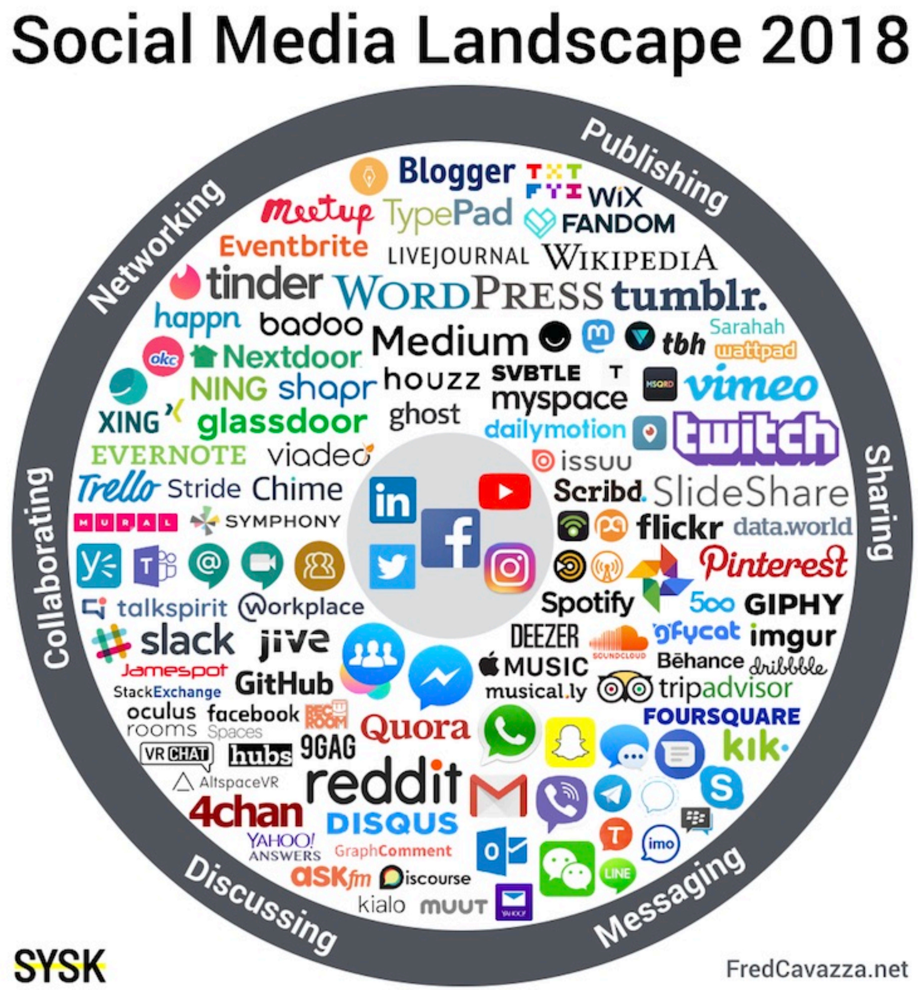
Exploring Human Interactions for Influence Modeling in Online Social Networks

Monika Rakoczy

Supervisors: Amel Bouzeghoub, Katarzyna Węgrzyn-Wolska, Alda Lopes Gancarski
Reviewers: Lynda Tamine Lechani, Przemysław Kazienko
Jury: Cedric Du Mouza, Bogdan Cautis, Salima Benbernou

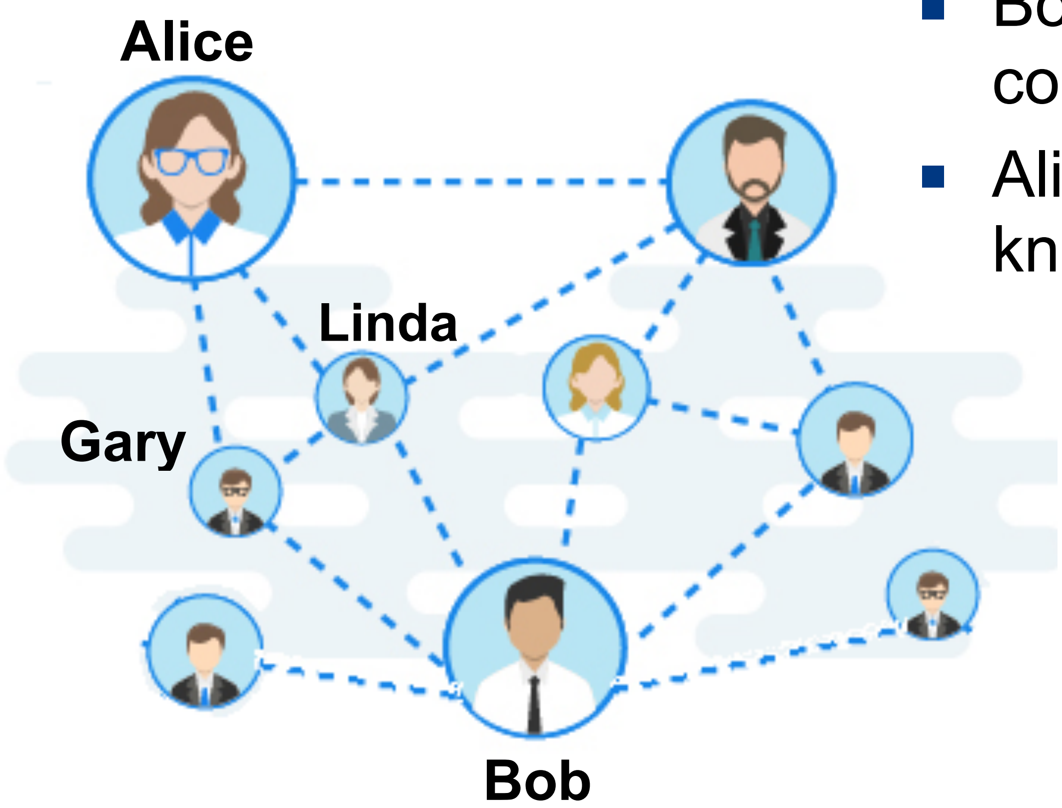
Context and Motivation

- Various usages
- Multiple topics:
  - applications (advertising, recommender systems)
  - social network analysis (data mining)
- Changes in how people interact with environment and each other
- Interactions have impact on Social Network (SN): members behavior, structure, transformation



TELECOM SudParis

Problematic

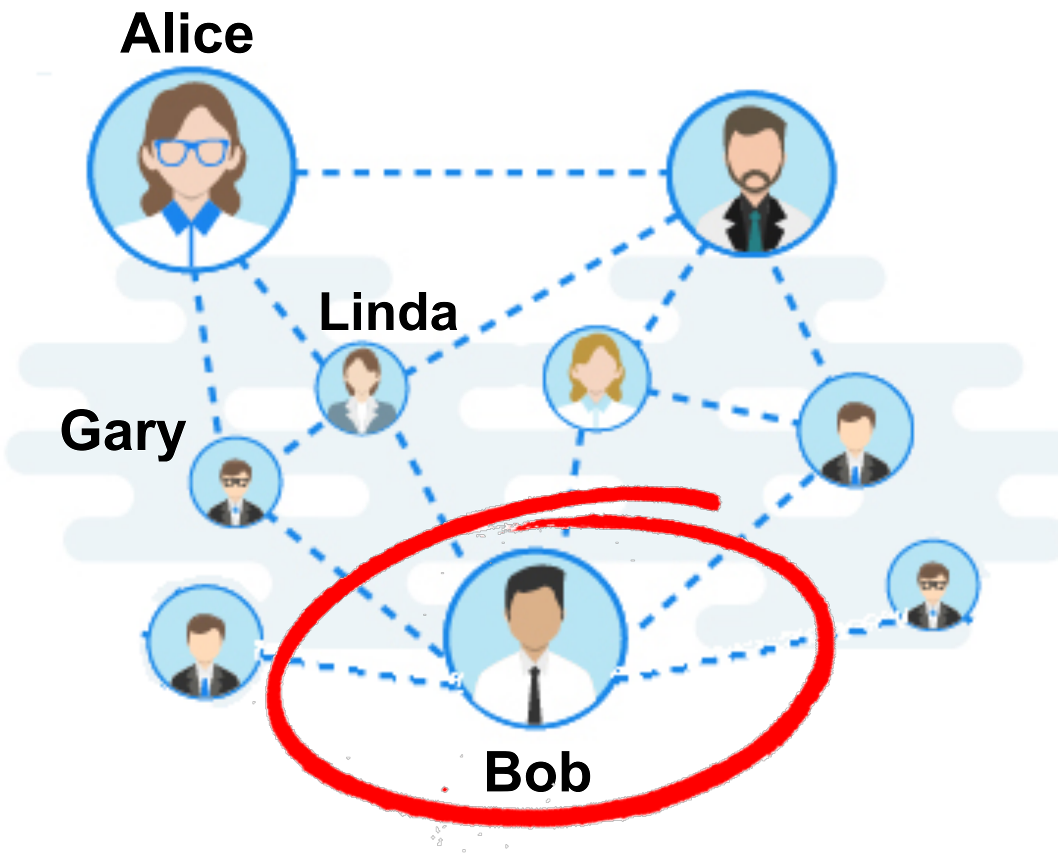


- Bob deals with computers
- Alice does not know Bob directly

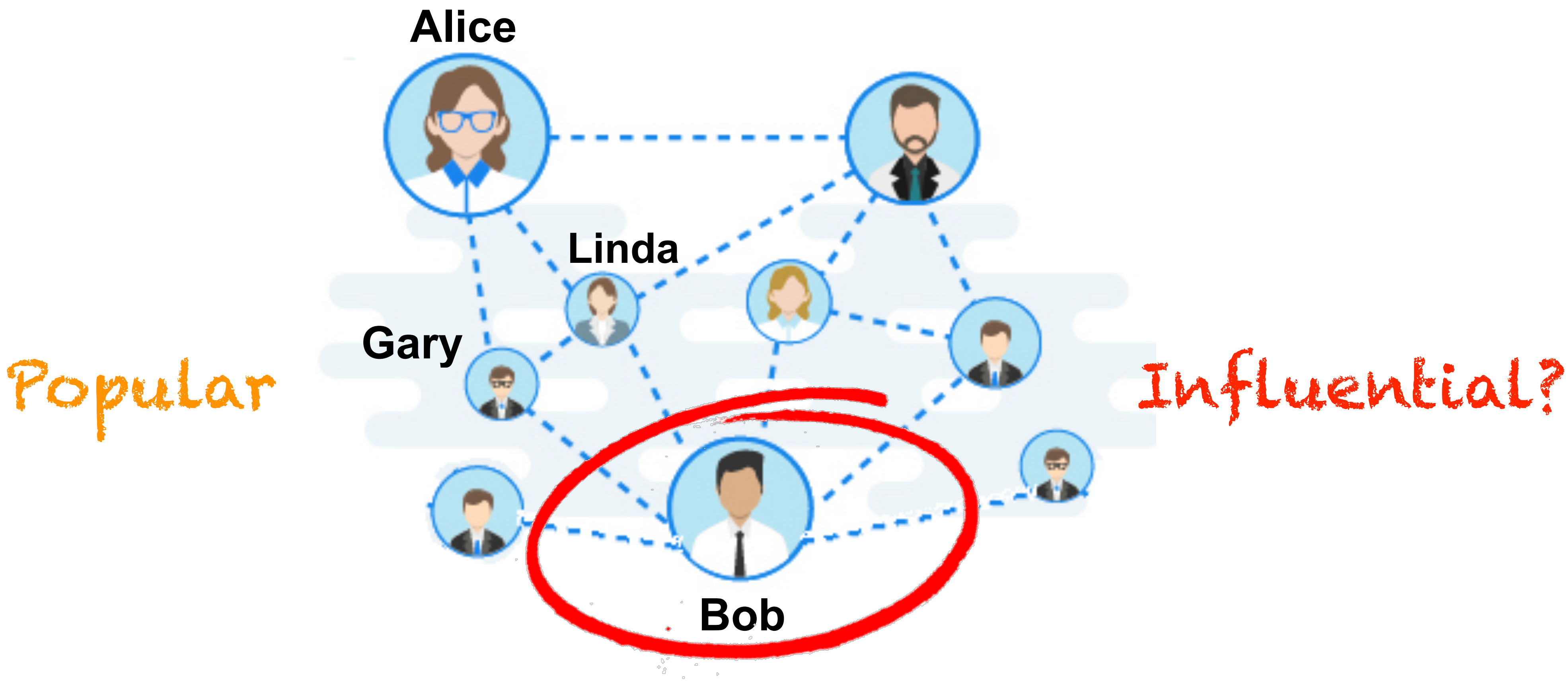
Alice wants information about a computer

Problematic

Popular

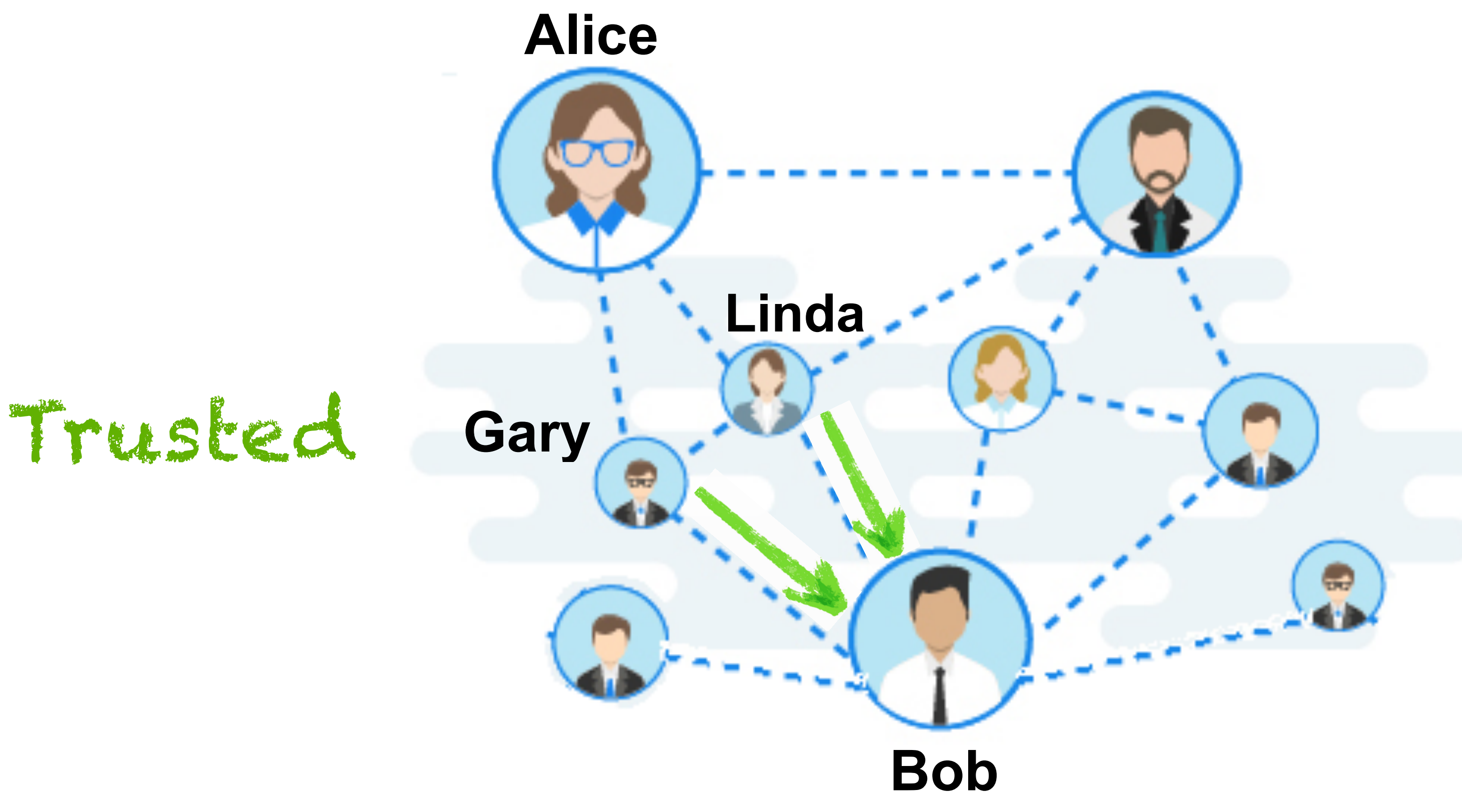


Problematic

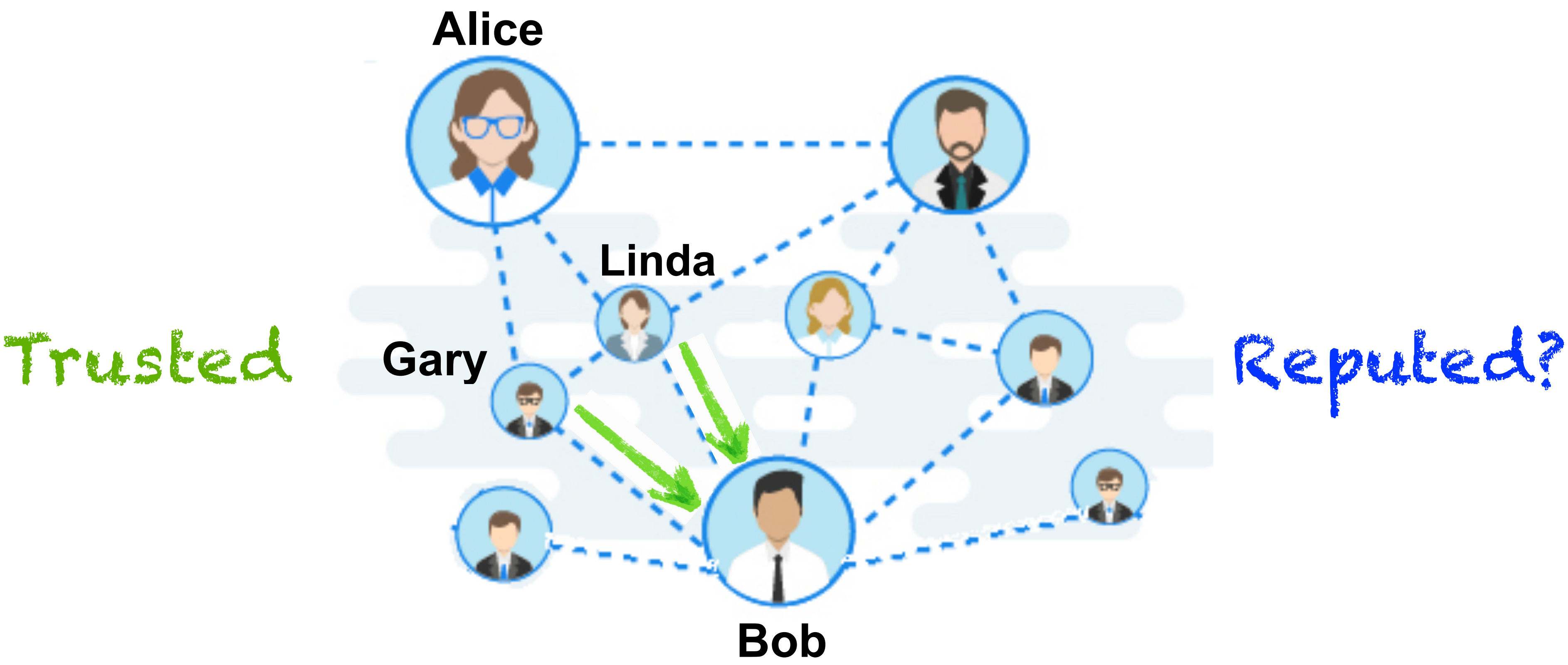


TELECOM SudParis

Problematic

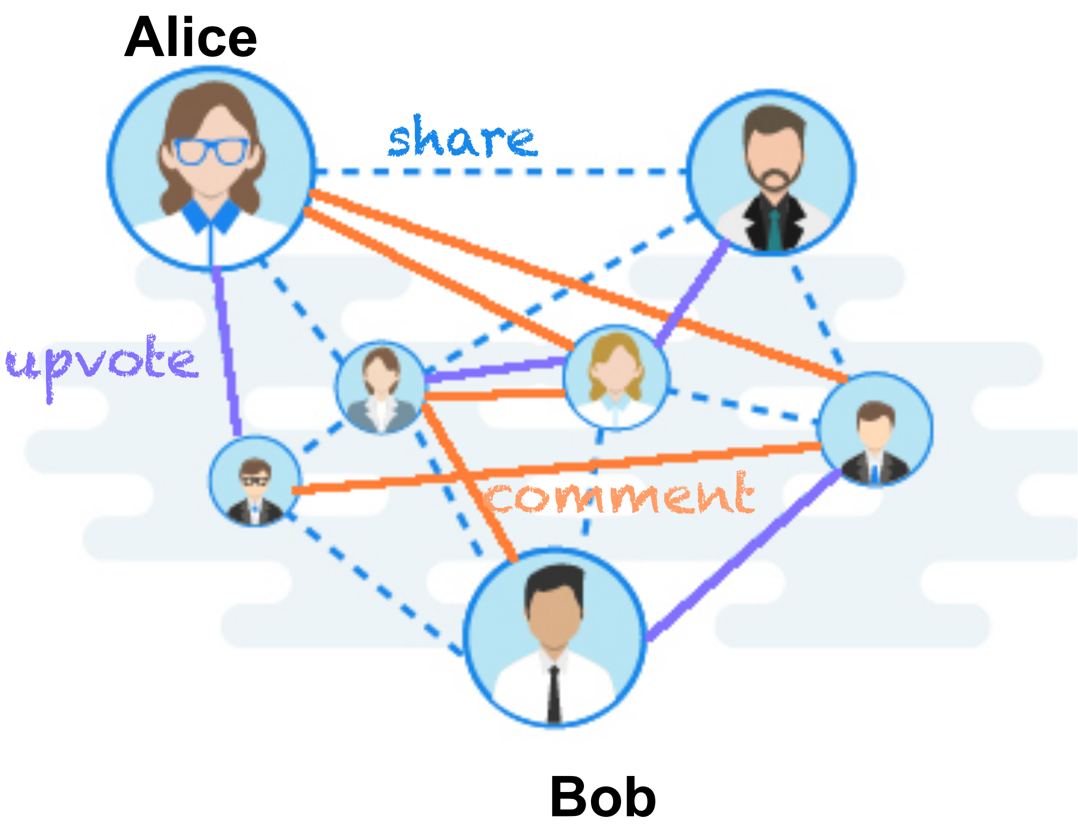


Problematic



TELECOM SudParis

Problematic



Who is the most influential?

- Different ways of interacting!
- What impact on the overall influence different interactions should have?
- What happens with influence when we consider time?

Agenda

1. Challenges
2. Related work
3. Contributions
    1. Modeling of Social Network Interactions
    2. Proposition of Theoretical Influence Model
    3. Action-Reaction Influence Model
    4. Micro-influence
    5. Time Dependent Influence Estimation (TiDIE)
    6. Inference of Reputation from Influence
4. Summary and Perspectives

Challenges

Challenges (1)

- The notions are elusive to quantify, unclear and imprecise in the literature, and are often confused with one another
  - **RQ 1:** How to **define**, **differentiate** and **specify properties** of each of the notions: **trust, popularity, influence, and reputation**?
  - **RQ 2:** Is there a **link** between those notions? If so, how to **model the linkage**, so we can use it for evaluation?

Challenges (2)

- Influence between different entities in SN is particularly used and useful
- But, as it is a compound notion, modelization and evaluation of influence still leaves open problems
  - **RQ3:** How to **modelize** influence capturing its **complexity**, while being **adaptive** to different social network types and consider **numerous methods of social interaction**?
  - **RQ4:** How to include **time** for influence evaluation? How to **quantify influence over time**? How can influence **causal effect** be represented?

TELECOM SudParis

Challenges (3)

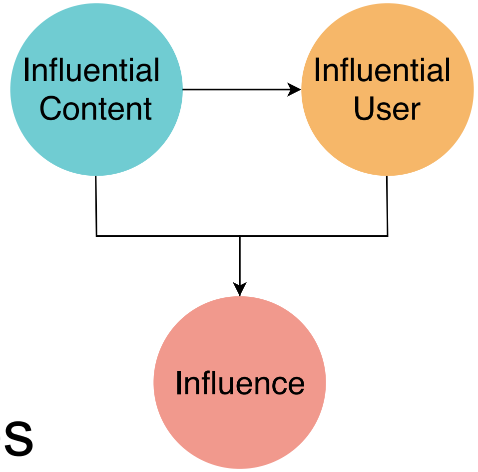
- Influence is broadly examined by searching for the most known and followed users, but we know that it exists as well for not widely-known entities
  - **RQ5:** How to find “promising” entities who could **still have influence but are invisible** (as they are less connected)?

Related Work

Influence

- Definition: *process of changing both feelings and behavior of a particular person, due to the interaction with others [resulting] from an adaptation of one's opinions, believes revision to change of the behavior* [Hwang, 2016]

- Influential content
  - Content Recognition
  - Activity Generation
  - Content Propagation



- Influential users
  - Connectivity
  - Immediacy

- Properties
  - Asymmetry [Page, 1999; Rao, 2015; Eirinaki, 2012]
  - Time-dependency [Yin, 2012; Chikhaoui, 2015]
  - Context-dependency [Bi, 2014; Cataldi, 2015]
  - Event Sensitivity [Xiao, 2014; Li, 2012]

Influence: literature comparison

Method	Connectivity	Immediacy (Intensity)	Content Recognition	Activity generation	Time dependency
Degree Centrality [Zafarani al, 2014]	✔	✘	✘	✘	✘
Closeness/Betweenness Centrality [Zafarani al, 2014]	✔	✔	✘	✘	✘
HITS [Manning, 2008]	✔	✔	✔	✘	✘
PageRank [Page, 1999]	✔	✔	✔	✘	✘
TSPR [Haveliwala, 2002]	✔	✔	✔	✘	✘
Cataldi et al. [Cataldi, 2015]	✔	✔	✔	✘	✘
MentionRank [Xiao, 2014]	✘	✘	✔	✘	✘
TOIM [Li, 2012]	✘	✔	✔	✘	✘
FLDA [Bi, 2014]	✔	✘	✔	✘	✘
Liu et al. [Liu, 2010]	✔	✘	✔	✘	✘
AWI [Yin, 2012]	✘	✘	✘	✔	✔
Li&Gillet [Li&Gillet, 2011]	✔	✘	✔	✔	✘
Chikhaoui et al. [Chikhaoui, 2015]	✔	✘	✘	✔	✔
H-index [Hirsch, 2005]	✔	✘	✘	✔	✘
iFinder [Agarwal, 2008]	✔	✔	✔	✘	✘
ProfileRank [Eirinaki, 2012]	✔	✘	✔	✘	✘
Klout [Rao, 2015]	✔	unavailable	✔	✔	½

Influence: literature comparison

Method	Connectivity	Immediacy (Intensity)	Content Recognition	Activity generation	Time dependency
Degree Centrality [Zafarani al, 2014]	✔	✘	✘	✘	✘
Closeness/Betweenness Centrality [Zafarani al, 2014]	✔	✔	✘	✘	✘
HITS [Manning, 2008]	✔	✔	✔	✘	✘
PageRank [Page, 1999]	✔	✔	✔	✘	✘
TSPR [Haveliwala, 2002]	✔	✔	✔	✘	✘
Cataldi et al. [Cataldi, 2015]	✔	✔	✔	✘	✘
MentionRank [Xiao, 2014]	✘	✘	✔	✘	✘
TOIM [Li, 2012]	✘	✔	✔	✘	✘
FLDA [Bi, 2014]	✔	✘	✔	✘	✘
Liu et al. [Liu, 2010]	✔	✘	✔	✘	✘
AWI [Yin, 2012]	✘	✘	✘	✔	✔
Li&Gillet [Li&Gillet, 2011]	✔	✘	✔	✔	✘
Chikhaoui et al. [Chikhaoui, 2015]	✔	✘	✘	✔	✔
H-index [Hirsch, 2005]	✔	✘	✘	✔	✘
iFinder [Agarwal, 2008]	✔	✔	✔	✘	✘
ProfileRank [Eirinaki, 2012]	✔	✘	✔	✘	✘
Klout [Rao, 2015]	✔	unavailable	✔	✔	½

Influence: literature comparison

Method	Connectivity	Immediacy (Intensity)	Content Recognition	Activity generation	Time dependency
Degree Centrality [Zafarani al, 2014]	✔	✘	✘	✘	✘
Closeness/Betweenness Centrality [Zafarani al, 2014]	✔	✔	✘	✘	✘
HITS [Manning, 2008]	✔	✔	✔	✘	✘
PageRank [Page, 1999]	✔	✔	✔	✘	✘
TSPR [Haveliwala, 2002]	✔	✔	✔	✘	✘
Cataldi et al. [Cataldi, 2015]	✔	✔	✔	✘	✘
MentionRank [Xiao, 2014]	✘	✘	✔	✘	✘
TOIM [Li, 2012]	✘	✔	✔	✘	✘
FLDA [Bi, 2014]	✔	✘	✔	✘	✘
Liu et al. [Liu, 2010]	✔	✘	✔	✘	✘
AWI [Yin, 2012]	✘	✘	✘	✔	✔
Li&Gillet [Li&Gillet, 2011]	✔	✘	✔	✔	✘
Chikhaoui et al. [Chikhaoui, 2015]	✔	✘	✘	✔	✔
H-index [Hirsch, 2005]	✔	✘	✘	✔	✘
iFinder [Agarwal, 2008]	✔	✔	✔	✘	✘
ProfileRank [Eirinaki, 2012]	✔	✘	✔	✘	✘
Klout [Rao, 2015]	✔	unavailable	✔	✔	½
Our Objective	✔	✔	✔	✔	✔

Reputation

- Definition: *what is generally said or believed about a person's or thing's character or standing* [Josang et al., 2007]
- ≈ *Global trust* → Collective measure;
  value based on many opinions of users
- Properties:
  - Collectivity [Hamdi, 2017; Song, 2005; Lee, 2015; Jha, 2017; Fu-Guo et al., 2009]
  - Dynamicity [Lee, 2015]
  - Long-term [Lee, 2015; Jha, 2017]
  - Context-dependency [Fu-Guo et al., 2009]

Reputation: literature comparison

Method	Collective	Dynamicity	Long-term	Context-dependence
Arithmetic mean	✔	✔	✘	✘
FCR [Hamdi, 2017]	✔	✘	✘	✘
FuzzyTrust [Song, 2005]	✔	✘	✘	✘
Binomial Rep Score [Josang, 2008]	✔	✘	½	✘
Multinomial Rep Score [Josang, 2016]	✔	½	½	✘
ReMSA [Lee, 2015]	✔	✔	✔	✘
Jha [Jha, 2017]	✔	✘	✔	½
Fu-Guo et al. [Fu-Guo et al., 2009]	✔	✘	✘	✔
O'Donovan&Smyth [ODonovan, 2005]	✔	✘	✘	✘
Advogato [Levien, 1998]	✔	✘	✘	✘
Appleseed [Ziegler, 2005]	✔	✘	✘	✘

Reputation: literature comparison

Method	Collective	Dynamicity	Long-term	Context-dependence
Arithmetic mean	✔	✔	✘	✘
FCR [Hamdi, 2017]	✔	✘	✘	✘
FuzzyTrust [Song, 2005]	✔	✘	✘	✘
Binomial Rep Score [Josang, 2008]	✔	✘	½	✘
Multinomial Rep Score [Josang, 2016]	✔	½	½	✘
ReMSA [Lee, 2015]	✔	✔	✔	✘
Jha [Jha, 2017]	✔	✘	✔	½
Fu-Guo et al. [Fu-Guo et al., 2009]	✔	✘	✘	✔
Odonovan&Smyth [ODonovan, 2005]	✔	✘	✘	✘
Advogato [Levien, 1998]	✔	✘	✘	✘
Appleseed [Ziegler, 2005]	✔	✘	✘	✘
Our Objective	✔	✔	✔	✔

Trust

- Definition: *a commitment to an action, based on a belief that the future actions of that person will lead to a good outcome* [Goldbeck, 2005]
- Properties:
  - Asymmetry [Jamali 2009; Alexandridis 2013; Bedi 2012; Jiang 2016; Lumbreras 2015; Golbeck 2005; Sarda 2008]
  - Transitivity [Jamali 2009; Alexandridis 2013; Bedi 2012, Jiang 2016; Lumbreras 2015; Golbeck 2005; Sarda 2008]
  - Dynamicity [Bedi 2012; Jiang 2016; Lumbreras 2015]
  - Context dependence [Sarda 2008]

Popularity

- Two major concepts from sociology [Stopfer et al., 2013]:
  - **perceived** popularity – well known
  - **sociometric** popularity – well liked
- Social Network Analysis: perceived popularity only!
- Topological measure

Contributions

Contribution I

- **RQ 1:** How to define, differentiate and specify properties of each of the notions: trust, popularity, influence, and reputation?
  - ➥ Proposition of **disambiguation** of the terms for several state-of-the-art methods
  - ➥ Proposition of the **hierarchical order of terms** from the abstract complexity point of view
  - ➥ **Definition** of the **network information scope** needed to infer the trusted/influential/popular users

Contribution I: Disambiguation

Method	Literature Terminology	Our Terminology
Degree Centrality	Influence	Popularity
Closeness Centrality	Influence	Popularity
Betweenness Centrality	Influence	Popularity
FollowerRank	Influence	Popularity
***O'Donovan&Smyth* [ODonovan, 2005]**	Trust	Reputation
***Fu-Guo et al.* [Fu-Guo et al., 2009]**	Trust	Reputation
Advogato [Levien, 1998]	Trust	Reputation
Appleseed [Ziegler, 2005]	Trust	Reputation

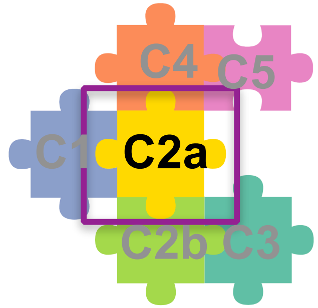
Contribution I: Hierarchy of terms

Abstraction Complexity ↑

Influence	Individual relations between users
	Spread of shared information
	Structure of network
Reputation	Group relations between users
	Individual relations between users
	Structure of network
Trust	Spread of shared information
	Structure of network
Popularity	Structure of network

📖 *Users Views on Others – Analysis of Confused Relation-Based Terms in Social Network*, OTM 2016 Conferences CoopIS, C&TC, and ODBASE 2016, Springer, 2016.

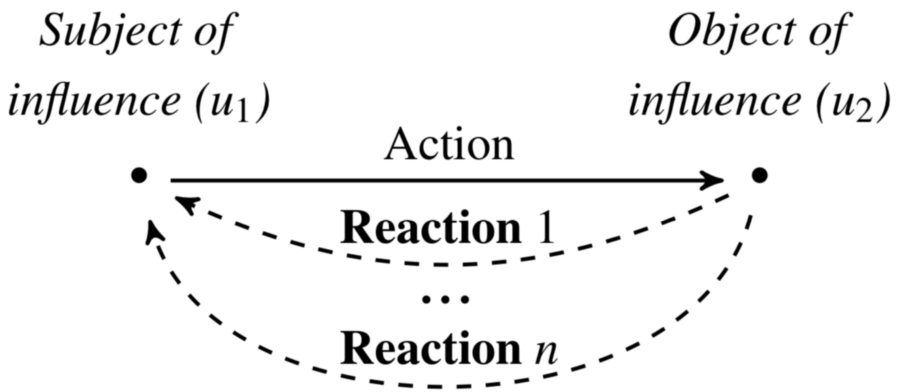
Contribution II



- **RQ3:** How to **modelize** influence capturing its **complexity**, while being **adaptive** to different social network types and consider **numerous methods of social interaction**?
  - ➥ Modelization of **influence adaptive** to multiple **different social networks**, and utilizing **numerous** ways of **users' interaction**
  - ➥ Practical **instantiations** and **experimentations** using the influence model

Contribution II: Influence Modelization

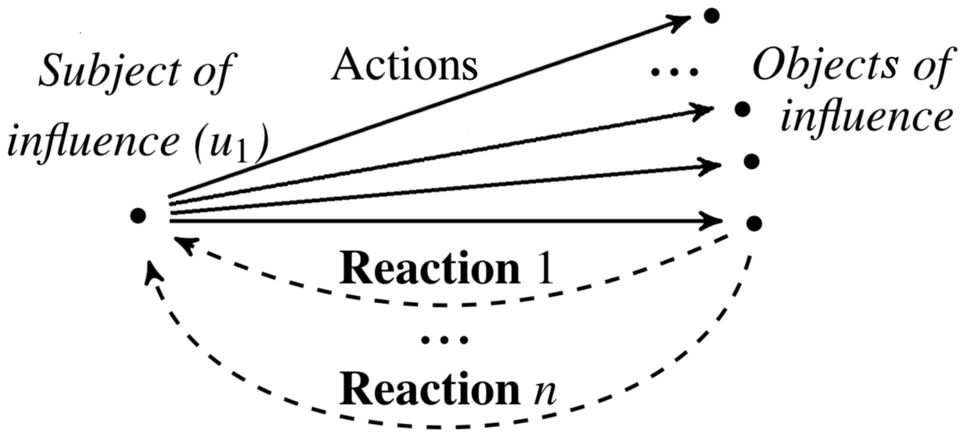
- **Action-Reaction** schema



- Actions:
  - text (message, post)
  - photo
  - video…
- Reactions:
  - upvote
  - comment
  - share…

Contribution II: Influence Modelization

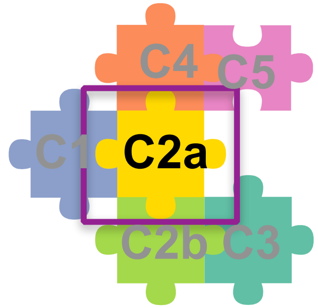
- **Action-Reaction** schema



- Actions:
  - text (message, post)
  - photo
  - video
  - …

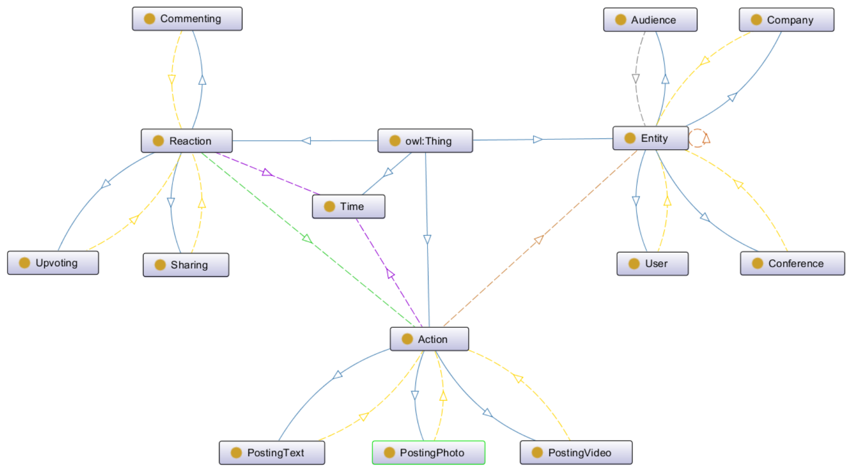
➥ not targeted at particular user → Audience

- Reactions:
  - upvote
  - comment
  - share
  - …



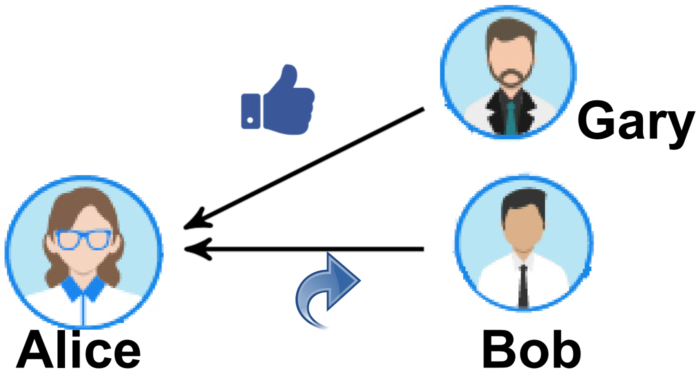
Contribution II: Influence Modelization

- **Modelizing influence** using Action-Reaction schema
- Proposition of **ontology** with new terms representing influence and influence-related terms
- Identification of **four influence components**:
  - time, intensity, spread, engagement
- Proposition of **definitions** of the terms **intensity, spread, and engagement**



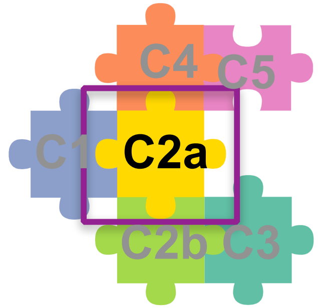
Contribution II: Influence Modelization

- **Intensity** - Property of influence relation determining the quantity of influencer strength per a reacting entity. It combines information about the number of reactions and their type. Depending on the type, the reaction can have different degree of importance.



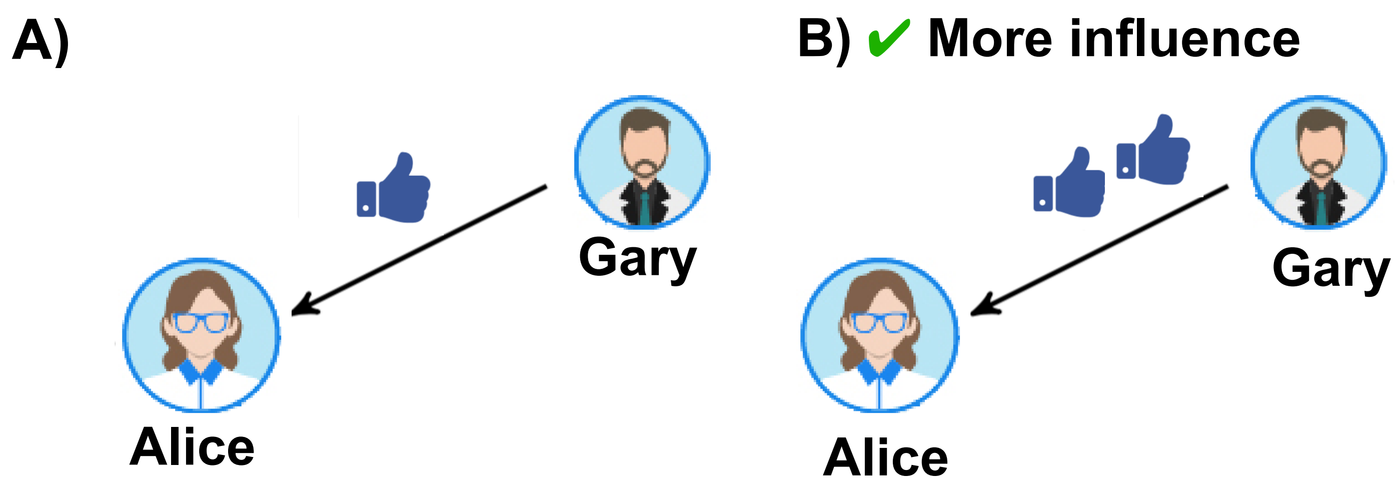
$$ActionAvgIntensity(a,T) = \frac{\sum_{e_i \in Audience(e_s,a,T)} ReactionsIntensity(a,e_i,T)}{|Audience(e_s,a,T)|}$$

$$ReactionsIntensity(a,e_t,T) = w_1 * |R_u(e_t,T)| + w_2 * |R_c(e_t,T)| + w_3 * |R_s(e_t,T)| + w_4 * |R_u(e_t)| * |R_c(e_t,T)| \\ w_5 * |R_u(e_t,T)| * |R_s(e_t,T)| + w_6 * |R_c(e_t,T) * |R_s(e_t,T)| + w_7 * |R_u(e_t,T)| * |R_c(e_t,T)| * |R_s(e_t,T)|$$



Contribution II: Influence Modelization

- **Spread and Engagement**

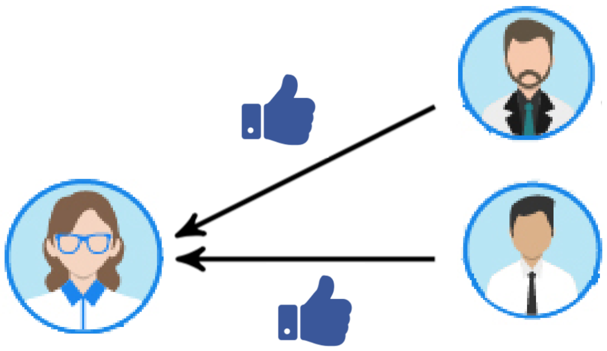


TELECOM SudParis

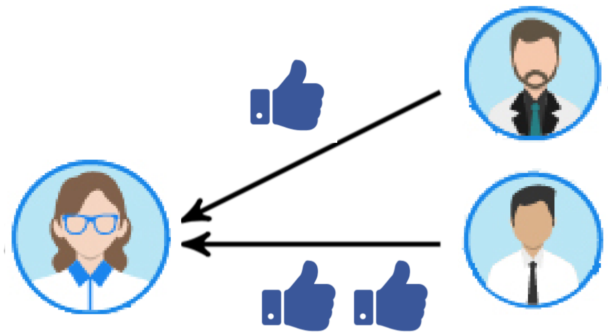
Contribution II: Influence Modelization

- **Spread and Engagement**

C)



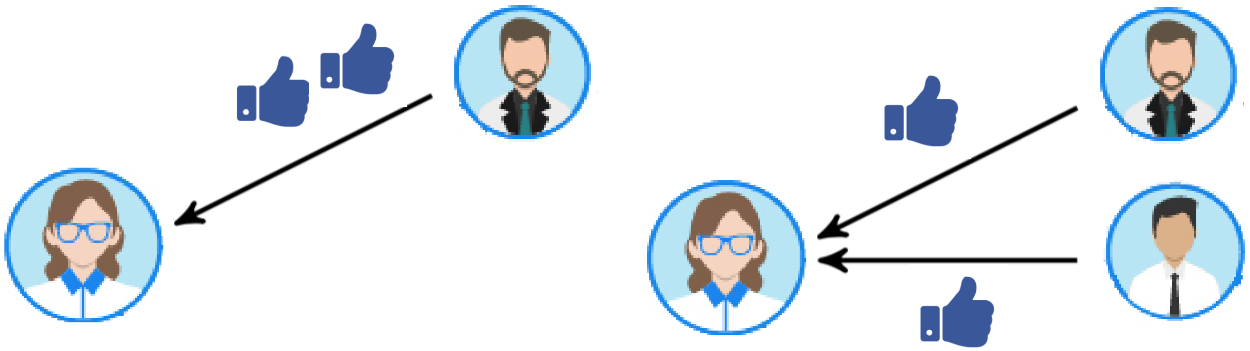
D) ✔ More influence



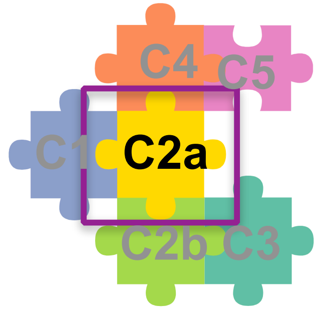
Contribution II: Influence Modelization

- **Spread and Engagement**

??More influence??

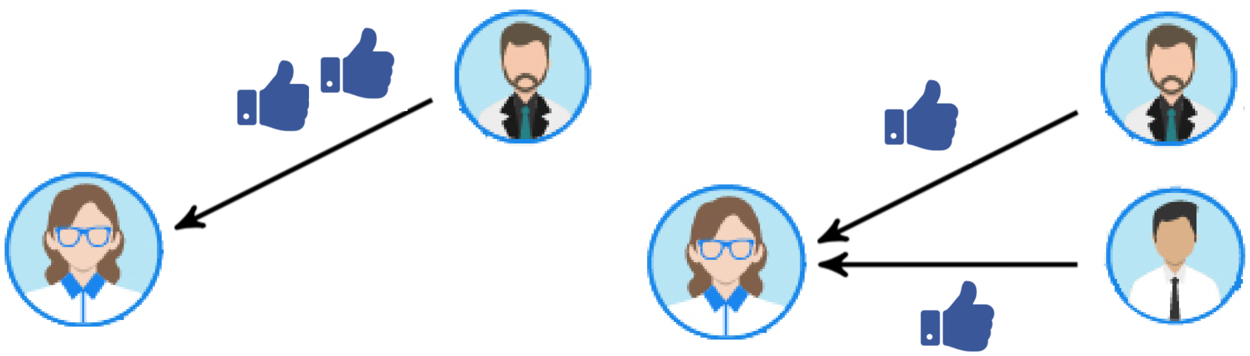


Contribution II: Influence Modelization



- **Spread** - Property of influence relation determining the number of audience members per action performed by an influencer i.e. the number of users affected by influencer action.

$$Spread(e_s, T) = \sum_{a_i \in A} |Audience(e_s, a_i, T)|$$

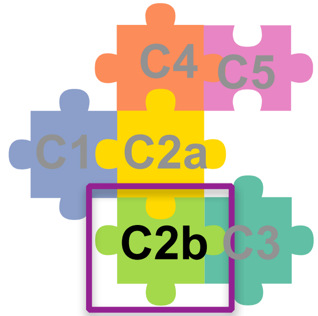


- **Engagement** - Property of influence relation determining the strength of the audience reactions per action performed by an influencer.

$$Engagement(e_s, T) = \frac{\sum_{a_i \in AllActions(e_s, T)} ActionAvgIntensity(a_i, T)}{|AllActions(e_s, T)|}$$

TELECOM SudParis

Contribution II: Action-Reaction Influence Model (ARIM)



- **A**ction-**R**eaction **I**nfluence **M**odel (ARIM)
- Usage of influence components
  - time, intensity, spread, engagement
- Utilization of whole time period and additional favoring of less frequent posting:

$$ActionFreq(e_s, T) = e^{\frac{1}{|A|}}$$

- Focus on **maximization** of all the parameters
- Evaluation of influence:

$$Influence(e_s, T) = Engagement(e_s, T) \times Spread(e_s, T) \times ActionFreq(e_s, T)$$

TELECOM SudParis

Contribution II: Action-Reaction Influence Model (ARIM)

- Experiments: Discovery of macro-influential users using three real-world datasets:
  - Facebook (social, reaction: comments)
  - Pinterest (social, reactions: upvotes, shares)
  - Microsoft Academic (scientific, reaction: citation)

Facebook Dataset

Parameter	Value
Number of acting users	1 067 026
Number of users that reacted	23 426 682
Number of posts	25 937 525
Number of comments	104 364 591

Pinterest Dataset

Parameter	Value
Number of acting users	1 307 527
Number of users that reacted	8 314 067
Number of posts	2 362 006
Number of shares	37 087 685
Number of comments	19 332 254

Microsoft Academic Dataset

Parameter	Value
Number of citations between papers	1 609 103
Number of papers	554 532

Contribution II: Action-Reaction Influence Model (ARIM)

C4 C5 C1 C2a C2b C3

- Facebook

Position	Engagement	Spread	#Actions
1	**1.039**	**66181**	**96**
2	**1.216**	**19793**	**549**
3	1.208	18093	148
4	1.204	17030	103
5	1.071	17817	200

- Pinterest

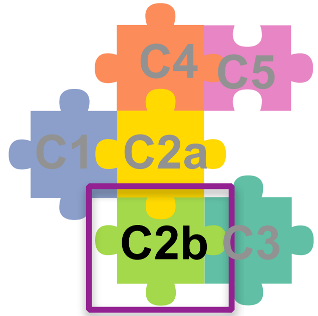
All reactions equal

Position	UID	Engagement	Spread	#Actions
1	2777	1.314	23386	1282
2	20703	1.249	19777	566
3	2367	1.367	13512	1025
4	5656	1.314	9843	535
5	4000	1.286	9908	360
6	**1731**	**1.442**	**8553**	**328**
7	5074	1.389	8876	465
8	**820**	**1.262**	**9735**	**615**
9	4968	1.301	9013	569

Shares more important

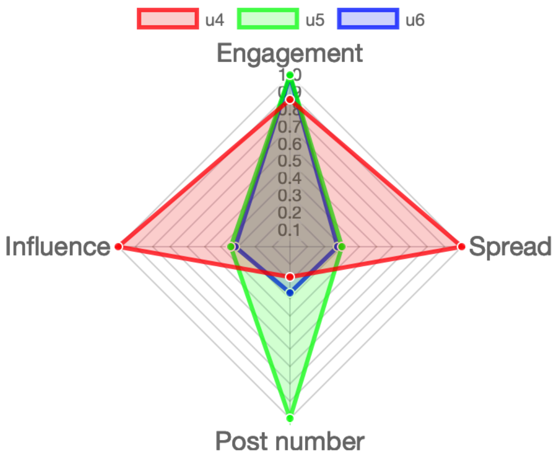
Position	UID	Engagement	Spread	#Actions
1	2777	2.263	23386	1282
2	20703	1.935	19777	566
3	2367	2.283	13512	1025
4	**820**	**2.224**	**9735**	**615**
5	4000	2.133	9908	360
6	**5656**	**2.133**	**9843**	**535**
7	4968	2.262	9013	569
8	1731	2.36	8553	328
9	5074	2.256	8876	465

TELECOM SudParis



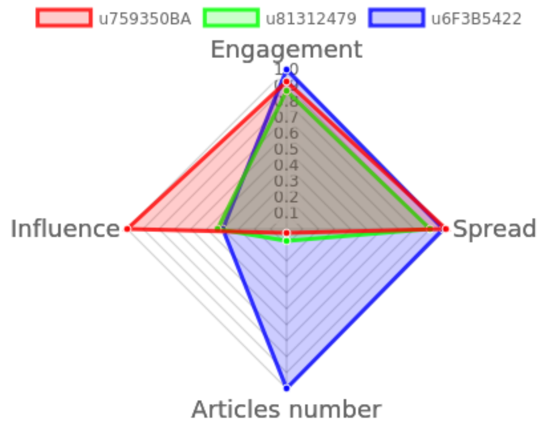
Contribution II: Action-Reaction Influence Model (ARIM)

Top three users comparison:



Facebook dataset

Pinterest dataset

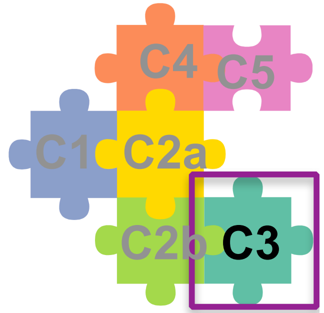


Microsoft Academic dataset

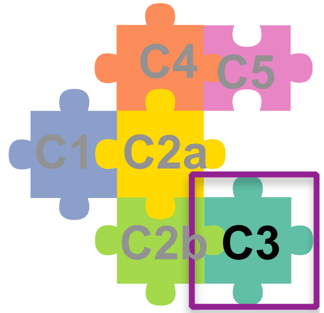
- ✓ Flexibility - different SN, various properties of dataset
- ✓ Explicability - possible analysis of users' order
- ✓ Easy to tune - depending on the usage possibility of stressing each of the components
- ✓ Captures intuitional understanding of influence

📖 *Exploring Interactions in Social Networks for Influence Discovery*, 22nd International Conference on Business Information Systems (BIS), Springer, 2019.

Contribution III



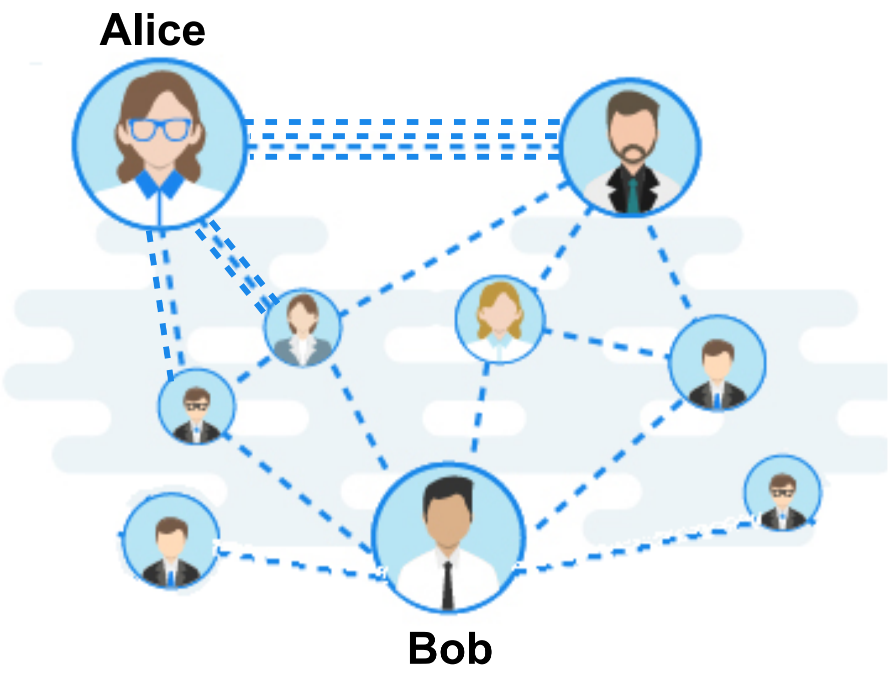
- **RQ5:** How to find “promising” entities who could **still have influence but are invisible** (as they are less connected)?
  - ➥ Definition and interpretation of the **notion of a micro-influence**
  - ➥ **Experimentation** using the proposed notion



Contribution III: Micro-influence Concept

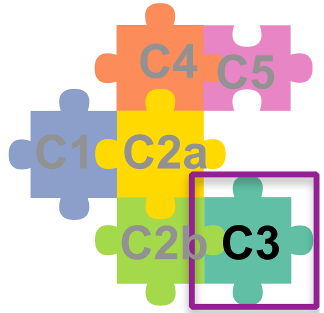
A micro-influencer is an influencer that has:

- a limited spread value, that is audience size that is both non-empty and greatly smaller than the maximal audience size observed in the SN,
- the highest possible engagement value.



TELECOM SudParis

Contribution III: Micro-influence Concept



- Tests using ARIM with focus on **maximization** of **engagement** and **limitation of spread**
  - Audience size between 100 and 500
- Experiments with Facebook and Pinterest datasets
- Comparison with PageRank with same limits

TELECOM SudParis

Contribution III: Micro-influence Concept

C4 C5 C1 C2a C2b C3

Facebook					
ARIM: Top 3 users	UID	ARIM positon	Corresponding PageRank position	Engagement	Audience size
	11jh44w613qww	1	48262	5.779887	118
	15rfcd2cgpdds	2	57692	3.085694	133
	eaa43njsf6yo	3	73208	3.053465	150
PageRank: Top 3 users	UID	PageRank position	Corresponding ARIM positon	Engagement	Audience size
	-1jy1nmhvcdgcg	1	33383	1.49695	496
	-qsiiojecsyyo	2	31415	1.150296	495
	-fswnrkmo4yrk	3	32253	1.132718	486

- Overall number of users with audience between 100 and 500: 82 972
- Engagement of top 5 users from previous ARIM experiments: ≅1.2

TELECOM SudParis

Contribution III: Micro-influence Concept

C4 C5 C1 C2a C2b C3

Facebook

ARIM: Top 3 users

UID	ARIM positon	Corresponding PageRank position	Engagement	Audience size
11jh44w613qww	1	48262	5.779887	118
15rfcd2cgpdds	2	57692	3.085694	133
eaa43njsf6yo	3	73208	3.053465	150

PageRank: Top 3 users

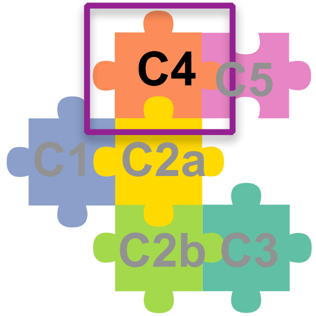
UID	PageRank position	Corresponding ARIM positon	Engagement	Audience size
-1jy1nmhvcdgcg	1	33383	1.49695	496
-qsiiojecsyyo	2	31415	1.150296	495
-fswnrkmo4yrk	3	32253	1.132718	486

- Overall number of users with audience between 100 and 500: 82 972
- Engagement of top 5 users from previous ARIM experiments: ≅1.2

Contribution IV

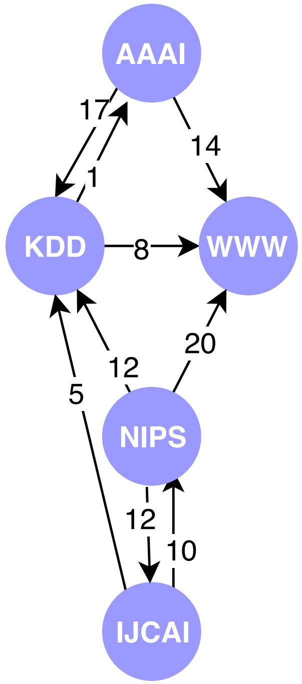
- **RQ4:** How to include **time** for influence evaluation? How to **quantify influence over time**? How can influence **causal effect** be represented?
  - ➥ **Instantiation** of the **theoretical influence model** targeted at **particularly time sensitive** SN with focus on **time effect** on influence evaluation
  - ➥ **Experimentation** using the time-dependent application of influence model

Contribution IV: Time Dependent Influence Estimation (TiDIE)



- For influence determination **time** is especially important

Citation network



- Of few works dealing with time-dependency aspect [Chikhaoui et al., 2015] focused on specific, **less dynamic and time embedded** type of network: **citation network**, using conferences as entities
- However, the method has **several drawbacks**:
  - lack of consideration of spread
  - lack of influence value → no possibility of comparing conferences
  - consideration of very specific conference set

➥ Our objective is to further investigate the idea and extend and improve the method

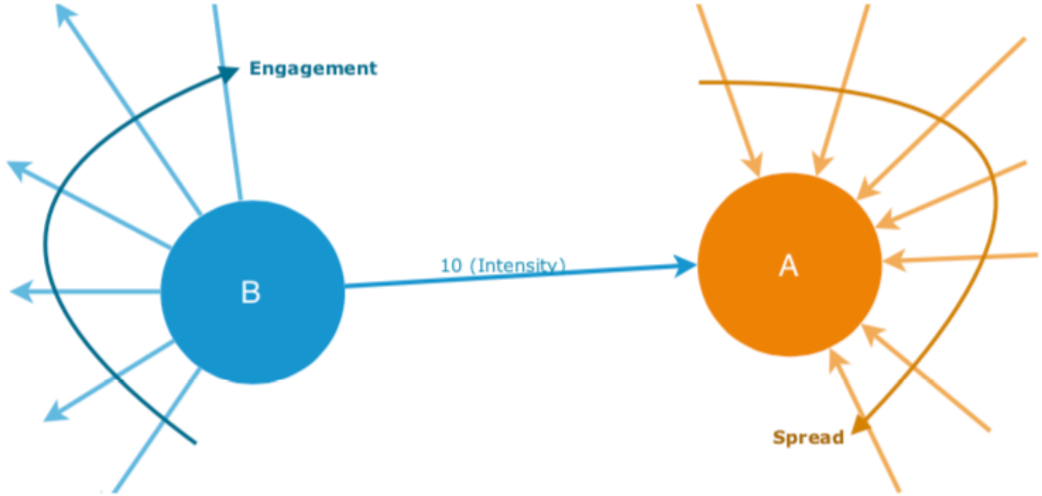
Contribution IV: Time Dependent Influence Estimation (TiDIE)

Time **D**ependent **I**nfluence **E**stimation (TiDIE):

1. Calculation of **intensity**, **engagement** and **spread** in one time snapshot
2. Pairwise measurement **time dependence between pair conferences**
3. Estimation of **influence value** of influential conferences, using time priority function

Contribution IV: Time Dependent Influence Estimation (TiDIE)

1. Calculation of intensity, engagement and spread in one time snapshot



- Citation Ratio
  - intensity
  - engagement

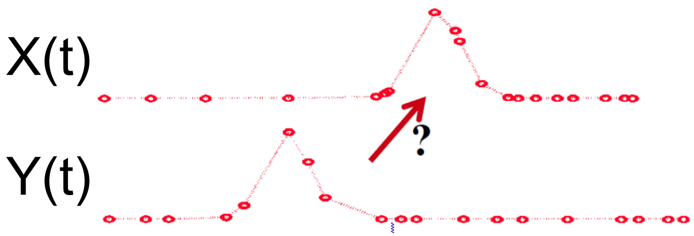
$$CR_{A\to B}(t) = \frac{|cit_{B\Rightarrow A}(t)|}{\sum_{i=1}^{|S|} |cit_{B\Rightarrow i}(t)|}$$

- Reference Ratio
  - intensity
  - spread

$$RR_{A\to B}(t) = \frac{|cit_{B\Rightarrow A}(t)|}{\sum_{i=1}^{|S|} |cit_{C_i\Rightarrow A}(t)|}$$

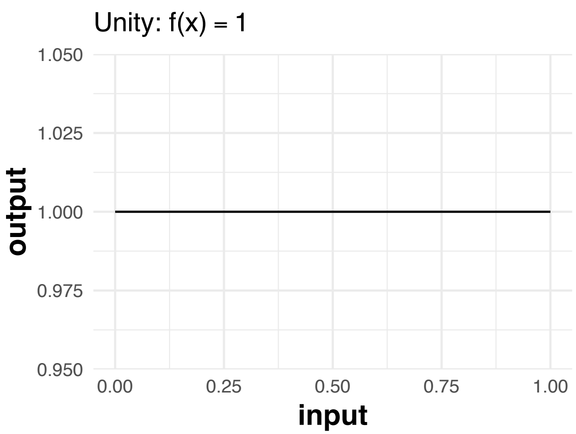
Contribution IV: Time Dependent Influence Estimation (TiDIE)

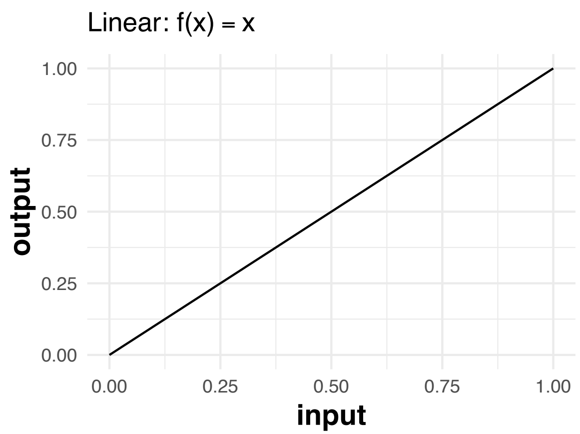
2. Pairwise measurement time dependence between pair conferences
   - Use of Citation Ratio/Reference Ratio per time snapshot for pair of conferences to create time series for time interval
   - Use of **Granger Causality** in order to use dependency
     - *Y(t) is causing X(t) if we are better able to predict X(t) using the history information of both X(t) and Y(t) than solely using the history information of only X(t)*
   - Obtaining the information about **pairwise influence**

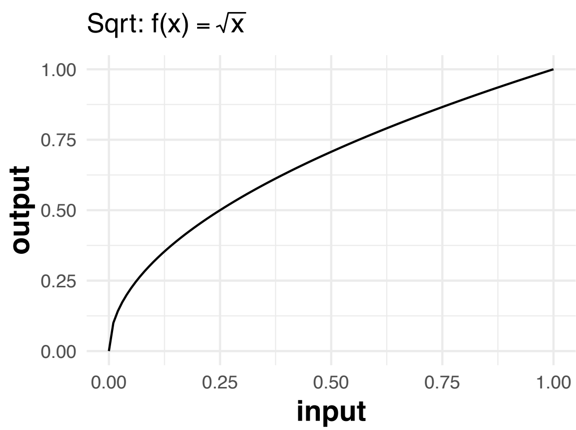


Contribution IV: Time Dependent Influence Estimation (TiDIE)

3. Estimation of **influence value** of influential conferences, using time priority function
   - Use of Exponential Moving Average to put more weight to recent citations
   - Use of **time priority function** to treat historical citations

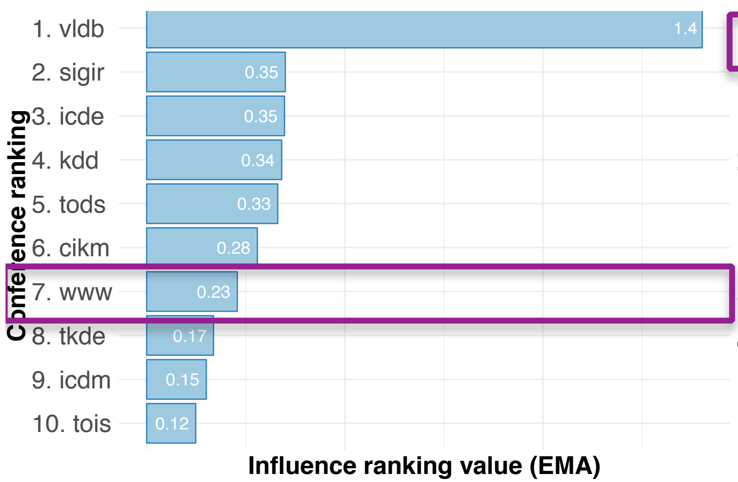




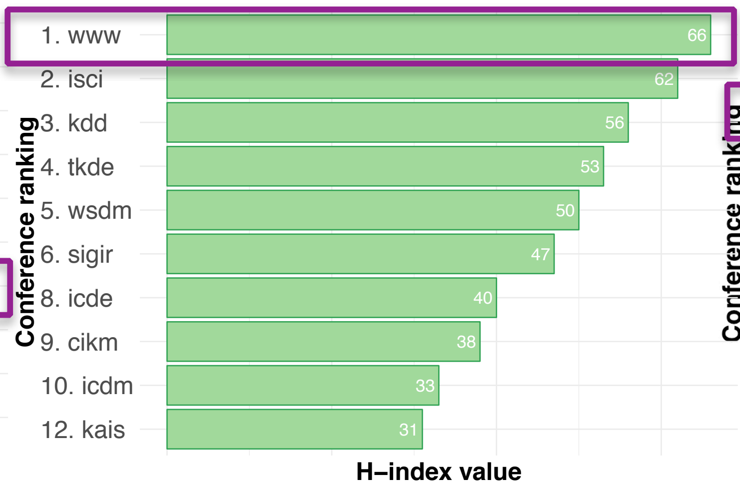


Contribution IV: Time Dependent Influence Estimation (TiDIE)

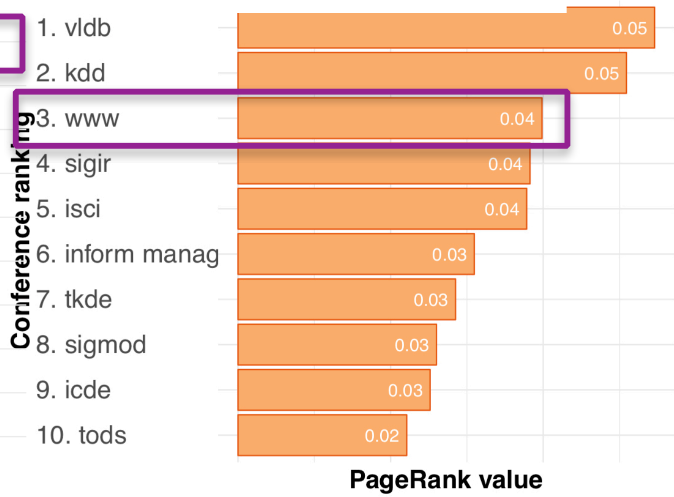
- Experiments: Microsoft Academic dataset
  - Comparison with H-Index and PageRank



Top 10 Conferences by TiDIE using Citation Ratio



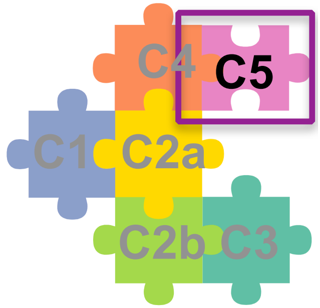
Top 10 Conferences by H-Index



Top 10 Conferences by PageRank

📖 *Influence in Time-Dependent Citation Networks*, 12th International Conference on Research Challenges in Information Science (RCIS), IEEE, 2018

📖 *Time-Dependent Influence Measurement in Citation Networks*, Complex Systems Informatics and Modeling Quarterly (CSIMQ 17), Vol 17, 2018.



Contribution V

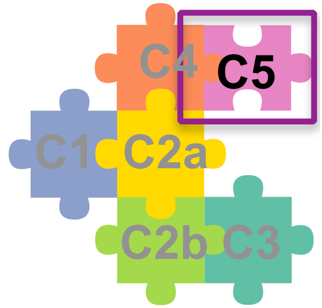
- **RQ 2:** Is there a **link** between those notions? If so, how to **model the linkage**, so we can use it for evaluation?
  - ➥ **Exploration** of the **link** between influence and reputation
  - ➥ Combination of the **influence information** in order to **obtain reputation** about an entity

Contribution V: Inferring Reputation from Influence

- Influence and Reputation studied **separately**, while:
  - Different studies [Anderson&Kilduff, 2009], [Berger et al., 1980] show the **connection** between **high levels of competence, skills and abilities and high position in a group**
  - Study by [Cheng et al., 2013] stated that **social influence** is strictly **connected** to the notion of ***"sharing of expertise or know-how to gain respect"***

➥ Our objective is to utilize this link in order to infer reputation from influence

Contribution V: Inferring Reputation from Influence



Reputation **TiDIE** (ReTiDIE):

1. Calculation of **influence rank** using TiDIE
2. Calculation of **H-index rank**
3. Creation of **Reputation Rank** by **merging** influence and H-index ranks, using one of the methods:
   a. Cross Entropy Monte Carlo algorithm
   b. Genetic algorithm with Spearman distance metrics

Contribution V: Inferring Reputation from Influence

C4 C5 C1 C2a C2b C3

- Experiments using Microsoft Academic dataset
  - Cross-Entropy Monte Carlo with Spearman distance metrics
  - Genetic Algorithm with Spearman distance metrics

Venue	Influence Rank	H-index	Reputation (CE)
ai	1	4	1
ijcv	10	3	2
neural netw	21	1	3
cvpr	6	13	4
ieee neural	8	12	5
prl	20	7	6
cviu	25	6	7
jair	17	10	8
jmlr	15	9	9
eccv	12	20	10

Venue	Influence Rank	H-index	Reputation (GA)
ai	1	4	1
nips	2	41	2
ijcv	10	3	3
acl	3	24	4
neural netw	21	1	5
dss	54	2	6
kbs	51	5	7
jmlr	15	9	8
ieee neural	8	12	9
prl	20	7	10

📖 *Reputation Prediction using Influence Conversion*, 17th IEEE International Conference On Trust, Security And Privacy In Computing And Communications, IEEE, 2018.

Conclusion

Summary

Influence

Reputation

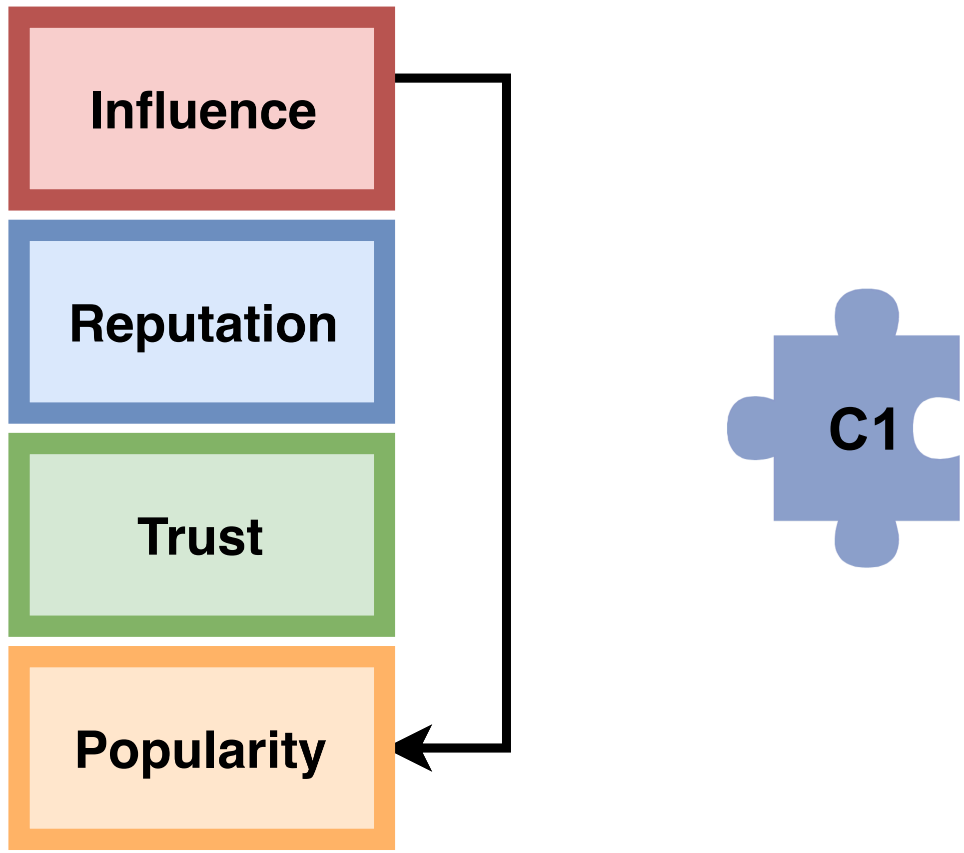
Trust

Popularity

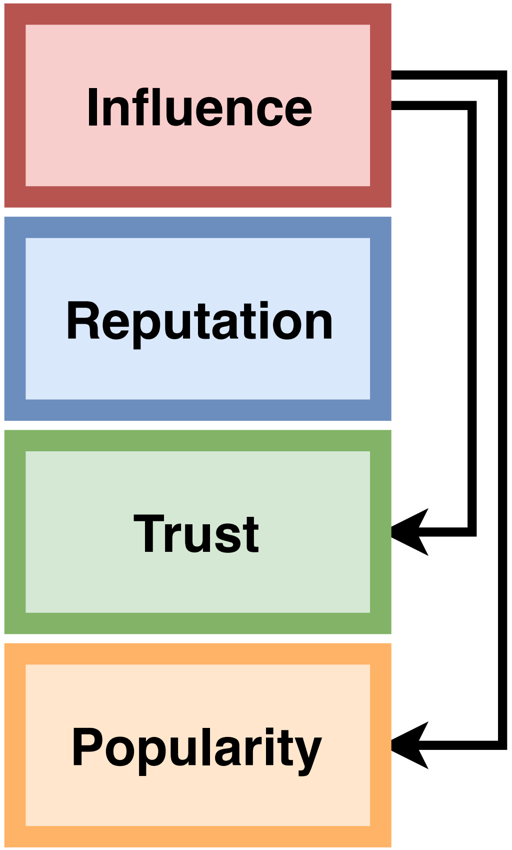
Clarification, differentiation, comparison of the notions and hierarchical order of terms

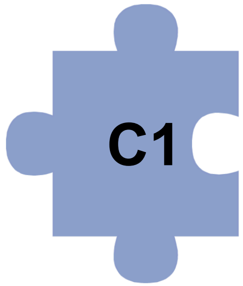
C1

Summary

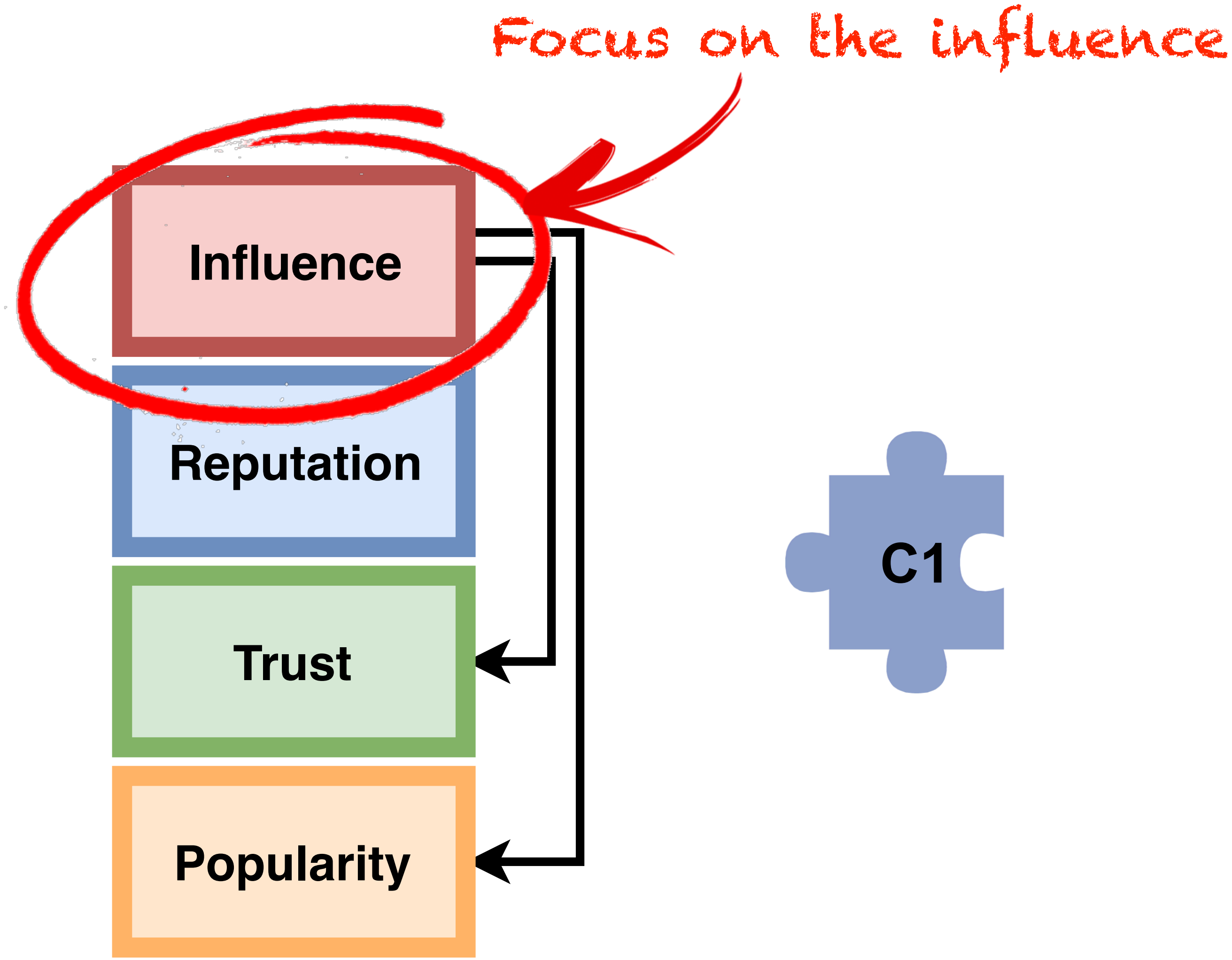


Summary





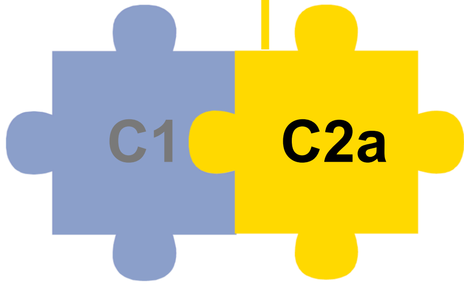
Summary


Focus on the influence
Influence
Reputation
Trust
Popularity
C1

Summary

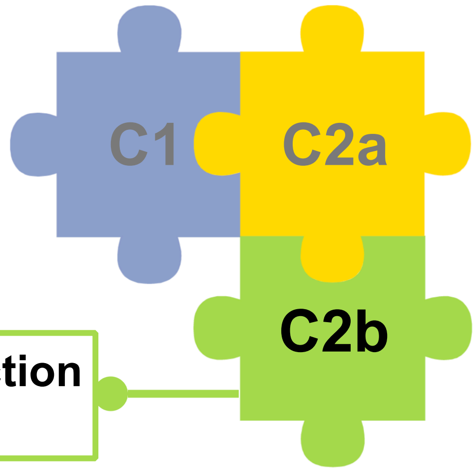
Influence

Theoretical model of influence: adaptive to different social networks, and utilizing numerous types of interactions



Summary

Influence

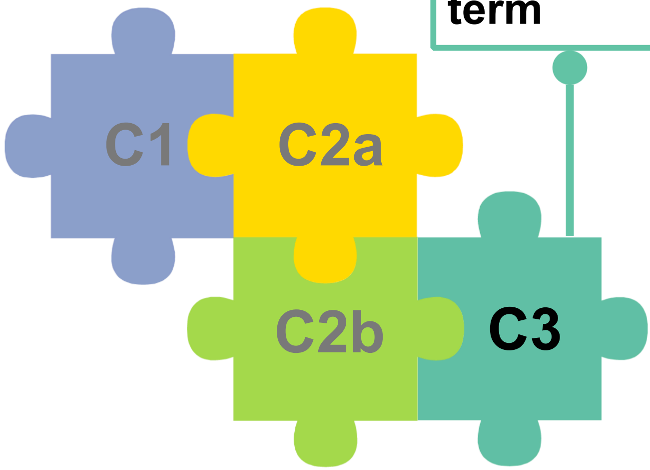


ARIM: Action-Reaction Influence Model

Summary

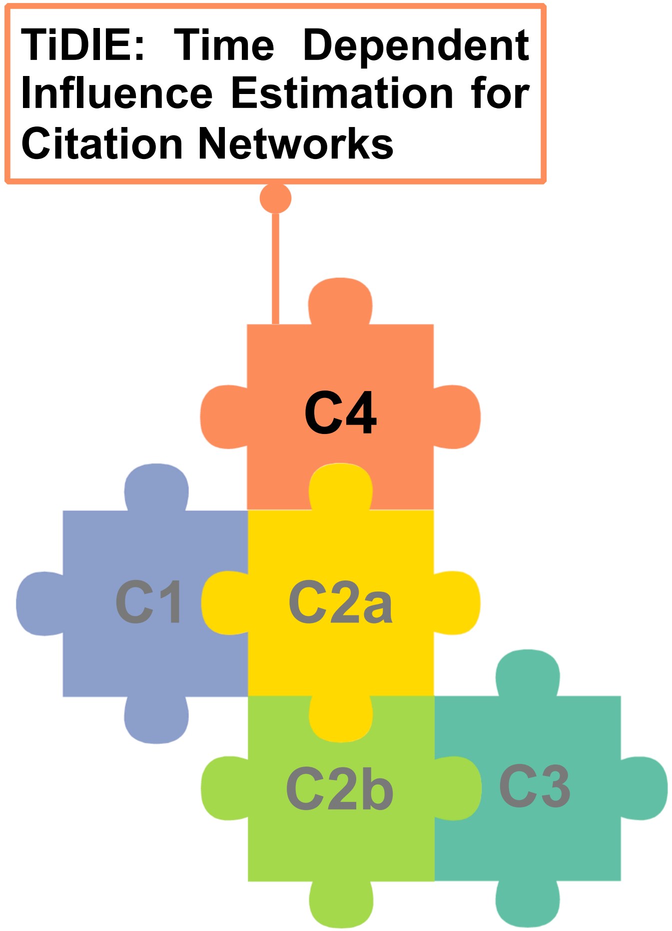
Influence

Micro-influence: Definition and experimentation using the new term

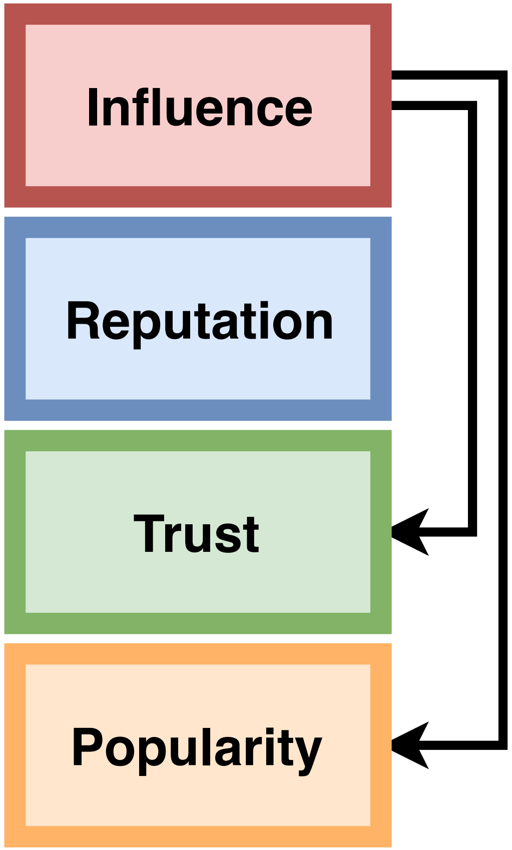


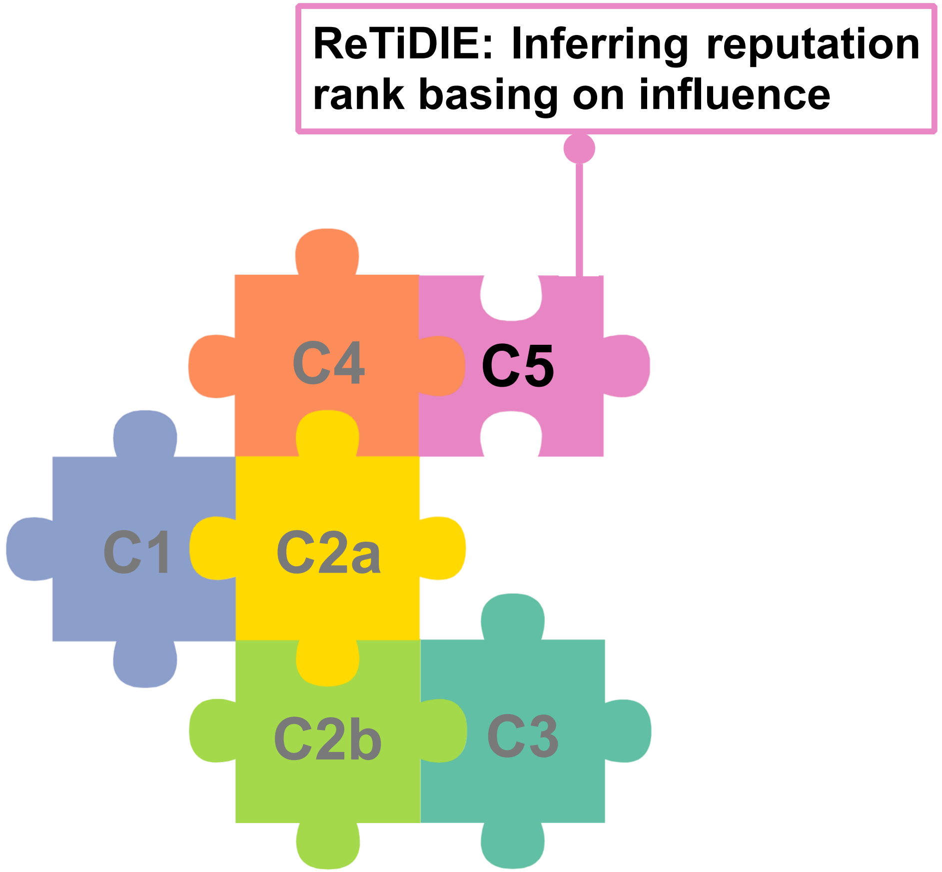
Summary

Influence

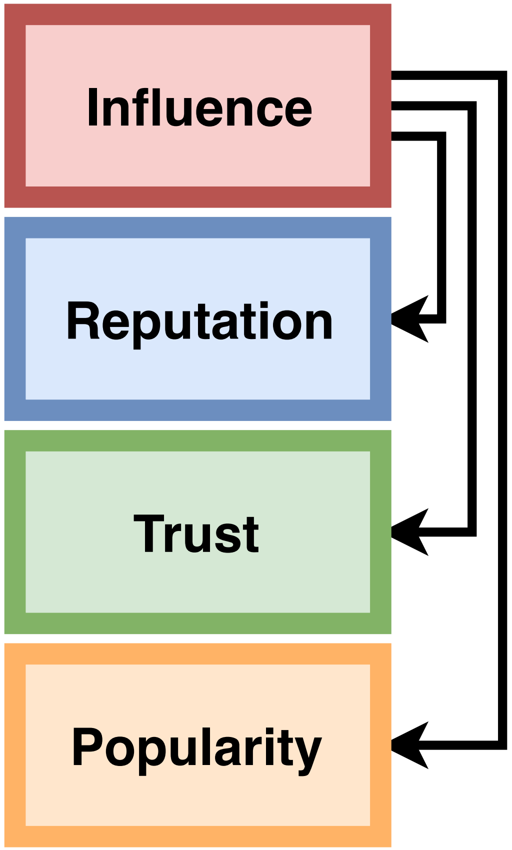


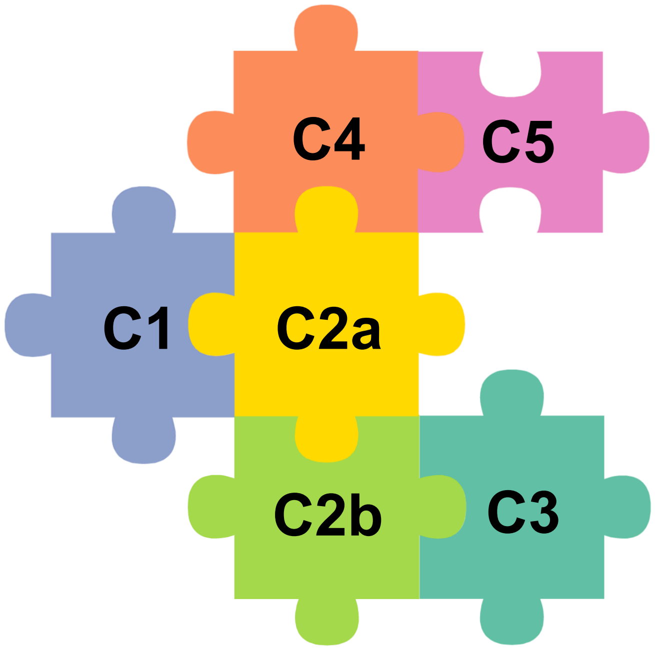
Summary


Influence
Reputation
Trust
Popularity


ReTiDIE: Inferring reputation rank basing on influence
C4
C5
C1
C2a
C2b
C3

Summary





TELECOM SudParis

Perspectives

- Further **adjustments** of **theoretical influence model** to future needs (e.g. new types of interactions)
- Experimental **evaluation** of ARIM using **other** types of **SNs**
- Analysis of **influence trends**
- **Forcasting** the **micro-influencers**
- Application to **Social Recommendation** and **Influence Diffusion**
- Development of **conference classification** based on TiDIE
- Combining current evaluation of influence (ARIM, TiDIE) with **sentiment analysis**

Publications

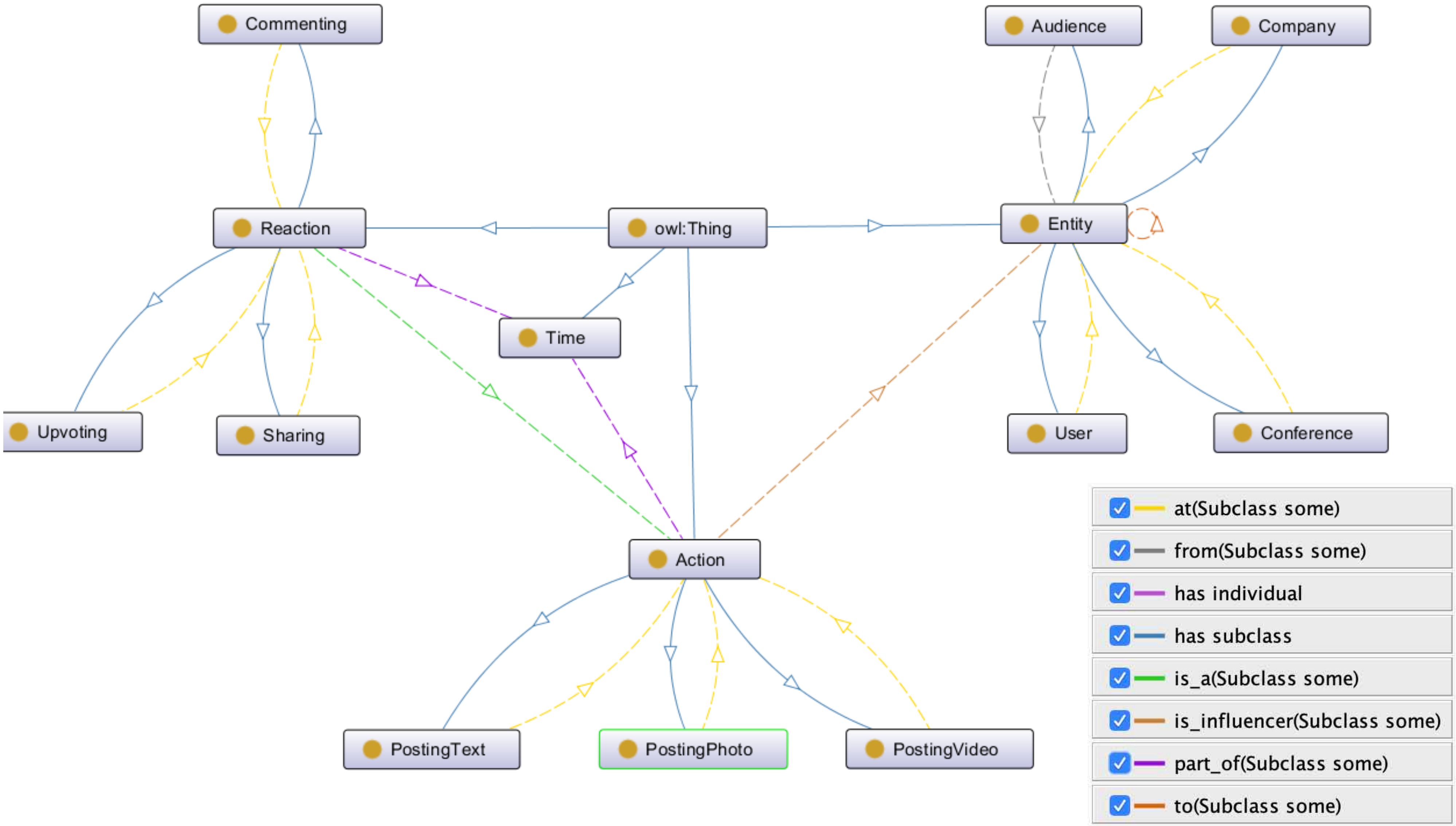
- ✓ M.Rakoczy, A.Bouzeghoub, K.Wegrzyn-Wolska, A.Lopes Gancarski, *Exploring Interactions in Social Networks for Influence Discovery*, 22nd International Conference on Business Information Systems (BIS), 2019.
- ✓ M.Rakoczy, A.Bouzeghoub, A.Lopes Gancarski, K.Wegrzyn-Wolska, *Time-Dependent Influence Measurement in Citation Networks*, Complex Systems Informatics and Modeling Quarterly (CSIMQ 17), Vol 17, 2018.
- ✓ M.Rakoczy, A.Bouzeghoub, K.Wegrzyn-Wolska, A.Lopes Gancarski, *In the Search of Quality Influence on a Small Scale – Micro-influencers Discovery*, OTM 2018 Conferences: Confederated International Conferences: CoopIS, C&TC, and ODBASE 2018, Springer, 2018.
- ✓ M.Rakoczy, A.Bouzeghoub, K.Wegrzyn-Wolska, A.Lopes Gancarski, *Reputation Prediction using Influence Conversion*, 17th IEEE International Conference On Trust, Security And Privacy In Computing And Communications (IEEE TrustCom-18), IEEE, 2018.
- ✓ M.Rakoczy, A.Bouzeghoub, K.Wegrzyn-Wolska, A.Lopes Gancarski, *Influence in Time-Dependent Citation Networks*, 12th International Conference on Research Challenges in Information Science (RCIS), IEEE, 2018;
- ✓ M.Rakoczy, A.Bouzeghoub, K.Wegrzyn-Wolska, A.Lopes Gancarski, *Users Views on Others – Analysis of Confused Relation-Based Terms in Social Network*, OTM 2016 Conferences: Confederated International Conferences: CoopIS, C&TC, and ODBASE 2016, Springer, 2016.

- **Thank you !**

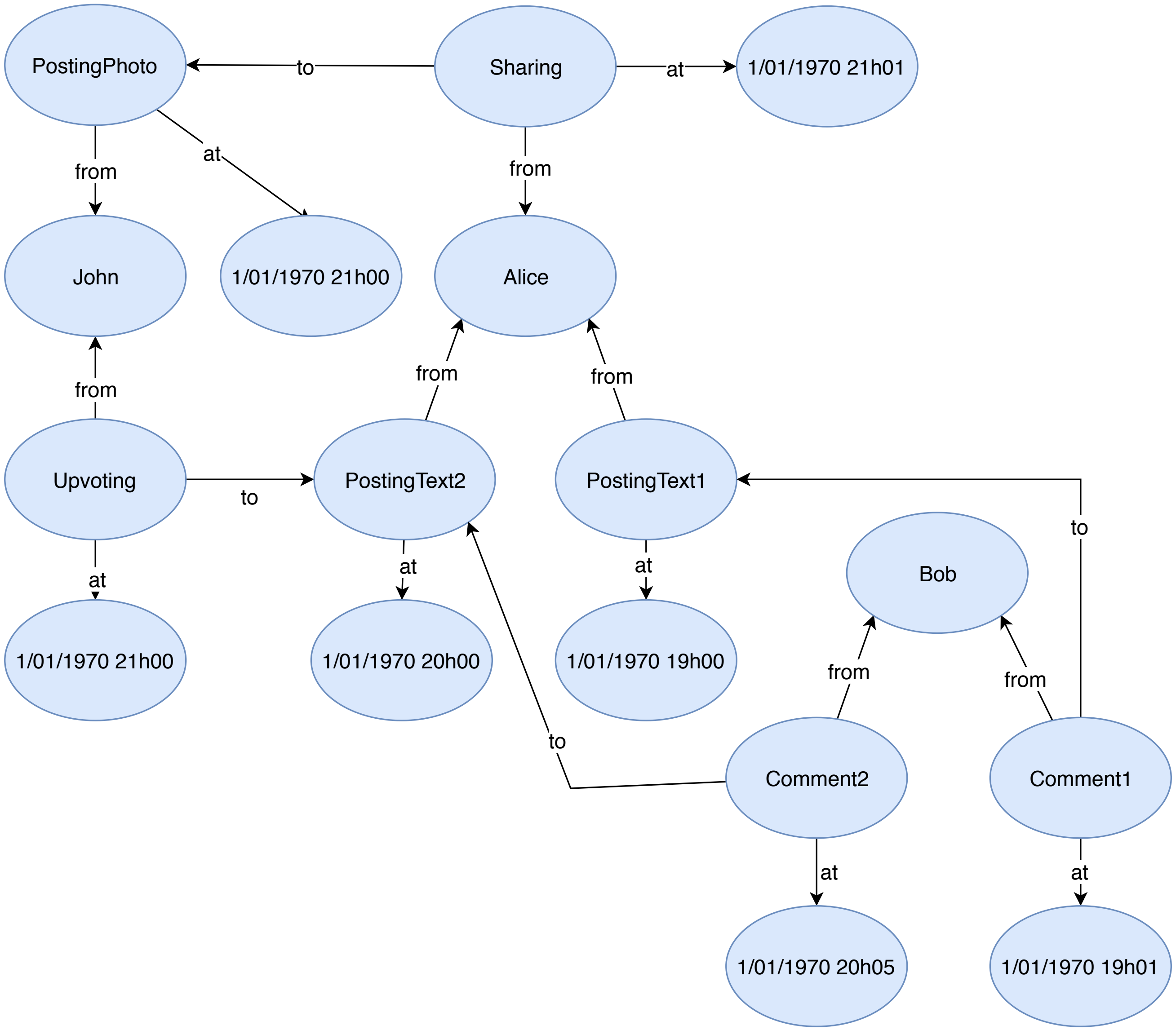
Influence: literature comparison (2)

Method	Asymmetry	Transitivity	Topic dependency	Time dependency	Event Sensitivity
Degree Centrality	✔	✘	✘	✘	✘
Closeness/Betweenness Centrality	✔	✘	✘	✘	✘
HITS	✔	✔	✘	✘	✘
PageRank [Page, 1999]	✔	✔	✘	✘	✘
TSPR [Haveliwala, 2002]	½	✔	✔	✘	✘
Cataldi et al. [Cataldi, 2015]	✔	✔	✔	✘	✘
RetweetRank [Xiao, 2014]	✔	✘	✔	✘	½
MentionRank [Xiao, 2014]	✔	✘	✔	✘	½
TOIM [Li, 2012]	✔	✔	✔	✘	½
FLDA [Bi, 2014]	✔	✔	✔	✘	✘
Liu et al. [Liu, 2010]	✔	✔	✔	✘	✘
AWI [Yin, 2012]	✔	✘	✘	✔	✘
Li&Gillet [Li, 2013]	✔	✘	✘	✘	✘
Chikhaoui et al. [Chikhaoui, 2015]	✔	✘	✘	✔	✘
H-index [Hirsch, 2005]	✔	✘	✘	✘	✘
iFinder [Agarwal, 2008]	✔	✘	✘	✘	✘
ProfileRank [Eirinaki, 2012]	✔	✘	✘	✘	✘
Klout [Rao, 2015]	✔	✘	✘	½	✘

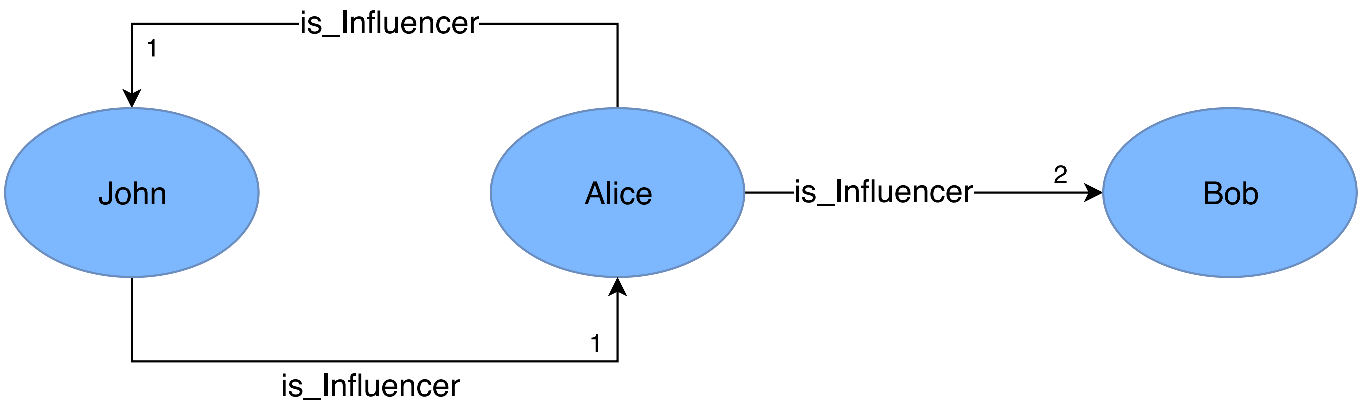
Ontology


Commenting
Audience
Company
Reaction
owl:Thing
Entity
Time
Upvoting
Sharing
User
Conference
Action
PostingText
PostingPhoto
PostingVideo
at(Subclass some)
from(Subclass some)
has individual
has subclass
is_a(Subclass some)
is_influencer(Subclass some)
part_of(Subclass some)
to(Subclass some)

Ontology example

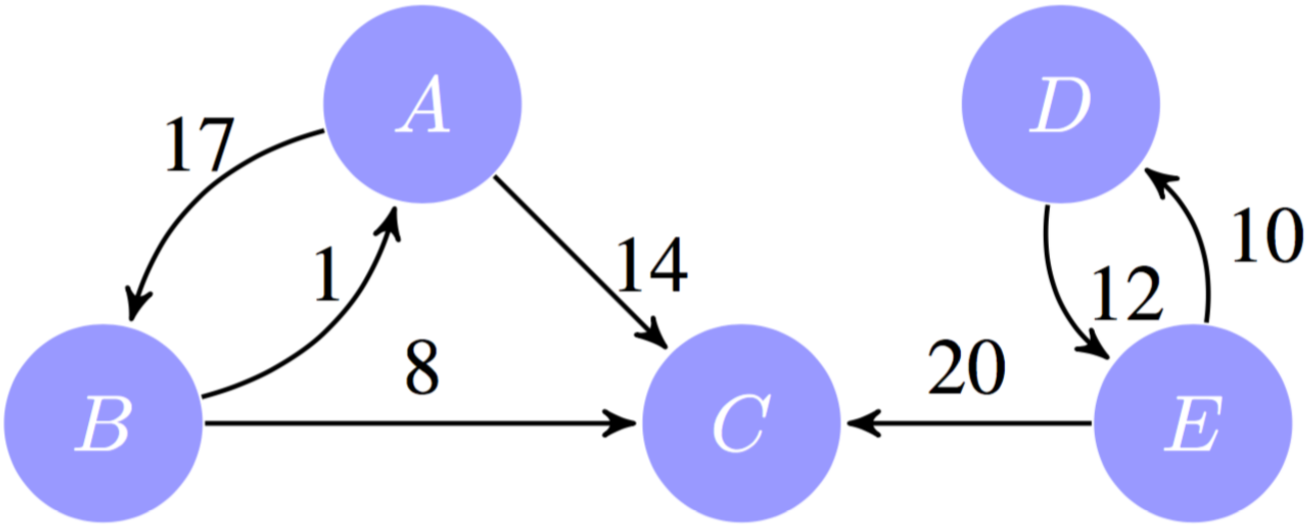


Ontology example (2)



Proposition: Time-focused Adaptation of Influence

- Time embedded
- Citation networks
- Predefined communities



TELECOM SudParis

Proposition: Time-focused Adaptation of Influence

- Influence identification problem - **useful**: political/ marketing campaigns, recommending
- Current focus on **individuals** - influencers (who is the most tweeted/shared…?) and **overall** ranking (e.g. PageRank)

BUT

- Loss of **particular influence** information (do I influence you/him/her?)
- Influencers ≠ **communities** !

TELECOM SudParis

Problem definition

- We **have:**
  - Time snapshots $\{t_1, ..., t_m\}$
  - Universe of conferences U
  - Set of predefined communities $S = \{C_1, ..., C_n\}$ $(S \subset U)$
- We **want:**
  - Determine pairwise Running Influence (RI) using citation information from each time
  - Estimate the value of the RI

TELECOM SudParis

Influence Discovery Steps: Step 1

- Pairwise Citation Ratio for each time snapshot based on the work of *Chikhaoui et al.*

$$CR_{A \to B}(t) = \frac{|cit_{B \Rightarrow A}(t)|}{\sum_{i=1}^{|S|} |cit_{B \Rightarrow i}(t)|}$$

- Global and Local Citation Ratio
- Additional use of weight function

Influence Discovery Steps: Step 2

- Using pairwise Citation Ratios in time period, we determine Running Influence using the notion of Granger Causality between them
  - Quick intuition behind Granger Causality:
  - *Y(t) is granger causing X(t) if we are better able to predict X(t) using the history information of both X(t) and Y(t) than solely using the history information of only X(t)*

- ➠ **Thus, we know if confA is influencing confB for time period**

Influence Discovery Steps: Step 3

- ➠ **Hence, we can create the influence dependency graph**
- Estimation of Running Influence value by using for each conference **set of conferences that it influences**
- ➠ **Thus, we have the RI value, and the overall rank**

Experiments

- **Microsoft Academic** database
  - 68 selected conferences
  - 930 000 papers
  - 2.8 million citations between papers

Results - Influence Dependencies