Political Dynamics in Large Scale online Data Sets: A Study of Content-Oriented User Behavior

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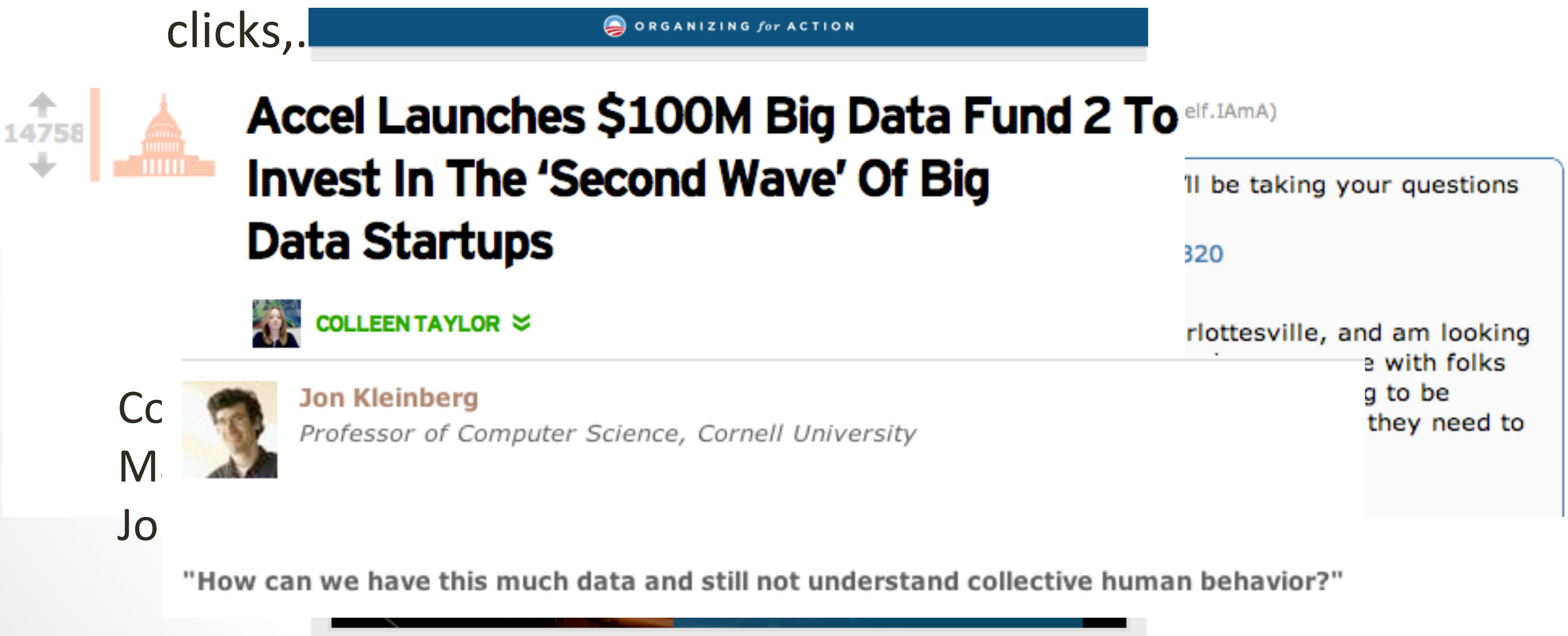
Big Data, Little Insight

- Growing shift to online interaction is affecting society
  - Example: opinion formation and decision making
  - Government, Industry, Academia have taken notice
- User → Thousands of small actions (tweets, likes, comments, clicks,.



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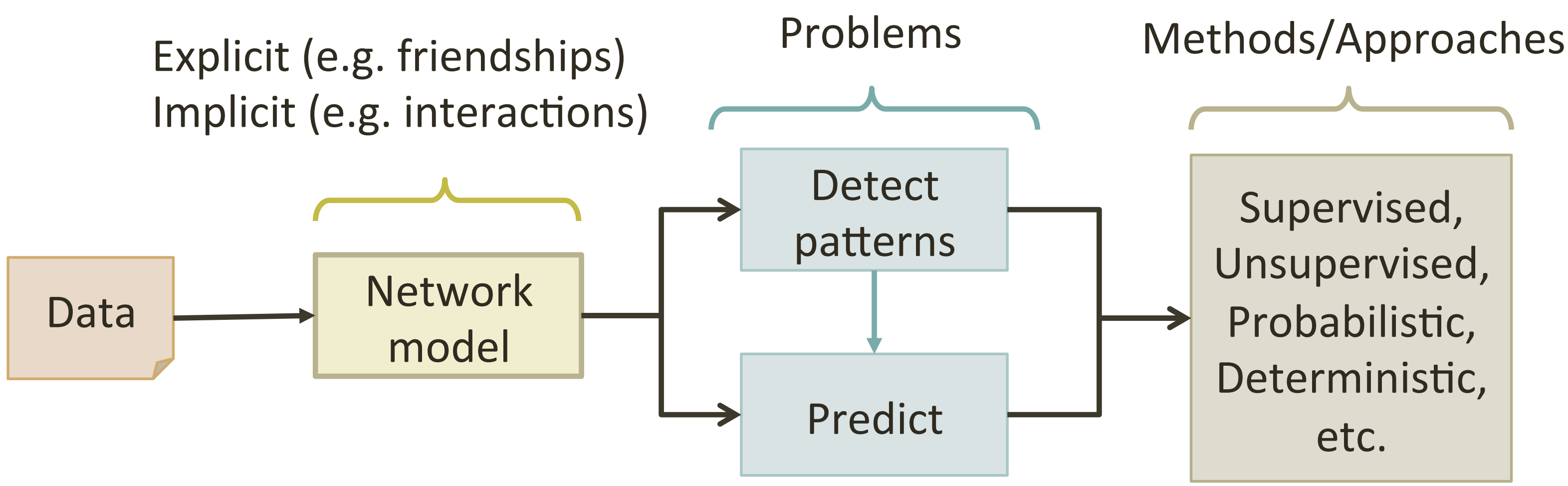
Background



- Examples:
  - Friendship recommendations
  - Prediction of popularity (e.g. films)

Promise for Social Sciences

- Access to highly granular, time-stamped data
- Datasets raise hopes for data-driven models in social sciences
  - Scale, complexity, and noisiness
  - Predicated on automated methods to extract *summative macroscopic observables*
    - Equivalents of pressure and temperature
- Current approaches:
  - Summarizing the network: e.g. graph-theoretic communities
  - Summarizing the content: e.g. Topic Modeling
    - Hidden topics derived through word co-occurrence across documents
    - Computationally intensive
    - Mathematical regularization rather than social regularization

Focus of Talk

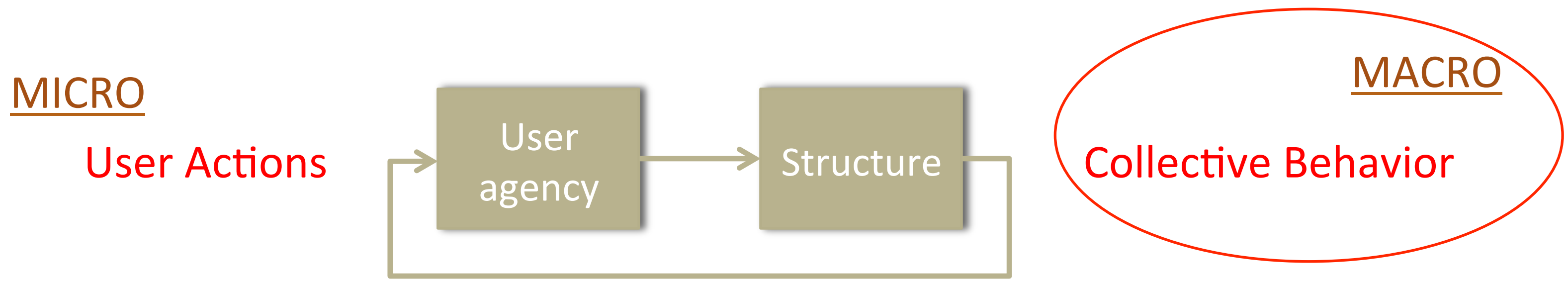
- Content oriented collective behavior
- Macroscopic observables to extract:
  - *Collective behavior*: different meanings across many traditions.
    - Here we use it in a general sense: attitudes and actions of groups of users
  - Collective behavior in social news
- *Content-oriented:* involving users' creation, sharing, and promotion of content and their attitudes toward content (text or other material)

Social News

- Social news aggregation sites have article submission, voting, and commenting capabilities
  - Examples: Reddit, Digg, Slashdot, Balatarin

Motivating Questions

- How would one begin to understand the user population?
- Theory of structuration (Anthony Giddens)
  - Emphasizes both agency and structure



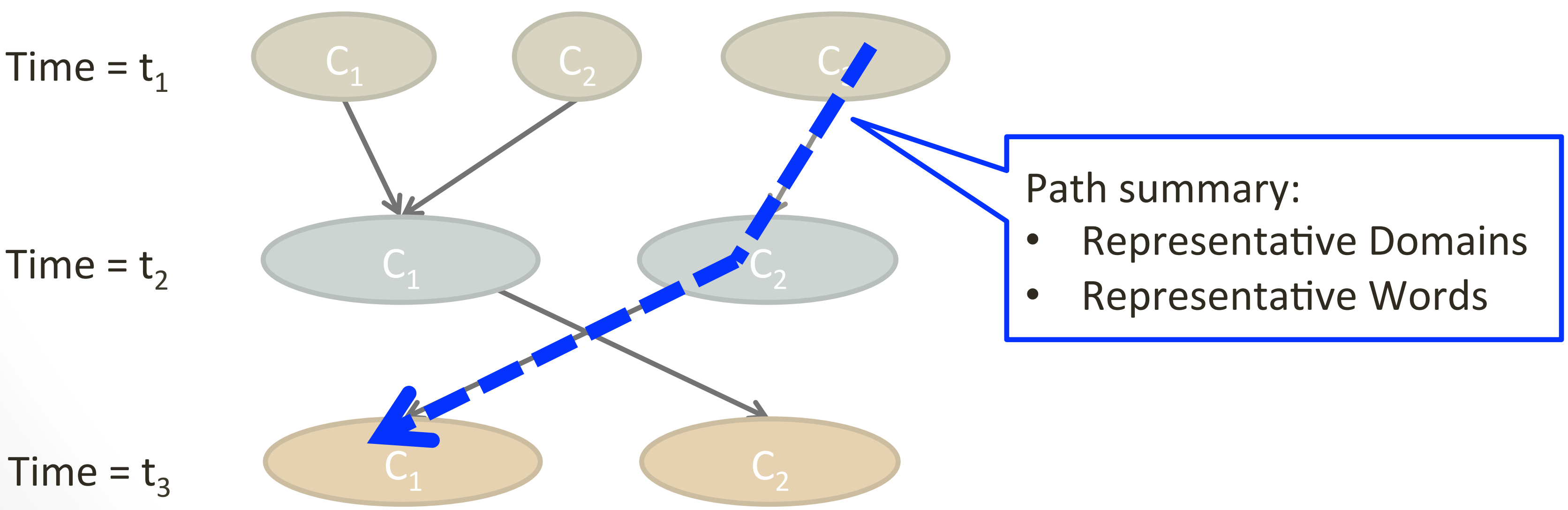
- If these structures exist they must manifest themselves in aggregated data.
- Once we can detect macro structures (collective behavior), we can answer other questions:
  - Do users form polarized and insular groups?
  - Does one group dominate or drive out other groups?
  - How do external events affect these dynamics?

Dataset and Methodology

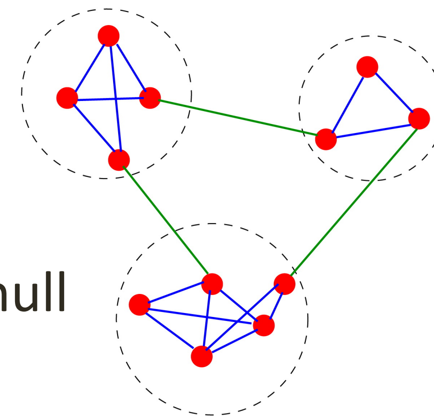
- Balatarin: popular Persian-language social news site
  - 4 years of data: users, articles, and user votes to articles
  - Politics Category: 26,000 users 350,000 articles, 9.2M votes
- Votes: user actions
  - Explicit indicators of user preference for content
  - Other examples: *Like* (Facebook), *up-vote* (Reddit), *+1* (G+), *Digg*
- Detect communities of users with similar voting patterns and track these communities' temporal evolution.
- Characterize evolving communities through their preferred content

Methodology

Divide data into consecutive overlapping time periods (30 days, 14 day overlap).



Communities



- Higher density of edges within communities than between them
- *Modularity** = fraction of edges that belong to the same community in the graph minus the null model

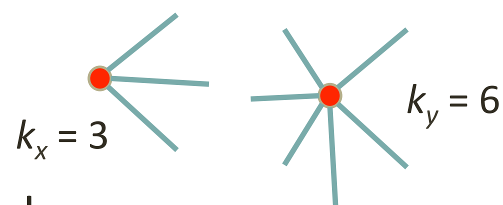
$$Q = \frac{1}{2m}\sum_{x,y}\left(A_{xy} - \boxed{\frac{k_x k_y}{2m}}\right)\delta(C^x, C^y)$$

Number of edges in the graph

$\boxed{P(A_{xy} = 1)}$

Communities that vertices x and y belong to

- Null model:
  - Graph with same degree sequence
  - Connect pairs of edge stubs (*2m*) at random

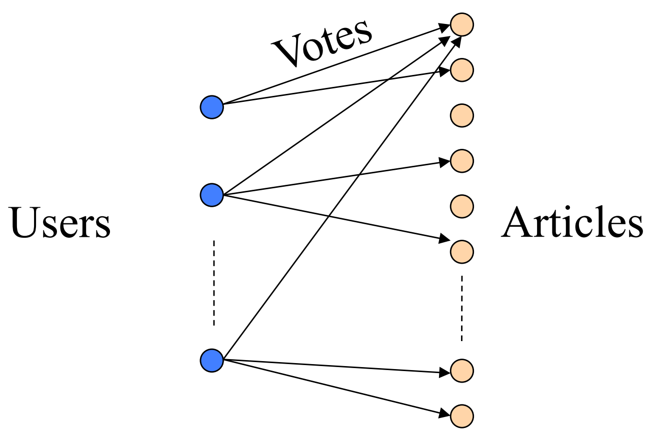


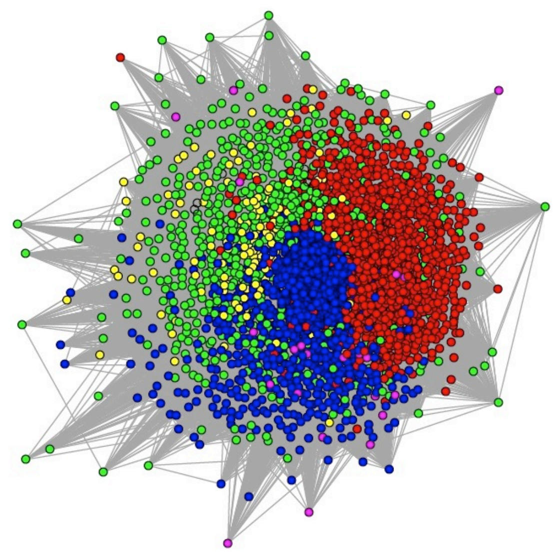
- Optimize by iteratively joining communities, starting with single-node communities.

* Developed by Girvan, Clauset, Newman

Bipartite Projection

- In each time period votes create a bipartite graph of articles and users
- Project to a weighted unipartite network





$$W_{jaccard} = \frac{n(X \cap Y)}{n(X \cup Y)}$$

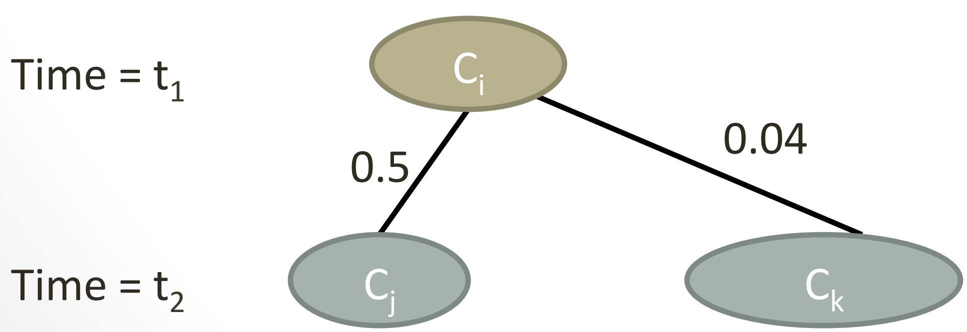
Weight between users x and y
X: set of articles voted for by user x
Y: set of articles voted for by user y
n: set cardinality

Detect and Map Communities

- For a weighted graph
  - Replace A_{xy} with W_{xy} and m with total weight in the graph, W.
  - Replace vertex degree k_x with vertex strength s_x

$$Q = \frac{1}{2W}\sum_{x,y}(W_{xy} - \frac{s_x s_y}{2W})\delta(C^x, C^y) \qquad \boxed{s_x = \sum_y W_{xy}}$$

- <u>Communities reflect users with similar content preference</u>
- Map consecutive communities based on user overlaps.

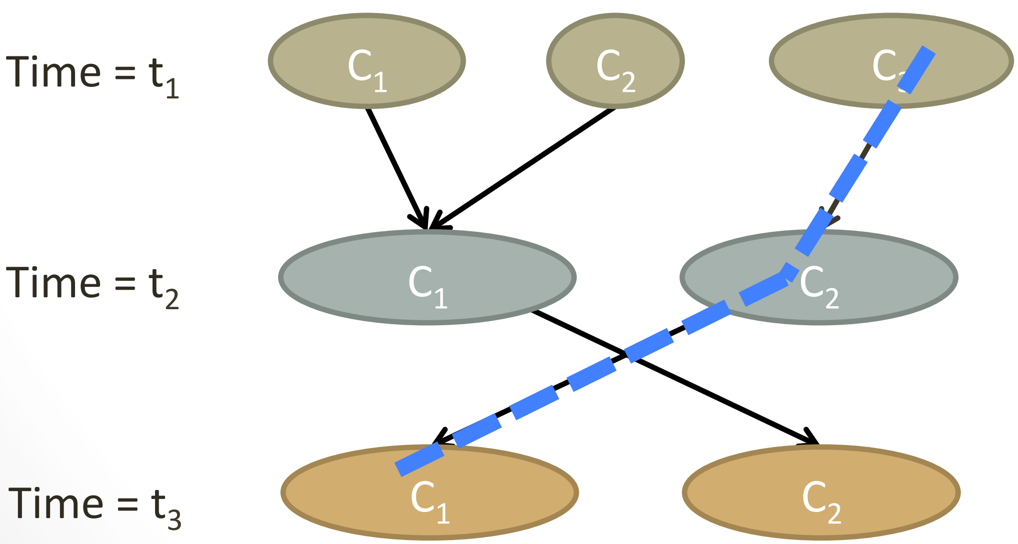


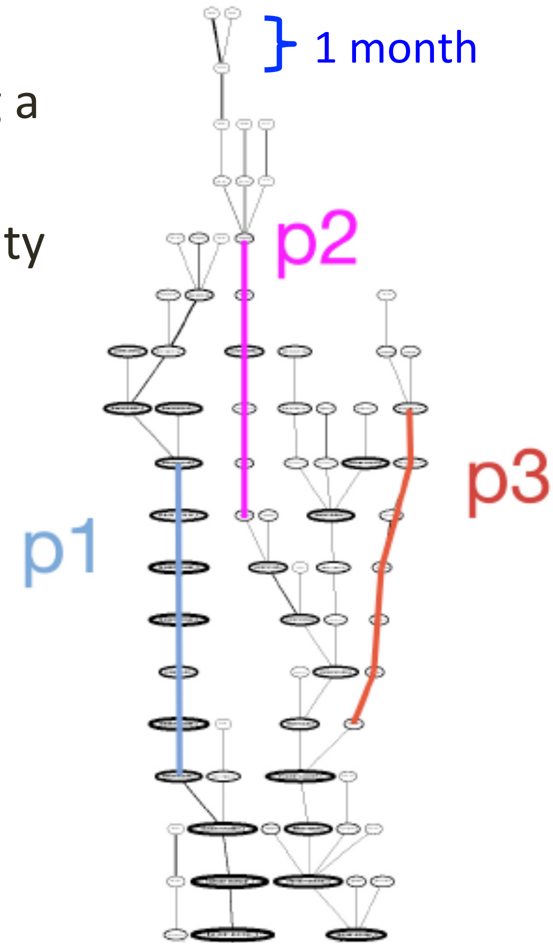
Users in community i

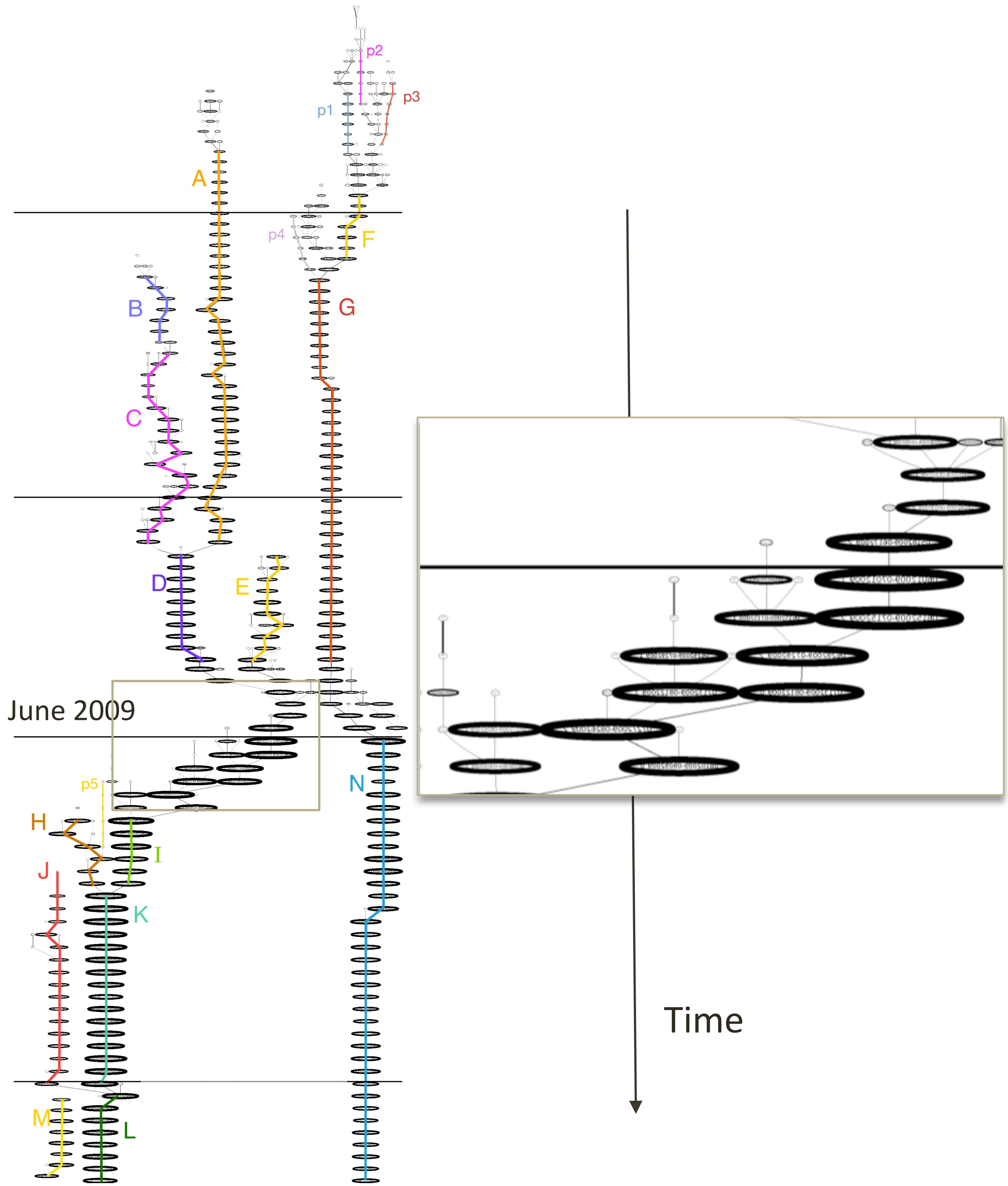
$$\frac{n(C_i \cap C_j)}{n(C_i)} \cdot \frac{n(C_i \cap C_j)}{n(C_j)}$$

Define an Evolution Path

- Define a path as consecutive mapping of communities with no merges or splits lasting a minimum duration (at least 3 months long)
- Size of each oval represents size of community







p2
p3
p1
A
p4
F
G
B
C
D
E
June 2009
p5
N
H
I
J
K
M
L
Time

Representative Content

- In each time window, find articles that are highly preferred by each community
- Assuming each community votes for articles at random with probability:

$$p_i = \frac{\overbrace{N_i}^{\text{Votes cast by community } i}}{\underbrace{N}_{\text{Votes cast by all communities}}}$$

- Then probability that o_{ij} of an article's N_j votes come from community *i*:

$$p(o_{ij}) = \binom{\underbrace{N_j}_{\text{Total votes received by article } j}}{\underbrace{o_{ij}}_{\text{Observed number of votes from community } i \text{ to article } j}} {p_i}^{o_{ij}} (1 - p_i)^{(N_j - o_{ij})}$$

- For $o_{ij} > p_i.N_j$, the lower this probability, the higher the preference of community *i* for article *j*

Representative Terms and Domains

- Representative *terms* (in articles preferred by a community)

Normalized term frequency of term T in community C

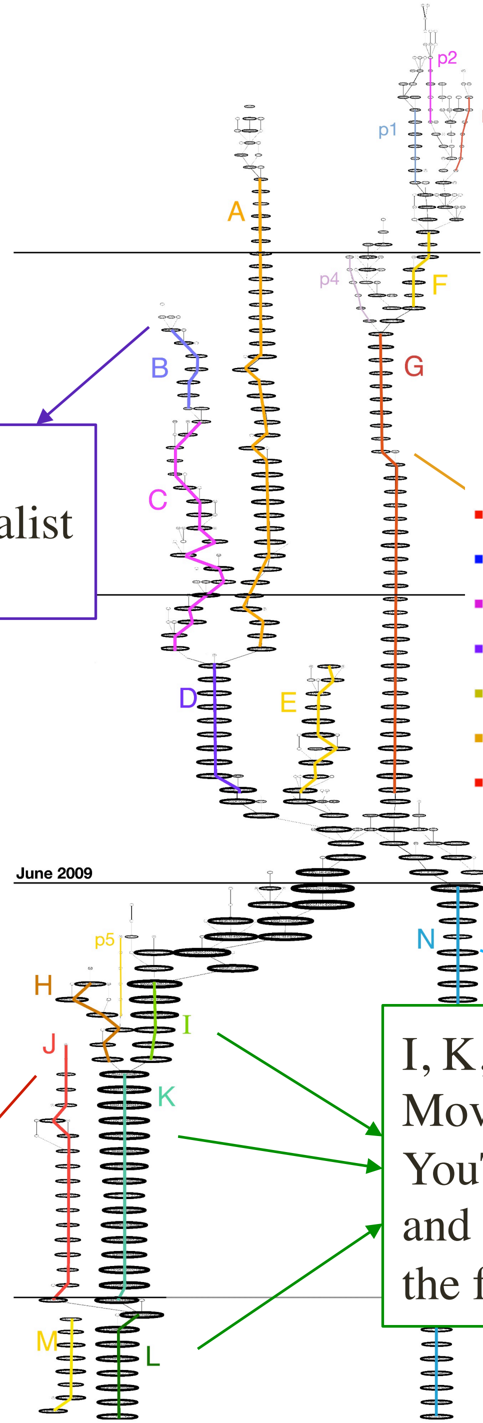
Normalized term frequency of term T in all communities in the period

$$\text{Score}(T) = \frac{\text{tf}(T, C)}{\max_t \text{tf}(t, C)} - \frac{\text{tf}(T)}{\max_t \text{tf}(t)}$$

- Aggregate these terms as well as the websites of preferred articles over each path

Representative domains and terms for one path

Domains	Terms
www.bbc.co.uk www.dw-world.de www.roozonline.com radiozamaaneh.com www.radiofarda.com	Minister, Nuclear, Spokesperson, Russia, Council, Continuation, Israel, Security, Iraq, Arrangement, Agency, Europe, America, Declare



G: Iran's foreign affairs: nuclear talks, US, Russia,

B: Articles published by conservative fundamentalist websites.

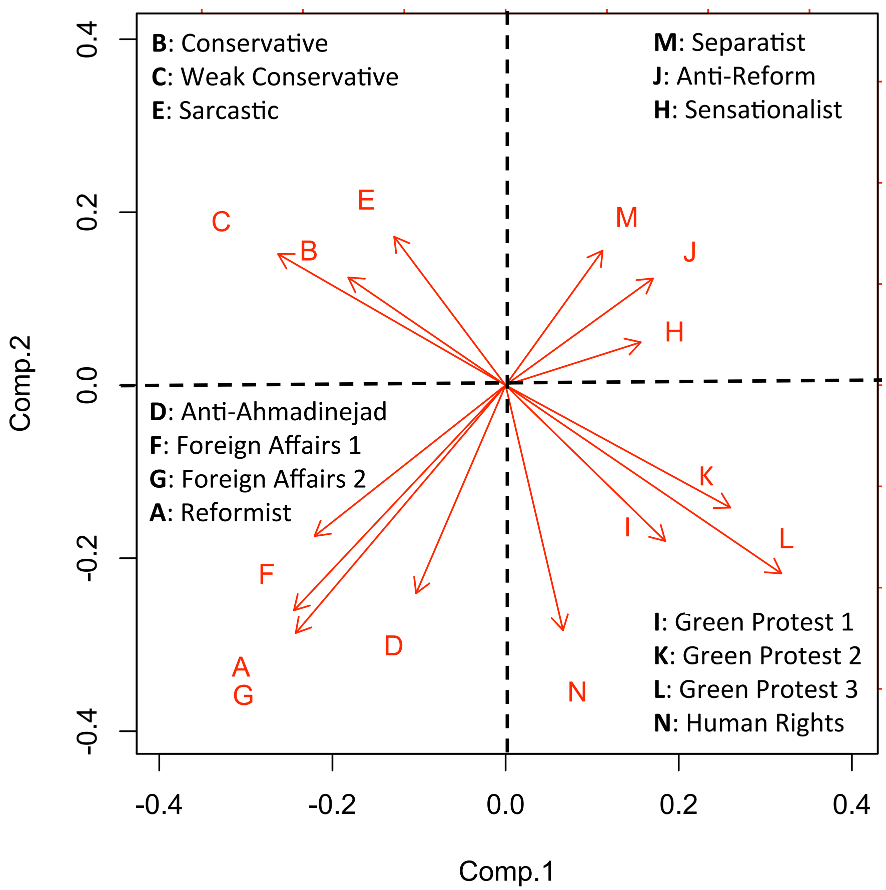
N: Articles about human rights violations committed against

rests of

I, K, L: Large pro-Green Movement consecutive paths. YouTube videos of protests and eyewitness accounts are the focal points.

J: Against prominent reformist figures.

Principal Component Analysis Corroborates Path Meanings



- PCA plot of core-user overlaps
- A temporal and a political dimension emerge as a result of PCA analysis on user overlaps in paths.
- First two components explain 43% of variance
- Contents of paths agree with path positions in the PCA political dimension.

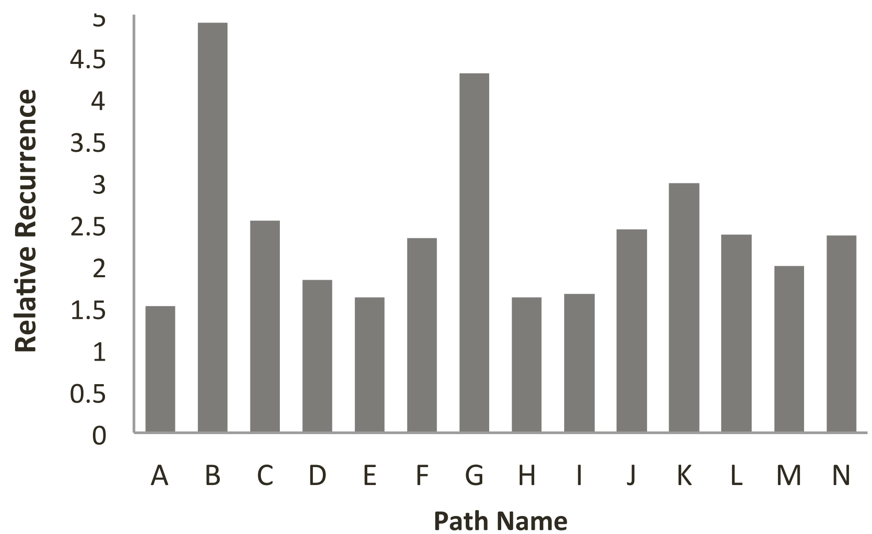
Domain Recurrence

- Are some domains repeatedly preferred in a path?
  - Aggregate domains over whole path and count their recurrence
  - Compare with count of domains if the votes were drawn at random
    - Draw votes at random and note their domains
- Higher relative recurrence = more uniformity in domains

$$\text{Entropy}(C) = -\sum_i p_i log_2(p_i)$$

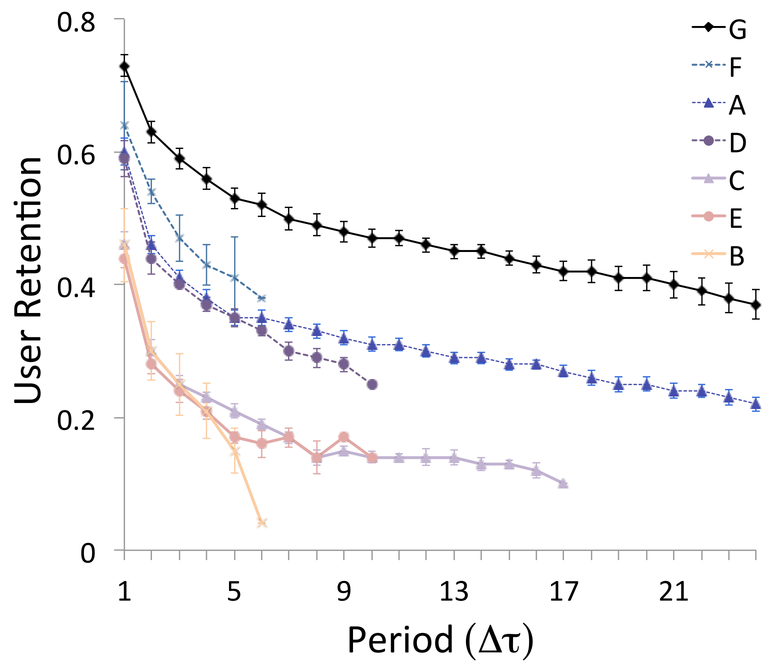
$$\text{Relative Recurrence} = \frac{2^{Entropy(random)}}{2^{Entropy(path)}}$$

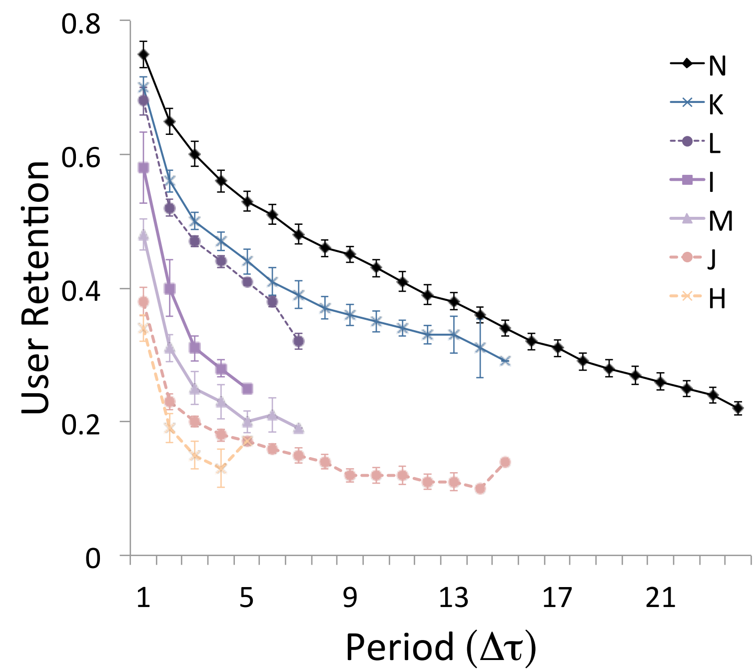
$\boldsymbol{p_i}$**:** Probability that an article from domain i is in the top n most preferred articles of a path.



Paths with high recurrence: B(conservative), G(foreign affairs), K(eyewitness)

User Retention





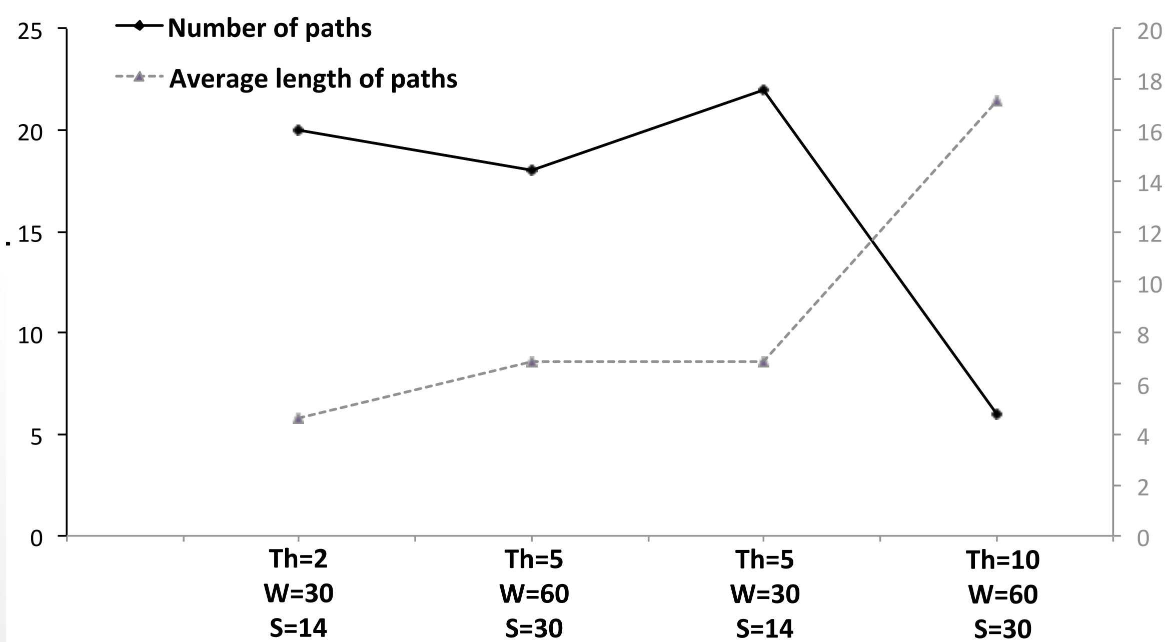
$$\mathrm{Retention}(P, \Delta\tau) = \frac{n(P(\tau_i) \cap P(\tau_i + \Delta\tau))}{n(P(\tau_i))}$$

where $P(\tau_i)$ is the set of users in path P at time τ_i.

- Paths with high retention: G, N, K
- Paths with low retention: B, C, E, J, H

Parameter variations

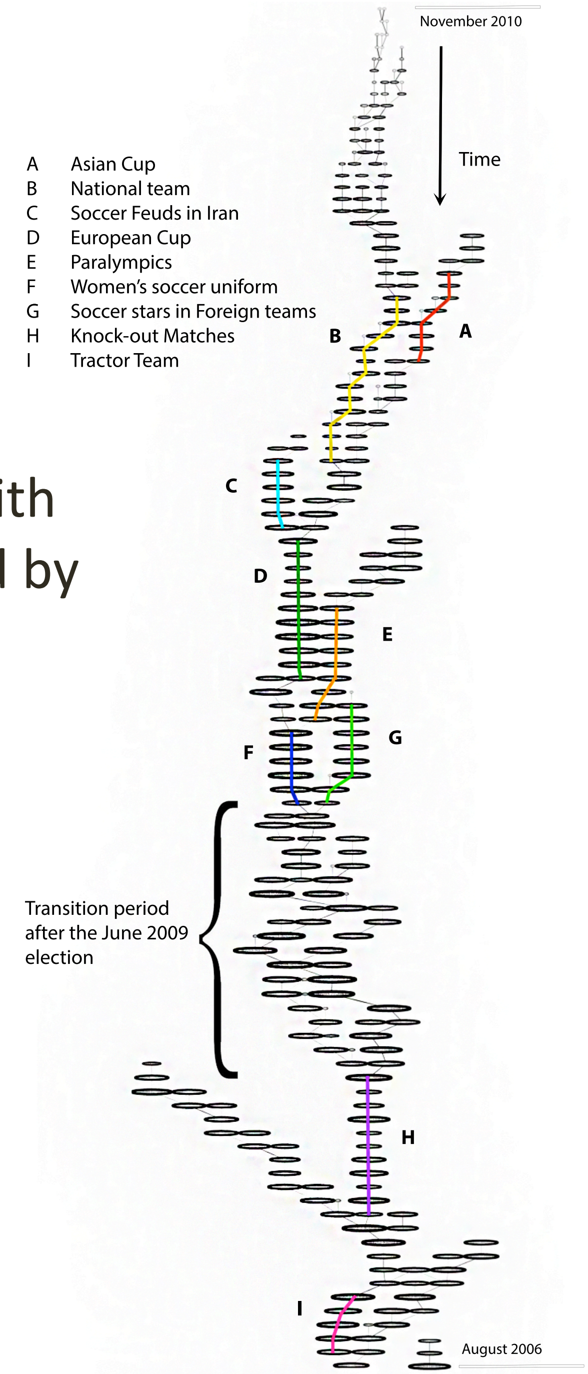
- Three parameters were chosen:
  - W : Window length for each time period
  - S : Shift length determines overlap between consecutive windows
  - Th: Threshold for elimination of low-vote users
- Overlapping windows of size W shifted S days at each period



- More paths: higher granularity
- Longer path: more consistency, easier interpretation
- Prefer *more* and *longer* paths

Alternative dataset: sports

- Method is applicable to different contexts
- Found that Sports is highly event-driven with some early adopters for each event, joined by the rest some periods later:
  - Asian (soccer) cup
  - National leagues
  - European cup
  - Paralympics



Gestalt Computing

From the Merriam-Webster dictionary: Gestalt is a structure, configuration, or pattern of physical, biological, or psychological phenomena so integrated as to constitute a functional unit with properties not derivable by summation of its parts.

- A macro structure
  - The parts create the whole but the whole adds to the parts → more than the summation of its parts.
  - Constructed from elementary user actions
  - More than sum of its parts:
    - Relationship between parts of the structure.
    - What is not there as well as what is there.

Gestalt principle in Design

- We began with elementary actions (votes) → obtained global structure → the context in the structure gives back meaning to individual actions

Structure Reveals a New Perspective

- Comparing two users: 2 of their top 20 domains are different.

  - User 1 Simpson Index: 0.41
    - Core users in paths A, F, G, N: Reformist, Foreign affairs, Human rights.

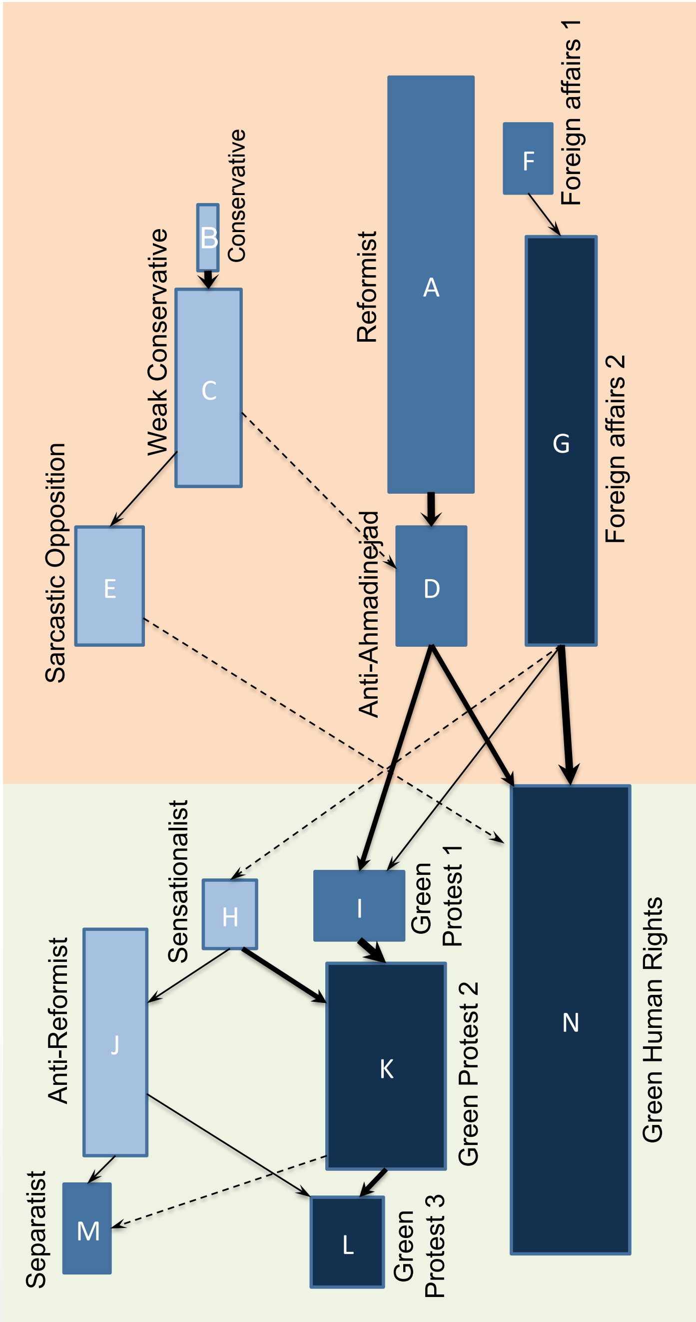
  - User 2 Simpson Index: 0.34
    - Core user in paths A, C, D, G, K, L, N: Reformist, Weakly conservative, Anti-Ahmadinejad, Foreign affairs, Eyewitness, Human rights.

User 1 is more consistent

www.youtube.com	13673	www.youtube.com	1042
www.bbc.co.uk	9012	www.bbc.co.uk	517
www.radiofarda.com	7264	www.radiofarda.com	430
www.roozonline.com	7104	www.roozonline.com	329

$$\text{Simpson's index} = \sum_{i \epsilon A:N} p_i^2$$

Proportion of a user's activity that is in path i



In Summary:

- Automated and unsupervised
  - Deriving the structure requires no expert knowledge of the forum under study
- Paths with <u>distinct</u> and <u>meaningful</u> preferences.
- Incorporates both users and content (vs. just one)
- Reveals a new perspective otherwise unknown
- Applicable to other contexts

- <u>Path width</u>: number of unique users in the path.
- <u>Arrows:</u> inter-path migrations.
- <u>Darkness:</u> user retention.

Concluding Remarks

- Automated and unsupervised method produced political paths with <u>distinct</u> and <u>meaningful</u> preferences.
- Questions:
  - Does the approach sacrifice complexity and sophistication?
  - Is this the “single” “True” structure?
  - Can one combine user actions with different/multiple/undefined intentions?
- Ethical considerations: surveillance and privacy

Thank You