1-Bit Matrix Completion

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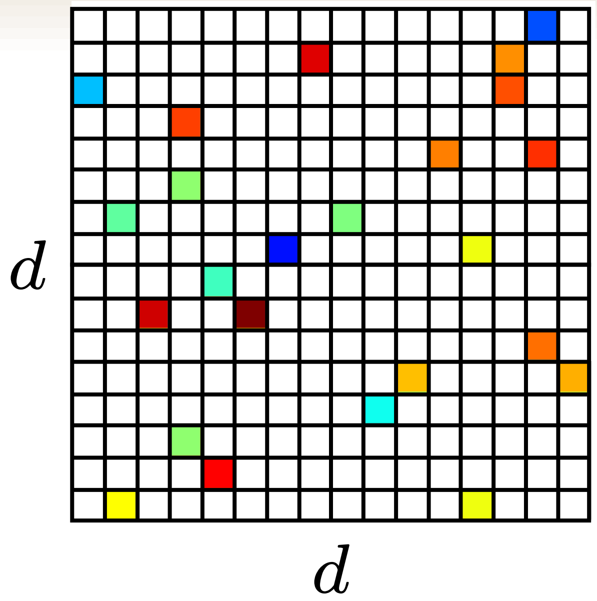
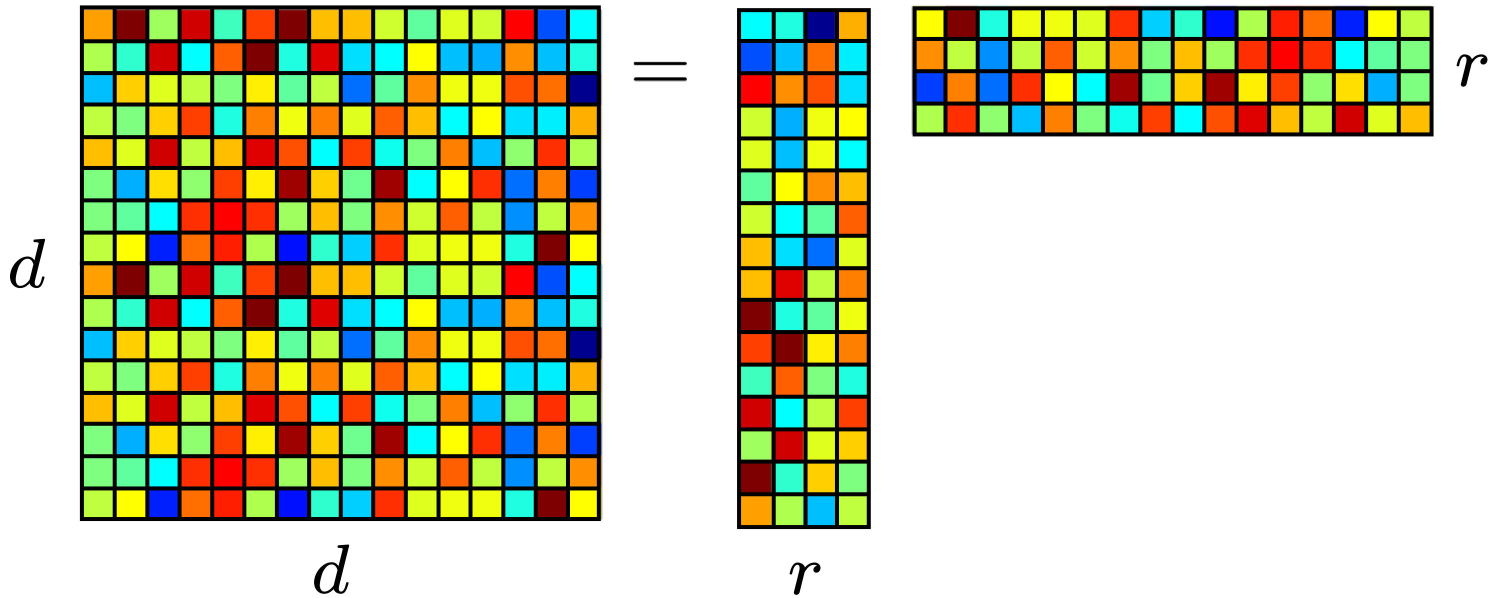
Matrix Completion



- 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

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

Beyond Netflix

- Recovery of incomplete survey data
- Analysis of voting data
- Sensor localization
- 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?

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

Can we replace this with something computationally feasible?

Nuclear Norm Minimization

Convex relaxation!

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

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

If $| \quad | = O(r\, d \log d)$, 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*

1-Bit Matrix Completion

Extreme case

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

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 $\lambda < 0$

1-Bit Matrix Completion

Extreme case

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

Claim: Recovering M from Y is impossible!

$$M = uv^*$$

$$\widetilde{u} = \mathrm{sign}(u) \qquad \widetilde{v} = \mathrm{sign}(v)$$

$$\widetilde{M} = \widetilde{u}\widetilde{v}^*$$

$$\Rightarrow \quad \mathrm{sign}(\widetilde{M}) = \mathrm{sign}(M)$$

Is There Any Hope?

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

$$Y = \text{sign}(M \;\; + Z \;\;)$$

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

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

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

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

- Probit regression / Gaussian noise

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

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

Assumptions

$$M = \begin{bmatrix} d & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

- If the upper-left corner of M is not sampled, we have no information

- Solution: Assume that M is “spread”

$$\|M\|_\infty = \max_{i,j} |M_{i,j}| \leq \alpha \approx O(1)$$

Maximum Likelihood Estimation

Log-likelihood function:

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

$$\begin{aligned} \widehat{M} = \arg\max_X F(X) \\ \text{s.t. } \operatorname{rank}(X) \leq r \\ \|X\|_\infty \leq \alpha \end{aligned}$$

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 $\mathbb{E}|\ \ | = m > d \log d$, 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 $|\ \ | = m$, 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!

Recovery of the Distribution

- It is also possible to establish bounds concerning the recovery of the distribution $f(M)$
- We obtain matching upper and lower bounds on the average Hellinger distance between $f(M)$ and $f(\widehat{M})$
- When $\lim_{\alpha \to \infty} L_\alpha < \infty$, we can recover the distribution $f(M)$ without any assumptions on $\|M\|_\infty$
  - logistic model
  - *not* probit model
  - any model where the noise has heavy tails

Proof Methods

- Upper bounds
  - Probability in Banach spaces
  - Random matrix theory

- Lower bounds
  - Information theoretic arguments
  - Fano's inequality
  - Packing sets of low-rank matrices

Tiny Sketch of Proof of Upper Bound

Recall that we maximize the log-likelihood $F(X)$

- For a fixed matrix X, $\mathbb{E}[F(M) - F(X)] = c \cdot D(f(X) || f(M))$
- Lemma: Let $K = \{X : \frac{1}{d\alpha}\|X\|_* \leq \sqrt{r}\}$. With high probability, $\sup_{X \in K} |F(X) - \mathbb{E}F(X)| \leq \delta$
- By definition, $F(\widehat{M}) \geq F(M)$

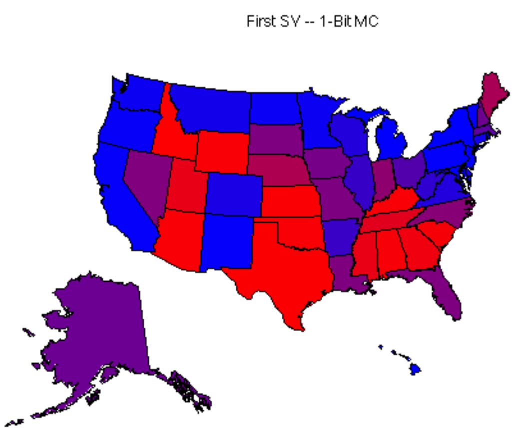
$$\begin{aligned} 0 &\geq F(M) - F(\widehat{M}) \\ &\geq \mathbb{E}\left[F(M) - F(\widehat{M})\right] - 2\delta \\ &= c \cdot D(f(\widehat{M}) || f(M)) - 2\delta \end{aligned}$$

- Thus, $D(f(\widehat{M}) || f(M)) \leq \frac{2}{c}\delta$

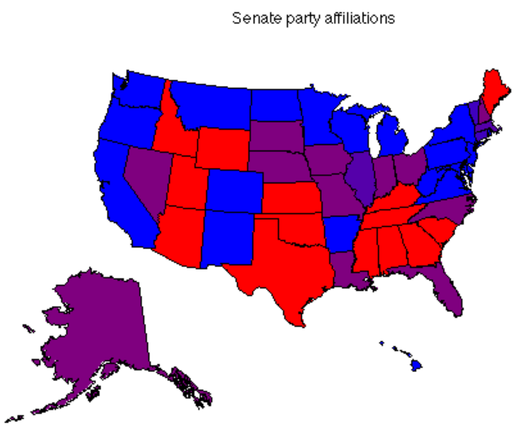
Voting Simulation

Binary (incomplete) data:

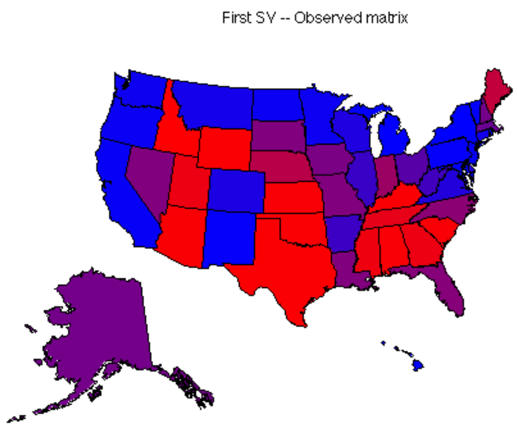
Voting history of 105 US senators on 299 bills from 2008-2010



First singular vector of $\widehat{M}$



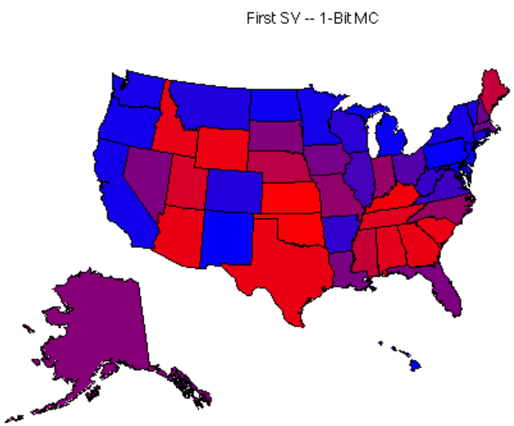
Senator party affiliations

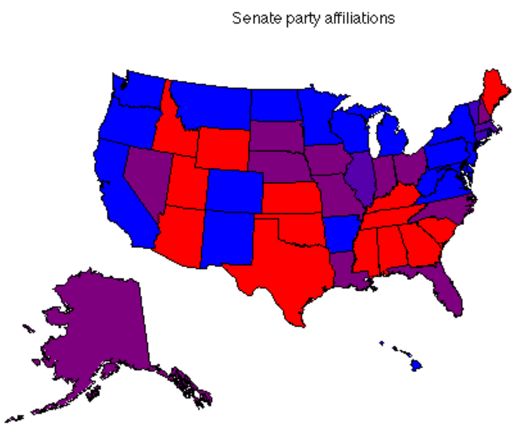


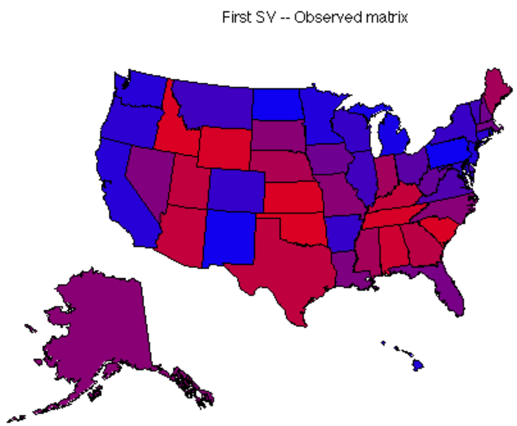
First singular vector of Y

Voting Simulation

Randomly delete 90% of the entries







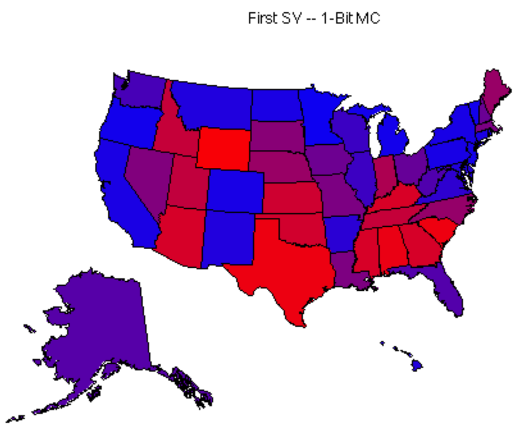
First singular vector of $\widehat{M}$

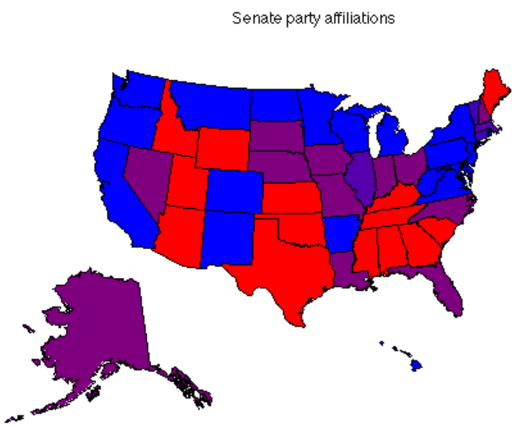
Senator party affiliations

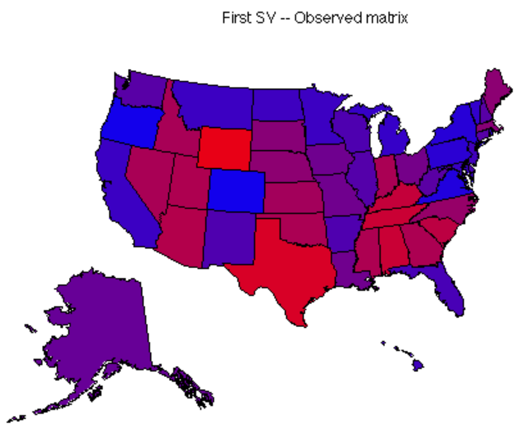
First singular vector of Y

Voting Simulation

Randomly delete 95% of the entries







First singular vector of $\widehat{M}$

Senator party affiliations

First singular vector of Y

86% of missing votes correctly predicted

MovieLens Data Set

- 100,000 movie ratings (1000 users, 1700 movies) 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: 68% accuracy
  - 1-bit matrix completion: 74% accuracy

Thank You!