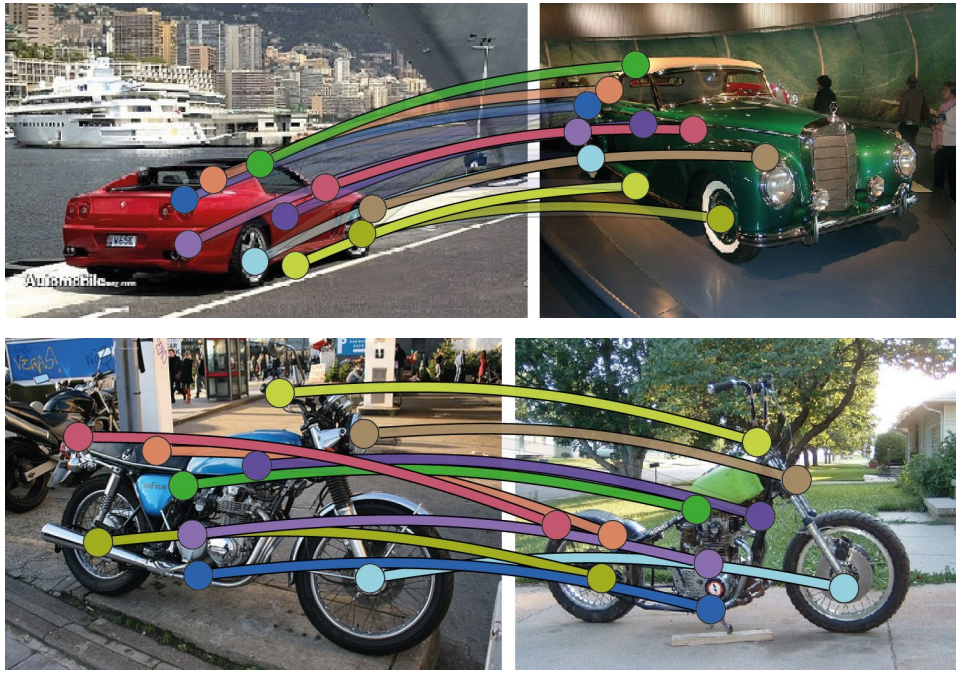

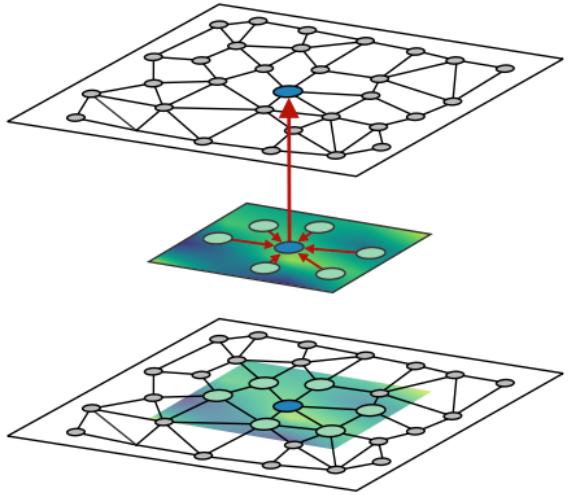

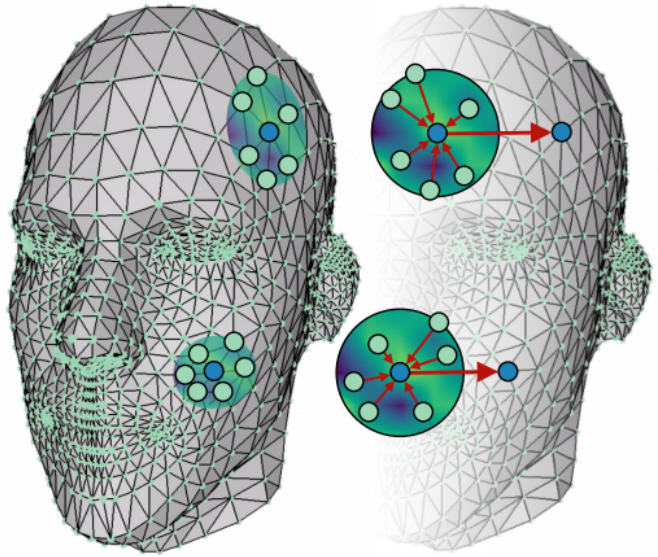

Graph Neural Networks in Vision and Graphics

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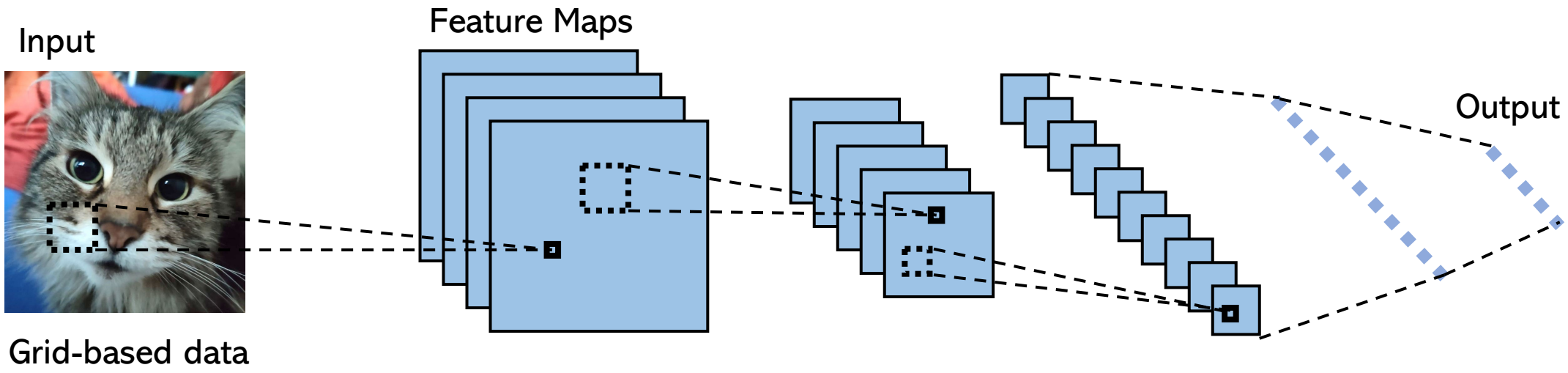
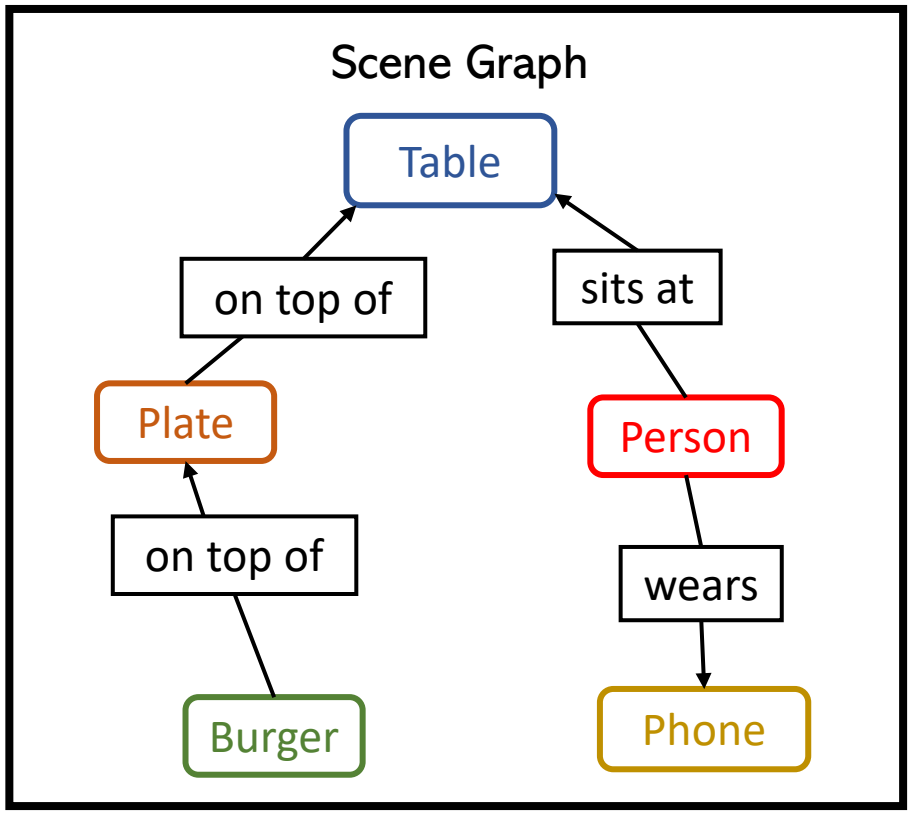
Differentiable programming in CV is dominated by CNNs



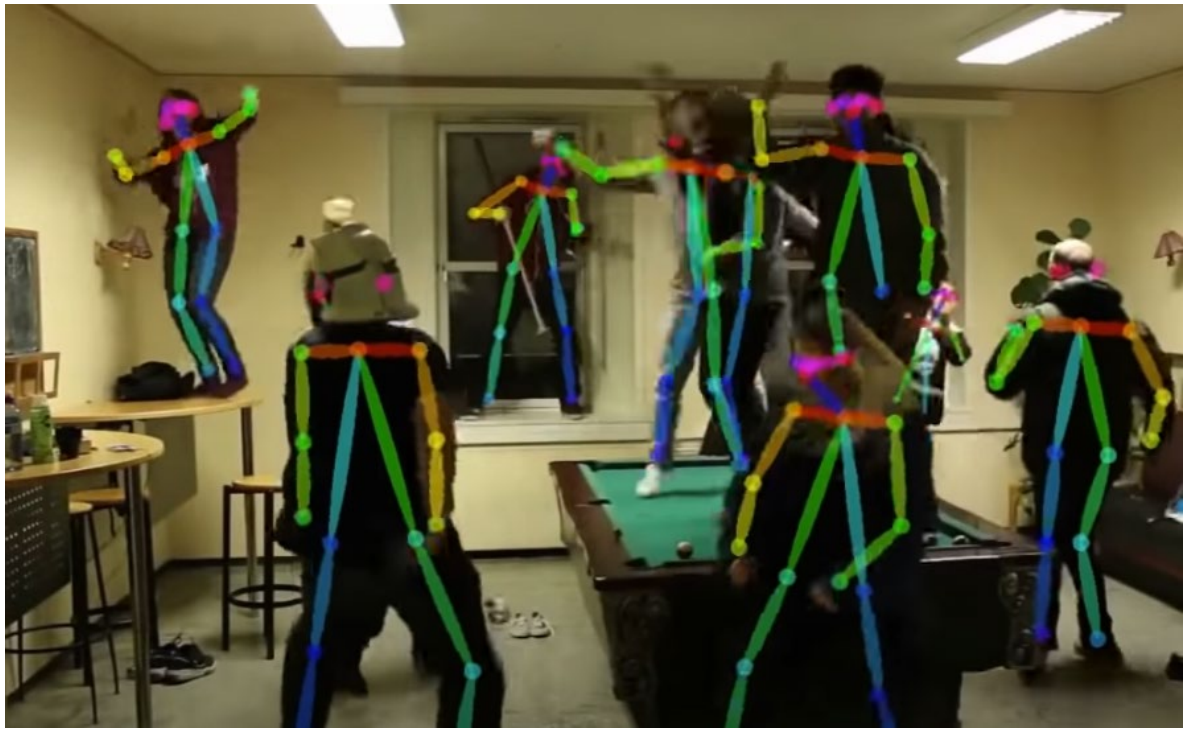
What about object hierarchies?

DIV2K dataset



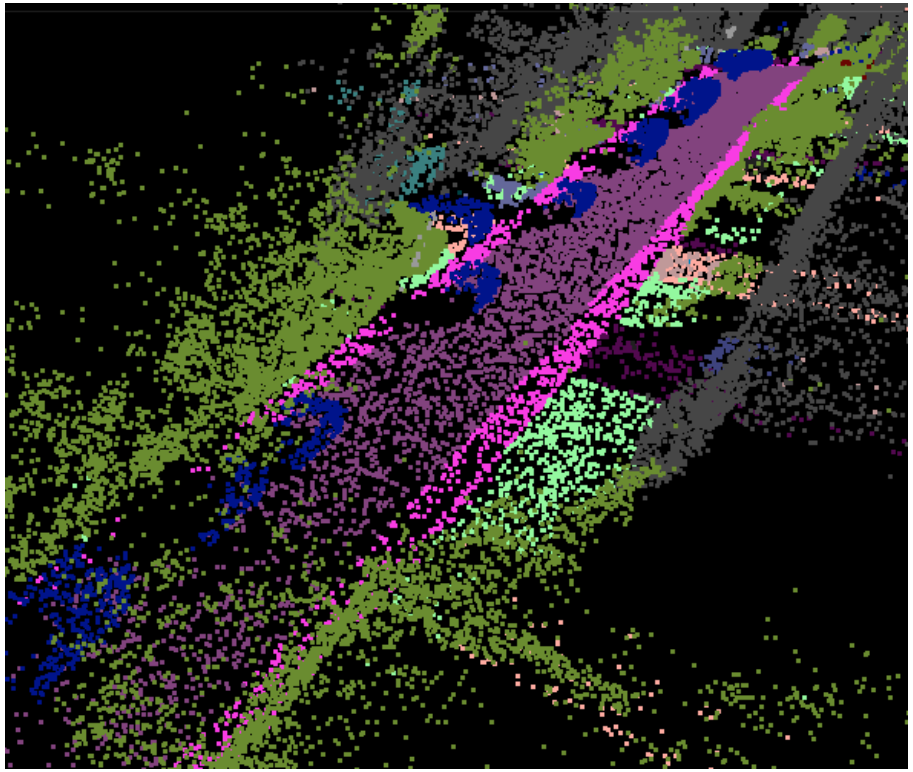
Or graphs with geometric information?

Fey et al., Deep Graph Matching Consensus, ICLR 2020

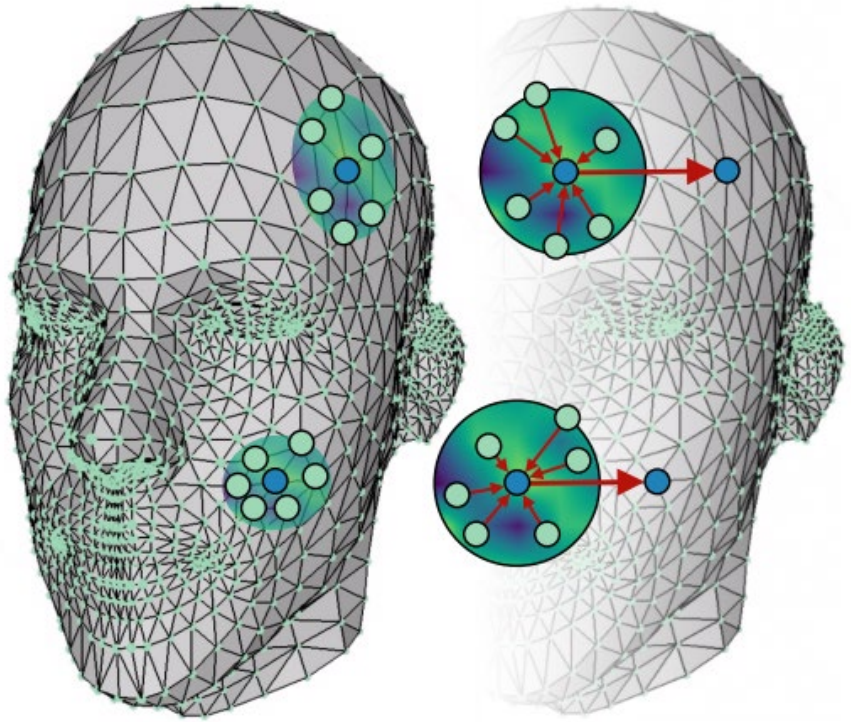


Cao et al., Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields, CVPR 2017

Point Clouds and Meshes?



KITTI dataset



Fey et al., SplineCNN, CVPR 2018

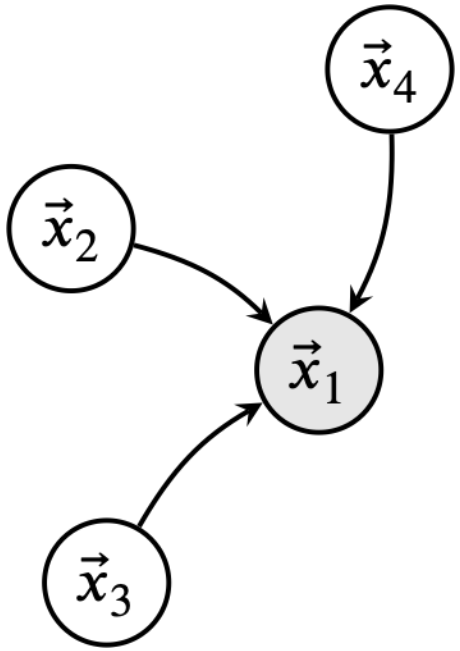
GNNs describe differentiable data flow between entities

Entities can be:

- Nodes
- 3D points
- Scene objects
- Keypoints

Relations can be:

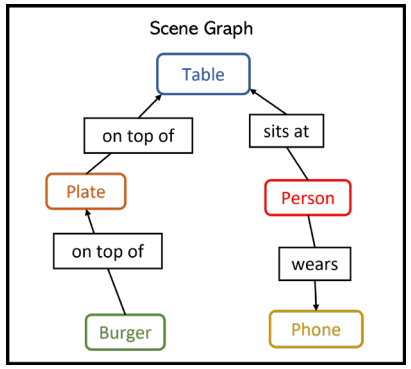
- Cartesian/Polar relationship
- Hierarchical relationship
- Mesh edges
- …



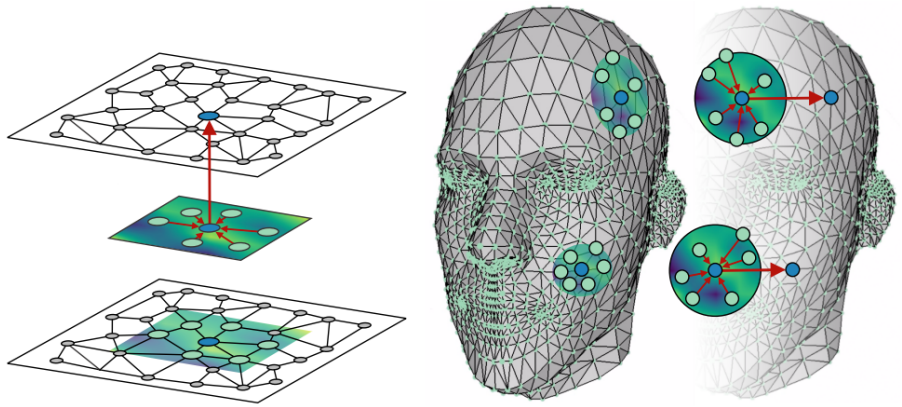
$$\vec{x}_i' = \text{UPDATE}\left(\vec{x}_i, \square_{j \in \mathcal{N}(i)} \text{MESSAGE}\left(\vec{x}_i, \vec{x}_j, \vec{e}_{j,i}\right)\right)$$

GNNs as building block for differentiable programmming

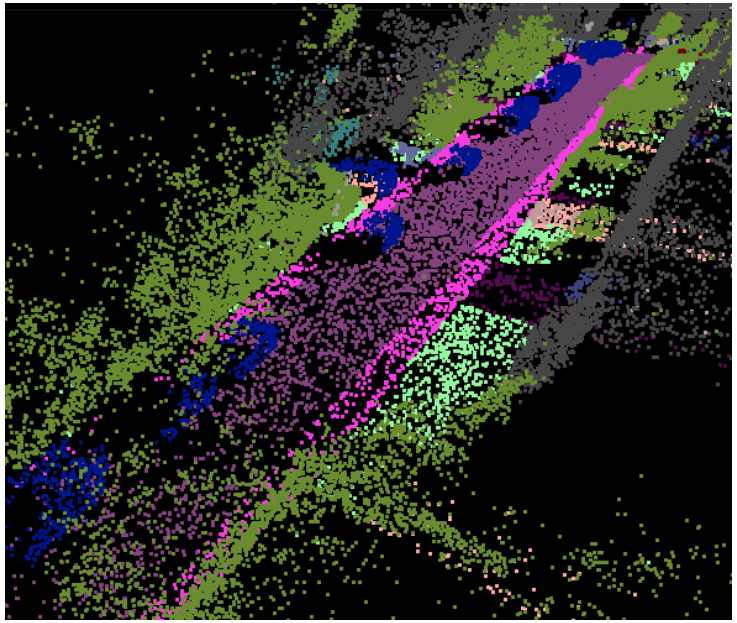
… to fuse data from multiple entities



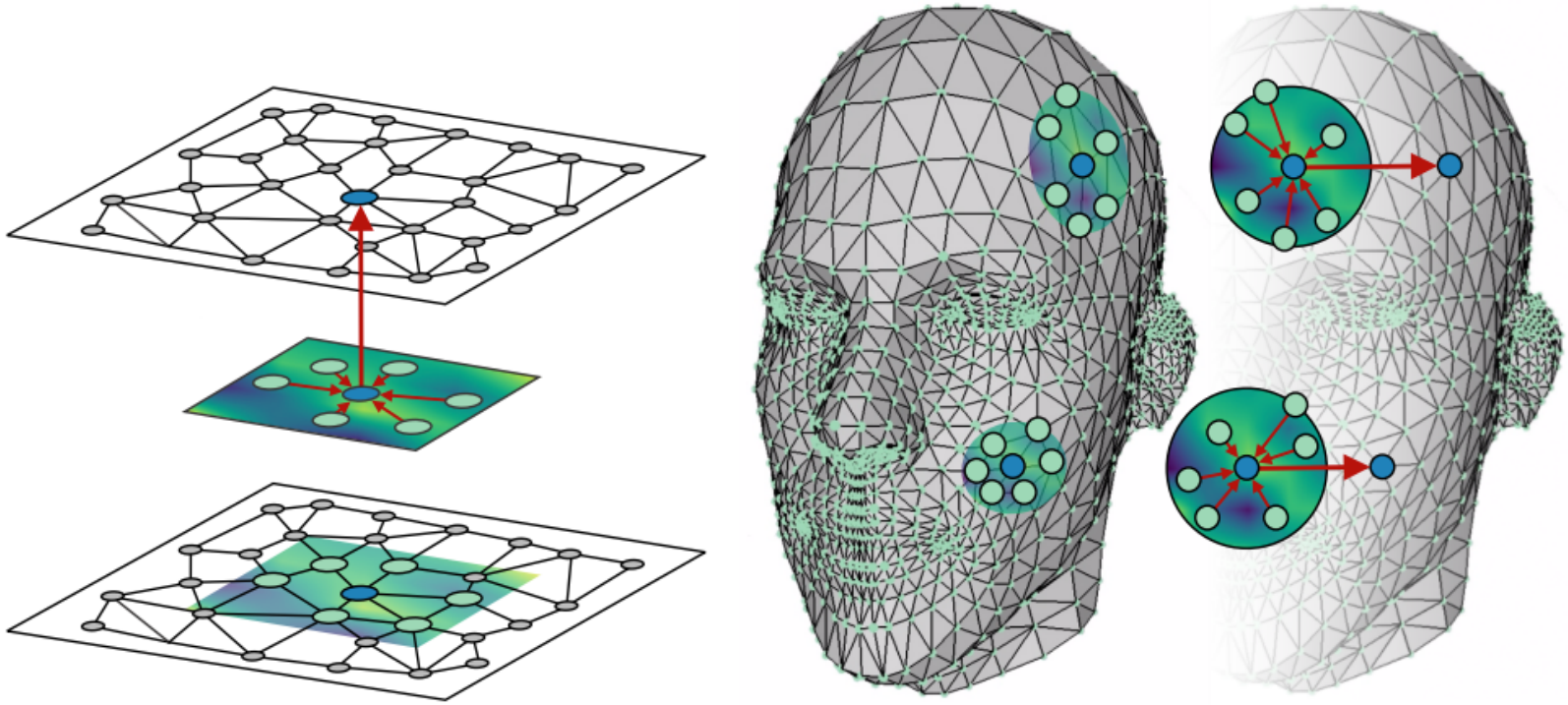
… to process data on irregular domains



… to analyze geometric structures

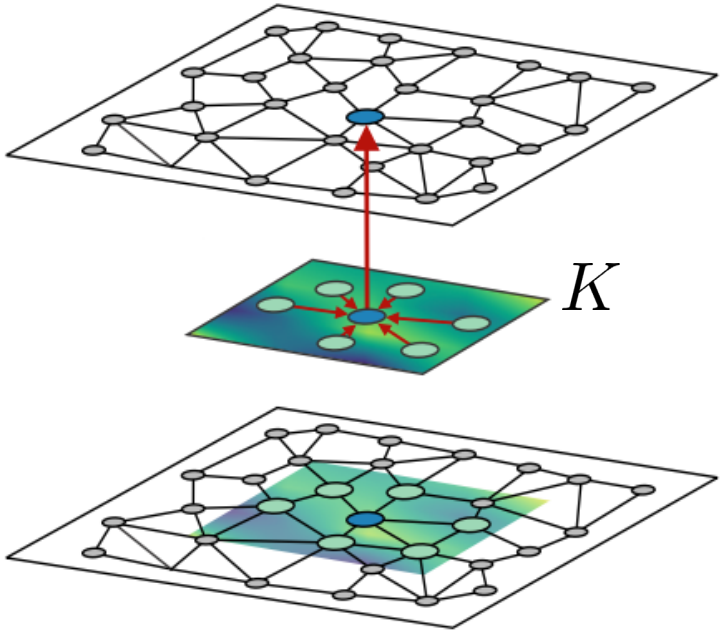


GNNs for Continuous Convolution



[1] Fey, Lenssen, Weichert, Müller: SplineCNN, CVPR 2018

GNNs for Continuous Convolution



Continuous Convolution:

$$\mathbf{x}_i = \sum_{j \in \mathcal{N}(i)} K(\mathbf{p}_j - \mathbf{p}_i) \cdot \mathbf{x}_j$$

Message Passing:

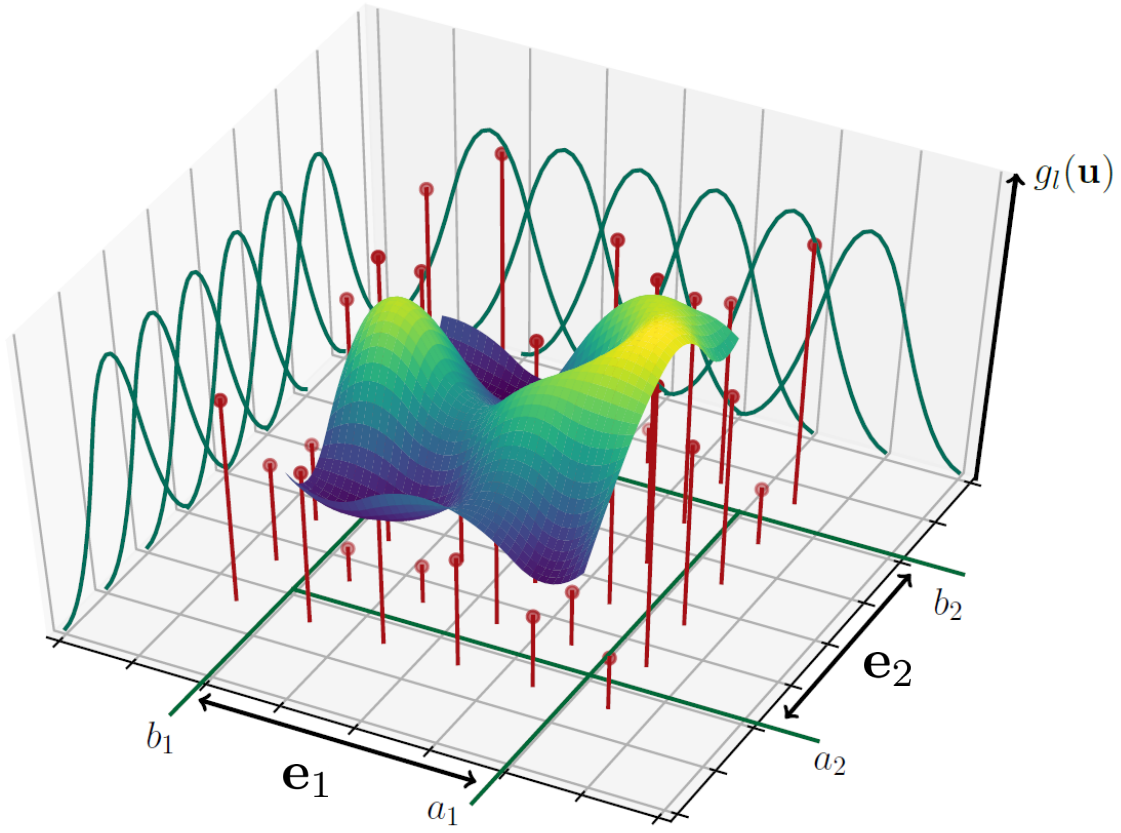
$$\mathbf{x}_i = \text{Update}\left(\mathbf{x}_i, \sum_{j \in \mathcal{N}(i)} \text{Message}(\mathbf{x}_i, \mathbf{x}_j, \mathbf{e}_{i,j})\right)$$

Message for Continuous Convolution:

$$\begin{aligned}\text{Message}(\mathbf{x}_j, \mathbf{e}_{j,i} = (\mathbf{p}_j - \mathbf{p}_i)) \\ = K(\mathbf{e}_{j,i}) \cdot \mathbf{x}_j\end{aligned}$$

[1] Fey, Lenssen, Weichert, Müller: SplineCNN, CVPR 2018

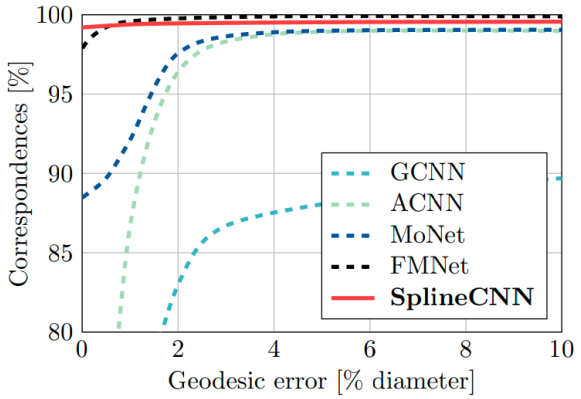
GNNs for Continuous Convolution

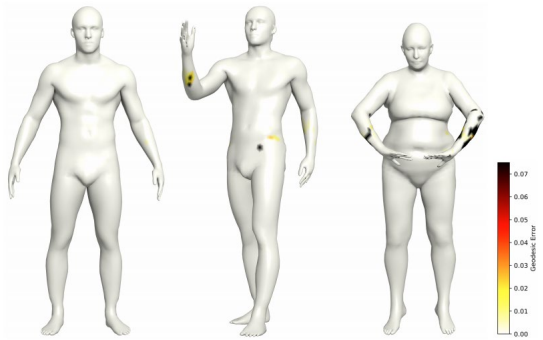


[1] Fey, Lenssen, Weichert, Müller: SplineCNN, CVPR 2018

Processing data on irregular, geometric domains

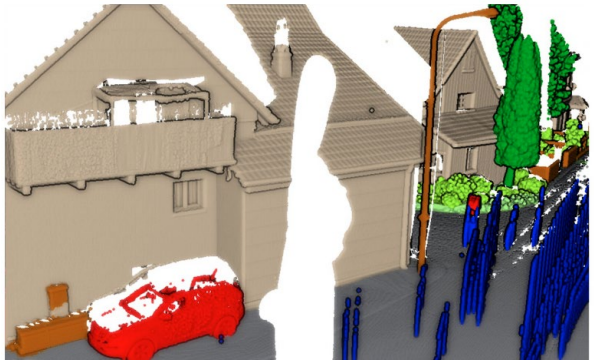
Shape Correspondence

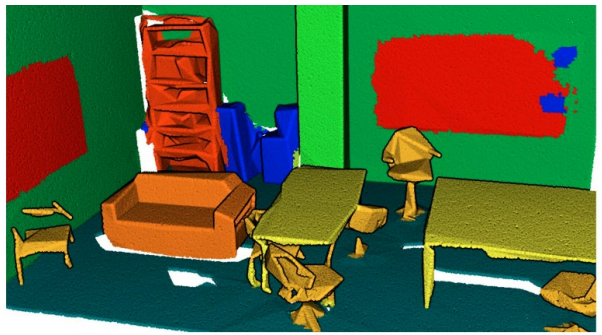




Fey et al., SplineCNN, CVPR 2018

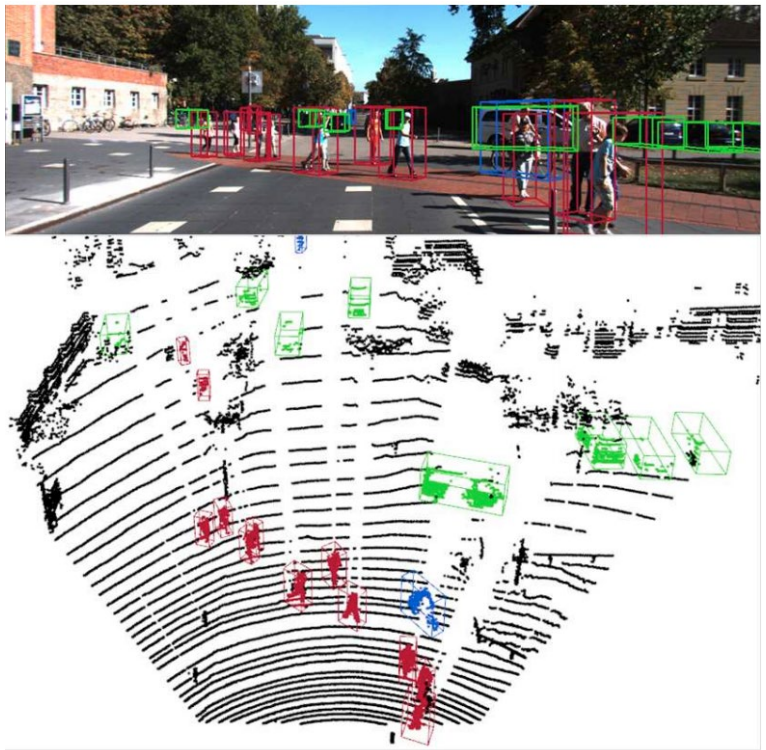
Semantic Segmentation





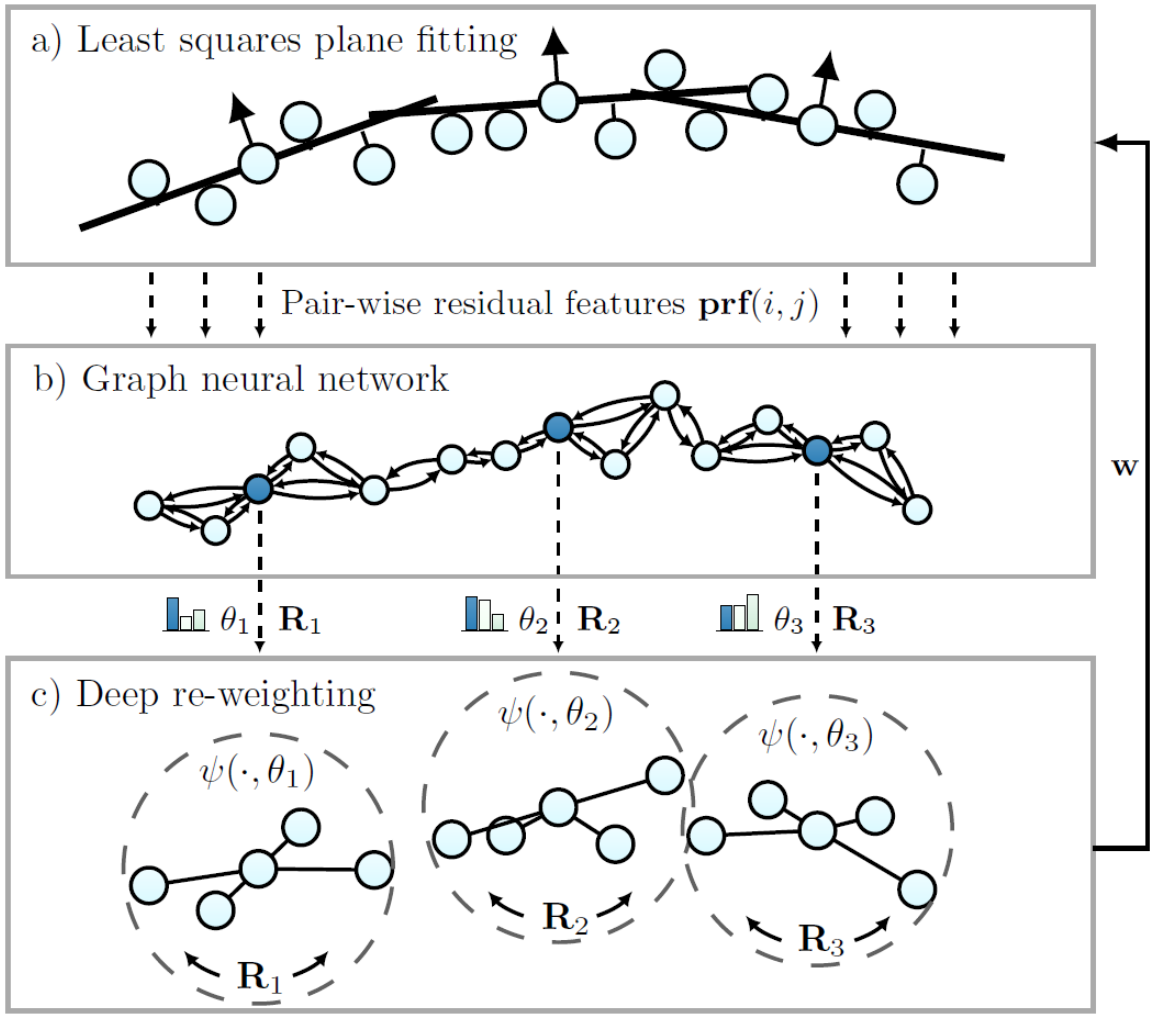
Thomas et al., KPConv, CVPR 2019

3D Object Detection



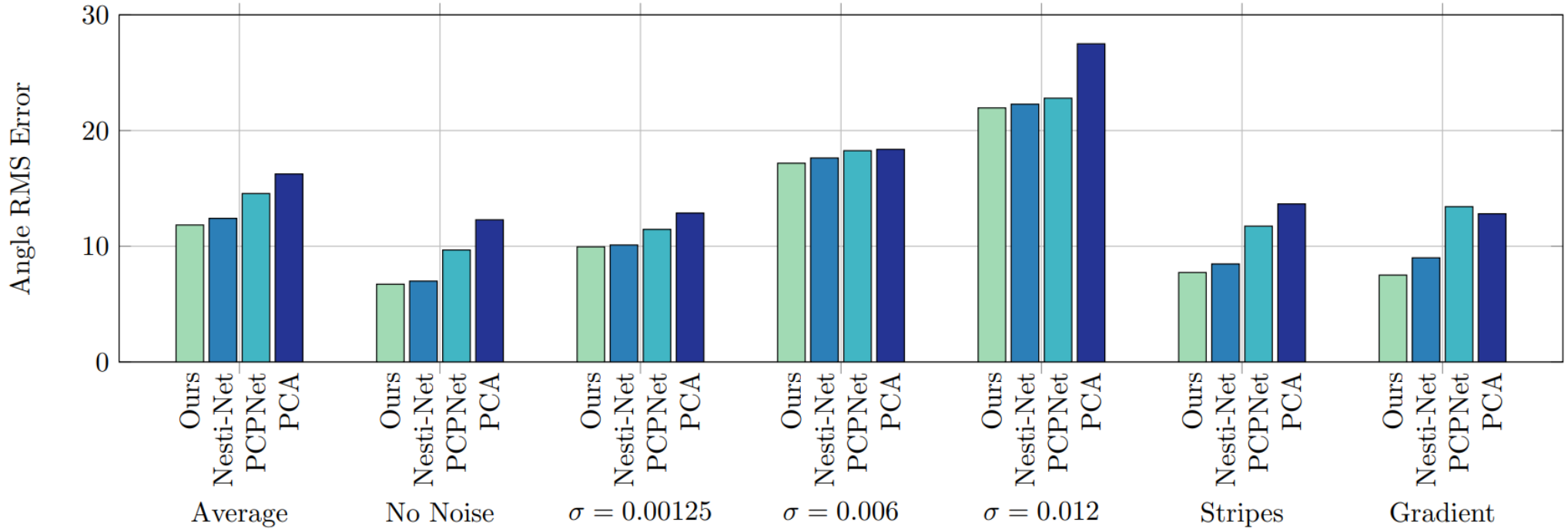
Shi et al., Point-GNN, CVPR 2020

Processing geometric structures



[3] Lenssen, Osendorfer, Masci; Deep Iterative Surface Normal Estimation, CVPR 2020

Processing geometric structures



	Ours	Nesti-Net	PCPNet
Number of network parameters	**7981**	179M	22M
Execution time for 100k points	**3.57 s**	1350 s	470 s
Relative execution time	**1**×	**378**×	**131**×

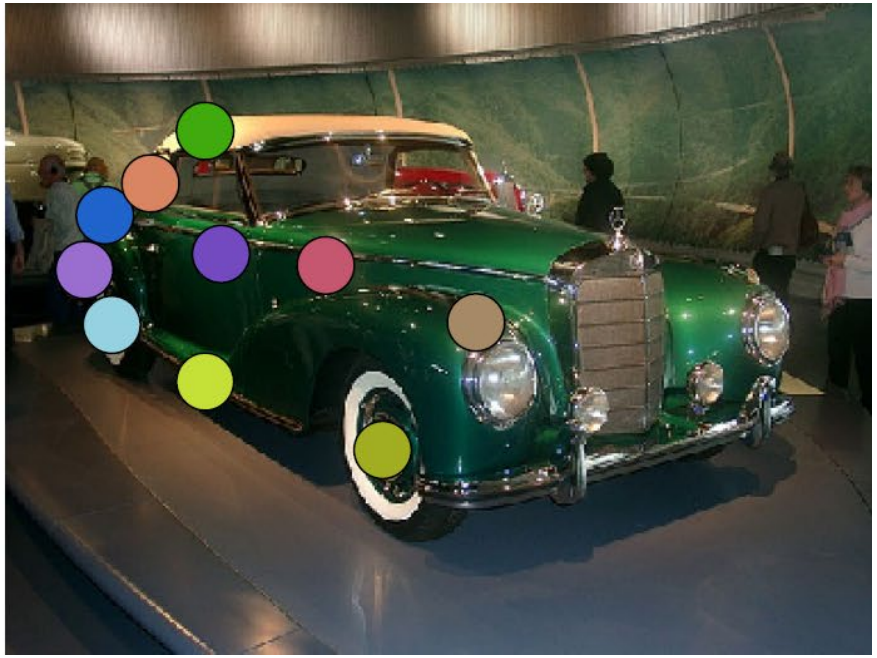
[3] Lenssen, Osendorfer, Masci; Deep Iterative Surface Normal Estimation, CVPR 2020

Matching geometric graphs

WILLOW-ObjectClass dataset

[2] Fey, Lenssen, Morris, Masci, Kriege: Deep Graph Matching Consensus, ICLR 2020

Matching geometric graphs



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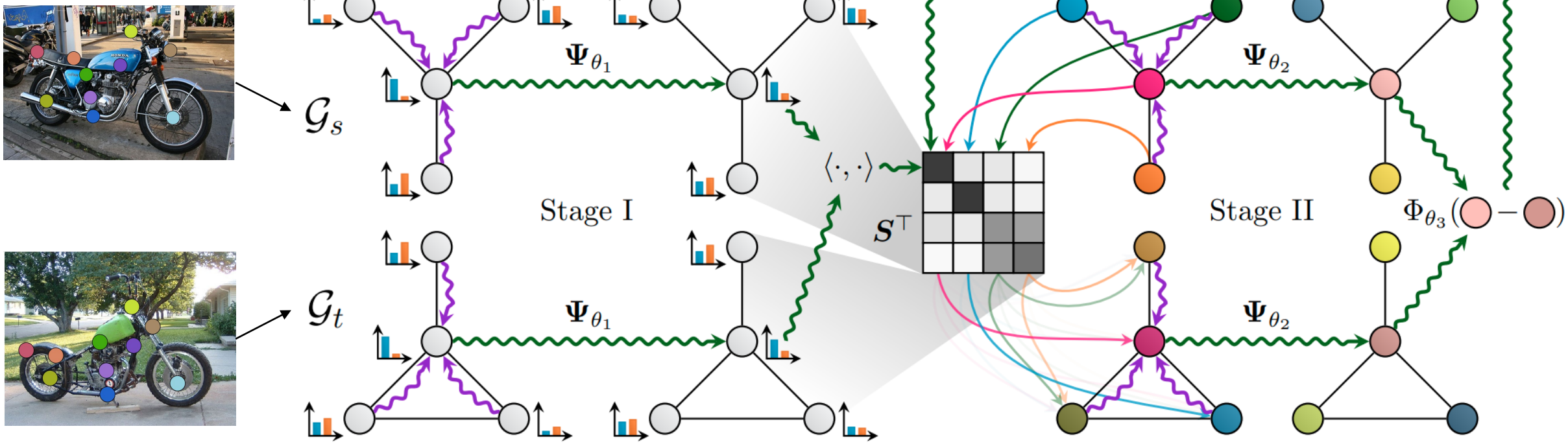
Matching geometric graphs



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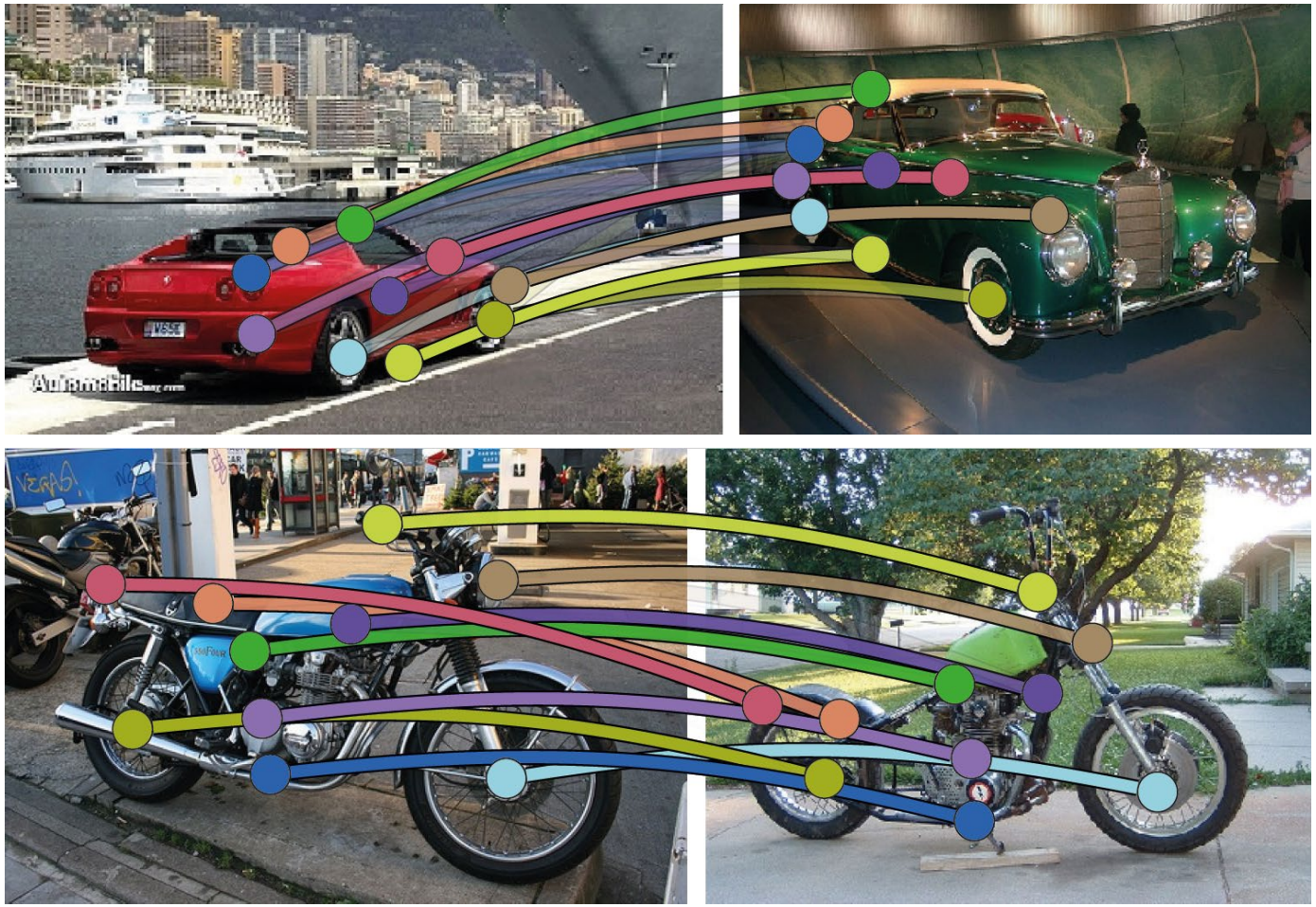
Matching geometric graphs



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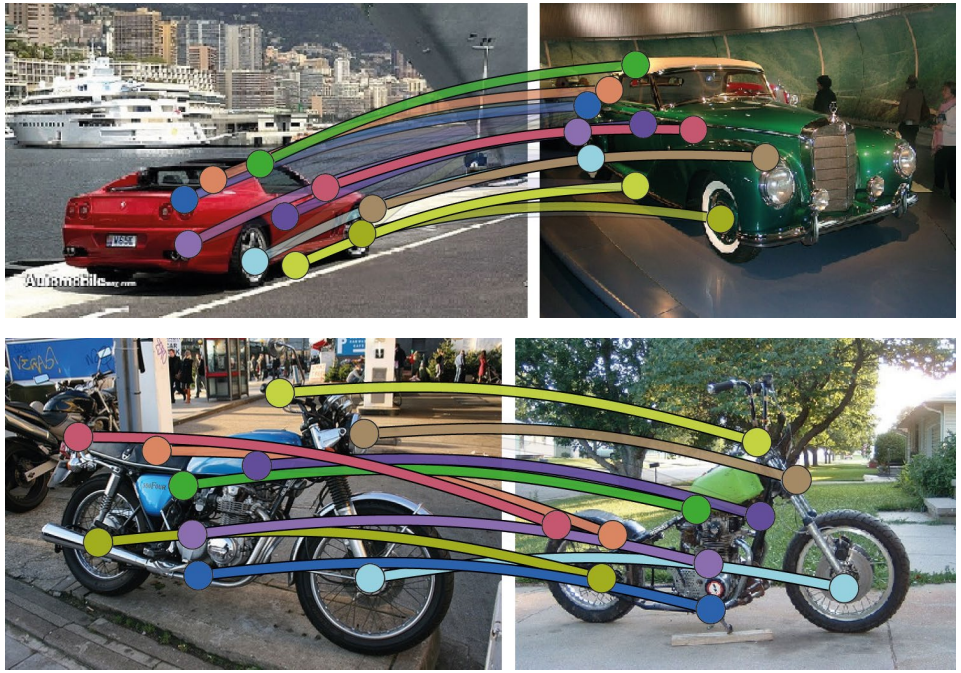

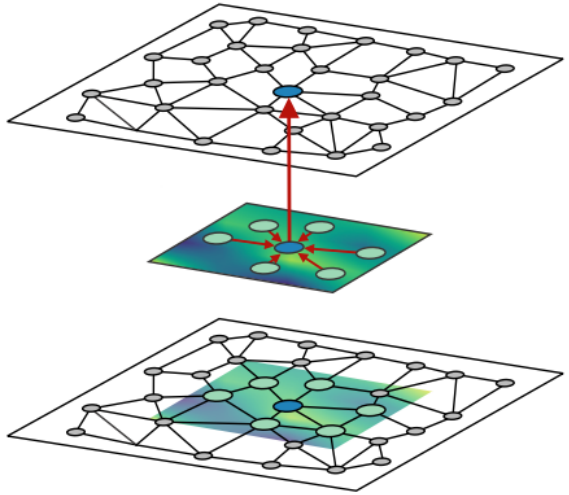

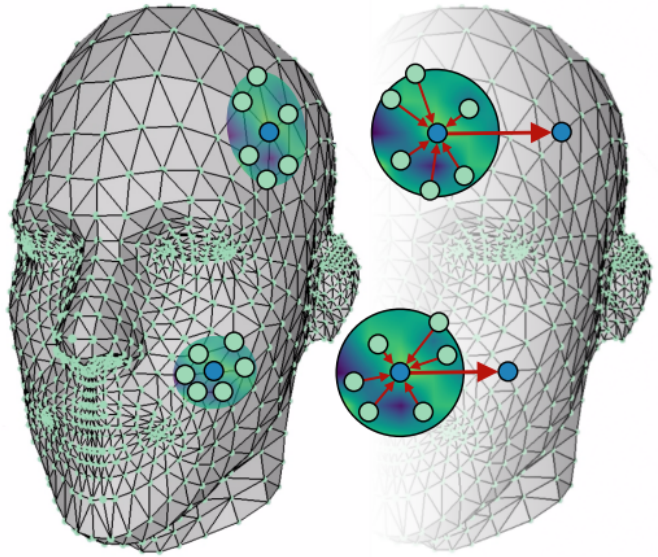

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