

A Characterization of Deterministic Sampling Patterns for Low-Rank Matrix Completion

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University of Wisconsin-Madison

Allerton, 2015

Outline

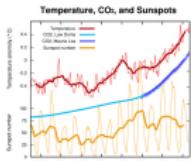
- ▶ Introduction
- ▶ When can we Low-Rank Matrix Complete?
- ▶ The Answer
- ▶ Implications
- ▶ Idea of the proof
- ▶ Conclusions
- ▶ Open questions (if time allows)

Outline

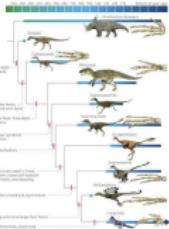
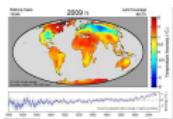
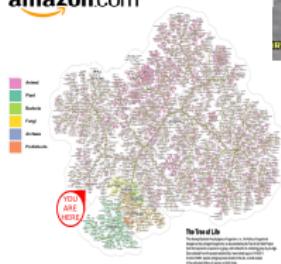
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Introduction

We have lots of data

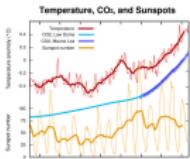


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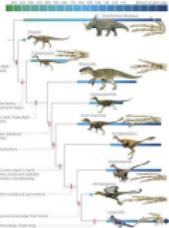
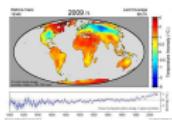
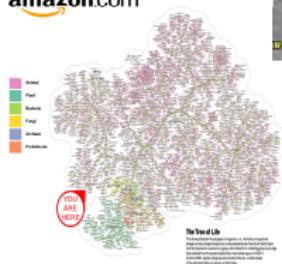


Introduction

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And we want to analyze it.

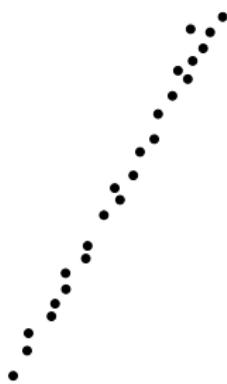
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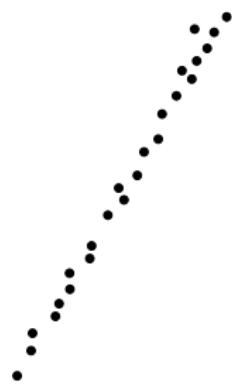


$$\begin{bmatrix} 1 & 2 & 1 & 3 & 2 & 1 & 3 & 1 & 2 & 2 \\ 2 & 4 & 2 & 6 & 4 & 2 & 6 & 2 & 4 & 4 \\ 3 & 6 & 3 & 9 & 6 & 3 & 9 & 3 & 6 & 6 \\ 1 & 2 & 1 & 3 & 2 & 1 & 3 & 1 & 2 & 2 \\ 2 & 4 & 2 & 6 & 4 & 2 & 6 & 2 & 4 & 4 \\ 3 & 6 & 3 & 9 & 6 & 3 & 9 & 3 & 6 & 6 \end{bmatrix}$$

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- ▶ We know how to find the subspace (e.g., using SVD).

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- ▶ We still want to find subspaces.

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Low-Rank Matrix Completion (LRMC) aims to find the **subspace** from **incomplete** datasets.

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$$S^* = \text{span} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}.$$

Outline

- ▶ Introduction ✓
- ▶ When can we Low-Rank Matrix Complete?
- ▶ The Answer
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But what if these assumptions are not met?

When can we Low-Rank Matrix Complete?

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- ▶ What makes a matrix *completable*?
- ▶ What conditions must a matrix satisfy?

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The Answer

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The Answer

Setup

- ▶ For any matrix Ω' formed with a subset of the columns in Ω :

$$\Omega' = \underbrace{\begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}}_{n(\Omega') := \# \text{columns}} \quad \left. \right\} m(\Omega') := \# \text{nonzero rows}$$

The Answer

Theorem (P.-A., Nowak, Boston (Allerton '15))

For almost every \mathbf{X} , there exist at most finitely many rank- r completions of \mathbf{X}_Ω if and only if every matrix Ω' formed with a subset of the columns in Ω satisfies

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For almost every \mathbf{X} , there exist at most **finitely** many rank- r completions of \mathbf{X}_Ω if and only if every matrix Ω' formed with a subset of the columns in Ω satisfies

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$$\mathbf{X}_\Omega = \begin{bmatrix} 1 & 1 & 3 & \cdot \\ 1 & 2 & \cdot & 1 \\ 3 & \cdot & 5 & 4 \\ \cdot & 7 & 6 & 5 \end{bmatrix} \Rightarrow \begin{cases} \mathbf{X} = \begin{bmatrix} 1 & 1 & 3 & 2 \\ 1 & 2 & 1 & 1 \\ 3 & 5 & 5 & 4 \\ 4 & 7 & 6 & 5 \end{bmatrix} \\ \mathbf{X} = \begin{bmatrix} 1 & 1 & 3 & 10 \\ 1 & 2 & \frac{21}{13} & 1 \\ 3 & \frac{53}{9} & 5 & 4 \\ \frac{68}{19} & 7 & 6 & 5 \end{bmatrix} \end{cases}$$

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$$\Omega = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \Rightarrow \text{Check: } \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The answer

Now we know when there are at most **finitely** many completions.

- ▶ Then what?

The Answer

Theorem (P.-A., Nowak, Boston (Allerton '15))

If in addition \mathbf{X}_Ω has an extra $(d - r)$ columns observed on $\hat{\Omega}$, such that every matrix Ω' formed with a subset of the columns in $\hat{\Omega}$ satisfies

$$m(\Omega') \geq n(\Omega') + r,$$

then \mathbf{X} can be uniquely recovered from \mathbf{X}_Ω .

The Answer (in words)

If a matrix does not satisfy our sampling conditions, then you **cannot** complete it.

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$$\mathbf{X}_\Omega = \begin{bmatrix} 1 & 1 & 3 & \cdot \\ 1 & 2 & \cdot & 1 \\ 3 & \cdot & 5 & 4 \\ \cdot & 7 & 6 & 5 \end{bmatrix}$$

Sometimes **finitely** completable = **uniquely** completable (e.g., rank= 1), but sometimes not.

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$$\mathbf{X}_\Omega = \begin{bmatrix} 1 & 1 & 3 & \cdot & -1 & 1 \\ 1 & 2 & \cdot & 1 & \cdot & -1 \\ 3 & \cdot & 5 & 4 & 3 & \cdot \\ \cdot & 7 & 6 & 5 & 5 & -2 \end{bmatrix}$$

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In essence:

r **complete** columns (linearly independent) uniquely define an r -dimensional subspace.

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r **complete** columns (linearly independent) uniquely define an r -dimensional subspace.

$(r + 1)(d - r)$ **incomplete** columns (observed in the right places) uniquely define an r -dimensional subspace.

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- ▶ **Implications**
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- ▶ Conclusions

Implications (coherence)

- ▶ P.-A., Nowak, Boston (Allerton '15):
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- ▶ P.-A., Nowak, Boston (Allerton '15):
 - ▶ For almost every matrix, $\mathcal{O}(\max\{r, \log d\})$ uniform random entries per column are sufficient for completion.
- ▶ Regardless of coherence!

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- ▶ Help answer an important open question:
 - ▶ The Sample Complexity of Subspace Clustering with Missing Data.

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- ▶ In lieu of **uniform sampling** assumptions.

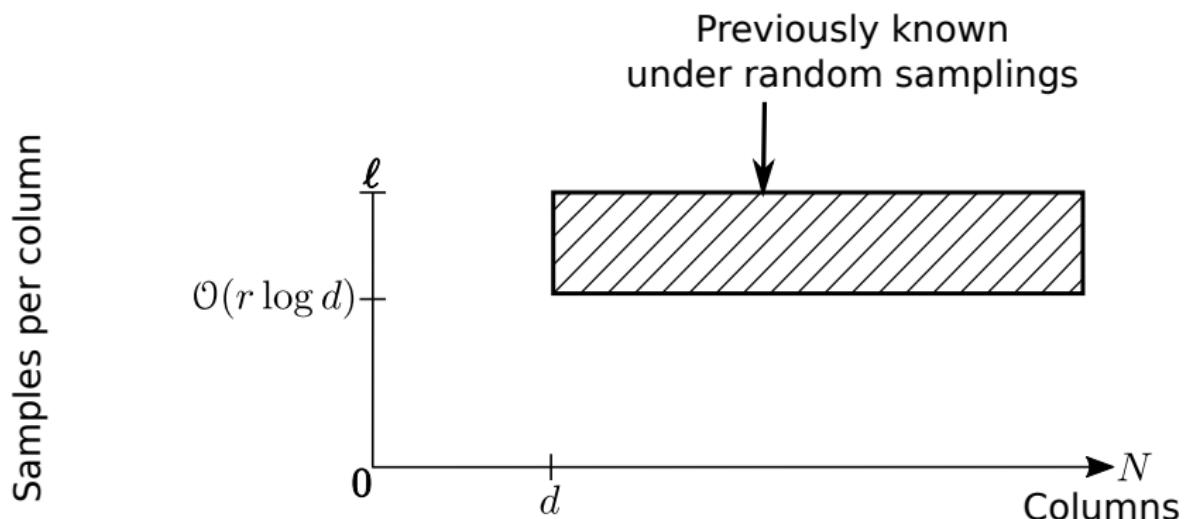
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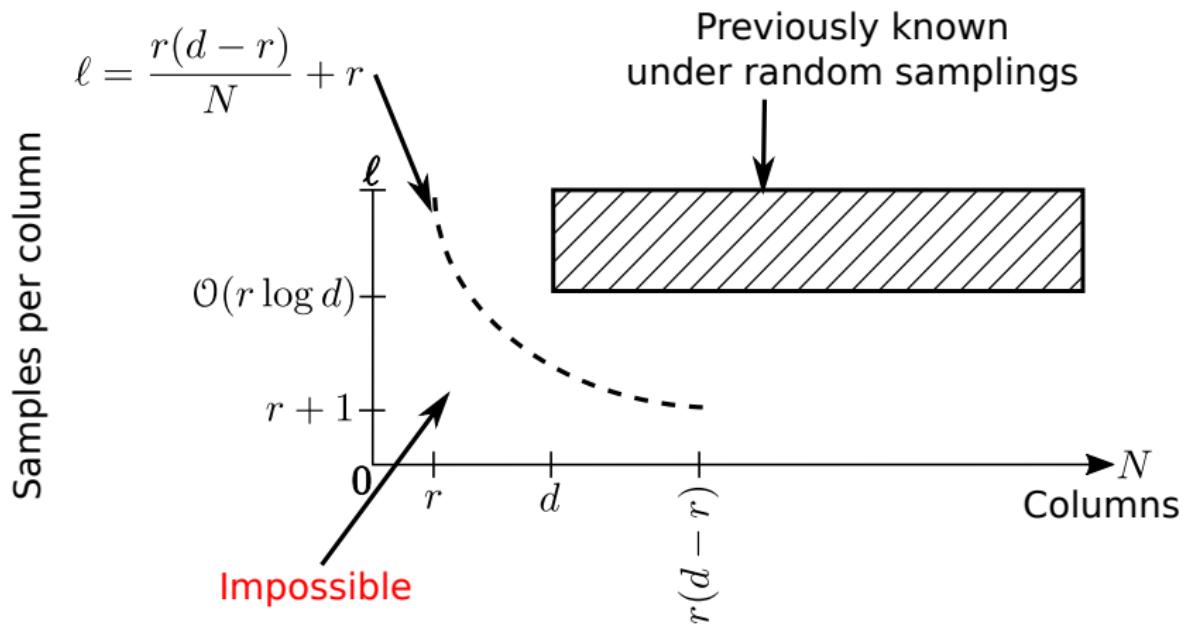
- ▶ Suppose you observe the right entries.
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- ▶ In lieu of coherence assumptions.
- ▶ In lieu of uniform sampling assumptions.
- ▶ With probability 1 (as opposed to with high probability).

Implications: better understanding of sampling regimes

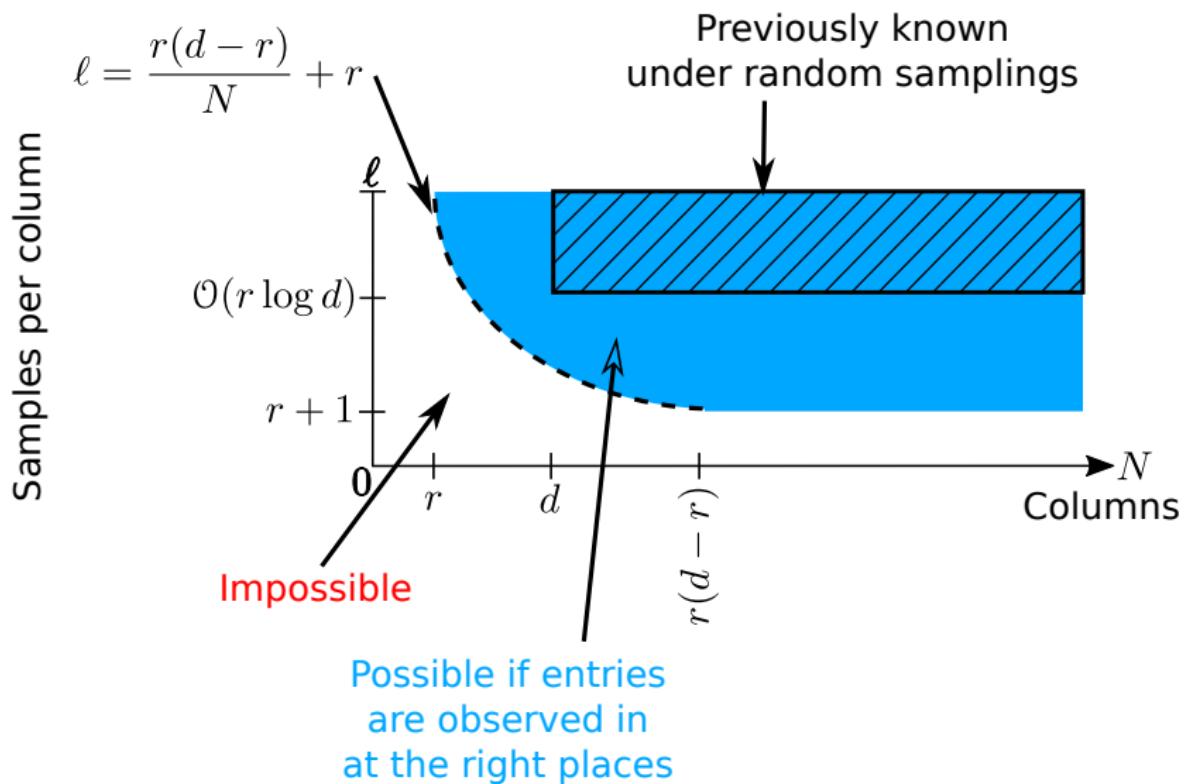
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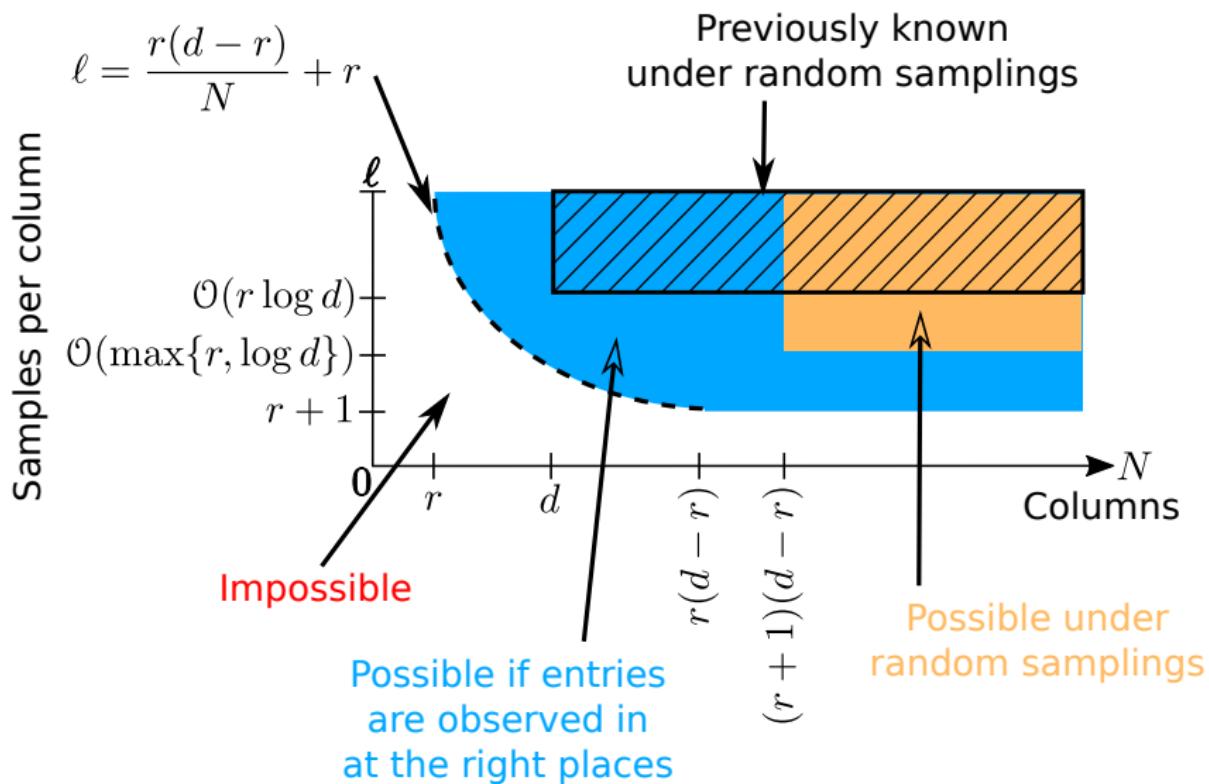
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Idea of the proof

A column with $r + 1$ samples imposes one **restriction** on what the subspace may be.

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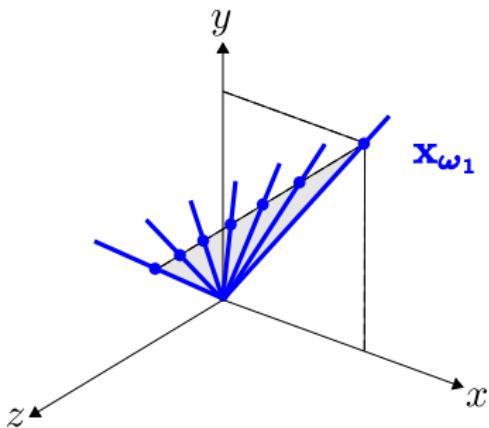
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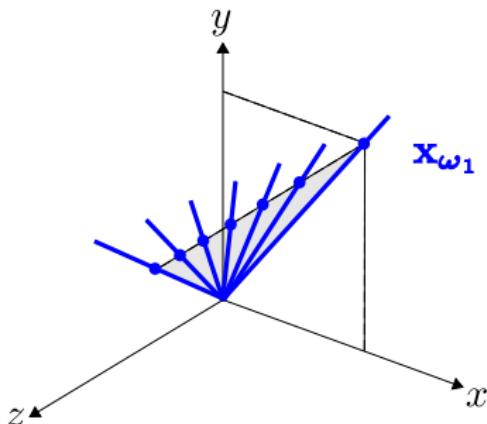
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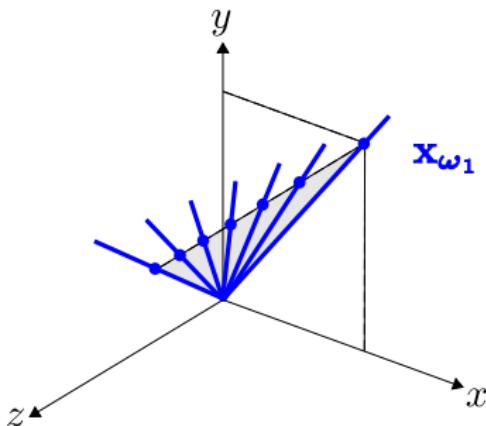


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$$\mathbf{X}_\Omega = \begin{bmatrix} \mathbf{x}_{\omega_1} \\ 1 \\ 1 \\ \cdot \end{bmatrix}$$



- ▶ A subspace S fits $\mathbf{x}_{\omega_1} \iff f_1(S) = 0$.
- ▶ This reduces one **degree of freedom** in the Grassmannian.

Idea of the proof

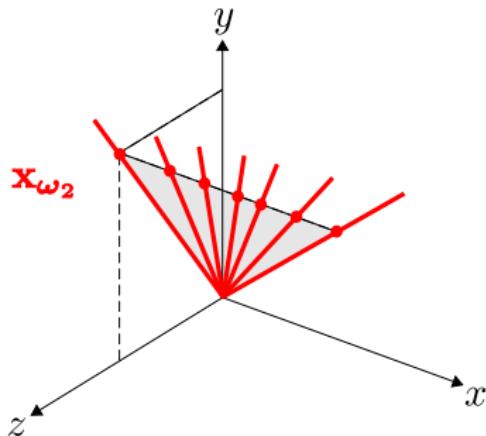
An other column with $r + 1$ samples imposes an other **restriction**.

$$\mathbf{X}_\Omega = \begin{bmatrix} \mathbf{x}_{\omega_2} \\ \vdots \\ 2 \\ 2 \end{bmatrix}$$

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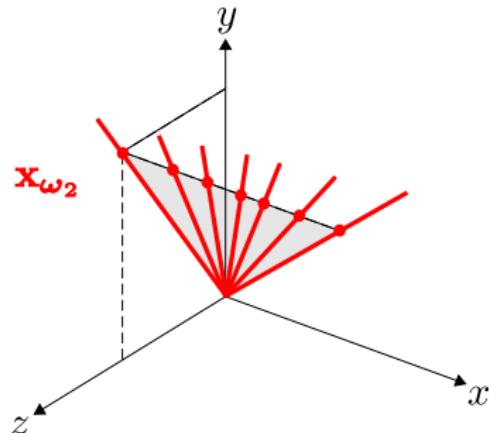
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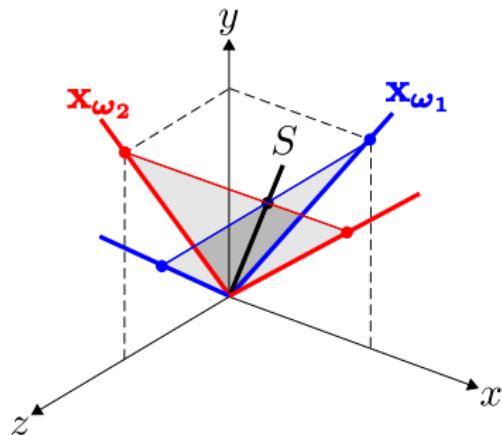
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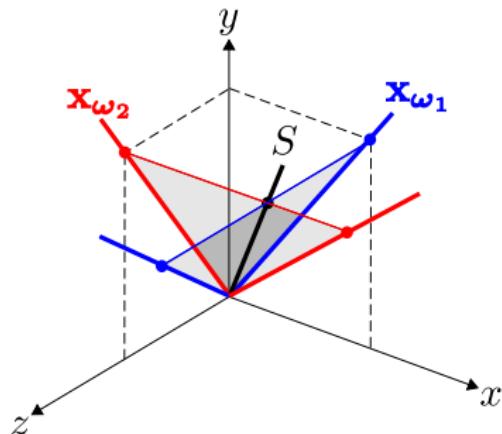
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- A subspace S fits $\mathbf{X}_\Omega \iff \left\{ \begin{array}{l} f_1(S) = 0 \\ f_2(S) = 0 \end{array} \right.$

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- ▶ The Grassmannian has $r(d - r)$ degrees of freedom.
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- ▶ $f_i(S)$ only involves the variables (of S) corresponding to the nonzero rows of ω_i .
- ▶ We want all sets of n polynomials to involve at least $n/r + r$ variables (otherwise they will be dependent)

Outline

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- ▶ When can we Low-Rank Matrix Complete? ✓
- ▶ The Answer ✓
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- ▶ This sheds new light on LRMC.

Thanks.

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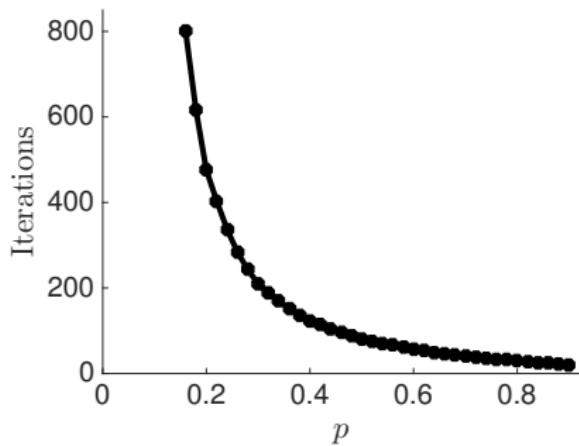
- ▶ P.-A., Nowak, Boston (Allerton '15):
 - ▶ New sampling regimes where you can **theoretically** complete a matrix.
 - ▶ This may involve solving a complex system of polynomial equations!
 - ▶ This is **computationally** prohibitive.

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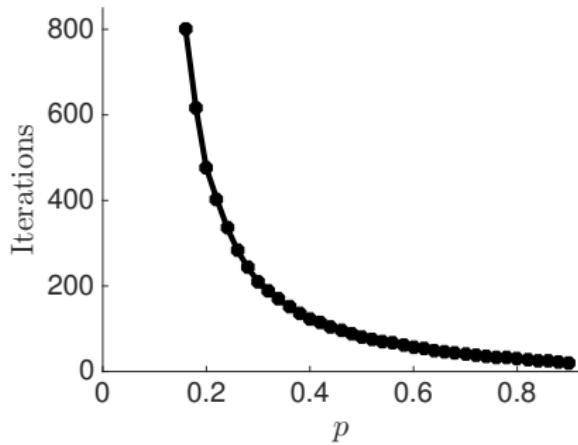
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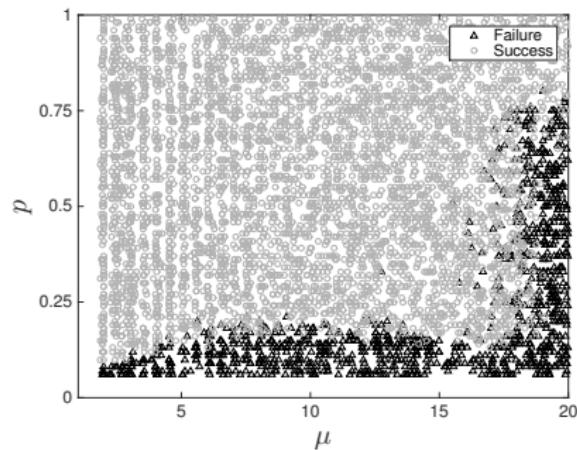
How much **missing data** can we handle and remain computationally efficient?

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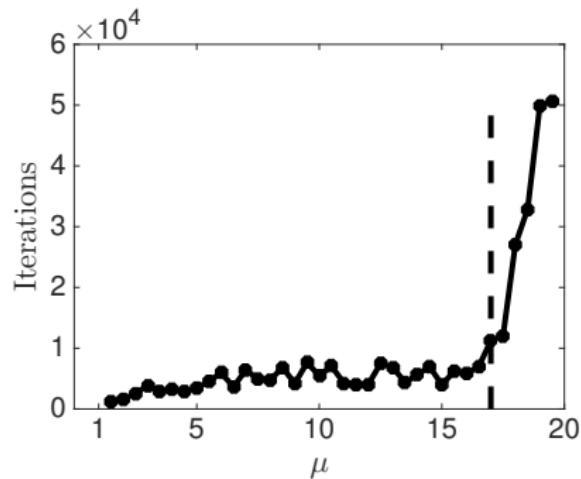


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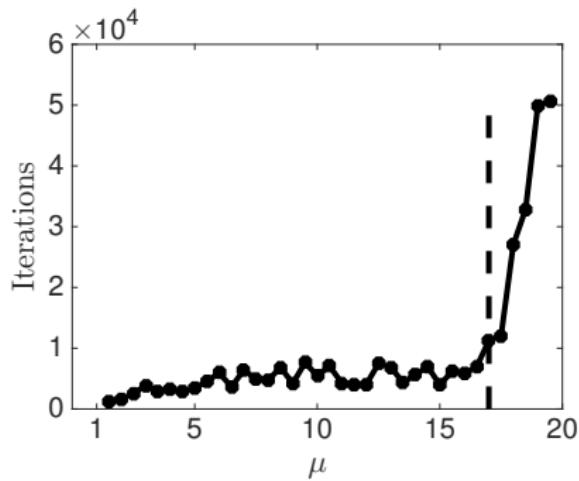
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How much coherence can we handle and remain computationally efficient?

Thanks again!

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(this time I'm really done)