

Embracing Domain Differences in Fake News: Cross-domain Fake News Detection using Multi-modal Data

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Abstract

With the rapid evolution of social media, fake news has become a significant social problem, which cannot be addressed in a timely manner using manual investigation. This has motivated numerous studies on automating fake news detection. Most studies explore supervised training models with different modalities (e.g., text, images, and propagation networks) of news records to identify fake news. However, the performance of such techniques generally drops if news records are coming from different domains (e.g., politics, entertainment), especially for domains that are unseen or rarely-seen during training. As motivation, we empirically show that news records from different domains have significantly different word usage and propagation patterns. Furthermore, due to the sheer volume of unlabelled news records, it is challenging to select news records for manual labelling so that the domain-coverage of the labelled dataset is maximized. Hence, this work: (1) proposes a novel framework that jointly preserves domain-specific and cross-domain knowledge in news records to detect fake news from different domains; and (2) introduces an unsupervised technique to select a set of unlabelled informative news records for manual labelling, which can be ultimately used to train a fake news detection model that performs well for many domains while minimizing the labelling cost. Our experiments show that the integration of the proposed fake news model and the selective annotation approach achieves state-of-the-art performance for cross-domain news datasets, while yielding notable improvements for rarely-appearing domains in news datasets.

Introduction

Motivation. Today, social media is considered as one of the leading and fastest media to seek news information online. Thus, social media platforms provide an ideal environment to spread fake news (i.e., disinformation). Many times the cost and damage due to fake news are high and early detection to stop spreading such information is of importance. For example, it has been estimated that at least 800 people died and 5800 were admitted to hospital as a result of false information related to the COVID-19 pandemic, e.g., believing alcohol-based cleaning products are a cure for the virus¹. Due to the high volumes of news generated on a daily basis,

it is not practical to identify fake news using manual fact checking. Therefore, automatic detection of fake news has recently become a significant problem attracting immense research effort.

Challenges. Nevertheless, most existing fake news detection techniques fail to identify fake news in a real-world news stream for the following reasons. First, most existing techniques (Silva et al. 2020; Zhou et al. 2020; Shu et al. 2019, 2020b; Ruchansky et al. 2017) are trained and evaluated using datasets (Shu et al. 2020a; Cui et al. 2020) that are limited to a single domain such as politics, entertainment, healthcare. However, a real news stream typically covers a wide variety of domains. We have empirically found that existing fake news detection techniques perform poorly for such a cross-domain news dataset despite yielding good results for domain-specific news datasets. This observation may be due to two reasons: (1) domain-specific word usage; and (2) domain-specific propagation patterns. For example, Figure 1 adopts two datasets from different domains, PoliFact for politics and GossipCop for entertainment, which are two widely used labelled datasets to train fake news detection models. Fig. 1 shows that there are significant differences in the frequently used words and propagation patterns of these two datasets. To address this challenge, some previous works (Wang et al. 2018; Castelo et al. 2019) learned models to overlook such domain-specific information and only rely on cross-domain information (e.g., web-markup and readability features) for fake news detection. However, domain-specific knowledge could be useful for accurate identification of fake news. As a solution, this work aims to address *how to preserve domain-specific and cross-domain knowledge in news records to detect fake news in cross-domain news datasets*. Second, the studies in (Han et al. 2020; Janicka et al. 2019) show that most fake news detection techniques are not good at identifying fake news records from unseen or rarely-seen domains during training. As a solution, fake news detection models can be learned using a dataset that covers as many domains as possible. Here we assume that the fake news detection model requires supervision as supervised techniques are known to be substantially better at identifying fake news compared to the unsupervised methods (Yang et al. 2019a). In such a supervised learning setting, each training (i.e., labelled) data point has an associated labelling cost. Thus, the total labelling budget

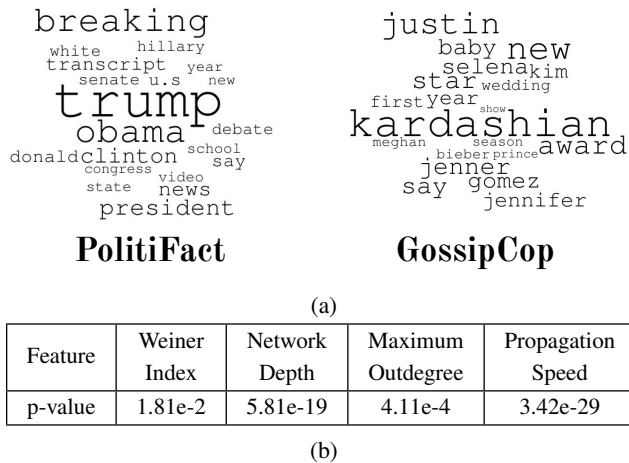


Figure 1: (a) Word clouds for the top 20 words in PolitiFact and GossipCop. (b) Two-sample t-test results conducted using different graph-level features extracted from the propagation networks in PolitiFact and GossipCop.

constrains the number of data instances that can be selected for manual labelling. Due to the sheer volume of unlabelled news records available, there is a need to *identify informative news records to annotate such that the labelled dataset ultimately covers many domains while avoiding any selection biases*.

Contribution. To address the aforementioned challenges, this work makes the following contributions:

- We propose a multimodal² fake news detection technique for cross-domain news datasets that learns domain-specific and cross-domain information of news records using two independent embedding spaces, which are subsequently used to identify fake news records. Our experiments show that the proposed framework outperforms state-of-the-art fake news detection models by as much as 7.55% in F1-score.
- We propose an unsupervised technique to select a given number of news records from a large data pool such that the selected dataset maximizes the domain coverage. By using such a dataset to train a fake news detection model, we show that the model achieves around 25% F1-score improvements for rarely-appearing domains in news datasets.

Related Work

Fake news detection methods mainly rely on different attributes (text, image, social context) of news records to determine their veracity. Text content-based approaches (Yang et al. 2016; Volkova et al. 2017; Pérez-Rosas et al. 2018; Pennebaker et al. 2015) mainly explore word usage and linguistic styles in the headline and body of news records to identify fake news. Some works analyse the images in news records along with the text content for fake news detection. For example, the studies in (Jin et al. 2017; Wang et al. 2018; Khattar et al. 2019) use pre-trained image models (e.g.,

²We define multimodality as information acquired from different sources/attributes following (Zhang et al. 2017), instead of restricting just for sensory media (e.g., text, image).

VGG-19, ResNet) to extract features from images, which are integrated with text features to identify fake news. Also, some works consider the social context of a news record, i.e., how the record is propagated across social media, as another modality to differentiate fake news records from real ones. Existing work in this line mostly applies various machine learning techniques to extract features from propagation patterns, including Propagation Tree Kernels (Ma et al. 2017), Recurrent Neural Networks (Wu et al. 2018; Liu et al. 2018), and Graph Neural Networks (Monti et al. 2019). However, all these modalities (i.e., text, propagation patterns) generally show notable differences (see Figure 1) for news records in different domains. Thus, most existing techniques perform poorly for cross-domain news datasets due to their inability to capture such domain-specific variations. Our model also relies on the text content and social context of news. However, the main objective of our model is to capture such domain-specific variations of news records.

Domain-agnostic Fake News Detection. Several previous works have attempted to perform fake news detection using cross-domain datasets. In (Wang et al. 2018), an event discriminator is learned along with a multimodal fake news detector to overlook domain-specific information in news records. The study in (Castelo et al. 2019) carefully selects a set of features (e.g., psychological features, readability features) from news records that are domain-invariant. These techniques rely only on cross-domain information in news records. In contrast, Han et al. (2020) consider cross-domain fake news detection as a continual learning task, which learns a model for a large number of tasks sequentially. This work adopts Graph Neural Networks to detect fake news using their propagation patterns and applies well-known continual learning approaches Elastic Weight Consolidation (Kirkpatrick et al. 2017) and Gradient Episodic Memory (Lopez-Paz et al. 2017) to address cross-domain fake news detection problem. This approach has two limitations: (1) it assumes that the news records from different domains arrive sequentially, though this is not always true for real-world streams; and (2) it requires the domain of news records to be known, which is not generally available. In contrast, our approach exploits both domain-specific and cross-domain knowledge of news records without knowing the actual domain of news records.

Active Learning for Fake News Detection. Almost all the aforementioned models are supervised. Although there are unsupervised fake news detection techniques (Yang et al. 2019b; Hosseinimotlagh et al. 2018), they are generally inferior to the supervised approaches in terms of accuracy. However, the training of supervised models requires large labelled datasets, which are costly to collect. Therefore, how to obtain fresh and high-quality labelled samples for a given labelling budget is challenging. Some works (Wang et al. 2020; Bhattacharjee et al. 2017) adopt conventional active learning frameworks to select high-quality samples, in which the model is initially trained using a small randomly selected dataset. Then, the beliefs derived from the initial model are used to select subsequent instances to annotate. This approach has two limitations: (1) it requires a pre-trained model to select instances; and (2) it is known

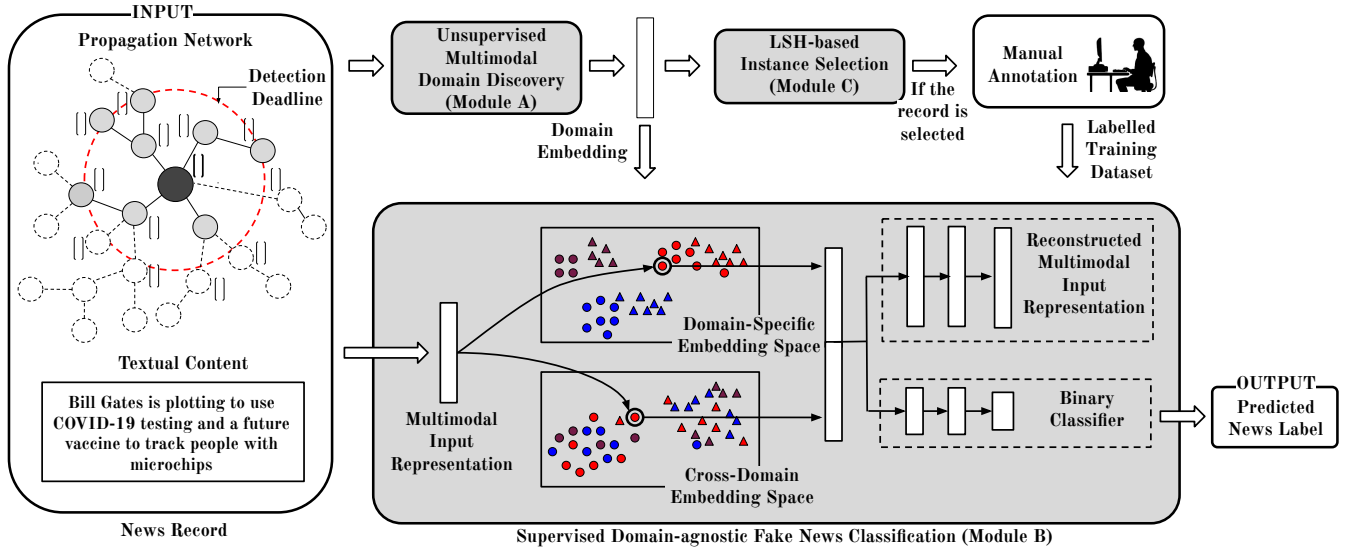


Figure 2: Overview of the proposed framework. In the illustrated embedding spaces, each data point’s colour and shape denote its domain label and veracity label (i.e., triangle for fake news and circle otherwise) respectively.

Table 1: Descriptive statistics of PolitiFact, GossipCop and CoAID datasets.

Dataset	PolitiFact	GossipCop	CoAID
# Fake News	269	1269	135
# Real News	230	2466	1568

to be highly vulnerable to the biases introduced by the initial model. In contrast, our instance selection approach does not depend on such an initial model. Also, none of the previous works attempted to explicitly maximize the domain-coverage of the labelled dataset, which is vital to train a model that perform equally well for multiple domains.

Problem Statement

Let R be a set of news records. Each record $r \in R$ is represented as a tuple $\langle t^r, W^r, G^r \rangle$, where (1) t^r is the timestamp when r is published online; (2) W^r is the text content of r ; and (3) G^r is the propagation network of r for time bound ΔT . We keep ΔT low (= five hours) for our experiments to evaluate early detection performance. Each propagation network G^r is an attributed directed graph (V^r, E^r, X^r) , where nodes V^r represent the tweets/retweets of r and the edges E^r represent the retweet relationships among them. X^r is the set of attributes of the nodes (i.e., tweets) in G^r . More details about E^r and G^r are given in (Silva et al. 2021).

Our problem consists of two sub-tasks: (1) select a set of instances R^L from R to label while adhering to the given labelling budget B , which constrains the number of instances in R^L . The labelling process assigns a binary label y^r for each record r : y^r is 1 if r is false and 0 otherwise; (2) learn an effective model using R^L to predict the label y^r for unlabelled news records $r \in R^U$ as false or real news records. In this work, R ($R^L \cup R^U$) is not constrained to a specific domain. To emulate such a domain-agnostic dataset, we combine three publicly available datasets: (1) PolitiFact (Shu

et al. 2020a), which consists of news related to politics; (2) GossipCop (Shu et al. 2020a), a set of news related to entertainment stories; and (3) CoAID (Cui et al. 2020), a news collection related to COVID-19. All three datasets provide labelled news records and all the tweets related to each news item. The statistics of the datasets are shown in Table 1.

Our Approach

As shown in Fig. 2, the proposed fake news detection model consists of two main components: (1) unsupervised domain embedding learning (Module A); and (2) supervised domain-agnostic news classification (Module B). These two components are integrated to identify fake news while exploiting domain-specific and cross-domain knowledge in the news records. In addition, the proposed instance selection approach (Module C) adopts the same domain embedding learning component to select informative news records for labelling, which eventually yields a labelled dataset that maximizes the domain-coverage.

Unsupervised Domain Discovery

For a given news record r , assume that its domain label is not available. The proposed unsupervised domain embedding learning technique exploits multimodal content (e.g., text, propagation network) of r to represent the domain of r as a low-dimensional vector $f_{domain}(r)$. Our approach is motivated by: (1) the tendency of users to form groups containing people with similar interests (i.e., homophily) (McPherson et al. 2001), which results in different domains having distinct user bases; and (2) the significant differences in domain-specific word usage as shown in Figure 1a.

We exploit the aforementioned motivations by constructing a heterogeneous network which consists of both users tweeting the news items and words in the news title as nodes, using the following steps (Line 1-9 in Algo. 1): (1) create a set S^r for each news record r by adding all the users U^r

Algorithm 1: Domain Embedding Learning

Input: A collection of news records R **Output:** Domain embeddings $f_{domain}(r)$ of $r \in R$

// Network construction

```
1 Initialize an empty graph  $G$ ;  
2 for  $r \in R$  do  
3    $S^r \leftarrow X^r \cup U^r$   
4   for each pair  $(s_1, s_2) \in S$  do  
5      $e \leftarrow (\{s_1, s_2\}, 1)$ ;  
6     if edge  $e$  exists in graph  $G$  then  
7       Increment edge  $e$  in graph  $G$  by 1;  
8     else  
9       Add edge  $e$  to graph  $G$ ;  
// Community Detection  
10  $C \leftarrow$  Find communities in  $G$  using Louvain;  
// Embedding Learning  
11 for  $r \in R$  do  
12   Compute  $f_{domain}(r)$  using Eq. 2  
13 Return  $f_{domain}(r)$  of  $r \in R$ .
```

in the propagation network G^r and all the words appearing in the news title W^r (tokenized using whitespaces); (2) for each pair of items in S^r , build a weighted edge e linking the two items in the graph; and (3) repeat Steps 1 and 2 for all the news records, until we obtain the final network G . Then, we adopt the Louvain algorithm³ (Blondel et al. 2008) to identify communities in G . Here, we select the Louvain algorithm as it was shown to be one of the best performing parameter-free community detection algorithms in (Fortunato 2010). At the end of this step, we obtain a set of communities/clusters C , each having either a highly connected set of users or words. As the nodes of G contain both users and words, such communities may have formed either due to a set of users engaging with similar news records or a set of words only appearing within a fraction of news records. Following the aforementioned motivations, this work assumes each community in C belongs to a single domain.

In the next step, we compute the soft membership $p(r \in c)$ of r in a cluster c using the following equation:

$$p(r \in c) = \sum_{v \in c \cap r} v_{deg} / \sum_{c \in C} \sum_{v \in r} v_{deg} \quad (1)$$

Here $p(r \in c)$ is proportional to the number of common users or words that r and c have. Each node (i.e., user or word) v is weighted using the degree v_{deg} in G (i.e., number of occurrences) to reflect their varying importance for the corresponding community. Finally, we produce the domain embedding $f_{domain}(r) \in \mathbb{R}^{|C|}$ of r as the concatenation of r 's likelihood belonging to communities in C :

$$f_{domain}(r) = p(r \in c_1) \oplus p(r \in c_2) \oplus \dots \oplus p(r \in c_{|C|}) \quad (2)$$

where \oplus denotes concatenation.

In Figure 3, we adopt t-SNE (Maaten et al. 2008) to visualize the domain embedding space of the proposed ap-

³Please see Supplementary Material in (Silva et al. 2021) for detailed pseudo code of the Louvain algorithm

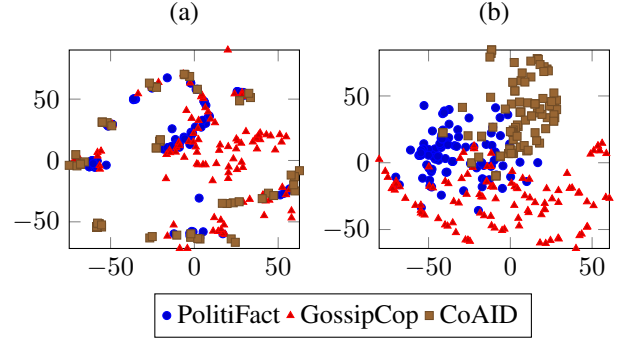


Figure 3: t-SNE visualization of domain embeddings from: (a) user-based domain discovery algorithm in (Chen et al. 2020) and (b) multimodal domain discovery approach proposed in this work.

proach and the user-based domain discovery algorithm proposed in (Chen et al. 2020). Due to space limitations, we present more details about the baseline in (Silva et al. 2021). As can be seen in Figure 3, the proposed approach yields a clear separation between the domains compared to the baseline. This may be mainly due to the ability of our approach to jointly exploit multimodalities, both users and text of news records to discover their domains. In addition, most previous works on domain discovery ultimately assign hard domain labels for news records, which could lead to substantial information loss. For example, some news records may belong to multiple domains, which cannot be captured using hard domain labels. Hence, by having a low-dimensional vector to represent embedding, our approach could preserve such knowledge related to the domains of news records.

Domain-agnostic News Classification

In our news classification model, each news record r is represented as a vector $f_{input}(r)$ using the textual content W^r and the propagation network G^r of r (elaborated in the section Experiments). Then, our classification model maps $f_{input}(r)$ into two different subspaces such that one preserves the domain-specific knowledge, $f_{specific} : f_{input}(r) \rightarrow \mathbb{R}^d$, and the other preserves the cross-domain knowledge $f_{shared} : f_{input}(r) \rightarrow \mathbb{R}^d$, of r . Here d is the dimension of the subspaces. Then, the concatenation $f_{specific}(r)$ and $f_{shared}(r)$ is used to recover the label y^r and the input representation $f_{input}(r)$ of r during training via two decoder functions g_{pred} and g_{recon} respectively.

$$\begin{aligned} \overline{y^r} &= g_{pred}(f_{specific}(r) \oplus f_{shared}(r)) \\ \overline{f_{input}(r)} &= g_{recon}(f_{specific}(r) \oplus f_{shared}(r)) \\ L_{pred} &= BCE(y^r, \overline{y^r}) \end{aligned} \quad (3)$$

$$L_{recon} = \|f_{input}(r) - \overline{f_{input}(r)}\|^2 \quad (4)$$

where $\overline{y^r}$ and $\overline{f_{input}(r)}$ denote the predicted label and the predicted input representation respectively. BCE stands for the Binary Cross-Entropy loss function. We minimize L_{pred} and L_{recon} to find the optimal parameters of $(f_{specific}, f_{shared}, g_{pred}, g_{recon})$.

However, L_{pred} and L_{recon} do not leverage domain differences in news records. Hence, we now discuss how the mapping functions for subspaces, $f_{specific}$ and f_{shared} , are further learned to preserve the domain-specific and cross-domain knowledge in news records.

Leveraging Domain-specific Knowledge To preserve the domain-specific knowledge, we introduce an auxiliary loss term $L_{specific}$ to learn a new decoder function $g_{specific}$ to recover the domain embedding $f_{domain}(r)$ of r using the domain-specific representation $f_{specific}(r)$. We minimize $L_{specific}$ to find the optimal parameters for $(f_{specific}, g_{specific})$ to capture the domain-specific knowledge by $f_{specific}$, and this process can be defined as follows:

$$L_{specific} = \|f_{domain}(r) - g_{specific}(f_{specific}(r))\|^2$$

$$(\hat{g}_{specific}, \hat{f}_{specific}) = \underset{(g_{specific}, f_{specific})}{\operatorname{argmin}} (L_{specific}) \quad (5)$$

Leveraging Cross-domain Knowledge In contrast, we learn f_{shared} to overlook domain-specific knowledge of the news records. Consequently, f_{shared} preserves the cross-domain knowledge in the news records. Here, we train a decoder function g_{shared} to accurately predict the domain of r using $f_{shared}(r)$. Meanwhile, we learn f_{shared} to fool the decoder g_{shared} by maximizing the loss of g_{shared} . Such a formulation forces f_{shared} to only rely on cross-domain knowledge, which are useful to transfer the knowledge across domains. This process can be defined as a minimax game between g_{shared} and f_{shared} as follows:

$$L_{shared} = \|g_{shared}(f_{shared}(r)) - f_{domain}(r)\|^2$$

$$(\hat{g}_{shared}, \hat{f}_{shared}) = \underset{f_{shared}}{\operatorname{argmin}} \underset{g_{shared}}{\operatorname{argmax}} (-L_{shared}) \quad (6)$$

Integrated Model Then the final loss function of the model is formulated as:

$$L_{final} = L_{pred} + \lambda_1 L_{recon} + \lambda_2 L_{specific} - \lambda_3 L_{shared} \quad (7)$$

where λ_1 , λ_2 and λ_3 controls the importance given to each loss term compared to L_{pred} (i.e., main task).

To learn the minimax game in L_{shared} , the final loss function L_{final} is sequentially optimized using the following two steps:

$$(\hat{\theta}_1) = \underset{\theta_1}{\operatorname{argmin}} L_{final}(\theta_1, \theta_2) \quad (8)$$

$$(\hat{\theta}_2) = \underset{\theta_2}{\operatorname{argmax}} L_{final}(\hat{\theta}_1, \theta_2) \quad (9)$$

where θ_1 and θ_2 denote the parameters in $(f_{specific}, f_{shared}, g_{specific}, g_{pred}, g_{recon})$ and g_{shared} respectively. The empirically studied convergence properties of the proposed optimization scheme are presented in (Silva et al. 2021).

LSH-based Instance Selection

The aforementioned model is able to exploit the domain-specific and cross-domain knowledge in news records to identify their veracity. Nevertheless, if the model is used to identify fake news records in unseen or rarely appearing domains during training, we empirically observe that the performance of the model substantially drops. This observation

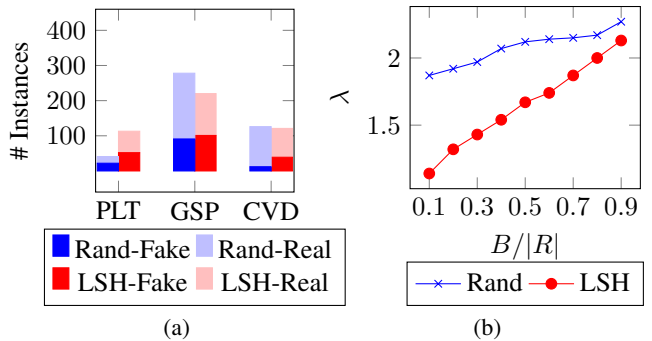


Figure 4: Statistics of datasets selected using random selection (Rand) and the proposed LSH-based technique (LSH). (a) Number of fake and real news records selected from each domain when $B/|R| = 0.1$ and (b) domain-coverage measure λ (lower λ is better) for different $B/|R|$ values.

is expected and is consistent with the findings in (Castelo et al. 2019), which could be due to the domain-specific word usage and propagation patterns as shown in Fig. 1. Hence, we propose an unsupervised technique to come up with a labelled training dataset for a given labelling budget B such that it covers as many domains as possible. The ultimate objective of this technique is to learn a model using such a dataset that performs well for many domains.

Our approach initially represents each news record $r \in R$ using its domain embedding $f_{domain}(r)$. Then, we propose a Locality-Sensitive Hashing (LSH) algorithm based on random projection to select a set of records in R that are distant in the domain embedding space, which can be elaborated using the following steps:

1. Create $|H|$ different hash functions such as $H_i(r) = \operatorname{sgn}(h_i \cdot f_{domain}(r))$, where $i \in \{0, 1, \dots, |H| - 1\}$ and h_i is a random vector, and $\operatorname{sgn}(\cdot)$ is the sign function. The random vectors h_i are generated using the following probability distribution, as such a distribution was shown to perform well for random projection-based techniques (Achlioptas 2001):

$$h_{i,j} = \sqrt{3} \times \begin{cases} +1 & \text{with probability } 1/6 \\ 0 & \text{with probability } 2/3 \\ -1 & \text{with probability } 1/6 \end{cases} \quad (10)$$

2. Construct an $|H|$ -dimensional hash value for each news record r as $H_0(r) \oplus H_1(r) \oplus \dots \oplus H_{|H|-1}(r)$, where \oplus defines the concatenation operation. According to the Johnson-Lindenstrauss lemma (Johnson et al. 1984), such hash values approximately preserve the distances between the news records in the original embedding space with high probability. Hence, neighbouring records in the domain embedding space are mapped to similar hash values.

3. Group the news records with similar hash values to construct a hash table.

4. Randomly pick a record from each bin in the hash table and add to the selected dataset pool.

5. Repeat steps (1), (2), (3) and (4) until the size of the dataset pool reaches the labelling budget B .

In Figure 4a, we compare 10% of the original dataset selected using the proposed approach and random selection.

As can be seen, random selection follows the empirical distribution of the datasets in Table 1 and picks few instances from rarely appearing domains (e.g., fake/real news in PolitiFact, fake news in CoAID). Thus, the model trained on such a dataset may poorly perform on rarely appearing domains. In contrast, the proposed approach provides a significant number of samples from even rarely occurring domains.

In addition, the proposed approach is efficient ($O(|H||R|)$ complexity) compared to the naive farthest point selection algorithms (e.g., k-Means (Lloyd 1982) with $O(|R|^2)$ complexity, where $|R| \gg |H|$). To measure the domain coverage of the instances selected from the proposed instance selection approach, we adopt the metric introduced in (Laib et al. 2017), which can be computed as follows for a given set of records r_1, r_2, \dots, r_n that are represented using their domain embeddings: $\lambda = \frac{1}{\bar{\delta}} (\frac{1}{n} \sum_{i=1}^n (\delta_i - \bar{\delta})^2)^{\frac{1}{2}}$, where $\delta_i = \min_k (L2 \text{ norm}(f_{\text{domain}}(r_i), f_{\text{domain}}(r_k)))$ and $\bar{\delta} = \sum \delta_i / n$. If the coverage is high, λ is small. Hence, the proposed approach yields a better domain-coverage compared to random instance selection as shown in Figure 4b.

Experiments

Experimental Setup

Encoding and Decoding Functions In our model, each record r is initially represented as a low-dimensional vector $f_{\text{input}}(r)$ using its text content and propagation network. We adopt RoBERTa-base, a robustly optimized BERT pre-training model (Liu et al. 2019) to learn the text-based representation $f_{\text{text}}(r)$ of r . The propagation network-based representation $f_{\text{network}}(r)$ of r is represented using the unsupervised network representation learning technique proposed in (Silva et al. 2020). Then, the final input representation $f_{\text{input}}(r)$ is constructed as $f_{\text{text}}(r) \oplus f_{\text{network}}(r)$, where \oplus denotes concatenation. All the other encoding and decoding functions, ($f_{\text{specific}}, f_{\text{shared}}, g_{\text{specific}}, g_{\text{shared}}, g_{\text{pred}}, g_{\text{recon}}$), are modelled as 2-layer feed-forward networks with sigmoid activation⁴.

Dataset We combine three disinformation datasets: (1) PolitiFact; (2) GossipCop; and (3) CoAID, to produce a cross-domain news dataset⁵. Then, we randomly choose 75% of the dataset as the candidate data pool R_{pool} for training and the remaining 25% for testing. For a given labelling budget B , we select B instances from R_{pool} to train the model. The same process is performed for 3 different training and test splits and the average performance is reported. We evaluate the performance for each domain separately using the testing instances from each domain. For the evaluation, we adopt four metrics: (1) Accuracy (Acc); (2) Precision (Prec); (3) Recall (Rec); and (4) F1 Score (F1).

Baselines In Table 2, we compare our approach with seven widely used fake detection techniques and their variants⁴.

⁴We present more details about implementations and parameter selections in the Supplementary Material in (Silva et al. 2021)

⁵Here we do not consider the existing datasets on rumour detection (Kochkina et al. 2018; Ma et al. 2017) as they are not consistent with the fake news definition (i.e., disinformation).

Parameter Settings After performing a grid search, we have set the hyper-parameters in our model as⁴: $\lambda_1 = 1$, $\lambda_2 = 10$, $\lambda_3 = 5$, $d = 512$. To satisfy the Johnson–Lindenstrauss lemma, we set $|H| = 10 (>> \log(|R|))$. For the specific parameters of the baselines, we use the default parameters mentioned in their original papers.

Results

Quantitative Results for Fake News Detection As shown in Table 2, the proposed approach yields substantially better results for all three domains, outperforming the best baseline by as much as 7.55% in F1-score. The best baseline, EANN-Multimodal, also adopts domain-information when determining fake news. This observation shows the importance of having domain-knowledge of news records when identifying fake news in cross-domain datasets. In addition to the architectural differences of the model, EANN-Multimodal is different from our approach for two reasons: (1) EANN-Multimodal only preserves cross-domain knowledge in news records. Thus, it overlooks domain-specific knowledge, which is shown to be useful in our ablation study in Table 2; and (2) EANN-Multimodal adopts a hard label (i.e., exclusive membership) to represent the domain of a news record. Our approach conversely uses a vector to represent the domain of a news record. Thus, our approach can accurately represent the likelihood of each record for different domains. These differences may explain the importance of our approach compared to the best baseline.

Out of the baselines, the multimodal approaches (except HPNF+LIWC) generally achieve better results compared to the uni-modal approaches. Thus, we can conclude that each modality (i.e., propagation network and text) of news records provides unique knowledge for fake news detection. In HPNF+LIWC, each news record is represented using a set of hand-crafted features. In contrast, other multimodal approaches including our approach learn data-driven latent representations for news records, which may be able to capture latent and complex information in news records that are useful to determine fake news. These observations further support two main design decisions in our model: (1) to exploit multimodalities of news records; and (2) to adopt a representation learning-based technique.

Ablation Study Our ablation study in Table 2 shows that without the domain-specific loss (Eq. 5) and the cross-domain loss (Eq. 6), the F1-score of the model substantially drops by around 6% and 3% for the PolitiFact dataset, which is the smallest domain of the training dataset. Hence, it is important to have a domain-specific layer to preserve the domain-specific knowledge and a separate cross-domain layer to transfer common knowledge between domains.

To check whether our model actually learns the aforementioned intuition behind each embedding layer, we visualize each embedding layer using t-SNE in Figure 5. As can be seen, the domain-specific embedding layer preserves the domain of the news records by mapping different domains into different clusters. In contrast, we cannot identify the domain labels of news records from the cross-domain embedding space. Hence, this embedding space is useful to share com-

Method	Type			Politifact				Gossipcop				CoAID			
	T	S	M	Acc	Prec	Rec	F1	Acc	Prec	Rec	F1	Acc	Prec	Rec	F1
LIWC (Pennebaker et al. 2015)	✓			0.488	0.680	0.565	0.432	0.662	0.550	0.516	0.472	0.903	0.586	0.531	0.538
text-CNN (Kim 2014)	✓			0.608	0.621	0.623	0.608	0.733	0.698	0.703	0.701	0.903	0.679	0.674	0.677
HAN (Yang et al. 2016)	✓			0.632	0.672	0.651	0.648	0.716	0.703	0.709	0.706	0.919	0.698	0.682	0.688
EANN-Unimodal (Wang et al. 2018)	✓			0.794	0.811	0.790	0.791	0.765	0.732	0.738	0.734	0.925	0.842	0.763	0.792
HPNF (Shu et al. 2020b)		✓		0.697	0.692	0.683	0.687	0.721	0.703	0.689	0.695	0.902	0.652	0.693	0.672
AE (Silva et al. 2020)		✓		0.784	0.783	0.774	0.779	0.834	0.828	0.802	0.812	0.928	0.686	0.673	0.677
HPNF + LIWC (Shu et al. 2020b)			✓	0.704	0.723	0.708	0.716	0.734	0.715	0.706	0.708	0.911	0.682	0.709	0.690
SAFE (Zhou et al. 2020)			✓	0.793	0.782	0.771	0.775	0.831	0.822	0.798	0.806	0.931	0.754	0.744	0.748
EANN-Multimodal (Wang et al. 2018)			✓	0.804	0.808	0.794	0.798	0.836	0.812	0.815	0.813	0.944	0.849	0.803	0.808
Our Approach ($B = 100\% R_{pool} $)			✓	0.840	0.836	0.831	0.835	0.877	0.840	0.832	0.836	0.970	0.876	0.863	0.869
Our Approach ($B = 50\% R_{pool} $)			✓	0.838	0.836	0.828	0.833	0.848	0.822	0.797	0.808	0.963	0.870	0.854	0.862
Ablation Study ($B = 100\% R_{pool}$)															
(-) Domain-shared loss				0.823	0.821	0.812	0.815	0.864	0.832	0.828	0.829	0.956	0.857	0.861	0.858
(-) Domain-specific loss				0.792	0.800	0.783	0.786	0.858	0.832	0.821	0.828	0.934	0.850	0.857	0.853
(-) Network modality				0.816	0.815	0.817	0.815	0.765	0.749	0.745	0.746	0.945	0.803	0.855	0.827
(-) Text modality				0.804	0.798	0.793	0.795	0.837	0.835	0.815	0.817	0.932	0.711	0.704	0.707

Table 2: Results for fake news detection of different methods, which are classified under three categories: (1) text content-based approaches (T); (2) social context-based approaches (S); and (3) multimodal approaches (M).

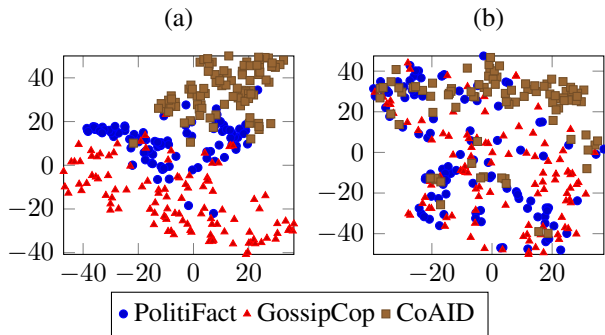


Figure 5: t-SNE visualization of the (a) domain-specific and (b) cross-domain embedding spaces.

mon knowledge between records from different domains.

Furthermore, we analyse the contribution of each modality. It can be seen that *network modality* is more useful to determine fake news in GossipCOP, while *text modality* is the most informative one for CoAID. This observation further signifies the importance of multimodal approaches to train models that generalize for multiple domains.

Evaluation of LSH-based Instance Selection As shown in Table 2, our model outperforms the baselines even with a constrained budget B ($50\%|R_{pool}|$) to select training data using the LSH-based instance selection technique. To verify its significance further, Figure 6 compares the proposed LSH-based instance selection approach with random instance selection for different B values. The proposed approach substantially outperforms the random instance selection for the rarely-appearing or highly imbalanced domains. It increases F1-score by 24% for Politifact and 27% for CoAID, when $B/|R_{pool}| = 0.1$. This may be due to the ability of our approach to maximize the coverage of domains when selecting instances (see Figure 4), instead of biasing towards a domain with larger number of records.

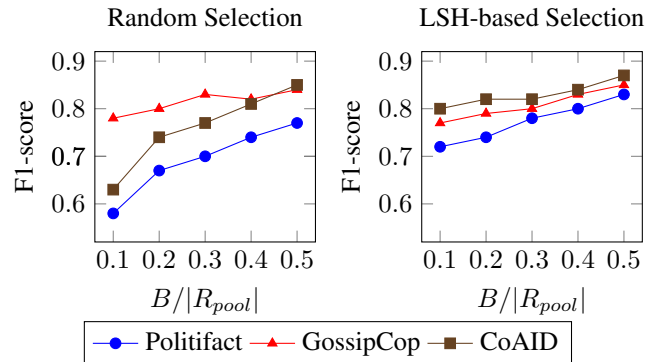


Figure 6: F1-scores for the fake news detection task with different instance selection strategies.

Conclusion

In this work, we proposed a novel fake news detection framework, which exploits domain-specific and cross-domain knowledge in news records to determine fake news from different domains. Also, we introduced a novel unsupervised approach to select informative instances for manual labelling from a large pool of unlabelled news records. The selected data pool is subsequently used to train a model that can perform equally for different domains. The integration of the aforementioned two contributions yields a model with low labelling budgets that outperforms existing fake news detection techniques by as much as 7.55% in F1-score.

For future work, we intend to extend our model as an on-line learning framework to determine fake news in a real-world news stream, which typically covers a large number of domains. This setting introduces new challenges such as capturing newly emerging domains and handling temporal changes in domains. Also, how to use the alignment in multimodal information to weakly guide the learning process of the proposed model is another interesting direction to explore, which may further reduce the labelling cost in a conventional supervised learning setting.

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