Signatures of subjective quantities

Data, measurements and models

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To Geetika, Medha and Chanda ... The three formidable pillars of my life

DECLARATION

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other University. This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration, except where specifically indicated in the text. The dissertation covers contributions for journals and conferences where I was the main contributor and primary investigator.

Sagar Joglekar
April 2019

Acknowledgements

And I would like to acknowledge ...

ABSTRACT

Research in the field of recommendation systems have shown that *subjective preferences tend to follow deterministic patterns, when looked at data in large sample sizes*. This principle underpins several of our present day applications like recommendations while shopping for items online or visiting places to eat or listening to music. With the ever pervasive nature of the internet, we as a society have gone beyond treating the online spaces as a tool to access information, and have started treating them as a natural extension of the self. We spend more time than before as a part of a larger networked community, exchanging thoughts, debating ideas, expressing creativity and "socializing". We also sometimes indulge in expression of human emotions like empathy, anger, sadness and sometimes seeking help. At such a juncture, I examine the thesis **Can we quantify entities of subjective nature, if the data is large enough, and originates from human responses?**. In this dissertation I develop data driven pipelines with the aim to quantify perceptions of subjective qualities, through two case studies. In the process, I provide a broad overview of how intangible subjective properties exhibit in data and develop metrics to quantify them. I also reason about the utility of said properties when it comes to developing interventions.

In the first study I analyse on-line formal networks where interactions between humans are purely with the intent of helping each other. I develop frameworks to abstract out the structure of these interactions. I then delve into investigating presence of perceived support by finding discriminative local structures in these abstractions. I reason about these local structures using established cross disciplinary theories. This informs my analysis about the nature of peer to peer support in these communities and paves the way to do actionable interventions in the area of peer support in online networks.

In the second study, I investigate utility of perception of aesthetics in physical spaces, by developing a pipeline that capitalizes on crowd sourced responses about urban aesthetics. I propose a deep-learning driven framework, which is able to quantify the perception of intangible abstract qualities like 'beauty' through a crowd sourced rating of google street view images. I show that a general pattern of beauty in urban spaces can be learnt through a crowd sourced opinion and deep learning models. I further develop a generative model

to simulate beautification of urban spaces. Through a detailed literature review of the field of urban design, I develop a measurement framework which can provide insights into the predictors of urban beauty on a case by case basis. I then develop the necessary tools to evaluate these metrics using computer vision techniques. I validate the value of these metrics through expert survey and also validate the interventions using crowd sourced perception experiments.

In the course of the work, I contribute original design and implementations of different data driven pipelines, which can be used to quantify signatures of subjective properties in a way that can drive interventions and impact real lives.

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CHAPTER 1

INTRODUCTION

There are things known and there are things unknown, and in between are the doors of perception - Aldous Huxley - *Doors of perception*

1.1 Introduction

We live in a world where information is being bombarded on our cognitive faculties from all sides, at all times. The internet is a continuous stream of information and each source is fighting with the other to get a piece of our attention budget. With the advent of machine learning and big-data sources, building systems that predict actions as a response to perceptual triggers is the bread and butter of many companies. The use cases may range from understanding which advertise made a visitor do an unscheduled purchases on amazon, or which string of music tracks recommendations maximized a users time on a particular music platform. But in the end it all boils down to understanding what triggers result in human action or lack there of [70]. Nonetheless the systems that surrounds a human interacting with the internet, are all figuring out the best triggers which are perceived by the human as worthy of attention. The term "Attention Economy" [22] was actually coined for this very reason. In the words of Matthew Crawford "*Attention is a resource, a person has only so much of it.*" [20]. We live in the age of distraction, and more often than not, our subjective perceptions are guiding our actions, than our conscious cognitive processes. Several studies have shown that engagement is almost always a game of stimulating our most basic urges, such as dopamine hits, presence of faces or simply arousal of emotions to increase the working memory. [6, 38] [64] [69].

An interesting side effect of dwindling attention budgets is the emergence of more formal topical spaces on the internet. The ever pervasive nature of the internet allow these formal spaces to function almost like physical communities, with moderated and effective peer to peer exchange of thoughts, ideas and empathy [34, 43, 71]. In such an environment, as computer scientists, it is worth asking the questions:

How do subjective human perceptions manifest in data?
Can quantifying these help us design better interventions ?

These two questions are going to be the guiding principles of my dissertation. But first of all, we need to clarify the relation between perception, affects and data. To do so we should try and understand each of these terms separately in the context of the field of application.

1.2 Perception and Affect

Across my work , I would try to build frameworks to capture subjective human perceptions in the realm of human to human interactions and subjective intangible qualities like the sense of beauty or the sense of perceived support. The utility of such an attempt, can only be justified if there is a real link between how humans function at the most fundamental cognitive level and how they perceive the intangible, including the aesthetic. There has been an ongoing effort to unravel this link, through psychological, neuro-evolutional and philosophical arguments. I will try to gain inspiration from them, but a detailed critique is beyond the scope of my dissertation and expertise

Affect [1]*: Any experience of feeling or emotion, ranging from suffering to elation, from the simplest to the most complex sensations of feeling, and from the most normal to the most pathological emotional reactions.*

[1] American Psychological Association definition.

Perception [2]*: The process or result of becoming aware of objects, relationships, and events by means of the senses, which includes such activities as recognizing, observing, and discriminating. These activities enable organisms to organize and interpret the stimuli received into meaningful knowledge and to act in a coordinated manner.*

Emotions or ‘affects’ and perceptions have long been discussed in the psychology, neuroscience and philosophical literature. Emanuel Kant in his prolific work, first discussed the utility and the philosophical reasoning behind presence of affects or emotions[39]. In his opinion, emotions are pre-cognitive involuntary states, termed as "mere perceptions of unspecified bodily states"[12]. But that does not mean they don’t influence our deepest level of well-being and influence our decision making processes. The link between affect and perception has also been explored in several other cases. An argument to link perception of affect producing aesthetics was made by Perlovsky[60], where they propose that the phenomenon of affects arousing from aesthetics, comes from a fundamental human need to enrich the knowledge about real world. An unexpected thing, stimuli or structure in physical space creates a dissonance between our expected model of the world and the perceived reality at some level and we perceive it as aesthetically pleasing. Another recent study by Zadra et.al[76] evaluated the relation between visual perception and emotions. They demonstrate that the conventional assumption of the disentangled functioning of perception and affects is not necessarily true. Humans are quite susceptible to perceiving different realities based on different aroused affects.

The discussion on the formal definition and process of affects will continue, but there seems to be a consensus, at-least among the computer science and information science community that affects do influence our decisions and we perceive information through a filter of affects. Affective triggers can be generated when information is formatted or packaged in a certain way. In such a setup, it is worth testing if certain affect driven interactions on the web leave a trail of patterns in the data of these interactions. Furthermore it is work asking if these patterns might in some way be used to improve our online and physical environments.

[2]American Psychological Association definition.

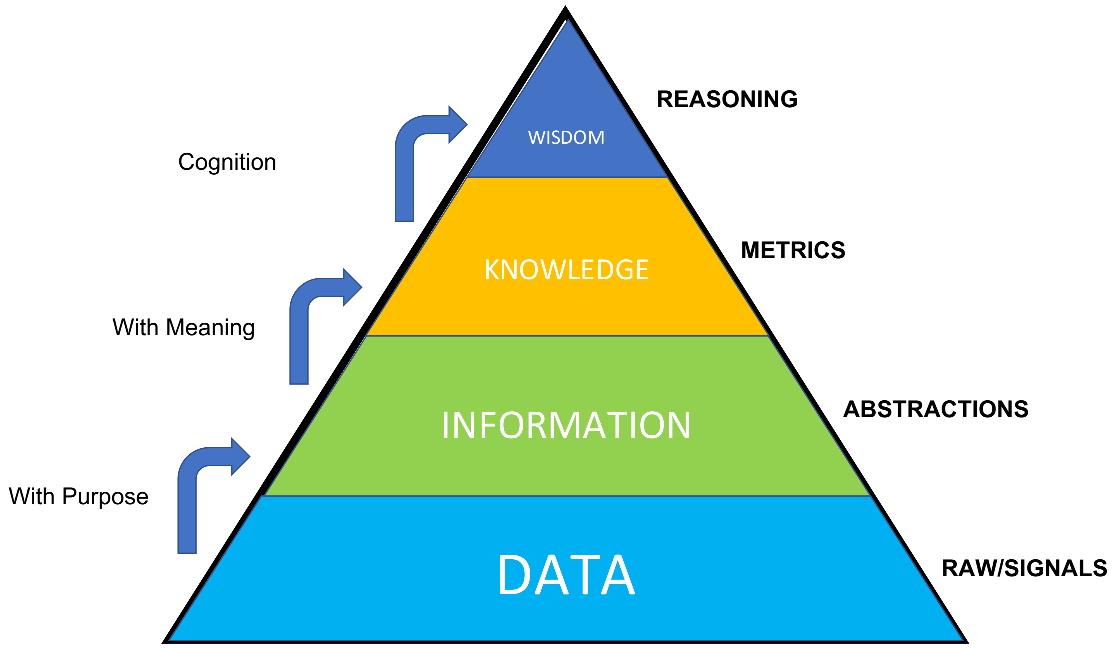


Fig. 1.1 The DIKW pyramid

But to arrive at these patterns, one needs to understand the frameworks of approaching such a problem. The journey from Data to subjective signatures, has to go through a series of operations.

1.3 Intervention and the DIKW model

In attempt to develop metrics and pipelines, one has to reflect on one of the fundamental frameworks about operations on data, that is the **Data , Information, Knowledge and Wisdom** model[62].In this dissertation I posit and demonstrate through case studies, that for any reasoning about subjective perceptions , you need to develop frameworks that extract knowledge from data in a format that is aligned with the ontological framework of the application. In the context of this dissertation, ontology implies a set of concepts, definitions and relations between entities defined around a common set of axioms. I show that if a set of relations and definitions of concepts in the area of intervention are present, 'a' solution can be reached provided that systems are designed to interpret metrics extracted from the data in relation to the ontology of the area of application. But to reach this step, the data needs to pass through the 4 layers of the DIKW pyramid model.

In this model, the most foundational layer consists of the pure form raw **data or signals** that come from a source. If we are measuring subjective perceptions of humans, this source needs to be tied back to humans in some way. To that extent, the data must ideally be a product of human to human interaction online. Or it needs to capture the human perceived responses, through explicit exercises like crowd sourcing or public surveys. In this dissertation, I present various data sources and methods of collecting and curating data, which pertain to human-human interactions or human responses.

The **information** layer is the result of the fact that any process done on the data is with a sense of purpose or an end goal. For example, if the goal is to understand how humans exchange messages at times of distress, you would most certainly need to express the raw information about sender and recipient of messages into some form of a networked abstraction. The abstraction preserves the organization of data, but at the same time allows information to be operated on. As a result, almost always the output of this process is some form of a data abstraction. You need to attach some meaning to the patterns in the information to extract knowledge about the fundamental processes that you want to measure.

Knowledge. Defining knowledge has been an ongoing effort in the field of philosophy. But in the context of information science, knowledge involves collation of diverse sources of information and mix of contextual information, values and metrics to deliver a coherent understanding of the real world. For example, if you need to know the most popular user among a social network of users exchanging messages; you would look for the most central user in the network(abstraction) along with several other temporal and structural metrics to arrive at a few candidates. In this particular case, these metrics, along with the context of the social network's design, dawns the meaning of popularity.

The final layer needs a cognitive process and an ontological framework, to extract actionable insights, which we can call **wisdom**. By classical definition of ontology, it defines properties of and relations between objects or concepts. For this very reason, these ontological frameworks need to be originating from the fields of intervention. In our example, lets assume we need to get some insights about the dynamics of popular users. Particularly in the context of optimizing advertising delivery. For example we need to understand how a particular piece of advertising, might percolate through the network if certain popular users advertise it [44]. However , to arrive at these insights we need to be grounded in the ontological frameworks of epidemiology, network physics and depending on the application, advertising or meme theory. Then using the abstractions of social networks, the metrics derived from them, and the ontological basis of all the aforementioned fields, one can design a pipeline that could deliver us these insights with reasonable accuracy.

Figure 1.1 shows an illustration of the adopted version of Rowley's DIKW model, which I would refer back as a repeating motif for my dissertation.

1.3.1 Data

Data is one of the most fundamental contribution of this work. To develop frameworks around quantification of human perceptions, such that we can do impactful interventions from this approach, we first need to make sure we formalize how we acquire, clean and condition our data. The most base level of this pyramid is the data that the frameworks would work with in order to progress on these lines. I work with diverse forms of data such as textual data , video data and image data to understand how these might exhibit signatures of human perceptive processes. The relation between data and subjective attributes needs to be examined using some proxy. For this reason, my research involved collecting data from sources where either human to human interactions happen or the data is generated on account of a human expressing their opinion about a subjective quality like beauty of a place, or how much someone "likes" an image or a video.

Interaction Data

In the first case study of this dissertation focusses on is online support communities, where human to human interaction is at the centre of the utility of these communities. It has been shown through several studies in medical informatics, that these communities play a very important role in providing support and respite in times of distress [4] [50, 59] [9, 35] [33].

The communities are especially helpful when it comes to people suffering from long term illnesses or mental health issues. The key element that impacts the users is the perceived social support [52], which delivers people in distress a sense of belonging to a group and empathy from the fellow supporters. To understand how users on these communities perceive social support, I work with data acquired from online health forums, where users share, give support and ask for support. I look at communities that deal with long term conditions like Lung illnesses, and communities where mental health patients seek support [37]. The data spans across a duration of 10 years, containing peer to peer support interactions of more than 30,000 users. I also crawled a popular forum based social network called reddit [3] to acquire a peer to peer support forum data regarding mental illness and suicidal thoughts. The data covers discussions about more than 30,000 calls to support, and incorporates the complete structure of the way people respond to these calls.

Media data

The other facet of my work looks for quantification of how we perceive physical spaces. Whether a street is considered beautiful is a matter of subjective opinion, yet research has shown that there are specific urban elements that are universally considered beautiful: from greenery, to small streets, to memorable spaces [2, 61, 63]. These elements are those that contribute to the creation of what the urban sociologist Jane Jacobs called 'urban vitality' [36]. Apart from vitality, these motifs in urban environments are also highly correlated with feeling of well-being, health and safety [40]. There have been studies where people have tried to use crowd sourcing to acquire subjective ratings of images [65] which have shown some reasonable progress on this front. But the real gap in these studies is understanding the impact of urban elements on the perception of these subjective qualities. E.g. How much does presence of a green garden affect the subjective rating of beauty of that particular area. For this reason, I work with google street view data and subjective ratings of various places around the world [51], with the aim to understand, how people perceive the sense of beauty in urban areas. Then using the ontological basis of urban design and architecture, developed

[3] www.reddit.com

by a detailed literature review, I aim to develop machine learning pipelines that can suggest interventions to change perceptions of physical spaces.

1.3.2 Abstractions

The act of aggregating information from data, almost always involves building organized abstractions. Throughout my dissertation, I either repurpose well known abstractions in computer science or develop my own using tools from fields like computer vision and Information theory. For the first study, I incorporate user meta data and the textual data of their activity, to build organized networked abstractions representing the conversation structures on the support forums. I use these abstractions to evaluate global and local structures in support communities, which would be discussed in detail in Chapter 2 and 3.

While working with media data, I use several pixel level abstractions to segment and group semantically similar pixels. I also use several state of the art object and scene detection to extract semantic information from an image, with the aim at analysing correlations with the perception of subjective attributes of images with these metrics. I also use deep convolutional networks and generative models, to abstract out a representation of beauty. A more detailed discussion of these abstractions would be done in the later chapters (Chapter **??**).

1.3.3 Knowledge

For extracting knowledge, we need to first associate meanings to certain computable metrics that we obtain from the abstractions. As discussed in the previous example, it could be as simple as associating the property of “popularity” to the metric of centrality. In my case, I develop several of these metrics to related subjective properties with measurable structures in data. Some of these metrics are based on intuitions which I validate, and some based on extensive literature survey. To give an example, I develop the concept of anchored triads, which combines local structures in interaction graphs of users, with the role of a user in a supportive conversation, to understand how these conversations evolve.

1.3.4 Wisdom

Finally the wisdom , in definition underlies insights that come for experience. The experience could come simply from the scale of data or from cross disciplinary literature that puts forth theories of subjective experience. E.g. The theory of social support puts forth four categories of social support 1)Affective/Perceived 2)Instrumental 3)Informational 4)Appraisal. Each type has its own specific traits. My dissertation looks at these theories from the lense of computational social science, and develops processes to quantify signatures of affective support.

1.4 Research Thesis and Research Questions

The overarching thesis question of interest that I would explore through the two case studies is:

> How do we quantify perceived qualities from data, if the data source is human and the scale is large?

But this thesis question is quite open ended, and answering it in a generalized manner seems impractical in the scope of one Ph.D. For this reason, I need to first contextualize my work in the realm of practical applications, by deriving more focussed research questions, such that I can acquire data and test my hypothesis in an effective time bound manner. More so, being an impact driven person, I would like to focus on applications which have the potential to have real world impact, either through interventions or through inspired interest in the field.

1.4.1 Supportive Interactions on the web

Humans are social animals in every aspect. The presence of social support systems in ones lives have shown to have huge quantifiable benefits. From speeding up recovery in cases of post-partum depression or in the cases of cancer survivors [8, 17, 28] , to signs of positive turn around among patients suffering from alcoholism and depression [14, 58], social support is a key predictor of positive prognosis for patients under distress. With the advent of internet, a lot of communities have sprung up, which provide a rich platform for patients to interact, exchange support as well as provide a perceived sense of community. These communities are moderated, only to an extent to curb toxic behaviour, but other than that are largely free form. Due to a very homogenous membership, where most members have either gone through or are going though similar distress, there is an emergent sense of support and affective empathy [26]. The idea of this case study was to quantify how supportive processes evolve over these communities, using abstraction methods from the fields of network science. The hope in doing so, is that the communities would be better poised to tackle any disturbances in the dynamics of these supportive communities as well as quantify the net utility these communities offer to the users.

The investigation of these would lead me to form the following research questions

RQ1 *How do support communities thrive?*
RQ2 *How do we quantify support on these communities?*
RQ3 *Are there any macroscopic signatures of supportive conversations?*
RQ4 *Are there any mesoscopic signatures of supportive conversations?*

To achieve this I first had to collect data from two different communities designed for online social support. The first community is dedicated for patients suffering from chronic lung diseases, such as Asthma or Chronic Obstructive Pulmonary Disorder (COPD). This community was moderated by self appointed moderators, and everyone on this community was either a survivor or a patient of these diseases. This community allowed patients to ask questions about symptoms and home remedies and sometimes just bond over social interactions. The second community I worked with dealt with people suffering from chronic depression and suicidal thoughts. This community was a safe haven for such people to vent out suicidal thoughts and get support from peers to manage these sudden flares of thoughts of self harm.

Through these two communities, I develop a pipeline to analyse the peer to peer interactions using abstractions derived from network science. The abstractions try to mimic the conversation structure which allows me to probe the evolution of such conversations both in terms of macroscopic properties as well as local interactions between users. I also develop metrics inspired from psychology and sociology literature to quantify how these interactions can be qualified as supportive or non supportive. Through a data driven analysis, I establish confidence on these metrics. Through this process, I also report my findings about the dynamics of users on these communities and key properties of user roles. I find that these conversations have a distinct nature when compared against regular baseline conversations over the web, and these distinct signatures could one day be used to curb toxicity as well as improve the support community interface.

1.4.2 Leveraging aesthetic perceptions of real spaces

Urban aesthetics and presence of certain elements in the physical spaces that we use, have shown to have lasting effects on our mental health[66] and physical well being[7, 31]. However, with the advent of large scale data access, and machine learning techniques, we have a unique opportunity to quantify what exactly comprises of urban aesthetics. In the next part of my dissertation, I aim at using the scale of the internet to try and improve how our cities are perceived. In this study, I investigate the following research question:

RQ5 *Can crowdsourcing and machine learning help us quantify how humans perceive aesthetics in urban settings?*

RQ6 *Can machine learning leverage this quantification to improve aesthetics of urban spaces?*

RQ7 *Do humans and practitioners find these interventions worth the effort?*

Crowdsourcing is a method through which one could get inputs, subjective or otherwise, about a particular set of questions from a large number of real humans using the internet. In return the participants could be offered a tangible compensation, or in some cases, a gamified incentive. The **RQ5** motivates me to investigate if we can use crowdsourcing to quantify how people perceive urban spaces. Research has shown that if a large number of people could vote on a set of images, regarding their aesthetic quality, a trend emerges that favours some objective metrics of beauty[21, 61**?**]. Can we link these metrics to urban elements? For this reason we work with google streetview images, where real people vote on aesthetic value of images through a large scale crowdsourced study. After evaluating for statistical trends in preference of aesthetic urban images amongst the voters, we answer **RQ5** by training a deep convolutional neural network model, which can discern between an aesthetically pleasing and unpleasant urban scene with a high degree of accuracy. Once we have a model that could "detect" beauty in urban scences, we could then use machine learning and deep learning techniques to understand how different urban elements relate to the notion of beauty (**RQ6**). I further try to build a tool, which could use the quantified notion of beauty in urban spaces, to hint practitioners about possible actions to beautify any given urban space. These hints are given in the form of suggested changes in different popular urban design metrics, which makes the whole process legible to practitioners in the field. In the pursuit of answering the **RQ6** and **RQ7**, I propose deep neural network and generative adversarial network models to make an end-to-end pipeline which can be then used to visualize how different urban elements affect the perception of beauty in the real world.

1.5 Thesis overview and original contributions

In Chapter 2, I examine how supportive communities evolve and sustain over a long period of time. I show presence of an anti-rich club effect on these support groups, which implies that experienced users are more interested in helping new comers rather than forming a clique of their own. I define a quantitative metric for “expertise” and show that as one becomes adept, one becomes more willing to help. All these original insights point towards answers for **RQ1** and **RQ2**. In Chapter 3, I look at global(macro-) and local(meso-) structures of supportive conversations. I show that mapping the conversation exchanges onto a topological structure exhibits keen preference for local supportive motifs, which I call “anchored motifs”. I discuss the utility of such a model of support conversation and draw parallels with the offline model of community support(Chapter 4) as per the mandate of **RQ3** and **RQ4**.

In the second study, I investigate utility of perceptions of real world places through a crowd sourced rating of google street view images. As per **RQ5**, I develop models to extract the perception of the crowds using data driven inference methods(Chapter 4). I then show that a general pattern of beauty in urban spaces can be learnt through a crowd sourced opinion and based on this finding, I develop a generative model to simulate beautification of urban spaces by using deep learning(Chapter 5). I validate the quantification of perception of real-world beauty using crowd validation. I contribute a way to use computer vision techniques to abstract out beautification process into explainable metrics used by architects and urban planners. The final contribution is a demo web application, that allows practitioners to examine and validate the utility of such a end to end system that captures citizen perceptions for urban design. These contributions are motivated by **RQ5** and **RQ7**. I close by enumerating the different research problems and future directions that my work would pursue as a early career scientist(Chapter 6)

1.6 List of peer reviewed publications

I would like to list all the publications which resulted from the past 4 years of work, as well as collaborations I was able to strike with a diverse group of researchers. The author lead publications have influenced different chapters of this dissertation.

1.6.1 Original author contributions

List of papers, published and in review, which were led by the author or where the author had fundamental contribution

1. **Joglekar, Sagar**, Nishanth Sastry, and Miriam Redi. "Like at First Sight: Understanding User Engagement with the World of Microvideos." International Conference on Social Informatics. Springer, Cham, 2017.

2. **Joglekar, Sagar**, et al. "How online communities of people with long-term conditions function and evolve: Network analysis of the structure and dynamics of the asthma UK and British lung foundation online communities." Journal of medical Internet research 20.7 (2018).

3. **Joglekar, Sagar**, et al. "Online discussions about mental health in Reddit exhibit signatures of supportive conversations" Under Review

4. **Joglekar, Sagar**, et al. "FaceLift: A transparent deep learning framework beautifying urban scenes" Under Review

5. Kauer, T., **Joglekar, S.**, Redi, M., Aiello, L. M., & Quercia, D. (2018). Mapping and Visualizing Deep-Learning Urban Beautification. IEEE computer graphics and applications, 38(5), 70-83.

1.6.2 Collaborative author contributions

List of papers, published and in review, where the contribution was significant, but were not led by the author

1. Bhatt, S., **Joglekar, S.**, Bano, S., & Sastry, N. (2018, April). Illuminating an ecosystem of partisan websites. In Companion of the The Web Conference 2018 on The Web Conference 2018 (pp. 545-554). International World Wide Web Conferences Steering Committee.

2. De Simoni, A., **Joglekar, S.**, Taylor, S. J., Patel, A., Duschinsky, R., Coulson, N., ... & Evans, M. J. (2017). Structure and dynamics of online patients' communities: the case of Asthma UK and BLF online fora.

3. YOUNG, A. P., **Joglekar, S.**, GARIMELLA, K., & SASTRY, N. (2018). Approximations to Truth in Online Comment Networks.

4. Agarwal, P , **Joglekar, S.**, Papadopoulos, P., , SASTRY, N. & Kourtellis, N. (2018) Hyper-partisan websites: Personalization of user experience on polarized websites.

5. Raman, A , **Joglekar, S.**, De Christofaro,E., SASTRY, N. & Tyson, G. (2018) Tooting Your Own Horn: Exploring the Impact of Decentralisation on the Mastodon Social Network.

CHAPTER 2

MACROSOPIC VIEW: PERCEIVED SOCIAL SUPPORT

> *"The original idea of the web was that it should be a collaborative space where you can communicate through sharing information... In an extreme view, the world can be seen as only connections, nothing else.*" - Tim Berners Lee[11]

Attention budgets pretty much govern how we as consumers interact with online social networks. It has been shown that the dearth of this budget, promotes an engagement behaviour that prioritizes perceptive features and immediacy in the content [38]. The scrolling user interface of platforms like Instagram and Facebook, allow mere seconds to decide whether a particular content is worth the user's attention [29].

However, there is a whole breed of online social networks, which aim at bringing the offline sense of networking, online. These networks are mostly designed around a specific purpose like technical discussions[1], subject specific questions[2] or simply around hobbies like knitting[3] or art[4]. These communities embody the true essence [11] of the internet, in that they strive at making geographical distance secondary, to the act of social networking and information sharing.

1 *According to the seminal work by Shumaker and Brownell [68], social support is defined as "an exchange of resources between two individuals perceived by the provider or the recipient to be intended to enhance the well-being of the recipient."*

[1] www.stackoverflow.com
[2] www.stackexchange.com
[3] www.ravelry.com
[4] www.artween.com/

Under this construct , these communities are apt Petri dishes to study the signatures of the online social support. Once you could quantify the social support signatures in terms of computable metrics, platforms could then empower the participants of these communities and design interventions to curb negative behaviour like trolling.

In the context of this dissertation, I wanted to know how signatures of a perceived entity like social support, manifests on these formal social networks. More specifically I develop methods and frameworks, to extract the signatures of perceived *social support* on communities designed around users who have underwent or are undergoing physical or mental distress. These methods and frameworks could bear significant potential impact on the health and utility of these forums. The first step us to understand the structure and utility of these communities. More over, having a primer on these communities would help the reader get an idea about the methods developed over the course of this dissertation.

2.1 Primer on online health communities

Recent work has proposed that online communities have the potential to influence health and health care sectors. Recent studies have suggested that the participation of people with long-term conditions (LTCs) in online communities (1) improves illness self-management [4], (2) produces positive health-related outcomes[5] [50, 59] , (3) facilitates shared decision-making with health care professionals [9, 35], and (4) may even reduce mortality [33].

There is also evidence that self-management support interventions can reduce health service utilization [54, 73]. This is especially a crucial point as the world health services are facing the brunt of an ageing population.

Online communities have experienced an upsurge in popularity among people with chronic respiratory conditions such as cystic fibrosis [42], asthma [72], pulmonary hypertension [45] and chronic obstructive pulmonary disease (COPD) [74]. More than 15 million people in England suffer from a long-term condition or disability, and they account for at least 50 percent of all general practitioner appointments[6]. Thus, assessing how these online

[5]https://bit.ly/2FLcs1F
[6]https://bit.ly/2EVFs9v

communities function, evolve and provide perceived support, can have important implications for health care sector. More so, understanding the dynamics of these online communities, have actual repercussions on how the platforms that host them, could become a better resource of self-management of LTCs.

On average, one in four people with an LTC who use the Internet tries to engage online with others with similar health-related concerns [30]. In particular, it has been suggested that the value of participating in an online community lies in the possibility of gaining access to a range of people and resources quickly, easily [5], and anonymously [59], as well as obtaining tailored information and emotional support [3, 18, 25, 26, 67]. However, most of this evidence comes from qualitative studies, whereas only recent years have witnessed an increasing interest in quantitative assessments of online communities as intervention mechanisms.

The potential future integration of online health support systems with formal health care provision should be underpinned by a better understanding of how they are used and by evidence of their effectiveness. Indeed, as suggested by the Medical Research Council [19], integrating online support systems with the more traditional health care provision would require the identification and comparative assessment of potential alternative intervention mechanisms.

In this chapter, I aim to uncover and understand how these communities function,evolve, and operate in the role of a supportive entity, from a macroscopic perspective. Further it is worth knowing if there exists any particular mechanism, by which individual users evolve into the role of support givers.

Ultimately, once we understand the mechanisms of peer support, we can proceeded in looking for discriminative signatures of these supportive exchanges. In this chapter, we would illuminate the answers for **RQ1** and **RQ2** using a large scale dataset of a pulmonary illness support group. The questions are:

RQ1 *How do support communities thrive?*

RQ2 *How do we quantify support on these communities?*

2.2 Dataset and properties

The data was collected from HealthUnlocked[7], the online platform provider of the Asthma UK and British Lung Foundation communities. Registered users can choose to either write posts publicly or send private posts to one another. In the latter case, posts are shared between 2 users only, whereas when posts are written publicly, a large number of users can become connected through threads of posts. A thread is a series of posts made on one root post, as a response to the root, or as a response to one of the responses to the root. This tree-like structure of posts can evolve indefinitely between posters. Only posts that were shared publicly were collected and analyzed. For this study, user identifiers (IDs) were anonymized by the HealthUnlocked platform, and no demographic information was collected. The data set included posts and their metadata (ie, the anonymized user ID numbers), user roles (eg, user, administrator, or moderator), date of posting, the hierarchical level of the post within the corresponding thread, and the dates in which the users joined and left the community. Both communities were moderated, and HealthUnlocked moderators (identified through metadata linked to posts) were included in the analysis to assess their contribution and compare it with other users. Online communities on the HealthUnlocked platform benefit from additional functionalities compared to other online forums, such as built-in patient groups that moderate the content. In particular, the content accessed by users is tailored to their interests, and profiles highlight users' condition, chosen community, medications and treatments they use or find interesting. No data were collected on participants' characteristics, though only people declaring themselves to be older than 16 years were permitted to create an account and take part in the online communities. Table 2.1 summarizes the salient features of the dataset used for this work.

[7]http://www.webcitation.org/70Y10rppl

Dataset Properties		
Property	**AsthmaUK**	**British Lung Foundation**
Time span of data	02/03/2006-06/09/2016	13/04/2012-06/09/2016
Total Time (weeks)	548	230
Total number of posts	32,780	875,151
Percentage of posts with at-least 1 reply	87.3%	93.1 %
Total number of users	3345	19,837
Users who contributed > 1 posts (%n)	1053 (31.5)	7814 (39.4)
Users who contributed exactly 1 post(%n)	331 (31.4) 722	1186 (15.2)
Registered users who never posted (ie, lurkers), n (%)	2292 (68.5)	12,023 (60.6)
Number of posts per user, $\mu(\sigma)$	14.2 (55.0)	66.9 (75.1)
Number of posts per users who posted >1, median (min - max)	5.1 (2-1068)	8.0 (2-8947)
Number of posts per users who posted >1, mean (SD)	20.4 (65.6)	88.1 (458.6)
Posts contributed by top 1% users by activity, n (%)	10,457 (31.9)	426,198 (48.7)

Table 2.1 The summary of salient attributes of the data used for this work

The data sets span, respectively, 10 years for the Asthma UK and 4 years for the BLF communities (see Table 1).

Despite the shorter time span, as a result of the larger number of users, the number of posts in the BLF community was higher than in Asthma UK, namely 875,151 compared to 32,780 respectively. Moreover, BLF users wrote a higher number of posts per user and were connected with a higher number of other users when compared with people in the Asthma UK forum (see Figure 2). In both communities, 60%-70% of registered users wrote no posts (ie, they were lurkers). Users who wrote more than one post contributed with a median of 8 (range 2-8947) and 5 (range 2-1068) posts in the BLF and Asthma UK communities, respectively.

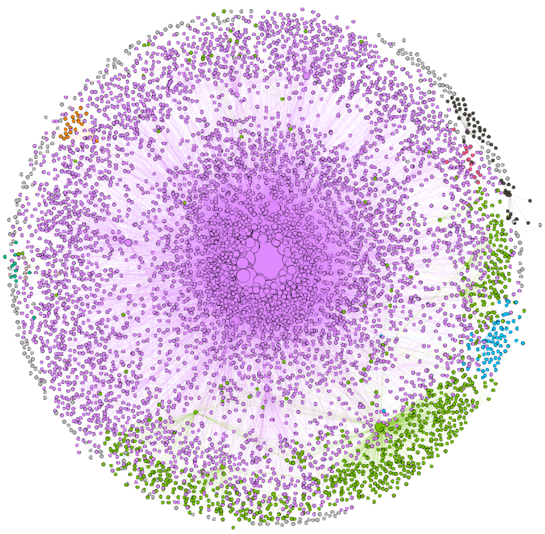
The number of official moderators among the highly active users was negligible; there were no moderators in the top 5% contributors to BLF and only 2 in the top 5% for Asthma UK. Thus, our network analysis predominantly reflects content originated from registered users. This also means that moderators on these forums have more of an observatory role and do not engage in active support.

When classified according to posting activity (ie, number of posts written to the forum), the top 5% users contributed to a substantial proportion of all posts: 58% and 79% in the Asthma UK and BLF communities, respectively. In the context of this thesis, *Superusers* were those who made high number of connections with other users across the lifetime of the community.

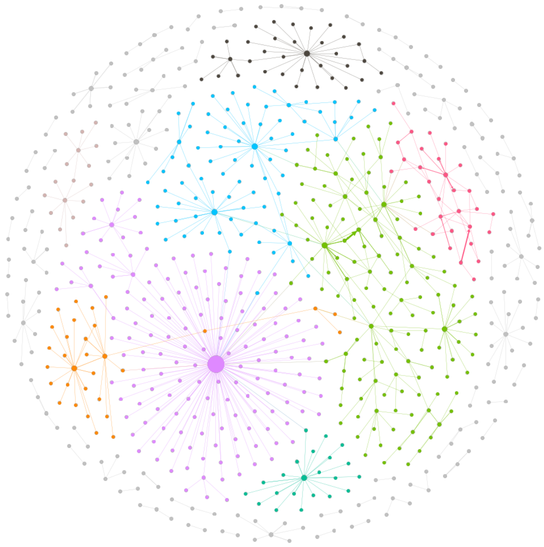
2.3 Interaction Graphs

To understand the reason behind how these communities thrive and in order to quantify the conversation structures, I convert all the message exchanges into graphs, where users are represented by nodes and messages are represented by edges between users. More formally imagine a directed graph $G(V,E)$ involving a set of users $V_i \forall i \in N$ where N is the total number of users interacting on a health community. For every message exchanged between a user i and a user j we create an edge E_{ij}. The complete community would form a global graph based off total interactions between all pairs of users which we call a global graph G_g. Similarly we may decide to only consider the users and messages exchanged across one particular thread discussing a particular issue. Such a graph is called a thread graph G_t.

These graphs are the abstractions of how users interacted on the community either around a particular query (Thread graphs) or over all as a part of the bigger community (Gobal graph). To understand the behaviour of these users, I evaluate several metrics on these graphs to understand the utility of these communities in terms of activity of sharing and support. This abstraction also makes it feasible for us to investigate how a particular community grows with time and how particular users evolve with time.



(a)



(b)

Fig. 2.1 Global graphs prepared from Asthama UK community2.1b and BLF community2.1a. The size of the node corresponds to the degree of the node and the color corresponds to the community membership

2.4 How do support communities thrive ?

This question sets the primer about the peculiarity of support communities. Do these communities have enough interest and activity, to sustain over long periods of time? Are all users equally involved in the vitality of the community or is this a group of users? How important are these users?

2.4.1 Activity Metrics

To calculate the activity patterns of users on these forum, we first work with the most basic of proxies, which is the weekly/daily activity. We arrive at it by calculating the amount of messages exchanged in a community across the whole life cycle of the data. This metric would expose how much activity is happening on a daily or weekly basis on a particular community. It is worth noting that this activity pattern, would also shed light on how users are engaging with the community. A continuous engagement is good for the vitality of a

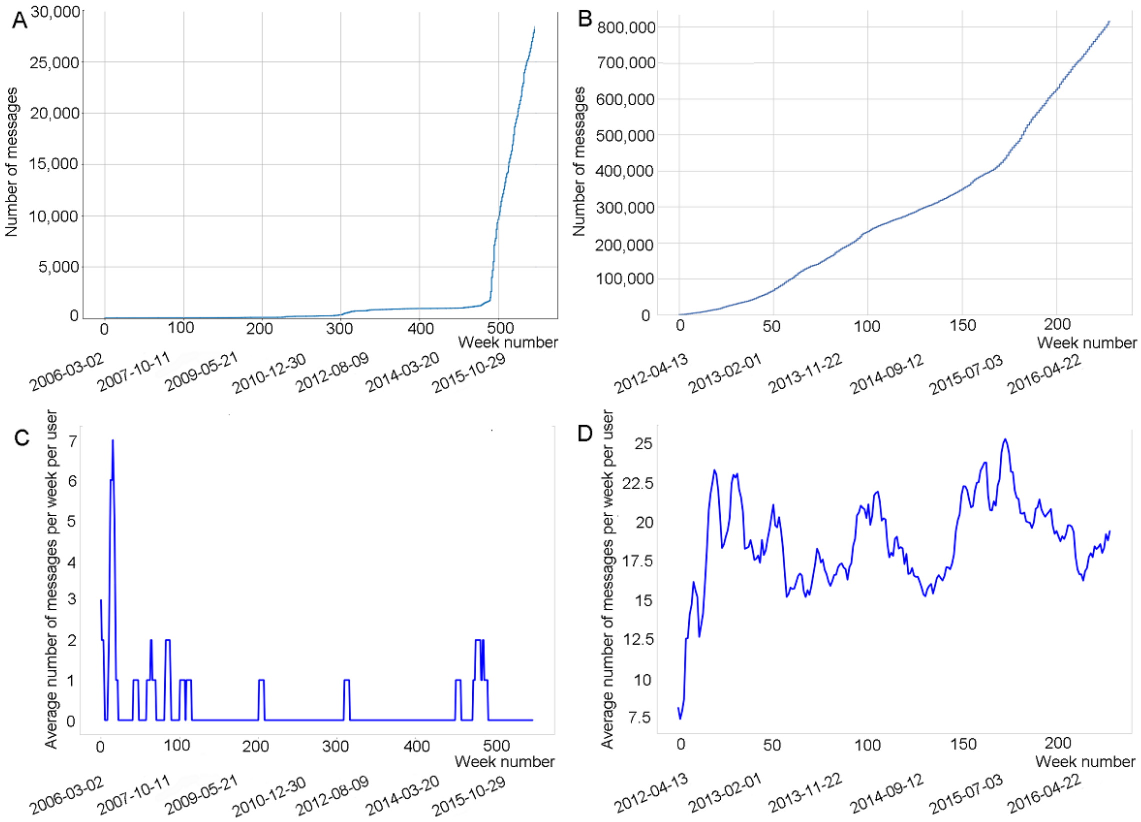


Fig. 2.2 Cumulative distributions of the number of posts as a function of time (weeks) within the Asthma UK (A) and the British Lung Foundation (B) communities. Calendars dates are reported below as week numbers (since the inception of the community). Panels C and D illustrate the average number of posts per user per week within Asthma UK and British Lung Foundation, respectively

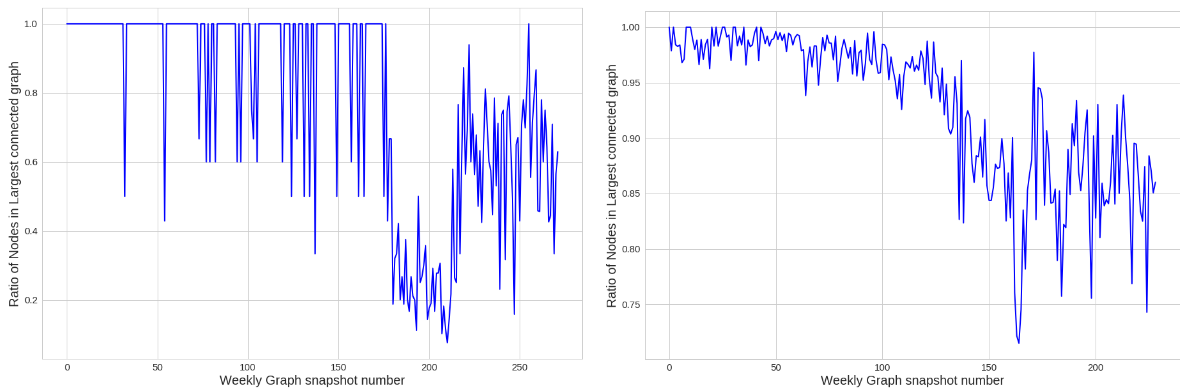
community, however if a community revolves around purely functional interactions, then you may see a bursty nature of communication [55]. From these basic analysis, it was quite evident that the BLF community was more active of the two, in that, the community exhibits a consistent engagement of the users across the lifetime of the data. Asthma forum however shows a bursty activity, despite being more than twice as old as the BLF community. The trends can be see in Figure 2.2.

Remark 1 *It is worth noting that as the activity on the community increases, you do see an increase in fragmented reply networks, which means concurrent discussions are happening with disjoint set of users interacting.*

2.4.2 Community resilience

The activity patterns does not tell the real story about the cohesiveness of any particular community. To answer the **RQ1**, it is first worth asking how the user interactions bind the community together. We would like to know if the user activity is highly concentrated or is it covering a large fraction of the user base. More so, it is worth asking if there are any special users who bear the mantle of providing support. This can be observed from the topological properties of the interaction graph. From table2.1, it is evident that a minority of users are generating a bulk of data on these communities. E.g. the top 1% users by activity contributed 32% posts to AsthamaUK community. Such level of activity makes these users extremely important in understanding the dynamics of support on these communities.

Cohesive conversations



(a) (b)

Fig. 2.3 Fraction of users that are part of the largest component as a function of time (weeks) for Asthma UK 2.3a and the British Lung Foundation 2.3b.

To understand the first aspect of the community's resiliance, I examine how is the coverage of communications between the users, on a weekly basis, given that messages are exchanged between the most active users within that week. To do so, imagine a sorted list of message interactions over a particular time period T_k, sorted in chronological order defined as $L_k = [E_{ij} \forall i, j \in N]$, where E_{ij} is a message between user i and user j, with N total users being active in a given time period T_k. Now imagine this time period T_k is of 7 days . I calculate such K lists for the K weeks the community has been active. For each such list, I induce a graph $G_k(V,E)$ such that the nodes in V are the active users in that particular list, and the edges in E are corresponding to the messages exchanged in the list L_k between any two users.

2 ***Largest Connected component*** *: A largest connected component of a Graph $G(V,E)$ is the largest possible subgraph $G_L(V_L,E_L)$ of G, such that each node in G_L has at least one valid connected path to every other node in G_L*

Now for each such graph G_k I calculate the largest connected subgraph $G_{\theta_k}(N_k,E_k)$ such that all nodes in N_k have at least one path between them. Calculating the fraction $\frac{N_k}{N}$ would give us the total fraction of users who are part of the same conversation network for a given week. After calculating and plotting these fractions across a total of 250 weeks for each community, we see that whenever there is an activity on these networks, almost always, the active nodes belong to the largest connected sub graph. This implies that activity on support forums is cohesive and even if bursty at times, is all encompassing with the users.

Fragile communication structure

Despite the exchange on a weekly basis is quite cohesive, it is pertinent to understand the resilience in terms of user responsibility in helping, in order to examine the health of such a community. Moreover, I want to know if the conversation network is held together by a more or less uniform contribution of nodes, or if there is a skew in the responsibility of nodes. This can be tested by using the sensitivity analysis methods, popular in the network science [1, 13], which measures the network's capacity to diffuse information as you remove nodes based on certain property. In our case, we want to understand the importance of the *Superusers*, or the users who are disproportionately more active. Hence we begin by first sorting all the

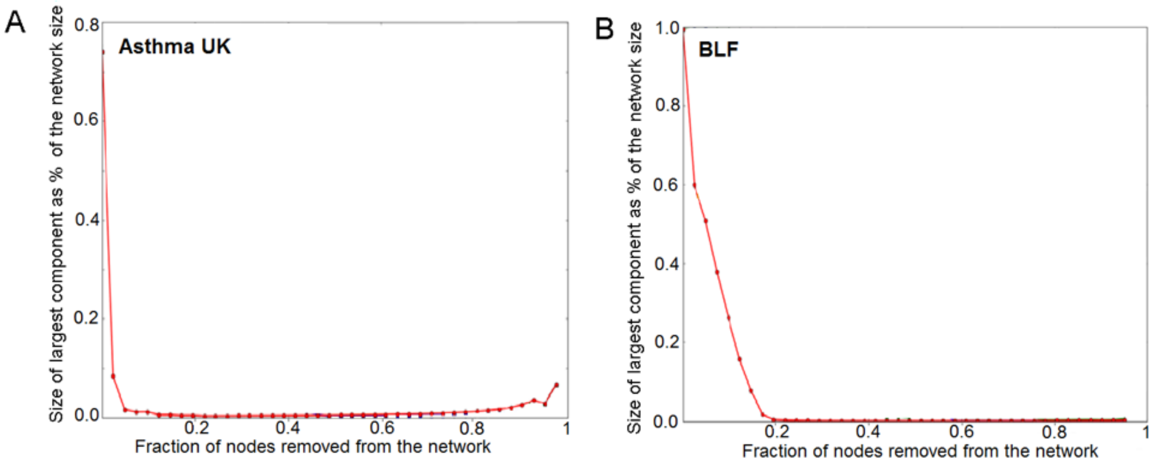
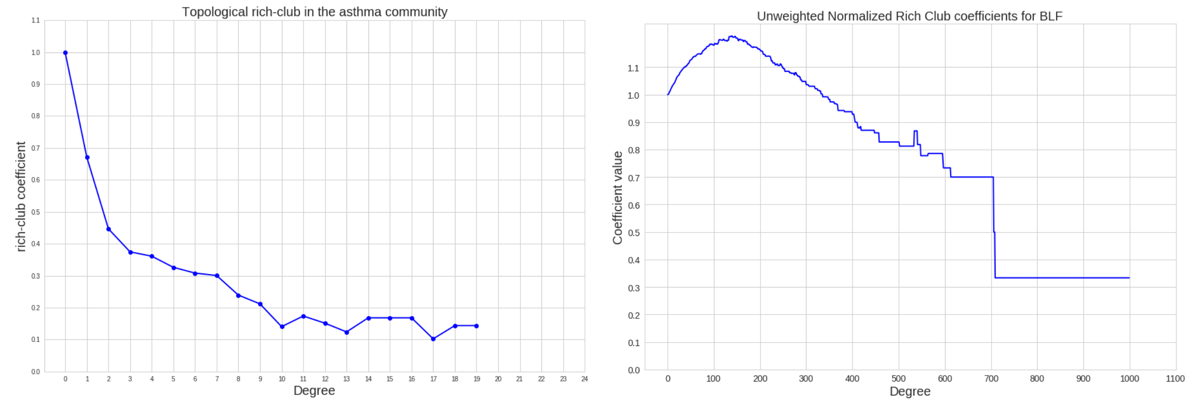


Fig. 2.4 Results of progressive removal of nodes based on connectivity. Both communities collapse drastically, in terms of connectivity, with BLF showing a little more resilience

nodes in the macroscopic graph $G(V,E)$ in order of their degrees. The degree of a node in the global graph is proportional to the diverse set of users that node has communicated with, over the period if the community's lifetime. We then start removing nodes from the top, by progressively removing nodes in increments of 1%. I then compute the size of the largest connected component G_k and compute the ration of number of nodes in G_k as compared to the original global undisturbed network. Figure 2.4 shows the performance of global graphs of both the communities to this attack. It is worth noting, that what we observe is that a top 10% nodes by activity are responsible for most of the cohesive connectivity of the community. This also means that the top 10% of these nodes have the most diverse connections in terms of number of users contacted. This gives hope to health care industry, since these nodes can act like efficient information diffusers, if used in a targeted fashion.

Anti-rich conversations

The "rich-club" coefficient is a metric designed to measure the extent to which well-connected users tend to connect with one another to a higher degree than expected by chance [16]. To this end, for each value k of a node's degree (ie, the number of other users a given user is connected with), we computed the ratio between the number of actual connections between nodes with degree k or larger and the total possible number of such connections [53]. We



(a) (b)

Fig. 2.5 Plots of rich-club coefficients for each viable degree in the respective communities.

then divided this ratio by the one obtained on a corresponding random network with the same number of nodes and degree distribution (ie, the probability distribution of the degrees over the whole network) as the real network, but in which links were randomly reshuffled between nodes.

Formally let $G(V,E)$ be a global graph representation of the community. Let $V_{>k}$ be the set of vertices in the graph having degree higher than k. Let there be $N_{>k}$ such vertices having $E_{>k}$ edges between them. In such case, the rich club coefficient for degree k in the graph G is given by

$$\phi(k) = \frac{2E_{>k}}{N_{>k}(N_{>k}-1)} \tag{2.1}$$

In this equation $\frac{N_{>k}(N_{>k}-1)}{2}$ represents the maximum number of edges possible between $N_{>k}$ nodes. These coefficients are highly dependent on the size of the network, which makes them hard to compare. So I normalize the network by comparing against a random null model of rich-club coefficients $\phi_{rand}(k)$. This is obtained by generating an ensemble of random networks, each having the same degree distribution as that of G, but with links randomly placed. The ratio $\frac{\phi(k)}{\phi_{rand}(k)}$, gives us an un-correlated trend about the rich-club effect in G.

Thus, the rich-club coefficients may take values lower or higher than 1, depending on whether the real network has a higher or lower tendency to coalesce into rich clubs than randomly expected. In particular, networks that display a high rich-club coefficient (ie, greater than 1, are also said to show a “rich-club effect,” namely the tendency to organise into a hierarchical structure in which highly connected nodes preferentially create tightly knit groups with one another [46]. .

Remark 2 *It is worth noting that most previous studies in base lining rich-club effect in technical and real world networks have shown a propensity to create rich-clubs. Thus these networks exhibit exclusive clubs of (topologically) rich nodes, as illustrated in previous work [16, 79]*

What we observe from this analysis is that communities in general have a less than 1 rich-club co-efficient value for a spectrum of degrees k. This means, rich nodes are exhibiting an anti-rich behaviour, where nodes which have a higher degree, prefer engaging with new nodes with lower degree. This implies an active information exchange from a well connected node to a sparsely connected node, which follows according to the definition of social support(definition 1).

2.5 How do we quantify support on these communities?

Once I establish that these support communities are thriving and are providing what seems to be an active supportive environment for the patrons, it is worth delving into the analytical methods for quantifying these supportive interactions. More so we would like to have concrete metrics that characterize a given community as a supportive one. To do so we need to understand how are the users on these communities driven to help each other, and whether there is a correlation between the “richness” of a user, as defined in previous section, and its propensity to help. More so we would like to know how consistent are these so called “rich” users in providing support.

2.5.1 Propensity to help

We would like to understand how users on support communities, as a group behave as they become more seasoned. Fortunately, there is an approximate way for us to capture a user’s role as a support seeker and as a support giver. As described in Section 2.2, the forum activity consists of a root poster, asking a question to the forum board, and the members responding to that question in a cascaded fashion. These responses, along with the original question constitute what is called as a *thread*. To that end, we define the following two roles on these communities[8]

3 *Support seeker: a user who begins a thread by posting on the forum, a question, or a query, to which others may respond to.*

4 *Support giver: a user who responds to any post by a support seeker.*

Using these definitions I aim at modelling the statistical propensity of someone being a support giver or a seeker, as a function of their "richness". We first begin by calculating across the dataset, the average number of questions per user and answers per user, by finding the mean number of questions or answers posted by any user on the forum. We consider an expected probability of answering a question by a user as P_a as 2/3 and the probability of posting a question as P_q as 1/3. With this information we modify the definition of "Z-score" to quantify the expertise, used by Adamic. et. al [77] to arrive at the expression of expertise in the context out our support community.

Proof 1 *Consider a Bernoulli process for a user to choose to answer or post a question on the forum, with asymmetric probabilities for answering (P_a) and posting a question (P_q). For any user i the total number of posts n_i are the sum of total number of questions posted q_i and answers posted a_i and $n_i = a_i + q_i$ For a Bernoulli process the variance for the whole forum is given as:*

$$\sigma_{forum} = \sqrt{nP_a(1-P_a)}$$

$$\sigma_{forum} = \frac{\sqrt{2n}}{3}$$

[8]There are other ways to qualify someone as support giver/seeker, mainly using language sturcture, but here we consider only the bare minimum requirement to be considered as one, using the position in conversation structure

Similarly the mean for this process can be written as :

$$\mu_{forum} = nP_a = \frac{2n}{3}$$

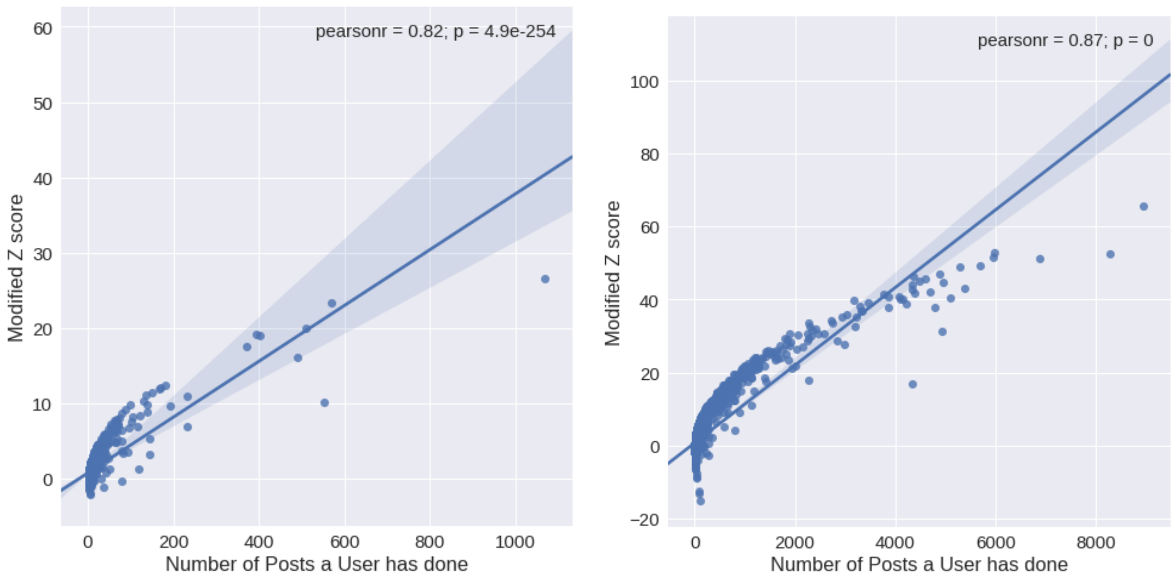
Z_{score} *of a random variable X is defined as*

$$Z_{score} = \frac{X - \mu}{\sigma}$$

Substituting the values for σ_{forum} *and* μ_{forum} *inside the expression for* Z_{score} *we arrive at the modified Z-score as*

$$Z_{score} = \frac{a - 2q}{\sqrt{2(a+q)}} \tag{2.2}$$

Equation 2.2 depicts the modified notion of Z-score for the question answering process of our support community. I calculate this particular metric for each user in both the communities based on their posting history.

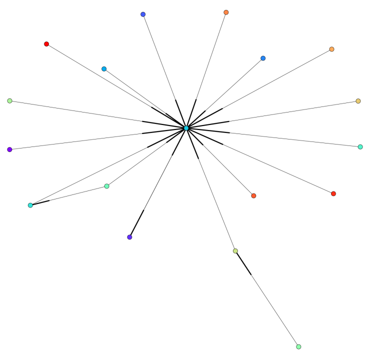


(a) (b)

Fig. 2.6

I then find the correlation between a users Z-score and the total number of posts a user has done in their lifetime on the forum. Figure 2.6a and Figure 2.6b shows the results of this analysis for both the communities. It is quite evident, that as the users become more seasoned and post more actively, they are more likely to answer on questions rather than post new ones. This also implies that based on the rich club results from Section 2.4.2, these communities are thriving not only for the “rich” users, but also for the sparse users. Users on these communities are more open to new members and provide active support to them.

2.6 Key takeaways, possible interventions



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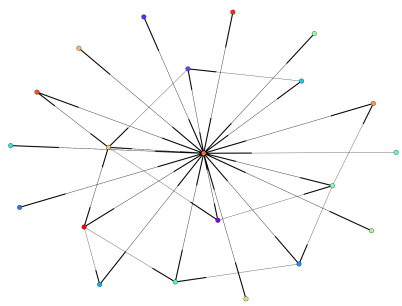

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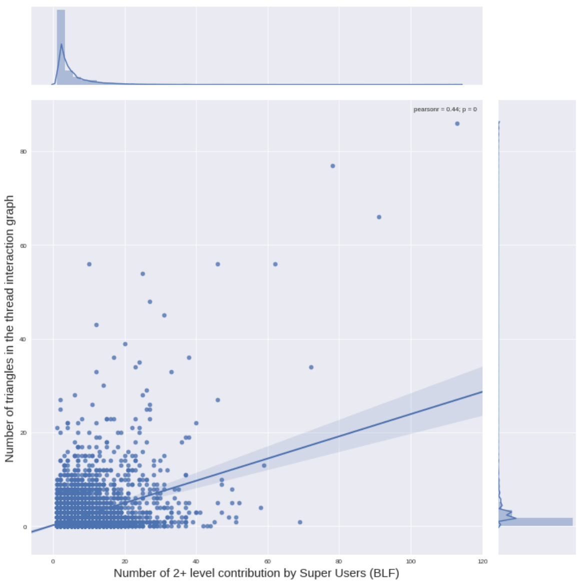
Fig. 2.7


pearsonr = 0.44; p = 0
Number of triangles in the thread interaction graph
Number of 2+ level contribution by Super Users (BLF)

Chapter 3

Mesoscopic View: Perceived social support

3.1 Introduction

The world has become more connected over the past decades thanks to the networked nature of the technologies of the day. It is seldom possible to spend a whole day without single interaction on the Internet. The Internet gives platforms where we can not only connect with our social counterparts but also exchange ideas and express opinions. These new mediums have become so ubiquitous, that some research suggests that they might be affecting our broader psychological state [15]. But on the positive side, studies have also proposed different ways in which this medium could be used for measuring and intervening in the matters of mental health[23, 24]. Online communities, or fora, offer a platform for users to directly interact with each other. Reddit[1] is one of the largest online communities which contains a number of sub-communities (so called *subreddits*) that can be about almost anything. On this platform, several subreddits are specifically tailored to mental health-related topics, such as *depression*, *anxiety* or *alcoholism*. These fora offer a unique opportunity to study the way people describe or discuss their problems in their own voice.

One of the most challenging, and devastating, global mental health concerns is suicide. Suicidal behaviour includes any thoughts, plans or acts someone makes towards ending their life. In health care services, preventing death by suicide is a priority, but accurately

[1]http://reddit.com/

predicting whether or not someone is at risk of committing suicide is difficult. Moreover, a large proportion of deaths by suicide occur in populations that have never been seen by health service providers.you could probably improve the section above...

Several online platforms are used for expressing suicidal thoughts and reaching out for support. On Reddit, the subreddit *SuicideWatch* currently[2] has almost 94k subscribers, and is a moderated forum that is intended to offer peer support for people at risk of, or are worried about others', suicidal behaviour. The moderators take the message of peer support seriously, and are governed by guidelines that prohibits false promises, abuse, tough love and other clinically frowned upon methods of conversations[3]

As such it is valuable to understand what characteristics supportive communities like SuicideWatch have, and in what aspects such communities are similar or dis-similar from other casual subreddit conversations.

Recent studies have shown promising results in modeling and measuring signals and patterns in reddit communities related to mental health. For instance, statistical relations of mental health and depression communities with suicidal ideation have been studied [23, 24]. The authors explored linguistic and social characteristics that evaluate user's propensity to suicidal ideation. Approaches to classify reddit posts as related to certain mental health conditions have also been successfully developed, showing that there are certain characteristics specific to mental health-related topics in posts that can be automatically captured[32]. Furthermore, in a study focused on reddit posts related to anxiety, depression and post-traumatic stress disorder, the authors show that these online communities exhibit themes of supportive nature, e.g. gratitude for receiving emotional support[57]. Positive effects in participation in such fora have also been shown by improvements in members' written communication[56]. The supportive nature of comments in the SuicideWatch forum has also been studied by automatic identification and classification of helpful comments with promising results[41].

Most previous studies have aimed at studying the *content* of posts and their characteristics in relation to other posts. One important aspect of online communities is its supportive

[2]As of 27th June 2018
[3]http://www.bbc.co.uk/newsbeat/article/35577626/social-media-and-suicide-what-its-like-being-a-moderato

function — users turn to these platforms not only to express their thoughts and concerns, but also to receive support from the community. More references to be added in the introduction. Also, we need to add something about the Online disinhibition effect somehow.

To our knowledge, there are no studies that have specifically focused on modeling the supportive *nature* of online fora related to mental health. This work takes a macroscopic perspective, to quantitatively characterise and model the nature of supportive conversations. SuicideWatch is particularly interesting because of its purpose to offer peer support to people with suicidal thoughts, and also because of the complexity of this clinical construct.

Our aims in this study are to

- Understand similarities and differences between a Suicide watch conversation and a generic conversation using these abstraction.

- Study global properties of these conversations in comparison with control conversations.

- User network metrics to reason about global differences in terms of local interactions between users.

To model the network topology in an online community, we represent conversations in a forum using graph-based abstractions (users and replies) as described in Section 3.3.2. To measure global structure of these conversations, we user network topological metrics such as centrality: which measures importance of nodes in a network in terms of relaying information, branching factor: which measures how a conversation fans our over time, return distance: which measures how soon do users return back to the conversation and symmetric edges: which measures reciprocity of users in a conversation. To measure measure local interactions, we measure inter response times: which measure urgency of response to a message, semantic alignment between messages and local interaction motifs known as Triadic motifs : which gives an idea about how distinctive are interactions between subgroups of users.

Terminology	**stands for**
RP	Root post which begins a new thread on a subreddit
OP	Original poster who posts the Root post for a thread
SW	The suicide watch Subreddit
FP	Front page of Reddit.

Table 3.1 Notations and Terms.

3.2 Results

Particularly Suicide watch community consists of over 78k subscribers and reader, however is supported by mere 12 Moderators according to the latest count. The moderators are mainly present to prevent any kind of abuse, trolling or non-clinical or non-productive advices. These moderators do not have any form of formal training. However through several accounts they have confessed to learn through interactions and mentorship from more senior moderators on the site[4] All the moderators have been in that role for at least 3 years and the oldest goes as far as December 2008.

Our study is based on all conversations on SuicideWatch. We represent these conversations through networked abstractions as described in 3.3.2.

Through our analysis we find several discriminatory factors among Suicide watch conversations and generic front page conversation. We show that some of these factors are predictive of suicide watch conversations to a very high degree. We also show that certain properties of these conversations can be backed by sociological theories of real life support conversations.

3.2.1 Peculiarity of threads of Support

We begin by characterizing the two networked abstractions, namely Reply Graphs and Interaction graphs as described in Section 3.3.2. We do so by first comparing these two abstractions with a baseline control conversation threads using certain macroscopic network properties. We first compare the number of unique users per thread. The two communities

[4]https://bbc.in/24rJYQH

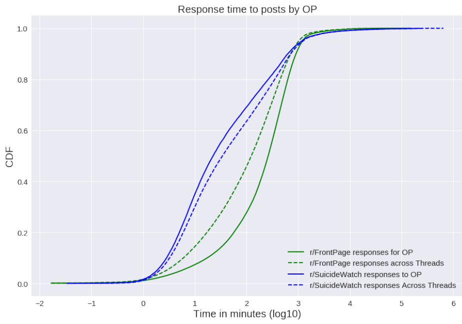
exhibit considerable difference. SW Sub-Reddit has a median of 5 users per thread and a mean of 6.7 users and BL threads have a median of 25 users and mean of 50 unique users. So this off the bat indicates that Suicide watch conversations are more intimate and involve less participants. Authors tend to participate on a similar level, with a median participation per author of Suicide Watch to be 5 and for baseline conversations to be 3.

How urgent are user responses?

Understanding the inter message times can act as a good proxy for the urgency in a conversation. To understand how Suicide watch subreddit users responds to a *OP* compared to other sub-reddit threads on the frontpage, we calculate differences between the posting times between consecutive messages in a reply graph. Figure 3.1a shows comparison using CDFs of inter-message response times for SW and FP threads. It can be seen that SW *OP* are responded with the highest urgency amongst the 4, especially compared to either the *OP* or any other users or sub-reddits.

How symmetric are the interactions?

Despite signs of urgency and engagement, we ask the question: what percentage of conversations happening on these subreddits are symmetric in nature ? For this The median value for U_{sym} for SW is 20% where as for AS is 0%. This shows that SW subreddit engages is a lot more symmetric conversation that the baseline threads. If we define a set of users who engage in symmetric activity with the *OP* , it would be worth while to investigate how much of the total message activity on the thread is carried out by these set of symmetric users . To calculate this we find the fraction of messages on each thread written as part of this symmetric conversation. Figure 3.1b shows the trend. It can be see that SW threads contain a higher prevalence of symmetric message exchanges compared to the baseline Frontpage threads. This shows a higher engagement from the *OP*s side when participating in a supportive conversations



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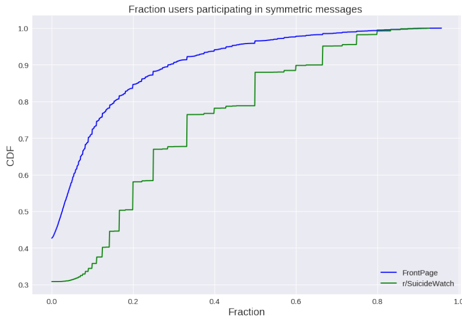

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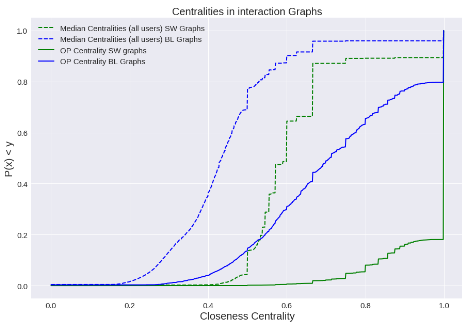

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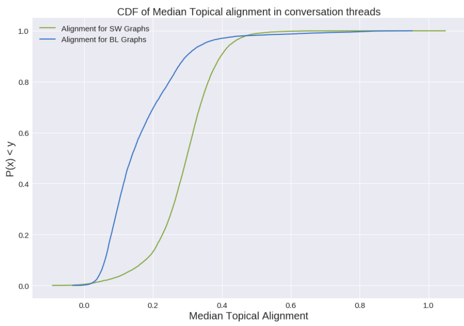
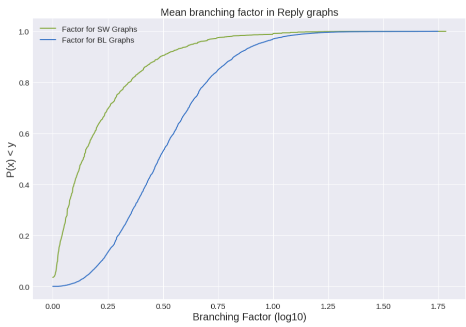


(d)



(e)

Fig. 3.1 Panel shows CDFs of different network metrics. Fig.3.1a shows the response time distributions, Fig.3.1b shows symmetrically engaged users, Fig.3.1d shows topical similarities across posts and 3.1e shows the branching factors of reply graphs.

How central are the users?

To understand how embedded is the *OP* in a conversation thread, we compare the betweenness centralities of *OPs* in the *SW* dataset with the baseline *FP* dataset. Betweenness centrality is a good proxy of understanding how closely linked is a node with the rest of the network. When we calculate this metric for the user graphs we see that Suicide watch *OP*s tend to have highest centralities compared to generic FP threads moth in terms of *OP* centrality as well as median centrality across all the users. The high centrality of *OP*s in *SW* conversations implies a high level of embedded-ness as well as a *OP* centric approach by other participants in the conversation. The Figure 3.1c shows the Empirical CDFs of centralities.

How semantically aligned are the responses?

We measure semantic alignment based on word embeddings of the source post and the reply post, at every edge of the reply graph. The detailed method of extracting semantic alignment along a post and its response is described in Section 3.3.3. Extracting such similarity metrics, we compare the trend in response text being in semantic alignment with the parent text in the reply graphs.

How branched do conversations become?

Branching in a conversation thread could be either a sign of digression or a sign interestingness resulting in more people joining in. To measure this phenomena, use the reply graphs, which resemble a n-ary directed acyclic graph, to evaluate the branching factor. By using the method described in Section 3.3.3, we found that Suicide watch threads, tend to branch in a much less as compared to our baseline conversations. This implies that suicide watch threads tend to remain a one-on-one conversation with the *OP* albeit many such dialogues may emerge, and hence that explains the high centrality of the *OP* in all interaction graphs. If the helpers on a thread seldom interact with each other, the corresponding interaction graph will have the *OP* as the most central node.

3.2.2 Patterns in local interactions

It is often a useful tool to express large interaction graphs, as the sum of local interactions between two or three nodes at a time. Such analysis is quite useful in expressing local structures in the graphs and has been used in several network analysis works For this reason we use a method more commonly known as network motif analysis (described in Section

3.3.4) to understand triads, or groups of three nodes, and the patterns of edges that exist between them.

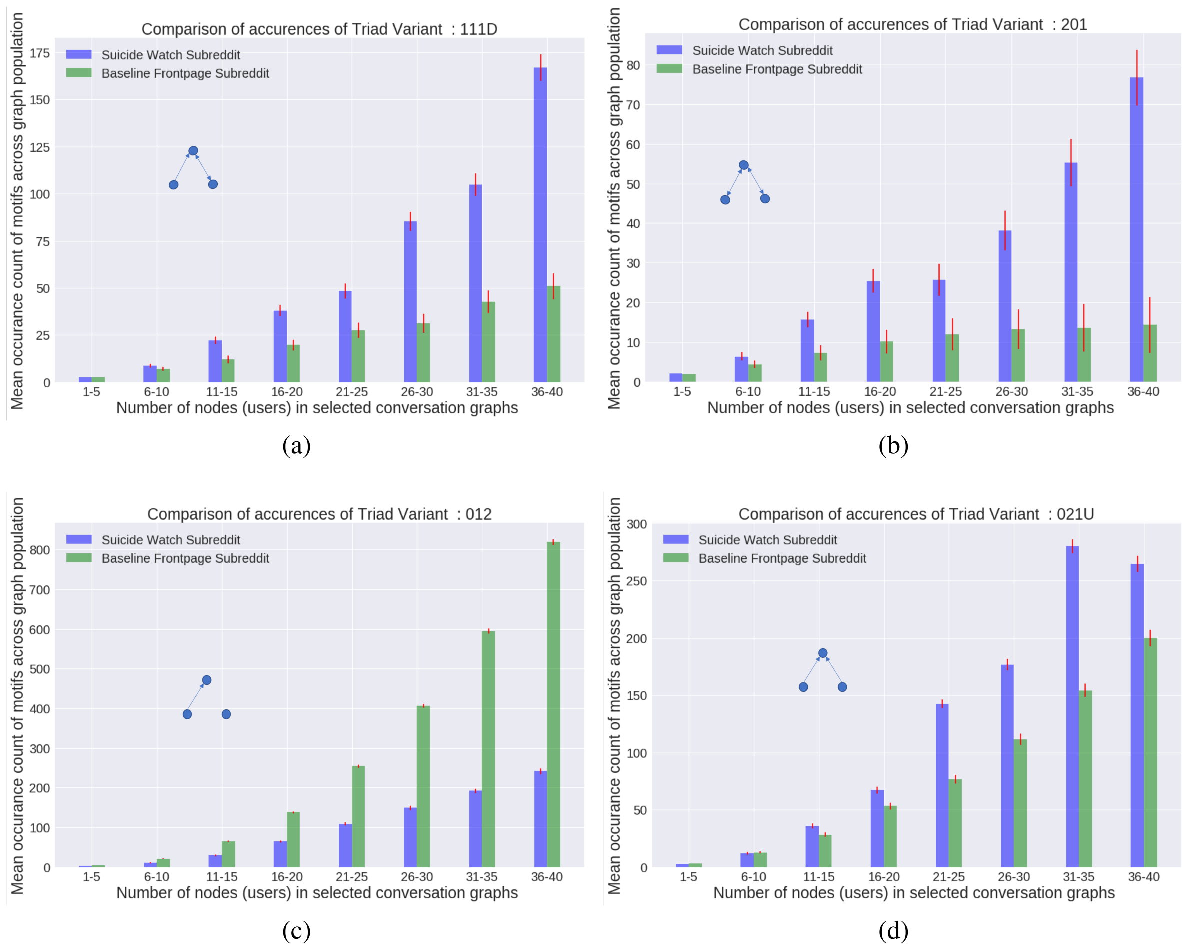


Fig. 3.2 This panel shows the statistical significance of the three over expressed and one under expressed triadic motif.

3.3 Methods

This section discusses the methodological devices used to extract insights from the fora data.

3.3.1 Data

We build on dataset that was used in [32] where they analyze textual content for the root posts in a Subreddit called Suicide Watch[5]. The dataset contains a dump of 53 thousand posts from the suicide watch sub-reddit. However the dataset did not contain the threaded conversations for each thread. Reddit is a platform where a user can create a post on a sub-reddit, to which several members of a given sub-reddit can interact with. The array of interactions may range from simple up or down votes or posting at different hierarchy of the thread. This creates a hierarchical threaded structure of posts where the conversations are organized as threads of posts. To understand the deeper structure that is present in these posts, we crawl Reddit to get the threaded conversations by pursuing each conversation at arbitrary depth. [6]. This results in a dataset of over 50 thousand threads totaling to around 500,000 individual posts on those threads.

To baseline our work and compare theorized supportive nature of conversations with the broader community, we also crawl other reddit threads. To avoid any bias towards a particular type of subreddit, which have their own culture, we acquire roughly 50 thousand baseline posts which have been popular enough to land on the front page [7]. We crawl the Frontpage posts for 2 weeks accumulating over 50 thousand reddit threads in the process. The median amount of responses for a Suicide watch thread were 6 and for baseline Frontpage posts were 8. To understand the structure of these two foras, and find discriminating factors between a supportive community like suicide watch and a general thread on Reddit, we need to build abstractions of the thread.

3.3.2 Abstractions

To understand the dynamics of supportive conversations, we first need to formalize the abstraction of networked conversations. In case of forum based platforms where users

[5] https://www.reddit.com/r/SuicideWatch/

[6] The code to crawl reddit for threads can be found at *https://github.com/sagarjoglekar/redditTools*

[7] The reddit front page algorithm is a combination of popularity and decay in popularity as a function of time. More can be found here https://goo.gl/uVdHjn

interact in a nested dialogue fashion, and original poster or *OP* posts a start of a thread. This thread is then open for comments by all the community users. In case of Reddit, such a community is called a Subreddit, which is a moderated collection of users who subscribe to it. These users may post new threads onto the subreddit as far as the post follows the subreddit rules. Enforcement of these rules is the responsibility of the moderators. The user who starts a thread is called the Original Poster or **OP** and the headlining post which the *OP* begins with is called the Root Post or *RP*.

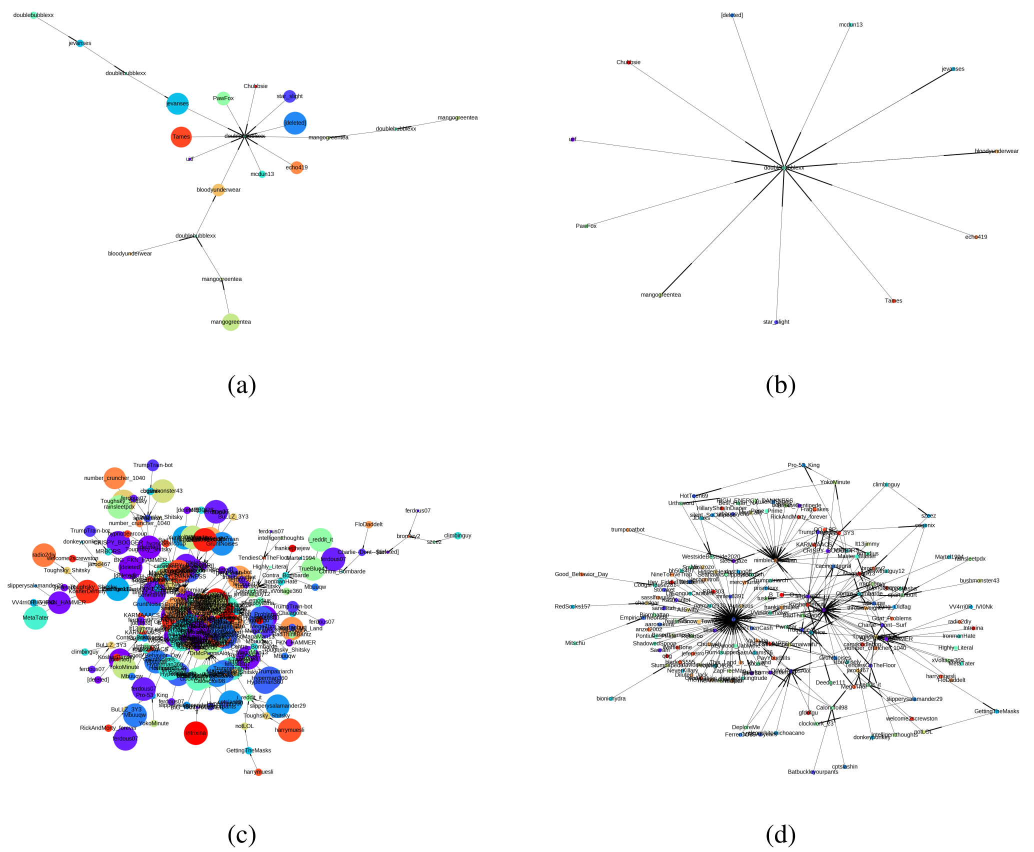


Fig. 3.3 Example UserGraphs and their corresponding Reply graphs, Figure 3.3b shows a random thread from the SW sub-reddit and 3.3a shows the corresponding reply graph that arises from the response structure of the same thread. In comparison we have Usergraph Fig 3.3d and its corresponding reply graph Fig 3.3c from one of the Front page threads

Reply Graphs

The first abstraction mimics directly the structure of conversation threads on Reddit. These abstractions are called Reply Graphs. We formulate a reply graph $R\{P,E,W\}$ as a thread of multi-layered posts in a thread in response to the root post *RP* in the sub-reddit. Each graph *R* consists of posts $P_i, P_j, i, j \in N$, where N+1 is the total number of responses in the thread and Edges E_{ij}such that and Edge E_{ij} exists iff post P_i was in response to post P_j in the hierarchy of responses. The weight of the edge E_{ij} is found by calculating the cosine similarity between topic vector T_i for post P_i and the topic vector T_j of post P_j. For a given dataset, the topic vectors are extracted using the model trained on that particular corpus (LDA_{BL}, LDA_{SW}). This abstraction works well in modeling the conversational nature of these forums. For convenience of the reader, we present a couple of example pairs from SW and Frontpage baseline datasets in Figure 3.3

Interaction Graphs

In this method, we represent each thread as a directed graph $G\{V,E,W\}$ where V is the set of all users participating in a particular thread and E are the directed edges which correspond to interactions between two users $V_i, V_j \in V$. The weight of each directed edge E_{ij} corresponds to the average of all the edges between $V_i, V_j \in V$ in the corresponding reply graph $R\{P,E,W\}$ as described above. This means that each reply graph is then mapped to a User graphs where the nodes are Users rather than posts. Another salient distinction between the two abstractions is that reply graphs resemble an n-ary tree and user graphs are directed cyclic graphs.

3.3.3 Macro and local metrics

The abstractions are used to extract certain structural metrics from the conversation threads. These metrics are then used to validate structural differences between supportive conversations and generic casual conversations from out baseline set.

Centrality

For this metric we use the User Graphs. Node centrality is a metric that measures how central a node is in a network. It directly reflects the importance of the node when it comes to membership of the shortest connecting paths between all the nodes in the graph. More formally, we use betweenness centrality of a node which is defined as Betweenness centrality of a node v is defined as

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where $\sigma_{st}(v)$ is the total number of shortest paths from node s to node t and σ_{st} is the number of those paths that pass through v. To understand whether the thread starters (OP) have a special place in the network, we evaluate both OP centrality as well as median centrality across all the nodes in a User graph.

Symmetrical users

We define a symmetric user and a symmetric edges for user graphs. For a user V_i in the user graph $G\{V,E,W\}$ as described in Section , a symmetric user is a user who interacts with V_o or the OP and receives a response back from the OP. We find the fraction

$$U_{sym} = \frac{total\ number\ of\ symmetric\ users}{Total\ users\ in\ a\ thread}$$

Urgency

To understand how Suicide watch subreddit users responds to the OP and each other, compared to other sub-reddit threads on the frontpage, we calculate differences between the posting times between consecutive messages in a reply graph. We compute the median response times per thread, for OP's posts and for all other posts.

Branching Factor

Branching factor is a quantity that reflects the fan out of a conversation as it evolves. To measure this phenomena, we use the reply graphs, which resemble a n-ary directed acyclic graph, to evaluate the branching factor. The branching factor is formally described as

$$\tau = \frac{1}{|D|} \sum_{d \in D} \frac{1}{|N_d|} \sum_{n \in N_d} InDeg(n)$$

Response distance

A user who interacts frequently with a thread, may contribute at different stages of hierarchy. Intuitively, for a one on one conversation to exist, the user needs to contribute back to the thread at alternate levels of hierarchy. To measure this phenomenon, we assume that a user U contributes in a reply graph at variable depths $d_i \forall i \in [0, D]$. We calculate the average difference between two consecutive contributions d_{avg}

$$d_{avg} = \frac{\sum_{i=0}^{D} d_{i+1} - d_i}{D}$$

We calculate the values of d_{avg} for both OP and other users in the thread.

Semantic similarity

We use a popular word embedding method called *Word2Vec* [48] which learns representations of a set of words from a corpus of text, which in our case is the text from Suicide Watch and baseline fora. These representations can be used to extract text embedding vectors for each post which belong to a N dimensional space R^N. These vectors are tested for their alignment using cosine distance in R^N, which corresponds to semantic similarity in the textual space. This method is quite popular and used in community based question answering[47], Medical semantic similarity [27] and other medical informatics applications[80].

3.3.4 Structural metrics

Network motifs are local sub-networks between 2 or 3 nodes. Such local patterns are highly useful in quantifying local interactions and the resulting macro structure of the network[49]. They gave been used in a variety of applications and networks, from economics [78] to cellular protein-protein interaction networks [75]. Hence we calculate census of 16 distinct *triadic motif* i.e. possible subgraphs that could be formed between any three chosen nodes.

This probably needs to be briefly introduced/explained earlier in the manuscript? To understand relation of local structures in interaction networks within a conversation with its , we compare the quantity called *motif occurrence ratio*. After calculating motif census across the dataset[10], we select progressive subsets of graphs from both datasets with nodes $n \in [k, k+4]\ \forall\ k \in \{1, 6, 11, 16, 21, 26, 31, 36\}$. This segmentation of the dataset is called binning, and it allows us to not only measure the differences in the census between the datasets, but also observe the trend as the size of the interaction graph becomes larger. We stop at 40 because beyond that, we start getting lower and lower number of graphs samples per bin.

We test each graph for the frequency of occurrence of the 16 possible triadic motifs as shown in Figure3.4a. We start by selecting the subset of graphs from Suicide watch and Frontpage belonging to a particular bin k. We then define the motif occurrence ratio as the fraction values for $\frac{\gamma_{BL}}{K_{BL}}$ and $\frac{\gamma_{SW}}{K_{SW}}$ for all the 16 motifs across all the chosen values of n.

3.4 Appendix

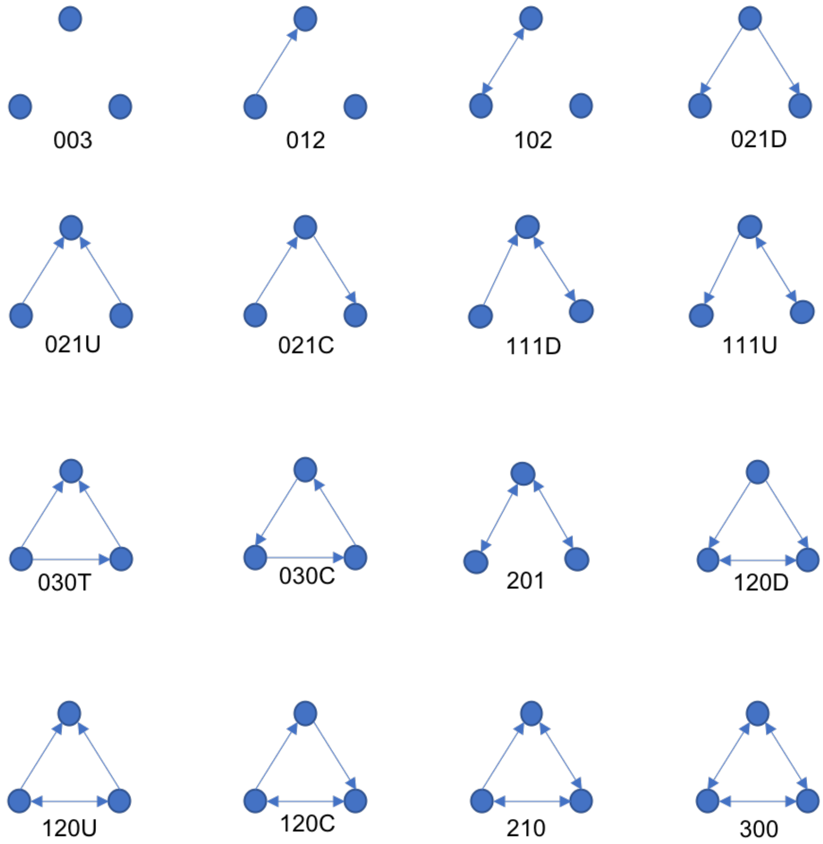
3.4.1 Triadic statistics for twitter conversations

3.4.2

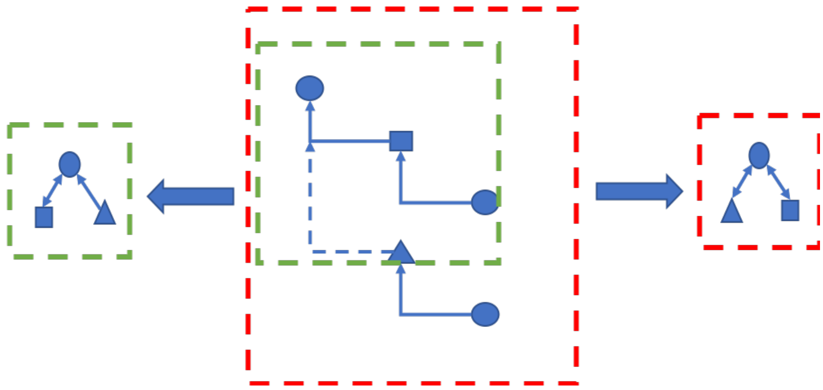
Replication of quantification of the topological metrics for twitter conversations for suicidal ideation and comparison with baseline threads. There are 5k threads for suicidal ideation and 6k for baseline. The baseline threads deal with discussion around westminster and manchester terrorist attacks in the uk.

3.4.3 Network characteristics

Figure 3.7a shows the distribution of maximum depths across all Reply graphs for SW and Baseline subreddits. The SW threads depths have a median depth of 2 and mean of 4



(a)



(b)

Fig. 3.4 Figure 3.4a shows the 16 different types of motifs that are looked for in the user graph data. Figure 3.4b shows how three unique users could produce different motifs. The three shapes represent different users and the dotted line means the message order is irrelevant.

compared to median depth of 2 for BL and a mean of 2.5. This shows that statistically the depths of Suicide watch and baseline graphs are quite similar.

Figure3.8 shows the CDF for the number of responses a Root post gets on a thread across the whole dataset. Figure 3.8 shows the CDF for number of comments per thread across the r/SuicideWatch subreddit dataset and the crawled frontpage subreddit.

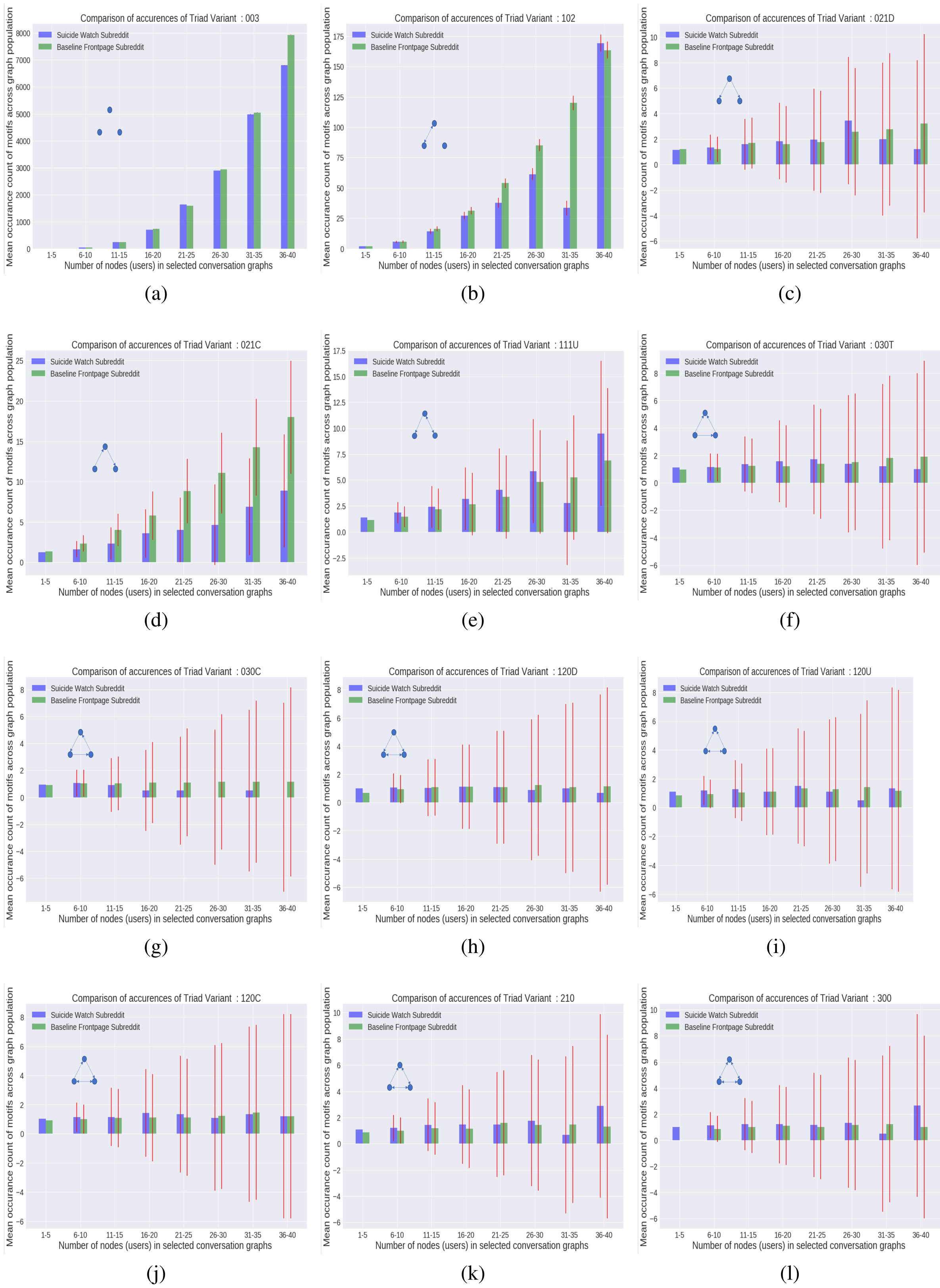
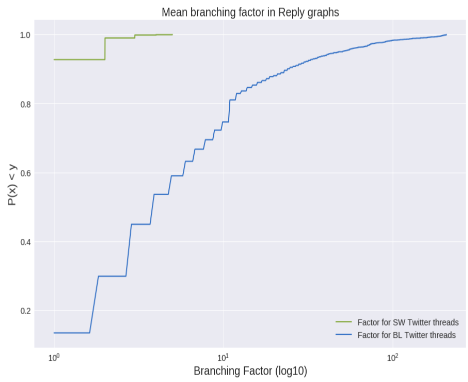
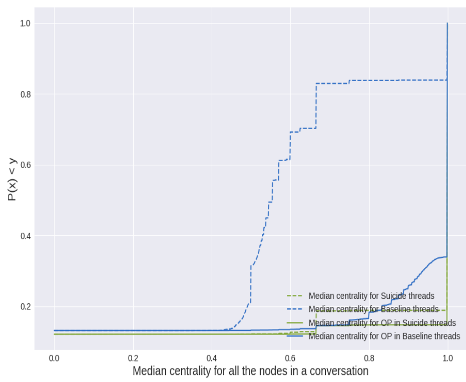


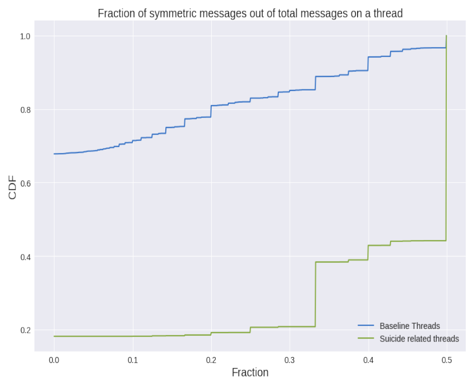
Fig. 3.5 The figure shows comparison of occurrence ratios of 9 insignificant motifs. Blue traces are for Suicide watch and Green traces are for Baseline Front page threads



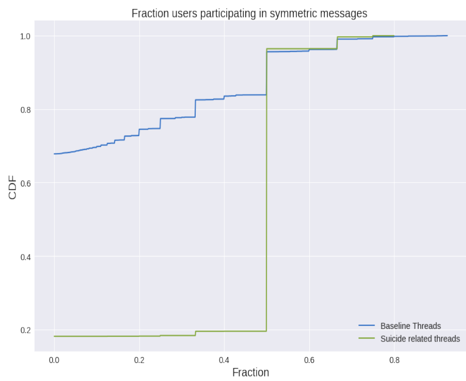
(a)



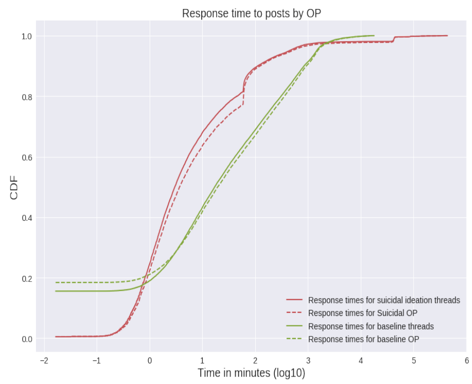
(b)



(c)

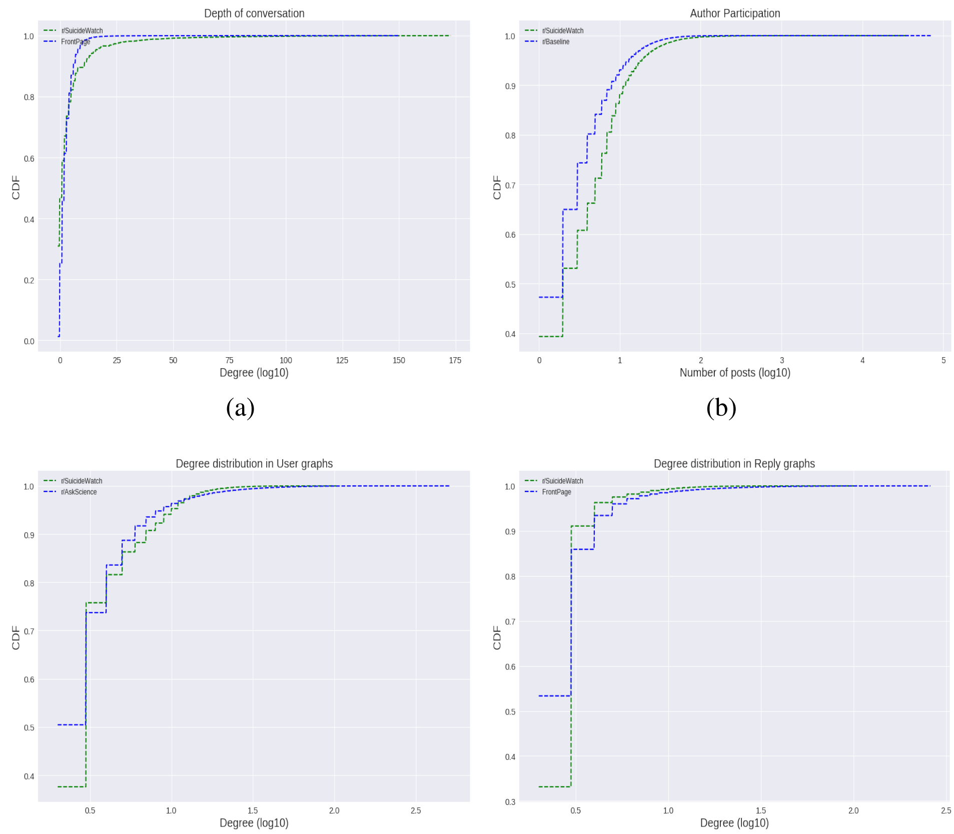


(d)



(e)

Fig. 3.6 *Fig 3.6a shows the branching factor for twitter threads that talk about suicidal tendencies against baseline threads. Fig 3.6b shows the distribution of median centralities per thread, for both the twitter crawls. Fig 3.6c shows Distribution of symmetric messages in reply graphs for both datasets. Fig 3.6d shows the distributions for users participating in a symmetric conversation Fig 3.6e shows he dustribution of reply urgency for suicide threads against baseline. The suicide median reponse time for suicide threads is 3 min as compared to 18 mins for non-suicide threads*



(a) (b)

(c) (d)

Fig. 3.7 *Fig 3.7a shows the distribution of maximum depths of Reply Graphs for Subreddit r/SuicideWatch and the baseline Frontpage conversations. Fig 3.7b shows the distribution of unique authors per thread in the two datasets. Fig 3.7d shows Distribution of degrees for Reply Graphs, r/SuicideWatch and FrontPage. Fig 3.7c shows the degree distributions for the reply graphs*

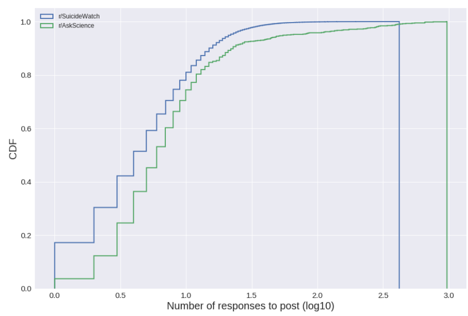


Fig. 3.8 *Distribution of responses per thread on Subreddits r/SuicideWatch and Frontpage*

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