Dipartimento Politecnico
di Ingegneria e Architettura

Multiple structures recovery

an application to scan2BIM

14th may 2018
Udine

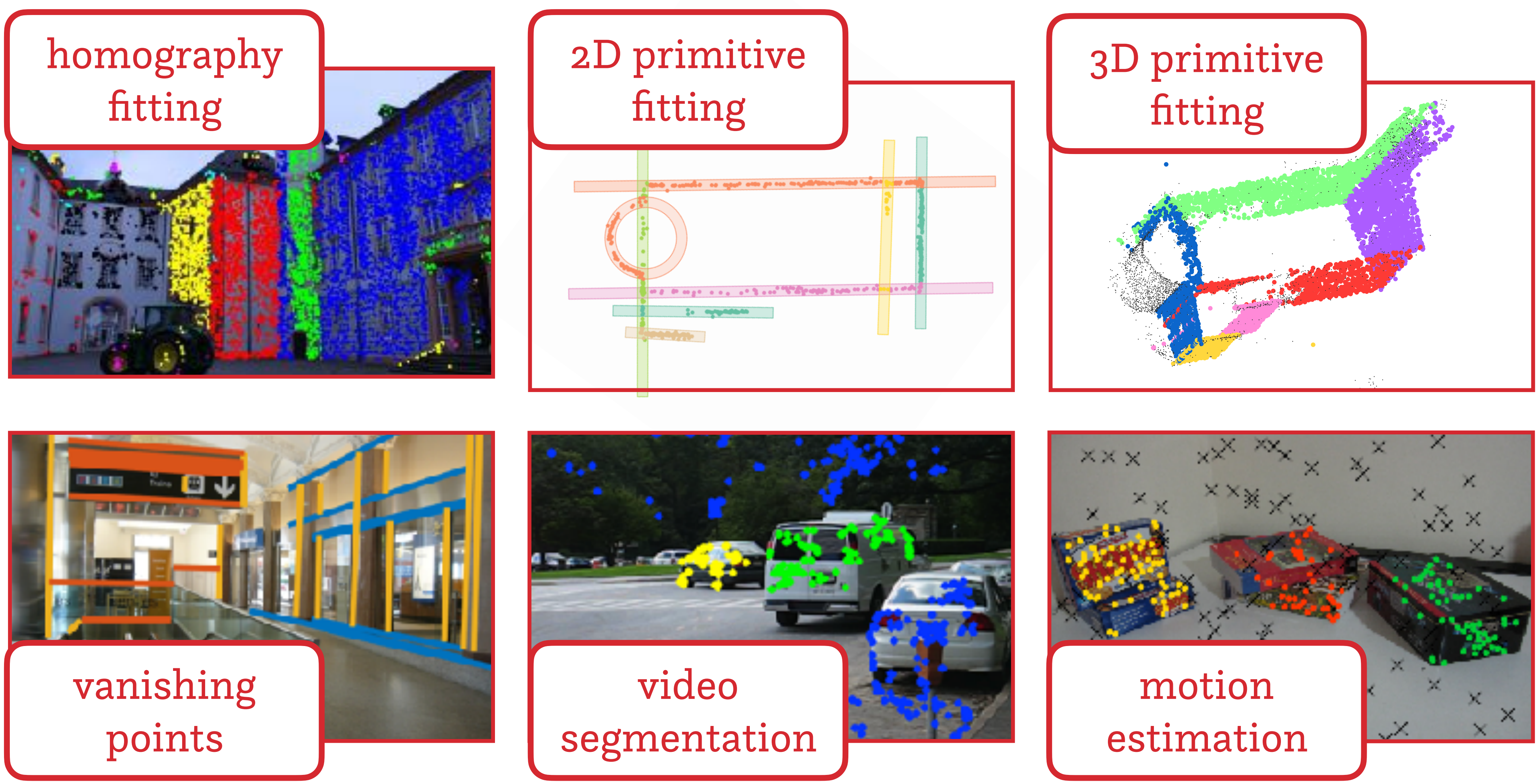
joint work with Andrea Fusiello

UNIVERSITÀ DEGLI STUDI DI UDINE
3DFLOW

The challenges of multi-structure recovery

Fitting multiple instances of a mathematical parametric model – also called "structures" – to measured data, which are invariably contaminated by noise and outliers.

- outliers
- pseudo-outliers
- chicken-&-egg-dilemma
- ill-posed



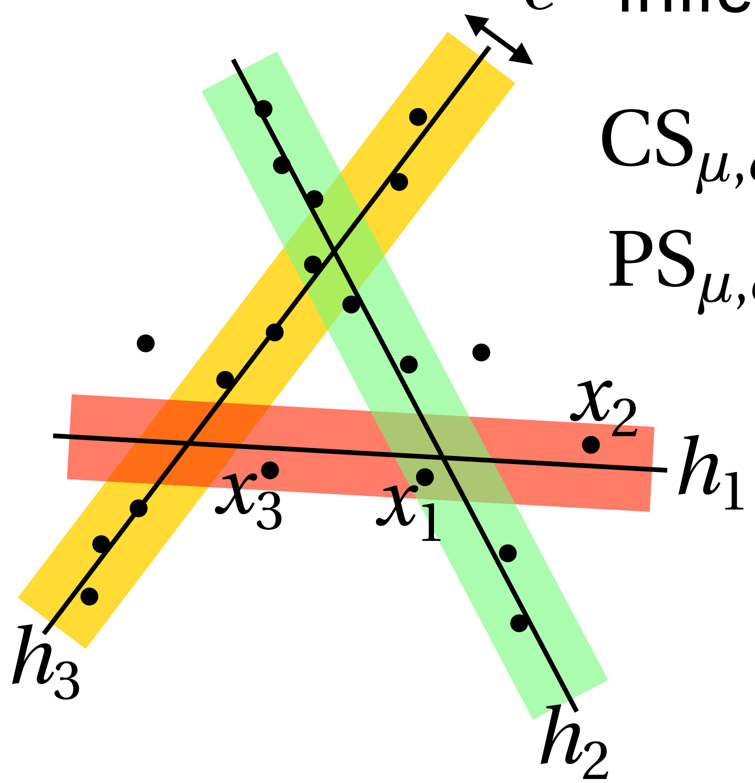
The setup

X data space

H pool of tentative structures

$\mathrm{err}_\mu : X \times H \longrightarrow \mathbb{R}$ residual point-structure

ϵ inlier threshold



$\mathrm{CS}_{\mu,\epsilon}(h_1) = \{x_1, x_2, x_3\}$

$\mathrm{PS}_{\mu,\epsilon}(x_1) = \{h_1, h_2\}$

Consensus set

the points supporting a given structure

$x : \mathrm{err}_\mu(x, h) \leq \epsilon$

Preference set

the structures describing a given point

$h : \mathrm{err}_\mu(x, h) \leq \epsilon$

Consensus Analysis

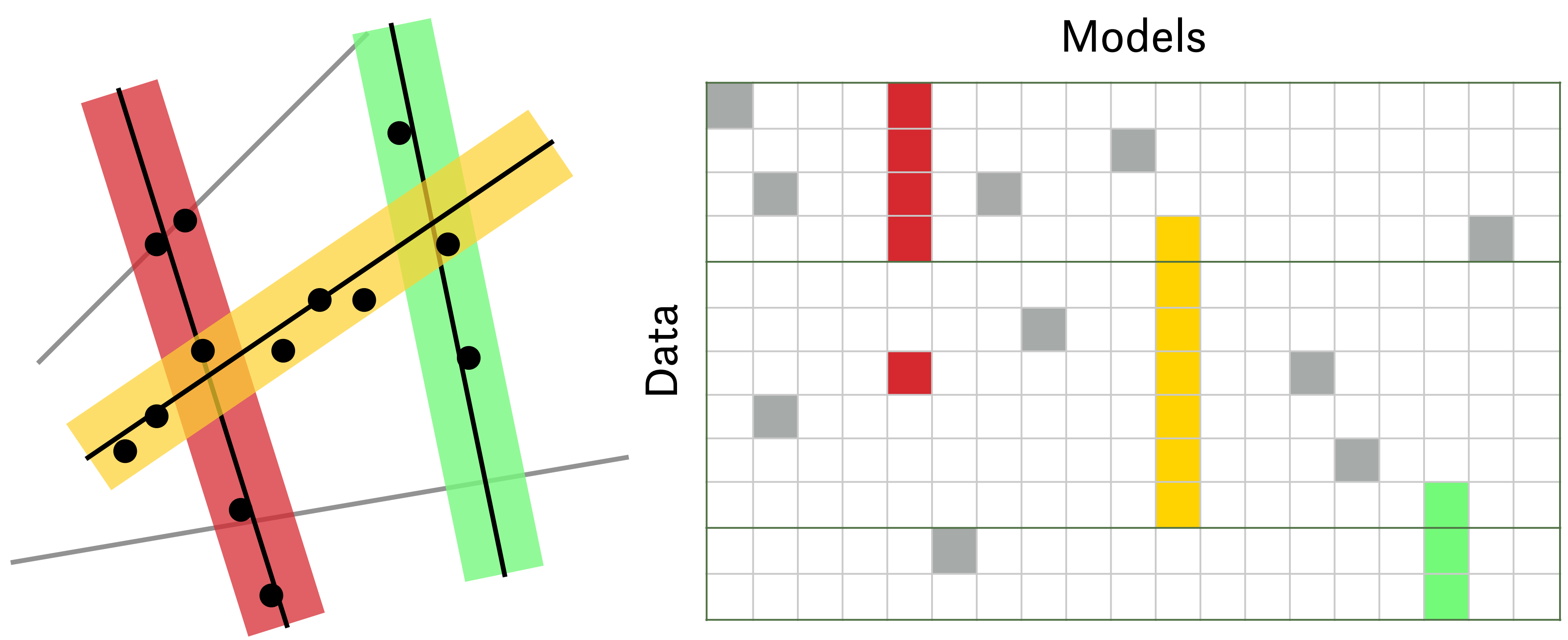
emphasis on model estimation

- Ransac & variants
- Sequential Ransac
- Multi-Ransac
- Hough Transform
- Ransacov

Preference Analysis

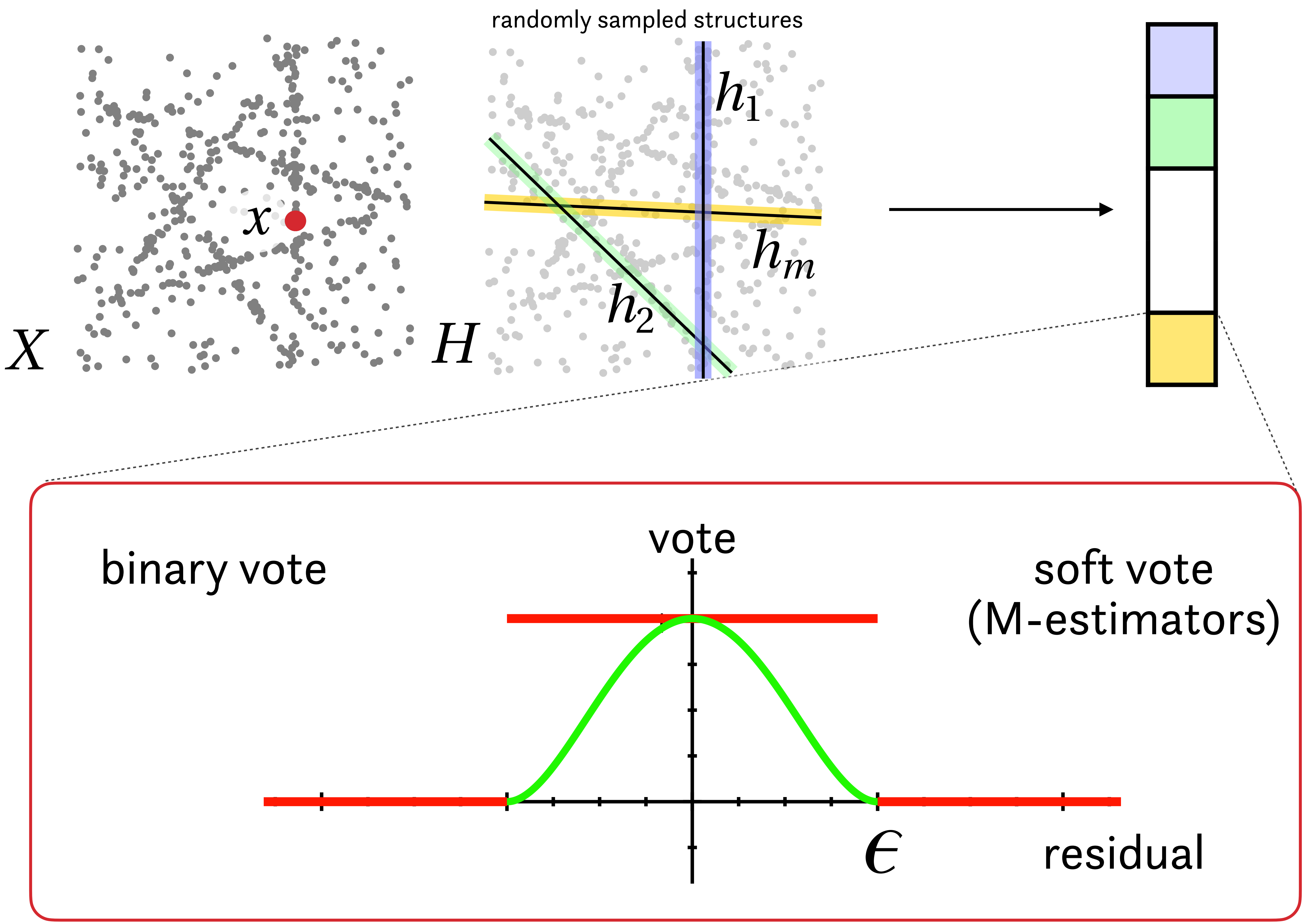
emphasis on segmentation

- Residual Histogram Analysis
- J-Linkage and T-Linkage
- Kernel Methods
- Higher order clustering
- Robust Preference Analysis



Consensus/Preference Matrix

First represent....



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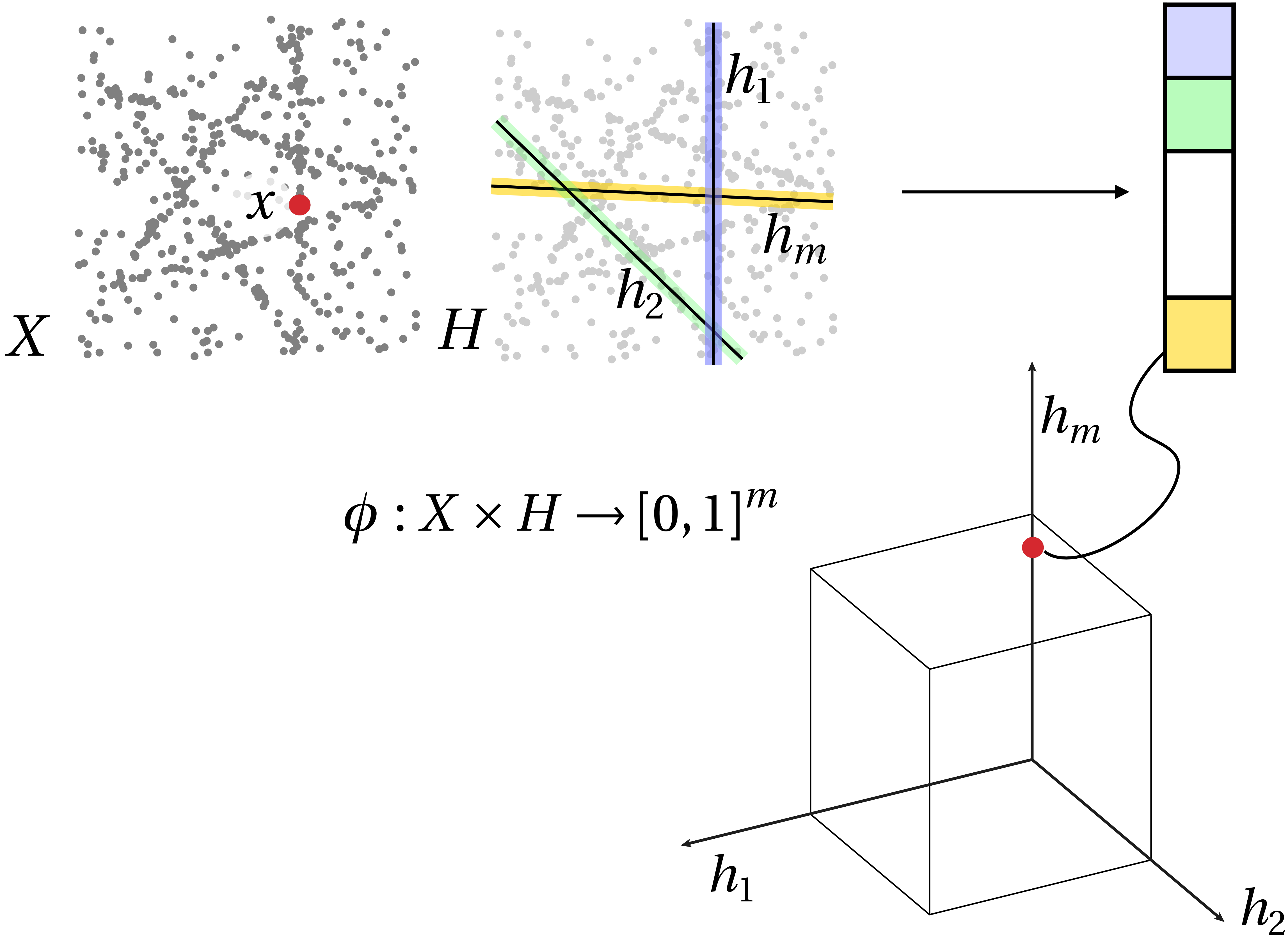
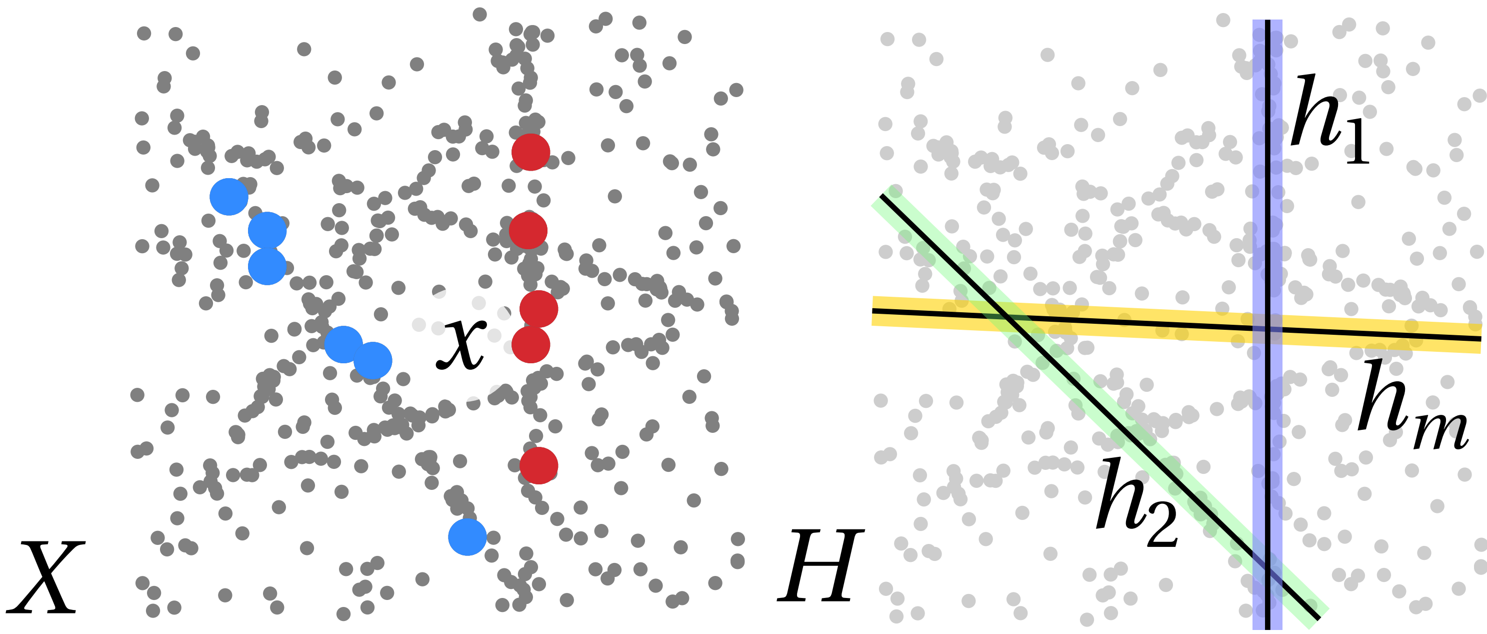
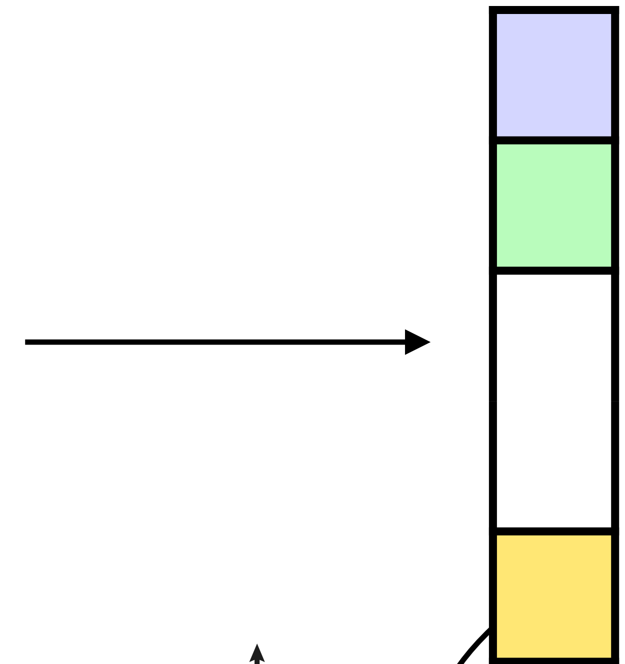


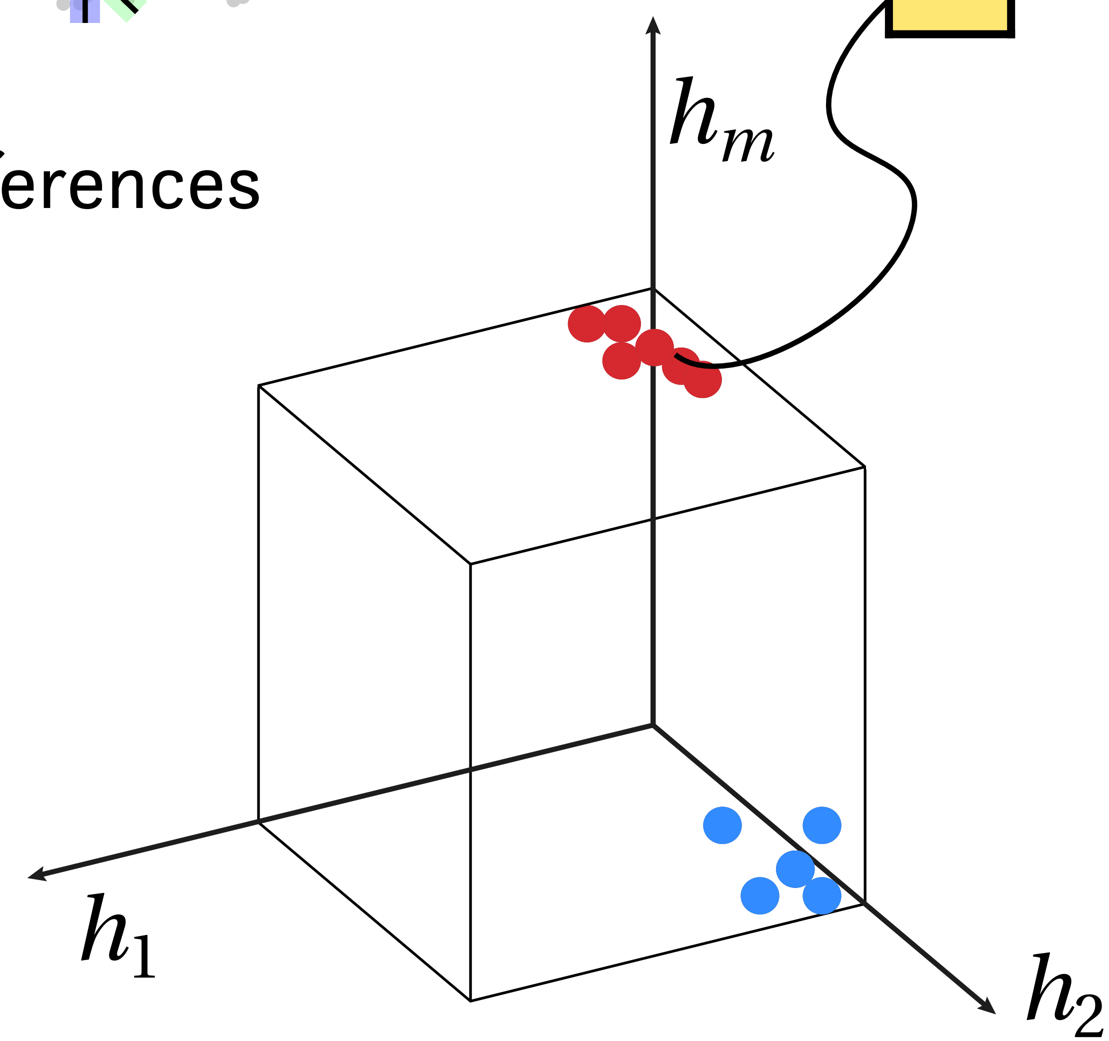
$$\phi : X \times H \longrightarrow [0,1]^m$$

First represent....



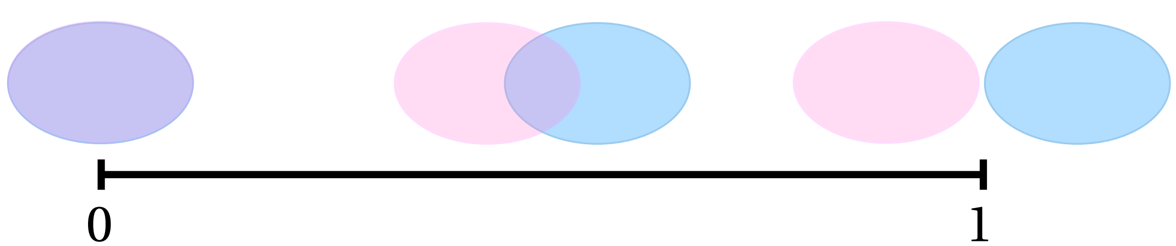


measure agreement between preferences



Jaccard distance

$$d_J(p,q) = 1 - \frac{|p \cap q|}{|p \cup q|}$$



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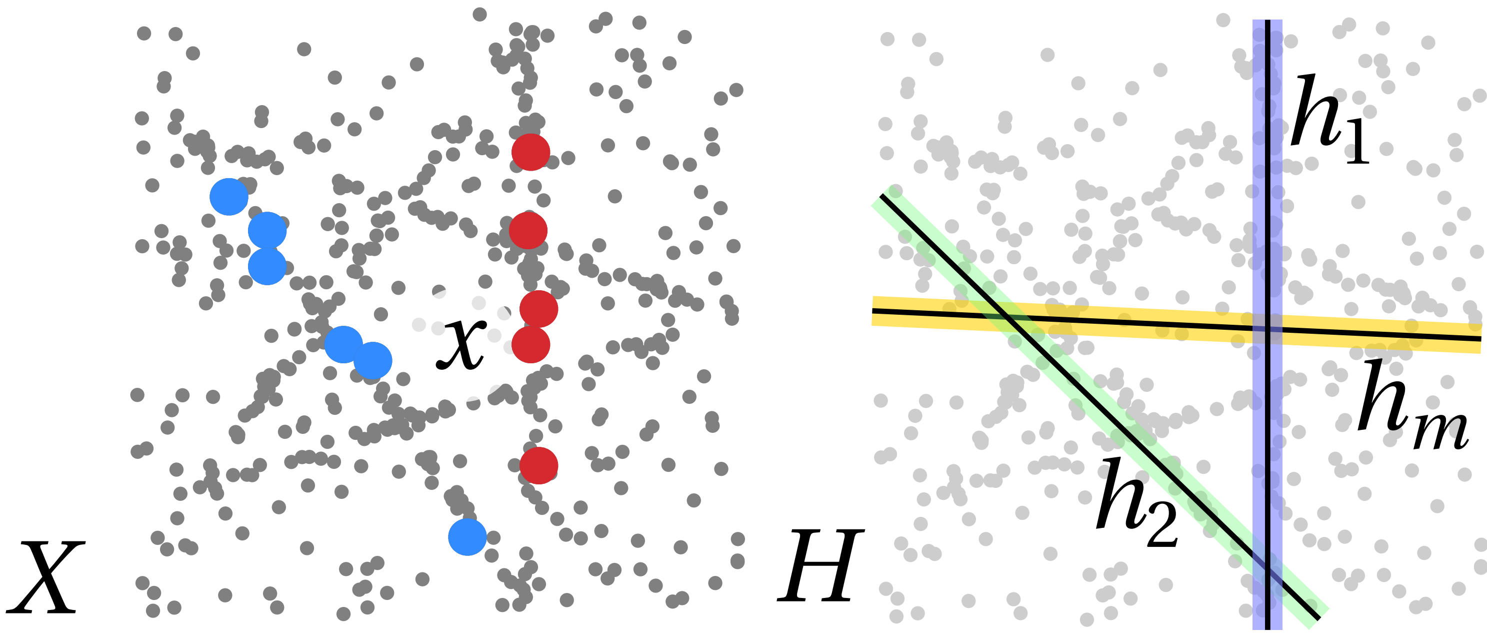
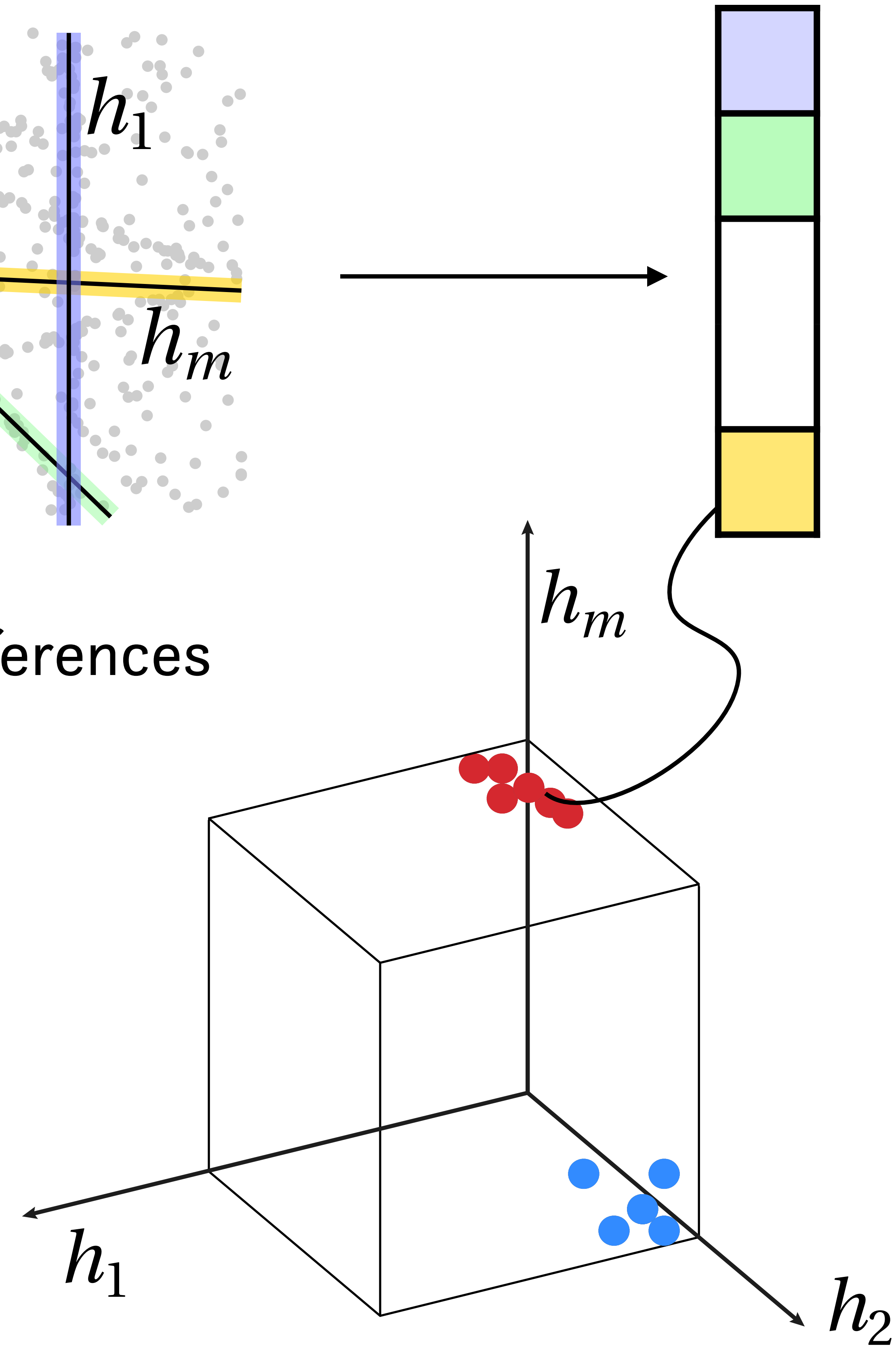




measure agreement between preferences

Tanimoto distance

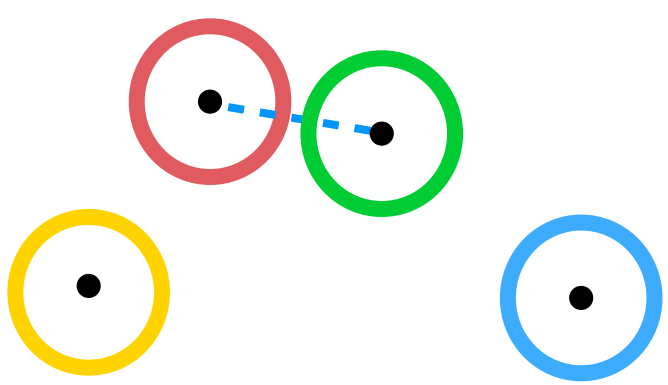
$$d_{\mathscr{T}}(p,q) = 1 - \frac{\langle p,q\rangle}{\|p\|^2 + \|q\|^2 - \langle p,q\rangle}$$

when votes are soft

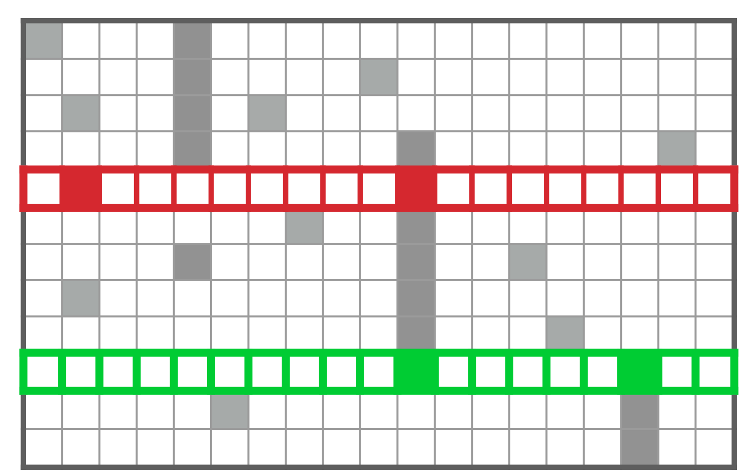
... then clusterize

- Bottom-up hierarchical clustering in the preference space
- The preferences of a cluster are:
  - the intersection of the preference set if votes are binary (J-linkage)
  - the component-wise minimum of the preference vectors if votes are soft (T-linkage)
- Preferences of clusters are merged until they are orthogonal
- The number of structure is automatically determined

put each point in its own cluster



find the closest cluster
w.r.t Tanimoto/Jaccard



... then clusterize

- Bottom-up hierarchical clustering in the Tanimoto space
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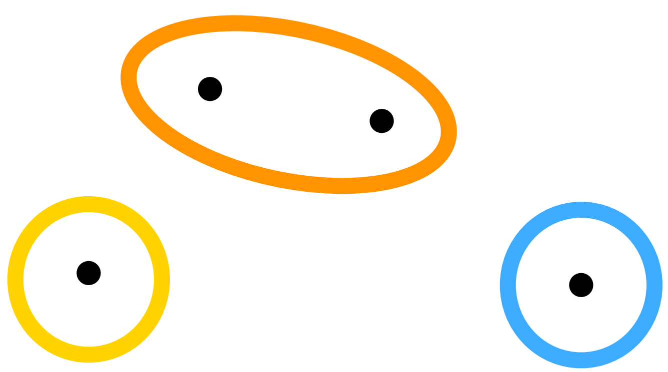
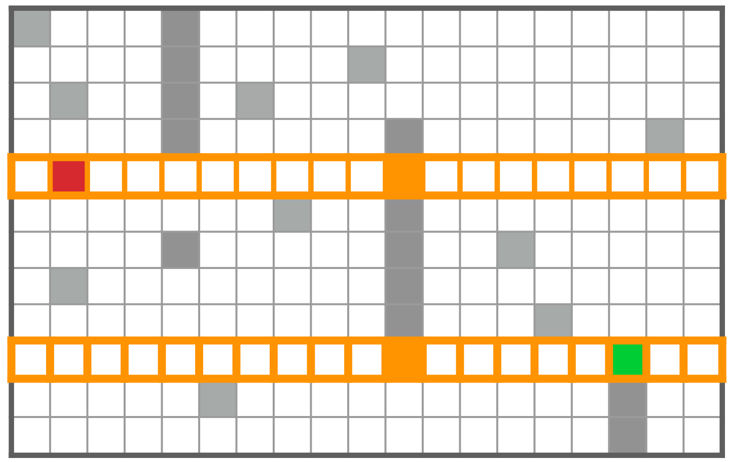
merge the cluster





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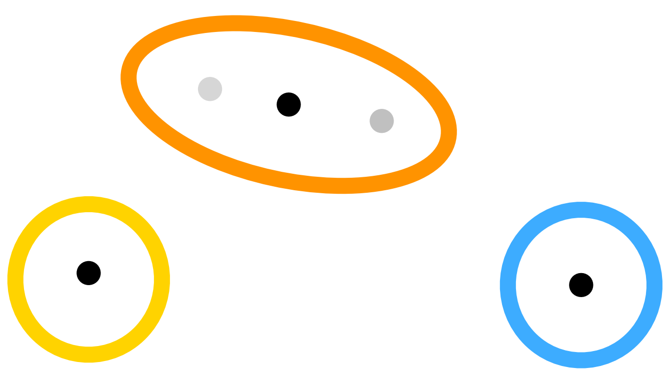
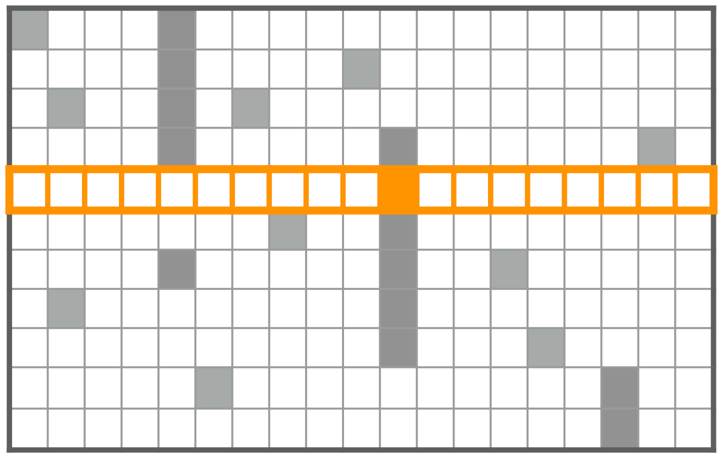




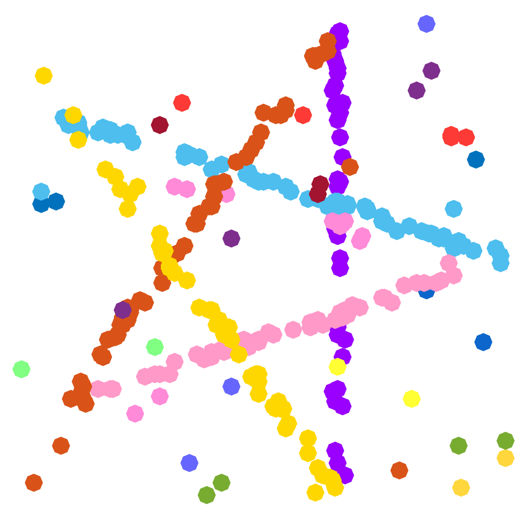
update the preference

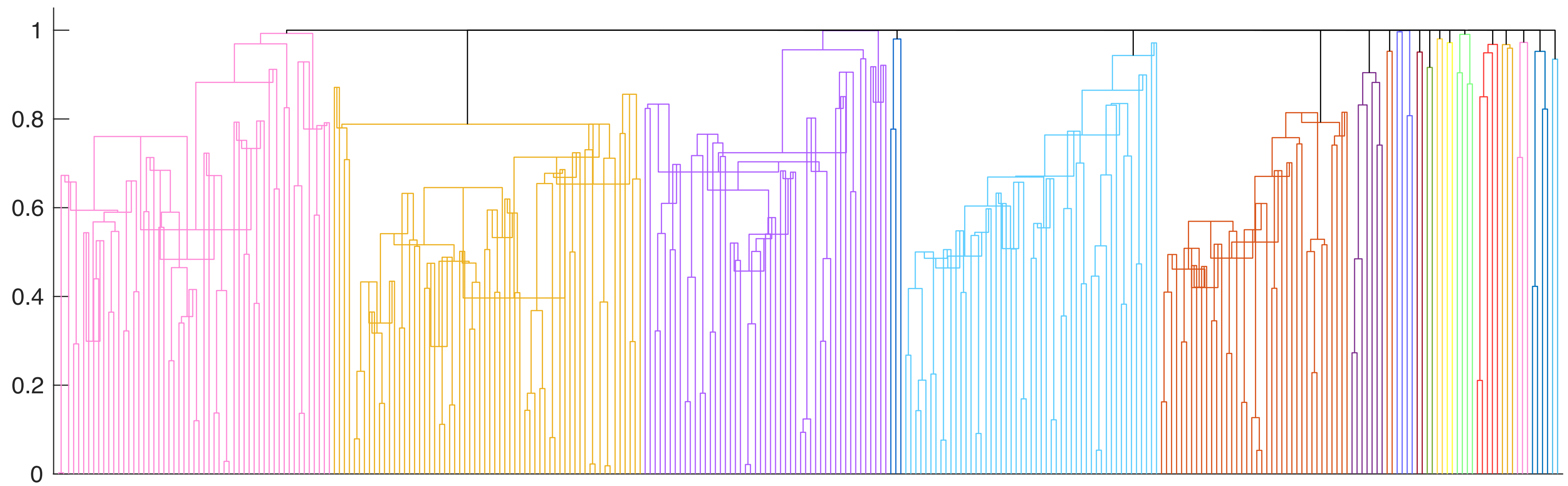
update distances

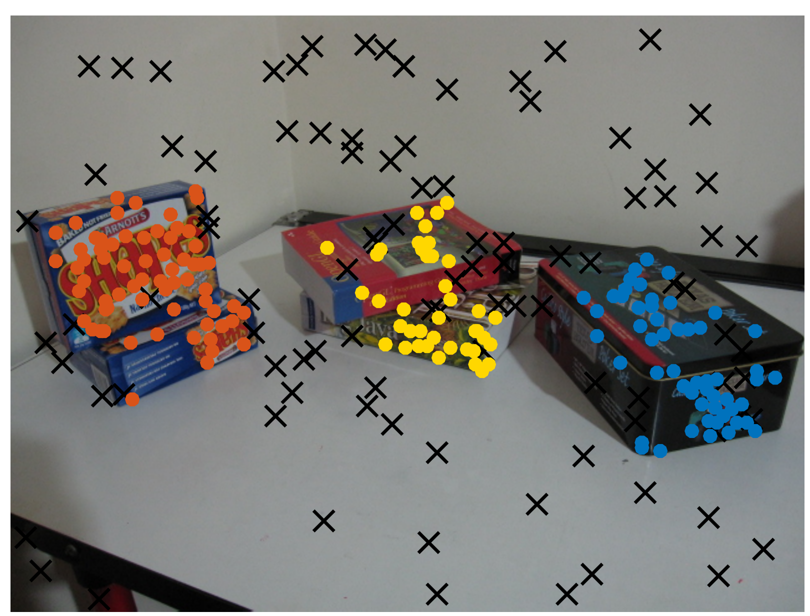
Robustness to outliers

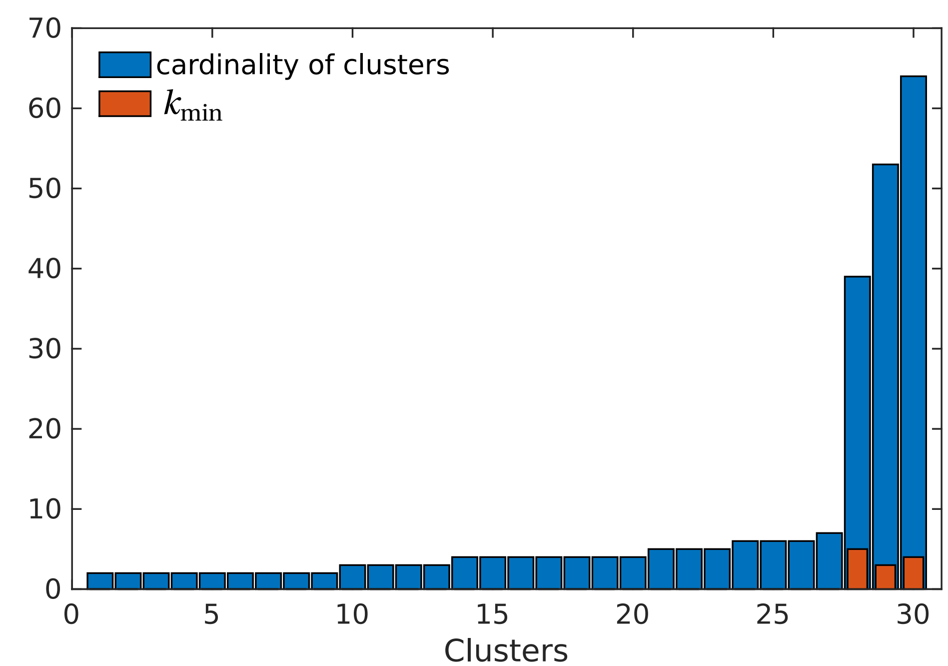
Outliers are:

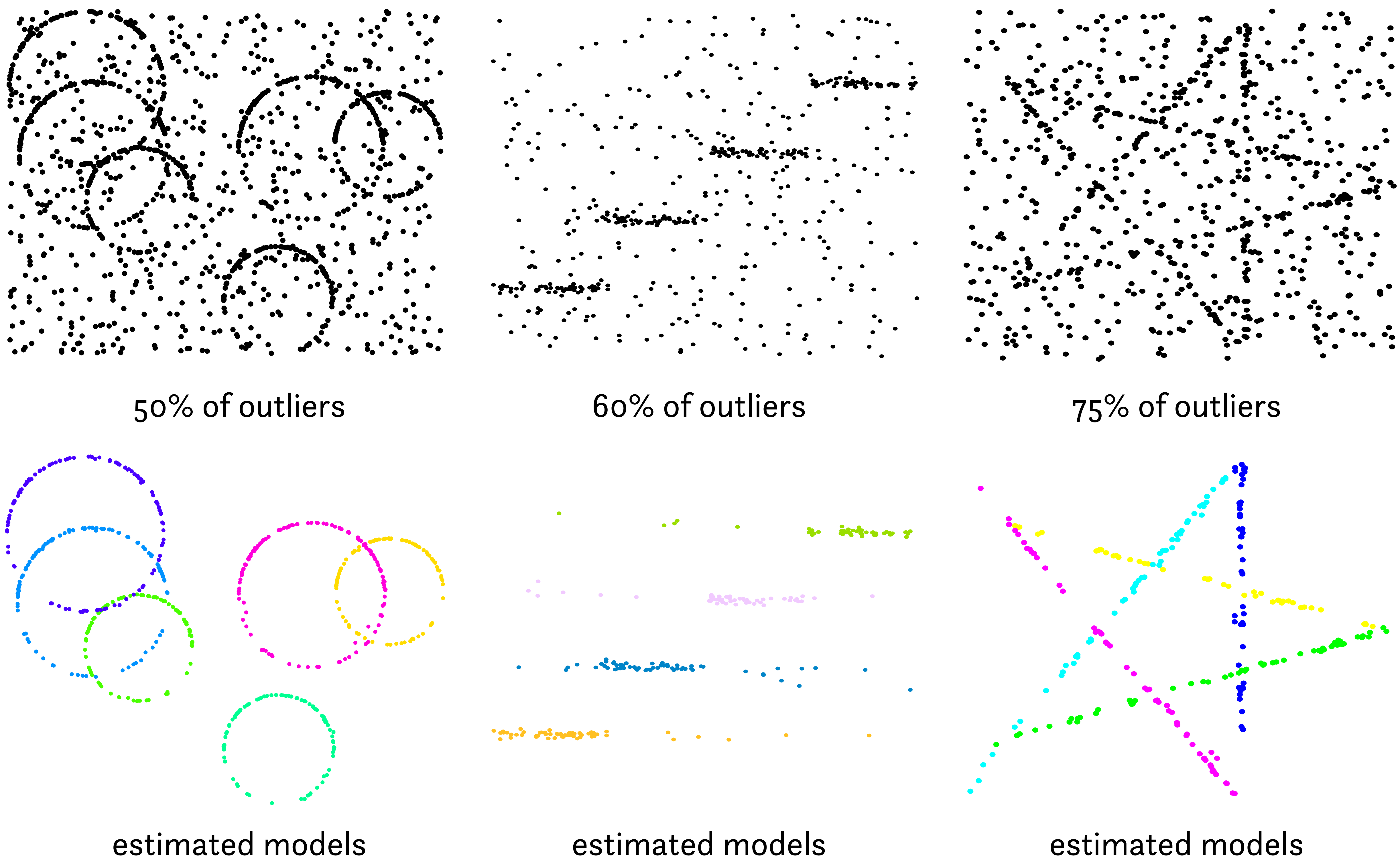
- sparse and well separate in the preference space
- tend to be merged in later stages of the clustering
- emerge as micro-clusters and can be pruned out with ad hoc post-processing.



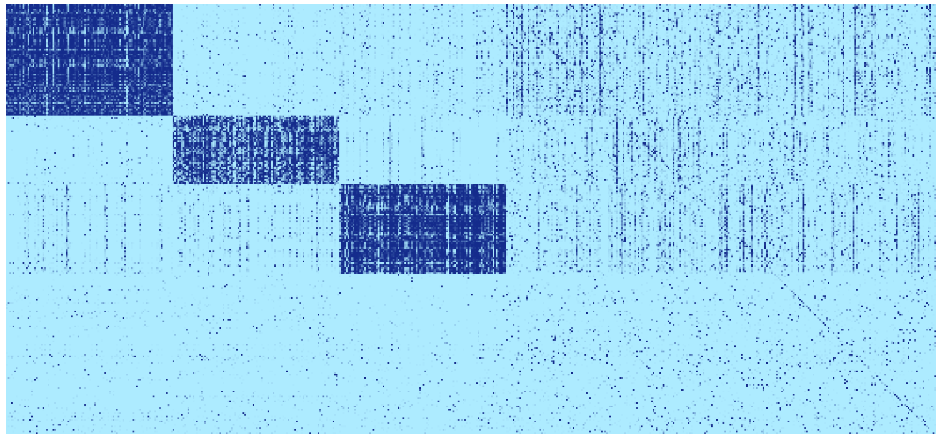







50% of outliers
60% of outliers
75% of outliers
estimated models
estimated models
estimated models

Other solutions explored



preference matrix

Linkage

- automatic number of models
- greedy clustering

Matrix factorization

- Low Rank & sparse decomposition + Non-Negative Matrix Factorization
- requires the number of models in advance

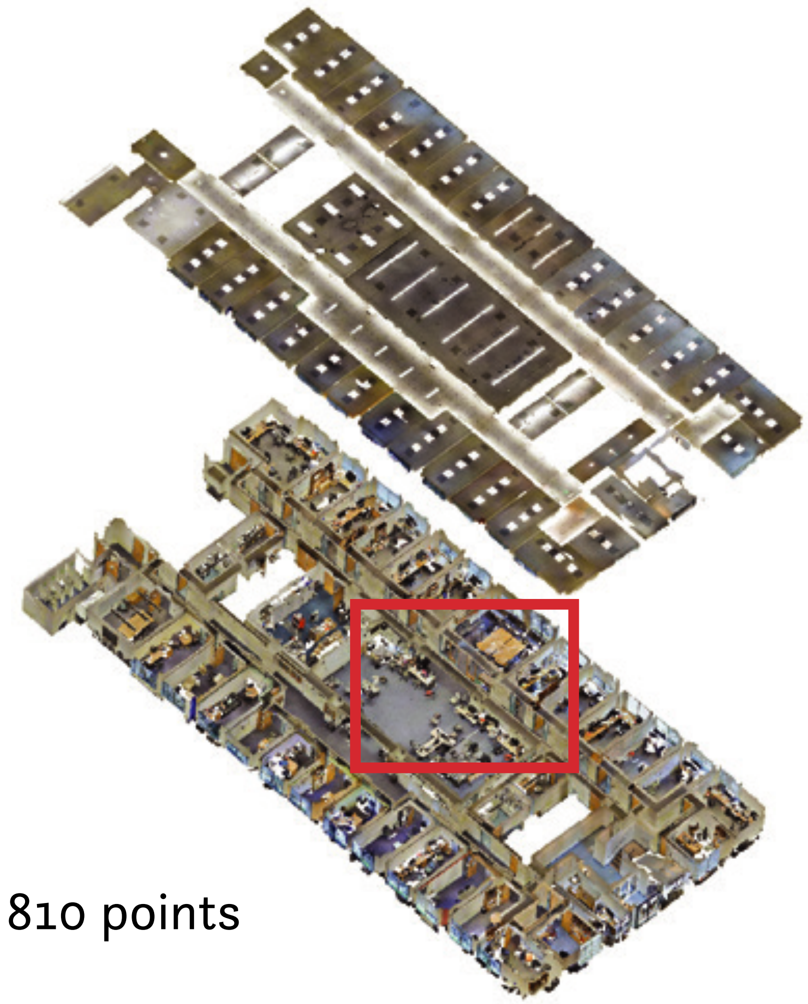
Coverage

- coverage to handle intersecting models
- well founded/integer linear programming
- does not scale well with the number of points

Towards large scale multiple structure recovery

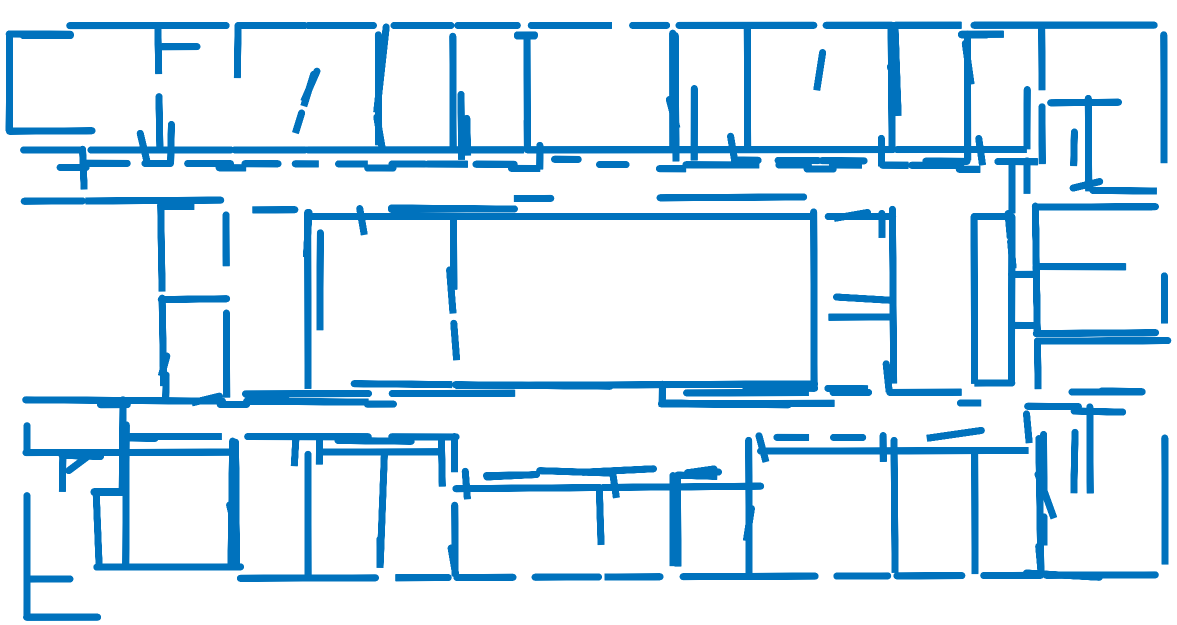
scan2bim: large indoor 3D point clouds
we want to extract a floorplan

- we don't know in advance the number of structures
- it is quite natural to set an inlier threshold



44 026 810 points

http://buildingparser.stanford.edu/dataset.html

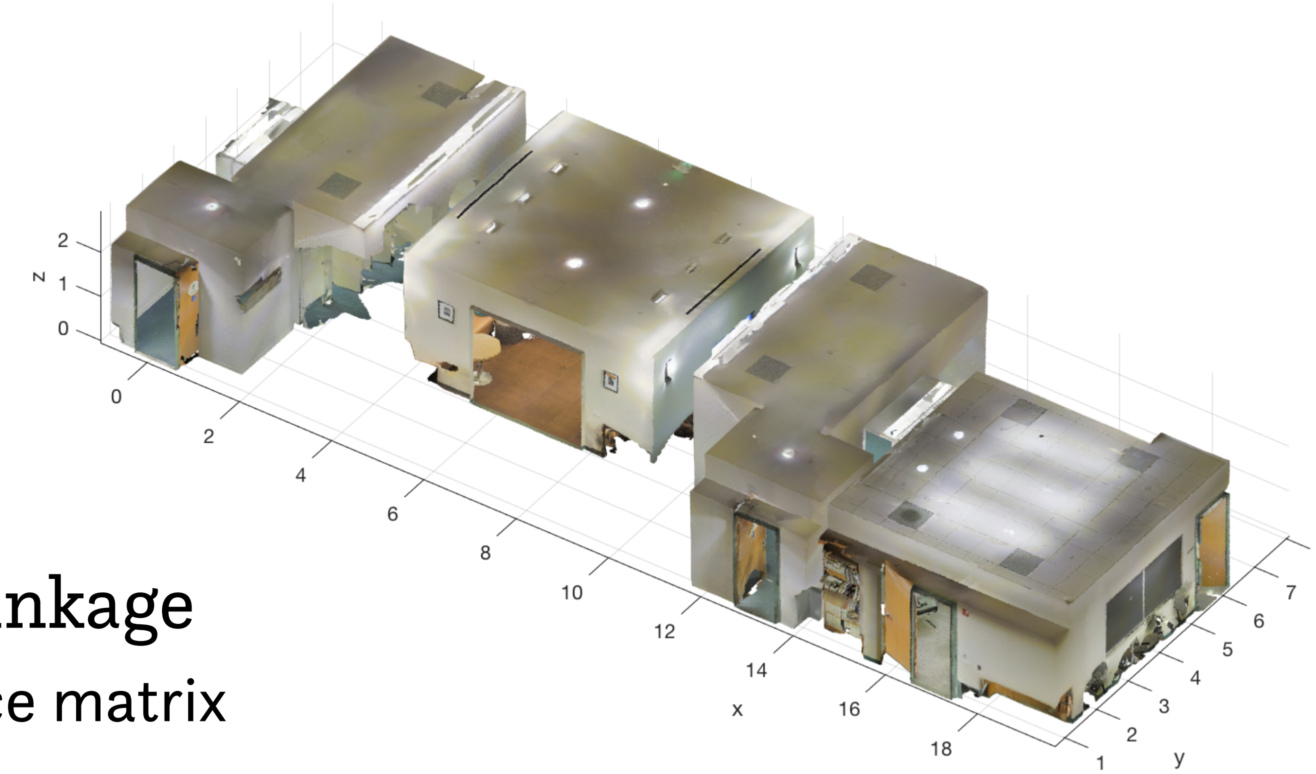


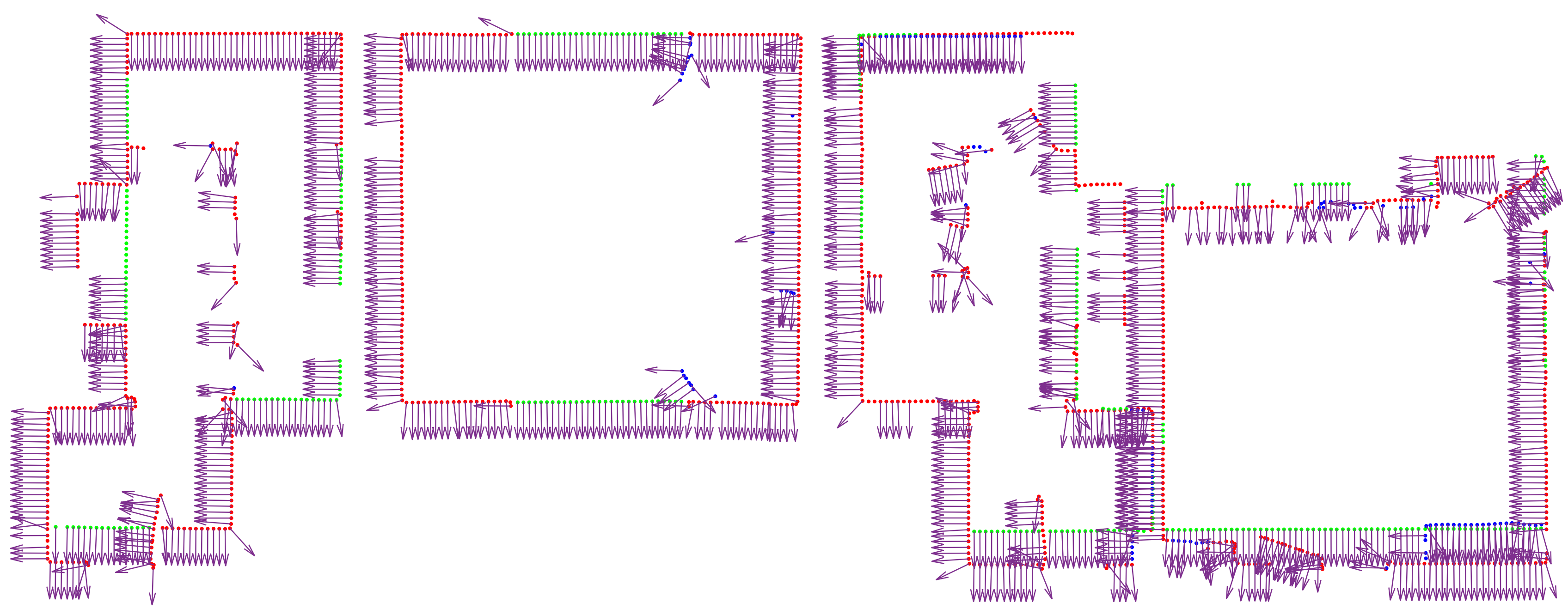
Towards large scale multiple structure recovery

1) remove floor/ceiling
- horizontal plane fitting
- peaks in the z-axis distribution

2) project points on the floor-plane
together with their normal information

3) multiple line recovery through J-linkage
normals are used to define the preference matrix





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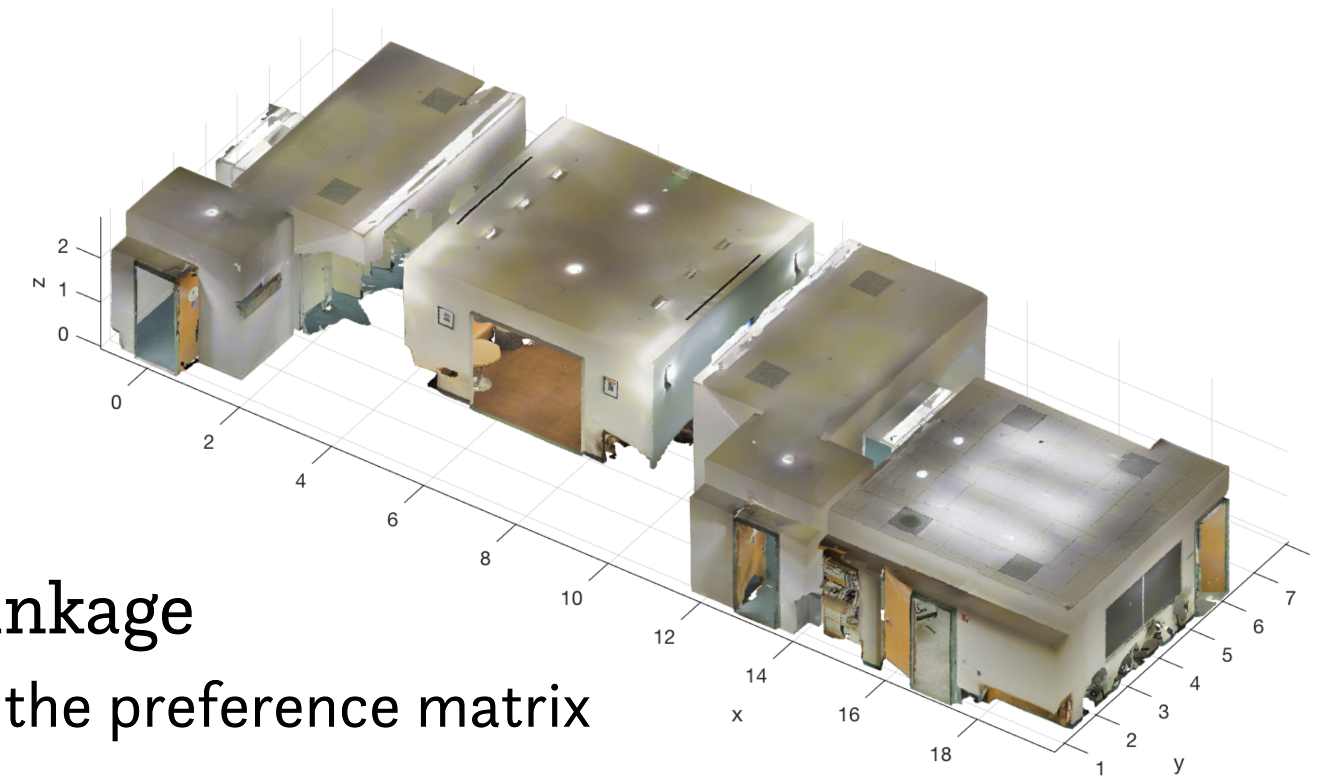
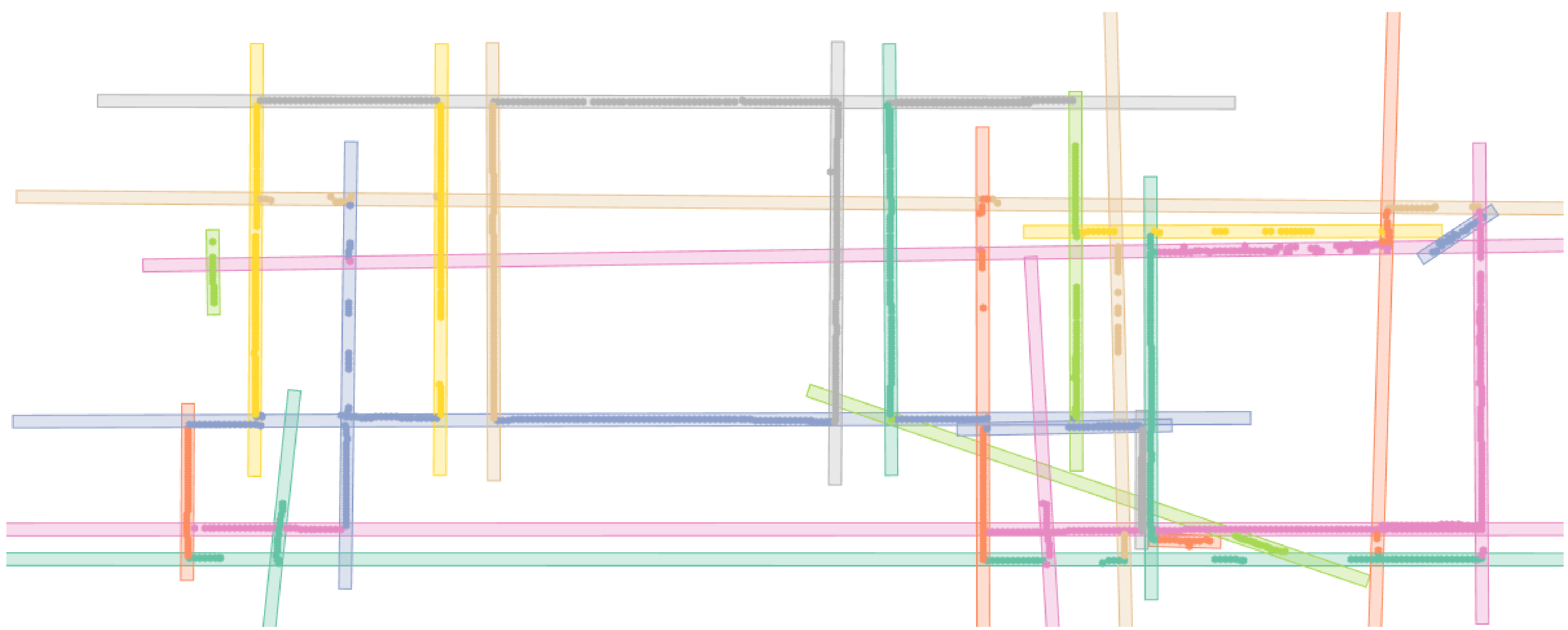




Towards large scale multiple structure recovery

work in progress:

- efficient construction of the preference matrix
  - exploit parallelism
  - exploit data spatial structures to compute residuals (e.g. kdtree/octree)

- efficient linkage clustering:
  - maintain a list of cluster nearest neighbours to speed up the computation of closest clusters

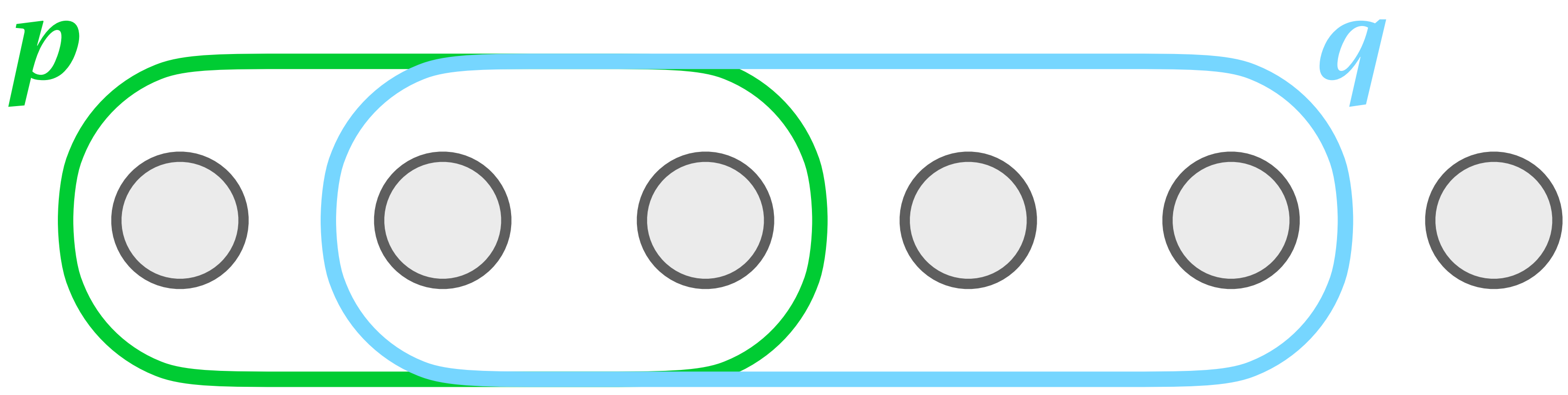
- efficient computation of Jaccard distance exploiting MinHash

MinHash

J-linkage need to update the Jaccard distances every time two clusters are merged.

We can alleviate the computational burden of this step exploiting MinHash to compute the distance between preference set:

$$d_J(p,q) = 1 - \frac{|p \cap q|}{|p \cup q|}$$



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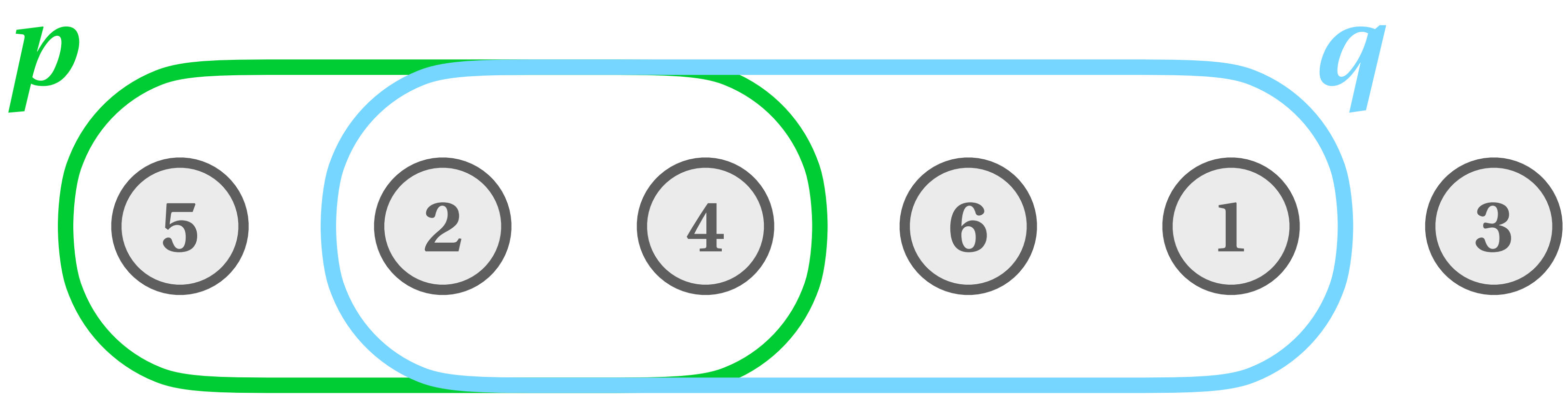
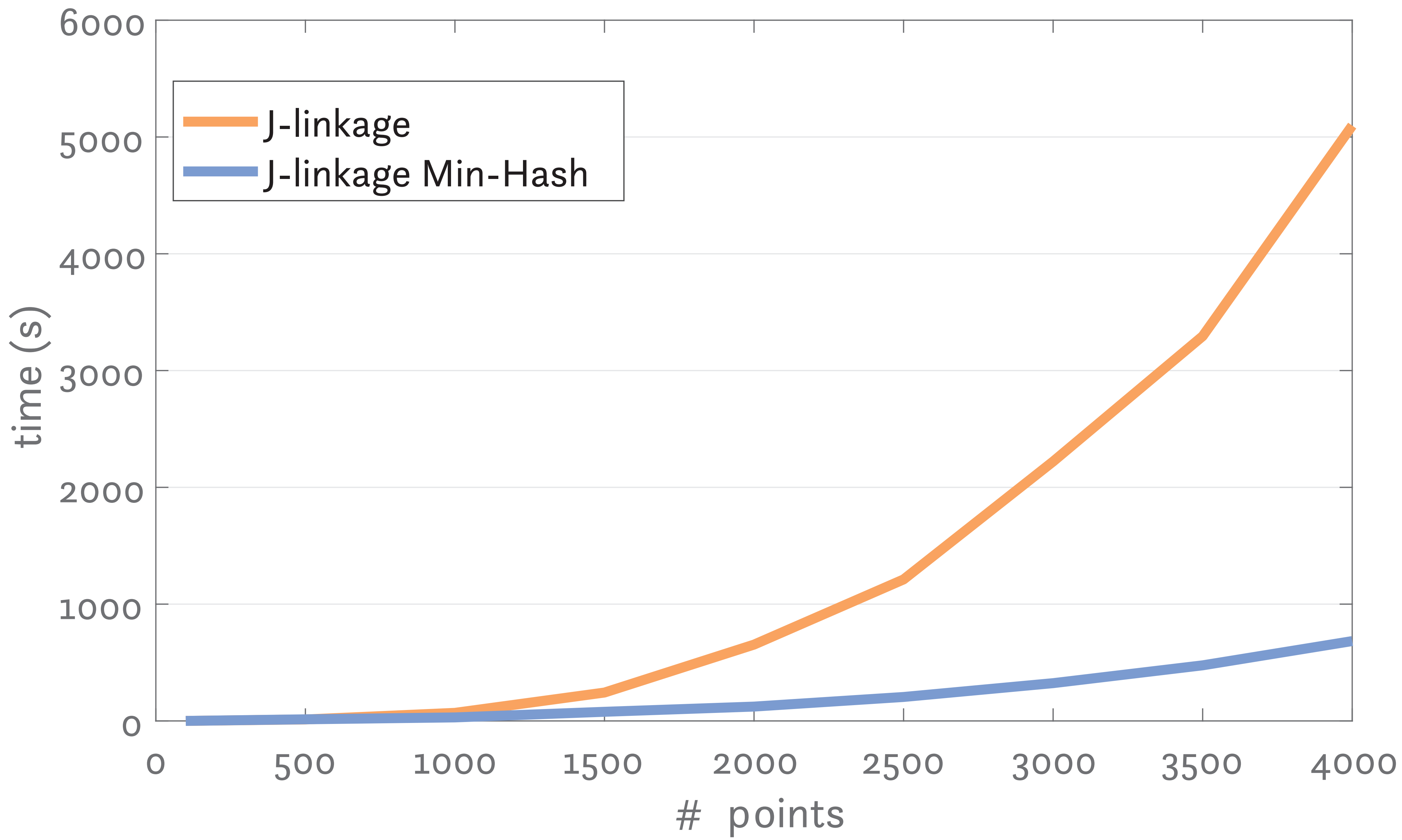


define a random permutation (hash function)

consider min(p) = 2
consider min(q) = 1

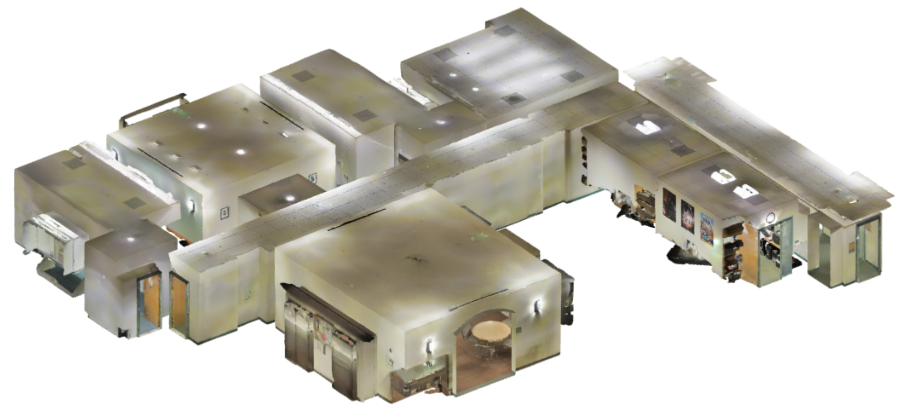
$$\text{Prob}\big(\min(p) = \min(q)\big) = \frac{|p \cap q|}{|p \cup q|}$$

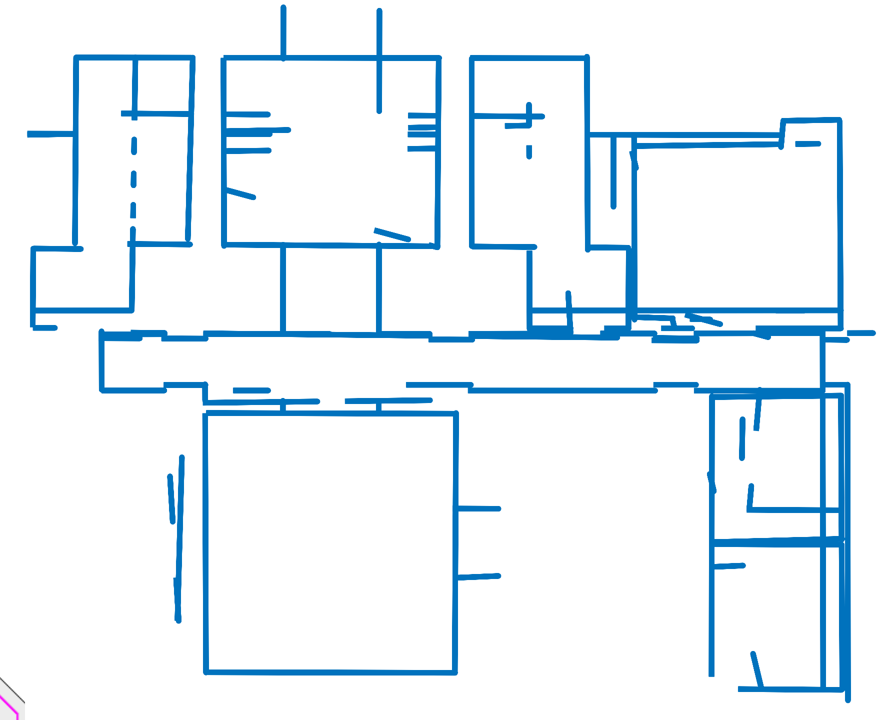
MinHash

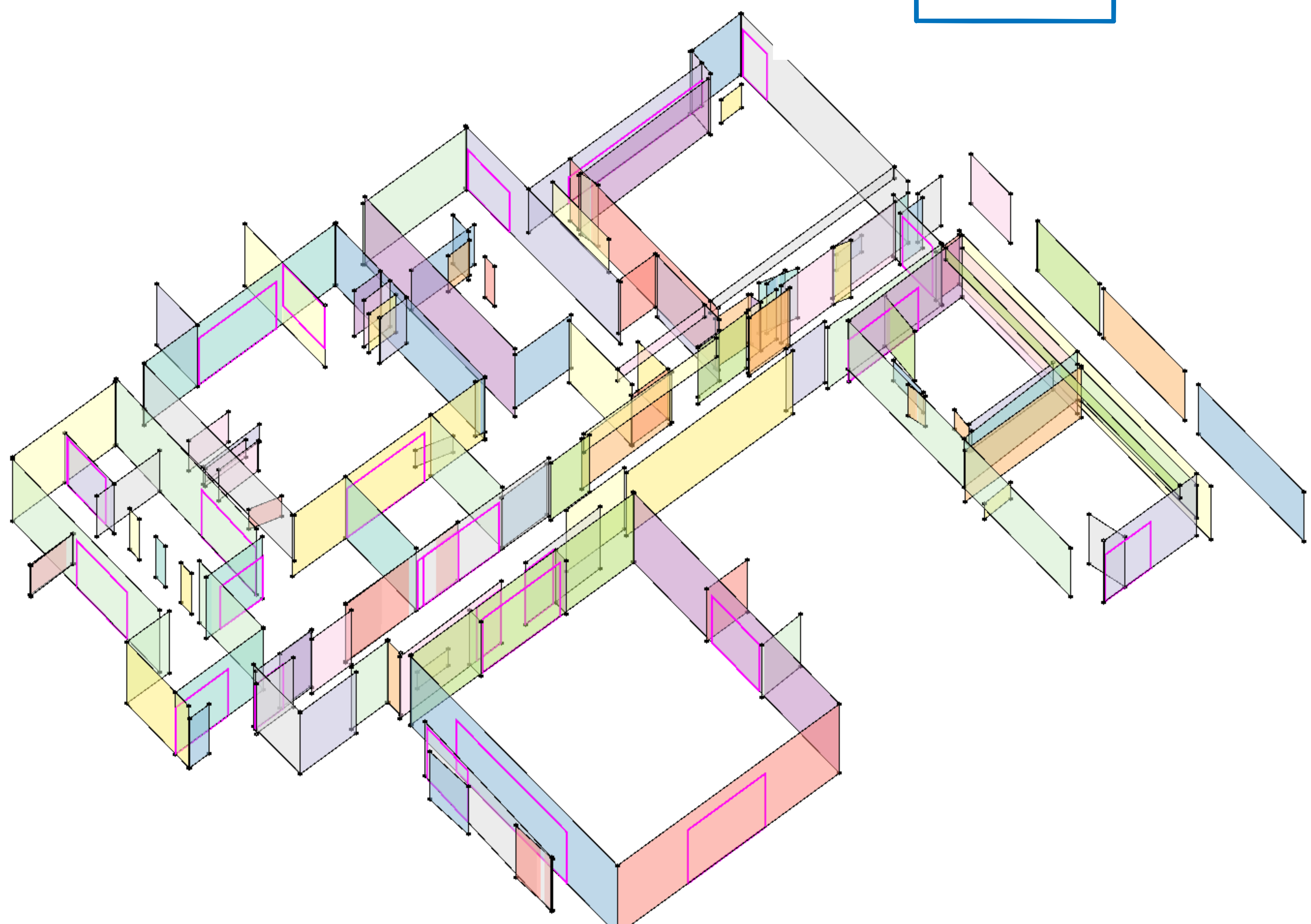

J-linkage
J-linkage Min-Hash
time (s)
6000
5000
4000
3000
2000
1000
0
0
500
1000
1500
2000
2500
3000
3500
4000
points

Sample results

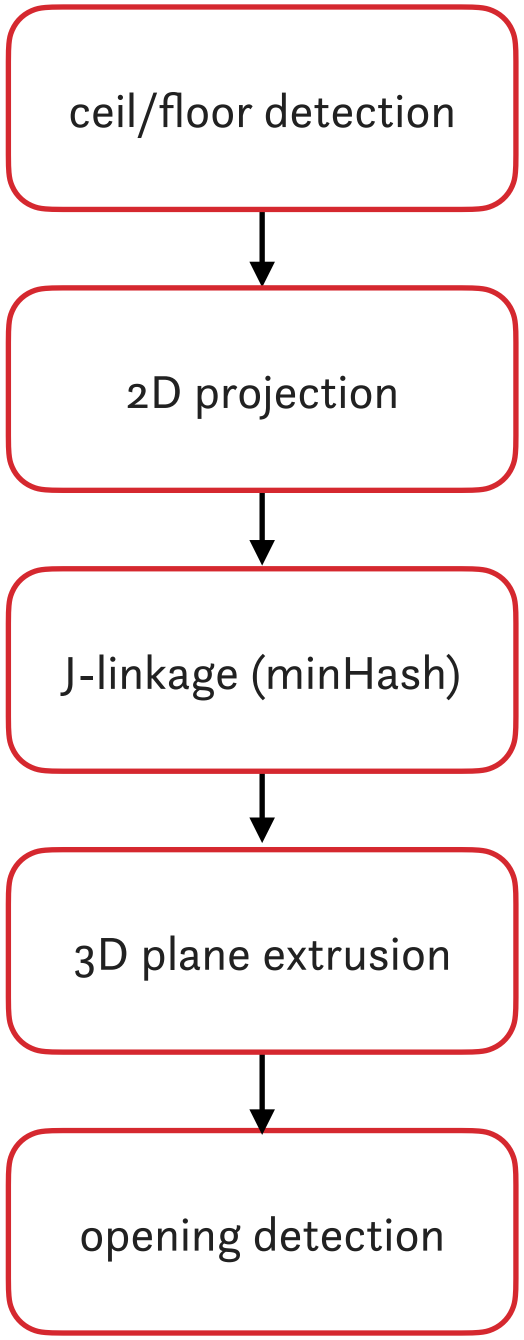
ceil/floor detection
↓
2D projection
↓
J-linkage (minHash)
↓
3D plane extrusion
↓
opening detection

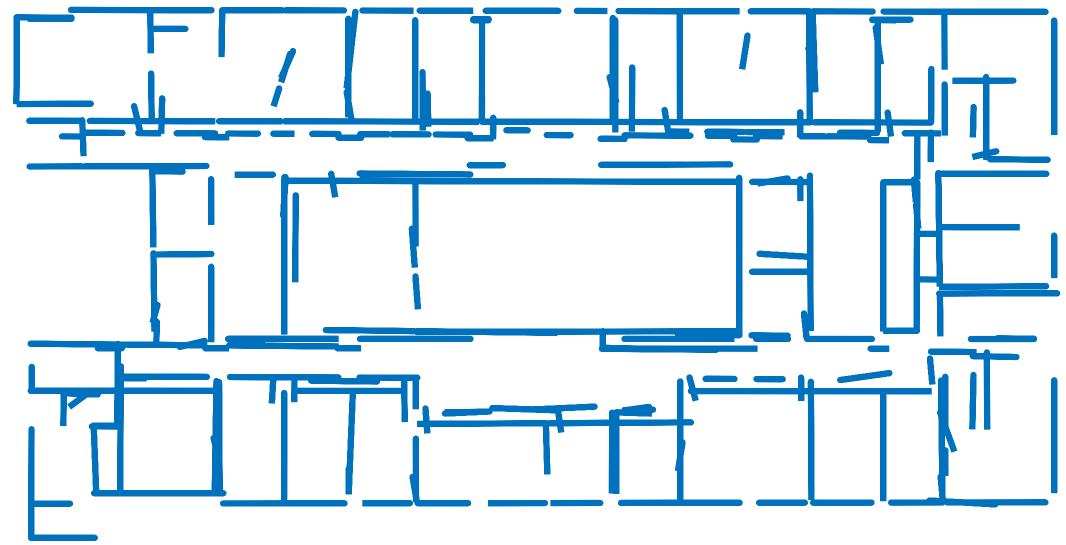


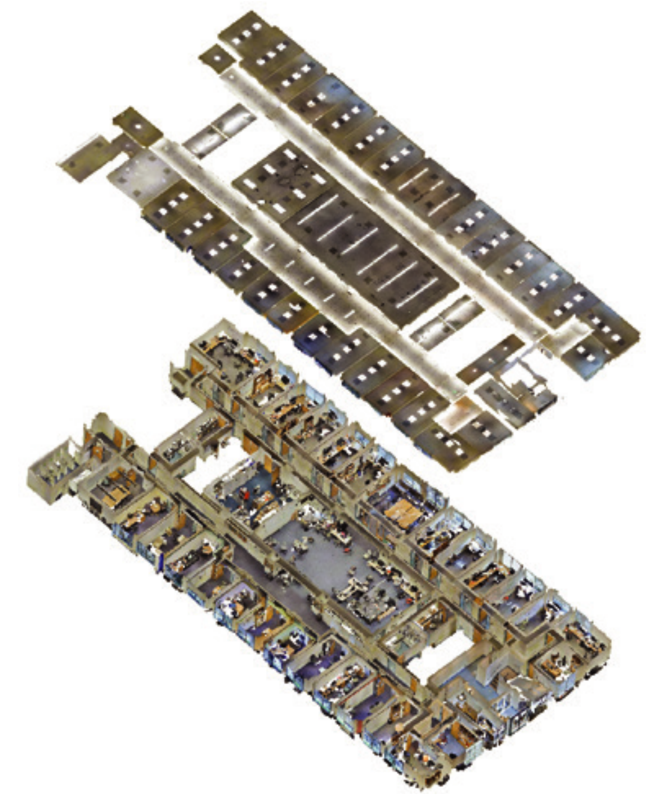


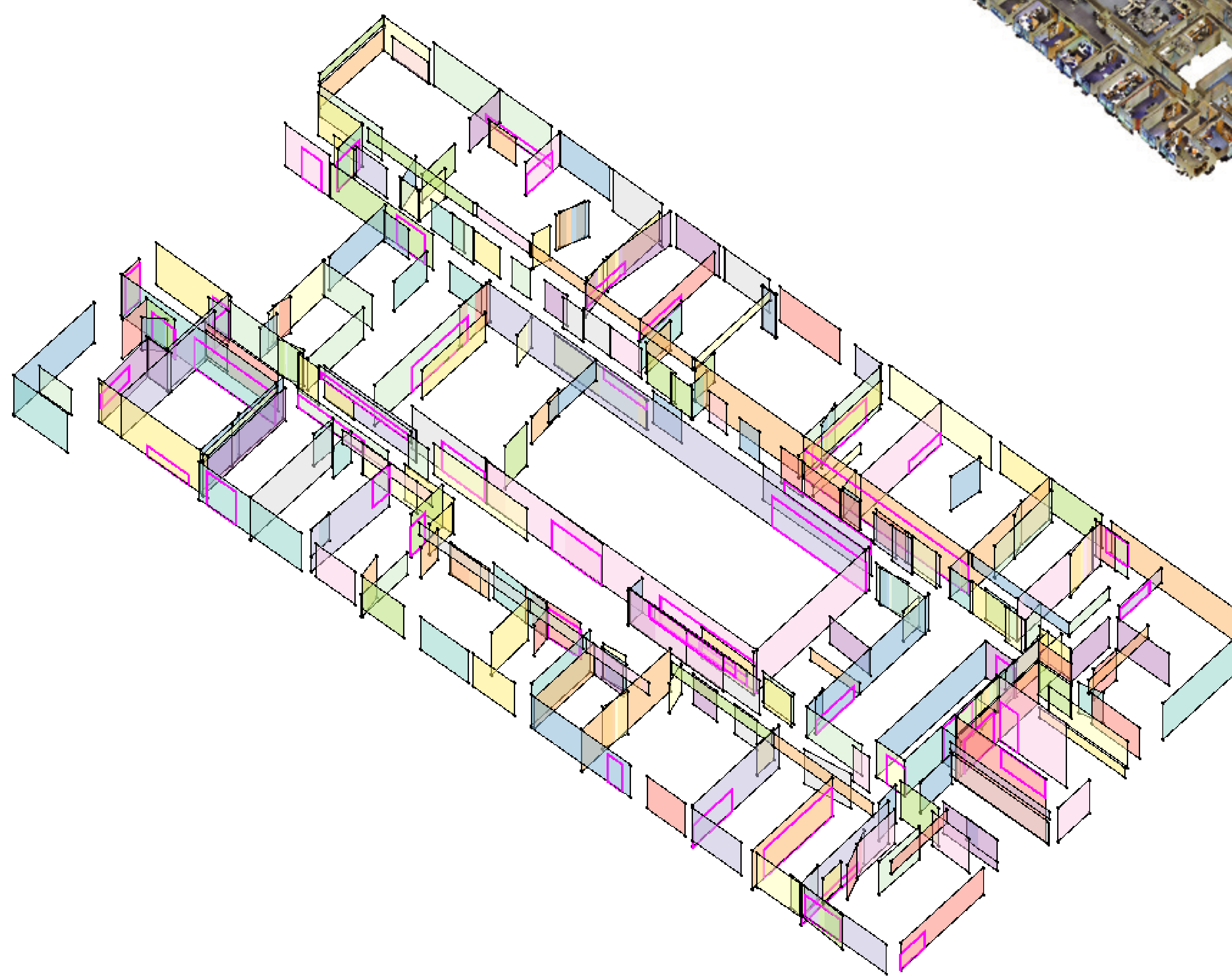


Sample results









thank you

Some references:

- Toldo, R. and Fusiello, A. Robust Multiple Structures Estimation with J-Linkage. In ECCV, 2008
- Magri, L. and Fusiello, A. Robust Multiple Model Fitting with Preference Analysis and Low-rank Approximation. In BMVC, 2015
- Magri, L. and Fusiello, A. T-Linkage: A Continuous Relaxation of J-Linkage for Multi-Model Fitting. In CVPR, 2014
- Magri, L. and Fusiello, A. Multiple Models Fitting as a Set Coverage Problem. In CVPR, 2016

Outlier pruning

They tend to be merged in late stages of the clustering

to emerge as micro-clusters and can be pruned out with ad hoc post-processing.
For example:

- compute the cardinality of its consensus set
- compute the probability p that an outlier falls in its inlier band
- compute the probability that k outliers fall in its inlier band as

$$\alpha(k) = 1 - F(n, k, p)$$

- compute $\alpha^{-1}(0.01)$ the minimum cardinality necessary to be not considered mere coincidence
- if the considered model is supported by less points it is rejected as outlier.