Proceedings of the Sixteenth International AAAI Conference on Web and Social Media (ICWSM 2022)

Twitter User Representation Using Weakly Supervised Graph Embedding

Tunazzina Islam, Dan Goldwasser

Department of Computer Science, Purdue University, West Lafayette, Indiana 47907
islam32@purdue.edu, dgoldwas@purdue.edu

Abstract

Social media platforms provide convenient means for users to participate in multiple online activities on various contents and create fast widespread interactions. However, this rapidly growing access has also increased the diverse information, and characterizing user types to understand people's lifestyle decisions shared in social media is challenging. In this paper, we propose a weakly supervised graph embedding based framework for understanding user types. We evaluate the user embedding learned using weak supervision over well-being related tweets from Twitter, focusing on 'Yoga', 'Keto diet'. Experiments on real-world datasets demonstrate that the proposed framework outperforms the baselines for detecting user types. Finally, we illustrate data analysis on different types of users (e.g., practitioner vs. promotional) from our dataset. While we focus on lifestyle-related tweets (i.e., yoga, keto), our method for constructing user representation readily generalizes to other domains.

Introduction

Social media has been rapidly evolved to make inferences about the real world, with application to health (Dredze 2012; De Choudhury et al. 2013; Pantic 2014), well-being (Schwartz et al. 2013a), politics (O'Connor et al. 2010), marketing(Gopinath, Thomas, and Krishnamurthi 2014). Over the last decade, we have witnessed a dramatic change in social media microblogging platforms, specifically Twitter. An increasing number of people access Twitter to express opinions, engage with friends, share ideas & thoughts, and propagate various contents in their social circles.

Motivation

Twitter is a highly influential and relevant resource for understanding lifestyle choices, health, and well-being (Schwartz et al. 2016; Yang and Srinivasan 2016; Amir et al. 2017; Reece et al. 2017; Islam 2019). The information provided is often shaped by people's underlying lifestyle choices, motivations, and interests. Besides, multiple commercial parties, practitioners, and interest groups use this platform to advance their interests and share their journey focusing on specific lifestyle decisions based on different motivations. Fig. 1 shows two different Twitter users' profile description and tweets focusing on keto diet. Though both users **susan** and **keto_collab** tweet about the keto diet, they have different intentions. User **susan** (yellow box) is a 'keto enthusiast' tweeting about her keto journey, while **keto_collab** (green box) focuses on collecting information from various keto channels and promoting keto recipes and ketogenic diet daily. In addition to the tweets' contents, the profile description of **susan** indicates that she is a practitioner. On the other hand, the profile description and tweets of **keto_collab** indicate that it is a promotional account (Fig. 1). Our goal is to automatically classify user types from well-being related tweets and analyze their textual content.

To demonstrate our proposed method to characterize user types, we consider two lifestyle-related activities: **Yoga** – a popular multi-faceted activity focusing on the body-mind-spirit connection (Goyeche 1979) having benefits of alleviating symptoms of anxiety and depression as well as promoting good physical fitness (Khalsa 2004; Yurtkuran, Alp, and Dilek 2007; Smith and Pukall 2009; Ross and Thomas 2010) and **Keto diet** – a low-carbohydrate, high-fat, adequate-protein diet helping weight loss (Johnstone et al. 2008), controlling $type - 2$ diabetes (McKenzie et al. 2017) as well as therapeutic potential in pathological conditions, such as PCOS, acne, neurological diseases, cancer, and the amelioration of respiratory and cardiovascular disease risk factors (Paoli et al. 2013). Despite the current popularity of yoga and keto, there is little research on analyzing users' lifestyle decision in social media. However, understanding user dynamics on social media is critical to analyze their lifestyle choice and motivation.

Challenges

First, social media users have massive and diverse information regarding topics, content, demographics. It is hard to obtain *large-scale annotated data* for training a machine learning models on such sophisticated content. Second, tweets are *short and often ambiguous*. So, a simple pattern-based analysis on text (tweets) using specific keywords is often inadequate for capturing relevant information. Third, user representation requires *multiview formulation* of data. A system solely relying on tweets' contents misses the rich auxiliary information from the available sources. In addition to the tweet, user's profile description and network are helpful. In this work, we suggest a graph embedding based approach

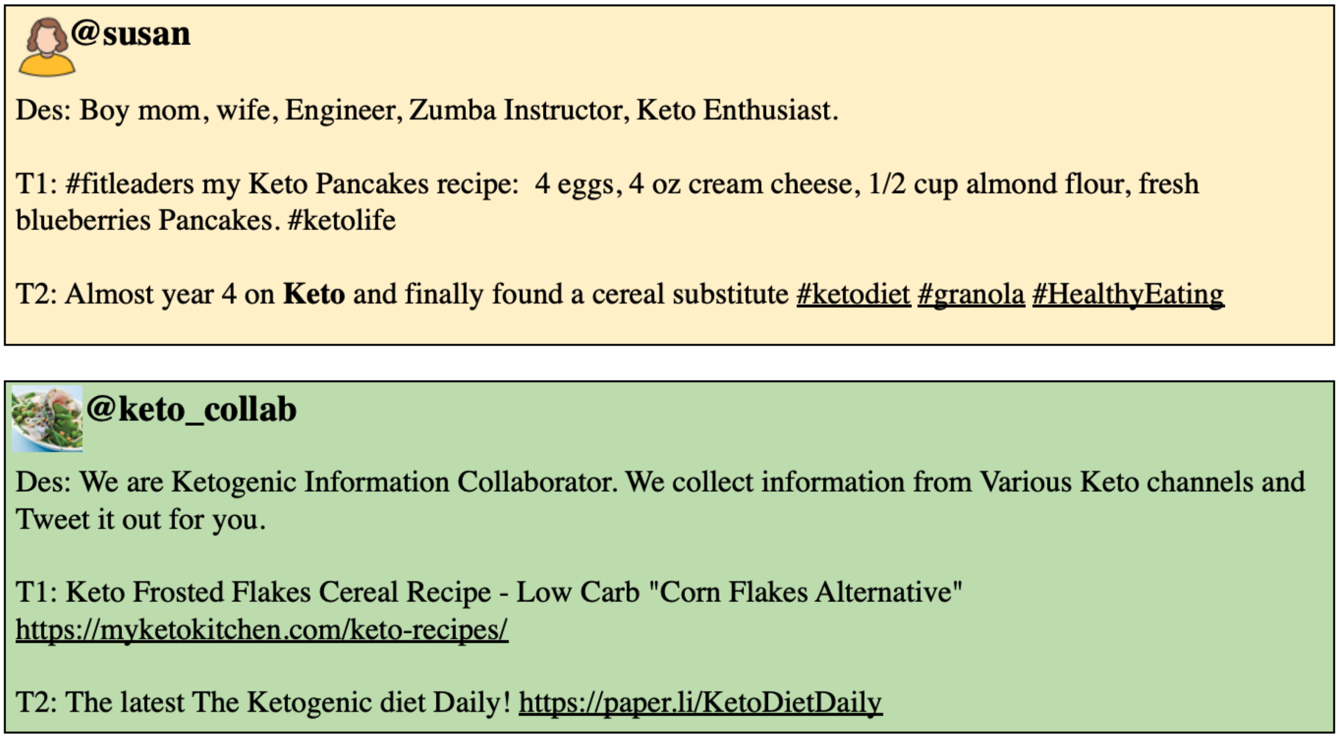


Figure 1: Two different Twitter users' profile sharing their interests on keto diet. Here, *Des* represents users' profile description and $T1, T2$ are users' tweets.

designed to address the above challenges for generating user representation by leveraging weak supervision from profile description.

Existing Work

Prior works infer many latent user characteristics like personality (Golbeck et al. 2011; Kosinski, Stillwell, and Graepel 2013; Schwartz et al. 2013b; Lynn, Balasubramanian, and Schwartz 2020), emotions (Wang and Pal 2015), happiness (Islam and Goldwasser 2020), mental health (Amir et al. 2017), mental disorders (De Choudhury et al. 2013; Reece et al. 2017) by analyzing the information in a user's social media account. Several works have been done on multiview formulation of data in social media analysis research. (Islam and Goldwasser 2020) investigated relationship between *practicing yoga* and *being happy* by incorporating textual and temporal information of users using Granger causality. (Mishra, Yannakoudakis, and Shutova 2018; Mishra et al. 2019) exploited user's community information along with textual features for detecting abusive instances. (Ribeiro et al. 2018) characterized hateful users using content as well as user's activity and connections. (Miura et al. 2017; Ebrahimi et al. 2018; Huang and Carley 2019) used a joint model incorporating different types of available information, including tweet text, user network, and metadata for geolocating Twitter users. These works are typically studied as a supervised learning task. Previous works aiming to understand Twitter users' types by combining their tweets, metadata, and social information (Del Tredici et al. 2019; Islam and Goldwasser 2021b,a) rely on large amounts of labeled instances to train supervised models. Such sizeable labeled training data is difficult to obtain. Semi-supervised methods can reduce dependence on labeled texts. Graph based semi-supervised algorithms achieved considerable attention over the years (Belkin, Niyogi, and Sindhwani 2006; Subramanya and Bilmes 2008; Talukdar et al. 2008). (Sindhwani and Melville 2008) used a polarity lexicon combined with label propagation (Zhu and Ghahramani 2002) for sentiment analysis. Several have used label propagation for polarity classification (Blair-Goldensohn et al. 2008; Brody and Elhadad 2010), community detection (Jokar and Mosleh 2019). Our challenge is to construct a user representation in a weakly supervised way relevant for characterizing nuanced activity and lifestyle-specific properties.

Contributions

In this paper, our goal is to explore the approach driven by the principle of social homophily (McPherson, Smith-Lovin, and Cook 2001), indicating individuals' tendency to form social ties with others who have common interests. (Yang and Eisenstein 2017) used this phenomenon to overcome language variation in sentiment analysis. Graph-based method such as label propagation (Zhu and Ghahramani 2002; Talukdar and Crammer 2009; Speriosu et al. 2011) provides a representation by exploiting such relationships to improve classification, often while requiring less supervision than with standard classification. In our settings, we follow the observation that the users' lifestyle choices expressed in the

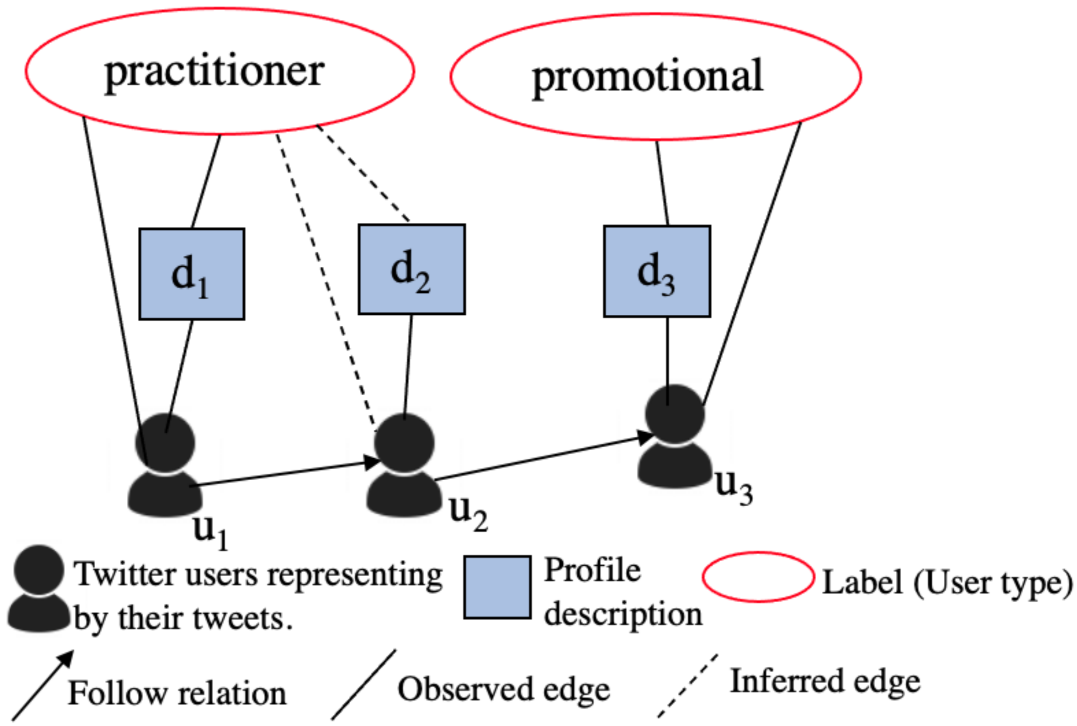


Figure 2: Information graph capturing relations among users, descriptions, user types.

text will be reflected in users' behavior engaging with it. The main insight of our work is that given two users with very similar behaviors and similar activity, their profile descriptions can be aligned. We define an objective that does the weak supervision - mapping profile descriptions to labels (i.e., user types) based on specific keywords.

Fig. 2 represents the relationship between users, descriptions, user types. To capture more hidden relationships that characterize user types through information graph, we suggest *inference function* to apply iteratively. Fig. 2 shows that users u_1 and u_3 have weak labels that we obtain from their profile descriptions d_1 and d_3 respectively by mapping with labels using specific keywords. Profile description of u_2 doesn't have label initially. Inference function infers the label of user u_2 and u_2's description, d_2 as 'practitioner' because u_1 and u_2 have similar tweets (Fig. 2).

From a technical viewpoint, we define our user type detection as a reasoning problem over an information graph that creates distributed representations of nodes contextualized by the graph structure, allowing us to transfer information from observed nodes to unknown nodes (**Step 1**). **Step 2** – we use inference function built on similarity metric defined by the learned graph embedding to increase the number of edges connecting the two node types. We suggest an Expectation–maximization (EM) approach for completing these two steps. Our contributions can be summarized as follows:

1. We formulate a novel problem of exploiting weak supervision for user type detection from social media.
2. We suggest a graph embedding based EM-style approach for learning and reasoning to construct like-minded users incrementally.
3. We describe how to generate weak labels from user's profile description along with quantitative quality assessment.
4. We conduct extensive experiments on real-world datasets to demonstrate the effectiveness of the proposed weakly supervised graph embedding method to detect user type over the baselines.

Model

In this section, we first describe how to create the information graph and learn the information. Next, we discuss about inference function. Then, we discuss an iterative EM-style approach that continually improves the user representation learned by the graph.

Information Graph Creation

We represent users' activity on social media as an information graph, connecting profile description to user representing by their tweets. In this process, we have following nodes: users representing by their tweets, profile descriptions, user types (practitioner, promotional). We have following observed edges: profile description-to-user type, user-to-user type, profile description-to-user, user-user. As most users' descriptions are not associated with the labels, our technical challenge is to infer the unknown label of the descriptions. To address this challenge, we learn a graph embedding to maximize the similarity between neighboring nodes (Perozzi, Al-Rfou, and Skiena 2014; Tang et al. 2015; Grover and Leskovec 2016).

Information Graph Embedding

We define the notion of information graph shown in Fig. 2. Let Graph, $G = (V, E)$, where V consists of the following nodes: (1) $D = \{d_1, d_2, ..., d_n\}$ represents user's profile description, (2) $U = \{u_1, u_2, ..., u_n\}$ are the Twitter users representing by their tweets, (3) $UT = \{ut_1, ut_2, .., ut_m\}$ represents user type (label) which is binary (i.e., practitioner and promotional) in our case. E contains following edges: (1) each Twitter user must have profile description so D connects with U, (2) profile description has connection with user type based on specific keywords resulting a connection between D and UT, (3) user U connects with user type UT if the user's description is already connected to user type, (4) U and U via follow link. For follow link, we consider those users from our dataset if they are retweeted and/or $@-$mentioned (Rahimi et al. 2015) in other users' (from our data) tweets. An edge is created between two users if either user mentioned the other from the data. We embed the following instances in a common embedding space - (a) users, (b) profile descriptions, (c) user types. We maximize the similarity between two instances in the embedding space if – (1) profile description has a type. (2) a user has a type.

Let define the embedding function, ϕ that maps the graph's nodes to vectors R^d. We train this by following a negative sampling approach. As we construct positive examples by associating each node u with all of its neighbors, (u, x^p) is a positive pair where x^p is a positive example. For each positive pair, we sample 5 negative examples (x^n) in such a way that u and x^n do not share an edge. Our goal is to maximize the similarity of a node embedding with a positive example and minimize the similarity with a negative example. We call a user type a positive example for a user if the user belongs to that type. Otherwise, the type is called a negative example. The embedding loss is designed to place u closer to x^p than x^n. We define the loss function as follows:

$$E_t = l(\mathrm{sim}(\phi(u), \phi(x^p)), \mathrm{sim}(\phi(u), \phi(x^n))) \quad (1)$$

where, E_t defines the embedding loss for specific objective function t (i.e., user to user type). Similarity function, $sim()$ is the dot product and $l()$ is the cross-entropy loss.

$$l(p, n) = -\log\left(\frac{e^{\mathrm{sim}(\phi(u),\phi(x^p))}}{e^{\mathrm{sim}(\phi(u),\phi(x^p))} + e^{\mathrm{sim}(\phi(u),\phi(x^n))}}\right) \quad (2)$$

We minimize the summed loss $\sum_{t \in T} \lambda_t E_t$, where T is the set of all objective functions and the weight, λ_t associates with each objective function.

We obtain user embeddings by running a Bi-LSTM (Schuster and Paliwal 1997) over the Glove (Pennington, Socher, and Manning 2014) word embeddings ($300d$) of the words of the user's tweets. Concatenating the hidden states of the two opposite directional LSTMs, we get representation over one time-stamp and average the representations of all time-stamps to obtain a single representation of the tweets. We train this Bi-LSTM jointly with embedding learning.

Inference Function

After learning the information from graph embedding, which captures the observed relations, we can obtain unobserved relations among nodes in the graph. Based on the similarity captured between non-connected nodes by graph embedding, we create new edges between them to use this knowledge in the future. We do this by defining an inference function that creates the edges based on information graph inferences. For example, we have users whose profile descriptions are not covered by specific keywords used to create a weak label. But those users may have similar tweet contents that match with the tweets of a labeled user. The graph embedding step learn this commonality between these users and represent them with similar embeddings. Using inference function, we directly connect the user and label with an edge as well as the user's description and label with an edge based on the user node similarity in the embedding space.

For the inference function, we make edge connections based on the node representations learned by computing similarity scores between all pairs of nodes (using the node embedding) and connecting the nodes with the top k scores.

EM-style Learning Approach

In this section, we describe overall EM-style graph learning framework that continually as follows:

Step 1: Learn node embedding. In this step, we learn the information graph embedding using the framework described in subsection named Information Graph Embedding to obtain initial graph representation.

Step 2: Infer unlabeled users. We apply inference function (see details in subsection named Inference Function) built on similarity metric based on the learned information graph representation.

Step 3: Stopping criterion. At each iteration, after Step 2, we check the predicted labels of all users. Our model converges when the change in predicted labels is less than a threshold between two consecutive iterations.

Dataset Details

To evaluate our model's ability to characterize user type, we use two lifestyle choice related data, i.e., yoga and keto diet from Twitter. We download tweets using Tweepy[1] by Twitter streaming API sub-sequentially from May to November, 2019. For yoga, we collect 419608 tweets related to yoga containing popular keywords : 'yoga', 'yogi', 'yogalife', 'yogalove', 'yogainspiration', 'yogachallenge', 'yogaeverywhere', 'yogaeveryday', 'yogadaily', 'yogaeverydamnday', 'yogapractice', 'yogapose', 'yogalover', 'yogajourney'. There are 297350 different users among them 15168 users have at least yoga-related tweets in their timelines. We have 35392177 timeline tweets in total. We discard those users who do not have profile description. So we have finally 13301 yoga users.

For ketogenic diet, we focus on several keywords i.e. 'keto', 'ketodiet', 'ketogenic', 'ketosis', 'ketogenicdiet', 'ketolife', 'ketolifestyle', 'ketogenicfood', 'ketogenicfoodporn', 'ketone', 'ketogeniclifestyle', 'ketogeniccommunity', 'ketocommunity', 'ketojourney' to extract 75048 tweets from 38597 different users. Among them 16446 users have at

[1]https://www.tweepy.org/

least two keto-related tweets in their timelines having total 39250716 timeline tweets. After discarding the users not having profile description, we have 14320 keto users finally.

Holdout Data

For testing purpose, we manually annotate 786 yoga users and 908 keto users using binary label 'practitioner', 'promotional'. For each user, we check both their profile description and timeline tweets (only yoga/keto-related). At first, we look at the user profile description for user type, whether they explicitly mention practicing a specific lifestyle (e.g., yogi, yogini, keto enthusiast, ketosis); then, we look into the timeline tweets of that user. If the user tweets about the first-hand experience of practicing yoga (e.g., *love doing yoga during weekend morning*)/keto diet (e.g., *lost 7lb in* 3^{rd} *week of keto dieting*), we annotate them as a 'practitioner'. After looking at the description and tweets, if we observe that they are promoting a gym/studio (e.g., *offering online yoga classes*), online shop (e.g., *selling yoga pants*), app (e.g., *keto diet recipe*), restaurant (e.g., *serving keto meal*) etc., rather than sharing their first-hand experience about a particular lifestyle, we annotate the user as a 'promotional' user.

Two graduate students from Computer Science department manually annotate a subset of tweets (10%) for calculating inter-annotator agreement. This subset has an inter-annotator agreement of 64.7%, which is substantial agreement using Cohen's Kappa coefficient (Cohen 1960). In case of a disagreement, we resolve it by discussion.

Information Graph

In our information graph, we have following nodes: users representing by their tweets, profile descriptions, user types and following observed edges: profile description-to-user type, user-to-user type, profile description-to-user, user-user. For yoga data, initially we have 33784 nodes with 8730 observed edges. After EM-style approach, we have total 19927 edges in our information graph for yoga. In our keto data, we have 28583 nodes and 132486 observed edges initially. After EM-style approach, we notice that our keto information graph contains total 145944 edges.

Constructing Weak Labels

In this section, we describe how to generate weak labels from users' profile descriptions that can be incorporated as weak sources in our model. We further evaluate the quality of the weak labels.

Generating Weak Labels

Keyword based knowledge extraction from profile description. In some cases, the user's profile description contains specific keywords indicating a particular user type (i.e., practitioner, promotional). We use those keywords to extract the label and utilize them as weak-supervision for our model. However, not to make our weak label too noisy, we do not assume that people with 'yoga' or 'keto' mentioned in their profile description would be 'practitioner' because other keywords that appear with them would be the indicator of being 'promotional'. Also, the exact keywords might appear in both user types. So we need to check other keywords appearing with them as separating criteria for 'practitioner' and 'promotional'. To handle these cases, we form the following rules based on more related keywords:

For yoga, if user description contains following words *('yoga' or 'yogi' or 'yogini' or 'guru' or 'sprituality' or 'asana' or 'meditation' or 'mindfulness' or 'fitness' or 'health') and not ('studio', 'gym', 'magazine', 'daily', 'channel', 'clothing', 'subscribe', 'training', 'shop', 'sale', 'discount', 'package', 'free', 'ship', 'retreat', 'resort', 'design', 'jewellery', 'handmade', 'business', 'spa', 'hotel', 'restaurant', 'activewear', 'beachwear', 'sportsfashion', 'festival', 'app', 'website', 'community', 'organizer', 'center', 'donate', 'support', 'fund', 'product', 'review', 'trend', 'healthcare')*, we consider them yoga practitioner. If profile description has following words *('gym' or 'studio' or 'magazine' or 'daily' or 'channel' or 'clothing' or 'subscribe' or 'training' or 'shop' or 'sale' or 'discount' or 'package' or 'free' or 'ship' or 'retreat' or 'resort' or 'design' or 'jewellery' or 'handmade' or 'business' or 'spa' or 'hotel' or 'restaurant' or 'activewear' or 'beachwear' or 'sportsfashion' or 'festival' or 'app' or 'website' or 'community' or 'organizer' or 'center' or 'donate' or 'support' or 'fund' or 'product' or 'review' or 'trend' or 'healthcare')*, we consider them promotional user. After applying keyword based knowledge extraction rule, we have 2104 weak labels for yoga data.

For keto diet, if user description contains following words *('keto' or 'ketogenic' or 'ketosis' or 'ketodiet' or 'ketogenicdiet' or 'lowcarb' or 'carnivore', 'pro-meat') and ('lifestyle', 'follower', 'teacher', 'instructor', 'fitness', 'bodybuilder', 'nutrition', 'coach', 'addict', 'enthusiast', 'health', 'body', 'mind', 'practitioner', 'guru', 'journey', 'life')*, we consider them keto practitioner. On the other hand, if user description has following words *('keto' or 'ketogenic' or 'ketosis' or 'ketodiet' or 'ketogenicdiet' or 'lowcarb') and ('collaborator', 'channel', 'restaurant', 'business', 'subscribe', 'sale', 'discount', 'offer', 'free', 'organizer', 'mealplan', 'recipe', 'trend', 'review', 'delivery', 'app', 'community', 'website')*, we label them as promotional keto users. Finally, 858 keto users have weak label.

Quality of Weak Labeling

To assess the weak label quality, we consider the data with both weak label and ground-truth label. For yoga data, we have 451 users and for keto, we have 56 users having both weak and true label. We compare the weak labels with the ground truth labels. The accuracy and macro-avg F1 score of the weak label are 0.79 and 0.78 respectively for yoga data. For keto data, the accuracy and macro-avg F1 score of the weak label are 0.86 and 0.67 correspondingly. We observe that the accuracy and macro-avg F1 score of the weak label both for yoga and keto data are significantly better than random (0.5) for binary classification, indicating that our weak labeling approach has acceptable quality.

Experiments

In this section, we present the experiments to evaluate the effectiveness of our model, baselines, hyperparameter tun-

Model	Yoga		Keto	
	Accuracy	Macro-avg F1	Accuracy	Macro-avg F1
LSTM_Glove	0.51	0.45	0.72	0.43
Fine-tuned BERT	0.47	0.47	0.72	0.42
Label propagation	0.78	0.75	0.66	0.42
EM-style approach	**0.78**	**0.76**	**0.72**	**0.64**

Table 1: The first two rows are supervised baselines. The last two rows show the user type detection results for weak supervision settings.

Model	Yoga		Keto	
	Accuracy	Macro-avg F1	Accuracy	Macro-avg F1
Label propagation (des)	0.721	0.711	0.715	0.398
EM-style approach (des)	0.781	0.761	0.664	0.635
Label propagation (net)	0.573	0.572	0.644	0.384
EM-style approach (net)	0.670	0.657	0.707	0.617
Label propagation (des + net)	0.781	0.753	0.663	0.418
EM-style approach (des + net)	**0.782**	**0.763**	**0.722**	**0.642**

des : profile description
net : user network
des + net : both profile description and user network

Table 2: Ablation study.

ing and text pre-processing details. We aim to answer the following evaluation questions (EQ):

- **EQ1:** Can our model improve user type detection task by leveraging weak supervision?
- **EQ2:** How effective to consider multiview information for improving prediction performance?
- **EQ3:** How meaningful our model's embeddings are? How does EM-style approach help?

Experimental Settings

We use accuracy and macro-average F1 score as the evaluation metrics. We show two versions of our model (weakly supervised) —(1) initial graph embedding without iterating multiple times (Label propagation), (2) EM-style approach. Both of them are trained on weakly labeled data and evaluated with the performance on holdout data (manually annotated ground-truth discussed in section named Dataset Details). Both of our weakly supervised models are repeated for 3 times and we report the average performance (3^{rd} and 4^{th} rows of Table 1). We compare our model with two supervised learning baselines. Table 1 shows that our EM-style graph embedding model achieves the highest performance both in accuracy (yoga = 78.2%, keto = 72.2%) and macro-avg F1 score (yoga = 76.3% , keto = 64.2%) than the supervised baselines which answer the **EQ1**.

Baselines. For supervised baselines, we train a model using the weak labels assigned by the keywords and make predictions about the users that do not match any keyword. From the weakly labeled training data, we randomly choose 20% data as validation set. Our first supervised baseline is referred to as LSTM_Glove, where we use $300d$ Glove word embeddings to obtain the embedding of user's tweets and forward these embeddings to LSTM (Hochreiter and Schmidhuber 1997). We use cross-entropy loss. We fine-tune the pre-trained BERT (base-uncased) (Devlin et al. 2019) model with user's tweets as our second supervised baseline. For both baselines, we use 3-fold cross-validation and the average is reported in Table 1.

Hyperparameter Details. We run our proposed model for characterizing user type on yoga and keto data. For both of them, we run the embedding learning (described in subsection named Information Graph Embedding) at most 100 epochs or stop the learning if the embedding learning loss does not decrease for 10 consecutive epochs. For inference function, we pick the top 20 most confident predictions based on majority voting and treat them as labeled users. For stopping criterion, we set the threshold to 10%. We end up running inference function for 2 iterations for yoga and 3 iterations for keto. We use optimizer= Adam (Kingma and Ba 2014), learning rate= 0.001, batch size = 16. The single layer Bi-LSTM takes $300d$ Glove word embeddings as inputs and maps to a $150d$ hidden layer. We initialize the embeddings of all of the other instances randomly in $300d$ space. We initialize the weight associates with each objective function, $\lambda_t = 1$, for all.

For LSTM_Glove baseline, the single layer LSTM takes $300d$ Glove word embeddings as inputs and maps to a $150d$ hidden layer with optimizer= Adam, learning rate= 0.01, batch size = 16, epochs = 20. For BERT fine-tuning, to encode our texts, for padding or truncating we decide maximum sentence length = 500. We use batch size = 32, learning rate

= $2e-5$, optimizer= AdamW (Loshchilov and Hutter 2018), epochs = 3, epsilon parameter = $1e-8$. Our stopping criterion for these two supervised baselines is the lowest validation loss.

Pre-processing. To pre-process the tweets, we first convert them into lower case, remove URLs, smiley, emoji, stopwords. To prepare the data for input to BERT, we tokenize the text using BERT's wordpiece tokenizer.

Does Multiview Information Help?

Social media user representation requires multiview formulation of data. To understand the contribution of the model components, we perform an ablation study. Table 2 shows the results of our ablation study both for yoga and keto data.

We train both initial graph embedding (Label propagation) and EM-style approach with user description only (1^{st} and 2^{nd} rows of Table 2). In this case, our information graph contains the following nodes: users representing by their tweets, profile descriptions, user types (practitioner, promotional). We have the following observed edges: profile description-to-user type, user-to-user type, profile description-to-user. For yoga data, initially, we have 26482 nodes with 2104 observed edges. After the EM-style approach, we have total 13301 edges in the information graph of yoga. For keto data, we have 28583 nodes and 855 observed edges initially. After the EM-style approach, we notice that our information graph contains total 14313 edges for keto. Table 2 (2^{nd} row) shows that EM-style graph embedding model with description only achieves 78.1% accuracy for yoga and 66.4% for keto as well as 76.1% macro-avg F1 score for yoga and 63.5% for keto.

Then, we train both Label propagation and EM-style approach with user network only (3^{rd} and 4^{th} rows of Table 2). Information graph contains the following nodes: users representing by their tweets, profile descriptions, user types (practitioner, promotional) and we have the following observed edges: profile description-to-user type, user-to-user type, user-user. In this case, we have 13304 nodes and 5811 observed edges initially for yoga data. After the EM-style approach, we obtain total 6469 edges in the yoga information graph. For keto data, initially, we have 14316 nodes with 126929 observed edges. After the EM-style approach, we have total 131631 edges in the information graph of keto. The 4^{th} row of Table 2 shows that the EM-style graph embedding model with user network only obtains 67.0% accuracy for yoga and 70.7% for keto as well as 65.7% macro-avg F1 score for yoga and 61.7% for keto.

Exploiting the knowledge from multiple views to represent the data, user's profile description, and network are helpful besides tweets. In our model, the following instances - tweets, user network, profile descriptions, user types are embedded in a common embedding space which creates distributed representations of nodes contextualized by the graph structure. This graph structure allows us to transfer information from observed nodes to unobserved nodes. The inference function built on similarity metric increases the number of edges connecting the two node types. 5^{th} and 6^{th} rows of Table 2 show two versions of our weakly supervised model i.e., Label propagation and EM-style approach respectively. Our EM-style approach obtains the highest accuracy and macro-avg F1 score both for yoga and keto data (6^{th} row of Table 2). From Table 2, we notice that considering multiview information improves prediction performance (answer to **EQ2**) compared to the models that are using only either profile description or user network information.

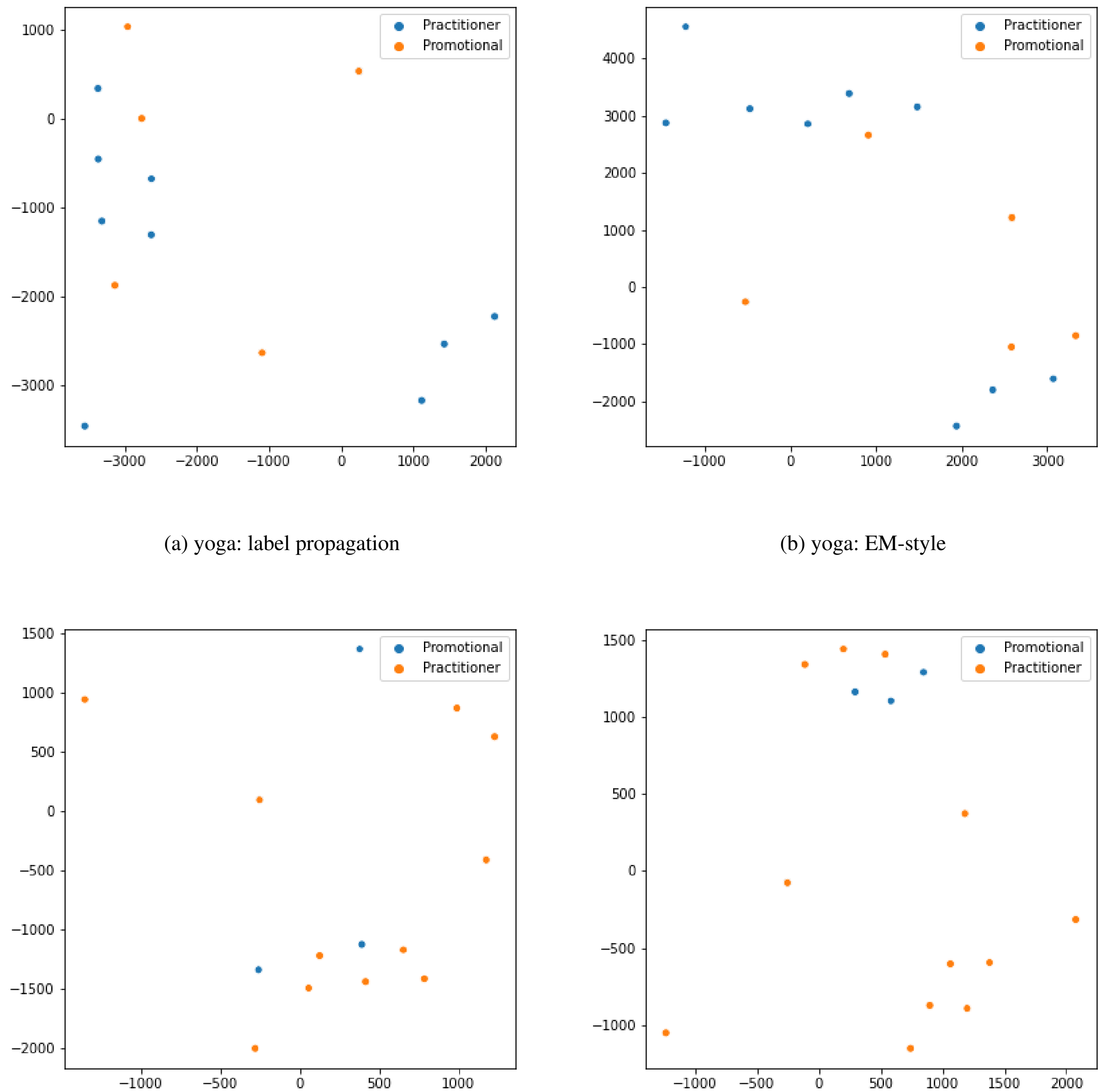
Embedding Analysis

Our model's embeddings are effective to characterize user types. Before our model is trained, user embeddings are random. To answer the **EQ3**, we project the embeddings to a $2D$ space using t-SNE (Van der Maaten and Hinton 2008) and use different colors to represent labels (Fig. 3). We plot the user embeddings after label propagation (Fig. 3a and Fig. 3c) and EM-style approach (Fig. 3b and Fig. 3d) based on ground truth data. The embeddings show that EM-style approach has better user representation both for yoga (Fig. 3b) and keto (Fig. 3d) dataset.

User Type Analysis

In this section, we perform analysis on predicted user types from our data. To understand the topic of the user's tweets, we run LDA (Blei, Ng, and Jordan 2003) based topic modeling over the tweets. Fig. 4 shows the wordclouds of top 10 keywords in each topic (we show 2 topics here) from practitioner and promotional users' tweets both from yoga and keto dataset. For visualization purpose, we filter out the word 'yoga' and 'keto' because of the apparent high occurrences. Looking at yoga practitioners' topics, we notice that they tweet mostly about their yoga practice, yoga pose, yoga class, yoga practice time (Topic 0 in Fig. 4a). On the other hand, topic 1 of practitioner mostly focus on practitioners' motivation of doing yoga, i.e., health and fitness benefit, spiritual connection, meditation. Topics from promotional yoga users mostly focus on joining yoga class, gym, fitness model, sport, yoga pant (Fig. 4b). For keto practitioners, the tweets' topics are mostly related to ketogenic diet, low carb high fat food (lchf), ketonemia (presence of abnormally high concentration of ketone bodies in the blood), budget friendly ketodiet (Fig. 4c). Promotional keto users tweet mostly about keto recipe, paleo diet, gluten-free meal, supplements, anti-aging medicine (Fig. 4d).

We perform text analysis of user's profile description to understand what kind of words users use in their description which can distinguish their types based on their lifestyle. We create wordcloud with the most frequent words (Fig. 5) from yoga and keto users' profile description, filtering out the word 'yoga' and 'keto' respectively, because of the apparent high occurrences. We observe the words {'teacher', 'instructor', 'coach', 'health', 'meditation', 'wellness', 'writer', 'yogi'} in yoga practitioners' descriptions (Fig. 5a). Promotional users have the following words in the description {'studio', 'fitness', 'health', 'wellness', 'class', 'offer', 'community', 'event', 'business'} (Fig. 5b). Fig. 5c shows the wordcloud of the profile description of keto practitioner having words {'food', 'nutrition', 'coach', 'author', 'writer', 'wife', 'mom', 'family'}. Promotional users' description contains {'free', 'food', 'recipe', 'health', 'share', 'blogger'} words. We notice that most users use {'love', 'life', 'live', 'health'} these



(a) yoga: label propagation

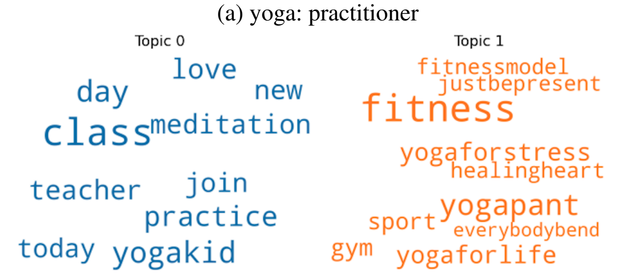
(b) yoga: EM-style

(c) keto: label propagation

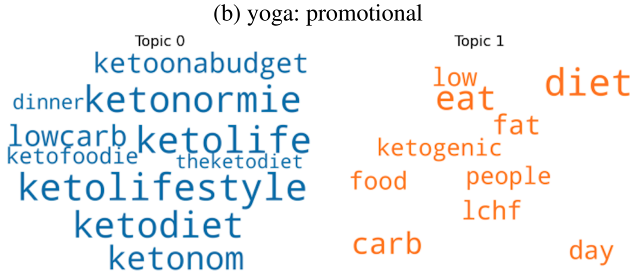
(d) keto: EM-style

Figure 3: User embeddings after label propagation and EM-style approach both for yoga and keto data in t-SNE visualization.

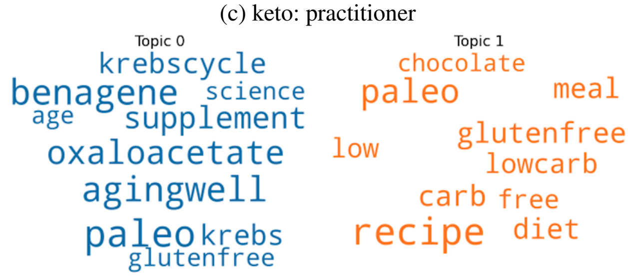
(a) yoga: practitioner



(b) yoga: promotional

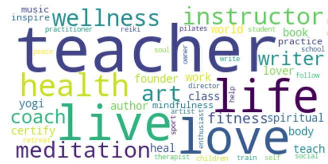


(c) keto: practitioner



(d) keto: promotional

Figure 4: Wordclouds of top 10 keywords in each topic from yoga and keto users' tweets. Only 2 topics from each dataset are shown here.



(a) yoga: practitioner

(b) yoga: promotional

(c) keto: practitioner

(d) keto: promotional

Figure 5: Wordcloud for yoga and keto users' profile description.

words in their profile descriptions frequently, regardless of types.

Users' Sentiment Analysis

We analyze the sentiment of practitioners' tweets both for yoga and keto using VADER (Hutto and Gilbert 2014) model which is used for text sentiment analysis that is sensitive to both polarity (positive/negative) and intensity (strength) of emotion.

For this analysis, we randomly select 350 yoga practitioners and 150 keto practitioners and choose their timeline tweets related to yoga and keto diet respectively. After running VADER sentiment analyzer, we obtain 9147 positive sentiment and 853 negative sentiment tweets for yoga practitioners. For keto practitioners, we have 7931 positive and 2069 negative sentiment tweets.

To understand the topic of the practitioners' tweets which have positive sentiment, we run LDA based topic modeling over the tweets. Fig. 6 shows the wordclouds of top 10 keywords in each topic (we show 2 topics here) from practitioners' tweets which have positive sentiment both from yoga (Fig. 6a) and keto (Fig. 6b) dataset.

For yoga practitioners positive sentiment tweets, Topic 0 (Fig. 6a) is mostly related to 'vinyasa' and 'hatha' yoga. Vinyasa is a style of yoga characterized by stringing postures together so that we can move from one to another, seamlessly, using breath. It is commonly referred to as 'flow' yoga. Hatha yoga allows for more stretching. Topic 1 is more about joining yoga class, studio. Looking at keto practitioners' (having positive sentiment) topics, we notice that they tweet mostly about the keto/lowcarb recipe, sugar free diet (Topic 0 in Fig. 6b). On the other hand, topic 1 of practitioner mostly focus on practitioners' positive sentiment about weight loss, diet, meal plan.

Conclusion and Future Work

In this paper, we propose a weakly supervised graph embedding based EM-style framework to characterize user types in social media. To demonstrate our model's effectiveness, we

(a) yoga: practitioner

(b) keto: practitioner

Figure 6: Wordclouds of top 10 keywords in each topic from yoga and keto practitioners' tweets having positive sentiment. Only 2 topics from each dataset are shown here.

perform extensive experiments on real-world datasets focusing on 'yoga' & 'keto diet' and our model outperforms the baselines. We perform data analysis on different user types from our data to show the topics from users' tweets and frequently used words in users' descriptions. Using our model with minimal tweaking in keywords selection for generating weak labels, we can distinguish any user types though they are not from the yoga/keto lifestyle communities. Our work can lead to new discussions on the analysis of health users' account types. While we focus specifically on lifestyle-related tweets, our approach is a general framework that can be adapted to other corpora. In the future, we aim to expand our work to detect communities based on different lifestyle decisions and understand their motivations.
Our code and the data are available here.[2]

Ethics Statement

To the best of our knowledge no code of ethics has been violated throughout the annotations and experiments done in this paper. We use illustrative examples to show the Twitter user profile descriptions, tweets in Fig. 1. As our dataset is comprised of tweets, we will share the original data based upon request for research purpose only.

Acknowledgments

We gratefully acknowledge Md Masudur Rahman and the anonymous reviewers for their insightful comments. We further thank our annotators. This work was partially supported by an NSF CAREER award IIS-2048001.

[2]https://github.com/tunazislam/WeakSupervised-GraphEmb-UserRep

References

Amir, S.; Coppersmith, G.; Carvalho, P.; Silva, M. J.; and Wallace, B. C. 2017. Quantifying mental health from social media with neural user embeddings. *arXiv preprint arXiv:1705.00335*.

Belkin, M.; Niyogi, P.; and Sindhwani, V. 2006. Manifold regularization: A geometric framework for learning from labeled and unlabeled examples. *Journal of machine learning research*, 7(11).

Blair-Goldensohn, S.; Hannan, K.; McDonald, R.; Neylon, T.; Reis, G.; and Reynar, J. 2008. Building a sentiment summarizer for local service reviews.

Blei, D. M.; Ng, A. Y.; and Jordan, M. I. 2003. Latent dirichlet allocation. *the Journal of machine Learning research*, 3: 993–1022.

Brody, S.; and Elhadad, N. 2010. An unsupervised aspect-sentiment model for online reviews. In *Human language technologies: The 2010 annual conference of the North American chapter of the association for computational linguistics*, 804–812.

Cohen, J. 1960. A coefficient of agreement for nominal scales. *Educational and psychological measurement*, 20(1): 37–46.

De Choudhury, M.; Gamon, M.; Counts, S.; and Horvitz, E. 2013. Predicting depression via social media. In *Seventh international AAAI conference on weblogs and social media*.

Del Tredici, M.; Marcheggiani, D.; Walde, S. S. i.; and Fernández, R. 2019. You Shall Know a User by the Company It Keeps: Dynamic Representations for Social Media Users in NLP. *arXiv preprint arXiv:1909.00412*.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 4171–4186.

Dredze, M. 2012. How social media will change public health. *IEEE Intelligent Systems*, 27(4): 81–84.

Ebrahimi, M.; ShafieiBavani, E.; Wong, R.; and Chen, F. 2018. A unified neural network model for geolocating twitter users. In *Proceedings of the 22nd Conference on Computational Natural Language Learning*, 42–53.

Golbeck, J.; Robles, C.; Edmondson, M.; and Turner, K. 2011. Predicting personality from twitter. In *2011 IEEE third international conference on privacy, security, risk and trust and 2011 IEEE third international conference on social computing*, 149–156. IEEE.

Gopinath, S.; Thomas, J. S.; and Krishnamurthi, L. 2014. Investigating the relationship between the content of online word of mouth, advertising, and brand performance. *Marketing Science*, 33(2): 241–258.

Goyeche, J. R. 1979. Yoga as therapy in psychosomatic medicine. *Psychotherapy and Psychosomatics*, 31(1-4): 373–381.

Grover, A.; and Leskovec, J. 2016. node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining*, 855–864.

Hochreiter, S.; and Schmidhuber, J. 1997. Long short-term memory. *Neural computation*, 9(8): 1735–1780.

Huang, B.; and Carley, K. M. 2019. A Hierarchical Location Prediction Neural Network for Twitter User Geolocation. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 4734–4744.

Hutto, C.; and Gilbert, E. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 8.

Islam, T. 2019. Yoga-Veganism: Correlation Mining of Twitter Health Data. *arXiv preprint arXiv:1906.07668*.

Islam, T.; and Goldwasser, D. 2020. Does yoga make you happy? analyzing twitter user happiness using textual and temporal information. In *2020 IEEE International Conference on Big Data (Big Data)*, 4241–4249. IEEE.

Islam, T.; and Goldwasser, D. 2021a. Analysis of Twitter Users' Lifestyle Choices using Joint Embedding Model. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 15, 242–253.

Islam, T.; and Goldwasser, D. 2021b. Do You Do Yoga? Understanding Twitter Users' Types and Motivations using Social and Textual Information. In *2021 IEEE 15th International Conference on Semantic Computing (ICSC)*, 362–365. IEEE.

Johnstone, A. M.; Horgan, G. W.; Murison, S. D.; Bremner, D. M.; and Lobley, G. E. 2008. Effects of a high-protein ketogenic diet on hunger, appetite, and weight loss in obese men feeding ad libitum. *The American journal of clinical nutrition*, 87(1): 44–55.

Jokar, E.; and Mosleh, M. 2019. Community detection in social networks based on improved Label Propagation Algorithm and balanced link density. *Physics Letters A*, 383(8): 718–727.

Khalsa, S. B. S. 2004. Treatment of chronic insomnia with yoga: A preliminary study with sleep–wake diaries. *Applied psychophysiology and biofeedback*, 29(4): 269–278.

Kingma, D. P.; and Ba, J. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Kosinski, M.; Stillwell, D.; and Graepel, T. 2013. Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the national academy of sciences*, 110(15): 5802–5805.

Loshchilov, I.; and Hutter, F. 2018. Decoupled Weight Decay Regularization. In *International Conference on Learning Representations*.

Lynn, V.; Balasubramanian, N.; and Schwartz, H. A. 2020. Hierarchical modeling for user personality prediction: The role of message-level attention. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 5306–5316.

McKenzie, A. L.; Hallberg, S. J.; Creighton, B. C.; Volk, B. M.; Link, T. M.; Abner, M. K.; Glon, R. M.; McCarter, J. P.; Volek, J. S.; and Phinney, S. D. 2017. A novel intervention including individualized nutritional recommendations reduces hemoglobin A1c level, medication use, and weight in type 2 diabetes. *JMIR diabetes*, 2(1): e5.

McPherson, M.; Smith-Lovin, L.; and Cook, J. M. 2001. Birds of a feather: Homophily in social networks. *Annual review of sociology*, 27(1): 415–444.

Mishra, P.; Del Tredici, M.; Yannakoudakis, H.; and Shutova, E. 2019. Abusive language detection with graph convolutional networks. *arXiv preprint arXiv:1904.04073*.

Mishra, P.; Yannakoudakis, H.; and Shutova, E. 2018. Neural character-based composition models for abuse detection. *arXiv preprint arXiv:1809.00378*.

Miura, Y.; Taniguchi, M.; Taniguchi, T.; and Ohkuma, T. 2017. Unifying text, metadata, and user network representations with a neural network for geolocation prediction. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 1260–1272.

O'Connor, B.; Balasubramanyan, R.; Routledge, B.; and Smith, N. 2010. From tweets to polls: Linking text sentiment to public opinion time series. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 4.

Pantic, I. 2014. Online social networking and mental health. *Cyberpsychology, Behavior, and Social Networking*, 17(10): 652–657.

Paoli, A.; Rubini, A.; Volek, J.; and Grimaldi, K. 2013. Beyond weight loss: a review of the therapeutic uses of very-low-carbohydrate (ketogenic) diets. *European journal of clinical nutrition*, 67(8): 789–796.

Pennington, J.; Socher, R.; and Manning, C. D. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, 1532–1543.

Perozzi, B.; Al-Rfou, R.; and Skiena, S. 2014. Deepwalk: Online learning of social representations. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*, 701–710.

Rahimi, A.; Vu, D.; Cohn, T.; and Baldwin, T. 2015. Exploiting Text and Network Context for Geolocation of Social Media Users. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 1362–1367.

Reece, A. G.; Reagan, A. J.; Lix, K. L.; Dodds, P. S.; Danforth, C. M.; and Langer, E. J. 2017. Forecasting the onset and course of mental illness with Twitter data. *Scientific reports*, 7(1): 13006.

Ribeiro, M. H.; Calais, P. H.; Santos, Y. A.; Almeida, V. A.; and Meira Jr, W. 2018. Characterizing and detecting hateful users on twitter. *arXiv preprint arXiv:1803.08977*.

Ross, A.; and Thomas, S. 2010. The health benefits of yoga and exercise: a review of comparison studies. *The journal of alternative and complementary medicine*, 16(1): 3–12.

Schuster, M.; and Paliwal, K. K. 1997. Bidirectional recurrent neural networks. *IEEE transactions on Signal Processing*, 45(11): 2673–2681.

Schwartz, H. A.; Eichstaedt, J. C.; Kern, M. L.; Dziurzynski, L.; Lucas, R. E.; Agrawal, M.; Park, G. J.; Lakshmikanth, S. K.; Jha, S.; Seligman, M. E.; et al. 2013a. Characterizing Geographic Variation in Well-Being Using Tweets. *ICWSM*, 13: 583–591.

Schwartz, H. A.; Eichstaedt, J. C.; Kern, M. L.; Dziurzynski, L.; Ramones, S. M.; Agrawal, M.; Shah, A.; Kosinski, M.; Stillwell, D.; Seligman, M. E.; et al. 2013b. Personality, gender, and age in the language of social media: The open-vocabulary approach. *PloS one*, 8(9): e73791.

Schwartz, H. A.; Sap, M.; Kern, M. L.; Eichstaedt, J. C.; Kapelner, A.; Agrawal, M.; Blanco, E.; Dziurzynski, L.; Park, G.; Stillwell, D.; et al. 2016. Predicting individual well-being through the language of social media. In *Biocomputing 2016: Proceedings of the Pacific Symposium*, 516–527. World Scientific.

Sindhwani, V.; and Melville, P. 2008. Document-word co-regularization for semi-supervised sentiment analysis. In *2008 Eighth ieee international conference on data mining*, 1025–1030. IEEE.

Smith, K. B.; and Pukall, C. F. 2009. An evidence-based review of yoga as a complementary intervention for patients with cancer. *Psycho-Oncology: Journal of the Psychological, Social and Behavioral Dimensions of Cancer*, 18(5): 465–475.

Speriosu, M.; Sudan, N.; Upadhyay, S.; and Baldridge, J. 2011. Twitter polarity classification with label propagation over lexical links and the follower graph. In *Proceedings of the First workshop on Unsupervised Learning in NLP*, 53–63.

Subramanya, A.; and Bilmes, J. 2008. Soft-supervised learning for text classification. In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, 1090–1099.

Talukdar, P.; Reisinger, J.; Pasca, M.; Ravichandran, D.; Bhagat, R.; and Pereira, F. 2008. Weakly-supervised acquisition of labeled class instances using graph random walks. In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, 582–590.

Talukdar, P. P.; and Crammer, K. 2009. New regularized algorithms for transductive learning. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, 442–457. Springer.

Tang, J.; Qu, M.; Wang, M.; Zhang, M.; Yan, J.; and Mei, Q. 2015. Line: Large-scale information network embedding. In *Proceedings of the 24th international conference on world wide web*, 1067–1077.

Van der Maaten, L.; and Hinton, G. 2008. Visualizing data using t-SNE. *Journal of machine learning research*, 9(11).

Wang, Y.; and Pal, A. 2015. Detecting emotions in social media: A constrained optimization approach. In *Twenty-fourth international joint conference on artificial intelligence*.

Yang, C.; and Srinivasan, P. 2016. Life satisfaction and the pursuit of happiness on Twitter. *PloS one*, 11(3): e0150881.

Yang, Y.; and Eisenstein, J. 2017. Overcoming language variation in sentiment analysis with social attention. *Transactions of the Association for Computational Linguistics*, 5: 295–307.

Yurtkuran, M.; Alp, A.; and Dilek, K. 2007. A modified yoga-based exercise program in hemodialysis patients: a randomized controlled study. *Complementary therapies in medicine*, 15(3): 164–171.

Zhu, X.; and Ghahramani, Z. 2002. Learning from Labeled and Unlabeled Data with Label Propagation. Technical report.