Venting Weight: Analyzing the Discourse of an Online Weight Loss Forum

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Abstract

Online social communities are becoming increasingly popular platforms for people to share information, seek emotional support, and maintain accountability for losing weight. Studying the discourse in these communities can offer insights on how users benefit from using these applications. This paper presents an analysis of language and discourse patterns in forum posts by users who lose weight and keep it off versus users with fluctuating weight dynamics. In contrast to prior studies, we have access to the weekly self-reported check-in weights of users along with their forum posts. This paper also presents a study on how goal-oriented forums are different from general online forums in terms of language markers. Our results reveal differences about how the types of posts made by users vary along with their weight-loss patterns. These insights are closely related to the power dynamics of social interactions and can enable better design of weight-loss applications thereby contributing to a healthy society.

1 Introduction

Obesity is a major public health problem; the number of people suffering from obesity has risen globally in the last decade (Ogden et al. 2014). The Centers for Disease Control and prevention (CDCP) defined an obese adult (`http://www.cdc.gov/obesity/adult/defining.html`) as a person with a body mass index (BMI) of 30 or higher. 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 (Must et al. 1999; Ngu 2012). Researchers have been trying to understand how certain factors are affecting the weight loss as large number of over-weight people are trying to lose weight and some 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 (Ballantine and Stephenson 2011).

Social media tools like weblogs, instant messaging platforms, video chat, social networks, online discussion forums, are reengineering the healthcare sector (Hawn 2009). Especially, social media is a promising tool for studying public health like tracking flu infections (Lamb, Paul, and Dredze 2013), studying post-partum depression (De Choudhury, Counts, and Horvitz 2013), dental pain (Heaivilin et al. 2011), etc. Tools like online discussion forums make it easier to find health-related information while at the same time provides support by maintaining accountability and some of the popular works like (Black, But, and Russell 2010) proved that weight loss can be supported through online interactions. Hence, studying the online discussion forums can help identify the people at risk who need more support and provide them access to appropriate services and support.

In this paper, 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 (Brownell and Rodin 1994; Hekler et al. 2014). 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 general 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 sig-

nals that makes a goal-oriented forum such as a 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 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.

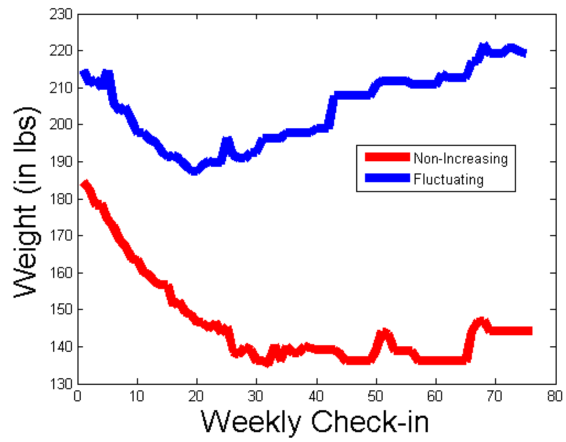

Figure 1: Example weight loss patterns from two individual users: non-increasing (bottom line), and fluctuating (top line). The x-axis ranges from the 1st through the 80th weekly check-in; the y-axis shows the weight, measured in lbs.

2 Related Work

There is a vast amount of literature about online forums – statistical and language analysis of the discussion threads (Gómez, Kaltenbrunner, and López 2008), summarizing the discussions (Backstrom et al. 2013), measuring the success and identifying the factors that make users participate (Kim 2000; Ludford et al. 2004) on these forums, addressing how the roles of users change (Yang et al. 2010), understanding the lurking behavior and predicting lurkers (Preece, Nonnecke, and Andrews 2004), etc. Different fields like marketing (Bickart and Schindler 2001), public health (Black, But, and Russell 2010), etc., considered online forums as influential sources of user information. Much of this literature focuses on studying the online communities and their users from different linguistic and social networking perspectives. Little attention has been given to analyze forums from the weight loss perspective.

However, most of the existing studies (Ballantine and Stephenson 2011; Leahey et al. 2012; Das and Faxvaag 2014) 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. Instead of choosing a small subset of a dataset and performing manual coding, our work is novel in automating the language analysis by handling a bigger dataset. Identifying and providing better assistance to users who need help can also have a significant impact on gaining the trust and confidence of users in these kinds of services through better decision making.

3 Dataset

We obtained an anonymized 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 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 1 shows the weekly weight check-ins of two individual users, one from each group. This grouping is coarse, but is motivated by studies (Kraschnewski et al. 2010; Wing and Phelan 2005) 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.

3.1 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 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 (Toutanova et al. 2003).

	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 1: 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 1. 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 atleast 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.

4.1 Lexical Categories

Studies (Pennebaker, Mehl, and Niederhoffer 2003) 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 2. 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 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 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 over time. As a part of that, previous literature (Bambina 2007) revealed that people on 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

	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 2: Results of statistical measures on linguistic class attributes; Med. refers to Median; SD refers to Standard Deviation

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.

4.3 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 (Socher et al. 2013). This analyzer

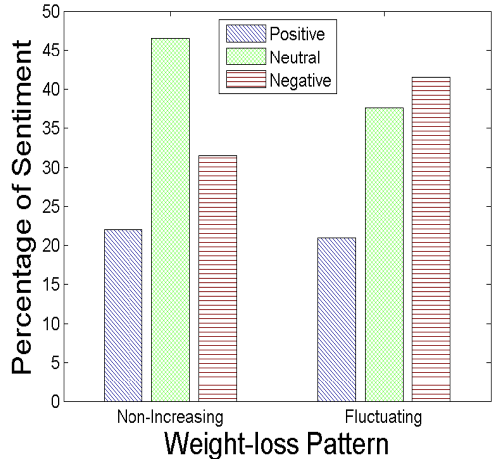

Figure 2: Proportion of sentiments for the two weight-loss patterns. For non-increasing users, percentage of posts with *Positive*, *Neutral* and *Negative* sentiments are: *22%*, *46.5%* and *31.5%* respectively. For fluctuating users, the percentage of posts with *Positive*, *Neutral* and *Negative* sentiments are: *20.9%*, *37.6%* and *41.5%* respectively.

classifies a text input into one of five sentiment categories – from *Very Positive* to *Very Negative*. We merge the five classes into three: *Positive*, *Neutral* and *Negative* (In 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 2, 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 fluctuating group might require more emotional support as they use more negative sentiment in their posts.

4.4 Politeness

Politeness is an important marker which often is a decisive factor in whether interactions go well or cease (Rogers and Lee-Wong 2003). 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 (Danescu-Niculescu-Mizil et al. 2013) that was constructed with a wide range of domain-independent lexical, sentiment and dependency features and there by 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 3 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 3: Statistics of users and politeness percentage posts

4.5 Excuses

Literature (Bambina 2007) 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 (Deppe and Harackiewicz 1996) 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 (Blei, Ng, and Jordan 2003) (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 (Hall et al. 2009) and svm-light (Joachims 1999) libraries to perform classification using Naive Bayes and SVM respectively. Based on the results shown in Table 4, 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: 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 at least 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 lose weight. This kind of in-

tervention by these applications can help gain the trust of its 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. Automated classifier can be very beneficial to design 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.

5 Comparison With General Forums

To contextualize this research, we want to understand if the goal-oriented forums exhibit any specific traits compared to the general forums. We define goal-oriented forums as the forums associated with applications that help set goals while building a social network of users who share similar goals. Here, we present an analysis of how the type of forum can affect the language used with a primary focus on understanding the lexical features and cohesiveness of the threads on these forums.

5.1 Forums Studied

We used threads from two other popular online forums that were used in (Biyani et al. 2012) – 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 the 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 total number of 609 threads (6591 total posts) and 621 threads (3603 total posts) for Tripadvisor and Ubuntu forums respectively. On an average, the thread length in terms of the number of posts is 10 and 5 for the tripadvisor and ubuntu forums respectively. The average number of users in a thread on tripadvisor forum is 1.98 and on ubuntu forum is 3.41. As stated in (Biyani et al. 2012), ubuntu forums have technical discussions which are non-subjective in nature where as trip advisor, a travel related discussion forum has discussions which tend to be subjective.

5.2 Lexical Features

Lexical features like Part-of-Speech (POS) tags are obtained for both the forums to understand the behavior of users in terms of using different categories of words. 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 5. 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 weight loss forum have a primary goal to seek information while maintaining accountability.

	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 5: 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 2. SD–Standard Deviation

5.3 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. Users on the online health forums mostly tend to seek information and if the main topic is drifted to some other topic, the main purpose of these discussion forums is lost. Hence, it is important for the system to automatically track non-cohesiveness in 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 previous post versus those who shift the topic.

Below is an example (paraphrased) showing 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, 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."*

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 (Miller 1995) 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 analysis, we consider this similarity score to be the measure of cohesion.

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 6) on the three forums – fit now data (weight loss forum), trip advisor and ubuntu

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**
  $[vb_i, nn_i] \leftarrow POS_{tagging}(P_i)$;
  $set_A \leftarrow set_A \cup [vb_i, nn_i]$;
  $set_A \leftarrow set_A \cup synset(vb_i) \cup synset(nn_i)$;
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

finds that the threads on weight loss forum are more cohesive compared to the other two forums.

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

Table 6: 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 the goal-oriented forums (like weight loss forums) have more cohesive threads compared to the general forums. Additionally, users on the goal-oriented forums tend to post more information about themselves. 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. Studying other language metrics can also help understand the contributions of different online forums and their impact on the public.

6 Implications

The different language metrics studied in the two main sections of this paper have a great potential to differentiate automatically between 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 `http://www.gym-pact.com/`), allowing other fitness applications to synchronize with the current application to keep track of exercise (MyFitnessPal `https://www.myfitnesspal.com/`), posting questions while doing grocery shopping to find out the calorie content (Fooducate `http://www.fooducate.com/`), etc. We envision tools that utilize the wealth of information present on the discussion forums along with the users activity to automatically estimate the degree to which a user's efforts will yield results. Predictions of success are not the end goals. The value of these types of predictions are when they are leveraged 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 as 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 the 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 (Estrin 2014). 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 this work initiates further research on these types of discussion forums to raise awareness about the different factors faced by individuals who are struggling to lose weight and thereby can help develop policies that can support them in losing weight.

7 Conclusions and Future Work

In this paper, we analyzed how the online discussion forums of weight loss applications can act as an important tool to detect and identify the different metrics that are associated with weight loss. As a first step, we identified the two types of weight loss patterns exhibited by the users on this forum and studied different factors like sentiment, politeness, excuses and questions. We took advantage of existing tools to study these different factors and correlations between these factors and the weight loss pattern. Specifically, this analysis reveals interesting insights about two populations of users who lose weight differently. Users who lose weight in a fluctuating manner are more active in these forums, give more excuses, post more questions and the majority of their posts contain negative sentiment. This shows the information seeking nature and suggests the possible need for more support to these kinds of users. As a secondary focus, we studied how the language metrics differ across goal-oriented forums and general forums. We found that users of goal-oriented forums usually contribute to a more cohesive posting threads and users on general forums tend not to reveal much information about themselves.

Our analyses provides valuable insights on how user behavior within online weight loss forums might correlate with the weight outcomes. These sorts of analyses, particularly when replicated, could provide valuable insights for developing new technologies that might facilitate more effective interactions about weight loss and can help gain trust of users in these kinds of systems. It could also provide valuable insights for improving theories about behavior change.

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