Style Compatibility For 3D Furniture Models

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Motivation
Motivation
Motivation

Stylistically incompatible
Motivation

Stylistically compatible
How likely is it that a person would put these two furniture pieces together, when furnishing an apartment?
Goal

\[ d(X_i, X_j) = \text{Scalar} \]
Previous work – shape style

[Xu et al. 2010]  [Li et al. 2013]
Previous work – virtual world synthesis

[Merrell et al. 2011] [Fisher et al. 2012] [Xu et al. 2013]
Concurrent work – style similarity

[Lun et al. 2015]
(previous talk in this session)
Challenges

• Hard to design a hand-tuned function
• Coupled with functionality
• Requiring comparisons across object classes
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Key ideas

• Crowdsourcing compatibility preferences
• Part-based geometric features
• Learning object-class specific embeddings
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Crowdsourcing compatibility preferences

Living room

Table lamp (28)
End table (42)
Chair (37)
Coffee table (49)
Armchair (36)
Couch (39)
Floor lamp (23)
Crowdsourcing compatibility preferences

Design of user study [Wilber et al. 2014]

Please select the two most compatible pairs.
Crowdsourcing compatibility preferences

Rater’s selection
Converted into 8 triplets

and 4 more triplets ...
Crowdsourcing compatibility preferences

Collected 63,800 triplets for living room and 20,200 for dining room
Key ideas

• Crowdsourcing compatibility preferences
• Part-aware geometric features
• Learning object-class specific embeddings
Part-aware geometric features

Contemporary

Antique
Part-aware geometric features

- Consistent segmentation
- Computing geometry features for each part
- Concatenating features of all parts
Part-aware geometric features

Step 1: Consistent segmentation [Kim et al. 2013]

<table>
<thead>
<tr>
<th></th>
<th>Armrest</th>
<th>Back</th>
<th>Legs</th>
<th>Seat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td><img src="image1.png" alt="Armrest" /></td>
<td><img src="image2.png" alt="Back" /></td>
<td><img src="image3.png" alt="Legs" /></td>
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<td>Image 2</td>
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<td><img src="image9.png" alt="Armrest" /></td>
<td><img src="image10.png" alt="Back" /></td>
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<td><img src="image15.png" alt="Legs" /></td>
<td><img src="image16.png" alt="Seat" /></td>
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Part-aware geometric features

Step 2: Computing geometry features for each part

Back

Curvature histogram

Bounding box dimensions

Shape diameter histogram

Normalized surface area
Part-aware geometric features

Step 3: Concatenating features of all parts

\[ x = [x_{back}, x_{legs}, ...] \]
Key ideas

• Crowdsourcing compatibility preferences
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Learning object-class specific embeddings

Previous approach [Kulis 2012]: *Symmetric embedding*

\[ d_{symm}(x_i, x_j) = \|W(x_i - x_j)\|_2 \]

\( d_{symm} \) is the compatibility distance

\( x_i, x_j \) are feature vectors of two shapes
Learning object-class specific embeddings

Previous approach [Kulis 2012]:

The quick brown fox jumps over the lazy dog.

Fonts [O’Donovan et al. 2014]

Illustration styles [Garces et al. 2014]
Learning object-class specific embeddings

Assumptions of the previous approach

• Feature vectors have same dimensionality.
• Corresponding dimensions are comparable.
Learning object-class specific embeddings

Our approach: **Asymmetric embedding**

\[ d_{\text{asym}}(x_i, x_j) = \left\| W_{c(i)}x_i - W_{c(j)}x_j \right\|_2 \]

- \( c(i) \) is the object class of \( x_i \)
- \( c(j) \) is the object class of \( x_j \)
Learning object-class specific embeddings
Learning object-class specific embeddings

Learning procedure [O’Donovan et al. 2014]

• Using a logistic function to model rater’s preferences
• Learning by maximizing the likelihood of the training triplets with regularization
Outline

• Key ideas
• Results of triplet prediction
• Applications
Results of triplet prediction

Test set: triplets that human agree upon

- 264 triplets from dining room
- 229 triplets from living room
## Results of triplet prediction

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• Applications
Applications

• Style-aware shape retrieval
• Style-aware furniture suggestion
• Style-aware scene building
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Style-aware shape retrieval

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Style-aware shape retrieval

Query model

Dining chair
Style-aware shape retrieval

Query model

Dining chair

(Most incompatible chairs)
Style-aware scene modeling
Style-aware scene building

User study

• 12 participants, each works on 14 tasks.
• Half of the tasks are assisted by our metric, and the other half are not.
• Results from both conditions are compared on Amazon Mechanical Turk
Style-aware scene building

Percentage of votes

Test scenes

- Random
- No preference
- Ours
Style-aware scene building
Style-aware scene building
Take-away messages

It is possible to learn a compatibility metric for furniture of different classes.

- Part-aware geometric features
- Asymmetric embedding of individual object classes

The learned compatibility metric is effective in style-aware scene modeling.

- Shape retrieval
- Interactive scene building
Take-away messages

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Limitations and future work

• Modeling fine-grained style variations

Duncan Phyfe style with eagle motif  
(Courtesy: Carswell Rush Berlin)  

Sheraton style with lyre motif
Limitations and future work

• Modeling fine-grained style variations
• Investigating how other properties determine style
Limitations and future work

- Modeling fine-grained style variations
- Investigating how other properties determine style
- Investigating style compatibility in other domains
Acknowledgements

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• Trimble and Digimation
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