Profiling User Interactions on Social Networks

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Outline

- Theoretical aspects of user interactions: theories from sociology and social network analysis to explain why users interact [1,2,3,4].

- Detecting users' inclination to interact with certain people: applying interaction forecasts in
  - privacy [5,6]
  - anomaly detection [7]

Outline 1

Theoretical aspects of user interactions

- Analysing data content for basic interactions [3]
- Theories to generalize and explain interactions[1,2,4]

Understanding basic Interactions

User generated content for user interactions

- the expressed sentiment
- entities mentioned
- grammar mistakes
- shared locations among users

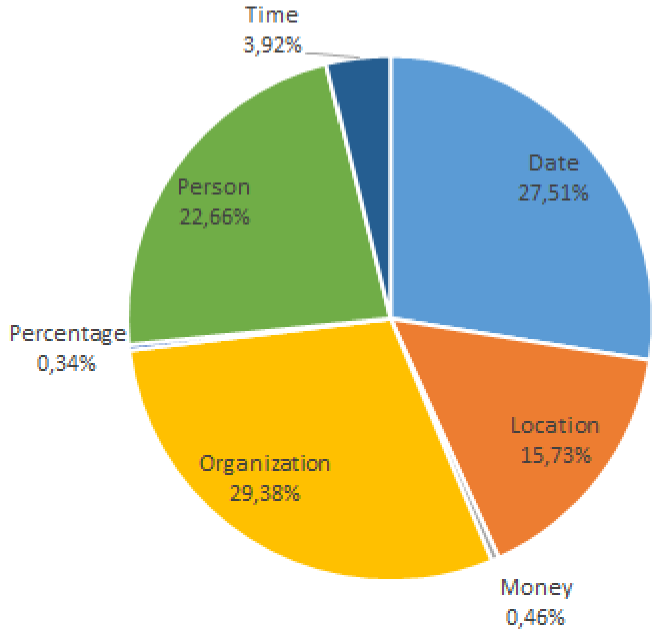
How these differ on different social networks?

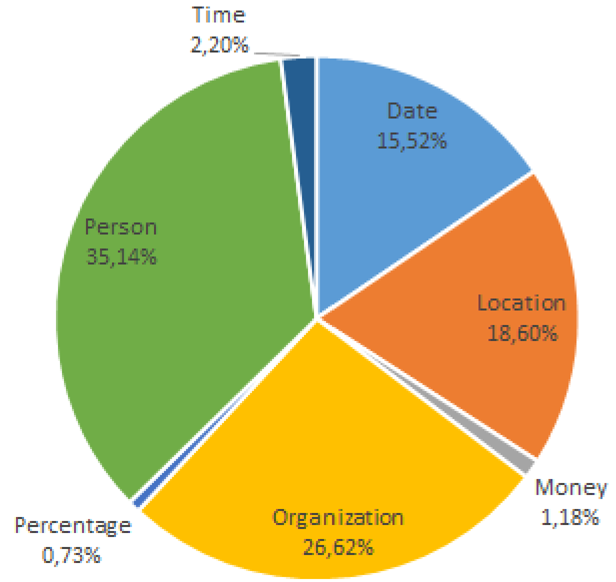
Understanding basic Interactions

Likes on Facebook.com, retweets on Twitter.com*

Both are used to spread posts of other users.

Interactions of 670K Facebook and 11M Twitter users [3].



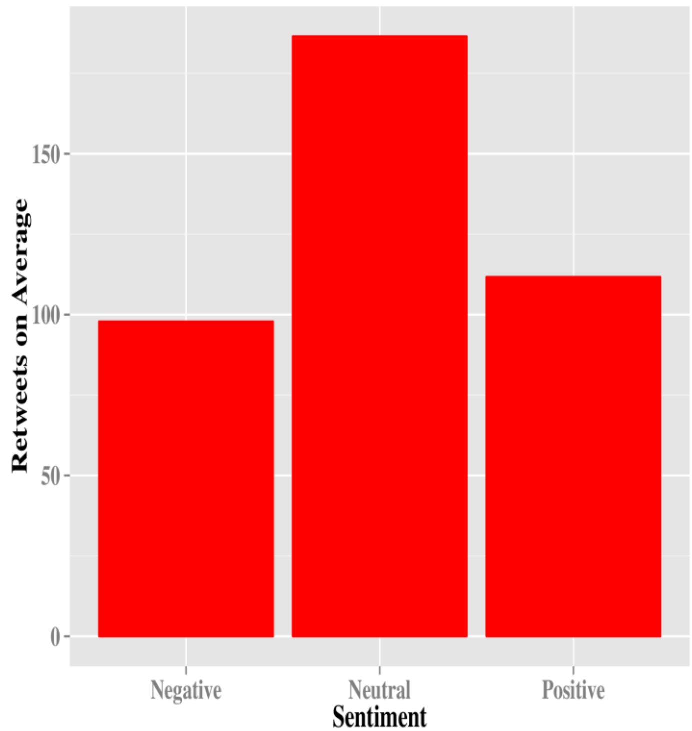


*Our data sets from Multi-dimensional Conversation Analysis across Online Social Networks, **IEEE SCA 2013**

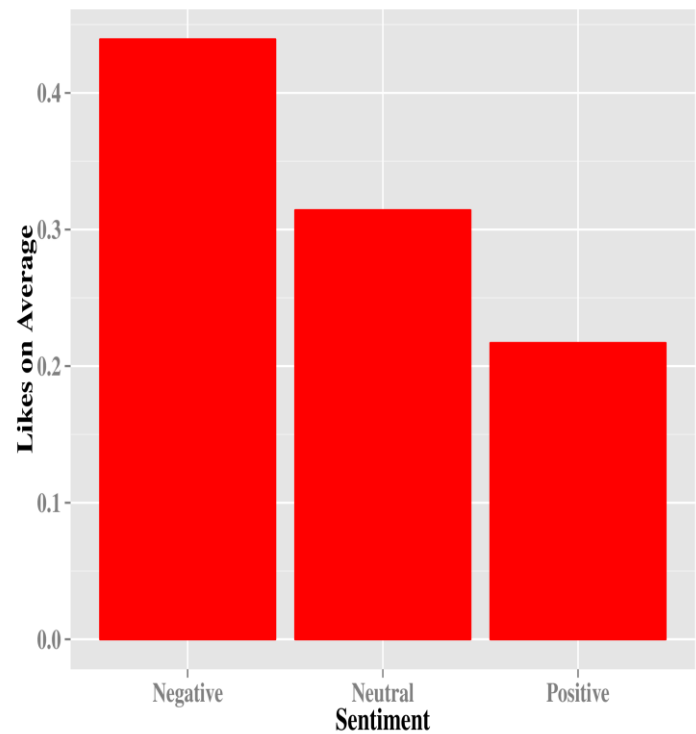
Understanding basic Interactions

Sentiments and like/retweet counts:

Twitter



Facebook



A like is not always a like:

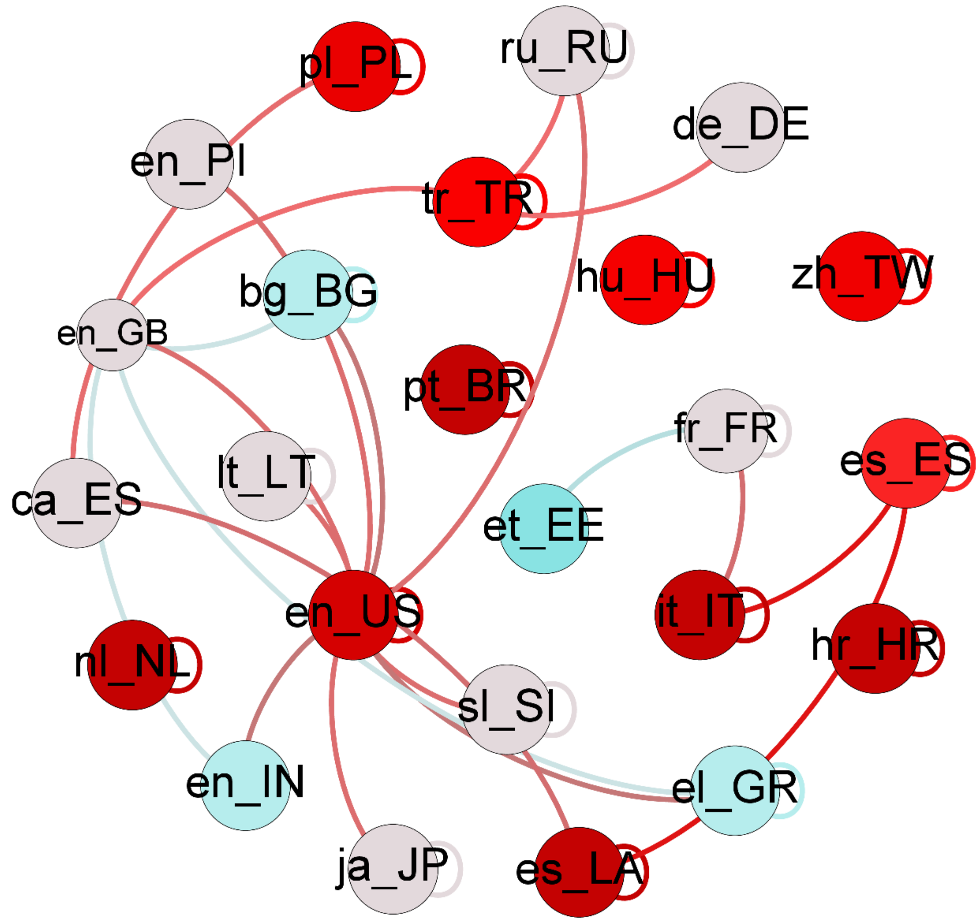
Lexi better not die tonight. :(

[96 likes]

Understanding basic Interactions

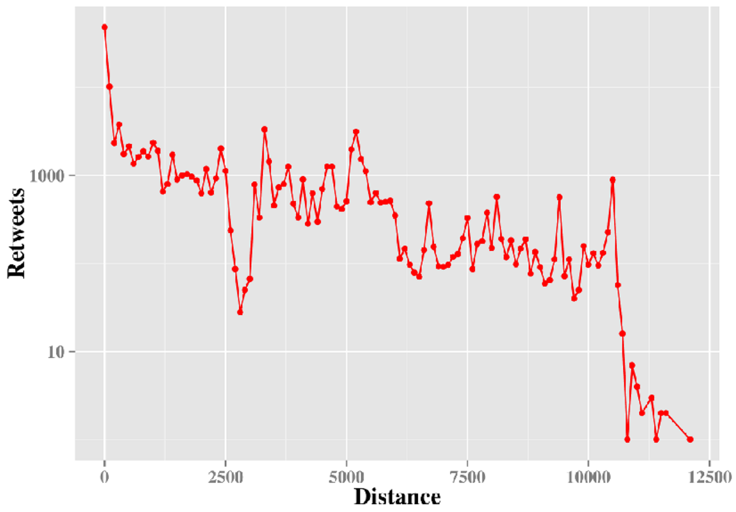
Facebook locale*

interactions

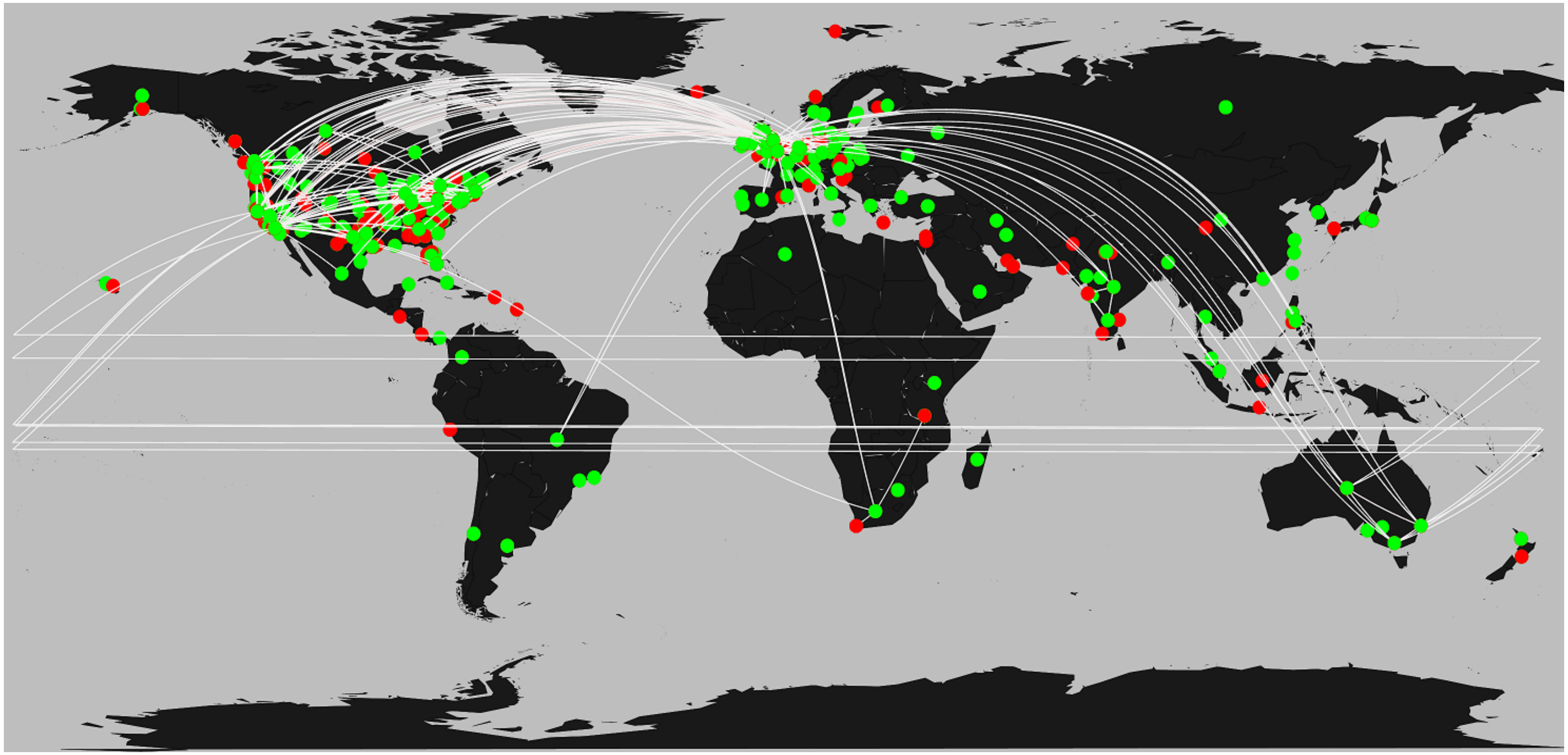


Locale: user interface language

Understanding basic Interactions



Twitter location* interactions



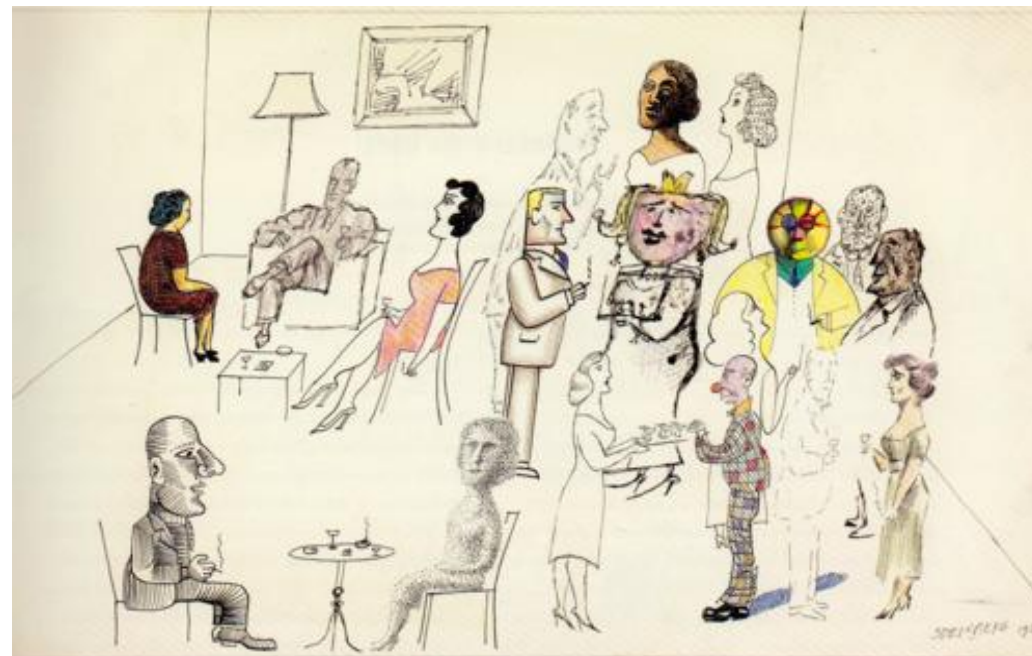
Location: bio location with Google maps API.

From micro to macro levels: Theoretical aspects

- Observing user generated data on social networks to understand interactions [1,2,4].
- We use two models from Sociology to explain user interactions:
  - Homophily: Being friends with similar people.
  - Heterophily: The tendency of individuals to collect in diverse groups.

Theoretical aspects

Homophily

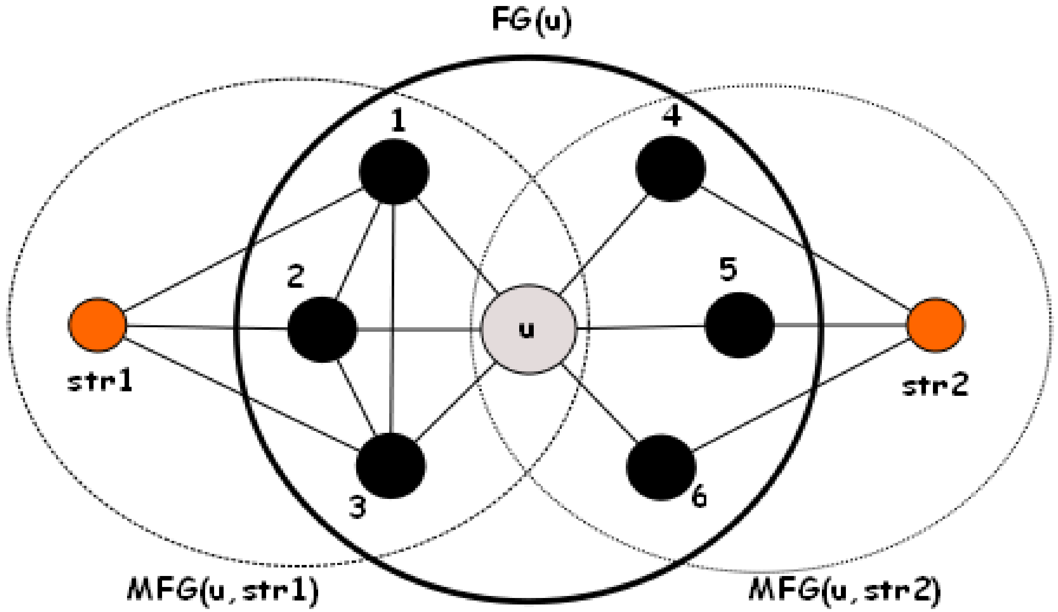


Heterophily

Theoretical aspects

- We use similarity measures to quantify homophily.
- Identification of user characteristics to find the similarity between users
  - On graph structure
  - With profile attributes
  - Working with incomplete profiles

Theoretical aspects – Network similarity

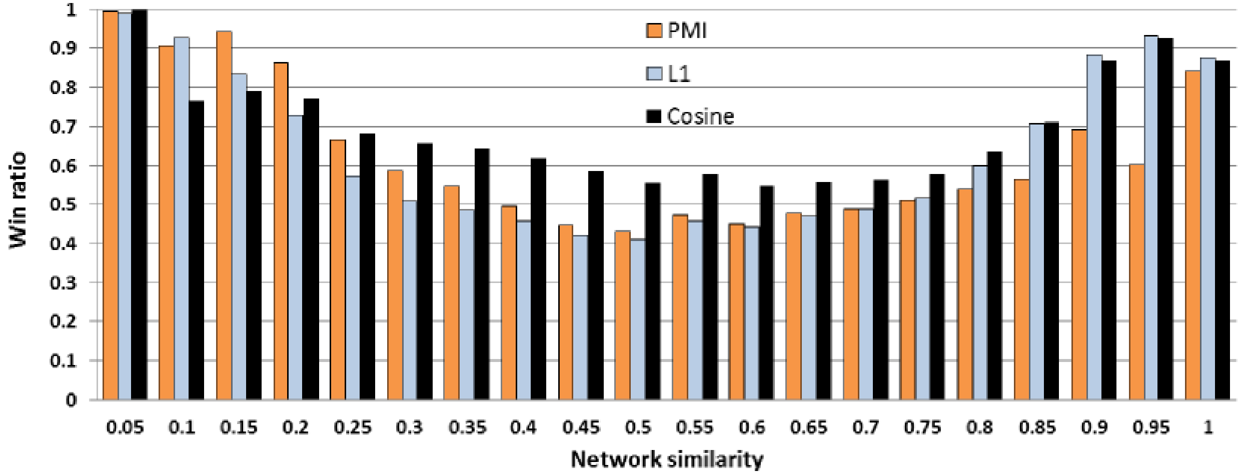


Mutual friends graph vs friendship graph

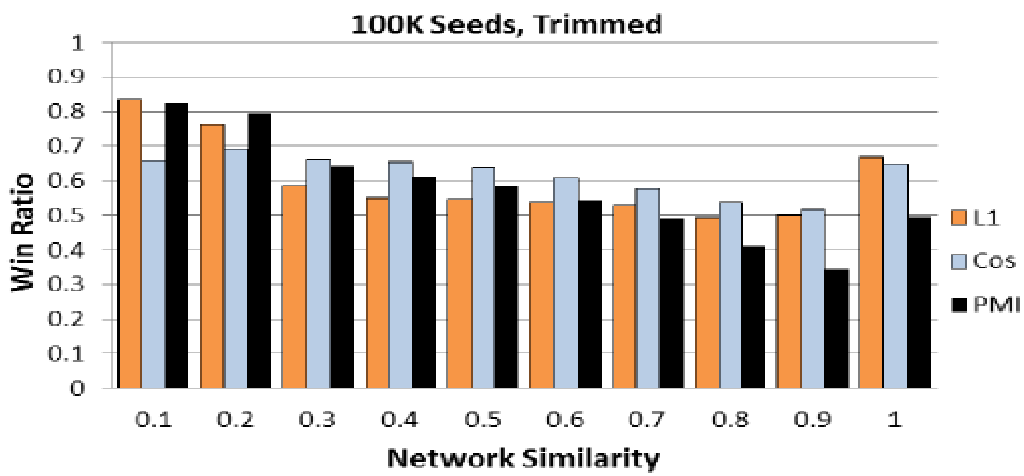
$$NS(u,x) = \frac{Log(|MFG(u,x).E|)}{Log(2\,|FG(u).E|)}$$

Theoretical aspects – Experimental results

Network similarity with undirected (Facebook, DBLP), directed (Youtube) and signed (Epinions) networks.



Link prediction on Facebook

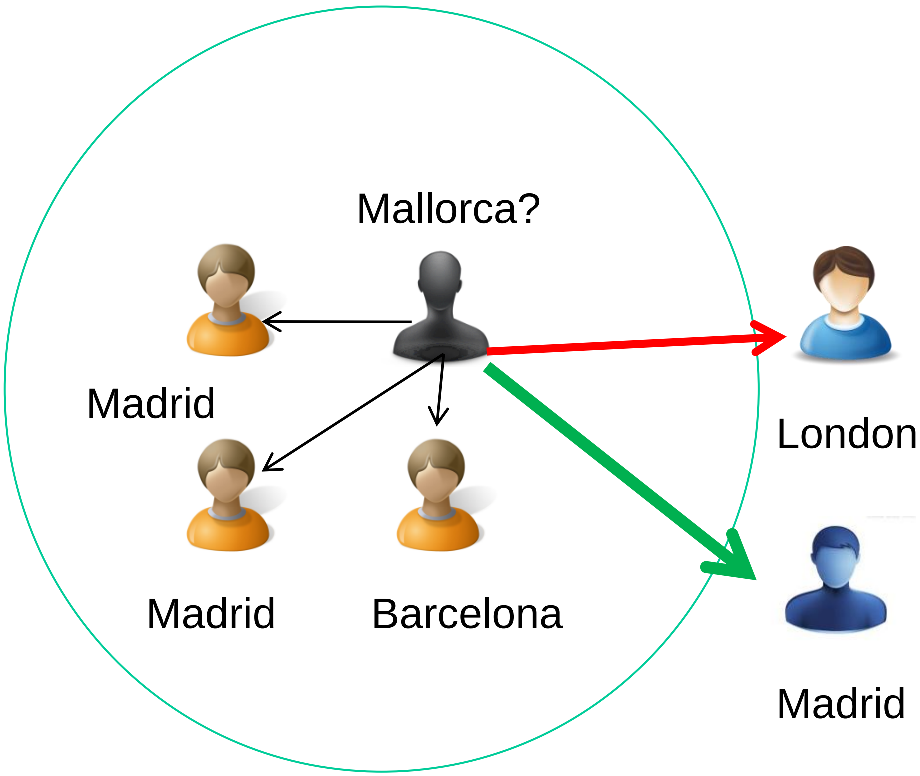


Link prediction on Youtube

*Data sets from Mislove et al. [10] and Leskovec et al. [11].

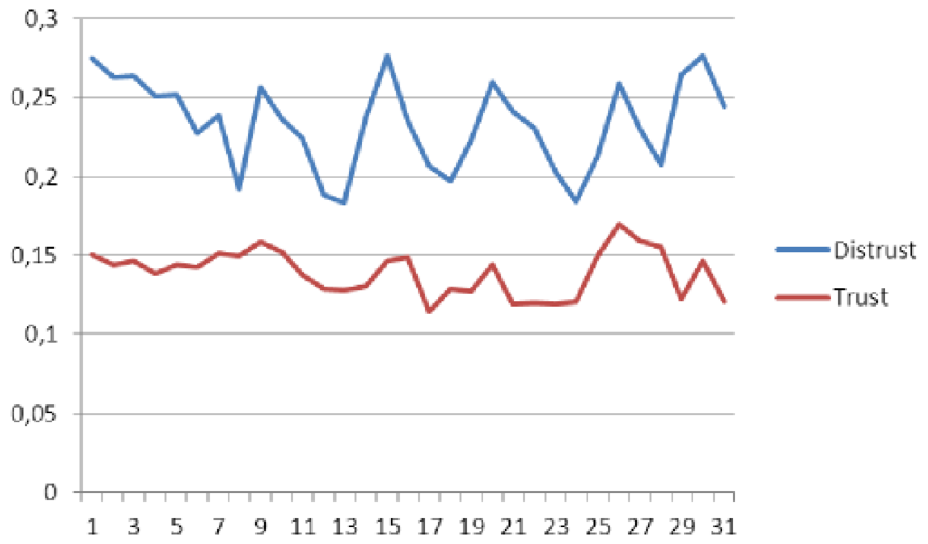
Theoretical aspects – Profile similarity

A social graph approach: Tell me who your friends are.



Theoretical aspects – Experimental results

We have used the profile similarity with undirected (Facebook, DBLP) networks.



Given trust/distrust ratings by profile similarity on Epinions

Outline 2

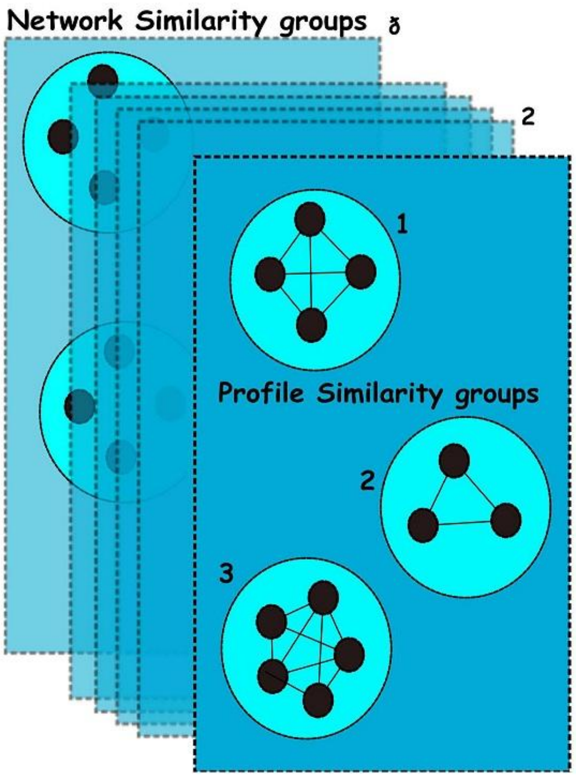
Interaction forecasts for

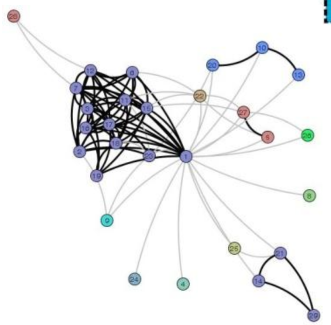
- Privacy [5,6]
- Anomaly detection [7]

Interactions in the privacy domain

- Things to Consider in a Risk Model [5]:
  - Subjective risk attitude of a user
  - Homophily
  - Heterophily
- Heterophily presents a user with some benefits like seeing others' profiles and social graphs.

Interactions in the privacy domain





Our idea is to cluster strangers (FOFs) based on their network connections and profiles.

Network Similarity Groups consist of disjoint sets of friends of friends

Profile Similarity Groups are prepared by using a custom clustering algorithm.

Interactions in the privacy domain

Random Walks:

Both labeled and unlabeled strangers are represented as nodes in a graph.

We assign edge weights based on strangers' profile similarity to the user.

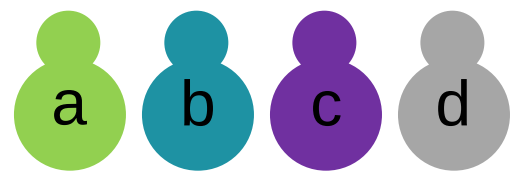
The classifier predicts similar labels for similar neighbors on the graph, by using a random walk strategy.

Interactions in the privacy domain

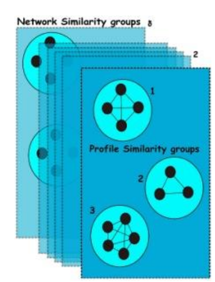
We solicit owner labels until a good accuracy is reached in successive iterations.

We receive labels for n strangers, and compute RMSE.

Pred. label				Iterations
2	2	2	2	0
1	1.5	1.3	1.8	1
	2	1.4	1.9	2
		1	1.85	3

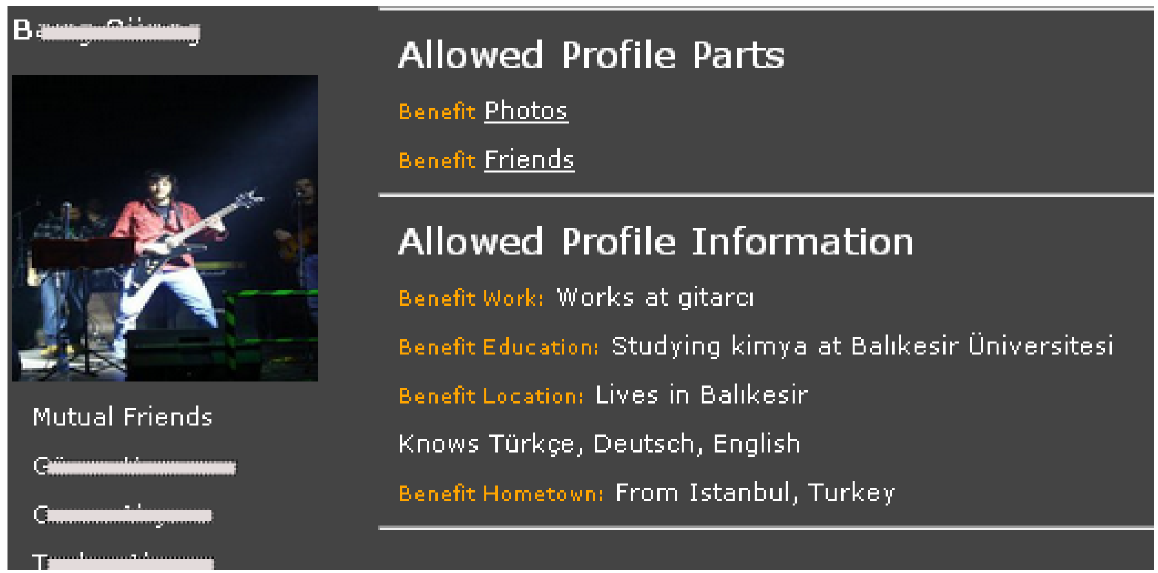


Furthermore we want stability in predictions. Predicted labels should not fluctuate too much. If they do, we ask for more labels.



Experimental results

- Sight application was given permission by 72 Facebook users, and 47 of them labeled strangers for our experiments.



- 32 users were males and 15 users were females, all aged in the range   [18-35]. 172,091 stranger profiles, and 4,013 user given risk labels

Experimental results: Mined v.s. User Given Weights for Benefits

User given weights do not really reflect the labeling pattern.

user given benefit weights

Importance	1	2	3	4	5	6	7	Avg
Photos	21	8	6	4	3	0	5	0.27
Education	11	9	4	3	10	4	6	0.143
Work	8	7	9	7	5	7	4	0.140
Friends	2	10	7	6	6	8	8	0.13
Hometown	0	7	9	11	6	9	5	0.11
Location	1	4	8	9	11	8	6	0.092
Wall	4	2	4	7	6	11	13	0.091

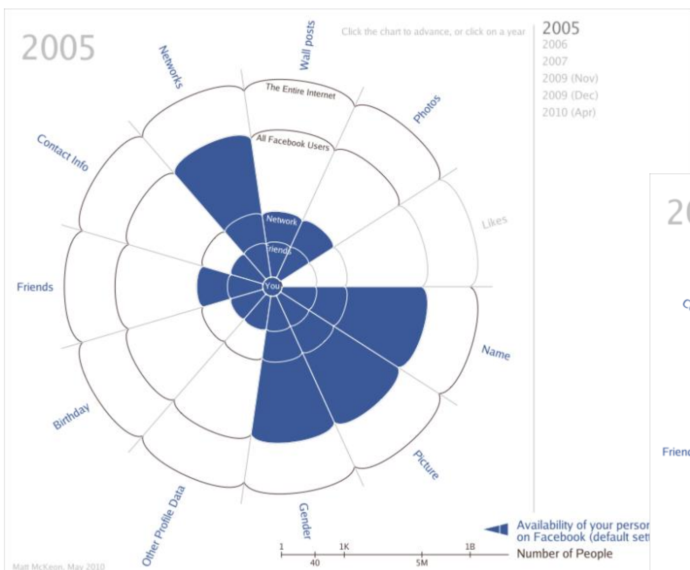
mined weights

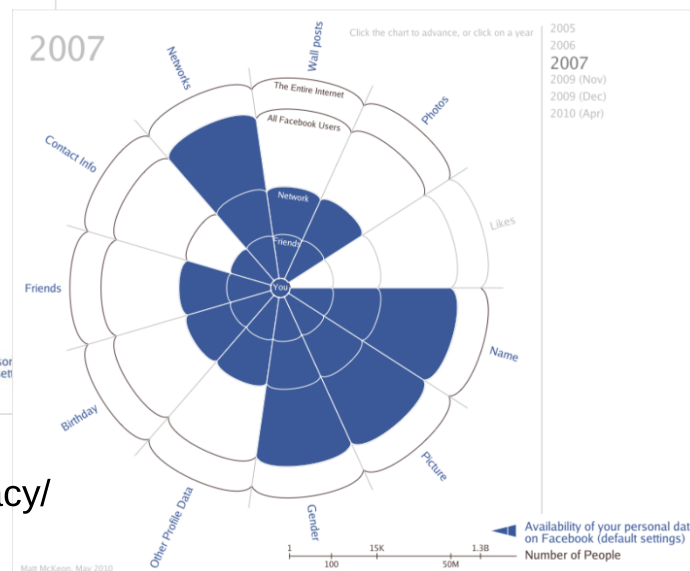
Item	Avg
Hometown	0.155
Friends list	0.149
Photos	0.147
Location	0.143
Education	0.139
Wall	0.133
Work	0.132

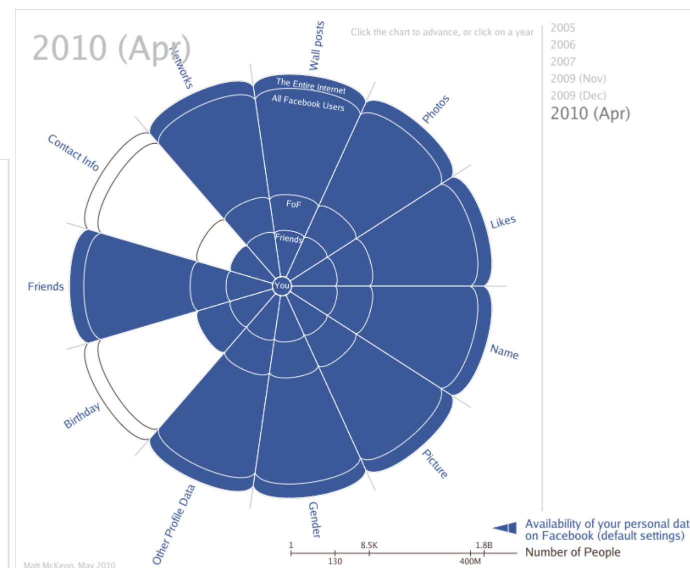
Experimental results: Visibility for benefits

- Once we learn the user’s risk attitude, these differences make it easier to generalize risk labels to unlabeled strangers.

	Wall	Photo	Friend	Loc	Edu.	Work	Hometown
Male	25%	88%	56%	42%	35%	20%	41%
Female	16%	87%	47%	32%	28%	12%	30%







http://mattmckeon.com/facebook-privacy/

Experimental results: Visibility for benefits

Benefit values depend very much on user characteristics, and different locale users have different settings. Similarly, there are differences between male and female profiles.

Item visibility for countries

	Wall	Photo	Friend	Loc	Edu.	Work	Hometown
TR	20%	84%	41%	36%	31%	15%	32%
DE	20%	77%	46%	34%	17%	17%	34%
US	17%	89%	52%	42%	34%	18%	37%
IT	27%	92%	68%	32%	38%	14%	41%
GB	12%	91%	46%	38%	25%	17%	32%
ES	22%	87%	63%	37%	28%	13%	37%
PL	31%	95%	72%	33%	23%	13%	31%

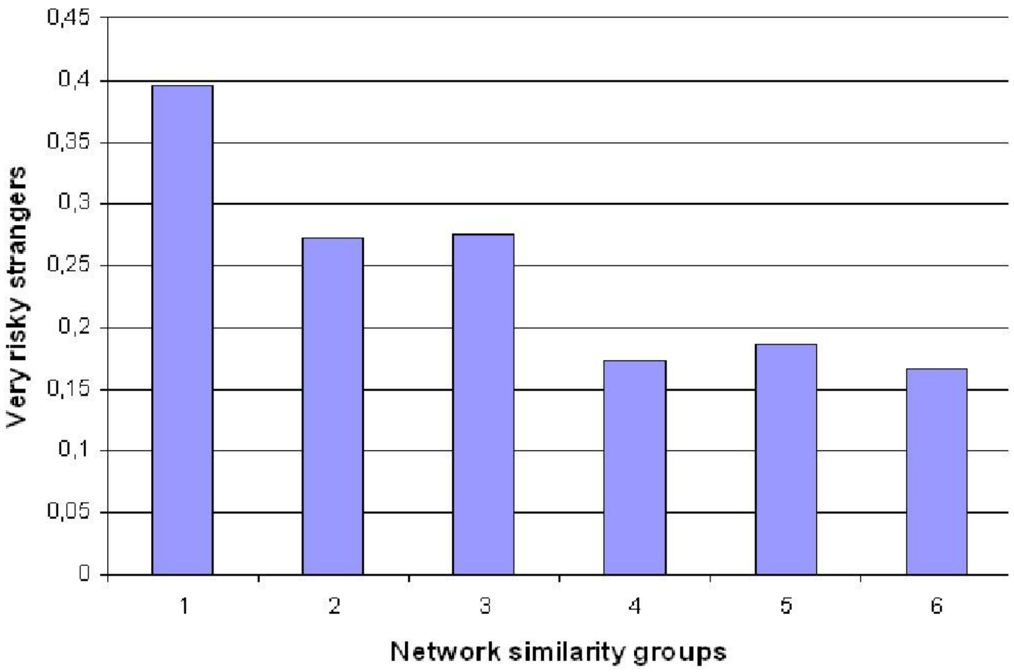
Item visibility correlations of countries

	Turkey	Germany	Spain	Britain	Poland	Italy	US
Turkey		0.95	0.94	0.98	0.90	0.93	0.98
Germany	0.95		0.97	0.97	0.94	0.93	0.96
Spain	0.94	0.97		0.95	0.97	0.98	0.96
Britain	0.98	0.97	0.95		0.90	0.92	0.99
Poland	0.90	0.94	0.97	0.90		0.96	0.91
Italy	0.93	0.93	0.98	0.92	0.96		0.94
US	0.98	0.96	0.96	0.99	0.91	0.94	

Experimental results: Stability and RMSE

Predictions need as little as 3 rounds of labeling.

Why are very risky labels given less often for higher network similarity groups?



Privacy: Risks of Friendships

- A friend is said to have a positive/negative impact on the social network experience of a user [6].

- Our clue is the risk labels given to friends of friends.

- We define four phases:
  - Baseline estimation for friend of friends in terms of risk
  - But we have to generalize friends of friends for more support.
  - Learn friend impacts on risk scores of friends of friends.
  - Assign risk labels to friends by analyzing the sign of his/her impact

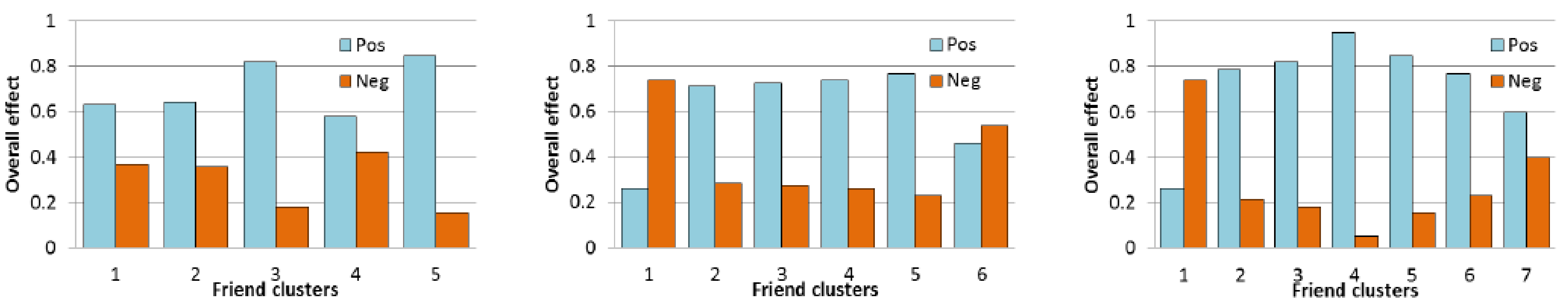
$$P(l = risky) = \pi = \frac{e^{(\alpha + \sum \beta_k X_k)}}{1 + e^{(\alpha + \sum \beta_k X_k)}}$$

$$\hat{l}_{us} = b_{us} + \sum_{FC_i \in FC} FI(FC_i, SC_j) \times Past(u, s)$$

Privacy: Risks of Friendships

- Cross validation and coefficient of correlation to choose best values for how many types of friends and friends of friends there are.

- We found 6 types of friends and 28 types of friends of friends to be the optimum setting.



(a) 5 friend clusters (b) 6 friend clusters (c) 7 friend clusters

Percentage of positive and negative impact values for friend clusters.

Privacy: What we learned?

- Friends and friends of friends can be generalized very well.

- Even friendships on undirected networks are becoming random (That we are connected to more friends than we know in real life will become more problematic in future).

- Visibility is a trade off that users are willingly taking.

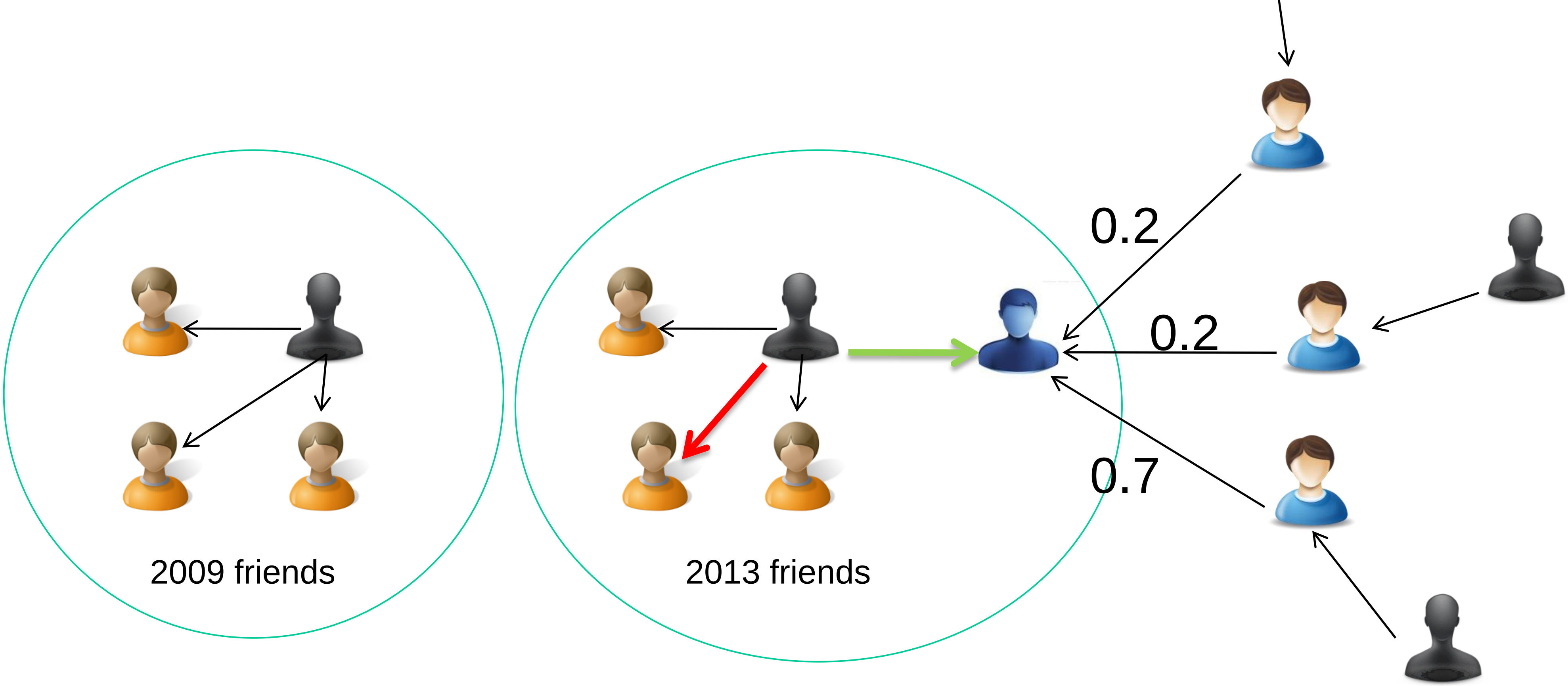
- Reaching out to very different people is not very common.

Anomaly work

- Analyze data interest patterns of social network users in time [7].
- Understand individual and collective user behavior on social networks.
- Two snapshots from the Twitter network in 2009 and 2013.
- Identify users whose data interests diverge from collective behavior.

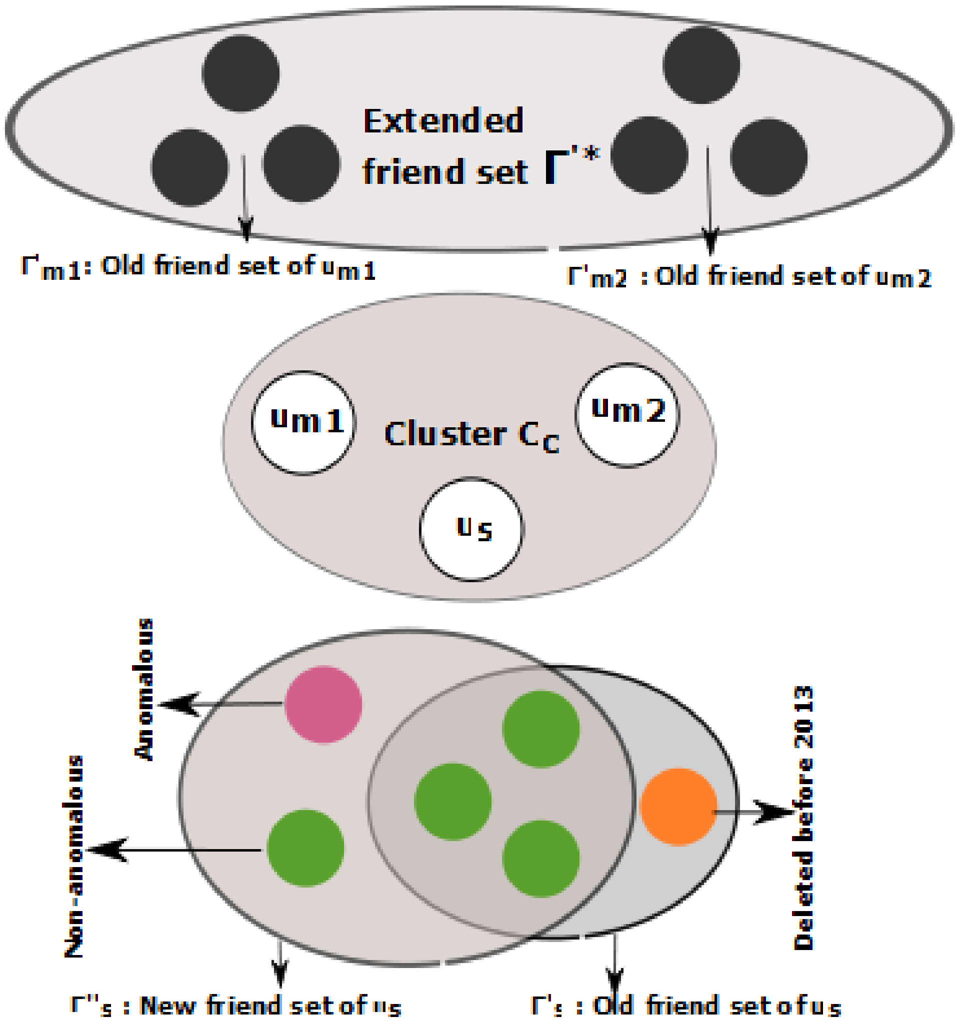
Anomaly work

- Working with two snapshots of Twitter.



Anomaly work

- Working with two snapshots of Twitter.



1- Individual anomaly: Deviation from past behavior

2- Collective anomaly: Deviation from collective behavior

Deviation is measured in terms of topic divergences.

Anomaly work

- LDA (Latent Dirichlet Allocation) to profile users.
- US Congress members:

Tweets: tweetLDA

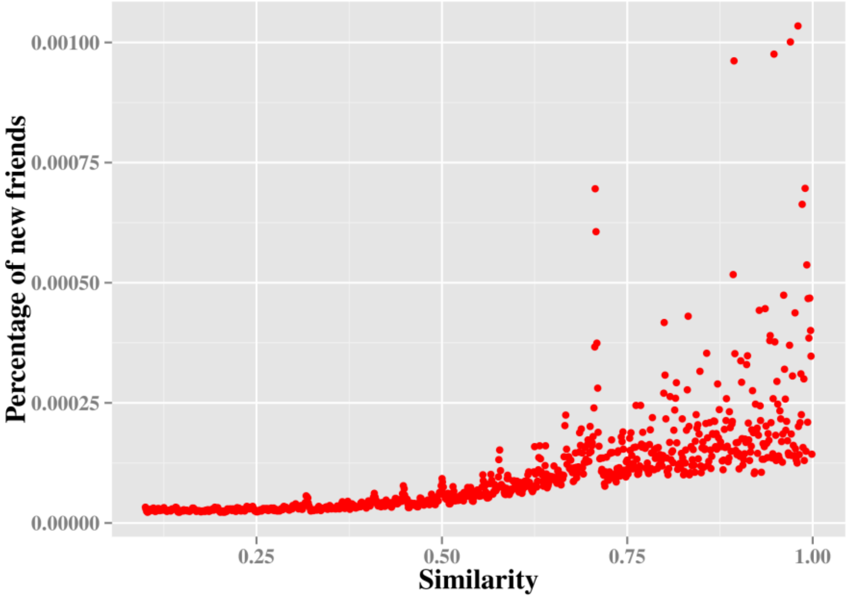
Democrat	Republican
Obama, president	Obama, president
city, park	tax, year
business, innovation	art, photo
energy, solar	war, Israel
great, love	live, show

Bios: bioLDA

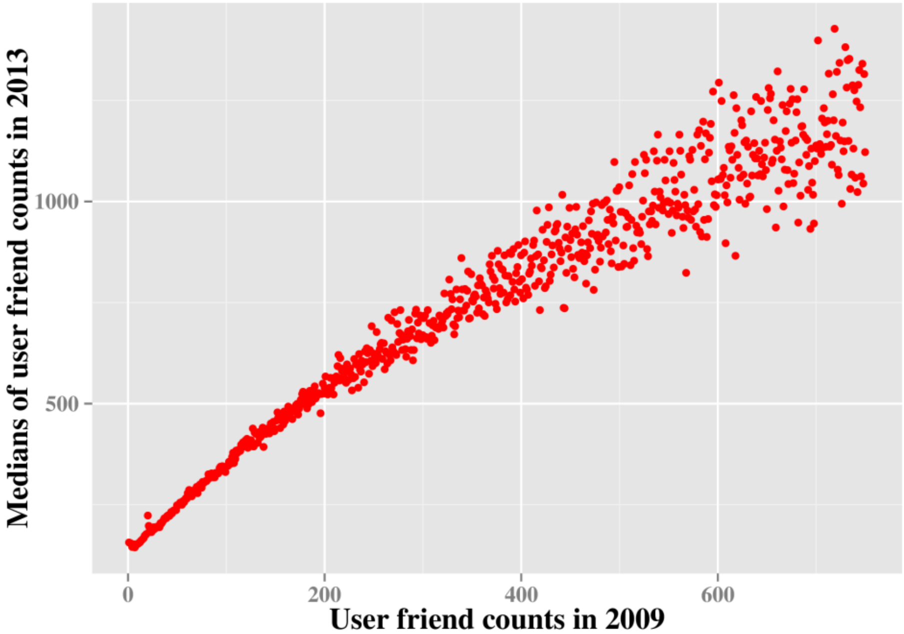
Democrat	Republican
city, area	city, area
official, account	official, account
news, latest	conservative, christian
conservative, christian	official, love
public, views	Facebook, Youtube

Anomaly work

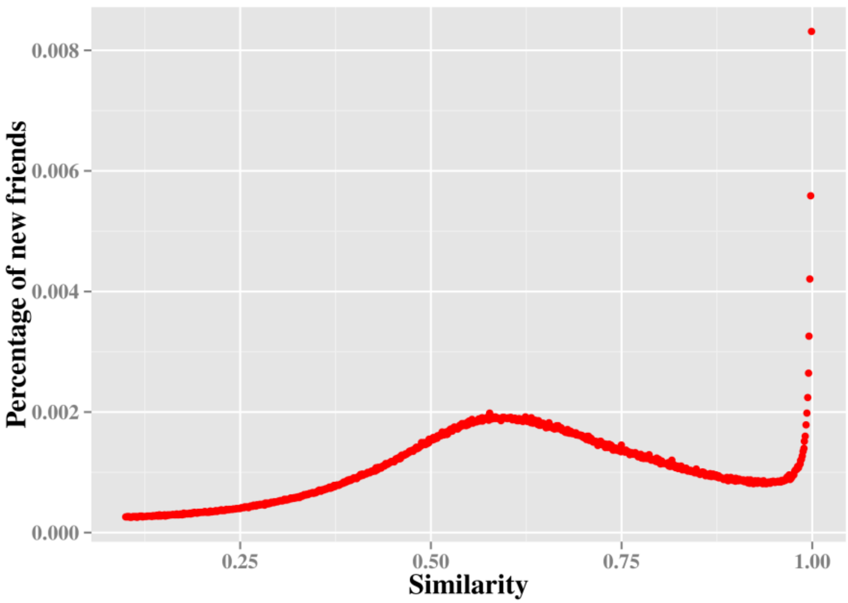
BioLDA



How friendships change?



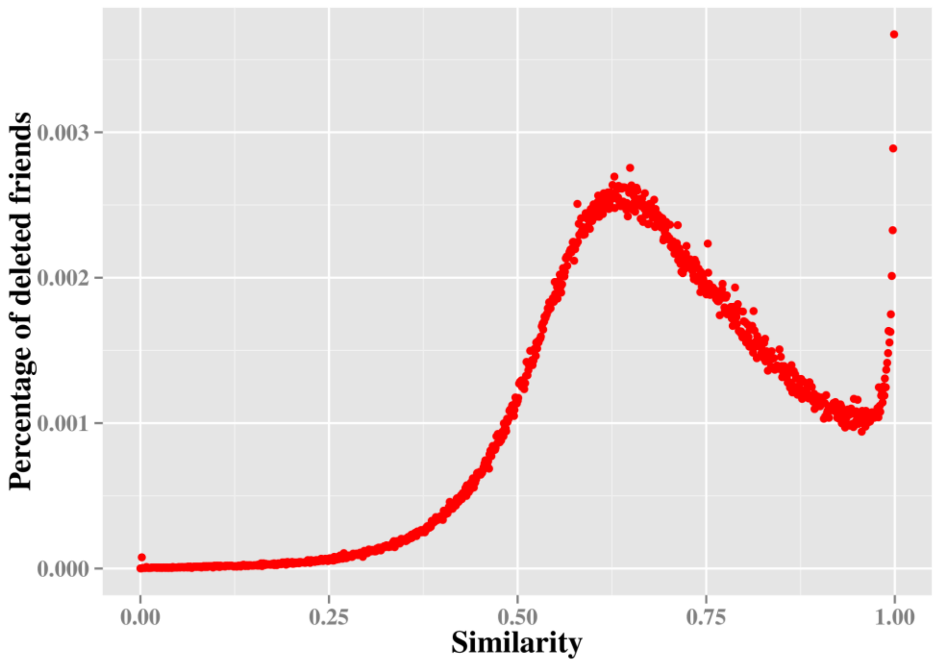
Similarity of new friendships.



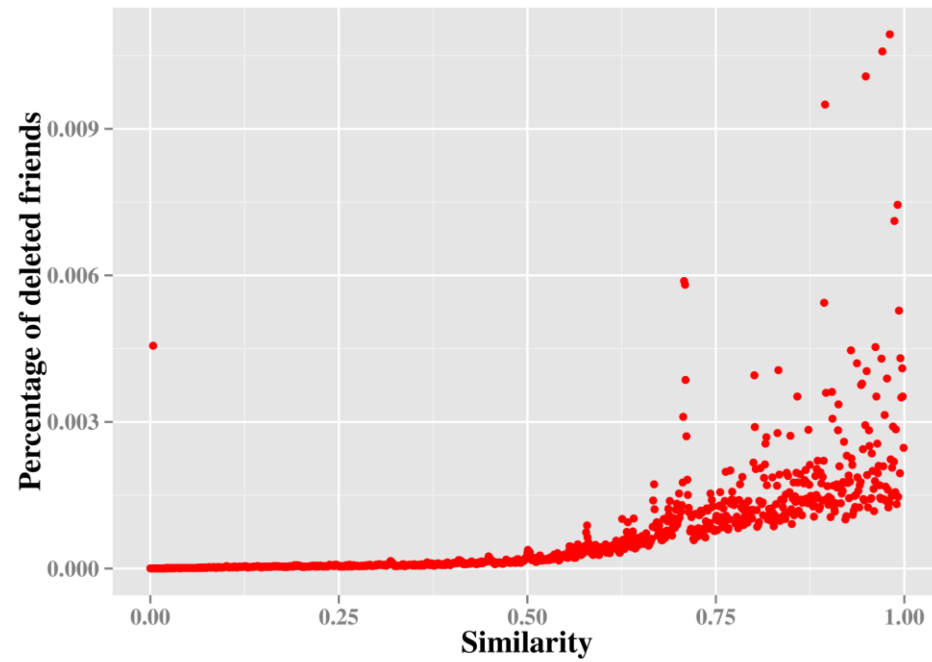
TweetLDA

Anomaly work

How deleted friendships look like.



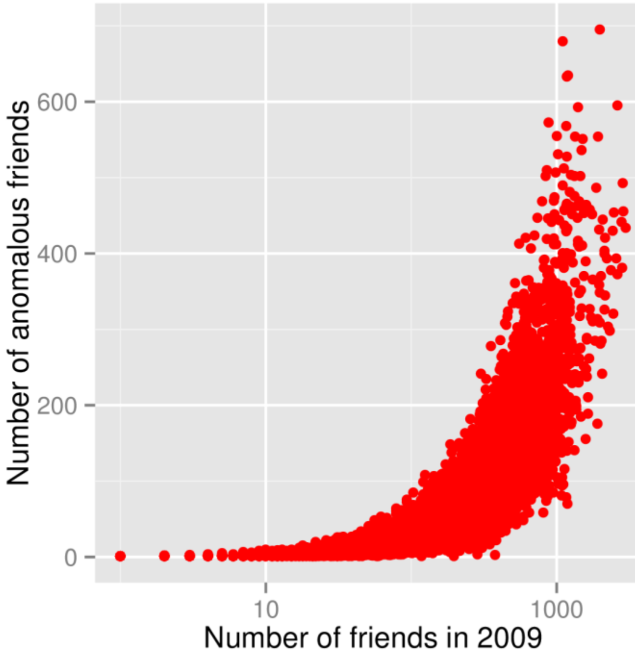
TweetLDA



BioLDA

Anomaly work

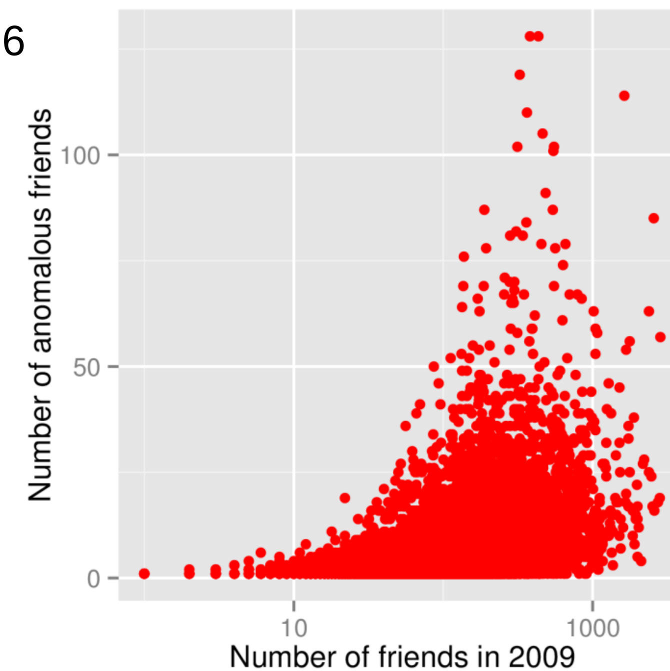
Threshold ξ=0.7



How anomalous friendships look like.

ξ	% users	% new friends judged as anomaly
0.1	0.20	0.01
0.2	0.40	0.01
0.3	0.60	0.02
0.4	0.76	0.04
0.5	0.82	0.08
0.6	0.83	0.15
0.7	0.83	0.22

Threshold ξ=0.6



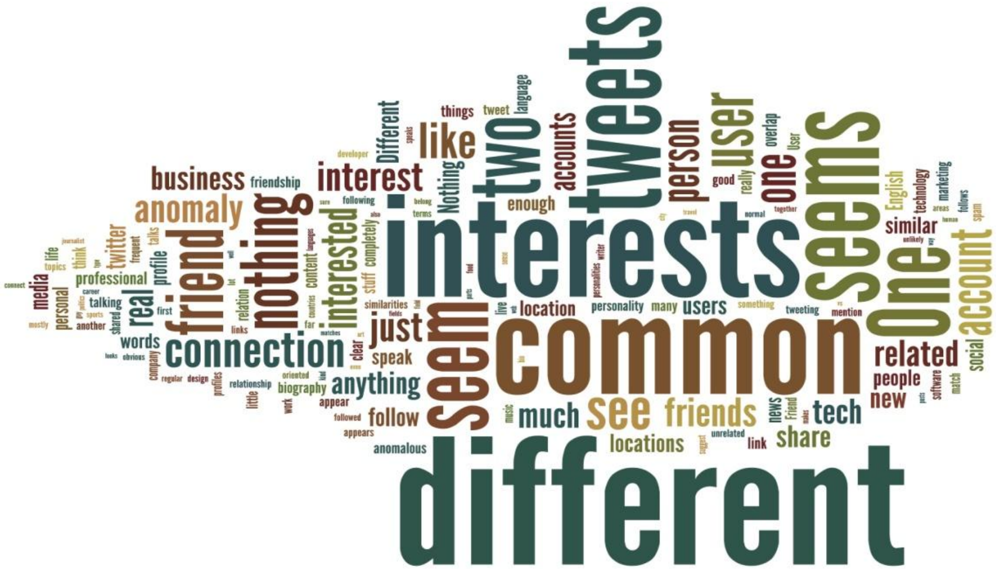
Anomaly work - Validation

amazon mechanical turk™
Artificial Artificial Intelligence

No, it is not an anomaly

Explanation Category	Freq.	Example
Same interests	29.4%	Language difference, but both are interested in public transport and trains
Same professions	16.6%	Both accounts are speakers and deal with the public.
Follows his/her interest	10.8%	Person likes geek and digital things, what he followed is a popular internet meme.
Same location	10.6%	Makes sense that a lawyer from Philade(l)phia would follow a local chef and restaurant owner.
Same backgrounds	6.0%	I know these people mentioned and they are real leftists. They are at least in solidarity.

Anomaly work - Validation



amazon mechanical turk™
Artificial Artificial Intelligence

No, it is not an anomaly

Explanation Category	Freq.	Example
Different interests	25.2%	E*** seems more interested in writing, nomad is more into marketing.
Different background	16.0%	One is stripper, and the other one is a working busy person
Different location	11.1%	H*** is from Netherlands, J** visited and probably met H***. He is not a typical friend.
Different profession	10.3%	One is a poet and one is a coder.
Unlikely interest	9.0%	M***** is a businesswoman and is unlikely to be interested in cats and products for cats

Anomaly work - What we learned?

Using both user generated text data and network connections can help us detect anomalous user behavior.

Anomaly detection models could be used with as few as 5 recent tweets of profile users.

Almost all users show anomalous behavior in long term (but there is a but.).

Non-anomalous friendships outweigh anomalies as expected (User interests are not so volatile).

If users assume that by not writing any tweets they protect their privacy, they are wrong.

Theoretical aspects 1

[1] C.G. Akcora, B. Carminati, and E. Ferrari.

Network and profile based measures for user similarities on social networks.

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[2] C.G. Akcora, B. Carminati, and E. Ferrari.

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Theoretical aspects 2

[3] William Lucia, CG Akcora, E. Ferrari

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[4] C.G. Akcora, E. Ferrari.

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Privacy works

[5] CG Akcora, B. Carminati, E. Ferrari.

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[6] CG Akcora, B. Carminati, E. Ferrari.

Risks of Friendships on Social Networks

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Anomaly work

[7] CG Akcora, B. Carminati, E. Ferrari, M. Kantarcioglu.

Detecting Anomalies in Social Network Data consumption.

Submitted to the Springer Journal On Social Network Mining and Analysis (SNAM)

Other work

[8] C.G. Akcora, B. Carminati, and E. Ferrari.

Building virtual communities on top of online social networks.

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[9] C.G. Akcora, E. Ferrari.

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Thanks for attending!

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[11] Massa and P. Avesani. **Trust-aware bootstrapping of recommender systems.** In Proceedings of ECAI 2006 Workshop on Recommender Systems, pages 29-33.