Twitter User Representation Using Weakly Supervised Graph Embedding

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How do people talk about Life-Style & Well-Being?

@susan

Description : Boy mom, wife, Engineer, Zumba Instructor, Keto Enthusiast.

Tweet1: #fitleaders my Keto Pancakes recipe: 4 eggs, 4 oz cream cheese, 1/2 cup almond flour, fresh blueberries Pancakes. #ketolife

Tweet2 : Almost year 4 on Keto and finally found a cereal substitute #ketodiet #granola #HealthyEating

@keto_collab

Description: We are Ketogenic Information Collaborator. We collect information from Various Keto channels and Tweet it out for you.

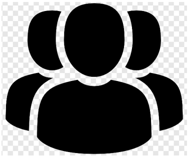
Tweet1: Keto Frosted Flakes Cereal Recipe - Low Carb "Corn Flakes Alternative" https://myketokitchen.com/keto-recipes/

Tweet2: The latest The Ketogenic diet Daily! https://paper.li/KetoDietDaily

Our Goal

- Formulate a novel problem of exploiting weak supervision for characterizing users in social media.
- Suggest a graph embedding based Expectation–maximization (EM)-style approach.
- Conduct extensive experiments on real-world datasets to demonstrate the effectiveness of the model.

Roadmap

	Brief Introduction to Graph Embedding Model
	Dataset Collection and Annotation
	Automatic User Characterization
	User Type Analysis

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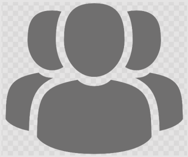	Automatic User Characterization
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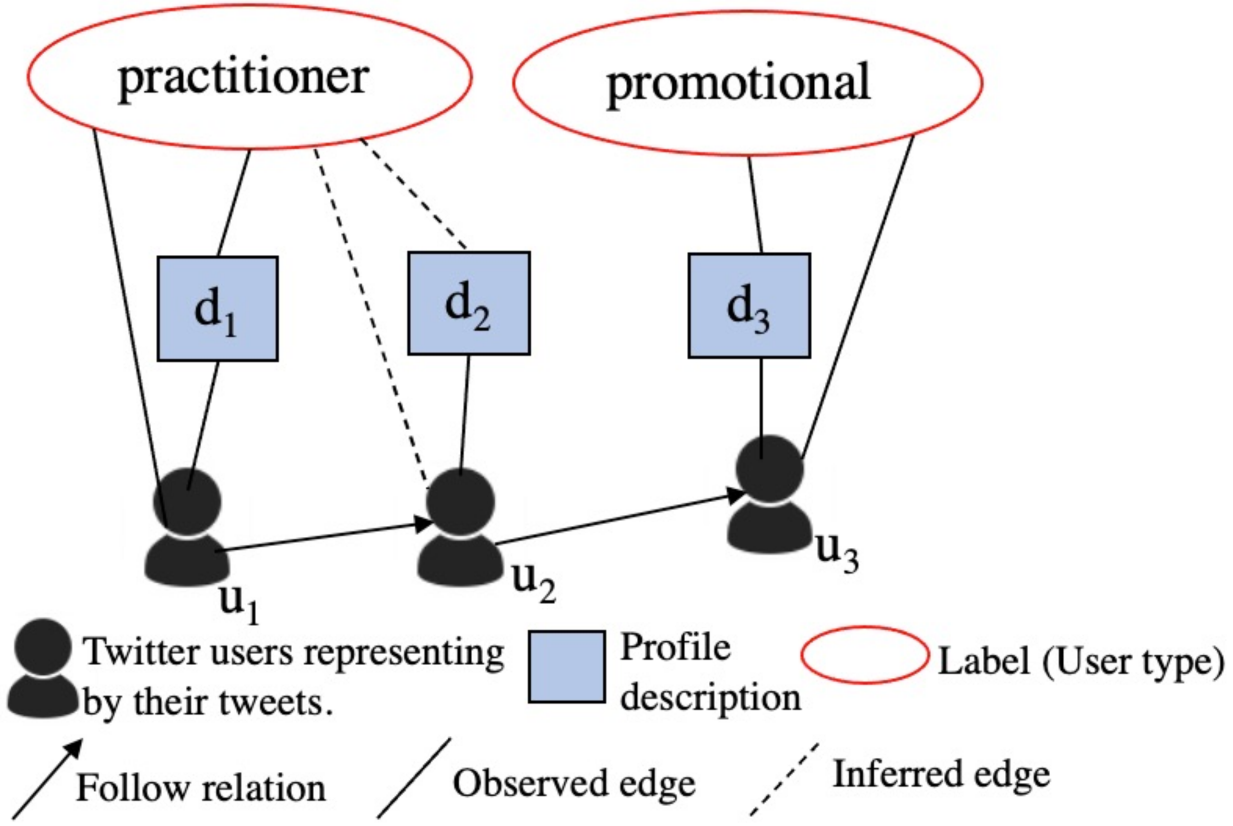
Information Graph Creation

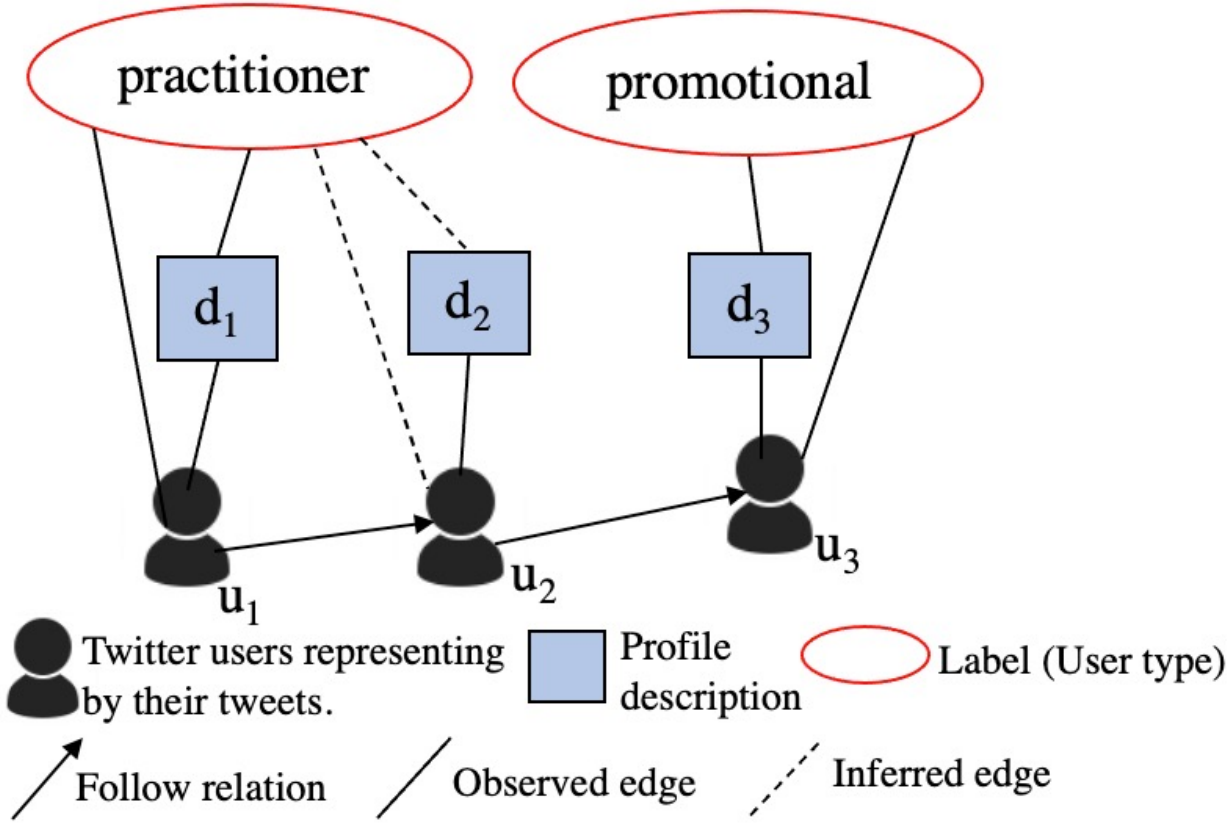
- Nodes:
  - users representing by tweets
  - profile description
  - user type

- Edges:
  - profile description-to-user type
  - user-to-user type
  - profile description-to-user
  - user-user



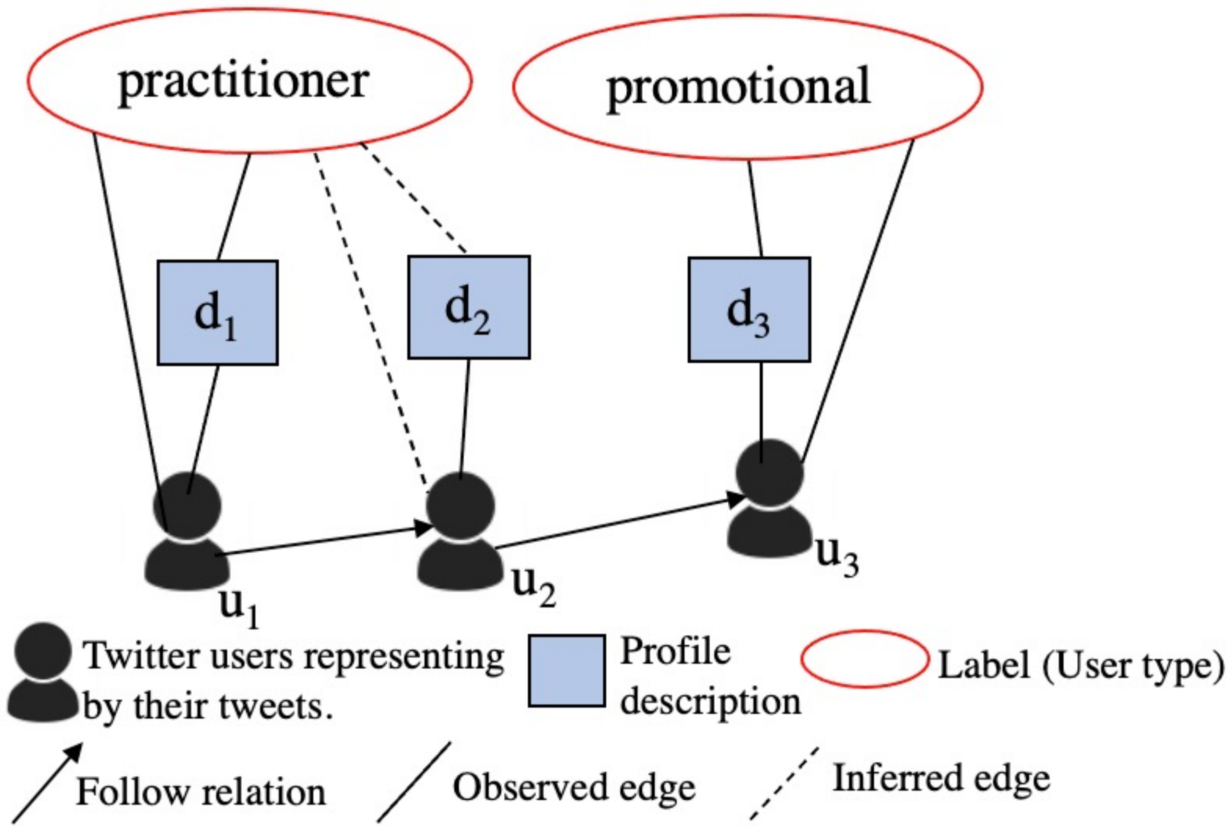
Information Graph Embedding

- Embed nodes in a common embedding space.
- Maximize similarity between two instances in the embedding space if –
  1. profile description has a type,
  2. a user has a type.
- Train embedding following a negative sampling approach.



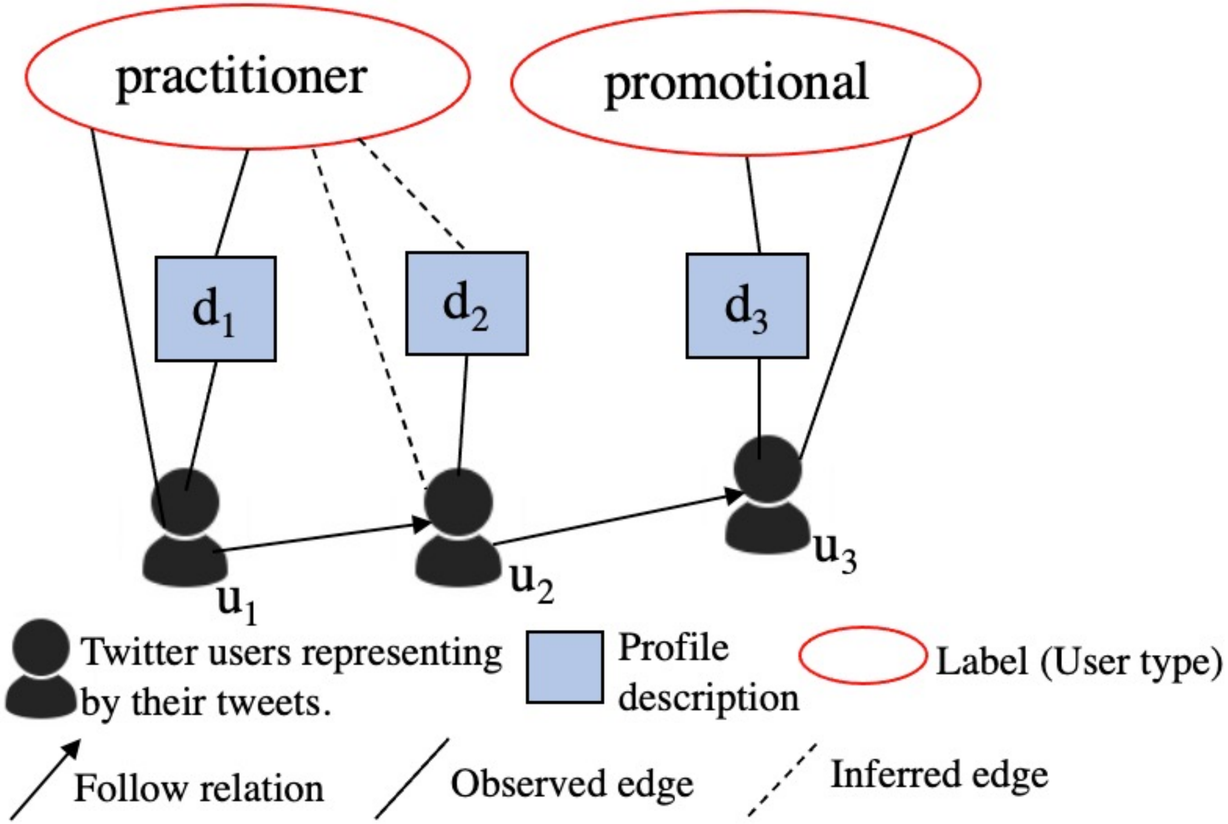
Inference Function

- Edge connections based on the learned node representations.
- Connecting the nodes with the top k scores.



EM-style Learning Approach

- **Step 1:** Learn information graph embedding.
- **Step 2:** Apply inference function to infer unlabeled users.
- **Step 3:** Stopping criterion.
  - At each iteration, after Step 2, check the model convergence.



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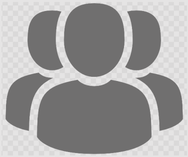

Automatic User Characterization

User Type Analysis

Dataset

- **13k yoga users** and **14k keto users** from May-November 2019 from Twitter.

- Holdout Data Annotation :
  - Manually annotated **786 yoga users** and **908 keto users** using binary label ‘practitioner’, ‘promotional’.
  - 1 annotator, with annotation instruction and examples provided.
  - To calculate % agreement, 2 graduate students annotate a subset of tweets having inter-annotator agreement 65% (substantial agreement).

- Constructing Weak Labels
  - Keyword based knowledge extraction from profile description.

- Quality of Weak Labeling:
  - 451 yoga users and 56 keto users have both weak and ground truth label
  - Yoga: accuracy 79%, macro-avg F1 score 78%
  - Keto: accuracy 86%, macro-avg F1 score 67%

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Models

- Our Model: **EM-Style Approach**
- Baseline Models:
  - Weakly Supervised Baseline:
    - Label Propagation
  - Supervised Baseline:
    - LSTM_Glove
    - Fine-tuned BERT

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**

EM-Style approach outperforms all baselines

- Our Model: EM-Style Approach
  - Yoga:
    - Accuracy: 78%
    - Macro-avg F1 score: 76%
  - Keto:
    - Accuracy: 72%
    - Macro-avg F1 score: 64%

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Does Multiview Information Help?

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

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Multiview information improves prediction performance compared to the models using only either profile description or user network information.

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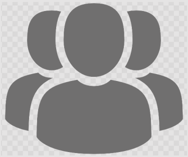	Automatic User Characterization
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Tweets and Labels

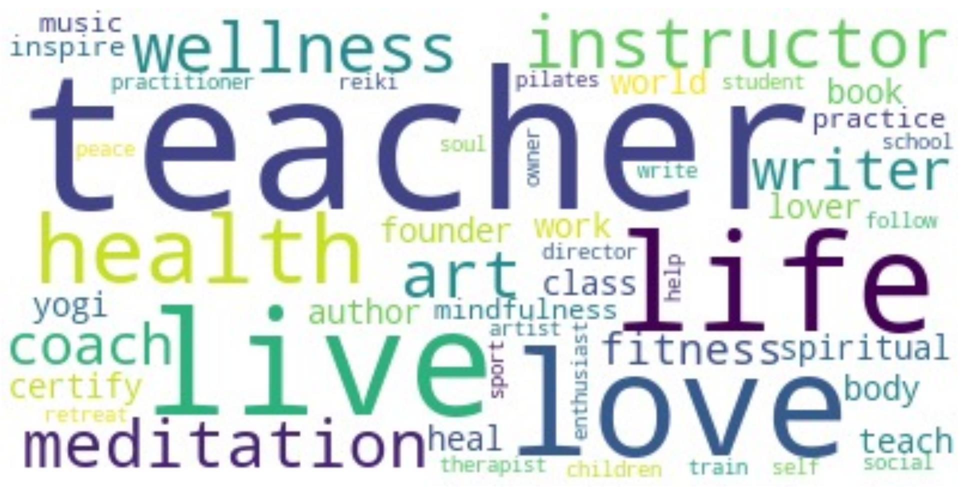
(a) yoga: practitioner

(b) yoga: promotional

(c) keto: practitioner

(d) keto: promotional

Profile Description and Labels



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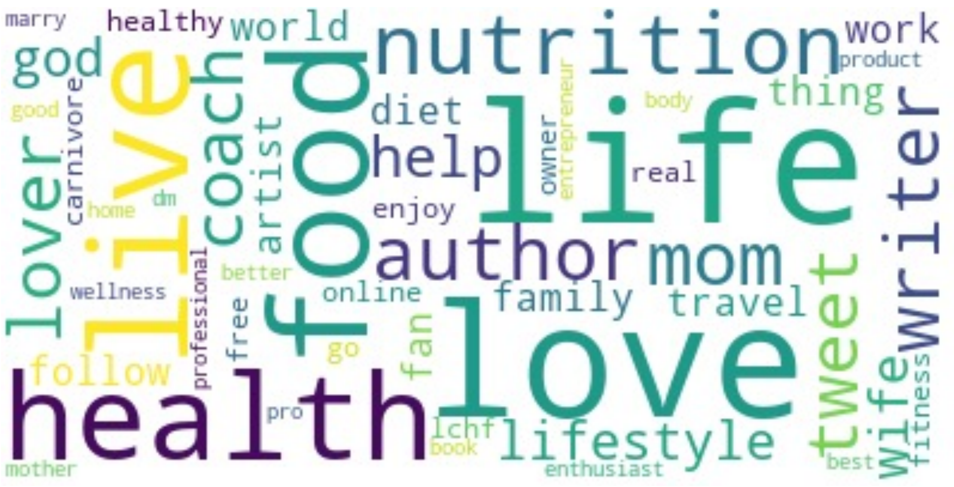

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(d) keto: promotional

Users' Sentiment Analysis

(a) yoga: practitioner

(b) keto: practitioner

Summary of Contributions

- Formulate a novel problem of exploiting weak supervision for characterizing users in social media.
- Suggest a graph embedding based EM-style approach for learning and reasoning to construct like-minded users incrementally.
- Generate weak labels from user's profile description along with quantitative quality assessment.
- Conduct extensive experiments on real-world datasets to demonstrate the effectiveness of the model.

THANK YOU ☺

Slide: https://tunazislam.github.io/files/ICWSM22_yoga_keto.pdf

Questions?

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