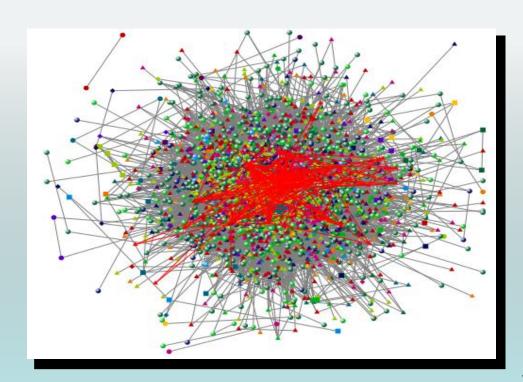




Comment-based communities in the Russian Livejournal and their topical coherence



Olessia Koltsova, Sergey Koltcov, Sergey Nikolenko

www.linis.hse.ru

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RESEARCH AGENDA

- Online discussions are socially important.
- In blogs, they develop in comments.
- Comment-based networks may contain denser areas communities – indicative of some (problematic) social issues.
- However, most research on communities in blogs has been on friendship networks (Lescovec 2008, Zakharov 2007).
- Comment-based network research uses authors, not posts as nodes (Adamic et al 2008, Ali-Hasan & Adamic 2009, Gomez et al 2008).





RESEARCH QUESTIONS

- Do comment-based communities exist?
 - Comment-based community in blogs: exists when a certain (fuzzy) set of posts or bloggers is commented by a certain set of bloggers
- If so, do they form around common topics of the commented posts or around authors of the commented posts?





NETWORK CONSTRUCTION

- For greedy community detection algorithms → bimodal post-commentator network projected to post-post network
- Two posts are considered connected if they have been commented by the same blogger
 - If they have been commented by two different bloggers, they gain two edges in common
 - If they have been commented twice y one blogger, they gain two edges in common
 - Self-commenting is excluded.





RUSSIAN BLOGOSPHERE AND LiveJournal

- Russian blogosphere: about 58 mln blogs, 7-8 mln posts a day(without microblogs).
- Commenting: mostly locked within blog platforms (around 100, 5-6 leading).
- Livejournal (most politicized): 2 (4) mln accounts, 60-70 thousand posts a day.
- Followers-based ratings of bloggers are important in Russia.
- At rating level of 150 thousand LJ produces less than 1 post per blogger per month.





DATA

- Top LJ 2000 bloggers (have 500+ followers, produce avg. 1 post per blogger per day, receive 20 times more comments).
- Time: April 1 April 7 2013 (reasonable period for an event life-cycle, also: computational complexity limits).
- 24619 posts total,19039 posts with comments,1653 excluded for technical reasons = 17 386 posts in analysis.
- 520 549 comments
- ≈ 4,5 mln edges "post-post", after self-comments are excluded; 391 posts had no shared commentators.
- 1667 authors, 56217 commentators



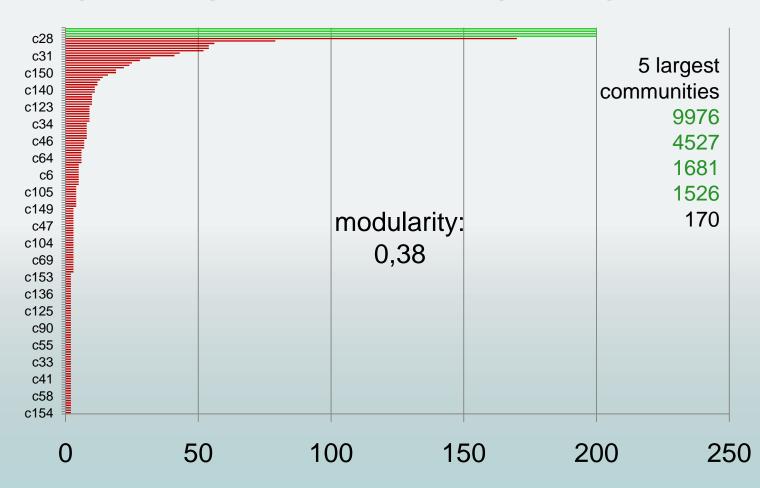
METHODS 1

- Data collection: Koltran / LINIS BlogMiner software (full-text & relational structure of LJ).
- Community detection: Louvain algorithm, developers' code.
- Community belonging / authorship correlation: SPSS, nominal measures of association.
- Topic similarity detection: LINIS TopicMiner & C++ codes:
 - Text clearing, cutting & lemmatization;
 - TF/IDF calculation (texts represented as lists of frequencies of words in them);
 - Cosine similarity calculation (each pair of texts compared on the basis of words frequencies in them);
 - Average similarity within comment communities compared to global average similarity.





COMMUNITY STRUCTURE



Number of posts in communities: communities 0-158; number range: 2-9976 Louvain, level 1.





AUTHORSHIP

			Asympt.Std.		Approx.
		Value	Error	Approx. T	sig.
Lambda	Symmetric	,209	,003	59,644	,000
	Dependent blogger	,057	,002	26,346	,000
	Dependent	,522	,007	56,832	,000
	community				
Goodman &	Dependent	,041	,001		,000
Kruskal Tau	blogger				
	Dependent	,510	,004		,000
	community				
Cramer's V		,466			,000
Contingency		,985			,000
Coefficient					

Belonging of a post to a community strongly depends on the post's authorship. I.e. communities tend to form around authors.





TOPICAL SIMILARITY 1

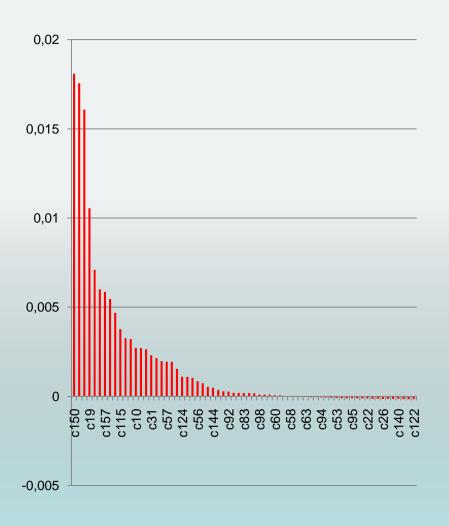


- •Global average cosine similarity: 0,00015924;
- •Intra-community average cosine similarity: 0,04916513.
- •Distribution of intra-community cosine similarity means (see above) is power-law: there are tighter and looser communities.





TOPICAL SIMILARITY 2



Middle part of intracommunity cosine similarity means distribution. X axis: global average cosine similarity

Below average are multiple, but extremely small numbers. I.e. topical similarity in a certain set of communities is manifest.





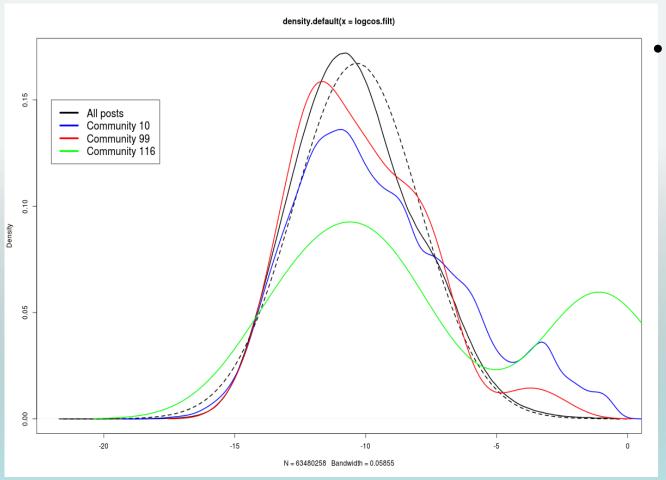
TOPICS IN COMMUNITIES: EXAMPLES

	num of authors in	num of posts in	
comm ID	comm	comm	description
c154	1	2	author: sontucio, one post is a cut version of another
c86	5	8	culture and privacy
c150	2	9	author: bragin_sasha - on politics in Ulianovsk region
			dominant author: lumbricus where she went and what
c39	5	20	pictures she took
			15 natashav, 7 orange_sky_bird, 14 pelageya, most are
			women; dominant topics: maternity, pregnancy, women
c52	8	43	problems; other private issues are present
			29 posts by hope1972, dominant topic: popstars and
c7	14	48	films; others also have a mixture of other issues.
			Post/author distr power law, short posts (mean 83
			words against global mean 375), private messages
c10	262	1135	dominate





TOPICS IN COMMUNITIES: INDICATORS



Distributions of logarithms of cosine distances in communities where dominant topics are clearly present, have additional peaks.





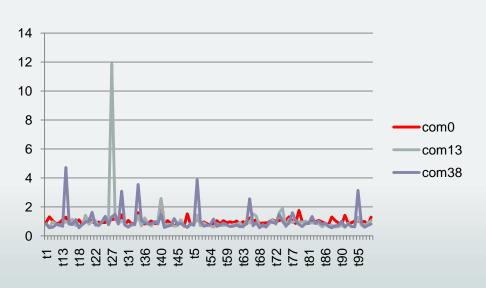
METHODS 2

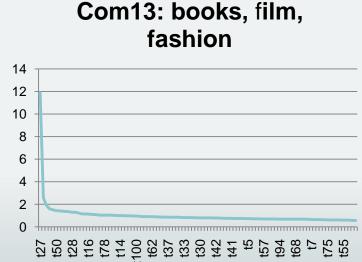
- LDA Gibbs-sampling 100-topic modeling (software: LINIS TopicMiner)
- Total weight of each topic calculated for each comment-based community
- Normalized
- Topics' weights variance calculated for each community
- Low variance = multitopic communities





MONO- AND MULTITOPICAL COMMUNITIES

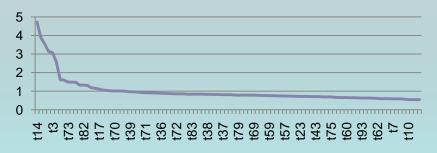




Com0: all topics



Com38: personal stories, travel, fashion, pets





CONCLUSIONS

- Comment-based communities in top LJ exist; community structure moderately manifest.
- Communities are uneven in size.
- Graph is sparse and interconnected by a minority of active commentators.
- Most comments are done by non-top bloggers (fandom commenting)
- Communities strongly tend to emerge around authors of posts.
- Communities have a less manifest tendency to form around topics.
- Some communities are clearly centered around a limited number of topics; they can be detected and described.





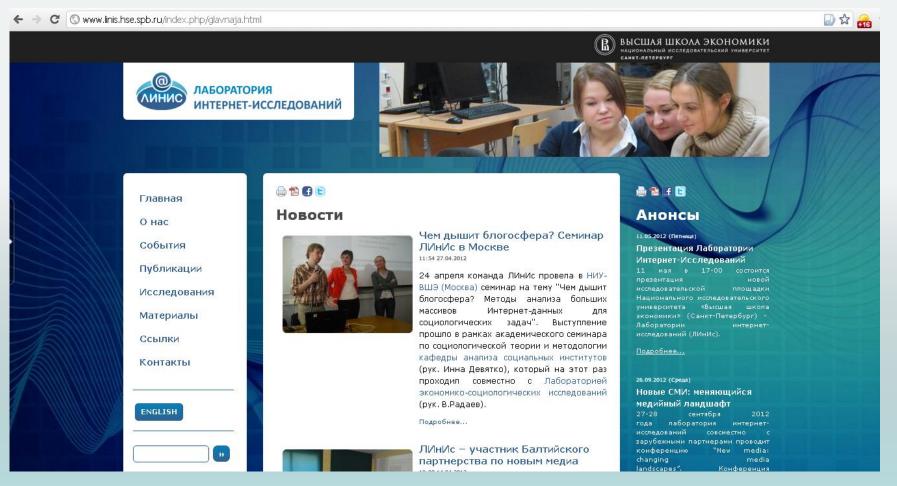
FUTURE RESEARCH

- Finalizing LDA results interpretation
- Inclusion of texts of comments into topic modeling.
- Bimodal post-commentator network clustering (inclusion of info about authors of comments).
- Author-commentator network analysis (fandom communities mining).





THANKS!



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CONTRIBUTORS







Sergey Nikolenko, mathematician, senior researcher



Sergei Koltcov,

Physicist, technical director



Anastasia Shimorina, Computer linguist, junior researcher





Yury Rykov, Sociologist, PhD student, intern



Victoria Seneva, Sociology MA student, intern

