Topic Detection and Tracking with Time-Aware Document Embeddings

Hang Jiang, Doug Beeferman, Weiquan Mao, Deb Roy
Massachusetts Institute of Technology, Stanford University
75 Amherst St, Cambridge, MA 02139
{hjian42, dougb5, dkroy}@mit.edu, mwq@stanford.edu

Abstract

The time at which a message is communicated is a vital piece of metadata in many real-world natural language processing tasks such as Topic Detection and Tracking (TDT). TDT systems aim to cluster a corpus of news articles by event, and in that context, stories that describe the same event are likely to have been written at around the same time. Prior work on time modeling for TDT takes this into account, but does not well capture how time interacts with the semantic nature of the event. For example, stories about a tropical storm are likely to be written within a short time interval, while stories about a movie release may appear over weeks or months. In our work, we design a neural method that fuses temporal and textual information into a single representation of news documents for event detection. We fine-tune these time-aware document embeddings with a triplet loss architecture, integrate the model into downstream TDT systems, and evaluate the systems on two benchmark TDT data sets in English. In the retrospective setting, we apply clustering algorithms to the time-aware embeddings and show substantial improvements over baselines on the News2013 data set. In the online streaming setting, we add our document encoder to an existing state-of-the-art TDT pipeline and demonstrate that it can benefit the overall performance. We conduct ablation studies on the time representation and fusion algorithm strategies, showing that our proposed model outperforms alternative strategies. Finally, we probe the model to examine how it handles recurring events more effectively than previous TDT systems.

Keywords: Topic Detection and Tracking, Online Clustering, Document Embedding, Temporal Embedding

1. Introduction

Following emerging news stories is crucial to making real-time decisions on important political and public safety matters. Amid the COVID-19 pandemic, for instance, media platforms and government agencies need to identify the emergence of misinformation in time and take action to protect the safety of the public. As humans cannot read all of the articles produced by the news media, automatic clustering of news articles into real-world events is needed to make this work tractable. Computational tools for this task are useful for organizing not just news articles, but also scientific papers, microblogs, online reviews, forum messages, and social media posts.

Allan et al. (1998) first introduced the topic detection and tracking (TDT) framework to address these needs. In this paper, we focus on the event detection part of TDT, where events are defined as real-world news stories and we want to categorize news articles into these events. Researchers have proposed both topic modeling and clustering-based methods for this task, in both retrospective and online streaming settings. In the retrospective setting, researchers process the news documents altogether, whereas in the online setting they are processed one by one as they appear in the stream.

Most real-world documents have a timestamp, the time at which it was written, spoken, or shared. TDT modelers use this metadata, at a minimum, to exploit the temporal locality inherent in news events. But beyond that, researchers tend to focus on improving text representations (Hu et al., 2017; Staykovski et al., 2019; Saravanakumar et al., 2021; Fan et al., 2021) instead of time representations. The time model is typically parameter-free or low capacity, and unconnected to the text. This overlooks important ways that the time may interact with the topic of the article to influence where it falls on the calendar and how long it lasts as an event. For example, stock reports happen daily, but corporate earnings releases may happen quarterly and be discussed over several days. Stories about a weather event are likely to be written over a short time period, while stories a movie release may be discussed over weeks or months.

In this paper, we address these gaps with a unified neural time-text model that fuses temporal and semantic embeddings to represent news documents. Our contributions are as follows:

- We propose a time-aware neural document embedding method that can be applied to topic detection and tracking and other NLP tasks.
- We build two TDT pipelines based on our time-aware model, for retrospective and online event clustering tasks respectively, achieving state-of-the-art performance in both settings for the corpus used as a benchmark by re-
cent prior work. Importantly, our retrospective model is free of the TF-IDF features that are needed by similar systems, allowing it to be adapted to new domains more easily.

- We conduct an ablation analysis on our time representation. We find that sinusoidal positional embedding outperforms two alternatives, learned positional embedding and Date2Vec, to encode timestamps for TDT.

- We analyze the event predictions of our model and baseline methods and find that our model can better handle recurring events that pose challenges to previous TDT systems.

2. Related Work

Topic detection and tracking (TDT) program (Liu, 2009; Fiscus and Doddington, 2002) focuses on building algorithms to organize multilingual, news oriented textual materials from the Internet. Apart from news, TDT techniques are also widely used in processing social media data (Xiong et al., 2022). Traditionally, some researchers (Allan et al., 1998; Yang et al., 1998; Xu et al., 2019; Liu et al., 2020) have focused on applying different topic models (e.g., LDA) for TDT. Other researchers (Hatzivasiloglou et al., 2000; Allan et al., 2003; Dai et al., 2010; Li et al., 2020) explored the use of text clustering algorithms on sparse features and word embeddings for TDT.

Recent approaches to TDT have explored both sparse and dense features. Miranda et al. (2018) proposes an online clustering method that represents documents with TF-IDF features, and demonstrates high performance on a benchmark news article data set. Building on this work, Staykovski et al. (2019) compares sparse TF-IDF features with dense Doc2Vec representations, showing a sizeable improvement on the standard data set according to the BCubed evaluation metric. Saravanakumar et al. (2021) is the first to include BERT contextual representations for the task and achieves further improvement. Specifically, they fine-tune an entity-aware BERT model on an event similarity task with a triplet loss function. They generate triplets for each document using the batch-hard regime (Hermans et al., 2017). In each document in a mini-batch, they mark documents with the same label as positive examples and different labels as negative examples. The hardest positive (biggest positive-anchor document distance) and negative (smallest anchor-negative document distance) examples are picked per anchor document to form a triplet. The entity-aware BERT model is trained to make the embedding distance between anchor and positive documents closer than anchor and negative documents. Overall, this fine-tuning process effectively improves the contextual embedding for the overall TDT system. Santos et al. (2022) simplified the multilingual news clustering process with multilingual document embeddings. Recent studies have also leveraged large language models (LLMs) for text clustering (Zhang et al., 2023; Viswanathan et al., 2023) and story discovery (Yoon et al., 2023a,b). This paper focuses on comparing our method against previous embedding-based methods with small language models such as BERT.

TDT systems vary in how they model the timestamps of the news stories. Some online approaches combine the time element implicitly by sorting documents in chronological order, dividing them with time slicing, and processing each slice (Allan et al., 1998; Yang et al., 1998; Dai et al., 2010; Hu et al., 2017). Other work uses decay functions to extract sparse time features (Yang et al., 1998; Brants et al., 2003; Li et al., 2005; He et al., 2010; Ribeiro et al., 2017; Miranda et al., 2018; Saravanakumar et al., 2021). However, none of the previous work has used temporal embeddings to represent time for the TDT task. This work aims to introduce a popular temporal embedding method from Devlin et al. (2018) to TDT such that the fused document embedding contains both temporal and semantic information for clustering.

3. Methodology

In this section we propose a novel method called T-E-BERT to encode news documents by fusing text and time information. We adopt a triplet loss function to train the model on the event similarity task and integrate the fine-tuned model into both retrospective and online TDT pipelines.

3.1. The Proposed Model

![Figure 1: The proposed T-E-BERT model.](image)

3.1.1. T-E-BERT Encoder

We design a simple time-text encoder (“T-E-BERT”) based on entity-aware BERT to combine textual...
and temporal information to encode news documents (shown in Figure 1). Following Saravanakumar et al. (2021), we add an entity presence-absence embedding layer to enhance BERT’s entity awareness, which can improve the text representation of news events. We use all the hidden output from the last layer as the textual matrix \( M_{text} \). To represent time, we convert the date time in each document into a time step (e.g. the number of days from the earliest date in the data) and transform the time step into a temporal embedding with the sinusoidal position encoding method introduced by Vaswani et al. (2017). The temporal embedding is repeated “sequence length” times to generate \( M_{time} \), which is the same shape as the \( M_{text} \). Afterwards, we introduce a fusion module based on multi-head attention to transform the concatenation of text and time embeddings into a text-time matrix. At last, the fused matrix is fed into the pooling layer to generate a news document embedding. The model is trained on a event similarity task to learn how to combine text and time information before this is used for downstream TDT tasks.

### 3.1.2. Fine-tuning

We follow the fine-tuning procedure suggested by Saravanakumar et al. (2021) to adapt the triplet network structure (Hoffer and Ailon, 2015) and fine-tune our T-E-BERT model on the event similarity task. The task aims to tune the model such that it can make the temporal-semantic similarity between same events smaller than the temporal-semantic similarity between different events. In Figure 2, we demonstrate how the training paradigm works. Given an anchor document \( d_a \), we sample a positive document \( d_p \) (from the same event as \( d_a \)) as well as a negative document \( d_n \) (from a different event). We compute the triplet loss function as follows:

\[
L_{triplet} = sim(d_a, d_n) - sim(d_a, d_p) + m \quad (1)
\]

where \( sim \) is the cosine similarity function and \( m \) is the hyper-parameter margin.

![Figure 2: This figures demonstrates the fine-tuning procedure of T-E-BERT on news event triplets.](Image)

We also experimented with SVM-triplet but our implementation performed worse than their reported performance (Saravanakumar et al., 2021).

### 3.2. Retrospective TDT Pipeline

The retrospective TDT pipeline is simple, consisting of a document encoder and a clustering module. At the document encoding step, we concatenate the title and the body of the news articles to form the input text. We then replace the original TF-IDF encoder (Yang et al., 1998; Allan et al., 1998; Schultz and Liberman, 1999) with the fine-tuned T-E-BERT to vectorize the news documents, considering both their timestamps and texts. These vectors are directly fed into a clustering algorithm to produce event clusters. We choose the HDBSCAN clustering algorithm\(^2\) (McInnes et al., 2017) for two reasons. First, HDBSCAN does not require the number of clusters as a hyperparameter, which is unknown to a TDT system in a real-world deployment. Second, HDBSCAN shows strong empirical performance in our experiments, even compared with K-Means and agglomerative clustering algorithms using the true number of clusters.

### 3.3. Online TDT Pipeline

We follow the previous work (Miranda et al., 2018; Saravanakumar et al., 2021) to adopt a variant of the streaming K-means algorithm (Figure 3) with a few key changes. This system consists of three main components: (1) a document encoder, (2) a document-cluster weighted similarity model, (3) a cluster creation model. At any point time \( t \), let \( n \) be the number of clusters in the cluster pool. For any input document, we assume it belongs to a single event cluster. We first represent this document with a set of vectors including \( 9 \) TF-IDF sparse vectors, one dense vector from T-E-BERT, and one time sparse vector (Saravanakumar et al., 2021). After the document representation is extracted, we use the document-cluster weighted similarity model to find the best matching event cluster \( C^* \) from the cluster pool. Finally we use a cluster creation model to decide whether a new cluster is needed. If the cluster \( C^* \) is predicted to be a good fit for the new document, we add the document to this cluster. Otherwise, we create a new cluster containing this document and add the cluster into the cluster pool.

We make two major changes to previous methods (Miranda et al., 2018; Saravanakumar et al., 2021). First, we switch the weighted similarity model from SVM-rank to a linear model with Margin-RankingLoss. This change boosts the performance of the weighted similarity model\(^3\). Second, we sample balanced positive and negative examples to train the cluster creation model. This alleviates the issue of data imbalance because only 5% of the

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\(^1\) \( M_{text} \) has a shape of [sequence length, hidden size].

\(^2\) [https://hdbscan.readthedocs.io/](https://hdbscan.readthedocs.io/)

\(^3\) We also experimented with SVM-triplet but our implementation performed worse than their reported performance (Saravanakumar et al., 2021).
training data points contain a positive label (create a new cluster).

4. Experiments

4.1. Data Sets

We use two data sets for our experiments, which we refer to as News2013 and TDT-1. News2013 refers to the English portion of the multilingual news data set produced in Miranda et al. (2018), which in turn derives from Rupnik et al. (2016). The News2013 data set contains a train set from 2013-12-18 to 2014-11-02, and a temporally disjoint test set from 2014-11-02 to 2015-08-25. TDT-1 refers to the pilot data set for the TDT initiative. We follow Saravanakumar et al. (2021) to generate its train set from 1994-07-09 to 1995-06-30 and a temporally overlapping test set from 1994-07-04 to 1995-06-28. Dataset statistics are shown in Table 1.

| Dataset          | Train | Test |
|------------------|-------|------|
| News2013 (Miranda et al., 2018) | 12,233 | 593 | 8,726 | 222 |
| TDT-1 (Allan et al., 1998) | 899 | 13 | 654 | 12 |

Table 1: Characteristics of the two TDT datasets. \(|D|\) and \(|E|\) denote the number of documents and topic events, respectively.

4.2. Retrospective TDT Experiments

We designed three experiments in retrospective TDT setting. First, we compare different representations with clustering algorithms that need the gold number of clusters (Table 2). We include two known baseline algorithms based on TF-IDF features including (a) the K-Means algorithm and (b) the augmented Group Average Clustering (GAC) (Yang et al., 1998). We then compare them against different BERT representations on GAC to understand the effect of representations. Second, we conduct experiments to compare these representations (TF-IDF, BERT, E-BERT, three variants of T-E-BERT) with HDBSCAN, which does not require the cluster number as an input. In Table 2, we also conduct experiments with three time encoding strategies (Date2Vec, LearnPE, SinPE). At last, we run some studies on the time-text fusion strategy and time granularity option. With the most performant time encoding method SinPE, we compare four time-text fusion methods (Table 3) and five time granularity choices on News2013 (Table 4).

4.2.1. Experiment Setup

We use the online BatchHardTriplet algorithm to fine-tune BERT models for 1-5 epochs and use the best model. The training adopts a batch size of 32 and a max sequence length 230 to best fit into an 11GB GTX 1080 Ti GPU.

4.2.2. Time Encoding Strategies

We explored three ways of encoding temporal information into dense embeddings: (1) Date2Vec; (2) learned position embedding (LearnPE); (3) sinusoidal position embedding (SinPE). The first method directly transforms a date-time string into a dense vector. The second and third methods transform a document timestamp into a position by calculating the time span (e.g., in days) between the target document and the earliest document, generating a position embedding from this relative position. Previous studies (Vaswani et al., 2017; Wang and Chen, 2020) show that (2) and (3) perform similarly for language modeling. To integrate these time encodings into the TDT system, we use the E-BERT text encoder and apply the concatenation + multi-head-attention fusion method described in the method section (Figure 1).

- **Date2Vec** is a pre-trained time encoder based on Time2Vec (Kazemi et al., 2019) that transforms a date and time into a dense vector, while preserving the time-specific characteristics (progression, periodicity, scale, etc). Kazemi et al. (2019) shows that Date2Vec is able to improve downstream NLP tasks. We use the pre-trained Date2Vec model\(^5\) released by Kazemi et al. (2019) in our experiments. We decided to update the Date2Vec module during training because we also tried to freeze the time module, leading to 2% decrease in F1 on News2013.

- **Learned position embedding (LearnPE)** is a learned position embedding method used by many Transformer-based models (Devlin et al., 2018; Liu et al., 2019; Radford et al., 2019). It randomly initializes an embedding layer and updates the look-up table during training.

- **Sinusoidal position embedding (SinPE)** uses the sine and cosine functions of different frequencies to encode positions (Vaswani et al., 2017). As shown in the following equations, \(i\) is the position index and \(j\) is the dimension index. Compared to the learned PE method, this approach assigns a fixed embedding to each position.

\(^4\)We follow their event splits, but get different train and test instances from Saravanakumar et al. (2021).

\(^5\)https://github.com/ojus1/Date2Vec
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Figure 3: Overview of the online TDT pipeline.

| Model                           | News2013 | TDT-1 |
|---------------------------------|----------|-------|
|                                 | Precision | Recall | F1 | CN | Precision | Recall | F1 | CN |
| TF-IDF + K-Means                | 87.00    | 53.94 | 66.60 | 222 | 84.23 | 69.01 | 75.87 | 12 |
| TF-IDF + GAC                    | 71.12    | 96.06 | 81.73 | 222 | 42.70 | 97.35 | 59.36 | 12 |
| BERT + GAC                      | 69.35    | 88.59 | 77.79 | 222 | 79.27 | 89.65 | 84.14 | 12 |
| E-BERT + GAC                    | 71.82    | 86.82 | 78.61 | 222 | 76.34 | 89.84 | 82.54 | 12 |
| SinPE-E-BERT + CM + GAC         | 83.09    | 95.04 | 88.66 | 222 | 80.79 | 91.96 | 86.01 | 12 |
| TF-IDF + HDBSCAN                | 88.45    | 58.58 | 70.48 | 301 | 93.05 | 89.34 | 91.16 | 11 |
| BERT + HDBSCAN                  | 81.93    | 69.22 | 75.04 | 208 | 83.57 | 90.95 | 87.10 | 12 |
| E-BERT + HDBSCAN                | 82.07    | 70.41 | 75.79 | 210 | 82.23 | 90.50 | 86.17 | 11 |
| Date2Vec-E-BERT + CM + HDBSCAN  | 78.68    | 88.99 | 83.52 | 156 | 62.83 | 58.32 | 60.49 | 10 |
| LearnPE-E-BERT + CM + HDBSCAN   | 83.33    | 54.24 | 65.71 | 252 | 79.51 | 59.36 | 67.97 | 13 |
| SinPE-E-BERT + CM + HDBSCAN     | 90.18    | 89.90 | 90.04 | 186 | 86.79 | 90.96 | 88.83 | 9  |

Table 2: Retrospective TDT performance comparison of baselines with our T-E-BERT variants. CN stands for the predicted cluster number. We adopt the B-Cubed F measure for precision, recall and F1. Note that CN is automatically determined by HDBSCAN but set to be the gold number of clusters for the K-Means and Group Agglomerative Clustering (GAC) algorithms. GAC and HDBSCAN are deterministic, whereas K-Means is stochastic. We run K-Means five times and pick the best run for the table. The average F1 and standard deviation of the K-Means algorithm on two data sets are 67.86 ± 1.00 (News2013) and 71.06 ± 4.81 (TDT-1).

\[
PE_{(i,2j)} = \sin\left(i/10000^{2j/d_{model}}\right) \tag{2}
\]

\[
PE_{(i,2j+1)} = \cos\left(i/10000^{2j/d_{model}}\right) \tag{3}
\]

4.2.3. Time-text Fusion Methods

We experiment with four methods to fuse the time and content embeddings. We repeat each document’s position embedding “sequence length” times to form the position matrix \(M_{time}\). \(M_{text}\) indicates the text matrix from the last layer of the BERT model. \(e_f\) indicates the fused document embedding, \(\oplus\) indicates addition operation of two matrices. \([M_1, M_2]\) indicates a concatenation operation of two matrices. \(\text{POOL}\) indicates the mean pooling layer. \(\text{ATT}\) indicates the multi-head attention layer. The third CM equation corresponds to the T-E-BERT diagram in Figure 1. Based on the results with the following four time-text fusion methods on News2013 (Table 3), the CM fusion method achieves the best results relative to the other three methods (A, AM, and ACM). As a result, we decide to adopt the SinPE-E-BERT + CM implementation for T-E-BERT in the later experiments.

- **additive (A):**
  \[
e_f = \text{POOL}(M_{text} \oplus M_{time})
\]

- **additive + multi-head attention (AM):**
  \[
e_f = \text{POOL}(\text{ATT}(M_{text} \oplus M_{time}))
\]

- **concatenate + multi-head attention (CM):**
  \[
e_f = \text{POOL}(\text{ATT}([M_{text}, M_{time}]))
\]

- **additive + concatenate + multi-head attention (ACM):**
  \[
e_f = \text{POOL}(\text{ATT}([M_{text}, M_{time}] \oplus M_{time}))
\]
We make three main observations from Table 2. First, we demonstrate that adding time-text fused embedding vectors for clustering to achieve reported performance. Second, SinPE-E-BERT consistently outperforms E-BERT and BERT on both data sets. With HDBSCAN, it substantially outperforms E-BERT (+14.25%) and BERT (+15.00%) on News2013, which challenges recent TDT systems to detect hundreds of fine-grain topic events over time. It also performs above par compared with E-BERT (+2.66%) and BERT (+1.73%) in TDT-1, where events are more broadly defined and spread in the data. At last, SinPE outperforms the other two ways to encode time information. We find that the offset from the earliest document in the data set, and hence a pair of documents that are in the same calendar month may yield different embedding vectors in a model with monthly granularity; and likewise for weekly.

Table 3: This tables shows the effect of four different fusion strategies to retrospective TDT on News2013. HDBSCAN is used in this experiment. CN stands for the predicted cluster number.

| Fusion Method       | Precision | Recall | F1   | CN  |
|---------------------|-----------|--------|------|-----|
| SinPE-E-BERT + A    | 88.44     | 86.54  | 87.48| 190 |
| SinPE-E-BERT + AM   | 89.03     | 89.29  | 89.16| 183 |
| SinPE-E-BERT + CM   | 90.18     | 89.90  | 90.04| 186 |
| SinPE-E-BERT + ACM  | 89.50     | 86.71  | 89.10| 188 |

Table 4: This table shows the effect of time granularity to retrospective TDT on News2013. SinPE-E-BERT + CM + HDBSCAN is used for this experiment. CN stands for the predicted cluster number.

| Time Granularity    | Precision | Recall | F1   | CN  |
|---------------------|-----------|--------|------|-----|
| SinPE-E-BERT + hourly| 85.95     | 82.58  | 84.23| 199 |
| SinPE-E-BERT + daily | 90.18     | 89.90  | 90.04| 186 |
| SinPE-E-BERT + bidaily | 88.92    | 88.75  | 88.84| 185 |
| SinPE-E-BERT + weekly | 86.55    | 83.62  | 85.06| 189 |
| SinPE-E-BERT + monthly | 82.63    | 72.45  | 77.20| 200 |

4.2.4. Time Granularity

The unit of time can be a crucial factor in the model’s performance. Our work follows the previous work (Miranda et al., 2018; Saravanakumar et al., 2021) and uses 1 day as the time granularity for the News2013 data set. We also experimented with hourly, bidaily, weekly (7-day), and monthly (30-day) granularity on this data set (Table 4). Similar experiments led us to choose a 3-month granularity for the TDT-1 data set.

4.2.5. Retrospective TDT Results

We make three main observations from Table 2. First, SinPE-E-BERT + CM + GAC outperforms the other methods based on K-Means and GAC on both data sets. This result provides some evidence that time information is helpful to the retrospective TDT task. Second, SinPE-E-BERT consistently improves E-BERT and BERT on both data sets. With HDBSCAN, it substantially outperforms E-BERT (+14.25%) and BERT (+15.00%) on News2013, which challenges recent TDT systems to detect hundreds of fine-grain topic events over time. It also performs above par compared with E-BERT (+2.66%) and BERT (+1.73%) in TDT-1, where events are more broadly defined and spread in the data. At last, SinPE outperforms the other two ways to encode time information. We find that the training data is insufficient to tune Date2Vec and LearnPE to fit the TDT task, for which a monotonic decrease in event similarity over time is the dominating characteristic for news articles. We will discuss the difference between Date2Vec and SinPE further in the “Probing Time in T-E-BERT” section.

It is worth noting that BERT-based methods underperform TF-IDF on News2013, but they slightly underperform TF-IDF on TDT-1. However, our retrospective TDT system with T-E-BERT + HDBSCAN is simple and efficient compared to the TF-IDF counterpart. TF-IDF is more complicated to construct and requires researchers to carefully choose vocabulary size and stop words for each data set. In contrast, T-E-BERT has a simple and standard fine-tuning procedure to adapt to new data sets. Moreover, TF-IDF features are high dimensional sparse features, whereas T-E-BERT embeddings are low dimensional dense vectors. That means that it takes significantly longer time for the HDBSCAN algorithm to converge with TF-IDF than T-E-BERT embeddings, especially for large data sets such as News2013.

4.3. Online TDT Experiments

In online TDT experiments, we integrate different BERT embeddings (BERT, E-BERT, SinPE-E-BERT) into the online TDT system and compare them with the baseline TF-IDF + TIME as well as previous works. The online TDT system has a document encoder, for which we pick the BERT model with the best performance from the retrospective TDT task (T-E-BERT with SinPE and concatenation + multi-head attention) and train the model with the same configuration for the online TDT system.

As for weighted similarity and cluster creation models, we follow the steps suggested by Miranda et al. (2018) to create the training data. The only difference is that we balance the training data for the cluster creation model, as suggested by Saravanakumar et al. (2021). Both the weighting and cluster creation models are trained using 5-fold cross validation to tune hyper-parameters and are applied with the best configuration for inference. The clustering output is evaluated against the gold event cluster labels. To be consistent with recent previous work (Staykovski et al., 2019; Saravanakumar et al., 2021) we use the B-Cubed measure for evaluation. B-Cubed is more suitable for cluster evaluation than the standard F measure, as it favors cluster homogeneity and cluster completeness.

4.3.1. Online TDT Results

We make three observations from Table 5. First, we demonstrate that adding time-text fused embed-
Table 5: Online Streaming TDT performance between prior work and our system with different features.

| Model                                  | Precision | Recall | F1  | CN  | Precision | Recall | F1  | CN  |
|----------------------------------------|-----------|--------|-----|-----|-----------|--------|-----|-----|
| Laban and Hearst (2017)               | 94.37     | 85.58  | 89.76 | 873 | -         | -      | -   | -   |
| Miranda et al. (2018)                 | 94.27     | 90.25  | 92.36 | 326 | 77.14     | 90.20  | 83.16 | 17  |
| Staykovski et al. (2019)              | 95.16     | 93.66  | 94.41 | 484 | -         | -      | -   | -   |
| Linger and Hajalej (2020)             | 94.19     | 93.55  | 93.86 | 298 | -         | -      | -   | -   |
| Saravanakumar et al. (2021)           | 94.28     | 95.25  | 94.76 | 276 | -         | -      | -   | -   |
| Ours - TF-IDF + TIME                  | 90.21     | 95.66  | 92.86 | 296 | 84.05     | 93.77  | 88.65 | 18  |
| Ours - TF-IDF + BERT + TIME           | 93.97     | 89.46  | 91.66 | 359 | 84.27     | 95.27  | 89.43 | 18  |
| Ours - TF-IDF + E-BERT + TIME         | 93.55     | 95.35  | 94.44 | 315 | 84.47     | 95.82  | 89.79 | 18  |
| Ours - TF-IDF + SinPE-E-BERT + TIME   | 93.20     | 97.14  | 95.13 | 253 | 84.69     | 97.48  | 90.63 | 16  |

5. Analysis

5.1. Probing Time in T-E-BERT

To understand the effect of time on the overall document embedding, we conduct a simple probing analysis on the Date2Vec-PE-E-BERT and SinPE-E-BERT models. We randomly pick one document from the News2013 dataset and tweak its timestamp from an anchor date to 1000 days later. We compute the cosine similarity $\text{sim}(d_0, d_t)$ of the same document between its document embeddings with the anchor date and another date $t$ to generate the Figure 4. On one hand, we observe that the similarity monotonously decrease for SinPE-E-BERT, despite some small oscillations in the later days. We suppose that the fluctuations in similarities are due to the limited data used for fine-tuning. News articles are not evenly distributed across time and some dates are associated with more articles. Therefore, it is possible that news articles from some dates are sampled less frequently than others when we dynamically sample triplets for fine-tuning the SinPE-E-BERT model. On the other hand, we notice that the similarity score changes periodically for Date2Vec-PE-E-BERT. Specifically, the similarity for Date2Vec-PE-E-BERT is in a decreasing trend within a month and a week 5, but the score will be similar for the same dates across months and years 4. For instance, Date2Vec-PE-E-BERT thinks a document that the label 2013-12-25 and 2014-12-25 to have a high similarity. However, such a periodic trait is not always beneficial for the TDT task, whereas the span of time from the beginning date is probably the most helpful signal. Therefore, the SinPE-E-BERT model based on position embedding is more suitable for the TDT task than Date2Vec-E-BERT.
Table 6: Selected clusters from the News2013 training set. The cells with → show the change in mean cosine similarity, averaged over all document pairs from the respective clusters, between the E-BERT embeddings (left) and the time-infused T-E-BERT embeddings (right). All dates are in 2014.

5.2. Qualitative Analysis

Both E-BERT and T-E-BERT are fine-tuned such that the embedding vectors produced for articles within the same training event are moved closer together, but T-E-BERT alone is sensitive to the times-tamp. Qualitatively, we find that the articles that are impacted the most by T-E-BERT are those that belong to recurring real-world events such as daily stock summaries and financial news updates, of which there are many semantically similar clusters in the training corpus. Table 6 shows four examples of clusters in the News2013 data set; the first two of these are the clusters most impacted by T-E-BERT, both representing daily stock updates. We see that the mean pairwise cosine similarity between the articles in the two clusters is much greater for E-BERT (0.45) than for T-E-BERT (0.16); whereas the within-cluster similarity is in both cases slightly greater for T-E-BERT.

5.3. Evaluation Metrics

The B-Cubed metric gives more weight to larger clusters and can obscure the impact that an algorithm has on smaller clusters. In order to weight every cluster equally, we use CEAF-e (Luo, 2005) metric to show that our model performs better on small clusters as well. In addition, other evaluation metrics (Table 7) show that our model’s superior performance is metric-agnostic.

Table 7: Performance across different evaluation metrics. Our Best represents the best model we have. SinPE-E-BERT + TF-IDF + TIME. Our model achieves an improvement of 2.95 points on the CEAF-e metric, compared to the best E-BERT + TF-IDF + TIME model in Saravanakumar et al. (2021).

5.4. Truncated Document Length

We also run ablation studies on triplet mining methods and truncated document length. We compare BatchHardTripletLoss against three other online methods including BatchHardSoftMarginTriplet-Loss, BatchSemiHardTripletLoss, and BatchAllTripletLoss and four offline methods including Easiest Positive and Easiest Negative(EPEN), Easiest Positive and Hardest Negative (EPHN), Hardest Positive, and Easiest Negative (HPEN), and Hardest Positive and Hardest Negative (HPHN), showing it outperforms the other triplet mining approaches for the retrospective TDT task on News2013. Besides, we find that keeping more than the first few hundred words is of limited help in improving clustering accuracy, confirming the inverted pyramid structure of news articles (Pöttker, 2003): the underlying event is usually summarized in the title and the first paragraph, and later paragraphs provide auxiliary information. This suggests that further increasing the sequence length is unlikely to improve the performance substantially.

6. Conclusion

We propose a simple yet effective neural approach to fuse time and text information to create document representations for the TDT task. We explore different time representations, fusion modules, and time granularities. Our T-E-BERT model SinPE-E-BERT uses sinusoidal positional embeddings to represent timestamps, and entity-aware BERT to represent content. We fine-tune this model with online BatchHardTripletLoss and daily time granularity to achieve state-of-the-art performance on the News2013 benchmark data set. After incorporating our T-E-BERT embeddings in TDT systems, we show superior performance compared to BERT and E-BERT features in both retrospective and online streaming TDT event detection tasks on two benchmark datasets. Finally, we probe our model to show the effectiveness of time module. We also find that SinPE is able to move the document embedding in a desirable direction to better handle recurring events (e.g. stock reports, climate events).
7. Bibliographical References

James Allan. 2002. Introduction to topic detection and tracking. In Topic detection and tracking, pages 1–16. Springer.

James Allan, Jaime G Carbonell, George Doddington, Jonathan Yamron, and Yiming Yang. 1998. Topic detection and tracking pilot study final report.

James Allan, Ao Feng, and Alvaro Bolivar. 2003. Flexible intrinsic evaluation of hierarchical clustering for tdt. In Proceedings of the twelfth international conference on Information and knowledge management, pages 263–270.

Thorsten Brants, Francine Chen, and Ayman Farahat. 2003. A system for new event detection. In Proceedings of the 26th annual international ACM SIGIR conference on Research and development in information retrieval, pages 330–337.

BSI. 1973a. Natural Fibre Twines, 3rd edition. British Standards Institution, London. BS 2570.

BSI. 1973b. Natural fibre twines. BS 2570, British Standards Institution, London. 3rd. edn.

A. Castor and L. E. Pollux. 1992. The use of user modelling to guide inference and learning. Applied Intelligence, 2(1):37–53.

J.L. Chercheur. 1994. Case-Based Reasoning, 2nd edition. Morgan Kaufman Publishers, San Mateo, CA.

N. Chomsky. 1973. Conditions on transformations. In A festschrift for Morris Halle, New York. Holt, Rinehart & Winston.

Margaret Connell, Ao Feng, Giridhar Kumaran, Hema Raghavan, Chirag Shah, and James Allan. 2004. Umass at tdt 2004. In Topic Detection and Tracking Workshop Report, volume 19.

Xiangying Dai, Yancheng He, and Yunlian Sun. 2010. A two-layer text clustering approach for retrospective news event detection. In 2010 International Conference on Artificial Intelligence and Computational Intelligence, volume 1, pages 364–368. IEEE.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Umberto Eco. 1990. The Limits of Interpretation. Indian University Press.

Rong-En Fan, Kai-Wei Chang, Cho-Jui Hsieh, Xiang-Rui Wang, and Chih-Jen Lin. 2008. Liblinear: A library for large linear classification. the Journal of machine Learning research, 9:1871–1874.

Wentao Fan, Zhiyan Guo, Nizar Bouguila, and Wenzhuan Hou. 2021. Clustering-based online news topic detection and tracking through hierarchical bayesian nonparametric models. In Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 2126–2130.

Jonathan G Fiscus and George R Doddington. 2002. Topic detection and tracking evaluation overview. In Topic detection and tracking: event-based information organization, pages 17–31. Springer.

Vasileios Hatzivassiloglou, Luis Gravano, and Ankineedu Maganti. 2000. An investigation of linguistic features and clustering algorithms for topical document clustering. In Proceedings of the 23rd annual international ACM SIGIR conference on Research and development in information retrieval, pages 224–231.

Qi He, Kuiyu Chang, Ee-Peng Lim, and Arindam Banerjee. 2010. Keep it simple with time: A reexamination of probabilistic topic detection models. IEEE Transactions on Pattern Analysis and Machine Intelligence, 32(10):1795–1808.

Alexander Hermans, Lucas Beyer, and Bastian Leibe. 2017. In defense of the triplet loss for person re-identification. arXiv preprint arXiv:1703.07737.

Paul Gerhard Hoel. 1971a. Elementary Statistics, 3rd edition. Wiley series in probability and mathematical statistics. Wiley, New York, Chichester. ISBN 0 471 40300.

Paul Gerhard Hoel. 1971b. Elementary Statistics, 3rd edition, Wiley series in probability and mathematical statistics, pages 19–33. Wiley, New York, Chichester. ISBN 0 471 40300.

Elad Hoffer and Nir Ailon. 2015. Deep metric learning using triplet network. In International workshop on similarity-based pattern recognition, pages 84–92. Springer.

Matthew Honnibal and Ines Montani. 2017. spacy 2: Natural language understanding with bloom embeddings, convolutional neural networks and incremental parsing. To appear, 7(1):411–420.

Linmei Hu, Bin Zhang, Lei Hou, and Juanzi Li. 2017. Adaptive online event detection in news streams. Knowledge-Based Systems, 138:105–112.
Otto Jespersen. 1922. *Language: Its Nature, Development, and Origin*. Allen and Unwin.

Seyed Mehran Kazemi, Rishab Goel, Sepehr Eghbali, Janahan Ramanan, Jaspreet Sahota, Sanjay Thakur, Stella Wu, Cathal Smyth, Pascal Poupart, and Marcus Brubaker. 2019. Time2vec: Learning a vector representation of time. *arXiv preprint arXiv:1907.05321*.

Philippe Laban and Marti A Hearst. 2017. newslens: building and visualizing long-ranging news stories. In *Proceedings of the Events and Stories in the News Workshop*, pages 1–9.

Ken Lang. 1995. Newsweeder: Learning to filter netnews. In *Proceedings of the Twelfth International Conference on Machine Learning*, pages 331–339.

Chuanzhen Li, Mingqiao Liu, Juanjuan Cai, Yang Yu, and Hui Wang. 2020. Topic detection and tracking based on windowed dbscan and parallel knn. *IEEE Access*, 9:3858–3870.

Zhiwei Li, Bin Wang, Mingjing Li, and Wei-Ying Ma. 2005. A probabilistic model for retrospective news event detection. In *Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 106–113.

Mathis Linger and Mhamed Hajaiej. 2020. Batch clustering for multilingual news streaming. *arXiv preprint arXiv:2004.08123*.

Huailan Liu, Zhiwang Chen, Jie Tang, Yuan Zhou, and Sheng Liu. 2020. Mapping the technology evolution path: a novel model for dynamic topic detection and tracking. * Scientometric*, 125:2043–2090.

Ning Liu. 2009. *Topic Detection and Tracking*, pages 3121–3124. Springer US, Boston, MA.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Xiaoliang Luo. 2005. On coreference resolution performance metrics. In *Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing*, pages 25–32.

Leland McInnes, John Healy, and Steve Astels. 2017. hdbscan: Hierarchical density based clustering. *Journal of Open Source Software*, 2(11):205.

Sebastiao Miranda, Artūrs Znotinš, Shay B Cohen, and Guntis Barzdins. 2018. Multilingual clustering of streaming news. *arXiv preprint arXiv:1809.00540*.

Hien M Nguyen, Eric W Cooper, and Katsuari Kamei. 2011. Borderline over-sampling for imbalanced data classification. *International Journal of Knowledge Engineering and Soft Data Paradigms*, 3(1):4–21.

Horst Pöttker. 2003. News and its communicative quality: the inverted pyramid—when and why did it appear? *Journalism Studies*, 4(4):501–511.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Swen Ribeiro, Olivier Ferret, and Xavier Tannier. 2017. Unsupervised event clustering and aggregation from newswire and web articles. In *Proceedings of the 2017 EMNLP Workshop: Natural Language Processing meets Journalism*, pages 62–67.

Jan Rupnik, Andrej Muhic, Gregor Leban, Primoz Skraba, Blaz Fortuna, and Marko Grobelnik. 2016. News across languages-cross-lingual document similarity and event tracking. * Journal of Artificial Intelligence Research*, 55:283–316.

João Santos, Afonso Mendes, and Sebástiao Miranda. 2022. Simplifying multilingual news clustering through projection from a shared space. *arXiv preprint arXiv:2204.13418*.

Kailash Karthik Saravanakumar, Miguel Balles- teros, Muthu Kumar Chandrasekaran, and Kathleen McKeown. 2021. Event-driven news stream clustering using entity-aware contextual embeddings. *arXiv preprint arXiv:2101.11059*.

J Michael Schultz and Mark Liberman. 1999. Topic detection and tracking using idf-weighted cosine coefficient. In *Proceedings of the DARPA broadcast news workshop*, pages 189–192. San Francisco: Morgan Kaufmann.

Milad Sikaroudi, Benyamin Ghojogh, Amir Safarpoor, Fakhri Karray, Mark Crowley, and Hamid R Tizhoosh. 2020. Offline versus online triplet mining based on extreme distances of histopathology patches. In *International Symposium on Visual Computing*, pages 333–345. Springer.

Charles Joseph Singer, E. J. Holmyard, and A. R. Hall, editors. 1954–58. *A history of technology*. Oxford University Press, London. 5 vol.
Todor Staykovski, Alberto Barrón-Cedeno, Giovanni Da San Martino, and Preslav Nakov. 2019. Dense vs. sparse representations for news stream clustering. In Text2Story@ ECIR, pages 47–52.

Jannik Strötgen and Michael Gertz. 2012. Temporal tagging on different domains: Challenges, strategies, and gold standards. In Proceedings of the Eight International Conference on Language Resources and Evaluation (LREC’12), pages 3746–3753, Istanbul, Turkey. European Language Resource Association (ELRA).

S. Superman, B. Batman, C. Catwoman, and S. Spiderman. 2000. Superheroes experiences with books, 20th edition. The Phantom Editors Associates, Gotham City.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008.

Vijay Viswanathan, Kiril Gashteovski, Carolin Lawrence, Tongshuang Wu, and Graham Neubig. 2023. Large language models enable few-shot clustering. arXiv preprint arXiv:2307.00524.

Yu-An Wang and Yun-Nung Chen. 2020. What do position embeddings learn? an empirical study of pre-trained language model positional encoding. arXiv preprint arXiv:2010.04903.

Jianshu Weng and Bu-Sung Lee. 2011. Event detection in twitter. In Proceedings of the International AAAI Conference on Web and Social Media, volume 5.

Fei Xiong, Shirui Pan, Xuzhen Zhu, et al. 2022. Collective behavior analysis and graph mining in social networks 2021.

Guixian Xu, Yueting Meng, Zhan Chen, Xiaoyu Qiu, Changzhi Wang, and Haishen Yao. 2019. Research on topic detection and tracking for online news texts. IEEE access, 7:58407–58418.

Yiming Yang, Tom Pierce, and Jaime Carbonell. 1998. A study of retrospective and on-line event detection. In Proceedings of the 21st annual international ACM SIGIR conference on Research and development in information retrieval, pages 28–36.

Susik Yoon, Dongha Lee, Yunyi Zhang, and Jiawei Han. 2023a. Unsupervised story discovery from continuous news streams via scalable thematic embedding. In Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 802–811.

Susik Yoon, Yu Meng, Dongha Lee, and Jiawei Han. 2023b. Scstory: Self-supervised and continual online story discovery. In Proceedings of the ACM Web Conference 2023, pages 1853–1864.

Yuwei Zhang, Zihan Wang, and Jingbo Shang. 2023. Clusterllm: Large language models as a guide for text clustering. arXiv preprint arXiv:2305.14871.