ONLINE SOCIAL NETWORKS

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WHERE ?

- **Social media**
- Web content in general
- Other internet protocols and applications

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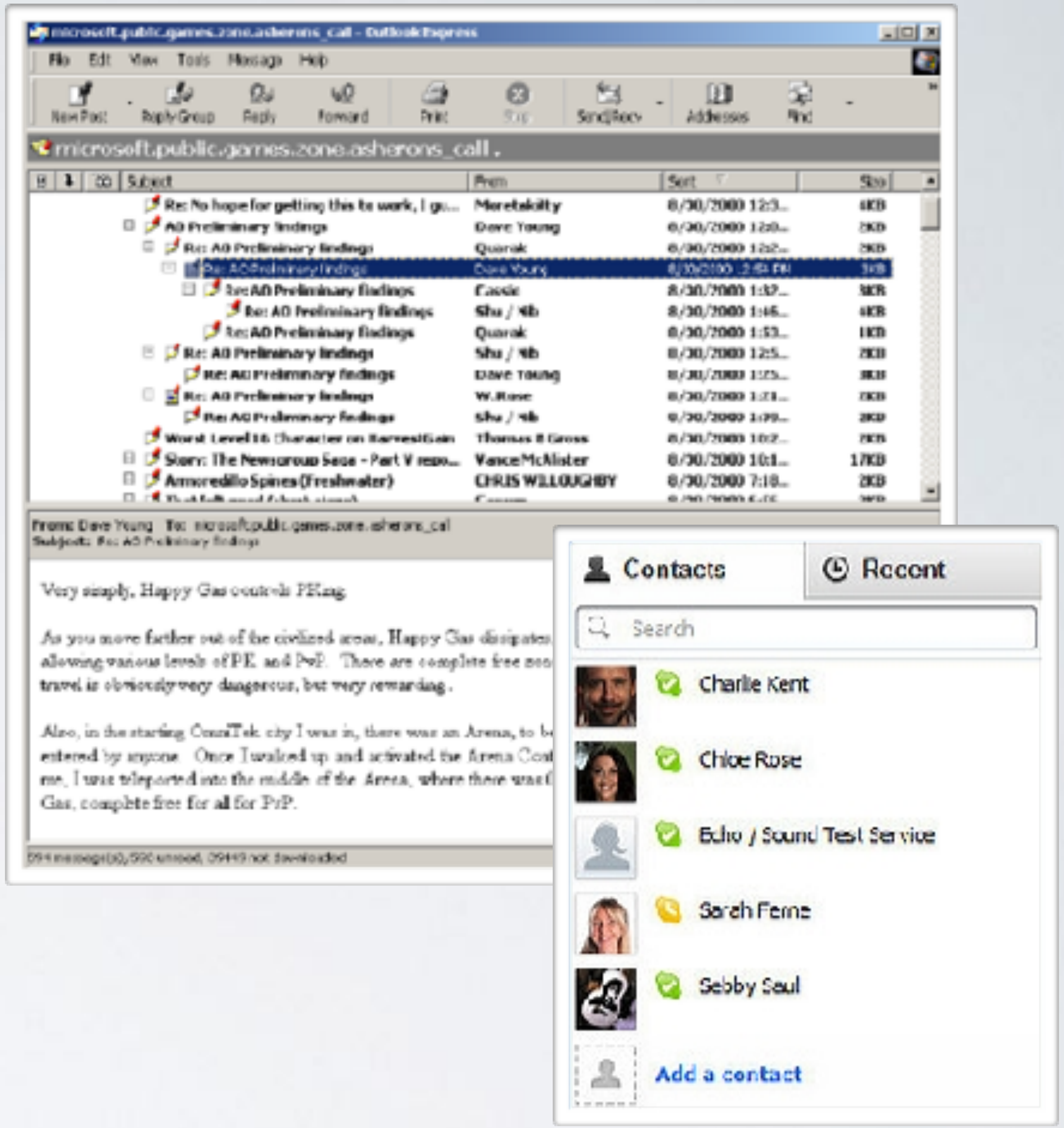
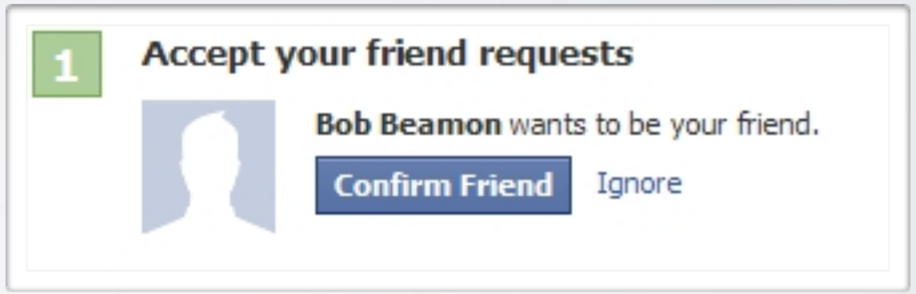


- Social media
- Web content in general
- **Other internet protocols and applications**

USENET (discussion forums), emails, messengers

WHAT ?

- **Confirmed reciprocal connections**
- Formal links
- Implicit networks



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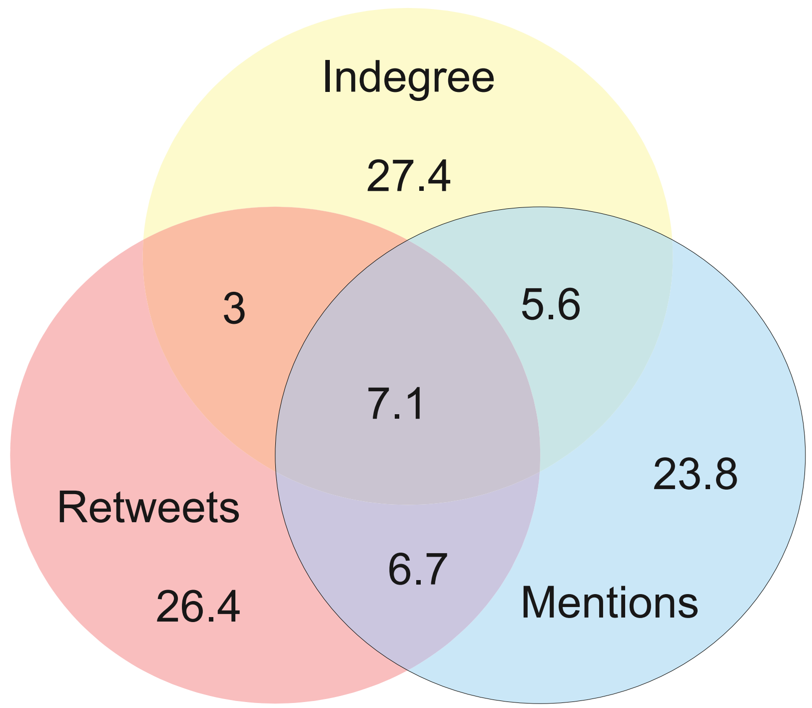


Venn diagram of the top-100 influentials

(Cha, Haddadi, Benevenuto, Gummadi, 2010)

WHAT ?

"Expressing Social Relationships on the Blog through Links and Comments"

(Ali-Hasan, Adamic, 2005)

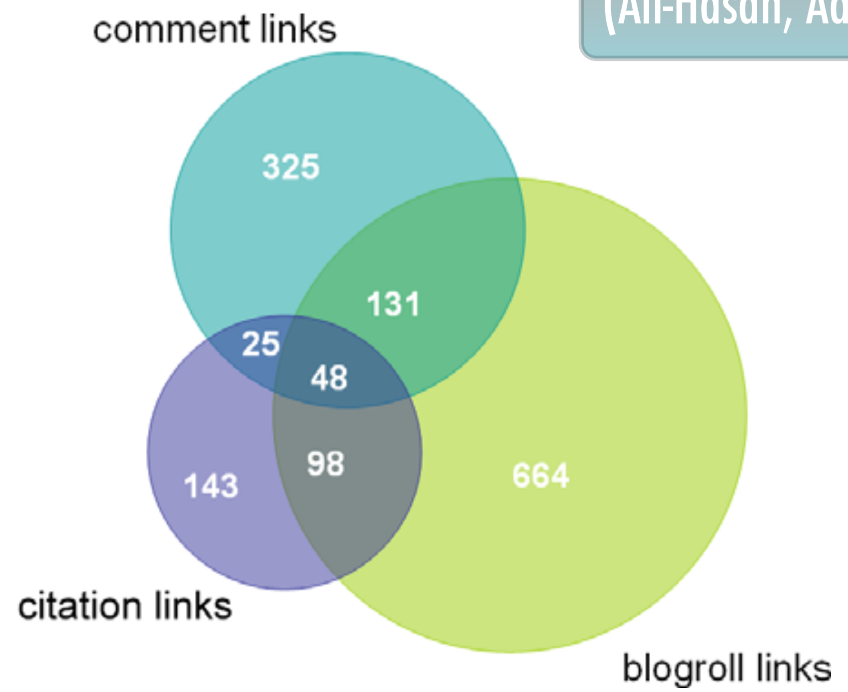
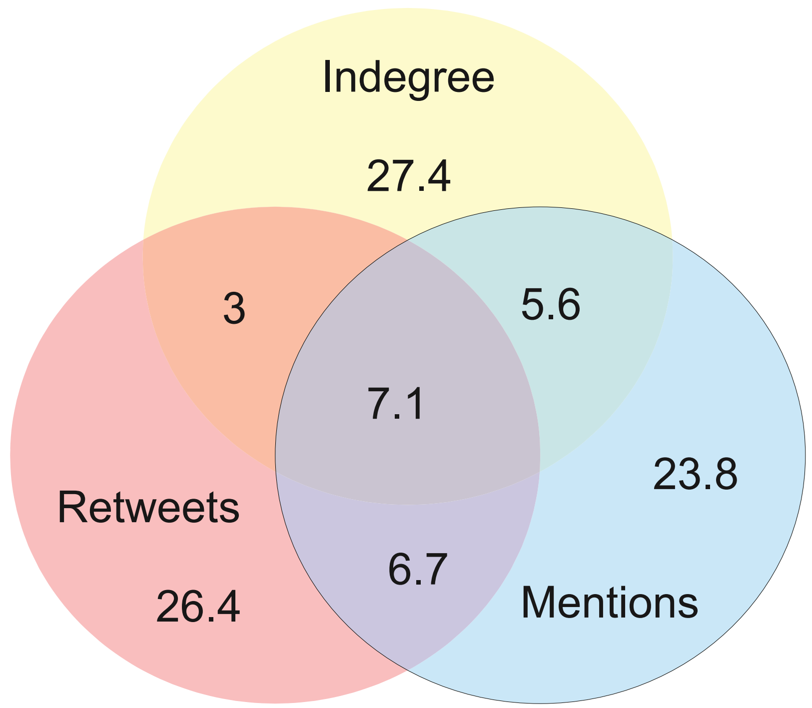


Figure 1. Venn diagram illustrating the overlap in different types of blog ties (comments, blogrolls, and citations) for Kuwait Blogs.

ocal connections

- **Implicit networks**



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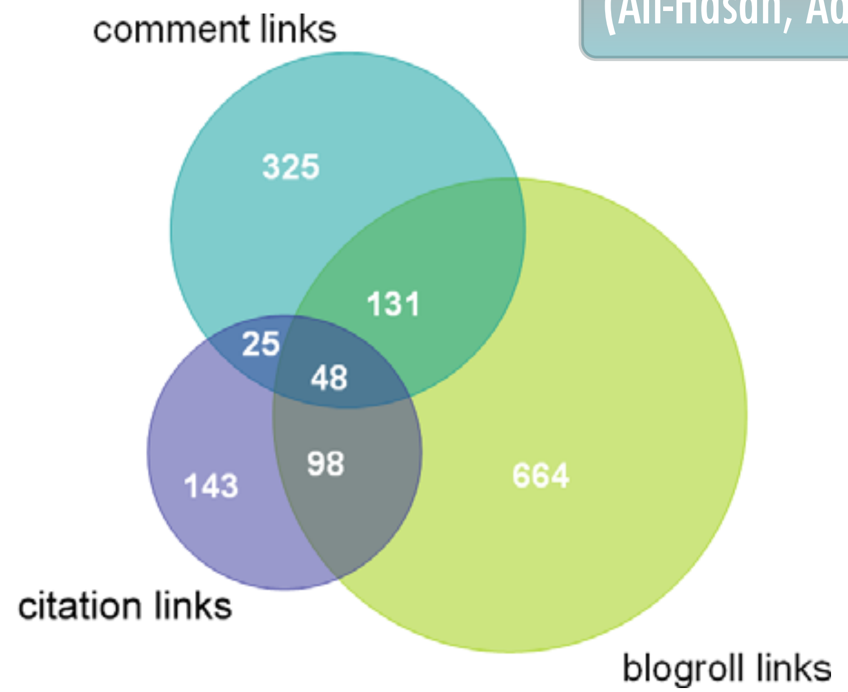

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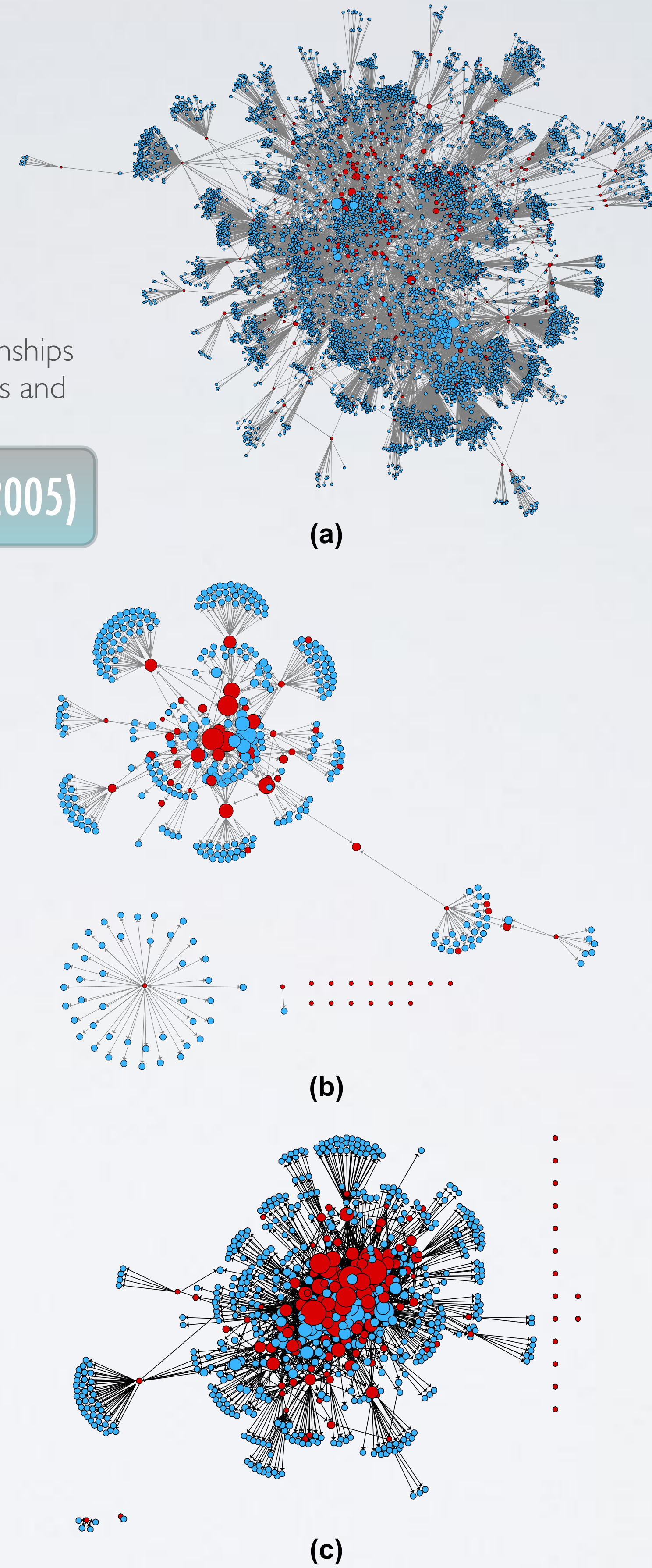


Figure 3. Blogroll and citation links for (a) DFW, (b) UAE, (c) Kuwait. Nodes are colored red if they are in the community and are sized by indegree.

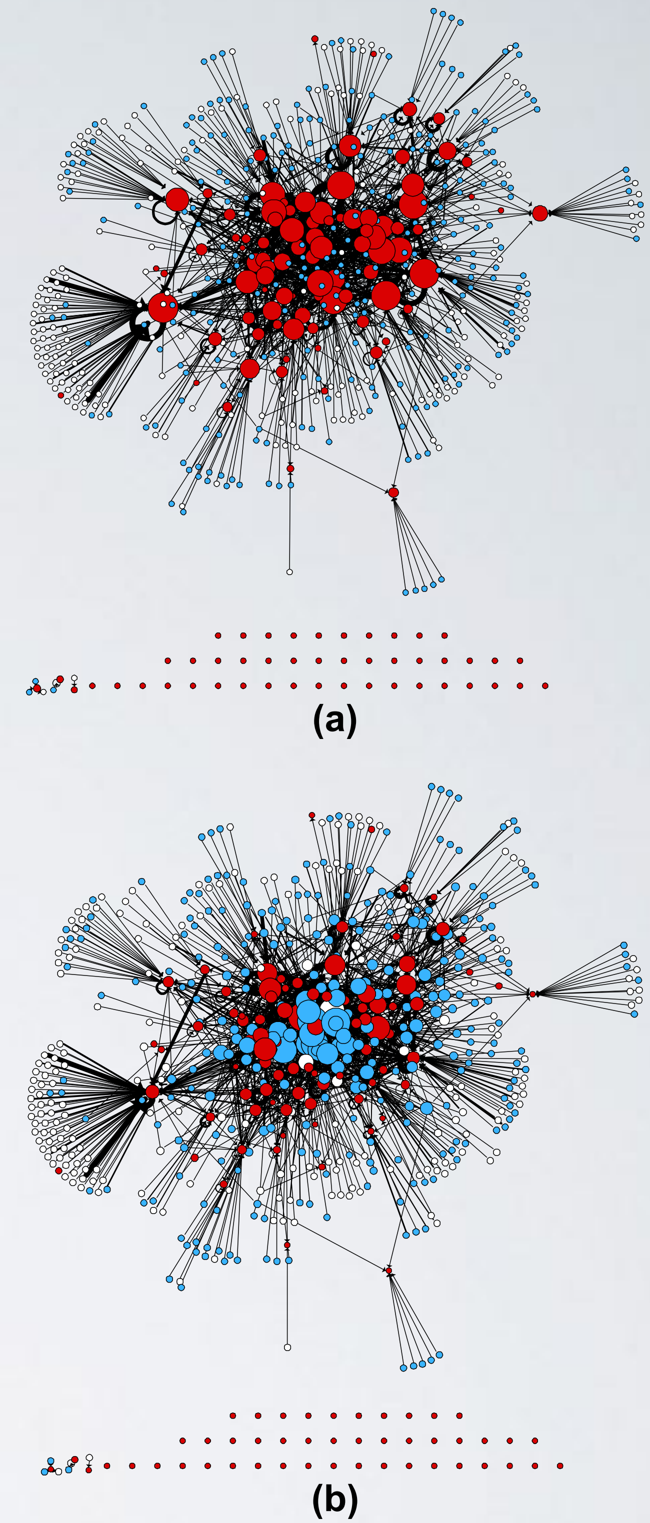
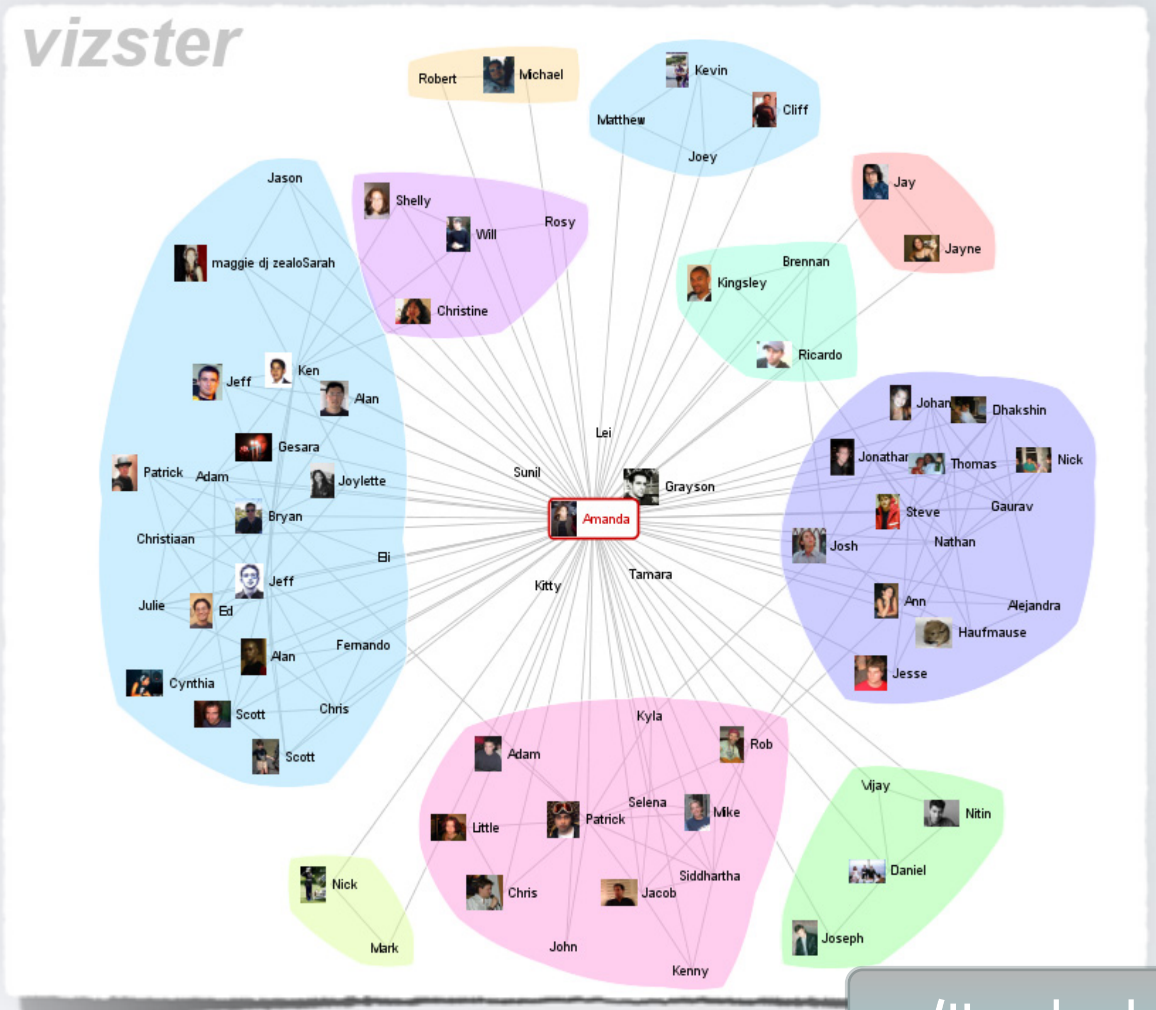


Figure 5. The network of comments in Kuwait blogs. Nodes are sized by (a) how many people commented on their posts (indegree) and (b) how many posts they left comments on (outdegree). The color of the nodes corresponds to their status in the community: Kuwait Blogs are red, other blogs are blue, and anonymous authors or non-bloggers are white.

COLLECTION PROTOCOLS

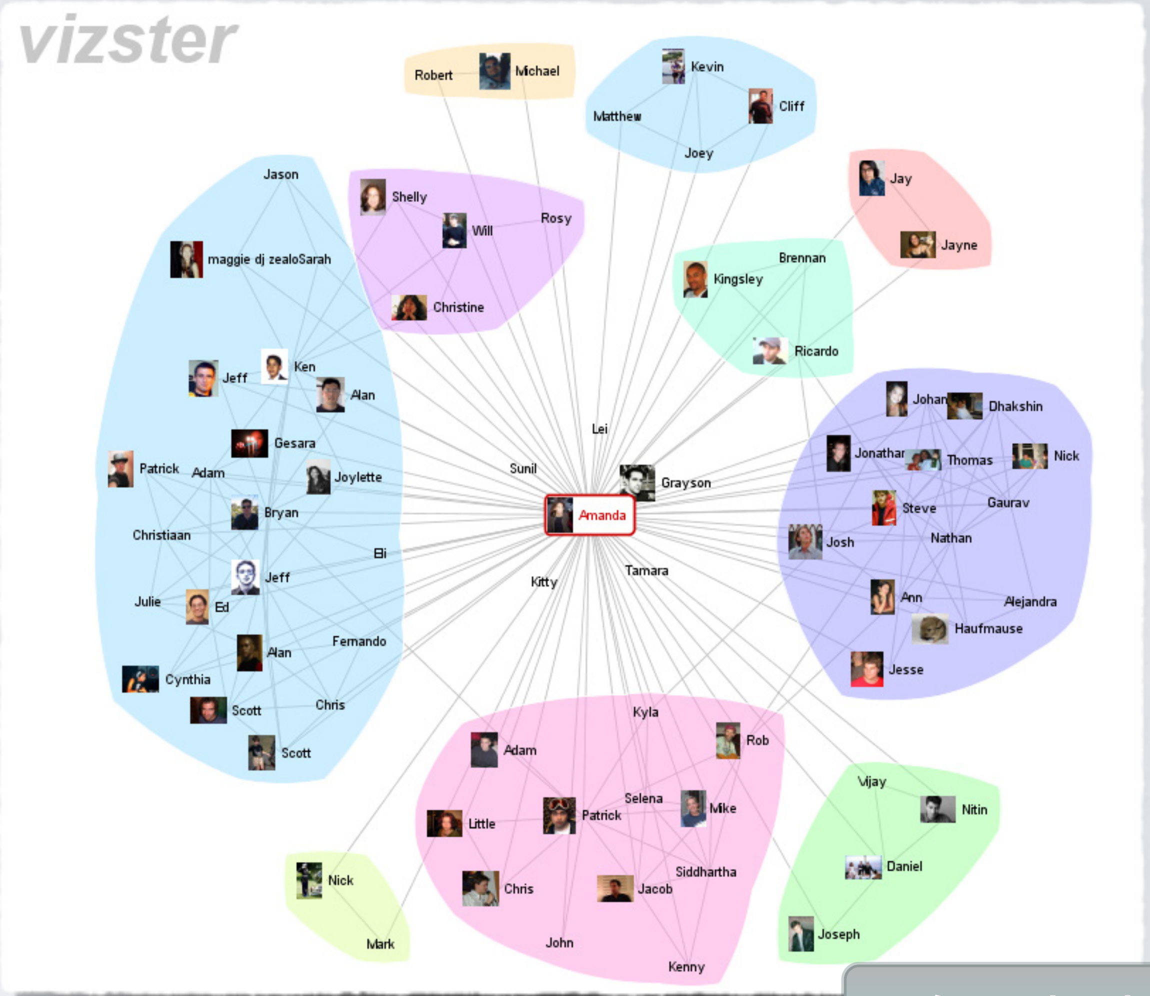
- **ego-centered**
- snowball
- holistic



(Heer, boyd, 2005)

"Vizster: Visualizing Online Social Networks"

COLLECTION PROTOCOLS



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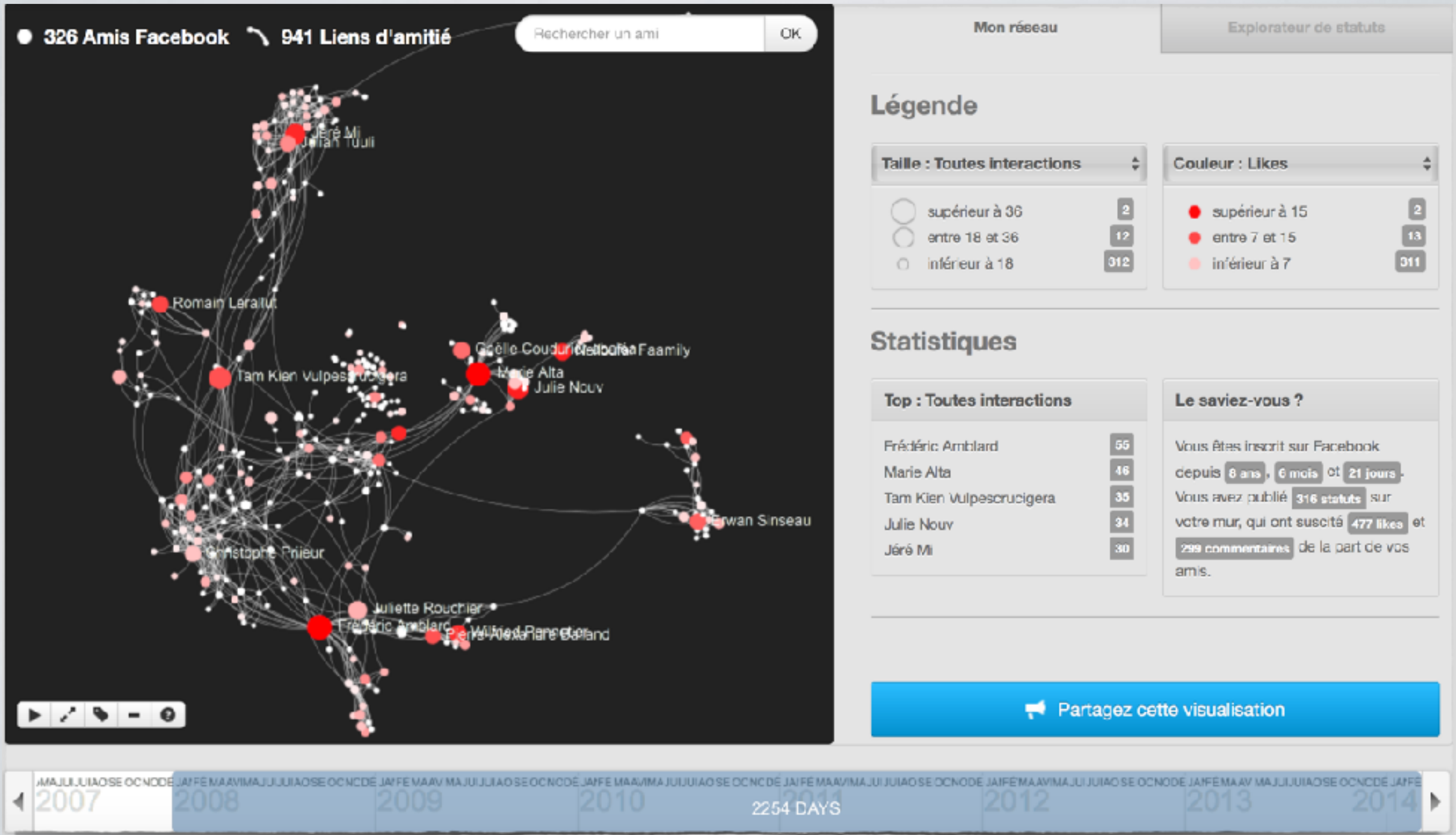

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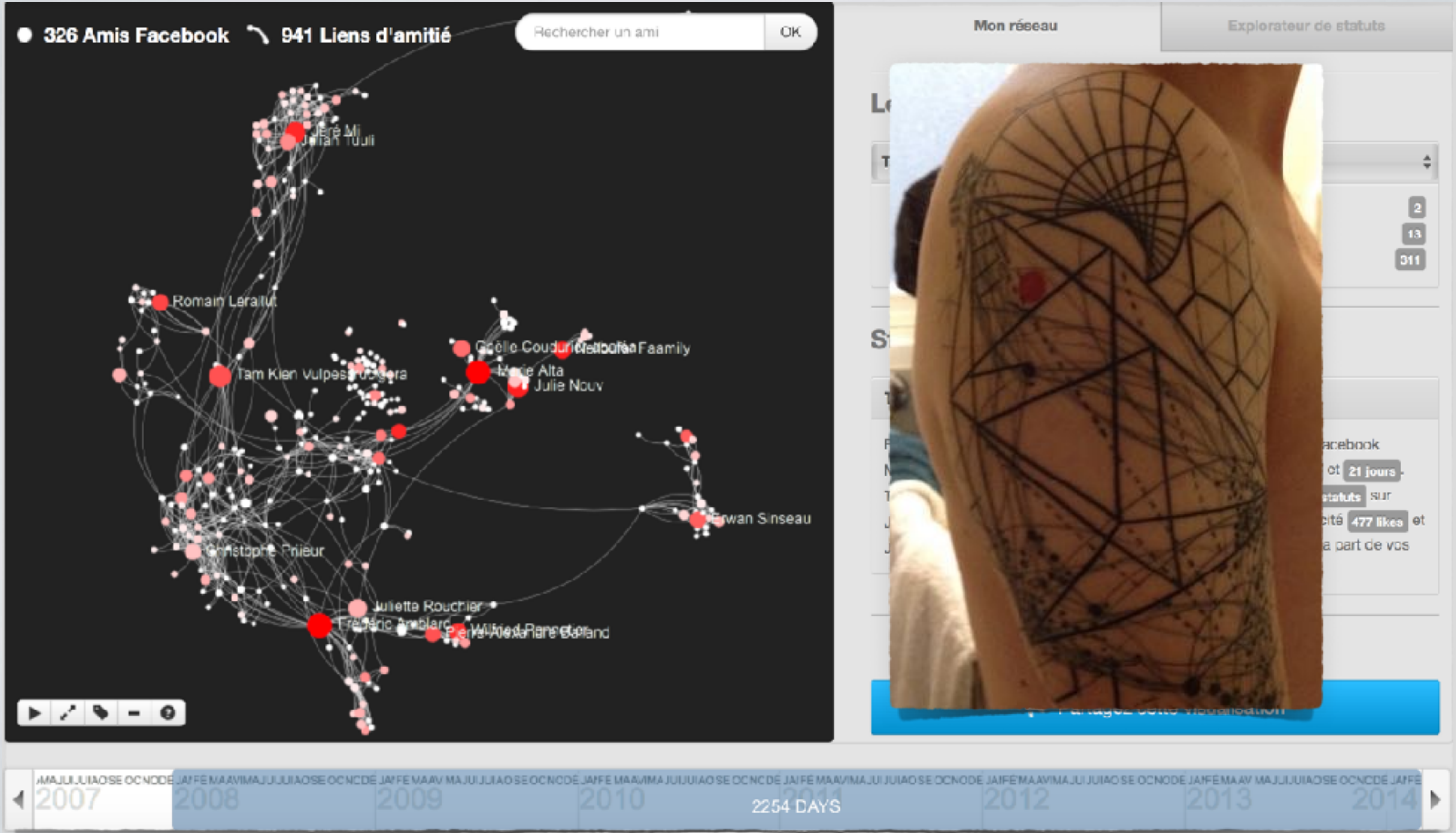

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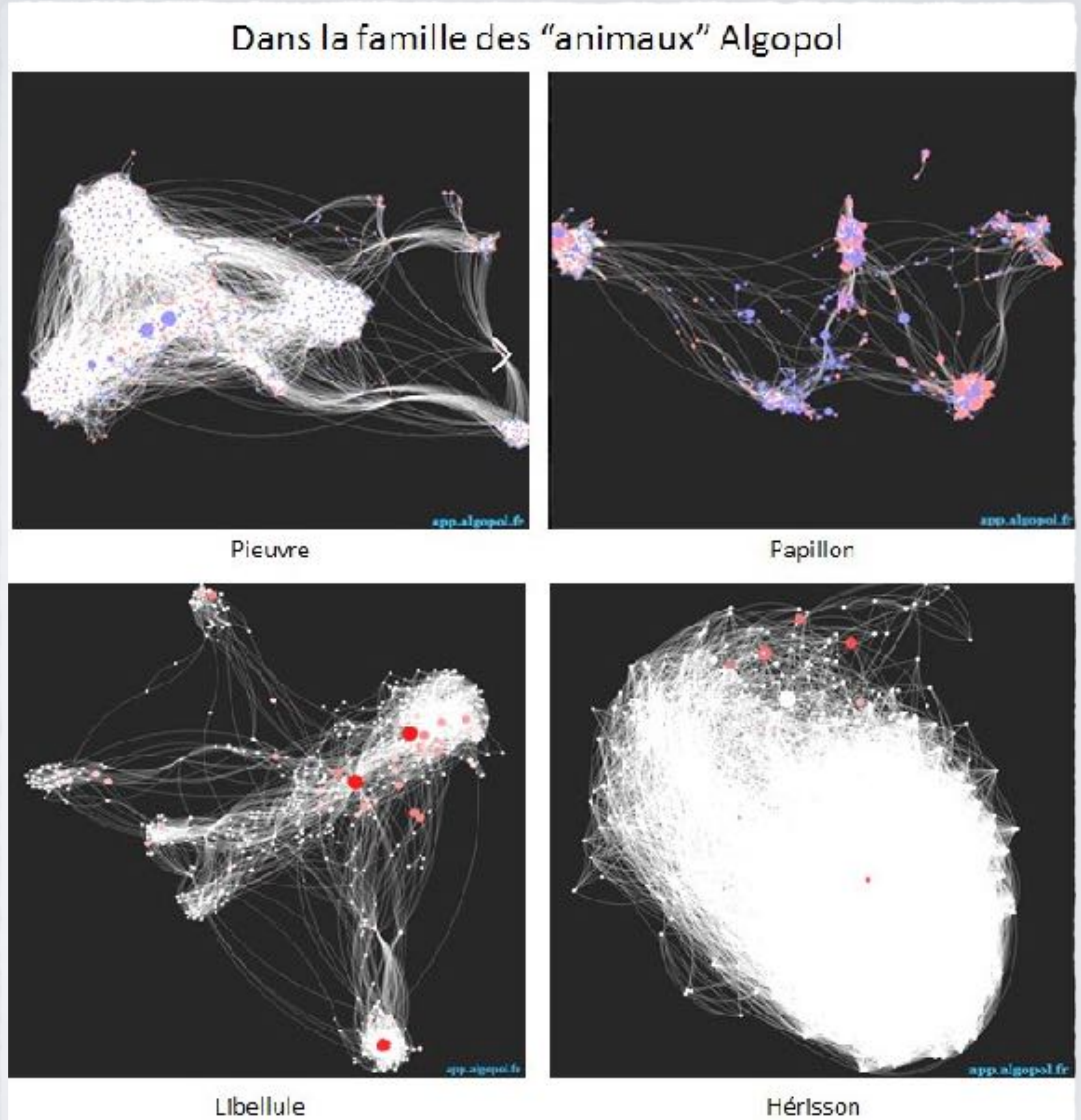

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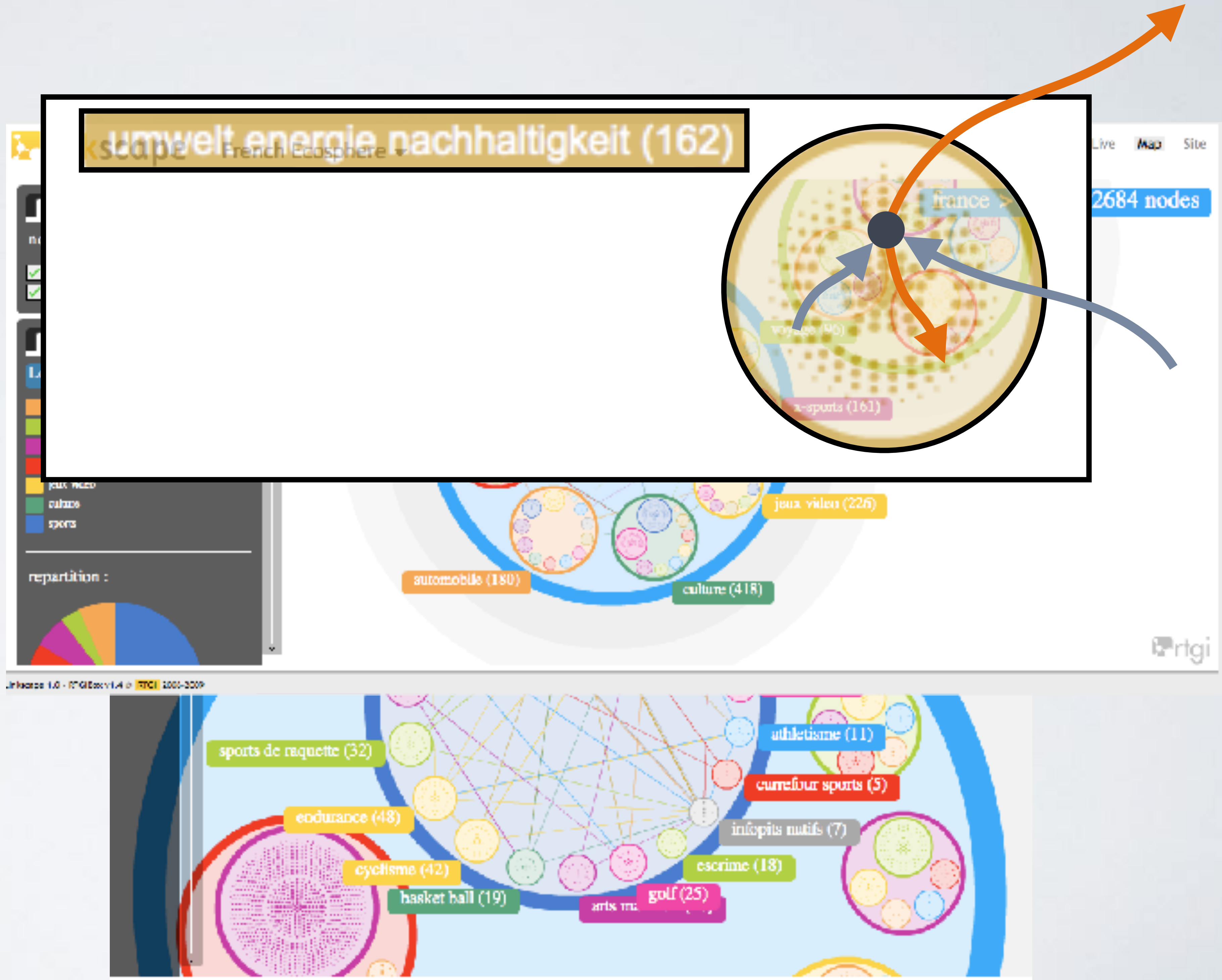

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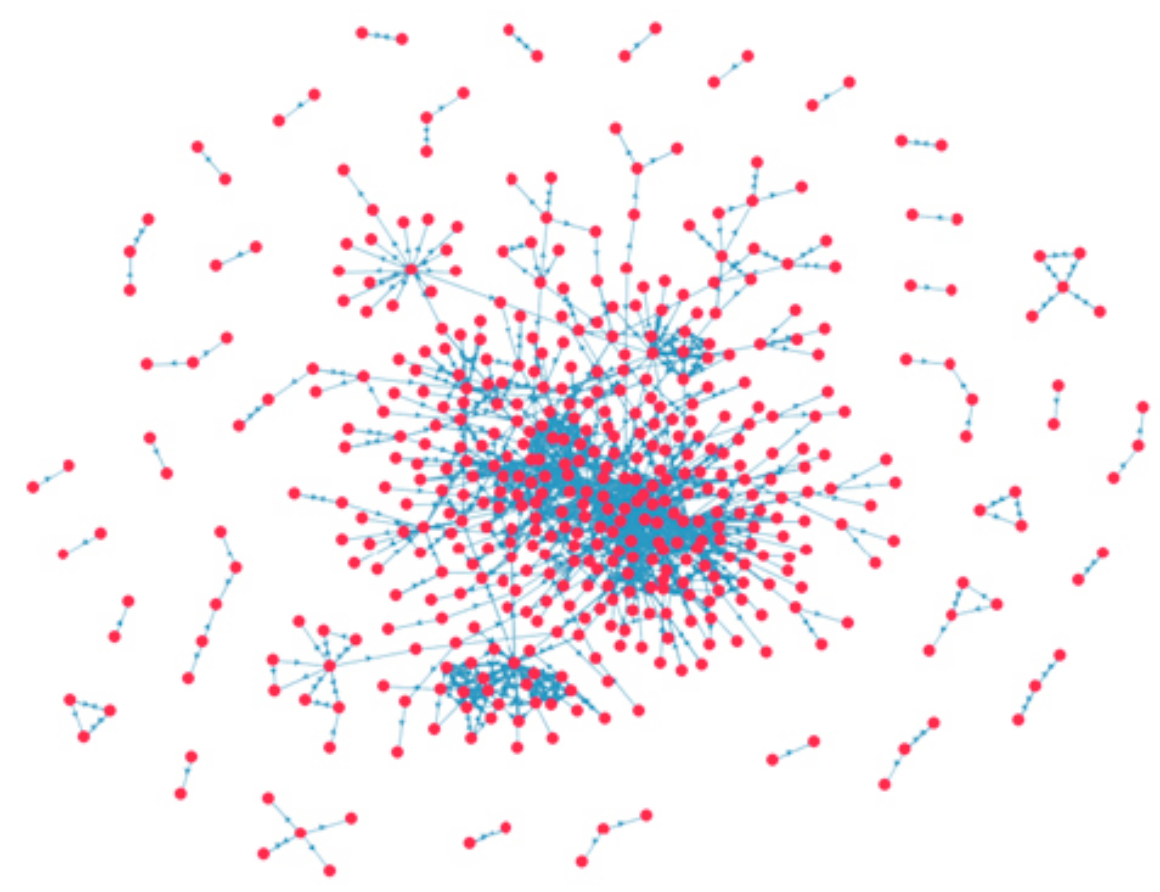


Figure 2: The FilmTrust social network.
Users who are not connected into the main component and are seen in the small clusters scattered around the edges.

(2007)

The dynamics of Web-based social networks: Membership, relationships, and change

by Jennifer Golbeck

COLLECTION PROTOCOLS

(Connover, Ferrara, Menczer, Flammini, 2013)

"The Digital Evolution of Occupy Wall Street"

To identify Occupy-related content, we deem relevant any tweet containing a hashtag matching either #ows or #occupy*, where * represents a wildcard character. This set includes high-profile tags such as #occupy as well as location-specific tokens such as #occupyoakland and #occupyseattle. While this approach does not allow us to study content that does not contain an Occupy-specific hashtag, we argue that it is appropriate for two reasons. As outlined above, hashtags allow a user to reach an audience beyond his or her immediate followers, and it is this kind of expressly public engagement in which we are primarily interested. Moreover, while topic modeling techniques may allow for the analysis of untagged tweets, their use would introduce noise that could cloud the interpretation of any analytical results [30]. Based on the criteria outlined above, we produce a corpus of all sampled tweets containing at least one of these hashtags from the year-long period between September 1st, 2011 to August 31st, 2012. Referred to hereafter as the *Occupy corpus*, this dataset contains approximately 1.82 million tweets produced by 447,241 distinct accounts.

- ego-centered
- snowball
- **holistic**

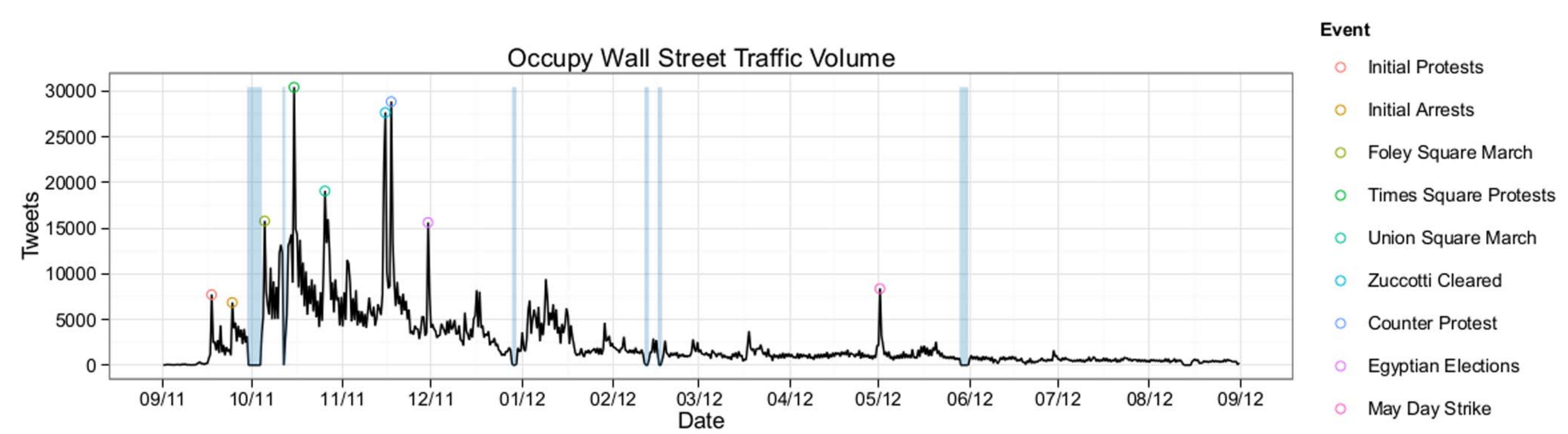
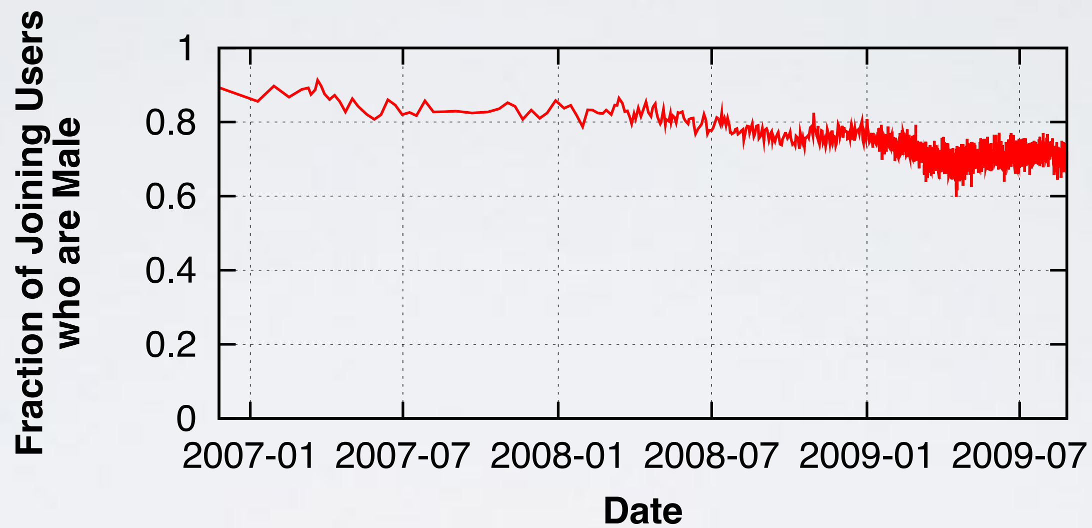


Figure 1. Total number of tweets related to Occupy Wall Street between September 2011 and September 2012. Each timestep represents a 12-hour period, with vertical blue bars overlaid on periods during which access to the Twitter streaming API was interrupted. Large bursts in activity tend to correspond to protest or police action on the ground, demarcated with circles. From left to right, the events are: initial Occupy Wall Street protest in Zuccotti Park; initial NYPD arrests of protesters; march from Foley Square to Zuccotti Park; protest at U.S. Armed Forces recruiting station in Times Square; protest in support of Iraq veteran injured by police-fired projectile; NYPD action to clear Zuccotti Park; protest against eviction from Zuccotti Park; first round of Egyptian elections; 'May Day' general strike and planned reoccupation of former encampments.

COLLECTION PROTOCOLS

- *sampling issues*



(Mislove, Lehmann, Ahn, Onnela, Rosenquist, 2012)

"Understanding the Demographics of Twitter Users"

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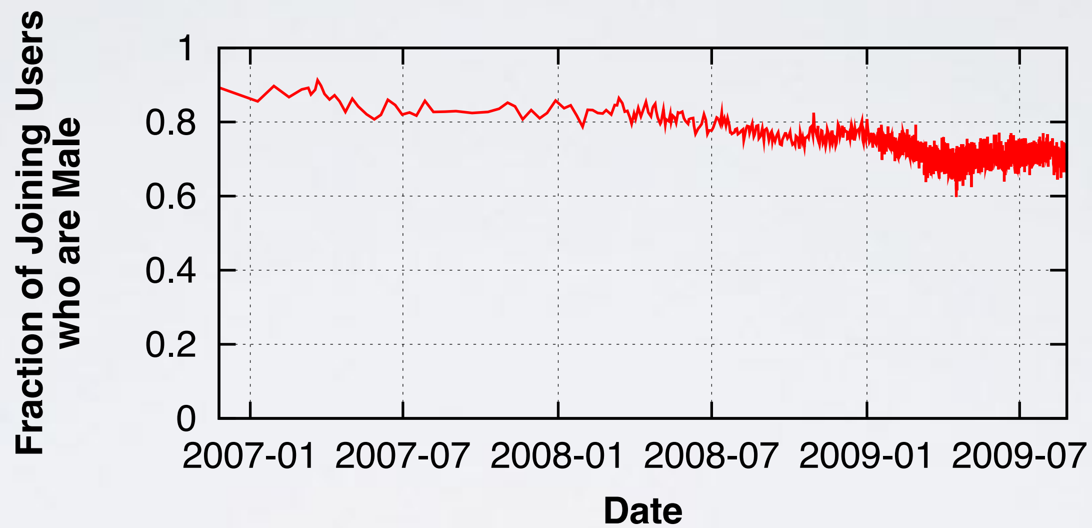

75.3% of the publicly visible users listed a location

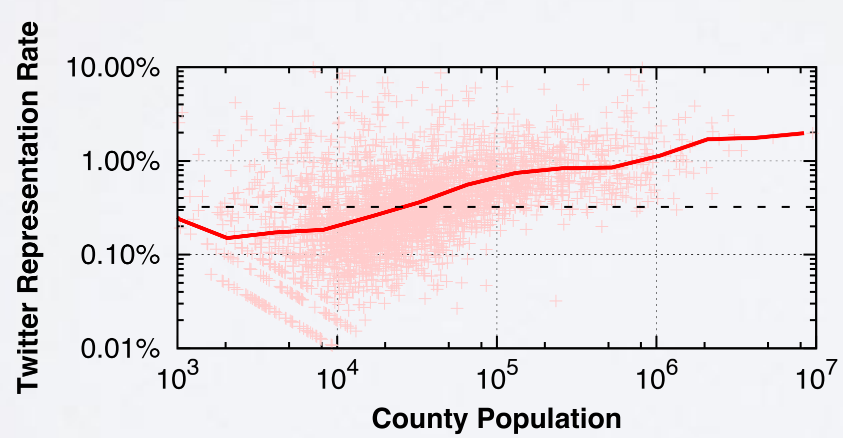

Figure 1: Scatterplot of US county population versus Twitter representation rate in that county. The dark line represents the aggregated median, and the dashed black line represents the overall median (0.324%). There is a clear overrepresentation of more populous counties.

<u>Twitter representation rate</u>: #Twitter users in that county divided by the number of people in that county in the 2000 U.S.

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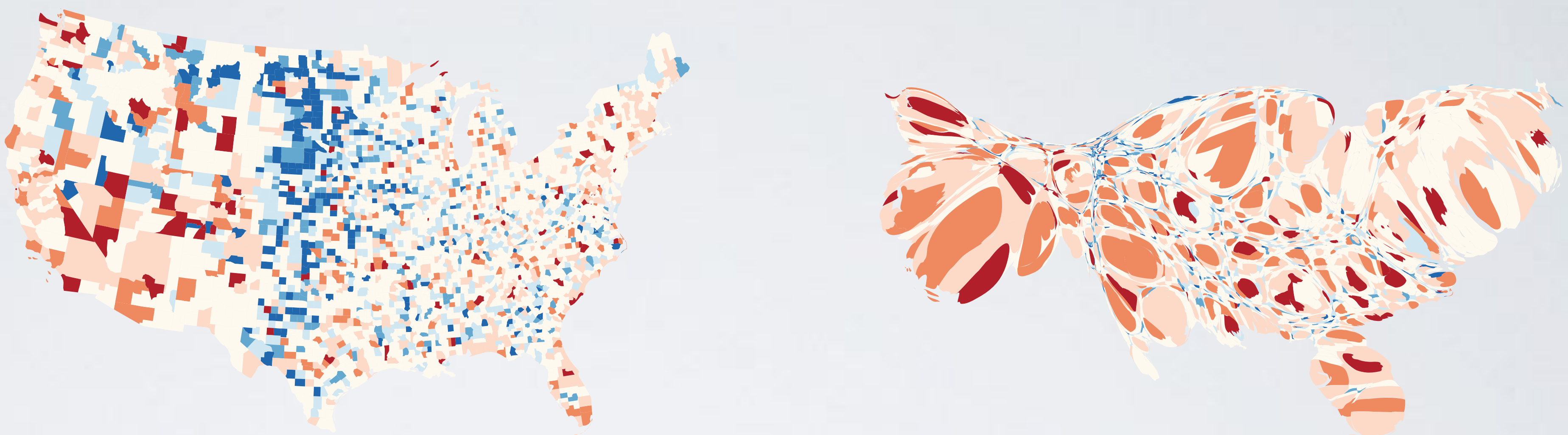

(a) Normal representation

(b) Area cartogram representation

Figure 2: Per-county over- and underrepresentation of U.S. population in Twitter, relative to the median per-county representation rate of 0.324%, presented in both (a) a normal layout and (b) an area cartogram based on the 2000 Census population. Blue colors indicate underrepresentation, while red colors represent overrepresentation. The intensity of the color corresponds to the log of the over- or underrepresentation rate. Clear trends are visible, such as the underrepresentation of mid-west and overrepresentation of populous counties.

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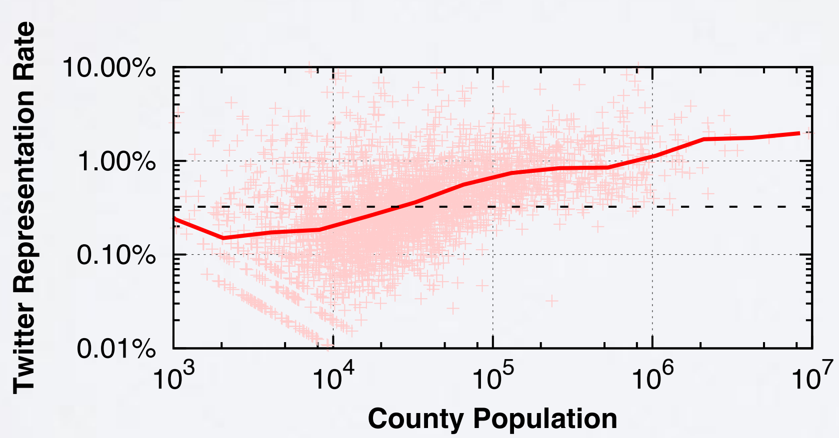

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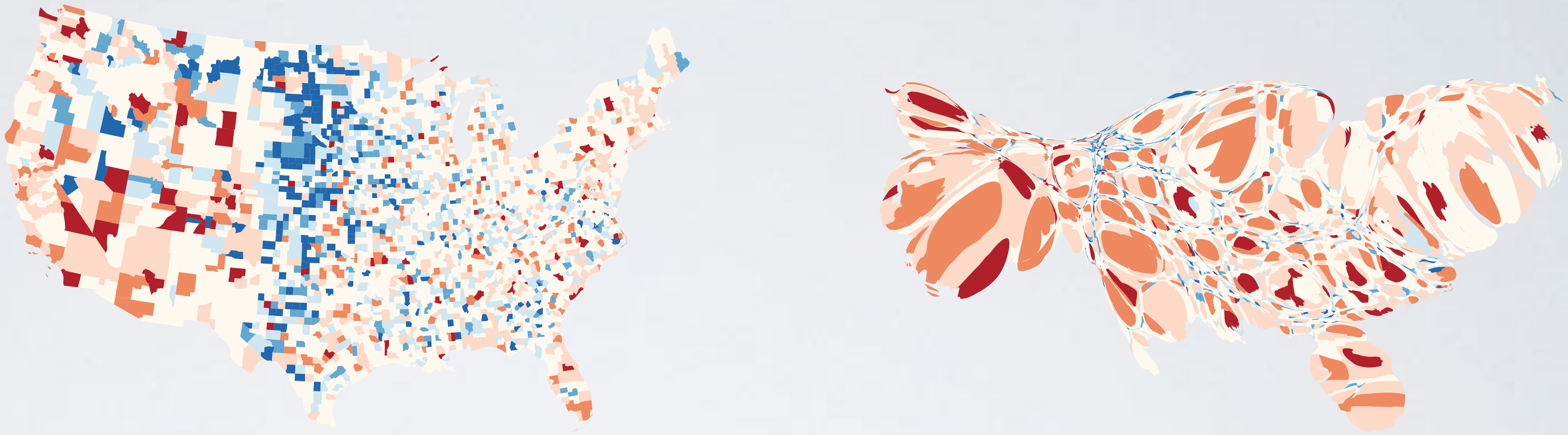

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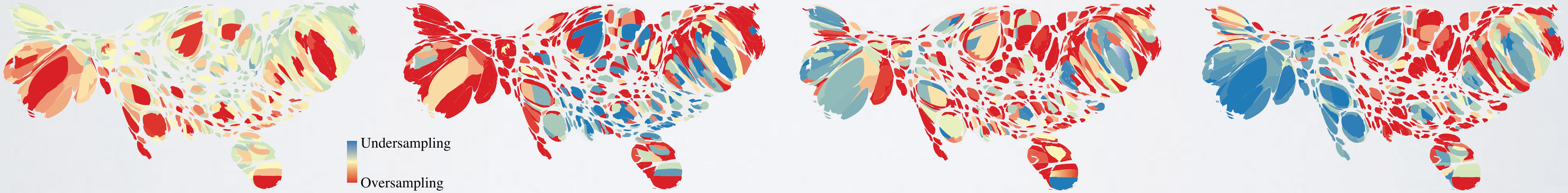

(a) Caucasian (non-hispanic) (b) African-American (c) Asian or Pacific Islander (d) Hispanic

Figure 4: Per-county area cartograms of Twitter over- and undersampling rates of Caucasian, African-American, Asian, and Hispanic users, relative to the 2000 U.S. Census. Only counties with more than 500 Twitter users with inferred race/ethnicity are shown. Blue regions correspond to undersampling; red regions to oversampling.

TYPICAL QUESTIONS

- **Shape of online interactions**

  – *is it much different ?*

  - Existence of hierarchies, of clustering, communities, aggregates, central people, etc.

  - Existence of specific roles (e.g. answer person in case of discussion forums)

  - In some cases, expected to be correlated to offline social networks (e.g. Facebook)

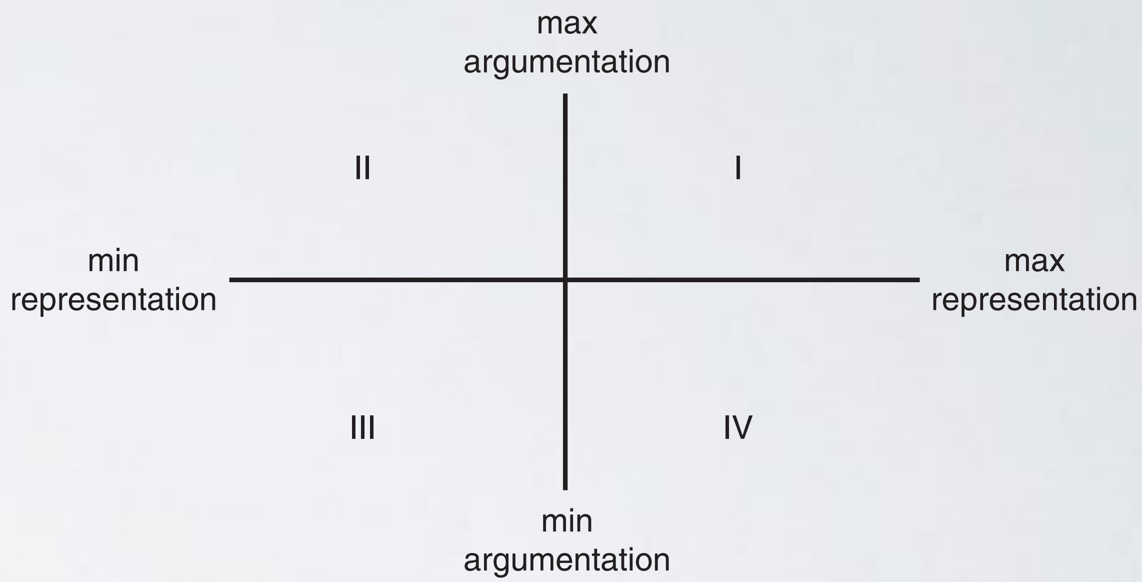

Figure 1 Prerequisites of deliberation.
Source: Adapted from Ackerman and Fishkin (2002).

The structure of political discussion networks: a model for the analysis of online deliberation

Sandra Gonzalez-Bailon[1], Andreas Kaltenbrunner[2], Rafael E Banchs[2]

Journal of Information Technology (2010), 1–14

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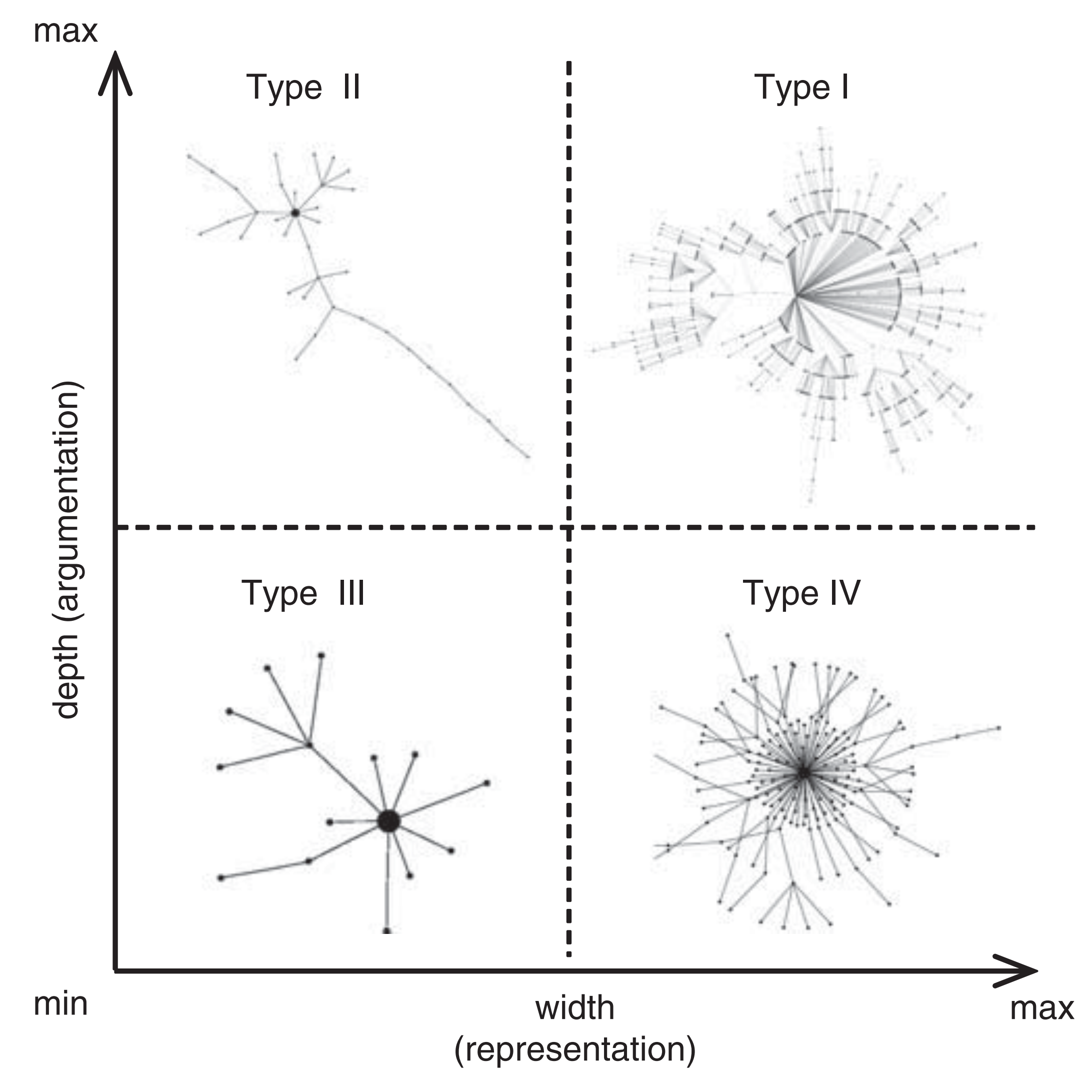
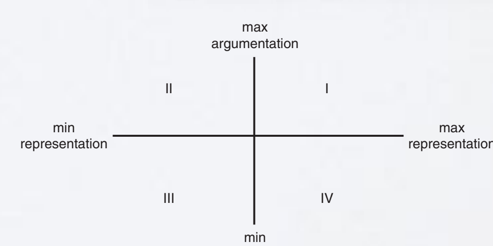


Figure 2 Types of discussions according to the width and depth of the interactions.



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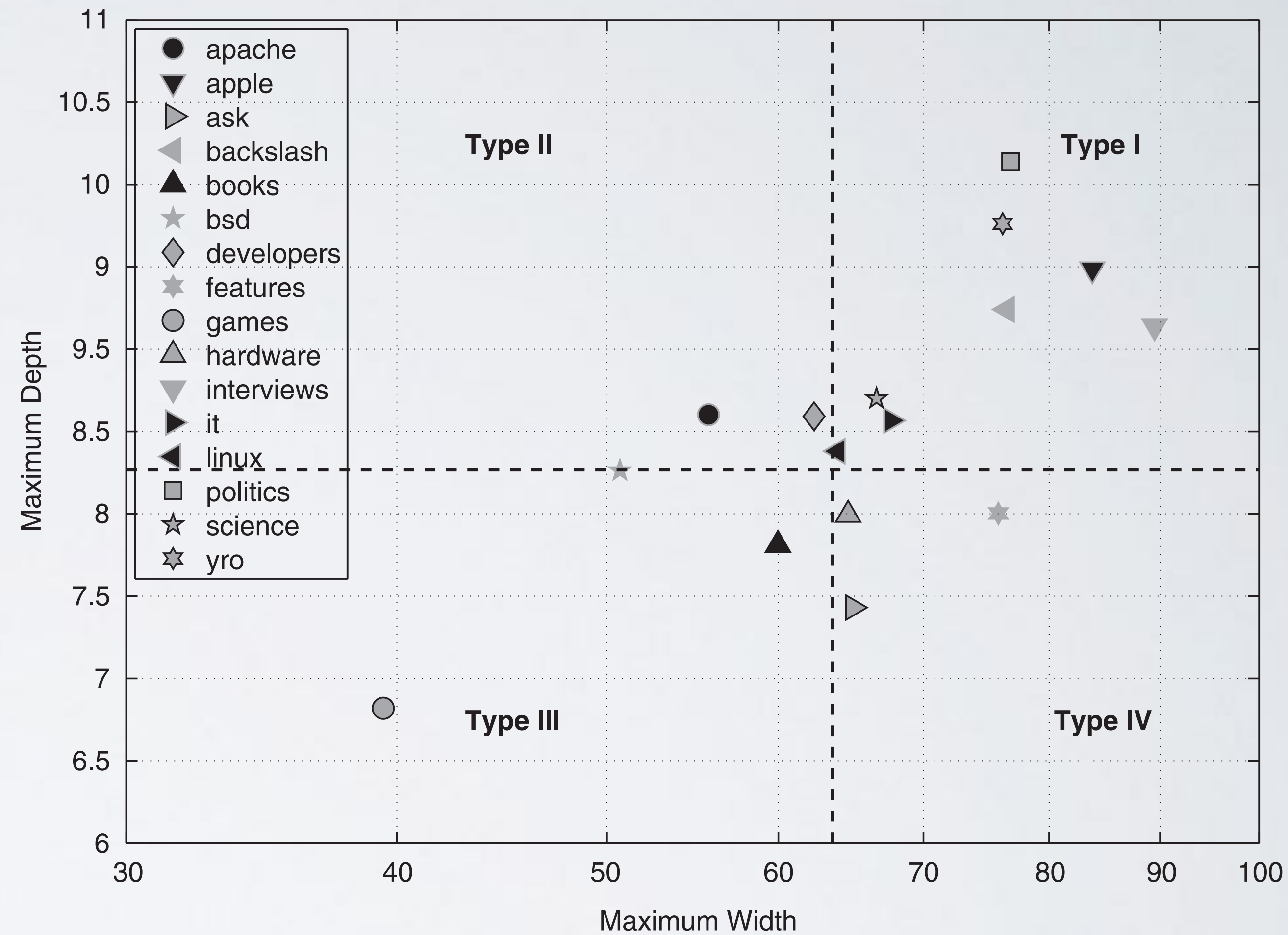
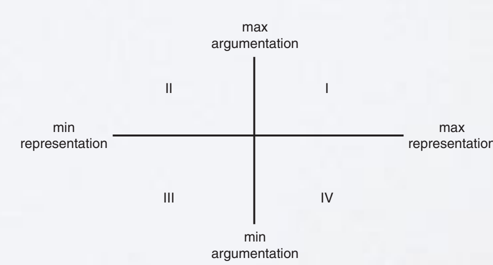


Figure 4 Width-depth distributions of computed centroids for all post categories.



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Bertelsmann Stiftung

spotlight europe

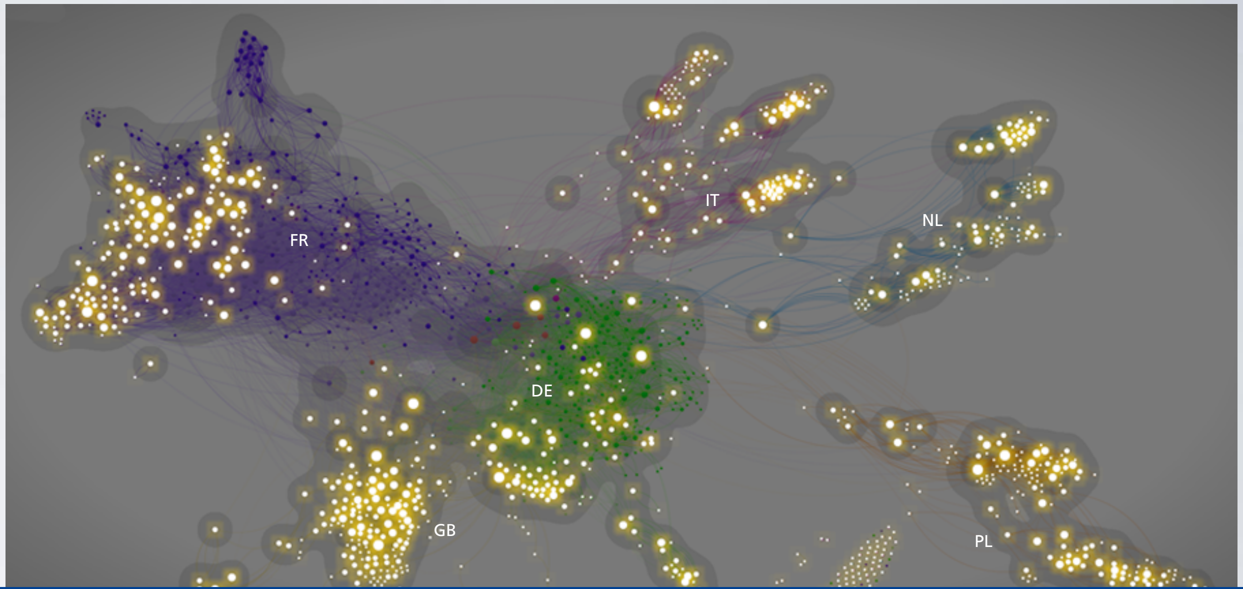
2014/02 — Mai 2014

Im Netz der Populisten

73 Prozent der Bevölkerung der Europäischen Union nutzten 2013 das Internet. Tendenz steigend. Kurz vor der Europawahl wollten wir daher wissen: Wie präsent und aktiv sind die antieuropäischen Populisten im Internet? Resultat: Die Anti-Europäer sind isoliert und zersplittert. Es gibt aber eine lebendige pro-europäische Netzöffentlichkeit. Nur zivilgesellschaftliche Initiativen brauchen noch mehr Unterstützung.

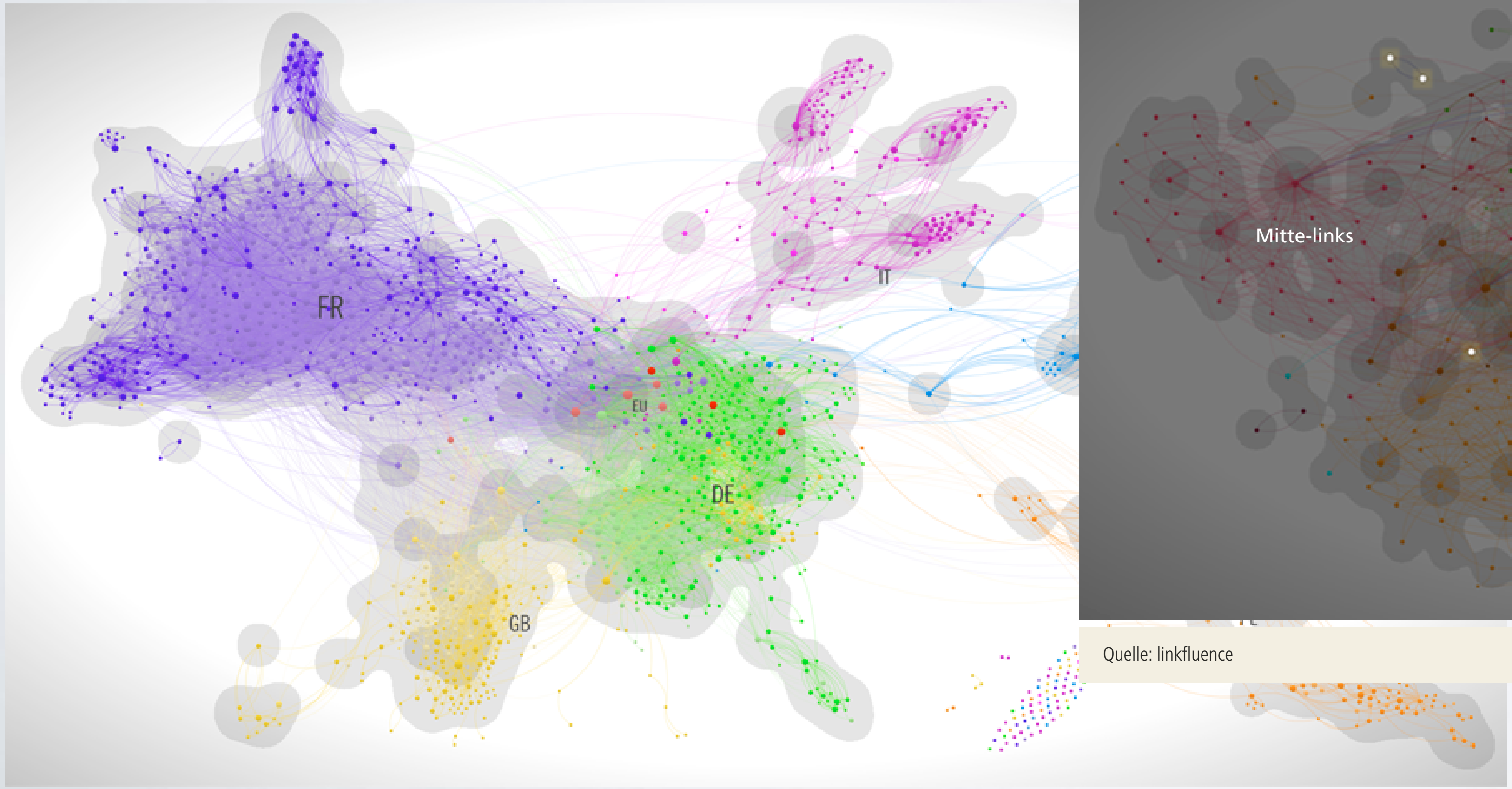
988 Internetseiten mit antieuropäischen Inhalten

In Deutschland, Frankreich, Großbritannien, Italien, den Niederlanden und Polen



1.638 europapolitische Internetseiten

In Deutschland und Frankreich mit pro- und antieuropäischen Inhalten;
in Großbritannien, den Niederlanden, Italien und Polen mit antieuropäischen Inhalte



Quelle: linkfluence

Deutschland

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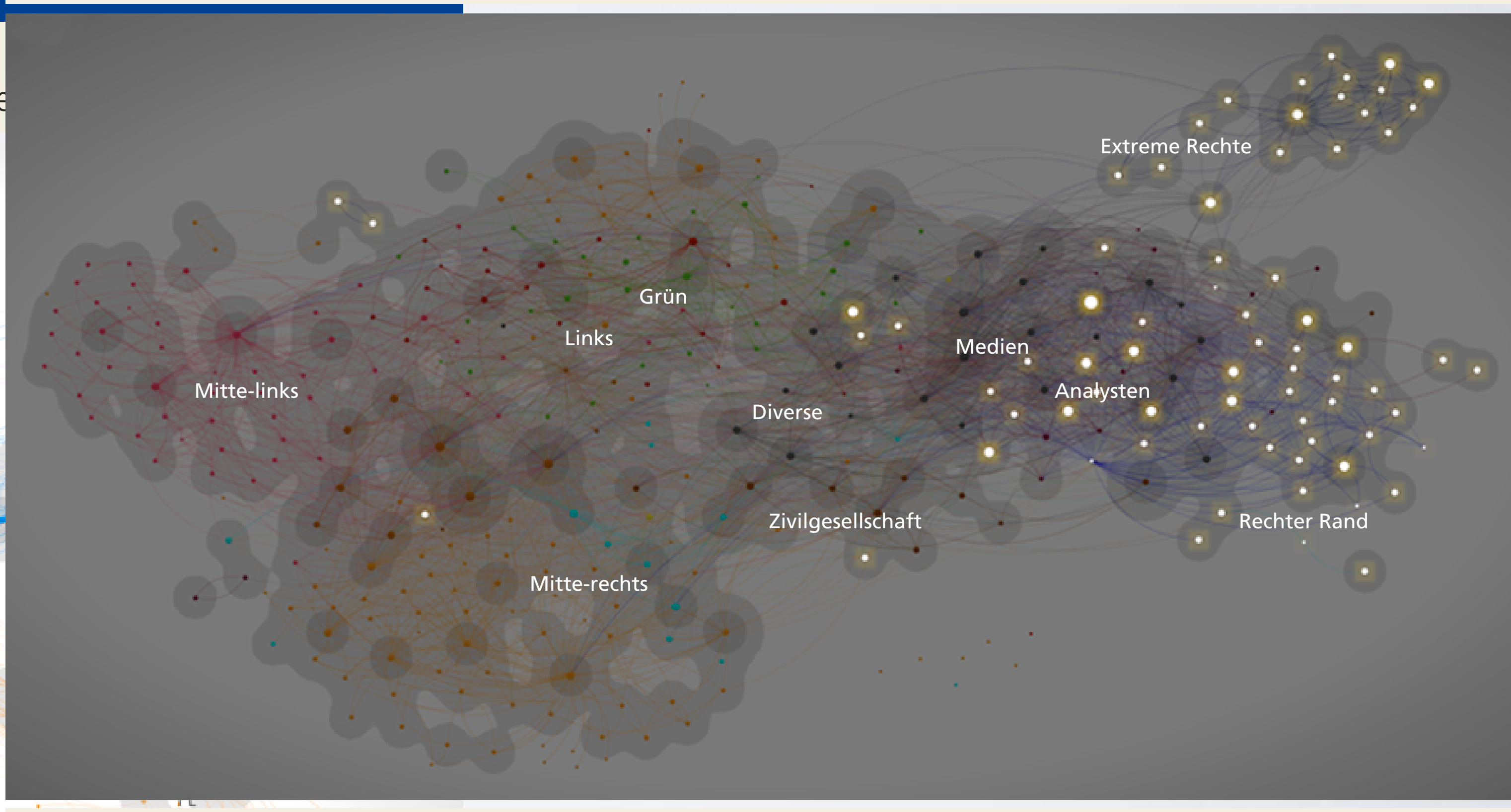

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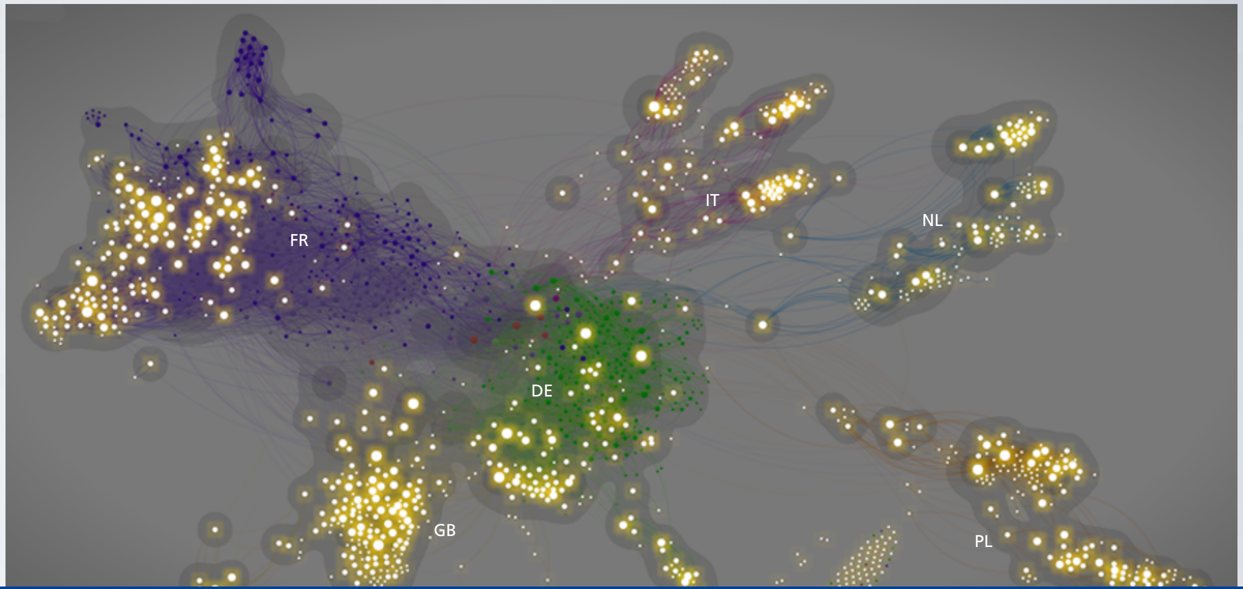

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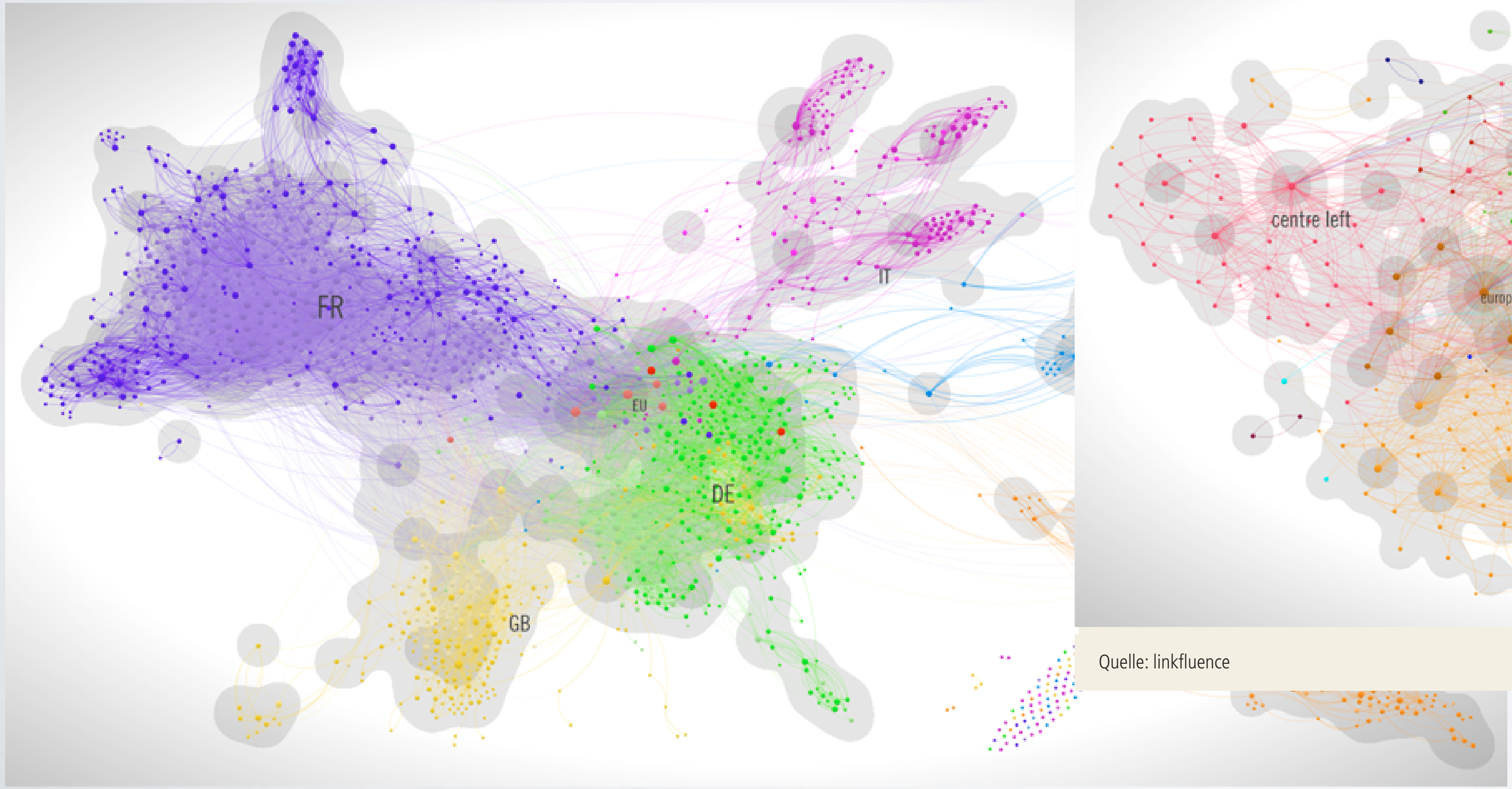

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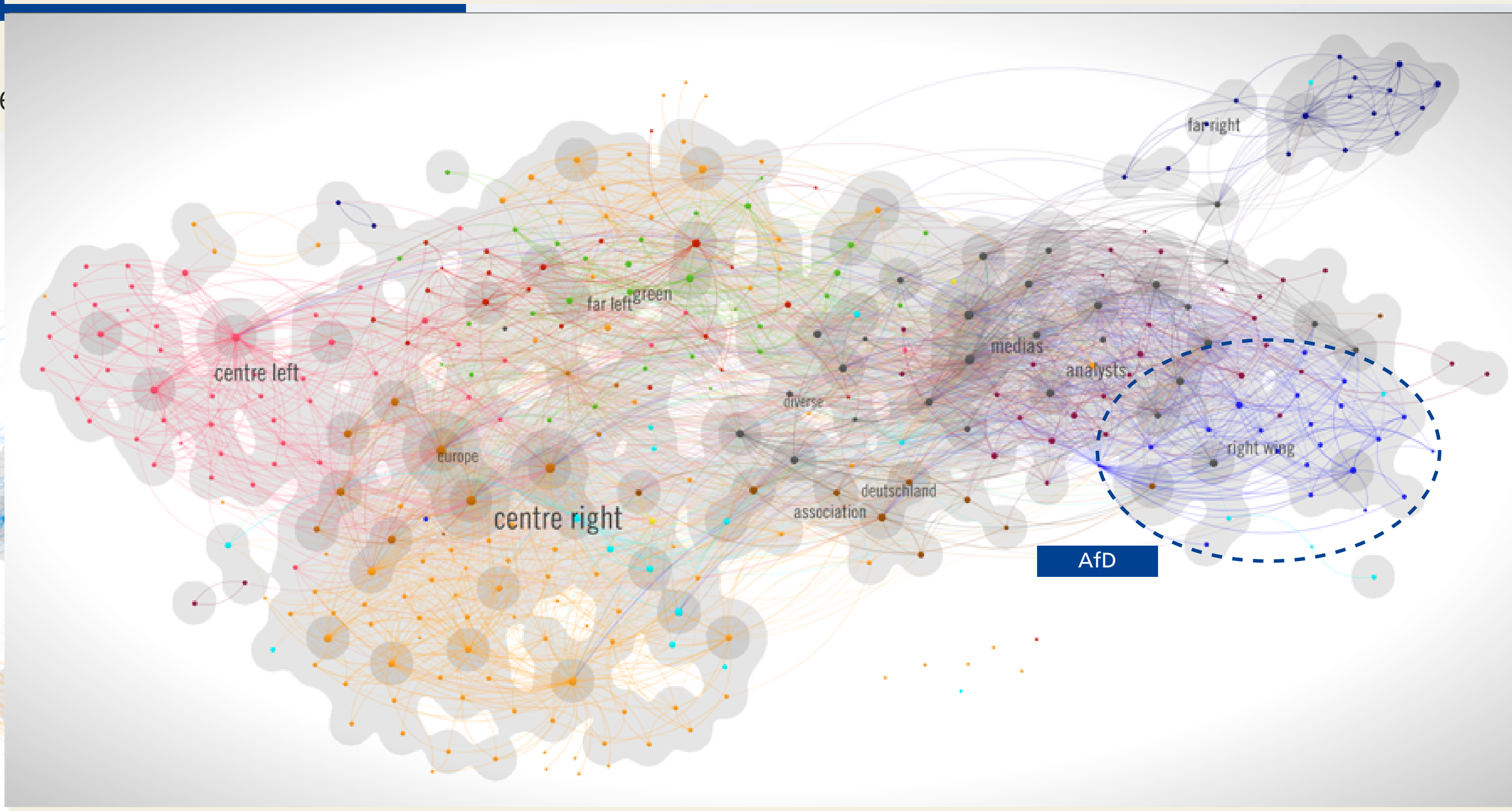
Deutschland

349 Internetseiten mit pro- und antieuropäischen Inhalten



Quelle: linkfluence

Political Polarization on Twitter

M. D. Conover, J. Ratkiewicz, M. Francisco, B. Gonçalves, A. Flammini, F. Menczer
Center for Complex Networks and Systems Research
School of Informatics and Computing
Indiana University, Bloomington, IN, USA

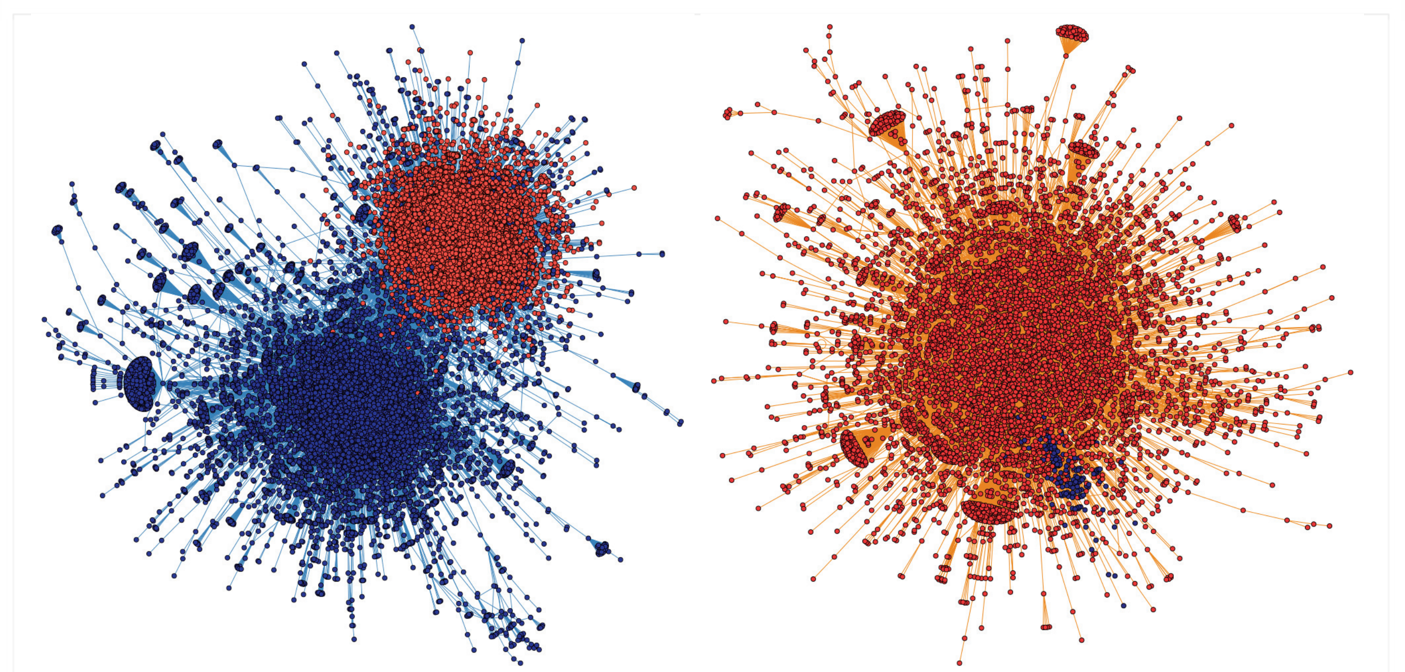


Figure 1: The political retweet (left) and mention (right) networks, laid out using a force-directed algorithm. Node colors reflect cluster assignments (see § 3.1). Community structure is evident in the retweet network, but less so in the mention network. We show in § 3.3 that in the retweet network, the red cluster A is made of 93% right-leaning users, while the blue cluster B is made of 80% left-leaning users.

"We demonstrate that the network of political retweets exhibits a highly segregated partisan structure, with extremely limited connectivity between left- and right-leaning users."

"Surprisingly this is not the case for the user-to-user mention network, which is dominated by a single politically heterogeneous cluster of users in which ideologically-opposed individuals interact at a much higher rate compared to the network of retweets."

"To explain the distinct topologies of the retweet and mention networks we conjecture that politically motivated individuals provoke interaction by injecting partisan content into information streams whose primary audience consists of ideologically-opposed users"

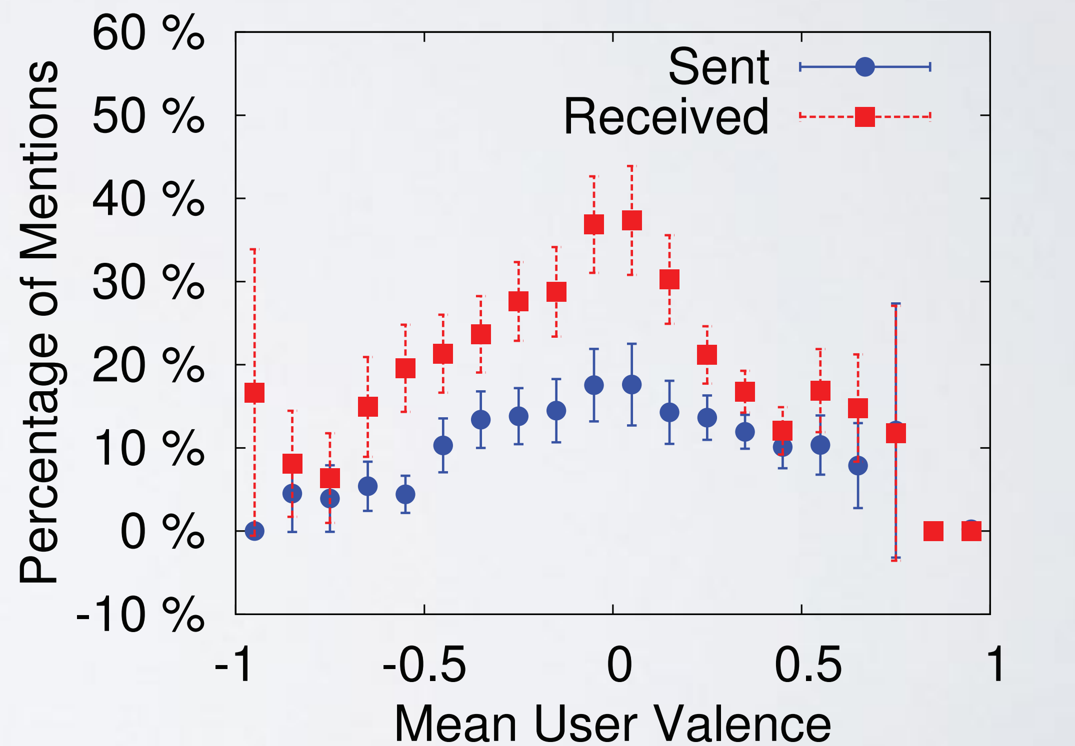


Figure 3: Proportion of mentions a user sends and receives to and from ideologically-opposed users relative to her valence. Points represent binned averages. Error bars denote 95% confidence intervals.

Diffusion observation

on Twitter with *hashtags*...

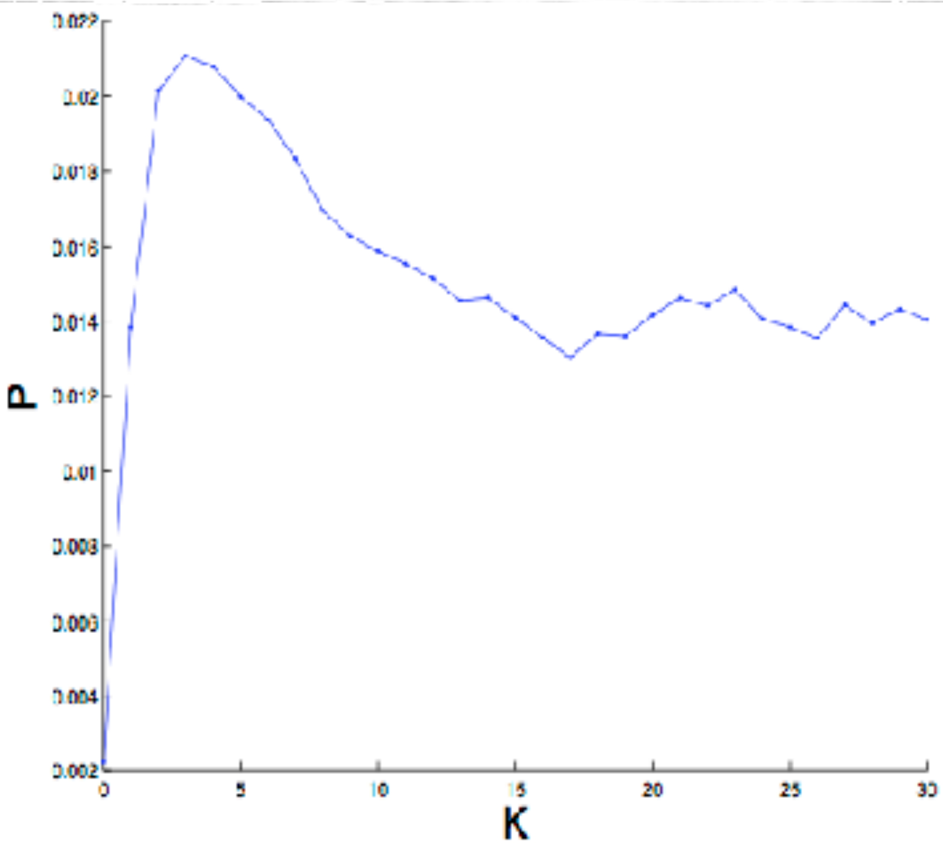
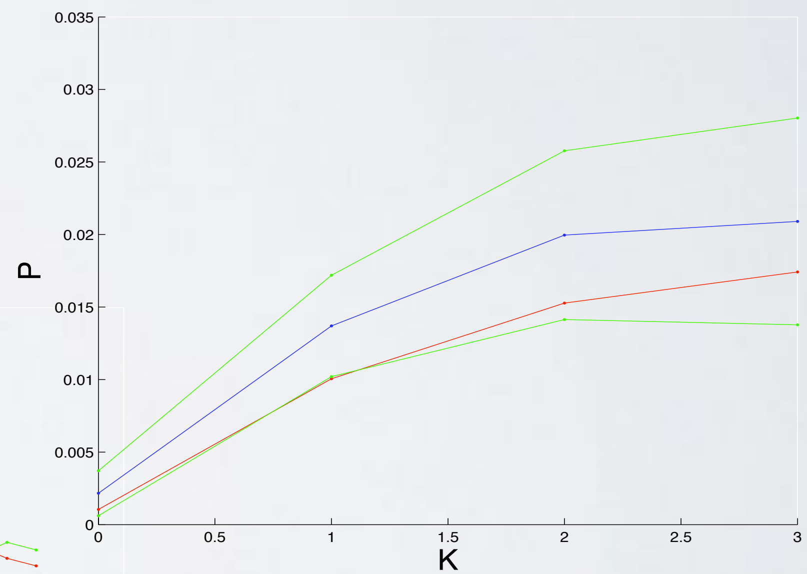


Figure 1: Average exposure curve for the top 500 hashtags. $P(K)$ is the fraction of users who adopt the hashtag directly after their k^{th} exposure to it, given that they had not yet adopted it

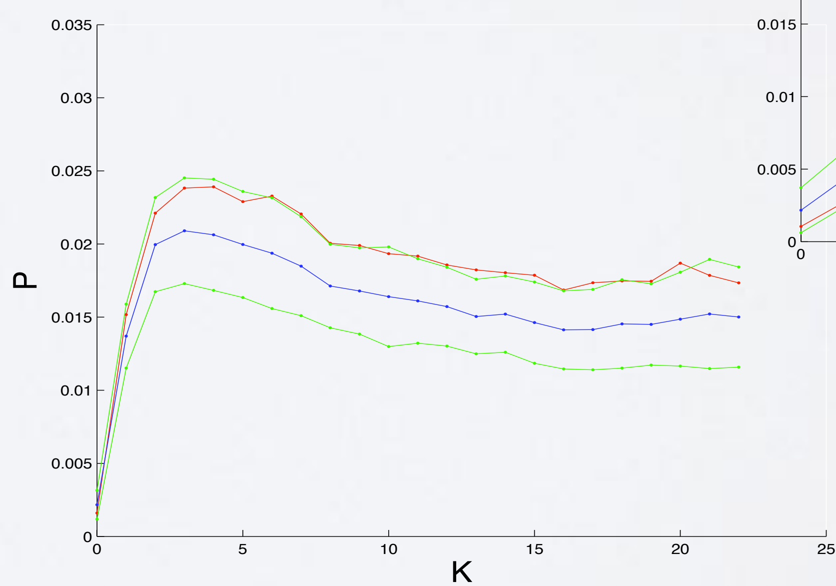
Differences in the Mechanics of Information Diffusion Across Topics: Idioms, Political Hashtags, and Complex Contagion on Twitter

WWW 2011, March 28–April 1, 2011, Hyderabad, India.

Daniel M. Romero   Brendan Meeder   Jon Kleinberg



(h) Games



(f) Political

Diffusion observation

...with respect to community structure

- effect of **clustered communities**?
  - contradictory influence of:
    - homophily (communities reinforcing contagion through multiple exposures)
    - clustering (slowing random information flows).

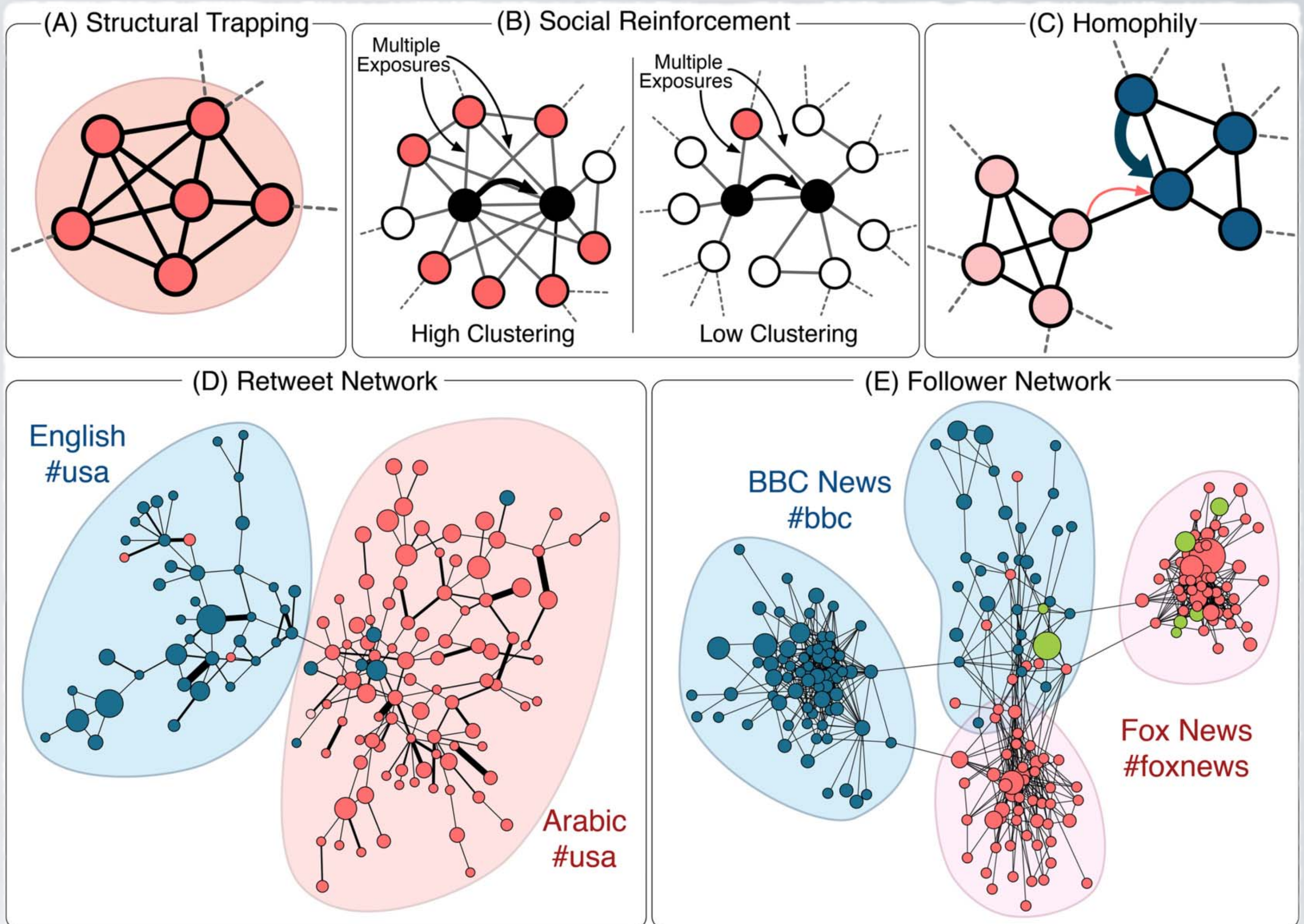


Table 1 | Baseline models for information diffusion

	Community effects			
	Network	Reinforcement	Homophily	Simulation implementation
M_1				For a given hashtag h, M_1 randomly samples the same number of tweets or users as in the real data.
M_2	✓			M_2 takes the network structure into account while neglecting social reinforcement and homophily. M_2 starts with a random seed user. At each step, with probability p, an infected node is randomly selected and one of its neighbors adopts the meme, or with probability $1 - p$, the process restarts from a new seed user ($p = 0.85$).
M_3	✓	✓		The cascade in M_3 is generated similarly to M_2 but at each step the user with the maximum number of infected neighbors adopts the meme.
M_4	✓		✓	In M_4, the simple cascading process is simulated in the same way as in M_2 but subject to the constraint that at each step, only neighbors in the same community have a chance to adopt the meme.

- "**viral**" (irrespective of community structure, disease-like spreading: clustering slows diffusion)
- vs. "**non-viral**" (community structure-dependent, clustering facilitates diffusion)

Diffusion observation

(Weng, Menczer, Ahn, 2013)

...with respect to community structure

- effect of **clustered communities**?
  - contradictory influence of:
    - homophily (communities reinforcing contagion through multiple exposures)
    - clustering (slowing random information flows).

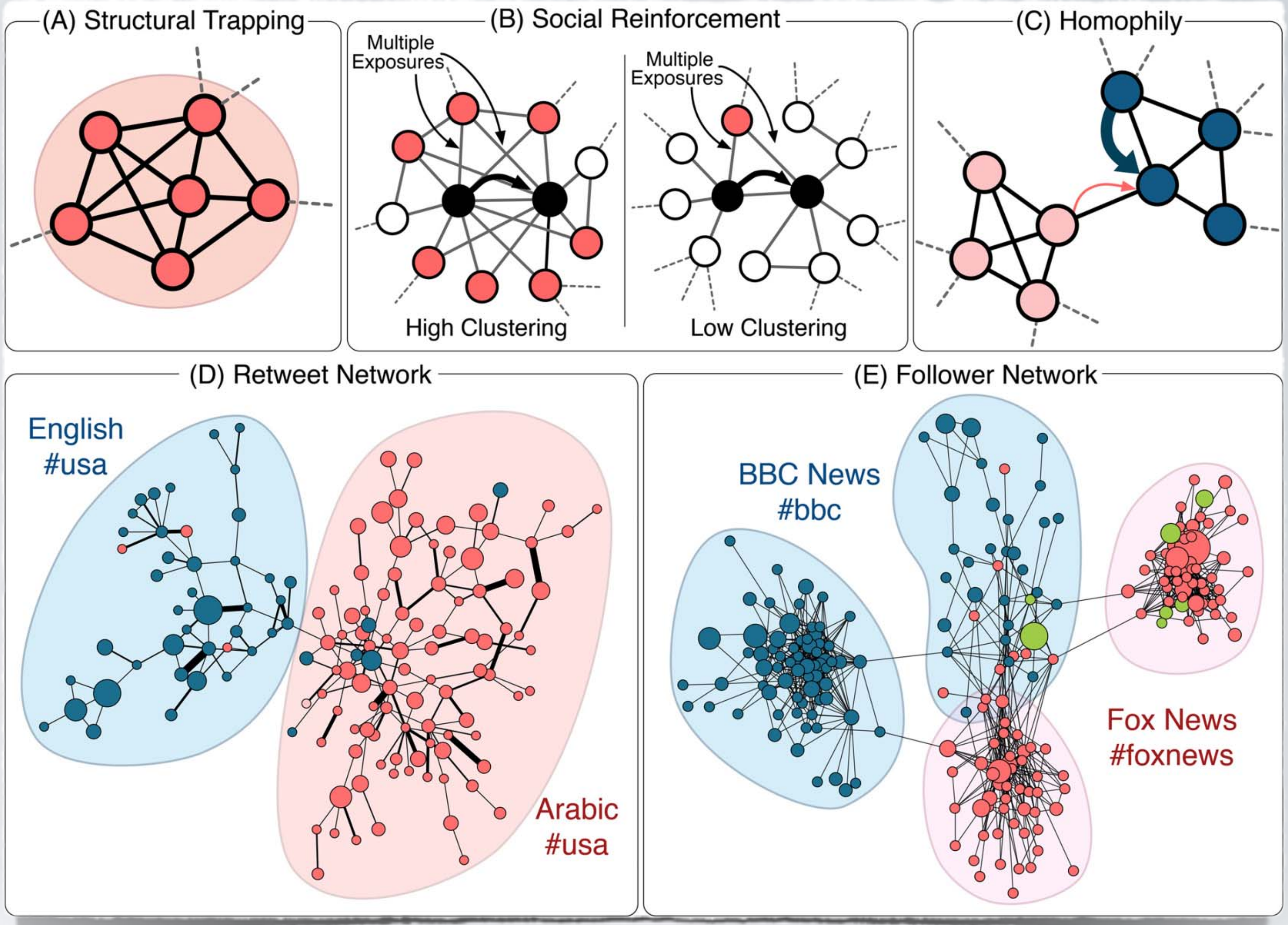


Table 1 | Baseline models for information diffusion

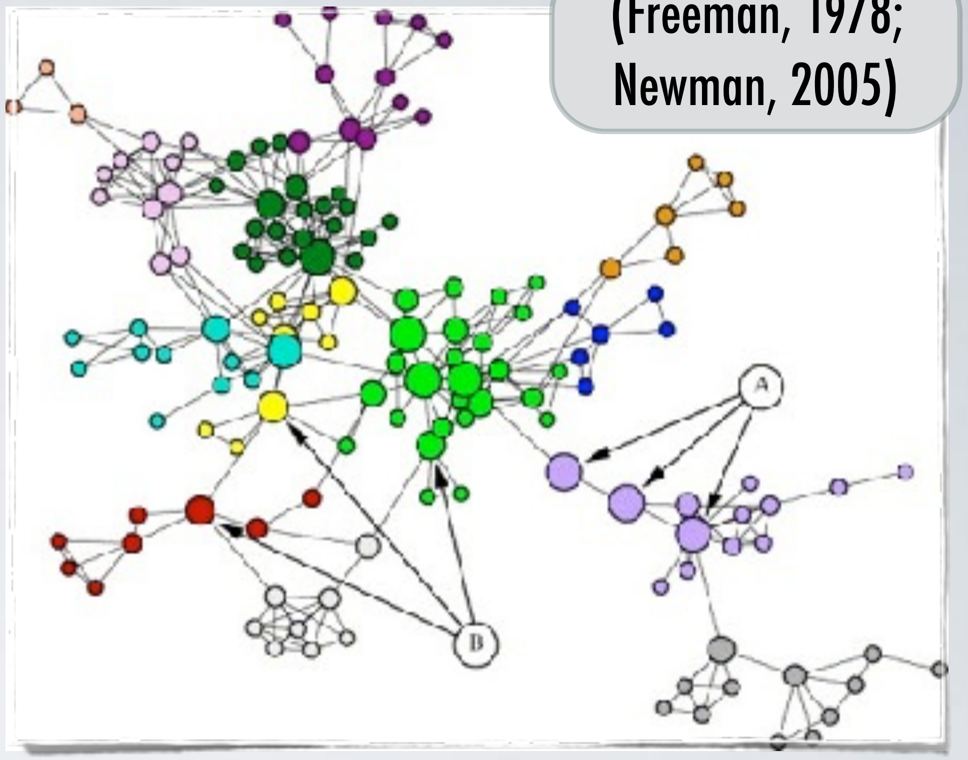
	Community effects			
	Network	Reinforcement	Homophily	Simulation implementation
M_1				For a given hashtag h, M_1 randomly samples the same number of tweets or users as in the real data.
M_2	✓			M_2 takes the network structure into account while neglecting social reinforcement and homophily. M_2 starts with a random seed user. At each step, with probability p, an infected node is randomly selected and one of its neighbors adopts the meme, or with probability $1 - p$, the process restarts from a new seed user ($p = 0.85$).
M_3	✓	✓		The cascade in M_3 is generated similarly to M_2 but at each step the user with the maximum number of infected neighbors adopts the meme.
M_4	✓		✓	In M_4, the simple cascading process is simulated in the same way as in M_2 but subject to the constraint that at each step, only neighbors in the same community have a chance to adopt the meme.

- "**viral**" (irrespective of community structure, disease-like spreading: clustering slows diffusion)
- vs. "**non-viral**" (community structure-dependent, clustering facilitates diffusion)

FRAGMENTATION

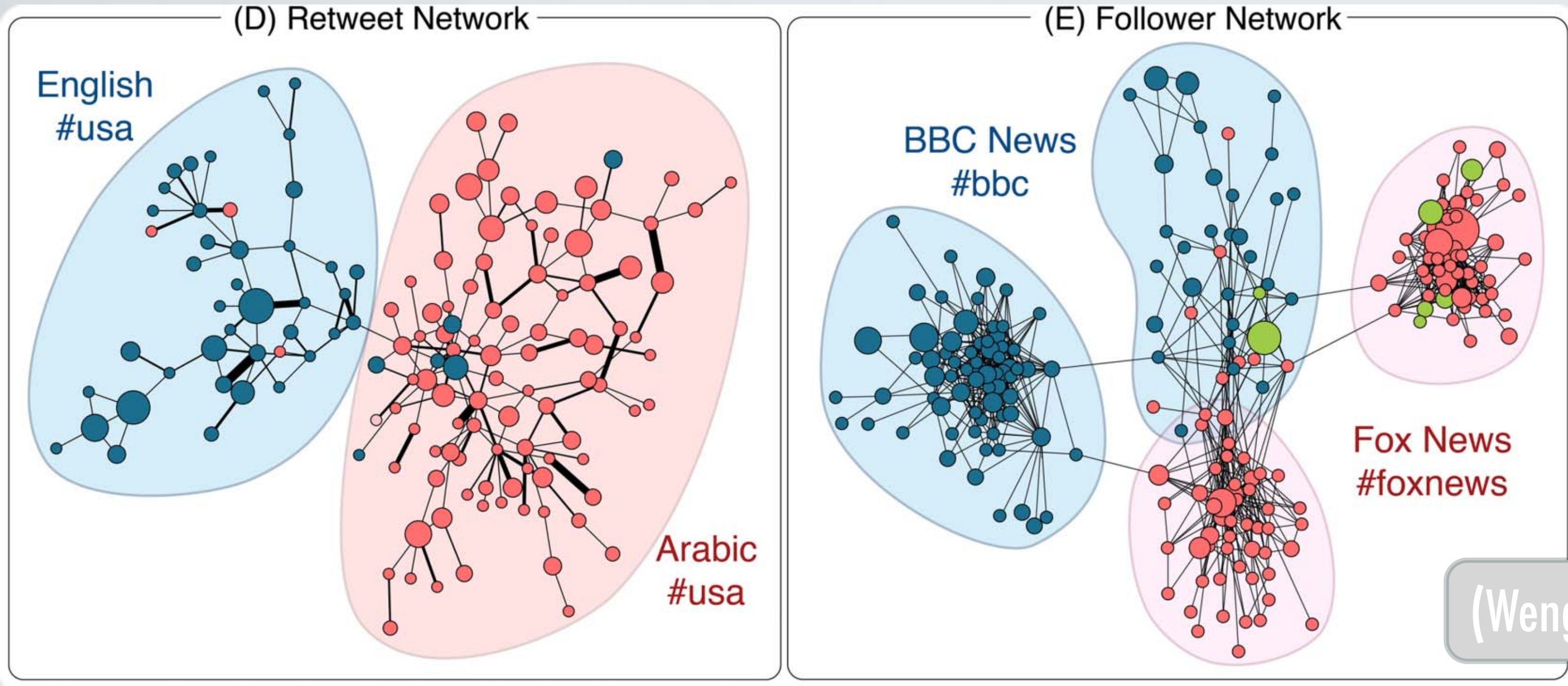
- Socio-Semantic Structure
- Algorithms

- **Aggregates**, be they **structural or semantic**, are **ubiquitous**

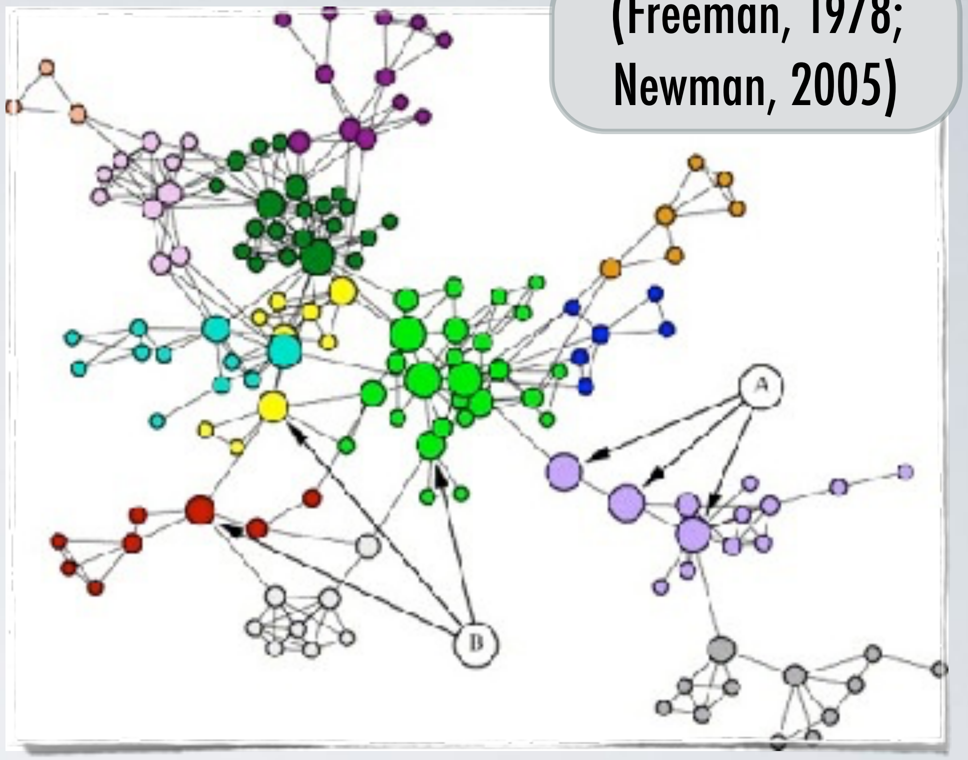


(Freeman, 1978; Newman, 2005)

- **Aggregates**, be they **structural or semantic**, are **ubiquitous**



(Weng, Menczer, Ahn, 2013)



(Freeman, 1978; Newman, 2005)

- **Aggregates**, be they **structural or semantic**, are **ubiquitous**

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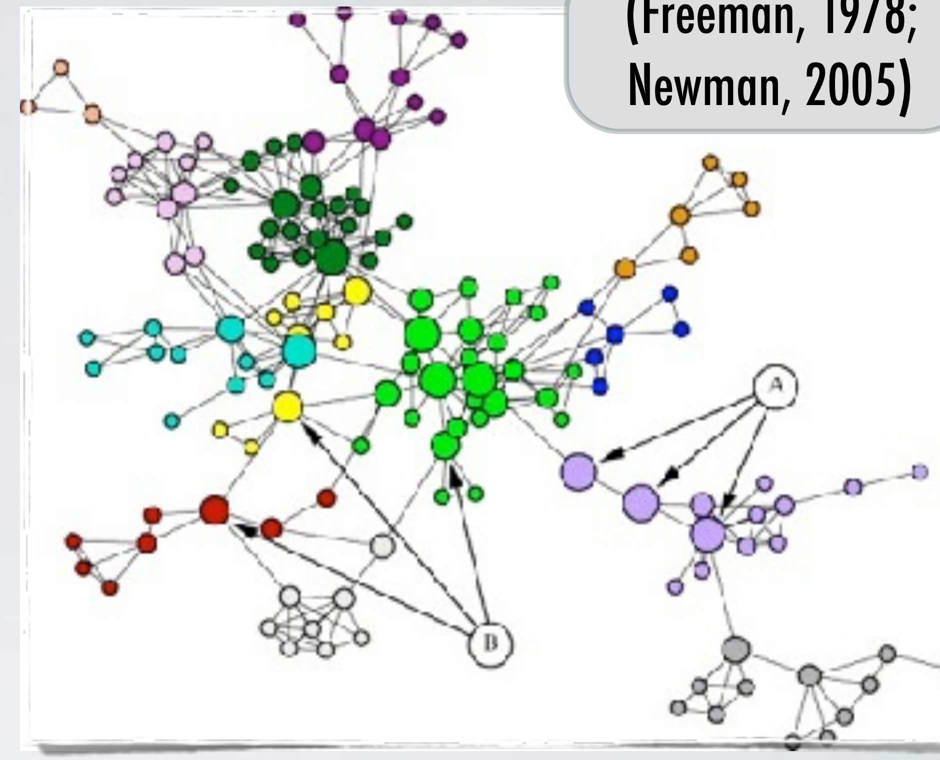
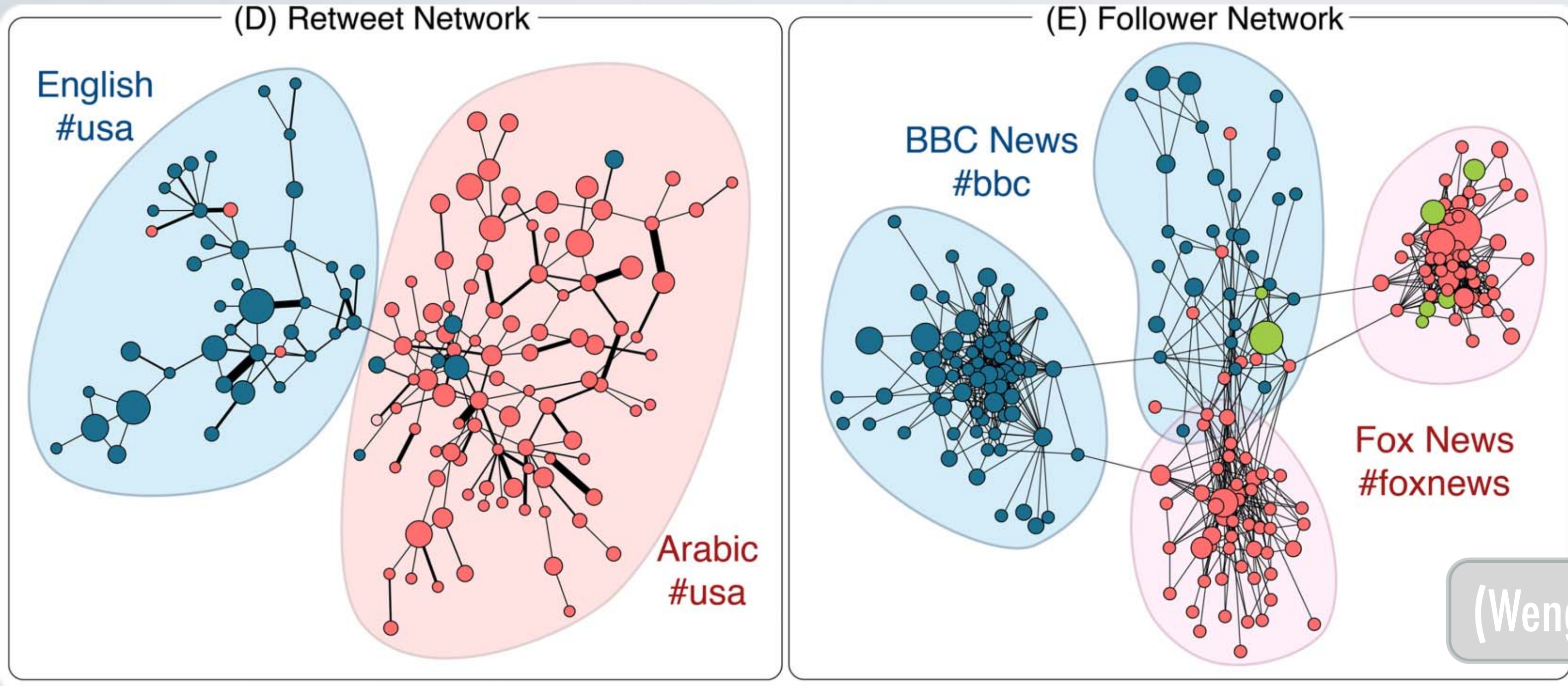




(Weng, Menczer, Ahn, 2013)

spotlight europe

Bertelsmann Stiftung

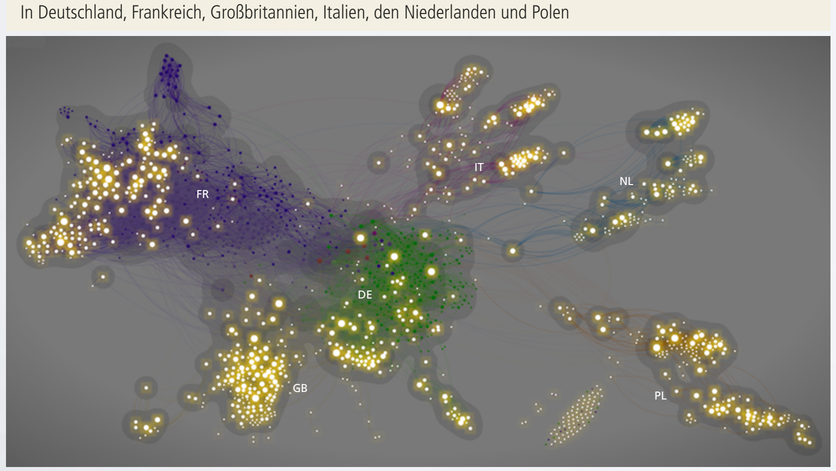
2014/02 — Mai 2014

Im Netz der Populisten

Wie präsent und aktiv sind die antieuropäischen Populisten im Internet? Resultat: Die Anti-Europäer sind isoliert und zersplittert. Es gibt aber eine lebendige pro-europäische Netzöffentlichkeit. Nur zivilgesellschaftliche Initiativen brauchen noch mehr Unterstützung.

988 Internetseiten mit antieuropäischen Inhalten

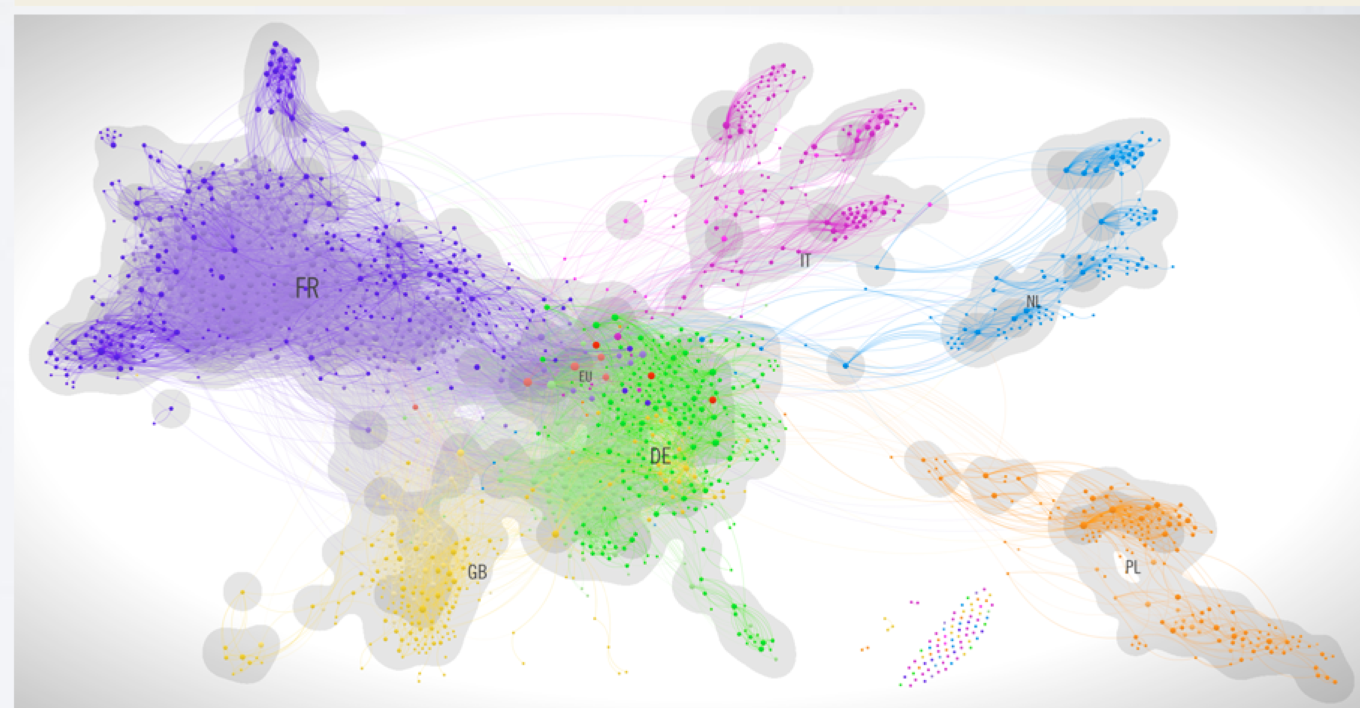
In Deutschland, Frankreich, Großbritannien, Italien, den Niederlanden und Polen



Quelle: linkfluence

1.638 europapolitische Internetseiten

In Deutschland und Frankreich mit pro- und antieuropäischen Inhalten;
in Großbritannien, den Niederlanden, Italien und Polen mit antieuropäischen Inhalten



Quelle: linkfluence

CONNECTING INTERACTIONS AND CONTENT

Studying the aNobii book rating/tagging social network

- semantic-structural proximity (bookshelf)

(Aiello, Barrat, Cattuto, Ruffo, Schifanella, 2010)

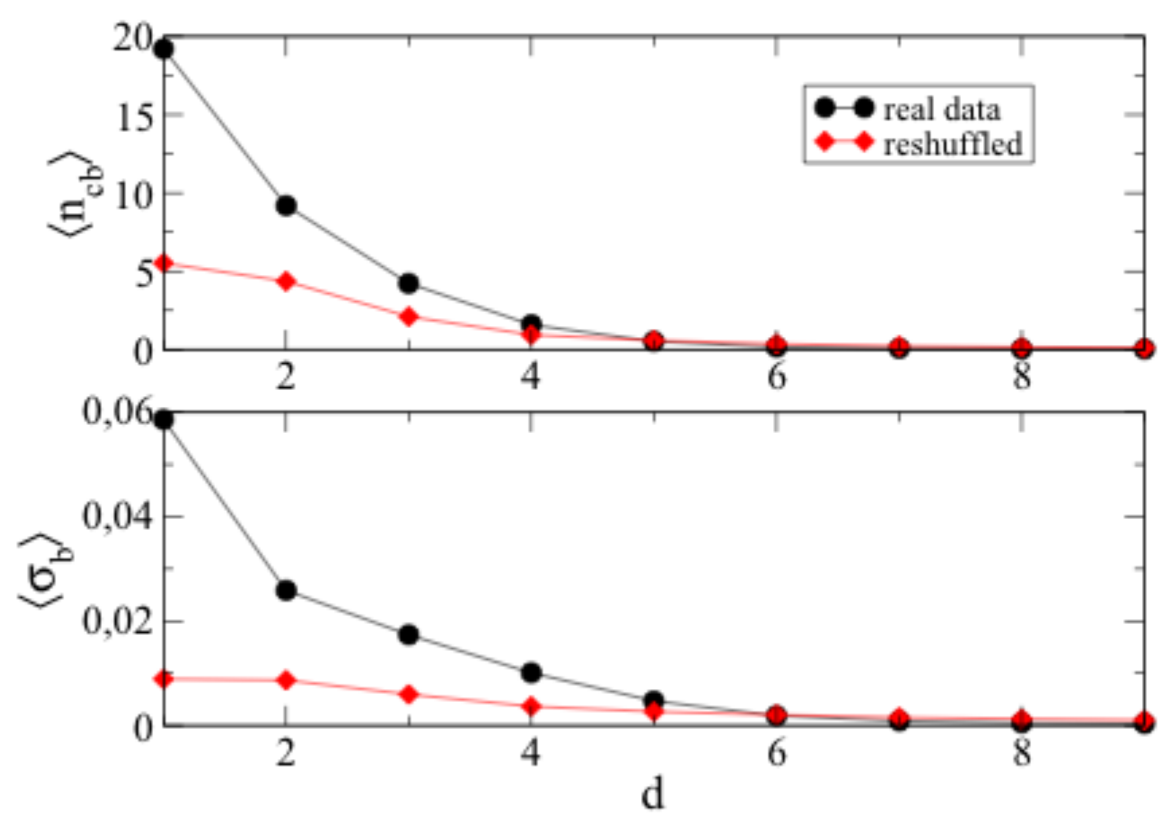


Fig. 3. Average similarity of the libraries of aNobii users as a function of their distance in the social network. The similarity is measured by the average number of common books (top, $\langle n_{cb} \rangle$), and by the average cosine similarity (bottom, $\langle \sigma_b \rangle$) between the book lists. In both cases data for the same social network with reshuffled booklists are shown.

CONNECTING INTERACTIONS AND CONTENT

- Studying the aNobii book rating/tagging social network
  - semantic-structural proximity (bookshelf)
  - spatial-structural homophily (location)

(Aiello, Barrat, Cattuto, Ruffo, Schifanella, 2010)

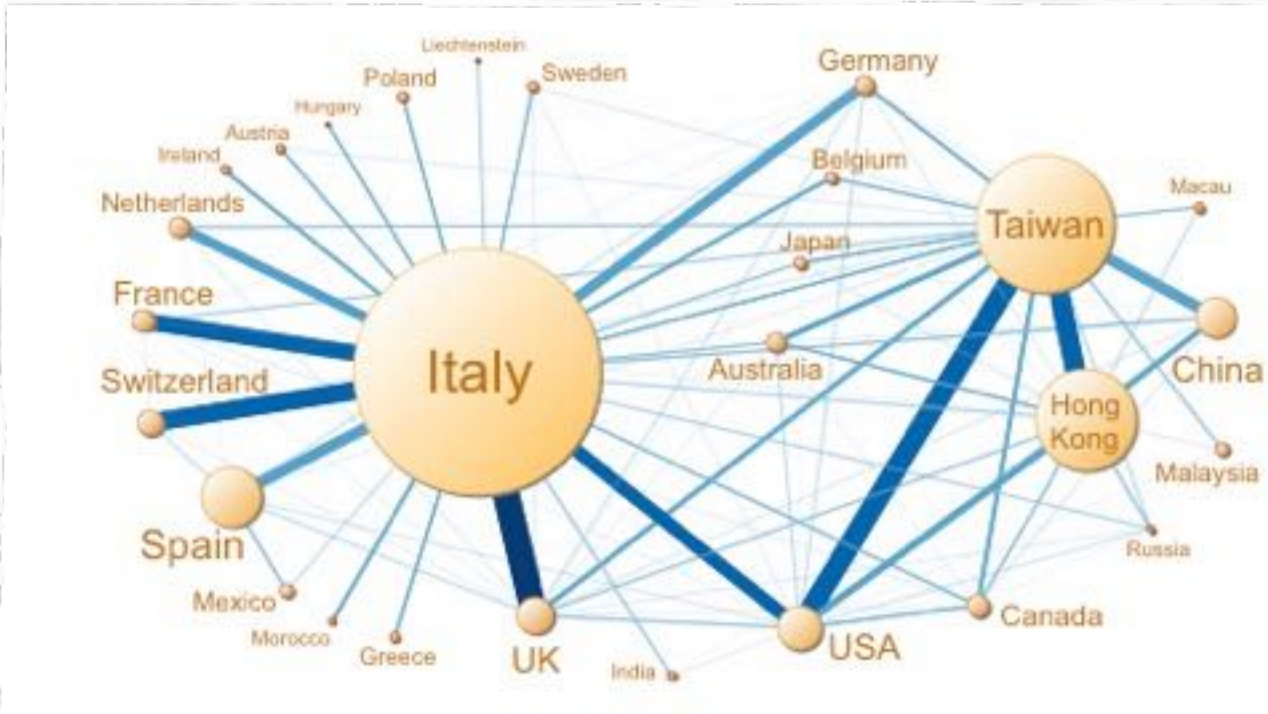


Fig. 5. Graph of aNobii countries. Nodes areas are scaled according to the size of the geographic communities and edges' width and colors are proportioned to the number of links that connects nodes between the countries.

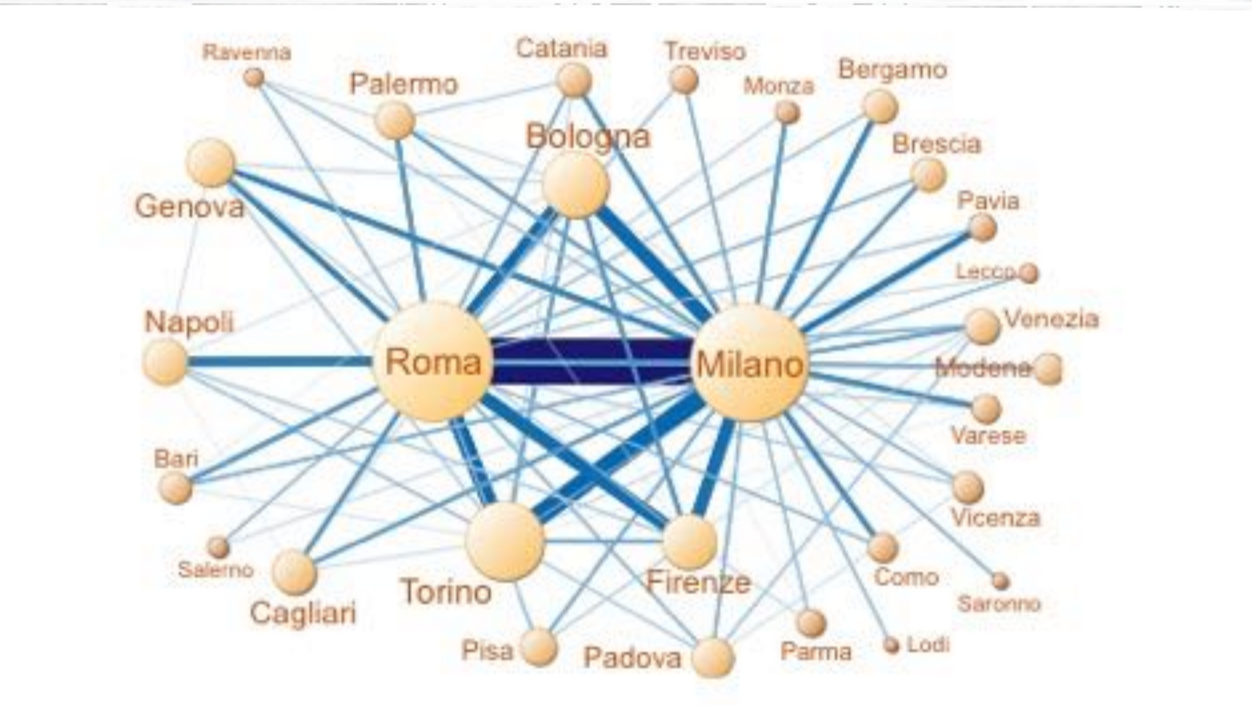


Fig. 6. Graph of aNobii Italian towns. Nodes areas and edges' width and colors are scaled like in Fig. 5. Small towns linked to others with less than 10 links are not represented.

CONNECTING INTERACTIONS AND CONTENT

- Studying the aNobii book rating/tagging social network
  - semantic-structural proximity (bookshelf)
  - spatial-structural homophily (location)
    - although not always, see Lin et al.

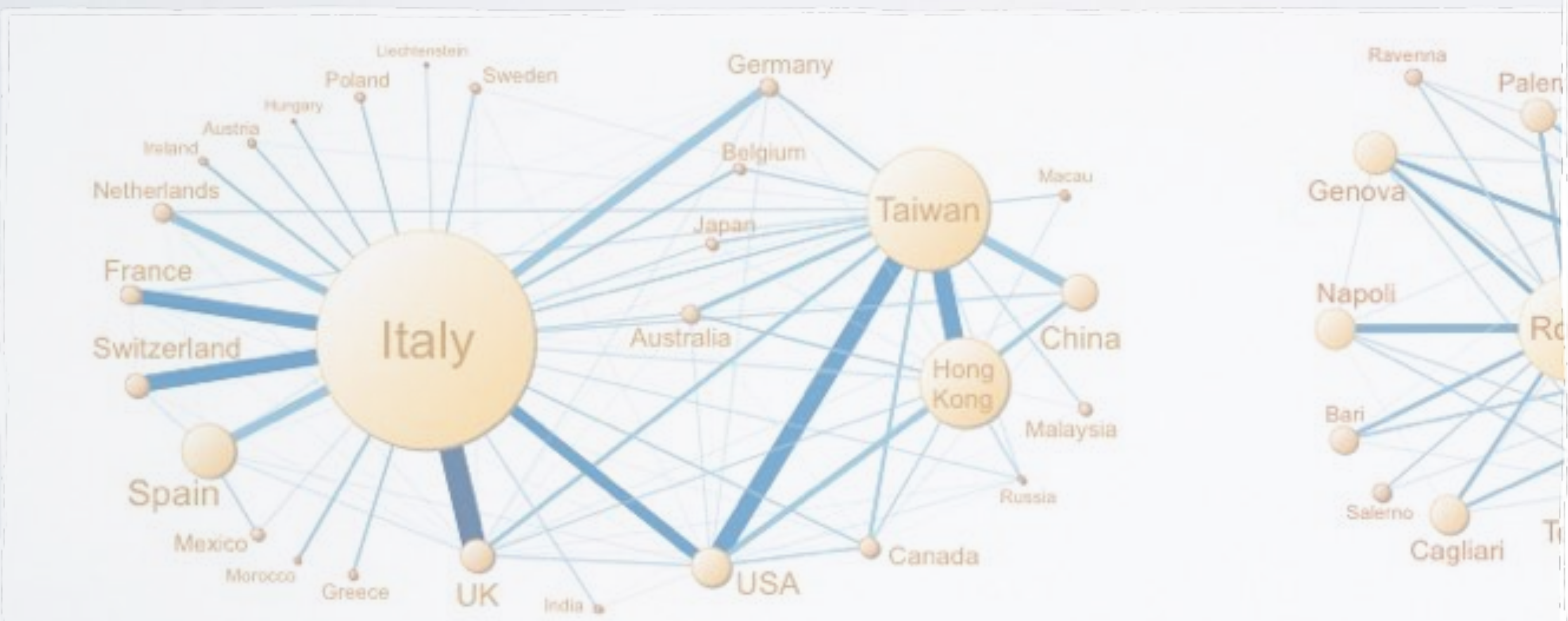
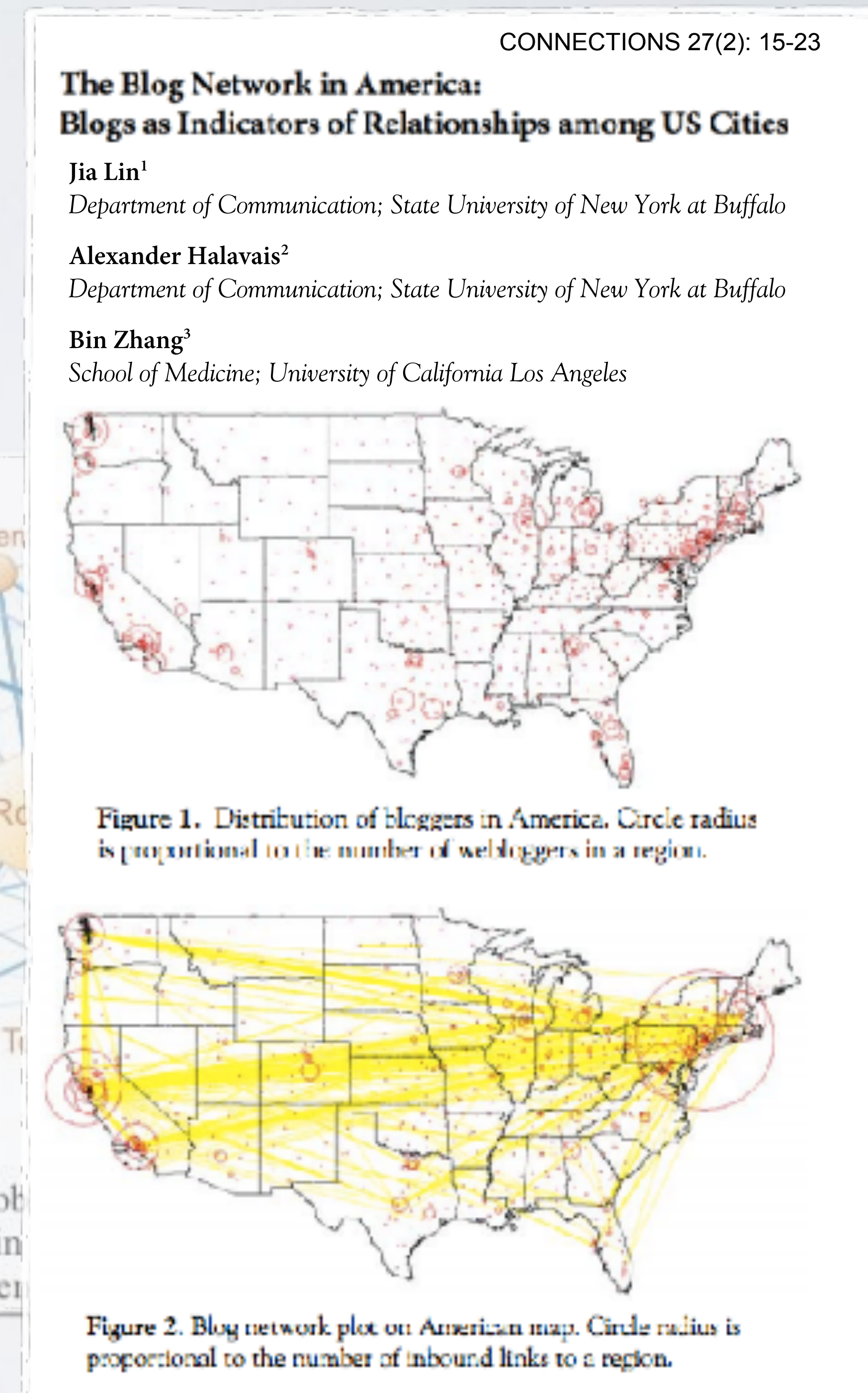


Fig. 5. Graph of aNobii countries. Nodes areas are scaled according to the size of the geographic communities and edges' width and colors are proportioned to the number of links that connects nodes between the countries.

Fig. 6. Graph of aNob colors are scaled like in 10 links are not represe



CONNECTIONS 27(2): 15-23

The Blog Network in America: Blogs as Indicators of Relationships among US Cities

Jia Lin[1]
Department of Communication; State University of New York at Buffalo

Alexander Halavais[2]
Department of Communication; State University of New York at Buffalo

Bin Zhang[3]
School of Medicine; University of California Los Angeles

Figure 1. Distribution of bloggers in America. Circle radius is proportional to the number of webloggers in a region.

Figure 2. Blog network plot on American map. Circle radius is proportional to the number of inbound links to a region.

Mapping the Arabic Blogosphere: Politics, Culture, and Dissent

By Bruce Etling, John Kelly, Robert Faris, and John Palfrey

Berkman
The Berkman Center for Internet & Society at Harvard University

JUNE 2009
Berkman Center Research Publication No. 2009-06

INTERNET & DEMOCRACY project

STRUCTURE OF THE NETWORK AND METHODS OVERVIEW

- **links:**
  citations (interactional)
- **colors:**
  co-citation communities ("topical")
- strong geographic coherence, *even though* national clusters not focused on national topics (e.g. youth, women's rights, bloggers' rights, poetry)
- *international clusters* related to international media and international political topics (including islam)

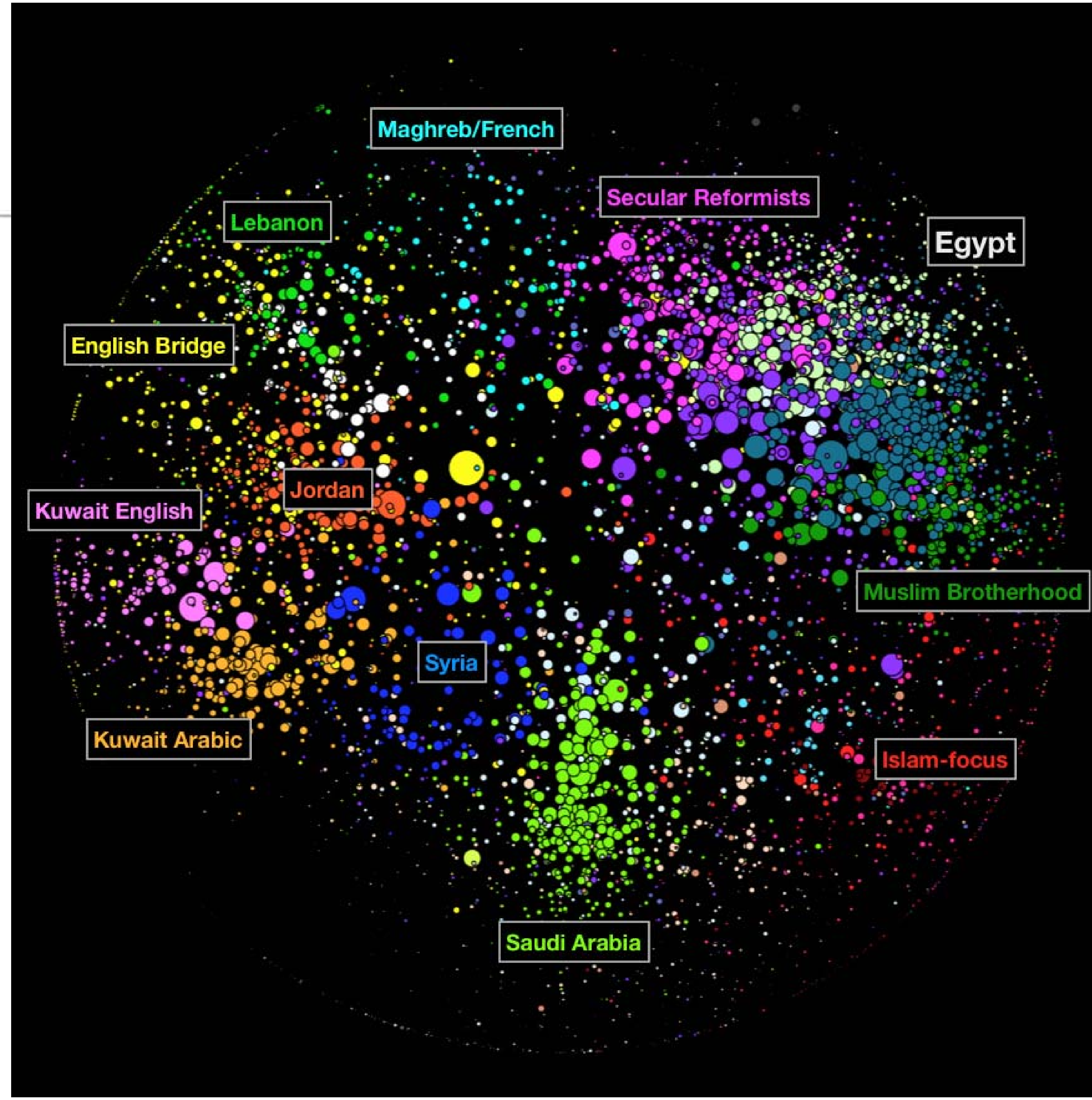


Fig. 1: Map of the Arabic Blogosphere

Multilingual use of Twitter: Social networks at the language frontier

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Computers in Human Behavior 41 (2014) 424–432

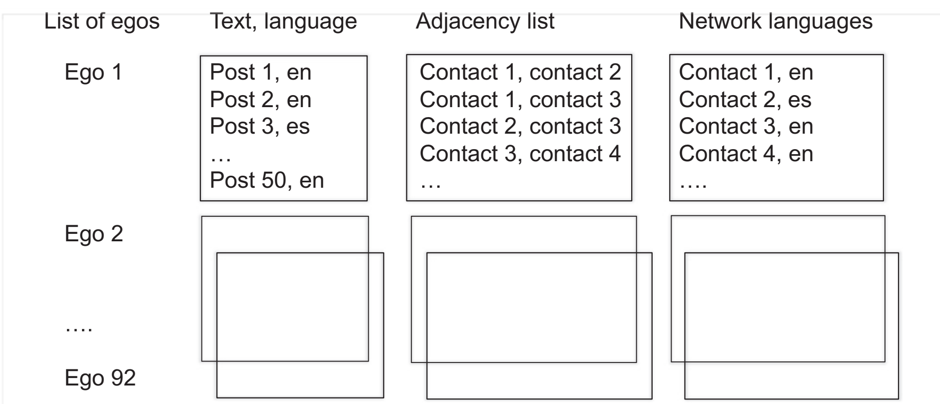

Fig. 1. The data comprises a list of 92 egos, with 50 posts each and language labels, their contacts with a language label, and the social network edges in an adjacency list.

Table 1
Properties of bilingual networks observed in the visualizations.

Properties	
(A) Degree of connection between language groups	(A1) Few connections
	(A2) Tightly connected
(B) Degree of integration of one language group inside another	(B1) Separated
	(B2) Partial integration
	(B3) Complete integration
(C) Relative size of one language group respect to the other	(C1) Similar size
	(C2) Very different size

Gatekeeper (Fig. 5.1): two language groups connected by a few nodes only, with properties A1, B1, and C1 (12 networks).

Language bridge (Fig. 5.2): two tightly connected language groups, but still separated, with properties A2, B1, and C1 (12 networks).

Peripheral language (Fig. 5.3): a dominant language group con- nected to a small or not cohesive language group, with properties A1 or A2, B1, and C2 (12).

Union (Fig. 5.4): two tightly connected language groups, where one language group has been penetrated by the other, with properties A2, B2, and C1 or C2 (9 networks).

Integration (Fig. 5.5): one language group inside another with properties A2, B3, and C1 or C2 (17 networks).

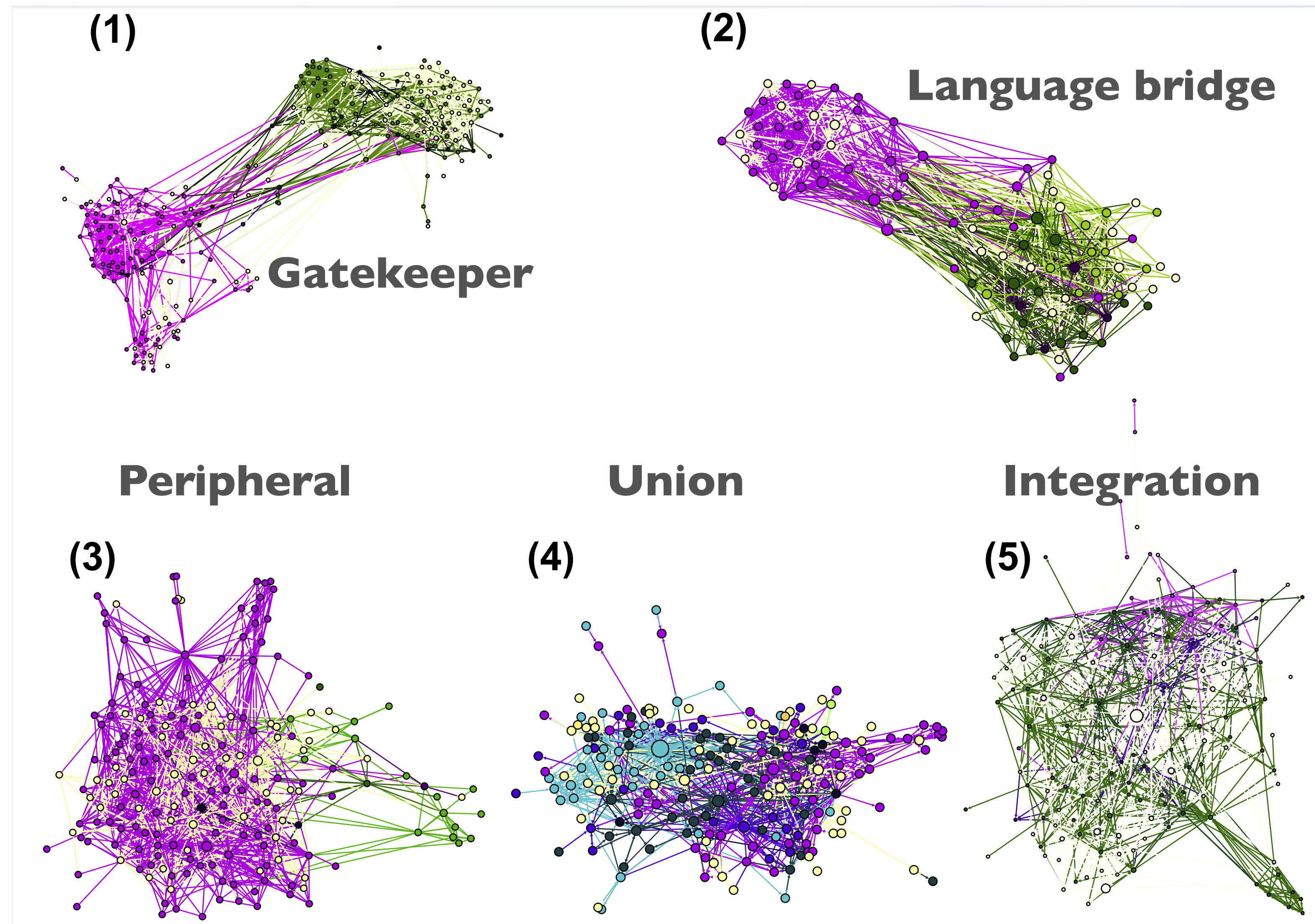

Fig. 5. Networks of five multilingual Twitter users exemplifying the network types. The nodes are their contacts and the edges represent the “follower/following” relationship. Pink nodes post in English and yellow/white is used for nodes with no data. (1) The gatekeeper type; there is a French group on the right side (green) loosely connected with an English group on the left. (2) Represents the language bridge type; in this network, the Japanese group on the right side (green) is tightly connected with the English group on the left, and intermingled with bilingual users (violet and dark green). (3) The peripheral language, Portuguese, on the right side (green) of the dominant English group. (4) Exemplifies the union type, where the Greek group on the left (turquoise) is merging and mixing with the English group on the right, and there are many bilinguals (violet and dark green). (5) Illustrates the integration type; the English group being inside the Arabic (green). Visualizations made with Gephi. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Sociolinguistic Analysis of Twitter in Multilingual Societies*

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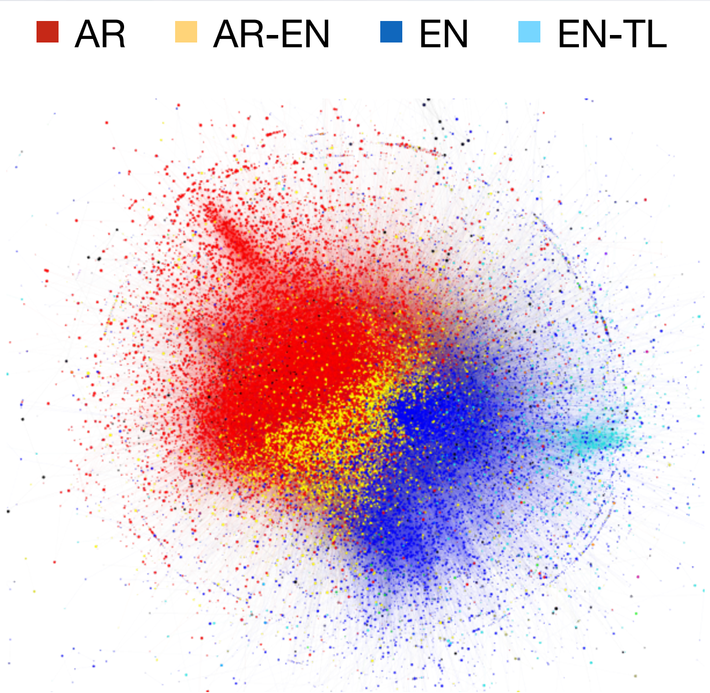

Figure 1: Visualization of Qatar Twitter network. Each node and edge represents user and followings in the Twitter networks. Each node is colored by the language usage from corresponding user's tweets. AR-EN Bilingual users are located between monolingual clusters.

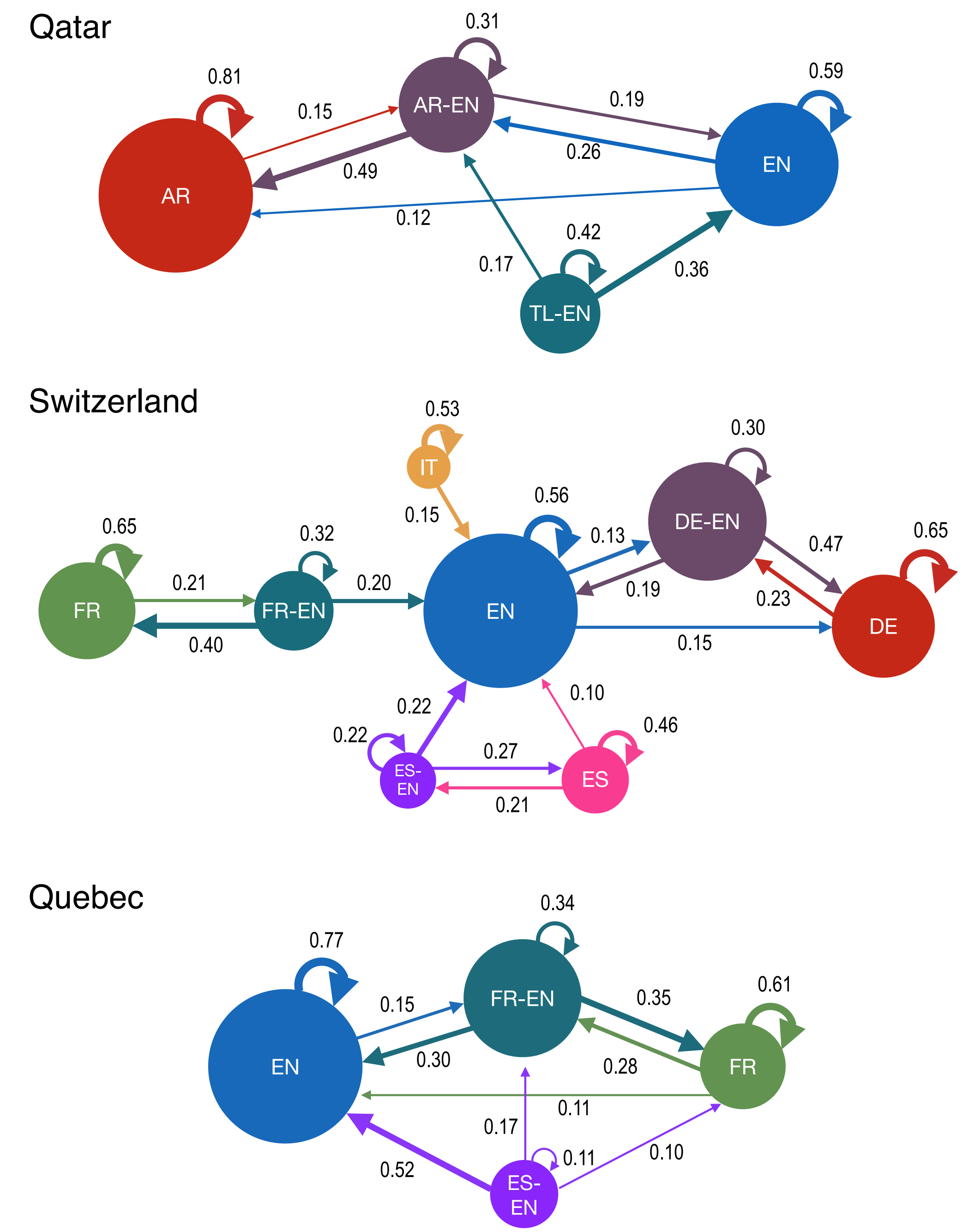

Figure 4: Following patterns among lingua groups. The color of an edge corresponds to the source color of the edge. Following

"We found that from all bilingual groups in three regions, bilingual users post informational and political tweets for the local audience in local language. They, on the other hand, post events, tourism, photography, and other leisure-related tweets in English for the non-local audience."