Learning User Embeddings from Temporal Social Media Data: A Survey

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Abstract

User-generated data on social media contain rich information about who we are, what we like and how we make decisions. In this paper, we survey representative work on learning a concise latent user representation (a.k.a. user embedding) that can capture the main characteristics of a social media user. The learned user embeddings can later be used to support different downstream user analysis tasks such as personality modeling, suicide risk assessment, substance use modeling, and depression detection. The temporal nature of user generated data on social media has largely been overlooked in much of the existing user embedding literature. In this survey, we focus on research that bridges the gap by incorporating temporal/sequential information in user representation learning. We categorize relevant papers along several key dimensions, identify limitations in the current work and suggest future research directions.

1 Introduction

The continual creation and archiving of rich user-generated content on social media sites has given us an opportunity to capture the main characteristics of social media users including their personality traits and decision-making processes. Past research has demonstrated that user embedding, a mostly unsupervised machine learning process to derive concise latent user representations from raw social media content (e.g. text and image posts, likes, and friendship relations) is an effective approach for user modeling [Pan and Ding, 2019; Ding et al., 2017; Pennacchiotti and Popescu, 2011]. These learned user embeddings can later be used in diverse downstream user analysis tasks such as user preference prediction [Pennacchiotti and Popescu, 2011], personality modeling [Kosinski et al., 2013], substance use detection [Ding et al., 2018], social connection recommendation [Liu et al., 2020] and depression detection [Amir et al., 2017].

An often overlooked aspect of social media based user embedding is the temporal nature of user-generated content, often spanning multiple years with precise timestamp annotations, which makes these data streams ideal for longitudinal analysis of human behavior. For example, by learning the social media posting patterns of individuals, it is possible to track episodic outbursts of angry posts and make inferences about their personality, such as their level of impulsivity. Incorporating temporal information has traditionally been explored in the signal processing, ubiquitous computing, and network science research communities. There is also a large body of work in the natural language processing (NLP) community on sequential data mining. We argue that by exploring different technologies developed in diverse communities, we may uncover new solutions for temporal user embedding.

Although smaller in number than papers on user embeddings that do not consider time, there has been a growing amount of research on temporal user embedding with social media data. Our survey is an attempt to summarize these emerging technologies and at the same time, provide the community some suggestions on how we can go forward.

2 Overview

Given the limited space, we define a relatively narrow scope to include only user embedding methods that incorporate temporal information. Our scope includes node embedding methods that use dynamic social networks (where each node represents a user). We exclude methods that do not use data from typical social media sites such as Facebook, Twitter, Flickr, Stack Overflow, Reddit, Google+, Digg, and Foursquare. We further refine the scope by including only methods published within the last ten years. Table 1 is an overview of these articles. We will occasionally discuss out-of-scope articles on temporal modeling methodology as they are applicable to social media data, but will not include them in the Table. We survey each article based on the input data type, output embedding type, and the downstream tasks that employ these embeddings.

3 Input Data & Output Embedding Type

In the literature, we found five categories of input data being used to learn user embeddings from temporal social media streams: (i) text, (ii) image, (iii) user activity, (iv) network/graph, and (v) multi-modal. Texts may include sequences of tweet streams or Facebook status updates, and...
| Paper | Input Data Type | Output Embedding Type | Downstream Task |
|-------|-----------------|-----------------------|-----------------|
|       |                 | Static/ Dynamic Single/Joint |                  |
| [Sang et al., 2015] | Text | Dynamic | Single | Personalized Information Recommendation, Long-term and Short-term Interest |
| [Liang et al., 2018] | Text | Dynamic | Joint (user-word) | Top-K Relevant and Diversified Keywords to Profile Users’ Dynamic Interests |
| [Yin et al., 2014] | User Activity | Dynamic | Joint (user-temporal) | Temporal Recommendation |
| [Khodadadi et al., 2018] | User Activity | Static | Joint (user-temporal) | Time Prediction, Mark Prediction |
| [Yin et al., 2015] | User Activity | Dynamic | Joint (user-temporal) | Temporal Recommendation |
| [Li et al., 2017] | Multimodal | Dynamic | Single | Node (User) Classification, Network Clustering |
| [Liu et al., 2020] | Multimodal | Static | Single | Node (User) Classification, Network Reconstruction, Link (Friendship) Prediction |
| [Noorshams et al., 2020] | Multimodal | Static | Single | Fake Account Detection, Misinformation Detection, Ad Payment Risk Detection |
| [Kumar et al., 2019] | Multimodal | Dynamic | Joint (user-item in separate space) | Future Interaction Prediction, User State Change Prediction |
| [Fani et al., 2020] | Multimodal | Static | Single | Personalized News Recommendation, User Prediction |
| [Costa et al., 2017] | User activity | Static | Single | Bot Detection |
| [Yu et al., 2018] | Network | Static | Single | Anomaly Detection |
| [Xiong et al., 2019] | Graph | Dynamic | Single | Link Prediction (Friendship), Link Reconstruction |
| [Gong et al., 2020] | Network | Dynamic | Single | Link Reconstruction, Changed Link Prediction |
| [Beladev et al., 2020] | Graph | Dynamic | Single | Anomaly Detection, Trend Analysis |
| [Gao et al., 2017] | Network | Static | Joint (user-info) | Information Diffusion Prediction |
| [Wu et al., 2017] | Image | Static | Joint (user-photo) | Photo Popularity Prediction |
| [Wu et al., 2016] | Multimodal | Static | Joint (user-item in separate space) | Photo Popularity Prediction |
| [Yin et al., 2013] | Multimodal | Static | Joint (user-temporal) | Stable and Temporal Topic Detection |
| [Diao et al., 2012] | Text | Static | Joint (user-temporal) | Finding Bursty Topic |
| [Xie et al., 2016] | Multimodal | Dynamic | Joint (user-POI) | POI Recommendation |
| [Zhuo et al., 2019] | Multimodal | Static | Single | Information Diffusion Prediction, Influence Relationship Prediction |
| [Qiu et al., 2020] | Multimodal | Static | Single | Link Prediction (Friendship), Node (User) Classification, Network Reconstruction |
| [Zhao et al., 2017] | User activity | Static | Joint (user-POI in separate space) | POI Recommendation |
| [Du et al., 2016] | User activity | Static | Joint (user-temporal) | Time Prediction, Event Prediction |
| [Yang et al., 2017] | Network | Static | Single | Temporal Link Prediction |
| [Xu, 2015] | Network | Dynamic | Single | Time Prediction |
| [Zhang et al., 2018] | Multimodal | Static | Single | Photo Popularity Prediction |
| [Nguyen et al., 2018] | Network | Static | Single | Temporal Link Prediction |

Table 1: High level summary of user embedding methods from temporal social media data

*images* are sequences of photos shared by users. User activity data refer to the timestamped records of users performing certain actions such as liking a post, rating a review, asking/answering a question (e.g., on Stack Overflow), and check-ins (e.g., on Facebook or Twitter). The dynamically created social networks (e.g., the friendship network on Facebook and the follower/reweet network on Twitter) constitute a sequence of networks at different timestamps. Finally, multi-modal data is a combination of multiple types of input data streams such as network-text, user activity-text, and image-user activity.

We also categorize output embeddings along two dimensions: (i) static vs. dynamic, (ii) single vs. joint-embedding.

**Static vs. Dynamic Embedding:** With a *static* user embedding, for a given user, the system outputs only one time-independent representation. In contrast, *dynamic* user embed-
Single vs. Joint Embedding: Single user embedding only learns user representations. Joint embedding, on the other hand, learns not only user representations but also representations of other related entities such as text, time, image, and item. Depending on whether different types of embeddings are in the same or separate space, joint embedding can be divided into two categories: (i) shared space, (ii) separate space. For example, [Liang et al., 2018] learn user and text representations jointly in the same shared embedding space, while [Kumar et al., 2019] learn user and item representation jointly but they are in separate embedding spaces. When user and entity embedding are in a shared space, in addition to user-user relations, we can also infer user-entity relations based on user and entity embeddings.

In the following, we summarize the methodology of learning temporal user embeddings. As the temporal representation plays an important role in determining proper temporal modeling methods, we first explain temporal representation.

4 Temporal Representation

There are various ways of encoding temporal information. We categorize them along two dimensions: (i) representation: discrete vs. continuous, (ii) duration: timestamp vs. interval-time vs. time-bin vs. time-window vs. temporal order.

Discrete vs. Continuous In order to learn user representations with temporal data, we need to decide how to represent time as a variable. With a discrete representation, time is discretized into regularly spaced intervals [Xu, 2015]. One may choose the granularity of these intervals (e.g., daily, monthly) based on the specific use case, sparsity of the events and the machine learning algorithms. The continuous representation of time, on the other hand, can accommodate irregularly spaced time intervals and allow the time variable to take the value of any real number. Therefore, within a time interval, in theory, there can be an infinite number of time points when an event can take place [Yin et al., 2014]

Timestamp vs. Interval time vs. Time-bin vs. Time-window vs. Temporal order The input representation can also be classified in terms of duration. A timestamp refers to the exact time of an action. For example, given a sequence of user posts created at different times $t$, we can record their timestamps as $(t_1, t_2, t_3, t_4, \ldots, t_i, \ldots, t_n)$. Since a timestamp is represented as a real number, by definition, it employs a continuous time representation. While timestamps can be directly used as an input to user representation learning algorithms, they can also be used for selecting input data in order to generate user embeddings at time $t$ [Li et al., 2017].

Interval time represents the time difference between two consecutive actions. For example, given a sequence of user posts at different times $(t_1, t_2, t_3, t_4, \ldots, t_i, \ldots, t_{n+1})$, the interval time $\Delta_t$ can be defined as $(\Delta_1, \Delta_2, \Delta_3, \ldots, \Delta_n) = (t_2 - t_1, t_3 - t_2, t_4 - t_3, \ldots, t_{n+1} - t_n)$. Since the sequence of time intervals is irregularly spaced, this is a continuous time representation [Yin et al., 2014; Noorshams et al., 2020].

A number of articles [Liang et al., 2018; Wu et al., 2016; Diao et al., 2012; Xie et al., 2016; Zhao et al., 2017] have also utilized a binning strategy to group input data in equal sized bins (e.g., weekly and monthly). Time-bins can be considered as either a discrete or continuous time representation, depending on the relative resolution between the size of the bin and the time span of the entire dataset. A daily time bin may be considered a continuous representation if the entire dataset spans over 10 years. It is typically considered discrete however if the time span of the entire dataset is only 10 days.

A time-window is defined as a fixed context window to select input features [Sang et al., 2015]. A time-window can be used to generate embeddings at time $t$ with the input data in the $t - \Delta$ to $t + \Delta$ range, where $\Delta$ is a configurable time-window size variable. Since it is regularly spaced, this is often considered a discrete-time representation.

A temporal order only preserves the sequential order of the inputs [Zhang et al., 2018]. A stream of tweets ordered by time falls into this category. Since it is not an explicit temporal representation, it is neither discrete nor continuous.

5 Methodology

In this section, we summarize the main methods for temporal user embeddings. We categorize them first in terms of machine learning methodology (shown in Table 2) and second in terms of temporal modeling methodology.

5.1 Machine Learning (ML) Methodology

The papers in our survey cover a wide variety of techniques originated from diverse fields such as statistical learning theory, probabilistic modeling, graph/network theory, and neural networks; they also vary widely in the amount of supervision they receive from labeled ground truth data, as well as their methods of modeling the input data space. Here, we categorize the machine learning methodology used in these papers along three dimensions:

Unsupervised vs. Self-supervised vs. Supervised The main difference between unsupervised and supervised ML pertains to the use of ground truth labels; the unsupervised approaches do not require any ground truth labels to derive embedding features while supervised methods require ground truth labels from the target task.

A self-supervised approach is a special case of supervised ML where training examples can be automatically constructed from raw input data (a.k.a. no human-provided ground truth labels are required). For this reason, self-supervised approaches are also sometimes referred to as unsupervised. Self-supervised approaches often rely on auxiliary training tasks for which a large number of training instances can be automatically constructed. Word2Vec [Mikolov et al., 2013] is a classic example of a self-supervised approach, learning the representation of words by predicting other words in its context (Skip-Gram). A user representation can be derived by aggregating all the words authored by the same user within a temporal context.
| Paper                          | Temporal Representations | ML Methologies          | Embedding Method                  |
|-------------------------------|--------------------------|-------------------------|-----------------------------------|
|                               | Continuous/Discrete      | Unsupervised/Supervised | Matrix-factorization/Neural Net   |
|                               | Interval time/Time-bin   | Discriminative/Generative | Hybrid                           |
|                               | Time window             |                         | LDA                               |
| [Sang et al., 2015]           | Discrete                 | Unsupervised Generative | Probabilistic                     |
| [Liang et al., 2018]          | Discrete                 | Self-supervised Hybrid  | Hybrid                            |
|                               | Time-bin                 |                         | Skip-gram extended by Kalman filter |
| [Yin et al., 2014]            | Continuous               | Unsupervised Generative | Probabilistic                      |
| [Khodadadi et al., 2018]      | Continuous               | Generative              | Topic Model                       |
| [Yin et al., 2015]            | Discrete                 | Unsupervised Generative | Probabilistic                      |
| [Li et al., 2017]             | Continuous               | N/A                     | Matrix-factorization              |
|                               | Timestamp                |                         | Matrix Decomposition              |
| [Liu et al., 2020]            | Continuous               | Unsupervised N/A        | Matrix-factorization              |
|                               | Time window             |                         | RNN, Attention                    |
| [Noorshams et al., 2020]      | Continuous               | Supervised Discriminative | Neural Net                        |
|                               | Interval time            |                         | Graph Embedding                   |
|                               |                          | Supervised Discriminative | Neural Net                        |
| [Yu et al., 2018]             | Continuous               | Unsupervised Discriminative | Neural Net                        |
| [Xiong et al., 2019]          | Continuous               | Supervised Discriminative | Neural Net                        |
| [Gong et al., 2020]           | Discrete                 | Unsupervised Discriminative | Neural Net                        |
|                               | Time window             |                          | GCN, LSTM                         |
| [Beladev et al., 2020]        | Continuous               | Supervised Discriminative | Neural Net                        |
|                               | Temporal order           |                          | Graph Embedding extended by CBOW  |
| [Gao et al., 2017]            | Continuous               | Self-supervised Discriminative | Neural Net                        |
| [Wu et al., 2017]             | Continuous               | Supervised Discriminative | Neural Net                        |
| [Wu et al., 2016]             | Discrete                 | Supervised N/A          | Matrix-factorization              |
| [Yin et al., 2013]            | Continuous               | Time window             | LDA                               |
| [Diao et al., 2012]           | Discrete                 | Unsupervised Generative | Probabilistic                      |
| [Xie et al., 2016]            | Discrete                 | Unsupervised Generative | Probabilistic                      |
| [Zhuo et al., 2019]           | Continuous               | Supervised Generative   | Graph Embedding                   |
|                               | Temporal order           |                          |                                  |
| [Qiu et al., 2020]            | Continuous               | Supervised Hybrid       | Neural Net                        |
| [Zhuo et al., 2017]           | Discrete                 | Self-supervised Discriminative | Neural Net                        |
| [Du et al., 2016]             | Continuous               | Supervised Hybrid       | Neural Net                        |
| [Yang et al., 2017]           | Continuous               | Unsupervised Generative | Probabilistic                      |
|                               | Time-bin                 |                          | Temporal Random Walk, Autoencoder |
| [Xu, 2015]                    | Discrete                 | Supervised Generative   | Temporal Point Process            |
| [Zhang et al., 2018]          | N/A                      | Temporal order          | Neural Net                        |
|                               | Supervised Discriminative | Neural Net                        |
| [Nguyen et al., 2018]         | Continuous               | Self-supervised Discriminative | Neural Net                        |

Table 2: Temporal representations and methodologies used in generating user embedding from temporal social media data

Supervised learning can be used to learn temporal user embeddings [Zhuo et al., 2019; Qiu et al., 2020; Wu et al., 2016; Wu et al., 2017; Noorshams et al., 2020], although this is uncommon. Unlike unsupervised or self-supervised embeddings, supervised user embeddings may not be generalizable as they are optimized specifically for only the target task.

In terms of the specific embedding methods employed, Latent Dirichlet Allocation (LDA) [Blei et al., 2003] is one of the most popular unsupervised feature learning methods employed in the survey articles to characterize a person using a mixture of topics conveyed in their social media posts [Sang et al., 2015; Yin et al., 2014; Yin et al., 2015; Yin et al., 2013; Diao et al., 2012]. Various extensions to LDA (e.g., Dynamic LDA [Blei and Lafferty, 2006]) have been proposed to model topic distributions across time. Other notable unsupervised methods include Temporal Point Process [Costa et al., 2017; Khodadadi et al., 2018], Spectral Embedding of Graphs [Li et al., 2017], and Singular Value Decomposition [Liu et al., 2020]. Recently, most
modern user embeddings approaches have used neural network-based self-supervised learning [Kumar et al., 2019; Beladev et al., 2020] due to the flexibility and scalability of these approaches.

### Discriminative vs. Generative

The main difference between generative and discriminative models boils down to how they model the input data distribution from a probabilistic perspective. Generative models learn the joint probability distributions of input and output, whereas discriminative models learn the conditional probability distribution of the output, given the input. Due to the generative model’s ability to model the distribution of the input data itself (as opposed to learning the mappings between the input and output), a large portion of the unsupervised methods follow a generative methodology such as LDA [Sang et al., 2015; Yin et al., 2015] and Temporal Point Process [Costa et al., 2017; Khodadadi et al., 2018].

Combining adversarial learning with generative models (as in GAN) has been gaining traction in modeling high-order proximity and temporal evolution in graph-structured data [Xiong et al., 2019] as these two properties were found to be particularly challenging to learn through a purely generative process [Zhou et al., 2018]. Under the GAN framework, a generator is tasked with creating a graph-based representation of the networks’ temporal evolution and the discriminator is used to assess the probability of the generated representation being real. Such models can be efficiently trained with back-propagation without relying on costly sampling strategy.

Dynamic graph embeddings can also be learned in a purely discriminative manner as long as sufficient ground truth for the training task is available [Noorshams et al., 2020; Fani et al., 2020; Yu et al., 2018; Beladev et al., 2020]. Other popular discriminative architectures include Word2Vec [Gao et al., 2017; Zhao et al., 2017] and autoregressive models (e.g. recurrent architectures) [Kumar et al., 2019; Gong et al., 2020; Wu et al., 2017].

Last but not least, several works have also had success with using a mixture of both generative and discriminative methodologies. For example, [Liang et al., 2018] extended a (discriminative) Skip-Gram model with a (generative) Kalman filter to capture the temporal dynamics of Twitter profiles. Similarly, [Qiu et al., 2020] combined a temporal random walk method with a supervised auto-encoding architecture to learn temporal network embeddings.

### Matrix-factorization vs. Probabilistic vs. Neural Network

Among the 29 articles we surveyed, around half of them use neural-networks as the underlying embedding-learning method. Others mostly follow a probabilistic approach, with only 3 utilizing matrix-factorization. Once a staple in text-based embedding learning and recommender systems, matrix decomposition techniques have fallen out of favor due to the prevalence of probabilistic (e.g. LDA) and neural-network based (e.g. Word2Vec) embedding methods. However, they are still used for constructing low dimensional representation of complex dynamic networks where the adjacency matrix remains incomplete and noisy [Li et al., 2017; Liu et al., 2020; Wu et al., 2016].

Among the probabilistic approaches, the works of [Diao et al., 2012; Yin et al., 2013; Yin et al., 2014; Yin et al., 2015; Sang et al., 2015] are notable for extending LDA across time to create temporal topic model. However, for more specialized use cases (e.g. predicting specific user action in time) we identified the usage of statistical processes such as Temporal Point Processes [Khodadadi et al., 2018; Costa et al., 2017; Yang et al., 2017], which we discuss further in Section 5.2.

### 5.2 Temporal Modeling Methodology

A large portion of the articles directly extends a well established method (e.g. LDA or Word2Vec) with a temporal aspect. Only a small portion of the literature has developed dedicated techniques to extract the temporal characteristics of data (e.g. temporal point processes [Khodadadi et al., 2018] and RNN/LSTM [Kumar et al., 2019; Gong et al., 2020]). In the following, we discuss these temporal modeling techniques in details.

#### Probabilistic models for discrete time

A common approach to extend a model designed for a static setting, e.g. LDA, to one that evolves in discrete time bins is to assume a hidden Markov model (HMM) structure. HMM models the observed data in each time bin using the static model but chains together the unobserved or latent parameters for different time bins using a Markov model. These models have been used to chain parameters in discrete user embedding for dynamic networks [Foulds et al., 2011; Xu and Hero, 2014] and a dynamic extension of LDA [Blei and Lafferty, 2006]. Many variants of HMMs such as hidden semi-Markov models, autoregressive HMMs — as well as their discriminative counterpart, Conditional random fields (CRF) — have been proposed to better model temporal structure. In the context of social media data, the stochastic block transition model [Xu, 2015] combined a dynamic discrete user embedding with an autoregressive HMM to model wall posts on Facebook over 90-day time bins.

#### Probabilistic models for continuous time

Unlike discrete-time models, which cannot capture changes in behavior within a time bin, continuous-time models capture user be-
havior at arbitrary time points. This is useful when modeling user activities on social media, which are often quite bursty. A temporal point process (TPP) is a generative model for a sequence of times \((\Delta_1, \Delta_2, \ldots)\) between events, e.g. posts on social media, from which one can obtain exact times of events \((t_1, t_2, \ldots)\) by summing inter-event times. In addition to being bursty, the distribution of inter-event times has also been found to be bimodal, which motivated the ACT-M model for temporal activity on social media [Costa et al., 2017].

A common TPP used to model user activities on social media is the Hawkes process [Hawkes, 2018], which is self-exciting so that the occurrence of an event increases the probability of another event occurring shortly thereafter. A multivariate Hawkes process models multiple time sequences that are mutually exciting. Multivariate Hawkes processes were combined with latent space models [Hoff et al., 2002] to learn user embeddings that decouple homophily and reciprocity from Facebook wall posts [Yang et al., 2017]. Marked TPPs augment TPPs with marks for events, which model additional information beyond event times, such as type of user action (e.g. like or dislike), text and other content types. User-specific marked multivariate Hawkes processes were used by [Khodadadi et al., 2018] to model questions and answers on Stack Overflow with marks denoting badges that users may earn. Unlike discrete-time probabilistic models, the user embeddings in continuous-time models are usually static.

Deep learning for discrete time As previously stated, recurrent neural networks (RNN) are a common choice in modeling dynamic user embeddings from temporal structured data [Kumar et al., 2019; Gong et al., 2020; Wu et al., 2017]. The RNN (and its variants GRU, LSTM) take a sequence of vectors as input and apply a recurrence formula at every discrete time step — same set of parameters are shared between these steps. For example, [Kumar et al., 2019] utilized RNN to project user and item embeddings at discrete time steps, eventually use the generated embeddings to predict future user–item interactions and also predict user state change (e.g. Reddit bans). However, RNNs can only model the embeddings at discrete intervals even if the temporal data itself can be used as continuous input [Kumar et al., 2019]—this makes it difficult to model the temporal dynamics of the embedding at any arbitrary timestamp.

Deep learning for continuous time As an alternative to RNN-based models, [Nguyen et al., 2018] proposed a continuous-time dynamic network embedding approach based on temporal random walks. The embedding is computed by using sampled random walks that follow a time ordering and fit within a minimum and maximum time window.

Recurrent Marked Temporal Point Process (RMTPP), a generative model for event times that combines marked temporal point processes with RNNs is presented in [Du et al., 2016]. Unlike the purely probabilistic TPP models, which typically specify a parametric model for the event times, the RMTTP uses an RNN to jointly model the times-tamp and mark sequences over time.

6 Current Limitation & Future Directions

We next identify several issues/limitations in the current research, which could be addressed in future research.

Continuous-time deep learning models In social media data user activities (e.g., posting) rarely happen at regular intervals. Traditional auto-regressive models (RNN/LSTM) are limited to learning representations at discrete steps, making it difficult for them to generate representations at arbitrary time points. There is emerging work on continuous-time deep learning approaches [Du et al., 2016; Nguyen et al., 2018], but this area is relatively understudied. As a recent alternative which could be employed, Neural Ordinary Differential Equations (Neural ODE) [Chen et al., 2018] are a new family of deep neural network models capable of building continuous-time series models. Neural ODE parameterizes the derivatives of hidden states using a neural network.

Fair and ethical temporal user embedding Recently, there is a surge of research interest in fair AI and machine learning. As demonstrated in a recent study [Islam et al., 2021], user embeddings learned from social media data exhibit biases (e.g., gender and age bias). So far, there has not been much work on developing fair AI/ML techniques to ensure that the temporal user embeddings learned from social media data are unbiased and will not encode prejudice against marginalized groups. Moreover, protecting the privacy of social media users is of utmost importance. There is thus a need for privacy-preserving user embedding and analysis.

Generalizable time embedding Currently, except for Time2Vec [Kazemi et al., 2019], there has not been much work that produces a model-agnostic vector representation of time that can easily be incorporated into existing machine learning architectures.

Learning user embeddings with multimodal data Most work in our survey uses only a single type of temporal user data (e.g., a sequence of text posts or a dynamic social network). Since there are diverse types of user data on social media, learning user embeddings from multimodal temporal data may allow us to build more comprehensive and more accurate user representations.

Dynamic user embedding Most existing work learns a static embedding from temporal user data. As user interests and behavior may evolve over time, the learned user representations should also vary with time. More work is needed to learn dynamic user embeddings that change with time.

Explainability As user embeddings are latent feature vectors that can be difficult to interpret, there is an urgent need to develop new explainable AI technologies (e.g. visualization) to help users to gain insight into the embedding models.

Resource consciousness Many of the state-of-the-art deep learning-based embedding models are very large (e.g., with billions of parameters ) and can be very expensive to train. For example, BERT [Devlin et al., 2018], a neural network model that is frequently used to learn text embeddings requires high-performance GPU or TPU servers to train. This can prevent those who do not have expensive hardware and resources from trying these models. To make embedding technologies more accessible, there is an urgent need to develop novel techniques to build more concise and more effi-
sient models that are resource conscious.

Conclusion User embeddings enable the automated understanding of social media users, with implications for e-commerce, social science, and social good applications. We surveyed work addressing the essential temporal nature of social media. As we have seen, many strides have been taken, but much remains to be done in this important research area.

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