

Orbit recovery problems

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Orbit recovery problems

We observe i.i.d. realizations of the model:

$$y_i = P(g_i \circ x) + \varepsilon_i, \quad i = 1, \dots, n,$$

where

- x is a fixed but unknown element of a vector space \mathcal{X}
- g_1, \dots, g_n are unknown elements of a (compact) group G
- $P: \mathcal{X} \mapsto \mathcal{Y}$ is a linear operator
- \mathcal{Y} is a finite dimensional measurement space
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Goal: Estimate/recover/reconstruct/learn the orbit

$$\{g \circ x : g \in G\}$$

from y_1, \dots, y_n .

First example: multi-reference alignment

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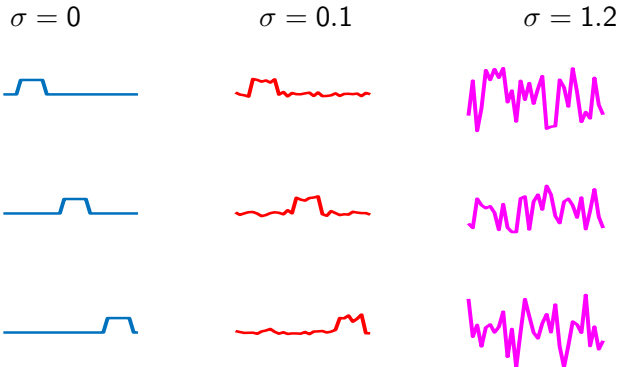
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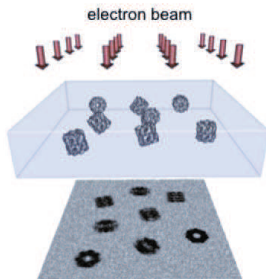
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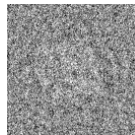
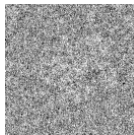
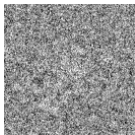
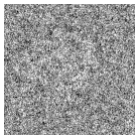
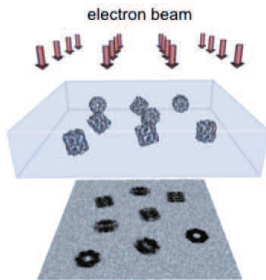


Single particle reconstruction using cryo-electron microscopy



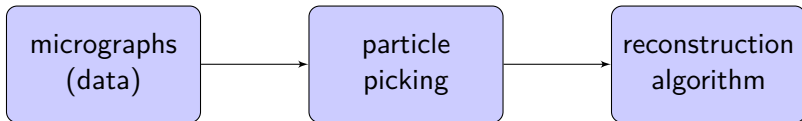
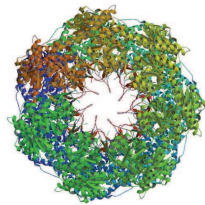
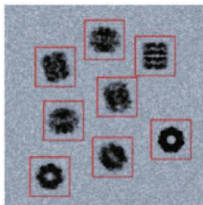
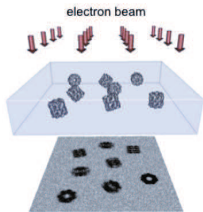
The images of *E. coli* 50S ribosomal subunit were provided by Dr. Fred Sigworth, Yale Medical School.

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The cryo-EM inverse problem



The cryo-EM inverse problem (perfect particle picking)

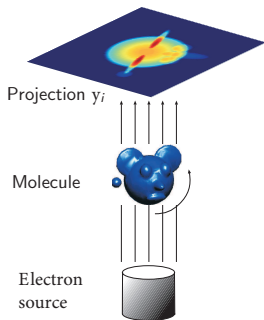


Image formation model

$$y_i = P(g_i \circ x) + \text{noise}, g_i \in SO(3)$$

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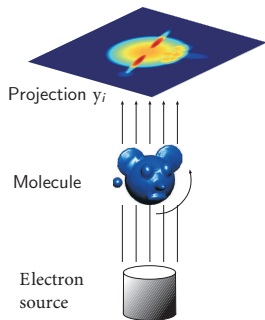


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Estimate (the orbit of) x from
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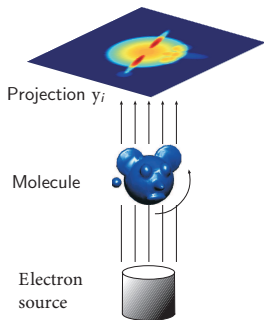


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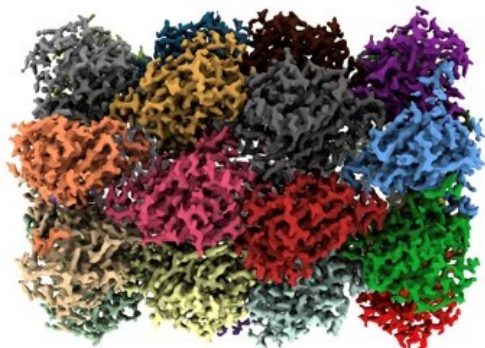
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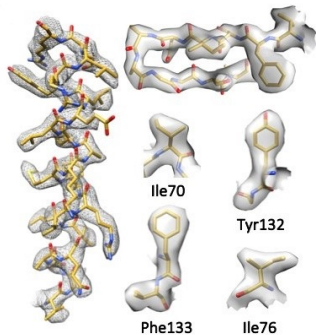
Estimate (the orbit of) x from
 y_1, \dots, y_N

- Can we accurately estimate the rotations?
- Can we accurately estimate the volume x ?
- And how?
- What is the optimal estimation rate?

Reconstruction of T20S proteasome



(a)



(b)

Taken from: Zhou, Moscovich, Bendory, and Bartesaghi. "Unsupervised particle sorting for high-resolution single-particle cryo-EM." *Inverse Problems*, (2019).

More examples

- Heterogeneous multi-reference alignment [Boumal, Bendory, Lederman, Singer, '18]
- Linear models with permuted data [Pananjady, Wainwright, Courtade, '17]
- Rotations and reflections (the orthogonal group) of a point cloud [Pumir, Singer, Boumal, '19]
- Boolean multi-reference alignment [Abbe, Pereira, Singer, '17]
- Low-rank covariance estimation under unknown translations [Aizenbud, Landa, Shkolnisky, '19; Landa, Shkolnisky, '19]
- Similar algebraic structures [Bendory, Boumal, Leeb, Levin, Singer, '19]

How to solve the problem?

$$y_i = P(g_i \circ x) + \varepsilon_i, \quad i = 1, \dots, n.$$

High SNR regime: Synchronization! Estimate g_1, \dots, g_n from y_1, \dots, y_n .



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Beautiful theory, near-optimal provable algorithms.

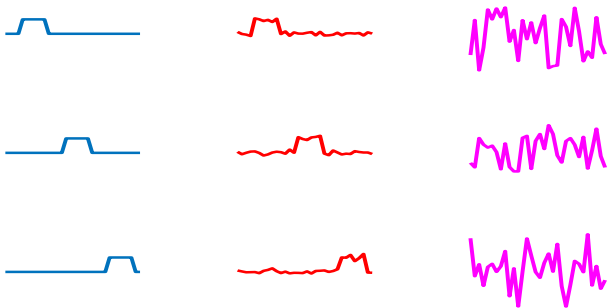
Literature:

- Singer. "Angular synchronization by eigenvectors and semidefinite programming." ACHA, '11.
- Singer, Shkolnisky. "Three-dimensional structure determination from common lines in cryo-EM by eigenvectors and semidefinite programming." SIIMS, '11.
- Boumal. "Nonconvex phase synchronization." SIPOT, '16.
- Perry, Wein, Bandeira, Moitra. "Message-Passing Algorithms for Synchronization Problems over Compact Groups." CPAM, '18.
- Zhong, Boumal. "Near-optimal bounds for phase synchronization." SIPOT, '18.
- Chen, Candes. "The projected power method: An efficient algorithm for joint alignment from pairwise differences" CPAM, '18.
- Bandeira, Chen, Singer. "Non-unique games over compact groups and orientation estimation in cryo-EM."

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Option 1: Optimize/sample the marginalized likelihood/posterior distribution (EM, MCMC, etc.)

$$L(x; y_1, \dots, y_n) = p(x) \cdot \prod_i \mathbb{E}_g \mathcal{N}(y_i - P(g \circ x), \sigma^2)$$

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Remark: The MLE of

$$L(x, g_1, \dots, g_n; y_1, \dots, y_n) = \prod_i \mathcal{N}(y_i - P(g_i \circ x), \sigma^2)$$

might be inconsistent as $n \rightarrow \infty$ (Neyman-Scott “paradox”).

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Option 2: Method of moments/group invariants

$$\frac{1}{n} \sum_{i=1}^n y_i \approx \mathbb{E}_{g, \varepsilon} \{y\} = p_1(x)$$

$$\frac{1}{n} \sum_{i=1}^n y_i y_i^T \approx \mathbb{E}_{g, \varepsilon} \{y y^T\} = p_2(x)$$

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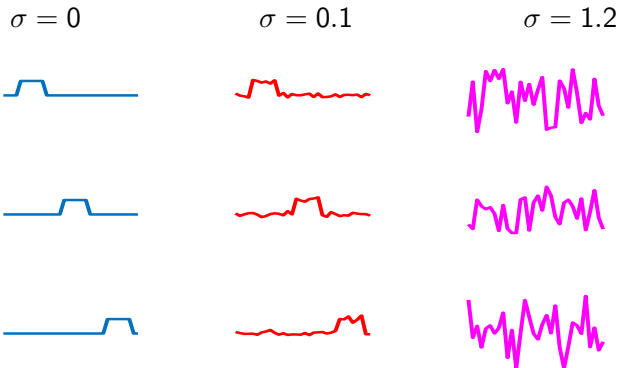
- One pass over the data
- Consistent
- Amenable to theoretical analysis

1-D multi-reference alignment

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Group invariants

For any $x \in \mathcal{X}$ and $g \in G$, invariants are functions (polynomials) that satisfy

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H.W: Is $|x|$ an invariant representation? If not, find an invariant representation h .

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Thus, it is very easy to construct invariants:

$\hat{x}[0]$	mean
$\hat{x}[k]\hat{x}[-k]$	power spectrum
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$\hat{x}[k_1]\hat{x}[k_2], \dots, \hat{x}[k_q]\hat{x}[-k_1 - k_2 - \dots]$	higher-order

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Question: What are the invariants of an image under $SO(2)$?

Estimating invariants

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Estimating the invariants:

$$\frac{1}{n} \sum_{i=1}^n \hat{y}[0] \rightarrow \hat{x}[0] \quad \text{var}(\sigma^2/n)$$

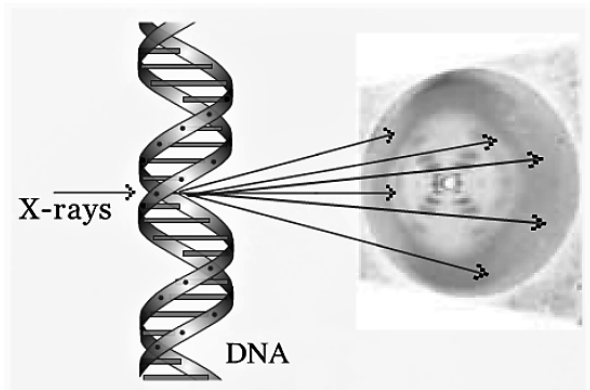
$$\frac{1}{n} \sum_{i=1}^n P_y[k] \rightarrow P_x[k] \quad \text{var}(\sigma^4/n)$$

$$\frac{1}{n} \sum_{i=1}^n B_y[k_1, k_2] \rightarrow B_x[k_1, k_2] \quad \text{var}(\sigma^6/n)$$

Many efficient algorithms to recover a signal from its bispectrum [Bendory et al., '17]

Phase retrieval

Phase retrieval is the problem of recovering a signal from its Fourier magnitudes.



Uncovering the double helix structure of the DNA with X-ray crystallography in 1951. Nobel Prize for Watson, Crick, and Wilkins in 1962 based on work by Rosalind Franklin.

Phase retrieval is also an orbit recovery problem

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One cannot recover x , but only its orbit. In particular, recovery is possible up to a cyclic shift \mathbb{Z}_L , reflection through the origin \mathbb{Z}_2 (together, they form the dihedral group D_{2L}), and global sign \mathbb{Z}_2 (global phase S^1 in the complex case).

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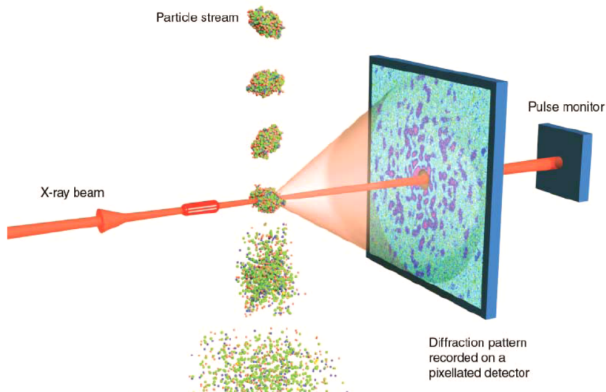
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Intricate geometry!

Single particle reconstruction using X-ray free-electron laser (XFEL)

XFEL \approx cryo-EM + phase retrieval



Thanks for your attention!