FeaStNet: Feature-Steered Graph Convolutions for 3D Shape Analysis

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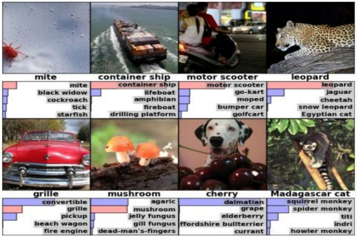
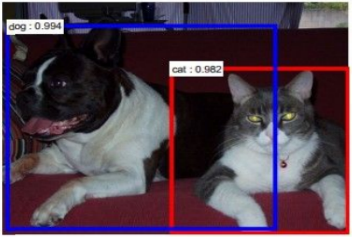
Computer Vision and Pattern Recognition, 2018

ConvNets are everywhere for 2D images



Classification



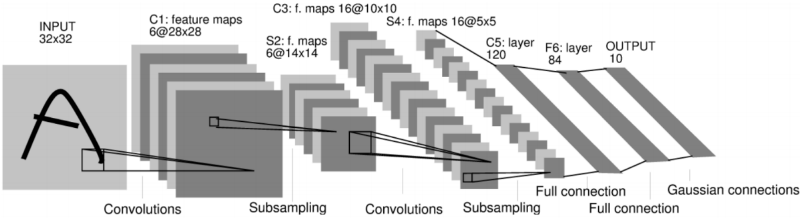
Detection

Retrieval

Segmentation

[Krizhevsky et al., 2012, Farabet et al., 2013, Ren et al., 2015, Gordo et al., 2016]

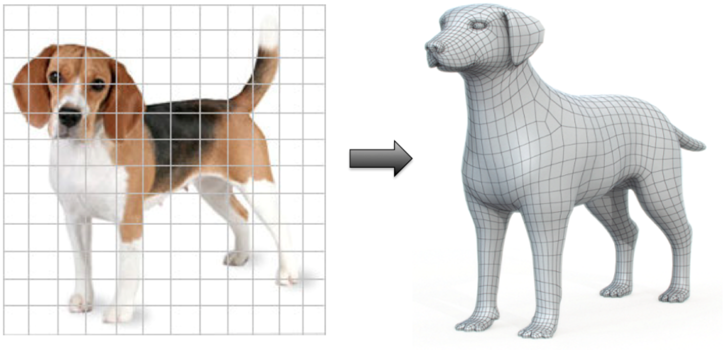
Convolutional Neural Networks (CNNs)



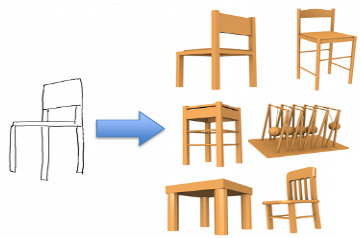
[LeCun et al., 1989]

How to generalize ConvNets to graph-structured data?

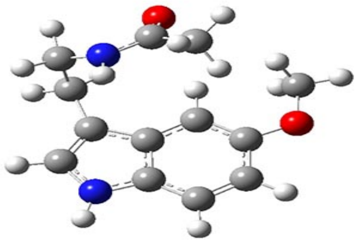
- RGB over regular grid of pixels
- XYZ(+RGB) over irregular graph of vertices



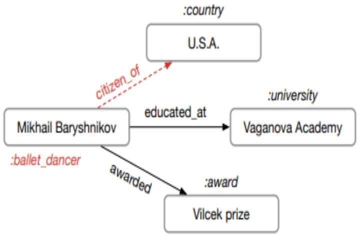
Applications



3D shape data



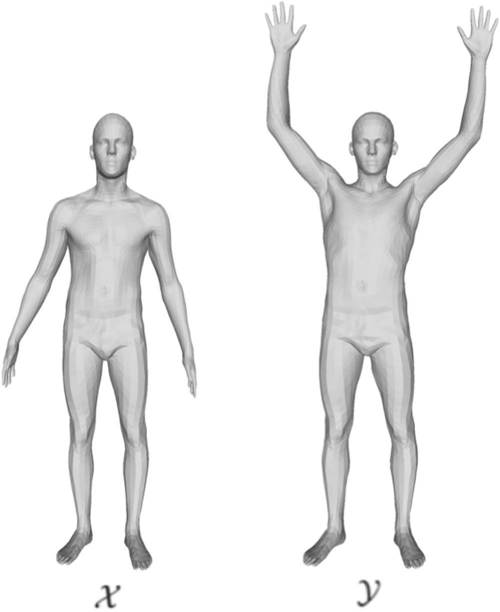
molecular graphs



knowledge graphs

social network analysis

Problem: Shape correspondence



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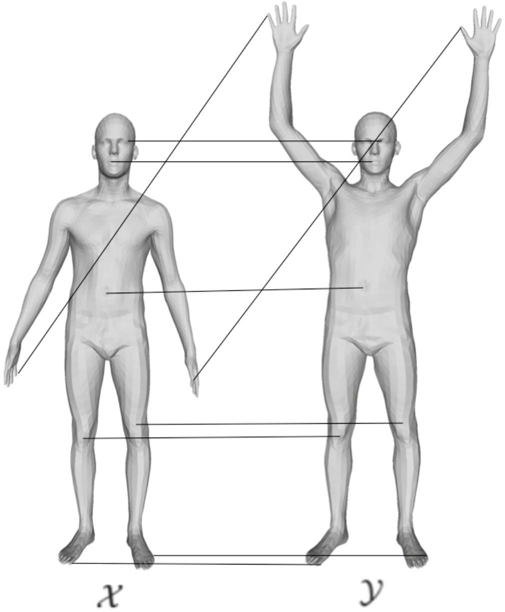
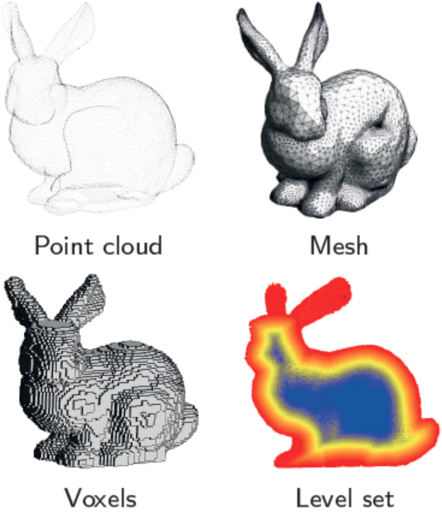


Representations for 3D shape data



Bronstein et al. 2016

Extrinsic *vs.* Intrinsic representations

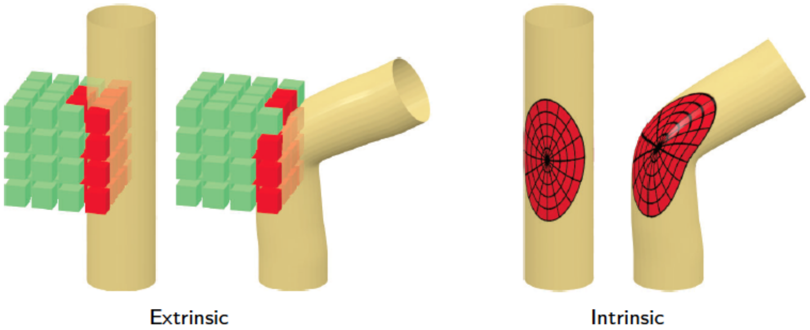
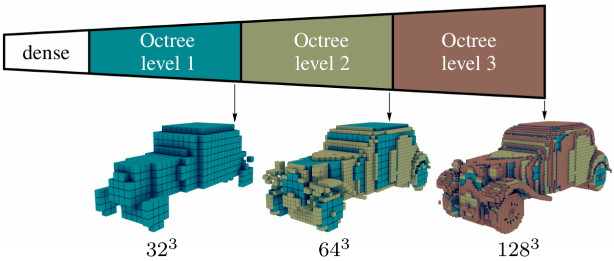


Figure from [Boscaini et al., 2016]

Extrinsic representation: Voxel grids

- Occupancy grids on input and/or output
- Quantize space rather than shape, lots of empty space
- 3D convolutions over grid, limited scalability
  - Sparse convolutions over input [Graham et al., 2018]
  - Octtrees on input and/or output [Tatarchenko et al., 2017]



Extrinsic representation: Point clouds

- Avoid quantization, ignore (most) structure
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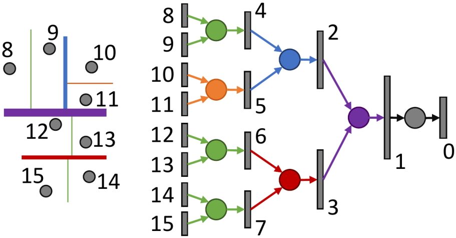
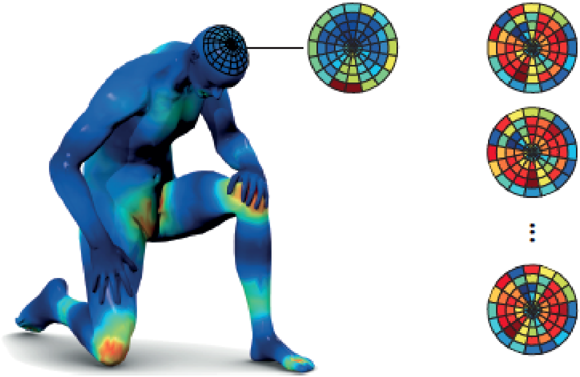
- Kd-Networks [Klokov and Lempitsky, 2017]
  - Propagate features across Kd-Tree over point cloud
  - Share parameters over branches with same split direction



Intrinsic representation: Geodesics over 3D mesh data

- Local geodesic polar coordinates
  [Masci et al., 2015, Boscaini et al., 2016]

$$\mathbf{u}(x, y) = (\rho(x, y), \theta(x, y))$$



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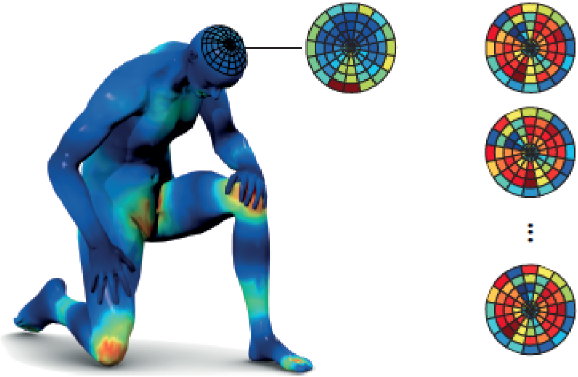

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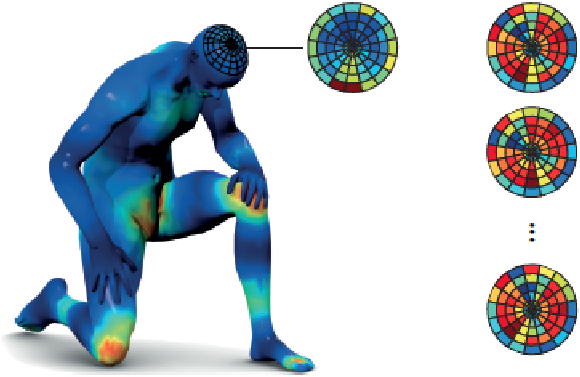

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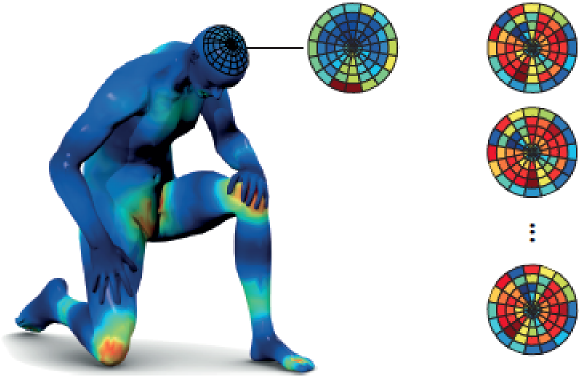
- Trained filters, hand-crafted patch function

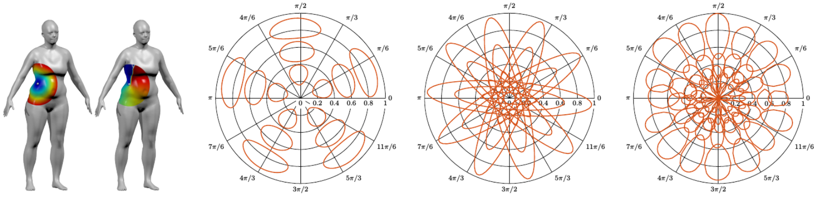


MoNet: Trainable patch function [Monti et al., 2017]

- Trainable Gaussian assignment to bin k of the patch

$$\mathbf{u}(x, y) = (\rho(x, y), \theta(x, y)) \tag{1}$$
$$w_k(\mathbf{u}) = exp((\mathbf{u} - \mu_k)^T \Sigma_k^{-1} (\mathbf{u} - \mu_k)) \tag{2}$$

- Trained filters, trained patch function, hand-crafted features for patch function



Polar coordinates ρ, θ GCNN ACNN MoNet

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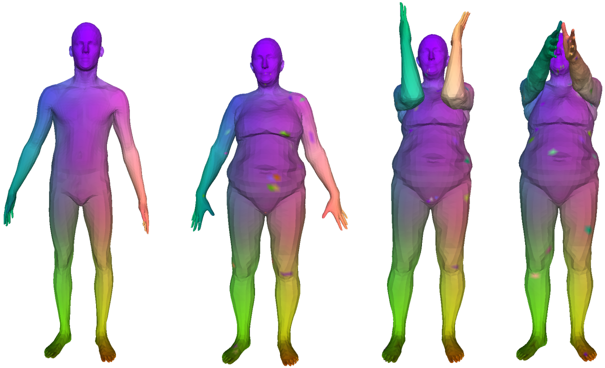
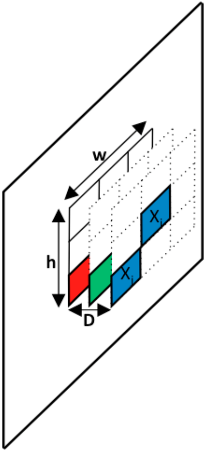
- Validation: 3D shape correspondence and part labeling



Template Texture transfer on test shapes

A brief recap of ConvNets



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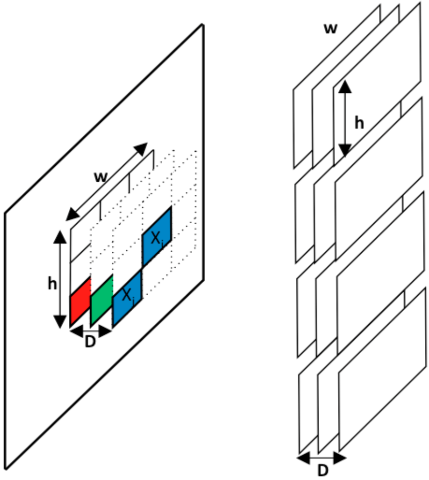

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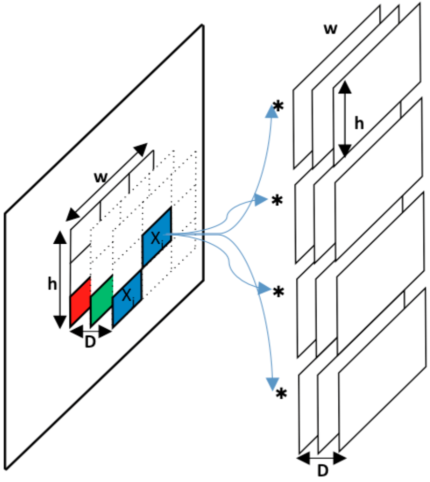

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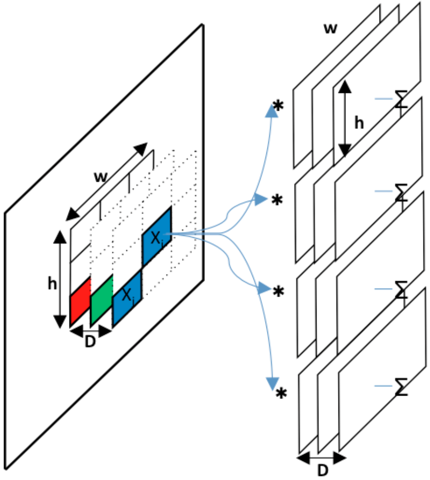

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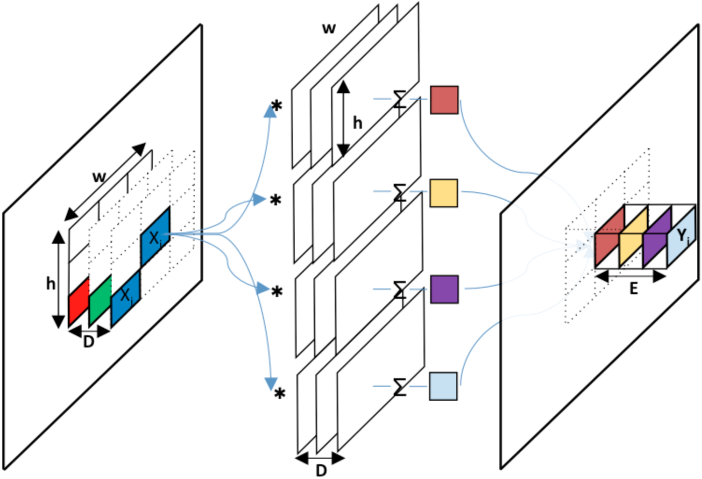
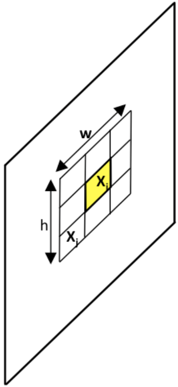


Reformulation of standard CNNs

$$y_i = b + \sum_{m=1}^{M} W_m x_{j(m,i)}$$



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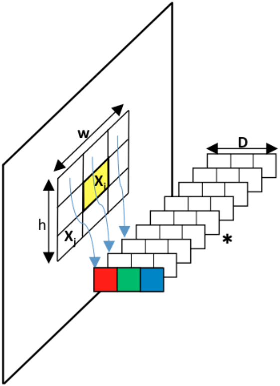

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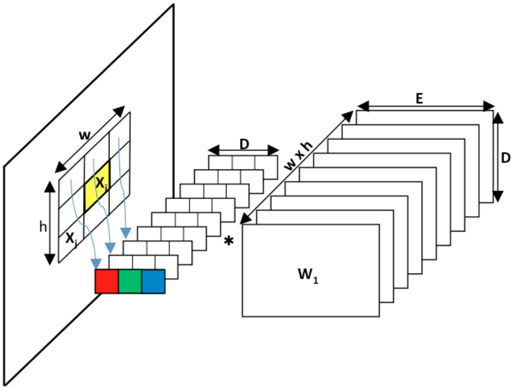

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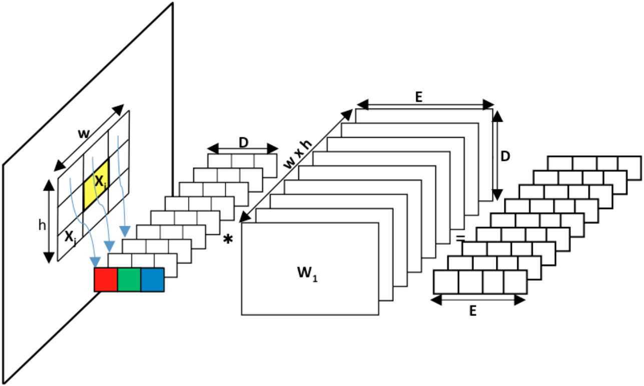

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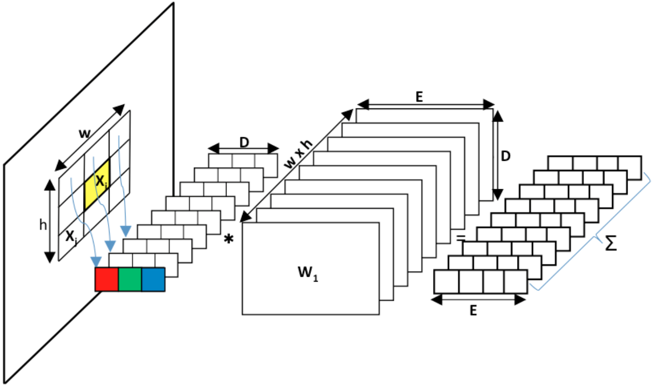

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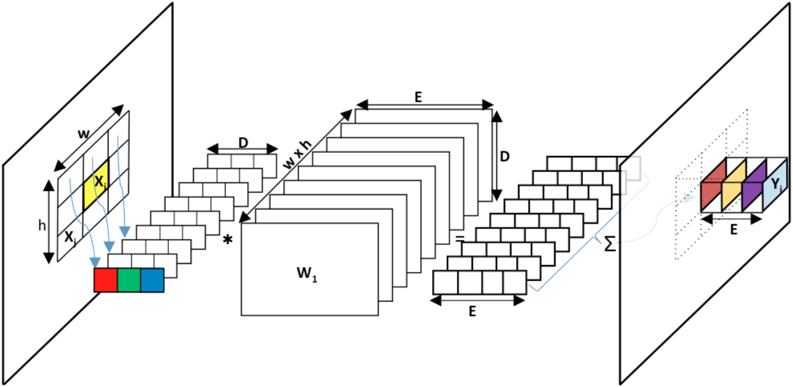
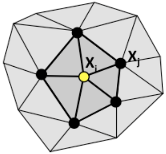


Graph convolutional approach in FeaStNet

- Varying number of neighbors, no intrinsic ordering
- No one-to-one mapping between neighbors and weights



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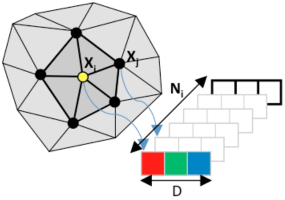

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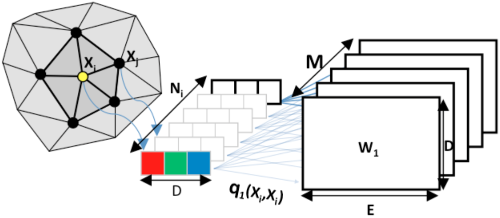

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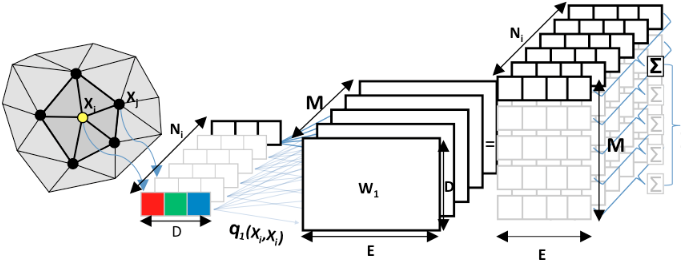

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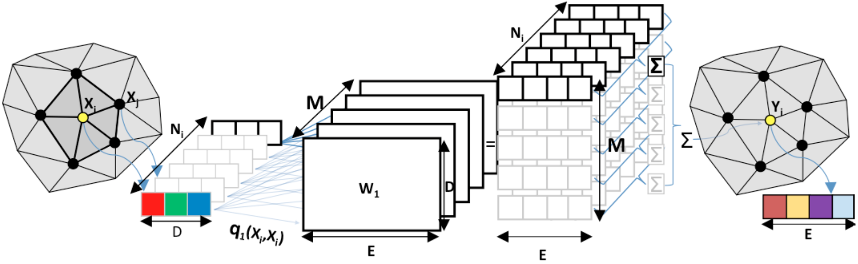

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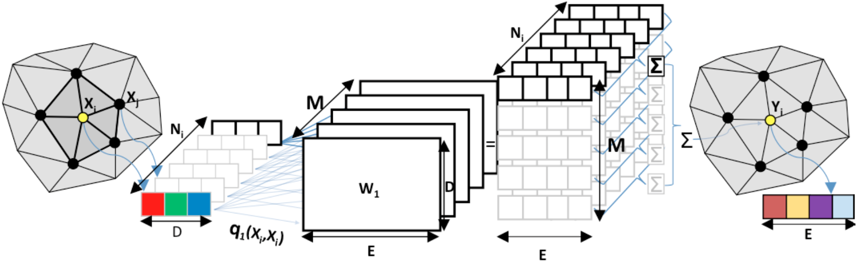
- Using ring-1 neighbors in practice, but can be different



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- Setting $u_m = -v_m$ in makes assignment translation invariant in feature space

$$q_m^{ij} \propto \exp\left(u_m^\top (x_j - x_i) + c_m\right)$$

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  - Computational cost increased from $O(NMED)$ to $O(NME(D + K))$

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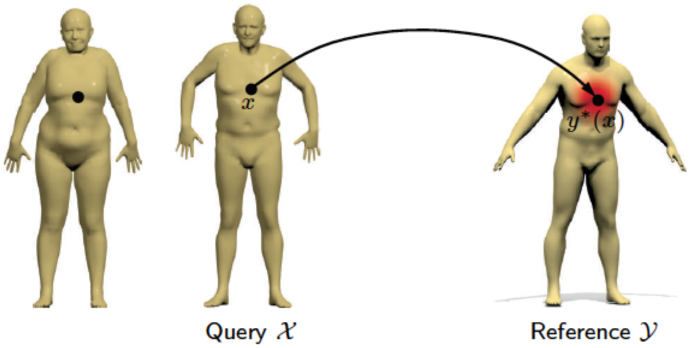
- Can be implemented by translation invariant linear-softmax assignment function

Experimental evaluation — Shape correspondence



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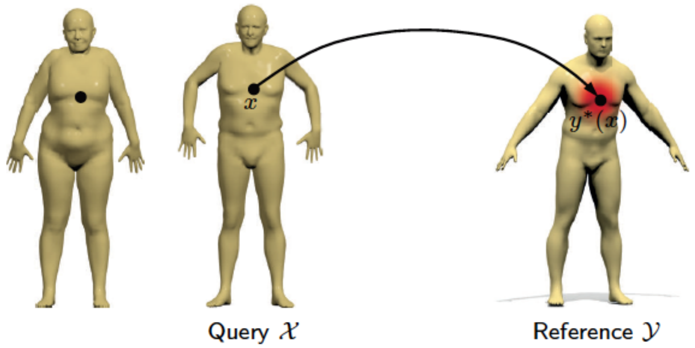

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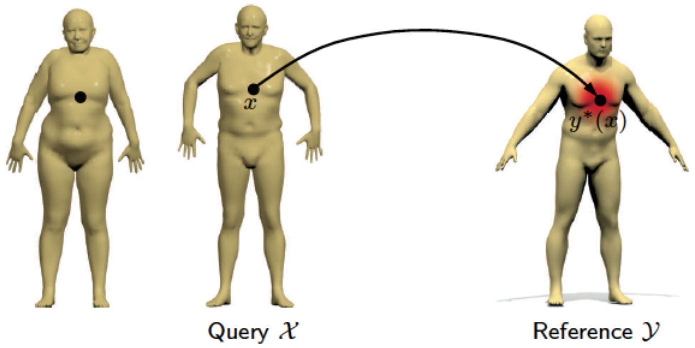
  - XYZ: raw vertex coordinates



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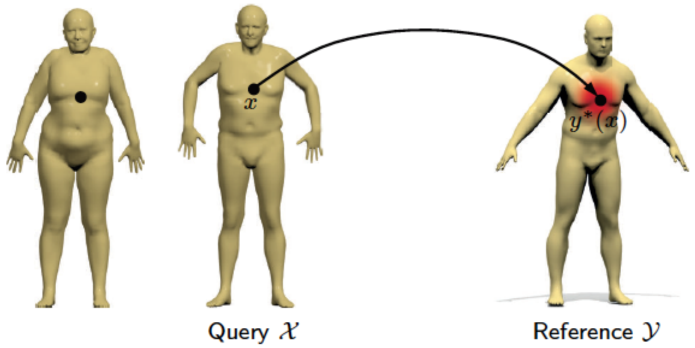
  - XYZ: raw vertex coordinates
- Correspondence as dense labeling problem
  - Like semantic segmentation, but with 6,890 classes



Shape correspondence: Architectures

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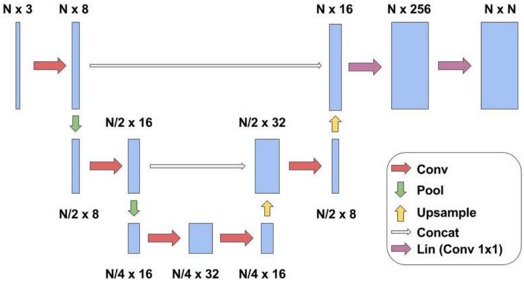
  - Lin16 + Conv32 + Conv64 + Conv128 + Lin256 + Lin6890
- Multi-scale architecture
  - Graph sub-sampling [Dhillon et al., 2007]
  - Max pooling, zero-pad up-sampling



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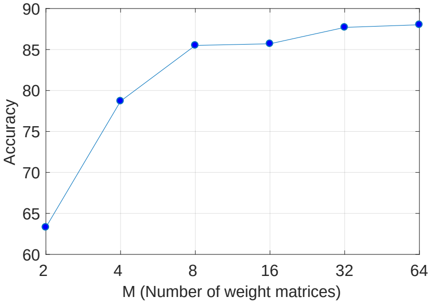
- Translation invariance helps, in particular for XYZ coordinates
- Learning from XYZ better than hand-crafted SHOT

Results single-scale architecture

- Metric: Percentage of correct (exact) correspondences

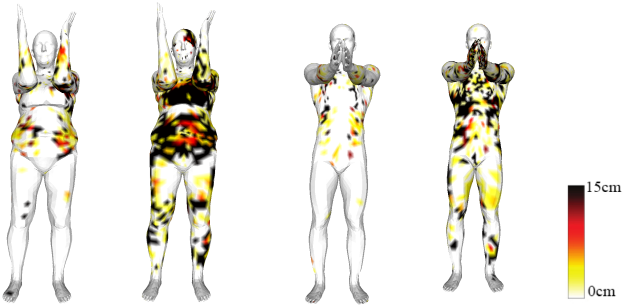
Trans.-inv.	yes	no
XYZ	86%	28%
SHOT	63%	58%

- Translation invariance helps, in particular for XYZ coordinates
- Learning from XYZ better than hand-crafted SHOT
- Impact nr. of weight matrices, using XYZ



Geodesic errors: SHOT *vs.* XYZ

- Geodesic distance between predicted and true correspondence
- Single-scale architecture in both cases



XYZ SHOT XYZ SHOT

Comparison to state of the art

- Metric: Percentage of correct (exact) correspondences

Method	Input	Accuracy
Logistic Regr., w/o refinement	SHOT	39.9%
GCNN [Masci et al., 2015], w/o refinement	SHOT	42.3%
PointNet [Qi et al., 2017], w/o refinement	SHOT	49.7%
ACNN [Boscaini et al., 2016], w/ refinement	SHOT	62.4%
GCNN [Masci et al., 2015], w/ refinement	SHOT	65.4%
MoNet [Monti et al., 2017], w/o refinement	SHOT	73.8%
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FeaStNet, w/o refinement	XYZ	88.1%

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FeaStNet, multi scale, w/o refinement	**XYZ**	**98.6%**
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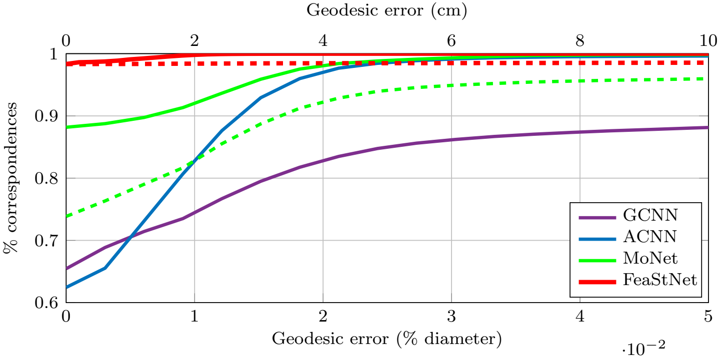
- New state of the art result, with both XYZ and SHOT
- Relative reduction of 89% in error rate w.r.t. Monti *et al.*

Geodesic errors

- Metric: Percentage of correspondences within tolerance
- Dashed curves: without refinement



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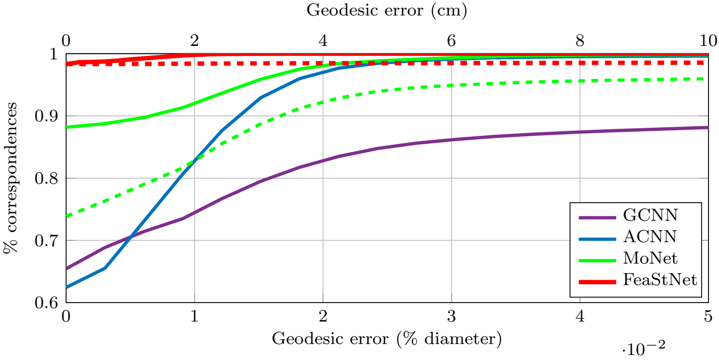

- Without refinement: very few, relatively big errors

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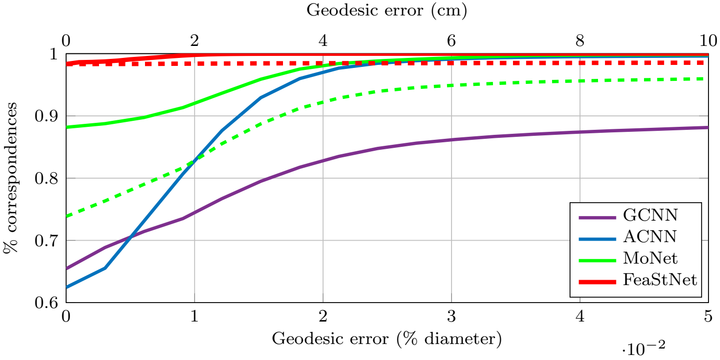
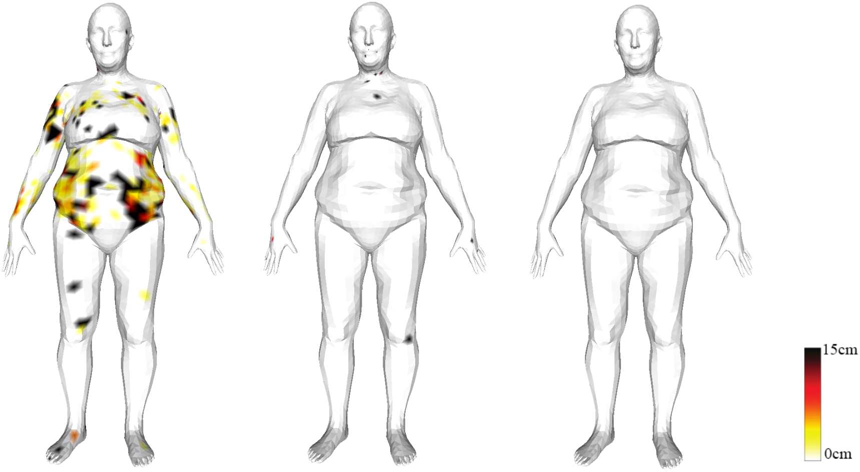


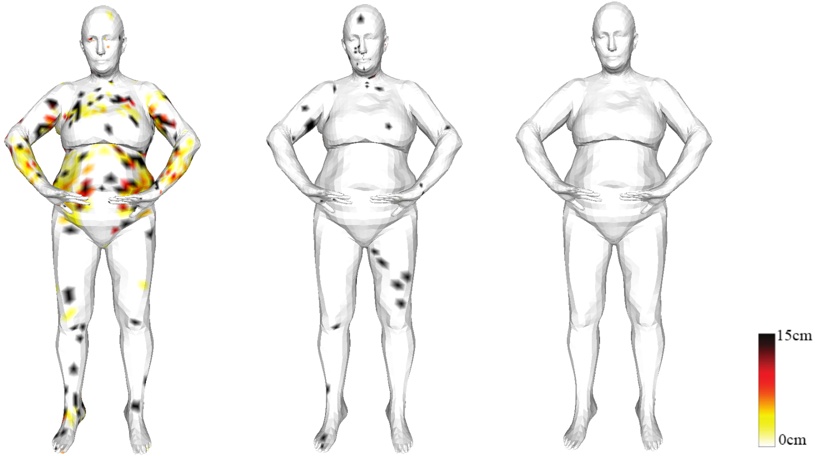
- Without refinement: very few, relatively big errors
- With refinement: very few, very small errors

Shape correspondence: Geodesic errors



Single-scale　　Multi-scale　　+ refinement

Shape correspondence: Geodesic errors



Single-scale Multi-scale + refinement

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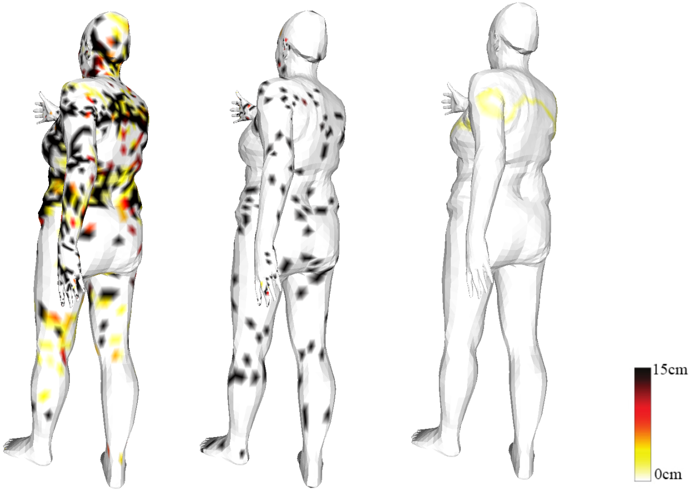

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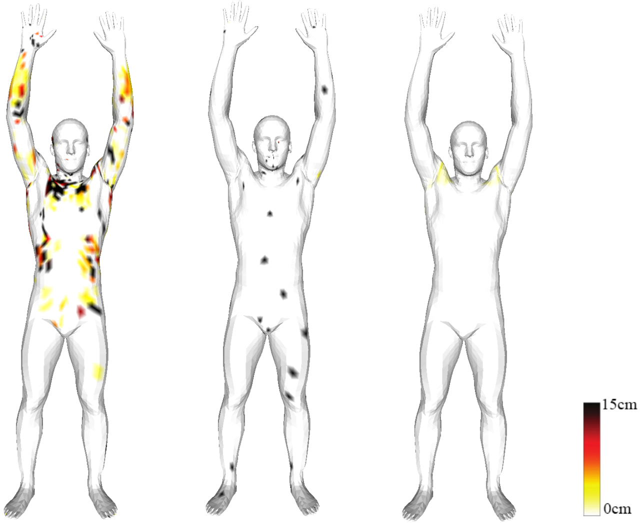

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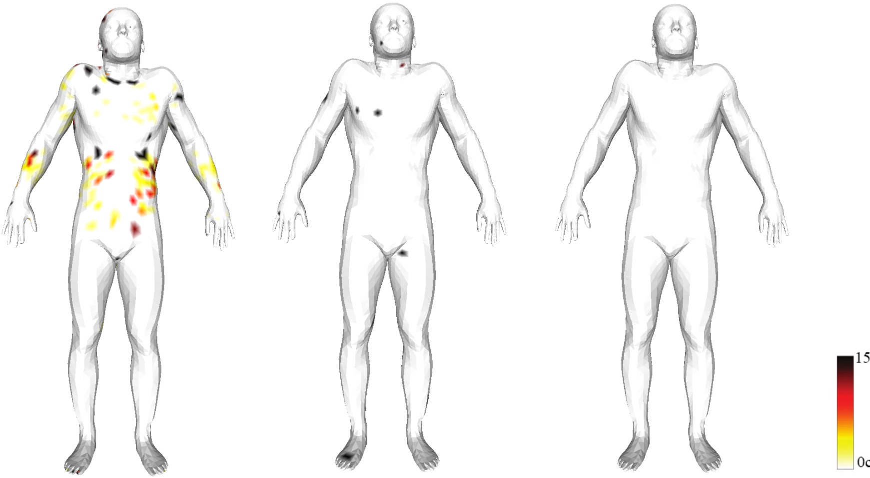
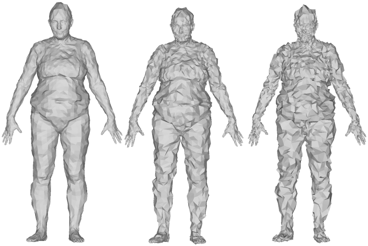


Single-scale   Multi-scale   + refinement

Shape correspondence: Noise robustness

- Gaussian noise on vertex coordinates, proportional to average distance to neighbors



0.1 0.2 0.3

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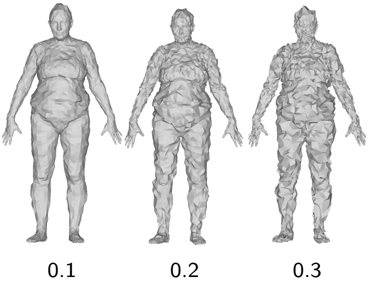
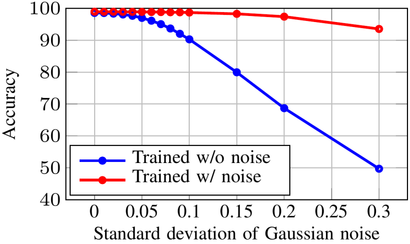
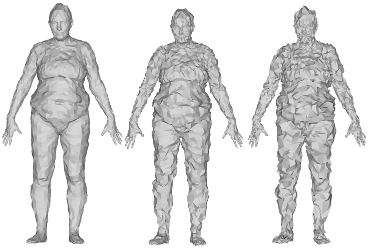




Shape correspondence: Noise robustness

- Gaussian noise on vertex coordinates, proportional to average distance to neighbors
- Robust model when training with noisy shapes



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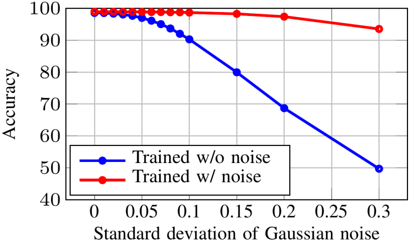
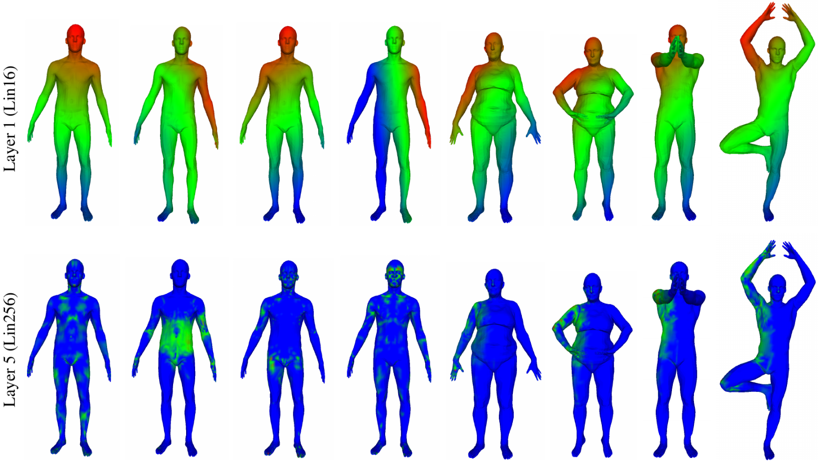


Feature activations

- Left: 4 features on same shape
- Right: same feature on 4 shapes



ShapeNet Part labeling benchmark

- 16,881 hand-designed shapes from 16 object categories
- Labeled with 50 parts across all categories
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- Single-scale architecture, with global max-pooling
- Descriptors: XYZ coordinates

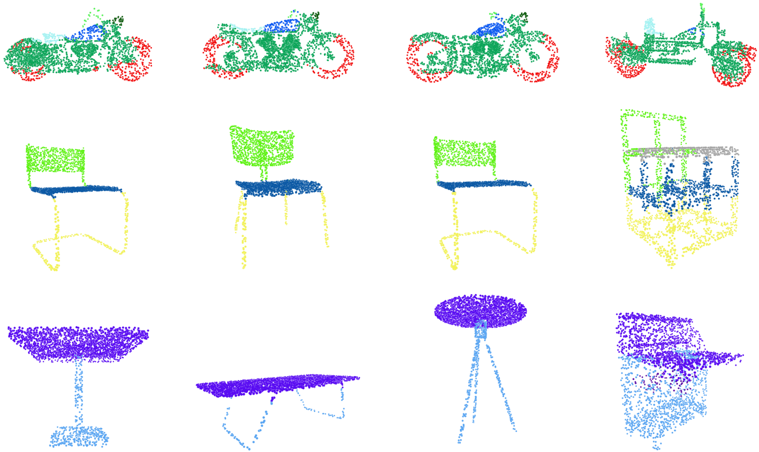
Part labeling: Quantitative results

- Performance similar to methods designed for point-cloud data

	overall	aero plane	car	chair	guitar	knife	lamp	laptop	motor bike	pistol	table
Number of shapes	16,881	2690	898	3758	787	392	1547	451	202	283	5271
PointNet [Qi et al., 2017]	83.7	83.4	74.9	89.6	91.5	85.9	80.8	95.3	65.2	81.2	80.6
KdNet [Klokov and Lempitsky, 2017]	82.3	80.1	70.3	88.6	90.2	87.2	81.0	94.9	57.4	78.1	80.3
FeaStNet	81.5	79.3	71.7	87.5	90.0	80.1	78.7	94.7	62.4	78.3	79.6

Part labeling examples

- Test shapes with accurate labeling,
  and one with worst labeling in category.



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- Perspectives
  - Application to raw/real scanned 3D meshes
  - Integrate global correspondence refinement
  - Generalize across meshes/templates: local correspondences
  - Modeling meshes in motion: (shape + pose) x time

FeaStNet: Feature-Steered Graph Convolutions for 3D Shape Analysis

Nitika Verma, Edmond Boyer, Jakob Verbeek
INRIA, Grenoble, France

Computer Vision and Pattern Recognition, 2018

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