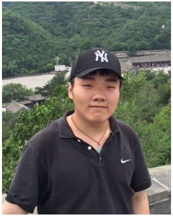
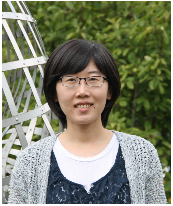
Bridging convex and nonconvex optimization in noisy matrix completion: Stability and uncertainty quantification

Cong Ma

ORFE, Princeton University

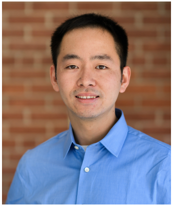


Yuling Yan
Princeton ORFE



Yuejie Chi
CMU ECE

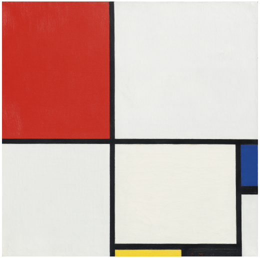
Jianqing Fan
Princeton ORFE



Yuxin Chen
Princeton EE

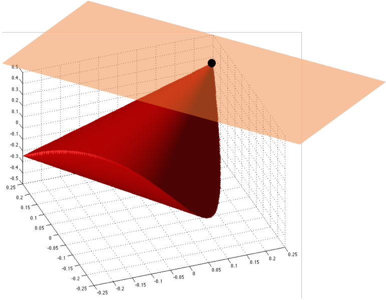
Convex relaxation for low-rank structure

$$\underset{Z}{\text{minimize}} \quad \|Z\|_*$$
$$\text{subj. to} \quad \text{noiseless data constraints}$$



low-rank matrix

figure credit: Piet Mondrian



semidefinite relaxation

Convex relaxation for low-rank structure

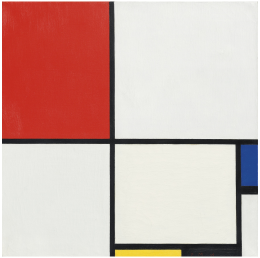
$$\begin{array}{ll} \underset{Z}{\text{minimize}} & \|Z\|_* \\ \text{subj. to} & \text{noiseless data constraints} \end{array}$$

- ✓ matrix sensing (Recht, Fazel, Parrilo '07)
- ✓ phase retrieval (Candès, Strohmer, Voroninski '11, Candès, Li '12)
- ✓ matrix completion (Candès, Recht '08, Candès, Tao '08, Gross '09)
- ✓ robust PCA (Chandrasekaran et al. '09, Candès et al. '09)
- ✓ Hankel matrix completion (Fazel et al. '13, Chen, Chi '13, Cai et al. '15)
- ✓ blind deconvolution (Ahmed, Recht, Romberg '12, Ling, Strohmer '15)
- ✓ joint alignment / matching (Chen, Huang, Guibas '14)

...

Stability of convex relaxation against noise

$$\begin{array}{rl} \underset{Z}{\text{minimize}} & \|Z\|_* \\ \text{subj. to} & \text{noisy data constraints} \end{array}$$



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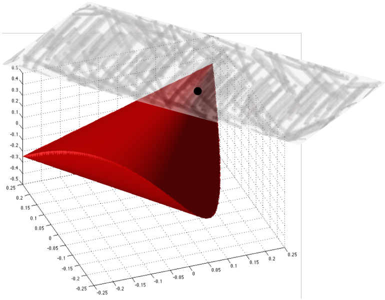
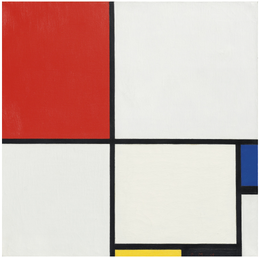


semidefinite relaxation

Stability of convex relaxation against noise

$$\underset{\boldsymbol{Z}}{\text{minimize}} \quad \underbrace{f(\boldsymbol{Z};\text{data})}_{\text{empirical loss}} + \lambda \|\boldsymbol{Z}\|_*$$



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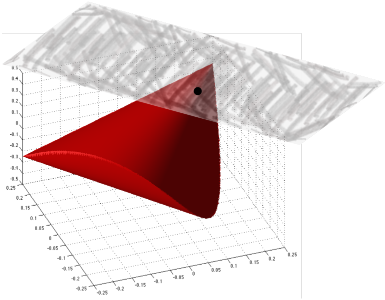

semidefinite relaxation

Stability of convex relaxation against noise

$$\underset{\boldsymbol{Z}}{\text{minimize}} \qquad \underbrace{f(\boldsymbol{Z};\text{data})}_{\text{empirical loss}} + \lambda \|\boldsymbol{Z}\|_*$$

✓ matrix sensing (RIP measurements) (Candès, Plan '10)

✓ phase retrieval (Gaussian measurements) (Candès et al. '11)

? matrix completion (Candès, Plan '09, Negahban, Wainwright '10, Koltchinskii et al. '10)

? robust PCA (Zhou, Li, Wright, Candès, Ma '10)

? Hankel matrix completion (Chen, Chi '13)

? blind deconvolution (Ahmed, Recht, Romberg '12, Ling, Strohmer '15)

? joint alignment / matching

...

Stability of convex relaxation against noise

$$\underset{\boldsymbol{Z}}{\text{minimize}} \qquad \underbrace{f(\boldsymbol{Z};\text{data})}_{\text{empirical loss}} + \lambda\|\boldsymbol{Z}\|_*$$

- ✓ matrix sensing (RIP measurements) (Candès, Plan '10)
- ✓ phase retrieval (Gaussian measurements) (Candès et al. '11)
- ? **this talk: matrix completion** (Candès, Plan '09, Negahban, Wainwright '10, Koltchinskii et al. '10)
- ? robust PCA (Zhou, Li, Wright, Candès, Ma '10)
- ? Hankel matrix completion (Chen, Chi '13)
- ? blind deconvolution (Ahmed, Recht, Romberg '12, Ling, Strohmer '15)
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...

Low-rank matrix completion

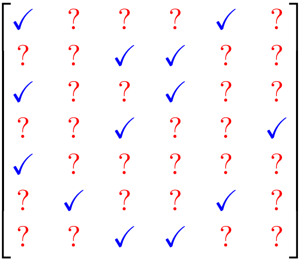
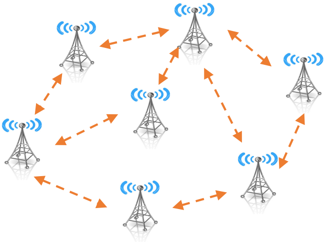


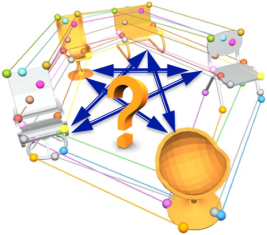
figure credit: E. J. Candès

Given partial samples of a low-rank matrix $M^\star$, fill in missing entries

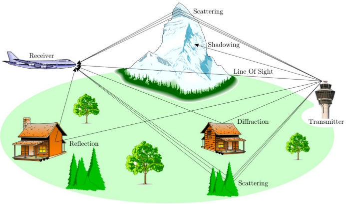
recommendation systems



localization



shape matching



channel estimation

Noisy low-rank matrix completion

observations: $M_{i,j} = M^\star_{i,j} + \text{noise}, \quad (i,j) \in \Omega$

goal: estimate $\boldsymbol{M}^\star$

unknown rank-r matrix $\boldsymbol{M}^\star \in \mathbb{R}^{n\times n}$

$$\begin{bmatrix} \checkmark & ? & ? & ? & \checkmark & ? \\ ? & ? & \checkmark & \checkmark & ? & ? \\ \checkmark & ? & ? & \checkmark & ? & ? \\ ? & ? & \checkmark & ? & ? & \checkmark \\ \checkmark & ? & ? & ? & ? & ? \\ ? & \checkmark & ? & ? & \checkmark & ? \\ ? & ? & \checkmark & \checkmark & ? & ? \end{bmatrix}$$

sampling set Ω

Noisy low-rank matrix completion

observations: $M_{i,j} = M^{\star}_{i,j} + \text{noise}, \quad (i,j) \in \Omega$

goal: estimate $\boldsymbol{M}^{\star}$

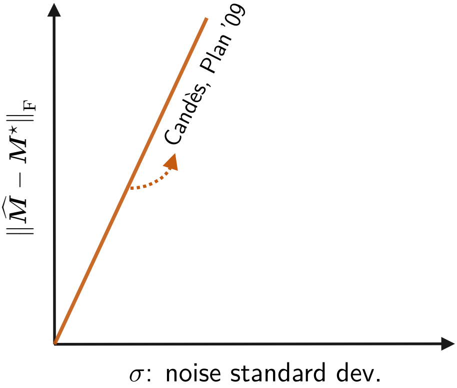
convex relaxation:

$$\underset{\boldsymbol{Z}\in\mathbb{R}^{n\times n}}{\text{minimize}} \quad \underbrace{\sum_{(i,j)\in\Omega} \left(Z_{i,j} - M_{i,j}\right)^2}_{\text{squared loss}} + \lambda \|\boldsymbol{Z}\|_*$$

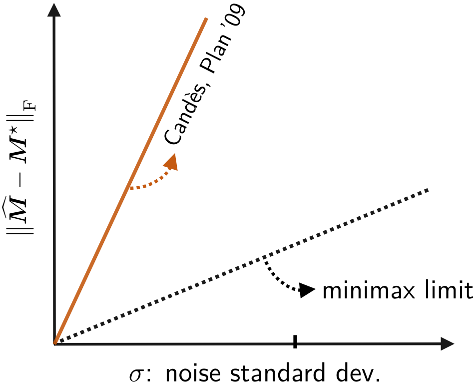
Prior statistical guarantees for convex relaxation

- **random sampling:** each $(i, j) \in \Omega$ with prob. p
- **random noise:** i.i.d. sub-Gaussian noise with variance σ^2
- true matrix $\boldsymbol{M}^\star \in \mathbb{R}^{n \times n}$: rank $r = O(1)$, incoherent, ...

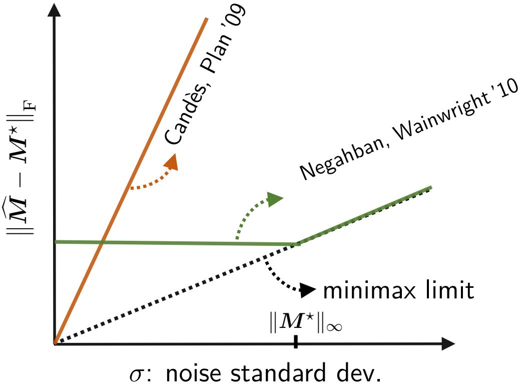
Candès, Plan '09	$\sigma n^{1.5}$



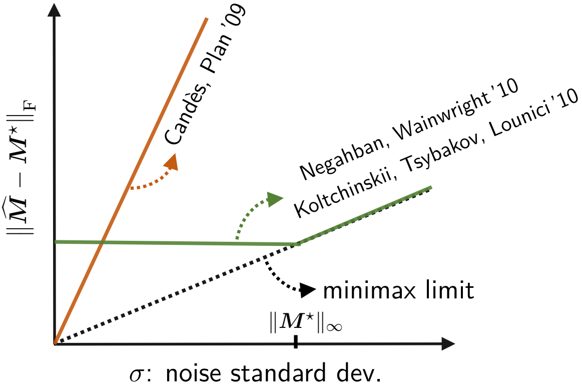
minimax limit	$\sigma\sqrt{n/p}$
Candès, Plan '09	$\sigma n^{1.5}$

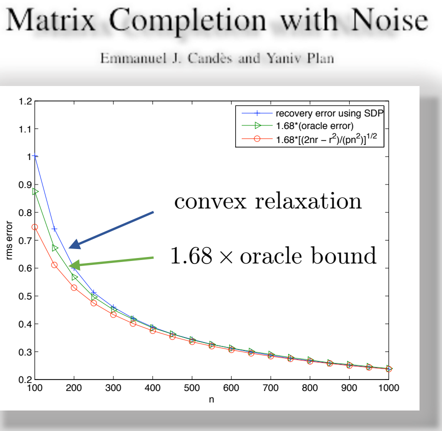


minimax limit	$\sigma\sqrt{n/p}$
Candès, Plan '09	$\sigma n^{1.5}$
Negahban, Wainwright '10	$\max\{\sigma, \|\boldsymbol{M}^\star\|_\infty\}\sqrt{n/p}$



minimax limit	$\sigma\sqrt{n/p}$
Candès, Plan '09	$\sigma n^{1.5}$
Negahban, Wainwright '10	$\max\{\sigma, \|\boldsymbol{M}^{\star}\|_{\infty}\}\sqrt{n/p}$
Koltchinskii, Tsybakov, Lounici '10	$\max\{\sigma, \|\boldsymbol{M}^{\star}\|_{\infty}\}\sqrt{n/p}$





Existing theory for convex relaxation does not match practice . . .

Matrix Completion with Noise

Emmanuel J. Candès and Yaniv Plan

with adversarial noise. Consequently, our analysis looses a $\sqrt{n}$ factor vis a vis an optimal bound that is achievable via the help of an oracle.

Existing theory for convex relaxation does not match practice . . .

What are the roadblocks?

Strategy: $\widehat{\boldsymbol{M}}_{\mathsf{cvx}}$ is optimizer if $\underbrace{\text{there exists } \boldsymbol{W}}_{\text{dual certificate}}$ s.t.

$(\widehat{\boldsymbol{M}}_{\mathsf{cvx}}, \boldsymbol{W})$ obeys KKT optimality condition

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Strategy: $\widehat{\boldsymbol{M}}_{\mathsf{cvx}}$ is optimizer if $\underbrace{\text{there exists } \boldsymbol{W}}_{\text{dual certificate}}$ s.t.

$(\widehat{\boldsymbol{M}}_{\mathsf{cvx}}, \boldsymbol{W})$ obeys KKT optimality condition

David Gross

- **noiseless case**: $\underbrace{\widehat{\boldsymbol{M}}_{\mathsf{cvx}} \leftarrow \boldsymbol{M}^{\star}}_{\text{exact recovery}}$; $\boldsymbol{W} \leftarrow$ golfing scheme

What are the roadblocks?

Strategy: $\widehat{\boldsymbol{M}}_{\mathsf{cvx}}$ is optimizer if $\underbrace{\text{there exists } \boldsymbol{W}}_{\text{dual certificate}}$ s.t.

$(\widehat{\boldsymbol{M}}_{\mathsf{cvx}}, \boldsymbol{W})$ obeys KKT optimality condition

David Gross

- **noiseless case**: $\underbrace{\widehat{\boldsymbol{M}}_{\mathsf{cvx}} \leftarrow \boldsymbol{M}^{\star}}_{\text{exact recovery}}$; $\boldsymbol{W} \leftarrow$ golfing scheme
- **noisy case**: $\widehat{\boldsymbol{M}}_{\mathsf{cvx}}$ is very complicated, hard to construct $\boldsymbol{W}$ ...

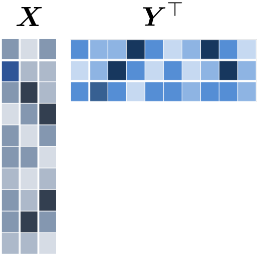
dual certification (golfing scheme)

dual certification (golfing scheme)

nonconvex optimization

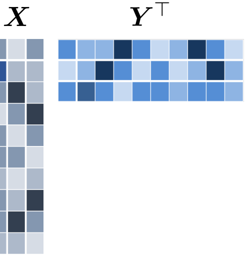
A detour: nonconvex optimization

Burer–Monteiro: represent Z by $\boldsymbol{X}\boldsymbol{Y}^\top$ with $\underbrace{\boldsymbol{X}, \boldsymbol{Y} \in \mathbb{R}^{n\times r}}_{\text{low-rank factors}}$



A detour: nonconvex optimization

Burer–Monteiro: represent $\boldsymbol{Z}$ by $\boldsymbol{X}\boldsymbol{Y}^\top$ with $\underbrace{\boldsymbol{X}, \boldsymbol{Y} \in \mathbb{R}^{n\times r}}_{\text{low-rank factors}}$



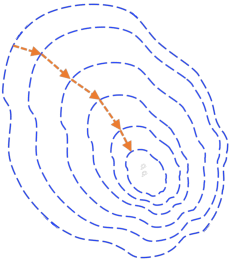
$$\underset{\boldsymbol{X},\boldsymbol{Y}\in\mathbb{R}^{n\times r}}{\text{minimize}} \quad f(\boldsymbol{X},\boldsymbol{Y}) = \underbrace{\sum_{(i,j)\in\Omega}\left[\left(\boldsymbol{X}\boldsymbol{Y}^\top\right)_{i,j} - M_{i,j}\right]^2}_{\text{squared loss}} + \text{reg}(\boldsymbol{X},\boldsymbol{Y})$$

A detour: nonconvex optimization

- Burer, Monteiro '03
- Rennie, Srebro '05
- Keshavan, Montanari, Oh '09 '10
- Jain, Netrapalli, Sanghavi '12
- Hardt '13
- Sun, Luo '14
- Chen, Wainwright '15
- Tu, Boczar, Simchowitz, Soltanolkotabi, Recht '15
- Zhao, Wang, Liu '15
- Zheng, Lafferty '16
- Yi, Park, Chen, Caramanis '16
- Ge, Lee, Ma '16
- Ge, Jin, Zheng '17
- Ma, Wang, Chi, Chen '17
- Chen, Li '18
- Chen, Liu, Li '19
- ...

A detour: nonconvex optimization

$$\underset{\boldsymbol{X},\boldsymbol{Y}\in\mathbb{R}^{n\times r}}{\text{minimize}} \quad f(\boldsymbol{X},\boldsymbol{Y}) = \sum_{(i,j)\in\Omega}\Big[\big(\boldsymbol{X}\boldsymbol{Y}^\top\big)_{i,j} - M_{i,j}\Big]^2 + \text{reg}(\boldsymbol{X},\boldsymbol{Y})$$



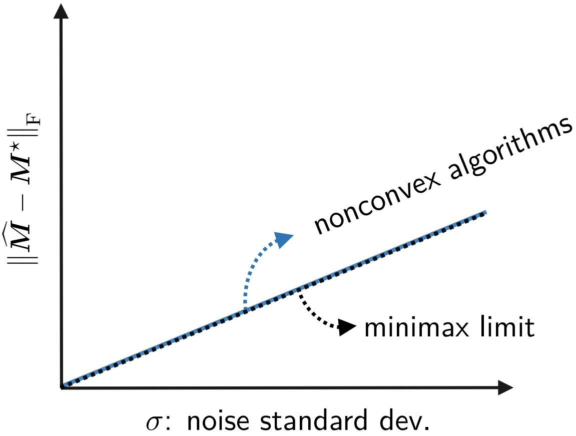
- **suitable initialization:** $(\boldsymbol{X}^0, \boldsymbol{Y}^0)$
- **gradient descent:** for $t = 0, 1, \ldots$

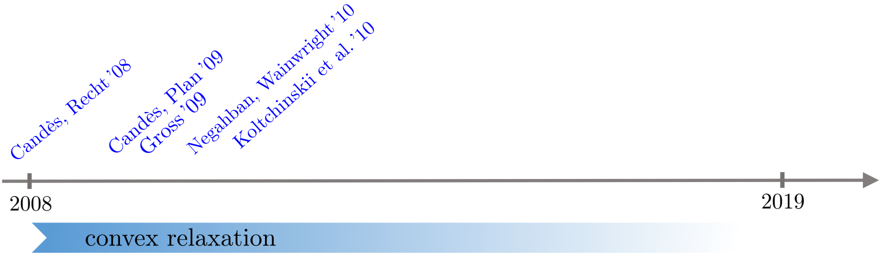
$$\boldsymbol{X}^{t+1} = \boldsymbol{X}^t - \eta_t \nabla_{\boldsymbol{X}} f(\boldsymbol{X}^t, \boldsymbol{Y}^t)$$
$$\boldsymbol{Y}^{t+1} = \boldsymbol{Y}^t - \eta_t \nabla_{\boldsymbol{Y}} f(\boldsymbol{X}^t, \boldsymbol{Y}^t)$$

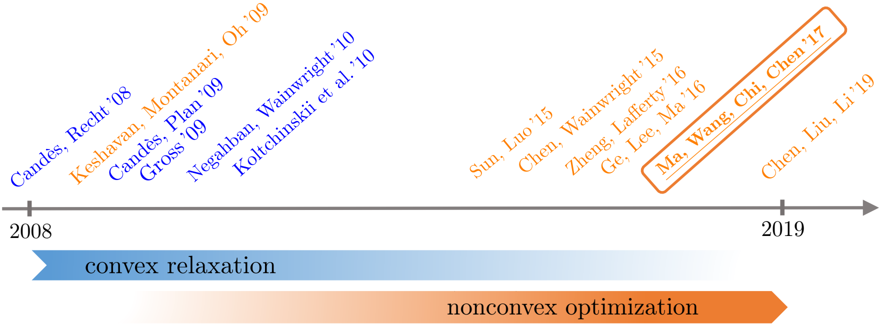
A detour: nonconvex optimization

- **random sampling:** each $(i, j) \in \Omega$ with prob. p
- **random noise:** i.i.d. sub-Gaussian noise with variance σ^2
- true matrix $\boldsymbol{M}^\star \in \mathbb{R}^{n \times n}$: $r = O(1)$, incoherent, ...

minimax limit	$\sigma\sqrt{n/p}$
nonconvex algorithms	$\sigma\sqrt{n/p}$ (optimal!)




Candès, Recht '08
Candès, Plan '09
Gross '09
Negahban, Wainwright '10
Koltchinskii et al. '10
2008
2019
convex relaxation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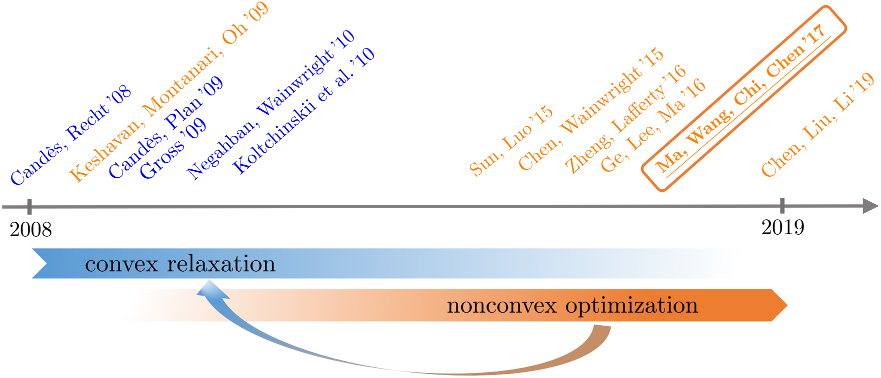

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2019
convex relaxation
nonconvex optimization

A motivating experiment

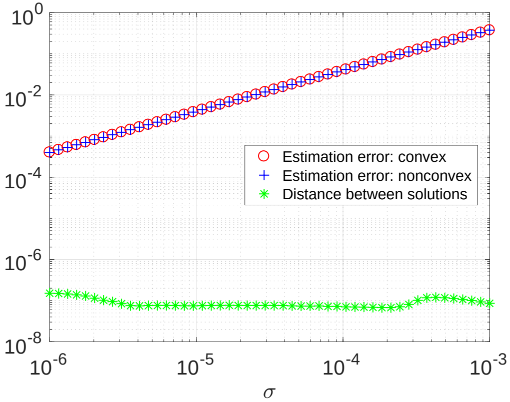
convex: $$\underset{\boldsymbol{Z}\in\mathbb{R}^{n\times n}}{\text{minimize}} \sum_{(i,j)\in\Omega}\left(Z_{i,j}-M_{i,j}\right)^2+\lambda\|\boldsymbol{Z}\|_*$$

nonconvex: $$\underset{\boldsymbol{X},\boldsymbol{Y}\in\mathbb{R}^{n\times r}}{\text{minimize}} \sum_{(i,j)\in\Omega}\left[\left(\boldsymbol{X}\boldsymbol{Y}^\top\right)_{i,j}-M_{i,j}\right]^2+\underbrace{\frac{\lambda}{2}\|\boldsymbol{X}\|_{\mathrm{F}}^2+\frac{\lambda}{2}\|\boldsymbol{Y}\|_{\mathrm{F}}^2}_{\text{reg}(\boldsymbol{X},\boldsymbol{Y})}$$

— $\|\boldsymbol{Z}\|_* = \min_{\boldsymbol{Z}=\boldsymbol{X}\boldsymbol{Y}^\top} \frac{1}{2}\|\boldsymbol{X}\|_{\mathrm{F}}^2+\frac{1}{2}\|\boldsymbol{Y}\|_{\mathrm{F}}^2$

A motivating experiment

$$n = 1000,\ r = 5,\ p = 0.2,\ \lambda = 5\sigma\sqrt{np}$$



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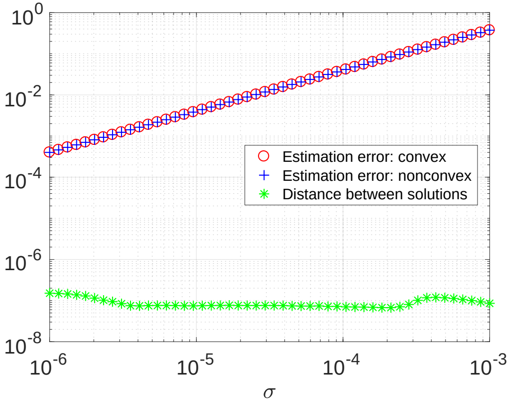

Convex and nonconvex solutions are exceedingly close!

convex  nonconvex

$$\Downarrow$$

$$\text{stability}\left(\boxed{\text{convex}}\right) \approx \text{stability}\left(\boxed{\text{nonconvex}}\right)$$

Main results: $r = O(1)$

- **random sampling:** each $(i,j) \in \Omega$ with prob. $p \gtrsim \frac{\log^3 n}{n}$
- **random noise:** i.i.d. sub-Gaussian noise with variance σ^2
- true matrix $\boldsymbol{M}^\star \in \mathbb{R}^{n\times n}$: $r = O(1)$, incoherent, well-conditioned

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$$\underset{\boldsymbol{Z}\in\mathbb{R}^{n\times n}}{\text{minimize}} \quad \sum_{(i,j)\in\Omega} \big(Z_{i,j} - M_{i,j}\big)^2 + \lambda \|\boldsymbol{Z}\|_* \qquad (\lambda \asymp \sigma\sqrt{np})$$

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Theorem 1 (Chen, Chi, Fan, Ma, Yan '19)

With high prob., any minimizer $\widehat{\boldsymbol{M}}_{\mathsf{cvx}}$ of convex program obeys

1. $\widehat{\boldsymbol{M}}_{\mathsf{cvx}}$ *is nearly rank-r*

$$\big\|\widehat{\boldsymbol{M}}_{\mathsf{cvx}} - \mathsf{proj}_r(\widehat{\boldsymbol{M}}_{\mathsf{cvx}})\big\|_{\mathrm{F}} \ll \frac{1}{n^5} \cdot \sigma\sqrt{\frac{n}{p}}$$

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2. $$\big\|\widehat{\boldsymbol{M}}_{\mathsf{cvx}} - \boldsymbol{M}^\star\big\|_{\mathrm{F}} \lesssim \sigma\sqrt{\frac{n}{p}}$$

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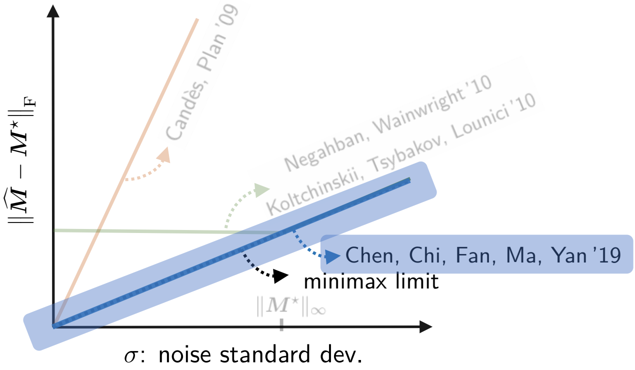
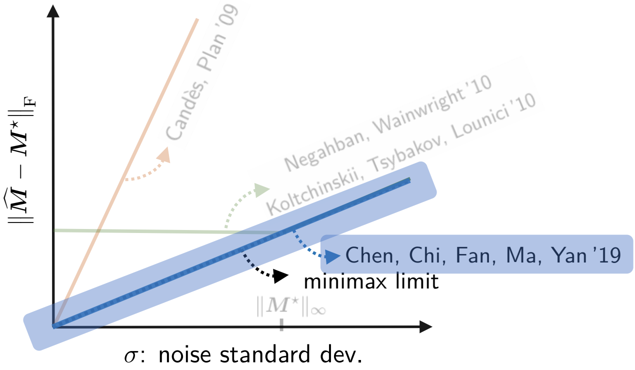
2. $$\big\|\widehat{\boldsymbol{M}}_{\mathsf{cvx}} - \boldsymbol{M}^\star\big\|_{\mathrm{F}} \lesssim \sigma\sqrt{\frac{n}{p}}$$
$$\big\|\widehat{\boldsymbol{M}}_{\mathsf{cvx}} - \boldsymbol{M}^\star\big\|_{\infty} \lesssim \sigma\sqrt{\frac{n\log n}{p}} \cdot \frac{1}{n}$$

$$\|\widehat{\boldsymbol{M}}_{\mathsf{cvx}} - \boldsymbol{M}^{\star}\|_{\mathrm{F}} \lesssim \sigma\sqrt{\frac{n}{p}}$$



- minimax optimal when $r = O(1)$

$$\|\widehat{M}_{\mathsf{cvx}} - M^\star\|_{\mathrm{F}} \lesssim \sigma\sqrt{\frac{n}{p}} \qquad \|\widehat{M}_{\mathsf{cvx}} - M^\star\|_{\infty} \lesssim \sigma\sqrt{\frac{n\log n}{p}} \cdot \frac{1}{n}$$



- minimax optimal when $r = O(1)$
- estimation errors are spread out across all entries

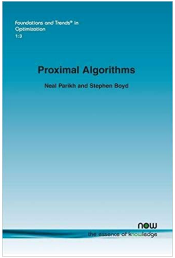
Implicit regularization

No need to enforce spikiness constraint as in Negahban & Wainwright

$$\underset{\|\boldsymbol{Z}\|_\infty \le \alpha}{\text{minimize}} \quad \sum_{(i,j)\in\Omega} \left(Z_{i,j} - M_{i,j}\right)^2 + \lambda \|\boldsymbol{Z}\|_* \qquad \text{(Negahban et al.)}$$

- convex programming automatically controls spikiness of solutions

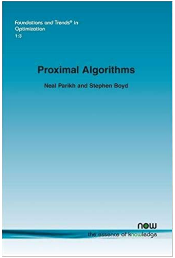
Statistical guarantees for iterative algorithms



$$\underset{Z}{\text{minimize}} \quad g(\boldsymbol{Z}) := \sum_{(i,j)\in\Omega} \left(Z_{i,j} - M_{i,j}\right)^2 + \lambda \|\boldsymbol{Z}\|_* \quad (1)$$

Many algorithms (e.g. SVT, SOFT-IMPUTE, FPC, FISTA) have been proposed to solve (1), typically without statistical guarantees

Statistical guarantees for iterative algorithms



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Many algorithms (e.g. SVT, SOFT-IMPUTE, FPC, FISTA) have been proposed to solve (1), typically without statistical guarantees

We provide statistical guarantees for any $\boldsymbol{Z}$ with $g(\boldsymbol{Z}) \leq g(\boldsymbol{Z}_{\mathsf{opt}}) + \varepsilon$ for some sufficiently small $\varepsilon > 0$

Main results: general case

- **random sampling:** each $(i, j) \in \Omega$ with prob. $p \gtrsim \frac{r^2 \log^3 n}{n}$
- **random noise:** i.i.d. sub-Gaussian noise with variance σ^2
- true matrix $\boldsymbol{M}^\star \in \mathbb{R}^{n \times n}$: incoherent, well-conditioned

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Theorem 2 (Chen, Chi, Fan, Ma, Yan '19)

With high prob., any minimizer $\widehat{\boldsymbol{M}}_{\mathsf{cvx}}$ of convex program obeys

1. $\widehat{\boldsymbol{M}}_{\mathsf{cvx}}$ *is nearly rank-r*
2. $$\begin{aligned} \|\widehat{\boldsymbol{M}}_{\mathsf{cvx}} - \boldsymbol{M}^\star\|_{\mathrm{F}} &\lesssim \frac{\sigma}{\sigma_{\min}(\boldsymbol{M}^\star)} \sqrt{\frac{n}{p}}\, \|\boldsymbol{M}^\star\|_{\mathrm{F}} \\ \|\widehat{\boldsymbol{M}}_{\mathsf{cvx}} - \boldsymbol{M}^\star\|_{\infty} &\lesssim \sqrt{r} \frac{\sigma}{\sigma_{\min}(\boldsymbol{M}^\star)} \sqrt{\frac{n \log n}{p}}\, \|\boldsymbol{M}^\star\|_{\infty} \\ \|\widehat{\boldsymbol{M}}_{\mathsf{cvx}} - \boldsymbol{M}^\star\| &\lesssim \frac{\sigma}{\sigma_{\min}(\boldsymbol{M}^\star)} \sqrt{\frac{n}{p}}\, \|\boldsymbol{M}^\star\| \end{aligned}$$

Main results: general case

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sample complexity bound $O(nr^2 \log^3 n)$ is suboptimal in r!

A little analysis:
connection between convex and nonconvex solutions

Link between convex and nonconvex optimizers

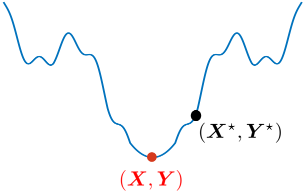
$(\boldsymbol{X}, \boldsymbol{Y})$ is nonconvex optimizer

Link between convex and nonconvex optimizers

$(\boldsymbol{X}, \boldsymbol{Y})$ is nonconvex optimizer $\overset{?}{\Longrightarrow}$ $\boldsymbol{X}\boldsymbol{Y}^\top$ is convex solution

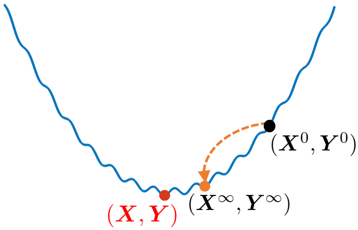
Link between convex and nonconvex optimizers

- $(\boldsymbol{X}, \boldsymbol{Y})$ is close to truth (in $\ell_{2,\infty}$ sense)
- a little condition on noise size



$(\boldsymbol{X}, \boldsymbol{Y})$ is nonconvex optimizer $\overset{\checkmark}{\Longrightarrow}$ $\boldsymbol{X}\boldsymbol{Y}^\top$ is convex solution

Approximate nonconvex optimizers



Issue: we do NOT know properties of nonconvex optimizers

- It is unclear whether nonconvex algorithms converge to optimizers (due to lack of strong convexity)

Approximate nonconvex optimizers

Strategy: resort to "$\underbrace{\text{approximate stationary points}}_{\nabla f(\boldsymbol{X},\boldsymbol{Y}) \approx \boldsymbol{0}}$" instead

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starting from $(\boldsymbol{X}^0, \boldsymbol{Y}^0) =$ truth or spectral initialization:

$$\begin{aligned} \boldsymbol{X}^{t+1} &= \boldsymbol{X}^t - \eta\,\nabla_{\boldsymbol{X}} f(\boldsymbol{X}^t, \boldsymbol{Y}^t) \\ \boldsymbol{Y}^{t+1} &= \boldsymbol{Y}^t - \eta\,\nabla_{\boldsymbol{Y}} f(\boldsymbol{X}^t, \boldsymbol{Y}^t) \end{aligned} \qquad t = 0, 1, \cdots, T$$

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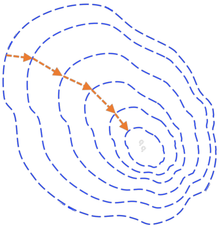
- when T is large: there exists point with $\underbrace{\text{very small gradient}}_{\|\nabla f(\boldsymbol{X},\boldsymbol{Y})\|_{\mathrm{F}} \lesssim \frac{1}{\sqrt{\eta T}}}$
- hopefully not far from $(\boldsymbol{X}^\star, \boldsymbol{Y}^\star)$

Gradient descent for nonconvex matrix completion

Gradient descent for nonconvex matrix completion



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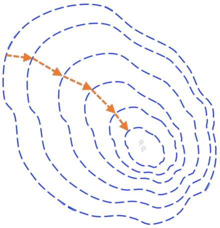
Prior works analyze regularized GD

- not guaranteed to return small-gradient solutions
- no $\ell_{2,\infty}$ error control

— *Keshavan et al. '09, Sun, Luo '15, Chen, Wainwright '15, Zheng, Lafferty '16*

Gradient descent for nonconvex matrix completion



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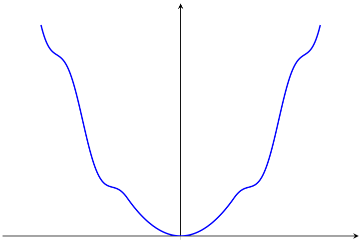
Our work and Chen et al. analyze vanilla GD

- regularization-free
- optimal $\ell_{2,\infty}$ error control

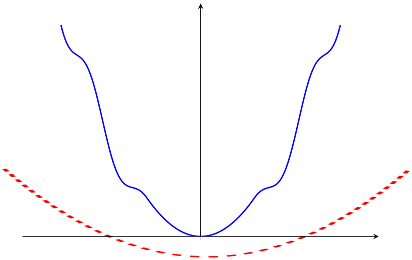
— *Ma, Wang, Chi, Chen '17, Chen, Liu, Li '19*

Gradient descent theory revisited



Two standard conditions that enable geometric convergence of GD

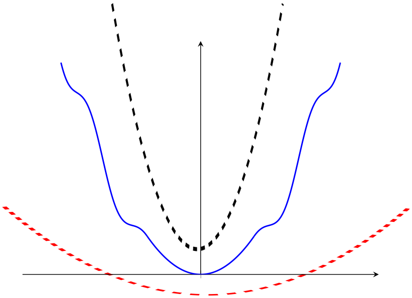
Gradient descent theory revisited



Two standard conditions that enable geometric convergence of GD

- (local) restricted strong convexity

Gradient descent theory revisited



Two standard conditions that enable geometric convergence of GD

- (local) restricted strong convexity
- (local) smoothness

Gradient descent theory revisited

f is said to be α-strongly convex and β-smooth if

$$\mathbf{0} \;\preceq\; \alpha \boldsymbol{I} \;\preceq\; \nabla^2 f(\boldsymbol{X}) \;\preceq\; \beta \boldsymbol{I}, \qquad \forall \boldsymbol{X}$$

ℓ_2 **error contraction:** GD with $\eta = 1/\beta$ obeys

$$\|\boldsymbol{X}^{t+1} - \boldsymbol{X}^\star\|_{\mathrm{F}} \le \left(1 - \frac{\alpha}{\beta}\right) \|\boldsymbol{X}^t - \boldsymbol{X}^\star\|_{\mathrm{F}}$$

Incoherence region

Which region enjoys both restricted strong convexity and smoothness?

Incoherence region

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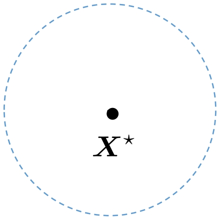

- X is not far away from $X^\star$

Incoherence region

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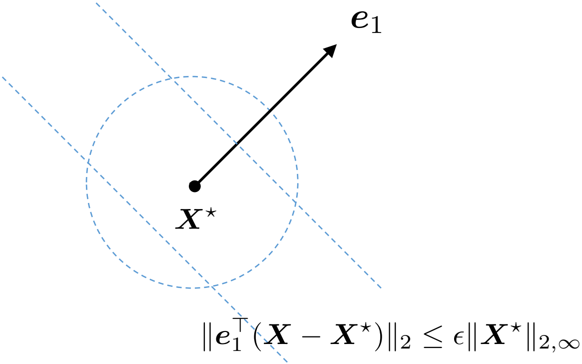

- X is not far away from $X^\star$
- X is incoherent w.r.t. standard basis vectors (incoherence region)

Incoherence region

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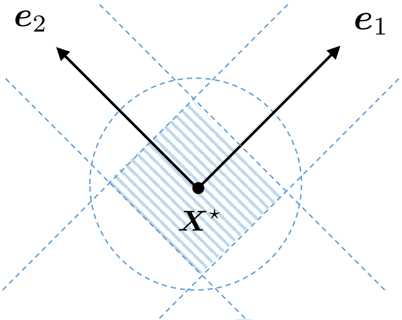
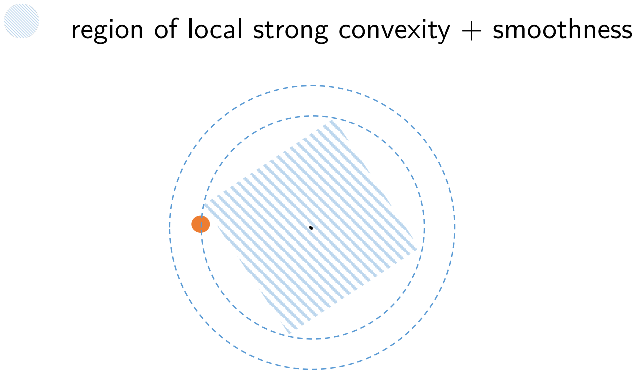


$$\|\boldsymbol{e}_2^\top(\boldsymbol{X}-\boldsymbol{X}^\star)\|_2 \le \epsilon\|\boldsymbol{X}^\star\|_{2,\infty} \quad \|\boldsymbol{e}_1^\top(\boldsymbol{X}-\boldsymbol{X}^\star)\|_2 \le \epsilon\|\boldsymbol{X}^\star\|_{2,\infty}$$

- $\boldsymbol{X}$ is not far away from $\boldsymbol{X}^\star$
- $\boldsymbol{X}$ is incoherent w.r.t. standard basis vectors (incoherence region)

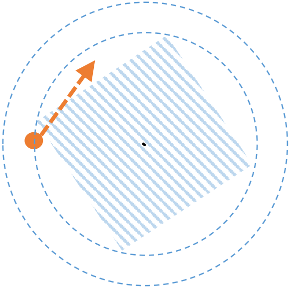
Inadequacy of generic gradient descent theory



- Generic optimization theory does NOT ensure GD stays in incoherence region

Inadequacy of generic gradient descent theory

region of local strong convexity + smoothness



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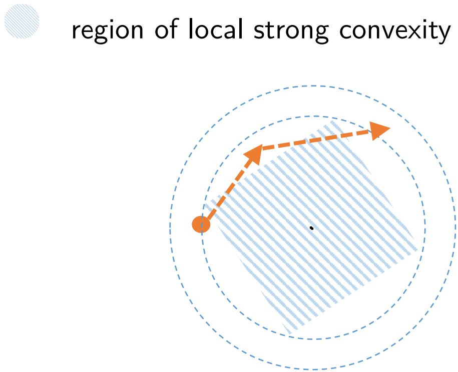

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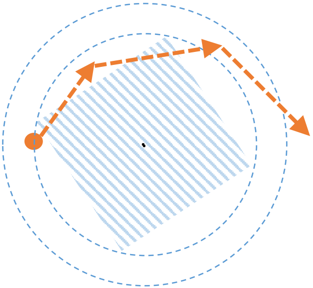


- Generic optimization theory does NOT ensure GD stays in incoherence region
- Calls for new analysis tools

Key proof idea: leave-one-out analysis

Leave out a small amount of information from data and run GD

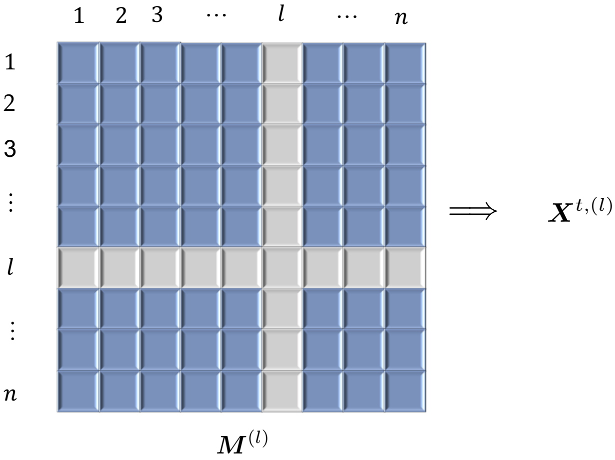
Key proof idea: leave-one-out analysis

Leave out a small amount of information from data and run GD

- Stein '72
- El Karoui, Bean, Bickel, Lim, Yu '13
- El Karoui '15
- Javanmard, Montanari '15
- Zhong, Boumal '17
- Lei, Bickel, El Karoui '17
- Sur, Chen, Candès '17
- Abbe, Fan, Wang, Zhong '17
- Chen, Fan, Ma, Wang '17
- Ma, Wang, Chi, Chen '17
- Chen, Chi, Fan, Ma '18
- Ding, Chen '18
- Dong, Shi '18
- Chen, Liu, Li '19

Key proof idea: leave-one-out analysis

For each $1 \leq l \leq n$, introduce leave-one-out iterates $\boldsymbol{X}^{t,(l)}$ by replacing l^{th} row and column with true values



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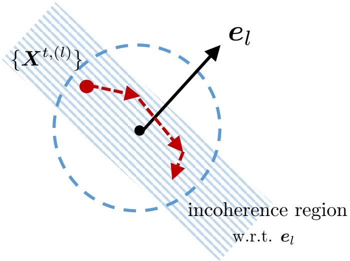
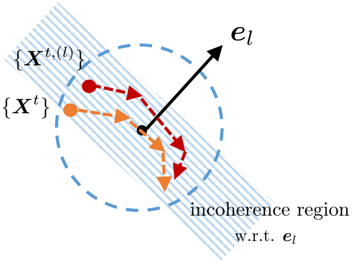


- Leave-one-out iterates $\{X^{t,(l)}\}$ contains more information of l^{th} row of truth; indep. of randomness in l^{th} row

Key proof idea: leave-one-out analysis



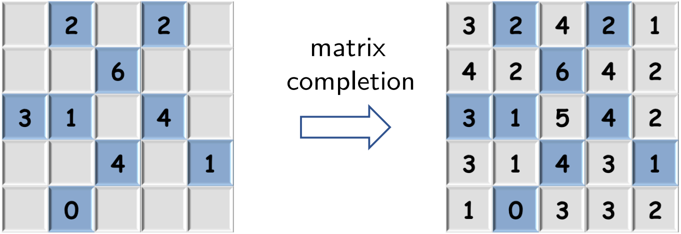
- Leave-one-out iterates $\{\boldsymbol{X}^{t,(l)}\}$ contains more information of l^{th} row of truth; indep. of randomness in l^{th} row
- Leave-one-out iterates $\{\boldsymbol{X}^{t,(l)}\} \approx$ true iterates $\{\boldsymbol{X}^{t}\}$

Inference and uncertainty quantification

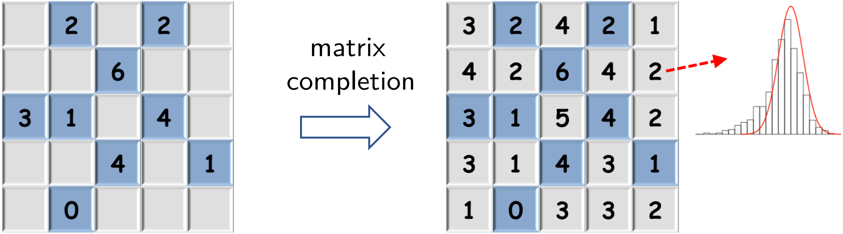
Reasoning about uncertainty

	2		2	
		6		
3	1		4	
		4		1
	0			

Reasoning about uncertainty



Reasoning about uncertainty



How to assess uncertainty, or “confidence”, of obtained estimates?

Inference in high dimensional regression

organized by
Peter Buehlmann, Andrea Montanari, and Jonathan Taylor

American Institute of Mathematics

(3) *Confidence intervals for matrix completion.* In matrix completion, the data analyst is given a large data matrix with a number of missing entries. In many interesting applications (e.g. to collaborative filtering) it is indeed the case that the vast majority of entries is missing. In order to fill the missing entries, the assumption is made that the underlying –unknown– matrix has a low-rank structure.

Substantial work has been devoted to methods for computing point estimates of the missing entries. In applications, it would be very interesting to compute confidence intervals as well. This requires developing distributional characterizations of standard matrix completion methods.

Challenges

$$\boldsymbol{M}^{\mathsf{cvx}} \triangleq \arg\min_{\boldsymbol{Z}\in\mathbb{R}^{n\times n}} \sum_{(i,j)\in\Omega} \big(Z_{i,j} - M_{i,j}\big)^2 + \lambda \|\boldsymbol{Z}\|_*$$

- convex estimate $\boldsymbol{M}^{\mathsf{cvx}}$ is biased towards small norm

Challenges

$$\boldsymbol{M}^{\mathsf{cvx}} \triangleq \arg\min_{\boldsymbol{Z}\in\mathbb{R}^{n\times n}} \sum_{(i,j)\in\Omega} \big(Z_{i,j} - M_{i,j}\big)^2 + \lambda\|\boldsymbol{Z}\|_*$$

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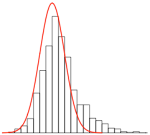
- convex estimate $\boldsymbol{M}^{\mathsf{cvx}}$ is biased towards small norm
- very challenging to pin down distributions of obtained estimates
- existing orderwise bounds come with unspecified (but huge) pre-constants

  $\longrightarrow$ overly wide confidence intervals

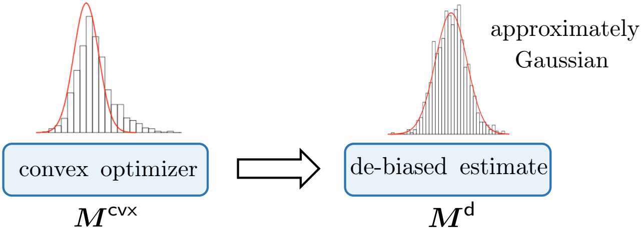
— *inspired by Zhang, Zhang '11, van de Geer et al. '13, Javanmard, Montanari '13*



convex optimizer

M^{cvx}

— *inspired by Zhang, Zhang '11, van de Geer et al. '13, Javanmard, Montanari '13*



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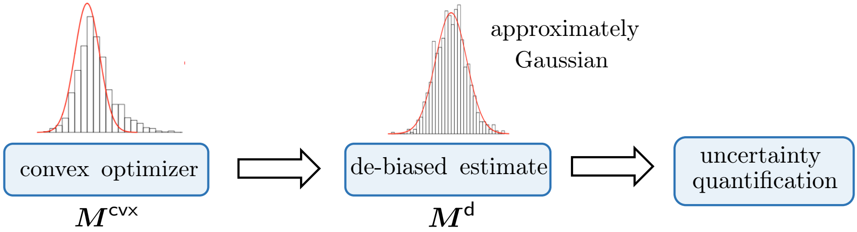

De-biasing convex estimate

$$\boldsymbol{M}^{\mathsf{cvx}} \quad \overset{\text{de-biasing}}{\longrightarrow} \quad \underbrace{\boldsymbol{M}^{\mathsf{cvx}} + \frac{1}{p}\mathcal{P}_{\Omega}(\boldsymbol{M}^{\star} + \boldsymbol{E} - \boldsymbol{M}^{\mathsf{cvx}})}_{\text{(nearly) unbiased estimate of } \boldsymbol{M}^{\star}}$$

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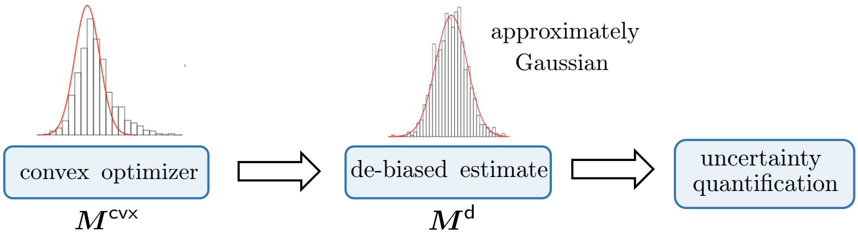
- **issue:** high-rank after de-biasing; statistical accuracy suffers

De-biasing convex estimate

$$\boldsymbol{M}^{\mathsf{cvx}} \overset{\text{de-biasing}}{\longrightarrow} \underbrace{\mathsf{proj}_{\mathsf{rank}\text{-}r}\Big(\boldsymbol{M}^{\mathsf{cvx}} + \frac{1}{p}\mathcal{P}_{\Omega}(\boldsymbol{M}^{\star} + \boldsymbol{E} - \boldsymbol{M}^{\mathsf{cvx}}) \Big)}_{\text{1 iteration of singular value projection (Jain, Meka, Dhillon '10)}} =: \boldsymbol{M}^{\mathrm{d}}$$

- **issue:** high-rank after de-biasing; statistical accuracy suffers
- **solution:** low-rank projection


approximately
Gaussian
convex optimizer
M^{cvx}
de-biased estimate
M^{d}
uncertainty
quantification

Distributional guarantees for low-rank factors

- **random sampling:** each $(i,j) \in \Omega$ with prob. $p \gtrsim \frac{\log^3 n}{n}$
- **random noise:** i.i.d. $\mathcal{N}(0,\sigma^2)$ (not too large)
- true matrix $\boldsymbol{M}^\star \in \mathbb{R}^{n\times n}$: $r = O(1)$, incoherent, well-conditioned
- regularization parameter: $\lambda \asymp \sigma\sqrt{np}$

$$\boldsymbol{X}^{\mathsf{d}}\boldsymbol{Y}^{\mathsf{d}\top} \leftarrow \underbrace{\text{balanced}}_{\boldsymbol{X}^{\mathsf{d}\top}\boldsymbol{X}^{\mathsf{d}}=\boldsymbol{Y}^{\mathsf{d}\top}\boldsymbol{Y}^{\mathsf{d}}} \text{ rank-}r \text{ decomp. of } \boldsymbol{M}^{\mathsf{d}}$$

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Theorem 3 (Chen, Fan, Ma, Yan '19)

With high prob., there exists global rotation matrix $\boldsymbol{H} \in \mathbb{R}^{r\times r}$ *s.t.*

$$\boldsymbol{X}^{\mathrm{d}}\boldsymbol{H} - \boldsymbol{X}^{\star} \approx \boldsymbol{Z}^{X}, \qquad \boldsymbol{Z}^{X}_{i,\cdot} \overset{\text{ind.}}{\sim} \mathcal{N}\Big(\boldsymbol{0}, \frac{\sigma^2}{p}(\boldsymbol{Y}^{\star\top}\boldsymbol{Y}^{\star})^{-1}\Big)$$

$$\boldsymbol{Y}^{\mathrm{d}}\boldsymbol{H} - \boldsymbol{Y}^{\star} \approx \boldsymbol{Z}^{Y}, \qquad \boldsymbol{Z}^{Y}_{i,\cdot} \overset{\text{ind.}}{\sim} \mathcal{N}\Big(\boldsymbol{0}, \frac{\sigma^2}{p}(\boldsymbol{X}^{\star\top}\boldsymbol{X}^{\star})^{-1}\Big)$$

Implications

$$\boldsymbol{X}^{\mathrm{d}}\boldsymbol{H}-\boldsymbol{X}^{\star} \;\approx\; \boldsymbol{Z}^{X}, \qquad \boldsymbol{Z}^{X}_{i,\cdot} \overset{\text{ind.}}{\sim} \mathcal{N}\big(\boldsymbol{0}, \tfrac{\sigma^2}{p}(\boldsymbol{Y}^{\star\top}\boldsymbol{Y}^{\star})^{-1}\big)$$

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- estimation errors for different rows of $\boldsymbol{X}^{\star}$ are nearly independent

$$\boldsymbol{X}^{\mathrm{d}}_{i,\cdot}\boldsymbol{H}-\boldsymbol{X}^{\star}_{i,\cdot} \quad \text{nearly ind. of} \quad \boldsymbol{X}^{\mathrm{d}}_{j,\cdot}\boldsymbol{H}-\boldsymbol{X}^{\star}_{j,\cdot}$$

Implications

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- accurate uncertainty quantification for low-rank factors, e.g.

$$\boldsymbol{X}^{\mathsf{d}}_{i,\cdot}\boldsymbol{H} - \boldsymbol{X}^{\star}_{i,\cdot} \sim \mathcal{N}\big(\boldsymbol{0}, \tfrac{\sigma^2}{p}(\boldsymbol{Y}^{\star\top}\boldsymbol{Y}^{\star})^{-1}\big) + \text{negligible term}$$

$$\boldsymbol{Y}^{\mathsf{d}}_{i,\cdot}\boldsymbol{H} - \boldsymbol{Y}^{\star}_{i,\cdot} \sim \mathcal{N}\big(\boldsymbol{0}, \tfrac{\sigma^2}{p}(\boldsymbol{X}^{\star\top}\boldsymbol{X}^{\star})^{-1}\big) + \text{negligible term}$$

Implications

$$\boldsymbol{X}^{\mathrm{d}}\boldsymbol{H} - \boldsymbol{X}^{\star} \approx \boldsymbol{Z}^{X}, \qquad \boldsymbol{Z}^{X}_{i,\cdot} \overset{\text{ind.}}{\sim} \mathcal{N}\big(\mathbf{0}, \tfrac{\sigma^2}{p}(\boldsymbol{Y}^{\star\top}\boldsymbol{Y}^{\star})^{-1}\big)$$

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$$\boldsymbol{X}^{\mathsf{d}}_{i,\cdot} - \boldsymbol{X}^{\star}_{i,\cdot}\boldsymbol{H}^{\top} \sim \mathcal{N}\big(\mathbf{0}, \tfrac{\sigma^2}{p}(\boldsymbol{Y}^{\mathrm{d}\top}\boldsymbol{Y}^{\mathrm{d}})^{-1}\big) + \text{negligible term}$$

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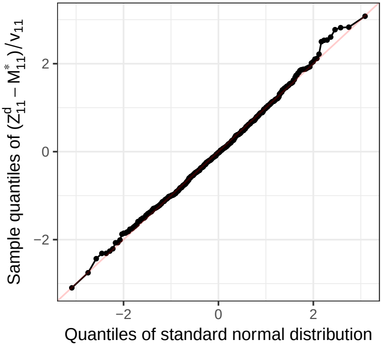
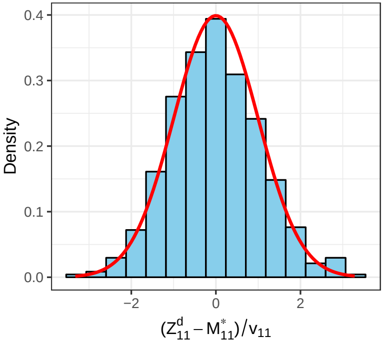
Numerical experiments





$$n = 1000,\ p = 0.2,\ r = 5,\ \|\boldsymbol{M}^\star\| = 1,\ \kappa = 1,\ \sigma = 10^{-3}$$

convex

nonconvex

convex

nonconvex

$$\text{inference}\left(\boxed{\text{convex}}\right) \approx \text{inference}\left(\boxed{\text{nonconvex}}\right)$$

Same inference procedures work for both cvx & noncvx estimates!

A bit of intuition

Consider rank-1 PSD case $\boldsymbol{M}^\star = \boldsymbol{x}^\star \boldsymbol{x}^{\star\top}$, $p = 1$ (no missing data)

$$\text{minimize}_{\boldsymbol{x}} \qquad \frac{1}{2}\|\boldsymbol{x}\boldsymbol{x}^\top - \boldsymbol{x}^\star \boldsymbol{x}^{\star\top} - \boldsymbol{E}\|_{\mathrm{F}}^2 + \lambda \|\boldsymbol{x}\|_2^2$$

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- first-order optimality condition

$$(\boldsymbol{x}\boldsymbol{x}^\top - \boldsymbol{x}^\star\boldsymbol{x}^{\star\top} - \boldsymbol{E})\boldsymbol{x} + \lambda\boldsymbol{x} = \boldsymbol{0}$$

A bit of intuition

$$(\boldsymbol{x}\boldsymbol{x}^\top - \boldsymbol{x}^\star\boldsymbol{x}^{\star\top} - \boldsymbol{E})\boldsymbol{x} \quad \underbrace{+\lambda\boldsymbol{x}}_{\text{causes bias}} \quad = \boldsymbol{0}$$

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$$\boldsymbol{x}^{\mathrm{d}} - \boldsymbol{x}^\star = \underbrace{\frac{1}{\|\boldsymbol{x}^{\mathrm{d}}\|_2^2}\boldsymbol{E}\boldsymbol{x}^{\mathrm{d}}}_{\text{nearly Gaussian}} + \underbrace{\frac{\left(\boldsymbol{x}^\star - \boldsymbol{x}^{\mathrm{d}}\right)^\top\boldsymbol{x}^{\mathrm{d}}}{\|\boldsymbol{x}^{\mathrm{d}}\|_2^2}\boldsymbol{x}^\star}_{\text{hopefully small}}$$

An alternative de-biased estimator

— *inspired by Zhang, Zhang '11, van de Geer et al. '13, Javanmard, Montanari '13*

$$\boldsymbol{M}^{\mathsf{cvx}} \triangleq \arg\min_{\boldsymbol{Z}\in\mathbb{R}^{n\times n}} \left\|\mathcal{P}_{\Omega}(\boldsymbol{Z}-\boldsymbol{M})\right\|_{\mathrm{F}}^{2} + \lambda\|\boldsymbol{Z}\|_{*}$$

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$$\widehat{\boldsymbol{M}}^{\mathrm{d}} = \boldsymbol{M}^{\mathsf{cvx}} + \text{linear-map}\Big(\mathcal{P}_{\Omega}(\boldsymbol{M}-\boldsymbol{M}^{\mathsf{cvx}})\Big)$$

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$$\Downarrow$$

$$\widehat{\boldsymbol{M}}^{\mathrm{d}} = \boldsymbol{M}^{\mathsf{cvx}} + \frac{1}{p}\mathcal{P}_{T}\Big(\mathcal{P}_{\Omega}\big(\boldsymbol{M}-\boldsymbol{M}^{\mathsf{cvx}}\big)\Big)$$

— $\mathcal{P}_T$: projection onto T (tangent space at $\mathsf{proj}_{\mathsf{rank\text{-}r}}(\boldsymbol{M}^{\mathsf{cvx}})$)

$\widehat{\boldsymbol{M}}^{\mathrm{d}} \approx \boldsymbol{M}^{\mathrm{d}}$!

Back to estimation: M^{d} is optimal

Distributional theory further allows to track the estimation accuracy

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Theorem 4 (Chen, Fan, Ma, Yan '19)

With high prob., the Euclidean estimation error of $\boldsymbol{M}^{\mathsf{d}}$ *obeys*

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- Precise characterization of estimation accuracy (including pre-constant)
- Asymptotically optimal!

Numerical evidence

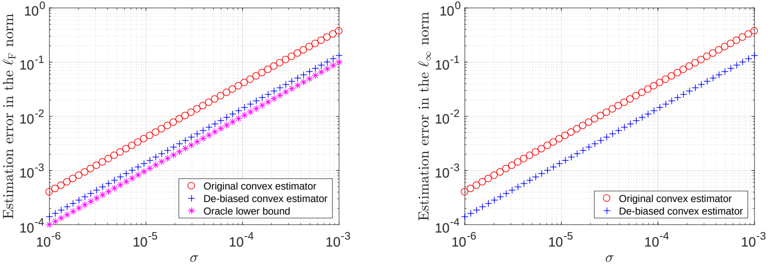
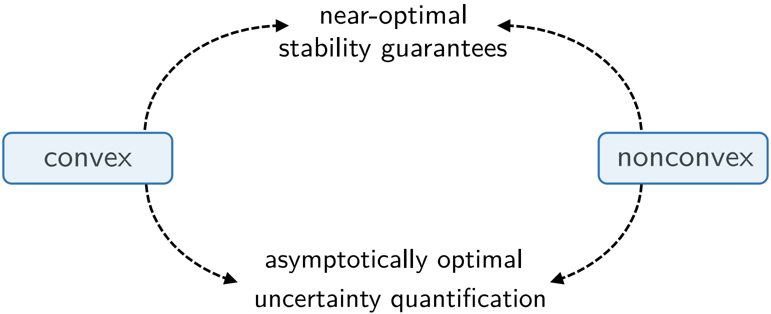
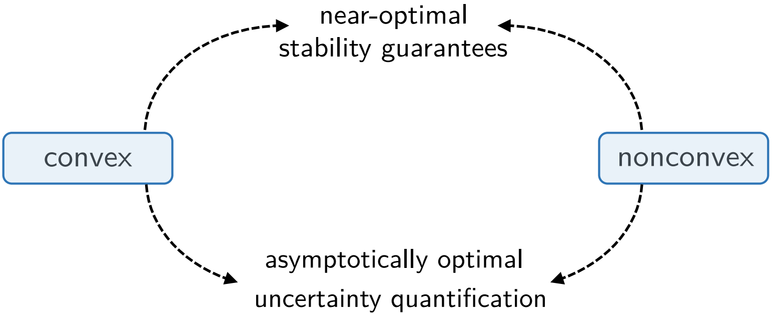


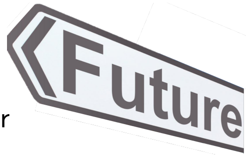
Figure 1: (left) Estimation error of $\boldsymbol{M}^{\mathsf{cvx}}$ vs. $\boldsymbol{M}^{\mathsf{d}}$ measured in the Frobenius norm. (right) Estimation error of $\boldsymbol{M}^{\mathsf{cvx}}$ vs. $\boldsymbol{M}^{\mathsf{d}}$ measured in the ℓ_∞ norm. The results are averaged over 20 independent trials for $r = 5$, $p = 0.2$ and $n = 1000$.

Concluding remarks

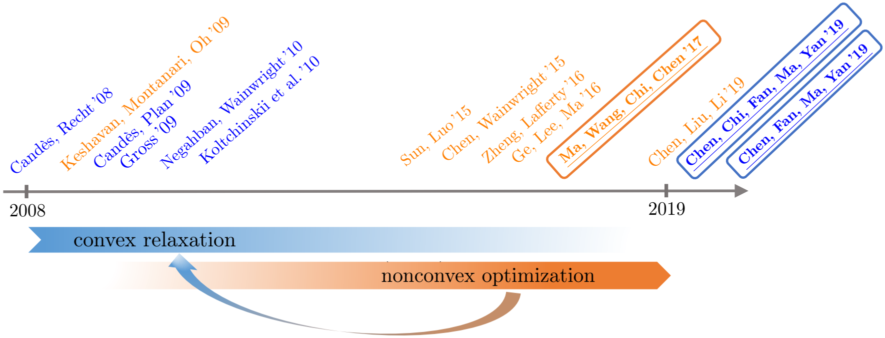


Concluding remarks





- improve dependency on rank & cond. number
- what if $M^\star$ is only approximately low-rank?
- more general sampling patterns



"Noisy matrix completion: understanding statistical guarantees for convex relaxation via nonconvex optimization," Y. Chen, Y. Chi, J. Fan, C. Ma, Y. Yan, 2019

"Inference and uncertainty quantification for noisy matrix completion," Y. Chen, J. Fan, C. Ma, Y. Yan, 2019