A METHOD FOR CHARACTERIZING COMMUNITIES IN DYNAMIC ATTRIBUTED COMPLEX NETWORKS

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Plan

1. Introduction

- 1. Community Detection
- 2. Community Characterization (Novel Problem)

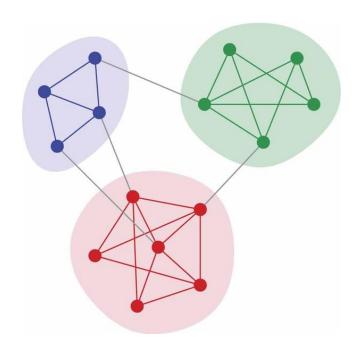
2. Problem Definition

- Sequence Mining
- Representing Dynamic Attributed Networks

Method

- 1. Community Detection
- Node Identification
- 3. Mining Closed Frequent Emerging Sequences
- 4. Selecting Characterizing Patterns and Finding Outliers
- 4. Empirical Results
- 5. Conclusion

1.1. Community Detection



A very active sector concentrated on detection task

What about community interpretation?

1.2. Community Characterization Novel Problem

- Community = group of nodes with common properties
 - Node description
 - Topology (via network)
 - Relational Information
 - Attributes
 - Individual Information
- Community = group of nodes with common behaviors
 - Temporal evolution of the descriptions

Interpreting communities in a systematic way by considering common changes on the node descriptions over the time

2. Problem Definition

 Identifying the discriminant features of the nodes of each community

1. What are the features?

 Encoding all the information describing the evolution of each node from each community in a complete and compact way

2. How to measure their typicality?

- Choosing objective criteria to measure the power of representation of each sequence
 - Informative
 - Prevalent
 - Distinctive

2.1. Sequence Mining

- Finding correlated elements in an ordered set of elements
- Given a set of sequences, finding the complete set of frequent sub-sequences

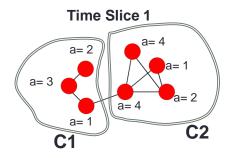
A sequence database

SID	Sequences
10	<a(<u>abc)(a<u>c</u>)d(cf)></a(<u>
20	<(ad)c(bc)(ae)>
30	<(ef)(<u>ab</u>)(df) <u>c</u> b>
40	<eg(af)cbc></eg(af)cbc>

- A sequence <(ef)(ab)(df)cb> is an ordered set of itemsets.
- $\alpha = \langle (ab)c \rangle$ is a *sub-sequence* of $\beta = \langle a(\underline{ab}c)(a\underline{c})d(cf) \rangle$

- Given support threshold min_{sup} = 2/4, <(ab)c> is a frequent sequence
- A sequence is *closed* if there is no other super-sequence of it with the same support

2.2. Representing Dynamic Attributed Networks

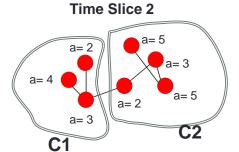


Items: Node descriptors with their values {a=1,a=2,a=3,a=4,a=5,a=6}

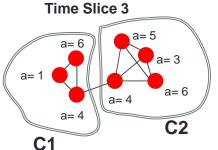
Node Sequence: *u(n1)=<(a=2)(a=2)(a=6)>*

Node Sequence concatenation:

$$u(n1) \bullet C(n1) = <(a=2)(a=2)(a=6)(C1)>$$

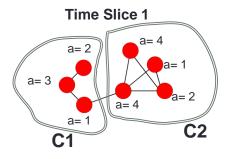


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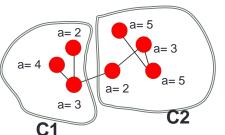


Node Sequence Database

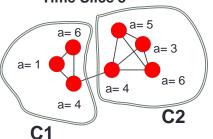
2.2. Representing Dynamic Attributed Networks



Time Slice 2



Time Slice 3



Choosing Criteria

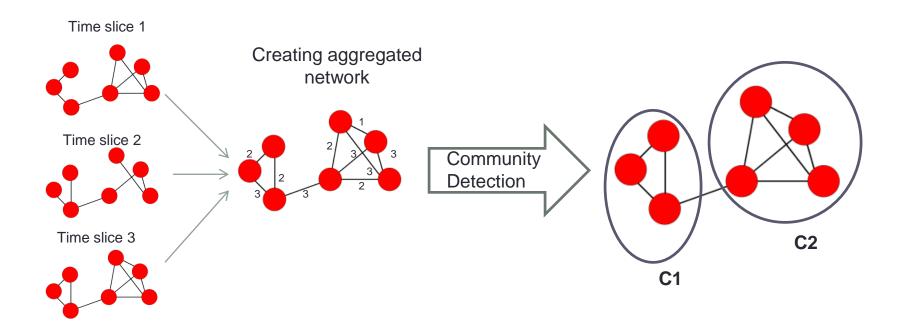
- Prevalent: Frequent sequences for min_{sup}
- Informative: Closed sequences
- What about distinctiveness?
 - Emerging Sequences
 - Growth rate of s relatively to a community C is
 - Gr(s,C) = sup(s,C)/(sup(s)-sup(s,C))
 - e.g., Gr(<(a=2)(a=2)>,C1)= ∞

3. Method

- Step1. Community Detection
- Step2. Mining Closed Frequent Emerging sequences
- Step3. Selecting characteristic patterns and finding outliers

3.1. Community Detection

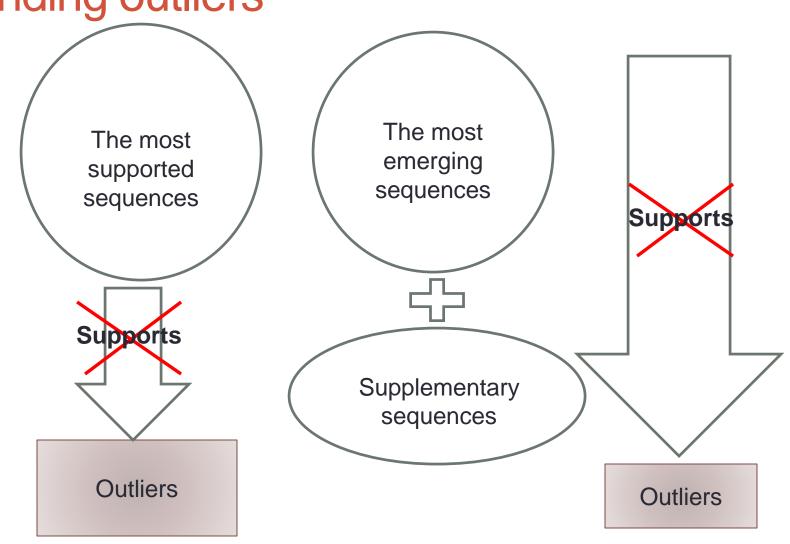
- Creating aggregated network
- Detecting communities by considering link weights
 - Louvain Method [Blondel et al. 2008, JSTAT Mech]



3.2. Mining Closed Frequent Emerging Sequences

- Creating sequence database
 - Attributes
 - 5 topological measures
 - internal degree, local transitivity, within module degree, participation coefficient and embeddedness
- Mining Closed Frequent Sequences
 - CloSpan [Yan et al. 2003,SDM] with min_{sup}
- Calculating emergence
 - PostProcessing [Plantevit and Cremilleux 2009, IDA]

3.3. Selecting characteristic patterns and finding outliers



4. Empirical Results

- DBLP Dynamic Attributed Network
 - Nodes=researchers
 - Links=co-authorship
 - 10 time slice from 1990 to 2012
 - Attributes :
 - Publication number in 43 journal/conferences
 - Total conference publication number
 - Total journal publication number
- Focus: Communities containing >40 nodes

4. Empirical Results

I- The most supported

 The majority of the nodes of each community has a nonhub community role

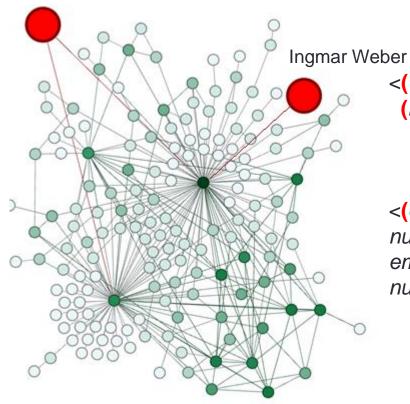
MOST SUPPORTED SEQUENCE SIZE FOR EACH COMMUNITY

Community	Community	Sequence	Support
ID	Size	Size	Support Value
38	335	2	0.99
40	43	8	0.97
77	41	7	1.00
115	125	1	1.00

Philip S. Yu, Jiawei Han, Beng C. Ooi Hans-Peter Kriegel

4. Empirical Results II- The most emerging

Anastasia Ailamaki



Representation of Community 45

<(VLDB publication number=3)
(having few connections and community non-hub)>
Gr. rate = 6.40 et sup=0.30

<(community non-hub and total conference publication number between 1 and 5) (community non-hub, embedded to its community and ICDE publication number =3)>

Gr. rate = 2.30 et sup=0.30

4. Empirical Results

- Both topology and attributes support the interpretation process
 - Main theme of communities
 - Relations of nodes
- Three types of outliers
 - Different theme
 - Changing theme
 - Rising actors

5. Conclusion & Perspectives

- Novel problem : community characterization
- Considering dynamic community detection
- Considering constraints on sequential patterns
 - Patterns including information both on topology and on attributes
- Application on different networks from different domains

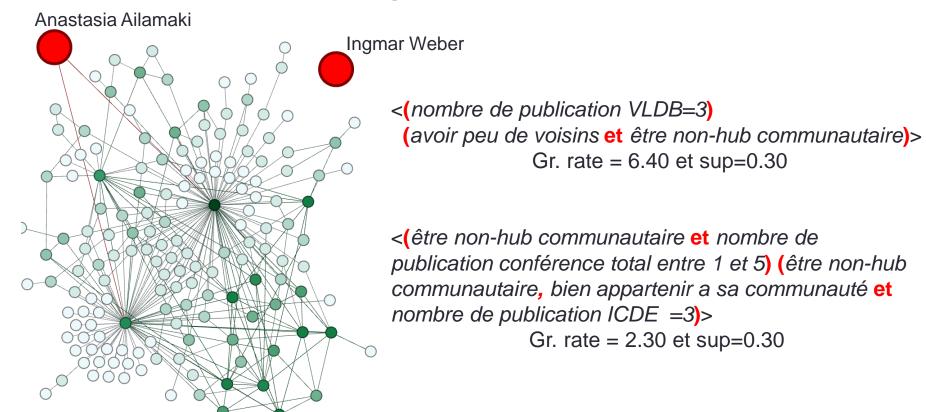
Questions

Discrétisation

Descripteurs	Ranges						
Dégrée	[0;3]]3;10]]10;30]]30; ∞[
	Non populaire	Peu populaire	Populaire	Très populaire			
Transitivité	[0;0.35]]0.35;0.5]]0.5;0.7]]0.7;1.0]			
Dégrée interne]-∞;2.5]]2.5, ∞[
normalisé	non-hub	Hub communautaire					
	communautaire						
Coefficient de	[0;0.05]]0.05;0.6]]0.6;0.8]]0.8;1.0]			
Participation	Ultra Périphaire	Périphaire	Connecteur	Kinless			
Enchaissement	[0;0.3]]0.3;0.7]]0.7;1.0]				
	Peu appartenance	Appartenance	Très haute				
			appartenance				
Conf./Journal Pub.	1	2	3	4	[5; ∞[
Total	[0;5[[5;10[[10;20[[20;50[[50; ∞[
Conf./Journal Pub.							
	Į						

3. Résultats

II- Les plus emergents



Représentation de la communauté 45 p.r.a graph global pondère