NewsBag: A Benchmark Dataset for Fake News Detection

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Student's Declaration

I hereby declare that the work presented in the report entitled **"NewsBag: A Benchmark Dataset for Fake News Detection"** submitted by me for the partial fulfillment of the requirements for the degree of *Bachelor of Technology* in *Computer Science & Engineering* at Indraprastha Institute of Information Technology, Delhi, is an authentic record of my work carried out under guidance of **Dr. Mayank Vatsa** and **Dr. Richa Singh**. Due acknowledgements have been given in the report to all material used. This work has not been submitted anywhere else for the reward of any other degree.

....
Sarthak Jindal

Place & Date: IIITD, 15/04/2019

Certificate

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

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Dr. Richa Singh

Place & Date: IIITD, 15/04/2019

Abstract

The spread of fake news poses a serious problem in today's world where the masses consume and produce news using online platforms. One main reason why fake news detection is hard is the lack of ground truth database for training classification models. In this paper, we present a benchmark dataset for fake news detection. The size of this dataset is an order of magnitude larger as compared to existing datasets for fake news detection. Moreover, we collect our training and testing datasets from different news sources to understand how well deep detection architectures generalize to unseen data. We also present an augmented training dataset generated using a custom data augmentation algorithm. The proposed dataset comprises of two modalities, image, and text; therefore, both unimodal and multimodal (deep learning) models can be trained. We also present baseline results of single modality and multimodal approaches. We observe that the multimodal approaches yield better results compared to unimodal approaches. We assert that availability of such large database can instigate research in this arduous research problem.

Acknowledgments

Contents

Chapter 1

Introduction

News consumption by people has increasingly grown over the years. The primary reason is the ease of accessibility of news. With the help of social networking sites such as Facebook and Twitter, people can not only share existing news with each other but also create "news" and then share it [34]. Moreover, the era of content driven websites is becoming increasingly visible. For example, there are many existing popular news websites and many more smaller websites come up every new day. These websites contain news articles written by mostly paid content writers. Even though it is good that news is so easily accessible, these days, both with respect to consumption and production, it poses a serious challenge in the form of fake news [19]. Fake news in simple terms can be defined as any news which is verified to be false [24]. This is slightly different from "rumours", which are news that cannot be verified as true [20]. There can be many ill intentions behind creating and spreading fake news. These include defamation of personalities [18], creating bias to change real world event outcomes [23], and decreasing trust in particular sections of social media.

Fake news is often written to defame certain famous personalities by spreading false information about them. These famous personalities could be politicians and movie stars. The LIAR [18] dataset which contains labelled short real world statements collected from fact checking website Politifact contains examples of such defamatory news with reference to a diverse range of political personalities. It becomes important to stop the spread of such defamation so as to protect the reputation of these famous personalities. For example, the fake news shown in Figure 1.1(a) is an example of a fake news written to defame a certain personality.

The effect of news on the outcome of important events such as Presidential elections in any country are far ranging. For example, fake news which favoured particular nominees in the 2016 US Presidential election was shared more than 37 million times on Facebook within the last three months of the election period [22]. Fake news can create a bias in the minds of people which in turn affects the outcome of these important events. This motivates one to stop the spread of fake news to isolate event outcomes from bias. For example, the fake news shown in Figure 1.1(b) is an example of a fake news written to create a bias in the minds of people during the event of US Presidential Elections. Social media is the most easily accessible platform for news exchange. The spread of fake news on social networking sites can lead to the daily user to stop trusting information on social media. This would be a major loss since the social media platform could be used very effectively, given that the trust factor is maintained. Fake news spread must hence be put to an end especially on social media.

The problem of detecting fake news is hard primarily because of two reasons: (i) the scarcity of labelled data [18] and (ii) deceptive writing style [25]. Most fake news websites come up shortly during events like elections and then disappear after publishing fake news. Also, fake news spreading on social media websites like Facebook is hard to obtain because the feeds of users are private. Another reason for data
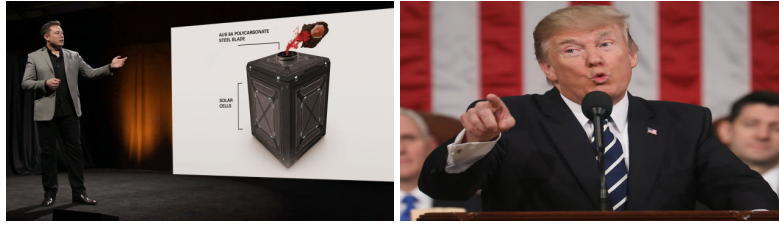
Figure 1.1: Example of defamatory news (a) Elon Musk Gives Saudi Investors Presentation On New Autonomous Beheading Machine For Adulterers. Example of a bias inducing news (b) Trump says "America Has Not Been Stronger Or More United Since I First Opened My Eyes And Created The Universe".

scarcity is that even if we scrape random news articles from the web, a lot of domain knowledge would be needed for human annotation of news as real or fake. Moreover, fake news creators use deception in the sense that they mimic the writing style of real news writers in order to avoid being caught. Therefore, it is hard sometimes for even human beings to identify if an article is fake just on the basis of writing style.

1.0.1 Contributions

In this research paper, we present a large-scale dataset to help build fake news detection algorithms. We initially scrape The Wall Street Journal and The Onion to create our training dataset, termed as News-Bag, which has 2,15,000 news articles. The proposed dataset contain both news text and images. Since this training dataset is imbalanced, we use a data augmentation algorithm to create a bigger and approximately balanced training dataset, NewsBag++, containing around 5,89,000 news articles with both text and image data. To show a real world evaluation of our models, we scrape our testing set- News-Bag Test from completely different news websites. We use state-of-the-art text and image classification models in our experiments and also extend the deep convolutional neural networks like ResNets [14], SqueezeNets [15], DenseNets [21] etc for multimodal fake news detection. This is done by parallely training the networks with image and text input. However, we infer from our experiments that even very deep networks cannot generalize well to unseen and differently written news in the testing dataset. This shows the hardness of the fake news detection problem as fake news can vary with respect to writing style, news content, source etc. However, if seen from a relative point of view we show that it's a good idea to use multiple modalities of data from fake news detection. Our best multimodal model is a Text-Image Resnet which beats our best single modality classification model, RCNN [10], by a significant margin. This provides inspiration for further work in the field of multimodal fake news detection.

Chapter 2

Background and Previous Work

The fake news problem is quite old. There are also many real world tasks similar to fake news detection like rumour detection [26] and spam detection [27]. Researchers have come up with various solutions belonging to different domains. The earliest solutions were purely using natural language processing for fake news detection [28] [30]. The lie detector [1] was one of the earlier major attempts in deception detection which used purely natural language processing techniques. Although, the problem of detecting fake reviews is slightly different from that of detecting fake news, sentiment analysis using NLP emerged as a method to detect fake review on E-commerce sites [2]. Research has also shown that just a word level analysis is not enough for deception detection tasks [3]. So, parse trees are created for sentences to analyse the syntax of a sentence for deception detection. Natural language processing based fake news detection depended on text data only and it's features [29]. For example, handcrafted rules could be written to point out explicit features such as large number of third person pronouns which were mostly common in fake news articles [5]. However, explicit handcrafted features extracted from text data depends upon news content and the event context in which the news is generated [24]. So, it is difficult to come up with discriminative textual features to get good detection results on fake news on new events. The next steps taken by the research community incorporated information from social networks in them. The social context of a news includes user interactions such as hastags, comments, reactions, retweets etc. [25]. A news that is spreading on social media can be said to be fake or real depending on the reactions of social media users [5]. For example, consider a news article which has been posted on Facebook and is becoming popular as many people are sharing it. However, if a credible user with a trusted account and activity, comments on the post describing it as fake then their is some probability that the post is fake [5]. Moroever, research has been done to analyse the propagation graphs of news on social media [31]. However, the shortcoming of social context based fake news detection lies in the noisy nature of these social feature.

It is only recently that researchers have started using images along with text for the fake news detection task. Multimodal deep learning has previously been successfully applied to related tasks like visual question answering [32] and image captioning [33]. With respect to fake news detection, TI-CNN [4] (Text-Image Convolutional Neural Network) is a very recent work in which the authors scrape fake and real news generated during the US 2016 Presidential elections. The authors have used parallel convolu-

tional neural networks to find reduced representations for both image and text in a data point. Then, they merge the representations to find a combined feature representation for image and text which is used for classification. The experiments make it clear that multimodal models perform better than single modality models (image or text) for the fake news detection task. Romour detection on microblogs [19] is another form of fake news detection. In this paper, the authors work with the Weibo [19] and Twitter [20] datasets, obtained from Chinese authoritative news agencies and Twitter respectively. The authors propose a multimodal fusion mechanism in which the image features are fused with the join features of text and social context produced by an LSTM(Long-Short Term Memory) network. They show that images fused with neural attention from the outputs of the LSTM, the att-RNN mechanism performs well on multimodal rumour detection task. EANN (Event-Adversarial Neural Network) [6] is another recent work which involves the use of both text and image, to find a combined feature representation for classification. The authors have used the Weibo [19] and Twitter [20] datasets which were originally collected for rumour detection on social media. The special characteristic of this model is that apart from using both text and image content, it uses an event discriminator to find event-independent features for classification of news as real or fake. This is important because fake news is generally dependent on the event that generated them but we do not want our models to learn event-dependent features, so that they can perform well on classifying any new news given as input.

Chapter 3

Dataset

The NewsBag dataset comprises of 2,00,000 real news and 15,000 fake news. The real news has been scraped from the Wall Street Journal. The fake news have been scraped from the Onion which is a fake news website. Such websites openly publish fake news but not to hurt someone's reputation. They do it for the purpose of creating humour. However, since the NewsBag dataset is highly imbalanced we create NewsBag++, an augmented training dataset. The NewsBag++ dataset contains 2,00,000 real news and 3,89,000 fake news. The data augmentation algorithm used for generating new fake news given a ground truth set of fake and real news is described in the following section. Apart from NewsBag and NewsBag++, we create a NewsBag Test dataset for testing while training models on either of NewsBag or NewsBag++. The NewsBag Test dataset contains 11,000 real news articles scraped from The Real News and 18,000 fake news articles scraped from The Poke. We have used completely different sources of news for the NewsBag Test dataset so that we can understand how well a model trained on NewsBag or NewsBag++ generalises to unseen and differently written news.

3.0.1 Intelligent Data Augmentation Algorithm for Generating Fake News

The simplest idea to generate fake news would be to combine any two random news from the existing 15,000 fake news scraped from websites. However, this poses two problems. One, the two combined pieces of fake news may be totally irrelevant and hence make no sense together. This is not good for our research because we want fake news to be the way it is actually written by people. The second drawback is that the number of fake news images would be limited, since we would only be picking from the existing set of 15,000 images. This is not good with respect to training a robust model. So, we decide to come up with an intelligent data augmentation algorithm for generating fake news. Figure 3.1 shows an example of the same.

First of all, we scrape 1,70,000 additional real news from the Wall Street Journal besides the 2,00,000 real news we already have. Then, we get a bag-of-words representation for each news in this additional set of 1,70,000 real news. We get a bag-of-words representation for each news in our 15,000 fake news set as well . These bag-of-words representations are found after removing stop words from the respective news whose representation it is. Then, we do the following for mutliple iterations: Pick a

random news from the 15,000 fake news set. Find all the fake news whose bag-of-words representation has an intersection above a threshold with the particular fake news picked from the 15,000 fake news set. Generate a new fake news by combining the text of each of these fake news with the fake news picked at first. Also, mark the pair so that it is never used for generation again. Find the real news from the additional 1,70,000 real news set whose bag-of-words representation has the largest intersection with the bag-of-words representation of this particular generated piece of fake news. Simply attach the image from this real news to the generated fake news.

Our augmentation algorithm generates fake news which is very similar to actual fake news written by people because of two main reasons. Firstly, the two fake news combined to generate a new one are very relevant to each other since their bag-of-words representation have the largest intersection with each other. This makes the generated news sound coherent and not completely senseless. And the second reason is that we attach an image from the real news whose bag-of-words representation has the largest in common with the bag-of-words representation of the generated fake news. This is actually the most intuitive way to write fake news since fake news writers must look for relevant real news images which can be attached to the fake news text they have written.

Figure 3.1: Example of fake news generation using Intelligent Data Augmentation Algorithm for generating fake news.

3.0.2 Nomenclature

We make our dataset publicly available in three different formats. The simplest is the Dataset Folder format which is commonly used by deep learning libraries like PyTorch. The image data is organised as two folders- fake and real. Each folder contains all images of that particular class. The same is the organisation for the text data.

FastText is a format used for data in text classification tasks. In the FastText Format, the three datasets- NewsBag Test, NewsBag and NewsBag++ exist as a text file each. Within the text file, each line represents a sample ie. two samples are separated by a newline character. Also, each line starts with __label__ followed by the target label for the sample. This prefix allows models to retrieve the class for a given sample during training or testing. The actual sample follows the label prefix after separation by a space followed by a comma followed by a space. This format is very well suited for text classification as it requires very little extra memory to store every sample's label.

Google Colaboratory is an openly available tool for researchers which provides a Tesla K80 GPU back-end. However, reading data folders from google drive with a lot of files or subfolders at the top level gives IO Error on Colab. Also, memory is limited on colab which calls for data compression. So, we provide our datasets- NewsBag.zip, NewsBag Test.zip and NewsBag++.zip in a format which we call the Google Colab format. We downsample our images to 28 by 28 so as to keep only the most useful visual information and limit memory requirement. We organise the text and images into numbered sub-directories with 500 text and image files each, respectively. The last subdirectory in the text and image folders may however have lesser than 500 files each. We prefix the label followed by a space to each filename to retrieve the target label during training or testing. Finally, we perform our experiments on Colab using this particular format and face no input/output errors.

3.0.3 Comparison with Other Existing Datasets

One of the main strengths of our database is it's size. Our NewsBag++ database stands at 5,89,000 data points with two classes- real and fake. This is an order of magnitude bigger than already existing fake news datasets. However, at the same time, the main weakness of our dataset is that it does not have any social context. By social context, we mean that there is no information on who is spreading the news on social media, what are the trends in the sharing of this news, what are the reactions and comments of users etc. This provides scope for further improvement where we can dig out the social context of news by searching similar posts on social media. Some of the already existing datasets for fake news detection are discussed below. Table 3.1 compares all the datasets.

- The FakeNews Net dataset [5] which is a recent work in fake news detection contains about 24,000 data points only. The main strength of this dataset is the presence of social context, for example, user reactions and comments etc.

- Similarly, the TI-CNN (Text-Image Convolutional Neural Network) [4] also has only 20,000 data points. The fake news revolve around the 2016 US Presidential elections.

- BuzzFeedNews is a small dataset collected from Facebook. It has been annotated by BuzzFeed journalists. BuzzFace [16] is simply an extension of BuzzFeedNews. Both the datasets have content based on the US 2016 elections just like the TI-CNN dataset.

- The FacebookHoax [17] as the name suggests has hoaxes and non-hoaxes collected from few of Facebook's scientific and conspiracy pages respectively.

- The LIAR dataset [18] is different from others because it is more fine-grained. Fake news are divided into fine classes- pants on fire, false and barely-true while real news are divided into fine classes- halftrue, mostly true, and true. This dataset contains real world short statements made by a diverse range of political speakers. It is collected from fact checking website Politifact, which uses manual annotation for the fine-grained classes.

- The Weibo dataset [19] is collected from Chinese authoritative news sources over a period of 4

years from 2012 to 2016. The annotation has been done by examining suspicious posts reported by credible users of the official rumour debunking system of Weibo.

- The Twitter dataset [20] is collected from Twitter, originally for detecting fake content on Twitter. The data not only has both text and images but also additional social context information from twitter users.

Table 3.1: Comparison of existing datasets for Fake News Detection

Dataset	No. of real news articles	No. of fake news articles	Visual Content	Social Context	Public Availability
BuzzFeedNews	826	901	No	No	Yes
BuzzFace	1,656	607	No	Yes	Yes
LIAR	6,400	6,400	No	No	Yes
Twitter	6,026	7,898	Yes	Yes	Yes
Weibo	4,779	4,749	Yes	No	Yes
FacebookHoax	6,577	8,923	No	Yes	Yes
TI-CNN	10,000	10,000	Yes	No	Yes
FakeNewsNet	18,000	6,000	Yes	Yes	Yes
NewsBag Test	**11,000**	**18,000**	Yes	No	Yes
NewsBag	**2,00,000**	**15,000**	Yes	No	Yes
NewsBag++	**2,00,000**	**3,89,000**	Yes	No	Yes

3.0.4 Analysis of the Dataset

In this section, we present key statistics about the NewsBag Test, NewsBag and NewsBag++ datasets. Each of these statistics can be used as handcrafted features that may be input to a machine learning model. However, one of the main reasons why fake news detection is hard is that these handcrafted features are not very discriminative. In other words, they are almost equal for both the classes- real and fake. This encourages the use of deep learning models which can learn hidden or latent features in the data. The significance, variation and lack of dicriminative property of the features for the different datasets is described below. Table 3.2 summarises the analysis of the dataset.

Vocabulary is the set of unique tokens in a text dataset, also called the set of types. It is a very important indicator of the diversity of a dataset. But, in the case of both of our approximately balanced datasets- NewsBag Test and NewsBag++, the vocabulary size is almost equal for fake and real classes. This shows that fake and real news are equally diverse. For the NewsBag dataset, the vocabulary size is higher for the real news samples simply because of their larger number compared to fake news samples in the dataset.

We analyze the news content of the three datasets with respect to both the classes separately. Word Cloud representations reflect the frequency of words in a particular dataset. We make two interesting observations on the word cloud representations shown in Figure 3.2. Firstly, the word clouds of real news for all of the three datasets reflect important real word entities. For example, we can easily observe the highly frequent words Israel, New York and China in the word cloud representations of the real news of NewsBag Test, NewsBag and NewsBag++ respectively. On the other hand, fake news contain mostly words not related to important entities. For example, we see words such as new, one, week and pictures in the word clouds of the fake news in the NewsBag Test, NewsBag and NewsBag++ dataset

Table 3.2: Analysis of the dataset

Textual Features/Dataset	NewsBag Test		NewsBag		NewsBag++	
	Fake	Real	Fake	Real	Fake	Real
Vocabulary Size (words)	29571	25286	40897	124243	109006	124243
Avg. number of characters per news	148	219	223	216	446	216
Avg. number of words per news	27	37	38	36	81	36
Avg. number of stopwords per news	9	11	13	11	27	11
Avg. number of punctuations per news	1	1	2	2	7	2

respectively. This disparity between the word clouds of fake and real news emphasizes the fact that fake news do not have much real world content to speak about. They simply try to create news by using attractive words, for example, 'New' rule on tax payment etc. Another observation to make is that the NewsBag Test has noticeably different word cloud representations than our training datasets, NewsBag and NewsBag++. This is because we have scraped the NewsBag Test dataset from different websites (TheRealNews and ThePoke) while the training datasets contain news from Wall Street Journal and The Onion. We use different sources of news for the testing and training datasets so that we can observe how well our models generalize to unseen data points.

The length of the fake or real news in terms of the number of characters or words is once again dependent on the source of news. There is no fixed pattern. As we see, the NewsBag Test dataset has longer real news as compared to fake news, in contrast to the NewsBag dataset which has longer fake news. This is another reason why fake news detection is non-trivial. The length of the news (characters or words) is an example of a handcrafted feature which follows opposite pattern in our training (NewsBag or NewsBag++) datasets and testing(NewsBag Test) dataset. Features like these can actually fool the model. This is reflected in the baseline results we present in the experiments section, where we see the testing accuracy of some models to be less than random.

Stopwords and punctuations are least informative in a text. Just like the length of the news, we see that these features follow different patterns in real and fake classes, across different sources of news. Hence, these handcrafted features are also not suitable for classification.
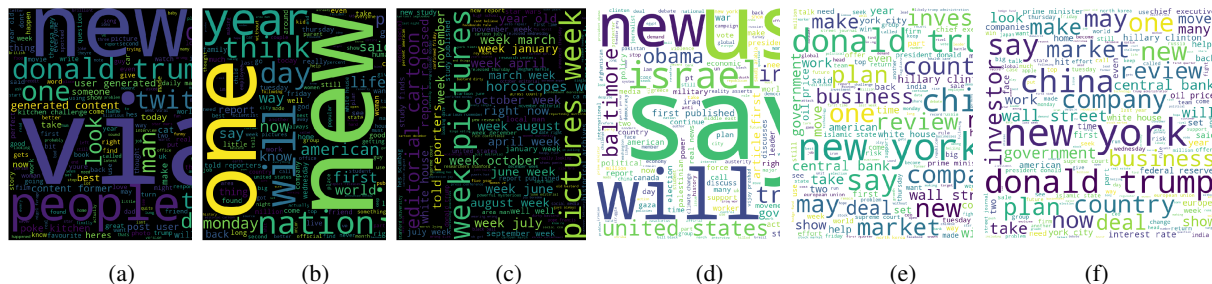

(a) (b) (c) (d) (e) (f)

Figure 3.2: Fake news word cloud representations for NewsBag Test, NewsBag and NewsBag++ are shown in black from (a)-(c) respectively. Real news word cloud representations for NewsBag Test, NewsBag and News-Bag++ shown in white from (d)-(f) respectively.

Chapter 4

Experiments

We train both single modality and multimodal models on our dataset. We show the training and testing accuracies for both NewsBag and NewsBag++. The test set is the same while training with either NewsBag or NewsBag++. All our experiments have been carried out on Google Colaboratory, an open source python notebook environment with a Tesla K80 GPU backend. The accuracies for each dataset and model are summarized in Table 4.1.

4.0.1 Single Modality - Text

We use the FastText data format for training our text classification models. The training setting for each model is described in detail below.

- FastText [7] is one of the simplest text classification methods known for it's efficiency. We use GloVe [8] word embeddings which have 300 dimensional vectors, 2.2M types in vocabulary and 840B tokens. We train the model for 30 epochs with a learning rate of 0.5 and batch size 128.

- TextCNN [9] had improved the state-of-the-art in sentiment analysis and question classification. Here, we train the model for fake news classification. We use the same embeddings as in the case of FastText but we train the model with a slower learning rate of 0.3 and a smaller batch size of 64. We use convolutional kernels of sizes 3x3, 4x4 and 5x5. The model is trained for 15 epochs.

- We use a bi-directional LSTM network for classification. The architecture is kept simple with only 2 hidden layers consisting of 32 units each. We use a maximum sentence length of 20 to enable faster training.

- Recurrent Convolutional Neural networks [10] capture context to learn better representations for words, thereby eliminating the requirement for handcrafted features. We train a simple RCNN with 1 hidden layer of size 64 using a dropout of 0.2. We keep the batch size as 128 and train the model for 15 epochs with a learning rate of 0.5.

- Neural Machine Translation [12] is a recent approach for end-to-end machine translation. It uses an encoder-decoder architecture with a soft attention mechanism to align words better to each other.

Table 4.1: Experiments carried out using NewsBag and NewsBag++ training sets

Model/Dataset	NewsBag		NewsBag++	
	Training Accuracy	Testing Accuracy	Training Accuracy	Testing Accuracy
fastText	0.95	0.47	0.98	0.52
TextCNN	0.96	0.50	0.98	0.45
TextRNN	**0.99**	0.51	0.99	0.40
RCNN	0.98	0.54	0.99	0.43
Seq2Seq (Attention)	0.98	0.48	**0.99**	0.43
Transformer	0.96	0.44	0.98	0.39
Image ResNet	0.93	0.38	0.66	0.38
Image SqueezeNet	0.93	0.38	0.66	0.38
Image DenseNet	0.92	0.38	0.65	0.38
Text-Image DenseNet	0.93	0.38	0.66	0.38
Text-Image SqueezeNet	0.93	0.38	0.66	0.38
Text-Image ResNet	0.93	**0.62**	0.66	**0.62**

In order to use the sequence to sequence model(with attention), we use only the representation of a news article generated by the encoder for classification. The encoder architecture is a simple bi-directional LSTM with 1 hidden layer of size 32.

- Transformers [13] eliminate the need for any RNN or CNN by using stacks of self-attention and position-wise feedforward neural networks for the machine translation task. The methodology to use transformer for fake news detection is the same as the sequence to sequence model. We use the self-attention and position-wise feedforward network in the encoder to get the data representation for classification.

4.0.2 Single Modality - Image

We use the Google Colaboratory data format for our image classification models. We show our results for very deep convolutional neural networks which have performed extremely well on image classification tasks.

- We use a ResNet [14] with 18 layers for classifying fake news on the basis of image only. ResNets have shown increase in accuracy and decrease in complexity in image classification tasks by learning residual functions with respect to the input layers. The final fully connected layer of the ResNet with 1000 dimensional output is replaced by another dense layer with 2 outputs to get the desired classification. We use a batch size of 128 and a learning rate of 0.01 decayed by a factor of 0.1 every 3 epochs. The model is trained for 7 epochs.

- We use SqueezeNet [15] as another model which takes less memory than AlexNet or ResNet, without sacrificing on accuracy. The training settings are kept same as ResNet. We see that when

trained on our NewsBag dataset, SqueezeNet perform as good as ResNet. We use a bigger batch size of 256 for SqueezeNet.

- DenseNets [21] take the idea of feature propagation and feature reuse to the extreme which is the reason why they achieve good classification accuracy. For a given layer, the feature maps from all the previous layers are used as input, leading to a total K*(K + 1)/2 direct connections, where K is the number of convolutional layers. DenseNets are effective in reducing the vanishing gradients problem.

4.0.3 Mutliple Modality - Image and Text

The training of multimodal models is carried out very similarly to the image only models. We employ very deep networks like ResNet, DenseNet and SqueezeNet with text input data. This makes sense because when tranformed to a 3d-tensor, even text has properties like an image. For example, characters belonging to the same word will occupy adjacent rows in the 3d-tensor. Hence, the conventional image classification models can be used to better capture spatial relationships of characters, which are nothing but words, context and sentences. We conduct our experiments for Text-Image ResNet, Text-Image DenseNet and Text-Image SqueezeNet. These networks run parallel ResNets, DenseNets and SqueezeNets respectively, for both image and text. Images can be directly input as 3d-tensors to the model. But, in order to feed the text to the Text-Image ResNet or Text-Image SqueezeNet we first get an embedding for every character, an idea very similar to CharCNN [11]. Once we have character level embedding, we reshape our text into a 3d-tensor of shape 3 x 224 x 224 which can be input to our models. To keep our models simple, we simply sum the final 2 dimensional prediction vectors for both image and text, for the final classification.

Chapter 5

Inferences

The results summarised in the table indicate the hardness of the fake news detection problem. We observe that the training accuracies are very high for the NewsBag training set, irrespective of the modality of the model. In the case of NewsBag++, however, training accuracy for image modality only models and multimodal models is very low. On the other hand, text modality only models yield very high training accuracy even on NewsBag++. This leads us to infer that it is specifically the image modality of the data which is fooling the models in case of NewsBag++ training set. The reason behind this is that our custom intelligent data augmentation algorithm for NewsBag++ generation tries to generate realistic fake news by using images from the additional 1,70,000 real news, scraped from Wall Street Journal specifically for this purpose. This inference empirically verifies exactly how fake news writers can fool detection models by attaching real news images to their fake text content.

We also observe that irrespective of the training dataset and model used, the testing accuracies are very low. Neither of the single modality or multi-modal models give a testing accuracy significantly above random accuracy of 0.5. This is because when the source of news varies, as in our NewsBag Test and NewsBag/NewsBag++ datasets, even the very basic latent feature learnt by the model from the training set vary in the testing set, across classes. Even data augmentation using already available ground truth data, as in NewsBag++, does not seem to solve the problem of effective generalisation to unseen data. So, in a way, the learning done by the model becomes useless when applied to the testing set. However, even on such unpredictable dataset, our best model- Text-Image ResNet achieves about 12% improvement over random accuracy.

Another takeaway is that using models which work on images only is not a good choice for the fake news detection task. This is verified empirically by the extremely low testing accuracy of around 0.38 for even very deep image classification models like ResNet and SqueezeNet. Images are not very discriminative across fake and real news unlike other standard image classification tasks, like ImageNet classification. Another important inference is that single modality models which take only text as input cannot achieve as good a classification accuracy as compared to the multi-modal classification models. We see that the RCNN model gives about 8% less accuracy as compared to the Text-Image ResNet. This observation guides us to infer that images, though when used only cannot give good classification accuracy, but when used with text, they enhance the accuracy.

Chapter 6

Conclusion

In this paper, we present Newsbag, a benchmark dataset for training and testing models for fake news detection. It is not only an order of magnitude larger than previously available datasets but also contains visual content for every data point. Our work brings forward the complexities involved in fake news detection due to unpredictable news content, the event context in which the news originated, author writing style, and news article sources. We show baseline results of state-of-the-art text classification and image classification models for single modality fake news detection. We also show results from multimodal fake news detection techniques. We indicate the hardness of the fake news detection problem by showing poor generalization capabilities of both single modality and multimodal approaches. We further support our claim about the non-trivial nature of the problem by presenting an augmentation algorithm which when used for fake news generation can fool very deep architectures, as empirically verified in our experiments. We infer that none of the single modality models achieve good improvement over a random coin toss. Multimodal approaches, however, achieve better performance by combining learning's from text and image modalities. Future work can be done in the direction of expanding the modality set for fake news detection datasets, for example, using social context, text, images, audio, and video for fake news detection.

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