Persistent Roles in Online Social Networks

ECML-PKDD 2016, M. Revelle, C. Domeniconi, and A. Johri

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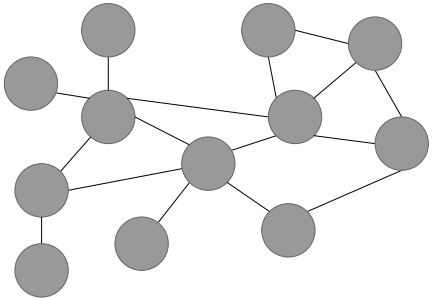
Introduction

Social Network Analysis

The study of relationship between actors.



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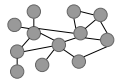

Persistent roles should occur in any social network
Based on the structure of the network

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Applications

graph mining
Targeted advertisement

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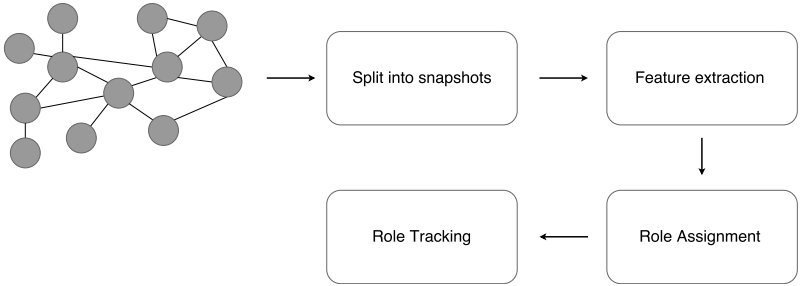
Methodology

The Approach



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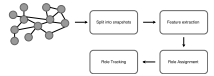


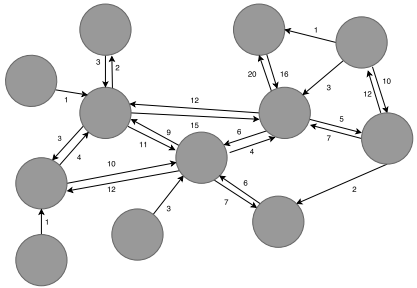
Feature-based approach

The Data

Datasets:

- Facebook - Wall posts from one user to another
- Scratch - Comments on uploaded programming projects

Directed, timestamps.



The Data

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- Facebook - Wall posts from one user to another
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Directed, timestamps.

Snapshot Split-up

The dataset is split into a total of 26 snapshots:

- 7 from facebook
- 19 from Scratch

Non-overlapping
Same length = observation window Ω.
Something with node interaction being smaller than Omega. (90th percentile?)

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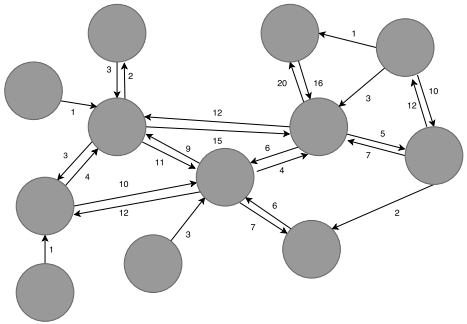
Feature Selection

12 features based upon the graph.



In-degree
Out-degree
Weighted in-degree
Weighted out-degree
Reciprocity
New activity
Social strategy
Betweenness centrality
PageRank
Weighted PageRank
Transitivity
Weighted transitivity

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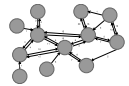

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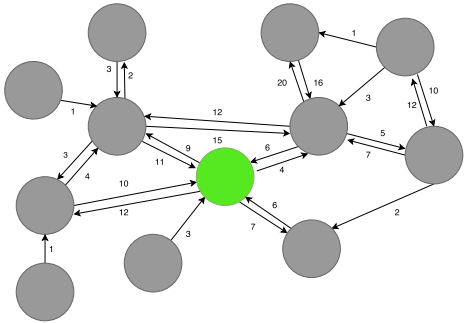
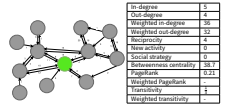
Feature Example



In-degree	5
Out-degree	4
Weighted in-degree	36
Weighted out-degree	32
Reciprocity	4
New activity	0
Social strategy	0
Betweenness centrality	38.7
PageRank	0.21
Weighted PageRank	-
Transitivity	$\frac{1}{3}$
Weighted transitivity	-

Feature Example

In-degree 5
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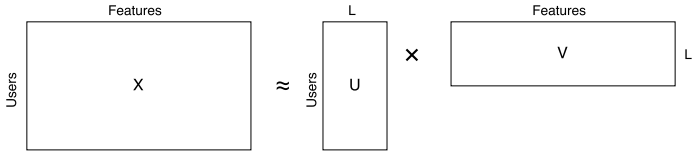
Weighted in-degree 36
Weighted out-degree 32
Reciprocity 4
New activity 0
Social strategy 0
Betweenness centrality 38.7
PageRank 0.21
Weighted PageRank -
Transitivity $\frac{1}{3}$
Weighted transitivity -

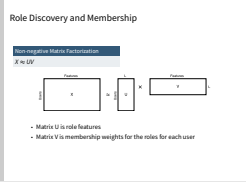
Role Discovery and Membership

Non-negative Matrix Factorization

$X \approx UV$



- Matrix U is role features
- Matrix V is membership weights for the roles for each user



- Frobenius NMF updated with euclidean distance
- U and V are initialized with left and right matrix from nndsvd (Modified svd)

Selection of L

Root Mean Squired Error

$$RMSE = \sqrt{\frac{1}{|X|} \sum_{(u,f) \in X} (X_{u,f} - X'_{u,f})}$$

Figure: Facebook

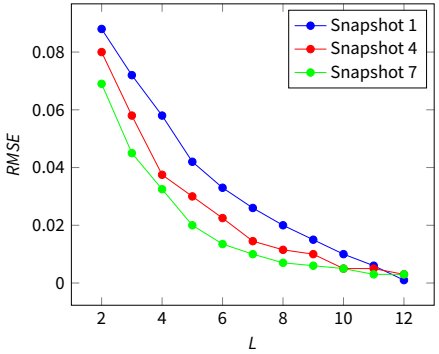
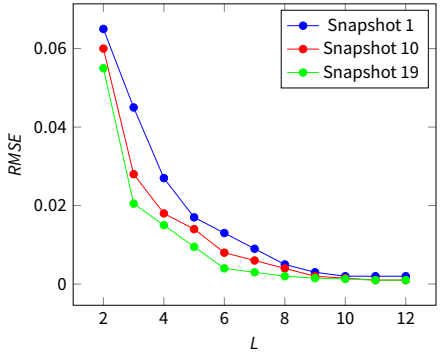
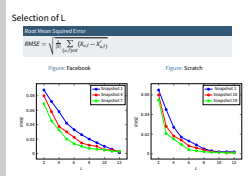


Figure: Scratch





Tracing Roles

The sim between snapshots.

Tracing Roles
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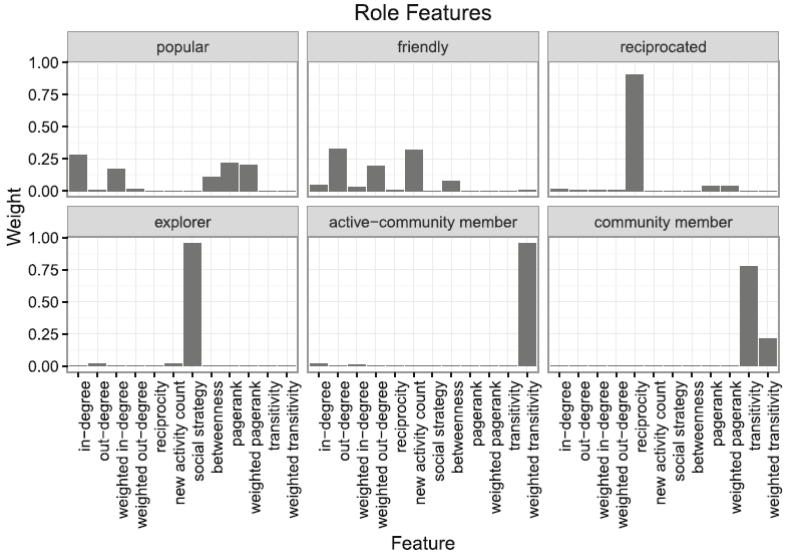
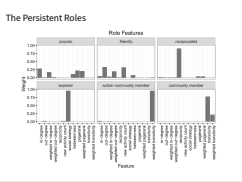
Results

Data Processing

The Roles

The Persistent Roles





Evidence of Roles

Affinity Analysis?

Affinity Analysis?

Role Transition

Conclusion

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Future Work?

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Shortcomings

They does not argue for their selection of features or give a reference to an article that does.
Number of snapshots.

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