MultiLink: Multi-class Structure Recovery via Agglomerative Clustering and Model Selection

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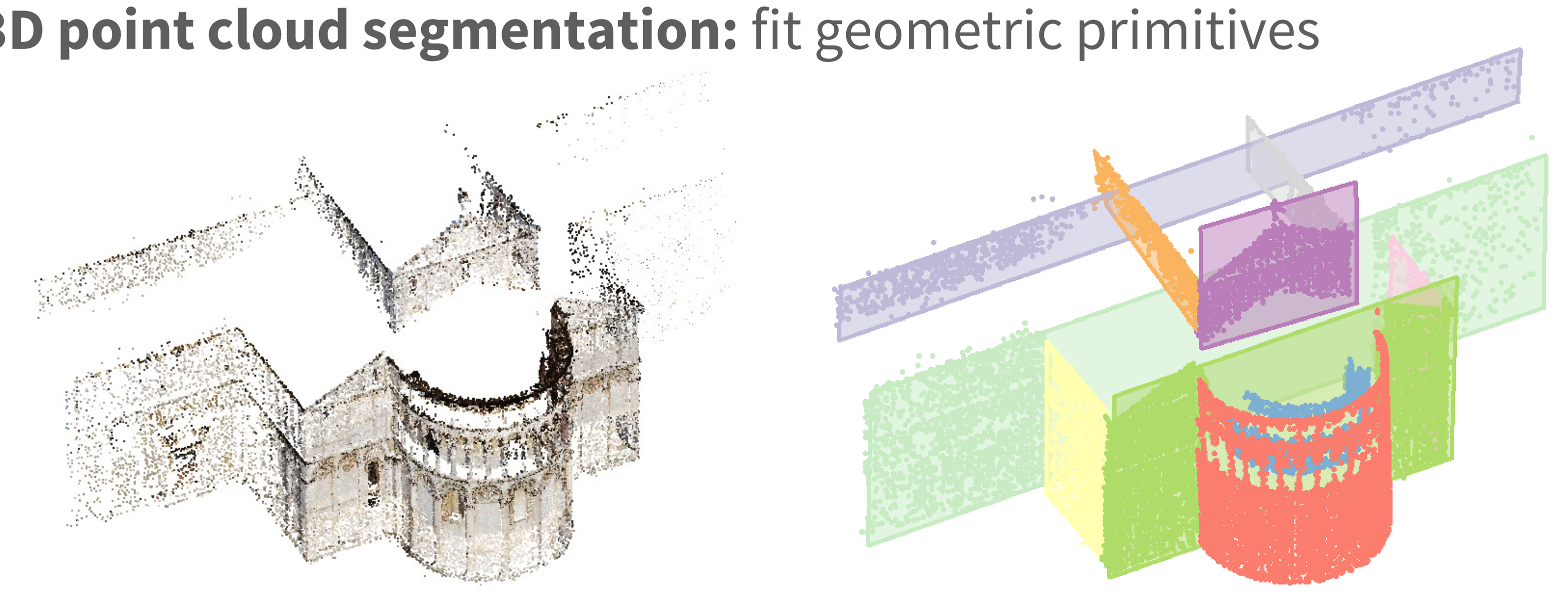
Multi-class multiple structure recovery

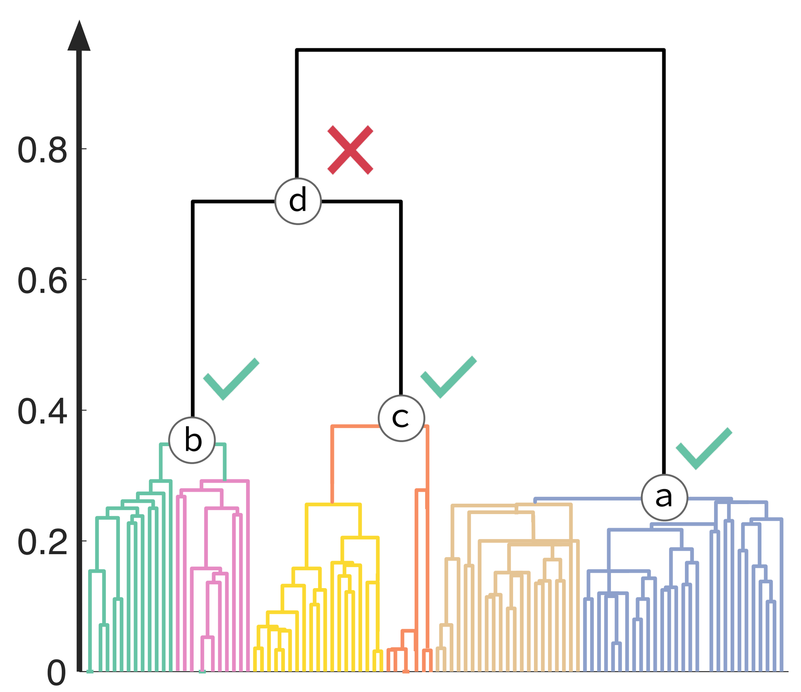
Recover structures described by a **mixture** of parametric models belonging to **multiple** classes from data contaminated by noise and outliers.

Applications:

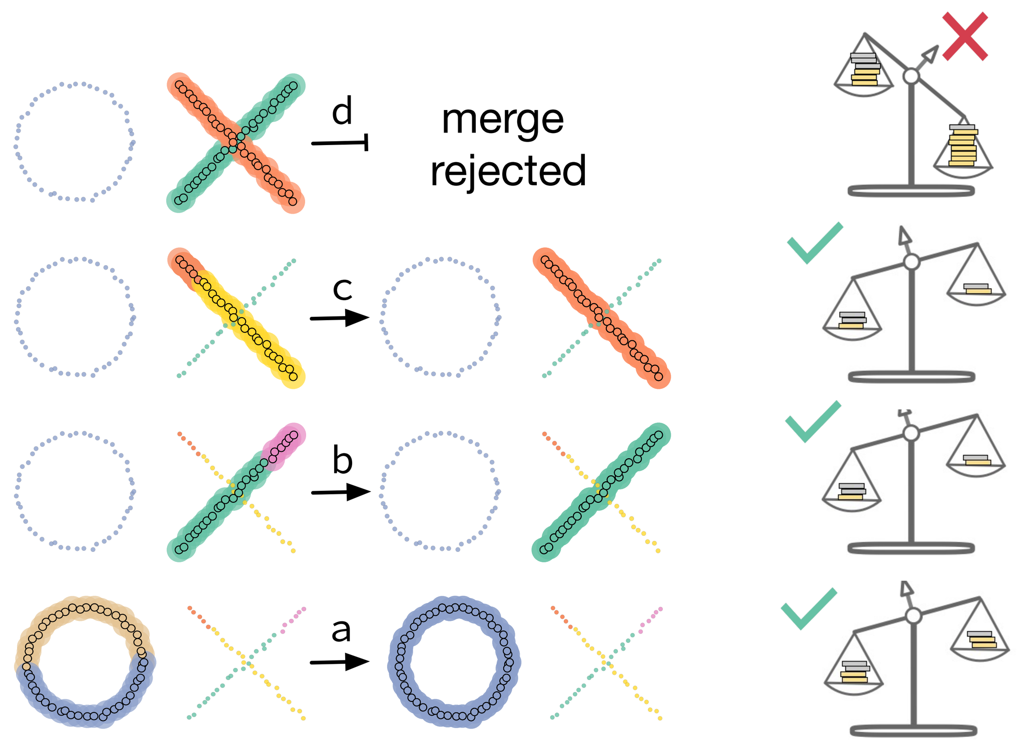
- **stereo geometry:** fit homography, fundamental and affine fundamental matrices on two view correspondences
- **motion segmentation:** segment trajectories in subspace of different dimension
- **3D point cloud segmentation:** fit geometric primitives



Idea: solve simple-model-selection problems guided by clustering



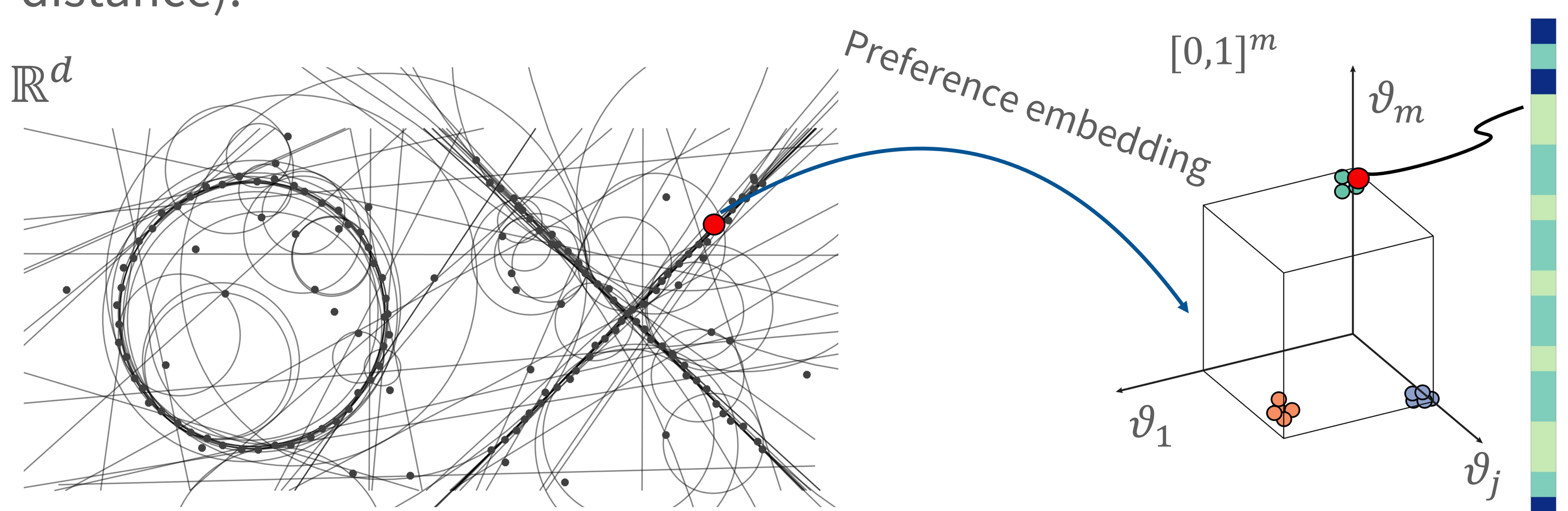
Dendrogram obtained by clustering preferences



Merging is controlled by model selection that decides whether to merge clusters and which class of model is the best

Clustering via preference embedding

A data point $x \in X$ is embed to a vector of preferences that measures its adherence to sampled models H from different classes $\Theta_1 \cup \cdots \cup \Theta_s$. Points of the same structure have similar preferences (Tanimoto distance).

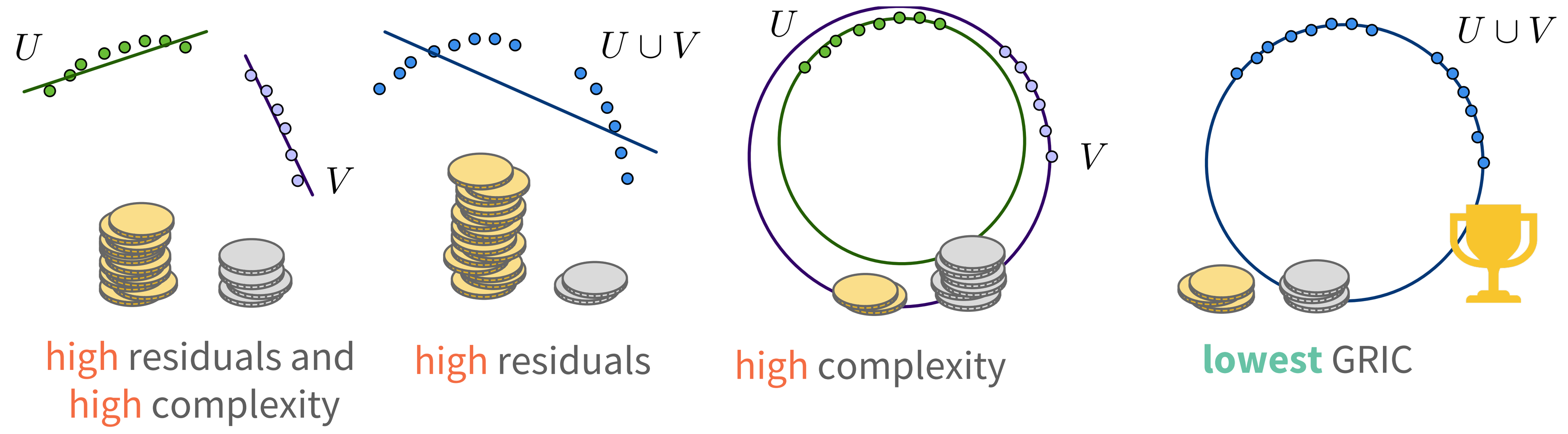


$$\mathcal{H} = H_l \cup H_c \subset \Theta_l \cup \Theta_c$$

$$p(x_i, \vartheta_j) = \begin{cases} \phi(e_{ij}) & \text{if } e_{ij} = \mathrm{err}(x_i, \vartheta_j) \leq \varepsilon \\ 0 & \text{otherwise} \end{cases}$$

Model selection

Models of different classes are **fitted on-the-fly**, this mitigates sampling imbalance in H. Then GRIC selects the configuration yielding the lowest cost



1-vs-2 model selection are simple to solve, it is not difficult to tune λ_1, λ_2.

Geometric Robust Information Criterion

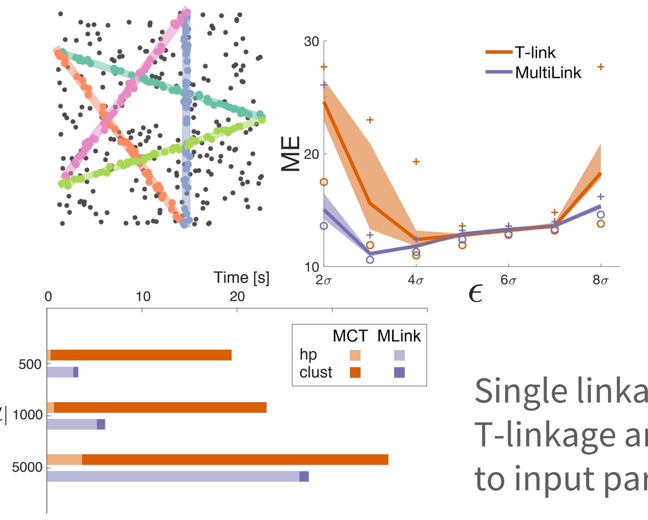
GRIC cost:

$$\underbrace{\sum_{x \in U} \rho\left(\frac{\mathrm{err}(x, \theta(U))}{\sigma}\right)^2}_{\text{Geometric residuals}} + \underbrace{\lambda_1 d|U| + \lambda_2 \mu}_{\text{Model complexity}}$$

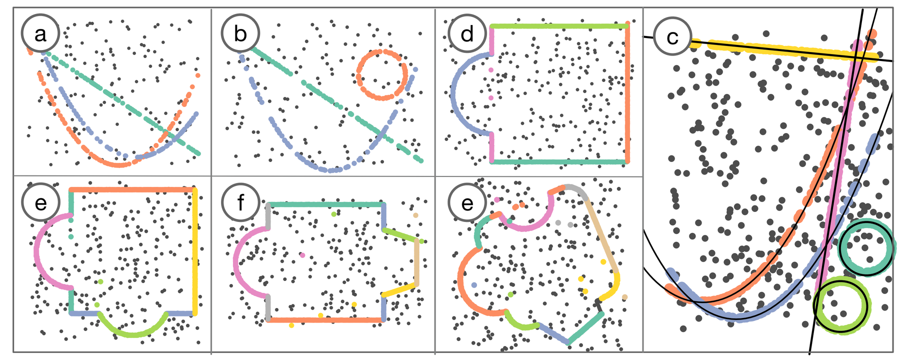
- U cluster
- ρ robust function
- σ noise estimate
- d dim. of model manifold
- μ # model parameters

Experiments

Synthetic data

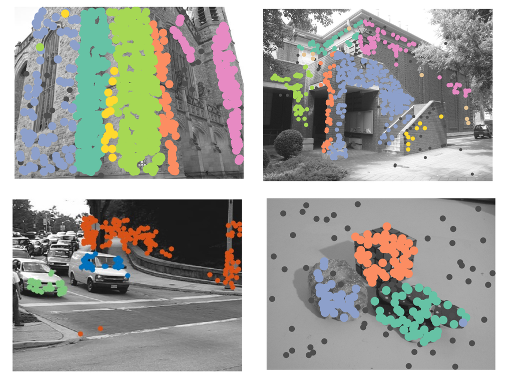


Single linkage is faster than T-linkage and less sensitive to input parameters



	(a)	(b)	(c)	(d)	(e)	(f)	(g)
PEARL	6.00	16.22	14.44	8.05	8.33	17.38	19.21
MCT	**0.67**	**2.00**	2.33	5.23	7.12	5.38	6.23
MLink	2.17	2.13	**1.55**	**1.83**	**0.87**	**2.46**	**4.28**

Real datasets



	PEARL	Multi-X	Prog-X	RPA	T-link	MLink
Mean	15.14	8.71	6.86	23.54	22.38	**6.46**
Std.	6.75	8.13	5.91	13.42	7.27	1.75

(a) Plane seg. *fixed parameters*

	T-link	MCT	MLink
Mean	6.60	6.13	**4.10**
Median	4.68	4.93	**2.70**

(b) Methods with ε *tuned* per-sequence

	Fundamental		Affine fund.		Mixed	
	Mean	Std.	Mean	Std.	Mean	Std.
MLink	8.59	4.67	9.84	4.09	**7.75**	4.54
T-link	32.20	50.33	41.90	7.95	38.78	8.21
Prog-X	10.73	8.73	-	-	-	-
Multi-X	17.13	12.23	10.5	2.90	9.53	1.43
PEARL	29.54	14.80	41.81	15.25	48.89	8.16

(c) Two-view seg. *fixed parameters*

	Mean	Std.
Multi-X	12.96	19.60
Prog-X	8.41	10.29
T-link +S (dim 3)	8.68	12.23
MCT +S	10.87	12.68
MLink +S (dim. 3)	**8.34**	11.93
MLink +S (mixed)	9.83	13.05

(d) Video seg. S= Silhouette index.

Conclusions

MultiLink is

- **General**: can cope with a variety of models and can be extended by modifying cluster-merging conditions to accommodate for specific constraints coming from an application at hand.
- **Faster and more stable:** less sensistive to sampling and to the inlier threshold than greedy alternatives based on preference analysis.
- **Accurate**: favorably compares with state-of-the-art optimization-based methods.

Code Available at https://github.com/magrilu/multilink

References:

Barath, Matas. Multi-class model fitting by energy minimization and mode-seeking. ECCV 2018

Barath, Matas. Progressive-x: Efficient, anytime, multi-model fitting algorithm. CVPR 2019

Delong, Veksler, Boykov.Fastfusion moves for multi-model estimation. ECCV, 2012

Isack, Boykov. Energy-based geometric multi-model fitting. IJCV, 2012

Magri, Fusiello. T-Linkage: A continuous relaxation of J-Linkage for multi-model fitting. CVPR, 2014

Magri, Fusiello. Fitting multiple heterogeneous models by multi-class cascaded t-linkage. CVPR, 2019

Torr. Geometric motion segmentation and model selection. Transactions of the Royal Society, 1998