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SOCNET 2018

Proceedings of the „Second International Workshop on Modeling, Analysis, and Management of Social Networks and Their Applications“

Kai Fischbach, Udo R. Krieger (eds.)

University of Bamberg Press

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Preface

In recent years, social networks have produced significant on-line applications running on top of a modern Internet infrastructure. The associated information exchange patterns that are caused by the underlying massive human interactions constitute a major driver of the fast growing Internet traffic observed in the last decade.

Generally speaking, a social network denotes the social structures emerging from interactions of human actors among each other and within their organizations. The modeling, analysis, control, and management of complex social networks represent an important area of interdisciplinary research in an advanced digitalized world. Over the years, scholars in the fields of anthropology, sociology, psychology, economics, and organizational theory have proposed different methods to reveal the underlying structures of these complex networks, to analyze their functioning and to determine the associated network outcomes. For this reason the practical application of social network analysis constitutes an important and rapidly growing scientific domain in our interconnected information societies. The related scientific concepts incorporate a variety of sophisticated techniques stemming from diverse areas such as computer science, control theory, graph theory, simulation, visualization, and statistics, among others.

To cover related research issues in the vibrant field of social networks, "The Second International Workshop on Modeling, Analysis and Management of Social Networks and Their Applications" (SOCNET 2018) was organized in cooperation with representatives of Deutsche Gesellschaft für Netzwerkforschung (German Association for Network Research, DGNet) and the organizing committee of the 19th International GI/ITG Conference on "Measurement, Modelling and Evaluation of Computing Systems" (MMB 2018). It toke place at Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany, on February 28, 2018. The workshop was co-located with MMB 2018 that was held during February 26–28, 2018.

SOCNET 2018 was an interdisciplinary, international event where authors from Belgium, Japan, South Africa, and Germany presented their new scientific results. After a careful review process the international program committee of SOCNET 2018 finally selected eight regular papers from different fields such as information systems, business administration, computational social science, and computer science. These papers covered important aspects of the modeling, the analysis, and the application of social networks. The topics ranged from theoretical oriented studies focusing on the structural inference of topic networks, the modeling of group dynamics, and the analysis of emergency response networks to the application areas of social networks such as social media used in organizations or social network applications and their impact on modern information society.

Apart of these contributed papers, the scientific program included the invited talk “From the Age of Emperors to the Age of Empathy” by Dr. Peter A. Gloor, Center for Collective Intelligence, Massachusetts Institute of Technology, USA.

The program was complemented by a tutorial “Network Analysis in Python - A Brief Introduction” offered by Dr. Oliver Posegga, University of Bamberg.

The program of SOCNET 2018 fulfilled its initial objective to reveal the rich methodological, technical, socio-economic and psychological aspects of social network analysis. As conference chairs, we thank all authors for their submitted papers and all the speakers, in particular the invited speaker, for their vivid presentations and lively discussions.

We are grateful for the support of all members of the program committee and thank all external reviewers for their dedicated service and the timely provision of their reviews.

We express our gratitude to Friedrich-Alexander-Universität Erlangen-Nürnberg as host of the workshop and the local organizing committees of SOCNET 2018 and MMB 2018 for their great efforts. We thank Technology Alliance Oberfranken (TAO) regarding its endorsement. We also acknowledge the support of the Easy-Chair conference system and express our gratitude to its management team.

We are indebted to University of Bamberg Press for an unceasing support of our publication effort. In particular, we are thankful to Mr. M. Großmann who prepared the proceedings by his powerful editorial tools.

Finally, we hope that the Proceedings of SOCNET 2018 will strongly stimulate the readers' future research on monitoring, modeling, and analysis of social networks and encourage their development efforts regarding social network applications of the next generation.

February 2018

Kai Fischbach
Udo R. Krieger

Tutorial

Network Analysis in Python

A Brief Introduction

Oliver Posegga

University of Bamberg,
An der Weberei 5, 96047 Bamberg, Germany
`http://www.uni-bamberg.de/sna/`

Abstract. This tutorial provides an entry-level introduction to social network analysis using Python and NetworkX. We discuss Python as a platform for network analysis and provide a systematic overview on the available libraries that elevate Python to a powerful toolbox for network research. Further, we introduce the fundamental concepts of network analysis and visualization, which we illustrate with practical examples based on a freely available dataset that we analyze with the software introduced in the beginning of the tutorial.

1 Goals

The goal of this tutorial is to provide a brief but comprehensive introduction to social network analysis using Python. After attending the tutorial, participants will be familiar with the basic concepts of network analysis, know how to analyze networks from a multi-level multi-theory perspective, understand the fundamentals of the Python ecosystem and know how to quickly setup their own Python environment. Further, they will be able to model, analyze, and visualize simple networks from freely available datasets using contemporary Python libraries.

2 Requirements

This course is designed to be an entry-level tutorial for individuals interested in social network analysis and serves as a starting point and overview on the topic. Participants are not required to be familiar with social network analysis and related software in general. Previous knowledge, however, will be beneficial to understand the topics of the tutorial. Participants who are already familiar with social network analysis and Python are not the primary target audience of the tutorial, but might be interested in some of the advanced topics (e.g. interactive network visualization using Python and d3.js [2]), which are briefly discussed and demonstrated as an outlook at the end of the tutorial.

3 Structure and Content

The tutorial covers three major topics, i.e. (1) the Python ecosystem, including network analysis and visualization libraries, (2) the fundamentals of network analysis, and (3) the fundamentals of network visualization. The contents discussed for each topic are briefly outlined in the following.

3.1 Python and Social Network Analysis

There are multiple readily available software solutions that come with many of the different methods and techniques falling into the domain of social network analysis, some of which have been around for decades (e.g. UCINET [8], Pajek [7], Gephi [4]). Recently, however, Python and the ecosystem evolving around it have gained popularity in the network community. As a programming language, Python is known for its intuitive syntax, readability, extensibility, versatility, cross-platform availability, high degree of customizability, and the large community that has emerged from it. As a platform for social network analysis, it primarily benefits from the extensive number of libraries and extensions contributed by this community, which elevate Python from a simple programming language to a flexible and powerful ecosystem with a wide range of scientific applications.

Over the course of the tutorial, we provide a brief overview of the various libraries that are necessary to use Python for social network analysis. For this tutorial, we use a freely available Python distribution, i.e. Anaconda [1], which provides a comprehensive scientific Python environment, including Jupyter [5], a web-based, interactive development environment, formerly known as iPython.

We briefly discuss the scientific Python environment and its setup, before we demonstrate how Anaconda [1] can be used in conjunction with Docker [3] to provide a flexible cross-platform environment for network analysis. Further, we provide an overview of the most commonly used network analysis libraries for Python and continue the tutorial with a practical introduction to the NetworkX [6] library using practical examples based on a freely available dataset.

3.2 The Fundamentals of Social Network Analysis

We discuss the basic concepts of network analysis using the previously introduced dataset based on simple analyses conducted with NetworkX [6]. Over the course of this introduction, we follow an exploratory analysis pattern [9], which comprises the following steps: *Definition* of nodes and edges, *manipulation* of the network, *computation* of network measures, *visualization* of the network.

In the definition step, we discuss the implicit and explicit assumptions that have to be made when modeling network structures from different types of network data. With regard to the manipulation step, we explain several approaches to querying and manipulating network structures using NetworkX [6]. After covering those steps, we proceed with the introduction of well-known network measures along a multi-level multi-theory framework [10], which systematically captures different units of analysis, ranging from the level of individual actors to the network level. Finally, we cover the visualization of networks in general, and in Python in particular, in a dedicated section of this tutorial.

3.3 The Fundamentals of Network Visualization

One of the profound strengths of network analysis lies within the beauty and intuitive nature of network visualizations. While it has become deceptively easy to visualize networks using tools like Gephi [4], which provide easy access to a variety of sophisticated layout algorithms and a plethora of useful visualization features, creating meaningful visualizations requires a systematic understanding of their building blocks.

We briefly discuss those building blocks and provide an overview of the most common layout algorithms used in practice. Using the dataset analyzed in the first part of this tutorial, we demonstrate how to create simple network visualizations using NetworkX [6].

The last part of this tutorial is dedicated to the discussion of the interactive visualization of networks. We demonstrate two approaches to create such visualizations: The first approach is based on exporting network data from Python and importing them into Gephi [4]. The second approach utilizes the d3.js [2] framework in conjunction with Python and NetworkX [6].

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Invited Talk

From the Age of Emperors to the Age of Empathy

Peter A. Gloor

Massachusetts Institute of Technology
Center for Collective Intelligence
5 Cambridge Center
Cambridge, MA 02138, USA
pgloor@mit.edu
http://cci.mit.edu/pgloor

Abstract

The age of imperial CEOs residing in the corner office is over, Mark Zuckerberg shares the same open office space with the rest of his Facebook employees. Today's Millennials do not want to be led by emperors high on testosterone and authority, but by leaders high on empathy and compassion.

This talk is based on my new books "SwarmLeadership" and "Sociometrics" . "SwarmLeadership" introduces a framework based on "social quantum physics", which explains how all living beings are connected through empathy in entanglement, and learning. To track empathy, entanglement, and learning we have developed "seven honest signals of collaboration" which can be used to measure empathy, entanglement, and learning on any level, from the global level on social media, inside the organization with e-mail, down to face-to-face entanglement using the body sensors of smartwatches. The talk will present the main concepts and the underlying algorithms and models, documenting them by numerous industry examples from our own work.

Key words:
Social quantum physics, Entanglement, Empathy, Learning, Collaborative Innovation Networks.

References:

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2. Gloor, P.: Sociometrics and Human Relationships: Analyzing Social Networks to Manage Brands, Predict Trends, and Improve Organizational Performance. Emerald Publishing, London 2017

Curriculum Vitae

Peter A. Gloor is a Research Scientist at the Center for Collective Intelligence at MIT's Sloan School of Management where he leads a project exploring Collaborative Innovation Networks. He is also Founder and Chief Creative Officer of software company galaxyadvisors, a Honorary Professor at University of Cologne, a lecturer at Aalto University in Helsinki, Distinguished Visiting Professor at P. Universidad Católica de Chile, and a Honorary Professor at Jilin University, Changchun, China. Earlier he was a partner with Deloitte and PwC, and a manager at UBS. He got his Ph.D in computer science from the University of Zurich and was a Post-Doc at the MIT Lab for Computer Science working on WWW-like systems before the Web existed.

He is currently focusing on quantum social physics, predicting social behavior from electronic communication patterns and trying to model collective consciousness and competitive collaboration.

Reviewed Papers

SOCNET 2018

A Framework for the Analysis of the Impact of the Use of Social Media by an Organization (FAIUSMO)

Patricia Gouws, Elmarie Kritzinger, and Jan Mentz

School of Computing, College of Science, Engineering and Technology,
University of South Africa

Abstract. This paper presents a proposed framework for the analysis of the impact of the use of social media by an organization (FAIUSMO). A design science research (DSR) approach was used to create awareness of the research problem, propose a solution, create and evaluate the research artefact (FAIUSMO), and to communicate the first iteration of the framework. The theoretical framework is proposed from the synthesis of extant literature using dimensional data modelling. The internal (organization), external (virtual community) and strategic (social media strategy) perspectives describe the analysis of the impact of the use. The measures of the use are the identified strategic social media metrics. The FAIUSMO framework comprises four stages, namely: process and scope, attribute perspectives (internal, external and strategic), measurement data and processing, and analysis and presentation. The framework may be used to transform social media metrics to strategic insights and social intelligence. The evaluation of the framework is ongoing.

Key words: organizational social media, social media strategy, virtual community

1 Introduction

Social media (SM) refers to a collection of web-enabled applications, used to communicate, to collaborate, and to create user-generated content [1]. Examples of current SM applications include: Facebook, Twitter, Instagram and YouTube. The background to the research problem is considered in terms of the impact of the use of SM and the analysis of use of SM by an organization.

The identified research problem is a lack of a comprehensive and integrated approach to the analysis of the impact of the use of SM by an organization. This paper reports on the design, creation and evaluation of a comprehensive and integrated framework to address the identified research problem.

1.1 Background to Problem

SM is a universal focus of the societal communications [2]. Organizations use SM for communication. However, SM has changed the ways in which communities and organizations communicate and interact [3]. The use of SM applications allows for the creation, sharing and exchange of information [1].

SM research is considered in terms of theories, constructs and conceptual frameworks [3]. The need for research pertaining to the impact of the use of organizational SM is identified [4]. However, there is a need for conceptual instruments to guide the approach and structure of SM knowledge [2]. The nature of SM data as big data from diverse subject matter domains is a focus of the research framework [2].

The review [3] presents groups of theories used in the formulation of conceptual frameworks within SM research, namely personal behaviours, social behaviours and mass communication. From the theories identified, a causal-chain framework of social media research on the adoption and use of SM is formulated, the attributes of which include [3]: inputs (e.g. social factors), mediators (e.g. platform attributes), moderators (e.g. user characteristics) and outcomes (e.g. organizational context). Thus, research considers a wider spectrum than merely quantitative measurement [5].

From the review presented, research gaps and opportunities were identified [3]. The focus on personal use suggests a gap in the study of SM adoption from an organization perspective. Organizational use of SM for daily operational and strategic use is limited [3]. It is recommended that the impact of the use of SM be investigated. The contribution of the impact of the use of SM on the organizational strategic performance is questioned. From the review [3], four areas for future SM research are identified, namely: the organizational orientation in the use of SM, the social power, the cultural diversity of the use of SM, and the impact of the use of SM. However, balance should be maintained to mitigate the negative impacts (e.g.

distraction, reduced productivity, lack of data control), and infrastructure should be deployed to manage data [3].

The use of SM creates both positive (communication, collaboration) and negative (security, risk) effects [3], and thus requires tracking to identify problems and discover solutions timeously. A better understanding of the use of SM may lead to an appreciation of the impact of the use of SM [3]. Thus, to understand the use of SM, some form of measurement of the use of SM is required.

The first gap identified is the analysis of the impact of the use of SM. The second gap identified is the analysis of use of SM by an organization. The problem considered by this research is the analysis of the impact of the use of SM by an organization. The proposed artefact is a comprehensive framework for a comprehensive and integrated approach to the analysis of the impact of the use of SM by an organization.

1.2 Organization of Paper

This paper presents an introduction (Section 1) and an overview of research methodology (Section 2), relevant literature (Section 3), and creation of artefact (Section 4). This paper concludes with recommendations for future research (Section 5 and 6).

2 Research Methodology

Design science research (DSR) in information systems (IS) research is considered a collection of techniques for the design and creation of artefacts to address a problem [6]. The first step of DSR is the awareness of the problem. In this research, a review of the extant literature leads to the definition of the problem.

The second step of the DSR approach is the proposal of the design criteria for a solution to address the problem. The Step 1 and Step 2 of the DSR approach are presented in Section 3.

The third step of the DSR approach is the design and creation of the research artefact, as a solution to address the problem. In this research, the framework FAIUSMO is proposed. The Step 3 of the DSR approach is presented in Section 4.

The fourth step is an evaluation of the utility of the research artefact, to determine the extent to which the artefact addresses the problem, as well as the evaluation of the design criteria specified. The Step 4 of the DSR approach is introduced in Section 5.

To address the need of iteration in the DSR approach, it is envisaged that future research may include multiple iterations of evaluation of utility and quality, where feedback from an evaluation may be used for the improvement of the FAIUSMO framework. The final step in the DSR approach requires the communication of the contribution of the research. Future research opportunities are also recommended.

3 Literature Overview

SM is the collective name for a number of SM applications. The purpose of use by an organization will determine the collection of SM applications that may be used by the organization. Each of the SM applications may be classified according to purpose. The definition and classification [1] of SM is evolving. Generic guidelines for the use of SM [1,5,7] are presented in the literature.

To present an awareness of the research problem, the literature is considered in terms of aspects of the analysis of the impact of the use of SM by an organization. These aspects include the measurement of the use of SM (Section 3.1). From the measurement options considered, the internal (organization) (Section 3.2), the external (virtual community) (Section 3.3) and strategic (SM strategy) (Section 3.4) perspectives are identified. For the strategic perspective, the identification of strategic metrics is required to evaluate the SM strategy.

To ensure that the use of SM is aligned to organizational strategies, SM data needs to be integrated with organization data (Section 3.5). This leads to the awareness of the identified research problem, namely: the lack of a comprehensive and integrated approach to the analysis of the impact of the use of SM by an organization.

3.1 Measurement of Impact of Use of SM

To analyze the impact of the use of SM, some form of measurement is required. The measurement of the use of SM is imperative to ensure success [8]. The contribution of SM may be considered in terms of the relevant metrics and methods [9]. Approaches to SM measurement include an iterative measurement process [8], a step-by-step SM measurement approach [10], an evaluation framework [11], and a performance measurement system [9]. This confirms the observation that an over-arching approach to SM measurement, and thus also analysis, is lacking [9].

A five-phase SM measurement process includes [8]:

- Concept Phase: During this phase, the goals, objectives and key performance indicators aligned with objectives are identified. Targets or performance benchmarks of success are recommended.
- Definition Phase: The social strategy is detailed in terms of indicators that quantify the reach, the discussion and the outcome.
- Design Phase: The tactics to achieve the SM goals are defined. The data collection methods are identified. Examples of types of SM data sources include: enterprise listening platforms, text mining partners, platform API tools and site analytic solutions.
- Deployment Phase: During the phase, data is collected from the SM applications that are used. The data must be quality assured, validated and aggregated for meaningful analysis.
- Optimization Phase: The data is analyzed and insights are reported.

However, the use of SM requires long term commitment [8]. Whilst the proposed planning includes the identification of strategic goals, the stakeholders and the needs of the stakeholders, these aspects are not detailed in the planning of the use of SM.

To provide more detail, an eight-step SM measurement process and a valid metrics framework are provided, albeit specifically for the public relations industry [10]. An Eight-Step SM Measurement Process includes [10]:

- Identification of the strategic goals.
- Prioritization of the stakeholders (internal and external to the organization).
- Identification of the objectives that are aligned to the goals.
- Link key performance indicators (as quantifiable measurements that may be used to assess strategic success) to objectives.
- Selection of SM applications (tools) and benchmarks.
- Analysis of results with reference to the SM effort and activities.
- Presentation of results.
- Iterative measurement and improvement.

Despite the increased level of detail presented in the literature, the eight-step approach has a public relations and marketing focus. Although the stakeholders are considered in the planning, the attributes of the stakeholders are not included in the analysis or in the presentation of the results. A more generic focus is required.

An evaluation framework to assess the impact and value of the use of SM is developed [11]. The evaluation is considered from an internal and external perspective and includes the strategic objectives of the organization. The key performance indicators (KPIs) are, however, not linked to specific metrics of specific SM applications.

Performance measurement systems for the measurement of SM is considered in terms of metrics and methods of measurement [9] and the measurement model required [12]. Information derived from the large volumes of SM data may contribute to the organizational decision-making processes [12]. Phases in which the SM information may be used include: planning, performance and action for improvement [12]. However, there exists a lack of a comprehensive and integrated approach to the analysis of the impact of the organizational use of SM.

The metrics are defined as the indicators that are used to quantify an entity, thus the SM and related activities [9]. The methods are defined as the approaches used to calculate the metrics, including the retrieval, collection and storage of the SM data [9]. This is required to quantify the contribution or impact of use of the SM, specifically by an organization.

The performance measurement system addresses the data collection and analysis [9]. Approaches to data collection include: default data collection (e.g. Google Analytics), manual data collection (e.g. number of likes) and automated data collection (e.g. web-crawling). Approaches to the analysis of SM data include content and sentiment analysis [9]. Both data collection and data analysis approaches need to be taken into account during the planning of the measurement of SM.

The planning for the use and measurement of SM considers the internal, external and strategic perspectives of the use of SM. The five-phase process [8], the eight-step approach [10] and the evaluation framework [11] include the following aspects in the planning for the use and measurement of the impact of the use of SM: internal (Section 3.2), external (Section 3.3) and strategic (Section 3.4) perspectives.

3.2 Internal Perspective – The Organization

This refers to the organization that uses the SM. Organization SM (OSM) is presented in the literature [13]. The users within an organization are considered the internal environmental perspective of use. An organization may use SM to communicate internally within the organization and externally to the virtual community. SM applications may be used by an organization to enhance the services of government, including marketing, customer care relations and health care [16,17]. SM is used in organisations for specific functions (in order of priority), including branding, information sharing, public relations, understanding customers, generation of leads, work collaboration, communication (internal) and support for sales [18].

A more strategic approach to the use of SM would promote and support the use of SM by the organization. Factors that could encourage SM use include allocated budgets and guidelines for the use of SM [19]. Factors to encourage rather than hinder the use of SM by an organization should be considered. However the analysis of use of SM by an organization tends to be challenged also by a focus on personal and individual use rather than an aggregated organizational level of use [13].

The organization social media (OSM) refers to actors, artefacts and activities, highlighting the need for more aggregated, organization focused analysis of the use of SM [13]. The organization type may influence the organizational actors in the artefacts (SM applications) used. Although organizational use of SM is considered a domain of IS research where limited research is available, empirical analysis of the use of SM with an organization may impact the use of SM and address one or more of the challenges identified in the use of SM by the organization.

3.3 External Perspective - The Virtual Community

This refers to the users of the SM that are stakeholders in the use of SM, albeit external to the organization. These users are considered members of the organization's virtual community. The virtual community (VC) is external to the organization. The members of the VC are also stakeholder in the planning of the use of SM. A VC may be described in terms of VC attributes that include a VC typology [14], a life-cycle stage of a VC [20], or the VC type [21]. These VC attributes may provide dimensions for comparative and deeper analysis of measures of the impact of the use of SM. The identified research gap is that the VC attributes of SM use, although described in the literature, should be included in the analysis of SM metrics. There is also the option of the comparative analysis of perceived (theoretical) and actual (empirical) community demographics.

3.4 Strategic Perspective - SM Strategy

Planning prior to the definition of a SM strategy is required. To ensure that the goals are achieved, required SM tactics are addressed in SM activities. These SM activities focus on content, community, resources, and support (e.g. skills, equipment, and governance). The recommended strategic objectives may include: to inspire adoption, to build community and to engage community. A SM strategy should be aligned to the organizational strategy [27].

A SM strategy ensures that the use of the SM is not merely ad hoc, but that an integrated use of these SM applications addresses the purpose of use as well as the strategic goals and objectives of the organization. A SM strategy must be defined for a given SM perspective, and quantified using strategic targets and benchmarks of use of SM applications. Each SM application generates its own specific format application data stream and metrics. However, the integration of these metrics is required to ensure that synergy of the defined SM strategy. Thus, the on-going measure and evaluation of the use of SM in terms of identified strategic metrics must be aligned within the SM strategy.

The limited availability of a comprehensive SM strategy that uses the integrated SM data to evaluate the strategy against targets is considered a gap. The organizations need to be guided in the formulation of a SM strategy from generic goals that can be customized according to the specifics of the application.

The SM strategy should also be aligned to the organizational or business strategy through generic business goals aligned to SM activities [15], and key performance indicators need to be linked to generic metrics [22].

3.5 Data and Data Processing Required for Analysis of Impact of Use

To address the need for the analysis of the impact of the use of SM by an organization, the SM data needs to be integrated with the organizational business data. To this end, a procedure is required to ensure that intelligence may be derived from SM data. The synthesis of accessible business intelligence (the process in which information is derived from organizational data) and SM data is investigated [23].

According to [23], the value of the SM data is attributed to the fact that the users generate the data. He continues that organizations pursue information to discover trends that may influence organizational performance [23]. The intention of the analysis of the SM data, is to go beyond analysis. The focus is the social business intelligence. Social business intelligence systems are defined as systems that are developed to derive information from SM data to support decision making [23]. Although business information systems derived the information from internal business (organizational) data, cognizance is given to the external SM data that may be included in the business intelligence process.

A procedure was developed to collect, process and analyze SM data for business intelligence [23]. SM is considered a new data domain, a novel source of useful data [24]. The integration of SM data from multiple SM applications is required to support the comprehensive and integrated analysis of the impact of the use of SM by an organization.

Organizational or enterprise data is stored in the enterprise data warehouse, and this data is traditionally analyzed using the technique of online analytical processing (OLAP). However, the enterprise data warehouse may be extended to accommodate SM data. Thus, OLAP may also be extended for the analysis of SM data. Although OLAP technology is considered under-exploited for the analysis of SM data and is thus under-represented in SM research [24], extensions to data warehouses and online analytical processing (OLAP) technology allow for analysis of emerging novel data domains [24]. The extensions include [24]: a five-layer data warehouse architecture, reinforcement of OLAP for the analysis of SM data, and a three-layer Social Business Intelligence (SBI) framework integrates the use of business intelligence with the analytics of SM. Social OLAP is defined as the use of OLAP for the multi-dimensional analysis of SM and business data [24].

The external SM data needs to be imported and stored in the organization's internal data structures, i.e. the enterprise data warehouse [24]. This allows for the analysis of the SM data integrated with the business data. The data warehouse that uses conformed dimensions will ensure that the analysis of impact of the use is within the defined internal, external and strategic perspectives and aligned to the organizational data. Thus, the gap is a comprehensive and integrated approach to the identification and transformation of the externally generated SM data. Within the warehouse, this SM data will be integrated with the organizational data to ensure that social business intelligence may be gleaned [24].

3.6 Summary of Literature Overview

The following are identified as design criteria for an artefact to address the problem: process and scope of purpose, perspectives, and the data (SM metrics) processing, analysis and presentation required for the analysis. The review of the extent literature, and thus awareness of the problem, leads to the creation of the proposed framework (FAIUSMO) to address the identified problem.

4 Design and Creation of Framework

The Framework for the Analysis of the Impact of the Use of SM by an Organization (FAIUSMO) is proposed to address the research problem identified. As the body of SM knowledge evolves, and the SM landscape changes accordingly, the needs for analysis of the impact of the use of SM by an organization will develop too.

It is envisaged that the FAIUSMO framework will be adapted to accommodate these changes. The eight-step SM measurement process [10] guides the synthesis of a proposed four-stage framework. The given eight steps are used in the mapping of the proposed four FAIUSMO stages, thus:

- **Step 1**: The initial purpose of use of SM is defined to address the needs of the users. The unit of use, strategy and time-frame need to be identified. This is addressed in Stage 1 of the framework.
- **Step 2, Step 3 and Step 4**: The internal, external and strategic perspective are identified. These details are addressed in Stage 2 of the proposed framework. Stage 2.1 considers the internal, organizational perspective, Stage 2.2 considers the external, virtual community, perspective, Stage 2.3 considers the strategic perspective (goals, objectives, key performance indicators and generic metrics), Stage 2.4 sets the weights of the strategic goals, and Stage 2.5 defines the strategic target ranges.
- **Step 5**: The data that will be used in the analysis of use is identified. As the data resides external to the organization, the data needs to be imported into the organizational data structure. Only the strategic metrics (i.e. a subset) are selected for import into the organizational data repository and used in the analysis. These details are addressed in Stage 3 of the proposed framework.

- **Step 6**, **Step 7 and Step 8**: The data that has been imported as strategic metrics must be processed, analyzed and presented for the identification of information and trend patterns. These details are presented in Stage 4.

The nine decision points of dimensional data modelling [25,26] guide the development of the FAIUSMO framework. In Section 4.9, a detail diagram is presented in Figure 1.

4.1 Stage 1: Process and Scope of Purpose

The process to analyze the use of a subset of SM for a given time by an organizational unit (for this research, a project) for a given purpose requires the definition of the scope of purpose of use. The definitions of the following entities are required: Time (to ensure that analysis trends and patterns may be detected and explored), organizational unit (e.g. a project) (to allow for comparison of use of SM across multiple units), and strategy (to identify for comparison purposes).

4.2 Stage 2.1: Internal Perspective - Organization

These attributes are considered sufficient to define the internal perspective: organization (type) (a synthesis of organization types describes an organization), organizational artefacts (SM applications) (organizational artefacts [13] are included as per the classification [1]), organizational actors and activities (strategic activities are included in Stage 2.3).

4.3 Stage 2.2: External Perspective - Virtual Community

These attributes are considered sufficient to define the external perspective: classification of virtual community (Classification is defined in terms of profiles [21]), typology of the virtual community (Typology is defined in terms of purpose, place, platform, population and profit. Identified benefits of using a typology includes a classification to understand a virtual community, to contribute to a growing knowledge base of virtual communities and to ensure rigor in the research of virtual communities [14]), and virtual community life-cycle stage (Identification of the stage in the life-cycle of a virtual community leads to a better understanding of the needs of the virtual community, guidance in the inclusion of SM applications, and conversant creation of the community [20]).

4.4 Stage 2.3: Strategic Perspective

For the framework, these attributes are considered sufficient to define the strategic perspective: goals (The goals of the social business strategy are generic business goals [15]. These are the long term goals), objectives (An objective is considered more short term. It refers to the SM objectives, the SM strategic theme that contributes to the social business goals [11,28], though linking the recommended aligned SM activities), activity (The aligned and generic SM activities are presented for each of the selected, prioritized goals [15]), key performance indicator (KPIs) (a goal may have multiple KPIs. An indicator may be linked to multiple goals [15]. Each KPI may be measured by multiple generic metrics [22], and are mapped (in this research) onto the strategic themes [11]), generic metrics (KPIs are linked to generic metrics [22]), and SM application metric. Each generic metric defined [22] may be linked (in this research) to a SM application metric (A number of such links may be recommended, however, due to the evolving user needs, these may be defined by users. A SM application metric is required to be linked to each strategic generic metric, for each of the SM applications used).

Each social business goal [15] is aligned to one or more SM activities. The definition of the KPI (and thus generic metric) [22] is used to derive KPIs from the descriptions of the SM metrics in this research. It is envisaged that this apparent link between a social business goal and a generic metric may be utilized in this research towards the analysis of the use of SM, specifically in the strategic perspective. By highlighting the focus of the SM activity, one or more indicators may be linked to the activity, and thus to the goal.

4.5 Stage 2.4: Strategic Perspective - Goal Weightings

The collection of SM business goals may not all be equally relevant in a SM application. The allocated weight may be considered an indication of priority of the goal within the strategy. These assigned relative weights of the strategic goals may, however, change. The sum of the goal weights must however be one. These goal weight values are considered sufficient to analyze the impact of use of SM by organizations that have varying strategic priorities.

4.6 Stage 2.5: Strategic Target Setting of the Strategic Metrics

The target ranges are defined in terms of minimum and maximum values for each of the strategic metrics that are included in the strategy. This ensures that the actual metric values can be compared to strategic values. Strategically, a metric value must be within range. Action may be deemed necessary when values occur out of range. These target values are considered sufficient to analyze the use of SM.

4.7 Stage 3: Data Measures and Processing

The measures to support the analysis of the impact of the use of SM are the actual SM data values of the identified strategic metrics. This data must be imported and loaded into the SM data warehouse. The structure of the SM data warehouse is developed according to the data warehouse architecture of conformed dimensions. The use of each of the SM applications deployed may be measured in terms of a range of metrics. Relevant metrics from appropriate data sources are identified. Each application may have a range of metrics that are generated. Metric values are quantitative and objective measures, and may be exported regularly and frequently.

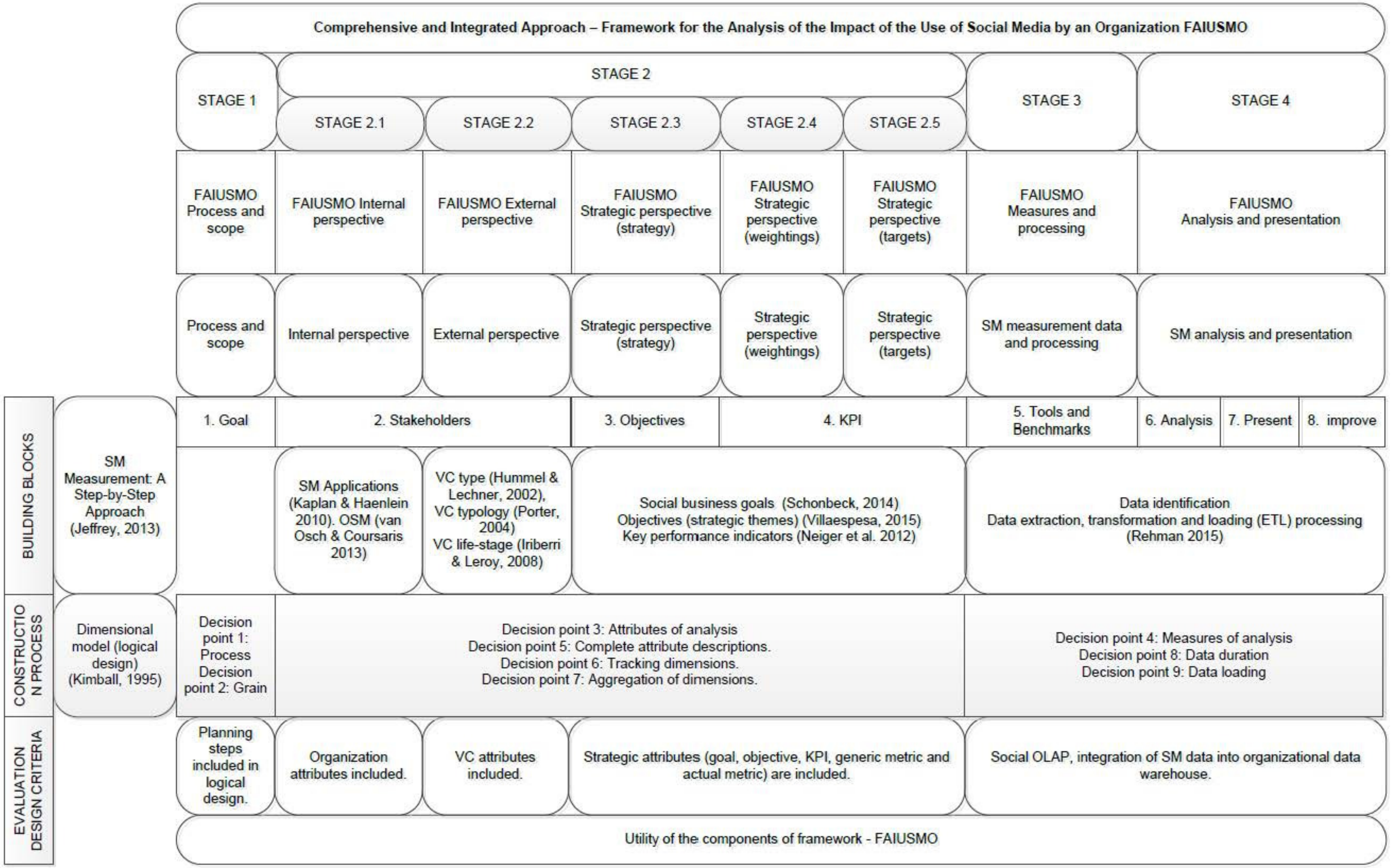
4.8 Stage 4: Analysis and Presentation

For each SM application used, the metric values are considered. These measures may be analyzed in terms of the attributes that describe the metrics. The analysis activities (compare, present and identified) must be supported to meet the data needs of all stakeholders in the use of SM by the organization. The SM metric values may need to be aggregated for the evaluation of the SM strategy and an integrated analysis of the strategic use of SM applications. The dimensions (defined in Stage 2) and the measures (derived from the data in Stage 3) are considered sufficient to analyze the impact of the strategic use of SM by an organization.

4.9 The FAIUSMO Framework

This completes Step 3 of the DSR approach that is followed. The FAIUSMO framework is defined in terms of the four stages presented above. A comprehensive diagram of the framework is presented in Figure 1 below.

The building blocks for FAIUSMO are synthesized from extant literature, and the construction process followed is guided by the nine decision points [25,26].



Comprehensive and Integrated Approach – Framework for the Analysis of the Impact of the Use of Social Media by an Organization FAIUSMO

STAGE 1 | STAGE 2 (STAGE 2.1, STAGE 2.2, STAGE 2.3, STAGE 2.4, STAGE 2.5) | STAGE 3 | STAGE 4

FAIUSMO Process and scope | FAIUSMO Internal perspective | FAIUSMO External perspective | FAIUSMO Strategic perspective (strategy) | FAIUSMO Strategic perspective (weightings) | FAIUSMO Strategic perspective (targets) | FAIUSMO Measures and processing | FAIUSMO Analysis and presentation

Process and scope | Internal perspective | External perspective | Strategic perspective (strategy) | Strategic perspective (weightings) | Strategic perspective (targets) | SM measurement data and processing | SM analysis and presentation

BUILDING BLOCKS

SM Measurement: A Step-by-Step Approach (Jeffrey, 2013)

1. Goal | 2. Stakeholders | 3. Objectives | 4. KPI | 5. Tools and Benchmarks | 6. Analysis | 7. Present | 8. improve

SM Applications (Kaplan & Haenlein 2010). OSM (van Osch & Coursaris 2013)

VC type (Hummel & Lechner, 2002), VC typology (Porter, 2004) VC life-stage (Iriberri & Leroy, 2008)

Social business goals (Schonbeck, 2014) Objectives (strategic themes) (Villaespesa, 2015) Key performance indicators (Neiger et al. 2012)

Data identification Data extraction, transformation and loading (ETL) processing (Rehman 2015)

CONSTRUCTIO N PROCESS

Dimensional model (logical design) (Kimball, 1995)

Decision point 1: Process Decision point 2: Grain

Decision point 3: Attributes of analysis
Decision point 5: Complete attribute descriptions.
Decision point 6: Tracking dimensions.
Decision point 7: Aggregation of dimensions.

Decision point 4: Measures of analysis
Decision point 8: Data duration
Decision point 9: Data loading

EVALUATION DESIGN CRITERIA

Planning steps included in logical design. | Organization attributes included. | VC attributes included. | Strategic attributes (goal, objective, KPI, generic metric and actual metric) are included. | Social OLAP, integration of SM data into organizational data warehouse.

Utility of the components of framework - FAIUSMO

Fig. 1: Stages of FAIUSMO (building blocks and construction process)

This initial design and creation of FAIUSMO requires evaluation of utility to ensure that the identified research problem has been addressed.

5 Initial Evaluation

In Step 4 of the DSR approach followed, an initial evaluation of utility of the research artefact is required. An application domain was identified, and participants from the domain volunteered to participate. The participants completed a questionnaire that required the evaluation of the utility of each of the stages included in the FAIUSMO framework, as well as the overall utility. Recommendations and suggestions will be used to design and create the next iteration of the research artefact.

6 Recommendations for Future Research

In Step 5 of the DSR approach follows, the research results are communicated. The results thus far are presented in this paper. From the study, the following are recommended as future research:

- The evaluation of FAIUSMO in different application domains. This may identify additional user needs, and may lead to the discovery of improvements and enhancements of the framework.
- The development of a more comprehensive (not merely demonstration) prototype with actual SM data. This may increase the clarity of concepts.
- The revision of the initial version of the proposed framework. This may require enhancement and adaptation to include additional SM data, identified environmental and strategic dimensions and strategic measures fact tables, as well as aggregations for comparative and trend analysis.

7 Conclusions

The contribution of this research is to address the research problem of a lack of a comprehensive and integrated approach to the analysis of the impact of the use of SM by an organization. The purpose of this study was to create awareness of the research problem. A comprehensive and integrated framework (FAIUSMO) that includes the internal (organizational), external (virtual community) and strategic (strategy) perspectives in the analysis use of SM by an organization, is designed and created in this research to address the identified research problem. An initial evaluation of utility was conducted that confirmed the utility of the FAIUSMO framework.

Subsequent iterations of the DSR approach will lead to refinement and enhancement of the FAIUSMO framework to ensure that the ongoing analysis of the (increasing) impact of the (evolving) use of SM by organizations.

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Bringing Structure to Interfirm Interaction – The Influence Nested Formal Organizations on Knowledge Transfer Patterns in Interorganizational Networks

Fabian Reck

University of Bamberg,
Kaerntenstraße 7, 96052 Bamberg, Germany
fabian.reck@uni-bamberg.de

Abstract. This study examines how managerial interventions impact structures of knowledge transfer. The work thereby focuses on one form of network management, the implementation of nested organizations. I develop a theoretical framework discerning two forms of nested organizations, namely platforms and projects, and propose distinct effects from these forms' unique features. I test the research hypotheses based network data from the biggest association of small and medium municipal utilities in Germany using exponential random graph models (ERGM). The results largely support the proposed hypotheses and indicate that platforms induce structural mechanisms of social embeddedness whereas projects induce mechanisms of task interdependence.

Key words: Interorganizational Networks, Knowledge Transfer, Network Management, ERGM

1 Introduction

Networks such as strategic alliances, regional clusters or industrial associations bear huge potential to provide firms with opportunities to share costs and risks of research and development, access complementary assets or profit from knowledge spillover. Hence, especially for small and medium firms for which innovation opportunities may exceed their own resource base, interorganizational networks represent an important strategic element in innovation management [17].

One essential mechanism through which interorganizational networks increase member firms' performance is knowledge transfer. Consequentially, in order for interorganizational networks to fulfill their innovation-enhancing effects, high levels of knowledge mobility – i.e., the "ease with which knowledge is shared, acquired, and deployed within the network" [10, p. 660] – are indispensable. As such, establishing, supporting and steering knowledge flows is a key task in network management [10,17]. As such, managerial intervention mechanisms need to be applied to ensure knowledge "transfer to other points in the network where it is needed" [10, p. 660]. One type of such interventions is the implementation of nested formal organizations within the broader scope of interorganizational networks. These nested organizations represent subsets of member firms which are formally constituted by clear membership boundaries and a defined purpose [34]. By establishing such formal structures, network management sets a frame for arranging encounters and as a consequence channeling knowledge flows between member firms [9]. Hence, nested formal organizations are likely to represent a mean to substantially shape the structure of knowledge flows. Thus, they represent a valuable element in the toolbox of interorganizational network management.

However, up to now little to no research examined managerial interventions in interorganizational networks, let alone providing empirical evidence on these interventions' effectiveness [30]. Network management thus represents a clearly underresearched topic that demands for deeper investigation [25]. Accordingly, also the effects of nested formal organizations on knowledge transfer in interorganizational networks remain somewhat unclear. Within this work, I therefore aim to explain how the installment of nested organizations within interorganizational networks shapes the structure of interfirm knowledge transfer. More specifically, I develop and test a theoretical model outlining the effects of two distinct types of nested organizations – platforms [1] and projects [36]. In all, this paper sheds light on the following research question: "How do nested formal organizations impact structural patterns of knowledge transfer and how do the effects of projects and platforms differ?".

2 Nested Organizations and their Effect on Knowledge Network Development

Network management which Provan and Kenis [30] describe as monitoring and controlling member firms' behaviour and aligning them towards an overarching network-level goal by definition aims to impact the "natural" endogenous tendencies in a network's development [33]. Accordingly, initiatives of network management represent exogenous interventionist forces that may impact interorganizational networks directly by establishing new structural logics as well as indirectly by enforcing, altering or diminishing the causal mechanisms endogenous to the network [6]. In doing so, network management steers network development towards new structural patterns [13].

By implementing nested organizations in a network of firms, network management may alter a network's structure substantially. Nested organizations comprise a certain number of formally associated member firms that group together to accomplish a specific goal [34]. In practice, especially two different types of nested organizations are prevalent: platforms and projects [15]. On the one hand, platforms represent communities of firms which collaboratively address a certain field of business or innovation [1]. On the other hand, projects are temporal forms of organization with the goal of producing a clearly specified outcome, e.g. the development of a new technology or product [34]. Both forms of nested organizations differ in two dimensions: temporal scope and functional scope. While platforms combine long-term interaction with a rather broad goal, projects are temporal and deal with a narrowly specified issue.

These types of nested formal organizations are likely to induce framing mechanisms shaping knowledge network structures. Framing describes the "behaviors used to arrange and integrate a network structure by facilitating agreement on participants' roles, operating rules, and network values." [23, p. 603]. By establishing nested formal structures, network management sets a task frame respectively a reference point to which network members can align their efforts [9]. With the creation of an organization with particular goals, interdependencies are created leading to a stimulation of knowledge transfer. Hence, network management facilitates the creation of internal structure in the knowledge network as well as the positioning of network members within this structure [27]. I argue that based on the features of the particular task frame that is created by the implementation of platforms and projects, the corresponding framing mechanisms will differ. As a consequence, platforms and projects will stimulate different structural tendencies in the knowledge network which I will outline in the following.

2.1 Platforms

A platform describes a form of nested formal organizations on which a number of firms comes together to make sense of a new field of technology respectively to create new visions and blueprints on how to set up commercial systems that address future trends in the industry [26]. Hence, their scope is rather targeting long-term developments in the particular market [1]. Firms that engage in innovation platforms are thus mostly focused on staying in touch with general technological developments and exchanging experiences with their peers in the industry. Still, such a platform creates a community of firms that are willing to learn about new knowledge in the market and enlarge their own knowledge base [22]. The firms engaging in it thus signal openness to external knowledge and interorganizational knowledge transfer in general. Hence, firms participating in the platform will probably be more likely to perceive other platform participants as accessible and willing to share their expertise.

In general, platforms possess a rather large temporal and functional scope. Concerning the former, platforms do not aim to address immediate problems for which a solution might be developed in the near future, but provide firms with a forum to discuss macrotrends within the particular industry [1]. Hence, rather than providing a closed time frame with clear points of beginning and ending, platforms enforce a rather cyclical time frame in which loops of learning and continuous development dominate [2]. Accordingly, the task frame of a platform includes a rather broad and open temporal scope, without deadlines or time restrictions. Concerning the latter, platforms also possess a rather broad and open functional scope. Their goal statement normally is vague so that participating firms jointly may shape the agenda to issues of interest and topicality [23]. Rather than projecting a clear vision of the future, these platforms provide an opportunity for firms to exchange experiences with other companies that face similar long-term challenges. Hence, platforms set the frame for firms jointly honing their own base of expertise and capabilities by the help of their peers [28].

Due to these broad scopes of time and function, I expect structural logics that depict social coordination mechanisms to be more prevalent than structural logics that might be induced by task characteristics. As the task frame is broad and ambiguous, there is no clear immediate goal to be achieved. In turn however, firms participating in a platform commit broadly to an overarching longterm vision [5].

This special context should account for the increased occurrence of a number of structural logics. First, I propose that firms will be more likely to accept indirect reciprocity within the platform. The long-term horizon and commitment to a broad vision could diminish potential source firms' need to be incentivized by counteroffer of relevant and new information as they may rely on generalized exchange in the platform. Second, firms might be less likely to acquire knowledge from other firms in the platform based on tendencies of homophily. Whereas in networks, firms tend to generally find similar others to be more accessible and their knowledge to be more valuable [24], the context of a platform is likely to reduce these tendencies. When two firms similar to each other commit to a nested organization with a broad overarching vision, they indicate similar preferences and worldviews thus altering the perception of accessibility. With the lack of a clear immediate goal, firms moreover possess the freedom to explore diverse areas of knowledge leading to a diminished preference towards similar firms [7]. Third and finally, transitive triads will be more likely to occur within platforms. All three logics behind the existence of transitive triads, namely clustering, bypassing and countering may be stimulated by a platform [21,19]. Clustering will be enhanced because of the common long-term vision of platforms members, bypassing might be more likely because of the social proximity created by the platform facilitating the formation of forming ties to third actors, and countering will be induced by short term self-interest. As a consequence, I propose the following hypotheses:

Hypothesis 1a: Firms in a platform are less likely to form reciprocal knowledge ties between each other and more likely to form cyclic triads.

Hypothesis 1b: Firms in a platform are less likely to acquire knowledge from similar others in the platform as well as firms located in close geographic distance.

Hypothesis 1c: Firms in a platform are more likely to form transitive triads.

2.2 Projects

Projects, the second form of formal nested organizations in interorganizational networks aim at exploring technology fields, identifying market opportunities or developing new products, processes or business models. Project members thereby agree to fulfill a specified task in a certain amount of time [12]. Expecting an impact of projects on the likelihood of a knowledge transfer tie existing between two member firms is reasonable. First, firms engaging in the same project will be more both visible to each other. Moreover, due to a clear collective goal, high levels of accessibility among project members as well as high motivation to share knowledge resources are likely [2]. Second, knowledge exchange among project members will be perceived as especially valuable and profitable due to task interdependencies and coordination needs [34].

In comparison to platforms, projects are nested organizations with clear temporal and functional boundaries. They group together firms in aiming to accomplish a unique, novel and complex task [29]. Though the goal of projects is most often clearly specified, the operational rules of how to achieve this goal are normally not [34]. Thereby, instead of pursuing a long-term vision, projects have immediate task and performance demands [12]. In sum, projects usually demand highly focused and fast knowledge work with specified goals and finite time horizon but ambiguity in terms of how to reach them [34]. In other words, interorganizational projects are the organizational equivalent of a one-night stand [12].

I argue that these features of projects will lead to different effects on knowledge transfer network structures than it was the case for platforms. Previous research found that the narrow temporal and functional scopes of projects lead member firms to predominantly focus on the task at hand. Due to performance and time pressures, the social system of project members is likely to immediately jump into a mode of action without first letting firms develop relationships or a common knowledge base [18,20]. This radical task focus leads to the emergence of distinct structural logics in the according knowledge exchange network [36]. First, research on social psychology has shown that in task-oriented contexts, centralized network structures tend to develop [3,16]. More recent studies support these notions in outlining the importance of lead organizations in providing for fast and easy communication linkages across interfirm networks [26]. Hence, we predict a tendency of open triadic structures occurring in project networks [12]. Second, via task focus, interdependencies in firms' activities emerge. It is likely that in a project network, knowledge network structures will reflect such interdependencies in order to minimize coordination failures [11]. As a consequence,firms might tend to not experiment with their partners and exchange knowledge more likely with similar others. Finally, due to the more transactional character of projects in comparison to platforms, firms might be less likely to rely on generalized exchange and thus to accept indirect reciprocity.

In sum, I propose the following hypotheses:

Hypothesis 2a: Firms in the same project are more likely to form reciprocal knowledge ties between each other and less likely to form cyclic triads.

Hypothesis 2b: Firms in the same project are more likely to acquire knowledge from similar others in the platform.

Hypothesis 2c: Firms in the same project are more likely to form open triads.

3 Nested Organizations and their Effect on Knowledge Network Development

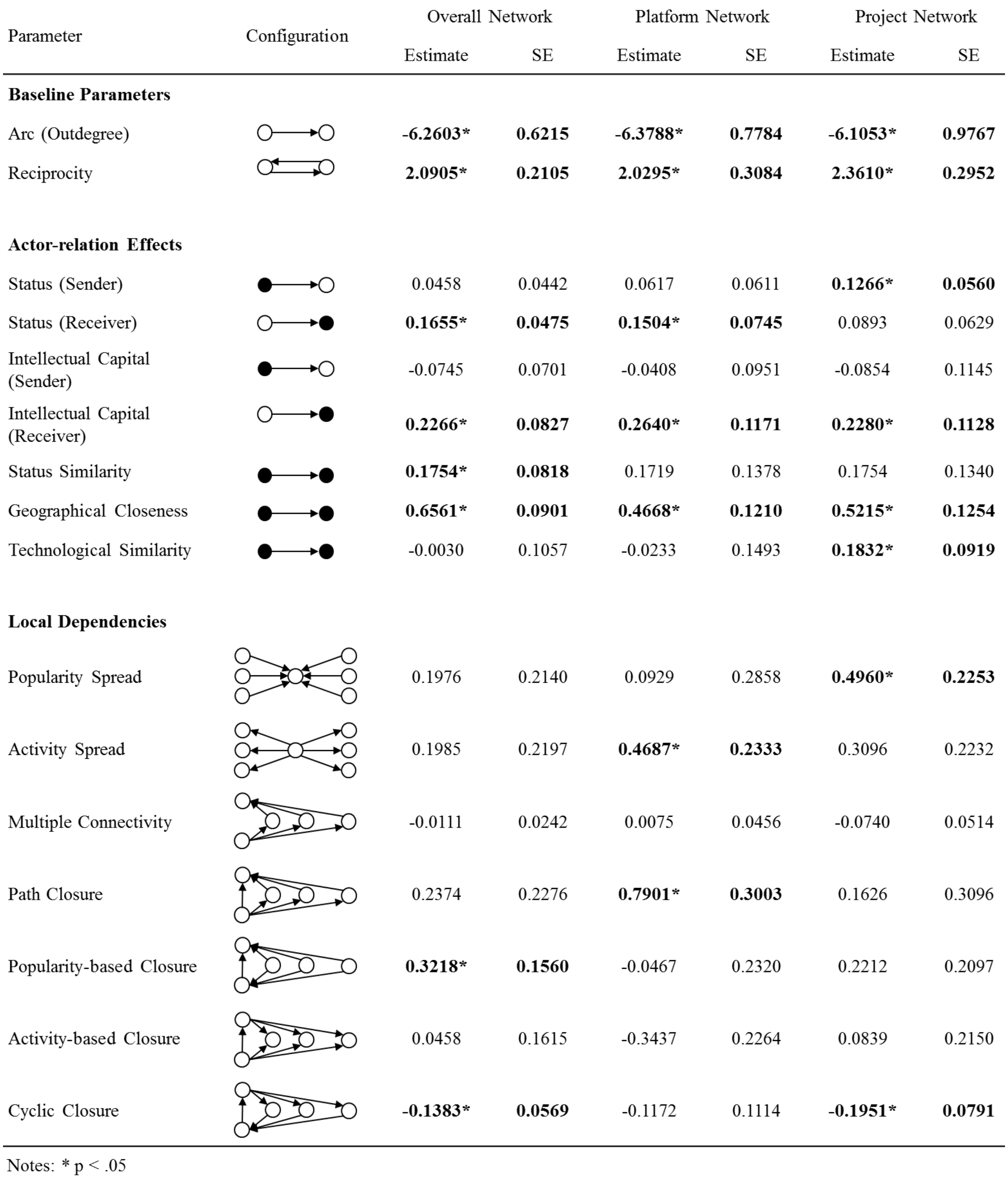
In order to test the research hypotheses proposed in this paper, I collected network data from the biggest association of municipal utilities in Germany. The 84 members of this association are local energy providers from all over the country. The data collection procedure was done via cross-sectional survey. I approached at least two key informants in all the association's member firms. Managers responsible for innovation management within their respective firms as well as C-level executives were contacted. In total, I was able to obtain contact information from 314 potential sources within the 84 member organizations. These were contacted via e-mail and telephone calls. In all, I received 147 completed questionnaires. The responses came from 74 of the 84 member organizations resulting in a response rate of 88.1 percent.

In the questionnaire I asked respondents to indicate 'flow relations' between the organizations [4]. To this end, sociometric techniques were applied [35]. These comprised a rooster-based approach to obtain data on a focal firm's knowledge sources. In addition to the surveys, the association's central management unit provided me with access to extensive archival data. I thereby obtained annual reports of all member firms, the association's quarterly magazine published to the member firms, internal newsletters, and project reports, all adding up to over 1,500 pages of text material. Based on this archival data, I was able to reconstruct the membership of firms in platforms and projects within the association's context. Concerning platforms, the central management unit installed two different long-term interest groups. The first one is dealing with the issues of digitalization and digital business models in the energy sector. In this platform 39 of the 84 association members participate. The second one addresses the future of energy production. Here, 11 member firms participate. Concerning projects, I identified 18 projects dealing with concrete tasks such as developing a rollout concept for smart meter solutions or creating an app for end users to monitor their homes energy consumption. This final list includes only projects which fell into the three year before the survey and had at least three firms participating.

In order to test my theoretical arguments with an appropriate statistical model, I consider each individual tie between two firms in the observed network as a random variable. Hence, I link my data structure to the p-star (p*) class of Exponential Random Graphs Models (ERGM) [31]. I follow usual approaches in the specification of ERGM in that I include both actor-relation effects and local dependencies in the estimation model. Concerning actor-relation effects, I used the status (measured by the firm's size [14]) and intellectual capital (measured by eight survey items based on [32] of firms for sender and receiver effects as well as organizational similarity (measured by size difference), geographical closeness (assigned if both firms are located in the same region in northern, central or southern Germany) and technology base similarity (measured by Pearson correlations between both firms' energy production mix (consisting of coal, nuclear energy, gas and renewables)) for homophily effects. As local dependencies I included popularity spread (A-in-S), activity spread (A-out-S), multiple connectivity (A2P-T), path closure (AT-T), popularity closure (AT-D), activity closure (AT-U) and cyclic closure (AT-C). For parameter estimation, Markov Chain Monte Carlo Maximum Likelihood simulations techniques were used. The model was estimated for the overall network, the platform network and the project network.

4 Results and Conclusion

The results confirm the impact of formal nested organizations on knowledge transfer structures in interorganizational networks. In general interorganizational knowledge networks seem to have a tendency towards reciprocity, status and expertise-based selection, homophily in terms of organizational similarity and geographical closeness as well as popularity-based closure ('Overall Network' in Fig. 1). In the platform network, reciprocity, status-based selection, expertise-based selection and geographic closeness effects are also existent, though the last is clearly lower than in the overall network. The effect of status similarity, the positive tendency towards popularity-based closure and the negative tendency for cyclic closure disappear whereas path closure and activity spread become significant ('Platform Net-



Parameter	Configuration	Overall Network		Platform Network		Project Network	
		Estimate	SE	Estimate	SE	Estimate	SE
Baseline Parameters							
Arc (Outdegree)	○→○	**-6.2603***	**0.6215**	**-6.3788***	**0.7784**	**-6.1053***	**0.9767**
Reciprocity	○⇄○	**2.0905***	**0.2105**	**2.0295***	**0.3084**	**2.3610***	**0.2952**
Actor-relation Effects							
Status (Sender)	●→○	0.0458	0.0442	0.0617	0.0611	**0.1266***	**0.0560**
Status (Receiver)	○→●	**0.1655***	**0.0475**	**0.1504***	**0.0745**	0.0893	0.0629
Intellectual Capital (Sender)	●→○	-0.0745	0.0701	-0.0408	0.0951	-0.0854	0.1145
Intellectual Capital (Receiver)	○→●	**0.2266***	**0.0827**	**0.2640***	**0.1171**	**0.2280***	**0.1128**
Status Similarity	●→●	**0.1754***	**0.0818**	0.1719	0.1378	0.1754	0.1340
Geographical Closeness	●→●	**0.6561***	**0.0901**	**0.4668***	**0.1210**	**0.5215***	**0.1254**
Technological Similarity	●→●	-0.0030	0.1057	-0.0233	0.1493	**0.1832***	**0.0919**
Local Dependencies							
Popularity Spread		0.1976	0.2140	0.0929	0.2858	**0.4960***	**0.2253**
Activity Spread		0.1985	0.2197	**0.4687***	**0.2333**	0.3096	0.2232
Multiple Connectivity		-0.0111	0.0242	0.0075	0.0456	-0.0740	0.0514
Path Closure		0.2374	0.2276	**0.7901***	**0.3003**	0.1626	0.3096
Popularity-based Closure		**0.3218***	**0.1560**	-0.0467	0.2320	0.2212	0.2097
Activity-based Closure		0.0458	0.1615	-0.3437	0.2264	0.0839	0.2150
Cyclic Closure		**-0.1383***	**0.0569**	-0.1172	0.1114	**-0.1951***	**0.0791**

Notes: * p < .05

Fig. 1. ERG model estimates on the presence of knowledge network ties

work' in Fig. 1). In the project network, reciprocity, expertise-based selection and geographical closeness effects are similar to the overall network. Cyclic closure becomes even less likely, status-based selection, status similarity effects and tendencies towards popularity-based closure disappear. In turn, popularity spread, sender effects of status and technology similarity effects emerge ('Project Network' in Fig. 1).

Partial support for the proposed hypotheses and revealing several additional structural logics is displayed. H1a proposed that in platforms, indirect reciprocity is more likely. In the platform network, the estimation score for direct reciprocity is only slightly lower than in the overall network, the score for cyclic closure is still negative but insignificant in contrast to the overall network. Hence, adequate support for this hypothesis can be stated. H1b suggests lowered similarity/proximity effects. These are clearly evident for size similarity and geographic proximity, but not for technological similarity. Hence, there is partial support for H1b. As proposed in H1c, transitivity in the form of path closure occurred at a significantly higher frequency whereas estimation scores for popularity - and activity-based closure are not significant. Hence, bypassing is a prevalent network dynamic in platforms. Concerning projects, H2a is confirmed in that the probability of indirect reciprocity is diminished in a task-oriented context whereas estimation scores for reciprocity are clearly higher than in the overall network. H2b which proposes that firms participating in the same project are more likely to acquire knowledge from similar others is partially confirmed in terms of firms in a project being more likely to acquire knowledge from other firms with a similar technological knowledge base. In contrast, the tendency towards geographic proximity is reduced also in the project network. Finally, H2c is partially confirmed. On the one hand, popularity spread is significantly more likely in the context of projects. On the other hand, there is no significant tendency towards activity spread or multiple connectivity.

With these results, the paper makes some important contributions to different streams of research. First, this work contributes to previous literature knowledge transfer networks. In this context, works such as [7] outlined the existence of a range of theories and causal mechanisms explaining in which structural patterns knowledge transfer among firms emerges. Furthermore, [19] provided evidence for the notion that features of the overall context in which firms operate determine the specific structural logics in place. The results of this paper further expands these pioneering insights by supporting the notion that a formal context connecting firms through a certain type of task frame has an impact on the particular emerging structural logics in the network. Second, the paper adds to research on the management of firm networks. I am able to provide empirical evidence for the actual impact of a concrete type of management measure, namely the initiation of nested organizations. Thereby, both platforms and projects serve to foster knowledge transfer in interorganizational networks. Besides these direct effects, both platforms and project induce indirect effects on knowledge network structure. More specifically, the broad functional and temporal scope of platforms induces a long term vision task frame fostering a social MBB structure geared towards interfirm learning. In contrast, the goal-oriented task frame of projects rather stimulates structural mechanisms that allow for communication efficiency. In sum, both forms of nested organizations thus complement each other as they foster the emergence of fairly different network patterns and characteristics. Future research should further specify these differences and validate the findings across interorganizational networks in different industrial and regional settings.

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Preferential Attachment in Social Media

The Case of Nico Nico Douga

Johannes Putzke[1] and Hideaki Takeda[2]

[1] University of Bamberg,
An der Weberei 5, 96047 Bamberg, Germany
[2] National Institute of Informatics (NII)
2-1-2, Hitotsubashi, Chiyoda-ku, Tokyo, 101-8430, Japan

Abstract. In the examination of evolving complex networks, the analysis of preferential attachment is a core research problem. However, the results of studies that examine whether preferential attachment operates in social media networks are conflicting. On the one hand, preferential attachment generally has been found to be a stable predictor of network evolution. On the other hand, IS researchers question the applicability of the preferential attachment hypothesis to social media networks. This study shows that preferential attachment also operates on Nico Nico Douga, a Japanese video sharing service similar to Youtube with more than 20 million registered users. However, this study also reveals that the attachment kernel differs substantially from the classically assumed log-linear form, when estimating the kernel with nonparametric maximum likelihood estimation (PAFit).

Key words: PAFit, preferential attachment, social media, social network analysis

1 Introduction

Social media radically have changed the way in which we create and consume content. During content creation and consumption we are embedded in networks of peers that leave their digital traces on the social media platforms that we use. Consequently, a number of recent papers applies methods from network science for the examination of social media, e.g. [1]. In this context, authors particularly tried to answer the research question what might be a good model to describe the evolution of a network. As a general network formation model, preferential attachment (PA) [2] has been found to be a stable predictor for network evolution. PA means that newly arriving nodes in a network connect with a higher probability to those nodes in the network that already have a large number of connections. However, since recent studies by information systems (IS) scholars [1][3] could not find evidence for PA in social media networks, these scholars question the applicability of the PA hypothesis to networks in social media. On the other hand, a recent study about friendship networks on the social media website *Flickr* [4] provides evidence for PA in social media networks, but not in the classically assumed log-linear form of the attachment kernel. Therefore, in this paper we try to shed further light on the question whether PA operates in social media networks. Particularly, we intend to examine whether [4]'s findings can be replicated on a data set from the social media website *Nico Nico Douga (NND)*. *NND* is a Japanese video sharing platform similar to *Youtube*. As of 2014, it has more than 20 million registered users [5]. However, *NND* has a unique feature that differentiates it from *Youtube*. In *NND*, users can add time-stamped comments to the videos. These comments are then overlaid to the original video when playing back the video. This commenting feature made *NND* famous for a new form of content co-creation. In this form of content co-creation, song writers and (3D) illustrates collaborate and create music videos. In doing so, they comment on their videos and (re-) use some content (e.g. music or graphics) from each other. When creating content and using the content of other videos, the creators frequently attribute credits to the videos which they used. In such a way a network of co-creation emerges. We analyze the PA hypothesis for this evolving co-creation network.

The remainder of this paper will be structured as follows. The next section, Background, will be structured into two sub-sections. In the first sub-section, we review the related literature about the PA hypothesis. In the second sub-section, we present [4]'s nonparametric maximum likelihood (ML)-based preferential attachment kernel estimation method (*PAFit*) as well as its application to a *Flickr* dataset. In the next section, Replication I, we describe the *NND* data set used for replicating the results of [4]'s study, the procedures used in the replication, as well as the comparative results of the application of *PAFit* to our data set (see also [6]). Since we could replicate [4]'s results with the *NND* data set, we performed another replication with a publicly available social media data from the Website *Digg*.[3] This replication will be presented in the section “Replication II”. Finally, the paper closes with a short Discussion section.

2 Background

2.1 The Preferential Attachment Hypothesis

The “preferential attachment hypothesis” has been examined in the literature under various names such as the “Yule distribution/process” [7], the “Mathew effect” [8], or “cumulative advantage” [9].[4] It states that subjects with an attribute X will acquire new units of this attribute X according to how many units of this attribute they already have. In network science, “preferential attachment is generally understood as a mechanism where newly arriving nodes have a tendency to connect with already-well connected nodes” [12]. Most researchers attribute the name “preferential attachment hypothesis” to [2] who published a highly influential paper in *Science* about the subject.[5] Considering the vast amount of papers on PA, it would not be meaningful to provide a complete (interdisciplinary) literature review on this subject at this place.[6] Rather, an appropriate literature review focusses on the groundbreaking works about PA (e.g., [13,14]), as well as on the works of IS researchers who conducted network studies and pointed out to the (missing) PA process in the context of social media. Concerning the groundbreaking works about PA, the reader is referred to the literature reviews in [15] and [16], as well as the corresponding sections in the work by [4]. Concerning the works by IS researchers, there were some interesting findings concerning PA in social media. For example, [3] could not find evidence for the PA hypothesis examining data from 28 online communities. Also [1] do not find evidence for PA examining enterprise social media networks such as an online social networking platform. On

[3] `http://digg.com/`, accessed on 02/28/2017.

[4] For the history of the PA hypothesis see also [10] and [11]. The interested reader is also referred to a lecture by Aaron Clauset (available at `http://tuvalu.santafe.edu/~aaronc/courses/5352/fall2013/csci5352_2013_L13.pdf`, accessed on 04/12/2017) in which Clauset explains the PA hypothesis and its history in detail.

[5] The paper has been cited more than 25,000 times as of a google scholar search on 04/17/2017.

[6] For example, a google scholar search for the term “preferential attachment” provided more than 24,000 search results as on 04/17/2017.

the other hand, PA is supposed to be a robust predictor of tie formation [1], and other IS researchers state that, for example, fundraising over social media is a PA process [17]. In the light of these contradicting results, it is evident that we need a clearer understanding about the "conditions under which preferential attachment operates (or not) in different network settings". Therefore, [1] call exactly for this type of research. In order to answer [1]'s call, a robust method for estimating PA in different network settings is needed. Such a method has been recently proposed by [4]. However, this method has never been applied in IS research. Therefore, in the following sub-section we highlight [4]'s method, as well as its application by [4] to a *Flickr* social network dataset [18].

2.2 Nonparametric Maximum Likelihood-Based Preferential Attachment Kernel Estimation and its Application to Flickr

Following [4], we denote an observable seed network at a time-step $t_0 = 0$ with G_0. This network grows from each period $t = 0, 1, ..., T$ with $n(t)$ nodes and $m(t)$ edges. At discrete points in time $t = 0, 1, ..., T$ we can observe these static network configurations G_t. In each time-step t, the probability that an existing node v with in-degree k acquires a new edge is given by

$$Pr(v \text{ acquires a new edge}) \propto A_k. \tag{1}$$

A_k is the value of the attachment kernel at degree k. A number of authors proposed estimation methods for the attachment kernel. A good overview of these methods can be found in Table 1 in [4].[7] However, most of these methods assume a log-linear form $A_k = k^\alpha$ of the attachment kernel. Notable exceptions are the works by [13] and [14] who base their estimation on histograms, and are thus nonparametric. However, also these two methods have their shortcomings. In contrast, [4] derive the ML estimator as[8]

$$A_k = \frac{\sum_{t=1}^{T} m_k(t)}{\sum_{t=1}^{T} \frac{m(t) n_k(t)}{\sum_{j=0}^{K} n_j(t) A_j}} \tag{2}$$

for $k = 1, ..., K$. The solution to this equation can be found using the Minorize-Maximization (MM) algorithm (e.g., [19]) that is beyond the scope of this paper.

[7] doi:10.1371/journal.pone.0137796.t001, accessed on 3/31/2017.

[8] For the details of derivations and proofs of the following paragraph see [4].

The interested reader is referred to the aforementioned literature. [4] apply their method to a publicly available *Flickr* social network dataset [18].[9] This dataset consists of 2,302,925 users and their 33,140,017 directed friendship relationships that grow over a period of 133 days. After the period $t = 0$, 815,867 new nodes and 16,105,211 new edges arrive in the data set. As convergence criterion for the MM algorithm, [4] use a value of $\epsilon = 10^{-7}$. Figure 1 [4] illustrates the results of the estimation of the attachment kernel. The plot is on a log-log scale, and a solid line illustrates $A_k = k$ as a visual guide. Although the results clearly indicate PA, they also indicate a clear signal of deviation from the log-linear model $A_k = k^{\alpha}$ [4].

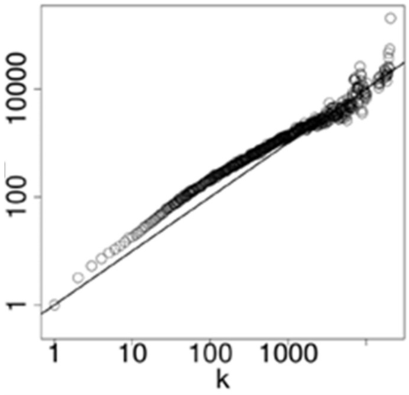

Fig. 1: Estimation of the attachment kernel in the *Flickr* social network dataset (doi:10.1371/journal.pone.0137796.g003)

3 Replication I

3.1 Data Set: Nico Nico Douga

We replicated [4]'s study using a data set of NND that was provided by [5], and that is partially available on figshare[10]. The data set contains the metadata of all videos uploaded on *NND* between January 2007 and December 2012 (i.e. the author, keywords, author's comment, number of views and the timestamp of the upload). In

[9] Available at `http://konect.uni-koblenz.de/networks/flickr-growth`, accessed 02/28/2017.

[10] Available at `https://dx.doi.org/10.6084/m9.figshare.2055597`, accessed 02/28/2017.

total, we extracted 2,622,495 VideoIDs from the data set that had at least one keyword associated to them, together with their timestamps. Out of these 2,6 million videos, 1,427,715 videos could be assigned to an author ID (see [5]). Our following analyses are based on these 1.4 million videos.

3.2 Methods

For the estimation of the *PAFit* model, we focused on the author co-creation network, i.e. we assumed a directed link from author *A* to author *B*, if an author *A* cited a video that had been created by author *B*. In this way, we obtained 4,773,163 directed edges. After excluding self-citations, 3,014,423 edges remained in the data set. When estimating the model in *R v. 3.2.2* with the package *PAFit v. 0.9.3* on the whole data set, we obtained an error due to memory problems. Therefore, we decided to split the data set into two (random) parts. The first part contains 2,016,458 random edges, the second part contains the remaining 997,965 edges. The size of the first part is the maximum number of edges for which the estimation worked on our system. The first part of the data set will be used for model estimation, and the second part of the data set will be used for cross-validation. The final data set consists of 124,996 authors and their relationships that grow over a period of 1,449 days. In the first part of the data set, after the period $t = 0$ 115,134 new nodes, and 1,635,827 new edges arrived. The node with the highest number of edges has a degree centrality of 38,234. In the second part of the data set, after period $t = 0$ 115,134 new nodes, and 808,740 new edges arrive. The node with the highest number of edges has a degree centrality of 19,037. Like [4] we use a value of $\epsilon = 10^{-7}$ as convergence criterion for the MM algorithm. Furthermore, we use logarithmic binning (with 200 bins) in order to stabilize the estimation of the attachment kernel.

3.3 Results

Figure 2 (a/b) illustrates the results of the estimation of the attachment kernel. Again, the plots are on a log-log scale, and solid lines illustrate $A_k = k$.

The estimated attachment exponents of the log-linear model $A_k = k^{\alpha}$ are (1) $\alpha = 0.8819457$ for the first part of the data set, and (2) $\alpha = 0.8841727$ for the second part of the data set. In summary, these results are very stable, and provide strong empirical evidence for preferential attachment in the *Nico Nico Douga* co-

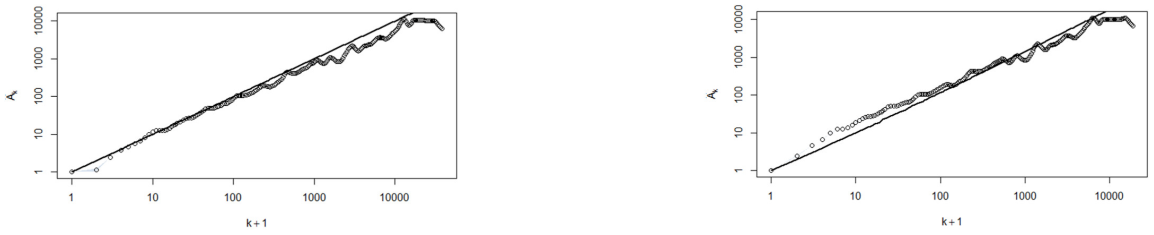

Fig. 2: **(a/b).**Estimation of the attachment kernel in the *NND* data set (first part, second part)

creation network. Nevertheless, like Pham et al. [4] we observe a deviance from the log-linear functional form of the attachment kernel, particularly in the high degree region.

4 Replication II

Since we could replicate [4]'s results with the *NND* data set, we performed another replication with a publicly available social media data. This data set comprises user interactions on the social media website *Digg* between 10/28/2008 and 11/12/2008.[11] In the data set, each node reflects a user in the network, and an edge between user A and user B reflects that user A replied to user B. The data set consists of 30,398 nodes, and 87,627 edges between them. Concerning the evolution of the network, there was only one edge with a timestamp 10/28/2008 in the dataset. Therefore, we assumed that the observable seed network at a time-step $t_0 = 0$ comprises all edges with a time-stamp ≤ 10/29/2008. During the evolution of the network, 30,382 new nodes and 59,655 new edges arrived. Since the maximum degree of the nodes was rather low (243), we did not apply logarithmic binning.

Figure 3 displays the estimation results. The estimated attachment exponent has a value of $\alpha = 0.3958123$. Again, the results indicate PA, but also not in log-linear form. The low value of the attachment exponent α is an interesting finding, particularly since the social news website *Digg* is used for professional as well as for private use.

[11] Available at `http://konect.uni-koblenz.de/networks/munmun_digg_reply`, accessed 02/28/2017.

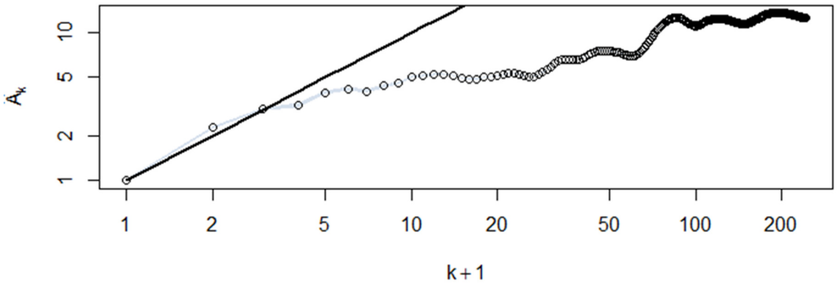

Fig. 3: Estimation of the attachment kernel in the *Digg* data set

5 Discussion

In this paper, we showed that the evolution of the co-creation network on *NND* is driven by PA. However, nonparametric ML-based estimation of the PA kernel revealed that the process does not follow the classically assumed log-linear form. Hence, this study makes at least the following contributions to the IS literature: First, we introduced a new method for attachment kernel estimation, *PAFit* [4], from physics to the IS literature. This is important, as our results show that the predominant praxis to estimate the attachment kernel with parametric methods falls short. Second, IS researchers argue that PA might be a structural feature that operates in a variety of physical and technical networks [20], but question the applicability of the PA hypothesis for social networks in social media (e.g. [1,3]). This study showed that PA also operates in social media networks such as the *NND* co-creation network. This is an interesting finding as it substantiates [1]'s call for research that we should figure out the conditions under which PA operates in social media. The proposed method, *PAFit* can help us to fulfil this aim. Using *PAFit*, we also made an interesting second finding. Although we could observe some deviance from the log-linear model in the *NND* data set, the deviance was even more pronounced in the *Digg* data set (see Figure 3). Despite the large deviance, however, there was a strong evidence for PA. Nevertheless, we suggest that future research should examine the functional forms of the attachment kernel for different social media data sets. In an exploratory study, future research should particularly figure out the conditions when the PA hypothesis holds in social media. For example, based on the results of the *NND* study and the *Flickr* study [4] one might speculate that the PA hypothesis holds in social media settings that focus on the creation of artistic goods (such as photos and videos), which people mainly use during their free time. On the other hand, based on the analyses of technology related discussion forums [3] and enterprise social media platforms [1] one might speculate that the PA hypothesis does not hold in social media settings that focus on increasing productivity (in enterprises). However, these conjectures still have to be substantiated by examining more social media data sets. We hope that this study will lie the basis for more work into this direction.

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Modelling Group Dynamics in Epidemic Opinion Propagation

Dieter Fiems

Ghent University, Department of Telecommunications and Information Processing
St-Pietersnieuwstraat 41, 9000 Gent, Belgium
http://telin.ugent.be

Abstract. Motivated by weblogs and discussion forums, epidemic opinion propagation on affiliation networks is investigated. An affiliation network is a bi-partite graph describing the connections between individuals and their affiliations. In contrast to epidemics on complex networks, the epidemic spreading process in the current setting is not the consequence of pairwise interactions among individuals but of a group dynamic. We derive a Markov model for the epidemic process and its fluid limit obtained by sending the population size to infinity while keeping the number of affiliations constant. This results in a set of modified SIR-like ordinary differential equations. Different types of group dynamics are studied numerically and the accuracy of the fluid limit is verified by simulation.

1 Introduction

With the emergence of social network services (SNS), the speed and outreach of information diffusion has reached unprecedented heights. In just over a decade, SNS's have attracted millions of users, many of them using these services on a daily basis [1]. A typical SNS allows users to create a profile and make connections to other users in the social network. A profile is a unique page where one can "type oneself into being" [2] and can be public or semi-public. SNS users can send private messages to their connections, inform their connections when their profile is updated, or pass on messages received from their connections, etc. Such functionality greatly facilitates quick dissemination of information.

This paper studies epidemic-like opinion propagation on social networks. While initial epidemiological models assumed well-mixed populations, it has been increasingly recognised that topological properties of the network of members of the population and their connections greatly affect the epidemic spreading process [3]. The interplay between topology and dynamics is one of the most pressing challenges in the development of network science [4] and runs in parallel with the increased research effort on complex networks [5]. Indeed, the large amount of scientific effort devoted to this subject [6, 7] has made it evident that dynamical processes (like epidemics) taking place on top of a complex network can be strongly influenced by the topological features of the network, especially in the case of scale-free networks, in which the degree distribution (the degree of a node is the number of nodes it is connected to) follows a power law [8].

In contrast to previous studies on epidemic processes on complex networks, we adopt the affiliation network (AN) paradigm [9], which was studied for SNSs in [10] and [11]. An AN describes the connections between individuals and their affiliations. An affiliation can be a shared interest or personal affinity, a common collective activity, etc. [12]. The AN is a bi-partite graph of individuals and affiliations. Such a graph consists of affiliations and individuals and only interconnections between individuals and affiliations are allowed. As opposed to standard complex networks, ANs allow for a considerably richer and a more intricate interaction between individuals. Whereas interaction between individuals is explicitly pairwise in complex networks, multiple individuals can interact jointly by sharing an affiliation in an AN.

The effects of such non-pairwise interaction is the subject of the present study. Borrowing from epidemiological terminology, it is assumed that the state of any individual is either susceptible (S), infected (I) or recovered (R). Such epidemiological models are usually referred to as SIR-type models. The SIR model assumes that an individual's state goes from susceptible to infected to recovered, an infection being the consequence from contact with infected individuals. This process can be directly reformulated in terms of the propagation of opinions on a particular topic: a susceptible individual has yet to form an opinion on a certain topic, whereas infected or opinionated individuals do have such an opinion and spread their opinion to other individuals. Finally, individuals loose their interest in the topic after some time and stop spreading their opinion, which corresponds to recovery in the epidemiological context [13]. While we retain the classical assumption of Markovian SIR models that individuals recover after an exponentially distributed amount of time, we modify the infection process as to reflect “group dynamics” associated with affiliations. We adopt the term “group dynamics” as introduced by Lewin [14] as the spreading process is not simply the result of the sum of individual interactions [15]. In particular, we assume that affiliations infect their members with a rate which is a generic function of the states of the affiliation’s members. That is, if an affiliation has x_S susceptible and x_I infected members, the affiliation’s susceptible members get infected with rate $\alpha(x_S, x_I)$, α being a generic function. Obviously, an individual can have multiple affiliations, and it is assumed that infection by the different affiliations are independent processes, such that the infection rate of an individual is the sum of the infection rates of this individual’s affiliations.

The remainder of this paper is organised as follows. The epidemic Markov model and the notational conventions of the paper are introduced in the next section. The fluid limit of the Markov model, which is obtained by increasing the population size while keeping the number of affiliations constant, is discussed in section 3 and numerically investigated in section 4. Finally, conclusions are drawn in section 5.

2 Markovian Epidemic Model

We consider epidemic opinion propagation on ANs. An AN is a bipartite graph, whose vertices are divided into affiliations and individuals and whose edges connect affiliations with individuals.

Let $\mathcal{A}$ be the set of all affiliations and let $\widehat{\mathcal{G}} = \mathcal{P}(\mathcal{A})$ be the power set of $\mathcal{A}$, that is $\widehat{\mathcal{G}}$ is the set of all subsets of $\mathcal{A}$. Further, let $\mathcal{X}$ be the set of individuals. Each individual can have multiple affiliations, for an individual $i \in \mathcal{X}$, let $g(i) : \mathcal{X} \to \widehat{\mathcal{G}}$ be the set of this individual’s affiliations. The mapping g induces a partition of $\mathcal{X}$, all individuals having the same affiliations in each subset of the partition. For $G \in \widehat{\mathcal{G}}$, let $\mathcal{X}_G = \{x \in \mathcal{X}, g(x) = G\}$ be the corresponding subset of $\mathcal{X}$ and let $N_G = |\mathcal{X}_G|$ be the number of individuals in this subset. For any set X, $|X|$ denotes its cardinality. We may exclude subsets G with $N_G = 0$ from further analysis. Therefore, let $\mathcal{G} = \{G \in \widehat{\mathcal{G}} : N_G > 0\}$.

With a slight abuse of notation, for any affiliation $a \in \mathcal{A}$, let $\mathcal{X}_a$ be the set of individuals having affiliation a, $\mathcal{X}_a = \{x \in \mathcal{X} : a \in g(x)\}$, and let $N_a = |\mathcal{X}_a|$ be the number of individuals in this set. Note that for $a_1 \neq a_2$ the intersection of $\mathcal{X}_{a_1}$ and $\mathcal{X}_{a_2}$ may be non-empty as individuals may have affiliations a_1 and a_2.

We adopt a Markovian SIR-type epidemic process. At any time, an individual is in one out of three possible states: susceptible, infected or recovered. Hence, the individuals can also be partitioned into susceptible, infected and recovered individuals. Let $\mathcal{S}(t)$, $\mathcal{I}(t)$ and $\mathcal{R}(t)$ be the sets of susceptible, infected and recovered individuals at time t, and let

$$S_G(t) = |\mathcal{S}(t) \cup \mathcal{X}_G|, \quad I_G(t) = |\mathcal{I}(t) \cup \mathcal{X}_G|, \quad R_G(t) = |\mathcal{R}(t) \cup \mathcal{X}_G|.$$

Individuals in the same partition $G \in \mathcal{G}$ are indiscernible. Moreover, affiliations inherit their state from the state of their members. Therefore, the state of the epidemic process is completely described by the number of susceptible and infected individuals in the different subsets $G \in \mathcal{G}$. Let $\mathbf{S}(t) = [S_G(t)]_{G \in \mathcal{G}}$ and $\mathbf{I}(t) = [I_G(t)]_{G \in \mathcal{G}}$ be the vectors whose elements represent the number of susceptible and infected individuals in the different partitions at time t. Here and in the remainder, we index vectors by the elements of $\mathcal{G}$ for ease of presentation. Moreover, let $\pi(\mathbf{s}, \mathbf{i}; t) = Pr[\mathbf{S}(t) = \mathbf{s}, \mathbf{I}(t) = \mathbf{i}]$, for $\mathbf{s} = [s_G]_{G \in \mathcal{G}}$ and $\mathbf{i} = [i_G]_{G \in \mathcal{G}}$, such that $(\mathbf{s}, \mathbf{i}) \in \mathcal{N}$. Here $\mathcal{N}$ denotes the state space of the Markov chain,

$$\mathcal{N} = \{([s_G]_{G \in \mathcal{G}}, [i_G]_{G \in \mathcal{G}}) : s_G, i_G \in , s_G + i_G \leq N_G\}.$$

For $a \in \mathcal{A}$ and given state vectors $\mathbf{s}$ and $\mathbf{i}$, let $s_a(\mathbf{s})$ and $i_a(\mathbf{i})$ be the fraction of susceptible and infected individuals that have affiliation a,

$$i_a(\mathbf{i}) = \frac{1}{N_a} \sum_{G \in \mathcal{G}, a \in G} i_G, \quad s_a(\mathbf{s}) = \frac{1}{N_a} \sum_{G \in \mathcal{G}, a \in G} s_G.$$

Affiliation $a \in \mathcal{A}$ infects its susceptible members with a rate $\alpha_a(s_a(\mathbf{s}), i_a(\mathbf{i}))$, α_a being a generic function. The infection rate experienced by individuals in the subset $G \in \mathcal{G}$ therefore equals,

$$\beta_G(\mathbf{s}, \mathbf{i}) = \sum_{a \in G} \alpha_a(s_a(\mathbf{s}), i_a(\mathbf{i})).$$

Let γ be the recovery rate of the individuals, the Chapman-Kolmogorov equations are then given by,

$$\begin{aligned}\frac{d}{dt}\pi(\mathbf{s},\mathbf{i};t) = &\sum_{G\in\mathcal{G}} \pi(\mathbf{s}+\mathbf{e}_G,\mathbf{i}-\mathbf{e}_G;t)\beta_G(\mathbf{s}+\mathbf{e}_G,\mathbf{i}-\mathbf{e}_G)(s_G+1)\\ &+\sum_{G\in\mathcal{G}} \pi(\mathbf{s},\mathbf{i}+\mathbf{e}_G;t)\gamma(i_G+1)-\pi(\mathbf{s},\mathbf{i};t)\sum_{G\in\mathcal{G}}(\gamma i_G+\beta_G(\mathbf{s},\mathbf{i})s_G)\ ,\end{aligned}$$

where we set $\pi(\mathbf{s},\mathbf{i};t) = 0$ for $(\mathbf{s},\mathbf{i}) \notin \mathcal{N}$ to simplify notation. Moreover $\mathbf{e}_G$ is a vector of zeros apart from the Gth element which equals 1. The first term on the right-hand side of the former expression corresponds to an infection of an individual in one of the sets $G \in \mathcal{G}$. The second term corresponds to having a recovery in these different sets.

3 Fluid Limit

Due to the considerable size of the state space $\mathcal{N}$, even for modest population sizes and a modest number of affiliations, direct computation of either transient or stationary distributions is quite forbidding. As we are mainly interested in the dynamics when the population is large, we focus on the fluid limit of the process. The present study scales the size of the population, while keeping the number of affiliations constant. Let $\mathcal{F}$ be the infinitesimal generator of the Markov process above, we then have,

$$\mathcal{F}h(\mathbf{s},\mathbf{i}) = \sum_{G\in\mathcal{G}}[h(\mathbf{s}-\mathbf{e}_G,\mathbf{i}+\mathbf{e}_G)-h(\mathbf{s},\mathbf{i})]\beta_G(\mathbf{s},\mathbf{i})s_G+[h(\mathbf{s},\mathbf{i}-\mathbf{e}_G)-h(\mathbf{s},\mathbf{i})]\gamma i_G\,.$$

We now consider a sequence of Markov chains with generators $\mathcal{F}_N$ such that the number of individuals is N for the Nth Markov chain, thereby equally scaling N_G for the different sets G; set $\nu_G = lim_{N\to\infty} N_G N^{-1}$. We track the fractions of populations, such that components of the state space $\mathcal{N}_N$ of the Nth Markov chain live on a lattice with step size $1/N$, the unit vectors having size $1/N$ as well. In contrast, the transition rates increase by N as we translate from population fractions to population sizes. Setting $\epsilon \doteq 1/N$, we get the following generator:

$$\begin{aligned}\mathcal{F}_{\epsilon^{-1}}h(\mathbf{s},\mathbf{i}) = \epsilon^{-1}&\sum_{G\in\mathcal{G}}[h(\mathbf{s}-\epsilon\mathbf{e}_G,\mathbf{i}+\epsilon\mathbf{e}_G)-h(\mathbf{s},\mathbf{i})]\beta_G(\epsilon^{-1}\mathbf{s},\epsilon^{-1}\mathbf{i})s_G\\ &+\epsilon^{-1}\sum_{G\in\mathcal{G}}[h(\mathbf{s},\mathbf{i}-\epsilon\mathbf{e}_G)-h(\mathbf{s},\mathbf{i})]\gamma i_G n\,.\end{aligned}$$

We can deduce the (candidate) fluid limit by Taylor expansion of this generator around $\epsilon = 0$. We find a limiting generator of the form $\hat{\mathscr{F}}h = \mathbf{f}(\mathbf{x}, \mathbf{y}) \cdot \nabla h$, for a certain $2|\mathcal{G}|$-dimensional vector function $\mathbf{f} = [\mathbf{f}_1, \mathbf{f}_2]$. Note that a generator of this form corresponds to a deterministic process satisfying the system of differential equations $\dot{\mathbf{x}}(t) = \mathbf{f}_1(\mathbf{x}(t), \mathbf{y}(t))$, $\dot{\mathbf{y}}(t) = \mathbf{f}_2(\mathbf{x}(t), \mathbf{y}(t))$.

In order to prove this limit rigorously, it needs to be checked that both the pre-limit processes and the limit process are Feller processes [16], which corresponds to checking the Hille-Yosida conditions. We believe that a careful proof falls outside the scope of this paper, but remark that due to the compactness of the state space the proof is not as involved as is sometimes the case. Below we detail the set of differential equations, where we have dropped the dependence on t for notational convenience. For all $G \in \mathcal{G}$, we have,

$$s'_G = -\hat{\beta}_G(\mathbf{i}, \mathbf{s}) s_G \,, \quad i'_G = \hat{\beta}_G(\mathbf{i}, \mathbf{s}) s_G - \gamma i_G \,, \quad r'_G = \gamma i_G \,,$$

where s_G, i_G and r_G are the fraction of susceptible, infected and recovered individuals that have affiliation set G, respectively. Here $\hat{\beta}$ couples the differential equations for the different affiliation sets as follows,

$$\hat{\beta}_G(\mathbf{i}, \mathbf{s}) = \sum_{a \in G} \alpha_a \left(\frac{1}{\nu_a} \sum_{H \in \mathcal{G}, a \in H} i_H, \frac{1}{\nu_a} \sum_{H \in \mathcal{G}, a \in H} s_H \right) \,,$$

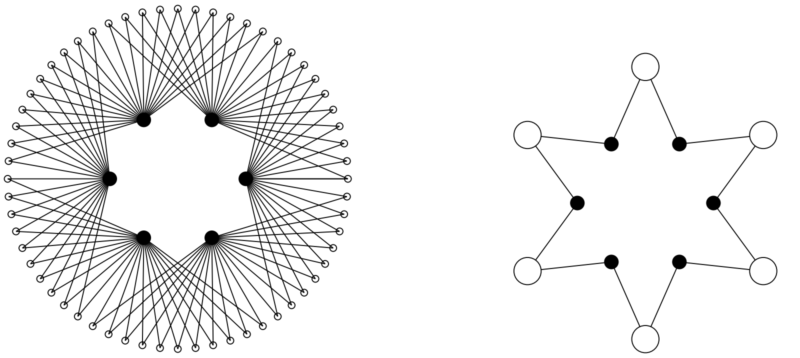
with $\nu_a = lim_{N \to \infty} N_a N^{-1}$.

4 Numerical Examples

We adopt the topology of Fig. 1 for the numerical examples. The affiliations and individuals live on circles, and an individual connects to its κ closest affiliations, the distance being measured in terms of difference in angle between individual and affiliation. In addition, we assume the same group dynamic in each affiliation and the infection rate of the affiliations only depends on the fraction of infected in the affiliation.

We focus on *regular* dynamics, in which case the infection rate is an increasing function of the number of infected, as well as on *early adopter dynamics* in which case the infection rate decreases if more members of the affiliation are infected.

Figure 2 assesses the accuracy of the fluid approximation by means of simulation. All plots depict the time-evolution of the percentage of susceptible (S), infected (I) and recovered (R) individuals in the population. The lines correspond to

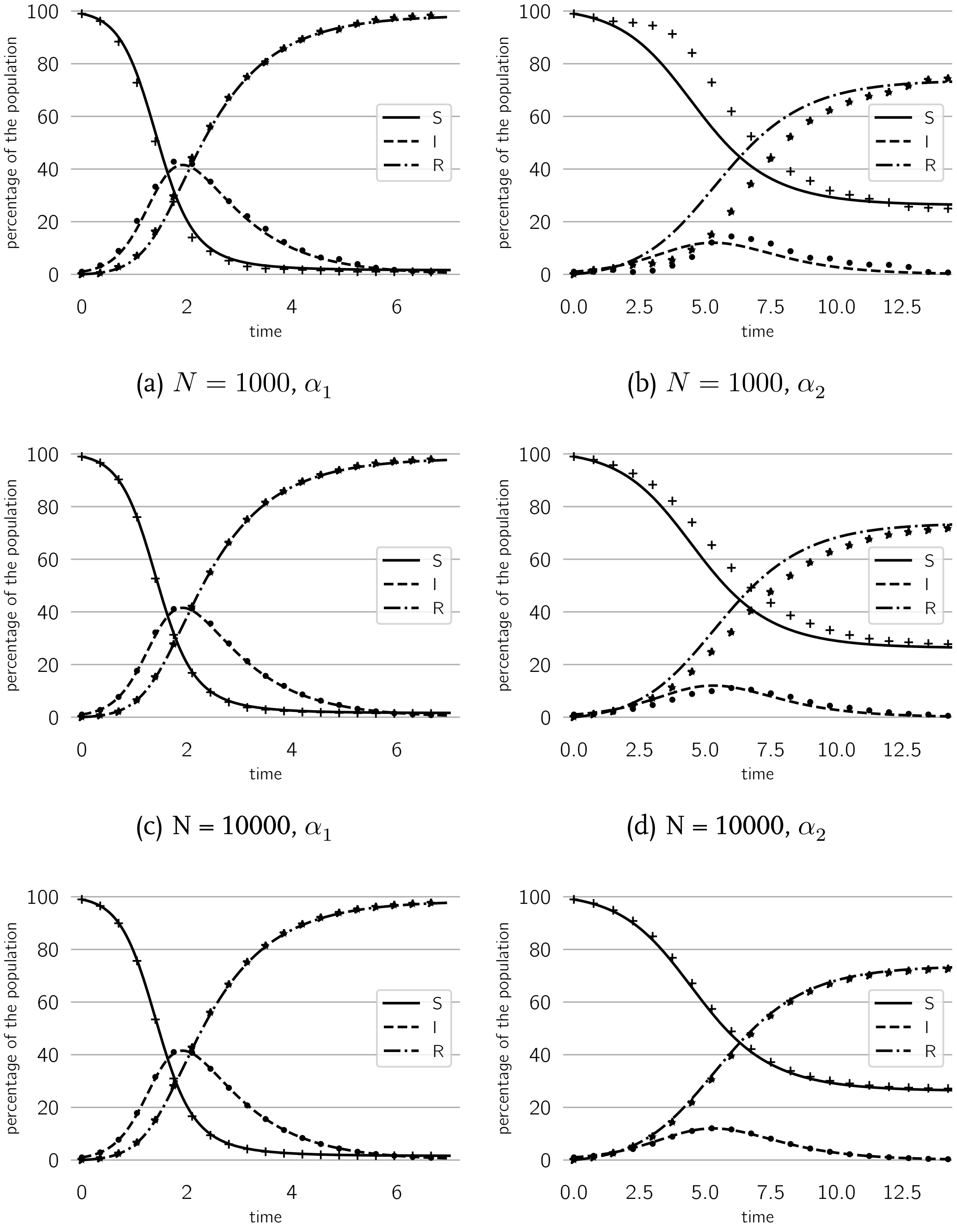


(a) individual connections (b) group connections

Fig. 1. Circular structure for a network with 60 individuals (outer circle) and 6 affiliations (inner circle), each individual having two affiliations. Figure (a) shows the individual connections, figure (b) groups the individuals with the same affiliations.

the fluid limit, whereas the markers correspond to a single trajectory of the epidemics, obtained by simulating the Markov chain. The population size is $N = 1000$ in figures 2(a) and 2(b), $N = 10000$ in 2(c) and 2(d), and $N = 100000$ in 2(e) and 2(f). All individuals have 3 affiliations, thereby assuming the topology of figure 1. The initial infection consists of 1% of infected individuals that share the same affiliations. All other individuals are susceptible. The infection rate function is regular and superlinear in Figs. 2(a), 2(c) and 2(e), $\alpha_1(i) = 1.4i - \mathbb{1}_{\{i>1/2\}} 0.8(i-1/2)$, and regular and sublinear in Figs. 2(b), 2(d) and 2(f), $\alpha_2(i) = 0.6i + \mathbb{1}_{\{i>1/2\}} 0.8(i-1/2)$. Finally the recovery rate is $\gamma = 1$ for all plots. There is clear discrepancy between the plots with super- and sublinear dynamics, the infection for the superlinear case being considerably more extensive. In either case, the fraction of infected is always less than 50% such that the slope of the infection rate function for $i < 1/2$ entirely determines the dynamics of the epidemic. Simulation confirms the accuracy of the fluid limit for $N = 10^5$.

We now compare regular and early adopter dynamics. Figure 3 depicts the time-evolution of the percentage of susceptible, infected and recovered individuals for regular ($\alpha_3(i) = 2i\nu + \mathbb{1}_{\{i>1/2\}} 2(1-2\nu)(i-1/2)$) dynamics and for early adopter dynamics ($\alpha_4(i) = 1-2i(1-\nu)+\mathbb{1}_{\{i>1/2\}} 2(1-2\nu)(i-1/2)$). Here, ν is the value of α for $i = 0.5$; different values of ν are assumed as indicated. A comparison of the curves of regular dynamics and early adopter dynamics reveals that the speed and the maximal size of the infection for early adopter dynamics is faster and larger



(a) $N = 1000$, α_1

(b) $N = 1000$, α_2

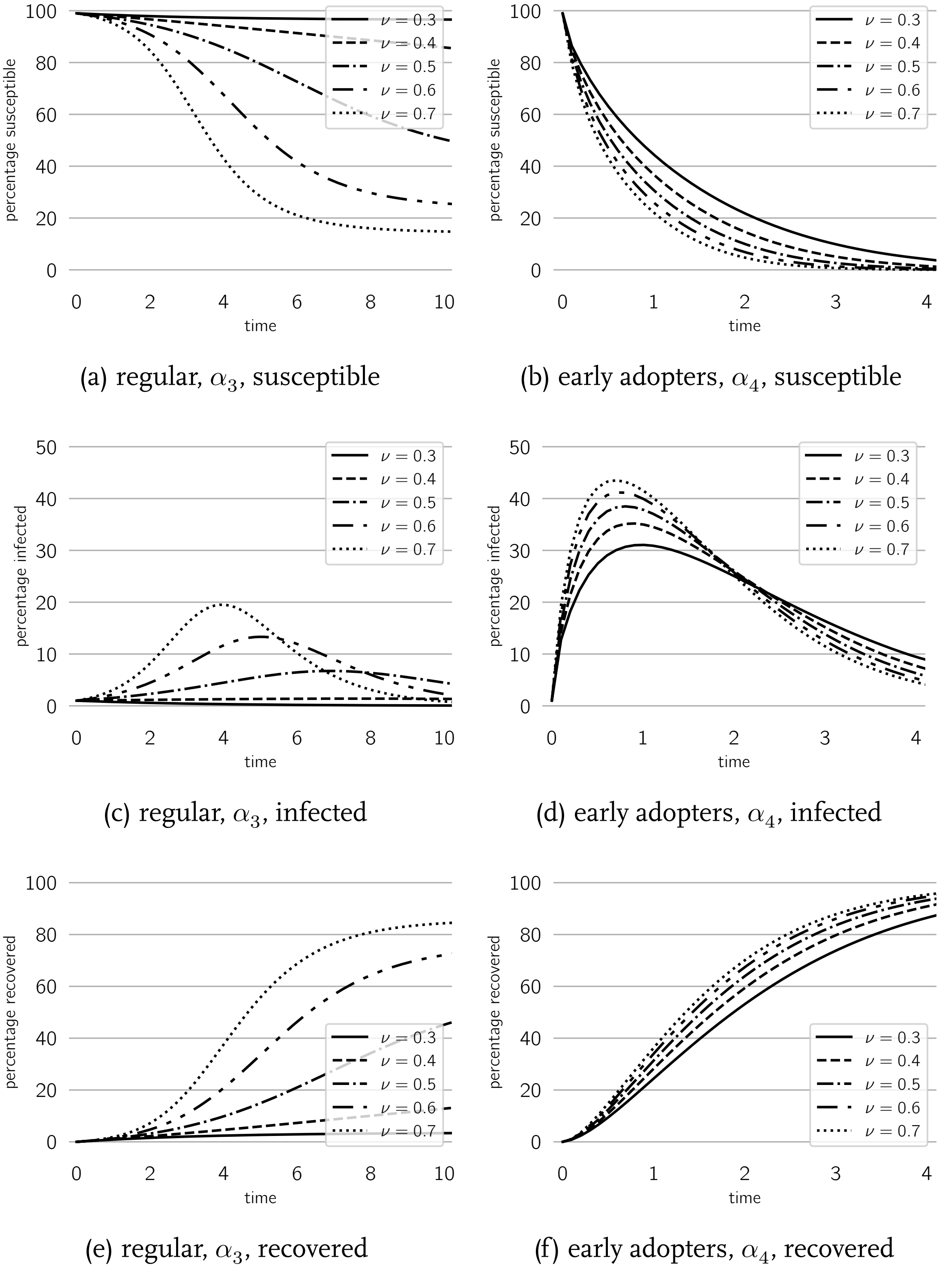
(c) N = 10000, α_1

(d) N = 10000, α_2

(e) N = 100000, α_1

(f) N = 100000, α_2

Fig. 2. Accuracy of the fluid limit for a sub- and super-linear infection rate function.



(a) regular, α_3, susceptible

(b) early adopters, α_4, susceptible

(c) regular, α_3, infected

(d) early adopters, α_4, infected

(e) regular, α_3, recovered

(f) early adopters, α_4, recovered

Fig. 3. Regular dynamics versus early adopter dynamics for different values of ν.

than regular dynamics. This is not unexpected as the infection rate is larger at the onset of the infection for early adopter dynamics.

5 Conclusion

We proposed an epidemic process on an affiliation network for modelling group dynamics for opinion propagation on social networks. Opinions are spread from one individual to another via shared affiliations: the opinions of the members of an affiliation determine the spread of the opinions to the (non-infected) members of the affiliation. We provided a continuous-time Markov process for SIR-like propagation, and studied its fluid limit. That is, we scaled the Markov process by sending number of individuals to infinity while keeping the number of affiliations constant. By numerical examples, we showed that the fluid limit is accurate when the number of individuals is sufficiently large, while the nature of the group dynamic can seriously affect spreading in the network.

Apart from the SIR epidemic, other epidemic models may apply to rumour spreading as well. For example, if the SIS model is adopted, individuals alternate between being susceptible and infected, i.e. between spreading and not spreading their opinion. In the SEIR model, individuals are exposed before they are infected, which introduces some time during which in individual has adopted the opinion, but does not yet spread. We aim at developing similar mathematical tools for these alternative epidemic processes on affiliation networks in the near future.

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Towards a DDC-based Topic Network Model of Wikipedia

Tolga Uslu[1]*, Alexander Mehler[1], Andreas Niekler[2], and Daniel Baumartz[1]

[1]Goethe University, TextTechnology Lab,
Robert-Mayer-Straße 10, 60325 Frankfurt am Main, Germany
uslu@em.uni-frankfurt.de
mehler@em.uni-frankfurt.de
https://hucompute.org/
[2]Leipzig University, Natural Language Processing Group
Augustusplatz 10, 04109 Leipzig, Germany
aniekler@informatik.uni-leipzig.de
http://asv.informatik.uni-leipzig.de/

Abstract. This paper presents a network-theoretical approach to modeling the semantics of large text networks. By example of the German Wikipedia we demonstrate how to estimate the structuring of topics focused by large corpora of natural language texts. Algorithms of this sort are needed to implement distributional semantics of textual manifestations in large online social networks. Our algorithm is based on a comparative study of short text classification starting from two state-of-the-art approaches: *Latent Dirichlet Allocation* (LDA) and *Neural Network Language Models* (NNLM). We evaluate these models by example of (i) OAI metadata, (ii) a TREC dataset and (iii) the Google Snippets dataset to demonstrate their performance. We additionally show that a combination of both classifiers is better than any of its constitutive models. Finally, we exemplify our text classifier by plotting the topic structuring of all articles of the German Wikipedia.

Key words: Topic model, topic networks, short text classification, LDA, NNLM, SVM

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1 Introduction

In this paper, we develop a simple algorithm for modeling the semantics of large text networks. This is done by example of the German Wikipedia. Our aim is to model the structure and networking of topics as manifested by large corpora of natural language texts. Algorithms serving this task are needed to implement a distributional semantics of textual manifestations in online social networks. One may want to know, for example, what topics are focused in a certain period of time in Twitter. Alternatively, one may want to know which fields of knowledge are either preferred or underrepresented in media such as Wikipedia or Wiktionary [20]. In order to answer questions of this sort, it is necessary to determine the topic distribution of each individual text aggregate of the focused media and to decide how the resulting distributions are to be networked. This is the task of the present paper.

Our algorithm for modeling the thematic structure of large text corpora utilizes a well-established topic classification, that is, the *Dewey Decimal Classification* (DDC). More specifically, we build on a comparative study of approaches to short text classification. Short texts (e.g. tweets) refer to situations in which only snippets (e.g., metadata, abstracts, summaries or only single sentences such as titles) are available as input for classification instead of full texts. One example of this is digital libraries working on OAI (Open Archives Initiative) metadata [28]. It also concerns text mining in online social media by example of chat messages, news feeds, tweets [24], or turn-taking in online discussions [7]. In all these cases the central information to be extracted is what the snippets are about in order to classify them thematically [29], to disambiguate or to classify their constituents [8] or to enrich them by means of external knowledge resources. The requirement to handle big data streams is another reason to process snippets instead of full texts even if being accessible. In each of these cases, classifiers are influenced more by the sparseness of the lexical content of short text. Therefore, one needs both fast and accurate classifiers that are expressive enough to overcome the problem of lexical sparseness.

In this paper, we present a network model of topic structuring that is based on a comparative study of text snippet classification starting from two state-of-the-art approaches: *Latent Dirichlet Allocation* (LDA) and *Neural Network Language Models* (NNLM). In the latter case we experiment with fastText [13], which has been developed to overcome problems of time-consuming deep learners. We test each of these approaches separately and also test a variant in which fastText is additionally fed with topics generated by LDA. We have found that both classifiers classify with similar quality. Feeding fastText with LDA-based topics has not accomplished any improvements. However, the combination of both classifiers has enabled us to improve the overall quality of classification.

As a gold standard of topic modeling we use the DDC, which is the most common thematic classification system in (digital) libraries. One advantage of this approach is that it provides access to extensive training and test data. In addition to that we consider two tasks of short text classification in order to enable comparisons with state-of-the-art approaches: the first uses the TREC (Text Retrieval Conference) dataset [26], the second the Google Snippets dataset [21]. As a result of these evaluations we receive a classifier that allows for determining the topic distribution of all articles of the German Wikipedia so that we can finally model the networking of these topics. In this way, we exemplify how to map text corpora on networks of topics described by them.

The paper is organized as follows: Section 2 discusses related work of text classification. Section 3 describes the series of topic classifiers with which we experiment in Section 3. In Section 5, the best performer of this evaluation is applied in order to visualize the thematic structure of Wikipedia. Finally, in Section 6 we draw a conclusion and give an outlook on future work.

2 Related Work

Since our paper deals with the DDC-related classification of short texts, we consider two areas of related work: text snippet classification and topic modeling used for content analysis of online social networks.

By exploring OAI Metadata, [28] present an SVM-based classifier that considers all three levels of the DDC. A basic restriction of this approach relates to the fact that it only processes OAI records of a certain minimal length. In contrast to this, we do not consider such a lower bound so that we face a more realistic scenario in which the topic of a snippet is highly underrepresented by its vocabulary. Thus, unlike [28], we consider all 2nd-level DDC categories: in the case of English texts this 2-level approach even deals with a larger set of target classes than the 3-level approach of [28] (who are considering only 88 classes in total). Likewise, we aim at overcoming problems of computational complexity as exemplified by the approach of [27]. This research shows that DDC-related text categorization, especially by example of short texts, has been a desideratum so far.

The classification of text snippets, regardless of the classification scheme, has made significant progress with the utilization of neural networks for text classification. [29] show that the projection of similar text snippets onto a matrix can be a very helpful input to training a convolutional neural network that outperforms approaches based on other neural networks [14,16], LDA [21,5] or SVMs [23]. These approaches concentrate on single aspects like syntactic rules, topic modeling of text snippets or semantic similarity measurement. Our case study examines sources of information that have not previously been investigated together in the context of classifying text snippets. This includes

1. information about n-grams,
2. information provided by dataset-external semantic knowledge as given by topic models derived from general corpora, and
3. information provided by NLP tools about tokens, lemmas and parts of speech.

We integrate these information sources into our model and compare the performance of a neural network and an SVM-based approach as two competing instances of our model.

The usage of topic models and thematic classifications as an input to graph structures has been explored in different ways. Mostly, the connections in such graphs are built by topical similarities of the documents [4,17]. In this way, one can observe, for example, which sources or authors are highly connected in the resulting graph. On the other hand, social networks can be analyzed with respect to topical preferences manifested by their textual content [19,3,9,25]. Our approach also adds the network perspective regarding topic distributions. However, we additionally explore the networking of topics as a function of the polysemy of the underlying textual aggregates.

3 Models of Topic Classification

In this section we describe the models that we used for topic-related text classification: based on LDA (Sec. 3.1), on neural networks (Sec. 3.2), on neural networks fed by LDA-based topics (Sec. 3.3), on neural networks fed by vectors representing word significance distributions (Sec. 3.4), and based on a combination of a SVM and a NNLM-based classifier (Sec. 3.5).

3.1 LDA-based classification (SVM-LDA)

Topic models, as the *Latent Dirichlet Allocation* (LDA) model, utilize large text corpora to infer a latent distribution of words over a given number of topics so that each document can be described as a mixture of those topics when exploring co-occurrences of their lexical constituents [2]. The parameters of the LDA model, ϕ (word-topic distribution) and θ (document-topic distribution) can be estimated using either a variational inference scheme or Gibbs samplers on a training set of documents [11]. One of the great benefits of topic models is the generalization of the model. The topic structure of documents which do not belong to the training set can be inferred using the fixed model parameters even if additional unknown vocabulary is included. In this way, each document of a corpus can be described in terms of its topic distribution regarding the parameters of a topic model that has been generated by means of a reference corpus.

In text classification, a vector space model is often used to derive elementary features for documents. The famous tf-idf scheme, entropy-based measures or the pointwise mutual information can be used as alternatives to weight the terms in the document vectors. In [27], lexical features are weighted using such term weights. The resulting feature vectors are used to train a *Support Vector Machine* (SVM) using a *Negative Euclidean Distance Kernel* (NDK) on a dataset of 4 000 German DDC classified documents. This approach achieves 0.723 in F-score with respect to the dataset.

Our approach uses additional information besides the tf-idf weights including the extraction of uni-, bi-, and trigrams and the additional use of topics as features within an SVM-classification scheme. That is, we informationally enrich each document in the training set. Unigram stop words are deleted from the set of features and words of the document collection were stemmed. Since a topic encodes an associated vocabulary context (e.g., the word-topic distribution), each document holds general information about other documents containing similar topics. This information can be useful in classification tasks if we augment the lexical features with the topic structure for a category. Our hope is to enhance the results of [27] by the use of such topic model-related features. The here described approach uses the LDA model of [2] to infer topics on the dataset.

We considered a novel strategy to augment the lexical features with topic information. An LDA-model with 100 topics is inferred on "general" language data and the topic distributions of documents from both, training and test datasets, are determined with respect to this model.[1] This gives us an additional topic distribution on each document in the training and test sets. The language resource to build our model is based on corpora from the Wortschatz[2] project. We chose 3 million sentences from news data which were crawled in 2015 from German and English websites to build the respective models. We did not use Wikipedia-based data because of the possible domain similarity to our OAI-datasets in Section 4.

Additionally, we apply the tf-idf weighting scheme to the document term vectors (uni-, bi- and trigrams) in order to reduce the influence of general vocabulary. Then, we append the topic distribution for a document as a vector of probabilities to its vector of lexical features. To train the SVM, we used the R-version of liblinear with an L2-regularized logistic regression and estimated the C-parameter heuristically [6,12].

3.2 Neural network-based classification (NN)

For the neural network-based approaches, we started with the simple but very efficient classifier of [13] called `fastText` (see Figure 1 for a visual depiction of this model in our context). `fastText` uses a *bag-of-words* (bow) model and defines the occurrences of words in a document as input of the neural network. Since the order of words is ignored in the bow-model, `fastText` uses n-grams to capture some information about the local order. To avoid being forced to use default parameter settings, we have written a parameter analyzer, which searches the parameter space for better performing settings (according to a hill-climbing algorithm). Since the input corpora were not preprocessed, we applied various NLP tools to obtain additional information about tokenization, lemmas and parts of speech. We also used pretrained word embeddings to initialize the neural network.

[1] Our experiments showed that 100 topics provided the best topic solution for the described experiments in terms of F1 performance of the final classifier. We tested 20, 50, 75, 100, 250 and 500 as values for the amount of topics to infer.

[2] `http://wortschatz.uni-leipzig.de/en/download`

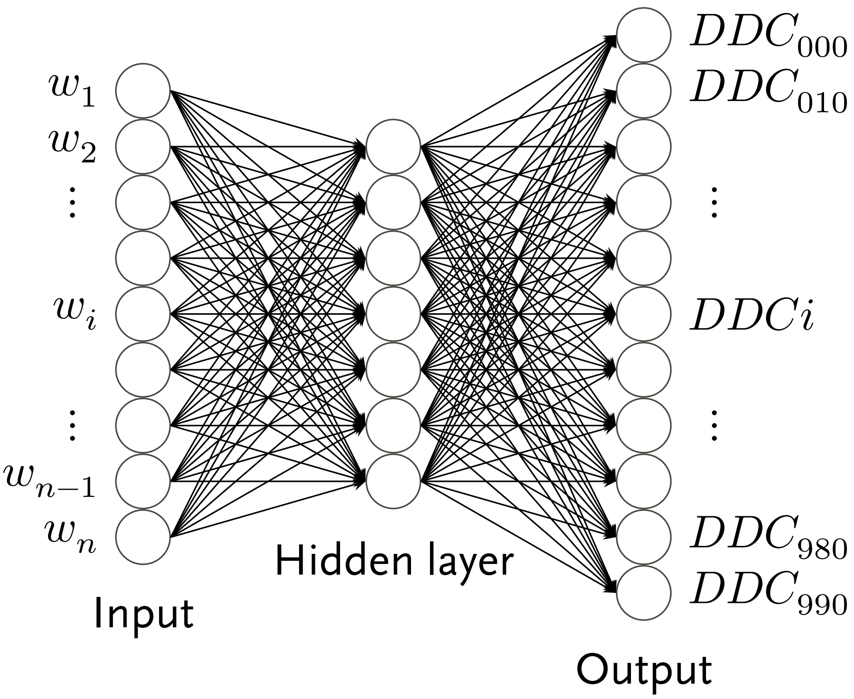


Fig. 1: Architecture of Model 3.2.

3.3 Neural Network based classification combined with LDA (NN-LDA)

Since `fastText` only accepts text as input, we adapted its architecture so that we can process the textual content in conjunction with the topic distribution of a document. To this end, we extended the neural network underlying `fastText` to include not only input nodes for words, but also for each topic provided by the model of Section 3.1. Thus, when considering a distribution of 100 LDA-based topics, we added 100 input nodes to the neural network, which are activated according to the topic values of the input document. In this way, our extension of `fastText` is additionally fed with numerical values signaling membership to topics derived from LDA.

3.4 Neural network-based classification combined with GSS (NN-GSS)

Taking profit of the fact that we adapted `fastText` to additionally accept numeric values as input, we calculated the GSS coefficient (*Galavotti-Sebastiani-Simi*) [10] for each pair of words in the input corpus and first-level categories of the DDC. In this way, each word of the input corpus is mapped onto a 10-dimensional feature vector whose dimensions denote the association of the word with respect to the given target category. Under this regime, the classifier uses feature vectors of GSS coefficients instead of the words themselves. This results in a neural network with $n \times m$ input nodes, where n is the size of the vocabulary of the input corpus and $m = 10$ the number of top-level DDC classes.

3.5 Combining both worlds (NN-SVM-LDA)

By means of an error analysis we found that the SVM and the NN-based classifiers make different errors, although achieving similar classification qualities. Therefore, we calculated a scoring for each document with respect to each target category based on the two best performing classifiers from the SVM- and NN-world, respectively, and experimented with two methods to combine their scorings:

1. voting for the target class as a function of the maximum score (not to be confused with majority voting) or
2. by means of the average score.

4 Classification Experiment

We test the models of Section 3 by example of four different data sets. Two of these samples represent OAI-based datasets (one in German and one in English) which were used regarding two classification tasks. The first task was to classify the first level of the DDC (10 classes in the English corpus (EN-10) and 10 classes in the German corpus (DE-10)). The second task was to classify the first two levels of the DDC (93 classes in the English corpus (EN-All) and 88 classes in the German corpus (DE-All)). The German corpus consists of 595 493 records with an average of 37.24 words per document. The English corpus consists of 1 222 948 records with an average of 50.69 words per document. Each corpus was randomly divided into training (70%) and test (30%) sets. In order to ensure comparability with state-of-the-art systems for classifying text snippets, we also evaluated our models using the TREC 2003 Question Answering dataset [18] and the Google Snippet dataset [22] as used in [29].

4.1 Classification

For the SVM-based classification using LDA-features we trained one SVM-model for each dataset and task. The results are shown in Table 1. The SVM-LDA model outperforms the models described in [27,28]. Furthermore, it performs as good as the NN-based model described in [29]. In examining the impact of all features, we find that the n-gram features have an impact similar to features provided by the topic model. The combination of both feature sets does not improve overall performance. In detail, the classification for the DE-10 dataset results in the following F1-scores for the different feature configurations: *1. unigrams – 0.786; 2. unigrams + topics – 0.805; 3. n-grams – 0.814; 4. n-grams + topics – 0.815.* In general, it can be shown that using topic model features improves the quality of the classification, albeit to a limited extent. From a classification point of view, n-grams and LDA-based topics seems to encode related information within the feature space. This may give rise to future research.

In the case of classifying with neural networks, we carried out a parameter study to detect optimal parameter settings. To this end, we examined the following parameters:

- Learning rate (0.025 - 0.1)
- n-grams (1 - 5)
- Dimension (50 - 100)
- Epochs (500 - 10000)

The results are shown in Table 1.

It shows that SVM-LDA performs better than its NN-based counterparts in the case of the English data sets, while the NN-based (lemma + POS) classifier outperforms its competitors in the case of the German data. However, the difference to SVM-LDA is very small. Additionally feeding the NN with LDA topics (NN-LDA) performs worse as does NN-GSS (DE-10). Further, lemma-level features perform very little better than token-level ones (DE-10 and DE-All).

Next, we selected the best classifiers of both areas (SVM and NN) and further analyzed their classification quality. Although both classifiers perform similarly (81.4% and 81.6%), they make different mistakes. When always knowing the right class of a snippet and then selecting the classifier voting for it, we would achieve an F-score of 89.6% as a kind of an upper bound of an algorithmic combination of SVM-LDA and NN (lemmas + POS). However, we cannot presuppose this knowledge. Thus, we need to apply one of the combinations of Section 3.5. This produces an the F-score of 82% in the DE-10 experiment using the method of averaging scores.

Corpus	Features	N-gram	F-scores
EN-10	NN: token-based	3	0.748
EN-10	SVM-LDA	1-3	0.771
EN-All	NN: token-based	3	0.698
EN-All	SVM-LDA	1-3	0.717
DE-10	NN: token-based	1	0.814
DE-10	NN: lemma + POS	2	0.816
DE-10	NN-GSS	–	0.792
DE-10	NN-LDA: lemma + POS + topics	2	0.795
DE-10	NN (lemma + POS) + SVM-LDA	1-3	0.820
DE-10	SVM	1-3	0.814
DE-10	SVM-LDA	1-3	0.815
DE-All	NN: lemma + POS	2	0.757
DE-All	NN: token-based	2	0.753
DE-All	SVM-LDA	1-3	0.750

Table 1: F-scores of text snippet classification based on four different corpora.

Method	Google Snippets	TREC
SVM-LDA (Section 3.1)	0.960	0.971
NN (Section 3.2)	0.962	0.974
[29]	0.851	0.972

Table 2: Comparison of our models to the best performing model in [29].

Finally, we compared the best performers of Table 1 with those documented by [29]: Table 2 shows that we also outperform these competitors by example of the Google and the TREC data by more than 10%. Obviously, our approach is more than just competitive.

4.2 Discussion

Although we worked with the complete DDC corpus (as described at the beginning of this section) and therefore had to classify many small texts, we achieved rather promising classification results. This holds for both the SVM-LDA and the NN-based classifier. Both classifiers outperform the approach of [28] (being based on a classical SVM) and the one of [27] (using a newly invented kernel function), even when using the full dataset rather than using only a subset of texts of a certain minimal length. In addition, both our classifiers outperform their competitors described in [29] (see Table 2).

In the case of SVM-LDA, we show that information provided by LDA has a positive impact on classification. The different errors generated by SVM-LDA and NN indicate that there is a high potential in the combination of both approaches. However, the neural network achieved worse results when directly using topic information provided by the LDA (NN-LDA – see Table 1). Therefore, information about topics as provided by LDA should be integrated into neural networks in other ways than by the one used here so that one can make better use of this information. The very same can be said about using GSS-weighted vectors (NN-GSS). Experiments of [15] and [16] show the potential of including word similarity information within a convolutional layer of a neural network. This type of semantic smoothing might also be interesting to explore similarities of documents that are used simultaneously for training the network. In this way, we may help to better integrate topic models and neural networks. This will also be an object of future research. In any event, we are now in a position to guess for any piece of text – down to the level of single words (supposed they have been seen during training) – what topic class of the DDC it likely belongs to. In this way, we have a very powerful topic model that can be used to study the topic distribution and topic networking of online social networks and related media.

5 A bird’s eye view of topic networks

In this section, we experiment with the best performing (non-combined) topic classifier of Section 4, that is, NN (lemma + POS, DE-All), to model inter-topic structures. This is done by example of a complete release of the German Wikipedia (download: January 20th, 2017). That is, each of the 1 760 875 Wikipedia articles in this release is mapped onto a subset of DDC categories and each of the 53 122 347 links between these articles is mapped onto arcs between nodes denoting these categories. We address two tasks:

- *Topic distribution and thematic dominance:* Firstly, we try to determine for each article of this release what topics it deals with. This means that we assume a multi-label classification scenario in which the same article possibly manifests several topics to varying degrees (measured by the strength μ of classification).

- *Topic linkage:* Secondly, we use this information to generate a network that shows how these topics are interlinked. Through this network we provide two types of information: about the salience of topics and about topics being jointly manifested by articles.
- *Visualization:* Our visual depiction of this topic network is based on the following statements:
  1. The more articles describing the same topic and the stronger they do, the more salient this topic becomes and the bigger its visual depiction.
  2. The more articles related to the topic A are linked with articles related to the topic B, the larger the visual representation of the arc from A to B.

The result of this visualization procedure is depicted in Figure 2 (a). It demonstrates that articles are usually so ambiguous (in terms of our classifier) that applying this algorithm of network induction to *all* Wikipedia articles ultimately brings us close to a completely connected topic network.

Thus, in order to reveal more structure, we additionally experiment with varying thresholds of minimal classificatory membership by analogy to α-cuts in fuzzy set theory. This is demonstrated in Figure 2 (b): it shows that for a threshold of maximum class membership, we arrive at an extremely sparse network in which only a tiny fraction of topic-to-topic links survive. At this level, inter-topic structure almost diminishes: a single highly salient category emerges, that is, DDC class 790 (*Recreational & performing arts*). Note that in Figure 2 (b), salience of vertices is *also* a function of α: only those categorizations are counted per DDC class whose membership value μ is at least α; the same constraint also concerns the linkage of topic nodes.

Now the question is raised how the network of Figure 2 (b) passes over into the one of Figure 2 (a): how does it move from crisp to fuzzy categorization? In order to answer this question, we compute networks according to our algorithm of network induction by taking only those mappings of articles x to DDC categories A into account, whose class membership $\mu_A(x)$ satisfies the inequality $\mu_A(x) \geq \alpha$ while reducing α stepwise from 1 to 0.01 (in steps of 0.01). Then, for each of these α values we induce a separate network for which we compute a subset of graph invariants as depicted in Figure 3:

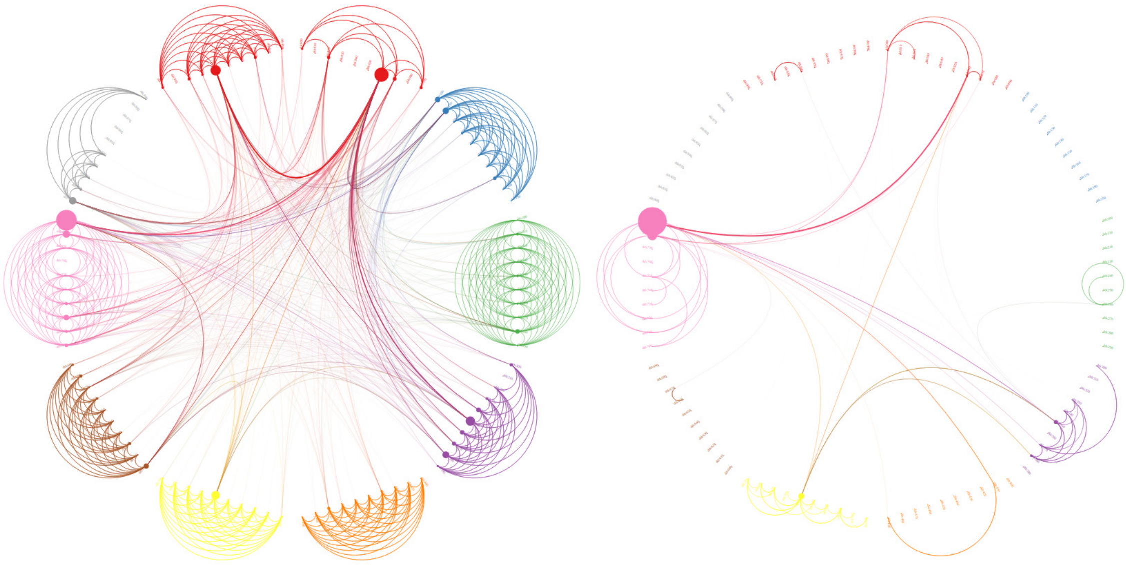
1. The unweighted C [30] and the weighted cluster value C_d^w of directed networks [1] estimating the probability with which nodes linked from the same node are

themselves connected, taking into account the weights of these arcs.

2. The proportion of vertices belonging to the largest strongly lcc_s and weakly lcc_w connected component.
3. The cohesion value coh, that is, the proportion of existing arcs in relation to the number of possible arcs.

Finally, we plot aggregated values of graph invariants, that is, the product of C_d^w and C on the one hand and of coh and lcc_s on the other. We observe that compared to C_d^w (C), the values of $C_d^w \cdot coh$ ($C \cdot coh$) are significantly smaller. This indicates that although clustering rapidly increases even for smallest decreases of maximum α, clustering rather concerns a small subset of vertices. At the same time, we observe that by weighting C_d^w with lcc_s, clustering does not decrease by far to the same extent (the same holds, though to a higher degree, for $C \cdot lcc_s$). This suggests that adding arcs as a result of reducing α contributes more to the connectivity than to the clustering of the underlying networks. In other words: increasing the level of allowable ambiguity rather leads to connected topic networks than to networks exhibiting many local (triadic) clusters. If we compare the distribution of C_d^w as a function of α with C, we observe that for smaller values of $\alpha = 0.4$ C_d^w starts shrinking as C continues to grow: for this threshold value, smaller weights of edges begin to overlay higher edge weights. In other words, at this level, the categorization quickly becomes too much blurred. In any event, we also observe that under our model of topic classification, articles tend to be highly polysemous so that one rapidly approximates a highly connected graph ($lcc_w \sim 1$) that also exhibits high cluster ($C > 0.8$) and cohesion values ($coh > 0.2$).

Obviously, this analysis provides both (i) a bird's eye view on topic structuring as manifested by text networks as large as Wikipedia and (ii) an assessment of its ambiguity. The latter is done by analyzing the transition dynamics starting from clear classifications to highly ambiguous ones, taking into account clustering and connectivity.



(a) alpha=0

(b) alpha=1

Fig. 2: Comparison of the Wikipedia based DDC network with alpha = 0 and 1.

● DDC 0, ● DDC 1, ● DDC 2, ● DDC 3, ● DDC 4, ● DDC 5, ● DDC 6, ● DDC 7, ● DDC 8, ● DDC 9

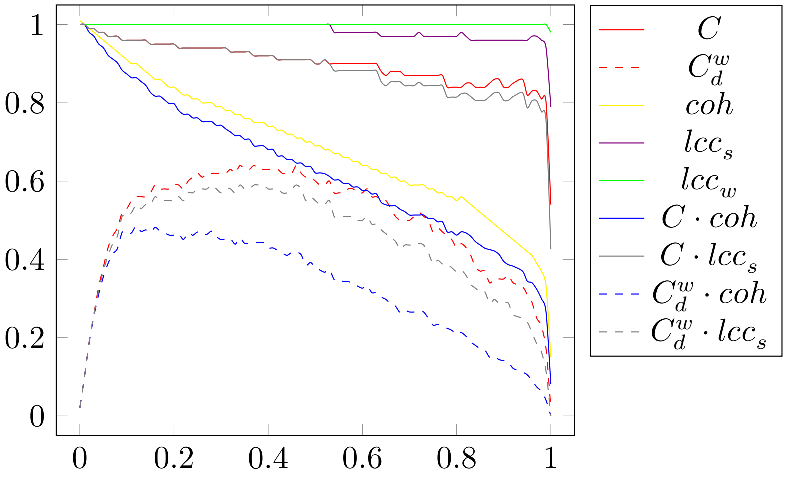


Fig. 3: Distribution of graph invariants of topic networks as a function of minimal class membership α.

6 Conclusion

In this paper, we developed a simple algorithm for analyzing and visualizing the topic structure of large text networks. To this end, we experimented with a series of classifiers in the context of three evaluation scenarios. This included an SVM-based classifier exploring topics derived from LDA, a NNLM-based classifier (i.e, `fastText`) as well as combinations thereof. Using the best performer of these experiments, we have shown how to generate a bird's eye view of the salience and linkage of topics as manifested by hundreds of thousands of texts. In this context, we observed a very high degree of thematic ambiguity, which makes it necessary to search for more precise, less ambiguous classifiers. This will be the task of future work. Nevertheless, our paper shows a way to automatically visualize the thematic dynamics of textual aggregates as produced by large online social networks.

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Using Social Network Analysis to Make Sense of Radio Communication in Emergency Response

Kathrin Eismann, Diana Fischer, Oliver Posegga, and Kai Fischbach

University of Bamberg,
An der Weberei 5, 96047 Bamberg, Germany
http://www.uni-bamberg.de/sna/

Abstract. In the wake of an increasing interest in the communication networks of emergency responders, radio communication systems have been recognized as an important source of digital trace data. In this paper, we explore how radio data can be used as part of social network analysis (SNA). In particular, we investigate how social networks can be modeled and analyzed based on digital trace data obtained from radio systems in the emergency response field. We outline SNA challenges and opportunities based on radio networks, following the work of [9]. Utilizing radio data from a recent emergency response field exercise, we illustrate an example of a workflow that can be applied for modeling social networks from emergency responders' radio communication and discuss the implications of our findings for the analysis and interpretation of radio network structures. Hence, this paper is a useful starting point for future research that applies tools and methods from the SNA repertoire to radio networks in the context of emergency response and beyond.

Key words: Social Network Analysis, Radio Communication, Digital Trace Data, Emergency Response

1 Introduction

Radio communication – that is, telecommunication by means of radio waves [11][1] – has largely disappeared from the public consciousness but remains a common communication medium in many fields of operation, such as in ground, air, and water transportation, in businesses with factories and other industrial sites, and in care facilities.

Naturally, radio data afford opportunities to apply tools and methods from the repertoire of social network analysis (SNA) to communication networks [1]. While such research was once rare, new interest in the communication networks of emergency responders has emerged in recent years [8,12,13,14,19]. Radio is crucial for emergency responders, especially when other communication infrastructures are compromised or destroyed by disasters or extreme events [10], and has thus remained the baseline communication tool of emergency services in many places [8,14]. Radio interoperability disruptions are still among the most severe communication problems emergency responders face [7,13,15]. Research also suggests that studying radio communication provides unique insights into the social structure of emergency response operations [2,17].

Utilizing radio as a basis for SNA is not without challenges, though. In this paper, we focus on the modeling and analysis of social networks based on radio communication as a special case of digital trace data. We outline key issues in utilizing digital trace data for SNA based on [9] (section 2). We then discuss the SNA challenges and opportunities for radio networks based on our experiences in a research project involving three major German relief organizations, and share our insights from a recent emergency response field exercise (section 3). Finally, we outline the contributions of our work (section 4).

2 SNA for Digital Trace Data

Digital trace data are “records of activity (trace data) undertaken through an online information system (thus, digital)” [9]. Unlike traditional network data, which are produced for research (e.g. from interviews, observations, or archival records

[1] In technical terms, radio communication is any transmission, emission, or reception of signs, signals, writings, images, sounds, or intelligence of any nature using radio waves (i.e., electromagnetic waves of frequencies arbitrarily lower than 3,000 GHz, transmitted in space without artificial guide such as wire) [11].

[16,20]), digital trace data are found. Furthermore, whereas traditional network data typically describe specific relationships, digital trace data are event-based, and they are longitudinal records of events instead of cross-sectional network snapshots. Digital trace data thus enable scholars to understand the structure and outcomes of social networks on an unprecedented scale. This type of data does, however, require scholars to make crucial assumptions regarding the nodes, ties, and structures they model from it [9].

According to [9], five steps are necessary to construct and analyze social networks from digital trace data such as radio communication. In the first step, digital trace data have to be understood and interpreted in alignment with the context and characteristics of the information systems they emerge from. In this context, issues relating to the reliability of the information systems from which communication events are to be extracted in the first place, as well as practical usage behaviors deviating from the intended information systems usage, need to be considered. In the second step, the network elements (i.e., the nodes and links of the network) have to be modeled from the identified communication events. In particular, digital trace data typically allow for different ways to handle the multiplexity, intensity, and directionality of ties. Furthermore, missing ties may be an issue when the records provided by the information system are incomplete or limited to a partial representation of the relationships and interactions within the context of a study. In the third step, the identified network elements have to be aggregated into a network, which may entail difficulties in the temporal aggregation of nodes and links. In the fourth step, appropriate network measures that align with both the intended theoretical construct to be analyzed and the social network at hand have to be selected. This can be challenging especially if there is mismatch between the temporal dynamics of constructs and network representation, or if software tools applied to support computation of measures yield invalid results. Finally, in the fifth step, the theoretical constructs inferred from the network measures have to be interpreted and generalized in a valid way, which is important for SNA-based research in general, but particularly challenging when working with digital trace data.

In the case of communication networks modeled from radio communication, it is necessary to initially extract communication events (i.e., instances of radio communication between two or more users of the radio communication system) from the electronic records of radio communication. Based on this, unique actors that constitute the nodes of the communication network have to be identified from the radio names of users (i.e., the aliases radio users rely on to address their peers). Furthermore, the trade-offs of considering directed and weighted communication links between these users as opposed to simple undirected and unweighted links, as well as the potential consequences of omitting unobserved communication events have to be discussed. In the next step, several options are available for the temporal aggregation of these network elements, in particular, aggregation of communication links over the entire period of observation, over limited periods using sliding windows, or over fixed periods focusing on specific events. Once a communication network has been generated from the identified nodes and edges, it is important to select appropriate network measures. In particular, we discuss the applicability of standard measures that are often applied to the analysis of digital trace data. Finally, we turn to the implications of the identified network structures for the interpretation of the communication network.

Figure 1 provides an overview on the chain of reasoning described by [9], which covers the major assumptions that have to be made in the process of modeling networks from digital trace data in general. In addition, the figure includes an adaption of this concept for radio communication networks in particular, which we use as an example to discuss the challenges and opportunities involved in modeling and analyzing such networks.

In the following section, we discuss in detail how digital trace data of emergency responders' radio communication can be utilized for SNA based on findings from a research project with relief organizations in Germany and insights from the analysis of empirical radio data obtained from a recent emergency response field exercise.

3 Challenges and Opportunities of SNA for Radio Networks in the Emergency Response Field

3.1 Case Description

We utilize data from a recent emergency response field exercise to illustrate SNA challenges with respect to radio networks. The exercise scenario was based on a past crisis event – a flash flooding of a river during a large festival in a medium-sized city in Germany. In the emergency response exercise, emergency responders

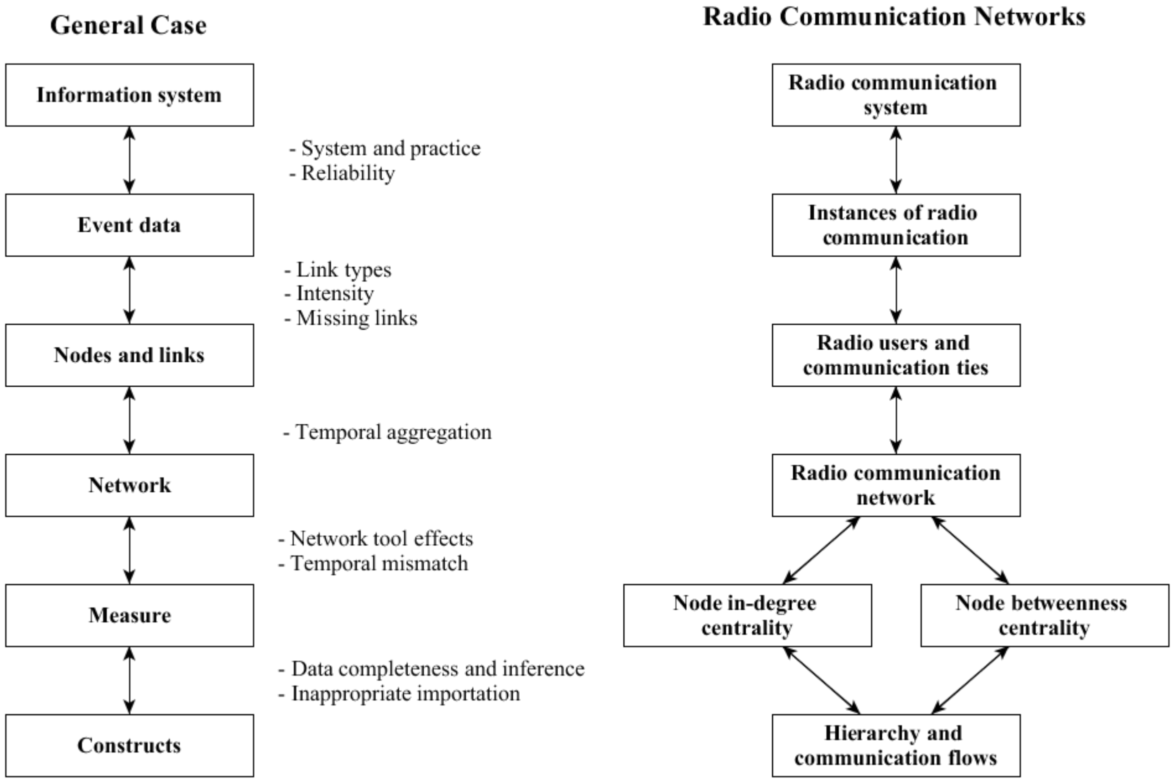
General Case
Information system
- System and practice
- Reliability
Event data
- Link types
- Intensity
- Missing links
Nodes and links
- Temporal aggregation
Network
- Network tool effects
- Temporal mismatch
Measure
- Data completeness and inference
- Inappropriate importation
Constructs
Radio Communication Networks
Radio communication system
Instances of radio communication
Radio users and communication ties
Radio communication network
Node in-degree centrality
Node betweenness centrality
Hierarchy and communication flows

Fig. 1: Conducting SNA based on Radio Communication Data (adapted from [9]).

from three German relief organizations simulated this incident with a particular focus on the evacuation of the festival venue. They were accompanied by representatives of the police, fire brigades, coastguard, local governmental authorities, and an observing research team, to which the authors belonged. In addition, the exercise involved groups of disaster volunteers spontaneously joining the relief efforts.

For the time of the exercise, the three relief organizations established a shared incident command system based on hierarchical relationships under a single director of operations. This structure of command and control based on a clear chain of command and control that is common in established relief organizations in Germany and that is manifested in their basic organizational routines and working rules, such as the“Dienstvorschrift 100” that has a counterpart also in the military service regulations.

The staffing of the exercise included a command center that was located several kilometers away from the exercise site and which hosted the operation controllers and the director of operations, who were responsible for planning and coordinating the response efforts in the field, as well as representatives of the other aforementioned organizations resuming advisory functions. Additionally, two operations control groups located in mobile command vehicles nearby the command center (in the following referred to as "‘mobile command units") were responsible for ensuring the radio communication flow and thus served as information hubs between the operation controllers and the responders in the field. The immediate area of operations was divided into three sub-areas, each of which was staffed with a local operation commander and approximately nine additional responders. Owing to the requirements of the exercise scenario, each response team worked on similar tasks related to the evacuation of persons and equipment simultaneously. Observers from other organizations and researchers were admitted to all locations at any time during the approximately three hours of operation.

Our data consist of personal observations of the operation controllers, mobile command units, and response operations in the field. Furthermore, we were given access to a dataset that contains all records of radio communication taking place during the exercise, including unique identifiers of the communicating individuals and the complete audio records of their conversations.[2] Hence, we could listen to the radio communication and observe when and between which radio users the communication took place in the aftermath of the event.

Below, we describe an exemplary workflow of conducting SNA research based on digital trace data as were obtained from this exercise.

3.2 Practical SNA Challenges and Opportunities for Radio Networks in the Emergency Response Field

Extracting communication events from the radio system. Initially, we identified from the radio system concrete instances of communication among users. These communication events are the basis for the extraction of network nodes and links and thus the first step of conducting SNA based on radio data.

In the emergency response field, radio systems that enable at least half-duplex communication – that is, non-simultaneous two-way communication, such as giving orders and receiving status updates – are common [3]. Responders taking part in the field exercise relied on a digital radio system that included an electronic interface by which the system can be connected to computers, making available

[2] Note, however, that recording emergency responders' radio communication can be problematic because German relief organizations require permission to do so. For the field exercise, the local authorities granted us permission to record emergency responders' radio communication.

electronic records of the communication, which includes detailed metadata, such as the technical identifiers of sending and receiving radio devices. While those identifiers are unique and exclusively assigned to specific individuals taking part in the emergency response field exercise, we had to employ qualitative coding techniques to match those technical identifiers with the corresponding radio names (used on the organizational level by the participants to address each other). Accordingly, we transcribed all radio communication records and manually coded the radio names of the senders and receivers of each radio message (i.e., the technical identifier and the radio names), the instant of time at which the message was sent, and the content of the message. This provides us with the necessary data to model the nodes of the network (defined by radio names and the corresponding technical identifiers) and the edges (defined by the recorded radio messages).

Further, based on the transcript of all radio messages, we identified events that occurred during the emergency response field exercise and which caused an increased amount of observable radio communication. A typical example of a communication event extracted from the digital record of radio communication is given in table 1 and refers to the launch of unmanned arealial vehicles (drones) to surveil the field.

Time	Sender	Receiver	Content of communication
10:01 AM	Responder 1	Responder 2	We will launch the drones in five minutes.
10:05 AM	Responder 1	Responder 2	We are launching the drones.
10:14 AM	Responder 1	Responder 2	The drones are back on the ground.
10:15 AM	Responder 2	Responder 1	Let us know when you are flying again.

Table 1: Radio communication example.

We experienced several issues during coding that we suspect are common problems when dealing with radio systems. The first has to do with *radio charts* and *radio discipline*. Members of relief organizations we talked to often praised radio for enabling reliable and standardized patterns of communication among responders. In particular, this is based on the common practice to prepare radio charts that define the radio name, operational role, and designated radio contacts of all users of a radio system prior to the actual emergency operations. This results in a well structured and hierarchical organizational chart of communication paths among the responders. Relief professionals we interviewed also expressed their intent to ensure compliance with radio discipline, meaning the avoidance of unnecessary calls and calls outside of the predefined routine.

Nevertheless, we witnessed cases in which radio charts were incorrect or incomplete, or in which inadequate flows of communication could not be prevented. During the field exercise, for instance, not all radio names and operational roles were predefined, which led to some confusion because some responders initially did not respond to their assigned radio names. Such unexpected patterns of radio usage can heavily complicate the practical identification of communication events from radio. This issue is, at least in part, related to the inter-organizational nature of emergency relief efforts. In this particular case, one of the relief organizations took the leading role in organizing the exercise. Due to organizational communication barriers, especially lack of trust and information sharing between the involved organizations, some members of other involved relief organizations did not receive all of the information that had been distributed beforehand. Such barriers, which manifest themselves as gaps in the inter-organizational flow of information, are a common phenomenon in this context [7,13,15].

Other problems arose from the *quality of the available audio records*. While common standards of radio communication (e.g., specifying the radio name of both senders and receivers at the beginning of a message) facilitate identifying users, we were not always able to do so because some recorded passages were inaudible. We were able, however, to identify senders and receivers and the timestamps of communication by relying on additional information from the electronic interface of the digital radio system.

Moreover, we noted that records of radio communication are almost necessarily incomplete. Relief organizations usually intend that all emergency-related communication take place via radio. During the field exercise, however, we could observe that communication, especially for longer messages, also took place via unrecorded channels, such as instant messaging, telephone, and face-to-face. Naturally, such communication is not covered by the radio system, which means that records might include non-random and possibly indiscernible *discontinuities in the communication flow*.

Modeling actors and communication ties from event data. The second challenge we faced was determining network nodes and ties from the event data. While radio users – as indicated by their radio names – could readily be regarded as nodes of the communication network, it was less clear when to assume a communication tie between them.

We discussed the modeling of different *types of communication ties* and decided to define a tie as the occurrence of a communication event between any pair of sender and (potentially multiple) receivers, under the condition that it referred to the ongoing emergency response operations. In our view, not incorporating additional information on the content of communication is acceptable in the restricted case of a simulated event with a narrow focus on the general structure of emergency responders' operational communications.

Next, we considered the *strength and direction of ties*. With regard to tie strength, we believe that dichotomization is mostly uncritical in the given context because radio communication essentially reproduced the predefined structures of the radio chart, with repeated communication stressing the role of the known information hubs in the network. As to the directionality of ties, including the directionality of the information flow enables insights into the role of specific users in the communication process. This information is relevant to our analysis for two reasons. First, including the direction of ties allows us to distinguish between simple (one-directional) commands and information exchanges (reciprocal ties). Second, the normative structure imposed by the participating organizations and emergency relief work in general suggests that the network shows strong hierarchical patterns resembling the information flows suggested by the radio charts. Those hierarchies define directed information flows, which can only be analyzed in directed radio communication networks. Therefore, we distinguish between the senders and receivers of messages and model edges as directed ties flowing from the former to the latter. Note, however, that we regarded receivers' affirmative responses to incoming calls – common in radio communications to signal that receivers are listening or have understood – to be part of the initial call directed towards them, which is part of the standard radio communication protocol that applies in this context.

Figure 2 illustrates different ways of modeling communication ties based on the radio communication recorded during the field exercise. Figure 2a is the directed, unweighted network on which our subsequent explanations are based. The directed edges indicate the flow of information from the sender (i.e., the radio user initiating the radio call) to the receiver (i.e., the radio user responding to the call). In contrast, figure 2b is the directed, weighted network in which the strength of a communication tie corresponds to the number of concrete instances of communication between two users. The tie strength indicates the sum of communication events between two users. Figure 2c is the undirected, weighted network and figure 2d is the undirected, unweighted network. With regard to the direction of ties, we can see that there are actors who serve primarily as senders or receivers of communication, which implies that they might fulfill specific roles in the communication networks (e.g., as coordinators [17]).

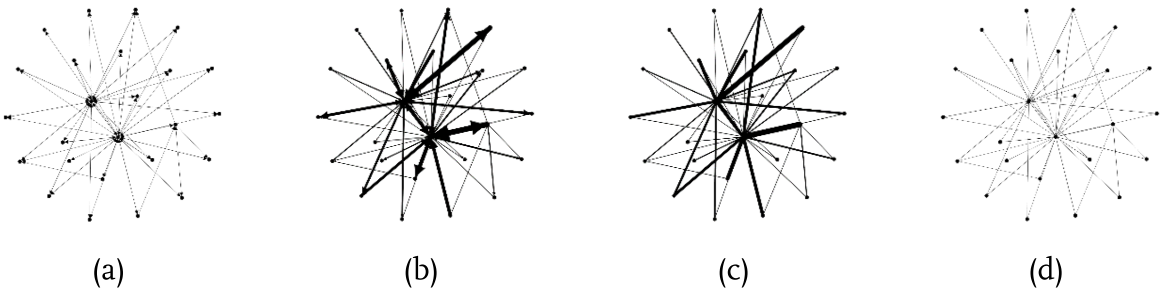

Fig. 2: Temporal aggregation of communication ties in a radio network.

Finally, *missing ties* were a minor problem for our analyses. As already pointed out, radio systems are systematically biased against unrecorded communication events. Such gaps in the records could be of considerable interest, however, because they indicate users' bypassing the designated structures of communication. Missing ties might furthermore derive from the partly untargeted nature of radio communication because emergency responders are used to listening in to bystanders' radio to keep up on the latest information. Therefore, it is not possible to define an exclusive set of receivers, even if the identity of active users is known.

Drawing from our experience, we recommend that radio data should be complemented by other sources, such as observations, interviews, and additional audio records wherever possible. During the field exercise, for instance, we collected additional data through observations and interviews. These additional data allowed us to validate our modeling decisions and verify the results we obtained through SNA. Ideally, network-based research in this context should follow a mixed methods design, which systematically integrates (quantitative) SNA and qualitative methods [6].

Modeling radio communication networks from actors and communication ties. In the next step, we aggregated the network elements extracted from the event data into a communication network. We were concerned in particular with the *temporal aggregation of network ties*. Our records of radio communication events included exact timestamps, which enabled us to investigate the dynamics of the radio communication network.

We decided to divide the dataset into activity-based timeframes – that is, we generated multiple snapshots of the network, each corresponding to a timeframe covering a specific event during the field exercise. This approach is common in the analysis of digital trace data that are collected in the wake of extreme events. For instance, previous research has aggregated social media messages that were initiated by the progress of crisis events or specific instances of communication (e.g., warning messages issued by the government) [4,5]. The timeframes were identified through a qualitative assessment of all available datasets: radio data, field observations, and interviews.

Figure 3 shows four network snapshots generated based on our approach. Network 3a represents the structure of radio communication between a local responder and a member of a mobile command unit while launching an unmanned aerial vehicle. It includes various status updates of the responder and covers a 15-minute period. Network 3b depicts the communication network of several local responders and an operation controller on the issue of coordinating a group of volunteers. In this case, the network illustrates the exchange of information and orders between users over an 8-minute period. Network 3c illustrates the final announcement of the upcoming end of operations by a member of a mobile command unit to all radio users in the last minutes of the field exercise. The specific events of radio communication on which these snapshots are based are described in table 2.

As these examples show, the network structure – and thus the outcomes of SNA based on these structures – depends strongly on the extent of temporal aggregation. Furthermore, the figure indicates that variations in the network structure can be captured well by an event-based approach.

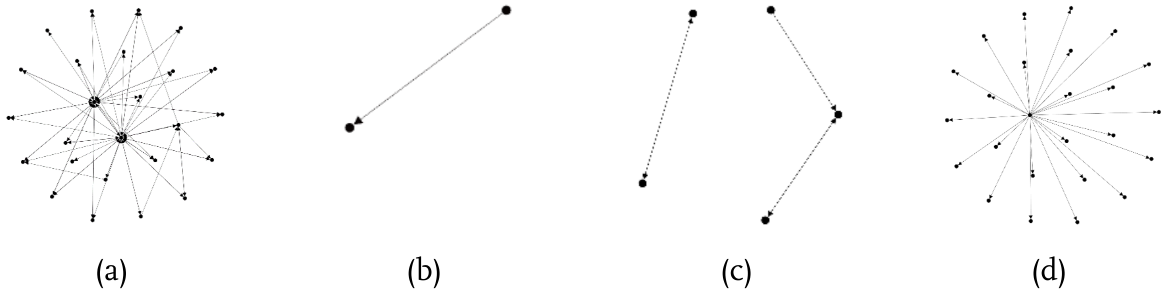

Fig. 3: Four (unweighted, directed) radio communication networks covering four different events.

It is noteworthy that radio data allow for precisely identifying the underlying patterns of peer-to-peer communication. Figure 3b, for instance, is an example of unicast communication, in which one sender targets one receiver. In contrast, figure 3c illustrates a case of concast communication, in which multiple senders address one receiver. Finally, figure 3d is an example for multicast communication in which one sender communicates to multiple receivers. While radio communication generally provides various opportunities for these types of communication between the radio users, the common practice of radio system usage prevents broadcast communication by suppressing interactions between users outside the predefined hierarchy.

Table 3 provides an overview of different communication patterns [21] enabled by radio communication in emergency response, to which we also added insights into the role of radio users in the communication process and example instances of this kind of communication.

Selecting appropriate network measures. Having generated a communication network from the radio data, we now focus on appropriate network measures. One instance that was of key interest to us was the hierarchical structure of the communication flows and the role of the mobile command units as central information hubs in the radio network. Although most activities involved only a few users (as figures 3b and 3c illustrate), almost all activities involved members of one or both

Figure	Time	Sender	Receiver	Content of communication
3a	10:34 AM	Responder 1	Responder 2	We have arrived at the operation area; We will report as soon as we are ready for the operation.
3b	11:35 AM	Responder 3	Responder 4	The coordinator of spontanous crisis volunteers informed me that there are no volunteers available for operation area 2. Is that right?
	11:35 AM	Responder 4	Responder 3	That is correct.
	11:36 am	Responder 5	Responder 4	We start with the pitching of the tents in area 2.
	11:37 AM	Responder 3	Responder 4	Request for security: Are there no volunteers for operation area 2?
	11:37 AM	Responder 4	Responder 3	We have four spontanous crisis volunteers, which are assigned exclusively to area 1 and 3. More are not available.
3c	12:14 PM	Responder 1	All responders	Mission accomplished; Lock up the vehicles and walk to the meeting place.

Table 2: Communication events.

Communication pattern	Roles of involved radio users	Functionality of communication (examples)
Unicast (1:1)	Both local responders and information hubs as senders and receivers of communication	Giving and receiving commands, sending and receiving status updates
Concast (m:1)	Both local responders and information hubs as senders and receivers of communication, but information hubs as coordinators of communication	Coordination of response activities and interactive reporting on the situation
Multicast (1:m)	Operation controllers or members of the mobile command units as senders as well as mobile command units and users on the ground as receivers	Announcements

Table 3: Communication patterns, roles, and examples of the field exercise.

of the mobile command units. This indicates that these users are essential for controlling the information flow in the network. The relative importance of the units seemed to vary, however, as they took turns answering and passing along calls. We suppose that computing user centralities for each activity-based window could help to clarify the role of key users. For instance, the in-degree centrality could assist in identifying users' respective workloads, as indicated by the number of incoming radio messages, and the betweenness centrality could indicate the importance of these users for information diffusion.

Inferring theoretical constructs from network measures. Finally, we discuss the insights of our example analysis of a radio network. At first glance, the overall network structure, as illustrated by figure 3a, resembles the information star network as identified by [18]. In particular, the network is highly centralized and characterized by two central information hubs – the mobile command units – that receive and distribute the larger share of information both horizontally and vertically within and between the organizational units. Apart from these hubs, only three other users have more than two communication ties to others. It follows that users mostly stuck to the predefined hierarchical communication structures as stipulated in the radio chart. This insight is not surprising since it mirrors the predefined hierarchical structure imposed by the radio chart that also reflects the hierarchical nature of relief organizations in general.

Considering specific action-based windows instead suggests a more dynamic view of both network structures and the role of the central users within them. Contrasting the degree and betweenness centralities within these windows suggests that the two information hubs alternated in their respective workloads and relevance for ensuring overall communication flow. While this finding is trivial for the small communication network obtained from the field exercise, such knowledge can be crucial during actual emergency response operations, for instance, to ensure an efficient flow of information among responders, design robust communication structures, and prevent information overload of central actors.

Since the field exercise was restricted to a timeframe of only three hours, the extent of observed network dynamics is, of course, limited. Furthermore, the field exercise was the result of a long planning process and involved only low degrees of stress and uncertainty for responders, which is atypical in emergency response operations. Nevertheless, operational tasks were chosen by experienced emergency managers and judged to be realistic by experts from all three relief organizations involved. Therefore, our results allow for initial insights into patterns of communication that might also be observed in a similar way under similar circumstances in a non-simulated emergency response. More importantly, however, we have described an example workflow of how radio data can be utilized for SNA, pointing to the challenges and opportunities of radio systems and indicating initial opportunities for future analyses.

4 Conclusion

Our paper's purpose was to discuss how SNA can be used to understand radio communication networks in the context of emergency response. In particular, we outline the importance of modeling and analyzing radio networks appropriately based on [9], experiences from a research project in the emergency management field, and a radio network obtained in an emergency response field exercise. We document and prototype a workflow that can be utilized for generating and analyzing emergency responders' radio communications from an SNA perspective.

Given the growing interest in emergency response communication in general [13,14,19], and emergency responders' radio communication in particular [2,17], our work is as a starting point for further SNA research based on such data.

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Analyzing the Missing Data of Online Travel Reviews Published in a Large Virtual Travel Community

Lisa Hepp

University of Bamberg,
An der Weberei 5, 96047 Bamberg, Germany
http://www.uni-bamberg.de

Abstract. In the present study, a data set of a virtual travel community is to be analyzed. The relationship between two variables of the data set is being examined with a regression model. The network was identified to contain a lot of missing data and the need to handle the missing data was presented. The missing data was found to be missing at random. A plan to handle the missing data in this specific data set by multiple imputation was developed.

Key words: Missing Data, Social Network Analysis, Multiple Imputation

1 Introduction

A huge data set of the virtual travel community trip advisor was generated by Roman Tilly [7] . It contains the user generated reviews of many accommodations worldwide. Using this data, we want to examine the relationship between the rating given for service and the rating given for check-in. The reviewers are given the option to rate several aspects of the accommodation such as the service or the location. Many users choose to only fill in some of these categories and leave others blank. This leads to a large amount of missing data in the network. Previous research has shown that simply ignoring missing data when analyzing social networks can lead to bias and lower the significance of the network analysis dramatically and should therefore be avoided [2]. It is therefore the aim of this work to prepare the given network data to allow further network analysis to be performed. In order to achieve this, the data was analyzed with a focus on the missing data. Reasons for the missing data and the missingness mechanism were identified.

The need for future work was outlined. The missing data will need to be implemented on the basis of a suitable multiple imputation method as presented by Huisman [4].

2 Methodology

2.1 Data

In the following, the data used in this study is being introduced. The reporting guidelines by Stef Buuren are used as an orientation here [1]. Roman Tilly developed a software to collect information available on the online travel platform tripadvisor. Using this method, around 7.89 million reviews in different languages on attractions worldwide were accumulated. The reviews in this data set were all published between 1999 and 2010. 26.564 randomly chosen reviews from this population were used as a sample for the here conducted study. The variables used in this study are listed in Table 1.

Compulsory	Variable	Description
x	*rating*	Overall rating of the property on a scale from 1 to 5
	reader_rating_helpful	Number of users who found this review helpful
x	*no_words_title*	Number of words in the title of the review
x	*no_words_content*	Number of words in the written review section
	detail_value	Value for money on a scale from 1 to 5
	detail_rooms	Evaluation of the room on a scale from 1 to 5
	detail_location	Evaluation of the location of the hotel on a scale from 1 to 5
	detail_cleanliness	Evaluation of the cleanliness on a scale from 1 to 5
	detail_service	Evaluation of the service on a scale from 1 to 5
	detail_check_in	Evaluation of the check in on a scale from 1 to 5
	detail_business_service	Evaluation of the business service on a scale from 1 to 5

Table 1: Description of the variables in the data set

Whenever the factor variables have levels from 1 to 5, then 1 corresponds to terrible, 2 corresponds to poor, 3 corresponds to average, 4 corresponds to very good and 5 corresponds to excellent.

To allow for quantitative analysis, the content in the fields *title* and *content* were transformend into integer variables only containing the number of words written in the corresponding section. Reviewers were obligated to fill in the categories *title* and *content* and hence there is no missing data here. Users are also required to fill in the category *rating* before submitting a review. Surprisingly, there are two values missing in this category, this is most likely due to technical issues. The category *reader_rating_helpful* is by default set to zero and hence this category does not have any missing values either. The value in this category can only be incremented when other users of the platform rate this specific review as being helpful and can thus not be rated by the reviewer itself. The amount of missingness of the categories with missing data is listed in Table 2.

Level	*rating*	*value*	*rooms*	*location*	*cleanliness*	*service*	*check_in*	*business_service*
1	10.9%	7.4%	6.5%	2.3%	4.8%	6.2%	5.0%	4.5%
2	10.5%	7.1%	7.2%	4.4%	5.3%	5.3%	5.8%	3.5%
3	11.2%	10.7%	12.1%	11.3%	9.9%	10.6%	13.1%	12.5%
4	26.1%	19.5%	20.8%	20.1%	17.8%	16.7%	16.7%	10.3%
5	41.2%	28.5%	27.8%	36.3%	36.7%	33.1%	33.2%	14.0%
NA rate	0%	27%	26%	25%	25%	28%	26%	55%

Table 2: Summary of all the categorical variables of the data set. The non-categorical variables of the data set don't have missing values and are therefore omitted here.

2.2 Data Analysis Method

At first the data set was investigated on a general level, summary statistics and frequency tables were generated. Then the focus was placed on the missing data of the data set. Again, frequency tables, combinatorics and plots were produced to gain a better understanding of the data. Reasons for the missing data and the missingness pattern need to be identified before further analysis can be conducted [1] [3]. Huisman distinguishes between data that are missing completely at random (MCAR), data that are missing at random (MAR) and data that are not missing at random (NMAR) [3]. When an item is missing completely at random, neither the (unknown) value of the missing item nor the observed items are related to the missigness of an item. In this case, the observed data is simply a random subset of the original set of oberservations, since there is no systematic bias. MAR means that the missingness of an item is not related to its value, but it is related to some of the observed data in the data set. The systematic bias can, in this case, be controlled as it is related to known values. The property MNAR describes the case in which the probability that an item is missing is related to the item's value. This mechanism can lead to a large bias and is hard to regulate. To determine the missingness mechanism in the data set, the following hypothesis is set up:

Hypothesis 1 H_0 *: The data is missing completely at random.*
H_1 *: The data is not missing completely at random.*

To test the null hypothesis, Little's test for MCAR was conducted using the R-package BaylorEdPsych on the entire data set [5] . The hypothesis is to be rejected if the corresponding p-value is less than 0.05.

In the next step, a further hypothesis was set up to investigate whether the reviewer's satisfaction of the attraction that is being reviewed and the thoroughness of the review are dependent.

Hypothesis 2 H_0 *: The overall rating of a review and the number of missing items in the review are not related.*
H_1 *: The overall rating of a rewiew and the number of missing items in the review are related.*

A Chi-Square test of independence was conducted on the value of the categorical variable rating and the number of missing values in the review to test this null hypothesis. The test was conducted with 26561 degrees of freedom at a significance level of 0.05.

After investigating the missing data, the complete cases of the data set were analyzed and summary statistics were computed.

2.3 Setting up the Analysis Model

In order to examine the relationship between the two variables *detail_service* and *detail_check_in* , a regression model is set up. Additionally to the above mentioned categories, the other variables of the data set (*rating, reader_rating_helpful, no_words-_title, no_words_content, detail_value, detail_rooms, detail_location, detail_cleanliness, detail_business_service*) were also taken into account.

Due to the mixed nature of the variables, some of them are of categorical nature and some are integers, a logistic regression model was chosen.

The logistic regression model is given by:

$$\begin{aligned} logitp(detail\_service) = y_0 + y_1 detail\_check\_in + y_2 rating + \\ y_3 reader\_rating\_helpful + y_4 no\_words\_title + y_5 no\_words\_content + \\ y_6 detail\_value + y_7 detail\_rooms + y_8 detail\_location + y_9 detail\_cleanliness + \\ y_{10} detail\_business\_service \end{aligned}$$

2.4 Imputation Methods

In the next step that has yet to be performed, an appropriate multiple imputation method will be chosen since Huisman identifies multiple imputation methods to perform the best when imputing missing data in social networks [4]. This imputed data set will then be compared to the complete cases and the performance of the imputation method and the usefulness of the imputed data set will be assessed. There are several imputation methods that could potentially be useful for the given data set.

3 Results

3.1 Missingness

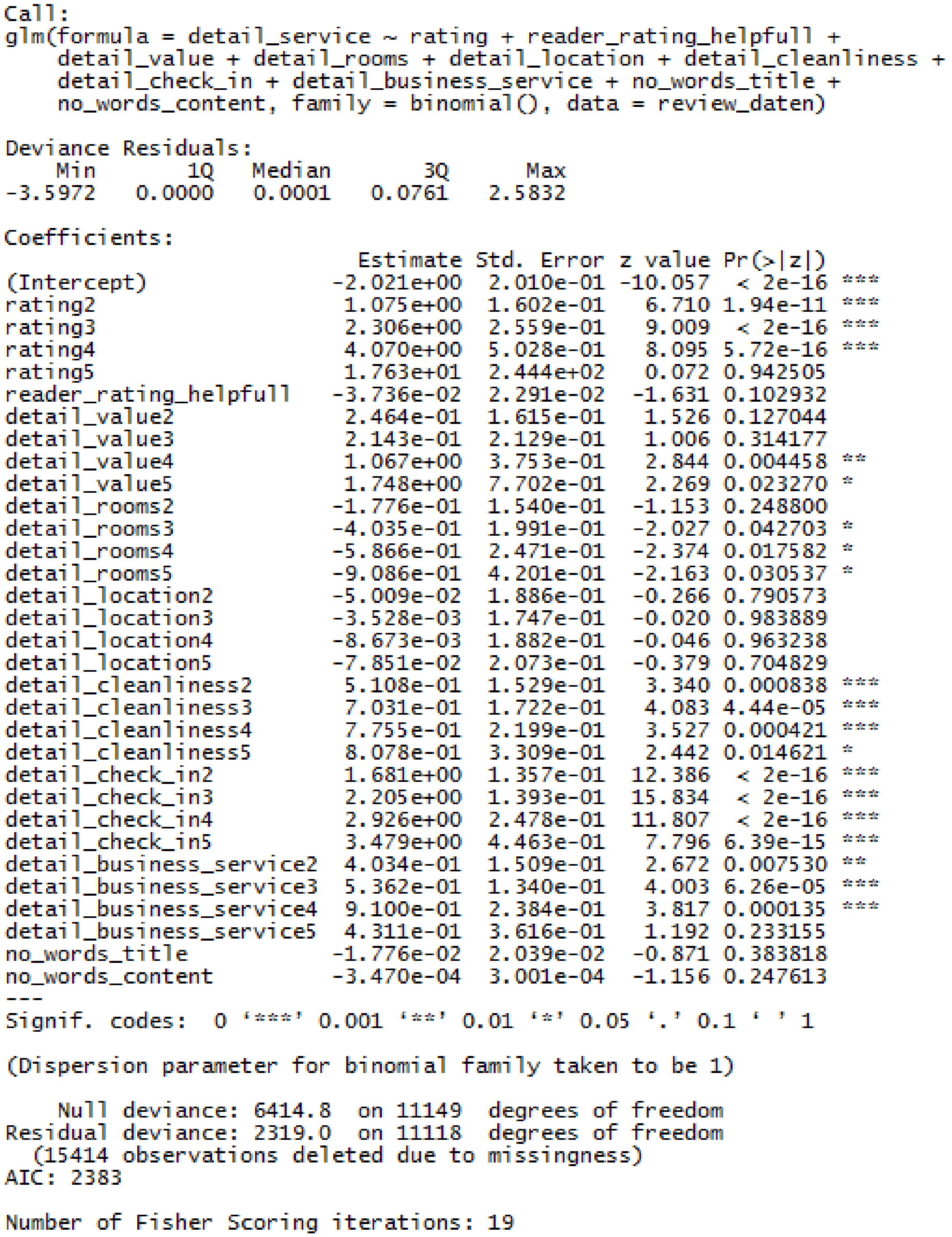
The data set used here contains 26.564 travel reviews with 11 categories each. These variables are listed in Table 1 and a summary of the categorical variables is given in Table 2. While the platform requires the user to fill in a rating, a title and a worded review, the other categories may be left blank. It can be seen that most categories suffer from missingness at a rate of approximately 25%. An exception to this is the variable detail_business_service with a missingness rate of 55%. The data set contains 11.150 complete cases, these are reviews without any item nonresponse. It is essential to observe the reasons for missingness and the missingness patterns and mechanisms before further analyzing the data set. Negligence and ambiguity may have led to missing data here [8]. Moreover, users may have omitted filling in some categories of the review if they felt they were closely related to another category and they wanted to avoid repetition. An example of such a pair of variables are *detail_service* and *detail_check_in*. The relationship of the missingness of the two variables is strong. Due to its nature of being a survey whose sample is chosen by self-selection, we do not have unit nonresponse here and only deal with item nonresponse. The hypothesis that the data are MCAR was strongly rejected with a p-value of zero when Little's test for MCAR was conducted [5] . Therefore, we assume the data to be MAR.

An interesting observation can be made that shows that there are two kinds of people writing reviews on this particular platform: Participants who fill in every single category or only miss out one rating and participants who only fill in the categories one needs to rate in order to submit a review. In fact, 42,0% are complete cases, 28,7% are only missing one item per review and 24,5% of the reviews are missing 7 values. Only 4,8% of the reviews have 2-6 missing items. This raises the question whether missingness only depends on the personality of the person writing the review and is independent of the accommodation that is being reviewed. To check this assumption, I first compared the values of the variable rating from the complete cases and the reviews with seven missing items ("obligatory data"). At first sight, the data looks very similar as can be seen in Table 4 and this strengthens the assumption that missingness is independent of the rating itself. Afterwards, a Chi-Squared test of independence was conducted to check whether rating and number of missing values per review are independent. With a p-value smaller than 2,2e-16 there is strong evidence that these factors are, in fact, dependent and the hypothesis was incorrect.

3.2 Logistic Regression Model

The logistic regression model for the dependent variable *detail_service* can be seen in the following figure 1.

The model output shows that not only the covariate *detail_check_in* but also the covariate *rating* is highly significant for every value of the categorical variable.



```
Call:
glm(formula = detail_service ~ rating + reader_rating_helpfull + 
    detail_value + detail_rooms + detail_location + detail_cleanliness + 
    detail_check_in + detail_business_service + no_words_title + 
    no_words_content, family = binomial(), data = review_daten)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-3.5972   0.0000   0.0001   0.0761   2.5832  

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)    
(Intercept)             -2.021e+00  2.010e-01 -10.057  < 2e-16 ***
rating2                  1.075e+00  1.602e-01   6.710 1.94e-11 ***
rating3                  2.306e+00  2.559e-01   9.009  < 2e-16 ***
rating4                  4.070e+00  5.028e-01   8.095 5.72e-16 ***
rating5                  1.763e+01  2.444e+02   0.072 0.942505    
reader_rating_helpfull  -3.736e-02  2.291e-02  -1.631 0.102932    
detail_value2            2.464e-01  1.615e-01   1.526 0.127044    
detail_value3            2.143e-01  2.129e-01   1.006 0.314177    
detail_value4            1.067e+00  3.753e-01   2.844 0.004458 ** 
detail_value5            1.748e+00  7.702e-01   2.269 0.023270 *  
detail_rooms2           -1.776e-01  1.540e-01  -1.153 0.248800    
detail_rooms3           -4.035e-01  1.991e-01  -2.027 0.042703 *  
detail_rooms4           -5.866e-01  2.471e-01  -2.374 0.017582 *  
detail_rooms5           -9.086e-01  4.201e-01  -2.163 0.030537 *  
detail_location2        -5.009e-02  1.886e-01  -0.266 0.790573    
detail_location3        -3.528e-03  1.747e-01  -0.020 0.983889    
detail_location4        -8.673e-03  1.882e-01  -0.046 0.963238    
detail_location5        -7.851e-02  2.073e-01  -0.379 0.704829    
detail_cleanliness2      5.108e-01  1.529e-01   3.340 0.000838 ***
detail_cleanliness3      7.031e-01  1.722e-01   4.083 4.44e-05 ***
detail_cleanliness4      7.755e-01  2.199e-01   3.527 0.000421 ***
detail_cleanliness5      8.078e-01  3.309e-01   2.442 0.014621 *  
detail_check_in2         1.681e+00  1.357e-01  12.386  < 2e-16 ***
detail_check_in3         2.205e+00  1.393e-01  15.834  < 2e-16 ***
detail_check_in4         2.926e+00  2.478e-01  11.807  < 2e-16 ***
detail_check_in5         3.479e+00  4.463e-01   7.796 6.39e-15 ***
detail_business_service2 4.034e-01  1.509e-01   2.672 0.007530 ** 
detail_business_service3 5.362e-01  1.340e-01   4.003 6.26e-05 ***
detail_business_service4 9.100e-01  2.384e-01   3.817 0.000135 ***
detail_business_service5 4.311e-01  3.616e-01   1.192 0.233155    
no_words_title          -1.776e-02  2.039e-02  -0.871 0.383818    
no_words_content        -3.470e-04  3.001e-04  -1.156 0.247613    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 6414.8  on 11149  degrees of freedom
Residual deviance: 2319.0  on 11118  degrees of freedom
  (15414 observations deleted due to missingness)
AIC: 2383

Number of Fisher Scoring iterations: 19
```

Fig. 1. Output from the logistic regression model

# items missing	0	1	2	3	4	5	6	7
# reviews	42.0%	28.7%	3.7%	0.5%	0.1%	0.1%	0.3%	24.5%

Table 3: Number of reviews that have 0, 1, 2, ... , 7 items missing expressed in percentages

Value of the variable rating	**Frequency datencC**	**Frequency datenOb**
1	9%	13%
2	9%	10 %
3	10%	10 %
4	26%	24 %
5	45%	43%

Table 4: Comparison of the relative frequency of a specific value of the variable rating from the data set containing only complete cases and the data containing only the obligatory fields.

4 Discussion

This work understands itself as making a first step towards dealing with the missing data of the trip advisor data set to allow for network analysis in subsequent research. The data set was analyzed and looked at with an open mind and reasons for and properties of the missing data of the data set were described and a further research plan was outlined. The next step of the analysis would be to find the most suitable imputation method from the comprehensive list of imputation methods listed by Huisman and Krause [4]. After imputing the missing data of the data set, it needs to be compared to the complete cases of the data set to evaluate the performance of the imputation method on this specific network. Older imputation methods do not perform well when the missing data is not MCAR and therefore a modern imputation method will be chosen to avoid bias [4]. The most crucial part when applying multiple imputation is the specification of the imputation model [6]. An exponential random graph model (ERGM) will be used here since this is a promising approach to multiple imputation [4].

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Modeling, analysis, control, and management of complex social networks represent an important area of interdisciplinary research in an advanced digitalized world. In the last decade social networks have produced significant online applications which are running on top of a modern Internet infrastructure and have been identified as major driver of the fast growing Internet traffic.

„The Second International Workshop on Modeling, Analysis and Management of Social Networks and Their Applications“ (SOCNET 2018) held at Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany, on February 28, 2018, covered related research issues of social networks in modern information society. The Proceedings of SOCNET 2018 highlight the topics of a tutorial on „Network Analysis in Python“ complementing the workshop program, present an invited talk „From the Age of Emperors to the Age of Empathy“, and summarize the contributions of eight reviewed papers. The covered topics ranged from theoretical oriented studies focusing on the structural inference of topic networks, the modeling of group dynamics, and the analysis of emergency response networks to the application areas of social networks such as social media used in organizations or social network applications and their impact on modern information society. The Proceedings of SOCNET 2018 may stimulate the readers‘ future research on monitoring, modeling, and analysis of social networks and encourage their development efforts regarding social network applications of the next generation.

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