ERC Advanced Grant 2018
Research proposal [Part B2]

An algorithmic framework for reducing bias and polarization in online media

(REBOUND)

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Part B2: The scientific proposal

Section a. State-of-the-art and objectives

a.1. Background and project overview

Social media play a critical role in today's information society, not only by connecting people with their friends, but also by providing a medium where information is disseminated and public opinion is shaped. In today's world, citizens have easy access not only to an abundance of information, but also to a podium where they can express their opinion and participate in public debates. In a survey conducted in May 2018 it is reported that in several European countries the majority of citizens get their news via social media.[1]

Initially it seemed that giving ordinary citizens the means to create content of their own and share their opinion publicly can lead to a whole lot of positive effects: traditional media would not hold a monopoly as news outlets, information would be democratized, and citizens would be exposed to a variety of ideas and viewpoints. It was argued that those effects would contribute to making the society more democratic and diverse. However, during the past few years we have witnessed that the rise of social media has led to a series of negative effects and undesirable phenomena.

First, as the internet has lowered the cost of content creation and as social-media sites provide mechanisms that facilitate information spreading, malicious actors attempt to manipulate the existing social-media platforms and inject fake news and misinformation into the information ecosystem. Second, instead of being exposed to novel viewpoints and diverse ideas, social-media users often end up being isolated in narrow informational silos, typically called *echo chambers* or *filter bubbles*, which in turn lead to *amplifying polarization* and creating environments where ideologically conflicting news circulate in separated parts of the system. The mechanisms that lead to this ideological segregation are often attributed to a number of cognitive biases, such as *selective exposure* (humans tend to favor information that reinforces their preexisting views, and they avoid contradictory information), and *confirmation bias* (humans tend to search for, favor, or recall information in a way that confirms their preexisting beliefs). Additionally, as social-media platforms aim to please their users and keep them engaged in the system, they fine-tuned their content-delivery and content-prioritization algorithms so that users see mainly content that matches their preferences, aligns with their world view, and confirms their beliefs. This *algorithmic personalization* intensifies the phenomena of filter bubbles and polarization.

An illustration of the phenomenon, coming from the research done in my research group [28], is shown in Figure 1, where we display the network structure ("retweet" network) of the discussions for two topics, which took place in twitter. The discussion on the left corresponds to a political topic and it is polarized, while the discussion on the right corresponds to a technology event and it is not polarized.

All these negative aspects of social media have drawn a lot of attention in the recent years. There has been a considerable amount of criticism, skepticism, discussion in public forums, as well as calls from

[1] www.journalism.org/2018/05/14/many-western-europeans-get-news-via-social-media-but-in-some-countries-substantial-minorities-do-not-pay-attention-to-the-source/

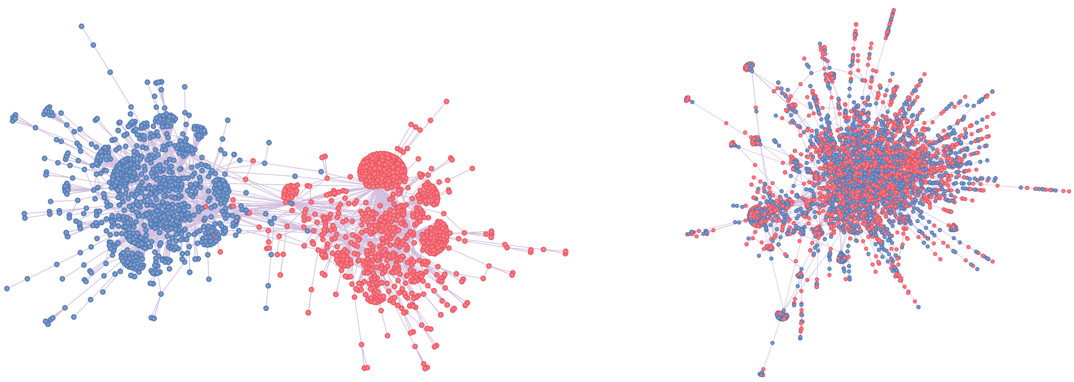

Figure 1: The "retweet" network of two discussions that took place in twitter. The discussion on the left corresponds to demonstrations in Russia and is polarized, while the one on the right corresponds to the SXSW conference and is not polarized.

advocates to fix the problems. Prominent media outlets, researchers, and think tanks have contemplated whether "*social media is a threat to democracy*."[2] Facebook's CEO Mark Zuckerberg, has acknowledged the shortcomings of the Facebook platform and has pledged to fix the issues,[3] while twitter's CEO Jack Dorsey has asserted that they are experimenting with features that would promote alternative viewpoints in twitter's timeline to address misinformation and reduce "echo chambers."[4]

Given all these concerns a natural question arises.

How can we address the deficiencies encountered in today's online platforms and how can we create environments in which social media enable exchange of alternative views and promote constructive deliberation?

This is certainly a complex problem that requires parallel work and cooperation of multiple parties: owners of social-media platforms and traditional media outlets, journalists, policy makers, educators, as well as *independent academics*. It is also a cross-disciplinary research challenge that requires expertise in sociology, political science, economics, engineering, design, and *computer science*.

Research in computer science can assist in developing methods for analyzing the available data in order to understand patterns of misinformation, biases, roles of individual actors, etc. It can also contribute with methods for designing novel online information systems that foster certain desirable properties, such as, less biased content, easier access to opposing ideas, incentives to explore and understand alternative viewpoints, reduced segregation, and so on.

Why is this a problem that concerns academic computer science? Although social-media companies employ highly-talented researchers, who have access to loads of data that can help them tackle the problem, we believe that cooperation with independent academics in computer science is essential for addressing this important societal issue, and it is needed to complement the efforts put in industrial research. There are several reasons for this. First, in many cases the primary incentive of social-media companies is to offer to the users content of their liking so as to increase engagement. Second, each social-media platform has a distinct character and focus on specific content and audience demographics. Thus, in-house solutions may lack generality.

On the other hand, academics in computer science can study the problem from an independent and abstract point of view. They can design methods that are applicable to a variety of different settings, provide proof of concepts with datasets coming from more than one source, and make their methods publicly available, to be tested, further developed, and/or deployed by any interested party.

This is precisely the goal of this project:

[2]For example, see www.economist.com/leaders/2017/11/04/do-social-media-threaten-democracy, or www.weforum.org/agenda/2016/08/the-biggest-threat-to-democracy-your-social-media-feed/

[3]www.facebook.com/notes/mark-zuckerberg/building-global-community/10154544292806634/

[4]www.washingtonpost.com/technology/2018/08/15/jack-dorsey-says-hes-rethinking-core-how-twitter-works/

High-level goal of REBOUND**:** We will develop theoretical foundations and a concrete set of algorithmic techniques to address deficiencies in today's online media. We will develop methods to discover structure and patterns of segregation, conflict, and closeness in social-media systems. We will address the issues of reducing bias and polarization, breaking information silos, and creating awareness of users to explore alternative viewpoints.

Challenges. Tackling successfully the project objectives is extremely challenging, for a number of reasons. First, we will be dealing with noisy data, generated by a diverse set of actors, who exhibit complex behavior, have multiple interests, use the system in different ways and for different purposes, and possibly have adversarial motives. Additionally, data are highly dynamic. New events are taking place, and interactions between actors are constantly evolving over time. Second, we will deal with concepts that are not well-understood and will need to develop novel abstractions and problem definitions. As a simple example, although one may have an intuitive understanding of the claim "*social media amplify the problem of echo chambers*," there is no well-accepted definition for what constitutes an echo chamber, nor how to measure it. Furthermore, while there is a well-motivated discussion about how to combat the problem of bias and polarization in online media, there is no understanding of what does this entail, what are the trade-offs, nor what are the side effects of possible remedial actions. Third, most of the computational problems that can be defined, even in simple scenarios and with many simplifying assumptions, lead to challenging optimization tasks, which are typically **NP**-hard. Thus, it is desirable to develop methods that offer approximation guarantees or other theoretical properties.

Methodological approach. We will pursue the project goal by following a methodology that aims to tackle the challenges outlined above. (1) We will develop abstractions that capture the semantics of the application domain and we will provide formal problem definitions that capture our objectives. (2) We will develop and work with theoretical frameworks that capture the noise and complexity of real-world data. (3) We will develop scalable algorithms with theoretical guarantees on the solution quality.

Research thrusts. To achieve the objectives of REBOUND, we have structured the project into three research thrusts. These thrusts specify domains in which one can develop concrete problem formulations. To a certain extent the research thrusts can be studied separately, however, there are several links and inter-dependencies. In particular, we consider the following research thrusts.

RT1. DISCOVERY: Analyze large-scale online-media data to discover structural patterns that indicate bias, polarization, conflict, and barriers in the information flow in online media. Identify the roles of individual users, and understand the interplay between individual-level decisions and the resulting system-level biases.

RT2. EXPLORATION: Develop methods and tools that help users understand better the global information landscape with respect to topics of interest, visualize stories with annotations about alternative viewpoints, and become more aware of the bias of the content they consume.

RT3. RECOMMENDATION: Develop methods and tools that help users gain control of their news diet, and receive recommendations for alternative viewpoints according to simple interfaces and knobs that they can understand and tune. Develop recommendation algorithms that aim to increase the overall diversity in the network and balance information exposure about conflicting views. Investigate the effect of different design features to the willingness of the users to explore viewpoints that conflict their opinion.

Timeliness, feasibility, and relevance of the PI. More and more people use the Internet and social media as a window to what is happening in the world. At the same time it is apparent that existing social-media platforms have been designed with no consideration to some important desirable properties, and as a result there are adverse consequences. Stakeholders have raised their concerns and companies have pledged to fix the issues. However, this is a challenging problem, which will require cooperation among companies, policy makers, and scientists in multiple disciplines, including academic computer scientists. In this respect, the project is extremely timely.

The PI is in a unique position to accomplish the goals of the project. His profile brings together theoretical work on algorithms design, with development of practical data-mining methods, and strong emphasis on applications. The practical aspect is further enhanced by the six-year experience in industrial research (Yahoo! Research) and a network of collaborators in big social-media companies.

The PI and his research team have pioneered a line of work on the project theme and have obtained several preliminary results [7, 25, 26, 28, 35, 40]. The objective of this project is to advance the state of the art in this important topic on multiple fronts. In particular, we aim to work on more realistic models, achieve stronger algorithmic results, and resolve open problems. We also aim to enlarge and strengthen the team with researchers of complementary skills, and establish collaborations with industrial partners and scientists in other disciplines. Without the support of this project it will not be possible to accomplish these ambitious goals.

The research team has strong experience in collecting data from platforms like twitter and reddit, and much of our recent work has built on extensive data gathering. In addition, we will seek to establish collaborations with international online-media companies so that we can test our methods on real-world scenarios. We will also will seek collaboration with local media companies in Helsinki, such as Yle (Finland's national public broadcasting company) and Sanoma (a leading media group in the Nordic countries).

Risk and potential impact. REBOUND is a *high-risk project*. The risks include providing conclusive evidence that we can design systems that can help combating the problems of bias, polarization, and information silos in online media. They also include making progress in fundamental research so as to devise novel algorithms and make smooth connections between theory and practice. A more detailed risk analysis is discussed in Section b.5.

Overall, given the importance of the topic, the project has the potential to make huge impact, both in computer-science research, as well as in our society.

a.2. State of the art

The study of the phenomena of bias and polarization predates the era of the internet and social media. The first works appear in the fields of psychology, social science, and political science.

A number of theories have been proposed in psychology and social sciences in an attempt to *explain the mechanisms* that result in various types of bias that are present in our society. For instance, the theory of *cognitive dissonance* was proposed by Festinger et al. [23] — it refers to the phenomenon according to which people experience positive feelings when presented with information that confirms their beliefs or decisions. *Selective exposure theory* [24] — which proposes the concepts of *selective exposure*, *selective perception*, and *selective retention* — is the tendency of individuals to favor information that aligns with their pre-existing views while avoiding contradictory information. *Biased assimilation* [39] is a related phenomenon, where an individual gets exposed to information from all sides, but has the tendency to interpret information in a way that supports a pre-existing opinion. All these psychological mechanisms, together with other biases, such as, *algorithmic filtering* and *personalization* [13], are connected to the phenomenon of echo chambers. Understanding how all these phenomena interact with each other and the precise causality relations is an open research domain.

Similarly, social-science researchers have attempted to provide working definitions of the concept of polarization. Esteban et al. propose axioms that a polarization measure should respect [22] — they also contrast polarization with social inequality, and they explain how the two concepts are different, mainly due to the fact that polarization takes into account the antagonism between different sides. Bramson et al. distinguish nine senses of polarization and provide formal measures for each one [14].

With the wide availability of online media data, a lot of work has been devoted in studying controversy, polarization, bias, and conflict in social media. In one of the first papers, Adamic and Glance study the link structure of blog posts on the 2004 US presidential election; they provide evidence that conservative blogs are linking to each other more frequently and in a denser pattern [2]. Conover et al. study twitter data from congressional midterm elections and identify a highly-segregated partisan network structure [17]. They also employ the concept of modularity and graph partitioning [44] in order to verify controversy structure on graphs extracted from discussion of political issues. Similarly, Guerra et al. propose an alternative graph-structure measure based on the analysis of the boundary between communities [32], while

Morales et al. apply graph-diffusion techniques [42]. In a different setting, Akoglu proposes a polarization metric that uses signed bipartite opinion graphs [3]. Linguistic-driven approaches have also been used for analyzing controversy in online discussions. Choi et al. apply sentiment-analysis techniques to detect controversy [15], while Mejova et al. identify a significant correlation between controversial issues and the use of negative affect and biased language [41].

The term "echo chambers" is used to describe situations where users consume content that already aligns with their opinions. Echo chambers have been shown to exist in various forms of online media such as blogs [29, 60], forums [21], and social-media sites [11, 31, 47]. An et al. analyzed the activity of twitter users who engage with political news and found that 90% of the users directly follow news media of only one political leaning [4]. In the context of Facebook, Bakshy et al. measure the degree to which users with declared political affiliations consume cross-cutting content, i.e., content predominantly posted by users of opposing political affiliation [9]. They find that even though users are exposed to a significant amount of cross-cutting content, users opt to engage with proportionately less cross-cutting content, a behavior compatible with the theory of *biased assimilation* [39]. In our recent work, we also find that twitter users are, to a large degree, exposed to political opinions that agree with their own [27]. We also analyze the different roles of twitter users in the process of information-dissemination and echo-chamber creation.

One simple way to mitigate the ill-fated consequences of bias and polarization in the society is to "nudge" individuals towards being exposed to opposing view-points, an idea that has motivated several publications. Liao et al. attempt to limit the echo-chamber effect by making users aware of other users' stance on a given issue, the extremity of their position, and their expertise [37, 38]. Their results indicate that participants who seek to acquire more accurate information about an issue are exposed to a wider range of views, and agree more with users who express moderately-mixed positions on the issue. In a similar spirit, Munson et al. create a browser widget that measures and displays the bias of users based on the news articles they read [43]. Their study concludes that showing users their bias nudges them to read articles of opposing views. In the spirit of REBOUND, in our previous work, we have studied the problem of reducing bias and polarization by the means of recommending links of users to follow [25], selecting users to promote campaigns [26], and maximizing diversity [7, 40].

In summary, the problem of reducing bias and polarization in online information has already received some attention in the literature. However, the area is still largely undeveloped and most works are preliminary. The topic has attracted a lot of attention in the public sphere, and there is exciting work ahead to be done in a range of disciplines, including with no doubt computer science.

a.3. Hypothesis and objectives

The project is grounded on the following hypothesis.

Hypothesis: We postulate that bias, conflict, polarization, and information silos are real phenomena in today's online media. We hypothesize that these deficiencies can be alleviated by designing and building appropriate tools, and that people can get interested to explore and engage with alternative viewpoints.

Our encompassing research objective is to test this hypothesis. To achieve this objective we will consolidate existing approaches, including our recent work, and push significantly the state-of-the-art in terms of models, novel problem formulations, improved algorithmic techniques, and applications. In particular, REBOUND has the following concrete objectives.

Models: Develop novel models for analyzing data on news dissemination and online discussions in online media, with the aim to obtain a deeper understanding on phenomena related to bias, polarization, and information bottlenecks. Extend standard data-mining problem formulations for this particular application domain, and formulate novel problem representations for the tasks specified in the three research thrusts of the project.

Algorithms: Develop efficient algorithmic solutions for the formulated problems. Our algorithms should take into account the rich available data representations as well as the stochastic and noisy nature of the problem domain. The proposed algorithms should be efficient, be able to deal with uncertainty, and offer theoretical guarantees.

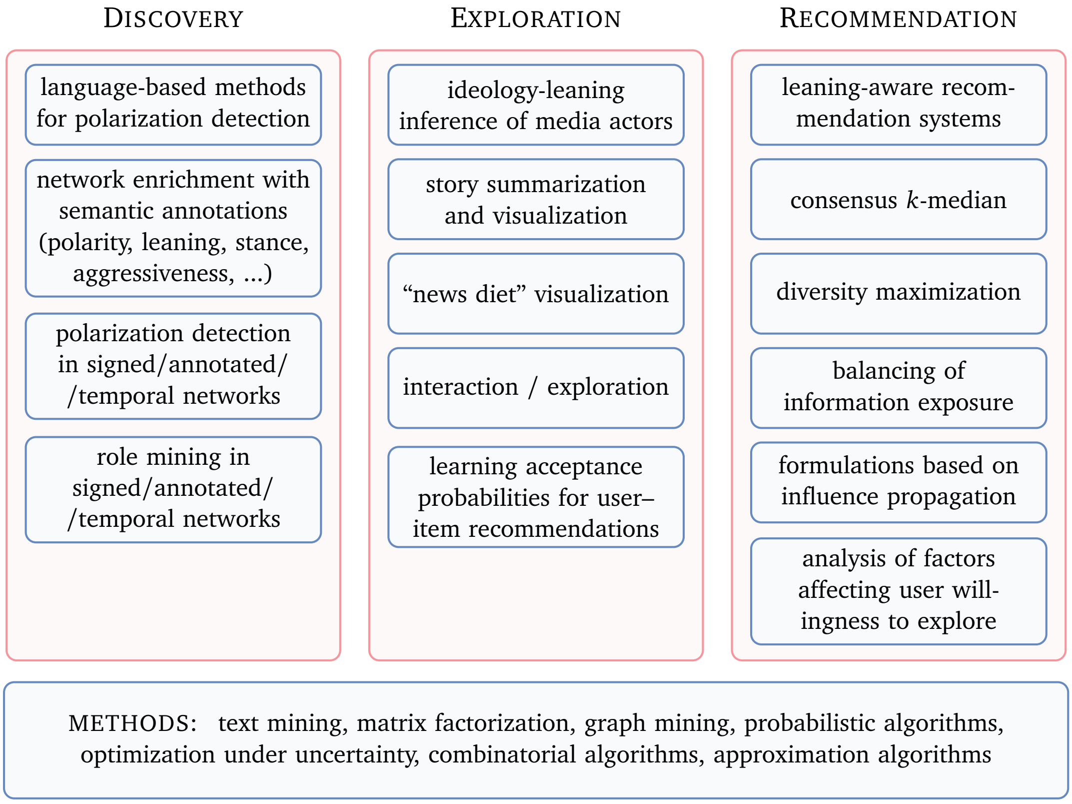

Figure 2: The structure of REBOUND, depicting the research thrusts of the project, the problem formulations we will consider, and the methods we will employ.

Applications: Apply the developed methodology on different application scenarios and evaluate the resulting algorithms on real-world datasets. Validate proof-of-concept by showcasing findings of the methods on different use cases. Implement the developed algorithms and make them available to the scientific community.

Education: Nurture doctoral students and postdoctoral researchers. Educate them about fundamental algorithmic techniques, teach them the value of identifying important data-analysis problems, and support them becoming independent researchers.

Before providing more details on how we will achieve those objectives, we note the interplay between *models*, *algorithms*, and *applications*: the data-mining problems we will define should be motivated by realistic application scenarios, and the algorithms we will develop should be evaluated on real-world datasets.

Section b. Methodology

b.1. Structure of the project

The structure of REBOUND is illustrated in Figure 2, where we depict the three research thrusts of the project, and the concrete research problems that we will address in each one of them. The figure also highlights the set of methods that will be used to tackle the research problems.

While each research thrust defines its own concrete problems, which to a large degree can be studied independently, there are also strong connections among the research thrusts and feedback from one will be used to obtain higher-quality results in the other.

RT1 ⟷ RT2 : The structure and models extracted from the DISCOVERY research thrust will be applied to provide visualizations and representations for the EXPLORATION research thrust. Vice versa, structural requirements by EXPLORATION will motivate novel problem definitions for DISCOVERY.

RT1 $\longleftrightarrow$ **RT3 :** Definitions for bias, polarization, conflict, and information silos, which will be formulated and evaluated in DISCOVERY will be used in RECOMMENDATION so as to provide recommendation actions that counter these deficiencies.

RT2 $\longleftrightarrow$ **RT3 :** There is strong dependency between these two research thrusts so as to provide recommendations that satisfy the exploration actions of the users. Vice versa, recommendations should be organically embedded within the EXPLORATION thrust.

b.2. Methods

To tackle the challenging computational problems of REBOUND we will employ a mix of different methods and algorithmic techniques. While some of the technical ideas will be applicable to all three research thrusts, each problem we consider poses unique challenges and it will require developing tailored methods.

Emphasis will be given to combinatorial algorithms. As demonstrated by the previous work of the PI, there is strong expertise in developing combinatorial methods for data-mining problems. For the problems defined in the DISCOVERY and RECOMMENDATION thrusts, we will consider techniques such as combinatorial optimization, optimization of submodular functions, local-search methods, greedy algorithms, dynamic programming, linear-programming and semidefinite-programming relaxations, primal-dual methods, convex optimization, etc. Our aim is not only to apply those methods as black boxes, but also to enrich the set of available algorithmic techniques. Our goal is to devise algorithms with provable approximation bounds, or other quality guarantees.

Given the stochastic nature of our data we will develop probabilistic models and algorithms that handle uncertainty. We will seek to optimize the expectation of our objective functions, consider adaptive policies, or minimize risk. We will also focus on designing efficient algorithms so that they can be applied to large-scale data. To achieve this goal we will apply techniques based on sampling and sketching [18].

In the DISCOVERY and EXPLORATION thrusts we will apply text-analysis, natural-language processing, and matrix-factorization methods. In EXPLORATION we will use visualization and user-interface design methods. In all three research thrusts we will conduct user studies to validate our assumptions, problem definitions, and proposed solutions. The PI does not have extensive expertise on these areas, so the needs of the project on these domains will be covered by hiring postdoctoral researchers with relevant expertise.

b.3. Description of research thrusts

Next we discuss in more detail the research thrusts of the proposal. We present the concrete problems we will study, preliminary work, and methodology.

Research thrust 1: DISCOVERY

In this research thrust we will develop novel computational methods to discover patterns and structure related to bias, polarization, conflict, and other deficiencies associated with information dissemination in online platforms. We will study complex information ecosystems, involving multiple actors, such as, media outlets, journalists, analysts, and everyday users, who are exposed to information, share content, engage in discussion with others, and shape their opinions accordingly. Data from such complex systems are highly heterogeneous. It consists of *network relationships* (who follows whom, who discusses with whom, etc.) and *textual information* of *varying structure and quality*. The data is also *highly dynamic*, with new events taking place constantly, public attention shifting, discussions developing around popular topics, and interactions among actors evolving over time.

The problem of mining social-media data in order to understand the dynamics of online discussions and information dissemination has attracted considerable attention in the recent years [2, 3, 17, 32, 42], including work in my research group [25, 26, 28, 27, 35]. Much of the research, however, relies on simplifications and case studies on controlled environments, such as focusing on carefully curated data centered around long-lasting major events, or annotating the data with ground-truth labels and external sources.

In the previous work conducted in my group, we have developed techniques aimed to overcome these limitations. In one of our first articles on the topic [28], we have focused on the problem of *identifying controversy* for topics in any domain (e.g., political, economical, or cultural), and in a general setting, i.e., without prior domain-specific knowledge about the topic in question. We have also addressed the question of devising a *measure of controversy*, which is applicable to any online discussion. The proposed solution follows a *graph-theoretic approach*: we first build a conversation graph about a topic, and then measure controversy via *clustering the graph* and performing an appropriately-defined *random walk*.

In a more recent article we study the phenomenon of political *echo chambers* in social media [27]. We propose a quantifiable approach to characterize echo chambers. By applying the analysis on a large-scale twitter dataset we find that twitter users are, to a large degree, exposed to political opinions that agree with their own. We also identify distinct *user types* (such as partisans, bi-partisans, and gatekeepers) and characterize their position and role in their local community.

These publications provide preliminary results and set the stage for a much deeper analysis and more advanced knowledge-discovery techniques that are yet to be developed. Below we outline the directions that we will pursue in REBOUND, and highlight the connections with our previous work.

The first observation is that while there is currently a lot of discussion about the negative effects of online media, there are no commonly-accepted definitions of these concepts. Thus, a first goal is to provide such definitions so as to establish a basis for algorithmic development. We will seek to provide definitions that incorporate textual information, network structure, and network dynamics. We will also perform large-scale user studies to validate the proposed definitions and select among alternatives.

Second, most of our current work relies on graph-theoretic techniques, such as analysis of the "follower graph" or the "retweet graph." On the one hand, this is an attractive approach as it results in language-independent methods. On the other hand, language contains a lot of extremely useful information that our current methods ignore. Thus, we will put significant effort in developing methods that incorporate text information into the mining process. First we will approach the question of detecting and quantifying bias, polarization, and conflict from a *natural-language processing* perspective. Second we will develop methods to extract *semantic annotations* from the textual data. In particular, we will extract information about: (i) *agreement* between pairs of users who participate on an online discussion, which can be positive or negative; (ii) *political leaning* of a user or a piece of text; (iii) *stance* with respect to an argument or position (agreement or disagreement); (iv) *aggressiveness* in the tone of discussion, and more. We will use the extracted pieces of information to *annotate* our graph representations. The goal is to enrich our graph data with those annotations and then *design mining algorithms for the semantically-annotated graphs*.

The next step is to design knowledge-discovery techniques for the annotated graphs we constructed. This objective leads to many novel algorithmic problems. As a simple example, consider a graph modeling the discussion between users of an online platform on a particular topic. Assume that we have successfully annotated the edges of the graph with *signs* so that positive signs ('+') indicate agreement and negative signs ('−') disagreement. This is a *signed graph* [56]. Finding a heated discussion in this graph, with $k = 2$ opposing views, corresponds to finding two sets of vertices so that there are (i) many '+' edges and few '−' edges between vertices in the same set, and (ii) few '+' edges and many '−' edges between vertices in different sets. Formulations of this task resemble the *correlation clustering* problem [10, 30], with the difference that we are not looking for a complete partition of the graph vertices. In other words, we are considering the problem of *correlation clustering with outliers*. The motivation is that the discussion of interest can be "masked" by many other discussions that take place in the network.

In the setting of signed conversation graphs, we are also interested in discovering alliances of users who share a common opinion and support each other. As a graph-mining problem we want to find a set of vertices in which there is high density of '+' edges and low density of '−' edges. The problem is related to our previous work on finding *densest subgraphs* [48, 55, 58, 59]. To our knowledge the problem has not been addressed in the context of signed graphs.

We will also study how to leverage the temporal dimension of the data. The main observation is that by considering the time that interactions between users and discussions take place it is possible to reveal information about the network structure and dynamics, which otherwise will be hidden. In my research group we have considered a number of problems related to mining temporal graphs, such as, finding dense subgraphs [51], reconstructing epidemics [50], and monitoring important nodes [49]. In REBOUND we will study formulations that allow to model and discover bias, polarization, and conflict in the setting of temporal networks. One interesting such formulation is to consider *signed temporal* graphs, and study the interplay between conflicting communities and influential nodes in each community, where nodes are deemed influential if other nodes are following their actions in time.

Going beyond signed and temporal graphs, we will exploit the other semantic annotations of the social graph, constructed by the text-analysis representations discussed above, and provide relevant and novel problem formulations. In particular we will consider formulations related to *motif discovery* [8, 16] and *role mining* [6], aiming to extend significantly our previous work, in terms of considering more realistic data models and developing more efficient and accurate methods.

Research thrust 2: EXPLORATION

According to recent studies polarization in the public sphere has intensified [20] and users increasingly live in their *echo chambers* [20, 27, 46], oblivious to alternative views and creating their own world-view of truth. A natural question to ask, then, is *how can we help users escape their filter bubble*? We argue that a first step is to *make users aware of the potential narrowness of their "news diet."*

The idea of increasing user awareness and raising a flag about information silos has appeared not only in research articles, but also in popular media outlets. There are already numerous "bubble bursting" applications and widgets available, however, they are largely ignored by the public.[5] One reason for the low popularity of these applications is that they are not prioritized by media outlets, which have no strong incentive to direct their readers there. Additionally, and very importantly, most of these applications are *elementary*, offering very limited functionality, and are mainly using pre-selected content or manually-annotated sources. To our view, the research area of developing methods that help users understand the global information landscape with respect to topics of their interest, visualize their content consumption, and become aware of their information silos, is largely unexplored, yet it is extremely interesting and has huge potential.

Efforts to push this area forward in my research group have resulted in a recent publication on the problem of *learning political-leaning scores* in social media [35]. The goal is to infer an *ideological stance* for entities in a social network, such as user accounts and media outlets. We are interested in learning scores that are expressed in a *shared latent space* for entities of different types, so that they are comparable to each other and, e.g., can be drawn together in the same figure. The motivation for learning automatically the political-leaning scores of users and content sources is motivated by the core theme in this research thrust, namely, using the inferred scores to build tools that can make users aware of their informational bias, and thus, help in reducing those biases.

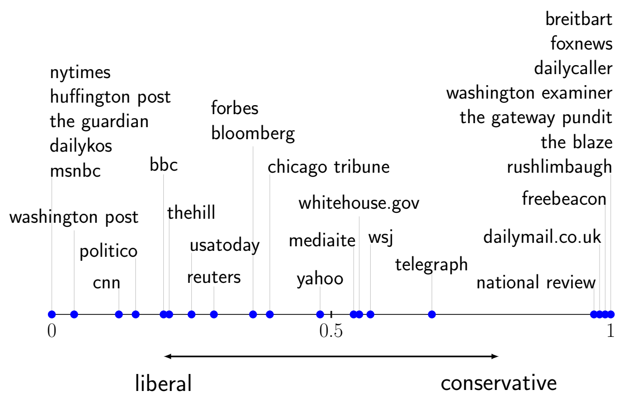

Figure 3: Popular media outlets and their *leaning scores* inferred by our recently-developed method [35], using a *joint non-negative matrix-factorization* approach.

Contrasted to state-of-the-art methods that use labeled data or ad-hoc heuristics, our solution requires no labeled data and uses simultaneously the network structure and information about content shared by users. It relies on the observation that a user's ideological stance on a topic depends on both the surrounding network structure and the content sources that the user is exposed to. Thus, we exploit the inherent connection between the two data types: Users are not only more likely to interact with or follow like-minded users, but also to share content of aligned ideological leaning. Quantitatively, the learning task is

[5] As an example see the '*Blue Feed, Red Feed*' page of the *Wall Street Journal*.

formulated as a *non-negative matrix-factorization* problem, which jointly decomposes the social network of users and the content they consume in a *shared latent space*.

An illustrative result of our work is depicted in Figure 3, which shows the top-30 popular media outlets and their leaning scores computed by our method. Contrasted with other methods in the literature, which estimate such scores, our approach is *unsupervised*, and thus, can potentially be *applied at scale in any online discussion*. Example applications of using the inferred leaning scores, such as visualization and recommendation, are demonstrated in our paper [35]. However, these preliminary results are only scratching the tip of the iceberg. Accomplishing the goals of this research thrust requires addressing a large number of novel and difficult problems in knowledge extraction and data summarization. It also requires developing methods for *computing a set of metrics* for users, content items, and media outlets, in line with, or complementary, to the leaning-score inference discussed above.

More concretely we will develop methods that produce *comprehensive and understandable summaries* of topics of interest discussed in online media. Our summaries will contain information regarding the *timeline of relevant events*, *important actors, entities, or concepts* involved in the story, *key persons* participating in the discussion, and *pointers to informative content*, such as news articles or opinion editorials. All this information will be extracted from large-scale online-media data by applying state-of-the-art data-mining techniques [5, 53, 54], or through novel problem formulations and methodological advances that will be accomplished within REBOUND, such as our recent work on constructing event timelines from a temporal network of entity interactions [52].

We will design methods for visualizing the extracted story summaries aided by representations computed in the DISCOVERY research thrust and by latent variables and metrics inferred in the EXPLORATION research thrust. In this way the users can obtain a holistic view of the stories they are interested in, based on which they can explore further concepts and drill down for more information. The summaries we will produce will help users answer the following questions:

(i) How polarized is the topic under consideration?

(ii) What is the spectrum of different opinions about the topic?

(iii) Who are the most authoritative actors supporting a given segment in the opinion space? Which is the best content for that opinion segment?

(iv) Which are the roles of the key actors in the discussion and how they are interacting with each other? For example, who are the most influential content producers, who are those who are followed by mostly members in their own community, and who interact mostly with members of other communities?

(v) Which are the key events in relation to a topic, or story, under consideration? Which are the different viewpoints related to these events, and which are authoritative articles expressing those viewpoints?

(vi) What is the position of media outlets in the opinion space and what is their coverage of the relevant events?

Exploration along the lines described by the questions above will help the users understand better the global information landscape and the different viewpoints with respect to their topics of interest. In addition, our own framework will allow users to visualize their own position in the opinion space and their role in the public discussion, based on the content they have been exposed, their interaction with other users, and the content they have shared.

Finally, it should be noted that the user characteristics inferred by our methods during the EXPLORATION research thrust, such as openness to opposing point-of-views, can be used not only to increase awareness and inform users about their own news diet, but also by our framework to make relevant suggestions, as in the RECOMMENDATION research thrust. In fact, one of our goals here is to develop methods to *learn the likelihood that a given user is interested in learning/exploring a given information item*.

Research thrust 3: RECOMMENDATION

In this research thrust we will develop recommendation algorithms that allow users to control better their news diet and explore more easily alternative viewpoints. To achieve this goal we will design novel methods to increase the overall network diversity, balance information exposure among conflicting views, and reduce polarization in the network. We distinguish between two types of recommendations: (i) *recommendations with utility to individual users*; (ii) *recommendations with utility to the whole network*. In both cases our goal is to recommend *relevant* and *interesting* content to users. However, while in the former case we consider the relevance and utility of a recommendation to each user in isolation, in the latter case we additionally consider the utility and the added benefits of each recommendation in the whole network.

Let us start our discussion with the first type of recommendations: recommendations with utility to individual users. There is certainly a vast amount of literature on the topic of *recommendation systems* and *personalized content delivery* in social media [1, 33, 36]. We will build on this existing work but we will also refine it and advance it towards the theme of the project.

One of the tasks that we will address is the following: Consider a user who has been informed about a controversial topic by reading articles that support mainly one side. *Can we identify and recommend a high-quality article on the same topic that supports the other side?* Additionally, how can we equip the user with the ability to control the polarity of the content they receive, for example, neutral, medium-opposing, or extreme-opposing? Such a functionality requires learning the polarity grades of content and users in the system, and thus, interacts with the methods developed in the EXPLORATION research thrust.

We will also develop techniques that allow users to control their profile and receive explainable recommendations. In particular, given a topic we will consider the problem of *learning to ask* a small set of questions the answer to which determine a particular point-of-view on the topic. Users can then receive recommendations that are relevant to that particular point-of-view. A similar learning-to-ask technique was used in our earlier work [19] to build a recommendation system that provides shopping advice.

Consider again a controversial topic that has attracted a lot of discussion and many news items have been written about it expressing different points of view. One idea to alleviate the problem of echo chambers is to present to the users a selection of news items encompassing different view points. We can formulate this task as a *clustering* or *summarization* problem: given a set of items X, select a subset $C \subseteq X$ of k items ($|C| = k$) that summarizes, or represents, best the set X. By assuming a distance function d between items in X, the *k-median clustering* formulation asks to find C so as to minimize $\sum_{x \in X} \min_{c \in C} d(x,c)$. In our application scenario though, we want to select a set of *non-polarized representative items*, i.e., items that are relatively close to each other. We can express this requirement by adding a second term to the objective and asking to minimize

$$\sum_{x \in X} \min_{c \in C} d(x,c) + \lambda \sum_{c \in C} \sum_{e \in C} d(c,e).$$

In our recent work we have developed efficient algorithms with *provable approximation guarantees* for this problem, which we call *consensus k-median*, and we have applied it with success for selecting items with reduced polarization in online media [45]. We plan to continue this line of work, both in terms of designing improved algorithms, as well as in terms of investigating other application scenarios.

Next we discuss the second type of recommendation systems that we will develop in REBOUND, namely, recommendations with utility to the whole network. Currently, in my research group, we have studied this kind of problems from different perspectives. In one of our first works in this direction [25], we considered the task of making recommendations of "users to follow" so as to *minimize the total controversy score* with respect to a topic discussed in the network. The controversy score here is quantified using the measure developed in our earlier publication [28]. An interesting feature of the recommendation algorithm is that it models the *acceptance probability* of the recommendation by the users, and thus, minimizes controversy in expectation. In this project, techniques for learning acceptance probability of users to recommendations will be developed in the EXPLORATION research thrust.

Recommending an item to a user in a social network may also have a *cascade* effect, and the recommended item may be seen by other users in the network. Following this idea, we recently addressed the problem of breaking information silos by *balancing information exposure* among users [26]. More concretely, we considered social-media discussions around a topic, characterized by two or more conflicting viewpoints. Our approach follows the popular paradigm of *influence maximization* [34]: we want to select a small number of seed users for each viewpoint so as to maximize the number of users who are *exposed to all viewpoints*. The problem is **NP**-hard, and approximation is challenging as the optimization function is not submodular. Yet for certain cases we are able to obtain algorithms with approximation guarantees.

More recently we have been studied the problem of making recommendations to social-network users so as to *maximize the overall diversity* in the network [7, 40]. We have considered both static and cascade-based formulations. Again for a number of cases we are able to obtain algorithms with approximation guarantees. We have also demonstrated the relevance of the formulations in real-world applications.

In one of our formulations we consider a set of different items I propagating in a network $G = (V, E)$ [7]. We also assume that for each item $i \in I$ we can estimate its leaning score $\ell(i)$, with respect to a debate or topic. We then consider the problem of making k recommendations of items to users, so as to maximize the overall network diversity, measured as the expectation of

$$\sum_{v \in V} \left(\max_{i \in I(v)} \ell(i) - \min_{i \in I(v)} \ell(i) \right),$$

where $I(v)$ is the set of items that user v is exposed in a random cascade of items in the network, according to a probabilistic propagation model. In other words, we assume that the diversity score of a user is the range of leaning scores of the items that the user is exposed, and the total network diversity is the sum over all user diversity scores. For this problem we can obtain a scalable algorithm with a provable approximation guarantee. Scalability is non trivial and relies on adapting the idea of reverse-reachable sets [12], and analysis based on martingales [57].

We consider our results in the problems discussed above as first steps, and we believe that the directions we have outlined open avenues for extremely interesting and practically-relevant work. First, as in the DISCOVERY research thrust, we will enrich our network data with semantic annotations extracted from text analysis and will approach the recommendation problems using realistic data models. For the problem of balancing information exposure we will study the setting of more than two viewpoints, and the setting where polarity is captured by a continuous score. We will also study different propagation models, discrete as well as temporal point processes, e.g., Hawkes processes.

With respect to maximizing diversity in social networks, we will seek to improve the theoretical guarantees of our methods. We will also extend our work to other diversity functions and propagation models, which capture better the real-life mechanics of a social network. We will also formulate and solve recommendation problems with different objectives, aiming to break information silos and minimize the amount of misinformation in the network.

Last but not least, the recommendation algorithms developed in this research thrust will be integrated with the story-summarization and visualization methods developed in EXPLORATION. Combined with user studies this will allow us to perform analysis so as to understand the effect of different design features to the willingness of the users to explore viewpoints that conflict their opinion.

b.4. Data and materials

All the data and materials that will be used in REBOUND will be publicly available, unless not permitted by the terms of service of the data sources. Our publications will be available via open access, in particular they will be shared via the `arxiv.org` repository. Similarly, the software we will develop and the other outputs of the project will become freely available to the scientific community via `github.com`.

With respect to datasets, we will validate our methods on data extracted from online platforms, such as `twitter` and `reddit`. My research team has strong experience in collecting data from these platforms, and much of our recent work has built on extensive data gathering. Use of such data sources is permitted for academic purposes under the EU general data protection regulation (GDPR). We will also validate our methods on benchmark networks, such as Koblenz network collection (KONECT),[6] Stanford network analysis project (SNAP),[7] and UC Irvine network data repository,[8] which are nowadays used by the majority of data-mining and social-network-analysis researchers.

We will seek to establish collaboration with big international social-media companies via our collaboration network, open calls for collaboration initiated often by these companies, and internships of doctoral

[6] konect.uni-koblenz.de
[7] snap.stanford.edu
[8] networkdata.ics.uci.edu/index.php

students. We will also seek collaboration with local media companies in Helsinki, such as Yle (Finland's national public broadcasting company) and Sanoma (a leading media group in the Nordic countries). There has already been interest from these companies on our work. Establishing such collaborations will allow us to perform our analysis on more diverse data, and may provide an opportunity to launch some of the algorithms developed in the project and validate their results on real-world scenarios.

In addition, we will work with political scientists to validate the project concepts. One path we will pursue is via our on-going collaboration with political scientists in the University of Helsinki.

Measures of success: Success in REBOUND will be quantified on the basis of (i) quality of doctoral dissertations, followed by success in the career paths of the PhD students; (ii) career path of the postdoctoral researchers; (iii) number and impact of publications in first-tier journals and conferences; and (iv) importance of the findings of the project; (v) release of software, which will be adopted by other scientists and practitioners. Target journals for disseminating the research developed in the project are IEEE TKDE, ACM TKDD, DMKD, etc. Target conferences are NIPS, ICML, VLDB, SIGMOD, KDD, WWW, etc.

Societal impact: In addition to scientific publications and software distribution, more opportunities will be sought to disseminate the output of the project to a wider audience and improve societal impact. From an educational point-of-view, the PI is often invited for tutorials in conferences. We will also make our work accessible to a wider audience. Much of our work has received coverage from media outlets or popular blogs.[9] Finally, we will seek for opportunities to collaborate with companies and start-ups on tasks related to the project themes. Aalto University provides an excellent environment to incubate such collaborations.

b.5. Risk management and contingency planning

REBOUND sets ambitious goals and has high potential, but at the same time it contains significant risks. Below we identify the highest risks of the project, we quantify their likelihood and their potential impact, and we suggest the measures we will take to mitigate those risks.

Risk 1. Project hypothesis: A potential risk is that we will find out that the majority of people prefer to receive biased content and are not interested to explore conflicting viewpoints. This would be an interesting finding for the project, which we will be able to establish via user studies or our collaborations with media companies. This risk implies that our results will not be relevant for a large population. Still, however, the methods we will develop in DISCOVERY will be relevant for content analysis, while the methods we will develop in EXPLORATION and RECOMMENDATION will be relevant for a smaller population.

Risk 2. Algorithms: Devising efficient algorithms with provable quality guarantees is a challenging task, which, however, gives the largest potential for scientific impact in the computer-science community. In cases that we will not be able to prove theoretical results, we will study problems with simplifying assumptions, abd we will focus on devising heuristic methods and providing thorough empirical validation.

Risk 3. Real-world deployment: We will seek to establish collaborations with different online media companies, either big international companies like twitter, or local (Helsinki) companies like Yle and Sanoma. The objective is to analyze additional sources of data. We will also seek to develop sandboxes with them in which we can implement our methods and evaluate their performance on realistic scenarios. Establishing this type of collaborations is challenging and depends also on factors beyond our control. The mitigation path is to perform analysis on public datasets that we collect or are available, and evaluate our algorithms with user studies.

Overall, the project is structured in a way that there are medium-risk paths, which will still make it highly successful. Furthermore, succeeding on the high-risk tasks will make the project groundbreaking.

b.6. Interaction between the project research thrusts, personnel, and time schedule

The time schedule of REBOUND is depicted in Figure 4. The project research thrusts are scheduled so as to allow for the interactions discussed in Section b.1.

[9] research.cs.aalto.fi/dmg/media.shtml

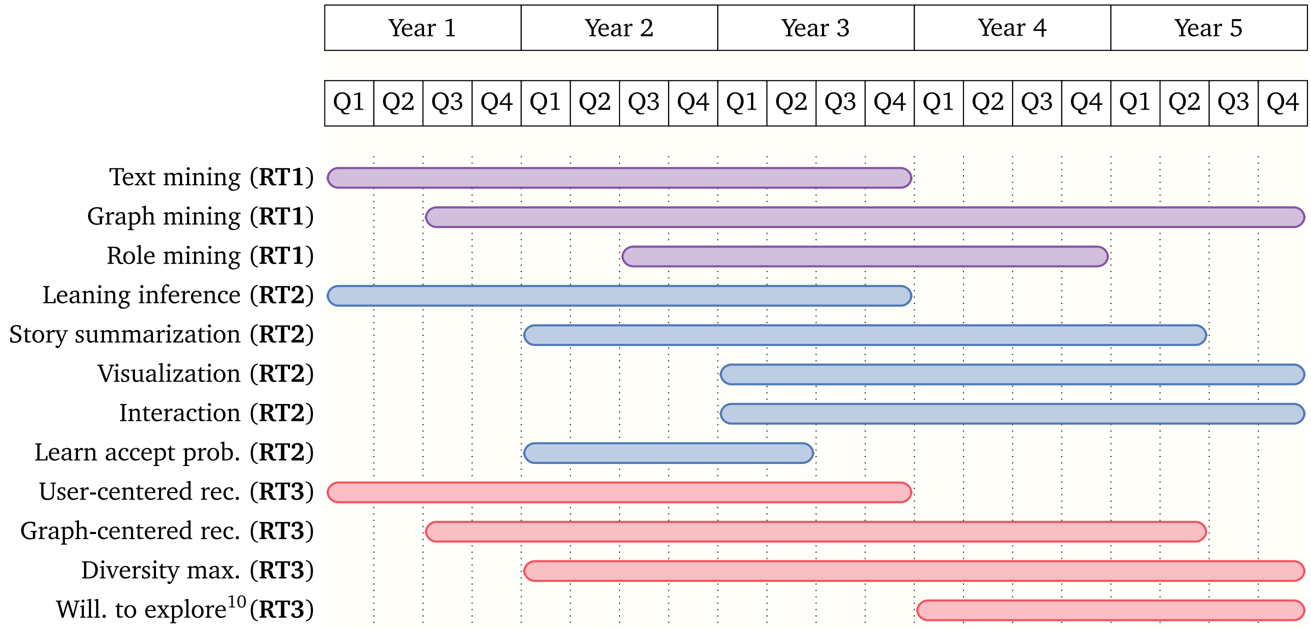

Figure 4: The time schedule of REBOUND.

The project will employ three doctoral students for four years each — the expected completion time for a doctoral degree in Aalto School of Science — for a total of 12 person-years of doctoral education. It will also employ three postdoctoral researchers during the whole duration of the project for a total of 15 person-years of postdoctoral training — most likely it will be more than 3 persons in total, as a typical postdoc residence is 2 to 4 years.

The topics of the doctoral students will be complementary so as to cover the different skills required in the project. In particular, one doctoral student will focus on text-mining methods and will contribute to all three research thrusts. The other two doctoral students will focus on graph-mining methods, one with emphasis on discovery problems, and the other with emphasis on recommendation problems.

Similarly, we will recruit postdocs with complementary background, to cover all skills required for the success of the project. Four person-years will be allocated to expert(s) in text mining and natural-language processing, who will contribute to problems in discovery, story summarization, and recommendation. Three person-years will be allocated to expert(s) in visualization and interactive methods. The rest eight person years will be allocated to experts in data mining, graph mining, and combinatorial optimization.

The postdocs will be supervising the doctoral students, but they will also be working independently on different parts of the project. In particular, the postdocs will be focusing on the more difficult and more risky parts of the project, such as developing algorithms with provable approximation guarantees. Overall, even though collaboration among the group members will be highly encouraged, each person in the project will have clearly assigned tasks so that there is accountability and fair assessment of progress.

The PI will devote 40% of his time in the project. He will supervise all the project members, take care of management issues, but will also allocate sufficient amount of time to technical problems.

During the hiring process we will support diversity and consider actions to achieve gender balance. Currently the gender ratio in the team is 3:5, while all members come from a different country.

b.7. Ethical issues

Research will be carried out in compliance with the European Code of Conduct for Research Integrity. To test our hypothesis and evaluate our methods we will contact user studies, either via Amazon Mechanical Turk, or via in-house participant recruitment. All participants in the user studies will be adult volunteers who will be given a full explanation of the study protocol and the purpose of the study. Their right to revoke the permission at any time will be clearly communicated. This research does not entail creation of registries featuring personal information.

[10] Analysis of factors that affect the willingness of users to explore alternative viewpoints.

Table 1: The REBOUND budget (in euros)

	Cost category	Year 1	Year 2	Year 3	Year 4	Year 5	Total
Direct costs	Personnel						
	PI (40%)	48 840	49 817	50 813	51 829	52 866	254 165
	Post docs	188 100	191 862	195 699	199 613	203 605	978 880
	Students	110 880	113 198	115 360	117 667	120 020	577 024
	Total personnel	347 820	354 776	361 872	369 109	376 492	1 810 069
	Other direct costs						
	Equipment	9 000	8 000				17 000
	Travel	30 000	30 000	30 000	30 000	30 000	150 000
	Other	1 000	1 000	1 000	1 000	11 000	15 000
	Total other direct costs	40 000	39 000	31 000	31 000	41 000	182 000
	Total direct costs	387 820	393 776	392 872	400 109	417 492	1 992 069
Indirect costs	Max 25% of direct costs	96 955	98 444	98 218	100 027	104 373	498 017
Total project costs		484 775	492 221	491 090	500 137	521 864	2 490 087
Requested grant		484 775	492 221	491 090	500 137	521 864	2 490 087

Section c. Resources

Research environment. The host institute is the Computer Science department of Aalto University, where the PI was appointed an associate professor in 2013 and promoted to full professor in 2017. With a wide range of computing resources and support services, a truly international community, and its commitment to high-quality research and teaching, Aalto University provides an excellent supporting environment for REBOUND. The department of Computer Science has long-standing tradition in the areas of machine learning and data mining, and it attracts a continuous stream of bright PhD students and postdoctoral researchers from Finland and abroad.

Budget. The budget details of REBOUND are provided in Table 1. The requested grant is 2.49 million euros for 60 months. The budget is divided into personnel costs, other direct costs, and overheads.

Personnel: Three doctoral students will be employed for four years each, and three postdoctoral researchers per year of the project lifetime. The salary cost of PhD students and postdoctoral researchers is calculated on the basis of 2 800 € /month and 3 800 € /month, respectively, which excludes side costs. The PI will devote **40%** of his total work time to the project.

Equipment: The proposed research framework does not require purchase of equipment, as the existing computing resources of the host institute are excellent. However, we have budgeted for one laptop computer for each project member.

Travel: We have budgeted travel costs so that all project members will be able to attend top international computer-science conferences. Additionally we will encourage all project members to travel pursuing international collaborations. Long-term academic collaborators of the PI include researchers in Boston University, University of Rome, Stockholm University, KTH, ISI Foundation in Turin, University of Pisa, University of Helsinki, and Ghent University. In fact there is strong tradition for the doctoral students in the group to pursue internship. Recent internship positions include Google, Facebook, Amazon, LinkedIn, MPI, etc.

Publications: We have not budgeted for open-access publication fees, as all resulting publications will be become openly available via green open access (`arxiv.org`).

User studies: To test our hypothesis and evaluate our methods we will contact user studies, either via Amazon Mechanical Turk, or via recruiting participants. We have budgeted 1 K€ /year for user studies.

Audit: We have budgeted 10 K€ in the last year for audit.

References

[1] F. Abel, Q. Gao, G.-J. Houben, and K. Tao. Analyzing user modeling on twitter for personalized news recommendations. In *International Conference on User Modeling, Adaptation, and Personalization*, pages 1–12, 2011.

[2] L. Adamic and N. Glance. The political blogosphere and the 2004 us election: divided they blog. In *Workshop on Link Discovery: Issues, Approaches and Applications (LinkKDD)*, pages 36–43, 2005.

[3] L. Akoglu. Quantifying political polarity based on bipartite opinion networks. In *Proceedings of the International AAAI Conference on Web and Social Media (ICWSM)*, 2014.

[4] J. An, D. Quercia, M. Cha, K. Gummadi, and J. Crowcroft. Sharing political news: the balancing act of intimacy and socialization in selective exposure. *EPJ Data Science*, 3(1):12, 2014.

[5] A. Angel, N. Sarkas, N. Koudas, and D. Srivastava. Dense subgraph maintenance under streaming edge weight updates for real-time story identification. *Proceedings of the VLDB Endowment*, 5(6):574–585, 2012.

[6] A. Arockiasamy, **A. Gionis**, and N. Tatti. A combinatorial approach to role discovery. In *Proceedings of the IEEE 16th International Conference on Data Mining (ICDM)*, pages 787–792, 2016.

[7] C. Aslay, E. Galbrun, **A. Gionis**, and A. Matakos. Maximizing the diversity of exposure in a social network. 2018.

[8] C. Aslay, A. Nasir, G. De Francisci Morales, and **A. Gionis**. Mining frequent patterns in evolving graphs. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management (CIKM)*, 2018.

[9] E. Bakshy, S. Messing, and L. Adamic. Exposure to ideologically diverse news and opinion on facebook. *Science*, 348(6239):1130–1132, 2015.

[10] N. Bansal, A. Blum, and S. Chawla. Correlation clustering. *Machine learning*, 56(1-3):89–113, 2004.

[11] P. Barberá, J. Jost, J. Nagler, J. Tucker, and R. Bonneau. Tweeting from left to right: Is online political communication more than an echo chamber? *Psychological science*, 26(10):1531–1542, 2015.

[12] C. Borgs, M. Brautbar, J. Chayes, and B. Lucier. Maximizing social influence in nearly optimal time. In *Proceedings of the twenty-fifth annual ACM-SIAM symposium on Discrete algorithms*, pages 946–957, 2014.

[13] E. Bozdag. Bias in algorithmic filtering and personalization. *Ethics and information technology*, 15(3):209–227, 2013.

[14] A. Bramson, P. Grim, D. J. Singer, S. Fisher, W. Berger, G. Sack, and C. Flocken. Disambiguation of social polarization concepts and measures. *The Journal of Mathematical Sociology*, 40(2):80–111, 2016.

[15] Y. Choi, Y. Jung, and S.-H. Myaeng. Identifying controversial issues and their sub-topics in news articles. In *Intelligence and Security Informatics*, pages 140–153. 2010.

[16] M. Coletto, K. Garimella, **A. Gionis**, and C. Lucchese. A motif-based approach for identifying controversy. 2017.

[17] M. Conover, J. Ratkiewicz, M. Francisco, B. Gonçalves, F. Menczer, and A. Flammini. Political polarization on twitter. In *Proceedings of the International AAAI Conference on Web and Social Media (ICWSM)*, 2011.

[18] G. Cormode, M. Garofalakis, P. J. Haas, C. Jermaine, et al. Synopses for massive data: Samples, histograms, wavelets, sketches. *Foundations and Trends® in Databases*, 4(1–3):1–294, 2011.

[19] M. Das, G. De Francisci Morales, **A. Gionis**, and I. Weber. Learning to question: leveraging user preferences for shopping advice. In *Proceedings of the ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 203–211, 2013.

[20] M. Dimock, J. Kiley, S. Keeter, and C. Doherty. Political polarization in the american public. pew research center. *Pew Research*, 2014.

[21] A. Edwards. (how) do participants in online discussion forums create “echo chambers”?: The inclusion and exclusion of dissenting voices in an online forum about climate change. *Journal of Argu-*

mentation in Context, 2(1):127–150, 2013.

[22] J.-M. Esteban and D. Ray. On the measurement of polarization. *Econometrica: Journal of the Econometric Society*, pages 819–851, 1994.

[23] L. Festinger. *A theory of cognitive dissonance*, volume 2. Stanford university press, 1962.

[24] D. Frey. Recent research on selective exposure to information. *Advances in experimental social psychology*, 19:41–80, 1986.

[25] K. Garimella, G. De Francisci Morales, **A. Gionis**, and M. Mathioudakis. Reducing controversy by connecting opposing views. In *ACM International Conference on Web Search and Data Mining (WSDM)*, pages 81–90, 2017.

[26] K. Garimella, **A. Gionis**, N. Parotsidis, and N. Tatti. Balancing information exposure in social networks. In *Advances in Neural Information Processing Systems (NIPS)*, pages 4663–4671, 2017.

[27] K. Garimella, G. D. F. Morales, **A. Gionis**, and M. Mathioudakis. Political discourse on social media: Echo chambers, gatekeepers, and the price of bipartisanship. In *Proceedings of the WebConference (WWW)*, 2018.

[28] K. Garimella, G. D. F. Morales, **A. Gionis**, and M. Mathioudakis. Quantifying controversy on social media. *ACM Transactions on Social Computing*, 1(1):3, 2018.

[29] E. Gilbert, T. Bergstrom, and K. Karahalios. Blogs are echo chambers: Blogs are echo chambers. In *International Conference on System Sciences*, pages 1–10, 2009.

[30] **A. Gionis**, H. Mannila, and P. Tsaparas. Clustering aggregation. *ACM Transactions on Knowledge Discovery from Data (TKDD)*, 1(1), 2007.

[31] M. Grömping. "echo chambers" partisan facebook groups during the 2014 Thai election. *Asia Pacific Media Educator*, 24(1):39–59, 2014.

[32] P. H. C. Guerra, W. Meira Jr, C. Cardie, and R. Kleinberg. A measure of polarization on social media networks based on community boundaries. In *Proceedings of the International AAAI Conference on Web and Social Media (ICWSM)*, 2013.

[33] I. Guy, N. Zwerdling, I. Ronen, D. Carmel, and E. Uziel. Social media recommendation based on people and tags. In *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*, pages 194–201, 2010.

[34] D. Kempe, J. Kleinberg, and É. Tardos. Maximizing the spread of influence through a social network. In *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2003.

[35] P. Lahoti, K. Garimella, and **A. Gionis**. Joint non-negative matrix factorization for learning ideological leaning on twitter. In *Proceedings of the ACM International Conference on Web Search and Data Mining (WSDM)*, pages 351–359, 2018.

[36] Q. Li, J. Wang, Y. P. Chen, and Z. Lin. User comments for news recommendation in forum-based social media. *Information Sciences*, 180(24):4929–4939, 2010.

[37] Q. V. Liao and W.-T. Fu. Can you hear me now?: mitigating the echo chamber effect by source position indicators. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW)*, pages 184–196, 2014.

[38] Q. V. Liao and W.-T. Fu. Expert voices in echo chambers: effects of source expertise indicators on exposure to diverse opinions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 2745–2754, 2014.

[39] C. G. Lord, L. Ross, and M. R. Lepper. Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence. *Journal of personality and social psychology*, 37(11):2098, 1979.

[40] A. Matakos and **A. Gionis**. Tell me something my friends do not know: Diversity maximization in social networks. 2018.

[41] Y. Mejova, A. X. Zhang, N. Diakopoulos, and C. Castillo. Controversy and sentiment in online news. *Symposium on Computation + Journalism*, 2014.

[42] A. Morales, J. Borondo, J. Losada, and R. Benito. Measuring political polarization: Twitter shows the

two sides of Venezuela. *Chaos*, 25(3), 2015.

[43] S. Munson, S. Lee, and P. Resnick. Encouraging reading of diverse political viewpoints with a browser widget. In *Proceedings of the International AAAI Conference on Web and Social Media (ICWSM)*, 2013.

[44] M. E. Newman. Modularity and community structure in networks. *Proceedings of the national academy of sciences*, 103(23):8577–8582, 2006.

[45] B. Ordozgoiti and **A. Gionis**. Consensus k-median. *Submitted for publication*, 2018.

[46] M. Prior. *Post-broadcast democracy: How media choice increases inequality in political involvement and polarizes elections*. Cambridge University Press, 2007.

[47] W. Quattrociocchi, A. Scala, and C. R. Sunstein. Echo chambers on facebook. 2016.

[48] P. Rozenshtein, A. Anagnostopoulos, **A. Gionis**, and N. Tatti. Event detection in activity networks. In *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1176–1185, 2014.

[49] P. Rozenshtein and **A. Gionis**. Temporal pagerank. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 674–689, 2016.

[50] P. Rozenshtein, **A. Gionis**, A. Prakash, and J. Vreeken. Reconstructing an epidemic over time. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1835–1844, 2016.

[51] P. Rozenshtein, N. Tatti, and **A. Gionis**. Finding dynamic dense subgraphs. *ACM Transactions on Knowledge Discovery from Data (TKDD)*, 11(3):27, 2017.

[52] P. Rozenshtein, N. Tatti, and **A. Gionis**. The network-untangling problem: From interactions to activity timelines. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases (ECML PKDD)*, pages 701–716, 2017.

[53] D. Shahaf, C. Guestrin, and E. Horvitz. Trains of thought: Generating information maps. In *Proceedings of the 21st international conference on World Wide Web (WWW)*, pages 899–908, 2012.

[54] D. Shahaf, C. Guestrin, E. Horvitz, and J. Leskovec. Information cartography. *Communications of the ACM*, 58(11):62–73, 2015.

[55] M. Sozio and **A. Gionis**. The community-search problem and how to plan a successful cocktail party. In *Proceedings of the ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 939–948, 2010.

[56] J. Tang, Y. Chang, C. Aggarwal, and H. Liu. A survey of signed network mining in social media. *ACM Computing Surveys (CSUR)*, 49(3):42, 2016.

[57] Y. Tang, Y. Shi, and X. Xiao. Influence maximization in near-linear time: A martingale approach. In *Proceedings of the ACM SIGMOD International Conference on Management of Data*, pages 1539–1554, 2015.

[58] N. Tatti and **A. Gionis**. Density-friendly graph decomposition. In *24th International Conference on World Wide Web (WWW)*, pages 1089–1099, 2015.

[59] C. Tsourakakis, F. Bonchi, **A. Gionis**, F. Gullo, and M. Tsiarli. Denser than the densest subgraph: Extracting optimal quasi-cliques with quality guarantees. In *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 104–112, 2013.

[60] K. Wallsten. Political blogs and the bloggers who blog them: Is the political blogosphere and echo chamber. In *American Political Science Association's Annual Meeting*, pages 1–4, 2005.