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Randomized First Order Algorithms with Applications to ℓ_1-minimization

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Abstract In this paper we propose randomized first-order algorithms for solving bilinear saddle points problems. Our developments are motivated by the need for sublinear time algorithms to solve large-scale *parametric* bilinear saddle point problems where cheap online assessment of the solution quality is crucial. We present the theoretical efficiency estimates of our algorithms and discuss a number of applications, primarily to the problem of ℓ_1 minimization arising in sparsity-oriented Signal Processing. We demonstrate, both theoretically and by numerical examples, that when seeking for medium-accuracy solutions of large-scale ℓ_1 minimization problems, our randomized algorithms outperform significantly (and progressively as the sizes of the problem grow) the state-of-the art deterministic methods.

1 Introduction

This paper is motivated by the desire to develop efficient *randomized* first-order methods for solving well-structured large-scale convex optimization problems. Our approach is based on saddle point (s.p.) reformulation of well-structured convex minimization problems and is applicable when the resulting s.p. problems are bilinear; in this respect, it goes back to the breakthrough paper of Nesterov [15]. The deterministic s.p. prototypes of the randomized algorithms we develop here were proposed in [12, 13], and the prototypes of our randomization scheme were proposed in [14, Section 3.3] and

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[10]. In this paper, we demonstrate that in the case of a bilinear s.p. problem, a better randomization is possible[1)], specifically, one allowing to assess in a computationally cheap fashion the quality of the resulting approximate solutions. This assessment is instrumental when solving parametric bilinear s.p. problems covering numerous applications.

As an application area, our primary (but not the only) target is the ℓ_1-minimization problem

$$\mathrm{Opt}_p = \min_u \{\|u\|_1 : \|Au - b\|_p \leq \delta\} \quad [A = [A_1, ..., A_n] \in \mathbf{R}^{m\times n}, m, n > 2], \qquad (1)$$

where $p = \infty$ ("uniform fit") or $p = 2$ ("ℓ_2-fit"). We are interested in the large-scale case, where the sizes m, n of (possibly dense) matrix A are in the range of thousands/tens of thousands. Efficient solutions to the problems of this type are of paramount importance for sparsity-oriented Signal Processing, in particular, in Compressed Sensing (see [2,3,5] and references therein). To give a flavor of our results, here is what our approach yields for (1):

Proposition 1 *Assume that* (1) *is feasible,* δ *is small enough, namely,* $2m^{\frac{1}{p}}\delta \leq \|b\|_p$. *Given* $\epsilon \in (0, \frac{1}{2}\mathrm{Opt}_p\|A\|_{1,p}]$ [2)], *let our goal be to find an* ϵ*-solution to (1), that is, a point* x_ϵ *satisfying*

$$\|x_\epsilon\|_1 \leq \mathrm{Opt}_p \ \& \ \|Ax_\epsilon - b\|_p \leq \delta + \epsilon.$$

Then, for every tolerance $\chi \in (0, 1/2]$, *the outlined goal can be achieved with probability* $\geq 1 - \chi$

(i) *in the case of* $p = \infty$ *(uniform fit) – in at most*

$$O(1)\left[\frac{\sqrt{\ln(m)\ln(n)}\|A\|_{1,\infty}\mathrm{Opt}_\infty}{\epsilon}\ln\left(\frac{\sqrt{\ln(m)\ln(n)}\|A\|_{1,\infty}\mathrm{Opt}_\infty}{\chi\epsilon}\right)\right]^2$$

steps of a randomized algorithm, with computational effort per step reduced to extracting from A *two columns and two rows, given their indexes, plus "computational overhead" of* $O(1)(m + n)$ *operations.*

(ii) *in the case of* $p = 2$ *(*ℓ_2 *fit) – in at most*

$$O(1)\left[\frac{\ln(mn)\Gamma(A)\|A\|_{1,2}\mathrm{Opt}_2}{\epsilon}\ln\left(\frac{\ln(mn)\Gamma(A)\|A\|_{1,2}\mathrm{Opt}_2}{\chi\epsilon}\right)\right]^2, \ \Gamma(A) = \frac{\sqrt{m}\|A\|_{1,\infty}}{\|A\|_{1,2}},$$

steps of a randomized algorithm with the same computational effort per step as in (i).

Furthermore, there exists a randomized preprocessing of the data $[A, b]$ *of the problem (1) of computational cost not exceeding* $O(1)mn\ln(m)$, *which ensures with probability* $\geq 1 - \chi$ *that* $\Gamma(A) \leq O(1)\sqrt{\ln(mn/\chi)}$.

Note that the best known so far complexity of finding ϵ-solution to a large-scale problem (1) by a *deterministic* algorithm is *at least* $O(1)\frac{\sqrt{\ln(m)\ln(n)}\|A\|_{1,\infty}\mathrm{Opt}_\infty}{\epsilon}$ $(p = \infty)$ or $O(1)\frac{\sqrt{\ln(n)}\|A\|_{1,2}\mathrm{Opt}_2}{\epsilon}$ $(p = 2)$ steps[3)] with complexity of a step dominated by the

[1)] In the hindsight, a particular case of this new randomization can be recognized in the sublinear time randomized algorithm for matrix games due to Grigoriadis and Khachiyan [7].

[2)] Here and below $\|A\|_{1,p} = \max_j \|A_j\|_p$ is the norm of the mapping $x \mapsto Ax$ induced by the norms $\|\cdot\|_1$ and $\|\cdot\|_p$ in the argument and the image spaces, respectively.

[3)] The bounds are attainable, provided Opt_p is known in advance.

necessity to perform $O(1)$ multiplications $x \mapsto Ax$, $y \mapsto A^T y$. When A is dense, full matrix vector product requires $O(mn)$ operations, and hence the total operations count is, up to log-factors, of order of $\frac{mn}{\nu}$, where $\nu = \frac{\epsilon}{\|A\|_{1,p}\mathrm{Opt}_p}$ can be naturally interpreted as relative accuracy. For the randomized algorithms underlying Proposition 1, this count, again up to log-factors, is of order of $\frac{m+n}{\nu^2}$ (uniform fit) and $\frac{m+n}{\nu^2} + mn$ (ℓ_2 fit). We see that when the relative accuracy ν is such that $1 \gg \nu \gg m^{-1} + n^{-1}$, the randomized algorithms outperform the deterministic ones, and the positive effect of randomization becomes more significant as the problem size grows, i.e., "$\gg$" in the above becomes "sharper." Numerical results presented in Section 5 demonstrate that this acceleration can be of real practical interest.

The main body of this paper is organized as follows. In Section 2, we present a saddle-point-based framework for our developments together with a sample of interesting optimization problems fitting this framework. This sample includes, along with ℓ_1 minimization, the (semidefinite relaxation of the) problem of low-dimensional approximation of a collection of points in $\mathbf{R}^d$. Randomized algorithms for the problems fitting to our framework are developed and analyzed in Sections 3 and 4. Section 5 presents encouraging preliminary results on numerical comparison of our randomized algorithms and their state-of-the-art deterministic counterparts as applied to large-scale ℓ_1 minimization problems.

2 Problems and Goals

We start with specifying and motivating two problems to be discussed in the paper and our goals.

2.1 A Bilinear Saddle Point Problem

The first problem we are interested in is a Bilinear Saddle Point (BSP) problem

$$\begin{array}{c} \mathrm{SV} = \min_{z_1 \in Z_1} \max_{z_2 \in Z_2} \phi(z_1, z_2), \\ \phi(z_1, z_2) = \upsilon + \langle a_1, z_1 \rangle + \langle a_2, z_2 \rangle + \langle z_2, B z_1 \rangle : \quad Z := Z_1 \times Z_2 \to \mathbf{R}, \end{array} \qquad (\mathcal{S})$$

where Z_i are nonempty convex compact sets in Euclidean spaces E_i, $i = 1, 2$. Recall that $(\mathcal{S})$ gives rise to two convex optimization programs that are dual to each other:

$$\begin{array}{ll} \mathrm{Opt}(P) = \min_{z_1 \in Z_1} [\overline{\phi}(z_1) := \max_{z_2 \in Z_2} \phi(z_1, z_2)] & (P) \\ \mathrm{Opt}(D) = \max_{z_2 \in Z_2} [\underline{\phi}(z_2) := \min_{z_1 \in Z_1} \phi(z_1, z_2)] & (D) \end{array} \qquad (2)$$

with $\mathrm{Opt}(P) = \mathrm{Opt}(D) = \mathrm{SV}$, and to the variational inequality (v.i.):

$$\text{find } z_* \in Z := Z_1 \times Z_2 \text{ such that } \langle F(z), z - z_* \rangle \geq 0 \ \text{ for all } z \in Z, \qquad (3)$$

where $F : Z \mapsto E_1 \times E_2$ is the affine monotone operator given by

$$\begin{array}{c} F(z_1, z_2) = \left[F_1(z_2) = \dfrac{\partial \phi(z_1, z_2)}{\partial z_1}; F_2(z_1) = -\dfrac{\partial \phi(z_1, z_2)}{\partial z_2} \right] \quad = a + \mathcal{A}[z_1; z_2], \\ a = [a_1; -a_2], \ \ \mathcal{A} = \left[\begin{array}{c|c} & B^* \\ \hline -B & \end{array} \right] \end{array} \qquad (4)$$

(here B^* stands for the conjugate of B). Note that $\mathcal{A}$ is skew-symmetric:

$$\langle z, \mathcal{A}z\rangle = 0 \ \forall z \in E := E_1 \times E_2. \tag{5}$$

It is well known that the solutions to $(\mathcal{S})$ — the saddle points of ϕ on $Z_1 \times Z_2$ — are exactly the pairs $z = [z_1; z_2]$ comprised of optimal solutions to problems (P) and (D) in (2). They are also exactly the solutions to the v.i. (3). We quantify the accuracy of candidate solutions $z = [z_1; z_2] \in Z$ to $(\mathcal{S})$ by the *saddle point residual*

$$\epsilon_{\text{sad}}(z) = \overline{\phi}(z_1) - \underline{\phi}(z_2) = \underbrace{\left[\overline{\phi}(z_1) - \text{Opt}(P)\right]}_{\geq 0} + \underbrace{\left[\text{Opt}(D) - \underline{\phi}(z_2)\right]}_{\geq 0}. \tag{6}$$

2.1.1 Assumptions and goal

When speaking about a BSP problem $(\mathcal{S})$, our goal is to solve it within a given accuracy $\epsilon > 0$, i.e., to find $z^\epsilon \in Z$ such that $\epsilon_{\text{sad}}(z^\epsilon) \leq \epsilon$. Deterministic first order algorithms achieve this goal by working with the values of the associated operator F at the iterates z_t, $t = 1, 2, ...$, generated by the method. When Z is simple and the problem is large-scale, computing the values $F(z_t)$ dominates the computational effort. Our goal in this paper is to replace relatively expensive (in the large scale case) exact values $F(z_t)$ with their computationally cheap unbiased random estimates. To this end we assume that

[P] every point $z \in Z$ is associated with a probability distribution P_z such that
- P_z is supported on Z and $\mathbf{E}_{\zeta \sim P_z}\{\zeta\} = z$;
- Given z, we can sample from the distribution P_z.

Under these assumptions, and due to the affinity of F, in order to get an unbiased estimate of $F(z_t)$, it suffices to draw a $\zeta_t \sim P_{z_t}$ and to take $F(\zeta_t)$ as a desired estimate of $F(z_t)$. To make this approach meaningful, the cost of generating ζ_t and subsequent computation of $F(\zeta_t)$ should be significantly less than the cost of a straightforward computation of $F(z_t)$. This requirement guided us in the selection of problems to be considered below and in building the s.p. reformulations of these problems.

Note that the deterministic algorithms remain in our scope, since there always is the option to define P_z as δ_z (the unit mass sitting at z).

2.1.2 Application example: low dimensional approximation

Consider the following problem (related to dimensionality reduction problem in statistics, see, e.g., [4]): given a collection $V = \{v_1, ..., v_N\}$ of unit vectors in $\mathbf{R}^n$, we want to find a linear subspace $E \subset \mathbf{R}^n$ of a given dimension $d < n$ which minimizes the *deviation* $\delta(V, E)$ of V from E, defined as the worst-case, w.r.t. $v_i \in V$, Euclidean distance from v_i to E: $\delta(V, E) = \max_{1 \leq i \leq N} \min_{u \in E} \|v_i - u\|_2$.

Let Π^d be the family of all orthonormal projectors of $\mathbf{R}^n$ onto subspaces of dimension d. Taking into account that v_i are unit vectors, we have for every $P \in \Pi^d$: $1 - \delta^2(V, \text{Im}\, P) = \min_i v_i^T P v_i$, so that

$$\delta_*^2 := \min_E\{\delta^2(V, E) : \dim E = d\} = 1 - \text{Opt}_*, \ \text{Opt}_* = \max_{P \in \Pi^d}[\min_i v_i^T P v_i].$$

Now, the set Π^d is nonconvex, so that the problem $\mathrm{Opt}_* = \max_{P\in\Pi^d}[\min_i v_i^T P v_i]$ is seemingly difficult; it, however, admits the tractable relaxation:

$$\mathrm{Opt}_* \le \mathrm{Opt} := \max_{Q\in\mathcal{P}^d} \min_{1\le i\le N} v_i^T Q v_i,\ \mathcal{P}^d = \{Q\in\mathbf{S}^n : 0\preceq Q\preceq I, \mathrm{Tr}(Q)=d\}. \tag{7}$$

We refer to (7) as to the *problem of low dimensional approximation*. We clearly have $\mathrm{Opt}_* \le \mathrm{Opt} \le 1$, whence $\delta^2 := 1-\mathrm{Opt} \le \delta_*^2$. Our relaxation admits some quality guarantees. Specifically, let Q be an optimal solution to (7) and let E be spanned by the d leading eigenvectors of Q. Then

$$\delta(V,E) \le \delta\sqrt{d+1} \le \delta_*\sqrt{d+1}. \tag{8}$$

Indeed, let $e_1,...,e_n$ be orthonormal system of eigenvectors of Q, and $\lambda_1\ge\lambda_2\ge...,\ge\lambda_n$ be the corresponding eigenvalues. Note that $\lambda_k\in[0,1]$ and $\lambda_{d+1}\le \mathrm{Tr}(Q)/(d+1) = d/(d+1)$. For every i we have $\mathrm{Opt}\le\sum_{k=1}^n\lambda_k(v_i^Te_k)^2 \le \sum_{k=1}^d(v_i^Te_k)^2 + \lambda_{d+1}\sum_{k=d+1}^n(v_i^Te_k)^2$ and $\sum_k(v_i^Te_k)^2=1$ (v_i are unit vectors), whence

$$(1-\lambda_{d+1})\textstyle\sum_{k=d+1}^n(v_i^Te_k)^2 \le 1-\mathrm{Opt} = \delta^2,$$

that is, $\sum_{k=d+1}^n(v_i^Te_k)^2\le(d+1)\delta^2$. Note that the left hand side in this inequality is the squared distance from v_i to E, and (8) follows.

Observe that (7) is nothing but the BSP problem:

$$\mathrm{Opt} = \max_{Q\in\mathcal{P}^d}\min_{\lambda\in\Delta_N}\left[\mathrm{Tr}\left(Q\textstyle\sum_{i=1}^N\lambda_i v_iv_i^T\right)\right],\ \ \Delta_N = \left\{\lambda\in\mathbf{R}^N_+ :\ \textstyle\sum_{i=1}^n\lambda_i = 1\right\}. \tag{9}$$

In terms of $(\mathcal{S})$, $Z_1=\Delta_N\subset E_1=\mathbf{R}^N$, E_2 is the space $\mathbf{S}^n$ of symmetric $n\times n$ matrices with Frobenius inner product, $Z_2=\mathcal{P}^d\subset E_2$. The associated operator F is

$$F(z_1,z_2) = F(\lambda,Q) = \big[\underbrace{[v_1^TQv_1;\ ...;\ v_N^TQv_N]}_{F_1(z_2)};\underbrace{-\sum_{i=1}^N\lambda_iv_iv_i^T}_{F_2(z_1)};\ \big]. \tag{10}$$

Assuming that the vectors v_i are dense, the arithmetic cost of computing the value of F at a given point is $O(n^2N)$. To reduce this cost by randomization, let us specify the distributions P_z for a given point $z=(\lambda,Q)\in Z=Z_1\times Z_2$. In order to generate $\zeta\sim P_{(\lambda,Q)}$, we proceed as follows:

- Given $\lambda\in\Delta_N$, we pick $\imath\in\{1,...,N\}$ at random, with $\mathrm{Prob}\{\imath=i\}=\lambda_i$, $1\le i\le N$, and set $\zeta_1^\imath := e_\imath$, where e_i, $i=1,...,N$, are standard basic orths in $\mathbf{R}^N$.
- Given $Q\in\mathcal{P}^d$, we build the eigenvalue decomposition $Q=U\mathrm{Diag}\{q\}U^T$. Note that $q\in\Delta_{n,d} := \{q\in\mathbf{R}^n :\ 0\le q_i\le 1\ \forall i,\ \sum_{i=1}^n q_i = d\}$. The extreme points of $\Delta_{n,d}$ are Boolean vectors with exactly d nonzero entries. There exists a simple algorithm (see Section A.1) which, given as input a vector $q\in\Delta_{n,d}$, builds in $O(1)\min\{d,\ln(n)\}n^2$ a.o. n extreme points q^j, $1\le j\le n$, of $\Delta_{n,d}$ along with weights $\mu_j\ge0$, $\sum_j\mu_j=1$, such that $q=\sum_j\mu_jq^j$. We run this algorithm to build $\{q^j,\mu_j\}_{j=1}^n$, pick $\jmath\in\{1,...,n\}$ at random, with $\mathrm{Prob}\{\jmath=j\}=\mu_j$, $j=1,...,n$, and set $\zeta_2^\jmath = U\mathrm{Diag}\{q^\jmath\}U^T$, which is a projection matrix.
- Finally, we set $\zeta=[\zeta_1^\imath;\zeta_2^\jmath]\in\mathcal{P}^d\times\Delta_N$.

The family of distributions $P_{(\lambda,Q)}$ clearly satisfies [P]. The "setup costs" for sampling from $P_{(\lambda,Q)}$ reduce to those of 1) computing the eigenvalue decomposition of Q, 2)

building $q^1, ..., q^n$, $\mu_1, ..., \mu_n$ (this cost is $O(n^3 + \min\{d, \ln(n)\}n^2)$ a.o.) and 3) computing the "cumulative distributions" $\{\lambda^i = \sum_{s=1}^i \lambda_s\}_{i=1}^N$ and $\{\mu^j = \sum_{s=1}^j \mu_s\}_{j=1}^n$ (what amounts to $O(n+N)$ a.o.). After the setup cost is paid, a sample $(\imath, \jmath)$ can be generated at the cost of just $O(\ln(n+N))$ a.o. Now let us look at the cost of computing $F(\zeta^{\imath\jmath})$ given $\imath, \jmath$. We have

$$F(\zeta^{\imath\jmath}) = \left[\{v_i^T U \mathrm{Diag}\{q^\jmath\} U^T v_i\}_{i=1}^N; -v_\imath v_\imath^T\right].$$

Since $q^\jmath$ has just d nonzero entries, all equal to 1, let the indices of these entries be $j_1, ..., j_d$, we have $v_i^T U \mathrm{Diag}\{q^\jmath\} U^T v_i = \sum_{\ell=1}^d (U_{j\ell}^T v_i)^2$, where U_j is j^{th} column of U. We see that computing $F(\zeta^{\imath\jmath})$ costs $O(n^2 + dnN)$ a.o. Thus, the total cost (including that of the setup) of drawing a sample ζ from $P_{(\lambda,Q)}$ and computing $F(\zeta)$ is

$$O(n^3 + \min\{d, \ln(n)\}n^2 + n^2 + dnN) = O(n^3 + dnN) \text{ a.o.}$$

When $d \ll n \ll N$, this cost is much smaller than the cost $O(n^2 N)$ of computing $F(z)$ at a "general position" point $z = (\lambda, Q) \in Z$.

2.2 A Generalized Bilinear Saddle Point Problem

2.2.1 The problem

Assume that we are given a *single-parameter family* of bilinear s.p. problems

$$\mathrm{SV}(\rho) = \min_{z_1 \in Z_1} \max_{z_2 \in Z_2} [\phi^\rho(z_1, z_2) := \phi(z_1, z_2) + \rho\psi(z_1, z_2)], \tag{11}$$

where $\rho \geq 0$ is a parameter and $\phi(z_1, z_2)$, $\psi(z_1, z_2)$ are bi-affine in z_1 and z_2. The *Generalized Bilinear Saddle Point* (GBSP) problem associated with this family is, by definition, the optimization program

$$\rho_* = \max\{\rho \geq 0 : \mathrm{SV}(\rho) \leq 0\} \tag{12}$$

A highly desirable property of a GBSP problem, relative to our approach, is the convexity of $\mathrm{SV}(\rho)$ as a function of $\rho \geq 0$. To ensure this property, from now on we make the following assumption on the structure of (11):

[A.1] *$Z_1 = Z_{11} \times Z_{12}$ is the direct product of two convex compact sets, and the bilinear functions $\phi(z_1, z_2)$, $\psi(z_1, z_2)$ in (11) are of the form*

$$\begin{array}{l} \phi(z_1 = [z_{11}; z_{12}], z_2) = \upsilon + \langle a_{11}, z_{11}\rangle + \langle b, z_2\rangle + \langle z_2, Bz_{11}\rangle, \\ \psi(z_1 = [z_{11}; z_{12}], z_2) = \chi + \langle a_{12}, z_{12}\rangle + \langle c, z_2\rangle + \langle z_2, Cz_{12}\rangle, \end{array} \tag{13}$$

that is, $\phi(z_1, z_2)$ and $\psi(z_1, z_2)$ as functions of z_1 depend each on its own "block" of z_1, and these blocks z_{11} and z_{12}, independently of each other, run through the respective convex compact sets Z_{11} and Z_{12}.

From now on, we denote by $F^\rho(z) = \Phi(z) + \rho\Psi(z)$ the affine monotone operator associated with ϕ^ρ according to (4), where $\Phi(\cdot)$ and $\Psi(\cdot)$ are the affine monotone operators associated with functions $\phi(\cdot)$ and $\psi(\cdot)$ respectively.

Lemma 1 *In the case of* **A.1** *the function* $\mathrm{SV}(\rho)$ *given by* (11) *is convex in* $\rho \geq 0$.

Proof. We have

$$
\begin{aligned}
&\mathrm{SV}(\rho) = \max_{z_2\in Z_2} \min_{z_1\in Z_1} \phi^\rho(z_1,z_2)\\
&= \max_{z_2\in Z_2} \min_{z_{11}\in Z_{11}, z_{12}\in Z_{12}} \Big[\upsilon + \rho\chi + \langle a_{11}, z_{11}\rangle + \langle b, z_2\rangle + \langle z_2, Bz_{11}\rangle\\
&\qquad\qquad + \rho\left[\langle a_{12}, z_{12}\rangle + \langle c, z_2\rangle + \langle z_2, Cz_{12}\rangle\right]\Big]\\
&= \max_{z_2\in Z_2} \Big[\upsilon + \rho\chi + \langle b, z_2\rangle + \rho\langle c, z_2\rangle + \min_{z_{11}\in Z_{11}} \big[\langle a_{11}, z_{11}\rangle + \langle z_2, Bz_{11}\rangle\\
&\qquad\qquad + \rho \overbrace{\min_{z_{12}\in Z_{12}} \left[\langle a_{12} + C^* z_2, z_{12}\rangle\right]}^{g(z_2)}\big]\Big]\\
&= \max_{z_2\in Z_2} \Big[\upsilon + \rho\chi + \langle b, z_2\rangle + \rho\langle c, z_2\rangle + \rho g(z_2) + \overbrace{\min_{z_{11}\in Z_{11}} \left[\langle a_{11}, z_{11}\rangle + \langle z_2, Bz_{11}\rangle\right]}^{h(z_2)}\Big]\\
&= \max_{z_2\in Z_2} \Big[\upsilon + \langle b, z_2\rangle + h(z_2) + \rho\left[\chi + \langle c, z_2\rangle + g(z_2)\right]\Big]
\end{aligned}
$$

and thus $\mathrm{SV}(\rho)$ is the supremum of affine functions of ρ. □

From now on we assume, in addition to **A.1**, that

[A.2] *Function* $\mathrm{SV}(\rho)$ *given by* (11) *is nonpositive somewhere on* $\mathbf{R}_{++}$ *and tends to* $+\infty$ *as* $\rho \to +\infty$,

which implies solvability of (12) and positivity of ρ_*.

The goal. Given a GBSP problem (11) – (12) and a tolerance $\epsilon > 0$, our goal will be to find an ϵ-solution to the problem, that is, a pair ρ_ϵ, $z_1^\epsilon \in Z_1$ such that

$$\rho_\epsilon \geq \rho_* \text{ and } \max_{z_2\in Z_2} \phi^{\rho_\epsilon}(z_1^\epsilon, z_2) \leq \rho_\epsilon \epsilon \tag{14}$$

We are about to point out several important application examples for GBSP problem.

2.2.2 Application example: ℓ_1 minimization with ℓ_p fit

Given an ℓ_p norm with $p \in [1,\infty]$ and a matrix $A \in \mathbf{R}^{m\times n}$, the problem of interest is

$$\mathrm{Opt} = \min_x \left\{\|x\|_1 : \ \|Ax - b\|_p \leq \delta\right\}. \tag{15}$$

Different versions of this problem arise in sparsity-oriented Signal Processing and Compressed Sensing. Setting $x = \frac{u}{\rho}$, $\|u\|_1 \leq 1$, we can rewrite the problem in (15) equivalently as

$$1/\mathrm{Opt} = \rho_* = \max\left\{\rho : \ \min_{\|u\|_1\leq 1} \|Au - \rho b\|_p - \rho\delta \leq 0\right\}. \tag{16}$$

Let $\varphi(u,\rho) := \|Au - \rho b\|_p - \rho\delta$. For any given u, let v_u be such that $Au - \rho b = \rho\delta v_u$. Whenever $\|v_u\|_p \leq 1$, we have $\varphi(u,\rho) = \|Au - \rho b\|_p - \rho\delta = \rho\delta\|v_u\|_p - \rho\delta \leq 0$. Moreover whenever $\varphi(u,\rho) \leq 0$, we see that there exists v_u satisfying $\|v_u\|_p \leq 1$ and $Au - \rho b - \rho\delta v_u = 0$. Hence we can alternatively write (16) as

$$1/\mathrm{Opt} = \rho_* = \max\left\{\rho : \ \Phi(\rho) = \min_{\|u\|_1\leq 1,\, \|v\|_p\leq 1} \|Au - \rho b - \rho\delta v\|_\infty \leq 0\right\}. \tag{17}$$

The advantage of formulation (17) as opposed to (16) (as well as to the original problem given in (15)) lies in the computational complexity of the corresponding first-order oracles. In particular, when computing F for the BSP's in (17), vector variables

participating in nontrivial matrix-vector products vary in unit ℓ_1 balls, which, as we shall see, makes an efficient randomization possible. Unfortunately we do not know of extensions of such a randomization for the unit balls of general ℓ_p norms.

Problem given in (17) is nothing but the GBSP problem (11) with $SV(\rho) = \min_{z_1\in Z_1}\max_{z_2\in Z_2}\phi^\rho(z_1,z_2)$,

$$\begin{array}{c}\phi^\rho(z_1(=[z_{11};z_{12}]),z_2) = z_2^T J_m^T\left(AJ_n z_{11} - \rho[b+\delta z_{12}]\right),\\ Z_1 = \underbrace{\Delta_{2n}}_{Z_{11}} \times \underbrace{\{z_{12}\in\mathbf{R}^m : \|z_{12}\|_p \le 1\}}_{Z_{12}},\ Z_2 = \Delta_{2m},\end{array} \tag{18}$$

where we denote $J_k = [I_k, -I_k]$, I_k being $k\times k$ identity matrix. This problem satisfies [**A.1**]; when $\|b\|_p > \delta$ (otherwise the optimal solution to (15) is $x = 0$), the problem satisfies [**A.2**] as well. The associated saddle value function is

$$\begin{aligned}\mathrm{SV}(\rho) &= \max_{z_2\in\Delta_{2m}}\min_{z_{11}\in\Delta_{2n},\, z_{12}\in Z_{12}}\left[z_2^T J_m^T\left(AJ_n z_{11} - \rho[b-\delta z_{12}]\right)\right]\\ &= \max_{w=J_m z_2,\, z_2\in\Delta_{2m}}\min_{u=J_n z_1,\, z_1\in\Delta_{2n}}\min_{z_{12}\in Z_{12}}\left[w^T(Au-\rho[b+\delta z_{12}])\right]\\ &= \max_{\|w\|_1\le 1}\min_{\|u\|_1\le 1}\min_{\|v\|_p\le 1}\left[w^T(Au-\rho[b+\delta v])\right] = \Phi(\rho).\end{aligned}$$

Suppose that we are given an ε-solution ρ_ε, $z_1^\varepsilon = [z_{11}^\varepsilon; z_{12}^\varepsilon]$ to the problem (14), (18) with $\varepsilon = \epsilon m^{-\frac{1}{p}}$. When setting $x_\varepsilon = \rho_\varepsilon^{-1} J_n z_{11}^\varepsilon$ and $v_\varepsilon = z_{12}^\varepsilon$ we get an approximate solution to (15) such that

$$\|x_\varepsilon\|_1 \le \mathrm{Opt} \ \ \& \ \ \|Ax_\varepsilon - b\|_p \le \|\delta v_\varepsilon\|_p + \|Ax_\varepsilon - b - \delta v_\varepsilon\|_p \le \delta + \varepsilon m^{1/p} = \delta + \epsilon.$$

Finally, we associate with $z = [z_{11}; z_{12}; z_2] \in Z = Z_1\times Z_2$ a distribution P_z satisfying condition [P] from Section 2.1.1 as follows. Note that for $z\in Z$, z_{11} and z_2 are vectors from the standard simplices and thus can be considered as probability distributions on the corresponding index sets $\{1,...,2n\}$, $\{1,...,2m\}$. To generate $\zeta = [\zeta_{11};\zeta_{12};\zeta_2]\sim P_z$, we draw at random index $\imath$ from the distribution z_{11} and make $[\zeta_{11}]_\imath = 1$ the only nonzero entry in ζ_{11}. ζ_2 is built similarly, with z_2 in the role of z_{11}, and ζ_{12} is nothing but z_{12}. It is immediately seen that it takes just $O(m+n)$ a.o. to generate a sample $\zeta\sim P_z$ and to compute the vector $F^\rho(\zeta)$.

It is worth to mention that in the important case $p=\infty$ the construction of the GBSP which corresponds to (15) can be substantially simplified. Indeed, one can see immediately that for $p=\infty$ (16) is equivalent to the GBSP problem on the direct product of just two unit ℓ_1-balls (since $\|Az_1 - b\|_\infty = \max_{\|z_2\|_1\le 1} z_2^T(Az_1 - b)$). It is more convenient to pass from ℓ_1-balls to the standard simplexes, as it was done in the case of (18). The resulting GBSP problem is given by

$$\begin{array}{c}\phi^\rho(z_1,z_2) = z_2^T J_m^T A J_n z_1 - \rho z_2^T J_m^T b - \rho\delta,\\ Z_1 = Z_{11} = \Delta_{2n},\ \ Z_{12} = \{0\},\ \ Z_2 = \Delta_{2m},\end{array} \tag{19}$$

and satisfies [**A.1**] and [**A.2**] when $\delta < \|b\|_\infty$.

3 Solving Bilinear Saddle Point Problem

We are about to present two randomized first order methods for solving BSPs; they will also be instrumental in solving GBSPs — the *Stochastic Approximation* (SA) and the *Stochastic Mirror Prox* (SMP) algorithms, which are the randomized versions of the methods proposed in [12] and [13] respectively. Both SA and SMP are directly applicable to a BSP problem which we consider in this section; the GBSP case will be considered in Section 4.

3.1 The Setup

Both SA and SMP algorithms are aimed at solving a BSP problem $(\mathcal{S})$. The setup for these methods is given by

- a norm $\|\cdot\|$ on the Euclidean space E where the domain $Z = Z_1 \times Z_2$ of $(\mathcal{S})$ lives, along with the conjugate norm $\|\zeta\|_* = \max_{\|z\|\le 1}\langle \zeta, z\rangle$;
- a *distance-generating function* (d.g.f.) $\omega(z)$ which is convex and continuous on Z, admits continuous on the set $Z^o = \{z \in Z : \partial\omega(z) \neq \emptyset\}$ selection $\omega'(z)$ of subgradient (here $\partial\omega(x)$ is a subdifferential of $\omega\big|_Z$ taken at z), and is strictly convex with modulus 1 w.r.t. $\|\cdot\|$:

$$\forall z', z'' \in Z^o : \ \langle \omega'(z') - \omega'(z''), z' - z''\rangle \ge \|z' - z''\|^2.$$

  We shall refer to the latter property as to *compatibility* of $\omega(\cdot)$ and $\|\cdot\|$.

A d.g.f. ω gives rise to several important for us entities:

1. *Bregman distance* $V_z(u) = \omega(u) - \omega(z) - \langle \omega'(z), u - z\rangle$, where $z \in Z^o$ and $u \in Z$;
2. *Prox-mapping* $\mathrm{Prox}_z(\xi) = \mathrm{argmin}_{w\in Z}\{\langle \xi, w\rangle + V_z(w)\} : E \to Z^o$; here $z \in Z^o$ is a "prox center;"
3. "ω-center" $z_\omega = \mathrm{argmin}_{z\in Z}\,\omega(z) \in Z^o$ of Z and the quantities

$$\Omega = \max_{z\in Z} V_{z_\omega}(z) \le \max_{z\in Z}\omega(z) - \min_{z\in Z}\omega(z), \quad \Theta = \sqrt{2\Omega}. \tag{20}$$

In the sequel, we set

$$\mathcal{R} := \max_{z\in Z}\|z - z_\omega\| \le \Theta, \tag{21}$$

where the concluding inequality follows from the fact that for every $z \in Z$ one has $\frac{1}{2}\|z - z_\omega\|^2 \le V_{z_\omega}(z)$ by strong convexity of $\omega(\cdot)$.

We also denote by $\mathcal{L}$ the $(\|\cdot\|, \|\cdot\|_*)$-Lipschitz constant of F:

$$\|F(z) - F(z')\|_* = \|\mathcal{A}(z - z')\|_* \le \mathcal{L}\|z - z'\|, \quad \forall z, z'; \tag{22}$$

and set

$$M_* = \max_{z,z'\in Z}\|F(z) - F(z')\|_* \le 2\mathcal{R}\mathcal{L} \le 2\Theta\mathcal{L}, \tag{23}$$

$$F_* = \max_{z\in Z}\|F(z)\|_* \le \|F(z_\omega)\|_* + 2\Theta\mathcal{L}. \tag{24}$$

3.2 The SA and SMP Algorithms

We assume that we have access to an "oracle" $\mathcal{O}$ which, at i-th call ($i = 1, 2, ...$), given an input point z_i, returns a vector $\xi_i \in E$ such that $\mathbf{E}_{\xi_i}[\xi_i] = F(z_i)$. This vector, ξ_i, can be random with distribution depending on previous calls and, more generally, on the history of our computational process before the call. In fact, in the case when ξ_i is random, the oracle can be interpreted as providing stochastic subgradient information of the saddle point objective at point z_i. Whenever this oracle is deterministic, i.e., $\xi_i = F(z_i)$, it is the usual first-order oracle providing subgradient information.

This oracle gives rise to two conceptual algorithms:

$$\begin{array}{l} (a): z_1 = z_\omega; \{z_t, \xi_t\} \mapsto \{z_{t+1} = \mathrm{Prox}_{z_t}(\gamma_t \xi_t), \xi_{t+1}\},\ t = 1, 2, ... \\ (b): z_1 = z_\omega; \{z_t, \xi_{2t-1}\} \mapsto \{w_t = \mathrm{Prox}_{z_t}(\gamma_t \xi_{2t-1}), \xi_{2t}\} \\ \qquad\qquad \mapsto \{z_{t+1} = \mathrm{Prox}_{z_t}(\gamma_t \xi_{2t}), \xi_{2t+1}\},\ t = 1, 2, ... \end{array} \tag{25}$$

here, in the case of (a), z_t are the search points, and ξ_t are the estimates of $F(z_t)$ as reported by $\mathcal{O}$; in the case of (b), z_t, w_t are search points, and ξ_{2t-1}, ξ_{2t} are the estimates of $F(z_t)$ and $F(w_t)$, respectively, as reported by $\mathcal{O}$. In both cases, $\gamma_1, \gamma_2, ...$ are positive stepsizes defined in a non-anticipative fashion, that is, γ_t depends on oracle's answers obtained prior to step t (i.e., γ_t depends solely on $\xi_1, ..., \xi_{t-1}$ in the case of (a), and solely on $\xi_1, ..., \xi_{2t-2}$ in the case of (b)). Note that these algorithms (25.a,b) can be perceived as the conceptual versions (with the possibility of working with stochastic oracles) of the Mirror Descent algorithm of [12] and Mirror Prox algorithm of [13] respectively. The main difference of (25.b) from (25.a) is the use of the extra subgradient information. Note that deterministic versions of extra-gradient type algorithms such as Mirror Prox have been shown to be optimal first-order methods (in terms of the number of iterations required for a fixed given accuracy) for structured non-smooth optimization problems, including s.p. problems over simple domains. For further details on the deterministic versions of these methods, we refer the reader to [12, 13]. Here the main difference of these conceptual algorithms from their deterministic counterparts is as follows: At each iteration, instead of using the exact subgradient information in generation of the next search point, an unbiased random estimate of the current point is built, from which the exact first-order information is gathered and used for computing the next iterate. As opposed to the deterministic versions or the earlier stochastic prototypes of these algorithms, which work with the actual search points, here we average these random estimates to construct the solutions. We refer to (25.a,b) as the Stochastic Approximation (SA) and Stochastic Mirror Prox (SMP) schemes, respectively. We will consider two implementations of these schemes, the *basic* and the *advanced* ones.

3.2.1 Basic implementation

Recall that we have associated with $(\mathcal{S})$ the affine operator $F(z) : Z \to E$ given by (3), and with every point $z \in Z$ — a probability distribution P_z supported on Z satisfying $\mathbf{E}_{\zeta \sim P_z}\{\zeta\} = z$. Suppose that

- the stepsizes $\gamma_t > 0$ are chosen in a non-anticipating fashion such that $\gamma_1 \geq \gamma_2 \geq ...$;
- in SA: ζ_t is drawn at random from the distribution P_{z_t}, and $\xi_t = F(\zeta_t)$;
- in SMP: $\xi_{2t-1} = F(\eta_t)$ with η_t drawn at random from the distribution P_{z_t}, and $\xi_{2t} = F(\zeta_t)$ with ζ_t drawn at random from the distribution P_{w_t}.

The approximate solution generated by the short-step SA/SMP in course of $t = 1, 2, ...$ steps is

$$z^t = t^{-1}\sum_{\tau=1}^{t}\zeta_\tau. \tag{26}$$

3.2.2 Advanced implementation

In Advanced implementation of SA and SMP, same as in the Basic one, the stepsizes $\gamma_t > 0$ still are chosen in a non-anticipating fashion, but the restriction $\gamma_1 \geq \gamma_2 \geq ...$ is now lifted. To explain how the oracle is built, observe that if $u \in Z$, then

$$\mathbf{E}_{\zeta\sim P_u}\{\langle F(\zeta), \zeta - u\rangle\} = 0$$

(recall that $F(z) = a + \mathcal{A}z$ with skew symmetric $\mathcal{A}$ and that $\mathbf{E}_{\zeta\sim P_u}\{\zeta\} = u$). It follows that given u and generating one by one independent samples $\eta^s \sim P_u$, $s = 1, 2, ...$, we will generate with probability 1 a ζ such that

$$\langle F(\zeta), \zeta - u\rangle \leq 0. \tag{27}$$

At step t of SA, in order to define ξ_t, the oracle draws one by one samples $\eta^s \sim P_{z_t}$, $s = 1, 2, ...$, until a sample $\zeta_t := \eta^s$ satisfying (27) with $u = z_t$ is generated; when it happens, the oracle returns $\xi_t = F(\zeta_t)$. At a step t of SMP, the oracle is invoked twice, first to generate $\xi_{2t-1} = F(\eta_t)$, and then to generate $\xi_{2t} = F(\zeta_t)$. ξ_{2t-1} is generated exactly as in the basic implementation — by drawing a sample $\eta_t \sim P_{z_t}$ and returning $\xi_{2t-1} = F(\eta_t)$. To generate ξ_{2t}, the oracle draws one by one samples $\eta^s \sim P_{w_t}$, $s = 1, 2, ...$, until a sample $\zeta_t = \eta^s$ satisfying (27) with $u = w_t$ is generated; when it happens, the oracle returns $\xi_{2t} = F(\zeta_t)$.

Finally, in the advanced implementation we replace the rule (26) for generating approximate solutions with the rule

$$z^t = \frac{1}{\sum_{\tau=1}^{t}\gamma_\tau}\sum_{\tau=1}^{t}\gamma_\tau\zeta_\tau. \tag{28}$$

3.2.3 Quantifying quality of approximate solutions

Observe that by construction at a step τ both ζ_τ and $F(\zeta_\tau)$ become known. Recalling that F is affine, it follows that after t steps we have at our disposal both the approximate solution $z^t = [z_1^t; z_2^t]$ and the vector $F(z^t)$. As a result, with both Basic and Advanced implementations of both SA and SMP, after $t = 1, 2, ...$ steps we have at our disposal the quantities

$$\begin{aligned}\overline{\phi}(z_1^t) &= \upsilon + \langle a_1, z_1^t\rangle + \max_{z_2\in Z_2}\langle z_2, -F_2(z_1^t)\rangle,\\ \underline{\phi}(z_2^t) &= \upsilon + \langle a_2, z_2^t\rangle + \min_{z_1\in Z_1}\langle z_1, F_1(z_2^t)\rangle\end{aligned} \tag{29}$$

(see (3)) and consequently we know the residual $\epsilon_{\text{sad}}(z^t) = \overline{\phi}(z^t) - \underline{\phi}(z^t)$ of the current approximate solution z^t. As we shall see in Section 4, this feature of our algorithms becomes instrumental when solving GBSP problems.[4)] This is in sharp contrast with

[4)] Of course, computing the quantities in (29) is not completely costless; note, however, that the cost of one step of the algorithm is dominated by the cost of computing the prox-mapping(s). Thus computing $\overline{\phi}(\cdot)$ and $\underline{\phi}(\cdot)$ represents a small fraction of the overall computational effort.

the prototypes of the SA and the SMP proposed, respectively, in [14, Section 3.3] and [10]. The approximate solutions z^t of those algorithms were computed according to the formula (28), but with z_τ [14] or w_τ [10] in the role of ζ_τ. As a result, in the prototype algorithms there is no universal and computationally cheap way to quantify the quality of approximate solutions.

3.3 Efficiency estimates for Basic implementation

The accuracy bounds for Basic SA and SMP algorithms are given by the following

Proposition 2 *Let the BSP problem $(\mathcal{S})$ be solved by the short-step SA or SMP algorithm with positive stepsizes $\gamma_1 \geq \gamma_2 \geq ...$ chosen in a non-anticipative fashion. Then*
(i) *For every $t \geq 1$, for both SA and SMP one has*

$$\epsilon_{\text{sad}}(z^t) \leq t^{-1}\left[\gamma_t^{-1}\Omega + R_t + S_t\right], \quad R_t := \sum\nolimits_{\tau=1}^{t} r_\tau, \quad S_t := \sum\nolimits_{\tau=1}^{t} s_\tau, \tag{30}$$

where

$$r_t = \begin{cases} \langle F(\zeta_t), \zeta_t - z_t\rangle & \text{in the case of SA,} \\ \langle F(\zeta_t), \zeta_t - w_t\rangle & \text{in the case of SMP,} \end{cases}$$

$$s_t = \begin{cases} \langle F(\zeta_t), z_t - z_{t+1}\rangle - \gamma_t^{-1} V_{z_t}(z_{t+1}), & \text{in the case of SA,} \\ \langle F(\zeta_t), w_t - z_{t+1}\rangle - \gamma_t^{-1} V_{z_t}(z_{t+1}), & \text{in the case of SMP.} \end{cases}$$

We have

$$s_t \leq \begin{cases} \frac{\gamma_t}{2}\|F(\zeta_t)\|_*^2, & \text{in the case of SA,} \\ \frac{\gamma_t}{2}\|F(\zeta_t) - F(\eta_t)\|_*^2 - \frac{1}{2\gamma_t}\|w_t - z_t\|^2, & \text{in the case of SMP,} \end{cases} \tag{31}$$

implying

$$s_t \leq \begin{cases} \frac{\gamma_t}{2} F_*^2, & \text{in the case of SA,} \\ \frac{\gamma_t}{2} M_*^2, & \text{in the case of SMP.} \end{cases} \tag{32}$$

In particular, if the stepsizes $\gamma_t > 0$ satisfy $S_t \leq \Omega/\gamma_t$, $t = 1, 2, ...$, then

$$\epsilon_{\text{sad}}(z^t) \leq \frac{2\Omega}{t\gamma_t} + \frac{R_t}{t}. \tag{33}$$

(ii) *Further, $\mathbf{E}\{R_t\} = 0$, and in the case of SMP, under additional assumption that*

$$\gamma_t \leq (\sqrt{3}\mathcal{L})^{-1}, \tag{34}$$

we have

$$s_t \leq \frac{3\gamma_t}{2}\left[\|\mathcal{A}(\zeta_t - w_t)\|_*^2 + \|\mathcal{A}(\eta_t - z_t)\|_*^2\right], \tag{35}$$

so that $\mathbf{E}\{s_t\} \leq 3\gamma_t\sigma^2$, where

$$\sigma^2 = \sup_{z\in Z} \mathbf{E}_{\zeta\sim P_z}\left\{\|\mathcal{A}(\zeta - z)\|_*^2\right\} \leq M_*^2. \tag{36}$$

In particular, if the stepsizes $\gamma_t > 0$ satisfy $\mathbf{E}\{S_t\} \leq \Omega/\gamma_t$ for $t = 1, 2, ...$, then

$$\mathbf{E}\{\epsilon_{\text{sad}}(z^t)\} \leq \frac{2\Omega}{t\gamma_t}.$$

Proof. $\mathbf{1}^0$. We need the following

Lemma 2 [cf. [13], Lemma 3.1.(b)] *Given $z \in Z^o$, $\gamma > 0$ and $\xi, \eta \in E$, let us set*

$$\begin{aligned} w &= \mathrm{Prox}_z(\gamma\xi) = \mathrm{argmin}_{v\in Z}\left\{\langle \gamma\xi - \omega'(z), v\rangle + \omega(v)\right\}, \\ z_+ &= \mathrm{Prox}_z(\gamma\eta) = \mathrm{argmin}_{v\in Z}\left\{\langle \gamma\eta - \omega'(z), v\rangle + \omega(v)\right\}. \end{aligned}$$

Then $w, z_+ \in Z^o$, and for every $u \in Z$ one has

$$\begin{array}{l} (a)\ \gamma\langle \eta, w-u\rangle \le V_z(u) - V_{z_+}(u) + \gamma\langle \eta, w - z_+\rangle - V_z(z^+) \\ (b)\ \le V_z(u) - V_{z_+}(u) + \gamma\langle \eta - \xi, w - z_+\rangle - V_z(w) - V_w(z_+) \\ (c)\ \le V_z(u) - V_{z_+}(u) + \gamma\|\eta - \xi\|_*\|w - z_+\| - \frac{1}{2}\left[\|w-z\|^2 + \|w - z_+\|^2\right] \\ (d)\ \le V_z(u) - V_{z_+}(u) + \frac{1}{2}\left[\gamma^2\|\eta - \xi\|_*^2 - \|w - z\|^2\right]. \end{array} \tag{37}$$

Proof of Lemma 2. The inclusions $w, z_+ \in Z^o$ are evident (a subgradient of $\omega(\cdot)$ at w, taken w.r.t. Z, is, e.g., $\omega'(z) - \gamma\xi$, and similarly for z_+). Now let $u \in Z$. z_+ is an optimal solution of certain explicit convex optimization problem; taking into account that $\omega'(\cdot)$ is continuous on Z^o, it is easily seen that the necessary optimality condition in this problem reads $\langle \gamma\eta + \omega'(z_+) - \omega'(z), u - z_+\rangle \ge 0$, whence $\gamma\langle \eta, w-u\rangle \le \gamma\langle \eta, w - z_+\rangle + \langle \omega'(z_+) - \omega'(z), u - z_+\rangle$, and the latter inequality, after rearranging terms in the right hand side, becomes (a). By similar reasons, $0 \le \langle \gamma\xi + \omega'(w) - \omega'(z), v - w\rangle$ for all $v \in Z$; setting $v = z_+$, summing up the resulting inequality with (a) and rearranging terms in the right hand side of what we get, we arrive at (b). (c) follows from (b) due to $V_a(b) \ge \frac{1}{2}\|a-b\|^2$ (recall that ω is strongly convex, modulus 1 w.r.t. $\|\cdot\|$, on Z). Finally, (d) follows from (c) due to $\mu\nu - \frac{1}{2}\mu^2 \le \frac{1}{2}\nu^2$. $\square$

$\mathbf{2}^0$**.** Let us prove the bound (30). Consider first the case of SMP. Applying Lemma 2 to $z = z_\tau$, $\gamma = \gamma_\tau$, $\xi = F(\eta_\tau)$, $\eta = F(\zeta_\tau)$, which results in $w = w_\tau$ and $z_+ = z_{\tau+1}$, we get for all $u \in Z$:

$$\gamma_\tau\langle F(\zeta_\tau), w_\tau - u\rangle \le V_{z_\tau}(u) - V_{z_{\tau+1}}(u) + [\gamma_\tau\langle F(\zeta_\tau), w_\tau - z_{\tau+1}\rangle - V_{z_\tau}(z_{\tau+1})]$$

whence for all $u \in Z$

$$\begin{array}{rl} \langle F(\zeta_\tau), \zeta_\tau - u\rangle \le \gamma_\tau^{-1}(V_{z_\tau}(u) - V_{z_{\tau+1}}(u)) + \overbrace{\langle F(\zeta_\tau), \zeta_\tau - w_\tau\rangle}^{r_\tau} + s_\tau, & \\ s_\tau = \langle F(\zeta_\tau), w_\tau - z_{\tau+1}\rangle - \gamma_\tau^{-1}V_{z_\tau}(z_{\tau+1}) & \\ \quad \le \frac{1}{2}\left[\gamma_\tau\|F(\zeta_\tau) - F(\eta_\tau)\|_*^2 - \gamma_\tau^{-1}\|w_\tau - z_\tau\|^2\right] & (*) \end{array} \tag{38}$$

with $(*)$ given by (37). When summing up inequalities (38) over τ and taking into account that $\gamma_1 \ge \gamma_2 \ge ..., V_z(u) \ge 0$ and $V_{z_1}(u) = V_{z_\omega}(u) \le \Omega$ by definition of Ω, we get

$$\textstyle\sum_{\tau=1}^t \langle F(\zeta_\tau), \zeta_\tau - u\rangle \le \gamma_t^{-1}\Omega + \sum_{\tau=1}^t [s_\tau + r_\tau]. \tag{39}$$

On the other hand, taking into account that $\mathcal{A}$ is skew symmetric,

$$\begin{array}{l} \sum_{\tau=1}^t \langle F(\zeta_\tau), \zeta_\tau - u\rangle = \sum_{\tau=1}^t \langle a + \mathcal{A}\zeta_\tau, \zeta_\tau - u\rangle = t\langle a, z^t - u\rangle - \sum_{\tau=1}^t \langle \mathcal{A}\zeta_\tau, u\rangle \\ = t\left[\langle a, z^t - u\rangle - \langle \mathcal{A}z^t, u\rangle\right] = t\left[\langle a, z^t - u\rangle + \langle \mathcal{A}z^t, z^t - u\rangle\right] = t\langle F(z^t), z^t - u\rangle. \end{array}$$

Thus, for all $u \in Z$ it holds

$$t\langle F(z^t), z^t - u\rangle \le \Omega\gamma_t^{-1} + \textstyle\sum_{\tau=1}^t [s_\tau + r_\tau] = \gamma_t^{-1}\Omega + S_t + R_t. \tag{40}$$

Setting $z^t = [z_1^t; z_2^t]$ and $u = [u_1; u_2]$, we get from the definition of $F(\cdot)$ and the bilinearity of the inner product $\langle F(z^t), z^t - u\rangle = \phi(z_1^t, u_2) - \phi(u_1, z_2^t)$; the supremum

of the latter quantity over $u \in Z$ is the s.p. residual $\epsilon_{\rm sad}(z^t)$. Since the right hand side in (40) is independent of u, we arrive at the SMP-version of (30).

3^0. Now consider the case of SA. Applying Lemma 2 to $\gamma = \gamma_\tau$, $z = z_\tau$, $\xi = 0$, $\eta = F(\zeta_\tau)$, which results in $w = z_\tau$ and $z_+ = z_{\tau+1}$, and acting exactly as in the case of SMP, we arrive at the SA-version of (30).

4^0. Let us prove (ii). The conditional to the "past" (the answers of the oracle prior to the call for $\xi_{2\tau}$) distribution of ζ_τ is P_{w_τ}, which combines with the affinity of F and the facts that the linear part of F is skew symmetric and the expectation of P_z is z, to imply that

$$\begin{aligned}\mathbf{E}\{\langle F(\zeta_\tau), \zeta_\tau - w_\tau\rangle\} &= \langle a, \mathbf{E}\{\zeta_\tau\} - w_\tau\rangle + \mathbf{E}\{\langle \mathcal{A}\zeta_\tau, \zeta_\tau - w_\tau\rangle\} = -\mathbf{E}\{\langle \mathcal{A}\zeta_\tau, w_\tau\rangle\} \\ &= \mathbf{E}\{\langle \mathcal{A}(w_\tau - \zeta_\tau), w_\tau\rangle\} = 0,\end{aligned}$$

whence $\mathbf{E}\{R_t\} = 0$ for all t. By completely similar reasoning, $\mathbf{E}\{R_t\} = 0$ in the case of SA. To complete the proof (ii), we need to prove (35). We have

$$\begin{aligned}s_t &\le \frac{\gamma_t}{2}\|F(\zeta_t) - F(\eta_t)\|_*^2 - \frac{1}{2\gamma_t}\|w_t - z_t\|^2 \qquad [\text{see } (31)] \\ &\le \frac{\gamma_t}{2}\left[\|F(w_t) - F(z_t)\|_* + \|F(\zeta_t) - F(w_t)\|_* + \|F(\eta_t) - F(z_t)\|_*\right]^2 - \frac{1}{2\gamma_t}\|w_t - z_t\|^2 \\ &\le \underbrace{\left[\frac{3\gamma_t}{2}\mathcal{L}^2 - \frac{1}{2\gamma_t}\right]}_{\le 0 \text{ by } (34)}\|w_t - z_t\|^2 + \frac{3\gamma_t}{2}\left[\|F(\zeta_t) - F(w_t)\|_*^2 + \|F(\eta_t) - F(z_t)\|_*^2\right].\end{aligned}$$

It remains to note that $\|F(\zeta_t) - F(w_t)\|_*^2 + \|F(\eta_t) - F(z_t)\|_*^2 \le 2M_*^2$ since $\zeta_t, w_t, \eta_t, z_t \in Z$ and that the expectations of $\|F(\zeta_t) - F(w_t)\|_*^2$ and $\|F(\eta_t) - F(z_t)\|_*^2$, conditional over the respective pasts, do not exceed σ^2. □

The bound of Proposition 2 allows to easily conceive stepsize policies. Let us start with *offline* policies, where γ_t are chosen in advance deterministic reals. If the number of steps N is fixed in advance, one can use constant stepsizes $\gamma_1 = ... = \gamma_N = \gamma$. In particular, when choosing

$$\gamma = \begin{cases} \frac{1}{F_*}\sqrt{\frac{2\Omega}{N}}, & \text{in the case of SA} \quad (a) \\ \min\left\{\frac{1}{\sigma}\sqrt{\frac{\Omega}{3N}}, \frac{1}{\sqrt{3}\mathcal{L}}\right\}, & \text{in the case of SMP} \quad (b)\end{cases} \tag{41}$$

(by (32), (24) this choice implies that $\mathbf{E}\{S_t\} \le \Omega/\gamma_t$, $1 \le t \le N$), Proposition 2 implies the efficiency bound

$$\mathbf{E}\{\epsilon_{\rm sad}(z^N)\} \le \begin{cases} F_*\sqrt{\frac{2\Omega}{N}}, & \text{in the case of SA} \quad (a) \\ \max\left\{2\sigma\sqrt{\frac{3\Omega}{N}}, \frac{2\sqrt{3}\Omega\mathcal{L}}{N}\right\}, & \text{in the case of SMP} \quad (b)\end{cases} \tag{42}$$

When the number of steps is not fixed in advance, one can use the decreasing stepsizes

$$\forall t \ge 1, \quad \gamma_t = \begin{cases} \frac{1}{F_*}\sqrt{\frac{\Omega}{t}}, & \text{in the case of SA,} \\ \min\left\{\frac{1}{\sigma}\sqrt{\frac{\Omega}{6t}}, \frac{1}{\sqrt{3}\mathcal{L}}\right\}, & \text{in the case of SMP,}\end{cases} \tag{43}$$

which result in the accuracy bound

$$\forall t \geq 1, \ \ \mathbf{E}\{\epsilon_{\rm sad}(z^t)\} \leq \left\{ \begin{array}{ll} 2F_* \sqrt{\frac{\Omega}{t}}\,, & \text{in the case of SA} \quad (a) \\ \max\left\{ 2\sigma\sqrt{\frac{6\Omega}{t}}, \ \frac{2\sqrt{3}\Omega\mathcal{L}}{t} \right\}, & \text{in the case of SMP} \ (b) \end{array} \right. \tag{44}$$

completely similar to (42).

3.3.1 Online stepsize policies

From theoretical viewpoint, the main advantage of the offline stepsize policies (41) and (43) is that in the framework of our approach they result in the best possible (and in fact – the best known under circumstances) efficiency estimates (42), (44). While they may appear attractive also from the practical viewpoint because of their apparent simplicity, their use may present several disadvantages: the quantity σ involved in the stepsize computation may not be available at hand and should be evaluated. Besides this, these policies are offline and worst-case oriented; we would prefer more flexible online adjustable stepsizes.

A natural way to adjust the stepsizes online would be to choose at each step $t \geq 1$ the largest $\gamma_t \leq \gamma_{t-1}$ ensuring the balance $\Omega/\gamma_t \geq S_t$, and thus the bound (33). This idea cannot be implemented "as is," since the stepsize policy should be non-anticipative, while s_t is not yet available when γ_t is computed. This difficulty can be easily circumvented by using instead of s_t its a priori upper bound, which is either $\frac{\gamma_t}{2}F_*$ for the SA algorithm or $\frac{\gamma_t}{2}M_*^2$ for the SMP, see (31). Specifically, consider the online policy of choosing $\gamma_t, \ t \geq 1$ as follows:

$$\Omega\gamma_t^{-2} = \left\{ \begin{array}{ll} 2\sum_{\tau=1}^{t-1}\gamma_\tau^{-1}[s_\tau]_+ + F_*^2 & \text{in the case of SA,} \\ 2\sum_{\tau=1}^{t-1}\gamma_\tau^{-1}[s_\tau]_+ + 8\Omega\mathcal{L}^2 & \text{in the case of SMP,} \end{array} \right. \tag{45}$$

where we set $\sum_{\tau=1}^{0}\gamma_\tau^{-1}[s_\tau]_+ = 0$. With this policy, one clearly has $\gamma_1 \geq \gamma_2 \geq ....$

Proposition 3 *Let positive stepsizes $\gamma_t, \ t = 1, 2, ...$ of the Basic SA/SMP implementation be chosen according to (45). Then the approximate solution z^t satisfies*

$$\epsilon_{\rm sad}(z^t) \leq \frac{(1+\sqrt{2})\Omega}{t\gamma_t} + \frac{R_t}{t}. \tag{46}$$

As a consequence, we have

$$\epsilon_{\rm sad}(z^t) \leq \left\{ \begin{array}{l} \frac{(1+\sqrt{2})\sqrt{\Omega}}{t}\left(F_*^2 + \sum_{\tau=1}^{t-1}\|F(\zeta_\tau)\|_*^2\right)^{1/2} + \frac{R_t}{t}, \text{ in the case of SA} \quad (a) \\ \frac{(1+\sqrt{2})\sqrt{\Omega}}{t}\left(8\Omega\mathcal{L}^2 + \sum_{\tau=1}^{t-1}\varsigma_\tau\right)^{1/2} + \frac{R_t}{t} \\ \qquad \leq \frac{7\Omega\mathcal{L}}{t} + \frac{R_t}{t} + \frac{(1+\sqrt{2})\sqrt{\Omega}}{t}\sqrt{\sum_{\tau=1}^{t-1}\varsigma_\tau}, \text{ in the case of SMP} \ (b) \end{array} \right. \tag{47}$$

where

$$\varsigma_t = 3\left[\|F(\zeta_t) - F(w_t)\|_*^2 + \|F(\eta_t) - F(z_t)\|_*^2\right]. \tag{48}$$

Recalling that $\mathbf{E}\{R_t\} = 0$ and $\mathbf{E}\{\varsigma_t\} \leq 6\sigma^2$ (see (36)), we arrive at

Corollary 1 *Under the premise of Proposition 3, for the SMP algorithm one has*

$$\mathbf{E}\{\epsilon_{\rm sad}(z^t)\} \leq \tfrac{7\Omega\mathcal{L}}{t} + \tfrac{6\sqrt{\Omega}\sigma}{\sqrt{t}}. \tag{49}$$

Proof of Proposition 3. Observe that (45) implies that $\gamma_1 \geq \gamma_2 \geq ....$
1^0. Let us verify first that with the choice (45) of $\gamma_\tau,\ \tau = 1,2,...$ we have for all $t = 1,2,...,$

$$\sqrt{2}\Omega\gamma_t^{-1} \geq S_t. \tag{50}$$

Indeed, for $t = 2,3,...$ we have (with $2S_0 = F_*^2$ in the case of SA and $2S_0 = 8\Omega\mathcal{L}^2$, $\geq M_*^2$ by (23), in the case of SMP)

$$\frac{\gamma_{t-1}^2}{\gamma_t^2} = \frac{\sum_{\tau=1}^{t-1} 2[s_\tau]_+/\gamma_\tau + 2S_0}{\sum_{\tau=1}^{t-2} 2[s_\tau]_+/\gamma_\tau + 2S_0} \leq 1 + \frac{2[s_{t-1}]_+/\gamma_{t-1}}{2S_0} \leq 2 \tag{51}$$

(recall that $2s_t/\gamma_\tau \leq 2S_0$ by (32)). On the other hand

$$\gamma_t^{-2} - \gamma_{t-1}^{-2} = \tfrac{2[s_{t-1}]_+}{\Omega\gamma_{t-1}}, \tag{52}$$

and

$$\gamma_t^{-1} - \gamma_{t-1}^{-1} \geq \tfrac{\gamma_t}{2}(\gamma_t^{-2} - \gamma_{t-1}^{-2}) = \tfrac{\gamma_t[s_{t-1}]_+}{\gamma_{t-1}\Omega} \geq \tfrac{[s_{t-1}]_+}{\sqrt{2}\Omega} \Rightarrow \sqrt{2}\Omega[\gamma_t^{-1} - \gamma_{t-1}^{-1}] \geq [s_{t-1}]_+ \tag{53}$$

where the second inequality follows from $\gamma_{t-1} \leq \sqrt{2}\gamma_t$ as implied by (51). By summing up the resulting inequalities in (53), we get

$$\sqrt{2}\Omega\gamma_t^{-1} \geq \textstyle\sum_{\tau=1}^{t-1} s_\tau + \sqrt{2}\Omega\gamma_1^{-1}. \tag{54}$$

In the case of SMP, we have $\gamma_1 = (2\sqrt{2}\mathcal{L})^{-1}$, whence $\sqrt{2}\Omega\gamma_1^{-1} = 4\Omega\mathcal{L} \geq \gamma_1 M_*^2 \geq \gamma_t M_*^2$ (see (23)), whence $\sqrt{2}\Omega\gamma_1^{-1} \geq s_t$ in view of (31), and (54) implies (50). In the case of SA, we have $\gamma_1 = \sqrt{\Omega}/F_*$, whence $\sqrt{2}\Omega\gamma_1^{-1} = \sqrt{2}\sqrt{\Omega}F_* \geq \gamma_1 F_*^2 \geq \gamma_t F_*^2$, whence $\sqrt{2}\Omega\gamma_1^{-1} \geq s_t$ by (31), and (50) again is given by (54).
2^0. Invoking (30), (50) implies (46). Now, by (31) in the case of SA we have $2[s_\tau]_+/\gamma_\tau \leq \|F(\zeta_\tau)\|_*^2$. In the case of SMP we have

$$\begin{aligned}
&\tfrac{2[s_\tau]_+}{\gamma_\tau} \leq \|F(\zeta_\tau) - F(\eta_\tau)\|_*^2 - \gamma_\tau^{-2}\|w_\tau - z_\tau\|^2 \quad \text{[see (31)]}\\
&\leq [\|F(\zeta_\tau) - F(w_\tau)\|_* + \|F(w_\tau) - F(z_\tau)\|_* + \|F(z_\tau) - F(\eta_\tau)\|_*]^2 - \gamma_1^{-2}\|w_\tau - z_\tau\|^2\\
&\leq 3\left[\|F(\zeta_\tau) - F(w_\tau)\|_*^2 + \|F(z_\tau) - F(\eta_\tau)\|_*^2\right] + \left[3\|F(w_\tau) - F(z_\tau)\|_*^2 - \gamma_1^{-2}\|w_\tau - z_\tau\|^2\right]\\
&\leq \underbrace{3\left[\|F(\zeta_\tau) - F(w_\tau)\|_*^2 + \|F(z_\tau) - F(\eta_\tau)\|_*^2\right]}_{:=\varsigma_\tau} \quad \text{[by (22) due to } \gamma_1^{-1} = 2\sqrt{2}\mathcal{L}]
\end{aligned}$$

Invoking (45), we get

$$\gamma_t^{-1} \leq \Omega^{-1/2} \cdot \begin{cases} \left(F_*^2 + \sum_{\tau=1}^{t-1}\|F(\zeta_\tau)\|_*^2\right)^{1/2}, & \text{in the case of SA}\\ \left(8\Omega\mathcal{L}^2 + \sum_{\tau=1}^{t-1}\varsigma_\tau\right)^{1/2}, & \text{in the case of SMP}\end{cases} \tag{55}$$

which combines with (46) to imply (47). □

Note that the bounds (47.a) and (49) within an absolute constant factor coincide with the respective bounds in (44), that is, our online stepsizes policy (which, in contrast to (43), does not require knowledge of σ) is not worse that the "theoretically optimal" stepsize policies underlying (44).

3.3.2 Discussion

By definitions of F_* and σ we have $\sigma \leq 2F_*$ (see (24), (36)). As a result, the SA efficiency estimate (44.a) for large t (and even for all t, provided that F_* is of order of $\sqrt{\Theta}\mathcal{L}$) can be better than the SMP efficiency estimate (44.b) by *at most* an absolute constant factor, and becomes much worse than the SMP estimate when t is large and $\sigma \ll \sqrt{\Omega}\mathcal{L}$. Besides this, when the noise level σ of the oracle is small enough (specifically, $\sigma^2 = O\left(\frac{\Omega\mathcal{L}^2}{N}\right)$), the efficiency estimate of SMP satisfies $\mathbf{E}\{\epsilon_{\rm sad}(z^t)\} \leq O(1)\frac{\Omega\mathcal{L}}{N}$, which, modulo expectation of the residual instead of the residual itself, coincides with the best known so far efficiency estimate of the deterministic first order algorithms for solving BSP problems. In addition to this, we do have a possibility to make σ small. The trivial way to do so is to use $P_z = \delta_z$, which results in $\sigma = 0$ and makes SMP a version of the Deterministic Mirror Prox algorithm (DMP) proposed in [13]. Another, more attractive, option to control σ is as follows. Given the family of distributions P_z supported on Z and such that $\mathbf{E}_{\zeta\sim P_z}\{\zeta\} = z$, and a positive integer k, we can convert P_z into the family of distributions $P_z^{(k)}$, also supported on Z and satisfying $\mathbf{E}_{\zeta\sim P_z}\{\zeta\} = z$, as follows. In order to generate a random vector $\zeta \sim P_z^{(k)}$ and to compute $F(\zeta)$, we draw a k-element sample $\zeta^1, ..., \zeta^k$ from the distribution P_z, compute $F(\zeta^1), ..., F(\zeta^k)$ and then set $\zeta = \frac{1}{k}\sum_{i=1}^k \zeta^i$, so that $F(\zeta) = \frac{1}{k}\sum_{i=1}^k F(\zeta^i)$. If, as in the examples of Section 2, drawing $\zeta^i \sim P_z$ and computing $F(\zeta^i)$ is much cheaper than computing $F(z)$, the outlined procedure with a "reasonably large" value of k is still significantly cheaper than the direct computation of $F(z)$. At the same time, for "good enough" norms $\|\cdot\|_*$, passing from P_z to $P_z^{(k)}$ can significantly reduce the noise level σ. Specifically, given a norm $\|\cdot\|_*$ on a finite-dimensional Euclidean space E, one can associate with it its *regularity parameter* $\varkappa \geq 1$ (see section A.2) to ensure the following: whenever $k > 0$ is an integer and $\xi^1, ..., \xi^k$ are independent vectors from E with $\mathbf{E}\{\xi^i\} = 0$ and $\mathbf{E}\{\|\xi^i\|_*^2\} \leq \alpha_i^2$ and $\alpha = \max_i \alpha_i$, then for $\xi = \frac{1}{k}\sum_{i=1}^k \xi^i$ the following holds

$$\mathbf{E}\{\|\xi\|_*^2\} \leq \min\left[\tfrac{1}{k}, \tfrac{\varkappa}{k^2}\right]\sum_{i=1}^k \alpha_i^2 \leq \min\left[1, \tfrac{\varkappa}{k}\right]\alpha^2.$$

Suppose now that when running SMP we sample ζ_t, η_t from the distributions $P_z^{(k)}$ for some $k > 0$. It follows that if $\|\cdot\|_*$ is $\varkappa$-regular with certain $\varkappa$, then, passing from P_z to $P_z^+ = P_z^{(k)}$, we can reduce the "original" value of σ to the value $\sigma^+ = \min[1, \sqrt{\frac{\varkappa}{k}}]\sigma$. We shall see in a while that in the applications we have mentioned so far, $\varkappa$ is "small" — at most logarithmic in $\dim Z$. The bottom line is that there is a tradeoff between the computational cost of a call to a stochastic oracle and the noise level σ. Consequently, in the case of SMP, it is possible to tradeoff the computational effort per iteration and the iteration count to obtain an approximate solution of the desired expected quality, and we can use this tradeoff in order to save on the overall amount of computations. This option (which is the major advantage of SMP as compared to SA) is especially attractive when among the two components of our computational effort per iteration — one related to computing η_t, ζ_t, $F(\eta_t)$ $F(\zeta_t)$, and the other aimed at computing the prox mappings – the second component is essentially more significant than the first one. In such a situation, we basically can only gain by passing from P_z to $P_z^{(k)}$ with k chosen to balance the outlined two components of the computational effort.

3.3.3 Large deviations

In the above efficiency estimates, say, in (49), we upper-bounded the *expected* inaccuracy of approximate solutions z^t. In fact, one can get exponential upper bounds on probabilities of large deviations for the inaccuracy of the approximate solution. Though we do not need such bounds to access the inaccuracy of solutions, they are still useful to provide *theoretical* guarantees for the complexity of our algorithms (cf. Theorem 1 in the next section).

For the sake of definiteness, when presenting large deviation results, we restrict ourselves to the SMP algorithm and the stepsize strategy (45). We can easily bound from above the probability of $\epsilon_{\rm sad}(z^t)$ to be larger than the bound (49) on its expectation using the Markov inequality. Moreover, let us fix the number t of iterations, run the algorithm m times and select the best, in terms of $\epsilon_{\rm sad}(\cdot)$, of the resulting approximate solutions. The probability that for this solution $\epsilon_{\rm sad}(\cdot)$ is worse than, say, twice the right hand side of (49) is at most 2^{-m} and thus can be made negligibly small for quite moderate values of m.

We also have the following bound on the deviations of the algorithm without restarts:

Proposition 4 *Assume we are solving problem $(\mathcal{S})$ by Basic implementation of SMP where ζ_t, η_t are sampled from the distributions $P_z^{(k)}$, $k \geq 1$ being a parameter of the construction. Assume also that the norm $\|\cdot\|_*$ is $\varkappa$-regular, and the online stepsize policy (45) is used. Then there are absolute constants K_0, K_1 such that the approximate solution z^t satisfies for all $t \geq 1$ and λ, $\Lambda \geq 0$*

$$\mathrm{Prob}\left\{\epsilon_{\rm sad}(z^t) \geq K_0\left[\frac{\Theta^2\mathcal{L}}{t} + \frac{\varkappa_*(k,\Lambda)\Theta^2\mathcal{L}}{\sqrt{kt}} + \Theta F_*\sqrt{\frac{\lambda}{kt}}\right]\right\} \leq e^{-\Lambda t} + e^{-\lambda}, \tag{56}$$

where $\varkappa_*(k,\Lambda) = \sqrt{\min[k,\,(\varkappa+\Lambda)]}$. In particular, one has for all $\varepsilon > 0$:

$$\begin{array}{l}\mathrm{Prob}\{\epsilon_{\rm sad}(z^N) \geq \varepsilon\} \leq e^{-\Lambda N} + e^{-\lambda} \quad \textit{for } N \geq N_\varepsilon, \textit{ where}\\ N_\varepsilon = K_1 \mathrm{Ceil}\left(\max\left[\Theta^2\mathcal{L}\varepsilon^{-1},\ \frac{\varkappa_*^2(k,\Lambda)\Theta^4\mathcal{L}^2}{k\varepsilon^2},\ \frac{F_*^2\Theta^2\lambda}{k\varepsilon^2}\right]\right).\end{array} \tag{57}$$

For proof, see section A.3.

3.4 Efficiency estimates for Advanced implementation

The efficiency of Advanced implementations of SA and SMP stem from the following result (we use the notation from section 3.1):

Proposition 5 *Let the BSP problem $(\mathcal{S})$ be solved by the advanced-step SA or SMP algorithms. Then for every $t \geq 1$, for both SA and SMP one has*

$$\epsilon_{\rm sad}(z^t) \leq \Gamma_t^{-1}\left[\Omega + R_t + S_t\right] = \Gamma_t^{-1}\left[\Omega + \sum\nolimits_{\tau=1}^t r_\tau + \sum\nolimits_{\tau=1}^t s_\tau\right], \tag{58}$$

where

$$\Gamma_t = \sum\nolimits_{\tau=1}^t \gamma_\tau,$$

$$r_t = \begin{cases}\gamma_t\langle F(\zeta_t), \zeta_t - z_t\rangle & \text{in the case of SA}\\ \gamma_t\langle F(\zeta_t), \zeta_t - w_t\rangle & \text{in the case of SMP}\end{cases}$$

$$s_t = \begin{cases}\left[\gamma_t\langle F(\zeta_t), z_t - z_{t+1}\rangle - V_{z_t}(z_{t+1})\right], & \text{in the case of SA}\\ \left[\gamma_t\langle F(\zeta_t), w_t - z_{t+1}\rangle - V_{z_t}(z_{t+1})\right], & \text{in the case of SMP}\end{cases}$$

with $r_t \leq 0$ *and*

$$s_t \leq \begin{cases} \frac{\gamma_t^2}{2}\|F(\zeta_t)\|_*^2 \leq \frac{\gamma_t^2}{2}F_*^2, & \text{in the case of SA} \\ \frac{\gamma_\tau^2}{2}\|F(\zeta_t)-F(\eta_t)\|_*^2 - \frac{1}{2}\|w_t - z_t\|^2 \leq \frac{\gamma_t^2}{2}M_*^2, & \text{in the case of SMP.} \end{cases} \tag{59}$$

Proof of Proposition 5 is completely similar to the one of Proposition 2 and is omitted.

In order to extract from (58) explicit efficiency estimates, we need to specify a stepsize policy. In this respect, the advanced implementations offer more freedom than the basic ones. With the advanced implementation, at each iteration t, we ensure that $r_t \leq 0$ and thus $R_t \leq 0$. This fact removes a technical complication from the analysis of the basic algorithm, namely we no longer need to ensure neither the martingale property of the random sums R_t, nor the monotonicity of the stepsizes. Therefore the step sizes in the advanced implementation can be far less restrictive than in the basic implementation. One option here is to use constant stepsize policy

$$\gamma_t = \sqrt{\frac{2\Omega}{N}} \cdot \begin{cases} \frac{1}{F_*}, & \text{in the case of SA} \\ \frac{1}{M_*}, & \text{in the case of SMP} \end{cases}, \; 1 \leq t \leq N.$$

As it is easily seen, with this policy, (58) results in efficiency estimate (cf. (44))

$$\forall t \geq 1, \quad \mathbf{E}\left\{\epsilon_{\text{sad}}(z^t)\right\} \leq O(1) \begin{cases} F_*\sqrt{\frac{\Omega}{t}}, & \text{in the case of SA} \quad (a) \\ \mathcal{R}\mathcal{L}\sqrt{\frac{\Omega}{t}}, & \text{in the case of SMP} \quad (b) \end{cases} \tag{60}$$

Our preliminary experiments, however, suggest to equip the advanced implementations of SA and SMP with the online stepsize policy as follows. Let us set

$$\delta_t = \frac{\Theta^2}{t}, \qquad S_t^* = \textstyle\sum_{\tau=1}^t \delta_\tau \quad [\leq \Theta^2(1+\ln t)] \tag{61}$$

and let us choose γ_τ according to the "greedy" rule (the larger, the better) under the restriction that for all $t = 1, 2, ...$ it holds

$$R_t + S_t \leq S_t^*, \tag{$*_t$}$$

see (58). Specifically, assume that we have already carried out $t-1$ steps of the algorithm ensuring the relations $(*_\tau)$, $\tau \leq t-1$, and are about to define γ_t in order to carry out step t and to ensure $(*_t)$. When deciding on the value of γ_t, we already know the values of $R_{t-1} \leq 0$ and S_{t-1}. Moreover we know in advance that whatever be our choice of $\gamma_t > 0$, we would have

$$R_t - R_{t-1} = r_t \leq 0, \;\; S_t - S_{t-1} = s_t \leq \theta\gamma_t^2, \;\; \theta = \begin{cases} \frac{F_*^2}{2}, & \text{in the case of SA} \\ \frac{M_*^2}{2} \leq 2\mathcal{L}^2\mathcal{R}^2, & \text{in the case of SMP} \end{cases}$$

(see (59)). Thus, we can be sure that $S_t + R_t \leq [S_{t-1} + R_{t-1}] + \theta\gamma_t^2$, meaning that when choosing

$$\gamma_t = \sqrt{[S_t^* - S_{t-1} - R_{t-1}]/\theta} \tag{62}$$

we guarantee the validity of $(*_t)$ and the inequality $\gamma_t \geq \sqrt{\delta_t/\theta}$. This observation combined with (58) and $(*_N)$ implies that

$$\begin{aligned} \forall N \geq 1: \quad \epsilon_{\text{sad}}(z^N) &\leq \frac{\Theta^2/2 + R_N + S_N}{\sum_{\tau=1}^N \sqrt{\delta_\tau/\theta}} \leq \frac{O(1)\Theta^2(1+\ln N)}{\sum_{\tau=1}^t \sqrt{\delta_\tau/\theta}} \\ &\leq O(1)(1+\ln N) \cdot \begin{cases} \Theta F_* N^{-1/2}, & \text{in the case of SA,} \\ \Theta\mathcal{R}\mathcal{L}N^{-1/2}, & \text{in the case of SMP.} \end{cases} \end{aligned} \tag{63}$$

Observe that (63) is, within the logarithmic in N factor $O(1)(1+\ln N)$, the same as the bound (60). In fact, we could somehow reduce this logarithmic gap by modifying S_t^*, but we do not think this is necessary; we may hope (and the experiments to be reported in Section 5 fully support this hope) that "in reality" the rule (62) is much better than it is stated by the above worst-case analysis. The rationale behind this hope is that while we indeed are conservative when thinking how large could $S_t - S_{t-1}$ be, we account, to some extent, for the "past conservatism:" when $S_{t-1} + R_{t-1}$ is essentially less than S_{t-1}^*, γ_t as given by (62) is essentially larger than its lower bound used in the complexity analysis.

Finally, we remark that the major theoretical disadvantage of the efficiency estimate (63) as compared to (44) is much more serious than an extra log-factor. While with the basic implementation, in course of N steps the stochastic oracle is called $O(1)N$ times, the number of oracle calls in course of N steps of the advanced implementation is random and can be much larger than $O(1)N$; it is unclear why it should be $O(1)N$ even on average. Though for the time being we cannot support the empirical evidence by a solid theoretical complexity analysis, in our experiments the advanced implementation by far outperformed its basic counterpart.

3.5 The Favorable Geometry Case

We are about to present the "favorable geometry" case where we can point out the setup for SA/SMP which results in (nearly) *dimension-independent* efficiency estimates. Specifically, assume that

[G.1] The domain Z of $(\mathcal{S})$ is a *subset* of the direct product $Z^+ = B_1 \times .... \times B_{p+q}$ of $r = p+q$ "standard blocks" as follows:

- for $1 \le i \le p$, B_i is the unit Euclidean ball in $F_i = \mathbf{R}^{n_i}$;
- for $1 \le j \le q$, B_{p+j} is a subset of the space F_{p+j} of $n_{p+j} \times n_{p+j}$ $(n_{p+j} > 1)$ symmetric block-diagonal matrices of a given block-diagonal structure and is the *spectahedron* of F_{p+j}, that is, the set of all positive semidefinite matrices from F_{p+j} with unit trace.
  In particular, B_{p+j} can be the standard simplex $\{x \in \mathbf{R}^k_+ : \sum_\ell x_\ell = 1\}$ (since the space of diagonal $k \times k$ matrices can be naturally identified with $\mathbf{R}^k$).

We equip $F_i = \mathbf{R}^{n_i}$, $i \le p$, with the standard Euclidean structure and the associated Euclidean norm $\|\cdot\|_{(i)}$, and F_{p+j} – with the Frobenius Euclidean structure and the trace-norm (the sum of singular values of a matrix) $\|\cdot\|_{(p+j)}$. In particular, the embedding space $E = F_1 \times ... \times F_r$ of Z^+ becomes equipped with the direct product of the indicated Euclidean structures. Note that the norm $\|\cdot\|_{(i,*)}$ conjugate to $\|\cdot\|_{(i)}$ is either the norm $\|\cdot\|_{(i)}$ itself (this is so when $i \le p$), or is the standard matrix norm (maximal singular value of a matrix) (this is so when $i > p$). We denote a vector form on E as $x = [x_1; ...; x_r]$, where x_ℓ is the F_ℓ-component of x.

[G.2] The decomposition $Z = Z_1 \times Z_2 \subset E_1 \times E_2$ is compatible with the decomposition $Z = B_1 \times ... \times B_r$, that is, E_1 is the direct product of some of F_ℓ, $1 \le \ell \le p+q$, and E_2 is the direct product of the remaining F_ℓ. Besides this, we assume that Z intersects the relative interior of Z^+.

We refer to this case as to the one of *favorable geometry* and associate with this case the setup for SA and SMP as follows (cf. [13, Section 5]):

– The skew-symmetric linear mapping $\mathcal{A}$ (see (3)) can be written down as

$$\mathcal{A}[x_1;...;x_r] = [\sum_{j=1}^r A^{1j}x_j;...;\sum_{j=1}^r A^{rj}x_j],$$

where A^{ij} is a linear mapping from F_j to F_i and $[A^{ij}]^* = -A^{ji}$. We denote by L_{ij} an a priori upper bound on $L^*_{ij} := \max_{x_j}\left\{\|A^{ij}x_j\|_{(i,*)} : \|x_j\|_{(j)} \le 1\right\}$ such that $L_{ij} = L_{ji}$.[5] We assume that the symmetric matrix $[L_{ij}]$ has no zero rows (this always can be enforced by replacing some of zero L_{ij}'s with small positive reals).

– Further, we set for $1 \le i \le p$ and $1 \le j \le q$:

$$\begin{array}{l}\omega_i(x_i) = \frac{1}{2}x_i^T x_i : B_i \to \mathbf{R},\ \Omega_i = \frac{1}{2},\\ \omega_{p+j}(x_{p+j}) = 2\sum_{\ell=1}^{n_{p+j}} \lambda_\ell(x_{p+j})\ln(\lambda_\ell(x_{p+j})) : B_{p+j} \to \mathbf{R},\ \Omega_{p+j} = 2\ln(n_j),\end{array}$$

where $\lambda_\ell(u)$ are the eigenvalues of a symmetric matrix u taken with their multiplicities. It is known that $\omega_\ell(\cdot)$ is a d.g.f. for B_ℓ compatible with the norm $\|\cdot\|_\ell$, $1 \le \ell \le r$.

– Finally, we define the norm $\|\cdot\|$ on E and the d.g.f. $\omega(\cdot)$ for Z according to

$$\mu_\ell = \frac{1}{\Omega_\ell}\frac{\sum_{j=1}^r L_{\ell j}\sqrt{\Omega_\ell\Omega_j}}{\sum_{i,j=1}^r L_{ij}\sqrt{\Omega_i\Omega_j}},\quad \|[x_1;...;x_r]\| = \sqrt{\sum_{\ell=1}^r \mu_\ell\|x_\ell\|^2_{(\ell)}},\quad \omega(x) = \sum_{\ell=1}^r \mu_\ell\omega_\ell(x_\ell), \tag{64}$$

which results in

$$\Omega \le 1,\quad \mathcal{R} \le \Theta \le \sqrt{2},\quad \mathcal{L} = \sum_{i,j=1}^r L_{ij}\sqrt{\Omega_i\Omega_j}, \tag{65}$$

see [13, Section 5].

Remark 1 From the results of [9] (see also section A.2) it follows that the norm $\|\xi\|_* = \sqrt{\sum_{\ell=1}^r \mu_\ell^{-1}\|\xi_\ell\|^2_{(i,*)}}$ is $\varkappa$-regular (see discussion in Section 3.3) with nearly dimension-independent $\varkappa$, namely, $\varkappa = 7\max_{1\le j\le q}\ln(n_{p+j}+1)+1$.

Note that our motivating application of ℓ_1 minimization presented in Section 2.2.2 is of favorable geometry. The same is true for the low dimension approximation problem of Section 2.1.2; being a BSP rather than GBSP, this problem is well suited to illustrate the results we have obtained so far.

3.6 Illustration: Low dimensional approximation via randomization

Passing in (9) from variable Q to variable $R = d^{-1/2}Q$, the problem reads

$$\begin{array}{c}\min_{z_1:=\lambda\in Z_1:=\Delta_N}\max_{z_2:=R\in Z_2}\left[d^{1/2}\mathrm{Tr}\left(R\sum_{i=1}^N\lambda_i v_i v_i^T\right)\right],\\ Z_2 = \{R\in\mathbf{S}^n : 0 \preceq R \preceq d^{-1/2}I, \mathrm{Tr}(R) = d^{1/2}\}.\end{array} \tag{66}$$

We equip the embedding space $E_1 = \mathbf{R}^N$ of Z_1 with $\|\cdot\|_1$, and $Z_1 = \Delta_N$ – with the entropy d.g.f. Further, we equip the embedding space $E_2 = \mathbf{S}^n$ of Z_2 with the Frobenius norm, and Z_2 (which clearly is a subset of the unit ball of this norm) – with the Euclidean d.g.f. $\frac{1}{2}\mathrm{Tr}(z_2^2)$. Taking into account that $\|v_i\|_2 = 1$ for all i, it

[5] The latter restriction is natural, since $L^*_{ij} = L^*_{ji}$ due to $[A^{ij}]^* = -A^{ji}$.

is immediately seen that we are in the Favorable Geometry case with $\Omega_1 = 2\ln(N)$, $\Omega_2 = 1/2$, $L_{12} = L_{21} = \sqrt{d}$ and $L_{11} = L_{22} = 0$.

Now assume that we want to solve (66) within a given accuracy $\epsilon > 0$. Consider t-step Basic implementation of SMP utilizing the distributions $P_z^{(k)}$, $k = \mathrm{Ceil}(t\ln(N))$ (see section 3.3.2) induced by the distributions P_z presented in section 2.1.2, the step-sizes being given by (45). Taking into account Remark 1 and (65), we are in the situation of Corollary 1 with $\Omega = O(1)$, $\mathcal{L} = 2\sqrt{d\ln(N)}$, $\sigma \leq O(1)\sqrt{\ln(N)/k}\mathcal{L} \leq O(1)\mathcal{L}/\sqrt{t}$, so that (49) implies that $\mathbf{E}\{\epsilon_{\mathrm{sad}}(z^t)\} \leq O(1)\sqrt{d\ln(N)}/t$. In particular, setting

$$t = t(\epsilon) = \mathrm{Ceil}\left(O(1)\sqrt{d\ln(N)}/\epsilon\right) \tag{67}$$

with properly chosen $O(1)$, we ensure that $\mathbf{E}\{\epsilon_{\mathrm{sad}}(z^t)\} \leq \epsilon/2$. Thus in course of running our algorithm, a solution of the required accuracy ϵ will be built with probability $\geq 1/2$. Running our $t(\epsilon)$-step randomized procedure several times, until the first approximate solution with $\epsilon_{\mathrm{sad}}(z^\tau) \leq \epsilon$ is built (recall that $\epsilon_{\mathrm{sad}}(z^\tau)$ is observable on-line), we conclude that the probability *not* to find the desired approximate solution in $mt(\epsilon)$ steps, $m = 1, 2, ...$, is as small as 2^{-m}.

Now let us look what, if any, is the gain of randomization. It is easily seen that in the case in question computing a value of the prox-mapping within machine precision costs $O(n^3 + N)$ a.o. As a result, the best known so far complexity of solving (66) within accuracy ϵ by any deterministic algorithm is, up to log-factors, $\mathcal{C}_{\mathrm{det}} = [n^3 + n^2N]\sqrt{d}\epsilon^{-1}$ a.o. According to section 2.1.2, when sampling from P_z, after a "setup cost" of $O(n^3 + dn^2 + N)$ a.o. is paid, generating a sample $\zeta \sim P_z$ and computing $F(\zeta)$ cost $O(dnN)$ a.o. Thus, an iteration of the randomized method costs $O(n^3 + dn^2 + dnN[\underbrace{t(\epsilon)\ln(N)}_{k}])$ a.o., and the overall cost of an ϵ-solution with this method, again up to log-factors, is $\mathcal{C}_{\mathrm{rand}} = \sqrt{d}\epsilon^{-1}\left[n^3 + \sqrt{d}\epsilon^{-1}dnN\right]$ a.o. Assuming $N \geq n$, we get $\mathcal{C}_{\mathrm{rand}}/\mathcal{C}_{\mathrm{det}} \leq O(1)[nN^{-1} + \epsilon^{-1}d^{3/2}n^{-1}]$. For fixed ϵ, this ratio tends to 0 as d, n, N grow in such a way that $n/d^{3/2} \to +\infty$ and $N/n \to +\infty$.

4 Solving the Generalized Bilinear Saddle Point Problem

Here we explain how a GBSP problem (11) – (12) can be reduced to a "small series" of BSP problems; the strategy to follow originates from [11]. ¿From now on we assume, in addition to **A.1-2**, that we have an a priori upper bound $\bar{\rho}$ on the optimal value ρ_* of (12). For example, it is immediately seen that when finding an ϵ-solution to ℓ_1 minimization problem with ℓ_p fit (Section 2.2.2) in the only nontrivial case $\|b\|_p > \delta$ relation (15) implies that

$$\bar{\rho} := \|A\|_{1,p}[\|b\|_p - \delta]^{-1} \geq \rho_* := 1/\mathrm{Opt}, \quad \|A\|_{1,p} = \max_j \|A_j\|_p, \tag{68}$$

where $A_1, ..., A_n$ are the columns of A.

For the sake of definiteness, we assume that we are in the Favorable Geometry case, and that the decomposition $Z = Z_{11} \times Z_{12} \times Z_2 \subset E$, see (13), is compatible with the decomposition $E = F_1 \times ... \times F_r$, that is, the embedding spaces of Z_{11}, Z_{12} and Z_2 are products of some of F_ℓ's. To save space, we restrict ourselves with the SMP algorithm; modifications in the case of SA are straightforward.

The algorithm solves the problem of interest (12) by applying to $\mathrm{SV}(\cdot)$ a Newton-type root finding routine, with (approximate) first order information on SV at a point ρ given by SMP as applied to the BSP problem specifying $\mathrm{SV}(\rho)$. Specifically, the algorithm works stage by stage. At a stage s, we have at our disposal an upper bound ρ_s on ρ_* and a piecewise linear function $\ell_{s-1}(\rho)$ which underestimates $\mathrm{SV}(\cdot)$:

$$\mathrm{SV}(\rho) \geq \ell_{s-1}(\rho) \ \ \forall \rho \geq 0.$$

here $\rho_1 = \bar{\rho}$, $\ell_0 \equiv -\infty$. At a stage, we apply SMP to the BSP problem

$$\mathrm{SV}(\rho_s) = \min_{z_1 \in Z_1} \max_{z_2 \in Z_2} \phi^{\rho_s}(z_1, z_2) \qquad (\mathcal{S}_s)$$

namely, act as follows.

A. We start stage s with building the setup for SMP as explained in Section 3.5. The affine operator associated with $(\mathcal{S}_s)$ is

$$\begin{aligned} F^{\rho_s}(z_1 = [z_{11}; z_{12}], z_2) &= \Phi(z_1, z_2) + \rho_s \Psi(z_1, z_2) \\ &= [[a_{11} + B^* z_2; \rho_s(a_{12} + C^* z_2)]\,; -b - Bz_{11} - \rho_s(c + Cz_{12})]\,, \end{aligned}$$

see (11), (13). In matrix $\mathcal{A} = \mathcal{A}_s$ of the linear part of F^{ρ_s}, some blocks A^{ij} are independent of ρ_s, while the remaining blocks are proportional to ρ_s. Consequently, the Lipschitz constant of F^{ρ_s} as given by (65) is

$$\mathcal{L} = \mathcal{L}(\rho_s) = \mathcal{M} + \rho_s \mathcal{N}, \quad \mathcal{M}, \mathcal{N} \geq 0. \tag{69}$$

Observe that by Remark 1, the regularity parameter of the norm $\|\cdot\|_* = \|\cdot\|_*^{(s)}$ conjugate to the norm $\|\cdot\| = \|\cdot\|^{(s)}$ participating in the SMP setup for s-th stage does not exceed

$$\varkappa = 7\ln(N+1) + 1, \tag{70}$$

where N is the largest size of the spectahedron blocks, if any (otherwise $N = 0$), participating in Z.

B. We apply to $(\mathcal{S}_s)$ either the basic, or the advanced implementation of the SMP. When running the basic SMP, we use the distributions $P_z^{(k)}$, see Section 3.3 (here $k \geq 1$ is a parameter of the construction) and the online stepsize policy (45), where we set $\mathcal{L} = \mathcal{L}_s := \mathcal{M} + \rho_s \mathcal{N}$ and $\Omega = 1$ (see (65)). In addition, we restart the basic SMP every

$$N_s(\rho_s \epsilon) := \mathrm{Ceil}\left(\max\left[\frac{102\mathcal{L}_s}{\rho_s \epsilon}, \left(\frac{272\mathcal{L}_s}{\rho_s \epsilon}\right)^2 \frac{\varkappa}{k}\right]\right) \tag{71}$$

steps, see below; here $\varkappa$ is given by (70). When $(\mathcal{S}_s)$ is solved by the advanced SMP, we use the online stepsize policy (61) – (62), with $\Theta = \sqrt{2}$ in (61).

B.1. Let $z^{ts} = [z_1^{ts}, z_2^{ts}]$ be the approximate solution to $(\mathcal{S}_s)$ generated after t steps of stage s; recall that along with this solution, we have at our disposal the quantities

$$\begin{aligned} \overline{\phi}^{ts} &= \max_{z_2 \in Z_2} \phi^{\rho_s}(z_1^{ts}, z_2) = \upsilon + \langle a_{11}, z_{11}^{ts} \rangle + \rho_s[\chi + \langle a_{12}, z_{12}^{ts} \rangle] \\ &\qquad + \min_{z_2 \in Z_2} \langle z_2, b + \rho_s c + Bz_{11}^{ts} + \rho C z_{12}^{ts} \rangle, \\ \underline{\phi}^{ts} &= \min_{z_1 \in Z_1} \phi^{\rho_s}(z_1, z_2^{ts}) = \overbrace{\upsilon + \langle b, z_2^{ts} \rangle + \min_{z_{11} \in Z_{11}} \langle a_{11} + B^* z_2^{ts}, z_{11} \rangle}^{p_{ts}} \\ &\qquad + \rho_s \overbrace{\left[\chi + \langle c, z_2^{ts} \rangle + \min_{z_{12} \in Z_{12}} \langle a_{12} + C^* z_2^{ts}, z_{12} \rangle\right]}^{q_{ts}} \end{aligned} \tag{72}$$

(cf. (29) and see (11), (13)). We set

$$u^{ts} = \min_{\tau\le t}\overline{\phi}^{\tau s},\ \ell^{ts} = \max_{\tau\le t}\underline{\phi}^{\tau s},\ \ell_{ts}(\rho) = \max[\ell_{s-1}(\rho), \max_{1\le\tau\le t}[p_{\tau s} + q_{\tau s}\rho]].$$

Note that u^{ts} is a nonincreasing in t upper bound on $\mathrm{SV}(\rho_s)$, ℓ^{ts} is a nondecreasing in t lower bound on $\mathrm{SV}(\rho_s)$, and $\ell_{ts}(\rho)$ underestimates $\mathrm{SV}(\rho)$ for all $\rho \ge 0$. In addition, $\ell_{ts}(\rho_s) \ge \ell^{ts}$. Note also that after t steps we have at our disposal vectors $w_1^{ts} \in Z_1$, $w_2^{ts} \in Z_2$ such that

$$\max_{z_2\in Z_2}\phi^{\rho_s}(w_1^{ts}, z_2) = u^{ts} \le \overline{\phi}^{ts}, \min_{z_1\in Z_1}\phi^{\rho_s}(z_1, w_2^{ts}) = \ell^{ts} \ge \underline{\phi}^{ts},$$

meaning that $w^{ts} = [w_1^{ts}; w_2^{ts}]$ is a feasible solution to $(\mathcal{S}_s)$ and $\epsilon_{\mathrm{sad}}(w^{ts}) = u^{ts} - \ell^{ts} \le \overline{\phi}^{ts} - \underline{\phi}^{ts} = \epsilon_{\mathrm{sad}}(z^{ts})$.

B.2. We proceed with solving $(\mathcal{S}_s)$ until one of the following three situations occurs:

A) We get $u^{ts} \le \epsilon\rho_s$. In this case we terminate with the claim that ρ_s, w_1^{ts} is the desired ϵ-solution to (11) – (12).

B) We get $\ell^{ts} \ge \frac{3}{4}u^{ts}$. When it happens, we set

$$\rho_{s+1} = \max\{\rho : \ell_{ts}(\rho) \le 0\},\ \ell_s(\cdot) \equiv \ell_{ts}(\cdot) \tag{73}$$

and pass to the stage $s+1$.

C) The iteration count t becomes a multiple of $N_s(\epsilon)$. When it happens *and if the basic implementation of SMP is used*, we restart SMP and proceed to step $t+1$ of stage s (that is, the next iterate of stage s will be z_ω, the subsequent approximate solutions will be weighted sums of the points w generated after the restart, etc.) If the advanced implementation of SMP is used, we do not restart the algorithm and proceed as at all other steps.

Theorem 1 *When solving a Generalized Bilinear Saddle Point problem* (11) – (12) *within the accuracy $\epsilon > 0$ by the outlined algorithm:*

(i) *The algorithm terminates in finite time with probability 1, and the resulting solution is an ϵ-solution, as defined in Section 2.2, to the GBSP problem in question;*

(ii) *The number of stages does not exceed the quantity $O(1)\ln\left(\frac{\|\phi\|_\infty+\bar\rho\|\psi\|_\infty}{\epsilon\rho_*} + 2\right)$, where $\|\phi\|_\infty = \max_{z\in Z}|\phi(z)|$, $\|\psi\|_\infty = \max_{z\in Z}|\psi(z)|$, ρ_* is the optimal value in the problem* (11) – (12)*, and $\bar\rho$ is an a priori upper bound on ρ_*, see the beginning of section 4.*

(iii) *The (random) number N_s of steps at every stage s of the basic implementation satisfies the relation*

$$\mathrm{Prob}\{N_s \ge mN_s(\rho_s\epsilon)\} \le 2^{-m},\ m = 1, 2, ... \tag{74}$$

with $N_s(\rho_s\epsilon)$ given by (71)*. Besides this,*

$$N_s(\rho_s\epsilon) \le O(1)\frac{\mathcal{L}+\rho_*\mathcal{N}}{\rho_*\epsilon}\left[1 + \varkappa\frac{\mathcal{L}+\rho_*\mathcal{N}}{\rho_*\epsilon k}\right] \tag{75}$$

with $\varkappa$ given by (70)*.*

The number of steps at every stage of the advanced implementation of the algorithm does not exceed

$$N_{\mathrm{adv}}(\epsilon) = O(1)\left[\frac{\mathcal{M}+\rho_*\mathcal{N}+2\epsilon\rho_*}{\epsilon\rho_*}\ln\left(\frac{\mathcal{M}+\rho_*\mathcal{N}+2\epsilon\rho_*}{\epsilon\rho_*}\right)\right]^2. \tag{76}$$

Proof. 1^0. From the description of the method it follows that

$$\forall t,s\geq 1,\ \forall \rho\geq 0:\quad u^{ts}\geq \mathrm{SV}(\rho_s)\geq \ell^{ts},\quad \ell_{ts}(\rho)\leq \mathrm{SV}(\rho),\quad \ell^{ts}\leq \ell_{ts}(\rho_s). \tag{77}$$

Let us prove by induction in s that $\rho_*\leq\rho_s\leq\rho_1$. The base $s=1$ is evident. Now let $\rho_*\leq\rho_s\leq\rho_1$, and let stage $s+1$ take place. When passing from stage s to stage $s+1$, we are in the case B) and thus have $u^{ts}>\epsilon\rho_s$, $\ell^{ts}\geq\frac{3}{4}u^{ts}>\frac{3}{4}\epsilon\rho_s$, whence, in view of (77),

$$\ell_s(\rho_s)=\ell_{ts}(\rho_s)\geq\ell^{ts}\geq\tfrac{3}{4}\max[\epsilon\rho_s,\mathrm{SV}(\rho_s)]\quad\text{thus}\quad \ell_s(\rho_s)>0. \tag{78}$$

This combines with $\ell_{ts}(\rho_*)\leq\mathrm{SV}(\rho_*)\leq 0$ and convexity of $\ell_{ts}(\cdot)$ to imply that $\rho_*\leq\rho_{s+1}<\rho_s$. Induction is complete.

Since $\rho_s\geq\rho_*$, u^{ts} is an upper bound on $\mathrm{SV}(\rho_s)$ and $u^{ts}\geq\overline{\phi}^{\rho_s}(w_1^{ts})$, we conclude that if the algorithm terminates at stage s, then the result ρ_s,w_1^{ts} is an ϵ-solution to the GBSP in question.

2^0. Let us prove (ii). The reasoning to follow goes back to [11]; we reproduce it here to make the paper self-contained. Let s be such that the stage $s+1$ takes place, and let u_s be the last bound u^{ts} built at stage s. Observe that

$$\tfrac{3}{4}\epsilon\rho_s<\tfrac{3}{4}u_s\leq\ell_s(\rho_s)\leq\mathrm{SV}(\rho_s)\leq u_s. \tag{79}$$

Since the convex function $\ell_s(\rho)$ is nonpositive at $\rho=\rho_{s+1}$ and is $\geq\frac{3}{4}u_s>0$ at $\rho=\rho_s>\rho_{s+1}$, we have $g_s:=\ell_s'(\rho_s)>0$ and

$$\rho_s-\rho_{s+1}\geq\ell_s(\rho_s)/g_s\geq\tfrac{3}{4}u_s/g_s. \tag{80}$$

Now assume that $s>1$ is an intermediate step, i.e., it is such that the stage $s+1$ also takes place. Applying (80) and (79) to $s-1$ in the role of s, we get $\rho_{s-1}-\rho_s\geq\frac{3}{4}u_{s-1}/g_{s-1}$ and $\frac{3}{4}u_s\leq\ell_s(\rho_s)$, whence, by convexity of $\ell_s(\cdot)$ and in view of (77), we have

$$u_{s-1}\geq\mathrm{SV}(\rho_{s-1})\geq\ell_s(\rho_{s-1})\geq\ell_s(\rho_s)+g_s(\rho_{s-1}-\rho_s)\geq\frac{3}{4}u_s+g_s\frac{3}{4}\frac{u_{s-1}}{g_{s-1}}.$$

Consequently, $\frac{4}{3}u_{s-1}\geq u_s+\frac{g_su_{s-1}}{g_{s-1}}$, or equivalently $\frac{u_s}{u_{s-1}}+\frac{g_s}{g_{s-1}}\leq\frac{4}{3}$, whence $\frac{u_sg_s}{u_{s-1}g_{s-1}}\leq(1/4)(4/3)^2=4/9$. It follows that

$$\sqrt{u_sg_s}\leq(2/3)^{s-1}\sqrt{u_1g_1}. \tag{81}$$

We have $\ell_s(\rho_*)\leq\mathrm{SV}(\rho_*)=0$, $\ell_s(\rho_s)\geq\frac{3}{4}u_s$ (see (79)) and $\ell_s(\rho_s)-\ell_s(\rho_*)\leq g_s(\rho_s-\rho_*)$ (by convexity of $\ell_s(\cdot)$), whence $g_s\geq\frac{3}{4}u_s(\rho_s-\rho_*)^{-1}\geq\frac{3}{4\rho_1}u_s$, and (81) implies that

$$u_s\leq(2/3)^{s-1}\sqrt{u_1g_1}\sqrt{4\rho_1/3}. \tag{82}$$

Now, $g_1=\ell_1'(\rho_1)$ and $\ell_1(\rho)\leq\mathrm{SV}(\rho)\leq\|\phi\|_\infty+\rho\|\psi\|_\infty$, and $g_1\leq\|\psi\|_\infty$, and clearly $u_1\leq\|\phi\|_\infty+\rho_1\|\psi\|_\infty$. At the same time, $u_s>\epsilon\rho_s\geq\epsilon\rho_*$, so that (82) implies that $\epsilon\rho_*\leq(2/3)^{s-1}[\|\phi\|_\infty+\rho_1\|\psi\|_\infty]$. The resulting upper bound on s implies (ii).

3^0. Let us prove (iii). Assume, first, that Basic SMP with stepsizes (45) is used. From the description of the algorithm it follows that at every stage s, before termination of the stage, the residual of current approximate solutions w^{ts} is $>\frac{1}{4}\epsilon\rho_s$ (since $u^{ts}>\epsilon\rho_s$ and $\ell^{ts}<\frac{3}{4}u^{ts}$). It follows that in order to prove (74), it suffices to verify that when applying to $(\mathcal{S}_s)$ $N=N_s(\rho_s\epsilon)$-step Basic SMP, we have $\epsilon_{\mathrm{sad}}(z^N)\leq\epsilon\rho_s/4$ with probability $\geq 1/2$; to this end, it is enough to verify that the expectation of $\epsilon_{\mathrm{sad}}(z^N)$

is $\leq \epsilon\rho_s/8$. By Corollary 1, this expectation is $\leq \alpha := 7\Omega\mathcal{L}_s/N + 6\sqrt{\Omega}\sigma/\sqrt{N}$, where $\sigma^2 = \sup_{z\in Z} \mathbf{E}_{\zeta\sim P_z^{(k)}} \left\{\|\mathcal{A}(\zeta - z)\|_*^2\right\} \leq \frac{\varkappa}{k}(2\mathcal{L}_s\Theta)^2$ (see (36) and discussion in section 3.3.2), that is, $\sigma \leq 2\Theta\mathcal{L}_s\sqrt{\varkappa/k}$. This inequality combines with the relations $\Omega = 1$, $\Theta = \sqrt{2\Omega}$ and the definition (71) of $N = N_s(\rho_s\epsilon)$ to imply the desired bound $\alpha \leq \epsilon\rho_s/8$. We have proved (74); (75) is readily given by (71) and the relation $\rho_s \geq \rho_*$.

For the advanced implementation of SMP, similar reasoning based on the bound (63) with $\mathcal{L} = \mathcal{M} + \rho_s\mathcal{N}$ justifies (76).

4^0. Combining (ii), (iii) and the concluding claim in item 1^0 above, we arrive at (i). □

The case of ℓ_1 minimization. In the case of ℓ_1 minimization problems with uniform and ℓ_2 fits, Theorem 1 as applied to the basic implementation of SMP with $k = 1$, initialized according to (68), after completely straightforward computations implies the complexity bounds stated in Proposition 1. The preprocessing mentioned in item (ii) of Proposition 1 is as follows: we choose an $m \times m$ orthogonal matrix U with moduli of entries not exceeding $O(1)/\sqrt{m}$ and such that multiplication of a vector by U takes $O(m \ln m)$ operations (e.g., U can be the matrix of the Cosine Transform). We then draw at random a ± 1 vector ξ from the uniform distribution on the vertices of the unit m-dimensional box and pass from the data $[A, b]$ to the data

$$[A' = U\mathrm{Diag}\{\xi\}A, \;\; b' = U\mathrm{Diag}\{\xi\}b],$$

thus obtaining an equivalent reformulation of the problem of interest. Note that this preprocessing costs $O(1)mn\ln(m)$ operations. We clearly have $\|A'\|_{1,2} = \|A\|_{1,2}$. Applying Hoeffding's inequality (see [8]), it is immediately seen that for every tolerance $\chi \in (0, 1/2)$ with probability $\geq 1-\chi$ one has $\|A'\|_{1,\infty} < O(1)\sqrt{\ln(mn/\chi)}m^{-1/2}\|A\|_{1,2}$, that is, $\Gamma(A') \leq O(1)\sqrt{\ln(mn/\chi)}$, as stated in Proposition 1.

5 Numerical Results

Below we report on a series of numerical experiments aimed at comparing the performances of the Stochastic Mirror Prox algorithm SMP (in its advanced implementation) and its prototype — Deterministic Mirror Prox algorithm (DMP) proposed in [13][6)]. The algorithms were tested on the GBSP problems of ℓ_1 minimization with uniform and ℓ_2 fits, see Section 2.2.2.

Test problems we use originate from Compressive Sensing. Specifically, given the sizes m, n of a test problem, we picked at random an $m \times n$ matrix B with i.i.d. entries taking values ± 1 with probabilities 0.5, and a sparse (with $\mathrm{Ceil}(\sqrt{m})$ nonzero entries randomly generated from standard Normal distribution) "true signal" x_* normalized to have $\|x_*\|_1 = 1$, thus giving rise to the test problem

$$\mathrm{Opt}_p = \min_x \{\|x\|_1 : \|Ax - y\|_p \leq \delta\}, \; A = m^{-1/p}B, \; y = Ax_* + \xi \qquad (P_p)$$

where $p = \infty$ (uniform fit) or $p = 2$ (ℓ_2 fit). The "observation noise" ξ was chosen at random (each entry is from an i.i.d. standard Normal distribution) and then normalized to have $\|\xi\|_p = \delta$, thus making sure that the true solution x_* is feasible to (P_p). Our

[6)] DMP is nothing but SMP with precise information (i.e., P_z is the unit mass sitting at z) and on-line stepsize policy described in [13, Section 6].

goal is to solve (P_p) within accuracy ϵ, i.e., to find x_ϵ satisfying $\|x_\epsilon\|_1 \leq \mathrm{Opt}_p$ and $\|Ax_\epsilon - y\|_p \leq \delta + \epsilon$. In all our experiments, $\delta = 0.005$ and $\epsilon = 0.0025$ were used.

Implementation of the algorithms. The GBSP reformulations of problems (P_p) were solved by SMP (in advanced implementation) and DMP according to the scheme presented in Section 4. In the case $p = \infty$ of uniform fit, both SMP and DMP used the GBSP problem reformulation given by (19). In the case $p = 2$ of ℓ_2 fit, SMP used the GBSP reformulation (18), while DMP was applied to the GBSP problem stemming directly from (16) with $p = 2$, namely, given by

$$\phi^\rho(z_1, z_2) = z_2^T(AJ_n z_1 - \rho b) - \rho\delta, Z_1 = Z_{11} = \Delta_{2n},\ Z_2 = \{\|z_2\|_2 \leq 1\}. \tag{83}$$

The rationale here is that the GBSP given by (83) "by itself" is easier than the GBSP given by (18): an ϵ-solution to the latter problem induces straightforwardly an ϵ-solution to the former one, but not vice versa. As a compensation, the problem (18), in contrast to (83), is better suited for randomization[7]. The latter fact, which is crucial for SMP, is irrelevant for DMP, this is why we apply this algorithm to the GBSP given by (83). In order to make a fair comparison, when running SMP for ℓ_2-fit, we terminate the run based on the ℓ_2-residual of the solution.

In our implementations, we have tested different policies for choosing the starting point at each stage and different choices of the distance generating function (d.g.f.) for the simplexes. Specifically, along with the entropy d.g.f. discussed in Section 3.5, we tested the power d.g.f. $\omega(x) = \frac{\mathrm{e}}{\kappa(1+\kappa)}\sum_{i=1}^n x_i^{1+\kappa} : \{x \in \mathbf{R}^n_+ : \sum_i x_i \leq 1\} \to \mathbf{R}$, with $\kappa = \frac{1}{\ln(n)}$; the theoretical complexity bounds associated with this choice of d.g.f. coincide, within absolute constant factors, with those for the entropy. The best policies we ended up with are as follows:

— for SMP: entropy d.g.f., restarts from the ω-center of Z ("C00E" implementation);

— for DMP, in the case of uniform fit: power d.g.f., restarts from the convex combination of the best (with the smallest ϵ_{sad}) point found so far and the ω-center of Z, the weights being 0.25 and 0.75, respectively ("B25P" implementation);

— for DMP, in the case of ℓ_2-fit: power d.g.f., restarts from the convex combination of the last search point of the previous stage and the ω-center of Z, the weights being 0.75 and 0.25, respectively ("L75P" implementation).

When implementing SMP, we utilized the option, discussed in Section 3.3, of building an estimate $F(\zeta)$ of $F(z)$ by generating k samples $\zeta^\ell \sim P_z$, $\ell = 1, ..., k$, and setting $\zeta = \frac{1}{k}\sum_{\ell=1}^k \zeta^\ell$. The "multiplicity" k was set to 40 for small instances and 100 for large (those with at least 10^8 nonzeros in A) instances.

The MATLAB 7.10.0 implementation of the algorithms was executed on an eight-core machine with two quad-core Intel Xeon E5345 CPU@2.33GHz, 8 MB L2 cache per quad-core chip and 12GB FB-DIMM total RAM (the computations were running single-core and single-threaded).

[7] Indeed, in the second problem all nontrivial matrix-vector multiplications required to compute $F^\rho(z)$ are multiplications of vectors from the ℓ_1-balls by A and A^T; since a vector from ℓ_1-ball is the expectation of an extremely sparse (just one nonzero entry) random vector taking values in the same ball, the required matrix-vector multiplications admit cheap randomized versions. In the first problem, some of the required matrix-vector multiplications involve vectors from the $\|\cdot\|_2$-ball, and such a vector typically cannot be represented as the expectation of a sparse random vector taking values in the ball.

The results, I. In order to avoid too time-consuming experimentation, we primarily dealt with "moderate size" test problems. These problems were split into four groups according to the total number of nonzeros in A ($2 \cdot 10^6$, $8 \cdot 10^6$, $32 \cdot 10^6$, $128 \cdot 10^6$). Every group was further split into two subgroups according to the ratio $n : m$ (8 and 2). For every one of the resulting pairs (m, n), we generated 5 instances of problem (P_2) and 5 instances of problem (P_∞) and solved them by DMP and SMP. Thus, the methods were compared on totally 80 problem instances split into 16 series of 5 experiments each, with common for all experiments of a series sizes m, n and the value of p. The results are presented in Tables 1 (uniform fit) and 2 (ℓ_2 fit). For every series of 5 experiments, we present the corresponding minimal, maximal and average values of several performance characteristics, specifically

- `CPU` — the CPU time (sec) of the entire computation
- `Calls` — the total number of computations of the values of F
- `FCalls` — the equivalent number of calls to the deterministic oracle for the randomized algorithm. This quantity is defined as follows. For DMP, computing a value of F at a point reduces to a pair of matrix-vector multiplications, one involving A and the other one involving A^T; the cost of this computation is $2mn$ operations. For SMP invoked with multiplicity k (see above), the computation of (an unbiased estimate of) $F(z)$ requires multiplying one vector with $\leq k$ nonzero entries by A, and another vector with $\leq k$ nonzero entries by A^T, the total cost of these two computations being $k(m+n)$ operations. Thus, the "deterministic equivalent" of the randomized computation of F used by SMP is $\frac{k(m+n)}{2mn}$. The quantity `FCalls` represents the equivalent number of calls to the deterministic oracle that we could afford for the same total computational cost involved with the queries to the stochastic oracle needed to solve the problem by SMP.

The data in Tables 1, 2 suggest the following interpretations:

1. As the sizes of instances grow, the randomized algorithm eventually outperforms its deterministic counterpart in terms of the CPU time, and the corresponding "savings" grow with the size $m \times n$ of the instance, and for instances of a given size – grow as the ratio n/m decreases. Both phenomena are quite natural: the larger is mn and the smaller is $n/m \geq 1$ for a given mn, the smaller is the deterministic equivalent $k\frac{m+n}{2mn}$ of a randomized computation of F.
2. Even for our "not too large" test problems, the savings stemming from randomization can be quite significant: for the 8000×16000 instances, SMP is, at average, nearly 4.6 times faster than the best version of DMP for problems with uniform fit and 2.1 times faster than DMP for problems with ℓ_2 fit.
   When interpreting the CPU time data one should keep in mind that oracle calls of DMP make use of very efficient MATLAB implementation of matrix-vector multiplication, while SMP relies upon much less efficient (with respect to, e.g., C language) implementation of long DO loops.
3. The advantages, if any, of SMP as compared to DMP are more significant in the case of uniform fit than in the case of ℓ_2 fit. This phenomenon is quite natural: as we have already explained, in the case of ℓ_2 fit the methods are applied to different GBSP reformulations of (P_2), and the reformulation DMP works with is easier than the one processed by SMP.

The results, II. In order to get impression of what happens when the matrix A in (P_p) is too large to be stored in RAM, we carried out two experiments where the goal was

to solve the ℓ_1 minimization problem with uniform and with ℓ_2 fits and fully dense $(m = 32000) \times (n = 64000)$ matrix A given by a simple analytical expression. This expression allows to compute a column/a row of A with a given index in $O(m)$, resp., $O(n)$ operations. Matrix $A = A_p$ was normalized to have $\|A\|_{1,p} = 1$. While the sizes of A make it impossible to store the matrix in the RAM of the computer we used for the experiments, we still can multiply vectors by A and A^T by computing all necessary columns and rows, and thus can run DMP and SMP. In our related experiments, we generated at random a sparse (64 nonzeros) "true" signal $x_* \in \mathbf{R}^{64000}$ with $\|x_*\|_1 = 1$, computed $y = Ax + \xi$, ξ, $\|\xi\|_p = \delta = 0.005$, being observation noise, and ran DMP and SMP in order to find an ϵ-solution x_ϵ, $\epsilon = 0.0025$, to the resulting problem (P_p); in particular, we should have $\|x_\epsilon\|_1 \leq \|x_*\|_1 = 1$ and $\|Ax_\epsilon - b\| \leq \delta + \epsilon = 0.0075$. In every experiment, each of the methods was allowed to run at most 7200 sec[8]. The results are as follows.

- In the allowed 7200 sec, the deterministic algorithms on every one of the two test problems ($p = 2$ and $p = \infty$) was able to carry out just about 30 steps with the total of about 67 computations of $F(\cdot)$; this is by far not enough to get meaningful results, see Table 3. In contrast to this, the numbers of steps and randomized computations of F carried out by the randomized algorithm in the same 7200 sec was in the range of tens of thousands, which was enough to fully achieve the required accuracy for both $p = \infty$ and $p = 2$.
- While the quality of approximation of x_* by the solution yielded by DMP is basically nonexisting, the SMP produced fairy reasonable approximations of x_*, see Table 3.

In our opinion, the preliminary numerical results we have reported suggest that "acceleration via randomization" possesses a significant practical potential when solving extremely large-scale convex programs of appropriate structure.

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A Appendix

A.1 Representing a vector from $\Delta_{n,d}$ as a convex combination of extreme points

We use the notations of Section 2.1.2. The case of $d = n$ is trivial, thus, let $d < n$. Let

$$q \in \Delta_{n,d} = \left\{ q \in \mathbf{R}^n_+ : \ 0 \leq q_i \leq 1 \ \forall i, \ \sum\nolimits_{i=1}^n q_i = d \right\}.$$

To represent q as a convex combination of n extreme points of $\Delta_{n,d}$ we act as follows:

- *Initialization:* We set $p^0 = [1; q]$, $\mu^0 = 1$. Note that $p^0 \in \Delta = \{p = [1; p_1; ...; p_n] \in \Delta_{n+1,d+1}\}$.
- *Step* $t = 1, 2, ...$: Given $p^{t-1} = [1; p_1^{t-1}; ...; p_n^{t-1}] \in \Delta$, we find the $d + 1$ largest among the entries p_i^{t-1}, $i = 1, ..., n$, let their indexes be $i_1, ..., i_{d+1}$, where $p_{i_1}^{t-1} \geq p_{i_2}^{t-1} \geq ... \geq p_{i_{d+1}}^{t-1}$.
  a) It may happen that $p_{i_\ell}^{t-1} = 1$ for $1 \leq \ell \leq d$; since $p^{t-1} \in \Delta$, $r^t := p^{t-1}$ is a Boolean

[8] The running time is compared with the limit of 7200 sec only at the end of an iteration, thus, with termination due to CPU limit, the actual running time was larger than this limit.

Table 1 Numerical Results for ℓ_1-minimization with $\|\cdot\|_\infty$-fit

		DMP		SMP				
Sizes		Calls	CPU	Calls	FCalls	CPU	I†	II‡
500	Mean (C00E)	2661.6	106.6	10511.0	236.5	57.2	11.89	1.98
x 4000	Min (C00E)	1683.0	50.0	8159.0	183.6	34.0	6.91	1.16
	Max (C00E)	4395.0	179.4	11783.0	265.1	83.4	23.94	4.14
	Mean (B25P)	1453.4	104.1				6.15	1.89
1000	Mean (C00E)	1830.8	64.0	10568.8	158.5	42.9	11.69	1.54
x 2000	Min (C00E)	1344.0	41.0	8434.0	126.5	28.8	7.82	1.02
	Max (C00E)	2507.0	91.5	11576.0	173.6	70.4	15.83	2.02
	Mean (B25P)	1530.6	97.9				9.64	2.48
1000	Mean (C00E)	2338.0	227.9	12406.6	139.6	113.2	16.68	1.99
x 8000	Min (C00E)	1453.0	119.4	11579.0	130.3	88.2	11.15	1.27
	Max (C00E)	2739.0	370.2	13895.0	156.3	168.9	18.99	2.39
	Mean (B25P)	1545.6	248.9				11.08	2.30
2000	Mean (C00E)	2691.6	227.6	12922.8	96.9	74.5	27.93	3.10
x 8000	Min (C00E)	1132.0	97.7	10934.0	82.0	56.6	12.24	1.37
	Max (C00E)	3355.0	313.1	15632.0	117.2	88.8	35.46	4.25
	Mean (B25P)	1426.4	207.8				14.74	2.84
2000	Mean (C00E)	2384.6	494.2	13174.8	74.1	184.9	32.30	2.68
x 16000	Min (C00E)	2288.0	486.3	11735.0	66.0	174.4	29.78	2.53
	Max (C00E)	2491.0	505.5	14729.0	82.9	195.3	34.66	2.84
	Mean (B25P)	1575.2	533.7				21.41	2.89
4000	Mean (C00E)	2923.6	798.7	19750.2	74.1	228.4	39.42	3.30
x 8000	Min (C00E)	2032.0	407.6	17262.0	64.7	159.0	28.86	2.34
	Max (C00E)	3895.0	1539.7	22945.0	86.0	343.1	48.61	4.49
	Mean (B25P)	1554.6	576.2				21.12	2.63
4000	Mean (C00E)	2482.8	2054.3	11973.2	84.2	515.8	29.47	3.98
x 32000	Min (C00E)	1826.0	1448.9	11331.0	79.7	499.9	22.39	2.90
	Max (C00E)	3479.0	2904.2	12715.0	89.4	525.0	42.65	5.70
	Mean (B25P)	1604.8	1736.3				19.19	3.36
8000	Mean (C00E)	2680.4	2227.7	12474.6	58.5	375.0	45.78	5.92
x 16000	Min (C00E)	2297.0	1890.1	11493.0	53.9	341.9	41.12	5.44
	Max (C00E)	3177.0	2609.0	13759.0	64.5	408.8	49.26	6.48
	Mean (B25P)	1615.8	1752.7				27.57	4.63

†: $\frac{\text{Calls,DMP}}{\text{FCalls,SMP}}$ ‡: $\frac{\text{CPU,DMP}}{\text{CPU,SMP}}$

vector with exactly $d+1$ entries equal to 1, and $q^t = [p_1^{t-1}; ...; p_n^{t-1}]$ is an extreme point of $\Delta_{n,d}$. We set $\nu_t = 1$, $p^t = 0$ and terminate.

b) When not all $p_{i_\ell}^{t-1}$, $1 \le \ell \le d$, are equal to 1, we set $\nu_t = \min[1 - p_{i_{d+1}}^{t-1}, p_{i_d}^{t-1}]$, define r^t as Boolean $(n+1)$-dimensional vector with $d+1$ entries equal to 1, the indexes of the entries being $0, i_1, ..., i_d$, set $p^t = [p^{t-1} - \nu_t r^t]/(1-\nu_t)$, $q^t = [r_1^t; ...; r_n^t]$ (note that q^t is an extreme point of $\Delta_{n,d}$) and pass to step $t+1$.

Observe that the algorithm is well defined. Indeed, $0 \le \nu_t \le 1$ by construction, and $\nu_t = 1$ if and only if $p_{i_{d+1}}^{t-1} = 0$ and $p_{i_d}^{t-1} = 1$, that is, when we terminate at step t according to a). Thus, p^t is well defined at every non-termination step t. Moreover, from b) it is immediately seen that at such a step we have $p_0^t = 1$, $0 \le p_i^t \le 1$ for all i and $\sum_{i=0}^n p_i^T = d+1$, that is, $p^t \in \Delta$ for all t for which p^t is well defined. Besides this, it is immediately seen that 0/1 entries in p^{t-1} remain intact when passing from p^{t-1} to p^t, and that the total number of these entries increases at every step of the algorithm by at least 1. The latter observation implies that the algorithm terminates in at most n steps. Finally, by construction $p^{t-1} = (1-\nu_t)p^t + \nu_t r^t$, whence, denoting by $\bar{t}$ the termination step, p^0 is a convex combination of $r^1, ..., r^{\bar{t}}$ with coefficients μ_t readily given by $\nu_1, ..., \nu_{\bar{t}}$. Discarding in $r^1, ..., r^{\bar{t}}$ the entries with index 0, we

Table 2 Numerical Results for ℓ_1-minimization with $\|\cdot\|_2$-fit

		DMP		SMP				
Sizes		Calls	CPU	Calls	FCalls	CPU	I†	II‡
500 x 4000	Mean (C00E)	579.8	21.0	4771.6	106.7	24.6	5.91	0.93
	Min (C00E)	410.0	14.5	3412.0	76.3	16.9	3.18	0.49
	Max (C00E)	722.0	40.3	6868.0	153.5	36.0	8.40	1.94
	Mean (L75P)	287.8	16.1				2.95	0.70
1000 x 2000	Mean (C00E)	553.0	19.0	3910.8	54.8	13.6	10.73	1.47
	Min (C00E)	463.0	9.1	3315.0	46.4	11.5	5.68	0.52
	Max (C00E)	664.0	30.1	5890.0	82.5	17.4	13.56	2.34
	Mean (L75P)	282.4	14.1				5.44	1.07
1000 x 8000	Mean (C00E)	617.0	56.6	5148.8	57.5	50.7	11.25	1.17
	Min (C00E)	486.0	34.7	3745.0	41.9	36.1	7.68	0.74
	Max (C00E)	794.0	87.1	6050.0	67.6	64.8	18.35	1.93
	Mean (L75P)	318.8	40.9				5.84	0.86
2000 x 8000	Mean (C00E)	634.8	39.8	5853.6	41.0	47.2	15.94	0.86
	Min (C00E)	487.0	30.0	3926.0	27.5	33.1	11.17	0.59
	Max (C00E)	796.0	51.0	6869.0	48.1	54.0	20.49	1.12
	Mean (L75P)	318.8	25.9				8.05	0.58
2000 x 16000	Mean (C00E)	531.8	150.7	5055.6	28.3	90.0	19.88	1.80
	Min (C00E)	438.0	108.3	3947.0	22.1	60.2	11.64	0.87
	Max (C00E)	608.0	180.3	6736.0	37.6	125.1	24.80	2.49
	Mean (L75P)	346.0	110.6				12.74	1.28
4000 x 8000	Mean (C00E)	675.2	138.5	6504.6	22.8	101.7	29.71	1.36
	Min (C00E)	531.0	99.1	5868.0	20.5	83.3	22.71	0.99
	Max (C00E)	810.0	193.6	7143.0	25.0	113.9	34.52	1.70
	Mean (L75P)	346.4	86.3				15.21	0.85
4000 x 32000	Mean (C00E)	672.2	486.0	5613.4	39.2	287.2	17.66	1.74
	Min (C00E)	506.0	382.5	3418.0	23.9	197.2	12.08	1.26
	Max (C00E)	817.0	579.1	6611.0	46.2	336.4	22.57	2.15
	Mean (L75P)	355.4	311.6				9.39	1.12
8000 x 16000	Mean (C00E)	592.4	591.4	5815.0	25.4	177.6	24.15	3.51
	Min (C00E)	509.0	472.4	3765.0	16.5	117.3	16.56	2.36
	Max (C00E)	696.0	798.1	7038.0	30.8	214.1	30.90	5.06
	Mean (L75P)	329.8	360.2				13.38	2.10

†: $\frac{\text{Calls,DMP}}{\text{FCalls,SMP}}$ ‡: $\frac{\text{CPU,DMP}}{\text{CPU,SMP}}$

Table 3 Experiments with dense 32000×64000 matrix A. Percents: $\|\widehat{x} - x_*\|/\|x_*\|$.

							$\|\widehat{x} - x_*\|_r$		
Method	p	Steps	Calls	FCalls	CPU	$\|A\widehat{x} - b\|_p$	$r = 1$	$r = 2$	$r = \infty$
DMP (C00E)	∞	30	71	71	7564	0.16018	1.406 (141%)	0.143 (89%)	0.041 (79%)
DMP (B25P)	∞	31	67	67	7363	0.15975	1.361 (136%)	0.136 (85%)	0.035 (69%)
SMP (C00E)	∞	7501	22141	25.9	5352	0.00744	0.048 (5%)	0.005 (3%)	0.002 (4%)
DMP (C00E)	2	29	67	67	7471	0.03653	1.455 (146%)	0.135 (84%)	0.035 (68%)
DMP (L75P)	2	30	67	67	7536	0.02480	0.976 (98%)	0.093 (58%)	0.022 (42%)
SMP (C00E)	2	2602	7749	8.5	2350	0.00715	0.264 (26%)	0.021 (13%)	0.004 (7%)

get extreme points $q^1, ..., q^{\bar{t}}$ of $\Delta_{n,d}$ such that $q = \sum_{i=1}^{\bar{t}} \mu_t q^t$. Finally, the computational effort per step clearly does not exceed $O(1)dn$. In fact, when $d > \ln(n)$, at each step we can first sort the components of p^{t-1} in nonincreasing order resulting in a complexity of $O(1)n\ln(n)$ per iteration instead of $O(1)dn$ complexity. That is, the total computational effort is at most $O(1)\min\{d, \ln(n)\}n^2$.

A.2 $\varkappa$-regular spaces

Due to space limitations, we present here a kind of "executive summary" which is fully sufficient for our purposes. For underlying definitions and proofs, see [9]; in a slightly different form, this material can be found also in [6,17]. Consider a finite-dimensional linear space E equipped with a norm $\|\cdot\|$. The pair $(E, \|\cdot\|)$ can be assigned with a well-defined *regularity parameter* $\varkappa \geq 1$ in such a way that whenever $\xi^1, \xi^2, ...$ are random vectors in E which form a martingale-difference, one has

$$\mathbf{E}\left\{\|\xi^1 + ... + \xi^N\|^2\right\} \leq \varkappa \sum_{i=1}^N \mathbf{E}\{\|\xi^i\|^2\},\ N = 1, 2, ...$$

In addition, if σ_i are positive deterministic reals such that $\mathbf{E}_{|i-1}\{\exp\{\|\xi^i\|^2/\sigma_i^2\}\} \leq \exp\{1\}$ almost surely for all i, where $\mathbf{E}_{|i-1}$ stands for conditional, $\xi^1, ..., \xi^{i-1}$ being fixed, expectation, then

$$\forall (N \geq 1, \gamma \geq 0) : \text{Prob}\left\{\|\xi^1 + ... + \xi^N\| > [\sqrt{2\varkappa} + \sqrt{2}\gamma]\sqrt{\sum_{i=1}^N \sigma_i^2}\right\} \leq \exp\{-\gamma^2/3\}.$$

In addition,

1. $(E, \|\cdot\|)$ is $(\dim E)$-regular;
2. If $(E, \|\cdot\|)$ is $\varkappa$-regular, so is $(E, \|\cdot\|_Q)$, where Q is a linear authomorphism of E and $\|x\|_Q = \|Qx\|$;
3. $(\mathbf{R}^N, \|\cdot\|_2)$ is regular with $\varkappa = 1$;
4. Let E be the space of $m \times n$ block-diagonal matrices x, $m \leq n$, of a given block-diagonal structure, and let the norm on E be defined as $|x|_p = \|\sigma(x)\|_p$, where $p \geq 2$ and $\sigma(x) \in \mathbf{R}^m$ is the vector of singular values of x. Then $(E, |\cdot\|_p)$ is regular with $\varkappa = O(1)\min[p, \ln(m+1)]$. In particular, when $n \geq 3$, $(\mathbf{R}^n, \|\cdot\|_\infty)$ is $(2\ln(n))$-regular (treat vectors as diagonals of diagonal matrices), while the space $\mathbf{R}^{n\times n}$ of $n \times n$ matrices equipped with the spectral norm (maximum singular value) is $6\ln(n)$-regular;
5. If $(E_1, \|\cdot\|_1), ..., (E_K, \|\cdot\|_K)$ are $\varkappa$-regular, the pair $(E = E_1 \times ... \times E_K, \|[x^1; ...; x^K]\| = \sqrt{\sum_{k=1}^K \|x^k\|^2})$ is $2(\varkappa + 1)$-regular.

A.3 Proof of Proposition 4

1^0. Let us denote

$$\varphi_t = 8\Omega\mathcal{L}^2 + \sum_{\tau=1}^{t-1} \varsigma_\tau, \quad \varsigma_t = 3\left[\|F(\zeta_t) - F(w_t)\|_*^2 + \|F(\eta_t) - F(z_t)\|_*^2\right] \tag{84}$$

(cf. (48)). Let us show that under the premise of Proposition 4

$$\forall \Lambda \geq 0 : \quad \text{Prob}\left\{\varphi_t \geq O(1)\left[\Omega\mathcal{L}^2 + \frac{M_*^2 t}{k}\varkappa_*^2(k, \Lambda)\right]\right\} \leq \exp\{-\Lambda t\}, \tag{85}$$

where $O(1)$ is an absolute constant factor. We use the following result (see, e.g., Theorem 2.1 (iii) of [9]): let $\xi^i, ..., \xi^k$ be k independent vectors from E with $\|\xi^i\|_* \leq \sigma$ and $\mathbf{E}\{\xi^i\} = 0$, where the norm $\|\cdot\|_*$ is $\varkappa$-regular, $\varkappa \geq 1$. Then for any $u \geq 0$

$$\text{Prob}\left\{\|\sum_{i=1}^k \xi^i\|_* \geq \left[\sqrt{2\varkappa} + u\sqrt{2}\right]\sigma\sqrt{k}\right\} \leq \exp\{-u^2/2\}. \tag{86}$$

When rewriting the above bound for $\xi^i = F(\zeta^i) - F(w)$ and $\xi^i = F(\eta^i) - F(z)$ and taking into account that $\|\xi^i\|_* \leq M_*$ we obtain

$$\forall u \geq 0 : \quad \text{Prob}\left\{\|\sum_{i=1}^k \xi^i\|_*^2 \geq M_*^2 k(\sqrt{2\varkappa} + \sqrt{2}u)^2\right\} \leq \exp\{-u^2/2\}. \tag{87}$$

So, if we denote Prob_t conditional probability over $\zeta_1, \eta_1, ..., \zeta_{t-1}, \eta_{t-1}$ being fixed, we get

$$\forall u \geq 0: \quad \mathrm{Prob}_t \left\{ \varsigma_t \geq \tfrac{24M_*^2}{k}(\varkappa + u) \right\} \leq 2\exp\{-u/2\}. \tag{88}$$

When setting $\nu_t = \frac{\varsigma_t k}{24M_*^2}$, we have for the conditional expectation $\mathbf{E}_t$ over $\zeta_1, \eta_1, ..., \zeta_{t-1}, \eta_{t-1}$ being fixed and $0 \leq \alpha < 1$

$$\begin{aligned}\mathbf{E}_t \left\{ \exp\{\frac{\alpha}{2}\nu_t\} \right\} &\leq e^{\frac{\alpha\varkappa}{2}} + \frac{\alpha}{2}\int_{\varkappa}^{\infty} e^{\frac{\alpha u}{2}} \mathrm{Prob}_t\{\nu_t \geq u\} du \\ &\leq e^{\frac{\alpha\varkappa}{2}} + \alpha \int_{\varkappa}^{\infty} \exp\{-\frac{(1-\alpha)u}{2}\} du = \frac{1+\alpha}{1-\alpha}\exp\{\frac{\alpha\varkappa}{2}\}\end{aligned}$$

When choosing $\alpha_* = \frac{\exp\{1\}-1}{\exp\{1\}+1}$ we get $\mathbf{E}_t \left\{ \exp\{\frac{\alpha_*\nu_t}{2}\} \right\} \leq \exp\{\frac{\alpha_*\varkappa}{2} + 1\}$, so that

$$\begin{aligned}\mathbf{E}\left\{ \exp\{\sum\nolimits_{\tau=1}^{t} \frac{\alpha_*\nu_\tau}{2}\} \right\} &= \mathbf{E}\left\{ \mathbf{E}_t \left\{ \exp\{\sum\nolimits_{\tau=1}^{t-1} \frac{\alpha_*\nu_\tau}{2}\} \exp\{\frac{\alpha_*\nu_t}{2}\} \right\} \right\} \\ &= \mathbf{E}\left\{ \exp\{\sum\nolimits_{\tau=1}^{t-1} \frac{\alpha_*\nu_\tau}{2}\} \mathbf{E}_t \left\{ \exp\{\frac{\alpha_*\nu_t}{2}\} \right\} \right\} \leq \exp\{t(\frac{\alpha_*\varkappa}{2} + 1)\}\end{aligned}$$

Hence, when applying the Tchebychev inequality we find

$$\forall \Lambda \geq 0: \quad \mathrm{Prob}\left\{ \sum\nolimits_{\tau=1}^{t} \nu_\tau \geq t\left(\varkappa + \tfrac{2}{\alpha_*}(1+\Lambda)\right) \right\} \leq \exp\{-\Lambda t\}. \tag{89}$$

When recalling that $\varsigma_t \leq 6M_*^2$, we conclude that

$$\forall \Lambda \geq 0: \quad \mathrm{Prob}\left\{ \sum\nolimits_{\tau=1}^{t-1} \varsigma_\tau \geq \min\left[6M_*^2 t,\ \tfrac{24M_*^2 t}{k}\left(\varkappa + \tfrac{2}{\alpha_*}(1+\Lambda)\right) \right] \right\} \leq \exp\{-\Lambda t\}. \tag{90}$$

Since $\varkappa \geq 1$, $\varkappa + \frac{2}{\alpha_*}(1+\Lambda) \leq O(1)\varkappa_*^2(k,\Lambda)$, and we arrive at (85).

2^0. We have

$$\forall \lambda \geq 0: \quad \mathrm{Prob}\left\{ \frac{R_t}{t} \geq O(1)F_*\sqrt{\frac{\Omega\lambda}{kt}} \right\} \leq e^{-\lambda}. \tag{91}$$

Indeed, since $\mathcal{A}$ is skew-symmetric, i.e. $\langle \mathcal{A}z, z\rangle = 0$,

$$r_t = \langle F(\zeta_t),\, \zeta_t - w_t\rangle = \langle a + \mathcal{A}\zeta_t,\, \zeta_t - w_t\rangle = \langle a + \mathcal{A}w_t, \zeta_t - w_t\rangle = \langle F(w_t), \zeta_t - w_t\rangle.$$

Let ζ_τ^i be the i-th sample drawn when evaluating ζ_τ. We conclude that

$$\begin{aligned}\frac{R_t}{t} &= \frac{1}{t}\sum\nolimits_{\tau=1}^{t} r_t = \frac{1}{t}\sum\nolimits_{\tau=1}^{t} \langle F(w_\tau), \zeta_\tau - w_\tau\rangle = \frac{1}{t}\sum\nolimits_{\tau=1}^{t} \left\langle F(w_\tau),\, \frac{1}{k}\sum\nolimits_{i=1}^{k} \zeta_\tau^i - w_\tau \right\rangle \\ &= \frac{1}{tk}\sum\nolimits_{\tau=1}^{t}\sum\nolimits_{i=1}^{k} \langle F(w_\tau),\, \zeta_\tau^i - w_\tau\rangle = \frac{1}{tk}\sum\nolimits_{\tau=1}^{t}\sum\nolimits_{i=1}^{k} \xi_\tau^i,\end{aligned}$$

where $\xi_\tau^i := \langle F(w_\tau),\, \zeta_\tau^i - w_\tau\rangle$ is a scalar martingale-difference with $|\xi_\tau^i| \leq 2\mathcal{R}F_* \leq 2\Theta F_*$ (cf. (21)). Then by the Azuma-Hoeffding inequality [1],

$$\forall \lambda \geq 0: \quad \mathrm{Prob}\left\{ \tfrac{R_t}{t} \geq 2\Theta F_*\sqrt{\tfrac{2\lambda}{kt}} \right\} \leq e^{-\lambda}, \tag{92}$$

which implies (91). We are done – when substituting the bounds (85) and (91) into (47) we get

$$\mathrm{Prob}\left\{ \epsilon_{\mathrm{sad}}(z^t) \geq O(1)\left[\frac{\Omega\mathcal{L}}{t} + M_*\varkappa_*(k,\Lambda)\sqrt{\frac{\Omega}{kt}} + \Theta F_*\sqrt{\frac{\lambda}{kt}} \right] \right\} \leq e^{-\Lambda t} + e^{-\lambda},$$

which is (56) (recall that $\Theta = \sqrt{2\Omega}$ and $M_* \leq 2\Theta\mathcal{L}$, see (23)). □

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ℓ_1 Minimization via Randomized First Order Algorithms

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Abstract

In this paper we propose randomized first-order algorithms for solving bilinear saddle points problems. Our developments are motivated by the need for sublinear time algorithms to solve large-scale *parametric* bilinear saddle point problems where cheap online assessment of solution quality is crucial. We present the theoretical efficiency estimates of our algorithms and discuss a number of applications, primarily to the problem of ℓ_1 minimization arising in sparsity-oriented Signal Processing. We demonstrate, both theoretically and by numerical examples, that when seeking for medium-accuracy solutions of large-scale ℓ_1 minimization problems, our randomized algorithms outperform significantly (and progressively as the sizes of the problem grow) the state-of-the art deterministic methods.

1 Introduction

This paper is motivated by the desire to develop efficient *randomized* first-order methods for solving well-structured large-scale convex optimization problems. Our primary (but not the only) target is the ℓ_1-minimization problem

$$\mathrm{Opt}_p = \min_u \{\|u\|_1 : \|Au - b\|_p \leq \delta\} \quad [A = [A_1, ..., A_n] \in \mathbf{R}^{m\times n}, m, n > 2], \tag{1}$$

where $p = \infty$ ("uniform fit") or $p = 2$ ("ℓ_2-fit"). We are interested in the large-scale case, where the sizes m, n of (possibly dense) matrix A are in the range of thousands/tens of thousands. Efficient solutions to the problems of this type are of paramount importance for sparsity-oriented Signal Processing, in particular, in Compressed Sensing (see [2, 3, 6] and references therein). To give an overview of our results, here is what our approach yields for (1):

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Proposition 1.1 *Assume that* (1) *is feasible,* δ *is small enough, namely,* $2m^{\frac{1}{p}}\delta \leq \|b\|_p$. *Given* $\epsilon \in (0, \frac{1}{2}\mathrm{Opt}_p\|A\|_{1,p}]$,[1] *let our goal be to find an* ϵ*-solution to (1), that is, a point* x_ϵ *satisfying*

$$\|x_\epsilon\|_1 \leq \mathrm{Opt}_p \ \& \ \|Ax_\epsilon - b\|_p \leq \delta + \epsilon.$$

Then, for every tolerance $\chi \in (0, 1/2]$, *the outlined goal can be achieved with probability* $\geq 1 - \chi$

(i) *in the case of* $p = \infty$ *(uniform fit) – in at most*

$$O(1)\left[\frac{\sqrt{\ln(m)\ln(n)}\|A\|_{1,\infty}\mathrm{Opt}_\infty}{\epsilon}\ln\left(\frac{\sqrt{\ln(m)\ln(n)}\|A\|_{1,\infty}\mathrm{Opt}_\infty}{\chi\epsilon}\right)\right]^2$$

steps of a randomized algorithm, with computational effort per step reduced to extracting from A *two columns and two rows, given their indexes, plus "computational overhead" of* $O(1)(m+n)$ *operations.*

(ii) *in the case of* $p = 2$ *(*ℓ_2 *fit) – in at most*

$$O(1)\left[\frac{\ln(mn)\kappa(A)\|A\|_{1,2}\mathrm{Opt}_2}{\epsilon}\ln\left(\frac{\ln(mn)\kappa(A)\|A\|_{1,2}\mathrm{Opt}_2}{\chi\epsilon}\right)\right]^2, \quad \kappa(A) = \frac{\sqrt{m}\|A\|_{1,\infty}}{\|A\|_{1,2}},$$

steps of a randomized algorithm with the same as in (i) *computational effort per step.*

Furthermore, there exists a randomized preprocessing of the data $[A, b]$ *of the problem (1) of computational cost not exceeding* $O(1)mn\ln(m)$, *which ensures with probability* $\geq 1 - \chi$ *that* $\kappa(A) \leq O(1)\sqrt{\ln(mn/\chi)}$.

Note that the best known so far complexity of finding ϵ-solution to a large-scale problem (1) by a *deterministic* algorithm is *at least* $O(1)\frac{\sqrt{\ln(m)\ln(n)}\|A\|_{1,\infty}\mathrm{Opt}_\infty}{\epsilon}$ $(p = \infty)$ or $\frac{\sqrt{\ln(n)}\|A\|_{1,2}\mathrm{Opt}_2}{\epsilon}$ $(p = 2)$ steps[2] with complexity of a step dominated by the necessity to perform $O(1)$ multiplications $x \mapsto Ax$, $y \mapsto A^Ty$. When A is dense, the resulting operations count is, up to logarithmic terms, of order of $N_{\mathrm{det}} = \frac{mn}{\nu}$, where $\nu = \frac{\epsilon}{\|A\|_{1,p}\mathrm{Opt}_p}$ can be naturally interpreted as relative accuracy. For the randomized algorithms underlying Proposition 1.1, this count, again, up to logarithmic terms, is of order of $N_{\mathrm{rand}} = \frac{m+n}{\nu^2}$ (uniform fit) and $N_{\mathrm{rand}} = \frac{m+n}{\nu^2} + mn$ (ℓ_2 fit). We see that when $\nu \ll 1$ is fixed and m, n grow, the randomized algorithms eventually outperform the deterministic ones, becoming more significant as the problem size grows. Numerical results presented in Section 5 demonstrate that this acceleration is not a purely academic phenomenon and can be of real practical interest.

Our approach is based on saddle point reformulation of well-structured convex minimization problems and is applicable when the resulting saddle point problems are bilinear; in this respect, it goes back to the breakthrough paper of Nesterov [14]. The deterministic saddle point prototypes of the randomized algorithms we develop here were proposed in

[1] Here and below $\|A\|_{1,p} = \max_j \|A_j\|_p$ stands for the norm of the mapping $x \mapsto Ax$ induced by the norms $\|\cdot\|_1$ and $\|\cdot\|_p$ in the argument and the image spaces, respectively

[2] The indicated bounds are attainable, provided Opt_p is known in advance.

[11] and [12] and the prototypes of our randomization scheme were proposed in [13, Section 3.3] and [9]. In this paper, we demonstrate that in the case of a bilinear saddle point problem, a better randomization is possible. The advantage of this new randomization over those prototypes lies in the immediate possibility to assess, in a computationally cheap fashion, the quality of the resulting approximate solutions. This possibility is instrumental when solving *parametric* bilinear saddle point problems. In particular many important applications including the problems of the form (1) reduce to the class of parametric bilinear saddle point problems which we introduce and study in Section 2.2. In the hindsight, one can recognize utilizing a particular case of this randomization technique leads to the sublinear time randomized algorithm for solving matrix games due to Grigoriadis and Khachiyan [7].

The main body of this paper is organized as follows. In Section 2, we present a saddle-point-based framework for our developments together with a sample of interesting optimization problems fitting this framework. This sample includes, along with ℓ_1 minimization, the (semidefinite relaxation of the) problem of low-dimensional approximation to a collection of points in $\mathbf{R}^d$ and a specific version of the Support Vector Machine problem. Randomized algorithms for the problems fitting to our framework are developed and analyzed in Sections 3 and 4. Section 5 presents encouraging results of preliminary numerical experiments aimed at comparing the performance of the proposed randomized algorithm and a state-of-the-art deterministic algorithm as applied to large-scale ℓ_1 minimization problem. All proofs are relegated to the appendix.

2 Problems and Goals

We start with specifying and motivating two problems to be discussed in the paper and our goals.

2.1 A Bilinear Saddle Point Problem

2.1.1 The problem

The first generic problem we are interested in is a Bilinear Saddle Point (BSP) problem

$$\begin{array}{rcl} \mathrm{SV} & = & \min\limits_{z_1\in Z_1}\max\limits_{z_2\in Z_2}\phi(z_1,z_2), \\ \phi(z_1,z_2) & = & \upsilon+\langle a_1,z_1\rangle+\langle a_2,z_2\rangle+\langle z_2,Bz_1\rangle: \quad Z[=Z_1\times Z_2]\to\mathbf{R}, \end{array} \qquad (\mathcal{S})$$

where Z_i are nonempty convex compact sets in Euclidean spaces E_i, $i=1,2$. Recall that $(\mathcal{S})$ gives rise to two dual to each other convex optimization programs

$$\begin{array}{rcll} \mathrm{Opt}(P) & = & \min\limits_{z_1\in Z_1}\overline{\phi}(z_1):=\max\limits_{z_2\in Z_2}\phi(z_1,z_2) & (P) \\ \mathrm{Opt}(D) & = & \max\limits_{z_2\in Z_2}\underline{\phi}(z_2):=\min\limits_{z_1\in Z_1}\phi(z_1,z_2) & (D) \end{array} \qquad (2)$$

with $\mathrm{Opt}(P)=\mathrm{Opt}(D)=\mathrm{SV}$, and to the variational inequality : find $z_*\in Z:=Z_1\times Z_2$ such that

$$\langle F(z),z-z_*\rangle\geq 0 \ \text{ for all } z\in Z, \qquad (3)$$

where $F:\ Z \mapsto E_1 \times E_2$, is an affine monotone operator given by

$$\begin{array}{rcl} F(z_1,z_2) & = & \left[F_1(z_2) = \dfrac{\partial\phi(z_1,z_2)}{\partial z_1}; F_2(z_1) = -\dfrac{\partial\phi(z_1,z_2)}{\partial z_2}\right] = a + \mathcal{A}[z_1;z_2], \\ & & a = [a_1;-a_2],\ \ \mathcal{A} = \left[\begin{array}{c|c} & B^* \\ \hline -B & \end{array}\right], \end{array}$$

(here B^* stands for the conjugate of B). Note that $\mathcal{A}$ is skew-symmetric: $\mathcal{A}^* = -\mathcal{A}$ and

$$\langle z, \mathcal{A}z\rangle = 0\ \forall z \in E := E_1 \times E_2. \tag{4}$$

It is well known that the solutions to $(\mathcal{S})$ — the saddle points of ϕ on $Z_1 \times Z_2$ — are exactly the pairs $z = [z_1; z_2]$ comprised of optimal solutions to problems (P) and (D) in (2), same as are exactly the solutions to the variational inequality (3). We quantify the accuracy of candidate solutions $z = [z_1; z_2] \in Z$ to $(\mathcal{S})$ by the *saddle point residual*

$$\epsilon_{\text{sad}}(z) = \overline{\phi}(z_1) - \underline{\phi}(z_2) = \underbrace{\left[\overline{\phi}(z_1) - \text{Opt}(P)\right]}_{\geq 0} + \underbrace{\left[\text{Opt}(D) - \underline{\phi}(z_2)\right]}_{\geq 0}. \tag{5}$$

2.1.2 Assumptions and goal

When speaking about a BSP problem $(\mathcal{S})$, our goal is to solve the problem within a given accuracy $\epsilon > 0$, that is, to find $z^\epsilon \in Z$ such that $\epsilon_{\text{sad}}(z^\epsilon) \leq \epsilon$. Deterministic first order algorithms achieve this goal by working with the values of the associated operator F at the iterates z_t, $t = 1, 2, ...$, generated by the method. When Z is simple and the problem is large-scale, computing the values $F(z_t)$ is the "leading term" in the computational effort. Our goal in this paper is to replace relatively expensive (in the large scale case) exact values $F(z_t)$ with their computationally cheap unbiased random estimates. Specifically, we assume that

> **[P]** every point $z \in Z$ is associated with a probability distribution P_z such that
>
> - P_z is supported on Z and $\mathbf{E}_{\zeta\sim P_z}\{\zeta\} = z$;
> - Given z, we can sample from the distribution P_z.

Under these assumptions, in order to get an unbiased estimate of $F(z_t)$, it suffices to draw a $\zeta_t \sim P_{z_t}$ and to take $F(\zeta_t)$ as a desired estimate of $F(z_t)$. In order to make this approach meaningful, the computational price of generating ζ_t and subsequent computation of $F(\zeta_t)$ should be significantly less than the price of a straightforward computation of $F(z_t)$. This requirement guided us in the selection of applications to be considered below as well as in building the corresponding saddle point reformulations .

Note that the deterministic algorithms remain in the scope of our approach since we always have an option to define P_z as δ_z (the unit mass sitting at z).

2.1.3 Application example: low dimensional approximation

We consider the following problem (related to a dimension reduction problem in statistics, see, e.g., [5]): let $V = \{v_1, ..., v_N\}$ be a collection of unit vectors in $\mathbf{R}^n$, and $d < n$ be a positive integer. We want to find a linear subspace $E \subset \mathbf{R}^n$ of dimension d such that the *deviation* $\delta(V, E)$ of the collection from E — the maximal, over i, Euclidean distance between v_i and E — is as small as possible.

Letting Π^d be the family of all orthogonal projectors of $\mathbf{R}^n$ onto d-dimensional linear subspaces, the problem reads

$$\mathrm{Opt}_* = \max_{\Pi \in \Pi^d} \min_{1 \le i \le N} v_i^T \Pi v_i$$

and seems to be computationally intractable. It, however, admits the tractable relaxation

$$\mathrm{Opt} = \max_{Q \in \mathcal{P}^d} \min_{1 \le i \le N} v_i^T Q v_i, \quad \mathcal{P}^d = \{Q \in \mathbf{S}^n : \ 0 \preceq Q \preceq I, \ \mathrm{Tr}(Q) = d\}. \tag{6}$$

We refer to (6) as to the *problem of low dimensional approximation*. We clearly have $\mathrm{Opt}_* \le \mathrm{Opt} \le 1$, whence $\delta^2 := 1 - \mathrm{Opt} \le \delta_*^2 := 1 - \mathrm{Opt}_*$; note that δ_* is the deviation of V from the "ideal" d-dimensional space E_* underlying Opt_*. It is easily seen (see Lemma A.1 of Section A.1) that if Q_* is an optimal solution to the relaxation (6) and E is spanned by the d leading eigenvectors of Q_*, then $\delta(V, E) \le \sqrt{d+1}\delta_*$, that is, approximation (6) admits some quality guarantees.

Now, (6) is nothing but the BSP problem:

$$1 - \mathrm{Opt} = \min_{Q \in \mathcal{P}^d} \max_{\lambda \in \Delta_N} \left[1 - \mathrm{Tr}\left(Q \sum\nolimits_{i=1}^N \lambda_i v_i v_i^T\right)\right], \ \ \Delta_N = \left\{\lambda \in \mathbf{R}_+^N : \ \sum\nolimits_i \lambda_i = 1\right\}. \tag{7}$$

In terms of $(\mathcal{S})$, E_1 is the space $\mathbf{S}^n$ of symmetric $n \times n$ matrices with Frobenius inner product, $Z_1 = \mathcal{P}^d \subset E_1$, $E_2 = \mathbf{R}^N$, $Z_2 = \Delta_N$. The associated operator F is

$$F(z_1, z_2) = F(Q, \lambda) = \big[\underbrace{-\sum\nolimits_{i=1}^N \lambda_i v_i v_i^T}_{F_1(z_2)}; \ \underbrace{[v_1^T Q v_1; \ ...; \ v_N^T Q v_N]}_{F_2(z_1)}\big]. \tag{8}$$

Assuming that v_i are dense, the arithmetic cost of computing the value of F at a given point is $O(n^2 N)$. Now let us specify the distributions P_z, $z = (Q, \lambda) \in Z = Z_1 \times Z_2$. In order to generate $\zeta \sim P_{(Q,\lambda)}$, we proceed as follows:

- Given $Q \in \mathcal{P}^d$, we build the eigenvalue decomposition $Q = U\mathrm{Diag}\{q\}U^T$. Note that $q \in \Delta_{n,d} = \{q \in \mathbf{R}^n : \ 0 \le q_i \le 1 \, \forall i, \sum_{i=1}^n q_i = d\}$. The extreme points of $\Delta_{n,d}$ are Boolean vectors with exactly d nonzero entries. There exists a simple algorithm (see Section A.1) which, given as input a vector $q \in \Delta_{n,d}$, builds in $O(1)dn^2$ a.o. n extreme points q^j, $1 \le j \le n$, of $\Delta_{n,d}$ along with weights $\mu_j \ge 0$, $\sum_j \mu_j = 1$, such that $q = \sum_j \mu_j q^j$. We run this algorithm to build $\{q^j, \mu_j\}_{j=1}^n$, pick $\jmath \in \{1, ..., n\}$ at random, with $\mathrm{Prob}\{\jmath = j\} = \mu_j$, $j = 1, ..., n$, and set $\zeta_1^\jmath = U\mathrm{Diag}\{q^\jmath\}U^T$.

- Given $\lambda \in \Delta_N$, we pick $\imath \in \{1, ..., N\}$ at random, with $\mathrm{Prob}\{\imath = i\} = \lambda_i$, $1 \le i \le N$, and set $\zeta_2^\imath := e_\imath$, where e_i, $i = 1, ..., N$, are standard basic orths in $\mathbf{R}^N$.

- Finally, we set $\zeta = \zeta^{\imath\jmath} := [\zeta_1^\jmath; \zeta_2^\imath] \in \mathcal{P}^d \times \Delta_N$.

The family of distributions $P_{(Q,\lambda)}$ clearly satisfies [P]. The "setup costs" for sampling from $P_{(Q,\lambda)}$ reduce to those of 1) computing the eigenvalue decomposition of Q, 2) building $q^1, ..., q^n,\ \mu_1, ..., \mu_n$ (this cost is $O(n^3 + dn^2)$ a.o.) and 3) computing the "cumulative distributions" $\{\mu^j = \sum_{s=1}^j \mu_s\}_{j=1}^n$ and $\{\lambda^i = \sum_{s=1}^i \lambda_s\}_{i=1}^N$ (what amounts to $O(n+N)$ a.o.). After the setup cost is paid, a sample $(\imath, \jmath)$ can be generated at the cost of just $O(\ln(n+N))$ a.o. Now let us look at the cost of computing $F(\zeta^{\imath\jmath})$ given $\imath, \jmath$. We have

$$F(\zeta^{\imath\jmath}) = \left[-v_\imath v_\imath^T; \{v_i^T U \mathrm{Diag}\{q^\jmath\} U^T v_i\}_{i=1}^N\right].$$

Since $q^\jmath$ has just d nonzero entries, all equal to 1, let the indices of the entries be $j_1, ..., j_d$, we have $v_i^T U \mathrm{Diag}\{q^\jmath\} U^T v_i = \sum_{\ell=1}^d (U_{j_\ell}^T v_i)^2$, where U_j is j^{th} column of U. We see that computing $F(\zeta^{\imath\jmath})$ costs $O(n^2 + dnN)$ a.o. Thus, the total cost (including that of the setup) of drawing a sample ζ from $P_{(Q,\lambda)}$ and computing $F(\zeta)$ is

$$O(n^3 + dn^2 + n^2 + dnN) = O(n^3 + dnN) \ \text{ a.o.}$$

When $d \ll n \ll N$, this cost is much smaller than the cost $O(n^2 N)$ of computing $F(z)$ at a "general position" point $z = (Q, \lambda) \in Z$.

2.2 A Generalized Bilinear Saddle Point Problem

2.2.1 The problem

Assume that we are given a *single-parameter family* of bilinear saddle point problems

$$\mathrm{SV}(\rho) = \min_{z_1 \in Z_1} \max_{z_2 \in Z_2} \phi^\rho(z_1, z_2) := \phi(z_1, z_2) + \rho\psi(z_1, z_2), \tag{9}$$

where $\rho \geq 0$ is a parameter and $\phi(z_1, z_2)$, $\psi(z_1, z_2)$ are bi-affine in z_1 and z_2. The *Generalized Bilinear Saddle Point* (GBSP) problem associated with this family is, by definition, the optimization program

$$\rho_* = \max\{\rho \geq 0 : \mathrm{SV}(\rho) \leq 0\} \tag{10}$$

A highly desirable property of a GBSP problem, relative to our approach, is the convexity of $\mathrm{SV}(\rho)$ as a function of $\rho \geq 0$. To ensure this property, we make from now on the following assumption on the structure of (9):

> **[A.1]** *$Z_1 = Z_{11} \times Z_{12}$ is the direct product of two convex compact sets, and the bilinear functions $\phi(z_1, z_2)$, $\psi(z_1, z_2)$ in (9) are of the form*
>
> $$\begin{array}{rcl} \phi(z_1 = [z_{11}; z_{12}], z_2) & = & \upsilon + \langle a_{11}, z_{11}\rangle + \langle b, z_2\rangle + \langle z_2, B z_{11}\rangle, \\ \psi(z_1 = [z_{11}; z_{12}], z_2) & = & \chi + \langle a_{12}, z_{12}\rangle + \langle c, z_2\rangle + \langle z_2, C z_{12}\rangle, \end{array} \tag{11}$$
>
> *that is, $\phi(z_1, z_2)$ and $\psi(z_1, z_2)$ as functions of z_1 depend each on its own "block" of z_1, and these blocks z_{11} and z_{12}, independently of each other, run through the respective convex compact sets Z_{11} and Z_{12}.*

From now on, we denote by $F^\rho(z) = \Phi(z) + \rho\Psi(z)$ the affine monotone operator associated with ϕ^ρ according to (3).

Lemma 2.1 *In the case of* **A.1** *the function* $\mathrm{SV}(\rho)$ *given by* (9) *is convex in* $\rho \geq 0$.

From now on we assume, in addition to **A.1**, that

[**A.2**] *Function* $\mathrm{SV}(\rho)$ *given by* (9) *is nonpositive somewhere on* $\mathbf{R}_{++}$ *and tends to* $+\infty$ *as* $\rho \to +\infty$,

which implies solvability of (10) and positivity of ρ_*.

The goal. Given a GBSP problem (9) – (10) and a tolerance $\epsilon > 0$, our goal will be to find an ϵ-solution to the problem, that is, a pair ρ_ϵ, $z_1^\epsilon \in Z_1$ such that

$$\rho_\epsilon \geq \rho_* \text{ and } \max_{z_2 \in Z_2} \phi^{\rho_\epsilon}(z_1^\epsilon, z_2) \leq \rho_\epsilon \epsilon \tag{12}$$

We are about to point out several important application examples for GBSP problem.

2.2.2 Application example: ℓ_1 minimization with ℓ_p fit

The problem of interest is

$$\mathrm{Opt} = \min_x \{\|x\|_1 : \|Ax - b\|_p \leq \delta\} \quad [A \in \mathbf{R}^{m \times n}]. \tag{13}$$

Different versions of this problem arise in sparsity-oriented Signal Processing and Compressed Sensing. Setting $x = \rho u$, $\|u\|_1 \leq 1$, we rewrite the problem equivalently as

$$\frac{1}{\mathrm{Opt}} = \rho_* = \max\left\{\rho : \min_{\|u\|_1 \leq 1} \|Au - \rho b\|_p - \rho\delta \leq 0\right\}, \tag{14}$$

or, which is the same as

$$\frac{1}{\mathrm{Opt}} = \rho_* = \max\left\{\rho : \ \Phi(\rho) = \min_{\|u\|_1 \leq 1,\, \|v\|_p \leq 1} \|Au - \rho b - \rho\delta v\|_\infty \leq 0\right\}.$$

This is nothing but the GBSP problem (9) with $SV(\rho) = \phi^\rho(z),\ z \in Z$, given by

$$\begin{array}{c} \phi^\rho(z_1(=[z_{11}; z_{12}]), z_2) = z_2^T J_m^T \left(AJ_n z_{11} - \rho[b + \delta z_{12}]\right), \\ Z_1 = \underbrace{\Delta_{2n}}_{Z_{11}} \times \underbrace{\{z_{12} \in \mathbf{R}^m : \|z_{12}\|_p \leq 1\}}_{Z_{12}},\ Z_2 = \Delta_{2m}, \end{array} \tag{15}$$

where we denote $J_k = [I_k, -I_k]$, I_k being $k \times k$ identity matrix. This problem satisfies [**A.1**]; when $\|b\|_p > \delta$ (otherwise the optimal solution to (13) is $x = 0$), the problem satisfies [**A.2**] as well. The associated saddle value function is

$$\begin{array}{rcl} \mathrm{SV}(\rho) & = & \max\limits_{z_2 \in \Delta_{2m}} \min\limits_{z_{11} \in \Delta_{2n},\, z_{12} \in Z_{12}} \left[z_2^T J_m^T \left(AJ_n z_{11} - \rho[b - \delta z_{12}]\right)\right] \\ & = & \max\limits_{w = J_m z_2,\, z_2 \in \Delta_{2m}} \min\limits_{u = J_n z_1,\, z_1 \in \Delta_{2n}} \min\limits_{z_{12} \in Z_{12}} \left[w^T (Au - \rho[b + \delta z_{12}])\right] \\ & = & \max\limits_{\|w\|_1 \leq 1} \min\limits_{\|u\|_1 \leq 1} \min\limits_{\|v\|_p \leq 1} \left[w^T (Au - \rho[b + \delta v])\right] = \Phi(\rho). \end{array}$$

Suppose that we are given an ε-solution ρ_ε, $z_1^\varepsilon = [z_{11}^\varepsilon; z_{12}^\varepsilon]$ to the problem (12), (15) with $\varepsilon = \epsilon m^{-\frac{1}{p}}$. When setting $x_\varepsilon = \rho_\varepsilon^{-1} J_n z_{11}^\varepsilon$ and $v_\varepsilon = z_{12}^\varepsilon$ we get an approximate solution to (13) such that

$$\|x_\epsilon\|_1 \leq \text{Opt} \ \& \ \|Ax_\epsilon - b\|_p \leq \|\delta v_\varepsilon\|_p + \|Ax_\varepsilon - b - \delta v_\varepsilon\|_p \leq \delta + \varepsilon m^{1/p} = \delta + \epsilon.$$

Finally, we associate with $z = [z_{11}; z_{12}; z_2] \in Z = Z_1 \times Z_2$ distribution P_z satisfying [P], namely, as follows. Note that for $z \in Z$, z_{11} and z_2 are vectors from the standard simplices and thus can be considered as probability distributions on the corresponding index sets $\{1, ..., 2n\}$, $\{1, ..., 2m\}$. To generate $\zeta = [\zeta_{11}; \zeta_{12}; \zeta_2] \sim P_z$, we draw at random index $\imath$ from the distribution z_{11} and make $[\zeta_{11}]_\imath = 1$ the only nonzero entry in ζ_{11}. ζ_2 is built similarly, with z_2 in the role of z_{11}, and ζ_{12} is nothing but z_{12}. It is immediately seen that it takes just $O(m+n)$ a.o. to generate a sample $\zeta \sim P_z$ and to compute the vector $F^\rho(\zeta)$.

It is worth to mention that in the important case $p = \infty$ the construction of the GBSP which corresponds to (13) can be substantially simplified. Indeed, one can see immediately that for $p = \infty$ (14) is equivalent to the GBSP problem on the direct product of just two unit ℓ_1-balls (since $\|Az_1 - b\|_\infty = \max\limits_{\|z_2\|_1 \leq 1} z_2^T(Az_1 - b)$). It is more convenient to pass from ℓ_1-balls to the standard simplexes, as it was done in the case of (15). The resulting GBSP problem is given by

$$\begin{array}{c} \phi^\rho(z_1, z_2) = z_2^T J_m^T A J_n z_1 - \rho z_2^T J_m^T b - \rho\delta, \\ Z_1 = Z_{11} = \Delta_{2n},\ Z_{12} = \{0\}, Z_2 = \Delta_{2m}, \end{array} \tag{16}$$

and satisfies **[A.1]** and **[A.2]** when $\delta < \|b\|_\infty$.

2.2.3 Application example: ℓ_1 Support Vector Machine.

One of the "statistically solid" SVM models (see [4] and [16, Section 2.3.3]) is as follows. We are given a *training sample* — a matrix $X \in \mathbf{R}^{m\times n}$ with rows representing feature vectors, and a vector $y \in \mathbf{R}^m$ with entries ± 1 representing labels. Setting $R = \|X\|_\infty := \max_{i,j} |X_{ij}|$, $Y = \text{Diag}\{y\}$ and $\mathbf{1} = [1; ...; 1] \in \mathbf{R}^m$, we want to solve the margin optimization problem

$$\text{Opt} = \max_{w,b,\rho} \left\{\rho : \|w\|_1 \leq 1, \|[\rho\mathbf{1} - Y[Xw + b\mathbf{1}]]_+\|_2 \leq R\right\}, \tag{17}$$

where $[z]_+$ is the vector with coordinates $[z_i]_+ := \max[z_i, 0]$. We can convert this problem into a GBSP one as follows. Observe first that

$$\begin{array}{rcl} \text{Opt} & = & \max\left\{\rho : \min\limits_{\|w\|_1\leq 1,\, \|v\|_2 \leq 1} \max\limits_{1\leq i\leq m} [\rho\mathbf{1} - Y[Xw + b\mathbf{1}] - Rv]_i \leq 0\right\} \\ & = & \max\left\{\rho : \min\limits_{\|w\|_1\leq 1,\, \|v\|_2 \leq 1, b} \max\limits_{u\in\Delta_m} u^T[\rho\mathbf{1} - Y[Xw + b\mathbf{1}] - Rv] \leq 0\right\}. \end{array}$$

Assuming that the entries of y contain both 1 and -1 and setting $\Delta_m^+ = \{u \in \Delta_m : y^T u = 0\}$, we have $\min\limits_b \max\limits_{u\in\Delta_m} u^T[\rho\mathbf{1} - Y[Xw + b\mathbf{1}] - Rv] = \max\limits_{u\in\Delta_m^+} u^T(\rho\mathbf{1} - YXw - Rv)$. Hence,

when setting $w = J_n s$, we come to

$$\text{Opt} \quad = \quad \max\left\{\rho : \min_{s\in\Delta_{2n},\|v\|_2\le 1} \max_{u\in\Delta_m^+} u^T[\rho\mathbf{1} - YXJ_n s - Rv] \le 0\right\}.$$

We see that (17) is equivalent to the GBSP problem given by

$$\begin{array}{c}\phi^\rho(z_1 = [z_{11} = s; z_{12} = v], z_2 = u) = u^T[\rho\mathbf{1} - YXJ_n s - Rv],\\ Z_1 = \{[s; v] : s \in \Delta_{2n}, \|v\|_2 \le 1\}, Z_2 = \Delta_m^+.\end{array}$$

Note that this problem clearly satisfies $\mathbf{A.1-2}$. Besides this, $\sqrt{m}\max_i[x_i]_+ \ge \|[x]_+\|_2$, so that an ϵ-solution $(\rho_\epsilon, z_1^\epsilon = [s^\epsilon; v^\epsilon])$ to the GBSP problem induces the approximate solution $(\rho_\epsilon, w^\epsilon = J_n s^\epsilon, b^\epsilon)$ to (17) such that

$$\rho_\epsilon \ge \text{Opt} \ \& \ \|[\rho_\epsilon\mathbf{1} - Y[Xw^\epsilon + b^\epsilon\mathbf{1}]]_+\|_2 \le R + \sqrt{m}\rho_\epsilon\epsilon,$$

whence $(\rho_\epsilon(1-\sqrt{m}\epsilon), w^\epsilon, b^\epsilon)$ is a feasible solution to (17) with the value of the objective $\ge (1-\sqrt{m}\epsilon)\text{Opt}$.

Finally, we associate with $z = [z_{11} = s; z_{12} = v; z_2 = u] \in Z = Z_1 \times Z_2$ a distribution P_z on $Z = Z_1 \times Z_2$ defined as follows. To generate $\zeta = [\zeta_{11}; \zeta_{12}; \zeta_2] \sim P_z$, we pick at random $\imath \in \{1, ..., 2n\}$, with $\text{Prob}\{\imath = i\} = [z_{11}]_i$, $1 \le i \le 2n$, and set $\zeta_{11} = e_\imath$, e_i being the basic orths in $\mathbf{R}^{2n}$. We always set $\zeta_{12} = v$. To generate ζ_2, we act as follows. Let $I = \{i : y_i = 1\}$, $J = \{i : y_i = -1\}$, and let $p := \sum_{i\in I} u_i = \sum_{j\in J} u_j$ (recall that $\sum_i y_i u_i = 0$, that is, $\sum_{i\in I} u_i = \sum_{j\in J} u_j$). Note that $p \le 1/2$ due to $\sum_{j=1}^m u_j \le 1$. We first flip a coin with probability $1-2p$ to get head; if head appears, we set $\zeta_2 = 0$. If tail appears, we pick at random $\imath \in I$ with $\text{Prob}\{\imath = i\} = u_i/p$, $i \in I$, pick at random $\jmath \in J$ with $\text{Prob}\{\jmath = j\} = u_j/p$, $j \in J$, and set $\zeta_2 = \frac{1}{2}[e_\imath + e_\jmath]$, e_i being the basic orths in $\mathbf{R}^m$. It is immediately seen that P_z satisfies [P], and that it takes just $O(m+n)$ a.o. to generate a sample $\zeta \sim P_z$ and to compute the vector $F^\rho(\zeta)$.

3 Solving Bilinear Saddle Point Problem

We are about to present two randomized first order methods for solving BSPs and hence will be utilized in solving GBSPs — the *Stochastic Approximation* (SA) and the *Stochastic Mirror Prox* (SMP) algorithms, which are the randomized versions of the methods proposed in [11] and [12] respectively. Both SA and SMP are directly applicable to a BSP problem, and this is the situation we are about to consider here; the GBSP case will be considered in Section 4.

3.1 The Setup

Both SA and SMP algorithms are aimed at solving a BSP problem $(\mathcal{S})$. The setup for these methods is given by

- a norm $\|\cdot\|$ on the Euclidean space E where the domain $Z = Z_1 \times Z_2$ of $(\mathcal{S})$ lives, along with the conjugate norm $\|\zeta\|_* = \max_{\|z\|\le 1}\langle\zeta, z\rangle$;

- a *distance-generating function* (d.g.f.) $\omega(z)$ which is convex and continuous on Z, admits continuous on the set $Z^o = \{z \in Z : \partial\omega(z) \neq \emptyset\}$ selection $\omega'(z)$ of subgradient (here $\partial\omega(x)$ is a subdifferential of $\omega\big|_Z$ taken at z), and is strictly convex with modulus 1 w.r.t. $\|\cdot\|$:

$$\forall z', z'' \in Z^o : \langle \omega'(z') - \omega'(z''), z' - z'' \rangle \geq \|z' - z''\|^2.$$

  We shall refer to the latter property as to *compatibility* of $\omega(\cdot)$ and $\|\cdot\|$.

A d.g.f. ω gives rise to several important for us entities:

1. *Bregman distance* $V_z(u) = \omega(u) - \omega(z) - \langle \omega'(z), u - z \rangle$, where $z \in Z^o$ and $u \in Z$;
2. *Prox-mapping* $\mathrm{Prox}_z(\xi) = \mathrm{argmin}_{w \in Z} \{\langle \xi, w \rangle + V_z(w)\} : E \to Z^o$; here $z \in Z^o$ is a "prox center;"
3. "ω-center" $z_\omega = \mathrm{argmin}_{z \in Z} \omega(z) \in Z^o$ of Z and the quantities

$$\Omega = \max_{z \in Z} V_{z_\omega}(z) \leq \max_{z \in Z} \omega(z) - \min_{z \in Z} \omega(z), \quad \Theta = \sqrt{2\Omega}. \tag{18}$$

In the sequel, we set

$$\mathcal{R} := \max_{z \in Z} \|z - z_\omega\| \leq \Theta, \tag{19}$$

where the concluding inequality follows from the fact that for every $z \in Z$ one has $\frac{1}{2}\|z - z_\omega\|^2 \leq V_{z_\omega}(z)$ by strong convexity of $\omega(\cdot)$. We also denote by $\mathcal{L}$ the $(\|\cdot\|, \|\cdot\|_*)$-Lipschitz constant of F:

$$\|F(z) - F(z')\|_* = \|\mathcal{A}(z - z')\|_* \leq \mathcal{L}\|z - z'\|, \quad \forall z, z'; \tag{20}$$

and set

$$M_* = \max_{z, z' \in Z} \|F(z) - F(z')\|_* \leq 2\mathcal{R}\mathcal{L} \leq 2\Theta\mathcal{L}, \tag{21}$$

$$F_* = \max_{z \in Z} \|F(z)\|_* \leq \|a\|_* + M_* \leq \|a\|_* + 2\Theta\mathcal{L}. \tag{22}$$

3.2 The SA and SMP Algorithms

Assume we have access to an "oracle" $\mathcal{O}$ which, at i-th call ($i = 1, 2, ...$), returns a vector $\xi_i \in E$ (this vector can be random with distribution depending on previous calls and, more generally, on the history of our computational process before the call). This oracle gives rise to two conceptual algorithms:

$$\begin{array}{ll} (a): & z_1 = z_\omega; \{z_t, \xi_t\} \mapsto \{z_{t+1} = \mathrm{Prox}_{z_t}(\gamma_t \xi_t), \xi_{t+1}\},\ t = 1, 2, ... \\ (b): & z_1 = z_\omega; \{z_t, \xi_{2t-1}\} \mapsto \{w_t = \mathrm{Prox}_{z_t}(\gamma_t \xi_{2t-1}), \xi_{2t}\} \mapsto \{z_{t+1} = \mathrm{Prox}_{z_t}(\gamma_t \xi_{2t}), \xi_{2t+1}\}, \\ & t = 1, 2, ... \end{array} \tag{23}$$

here $\gamma_1, \gamma_2, ...$ are positive stepsizes defined in a non-anticipative fashion, that is, γ_t depends on oracle's answers obtained prior to step t (i.e., γ_t depends solely on $\xi_1, ..., \xi_{t-1}$ in the case of (a), and solely on $\xi_1, ..., \xi_{2t-2}$ in the case of (b)). We refer to (23.a,b) as the Stochastic Approximation (SA) and Stochastic Mirror Prox (SMP) schemes, respectively. We will consider two implementations of these schemes, the *basic* and the *advanced* ones.

3.2.1 Basic implementation

Recall that we have associated with $(\mathcal{S})$ the affine operator $F(z) : Z \to E$ given by (3), and with every point $z \in Z$ — a probability distribution P_z supported on Z satisfying $\mathbf{E}_{\zeta\sim P_z}\{\zeta\} = z$. Suppose that

- the stepsizes $\gamma_t > 0$ are chosen in a non-anticipating fashion such that $\gamma_1 \geq \gamma_2 \geq ...$;
- in SA: ζ_t is drawn at random from the distribution P_{z_t}, and $\xi_t = F(\zeta_t)$;
- in SMP: $\xi_{2t-1} = F(\eta_t)$ with η_t drawn at random from the distribution P_{z_t}, and $\xi_{2t} = F(\zeta_t)$ with ζ_t drawn at random from the distribution P_{w_t}.

The approximate solution generated by the short-step SA/SMP in course of $t = 1, 2, ...$ steps is

$$z^t = t^{-1} \sum_{\tau=1}^{t} \zeta_\tau. \tag{24}$$

3.2.2 Advanced implementation

In Advanced implementation of SA and SMP, same as in the Basic one, the stepsizes $\gamma_t > 0$ still are chosen in a non-anticipating fashion, but the restriction $\gamma_1 \geq \gamma_2 \geq ...$ is now lifted. To explain how the oracle is built, observe that if $u \in Z$, then

$$\mathbf{E}_{\zeta\sim P_u}\{\langle F(\zeta), \zeta - u\rangle\} = 0$$

(recall that $F(z) = a + \mathcal{A}z$ with skew symmetric $\mathcal{A}$ and that $\mathbf{E}_{\zeta\sim P_u}\{\zeta\} = u$). It follows that given u and generating one by one independent samples $\eta^s \sim P_u$, $s = 1, 2, ...$, one with probability 1 eventually generates ζ such that

$$\langle F(\zeta), \zeta - u\rangle \leq 0. \tag{25}$$

At step t of SA, in order to define ξ_t, the oracle draws one by one samples $\eta^s \sim P_{z_t}$, $s = 1, 2, ...$, until a sample $\zeta_t := \eta^s$ satisfying (25) with $u = z_t$ is generated; when it happens, the oracle returns $\xi_t = F(\zeta_t)$. At a step t of SMP, the oracle is invoked twice, first to generate $\xi_{2t-1} = F(\eta_t)$, and then to generate $\xi_{2t} = F(\zeta_t)$. ξ_{2t-1} is generated exactly as in the basic implementation — by drawing a sample $\eta_t \sim P_{z_t}$ and returning $\xi_{2t-1} = F(\eta_t)$. To generate ξ_{2t}, the oracle draws one by one samples $\eta^s \sim P_{w_t}$, $s = 1, 2, ...$, until a sample $\zeta_t = \eta^s$ satisfying (25) with $u = w_t$ is generated; when it happens, the oracle returns $\xi_{2t} = F(\zeta_t)$.

Finally, in the advanced implementation we replace the rule (24) for generating approximate solutions with the rule

$$z^t = \frac{1}{\sum_{\tau=1}^{t} \gamma_\tau} \sum_{\tau=1}^{t} \gamma_\tau \zeta_\tau. \tag{26}$$

3.2.3 Quantifying quality of approximate solutions

Observe that by construction at a step τ both ζ_τ and $F(\zeta_\tau)$ become known. Recalling that F is affine, it follows that after t steps we have at our disposal both the approximate solution $z^t = [z_1^t; z_2^t]$ and the vector $F(z^t)$. As a result, with both Basic and Advanced implementations of both SA and SMP, after $t = 1, 2, ...$ steps we have at our disposal the quantities

$$\overline{\phi}(z_1^t) = \upsilon + \langle a_1, z_1^t \rangle + \max_{z_2 \in Z_2} \langle z_2, -F_2(z_1^t) \rangle, \ \underline{\phi}(z_2^t) = \upsilon + \langle a_2, z_2^t \rangle + \min_{z_1 \in Z_1} \langle z_1, F_1(z_2^t) \rangle \quad (27)$$

(see (3)) and consequently we know the residual $\epsilon_{\text{sad}}(z^t) = \overline{\phi}(z^t) - \underline{\phi}(z^t)$ of the current approximate solution z^t. As we shall see in Section 4, this feature of our algorithms becomes instrumental when solving GBSP problems.[3] This is in sharp contrast with the prototypes of the SA and the SMP proposed, respectively, in [13, Section 3.3] and [9]. The approximate solutions z^t of those algorithms were computed according to the formula (26), but with z_τ [13] or w_τ [9] in the role of ζ_τ. As a result, in the prototype algorithms there is no computationally cheap way to quantify the quality of approximate solutions.

3.2.4 Efficiency estimates for Basic implementation

The accuracy bounds for Basic SA and SMP algorithms are given by the following

Proposition 3.1 *Let the BSP problem $(\mathcal{S})$ be solved by the short-step SA or SMP algorithm with positive stepsizes $\gamma_1 \geq \gamma_2 \geq ...$ chosen in a non-anticipative fashion. Then*

(i) *For every $t \geq 1$, for both SA and SMP one has*

$$\epsilon_{\text{sad}}(z^t) \ \leq \ t^{-1} \left[\gamma_t^{-1} \Omega + R_t + S_t \right], \ R_t := \sum_{\tau=1}^{t} r_\tau, \ S_t := \sum_{\tau=1}^{t} s_\tau, \quad (28)$$

where

$$r_t = \begin{cases} \langle F(\zeta_t), \zeta_t - z_t \rangle & \text{in the case of SA,} \\ \langle F(\zeta_t), \zeta_t - w_t \rangle & \text{in the case of SMP,} \end{cases}$$

$$s_t = \begin{cases} \langle F(\zeta_t), z_t - z_{t+1} \rangle - \gamma_t^{-1} V_{z_t}(z_{t+1}), & \text{in the case of SA,} \\ \langle F(\zeta_t), w_t - z_{t+1} \rangle - \gamma_t^{-1} V_{z_t}(z_{t+1}), & \text{in the case of SMP.} \end{cases}$$

We have

$$s_t \leq \begin{cases} \frac{\gamma_t}{2} \|F(\zeta_t)\|_*^2, & \text{in the case of SA,} \\ \frac{\gamma_t}{2} \|F(\zeta_t) - F(\eta_t)\|_*^2 - \frac{1}{2\gamma_t} \|w_t - z_t\|^2, & \text{in the case of SMP,} \end{cases} \quad (29)$$

with

$$s_t \leq \begin{cases} \frac{\gamma_t}{2} F_*^2, & \text{in the case of SA,} \\ \frac{\gamma_t}{2} M_*^2, & \text{in the case of SMP.} \end{cases} \quad (30)$$

[3] Of course, computing the quantities in (27) is not completely costless; note, however, that the cost of this computation is dominated by the cost of computing the prox-mapping(s) at a step and thus is a small fraction of the overall computational effort.

In particular, if the stepsizes $\gamma_t > 0$ satisfy $S_t \leq \Omega/\gamma_t$, $t = 1, 2, ...$, then

$$\epsilon_{\rm sad}(z^t) \leq \frac{2\Omega}{t\gamma_t} + \frac{R_t}{t}. \tag{31}$$

(ii) *Further, $\mathbf{E}\{R_t\} = 0$, and in the case of SMP, under additional assumption that*

$$\gamma_t \leq (\sqrt{3}\mathcal{L})^{-1}, \tag{32}$$

we have

$$s_t \leq \frac{3\gamma_t}{2}\left[\|\mathcal{A}(\zeta_t - w_t)\|_*^2 + \|\mathcal{A}(\eta_t - z_t)\|_*^2\right], \tag{33}$$

so that $\mathbf{E}\{s_t\} \leq 3\gamma_t\sigma^2$, where

$$\sigma^2 = \sup_{z\in Z} \mathbf{E}_{\zeta\sim P_z}\left\{\|\mathcal{A}(\zeta - z)\|_*^2\right\} \leq M_*^2. \tag{34}$$

In particular, if the stepsizes $\gamma_t > 0$ satisfy $\mathbf{E}\{S_t\} \leq \Omega/\gamma_t$ for $t = 1, 2, ...$, then

$$\mathbf{E}\{\epsilon_{\rm sad}(z^t)\} \leq \frac{2\Omega}{t\gamma_t}.$$

The bound of Proposition 3.1 allows to easily conceive stepsize policies. Let us start with *offline* policies, where γ_t are chosen in advance deterministic reals. If the number of steps N is fixed in advance, one can use constant stepsizes $\gamma_1 = ... = \gamma_N = \gamma$. In particular, when choosing

$$\gamma = \begin{cases} \frac{1}{F_*}\sqrt{\frac{2\Omega}{N}}, & \text{in the case of SA} \quad (a) \\ \min\left\{\frac{1}{\sigma}\sqrt{\frac{\Omega}{3N}}, \frac{1}{\sqrt{3}\mathcal{L}}\right\}, & \text{in the case of SMP} \quad (b) \end{cases} \tag{35}$$

(by (30), (22) this choice implies that $\mathbf{E}\{S_t\} \leq \Omega/\gamma_t$, $1 \leq t \leq N$), Proposition 3.1 implies the efficiency bound

$$\mathbf{E}\{\epsilon_{\rm sad}(z^N)\} \leq \begin{cases} F_*\sqrt{\frac{2\Omega}{N}}, & \text{in the case of SA} \quad (a) \\ \max\left\{2\sigma\sqrt{\frac{3\Omega}{N}}, \frac{2\sqrt{3}\Omega\mathcal{L}}{N}\right\}, & \text{in the case of SMP} \quad (b) \end{cases} \tag{36}$$

When the number of steps is not fixed in advance, one can use the decreasing stepsizes

$$\forall t \geq 1, \;\; \gamma_t = \begin{cases} \frac{1}{F_*}\sqrt{\frac{\Omega}{t}}, & \text{in the case of SA,} \\ \min\left\{\frac{1}{\sigma}\sqrt{\frac{\Omega}{6t}}, \frac{1}{\sqrt{3}\mathcal{L}}\right\}, & \text{in the case of SMP,} \end{cases} \tag{37}$$

which result in the accuracy bound

$$\forall t \geq 1, \;\; \mathbf{E}\{\epsilon_{\rm sad}(z^t)\} \leq \begin{cases} 2F_*\sqrt{\frac{\Omega}{t}}, & \text{in the case of SA} \quad (a) \\ \max\left\{2\sigma\sqrt{\frac{6\Omega}{t}}, \frac{2\sqrt{3}\Omega\mathcal{L}}{t}\right\}, & \text{in the case of SMP} \quad (b) \end{cases} \tag{38}$$

completely similar to (36).

3.2.5 Online stepsize policies

From theoretical viewpoint, the main advantage of the outlined versions of SA and SMP with the "theoretically optimal" offline stepsize policies (35) and (37) are the explicit (and in fact — the best known under circumstances) efficiency estimates (36), (38). While they may appear attractive also from the practical viewpoint because of their apparent simplicity, their use may present several disadvantages: the quantity σ involved in the stepsize computation may not be available at hand and should be evaluated. Besides this, these policies are offline and worst-case oriented; we would prefer more flexible on line adjustable stepsizes.

A natural way to adjust the stepsizes online would be to choose at each step $t \geq 1$ the largest $\gamma_t \leq \gamma_{t-1}$ ensuring the balance $\Omega/\gamma_t \geq S_t$, and thus the bound (31). This idea cannot be implemented "as is," since the stepsize policy should be non-anticipative, while s_t is not yet available when γ_t is computed. This difficulty can be easily circumvented by using instead of s_t its a priori upper bound, which is either $\frac{\gamma_t}{2}F_*$ for the SA algorithm or $\frac{\gamma_t}{2}M_*^2$ for the SMP, see (29). Specifically, consider the online policy of choosing $\gamma_t,\ t \geq 1$ as follows:

$$\Omega\gamma_t^{-2} = \begin{cases} 2\sum_{\tau=1}^{t-1}\gamma_\tau^{-1}[s_\tau]_+ + F_*^2 & \text{in the case of SA,} \\ 2\sum_{\tau=1}^{t-1}\gamma_\tau^{-1}[s_\tau]_+ + 8\Omega\mathcal{L}^2 & \text{in the case of SMP,} \end{cases} \tag{39}$$

where we set $\sum_{\tau=1}^{0}\gamma_\tau^{-1}[s_\tau]_+ = 0$. With this policy, one clearly has $\gamma_1 \geq \gamma_2 \geq ....$

Proposition 3.2 *Let positive stepsizes $\gamma_t,\ t = 1, 2, ...$ of the Basic SA/SMP implementation be chosen according to (39). Then the approximate solution z^t satisfies*

$$\epsilon_{\text{sad}}(z^t) \leq \frac{(1+\sqrt{2})\Omega}{t\gamma_t} + \frac{R_t}{t}. \tag{40}$$

As a consequence, we have

$$\epsilon_{\text{sad}}(z^t) \leq \begin{cases} \frac{(1+\sqrt{2})\sqrt{\Omega}}{t}\left(F_*^2 + \sum_{\tau=1}^{t-1}\|F(\zeta_\tau)\|_*^2\right)^{1/2} + \frac{R_t}{t}, & \text{in the case of SA} \quad (a) \\ \frac{(1+\sqrt{2})\sqrt{\Omega}}{t}\left(8\Omega\mathcal{L}^2 + \sum_{\tau=1}^{t-1}\varsigma_\tau\right)^{1/2} + \frac{R_t}{t} & \\ \qquad \leq \frac{7\Omega\mathcal{L}}{t} + \frac{R_t}{t} + \frac{(1+\sqrt{2})\sqrt{\Omega}}{t}\sqrt{\sum_{\tau=1}^{t-1}\varsigma_\tau}, & \text{in the case of SMP} \quad (b) \end{cases} \tag{41}$$

where

$$\varsigma_t = 3\left[\|F(\zeta_t) - F(w_t)\|_*^2 + \|F(\eta_t) - F(z_t)\|_*^2\right]. \tag{42}$$

Recalling that $\mathbf{E}\{R_t\} = 0$ and $\mathbf{E}\{\varsigma_t\} \leq 6\sigma^2$ (see (34)), we arrive at

Corollary 3.1 *Under the premise of Proposition 3.2, for the SMP algorithm one has*

$$\mathbf{E}\{\epsilon_{\text{sad}}(z^t)\} \leq \frac{7\Omega\mathcal{L}}{t} + \frac{6\sqrt{\Omega}\sigma}{\sqrt{t}}. \tag{43}$$

Note that the bounds (41.a) and (43) within an absolute constant factor coincide with the respective bounds in (38), that is, our online stepsizes policy (which, in contrast to (37), does not require knowledge of σ) is not worse that the "theoretically optimal" stepsize policies underlying (38).

3.2.6 Discussion

Since $F_* \geq \mathcal{RL} \geq \sigma/2$ (cf. (19)), the SA efficiency estimate (38.a) is at most within an absolute constant factor better than the corresponding estimate for the SMP. Besides this, the SMP bound (38.b) says that when the noise level σ of the oracle is small enough (specifically, $\sigma^2 = O\left(\frac{\Omega\mathcal{L}^2}{N}\right)$), then $\mathbf{E}\{\epsilon_{\text{sad}}(z^t)\} \leq O(1)\frac{\Omega\mathcal{L}}{N}$, which, modulo expectation of the residual instead of the residual itself, coincides with the best known so far efficiency estimate of the deterministic first order algorithms solving bilinear saddle point problems. On the other hand, we do have a possibility to make σ small. The trivial way to do so is to use $P_z = \delta_z$, which results in $\sigma = 0$ and makes SMP a version of the Deterministic Mirror Prox algorithm (DMP) proposed in [12]. Another, more attractive, option to control σ is as follows. Given the family of distributions P_z supported on Z and such that $\mathbf{E}_{\zeta\sim P_z}\{\zeta\} = z$, and a positive integer k, we can convert P_z into the family of distributions $P_z^{(k)}$ with the same property as follows: in order to generate a random vector $\zeta \sim P_z^{(k)}$ and to compute $F(\zeta)$, we draw a k-element sample $\zeta^1, ..., \zeta^k$ from the distribution P_z, compute $F(\zeta^1), ..., F(\zeta^k)$ and then set $\zeta = \frac{1}{k}\sum_{i=1}^k \zeta^i$, so that

$$F(\zeta) = \frac{1}{k}\sum_{i=1}^k F(\zeta^i).$$

If, as in the examples of Section 2, drawing $\zeta^i \sim P_z$ and computing $F(z^i)$ is much cheaper than computing $F(z)$, the outlined procedure with a "reasonably large" value of k is still significantly cheaper than the direct computation of $F(z)$. At the same time, for "good enough" norms $\|\cdot\|_*$, passing from P_z to $P_z^{(k)}$ can significantly reduce the noise level σ. Specifically, given a norm $\|\cdot\|_*$ on a finite-dimensional Euclidean space E, one can associate with it its *regularity parameter* $\varkappa \geq 1$ (see Section 2.2, [8] for details) to ensure the following: whenever $k > 0$ is an integer and $\xi^1, ..., \xi^k$ are independent vectors from E with $\mathbf{E}\{\xi^i\} = 0$ and $\mathbf{E}\{\|\xi^i\|_*^2\} \leq \alpha_i^2$ and $\alpha = \max_i \alpha_i$, for $\xi = \frac{1}{k}\sum_{i=1}^k \xi_i$ it holds

$$\mathbf{E}\{\|\xi\|_*^2\} \leq \min\left[\frac{1}{k}, \frac{\varkappa}{k^2}\right]\sum_{i=1}^k \alpha_i^2 \leq \min\left[1, \frac{\varkappa}{k}\right]\alpha^2.$$

Suppose now that when running SMP we sample ζ_t, η_t from the distributions $P_z^{(k)}$ for some $k > 0$. It follows that if $\|\cdot\|_*$ is $\varkappa$-regular with certain $\varkappa$, then, passing from P_z to $P_z^+ = P_z^{(k)}$, we can reduce the "original" value of σ to the value $\sigma^+ = \min[1, \sqrt{\frac{\varkappa}{k}}]\sigma$. We shall see in a while that in the applications we have mentioned so far, $\varkappa$ is "small" — at most logarithmic in $\dim Z$. The bottom line is that there is a tradeoff between the computational cost of a call to a stochastic oracle and the noise level σ. Consequently, in the case of SMP, it is possible to tradeoff the computational effort per iteration and the iteration count to obtain an approximate solution of the desired expected quality, and we can use this tradeoff in order to save on the overall amount of computations. This option (which is the major advantage of SMP as compared to SA) is especially attractive when among the two components of our computational effort per iteration — one related to

computing η_t, ζ_t, $F(\eta_t)$ $F(\zeta_t)$, and the other aimed at computing the prox mappings – the second component is essentially more significant than the first one. In such a situation, we basically can only gain by passing from P_z to $P_z^{(k)}$ with k chosen to balance the outlined two components of the computational effort.

3.2.7 Large deviations

In the above efficiency estimates, say, in (43), we upper-bounded the *expected* inaccuracy of approximate solutions z^t. In fact, one can get exponential upper bounds on probabilities of large deviations for the inaccuracy of the approximate solution. Though we do not need such bounds to access the inaccuracy of solutions, they are still useful to provide theoretical guarantees for the complexity of our algorithms (cf. Theorem 4.1 in the next section).

For the sake of definiteness, when presenting large deviation results, we restrict ourselves to the SMP algorithm and the stepsize strategy (39). Note that one can easily derive a deviation bound from the bound (43) on the expectation of $\epsilon_{\rm sad}(z^t)$ in the previous section. Indeed, let us fix the number t of iterations, run the algorithm m times and select the best, in terms of $\epsilon_{\rm sad}(\cdot)$, of the resulting approximate solutions. The probability that for this solution $\epsilon_{\rm sad}(\cdot)$ is worse than, say, twice the right hand side of (43) is at most 2^{-m} and thus can be made negligibly small with quite moderate values of m.

We also have the following bound on the deviations of the algorithm without restarts:

Proposition 3.3 *Assume we are solving problem* $(\mathcal{S})$ *by Basic implementation of SMP where* ζ_t, η_t *are sampled from the distributions* $P_z^{(k)}$, $k \geq 1$ *being a parameter of the construction. Assume also that the norm* $\|\cdot\|_*$ *is* $\varkappa$*-regular, and the online stepsize policy (39) is used. Then there are absolute constants* K_0, K_1 *such that the approximate solution* z^t *satisfies for all* $t \geq 1$ *and* λ, $\Lambda \geq 0$

$$\mathrm{Prob}\left\{\epsilon_{\rm sad}(z^t) \geq K_0\left[\frac{\Theta^2\mathcal{L}}{t} + \frac{\varkappa_*(k,\Lambda)\Theta^2\mathcal{L}}{\sqrt{kt}} + \Theta(\|a\|_* + \Theta\mathcal{L})\sqrt{\frac{\lambda}{kt}}\right]\right\} \leq e^{-\Lambda t} + e^{-\lambda}, \quad (44)$$

where $\varkappa_*(k,\Lambda) = \sqrt{\min[k,\,(\varkappa+\Lambda)]}$. *In particular, one has for all* $\varepsilon > 0$*:*

$$\begin{array}{l}\mathrm{Prob}\{\epsilon_{\rm sad}(z^N) \geq \varepsilon\} \leq e^{-\Lambda N} + e^{-\lambda} \quad \textit{for } N \geq N_\varepsilon, \textit{ where}\\ N_\varepsilon = K_1 \mathrm{Ceil}\left(\max\left[\Theta^2\mathcal{L}\varepsilon^{-1},\ \frac{\varkappa_*^2(k,\Lambda)\Theta^4\mathcal{L}^2}{k\varepsilon^2},\ \frac{(\|a\|_*+\Theta\mathcal{L})^2\Theta^2\lambda}{k\varepsilon^2}\right]\right).\end{array} \quad (45)$$

3.3 Efficiency estimates for Advanced implementations of SA and SMP

The efficiency of Advanced implementations of SA and SMP stem from the following result (we use the notation from section 3.1):

Proposition 3.4 *Let the BSP problem* $(\mathcal{S})$ *be solved by the advanced-step SA or SMP algorithms. Then for every* $t \geq 1$*, for both SA and SMP one has*

$$\epsilon_{\mathrm{sad}}(z^t) \leq \Gamma_t^{-1}\left[\Omega + R_t + S_t\right] = \Gamma_t^{-1}\left[\Omega + \sum_{\tau=1}^{t} r_\tau + \sum_{\tau=1}^{t} s_\tau\right], \tag{46}$$

where

$$\begin{array}{rcl} \Gamma_t & = & \displaystyle\sum_{\tau=1}^{t} \gamma_\tau, \\ r_t & = & \left\{ \begin{array}{ll} \gamma_t \langle F(\zeta_t), \zeta_t - z_t \rangle & \text{in the case of SA} \\ \gamma_t \langle F(\zeta_t), \zeta_t - w_t \rangle & \text{in the case of SMP} \end{array} \right. \\ s_t & = & \left\{ \begin{array}{ll} \left[\gamma_t \langle F(\zeta_t), z_t - z_{t+1} \rangle - V_{z_t}(z_{t+1})\right], & \text{in the case of SA} \\ \left[\gamma_t \langle F(\zeta_t), w_t - z_{t+1} \rangle - V_{z_t}(z_{t+1})\right], & \text{in the case of SMP} \end{array} \right. \end{array}$$

with $r_t \leq 0$ *and*

$$s_t \leq \left\{ \begin{array}{ll} \frac{\gamma_t^2}{2}\|F(\zeta_t)\|_*^2 \leq \frac{\gamma_t^2}{2} F_*^2, & \text{in the case of SA} \\ \frac{\gamma_\tau^2}{2}\|F(\zeta_t) - F(\eta_t)\|_*^2 - \frac{1}{2}\|w_t - z_t\|^2 \leq \frac{\gamma_t^2}{2} M_*^2, & \text{in the case of SMP.} \end{array} \right. \tag{47}$$

In order to extract from (46) explicit efficiency estimates, we need to specify a stepsize policy. In this respect, the advanced implementations offer more freedom than the basic ones, since now we should not ensure neither the martingale property of the random sums R_t, nor the monotonicity of the stepsizes. One option here is to use constant stepsize policy

$$\gamma_t = \sqrt{\frac{2\Omega}{N}} \cdot \left\{ \begin{array}{ll} \frac{1}{F_*}, & \text{in the case of SA} \\ \frac{1}{M_*}, & \text{in the case of SMP} \end{array} \right., \; 1 \leq t \leq N.$$

As it is easily seen, with this policy, (46) results in efficiency estimate (cf. (38))

$$\forall t \geq 1, \;\; \mathbf{E}\left\{\epsilon_{\mathrm{sad}}(z^t)\right\} \leq O(1) \left\{ \begin{array}{lll} F_* \sqrt{\frac{\Omega}{t}}, & \text{in the case of SA} & (a) \\ \mathcal{RL}\sqrt{\frac{\Omega}{t}}, & \text{in the case of SMP} & (b) \end{array} \right. \tag{48}$$

Our preliminary experiments, however, suggest to equip the advanced implementations of SA and SMP with the online stepsize policy as follows. Let us set

$$\delta_t = \frac{\Theta^2}{t}, \quad S_t^* = \sum_{\tau=1}^{t} \delta_\tau \quad [\leq \Theta^2(1 + \ln t)] \tag{49}$$

and let us choose γ_τ according to the "greedy" rule (the larger, the better) under the restriction that for all $t = 1, 2, ...$ it holds

$$R_t + S_t \leq S_t^*, \tag{$*_t$}$$

see (46). Specifically, assume that we have already carried out $t-1$ steps of the algorithm ensuring the relations $(*_\tau)$, $\tau \leq t-1$, and are about to define γ_t in order to carry out step t and to ensure $(*_t)$. At this time, we know $R_{t-1} \leq 0$ and S_{t-1}, same as know for sure that whatever be our choice of $\gamma_t > 0$, we would have

$$R_t - R_{t-1} = r_t \leq 0, \quad S_t - S_{t-1} = s_t \leq \theta\gamma_t^2, \quad \theta = \begin{cases} \frac{F_*^2}{2}, & \text{in the case of SA} \\ \frac{M_*^2}{2} \leq 2\mathcal{L}^2\mathcal{R}^2, & \text{in the case of SMP} \end{cases}$$

(see (47)). Thus, we can be sure that $S_t + R_t \leq [S_{t-1} + R_{t-1}] + \theta\gamma_t^2$, meaning that when choosing

$$\gamma_t = \sqrt{[S_t^* - S_{t-1} - R_{t-1}]/\theta} \tag{50}$$

we guarantee the validity of $(*_t)$ and the inequality $\gamma_t \geq \sqrt{\delta_t/\theta}$. This observation combined with (46) and $(*_N)$ implies that

$$\begin{aligned} \forall N \geq 1: \quad \epsilon_{\text{sad}}(z^N) &\leq \frac{\Theta^2/2 + R_N + S_N}{\sum_{\tau=1}^N \sqrt{\delta_\tau/\theta}} \leq \frac{O(1)\Theta^2(1+\ln N)}{\sum_{\tau=1}^t \sqrt{\delta_\tau/\theta}} \\ &\leq O(1)(1+\ln N) \cdot \begin{cases} \Theta F_* N^{-1/2}, & \text{in the case of SA,} \\ \Theta\mathcal{R}\mathcal{L}N^{-1/2}, & \text{in the case of SMP.} \end{cases} \end{aligned} \tag{51}$$

Observe that (51) is, within the logarithmic in N factor $O(1)(1+\ln N)$, the same as the bound (48). In fact, we could somehow reduce this logarithmic gap by modifying s_t^*, but we do not think this is necessary; we may hope (and the experiments to be reported in Section 5 fully support this hope) that "in reality" the rule (50) is much better than it is stated by the above worst-case analysis. The rationale behind this hope is that while we indeed are conservative when thinking how large could $S_t - S_{t-1}$ be, we account, to some extent, for the "past conservatism:" when $S_{t-1} + R_{t-1}$ is essentially less than S_{t-1}^*, γ_t as given by (50) is essentially larger than its lower bound used in the complexity analysis.

Finally, we remark that the major theoretical disadvantage of the efficiency estimate (51) as compared to (38) is much more serious than an extra log-factor. While with the basic implementation, in course of N steps the stochastic oracle is called $O(1)N$ times, the number of oracle calls in course of N steps of the advanced implementation is random and can be much larger than $O(1)N$; it is unclear why it should be $O(1)N$ even on average. Though for the time being we cannot support the empirical evidence by a solid theoretical complexity analysis, in our experiments the advanced implementation by far outperformed its basic counterpart.

3.4 The Favorable Geometry Case

We are about to present the "favorable geometry" case where we can point out the setup for SA/SMP which results in (nearly) *dimension-independent* efficiency estimates. Specifically, assume that

[G.1] The domain Z of $(\mathcal{S})$ is a *subset* of the direct product $Z^+ = B_1 \times .... \times B_{p+q}$ of $r = p+q$ "standard blocks" as follows:

- for $1 \leq i \leq p$, B_i is the unit Euclidean ball in $F_i = \mathbf{R}^{n_i}$;

- for $1 \le j \le q$, B_{p+j} is a subset of the space F_{p+j} of $n_{p+j} \times n_{p+j}$ ($n_{p+j} > 1$) symmetric block-diagonal matrices of a given block-diagonal structure and is the *spectahedron* of F_{p+j}, that is, the set of all positive semidefinite matrices from F_{p+j} with unit trace.

  In particular, B_{p+j} can be the standard simplex $\{x \in \mathbf{R}^k_+ : \sum_\ell x_\ell = 1\}$ (since the space of diagonal $k \times k$ matrices can be naturally identified with $\mathbf{R}^k$).

We equip $F_i = \mathbf{R}^{n_i}$, $i \le p$, with the standard Euclidean structure and the associated Euclidean norm $\|\cdot\|_{(i)}$, and F_{p+j} – with the Frobenius Euclidean structure and the trace-norm (the sum of singular values of a matrix) $\|\cdot\|_{(p+j)}$. In particular, the embedding space $E = F_1 \times ... \times F_r$ of Z^+ becomes equipped with the direct product of the indicated Euclidean structures. Note that the norm $\|\cdot\|_{(i,*)}$ conjugate to $\|\cdot\|_{(i)}$ is either the norm $\|\cdot\|_{(i)}$ itself (this is so when $i \le p$), or is the standard matrix norm (maximal singular value of a matrix) (this is so when $i > p$). We denote a vector form on E as $x = [x_1; ...; x_r]$, where x_ℓ is the F_ℓ-component of x.

G.2. The decomposition $Z = Z_1 \times Z_2 \subset E_1 \times E_2$ is compatible with the decomposition $Z = B_1 \times ... \times B_r$, that is, E_1 is the direct product of some of F_ℓ, $1 \le \ell \le p+q$, and E_2 is the direct product of the remaining F_ℓ. Besides this, we assume that Z intersects the relative interior of Z^+.

We refer to this case as to the one of *favorable geometry* and associate with this case the setup for SA and SMP as follows (cf. [12, Section 5]):

- The skew-symmetric linear mapping $\mathcal{A}$ (see (3)) can be written down as

$$\mathcal{A}[x_1; ...; x_r] = [\sum_{j=1}^r A^{1j} x_j; ...; \sum_{j=1}^r A^{rj} x_j],$$

  where A^{ij} is a linear mapping from F_j to F_i and $[A^{ij}]^* = -A^{ji}$. We denote by L_{ij} an a priori upper bound on $L^*_{ij} := \max\limits_{x_j} \left\{\|A^{ij}x_j\|_{(i,*)} : \|x_j\|_{(j)} \le 1\right\}$ such that $L_{ij} = L_{ji}$.[4]

- Further, we set

$$\begin{array}{l} \omega_i(x_i) = \frac{1}{2} x_i^T x_i : \ B_i \to \mathbf{R},\ \Omega_i = \frac{1}{2},\ 1 \le i \le p \\ \omega_{p+j}(x_{p+j}) = 2\sum_{\ell=1}^{n_{p+j}} \lambda_\ell(x_{p+j}) \ln(\lambda_\ell(x_{p+j})) : B_{p+j} \to \mathbf{R},\ \Omega_{p+j} = 2\ln(n_j),\ 1 \le j \le q \end{array}$$

  where $\lambda_\ell(u)$ are the eigenvalues of a symmetric matrix u taken with their multiplicities. It is known that $\omega_\ell(\cdot)$ is a d.g.f. for B_ℓ compatible with the norm $\|\cdot\|_\ell$, $1 \le \ell \le r$.

- Finally, we define the norm $\|\cdot\|$ on E and the d.g.f. $\omega(\cdot)$ for Z according to

$$\mu_\ell = \frac{1}{\Omega_\ell} \frac{\sum_{j=1}^r L_{\ell j}\sqrt{\Omega_\ell \Omega_j}}{\sum_{i,j=1}^r L_{ij}\sqrt{\Omega_i \Omega_j}},\ \|[x_1; ...; x_r]\| = \sqrt{\sum_{\ell=1}^r \mu_\ell \|x_\ell\|^2_{(\ell)}},\ \omega(x) = \sum_{\ell=1}^r \mu_\ell \omega_\ell(x_\ell), \tag{52}$$

[4]The latter restriction is natural, since $L^*_{ij} = L^*_{ji}$ due to $[A^{ij}]^* = -A^{ji}$.

which results in

$$\Omega \leq 1,\ \mathcal{R} \leq \Theta \leq \sqrt{2},\ \mathcal{L} = \sum_{i,j=1}^{r} L_{ij}\sqrt{\Omega_i \Omega_j}, \tag{53}$$

see [12, Section 5].

Remark 3.1 *From the results of [8] it follows that the norm* $\|\xi\|_* = \sqrt{\sum_{\ell=1}^{r} \mu_\ell^{-1} \|\xi_\ell\|_{(i,*)}^2}$ *is* $\varkappa$*-regular (see discussion in Section 3.2.4) with nearly dimension-independent* $\varkappa$*, namely,* $\varkappa = 3 \max\limits_{1\leq j\leq q} \ln(n_{p+j})$.

Note that the applications presented in Sections 2.2.2 and 2.2.3 are of favorable geometry; the same is true for the low dimension approximation problem of Section 2.1.3 after passing from the variable Q to the variable $R = d^{-1}Q$.

4 Solving the Generalized Bilinear Saddle Point Problem

Here we explain how a GBSP problem (9) – (10) can be reduced to a "small series" of BSP problems; the strategy to follow originates from [10]. From now on we assume, in addition to **A.1-2**, that we have an a priori upper bound $\bar{\rho}$ on the optimal value ρ_* of (10). For example, it is immediately seen that when finding an ϵ-solution to ℓ_1 minimization problem with ℓ_p fit (Section 2.2.2) in the only nontrivial case $\|b\|_p > \delta$ relation (13) implies that

$$\bar{\rho} := \frac{\|A\|_{1,p}}{\|b\|_p - \delta} \geq \rho_* := \frac{1}{\mathrm{Opt}},\ \|A\|_{1,p} = \max_j \|A_j\|_p, \tag{54}$$

where $A_1, ..., A_n$ are the columns of A. In particular, when finding an ϵ-solution to ℓ_1 minimization problem with the uniform fit in the only nontrivial case $\|b\|_\infty > \delta$ we have

$$\bar{\rho} := \frac{\|A\|_{1,\infty}}{\|b\|_\infty - \delta} \geq \rho_* := \frac{1}{\mathrm{Opt}},\ \|A\|_{1,\infty} = \max_{i,j} |A_{ij}|; \tag{55}$$

.

For the sake of definiteness, we assume that we are in the Favorable Geometry case, and that the decomposition $Z = Z_{11} \times Z_{12} \times Z_2 \subset E$, see (11), is compatible with the decomposition $E = F_1 \times ... \times F_r$, that is, the embedding spaces of Z_{11}, Z_{12} and Z_2 are products of some of F_ℓ's. To save space, we restrict ourselves with the SMP algorithm; modifications in the case of SA are straightforward.

The algorithm solves the problem of interest (10) by applying to $\mathrm{SV}(\cdot)$ a Newton-type root finding routine, with (approximate) first order information on SV at a point ρ given by SMP as applied to the saddle point problem specifying $\mathrm{SV}(\rho)$. Specifically, the algorithm works stage by stage. At a stage s, we have at our disposal an upper bound ρ_s on ρ_* and a piecewise linear function $\ell_{s-1}(\rho)$ which underestimates $\mathrm{SV}(\cdot)$:

$$\mathrm{SV}(\rho) \geq \ell_{s-1}(\rho)\ \ \forall \rho \geq 0.$$

here $\rho_1 = \bar{\rho}$, $\ell_0 \equiv -\infty$. At a stage, we apply SMP to the BSP problem

$$\mathrm{SV}(\rho_s) = \min_{z_1 \in Z_1} \max_{z_2 \in Z_2} \phi^{\rho_s}(z_1, z_2) \qquad (\mathcal{S}_s)$$

namely, act as follows.

A. We start stage s with building the setup for SMP as explained in Section 3.4. The affine operator associated with $(\mathcal{S}_s)$ is

$$\begin{array}{rcl} F^{\rho_s}(z_1 = [z_{11}; z_{12}], z_2) & = & \Phi(z_1, z_2) + \rho_s \Psi(z_1, z_2) \\ & = & [[a_{11} + B^* z_2; \rho_s(a_{12} + C^* z_2)]; -b - Bz_{11} - \rho_s(c + Cz_{12})], \end{array}$$

see (9), (11). In matrix $\mathcal{A} = \mathcal{A}_s$ of the linear part of F^{ρ_s}, some blocks A^{ij} are independent of ρ_s, while the remaining blocks are proportional to ρ_s. Consequently, the Lipschitz constant of F^{ρ_s} as given by (53) is

$$\mathcal{L} = \mathcal{L}(\rho_s) = \mathcal{M} + \rho_s \mathcal{N}, \ \mathcal{M}, \mathcal{N} \geq 0. \qquad (56)$$

An analogous decomposition holds for vector $a = a_s$:

$$\|a\|_* = \mu + \rho_s \nu, \ \mu, \nu \geq 0.$$

B. We apply to $(\mathcal{S}_s)$ either the basic, or the advanced implementation of the SMP. When running the basic SMP, we use the distributions $P_z^{(k)}$, see Section 3.2.4 (here $k \geq 1$ is a parameter of the construction) and use the online stepsize policy (39), where we set $\mathcal{L} = \mathcal{M} + \rho_s \mathcal{N}$ and $\Omega = 1$ (see (53)). When $(\mathcal{S}_s)$ is solved by the advanced SMP, we use the online stepsize policy (49) – (50), with $\Theta = \sqrt{2}$ in (49).

B.1. Let $z^{ti} = [z_1^{ti}, z_2^{ti}]$ be the approximate solution to $(\mathcal{S}_s)$ generated after t steps of stage s; recall that along with this solution, we have at our disposal the quantities

$$\begin{array}{rcl} \overline{\phi}^{ts} & = & \max_{z_2 \in Z_2} \phi^{\rho_s}(z_1^{ts}, z_2) = \upsilon + \langle a_{11}, z_{11}^{ts} \rangle + \rho_s[\chi + \langle a_{12}, z_{12}^{ts} \rangle] \\ & & \qquad + \min_{z_2 \in Z_2} \langle z_2, \overbrace{b + \rho_s c + Bz_{11}^{ts} + \rho C z_{12}^{ts}}^{p_{ts}} \rangle, \\ \underline{\phi}^{ts} & = & \min_{z_1 \in Z_1} \phi^{\rho_s}(z_1, z_2^{ts}) = \overbrace{\upsilon + \langle b, z_2^{ts} \rangle + \min_{z_{11} \in Z_{11}} \langle a_{11} + B^* z_2^{ts}, z_{11} \rangle}^{q_{ts}} \\ & & \qquad + \rho_s \overbrace{\left[\kappa + \langle c, z_2^{ts} \rangle + \min_{z_{12} \in Z_{12}} \langle a_{12} + C^* z_2^{ts}, z_{12} \rangle\right]} \end{array} \qquad (57)$$

(cf. (27) and see (9), (11)). We set

$$u^{ts} = \min_{\tau \leq t} \overline{\phi}^{\tau s}, \ \ell^{ts} = \max_{\tau \leq t} \underline{\phi}^{\tau s}, \ \ell_{ts}(\rho) = \max[\ell_{s-1}(\rho), \max_{1 \leq \tau \leq t} [p_{\tau s} + q_{\tau s} \rho]].$$

Note that u^{ts} is a nonincreasing in t upper bound on $\mathrm{SV}(\rho_s)$, ℓ^{ts} is a nondecreasing in t lower bound on $\mathrm{SV}(\rho_s)$, and $\ell_{ts}(\rho)$ underestimates $\mathrm{SV}(\rho)$ for all $\rho \geq 0$. In addition, $\ell_{ts}(\rho_s) \geq \ell^{ts}$. Note also that after t steps we have at our disposal vectors $w_1^{ts} \in Z_1$, $w_2^{ts} \in Z_2$ such that

$$\max_{z_2 \in Z_2} \phi^{\rho_s}(w_1^{ts}, z_2) = u^{ts} \leq \overline{\phi}^{ts}, \min_{z_1 \in Z_1} \phi^{\rho_s}(z_1, w_2^{ts}) = \ell^{ts} \geq \underline{\phi}^{ts},$$

meaning that $w^{ts} = [w_1^{ts}; w_2^{ts}]$ is a feasible solution to $(\mathcal{S}_s)$ and $\epsilon_{\rm sad}(w^{ts}) = u^{ts} - \ell^{ts} \leq \overline{\phi}^{ts} - \underline{\phi}^{ts} = \epsilon_{\rm sad}(z^{ts})$.

B.2. We proceed with solving $(\mathcal{S}_s)$ until one of the following two situations occurs:

A) We get $u^{ts} \leq \epsilon\rho_s$. In this case we terminate with the claim that ρ_s, w_1^{ts} is the desired ϵ-solution to (9) – (10).

B) We get $\ell^{ts} \geq \frac{3}{4}u^{ts}$. When it happens, we set

$$\rho_{s+1} = \max\left\{\rho : \ell_{ts}(\rho) \leq 0\right\}, \ \ell_s(\cdot) \equiv \ell_{ts}(\cdot) \tag{58}$$

and pass to the stage $s+1$.

Theorem 4.1 *When solving a Generalized Bilinear Saddle Point problem* (9) – (10) *by the outlined algorithm:*

(i) *The algorithm terminates in finite time with probability 1, and the resulting solution is an ϵ-solution, as defined in Section 2.2, to the GBSP problem in question;*

(ii) *The number of stages does not exceed the quantity* $O(1)\ln\left(\frac{\|\phi\|_\infty + \bar{\rho}\|\psi\|_\infty}{\epsilon\rho_*} + 2\right)$, *where* $\|\phi\|_\infty = \max_{z\in Z}|\phi(z)|$, $\|\psi\|_\infty = \max_{z\in Z}|\psi(z)|$, *see* (9).

(iii) *The (random) number N_s of steps at every stage s of the basic implementation satisfies for all $\varepsilon > 0$ the relation*

$$\mathrm{Prob}\{N_s \geq N(\epsilon)\} \leq e^{-\Lambda N(\epsilon)} + e^{\lambda},$$

where

$$N(\epsilon) = O(1)\mathrm{Ceil}\left[\frac{\mathcal{M} + \rho_*\mathcal{N}}{\epsilon\rho_*} + \frac{\varkappa_*(k,\Lambda)^2}{k}\left(\frac{\mathcal{M} + \rho_*\mathcal{N}}{\epsilon\rho_*}\right)^2 + \frac{\lambda}{k}\left(\frac{\mu + \rho_*\nu}{\epsilon\rho_*}\right)^2\right]. \tag{59}$$

The number of steps at every stage of the advanced implementation of the algorithm does not exceed

$$N_{\rm adv}(\epsilon) = O(1)\left[\frac{\mathcal{M} + \rho_*\mathcal{N} + 2\epsilon\rho_*}{\epsilon\rho_*}\ln\left(\frac{\mathcal{M} + \rho_*\mathcal{N} + 2\epsilon\rho_*}{\epsilon\rho_*}\right)\right]^2. \tag{60}$$

For proof, see Section A.4.

In the case of ℓ_1 minimization problems with uniform and ℓ_2 fits, Theorem 4.1 as applied to the basic implementation of SMP with $k = 1$, initialized according to (55), resp., (54), after completely straightforward computations implies the complexity bounds stated in Proposition 1.1. The preprocessing mentioned in item (ii) of Proposition is as follows: we choose an $m \times m$ orthogonal matrix U with moduli of entries not exceeding $O(1)/\sqrt{m}$ and such that multiplication of a vector by U takes $O(m\ln m)$ operations (e.g., U can be the matrix of the Cosine Transform). We then draw at random a ± 1 vector ξ from the uniform distribution on the vertices of the unit m-dimensional box and pass from the data $[A, b]$ to the data

$$[A' = U\mathrm{Diag}\{\xi\}A, \ \ b' = U\mathrm{Diag}\{\xi\}b],$$

thus obtaining an equivalent reformulation of the problem of interest. Note that this preprocessing costs $O(1)mn\ln(m)$ operations. We clearly have $\|A'\|_{1,2} = \|A\|_{1,2}$. Applying the Hoeffding inequality, it is immediately seen that with probability $\geq 1 - \chi$ one has $\|A'\|_{1,\infty} < O(1)\sqrt{\ln(mn/\chi)}m^{-1/2}\|A\|_{1,2}$, that is, $\Gamma(A') \leq O(1)\sqrt{\ln(mn/\chi)}$, as stated in Proposition 1.1.

5 Numerical Results

Below we report on a series of numerical experiments aimed at comparing the performances of the Stochastic Mirror Prox algorithm SMP (in its advanced implementation) and its prototype — Deterministic Mirror Prox algorithm (DMP) proposed in [12][5]. The algorithms were tested on the GBSP problems of ℓ_1 minimization with uniform and ℓ_2 fits, see Section 2.2.2.

Test problems we use are of the "Compressive Sensing" origin. Specifically, given the sizes m, n of a test problem, we picked at random an $m \times n$ matrix B with i.i.d. entries taking values ± 1 with probabilities 0.5, and a sparse (with $\mathrm{Ceil}(\sqrt{m})$ nonzero entries) "true signal" x_* normalized to have $\|x_*\|_1 = 1$, thus giving rise to the test problem

$$\mathrm{Opt}_p = \min_x \{\|x\|_1 : \|Ax - y\|_p \leq \delta\}, \; A = m^{-1/p}B, \; y = Ax_* + \xi \qquad (P_p)$$

where $p = \infty$ (uniform fit) or $p = 2$ (ℓ_2 fit). The "observation noise" ξ was chosen at random and then normalized to have $\|\xi\|_p = \delta$. Our goal is to solve (P_p) within accuracy ϵ, i.e., to find x_ϵ satisfying $\|x_\epsilon\|_1 \leq \mathrm{Opt}_p$ and $\|Ax_\epsilon - y\|_p \leq \delta + \epsilon$. In all our experiments, $\delta = 0.005$ and $\epsilon = 0.0025$ were used.

Implementation of the algorithms. The GBSP reformulations of problems (P_p) were solved by SMP (in advanced implementation) and DMP according to the scheme presented in Section 4. In the case $p = \infty$ of uniform fit, both SMP and DMP used the GBSP problem reformulation given by (16). In the case $p = 2$ of ℓ_2 fit, SMP used the GBSP reformulation (15), while DMP was applied to the GBSP problem stemming directly from (14) with $p = 2$, namely, given by

$$\phi^\rho(z_1, z_2) = z_2^T(AJ_n z_1 - \rho b) - \rho\delta, Z_1 = Z_{11} = \Delta_{2n}, \; Z_2 = \{\|z_2\|_2 \leq 1\}. \qquad (61)$$

The rationale here is that the GBSP given by (61) "by itself" is easier than the GBSP given by (15): an ϵ-solution to the latter problem induces straightforwardly an ϵ-solution to the former one, but not vice versa. As a compensation, the problem (15), in contrast to (61), is better suited for randomization[6]. The latter fact, which is crucial for SMP, is irrelevant for DMP, this is why we apply this algorithm to the GBSP given by (61). In order to make a fair comparison, when running SMP for ℓ_2-fit, we terminate the run based on the ℓ_2-residual of the solution.

In our implementations, we have tested different policies for choosing the starting point at each stage and different choices of the distance generating function (d.g.f.) for

[5] DMP is nothing but SMP with precise information (i.e., P_z is the unit mass sitting at z) and on-line stepsize policy described in [12, Section 6].

[6] Indeed, in the second problem all nontrivial matrix-vector multiplications required to compute $F^\rho(z)$ are multiplications of vectors from the ℓ_1-balls by A and A^T; since a vector from ℓ_1-ball is the expectation of an extremely sparse (just one nonzero entry) random vector taking values in the same ball, the required matrix-vector multiplications admit cheap randomized versions. In the first problem, some of the required matrix-vector multiplications involve vectors from the $\|\cdot\|_2$-ball, and such a vector typically cannot be represented as the expectation of a sparse random vector taking values in the ball.

the simplexes. Specifically, along with the entropy d.g.f. discussed in Section 3.4, we tested the power d.g.f. $\omega(x) = \frac{\mathrm{e}}{\kappa(1+\kappa)} \sum_{i=1}^n x_i^{1+\kappa} : \{x \in \mathbf{R}^n_+ : \sum_i x_i \leq 1\} \to \mathbf{R}$, with $\kappa = \frac{1}{\ln(n)}$; the theoretical complexity bounds associated with this choice of d.-g.f. coincide, within absolute constant factors, with those for the entropy. The best policies we ended up with are as follows:

— for SMP: entropy d.g.f., restarts from the ω-center of Z ("C00E" implementation);

— for DMP, in the case of uniform fit: power d.g.f., restarts from the convex combination of the best (with the smallest ϵ_{sad}) point found so far and the ω-center of Z, the weights being 0.75 and 0.25, respectively ("B75P" implementation);

— for DMP, in the case of ℓ_2-fit: power d.g.f., restarts from the convex combination of the last search point of the previous stage and the ω-center of Z, the weights being 0.25 and 0.75, respectively ("L25P" implementation).

When implementing SMP, we utilized the option, discussed in Section 3.2.4, of building an estimate $F(\zeta)$ of $F(z)$ by generating k samples $\zeta^\ell \sim P_z$, $\ell = 1, ..., k$, and setting $\zeta = \frac{1}{k} \sum_{\ell=1}^k \zeta^\ell$. The "multiplicity" k was set to 40 for small instances and 100 for large (those with at least 10^8 nonzeros in A) instances.

The MATLAB 7.10.0 implementation of the algorithms was executed on an eight-core machine with two quad-core Intel Xeon E5345 CPU@2.33GHz, 8 MB L2 cache per quad-core chip and 12GB FB-DIMM total RAM (the computations were running single-core and single-threaded).

The results, I. In order to avoid too time-consuming experimentation, we primarily dealt with "moderate size" test problems. These problems were split into four groups according to the total number of nonzeros in A ($2 \cdot 10^6$, $8 \cdot 10^6$, $32 \cdot 10^6$, $128 \cdot 10^6$). Every group was further split into two subgroups according to the ratio $n : m$ (8 and 2). For every one of the resulting pairs (m, n), we generated 5 instances of problem (P_2) and 5 instances of problem (P_∞) and solved them by DMP and SMP. Thus, the methods were compared on totally 70 problems split into 14 series of 5 experiments each, with common for all experiments of a series sizes m, n and the value of p. The results are presented in Tables 1 (uniform fit) and 2 (ℓ_2 fit). For every series of 5 experiments, we present the corresponding minimal, maximal and average values of several performance characteristics, specifically

- `CPU` — the CPU time (sec) of the entire computation
- `Calls` — the total number of computations of the values of F
- `FCalls` — the equivalent number of calls to the deterministic oracle for the randomized algorithm. This quantity is defined as follows. For DMP, computing a value of F at a point reduces to a pair of matrix-vector multiplications, one involving A and the other one involving A^T; the cost of this computation is $2mn$ operations. For SMP invoked with multiplicity k (see above), the computation of (an unbiased estimate of) $F(z)$ requires multiplying one vector with $\leq k$ nonzero entries by A, and another vector with $\leq k$ nonzero entries by A^T, the total cost of these two computations being $k(m+n)$ operations. Thus, the "deterministic equivalent" of the randomized computation of F used by SMP is $\frac{k(m+n)}{2mn}$. The quantity `FCalls` is the induced by this definition deterministic equivalent of all randomized computations of F in a run of the SMP.

The data in Tables 1, 2 suggest the following interpretations:

1. As the sizes of instances grow, the randomized algorithm eventually outperforms its deterministic counterpart in terms of the CPU time, and the corresponding "savings" grow with the size $m \times n$ of the instance, and for instances of a given size – grow as the ratio n/m decreases. Both phenomena are quite natural: the larger is mn and the smaller is $n/m \geq 1$ for a given mn, the smaller is the deterministic equivalent $k\frac{m+n}{2mn}$ of a randomized computation of F.

2. Even for our "not too large" test problems, the savings stemming from randomization can be quite significant: for the 8000×16000 instances, SMP is, at average, nearly 4.6 times faster than the best version of DMP for problems with uniform fit and 2.0 times faster than DMP for problems with ℓ_2 fit.

   When interpreting the CPU time data one should keep in mind that oracle calls of DMP make use of very efficient MATLAB implementation of matrix-vector multiplication, while SMP relies upon much less efficient (with respect to, e.g., C language) implementation of long DO loops.

3. The advantages, if any, of SMP as compared to DMP are more significant in the case of uniform fit than in the case of ℓ_2 fit. This phenomenon is quite natural: as we have already explained, in the case of ℓ_2 fit the methods are applied to different GBSP reformulations of (P_2), and the reformulation DMP works with is easier than the one processed by SMP.

The results, II. In order to get impression of what happens when the matrix A in (P_p) is too large to be stored in RAM, we carried out two experiments where the goal was to solve the ℓ_1 minimization problem with uniform and with ℓ_2 fits and fully dense $(m = 32000) \times (n = 64000)$ matrix A given by a simple analytical expression. This expression allows to compute a column/a row of A with a given index in $O(m)$, resp., $O(n)$ operations. Matrix $A = A_p$ was normalized to have $\|A\|_{1,p} = 1$. While the sizes of A make it impossible to store the matrix in the RAM of the computer we used for the experiments, we still can multiply vectors by A and A^T by computing all necessary columns and rows, and thus can run DMP and SMP. In our related experiments, we generated at random a sparse (64 nonzeros) "true" signal $x_* \in \mathbf{R}^{64000}$ with $\|x_*\|_1 = 1$, computed $y = Ax + \xi$, ξ, $\|\xi\|_p = \delta = 0.005$, being observation noise, and ran DMP and SMP in order to find an ϵ-solution x_ϵ, $\epsilon = 0.0025$, to the resulting problem (P_p); in particular, we should have $\|x_\epsilon\|_1 \leq \|x_*\|_1 = 1$ and $\|Ax_\epsilon - b\| \leq \delta + \epsilon = 0.0075$. In every experiment, each of the methods was allowed to run at most 7,200 sec. The results are as follows.

- In the allowed 7,200 sec, the deterministic algorithms on every one of the two test problems ($p = 2$ and $p = \infty$) was able to carry out just about 30 steps with the total of about 67 computations of $F(\cdot)$; this is by far not enough to get meaningful results, see Table 3. In contrast to this, the numbers of steps and randomized computations of F carried out by the randomized algorithm in the same 7,200 sec was in the range

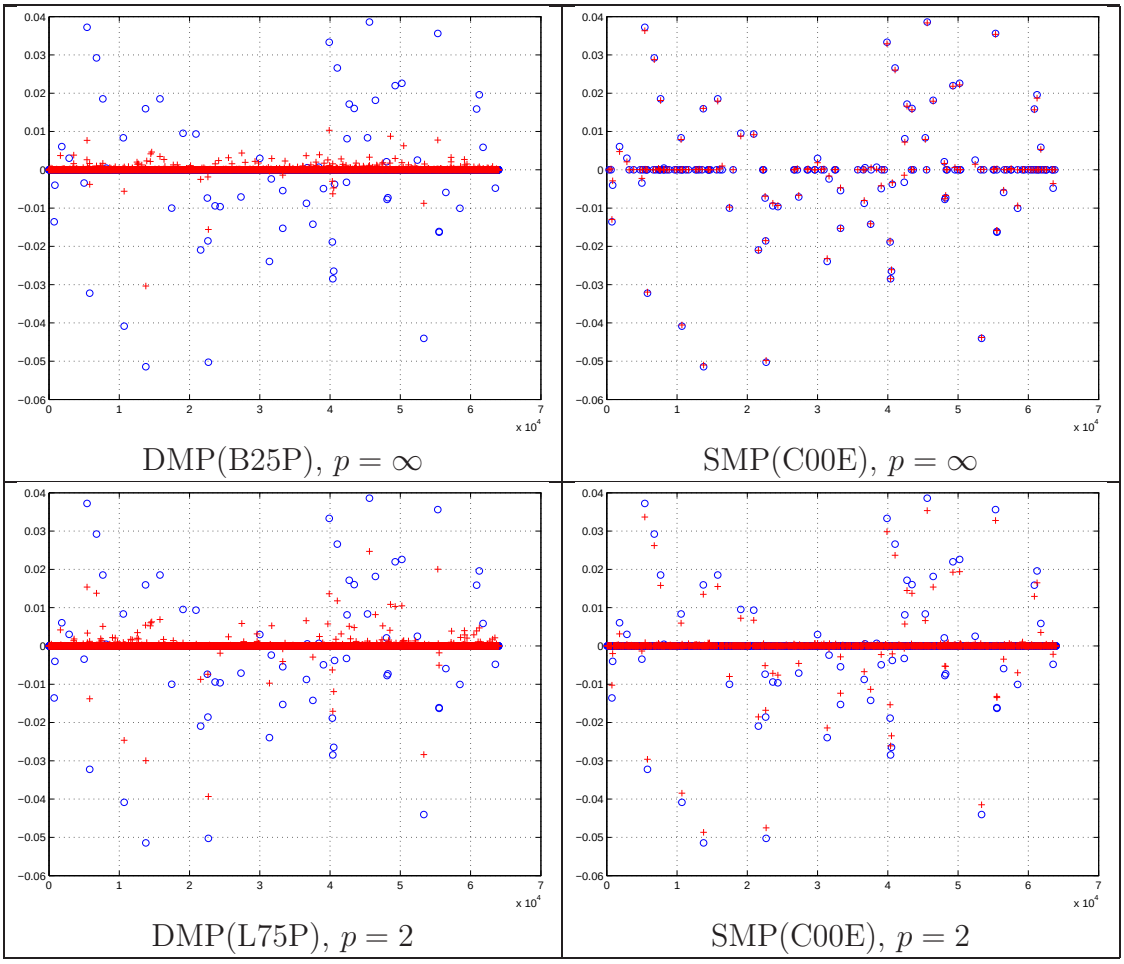

Figure 1: DMP-based (left) and SMP-based (right) recovery of sparse signals in the $32,000 \times 64,000$ experiment, entries vs. their indexes. Circles: x_*; crosses: recovery.

of tens of thousands, which was enough to fully achieve the required accuracy for both $p = \infty$ and $p = 2$.

- While the quality of approximation of x_* by the solution yielded by DMP is basically nonexisting, the SMP produced fairy reasonable approximations of x_*, see Table 3 and Figure 1.

In our opinion, the preliminary numerical results we have reported suggest that "acceleration via randomization" possesses a significant practical potential when solving extremely large-scale convex programs of appropriate structure.

		DMP		SMP				
Sizes		Calls	CPU	Calls	FCalls	CPU	$\frac{\text{Calls,DMP}}{\text{FCalls,SMP}}$	$\frac{\text{CPU,DMP}}{\text{CPU,SMP}}$
500 x 4000	Mean (C00E)	2661.6	106.6	10511.0	236.5	57.2	11.25	1.87
	Min (C00E)	1683.0	50.0	8159.0	183.6	34.0	9.17	1.47
	Max (C00E)	4395.0	179.4	11783.0	265.1	83.4	16.58	2.15
	Mean (B25P)	1453.4	104.1				6.15	1.82
1000 x 2000	Mean (C00E)	1830.8	64.0	10568.8	158.5	42.9	11.55	1.49
	Min (C00E)	1344.0	41.0	8434.0	126.5	28.8	10.62	1.42
	Max (C00E)	2507.0	91.5	11576.0	173.6	70.4	14.44	1.30
	Mean (B25P)	1530.6	97.9				9.65	2.28
1000 x 8000	Mean (C00E)	2338.0	227.9	12406.6	139.6	113.2	16.75	2.01
	Min (C00E)	1453.0	119.4	11579.0	130.3	88.2	11.15	1.35
	Max (C00E)	2739.0	370.2	13895.0	156.3	168.9	17.52	2.19
	Mean (B25P)	1545.6	248.9				11.07	2.20
2000 x 8000	Mean (C00E)	2691.6	227.6	12922.8	96.9	74.5	27.77	3.05
	Min (C00E)	1132.0	97.7	10934.0	82.0	56.6	13.80	1.73
	Max (C00E)	3355.0	313.1	15632.0	117.2	88.8	28.62	3.53
	Mean (B25P)	1426.4	207.8				14.72	2.79
2000 x 16000	Mean (C00E)	2384.6	494.2	13174.8	74.1	184.9	32.18	2.67
	Min (C00E)	2288.0	486.3	11735.0	66.0	174.4	34.66	2.79
	Max (C00E)	2491.0	505.5	14729.0	82.9	195.3	30.07	2.59
	Mean (B25P)	1575.2	533.7				21.25	2.89
4000 x 8000	Mean (C00E)	2923.6	798.7	19750.2	74.1	228.4	39.48	3.50
	Min (C00E)	2032.0	407.6	17262.0	64.7	159.0	31.39	2.56
	Max (C00E)	3895.0	1539.7	22945.0	86.0	343.1	45.27	4.49
	Mean (B25P)	1554.6	576.2				20.99	2.52
4000 x 32000	Mean (C00E)	2482.8	2054.3	11973.2	84.2	515.8	29.49	3.98
	Min (C00E)	1826.0	1448.9	11331.0	79.7	499.9	22.92	2.90
	Max (C00E)	3479.0	2904.2	12715.0	89.4	525.0	38.91	5.53
	Mean (B25P)	1604.8	1736.3				19.06	3.37
8000 x 16000	Mean (C00E)	2680.4	2227.7	12474.6	58.5	375.0	45.84	5.94
	Min (C00E)	2297.0	1890.1	11493.0	53.9	341.9	42.64	5.53
	Max (C00E)	3177.0	2609.0	13759.0	64.5	408.8	49.26	6.38
	Mean (D-B25P)	1615.8	1752.7	12474.6	58.5	375.0	27.63	4.67

Table 1: ℓ_1 minimization with $\|\cdot\|_\infty$-fit.

Sizes		DMP Calls	DMP CPU	SMP Calls	SMP FCalls	SMP CPU	$\frac{\text{Calls,DMP}}{\text{FCalls,SMP}}$	$\frac{\text{CPU,DMP}}{\text{CPU,SMP}}$
500 x 4000	Mean (C00E)	579.8	21.0	4771.6	106.7	24.6	5.44	0.85
	Min (C00E)	410.0	14.5	3412.0	76.3	16.9	5.38	0.86
	Max (C00E)	722.0	40.3	6868.0	153.5	36.0	4.70	1.12
	Mean (L75P)	287.8	16.1				2.70	0.66
1000 x 2000	Mean (C00E)	553.0	19.0	3910.8	54.8	13.6	10.10	1.40
	Min (C00E)	463.0	9.1	3315.0	46.4	11.5	9.98	0.79
	Max (C00E)	664.0	30.1	5890.0	82.5	17.4	8.05	1.73
	Mean (L75P)	282.4	14.1				5.16	1.04
1000 x 8000	Mean (C00E)	617.0	56.6	5148.8	57.5	50.7	10.72	1.12
	Min (C00E)	486.0	34.7	3745.0	41.9	36.1	11.61	0.96
	Max (C00E)	794.0	87.1	6050.0	67.6	64.8	11.74	1.34
	Mean (L75P)	318.8	40.9				5.54	0.81
2000 x 8000	Mean (C00E)	634.8	39.8	5853.6	41.0	47.2	15.49	0.84
	Min (C00E)	487.0	30.0	3926.0	27.5	33.1	17.72	0.91
	Max (C00E)	796.0	51.0	6869.0	48.1	54.0	16.56	0.95
	Mean (L75P)	318.8	25.9				7.78	0.55
2000 x 16000	Mean (C00E)	531.8	150.7	5055.6	28.3	90.0	18.82	1.67
	Min (C00E)	438.0	108.3	3947.0	22.1	60.2	19.85	1.80
	Max (C00E)	608.0	180.3	6736.0	37.6	125.1	16.15	1.44
	Mean (L75P)	346.0	110.6				12.25	1.23
4000 x 8000	Mean (C00E)	675.2	138.5	6504.6	22.8	101.7	29.66	1.36
	Min (C00E)	531.0	99.1	5868.0	20.5	83.3	25.85	1.19
	Max (C00E)	810.0	193.6	7143.0	25.0	113.9	32.40	1.70
	Mean (L75P)	346.4	86.3				15.22	0.85
4000 x 32000	Mean (C00E)	672.2	486.0	5613.4	39.2	287.2	17.14	1.69
	Min (C00E)	506.0	382.5	3418.0	23.9	197.2	21.19	1.94
	Max (C00E)	817.0	579.1	6611.0	46.2	336.4	17.69	1.72
	Mean (L75P)	355.4	311.6				9.06	1.09
8000 x 16000	Mean (C00E)	592.4	591.4	5815.0	25.4	177.6	23.29	3.33
	Min (C00E)	509.0	472.4	3765.0	16.5	117.3	30.90	4.03
	Max (C00E)	696.0	798.1	7038.0	30.8	214.1	22.60	3.73
	Mean (L75P)	329.8	360.2				12.96	2.03

Table 2: ℓ_1 minimization with $\|\cdot\|_2$-fit.

Method	p	Steps	Calls	FCalls	CPU, sec	$\|A\widehat{x}-b\|_p$	$\|\widehat{x}-x_*\|_1$	$\|\widehat{x}-x_*\|_2$	$\|\widehat{x}-x_*\|_\infty$
DMP (C00E)	∞	30	71	71	7564	0.16018	1.406 (141%)	0.143 (89%)	0.041 (79%)
DMP (B25P)	∞	31	67	67	7363	0.15975	1.361 (136%)	0.136 (85%)	0.035 (69%)
SMP (C00E)	∞	7501	22141	25.9	5352	0.00744	0.048 (5%)	0.005 (3%)	0.002 (4%)
DMP (C00E)	2	29	67	67	7471	0.03653	1.455 (146%)	0.135 (84%)	0.035 (68%)
DMP (L75P)	2	30	67	67	7536	0.02480	0.976 (98%)	0.093 (58%)	0.022 (42%)
SMP (C00E)	2	2602	7749	8.5	2350	0.00715	0.264 (26%)	0.021 (13%)	0.004 (7%)

Table 3: Experiments with dense $32,000 \times 64,000$ matrix A. Percents: $\|\widehat{x}-x_*\|/\|x_*\|$.

A Appendix: Proofs

A.1 Low dimensional approximation

We use the notations of Section 2.1.3.

Lemma A.1 *Let Q_* be an optimal solution to (6), $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_n$ be the eigenvalues of Q_*, $e_1, ..., e_n$ be the corresponding eigenvectors of Q_*, and $E = \mathrm{Lin}(e_1, ..., e_d)$. Then for any $v \in V$, $\mathrm{dist}(v, E) \leq \delta_* \sqrt{d+1}$ (here $\mathrm{dist}(x, E)$ stands for the Euclidean distance from v to E).*

Proof. Note that $0 \leq \lambda_j \leq 1$ and $\sum_j \lambda_j = d$, so that $\lambda_j \leq \frac{d}{d+1}$ when $j \geq d+1$. Denoting by $y_j(x)$ the coordinates of x in the eigenbasis $\{e_j\}$, we have

$$\begin{array}{l}
\mathrm{dist}^2(v, E) = 1 - \sum_{j=1}^d y_j^2(v) \leq 1 - \sum_{j=1}^d \lambda_j y_j^2(v) \text{ [since } \lambda_j \leq 1] \\
\leq 1 - \sum_{j=1}^n \lambda_j y_j^2(v) + \lambda_{d+1} \sum_{j=d+1}^n y_j^2(v) = 1 - v^T Q v + \lambda_{d+1} \mathrm{dist}^2(v, E) \\
\Rightarrow \quad (1 - \lambda_{d+1}) \mathrm{dist}^2(v, E) \leq 1 - v^T Q v \leq 1 - \mathrm{Opt} \leq 1 - \mathrm{Opt}_* = \delta_*^2 \\
\Rightarrow \quad \mathrm{dist}^2(v, E) \leq (d+1)\delta_*^2 \text{ [since } \lambda_{d+1} \leq \frac{d}{d+1}],
\end{array}$$

as claimed. □

Representing a vector from $\Delta_{n,d}$ as a convex combination of extreme points. The case of $d = n$ is trivial, thus, let $d < n$. Let

$$q \in \Delta_{n,d} = \left\{ q \in \mathbf{R}_+^n : \ 0 \leq q_i \leq 1 \, \forall i, \ \sum_{i=1}^n q_i = d \right\}.$$

To represent q as a convex combination of n extreme points of $\Delta_{n,d}$ we act as follows:

- *Initialization:* We set $p^0 = [1; q]$, $\mu^0 = 1$. Note that $p^0 \in \Delta = \{p = [1; p_1; ...; p_n] \in \Delta_{n+1,d+1}\}$.
- *Step $t = 1, 2, ...$:* Given $p^{t-1} = [1; p_1^{t-1}; ...; p_n^{t-1}] \in \Delta$, we find the $d+1$ largest among the entries p_i^{t-1}, $i = 1, ..., n$, let their indexes be $i_1, ..., i_{d+1}$, where $p_{i_1}^{t-1} \geq p_{i_2}^{t-1} \geq ... \geq p_{i_{d+1}}^{t-1}$.
  a) It may happen that $p_{i_\ell}^{t-1} = 1$ for $1 \leq \ell \leq d$; since $p^{t-1} \in \Delta$, $r^t := p^{t-1}$ is a Boolean vector with exactly $d+1$ entries equal to 1, and $q^t = [p_1^{t-1}; ...; p_n^{t-1}]$ is an extreme point of $\Delta_{n,d}$. We set $\nu_t = 1$, $p^t = 0$ and terminate.
  b) When not all $p_{i_\ell}^{t-1}$, $1 \leq \ell \leq d$, are equal to 1, we set $\nu_t = \min[1 - p_{i_{d+1}}^{t-1}, p_{i_d}^{t-1}]$, define r^t as Boolean $(n+1)$-dimensional vector with $d+1$ entries equal to 1, the indexes of the entries being $0, i_1, ..., i_d$, set $p^t = [p^{t-1} - \nu_t r^t]/(1 - \nu_t)$, $q^t = [r_1^t; ...; r_n^t]$ (note that q^t is an extreme point of $\Delta_{n,d}$) and pass to step $t+1$.

Observe that the algorithm is well defined. Indeed, $0 \leq \nu_t \leq 1$ by construction, and $\nu_t = 1$ if and only if $p_{i_{d+1}}^{t-1} = 0$ and $p_{i_d}^{t-1} = 1$, that is, when we terminate at step t according to a). Thus, p^t is well defined at every non-termination step t. Moreover, from

b) it is immediately seen that at such a step we have $p_0^t = 1$, $0 \le p_i^t \le 1$ for all i and $\sum_{i=0}^n p_i^T = d+1$, that is, $p^t \in \Delta$ for all t for which p^t is well defined. Beside this, it is immediately seen that those entries in p^{t-1} which are zeros and ones remain zeros and ones in p^t as well, and that the total number of these entries increases at every step of the algorithm by at least 1. The latter observation implies that the algorithm terminates in at most n steps. Finally, by construction $p^{t-1} = (1-\nu_t)p^t + \nu_t r^t$, whence, denoting by $\bar{t}$ the termination step, p^0 is a convex combination of $r^1, ..., r^{\bar{t}}$ with coefficients μ_t readily given by $\nu_1, ..., \nu_{\bar{t}}$. Discarding in $r^1, ..., r^{\bar{t}}$ the entries with index 0, we get extreme points $q^1, ..., q^{\bar{t}}$ of $\Delta_{n,d}$ such that $q = \sum_{i=1}^{\bar{t}} \mu_t q^t$. Finally, the computational effort per step clearly does not exceed $O(1)dn$, that is, the total computational effort is at most $O(1)dn^2$.

A.2 Proof of Lemma 2.1

We have

$$\begin{aligned}
\mathrm{SV}(\rho) &= \max_{z_2 \in Z_2} \min_{z_1 \in Z_1} \phi^\rho(z_1, z_2) \\
&= \max_{z_2 \in Z_2} \min_{z_{11} \in Z_{11}, z_{12} \in Z_{12}} \Big[\upsilon + \rho\chi + \langle a_{11}, z_{11} \rangle + \langle b, z_2 \rangle + \langle z_2, B z_{11} \rangle \\
&\qquad\qquad + \rho \left[\langle a_{12}, z_{12} \rangle + \langle c, z_2 \rangle + \langle z_2, C z_{12} \rangle \right] \Big] \\
&= \max_{z_2 \in Z_2} \Big[\upsilon + \rho\chi + \langle b, z_2 \rangle + \rho \langle c, z_2 \rangle + \min_{z_{11} \in Z_{11}} \big[\langle a_{11}, z_{11} \rangle + \langle z_2, B z_{11} \rangle \\
&\qquad\qquad + \rho \overbrace{\min_{z_{12} \in Z_{12}} \left[\langle a_{12} + C^* z_2, z_{12} \rangle \right]}^{g(z_2)} \big] \Big] \\
&= \max_{z_2 \in Z_2} \big[\upsilon + \rho\chi + \langle b, z_2 \rangle + \rho \langle c, z_2 \rangle + \rho g(z_2) + \overbrace{\min_{z_{11} \in Z_{11}} \left[\langle a_{11}, z_{11} \rangle + \langle z_2, B z_{11} \rangle \right]}^{h(z_2)} \big] \\
&= \max_{z_2 \in Z_2} \big[\upsilon + \langle b, z_2 \rangle + h(z_2) + \rho \left[\chi + \langle c, z_2 \rangle + g(z_2) \right] \big]
\end{aligned}$$

and thus $\mathrm{SV}(\rho)$ is the supremum of affine functions of ρ. □

A.3 Proofs for Section 3

We start with the following

Lemma A.2 [cf. [12], Lemma 3.1.(*b*)] *Given $z \in Z^o$, $\gamma > 0$ and $\xi, \eta \in E$, let us set*

$$\begin{aligned}
w &= \mathrm{Prox}_z(\gamma\xi) = \mathrm{argmin}_{v \in Z} \left\{ \langle \gamma\xi - \omega'(z), v \rangle + \omega(v) \right\}, \\
z_+ &= \mathrm{Prox}_z(\gamma\eta) = \mathrm{argmin}_{v \in Z} \left\{ \langle \gamma\eta - \omega'(z), v \rangle + \omega(v) \right\}.
\end{aligned}$$

Then $w, z_+ \in Z^o$, and for every $u \in Z$ one has

$$\begin{array}{ll}
(a) & \gamma \langle \eta, w - u \rangle \le V_z(u) - V_{z_+}(u) + \gamma \langle \eta, w - z_+ \rangle - V_z(z^+) \\
(b) & \le V_z(u) - V_{z_+}(u) + \gamma \langle \eta - \xi, w - z_+ \rangle - V_z(w) - V_w(z_+) \\
(c) & \le V_z(u) - V_{z_+}(u) + \gamma \|\eta - \xi\|_* \|w - z_+\| - \frac{1}{2} \left[\|w - z\|^2 + \|w - z_+\|^2 \right] \\
(d) & \le V_z(u) - V_{z_+}(u) + \frac{1}{2} \left[\gamma^2 \|\eta - \xi\|_*^2 - \|w - z\|^2 \right].
\end{array} \tag{62}$$

Proof. The inclusions $w, z_+ \in Z^o$ are evident (a subgradient of $\omega(\cdot)$ at w, taken w.r.t. Z, is, e.g., $\omega'(z) - \gamma\xi$, and similarly for z_+). Now let $u \in Z$. z_+ is an optimal solution of certain explicit convex optimization problem; taking into account that $\omega'(\cdot)$ is continuous on Z^o, it is easily seen that the necessary optimality condition in this problem reads $\langle \gamma\eta + \omega'(z_+) - \omega'(z), u - z_+\rangle \geq 0$, whence $\gamma\langle \eta, w-u\rangle \leq \gamma\langle \eta, w-z_+\rangle + \langle \omega'(z_+) - \omega'(z), u - z_+\rangle$, and the latter inequality, after rearranging terms in the right hand side, becomes (a). By similar reasons, $0 \leq \langle \gamma\xi + \omega'(w) - \omega'(z), v - w\rangle$ for all $v \in Z$; setting $v = z_+$, summing up the resulting inequality with (a) and rearranging terms in the right hand side of what we get, we arrive at (b). (c) follows from (b) due to $V_a(b) \geq \frac{1}{2}\|a-b\|^2$ (recall that ω is strongly convex, modulus 1 w.r.t. $\|\cdot\|$, on Z). Finally, (d) follows from (c) due to $\mu\nu - \frac{1}{2}\mu^2 \leq \frac{1}{2}\nu^2$. $\square$

A.3.1 Proof of Proposition 3.1

Let us prove the bound (28). Consider first the case of SMP. Applying Lemma A.2 to $z = z_\tau$, $\gamma = \gamma_\tau$, $\xi = F(\eta_\tau)$, $\eta = F(\zeta_\tau)$, which results in $w = w_\tau$ and $z_+ = z_{\tau+1}$, we get for all $u \in Z$:

$$\gamma_\tau\langle F(\zeta_\tau), w_\tau - u\rangle \leq V_{z_\tau}(u) - V_{z_{\tau+1}}(u) + [\gamma_\tau\langle F(\zeta_\tau), w_\tau - z_{\tau+1}\rangle - V_{z_\tau}(z_{\tau+1})]$$

whence for all $u \in Z$

$$\begin{array}{rcl} \langle F(\zeta_\tau), \zeta_\tau - u\rangle & \leq & \gamma_\tau^{-1}(V_{z_\tau}(u) - V_{z_{\tau+1}}(u)) + r_\tau + s_\tau, \\ s_\tau & = & \langle F(\zeta_\tau), w_\tau - z_{\tau+1}\rangle - \gamma_\tau^{-1}V_{z_\tau}(z_{\tau+1}) \\ & \leq & \frac{1}{2}\left[\gamma_\tau\|F(\zeta_\tau) - F(\eta_\tau)\|_*^2 - \gamma_\tau^{-1}\|w_\tau - z_\tau\|^2\right], \quad (*) \\ r_\tau & = & \langle F(\zeta_\tau), \zeta_\tau - w_\tau\rangle. \end{array} \tag{63}$$

with $(*)$ given by (62). When summing up inequalities (63) over τ and taking into account that $\gamma_1 \geq \gamma_2 \geq ...$, $V_z(u) \geq 0$ and $V_{z_1}(u) = V_{z_\omega}(u) \leq \Omega$ by definition of Ω, we get

$$\sum_{\tau=1}^t \langle F(\zeta_\tau), \zeta_\tau - u\rangle \leq \gamma_t^{-1}\Omega + \sum_{\tau=1}^t [s_\tau + r_\tau]. \tag{64}$$

On the other hand,

$$\begin{array}{rl} \displaystyle\sum_{\tau=1}^t \langle F(\zeta_\tau), \zeta_\tau - u\rangle = \sum_{\tau=1}^t \langle a + \mathcal{A}\zeta_\tau, \zeta_\tau - u\rangle & \\ = & t\langle a, z^t - u\rangle - \displaystyle\sum_{\tau=1}^t \langle \mathcal{A}\zeta_\tau, u\rangle \quad [\mathcal{A} \text{ is skew symmetric}] \\ = & t\left[\langle a, z^t - u\rangle - \langle \mathcal{A}z^t, u\rangle\right] = t\left[\langle a, z^t - u\rangle + \langle \mathcal{A}z^t, z^t - u\rangle\right] \\ = & t\langle F(z^t), z^t - u\rangle. \end{array}$$

Thus, for all $u \in Z$ it holds

$$t\langle F(z^t), z^t - u\rangle \leq \Omega\gamma_t^{-1} + \sum_{\tau=1}^t [s_\tau + r_\tau] = \gamma_t^{-1}\Omega + S_t + R_t. \tag{65}$$

Setting $z^t = [z_1^t; z_2^t]$ and $u = [u_1; u_2]$, we get from (3) $\langle F(z^t), z^t - u\rangle = \phi(z_1^t, u_2) - \phi(u_1, z_2^t)$; the supremum of the latter quantity over $u \in Z$ is nothing that the saddle point residual $\epsilon_{\text{sad}}(z^t)$. Since the right hand side in (65) is independent of u, we arrive at the SMP-version of (28).

Now consider the case of SA. Applying Lemma A.2 to $\gamma = \gamma_\tau$, $z = z_\tau$, $\xi = 0$, $\eta = F(\zeta_\tau)$, which results in $w = z_\tau$ and $z_+ = z_{\tau+1}$, and acting exactly as in the case of SMP, we arrive at the SA-version of (28).

Let us prove (ii). The conditional to the "past" (the answers of the oracle prior to the call for $\xi_{2\tau}$) distribution of ζ_τ is P_{w_τ}, which combines with the affinity of F and the facts that the linear part of F is skew symmetric and the expectation of P_z is z, to imply that

$$\begin{aligned}\mathbf{E}\{\langle F(\zeta_\tau), \zeta_\tau - w_\tau\rangle\} &= \langle a, \mathbf{E}\{\zeta_\tau\} - w_\tau\rangle + \mathbf{E}\{\langle \mathcal{A}\zeta_\tau, \zeta_\tau - w_\tau\rangle\} = -\mathbf{E}\{\langle \mathcal{A}\zeta_\tau, w_\tau\rangle\} \\ &= \mathbf{E}\{\langle \mathcal{A}(w_\tau - \zeta_\tau), w_\tau\rangle\} = 0,\end{aligned}$$

whence $\mathbf{E}\{R_t\} = 0$ for all t. By completely similar reasoning, $\mathbf{E}\{R_t\} = 0$ in the case of SA. To complete the proof (ii), we need to prove (33). We have

$$\begin{aligned} s_t &\leq \frac{\gamma_t}{2}\|F(\zeta_t) - F(\eta_t)\|_*^2 - \frac{1}{2\gamma_t}\|w_t - z_t\|^2 \text{ [see (29)]} \\ &\leq \frac{\gamma_t}{2}\left[\|F(w_t) - F(z_t)\|_* + \|F(\zeta_t) - F(w_t)\|_* + \|F(\eta_t) - F(z_t)\|_*\right]^2 - \frac{1}{2\gamma_t}\|w_t - z_t\|^2 \\ &\leq \underbrace{\left[\frac{3\gamma_t}{2}\mathcal{L}^2 - \frac{1}{2\gamma_t}\right]}_{\leq 0 \text{ by (32)}}\|w_t - z_t\|^2 + \frac{3\gamma_t}{2}\left[\|F(\zeta_t) - F(w_t)\|_*^2 + \|F(\eta_t) - F(z_t)\|_*^2\right]. \end{aligned}$$

It remains to note that $\|F(\zeta_t) - F(w_t)\|_*^2 + \|F(\eta_t) - F(z_t)\|_*^2 \leq 2M_*^2$ since $\zeta_t, w_t, \eta_t, z_t \in Z$ and that the conditional, over the respective pasts, expectations of $\|F(\zeta_t) - F(w_t)\|_*^2$ and $\|F(\eta_t) - F(z_t)\|_*^2$ do not exceed σ^2. □

A.3.2 Proof of Proposition 3.2

We start with observing that (39) $\gamma_1 \geq \gamma_2 \geq ....$

1⁰. Let us verify first that with the choice (39) of γ_τ, $\tau = 1, 2, ...$ we have for all $t = 1, 2, ...,$

$$\sqrt{2}\Omega\gamma_t^{-1} \geq S_t. \tag{66}$$

Indeed, for $t = 2, 3, ...$ we have (with $2S_0 = F_*^2$ in the case of SA and $2S_0 = 8\Omega\mathcal{L}^2$, $\geq M_*^2$ by (21), in the case of SMP)

$$\frac{\gamma_{t-1}^2}{\gamma_t^2} = \frac{\sum_{\tau=1}^{t-1} 2[s_\tau]_+/\gamma_\tau + 2S_0}{\sum_{\tau=1}^{t-2} 2[s_\tau]_+/\gamma_\tau + 2S_0} \leq 1 + \frac{2[s_{t-1}]_+/\gamma_{t-1}}{2S_0} \leq 2 \tag{67}$$

(recall that $2s_t/\gamma_\tau \leq 2S_0$ by (30)). On the other hand

$$\gamma_t^{-2} - \gamma_{t-1}^{-2} = \frac{2[s_{t-1}]_+}{\Omega\gamma_{t-1}},$$

and

$$\gamma_t^{-1} - \gamma_{t-1}^{-1} \geq \tfrac{\gamma_t}{2}(\gamma_t^{-2} - \gamma_{t-1}^{-2}) = \tfrac{\gamma_t [s_{t-1}]_+}{\gamma_{t-1}\Omega} \geq \tfrac{[s_{t-1}]_+}{\sqrt{2}\Omega} \Rightarrow \sqrt{2}\Omega[\gamma_t^{-1} - \gamma_{t-1}^{-1}] \geq [s_{t-1}]_+$$

where the second inequality in this chain follows from $\gamma_{t-1} \leq \sqrt{2}\gamma_t$ which is implied by (67). By summing up the resulting inequalities in the above chain, we get

$$\sqrt{2}\Omega\gamma_t^{-1} \geq \sum_{\tau=1}^{t-1} s_\tau + \sqrt{2}\Omega\gamma_1^{-1}. \tag{68}$$

In the case of SMP, we have $\gamma_1 = (2\sqrt{2}\mathcal{L})^{-1}$, whence $\sqrt{2}\Omega\gamma_1^{-1} = 4\Omega\mathcal{L} \geq \gamma_1 M_*^2 \geq \gamma_t M_*^2$ (see (21)), whence $\sqrt{2}\Omega\gamma_1^{-1} \geq s_t$ in view of (29), and (68) implies (66). In the case of SA, we have $\gamma_1 = \sqrt{\Omega}/F_*$, whence $\sqrt{2}\Omega\gamma_1^{-1} = \sqrt{2}\sqrt{\Omega}F_* \geq \gamma_1 F_*^2 \geq \gamma_t F_*^2$, whence $\sqrt{2}\Omega\gamma_1^{-1} \geq s_t$ by (29), and (66) again is given by (68).

2^0. Invoking (28), (66) implies (40). Now, by (29) in the case of SA we have $2[s_\tau]_+/\gamma_\tau \leq \|F(\zeta_\tau)\|_*^2$. In the case of SMP we have

$$\begin{aligned}
&2[s_\tau]_+/\gamma_\tau \leq \|F(\zeta_\tau) - F(\eta_\tau)\|_*^2 - \gamma_\tau^{-2}\|w_\tau - z_\tau\|^2 \text{ [see (29)]}\\
&\leq \left[\|F(\zeta_\tau) - F(w_\tau)\|_* + \|F(w_\tau) - F(z_\tau)\|_* + \|F(z_\tau) - F(\eta_\tau)\|_*\right]^2 - \gamma_1^{-2}\|w_\tau - z_\tau\|^2\\
&\leq 3\left[\|F(\zeta_\tau) - F(w_\tau)\|_*^2 + \|F(z_\tau) - F(\eta_\tau)\|_*^2\right] + \left[3\|F(w_\tau) - F(z_\tau)\|_*^2 - \gamma_1^{-2}\|w_\tau - z_\tau\|^2\right]\\
&\leq \varsigma_\tau := 3\left[\|F(\zeta_\tau) - F(w_\tau)\|_*^2 + \|F(z_\tau) - F(\eta_\tau)\|_*^2\right] \text{ [by (20) due to } \gamma_1^{-1} = 2\sqrt{2}\mathcal{L}]
\end{aligned}$$

Invoking (39), we get

$$\gamma_t^{-1} \leq \Omega^{-1/2} \cdot \begin{cases} \left(F_*^2 + \sum_{\tau=1}^{t-1}\|F(\zeta_\tau)\|_*^2\right)^{1/2}, & \text{in the case of SA}\\ \left(8\Omega\mathcal{L}^2 + \sum_{\tau=1}^{t-1}\varsigma_\tau\right)^{1/2}, & \text{in the case of SMP}\end{cases} \tag{69}$$

which combines with (40) to imply (41). □

A.3.3 Proof of Proposition 3.3

1^0. Let us denote

$$\varphi_t = 8\Omega\mathcal{L}^2 + \sum_{\tau=1}^{t-1}\varsigma_\tau,$$

where $\varsigma_t = 3\left[\|F(\zeta_t) - F(w_t)\|_*^2 + \|F(\eta_t) - F(z_t)\|_*^2\right]$ (cf. (42)). Let us show that under the premise of Proposition 3.3

$$\forall \Lambda \geq 0: \quad \text{Prob}\left\{\varphi_t \geq O(1)\left[\Omega\mathcal{L}^2 + \frac{M_*^2 t}{k}\varkappa_*^2(k,\Lambda)\right]\right\} \leq \exp\{-\Lambda t\}, \tag{70}$$

where $O(1)$ is an absolute constant factor. We use the following result (see, e.g., Theorem 2.1 (iii) of [8]): let $\xi^i, ..., \xi^k$ be k independent vectors from E with $\|\xi^i\|_* \leq \sigma$ and $\mathbf{E}\{\xi^i\} = 0$, where the norm $\|\cdot\|_*$ is $\varkappa$-regular, $\varkappa \geq 1$. Then for any $u \geq 0$

$$\text{Prob}\left\{\|\sum_{i=1}^k \xi^i\|_* \geq \left[\sqrt{2\varkappa} + u\sqrt{2}\right]\sigma\sqrt{k}\right\} \leq \exp\{-u^2/2\}.$$

When rewriting the above bound for $\xi^i = F(\zeta^i) - F(w)$ and $\xi^i = F(\eta^i) - F(z)$ and taking into account that $\|\xi^i\|_* \leq M_*$ we obtain

$$\forall u \geq 0: \quad \mathrm{Prob}\left\{ \|\sum_{i=1}^k \xi^i\|_*^2 \geq M_*^2 k(\sqrt{2\varkappa} + \sqrt{2}u)^2 \right\} \leq \exp\{-u^2/2\}.$$

So, if we denote Prob_t conditional probability over $\zeta_1, \eta_1, ..., \zeta_{t-1}, \eta_{t-1}$ being fixed, we get

$$\forall u \geq 0: \quad \mathrm{Prob}_t\left\{ \varsigma_t \geq \frac{24M_*^2}{k}(\varkappa + u) \right\} \leq 2\exp\{-u/2\},$$

where $\varsigma_t = 3\left[\|F(\zeta_t) - F(w_t)\|_*^2 + \|F(\eta_t) - F(z_t)\|_*^2\right]$ (cf. (42)). When setting $\nu_t = \frac{\varsigma_t k}{24M_*^2}$, we have for the conditional expectation $\mathbf{E}_t$ over $\zeta_1, \eta_1, ..., \zeta_{t-1}, \eta_{t-1}$ being fixed and $0 \leq \alpha < 1$

$$\begin{aligned} \mathbf{E}_t\left\{\exp\{\frac{\alpha}{2}\nu_t\}\right\} &\leq e^{\frac{\alpha\varkappa}{2}} + \frac{\alpha}{2}\int_{\varkappa}^{\infty} e^{\frac{\alpha u}{2}}\mathrm{Prob}_t\{\nu_t \geq u\}du \\ &\leq e^{\frac{\alpha\varkappa}{2}} + \alpha\int_{\varkappa}^{\infty}\exp\{-\frac{(1-\alpha)u}{2}\}du = \frac{1+\alpha}{1-\alpha}\exp\{\frac{\alpha\varkappa}{2}\} \end{aligned}$$

When choosing $\alpha_* = \frac{\exp\{1\}-1}{\exp\{1\}+1}$ we get $\mathbf{E}_t\left\{\exp\{\frac{\alpha_*\nu_t}{2}\}\right\} \leq \exp\{\frac{\alpha_*\varkappa}{2} + 1\}$, so that

$$\begin{aligned} \mathbf{E}\left\{\exp\{\sum_{\tau=1}^t \frac{\alpha_*\nu_\tau}{2}\}\right\} &= \mathbf{E}\left\{\mathbf{E}_t\left\{\exp\{\sum_{\tau=1}^{t-1}\frac{\alpha_*\nu_\tau}{2}\}\exp\{\frac{\alpha_*\nu_t}{2}\}\right\}\right\} \\ &= \mathbf{E}\left\{\exp\{\sum_{\tau=1}^{t-1}\frac{\alpha_*\nu_\tau}{2}\}\mathbf{E}_t\left\{\exp\{\frac{\alpha_*\nu_t}{2}\}\right\}\right\} \leq \exp\{t(\frac{\alpha_*\varkappa}{2} + 1)\} \end{aligned}$$

Hence, when applying the Tchebychev inequality we find

$$\forall \Lambda \geq 0: \quad \mathrm{Prob}\left\{\sum_{\tau=1}^t \nu_\tau \geq t\left(\varkappa + \frac{2}{\alpha_*}(1+\Lambda)\right)\right\} \leq \exp\{-\Lambda t\}.$$

When recalling that $\varsigma_t \leq 6M_*^2$, we conclude that

$$\forall \Lambda \geq 0: \quad \mathrm{Prob}\left\{\sum_{\tau=1}^{t-1}\varsigma_\tau \geq \min\left[6M_*^2 t,\ \frac{24M_*^2 t}{k}\left(\varkappa + \frac{2}{\alpha_*}(1+\Lambda)\right)\right]\right\} \leq \exp\{-\Lambda t\}.$$

Since $\varkappa \geq 1$, $\varkappa + \frac{2}{\alpha_*}(1+\Lambda) \leq O(1)\varkappa_*^2(k,\Lambda)$, and we arrive at (70).

2^0. We have

$$\forall \lambda \geq 0: \quad \mathrm{Prob}\left\{\frac{R_t}{t} \geq O(1)F_*\sqrt{\frac{\Omega\lambda}{kt}}\right\} \leq e^{-\lambda}. \tag{71}$$

Indeed, since $\mathcal{A}$ is skew-symmetric, i.e. $\langle \mathcal{A}z, z\rangle = 0$,

$$r_t \;=\; \langle F(\zeta_t),\, \zeta_t - w_t\rangle = \langle a + \mathcal{A}\zeta_t,\, \zeta_t - w_t\rangle = \langle a + \mathcal{A}w_t, \zeta_t - w_t\rangle = \langle F(w_t), \zeta_t - w_t\rangle.$$

We conclude that

$$\begin{aligned}\frac{R_t}{t} &= \frac{1}{t}\sum_{\tau=1}^{t} r_t = \frac{1}{t}\sum_{\tau=1}^{t}\langle F(w_\tau), \zeta_\tau - w_\tau\rangle = \frac{1}{t}\sum_{\tau=1}^{t}\left\langle F(w_\tau),\, \frac{1}{k}\sum_{i=1}^{k}\zeta_\tau^i - w_\tau\right\rangle \\ &= \frac{1}{tk}\sum_{\tau=1}^{t}\sum_{i=1}^{k}\langle F(w_\tau),\, \zeta_\tau^i - w_\tau\rangle = \frac{1}{tk}\sum_{\tau=1}^{t}\sum_{i=1}^{k}\xi_\tau^i,\end{aligned}$$

where $\xi_\tau^i := \langle F(w_\tau),\, \zeta_\tau^i - w_\tau\rangle$ is a scalar martingale-difference with $|\xi_\tau^i| \le 2\mathcal{R}F_* \le 2\Theta F_*$ (cf. (19)). Then by the Azuma-Hoeffding inequality [1],

$$\forall \lambda \ge 0: \;\; \mathrm{Prob}\left\{\frac{R_t}{t} \ge 2\Theta F_*\sqrt{\frac{2\lambda}{kt}}\right\} \le e^{-\lambda},$$

which implies (71).

Now we are done – when substituting the bounds (70) and (71) into (41) we get

$$\mathrm{Prob}\left\{\epsilon_{\mathrm{sad}}(z^t) \ge O(1)\left[\frac{\Omega\mathcal{L}}{t} + M_*\varkappa_*(k,\Lambda)\sqrt{\frac{\Omega}{kt}} + \Theta F_*\sqrt{\frac{\lambda}{kt}}\right]\right\} \le e^{-\Lambda t} + e^{-\lambda},$$

which is (44) if we recall that $\Theta = \sqrt{2\Omega}$ and $F_* \le \|a\|_* + 2\Theta\mathcal{L}$ (cf. (22)). □

A.3.4 Proof of Proposition 3.4

This proof is completely similar to the one of Proposition 3.1 and is omitted.

A.4 Proof of Theorem 4.1

1⁰. From the description of the method it follows that

$$\forall t, s \ge 1, \rho \ge 0: u^{ts} \ge \mathrm{SV}(\rho_s) \ge \ell^{ts},\; \ell_{ts}(\rho) \le \mathrm{SV}(\rho), \ell^{ts} \le \ell_{ts}(\rho_s). \tag{72}$$

Let us prove by induction in s that $\rho_* \le \rho_s \le \rho_1$. The base $s = 1$ is evident. Now let $\rho_* \le \rho_s \le \rho_1$, and let stage $s+1$ take place. When passing from stage s to stage $s+1$, we are in the case B) and thus have $u^{ts} > \epsilon\rho_s$, $\ell^{ts} \ge \frac{3}{4}u^{ts} > \frac{3}{4}\epsilon\rho_s$, whence, in view of (72),

$$\ell_s(\rho_s) = \ell_{ts}(\rho_s) \ge \ell^{ts} \ge \frac{3}{4}\max[\epsilon\rho_s, \mathrm{SV}(\rho_s)] \;\&\; \ell_s(\rho_s) > 0. \tag{73}$$

This combines with $\ell_{ts}(\rho_*) \le \mathrm{SV}(\rho_*) \le 0$ and convexity of $\ell_{ts}(\cdot)$ to imply that $\rho_* \le \rho_{s+1} < \rho_s$. Induction is complete.

Since $\rho_s \ge \rho_*$, u^{ts} is an upper bound on $\mathrm{SV}(\rho_s)$ and $u^{ts} \ge \overline{\phi}^{\rho_s}(w_1^{ts})$, we conclude that if the algorithm terminates at stage s, then the result ρ_s, w_1^{ts} is an ϵ-solution to the GBSP in question.

2^0. Let us prove (ii). The reasoning to follow goes back to [10]; we reproduce it here to make the paper self-contained. Let s be such that the stage $s+1$ takes place, and let u_s be the last bound u^{ts} built at stage s. Observe that

$$\frac{3}{4}\epsilon\rho_s < \frac{3}{4}u_s \leq \ell_s(\rho_s) \leq \mathrm{SV}(\rho_s) \leq u_s. \tag{74}$$

Since the convex function $\ell_s(\rho)$ is nonpositive at $\rho = \rho_{s+1}$ and is $\geq \frac{3}{4}u_s > 0$ at $\rho = \rho_s > \rho_{s+1}$, we have $g_s := \ell_s'(\rho_s) > 0$ and

$$\rho_s - \rho_{s+1} \geq \ell_s(\rho_s)/g_s \geq \frac{3}{4}u_s/g_s. \tag{75}$$

Now assume that $s > 1$ is such that the stage $s+1$ takes place. Applying (75) and (74) to $s-1$ in the role of s, we get $\rho_{s-1} - \rho_s \geq \frac{3}{4}u_{s-1}/g_{s-1}$ and $\frac{3}{4}u_s \leq \ell_s(\rho_s)$, whence, by convexity of $\ell_s(\cdot)$ and in view of (72), $u_{s-1} \geq \mathrm{SV}(\rho_{s-1}) \geq \ell_s(\rho_{s-1}) \geq \ell_s(\rho_s) + g_s(\rho_{s-1} - \rho_s) \geq \frac{3}{4}u_s + g_s\frac{3}{4}\frac{u_{s-1}}{g_{s-1}}$, so that $\frac{4}{3}u_{s-1} \geq u_s + \frac{g_s u_{s-1}}{g_{s-1}}$, or $\frac{u_s}{u_{s-1}} + \frac{g_s}{g_{s-1}} \leq \frac{4}{3}$, whence $\frac{u_s g_s}{u_{s-1}g_{s-1}} \leq (1/4)(4/3)^2 = 4/9$. It follows that

$$\sqrt{u_s g_s} \leq (2/3)^{s-1}\sqrt{u_1 g_1}. \tag{76}$$

We have $\ell_s(\rho_*) \leq \mathrm{SV}(\rho_*) = 0$, $\ell_s(\rho_s) \geq \frac{3}{4}u_s$ (see (74)) and $\ell_s(\rho_s) - \ell_s(\rho_*) \leq g_s(\rho_s - \rho_*)$ (convexity of $\ell_s(\cdot)$), whence $g_s \geq \frac{3}{4}u_s(\rho_s - \rho_*)^{-1} \geq \frac{3}{4\rho_1}u_s$, and (76) implies that

$$u_s \leq (2/3)^{s-1}\sqrt{u_1 g_1}\sqrt{4\rho_1/3}. \tag{77}$$

Now, $g_1 = \ell_1'(\rho_1)$ and $\ell_1(\rho) \leq \mathrm{SV}(\rho) \leq \|\phi\|_\infty + \rho\|\psi\|_\infty$, whence $g_1 \leq \|\psi\|_\infty$, and clearly $u_1 \leq \|\phi\|_\infty + \rho_1\|\psi\|_\infty$. At the same time, $u_s > \epsilon\rho_s \geq \epsilon\rho_*$, so that (77) implies that $\epsilon\rho_* \leq (2/3)^{s-1}[\|\phi\|_\infty + \rho_1\|\psi\|_\infty]$. The resulting upper bound on s implies (ii).

3^0. Let us prove (iii). From the description of the algorithm it follows that at every stage s before termination of the stage the residual of current approximate solutions w^{ts} is $\geq \frac{1}{4}\epsilon\rho_s$ (since $u^{ts} > \epsilon\rho_s$ and $\ell^{ts} < \frac{3}{4}u^{ts}$). In the case of short-step implementation we use the result of Proposition (3.3) with $\varepsilon = \epsilon\rho_s$. Let us denote $N_s(\epsilon)$ the corresponding value of N_ε as in (45). We conclude that the number N_s of steps at stage s is finite with probability 1 and satisfies $\mathrm{Prob}\{N_s > N_s(\epsilon)\} \leq \exp\{-\Lambda N_s(\epsilon)\} + \exp\{-\lambda\}$. As we have seen, $\rho_* \leq \rho_s$ for all s, and therefore $N_s \leq N(\epsilon)$ for all s, provided that the absolute constant $O(1)$ in (59) is properly chosen.

For the aggressive-step implementation, similar reasoning based on the bound (51) with $\mathcal{L} = \mathcal{M} + \rho_s\mathcal{N}$ justifies (60).

4^0. Combining (ii), (iii) and the concluding claim in item 1^0 above, we arrive at (i). $\square$

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