Multi-State Survival Framework for Modeling Sentiment Shifts in Social Media

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Abstract. Sentiment on social media is dynamic and context-sensitive, often shifting over time among various emotional or evaluative states. In this work, we introduce a multi-state Cox regression framework to model time-dependent transitions in sentiment shifts. Unlike traditional sentiment analysis methods, our approach incorporates transition-specific hazard functions with time-varying covariates derived from an evolving graph-based structure that learns novel, discriminative descriptors of sentiment beyond standard sentiment indicators. Each transition between sentiment states is associated with unique baseline hazards and regression coefficients, enabling precise modeling of state-specific effects. Leveraging the Cox model's ability to handle time-dependent transition matrices, our framework robustly predicts both the timing and direction of sentiment shifts. Tested on social media datasets spanning multiple contexts, our approach captures the complex temporal dynamics of sentiment evolution.

Keywords: Cox regression, sentiment analysis, social media

1 Introduction

The widespread adoption of social media has led to a surge in user-generated content, providing a dynamic view of evolving public sentiment [1–3]. Public sentiment, expressed through diverse interactions, reflects collective user responses to events and announcements. Unlike static classification approaches, real-world sentiment is fluid, shifting across emotional states due to contextual and external factors [4, 5]. This dynamic nature calls for advanced modeling to track and anticipate sentiment trends, with implications for political monitoring, market analysis, and crisis response.

Sentiment analysis has evolved from traditional feature-based methods like Bag-of-Words and TF-IDF combined with classifiers [6–8] to advanced deep learning models. RNNs, including LSTMs [9, 10] and GRUs [11, 12], capture temporal dependencies in text, while CNNs [13, 14] extract localized sentiment cues. Transformer-based models like BERT [15, 16] and RoBERTa [17] leverage contextual embeddings for deep semantic understanding. Attention mechanisms and hierarchical structures such as HAN [18] further enhance interpretability, and GNNs [19] incorporate social interactions into sentiment modeling. However, challenges persist in handling textual variation, domain adaptation, and model interpretability.

Survival-based models, such as recurrent survival networks and Cox regression, enhance NLP approaches by predicting not only the likelihood but also the timing of sentiment transitions [20–22]. These models incorporate time-varying covariates and contextual features, aligning well with the dynamic nature of sentiment on social media. By merging the interpretability of survival analysis with the expressiveness of modern NLP embeddings, they offer a more comprehensive and temporally-aware framework for sentiment prediction—bridging the gap between event occurrence and its timing in dynamic sentiment analysis.

Although advanced models have been designed for predicting sentiment on social media, most of these models face one or more of the following primary challenges:

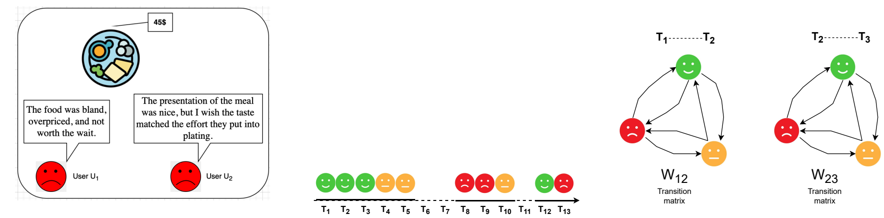
Textual discrepancies: User-generated content often contains implicit cues, sarcasm, or evolving sentiment interpretations that traditional feature extraction methods struggle to capture. Variations in expression, tone, and context make it challenging to identify consistent sentiment patterns, especially in dynamic environments where context or interactions evolve rapidly. These discrepancies significantly impact model accuracy and highlight the need for robust methods capable of handling linguistic nuance in diverse, unstructured social media data.

Intermittent chronological features: Sentiment dynamics on social platforms are frequently characterized by irregular and sporadic observations—whether due to inconsistent user engagement or external event-driven variability. Most existing models are ill-equipped to represent this non-uniform temporal behavior, limiting their ability to capture the true progression of sentiment. The absence of mechanisms to address such intermittency reduces the temporal resolution and interpretability of sentiment evolution.

Lack of sentiment switch modeling: Many sentiment prediction models adopt a uniform parameterization for transitions between all sentiment states, overlooking the unique triggers and trajectories associated with each switch (e.g., from negative to positive vs. positive to neutral). This oversimplified treatment neglects the asymmetry and context sensitivity inherent in sentiment shifts, thereby limiting the model's ability to faithfully represent sentiment dynamics in response to evolving discourse or news propagation.

2 Motivations and Contributions

To further illustrate the limitations discussed, consider the scenarios depicted in Fig. 1. In Fig. 1(a), we observe examples of negative sentiments expressed by two users (U_1 and U_2). The comment from U_1 provides clear descriptors of dissatisfaction (e.g., bland food, overpriced, long wait), which can be effectively captured by an NLP model to distinguish its sentiment. This clarity arises from the comment's direct emphasis on strongly negative attributes. In contrast, U_2's comment, while ultimately negative, begins with a seemingly positive remark



(a) Textual discrepancies. (b) Intermittent chronological features. (c) Sentiment switch.

Fig. 1

(e.g., nice presentation) before subtly transitioning into criticism. This mixed tone introduces textual discrepancies, potentially diluting the representation of negativity in certain embedding methods and making accurate sentiment modeling more challenging.

In Fig. 1(b), we observe a sequence of sentiments (happy, neutral, sad) shifting sporadically and irregularly across the time intervals T_1 to T_{13}. This inconsistent and non-uniform pattern of time-dependent features highlights the challenges models face in capturing and interpreting fluid temporal dynamics. The irregularities and gaps in the data hinder the ability of models to comprehensively represent the progression of sentiments over time, reducing their effectiveness in tracking and predicting sentiment evolution.

The irregular sentiment shifts shown in Fig. 1(b) highlight the limitations of traditional models like the Markov model [23], which assume uniform state transitions and struggle to capture sporadic changes. To address this, Fig. 1(c) introduces distinct transition matrices, W_{12} and W_{23}, for intervals $T_1 \rightarrow T_2$ and $T_2 \rightarrow T_3$, respectively. These matrices enable time-specific modeling of sentiment transitions, providing a more flexible and accurate representation of evolving sentiment dynamics often overlooked by conventional approaches.

To overcome the limitations of current sentiment prediction models; particularly their sensitivity to textual variability and inability to capture temporal sentiment shifts, we propose a framework that incorporates two key components:
Time-sequential feature smoothing for comment normalization: At each time interval, a synthetic graph is constructed by linking users with similar sentiment labels, reducing discrepancies caused by divergent expressions. This smoothing process emphasizes shared sentiment patterns and generates robust, uniform features by aggregating sentiment cues across users (e.g., “Great job!” and “Not bad at all”). The result is a more stable and discriminative representation of sentiment classes, less affected by textual noise.
Transition-specific modeling: A multi-state Cox regression (MSCR) model is employed within a multi-task learning framework to characterize sentiment dynamics over time. MSCR captures transitions between sentiment states (e.g., positive, neutral, negative) by assigning distinct hazard functions and covariate effects to each type of transition. This approach enables a detailed analysis of

the mechanisms underlying sentiment shifts, even in the presence of intermittent or missing data. By modeling how and when transitions occur, the framework provides deeper insight into the evolving nature of sentiment in social media contexts.

The significance of this work can be summarized as follows:

1. We introduce a longitudinal modeling framework that captures time-evolving user sentiments by leveraging multi-state Cox regression to effectively model and handle sentiment shifts over time.
2. We develop a robust graph-based feature smoothing methodology to enhance sentiment discrimination by integrating contextual relationships among users.
3. We demonstrate the effectiveness of our approach on real-world datasets, showing that the extracted descriptors can accurately predict user sentiments for future time intervals.

3 Preliminaries

Problem statement: Given a set of users who engage on social media through comments at distinct time intervals $T_1, T_2, \ldots, T_m$. At each interval T_j, a subset of users $\mathbf{U}_j$ is present, with each user $u \in \mathbf{U}_j$ generating comments that reflect their current sentiment or evaluative state. These sentiments may change over time in response to contextual factors, user interactions, or external events. To capture these dynamics, we group users at any interval T_j based on their respective sentiment states, such that $\mathbf{U}_j = \bigcup_{s \in \mathcal{S}} \mathbf{U}_{s,j}$, where $\mathcal{S}$ denotes the set of possible sentiment states, and $\mathbf{U}_{s,j}$ represents the users presenting sentiment s at time t_j. Our objective is to model the temporal evolution of these collective sentiment states, taking into account fluctuations in user engagement over time.

Standard Cox proportional hazards (CPH) model: The Cox proportional hazards model is a semi-parametric method for analyzing survival data [24]. The hazard function for an individual u at a time interval T is modeled as:

$$h_u(T) = h_0(T) \exp(\beta_1 x_{u1} + \beta_2 x_{u2} + ... + \beta_p x_{up}) \tag{1}$$

where $h_0(T)$ represents the baseline hazard function (left unspecified), while $x_{u1}, ..., x_{up}$ denote the predictor variables, and $\beta_1, ..., \beta_p$ are the corresponding regression coefficients. The model's strength lies in its semi-parametric nature, as it makes no assumptions about the shape of the baseline hazard function $h_0(T)$. A fundamental assumption is that hazard ratios remain constant over time, known as the proportional hazards assumption. The model parameters are estimated through partial likelihood maximization, allowing for efficient computation without specifying the baseline hazard.

Multi-state Cox regression model: Multi-state Cox models extend the standard model to handle transitions between multiple states [25,26]. For a transition from state r to state s, the hazard function takes the form:

$$h_{rs,u}(T) = h_{rs,0}(T)\exp(\beta'_{rs} x_u(T)) \tag{2}$$

where $h_{rs,0}(T)$ represents the baseline hazard for the transition from state r to state s, β_{rs} are the transition-specific regression coefficients, and $x_u(T)$ represents the possibly time-dependent covariates [27]. This extension allows for different covariate effects across different transitions, accommodating both progressive and reversible state changes. The model typically operates under the Markov assumption, where future transitions depend only on the current state, though semi-Markov variants can be employed when transition hazards need to account for the time spent in the current state. This flexibility makes multi-state Cox models particularly valuable in analyzing competing risks scenarios.

4 Proposed framework

In this section, we detailed the overall proposed framework. That is first detailing how descriptors enabling the discrimination of sentiments are identified. Then present how we model sentiment shift we may have as time goes.

4.1 Identifying discriminative sentiment descriptors

Due to text discrepancies that advanced NLP models may struggle to capture accurately, often due to insufficient contextual information, the objective is to build a time-sequential graph where users with similar sentiments (*positive, neutral, negative*) are densely interconnected, while those with differing sentiments are sparsely linked. This approach aims to mitigate textual inconsistencies and harmonize divergent comments.

Graph construction Given a time interval T_j, using a pretrained NLP or generative model $\mathcal{NLP}()$ (e.g., BERT, RoBERTa, ChatGPT) embeddings from each user's u with comment C_j^u is extracted:

$$f_j^u = \mathcal{NLP}(C_j^u) \in \mathbb{R}^p \tag{3}$$

where f_j^u is the embedding vector for user $u \in \mathbf{U}_j$, and p is the dimensionality of the embedding.

Based on the set of features $\mathbf{F}_j = \{f_j^u | \forall u \in \mathbf{U}_j, f_j^u = \mathcal{NLP}(C_j^u)\}$ extracted from users at time intervals T_j and their corresponding labels (that is $\mathbf{U}_j = \bigcup_{s\in\mathcal{S}} \mathbf{U}_{s,j}$), we use the function $\mathcal{R}(\mathbf{F}_j|\mathbf{U}_j)$ to randomly generate a graph G_j as,

$$\mathcal{R}(\mathbf{F}_j|\mathbf{U}_j) = \mathrm{G}_j = (\mathbf{U}_j, \mathbf{E}_j, \mathbf{F}_j) \tag{4}$$

with $\mathbf{E}_j = \{(u,v)|u,v \in \mathbf{U}_j, Pr((u,v)) > \epsilon\}$ with Pr a mixture probability function of forming an edge between u and v given as,

$$Pr((u,v)) = w_{\text{intra}} \cdot \mathbb{I}[l(u) = l(v)] \cdot P_{\text{intra}} + w_{\text{inter}} \cdot \mathbb{I}[l(u) \neq l(v)] \cdot P_{\text{inter}} \tag{5}$$

where, $\mathbb{I}[l(u) = l(v)]$ is the indicator function that evaluates to 1 if the labels of nodes u and v are the same, and 0 otherwise. $\mathbb{I}[l(u) \neq l(v)]$ is the indicator function that evaluates to 1 if the labels of nodes u and v are different, and 0 otherwise. P_{intra} is the probability of connecting nodes within the same class. P_{inter} is the probability of connecting nodes between different classes. w_{intra} and w_{inter} are Weights for intra-class and inter-class probabilities, satisfying $w_{\text{intra}} + w_{\text{inter}} = 1$.

Generating descriptors Each constructed graph G_j is processed by a graph encoder $\mathcal{G}$, parameterized by $\Theta_{\mathcal{G}}$, to produce a set of node descriptors $\mathbf{X}_j = \{x_j^u \in \mathbb{R}^p \mid \forall u \in U\}$ as follows:

$$\mathcal{G}(\mathrm{G}_j \mid \Theta_{\mathcal{G}}) = \mathrm{GCN}(G_j, \Theta_{\mathcal{G}}) = \mathbf{X}_j. \tag{6}$$

Learning process To ensure that the output descriptors $\mathbf{X}_j$ can effectively discriminate between different sentiment classes, we employ a variational approach. Specifically, we assume that the latent descriptors $\mathbf{X}_j$ corresponding to each sentiment class follow distinct probability distributions $P_s(\mathbf{X}_j)$, $\forall s \in \mathcal{S}$. To enforce divergence between these distributions, we define the following loss function based on the Kullback-Leibler (KL) divergence:

$$\mathcal{L}_{\text{KL}} = \mathbb{E}_{\mathbf{X}_j \sim P(\mathbf{X}_j)} \left[\frac{1}{|\mathbf{U}_j|} \sum_{u \in \mathbf{U}_j} \Big(\sum_{s \in \mathcal{S}} \sum_{r \in \mathcal{S} \setminus \{s\}} \mathrm{KL}(P_s(x_j^u) \parallel P_{\mathrm{r}}(x_j^u)) \Big) \right]. \tag{7}$$

4.2 Sentiment switch

Modeling transitions We encode each sentiment transition with a vector $\mathbf{V} \in \{0,1\}^{2 \times |\mathcal{S}|}$, where the first $|\mathcal{S}|$ entries indicate the user's initial sentiment state, and the subsequent $|\mathcal{S}|$ entries represent the sentiment at the next time step. For instance, if $\mathcal{S} = \{\text{positive}, \text{neutral}, \text{negative}\}$ and a user transitions from positive at time interval T_1 to negative at time interval T_2, the corresponding transition vector is $\mathbf{V} = (1, 0, 0, 0, 0, 1)$. This binary representation succinctly captures both the initial and subsequent sentiment states. We will use $\mathcal{V}$ to denote the set of all possible transition vectors.

To model the time-evolving sentiment that a user may experience, the proposed framework utilizes multi-state Cox regression to capture the risk of transitioning between two sentiment states, represented by the vector V, over consecutive time intervals. For a single user u whose sentiment is known at T_{j-1}, the risk of transitioning his sentiment at T_j is calculated as,

$$h(T_j|\beta, \mathrm{V}, u) = \begin{cases} \bullet h_0(T_j, \mathrm{V}|\beta_0) \text{ if } u \notin \mathbf{U}_j, \\ \bullet h_0(T_j, \mathrm{V}|\beta_0)\sigma\left(x_j^u|\beta_{\mathrm{V}}\right) \text{ else}, \end{cases} \tag{8}$$

with $\beta = \{\beta_0, \beta_{\mathrm{V}}\}$.

Eq. (8) defines a hazard function that combines a baseline hazard $h_0(T_j, \mathrm{V}|\beta_0)$, modeled using a recurrent neural network parameterized by β_0, and a user-specific adjustment factor $\sigma(x_j^u|\beta_\mathrm{V})$, approximated by a neural network with parameters β_V. The baseline hazard h_0 captures general transition dynamics based on the transition vector V and applies when user features are unknown or unavailable (i.e., $u \notin \mathbf{U}_j$, the set of users active at time T_j). When a user u is active (i.e., $u \in \mathbf{U}_j$), the baseline hazard is scaled by $\sigma(x_j^u|\beta_\mathrm{V})$, which processes the user's feature vector x_j^u to reflect individual-level risks of sentiment transition. This formulation ensures a hybrid approach that captures both global sentiment transition patterns through h_0 and personalized adjustments via σ, effectively modeling sentiment dynamics across diverse contexts.

Using relation given in Eq. (8), we calculate the global transition risk as,

$$h(T_j|\beta, \mathrm{V}) = h_0(T_j, \mathrm{V}|\beta_0)\left(1 + \frac{1}{|\mathbf{U}_{j-1} \cap \mathbf{U}_j| + 1} \times \sum_{u \in \mathbf{U}_{j-1} \cap \mathbf{U}_j} \sigma\left(x_j^u|\beta_\mathrm{V}\right)\right). \quad (9)$$

Eq. (9) introduces a correction term that adjusts the baseline hazard. This term depends on the number of users present at both time intervals T_{j-1} and T_j, denoted by $|\mathbf{U}_{j-1} \cap \mathbf{U}_j|$, and the non-linear function $\sigma()$. The sum over all users in the intersection set $\mathbf{U}_{j-1} \cap \mathbf{U}_j$ indicates that the risk of transitioning from one sentiment state to another is influenced by the collective sentiment of the overlapping users. This term is normalized by $|\mathbf{U}_{j-1} \cap \mathbf{U}_j| + 1$, preventing overly large adjustments when there are few overlapping users.

Learning transition process The learning process for the proposed multi-state Cox regression relies on optimizing the parameters $\beta = \{\beta_0, \beta_\mathrm{V}\}$ to accurately predict sentiment transitions over time. The key objective is to minimize the discrepancy between the predicted transition risk, as defined by Eq. (9), and the observed transitions in the data.

To achieve this, for the observed period ranging from T_1 to T_m, we define the loss function formulated based on the log-likelihood of the observed transitions given as,

$$\mathcal{L}(\beta) = \sum_{j=1}^{m} \Big[\log h(T_j|\beta, \mathrm{V}) - H(T_j|\beta, \mathrm{V})\Big] + \lambda \cdot ||\beta||^2 \quad (10)$$

with

$$H(T_j|\beta, \mathrm{V}) = \int_{T_1}^{T_j} h(t|\beta, \mathrm{V})\, d\, t\,,$$

where $H(T_j|\beta, \mathrm{V})$ is the cumulative hazard function up to time T_j, representing the accumulated risk of transition from the initial state up to T_j.

5 Sentiment lifespan

To this point, we have developed a model that effectively captures the likelihood of tracking user sentiment over time. Using the time-evolving mechanism described in Eq. (9), we have characterized the dynamics governing sentiment transitions across time intervals. In this section, we extend the model to predict the sentiment a user is likely to exhibit in future time intervals beyond the observed range T_1 to T_m (i.e., T_{m+1}, T_{m+2}, ...). To achieve this, it is necessary to estimate the user descriptors for these future time intervals.

These descriptors can be forecasted using any auto-regressive function $g()$. With this setup, assuming a user u exhibits a sentiment state $s \in \mathcal{S}$ at time T_m, they may transition to any sentiment state at the subsequent time interval t_{m+1}. Given a user u that present a sentiment r at time t_m, to predict what sentiment he may present at subsequent time, we first calculate the probability of this user to present each of the sentiment $s \in \mathcal{S}$. To do this we exploit historical risk he or she has been exposed to present this sentiment. This calculation is done based on the survival function and the corresponding vector V relating the transition from sentiment r to sentiment s given as,

$$\mathrm{Srv}(T_{m+1}|\beta, r \to s, u) = \exp\Bigg\{ - \int_{T_1}^{T_m} h(T|\beta, \mathrm{V}, u)\, dT - \int_{T_m}^{T_{m+1}} h_0(T, \mathrm{V}|\beta_0) \times \sigma\left(g(T|x_T^u, \ldots, x_{T-k}^u)|\beta_{\mathrm{V}} \right)\, dT \Bigg\}, \tag{11}$$

with k the number of historical feature values taken to predict the current feature value.

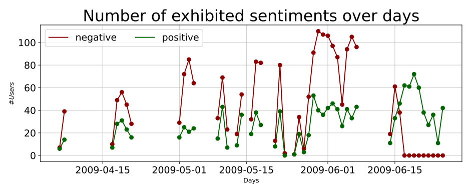
Relying on the survival relation Eq. (11), we predict the next user sentiment as,

$$P(T_{m+1}|u) = \hat{s} = \underset{s}{\mathrm{argmax}}\{\mathrm{Srv}(t_{m+1}|\beta, r \to s, u) \forall s \in \mathcal{S}\} \tag{12}$$

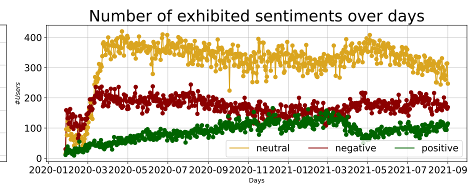
6 Experiment

6.1 Data description

Sentiment140 (ST140): This dataset is a collection curated for sentiment analysis, consisting of tweets automatically labeled as positive or negative based on the presence of emoticons. Each entry provides the tweet text, sentiment polarity, timestamp, and user identifiers. Widely recognized as a benchmark for sentiment analysis, the dataset also facilitates the study of temporal sentiment trends on social media platforms. For our analysis, we focused on 160 users who had posted over 100 tweets within the dataset's timeframe. User comments were aggregated on a daily basis, assigning each day the predominant sentiment displayed by the user. The dataset covers the period from April 6, 2004, to June



(a) ST140



(b) CVD19

Fig. 2: Daily count of users exhibiting sentiment.

25, 2004 (a total of 81 days), with inactive users during this timeframe excluded from consideration.

COVID-19 (CVD19): This dataset, sourced from the openICPSR repository, captures public conversations on Twitter during the COVID-19 pandemic, spanning January 28, 2020, to September 1, 2021—a period of 584 days. The dataset includes tweets from ten countries: Australia, France, Germany, United Kingdom, Ireland, Spain, Canada, United States, Mexico, and Brazil, providing a diverse geographical and cultural perspective on sentiment and emotional analysis. To ensure robust and meaningful insights, we filtered for users active on more than 400 days during the specified period. For each user, a single sentiment entry per day was recorded based on the dominant sentiment in their tweets, categorized into positive, negative, and neutral classes. Additionally, the dataset includes five emotional intensity scores—valence, fear, anger, happiness, and sadness—allowing for an in-depth analysis of emotional dynamics and their evolution over time. This dataset facilitates the study of temporal sentiment patterns and emotional trends, offering valuable insights into public reactions across different countries during the pandemic.

To provide a more detailed description of the dataset, Fig.2 illustrates the number of users expressing various sentiments across days in both the ST140 (Fig.2(a)) and CVD19 (Fig.2(b)) datasets. Notably, the gaps in the time series shown in Fig.2(a) indicate days where no data was recorded, reflecting missing activity. Despite the presence of these gaps, it is evident that the number of users expressing each sentiment fluctuates significantly over time. This variation highlights the dynamic nature of sentiment expression, as users frequently shift their sentiments in response to changing contexts, events, or personal experiences, demonstrating the evolving sentiment trends within the datasets.

6.2 Experiment settings

Recall that the proposed framework is composed of five core components: (1) an NLP module for text descriptor extraction, (2) a random graph generator for structural representation, (3) a graph neural network to smooth and refine the extracted descriptors via graph-based representation, (4) a transition risk module for evaluating sentiment transition probabilities, and (5) a sentiment forecasting module to predict user sentiment beyond the current timestamp. The subsequent paragraphs detail the experimental setup utilized.

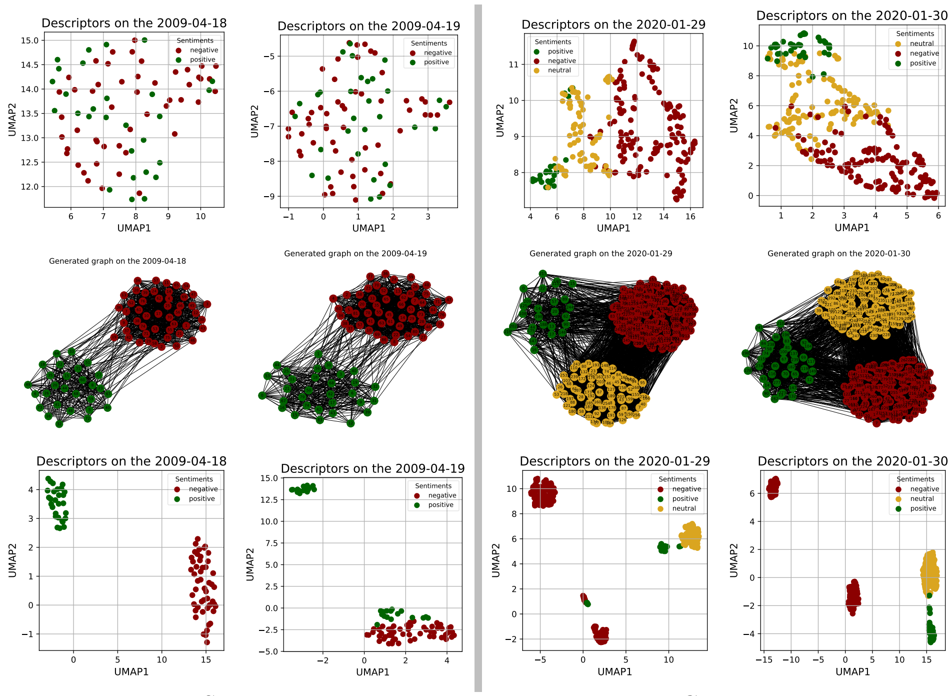


Fig. 3: Descriptor identification for ST140 and CVD19 datasets. The first row presents feature visualizations, the second row shows generated graphs, and the third row demonstrates smoothed features for different dates in both datasets.

Component 1 – Text descriptor extraction For the ST140 dataset, we employ the BERT-base-uncased model from Hugging Face. This model leverages a transformer-based bidirectional encoder architecture to process input text. The text undergoes WordPiece tokenization, with special tokens [CLS] and [SEP] marking the beginning and end of the sequences, respectively. From the final layer, we extract features specifically from the [CLS] token, which provides a 768-dimensional aggregate representation of the entire sequence, effectively capturing the contextual semantics of the input text. It is worth noting that this text feature extraction process is not applied to the CVD19 dataset, as the features for this dataset were pre-extracted and provided.

Component 2 – Graph generator This component exploits the mixture function given in relation Eq. (5) to randomly generate edges between different user sentiments. In this relation, for all datasets, we fixed the intra w_{intra} and inter w_{inter} mixture weights to .75 and .25 respectively. Probabilities to connect nodes representing users with the same sentiment P_{intra} and nodes representing users with different sentiment P_{inter} were fixed to .8 and .2 respectively. These values ensure that nodes representing users with similar sentiment should be densely connected while being sparsely connected to others.

Component 3 – Descriptor smoother For all datasets, we used a GCN neural network. The neural network architecture consists of two hidden layers, each containing 50 neurons, followed by an output layer with 125 neurons to produce the final node embeddings. A ReLU activation function is applied after each layer to introduce non-linearity, enabling the network to capture complex relationships between descriptors. The architecture is designed to prevent overfitting by incorporating a dropout rate of 0.5, which randomly deactivates a subset of neurons during training, ensuring that the network does not rely too heavily on specific features.

Component 4 – Transition risk evaluator The transition risk evaluator component is designed with two neural networks, each serving a distinct purpose. The first neural network models the baseline hazard and is implemented as an LSTM with a single hidden layer comprising 30 neurons. The second neural network evaluates user-specific sentiment risk and consists of two hidden layers with 15 and 30 neurons, respectively. Both networks employ ReLU activation functions to introduce non-linearity, enabling them to model complex dependencies effectively. To ensure the output values are non-negative and suitable for risk evaluation, a Softplus activation function is applied to the final layers of both networks. This configuration is uniformly applied across all datasets, ensuring consistency and comparability in evaluating sentiment transition risks across different data sources.

Component 5 – Sentiment forecasting This module uses a regressor $g()$ to forecast user sentiment descriptors at future timestamps. We adopt the Temporal Fusion Transformer (TFT) [28] for its effectiveness in capturing short- and long-term dependencies in temporal data. To address missing values, we first apply linear interpolation for continuity, followed by FFT-based smoothing to reduce noise and stabilize the input sequences.

6.3 Feature smoothing

Figure 3 presents UMAP projections of sentiment descriptors for ST140 (April 18–19, 2009) and CVD19 (January 29–30, 2020) in three stages: raw BERT features, graph-based embeddings, and smoothed features. In the first row, raw features form entangled clusters that blur positive, negative, and neutral sentiments. Graph-based embeddings (second row) improve separation but still mix neutral points. After smoothing (third row), all three sentiment categories appear as well-defined, non-overlapping clusters, illustrating how feature smoothing sharply enhances sentiment discrimination.

6.4 Transition risk

Through the description of the dataset, we have observed that the number of users presenting various sentiments over time is not constant. This suggests that some users may change their sentiment over time. In Fig. 4, we present examples

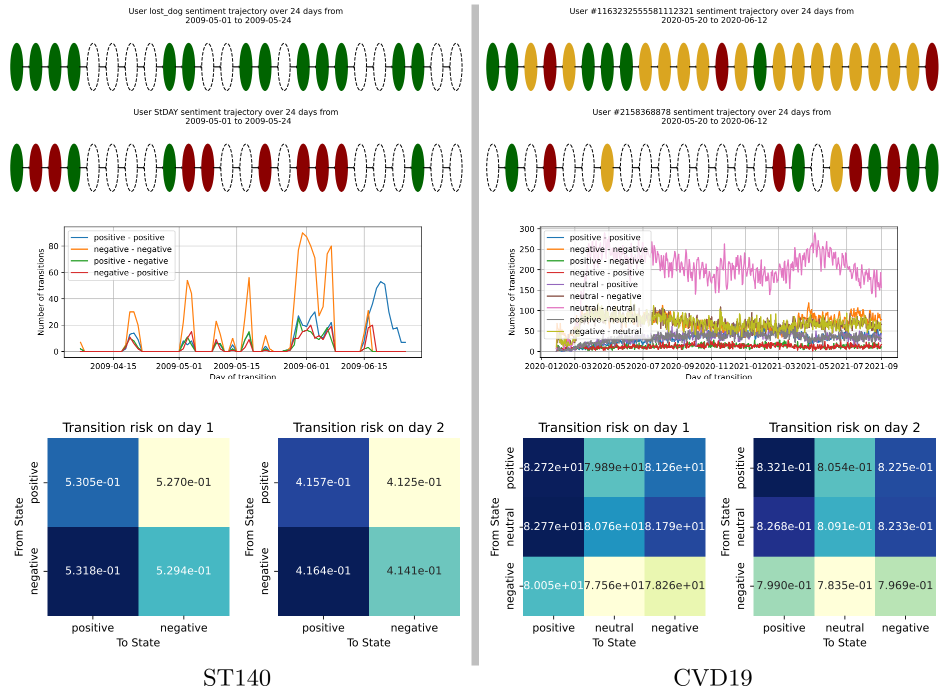


Fig. 4: Sentiment transitions in ST140 and CVD19 datasets.

of two different users randomly selected from the ST140 and CVD19 datasets. As the days advance, we note that the user "StDAY" in ST140, as well as users "#1163232555581112321" and "#2158368878" in CVD19, do not maintain the same sentiment throughout the 24-day period. These users exhibit alternating sentiments, switching between positive, negative, and sometimes neutral sentiments over time.

In contrast, user "lost dog" in ST140 consistently maintains the same sentiment, specifically positive, throughout the entire 24-day period. This example demonstrates how some users exhibit stable sentiments while others undergo changes in their emotional states. One important observation to note, however, is not just the alternating sentiments, but also the periods during which users remain inactive. This inactivity is illustrated by the presence of white ellipses with dashed borders in the sentiment trajectories of most users. Interestingly, user "#1163232555581112321" remains active throughout the 24 days, showing a continuous sentiment without any inactivity.

6.5 Sentiment forecasting

To show how likely the proposed survival function enable sentiment prediction not only at one time interval but more, we need to make sure that covariates are first of predicted. In Fig. 5 we have an example of two smoothed descriptors

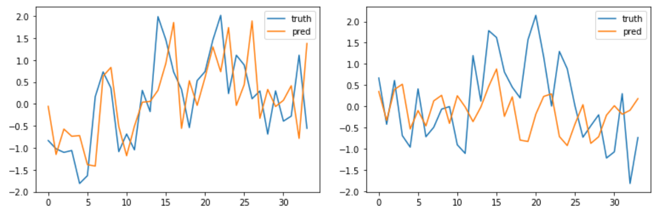


Fig. 5: Example of descriptors' forecasting

Table 1: Sentiment analysis performance (mean ± std) for ST140 and CVD19 over different forecast horizons. For each metric column, the best result is **underlined & bold** and the second-best is **bold**. The proposed approach is on task with different time series regression function: DLinear [29], LSTM, AR and SVR.

Model	Horizon	ST140			CVD19		
		F1	Acc	ROC	F1	Acc	ROC
DLinear	1-time ahead	**85%±1.5%**	**84%±1.2%**	**82%±1.3%**	**84%±1.4%**	**83%±1.5%**	**81%±1.2%**
	2-time ahead	**83%±1.6%**	**82%±1.3%**	**80%±1.5%**	**82%±1.7%**	**81%±1.4%**	**79%±1.6%**
	4-time ahead	81%±1.8%	80%±1.4%	78%±1.7%	80%±1.6%	79%±1.5%	77%±1.7%
	8-time ahead	79%±2.0%	78%±1.8%	76%±2.0%	78%±1.9%	77%±2.1%	75%±2.2%
LSTM	1-time ahead	**82%±1.6%**	**81%±1.5%**	**79%±1.6%**	**81%±1.5%**	**80%±1.7%**	**78%±1.6%**
	2-time ahead	80%±1.8%	79%±1.7%	77%±1.8%	79%±1.8%	78%±1.6%	76%±1.9%
	4-time ahead	78%±1.9%	77%±1.8%	75%±1.9%	77%±2.0%	76%±1.9%	74%±2.1%
	8-time ahead	74%±2.2%	73%±2.1%	71%±2.2%	73%±2.3%	72%±2.2%	70%±2.4%
AR	1-time ahead	80%±1.7%	79%±1.6%	77%±1.8%	79%±1.7%	78%±1.6%	76%±1.9%
	2-time ahead	78%±1.9%	77%±1.8%	75%±2.0%	77%±2.0%	76%±1.9%	74%±2.2%
	4-time ahead	75%±2.1%	74%±2.0%	72%±2.2%	74%±2.1%	73%±2.0%	71%±2.3%
	8-time ahead	70%±2.4%	69%±2.3%	67%±2.5%	69%±2.5%	68%±2.4%	66%±2.6%
SVR-RBF	1-time ahead	77%±2.0%	76%±1.9%	74%±2.1%	76%±2.0%	75%±2.1%	73%±2.3%
	2-time ahead	73%±2.2%	72%±2.0%	70%±2.3%	72%±2.4%	71%±2.3%	69%±2.5%
	4-time ahead	68%±2.6%	67%±2.4%	65%±2.6%	67%±2.6%	66%±2.5%	64%±2.7%
	8-time ahead	62%±2.8%	61%±2.7%	59%±2.9%	61%±2.9%	60%±2.8%	58%±3.0%

predicted. Though the forecasting is not perfectly aligned with the real evolution of the sentiment descriptors, we can note that the regressive function can capture the trend of the series.

To assess the influence of forecast range on user sentiment modeling, we conduct multi-step sentiment prediction on the ST140 and CVD19 datasets across 1-, 2-, 4-, and 8-step horizons, evaluating F1-score, accuracy, and ROC-AUC (Table 1). All models show their strongest performance at 1-step ahead, with **DLinear** leading (ST140: F1 ≈ 85%, Acc ≈ 84%, ROC ≈ 82%; CVD19: F1 ≈ 84%, Acc ≈ 83%, ROC ≈ 81%). As the forecast horizon increases, performance consistently declines and variability grows, especially for classical models like **AR** and **SVR**. Despite this, **DLinear** and **LSTM** remain comparatively robust over longer horizons, while ST140 exhibits more stable trends than CVD19, confirming the growing difficulty of long-range sentiment forecasting and the benefit of temporal-aware models.

7 Conclusion

We introduced a framework for modeling sentiment dynamics by combining temporal smoothing with multi-state Cox regression. This approach captures fine-grained sentiment transitions and offers interpretable insights into sentiment evolution. Results highlight the value of sentiment shifts in anticipating user behavior, paving the way for future exploration.

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