Sketchy Decisions: Convex Low-Rank Matrix Optimization with Optimal Storage

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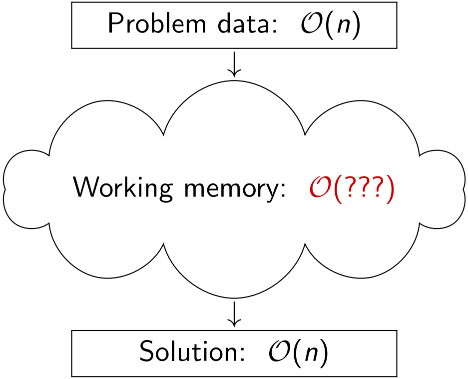
Desiderata

Suppose that the solution to a convex optimization problem has a **compact representation**.



Can we develop algorithms that provably solve the problem using **storage** bounded by the size of the **problem data** and the size of the **solution**?

Model problem: low rank matrix optimization

consider a convex problem with decision variable $X \in \mathbb{R}^{m \times n}$

compact matrix optimization problem:

$$\begin{array}{ll} \text{minimize} & f(\mathcal{A}X) \\ \text{subject to} & \|X\|_{S_1} \leq \alpha \end{array} \qquad \text{(CMOP)}$$

- $\mathcal{A} : \mathbb{R}^{m \times n} \to \mathbb{R}^d$
- $f : \mathbb{R}^d \to \mathbb{R}$ convex and smooth
- $\|X\|_{S_1}$ is Schatten-1 norm: sum of singular values

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assume

- **compact specification**: problem data use $\mathcal{O}(n)$ storage
- **compact solution**: $\operatorname{rank} X_\star = r$ constant

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- **compact specification**: problem data use $\mathcal{O}(n)$ storage
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Note: Same ideas work for $X \succeq 0$

Are desiderata achievable?

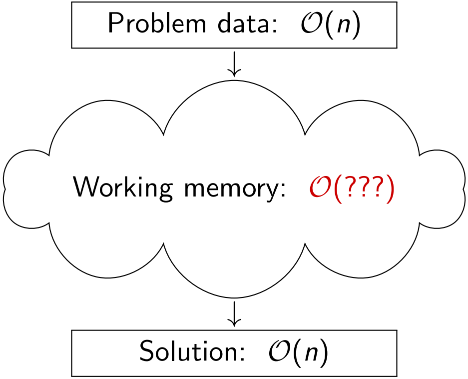
$$\begin{array}{ll} \text{minimize} & f(\mathcal{A}X) \\ \text{subject to} & \|X\|_{S_1} \leq \alpha \end{array}$$

CMOP, using any first order method:

$$\boxed{\text{Problem data: } \mathcal{O}(n)}$$
$$\downarrow$$
$$\boxed{\text{Working memory: } \mathcal{O}(n^2)}$$
$$\downarrow$$
$$\boxed{\text{Solution: } \mathcal{O}(n)}$$

Are desiderata achievable?

CMOP, using **???**:



Application: matrix completion

find X matching M on observed entries

$$\begin{array}{ll} \text{minimize} & \sum_{(i,j)\in\Omega}(X_{ij} - M_{ij})^2 \\ \text{subject to} & \|X\|_{S_1} \leq \alpha \end{array}$$

- $m =$ rows, $n =$ columns of matrix to complete
- $d = |\Omega|$ number of observations
- $\mathcal{A}$ selects observed entries X_{ij}, $(i, j) \in \Omega$
- $f(\mathcal{A}X) = \|\mathcal{A}X - \mathcal{A}M\|^2$

compact if $d = \mathcal{O}(n)$ observations and $\text{rank}(X^\star)$ constant

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why is there a good approximation to M with constant rank?

Nice latent variable models

Suppose matrix $A \in \mathbb{R}^{m \times n}$ generated by a latent variable model:

- $\alpha_i \sim \mathcal{A}$ iid, $i = 1, \ldots, m$
- $\beta_j \sim \mathcal{B}$ iid, $j = 1, \ldots, n$
- $A_{ij} = g(\alpha_i, \beta_j)$

We say latent variable model is **nice** if

- distributions $\mathcal{A}$ and $\mathcal{B}$ have bounded support
- g is piecewise analytic and on each piece: for some $M \in \mathbb{R}$,

$$\|D^\mu g(\alpha, \beta)\| \leq C M^{|\mu|} \|g\|.$$

($\|g\| = \sup_{x \in \mathbf{dom}\, g} g(x)$ is sup norm.)

Examples: $g(\alpha, \beta) = \text{poly}(\alpha, \beta)$ or $g(\alpha, \beta) = \exp(\text{poly}(\alpha, \beta))$

Rank of nice latent variable models?

Question: How does rank of ϵ-approximation to $A \in \mathbb{R}^{m \times n}$ change with m and n?

$$\begin{array}{ll} \text{minimize} & \operatorname{rank}(X) \\ \text{subject to} & \|X - M\|_\infty \leq \epsilon \end{array}$$

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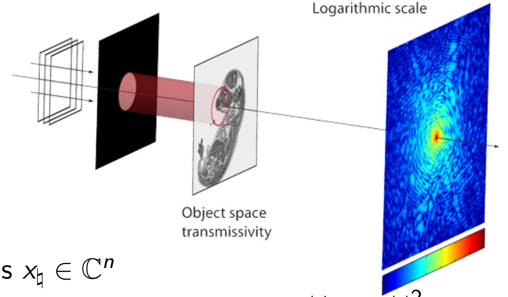
Theorem (Udell and Townsend, 2017)

Nice latent variable models are of log rank.

Application: Phase retrieval



- image with n pixels $x_\natural \in \mathbb{C}^n$
- acquire noisy nonlinear measurements $b_i = |\langle a_i, x_\natural \rangle|^2 + \omega_i$
- relax: if $X = x_\natural x_\natural^*$, then

$$|\langle a_i, x_\natural \rangle|^2 = x_\natural a_i^* a_i x_\natural^* = \mathrm{tr}(a_i^* a_i x_\natural^* x_\natural) = \mathrm{tr}(a_i^* a_i X)$$

- recover image by solving

$$\begin{array}{ll} \text{minimize} & f(\mathcal{A}X; b) \\ \text{subject to} & \mathrm{tr}\, X \le \alpha \\ & X \succeq 0. \end{array}$$

compact if $d = \mathcal{O}(n)$ observations and $\mathrm{rank}(X^\star)$ constant

Why compact?

why a compact specification?

- data is expensive
- collect constant data per column (=user or sample)
- if solution is compact, compact specification should suffice

why a compact solution?

- the world is simple and structured
- nice latent variable models are of log rank
- given d observations, there is a solution with rank $\mathcal{O}(\sqrt{d})$
  (Barvinok 1995, Pataki 1998)

Optimal Storage

What kind of storage bounds can we hope for?

- Assume black-box implementation of

$$\mathcal{A}(uv^*) \qquad u^*(\mathcal{A}^*z) \qquad (\mathcal{A}^*z)v$$

  where $u \in \mathbb{R}^m$, $v \in \mathbb{R}^n$, and $z \in \mathbb{R}^d$
- Need $\Omega(m+n+d)$ storage to apply linear map
- Need $\Theta(r(m+n))$ storage for a rank-r approximate solution

Definition. An algorithm for the model problem has **optimal storage** if its working storage is

$$\Theta(d + r(m+n)).$$

Goal: optimal storage

We can specify the problem using $\mathcal{O}(n) \ll mn$ units of storage.

Can we solve the problem using only $\mathcal{O}(n)$ units of storage?

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We can specify the problem using $\mathcal{O}(n) \ll mn$ units of storage.

Can we solve the problem using only $\mathcal{O}(n)$ units of storage?

If we write down X, we've already failed.

A brief biased history of matrix optimization

- 1990s: **Interior-point methods**
  - Storage cost $\Theta((m+n)^4)$ for Hessian
- 2000s: **Convex first-order methods (FOM)**
  - (Accelerated) proximal gradient and others
  - Store matrix variable $\Theta(mn)$

(**Interior-point:** Nemirovski & Nesterov 1994; . . . ; **First-order:** Rockafellar 1976; Auslender & Teboulle 2006; . . .)

A brief biased history of matrix optimization

- 2008–Present: **Storage-efficient convex FOM**
  - Conditional gradient method (CGM) and extensions
  - Store matrix in low-rank form $\mathcal{O}(t(m+n))$ after t iterations
  - Requires storage $\Theta(mn)$ for $t \geq \min(m, n)$
  - Variants: prune factorization, or seek rank-reducing steps

- 2003–Present: **Nonconvex heuristics**
  - Burer–Monteiro factorization idea + various opt algorithms
  - Store low-rank matrix factors $\Theta(r(m+n))$
  - For guaranteed solution, need unrealistic + unverifiable statistical assumptions

(**CGM:** Frank & Wolfe 1956; Levitin & Poljak 1967; Hazan 2008; Clarkson 2010; Jaggi 2013; . . . ; **CGM + pruning:** Rao Shah Wright 2015; Freund Grigas Mazumder 2017; . . . ; **Heuristics:** Burer & Monteiro 2003; Keshavan et al. 2009; Jain et al. 2012; Bhojanapalli et al. 2015; Candès et al. 2014; Boumal et al. 2015; . . .)

The dilemma

- convex methods: slow memory hogs with guarantees
- nonconvex methods: fast, lightweight, but brittle

The dilemma

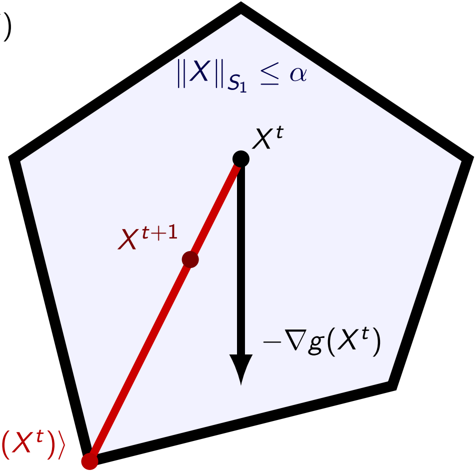
- convex methods: slow memory hogs with guarantees
- nonconvex methods: fast, lightweight, but brittle

low memory or guaranteed convergence

. . . but not both?

Conditional Gradient Method

$$\begin{array}{ll} \text{minimize} & f(\mathcal{A}X) = g(X) \\ \text{subject to} & \|X\|_{S_1} \leq \alpha \end{array}$$



$$H^t = \underset{\|X\|_{S_1} \leq \alpha}{\text{argmax}} \ \langle X, -\nabla g(X^t) \rangle$$

Conditional Gradient Method

$$\begin{array}{ll} \text{minimize} & f(\mathcal{A}X) \\ \text{subject to} & \|X\|_{S_1} \le \alpha \end{array}$$

CGM. set $X^0 = 0$. for $t = 0, 1, \ldots$

- compute $G^t = \mathcal{A}^* \nabla f(\mathcal{A}X^t)$
- set search direction

$$H^t = \underset{\|X\|_{S_1} \le \alpha}{\operatorname{argmax}} \langle X, -G^t \rangle$$

- set stepsize $\eta^t = 2/(t+2)$
- update $X^{t+1} = (1 - \eta^t) X^t + \eta^t H^t$

Conditional gradient method (CGM)

features:

- relies on efficient **linear optimization oracle** to compute

$$H^t = \underset{\|X\|_{S_1} \leq \alpha}{\operatorname{argmax}} \langle X, -G^t \rangle$$

- bound on suboptimality follows from subgradient inequality

$$\begin{aligned} f(\mathcal{A}X^t) - f(\mathcal{A}X^\star) &\leq \langle X^t - X^\star, G^t \rangle \\ &\leq \langle X^t - X^\star, \mathcal{A}^* \nabla f(\mathcal{A}X^t) \rangle \\ &\leq \langle \mathcal{A}X^t - \mathcal{A}X^\star, \nabla f(\mathcal{A}X^t) \rangle \\ &\leq \langle \mathcal{A}X^t - \mathcal{A}H^t, \nabla f(\mathcal{A}X^t) \rangle \end{aligned}$$

  to provide stopping condition
- faster variants: linesearch, away steps, ...

Linear optimization oracle for MOP

compute search direction

$$\underset{\|X\|_{S_1}\leq\alpha}{\operatorname{argmax}}\langle X, -G\rangle$$

Linear optimization oracle for MOP

compute search direction

$$\underset{\|X\|_{S_1} \leq \alpha}{\operatorname{argmax}} \langle X, -G \rangle$$

- solution given by maximum singular vector of $-G$:

$$-G = \sum_{i=1}^{n} \sigma_i u_i v_i^* \quad \Longrightarrow \quad X = \alpha u_1 v_1^*$$

- use Lanczos method: only need to apply G and G^*

Conditional gradient descent

Algorithm 1 CGM for the model problem (CMOP)

Input: Problem data for (CMOP); suboptimality ε
Output: Solution $X_\star$

```
function CGM
    X ← 0
    for t ← 0, 1, ... do
        (u, v) ← MaxSingVec(−𝒜*(∇f(𝒜X)))
        H ← −α uv*
        if ⟨𝒜X − 𝒜H, ∇f(𝒜X)⟩ ≤ ε then break for
        η ← 2/(t + 2)
        X ← (1 − η)X + ηH
    return X
```

Two crucial ideas

To solve the problem using optimal storage:

- Use the low-dimensional "dual" variable

$$z_t = \mathcal{A}X_t \in \mathbb{R}^d$$

  to drive the iteration.
- Recover solution from small (randomized) sketch.

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Never write down X until it has converged to low rank.

Conditional gradient descent

Algorithm 2 CGM for the model problem (CMOP)

Input: Problem data for (CMOP); suboptimality ε
Output: Solution $X_\star$

function CGM
  $X \leftarrow 0$
  for $t \leftarrow 0, 1, \ldots$ **do**
    $(u, v) \leftarrow \texttt{MaxSingVec}(-\mathcal{A}^*(\nabla f(\mathcal{A}X)))$
    $H \leftarrow -\alpha\, uv^*$
    if $\langle \mathcal{A}X - \mathcal{A}H, \nabla f(\mathcal{A}X)\rangle \leq \varepsilon$ **then break for**
    $\eta \leftarrow 2/(t+2)$
    $X \leftarrow (1-\eta)X + \eta H$
  return X

Conditional gradient descent

Introduce "dual variable" $z = \mathcal{A}X \in \mathbb{R}^d$; eliminate X.

Algorithm 3 Dual CGM for the model problem (CMOP)

Input: Problem data for (CMOP); suboptimality ε
Output: Solution $X_\star$

```
function dualCGM
    z ← 0
    for t ← 0, 1, ... do
        (u, v) ← MaxSingVec(−A*(∇f(z)))
        h ← A(−α u v*)
        if ⟨z − h, ∇f(z)⟩ ≤ ε then break for
        η ← 2/(t + 2)
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Conditional gradient descent

Introduce "dual variable" $z = \mathcal{A}X \in \mathbb{R}^d$; eliminate X.

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        if $\langle z - h,\, \nabla f(z)\rangle \leq \varepsilon$ **then break for**
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        $z \leftarrow (1-\eta)z + \eta h$

we've solved the problem... but where's the solution?

Two crucial ideas

1. Use the low-dimensional "dual" variable

$$z_t = \mathcal{A}X_t \in \mathbb{R}^d$$

   to drive the iteration.
2. Recover solution from small (randomized) sketch.

How to catch a low rank matrix

if $\hat{X}$ has the same rank as $X^\star$,
and $\hat{X}$ acts like $X^\star$ (on its range and co-range),
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How to catch a low rank matrix

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- see a series of additive updates
- remember how the matrix acts
- reconstruct a low rank matrix that acts like $X^\star$

Single-pass randomized sketch

- Draw and fix two independent standard normal matrices

$$\Omega \in \mathbb{R}^{n \times k} \quad \text{and} \quad \Psi \in \mathbb{R}^{\ell \times m}$$

with $k = 2r + 1$, $\ell = 4r + 2$.

Single-pass randomized sketch

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- The sketch consists of two matrices that capture the range and co-range of X:

$$Y = X\Omega \in \mathbb{R}^{n\times k} \quad \text{and} \quad W = \Psi X \in \mathbb{R}^{\ell\times m}$$

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- Rank-1 updates to X can be performed on sketch:

$$X' = \beta_1 X + \beta_2 uv^*$$
$$\Downarrow$$
$$Y' = \beta_1 Y + \beta_2 uv^*\Omega \quad \text{and} \quad W' = \beta_1 W + \beta_2 \Psi uv^*$$

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- Both the storage cost for the sketch and the arithmetic cost of an update are $\mathcal{O}(r(m+n))$.

Recovery from sketch

To recover rank-r approximation $\hat{X}$ from the sketch, compute

1. $Y = QR$ (tall-skinny QR)
2. $B = (\Psi Q)^\dagger W$ (small QR + backsub)
3. $\hat{X} = Q[B]_r$ (tall-skinny SVD)

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Theorem (Reconstruction (Tropp Yurtsever U Cevher, 2016))

Fix a target rank r. Let X be a matrix, and let (Y, W) be a sketch of X. The reconstruction procedure above yields a rank-r matrix $\hat{X}$ with

$$\mathbb{E}\,\|X - \hat{X}\|_{\mathrm{F}} \leq 2\,\|X - [X]_r\|_{\mathrm{F}}\,.$$

Similar bounds hold with high probability.

Previous work (Clarkson Woodruff 2009) algebraically but not numerically equivalent.

Recovery from sketch: intuition

recall

$$Y = X\Omega \in \mathbb{R}^{n \times k} \quad \text{and} \quad W = \Psi X \in \mathbb{R}^{\ell \times m}$$

- if Q is an orthonormal basis for $\mathcal{R}(X)$, then

$$X = QQ^* X$$

- if $QR = X\Omega$, then Q is (approximately) a basis for $\mathcal{R}(X)$
- and if $W = \Psi X$, we can estimate

$$\begin{aligned} W &= \Psi X \\ &\approx \Psi Q Q^* X \\ (\Psi Q)^\dagger W &\approx Q^* X \end{aligned}$$

- hence we may reconstruct X as

$$X \approx QQ^* X \approx Q(\Psi Q)^\dagger W$$

SketchyCGM

Algorithm 5 SketchyCGM for the model problem (CMOP)

Input: Problem data; suboptimality ε; target rank r
Output: Rank-r approximate solution $\hat{X} = U\Sigma V^*$

function $\textsc{SketchyCGM}$
  $\textsc{Sketch.Init}(m, n, r)$
  $z \leftarrow 0$
  for $t \leftarrow 0, 1, \ldots$ **do**
    $(u, v) \leftarrow \texttt{MaxSingVec}(-\mathcal{A}^*(\nabla f(z)))$
    $h \leftarrow \mathcal{A}(-\alpha uv^*)$
    if $\langle z - h, \nabla f(z)\rangle \leq \varepsilon$ **then break for**
    $\eta \leftarrow 2/(t + 2)$
    $z \leftarrow (1 - \eta)z + \eta h$
    $\textsc{Sketch.CGMUpdate}(-\alpha u, v, \eta)$
  $(U, \Sigma, V) \leftarrow \textsc{Sketch.Reconstruct}(\,)$
  return (U, Σ, V)

Guarantees

Suppose

- $X_{\mathrm{cgm}}^{(t)}$ is tth CGM iterate
- $\lfloor X_{\mathrm{cgm}}^{(t)} \rfloor_r$ is best rank r approximation to CGM solution
- $\hat{X}^{(t)}$ is SketchyCGM reconstruction after t iterations

Theorem (Convergence to CGM solution)

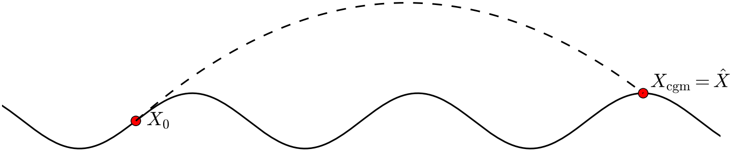
After t iterations, the SketchyCGM reconstruction satisfies

$$\mathbb{E}\,\|\hat{X}^{(t)} - X_{\mathrm{cgm}}^{(t)}\|_{\mathrm{F}} \leq 2\,\|\lfloor X_{\mathrm{cgm}}^{(t)} \rfloor_r - X_{\mathrm{cgm}}^{(t)}\|_{\mathrm{F}}\,.$$

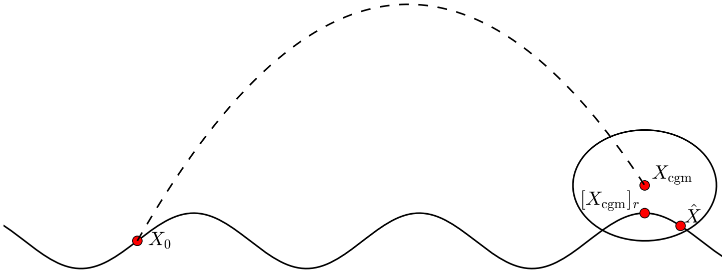
If in addition $X^\star = \lim_{t\to\infty} X_{\mathrm{cgm}}^{(t)}$ has rank r, then RHS $\to 0$!

(Tropp Yurtsever U Cevher, 2016)

Convergence when $\text{rank}(X_{\mathbf{cgm}}) \leq r$



Convergence when $\mathrm{rank}(X_{\mathbf{cgm}}) > r$



Guarantees (II)

Theorem (Convergence rate)

Fix $\kappa > 0$ and $\nu \geq 1$. Suppose the (unique) solution $X_\star$ of (CMOP) *has* $\operatorname{rank}(X_\star) \leq r$ *and*

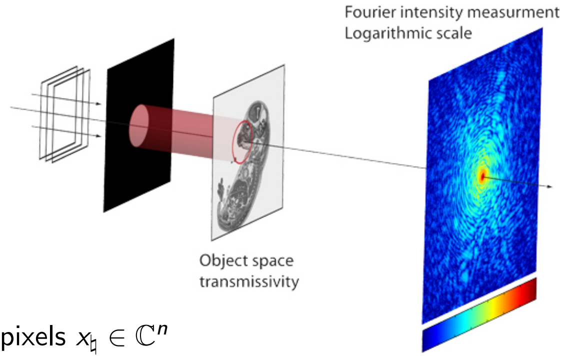
$$f(\mathcal{A}X) - f(\mathcal{A}X_\star) \geq \kappa \, \|X - X_\star\|_{\mathrm{F}}^{\nu} \quad \text{for all} \quad \|X\|_{S_1} \leq \alpha. \qquad (1)$$

Then we have the error bound

$$\mathbb{E}\, \|\hat{X}_t - X_\star\|_{\mathrm{F}} \leq 6 \left(\frac{2\kappa^{-1} C}{t+2} \right)^{1/\nu} \quad \text{for } t = 0, 1, 2, \ldots$$

where C is the curvature constant (Eqn. (3), Jaggi 2013) of the problem (CMOP).

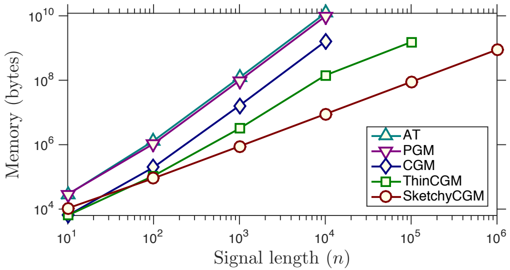
Application: Phase retrieval



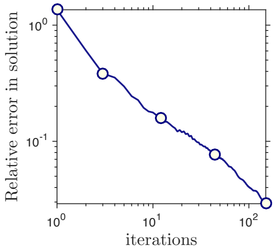
- image with n pixels $x_\natural \in \mathbb{C}^n$
- acquire noisy measurements $b_i = |\langle a_i, x_\natural \rangle|^2 + \omega_i$
- recover image by solving

$$\begin{array}{ll} \text{minimize} & f(\mathcal{A}X; b) \\ \text{subject to} & \operatorname{tr} X \leq \alpha \\ & X \succeq 0. \end{array}$$

SketchyCGM is scalable



(A) Memory usage for five algorithms



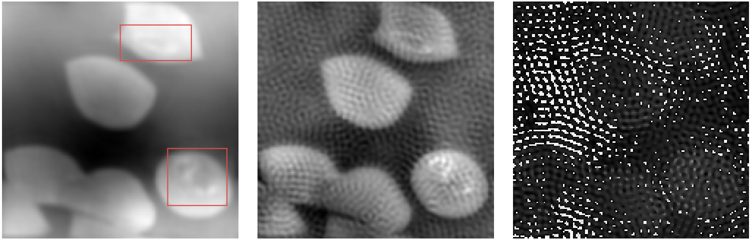
(B) Convergence for $n = 8 \cdot 10^6$.

PGM	=	proximal gradient (via TFOCS (Becker Candès Grant, 2011))
AT	=	accelerated PGM (Auslander Teboulle, 2006) (via TFOCS),
CGM	=	conditional gradient method (Jaggi, 2013)
ThinCGM	=	CGM with thin SVD updates (Yurtsever Hsieh Cevher, 2015)
SketchyCGM	=	ours, using $r = 1$

SketchyCGM is reliable

Fourier ptychography:

- imaging blood cells with $\mathcal{A}$ = subsampled FFT
- $n = 25,600$, $d = 185,600$
- $\text{rank}(X_\star) \approx 5$ (empirically)



(A) SketchyCGM (B) Burer–Monteiro (C) Wirtinger Flow

- brightness indicates phase of pixel (thickness of sample)
- red boxes mark malaria parasites in blood cells

Conclusion

SketchyCGM offers a proof-of-concept **convex method** with **optimal storage** for low rank matrix optimization using two new ideas:

- Drive the algorithm using a smaller (dual) variable.
- Sketch and recover the decision variable.

References:

- J. A. Tropp, A. Yurtsever, M. Udell, and V. Cevher. Randomized single-view algorithms for low-rank matrix reconstruction. SIMAX (to appear).
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