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Local Context Selection for Outlier Ranking in Graphs with Multiple Numeric Node Attributes

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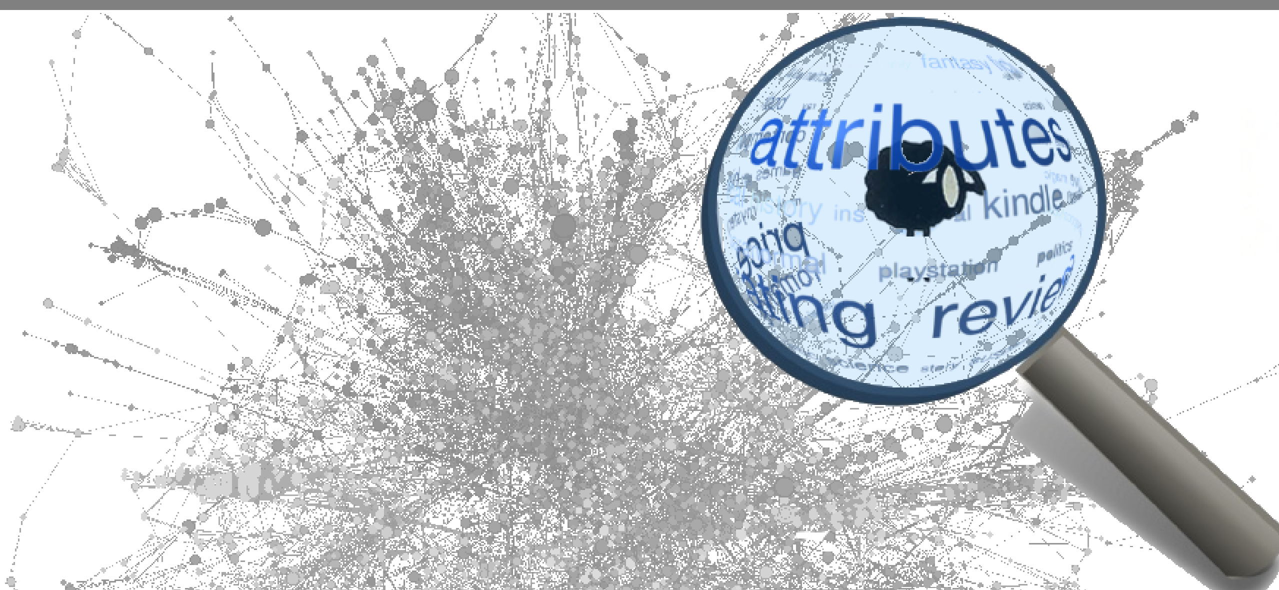
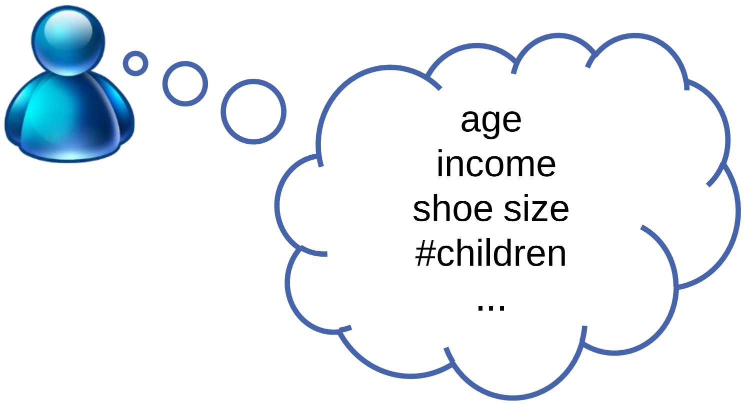
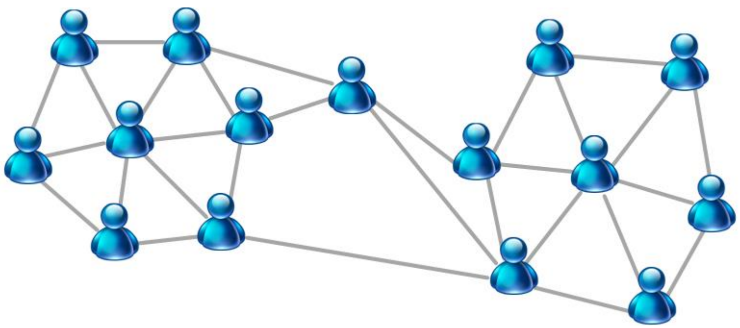


Attributed Graphs

- Complex databases: Attributed graphs



attributes



graph structure

- Several application domains:
  - Communication networks, co-purchased networks, social networks
  - Bibliographic networks, biological networks
- Outlier mining:
  - Fraud detection, network intrusion, data cleaning...

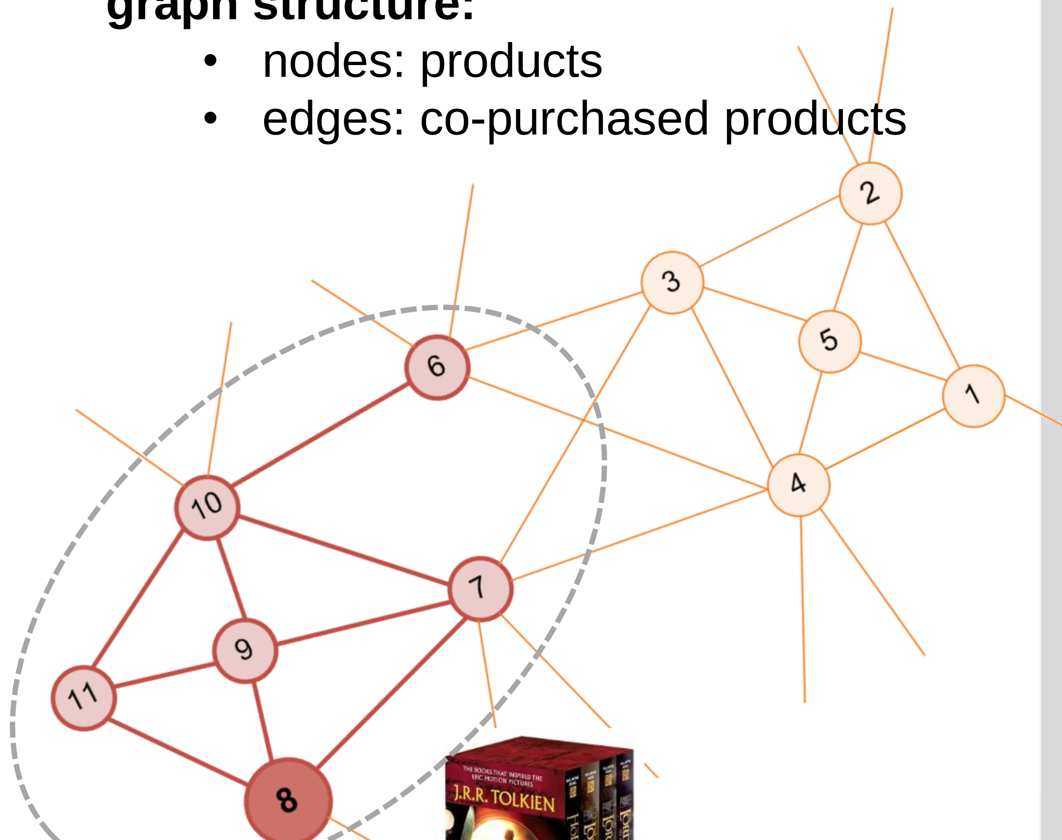
Problem Overview: Example

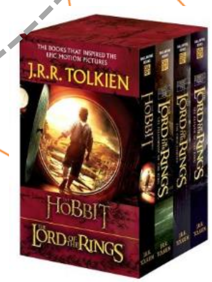
attributes: product description

Node	sales	#reviews	price
1	262	76	25
2	25	30	30
3	155	47	150
4	69	105	20
5	80	8	35
6	182	7	15
7	22	5	8
8	234	**28**	12
9	102	8	5
10	248	6	13
11	10	4	10
…	…	…	…

graph structure:

- nodes: products
- edges: co-purchased products



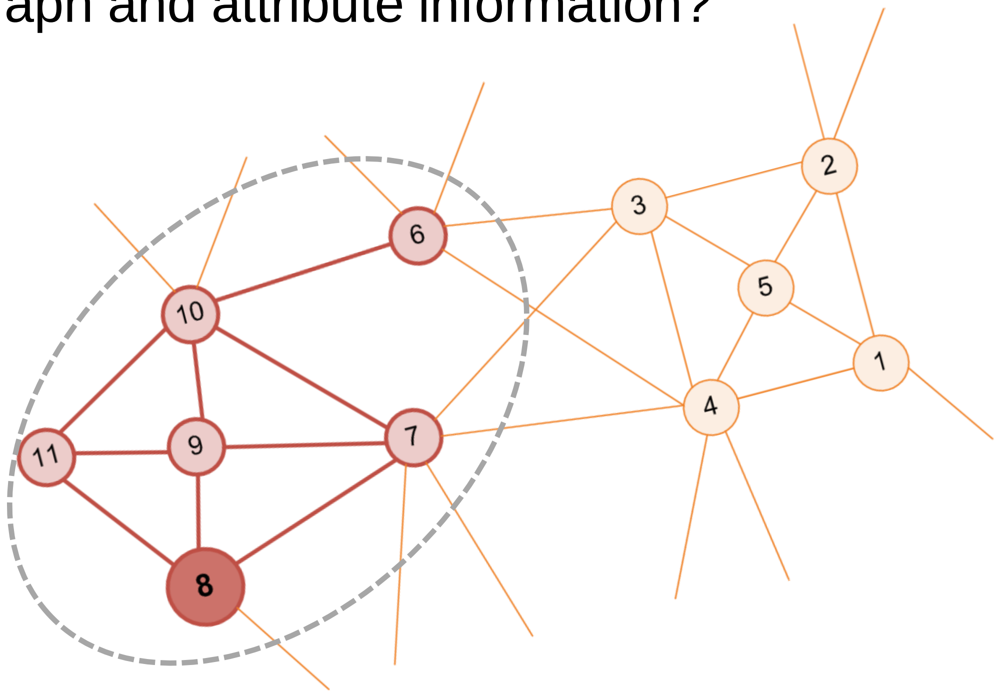


Tolkien Books

Challenges

- How to **define a local context** for each node?
- How to **efficiently** select only the **relevant attributes**?
- How to **rank** each node w.r.t. graph and attribute information?

Node	#reviews	price
6	7	15
7	5	8
8	**28**	12
9	8	5
10	6	13
11	4	10



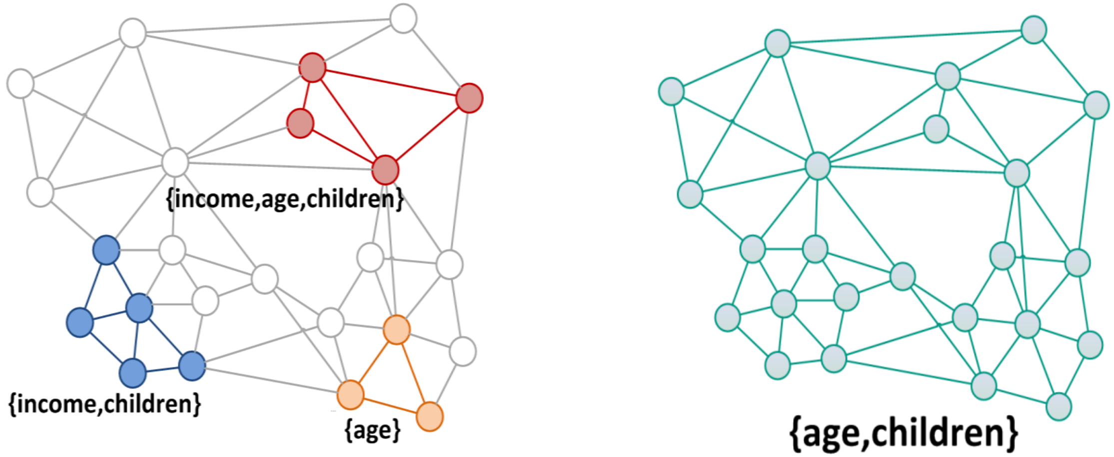
Comparison: Outlier Mining on Attributed Graphs

Algorithm	Local	Selection of attributes	Ranking	Time Complexity (#attributes)
CODA [Gao 2010]	✗	✗	✗	$O(d^2)$
CONSUB [Iglesias 2013]	✗	✓	✓	$O(2^d)$
GoutRank [Müller 2013]	✗	✓	✓	$O(2^d)$
ConOut	✓	✓	✓	$O(d)$

[Gao 2010] Gao et al. “On community outliers and their efficient detection in information networks" In ACM SIGKDD 2010
[Iglesias 2003] Iglesias et al. Statistical Selection of Congruent Subspaces for Mining Attributed Graphs. In IEEE ICDM. 2013
[Müller 2013] Müller et al. “Ranking outlier nodes in subspaces of attributed graphs” In GDM at IEEE ICDE 2013

Our Approach: ConOut

- Local vs. global



- Attribute projection vs. subspace selection
  - Avoid exponential runtimes w.r.t. the number of the attributes
  - Time complexity: Linear

- Ranking vs. Binary
  - Assessment of the outlierness w.r.t. both: graph and attributes

ConOut I: Context Definition

- **Local Context** of object o**:**
  - **C(o), R(o)**

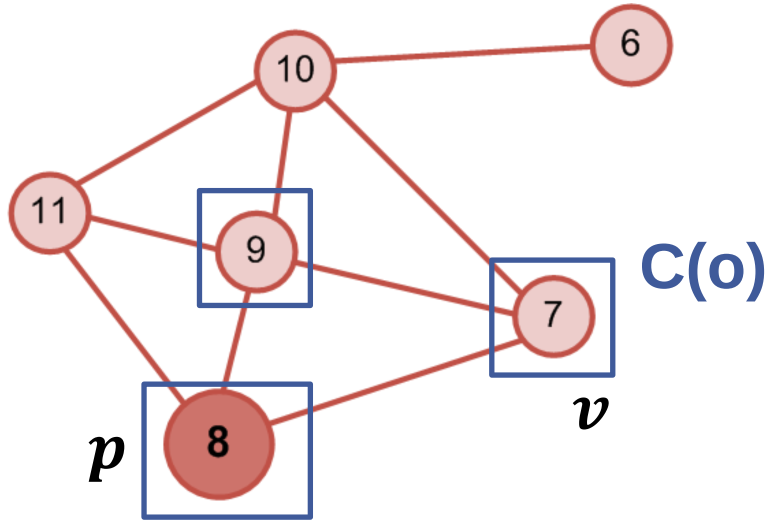
- **Graph Context** C(o)
  - Nodes similar w.r.t. graph structure
  - Graph similarity based on shared nearest neighborhood (SNN):

$$sim(v,p) = \frac{|Adj(v)| \cap |Adj(p)|}{\sqrt{|Adj(v)| \cdot |Adj(p)|}}$$

$$Adj(v) = \{p \in E \mid \exists (v,p) \in E\} \cup \{v\}$$

  - Other local graph context definitions possible

- **Relevant Attributes** R(o)?



Node	#reviews	price
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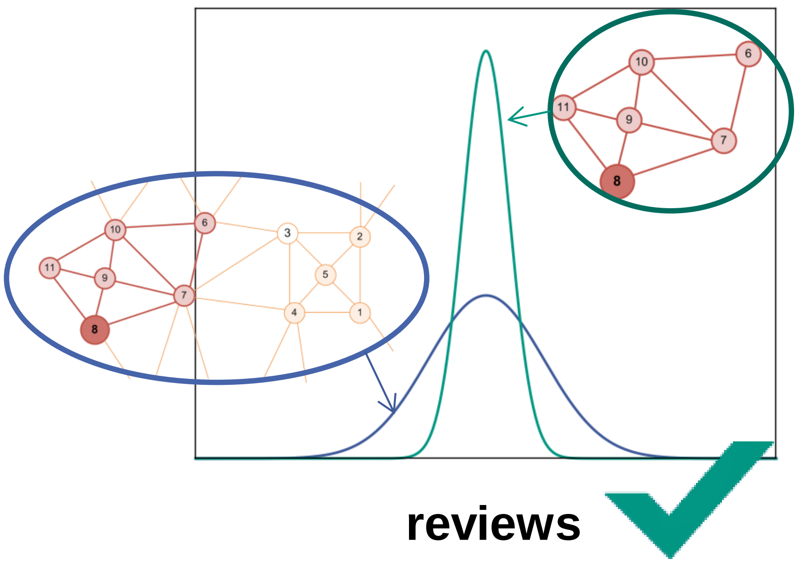
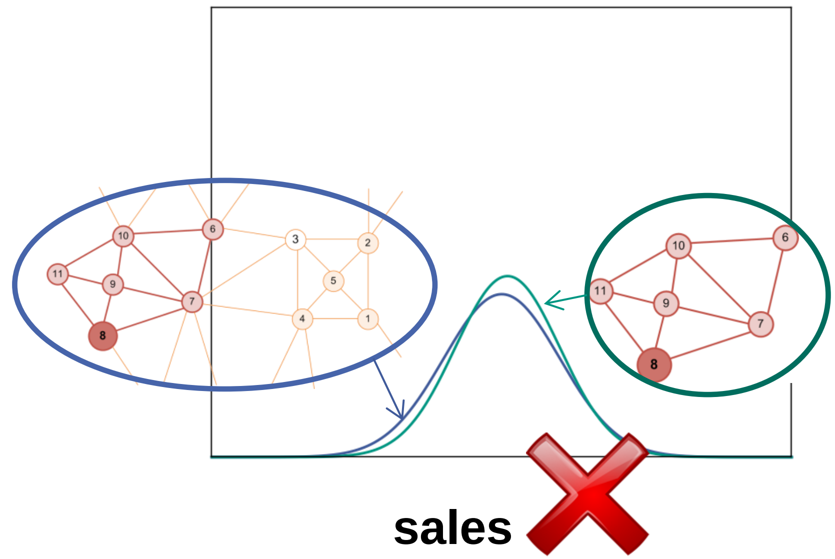
R(o)

ConOut II: Statistical Selection

- Attribute A_i has significantly lower variance in C(o) than the overall database





- Statistical test: Example of instantiation

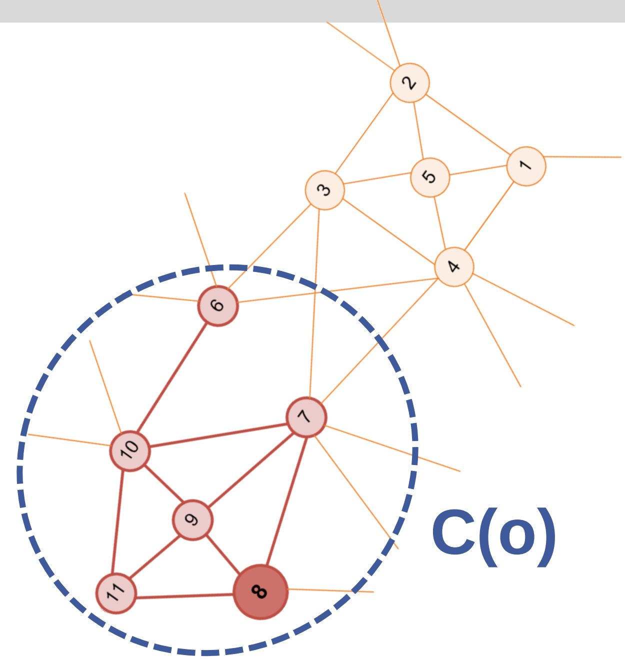
$$H_0 : \sigma^2_{local} = \sigma^2_{global}$$
$$\boldsymbol{H_1 : \sigma^2_{local} < \sigma^2_{global}}$$
$$P(H_o \, is \, rejected | H_o = true) \leq \alpha$$

ConOut III: Context Based Ranking

- Local context selection enables a **high contrast** between inliers and outliers

- **Goal:** Compare deviation of the attribute values and the graph density of each node to its local context
  - Local attribute deviation (LAD(o))
  - Local graph density (LGD(o))

- Context based score combines both:
  - $score(o) = LGD(o) \cdot LAD(o)$



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R(o)

Experimental Setup

- Synthetic data
- Real world data

Traditional Algorithms:

- LOF [Breunig 2001]: attributes
- SOF [Aggarwal 2001]: attributes
- SCAN [Xiu 2007]: graph

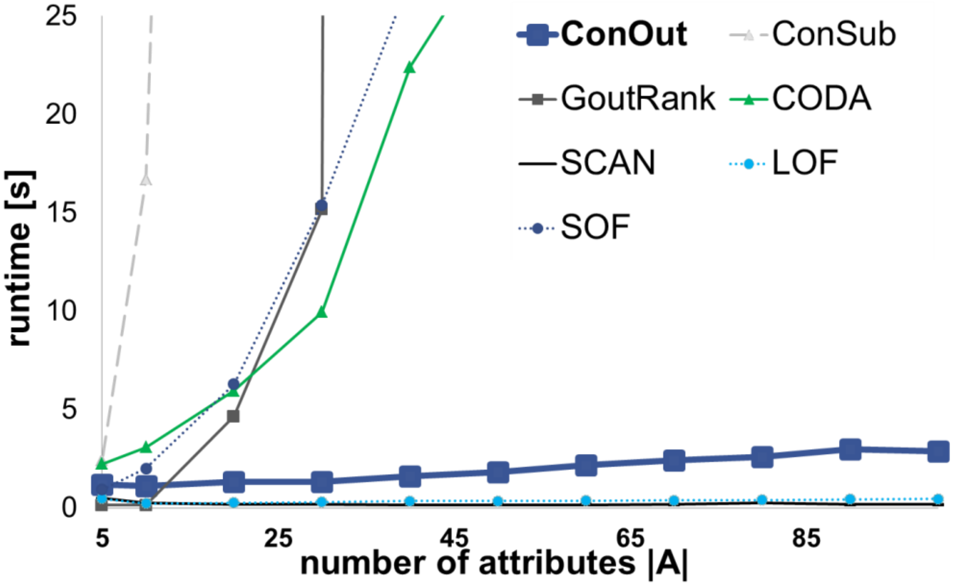
Algorithms for attributed graphs:

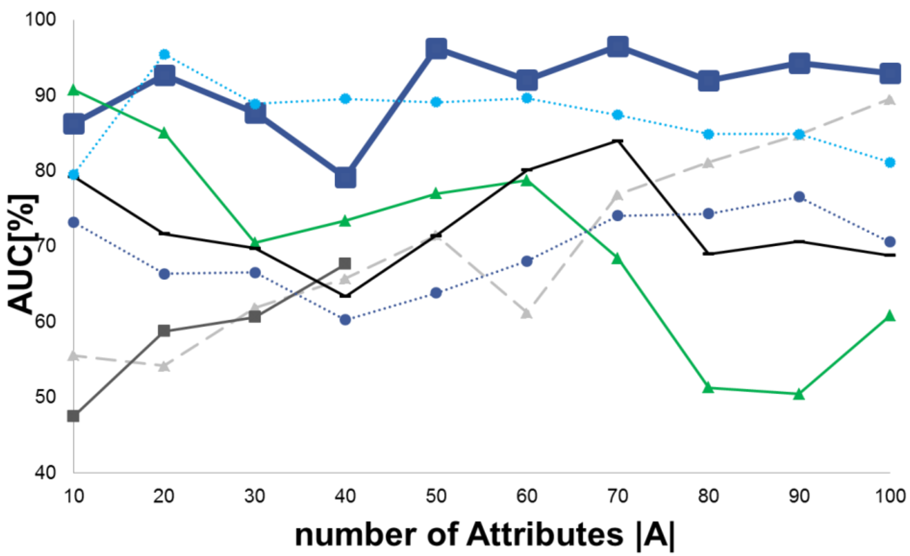
- CODA [Gao 2010]
- GOutRank [Müller 2013]
- ConSub [Iglesias 2013]

☑ **quality (AUC)** ☑ **runtime**

[Breunig 2001] Breunig et al. "LOF: identifying density-based local outliers." In *ACM SIGMOD* 2000
[Aggarwal 2001] Aggarwal et al. "Outlier detection for high dimensional data." In *ACM SIGMOD* 2001
[Xiu 2007] Xiu et al. "Scan: a structural clustering algorithm for networks." In ACM SIGKDD 2007

Synthetic Data





- Scalability w.r.t. increasing **number of attributes** and **graph size**
- **High quality** for the detection of contextual outliers

Real World Data

- Benchmark [Müller 2013]
  - 124 nodes, 333 edges and 28 attributes

		Algorithm	AUC [%]	run.[ms]
Attributes				
	full space	LOF	56.85	41
	subspace selection	SOF	65.88	825
Graph				
	graph clustering	SCAN	52.68	4
Both				
	full space	CODA	50.56	2596
	subspace cluster analysis	GOutRank	86.86	26648
	global subspace selection	ConSub	81.77	8930
	Local context selection	ConOut	81.21	199

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	global subspace selection	**ConSub**	**81.77**	8930
	Local context selection	**ConOut**	**81.21**	199

Real World Data

- Benchmark on a co-purchased network [Müller 2013]
  - 124 nodes, 333 edges and 28 attributes

		Algorithm	AUC [%]	run.[ms]
Attributes				
	full space	LOF	56.85	41
	subspace selection	SOF	65.88	825
Graph				
	graph clustering	SCAN	52.68	4
Both				
	full space	CODA	50.56	2596
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Conclusions & Future Work

- Challenge: attributed graphs ✓ **Local context definition**
- Irrelevant Attributes ✓ **Statistical selection**
- Outlierness Scoring ✓ **Combined ranking functions**
- Algorithm ✓ **Efficiency**

Future Work

- Mixed attribute types
- Local correlations between attributes
- Other graph definitions (directed, weighted, …)

Thank you for your attention

Our datasets and parameter settings are available online:

http://www.ipd.kit.edu/~muellere/conout/