

Rank aggregation via nuclear norm minimization

SAND2011-4281C

David F. Gleich

Sandia National Laboratories

Lek-Heng Lim

University of Chicago

Householder Symposium 18

Tahoe City, (Barely) CA

Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

Which is a better list of good DVDs?

Lord of the Rings 3: The Return of ...	Lord of the Rings 3: The Return of ...
Lord of the Rings 1: The Fellowship	Lord of the Rings 1: The Fellowship
Lord of the Rings 2: The Two Towers	Lord of the Rings 2: The Two Towers
Lost: Season 1	Star Wars V: Empire Strikes Back
Battlestar Galactica: Season 1	Raiders of the Lost Ark
Fullmetal Alchemist	Star Wars IV: A New Hope
Trailer Park Boys: Season 4	Shawshank Redemption
Trailer Park Boys: Season 3	Star Wars VI: Return of the Jedi
Tenchi Muyo!	Lord of the Rings 3: Bonus DVD
Shawshank Redemption	The Godfather

Standard
rank aggregation
(the mean rating)

Nuclear Norm
based rank aggregation

Ranking is *really* hard

Ken Arrow



All rank aggregations involve some measure of compromise

John Kemeny



A good ranking is the “average” ranking under a permutation distance

Dwork, Kumar, Naor, Sivikumar



NP hard to compute Kemeny’s ranking

*Given a hard problem,
what do you do?*

Numerically relax!

It'll probably be easier.

Embody chair
John Cantrell (flickr)



Suppose we had scores

Let s_i be the score of the i th movie/song/paper/team to rank

Suppose we can compare the i th to j th:

$$Y_{i,j} = s_i - s_j$$

Then $\mathbf{Y} = \mathbf{se}^T - \mathbf{es}^T$ is skew-symmetric, rank 2.

Also works for $Y_{i,j} = s_i/s_j$ with an extra log.

*Numerical ranking is intimately intertwined
with skew-symmetric matrices*

Kemeny and Snell, Mathematical Models in Social Sciences (1978)

Using ratings instead of comparisons



Ratings induce various skew-symmetric matrices.

$$Y_{i,j} = \frac{\sum_u R_{u,i} - R_{u,j}}{|\{u|R_{u,i} \text{ and } R_{u,j} \text{ exist}\}|} \quad \text{Arithmetic Mean}$$

$$Y_{i,j} = \log \frac{\Pr_u(R_{u,i} \geq R_{u,j})}{\Pr_u(R_{u,i} \leq R_{u,j})} \quad \text{Log-odds}$$

David 1988 – The Method of Paired Comparisons

Extracting the scores

Given \mathbf{Y} with all entries, then

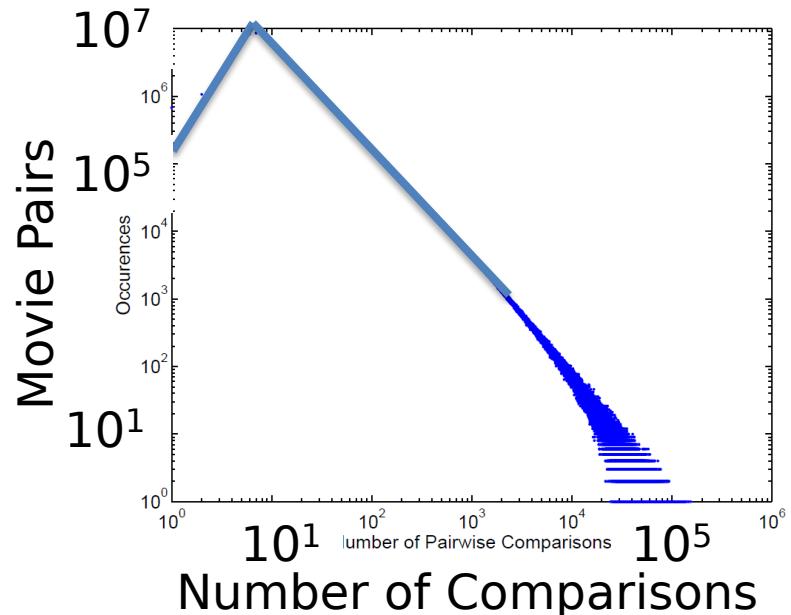
$\mathbf{s} = \frac{1}{n} \mathbf{Y} \mathbf{e}$ is the *Borda count*, the least-squares solution to \mathbf{s}

How many $Y_{i,j}$ do we have?

Most.

Do we *trust* all $Y_{i,j}$?

Not really.



Netflix data 17k movies,
500k users, 100M ratings-
99.17% filled

Only partial info? Complete it!

Let $\hat{Y}_{i,j}$ be known for $(i, j) \in \Omega$ We trust these scores.

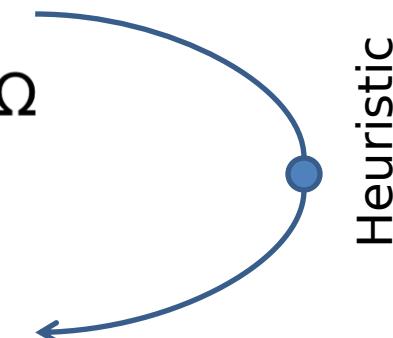
Goal Find the simplest skew-symmetric matrix that matches the data $\hat{Y}_{i,j}$

NP hard

$$\begin{aligned} & \text{minimize} && \text{rank}(\mathbf{Y}) \\ & \text{subject to} && \mathbf{Y} = -\mathbf{Y}^T \\ & && Y_{i,j} = \hat{Y}_{i,j} \text{ for all } (i, j) \in \Omega \end{aligned}$$

Convex

$$\begin{aligned} & \text{minimize} && \|\mathbf{Y}\|_* \\ & \text{subject to} && \mathbf{Y} = -\mathbf{Y}^T \\ & && Y_{i,j} = \hat{Y}_{i,j} \text{ for all } (i, j) \in \Omega \end{aligned}$$



$$\|\mathbf{Y}\|_* = \sum \sigma_i(\mathbf{Y}) \quad \text{best convex underestimator of rank on unit ball.}$$

Solving the nuclear norm problem

Use a LASSO formulation

$$\mathbf{b} = \text{vec}(\hat{Y}_{i,j})$$

$$\text{minimize} \quad \|\Omega(\mathbf{Y}) - \mathbf{b}\|$$

$$\text{subject to} \quad \|\mathbf{Y}\|_* \leq 2$$
$$\mathbf{Y} = -\mathbf{Y}^T$$

Jain et al. propose SVP for
this problem without
 $\mathbf{Y} = -\mathbf{Y}^T$

1. $\mathbf{Y}_0 = 0, t = 0$
2. REPEAT
3. $\mathbf{U}_t \mathbf{\Sigma}_t \mathbf{V}_t^T$ = rank-k SVD of
 $\Omega(\mathbf{Y}_t) - \eta(\Omega(\mathbf{Y}_t) - \mathbf{b})$
4. $\mathbf{Y}_{t+1} = \mathbf{U}_t \mathbf{\Sigma}_t \mathbf{V}_t^T$
5. $t = t + 1$
6. UNTIL $\|(\Omega(\mathbf{Y}_t) - \mathbf{b})\| < \varepsilon$

Skew-symmetric SVDs

Let $\mathbf{A} = -\mathbf{A}^T$ be an $n \times n$ skew-symmetric matrix with eigenvalues $i\lambda_1, -i\lambda_1, i\lambda_2, -i\lambda_2, \dots, i\lambda_j, -i\lambda_j$, where $\lambda_i > 0, \lambda_i \geq \lambda_{i+1}$ and $j = \lfloor n/2 \rfloor$. Then the SVD of \mathbf{A} is given by

$$\mathbf{A} = \mathbf{U} \begin{bmatrix} \lambda_1 & & & & & \\ & \lambda_1 & & & & \\ & & \lambda_2 & & & \\ & & & \lambda_2 & & \\ & & & & \ddots & \\ & & & & & \lambda_j \\ & & & & & & \lambda_j \end{bmatrix} \mathbf{V}^T$$

for \mathbf{U} and \mathbf{V} given in the proof.

Proof Use the Murnaghan-Wintner form and the SVD of a 2x2 skew-symmetric block

This means that SVP will give us the skew-symmetric constraint “for free”

Exact recovery results

David Gross showed how to recover Hermitian matrices.
i.e. the conditions under which we get the exact \mathbf{s}

Note that $i\mathbf{Y}$ is Hermitian. Thus our new result!

THEOREM 5. *Let \mathbf{s} be centered, i.e., $\mathbf{s}^T \mathbf{e} = 0$. Let $\mathbf{Y} = \mathbf{s}\mathbf{e}^T - \mathbf{e}\mathbf{s}^T$ where $\theta = \max_i s_i^2 / (\mathbf{s}^T \mathbf{s})$ and $\rho = ((\max_i s_i) - (\min_i s_i)) / \|\mathbf{s}\|$. Also, let $\Omega \subset \mathcal{H}$ be a random set of elements with size $|\Omega| \geq O(2n\nu(1 + \beta)(\log n)^2)$ where $\nu = \max((n\theta + 1)/4, n\rho^2)$. Then the solution of*

$$\text{minimize } \|\mathbf{X}\|_*$$

$$\text{subject to } \text{trace}(\mathbf{X}^* \mathbf{W}_i) = \text{trace}((i\mathbf{Y})^* \mathbf{W}_i), \quad \mathbf{W}_i \in \Omega$$

is equal to $i\mathbf{Y}$ with probability at least $1 - n^{-\beta}$.

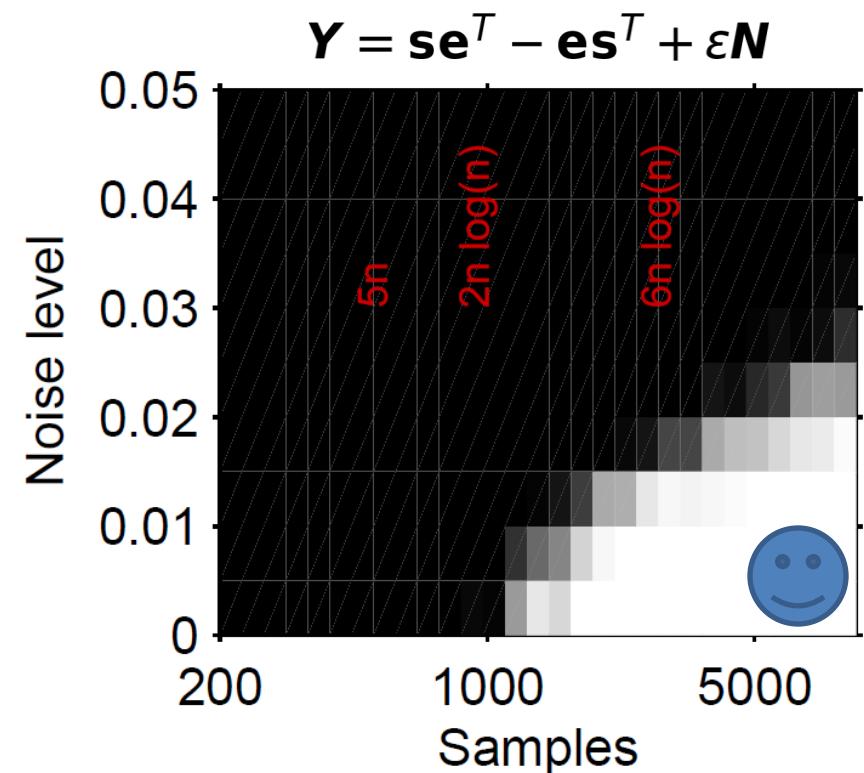
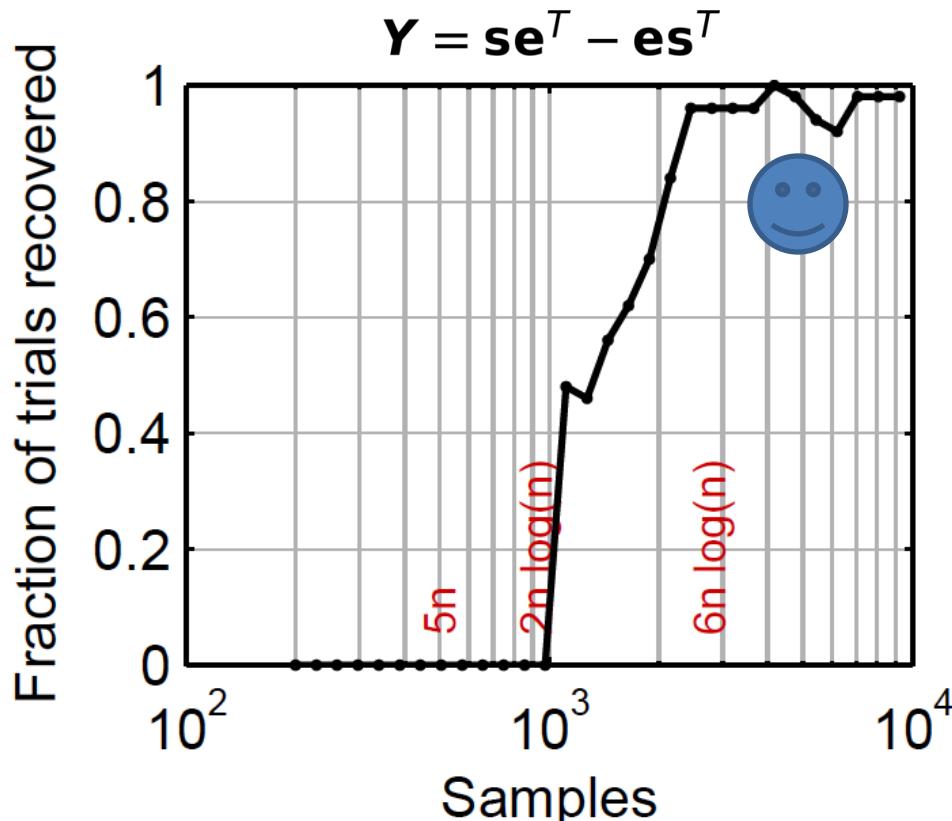
“ $n \log(n)$ ”

Gross arXiv 2010.

Recovery Discussion and Experiments

If $\mathbf{Y} = \mathbf{s}\mathbf{e}^T - \mathbf{e}\mathbf{s}^T$, then just look at differences from a connected set. Constants? Not very good.

“ $n \log(n)$ ” **Intuition for the truth.**

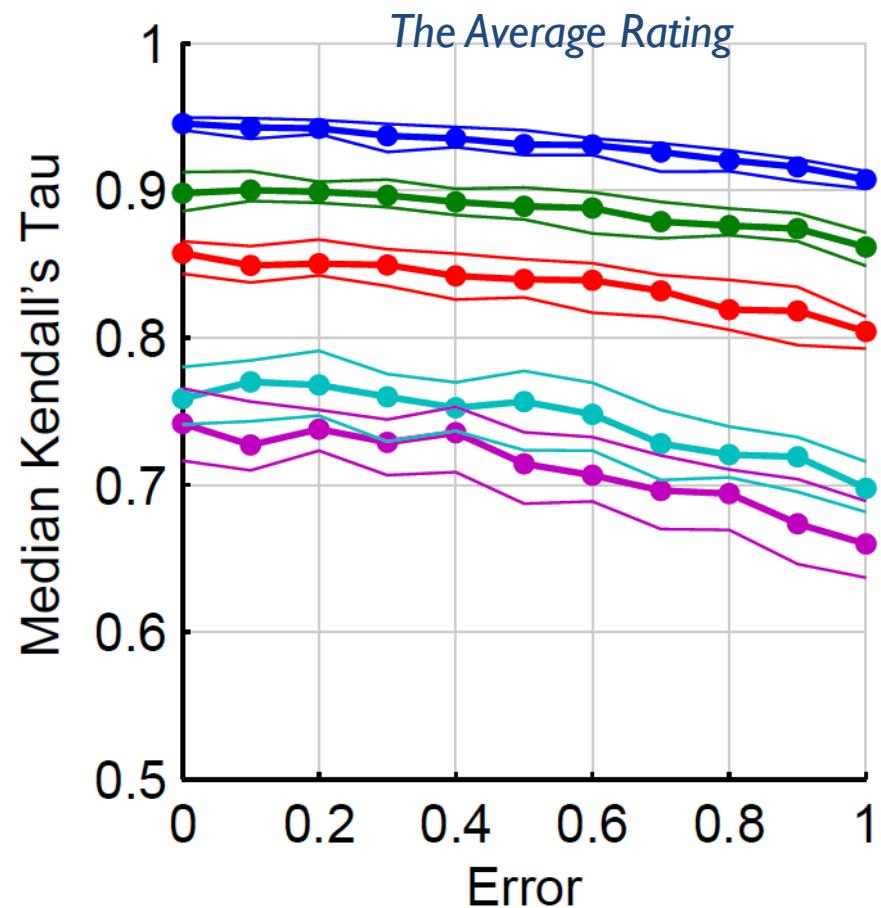
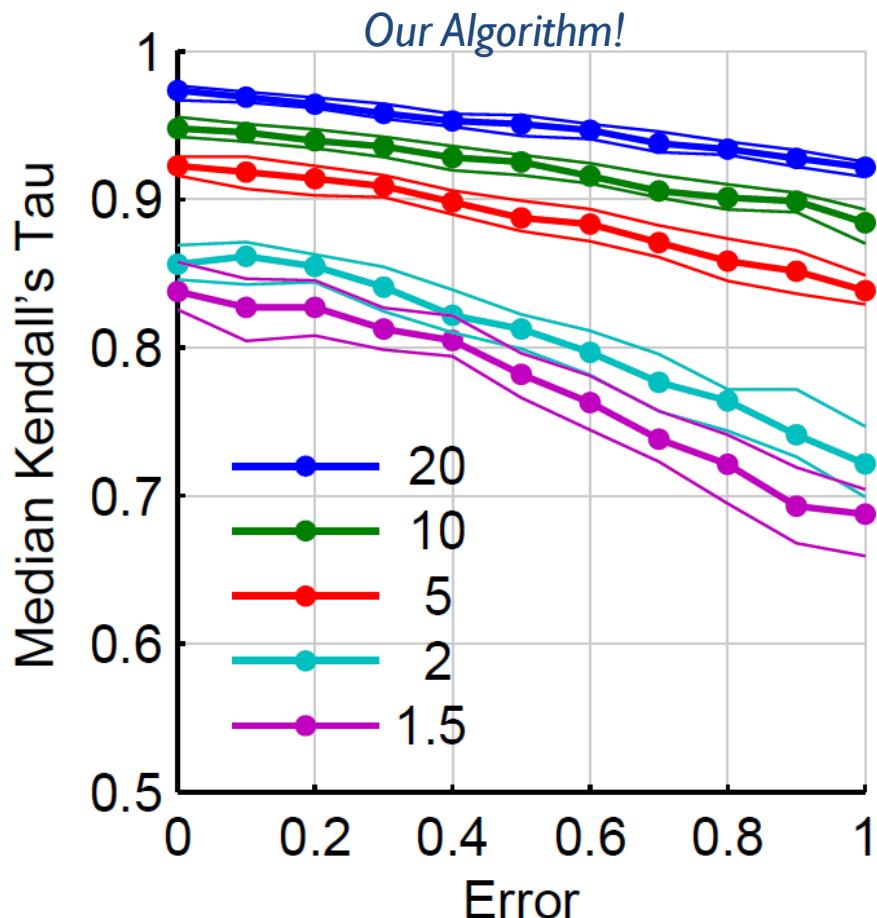


The Ranking Algorithm

0. INPUT \mathbf{R} (ratings data) and c (for trust on comparisons)
1. Compute \mathbf{Y} from \mathbf{R}
2. Discard entries with fewer than c comparisons
3. Set Ω , \mathbf{b} to be indices and values of what's left
4. $\mathbf{U}, \mathbf{S}, \mathbf{V}^T = \text{SVP}(\Omega, \mathbf{b}, 2)$
5. OUTPUT $\mathbf{s} = (1/n)\mathbf{U}\mathbf{S}\mathbf{V}^T\mathbf{e}$

Synthetic Results

Construct an Item Response Theory model. Vary number of ratings per user and a noise/error level



Conclusions and Future Work

Rank aggregation with the nuclear norm is:

principled

easy to compute

The results are much better than simple approaches.

1. Compare against others
van Dooren (fitting)
Massey (direct least squares for \mathbf{s})
2. Noisy recovery! More realistic sampling.
3. Skew-symmetric Lanczos based SVD?

Google nuclear ranking gleich

<https://dgleich.com/projects/skew-nuclear>

To appear KDD2011

Approximation Residuals

