Learning to Group Discrete Graphical Patterns



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Pattern Grouping Problem: motivation



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Input Pattern

Symmetry rule wins

Similarity rule wins

Challenges (2): various noises



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Challenges (3): Rich Variations and Complexity



Applications of Pattern Grouping

□ Pattern Editing



Inverse Procedural Modeling by Automatic Generation of L-systems. O. Stava, et al. 2010

Pattern EditingPattern Exploration



PATEX: Exploring Pattern Variations. P. Guerrero, et al. 2016

Pattern Editing Pattern Exploration Layout Optimization



GACA: Group-Aware Command-based Arrangement of Graphic Elements. P. Xu, et al. 2015

Related Work: Model & Rule Driven

□ Gestalt-based pattern grouping

- > Conjoining Gestalt Rules for Abstraction of Architectural Drawings. Nan et al. TOG, 2011.
- > Perceptual grouping by selection of a logically minimal model, Feldman, ICCV, 2003.
- > The whole is equal to the sum of its parts: A probabilistic model of grouping by proximity and similarity in regular patterns, Kubovy & Berg. Psychological Review, 2008.

□ Symmetry-based pattern grouping

- > Folding meshes: hierarchical mesh segmentation based on planar symmetry. Simari et al. SGP, 2006.
- > Co-Hierarchical Analysis of Shape Structures. O. Kaick et al. TOG, 2013.
- Symmetry Hierarchy of Man-Made Objects. Wang et al. Computer Graphics Forum, CGF, 2011.
- > Layered Analysis of Irregular Facades via Symmetry Maximization. Zhang et al. TOG, 2013.

Related Work: Gestalt-Based Pattern Grouping



Conjoining gestalt rules for abstraction of architectural drawings, Nan et al. TOG, 2011. □ Hand-engineering rules to quantify grouping models

□ Hand-tuning relative importance of rules





Our Work: First data-driven approach

- □ Learning to group discrete graphical patterns from human annotations
- □ Loosely consider Gestalt principles
- □ Learn relative importance of features, without hand-engineer rules
- □ Robust noise handling thanks to learning approach





Our Strategy

- □ Learning to group discrete graphical patterns from human annotations
- □ Loosely consider Gestalt principles
- Learn relative importance of features, without hand-engineer rules
- Robust noise handling thanks to learning approach



- □ Learned feature descriptor for each elements
- **Clustering in learned feature space**

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- □ Not optimize the clustering algorithm itself
- □ Learn a feature space suitable for clustering

Our Solution

- □ Element -> learned feature descriptor
- **Clustering in learned feature space**
- □ Not optimize the clustering algorithm itself
- □ Learn a feature space suitable for clustering







Similar & close-by



Horizontal Alignment



How can we **migrate** human experience into machine learning?

Feature Learning: local Information



Feature Learning: global Information



Local feature: Atomic Element Encoder



Local feature: Atomic Element Encoder



Local feature: Atomic Element Encoder



Local feature: Structure Encoder



Global feature: Structure Encoder



Network Architecture

Network Architecture



Data Collection: Lack of suitable patterns on the web



Black & White

Color Gradient

Lack Structural Variety

Layout Templates Based Training Data Collection



Training Data: element collection



- □ ~800 pattern layout templates
- □ ~8K pattern images
- □ 500 positive and 500 negative pairs of elements
- □ ~ 8M training pairs

Results on synthesized patterns



Grouping Results on synthesized patterns



Results on synthesized patterns



Noise level increase

Results on **downloaded patterns**



Results on **downloaded patterns**



Results on downloaded **Challenging** patterns



Results on downloaded **Challenging** patterns



	preset #group		auto #group	
	Rand index	purity	Rand index	purity
geometry distance	77.62%	73.13%	76.47%	76.64%
AlexNet	76.60%	70.96%	74.41%	71.16%
fine-tuned AlexNet	77.72%	73.12%	77.59%	80.21%
element encoder	78.34%	74.59%	77.72%	78.82%
structure encoder	78.79%	73.24%	77.35%	74.68%
element+structure enc.	80.28%	75.75%	80.03%	81.84%
our full measure	83.05%	80.24%	83.58%	85.76%

Greater score mean better grouping results

	Rand index	purity
affinity propagation	83.05%	80.24%
agglomerative (average linkage)	75.93%	71.13%
agglomerative (single linkage)	71.11%	68.38%
agglomerative (complete linkage)	76.76%	71.79%
k-means	80.85%	75.58%
Gaussian Mixture Models	80.92%	74.91%
normalized cuts	77.48%	71.72%
Tagger [Greff et al. 2016]	66.54%	55.21%

Results of User Study



Limitation on model



Limitation on input data



Future work: Unified Framework for Various types of Input Data



Other Future Directions: Hierarchical Grouping



The optimal result

Other Future Directions: learn to rank grouping results



Which Grouping Results is better?

Other Future Directions: learn to rank grouping results



Ranking order Changed

□ First (data-driven + deep CNN) for discrete 2D patterns.

Learned shape-, context-, and structure-aware descriptors for graphical elements.

A large, annotated dataset is provided online.
<u>http://people.cs.umass.edu/~zlun/papers/PatternGrouping/</u> (source code + dataset)

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- □ NSERC Canada.
- Gift funds from Adobe Research.

Thanks!

Q&A

<u>http://people.cs.umass.edu/~zlun/papers/PatternGrouping/</u> (Source code & Dataset)