Graph Neural Networks with Continual Learning for Fake News Detection from Social Media

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ABSTRACT
Although significant effort has been applied to fact-checking, the prevalence of fake news over social media, which has profound impact on justice, public trust and our society as a whole, remains a serious problem. In this work, we focus on propagation-based fake news detection, as recent studies have demonstrated that fake news and real news spread differently online. Specifically, considering the capability of graph neural networks (GNNs) in dealing with non-Euclidean data, we use GNNs to differentiate between the propagation patterns of fake and real news on social media. In particular, we concentrate on two questions: (1) Without relying on any text information, e.g., tweet content, replies and user descriptions, how accurately can GNNs identify fake news? Machine learning models are known to be vulnerable to adversarial attacks, and avoiding the dependence on text-based features can make the model less susceptible to the manipulation of advanced fake news fabricators. (2) How to deal with new, unseen data? In other words, how does a GNN trained on a given dataset perform on a new and potentially vastly different dataset? If it achieves unsatisfactory performance, how do we solve the problem without re-training the model on the entire data from scratch, which would become prohibitively expensive in practice as the data volumes grow? We study the above questions on two datasets with thousands of labelled news, and our results show that: (1) GNNs can indeed achieve comparable or superior performance without any text information to state-of-the-art methods. (2) GNNs trained on a given dataset may perform poorly on new, unseen data, and direct incremental training cannot solve the problem—this issue has not been addressed in the previous work that applies GNNs for fake news detection. In order to solve the problem, we propose a method that achieves balanced performance on both existing and new datasets, by using techniques from continual learning to train GNNs incrementally.

CCS CONCEPTS
• Computing methodologies → Supervised learning by classification. Neural networks.

KEYWORDS
fake news detection, graph neural networks, graph convolutional networks, continual learning, social media

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1 INTRODUCTION
While social media has facilitated the timely delivery of various types of information around the world, a consequence is that news is emerging at an unprecedentedly high rate, making it increasingly difficult to fact-check. A series of incidents over the recent years have demonstrated the significant damage fake news can cause to society. Therefore, how to automatically and accurately identify fake news before it is widespread has become an urgent challenge for research. Here we use the definition in [59]: fake news is intentionally and verifiably false news published by a news outlet—similar definitions have also been used in previous studies on fake news detection [22, 34, 36, 39].

In our work, we focus on a propagation-based approach for fake news detection. In other words, we use the propagation pattern of news on social media, e.g., tweets and retweets of news on Twitter, to determine whether it is fake or not. The feasibility of this approach builds on (1) empirical evidence that fake news and real news spread differently online [45]; and (2) the latest development in graph neural networks (GNNs) [3, 24, 52, 56] that has enhanced the performance of machine learning models on non-Euclidean data. In addition, as pointed out in [22], whereas content-based approaches require syntactic and semantic analyses, propagation-based approaches are language-agnostic, and can be less vulnerable to adversarial attacks [6, 41], where advanced news fabricators carefully manipulate the content in order to bypass detection.

The idea of using propagation patterns to detect fake news has been explored in a number of previous studies [17, 19, 38, 49, 50, 60], where different types of models have been considered: Wu et al. [49] use a hybrid Support Vector Machine (SVM), Ma et al. [19] use Propagation Tree Kernel; Wu et al. [50] incorporate Long Short-Term Memory (LSTM) cells into the Recurrent Neural Network (RNN) model; Liu et al. [17] use both RNNs and Convolutional Neural Networks (CNNs); Shu et al. [38] and Zhou et al. [60] propose different types of features and compare multiple commonly used machine learning models. The most relevant work is [22], which also applies GNNs to study propagation patterns. However, in addition to selecting a different GNN algorithm specifically designed for graph
classification (refer to Section 2 for further explanation), our work mainly focuses on the following questions:

- **Section 3: Without relying on any text information, e.g., tweet content, replies and user descriptions, how accurately can GNNs identify fake news?** It is demonstrated in Section 3 that even though our model is limited to a restricted set of eight features obtained from social context—(1) whether the Twitter user is verified, (2) the timestamp when the user is created, (3) the number of followers, (4) the number of friends, (5) the number of lists, (6) the number of favourites, (7) the number of statuses and (8) the timestamp of the tweet—GNNs can be trained on propagation patterns and these features to achieve comparable or superior performance to state-of-the-art methods that require sophisticated analyses on tweet content, user replies, etc. We argue that the limited set of features can further enhance the security of our models against adversarial attacks, as previous work has shown that high dimensionality facilitates the generation of adversarial samples, resulting in an increased attack surface [46]. In addition, we do not rely on the follower or following relations between Twitter users, since these types of information are more difficult to obtain in real time due to the rate limit of Twitter APIs. Therefore, our model is more suitable to online detection;

- **Section 4: How to deal with new, unseen data?** The above question is only concerned with the performance of GNNs on a single dataset. However, a trained model may face vastly different data in practice, and it is important to further investigate how models perform in this scenario. Specifically, we find that GNNs trained on a given dataset may perform poorly on another dataset, and direct incremental training cannot solve the problem—this issue has not been discussed in the previous work that uses GNNs for fake news detection. In order to solve the problem, we propose a method that applies techniques from continual learning to train GNNs incrementally, so that they achieve balanced performance on both existing and new datasets. The method avoids re-training the model on the entire data from scratch—new data always exist, and this becomes prohibitively expensive as data volumes grow.

The remainder of this paper is organised as follows: Section 2 briefly introduces the background on graph neural networks; Section 3 describes our content-free, GNNs-based fake news detection algorithm; Section 4 investigates how to deal with new, unseen data, and proposes a solution to achieve balanced performance on both existing and new data by applying techniques from continual learning; Section 5 reviews previous work in fake news detection on social media; and finally Section 6 concludes the paper and offers directions for future work.

## 2 BACKGROUND ON GRAPH NEURAL NETWORKS

Although deep learning has witnessed tremendous success in a wide range of applications, including image classification, natural language processing and speech recognition, it mostly deals with data in Euclidean space. GNNs [3, 24, 52, 56], by contrast, are designed to process data generated from non-Euclidean domains.

Consider a graph \( G = (A, F) \) with \( n \) vertices/nodes and \( m \) edges, where \( A \in \{0, 1\}^{n \times n} \) is the adjacency matrix, \( A_{i,j} = 1 \) if there is an edge from node \( i \) to node \( j \), and \( A_{i,j} = 0 \) otherwise; \( F \in \mathbb{R}^{n \times d} \) is the feature matrix, i.e., each node has \( d \) features. Given \( A \) and \( F \) as inputs, the output of a GNN, i.e., node embeddings, after the \( k^{th} \) step is: \( H^{(k)} = f \left( A, H^{(k-1)}; \theta(k) \right) \in \mathbb{R}^{n \times d} \), where \( f \) is the propagation function parameterised by \( \theta \), and \( H^{(0)} \) is initialised by the feature matrix, i.e., \( H^{0} = F \).

There have been a number of implementations for the propagation function. A simple form of the function is: \( f \left( A, H^{(k)} \right) = \sigma \left( AH^{(k-1)}W^{(k)} \right) \), where \( \sigma \) is a non-linear activation function, e.g., the rectified linear unit (ReLU) function, and \( W^{(k)} \) is the weight matrix for layer \( k \). A popular implementation of the function is [14]: \( f \left( A, H^{(k)} \right) = \sigma \left( \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(k-1)}W^{(k)} \right) \), where \( \tilde{A} = A + I, \tilde{D} = \sum_{j} \tilde{A}_{jj} \). Please refer to [52] for more choices of the function.

GNNs can perform node regression, node classification, link prediction, edge classification or graph classification depending on the requirements. In our work, since the goal is to label the propagation pattern of each item of news, which is a graph, we choose the algorithm of DiffPool [56] that is specifically designed for graph classification. DiffPool extends any existing GNN model by further considering the structural information of graphs. At each layer DiffPool takes the original output \( H^{(k)} \) and the adjacency matrix \( A \), and learns a coarsened graph of \( n' < n \) nodes, with the adjacency matrix \( A' \in \mathbb{R}^{n' \times n'} \) and the node embeddings \( H' \in \mathbb{R}^{n' \times d} \).

## 3 PROPAGATION-BASED FAKE NEWS DETECTION

As mentioned in the introduction, we use the definition in [59] that fake news is intentionally and verifiably false news published by a news outlet. Once an item of news is published, it may be tweeted by multiple users. We call these tweets that directly reference the news URL initial/source tweets. Each of them and their retweets form a separate cascade [45], and all the cascades form the propagation pattern of an item of news. The purpose of this work is to determine the validity of an item of news using its propagation pattern.

Formally, we define the propagation-based fake news detection problem as follows: given a set of labeled graphs \( \mathcal{D} = \{(G_1, y_1), (G_2, y_2), \ldots, (G_i, y_i) \ldots\} \), where \( G_i \in \mathcal{G} \) is the propagation pattern for news \( i \), and \( y_i \in \mathcal{Y} = \{0 \text{ (Real)}, 1 \text{ (Fake)} \} \) is the label of graph \( G_i \), the goal is to learn a mapping \( g : \mathcal{G} \rightarrow \mathcal{Y} \) that labels each graph.

In the remaining of this section, we first explain how we generate a graph in Section 3.1, i.e., the adjacency matrix and the feature matrix, and present the experimental results to verify the effectiveness of the GNN-based detection algorithm in Section 3.2.

### 3.1 Data Generation

In order to generate the news propagation pattern, we use the dataset of FakeNewsNet [37], which is especially collected for the purpose of fake news detection. FakeNewsNet contains labelled news from two websites: politifact.com¹ and gossipcop.com²—the news content includes both linguistic and visual information, all

1 https://www.politifact.com/
2 https://www.gossipcop.com/
### 3.2 Experimental Verification

Using the method introduced in the previous subsection to generate the graphs (the adjacency and feature matrices), we test multiple DiffPool models with a range of different architectures: 2-4 pooling layers, 16-128 hidden dimensions and 16-128 embedding dimensions. As recommended by the authors in [56], we use DiffPool built on top of GraphSage [8].

In addition, we train GNNs first on the whole dataset of PolitiFact/GossipCop, and then on the clipped dataset that contains only the first 100 tweets or tweets from the first five hours, whichever is smaller, for each item of news—it is more critical to detect fake news at an early stage before it becomes widespread, since the wider fake news spreads, the more likely people would trust it [2], and once the first impression is formed, it is difficult to correct people’s perceptions [12].

In order to make our results comparable with those reported in [36] (as they also tested fake news detection algorithms on the same dataset), we follow the same procedure to train and test the GNNs: randomly choose 75% of the news as the training data while keeping the rest as the test data, and the final result is the average performance over five repeats. In addition, the model is evaluated with the following commonly used metrics: accuracy, precision, recall and F1 score.

The experimental results are presented in Figs. 2 and 3, where (1) The first eight bars correspond to the results of eight fake news detection algorithms as reported in [36] on the same dataset—Rhetorical Structure Theory (RST) [33], Linguistic Inquiry and Word Count (LIWC) [26], Hierarchical Attention Networks (HAN) [55], text-CNN [13], TCNN-URG [31], HIPA-BLSTM [7], CSI [34] and dEFEND [36]. Note that all of these methods require analysis on textual information, e.g., tweet content, user replies. (2) The second last bar is the result of our propagation-based method trained on the whole dataset. (3) The last bar is the result of our method trained on the clipped dataset.

As we can see from the figures, by only relying on the limited features as introduced in Section 3.1, our model can achieve comparable performance on the dataset of PolitiFact, and the best result on the dataset of GossipCop, not only when trained on the complete dataset, but also when trained using the first 100 tweets or the tweets from the first five hours for each item of news.

In addition, we have also tested clipped datasets that contain the first 100 (without the five hour time limit), 200, 500, 1000 and 1500 tweets for each item of news. Table 1 presents the performance of models trained on these datasets. The results further demonstrate the effectiveness of our proposed method.

**Model efficiency.** When training and testing our models, we also find that GNNs converge very quickly—most of the time it only takes dozens of epochs for the model to reach similar performance to the final model in terms of the four metrics, while each epoch lasts from only a couple of seconds to several minutes, depending on the different model structures and sizes of the datasets.

All these results provide strong support for applying GNNs in propagation-based fake news detection.

### 4 DEALING WITH NEW DATA

While the above results demonstrate the effectiveness of our proposed method on a single dataset, this section further studies the model performance on new data.

Let one dataset, e.g., PolitiFact, represent the existing data that our model has been trained on, and the other dataset, e.g., GossipCop, represent the unknown data that our model will face in the future, we find that models trained on PolitiFact do not perform...
well on GossipCop (Fig. 4), and vice versa (the figure for this case is omitted due to similarity).
Table 1: Performance of the GNN-based fake news detection algorithm on the clipped datasets that contain the first 100 (without the five hour time limit), 200, 500, 1000 and 1500 tweets for each item of news.

| Dataset   | Metric | 100  | 200  | 500  | 1000 | 1500 |
|-----------|--------|------|------|------|------|------|
| PolitiFact| Accuracy | 0.850| 0.861| 0.860| 0.883| 0.890|
|           | Precision | 0.846| 0.852| 0.852| 0.876| 0.873|
|           | Recall | 0.852| 0.858| 0.860| 0.880| 0.890|
|           | F1 | 0.846| 0.854| 0.855| 0.876| 0.880|
| GossipCop | Accuracy | 0.882| 0.881| 0.894| 0.889| 0.902|
|           | Precision | 0.876| 0.877| 0.893| 0.889| 0.897|
|           | Recall | 0.884| 0.877| 0.894| 0.891| 0.900|
|           | F1 | 0.879| 0.877| 0.893| 0.888| 0.899|

We first test incremental training, i.e., further train the model obtained from PolitiFact (or GossipCop) on the other dataset of GossipCop (or PolitiFact). However, as shown in Fig. 5, then the models only perform well on the latter dataset on which they are trained, i.e., GossipCop.

while achieve degraded results on the former dataset (the figure for models first trained on GossipCop and then on PolitiFact is omitted due to similarity). Note that during incremental training, we still randomly choose 75% of graphs as the training data and the rest as the test data.

This is similar to the problem of catastrophic forgetting [5, 20, 21, 32] in the field of continual learning: when a deep neural network is trained to learn a sequence of tasks, it degrades its performance on the former tasks after it learns new tasks, as the new tasks override the weights.

In our case, each new dataset can be considered as a new task. In the next subsection, we investigate how to solve the problem by applying techniques from continual learning.

4.2 Continual Learning

In order to deal with catastrophic forgetting, a number of approaches have been proposed, which can be roughly classified into three types [25]: (1) regularisation-based approaches that add extra constraints to the loss function to prevent the loss of previous knowledge; (2) architecture-based approaches that selectively train a part of the network for each task, and expand the network when necessary for new tasks; (3) dual-memory-based approaches that build on top of complementary learning systems (CLS) theory [16, 20], and replay samples for memory consolidation.

In this paper, we choose the following two popular methods:

- Gradient Episodic Memory (GEM) [18]—GEM uses episodic memory to store a number of samples from previous tasks, and when learning a new task, it does not allow the loss over those samples held in memory to increase compared to when the learning of task \( t - 1 \) is finished;
- Elastic Weight Consolidation (EWC) [15]—its loss function consists of a quadratic penalty term on the change of the parameters, in order to prevent drastic updates to those parameters that are important to the old tasks.

In our case, the learning on the two datasets (\( D_1 \) and \( D_2 \)) are considered as two tasks. When the model learns the first task, it is trained as usual; then during the learning of the second task, we apply GEM and EWC:

- Let \( \theta_1 \) be the model parameters after the first task, and \( M \) be the set of instances sampled from the first dataset, then the optimisation problem under GEM becomes:
The results demonstrate that while all these models can achieve a relatively balanced performance over the two datasets, GEM trained models work better than EWC trained models in general. In addition, from the results in Appendix A.1 we can see that when the model is incrementally trained using GEM on the whole dataset, the performance can be further improved.

Another point worth mentioning is that it requires more fine-tuning during the EWC training process. For example, we need to apply early stopping to ensure balanced results on both datasets when the model is trained with EWC.

Efficiency. In terms of efficiency, the following observations can be made from our experiments on both datasets: (1) compared with the normal training process, training with GEM and EWC requires slightly more time; (2) there is no significant difference in training time between GEM and EWC; and (3) the impact of the parameters, i.e., sample size and $\lambda$, on the training time is also not significant.

5 RELATED WORK

Detecting fake news on social media has been a popular research problem over recent years. In this section, we briefly review the prior work on this topic. Specifically, similar to [27, 39], we classify existing work into three categories: content-based approaches, context-based approaches and mixed approaches, the first two of which, as suggested by their names, mainly rely on news content and social context to extract features for detection, respectively.

5.1 Content-based Approaches

Content-based approaches use news headlines and body content to verify the validity of the news. It can be further classified into two categories: knowledge-based and style-based [39, 59].

5.1.1 Knowledge-based Detection. In order for this type of method to work, a knowledge base or knowledge graph [23] has to be built first. Here, knowledge can be represented in the format of a triple: (Subject, Predicate, Object), i.e., SPO triple [1]. Then, to verify an item of news, knowledge extracted from its content is compared with the facts in the knowledge graph [4, 35, 51]. If a triple $(S, P, O)$ is missing in the knowledge graph, different link

\[
\min_{\theta} \sum_{(G_i, y_i) \in D_2} \text{loss} \left( f(A_i, H_i; \theta(k)), y_i \right)
\]

subject to

\[
\sum_{(G_j, y_j) \in M} \text{loss} \left( f(A_j(k), H_j; \theta(k)), y_j \right) \leq \sum_{(G_j, y_j) \in M} \text{loss} \left( f(A_j(k), H_j; \theta_1(k)), y_j \right)
\]

- Let $\lambda$ be the regularisation weight, $F$ be the Fisher information matrix, and $\theta^*_D$ be the parameters of the Gaussian distribution used by EWC to approximate the posterior of $p(\theta|D_1)$, then the loss function under EWC is:

\[
\sum_{(G_i, y_i) \in D_2} \text{loss} \left( f(A_i, H_i; \theta(k)), y_i \right) + \frac{\lambda}{2} F(\theta - \theta^*_D)^2
\]

Note that when estimating the Fisher information matrix $F$, we sample a set of instances $M$ and compare the model performance under different sample sizes.

In terms of parameters, we test sample size $|M| = 100, 200, 300$ (all the samples are chosen randomly), and $\lambda = 10^2, 10^3, 10^4, 10^5, 10^6$ (for EWC only).

Figs. 6 and 7 show the performance of models first trained on PolitiFact and then (incrementally) on GossipCop using GEM and EWC ($\lambda = 10^5$), respectively (the remaining results are given in Appendices A.2, A.3). The results demonstrate that while all these models can achieve a relatively balanced performance over the two datasets, GEM trained models work better than EWC trained models in general. In addition, from the results in Appendix A.1 we can see that when the model is incrementally trained using GEM on the whole dataset, the performance can be further improved.

Figure 6: Performance of models first trained on the clipped dataset of PolitiFact and then on GossipCop using GEM.

Figure 7: Performance of models first trained on the clipped dataset of PolitiFact and then on GossipCop using EWC ($\lambda = 10^5$).
prediction algorithms can be used to calculate the probability of an edge labelled \( P \) existing from node \( S \) to node \( O \).

5.1.2 Style-based Detection. According to forensic psychological studies [45], statements based on real-life experiences differ significantly in both content and quality from those derived from fabrication or fiction. Since the purpose of fake news is to mislead the public, they often exhibit unique writing styles that are rarely seen in real news. Therefore, style-based methods aim to identify these characteristics. For example, Perez-Rosas et al. [30] train linear SVMs on the following linguistic features to detect fake news: unigrams, bigrams, punctuation, psycholinguistic, readability and syntax features. Other methods that fall into this category include [9, 29, 44, 47].

In addition to textual information, images posted in social media have also been investigated to facilitate the detection of fake news [11, 48, 54, 58].

5.2 Context-based Approaches

Social context here refers to the interactions between users, including tweet, retweet, reply, mention and follow. These engagements provide valuable information for identifying fake news spread on social media.

Jin et al. [10] build a stance network where the weight of an edge represents how much each pair of posts support or deny each other. Then fake news detection is based on estimating the credibility of all the posts related to the news item, which can be formalised as a graph optimisation problem.

Tacchini et al. [42] propose to detect fake news based on user interactions, i.e., users who liked them on Facebook. Their experiments show that both the logistic regression based and the harmonic Boolean label crowdsourcing based methods can achieve high accuracy.

Unlike the above supervised methods, an unsupervised approach is proposed in Yang et al. [53]. It builds a Bayesian probability graphical model to capture the generative process among the validity of news, user opinions and user credibility.

Note that propagation-based approaches as mentioned in the introduction also belong to this category.

5.3 Mixed Approaches

Mixed approaches use both news content and associated user interactions over social media to differentiate between fake news and real news.

Ruchansky et al. [34] design a three-module architecture that combines the text of a news article, the received user response and the source of the news: (1) the first module takes the user response, news content and user feature as the input, and trains a Recurrent Neural Network (RNN) to capture temporal representations of articles; (2) the second module is fed with user features to generate a score and a low-dimensional representation for each user; (3) the third module takes the output of the first two modules and trains a neural network to label the news item.

Zhang et al. [57] propose to use a pre-extracted word set to construct explicit features from the news content, user profile and news subject description, and meanwhile use a RNN to learn latent features, such as news article content information inconsistency and profile latent patterns. Once the features are obtained, a deep diffusive network is built to learn the representations of news articles, creators and subjects. Shu et al. [40] use the tri-relationship among publishers, news articles and users to detect false news. Specifically, non-negative matrix factorization is used to learn the latent representations for news content and users, and the problem is formalised as an optimisation over the linear combination of each relation. Multiple machine learning algorithms are tested to solve the optimisation problem, and the results demonstrate its effectiveness.

In addition to the above work, two recent papers have started to work on explainability, i.e., why their model labels certain news items as fake [28, 36].

6 CONCLUSIONS AND FUTURE WORK

The prevalence of fake news over social media has become a serious social problem. In this paper, we propose a context-based approach for fake news detection, more specifically a propagation-based method that uses GNNs to distinguish between the different propagation patterns of fake news and real news over social networks. Even though the method only requires a limited number of features obtained from the social context, and does not rely on any text information, it can achieve comparable or superior performance to state-of-the-art methods that require syntactic and semantic analyses.

In addition, we identify the problem that GNNs trained on a given dataset may not perform well on new data where the graph structure is vastly different, and direct incremental training cannot solve the issue. Since this is similar to the catastrophic forgetting problem in continual learning, we propose a technique that applies two popular approaches, GEM and EWC, during the incremental training, so that balanced performance can be achieved on both existing and new data. This avoids re-training on the entire data, as it becomes prohibitively expensive as data size grows.

For future work, we will investigate whether, to some extent, the catastrophic forgetting phenomenon in this case can be mitigated by the choices of features—either increase the number of features, or find "universal" features that can work well despite the different graph structures.

REFERENCES

[1] 1999. Resource Description Framework (RDF) Model and Syntax Specification. https://www.w3.org/TR/PR-rdf-syntax/.
[2] Lawrence E. Boohan. 1994. The Validity Effect: A Search for Mediating Variables. Personality and Social Psychology Bulletin 20, 3 (1994), 285–293.
[3] Joan Bruna, Wojciech Zaremba, Arthur Szlam, and Yann LeCun. 2013. Spectral Networks and Locally Connected Networks on Graphs. arXiv e-prints (2013), arXiv:1312.6203.
[4] Giovanni Luca Ciampaglia, Prashant Shiralkar, Luis M. Rocha, Johan Bollen, Filippo Menczer, and Alessandro Flammini. 2015. Computational Fact Checking from Knowledge Networks. PLOS ONE 10, 6 (2015), 1–13.
[5] Robert M. French. 1999. Catastrophic forgetting in connectionist networks. Trends in Cognitive Sciences 3, 4 (1999), 128 – 135.
[6] Ian J. Goodfellow, Jonathon Shlens, and Christian Szegedy. 2014. Explaining and Harnessing Adversarial Examples. spritz arXiv:1412.6572 (2014).
[7] Han Guo, Jiao Cao, Yazi Zhang, Junbo Guo, and Jintao Li. 2018. Rumor Detection with Hierarchical Social Attention Network. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management (CIKM’18). Turin, Italy, 943–951.
[8] Will Hamilton, Zhitao Yang, and Jure Leskovec. 2017. Inductive Representation Learning on Large Graphs. In Advances in Neural Information Processing Systems 30. Curran Associates, Inc., 1024–1034.
Figure 8: Models trained on the whole dataset of GossipCop perform poorly on the dataset of PolitiFact.

Figure 9: Models first trained on the whole dataset of GossipCop and then on PolitiFact only perform well on the latter dataset on which it is trained, i.e., PolitiFact.

Figure 10: Performance of models first trained on the whole dataset of PolitiFact and then on GossipCop using GEM.

Figure 11: Performance of models first trained on the whole dataset of GossipCop and then on PolitiFact using GEM.
A. ADDITIONAL EXPERIMENTAL RESULTS

Here we present the remaining experimental results.

A.1 Results of Models Trained on the Whole Dataset

We have run the same experiments on the whole datasets of PolitiFact and GossipCop, and our results also suggest that: (1) these models perform well only on the dataset on which they are trained (e.g., Fig. 8); (2) direct incremental training suffers from catastrophic forgetting (e.g., Fig. 9); (3) incremental training using GEM can mitigate the problem (Figs. 10 and 11). We did not run further experiments with EWC on the whole dataset, as the previous results in Section 4 have demonstrated that GEM works better than EWC in our case.

A.2 Results of Incrementally Trained Models using GEM on the Clipped Dataset

Fig. 12 demonstrates the performance of the models first trained on the clipped dataset of GossipCop and then incrementally on PolitiFact using GEM.
Figure 12: Performance of models first trained on the clipped dataset of GossipCop and then on PolitiFact using GEM.

Table 2: Performance of models first trained on PolitiFact and then on GossipCop using EWC.

| sample size | λ   | Accuracy | Precision | Recall | F1   | Accuracy | Precision | Recall | F1   |
|-------------|-----|----------|-----------|--------|------|----------|-----------|--------|------|
| 100         | $10^{-4}$ | 0.787   | 0.735    | 0.683  | 0.693 | 0.801   | 0.782    | 0.755  | 0.778 |
|             | $10^{-3}$ | 0.780   | 0.728    | 0.674  | 0.688 | 0.787   | 0.775    | 0.741  | 0.746 |
|             | $10^{-2}$ | 0.815   | 0.791    | 0.713  | 0.736 | 0.764   | 0.758    | 0.741  | 0.746 |
|             | $10^{-1}$ | 0.823   | 0.797    | 0.732  | 0.753 | 0.751   | 0.750    | 0.734  | 0.737 |

| sample size | λ   | Accuracy | Precision | Recall | F1   | Accuracy | Precision | Recall | F1   |
|-------------|-----|----------|-----------|--------|------|----------|-----------|--------|------|
| 200         | $10^{-4}$ | 0.782   | 0.746    | 0.649  | 0.667 | 0.800   | 0.790    | 0.792  | 0.791 |
|             | $10^{-3}$ | 0.812   | 0.806    | 0.689  | 0.714 | 0.754   | 0.746    | 0.737  | 0.739 |
|             | $10^{-2}$ | 0.798   | 0.768    | 0.685  | 0.705 | 0.764   | 0.760    | 0.743  | 0.747 |
|             | $10^{-1}$ | 0.803   | 0.769    | 0.708  | 0.725 | 0.752   | 0.740    | 0.725  | 0.730 |
|             | $10^{0}$  | 0.819   | 0.786    | 0.736  | 0.753 | 0.762   | 0.754    | 0.744  | 0.746 |

| sample size | λ   | Accuracy | Precision | Recall | F1   | Accuracy | Precision | Recall | F1   |
|-------------|-----|----------|-----------|--------|------|----------|-----------|--------|------|
| 300         | $10^{-4}$ | 0.783   | 0.749    | 0.672  | 0.690 | 0.779   | 0.777    | 0.762  | 0.766 |
|             | $10^{-3}$ | 0.797   | 0.755    | 0.700  | 0.717 | 0.768   | 0.763    | 0.745  | 0.748 |
|             | $10^{-2}$ | 0.804   | 0.765    | 0.706  | 0.725 | 0.753   | 0.743    | 0.730  | 0.734 |
|             | $10^{-1}$ | 0.809   | 0.774    | 0.720  | 0.737 | 0.753   | 0.748    | 0.729  | 0.732 |
|             | $10^{0}$  | 0.801   | 0.757    | 0.711  | 0.727 | 0.755   | 0.750    | 0.724  | 0.729 |

Table 3: Performance of models first trained on GossipCop and then on PolitiFact using EWC.

| sample size | λ   | Accuracy | Precision | Recall | F1   | Accuracy | Precision | Recall | F1   |
|-------------|-----|----------|-----------|--------|------|----------|-----------|--------|------|
| 100         | $10^{-4}$ | 0.822   | 0.823    | 0.724  | 0.749 | 0.756   | 0.747    | 0.743  | 0.744 |
|             | $10^{-3}$ | 0.808   | 0.810    | 0.722  | 0.739 | 0.744   | 0.737    | 0.726  | 0.728 |
|             | $10^{-2}$ | 0.820   | 0.780    | 0.722  | 0.740 | 0.764   | 0.758    | 0.743  | 0.747 |
|             | $10^{-1}$ | 0.849   | 0.794    | 0.782  | 0.788 | 0.763   | 0.759    | 0.739  | 0.744 |
|             | $10^{0}$  | 0.808   | 0.778    | 0.719  | 0.735 | 0.755   | 0.750    | 0.731  | 0.735 |

| sample size | λ   | Accuracy | Precision | Recall | F1   | Accuracy | Precision | Recall | F1   |
|-------------|-----|----------|-----------|--------|------|----------|-----------|--------|------|
| 200         | $10^{-4}$ | 0.835   | 0.805    | 0.741  | 0.763 | 0.707   | 0.697    | 0.677  | 0.681 |
|             | $10^{-3}$ | 0.789   | 0.733    | 0.707  | 0.716 | 0.734   | 0.727    | 0.707  | 0.712 |
|             | $10^{-2}$ | 0.835   | 0.787    | 0.738  | 0.756 | 0.783   | 0.777    | 0.766  | 0.768 |
|             | $10^{-1}$ | 0.817   | 0.774    | 0.697  | 0.716 | 0.717   | 0.714    | 0.723  | 0.713 |
|             | $10^{0}$  | 0.775   | 0.736    | 0.643  | 0.657 | 0.780   | 0.774    | 0.783  | 0.776 |

| sample size | λ   | Accuracy | Precision | Recall | F1   | Accuracy | Precision | Recall | F1   |
|-------------|-----|----------|-----------|--------|------|----------|-----------|--------|------|
| 300         | $10^{-4}$ | 0.817   | 0.783    | 0.734  | 0.749 | 0.744   | 0.736    | 0.727  | 0.729 |
|             | $10^{-3}$ | 0.817   | 0.774    | 0.720  | 0.737 | 0.754   | 0.746    | 0.737  | 0.740 |
|             | $10^{-2}$ | 0.866   | 0.821    | 0.768  | 0.780 | 0.747   | 0.736    | 0.734  | 0.735 |
|             | $10^{-1}$ | 0.822   | 0.805    | 0.729  | 0.747 | 0.787   | 0.780    | 0.786  | 0.781 |
|             | $10^{0}$  | 0.789   | 0.737    | 0.679  | 0.691 | 0.701   | 0.698    | 0.705  | 0.696 |