Analysis and Decision-Making with Social Media

by

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ABSTRACT

The rapid advancements of technology have greatly extended the ubiquitous nature of smartphones acting as a gateway to numerous social media applications. This brings an immense convenience to the users of these applications wishing to stay connected to other individuals through sharing their statuses, posting their opinions, experiences, suggestions, etc on online social networks (OSNs). Exploring and analyzing this data has a great potential to enable deep and fine-grained insights into the behavior, emotions, and language of individuals in a society. This proposed dissertation focuses on utilizing these online social footprints to research two main threads – 1) *Analysis*: to study the behavior of individuals online (content analysis) and 2) *Synthesis*: to build models that influence the behavior of individuals offline (incomplete action models for decision-making).

A large percentage of posts shared online are in an unrestricted natural language format that is meant for human consumption. One of the demanding problems in this context is to leverage and develop approaches to automatically extract important insights from this incessant massive data pool. Efforts in this direction emphasize mining or extracting the wealth of latent information in the data from multiple OSNs independently. The first thread of this dissertation focuses on analytics to investigate the differentiated content-sharing behavior of individuals. The second thread of this dissertation attempts to build decision-making systems using social media data.

The results of the proposed dissertation emphasize the importance of considering multiple data types while interpreting the content shared on OSNs. They highlight the unique ways in which the data and the extracted patterns from text-based platforms or visual-based platforms complement and contrast in terms of their content. The proposed research demonstrated that, in many ways, the results obtained by focusing on either only text or only visual elements of content shared online could lead to biased insights. On the other hand, it also shows the power of a sequential set of patterns that have some sort of precedence relationships and collaboration between humans and automated planners.

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Chapter 1

INTRODUCTION

Given the ubiquitous nature of technology, online social media platforms (or online social networks (OSNs)) play a key role in the everyday lives of individuals. According to a recent report by the Pew Research Center [162], in the United States alone about 68% of individuals use Facebook, 24% use Twitter, 29% use Pinterest, 35% use Instagram and 25% use LinkedIn. Individuals utilize social media platforms for a variety of purposes. These venues have emerged to be conducive means of sharing opinions, seeking information, making connections, maintaining one's professional reputation, etc [93, 95, 115, 136]. Diverse motives along with the pervasive use of social media have led to a rich mixture of content in various data formats that raised several challenges with the structure of data.

Since content is generated on social media platforms at an unprecedented rate, this rising volume of data has been adopted as a lens to provide insight into the language [62, 89], behaviors [151, 154], physical well-being [80, 143, 160] and social interactions of individuals [14, 113, 167]. Since most of these aspects of individuals are of primary interest in fields such as social sciences, psychology and medicine, there is already a large amount of published qualitative research conducted through surveys or interviews and providing questionnaires and epistemological analysis [16, 18, 47, 120, 123]. On the other hand, a growing body of work in computational social science is leveraging linguistic data to gain access to the latent patterns of individuals or to predict different interactions and traits of individuals, their culture and society at large [67, 142, 149, 159].

From the perspective of data collection, specifically in the field of social sciences, it is a norm to collect data through surveys and interviews. This data is limited in different aspects, tedious and manually impossible to expand to billions of human subjects from whom the data is collected. This dataset focuses on smaller sample sizes for a deeper understanding but does not always represent the total population. The automated approaches crawling billions of data tuples from social media data are more prevalent in collecting linguistic data. As photo-sharing platforms are rapidly expanding and gaining popularity, visual-based platforms can add rich data expressing patterns along with linguistic data because an image can say a thousand words. From the methodological front, utilizing supervised learning methods is gaining prominence but their success is contingent up on a large amount of data that is often noisy and inaccurate [19, 56] especially the data crawled from social media. Utilizing groud truth data to not only identify the efficient learning methods but also to infer aggregated summaries is very helpful. From the modelling perspective, given a particular domain it is not always possible to obtain information to build a complete model that is fully aware of the attributes and dynamics of that domain. Bringing humans into the loop could help alleviate the incompleteness of the model. The limitations of these aspects call for robust and reliable analytics and models that are able to detect and improve on the existing methodologies.

To address the drawbacks on different fronts of the existing approaches, this dissertation proposes different analytics and models categorized into two threads – *analysis* and *synthesis*. Both these categories are further subdivided into sub-categories as shown in Figure 1.1. *Analysis* focuses on analyzing the different types of data collected from the social media platforms to answer the research questions proposed in the subcategories whereas *synthesis* aims at utilizing the data shared on social media platforms to build decision-making

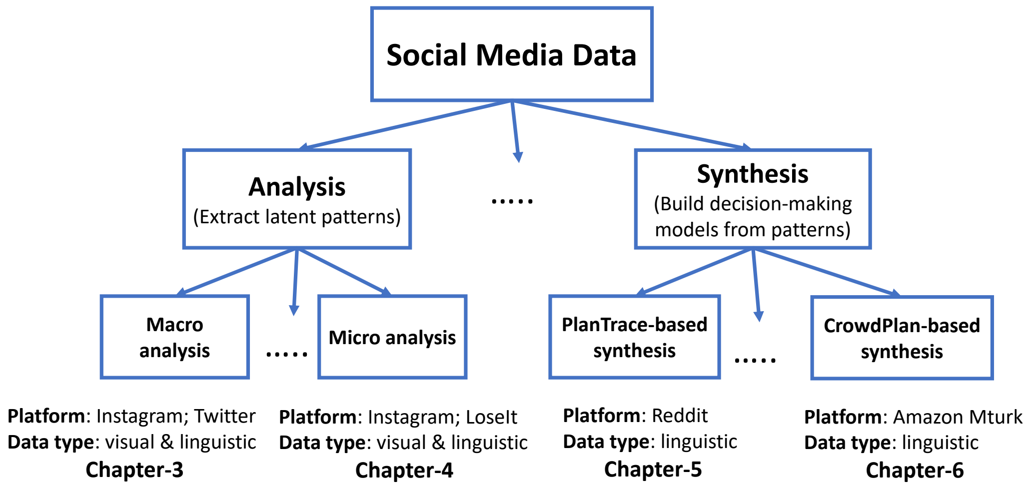


Figure 1.1: Organization of This Dissertation

models. A high-level summary of these categorizations is described below.

1.1 Thesis Overview

1.1.1 Analysis

In this thesis, we conduct an investigation to address the online differentiated content sharing behaviors through aggregated analytics, specifically to answer questions related to public health issues such as mental health and weight loss, and personal interests such as fashion, technology and travel. We focus on the data that is shared online in a "public" mode and is in the form of either natural language or images. However, with an appropriate methodology, we could extend these approaches and algorithms to handle any other type of data in a different domain that we didn't consider in this thesis.

Micro Analysis: There are several dimensions of conducting social media content analysis. As mentioned in the earlier section, much of the existing research attempts to conduct analysis using linguistic data which may not be sufficient to answer questions related to language, behavior, interactions, culture, etc. To fill this gap, our research utilizes visual data where the main motivation is to infer the objectives behind using photo-sharing platforms (primarily Instagram). By utilizing the public profiles of general users (see the definition in Chapter 3.2), we leveraged a 2-step human-machine approach. In this approach, computer vision techniques are utilized first to obtain the clustering automatically. Then, a set of human coders were involved to refine the clustering that eventually led to identifying the high-level clusters of images that represent different themes or types of photos shared on these photo-sharinga platforms. We evaluate the credibility of this platform using statistical significance tests as well as using sampling approaches. This raised the obvious question about the content-sharing behavior of users who maintain accounts on multiple social media platforms that provide a similar set of functionalities. To answer this question, we consider two popular platforms – Instagram and Twitter – to compare each individual's content on both these platforms in both data formats – images and text. This analysis infered that Twitter is primarily used to share posts about generally serious topics whereas Instagram is used to share light-hearted personal moments. This research inspired different threads of research – social media and loneliness [146], narcissism [133, 59], social media and food [84], etc.

Macro Analysis: To address the missing gaps in the existing research , we conducted analysis at a task-specific level on self-disclosures and health, primarily aspects such as mental health and weight loss. Social media platforms have become widely adopted in coping with health-related issues. This is because they allow anonymous or semi-anonymous accounts that enable individuals to hide their real identity to protect their privacy but to act as their true-self when sharing about their health [50, 129]. Extracting and characterizing the expressive meanings conveyed in imagery shared around health disclosures on social media can raise the quality of language-only studies of health-related disclosures. Towards these goals and the given potential of social media data related to health disclosures, we investigate how the disclosures of health could be characterized via shared visual imagery (mental health) and textual posts (weight loss). From the visual imagery used to characterize mental health disclosures, we extract the visual features, visual themes and linguistic themes (to compare and contrast with visual themes). We evaluate the inferences through crossvalidating with the existing literature from psychiatry as well as bringing experts into the loop. To characterize weight loss disclosures, we analyze the discourse of discussions posted in natural language. To make the inferences, we correlate the observed discourse patterns with the weight loss category (*Fluctuating* or *Non-increasing*) that was extracted as part of this study. We evaluate the approaches utilized to make these inferences using a *k*-fold cross-validation.

1.1.2 Synthesis

The second main thread of this research focuses on building incomplete action models to perform decision-making. In this thesis, we propose two different types of decision-making frameworks – one that leverages automated planning to improve crowdsourcing and a second that predicts the best plan or action to taken given a starting action in order to achieve a personal goal. Given the wide spread popularity of using social media to successfully achieve personal goals such as visiting a new city, running a marathon, quit smoking, etc., we utilize the shared posts for a domain (that is related to the goal) to extract aggregated plans that might help a new individual sharing the similar goal. There is literature that focuses on similar dimensions to address the problem, but much of these are aimed towards prediction or building a recommendation engine while this work considers the aspects of precedence relationships between any given set of two actions. This research adds to literature by proposing two types of framework – 1) *crowdplan-based synthesis* – leverage automated planning to improve crowdsourcing which is utilized for planning and scheduling, 2) *PlanTrace-based Synthesis* – build and train machine learning models to conduct predictive analytics to help individuals achieve goals. Both these frameworks can be used to extract a plan or a sequential set of actions that have precedence relationships between each other. We evaluate these frameworks by using metrics based on the human subject evaluations.

1.2 Contributions

The contributions of this thesis are:

1. We conduct the first in-depth study of content and users on a photo-sharing platform – Instagram. This study revealed that there are primarily 8 types of photo categories (at a high-level) on Instagram – Selfies (Self-portraits), Friends (Users posing with other friends), Captioned Photos (Pictures with embedded text), Pets (Animals), Activity (Both outdoor and indoor activities), Fashion (Shoes, costumes, makeup, etc), Food (Recipes, drinks, cakes, etc) and Gadget (Electronic goods, motorbikes, tools, etc). The categorization developed in this paper was deemed by the Instagram photo contest[1] and got a wide attention from media and academia.

2. We study differentiated content sharing behavior by the same set of individuals who maintain accounts on multiple social media platforms providing similar kinds of functionalities – Twitter vs Instagram. We observed that the differences are deeply rooted in the very intention with which users post on these platforms with *Twitter* being a *venue for serious posts* about news, opinions and business life while *Instagram* serves as the *host for light-hearted personal moments* and posts on leisure activities.

3. The macro and micro analysis conducted in this research revealed the importance of employing both visual as well as linguistic data. Specifically in the context of

[1]https://www.photocontestinsider.com/2014/10/insta-photo-awards/

revealing sensitive health disclosures, analyses shows that users are appropriating visual channels to communicate their emotions and feelings with the visual imagery.

4. We propose a novel framework – AI-MIX that implements a general architecture for human computation systems aimed at planning and scheduling tasks. We launched this framework in the travel planning domain on Amazon mechanical turk and evaluate if the plans generated are complete and meaningful by human raters. This system forecasts the types of roles an automated planner can play in human computation systems and the challenges involved in facilitating those roles.

5. We propose a novel framework to obtain aggregated plans from unstructured data repositories such as goal-oriented subreddits by leveraging machine learning and automated planning techniques.

1.3 Chapter Structure

The structure of this thesis is as follows.

Chapter 2 presents the background on the different dimensions of the analysis to identify the efforts towards differentiated content sharing behaviors, social media and public health, interpretation with incomplete action models for decision-making and crowdsourced planning. We describe the approaches and inferences made by the existing work at a high-level to provide a context for the research presented in this dissertation and emphasize the gaps in the literature that this research aims to fill.

Chapter 3 presents the investigation of motivations behind why users utilize specific photo-sharing social media platforms such as Instagram and the differentiated content sharing behaviors on platforms that are providing similar kinds of functionalities. This sharing behavior is investigated both at an individual level as well as an organizational level (fashion brands). The results emphasize that these online account holders specifically use platforms such as Twitter to share posts about general topics and Instagram to share light-hearted personal moments.

Unlike the previous chapter, Chapter 4 specifically investigates the content sharing behavior at the level of a specific task – here, public health. For the two subtasks, we consider two types of platforms – one a photo-sharing platform that has both visual and linguistic content (mental health), the other an online discussion forum primarily consisting of a linguistic content (weight loss). The main goal of this investigation is to answer a specific set of research questions that are directed towards the user's health condition and self-disclosures, where different aspects of the content are studied to characterize the self disclosures.

tChapter 5 introduces new models leveraging automated planning to perform decision-making. The main goal of these models is proposed from textual posts shared on a goal-oriented online discussion forum to infer structured plans with a precendence relationship. Individuals participating in this discussion forum share the same goal, and the posts reflect their own personal plans, what worked, what didn't work, etc shared in the natural language format that was mainly for human consumption. We propose two different models here - one that is structured as a directed graph and the other as a trained recurrent neural network. We evaluate these models by using metrics such as soundness and completeness through the ratings provided by the human subjects.

Chapter 6 proposes a collaborative human-in-the-loop framework where the requester, crowd and the automated planner interact through a distributed blackboard to perform planning and scheduling. We call this framework as AI-MIX (Automated Improvement of Mixed Initiative eXperiences) that implements a general architecture for human computation systems aimed at planning and scheduling tasks. This system is a tour plan generation system that uses automated checks and alerts to improve the quality of plans created by human workers. We present a preliminary evaluation of the effectiveness of steering provided by automated planning.

Chapter 7 summarizes the thesis, findings and contributions of this research and discusses potential future directions for research.

Chapter 2

FOUNDATIONS AND PRELIMINARIES

Social data (or *social media data*) – the content shared on social media platforms has enabled access to the opinions and perceptions of individuals or the society at a scale that is impractical with the conventional data collection techniques that include surveys and interviews [156]. These platforms enable users to share, seek and interact with other users on a rich mix of topics such as politics [60, 150, 174], health [28, 51, 16], food [5, 53], relationships [68, 124, 138], work [61], etc. These diverse reasons that individuals are utilizing social media platforms result in a rich variety of content. This data, the – “wisdom of crowd”, has been valuable in opening unprecedented opportunities to answer significant questions about the individuals and society at large. Research [136, 152] on Twitter shows that the majority of the posts shared online contain a significant percentage of posts about an individual’s own experiences.

2.1 Differentiated Content Sharing Behavior

Text-based platforms like Twitter (Twitter which was a text-based communication platform when it was originally launched) have been explored extensively with respect to their content [86], and language [87]. However, in spite of the fact that photo capturing and sharing platforms are rapidly growing in terms of the number of users, they have attracted less attention from the research community compared to platforms like Twitter and other text-based social media venues [45, 136]. Having a deeper understanding of photo-based platforms is important because it will help us gain deep insights about social, cultural and environmental issues about people’s activities (through the lens of their photos). After all, a picture is worth a thousand words.

It is established that Twitter is primarily a news medium [113]. Research on Instagram has focused mostly on understanding user behavior through analyzing color palettes [83], categories [88], filters [13], etc. On the other hand, it has been of significant interest to the researchers to investigate the behavior of a user [21], map same user accounts [184], study how users reveal their personal information [35], etc all across multiple OSNs. This dissertation extends the current state-of-the-art research by examining the nature of a given user's behavior manifested across Twitter and Instagram. Close to this research is the work of Raphael et al. [141] that compared Pinterest and Twitter, Bang et al. [122] where six OSNs were studied to analyze the temporal and topical signature (only w.r.t user's profession) of user's sharing behavior. However, they did not focus on studying the comparative linguistic aspects and visual cues across the platforms. Here we employ both textual and visual techniques to conduct a deeper comparative analysis of content on both Twitter and Instagram.

2.2 Social Media and Public Health

There is ample previous work in building computational approaches to address different public health scenarios by building models via graph theory, differential equations, aggregated data-driven approaches, etc. Most of the prior work on using data about user's online behavior on social media platforms was to estimate the cumulative disease trends. Some of these works focused on influenza tracking [6, 41, 29, 28], mental health and depression [71, 51, 52], weight loss [24, 16, 47], and a broad range of diseases [30, 143]. These platforms enable individuals to self-disclose their personal experiences by maintaining anonimity. Self-disclosure has been widely investigated both in the psychology and the computer mediated communication (CMC) literature. This body of work has argued self-disclosure to be beneficial: having been linked to trust and group identity, as well as playing an important role in social interactions by reducing uncertainty [7, 40, 96].

Most of the existing studies [24, 16, 120, 47] on online weight loss discussion forums focused on why people participate and how the social support can help them to lose weight. These studies are conducted from the perspective of medical and psychological domains, where the data are collected via interviews or a small set of online forum data that are manually analyzed by human experts. Unlike the existing literature, our work considers the weekly check-in weights of users along with their posts to understand the behavior of users who want to lose weight and detect the variables that classify users who need additional support and service.

In the context of mental health, Ellis [63] reported that discourse on emotionally laden traumatic experiences can be a safe way of confronting mental illness. Jourard [97] also reported that self-disclosure was a basic element in the attainment of improved mental health. This is because painful events that are not structured into a narrative format may contribute to the continued experience of negative thoughts and feelings that underlie many mental illnesses. Self-disclosure facilitates a sense of resolution, which results in less rumination and eventually allows disturbing experiences to subside gradually from conscious thought. A seminal work [144] found that participants assigned to a trauma-writing condition showed immune system benefits. Self-disclosure has also been associated with reduced visits to medical centers and psychological benefits in the form of improved affect [163]. This dissertation builds on these observations and examines the manner in which individuals might be appropriating the photo-sharing capability of social media platforms like Instagram to self-disclose about mental health challenges.

2.3 Interpretation with Incomplete Action Models

There is a growing interest in exploiting the burgeoning amount of user-generated data on the Internet – especially on social media platforms – to provide data-based decision support. While the initial wave of work in this direction [6, 11, 26, 38, 69, 157, 178, 181] was limited to supporting single labeling decisions (e.g. recommendations), there is an increasing interest in supporting more complex scenarios that require planning and other forms of sequential decision making [107, 140]. A prime example is the category of tasks that are classified as "self-help" and that involve a number of steps and often complicated sequences of actions. Examples here include quitting smoking, losing weight, or traveling the world. A number of online groups contain a plethora of crowd-generated wisdom about appropriate courses of action that have worked for a variety of different individuals. The main problem we consider in this thread of research is the extraction of such information so that it can be applied towards an automated way of helping new users with similar goals [65, 72, 91, 165]. Such automated approaches need not be restricted to plan synthesis alone [101, 134, 176]; they can also include a number of other sequential decision making problems including plan critiquing, plan ranking, and even merely the extraction of plan traces (where the existing work [191, 189, 74] in the automated planning community, performs planning without learning the traces) that can be used as input to existing model learning methods.

2.4 Crowdsourced Planning

Research in planning and crowd-sourcing intersect paths in three different ways: (i) to use the crowd to do planning tasks (ii) to use the crowd to provide planning knowledge to be used by an automated planner, and (iii) to use the planning technology to manage the crowd and their activities (e.g. monitor the crowd quality, allocate Human Intelligent Tasks (HITs)[1], optimize the workflow etc.) A number of other implemented human computation systems that use automated technology to assist with and improve the quality of tasks other than planning are listed in a wide-ranging survey [148] of the field. Both the challenges of interpreting the crowd's plan and the challenge of steering it can have primitive solutions

[1]Human Intelligence Task (HIT) is the individual task that the turkers work on.

(e.g. force structure and critique the plan in terms of lower level consistency checks), and more ambitious solutions (e.g. interpret structure by extracting actions and plans from text, and evaluate the extracted plan in terms of the planning model to provide constructive extensions or alternatives for the crowd's consideration).

Most existing work uses the primitive solutions for interpretation and steering. Mobi [186] takes a planning mission that consists of both preferences and constraints as input from a requester, and generates a plan or itinerary by allowing workers in the crowd to plan in a shared manner. Another system proposed in [119] which introduces CrowdPlan, a collaborative planning algorithm, takes as input a high-level mission from the user and provides web-based resources for accomplishing that mission. To facilitate this, CrowdPlan uses human workers to decompose the high-level mission into goals (like "stop smoking", "eat healthier food"). Although the decomposition process has similarities to HTN planning [137], CrowdPlan itself doesn't have any automated planning component overseeing the human workers. On the other hand, there are systems like CrowdPlanr [125] that focus more on sequencing the steps in a plan once the actions themselves have been selected.The Cobi [185] system employs the same basic idea – that the *crowd* assisting with the planning already has a built-in model of preferences and constraints. Cobi sought to "communitysource" the scheduling of a large-scale conference (CHI 2013) by taking input from organizers as well as authors and attendees in order to come up with a schedule (plan) of good quality that violates a fewer number of constraints while being feasible. The system proposed (but not yet implemented) by [116] is the closest in spirit and idea to applying automated planning methods on a distributed interaction platform to aid crowdsourced planning.

The role played by automated planning in crowdsourced planning problems has interesting connections and contrasts to the role of planners in mixed-initiative planning [64] and human-in-the-loop planning [102]. Broadly speaking, mixed-initiative planning work involved humans entering the land of planners, while crowdsourced planning requires the planner to enter the land of humans. For example, in mixed-initiative planning, the ”interpretation” problem is punted away by expecting the human in the loop to interact with the plan on the planner's terms; this will certainly not work in crowdsourced planning. Further, in mixed-initiative and human-robot teaming scenarios, the planner is expected to have a complete model of the planning problem – which is rarely the case in crowdsourced planning. Instead, the planner must deal with a model-lite [101] spectrum, where models may range from simple feasibility constraints, through incomplete theories of the task domain and, very rarely, preferences specified in a standardized format. Planning techniques that have so far expected input in standard forms (like PDDL) must also change to take this model-lite spectrum into account.

There are several research efforts that use planning and scheduling techniques to manage the crowd, regardless of the specific task being supported by the crowd-sourced system. The work proposed in [44] is an example of the strand of research where planning techniques are used to manage the crowd resources. The TurKontrol project, which is an end-to-end system that dynamically optimizes live crowdsourcing tasks, deals with the problem of assigning HITs to both improving the quality of a solution, as well as checking the current quality. This work also concentrates on optimizing iterative, crowdsourced workflows by learning the model parameters [177] from real Mechanical Turk data and modeling worker and his accuracy (for quality improvement) [99] and voting patterns and incentives [130] (to check the quality of work done.) Such systems are independent of the actual task at hand – whether that be text improvement or human intelligence to produce plans – and focus more on worker-independent parameters to assign improvement and voting jobs instead.

Chapter 3

COMPUTATIONAL ANALYSIS AT A MACRO-LEVEL

In this chapter, we investigate the motivations behind why users utilize social media platforms, especially the differentiated content sharing behaviors on two different platforms that provide similar functionalities. We investigate the sharing patterns of both individuals as well as organizations (in this case, different fashion brands) from the perspectives of textual as well as linguistic data. First, we present a case study on why individuals utilize photo-sharing social media platforms followed by addressing the content sharing behaviors at different levels.

3.1 What do users Instagram?

Interpretation could influence new interventions to leverage the rich information embedded in visual imagery as an image is worth a thousand words. With image (or video) sharing platforms quickly emerging as the new medium in the spotlight in recent years, we need systems that could automatically examine the visual content. Instagram, a mobile photo (and video) capturing and sharing service, is one of such popular platforms that is gaining traction. It provides users an instantaneous way to capture and share their life moments with friends through a series of (filter manipulated) pictures and videos. Since its launch in October 2010, it has attracted more than 150 million active users, with an average of 55 million photos uploaded by users per day, and more than 16 billion photos shared so far [90].

Despite its popularity, to date, little research has been focused on Instagram [1]. We advocate that Instagram deserves attention from the research community that is comparable

[1] We are aware of the small section of research on Instagram

to the attention given to Twitter and other social media platforms [136, 27]. Having a deep understanding of Instagram is important because it will help us gain deep insights about social, cultural and environmental issues about people's activities (through the lens of their photos). After all, a picture is worth a thousand words (in contrast, Twitter is mainly a text-based communication platform.) To address the gap, in this research, we aim to acquire an initial understanding of the type of photos shared by individuals on Instagram through investigating the fundamental and critical questions:

- What types of photos and videos do people usually post on Instagram?
- What are the differences between users in terms of the images they post?

Our analysis based on the Instagram data collected using the Instagram API, is a qualitative categorization of Instagram photos and a quantitative examination of users' characteristics with respect to their photos. The data includes profile information, photos, captions and tags associated with photos and users' social network that includes friends and followers.

3.1.1 Data Collection Methodology

We first got the IDs of users who had media (photos or videos) that appeared on Instagram's public timeline, which displays a subset of Instagram media that was most popular at the moment resulting in a set of 37 unique users. We found that these users were mostly celebrities (which may explain why their posts were popular.) We then crawled the IDs of both their followers and friends and later merged these two lists to form one unified list that contained 95,343 unique seed users. We extracted regular active users who are 1) not organizations, brands, or spammers, and 2) had ≥ 30 friends, ≥ 30 followers, and had posted ≥ 60 photos.[2] We found 13,951 users (14.6% of the seed users) who *satisfied* those criteria, out of which we randomly selected 50 users and downloaded their profiles, 20 recent photos, and their social network (lists of friends and followers). We chose to sample only 50 users here since we are performing semi-manual coding of their photos which is not feasible over a large number of users. This dataset allows us to make predictions with a 95% confidence level and a 13% confidence interval for typical users, accurate enough for the analysis in this paper (i.e., the sample is representative).

3.1.2 RQ1: Visual Content Categories

Coding Process:

To characterize the types of photos posted on Instagram we used a grounded approach to thematize and code (i.e., categorize) a sample of 200 photos from 1,000 photos we obtained (50 users by 20 photo per user). Coming up with good meaningful content categories is known to be challenging, especially for images since they contain much richer features than text. Therefore, as an initial pass, we sought help from computer vision techniques to get an overview of what categories exist in an efficient manner. Specifically, we first used the classical Scale Invariant Feature Transform (SIFT) algorithm [126] to detect and extract local discriminative features from photos in the sample. The feature vectors for photos are of 128 dimensions. Following the standard image vector quantization approach (i.e., SIFT feature clustering [169]), we obtained the *codebook* vectors for each photo [3]. Finally, we used k-means clustering to obtain 15 clusters of photos where the similarity between two

[2]It is worth noting that during our crawling process, many users (about 9.4%) changed their privacy settings from public to private which made their profiles and photos unretrievable.

[3]A photo I of a dog can have 125 SIFT features corresponding to the dog's eyes, legs, ears and so on, which are expressed in terms of the codebook vector (of size n) as $I =< C_1 : f_1, C_2 : f_2, C_3 : f_3, ..., C_n : f_n >$, where $\sum_{0 \leq i \leq n} f_i = 125$ and C_i is the cluster of all the features about specific characteristic of an object in the image.

photos is calculated in terms of Euclidean distance between their codebook vectors. These clusters served as an initial set of our coding categories, where each photo belongs to only one category.

To further improve the quality of this automated categorization, we asked two human coders who are regular users of Instagram to independently examine photos in each one of the 15 categories. They analyzed the affinity of the themes within the category and across categories, and manually adjusted categories if necessary (i.e., move photos to a more appropriate category or merge two categories if their themes are overlapped). Finally, through a discussion session where the two coders exchanged their coding results, discussed their categories and resolved their conflicts, we concluded with an 8-category coding scheme of photos (see Table 3.1) that both coders agreed on, i.e., the Fleiss' kappa is $\kappa = 1$. It is important to note that the stated goal of our coding was to manually provide a descriptive evaluation of photo content, not to hypothesize on the motivation of the user who is posting the photos.

Categorization:

Based on our 8-category coding scheme, the two coders independently categorized the rest of the 800 photos based on their main themes and their descriptions and hashtags if any (e.g., if a photo has a girl with her dog, and the description of this photo is "look at my cute dog", then this photo is categorized into "Pet" category.) The coders were asked to assign a single category to each photo (i.e., we avoid dual assignment.) The initial Fleiss' kappa is $\kappa = 0.75$. To resolve discrepancies between coders, we asked a third-party judge to view the unresolved photos and assign them to the most appropriate categories.

Fig. 3.1 shows the different proportions of photo categories. As shown in this figure, nearly half (46.6%) of the photos in our dataset belong to *Selfies* and *Friends* categories with slightly more self-portraits (24.2% vs. 22.4%). We also notice that *Pet* and *Fashion* are the least popular categories with less than 5% of the total number of images. This

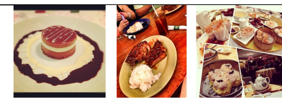
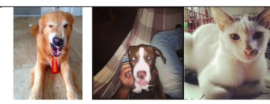
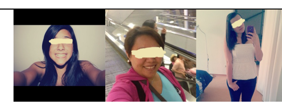
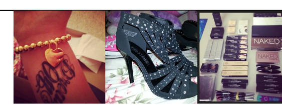
Category	Exemplary Photos
Friends (users posing with other friends; At least two human faces are in the photo)	
Food (food, recipes, cakes, drinks, etc.)	
Gadget (electronic goods, tools, motorbikes, cars, etc.)	
Captioned Photo (pictures with embed text, memes, and so on)	
Pet (animals like cats and dogs which are the main objects in the picture)	
Activity (both outdoor & indoor activities, places where activities happen, e.g., concert, landmarks)	
Selfie (self-portraits; only one human face is present in the photo)	
Fashion (shoes, costumes, makeup, personal belongings, etc.)	

Table 3.1: 8 Photo Categories

corroborates some of the recent discoveries in popular news media[4]. Other categories – *Food*, *Gadget* and *Captioned photo* – contributes to more than 10% individually but are approximately the same among themselves. This is in line with the conventional wisdom that Instagram is mostly used for self promoting and social networking with one's friends.

[4]http://newsfeed.time.com/2013/12/02/this-collar-camera-lets-your-pet-take-pics-and-post-them-to-instagram/ and http://digiday.com/brands/fashion-brands-instagram/

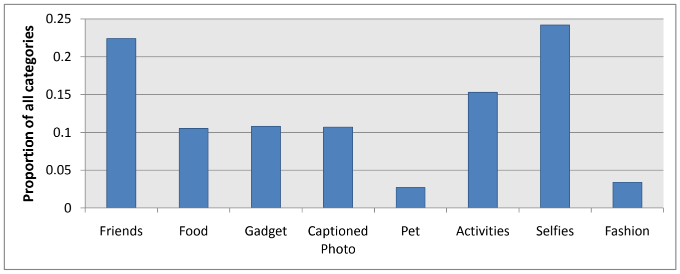


Figure 3.1: Proportion of Categories

3.1.3 RQ2: Users vs Posts

We perform an analysis to investigate whether there exist different types of users on Instagram based on the content they post. To start with, we first create an 8-dimensional vector for each user (since we have 8 categories of photos), where each dimension represents the proportion of user's photos in the corresponding category. After that, we utilize *k*-means clustering to generate clusters of users accordingly. We perform the clustering multiple times to determine the best *k* – the number of clusters, whose root mean square error is minimized.

Fig. 3.2 shows the clustering results that distinguish 5 types of users where, C1 to C5 represent five different user clusters. Within each cluster, the histograms indicate the proportion of each of the 8 content categories (C1 (n=11, 22%), C2 (n=7, 14%), C3 (n=7, 14%), C4 (n=3, 6%), and C5 (n=22, 44%)). The users on Instagam clearly exhibit distinctive characteristics in terms of the photos they share. For example, there exists "selfies-lovers" (C4) who almost post self-portraits exclusively (C4's entropy is $H(x)=1.4$). Similarly, people in C2 post mostly captioned photos whose embedded text mentions quotes, mottos, poetries or even popular hashtags (C2's entropy $H(x)=1.6$). On the other hand, there exist common users like C1 where even though they focus (slightly) more on posting photos of food, they like to post other categories of photos as well. Therefore, C1's entropy is the highest ($H(x)=1.96$). Also, it is interesting to know that people in C5 (22 users in

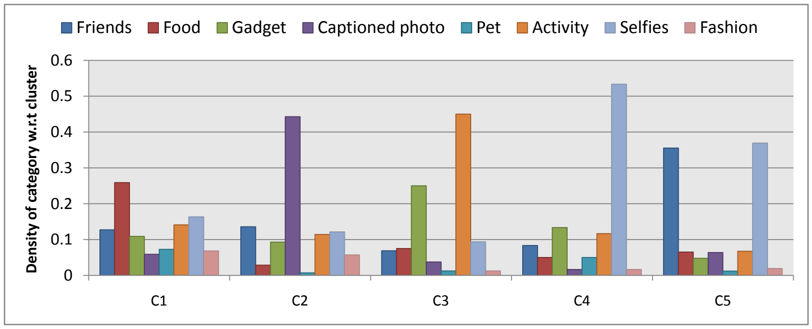


Figure 3.2: Clustering Users Based on the Categories of Their Photos

total) care about their friends as seriously as caring about themselves, by posting nearly equal number of photos from both categories (while ignoring the other categories) (C5's entropy is *H(x)=1.54*).

3.2 Differentiated Content Sharing – Individual-level

Understanding the usage of multiple Online Social Networks (OSNs) is of significant research interest as it helps in identifying the distinguishing traits of each social media platform that contribute to its continued existence. A comparison between two OSNs is particularly useful when it is done on the representative set of users holding active accounts on both the platforms. Twitter and Instagram are popular microblogging services with many users having active accounts on both these sites (or platforms) [122, 36]. While research has recognized immense practical value in understanding the user behavioral characteristics on these platforms separately, there is no existing research that has examined *how the content posted by the same set of individuals differs across these two platforms*. Instagram is a photo-sharing application whereas Twitter emerged as a text-based application which currently lets users post both text and multimedia data. Of particular interest is the question of *why and how a particular individual uses these two sites when both of them are similar in their current functionalities.* We aim to answer this question by analyzing content from the same set of individuals across these two popular platforms and quantifying their posting patterns.

3.2.1 Data Collection Methodology

To get a set of users maintaining accounts on both OSNs, we use a personal web hosting service called *About.me* (http://about.me/). This service enables individuals to create an online identity by letting them provide a brief biography, connections to other individuals and their personal websites. Using its API, we initially crawled a set of 10,000 users and pruned users who do not maintain accounts on both the platforms. The final crawl includes 963 users with a total of 1,035,840 posts from Twitter (using the Twitter API `https://dev.twitter.com/overview/api`) and 327,507 posts from Instagram (using the Instagram API `https://www.instagram.com/developer/`). Each post in this dataset is public and the data include user profiles along with their followers and friends list, tweets (insta posts), meta data for tweets that include favorites (likes), retweets (Instagram has no explicit reshares; so we use comments as a measure of the attention the post receives), geo-location tagged, date posted, media content attached and hashtags.

3.2.2 RQ1: Latent Topic Analysis

To analyze the types of content posted by a user across Twitter and Instagram, we first mine the latent topics from the corpus of Twitter (aggregated posts on Twitter of all users) and corpus of Instagram (aggregated posts on Instagram of all users where we use captions associated with posts for this analysis). Topic analysis is meaningful as it is pertinent to understand the reasons behind users joining the two platforms and making posts actively. We use TwitterLDA [5] developed for topic modeling of short text corpora to mine the latent topics.

The topic vocabulary listed for both the platforms in Table 3.2 indicates the unique top-

[5] `https://github.com/minghui/Twitter-LDA`

Twitter Topic Vocabulary		Instagram Topic Vocabulary	
ID	Terms	ID	Terms
0	stories, international, food, web, não, angelo, já	0	#food, delicious, coffee, sunset, beautiful, happy, #wedding
1	time, people, love, work, world, social, life	1	#streetart, #brightongraffiti, #belize, #sussex, #hipstamatic, #urbanart, #lawton
2	happy, love, home, birthday, weekend, beautiful, park	2	#fashion, #hair, #makeup, #health, #workout, #vegan, #fit
3	más, día, vía, gracias, mi, si, las	3	#instagood, #photooftheday, #menswear, #style, #travel, #beach, #summer
4	#football, #sports, #news, #art, facebook, google, iphone	4	birthday, beautiful, love, christmas, friends, fun, home

Table 3.2: Words Corresponding to the 5 Latent Topics from Twitter and Instagram

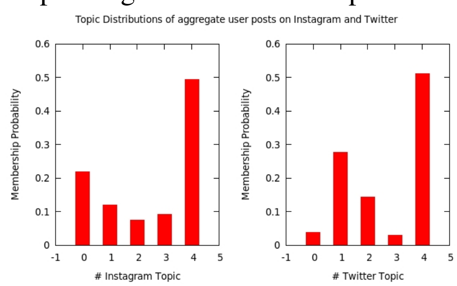


Figure 3.3: Topic Distributions of All the User Posts on Twitter and Instagram

ics for each site as well as the overlapping topics. For instance topics 0 and 4 on Instagram are similar to the topics 1 and 2 on Twitter. However, a significant difference is that Instagram is predominantly used to post about art, food, fitness, fashion, travel, friends and family but Twitter hosts a significantly higher percentage of posts on sports, news and business. Another notable difference is that the vocabulary from non-English language posts like French and Spanish is higher on Twitter as compared to the captions on Instagram mostly using English as the language medium. The topic distributions obtained from the two corpora listed in Figure 3.3 show that friends and food are the most frequently posted topics on Instagram as against sports and news followed by work and social life being popular on Twitter.

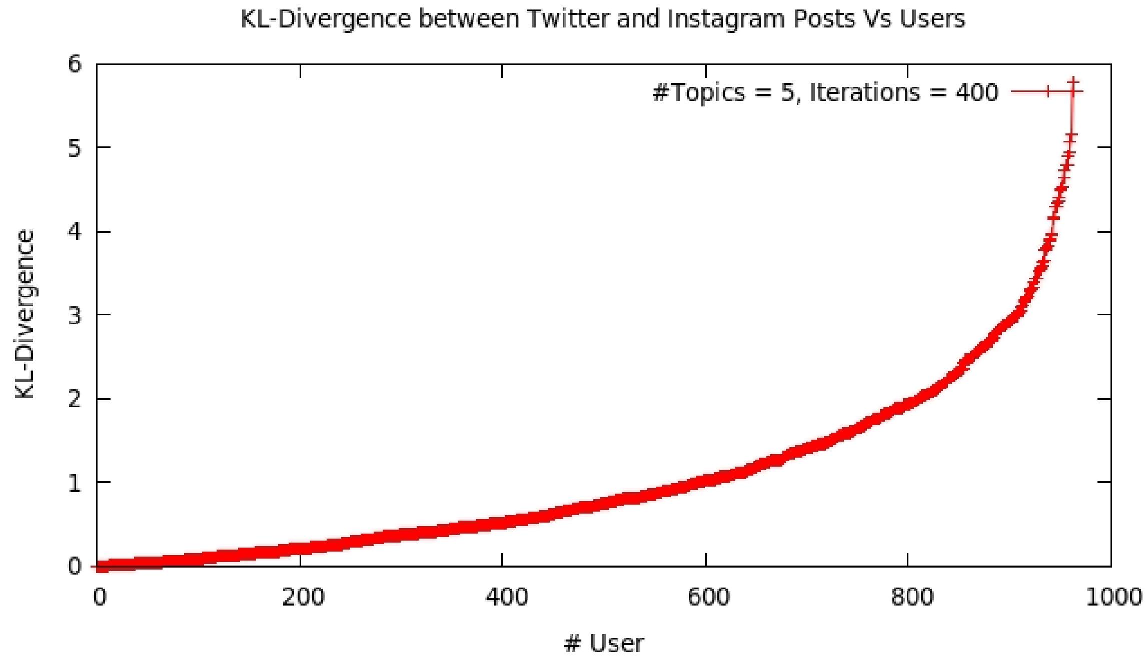
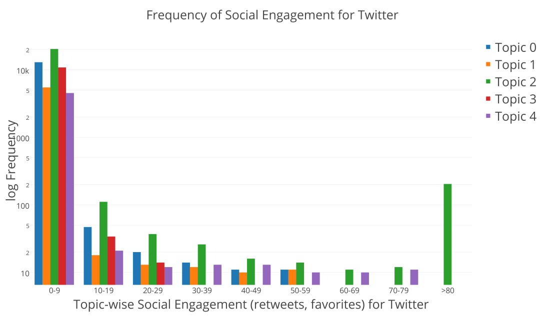


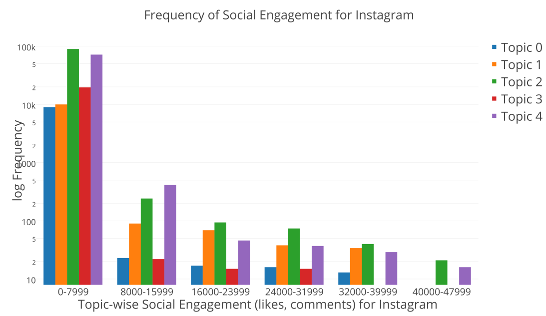
Figure 3.4: Sorted Entropies Between the Topic Distributions of the User Posts on Twitter and Instagram

$$D_{KL}(P||Q) = \sum_i P(i)log(\frac{P(i)}{Q(i)}) \tag{3.1}$$

To further validate the observations made about the distinctive topical content across the two platforms, we compared the topic distributions for each individual on the two platforms by estimating the *KL-Divergence* (Equation 3.1) between the topic distributions on each platform. We do this by first building a unified topic model on the combined corpus of tweets and captions of Instagram posts. The unified topics are listed in the description of Figure 3.5. The resultant entropy plot in Figure 3.4 shows a significant fraction of the users posting distinct content on the two platforms. This distinction is statistically significant with an estimated p-value $< 10^{-15}$ for each user.



(a) Twitter



(b) Instagram

Figure 3.5: Social Engagement Vs Post Frequency Where the Topics Are – Topic :{People, Life, World, Social, App, Game, Business}, Topic 1:{Stories, Artists, #lastfm, Level, #football, #sports, News}, Topic 2:{Birthday, Beautiful, Work, Weekend, Park, Dinner, Christmas}, Topic 3:{ Yang, Run, #fitness, #runkeeper, #art, Sale, #menswear}, Topic 4:{#instagood, #photooftheday, #love, MáS, #fashion, #travel, #food}

3.2.3 RQ2: Social Engagement

Since our findings revealed that the topics across the two platforms are significantly different, we investigate how the posts made by the same user engage other individuals on the two sites. We define the social engagement as the attention received by a user's post on the social media platform. It can be quantified in various ways varying from the sum of likes and comments on Instagram to the sum of favorites and reshares on Twitter. For each topic in the unified topic model for both Twitter and Instagram, the logarithmic frequency of posts is plotted against the magnitude of social engagement that is binned to discrete ranges as shown in Figure 3.5.

An interesting observation is that the socially engaging topics in the combined model are same as the overlapping topics from the topic models built in isolation on the Twitter and Instagram posts (Figure 3.3). The dominating topic on Twitter is about sports, news and business and on Instagram it is about love, fashion and food. Surprisingly, we found that the overlapping topics (Topics 2 and 3) focusing on social and personal life fetched predominant social engagement on both the platforms. A notable difference between the platforms with respect to social engagement is that the magnitude of attention received for Instagram posts is significantly higher than the level of attention received on Twitter. We can see this from the ranges plotted on the x-axes in Figure 3.5.

On average, there are 30% more hashtags for a Twitter post compared to an Instagram post (Pearson correlation coefficient = 0.34 between distributions with p-value $< 10^{-15}$). This may also indicate that since the main content on Instagram is imagery, textual captions may not receive as much attention from the user.

3.2.4 RQ3: Linguistic Nature

To characterize and compare the type of language used on both platforms, we use the psycholinguistic lexicon LIWC (`(http://liwc.wpengine.com/)`) on the text associated with Twitter posts and Instagram posts. We obtain measures of attributes related to user behavior – *emotionality* (how people are reacting to different events), *social relationships* (friends, family, other humans) and *individual differences* (attributes like bio, gender, age, etc).

It is clear from Table 3.3 that posts on Twitter have more negative emotions and contain more work-related and swear words. In contrast, positive social patterns are more evident on Instagram. By relating these results to the topic analysis results in the previous section, we note that on Instagram users share more light-hearted, happy personal updates.

3.2.5 RQ4: Visual Categories

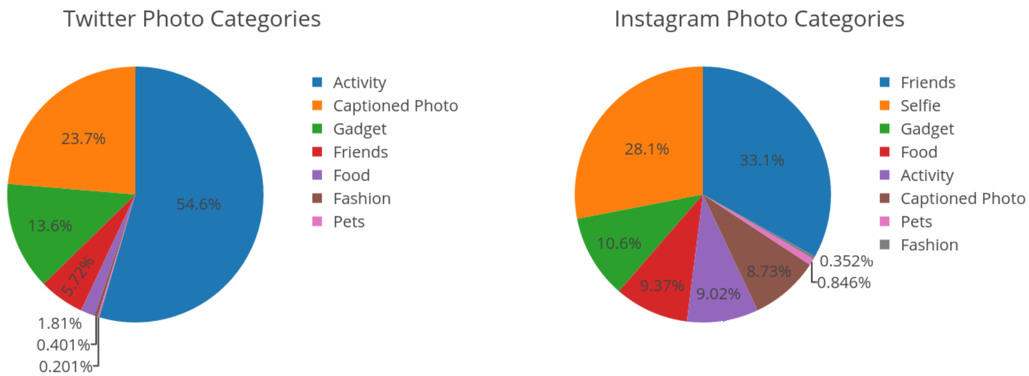
We further investigated if the visual categories of the posts made on Twitter and Instagram are different. We first sampled two sets of 5000 images from both platforms separately. Using the OpenCV library (`http://opencv.org/`) on these two datasets, we

	Platform	
	Twitter	Instagram
Emotionality		
Negemo	0.60	0.49
Posemo	0.19	0.19
Social Relationships		
home	0.15	0.30
family	0.14	0.21
friend	0.05	0.1
humans	0.17	0.21
Individual Differences		
work	0.81	0.5
bio	0.6	0.93
swear	0.08	0.06
death	0.07	0.04
gender	0.16	0.2

Table 3.3: Linguistic Attributes Across Twitter Vs Instagram. Each Value Indicates the Fraction of a Post Belonging to the Corresponding Attribute

extracted Speeded Up Robust Features (SURF) for each image. We used the vector quantization approach on these features that eventually converted each image into a codebook format. Using the codebook, we clustered images using k-means algorithm (best value of k is found by SSE (Sum of Squared Error)) which are refined and considered as the overall visual themes or categories.

Visual categories on Instagram agree with our previous work [88] which detected eight different categories of images. On the other hand, Twitter has four prominent cluster categories. Figure 3.6 shows that the percentage of photos in the activity category outnumbered any other category followed by captioned photos. These categories show that the topics of photos on Twitter are mainly related to news, opinions or other general user interests. In contrast, on Instagram users seem to mainly share the joyful and happy moments of their personal lives.



(a) Twitter (b) Instagram

Figure 3.6: Visual Categories

3.3 Differentiated Content Sharing – Organization-level

Fashion has a tremendous impact on our society and the increased interest in fashion displays the sign of its importance and generality [55, 104]. It is at the intersection of different fields to understand the collective identity dynamics, production patterns and consumer personality dynamics. Especially today, billions of users on social media make posts that are related to fashion on various platforms such as Instagram, Twitter, Facebook, Pinterest, Tumblr, etc. Social media is not only a dynamic platform for the users but also for businesses where it has transformed the landscape of business communication. This tranformation has made it easy for these businesses in relaying information to thousands of consumers promptly, globally and inexpensively. Because of this accessibility, different brands are relying on social media to promote their products and services, market information and consumer feedback.

There are several studies [57, 109, 108] that focus on understanding the growing interest in social media marketing. Different factors of social media have been studied to understand why it is the new hybrid element of promoting products. A study [39] shows that users on social media believe that companies should have a social media presence and interact with their customers. Other studies [22, 12] focused on the trends in cultural markets and especially sought to understand this phenomenon using social media data.

The importance of fashion branding on social media is becoming even more pronounced as networks like Instagram are revolutionizing this field. According to the well-analyzed editorials in The Guardian [32, 31] and The New York Times [66], it is social media that decides what you wear. Specifically Instagram is titled as *fashion's new front row*. Instagram alone has a significant share of posts that belong to fashion category [88]. During the runway shows as nearly every show attendee attends the show with a smartphone with Instagram account primed [3], it is important for the brands to understand how the trends and other competitors are utilizing this platform.

In this study we consider the top-20 fashion brands and investigate how they use Twitter and Instagram. We first analyze the text associated with the posts (either tweets or captions of photos on Twitter and Instagram) and identify the topics on which the brands are focusing. To perform this, we utilize the Latent Dirichlet Allocation (LDA) approach that helps in automatically discovering the topics present in the text. We then analyze the images where we extract deep features similar to those extracted by Khosla et al. [106]. These deep features are the last layer neuron activations of a large convolutional neural network that was trained on a common object detection task in a large dataset. In particular, we use the 22nd layer activation of the overfeat convolutional neural network [161]. These features transform the images into vectors on a 4096 dimensional representation space where object and color semantics are represented. Although these semantics are trained on tasks such as object detection and localization, the ImageNet dataset on which the network was trained provides enough semantics to perform even abstract tasks.

Using the deep image features, we conducted two experiments where in the first experiment we wanted to find out how the two types of brand marketing strategies – *direct* *marking* and *indirect marketing* are used. Our analysis revealed that brands that have a larger number of visibility tend to utilize the direct marketing strategy. We hope that the distinctions discovered in this paper can inspire marketing researchers to study the reason behind these inferences.

The summary of our contributions is as follows:

- A characterization of how top-20 fashion brands use social media primarily to compare and contrast the posts on Twitter and Instagram.

- An examination of the contributions made by the linguistic and deep image features of brands' posts on direct marketing and indirect marketing.

3.3.1 Data Collection Methodology

We consider the top-20 brands in terms of the number of followers on Instagram (shown in Table 3.4) according to the survey [1] conducted by Harper's Bazaar [2]. Harper's Bazaar is a monthly fashion magazine that delivers a perspective into the world of fashion, beauty and popular culture and is considered as a good style resource for women. Consider the dataset as $D = \{b_1, b_2, ...b_{20}\}$ where $b_1, \ldots, b_{20}$ are the brands that we consider for analysis on both Twitter and Instagram.

To download the tweets and meta information associated with each tweet for these brands in D on Twitter, we use the Twython API [6]. We downloaded all the tweets including metadata w.r.t followers, friends and media posted. On Instagram, we used the programming API [7] to collect the data for brands present in D that includes photos along with the meta data associated with the photo – number of likes, comments, caption, geolocation, hashtags, etc. Figure 3.7 shows the timeline of these brands when they started their accounts and first posted their tweet or photo on Twitter or Instagram respectively. Since

[6] https://twython.readthedocs.org/en/latest/
[7] http://instagram.com/developer/

Nike – b_1	Adidas Originals (AO) – b_2
Louis Vuitton (LV) – b_3	Dolce Gabbana (DG) – b_4
Michael Kors (MK) – b_5	Adidas – b_6
Dior – b_7	Louboutin World (LW) – b_8
Gucci – b_9	Prada – b_{10}
Burberry (Brb) – b_{11}	Vans – b_{12}
Fendi – b_{13}	Armani – b_{14}
Converse – b_{15}	Jimmy Choo (JC) – b_{16}
Free People (FP) – b_{17}	Calvin Klein (CK) – b_{18}
Ralph Lauren (RL) – b_{19}	Cartier – b_{20}

Table 3.4: Top-20 Brands Used in This Study

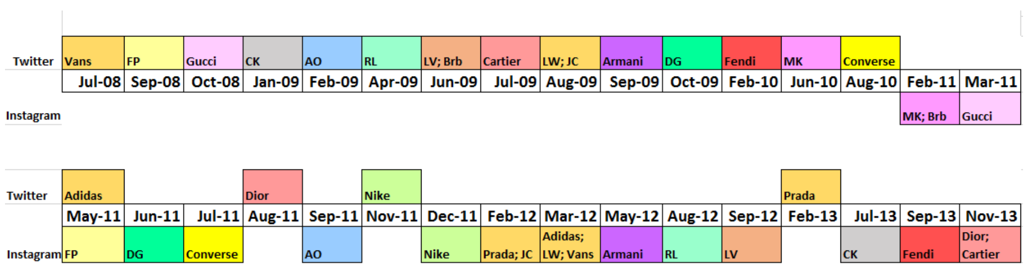


Figure 3.7: A Timeline Showing the Creation Dates of Accounts by the Brands on Twitter and Instagram

Twitter was founded in 2006 and Instagram in 2010, we can see in the timeline (shown in Figure 3.7) most brands have their accounts created on Twitter first. Among all these brands the first post was made by Vans in 2008 on Twitter and by Michael Kors in 2011 on Instagram.

A minimum of 18 posts and a maximum of 124 posts on Instagram and a minimum of 20 posts and a maximum of 619 posts on Twitter were made by these brands on average

–	Instagram	Twitter
mean #followers	5,264,421	2,405,283
mean #friends	207	425
mean #posts	1733	8995
total posts	34,659	179,902

Table 3.5: Statistics of the Data Obtained over the Top-20 Brands Used for This Study

every month. Table 3.5 gives some statistics of the data we collected over the time period of 2008–2015 on Twitter and 2011–2015 on Instagram for all these brands.

3.3.2 RQ 1: Brand behavior on Instagram

To investigate how these brands use Instagram, we first compute the frequency of posts per month by each brand (using eq. 3.3). Then we compute the average number of likes, average number of comments and average number of hashtags for all posts of brands which are shown in Figure 3.8.

Suppose $n_j^{(t,b)}$ and $n_j^{(i,b)}$ are the number of posts made on Twitter and Instagram by the brand b respectively in the time period j[8]. $p = \{t, i\}$ refer to the platforms Twitter and Instagram respectively,

$$M_i^{(p)} = \mathbb{1}\{\sum m_i^{(p)}\}\forall i, \tag{3.2}$$

is the vector that is an indicator function ($\mathbb{1}$) for each time period, indicating whether any posts at all were made during that time period. It is 1 if any posts were made and 0 if not.

[8]For the sake of convenience, we use a monthly time period

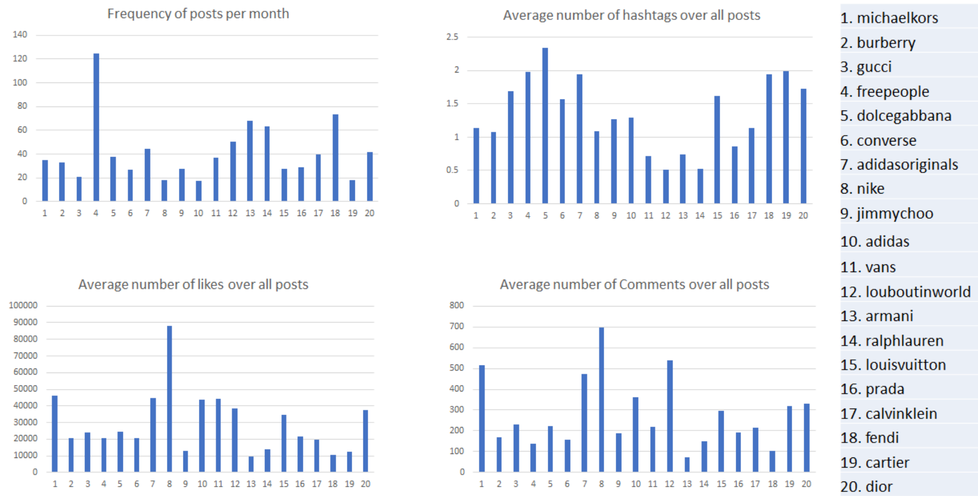


Figure 3.8: Different Statistics Showing the Brand Behavior on Instagram

Then,

$$\omega_p = \frac{P_t}{\sum M_i^{(p)}}, \tag{3.3}$$

is the average frequency of posts made by a brand on the platform p.

Based on the results shown in Table 3.8, we notice that the brands Michael Kors (MK) and Burberry (Brb) created their accounts at the same time and have a similar number of posts. But in terms of the number of followers, MK has 24% more followers than Brb and MK follows twice the number of people followed by Brb. When we consider the number of likes and comments, MK gets 3 times as many likes and comments as Brb receives. From the table we also notice that hashtags do not provide an answer for this behavior. One reason can be that the primary focus is on the product for photos posted by MK where as for Brb it is not the main focus. Users may tend to like the posts which focus on products more. Price can also be another factor as the products of MK are relatively very cheap compared to Brb. Brands like Free People (FP) created an instagram account during summer of 2011 and post pictures with a very high frequency (124 pictures on average every month). When

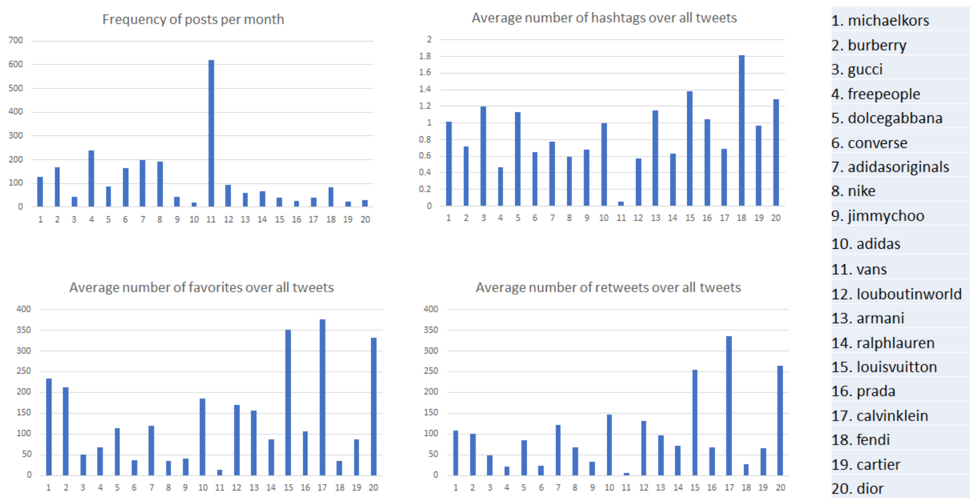


Figure 3.9: Different Statistics Showing the Brand Behavior on Twitter

we observe the number of likes and comments, they are around 20k and 136 respectively which are neither high nor low compared to other brands. This example may suggest that frequency rate doesn't affect the visibility (likes and comments) of posts.

3.3.3 RQ 2: Brand behavior on Twitter

On Twitter, users can submit content through (a) self (text) submissions that are stored on Twitter itself and (b) through links to external web content. The majority of these brands posted content that is stored on Twitter itself. On average, all of these brands have 87% of their tweets containing pictures of their products or models showcasing the brand's products. Some of these brands have links to external web content. For example, the majority of posts made by Gucci have images hosted on Instagram. Figure 3.9 gives information about the frequency of posts, hashtags, favorites and retweets of posts for the brands in D.

3.3.4 RQ 3: Instagram vs Twitter: Non-Visual Features

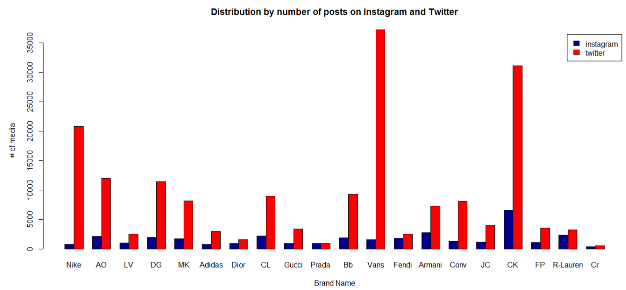
In this section we compare posts on Instagram and Twitter by considering the non-visual content which is the caption for a post on Instagram and the text of a tweet on Twitter. As a first step, we compare the number of posts, followers and friends on both the platforms of all the brands which are displayed in Figure 3.10. The key observation is that the posts made on Instagram get very large number of likes compared to the favorites of posts on Twitter. This can be due to the fact that on Instagram a post is a photo which speaks better than words. Also, Twitter allows posting photos that are hosted on external sources like Instagram, which can lead people to migrate to join those external photo-sharing platforms. This will be explored as a part of our future study.

These plots clearly suggest that the number of posts do not determine the number of followers (for example, Vans). It is very interesting to notice that all the brands have more followers on Instagram than on Twitter except Free People and Burberry. This suggests that following a large number of users does not guarantee a large number of followers.

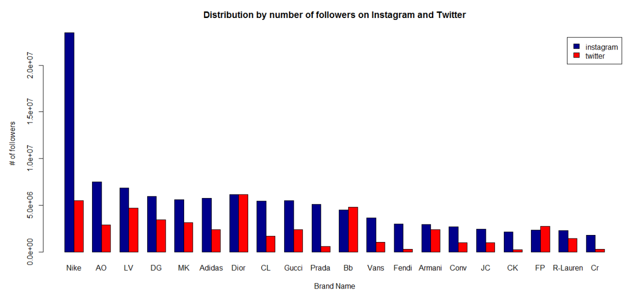
Popular Trends or topics:

We use the LDA approach [25] to understand how the brands focus on different topics using the textual features. To discover the topics, we use the Twitter LDA package [147]. We consider the captions or text attached with all the posts of a brand and try to understand how the topics vary across all the brands on the two platforms. Using LDA, we found 10 topics overall across all the brands on both platforms. Table 3.6 presents the 10 words associated with the discovered topics.

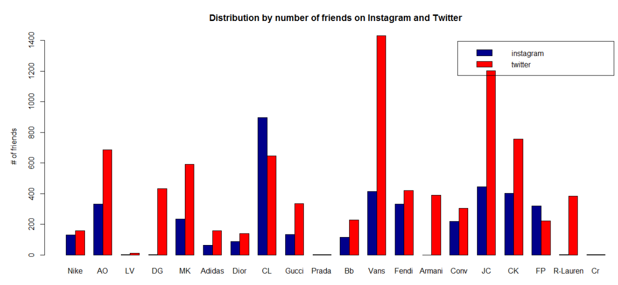
Using the topic distributions obtained through LDA, Table 3.7 shows the topics of focus for each of these brands on Twitter and Instagram. We can notice that the runway luxury fashion brands like Louis Vuitton, Dolce Gabbana, Burberry, etc., focus on the same topics on Twitter and Instagram. Only brands like Nike, Adidas Originals, Vans, Converse and Free People focus on different topics on the two platforms. Nike, the most popular brand on Instagram, focuses mainly on topic 7; whereas on Twitter, Nike focuses on topic 0 where the words associated with topic 0 suggest that Twitter might be used for correspondence or queries. We find that brands like Burberry focus mainly on British style and include men's



(a) Media



(b) Followers



(c) Friends

Figure 3.10: Comparison Between Instagram and Twitter on Three Attributes (a) Media (B) Followers (C) Friends

collections, while Michael Kors focuses on styles and accessories. The most active brand according to the number of friends, Louboutin World uses both the networks to contact their customers online – similar to Cartier. This analysis discovered that certain brands use Twitter to contact customers but use Instagram for advertising their products. Also these networks have posts of celebrities wearing certain brands, thereby promoting these brands – Dolce Gabbana, Armani and Prada.

3.3.5 RQ 4: Instagram vs Twitter: Visual Features

To analyze the visual content of both the social networks, we use the dataset of images and extract deep features. Deep learning is being used to convert data of various modalities into representations where the entropy is structured and ordered according to some tasks they are trained for. For instance, if a deep Convolutional Neural Network is trained for some prosaic task such as object recognition, they learn a distributed representation and map the images onto a vector space that carries details related to arbitrary semantics such as objectness, color, texture etc. Depending on the layer at which these representations are probed, one can glean a reasonable semantics. For instance, the earlier layers of a deep CNN seem to encode more edge and Gabor-like features while the latter layers seem to encode more meaningful features.

Often times deep features are used in transfer learning, where the networks are trained on one task and are used to create representation and analysis on other tasks. The transferability of CNN features was well-studied by Yosinski et al [183]. Following this line of thought, one could essentially train a deep CNN on a large enough dataset such as the Imagenet and use the learned network to extract image features for arbitrary task such as unsupervised clustering [112]. Most networks that are used in the Imagenet competition are made public. It is a common practice to use these *off-the-shelf* networks to extract imaging features.

In this article, we use the overfeat networks' image features [161]. Overfeat is a very popular network and is considered one of the state-of-the-art in image classification. We chose overfeat for two reasons. As argued by Khosla et al., overfeat-type features are particularly capable of extracting representations that are well-suited for Internet images and abstract tasks. Overfeat is a stable implementation that makes use of GPU in the efficient extraction of features for large scale image datasets. We use the network's 22^{nd} layer representation for each image as the feature vector corresponding to the image. We then perform clustering on this space and use those clusters' results to study the different marketing strategies utilized by the brands and how it affects the visibility of their products.

3.3.6 RQ 5: Marketing Strategies

In this section we study how brands use the two marketing strategies – direct marketing and indirect marketing. Direct marketing focuses on the product more and less on other attributes, which is vice-versa in indirect marketing. We first conduct an analysis along both brand and cluster category to understand these strategies. Figure 3.11 displays the brands b_1 – Dolce Gabbana, b_2 – Gucci, b_3 – Michael Kors along the cluster types – C_1 – Products, C_2 – Runway/Redcarpet events, C_3 – Portraits for both Instagram (top row) and Twitter (bottom row). Brand b_1 focuses on direct marketing on Instagram but doesn't make posts of category C_1, whereas it focuses on indirect marketing w.r.t category C_3. Brand b_2 follows the similar trend as b_1. Whereas, brand b_3 primarily focuses on direct marketing no matter what category it is.

Now we analyze how the brands which focus on similar topics according to Table 3.7 conduct marketing. Among all the brands, Nike has the largest number of followers and the number of likes received for a post. Adidas focuses on the same topics as Nike, and we measure how the photos differ among these two brands. Each row in Figure 3.12 corresponds to a cluster category where Nike and Adidas both post similar kinds of photos, except that Nike and Adidas have a unique cluster focusing on their tank tops and track jackets respectively. Both the brands focus on direct and indirect marketing, and it would be interesting to explore the factors that contribute to the greater visibility of posts made by Nike.

Figure 3.11: Brands (b_1 – Dolce Gabbana, b_2 – Gucci, b_3 – Michael Kors) and Types of Clusters on Twitter & Instagram

Figure 3.12: Nike Vs Adidas

We now analyze two runway brands Prada and Armani which focus on the same topics. Figure 3.13 shows that even if both brands have some common themes of pictures, there exist distinct themes. Prada (which has larger number of followers and their posts receive more likes than Armani) posts contain floral patterns with no architecture and not much focused on products; whereas Armani has photos with text, photos that focus on indoor architecture and photos of products. This reveals that posts made by brands practicing indirect marketing strategies can have more visibility. This shows that We hope that these explorations could draw the attention of market researchers to study whether this type of

Figure 3.13: Prada Vs Armani

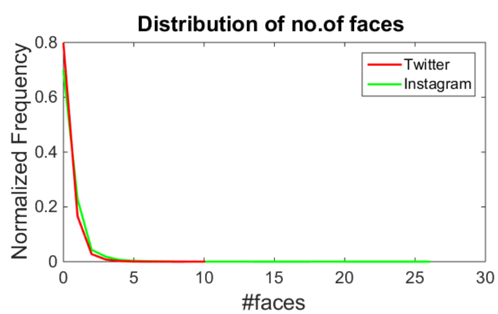


Figure 3.14: Distribution of Faces on Instagram Vs Twitter

marketing could lead to more visibility in terms of obtaining more likes and comments for posts on Instagram.

3.3.7 RQ 6: Faces vs Visibility

In this subsection we study whether photos that have people (either fashion models or celebrities endorsing the brand or the personnel) will get more visibility. To count the number of faces, we use the reliable Viola-Jones face detector algorithm [175]. The face detector works on collecting Haar-like features and uses a cascade of boosted trees to identify and count faces [121]. This detector is run over an image in overlapping patches and after a non-maximal suppression, we get a count and locations of all the faces in the image. One stable implementation of this is the OpenCV Library's face detector[9]. This is a stable state-of-the-art implementation; ergo we trust its reliability in detecting the number of faces. Results across all the brands in Figure 3.14 show that photos posted on Twitter contain more faces than the photos posted on Instagram.

In this chapter, our investigation showed that there are primarily 8 different content categories of images that are shared on a photo-sharing platform such as Instagram.

[9] http://docs.opencv.org/master/d7/d8b/tutorial_py_face_detection.html

ID	Words
0	*red*, *contact*, *make*, *pack*, *collection*, *team*, *hit*, *online*, *time*, *stores*
1	*show*, *louis*, *fashion*, *vuitton*, *men's*, *collection*, *gucci*, *watch*, *opening*, *live*
2	*collection*, *bag*, *discover*, *show*, *shoeoftheday*, *style*, *botique*, *fashion*, *wearing*, *watch*
3	*show*, *live*, *personalized*, *moment*, *autumn/winter*, *runway*, *wearing*, *collection*, *british*, *london*
4	*win*, *photo*, *pair*, *signed*, *metro*, *entered*, *sean*, *big*, *attitudes*, *submission*
5	*armani*, *giorgio*, *wearing*, *show*, *fashion*, *celebs*, *summer*, *emporio*, *collection*, *awards*
6	*rl*, *collection*, *regram*, *polo*, *vans*, *rad*, *photo*, *mix*, *fall*, *hope*
7	*styletip*, *conditions*, *merci*, *accessories*, *gnrales*, *live*, *peux-tu*, *participation*, *jetsetgo*, *timeless*
8	*fashion*, *blog*, *love*, *streetstyle*, *photo*, *today*, *fashionista*, *happy*, *inspiration*, *fashionphotography*
9	*collection*, *show*, *spring*, *runway*, *fall*, *discover*,*fashion*, *live*, *dress*, *backstage*

Table 3.6: Topic Ids and Their Corresponding Words

Brand	Instagram	Twitter
Nike	7	0
Adidas Originals	0	4
LouisVuitton	1	1
Dolce Gabbana	5	5
Michael Kors	7	7
Adidas	7	7
Dior	9	9
Louboutin World	0	0
Gucci	2	2
Prada	5	5
Burberry	3	3
Vans	6	0
Fendi	2	2
Armani	5	5
Converse	7	4
Jimmy Choo	2	2
Free People	8	6
Calvin Klein	9	9
Ralph Lauren	6	6
Cartier	0	0

Table 3.7: Topics Focused on by the Brands on Twitter and Instagram Obtained Using Lda Approach. The Ids Can Be Mapped to the Words as Shown in Table 3.6

Chapter 4

MICROANALYSIS

Using case studies from public health, this chapter presents the details of our investigation on social media data from the perspectives of self-disclosures and content analysis. The two main types of conditions that we consider as part of this study are mental health and weight-loss.

4.1 Self-Disclosures and Mental Health

Since many social media platforms like Instagram, Tumblr or Reddit allow anonymous or semi-anonymous discourse, they have come to be adopted widely in helping cope with mental health challenges [9, 50], conditions known to be associated with high social stigma. Recent research studying mental health disclosures through the lens of social media [8, 33, 51] has largely explored the ways in which linguistic attributes such as affect, cognition, and linguistic style may reveal cues about one's psychological state. We note that other modalities of mental health disclosure, such as visual imagery shared on social media, are under-explored. The rich literature in visual sociology situates imagery to be a powerful means of enabling emotional expression related to mental illnesses, especially those feelings and experiences that individuals may struggle to express verbally or through written communication [155]. Thus, visual imagery are likely to evoke deeper elements of psychological consciousness than do words or writing [105].

Extracting and characterizing the expressive meanings conveyed in the imagery shared around mental health disclosures on social media can provide rich information grounded in individuals' everyday experiences and interactions. Thus these approaches could raise the quality of language-only studies of mental health disclosures. We leverage the recent uptake of photo sharing practices on different social media platforms such as Instagram and Tumblr to investigate this research problem [58]. We are observing a shift in online user-generated content from predominantly text-based data to richer forms of image-based media. As Tifentale and Manovich [172] rightly noted, these image sharing practices open up fascinating opportunities for the study of "digital visual culture." Our broad research goal in this paper revolves around investigating *how social media disclosures of mental health challenges could be characterized via shared visual imagery*.

Specifically, as part of the microanalysis, the following three research questions are investigated.

(RQ 1) What *visual features* characterize images of mental health disclosures shared on social media?

(RQ 2) What are the kinds of *visual themes* manifested in these images, and what is the nature of *emotional expression* associated with these visual themes?

(RQ 3) How do visual themes of mental health images complement and contrast with themes manifested in the language of these social media posts?

4.1.1 Data Collection Methodology

We utilized Instagram's official API[1] to obtain the dataset used in this paper. Each post in this dataset is public and contains post-related information, such as the image, caption, likes, comments, hashtags, filter and geolocation, if tagged.

Referring to prior literature [33], we adopted an iterative approach to first identify a set of appropriate, distinguishing hashtags around different prominent mental illnesses prevalent in social media. With the seed tags, we performed an initial data collection of 1.5 million posts shared on Instagram between Dec 2010 and Nov 2015. Then by leveraging an association rule mining approach, we compiled the top k (k = 39, frequency $\geq$ 5000)

[1] https://www.instagram.com/developer/

anxiety	depression	mentalillness
bipolar	bpd	schizo
selfharm	paranoia	anorexic
depressed	bingeeatingdisorder	thinstagram
socialanxiety	unwanted	blades

Table 4.1: Sample Tags Used to Obtain Our Instagram Dataset

co-occurring tags in the 1.5M posts, and then appended them to the original seed tag list for further data collection. Table 4.1 lists a sample set of tags used to crawl the dataset.

This final list of 45 tags was thereafter passed on to a psychiatry researcher to be categorized into different disorder types. For tags that described experiences or symptoms cross-cutting across different conditions (e.g., "anxiety"), they were counted toward each disorder type. Table 4.2 gives a list of the ten different disorders identified in our data. We additionally consulted the Diagnostic and Statistical Manual of Mental Health Disorders (DSM-V [10]), that indicates these disorders to be prominent mental health challenges in populations. This categorization of the mental health challenges was conducted to ensure that our data used in the ensuing analysis focused on well-validated and clinically recognized conditions. At the same time, it allowed us to focus on a diverse range of disorders expressed on social media, rather than specific ones studied in prior work [49, 50, 85], thus enabling us to discover generalized patterns in visual disclosures of mental health challenges in social media. Our final crawl included 2,757,044 posts from 151,638 users spanning these disorders.

Data Reliability

Next, we assessed the suitability and reliability of our collected corpus of Instagram posts and users for our later analyses. For this purpose, we extracted *n*-grams (n=3) from the pro-

Anxiety Disorder	Depressive Disorder	PTSD
Bipolar Disorder	Panic Disorder	Suicide
Eating Disorder	OCD	Schizophrenia
Non-suicidal Self-injury		

Table 4.2: Disorder Categorization

file biographies of users. The top 10 *uni-*, *bi-* and *tri-* grams are shown in Table 4.3. They show that users are appropriating Instagram to seek and provide social and emotional support around different mental health concerns ("need someone talk," "feel free dm"). There are also explicit mentions of specific psychological challenges around mental health ("depression anxiety," "telling suicidal kids"), including warnings for profile visitors ("trigger warning") and personal experiences of the condition ("alone alone alone").

We corroborated these observations with a licensed psychiatrist and concluded that the users in our dataset are engaging in genuine mental health disclosures, tend to demonstrate disinhibition towards sharing their mental health experiences, and are appropriating the platform specifically for this purpose via the chosen account.

4.1.2 RQ 1: Visual Features

Towards examining the visual features of images relating to mental health disorders, we employ the extraction of color profiles, i.e., *grayscale histograms* [168]. Grayscale histograms provide us intuition about the brightness, saturation, and contrast distribution of images. In these histograms, images with high contrast pixels are binned in bins with lower numbers (near 0), whereas images with brighter pixels are binned in higher number bins (near 255). We utilize the OpenCV library[2] to extract these color histograms of images in our dataset.

[2]https://opencv-python-tutroals.readthedocs.io/en/latest/

Trigrams	Bigrams	Unigrams
need someone talk	days clean	love
just another depressed	report just	follow
ever need talk	self harm	like
depression self harm	secret account	account
telling suicidal kids	stay strong	days
feel free dm	mental health	need
one dat time	depression anxiety	one
dm need talk	need talk	years
report just unfollow	just block	depression
mine unless stated	trigger warning	dm

Table 4.3: Top Mentioned Tri-, Bi- and Uni-grams of Bios Extracted from User Profiles Sharing Mental Health Posts

	Anxiety	Bipolar	Depression	ED	NSSI	OCD	PD	PTSD	Schizophrenia	Suicide
Proportion of High contrast images	0.101	0.113	0.12	0.08	0.122	0.073	0.104	0.092	0.106	0.116
Proportion of High saturation images	0.58	0.644	0.577	0.669	0.481	0.751	0.601	0.733	0.63	0.577
Proportion of High brightness images	0.32	0.243	0.30	0.25	0.396	0.175	0.295	0.1743	0.263	0.306

Table 4.4: Proportion of Different Mental Health Category Posts Belonging to the Three Color (Pixel) Distributions. Here Ed=eating Disorder; Nssi=non-suicidal Self-injury; Pd=panic Disorder

Table 4.4 shows the proportion of posts belonging to the three color categories (all columns sum to 100%). We observe that a large number of images across the disorders are of high saturation (48-75%), i.e., these images contain different types of colors. However a considerable fraction *does* belong to the extreme ends as well, i.e., the high contrast and high brightness categories (25-52%). Thus, unlike prior findings where 90% of Instagram images were observed to *not* have dominant colors [128], in our case, we observe a contrasting pattern.

We also assess the *visual saliency* of images (using OpenCV) – a distinct subjective

	Contrast	Saturation	Brightness
saliency	45302 (45340)	59500 (55027)	41995 (42650)
hashtags	13 (13.4)	6 (10.2)	10 (12)

Table 4.5: Median (and Mean) Values of Saliency and Hashtag Counts of Images Associated with the Three Color Categories

perceptual quality that makes some images stand out from their neighbors [78]. A typical image in our dataset is of size 612px $\times$ 612px, so by using a saliency metric, we obtain a 612×612 grid matrix. For each image in these three visual feature categories, we obtain an empirical threshold that ensures $1/3^{rd}$ of the pixels will be greater than this value when sorted based on their saliency.

We find that (Table 4.5) the high saturation mental health images have higher saliency compared to the other categories ($\chi^2(2) = 19.7$; $p < 10^{-15}$; eta-squared estimate of effect size $E_r^2 = .52$, based on a Kruskal-Wallis test). This implies that these mental health images are likely to trigger greater cognitive and perceptual stimulus to viewers [78]. Further, high contrast and high brightness images tend to have more hashtags attached ($\chi^2(2) = 13.6$; $p < 10^{-15}$; $E_r^2 = .35$), indicating that the authors of these posts attempt to engage with the Instagram audience by associating their posts with a wide range of topics and content indicators. We conjecture this might be a way for the authors of these posts to increase their likelihood of discoverability and visibility on Instagram.

4.1.3 RQ 2a: Visual Themes

Identifying meaningful themes from images is known to be challenging as they contain richer features compared to text [70]. To examine the themes manifested in different mental health images that is posed as RQ 2, we used a 2-step human-machine approach. The first step employed automated computer vision techniques to perform initial clustering. The second step involved human raters to refine and label the automatically generated clusters, wherein they independently reorganized the clusters to obtain coherent descriptor labels. Our human-machine methodology is motivated by two observations: Human coding can help extract semantically meaningful and contextually relevant image themes, but it is difficult to scale in the face of datasets as large as ours. Automated clustering techniques can address the issue of scalability, but, on their own, they may not provide reliable or meaningful themes. We describe our two step method below:

Step I. In the first step, we used OpenCV to extract the Speeded Up Robust Features of the mental health images (SURF: [20]). SURF is a speeded-up local feature detector and descriptor that is good at handling images with rotation and blurring. More elaborately, the method uses a blob detector based on the Hessian matrix to find points of interest. It then develops a unique and robust description of an image feature, e.g., by describing the intensity distribution of the pixels within the neighborhood of the point of interest. It is typically used to locate and recognize objects, people or faces, to make 3D scenes, to track objects and to extract points of interest. Thus, these are likely to be helpful in characterizing the visual attributes of our mental health image data.

The extracted SURF vectors for all images are of 64 dimensions. Following the standard image vector quantization approach (i.e., SURF feature clustering) [20], we obtained the codebook vector for each image[3]. Finally, we used the k-means clustering algorithm (with Euclidean distance metric) to obtain 20 clusters, where we determine k in an empirical data driven manner that improves cluster consistency.

Step II. Next, with the help of two researchers familiar with mental health content on social media, the images in the 20 clusters and the affinity of themes were independently ex-

[3]For a given image I, it can have 96 SURF features corresponding to the different segments of an image. These features are expressed in terms of the codebook vector (of size n) as $I = <C_1 : f_1, C_2 : f_2, C_3 : f_3, dots, C_n : f_n>$ where, C_1 is the cluster of all features about specific characteristic of an object in the image.

amined, so as to refine the clusters as well as develop semantic descriptors characterizing them. The researchers adopted a semi-open coding approach, borrowing from the literature on mental health self-disclosure [96, 7, 40] and recent work in characterizing mental health images shared on different social media platforms [8, 9]. The annotators first independently coded all of the 20 clusters. Then following mutual discussion and resolution of inconsistencies, they merged the 20 clusters and readjusted them (shifting some images to other appropriate clusters) to eventually identify six major visual themes of mental health images.

What kind of textual cues characterize these visual clusters? In Table 4.6 we present the top 30 tags associated with each of these themes. We do not observe as much difference across them. For instance, inspection of the content of these tags across the visual themes reveals that many of these top tags include the tags we used to collect our data around the 10 mental health disorders (“depression,” “anxiety,” “eating disorder,” ‘suicide.”) Moreover, tags like “pain,” “broken,” “lonely,” “‘death” appear consistently across multiple themes, likely because the content associated with the different themes relates to the topic of mental health concerns. Our observations can further be quantified through the high value of the mean Spearman rank correlation (ρ=.21 (σ=.19), $p < .001$; ref. Table 4.7) between the tags and their frequency ranks in each visual theme.

4.1.4 RQ 2b: Linguistic Emotions of Visual Themes

Next, we employ the psycholinguistic lexicon LIWC (http://liwc.wpengine.com/) on the text associated with our mental health images spanning the different visual themes. We use the following five emotional attributes, motivated from prior work on mental health and social media [50, 15], *anger, anxiety, sadness, positive affect* and *negative affect*, and a measure of attributions to loss of life, indicated by the *death* category.

Figure 4.1 summarizes the distributions of the measures of six emotions across each

Visual Theme	Top Tags
Captioned Images	depression, anxiety, depressed, suicide, suicidal, sad, anorexia, selfharmmm, ana, alone, bipolar, worthless, bulimia, broken, anorexic, selfhate, ptsd, pain, schizophrenia, lonely, recovery, killme, sadness, love, death, hurt, help, quotes, suicidalthoughts, emo, depressionquotes
Selfie Images	depression, anxiety, depressed, suicide, suicidal, bipolar, anorexia, selfharmmm, ana, bulimia, ocd, schizophrenia, fat, ptsd, mia, ugly, anorexic, grunge, recovery, panicattack, love, blithe, ednos, secret_society123, bulimic, emo, ed, mentalillness, mentalhealth, eatingdisorder
Social	depression, anxiety, depressed, suicide, suicidal, anorexia, ocd, panicattack, ana, ptsd, bipolar, bulimia, mia, worthless, recovery, anorexic, emo, love, eatingdisorder, ednos, mentalillness, blithe, schizophrenia, grunge, mentalhealth, depressing, bulimic, skinny, ed, death
Food	depression, anxiety, depressed, suicide, sad, bipolar, suicidal, ptsd, ana, ocd, anorexia, schizophrenia, mentalhealth, alone, mia, broken, mentalillness, fat, ugly, bulimia, recovery, panicattack, anorexic, eatingdisorder, bulimic, calories, help, emo, sue, fitness
Physical Perceptions	depression, depressed, suicide, suicidal, anorexia, anxiety, ana, bulimia, sad, mia, anorexic, fat, bulimic, eatingdisorder, ed, worthless, skinny, ugly, blithe, lonely, broken, purge, mentalillness, ednos, pain, emo, ptsd, hurt, thin, workout
Graphic Images	depression, depressed, anxiety, suicide, suicidal, cutting, selfharmmm, blithe, cuts, suicidalthoughts, cut, starve, sad, blood, secret_society123, triggerwarning, f4f, fat, pathetic, empty, blades, numb, depressing, bruise, brain, razors, alternative, boyscanbedepressedtoo, scared, hated

Table 4.6: Top 30 Tags Associated with Each of the Six Visual Themes

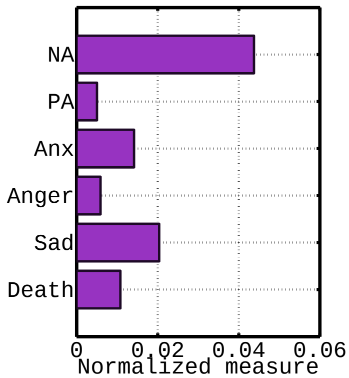
	Captioned	Selfie	Social	Food	Phys Perc	Graphic
Captioned	1	0.189	0.272	0.107	0.282	0.217
Selfie		1	0.674	0.091	0.260	0.247
Social			1	0.249	0.141	-0.165
Food				1	0.161	-0.056
Phys Perc					1	0.459
Graphic						1

Table 4.7: Spearman Rank Correlation Coefficients ρ Comparing the Most Frequent Tags Across All Pairs of Visual Themes

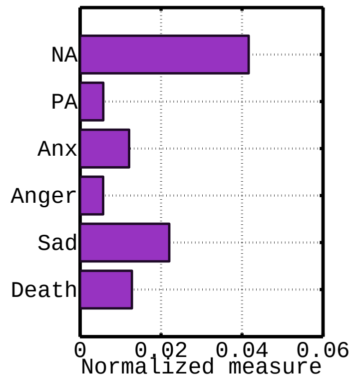
visual theme described above. Broadly, the different visual themes express diverse emotions. Expectedly, levels of Negative Affect (NA), Anger, Anxiety, Sadness and Death are relatively higher in all themes, compared to Positive Affect (PA). However, we observe notable differences in how specific emotions are expressed in the different visual themes. We discuss them below:

First, NA is consistently the largest emotion expressed in all the six visual themes ($H(1433663, 6) = 5.7; p < .001$ based on a Kruskal Wallis test). It is highest in the Graphic Images visual theme (+8.7%), followed by Captioned Images (+8.0%). We note similar trends for Sadness; it is higher by +28% in the Captioned Images theme, compared to others. As observed earlier (also see Table 4.6), the images associated with the Captioned Images tend to act as an outlet of deep-seated feelings and emotional distress—this can explain the high measures of NA and Sadness in it.

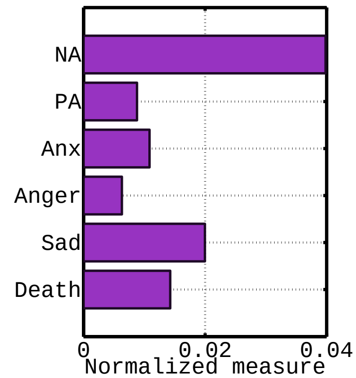
Anxiety is the highest in the Social theme (+60%; $H(1433663, 6) = 6.4; p < .001$); its second highest value is observed for the Graphic Images theme (+48%). Since per Table 4.6, many of the tags associated with Graphic Images relate to self-injurious behaviors known to be commonly associated with anxiety challenges [110], we see that manifested



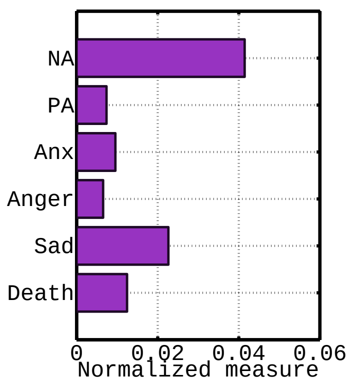
(a) Captioned Images



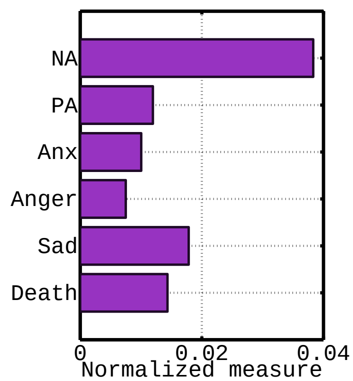
(b) Selfie Images



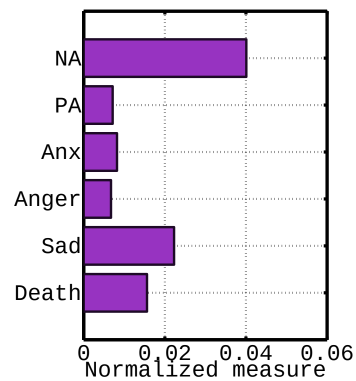
(c) Social



(d) Food



(e) Physical Perceptions



(f) Graphic Images

Figure 4.1: Distribution of Emotions for Each of the Six Visual Themes Extracted in This Study

via the Anxiety measure.

Next, we find that Anger is highest in the Food and Social themes (+18% and +12% respectively; $H(1433663, 6) = 2.7; p < .01$). Recall that our data consists of images associated with the topics of eating disorders and anorexia; hence the manifested anger in the Food theme may indicate self-conflicting thoughts about diet and food. On the other hand, high Anger in the Social theme may be attributed to limited access to social support, an aspect that characterizes much mental health related content on social media [51].

Somewhat surprisingly, we observe that the Food theme also includes the highest manifestation of PA (+108%; $H(1433663, 6) = 10.5; p < .0001$). This shows that, for some individuals, sharing Food related content may relate to a desire to adopt healthy and functional dietary habits and positive perspectives towards physical health. Moreover, many individuals in mental health recovery tend to share diet images as a way to identify with this behavior change process (ref. tags in Table 4.6). This might also be the underlying reason behind high PA.

Next, PA is lowest in the Graphic Images (-52%; $H(1433663, 6) = -5.9; p < .001$). Due to the large volume of images in the Graphic Images theme relating to deliberate harm to one's bodies, the emotion expressed in these images tends to be of largely negative tonality (and thus low PA). Finally the theme of Physical Perceptions stands out from the rest of the themes with respect to the expression of Death related emotions (+50%; $H(1433663, 6) = 6.2; p < .001$).

4.1.5 RQ 3: Linguistic Themes

Finally, to complement the visual themes (our research goal RQ 3), we identify themes from the captions and hashtags (textual data) associated with the Instagram images in our dataset. We refer to these latent topics as *linguistic themes*. Existing literature [144] emphasizes the importance of studying language, since it reflects a variety of thoughts, functions as a signal of identity, and emphasizes the social distance. We believe the linguistic themes may therefore help us contrast the visual themes around how individuals engage in mental health disclosure on Instagram.

We used TwitterLDA[4] to extract these linguistic themes. This method was developed for topic modeling of short text corpora for mining the latent topics. As typically done in topic modeling, we pre-processed the data by removing a standard list of stop words,

[4]https://github.com/minghui/Twitter-LDA

Topic id	Top Words
1	[non-English posts] con, amo, por, para, feliz, dia, pra, mais, meu, minha, mi, na, nao, los, amor, vida, em, como, narcissist, mas
2	[anorexia and body image] suicide, anorexia, ana, bulimia, mia, anxiety, anorexic, sad, fat, blithe, worthless, selfhate, sue, ugly, ednos, scars, skinny, ed, secret_society123
3	[fitness and workout] mentalhealth, ptsd, health, fitness, motivation, thinstagram, inspiration, workout, fitspo, veterans, fit, healthy, awareness, gym, support, weightloss
4	[everyday feelings and updates] feel, people, life, time, day, me, make, today, good, hate, anxiety, make, back, things, it, love, sad, fucking, mentalhealth, im, hope, hard, school
5	[self-hatred, self-harm and suicidality] sad, cutting, worthless, selfharm, broken, selfhate, lonely, ugly, cut, scars, fat, sadness, scars, pain, killme, death, hurt, dead
6	[general Instagram audience oriented content] love, instagood, follow, followme, photooftheday, tagsforlikes, beautiful, picoftheday, girl, cute, instadaily, fashion, happy, smile
7	[negative emotion] grunge, emo, sad, bands, tumblr, scene, ana, selfharm, music, softgrunge, punk, alternative, goth, bmth, sadness, pastel, ptv, pale, piercetheveil, emogirl
8	[positive emotion] love, happy, day, lol, good, birthday, tbt, time, night, fun, beautiful, family, baby, work, great, cute, snow, morning, selfie, friends, miss, home, made
9	[art, poetry, memes] art, dankmemes, drawing, memes, anime, fnaf, poetry, emo, bipolar, autism, sketch, filthyfrank, artist, kidzbop, sad, selfharmmm, feminism, love, dank, lol
10	[mental health recovery] depression, anxiety, recovery, anorexia, bulimia, ednos, eatingdisorder, edrecovery, ed, ana, hope, suicide, staystrong, anorexiarecovery, mia

Table 4.8: Linguistic Theme Distributions Generated Using the Latent Dirichlet Allocation (Lda). The Human Annotations of the Topics Are Included Inside the Square Brackets

words with very high frequency ($> 0.25\times$ datasize), and words that occur fewer than five times. Since LDA is an unsupervised learning approach, identifying the correct number of topics is challenging. We used the default hyper-parameter settings and 10 topics, which we determined based on the value of average corpus likelihood over ten runs.

These 10 topics constituted what is known as lifted forms of linguistic vocabulary [187]. On these extracted linguistic vocabulary, to arrive at interpretative descriptions (we call them linguistic themes), we adopted a similar semi-open coding approach as the visual themes that involved the same two researchers as above. The raters referred to the mental health literature [7, 40, 96] and identified the best possible description that characterized the tokens in the linguistic vocabulary corresponding to each of the 10 linguistic topics.

The extracted 10 linguistic themes and their associated vocabulary are presented in Table 4.8. All of the linguistic themes are highly semantically coherent within themselves, as noted from the themes' annotations in Table 4.8. Further, none of the linguistic themes overlap conceptually with any of the visual themes, as noted in the human annotations. In fact, mean Spearman rank correlation between the top 100 tags of each linguistic and visual theme is only .14 ($p < .01$), indicating that the sets of themes provide complementary perspective in understanding the different mental health disclosures of individuals on Instagram.

Going deeper into specific linguistic themes, we notice two themes (7 and 8) specifically expressing positive and negative emotion respectively. Example tags for the two themes include "sadness," "emo," "emogirl," and "good", "happy," "fun," "beautiful" respectively. Expectedly, two themes (2 and 5) relate to specific mental health challenges, ranging from anorexia and self-harm (tags like "blithe," "selfhate," "anorexia") to expressions of suicidality ("cutting," "worthless," "killme").

At the same time, we find the presence of a few linguistic themes that do not particularly relate to mental health issues. For instance, theme 6 spans content shared with the typical

Instagram audience [88] (note tags like “instadaily,” “smile,” “bestoftheday,” “instamood,” “selfie,” “tagsforlikes”). Another example is theme 4 that expresses feelings and thoughts around everyday activities and experiences (example tags include “life,” “people,” “today,” “good,” hope,” school”). Together, these themes indicate that despite primarily maintaining mental health focused accounts on Instagram, certain individuals do involve themselves in generic discourse as well. Again, this is in contrast to the visual themes, where we observed some mental health challenge manifested in every theme.

Finally, we find two linguistic themes that relate specifically to more uplifting content, such as relating to fitness (theme 3) and mental health recovery (theme 10). The former consists of tags like “workout,” “healthy,” “support,” “motivation,” “gym,” “exercise” and “mentalhealthawareness”. This indicates that the posts associated with this theme encourage and promote behaviors around improved physical health, known to bear links to better mental well-being [166]. Theme 10 includes the majority of content around recovery from eating disorder behaviors, as observed through tags like “anorexiarecovery,” “eatingdisorderrecovery” and “staystrong”. By sharing the posts associated with this theme, individuals may be aiming to seek and provide emotional support or to share their personal stories and experiences. Further inspection reveals that some of the posts associated with these two themes (3 and 10) tend to also be generated by a range of mental health support groups on Instagram. We note that such recovery related information was not discoverable through the visual themes.

4.1.6 Discussion and Conclusions

Our work indicates the adoption of the visual modality of photo-sharing social media platforms for mental health disclosure. In fact, many of the shared mental health images bear specific visual signatures, such as with high brightness or high contrast pixels. To explain this finding, we draw on Berger [79]: *“black-and-white photography is paradox-*

ically more evocative than colour photography. It stimulates a faster onrush of memories because less has been given, more has been left out." Individuals might be choosing these minimalist visual techniques to draw attention to their psychological state. The specific visual signatures may also indicate that the individuals want their emotions and experiences to be *visible* to others [155] beyond linguistic descriptions, although displaying these emotions can make them susceptible to both judgment and encouragement. We acknowledge that there are some limitations to our work, as the analysis and the inferences obtained are purely data-driven and relied on public posts shared on Instagram around mental health challenges. Specifically, to obtain disclosures of mental health issues, we utilized hashtags attached to posts. We presume self-selection biases in users who make public posts and link them to different mental health hashtags.

As a summary, we presented one of the first quantitative analyses of visual imagery shared on the photo-sharing social media Instagram around a variety of mental health challenges. We characterized different forms of self-disclosure as enabled via the visual imagery medium and contrasted them with that enabled via linguistic expression. We found that individuals were appropriating the photo-sharing affordances of Instagram to vent their discontentment around mental health challenges, seek support, and disclose sensitive and vulnerable information about their emotional distress. We believe our approach and findings can influence the design of new health interventions that leverage the rich information embedded in the visual imagery of mental health disclosures.

4.2 Online Discussion Forums of a Weight-Loss Program

Obesity is a major public health problem; the number of people suffering from obesity has risen globally in the last decade [139]. The Centers for Disease Control and prevention (CDCP) defined an obese adult[5] as a person with a body mass index (BMI) of 30 or higher.

[5] `http://www.cdc.gov/obesity/adult/defining.html`

Many obese people are trying to lose weight as diseases such as metabolic syndromes, respiratory problems, coronary heart disease, and psychological challenges are closely associated with obesity [135, 4]. Researchers have been trying to understand how certain factors are affecting weight loss as large number of over-weight people are trying to lose weight and others are trying to avoid gaining weight. Internet services are gaining popularity to support weight loss as they provide users with the opportunities to seek information by asking questions, answering questions, sharing their experiences and providing emotional support where people feel more comfortable by openly expressing their problems and concerns [16].

Social media tools like weblogs, instant messaging platforms, video chat, social networks and online discussion forums are reengineering the healthcare sector [80]. Especially, social media is a promising tool for studying public health like tracking flu infections [114], studying post-partum depression [48], dental pain [81], etc. Tools like online discussion forums make it easier to find health-related information while at the same time provide support by maintaining accountability, and some of the popular works like [117] proved that weight loss can be supported through online interactions. Hence, studying online discussion forums can help identify the people at risk who need more support and provide them access to appropriate services and support.

As part of this research problem, we explore the weight loss patterns of users who participate in online discussions and ground truth in terms of the weekly check-in weights of users. We perform different analyses on the users' language in correlation to their weight loss dynamics. From the overall dataset we identify two preliminary patterns of weight dynamics: (1) users who lose weight and successfully maintain the weight loss (*i.e.*, from one week to the next, weight is lost or weight remains the same) and (2) users whose weight pattern fluctuates (*i.e.*, from one week to the next, weight changes are erratic). While there are many possible groupings that we could have utilized, we chose this grouping because of the known problems with "yo-yo" dieting (diet that leads to cyclical loss and gain of weight) compared to a more steady weight-loss [82]. Our work is novel in terms of automating the language analysis by handling a bigger dataset and can help classify the user type based on the language efficiently. As a follow-up work, linguistic insights are explored which distinguish goal-oriented forums from non goal-oriented forums.

Our research contributions in this paper are divided into two main sections where each focuses on a broader perspective as described below:

1. How does the language of users vary within the weight loss forum based on their patterns of weight loss. Specifically, to understand the patterns of asking questions, using a specific sentiment, politeness and making excuses.

2. Are there any interesting insights about the linguistic signals that makes a goal-oriented forum such as weight-loss forum different from other general online forums.

Our analysis resulted in interesting insights as below:

1. users who lose weight in a *fluctuating manner* are *more active* on the discussion forums.

2. users losing weight in a *fluctuating manner* appear to talk about themselves as they use higher number of personal pronouns and adverbs.

3. users of *non-increasing weight loss pattern* mostly *reply to the posts* made by other users and *fluctuating users* post *more questions*.

4. posts from users of *fluctuating weight loss pattern* contain *more excuses*.

5. *politeness of posts* seems to be *uncorrelated* with the weightloss pattern.

6. *u*sers on *goal-oriented forums* contribute to a *cohesive thread of posts* compared to users on general online forums which suffer from non-cohesiveness.

We believe that this research can bring forth the different variables related to people who need additional support in terms of losing weight and thereby can stay healthy in maintaining their weight. Also, we envision building personalized weight loss applications that can cater to the needs of individuals who need additional support. We hope that this study will help in bringing more attention from the research community to study online weight loss communities and understand both the constructive and destructive dimensions of weight loss so that we can build a healthy society.

4.2.1 Data Collection Methodology

We obtained a text corpus of online discussion forums from *Fit Now, Inc.* who developed a popular mobile and web-based weight loss application. Along with the text corpus, we also obtain weekly weight check-in data for a subset of users. The entire corpus consists of eight different forums that are subdivided into conversation topic threads. Each thread consists of several posts made by different users. The forum data in our corpus consists of 884 threads, with a median length of 20 posts per thread. The posts were made between January 1, 2010 and July 1, 2012. We identify the subset of users for whom we have weight check-in data and who made at least 25 weight check-ins during this time period. This results in a total of 2,270 users.

We partition the users into two groups based on their dynamic weight loss patterns: a *non-increasing* group and a *fluctuating* group.

1. **Non-increasing**: These are the users who lose weight and keep it off. For each week j, the user's check-in weight w_j is less than or equal to their past week's weight w_{j-1}, within a small margin Δ. That is, $w_j \leq (1 + \Delta)w_{j-1}$.

2. **Fluctuating**: These are the users who do not lose weight. If the difference between two consecutive weekly check-in weights do not follow the non-increasing

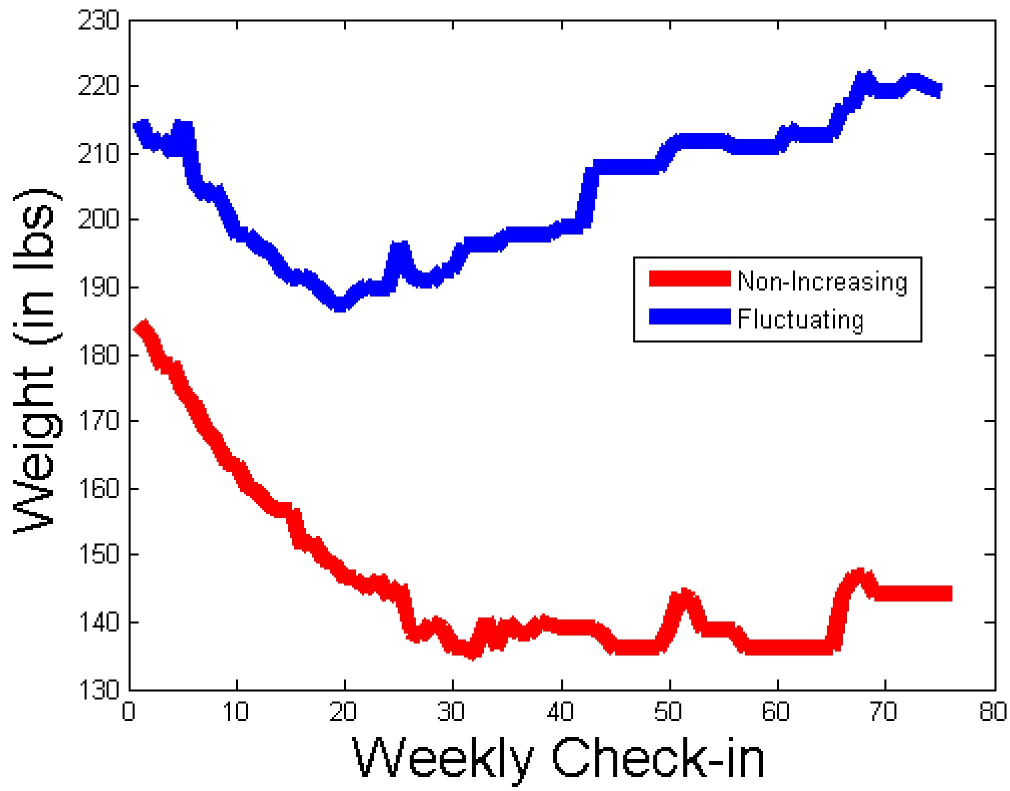


Figure 4.2: Example Weight Loss Patterns from Two Individual Users: Non-increasing (Bottom Line), and Fluctuating (Top Line). The x-axis Ranges from the 1st Through the 80th Weekly Check-in; The y-axis Shows the Weight, Measured in Lbs

constraint, users are grouped into this category.

We empirically set $\Delta = 0.04$ to divide the users in our dataset into two groups of similar size. To illustrate the two patterns of weight change, Figure 4.2 shows the weekly weight check-ins of two individual users, one from each group. This grouping is coarse, but is motivated by studies [111, 179] acknowledging that approximately 80% of people who set out to lose weight are successful at long-term weight loss maintenance, where successful maintenance is defined as losing 10% or more of the body weight and maintaining that for at least an year. In the future for further analysis, we aim to separate users less coarsely, e.g., users who maintain their weight neither gaining nor losing weight, users who lose weight and maintain it and finally, users who gain weight.

The main distinctive feature of this weight loss application is that users are encouraged to set goals to regularly log their weight, diet, and exercise. For a subset of users, this application included a weekly weight “check-in,” an average of the user’s weight check-ins during the week, for the January 1, 2010 through July 1, 2012 period. This allows us to juxtapose the weekly weights of the users with their posts on the discussion forums.

4.2.2 RQ1: Characteristics of Online Community

This weight loss application helps users set a personalized daily calorie budget, track the food they are eating, their exercise and log their weekly weight. It also helps users to stay motivated by providing an opportunity to connect with other users who want to lose weight and support each other. Example snippets from forum threads are shown below. The *“Can’t lose weight!”* thread demonstrates users supporting each other and offering advice. The *“Someday I will”* thread highlights the complex relationship between text, semantics, and motivation in the forums.

Example thread: “Can’t lose weight!”

User 1: *“I gained over 30 lbs in the last year and am stressed about losing it. I eat 1600 calories a day and burn more than that in exercise, but I havent lost any weight. I am so confused.”*

User 2: *“You’ve only been a member for less than 2 months. I suggest you relax. Set your program to 1 pound weight loss a week. Adjust your habits to something you can live with. . . long term.”*

User 3: *“You sound just like me. I think your exercise is good but maybe you are eating more than you think. Try diligently logging everything you consume.”*

User 1: *"Thanks for the suggestions! I am going to get back to my logging."*

Example thread: "Someday I will…"

User 1: *"Do a pull-up :-)"*

User 2: *"…actually enjoy exercising."*

User 3: *"Someday I will stop participating in these forums, but obviously not today."*

User 4: *"I hope you fail :-)"*

4.2.3 RQ 2: Empirical Analysis of Weight Loss Forum

In this section, we present preliminary observations on how the language and discourse patterns of forum posts vary with respect to weight loss dynamics. As an initial step, part-of-speech (POS) tagging is performed on all forum posts using the Stanford POS Tagger [173].

	Weight Pattern	
	Non-increasing	Fluctuating
# Total users	1127	1143
# Forum users	29	68
# Forum posts	99	1279
Posts per user	3.5	18.2
Words per post	49.1	77.3

Table 4.9: Statistics of Users and Forum Posts

From the weekly check-in data we identified the number of users and the number of posts from each weight-loss pattern cluster which are shown in Table 4.9. In our dataset, out of 1127 users who are expressing non-increasing weight loss pattern (1143 fluctuating weight loss pattern) only 29 of them (68 of them respectively) made at least one post on the discussion forums. We see that the average number of posts by fluctuating users is greater than the average number of posts by non-increasing users. Our data also suggest that the posts made by non-increasing users are shorter compared to those made by fluctuating users. Both these suggest the possible loss of social connectedness once users achieve their goal.

4.2.4 RQ 2a: Lexical Categories

Studies [145] show that the language defines an individual and his/her behavior. We use the measures that characterize the weight loss pattern by using the linguistic classes in posts made by these users on the forum. Specifically, *verbs*, *conjunctions*, *adverbs*, *personal pronouns* and *prepositions* are considered as shown in Table 4.10. We collected all the individual posts made by all the users belonging to each weight loss pattern and measured the average frequency of a linguistic class per post. Fluctuating users appear to talk more about themselves and interact with other individuals one-on-one as they are using a relatively higher number of personal pronouns. Additionally, we observe that users who lose weight in a fluctuating manner use greater fraction of prepositions and adverbs. Adverbs are primarily used to tell how someone did something [6] which means these users who lose weight in a fluctuating manner explain more about themselves, perhaps in an attempt to seek more information.

4.2.5 RQ 2b: Asking Questions

In order to build and maintain vibrant online communities, it is very important to understand the complex ways in which the members interact and how the communities evolve

[6](definition at `http://io9.com/5437610/seriously-whats-so-bad-about-adverbs`)

	Weight Pattern					
	Non-increasing			Fluctuating		
Ling. class	Mean	Med.	SD	Mean	Med.	SD
Adverbs	3.85	2.0	4.11	6.27	4.0	6.81
Verbs	3.44	3.0	3.51	4.53	3.0	5.04
Conjunctions	2.21	1.0	2.87	3.24	2.0	3.74
PersonalPron.	4.94	3.0	5.42	8.65	6.0	8.59
Prepositions	5.44	4.0	5.40	9.67	6.0	10.51

Table 4.10: Results of Statistical Measures on Linguistic Class Attributes; Med. Refers to Median; Sd Refers to Standard Deviation

over time. As a part of that, previous literature [17] revealed that people in online health communities mainly engage in two activities: (*i*) seeking information and (*ii*) getting emotional support. People usually ask questions or just browse through the community forums to collect information. If we can understand how users post questions and how the other members respond to those questions, it will be very useful in developing personalized profiles of users so that the system is able to help them get sufficient information even before they post any questions. Below is an example (paraphrased) showing how users ask and respond to questions.

Example thread: "New user"

User 1: *"Did anyone upgrade to the premium app? What do you like about it?"*

User 2: *"I upgraded to the premium. I LOVE the functionality to log food in advance. I can track and set goals that are not related to weight like how much*

I sleep, how much water I drink, etc.”

User 3: *“I upgraded my account to premium too. I really liked the added features because it helped me keep track of my steps and participate in challenges.”*

We are interested in knowing whether these two types of users are actively seeking information. We deem a forum post to be a question if it meets one of these two conditions:

1. ***Wh*-question words:** If a sentence in the post starts with a question word: *Wh-Determiner (WDT)*, *Wh-pronoun (WP)*, *Possessive wh-pronoun (WP$)*, *Wh-adverb (WRB)*.

2. **Punctuation:** If the post contains a question mark (‘?’).

We computed the ratio of question-oriented posts made by each user in the two clusters. After averaging these ratio values across all the users in each cluster separately, we found that on average, **32.6%** of the posts made by non-increasing users were questions ($StandardError(SE) = 0.061$) while **37.7%** of the posts made by fluctuating users were questions ($SE = 0.042$). This shows that on an average fluctuating users do post relatively larger number of questions than the non-increasing users. We conjecture this could be a reflection of the fluctuating users’ aim to seek more information from the forum.

4.2.6 RQ 2c: Sentiment of Posts

Analyzing the sentiment of user posts in the forums can provide a suprisingly meaningful sense of how the loss of weight impacts the sentiment of user’s post. In this analysis, we report our initial results on extracting the sentiments of user’s posts. In order to achieve this, we utilize the Stanford Sentiment Analyzer [164]. This analyzer classifies a text input into one of five sentiment categories – from *Very Positive* to *Very Negative*. We merge the

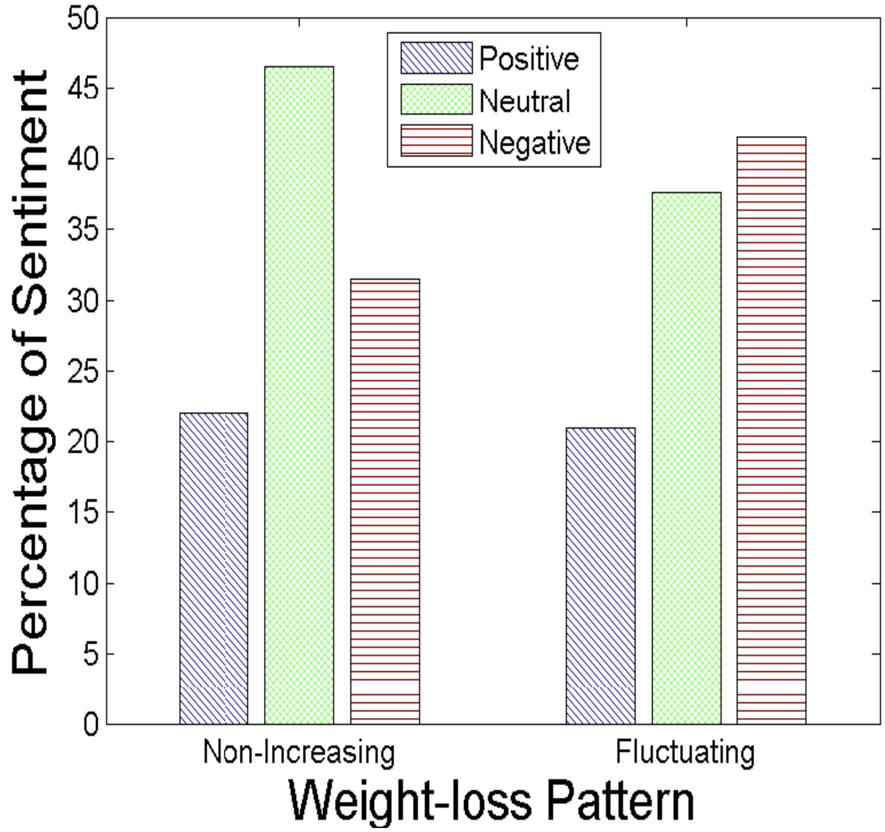


Figure 4.3: Proportion of Sentiments for the Two Weight-loss Patterns. For Non-increasing Users, Percentage of Posts with *Positive*, *Neutral* and *Negative* Sentiments Are: *22%*, *46.5%* and *31.5%* Respectively. For Fluctuating Users, the Percentage of Posts with *Positive*, *Neutral* and *Negative* Sentiments Are: *20.9%*, *37.6%* and *41.5%* Respectively

five classes into three: *Positive*, *Neutral* and *Negative*. (In the future, we may consider specific (health and nutrition) sentiment lexicons).

We analyzed the sentiment of posts contributed by the users from the two clusters. As shown in Figure 4.3, posts of users belonging to the non-increasing cluster are more *neutral* whereas the posts made by users from the fluctuating cluster are mainly of *negative* sentiment. This gives an interesting intuition that the users of the fluctuating group might require more emotional support as they use more negative sentiment in their posts.

4.2.7 RQ 2d: Politeness

Politeness is an important marker which often is a decisive factor in whether interactions go well or cease [158]. Based on this metric, we can understand if correlation exists between the politeness of posts made by users and their weight loss pattern. Politeness according to the Webster's Dictionary is to show good manners towards others, as in behavior, speech, etc. We measured how polite the posts are with respect to the weight loss pattern. We use the politeness classifier [46] that was constructed with a wide range of domain-independent lexical, sentiment and dependency features and thereby operationalizes the key components of politeness theory. It was proven that this classifier achieves near human-level accuracy across domains (shown 83.79% classification accuracy on in-domain wiki). Below are some examples obtained after the classification of posts on this forum.

1. **Polite text**: "Good for you! I started out obese. Now, Im not even overweight. Its a great feeling. Congrats to you on your milestone!"
   - *Polite Score:* 0.870
   - *Impolite Score:* 0.130
2. **Impolite text**: "Grrrr.... I wish I could screen these posts so that I dont even have to SEE those darn posts about HCG or 500 calorie diets any more. :twisted: And why did my search for Grumpy or Rant or McRant come up empty?????? Grrrrr......"
   - *Polite Score:* 0.250
   - *Impolite Score:* 0.750

The results of the politeness analysis in Table 4.11 shows that users on this weight-loss forum are polite overall. We speculate that users on weight-loss related forums act polite to get more information and emotional support. Further investigation is needed to conclude if users on goal-oriented communities talk politely.

Type	Polite	Impolite
Non-increasing	70.6%	29.4%
Fluctuating	75%	25%

Table 4.11: Statistics of Users and Politeness Percentage Posts

4.2.8 RQ 2e: Excuses

Literature [17] suggests that people use online forums to maintain accountability. This application mainly serves the user community to set goals and help the members achieve those goals. It is important to understand if there is a correlation between the weight loss pattern of the users and the way they are making excuses as they are accountable for not losing weight. In general, excuses are put forward when people experience questions about their conduct or identity in case of failing at an assigned task, violating a norm, etc. Existing research [54] demonstrates that people who are provided with the opportunity to make excuses do seem to perform better on a variety of tasks. In this analysis, we wanted to verify if the hypothesis that users when given an opportunity to make excuses are better at losing weight. Here is an example that shows how *User 1* posts excuses in a forum thread.

Example thread: "Trouble sticking to a diet"

User 1: *"I am out of town with the family and making the right food choices is impossible right now."*

User 2: *"I think we all have to find our own motivation and drive to succeed in weight loss. We just have to let the motivation be louder than the excuses."*

To the best of our knowledge, there is no prior work on automatic classification of a post as an excuse or a non-excuse. In this regard, we initially wanted to find if excuse classification is simply a special case of text-based categorization or any special classification approaches need to be developed. We performed experiments with two standard algorithms: Naive Bayes Classification and Support Vector Machines, which were shown to be effective in previous text categorization studies. In order to implement these two algorithms we considered the standard bag-of-words where a document d can be expressed in terms of the frequency of each of the n features as $\vec{d} = (f_1(d), (f_2(d), \ldots, (f_n(d)), f_i(d)$ is the number of times feature i occurs in document d.

We also extended the Latent Dirichlet Allocation [25] (LDA) to build a classifier that also uses majority class voting approach to provide labels to the posts. Initially, LDA is used to extract the latent topic distribution over each of the posts present in the training dataset that are already labeled as excuses and non-excuses. Later, each post from the testing dataset is represented in this topic space. For a given post in the testing dataset, the final class label is the majority class of the k-closest points in the topic space. The entire process of classifying a post as an excuse or non-excuse is described in Algorithm 1.

Data: Labelled dataset – Excuses (ef) and Non-excuses (nef); j^{th}post – a post with no class label

Result: Labelled Testing data

$\theta^e ne \leftarrow LDA_{estimation}(ef, nef)$;

$\phi_k^{ene} \leftarrow LDA_{inference}(k^{th}\text{post}, \theta_i^{ene})$;

$L \leftarrow \emptyset$;

for $i := 1\ to\ |ef| + |nef|$ **do**

  $dist \leftarrow KLdivergence(\theta_i^{ene}, \phi_j^{ene})$;

  $append(L, \text{dist})$;

end

$label\_jth\_post \leftarrow max\_class(k\text{-}nearestpoints(fullist))$;

Algorithm 1: Classification Approach

We utilized Weka [76] and svmlight [94] libraries to perform classification using Naive Bayes and SVM respectively. Based on the results shown in Table 4.12, LDA-based supervised classifier outperforms the other two approaches and so we use it for measuring the correlation between the frequency of excuses posted by users and their weight loss patterns.

Approach	Cond-1	Cond-2
Naive Bayes	57.8% (Uni)	63.1% (Uni + Bi)
SVM	50% (Uni)	46.15% (Uni + Bi)
LDA-based	65% (80-20 split)	50% (50-50 split)

Table 4.12: Classification Results in Terms of Accuracy with Different Approaches and Conditions (Uni – Unigrams; Bi – Bigrams; 80-20 Split – 80% Training and 20% Testing; 50-50 Split – 50% Training and 50% Testing Data) and Classifiers

We identified that **46%** of the users who make at least one post in the forum give excuses. If we consider the category-wise statistics, **48%** of the users who lose weight in a non-increasing pattern and **54%** of the posts made by the users of fluctuating weight loss pattern made excuses in atleast one post. It is surprising to notice that users exhibit excuse–giving behavior on this weight loss community where accountability is one of its characteristics. Early detection of these kinds of users and providing more assistance to help them stay motivated can help them lose weight. This kind of intervention by these applications can help gain the trust of their users.

Overall, in this section we have explored how the basic lexical classes, questions, sentiment, politeness and excuses are correlated with the weight loss patterns of users. As we got a good level of understanding about these associations, we can now use these different attributes as a set of features in order to predict whether a new user can lose weight or not, based only on the language he/she is using on these forums. An automated classifier can be very beneficial to designing effective weight loss applications that can help users get additional support. It can also help the users to pay more attention to their diet and exercise to lose weight effectively.

4.2.9 RQ 3: Comparative Analysis With General Forums

As a follow-up research, we want to understand if the goal-oriented forums (that are associated with apps that help set goals) exhibit any specific traits compared to the general non-goal oriented forums. Here, we present the details of our analysis on how the type of forum can have an affect on the language used with a primary focus on understanding the lexical features and cohesiveness of the threads on these forums.

Forums Studied

We used threads from two other popular online forums that were used in [23] – 1) Trip Advisor - New York city travel forum that contains travel related discussions for New

York City and 2) Ubuntu forum dataset that contains discussions about ubuntu operating system. There are multiple threads of discussions in both these forums and each thread has multiple posts by several users. The dataset contains a total number of 609 (6591 total posts) and 621 (3603 total posts) threads for TripAdvisor and Ubuntu forums respectively. On average, the thread length in terms of the number of posts is 10 and 5 for TripAdvisor and Ubuntu forums respectively. The average number of users in a thread on a TripAdvisor forum is 1.98 and on an Ubuntu forum is 3.41. As stated in [23], Ubuntu forums have technical discussions which are non-subjective in nature; whereas TripAdvisor, a travel related discussion forum, has discussions which tend to be subjective.

Lexical Features

Lexical features like parts-of-speech tags are obtained for both the forums to understand the behavior of users in terms of using different categories of word usage. Analysis similar to the earlier section was conducted using the Stanford pos tagger to find the number of *verbs*, *conjunctions*, *adverbs*, *personal pronouns* and *prepositions* appearing in the posts as shown in Table 4.13. As we compare these results with the weight loss forum, we notice that users on these two forums don't use as many personal pronouns and adverbs as users on the weight loss forums. This is understandable as users on a weight loss forum have a primary goal to seek more information by providing more details about their situation.

Cohesion with Previous Posts

It is very important for the discussion forums to capture as much participation as possible to reach their full potential. When multiple conversations occur simultaneously, it is difficult to decide which utterance belongs to a specific conversation. On the online health forums where users mostly tend to seek information, if the main topic drifts to some other topic, the main purpose of these discussion forums is lost. In this regard, it is important for the

	Forum Name			
	Trip Advisor		Ubuntu	
Ling. class	Mean	SD	Mean	SD
Adverbs	2.37	4.9	2.04	6.06
Verbs	1.87	3.6	1.86	3.76
Conjunctions	1.42	3.19	1.0	2.17
PersonalPron.	2.69	5.7	2.24	4.4
Prepositions	4.25	8.56	2.78	6.52

Table 4.13: Results of Statistical Significance Tests on Linguistic Class Attributes for Trip Advisor and Ubuntu Forums. For the Results on Weight Loss Forum, Please Refer to Table 4.10. Sd– standard Deviation

system to automatically verify non-cohesive posts. Cohesion is the property of a well-written document that links together sentences in the same context. As a first step, we want to find out how similar a user's post is with respect to the previous posts in a thread from the weight loss forum. This can also help identify users in a given thread who elaborate on a previous post versus those who shift the topic. Below is an example (paraphrased) showing a cohesive post made by the users on the weight loss forum.

Example thread: "changing life for a healthier self" showing cohesive post by User 2

User 1: *"Did you remove any commitments in your life to make time to be healthier? If you have done was it a good choice or did you regret it?"*

User 2: *"Yes I've done it and never regretted it."*

User 3: *"Trying to do everything at once means doing nothing - Georg Christoph"*

User 2: *"I'm not sure which entrepreneur said this but focus only on what you need to do."*

In this context, we focus only on content words: verbs and nouns (part-of-speech tags *VB*, *VBZ*, *VBP*, *VBD*, *VBN*, *VBG*, *NN*, *NNP*, *NNPS*) and use WordNet [132] to identify synonyms of the content words. We compute similarity between the current post and previous posts of other users in the thread, in terms of commonly shared verbs and nouns including synonyms. In our current, preliminary analysis, we consider this similarity score to be the measure of cohesion.

Data: Posts $P_1, \ldots, P_{k-1}, P_k$

Result: $CohScore(P_k)$

$set_A \leftarrow \emptyset$;

for $i := 1$ *to* $(k-1)$ **do**

$\quad [vb_i, nn_i] \leftarrow POS_{tagging}(P_i)$;

$\quad set_A \leftarrow set_A \cup [vb_i, nn_i]$;

$\quad set_A \leftarrow set_A \cup synset(vb_i) \cup synset(nn_i)$;

end

$set_B \leftarrow \emptyset$;

$[vb_k, nn_k] \leftarrow POS_{tagging}(P_k)$;

$set_B \leftarrow set_B \cup [vb_k, nn_k]$;

$set_B \leftarrow set_B \cup synset(vb_k) \cup synset(nn_k)$;

$CohScore(P_k) \leftarrow \frac{|set_A \cap set_B|}{|set_B|}$

Algorithm 2: Calculating the Cohesive Score of a Post

We consider all posts that are not thread-initial. To approximate whether a post is cohesive or not, we compare the nouns and verbs of the current post to the list of nouns and verbs (plus synonyms) obtained from the previous posts of the thread. Our analysis

(Table 4.14) on the three forums – Fit Now data, TripAdvisor and Ubuntu finds that the threads on weight loss forums are more cohesive compared to the other two forums.

	Fit Now data	*TripAdvisor*	*Ubuntu*
Cohesiveness	0.46	0.42	0.30
S.E ($\times 10^{-4}$)	2.22	3.64	3.87

Table 4.14: Average Value of Cohesiveness (along with Standard Error (S.E)) Across All the Threads in a given Forum. Extreme Values Are: 0 – Non-cohesive; 1 – Cohesive

Overall, it is interesting to see that goal-oriented forums have more cohesive threads compared to non-goal oriented forums. Additionally, users on the goal-oriented forums tend to post more information about themselves and their situations. This is not very surprising as the users have a specific goal to achieve in using the goal-oriented application that also provides a discussion forum. In the future it will be worth studying if language cues can help in predicting auto tagging of threads to a specific type of forum and studying other language metrics that can bring distinction between these different types of online forums while measuring their impact on the public.

Implications

The different language metrics studied in the two main sections of this paper have a great potential to differentiate automatically between the users who are struggling to lose weight and the users who lost weight and are keeping it off. There are, for example, other existing technologies that help users lose weight by – providing incentives if they lose weight (PACT[7]), allowing other fitness applications to sync with the existing application to keep track of exercise (myfitnesspal[8]), posting questions while doing grocery shopping to find

[7] `http://www.gym-pact.com/`

[8] `https://www.myfitnesspal.com/`

out the calorie content (fooducate[9]), etc. We envision tools that utilize the wealth of information present on the discussion forums along with the user's activity to automatically estimate the degree to which a user's efforts will yield results. Predictions of success are not the end goal; the value of these types of predictions lies in leveraging them to generate alternative behaviors and actions that a user can take to improve their chances of weight loss success. Designing systems that rely on features studied in this paper could improve weight loss applications and thereby enhance the quality of life.

People are taking advantage of these kinds of applications since they can preserve their anonymity and provide genuine information about their food intake, exercise levels, etc. to safely collect as much information as they can. Even though their real identity can be hidden, it is important that the tools being envisioned provide support in a very ethical manner. On the other hand, deciphering the genuineness of the information provided is an area of research that can be worth pursuing. On the whole, we believe that it is important to understand the different attributes that affect the behavior of individuals on the weight loss forums and help them successfully lose weight. We hope that work initiates further research on these types of discussion forums to increase awareness about the different factors faced by individuals who are struggling to lose weight and thereby help develop policies that can support them in losing weight.

[9]`http://www.fooducate.com/`

Chapter 5

LEARNING INCOMPLETE ACTION MODELS FROM SOCIAL DATA

Individuals utilize social media platforms to archive their journies of achieving their personal goals [188]. These posts shared online could help other individuals with similar goals who are also interested in understanding the popular ways of achieving these goals. Some of these questions could include: how to successfully quit smoking, how to run a 5K when someone has no experience of running, how to lose weight, etc. To find answers to such types of questions, individuals are turning to the Internet, especially online social media platforms [107]. Despite increasing interest in leveraging the wealth of online social media data to support data-based decision making, much work in this direction has focused on tasks with straightforward "labeling" decisions. A much richer class of tasks can benefit from the power of sequential decision making. However, supporting such tasks requires learning some form of action or decision models from unstructured data – a problem that had not received much attention. Existing literature [37, 107] focuses on decision-making and goal achievement tasks utilizing the data from online social media platforms. However, these works do not focus on automatic extraction of action traces from the unstructured social media data or do not address the issue of establishing sequentiality (or some sort of precedence relationship) between the actions.

The section of research presented in this chapter aims to interpret the plans of individuals trying to achieve their personal goals shared in the form of unstructured posts on online social media platforms. These high-level plans or sequence of actions could also explain the motivations behind individuals utilizing these goal-oriented platforms. The approaches proposed in this research could be generalized to any real world domain. Towards this goal, given a start state (or an action in this context), we propose two types of frameworks with different models. The first framework builds a plan trace graph to extract workflows and second framework trains a recurrent neural network to extract the aggregated plans.

Figure 5.1: 6-phase Pipeline That Takes Unstructured Social Media Data as the Input and Generates Incomplete Action Models to Guide the Decision Making

5.1 Dataset Collection Methodology

Through the proposed automated frameworks, we mainly aim to investigate these two research questions.

- **RQ1:** How are individuals trying to achieve their goals?
- **RQ2:** Why are individuals joining these goal-oriented forums?

5.1.1 Problem Statement and Dataset

Given a set of unstructured posts P from a user set U, for each post $p_{i,k}$ made by an i^{th} user, the main goal is to build an incomplete action model M. The framework we proposed in this paper first learns the plan trace structure and establishes precedence relationships between actions. Each post ($p_{i,k}$) made by a user (u_i), is used to extract a unique plan trace. Then these related actions (we call a set of sequentially related actions as a plan trace) are thereby used to learn the model (M). M learns the probability ($P(a_t|oa_{t-1})$) of choosing a particular action (a_t) given an observed action (oa_{t-1}). The model (M) is built using all these plan traces which is used to generate the aggregated plans.

Datasets:

In this paper we focus on real world datasets that are crawled from goal-oriented subreddits. The main motivation behind choosing these datasets is to measure the performance of the proposed framework to interpret two types of natural language data – unstructured and semi-structured data.

With the motivation from the existing literature [107, 171], we consider subreddits where the posts are comparatively longer than Twitter posts that have a 140 character limit. The social news website "Reddit" (http://www.reddit.com) is designed in such a way that based on the category or interest, a subreddit exists. These categories or interests could range from personal to professional. In each subreddit, users can post in multiple formats – natural language, web urls, visual entities such as images and videos. The important challenge is to handle the unstructuredness of the data.

This paper utilizes user posts from three different subreddits that are targeted to – 1) quit smoking (/r/stopsmoking/), 2) to running a 5K (/r/couch25k/) and 3) quit drinking (/r/stopdrinking/). A Reddit user can join any number of subreddits and can comment on any post unless there it is a post from a private subreddit. In order to crawl the data, we utilize the Python wrapper for Reddit API (PRAW[1]) to crawl the Reddit posts and their metadata. The final data has 1571 users from /r/stopsmoking domain (we denote this as QS in the rest of this paper), 622 users from /r/couch25K (C25K) and 2176 users from /r/stopdrinking (SD). As mentioned earlier, each user can make multiple posts in a subreddit. There are 5258, 2118 and 27124 total posts in QS, C25K and SD respectively.

Data Reliability

Before we build the frameworks and use them to interpret the posts shared on the goal-oriented platforms, we assess the reliability of the data. For this purpose, we extract the *n*-grams from these posts. The top-5 *tri*-, *bi*- and *uni*-grams for the three domains that we consider in this paper are shown in Table 5.1. These $n-$grams show that individuals are seeking help by joining these forums (e.g., *embarrassed questions sometimes*, *seek advice*

[1] https://praw.readthedocs.io/en/latest/index.html

Trigrams	Bigrams	Unigrams
embarrassed questions		
sometimes	rest day	run
brag little accomplish	feel like	week
need rest day	brag little	time
rest day runs	embarrassed	
questions	minutes	
walking easy pace	accomplish week	day
quit cold turkey	feel like	smoking
allen carrs book	quit smoking	quit
smoke free app	cold turkey	smoke
pack a day	smoke free	day
since I quit	right now	like
will drink today	drink today	drinking
next 24 hours	will drink	day
one day time	feel like	can
conscious decision drink	last night	sober
seek advice share	days sober	time

Table 5.1: Top Mentioned Tri-, Bi- and Uni-grams of Bios Extracted from the Posts Shared on Goal-oriented Forums

share), are accountable to each other honestly (e.g., *brag little accomplish*, *quit cold turkey*, *will drink today*), and sharing their tips on succeeding (e.g., *walking easy pace*, *smoke free app*, *one day [at a] time*), etc. These different purposes or topics of discussion show that for the kind of analysis this chapter focuses on, the data from Reddit might be reliable. More detailed understanding about what the users post on these forums is investigated in the later sections.

5.2 Model-1: Plan Graph

Towards addressing the main goals of this paper, for the first proposed model we utilize automated planning and NLP techniques to build a six-phase pipeline (as shown in Figure 5.1). This pipeline utilizes raw unstructured social media data to extract structured shallow workflows. The main contributions or challenges addressed by this pipeline are: 1) extract the plan traces from the raw unstructured data as most of the existing work (e.g., [75, 171, 180, 182]) assumes that the required plan traces are readily available and 2) utilize the plan traces to build an incomplete action model that is capable of generating workflows that are near optimal. Our main contribution lies in utilizing unstructured social media data to build shallow models that are capable of generating near-optimal plans.

Phase-1: Fragment Extractor

The main goal of this component is to extract fragments from the corresponding subreddit. We define a fragment as the relevant post that contains information about achieving the given goal of a given subreddit. An individual fragment may contain more than one action that helps achieve the goal. To do this, we first crawl the individuals who are actively participating on a subreddit associated with a given goal. We crawl the timelines of these individuals. We assume that these timelines are the sequence of actions or a workflow that helps these individuals to achieve the given goal. We define *timeline* as the set of goal-related posts shared by the same user chronologically.

Running example [relevant posts]: I spent few weeks drinking and partying. In a similar situation in the past, I take a cigarette and used to smoke pretty much non-stop. But this season I was assaulted by the triggers. Smoking in restaurants, communal areas. Many times I thought I can get a cigarette now. But those thoughts were always chased by reason and the power of conviction I have to quit smoking.

The running example is taken from the *Quit Smoking* domain. This example is an excerpt of a post shared by a user on Reddit whose main goal is to quit smoking. In this work, we consider each post made by a user as a plan trace and posts made by all users on this subreddit are aggregated to build the model in later steps.

Phase-2: Action Extractor

Each post may have more than one sentence and each sentence may have more than one action. For each sentence, we extract the actions (verbs) and their corresponding predicates (nouns) using the Stanford part of speech tagger [173], a state of the art tagger with reported 97.32% accuracy. The extracted verbs are the candidate list of action names. We make an important assumption that the temporal order of sentences in a post is indicative of the order of actions we extract from them. We then attach the most frequently co-occurring action parameter (noun) with a given action name (verb).

For this pipeline, we assume that each action (verb) will have only one action parameter (noun) and two action words can have the same action parameter. For example, assume that there is an action a_i in our dataset which occurs in multiple plan traces and co-occurs with nouns n_a, n_b and n_c. Noun with the largest co-occurrence frequency with a_i is chosen to be the action parameter for a_i. In the examples provided in this paper, action parameters are attached to an action as *<action_name>_<action_parameter_name>*. Since certain English words can be classified as multiple parts of speech tags, we make similar assumptions.

Running example: [action names]: spent_smoke drink_beer party_hard take_day smoke_day assault_trigger smoke_day thought_smoke chase_life quit_smoke

From the post made by the user obtained in phase-1, the running examples shows that we extract all the verbs and their associated nouns. We assume that the sequentiality among actions is pre-established in the original post made by the user. This assumption sets a constraint that all the verbs extracted are ordered in the same way they occur in the post made by the Reddit user. Since the word 'smoke' can be either a noun or verb, we see the similar pattern in this extracted set of actions and their corresponding parameters.

Phase-3: Generalizer

Since we are handling unrestricted natural language text, it is possible that a given action name has multiple synonyms. These kinds of hierarchical relationships motivated us to use hierarchical agglomerative clustering approach [77] where low-level actions are expressed in high level format. Performing this operation helps reduce the redundancy as well as increase the uniformity of actions.

While clustering the actions, only the action names are considered and their parameters (or predicates) are ignored. We utilize Leacock Chodorow similarity metric (*lch* for short)[2] to measure the distance between any two given actions (W_i and W_j – action words). This is one of the popular metrics utilized to compute the semantic similarity between a given pair of words. The *l*ch similarity is computed as follows:

$$Sim(W_i, W_j) = Max[log2D - logDist(c_i, c_j)] \tag{5.1}$$

where $Dist(c_i, c_j)$ is the shortest distance between concepts c_i and c_j (a concept is the general notion or abstract idea) and D is the maximum depth of a taxonomy.

We consider a threshold metric (or closeness metric) α to verify the quality and stop the agglomerative process. The agglomerative clustering algorithm terminates when the closeness metric is greater than the linkage metric at any given point of time. In hierarchical clustering, there are three different types of linkage metrics – *single*, *complete* and *average*. In this paper, we utilize the *complete* linkage metric as the Clustering Quality (we refer to as *cq*) measured is higher (*cq*=8.33) compared to the other linkage metrics (single

[2] `http://www.nltk.org/howto/wordnet.html`

(cq=5.23) and average (cq=7.17)). The formal equation to compute the complete linkage metric is $max\{d(a,b) : a \in A, b \in B\}$, where $d(a,b)$ is the distance metric and A and B are two separate clusters. We envision that when the algorithm terminates, semantically similar actions will be grouped into the same cluster. By putting a few conditions on the distribution of cluster sizes, lopsided clusters can be avoided.

Each cluster may have more than a single action that requires us to find a unique cluster representative. To do this, we utilize a popular statistic from the Information Retrieval community – *Term Frequency–Inverse Document Frequency* to rank the actions present in a cluster. For each cluster, we choose the top-ranked action with the highest *tfidf* value to be the representative of the respective cluster. The original parameter (or predicate) associated with this action word will continue to be the parameter after this action word is chosen to be the cluster representative. The statistic can be computed as shown in equation 5.4 that uses the *TF* and *IDF* equations in 5.2 and 5.3 respectively.

$$tf(t,d) = \frac{f_{t,d}}{max f_{t',d} : t' \in d} \tag{5.2}$$

$$idf(t,D) = log \frac{N}{|d \in D : t \in d|} \tag{5.3}$$

$$tfidf(t,d,D) = tf(t,d) * idf(t,D) \tag{5.4}$$

where t is the given action; d is the set of raw posts shared by a given user; D is the super set of all sets of raw posts made by all the users in our raw dataset (where $|D|$ will be equal to the number of unique users in our dataset). Each cluster will be represented by a unique top-ranked action word.

Running example: [clustering]: We map the action names to the cluster representatives of their corresponding cluster. spent → spend, drink → party, take → taken

Phase-4: Trace Builder

The initial plan fragments are converted into plan traces by replacing the action names with their corresponding cluster representatives[3]. This process is repeated on all the posts to build the traces.

Running example: [rebuilding plan traces]: initial plan fragment: [spent_smoke, drink_beer, party_hard, take_day, smoke_day, assault_trigger, smoke_day, thought_smoke, chase_life, quit_smoke], plan trace: [spend_time, party_hard, taken_hold, smoke_day, assault_trigger, smoke_day, thought_smoke, chase_life, quit_smoke]

The actions in the running example such as *spent*, *drink*, *take* are represented in their corresponding high level mapped format. Since *drink* is mapped to *party*, *drink_beer* is represented as *party_hard*. In the plan fragment, [*spend_time*, *party_hard*, *party_hard*, *taken_hold*, ...], two '*party*' actions are occurring sequentially. We remove repetitions and include only one such instance. However, in general a plan may include repeated actions and we acknowledge that our system may miss out on those plans with repeated actions.

Phase-5: Sequence Probability Learner

After extracting the plan traces, we then extract the pre-actions and post-actions for any given action. Due to co-occurrence in the plan traces, actions are inter-related to other actions with a probability ($p(a_i, a_j)$) describing the chance of action a_j following action a_i. This probability is computed purely in a data-driven fashion. This procedure considers a constraint metric θ that decides whether a co-occurring relation should be included in the

[3]Note, it is possible to replace two sequential action names by the same cluster representative. In that case we remove the repeated action name; hence, reducing the length of the plan trace. For example, if the representation of a plan trace is: [a_1, a_2, a_2, a_5, a_8], after post-processing it will be converted to [a_1, a_2, a_5, a_8].

model. We compute the conditional probability $p(a_i \mid a_j)$ using the following equation:

$$p(a_i \mid a_j) = \frac{p(a_i \cap^* a_j)}{p(a_j)} \tag{5.5}$$

Let a_1 and a_2 equal two actions where a_1 is an effect of a_2 which indicates that unless a_2 is executed, a_1 cannot be executed. The support-based probability then is computed where a_1 will be the postcondition of a_2 if $p(a_1 \mid a_2) > \theta$ and a_2 will be the precondition of a_1. The $\cap^*$ in Equation 5.5 represents an ordered conjunction that considers the sequentiality of a_1 and a_2 while computing the frequency of their occurrence together.

Once we extract the pre-actions and post-actions for every action in the data set, we represent the relationships in the form of an Action Graph (AG) as our incomplete action model (M) to generate shallow workflows. AG consists of actions as *nodes* and each *edge* is a transition between two actions a_i and a_j. The edge weight between any two nodes a_i and a_j is the support-based probability $p(a_i, a_j)$.

Running example: [data-driven probabilities]: In the plan trace dataset, we compute the sequential probabilities for any given action pairs. This results in generating a precedence graph shown in Figure 5.2 for the "Quit Smoking" domain, where the sink node is the action quit with no subsequent effect.

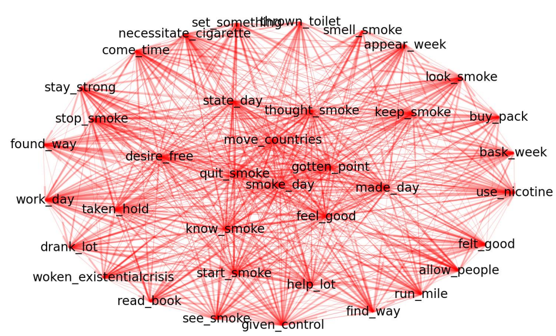


Figure 5.2: Part of the Directed Graph g for the $quitSmoking$ Domain with *Quit_smoke* as the Sink Node

Phase-6: Model Validator

We divide the set of plan traces D into training data, D_{tr}, and testing data, D_{te}. By this step, we have the set of plan traces represented in the lifted action format. This common lifted representation ensures that a given action uses the same name in both D_{tr} and D_{te}. We use D_{tr} to build the model M. Let T be the set of transitions present in M and $T^{'}$ be the set of transitions in the test dataset. Since M is used to generate workflows, the goodness of this model should be measured to trust the quality of these plans. To determine the goodness of M, we define a new metric called *explainability* that can be computed as shown in Equation 5.6.

$$\begin{aligned} T^{''} &= T \cap T^{'} \\ Explainability &= \frac{|T^{''}|}{|T^{'}|} \end{aligned} \tag{5.6}$$

Evaluation Methodology

We evaluate the pipeline from two perspectives: 1) data and approach employed to construct the incomplete action model in terms of explainability 2) workflows generated by the incomplete action model in terms of soundness and completeness. The incomplete action models follow this particular format: *pre-action* $\longrightarrow$ *action* $\longrightarrow$ *post-action*. A sample of these models extracted for the three domains is show in Table 5.2.

Evaluation-1 – Explainability

Prior to analyzing the pipeline, it is important to examine whether the data we are utilizing to construct the incomplete action models is consistent across all the experiential posts shared online by the users. Earlier we utilized the n-grams approach to examine if all the posts focus on the domain topic. But in this section, we evaluate if the posts made by all the users have anything in common between them in terms of having similar experiences.

Quit Smoking
(:action change(ability)
[:pre-action eat(gross) crave(succeed) dealt(reality)]
[:post-action set(goal) run(mile) quit(smoke)])
Possible explanation: Someone is craving for success and is dealing with the reality of eating gross food who wants to change his abilities that led that person to set some goals, run miles and quit smoking.

Couch to 5K
(:action sign(race)
[:pre-action recommend(c25k) push(run) refer(program)]
[:post-action begin(week) run(minute) cover(mile) know(battle) kept(pace)])
Possible explanation: A person was recommended the couch to 5K reddit forum and was being pushed to run. So, he refers to a program and signs up for the race. After this, he begins from the next week to run few minutes and cover few miles. The person knows the battle but he kept the pace.

Wedding Planning
(:action hate(dress)
[:pre-action pick(dress) saw(dress) blame(problem) cost(much) prove(difficult)]
[:post-action kill(wed) find(dress) move(wed)])
Possible explanation: The person sees and picks her dress. It may cost a lot but starts blaming someone for the problem and now hates the dress. The next steps could be to kill the wedding at the moment, find a new dress and move the wedding date.

Table 5.2: Sample Actions from the Incomplete Models Extracted for the 3 Domains **Automatically** by This Pipeline and Their Possible Explanations Provided by the Human Subjects

To evaluate this, we measure the explainability of the incomplete action model by varying the α value (clustering threshold). α decides on the amount of redundancy to be removed from the posts. The smaller the value of α, the larger the redundancy present in the data considered. We fix the size of the training data (D_{tr}) to 80% of the entire set of plan traces and the remaining as the test data set (D_{te}). We then conduct experiments on all three domains separately. The dataset from each domain consists of a set of plans that are aimed at achieving the primary goal of the corresponding domain. The pipeline first utilizes D_{tr} to build the incomplete action model M and then uses the test dataset D_{te} to evaluate the explainability of M.

α	**Quit Smoking**	**Couch to 5K**	**Wed. Planning**
2.50	65.66%	64.5%	73.39%
2.25	65.66%	64.59%	73.39%
2.0	68.41%	69.78%	77.7%
1.75	69.33%	70.67%	78.39%
1.50	80.58%	82.06%	84.68%
1.25	90.42%	89.43%	91.6%
1.0	89.31%	89.91%	91.04%

Table 5.3: Average Explainability Measured by Eq. 6 as We Vary α Through 10-fold Cross-validation

As shown in Table 5.3, the maximum explainability value was reached at $\alpha = 1.25$. It is expected that if the data and the approach are correct, the explainability value should be directly proportional to the value of α. This trend is clearly visible in the results shown in Table 5.3. This trend also positions more confidence in building the best incomplete model used to generate shallow workflows. Also, we focus on how well these incomplete domain models can explain the newly seen data to decide the consistency of goal-oriented experiences shared by users. The results obtained through 10-fold cross-validation show that *M* has the potential to obtain 90% accuracy. The results display the strength of employing unstructured data from social media platforms like Reddit to build incomplete models.

Evaluation-2 – Soundness & Completeness Next, we examine the "goodness" of the incomplete action models by evaluating the generated shallow workflows. Each workflow is generated by representing the incomplete model as a directed graph and finding the shortest path in this graph from a given source node to the goal node. For example, in *Quit Smoking* domain, the source node can be *start(smoke)* and the goal node is *quit(smoke)*. To identify the best path, we utilized the weight-based Djikstra's shortest path algorithm from the *NetworkX* (`https://networkx.github.io/`) Python library. We rate each plan on a binary-scale evaluating its soundness and completeness metrics.

Domain	Soundness	Completeness
Quit Smoking	42%	38%
Couch to 5K	66%	45%
Wedding Planning	36%	43%

Table 5.4: Soundness and Completeness as Evaluated by the Human Subjects. Note That Higher the Percentage Values, the Better the Workflows That Are Generated

> **Soundness:** is defined as whether a given shallow workflow is meaningful and can help achieve the goal.
>
> **Completeness:** is defined as if a given shallow workflow is missing any important actions to achieve the goal.

We recruited 10 human test subjects who evaluated the top-5 workflows generated by *M*. We provide instructions to the test subjects and ask them to rate the soundness and completeness of each workflow. Each subject evaluates all the top-5 workflows from the three domains, and the combined statistics are shown in Table 5.4. Each percentage value in this table is the average value of all the votes gathered by the plans in a given domain.

The best plan among these 15 plans (combined all top-5 plans from the 3 domains considered) is from the *Couch to 5K* domain – *inhale(nose)* → *exhale(mouth)* → *aid(loss)* → *transform(life)* → *outpaced(brain)* → *slow(pace)* → *run(minutes)*. This shallow workflow was described by the human subjects as "If you inhale through nose and exhale from mouth (a powerful breathing pattern[4]) that will help you relax and transforms by keeping your slow pace to run the 5K in minutes." Notice that these workflows are not partially meaningful. However, the evaluation results showed that they make sense to humans as shown by the results presented in Table 5.4. The table shows that the *Couch to 5K* domain has the highest soundness and completeness values which might be due to the fact that

[4]https://goo.gl/BiKvGG

the number of original number of actions are relatively lower that led to a model with less redundancy. Another reason could be the workflows generated from this domain are more meaningful to the human test subjects. With regard to completeness, test subjects expressed the difficulty of not being completely aware of the domains and so by default assumed that there should be a missing action in the plan.

5.3 Model-2: Trained Recurrent Neural Network

In this framework, we train a recurrent neural network to explain the discussions on subreddits as well as explore the plans that users follow to achieve their domain-related goal. First, we build the trace extractor by leveraging the natural language processing as well as unsupervised learning approaches. By parsing a given post, the actions along with their predicates are extracted by considering the part of speech tags. The framework then considers these actions and establishes a sequential relationship between them through agglomerative clustering. To measure the similarity between any given actions during the clustering, we utilize the popular Word2Vec model. Once the plan traces are extracted for each post of the user, all these traces for a given domain are utilized to build the incomplete action model to generate plans. The framework takes advantage of the Recurrent Neural Networks (RNNs) that acts as a language model. The entire framework is shown in Figure 5.3.

Framework

Phase-1: Trace Extraction

To extract a related sequential set of actions from sentence-sized posts, existing literature [34, 107] adopted temporal or graphical model based approaches. In this framework, the main aim is to handle the unstructured data without much loss of information. We need to extract a structured sequence of actions. In other words, this first step takes the raw

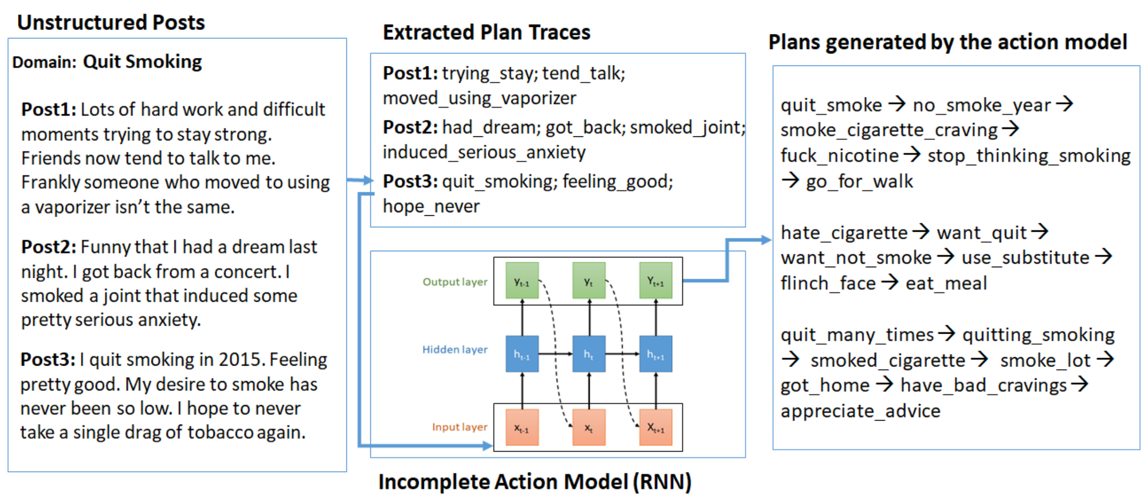


Figure 5.3: The Workflow of Our Proposed Framework

natural language text as an input and extracts a list of actions as well as their predicates where two adjacent actions in this list are related. To achieve this goal, the extractor leverages techniques such as linguistic parsing, word2vec embeddings, unsupervised learning approaches, neural networks, etc.

We define the user set (U) in our dataset as a set of each users posts($P = \{P_1, P_2, \cdots P\_M\}$) assuming that there are M users. Each post ($p_{i,k}$) in our dataset may have more than one sentence and has no restrictions on the length of the post. Given a post ($p_{i,k}$), the extractor first builds a parse tree for each sentence in the post to extract the action word that is a verb and its corresponding predicate that is a noun. All these verbs constitute the candidate set C_A. However, not all the actions are considered to build the final action set. We use a rule-based approach to identify the predicate for a given action. If in any case an action doesn't have a corresponding predicate, it will not be included in the final action set. The action set extracted through this process has actions sorted in a temporal fashion, which means the order in which they are described by the author of the post.

Once the final action set is extracted, the next step is to establish the precedence relationships between the sequence of actions. We look at this relationship as a form of

Data: Given U, P, W, win_size

$MAX\_PLEN \geq 2; |U| \geq 1$;

$A_U \leftarrow \emptyset$;

for $u_i \in U$ **do**

  for $p_{i,k} \in p_i$ **do**

    $A \leftarrow \emptyset$;

    for $s_{i,k} \in p_{i,k}$ **do**

      $A \leftarrow A \cup extractVerbs(s_{i,k})$;

    end

    $A_i \leftarrow EXTRACT - PRECEDE(A, W, win\_size)$;

  end

  $A_U \leftarrow A_U \cup A_i$;

end

Algorithm 3: Trace Extractor; Input – User Set (U); Posts (p_i) Made by Each User i – $u_i = \{\, p_{I,1}, P_{I,2}, \cdots P_{I,N}\}$, Where N $\in$ [1,*max_plen*], *max_plen* Is the Maximum Number of Posts Made by a given User in Our Dataset; Wikipedia Dump w to Train the Word2vec Model; *win_size* Is the Window Size Used While Establishing the Precedence Relationship

hierarchy and so we utilize the Word2Vec [131] approach to generate the word embeddings that are used to establish a hierarchical relationship between the actions. The way we perform this is to utilize the continuous-bag-of-words (CBOW) neural network structure in Word2Vec to learn the distributed representations. To build the Word2Vec model, we have to define the primary parameters used in the process – number of dimensions (N_{CBOW}), the context window size C_{CBOW} and the learning rate α_{CBOW}. This is a simple neural network with a single hidden layer whose goal is to just learn the weights of the hidden layer. These weights are actually the word vectors or the distributed representations for the given vocabulary V. We use the Word2Vec model to cluster the most similar words sequentially similar to the hierarchical clustering algorithm as shown in Algorithm 4.

Phase-2: Incomplete Action Model for Planning

The success of recurrent neural networks (RNNs) in terms of generating sequences [73] in the fields of Computer Vision (CV) and Natural Language Processing (NLP) is the main motivation for us to utilize them as part of our framework. Especially, the machine generated texts or articles that are very similar to human written texts are quite an accomplishment. Leveraging this idea, we build a language model that could generate sequence of actions where the language model is essentially a multi-layer recurrent neural network [103]. In this framework we utilize the word-level RNN as the language model that generates text in the form of a sequence of words.

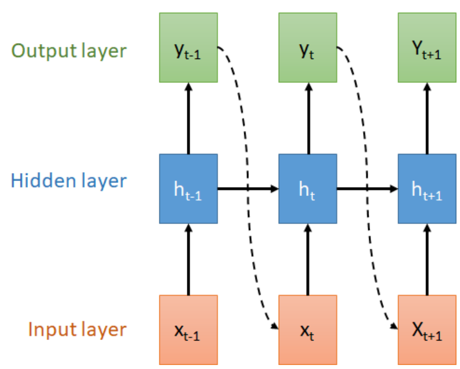


Figure 5.4: The Framework of Rnn. x_{T-1} Represents the Input at Time (T-1). Through Forward Activation, the Input Is Passed Through the Hidden Layers to Generate the Output Where the Error Is Back Propagated to Predict the Correct Output y_{T-1}. This Output Is Sent along with the Input at Time $t - x_t$ to Predict the Output y_t

Given the training data, the language model (M) is built in such a way that each word is encoded into a vector representation and the vocabulary is fed into the RNN. As shown in Figure 5.4, a future action sequence ($a_{t+1:T}$) is generated by using the observations ($a_{1:t}$)

Data: A, W, win_size

$TrainWord2Vec(W)$;

$A_U \leftarrow \emptyset$;

$elm1 \leftarrow \emptyset$;

$A_U \leftarrow A_U \cup MAX\_PAIR(Word2VecSim(A))$;

for $i \in [2, n), where\ n = |A|$ **do**

  $minSim \leftarrow INT\_MAX$;

  for $j \in [i, i + win), where\ m = |A|$ **do**

    for $k \in [0, l), where\ l = |A_U|$ **do**

      if $word2vec.sim(A[j], A_U[k]) \geq minSim$ **then**

        $elm1 \leftarrow A[j]$;

        $minSim \leftarrow word2vec.sim(A[j], A_U[k])$;

      end

    end

  end

  $A_U \leftarrow A_U elm1$;

  $A \leftarrow A \setminus \{elm1\}$;

end

Algorithm 4: Extract-precede; Input:- Actions Extracted from a given Post – A; Wikipedia Dump to Train the Word2vec Model – W; Window Size Used While Establishing Precedence Relationships Between Actions – Win_size

generated until time t. The main aim during the training is to minimizing the entropy ($-\sum log(P(gt_{t+1}|a_t))$) between the predicted action (a_t) and the next action from the ground truth (gt_{t+1}). When the model is fully trained, given a start action it is then used to predict the sequences – we call them plans. The incomplete action model is used to generate a sequence in a recursive fashion as it generates one action at a time, using an observed action.

Interpretation of Goal-Oriented Forums

We first identify a set of important queries relevant to the domain and use the RNN model to generate the responses for these queries that provide a deeper insight about the particular subreddit considered.

Couch to 5K:

1. *Query: start_c25k* The model responded that individuals who started participating in the subreddit C25K have performed certain actions with high probabilities. Some of them include – *push_little_bit*, *hit_threadmill*, *run_midnight*, *began_heal*, *get_outdoors*, *map_course_run*.

2. *Query: complete_c25k* The model suggests that individuals tend to celebrate and try to look for other motivating scenarios to participate in more runs. And they hope to keep up with the motivation they obtained through participating in this forum. Interestingly some users start reading the forums after achieving the goal. Some of the actions include – *hope_to_keepup*, *read_alot*, etc.

These associated actions describe the positive approaches and ideas to get motivated so that they can achieve the final goal.

Stop Smoking:

1. *Query: quit_smoking* Users mentioned that they love smoking but tried to get themselves distracted from the cravings. Some of the actions that have high probability of appearing after this action includes – *love_smoke*, *thought_meh*, *look_back*, etc.

2. *Query: quit_many_times* Users complained about catching flu, bothering people, hate the idea of smoking again. Actions include – *caught_flu*, *bother_people*, *hate_idea*, etc.

The associated actions describe the kinds of activities that users are taking up to stay on track to achieve their goal. When carefully observed, most of these extracted actions describe their ways to get motivated and their experiences. This shows the level of gravity at which users are involved to achieve their goal. At the same time, these associations also show that subreddits are the platforms where there are mostly serious users or this moderator-controlled forum is doing a great job at controlling unrelated posts.
Both these models show the power of leveraging trained models built from unstructured social media data to perform sequential decision-making. While these models lack different properties such as guaranteed optimal workflows, perfect correctness and soundness, they answer fundamental questions related to users and their participation on these platforms. The lack of properties listed above also calls for a more focused interest in building models for sequential decision-making.

Keyword	/r/c25k	/r/stopsmoking	/r/stopdrinking
Subreddit	support 0.98 encouragement 0.97 daily 0.96 partner 0.96 hope 0.95	helpful 0.82 owe 0.77 thank 0.76 support 0.75 stories 0.68	inspired 0.71 lurking 0.71 resource 0.67 successes 0.66 invaluable 0.64
Exercise	faster 0.86 stretching 0.81 running 0.78 jogging 0.76 anxiety 0.71	improving 0.90 coping 0.80 improvement 0.80 losing 0.78 diet 0.76	eating 0.68 meditation 0.65 healthy 0.60 balance 0.53 selfimprovement 0.52
Excuses	rain 0.97 stop 0.97 routes 0.96 gps 0.96 ice 0.96	convinced 0.86 cheat 0.86 reminding 0.82 prefer 0.79 rush 0.79	justify 0.55 obsessing 0.50 rationalizing 0.46 insecure 0.46 resentful 0.46
Advice	thanks 0.96 progress 0.95 suggestions 0.94 apps 0.93 encouragement 0.93	appreciate 0.91 stories 0.91 tips 0.90 encouragement 0.90 community 0.90	seek 0.75 stories 0.66 share 0.62 appreciated 0.56 insight 0.54
Quit	determined 0.96 skipping 0.95 admit 0.94 injury 0.94 tough 0.94	accountable 0.57 effective 0.52 history 0.49 struggled 0.47 birthday 0.45	unsuccessfully 0.59 failed 0.53 pregnancy 0.51 relapsed 0.49 started 0.48
Fail	tired 0.94 almost 0.94 hurts 0.93 issues 0.92 worth 0.92	struggled 0.76 intentions 0.76 question 0.76 encourage 0.73 contemplating 0.72	rationalize 0.59 justify 0.58 convince 0.58 ruin 0.57 scares 0.55

Table 5.5: Reddit Topic Vocabulary

Chapter 6

MIXED-INITIATIVE APPROACH TO INFLUENCE THE BEHAVIOR OF A USER

One other thread of research that influences the behavior of individuals is crowdsourced planning for scheduling a specific task (for example, to generate travel itineraries). For individuals who are in need of scheduling a specific task with certain budget and time constraints, one subclass of human computation application, crowdsourced planning, is a great solution. Human computation [118] is emerging as one of the fastest growing fields to solve computationally hard problems, because it offers a powerful and inexpensive alternative that helps combine the relative strengths of humans and computers [43, 44, 98, 125]. One such core class of problems is *planning*. Several recent efforts have started looking at crowd-sourced planning tasks [119, 186, 185, 116] which attempt to optimize the workflows used in crowdsourcing [100, 42], learning and planning to guide the best use of people and machines in hierarchical tasks [99], etc. Just as in a formal organization, the quality of the resulting plan depends on effective leadership. We observe that in most of these existing systems, workers are steered by primitive automated components that merely enforce checks and ensure satisfaction of simple constraints. Encouragingly, experiments show that even these primitive automated components improve plan quality for little to no investment in terms of cost and time [186].

This begs the obvious question: *is it possible to improve the effectiveness of crowd-sourced planning even further by using more sophisticated automated planning technologies?* It is reasonable to expect that a more sophisticated automated planner can do a much better job of steering the crowd (much as good human managers "steer" their employees more effectively). There exists a vibrant body of literature on automated plan generation, and automated planners have long tolerated humans in their decision cycle – be it mixed initiative planning [64] or planning for teaming [170]. The context of crowdsourced planning scenarios, however, introduces a *reversed mixed initiative planning* problem – the planner must act as a guide to the humans who are doing the actual planning. The humans in question can be either experts who have a stake in the plan that is eventually created or crowd workers demonstrating collective intelligence.

We present **`AI-MIX`** (Automated Improvement of Mixed Initiative eXperiences), a new system that implements a general architecture for human computation systems aimed at planning and scheduling tasks. **`AI-MIX`** foregrounds the types of roles an automated planner can play in such systems and the challenges involved in facilitating those roles. The aim of our research is to implement and evaluate a spectrum of solutions for the most critical challenges in the **`AI-MIX`** system which include:

Interpretation: Understanding the requester's goals as well as the crowd's plans from semi-structured or unstructured natural language input.

Steering with Incompleteness: Guiding the collaborative plan generation process with the use of incomplete models of the scenario dynamics and preferences.

The *interpretation* challenge arises because human workers find it most convenient to exchange or refine plans expressed in a representation as close to natural language as possible, while automated planners typically operate on more structured plans and actions. The challenges in *steering* are motivated by the fact that an automated planner operating in a crowdsourced planning scenario cannot be expected to have a complete model of the domain and the requester's preferences. If it does, then there is little need or justification for using human workers as it can automatically generate the best plan that meets the requester's preferences and also knows which type of plan to generate. Both of these challenges are further complicated by the fact that the (implicit) models used by the human workers and the automated planner are very likely to differ in many ways, making it challenging for the

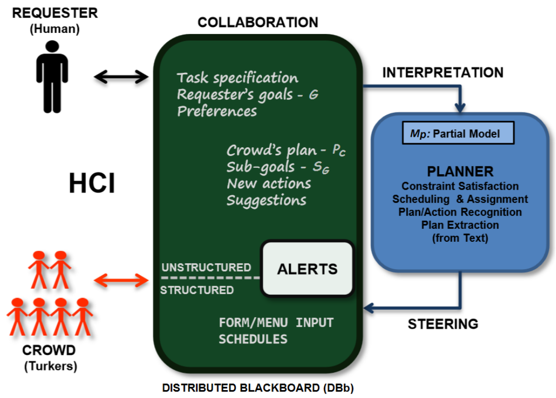


Figure 6.1: A Generalized Architecture for Crowdsourced Planning Systems That Includes Requester, Crowd, Distributed Blackboard (Dbb) and Planner

planner to critique the plans being developed by the human workers.

6.1 Planning for Crowdsourced Planning

The crowdsourced planning problem involves constructing a plan from a set of activities suggested by the crowd as a solution to a task, usually specified by a user called the *requester*. The requester provides a high-level description of the task - most often in natural language - which is then forwarded to the *crowd workers* (*or turkers*. In this paper, we use these terms interchangeably.) The turkers can perform various roles, including breaking down the high-level task description into more formal and achievable sub-goals [119] or adding actions into the plan that support those sub-goals [186]. The term *planner* is used to refer to the automated component of the system, which performs various tasks ranging from constraint checking, to optimization and scheduling, and action recognition. The entire planning process must itself be iterative, proceeding in several rounds which serve to refine the goals, preferences and constraints further until a satisfactory plan is found. A general architecture for solving a crowdsourced planning problem is shown in Figure 6.1.

Roles of the planner

The planning module, or the automated component of the system, can provide varying levels of support. It accepts both the sub-goals S_G, and crowd's plan P_C, as input from the turkers. This module analyzes the current plan generated by the crowd, as well as the sub-goals, and determines constraint and precondition violations according to the model M_P of the task that it has. The planner's job is to steer the crowd towards more effective plan generation.

However, the three main actors – turkers, requester, and planner – need a common space in which to interact and exchange information. This is achieved through a common interactive space – the *Distributed Blackboard* (DBb) – as shown in Figure 6.1. The DBb acts as a collaborative space where information related to the task and the plan that is currently being generated are stored and exchanged between the various system components.

In contrast to the turkers, the planner cannot hope for very complex, task-specific models, mostly due to the difficulty of creating such models. Instead, a planner's strong-suit is to automate and speed-up the checking of plans against whatever knowledge it *does* have. The planner's model M_P can thus be considered shallow with respect to preferences but may range the spectrum from shallow to deep where domain physics and constraints are concerned [190]. The planning process itself continues until one of the following conditions (or a combination thereof) is satisfied:

- The crowd plan P_C reaches some satisfactory threshold and the requester's original goal G is fulfilled; this is a subjective measure and is usually determined with intervention from the requester.

- There are no more outstanding alerts, and all the sub-goals in S_G are supported by one (or more) actions in P_C.

6.2 Planning Challenges

In the current system's architecture that is depicted in the Figure 6.1, a planner (automated system) would interact with the rest of the system to perform one of two tasks: (1) **interpretation** and (2) **steering**. Interpretation is required for the planner to inform itself about what the crowd *is* doing; steering is required for the planner to tell the crowd what it *should* be doing. In the next section, we will describe specific components of the **AI-MIX** system which solve some of the planning challenges listed here in more detail.

6.2.1 Interpretation of the Crowd's Evolving Plan

The planner must interpret the information that comes from the requester, and from the crowd, in order to act on that information. There are two ways in which the planner can approach this problem.

Force Structure: The system can enforce a pre-determined structure on the input from both the requester and the crowd. This can by itself be seen as part of the model M_P, since the planner has a clear idea about what kind of information can be expected through which channels. The obvious disadvantage is that this reduces flexibility for the turkers. In a given planning scenario (we consider *tour planning* as our main application domain), for example, we might force the requester to number his/her goals and force the turkers to explicitly state which goals their proposed plan aims to handle (c.f. [186]). The turkers could also be required to add other structured attributes to their plans, such as the duration and cost of various activities (actions) that are part of the plan.

Extract Structure: The planner can also *extract* structure from the turker inputs to look for specific action descriptions that are part of the planner's model M_P, in order to understand what aims a specific plan is looking to achieve. Although this problem has connections to plan recognition [153], it is significantly harder as it needs to recognize plans not from actions, but rather textual descriptions. Thus it can involve first recognizing actions and their ordering from text and then recognizing plans in terms of those actions. Unlike traditional plan recognition that starts from observed plan traces in terms of actions or actions and states, the interpretation involves first extracting the plan traces. Such recognition is further complicated by the impedance mismatch between the (implicit) planning models used by the human workers and the model available to the planner.

Our proposed system uses both the techniques described above to gather relevant information from the requester and the turkers. The requester provides structured input that lists their constraints as well as goals (and optionally cost and duration constraints) and can also provide a free, unstructured text description for the task. The turkers in turn also provide semi-structured data - they are given fields for activity title, description, cost and duration. The turkers can also enter free text descriptions of their suggestions; the system can then automatically extract relevant actions by using Natural Language Processing (NLP) methods to match the input against the planner's model M_P.

6.2.2 Steering the Crowd's Plan

The planner can steer the turkers by offering helpful suggestions, alerts, and perhaps even its own plan. There are two main kinds of feedback an automated planner can provide to the human workers:

Constraint Checking: One of the simplest ways of generating helpful suggestions for the crowd is to check for quantitative constraints imposed by the requester that are violated in the suggested activities. In terms of the tour planning scenario, this includes: (i) cost of a particular activity and (ii) the approximate duration of an activity. If the requester provides any such preferences, our system is able to check if they are satisfied by the crowd's inputs.

Constructive Critiques: Once the planner has some knowledge about the plan that the turkers are trying to propose (using the extraction and recognition methods described above),

-	**C2**	**C3**
minimum	*47 secs*	*59 secs*
maximum	*8 mins 26 secs*	*2 mins 43 secs*
Average	*3 mins 9 secs*	*1 mins 26 secs*

Table 6.1: HIT Completion times for the Two Conditions: C2 and C3

it can also try to actively help the creation and refinement of that plan by offering suggestions as part of the alerts. These suggestions can vary depending on the depth of the planner's model. Some examples include: (i) simple notifications of constraint violations, as outlined previously; (ii) plan critiques (such as suggestions on the order of actions in the plan and even what actions must be present); (iii) new plans or plan fragments because they satisfy the requester's stated preferences or constraints better; (iv) new ways of decomposing the current plan [137]; and (v) new ways of decomposing the set of goals S_G.

6.3 Evaluation on Amazon Mechanical Turk

In this subsection, we present details about the performance of the proposed system with respect to different experimental conditions that were all deployed on Amazon mechanical turk.

6.3.1 Experimental Setup

For our study, HITs were made available to all US residents (since the requests involved locations inside the US) with a HIT approval rate greater than 50%. Turkers were paid 20 cents for each HIT, and each turker could submit 10 HITs per task. We used tour planning scenarios for six major US cities reused from the Mobi system's evaluation [186]. To

Plan ID	Plan Suggestions	Our Observations
1	**Show:** Go to TKTS half ticket discount booth. You have to stand in line early but it's an authentic nyc experience #show(3 hours)(200.0 $) **Show:** Go to show #show(3 hours)(200.0 $) **Show:** ABSOLUTELY CANNOT go wrong with Phantom of the Opera #show(3 hours)(200.0 $) **Lunch:** Alice's Tea Cup #lunch(20.0 $) **Design:** Walk around the Garment District (go into shops) just south of Times Square. They often print their own fabrics. #design(2 hours)(0.0 $) **Dessert:** Serendipity #dessert(1 hours)(10.0 $)	1) Redundant suggestions – In this example, the action *show* has multiple similar suggestions 2) Shorter plan suggestions 3) Vague suggestions – In this example, the action *show* has very high level descriptions to go and watch a show
2	**piccolo angolo:** Italian in the Village - real deal #italiandinner(2 hours)(60.0 $) **Lombardi's Pizza:** #italian_dinner #italiandinner_todo1 **Ice Cream:** http://www.chinatownicecreamfactory.com/ #italiandinner_todo0 **#lunch:** Mangia Organics #lunch_todo0 **watch Wicked (musical):** Do watch Wicked the musical. It's a fantastic show and one of the most popular on Broadway right now! #broadwayshow(3 hours)(150.0 $) **watch How to Succeed in Business:** Also a great show, a little less grand than Wicked. #broadwayshow(3 hours)(150.0 $) **Activity Steamer:** #lunch #lunch_todo1 **Paradis To-Go:** Turkey & Gruyere is pretty delicious. The menu is simple, affordable, but certainly worth the time #lunch(1 hours)(10.0 $) **cupcakes!:** Magnolia Bakery on Bleecker in the Village #dessert(1 hours)(10.0 $)	1) Very detailed 2) Handling all the requester's preferences 3) Better utilization of the day

Table 6.2: Sample Activity Suggestions from Turkers for the Two Conditions: C2 (Top) and C3 (Bottom). For Both of These Conditions, Same Amount of Money Has Been Paid to Each Turker

measure the impact of automated critiquing on generated plans, we compared results from three experimental conditions:

C1: Turkers could give suggestions in free text after reading the task description - there were no automated critiques.

C2: Turkers quantified their suggestions in terms of cost and duration, and the system checked these constraints for violations with respect to the requester demands.

C3: In addition to C2, the system processed free-form text from turker input and extracted actions to match with our planning model in order to generate alerts for sub-goals and missing preconditions.

We note here that in terms of planning support, Mobi system corresponds to the condition C2 in our framework (as it only supported constraint checking). C1 and C2 were compared to the *proposed approach*, C3, separately. Each set was uploaded at the same time, with the same task description and HIT parameters. In the first run, C3 and C2 were compared on 6 scenarios (New York, Chicago, San Francisco, Las Vegas, Washington and Los Angeles) and were given 2 days before the HITs were expired. The interfaces for both C3 and C2 were made identical to eliminate any bias. In the second run, the conditions C1 and C3 were run over a period of one day for the two scenarios which were most popular in the first run: New York and Chicago. For each of these tasks, the requester prepopulated the existing activities with one or two dummy inputs that reflect the kinds of suggestions she was looking for. In sum, we had more than 150 turkers who responded to our HITs. The analysis that follows is from the 35 turkers who contributed to the final comparisons (only for New York City) among C1, C2, and C3.

6.3.2 Task Completion Latency

When C3 was compared to C1 over a period of one day, we found that C3 received four responses from 3 distinct turkers, whereas C1 failed to attract any responses. To receive responses for a HIT, the turkers have to accept the HIT before providing responses. In our scenario, C1 HITS were not accepted by any turker. This might indicate that the presence of the "TO DO" tags generated by the automated critiquing component was helpful in engaging the turkers and guiding them towards achieving specific goals. However, there may also be alternate explanations for the fact that C1 did not receive any inputs, such as turker fatigue or familiarity with the C3 interface from previous runs.

We also looked at the number of HITs taken to complete the tasks for each of the scenarios. After the HITs were expired, none of the tasks were entirely complete (a task is "completed" when there are no more outstanding to-do items), but C2 had 3.83 unfulfilled tags per HIT as compared to 10.5 for C3. As expected, the task completion latency seems to have increased for C3, since alerts from the system drive up the number of responses required before all the constraints are satisfied. We also verified the HIT completion time for a turker that we define as the difference between the time when he accepted the HIT and the time he submitted the same HIT. The average HIT completion time for C2 is 3 minutes 9 seconds, whereas for C3 it is 1 minute 26 seconds. For C3, the task latency is higher, but the HIT completion time is lower as shown in Table 6.1. These results show that in the case of C3, the probability of turker fatigue is low. As shown in the following section, the increased quality of generated plans may justify the task latency.

6.3.3 Generated Tour Plan Quality

We see that the quality of the plans, in terms of detail and description, seems to increase in C3, since we now have users responding to planner critiques to further qualify suggested activities. We consider the plan comparisons as we are conducting an ablation study to recognize the importance of automated planning technology on two similar systems (C2 and C3). For example, a turker suggested "not really fun, long lines and can not even go in and browse around" in response to a planner generated tag (related to a "fun club" activity suggested previously), while another suggested a "steamer" in response to a planner alert about "what to eat for lunch." A comparison between the plans generated for C2 and C3 (for New York City) is given in Table 6.2. This seems to indicate that including a domain description in addition to the simplistic quantity and constraint checks increases the plan quality.

6.3.4 Role Played by the Planner Module

We now look at some statistics that indicate the role played by the automated module in the tasks. We received a total of 31 new activity suggestions from turkers, of which 5 violated quantity constraints. The C3 setting attracted 39 responses, compared to 28 for C2, which may indicate that the planner tags encouraged turker participation. As shown by the HIT completion latencies, the planner module helped in reducing the probability of turker fatigue by requesting goal suggestions clearly. On the other hand, even though there is a task latency due to the planner generating more subgoals to be fulfilled, the overall quality of the plans is significantly improved.

Note that in the **AI-MIX** interface, there is no perceptual difference between the critiques generated by the planner and the critiques suggested by humans. So it is interesting to see how the critiques are received by the other turkers. There were 8 flaws pointed out by humans, but none were acted upon by other turkers; the planner on the other hand generated 45 critiques, and 7 were acted upon and fixed by turkers. This seems to indicate that turkers consider the planner's critiques more relevant to the generation of a high quality plan than those suggested by other turkers. Even if we consider alternate explanations (e.g. the critiques of the planner were received better as they were easier to respond to), there is enough evidence to suggest that the presence of an automated system does help to engage and guide the focus of the crowd.

Chapter 7

CONCLUSIONS AND FUTURE WORK

In different scientific and societal applications, data plays a key role in various decision-making scenarios. Analyzing the data will help extract important and useful insights about the data in order to make the right decisions. Given this fact, when individuals in a society are sharing their statuses, connecting with others and seeking information on online social media platforms, the data that is generated on these platforms is valuable. This dissertation focuses on utilizing machine learning and automated planning techniques to interpret social media data to help understand the perceptions of public, content-sharing behaviors, stigmatized mental health-related disclosures, individual privacy, etc. Once the interpretation is performed, these lessons are utilized to propose systems that could be used for decision-making.

One of the more demanding problems is to leverage and develop approaches to automatically extract important insights from this incessant massive data shared on social media platforms. The current efforts in this direction emphasize mining or extracting the wealth of information latently present in the data. This wealth of information could uncover the reasons behind the online activities of individuals. However, there are multiple levels of challenges, specifically the type of data – text, image, video, etc. – and the format of the data – structured, unstructured, semi-structured, etc. Even though the content shared on these platforms is for human consumption, manual analysis is non-trivial and highly implausible, requiring approaches similar to the ones that are utilized and proposed as the first thread of research (*Analysis*) in this dissertation. It attempts to identify the value and potential benefits of utilizing differentiated content along with building automated systems in different fields, including public health and personal goals, to conduct meaningful interpretation of this content shared on online social media platforms.

The second thread (*Synthesis*) of this dissertation attempts to utilize the lessons learned through interpretation to build decision-making systems for applications focused on planning and decision-making. To build such systems that help mine patterns efficiently, existing research focuses on detecting patterns that are independent of each other. Given no precedence relationships between these patterns, the developed techniques can miss important insights that could be drawn from these relationships between patterns. Especially in a goal-oriented domain (for example, *a personal goal to quit smoking*), extracting a set of patterns that have precedence relationships could predict the probability of achieving the goal. This could be an invaluable approach in many decision-making scenarios for goal-oriented domains by proposing frameworks based out of machine learning, automated planning and crowdsourcing.

7.1 Future Work

This dissertation defines a new research methodology of interpreting data shared on online social media platforms, showing its potential and significance but only emphasizing certain applications and data types in this vast research domain. There are many extensions that are worth exploring, such as interpretation through shallow action models and measuring bias. We summarize the tasks to be finished and the plan in the near future.

In the course of this current research, I have noticed the need for end-to-end generalizeable intelligent systems to perform automated interpretation of the data. This could be due to multiple factors. First, the lack of structure in social media data is intractable. So these systems could be highly useful to establish inter-disciplinary research between machine learning, information extraction and natural language processing. Second, given the freedom afforded by these social media platforms, the format of the data could be hard to handle. This could establish ways to combine the techniques from computer vision, social computing and data mining. I envisage that building automated systems to interpret online social media data has the potential to inspire novel threads of research that are highly beneficial to the society.

Towards this goal, some of the problems that could come out of this dissertation include:

1. **Mining patterns for decision-making**: The existing research in mining social media essentially focuses on detecting patterns independently. The precedence relationships between these patterns can help gain important insights. For example, in a domain such as *running a marathon*, there are multiple steps of actions that a runner could take to successfully run a marathon. This may include starting the run with a slow pace and short distances which will gradually lead to increased pace as well as long distance runs. Detecting these kinds of sequential set of relationships from the experiences of other users shared on these platforms is extremely valuable for future runners or anyone interested in running a marathon successfully. In the same context, these relationships could be utilized to predict whether a runner who is trying to achieve a goal (in this example, training for a marathon) is on the right track.

2. **Explanations through Data Analysis**: There have been rising concerns about the intelligent systems that are leveraging AI techniques being biased as well as compromising the privacy of users. For example, with the advent of generative adversarial networks (GANs), companies and individuals are utilizing GANs to perform data augmentation that is highly vulnerable to perpetuating biases present in the data utilized for training [92] the GAN. Since training the predictive models using the data posted on social media platforms is gaining traction, explaining the behavior of a system through a deeper analysis of training data could be beneficial. At the same time, in certain aspects bringing the humans into the loop to train the automated systems to generate the outputs with explanations is crucial (my work on building hybrid sys-

tems [127] that includes both humans and machines has **won the People's Choice Award for the best demo in ICAPS 2014**).

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BIOGRAPHICAL SKETCH

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