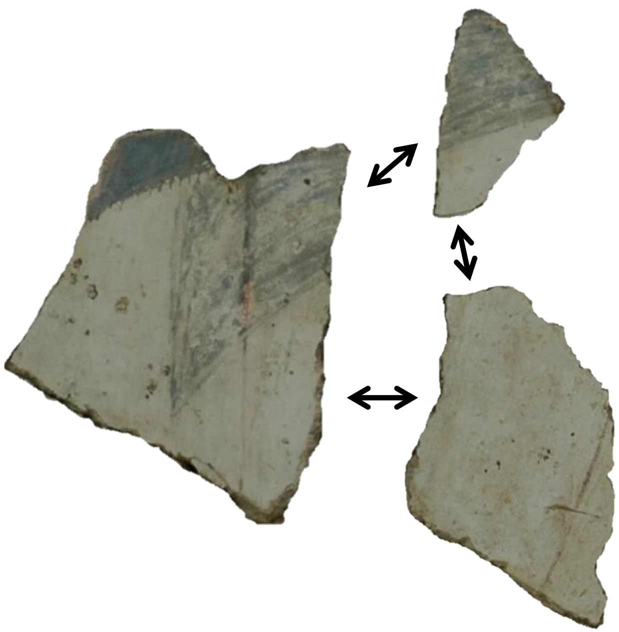
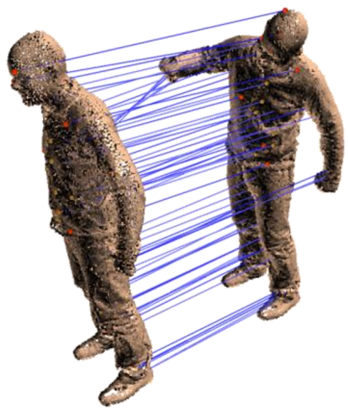
Data-Driven Shape Correspondence

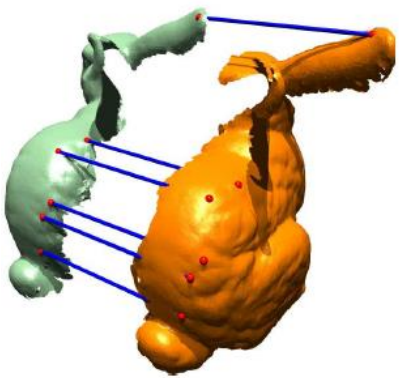


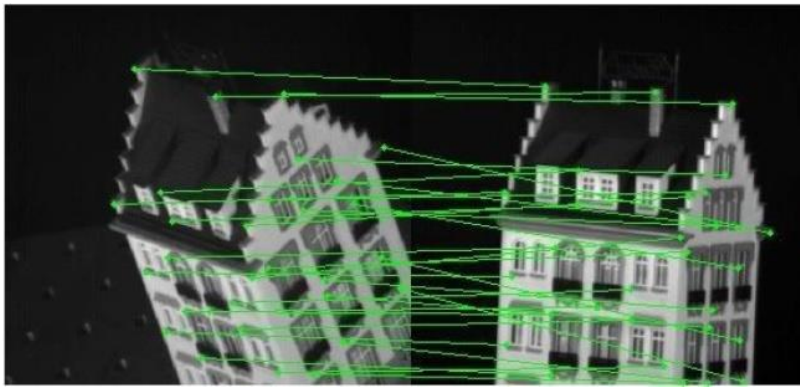
Qixing Huang

December 5th 2016

Maps between objects

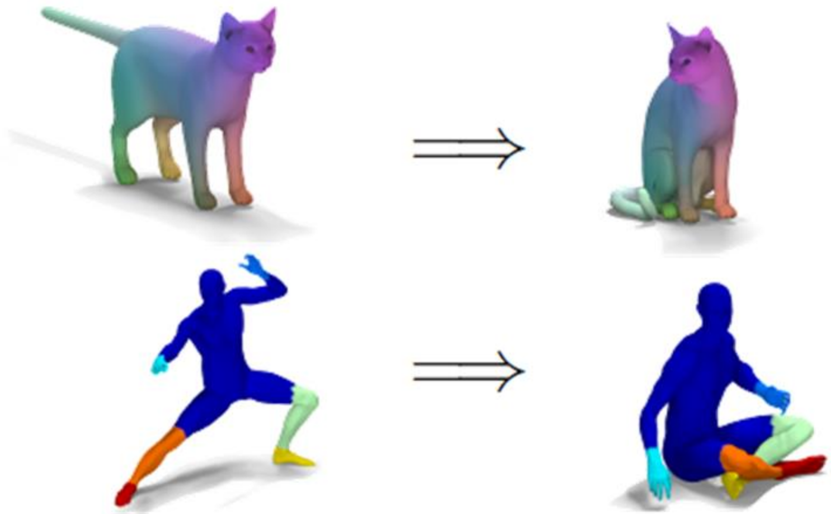




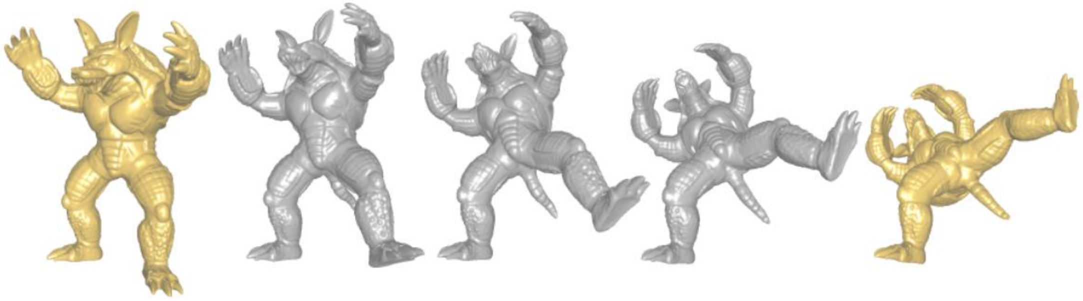


Maps for propagation and interpolation

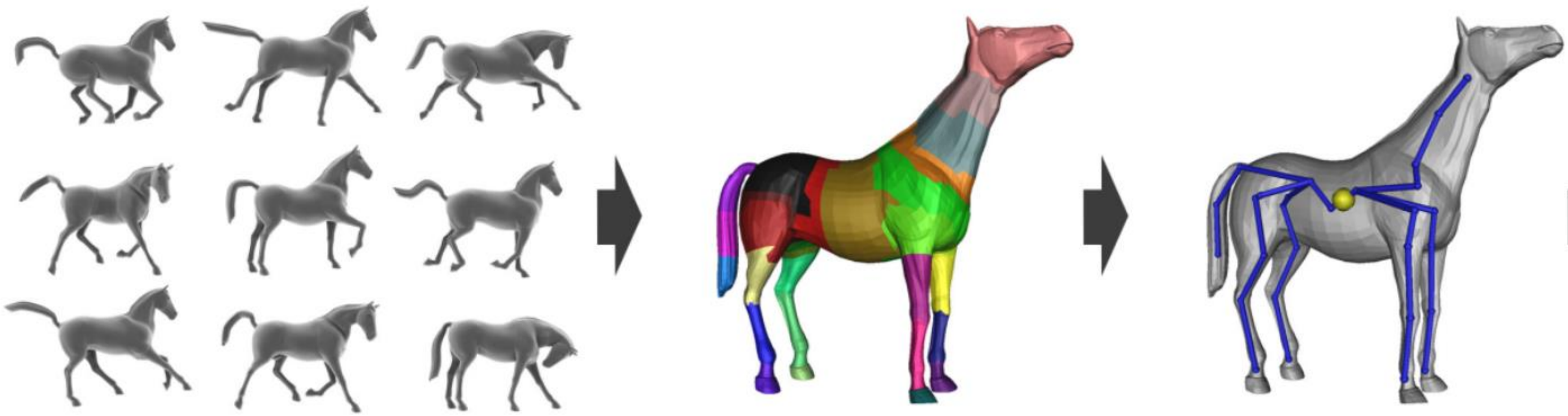
Propagation:



Interpolation:

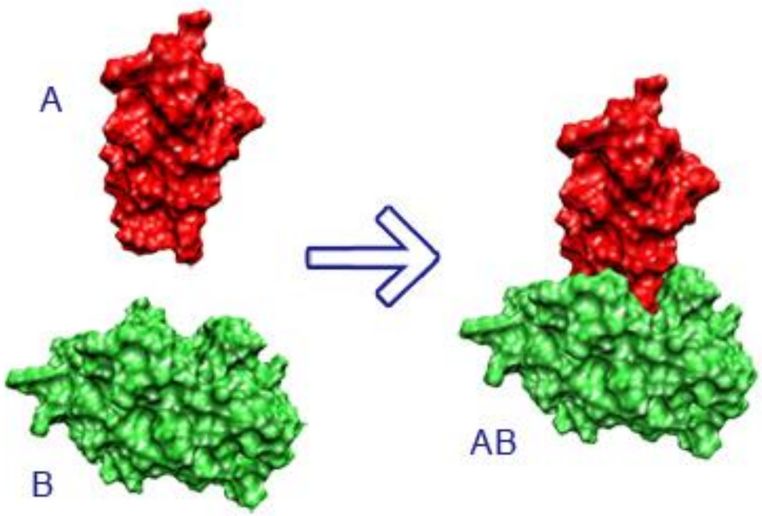


Aggregating information

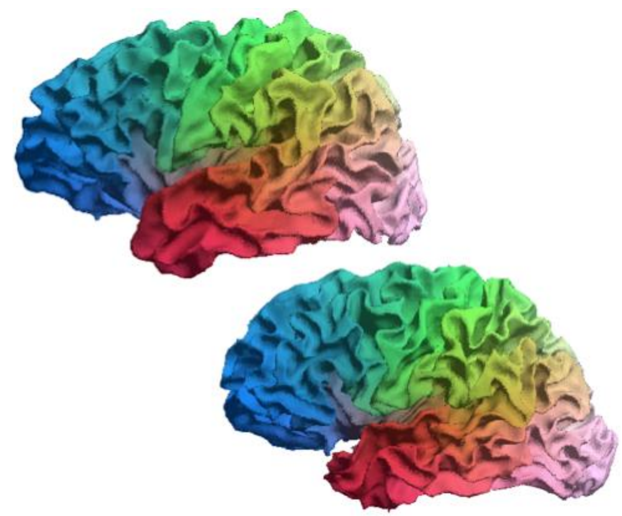


Segmentation and Skeleton Extraction

Matching in other domains



Protein docking

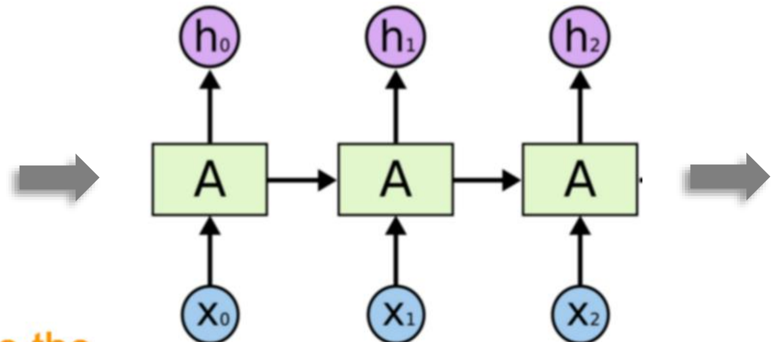


Brain matching

http://zbi-www.bioinf.uni-sb.de/en/about-bioinformatics/docking.html
http://step.polymtl.ca/~rv101/images/research-brains.png

Mapping between different domains

English *Chinese*



Li Keqiang will initiate the annual dialogue mechanism between premiers of China and Canada during this visit, and hold the first annual dialogue with Premier Trudeau of Canada.

李克強此行將啟動中加總理年度對話機制，與加拿大總理杜魯多舉行兩國總理首次年度對話。

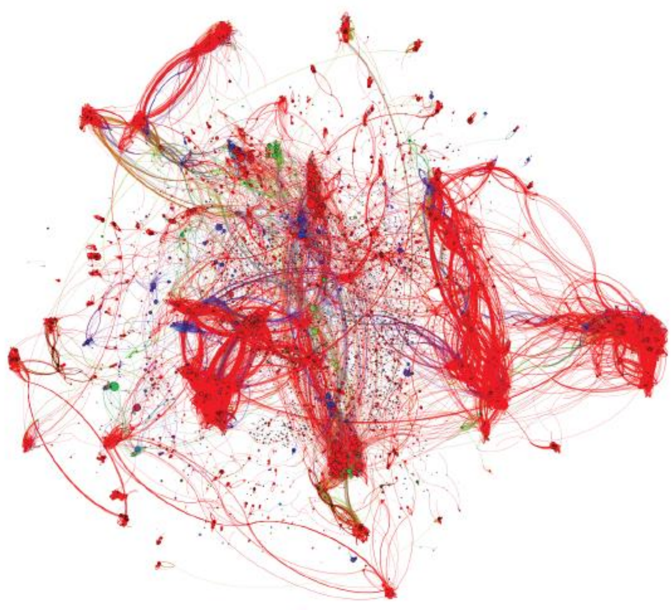
Matching is ubiquitous

- Introduction to machine learning (Coursera)
  - 40K code submissions for linear SVM

Credit: Jonathan Huang

Matching is ubiquitous

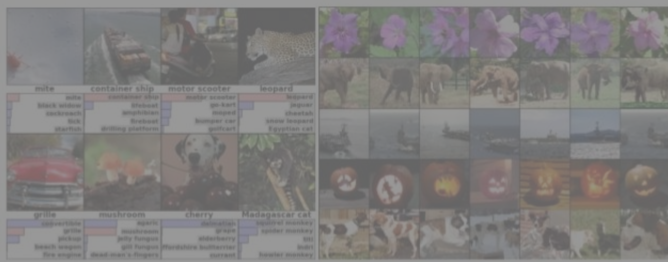
- Grading using maps between AST trees
  - Graders mark a very small portion of them
  - Propagate labels to other programs



Credit: Jonathan Huang

Matching is Hard!

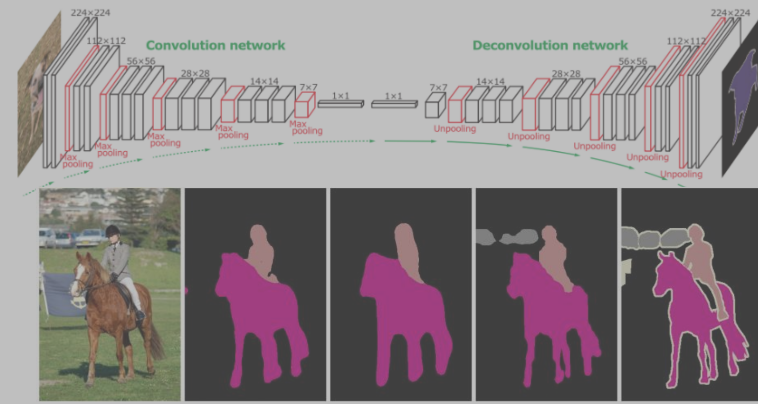
IMAGENET



1000 classes

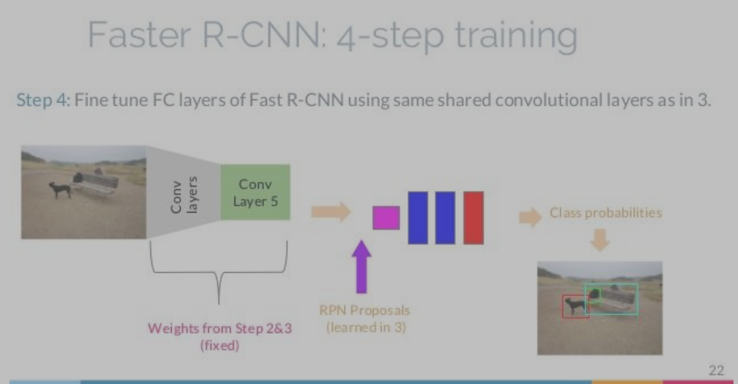
[He et al. 16]

Classification



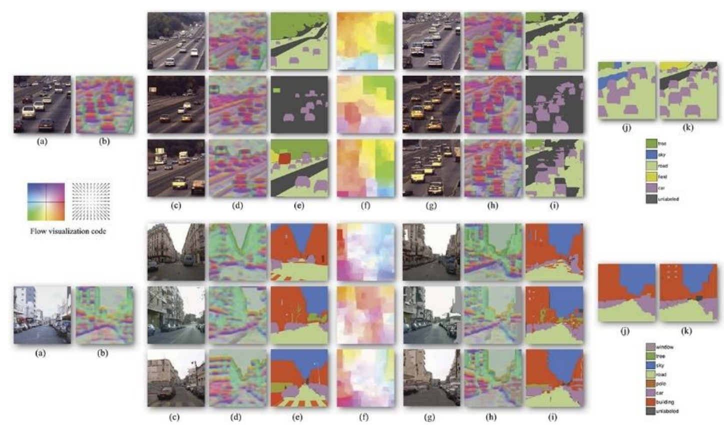
[Zheng et al. 16]

Segmentation



[Ren et al. 16]

Recognition

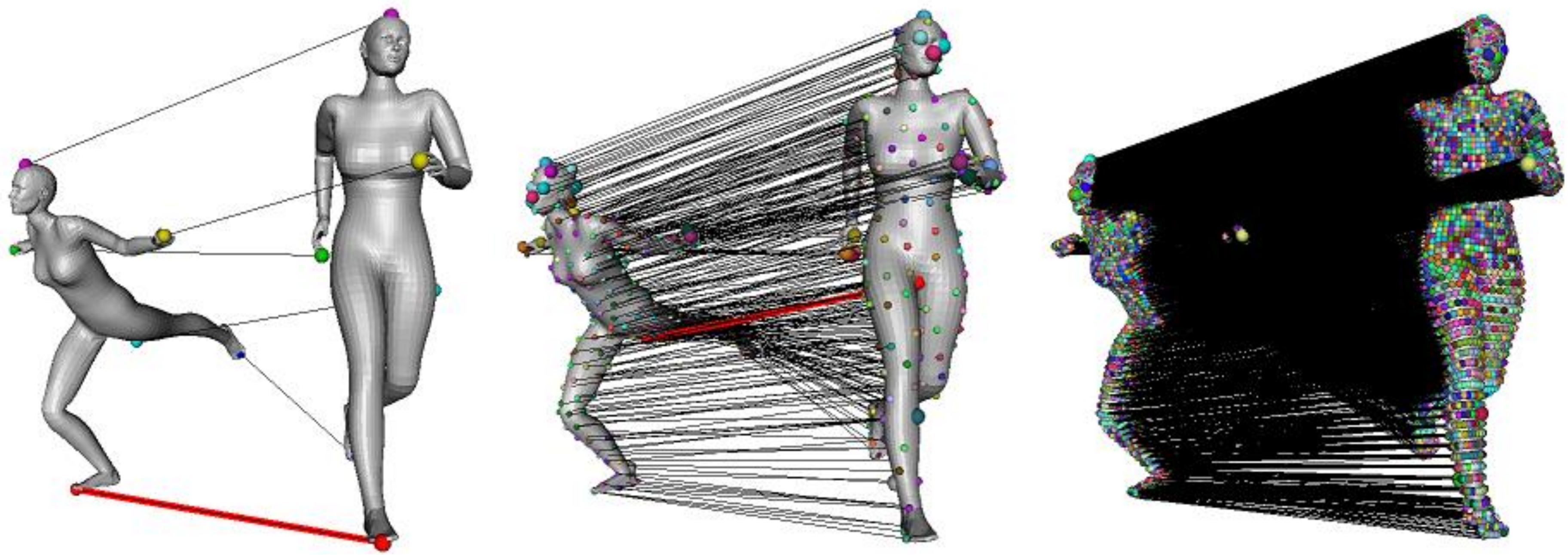


[Liu et al. 08]

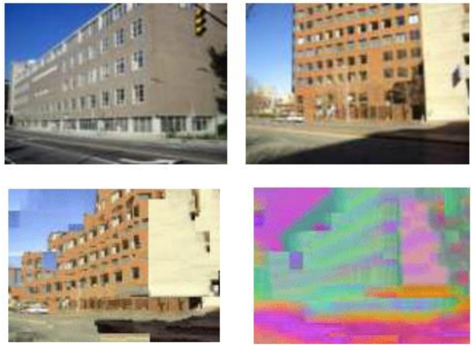
Correspondence

Fundamental Challenge: Lack of Training Data

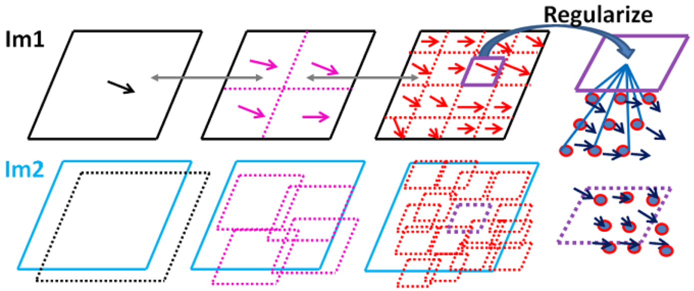
Hard to label dense correspondences



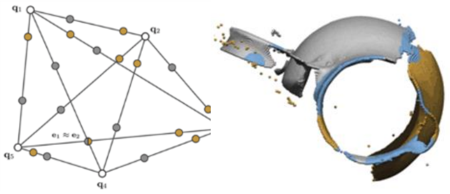
State-of-the-art pair-wise methods



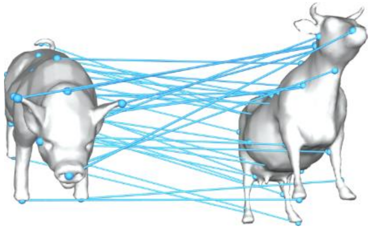
SIFTFlow [Liu et al. 08]



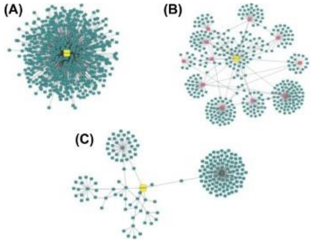
DSP [Kim et al. 13]



4-points voting
[Aigor et al. 08]

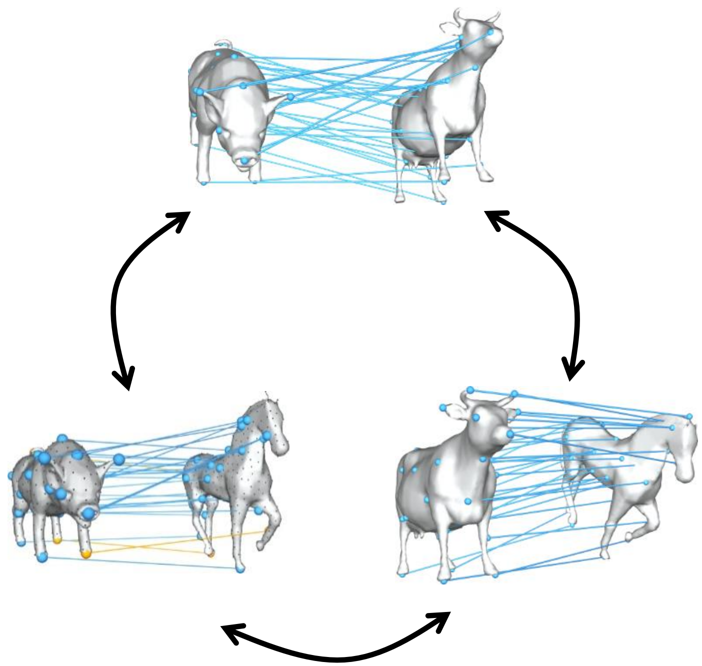


Blended intrinsic maps
[Kim et al. 11]

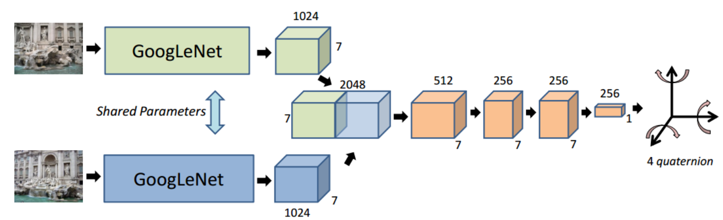


HubAlign
[Hashemifar et al. 14]

Outline



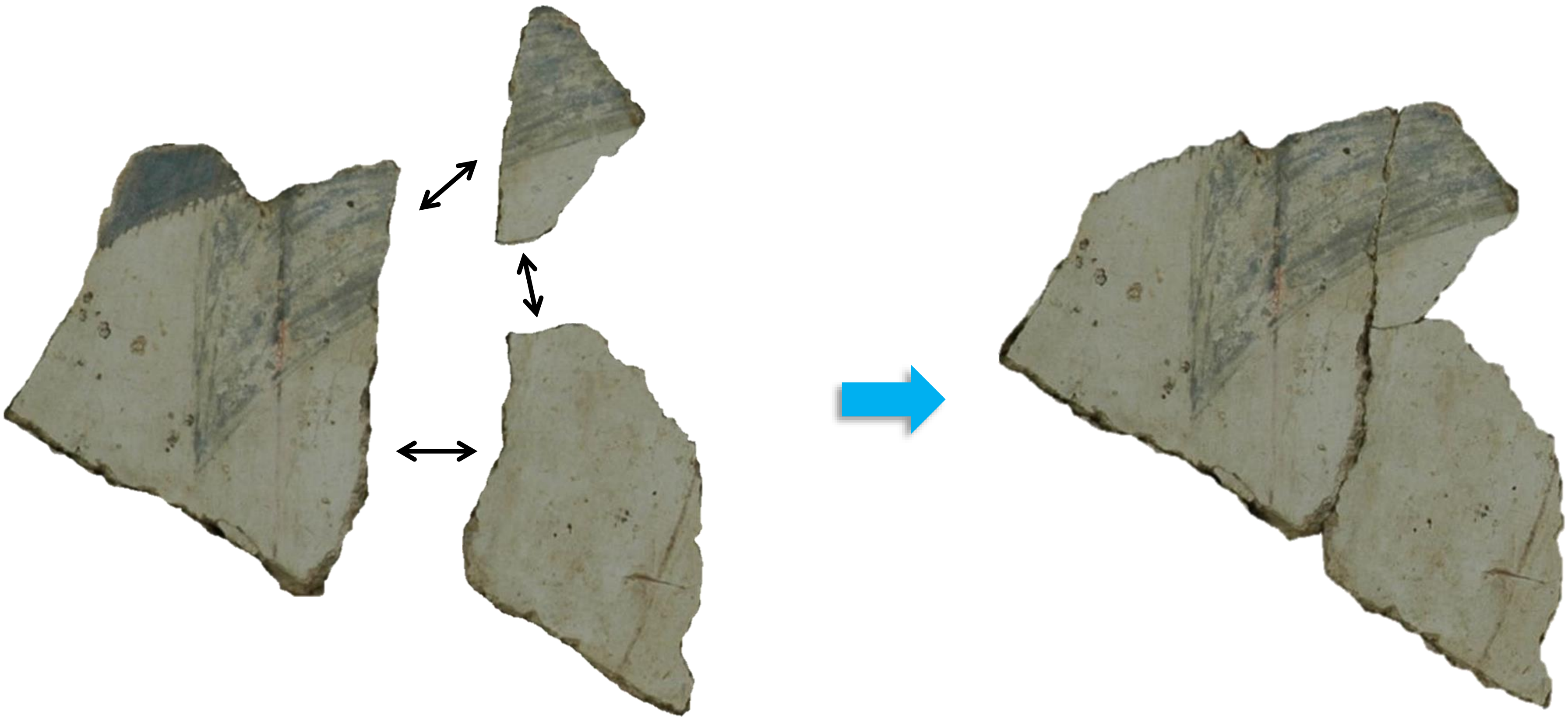
Map synchronization



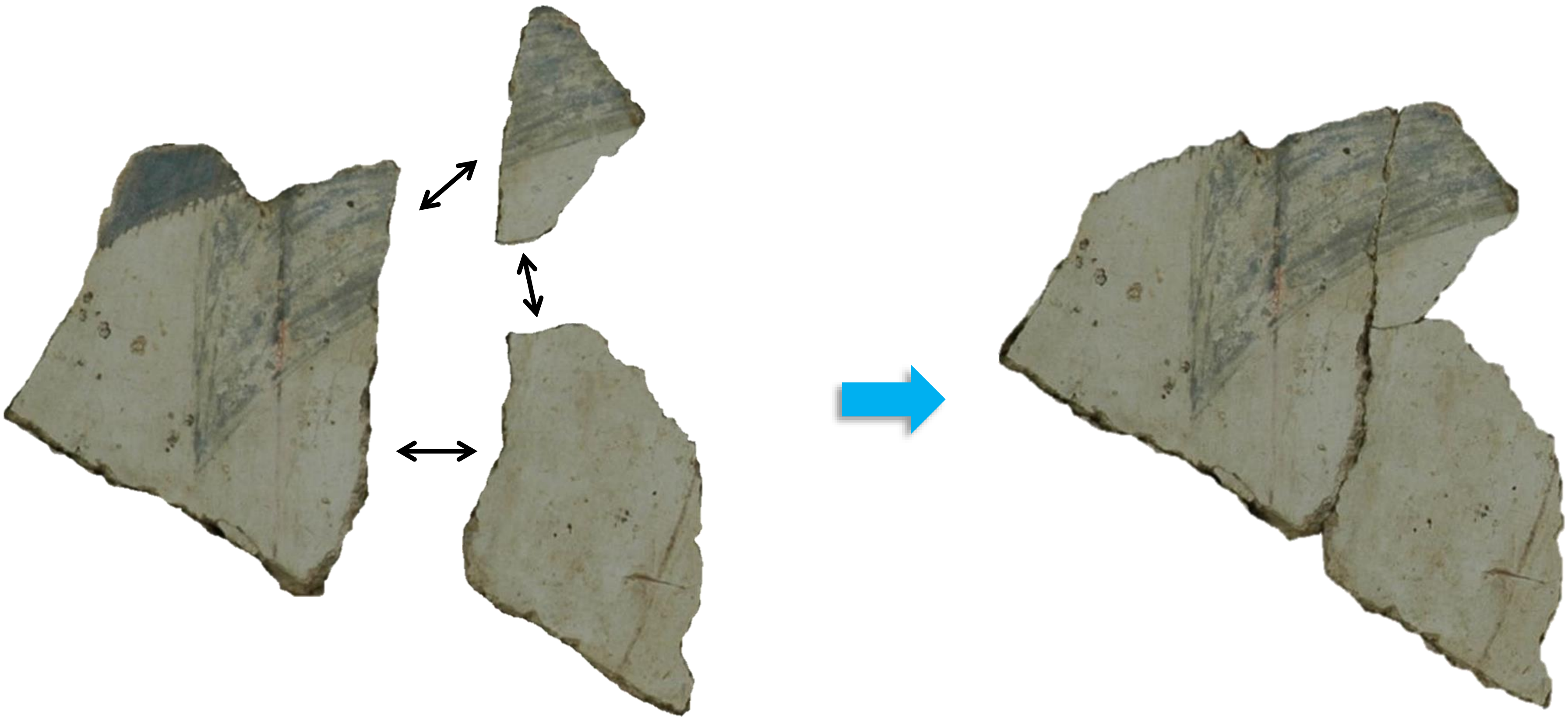
Supervising neural networks

Ambiguities in assembling pieces

Resolving ambiguities by looking at additional pieces

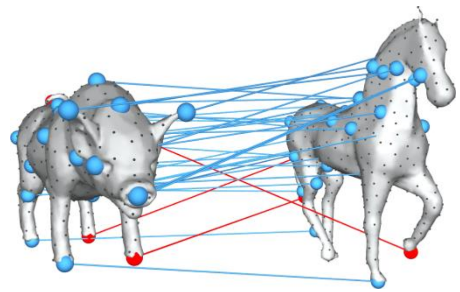


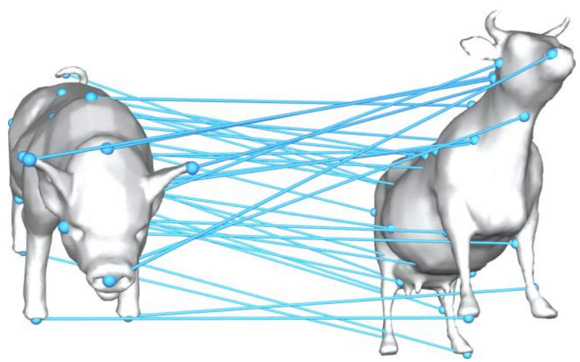
Resolving ambiguities by looking at additional pieces



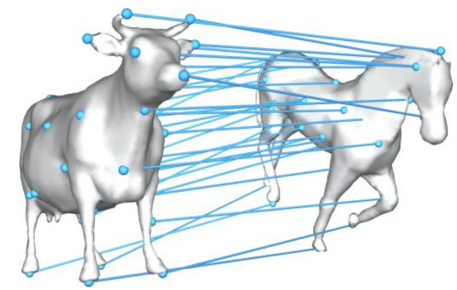
Matching through intermediate objects --- map propagation

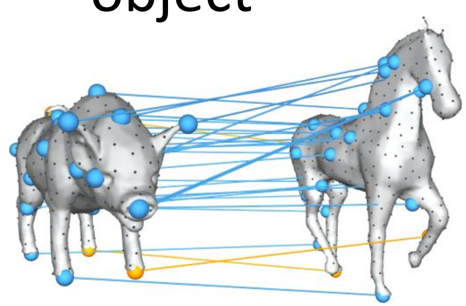
Blended intrinsic maps
[Kim et al. 11]





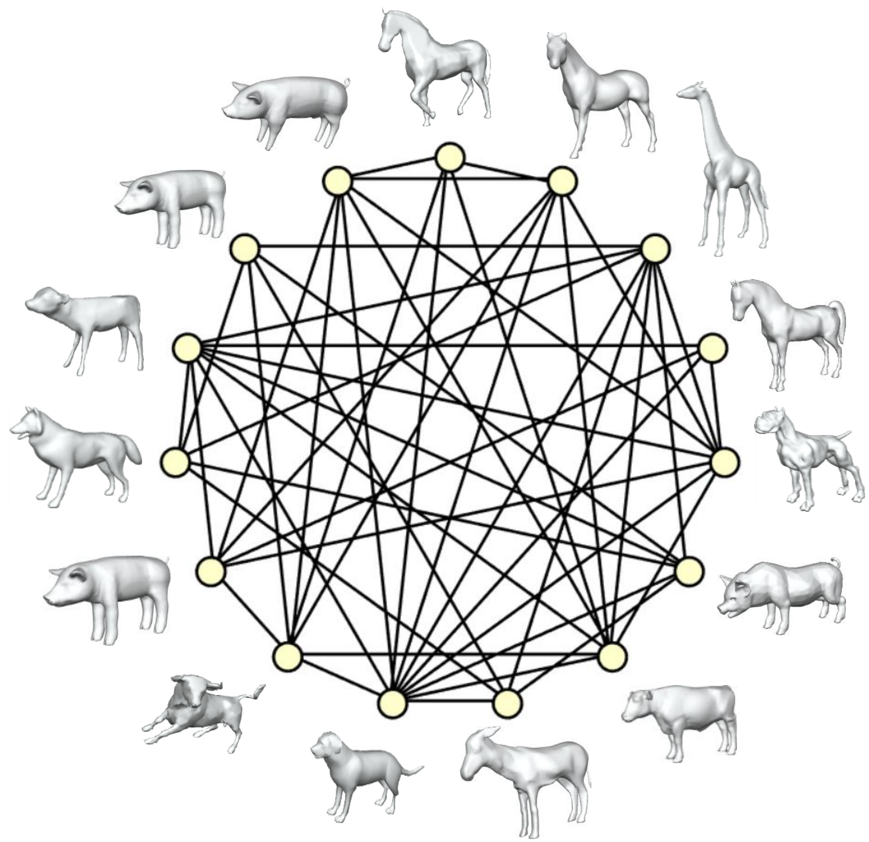
← Intermediate object →





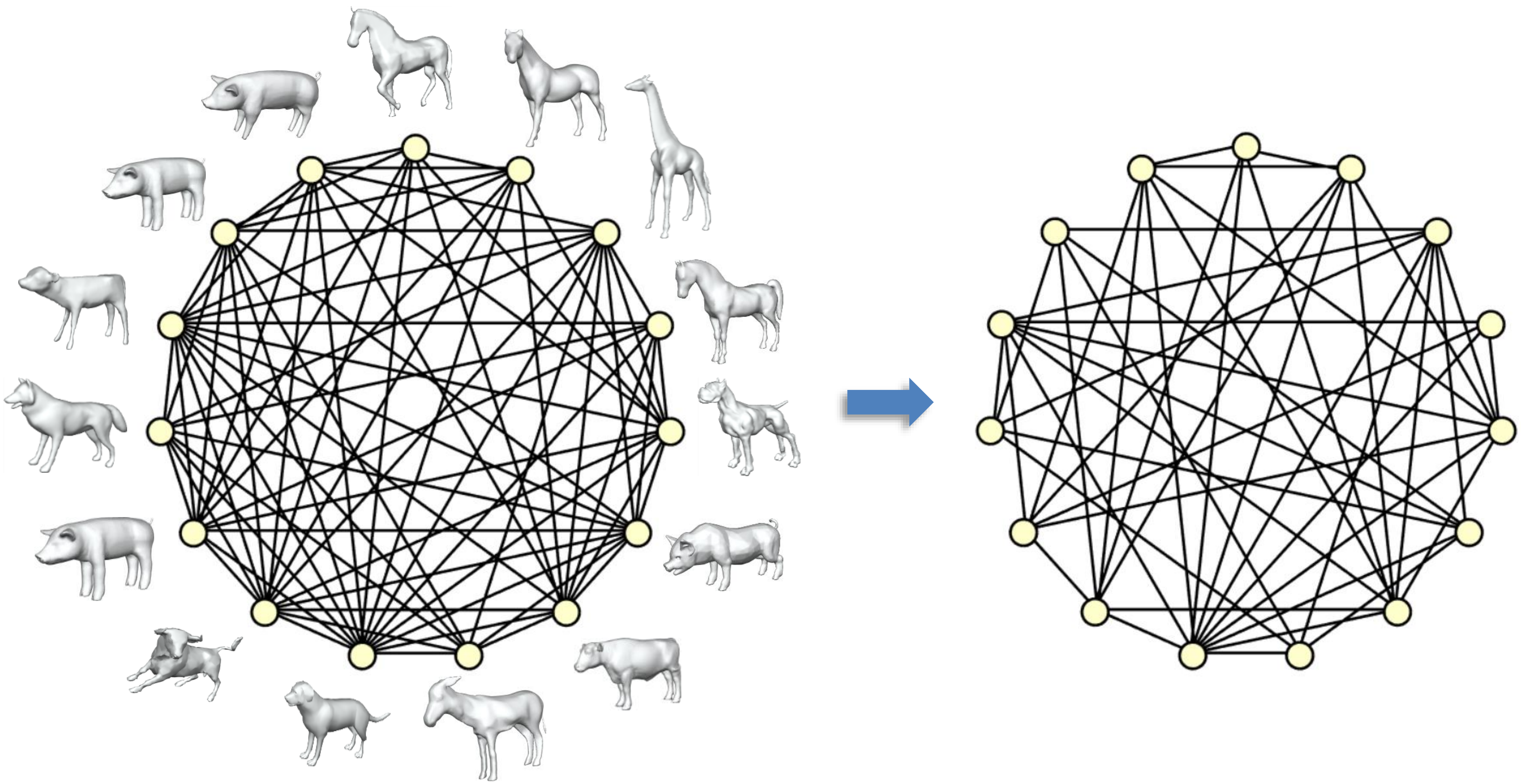
Composite

Pair-wise maps usually contain sufficient information



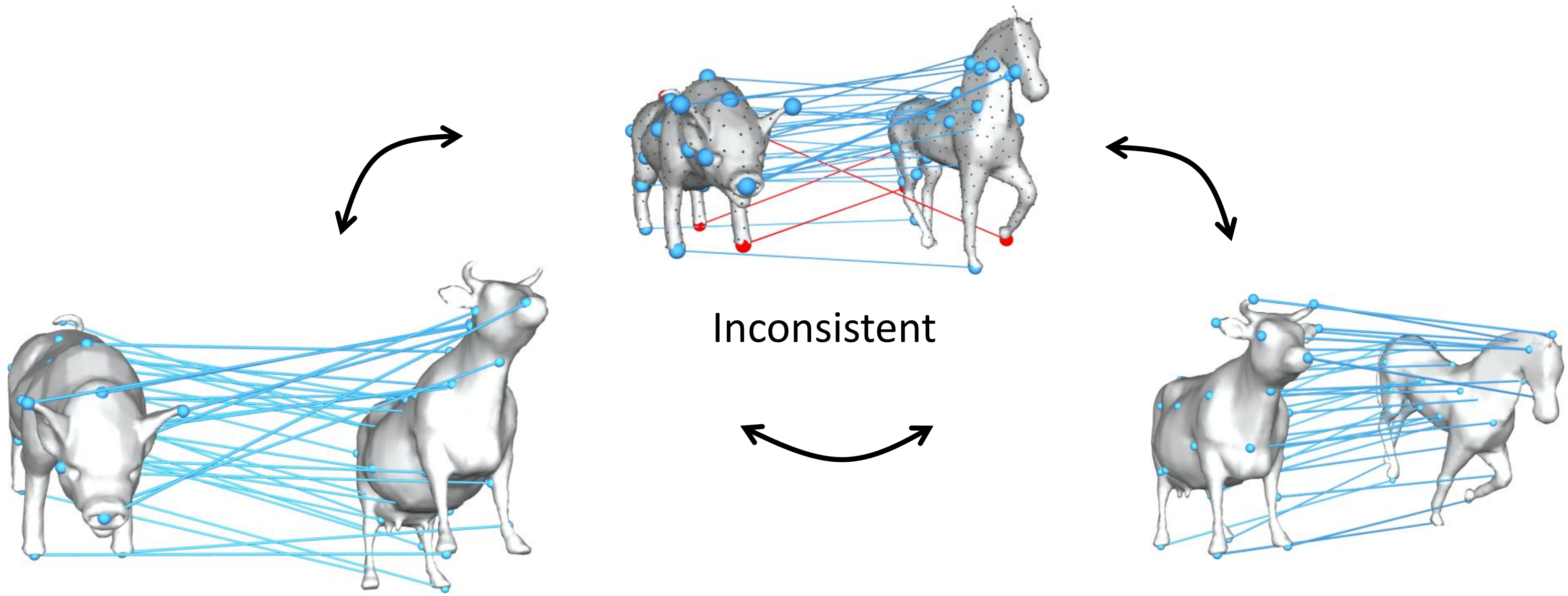
Network of approximately correct blended intrinsic maps

Map synchronization problem



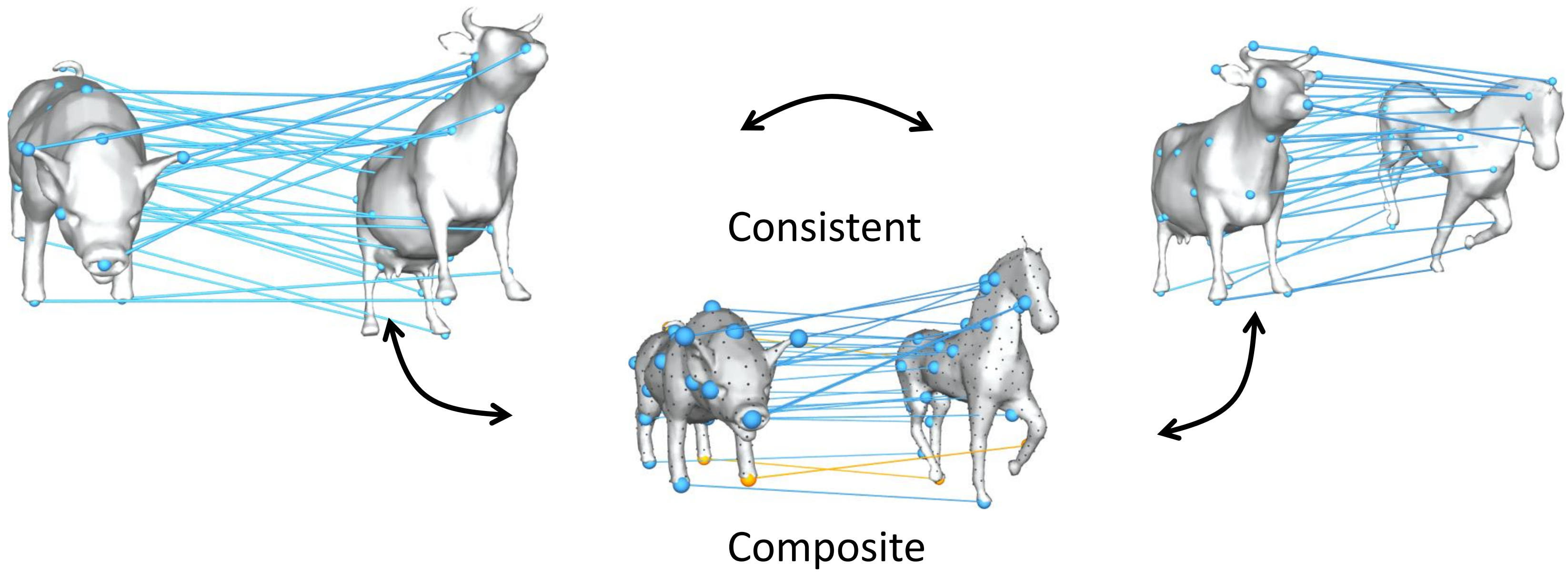
Identify correct maps among a (sparse) network of maps

A natural constraint on maps is that they should be consistent along cycles



Q. Huang, G. Zhang, L. Gao, S. Hu, A. Bustcher, and L. Guibas. *An Optimization Approach for Extracting and Encoding Consistent Maps in a Shape Collection*, SIGGRAPHAsia' 12

A natural constraint on maps is that they should be consistent along cycles



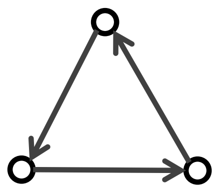
Q. Huang, G. Zhang, L. Gao, S. Hu, A. Bustcher, and L. Guibas. *An Optimization Approach for Extracting and Encoding Consistent Maps in a Shape Collection*, SIGGRAPHAsia' 12

Literature on utilizing the cycle-consistency constraint

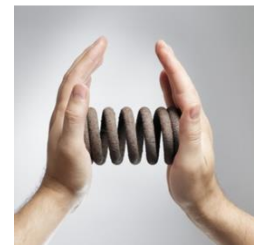
- Spanning tree optimization [Huber et al. 01, Huang et al. 06, Cho et al. 08, Crandel et al. 11, Huang et al. 12]

- Sampling inconsistent cycles [Zach et al. 10, Nyugen et al. 11, Zhou et al. 15]

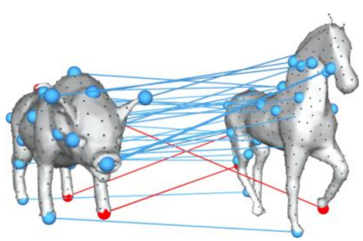
Compressive sensing view of map synchronization



Cycle-consistency



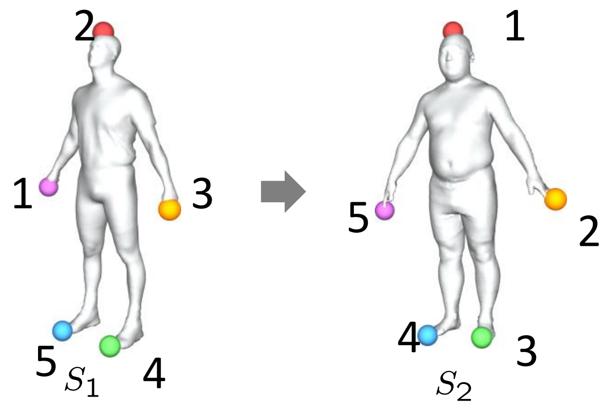
Compressible



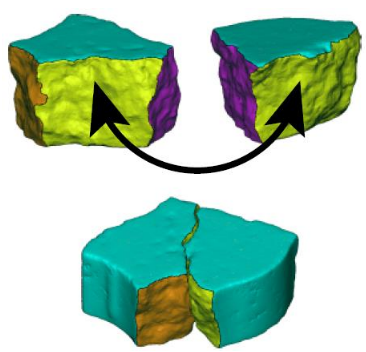
Input maps

Noisy observations

Matrix representation of maps



$$X_{12} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$



$$T_{12} = \begin{bmatrix} R_{12} & \boldsymbol{t}_{12} \\ 0 & 1 \end{bmatrix}$$

Map synchronization as constrained matrix recovery

$$X = \begin{bmatrix} I_m & X_{12} & \cdots & X_{1n} \\ X_{21} & I_m & \cdots & \vdots \\ \vdots & \vdots & \ddots & X_{n-1,n} \\ X_{n1} & \cdots & X_{n,n-1} & I_m \end{bmatrix} \qquad X_{ij} = X_{j1} X_{i1}^T$$

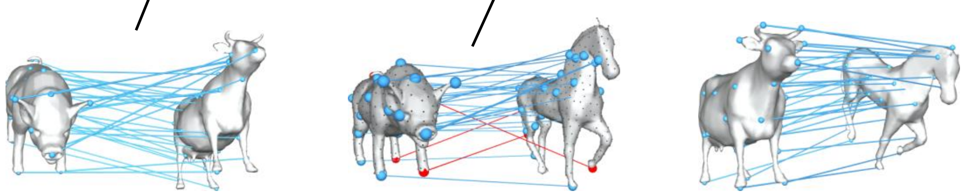
$$= \begin{bmatrix} I_m \\ \vdots \\ X_{n1} \end{bmatrix} \begin{bmatrix} I_m & \cdots & X_{n1}^T \end{bmatrix}$$

Map synchronization as constrained matrix recovery

$$X = \begin{bmatrix} I_m & X_{12} & \cdots & X_{1n} \\ X_{21} & I_m & \cdots & \vdots \\ \vdots & \vdots & \ddots & X_{n-1,n} \\ X_{n1} & \cdots & X_{n,n-1} & I_m \end{bmatrix}$$

Parameter-free

Theoretical guarantees



Noisy measurements of matrix blocks

Q. H and L. Guibas, *Consistent Shape Maps via Semidefinite Programming*, Sym. on Geometry Processing'13

Y. Chen, L. Guibas, Q. H, *Near-Optimal Joint Object Matching via Convex Relaxation*, ICML'14

Q. H, F. Wang, L. Guibas, Functional Map Networks for Analyzing and Exploring Large Shape Collections, SIGGRAPH' 14

S. Shen, Q.H., N. Srebro, S. Sunghavi, Normalized Spectral Map Synchronization, NIPS' 16

Permutation synchronization

Objective function:

$$\text{minimize} \sum_{(i,j)\in\mathcal{G}} \|X_{ij}^{\text{input}} - X_{ij}\|_1$$

Observation graph

Constraints:

$$X \succeq 0$$

cycle-consistency

Semidefinite Program

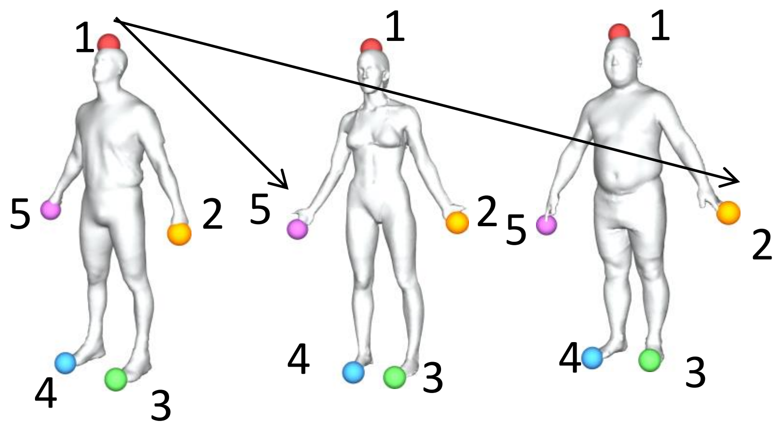
$$\boxed{\begin{aligned} & X_{ii} = I_m, \quad 1 \leq i \leq n \\ & X_{ij}\mathbf{1} = \mathbf{1}, X_{ij}^T\mathbf{1} = \mathbf{1}, \quad 1 \leq i < j \leq n \\ & 0 \leq X \leq 1 \end{aligned}}$$

mapping constraint

Deterministic guarantee

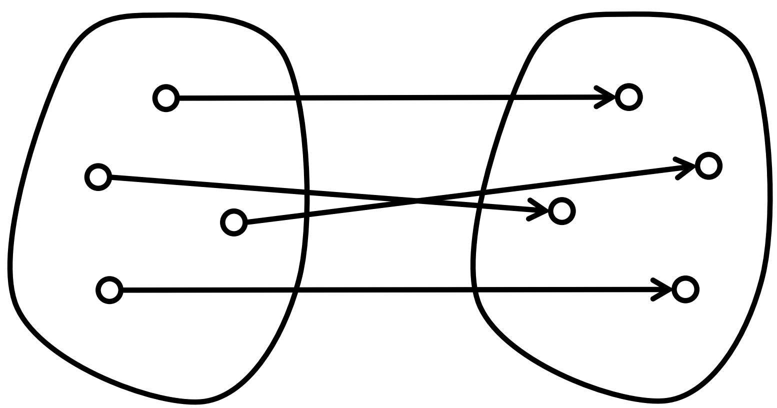
- *Theorem: Given noisy input maps, permutation synchronization recovers the underlying maps if*

#incorrect corres. of each point $< \frac{\lambda_2(G)}{4}$



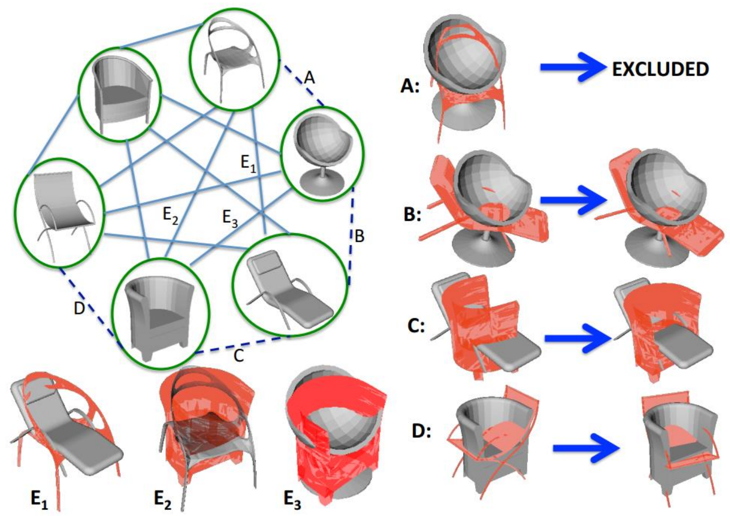
Optimality when the object graph *G* is a clique

- 25% incorrect correspondences
- Worst-case scenario
  - Two clusters of objects of equal size
  - Wrong correspondences between objects of different clusters only (50%)



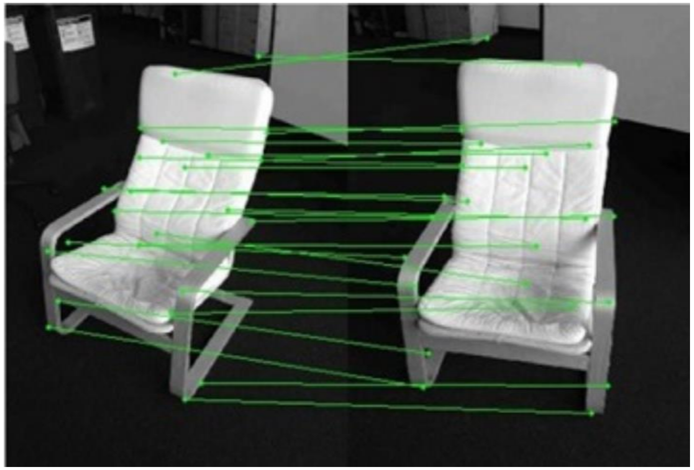
Justification of maximizing $\lambda_2(G)$ for map graph construction

Imageweb [Heath et al 10]



Fuzzy correspondences on shapes [Kim et al 12]

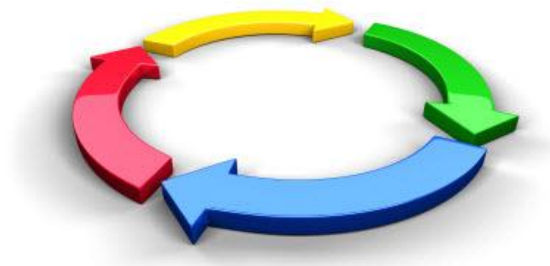
Variants



Partial maps [CGH'14]

Spectral Sync. [SHSS'16]

Near-optimal!

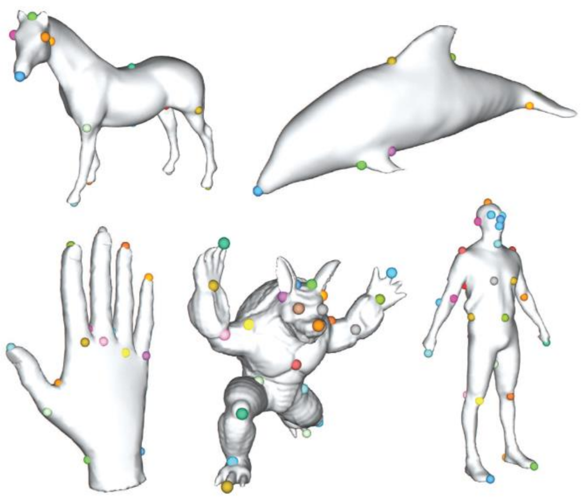


Rotation Sync.
[Wang and Singer'14,...]

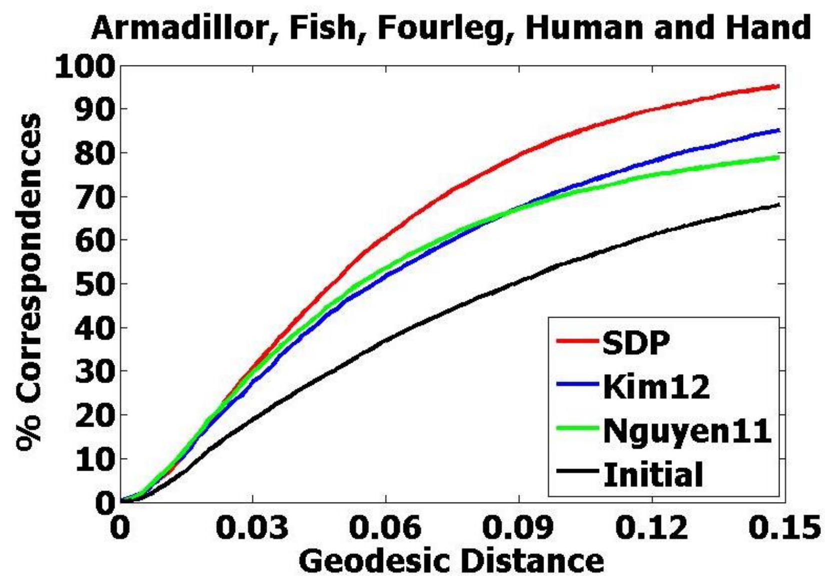
Near-optimal?

Experimental Results

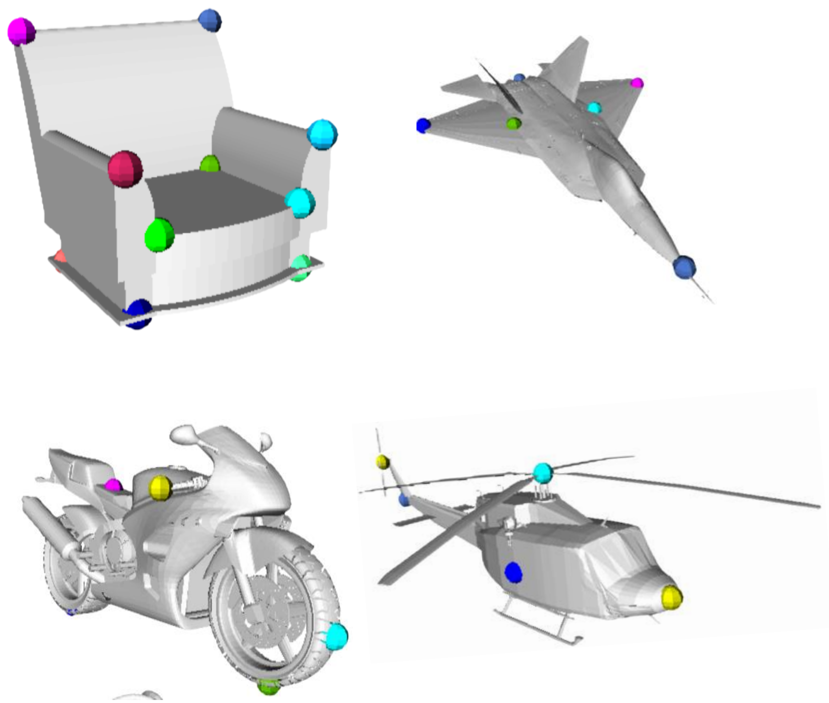
Constrained matrix recovery achieves state-of-the-art performance

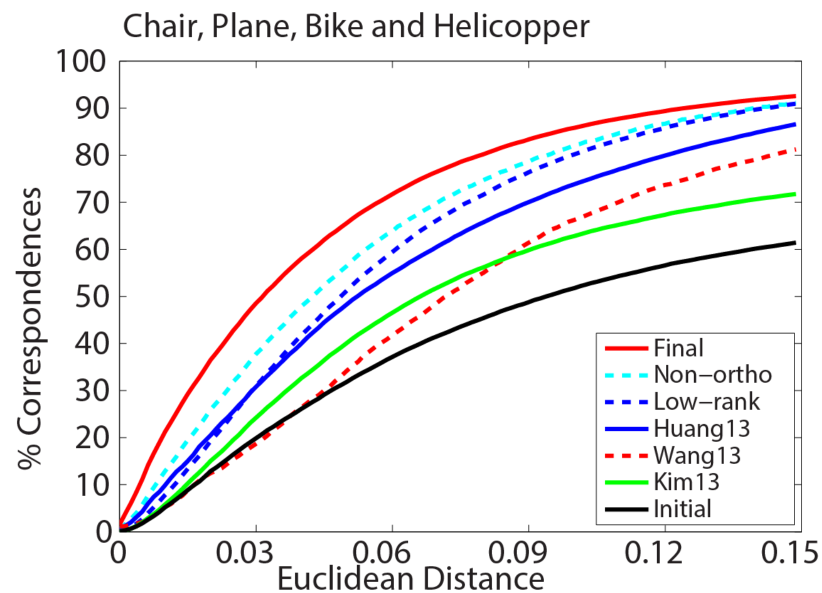


SHREC07-UnSym

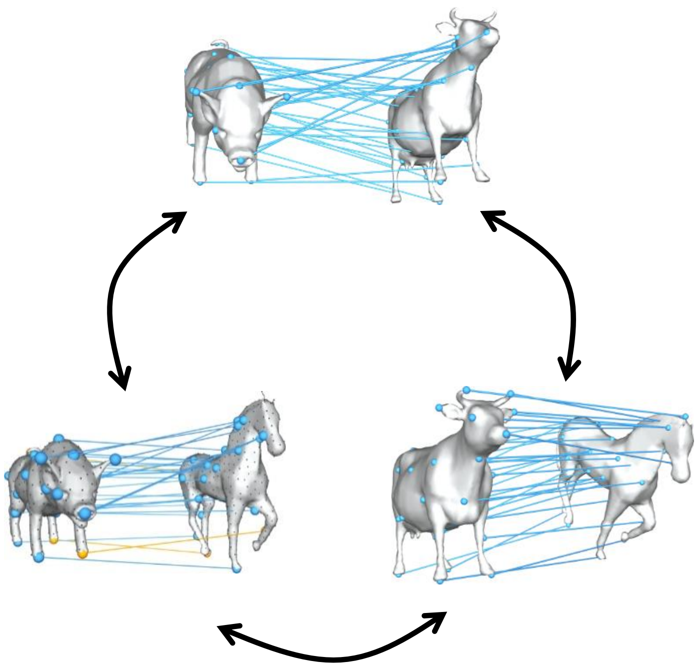


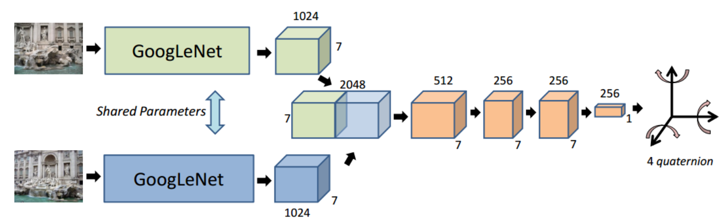
Constrained matrix recovery achieves state-of-the-art performance





Outline

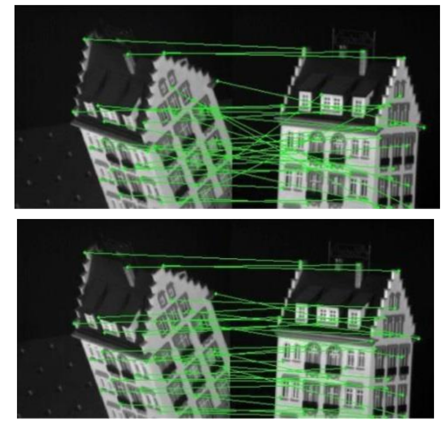




Supervising
neural networks

Matrix recovery perspective

Map synchronization versus learning pair-wise matching

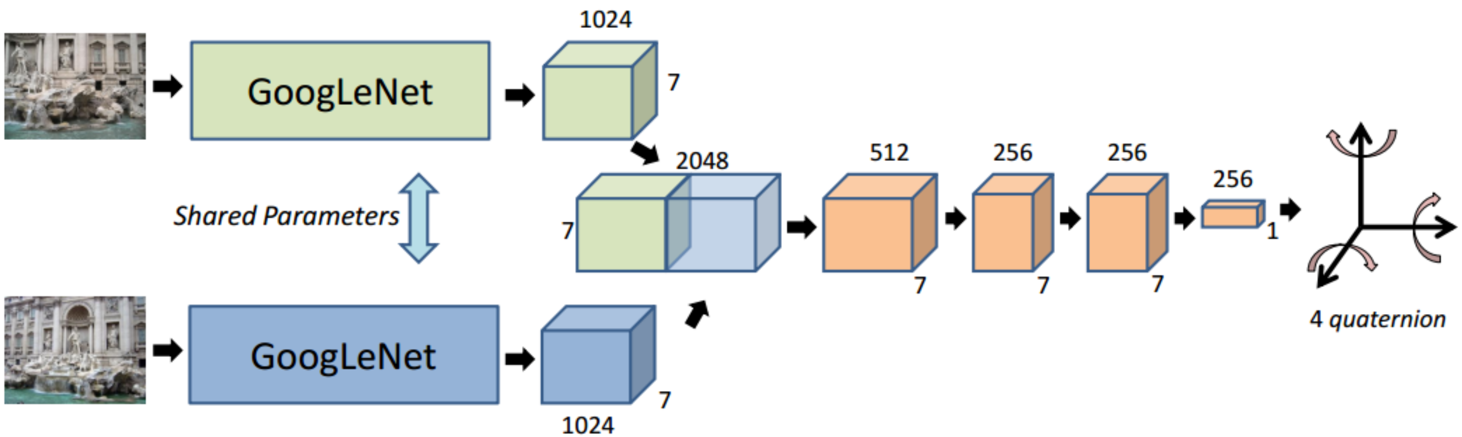


CMU Hotel dataset

Pair-wise (RANSAC)	Joint Matching (from RANSAC)	Pairwise (Learning) Leordeanu et al. 12
64.1%	97.4%	94.6%

Joint Matching (from Learning)	Pairwise (Learning) Leordeanu et al. 12	Joint Matching (from Learning)
100%	95.1%	100%

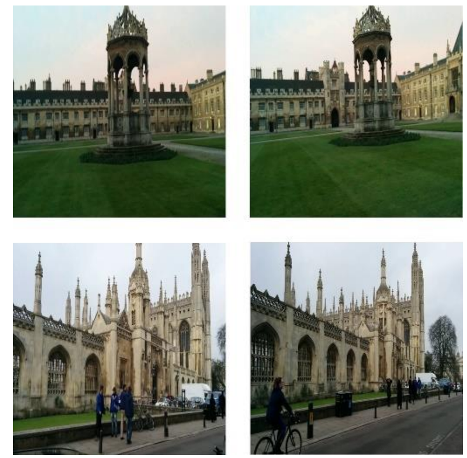
Unsupervised Learning of Relative Camera Poses Using Neural Networks



Alternating minimization converges

SydneyHouse [Chu et al.16]

125K Training, 30K Testing

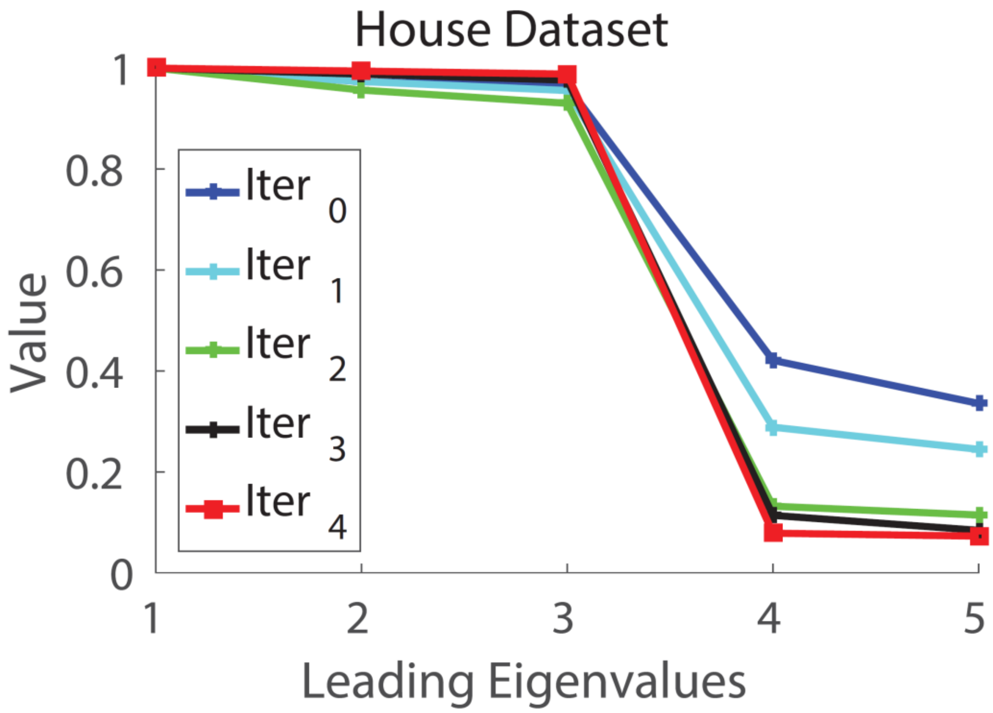


PoseNet [Kendall et al.15]

390K Training, 91K Testing

Network	Iter. 0	Iter. 1	Iter. 2	Iter. 3	Iter. 4
PoseNet	13.35	10.14	9.23	8.94	8.92
SydneyHouse	6.13	5.02	4.95	4.89	4.87

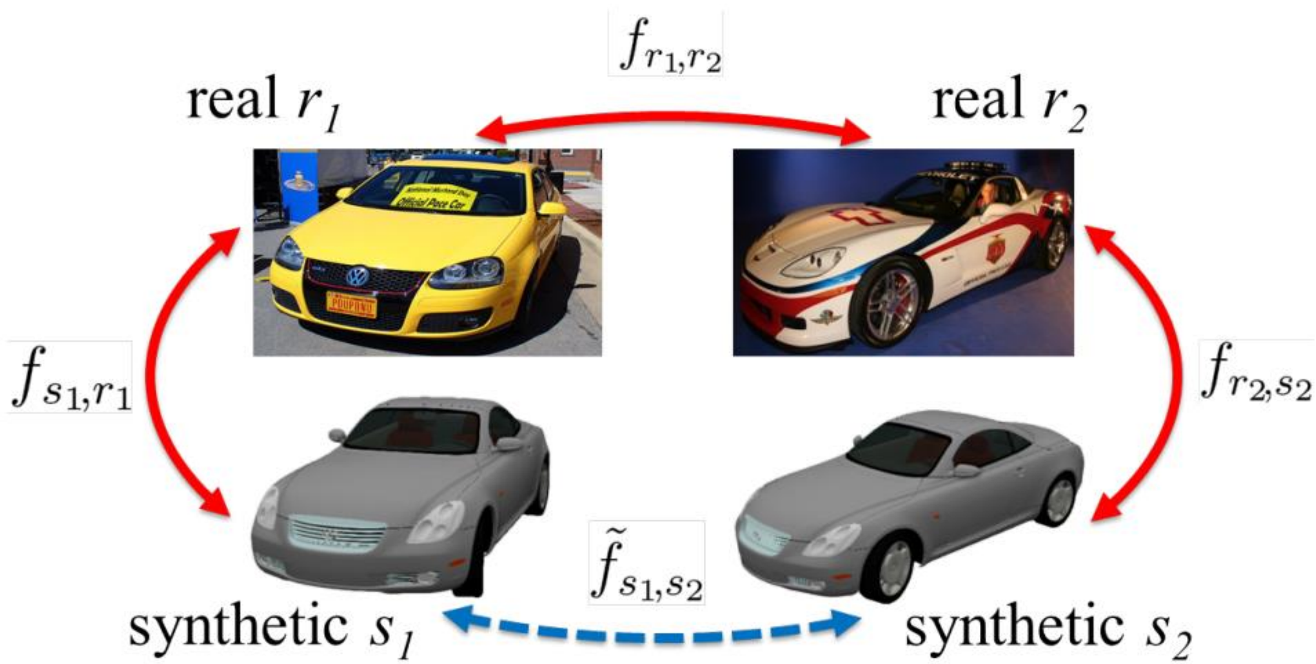
Predicted maps become more consistent



Cycle-consistency perspective

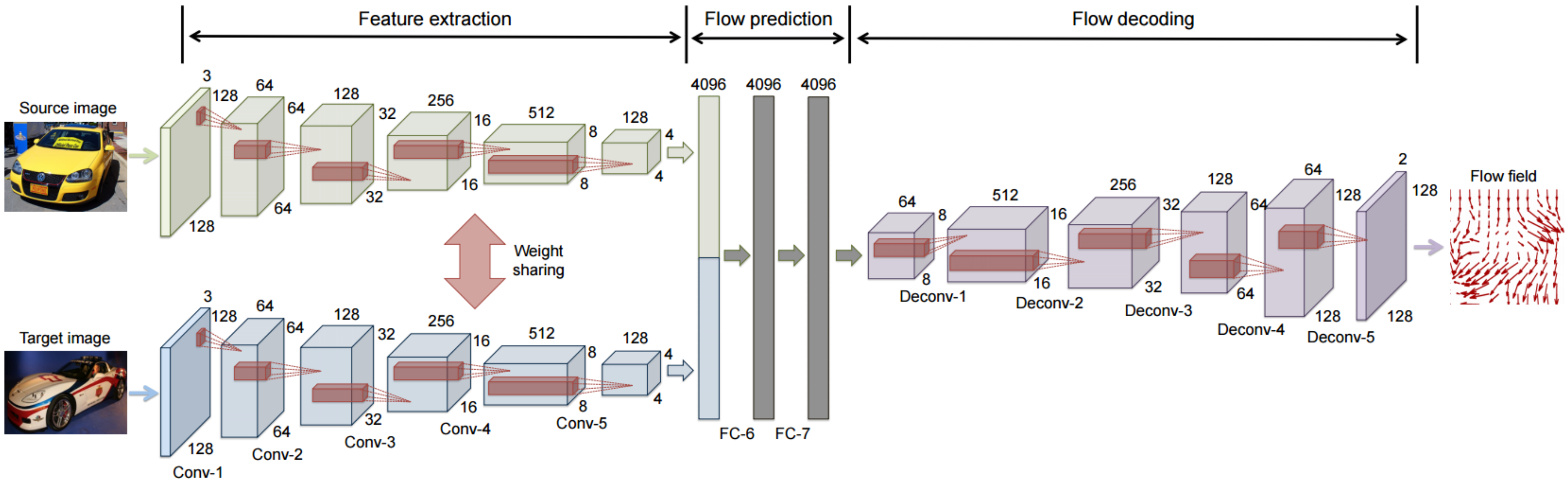
[Zhou-Krähenbühl-Abruy-Huang-Efros, CVPR’ 16]

Connecting real images through synthetic images



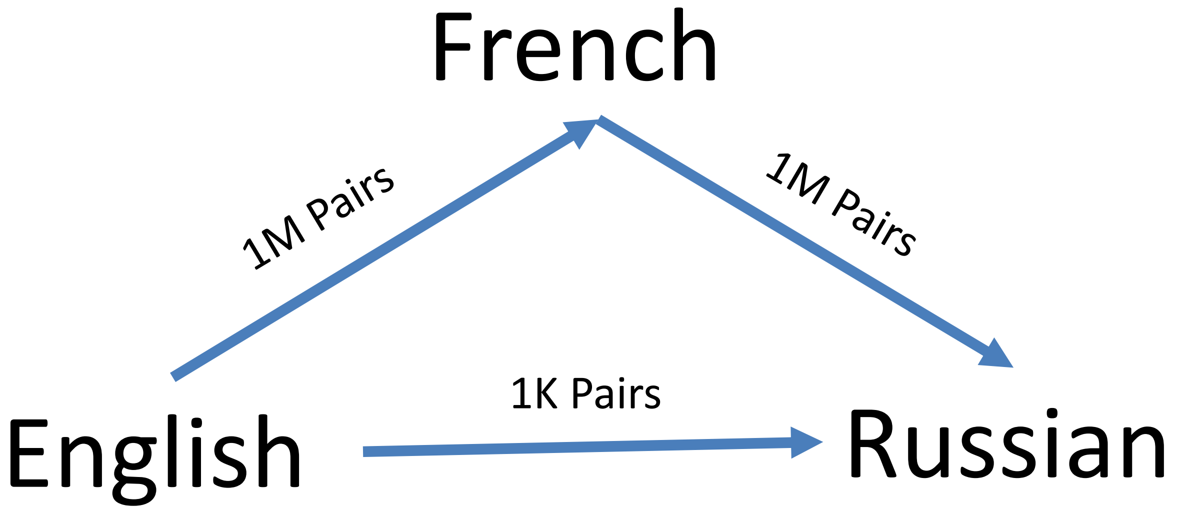
$$\tilde{f}_{s_1,s_2} = f_{s_1,r_1} \circ f_{r_1,r_2} \circ f_{r_2,s_2}$$

Flow architecture



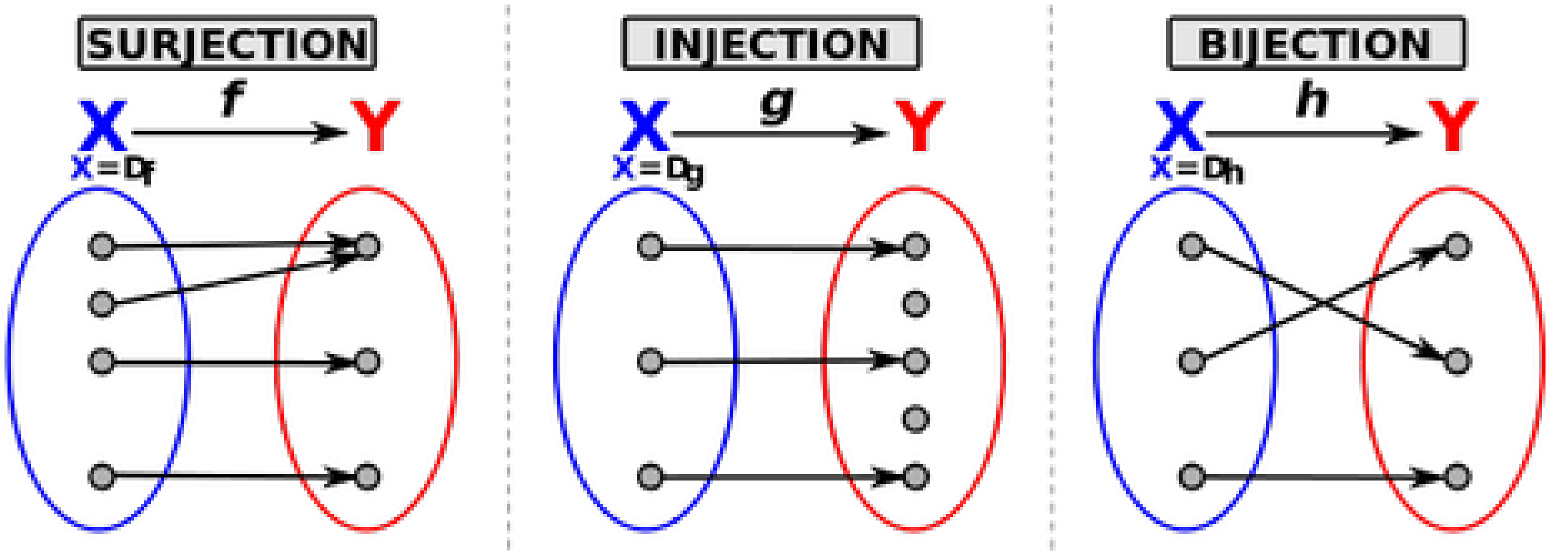
FlowNet [Fischer et al 15]

Multi-lingual Translation [Cho et al.]

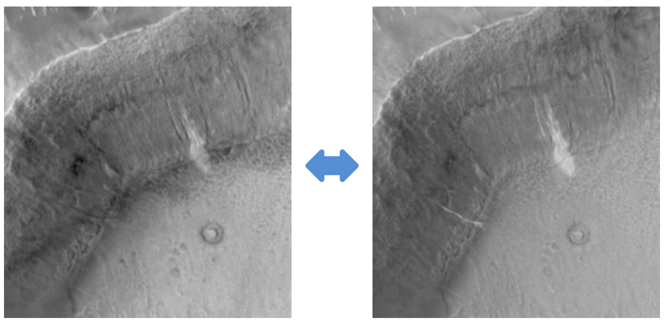


Looking Ahead

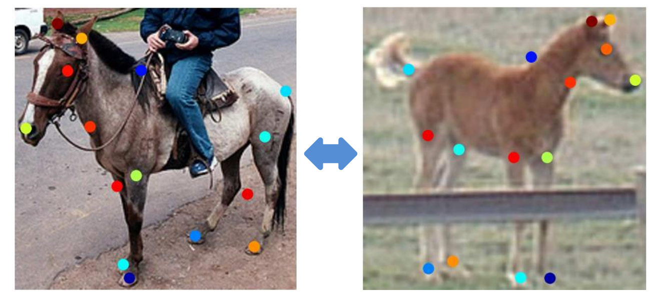
Maps as functions between sets



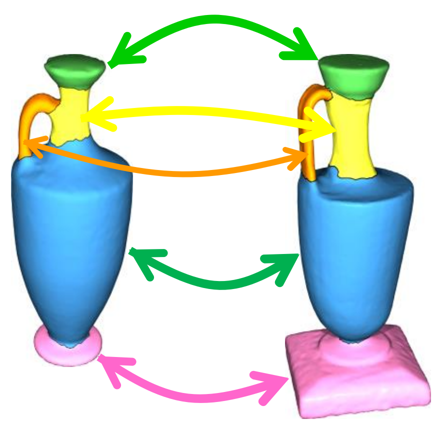
How to define sets on objects?



Pixels

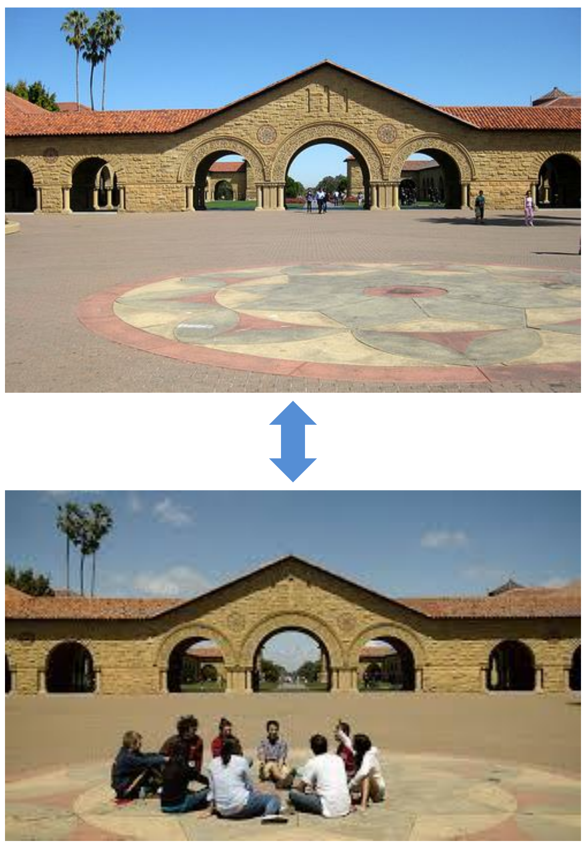


Key points

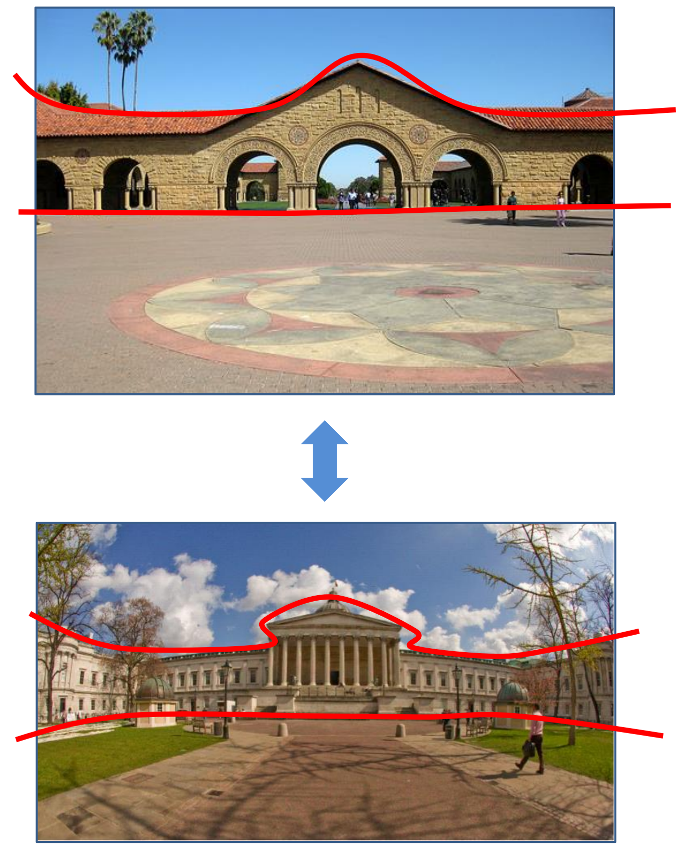


Parts

Sets (or representations) and maps should be optimized together



Pixel-wise correspondences



Segment correspondences

Questions?