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
May 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 due process, I provide a broad overview of how intangible subjective quantities manifest in data and develop metrics to quantify them. I also reason about the utility of said subjective quantities when it comes to developing interventions to improve our online and offline lives.

In the first study I analyse on-line spaces involving social networks where interactions between humans are purely with the intent of helping each other. I develop frameworks to abstract out the graphical structure of these interactions. I then investigate presence of support by finding discriminative local structures in these abstractions. Using established inter disciplinary theories, I argue that these local structures, which we call motifs, are the signatures of a supportive processes in online conversations. 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. I do so, by developing a pipeline that capitalizes on crowd sourced responses about perception of urban aesthetics. I develop a deep-learning driven framework, which is able to quantify the perception of intangible qualities like 'beauty of a space' 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 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. 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 due course of 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, online and offline.

TABLE OF CONTENTS

List of figures

List of Tables

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 [116]. 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" [30] 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.*" [28]. 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. [10, 61] [108] [115].

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 [57, 68, 118]. 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

1 ***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.*

2 ***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[62]. In his opinion, emotions are pre-cognitive involuntary states, termed as "mere perceptions of unspecified bodily states"[16]. 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[99], 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[132] 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

[1]American Psychological Association definition.
[2]American Psychological Association definition.

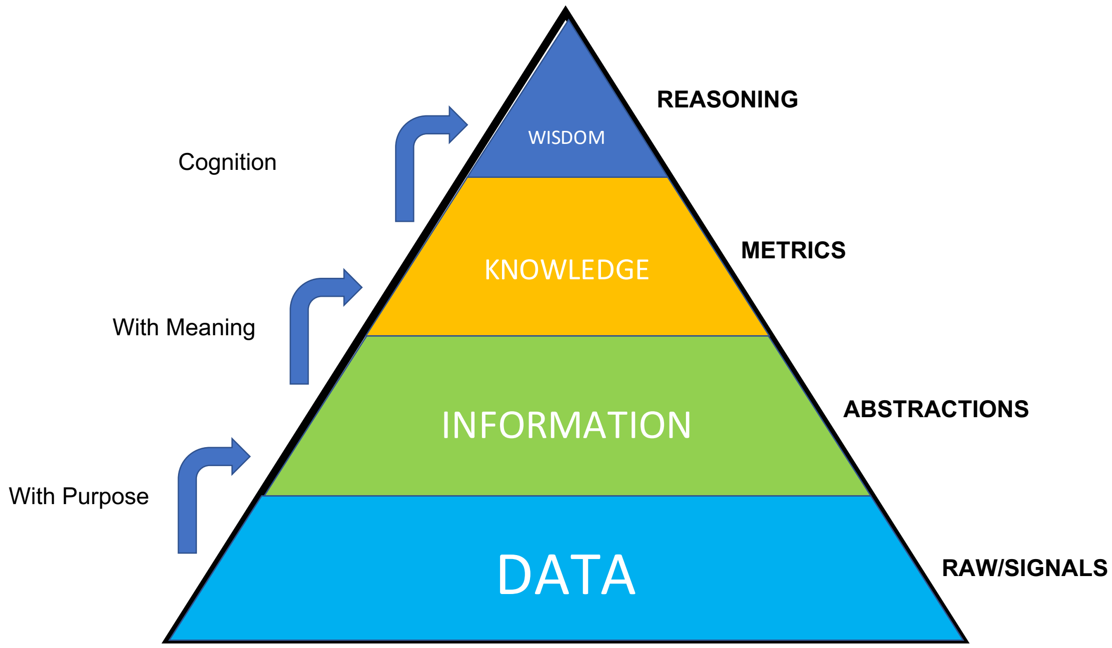


Fig. 1.1 The DIKW pyramid

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. 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 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[105].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. This is provided that the frameworks 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 [74]. 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 [5] [84, 98] [13, 58] [53]. 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 [88], 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 [60]. 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, 101, 106]. These elements are those that contribute to the creation of what the urban sociologist Jane Jacobs called ‘urban vitality’ [59]. Apart from vitality, these motifs in urban environments are also highly correlated with feeling of well-being, health and safety [63]. There have been studies where people have tried to use crowd sourcing to acquire subjective ratings of images [109] which have shown some reasonable progress on this front. But the real gap in these studies is understanding the

[3] www.reddit.com

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 [87], 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 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 4).

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 PART 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 [12, 25, 42] , to signs of positive turn around among patients suffering from alcoholism and depression [18, 97], 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 [38]. 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 PART 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[110] and physical well being[11, 48]. 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[29, 101]. 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

PART 1 : THE ACTORS OF 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[15]

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 [61]. 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 [43].

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 [15] of the internet, in that they strive at making geographical distance secondary, to the act of social networking and information sharing.

3 *According to the seminal work by Shumaker and Brownell [114], 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 [5], (2) produces positive health-related outcomes[5] [84, 98] , (3) facilitates shared decision-making with health care professionals [13, 58], and (4) may even reduce mortality [53].

There is also evidence that self-management support interventions can reduce health service utilization [92, 125]. 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 [66], asthma [120], pulmonary hypertension [79] and chronic obstructive pulmonary disease (COPD) [129]. 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 [46]. 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 [7], and anonymously [98], as well as obtaining tailored information and emotional support [4, 26, 37, 38, 113]. 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 [27], 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.

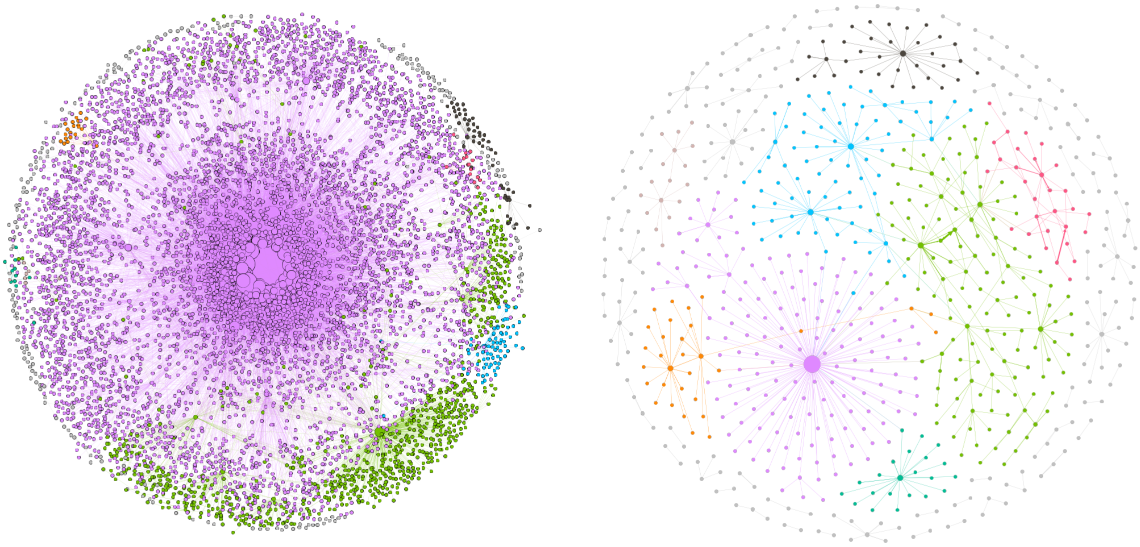
The number of official moderators among the highly active users was negligible; there were no moderators in the top 5% contributors to BLF and only 2 in the top 5% for Asthma UK. Thus, our network analysis predominantly reflects content originated from registered users. This also means that moderators 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

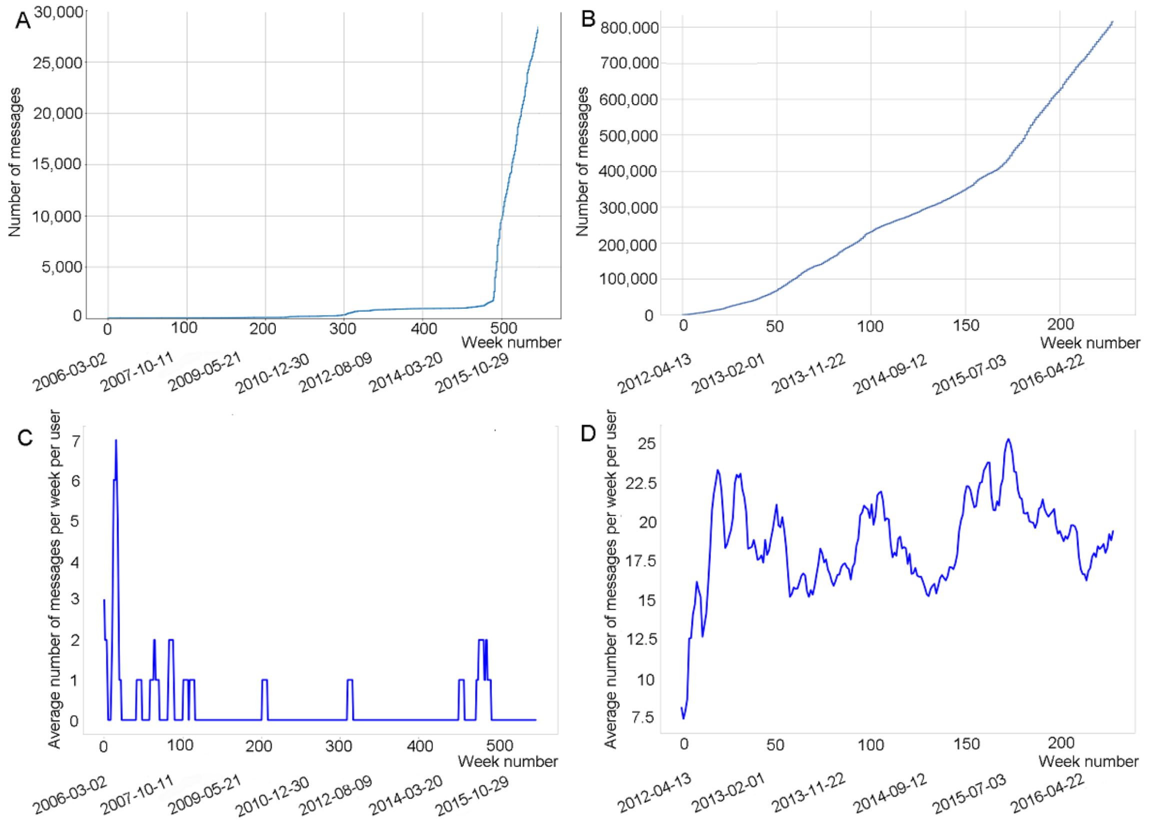


Fig. 2.2 Cumulative distributions of the number of posts as a function of time (weeks) within the Asthma UK (A) and the British Lung Foundation (B) communities. Calendars dates are reported below as week numbers (since the inception of the community). Panels C and D illustrate the average number of posts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

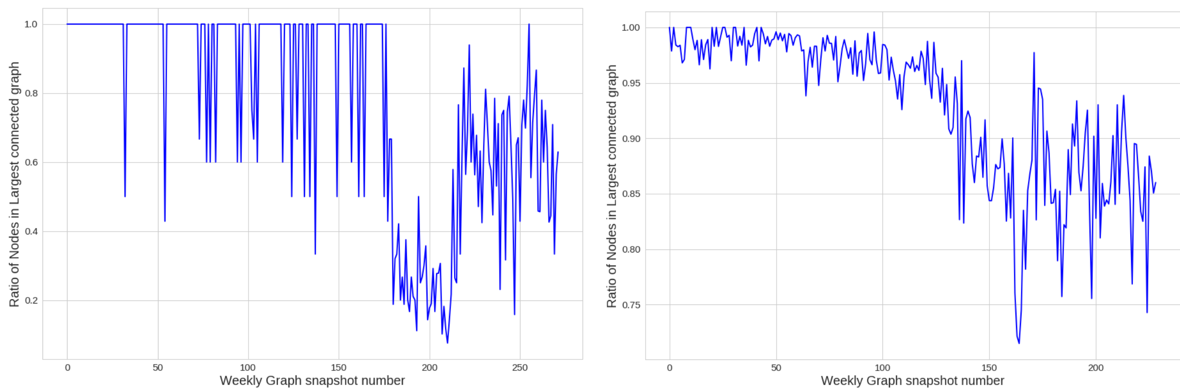
community, however if a community revolves around purely functional interactions, then you may see a bursty nature of communication [93]. From these basic analysis, it was quite evident that the BLF community was more active of the two, in that, the community exhibits a consistent engagement of the users 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.

4 ***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, 17], 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

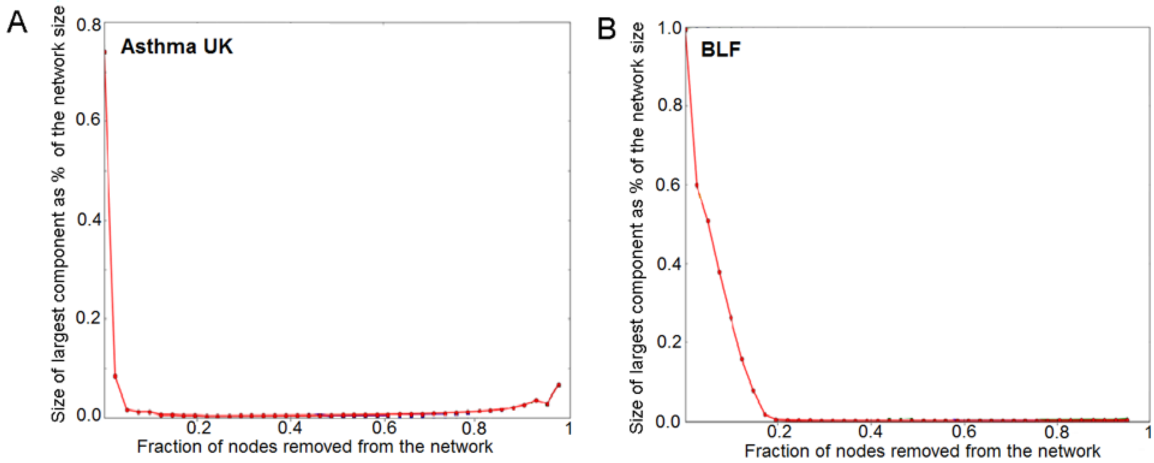
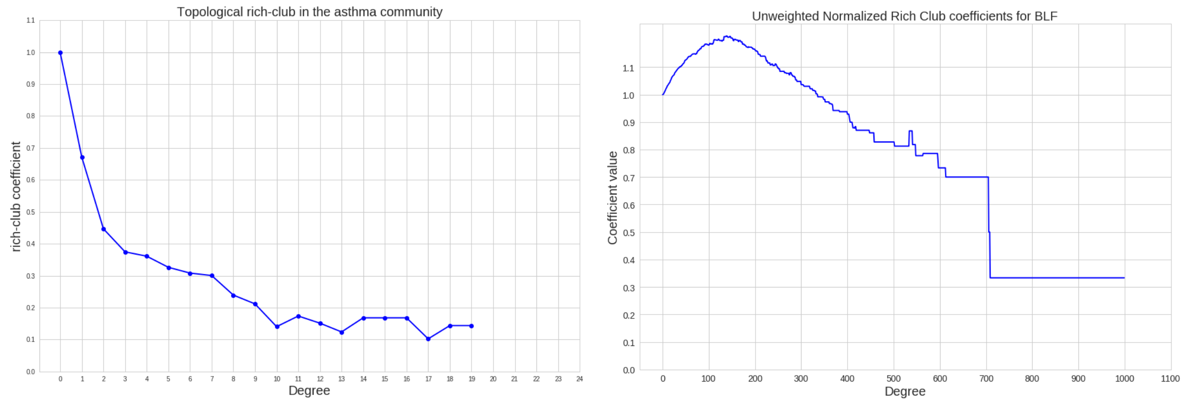


Fig. 2.4 Results of progressive removal of nodes based on connectivity. Both communities collapse drastically, in terms of connectivity, with BLF showing a little more resilience

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 [24]. 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 [91]. 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 [80]. .

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 [24, 136]*

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 3).

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]

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

6 *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 [133] 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 :

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

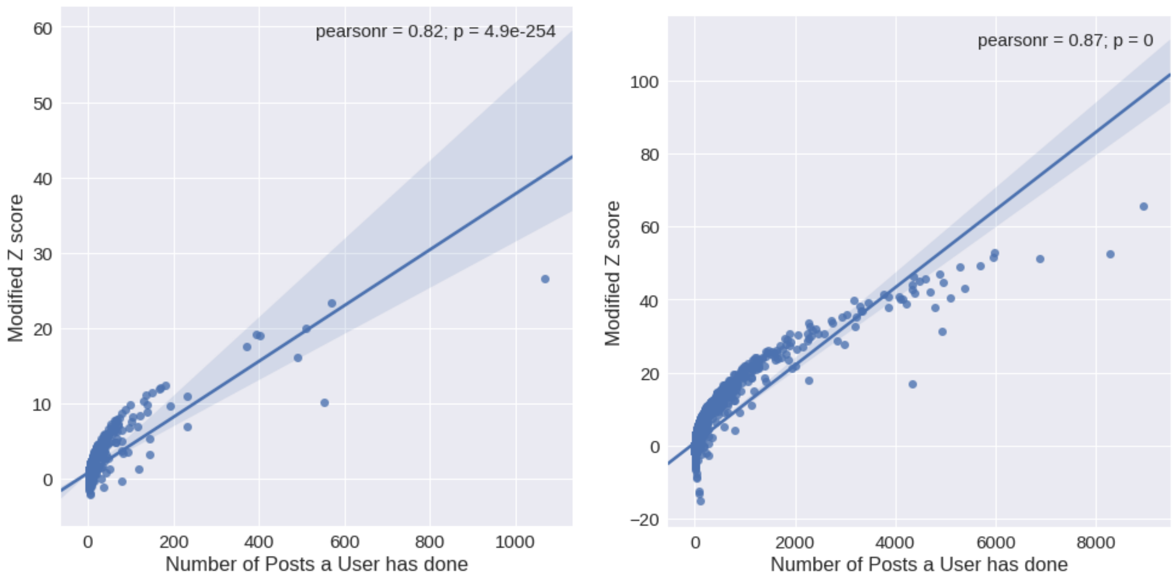
Z_{score} of a random variable X is defined as

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

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. Developing metrics like this makes quantifying whether a particular community works for the subscribers a tractable problem.

2.6 Rich users and structural holes

One of the key aspects of utility of any social network is driven from the social capital offered as a result of the subscription.

7 ***Social capital*** *(Sociology): Social capital is defined as those features of social structures , such as interpersonal trust and norms of reciprocity and mutual aid, which act as resources for individuals and facilitate collective action [23, 25]*

It is common to quantify social capital in the context of social networks, by looking at structural holes, or unmet potential social links in the network. This is where ties between otherwise unconnected neighbours are filled in, sometimes called as closures, thereby benefiting the broker and the two neighbours by adding an extra link for information to diffuse. Such mechanisms have been studied in the sociology literature for decades. Work by Granovetter [51] explored these structural holes and proposed that they are detrimental for efficient diffusion of information and resources in social networks. He also at times called these the "forbidden triad", referring to their propensity to close up. Such closures are, according to Ronald Burt [19, 20], necessary for information brokerage, and at times directly equate to social capital of these broker nodes. In our case, as so much evidence has shown that the brokers of social support are often the "rich" nodes or the super-users, we would certainly want to investigate how these agents affect the local cohesion and structural holes.

Till now we looked at the global macro structural properties of this support graph using the global graphs G_g, where we look at the user's interactions with other users across the lifetime of the community. But often the supportive interactions happen in a lifetime of a single thread, revolving around a topic or query. So to examine the effect of the rich users on the social cohesion, we correlate the total number of posts done by super users on any given thread, to the amount of closed triangles found in the corresponding thread graph G_t.

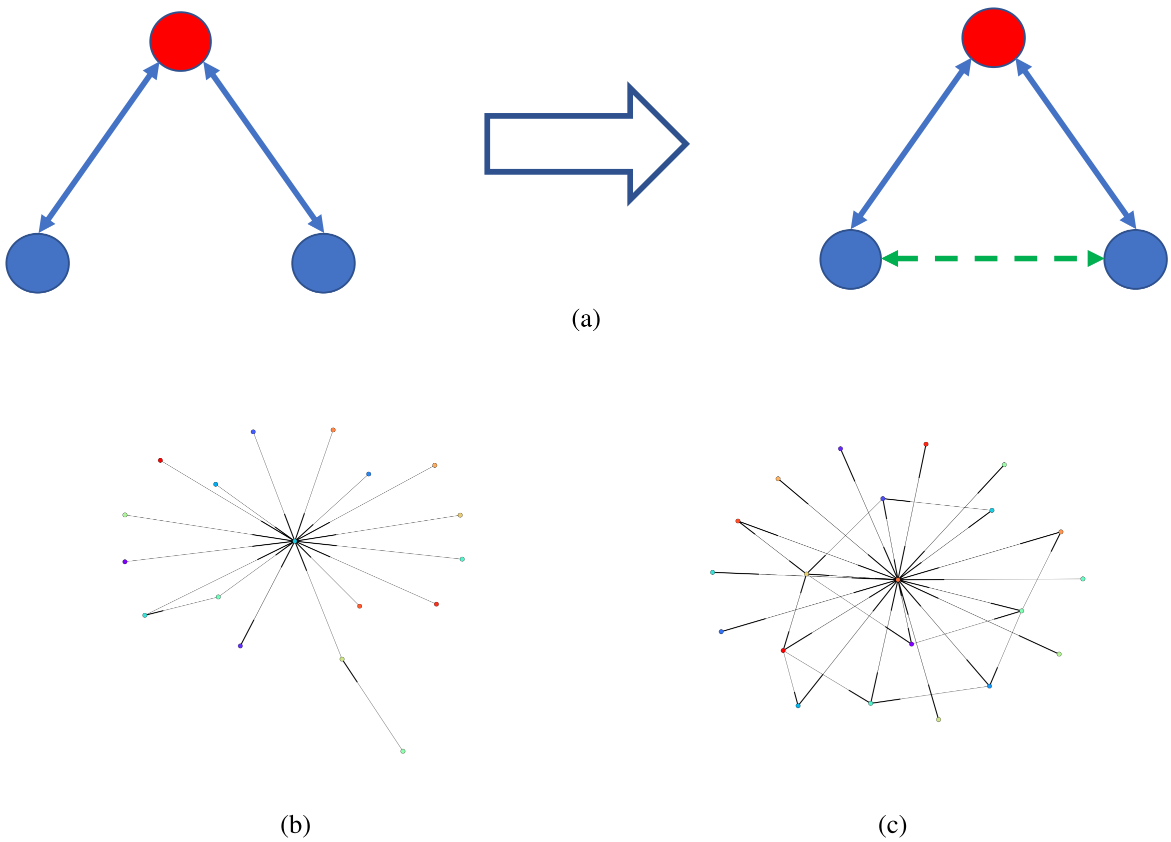


Fig. 2.7 Figure 2.7a shows an example of closure among three nodes, where a structural hole between a cluster of three nodes is closed by addition of the green link. Figure 2.7b shows a thread level interaction graph showing lots of structural holes between participating nodes. On the other hand Figure 2.7c shows an example of a thread level interaction graph where a 'rich' user has contributed multiple times. This graph also shows more closures

The resultant scatter plot can be seen in Figure 2.8, where we can see a net positive correlation of 0.44, with a very low p-value. This means there is a general trend of higher triadic closures in a conversation, with the amount of rich user participation.

The research questions asked at the beginning of this chapter, required us to look at these communities from the perspective of its users. It was evident, that these communities do provide a supportive space. When looking at macroscopic structure of a support network,

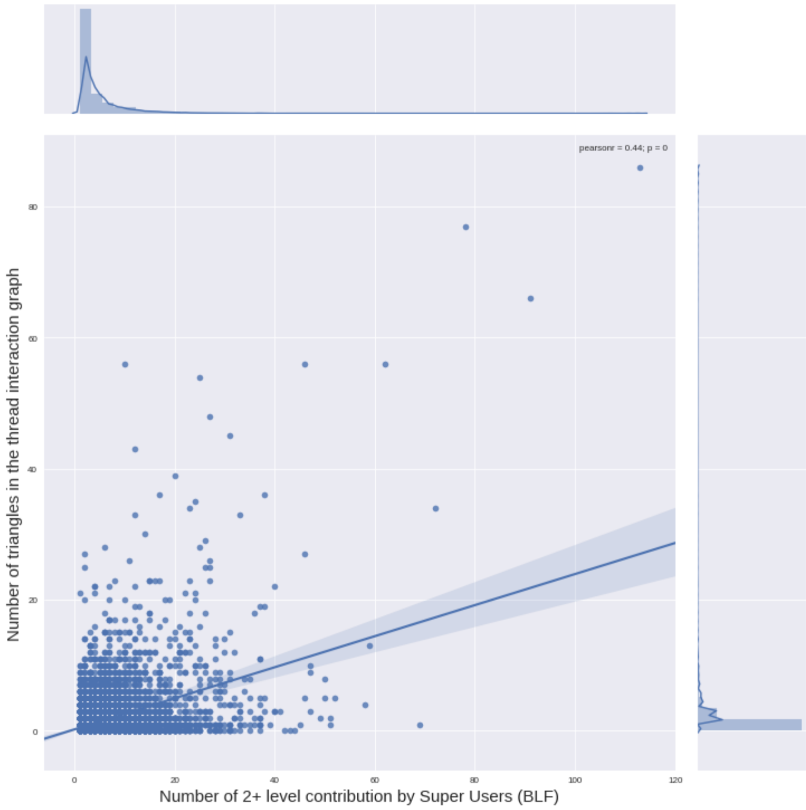


Fig. 2.8 Scatter plot between the number of closed triangles in a conversation thread, with the total number of posts done by rich users in that thread. A positive correlation of 0.44, with a p-value of 0 is observed

we find that certain groups of users are highly crucial for the vitality and survival of the whole exchange process. But we also observe that these groups are in flux, and users tend to become more supportive with experience. The idea of perceived support stems from the fact that the user in distress is not only getting the instrumental information, but also benefits from the social capital of the allied users. We observe that supportive users tend to have a positive effect on the social capital of a conversation, promoting more social cohesion.

Social support is a multi-dimensional perceived entity, and I am attempting to capture the mechanics of support through online conversations. It has been an active area of study from a sociological and psychological perspective. There is immense value in understanding how social support thrives on the internet, especially because of its potential of relieving some burden from the ever so burdened health services. The work till now did focus on the global interactions of support givers and seekers on a community. However, the actual action of peer support happens over a single thread of conversation. Aggregating these conversations over a period of time, allows us to look at how users behave by and large across different conversations. What is interesting and important to understand is how can we measure the act of peer support in an individual supportive conversation. How does a supportive conversation evolve, and are there any peculiar signatures we could observe in comparison with generic conversations? For this reason, it is important to look at a finer granularity of interaction, what we term as *mesoscopic* view of the conversation. In the following chapter, we would do exactly that, and unravel the discriminative patterns in meso and macro representations of conversation threads.

CHAPTER 3

PART 1 : SIGNATURES OF SUPPORT: FROM MACRO TO MESO

The global structure of social support communities, allude to the fact that these communities are exhibiting some mechanisms different than generic communities. They also seem to have an effect on how people perceive support when in distress. In the past chapter, we saw the behavioural signatures of support groups. The utility of 'rich' users who are the most active and promiscuous when it comes to responding. The dynamic of evolution of users from support seekers to support givers. We also saw the way brokerage works in providing closures in the conversation threads, adding more closed triangles between people as 'rich' or expert users contribute. These results make it relevant for us to investigate the signatures of social support when it comes to individual conversations on the web. Quantifying how support manifests in terms of structure in conversation, might gives us more insights in how online support can be utilised properly for health care. This may also point to the features to look at, if we need to automate the process of quashing online toxic behaviour. Inspired from the DIKW pyramid, we have now experienced the transformation of raw social network interaction data, into abstractions that bring out peer to peer interaction patters as well as the structure of dialogue between users. We have also extracted the knowledge about emergent behaviours of users using topological metrics. In this chapter we will look into the the macro and the micro signatures of a supportive dialogue on these communities.

A valid criticism of the results from Chapter 2 is that the results were driven by a support community which is highly moderated. This sort of moderation is often absent on more popular open platforms. One such popular and open platform is Reddit[1]. Reddit offers its users, anonymity and very limited moderation. The limited amount of moderation comes from volunteers appointed by a particular community, or in the case of Reddit, a sub-reddit. A sub-reddit is a sub-section of Reddit, which is a topical community, where only topical conversation threads can be posted. Any user can subscribe and post to such a topical sub-reddit, provided they abide by the simple rules of the sub-reddit. For example, if a sub-reddit deals with politics, like r/politics, one must make sure that the threads posted on this subreddit deals with political subject matters. There are several sub-reddits on this platform that deal with peer to peer support. A few examples include r/SuicideWatch[2] , r/Depression[3],r/Bipolar[4]. Utility of these communities in providing a support, and a place to vent have been explored before [34, 35]. However, in the context of my dissertation, I want to understand how such peer to peer support mechanisms are manifested in the dialogue structure. To do so, I need to look at these conversation threads from a over-all structural perspective(macro) as well as from a user-centric local perspective(meso).

3.1 An argument for studying mental health forums

The new platforms like facebook and reddit have become so ubiquitous, that some research suggests that they might be affecting our broader psychological state [21]. 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 [34, 35]. These platform define the way humans interact in the present age, and developing an understanding of their effects and utility is of high importance. Reddit is one of the largest online communities which contains a number of topical sub-communities. 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. This has motivated several researchers to probe the different aspects

[1]http://reddit.com/
[2]https://www.reddit.com/r/SuicideWatch/
[3]https://www.reddit.com/r/Depression/
[4]https://www.reddit.com/r/Bipolar/

of support online, like language [22], anonymity in social support [34] or risk factors [49]. Recent studies have shown promising results in modelling 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 [34, 35]. 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[49]. 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[95]. Positive effects in participation in such fora have also been shown by improvements in members' written communication[94]. The supportive nature of comments in the SuicideWatch forum has also been studied by automatic identification and classification of helpful comments with promising results[65].

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 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. Several online platforms are used for expressing suicidal thoughts and reaching out for support. On Reddit, the subreddit *SuicideWatch* currently[5] has almost 94k subscribers, and is a lightly 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 intent of peer support seriously, and are governed by guidelines that prohibits false promises, abuse, tough love and other clinically frowned upon methods of conversations[6] This setup gives us an ideal petri-dish to measure what constitutes a supportive conversation. More specifically, owing to the results from Chapter2, we would like to develop methods that would allow us to understand the macroscopic and mesoscopic signatures of support. Formulating this problem

[5]As of 27th June 2018

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

needs to follow the methodological framework discussed in Chapter 1, whereby we collect the necessary data and device appropriate abstraction/s, to quantify how the macroscopic and mesoscopic signatures of support in these conversations manifests. These signatures could be captured using different metrics that signify a particular behaviour of interaction.

3.1.1 Research questions

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 *function* — users turn to these platforms not only to express their thoughts and concerns, but also to receive support (instrumental or perceived) from the community. In the previous chapter, we looked at how this received support, manifests in the network structure in the short term and long term users. What remains to be explored is how these supportive conversations themselves look on a macro as well as local (meso) scale. More specifically, in this chapter we would like to arrive at answers to the following two research question, discussed in Chapter 1

RQ3 *Are there any macroscopic signatures of supportive conversations?*
RQ4 *Are there any mesoscopic signatures of supportive conversations?*

To model the network topology in an online community, we represent each conversation happening over these forums using graph-based abstractions (users and replies) as described in Section 3.3. 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

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.

known as Triadic motifs : which gives an idea about how distinctive are interactions between subgroups of users.

3.2 Data

Reddit is a platform where a user can create a post on a subreddit, and other reddit users can interact by posting at different levels of the thread or by up or down voting posts. We analyzed root posts in the SuicideWatch subreddit (SW)[7], building on the work of Gkotsis et al. [49]. We crawled SW to get hierarchical threaded conversations, by iteratively pursuing each conversation at progressively deeper levels until the whole thread had been obtained. [8]. This resulted in a dataset of over 50k SW threads totaling around 500k individual posts.

To provide a baseline against which to compare the hypothesized supportive nature of the SW sub-reddit, we acquired 50k baseline posts from any other subreddit popular enough to land on the frontpage.

We crawl the Frontpage posts for 2 weeks accumulating over 50 thousand reddit threads in the process. Comparing the suicide watch threads with the baseline, gives us confidence over our network metrics, and any claims made there forth. The two conversation datasets from r/SuicideWatch and Frontpage are very similar in terms of pure macro statistics. E.g. the median amount of responses for a Suicide watch thread were 6 and for baseline Frontpage posts were 8. The median conversation depth (the depth of the hierarchy of the responses) is 2 for all the datasets. The median amount of unique authors participating in a post are 2. Owing to the long tailed nature of the datasets, we perform our analysis on threads which

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

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

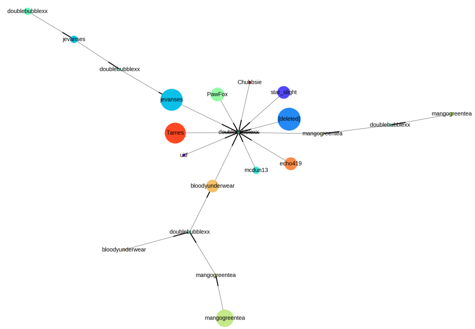
have been conversed on at least 5 times. Which means we consider graphs which have more than 5 posts on the root post. This results in our datasets to shrink to 25k threads for suicide watch and 30k threads for Baseline. We further clean the dataset, by removing threads where the root author has deleted their user account, which is a common practice to preserve anonymity in more controversial posts. The resulting dataset has 20k threads in Suicide watch and 23k threads in the baseline.

3.3 Abstractions

To understand the dynamics of supportive conversations, we first need to formalize the abstraction of networked conversations as well as the content posted in these conversations. In case of forum based platforms where users 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*.

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 semantic vector V_i for post P_i and the semantic vector V_j of post P_j. 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 3.1



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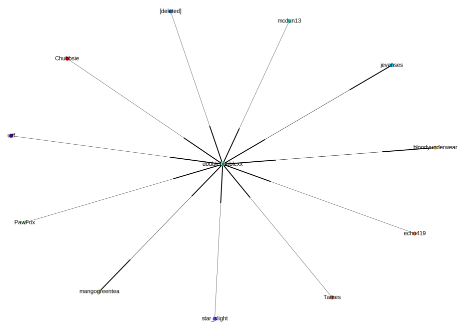

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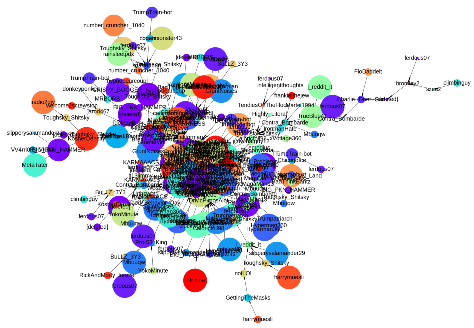

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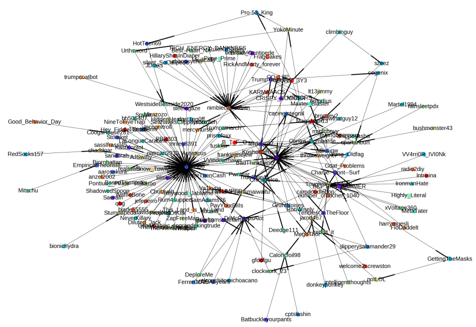


(d)

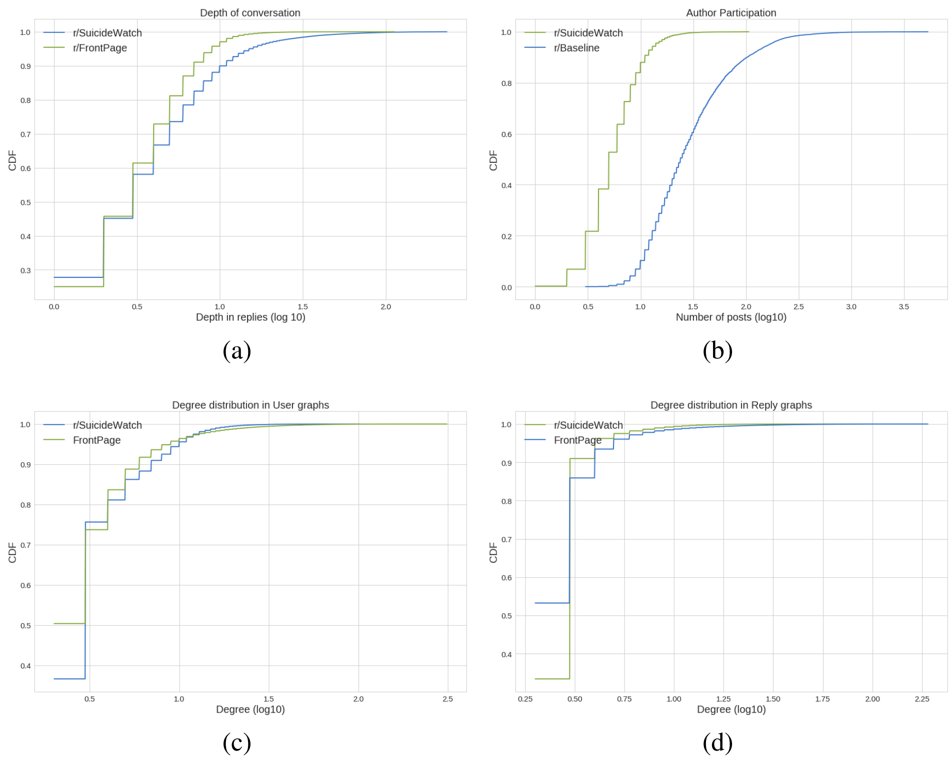
Fig. 3.1 Example User graphs and their corresponding Reply graphs, Figure 3.1a shows a random thread from the Suicide Watch sub-reddit along with the preserved structure of posts in the thread and 3.1b shows the corresponding user graph that arises by capturing the user to user interaction in the thread from the reply graph. In comparison we have user graph Fig 3.1d and its corresponding reply graph Fig 3.1c from one of the Front page threads

User 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 edge weights 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.

3.3.1 Network characteristics

Figure 3.2a 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 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.



(a) (b) (c) (d)

Fig. 3.2 *Fig 3.2a shows the distribution of maximum depths of Reply Graphs for Subreddit r/SuicideWatch and the baseline Frontpage conversations. Fig 3.2b shows the distribution of unique authors per thread in the two datasets. Fig 3.2d shows Distribution of degrees for Reply Graphs, r/SuicideWatch and FrontPage. Fig 3.2c shows the degree distributions for the reply graphs*

3.4 Metrics

Once you are able to develop abstractions from the data, it becomes possible to develop metrics on these abstractions so as to derive insights about the mechanics of support. These metrics are then used to validate structural differences between supportive conversations and generic casual conversations from our baseline set, and come up with a theory for links between supportive conversations and the structure of the conversation, if we find any.

Semantic Alignment

We use a popular word embedding method called *Word2Vec* [82] 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 from literature is shown to correspond to the semantic similarity in the textual space. This method is quite popular and used in community based question answering[81], Medical semantic similarity [39] and other medical informatics applications[137]. We first train two independent word2vec models on the Suicide watch and Front page post corpora. We then extract the word embedding vectors for each post using Doc2Vec[71], which extends the word embeddings to represent a whole document or paragraph. We extract these embedding vectors for each post in R^N for all the posts across the complete hierarchy of threads. We then quantify the edge weights of each interaction amongst the reply tree as the cosine distance between the response post and the hierarchically higher post, to which the responder has posted to. This captures the semantic alignment between the hierarchically adjacent responses. More formally, if user V_i has responded with post P_i to a post P_j by user V_j, the edge weight of of edge E_{ij} in the corresponding reply graph would be

$$W_{ij} = \frac{V_i.V_j}{||V_i||_2||V_j||_2}$$

This metric standardizes all edge weights between 0.0 and 1.0, 1.0 implying that the posts P_i and P_j are most aligned, and 0.0 implying the post have least semantic similarity. This metric abstracts out the content of the post, in terms of semantics which can then be used as edge weights in the graph abstractions.

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

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

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 centrality of the node corresponding to the *OP*, 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 any user V_o or the *OP* and receives a response back from that user or the *OP*. We find the fraction

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

Urgency

To understand the urgency in how Suicide watch subreddit users responds to the *OP* and each other, compared to the baseline threads on the Frontpage, we calculate differences between the posting times between consecutive response messages in a reply graph. We then compute the median response times per thread, for posts in response to any *OP* authored posts and in general across all other post responses.

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 tree, to evaluate the branching factor. The branching factor is formally described as

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

Median semantic alignments

This metric quantifies the overall semantic alignment between response posts across a particular conversation thread. For any reply graph $R\{P,E,W\}$, we compute The median of all the edge weights calculated using the definition of semantic alignment This metric quantifies the overall semantic alignment in a conversation. We also do the same calculation between responses to any post authored by the *OP* to test whether responses to *OP* demonstrate any special pattern of all alignment in supportive vs generic threads.

3.5 Macroscopic analysis: at conversational level

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 archetypal of suicide watch conversations such that they are over-expressed in 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.

3.5.1 Peculiarity of threads of Support

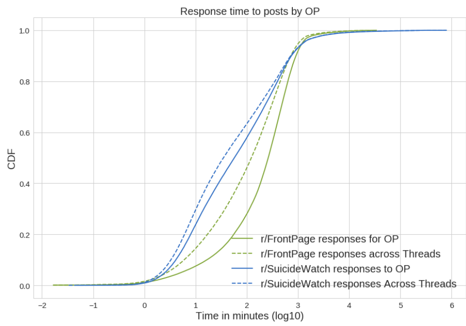
We begin by characterizing the two networked abstractions, namely Reply Graphs and Interaction graphs as described in Section 3.3. We do so by first comparing these two abstractions with a baseline control conversation threads using certain macroscopic network properties.

Responses to *OP* are very urgent in supportive setting

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* and other users as compared to other sub-reddit threads on the frontpage, we calculate differences between the posting times between consecutive messages in a reply graph. Figure 3.3a 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.

Interactions on suicide watch forums are statistically more symmetric

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 3.3b 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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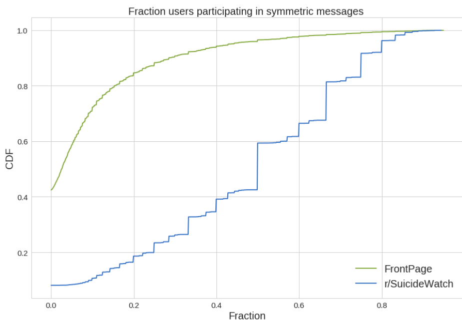

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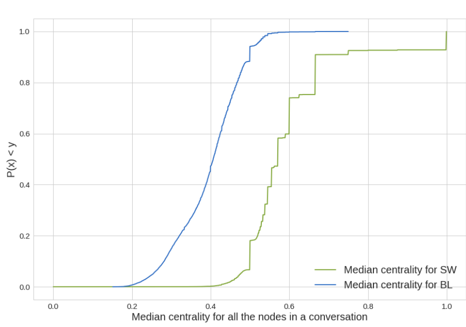

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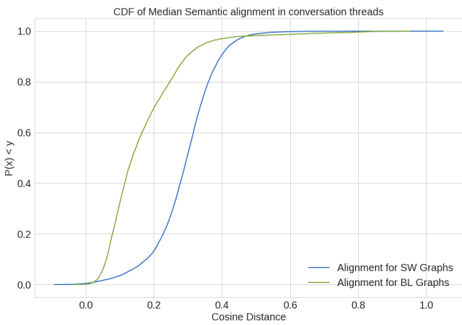

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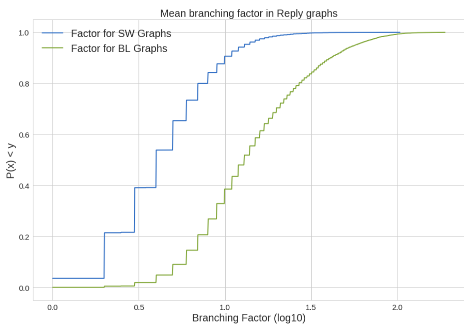


(e)

Fig. 3.3 Panel shows CDFs of different network metrics. Fig.3.3a shows the response time distributions, Fig.3.3b shows symmetrically engaged users, Fig.3.3d shows topical similarities across posts and 3.3e shows the branching factors of reply graphs.

OP is the most central user in supportive conversations

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 3.3c shows the Empirical CDFs of centralities.

Supportive responses are semantically aligned, more so when they are in response to the *OP*

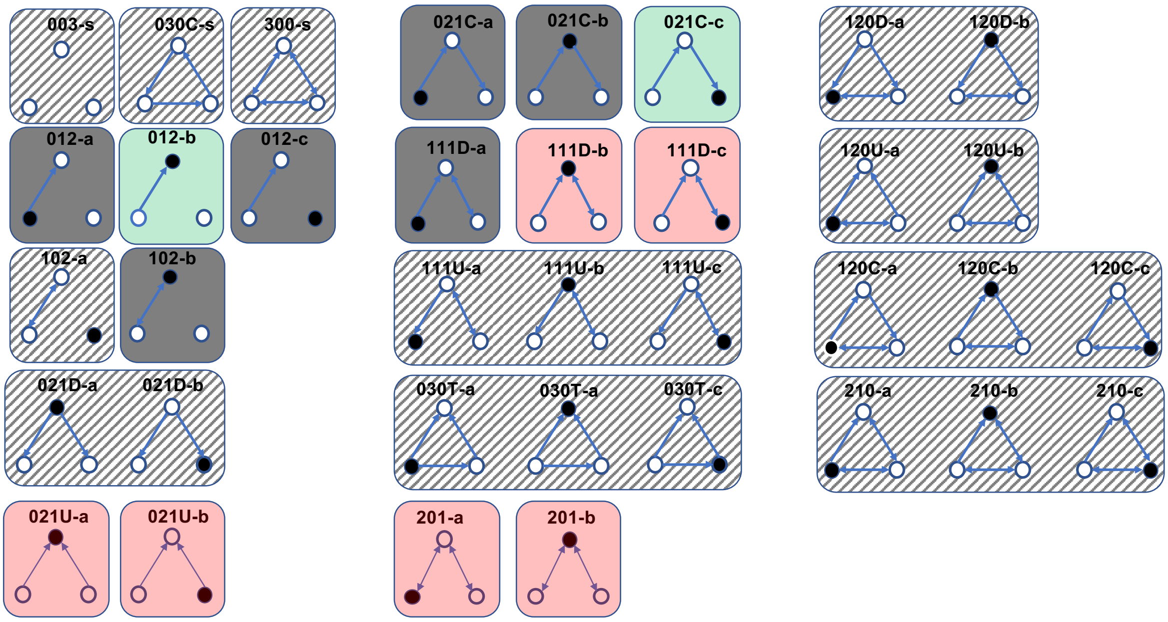
We measure semantic alignment based on word embeddings of the source post and the reply post, at every edge of the reply graph. The detailed method of extracting semantic alignment along a post and its response is described in Section 3.4. Extracting such similarity metrics, we compare the trend in response text being in semantic alignment with the parent text in the reply graphs.

Supportive conversations branch out considerably less compared to baseline

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, we use the reply graphs, that mimic the conversation structure of the threads. By using the method described in Section 3.4, we found that Suicide watch threads, tend to branch less as compared to our baseline conversations. This implies that suicide watch threads tend to remain on topic and more often than not, a one-on-one conversation. Albeit many such dialogues may emerge with many participants, and hence that explains the high centrality of the *OP* in all user interaction graphs. If the participants on a thread seldom interact amongst themselves, the corresponding interaction graph will have the *OP* as the most central node.

3.6 Mesoscopic analysis: Anchored triadic motifs.

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[83]. They have been used in a variety of applications and networks, from economics [134] to



(a)

Fig. 3.4 Figure 3.4a shows the 36 different types of Anchored Triadic motifs that are looked for in the user graph data. The motifs with **green boxes** are **over expressed in the baseline dataset** by significant amount. The motifs with **red boxes** are **over-expressed in the Suicide watch dataset** by significant amount. The motifs with **grey boxes** are present in significant numbers in both datasets, but neither over nor under expressed in any datasets based on their Z scores. The motifs in **grey hatched boxes** are very rare in both the baseline and suicide watch datasets, with less than 5 mean occurrences per graph per bin.

cellular protein-protein interaction networks [131]. These local interaction patterns have been studied before, and have been fundamental in the study of social structural processes[45]. They help social scientists quantify the type of hierarchies in the social network[31, 32]. But in the setup of a typical support community network like r/SuicideWatch, the conversation shows clear distinction between the users who respond to a call for help and the user/s who are asking for help. In the case of Reddit we define the former as the *OP* who starts the conversation thread. For this reason, we changed the definition of the triadic motifs to accommodate the role of a node around which the motif is developed in the due course of the conversation. In conventional literature, the local interactions are measured in terms of census of 16 triadic motifs[45], which cover all possible patterns of non-isomorphic graphs, or graphs which cannot be mapped or morphed into each other. In this method, there is no special treatment to any node, and positional parity of all nodes is treated equally. This means, role of a node in the conversation cannot be incorporated in this analysis. For this reason, we build on top of this methodology but by introducing anchors, or nodes with special importance. This is because, we would like to know how a graph evolves around the person in distress or the *OP* in our case. A symmetric link with the *OP* implies that the *OP* is part of a to and fro communication, however a triad with a symmetric link between two non-*OP* nodes implies that the conversation does not involve the *OP*. By fixing a role for a node in a motif, each of the 16 triadic motifs as seen and developed in the field[45, 56], can be unravelled into 36 sub-variants of these motifs by varying the anchored node, as seen in Fig 3.4. Each sub-variant is different from the other from the perspective of the anchored node. The resulting motifs to measure grow from 16 to 36, since some anchored motifs are iso-morphic, which means they look identical to some other motif from the perspective of the anchor. These motifs are then counted using custom tweaked census methods based on Bataglej et.al's work[14]. Each motif as seen in Figure 3.4a is named using a particular recipe. The first three letters, follow a M-A-N pattern which signifies the number of "**M**utual" , "**A**symmetric" or "**N**ull" edges present in that particular triad. E.g. the motif 030 has 0-Mutual(bi-directional), 3-Asymmetric(unidirectional) and 0-Null(disconnected) edges. There are some motifs with an added letter modifier attached, to signify the flow of information in the triad. The naming is done in accordance with Holland et. al's work[54].

To methodically understand the over or under expression of these anchored triadic motifs in the suicide watch community, we use the user interaction graphs for the Front page baseline posts as a control group. We analyse 10,000 user interaction graphs each for the baseline and the suicide watch datasets. We progressively select graphs with variable sizes i.e. number of users present in the interaction graphs. We do so by binning each dataset in ranges of graph sizes in increments of 5 nodes per bin. The resulting graphs would fall in the following 7 bins, with increasing number of nodes present : 1 - 5 , 6 - 10 , 11 - 15 , 16 - 20 , 21 - 25, 26 - 30, 31 - 35 and 36 - 40. We stop sampling above 40 nodes per graph, as the population of conversations that contain more than 40 unique users participating is extremely scarce for both the datasets. We then do the census for the 36 unrolled motifs for each of these bins, for both the datasets. Once the census is done, we calculate Z_{scores} for the Suicide watch conversations, using Baseline conversations as the null model, to understand over or under expressions of certain motifs. For any given bin B_I, let there be k baseline graphs that fall in that particular bin noted by G_{BL} , and let there be n suicide watch graphs falling in the same bin signified by G_{SW}. For such a setup, let M_{BL} signify a vector of k elements, where each element is the total number of occurrences of particular motif m in each graph from the set G_{BL}. With this sample of graphs as the null model, the mean would be $\mu_{null} = \frac{1}{k}\sum_{m_i \in M_{BL}} m_i$, where m_i is the count of motif m in the i^{th} graph in G_{BL}. The standard deviation σ_{null} is $std(M_{BL})$ Once we have the null model parameters for the baseline graphs for a particular bin, we calculate Z_{scores} for all the graphs from suicide watch samples G_{SW} from the same corresponding bin as random variable Z where the i^{th} element is the Z_{score} for graph i in G_{SW}. The score is calculated by the following formula

$$Z_i = \frac{m_i^{sw} - \mu_{null}}{\sigma_{null}}$$

where m_i^{sw} is the total number of occurrences for motif m in the i^{th} graph for the suicide watch samples. We then plot the mean of random variable Z and the standard error in Z to understand the over/under expression trends.

3.6.1 Patterns in local interactions

It is often useful to express large interaction graphs, as the sum of local interactions between two or three nodes at a time. This method is quite prevalent in the Social sciences, for studying social structures by looking at local interaction between agents[45]. Such analysis is quite useful in expressing local structures in the graphs and has been used in several network analysis works[112, 128]. For this reason we conduct a census of the 36 Anchored triadic motifs (described in Section 3.6) across all the selected graphs. From the amount of over or under expression of the network motifs, researchers have made inferences about the nature of local interaction. They do so by comparing the amount of density of each triad in a real network as against the expected quantity in a null model based on the number of edges[45]. We perform binning of user graphs as described before in Section 3.6, and perform over or under expression analysis in comparison with the baseline null model, using Z-scores of the motif occurrences.

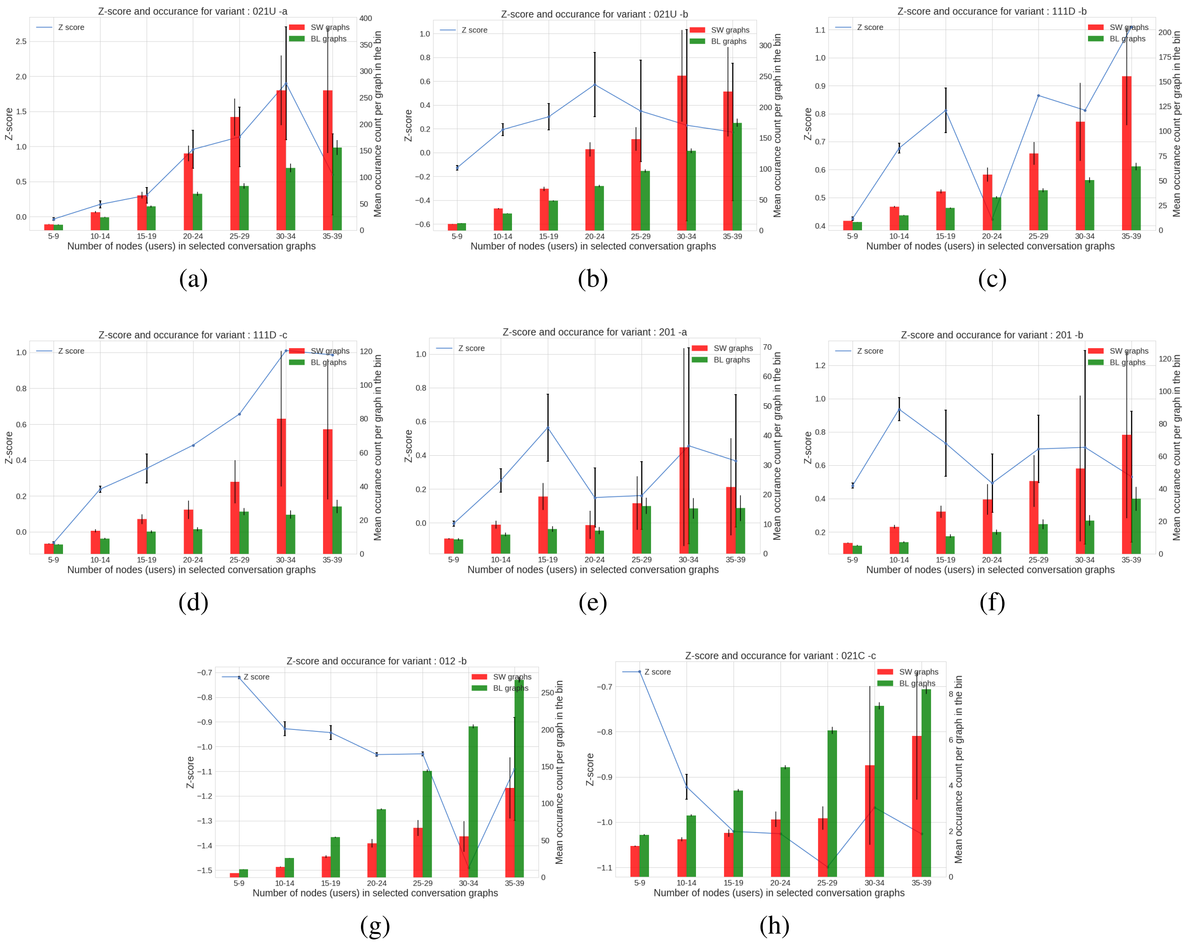
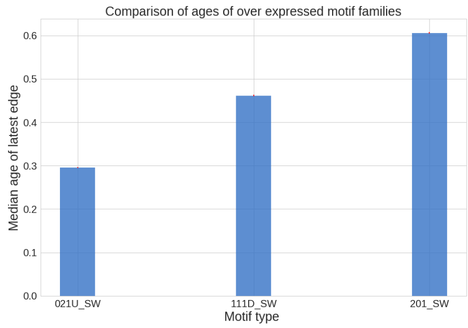


Fig. 3.5 This panel shows the Z-scores of the abundant and over expressed Anchored motifs found in both datasets. There are variants which are over expressed in Suicide watch (Like figures 3.5a,3.5b,3.5c,3.5d, 3.5e,3.5f), which form the top six plots. The bottom 2 plots show motifs which are over expressed in the Baseline over Suicide watch, as their Z-scores are negative. Figure 3.5g and Figure 3.5h.

We find that anchored motif variants **021U-a, 021U-b, 111D-b, 111D-c, 201-a and 201-b** are significantly over expressed in suicide watch conversations across all sizes of graphs as seen from figures 3.5a,3.5b,3.5c,3.5d, 3.5e,3.5f. Similarly anchored motif variants **012-b and 021C-c** are significantly over expressed in the null model(baseline) graphs across all sizes.



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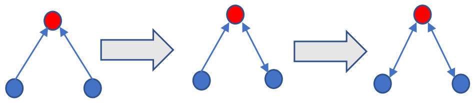


(b)

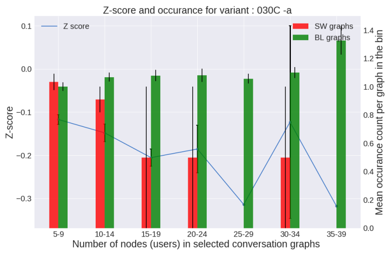
Fig. 3.6 *Figure 3.6a shows the plot for mean motif life times as a fraction of the entire thread life. The lifetime is measured as the time at which the latest edge of motif is formed. The Figure 3.6b shows a toy example of what sort of dialogue exchange could lead to the motif lifetime distributions seen in Figure 3.6a*

From previous studies on triadic structure, it was inferred that transitive triads are naturally more common than expected in social structures of human social networks. Interestingly, our analysis shows that transitive triads are rarer in Suicide watch, as against the baseline conversations. But in the defence of previous studies, the networks we study are of human conversations and not of human social ties. Also these conversations are happening with an intent of providing support, which makes one user (the one in distress) the centre of conversation. These conversational preferences make the macro and meso level structural signatures peculiar.

3.7 Conclusions and Outlook

These patterns in local interactions indicate that conversations in suicide watch tend to be more *OP* centric, with non-transitive dialogues between users who respond to a call for help. More so, the *OP* tends to be highly central in the conversation as well as part of several mutual interactions. These behaviours are highly particular to r/Suicidewatch when compared with the baseline conversations. Further investigation of local structures in graphs show that there is a radically different way the conversation graphs evolve. The difference is not only between supportive conversation graphs and generic conversations, but also overall in supportive conversations and any social graphs. Several studies have looked at the social-tie structures and shown certain triadic motifs to be important in maintaining social hierarchy [54, 55, 111, 112], but these expected structures are not the ones prevalent in supportive conversations. Transitive triads like *030T* and *210C* are shown to be overexpressed in ties that show social hierarchies. These and many of other relevant triads are not even active in supportive conversations as seen from Figure 3.6. This points of a very different approach at interaction with distressed users, and may have great implications on detection of toxic behaviour and enabling of helpful online conversations. Further work needs to be done in modelling these conversations. With the advances in machine learning, both the language and the network structure could be used in compliment to develop unique embeddings for support. A true inter disciplinary aim is to enable use of such frameworks, to understand at risk individuals online and offline.

In conclusion, quantifying perceived social support is an ongoing effort. But my work has shown that there are computable methods, which could capture the mechanics of support in online conversations.



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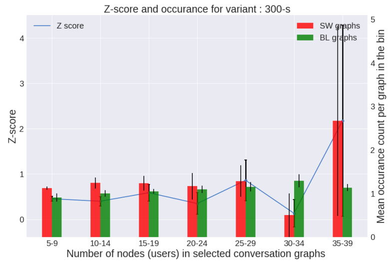

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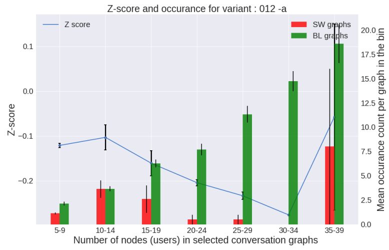

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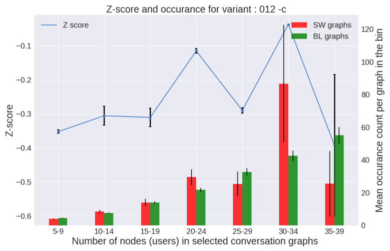

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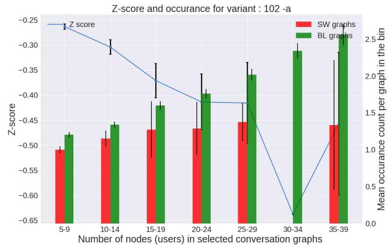

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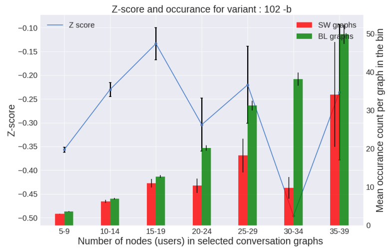

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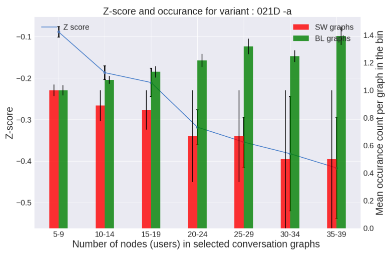

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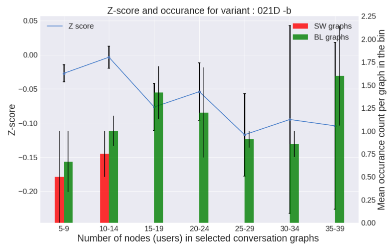

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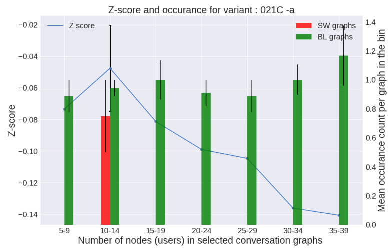

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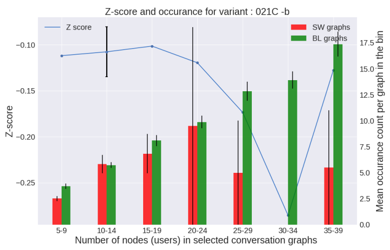

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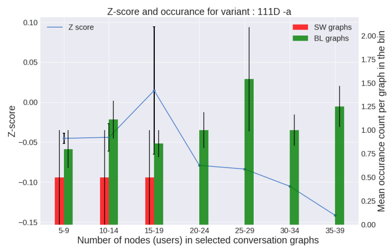

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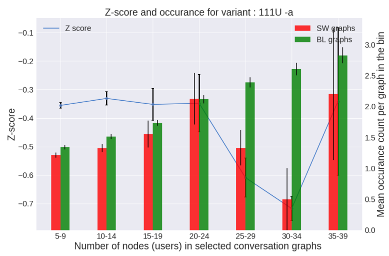

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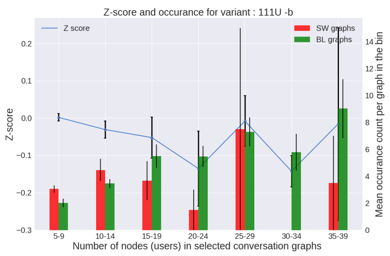

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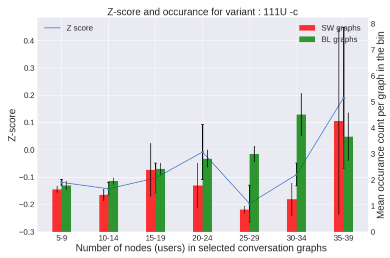

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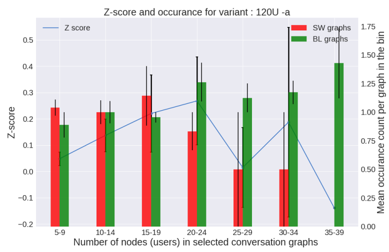

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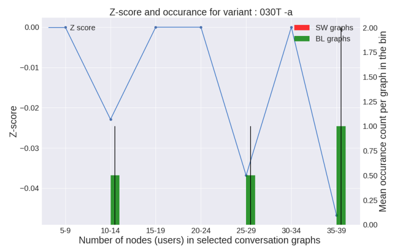

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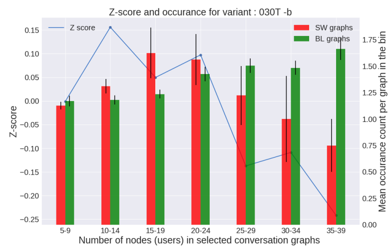

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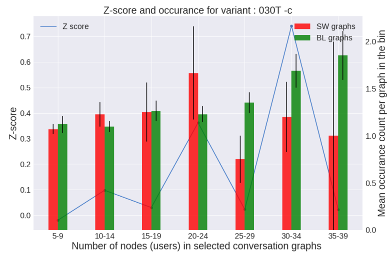

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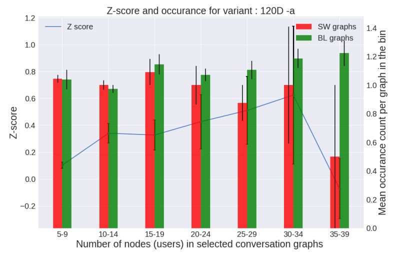

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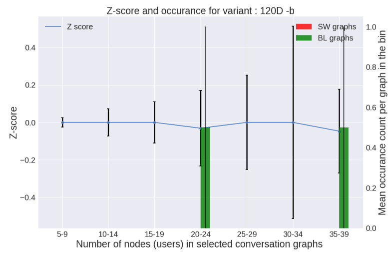

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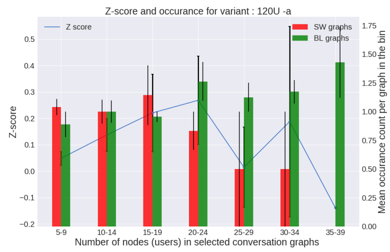

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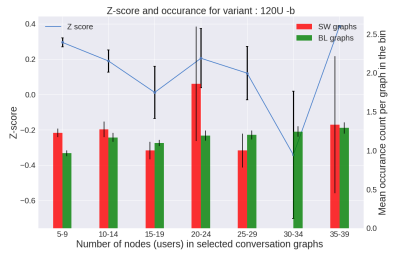

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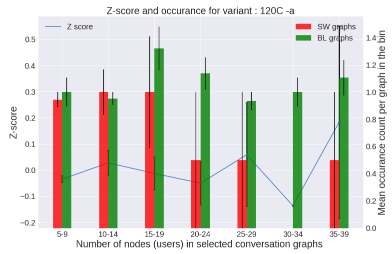

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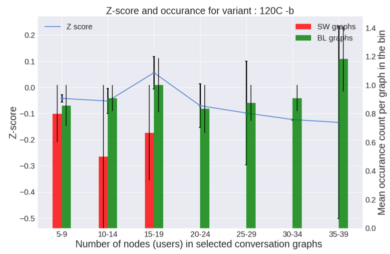

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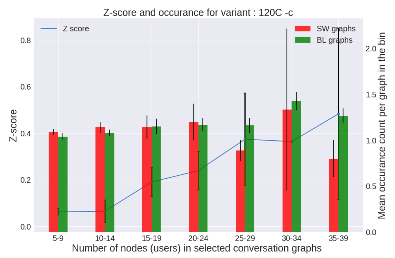

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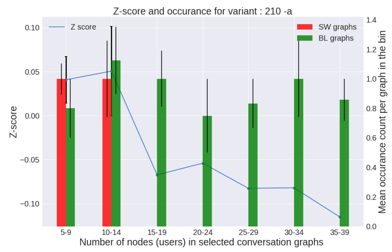

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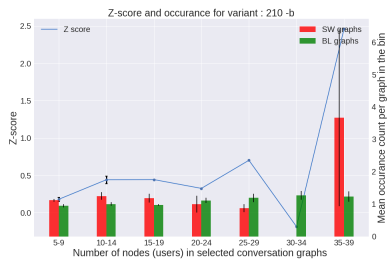

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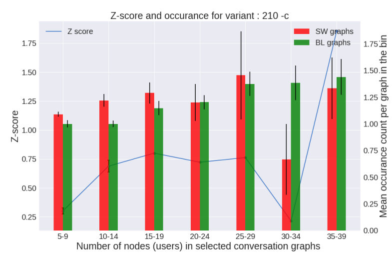


(10.a)

Fig. 3.6 This figure lists out all the insignificant Anchored motifs, either by the virtue of rare occurance (<5 mean motifs per bin) or by account of low Z-score.

CHAPTER 4

PART 2: REAL WORLD PERCEPTION OF BEAUTY

Beauty is nothing other than the promise of happiness – Stendhal, *On Love*

In part one, I delved deeper into the problem of quantification of perceived social support - online. This work showed that there are quantifiable signatures of social support, and these can be exploited to build models of support and safe interactions online, which could directly benefit persons at distress. Capturing the signatures of a subjective quantity, like the perception of social support, through the analysis of online conversations has implications on how we design online spaces in the future. In the second part of my thesis, I extend the spirit of perception driven design of spaces, to the offline world. The core idea is about asking a similar question, that is: **"Can we quantify the signatures of subjective perception of the real world, to design better spaces for ourselves?"**.

It has been shown through multiple studies, that the physical spaces that we use have measurable effect on our health [73, 78], our outlook towards exercise [124], health of seniors [123] and general all round well being [47, 90]. More importantly, all these studies point to the value of aesthetically pleasing spaces for an overall liveable city. This provokes the choice of quantification of perception of real spaces as my second case study. However, the question of whether an urban space is considered beautiful or not, is a subjective one. Yet research has shown that there are specific urban elements that are universally considered beautiful: from greenery, to small streets, to memorable spaces [2, 101, 106]. These elements are those that contribute to the creation of what the urban sociologist Jane Jacobs called 'urban vitality' [59]. Throughout the literature we find that there are certain patterns or motifs in the real world, predictive of whether a place would be considered aesthetically pleasing or not. The presence of these patterns point to a quantifiable nature of perception of real spaces. To the very least, there is a gap in quantifying what is "perceived" as pleasing or beautiful. To solve this gap, I try to answer the fifth research question of my thesis in this chapter, which is :

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

In this work, I will try to answer this question using the up and coming machine learning techniques. I use google streetview images as the data used for the analysis of beauty. An estimate of how 'beautiful' a street view image is, is arrived at using a crowd sourced approach. To understand the approach and the original contribution, lets first explore the related state of the art.

4.1 Related Work

Previous work has focused on collecting ground truth data about how people perceive urban spaces, on predicting urban qualities from visual data, and on generating synthetic images that enhance a given quality (e.g., beauty).

Perception of physical spaces. From Jane Jacobs's seminal work on urban vitality [59] to Christopher Alexander's cataloging of typical "patterns" of good urban design [2], there has been a continuous effort to understand what makes our cities livable and enjoyable. In the fields of psychology, environmental design and behavioral sciences, research has studied the relationship between urban aesthetics [104] and a variety of objective measures (e.g., scene complexity [64], presence of nature [63]) and subjective ones (e.g., people's affective responses [126]).

Ground truth of urban perceptions. So far, the most detailed studies of perceptions of urban environments and their visual appearance have relied on personal interviews and the observation of city streets: for example, some researchers relied on annotations of video recordings by experts [107], while others have used participant ratings of simulated (rather than existing) street scenes [75]. The Web has recently been used to survey a large number of individuals. Place Pulse is a website that asks a series of binary perception questions (such as 'Which place looks safer [between the two]?') across a large number of geo-tagged images [106]. In a similar way, Quercia *et al.* collected pairwise judgments about the extent to which urban scenes are considered quiet, beautiful and happy [101] to then recommend pleasant paths in the city [103]. They were then able to analyze the scenes together with their ratings using image-processing tools, and found that the amount of greenery in any given scene was associated with all three attributes and that cars and fortress-like buildings were associated with sadness. Taken all together, their results pointed in the same direction: urban elements that hinder social interactions were undesirable, while elements that increase interactions were the ones that should be integrated by urban planners to retrofit cities for happiness. Urban perceptions translate in concrete outcomes. Based on 3.3k self-reported survey responses, Ball et al. [11] found that urban scenes with positive aesthetics properties not only are visually pleasurable but also promote walkability. Similar findings were obtained by Giles et al. [48].

Deep learning and the city. Computer vision techniques have increasingly become more sophisticated. Deep learning techniques, in particular, have been recently used to accurately predict urban beauty [41, 110], urban change [86], and even crime [6, 36]. Recent works have also showed the utility of deep learning techniques in predicting house prices from urban frontages [70], and from a combination of satellite data and street view images [69].

Generative models. Since the introduction of Generative Adversarial Networks (GANs) [50], deep learning has been used not only to analyze existing images but also to generate new ones altogether. This family of deep networks has evolved into various forms, from super resolution image generators [72] to fine-grained in-painting technologies [96]. Recent approaches have been used to generate images conditioned on specific visual attributes [130], and these images range from faces [122] to people [77]. In a similar vein, Nguyen *et al.* [89] used generative networks to create a natural-looking image that maximizes a specific neuron. This method was used to bring out the latent representation of an image, that maximizes its probability of a particular class. In theory, the resulting image is the one that "best activates" the neuron under consideration. In practice, it is still a synthetic template that needs further processing to look realistic. Finally, with the recent advancement in Augmented Reality, the application of GANs to generate urban objects in simulated urban scenes have also been successfully shown [3].

To sum up, a lot of work has gone into collecting ground truth data about how people tend to perceive urban spaces, and into building accurate predictions models of urban qualities. However, little work has gone into models that generate realistic urban scenes and that offer human-interpretable explanations of what they generate.

4.2 A callback to DIKW

To quantify the subjective, I need to call back to the DIKW pyramid, which enumerates the different stages through which "Subjective" wisdom is extracted from the data.

Given that, it comes as no surprise that computer vision techniques can automatically analyse pictures of urban scenes and accurately determine the extent to which these scenes are considered, *on average*, beautiful. Deep learning has greatly contributed to increase these techniques' accuracy [41].

However, urban planners and architects are interested in urban interventions and, as such, they wish to go beyond technologies that are only able to predict beauty scores. They have often called for technologies that would make easier to recreate beauty in urban design [33]. Deep learning, by itself, is not fit for purpose. It is not meant to recreate beautiful scenes, not least because it cannot provide any explanation on why a scene is deemed beautiful, or which urban elements are predictors of beauty.

To partly fix that, we propose a deep learning framework (which we name FaceLift) that is able to both *generate* a beautiful scene (or, better, *beautify* an existing scene) and *explain* why that scene is beautiful. In so doing, we make two main contributions:

- We propose a deep learning framework that is able to learn whether a particular set of Google Street Views (urban scenes) are beautiful or not, and based on that training,

Symbol	**Meaning**
I_i	Original urban scene
Y	Set of annotation classes for urban scenes (e.g., beautiful, ugly)
y_i	Annotation class in Y (e.g., beautiful)
$\hat{I}_j$	Template scene (synthetic image)
I'	Target Image
C	Beauty Classifier

Table 4.1 Notations

the framework is then able to both *beautify* existing views and *explain* which urban elements make them beautiful (Section 4.3). These explanations are automatically extracted with computer vision tools.

- We quantitatively evaluate whether the framework is able to actually produce beautified scenes (Section 5.1). We do so by proposing a family of five urban design metrics that we have formulated based on a thorough review of the literature in urban planning. For all these five metrics, the framework passes with flying colors: with minimal interventions, beautified scenes are twice as walkable as the original scenes, for example. Also, after building an interactive tool with "FaceLifted" scenes in Boston and presenting it to twenty experts in architecture, we found that the majority of them agreed on three main areas of our work's impact: decision making, participatory urbanism, and the promotion of restorative spaces.

4.3 FaceLift Framework

The main goal of FaceLift is to beautify an existing urban scene. To meet that goal, it performs five steps:

Step 1 Curating urban scenes. Deep learning systems need considerable amounts of training data. To augment our initial set of data, we develop a new way of curating and augmenting the number of annotated images.

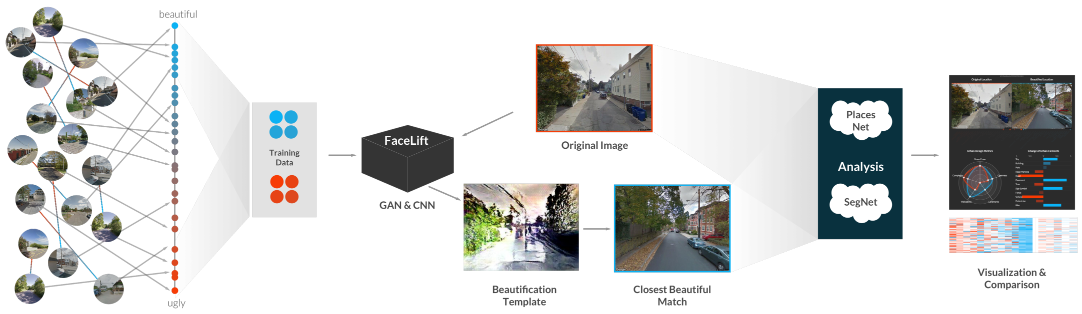


Fig. 4.1 An illustration of the FaceLift framework.

Step 2 Training a beauty classifier. We design and train a deep learning model that is able to distinguish beautiful urban scenes from non-beautiful ones.

Step 3 Generating a synthetic beautified scene. Based on our classifier's learned representation of beauty, we train a generative model that is able to generate a beautified version of an urban scene in input.

Step 4 Retrieving a realistic beautified scene. The generated image has a "synthetic look" and, as such, does not look realistic (Figure4.1). To fix that, we retrieve the image in our set most similar to the generated image.

Step 5 Identifying the urban elements characterizing the beautified scene. In the final step, the framework explains changes introduced in the transformation process in terms of addition and removal of specific urban elements.

Step 1 Curating Urban Scenes

To begin with, we need highly curated training data with labels reflecting urban beauty. We start with the Place Pulse dataset that contains 100k Google Street Views across 56 cities around the world [41]. These scenes are labeled in terms of whether the corresponding places are likely to be perceived beautiful, depressing, rich, and safe. We focus only on those scenes that are labeled in terms of beauty and that have at least three judgments. This leave us with roughly 20,000 scenes. To transform judgments into beauty scores, we use the TrueSkill algorithm [52], which gives us a way of partitioning the scenes into two sets (Figure 4.2):

one containing beautiful scenes, and the other containing ugly scenes. The resulting set of scenes is too small for training any deep learning model without avoiding over-fitting though. As such, we need to augment such a set.

We do so in two ways. First, we feed each scene's location into the Google Streetview API to obtain the snapshots of the same location at different camera angles (i.e., at $\theta \in -30°, -15°, 15°, 30°$). However, the resulting dataset is still too small for robust training. Therefore, again, we feed each scene's location into the Google Streetview API, but we now do so to obtain other scenes at distance $d \in \{10, 20, 40, 60\}$ meters. This will greatly expand our set of scenes, but it might do so at the price of introducing scenes whose beauty scores have little to do with the original scene's. To fix that, we take only the scenes that are *similar* to the original one (we call this way of augmenting "conservative translation"). To compute the similarity between a pair of scenes, we represent the two scenes with visual features derived from the FC7 layer of PlacesNet and compute the similarity between the two corresponding feature vectors [135]. For all scenes at increasing distance $d \in \{10, 20, 40, 60\}$ meters, we take only those whose similarity scores with the original scene is above a threshold. In a conservative fashion, we choose that threshold to be the median similarity between rotated and original scenes (those of the first augmentation step).

To make sure this additional augmentation has not introduced any unwanted noise, we consider two sets of scenes: one containing those that have been taken during this last step, i.e., the one with high similarity to the original scenes (*taken-set*), and the other containing those that have been filtered away (*filtered-set*). Each scene is then scored with PlacesNet [135] and is represented with the five most confident scene labels. We then aggregate labels at set level by computing each label's frequency on the *taken-set* and on the *filtered-set*. Finally, we characterize each label's propensity to be correctly augmented as: $\text{prone}(label) = fr(label, \textit{taken-set}) - fr(label, \textit{filtered-set})$. This reflects the extent to which a scene with a given label is prone to be augmented or not. From Figure 4.4, we find that, as one would expect, scenes that contain highways, fields and bridges can be augmented at increasing distances while still showing resemblances to the original scene; by contrast, scenes that contain gardens, residential neighborhoods, plazas, and skyscrapers cannot be

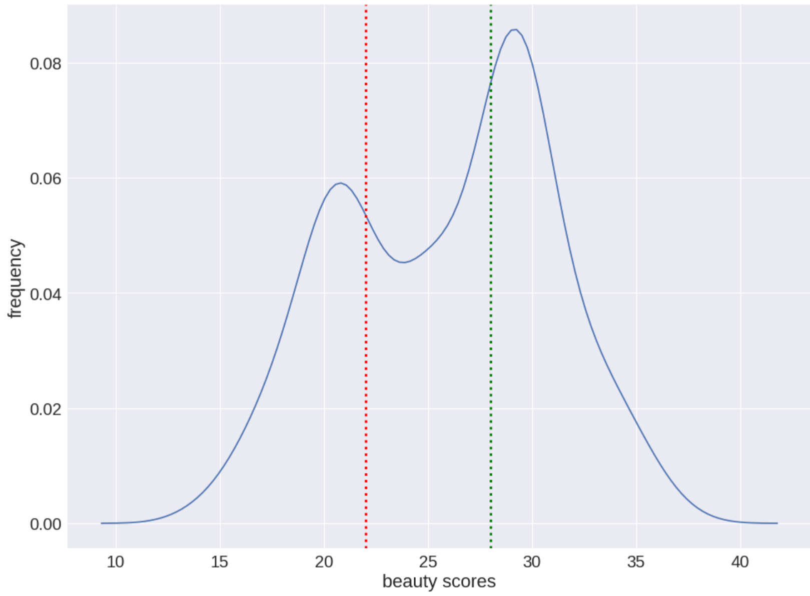


Fig. 4.2 Frequency distribution of beauty scores. The red and green lines represent the thresholds below and above which images are considered ugly and beautiful. Conservatively, images in between are discarded.

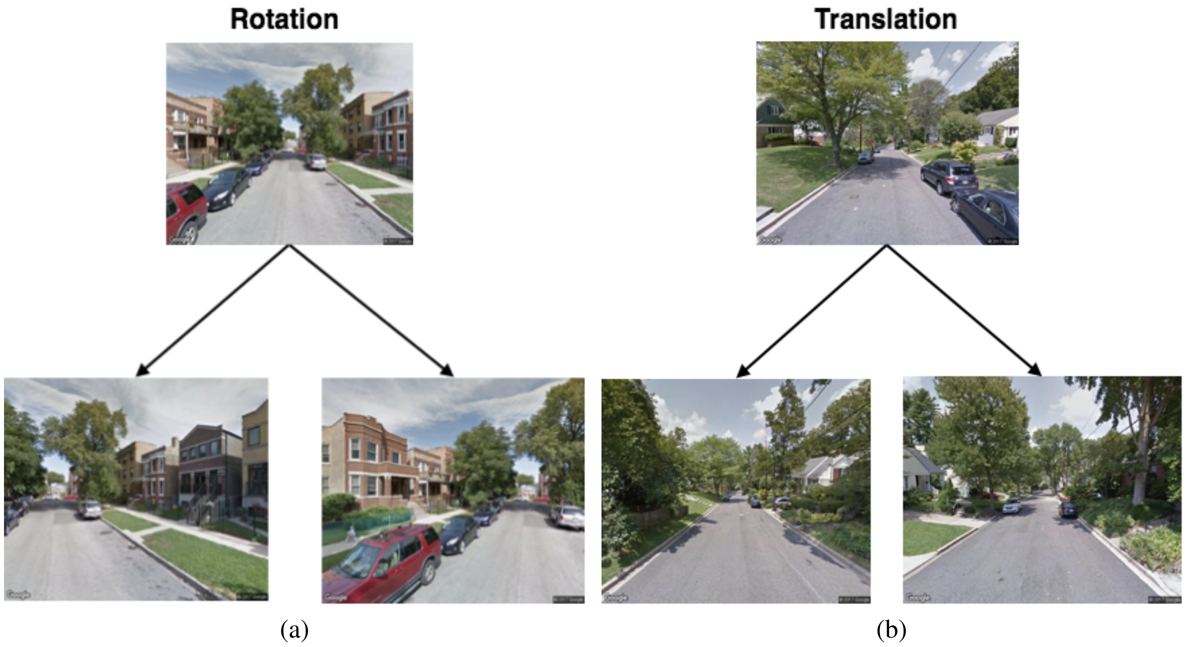


Fig. 4.3 Two types of augmentation: (a) rotation of the Street Views camera (based on rotation); and (b) exploration of scenes at increasing distances (based on translation).

easily augmented, as they are often found in high density parts of the city in which diversity within short distances might well be experienced.

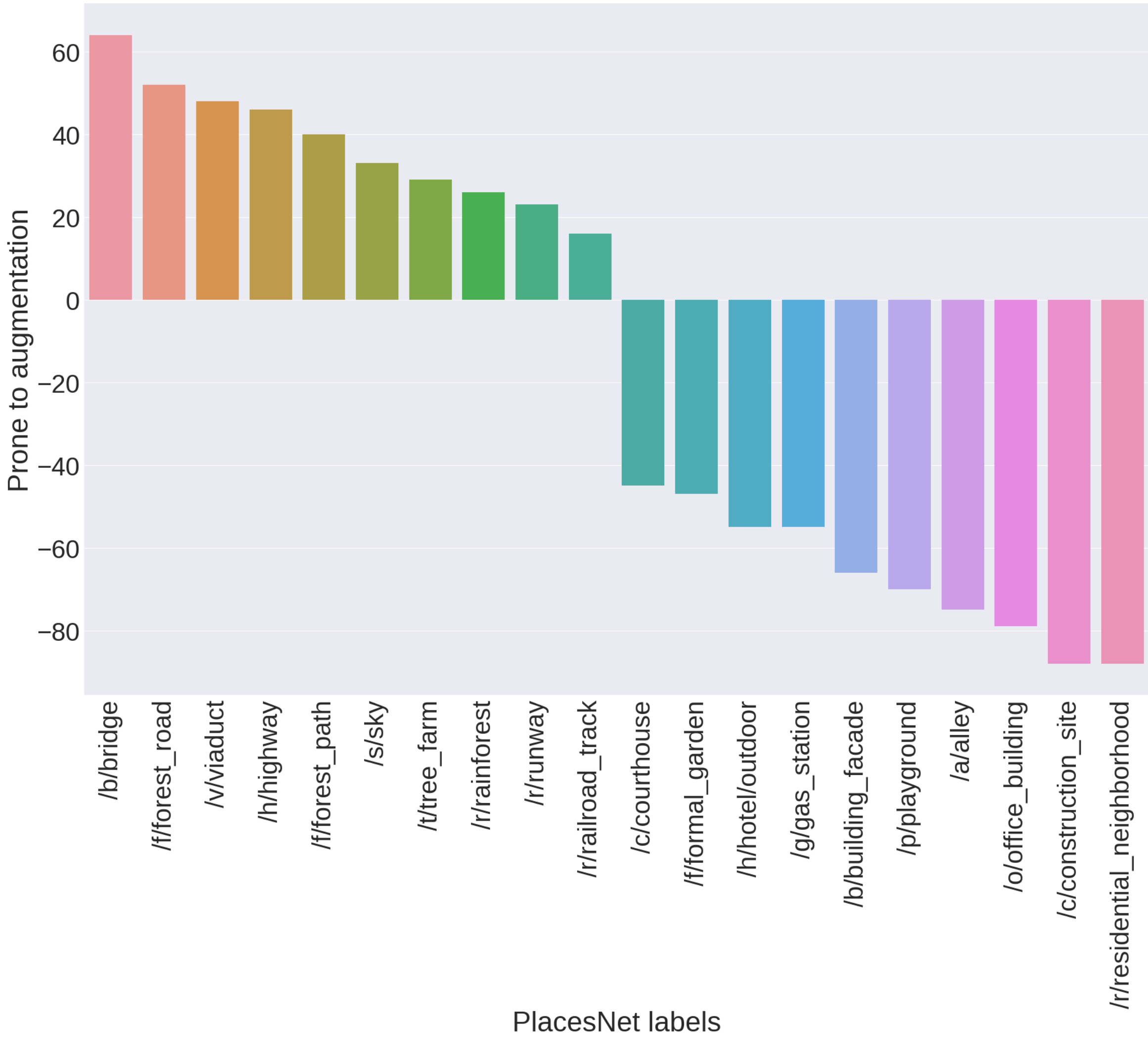


Fig. 4.4 The types of scene that have greater propensity to be correctly augmented with similar scenes at increasing distances.

Augmentation	**Accuracy (Percentage)**
None	63
Rotation	68
Rotation + Translation	64
Rotation + Conservative Translation	73.5

Table 4.2 Percentage accuracy for our beauty classifier trained on differently augmented sets of urban scenes.

Step 2 Training a beauty classifier

Having this highly curated set of labeled urban scenes, we are now ready to train classifier C with labels reflecting our beauty assessments.

As for classifier C, we use the CaffeNet architecture, a modified version of AlexNet [67, 121]. This has a conventional architecture with 5 convolutional layers; interleaved with max pooling and normalization layers; and terminated by: *(i)* two 4096 dimensional fully connected layers interleaved with dropout layers [119] (the dropout ratio is set to 0.5 to prevent over-fitting), and *(ii)* by a Softmax layer that classifies the input image into one of two classes of beautiful(1) and ugly(0).

Having C at hand, we now turn to training it. The training is done on a 70% split of the data, and the testing on the remaining 30%. All this is done on increasingly augmented sets of data. We start from our 20k images and progressively augment them with the snapshots obtained with the 5-angle camera rotations, and then with the exploration of scenes at increasing distance $d \in \{10, 20, 40, 60\}$ meters. The idea behind this data augmentation is that the model's accuracy should increase with increasing levels of augmentation. Indeed it does (Table 4.2): it goes from 63% on the set of original scenes to a value as high as 73.5% on the set of fully augmented scenes, which is a notable increase in accuracy for this type of classification tasks. Furthermore, our results match previous ones: for example, Dubey et.al's [41] model showed an accuracy of 70%, which is comparable to ours.

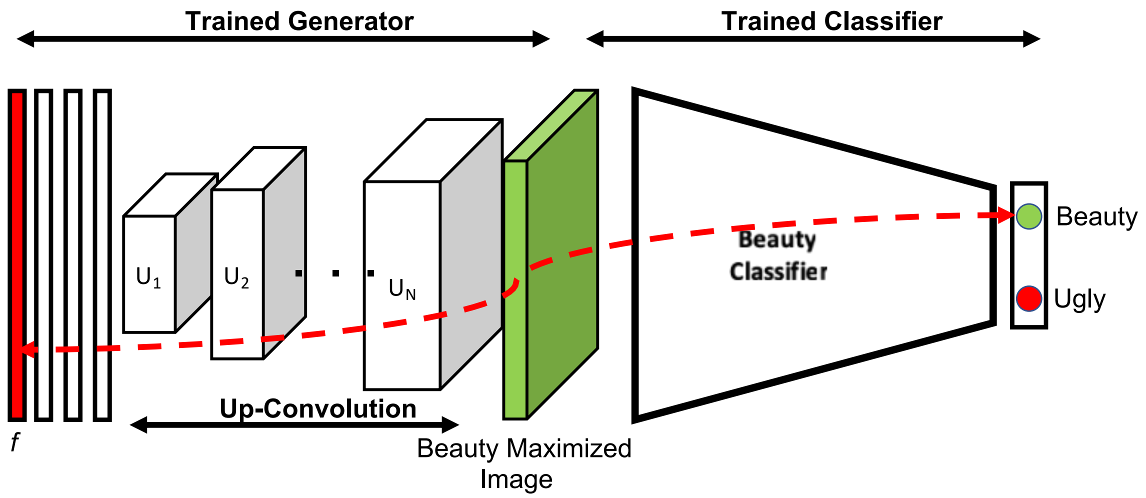


Fig. 5.1 Architecture of the synthetic beauty generator. This consists of a generator of synthetic scenes concatenated with a beauty classifier. The green block is the beauty maximized template $\hat{I}_j$, which is subject to forward and backward passes (red arrow) when optimizing for beauty.

Chapter 5

Part 2: Recreating the urban perceptions

Step 3 Generating a synthetic beautified scene

Having this trained classifier at hand, we can then build a generator of synthetic beautified scenes. To build such a generator, we retrain the GAN described by Dosovitskiy and Brox [40] on our curated urban scene dataset. This network is trained by maximizing the confusion for the discriminator between the generated images $G(f)$ and the original ones I_f [50]. The resulting generator is concatenated with our beauty classifier (Figure 5.1). As a

Original	Generated
	
	
	

Table 5.1 Examples of our generator's outputs. The original scenes and the generated ones are shown side by side.

result, given the two classes ugly y_i and beautiful y_j, the end-to-end model transforms any original scene I_i of class y_i (e.g., ugly scene) into template scene $\hat{I}_j$ that maximizes class y_j (e.g., beautified template scene).

More specifically, given an input image I_i known to be of class y_i (e.g., ugly), our technique outputs $\hat{I}_j$, which is a more beautiful version of it (e.g., I_i is morphed towards the average representation of a beautiful scene) while preserving I_i's details. The technique does so using the "Deep Generator Network for Activation Maximization" (*DGN-AM*) [89]. Given an input image I_i, *DGN-AM* iteratively re-calculates the color of I_i's pixels in a way the output image $\hat{I}_j$ both maximizes the activation of neuron y_j (e.g., the "beauty neuron") and looks "photo realistic", which is done by conditioning the maximization to an "image prior". This is equivalent to finding the feature vector f that maximizes the following expression:

$$\hat{I}_j = G(f) : \arg\max_f (C_j(G(f)) - \lambda ||f||) \tag{5.1}$$

where:

- $G(f)$ is the image synthetically generated from the candidate feature vector f;
- $C_j(G(f))$ is the activation value of neuron y_j in the scene classifier C (the value to be maximized);
- λ is a L_2 regularization term.

Here the initialization of f is key. If f were to be initialized with random noise, the resulting $G(f)$ would be the average representation of category y_j (of, e.g., beauty). Instead, since f is initialized with the feature vector corresponding to I_i, then the resulting maximized $G(f)$ is I_i's version "morphed to become more beautiful".

The input image is also key. It makes little sense to beautify an already beautiful image, not least because such beautification process would result in a saturated template $\hat{I}_j$ in our framework. For this reason, to generate an image that maximizes the beauty neuron in the classifier C, we restrict the corresponding input image to be in class y_i (i.e., ugly scenes as per the divisions in Figure 4.2). We do the opposite when maximizing the ugly neuron.

Step 4 Returning a realistic beautified scene

We now have template scene $\hat{I}_j$ (which is a synthetic beautified version of original scene I_i) and need to retrieve a realistic looking version of it. We do so by: *i)* representing each of our original scenes in Step 1 (including $\hat{I}_j$) as a 4096 dimensional feature vector derived from the FC7 layer of the PlacesNet [135]; *ii)* computing the distance (as L_2 Norm) between $\hat{I}_j$'s feature vector and each of the original scene's feature vector; and *iii)* selecting the original scene most similar (smaller distance) to $\hat{I}_j$. This results into the selection of the beautified scene I_j.

Step 5 Identifying characterizing urban elements

Since original scene I_i and beautified scene I_j are real scenes with the same structural characteristics (e.g., point of view, layout), we can easily compare them in terms of presence or absence of urban elements extracted by computer vision tools such as SegNet and PlacesNet. That is, we can determine how the original scene and its beautified version differ in terms of urban design elements.

5.1 Evaluation

The goal of FaceLift is to transform existing urban scenes into versions that: *i)* people perceive more beautiful; *ii)* contain urban elements typical of great urban spaces; *iii)* are easy to interpret; and *iv)* architects and urban planners find useful. To ascertain whether FaceLift meets that composite goal, we answer the following questions next:

Q1 Do individuals perceive "FaceLifted" scenes to be beautiful?

Q2 Does our framework produce scenes that possess urban elements typical of great spaces?

Q3 Which urban elements are mostly associated with beautiful scenes?

Q4 Do architects and urban planners find FaceLift useful?

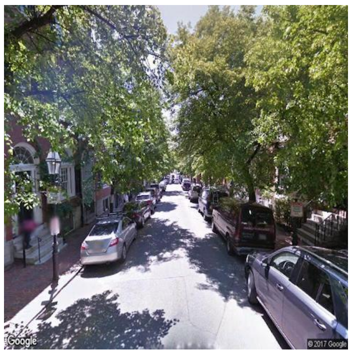
Original (I_i)	Latent Beauty representation ($\hat{I}_j$)	Beautified (I_j)
		
		
		
		
		

Table 5.2 Examples of the "FaceLifting" process, which tends to add greenery, narrow roads, and pavements.

Q1 People's perceptions of beautified scenes

To ascertain whether "FaceLifted" scenes are perceived by individuals as they are supposed to, we run a crowd-sourcing experiment on Amazon Mechanical Turk. We randomly select 200 scenes, 100 beautiful and 100 ugly (taken at the bottom 10 and top 10 percentiles of the Trueskill's score distribution of Figure 4.2). Our framework then transforms each ugly scene into its beautified version, and each beautiful scene into its corresponding 'uglified'. These scenes are arranged into pairs, each of which contains the original scene and its beautified or uglified version. On Mechanical Turk, we only select verified masters as our crowd-sourcing workers (those with an approval rate above 90% during the past 30 days), pay them $0.1 per task, and ask each of them to choose the most beautiful scene for each given pair. We make sure to have at least 3 votes for each scene pair. Overall, our workers end up selecting the scenes that are actually beautiful 77.5% of the times, suggesting that "FaceLifted" scenes are indeed perceived to be more beautiful by people.

Q2 Are beautified scenes great urban spaces?

To answer that question, we need to understand what makes a space great. After reviewing the literature in urban planning, we identify four factors associated with great places [2, 44] (Table 5.3): they mainly tend to be walkable, offer greenery, feel cozy, and be visually rich.

To automatically extract visual cues related to these four factors, we select 500 ugly scenes and 500 beautiful ones at random, transform them into their opposite aesthetic qualities (i.e., ugly ones are beautified, and beautiful ones are 'uglified'), and compare which urban elements related to the four factors distinguish uglified scenes from beautified ones.

We extract labels from each of our 1,000 scenes using two image classifiers. First, using PlacesNet [135], we label each of our scenes according to a classification containing 205 labels (reflecting, for example, landmarks, natural elements), and retain the five labels with highest confidence scores for the scene. Second, using Segnet [8], we label each of our scenes according to a classification containing 12 labels. Segnet is trained on dash-cam images, and

Metric	Description
Walkability	Walkable streets support people's natural tendency to explore spaces [44, 100, 117].
Green Spaces	The presence of greenery has repeatedly been found to impact people's well-being [2]. Under certain conditions, it could also promote social interactions [101]. Not all types of greenery have to be considered the same though: dense forests or unkempt greens might well have a negative impact [59].
Landmarks	Feeling lost is not a pleasant experience, and the presence of landmarks have been shown to contribute to the legibility and navigability of spaces [44, 76, 101, 102].
Privacy-Openness	The sense of privacy conveyed by a place's structure (as opposed to a sense of openness) impacts its perception [44].
Visual Complexity	Visual complexity is a measure of how diverse an urban scene is in terms of design materials, textures, and objects [44]. The relationship between complexity and preferences generally follows an 'inverted-U' shape: we prefer places of medium complexity rather than places of low or high complexity [126].

Table 5.3 Urban Design Metrics

classifies each scene pixel with one of these twelve labels: road, sky, trees, buildings, poles, signage, pedestrians, vehicles, bicycles, pavement, fences, and road markings.

Having these two ways of labeling scenes, we can now test whether the expectations set by the literature describing metrics of great urban spaces (Table 5.3) are met in the FaceLifted scenes.

H1 Beautified scenes tend to be walkable. We manually select only the PlacesNet labels that are related to walkability. These labels include, for example, *abbey, plaza, courtyard, garden, picnic area, and park*. To test hypothesis *H1*, we count the number of walkability-related labels found in beautified scenes as opposed to those found in uglified scenes (Figure 5.2): the former contain twice as many walkability labels than the latter. We then determine which types of scenes are associated with beauty (Figure 5.3). Unsurprisingly, beautified scenes

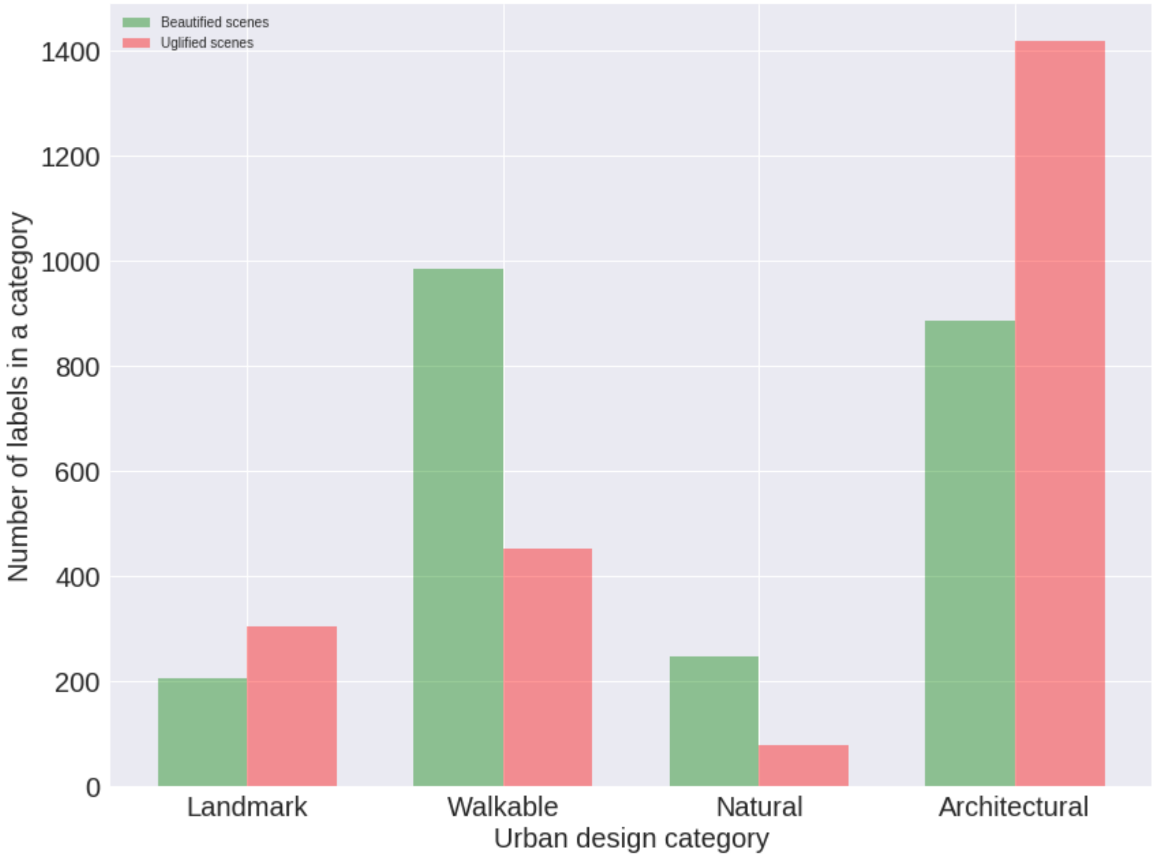


Fig. 5.2 Number of labels in specific urban design categories (on the x-axis) found in beautified scenes as opposed to those found in uglified scenes.

tend to show gardens, yards, and small paths. By contrast, uglified ones tend to show built environment features such as shop fronts and broad roads.

H2 Beautified scenes tend to offer green spaces. We manually select only the PlacesNet labels that are related to greenery. These labels include, for example, *fields, pasture, forest, ocean, and beach*. Then, in our 1,000 scenes, to test hypothesis *H2*, we count the number of nature-related labels found in beautified scenes as opposed to those found in uglified scenes (Figure 5.2): the former contain more than twice as many nature-related labels than the latter. To test this hypothesis further, we compute the fraction of ‘tree’ pixels (using SegNet’s label ‘tree’) in beautified and uglified scenes, and find that beautification adds 32% of tree pixels, while uglification removes 17% of them.

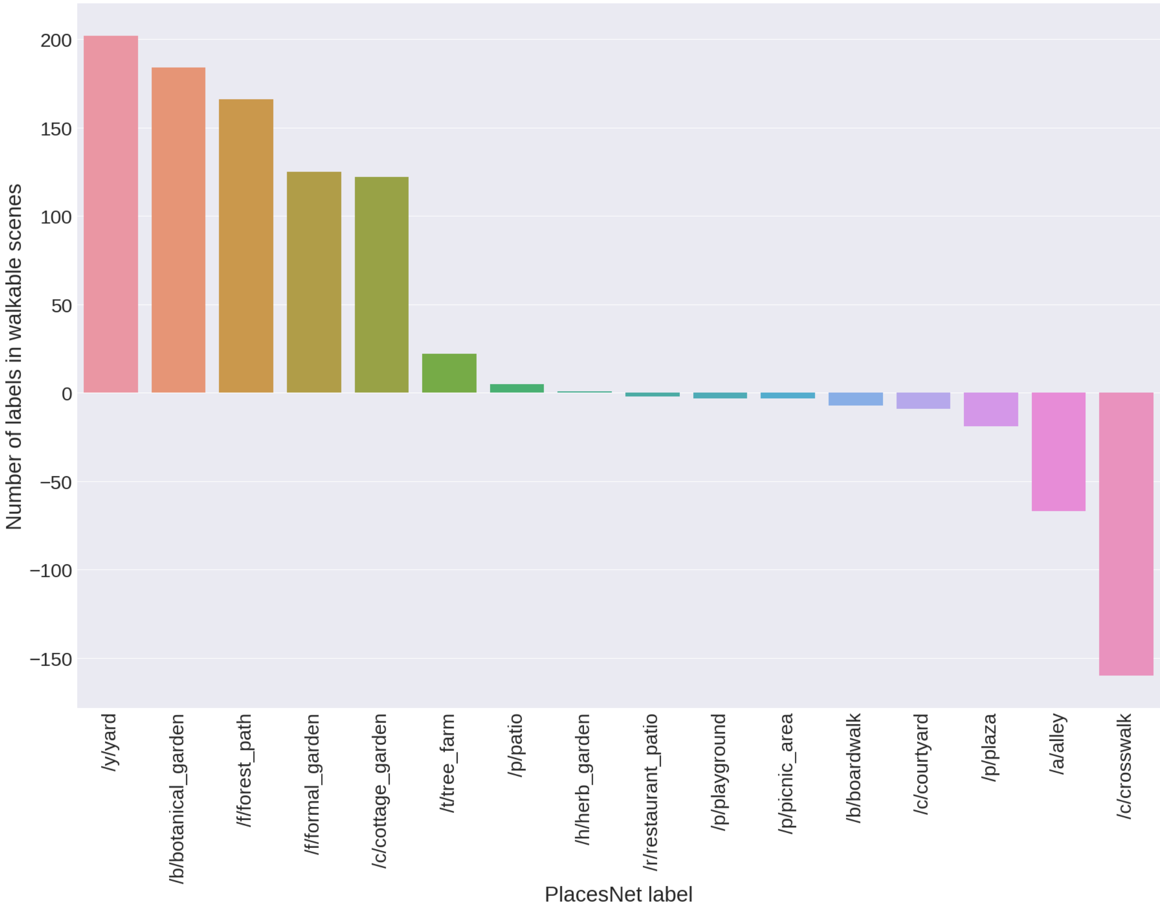


Fig. 5.3 Count of specific walkability-related labels (on the x-axis) found in beautified scenes minus the count of the same labels found in uglified scenes.

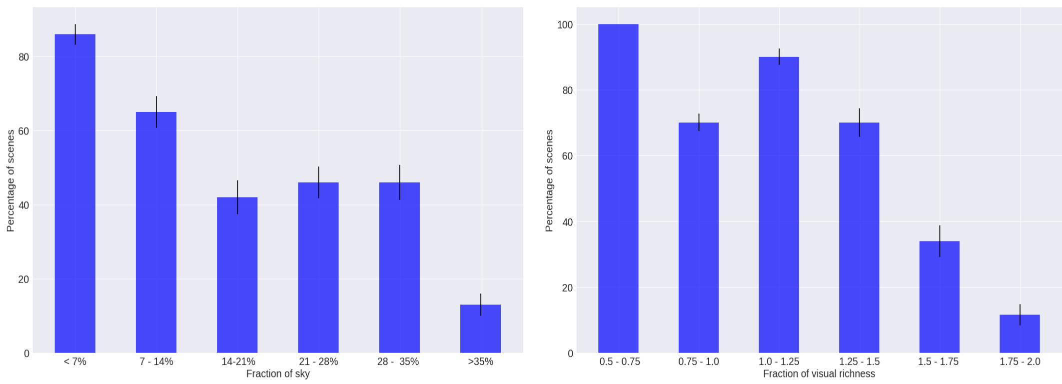


Fig. 5.4 The percentage of beautified scenes (y-axis): (a) having an increasing presence of sky (on the x-axis); and (b) having an increasing level of visual richness (on the x-axis). The error bars represent standard errors obtained by random re-sampling of the data for 500 iterations.

H3 Beautified scenes tend to feel private and 'cozy'. To test hypothesis *H3*, we count the fraction of pixels that Segnet labeled as 'sky' and show the results in a bin plot in Figure 5.4a: the x-axis has six bins (each of which represents a given range of sky fraction), and the y-axis shows the percentage of beautified *vs.* uglified scenes that fall into each bin. Beautified scenes tend to be cozier (lower sky presence) than the corresponding original scenes.

H4 Beautified scenes tend to be visually rich. To quantify to which extent scenes are visually rich, we measure their visual complexity [44] as the amount of disorder in terms of distribution of (Segnet) urban elements in the scene:

$$H(X) = -\sum p(i) \log p(i) \tag{5.2}$$

where i is the i^{th} Segnet's label. The total number of labels is twelve. The higher $H(X)$, the higher the scene's entropy, that is, the higher the scene's complexity. It has been suggested that the relationship between complexity and pleasantness follows an 'inverted U' shape [126]: we prefer places of medium complexity rather than places of low or high complexity. To test that, we show the percentage of beautified scenes that fall into each complexity bin (Figure 5.4b): we do not find a strong evidence of the 'inverted U' shape hypothesis, in that, beautified scenes are of low to medium complexity, while uglified ones are of high complexity.

Q3 Urban elements of beautified scenes

To determine which urban elements are the best predictors of urban beauty and the extent to which they are so, we run a logistic regression, and, to ease interpretation, we do so on one pair of predictors at the time:

$$Pr(\text{beautiful}) = logit^{-1}(\alpha + \beta_1 * V_1 + \beta_2 * V_2 + \beta_3 * V_1.V_2) \tag{5.3}$$

Pair of urban elements	β_1	β_2	β_3	Error Rate (Percentage)
Buildings - Trees	-0.032	0.084	0.005	12.7
Sky - Buildings	-0.08	-0.11	0.064	14.4
Roads - Vehicles	-0.015	-0.05	0.023	40.6
Sky - Trees	0.03	0.11	-0.012	12.8
Roads - Trees	0.04	0.10	-0.031	13.5
Roads - Buildings	-0.05	-0.097	0.04	20.2

Table 5.4 Coefficients of logistic regressions run on one pair of predictors at the time.

where $V1$ is the fraction of the scene's pixels marked with one Segnet's label, say, "buildings" (over the total number of pixels), and $V2$ is the fraction of the scene's pixels marked with another label, say, "trees". The result consists of three beta coefficients: β_1 reflects $V1$'s contribution in predicting beauty, β_2 reflects $V2$'s contribution, and β_3 is the interaction effect, that is, it reflects the contribution of the dependency between $V1$ and $V2$ in predicting beauty. We run logistic regressions on the five factors that have been found to be most predictive of urban beauty [2, 44, 101], and show the results in Table 5.4.

Since we are using logistic regressions, the quantitative interpretation of the beta coefficients is eased by the "divide by 4 rule" [127]: we can take the β coefficients and "divide them by 4 to get an upper bound of the predictive difference corresponding to a unit difference" in beauty [127]. For example, take the results in the first row of Table 5.4. In the model $Pr(beautiful) = logit^{-1}(\alpha - 0.032 \cdot buildings + 0.084 \cdot trees + 0.005 \cdot buildings \cdot trees)$, we can divide - 0.032/4 to get -0.008: a difference of 1 in the fraction of pixels being buildings corresponds to no more than a 0.8% *negative* difference in the probability of the scene being beautiful. In a similar way, a difference of 1 in the fraction of pixels being trees corresponds to no more than a 0.021% *positive* difference in the probability of the scene being beautiful. By considering the remaining results in Table 5.4, we find that, across all pairwise comparisons, trees is the most positive element associated with beauty, while roads and buildings are the most negative ones. These results match previous literature in urban design of what makes spaces great, adding further external validity to our framework's beautification.

Use case	Definitely Not	Probably Not	Probably	Very Probably	Definitely
Decision Making	4.8%	9.5%	38%	28.6%	19%
Participatory Urban Planning	0%	4.8%	52.4%	23.8%	19%
Promote Green Cities	4.8%	0%	47.6%	19%	28.6%

Table 5.5 Urban experts polled about the extent to which an interactive map of "FaceLifted" scenes promotes: (a) decision making; (b) citizen participation in urban planning; and (c)

Fig. 5.5 Interactive map of FaceLifted scenes in Boston.

Q4 Do architects and urban planners find it useful?

To ascertain whether practitioners find FaceLift potentially useful, we build an interactive map of the city of Boston in which, for selected points, we show pairs of urban scenes before/after beautification (Figure 5.5). We then send that map along with a survey to 20 experts in architecture, urban planning, and data visualization around the world. Questions were asked with a non-neutral response Likert scale (Table 5.5). That is because previous work [9, 85] has shown that such a scale: *(i)* pushes respondents to "take a stance", given the absence of a neutral response; and *(ii)* works best if respondents are experts in the subject matter of the survey as responses of the "I don't know" type tend to be rare (as it is has been the case for our survey). The experts had to complete tasks in which they rated FaceLift based on how well it supports decision making, participatory urbanism, and the promotion of green spaces. According to our experts (Table 5.5), the tool can very probably supports decision making, probably support participatory urbanism, and definitely promote green spaces. These results are also qualitatively supported by our experts' comments, which include: "*The maps reveal patterns that might not otherwise be apparent*", "*The tool helps focusing on parameters to identify beauty in the city while exploring it*", and "*The metrics are nice. It made me think more about beautiful places needing a combination of criteria, rather than a high score on one or two dimensions. It made me realize that these criteria are probably spatially correlated*".

5.2 Conclusion

FaceLift is a framework that automatically beautifies urban scenes by combining recent approaches of Generative Adversarial Networks and Deep Convolutional Networks. To make it usable by practitioners, the framework is also able to explain which urban elements have been added/removed during the beautification process.

There are still important limitations though. One is data bias. The framework is as good as its training data, and more work has to go into collecting reliable ground truth data on human perceptions. This data should ideally be stratified according to the people's characteristics that impact their perceptions. The other main limitation is that generative models are hard to control, and more work has to go into offering principled ways of fine-tuning the generative process.

Despite these limitations, FaceLift has the potential to support urban interventions in scalable and replicable ways: it can be applied to an entire city (scalable), across a variety of cities (replicable). To turn existing spaces into something more beautiful, that will still be the duty of architecture. Yet, with technologies similar to FaceLift more readily available, the complex job of recreating restorative spaces in an increasingly urbanized world will be greatly simplified.

After all, "we delight in complexity to which genius have lent an appearance of simplicity." [33] In the context of future work, that genius is represented by future technologies that will help us deal with the complexity of our cities.

5.2.1 Limitations and biases

Like any supervised deep learning based framework, this work is only able to learn what is present in the data. Hence the method of acquiring annotations for urban images can introduce huge biases in the model. The current model is trained on images acquired from the study on streetscore [87]. However their annotation is open to general public and there is not way we can remove biases that come with culture and location, in a highly subjective effect like beauty. Moreover because the pair wise choice is simply done by clicking one of the two images, the data might have noise introduced by non-serious participants. Such biases are bound to be picked up by the deep learning model. One can argue that the preference of our model for greenery , is a form of bias in the data. Another bias introduced because of data is the model's lack of preference to pedestrians. This bias was established well in advance because Google tries to remove most of the people from their street view images for privacy reasons. Hence people, which make up a major aspect of urban vitality, are completely missing from most dataset images and hence from the facelift transformations. Another Limitation of our work is in the metric formation. The computational metrics developed to capture the real urban design metrics are designed using heuristics. There needs to be more crowd and expert validation to establish the validity of their formulation.

5.2.2 Future work

The framework is generalizable for geotagged and annotated images. The aim of this paper is to propose a framework with uses state of art methods in generative models to understand perception of emotions in urban images and explain them. As an extension, understanding how intervention would look like against outcome variables such as depression, safety or mental well-being in general would be very valuable.

CHAPTER 6

CLOSING NOTES AND FUTURE OUTLOOK OF THIS WORK

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