AUTOMATIC IDENTIFICATION OF FAKE NEWS

SUPERVISOR: **Dr. Gagandeep Kaur**

SUBMITTED TO: **Dr. Sandeep Kumar Singh**
Dr. P. Raghu Vamsi

GROUP MEMBERS:

Nikita Jain 14103010

Saumya Pandey 14103078

Aditi Bhardwaj 14103108

ACKNOWLEDGEMENT

Every work accomplished is a pleasure – a sense of satisfaction. A number of people have motivated and encouraged us in accomplishing our project. So we take this opportunity to thank all those who have directly or indirectly helped us during the completion this project.

Firstly, we would like to thank **Dr. Gagandeep Kaur** ma'am our mentor without whose support this project could not be accomplished. We express our sincere gratitude to our mentor who in spite of being extraordinarily busy with her duties, took time out to hear us, guide us, keep us on the correct path extending all the help and keeping us motivated all along the way. Next we would like to thank all those who gave their valuable time and feedback to this project. We would also thank the college faculties to provide with resources which beyond any doubt have helped us.

Let us also use this opportunity to thank our team members who have contributed to this project with their invaluable opinions and suggestions, which has gone a long way in soothing our rough edges as teammates. Lastly, we would like to thank the almighty and our parents for their moral support with whom we shared our day-to-day experiences and received lots of suggestions that improved our quality of work.

CERTIFICATE

This is to certify that this project report entitled "**Automatic Fake News Detection using Neural Networks**" submitted to "**JAYPEE INSTITUTE OF INFORMATION TECHNOLOGY**", Noida Sector-62 UP is a bonafide record of work done by "Saumya Pandey, Aditi Bhardwaj and Nikita Jain" under my supervision.

SIGNATURE

TABLE OF CONTENTS

1. Introduction

The spread of fake news articles has generated noticeable concern recently, as false or misleading stories can spread faster and reach a wider audience over social media. Fake news are online stories that appear to be factual but are not. They may appear in websites that appear to be legitimate, although often they are often found on websites with little or no real news. Unfortunately, sometimes fake news stories are picked up by legitimate media houses and appear on their websites. Given that rapidly changing technology has played a major role in enabling the spread of fake news, a natural question is whether technology can also help warn users about misleading news [1]. While technology is certainly not advanced enough to evaluate the truth of a claim on its own, it could be used to aid journalists and make it easier for them to detect and debunk false statements.

While automated fact checking and stance detection has not yet gathered much attention from researchers, previous research in Natural Language Inference (NLI) has worked on problems that are very similar to ours. NLI attempts to identify the relationship between two statements, by identifying whether two bodies of text support, contradict, or are neutral towards one another. Researchers in NLI have achieved reasonable success on this task using neural network models, and almost all of the best performing models on the benchmark Stanford SNLI corpus have incorporated neural networks. Matching LSTMs were successfully used for NLI to achieve a performance of 86.1% on the SNLI dataset. Tests a LSTM model, attention model, and a word-by-word attention model on the SNLI corpus. In their paper, word-by-word attention achieves the highest test accuracy of 83.5% on the SNLI dataset. A sequential LSTM-based model combined with a syntactic parsing model was used by to achieve 88.3% accuracy on the SNLI corpus [2].

With the advent of fake news being used to influence elections and negatively impacting the decision making of the readers, the identification of fabricated information has become an important task. Governments, newspapers and social media platforms are working hard on distinguishing credible news from fake news. The goal of the Fake News detection is to automate the process of identifying fake news by using machine learning and natural language processing. This process can be broken down into several stages. A first helpful step towards the identification of fake news is to understand what other news sources are saying about the same topic. That is why we initially focus on stance detection. Specifically, the task is to estimate the stance of a news headline, relative to the contents of a news article which can but does not have to address the same topic. Thus, the relative stance of each headline-article pair has to be classified as either unrelated, discuss, agree or disagree. The discovery of a disagreeing headline-article pair does not necessarily correspond to the discovery of a fake article, but it is an automated first step which could make human reviewers aware of a discrepancy.

1.1 Relevant problems with fake news

It is said that " False travels around the whole world while truth is about to put on shoes"**.** With many individuals relying on the internet for daily news, fake news continues to be circulated on search engines and social media, which leads to inaccurate stories being virally shared worldwide. All of these fake articles being circulated contains outrageous headlines which were meant to attract the greatest amount of engagement from users, as well as pretending to be legitimate to gain credibility — at least at first glance[3]. This led to exponential engagement to millions of users through mindless sharing on social media such as Facebook. Social media has surged exponentially in last decade. The growing internet and smartphone users have given birth to new threat of FAKE NEWS on the social media. People spreading and blindly believing the same is disastrous.

Social media has become an integral part of modern society as all are very keen to increase their social footprints and make their presence felt in the virtual communities and networks. But suddenly the very primary cause of this social media like creation and sharing of information, news, trends, best practices and opinions are being sidetracked as the menace of fake news is popping up its head out. The reasons for the fake news gaining the prominence are:
1. Anti-social elements of the society are purposely spreading such fake news due to some vested interest and gaining benefits.
2. Some users who are blind followers of important persons like celebrities or political figures often don't take pain to check the authenticity of news and blindly do like/comment/share.
3. The present form of IT Act is not equipped with proper provisions to check the spreading of fake news.
4. Also the growing smart phones penetration can be hold responsible as it is extending the free access to social media through internet connectivity it offers[4].

1.2 Problem statement

The spread of fake news articles has generated noticeable concern recently, as false or misleading stories can spread faster and reach a wider audience over social media. Given that changing technology has played a major role in enabling the spread of fake news, a natural question is whether technology can also help warn users about false claims. While technology is certainly not advanced enough to evaluate the truth of a claim on its own, it could be used to aid journalists and make it easier for them to detect and debunk false statements.
There are several applications which have been designed for this purpose. Our application will explore the use Natural Language Processing techniques to determine whether a body of text agrees, disagrees, discusses, or is unrelated to another. This model could be applied as an automatic fact checker that could read an article, and then find other articles that either disagree or agree with its content. For this we will use methods from the field of Natural Language Inference to build a model that classifies the relationship between a news article headline and the body of a different news article.
With the advent of fake news being used to influence elections, the identification of false information has become an important task. Governments, newspapers and social media platforms are working hard on distinguishing credible news from fake news. And for this people developed the Fake News Challenge with the goal to automate the process of identifying fake news by using machine learning and natural language processing. This process can be broken down into several stages. A first helpful step towards the identification of fake news is to understand what other news sources are saying about the same topic. This is a problem which needs to be dealt with so we have also applied some of the concepts of deep learning to detect fake news and stance.

1.3 Solution and approach

Our solution approach is mainly based on the key fact that through our proposed idea we will be able to find out a key relation between the given headline and its corresponding body text. Hand-crafted features of headline-body pair, including bag of words and n-grams matching, have already been used to achieve moderate accuracy for stance classification and now recently neural-based encoder architectures are also been introduced to classify the problem. So, basically our approach to identify the fake news can be categorized under various models.
We train 3 different models after applying linear SVM for initial classification: a Bag of Vectors Model, LSTM, and RNN with Attention:

1. Baseline Model: Bag of Vectors

The baseline model utilizes a straightforward bag of vectors approach[5]. The model creates a L2-normalized sum of the embedding vectors for each of the words in the headline and body text.[5] This new vector naively captures the meaning between the texts through summing their embedding vectors[5]. To determine the prediction of the relationships between the headline and the body, the result is passed through a multilayer perceptron and softmax classifier to generate the final output[5]. The intent of this model was to have a working baseline that has shown success in Natural Language Inference applications. Several MLP architectures with both tanh and relu activations were constructed for training[5].

2. Long Short Term Memory (LSTM)

The LSTM model is a sequence-to-sequence model replicated from and modified to our task. It uses two LSTM encoders to generate separate encodings of the headline and body text of dimension d[6]. Next, the encodings are concatenated to form a vector of dimension 2d[6]. Like the baseline model, the concatenated vector is passed through a multilayer perceptron and finally a softmax classifier to generate the final output[6]. However, we modify this model from the original by treating the dimensions as hyper parameters, especially since our headlines and bodies are of significantly different lengths[6]. We experiment by allowing the LSTM processing body text to be a much higher dimension than 100d, hoping that it will allow a better representation of the longer body[6].

3. RNN with Attention

An often used extension to the sequence-to-sequence LSTM model mentioned above is to add an attention mechanism that allows the body text to attend to the LSTM output layer from the headline to make the final prediction[7].

We also test multi-layer LSTMs with attention. Here the attention mechanism acts on the LSTM output in essentially the same manner, but the input article headlines and bodies pass through multiple layers of LSTMs before they are output[7]. This may help us learn higher level structures in the text, at the cost of more parameters and more potential overfitting[7].

2. Literature Survey(Integrated Summary)

New Media, including online newspapers and social media, not only enable people around the world easily receive news and share information in real-time, but also lets fake news and rumors spread quickly under no verification and time[20]. Mistaking fake news for authentic reports can have costly consequences, as being misled or misinformed negatively impacts our decision-making and its consequent outcomes[8]. Fake, fabricated, falsified, disingenuous, or misleading news reports constitute instances of digital deception or deliberate misinformation [8]. “Digital deception”, a term signifying deception in the context of information and communication technology, is defined here as an intentional control of information in a technologically mediated environment to create a false belief or false conclusion[8].While human fact checkers fail to verify to verify the credibility of the news due to the sheer volume of the information out there leveraging AI and machine learning techniques seems the only possible solution for automatic fake news detection in this era[20].Therefore we examined several papers regarding this issue to get greater insight into the problem.

Firstly, we researched the papers that approached the problem of fake news via stance detection In February 2017, the Fake News Challenge 1 (FNC-1) was launched by a non-profit organization with the goal of developing tools to help fact checkers tag fake news [9].The papers utilizes the dataset provided by FNC-1 to approach this problem. We developed our baseline models based on detailed analysis of the papers which involved the main task of classifying the headline-article pair into agree, disagree, discuss or unrelated. Thus, stance detection for fake news is split into a two classification problem in which the first baseline model was a Lexicalized Linear Classifier. This classifier for each article,headline pair we extracted features such as the cosine distance between TF-IDF vectors, max BLEU score, cross-grams, and Jaccard Distance[9]. Then SVM classifier with a radial basis function (RBF) kernel is applied based on the highest correlation value.The researcher then employed various neural network architectures built on top of Long-Short-Term-Memory Models(LSTMs) to label the pairing as agree, disagree, or discuss[9]. Therefore, second baseline model was a BOW MLP that utilized 300 Dimensional GloVe Embeddings to represent the headline and article in vector space[9].Softmax classification was implemented on the final hidden state of LSTM with concatenated inputs that produced least accurate results which lead to author resorting to better models after pre-processing the dataset that involved truncating the articles to reduce the timesteps.

To improve the accuracy of results the author moved on to a conditionally encoded LSTM model that involves two separate LSTMs, one for the headline and one for the article. The headline is fed through the first LSTM to extract the final hidden vector hn. This hidden state is used to initialize the LSTM of the article, thus ”conditioning” the article LSTM on the headline[9] and then adding different forms of attention to the LSTM. The paper constantly evaluates the accuracy of each model and based on the results implements models that yield highest accuracy while taking into account the constraints like reduction of timestamps etc[9]. As the culminating model in this series of LSTM-based architectures, the author implemented the Conditionally Encoded LSTM with Bidirectional Global Attention using Bidirectional RNNs (thus reading the text both forward and backward)[9].This was the best performing model among all the models which yielded highest accuracy and successfully dealt with stance detection for fake news.

Secondly, we researched the paper that identified deception in textual data by identifying verbal predictors of deception with text processing and machine learning techniques[10].The paper intensively focuses on what is fake news, explores and identifies the sources of fake news like citizen journalism as Citizen journalists are not obliged to follow the guidelines of source-checking and fact checking cultivated in professional journalism [11] which leads to creation and dissemination of unverified news and looking to develop solution for detection of deception in news.In this paper Rhetorical Structure Theory (RST) and Vector Space Modeling (VSM) are the two theoretical components used in the analysis of deceptive and truthful news[10]. RST is used to analyze news discourse and VSM is used to interpret discourse features into an abstract mathematical space [10].This model aims to identify rhetorical relationships between the more and the less emphasized texts in the articles functional relations among different meaningful text units, and describes a hierarchical structure for each story [12].While the VSM each news text is represented as vectors in a high dimensional space [13], [14]. Then, each dimension of the vector space is equal to the number of rhetorical relations in a set of all news reports under consideration[10].The vectors represented in space are put into 2 clusters that is truthful and deceptive The element of a cluster is a news story, and a cluster is a set of elements that share enough similarity to be grouped together, as deceptive news or truthful news [15].The paper utilized the datasets of the National public radio show “Bluff The Listener” which was in the radio announcement style.The researcher performs in depth analysis by describing the procedures involved in RST analysis like-Inter-coder reliability test methods and calculations with consequent data manipulations, Statistical Procedures for Predictive Modeling using R etc [10].This was followed by application of logistic regression model for testing the accuracy on the training and the test set to calculate the accuracy achieved.

While the RST-SVM clustering technique for the NPR’s “Bluff the Listener” news reports was only in part successful (63% accuracy), further steps need to be taken to find predictors of deception for a news verification system as predictive model is comparable to average human lie detection abilities (54% accuracy)[10].Thus the results were promising but inconclusive and better models and research will be needed to achieve higher accuracy in the future[10].

In another research paper researchers have actually tried out to find a link between the headline and its corresponding body by applying various neural network algorithms such as RNN (Recurrent neural networks) and some of them have even used LSTM to identify fake news [19]. This research paper firstly involved the pre-processing of the dataset that they had and then applying different models and seeing the expected outcomes. They analyzed their dataset using various models such as bag of words and LSTMs and attention algorithms and predicted the results. They have applied all the algorithms and every time any one of the algorithms prove to work better than the previous one. The attention models outperformed the simpler models on all performance metrics on the test set. In particular the models with neural attention were able to achieve significantly higher F1 scores predicting the infrequent stances Agrees and Disagrees.

Furthermore we scrutinized the research paper in which they have basically applied different forms of Recurrent Neural Networks and analyzed their results. Recurrent neural networks basically have loops in them, allowing information to persist. A recurrent neural network can be thought of as multiple copies of the same network, each passing a message to a successor. The main task focused upon on Stance detection is identifying good features to find out the relation between headline and body text. If we are given a pair of headline and body text, the goal is to identify whether the body text is related to the headline or not, and in which of the four categories the exact relationship between them lies. Four different labels were assigned to each headline-body pair: Unrelated, Discuss, Agree and Disagree [20]. In this research paper a score metric is also calculated for the task of stance detection. Since relationship identification plays a major role in detection of fake news, a correct prediction or if the headline and the body text are related carries a major portion of the score, while discrimination over related/unrelated is less weighted. More specifically, 25% weighted score is for correct prediction on relatedness, and another 75% weighted score is for correct prediction on relationship.

A direct bidirectional encoder was able to achieve more accurate prediction results for agree category, though there was a lot of leakage of misclassification in discuss category. By using Attentive Reader with full attention, the recall on agree category was improved significantly, though the precision was still not high enough. In all cases, they notice that disagree category was poorly predicted. Their result suggests that all neural network based methods outperformed the hand-crafted feature based approach. In addition, they tried to improve the existing Attentive Reader with a full attention mechanism between words in body text and headlines. Evaluation result shows that this algorithm gave the best performance over other explored methods.

To further improve the performance, one needs to first improve the precision on agree category, and further improve the accuracy on disagree category. One possible approach is the combination of hand-crafted features and hidden features learnt by RNN to find more accurate results in the disagree category as this category provided the least accurate results. Their results in all of these categories were considerably good except the disagree category which somehow had a negative impact as the main task to be addressed was to find unrelated headline and the body text.

With the advent of fake news being used to influence people, the identification of false information has become an important task. Governments, newspapers and social media platforms are working hard on distinguishing credible news from fake news. The goal of this paper is to automate the process of identifying fake news by using machine learning and natural language processing. This process can be broken down into several stages. A first helpful step towards the identification of fake news is to understand what other news sources are saying about the same topic and analyzing the results.

The main task focused in these research papers was to identify relationship between headline and the body-text. To address this problem, they have begun with stance detection, which is considered to be a first step towards identifying fake news. The goal of this project is to identify whether given headline-article pairs: (1) agree, (2) disagree, (3) discuss the same topic, or (4) are not related at all. The method they have applied feeds the headline-article pairs into a bidirectional LSTM which first analyzes the article and then uses the acquired article representation to analyze the given headline.

After performing all the training and testing on the datasets they evaluated their results by designing a table in which they discovered how the headlines and the sub-articles are related based on some parameters. They evaluated as whether they are headline and body text are agree, disagree, unrelated or discussable. To their surprise, results were quiet astonishing, processing the article first and conditioning the headline on the article encoding worked better than vice versa for their dataset. Just by switching the order in which the article and headline are processed, they were able to increase their performance and F1 score.

3. Analysis, Design and Modelling

3.1 Overall Description of the project

3.1.1. Datasets

This project utilizes the datasets from two source Kaggle Fake news data set ,Signal media 1 Million articles dataset along with dataset released under Fake news challenge in February 2017. Kaggle Fake News Dataset-The UCI Machine Learning Repository maintains 351 data sets as a service to the machine learning community[16].

In February, the Fake News Challenge 1 (FNC-1) was launched by a non-profit organization with the goal of developing tools to help fact checkers tag fake news[9]. The FNC-1 Dataset consists of 1648 distinct headlines, 1683 distinct articles, and 49972 distinct headline-article pairings. The headlines had various lengths ranging from 10 to 220 words, while articles had lengths ranging from 25 to 5000 words[9].

Signal Media One-Million News Articles Dataset- This dataset is released by Signal Media to facilitate conducting research on news articles. It can be used for submissions to the NewsIR'16 workshop, but it is intended to serve the community for research on news retrieval in general[17].The format of this dataset is as follows:

- id
- title
- content
- source
- published
- media-type

3.1.2. Methodology

3.1.2.1. Data Pre-Processing

We also preprocessed our dataset extensively using NLTK of Stanford for NLP in order to split sentences, normalize casing, handle punctuation and other non-alphabetic symbols, and otherwise improve token consistency. The complete training set consists of just under 50,000 "stance" tuples, 2 with each tuple consisting of [18]:

1. A headline that is to be compared against an article to determine its stance toward the article. Word counts for the headlines range from 2 to approximately 40, with an average length of ~11 [18].
2. The (integer) ID of an article against which the headline is to be compared, which can be used to find the text of the article body in a separate file. Article lengths range from 2 to nearly 5000 words, with an average length of around 360 words[18].

3.1.2.2 Modelling Approach

Our goal in approaching the stance detection problem was to experiment with a wide range of the deep learning and NLP techniques:

1. Building a Linear SVM classifier and calculation Cosine TF-IDF vectors, Jaccard distance for each of the headline-article pair thereby classifying the data into related and unrelated.
2. Calculating highest correlation value for this pair of headline and article.
3. Training the filtered dataset of related articles to the LSTM
4. Input is the headline to the CE LSTM and the final hidden layer vector obtained is used to initialize the LSTM of the article.
5. The final hidden state which is obtained is then passed on to the two layer multi-layer perceptron.

3.2 Functional Requirements

3.2.1.Neural Networks

3.2.1.1 Linear SVM

3.2.1.2. Bag Of Word(BOW) Multi Layer Perceptron

3.2.1.3. Conditionally Encoded LSTM

3.2.1.4. Bidirectional Conditional LSTM with Bidirectional Global Attention

3.2.2 Comparison of accuracy of different models

3.3 Non-Functional Requirements

3.3.1. Hardware Requirements

- **Microsoft Windows 7 Professional/ Windows 8.1/ Windows 10**

- **Processor:** 2.6 GHz Intel Core i3 or greater
- **Memory:** 512 MB
- **Disk space:** 750 MB of free disk space
- **Graphics Card:** NVIDIA GeForce GTX860 and GTX870

3.3.2. Performance Requirements

In order to train the models quicker and faster processing of epochs we need to install GPU version of Tensorflow as GPU version outperforms in terms of speed. The large timesteps sometimes lead to inability to test some models thus GPU version becomes a necessity though it has no effect on enhancing the accuracy.

3.4 Overall architecture with component description and dependency details

To have things working smoothly and efficiently our system should be having the following requirements satisfied along with the mentioned software installed in it:

CuDNN:
NVIDIA cuDNN is a GPU-accelerated library of primitives for deep neural networks (DNNs). It provides tuned implementations of routines that arise frequently in DNN applications, such as convultion, pooling, softmax, neuron activations[21].When a developer leverages CuDNN, they are guaranteed reliable high performance on current and future NVIDIA GPUs, and benefit from new GPU features and capabilities in the future[21].

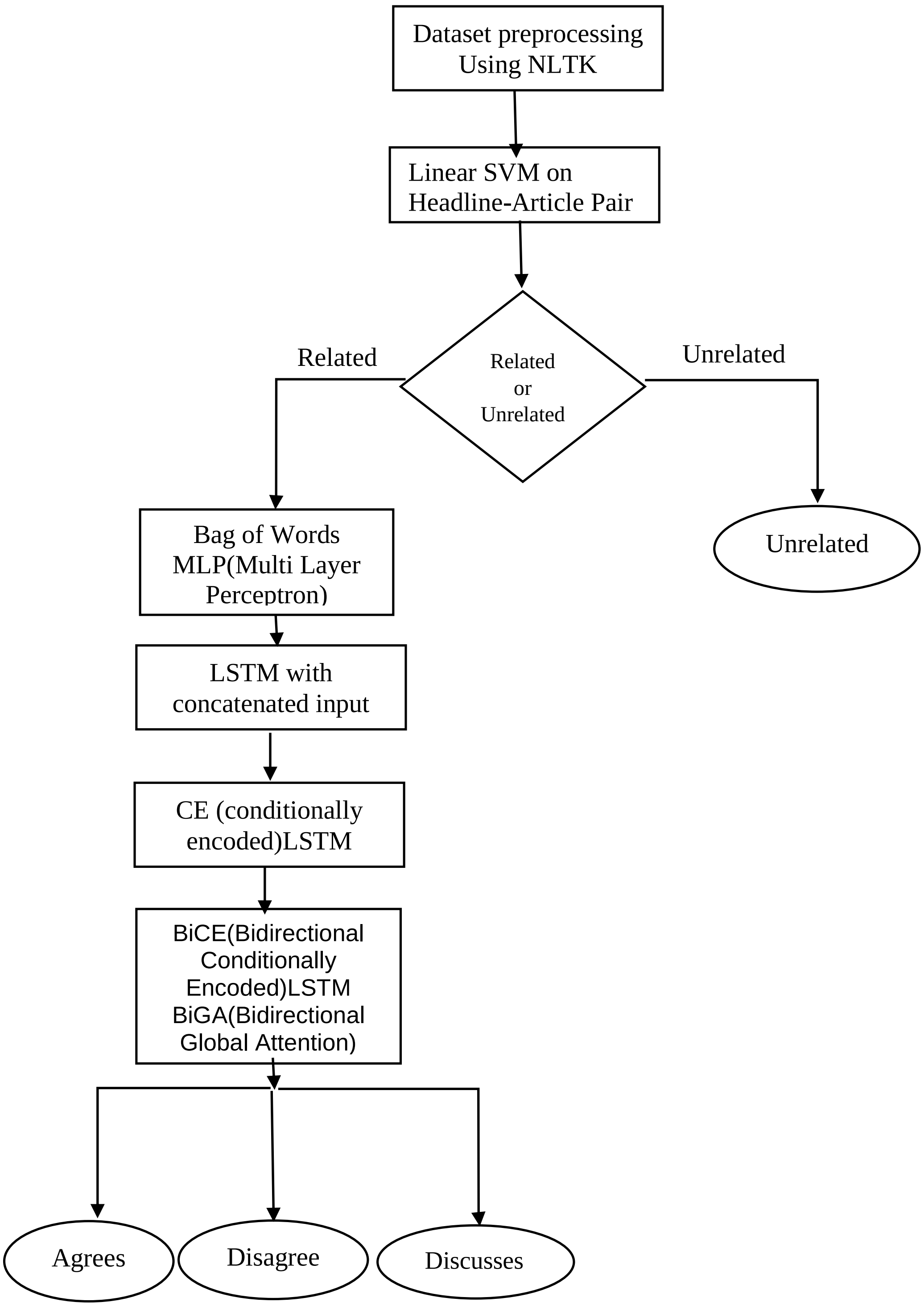
CUDA:

CUDA is a parallel computing platform and application programming interface (API) model created by Nvidia[22]. It allows software developers and software engineers to use a CUDA-enabled graphics processing unit (GPU) for general purpose[22].

TensorFlow:

TensorFlow is an open source software library used for the purpose of conducting machine learning and deep neural networks research and for numerical computation using data flow graphs[23]. Nodes in the graph represent mathematical operations, while the graph edges represent the multidimensional data arrays (tensors) communicated between them. The flexible architecture allows you to deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a single API [23].

3.5 Proposed Algorithm



3.6 Testing

3.6.1.Black Box Testing

Black-box testing is a method of software testing that examines the functionality of an application without peering into its internal structures or workings. This method of test can be applied virtually to every level of software testing: unit, integration, system and acceptance[24].We will split the dataset into 80-20 and examine the results of the test set obtained after training the model on the test set.

3.6.2.White Box Testing

White-box testing (or structural testing) is a method of testing software that tests internal structures or workings of an application[25].Analyzing the run time of the timesteps and identifying the models that require over 1000 timesteps.

3.7.Implemetation

This model currently achieves an accuracy of 51%. It is trained on 8000 headlines and articles pair.It takes as input a 2-column CSV file, where the first column corresponds to the headlines and second one corresponds to the article texts. The output file contains a third column with the label - 1 if the input is categorized as related, 0 if not.

The classifier is a non-linear SVM, and it uses the following features:

1. POS tags (unigrams and bigrams)
2. Punctuation counts
3. Average sentence length
4. Number of words that overlap

This model is used to contains the train a model and to classify new data, the data used for training, and a sample of test data (a held-out set) with different labels.

4. Appendices

4.1 Project Plan

Work Breakdown Structure is as follows:

1. Automatic Identification of Fake News using Neural Networks
  - 1.1 Initiation
    - 1.1.1 Project Title and Discussion
    - 1.1.2 Project Charter development
    - 1.1.3 Project Charter Discussed with mentor
  - 1.2 Planning
    - 1.2.1 Preliminary Scope of project
    - 1.2.2 Project Team Kick-off Meeting
    - 1.2.3 Project Milestones: Approved within the group and mentor
  - 1.3 Execution
    - 1.3.1 Design Discussed
    - 1.3.2 Background Study
    - 1.3.3 Algorithms Identified
    - 1.3.4 Algorithms Study
    - 1.3.5 Research on algorithms
    - 1.3.6 Installation of required software
    - 1.3.7 Physical execution on Tools
    - 1.3.8 LSTM Architecture Study
    - 1.3.9 Testing Phase
    - 1.3.10 Final Submission
  - 1.4 Control
    - 1.4.1 Project Management
    - 1.4.2 Risk Management
    - 1.4.3 Update Project Plan(if required)
  - 1.5 Project Closure

1.5.1 Update files/records
1.5.2 Gain Formal Acceptance

4.2 Details of Practice with New Technology

4.2.1.Referred YouTube videos and official documentation for installing the software.

4.2.2 Introduction to Machine Learning by Andrew Ng-
http://www.andrewng.org/courses/

4.2.3. Convolutional Neural Networks- http://cs231n.stanford.edu/

4.3 References

[1] http://guides.library.usciences.edu/CurrentIssues/FakeNews

[2] *RNNs for Stance Detection between News Articles*
- https://web.stanford.edu/class/cs224n/reports/2757443.pdf

[3] http://www.bbc.com/news/blogs-trending-37846860
[4] http://www.insightsonindia.com/2016/11/21/6-issue-fake-news

[5] *Stance Detection for Fake News Identification*
https://web.stanford.edu/class/cs224n/reports/2760496.pdF

[6] http://colah.github.io/posts/2015-08-Understanding-LSTMs/
[7] https://talbaumel.github.io/attention/
[8]- J.T. Hancock, "Digital deception: When, where & how people lie online," *The Oxford handbook of Internet psychology*, A. N. Joinson, et al., eds., Oxford University Press, 2012, pp. 508.

[9]- *Towards Automatic Identification of Fake News:Headline-Article Stance Detection with LSTM Attention Models-https*://web.stanford.edu/class/cs224n/reports/2761028.pdf

[10]- *Towards News Verification: Deception Detection Methods for News Discourse* **Victoria L. Rubin, NiallJ. Conroy, and Yimin Chen-**
http://onlinelibrary.wiley.com/doi/10.1002/pra2.2015.145052010082/pdf

[11] D. Gillmore, "We the media: The rise of citizen journalists," *National Civic Review*, vol. 93, no. 3, 2004, pp. 58-63.

[12] W.C. Mann & S.A. Thompson, "Rhetorical Structure Theory: Toward a Functional Theory of Text Organization,"*Text*, vol. 8, no. 3, 1988, pp. 243-281.

[13] C.D. Manning & H. Schutze, *Foundations of Statistical Natural Language Processing*, The MIT Press, 1999.

[14] G. Salton & M.J. McGill, *Introduction to Modern Information Retrieval*, McGraw-Hill, 1983.

[15] P. Berkhin, "Survey of clustering data mining techniques.," 2002; DOI: 10.1.1.18.3739.

[16]-UCI Machine Learning | Kaggle -https://www.kaggle.com/uciml |https://www.kaggle.com/mrisdal/fake-news/data

[17]- http://research.signalmedia.co/newsir16/signal-dataset.html

[18]- *Stance Detection for the Fake News Challenge:Identifying Textual Relationships with Deep Neural Nets-https*://web.stanford.edu/class/cs224n/reports/2760230.pdf

[19]- *Stance Detection for the Fake News Challenge with Attention and Conditional Encoding-https*://web.stanford.edu/class/cs224n/reports/2748568.pdf

[20]-*Neural Stance Detectors for Fake News Challenge*-https://web.stanford.edu/class/cs224n/reports/2761936.pdf

[21] https://developer.nvidia.com/cudnn

[22] https://developer.nvidia.com/about-cuda

[23] https://www.tensorflow.org/about

[24] https://en.wikipedia.org/wiki/Black-box_testing

[25] https://en.wikipedia.org/wiki/White-box_testing