

Analysis of Twitter Users' Lifestyle Choices using Joint Embedding Model

.

.

Tunazzina Islam. Dan Goldwasser

Department of Computer Science, Purdue University, West Lafayette, IN-47907

Background

Motivation

- Multiview representation of social media data.
- Construct coherent and contextualized user representations.
- Analyze users' activity type and motivation for specific lifestyle. Contribution
- Annotated dataset related to 'voga' and 'keto diet'.
- A joint embedding model incorporating users' social and textual information.
- Extensive empirical experiments.
- Qualitative analysis to describe relationship between output labels and several different indicators, i.e., tweets, descriptions, location,
 - Downstream Tasks
- Finding user type, i.e., Practitioner, Promotional, Other,
- Finding user motivation, i.e., Health, Spiritual, Other.

Data

Collection

- Yoga data
 - ~ 0.4 million yoga-related tweets from Twitter.
 - 1298 users: at least 5 yoga-related tweets.
- Keto data
 - ~ 75k keto-related tweets from Twitter .
 - 1300 users: at least 2 keto-related tweets.

Pre-processing

- Convert to lower case.
- Remove URLs, smiley, emoji,
- Tokenize text using BERT and RoBERTa's wordpiece tokenizer.

Annotation

- 1 annotator, with annotation instruction and examples provided.
- To calculate % agreement, 2 graduate students annotate a subset of tweets having inter-annotator agreement 64.7%.

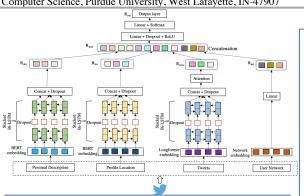
Model

Tweets Representation, Rtwts

- Concatenate all yoga/keto-related tweets representing long documents.
- Embedding with longformer-base-4096.
- Pass to stacked Bi-LSTM with dropout (0.5).
- Hidden representation by concatenating forward and backward directions with dropout (0.5).
- Use context-aware attention

Metadata Representation, Rdes and Rloc

- Embedding with uncased BERTbase.
- Pass to stacked Bi-LSTM with dropout (0.5).
- Hidden representation by concatenating forward and backward directions with dropout (0.5).



Network Representation, Rnet

- Dense user network considering users from dataset if they are @-mentioned.
- Nodes: all users in the dataset.

- An edge: if either user mentions/retweets the other (from our data). .
- Use Node2Vec for computing node embedding. .
- Pass through a linear layer.

User Representation, Ruser

- Concatenate four representations: Ruser = [Rdes, Rloc, Rtwts, Rnet]
- Feed to a fully connected two-layer classifier activated by ReLU and softmax.
- Use dropout between individual neural network layers.
- SGD over shuffled mini-batches with Adam. .
- Cross-entropy loss as the objective function for classification. •

Results

Model	User type		User motivation	
	Accuracy	Macro-avg F1	Accuracy	Macro-avg F1
Description	0.694	0.611	0.707	0.523
Location	0.639	0.520	0.694	0.517
Tweets	0.795	0.704	0.786	0.595
Network	0.726	0.561	0.798	0.590
Des_BF	0.718	0.681	0.771	0.528
Loc_BF	0.679	0.606	0.695	0.476
Twts_BF	0.760	0.669	0.805	0.551
Des + Loc	0.734	0.653	0.806	0.661
Des + Net	0.808	0.702	0.823	0.653
Des + Loc + Twt	0.778	0.705	0.808	0.603
Des + Loc + Net	0.774	0.725	0.806	0.663
Word2Vec based joint embedding	0.790	0.742	0.844	0.610
Our Model	0.802	0.757	0.853	0.708

- Yoga user type: Accuracy: 80.2%, Macro-avg F1: 75.7%
- Yoga user motivation: Accuracy: 85.3%, Macro-avg F1: 70.8%
- Keto user type: Accuracy: 71.9%, Macro-avg F1: 67.6%

- Analysis **Top Hashtags** In yoga dataset, the popular hashtag #namaste ('bow me you' or 'I bow to you'), #gfyh ('Go 4 Yoga Health'), #mantra ('vehicle of the mind'). Keto diet is related to low carb high-fat diet having common hashtag #lchf. **Relationship between Tweets and Labels** Yoga practitioners' wordcloud: practice, love, pose, class, meditation, mind, mantra, thank, gfyh, vogaevervwhere. Yoga promotionals' wordcloud: class, studio, come, train, teacher, workshop, free, mat, offer. Other users mostly retweet and share news of yoga/yogi rather than directly practicing or promoting yoga. They have noticeable words such as rt, reiki, sadhguru, isha, yogaday in wordcloud. Keto practitioners' wordcloud: diet, low carb, fat, carnivore, ketosis, start, go, try, love, fast, protein, meat, egg. Keto promotionals' wordcloud: recipe, paleo, weight loss, delicious, meal prep, money, healthy, organic, yummy.
- Other keto users: rt, ketodietapp, ketogenic diet, ketone, low carb, cook, health benefit.

Relationship between Descriptions and Labels

- Yoga practitioners' wordcloud: yoga, teacher, health, fitness, meditation, lover, coach, founder, author, writer, instructor. certify.
- Yoga promotionals' wordcloud: yoga, fitness, wellness, community, event, offer, free, product, market, business, program, design.
- Users who practice yoga for health benefits have similar wordcloud to yoga practitioners' descriptions.
- Spiritually motivated yoga user having words like yoga, spiritual, spirituality, devotee, wisdom, peace, seeker, vogi, meditator, Indian.
- Keto practitioners' wordcloud: keto, love, life, food, family.
- Keto promotionals' wordcloud: food, health, keto, meal, recipe, product, online, free.

Relationship between Location and Labels

- We observe that we have more practitioners and promotional yoga users from the USA than the rest of the world.
- We find South-Asian users mostly retweet about voga. We notice more 'others' users than practitioners in India.
- Most of the yoga users from India are motivated spiritually
 - For keto, we notice that our data is skewed towards the USA

Error Analysis

- Profile description, tweets, and network field contribute mainly to the classification task.
- Some prediction errors arise when description fields are absent or misleading.
- User location has relatively low accuracy and macro-avg F1 score according to ablation study.
- As Longformer supports sequences of length up to 4096, we might lose some information from tweets if the size of concatenated tweets > 4096.
- We construct @-mentioned network directly from retweets/mentions in tweets, which is less expensive to collect than the following network

Conclusion & Future Work

- We propose a BERT based joint embedding model that explicitly learns contextualized user representations by leveraging users' social and textual information.
- We show that our model outperforms multiple baselines.
- Besides voga, we demonstrate that our model can effectively predict user type on another lifestyle choice, e.g., 'keto diet' and our approach is a general framework that can be adapted to other corpora.
- In the future, we aim to investigate our work to a broader impact like community detection based on different lifestyle decisions using minimal supervision.