Pyramidal Stochastic Graphlet Embedding for Document Pattern Classification

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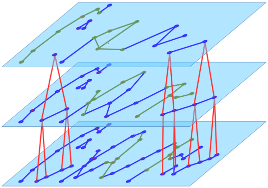

Horizon 2020
European Union funding
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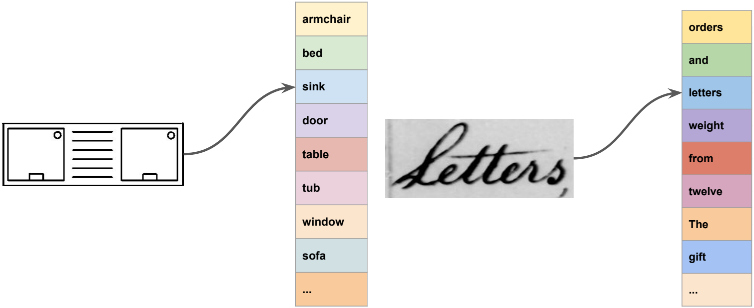
Outline

Introduction

Introduction

Document pattern classification

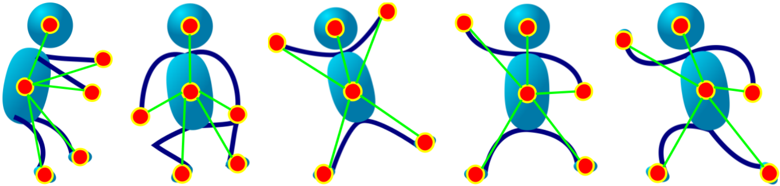
- Word and symbol classification.
- Application: document feature generation, document categorization, spam filtering etc.



Introduction

Graph based representation

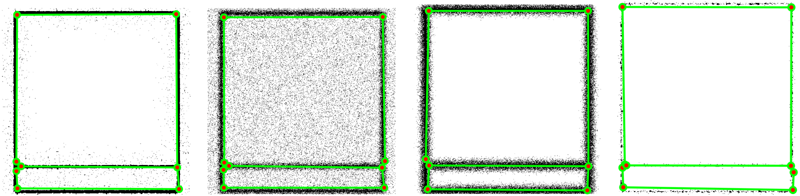
- Limitations of statistical pattern recognition.
- Advantages of structural pattern recognition.
- Graph based representation: relation between object parts.
- Invariant to rotation and affine transformation.
- Comparing graphs: graph matching, graph kernel.



Introduction

Motivation

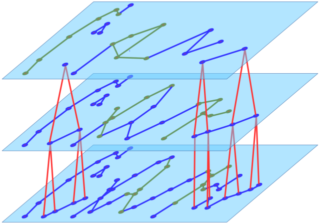
- Document part $\rightarrow$ graph $\Rightarrow$ noisy conversion
- Unstable representation.

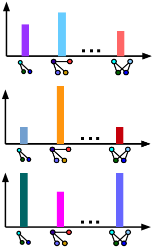


Introduction

Contribution

- Graph pyramid: multi-scale graph, tolerate noise, stable representation.
- Stochastic graphlet embedding: avoid graph matching, allows application of machine learning techniques, low to high order graphlets statistics.

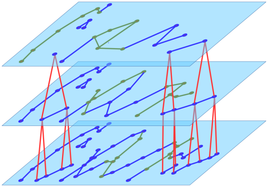




Pyramidal Graph Representation

Pyramidal Graph Representation

- Multi-scale graph, information at different resolutions.
- Higher leveled graphs contain abstract information.
- Graph pyramid construction techniques:
  1. Girvan-Newman
  2. grPartition



Girvan-Newman Algorithm

- Algorithm for graph clustering (Girvan and Newman NAS 2002).
- Basic principle:
  1. Compute edge centrality.
  2. Remove edge with highest score.
  3. Recompute all scores.
  4. Repeat 2^{nd} step.
- Results in a dendogram where each node is an independent cluster.
- Algorithm stops when the given number of clusters is reached.

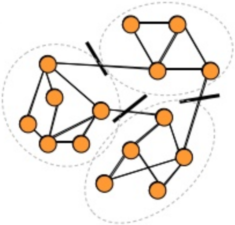
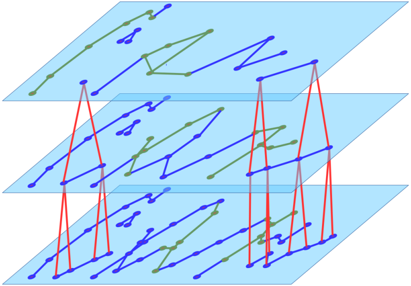


Figure credit: S. Papadopoulos, CERTH-ITI, 2011.

Pyramid Generation

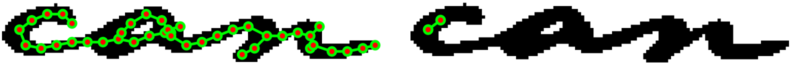
- Pyramid construction: at a higher level each cluster is represented as a node.
- Hierarchical edges: clustered nodes to their representative in the higher level.



Stochastic Graphlet Embedding

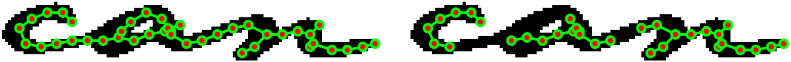
Stochastic Graphlets Sampling

- Graphlet sampling is a stochastic and recurrent procedure.
- It is controlled by two parameters M and T.
- Basic principles:
  1. Randomly select a node v from G.
  2. Add the node v to an empty graph $\mathcal{G}$.
  3. Recursively add T connected edges to $\mathcal{G}$.
  4. Restart 1$^{\text{st}}$ step M times.
- Animation: $M = 10$, $T = 6$.



Stochastic Graphlets Sampling

- A random walk process with a restart.
- Samples $M \times T$ connected graphlets, with edges varying from 1 to T.
- Hypothesis: empirical distribution of large amount of sampled graphlets will be same to actual distribution.

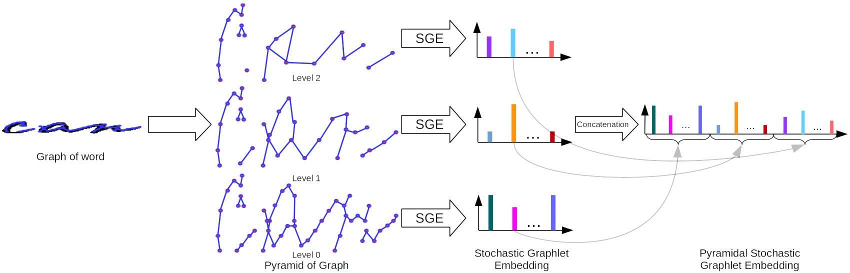


Hashed Graphlets Distribution

- Graph hash functions:
  1. Degree of nodes
  2. Betweenness centrality
  3. Core numbers
  4. Clustering coefficients
- Probability of collision (Dutta and Sahbi, ArXiv, 2017)
- Hash functions with low probability of collision: degree of nodes, betweenness centrality.
- Hash function $= \begin{cases} \text{degree of nodes,} & \text{if } t \leq 4 \\ \text{betweenness centrality,} & \text{otherwise} \end{cases}$

Pyramidal Stochastic Graphlet Embedding

Summary

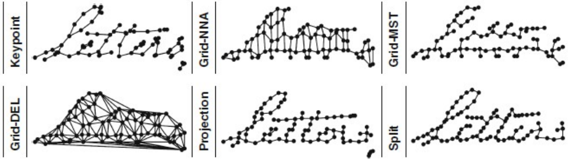


Experimental Validation

Datasets

HistoGraph

- Perfectly segmented word images from George Washington (GW) dataset.
- 30 different words and six different representations:



- Three independent subsets: training (90 words), validation (60 words) and test (143 words).
- Frequency: train and validation set (2 to 3), test set (3 to 5).

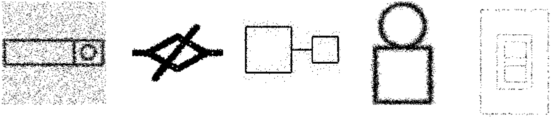
Figure credit: Stauffer *et al.* S+SSPR 2016

Results
HistoGraph

Subset	Acc. GED	Acc. SGE	Acc. PSGE	
			Level 2	Level 3
Keypoint	77.62	78.32	**80.42 (+2.10)**	78.32 (+0.00)
Grid-NNA	65.03	72.73	72.73 (+0.00)	**74.13 (+1.40)**
Grid-MST	74.13	**76.92**	75.52 (-1.40)	74.83 (-2.09)
Grid-DEL	62.94	74.83	**79.02 (+4.19)**	**79.02 (+4.19)**
Projection	**81.82**	79.02	79.72 (+0.70)	80.42 (+1.40)
Split	80.42	77.62	**80.42 (+2.80)**	77.62 (+0.00)

Datasets
GREC

- Graphs representing symbols from architectural and electronic drawings.
- 22 different classes and five different distortion levels:



- Preprocessing applied for cleaning the images and converting them to graphs.
- Three independent subsets: training and validation (286 symbols), test (528 symbols).
- Frequency: train and validation set (13), test set (24).

Figure credit: Riesen and Bunke SSPR 2008

Results

GREC

Method	Unlabelled	Labelled	
Dissimilarity Embedding (Bunke and Riesen PR 2010)	-	95.10	
Node Attribute Statistics (Gibert *et al.* PR 2012)	-	99.20	
Fuzzy Graph Embedding (Luqman *et al.* PR 2013)	-	97.30	
SGE (Dutta and Sahbi ArXiv 2017)	92.80	99.62	
		Level 2	Level 3
PSGE	93.18 (+0.38)	99.62 (+0.00)	**99.81 (+0.19)**

Conclusions and Future Work

Conclusions and Future Work

- Proposal of pyramidal stochastic graphlet embedding.
- Pyramidal representation of graph tolerates noise and distortion.
- SGE samples low to high order graphlets providing robust structural statistics.
- Consideration of hierarchical edges as a future line of work.

Thanks for your attention!

Questions?

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