A Parallel Neural Network Approach for Faster Rumor Identification in Online Social Networks

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ABSTRACT

The unprecedented scale of rumor propagation in online social networks urges the necessity of faster rumor identification and control. The identification of rumors in the inception itself is imperative to bring down the harm it could cause to the society at large. But, the available information regarding rumors in inception stages is minimal. To identify rumors with data sparsity, we have proposed a twofold convolutional neural network approach with a new activation function which generalizes faster with higher accuracy. The proposed approach utilizes prominent features such as temporal and content for the classification. This rumor detection method is compared with the state-of-the-art rumor detection approaches and results prove the proposed method identifies rumor earlier than other approaches. Using this approach, the detected rumors with 88% accuracy and 92% precision for experimental datasets is 5% to 35% better than the existing approaches. This automated approach provides better results for larger and scale-free networks.

KEYWORDS
Automatic Identification, Convolutional Neural Networks, Cybersecurity, Deep Learning, Early Detection, Online Social Networks, Rumor Identification

1. INTRODUCTION

In recent years, online social networks (OSNs) has become a widely accepted medium for real-time information propagation across the globe (Shearer & Gottfried, 2017; Bakshy et al., 2012). Although OSNs preferred to be an easier platform for real-time information sharing, the explosive propagation of rumors in these networks creates harm to society (Takayasu et al., 2015; Wen et al., 2015). Normally, the rumor spreads faster than the normal information in online mediums like OSNs (Doerr et al., 2011). Identifying such rumors earlier and controlling it can prevent major damages to the network and society. Consequently, researches on identifying the rumors have been a rising research interest among the industry experts and academicians.

Rumors in OSNs can be defined as an information or a study whose authenticity source is unknown or not verified at the time of circulation in the network (DiFonzo & Bordia, 2007). Basically, rumor identification is predicting from the available information whether a post or set of posts related to an event is a rumor or not. This rumor identification task can be categorized as a binary classification (Castillo et al., 2011; Chen et al., 2017) or a higher order classification approach (Ma et al., 2017; Hassan et al., 2015). These approaches use various types of features available in the information to identify the rumor. The features include the content of the post, propagation structure, structural

DOI: 10.4018/IJSWIS.2019100105

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Aspects and so on. Detecting the rumors during their initial stages can be of a greater benefit to reduce the harm in rumor propagation.

Earlier rumor identification in this work is to classify the event underlying to the set of posts is a rumor or not. For example, in 2013, there was a rumor related to Barack Obama injury in an explosion at the White House has made a major crackdown in the U.S stock market (Domm, 2013). This news exploded the OSNs and reached millions of people in a short span of time before it debunked as false. This work aims to classify the event “Explosion in the White House” is a rumor or not. This is a binary classification approach. Unlike other rumor identification approaches, this approach uses contextual information of content and temporal features for the classification. i.e., the set of posts consists of content, temporal features related to an event and their contextual information are considered as input for the proposed rumor classifier. The contextual information from content and temporal features is obtained by applying it to context-aware unsupervised vectorization approaches which result in contextual vectors.

Previously, some conventional models were proposed to identify the rumors through handcrafted features such as content (Castillo et al., 2011), user behavior (Liang et al., 2015) and various other factors (Qazvinian et al., 2011) (Kwon et al., 2013; Ma et al., 2015; Ratkiewicz et al., 2011). But handcrafted features may not be feasible for the dynamic and high-level interactive systems like OSNs. Also, handcrafted features are labor intensive and take more time. So, the automated approaches for rumor detection were proposed and some of which dealt with earlier rumor detection tasks. The first semi-automated rumor detector was proposed by Zhao et al. (2015). This tracks the questioning nature of users in the network. Then, deep learning approaches reduce the manual feature-engineering process which can serve as a perfect solution for automating the huge tasks (Chen et al., 2017; Ma et al., 2016; Ma et al., 2018; Yu et al., 2017). There are some deep learning-based approaches to identify rumors at the earliest (Wu et al., 2017; Ma et al., 2016; Chen et al., 2017). All these deep learning approaches consider the content or temporal features of a post or set of posts. But they failed to understand the contextual importance of features against the event and do not consider the rumor detection with minimal amount of data. Also, most of these approaches use the Recurrent Neural Network (RNN) based methods for rumor classification. However, previous researches claim that Convolutional Neural Network (CNN) is shown to be a practical approach for Natural Language Processing (Vu et al., 2016; Adel et al., 2016) and a large temporal feature classification (Krizhevsky et al., 2012). So, the proposed work utilizes CNN for rumor classification which accepts the contextual input vectors.

The proposed work aims to provide better results when available information about the rumors is minimal. To achieve this purpose, we have employed a few measures that fully utilize the data and perform better with data sparsity. Those measures are 1. Two input vectorization approaches are employed to vectorize the content as well as temporal features of information. These vectorization approaches are fully automated to avoid manual feature-engineering. 2. A new activation function is employed in CNN to arrive at better generalization faster. This activation function is extended from certain-factor activation functions. 3. Two parallel CNNs are deployed to accept the content and temporal vectors and provide enhanced results. Two CNNs are employed to leverage the efficient extraction of key features from different input sets and classify with higher accuracy. Two parallel CNNs has the benefit of handling the imbalance in input data.

In this paper, a novel Two Parallel Convolutional Neural Network (TP-CNN) approach is proposed to automatically identify rumors at the earliest. The proposed approach utilizes two CNNs in parallel to extract the key features from the input sequence and flexibly order the input to reduce the feature exclusion in neural networks. This binary classification approach processes the inputs automatically to arrive at faster classification results. First, the set of posts related to an event is collected and converted to two different vectors based on content and temporal features respectively. Then, these vectors are provided to the parallel CNNs separately to obtain the classification outputs. Finally, these two classification outputs are fused for the final classification result that demonstrates whether the event is a rumor or not. The novelty of the proposed approach lies in 1. Deploying two parallel
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