Abstract

Rumors are often associated with newly emerging events, thus, an ability to deal with unseen rumors is crucial for a rumor veracity classification model. Previous works address this issue by improving the model’s generalizability, with an assumption that the model will stay unchanged even after the new outbreak of an event. In this work, we propose an alternative solution to continuously update the model in accordance with the dynamics of rumor domain creations. The biggest technical challenge associated with this new approach is the catastrophic forgetting of previous learnings due to new learnings. We adopt continual learning strategies that control the new learnings to avoid catastrophic forgetting and propose an additional strategy that can jointly be used to strengthen the forgetting alleviation.

1 Introduction

Social media facilitates easy and rapid information sharing that inevitably includes false rumors. A study discovered that false rumors spread farther, faster, and deeper than true rumors (Vosoughi et al., 2018). It is, thus, important to devise an automatic system to facilitate the early detection of false rumors before they spread – rumor veracity classification. Since rumors are often associated with newly emerging breaking news (Zubiaga et al., 2018), a crucial technical challenge is to deal with new rumors unseen during the training phase.

Previous works (Kochkina et al., 2018a; Li et al., 2019a; Yu et al., 2020; Lee et al., 2021b) have attempted to address this challenge by focusing on the model generalizability in a static setup. As illustrated in Figure 1 (a), their objective is to improve the generalizability of the model $M_{t=1}$, trained at $t = 1$, to perform well on unseen domains (“Gurlitt” and “Putin Missing”) without updating the model. However, enhancing model generalizability is a hard problem, especially for tasks that always involve the introduction of new topics and vocabulary.

Therefore, as an alternative solution, we propose to tackle unseen rumors in a dynamic setup by training a classifier that can continuously adapt to newly emerging rumors (Figure 1 (b)). In this way, regardless of the large distributional gap between seen and unseen rumors, we can identify false rumors in a timely manner.

The main challenge of the dynamic setting is the catastrophic forgetting (McCloskey and Cohen, 1989) of previously learned domains while new domains are learned. In this work, to solve the catastrophic forgetting problem, we adopt rehearsal-based continual learning (CL) strategies (Robins, 1995; Lopez-Paz and Ranzato, 2017) that use episodic memory from the previously encountered domains to constrain the future learnings, and we additionally propose a simple technique TTKENS that can jointly be used to further reduce catastrophic forgetting. Through experiments, we empirically illustrate the benefit of the dynamic
setup in comparison to the static setup. To the best of our knowledge, we are the first to address the unseen rumors by continually updating the classifiers with in-domain data.

2 Methodology

In this section, we describe the task definition, the model that serves as a basis of this work, and the training strategies adopted to minimize the catastrophic forgetting and allow effective handling of unseen domains.

2.1 Task Definition

Rumor veracity classification is the task of identifying whether a given rumor text $X$ is true, false, or unverifiable. More formally, we define a dataset of rumors with their corresponding labels as the set $D = \{(X_i, y_i, Rm_i)\}_{i=1}^{N}$, where $y_i \in \{\text{True}, \text{False}, \text{Unverifiable}\}$, $Rm_i$ is the rumor-domain tag and $N$ is the size of the dataset.

The main objective is to train a rumor veracity classification model $M$ that can learn from a stream of rumor-domains through time $t$ without catastrophic forgetting. We define the stream of rumor-domains as $S = \{D_1, \cdots , D_T\}$, where $D_t$ represents the dataset of $t$-th rumor domain in the stream and $T$ is the length of the stream. $T$ is also equal to the length of timestamp and the number of rumor domains. At every timestamp, a new rumor domain dataset $D_t$ is used to sequentially train the model $M$, and we denote the model’s parameters after training with the rumor domain at time $k$ with $\theta_{t=k}$.

2.2 Base Model

Our base model consists of a BERT-base (Devlin et al., 2019) encoder and a classification head on top. More formally, given the input rumor $X = x_1, \cdots , x_m$, the model computes:

$$H = \text{BERT}([\text{CLS}]+X)$$  \hspace{1cm} (1)

$$P(y|X) = \text{Softmax}(WH_{[\text{CLS}]} + b)$$  \hspace{1cm} (2)

where, $H_{[\text{CLS}]}$ is the embedding of the [CLS] token and the trainable parameters are $\theta = [W,b]$. During training, the encoder layers are frozen and only the classifier parameters $\theta$ are trained using the cross-entropy loss:

$$L_{\theta_t}(D_t) = - \sum_{j}^{D_t} \log P(y|X)$$  \hspace{1cm} (3)

2.3 Rehearsal-based CL Strategies

Rehearsal-based CL strategies rely on an “episodic memory” $M$ to store previously encountered samples. $M$ is periodically replayed to avoid catastrophic forgetting and strengthens a connection between past and new knowledge.

**REPLAY (Robins, 1995)** One simple utilization of the memory $M$ for CL is to extend the current task data $D_t$, and optimize the models’ parameters using $L_{\theta_t}(D_t + M)$. Basically, it can be viewed as a data-efficient multi-tasking framework that only leverages a small subset of datasets bounded by the size of the memory $M$.

**Gradient Episodic Memory (GEM) (Lopez-Paz and Ranzato, 2017)** Another utilization approach is to constrain the gradient updates using current domain samples, so that the loss of the samples in memory $M$ never increases:

$$L_{\theta_t}(D_t) \text{ s.t. } L_{\theta_t}(M) \leq L_{\theta_{t-1}}(M).$$  \hspace{1cm} (4)

GEM computes the gradient constraint via a quadratic programming solver that scales with the number of parameters of the model.

2.4 Task-Specific Tokens (TTOKENS)

Various works (Petroni et al., 2019; Brown et al., 2020; Lee et al., 2021a) illustrated that a context of the input to large pre-trained language models has a huge impact on the outcomes of a model (i.e. representation, generation). In other words, we can leverage this context-dependent characteristic of LM/MLM to intentionally control/distinguish the representation for differing domains.

To apply this strategy, we pre-process the input text $X$ to start with its corresponding rumor-domain tag $Rm$. Formally, given the $t$-th rumor-domain $Rm$, Eq. 1 is replaced with:

$$H = \text{BERT}([\text{CLS}] + Rm + X)$$  \hspace{1cm} (5)

| Domain          | True | False | Unverified | Total |
|----------------|------|-------|------------|-------|
| Ebola Essien   | 0    | 14    | 0          | 14    |
| Gurlitt        | 59   | 0     | 2          | 61    |
| Putin missing  | 0    | 9     | 117        | 126   |
| Prince Toronto | 0    | 222   | 7          | 229   |
| Germanwings-crash | 94  | 111   | 33         | 238   |
| Ferguson       | 10   | 8     | 266        | 284   |
| Charlie Hebdo  | 193  | 116   | 149        | 458   |
| Ottawa Shooting| 329  | 72    | 69         | 470   |
| Sydney Siege   | 382  | 86    | 54         | 522   |
| **Total**      | 1067 | 638   | 697        | 2402  |

Table 1: PHEME Dataset Statistics
| MODEL         | ACC   | BWT   |
|--------------|-------|-------|
| BERT-BL      | 33.8% | -46.6%|
| M2-BL        | 44.3% | -29.2%|
| REPLAY       | 70.2% | -0.6% |
| REPLAY+TOKENS| 75.7% | 4.6%  |
| GEM          | 62.0% | -3.2% |
| GEM+TOKENS   | 68.5% | 2.9%  |

(a) CL metric at $t = 9$. ACC is the average accuracy through time as we do continual learning, and BWT is the measure for catastrophic forgetting; a negative BWT score indicates the existence of catastrophic forgetting, and a positive BWT score indicates the gain in performance for past domain due to future trainings.

Figure 2: Main results. Table a) presents the continual learning performance at $t = 9$, and Figure (b) illustrates the plot of ACC through time.

This strategy can easily be used together with other CL strategies since it is done in the data-processing step.

3 Experiments

3.1 Dataset and Dynamic Setup

We use the rumor veracity classification dataset PHEME, extended and publicly released by Kochkina et al. (2018a). A notable characteristic of PHEME is its categorization by rumor events. In total, there are nine different events/domains and further details are reported in Table 1.

Previous works utilize this dataset in a static setup, where eight domains are combined to be one training set and the remaining one domain is used as a single unseen test domain. In this work, our task is carried in a dynamic setup. To incorporate with the dynamic setup, we treat each domain of PHEME to be a separate domain-specific dataset $D_t$, and split them into train/dev/test with the ratio of 0.4/0.1/0.5.

3.2 Evaluation Method

After the model finishes learning about the $k$-th domain, we evaluate its test performance on all $T$ domain test sets. The result of this step is a matrix $R \in \mathbb{R}^{T \times T}$, where $R_{i,j}$ is the test classification accuracy of the model on the $j$-th domain after observing the last sample from $i$-th domain. Based on this matrix, we compute two CL-specific metrics Lopez-Paz and Ranzato (2017):

- **Avg. Accuracy (ACC)** is useful for understanding how the performance of the model changes while it is learning new domains. This metric is computed as follows:

  \[
  \text{ACC} = \frac{1}{T} \sum_{i=1}^{T} R_{T,i}
  \]  

  Note that at the end of the stream, $t=9$, the Avg. Accuracy (ACC) is exactly the average accuracy of all the tasks.

- **Backward Transfer (BWT)** is a CL metric used to measure the influence of newly learned tasks to the previously learned ones. This metric is computed as:

  \[
  \text{BWT} = \frac{1}{T-1} \sum_{i=1}^{T-1} R_{T,i} - R_{i,i}.
  \]  

  Notably, negative BWT indicates that the model has catastrophically forgotten the previous tasks.

3.3 Models

We report two baseline models trained without CL strategy and evaluated in our dynamic setup. BERT-BL refers to BERT-base model fine-tuned on PHEME dataset. M2-BL refers to another baseline that fine-tunes the unified misinformation representation (Lee et al., 2021b) that is shown to be effective in improving the generalizability to unseen domains.

For our proposed models, we have BERT-based classifiers trained with various combinations of CL strategies explained in section 2.3 and 2.4 to evaluate the effectiveness of the adopted strategies on the robustness to unseen domains.
3.4 Training Details

We ran all our experiments 3 times with different orders of domains and report the average since there can be a big variance in the overall performance depending on the order of the dataset. For all methods, we used the SGD optimizer (Kiefer et al., 1952) with a mini-batch size of 4, a learning rate of 0.01, and the maximum epoch count of 10. For GEM, we used $\lambda = 0.5$, which was searched over the $\{0.1, 0.3, 0.5, 0.7, 1.0\}$. For REPLAY, we used $M = 25$ which is found over $\{25, 50, 70\}$. These two hyper-parameters were obtained based on the validation-set performance. We ran all experiments with one NVIDIA 2080Ti GPU with 16 GB of memory.

4 Results and Analysis

4.1 Main Results

Our main results are reported in Table 2a and Figure 2b. Firstly, BERT-BL-based classifiers are known to be strong baselines, and this is shown to be true from the good performance at $t = 1$ (82% ACC). However, its performance degrades through time, achieving only 33.8% at the last timestamp ($t = 9$). The main cause behind this degradation is, obviously, the effect of catastrophic forgetting, and this is implied from an extremely negative BWT score ($-46.6\%$). Our second baseline, M2-BL, shows better robustness in comparison to BERT-BL with 11.5% and 17.4 gains in the final ACC and BWT scores. However, there still exists a substantial amount of catastrophic forgetting as shown from the halved ACC score and low BWT score ($-29.20\%$) at $t = 9$.

In contrast, all of our dynamic models with CL strategies illustrate better robustness towards catastrophic forgetting. As shown in Figure 2b, these models start off with a similar performance to the baselines at $t = 1$ but manage to maintain their performance relatively high (i.e., gentler downward slope of the performance). Among our models, REPLAY+TTokens performs the best with 75.7% ACC in $t = 9$, which is almost double of M2-BL. Moreover, it achieves a positive score for the BWT score (4.57%), indicating that it did not only avoid catastrophic forgetting but also managed to transfer additional knowledge from other domains.

Effect of TTokens

The proposed approach of adding TTokens shows a rather impressive effect. Despite its simplicity, we can observe the consistent performance gain from adding it; approximately 5% gains in ACC and BWT for both CL strategies. Such helpfulness of TTokens can also be highlighted from Figure 2b, where the dotted lines (models with TTokens) are always higher than that the solid lines (models without TTokens). In addition, when we compare the heatmap patterns of the performance between REPLAY and REPLAY+TTokens (Figure 3a vs Figure 3b), the colors of REPLAY+TTokens’ heatmap are clearly darker (darker color indicate better performance).

We have two hypotheses for the reasoning behind the success of TTokens: 1) TTokens implicitly served as a signal for the difference in the domain and encouraged the model to learn separate knowledge for each domain. Or, 2) TTokens served as a good start “context” that helped the LM-based encoder to encode the input to be
more separable when necessary – meaning, input from the same domain to be closer in the vector space than those from the differing domain.

5 Related Work

Rumor Veracity Detection The problem of rumor veracity detection has been actively explored by the NLP community (Kwon et al., 2013; Ma et al., 2017; Derczynski et al., 2017; Kochkina et al., 2018b; Wu et al., 2019; Li et al., 2019a; Yu et al., 2020; Yang et al., 2020; Bang et al., 2021; Lee et al., 2021b). Some leveraged multi-task learning with stance detection (Kochkina et al., 2018b; Wu et al., 2019) or with other misinformation tasks to enrich the learning (Lee et al., 2021b). More recent work utilized advanced architecture such as graph neural network (Yang et al., 2020) and hierarchical transformer (Yu et al., 2020). However, these works have only explored rumor veracity detection in a static setup.

CL in NLP Continual Learning has been explored for various classification tasks (d’Autume et al., 2019; Sprechmann et al., 2018; Wang et al., 2020), generation tasks (Sun et al., 2019; Hu et al., 2020), sentence encoding (Liu et al., 2019), composition language learning (Li et al., 2019b) and relation learning (Han et al., 2020). Howbeit, to the best of our knowledge, no exploration is done in the rumor verification.

6 Conclusion

In this work, we proposed the dynamic way of handling unseen rumor domains via continual learning. Through experiments, we show that our models with continual learning strategies outperform the strong baselines. Moreover, we highlight the effectiveness of our proposed TTOKENS in further enhancing the overall model performance through time. Aside from TTOKENS’s effectiveness, its ease of usage makes it more appealing. We believe our work suggests a new promising direction to solve the important challenge associated with rapidly evolving rumors.

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