1-Bit Matrix Completion

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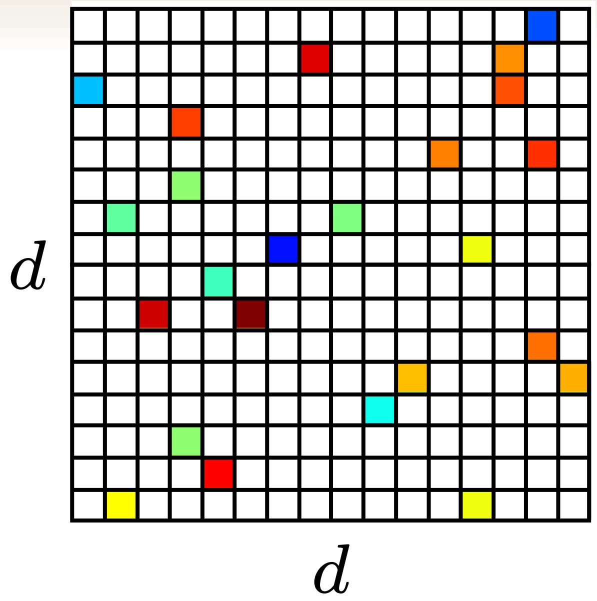
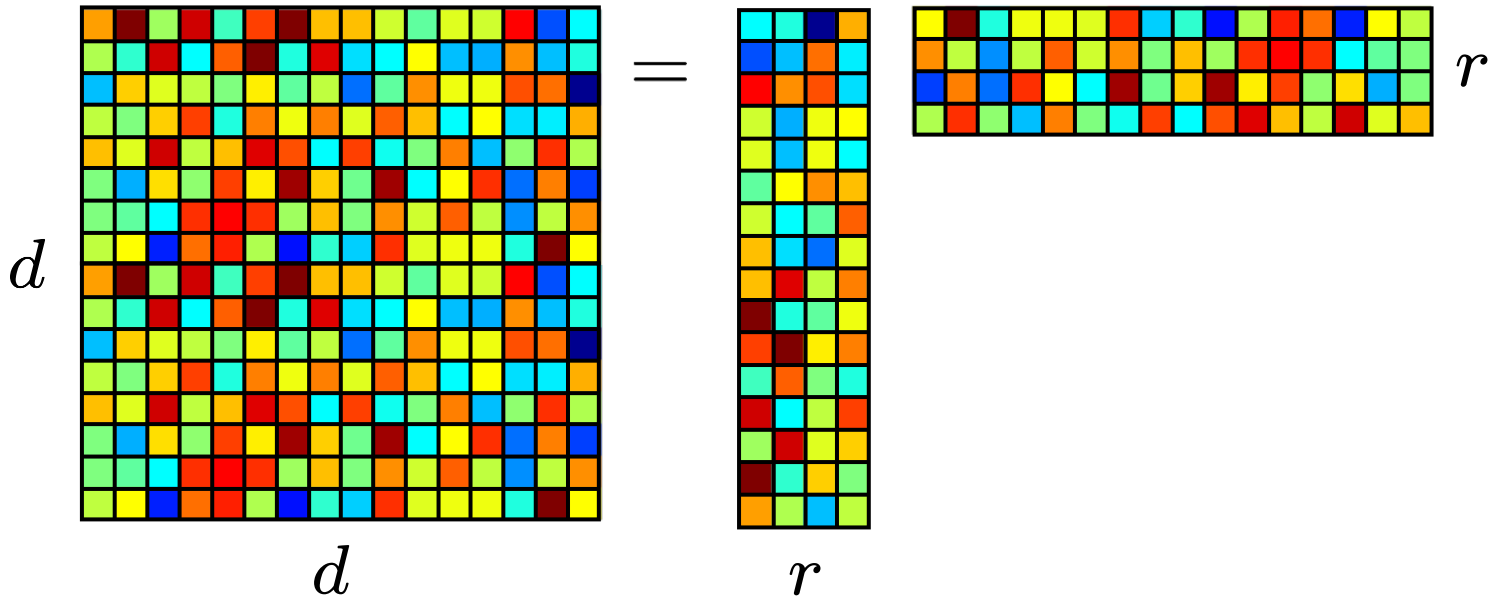
Matrix Completion



- When is it possible to recover the original matrix?
- How can we do this efficiently?
- How many samples will we need?

Low-Rank Matrices



Singular value decomposition:

$$M = U\Sigma V^* \quad \Rightarrow \quad \approx dr \ll d^2$$

degrees of freedom

Collaborative Filtering

The "Netflix Problem"

$M_{i,j}$ = how much user i likes movie j

Rank 1 model: u_i = how much user i likes romantic movies

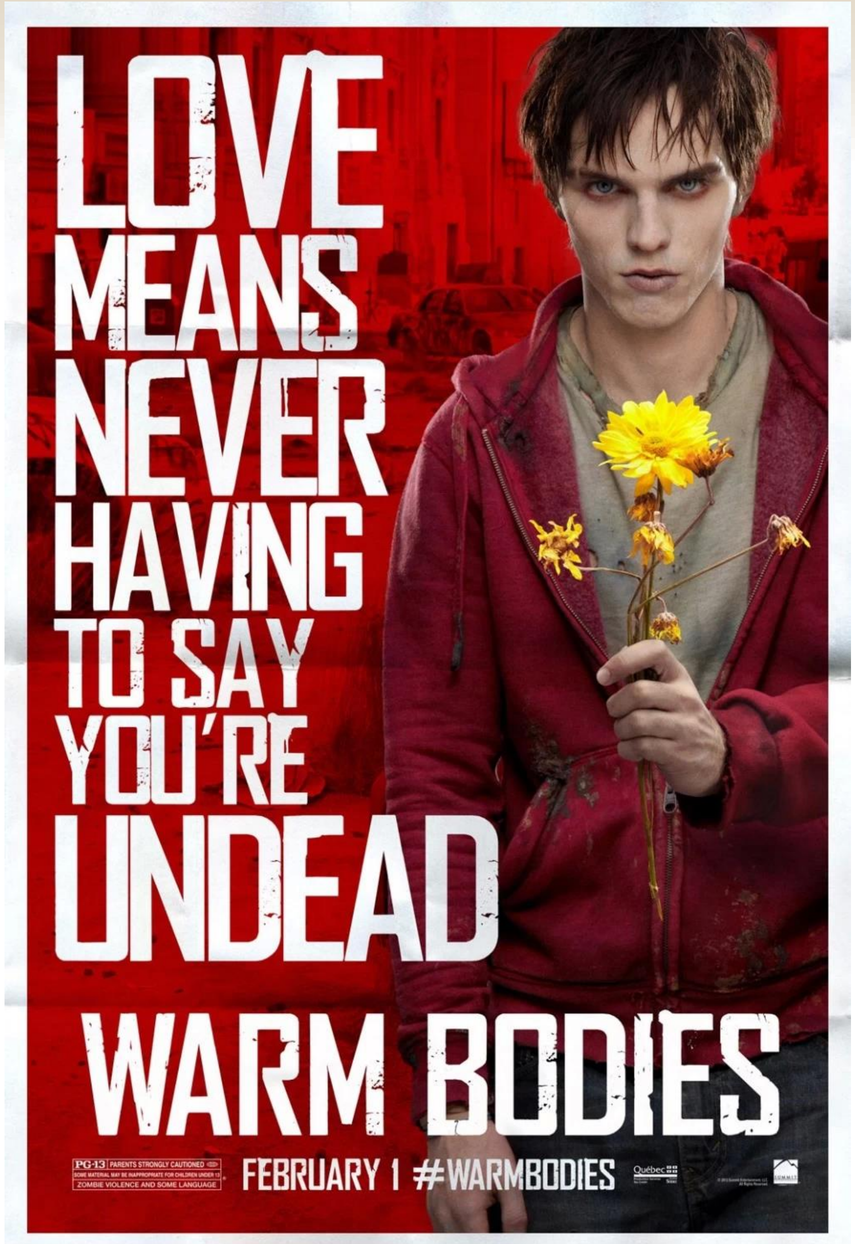
v_j = amount of romance in movie j

$$M_{i,j} = u_i v_j$$

Rank 2 model: w_i = how much user i likes zombie movies

x_j = amount of zombies in movie j

$$M_{i,j} = u_i v_j + w_i x_j$$


LOVE
MEANS
NEVER
HAVING
TO SAY
YOU'RE
UNDEAD
WARM BODIES
PG-13 PARENTS STRONGLY CAUTIONED
SOME MATERIAL MAY BE INAPPROPRIATE FOR CHILDREN UNDER 13
ZOMBIE VIOLENCE AND SOME LANGUAGE
FEBRUARY 1 #WARMBODIES
Québec

Beyond Netflix

- Recovery of incomplete survey data
- Analysis of voting data
- Sensor localization
- Student response data
- Quantum state tomography
- …

Low-Rank Matrix Recovery

Given:

- a $d \times d$ matrix M of rank r
- samples of M on the set : $Y = M$

How can we recover M?

$$\widehat{M} = \arg\inf_{X : X \quad = Y} \operatorname{rank}(X)$$

Can we replace this with something computationally feasible?

Nuclear Norm Minimization

Convex relaxation!

Replace $\mathrm{rank}(X)$ with $\|X\|_* = \sum_{j=1}^{d} |\sigma_j|$

$$\widehat{M} = \underset{X:X\ \ =Y}{\arg\inf}\ \|X\|_*$$

If $|\ \ | = O(r\,d\,\log d)$, under certain assumptions, this procedure can recover M !

Matrix Completion in Practice

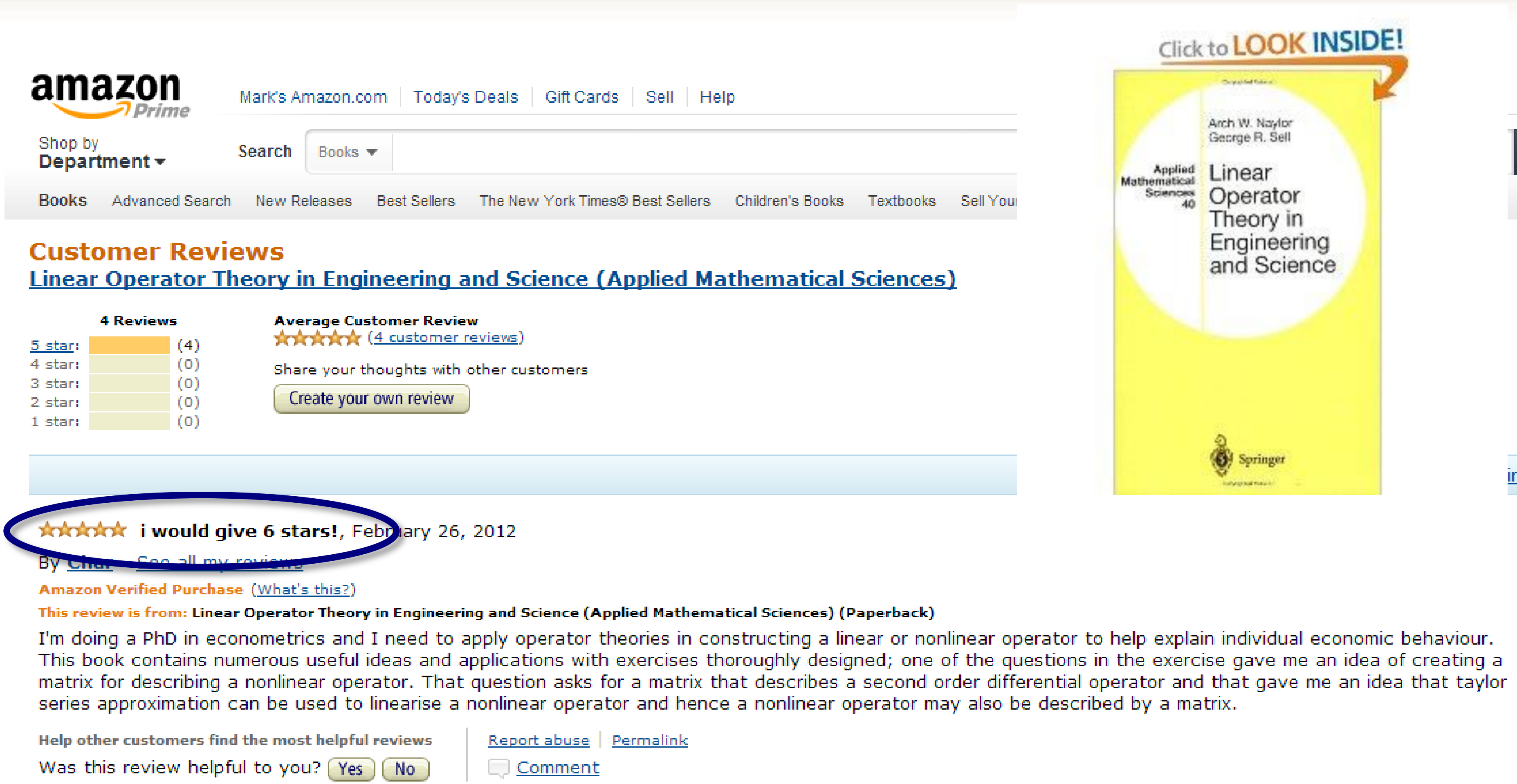
- Noise

$$Y = (M + Z)$$

- ***Quantization***
  - Netflix: Ratings are integers between 1 and 5
  - Survey responses: True/False, Yes/No, Agree/Disagree
  - Voting data: Yea/Nay
  - Quantum state tomography: Binary outcomes

Extreme quantization *destroys low-rank structure*

What’s the Problem?



1-Bit Matrix Completion

Extreme case

$$Y = \text{sign}(M\ \ )$$

Claim: Recovering M from Y is impossible!

$$M = \begin{bmatrix} \lambda & \lambda & \lambda & \lambda \\ \lambda & \lambda & \lambda & \lambda \\ \lambda & \lambda & \lambda & \lambda \\ \lambda & \lambda & \lambda & \lambda \end{bmatrix}$$

No matter how many samples we obtain, all we can learn is whether $\lambda > 0$ or $\lambda < 0$

Is There Any Hope?

If we consider a noisy version of the problem, recovery becomes feasible!

$$Y = \mathrm{sign}(M \quad + Z \quad)$$

$$M + Z = \begin{bmatrix} \lambda + Z_{1,1} & \lambda + Z_{1,2} & \lambda + Z_{1,3} & \lambda + Z_{1,4} \\ \lambda + Z_{2,1} & \lambda + Z_{2,2} & \lambda + Z_{2,3} & \lambda + Z_{2,4} \\ \lambda + Z_{3,1} & \lambda + Z_{3,2} & \lambda + Z_{3,3} & \lambda + Z_{3,4} \\ \lambda + Z_{4,1} & \lambda + Z_{4,2} & \lambda + Z_{4,3} & \lambda + Z_{4,4} \end{bmatrix}$$

Fraction of positive/negative observations tells us something about λ

Example of the power of *dithering*

Observation Model

For $(i, j) \in$ we observe

$$Y_{i,j} = \begin{cases} +1 & \text{with probability } f(M_{i,j}) \\ -1 & \text{with probability } 1 - f(M_{i,j}) \end{cases}$$

If f behaves like a CDF, then this is equivalent to

$$Y_{i,j} = \text{sign}(M_{i,j} + Z_{i,j})$$

where $Z_{i,j}$ is drawn according to a suitable distribution

We will assume that is drawn uniformly at random

Examples

- Logistic regression / Logistic noise

$$f(x) = \frac{e^x}{1 + e^x}$$

$Z_{i,j} \sim$ logistic distribution

- Probit regression / Gaussian noise

$$f(x) = \Phi(x/\sigma)$$

$$Z_{i,j} \sim \mathcal{N}(0, \sigma^2)$$

Maximum Likelihood Estimation

Log-likelihood function:

$$F(X) = \sum_{(i,j)\in \quad +} \log(f(X_{i,j})) + \sum_{(i,j)\in \quad -} \log(1 - f(X_{i,j}))$$

$$\widehat{M} = \arg\max_{X} F(X)$$

$$\text{s.t. } \frac{1}{d\alpha}\|X\|_* \leq \sqrt{r}$$

$$\|X\|_\infty \leq \alpha$$

Recovery of the Matrix

***Theorem** (Upper bound achieved by convex ML estimator)*

Assume that $\frac{1}{d\alpha}\|M\|_* \leq \sqrt{r}$ and $\|M\|_\infty \leq \alpha$. If is chosen at random with $\mathbb{E}|\quad| = m > d\log d$, then with high probability

$$\frac{1}{d^2}\|\widehat{M} - M\|_F^2 \leq C\alpha L_\alpha \beta_\alpha \sqrt{\frac{rd}{m}}$$

where

$$L_\alpha := \sup_{|x|\leq\alpha} \frac{|f'(x)|}{f(x)(1-f(x))} \qquad \beta_\alpha := \sup_{|x|\leq\alpha} \frac{f(x)(1-f(x))}{(f'(x))^2}$$

Is this bound tight?

Recovery of the Matrix

Theorem *(Upper bound achieved by convex ML estimator)*

Assume that $\frac{1}{d\alpha}\|M\|_* \leq \sqrt{r}$ and $\|M\|_\infty \leq \alpha$. If is chosen at random with $\mathbb{E}| \quad | = m > d \log d$, then with high probability

$$\frac{1}{d^2}\|\widehat{M} - M\|_F^2 \leq C\alpha L_\alpha \beta_\alpha \sqrt{\frac{rd}{m}}$$

Theorem *(Lower bound on any estimator)*

There exist M satisfying the assumptions above such that for any set with $| \quad | = m$, we have (under mild technical assumptions) that

$$\inf_{\widehat{M}} \mathbb{E}\left[\frac{1}{d^2}\|\widehat{M} - M\|_F^2\right] \geq c\alpha\sqrt{\beta_{\frac{3}{4}\alpha}}\sqrt{\frac{rd}{m}}$$

Logistic Model

$$L_\alpha = 1 \qquad \beta_\alpha \approx e^{\alpha}$$

***Theorem** (Upper bound achieved by convex ML estimator)*

$$\frac{1}{d^2}\|\widehat{M} - M\|_F^2 \leq C\alpha e^{\alpha}\sqrt{\frac{rd}{m}}$$

***Theorem** (Lower bound on any estimator)*

$$\inf_{\widehat{M}} \mathbb{E}\left[\frac{1}{d^2}\|\widehat{M} - M\|_F^2\right] \geq c\alpha e^{\frac{3}{8}\alpha}\sqrt{\frac{rd}{m}}$$

Probit Model

$$L_\alpha \approx \frac{\frac{\alpha}{\sigma} + 1}{\sigma} \qquad \beta_\alpha \approx \sigma^2 e^{\alpha^2/2\sigma^2}$$

***Theorem** (Upper bound achieved by convex ML estimator)*

$$\frac{1}{d^2}\|\widehat{M} - M\|_F^2 \leq C\left(\frac{\alpha}{\sigma} + 1\right) e^{\alpha^2/2\sigma^2} \sigma\alpha\sqrt{\frac{rd}{m}}$$

Two regimes

- High signal-to-noise ratio: $\sigma \leq \alpha$
- Low signal-to-noise ratio: $\sigma \geq \alpha$

Compare to how well we can estimate M from unquantized, noisy measurements

Probit Model (High SNR)

Theorem *(Upper bound achieved by convex ML estimator)*

$$\frac{1}{d^2}\|\widehat{M} - M\|_F^2 \leq C\alpha^2 e^{\alpha^2/2\sigma^2}\sqrt{\frac{rd}{m}}$$

Theorem *(Lower bound on any estimator with unquantized measurements)*

$$\inf_{\widehat{M}} \mathbb{E}\left[\frac{1}{d^2}\|\widehat{M} - M\|_F^2\right] \geq c\alpha\sigma\sqrt{\frac{rd}{m}}$$

Probit Model (Low SNR)

Theorem *(Upper bound achieved by convex ML estimator)*

$$\frac{1}{d^2}\|\widehat{M} - M\|_F^2 \leq C\alpha\sigma\sqrt{\frac{rd}{m}}$$

Theorem *(Lower bound on any estimator with unquantized measurements)*

$$\inf_{\widehat{M}} \mathbb{E}\left[\frac{1}{d^2}\|\widehat{M} - M\|_F^2\right] \geq c\alpha\sigma\sqrt{\frac{rd}{m}}$$

More noise can lead to *improved* performance!

Implementation

$$\underset{x}{\text{minimize}} \;\; f(x) \quad \text{subject to} \quad x \in \mathcal{C}$$

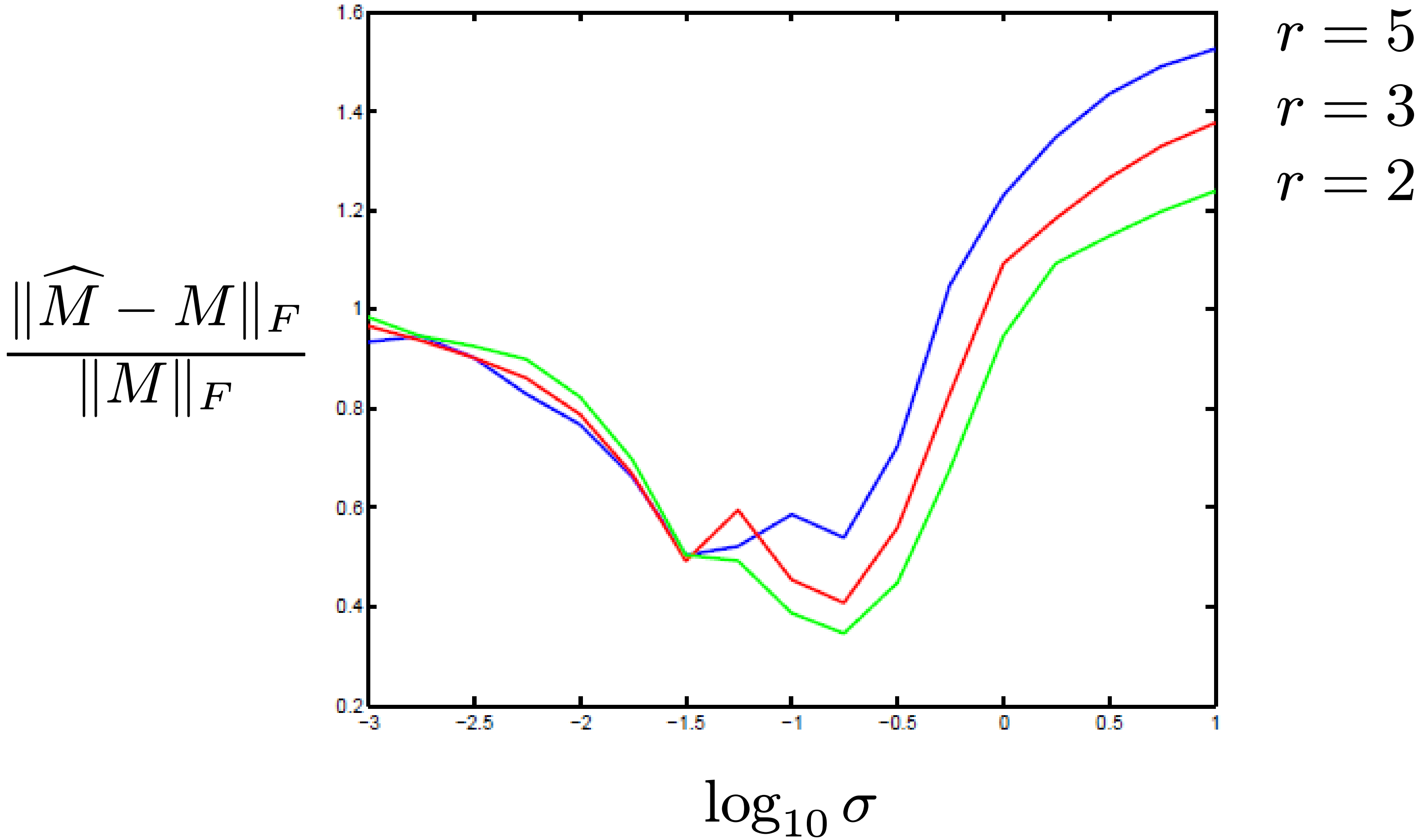
- $f(x)$ is smooth, convex
- $\mathcal{C}$ is a closed, convex set

- Nonmonotone spectral projected-gradient (SPG) algorithm

- Iterative algorithm, each iteration requires computation of
  - $f(x)$
  - $\nabla f(x)$

Synthetic Simulations

$$d = 500 \qquad m = .15d^2$$



MovieLens Data Set

- 100,000 movie ratings on a scale from 1 to 5
- Convert to binary outcomes by comparing each rating to the average rating in the data set
- Evaluate by checking if we predict the correct sign
- Training on 95,000 ratings and testing on remainder
  - "standard" matrix completion: 60% accuracy

1: 64%	2: 56%	3: 44%	4: 65%	5: 74%

  - 1-bit matrix completion: 73% accuracy

1: 79%	2: 73%	3: 58%	4: 75%	5: 89%

Conclusions

- 1-bit matrix completion is hard!
- What did you really expect?
- Sometimes 1-bit is all we can get…
- We have algorithms that are near optimal
- Open questions
  - Are there simpler/better/faster/stronger algorithms?
  - What about 2.32-bit matrix completion?

Thank You!