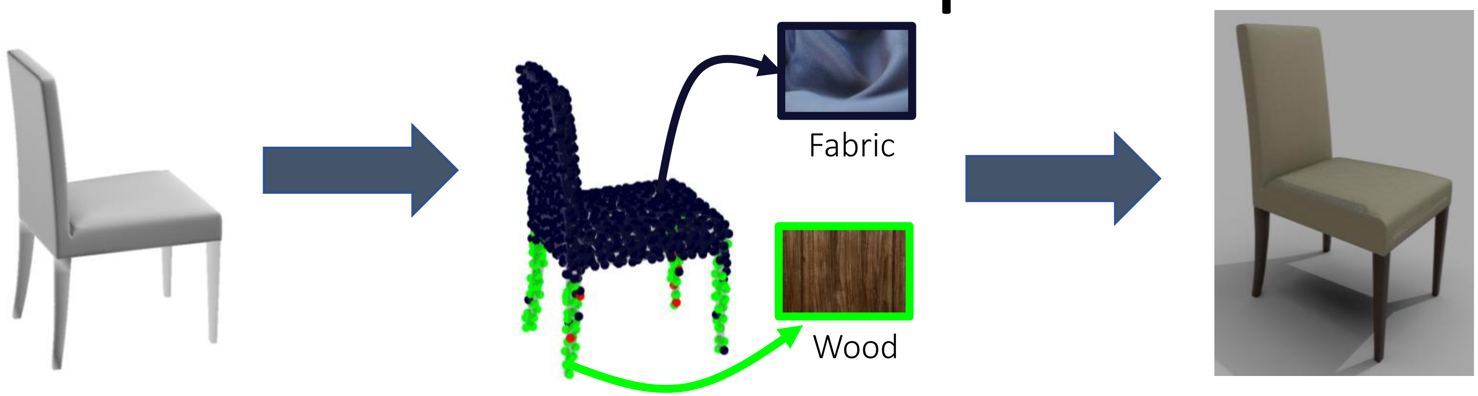
Learning Material-Aware Local Descriptors for 3D Shapes



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Outline

1. Goal
2. Motivation
3. Related Work
4. Data Collection
5. Network Architecture and Training Pipeline
6. Post-Processing
7. Results
8. Future Directions

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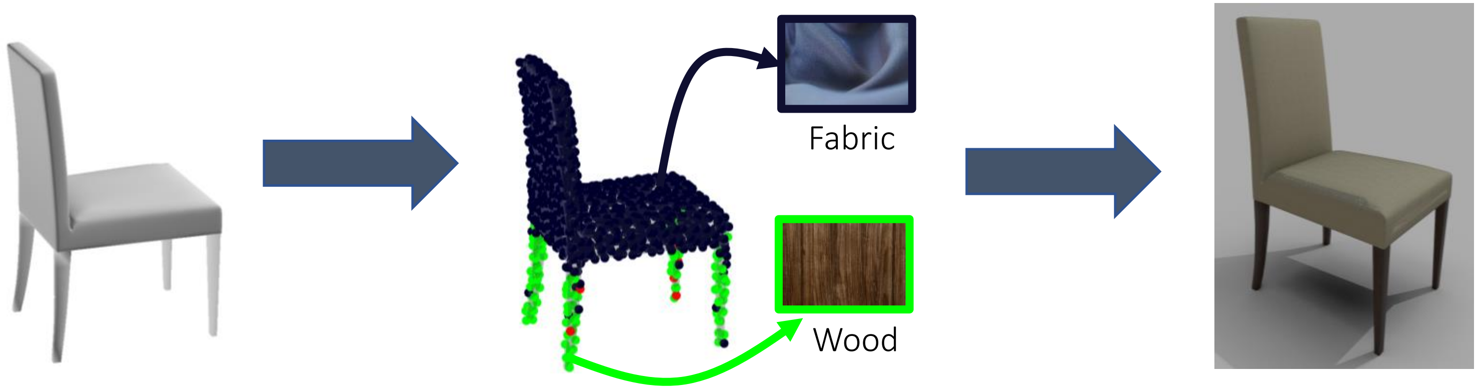
Goal: Learn local shape descriptors sensitive to physical material



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Motivation

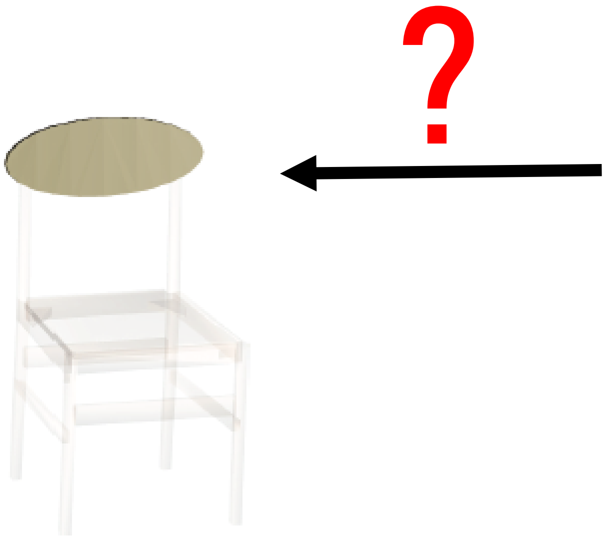
Understanding physical material properties from 3D geometry:

- Jointly reason about materials and geometry
- Interactive design tool
- Robotic perception
- …

[Morrison et al 2018]

Motivation

Jointly reason about materials and geometry



What material is typically used for an object part like this?

How can we retrieve objects that are composed of similar materials?

…

Motivation

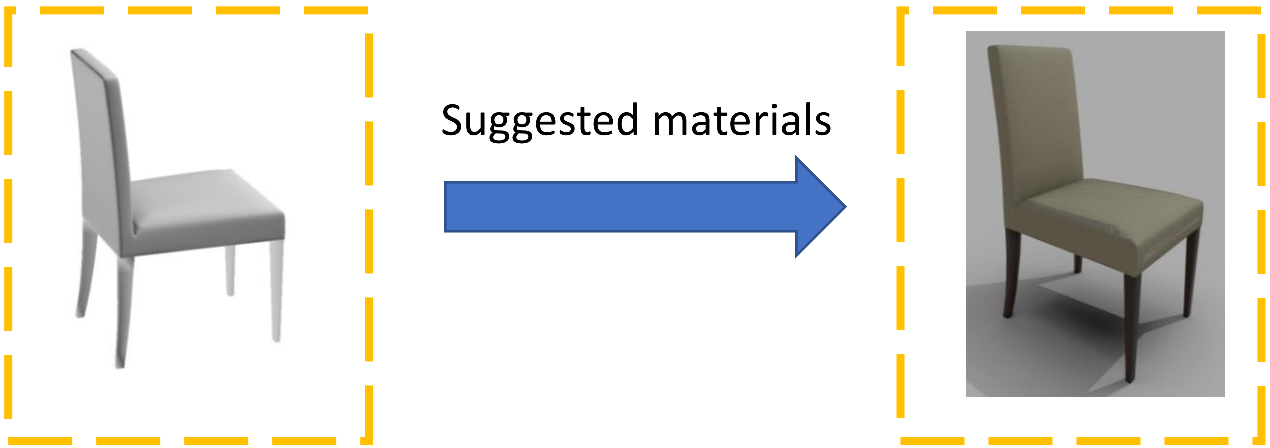
Design and fabrication

Which material is suitable for fabrication?

Wood ✓
Metal ✓
Glass ✗

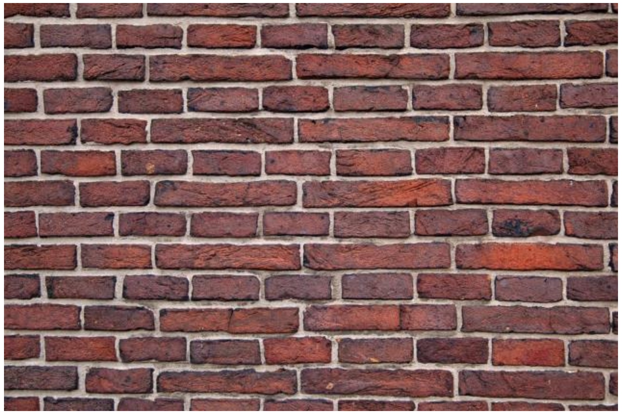
Motivation

Design and fabrication



Motivation

Robotic Perception



Which one is better for an emergency collision?

Which one requires more gentle handling?

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Related Work

1. Shape databases
2. Deep learning for shape analysis
3. Material understanding for shapes
4. Material understanding for images

Shape Databases

ShapeNet

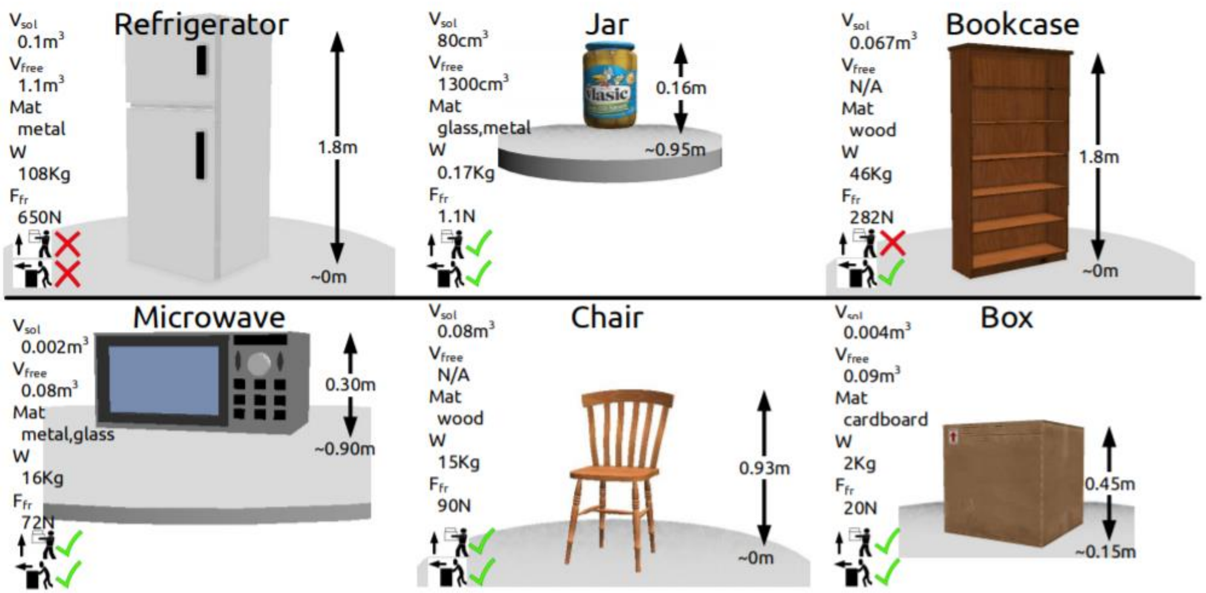
- Large-scale database with many object classes
- Some shapes are textured; part segmentation

[https://www.shapenet.org]

Shape Databases

Semantically-Enriched 3D Models for Common-sense Knowledge

- Many different annotations, including category-level priors over material labels

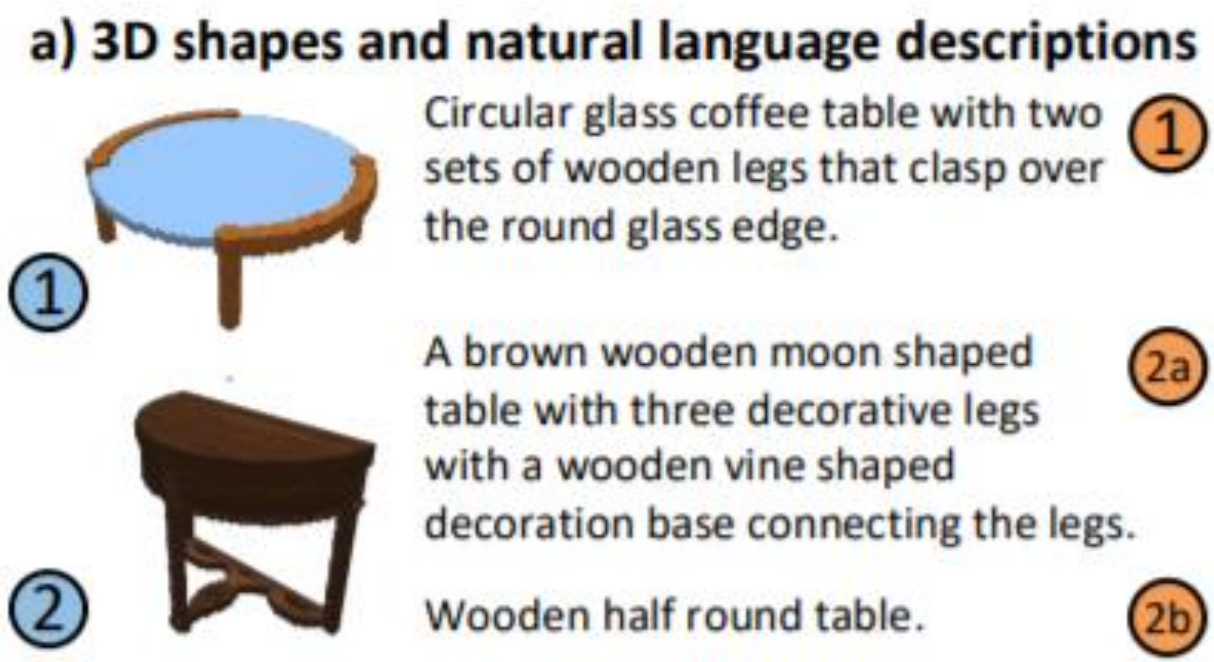


[Savva et al 2015]

Shape Databases

Text2Shape

- Natural language descriptions for 3D shapes
- Joint text / shape embedding



[Chen et al 2018]

Deep Learning for Shape Analysis

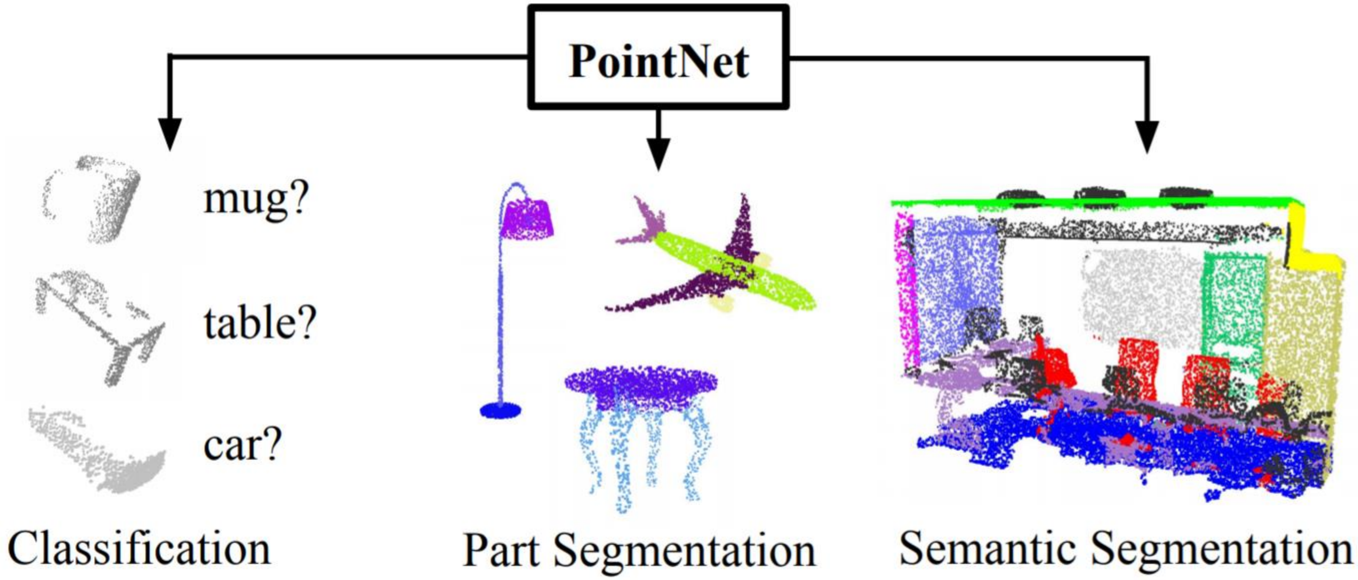
Based on…

- Mesh
- Canonicalized meshes
- 2D renderings
- Point sets
- Dense Voxels
- Voxel octrees
- Spectral alignment
- Surface patch collection

And more…

Deep Learning for Shape Analysis

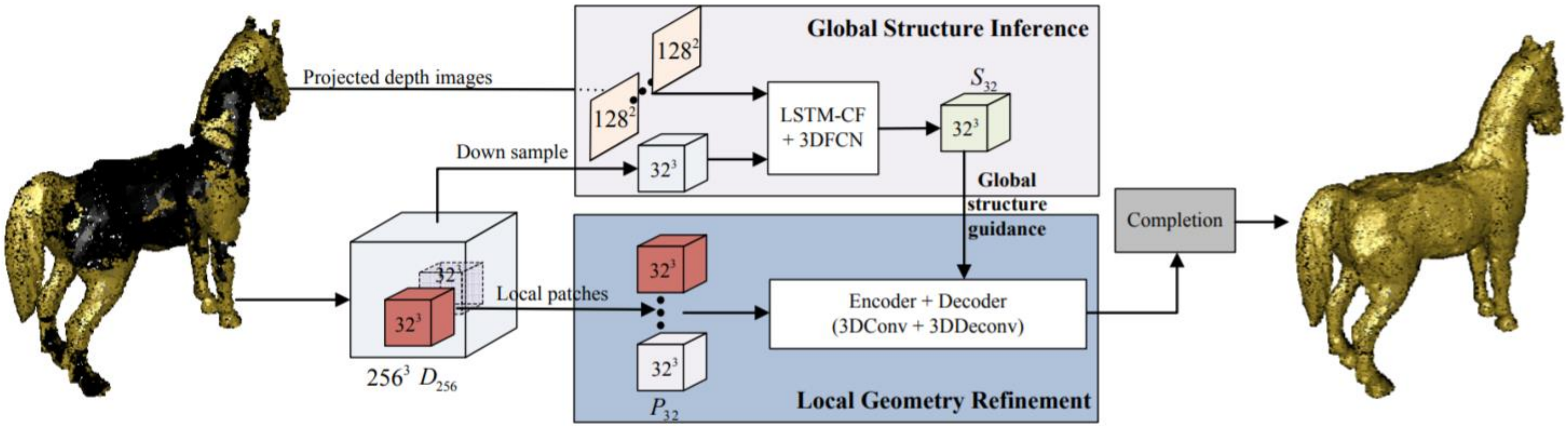
- Segmentation, classification



[Qi et al 2017]

Deep Learning for Shape Analysis

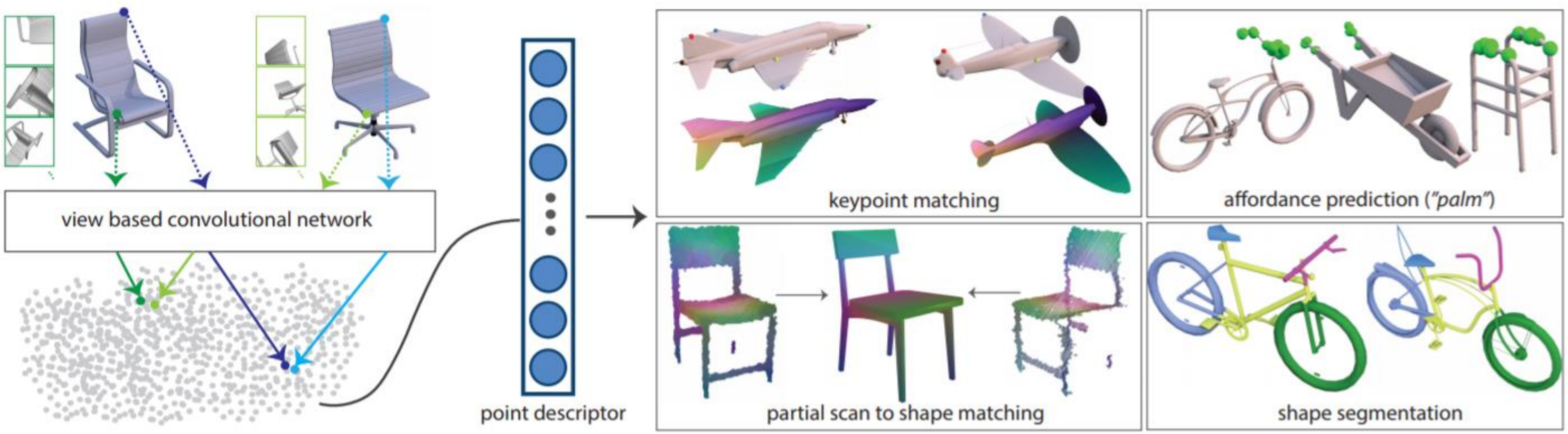
- Shape completion



[Han et al 2017]

Deep Learning for Shape Analysis

- Geometric descriptors



[Huang et al 2018]

Material Understanding for Shapes

Material Memex

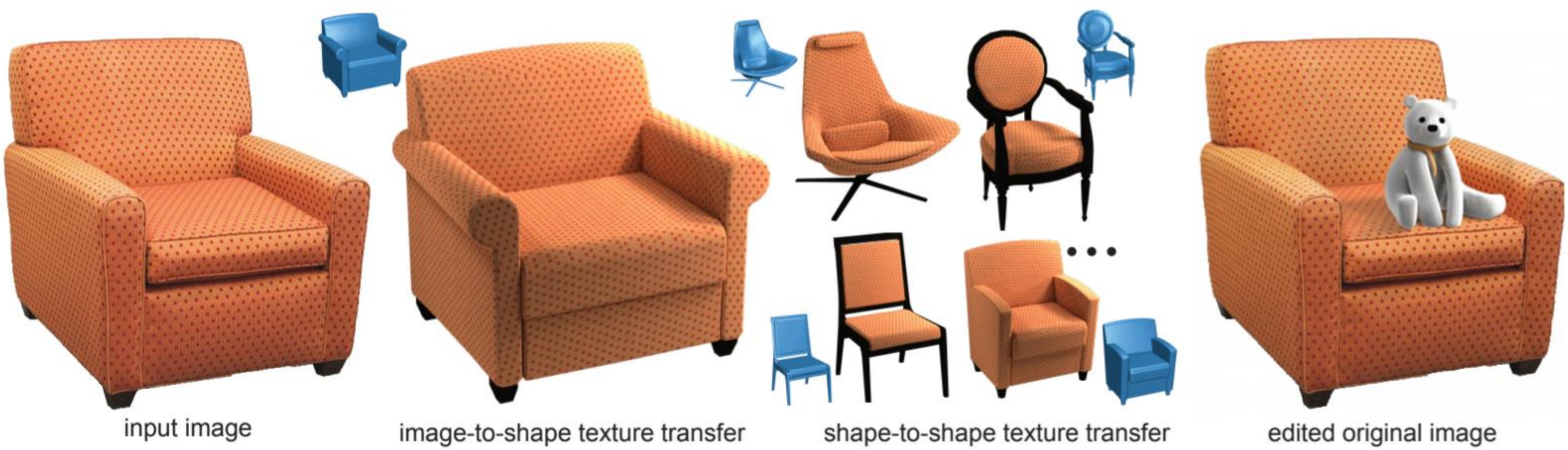
- Automatic material suggestion for parts
- Requires database of with known part properties

[Jain et al 2012]

Material Understanding for Shapes

Unsupervised Texture Transfer from Images to Shapes

- Image-to-shape, shape-to-shape texture transfer
- Aligns user-specified image to shape



[Wang et al 2016]

Material Understanding for Shapes

Magic Decorator: Indoor Material Suggestion

- Automatically suggest textures for indoor 3D scene
- Used color / texture statistics of 2D images
- Requires scene segmented and labeled

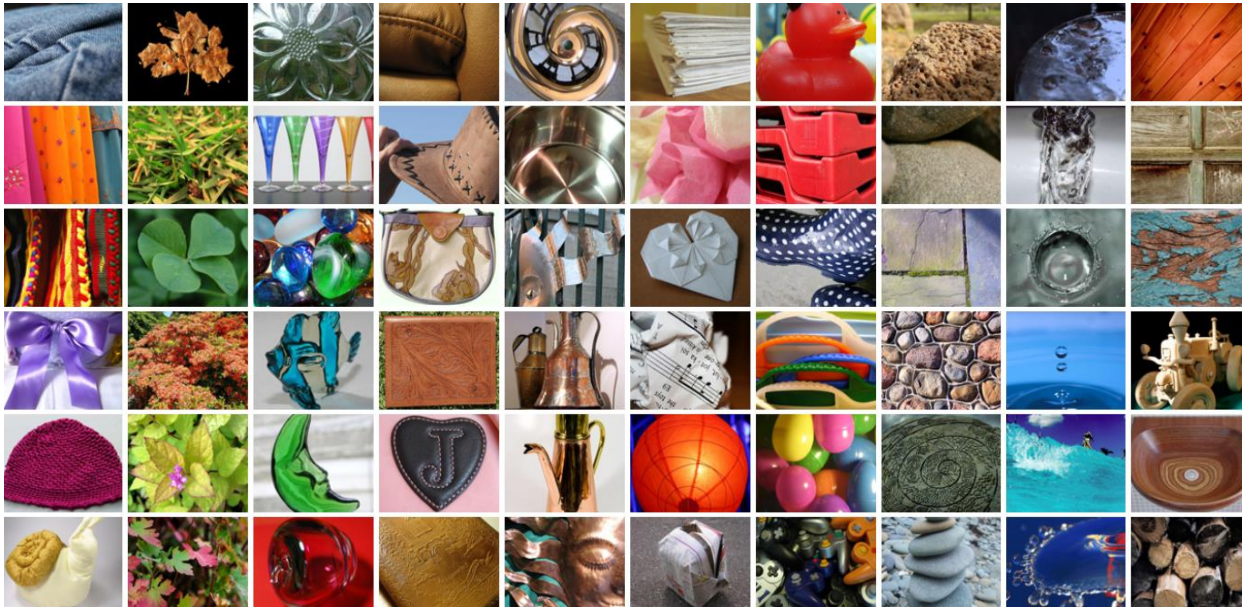
Input Scene Suggestion 1 Suggestion 2 Suggestion 3

[Chen et al 2015]

Material Understanding for Images

Flickr Material Database

- Surfaces of common materials; manually curated
- Relatively small dataset (100 per category)



[Sharan et al 2014]

Material Understanding for Images

Describable Textures Dataset

- Textures described by attributes (“striped”, …)
- Dataset of representative textures

[Cimpoi et al 2014]

Material Understanding for Images

OpenSurfaces

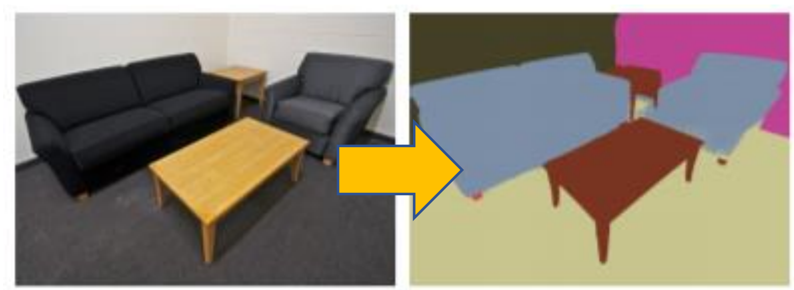
- Segmented surfaces from consumer photographs labelled with material and appearance properties

[Bell et al 2013]

Material Understanding for Images

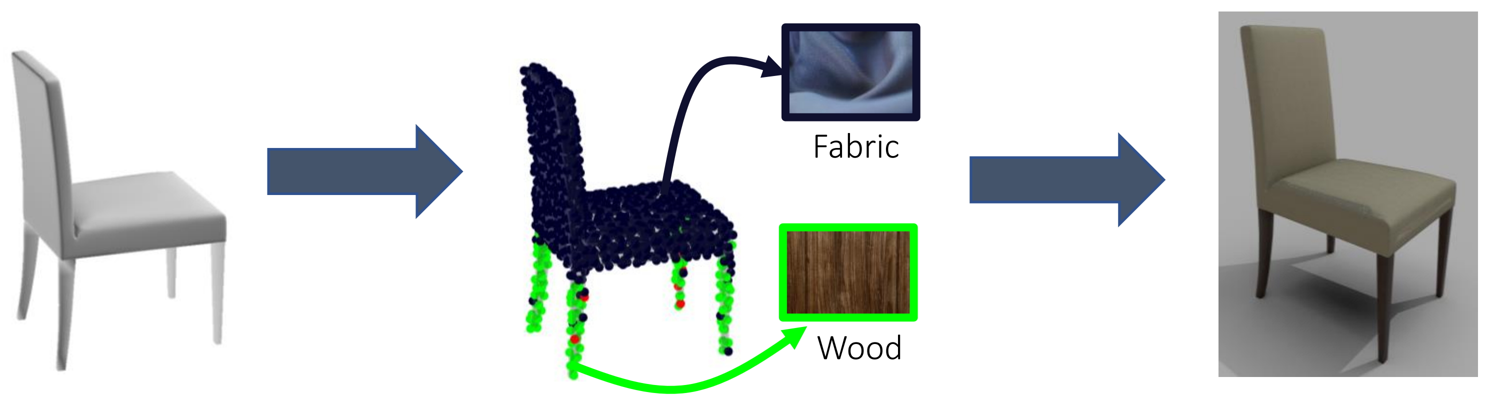
Materials in Context Database

- Millions of material points in real-world images
- Strong material recognition performance with deep learning



[Bell et al 2015]

Reminder: Learn local shape descriptors sensitive to physical material



Our work :

- Focuses on physical material rather than appearance
- Does not strictly require additional input (such as semantic segmentation, image-to-shape matching, parts, …)
- Only uses shape geometry as input
- Leverages existing deep learning approaches

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Challenge: Existing data is insufficient

Crowdsourced Data

- Selected 17K chairs, tables, cabinets from ShapeNet
- Remove hard-to-label shapes for reliable crowdsourced annotations

- **Remaining shapes (17K)**

Crowdsourced Data

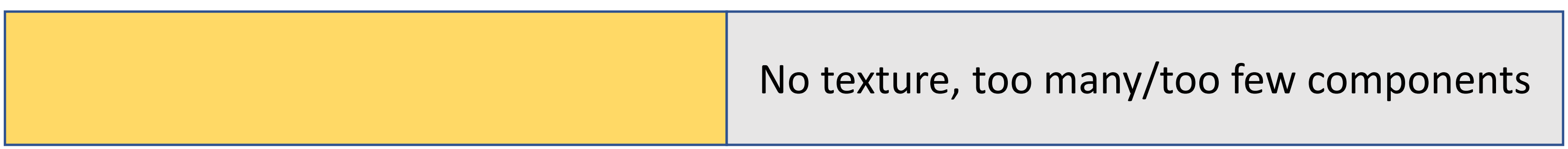
- Selected 17K chairs, tables, cabinets from ShapeNet
- Remove hard-to-label shapes for reliable crowdsourced annotations

- **Remaining shapes (12K)**

Crowdsourced Data

- Selected 17K chairs, tables, cabinets from ShapeNet
- Remove hard-to-label shapes for reliable crowdsourced annotations

- **Remaining shapes (8K)**



Crowdsourced Data

- Selected 17K chairs, tables, cabinets from ShapeNet
- Remove hard-to-label shapes for reliable crowdsourced annotations

- **Remaining shapes (3K)**

No texture, too many/too few components,
low-quality mesh, duplicates

Crowdsourced Data

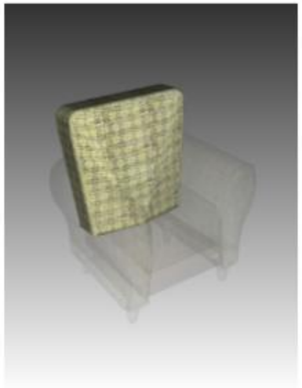
Material categories (commonly found in furniture):

1. Wood
2. Plastic
3. Metal
4. Glass
5. Fabric (including leather)
6. ~~Stone~~

Crowdsourced Data

Here are a few views of a 3D object:

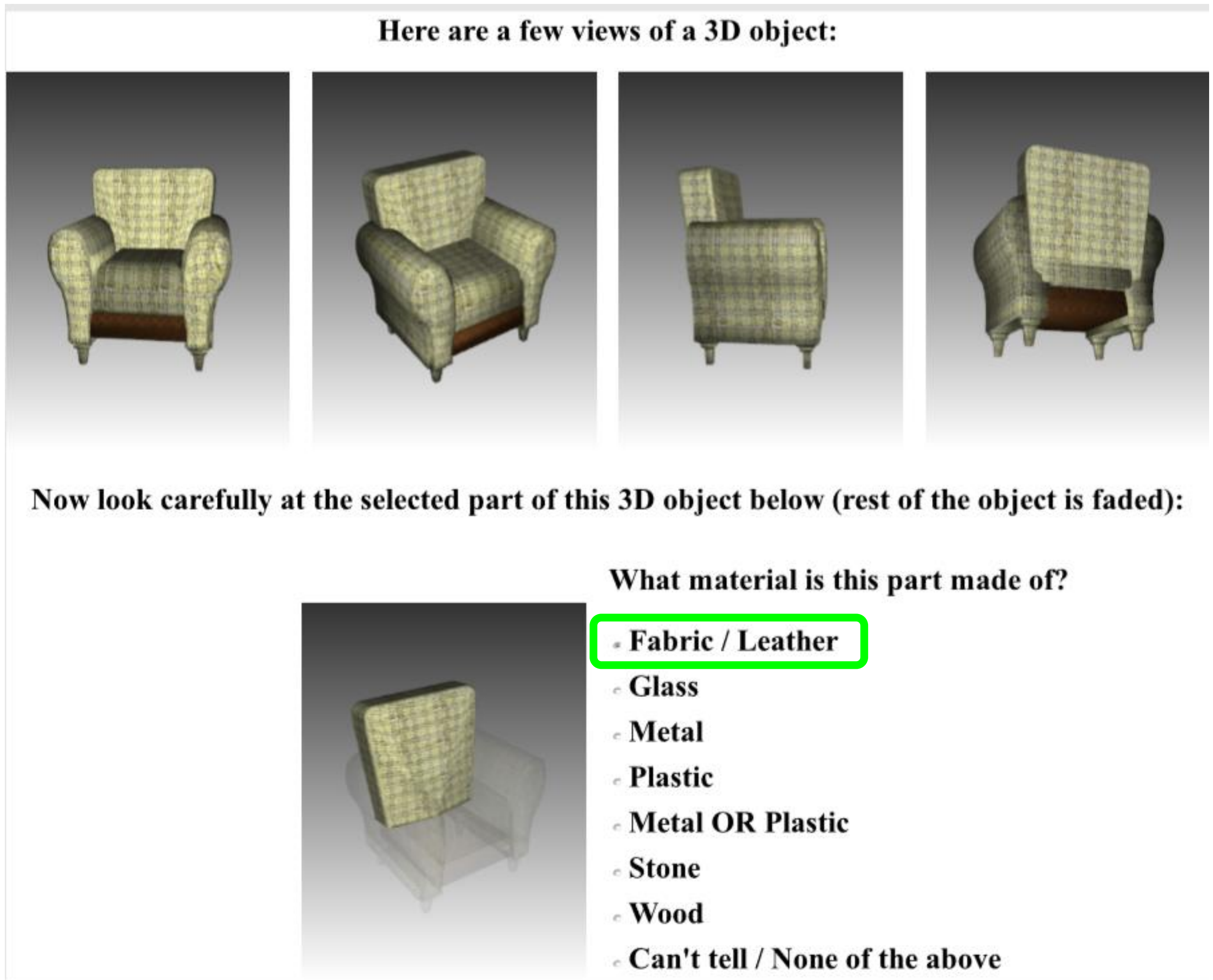
Now look carefully at the selected part of this 3D object below (rest of the object is faded):



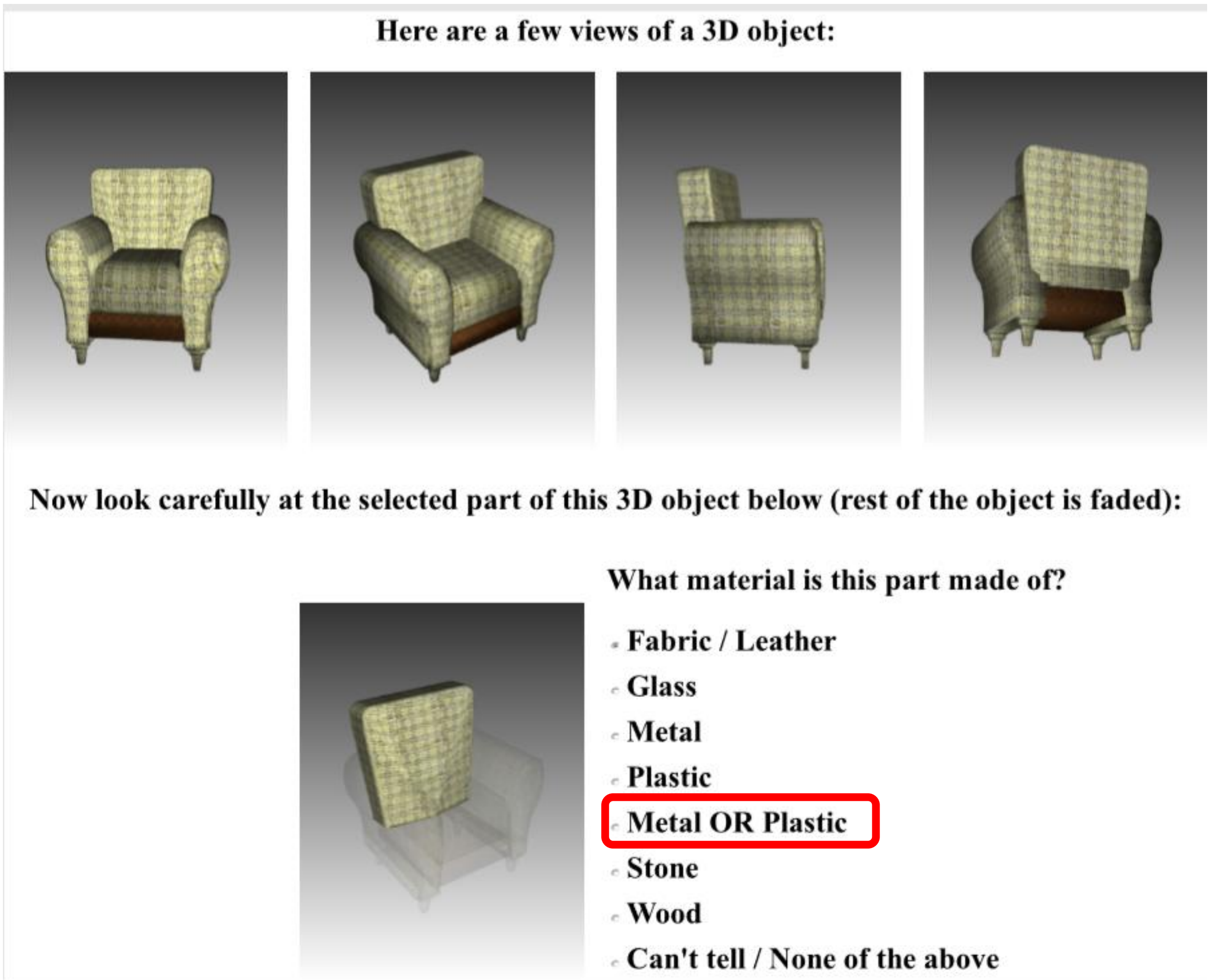
What material is this part made of?

- **Fabric / Leather**
- **Glass**
- **Metal**
- **Plastic**
- **Metal OR Plastic**
- **Stone**
- **Wood**
- **Can't tell / None of the above**

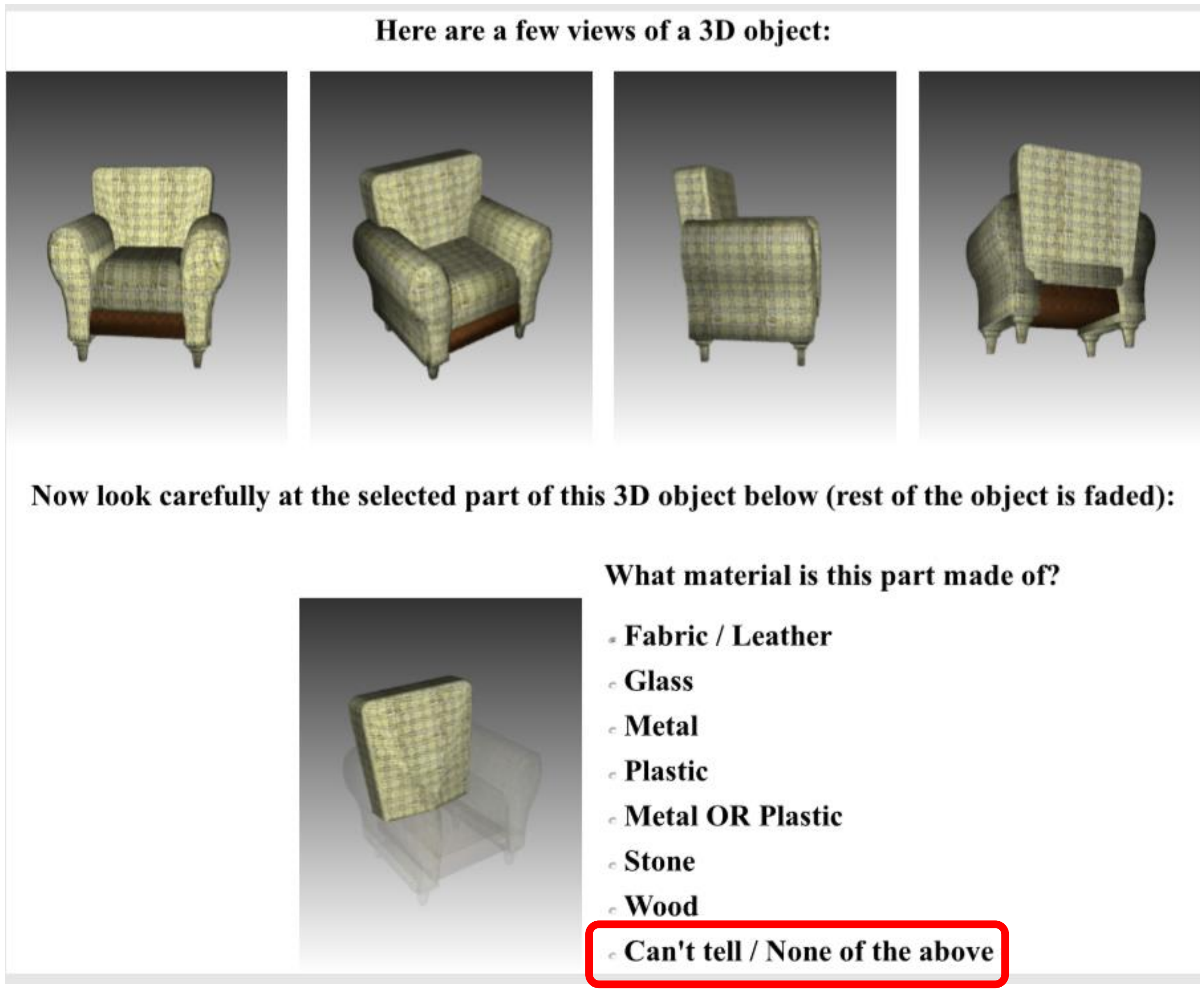
Crowdsourced Data



Crowdsourced Data



Crowdsourced Data



Crowdsourced Data

- 20 questions per task
- 3 sentinels per task
- Ignored labels from workers who incorrectly labeled sentinels or selected “Can’t tell” too often
- 5 votes per part, with 4+/5 considered reliable

- Parts with transparent textures labelled as glass (manually checked)

Expert-Annotated Data

- Crowdsourced data is noisy
- Only one label assigned per part, but…

e.g. This seat body can be made of wood or plastic.

- Need high quality annotations for evaluation
- Selected 115 chairs, tables, cabinets from 3D Warehouse and Herman Miller

[https://3dwarehouse.sketchup.com/]
[https://www.hermanmiller.com/resources/models/3d-models]

Expert-Annotated Data

Expert annotators reference product images and descriptions for accurate labelling

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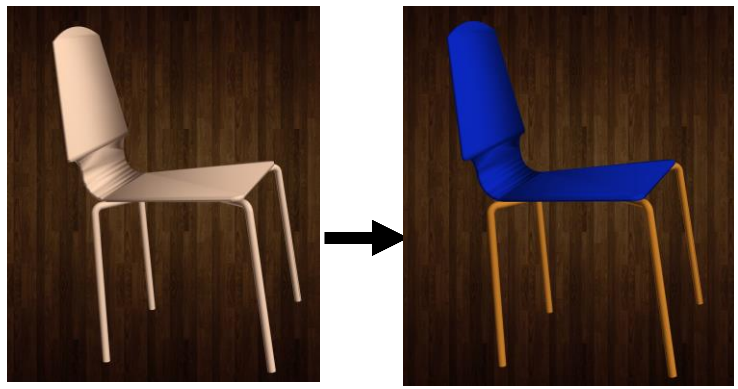
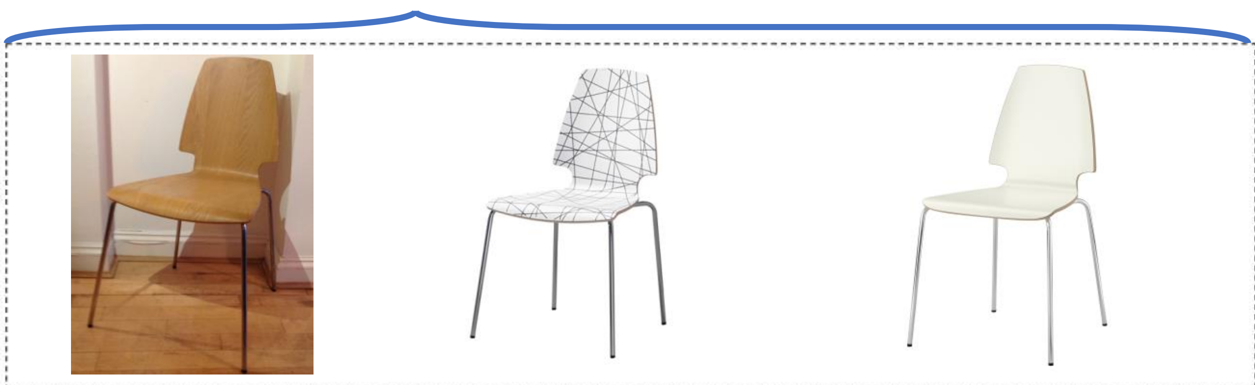


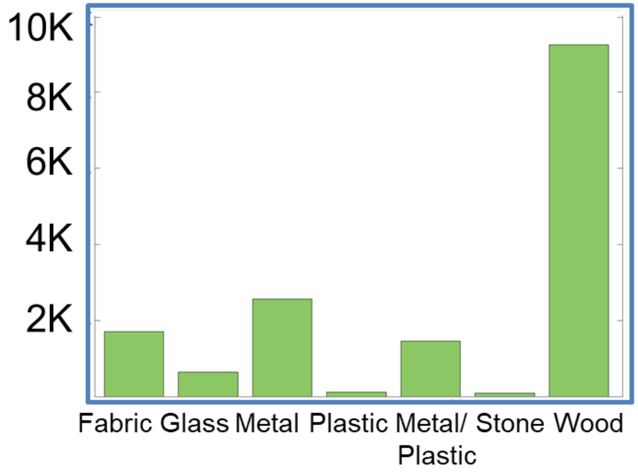
WOOD or PLASTIC
METAL

Manufacturer
Product Images

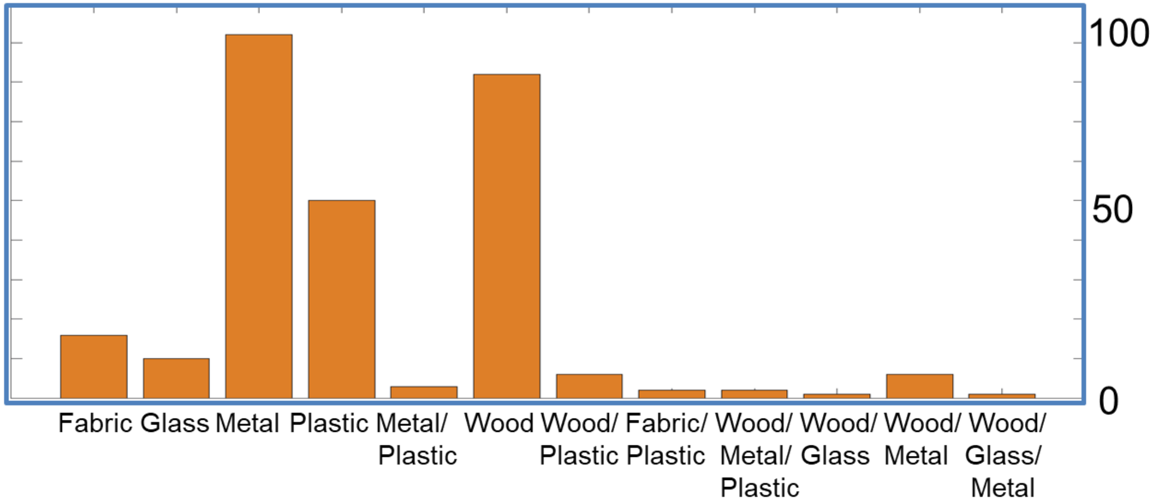


Label Distribution (# Parts / Label)

(Left) Crowdsourced Dataset



(Right) Expert Labeled Dataset



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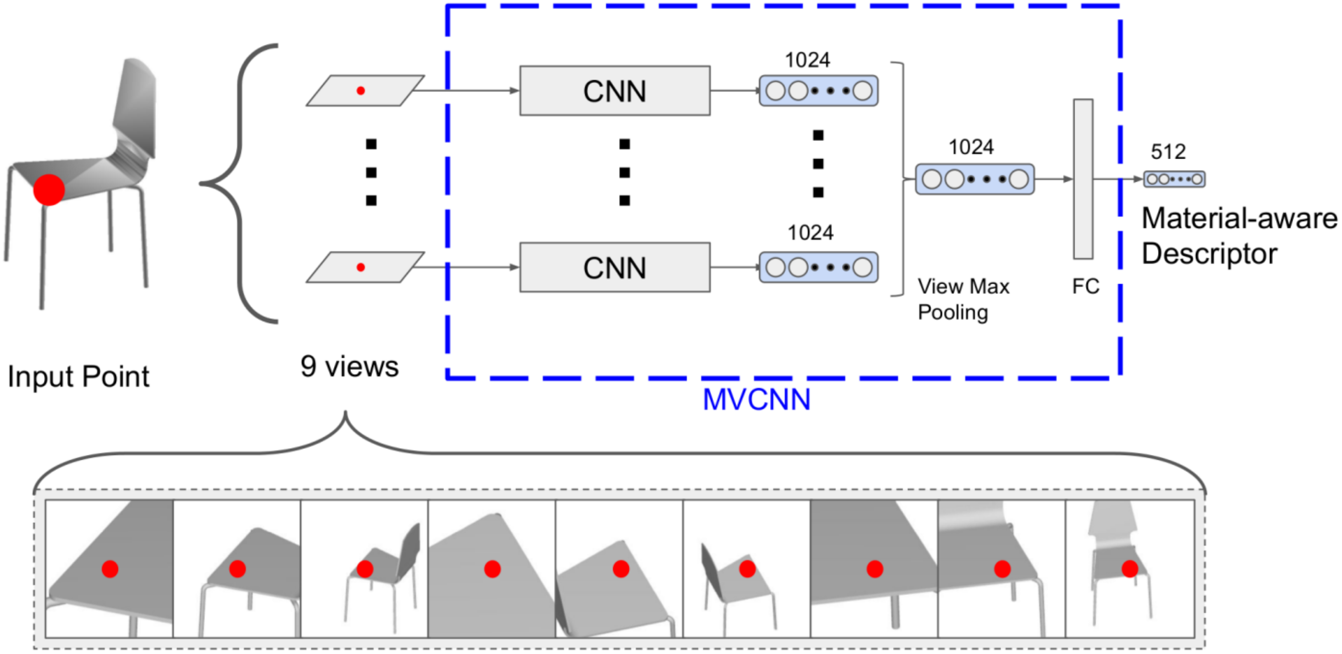
Challenge: Learning Pipeline

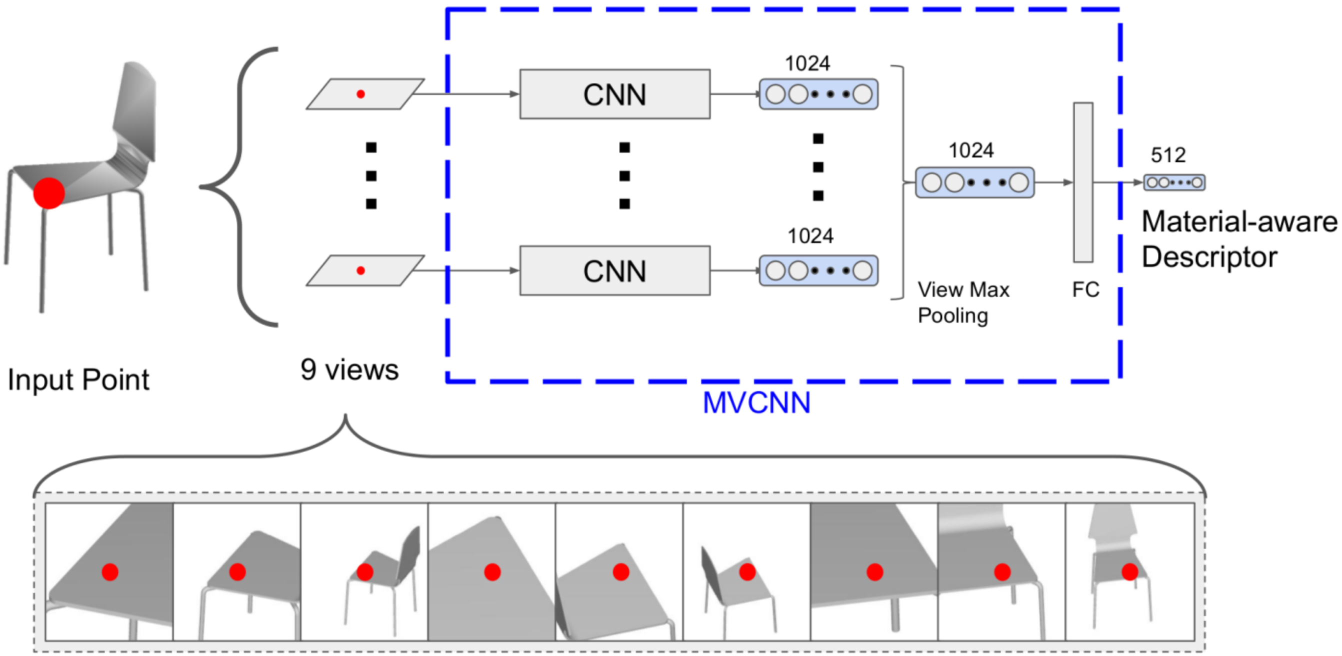
Architecture

Based on MVCNN architecture [Huang et al. 2018]



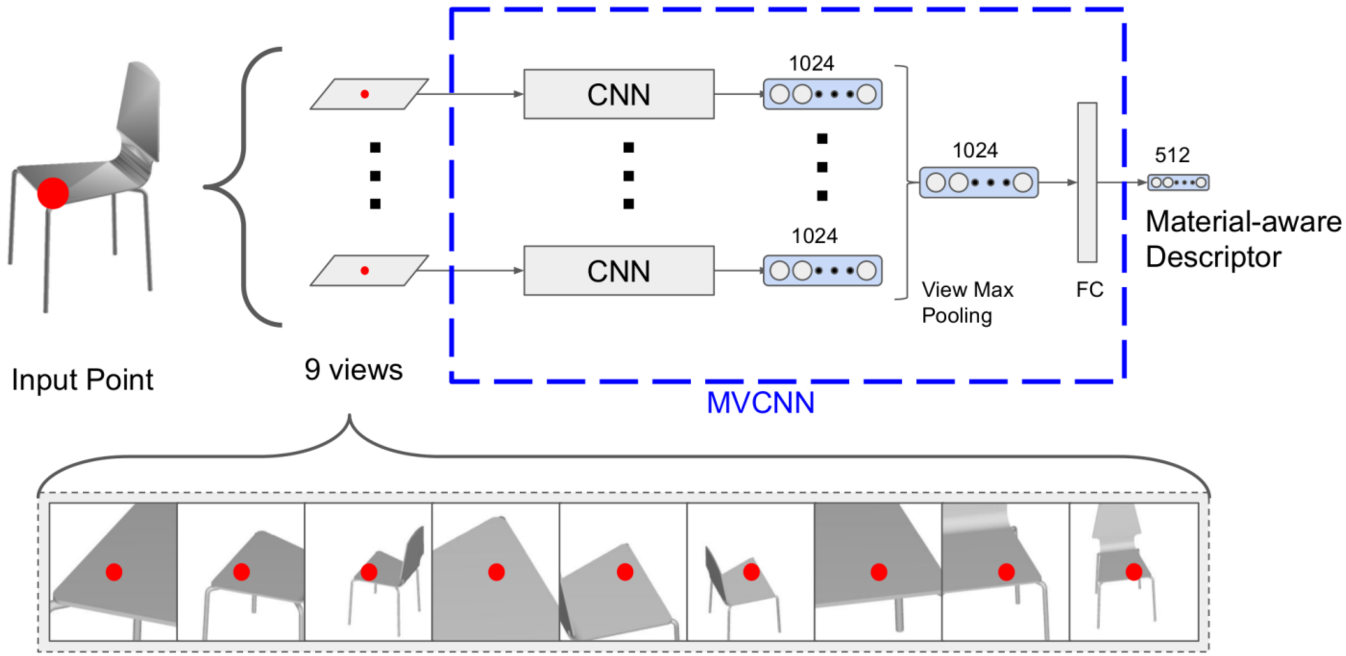
Architecture

- CNN backbone is Googlenet (VGG etc also works)



Architecture

- Input is 9 rendered views around surface point



Architecture

- Input is 9 rendered views around surface point
- Views are selected to maximize surface coverage
- 3 viewing directions at 3 viewing distances

- Camera is oriented upright wrt shape

- Also tried 36 views

Training

Loss function:

1) Contrastive loss [Hadsell et al. 2006] + classification loss
2) Classification loss only

Training

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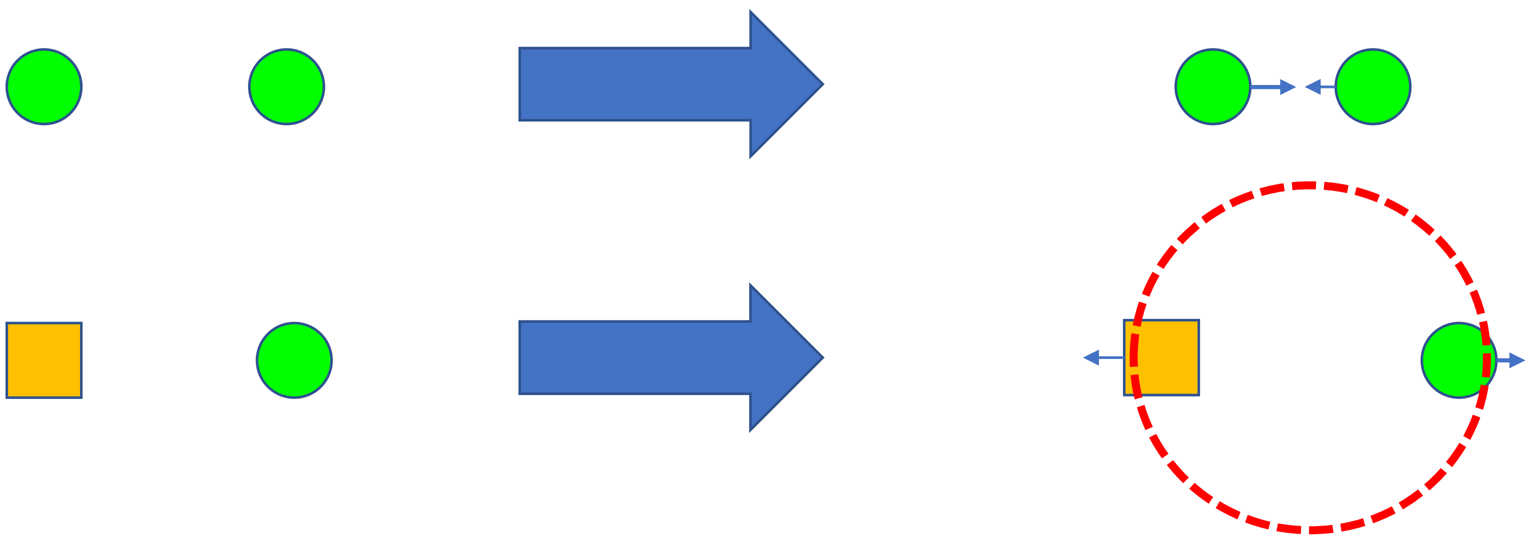

Training

Loss function:

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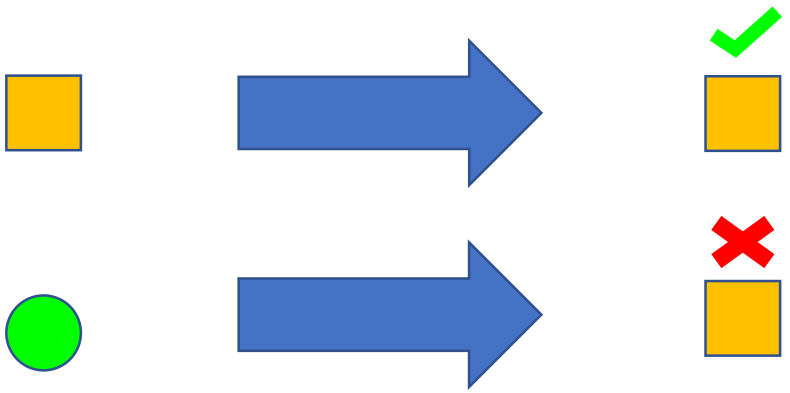


Training

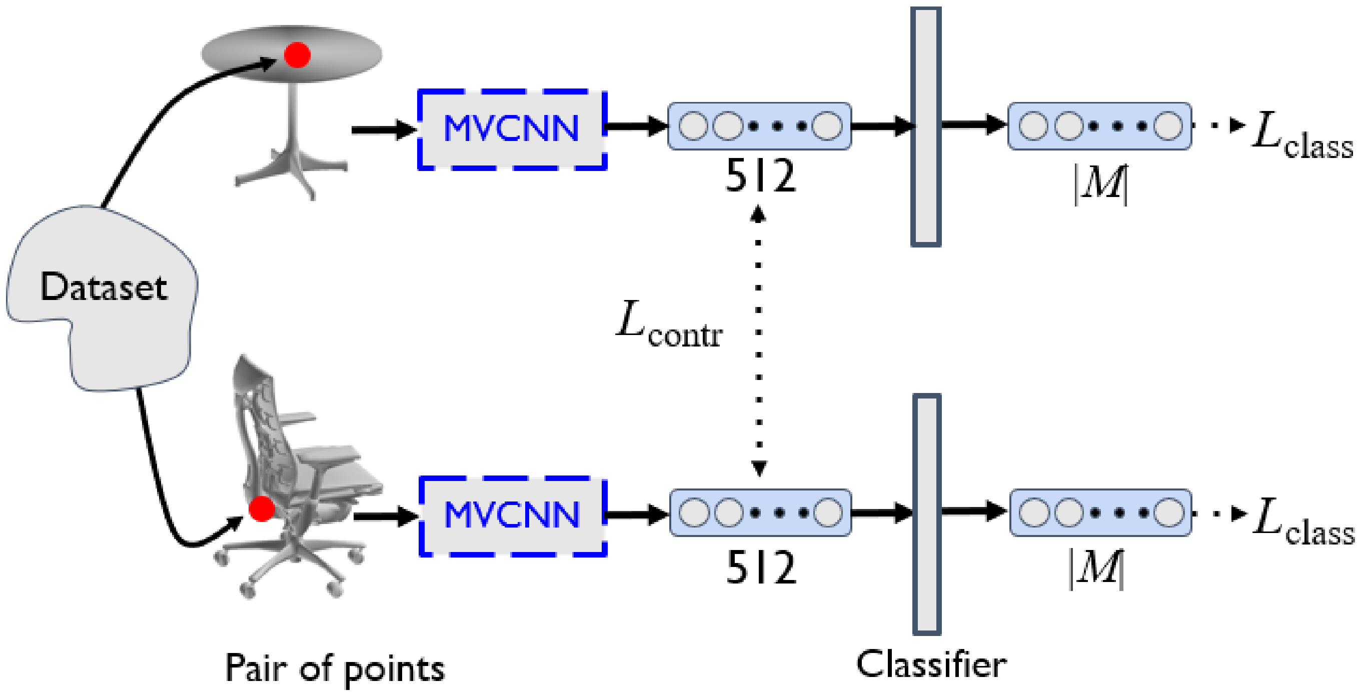
Loss function:

1) Contrastive loss [Hadsell et al. 2006] + classification loss
2) Classification loss only

These two variants produced the best results.

Training

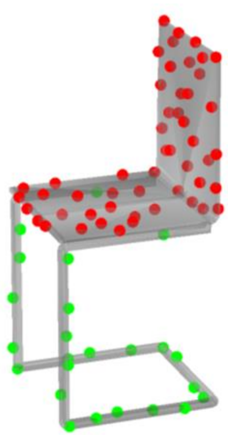
Trained in Siamese fashion

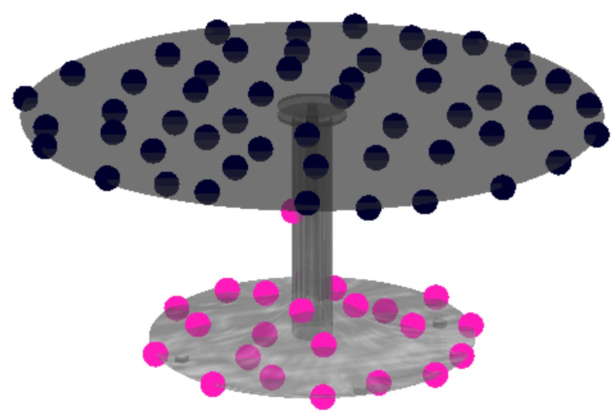


Training

Training set is sampled from crowdsourced data (>50% parts labeled)

- 75 uniformly separate points are sampled from each shape (occluded points ignored)
- Final training set consists of ~150K points.





Training

- Dataset is biased / imbalanced
- Class-balanced training – explicitly cycle through each combination of label pairs when sampling

e.g. (wood, wood)

(wood, metal)

(wood, fabric)

…

Training

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e.g. ~~(wood, wood)~~

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e.g. ~~(wood, wood)~~

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…

Training

- Dataset is biased / imbalanced
- Class-balanced training – explicitly cycle through each combination of label pairs when sampling

e.g. ~~(wood, wood)~~

~~(wood, metal)~~

~~(wood, fabric)~~

…

- Sample same class pairs 20% of time, sample different class pairs 80% of time

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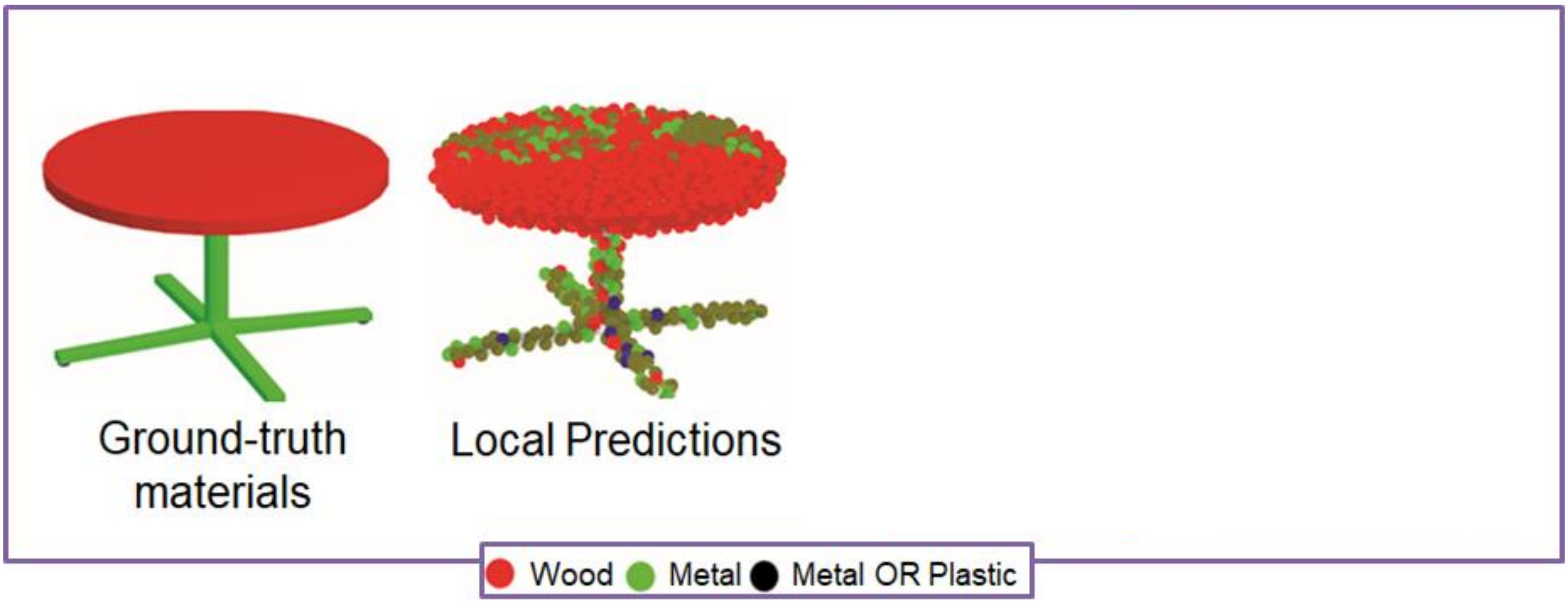
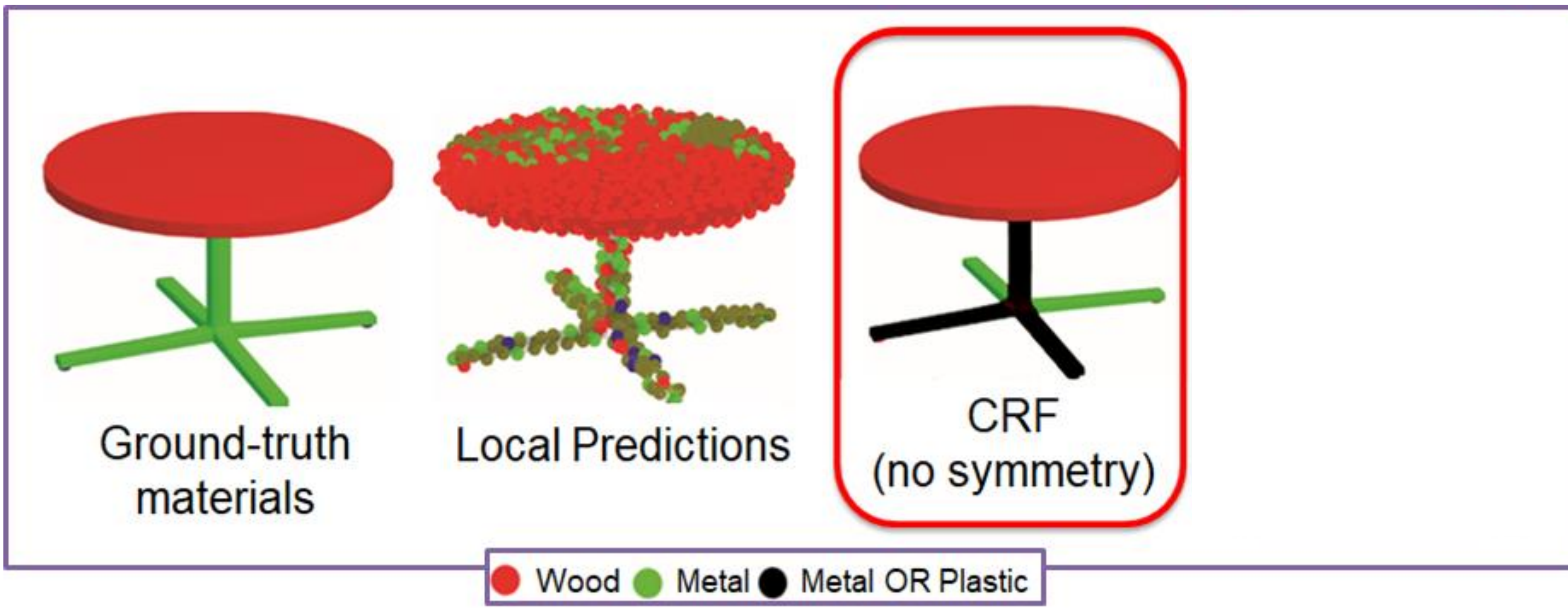
Challenge: Global Reasoning

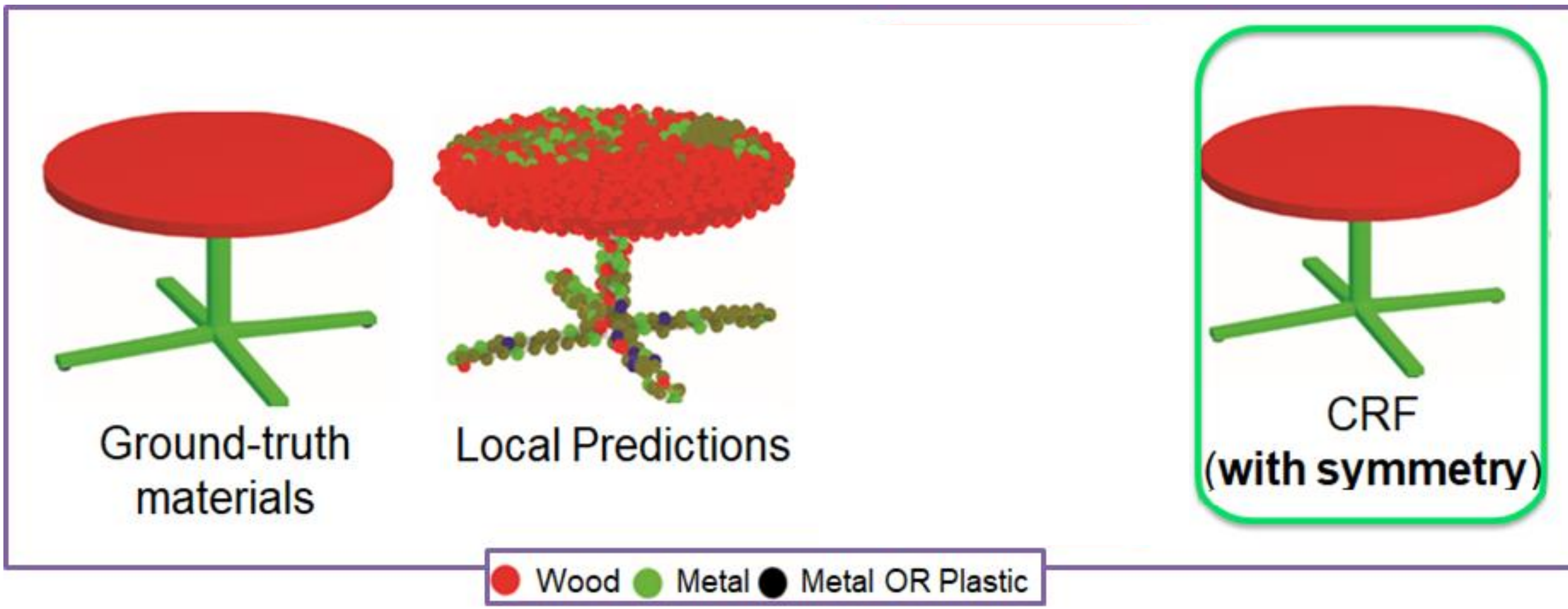
Local Material Predictions



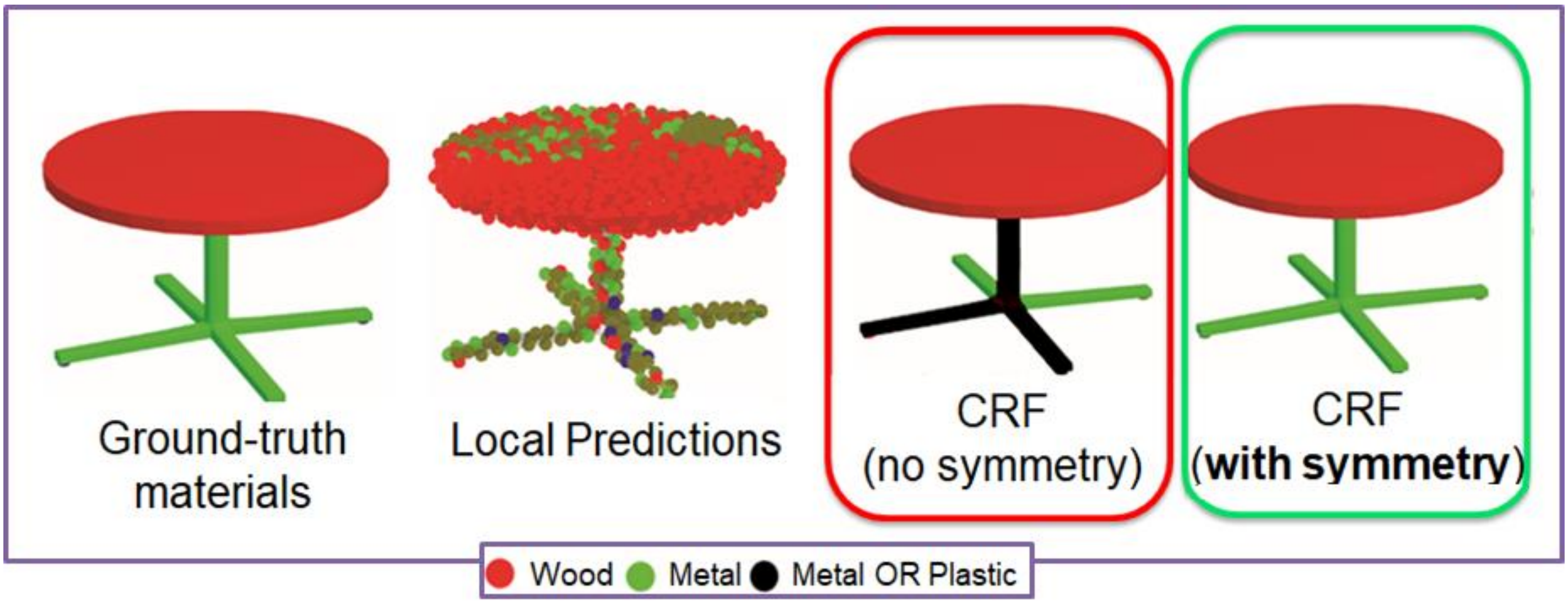
CRF


Ground-truth materials
Local Predictions
CRF (no symmetry)
Wood
Metal
Metal OR Plastic

CRF with symmetry



Comparison



Ground-truth materials
Local Predictions
CRF (no symmetry)
CRF (**with symmetry**)
Wood
Metal
Metal OR Plastic

CRF

- Use CRF to smooth local material predictions
- Three pairwise factors between polygons:
  - Low dihedral angle → same material
  - Low geodesic distance →same material
  - Rotational / reflective symmetry →same material

CRF

- Use CRF to smooth local material predictions
- Three pairwise factors between polygons:
  - Low dihedral angle ➔ same material
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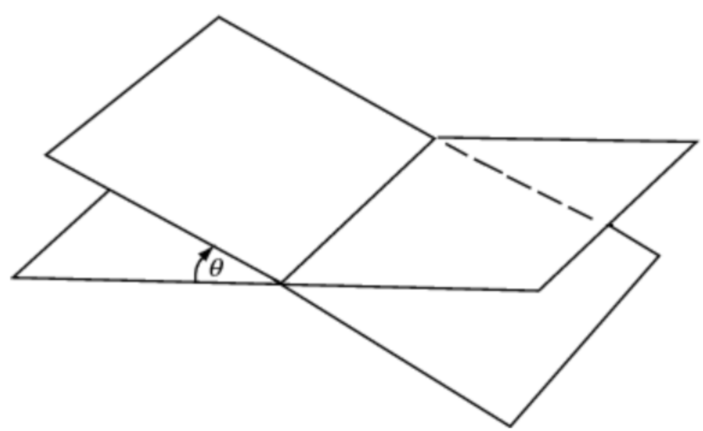

Fig from http://mathworld.wolfram.com/DihedralAngle.html

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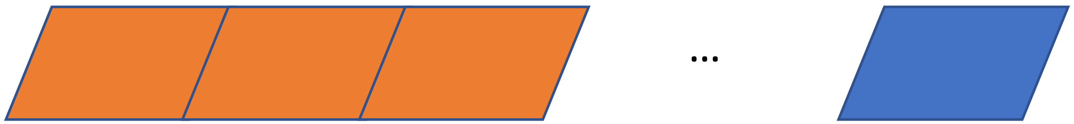

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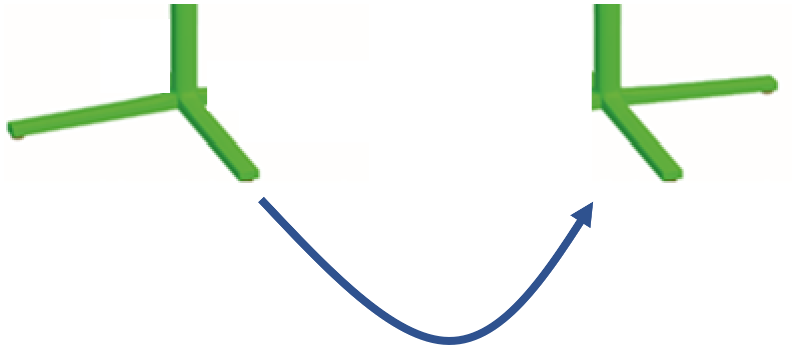

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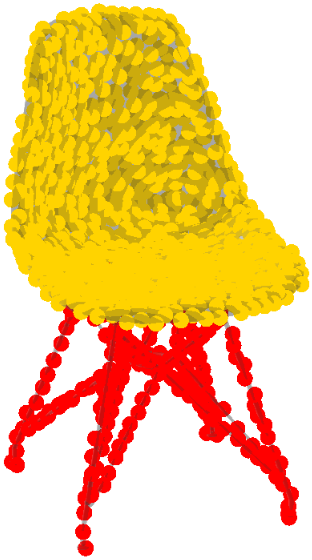
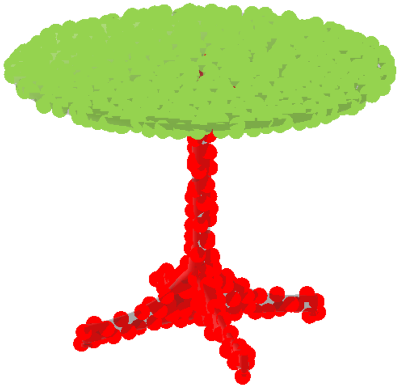
Test Set

1024 uniformly separated points sampled from each benchmark shape:

- Occluded points are discarded
- Final test set consists of 117K points





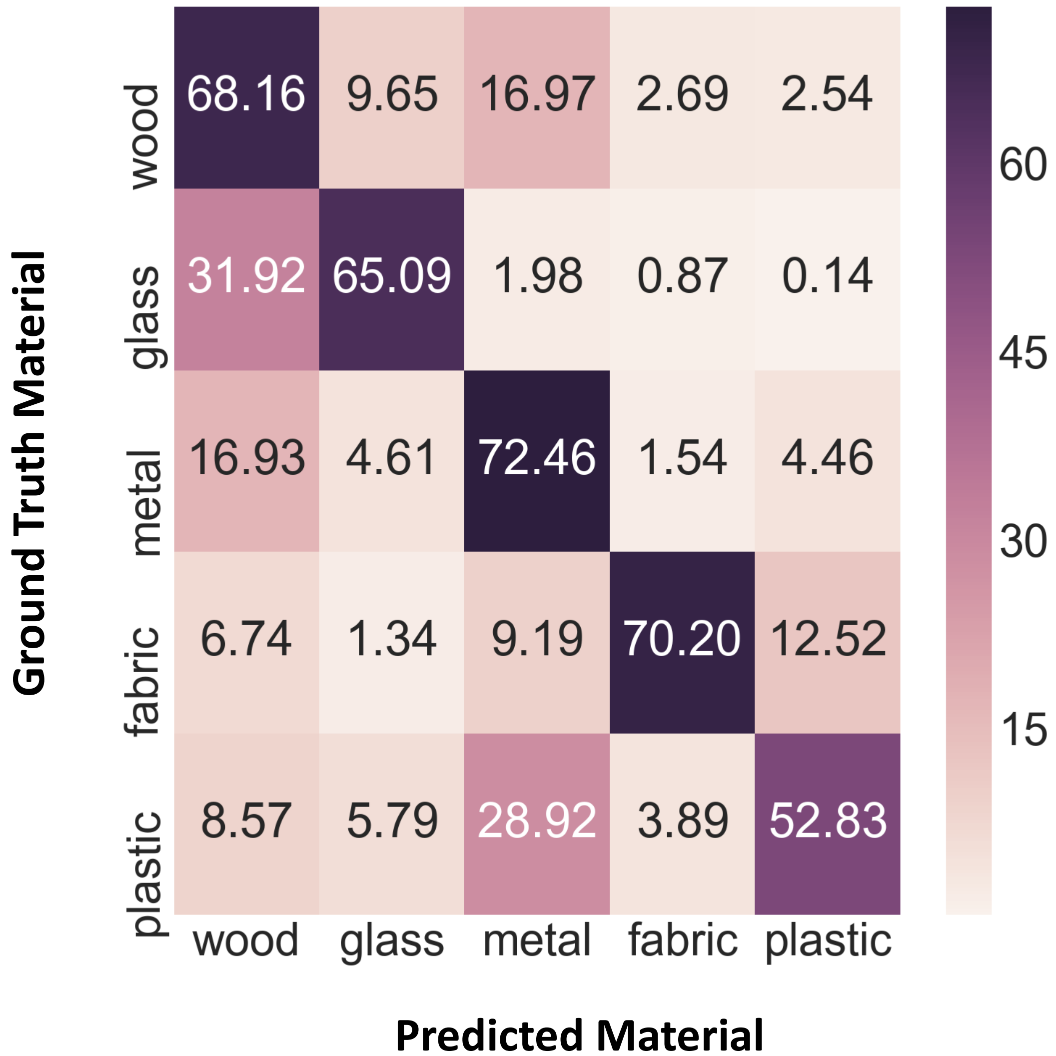
Material Prediction
Mean Class (Top 1) Accuracy

- Multitask has more balanced predictions and highest mean accuracy
- +CRF boosts performance across all categories except glass

Network	Mean	Wood	Glass	Metal	Fabric	Plastic
Classification	65	82	53	72	62	55
Classification +CRF	66	85	36	77	66	65
Multitask	66	68	65	72	70	53
Multitask +CRF	71	75	64	74	74	68

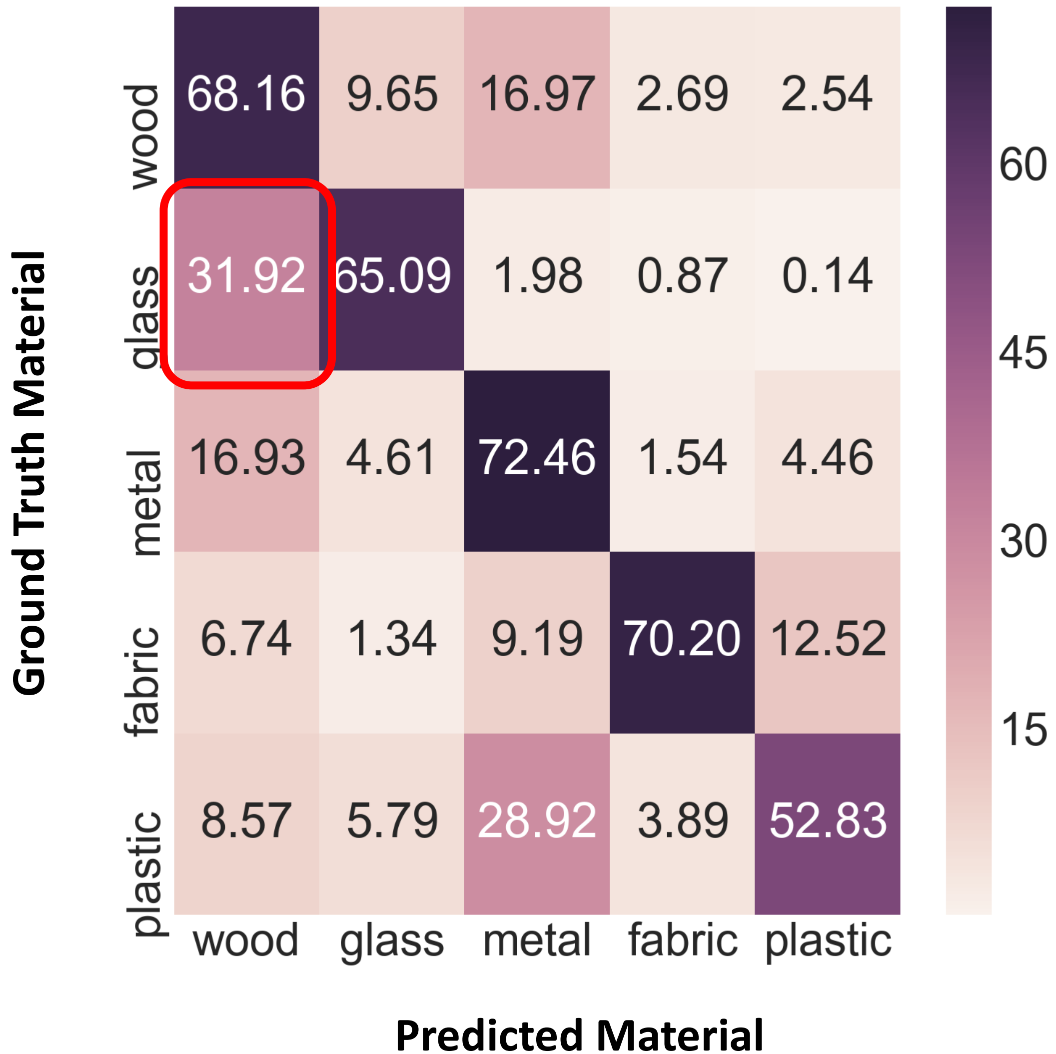
Material Prediction

Multitask (No CRF)



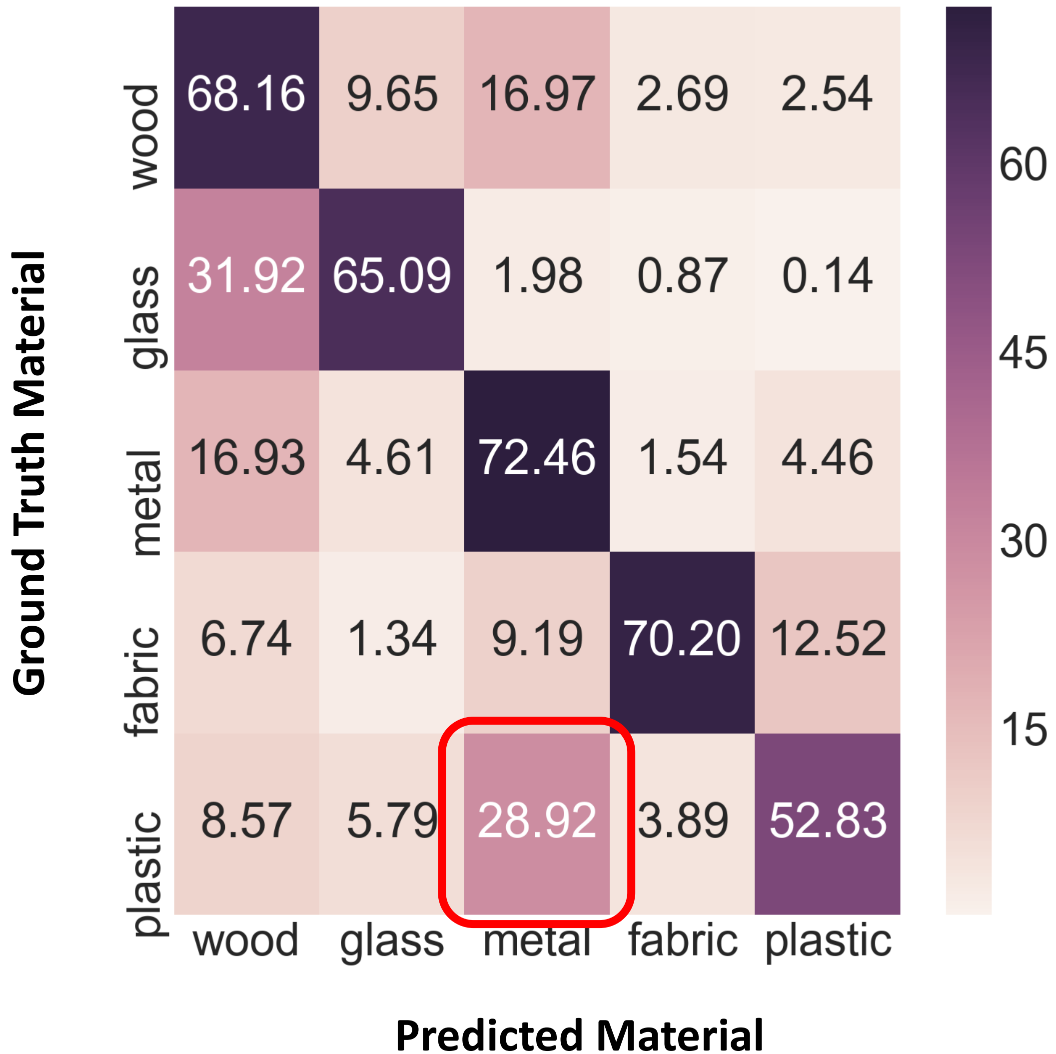
Material Prediction

Multitask (No CRF)



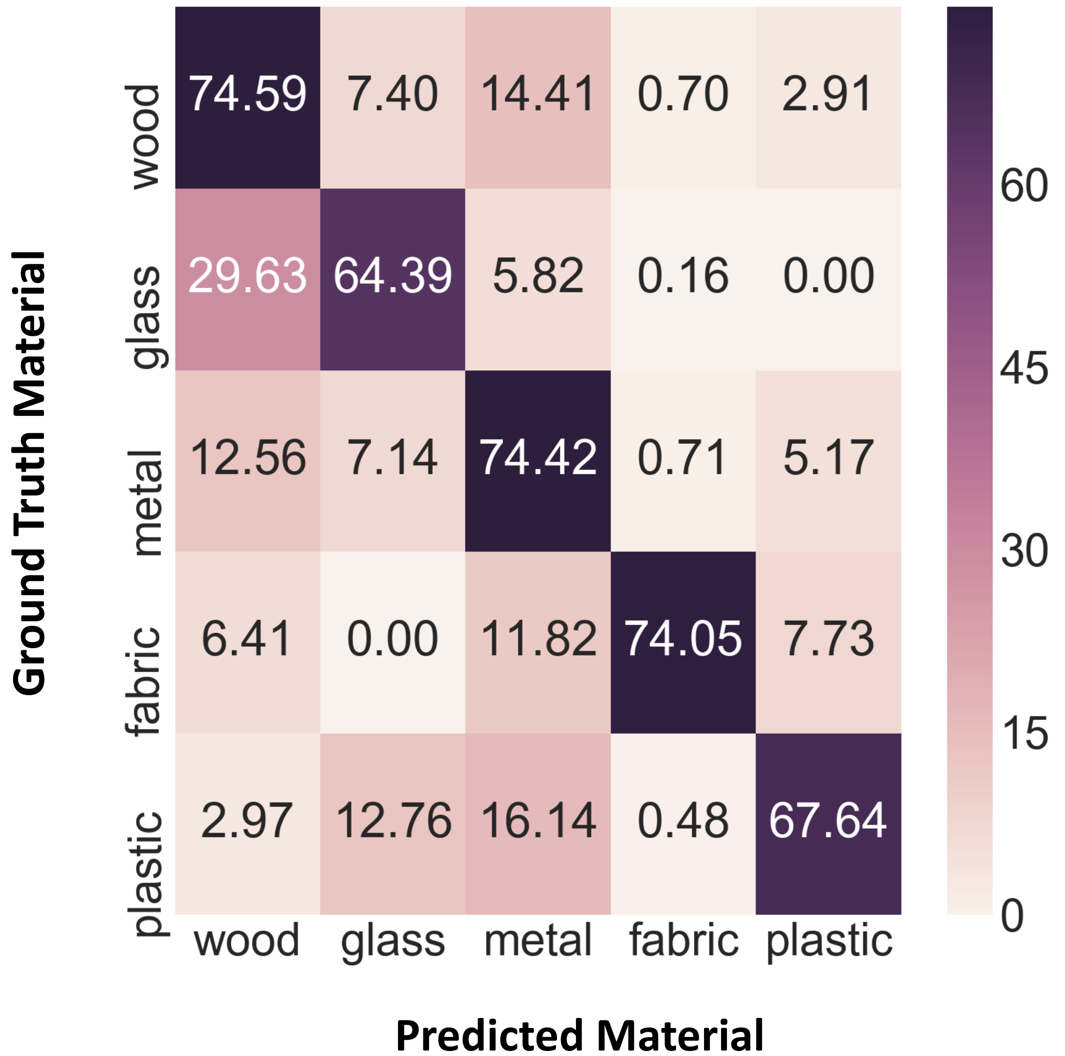
Material Prediction

Multitask (No CRF)



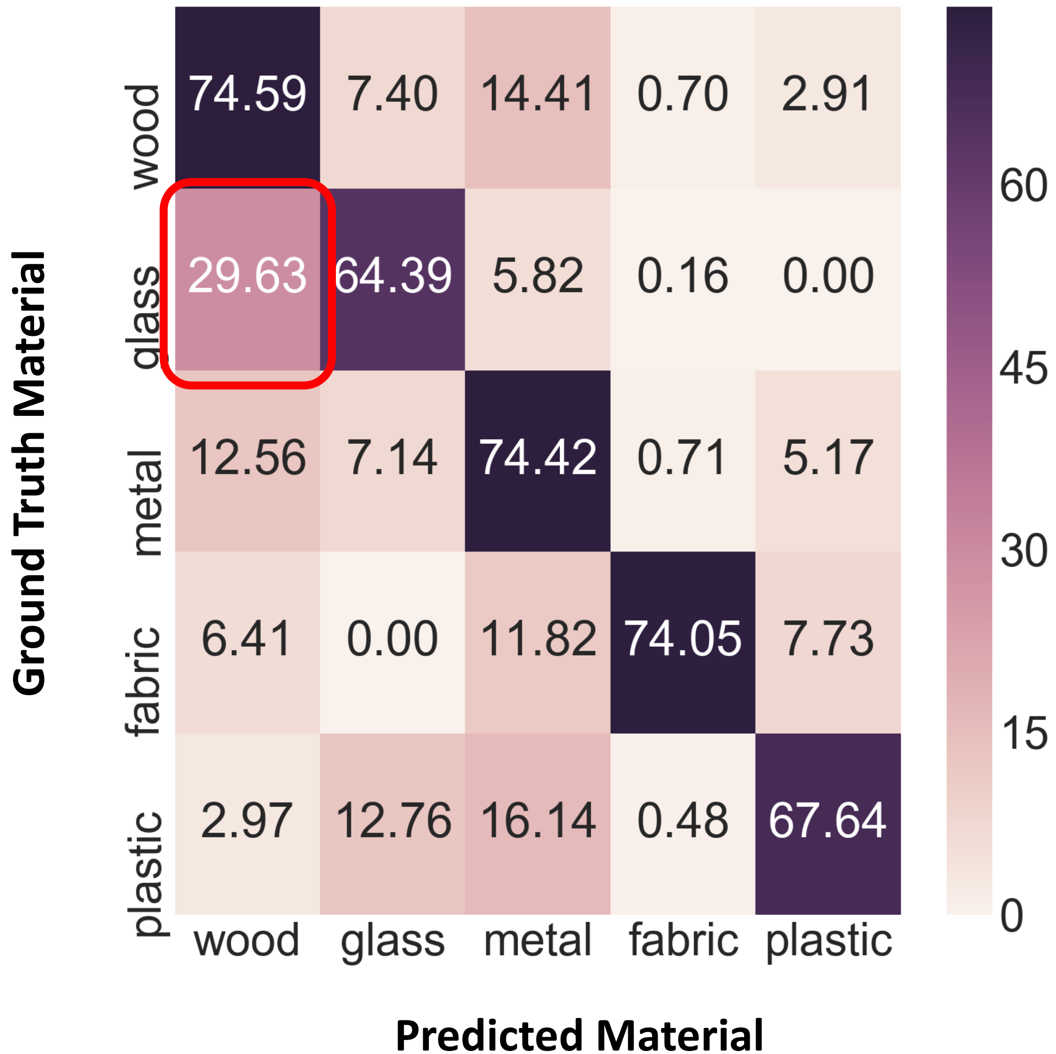
Material Prediction

Multitask+CRF:



Material Prediction

Multitask+CRF:



Material Prediction

Multitask+CRF:

Ground Truth Material \ Predicted Material	wood	glass	metal	fabric	plastic
wood	74.59	7.40	14.41	0.70	2.91
glass	29.63	64.39	5.82	0.16	0.00
metal	12.56	7.14	74.42	0.71	5.17
fabric	6.41	0.00	11.82	74.05	7.73
plastic	2.97	12.76	16.14	0.48	67.64

Predicted Material

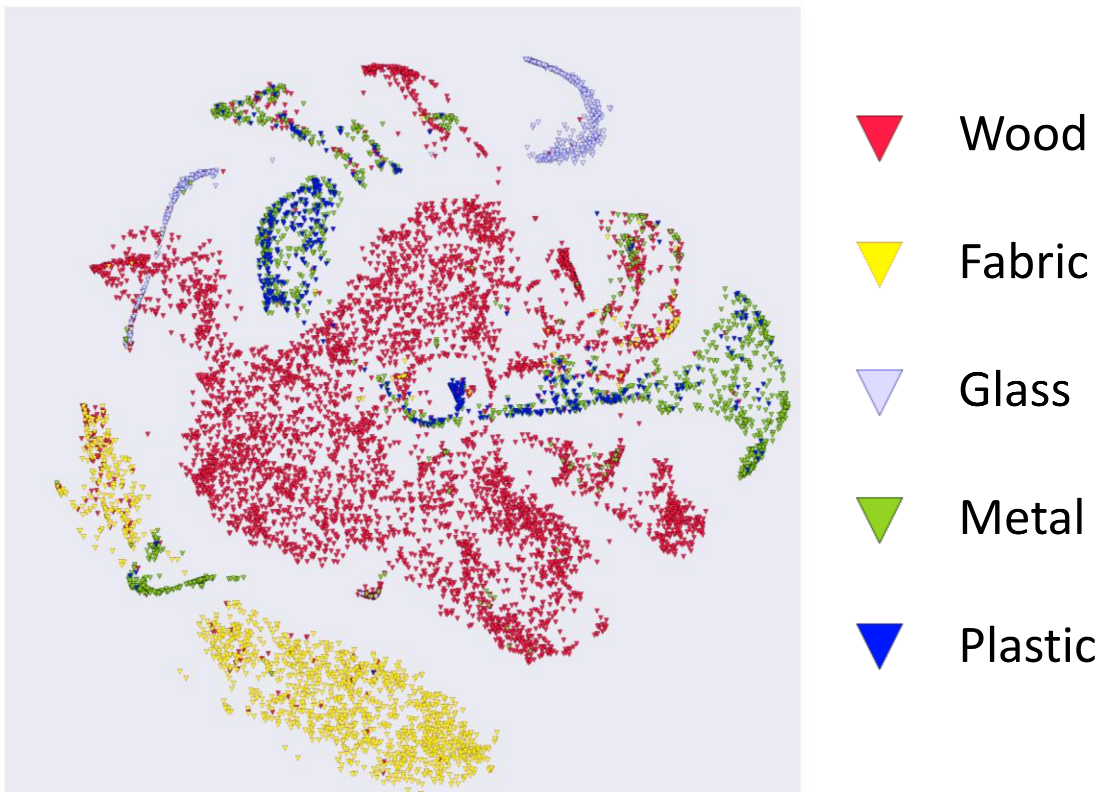
Descriptor Retrieval Mean Class Precision

- Similar mean class performance
- Multitask outperforms Classification for all materials except wood

Network	Mean	Wood	Glass	Metal	Fabric	Plastic
Classification						
k=1	55.7	76.4	34.3	65.0	56.1	46.7
k=30	56.9	75.3	41.1	64.9	55.3	47.6
k=100	57.3	75.1	43.0	64.9	55.5	48.0
Multitask						
k=1	56.2	62.2	40.8	68.6	58.0	51.2
k=30	56.2	61.0	42.6	68.9	57.4	51.1
k=100	56.6	60.7	44.7	68.7	57.4	51.5

Embedding Visualization (tSNE)

Multitask Descriptor Space



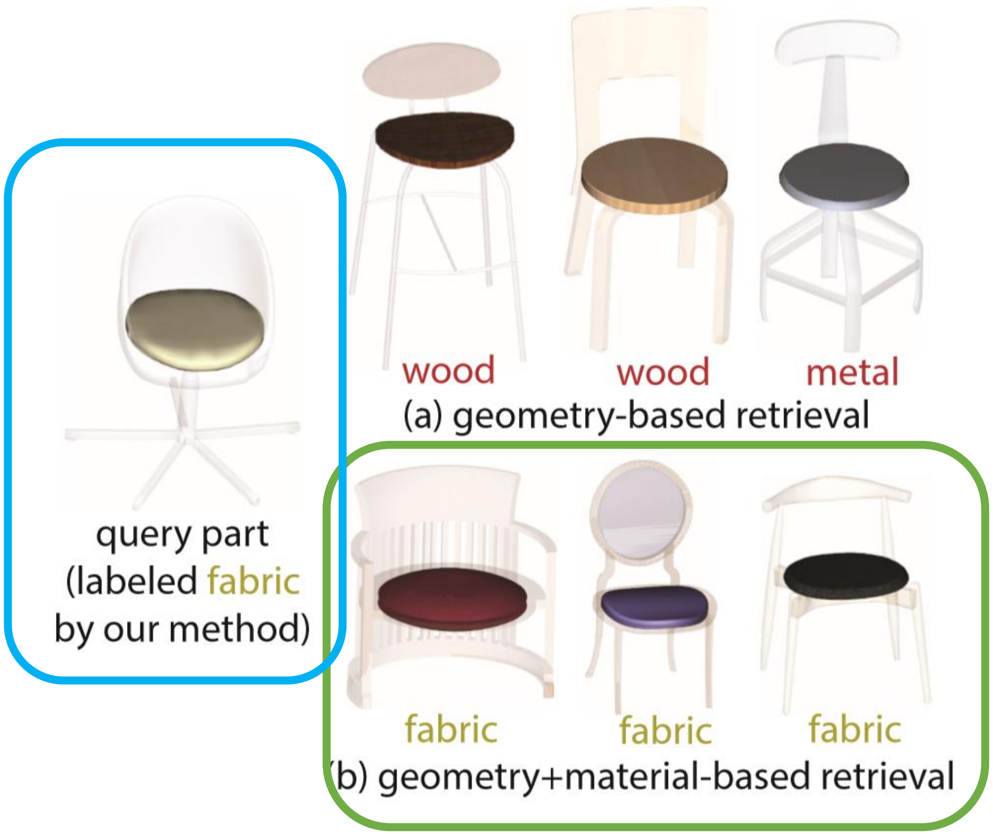
Effect of # of Input Views

3 views (1 direction, 3 distances) vs 9 views (3, 3)

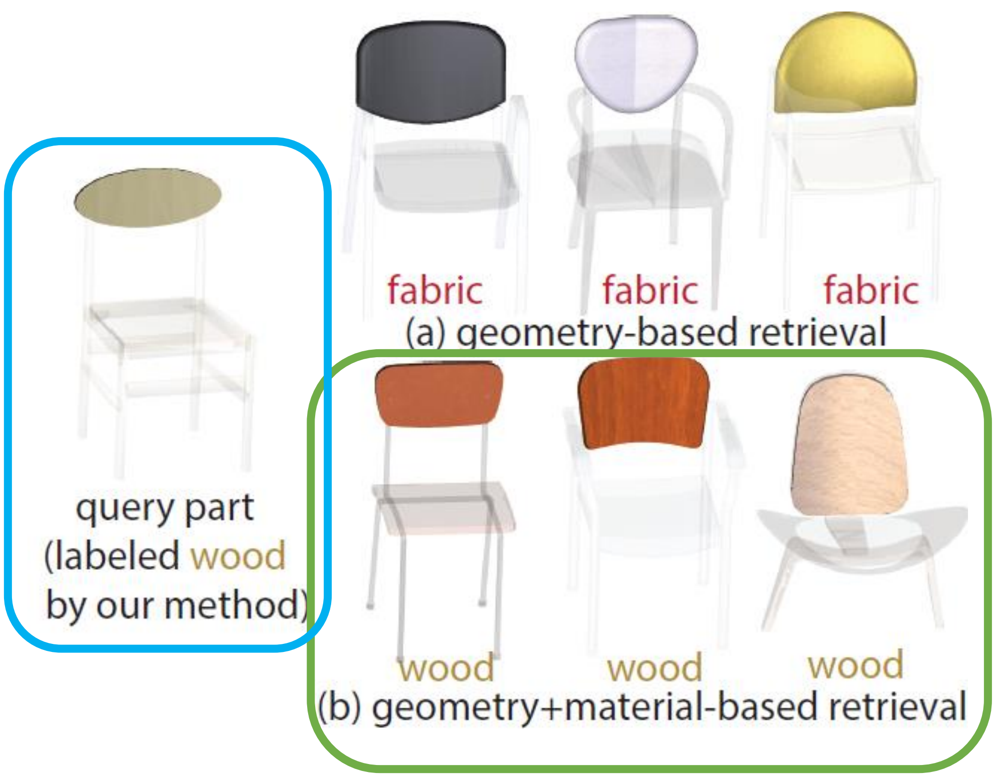
- Multiple view directions are advantageous
- Top 1 classification accuracy:

Network	Mean	Wood	Glass	Metal	Fabric	Plastic
Classification 3 views	59	81	41	71	60	40
Classification 9 views	65	82	53	72	62	55
Multitask 3 views	56	45	71	85	65	15
Multitask 9 views	66	68	65	72	70	53

Material-Aware Part Retrieval

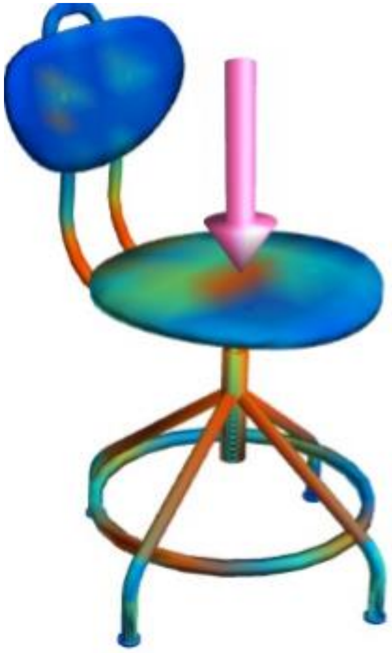


Material-Aware Part Retrieval



Material-Aware Automatic Texturing

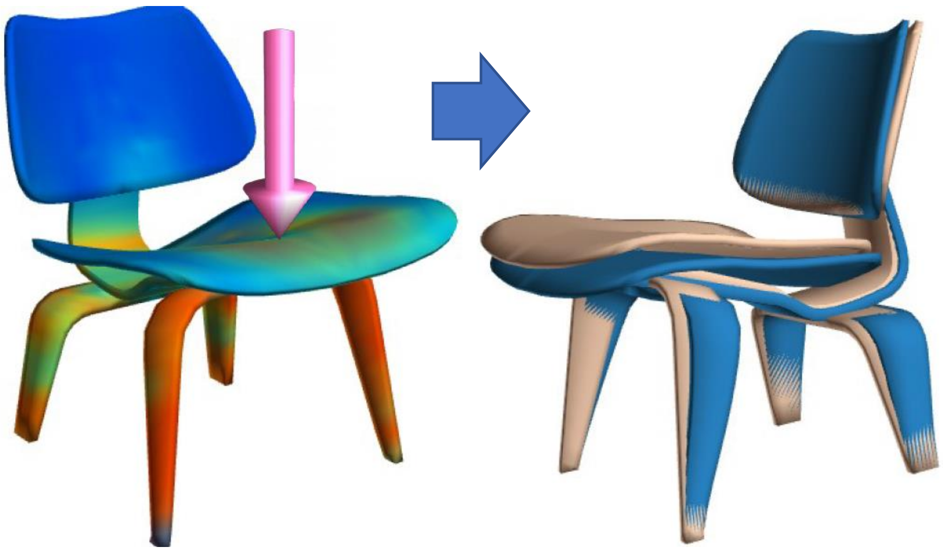
Material-Aware Physics Simulation



Applied force

Deformation

Material-Aware Physics Simulation



Applied force Deformation

Conclusion

- Two shape datasets with per-part material labels through crowdsourcing and expert-labelling
- Material-aware local descriptors computed through supervised learning pipeline
- Symmetry-aware CRF for global reasoning

Future Directions

- Increase variety of shapes and materials
- Learn smooth predictions end-to-end without CRF
- Fine-grained materials
- 2D material classification has good performance. Leverage this to improve 3D understanding.

Thank you!