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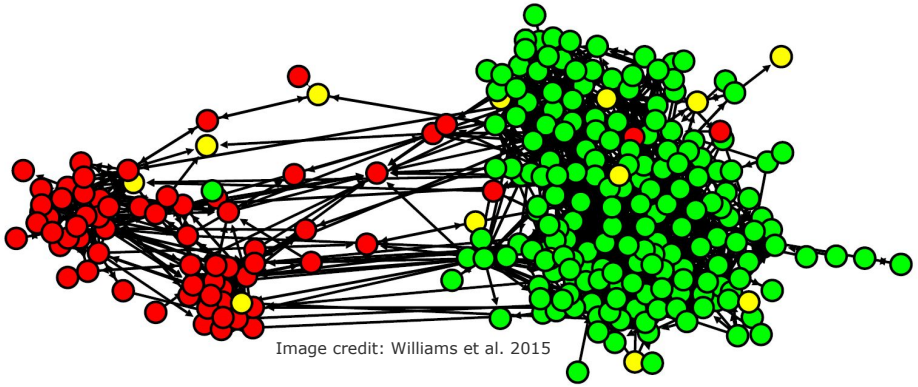

Image credit: Williams et al. 2015

Detecting Change Processes in Dynamic Networks by Frequent Graph Evolution Rule Mining

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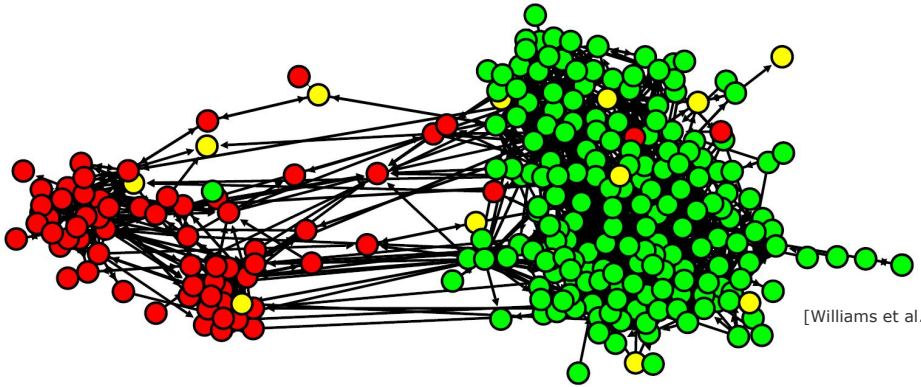
Motivation



[Williams et al. 2015]

question: which microscopic processes drive network evolution?

- understand and model social/biological/... mechanisms
- discriminate between networks by evolution

Change processes: Triadic closure

Markovian

microscopic

localized

(almost) arbitrary dynamics

Change processes: Homophilic rewiring

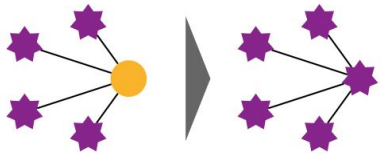
Markovian

microscopic

localized

(almost) arbitrary dynamics

Change processes: Opinion adoption



Markovian

microscopic

localized

(almost) arbitrary dynamics

Frequent graph evolution rule mining

dynamic network $(G_1, G_2, \ldots, G_T)$

graph evolution rule $G \blacktriangleright G'$ G evolves into G′

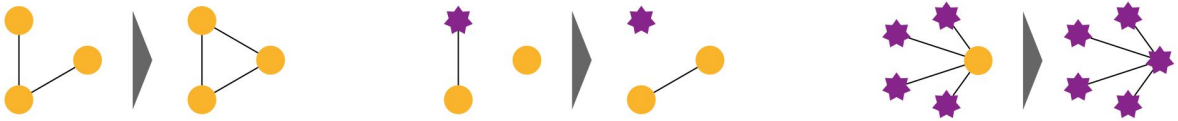
left hand side

right hand side

frequent graph evolution rule mining

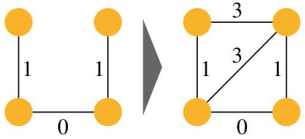
find all rules that appear a minimum number of times during network evolution

Related work



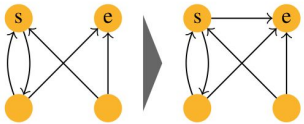
EvoMine
[this work]

GERM
[Berlingerio et al. 2009]



non-Markovian

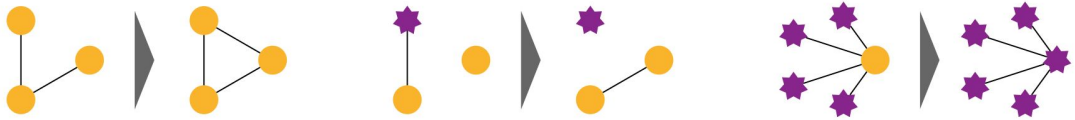
LFR-Miner
[Leung et al. 2010]



single link formation

Contribution: EvoMine

1. novel kind of rules



2. two new support measures

   embedding-based and *event-based*

3. comparative empirical evaluation on real data

How to count rule occurrences?

strategy

reduce the rule mining problem to frequent subgraph mining

observation

support measure is critical part

rule support measure

subgraph support measure

$$\sigma(r \mid DN) := \sigma'(S(r) \mid S'(DN))$$

single graph

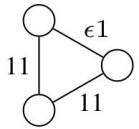
single graph - *or* - database of graphs

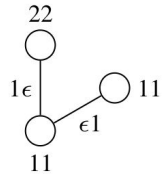
Rule representation

$\sigma(r \mid DN) := \sigma'(S(r) \mid S'(DN))$

rule

union graph

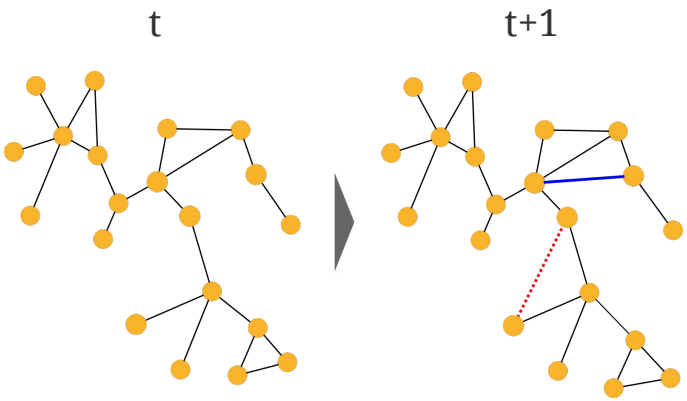




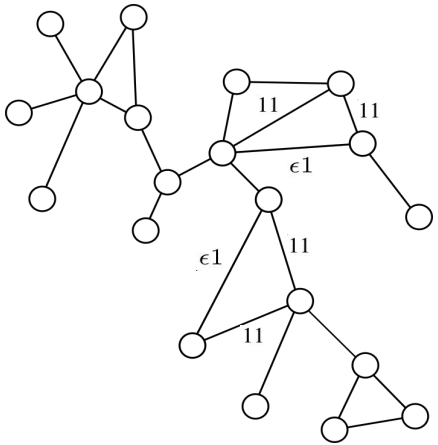
Network representation

$\sigma(r \mid DN) := \sigma'(S(r) \mid S'(DN))$

snapshots from network

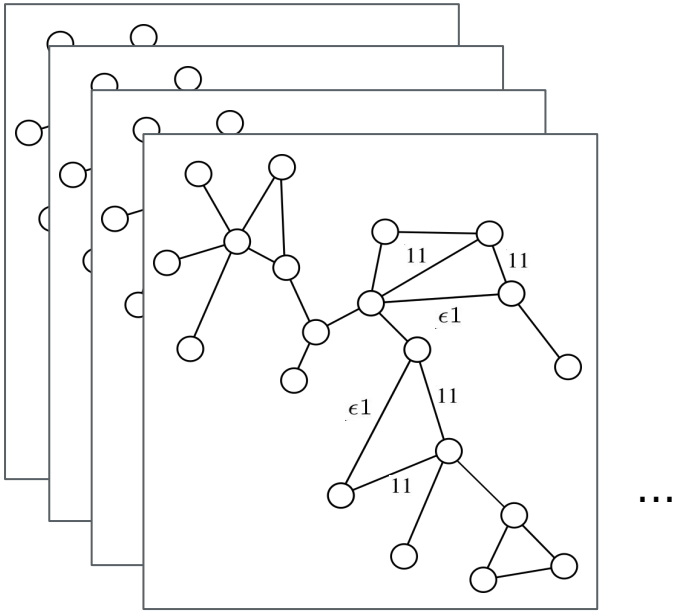


union graph



Network representation

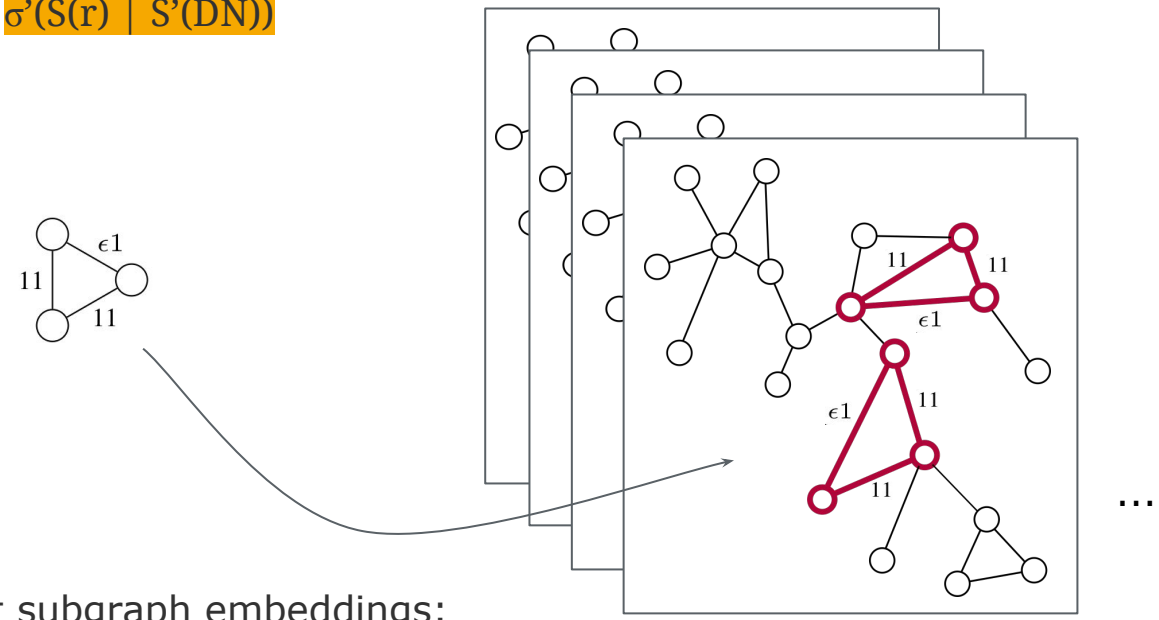
$\sigma(r \mid DN) := \sigma'(S(r) \mid S'(DN))$



...

Embedding-based support

$\sigma(r \mid DN) := \sigma'(S(r) \mid S'(DN))$



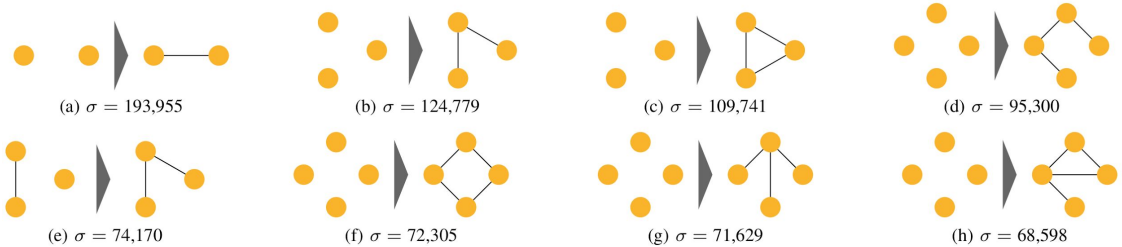
count subgraph embeddings:

minimum image based support

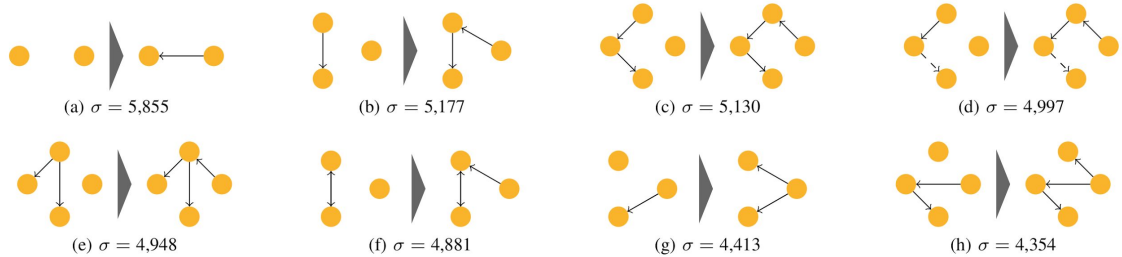
[Bringmann et al. 2008]

Results on real data sets

DBLP 92-02 co-authorship network



Epinions trust network



minSup = 5000 (100), max edges = 5 (3)
σ_{emb} with a simple compression for memory efficiency

Summary and outlook

paper

- graph evolution rules by frequent subgraph mining
- empirical comparison with GERM/LFR-Miner
- results on DBLP co-authorship and Epinions trust network

future work

- comparison of rules across datasets
- rule significance
- rule confidence for predictions

https://hpi.de/mueller/evomine