Random Consensus Robust PCA

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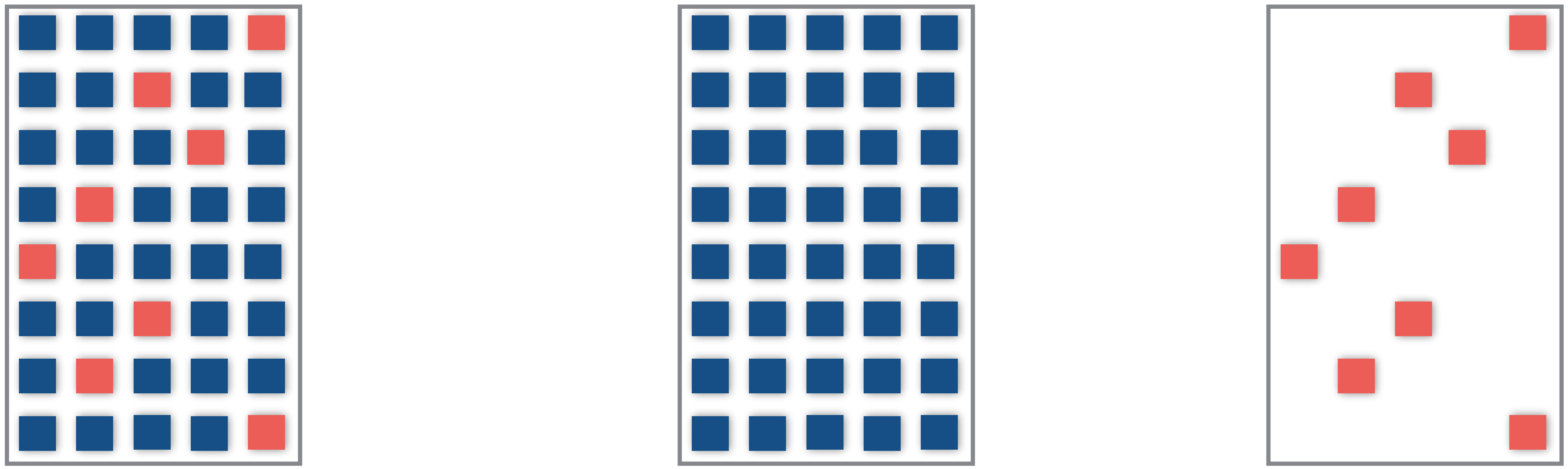
AISTATS 2017

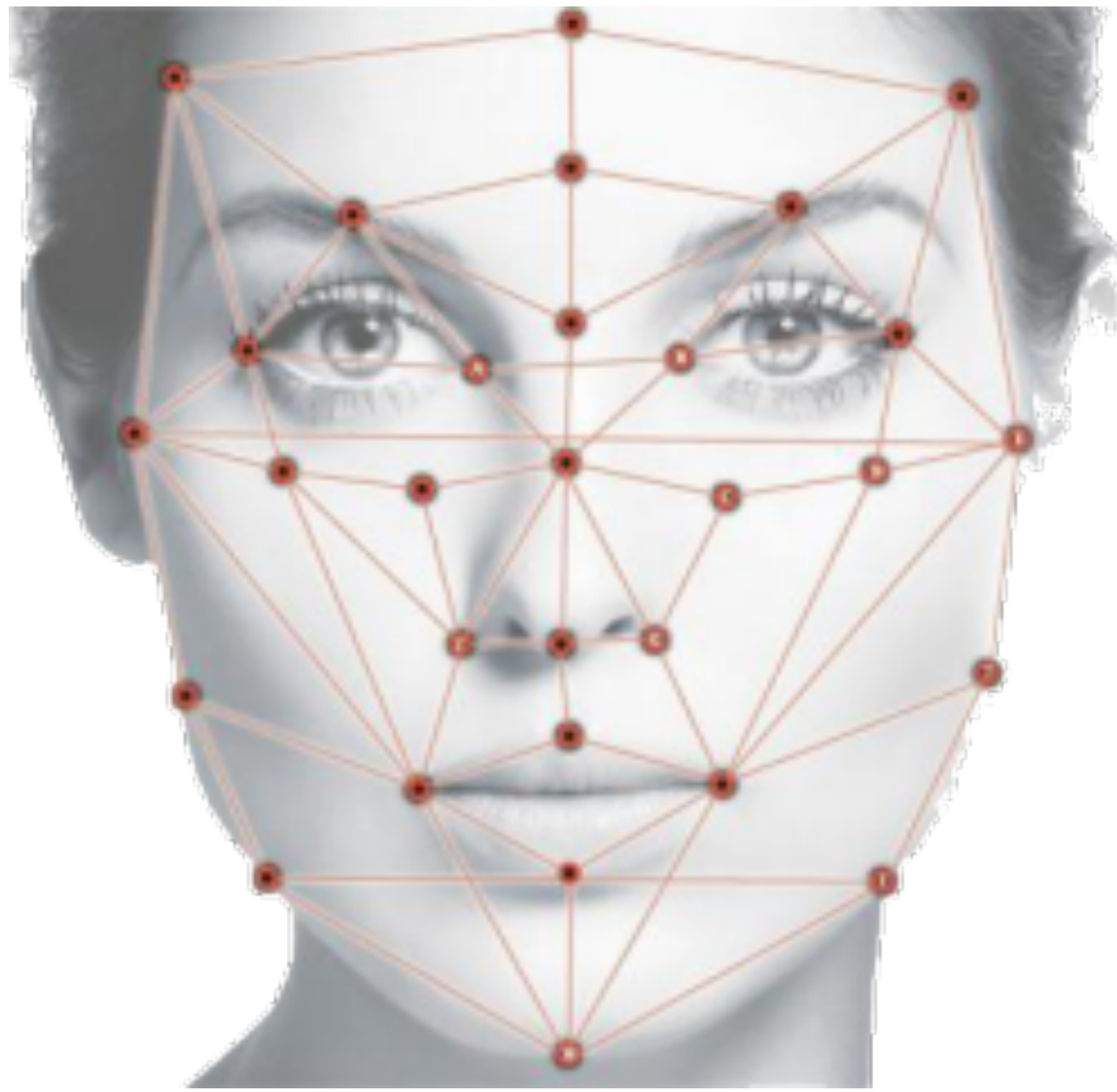


$$X = L + S$$

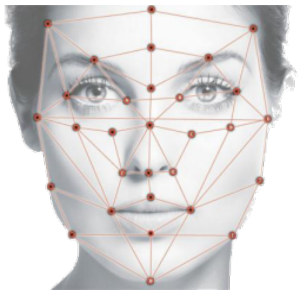
Low-Rank Sparse

Robust PCA


What is this good for?



Lots of Applications



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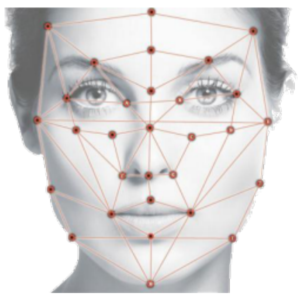

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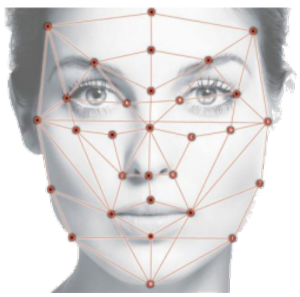

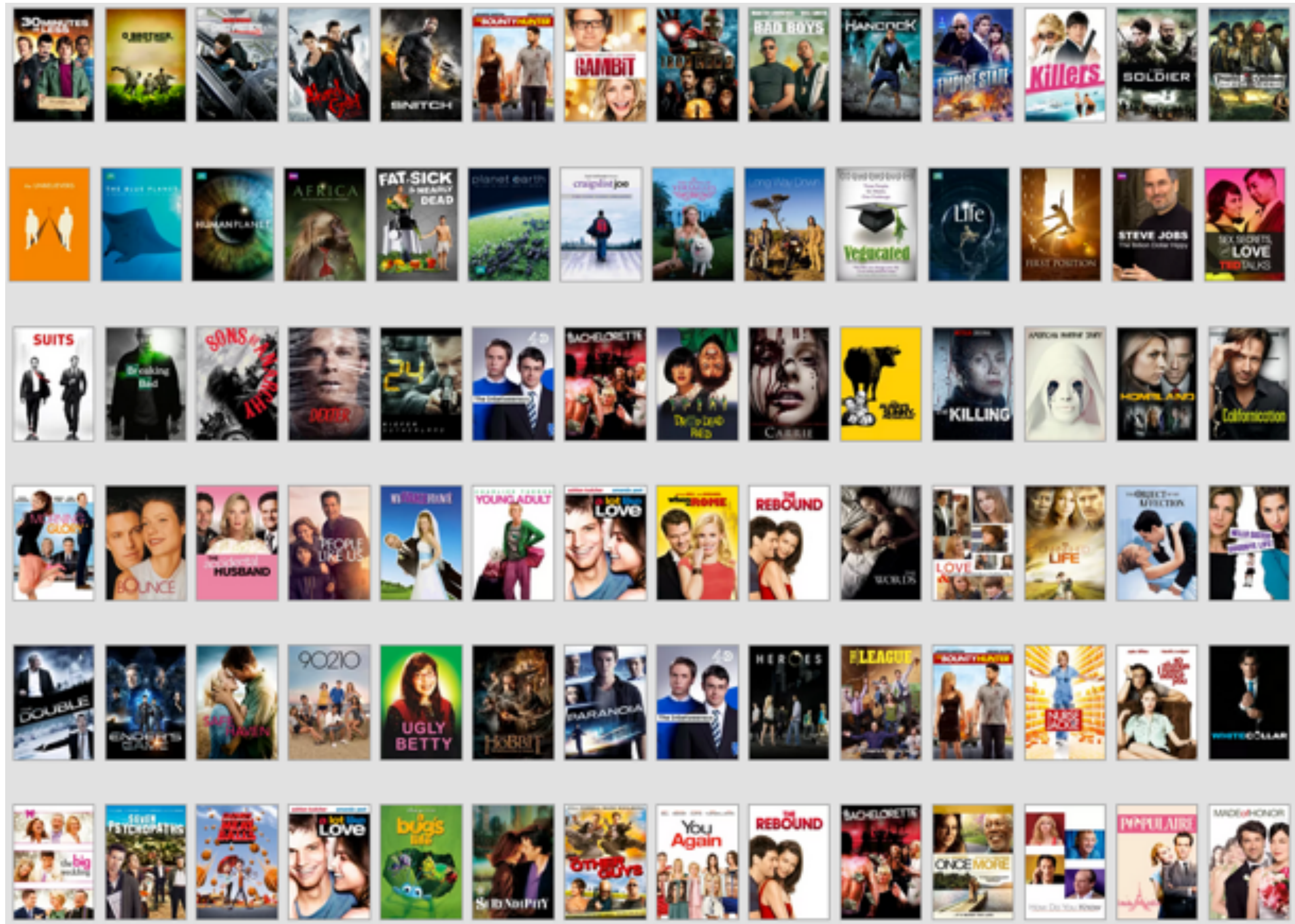

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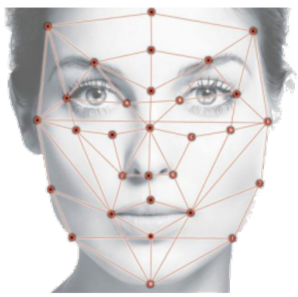


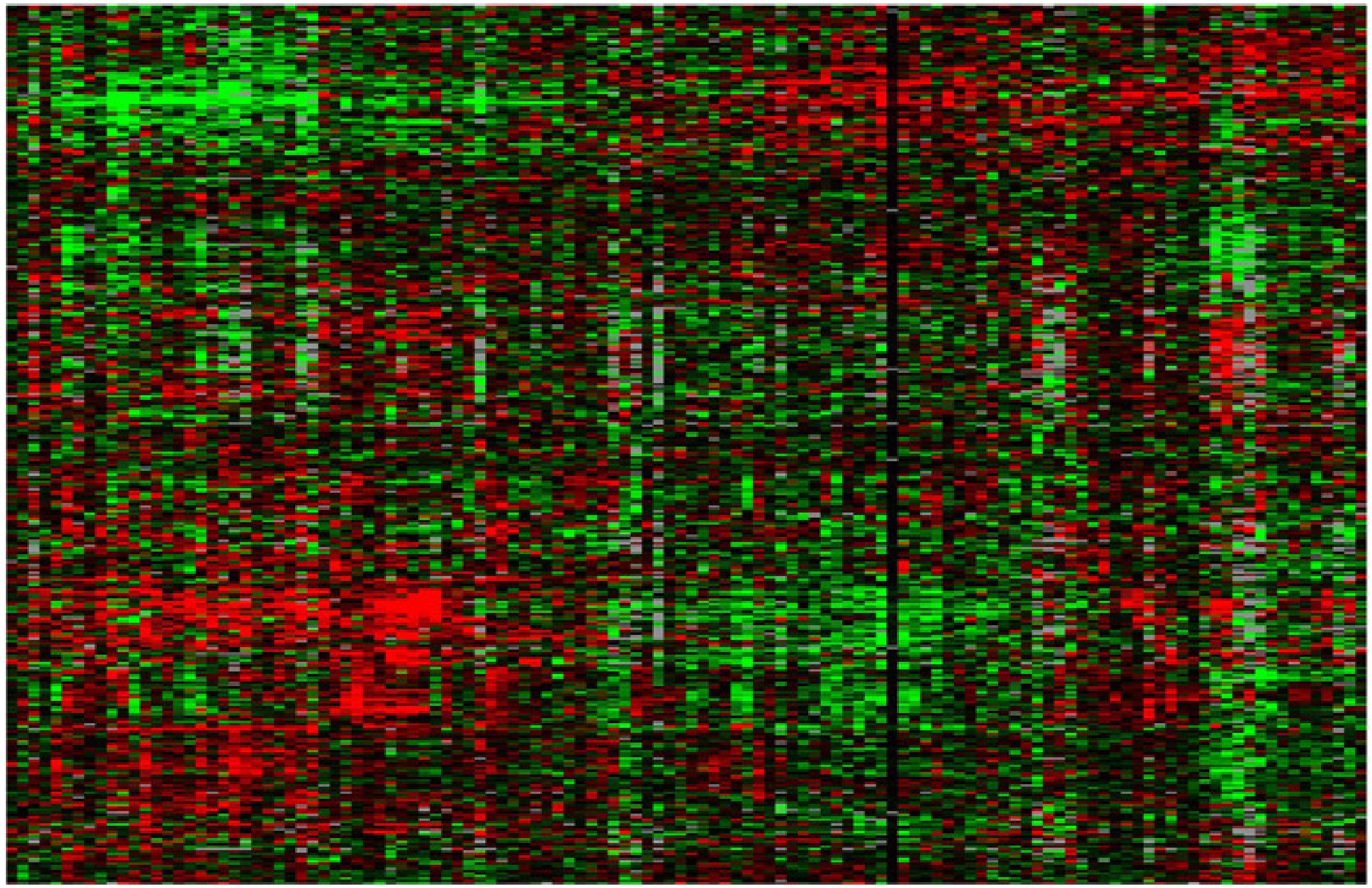
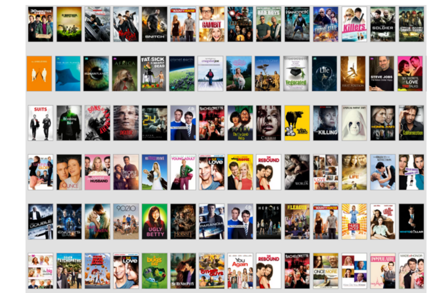

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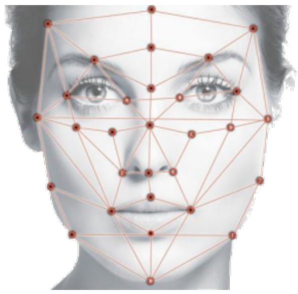

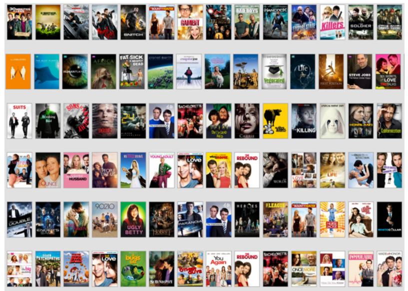

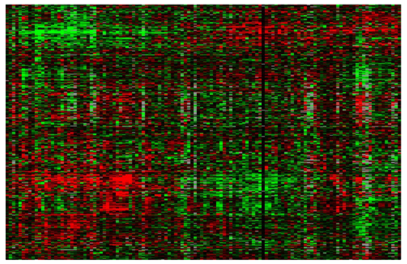

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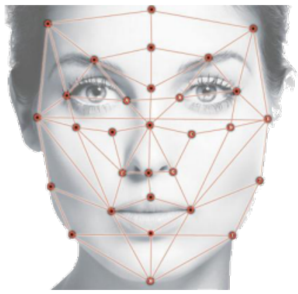
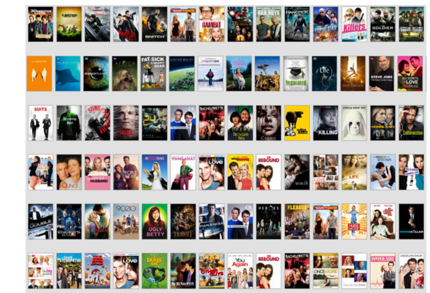
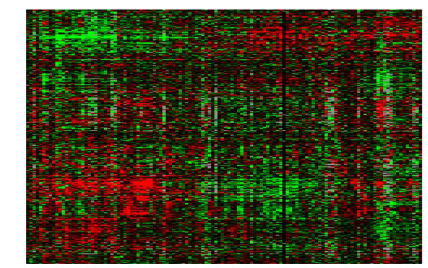
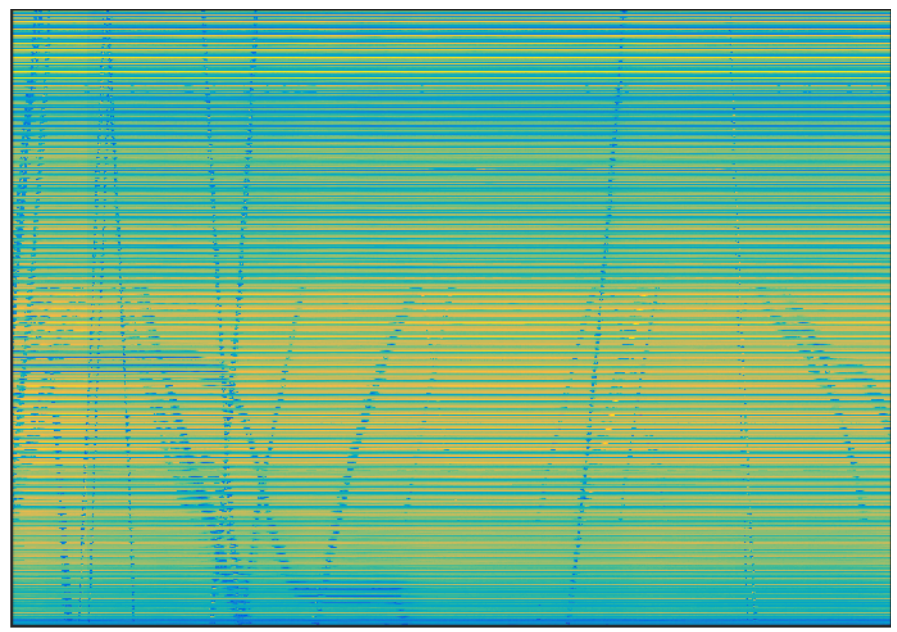




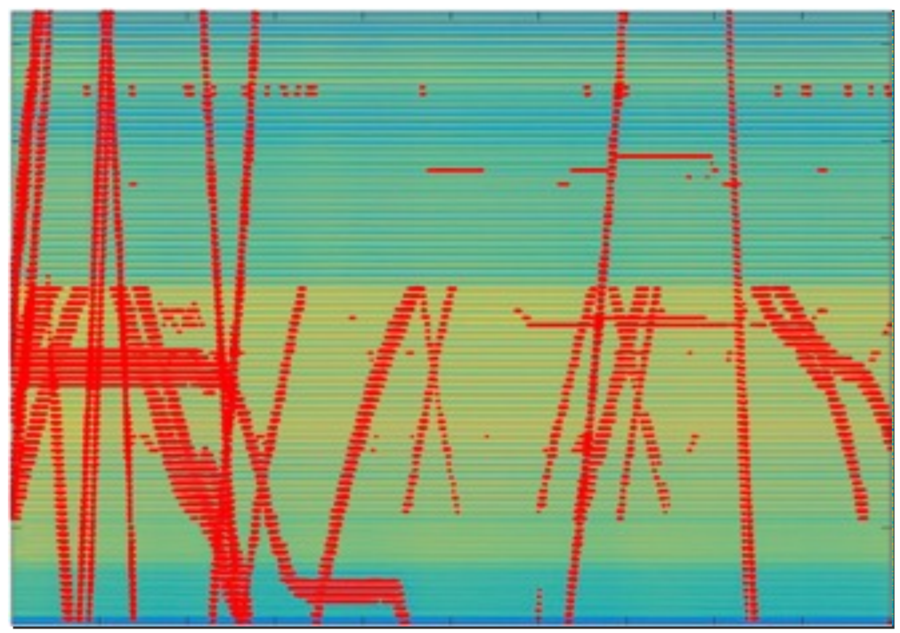




Lots of Applications

Background segmentation



Background segmentation



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$$\boxed{\begin{array}{ll}\text{minimize} & \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1 \\ \text{subject to} & \mathbf{X} = \mathbf{L} + \mathbf{S}\end{array}}$$

Existing theory

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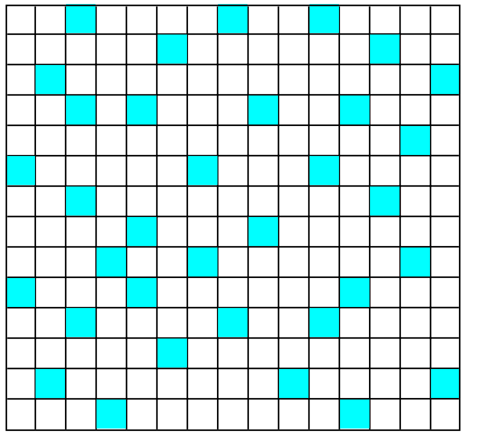

Uniform Sampling

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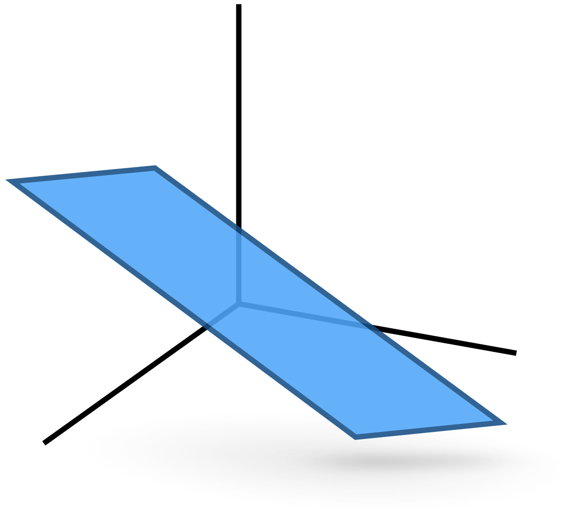
Incoherence



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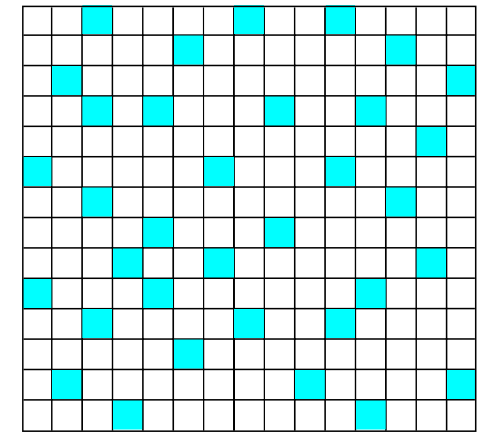

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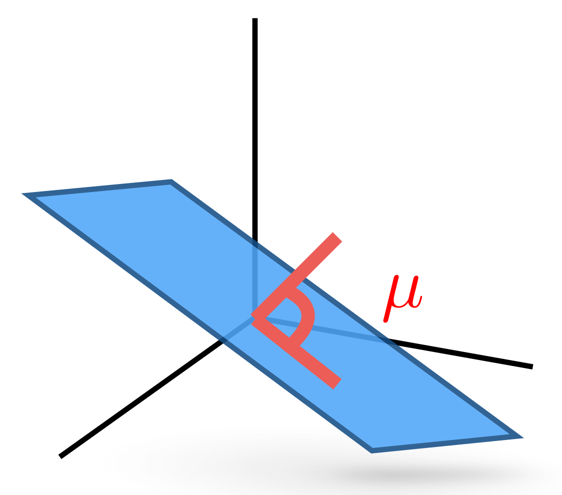

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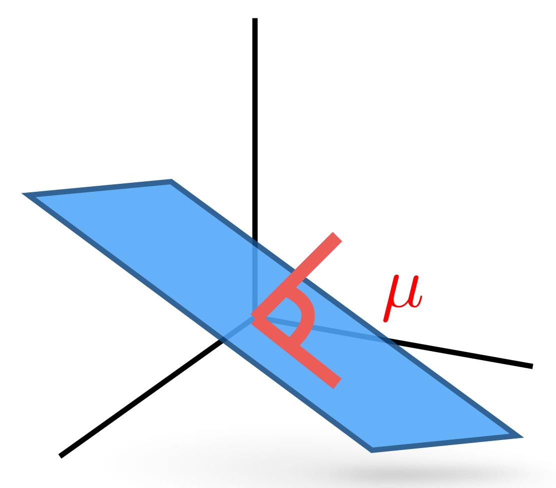

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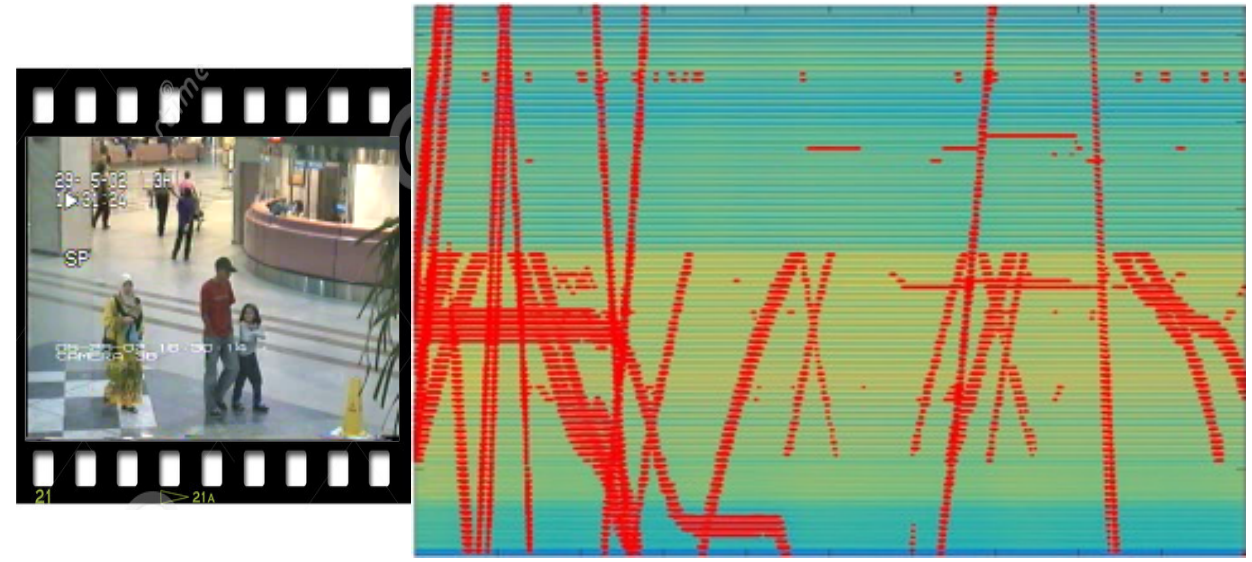

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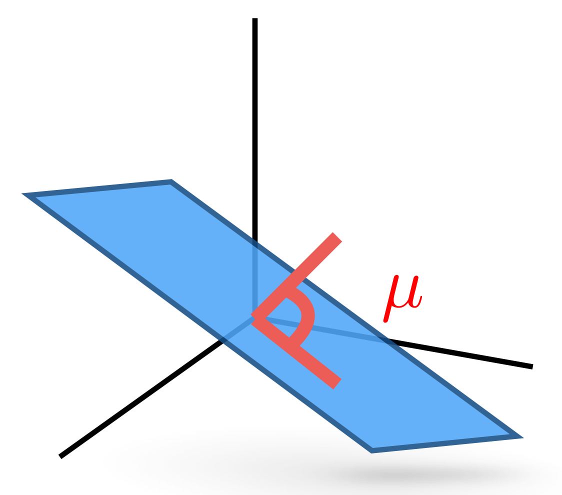

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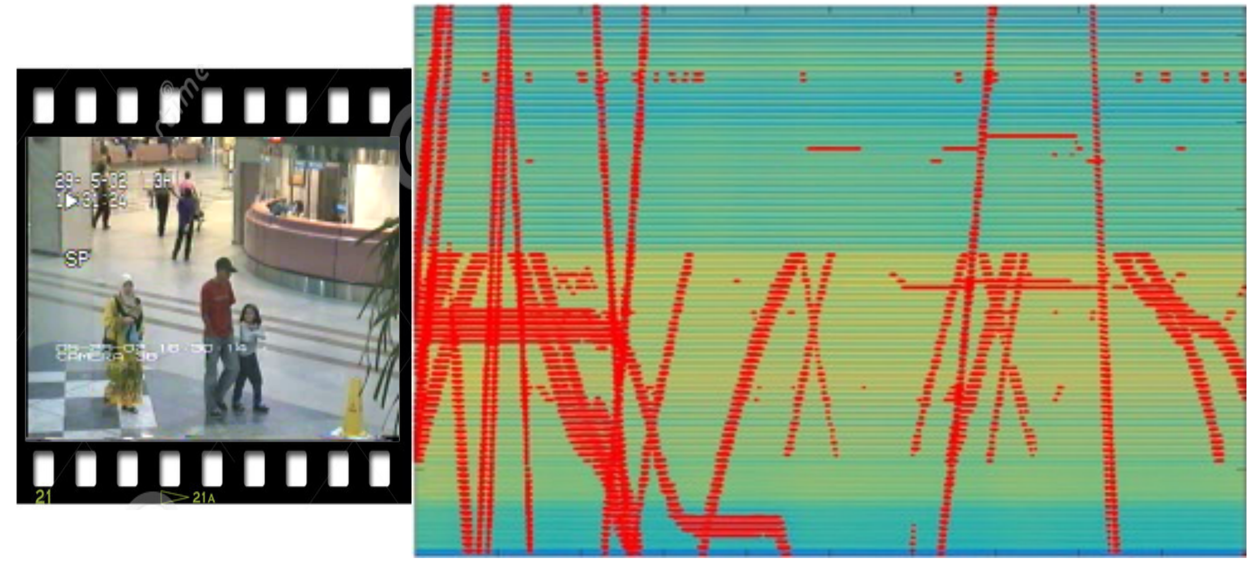

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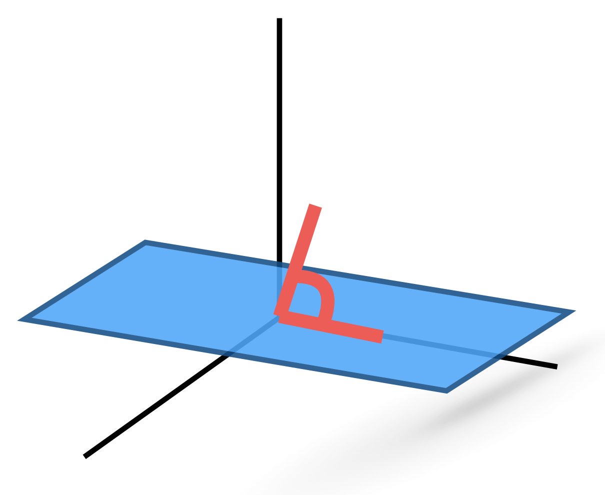

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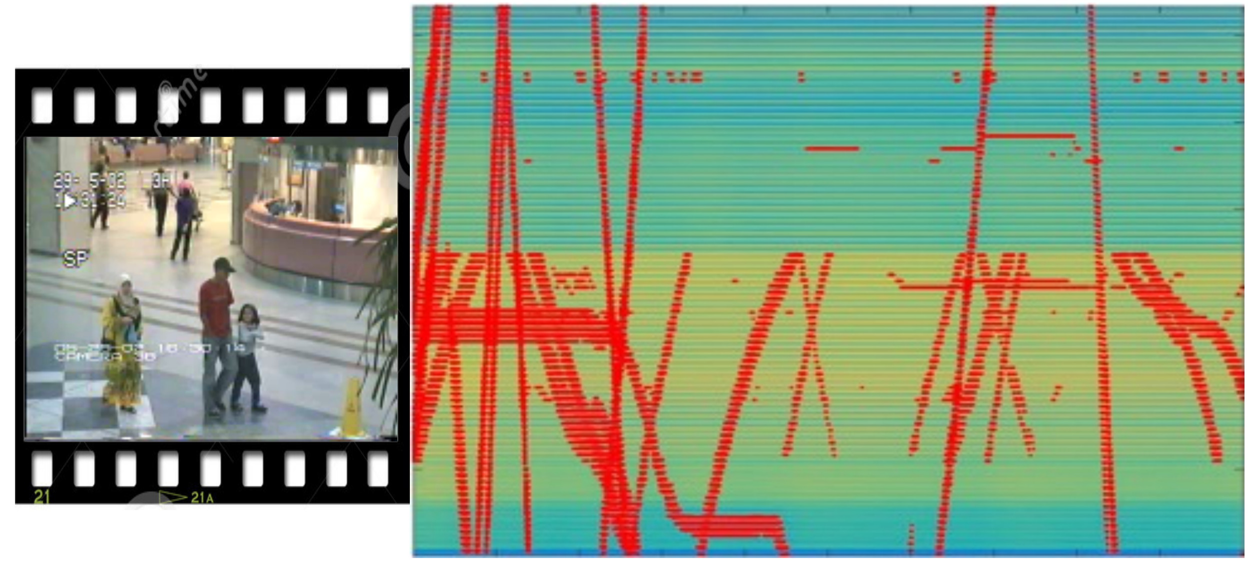

Uniform Sampling

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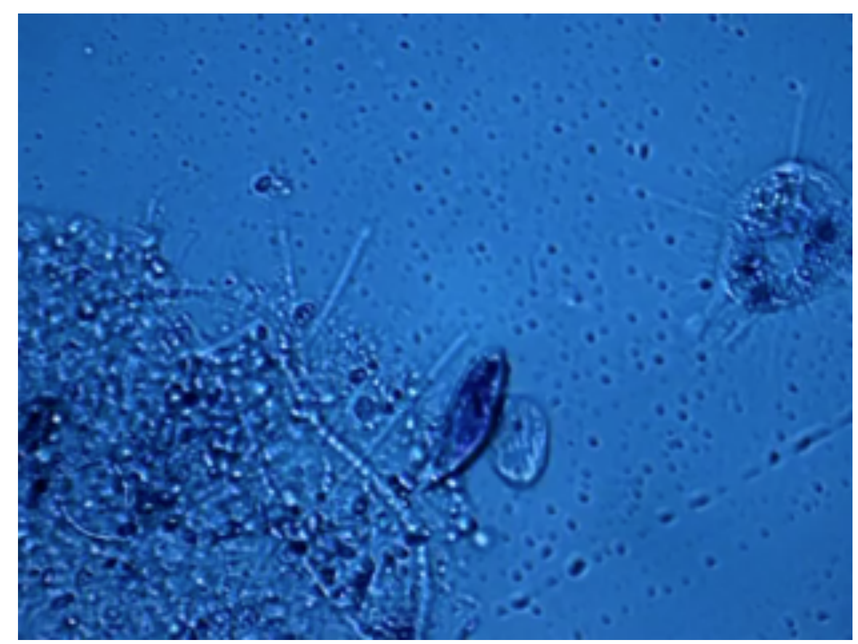
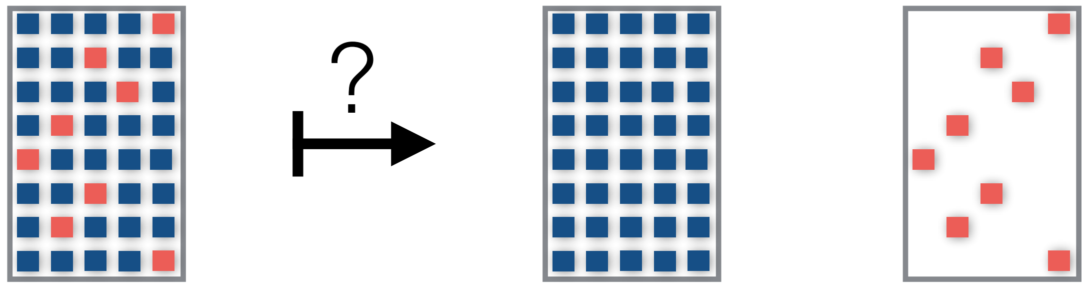
Incoherence



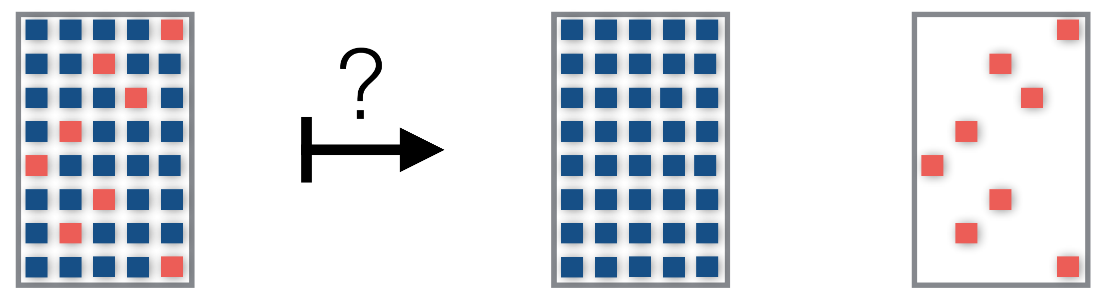
Existing theory

In general



$$X = L + S$$

In general



$$X \quad = \quad L \quad + \quad S$$

To answer this:

Totally different way to think about the problem

- ~~Incoherence~~
- ~~Uniform~~
- ~~With high probability~~
- ~~Optimization~~

- Arbitrary
- Deterministic
- With probability 1
- Algebraic/Geometric

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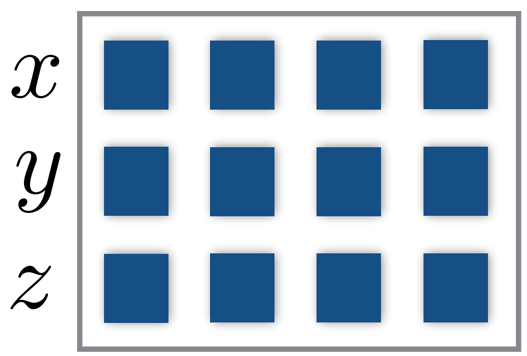
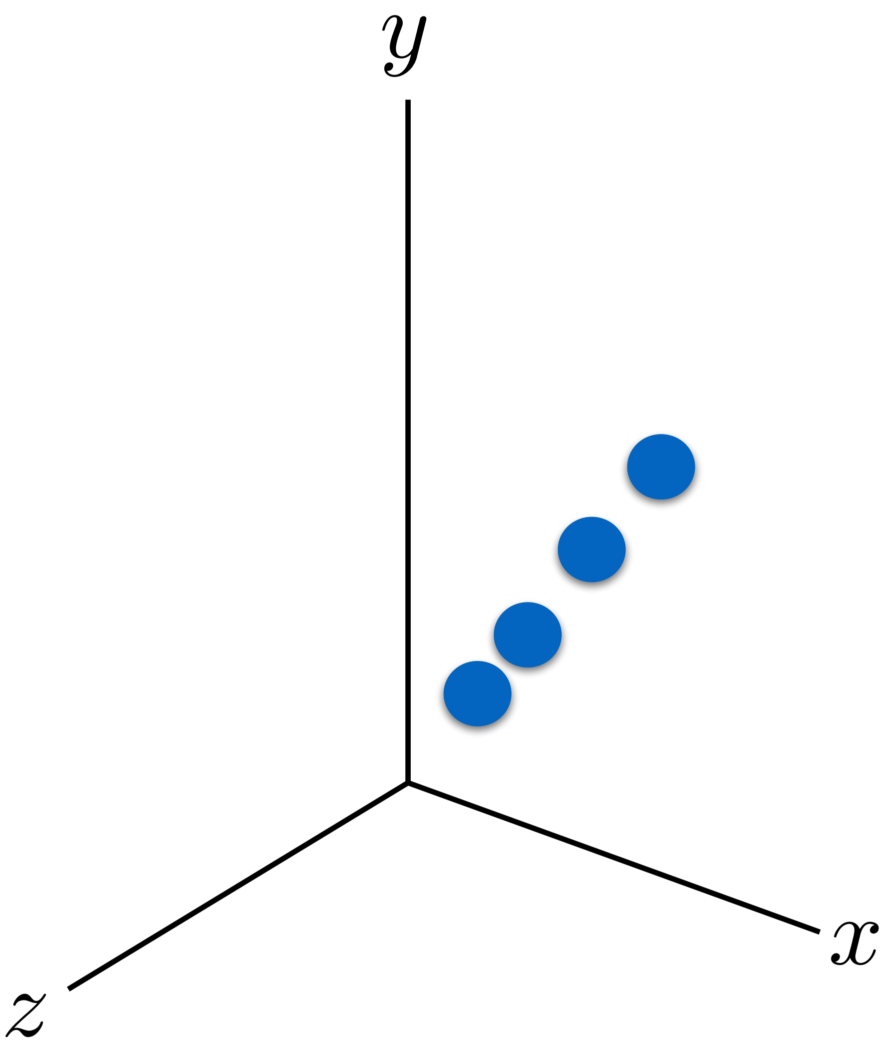
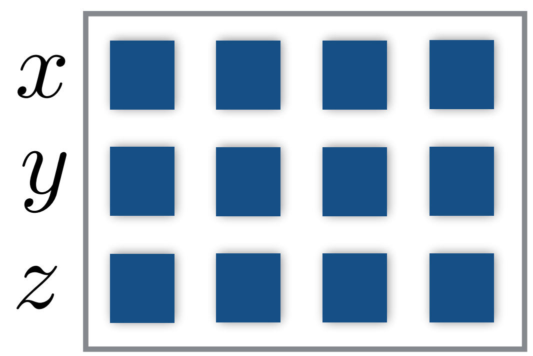
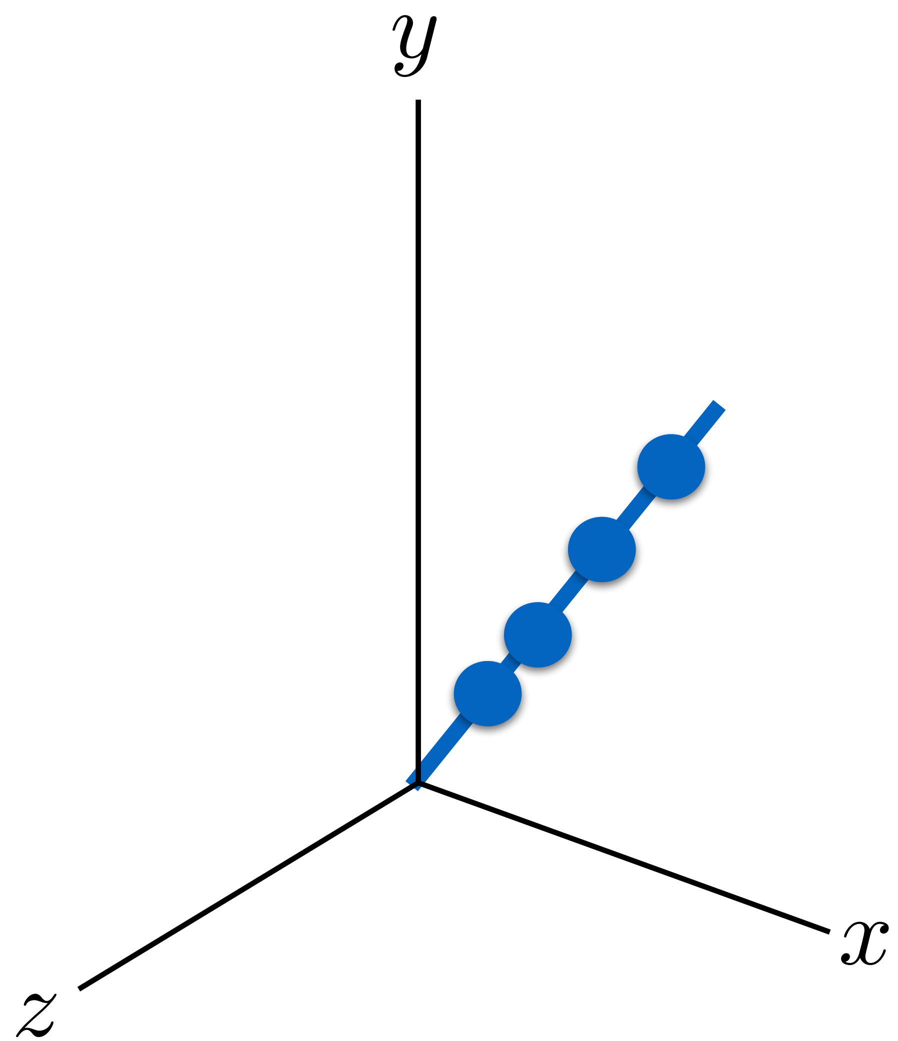




- **PCA**: Finds Subspace that Explains Data.





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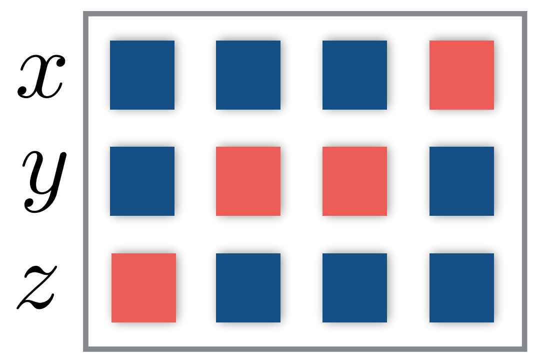

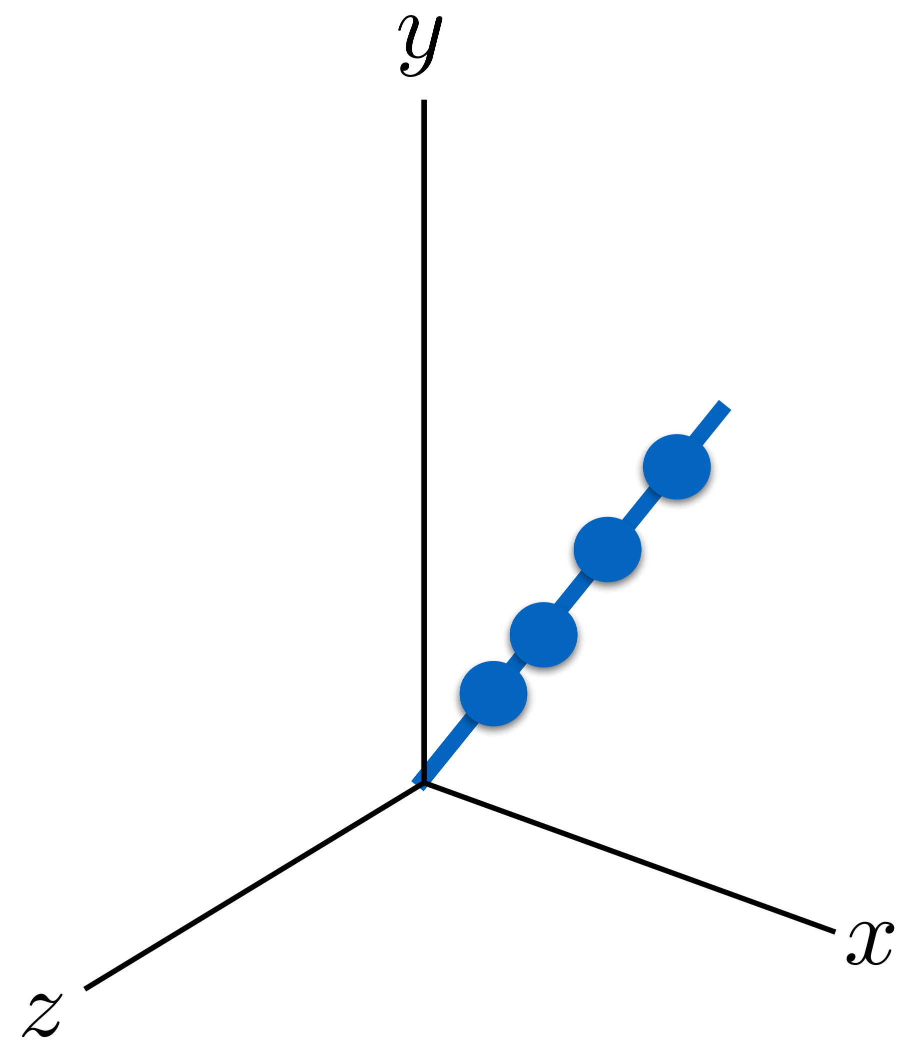

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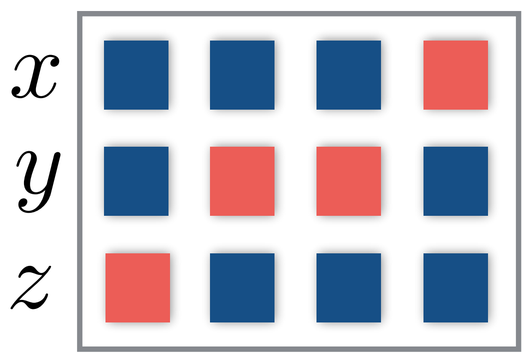

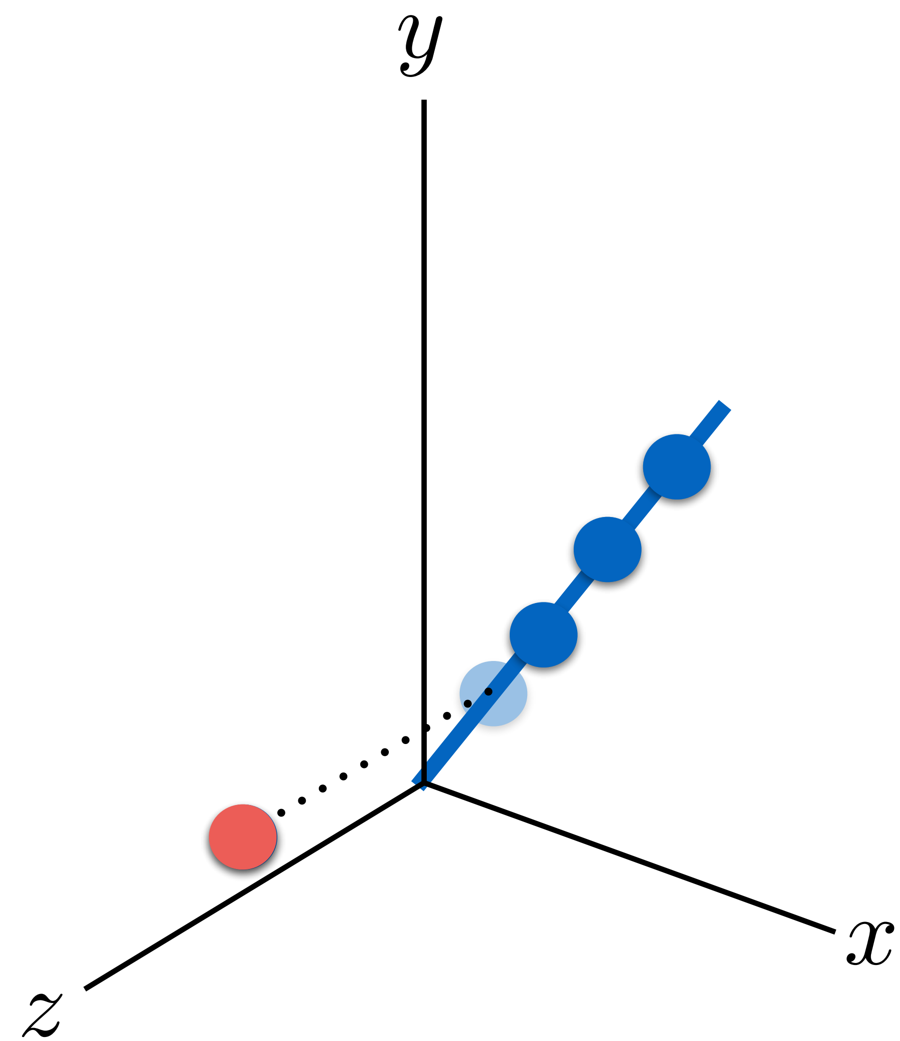

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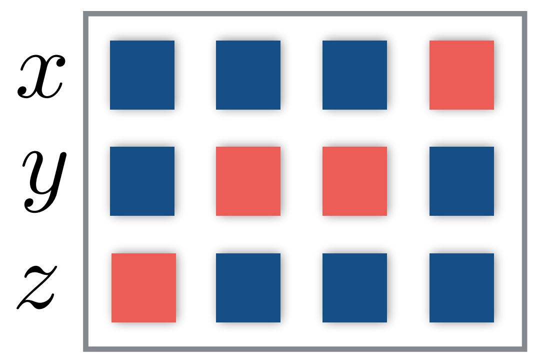

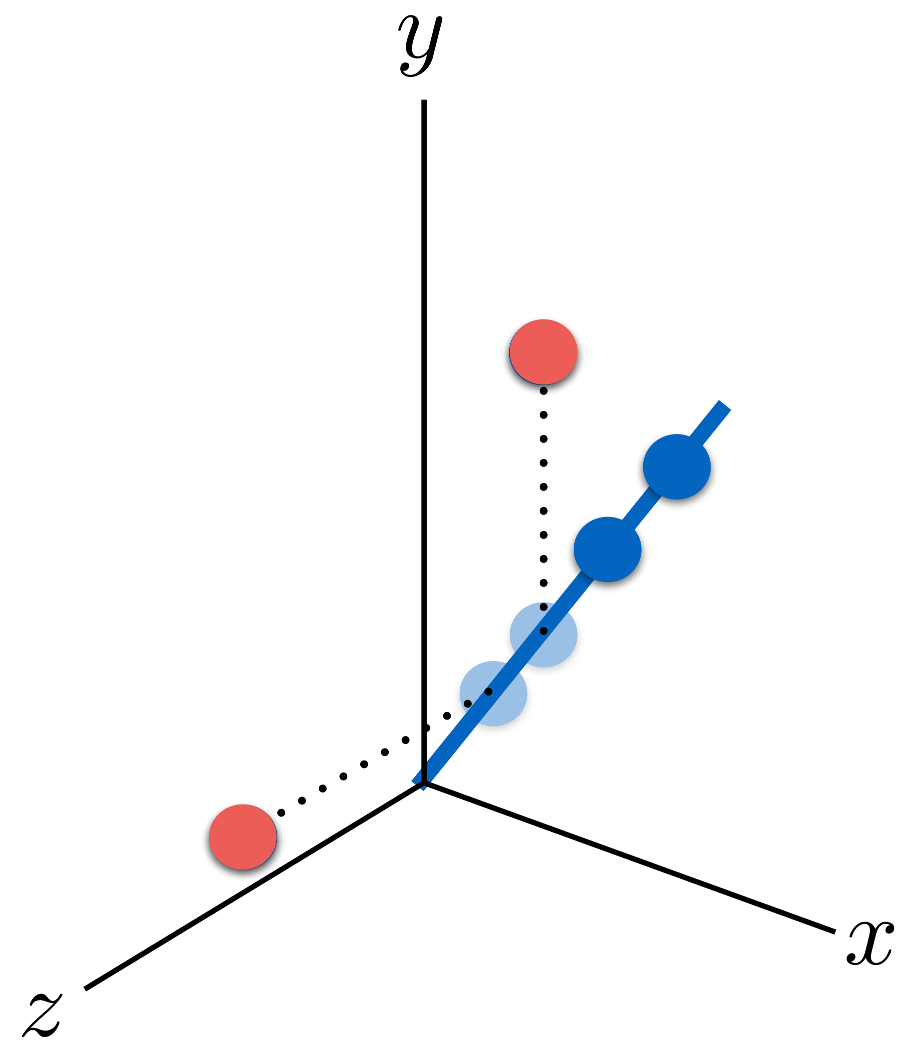

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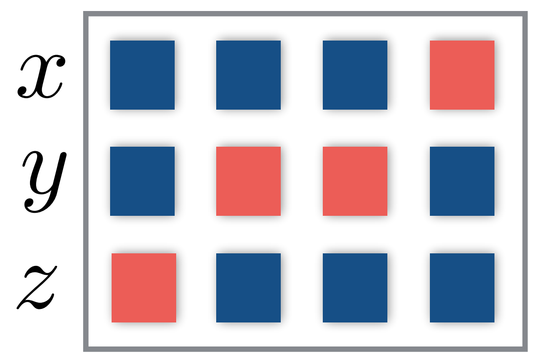

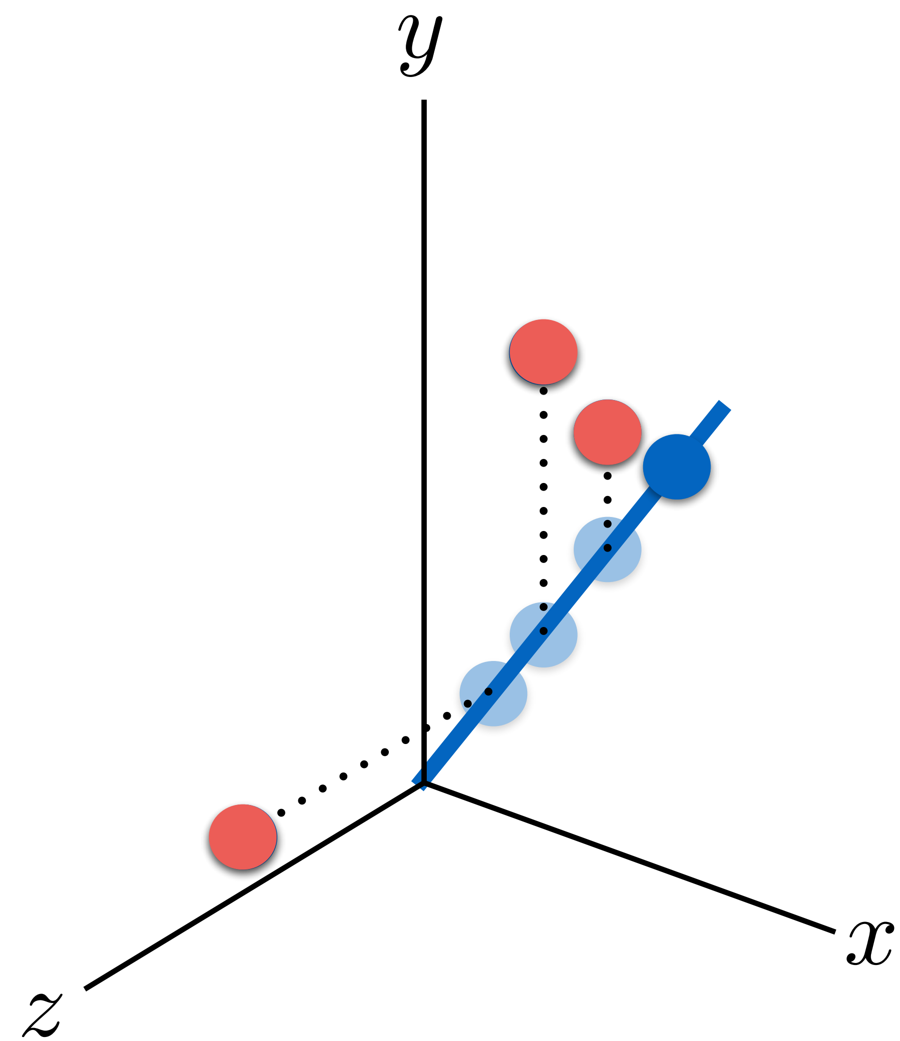

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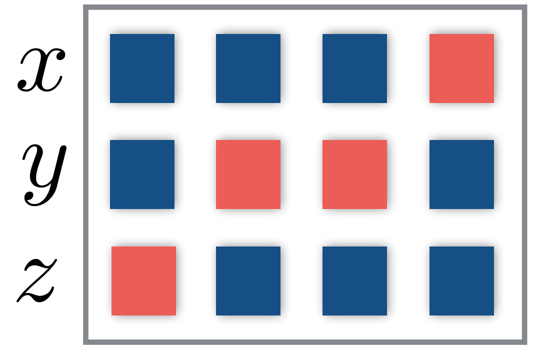

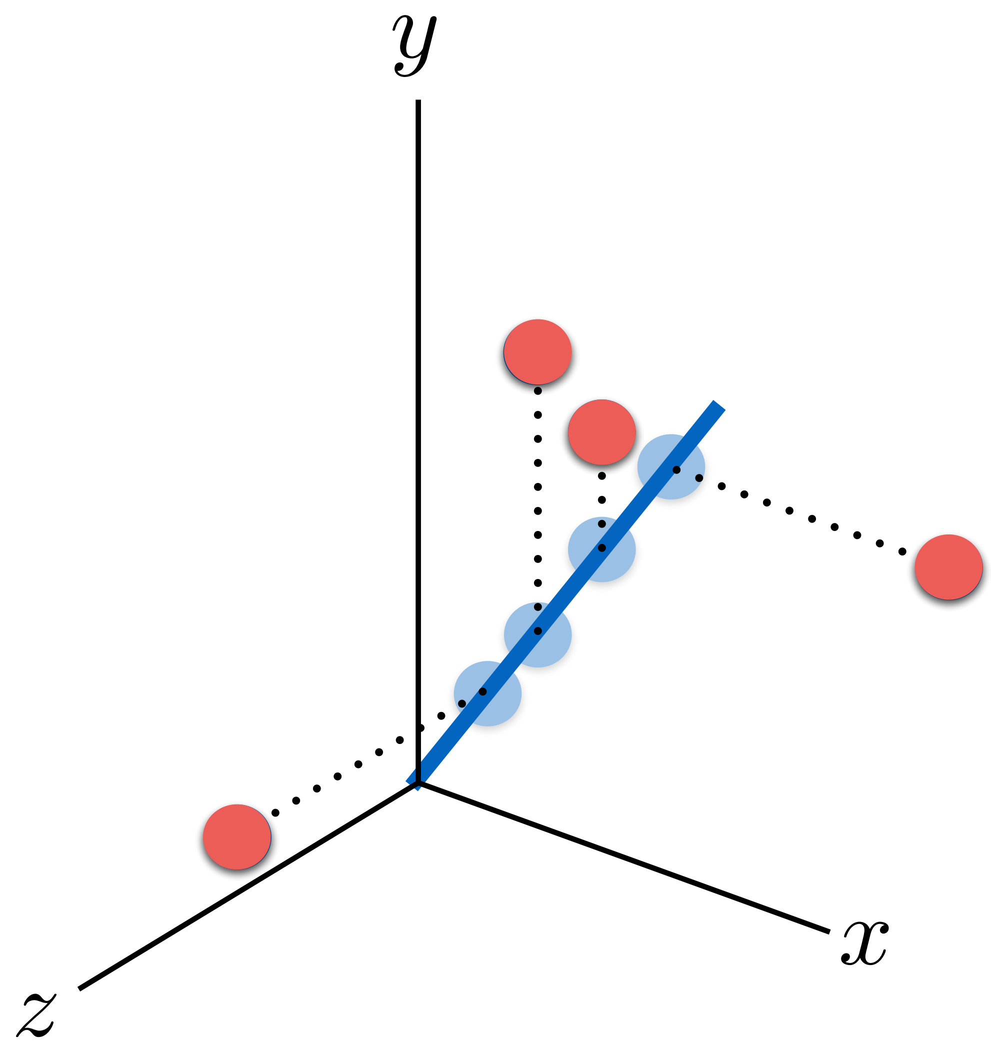

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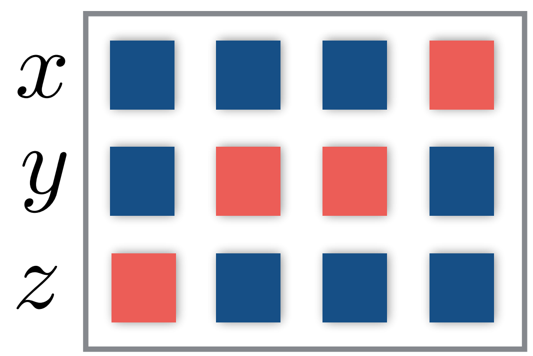

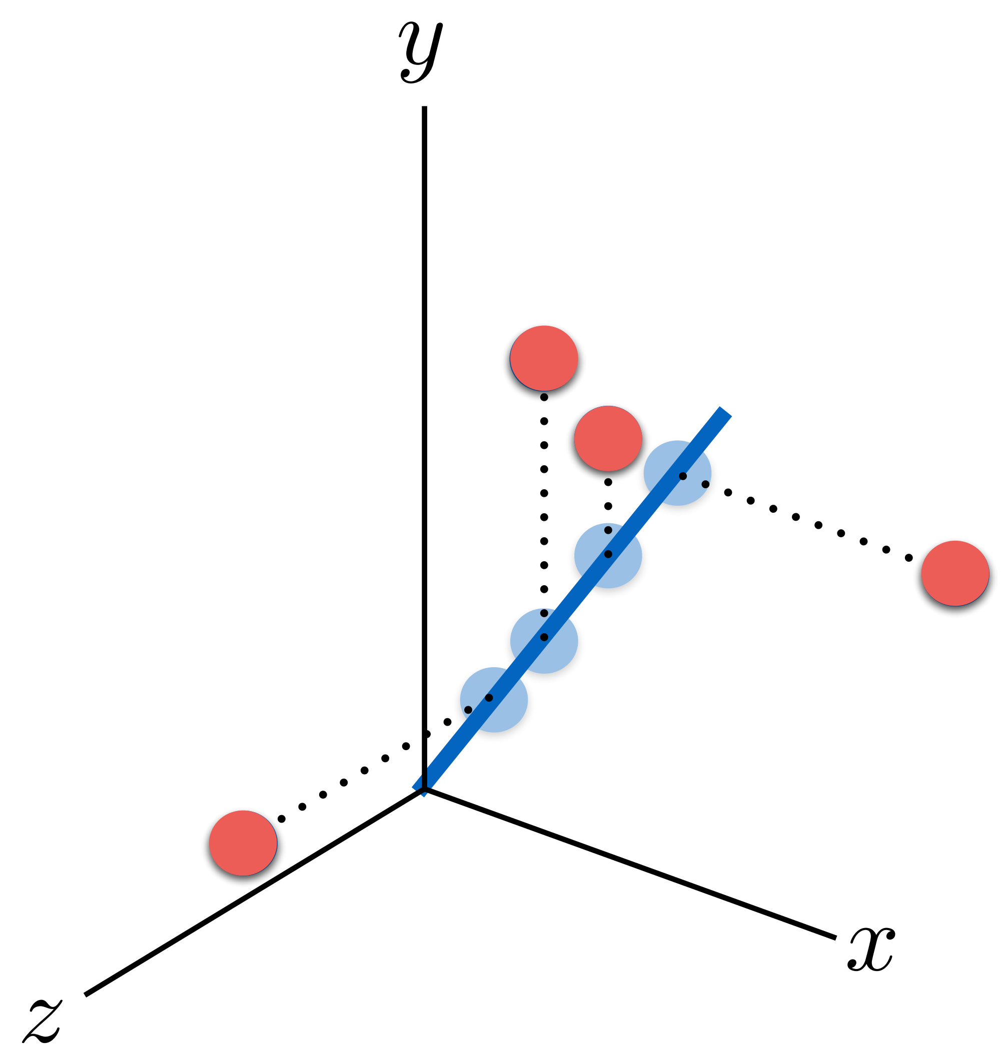

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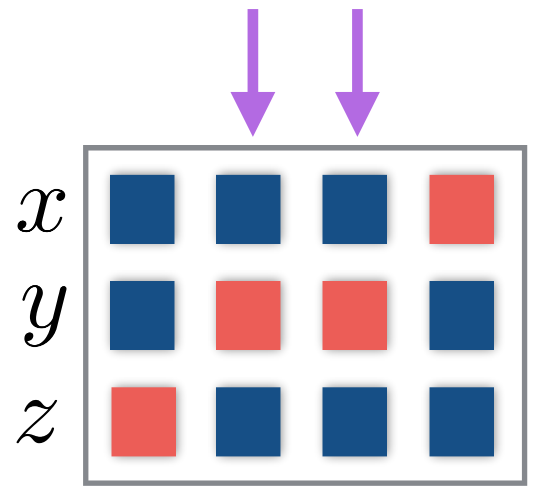

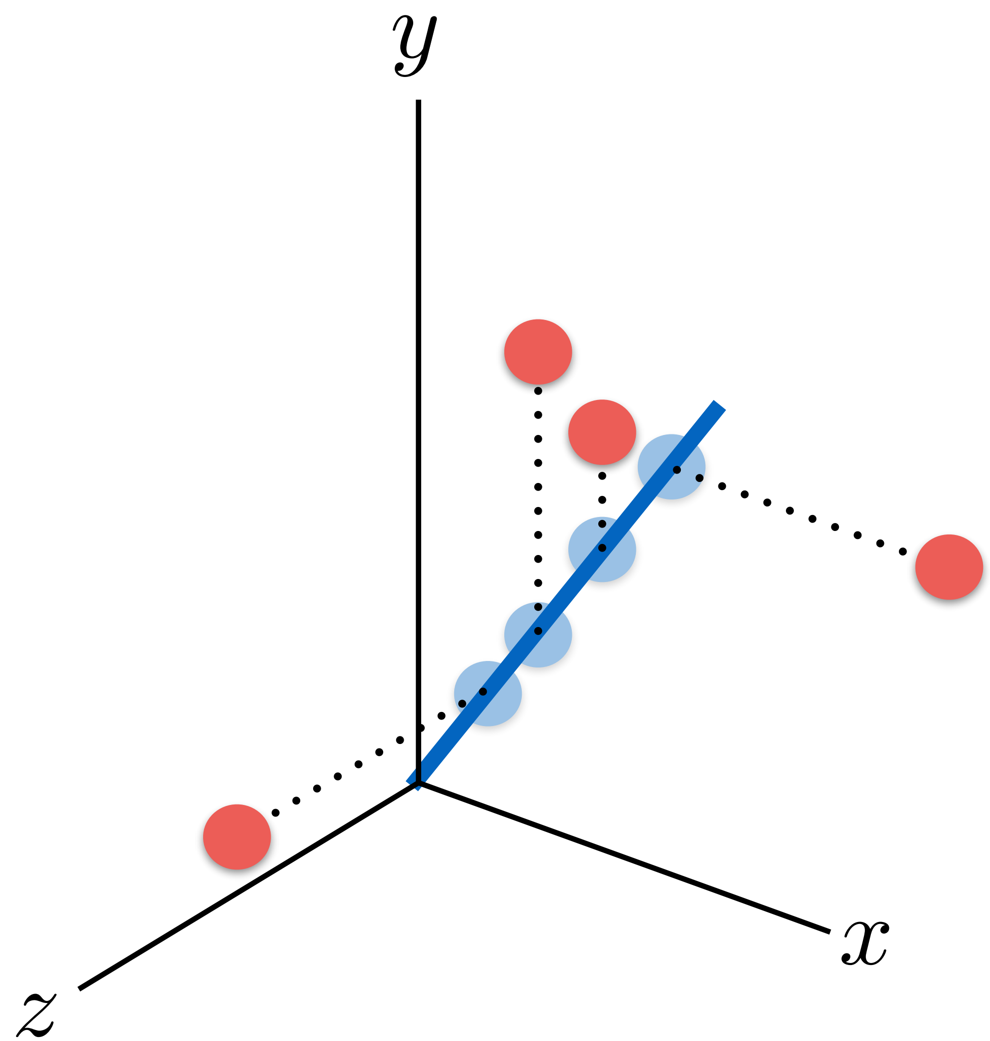

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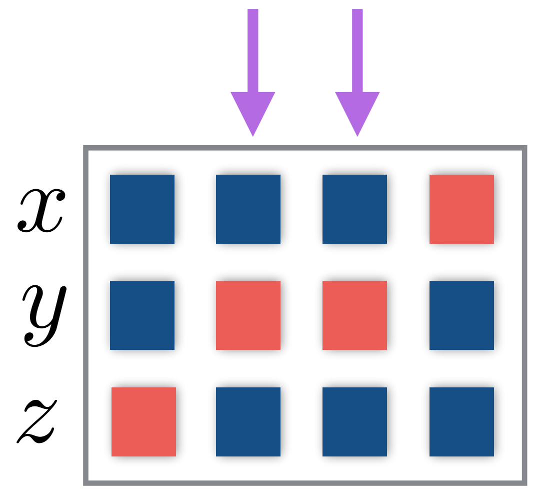

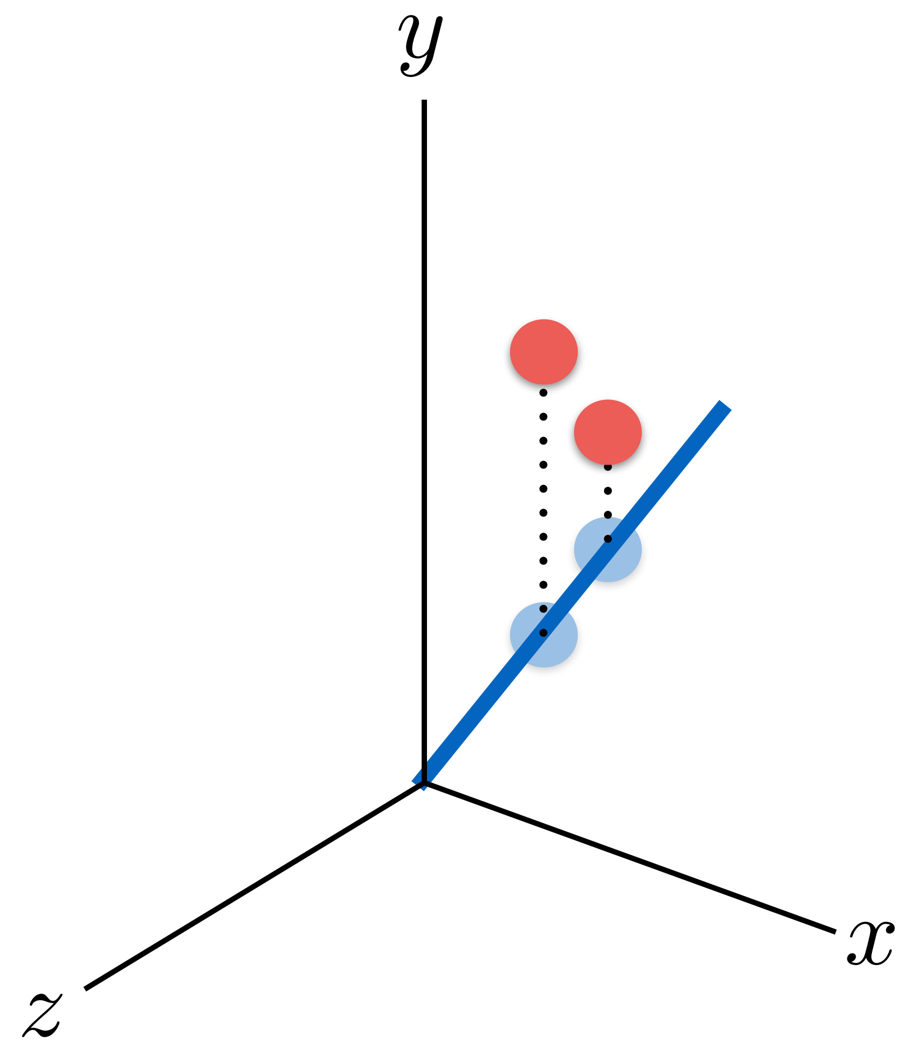

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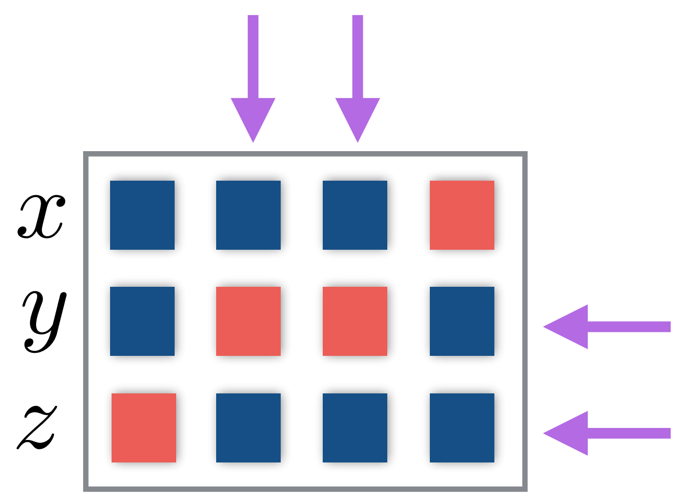

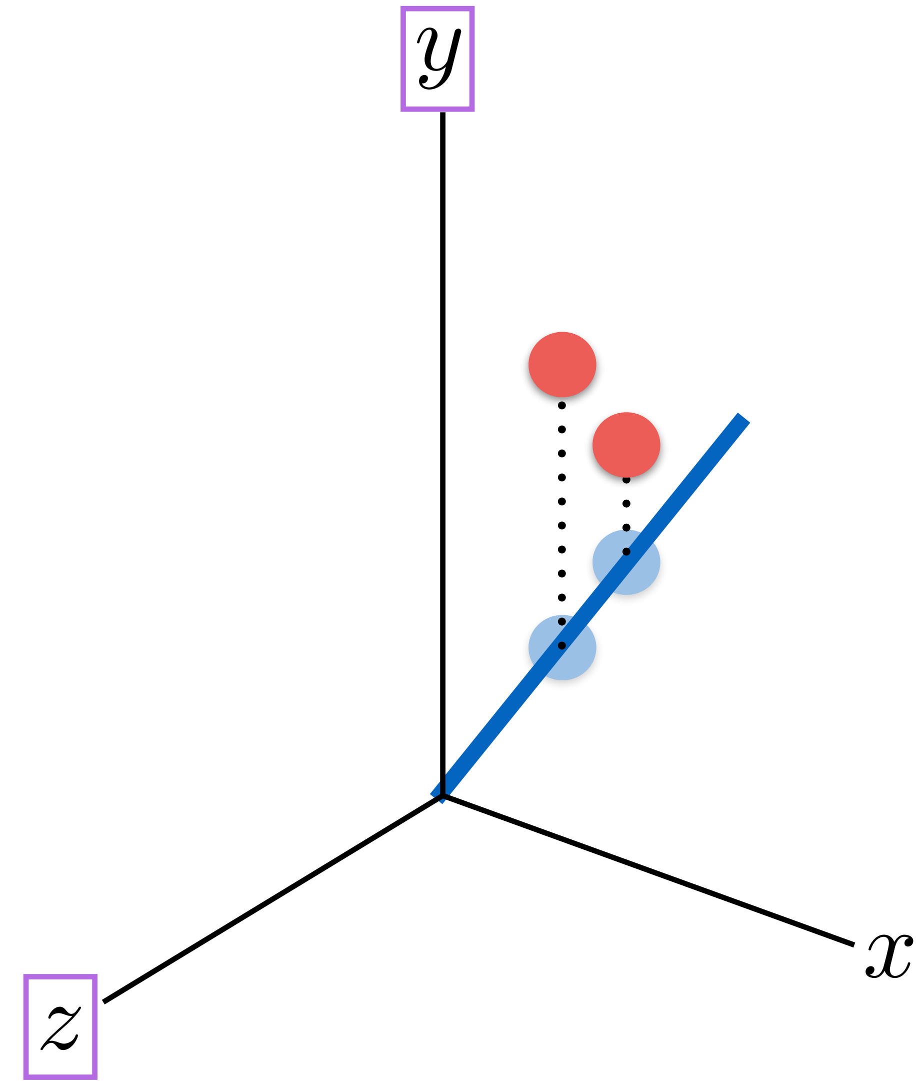

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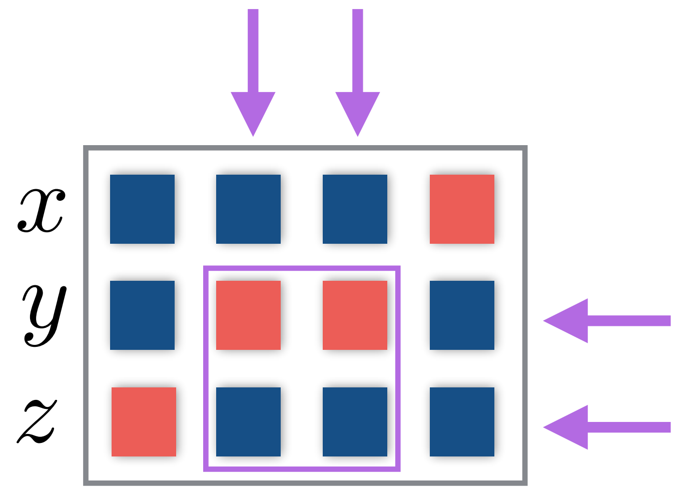

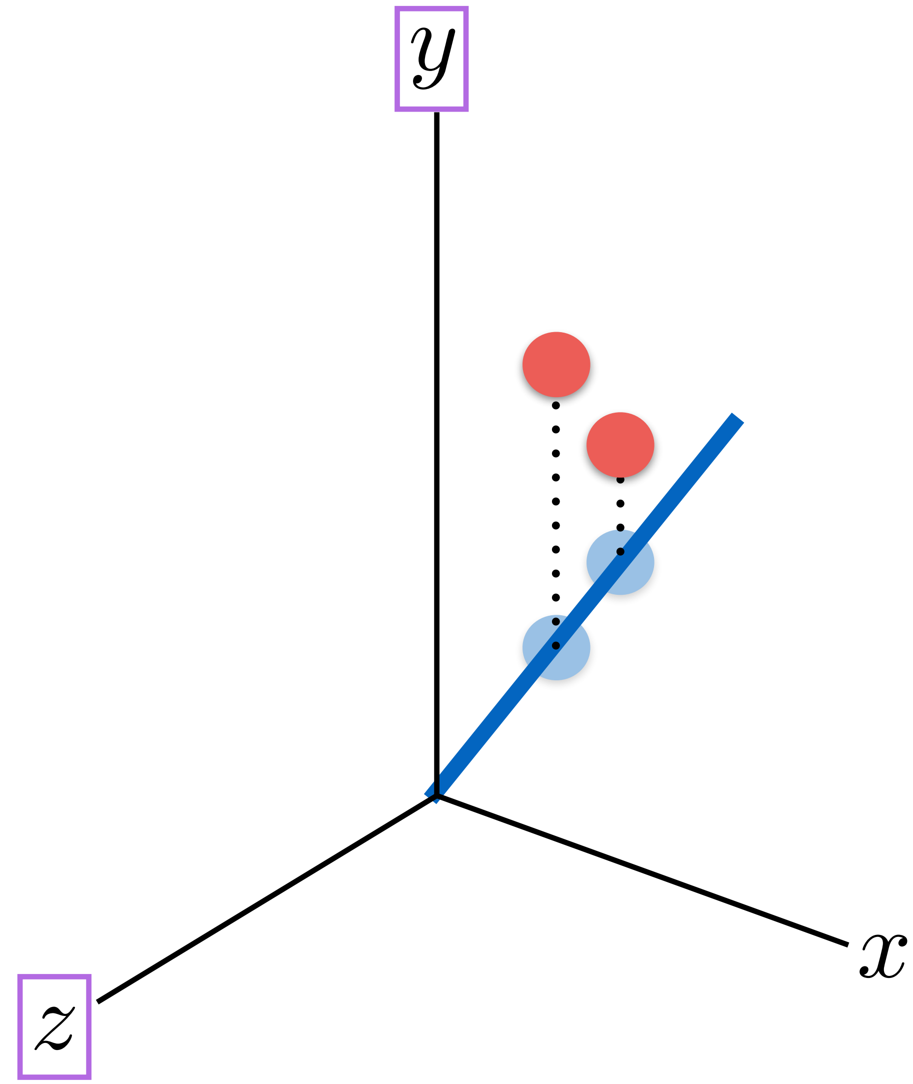

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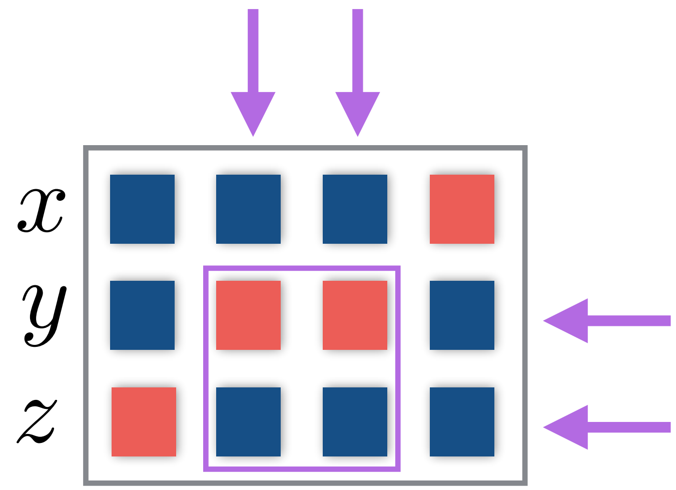

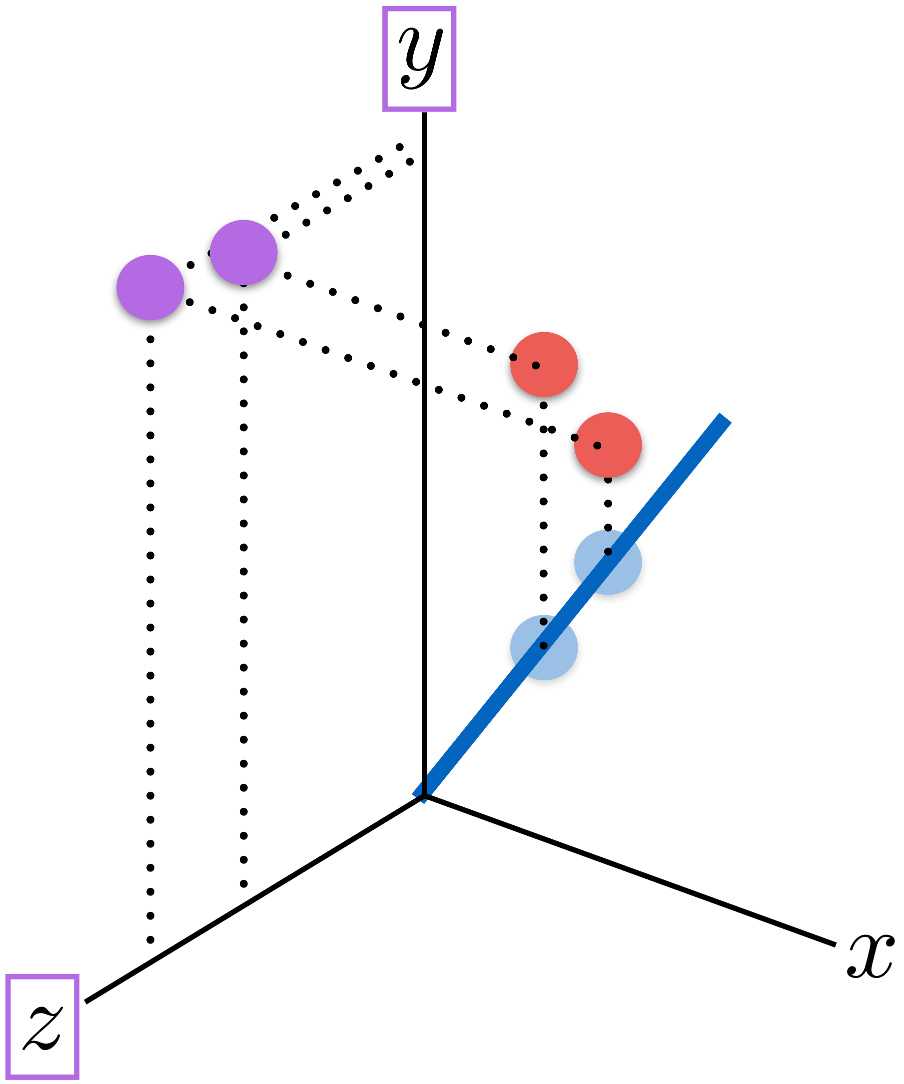

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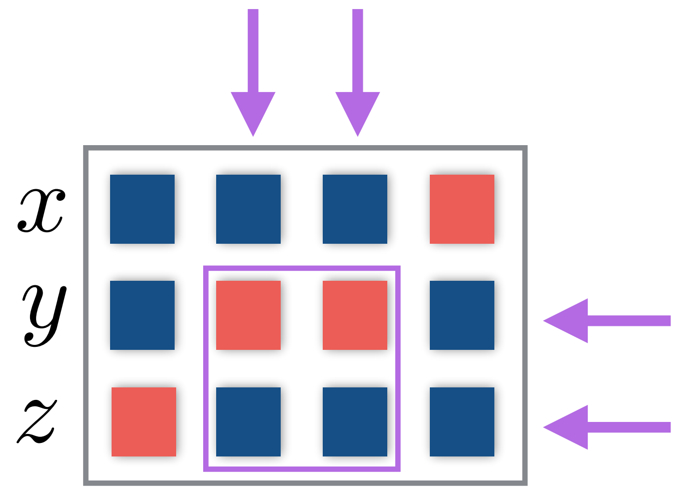

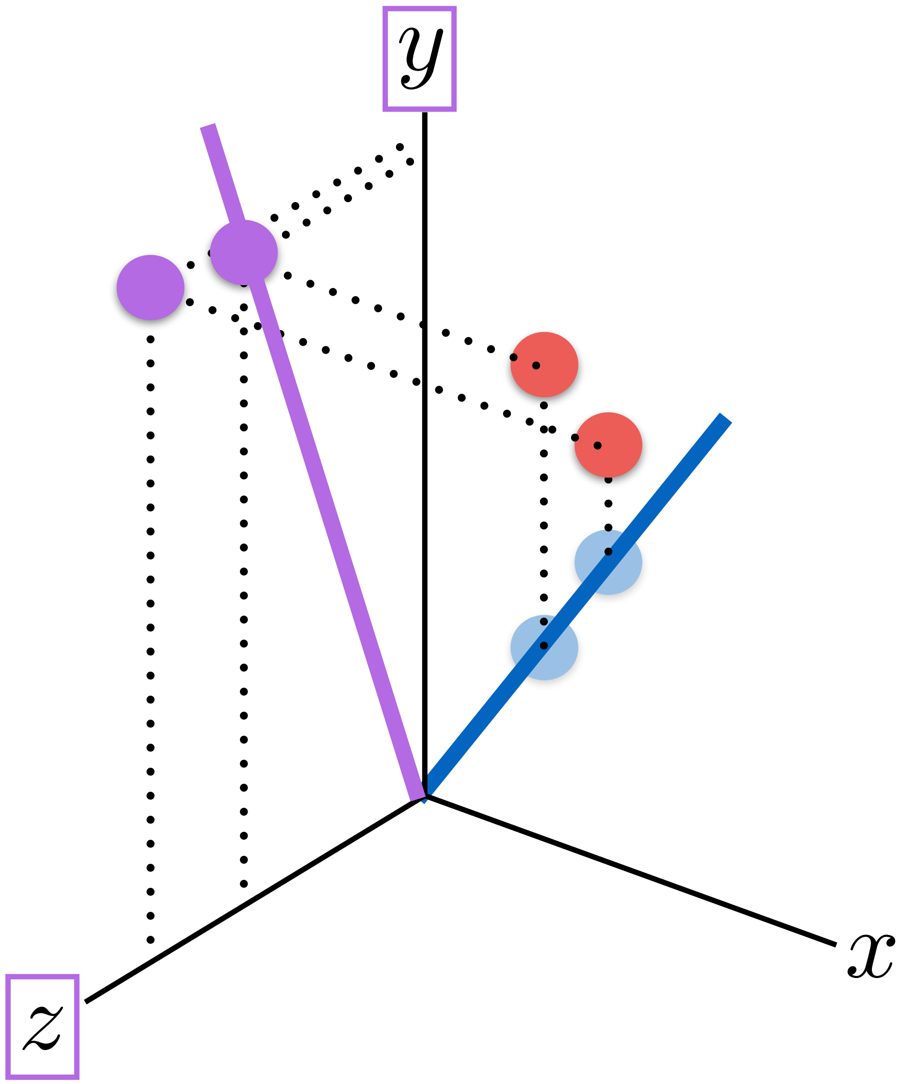

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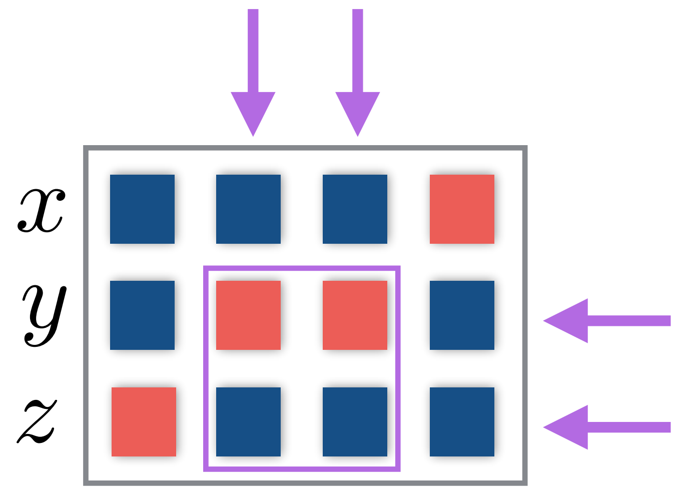

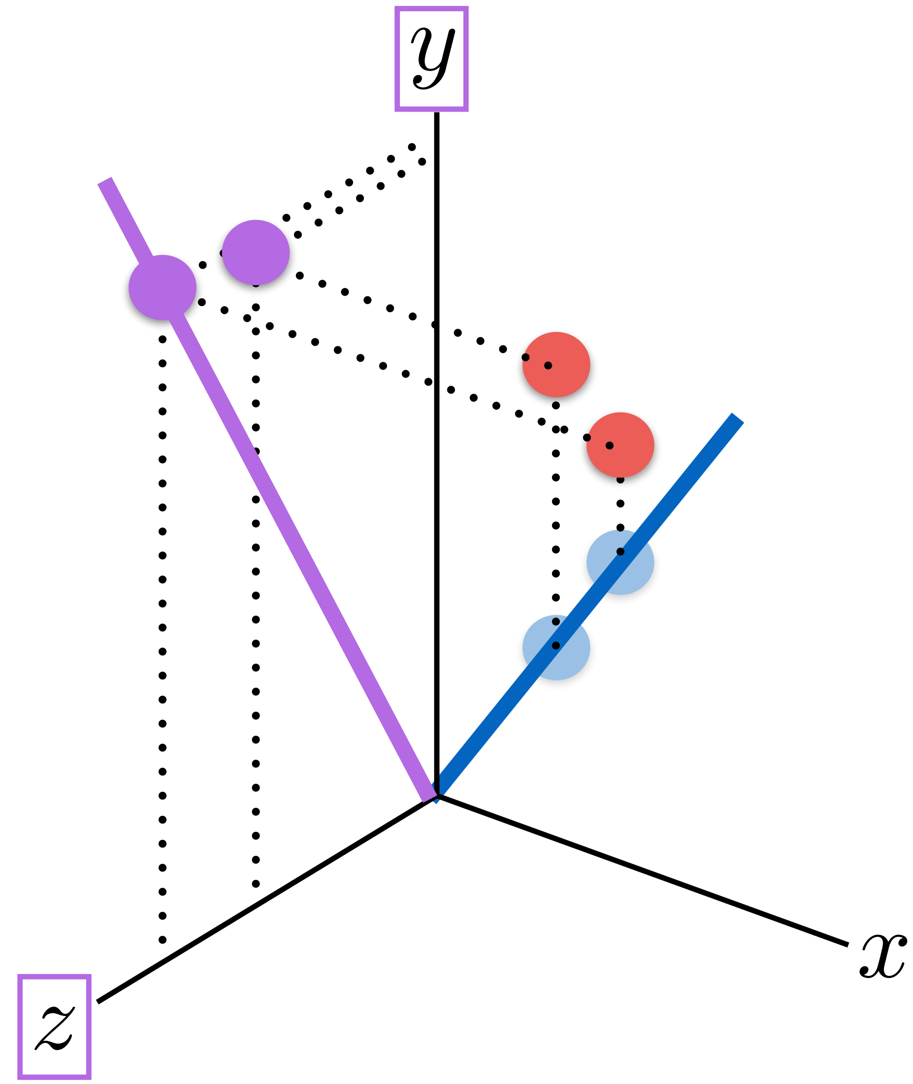

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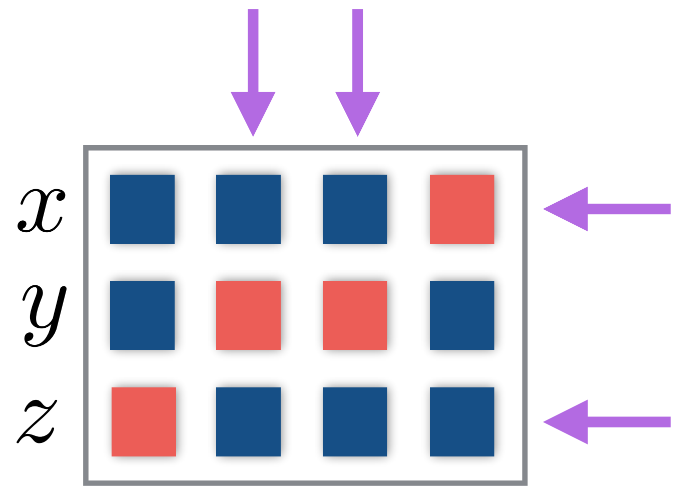

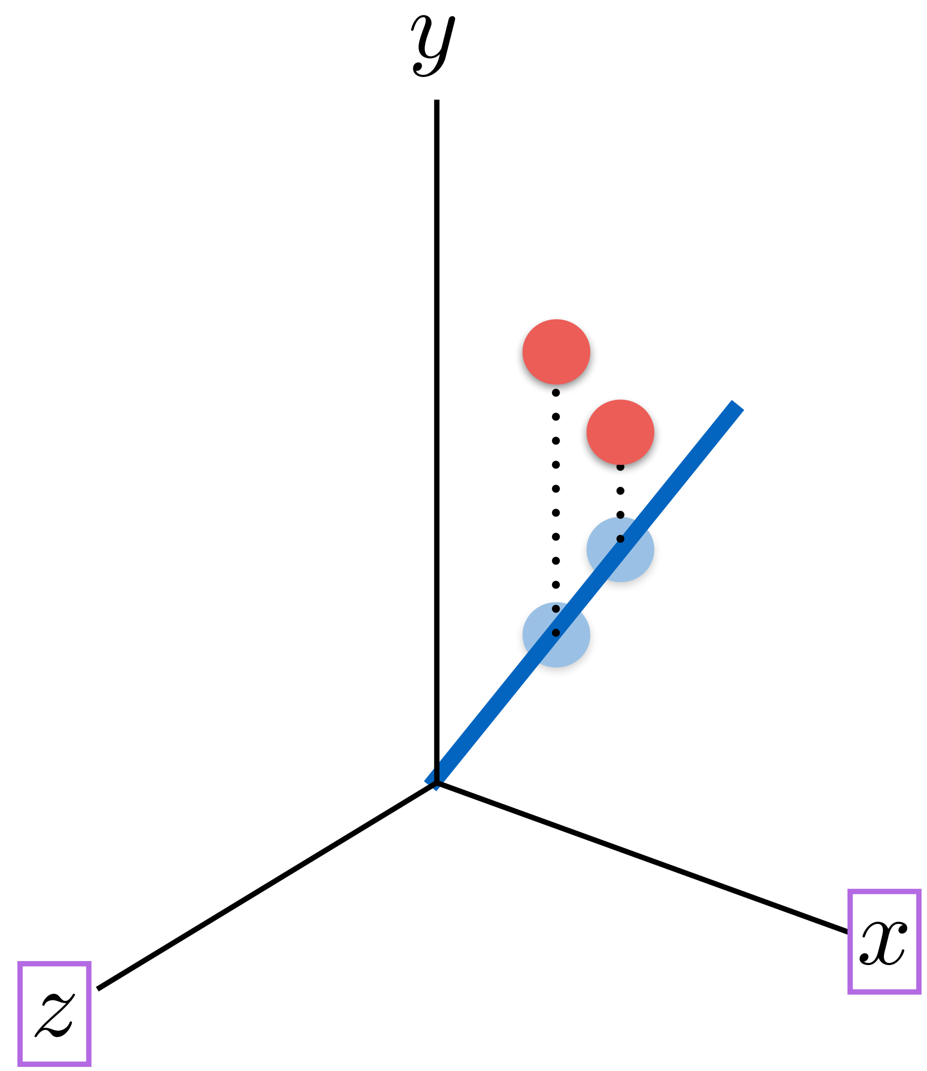

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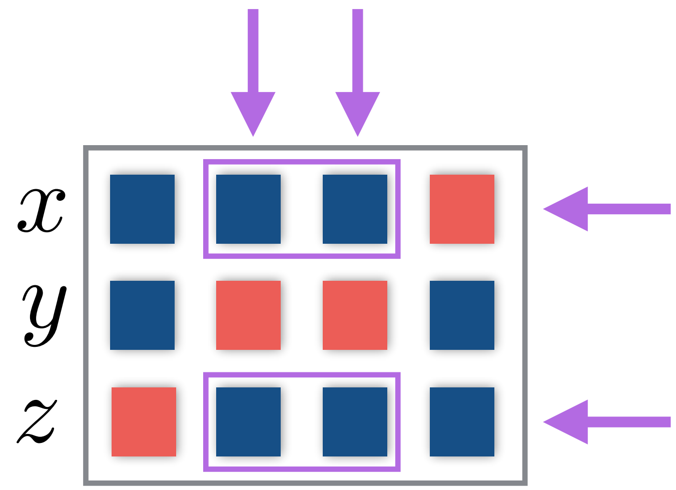

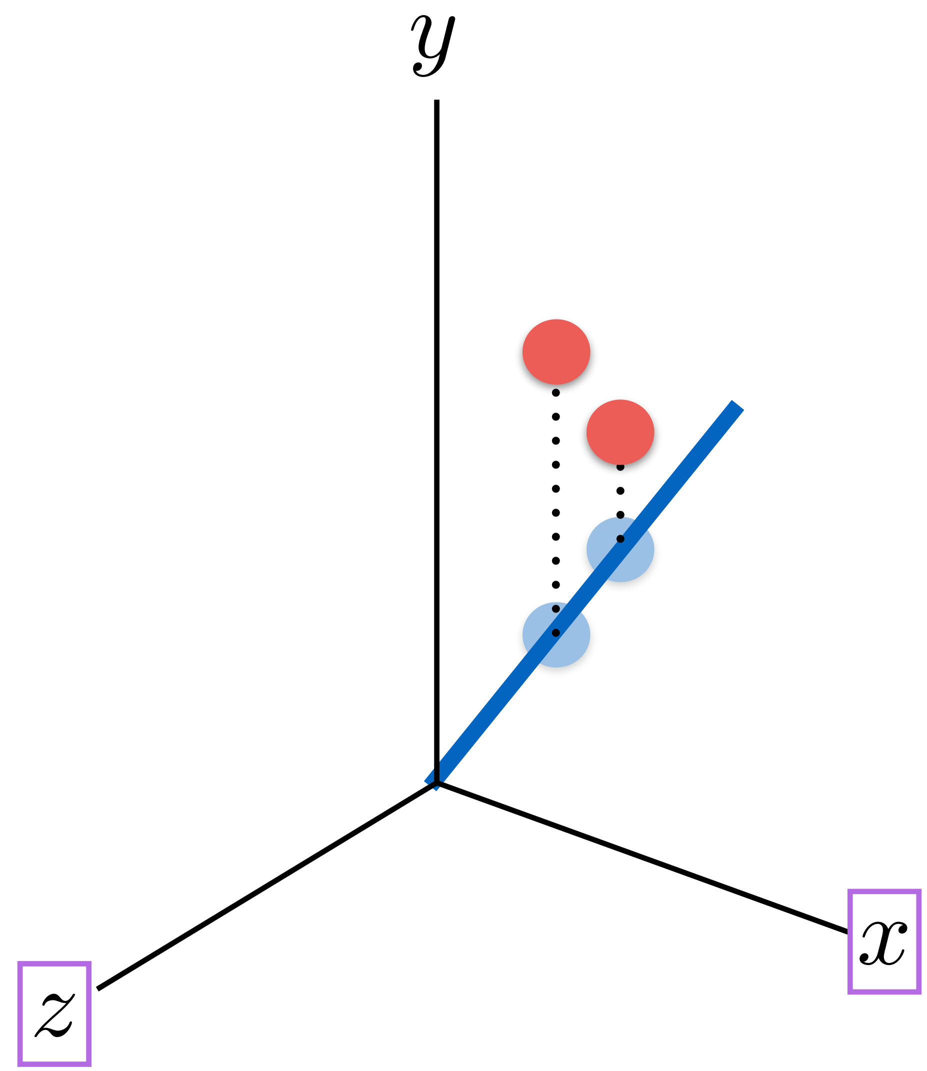

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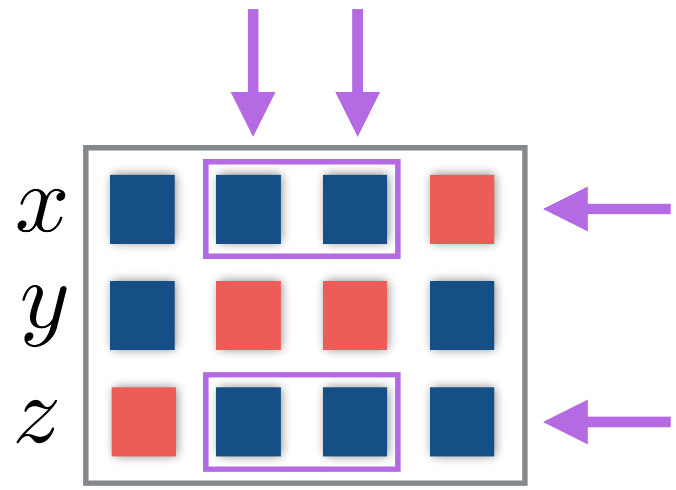

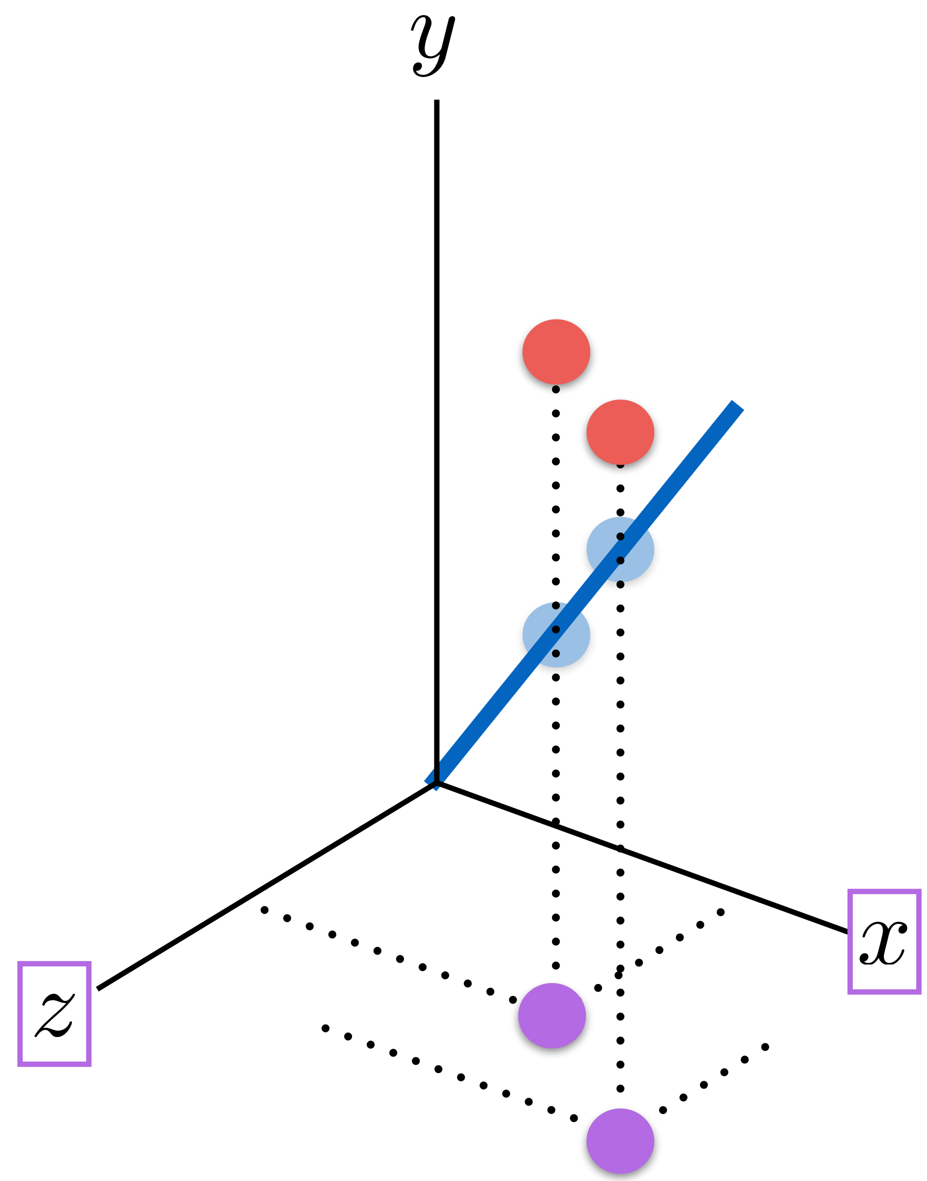

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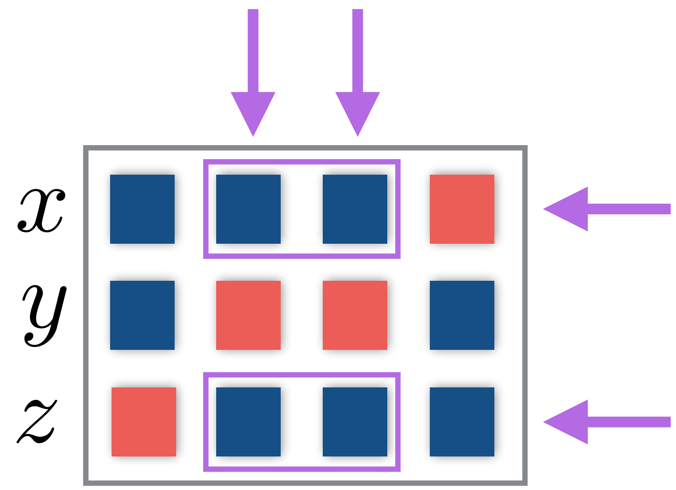

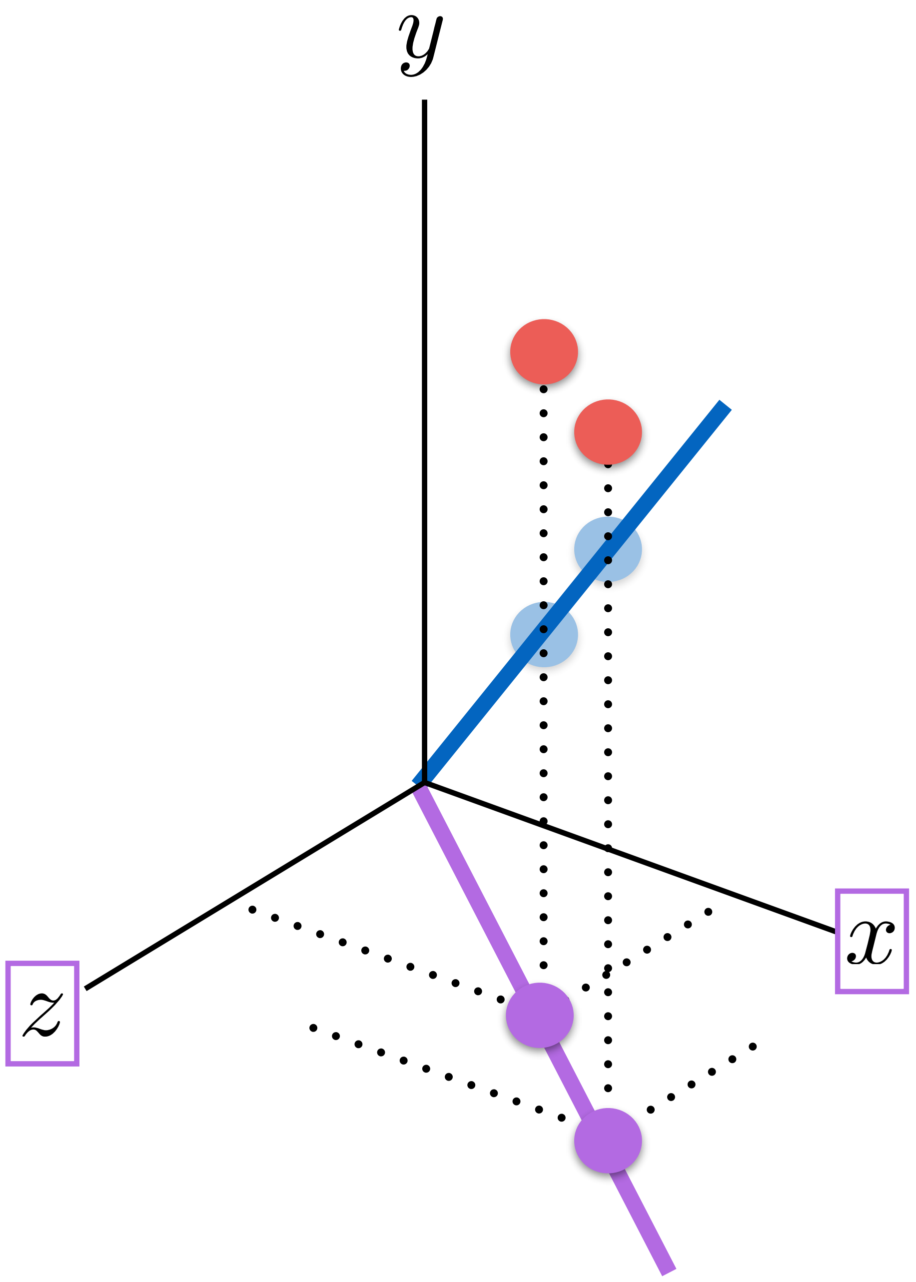

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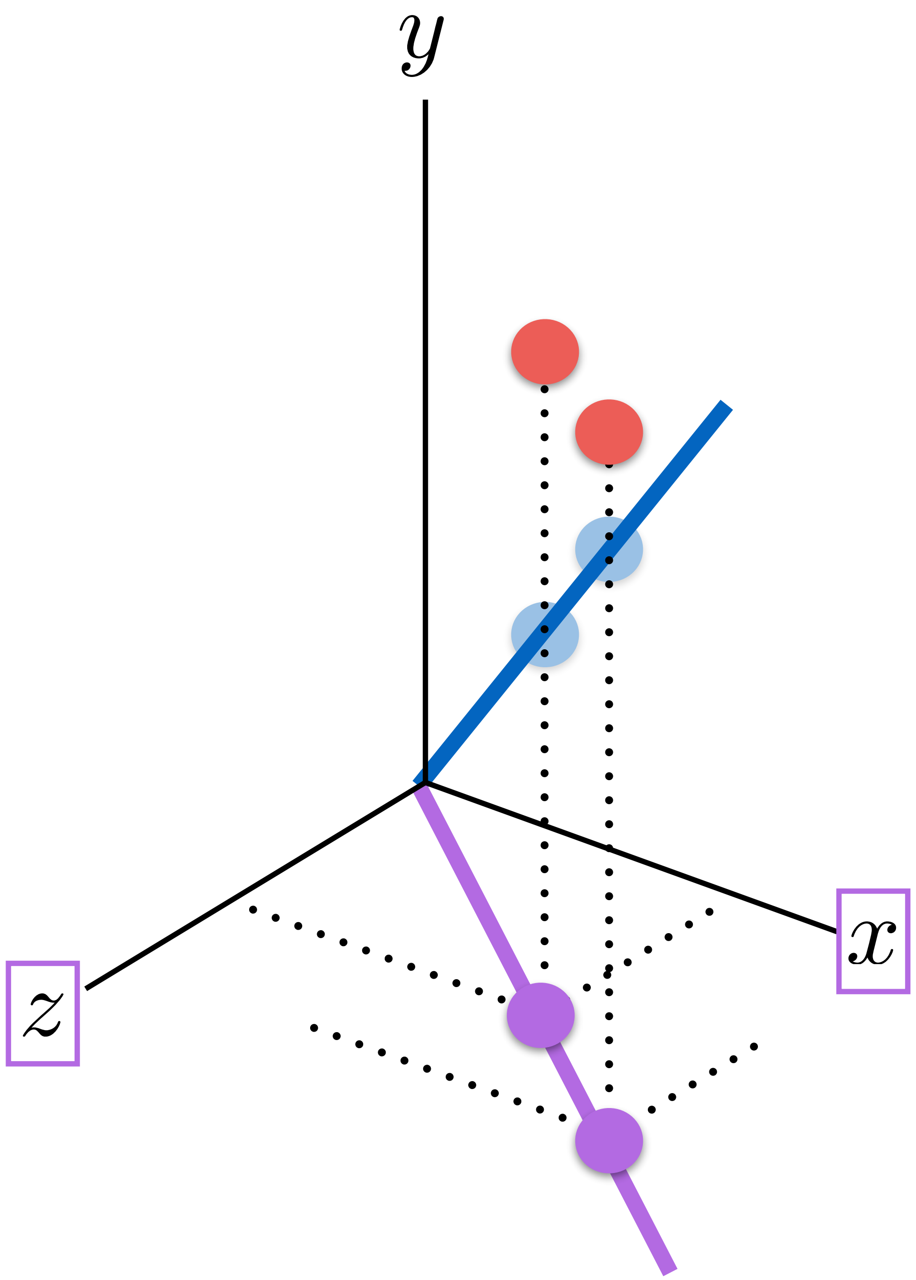

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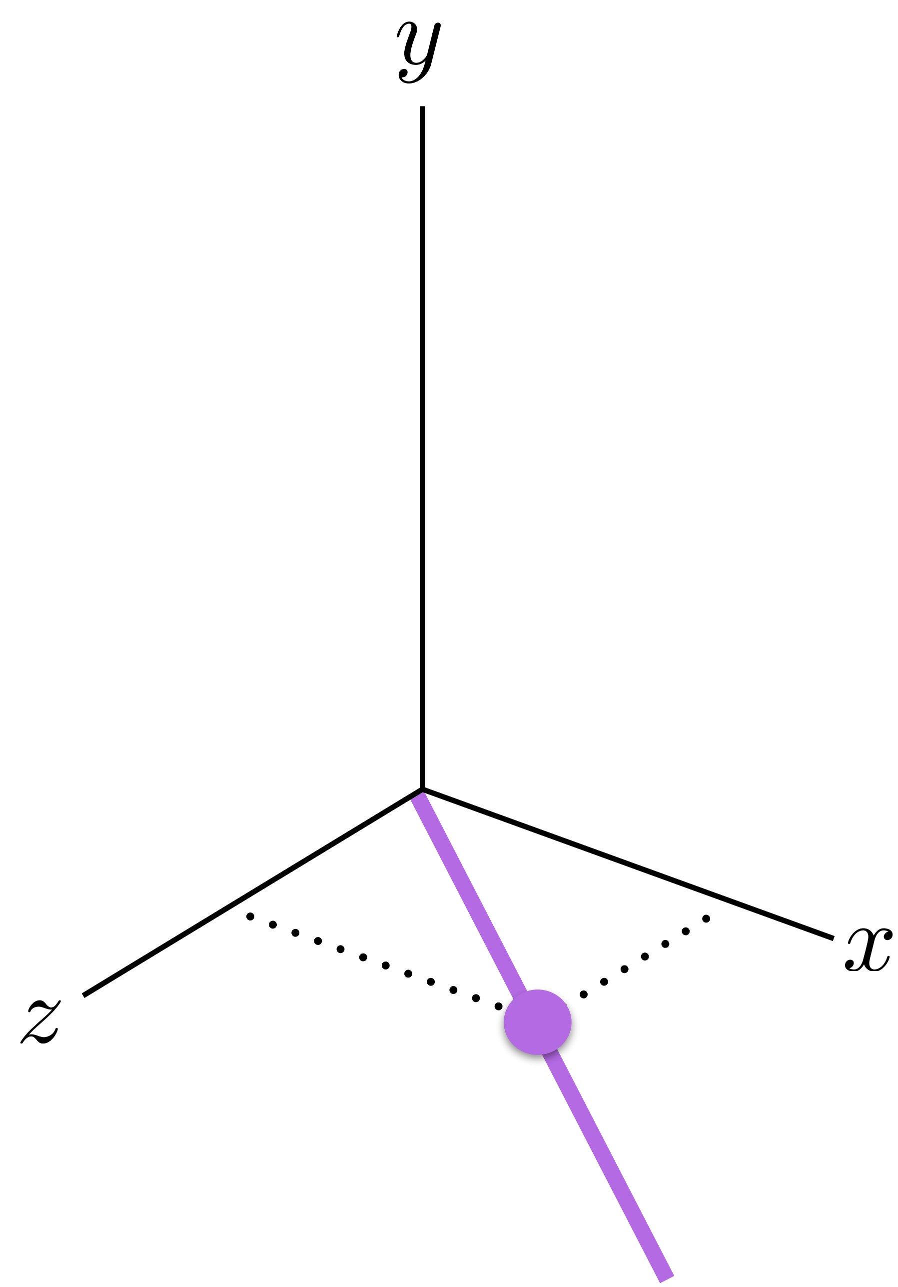

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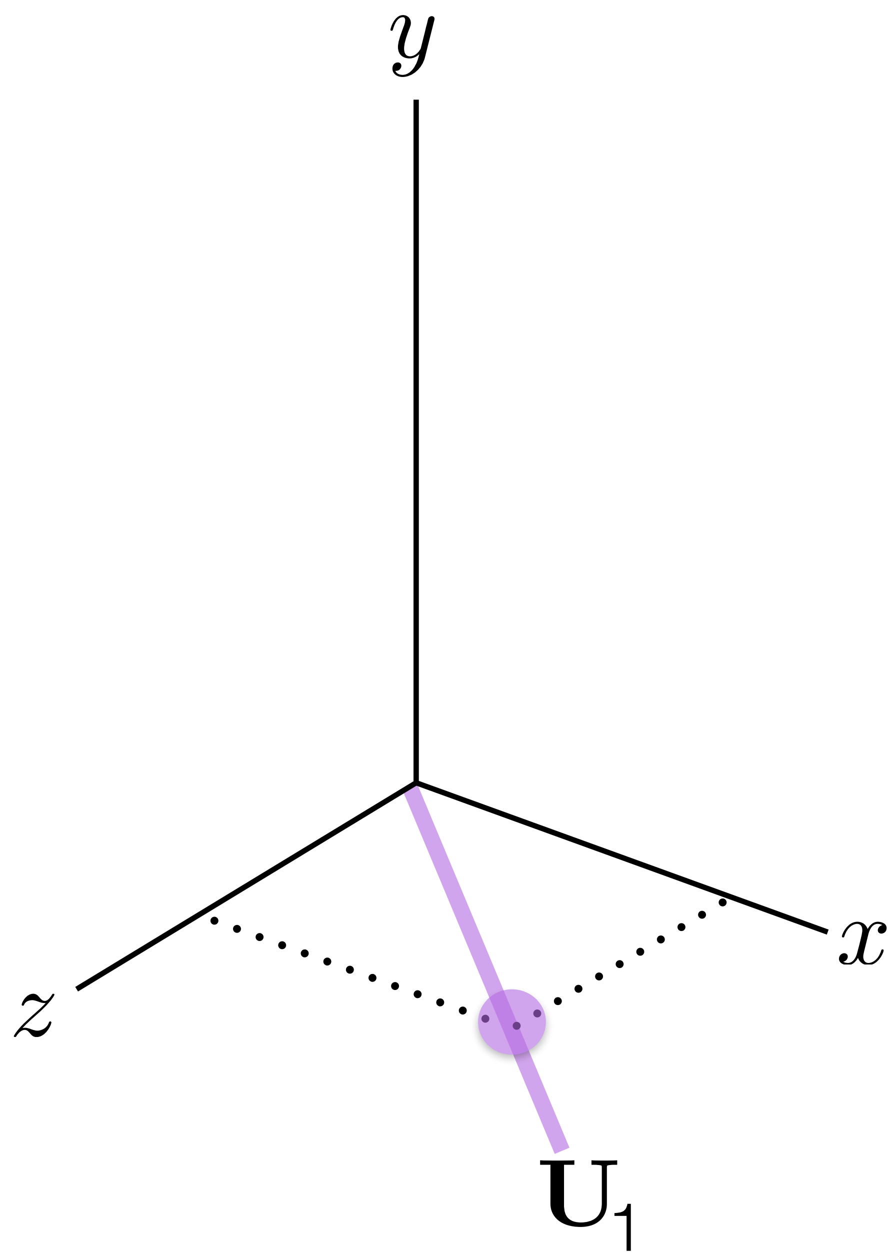

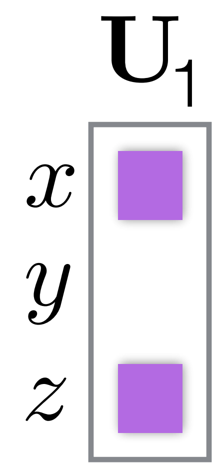

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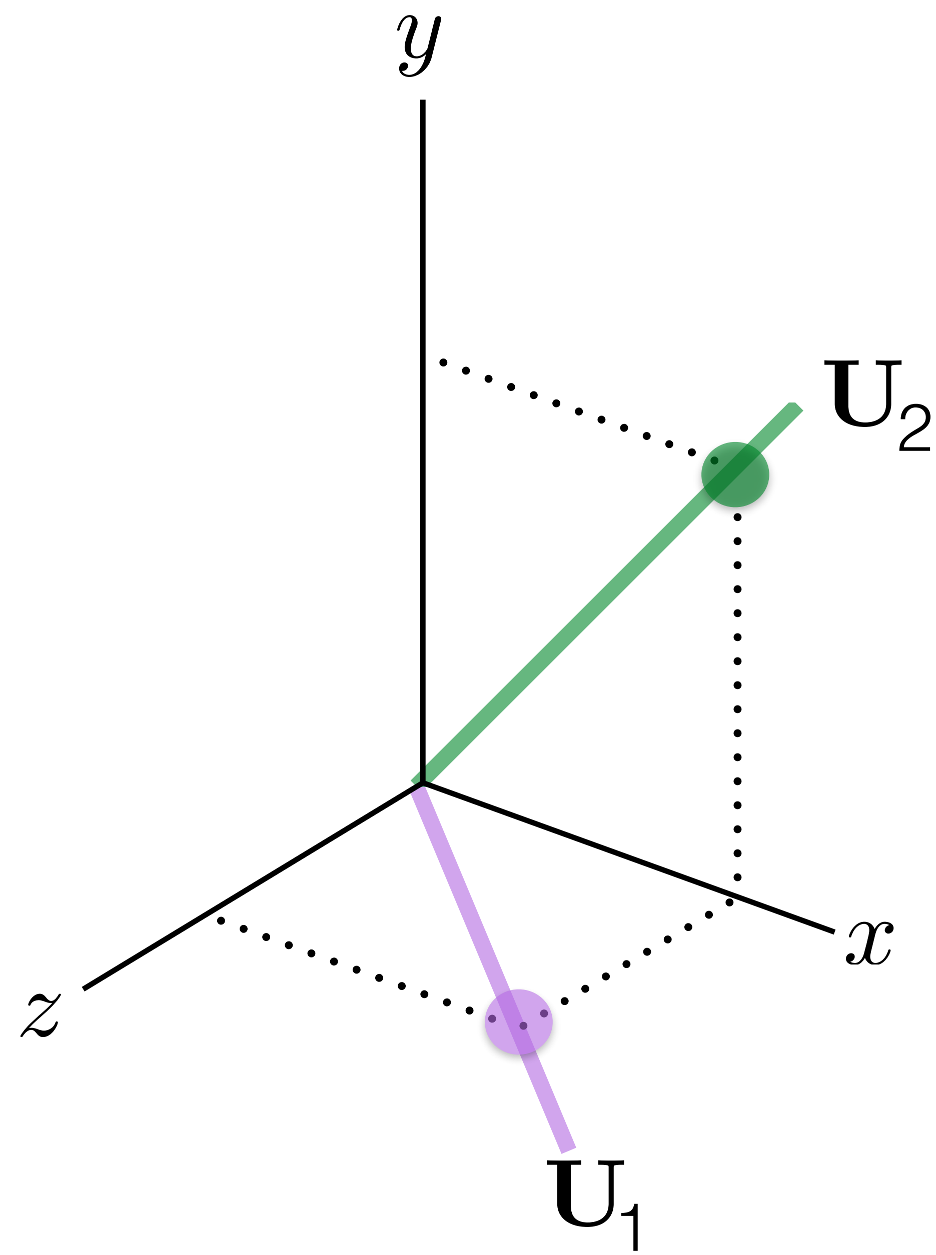

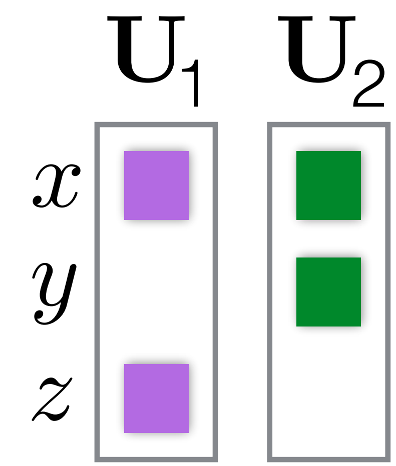

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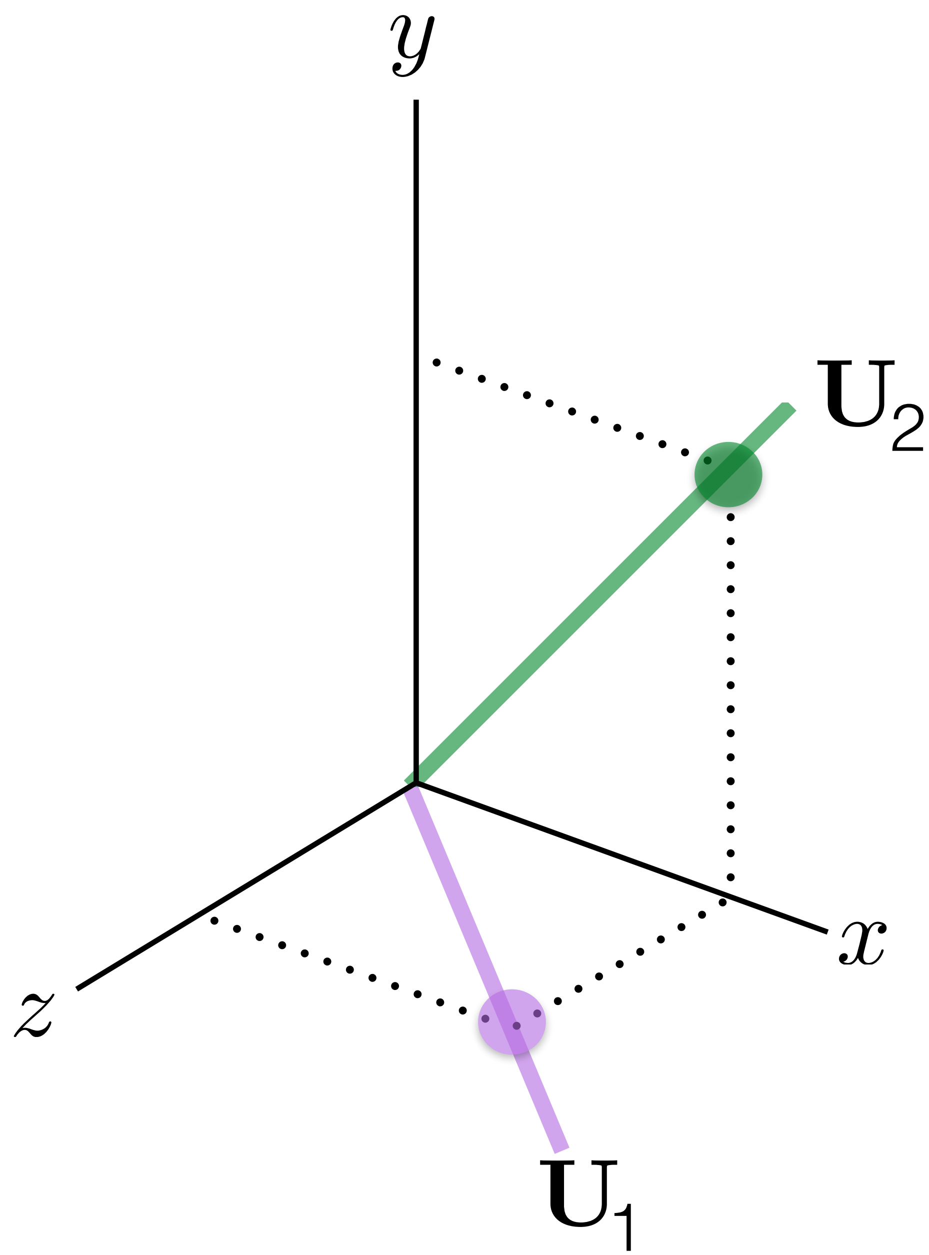
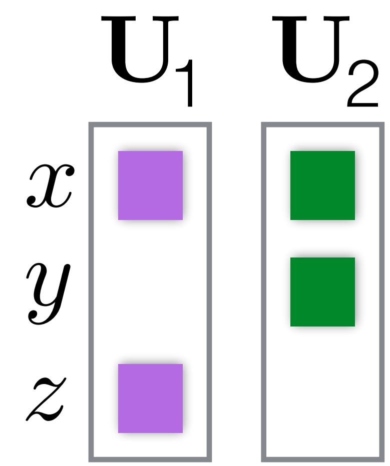
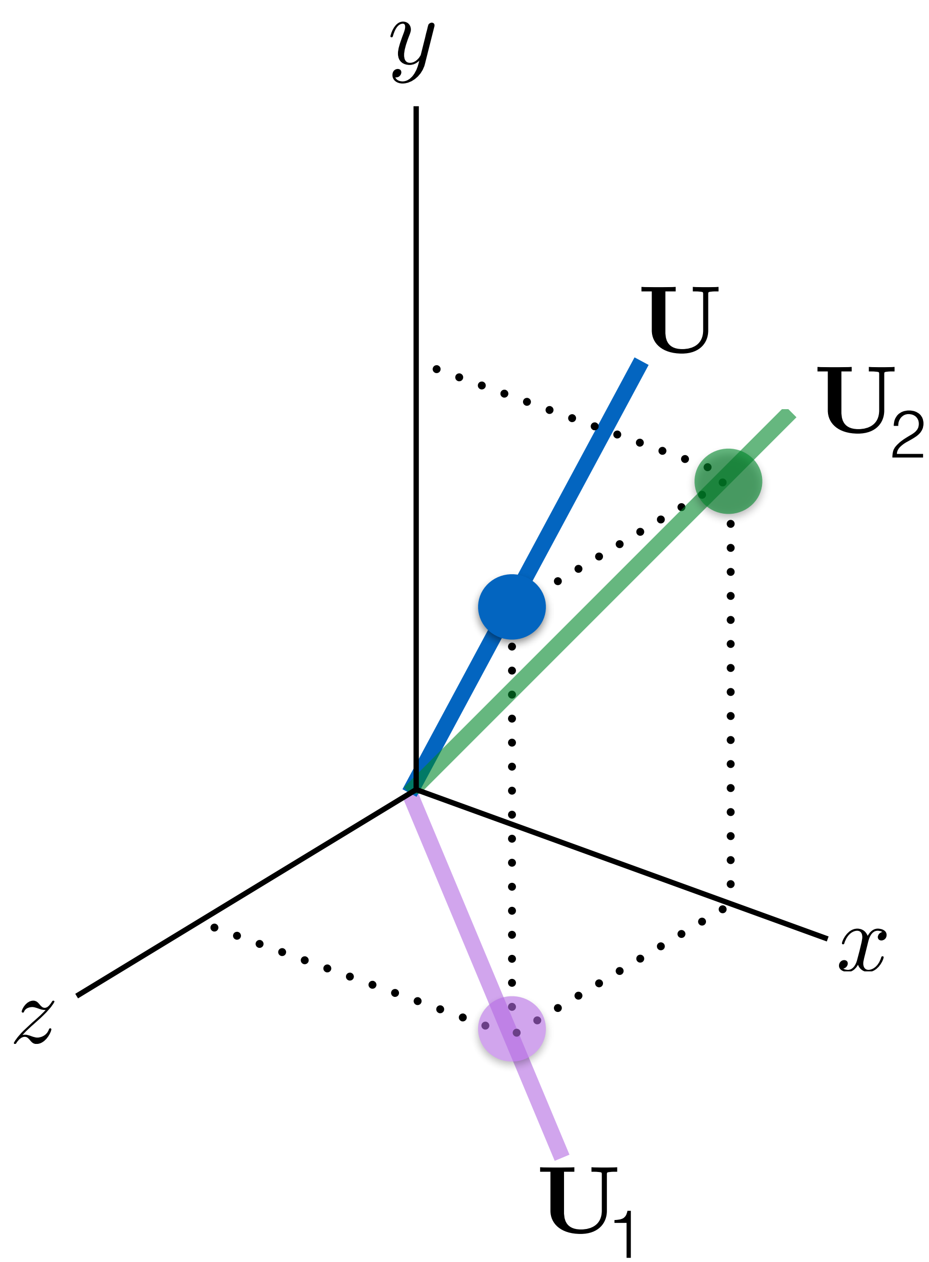
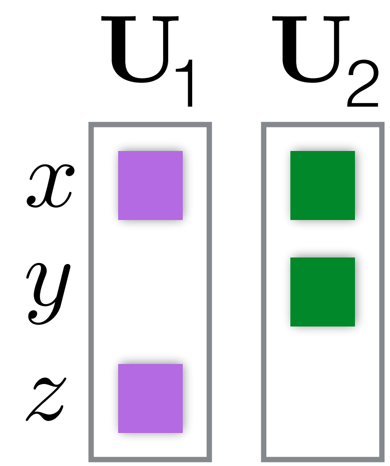




Now the question is:

Given canonical projections, can I find the subspace?





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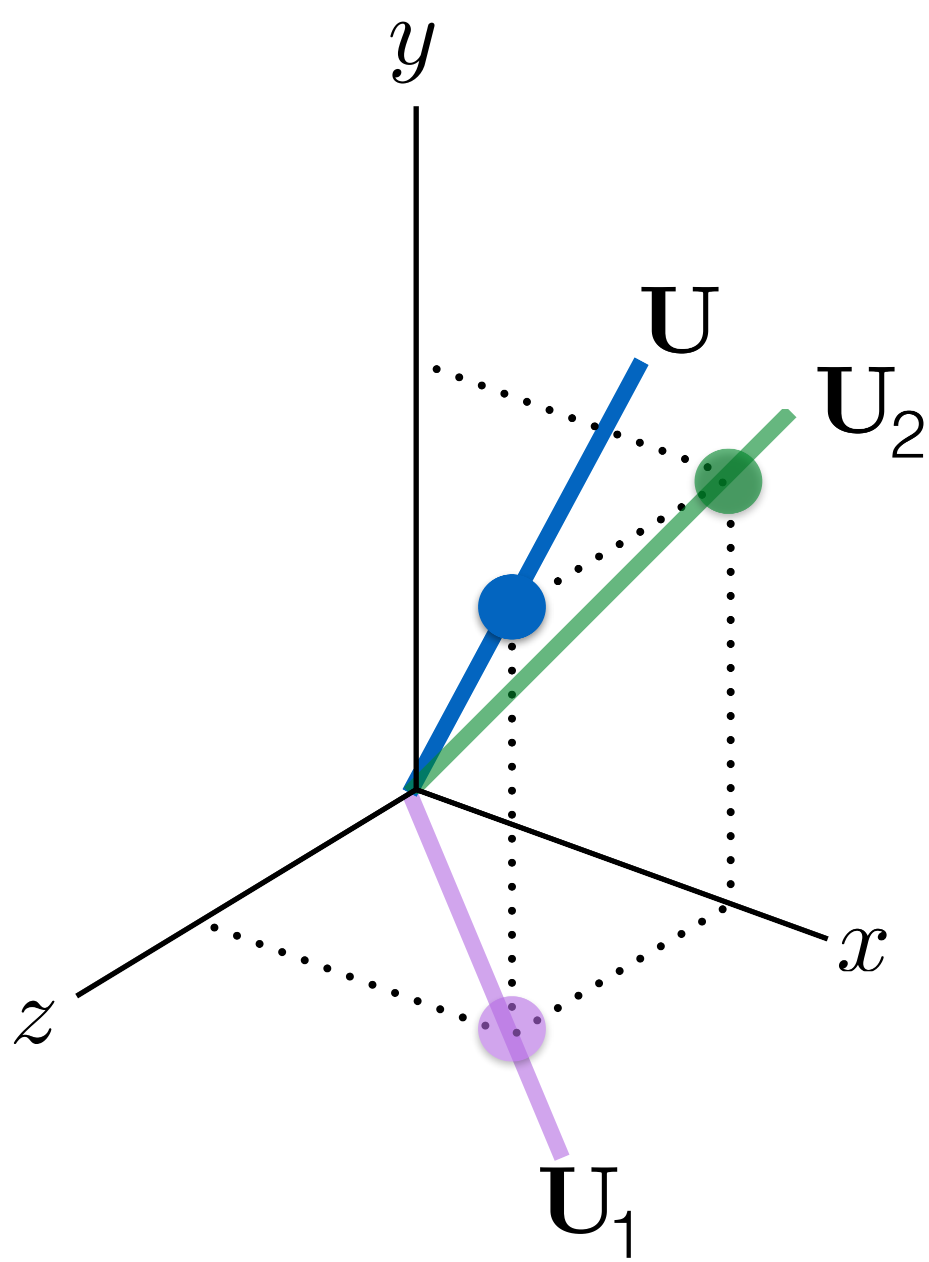

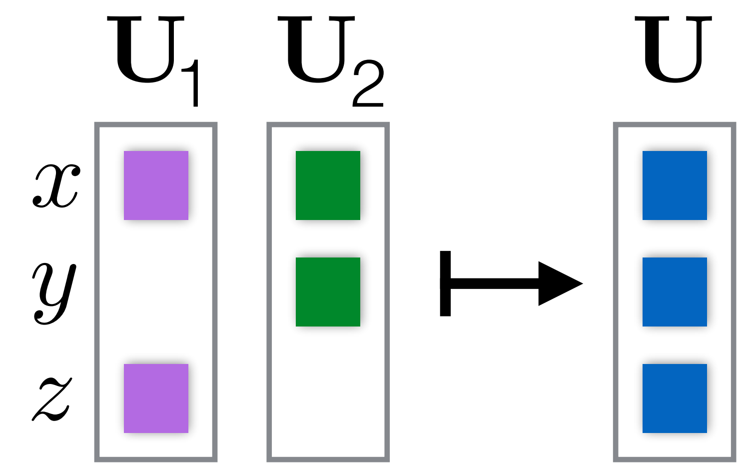

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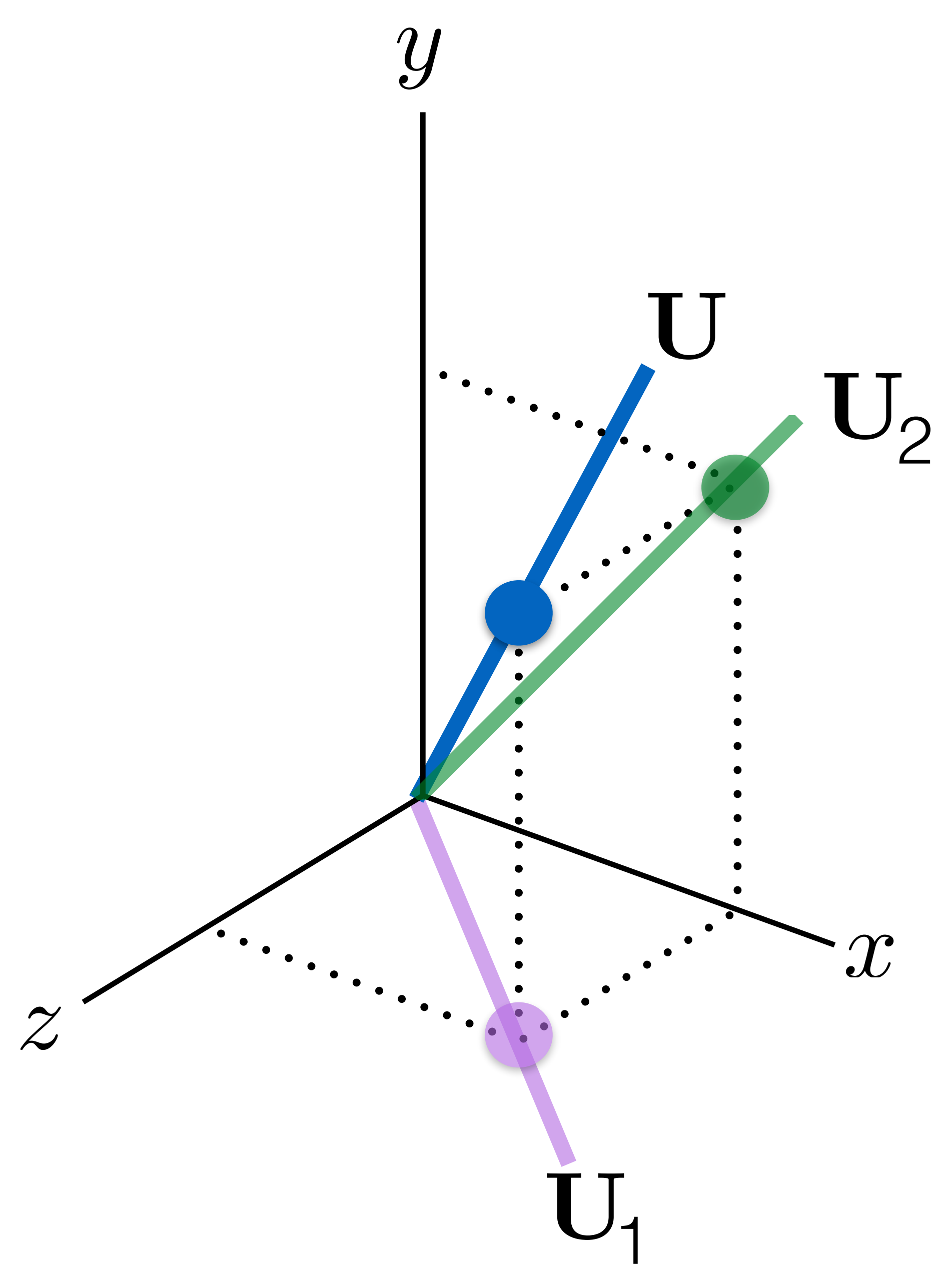

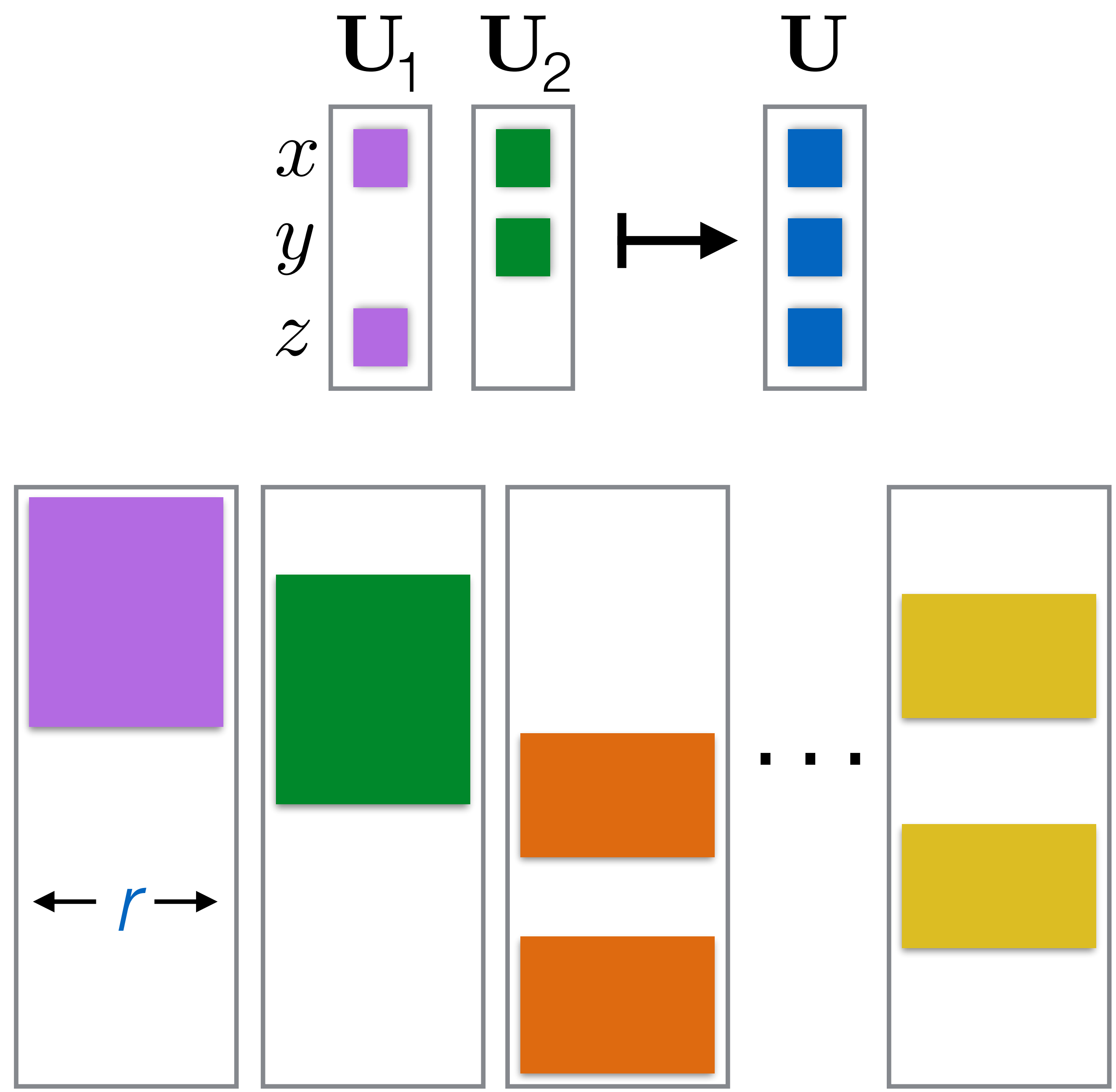

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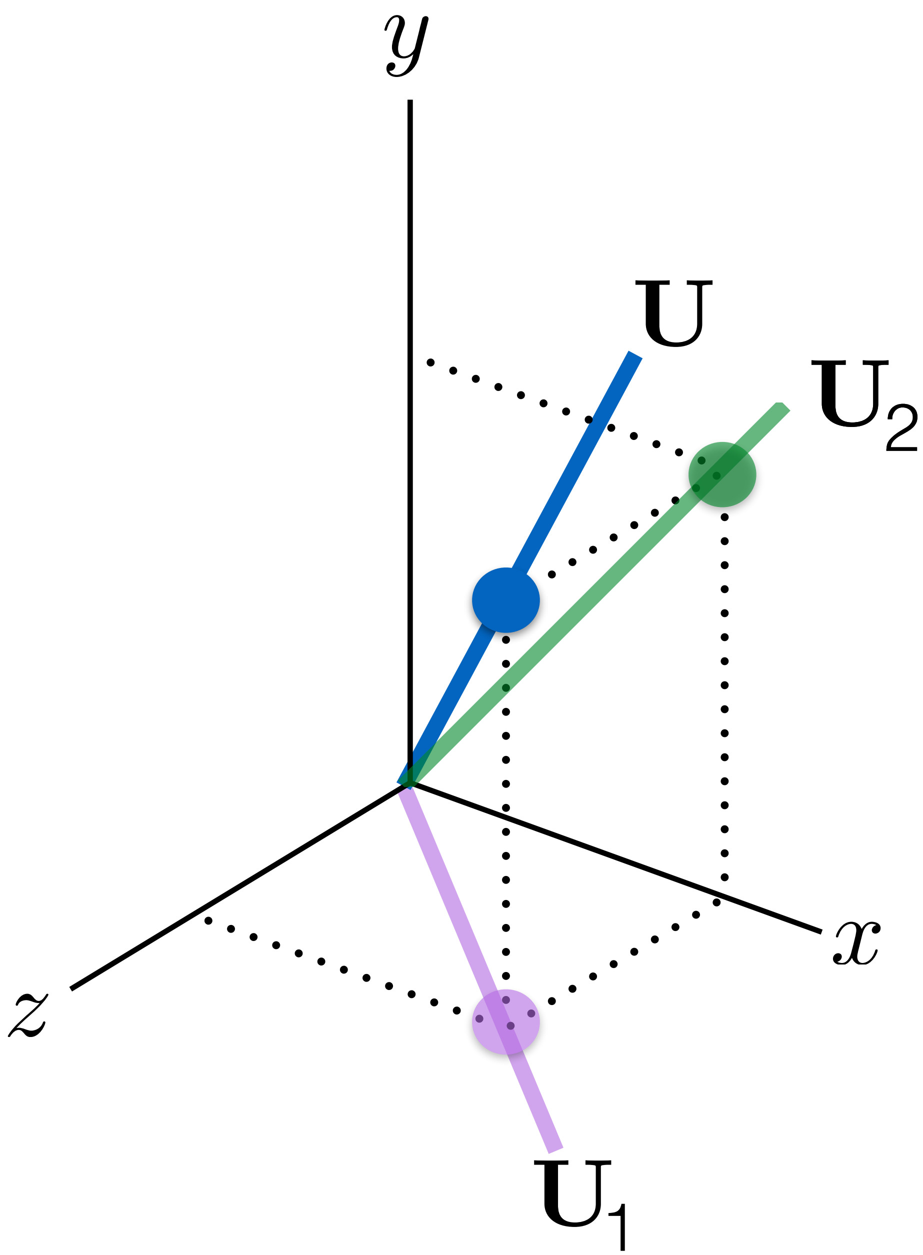

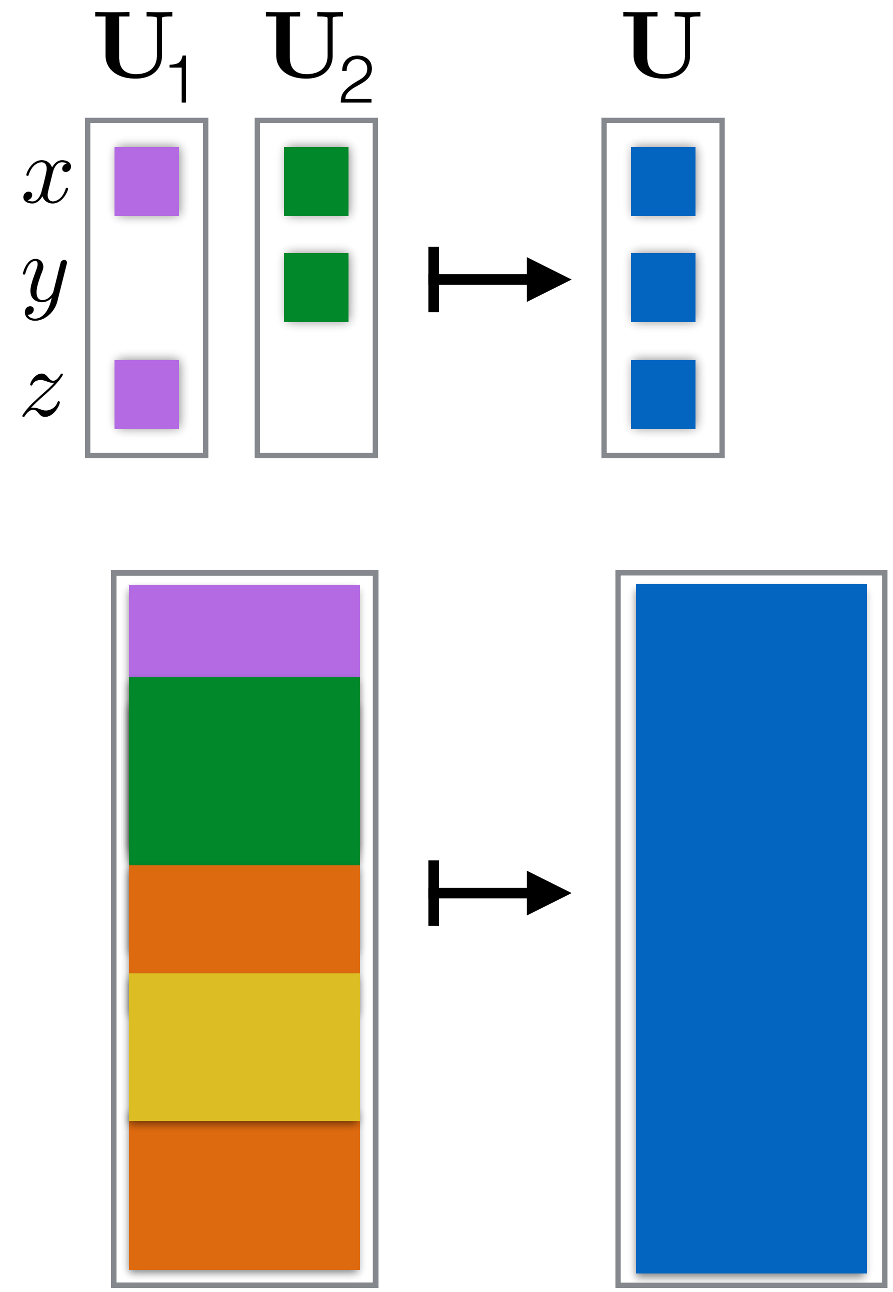

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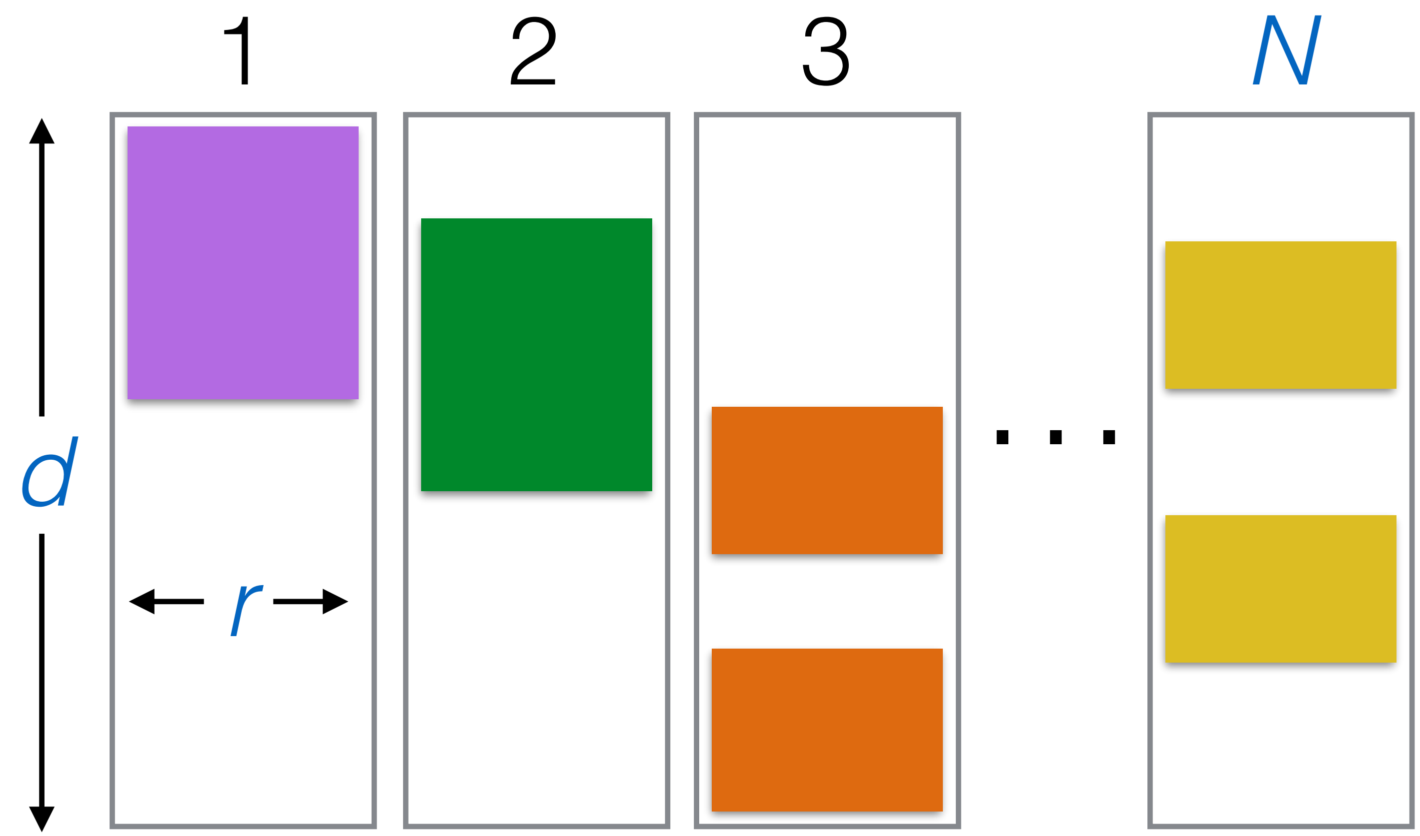
Given canonical projections, can I find the subspace?

Theorem (Pimentel, Boston, Nowak, ISIT, 2015)

A subspace can be recovered from $N = d - r$ canonical projections if and only if every subset of n projections involves at least $n + r$ coordinates.



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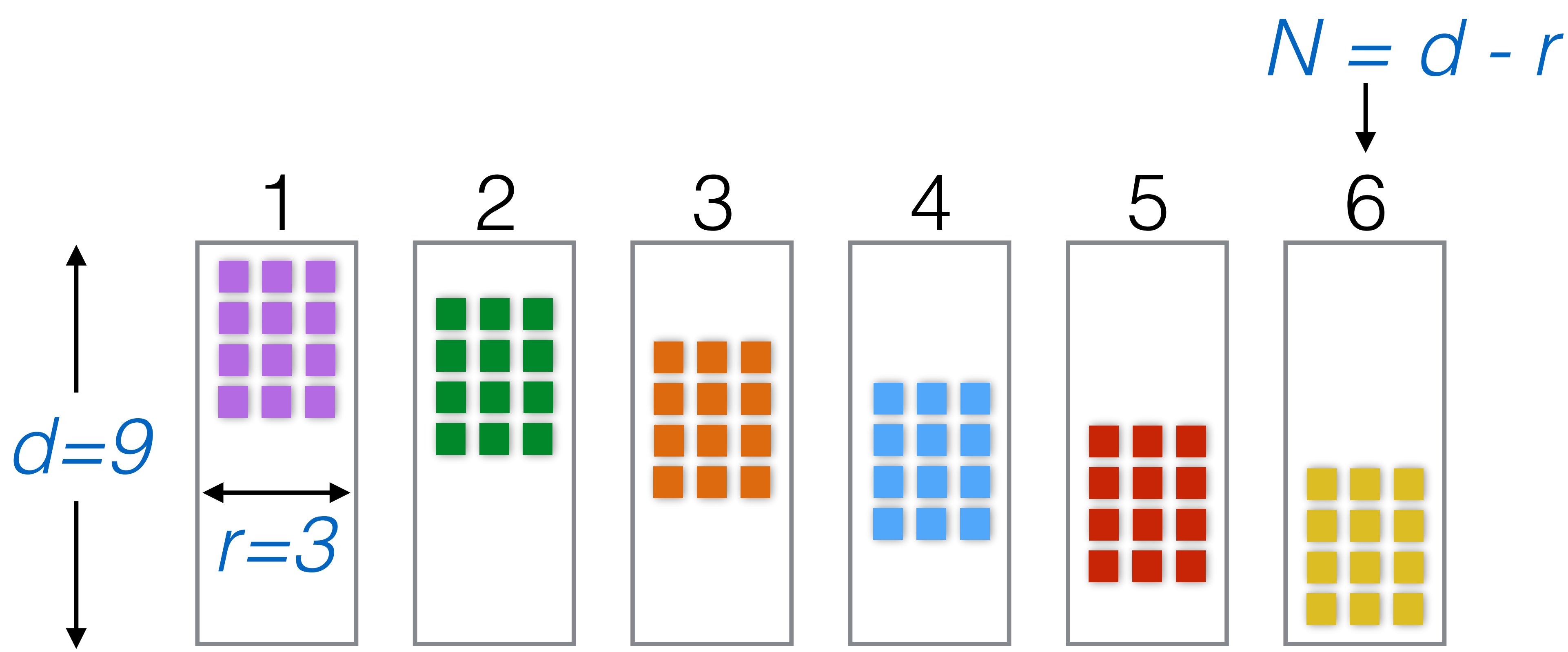
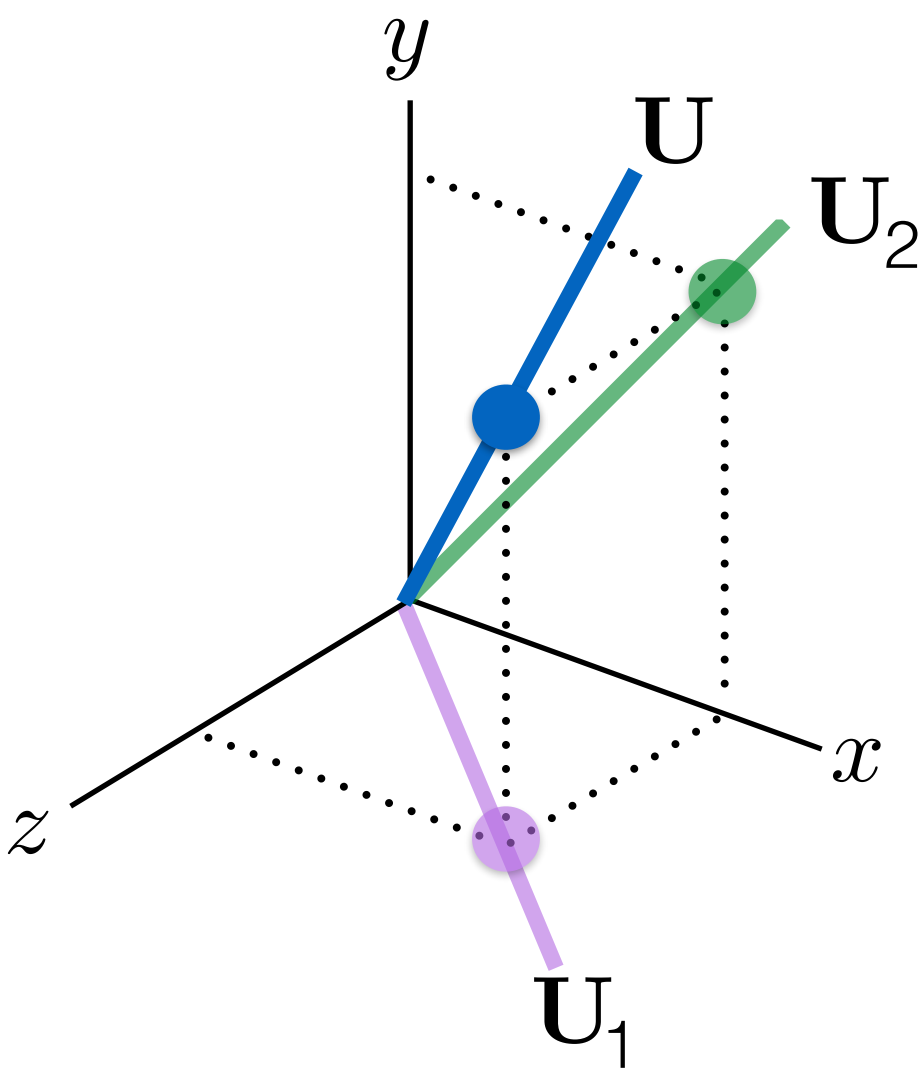
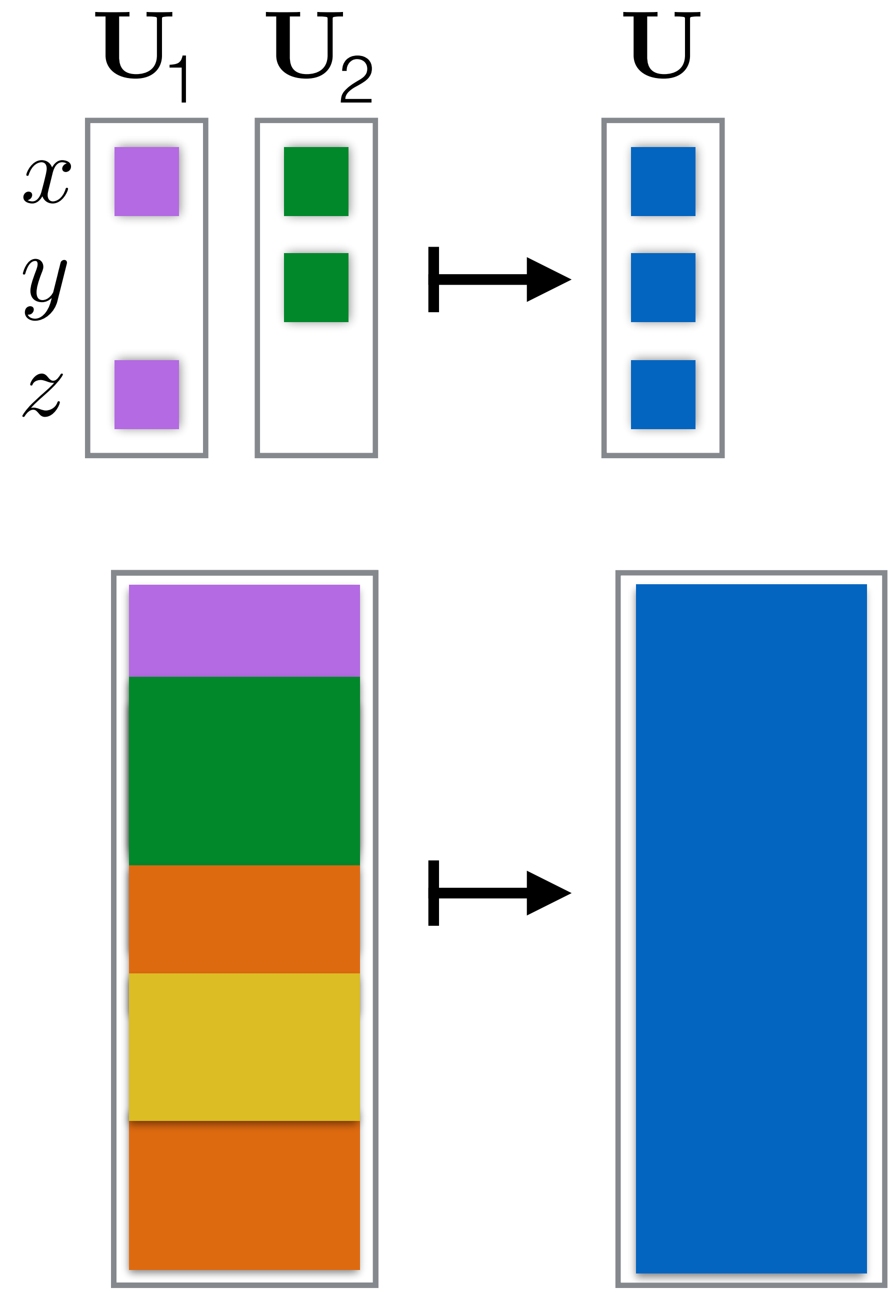




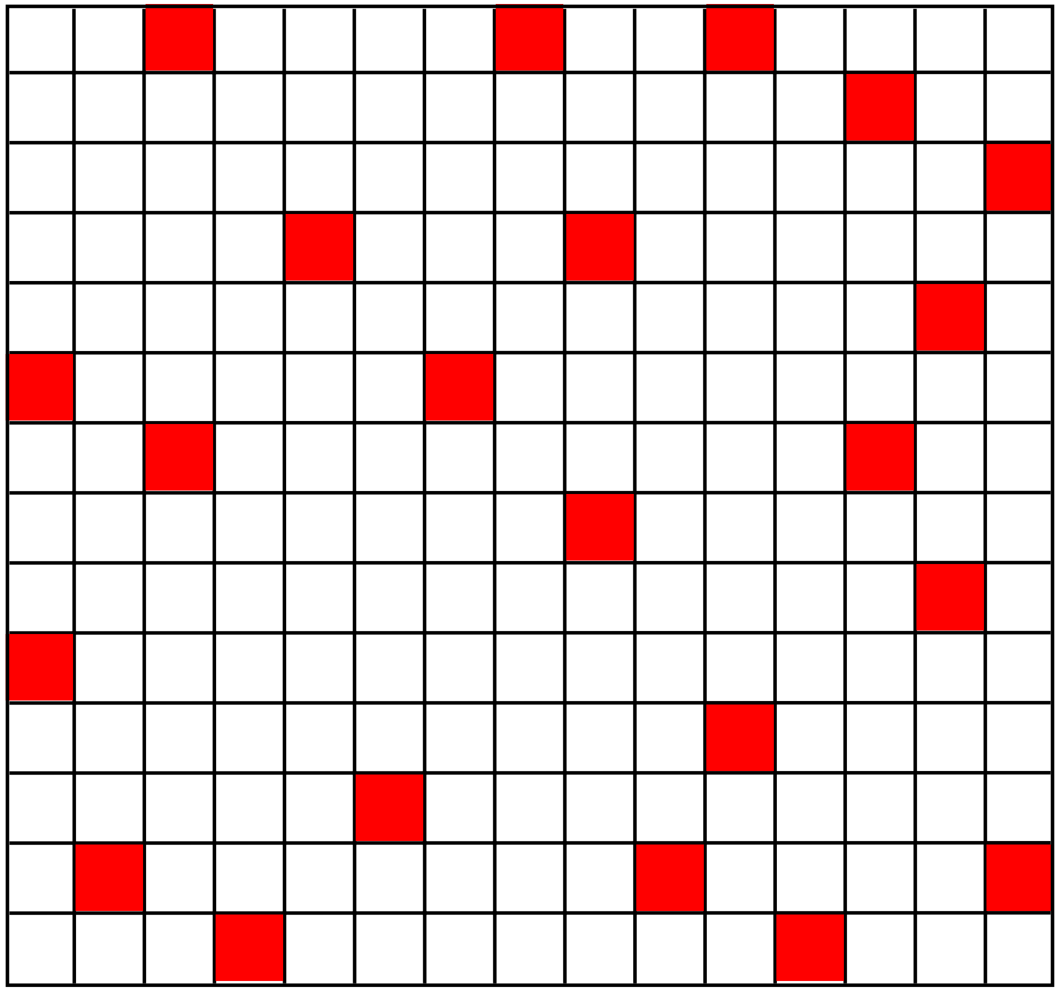


This tells me

Which projections I need to reconstruct the subspace.

Our Algorithm: R2PCA

(Ransac Robust PCA)



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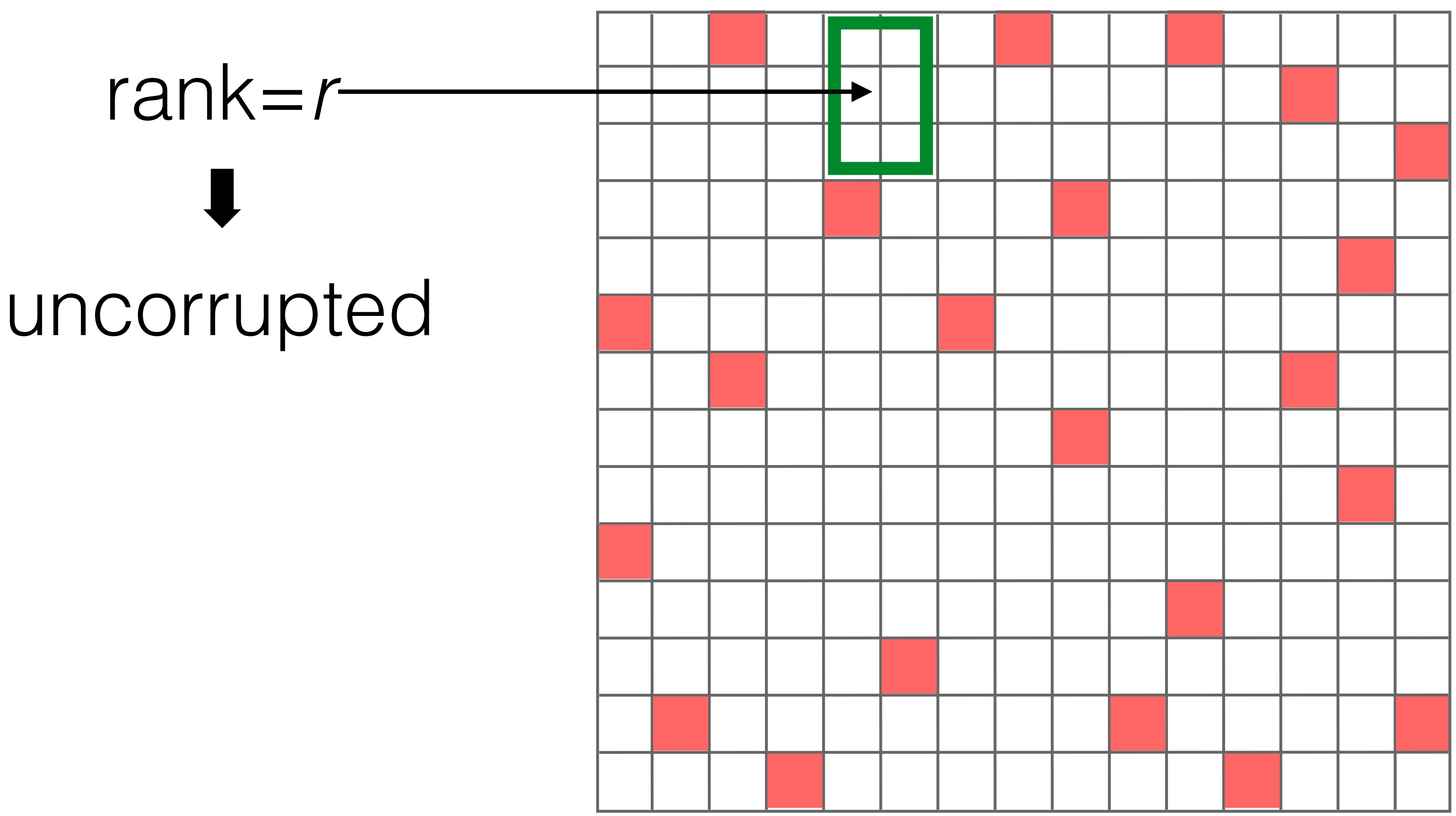

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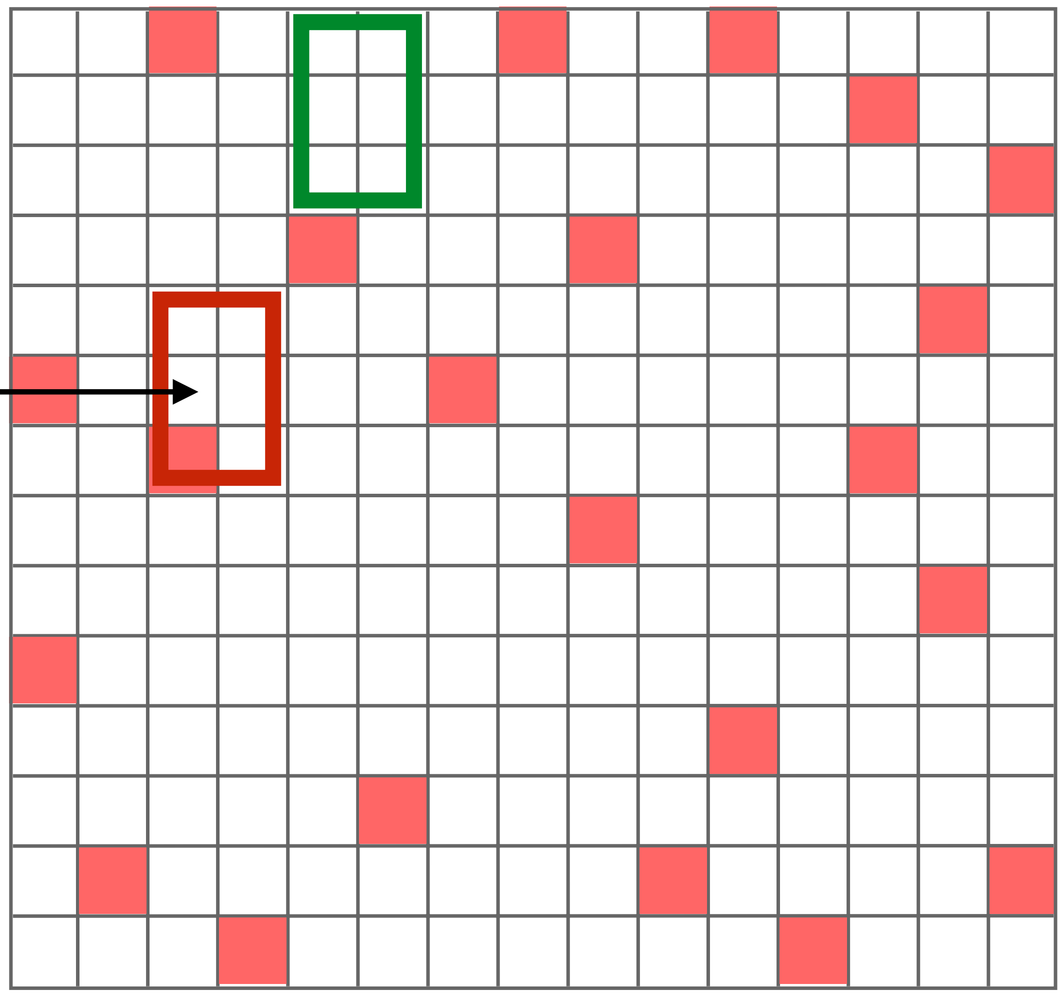
rank>r

⬇

corrupted



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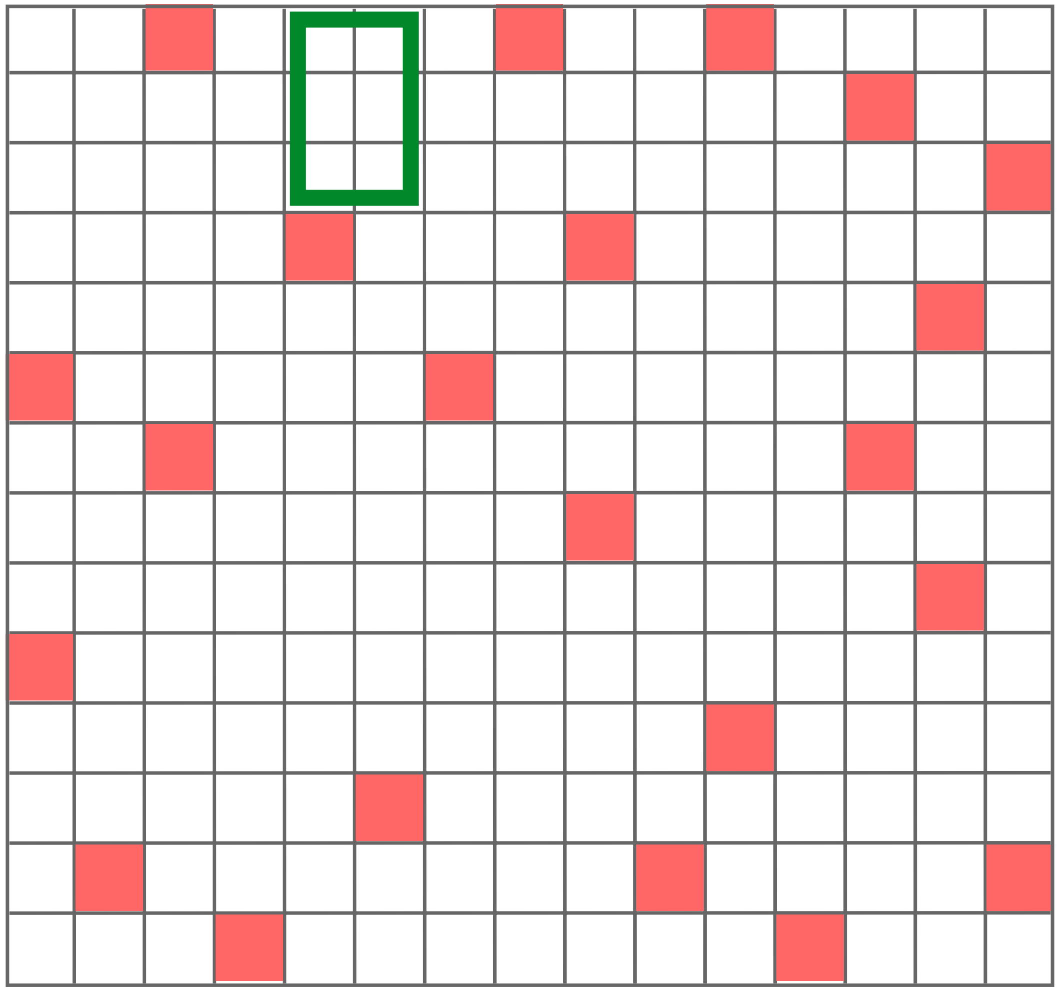

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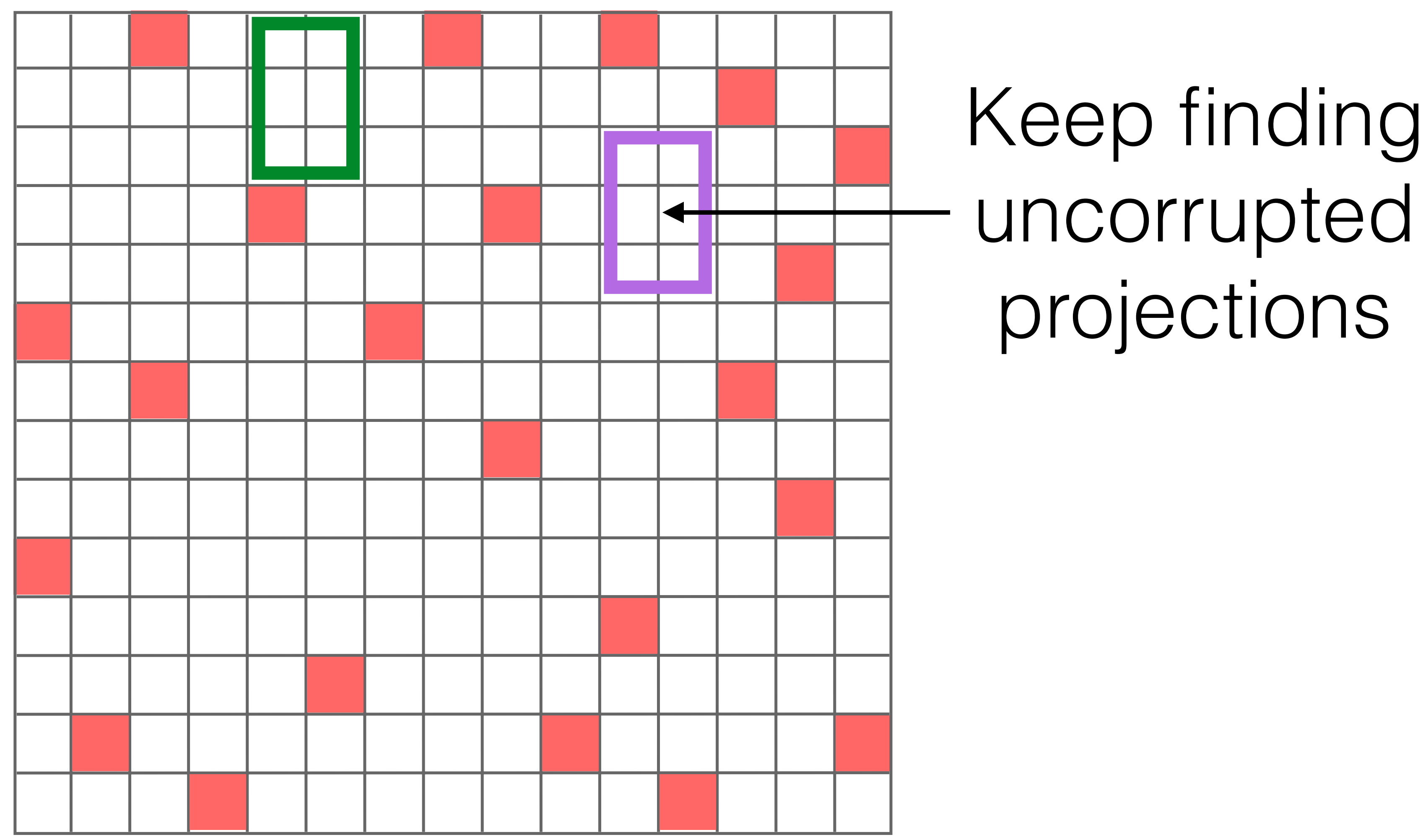

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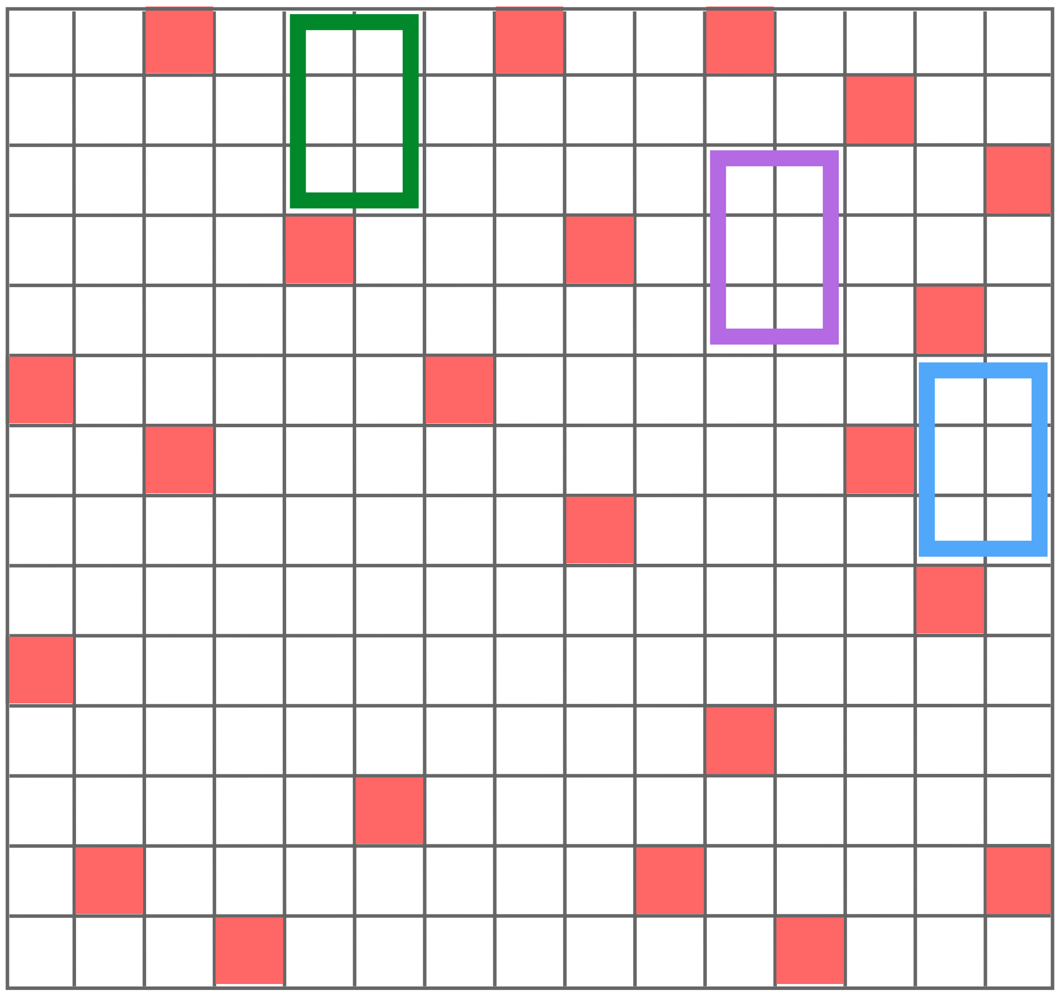

Keep finding uncorrupted projections

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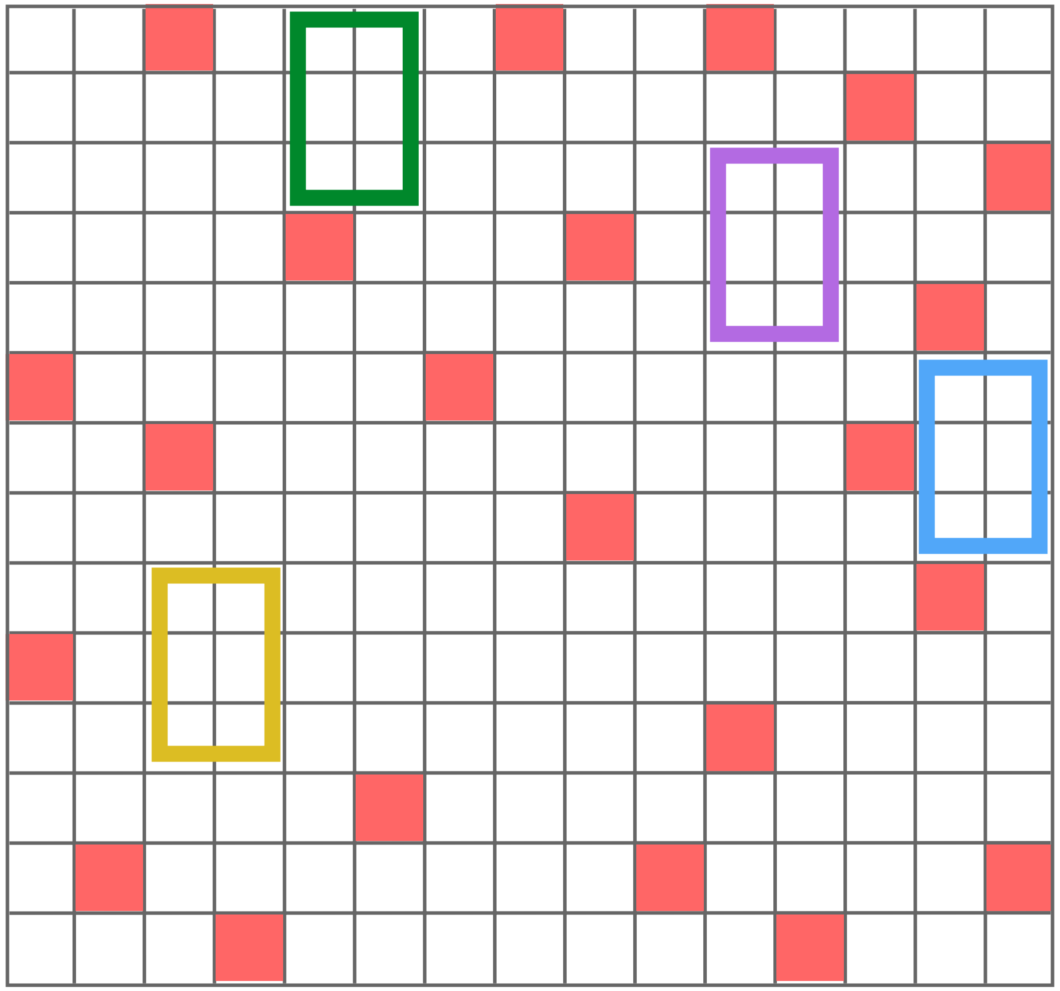

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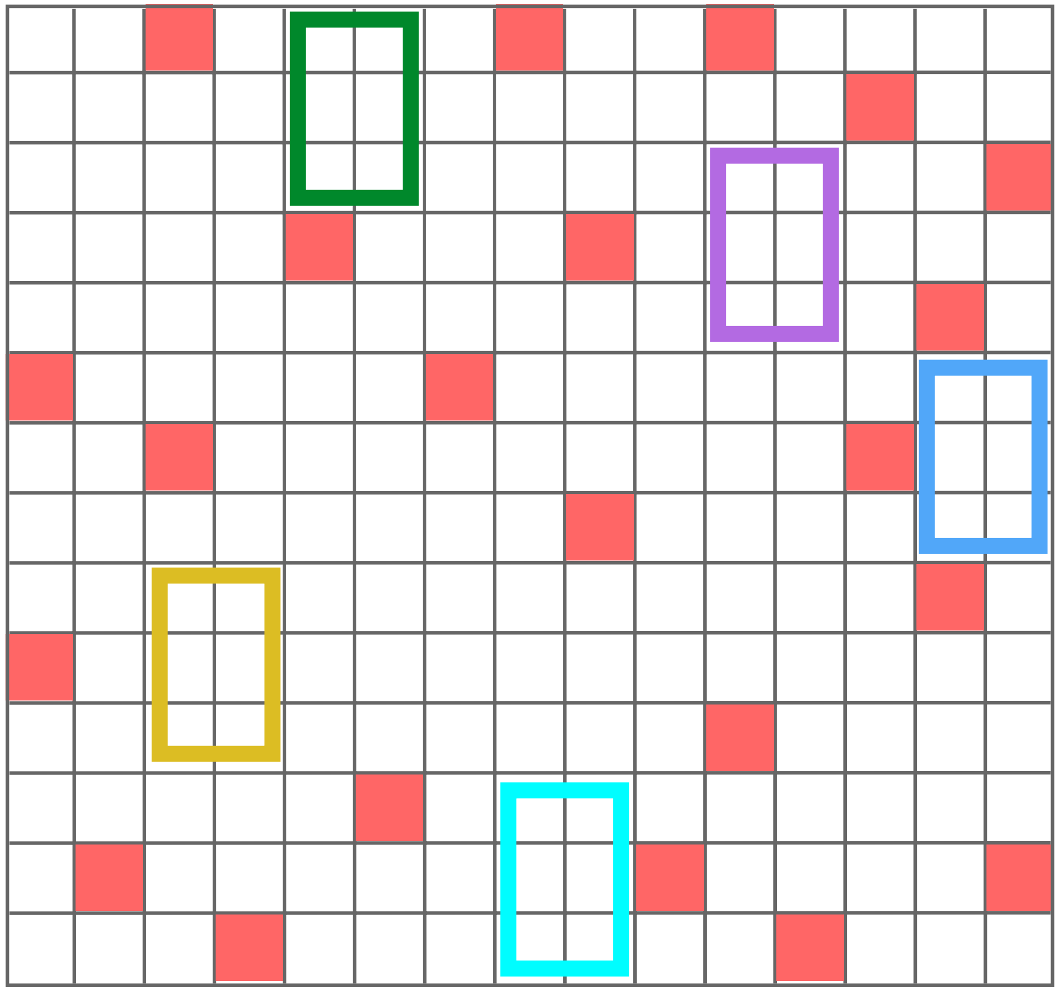

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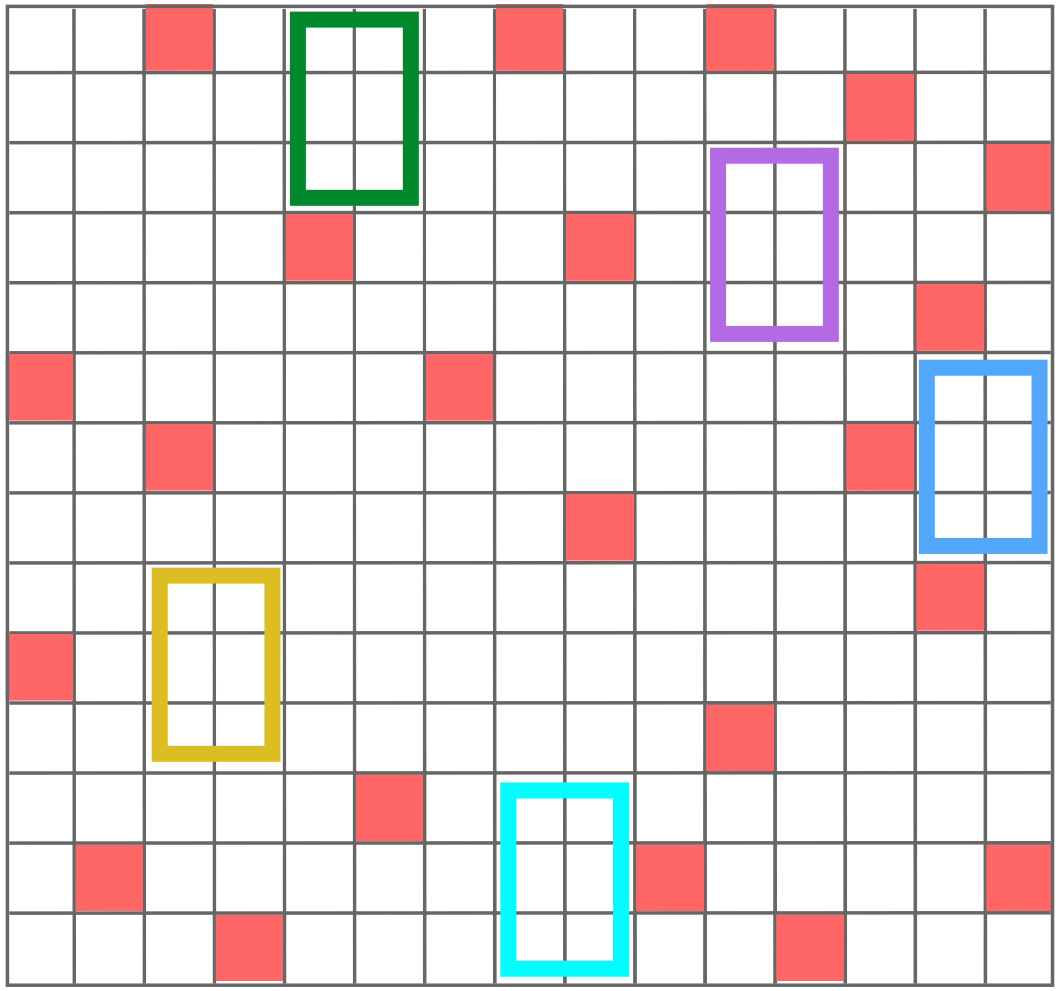
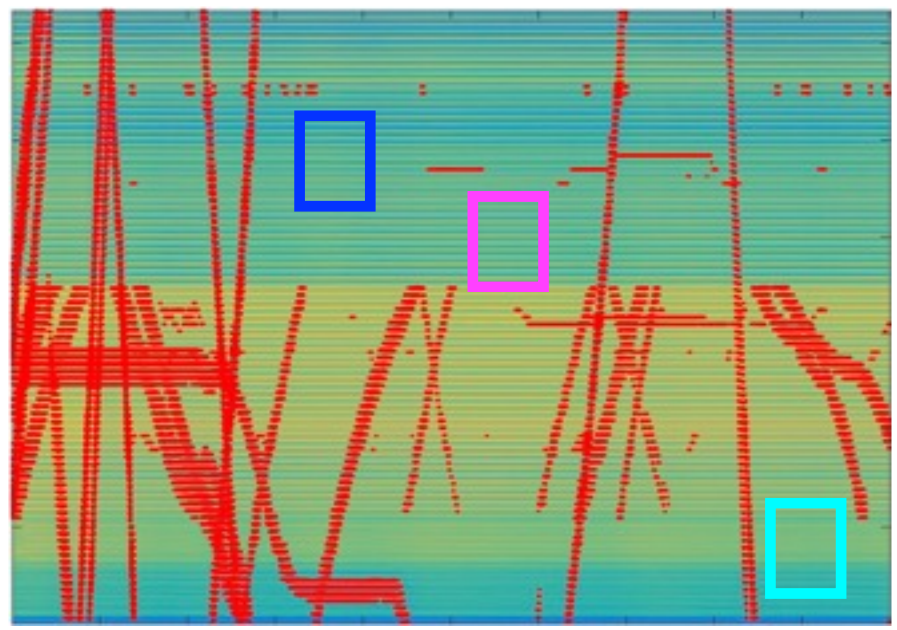


Keep finding uncorrupted projections

If we find *the right projections*, we can find the subspace



Background segmentation

Original Frame | This Work (Pimentel, Nowak, 2017) | RPCA-ALM (RPCA-ALM (Lin et. al, 2011-2016))

In many cases, similar results

Original Frame

This Work

(Pimentel, Nowak, 2017)

RPCA-ALM

RPCA-ALM (Lin et. al, 2011-2016)

In other cases, better

Original Frame

This Work

(Pimentel, Nowak, 2017)

RPCA-ALM

RPCA-ALM (Lin et. al, 2011-2016)

In other cases, better

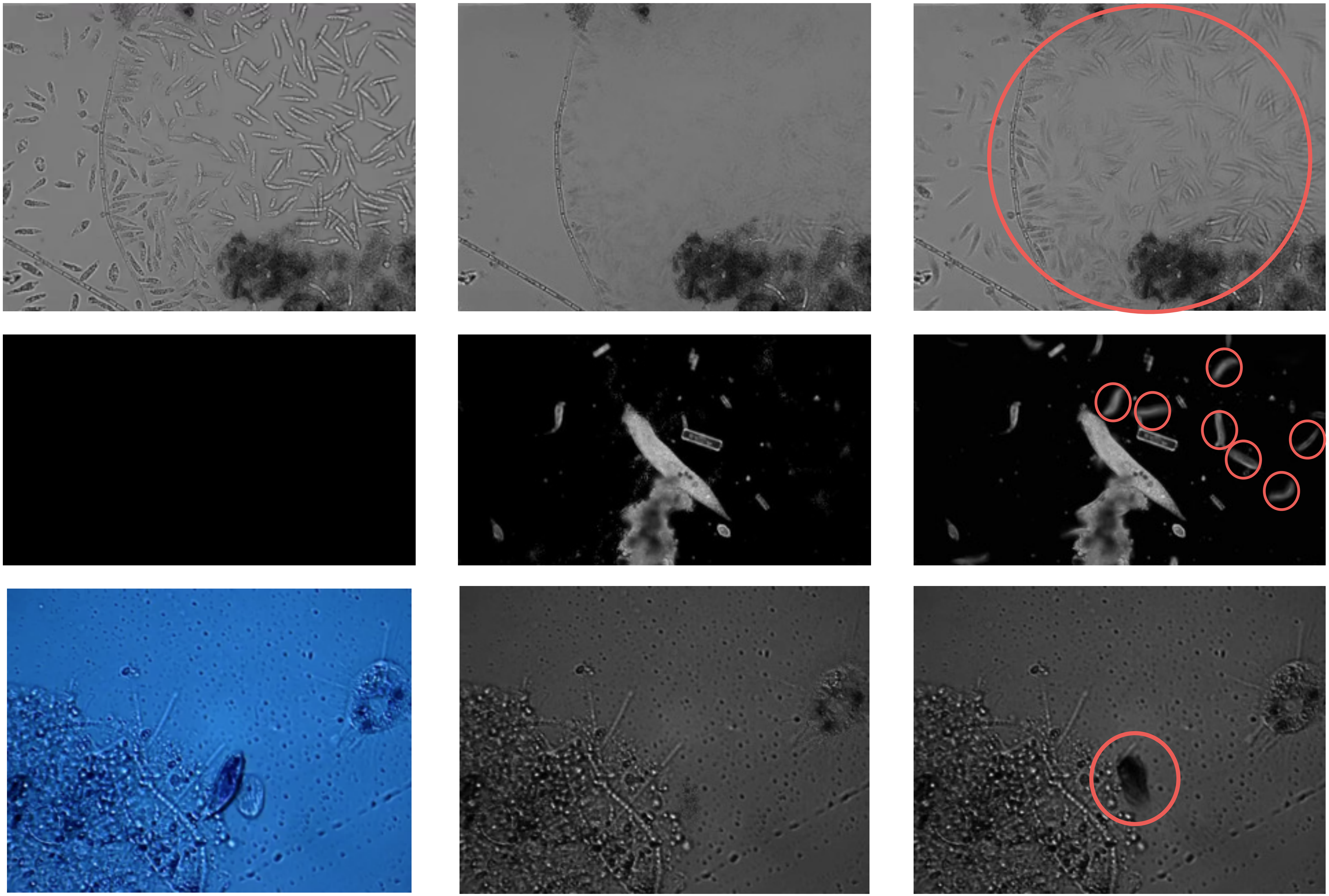
Original Video

This Work

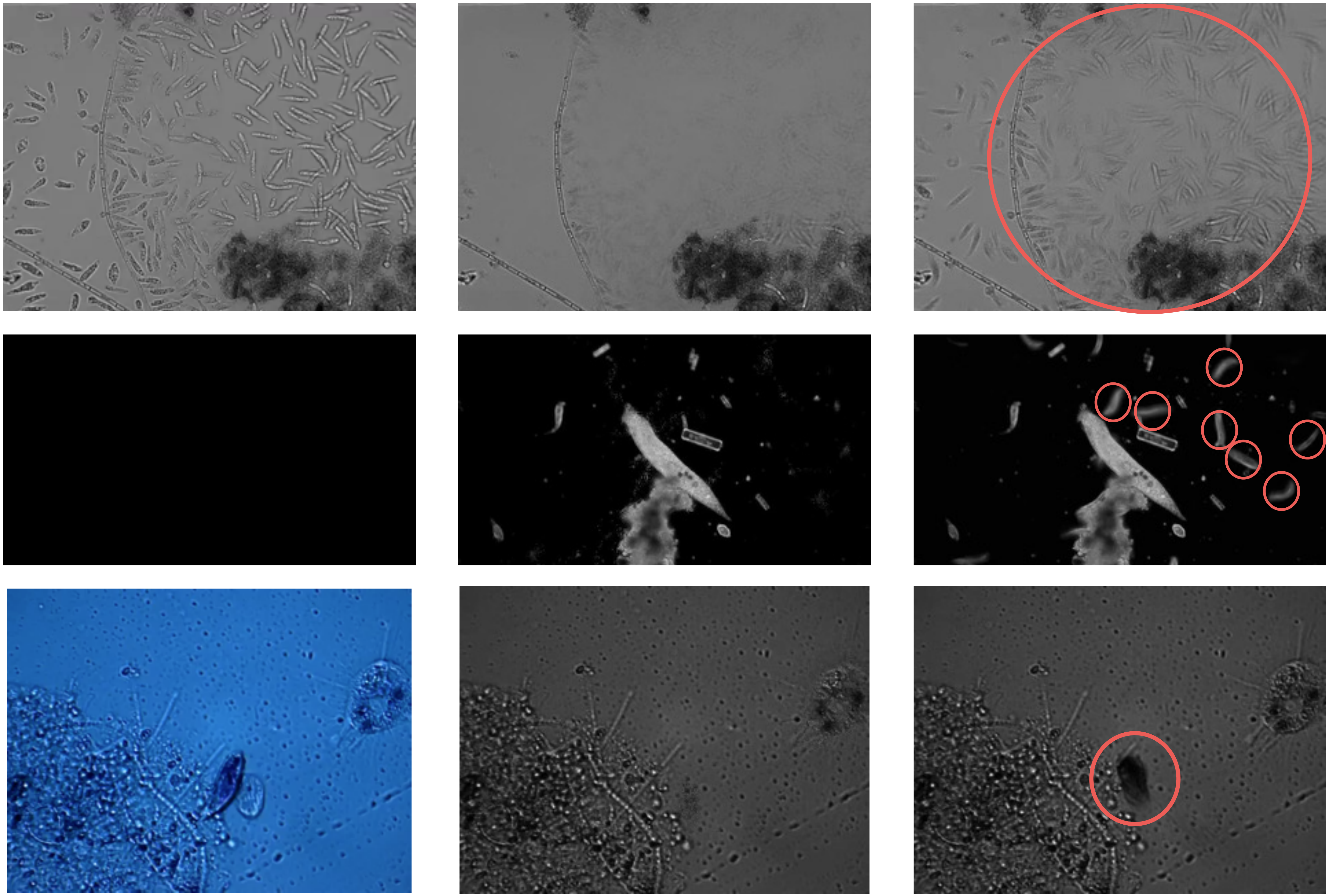
(Pimentel, Nowak, 2017)

RPCA-ALM

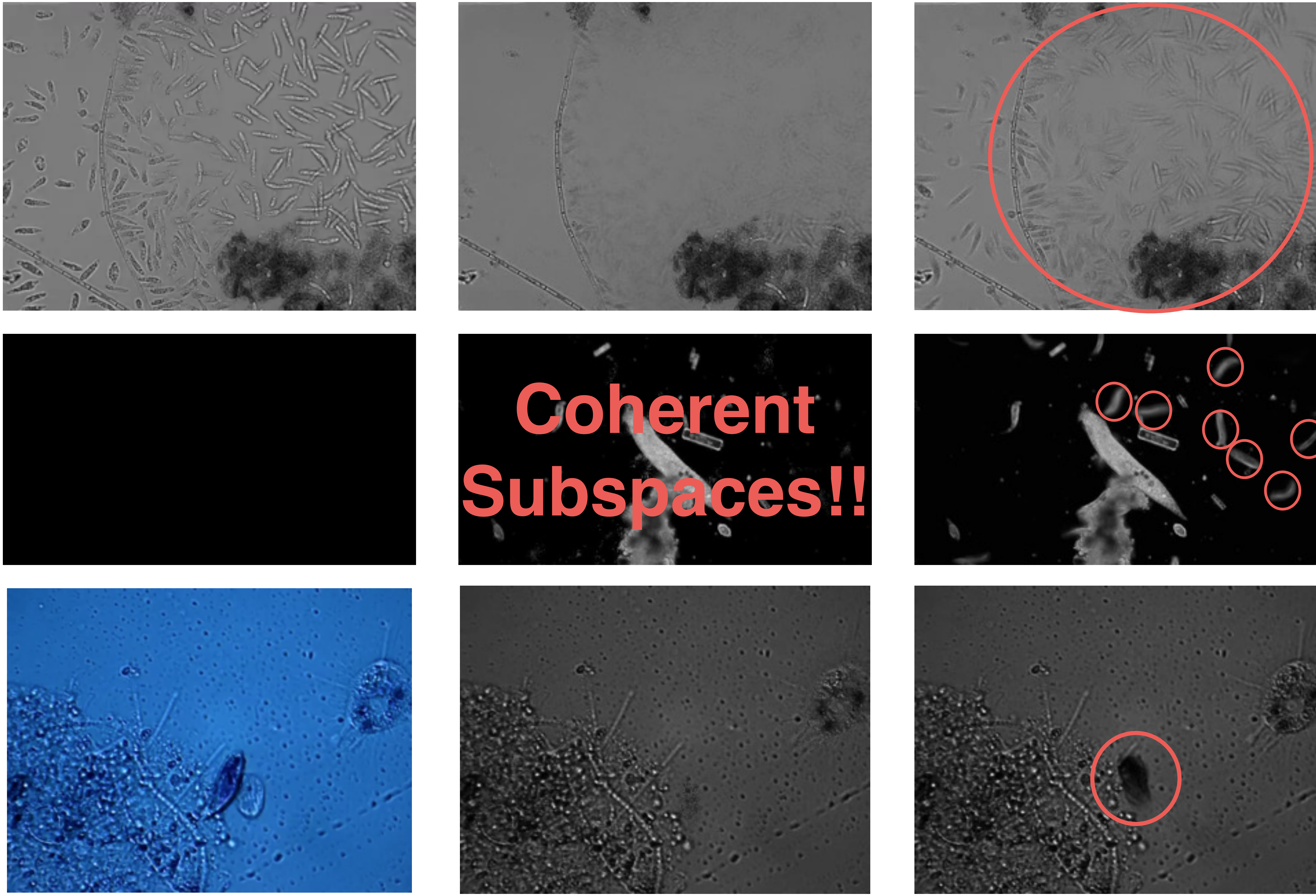
RPCA-ALM (Lin et. al, 2011-2016)



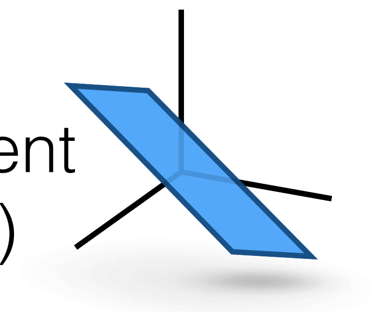
Original Video | This Work (Pimentel, Nowak, 2017) | RPCA-ALM RPCA-ALM (Lin et. al, 2011-2016)

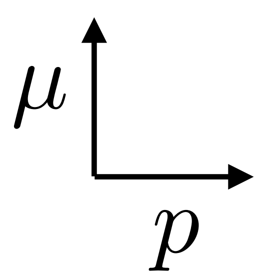


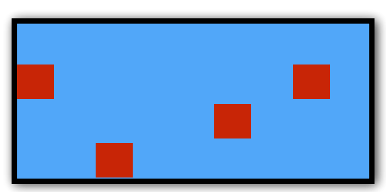
Original Video | This Work (Pimentel, Nowak, 2017) | RPCA-ALM RPCA-ALM (Lin et. al, 2011-2016)



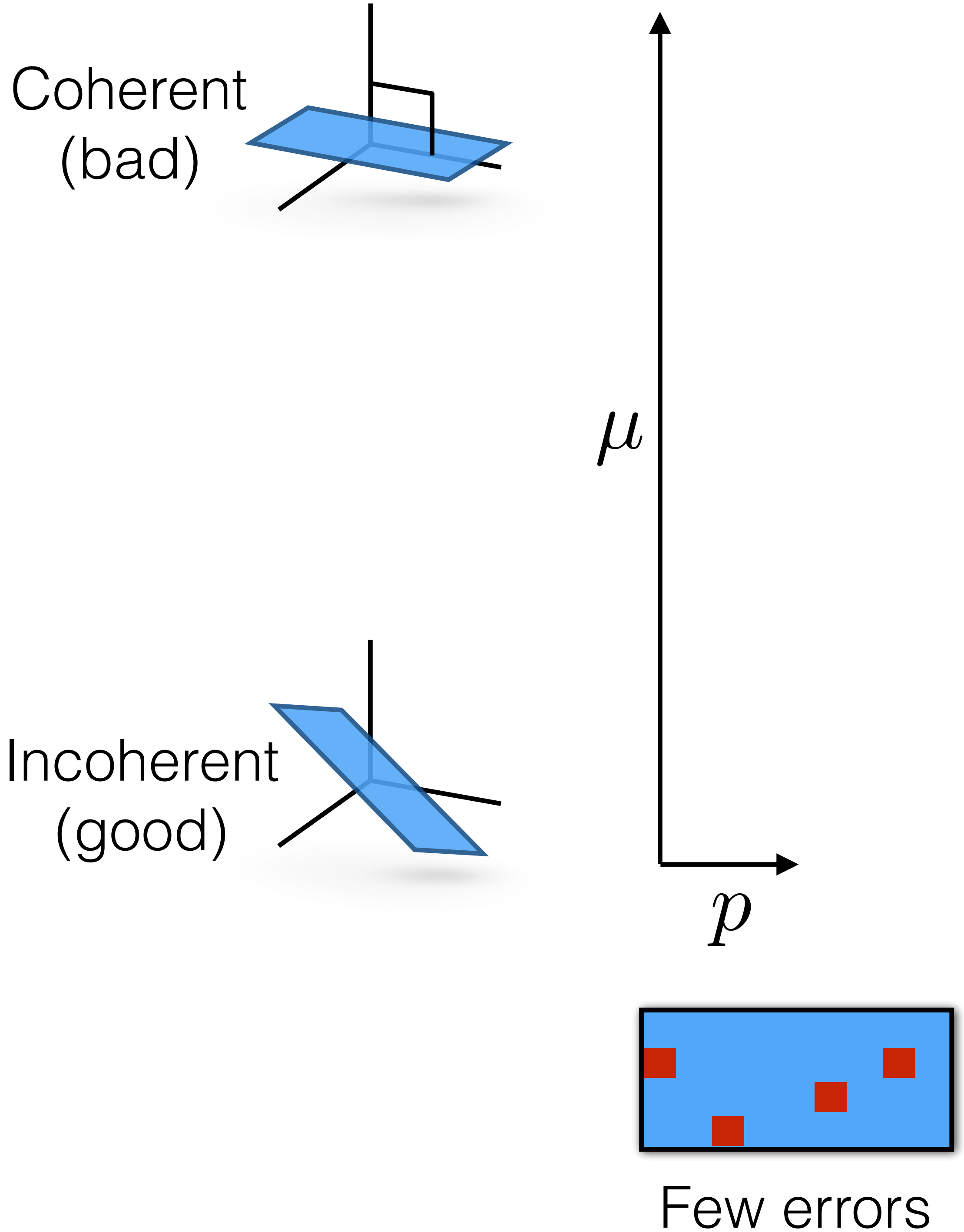
Incoherent
(good)



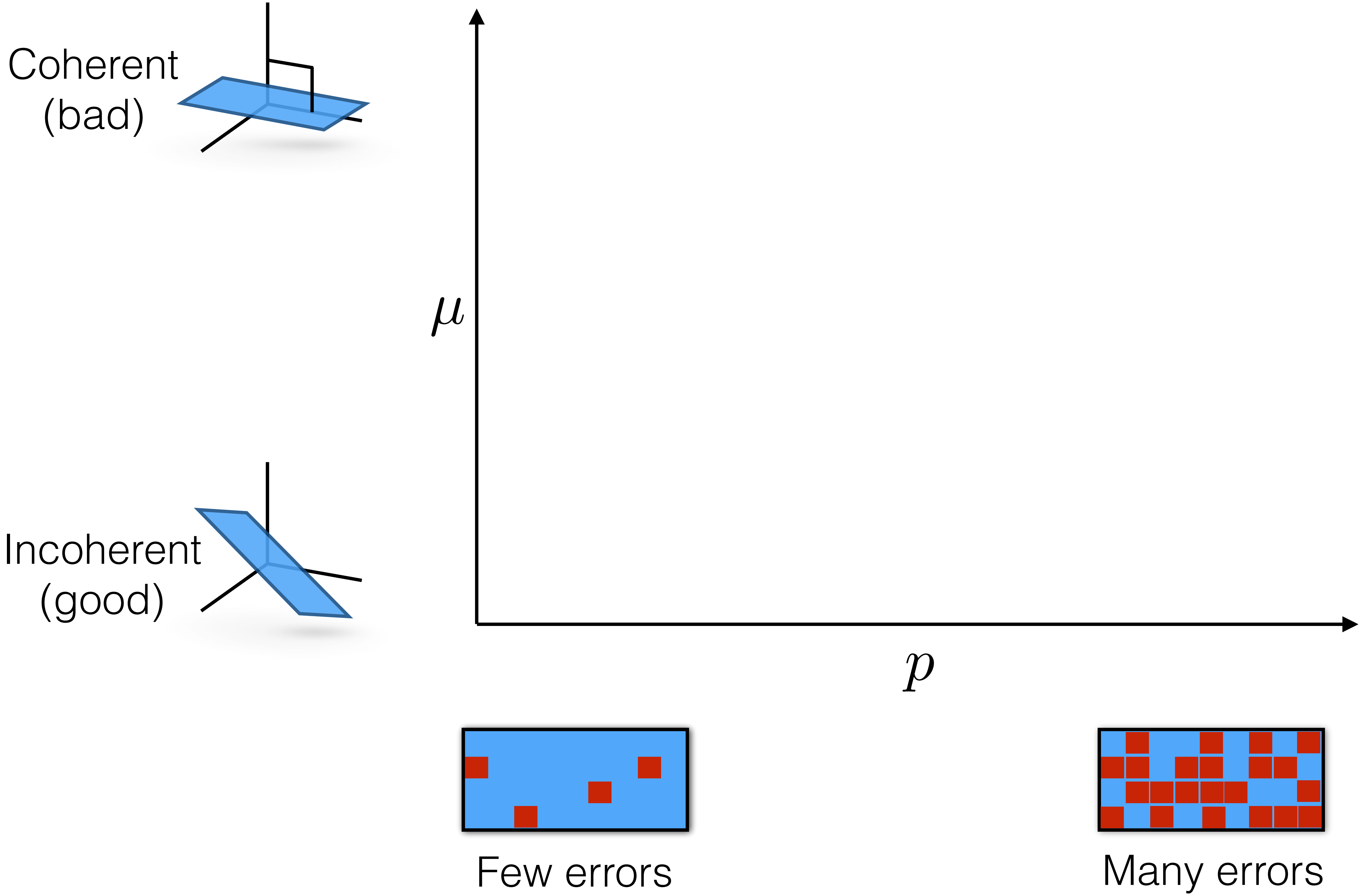




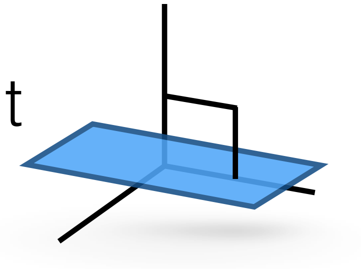
Performance Analysis

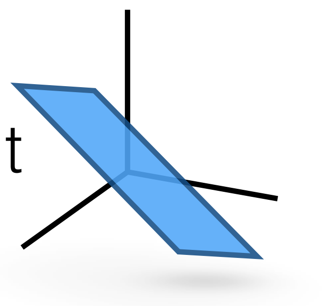


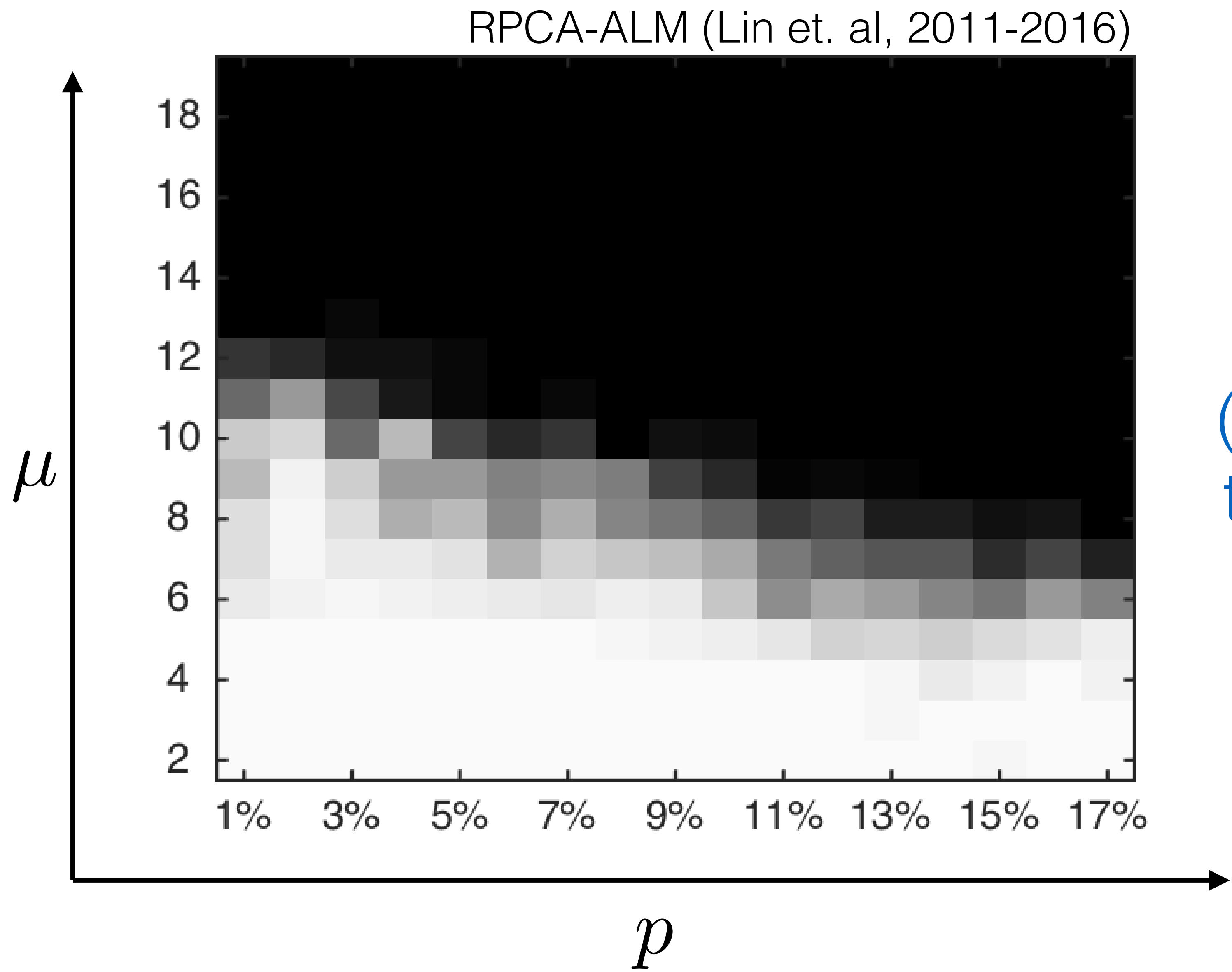
Performance Analysis



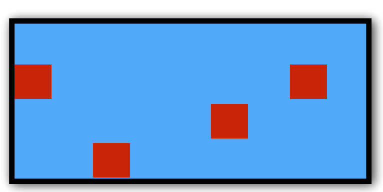
Performance Analysis



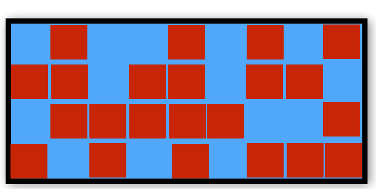




(the lighter the better)



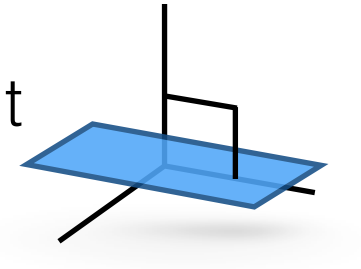
Few errors



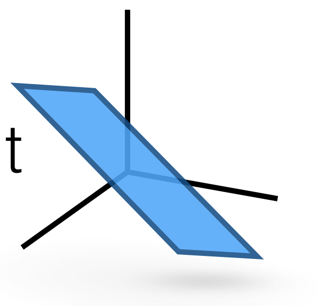
Many errors

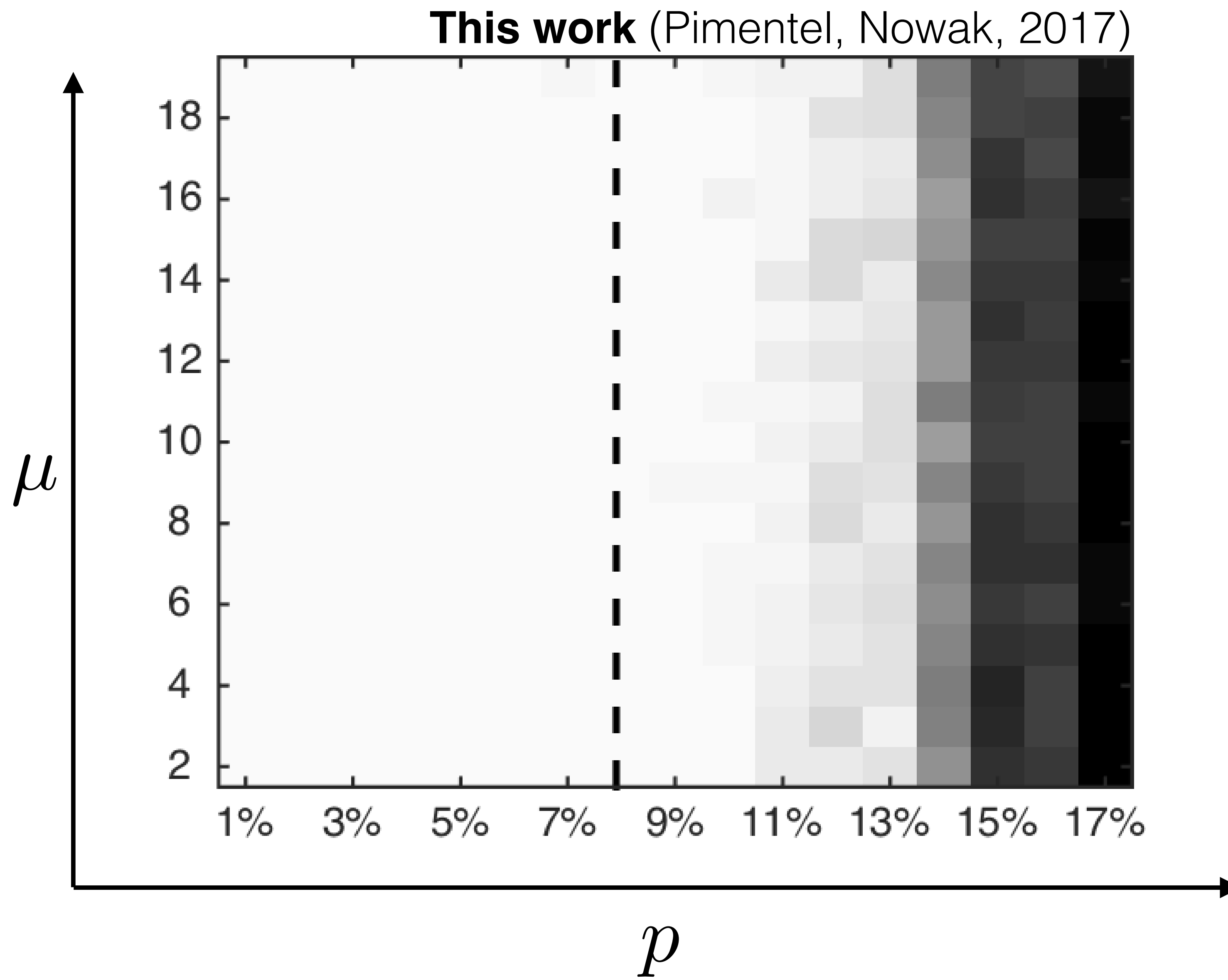
Performance Analysis

Coherent
(bad)



Incoherent
(good)





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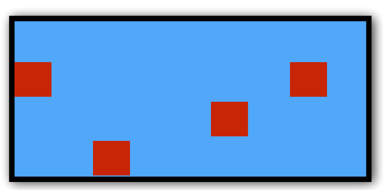
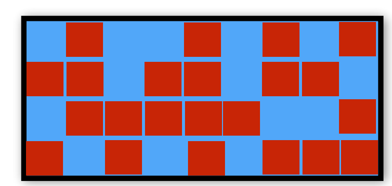


Few errors



Many errors

Performance Analysis

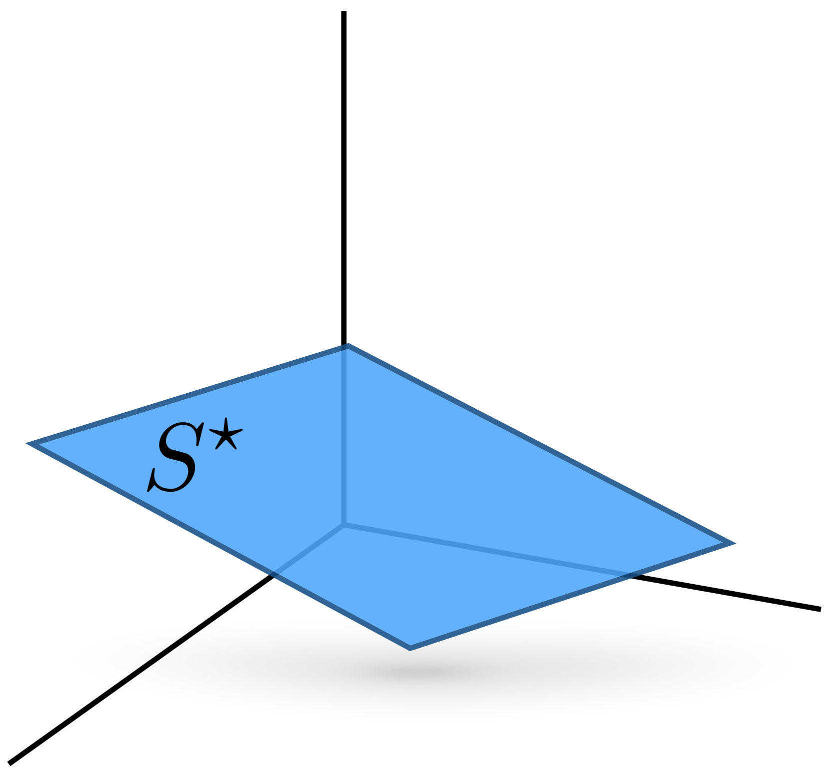
We can find the subspace,
and fast, **unless**
there are too many errors

Our main result in a nutshell

Pimentel, Nowak, AISTATS, 2017

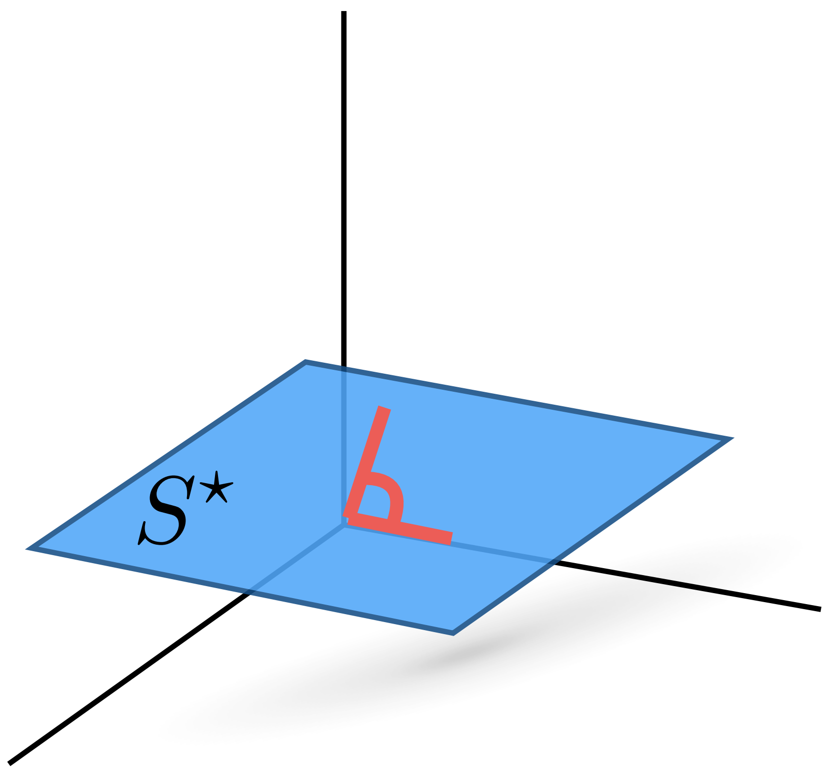

WOW, AMAZING
PLEASE TELL
ME MORE

S^* = r-dimensional subspace in general position.



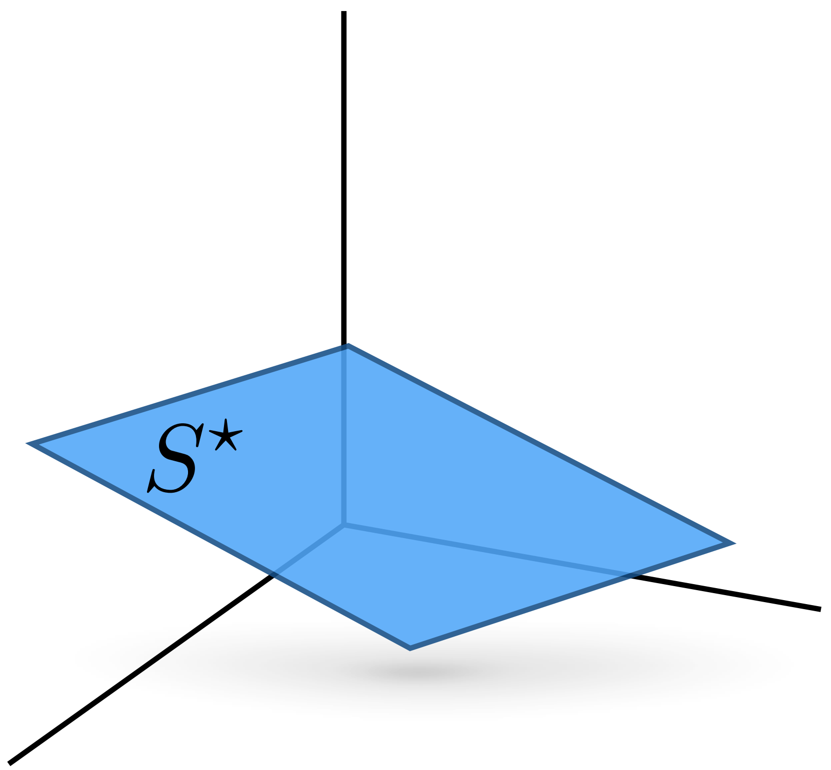
Assumptions

S^* = r-dimensional subspace in general position.



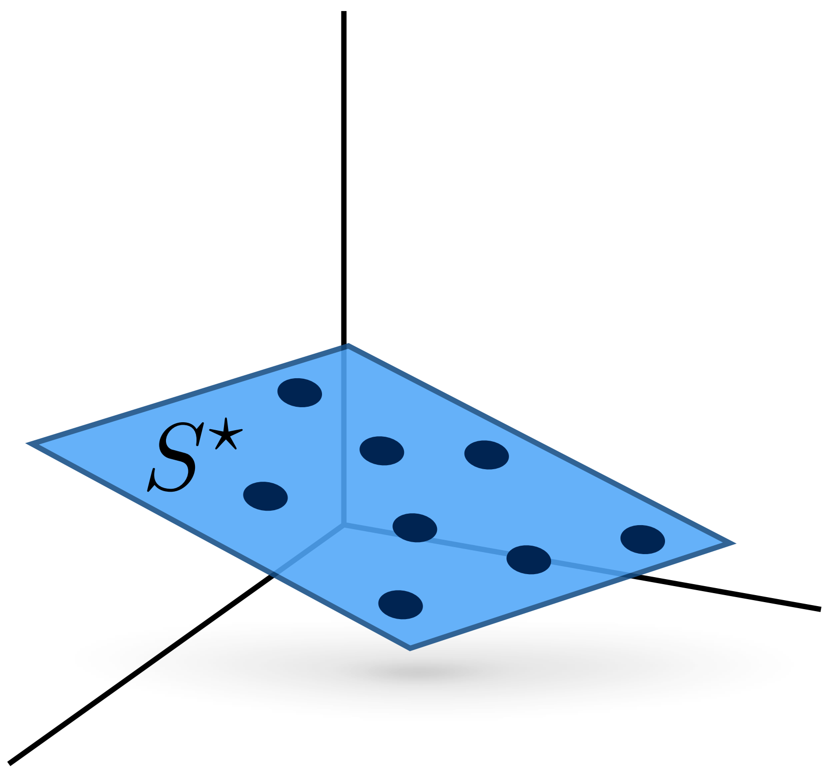
Assumptions

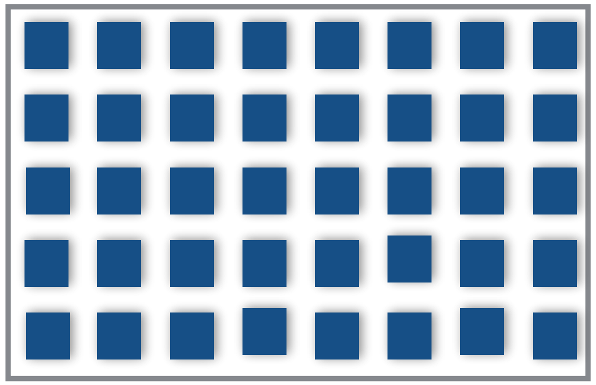
$S^\star$ = r-dimensional subspace in general position.



Assumptions

S^* = r-dimensional subspace in general position.

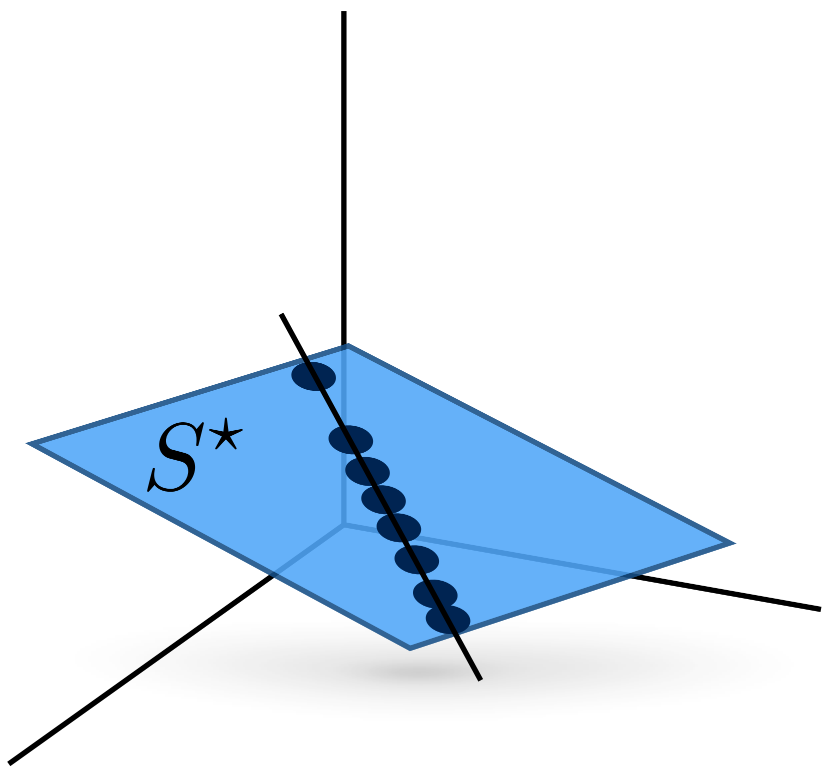


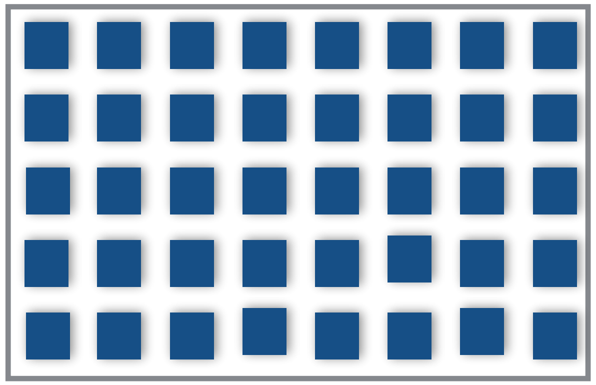


Columns lie in S^* generically.

Assumptions

S^* = r-dimensional subspace in general position.





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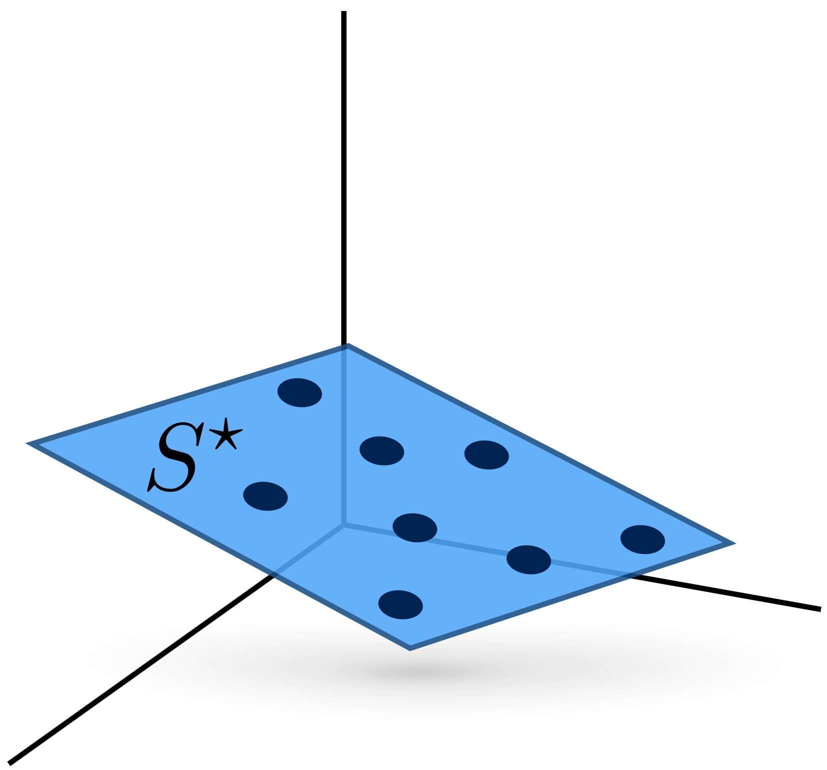
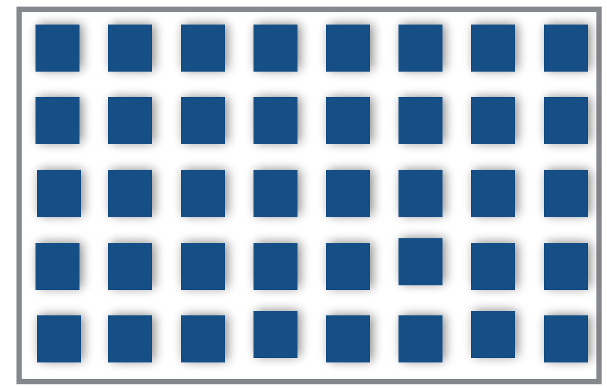
Assumptions

S^* = r-dimensional subspace in general position.





Columns lie in S^* generically.

Assumptions

Take-home Message

- New (algebraic) method for Robust PCA.
- Arbitrary (non-uniform, even adversarial) sparsity patterns.
- No coherence assumptions.

Rob Nowak

Nigel Boston

Joint work with:

Thank you!