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Tracking User Sentiment Changes on Social Networks

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***Abstract*—We present a time-dependent approach for learning temporal co-variates explaining the subsequent user sentiments in social networks. In most of the existing approaches, we note that the underlying text classification setting, generally used to model user sentiments, is designed to ingest a user comment generated at time t to predict his corresponding sentiment at the same time. Under such constraint, user sentiments can only be given whenever she or he has generated a comment. Furthermore, the evolving historical sentiments are omitted and no anticipation of subsequent sentiments could be made. To alleviate this limitation, we propose a time-dependent approach that takes advantage of historical user comments to learn temporal co-variates that explain their evolving sentiments. We demonstrate that our approach could be used to predict user sentiments at subsequent times ahead. Experimental results on Tweets data, during the Covid-19 pandemic, illustrate the suitability of our approach.**

***Index Terms*—Graph representation learning, Time series, Prediction.**

I. Introduction

The user sentiment on social networks [1] can be tracked by measuring the expressed sentiment of users towards specific subjects. This sentiment can be measured and learned by analyzing user interactions, via comments, towards subjects and can be applied to several situations such as hate speech recognition [2], user radicalization [3] or deliberate self-injury behaviors [4]. It can also be useful in cases of measuring public opinions towards issues like Covid-19 or an electoral candidate.

To identify user sentiments on social networks, text classification algorithms are used to model class separations over the generated comments [5], [6]. Using natural language processing (NLP) models, the comments are ingested into a classifier, and global descriptors of each class, representing the sentiment or behavior, are learned. The generated comments are projected into a latent space through vectorization. Vectors

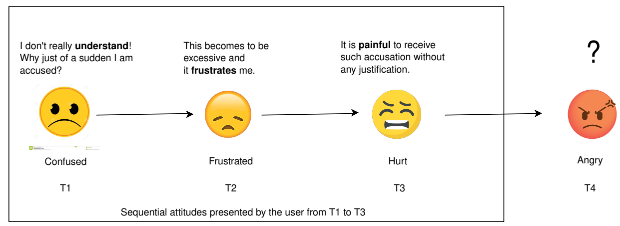

Fig. 1: Evolving user sentiment through time.

representing user comments are learned in such a way that they should distinctly identify the different underlying sentiments users may exhibit whenever they make a comment. In fact, from the vast majority of existing approaches [7], [8], the overall historical user comments are ingested directly into an NLP model to capture descriptors that may explain their attitudes.

However, in such settings, we note:

1) The evolution of sentiment with time is not taken into account. Ignoring the time dependency by not capturing the moment the sentiment was exhibited will yield frozen descriptors that may not be able to represent how sentiments evolve over time.

2) The learning model will tag keywords that allow the understanding of the user sentiment while omitting the context. Leveraging the chronological comments will better capture the context and harness the gradual changes that may occur in the user's attitude.

3) The user comment can only be determined whenever she/he has generated a comment. In other words, no anticipation could be made about its subsequent sentiment by knowing and analyzing what was exhibited in the past.

To further illustrate our claim, in Fig. 1 we have an example of a user whose sentiment is gradually changing from a *confused* state to a *hurt* state at time intervals T_1 to T_3. In most existing approaches, keywords in boldface (i.e., **"understand", "frustrates", "painful"**) will be exploited to ease the detection of corresponding user attitudes (i.e., "Confused", "Frustrated", "Hurt"). However, in the absence of the user comment (such as at time T_4 in Fig. 1), it will not be possible to know what its corresponding attitude would be. While, by tracing his/her immediate previous sentiments from T_1 to T_3, even with no comment at T_4, one may guess that

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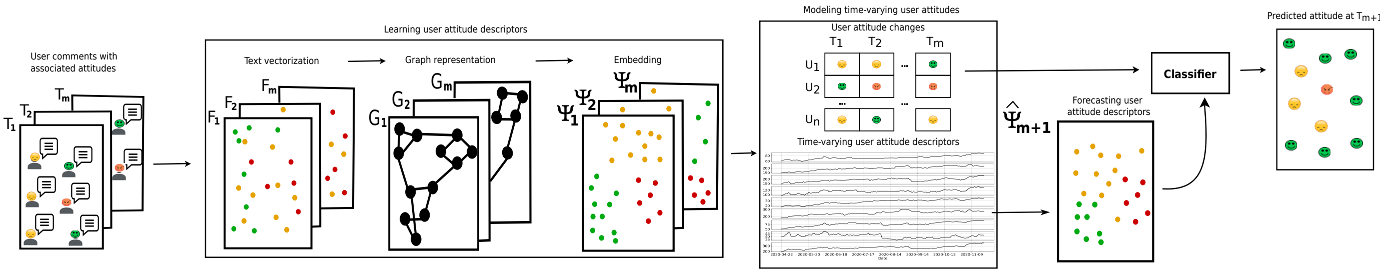


Fig. 2: Proposed framework. From left to right, user comments are first vectorized. The obtained vectors are fine-tuned via graph embeddings, then traced over time to anticipate plausible attitudes users may present at the subsequent time ahead.

this user may finally get angry. Moreover, though the user's comment might be available, it may not always have explicit terms or keywords that will ease to know his attitude.

To overcome the aforementioned issues, our approach proposes building a time-varying user sentiment graph that learns meaningful descriptors explaining the gradual user sentiment changes by capturing the graph substructure and links between users. The learning process is done in such a way that the identified descriptors should be traceable over time via a regressive model. Hence, even in the absence of the user comment at a given time, it will be possible to generate descriptor values, and thus deduce its corresponding sentiment. For the purpose of illustration, Fig. 2 provides an overview of the different steps of the proposed framework.

II. METHODOLOGY AND PRELIMINARY RESULTS

a) ***Case study:*** We tested our approach in tweets that reflect user conversations surrounding the COVID-19 pandemic for the period ranging from January 28^{th}, 2020 to September 1^{st}, 2021. Collected from the open ICPSR repository (icpsr.umich.edu), the data set comprises the time-dependent user comments projected into a $5-$dimensional space where each dimension represents intensities of valence, fear, anger, happiness, and sadness in the user comments. Each vector represents one of the three sentiments $\{positive, negative, neutral\}$. Looking at the daily comments of users, we work with a total of 583 days. We focused our research on users who actively exhibited feelings for at least 400 days within the examination period.

b) ***Graph construction:*** for a set of users $\boldsymbol{U} = \{U_u, \,|\, u = 1, 2, \ldots, n\}$ who interacted, using comments, on a social network in a specified, daily in our case, time interval T_j, $(j = 1, 2, \ldots, m)$. As time evolves, the vectorization of user comments is performed using NLP models such as Word2Vec and then the vectors are cast as a set of features $F_j = \{f_{u,j} | U_u \in \boldsymbol{U}_j\}$ with $\boldsymbol{U}_j \subseteq \boldsymbol{U}$ the set of users who commented at T_j. Each user is classified into one of the sentiment set B^κ, $(\kappa = 1, 2, \ldots, K)$, we construct a user sentiment graph $G_j = (U_j, E_j, F_j, \Omega_j)$. Where, $E_j = \{(U_u, U_v) | U_u, U_v \in \boldsymbol{U}_j\}$ is the set of edges that associate users who made a comment at that time; $\Omega_j = \{\omega_{(u,v),j} | \forall U_u, U_v \in E_j, \, \omega_{(u,v),j} \in [0, 1]\}$ the weights on the edges quantifying the similarity between two user reactions. Note that, in our experiments, at each time interval T_j, we evaluate the attitude similarity between two users U_u and U_v as,

$$mes(U_u, U_v \,|\, f_{u,j}, f_{v,j}) = \omega_{(u,v),j} = \frac{\|f_{u,j} - f_{v,j}\|}{max(\|f_{u,j}\|, \|f_{v,j}\|)} \quad (1)$$

where $\|\cdot\|$ is the norm. The resulting graph densely connects users who exhibit the same sentiment and sparsely connects users who exhibit dissimilar sentiments. The associated weights reflect the similarity as Ω_j, where, the more $\omega_{(u,v),j}$ tends to 1 (resp. 0) the more users U_u and U_v present the same (resp. different) sentiment at T_j.

In Fig. 3(a) and Fig. 3(c) we have examples of the initial vectorized Tweets taken from Australia and Canada in February 2^{nd}, 2020. Through our proposed graph construction strategy, we have the corresponding topological structure given in Fig. 3(b) and Fig. 3(f) for Australia and Canada, respectively. As we can see, the initial vectorized data present some overlapping areas that are hidden in the graph representation via the sparse relationships between subgraphs tagged in green, red, and yellow, respectively.

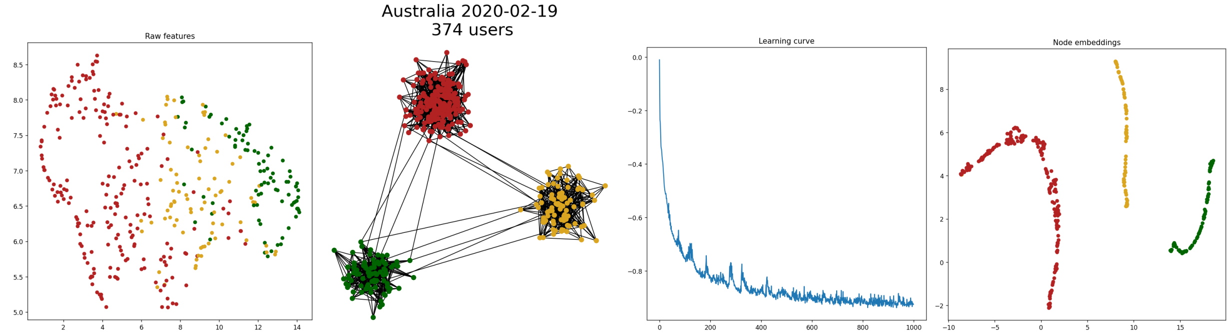
c) ***Learning user sentiment descriptors:*** Based on the constructed graph that strengthening the proximity between users presenting similar sentiments while weakening the proximity between users presenting different sentiments, we design an autoencoder graph neural network. The encoder side will project nodes in a latent space; whereas the decoder side will attempt to associate each of the encoded nodes (embedded node representation) to its right class (that is, the corresponding sentiment). In our experiments, we exploit the GraphSAGE [9] principle to build layers of our encoder and a perceptron for our decoder as follows,

$$\mathcal{E}nc = SAGE(G_j) = \Psi_j \quad (2)$$

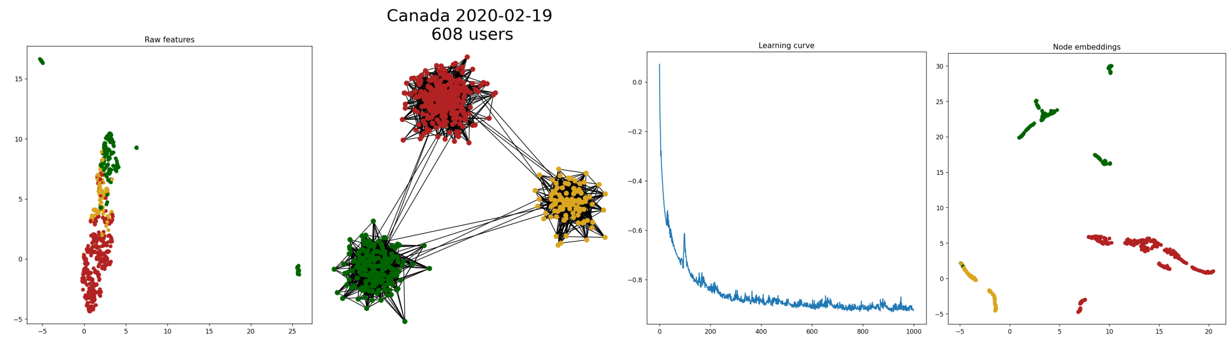
$$\mathcal{D}ec = MLP(\Psi_j) = \Delta_{j|B} \quad (3)$$

where $\Delta_{j|B} \in \{0, 1\}^{n \times K}$ is a binary matrix discriminating each user at time interval T_j with respect to the set of sentiments $B = \{B^\kappa | \kappa = 1, \ldots, K\}$.

Using stochastic gradient descent, we trained our model in discriminating user sentiments while learning descriptors that can better dissociate users based on their sentiments. In figures 3(c) and (g) we have curves that illustrate the learning process in the data sample from Australia and Canada, respec-



(a) Raw features (b) Built graph (c) Learning curve (d) Embedding



(e) Raw features (f) Built graph (g) Learning curve (h) Embedding

Fig. 3: Learning covariates process. From left to right, we provide an example of the process used to identify novel descriptors using GraphSage. Here, only the day 2020-02-19 is depicted for Australia. The UMAP projection is used to visualize in a two-dimensional space the raw features and the embeddings.

tively. Figures 3(d) and (h) depict the learned descriptors. Note that, in our experiments, in contrast of 5 descriptors originally given, we learned 123 descriptors that better discriminate user sentiments. Unlike the original descriptors given in figures 3(a) and (e), we can clearly see that the learned descriptors do not overlap.

d) ***Modeling time-varying user sentiments:*** As time goes on, our assumption is that the exhibited sentiment by a user at time T_j is impacted by the user sentiment exhibited previously, as well as the graph substructure representing the effect of other user interactions. Therefore, using a regressive model $\sigma()$, we then generate subsequent descriptors at any time interval as

$$\hat{\psi}_{u,j} = \sigma(\psi_{u,(j-1)}, \ldots, \psi_{u,(j-p)}|W)\,,$$

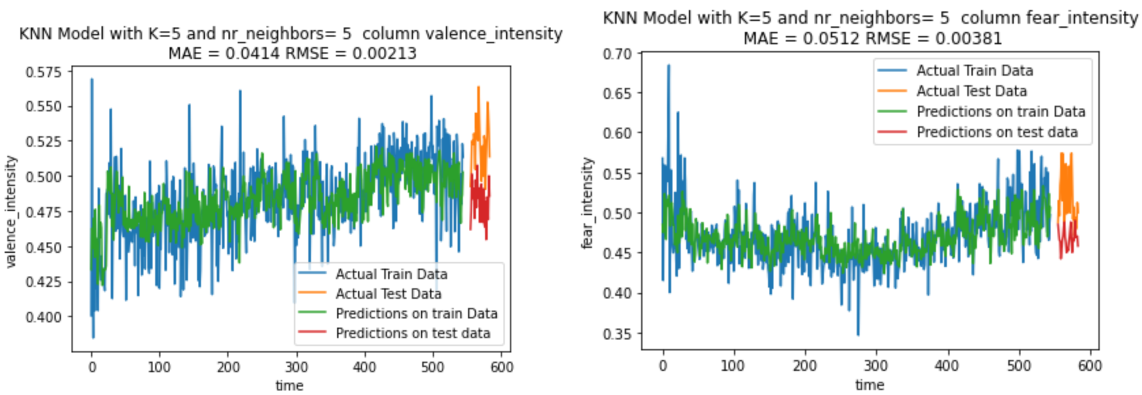
where W is the model parameter. In our study, we used a KNN regressor model, to trace the corresponding user descriptors and predict their subsequent values, as shown in Fig. 4. Here, we attempt generating initial descriptors (Fig. 4(a)) as well as learned descriptors (Fig. 4(b)). In both cases, we can see that, during the phase, the KNN-regressor can capture the time evolving descriptor trends. However, when forecasting unseen time ahead, in the case of the initial descriptors, values generated by the regressor seems deviating from truth trends followed by the original descriptors. With the learned descriptors, values generated by the regressor follows continuously the evolving trend of the learned descriptors. This, shows that the learned descriptors present a pattern enabling the generation of its subsequent values at unseen time ahead.

e) ***Predicting user sentiment:*** By daily tracing user sentiments, we can note that there are users that present different sentiments towards Covid-19 over different days. Maps in Fig. 5 for instance, illustrate the number of users presenting the different sentiments over time in Canada and Australia. Here, though the majority of users are idles, fact remains that we have a high variation on the number of users presenting the different sentiments from one day to another. To further illustrate our claim in Fig. 6 we have a case of user #64657405 in the Ireland data that changes its behavior across days.

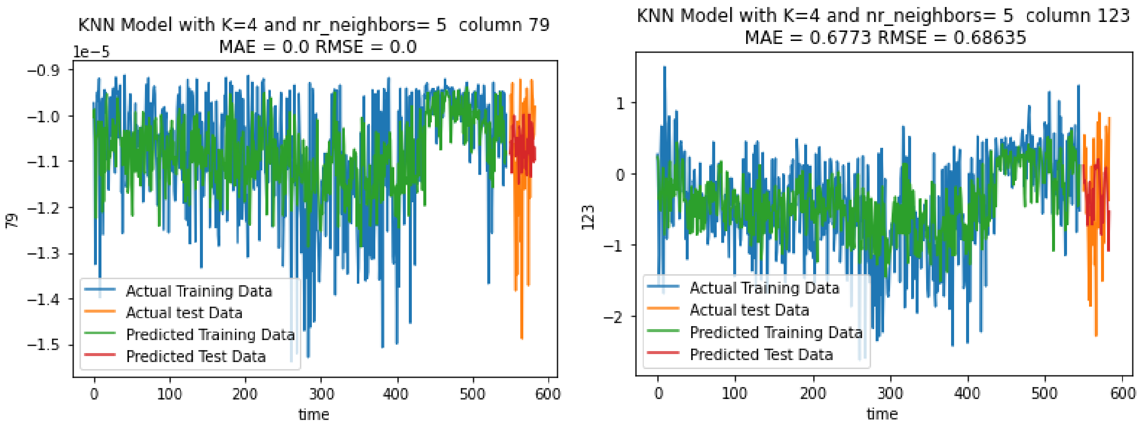
In the example shown in Fig. 6 the observed sentiments do not present a steady pattern from which we can simply deduce what could happen the next day. However, by exploiting the novel learned descriptors, via a KNN regressor model, we can trace the corresponding user descriptors and predict their subsequent values. To be able to track user sentiments via a regressive function σ, we use a classifier $\mathcal{C}()$ to predict user sentiments as

$$\mathcal{C}(U_u \,|\, \hat{\psi}_{u,j}) = \underset{B^{\kappa}}{argmax}\left(P_{\mathcal{C}}(A^{\kappa}|\hat{\psi}_{u,j})\right) \tag{4}$$

where $P_{\mathcal{C}}()$ is the underlying classifier discrimination's likelihood.

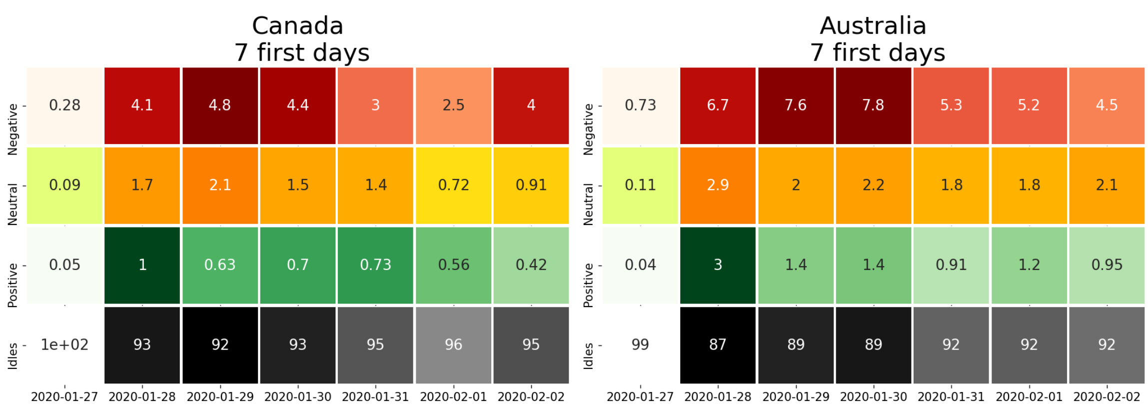


(a) Generating the initial *valence* and *fear* descriptors.



(b) Generating the 79^{th} and 123^{th} learned descriptors.

Fig. 4: Example of Generated descriptors.



(a) Canada (b) Australia

Fig. 5: Behavior map for users that had been active for more than 100 days. Reported values are in percentage.

To view how accurately the regressor generates user behavior descriptors, in our case study, we set 500 historical days as training data from which we learn novel descriptors and generate their subsequent values using the KNN model at two months. Based on the previously exhibited behaviors, we found that we could predict user behaviors with different accuracies (resp. F1-score) according to the given classifier. In Fig. 7 we have an illustration of our results. In all cases, the SVM with linear as well as RBF kernels seems to be best in contrast to other tested classifiers.

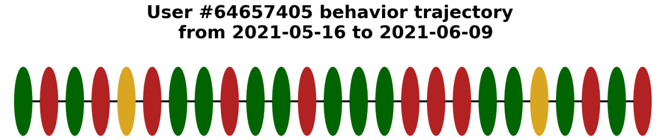
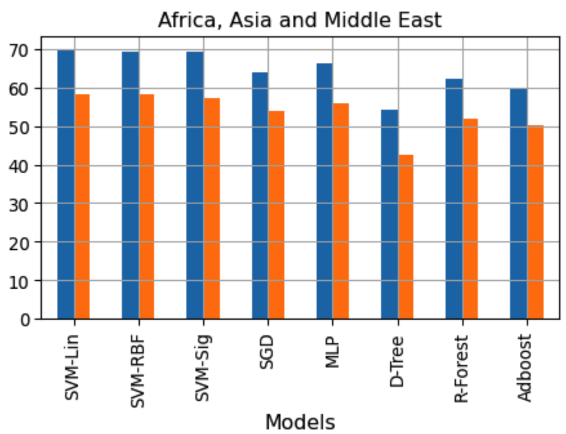
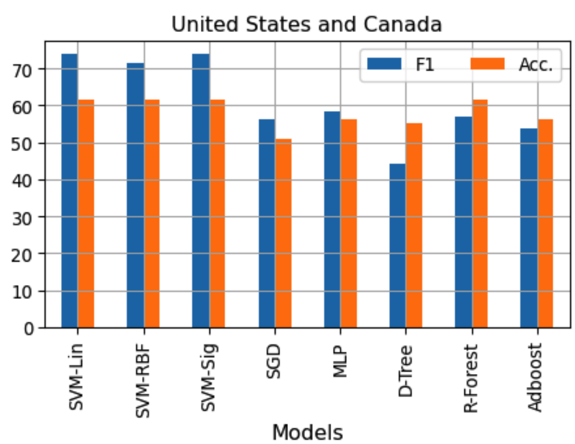


Fig. 6: Examples of user sentiment trajectories in Ireland from day 2021-05-16 till day 2021-06-09.



(a) Africa, Asia and Middle East



(b) USA and Canada

Fig. 7: Performance of the proposed approach.

III. Conclusion

We proposed a time-dependent approach to model the continuous sentiment changes users can present through social networks. Moreover, we found that our approach could be exploited to foresee subsequent sentiments users may present at an unseen time ahead. A study case on Twitter user conversations surrounding the Covid-19 pandemic has been presented. Although inductive, further research on graph construction and its learning process constitutes the backbone of the perspective of this current work.

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