VISVESVARAYA TECHNOLOGICAL UNIVERSITY

JNANA SANGAMA, BELAGAVI-590018, KARNATAKA

A Project Report
on

Detection of fake news articles in social network

Submitted in partial fulfillment of the requirements for the VIII Semester of degree of ***Bachelor of Engineering in Information Science and Engineering*** *of Visvesvaraya Technological University, Belagavi*

by

Adarsha NP	**1RN16IS003**	**Ajay L Gowda**	**1RN16IS010**
Aishwarya Arvind	**1RN16IS007**	**Harshith Kumar VS**	**1RN16IS036**

Under the Guidance of

Mrs.Vanishri V S
Assistant Professor
Department of ISE

Department of Information Science and Engineering

RNS Institute of Technology

Dr. Vishnuvaradhan Road, Rajarajeshwari Nagar post,
Channasandra, Bengaluru-560098

2019-2020

RNS INSTITUTE OF TECHNOLOGY

Dr. Vishnuvaradhan Road, Rajarajeshwari Nagar post,
Channasandra,Bengaluru - 560098

DEPARTMENT OF INFORMATION SCIENCE AND ENGINEERING

CERTIFICATE

Certified that the project work entitled ***Detection of fake news articles in social network*** has been successfully completed by **Adarsha NP (1RN16IS003), Aishwarya Arvind (1RN16IS007), Ajay L Gowda (1RN16IS010) and Harshaith Kumar VS (1RN16IS036),** bonafide students of **RNS Institute of Technology, Bengaluru** in partial fulfillment of the requirements for the award of degree in **Bachelor of Engineering in Information Science and Engineering** of **Visvesvaraya Technological University, Belagavi** during academic year **2019-2020**. The project report has been approved as it satisfies the academic requirements in respect of project work for the said degree.

Mrs Vanishri V S	**Dr. M V Sudhamani**	**Dr. M K Venkatesha**
Assistant Professor	Department of ISE	Principal
Department of ISE	RNSIT	RNSIT

External Viva

Name of the Examiners	**Signature with Date**
1. ______________________	1.____________________
2.______________________	2.____________________

DECLARATION

We, **Adarsha NP [USN: 1RN16IS003], Aishwarya Arvind [USN: 1RN16IS007]**, **Ajay L Gowda [USN: 1RN16IS010] and Harshith Kumar VS [USN: 1RN16IS036]** students of VIII Semester BE, in Information Science and Engineering, RNS Institute of Technology hereby declare that the Project entitled ***Detection of fake news articles in social networkg*** has been carried out by us and submitted in partial fulfillment of the requirements for the *VIII Semester of degree of* ***Bachelor of Engineering in Information Science and Engineering*** *of Visvesvaraya Technological University, Belagavi* during academic year 2019-2020.

Place: Bengaluru

Date:

Adardha NP	**(1RN16IS003)**
Aishwarya Arvind	**(1RN16IS007)**
Ajay L Gowda	**(1RN16IS010)**
Harshith Kumar VS	**(1RN16IS036)**

ACKNOWLEDGEMENT

At the very onset we would like to place our gratefulness to all those people who helped us in making this project a successful one.

Coming up, this project to be a success was not easy. Apart from the shear effort, the enlightenment of our very experienced teachers also plays a paramount role because it is they who guide us in the right direction.

First of all, we would like to thank **Management of RNS Institute of Technology** for providing such a healthy environment for the successful completion of project work.

In this regard, we express our sincere gratitude to the Director **Dr. H N Shivashankar** and the principal **Dr. M K Venkatesha,** for providing us all the facilities in this college.

We are extremely grateful to our own and beloved Professor and Head of Department of Information science and Engineering, **Dr. M V Sudhamani**, for having accepted to patronize us in the right direction with all her wisdom.

We place our heartfelt thanks to **Mrs. Vanishri V S,** Assistant Professor, Department of information science and Engineering for having guided for project and all the staff members of our department for helping us out at all times.

We thank **Mrs. Kusuma S** and **Mr. R Rajkumar ,** Project coordinators, teaching and technical staff of Department of Information Science and Engineering. We thank our beloved friends for having supported us with all their strength and might. Last but not the least, we thank our parents for supporting and encouraging us throughout. We made an honest effort in this assignment.

Adarsha NP

Aishwarya Arvind

Ajay L Gowda

Harshith Kumar VS

ABSTRACT

The rapid growth of fake news, especially in social media has become a challenging problem that has negative social impacts on a global scale. In contrast to fake news which intends to deceive and manipulate the reader, satirical stories are designed to entertain the reader by ridiculing or criticizing a social figure. Due to its serious threats of misleading information, researchers, governments, journalists and fact- checking volunteers are working together to address the fake news issue and increase the accountability of digital media. The automatic fake news detection systems enable identification of deceptive news. Low accuracy remains the main drawback of these systems.

The automatic detection of fake news using only news content is a technically challenging task as the language used in these articles is made to bypass the fake news detectors. This becomes even more complicated when the task is to differentiate the satirical stories from fake news. The project work implements a Machine Learning model that is made to help the fact checkers and not to replace them. It reduces the time to check articles by giving insights to the fact checker as to what level of scrutiny it should use for the particular article. The entire project can be categorized under two words 'stance detection' and 'SGD Classifier'. The stance detection model is an end-to-end model with lexical and feature extractors that feed the multilayer preceptor. SGD Classifier is an iterative method for optimizing a differentiable objective function and a stochastic approximation of gradient descent optimization.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

NLP	Natural Language Processing
SVM	Support Vector Machine
SGD	Stochastic Gradient Descent
DFD	Data Flow Diagram
AUC	Area Under Curve
ROC	Receiver Operating Characteristic
FRS	Functional Requirement Specification
SRS	System Requirement Specification

Chapter 1

INTRODUCTION

These days fake news is creating different issues from sarcastic articles to a fabricated news and plan government propaganda in some outlets. Fake news and lack of trust in the media are growing problems with huge ramifications in our society. Obviously, a purposely misleading story is “fake news” but lately blathering social media’s discourse is changing its definition. Some of the now use the term to dismiss the facts counter to their preferred viewpoints.

Machine Learning

Machine learning is the science of getting computers to act without being explicitly programmed. In the past decade, machine learning has given us self-driving cars, practical speech recognition, effective web search, and a vastly improved understanding of the human genome. Machine learning is so pervasive today that you probably use it dozens of times a day without knowing it. Many researchers also think it is the best way to make progress towards human-level AI.

Natural Language Processing (NLP)

Natural language processing (NLP) is a collective term referring to automatic computational processing of human languages. This includes both algorithms that take human-produced text as input, and algorithms that produce natural looking text as outputs.

Background

Fake news detection topic has gained a great deal of interest from researchers around the world. When some event has occurred, many people discuss it on the web through the social networking. They search or retrieve and discuss the news events as the routine of daily life. Some types of news such as various bad events from natural phenomenal or climate are unpredictable. When the unexpected events happen there are also fake news that are broadcasted that creates confusion due to the nature of the events. Very few people know the real fact of the event while the most people believe the forwarded news from their credible friends or relatives. These are difficult to detect whether to believe or not when they receive the news information. So, there is a need of an automated system to analyze truthfulness of the news

For example during the 2016 US president election, various kinds of fake news about the candidates widely spread in the online social networks, which may have a significant effect on the election results. According to a post-election statistical report, online social networks account for more than 41.8% of the fake news data traffic in the election, which is much greater than the data traffic shares of both traditional TV/radio/print medium and online search engines respectively. An important goal in improving the trustworthiness of information in online social networks is to identify the fake news timely.

By fake it refer to intentional media manipulation by changing its content and context to bring changes that influence opinions, facts and representations of real world events.

Fake can be achieved with a multitude of different manipulation techniques:

- Adding details into media by inserting regions or object from the same image or from another images and adapting them to fit into the entire media environment.
- Deletion of media details, by removing scene elements (regions) and replacing them by others.
- Incorrect classification, ordering and placement in presentations of media collections.
- Generating montages by combining separate images, also called composition and splicing in literature.

Facebook has been at the epicenter of much critique following media attention. They have already implemented a feature for users to flag fake news on the site ; however, it is clear from their public announcements that they are actively researching their ability to distinguish these articles in an automated way. And it is not an easy task. A given algorithm must be politically unbiased - since fake news exists on both ends of the spectrum - and also give equal balance to legitimate news sources on either end of the spectrum. In addition, the question of legitimacy is a difficult one. Need to determine what makes a new site 'legitimate' and a method to determine this in an objective manner.

The biggest benefit of this model would be reliability. With the help of this model people can accept the news they receive online with no doubts . And not just direct deception but also opinion biases and false critics would be easily identified, hence people would be clear of those as well.

The downside would be misuse of the model that is if the model could be used to promote sponsored content if the wrong hands gain control over it. It can be used to promote fake rumors, sponsored content or basically any other source of information on the internet. With the increasing use of the internet and online news and information the need for distinguishing reliable sources from the unreliable ones is expected to increase drastically and being confident in the news receive will certainly be a requirement in the future.

Problem Statement

The project aims at building a model that can detect fake news in all its forms on its own after. It has been trained with the appropriate dataset.
The aim is to achieve this using:

- Machine learning.
- Natural language processing.
- Context Matching.

In the first phase the features that will be used for classification are selected using NLP techniques such as,

- **Count Vectorizer**

  Count Vectorizer is used during the feature extraction phase. It is a simplifying representation used in natural language processing and information retrieval. In this model, a text (such as a sentence or a document) is represented as the bag (multiset) of its words, disregarding grammar and even word order but keeping multiplicity. The count vectorizer model has also been used for computer vision.

- **TF-IDF**

  Term frequency–inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is used in feature selection from the news article which will be used by the classifier algorithms in the next phase.

The extracted features are fed into optimized algorithms such as,

- **Support Vector Machines**

  In machine learning, support-vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible.

- **Stochastic Gradient Descent**

  Stochastic gradient descent , also known as incremental gradient descent, is an iterative method for optimizing a differentiable objective function. It is called stochastic because samples are selected randomly instead of as a single group or in the order they appear in the training set.

- **Random Forest**

  Random forests random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

The context of the article's is also taken into consideration with context matching,

- **Context Matching**

  In context matching the essence of what the article means to convey is extracted and then it is compared with the heading of the article to determine how much they match. This contributes to the final truthfulness score of the article.

Motivation

Over the last decade the Internet has spread to a almost all the corners of the world and the population has been increasingly relying on the Internet to keep up with the news. The large use of social media has tremendous impact on our society, culture, business with potentially positive and negative effects. Now-a-days, due to the increase in use of online social networks, the fake news for various commercial and political purposes has been emerging in large numbers and widely spread in the online world. Social media and the internet is suffering from fake accounts, fake posts, and fake news. The intention is often to mislead readers and or manipulate them into purchasing or believing something that isn't real.

Fake news detection topic has gained a great deal of interest from researchers around the world. When some event has occurred, many people discuss it on the web through the social networking. They search or retrieve and discuss the news events as the routine of daily life. Some types of news such as various bad events from natural phenomenal or climate are unpredictable. When the unexpected events happen there are also fake news that are broadcasted that creates confusion due to the nature of the events. Very few people know the real fact of the event while the most people believe the forwarded news from their credible friends or relatives.

Objectives

The main objective is to detect the fake news, which is a classic text classification problem with a straight forward proposition the model should be able to differentiate between “Real” and “Fake” news.

The functionalities to be implemented it this system to achieve the given objective are:

- **Text Extraction -** Extracting the body of an article with just the URL.
- **Feature Selection -** Selecting the most effective features from the data.
- **Model Selection -** By comparing the performance of various ML algorithms.
- **Classification -** Using the trained model to classify the news into Fake and Real.
- **Click Bait -** Identification of articles with misleading headlines.

Existing System

There exists a large body of research on the topic of machine learning methods for deception detection, most of it has been focusing on classifying online reviews and publicly available social media posts. Particularly since late 2016 during the American Presidential election, the question of determining 'fake news' has also been the subject of particular attention within the literature.

Conroy, Rubin, and Chen outlines several approaches that seem promising towards the aim of perfectly classify the misleading articles. They note that simple content-related n-grams and shallow parts-of-speech (POS) tagging have proven insufficient for the classification task, often failing to account for important context information. Deep Syntax analysis using Probabilistic Context Free Grammars (PCFG) have been shown to be particularly valuable in combination with n-gram methods.

Feng, Banerjee, and Choi are able to achieve 85%-91% accuracy in deception related classification tasks using online review corpora. Feng and Hirst implemented a semantic analysis looking at 'object:descriptor' pairs for contradictions with the text on top of Feng's initial deep syntax model for additional improvement.

Table 1.1 : News Sources Classification

Top Five unreliable news sources	count	Top five reliable news source	count
Before it's news	2066	Reuters	3898
Zero Hedge	149	BBC	830
Raw story	90	USA Today	824
Washington Examiner	79	Washington post	820

Shloka Gilda presented concept approximately how NLP is relevant to stumble on fake information. They have used time period frequency-inverse record frequency (TF-IDF) of bi- grams and probabilistic context free grammar (PCFG) detection. They have examined their dataset over more than one class algorithms to find out the great model. They locate that TF-IDF of bi-grams fed right into a Stochastic Gradient Descent model identifies non-credible resources with an accuracy of 77.2%.

Proposed System

For this project, try to create model that can classify news articles into fake and real with maximum accuracy. The main aim is to achieve this using Artificial Intelligence(AI) and Natural Language Processing(NLP).

The proposed system will have two major modules

- Classifier
- Predictor

➢ **Classifier**

The classifier will be used the initial phase to train the model on the required dataset. The classifier uses features selected from a dataset using NLP techniques such as TF-IDF to train five different models as different datasets may be better suited to specific algorithms. The algorithms used are Naïve Bayes, Logistic regression, Random Forest, Stochastic Gradient Descent and Linear Support Vector Machines (SVM).

- **Naive Bayes Classification**

  Naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes theorem with strong (naive) independence assumptions between the features. The featured image is the equation—with P(A|B) is posterior probability, P(B|A) is likelihood, P(A) is class prior probability, and P(B) is predictor prior probability. Once the models are trained the model with the best performance is chosen as the final model that will be used as the predictor.

- **Logistic Regression**

  Logistic regression is a powerful statistical way of modeling a binomial outcome with one or more explanatory variables. It measures the relationship between the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic function, which is the cumulative logistic distribution.

- **Support Vector Machines**

  SVM is binary classification algorithm. Given a set of points of 2 types in N dimensional place, SVM generates a (N—1) dimensional hyper plane to separate those points into 2 groups. Say you have some points of 2 types in a paper which are linearly separable. SVM will find a straight line which separates those points into 2 types and situated as far as possible from all those . In terms of scale, some of the biggest problems that have been solved using SVMs (with suitably modified implementations) are display advertising, human splice site recognition, image-based gender detection, large-scale image classification.

- **Stochastic Gradient Descent**

  Stochastic gradient descent (SGD), also known as incremental gradient descent, is an iterative method for optimizing a differentiable objective function, a stochastic approximation of gradient descent optimization. It is called stochastic because samples are selected randomly instead of as a single group (as in standard gradient descent) or in the order they appear in the training set.

➢ **Predictor**

The predictor module contains the trained module from the previous stage ready to be used for news prediction. It takes as input the body and headline of the article as input and uses the trained module for assigning it a probability of truthfulness. Based on the probability the news can be deemed either real or deceptive.

The probability will also take into account the publisher rating which a score given to the author well is known sources such as Fox news and CNBC will be given high ratings and sources known for fake news such as the ONION will be given zero rating. Based on the final probability the news can be deemed either real or deceptive.

Chapter 2

LITERATURE REVIEW

A **Literature Survey** or **Narrative Survey** is a type of survey article. A literature survey is a scholarly paper, which includes the current knowledge including substantive findings, as well as theoretical and methodological contributions to a particular topic.

In Paper [1], the author explores the application of natural language processing techniques for the detection of 'fake news', that is, misleading news stories that come from non-reputable sources. Using a dataset obtained from Signal Media and a list of sources from OpenSources.co, author applied term frequency-inverse document frequency (TF-IDF) of bi-grams and probabilistic context free grammar (PCFG) detection to a corpus of about 11,000 articles. The dataset is tested on multiple classification algorithms - Support Vector Machines, Stochastic Gradient Descent, Gradient Boosting, Bounded Decision Trees, and Random Forests and find that TF-IDF of bi-grams fed into a Stochastic Gradient Descent model identifies non- credible sources with an accuracy of 77.2%, with PCFGs having slight effects on recall.

As per the discussion in paper [2], the author shows a simple approach for fake news detection using naive baye's classifier. This approach was implemented as a software system and tested against a data set of Facebook news posts. This model achieved classification accuracy of approximately 74% on the test set which is a decent result considering the relative simplicity of the model. This results may be improved in several ways, that are described in the article as well. Received results suggest, that fake news detection problem can be addressed with artificial intelligence methods.

According to the author in paper [3], Fake News has been around for decades and with the advent of social media and modern day journalism at its peak, detection of media-rich fake news has been a popular topic in the research community. Given the challenges associated with detecting fake news research problem, researchers around the globe are trying to understand the basic characteristics of the problem statement. This model aims to solve through text classification approach.

In Paper [4], Social media for news consumption is a double-edged sword. On the one hand, its low cost, easy access, and rapid dissemination of information lead people to seek out and consume news from social media. On the other hand, it enables the wide spread of fake news" i.e., low quality news with intentionally false information. The extensive spread of fake news has the potential for extremely negative impacts on individuals and society. Therefore, fake news detection on social media has recently become an emerging research that is attracting tremendous attention. Fake news detection on social media presents unique characteristics and challenges that make existing detection algorithms from traditional news media ineffective or not applicable.

First, fake news is intentionally written to mislead readers to believe false information, which makes it difficult and nontrivial to detect based on news content; therefore, there is need to include auxiliary information, such as user social engagements on social media, to help make a determination. Second, exploiting this auxiliary information is challenging in and of itself as users' social engagements with fake news produce data that is big, incomplete, unstructured, and noisy. Because the issue of fake news detection on social media is both challenging and relevant, author conducted this survey to further facilitate research on the problem. In this survey, social theories, existing algorithms from a data mining perspective, evaluation metrics and representative datasets. The author also discuss related research areas, open problems, and future research directions for fake news detection on social media.

The author in paper [5], discuss about the rapid growth of fake news, especially in social media has become a challenging problem that has negative social impacts on a global scale. In contrast to fake news which intend to deceive and manipulate the reader, satirical stories are designed to entertain the reader by ridiculing or criticizing a social figure due to its serious threats of misleading information, researchers, governments, journalists and fact-checking volunteers are working together to address the fake news issue and increase the accountability of digital media. The automatic fake news detection systems enable identification of deceptive news. Low accuracy remains the main drawback of these systems. The automatic detection using only news’ content is a technically challenging task as the language used in these articles is made to bypass the fake news detectors.

This becomes even more complicated when the task is to differentiate the satirical stories from fake news. On the other side, human cognitive skills have shown to over perform machine-based systems when it comes to such tasks. In this paper author address the fake news and satire detection by proposing a method that uses a hybrid machine-crowd approach for detection of potentially deceptive news. This system combines the human factor with the machine learning approach and a decision-making model that estimates the classification confidence of algorithms and decides whether the task needs human input or not. Proposed approach achieves reasonably higher accuracy compared to the reported baseline results, in exchange of cost and latency of using the crowd sourcing service.

As per the discussion in paper [6], Research surveys the current state-of-the-art technologies that are instrumental in the adoption and development of fake news detection. “Fake news detection” is defined as the task of categorizing news along a continuum of veracity, with an associated measure of certainty. Veracity is compromised by the occurrence of intentional deceptions. The nature of online news publication has changed, such that traditional fact checking and vetting from potential deception is impossible against the flood arising from content generators, as well as various formats and genres.

The paper provides a typology of several varieties of veracity assessment methods emerging from two major categories – linguistic cue approaches (with machine learning), and network analysis approaches. The author sees promise in an innovative hybrid approach that combines linguistic cue and machine learning, with network-based behavioral data. Although designing a fake news detector is not a straightforward problem, proposed operational guidelines for a feasible fake news detecting system.

According to the author in paper [7], Consuming news from social media is becoming increasingly popular nowadays. Social media brings benefits to users due to the inherent nature of fast dissemination, cheap cost, and easy access. However, the quality of news is considered lower than traditional news outlets, resulting in large amounts of fake news. Detecting fake news becomes very important and is attracting increasing attention due to the detrimental effects on individuals and the society. Thus it necessitates an in-depth understanding of the correlation between user profiles on social media and fake news.

In this paper, author construct real-world datasets measuring users trust level on fake news and select representative groups of both “experienced” users who are able to recognize fake news items as false and “naive” users who are more likely to believe fake news. The author performs a comparative analysis over explicit and implicit profile features between these user groups, which reveal their potential to differentiate fake news. The findings of this paper lay the foundation for future automatic fake news detection research.

The author in paper [8], discuss about the Online social networking sites which are experimenting with the following crowd-powered procedure to reduce the spread of fake news and misinformation: whenever a user is exposed to a story through her feed, she can flag the story as misinformation and, if the story receives enough flags, it is sent to a trusted third party for fact checking. If this party identifies the story as misinformation, it is marked as disputed. However, given the uncertain number of exposures, the high cost of fact checking, and the trade-off between flags and exposures, the above mentioned procedure requires careful reasoning and smart algorithms which, to the best of knowledge, do not exist to date.

In this paper, author first introduces a flexible representation of the above procedure using the framework of marked temporal point processes. Then, author develop a scalable online algorithm, Curb, to select which stories to send for fact checking and when to do so to efficiently reduce the spread of misinformation with provable guarantees. In doing so, their is need to solve a novel stochastic optimal control problem for stochastic differential equations with jumps, which is of independent interest. Experiments on two real-world datasets gathered from Twitter and Weibo show that the algorithm may be able to effectively reduce the spread of fake news and misinformation.

According to the author in paper [9], Different language markers can be used to reveal the differences between structures of truthful and deceptive (fake) news. Two experiments are held: the first one is based on lexics level markers, the second one onand deceptive news stories in Russian. Support Vector Machines and Random Fores Classifier were used for text classification. The best results for lexical markers got by using Support Vector Machines with rbf kernel (f-measure 0.65). The model could be developed and be used as a preliminary filter for fake news detection.

As per the discussion in Paper [10], Fake News has been around for decades and with the advent of social media and modern day journalism at its peak, detection of media-rich fake news has been a popular topic in the research community. Given the challenges associated with detecting fake news research problem, researchers around the globe are trying to understand the basic characteristics of the problem statement.

This paper aims to present an insight on characterization of news story in the modern diaspora combined with the differential content types of news story and its impact on readers.

Subsequently, dive into existing fake news detection approaches that are heavily based on text-based analysis, and also describe popular fake news data-sets. The author conclude the paper by identifying 4 key open research challenges that can guide future research.

The author in paper[11], Different language markers can be used to reveal the differences between structures of truthful and deceptive (fake) news. Two experiments are held: the first one is based on lexics level markers, the second one on discourse level is based on rhetorical relations categories (frequencies). Corpus consists of 174 truthful and deceptive news stories in Russian. Support Vector Machines and Random Forest Classifier were used for text classification. The best results for lexical markers is got by using Support Vector Machines with rbf kernel (f-measure 0.65). The model could be developed and be used as a preliminary filter for fake news detection.

News verification and automated fact checking tend to be very important issues in this world, with its information warfare. The research is initial. This collected a corpus for Russian (174 news reports, truthful and fake). The two experiments are held, for both applied SVMs algorithm (linear/rbf kernel) and Random Forest to classify the news reports into 2 classes: truthful/deceptive. The 18 markers are used on lexics level, mostly frequencies of POS tags in texts. On discourse level , used frequencies of RST relations in texts. The classification task in the first experiment is solved better by SVMs (rbf kernel) (f-measure 0.65). The model based on RST features shows best results with Random Forest Classifier (f-measure 0.54) and should be modified. In the next research, the combination of different deception detection markers for Russian should be taken in order to make a better predictive model.

In paper [12], author's work considers leveraging crowd signals for detecting fake news and is motivated by tools recently introduced by Facebook that enable users to flag fake news. By aggregating users' flags, goal is to select a small subset of news every day, send them to an expert (e.g., via a third-party fact-checking organization), and stop the spread of news identified as fake by an expert. The main objective of the work is to minimize the spread of misinformation by stopping the propagation of fake news in the network. It is especially challenging to achieve this objective as it requires detecting fake news with high-confidence as quickly as possible. This shows that in order to leverage users' flags efficiently, it is crucial to learn about users' flagging accuracy.

The novel algorithm is developed, Detective that performs Bayesian inference for detecting fake news and jointly learns about users' flagging accuracy over time. This algorithm employs posterior sampling to actively trade off exploitation (selecting news that maximize the objective value at a given epoch) and exploration (selecting news that maximize the value of information towards learning about users' flagging accuracy). Demonstrate the effectiveness of this approach via extensive experiments and show the power of leveraging community signals for fake news detection.

In this paper the important problem is considered of leveraging crowd signals for detecting fake news. The approach is demonstrated that is not learning about users' flagging behaviour is prone to failure in the presence of adversarial/spam users (who want to "promote" fake news). The algorithm Detective is proposed that performs Bayesian inference for detecting fake newsand jointly learns about users over time. This experiments demonstrate that Detective is competitive with the fictitious algorithm Opt, which knows the true users' flagging behaviour. Importantly, Detective (thanks to learning about users) is robust in leveraging flags even if a majority of the users is adversarial. There are some natural extensions for future work. For instance, it would be useful to extend the approach to model and infer the trustworthiness of sources. It would also be important to conduct user studies by deploying algorithm in a real-world social system.

According to the author in paper [13], construction of real-world datasets measuring users trust level on fake news and select representative groups of both "experienced" users who are able to recognize fake news items as false and "naive" users who are more likely to believe fake news. Performance of a comparative analysis over explicit and implicit profile features between these user groups, which reveals their potential to differentiate fake news.

Fake news has significant detrimental effects on individuals and the society. First, fake news intentionally misleads people to believe false information. Second, fake news change the way people respond to real news. For example, people are confused about the news they read, which impedes their abilities to differentiating the truth from falsehood. Third, the trustworthiness of entire news ecosystem is broken due to fake news.

Thus, it's critical to detect fake news on social media to mitigate these negative effects and to benefit the public and the news ecosystem. Due to the potential of using user engagements on social media to help fake news detection, the investigation of correlation between user profiles and fake/real news. Experimental results on real-world datasets demonstrate that: i) there are specific users who are more likely to trust fake news than real news; and ii) these users reveal different features from those who are more likely to trust real news. These observations ease the feature construction of profiles features for fake news detection.

As per the discussion in paper [14], the author aims to present an insight on characterization of news story in the modern diaspora combined with the differential content types of news story and its impact on readers. Subsequently, dive into existing fake news detection approaches that are heavily based on text-based analysis, and also describe popular fake news data-sets. Conclude the paper by identifying 4 key open research challenges that can guide future research.

To leverage the power of crowd sourcing, design and implement a Crowd sourcing Data Analytics System, CDAS. CDAS is a framework designed to support the deployment of various crowd sourcing applications. The core part of CDAS is a quality-sensitive answering model, which guides the crowd sourcing engine to process and monitor the human tasks. This paper introduce the principles of quality-sensitive model. To satisfy user required accuracy, the model guides the crowd sourcing query engine for the design and processing of the corresponding crowd sourcing jobs. It provides an estimated accuracy for each generated result based on the human workers' historical performances.

When verifying the quality of the result, the model employs an online strategy to reduce waiting time. To show the effectiveness of the model, implement and deploy two analytics jobs on CDAS, a twitter sentiment analytics job and an image tagging job. Use real Twitter and Flickr data as queries respectively and compare approaches with state-of-the-art classification and image annotation techniques. The results show that the human-assisted methods can indeed achieve a much higher accuracy. By embedding the quality sensitive model into crowd sourcing query engine, effectively reduce the processing cost while maintaining the required query answer quality.

In Paper [15], introduced the quality-sensitive answering model in Crowd sourcing Data Analytics System, CDAS. The model guides the query engine to generate proper query plans based on the accuracy requirement. It consists of two sub-models, the prediction model and the verification model. The prediction model estimates the number of workers required for a specific task while the verification model selects the best answer from all returned ones. To improve users' experience, when verifying the results, model embraces online processing techniques to update answers gradually. By adopting the models, CDAS can provide high-quality results for different crowd sourcing jobs. In this paper, author implemented a twitter sentiment analytics job and an image tagging job on CDAS and used real Twitter data and Flickr data as queries. Amazon Mechanical Turk was employed as crowd sourcing platform. The results show that the proposed model can provide high-quality answers while keeping the total cost low.

This paper present LIAR: a new, publicly available dataset for fake news detection. Collecte a decade-long, 12.8K manually labeled short statements in various contexts from POLITIFACT.COM, which provides detailed analysis report and links to source documents for each case. This dataset can be used for fact-checking research as well. Notably, this new dataset is an order of magnitude larger than previously largest public fake news datasets of similar type. Empirically, investigate automatic fake news detection based on surface-level linguistic patterns. The designed novel, hybrid convolutional neural network to integrate metadata with text. This show that hybrid approach can improve a text-only deep learning model

LIAR is introduced, a new dataset for automatic fake news detection. Compared to prior datasets, LIAR is an order of a magnitude larger, which enables the development of statistical and computational approaches to fake news detection. LIAR's authentic, real-world short statements from various contexts with diverse speakers also make the research on developing broad-coverage fake news detector possible. This shows that when combining meta-data with text, significant improvements can be achieved for fine-grained fake news detection. Given the detailed analysis report and links to source documents in this dataset, it is also possible to explore the task of automatic fact-checking over knowledge base in the future. The corpus can also be used for stance classification, argument mining, topic modeling, rumor detection, and political NLP research.

According to the author in paper [16], present Emergent, a novel data-set derived from a digital journalism project for rumour debunking. The data-set contains 300 rumoured claims and 2,595 associated news articles, collected and labelled by journalists with an estimation of their veracity (true, false or unverified). Each associated article is summarized into a headline and labelled to indicate whether its stance is for, against, or observing the claim, where observing indicates that the article merely repeats the claim. Thus, Emergent provides a real-world data source for a variety of natural language processing tasks in the context of fact-checking. Further to presenting the dataset, address the task of determining the article headline stance with respect to the claim. For this purpose use a logistic regression classifier and develop features that examine the headline and its agreement with the claim. The accuracy achieved was 73% which is 26% higher than the one achieved by the Excitement Open Platform (Magnini et al., 2014).

This paper proposes to use data from the Emergent Project (Silverman, 2015), a rumour debunking project carried out in collaboration with the Tow Center for Digital Journalism at Columbia Journalism School2. Leverage the Emergent dataset to investigate the task of classifying the stance of a news article headline with respect to its associated claim, i.e. for each article headline assign a stance label which is one of for, against, or observing, indicating whether the article is supporting, refuting, or just reporting the claim, respectively.

This paper proposed Emergent, a new real world dataset derived from the digital journalism project Emergent which can be used for a variety of NLP tasks in the context of fact-checking. Focus on stance detection, for which the large number of claims in the dataset compared to previous work allows for more reliable assessment of the generalization capabilities of the methods evaluated. Then proceed to develop a model for stance classification using multiclass logistic regression and show how features beyond the typically used bag of words can be beneficial, achieving accuracy 26% better than an RTE system trained on the same data. Both the datasets and code are available.

In paper [17], author propose using profile compatibility to differentiate genuine and fake product reviews. For each product, a collective profile is derived from a separate collection of reviews. Such a profile contains a number of aspects of the product, together with their descriptions. For a given unseen review about the same product, build a test profile using the same approach. Then perform a bidirectional alignment between the test and the collective profile, to compute a list of aspect-wise compatible features. Adopt Ott et al. (2011)'s op spam v1.3 dataset for identifying truthful vs. deceptive reviews. Extend the recently proposed N-GRAM+SYN model of Feng et al. (2012a) by incorporating profile compatibility features, showing such an addition significantly improves upon their state-ofart classification performance.

With the rapid development of e-commerce and the increasing popularity of various product review websites, people are more and more used to making purchase decisions based on the reported experience of other customers. A product rated positively by its previous users is able to attract potential new customers, while a poorly rated product is certainly not a good option for most new customers. Given this influential power of product reviews, there comes a huge potential for deceptive opinion spam to distort the true evaluation of a product. The promoters of a product may post false complimentary reviews, and competitors may post false derogatory reviews.

This paper proposed the use of profile alignment compatibility as an indicator of truthfulness in product reviews. Define two types of compatibility between product profiles, and designed a methodology to tackle them by extracting aspects and associated descriptions from reviews.

As per the discussion in paper [18], the application of natural language processing techniques for the detection of 'fake news', that is, misleading news stories that come from non-reputable sources. Using a dataset obtained from Signal Media and a list of sources from OpenSources.co, apply term frequency-inverse document frequency (TF-IDF) of bi-grams and probabilistic context free grammar (PCFG) detection to a corpus of about 11,000 articles. Test dataset on multiple classification algorithms - Support Vector Machines, Stochastic Gradient Descent, Gradient Boosting, Bounded Decision Trees, and Random Forests. found that TF-IDF of bi-grams fed into a Stochastic Gradient Descent model identifies non-credible sources with an accuracy of 77.2%, with PCFGs having slight effects on recall.

This paper, compare the performance of models using three distinct feature sets to understand what factors are most predictive of fake news: TF-IDF using bi-gram frequency, syntactical structure frequency (probabilistic context free grammars, or PCFGs), and a combined feature union. In doing so, follow the existing literature on deception detection through natural language processing (NLP), particularly the work of Feng, Banerjee, and Choi with deceptive social media reviews. This find that while bi-gram TF-IDF yields predictive models that are highly effective at classifying articles from unreliable sources, the PCFG features do little to add to the models' efficacy. Instead, findings suggest that, contrary to the work done in [3], PCFGs do not provide meaningful variation for this particular classification task. This suggests important differences between deceptive reviews and so-called 'fake news'. Then suggest additional routes for work and analysis moving forward.

The results obtained above are very promising. This method demonstrates that term frequency is potentially predictive of fake news - an important first step toward using machine classification for identification. The best performing models by overall ROC AUC are Stochastic Gradient Descent models trained on the TF-IDF feature set only. Then observe that PCFGs do not add much predictive value, but balance the Recall for top performing model. This indicates that PCFGs are good for a Fake-News Filter type implementation versus, say, targeting fake news sites for review. TF-IDF shows promising potential predictive power, even when ignoring named entities, but remain skeptical that this approach would be robust to changing news cycles. However, this would require a more complete corpus.

In paper [19], investigate syntactic stylometry for deception detection, adding a somewhat unconventional angle to prior literature. Over four different datasets spanning from the product review to the essay domain, demonstrate that features driven from Context Free Grammar (CFG) parse trees consistently improve the detection performance over several baselines that are based only on shallow lexico-syntactic features. Resultant results improve the best published result on the hotel review data (Ott et al., 2011) reaching 91.2% accuracy with 14% error reduction.We investigated syntactic stylometry for deception detection, adding a somewhat unconventional angle to previous studies. Experimental results consistently find statistical evidence of deep syntactic patterns that are helpful in discriminating deceptive writing.

According to the author in paper [20], the current state-of-the-art method for generating educational content, such as math word problems and hints, is manual authoring by domain experts. Unfortunately, this is costly, time consuming, and produces content that lacks diversity. Attempts to automatically address the time and diversity issues through natural language generation still do not produce content that is sufficiently creative and varied. Crowd sourcing is a viable alternative - there has been a great deal of research on leveraging human creativity to solve complex problems, such as user interface design. However, these systems typically decompose complex tasks into subtasks. Writing a single word problem or hint is a small enough problem that it is unclear how to further break it down, but also far more complex than typical micro tasks like image labeling.

Therefore, it is not obvious how to apply these worker improvement methods or which ones are most effective (if at all). Large quantities of diverse content are important to math education. Explore the application of crowd sourcing to the new setting of math word problems and hints; examine various design factors to improve worker creativity and submission quality, showing how one can adapt techniques from prior work to improve worker accuracy and creativity. Hundreds of word problems and hints produced by workers through systems have been augmented into Riddlebooks, which has been played by thousands of students in a recent algebra challenge. Additionally, results from both studies suggest further avenues of research into designing tasks that attract individual prolific workers, which can from other lead to higher volumes and success rates of task completion in crowd sourcing work domains

Chapter 3

ANALYSIS

Goal of the project is to classify a news item as reliable or fake; in this section, author first describe the datasets used for tests, then he present the content-based approach implemented and the proposed method to combine it with a social-based approach available in the literature.

Data Set

The dataset is used from kaggle community. It consists of 3 columns such as id, statement and label. Labels are classified as either true or false.

Training set (75%)-train the model

Test set (25%)- evaluate the model

	A	B
1	Statement	Label
2	Building a wall on the U.S.-Mexico border will take literally years.	TRUE
3	Wisconsin is not on pace to double the number of layoffs this year and so on.	FALSE
4	Says John McCain has done nothing to help the vets.	FALSE
5	Suzanne Bonamici supports a plan that will cut choice for Medicare Advantage seniors.	TRUE
6	When asked by a reporter whether hes at the center of a criminal scheme to violate campaign laws, Gov.	FALSE
7	Over the past five years the federal government has paid out $601 million in retirement and disability be	TRUE
8	Says that Tennessee law requires that schools receive half of proceeds -- $31 million per year -- from a ha	TRUE
9	Says Vice President Joe Biden "admits that the American people are being scammed" with the economic	FALSE
10	Donald Trump is against marriage equality. He wants to go back.	TRUE
11	We know that more than half of Hillary Clintons meetings while she was secretary of state were given to	FALSE
12	We know there are more Democrats in Georgia than Republicans. We know that for a fact.	FALSE
13	PolitiFact Texas says Congressman Edwards attacks on Bill Flores are false.	FALSE
14	Denali is the Kenyan word for black power.	FALSE
15	Says 57 percent of federal spending goes to the military and just 1 percent goes to food and agriculture, i	FALSE
16	On residency requirements for public workers	TRUE
17	Says the unemployment rate for college graduates is 4.4 percent and over 10 percent for noncollege-edu	TRUE
18	Unfortunately we have documented instances where people defecated in the (Statehouse) building.	FALSE
19	A recent Gallup poll found that 72 percent of Americans and 56 percent of Democrats say the biggest thre	TRUE
20	Each year, 18,000 people die in America because they don't have health care.	TRUE
21	Ronald Reagan faced an even worse recession than the current one.	FALSE
22	There have not been any public safety issues in cities that allow transgender people to use the bathroom	TRUE
23	Says Mitt Romney was one of the first national Republican leaders to endorse Marco Rubio.	TRUE
24	The number of illegal immigrants could be 3 million. It could be 30 million.	FALSE
25	Marijuana is less toxic than alcohol.	TRUE

test

Figure 3.1: Sample data set

Confusion matrix

A confusion matrix is a summary of prediction results on a classification problem. The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix. The confusion matrix shows the ways in which your classification model is confused when it makes predictions. It gives us insight not only into the errors being made by a classifier but more importantly the types of errors that are being made.

Here,

Class 1: True

Class 2: Fake

	Class 1 Predicted	Class 2 Predicted
Class 1 Actual	TP	FN
Class 2 Actual	FP	TN

Figure 3.2: Confusion Matrix

Definition of terms

- Positive(P): Observation is positive.
- Negative(N): Observation is not positive.
- True Positive(TP): Observation is positive, and is predicted to be positive.
- True Negative(TN): Observation is negative, and is predicted to be negative.
- False Positive(FP): Observation is negative, but is predicted positive.
- False Negative(FN): Observation is positive, but is predicted negative.

Accuracy

Accuracy is given by the relation

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad \text{.................................(1)}$$

However, there are problems with accuracy. It assumes equal costs for both kinds of errors. 99% accuracy can be excellent, good, mediocre, poor or terrible depending upon the problem.

Recall

Recall can be defined as the ratio of the total number of correctly classified positive examples divide to the total number of positive examples. High recall means that an algorithm returned most of the relevant results.

Recall is given by the relation:

$$\textit{Recall} = \frac{TP}{TP + FN} \quad \text{...(2)}$$

Precision

To get the value of precision, divide the total number of correctly classified positive examples by the total number of predicted positive examples. High Precision indicates an example labeled as positive is indeed positive (small number of FP).

Precision is given by the relation:

$$\textit{Precision} = \frac{TP}{TP + FP} \quad \text{...(3)}$$

Anaconda

Anaconda is a free and open source distribution of the python and R programming languages for data science and machine learning related applications, that aims to simply package management and deployment. Package versions are managed by the package management system conda. The Anaconda distribution is used by over 6 million users, and it includes more than 250 popular data science packages suitable for Windows, Linux and MacOS.

Anaconda distribution comes with more than 1,000 data packages as well as the Conda package and virtual environment manager, called Anaconda Navigator, so it eliminates the need to learn to install each library independently.

The open source data packages can be individually installed from the Anaconda repository with the conda install command or using the pip install command that is installed with Anaconda. Pip packages provide many of the features of conda packages and in most cases, they can work together.

One can also make his own custom packages using the conda build command, and he can share them with others by uploading them to Anaconda Cloud, PyPI or other repositories. The default installation of Anaconda2 includes Python 2.7 and Anaconda3 includes Python 3.6. However, can create new environments that include any version of Python packaged with conda.

Anaconda navigator

Anaconda Navigator is a desktop graphical user interface (GUI) included in Anaconda distribution that allows users to launch applications and manage conda packages, environments and channels without using command-line commands. Navigator can search for packages on Anaconda Cloud or in a local Anaconda Repository, install them in an environment, run the packages and update them. It is available for Windows, macOS and Linux. Navigator is automatically include with Anaconda version 4.0.0 or higher.

The following applications are available by default in Navigator:

- JupyterLab
- Jupyter Notebook
- QtConsole
- Spyder
- Glueviz
- Orange
- Rstudio
- Visual Studio Code

Jupyter Notebook

Jupyter Notebook (Formerly IPython Notebooks) is a web-based interactive computational environment for creating Jupyter notebooks documents. The “notebook” term can colloquially make reference to many different entities, mainly the Jupyter web application, Jupyter python web server, or Jupyter document format depending on context. A Jupyter Notebook document is a JSON document, following a versioned schema, and containing an ordered list of input/output cells which can contain code, text (using Markdown), mathematics, plots and rich media, usually ending with the “. ipynb” extension. jupyter Notebook provides a browser-based REPL built upon a number of popular open-source libraries:

- IPython
- Tornado
- jQuery
- Bootstrap (front-end framework)
- MathJax

Jupyter Notebook can connect to many kernels, to allow programming in many languages. As of the 2.3 release(October 2014),there are currently 49 Jupyter- compatible kernels for as many programming languages, including Python, R, Julia and Haskell. The Notebook interface was added to IPython in the 0.12 release (December 2011), renamed to Jupyter notebook in 2015. Jupyter Notebook is similar to the notebook interface of other programs such as Maple, Mathematica and SageMath.

Jupyter kernels

A Jupyter kernel is a program responsible for handling various types of request, and providing a reply. Kernels talks to the other components of Jupyter using ZeroMQ over the network, and thus can be on the same or remote machines. Usually Kernels are implemented and allow execution of a single language with a couple of exceptions.

Jupyter hub

Jupyter Hub is a multi-user server for Jupyter Notebooks. It is designed to support many users by spawning, managing, and proxying many singular Jupyter Notebook servers.

Jupyter lab

Jupyter Lab is the next-generation user interface for Project Jupyter. It offers all the familiar building blocks of the classic Jupyter Notebook in a flexible and powerful user interface.The first stable release was announced on February 20, 2018.

Front-end Design

HTML5, CSS3 and JavaScript, along with PHP, will be used to create the front-end UI. **HTML5** is a markup language used for structuring and presenting content on the World Wide Web. Its goals are to improve support for the latest multimedia and other new features.

Cascading Style Sheetsversion 3 (**CSS3**) is a style sheet language used for describing the presentation of a document written in a markup language like HTML5. CSS3 is designed to enable the separation of presentation and content, including layout, colors, and fonts. Separation of formatting and content also makes it feasible to present the same markup page in different styles for different rendering methods, such as on-screen, in print, by voice (via speech-based browser or screen reader), and on Braille-based tactile devices.

PHP, which stands for Hypertext Preprocessor (or simply PHP) is a server-side scripting language designed for Web development, and also used as a general-purpose programming language. PHP code will be embedded into HTML5 code. PHP code will be processed by a PHP interpreter implemented as a module in the Apache Web. The web server combines the results of the interpreted and executed PHP code, which may be any type of data, including images, with the generated web page.

Back-end Design

MongoDB is a NoSQL database which stores the data in form of key-value pairs. It is an Open Source, Document Database which provides high performance and scalability along with data modelling and data management of huge sets of data in an enterprise application.
MongoDB also provides the feature of Auto-Scaling. Since, MongoDB is a cross platform database and can be installed across different platforms like Windows, Linux etc.

Python 3

Python 3.0 (also called "Python 3000" or "Py3K") was released on December 3, 2008. It was designed to rectify fundamental design flaws in the language—the changes required could not be implemented while retaining full backwards compatibility with the

2.x series, which necessitated a new major version number. The guiding principle of Python 3 was: "reduce feature duplication by removing old ways of doing things".

Python 3.0 was developed with the same philosophy as in prior versions. However, as Python had accumulated new and redundant ways to program the same task, Python 3.0 had an emphasis on removing duplicative constructs and modules, in keeping with "There should be one— and preferably only one —obvious way to do it".

Nonetheless, Python 3.0 remained a multi-paradigm language. Coders still had options among object-orientation, structured programming, functional programming and other paradigms, but within such broad choices, the details were intended to be more obvious in Python 3.0 than they were in Python 2.x.

Python 3.0 broke backward compatibility, and much Python 2 code does not run unmodified on Python 3. Python's dynamic typing combined with the plans to change the semantics of certain methods of dictionaries, for example, made perfect mechanical translation from Python 2.x to Python 3.0 very difficult. A tool called "2to3" does the parts of translation that can be done automatically. At this, 2to3 appeared to be fairly successful, though an early review noted that there were aspects of translation that such a tool would never be able to handle. Prior to the roll-out of

Python 3, projects requiring compatibility with both the 2.x and 3.x series were recommended to have one source (for the 2.x series), and produce releases for the Python 3.x platform using 2to3. Edits to the Python 3.x code were discouraged for so long as the code needed to run on Python 2.x. This is no longer recommended as of 2012 the preferred approach is to create a single code base that can run under both Python 2 and 3 using compatibility modules.

Features

Some of the major changes included for Python 3.0 were:

- Changing print so that it is a built-in function, not a statement. This made it easier to change a module to use a different print function, as well as making the syntax more regular. In Python 2.6 and 2.7 print () is available as a built-in but is masked by the print statement syntax,which can be disabled by entering from future import print function at the top of the file.
- Removal of the Python 2 input function, and the renaming of the raw input function to input. Python 3's input function behaves like Python 2's raw input function, in that the input is always returned as a string rather than being evaluated as an expression.
- Adding support for optional function annotations that can be used for informal type declarations or otherpurposes.

Unifying the str Unicode types, representing text, and introducing a separate immutable bytes type and a mostly corresponding mutable byte array type, both of which represent arrays of bytes.

- Removing backward-compatibility features, including old-style classes, string exceptions and implicit relativeimports.
- A change in integer division functionality: in Python 2, 5/2 is 2; in Python 3, 5/2 is 2.5. (In both Python 2 (2.2 onwards) and Python 3, 5//2 is 2).

SciKit-learn

Scikit-learn is a free software machine learning library for the Python programming language. It features various classification, regression and clustering algorithms including support vector machines, random forests, gradient boosting, k- means and DBSCAN, and is designed to interoperate with the Python numerical and scientific libraries NumPy andSciPy.

The scikit-learn project started as scikits-.learn, a Google Summer of Code project by David Cournapeau. Its name stems from the notion that it is a "SciKit" (SciPy Toolkit), a separately-developed and distributed third-party extension to SciPy. The original codebase was later rewritten by other developers. In 2010 Fabian Pedregosa, Gael Varoquaux, Alexandre Gramfort and Vincent Michel, all from INRIA took leadership of the project and made the first public release on February the 1st 2010. Of the various scikits, scikit-learn as well as scikit-image were described as "well-maintained and popular" in November2012.

Numpy

NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays. The ancestor of NumPy, Numeric, was originally created by Jim Huguninwith contributions from several other developers. In 2005, Travis Oliphant created NumPy by incorporating features of the competing Numarray into Numeric, with extensive modifications. NumPy is open-source software andhasmanycontributors.Byusingthem in Pythonprogramming, theycanbe used with two simple

commands:

>>> import numpy

The core functionality of NumPy is its "ndarray", for n-dimensional array, data structure. These arrays are strided views on memory. In contrast to Python's built-in list data structure (which, despite the name, is a dynamic array), these arrays are homogeneously typed: all elements of a single array must be of the same type.

Pandas

Pandas is a software library written for the Python programming language for data manipulation and analysis. In particular, it offers data structures and operations for manipulating numerical tables and time series. It is free software released under the three clause BSD license. The name is derived from the term "panel data", an econometrics term for data sets that include observations over multiple time periods for the same individuals.

Library features are:

- DataFrame object for data manipulation with integrated indexing.
- Tools for reading and writing data between in-memory data structures and different file formats.
- Data alignment and integrated handling of missing data.
- Reshaping and pivoting of data sets.
- Label-based slicing, fancy indexing, and subsetting of large data sets.
- Data structure column insertion and deletion.
- Group by engine allowing split-apply-combine operations on data sets.
- Data set merging and joining.
- Hierarchical axis indexing to work with high-dimensional data in a lower-dimensional
- Time series-functionality: Date range generation and frequency conversion, moving window statistics, moving window linear regressions, date shifting and lagging.

Matplotlib

Matplotlib is a plotting library for the Python programming language and its numerical mathematics extension NumPy. It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits like Tkinter, wxPython, Qt, or GTK+.There is also a procedural "pylab" interface based on a state machine (like OpenGL), designed to closely resemble that of MATLAB, though its use is discouraged. SciPy makes use of matplotlib.

Matplotlib was originally written by John D. Hunter, has an active development community, and is distributed under a BSD-style license. Michael Droettboom was nominated as matplotlib's lead developer shortly before John Hunter's death in August 2012, and further joined by ThomasCaswell.

As of 23 June 2017, matplotlib 2.0.x supports Python versions 2.7 through 3.6. Matplotlib 1.2 is the first version of matplotlib to support Python 3.x. Matplotlib 1.4 is the last version of matplotlib to support Python 2.6.

System Requirements Specification

A **System Requirements Specification** (SRS) is a description of a software system to be developed. It lays out functional and non-functional requirements and may include a set of use cases that describe user interactions that the software must provide.

Software requirements specification establishes the basis for an agreement between customers and contractors or suppliers on how the software product should function. Software requirements specification is a rigorous assessment of requirements before the more specific system design stages, and its goal is to reduce later redesign. It should also provide a realistic basis for estimating product costs, risks, and schedules. Used appropriately, software requirements specifications can help prevent software project failure.

Hardware Requirements Specification

- 64-bit CPU
- Intel i5 processor
- 4-8 GB Memory

Software Requirements Specification

- OS (eg. Windows 10)
- FLASK
- CSS3
- HTML5
- Apache Web server
- JavaScript

Performance requirements

The PCs used must be at least be INTEL CORE i7 machines so that they can give optimum performance of the product. In addition to these requirements, the system should also embrace the following requirements:-

- **Reliability:** The system should have little or no downtime.
- **Ease of Use:** The general and administrative views should be easy to use and intuitive.

Chapter 4

SYSTEM DESIGN

System Design is the process of defining the architecture, modules, interfaces, and data for a system to satisfy specified requirements. Systems design could be seen as the application of systems theory to product development.

Architectural design

Following is the architecture of the proposed system. It has three modules which are used to classify a given article into fake news or real news.

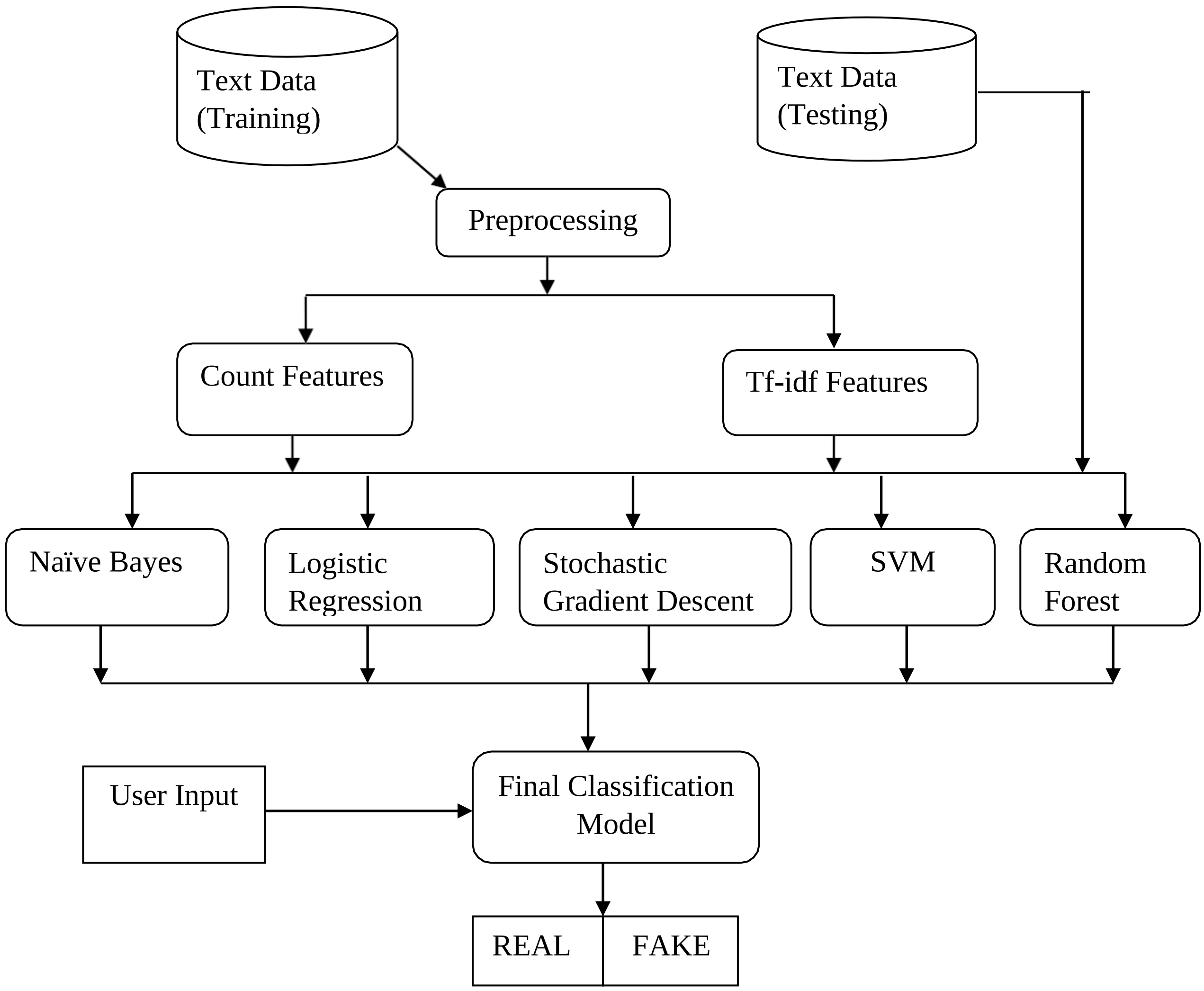


Figure 4.1: Architecture Diagram

The model has built all the classifiers for predicting the fake news detection. The extracted features are fed into different classifiers. They have used Naive-bayes, Logistic

Regression, Linear SVM, Stochastic gradient decent and Random forest classifiers from sklearn. Once fitting the model, compared the f1 score and checked the confusion matrix

Data Flow Diagram

Next is the level 0 DFD, it shows the how the data from the article is fed into the trained model and used to predict the probability of it being true.

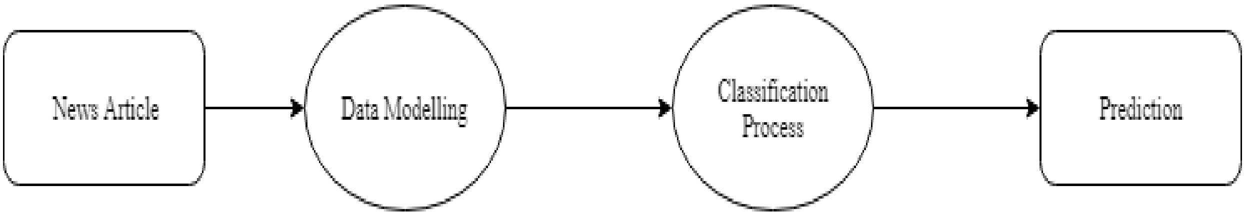


Figure 4.2: Level 0 DFD

The project design involves creation of a model to which the test, train and validation dataset will be fed as the input. The model will be trained using this dataset to classify the news as fake or not fake. The output will the prediction if the news is fake or not with the truth probability score. The figure 4.3 below illustrates flow of information between the various processes and components present in the system, in the form of a data flow diagram.

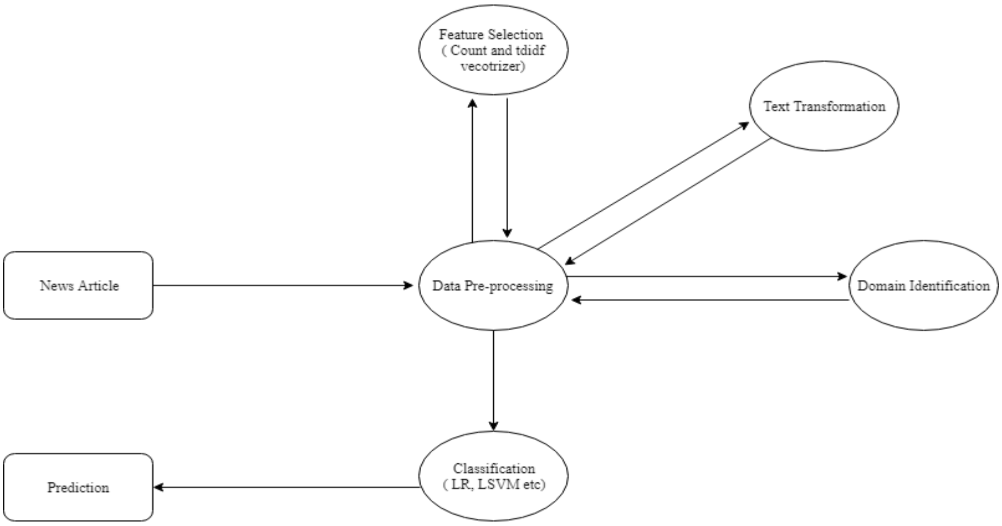


Figure 4.3: Level 1 DFD

Component design

The components of this system are

- Data

- Model
- Prediction

Data is generated constantly but a fixed set of data is used to uniformly train the model so that it can predict the class of the input accordingly. The dataset used for this project is the LIAR dataset. The model is trained using the LIAR dataset stripped to 2 attributes (statement and label) for simplicity. The features extracted are fed to different classifiers and the best one is chosen. The module also uses context matching to calculate the final rating. The body of the article is with the headline of the article to verify how much the context of the article matches the headline. Context matching contributes 15% to the final probability.

The final probability also has a small contribution from the reputation of the publisher. Based on the reputation of publishers, they are assigned a rating. Publishers well known for fake news will be given a bad rating. This rating contributes 5% to the overall probability of truthfulness of the article.

Prediction is the final result of whether the news is classified as true or false, the prediction is done by testing the input against the trained model and this contributes 80% of the probability

Behavioral design

In software engineering, behavioral designs are design patterns that identify common communication patterns between objects and realize these patterns. By doing so, these patterns increase flexibility in carrying out this communication

The system pipeline is as follows

- The Dataset is used is prepared and used to train the model.
- Then based on the performance of the models with different algorithms the best one is selected as the classifier.
- The URL of the article is fed into the UI which extracts the text by scraping it's content
- The content of the article is matched with the headline of the to find out how well the context matches rating.
- The name of the publisher is used to further improve the probability score based on their rating.
- The model is then used to predict the probability of truthfulness of the article.
- Base on the probability the news is classified.

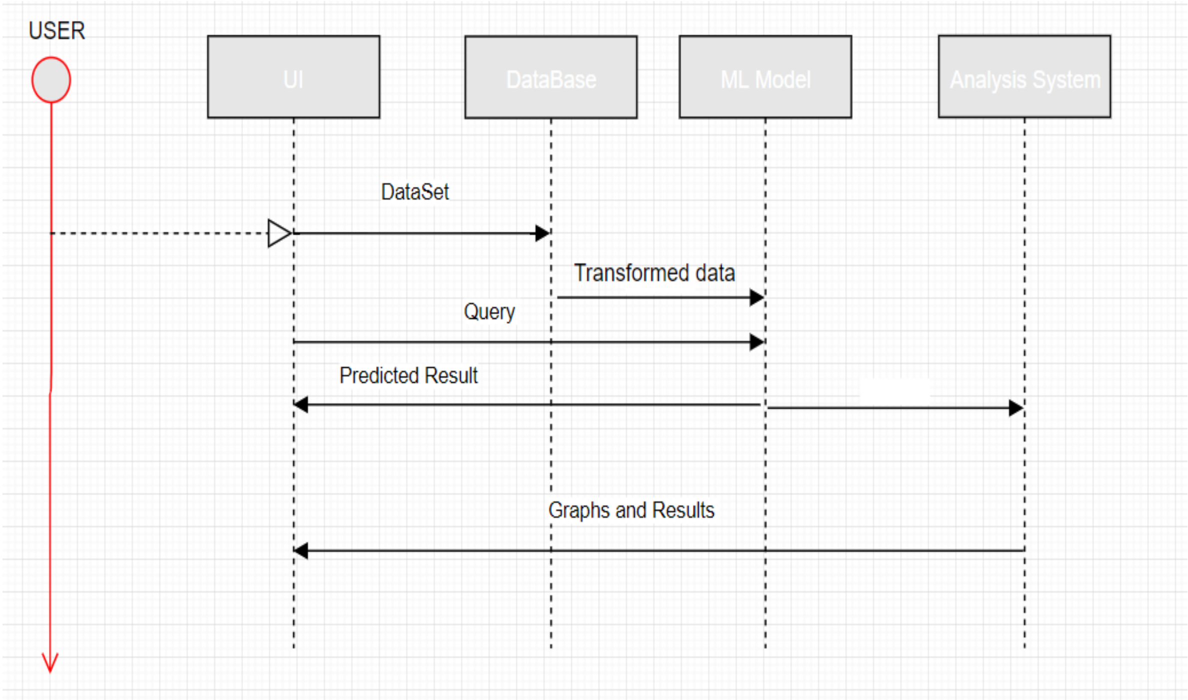


Figure 4.4: Sequence diagram

Chapter 5

IMPLEMENTATION

Implementation is the process of defining how the system should be built, ensuring that it is operational and meets quality standards. It is a systematic and structured approach for effectively integrating a software-based service or component into the requirements of end users.

Performance Analysis

For performance analysis different scoring methods are used which are,

- F1 score
- AUC-ROC score

F1 score

F1-score is a simple formula to gather the scores of precision and recall. Imagine you want to predict labels for a binary classification task (positive or negative).

There are 4 types of predictions:

- true positive: correctly assigned as positive.
- true negative: correctly assigned as negative.
- false positive: wrongly assigned as positive.
- false negative: wrongly assigned as negative.

Precision is the proportion of true positive on all positives predictions. A precision of 1 means that you have no false positive, which is good because you never says that an element is positive whereas it is not.

Recall is the proportion of true positives on all actual positive elements. A recall of 1 means that you have no false negative, which is good because you never says an element belongs to the opposite class whereas it actually belongs to your class. In essence f1-score is the harmonic mean of the precision and recall. As when create a classifier always make a compromise between the recall and precision, it is hard to compare a model with high recall and low precision versus a model with high precision but low recall. f1- score is measure that can use to compare two models.

AUC- ROC Score

ROC (Receiver Operating Characteristic) Curve tells us about how good the model can distinguish between two things. Better models can accurately distinguish between the two. Whereas, a poor model will have difficulties in distinguishing between the two. AUC ROC rating helps you identify the tradeoffs between sensitivity and specificity of a model.

In simple terms, the proportion of patients that were identified correctly to have the disease (True Positive) upon the total number of patients who actually have the disease is called as Sensitivity or Recall.Similarly, the proportion of patients that were identified correctly to not have the disease (True Negative) upon the total number of patients who do not have the disease is called as Specificity.

Now to understand the tradeoffs between sensitivity and specificity consider the following, when decrease the threshold, get more positive values thus increasing the sensitivity. Meanwhile, this will decrease the specificity. Similarly, when increase the threshold, get more negative values thus increasing the specificity and decreasing sensitivity.

To evaluate the performance of the models initially used F1 and AUC ROC score. Once fitting the model, compared the f1 score and checked the confusion matrix for all the models. After fitting all the classifiers, two best performing models were selected as candidate models for fake news. have performed parameter tuning by implementing GridSearchCV methods on these candidate models and chose the best performing parameters for this classifier. Parameter tuning increased the performance of the logistic regression model around 8%.

Logistic regression was found to be the best performing out of the according to the F1- score. Other algorithms may perform better on different datasets based on the nature of the dataset. Overall performance of the algorithms was around 85%.

The final trained model along with the added contribution of publisher rating and Context matching for the chosen news base was over around 85%. The system can further be improved by using better data sets and taking into account linguistic cues likes context of words.

Front-end – HTML5 and CSS3

HTML5 is a software solution stack that defines the properties and behaviors of web page content by implementing a markup based pattern to it.

Cascading Style Sheets (CSS) **3** is a style sheet language used for describing the presentation of a document written in a markup language like HTML. CSS is designed to enable the separation of presentation and content, including layout, colors, and fonts.

This separation can improve content accessibility, provide more flexibility and control in the specification of presentation characteristics, enable multiple web pages to share formatting by specifying the relevant CSS in a separate .css file, and reduce complexity and repetition in the structural content.

Separation of formatting and content also makes it feasible to present the same markup page in different styles for different rendering methods, such as on-screen, in print, by voice (via speech-based browser or screen reader), and on Braille-based tactile devices. CSS also has rules for alternate formatting if the content is accessed on a mobile device.

Algorithms

An algorithm is a step by step method of solving a problem. It is commonly used for data processing, calculation and other related computer and mathematical operations .An algorithm is also used to manipulate data in various ways, such as inserting a new data item, searching for a particular item or sorting an item. An algorithm is a detailed series of instructions for carrying out an operation or solving a problem.

In a non-technical approach, use algorithms in everyday tasks, such as a recipe to bake a cake or a do-it-yourself handbook. Technically, computers use algorithms to list the detailed instructions for carrying out an operation. For example, to compute an employee's paycheck, the computer uses an algorithm. To accomplish this task, appropriate data must be entered into the system. In terms of efficiency, various algorithms are able to accomplish operations or problem solving easily and quickly.

Logistic Regression

Logistic Regression is a Machine Learning technique used to estimate relationships among variables using statistical methods. This algorithm is great for binary classification problems as it deals with predicting probabilities of classes, and hence our decision to choose this algorithm as base- line run. It relies on fitting the probability of true scenarios to the proportion of actual true scenarios observed. Also, this algorithm does not require large sample sizes to start giving fairly good results.

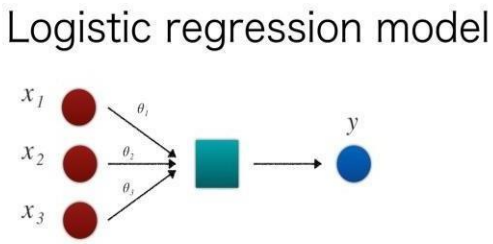


Figure 5.1: Logistic Regression Model

The Logistic Regression algorithm works by assigning ob- servations to a discrete set of classes and then transforms it using a sigmoid function to give the probability value which can be mapped to a discrete class.

Linear Regression Equation

$$y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots\ldots + \beta nXn$$

Where, y is dependent variable and x1, x2 ... and Xn are explanatory variables.

Pseudo code

- Initialize a= (1,..,1)^t
- Perform feature scaling on examples attributes
- Repeat until convergence
  - For each j=0,..,n:
    - aj=aj+α∑i(yi-ha(xi))xj
  - For each j=0,..,n:
    - aj=aj
- Output a

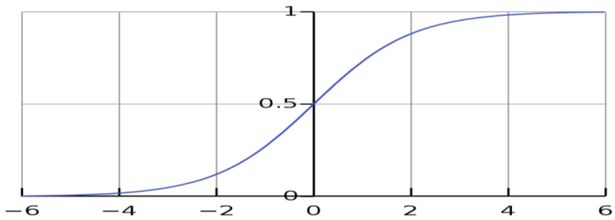


Figure 5.2 Sigmoid Function

Naïve Bayes

This is a simple yet powerful classification model that works remarkably well. It uses probabilities of the elements belonging to each class to form a prediction. The underlying assumption in the Naïve Bayes model is that the probabilities of an attribute belonging to a class is independent of the other attributes of that class. Hence the name 'Naive'.

In this model multiply the conditional probabilities of each attribute given the class value, to get the probability of the test data belonging to that class. Arrive at the final prediction by selecting the class that has the highest of the probabilities for the instance belonging to that class. The advantages of using Naïve Bayes is that it is simple to compute, and it works well in categorizing data as are using ratios for computation.

Pseudo code

Input: Training dataset T,

F=(f1,f2,f3,….,fn)

Output: A class of testing dataset.

Steps:

1. Read the training dataset T;
2. Calculate the mean and standard deviation of the predictor variables in each class;
3. Repeat
   Calculate the probability of fi using the gauss density equation in each class;
   Until the probability of all predictor variables(f1,f2,f3,..,fn) has calculated.
4. Calculate the likelihood for each class;
5. Get the greatest likelihood;

Random Forrest

Random Forests are a machine learning method of classification that work by building several decision trees while training the model. It is a kind of additive model that makes predictions from a combination of decisions from base models. Decision trees have huge depth and tend to over fit results. Random forest utilizes multiple decision trees to average out the results. The Random forest classifier creates a set of decision trees from a subset of the training data. It aggregates the results from different decision trees and then decides the final classification of the test data. The subsets of data used in the decision trees may overlap.

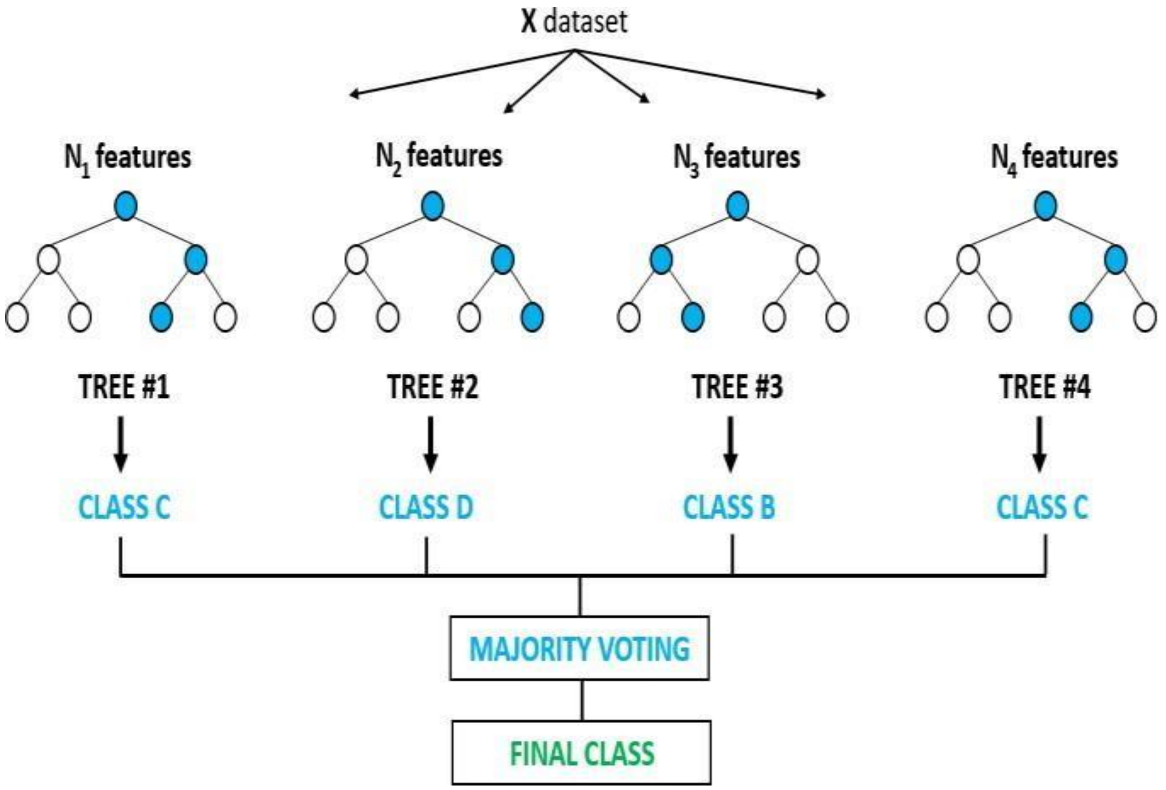


Figure 5.3: Random Forest Model

Pseudo code

1. Select randomly M features from the feature set.

2. For each x in M

   a. calculate the Information Gain

      Gain (t,x)=E (t) - E (t,x)

      E (t)=∑ i=1 - Pi log2 Pi

      E (t,x)=∑ c€x P(c)E(c)

   b. Select the node d which has the highest information gain.

   c. Split the node into sub-nodes.

   d. Repeat steps a, b and c to construct the tree until reach minimum number of samples.

3. Repeat steps 1 and 2 for N times to build forest of N trees

Support Vector Machine

Support Vector Machines are machine learning models that perform supervised learning on data for classification and regression. When given a labeled training dataset, it com- putes the optimal hyper plane that categorizes the test data.

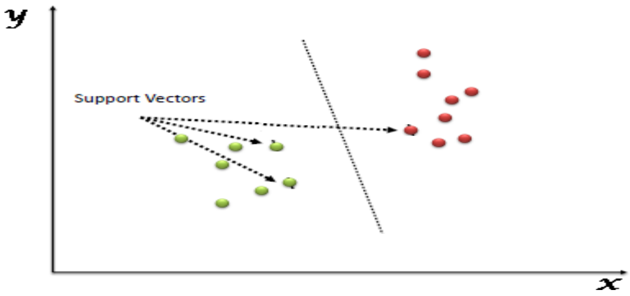


Figure 5.4: Support vector

Data points are plotted in a multidimensional space, where the dimension is determined by the number of features at disposal. The value of each feature is mapped to a point in the coordinate system. The algorithm then performs classification by finding the hyper plane that differentiates the two classes well. The hyper plane having the maximum margin between the two classes in chosen. The advantages of the SVM model are that it performs very well for high dimensional spaces and also creates a clear margin of separation between data points.

Pseudo code

Input: X: Training set. δ: Threshold. Output: Xr: Xr c Xs.t.

Xr<<X. Begin Train a decision tree T;

For each leaf Li of T do

For each opposite class neighbor Li do

if entropy of Li low then

use Li and Lj to build X+;

compute w (Eq. (12));

Add xi € Lj to Xr according to (12);

end for

else

Xr←XrU Lj;

end if

Stochastic Gradient Descent

The word '*stochastic*' means a system or a process that is linked with a random probability. Hence, in Stochastic Gradient Descent, a few samples are selected randomly instead of the whole data set for each iteration.

In Gradient Descent, there is a term called "batch" which denotes the total number of samples from a dataset that is used for calculating the gradient for each iteration. In typical Gradient Descent optimization, like Batch Gradient Descent, the batch is taken to be the whole dataset. Although, using the whole dataset is really useful for getting to the minima in a less noisy or less random manner, but the problem arises when our datasets get really huge.

Suppose, there is million samples in the dataset, so if typical Gradient Descent optimization technique is used, will have to use all of the one million samples for completing one iteration while performing the Gradient Descent, and it has to be done for every iteration until the minima is reached. Hence, it becomes computationally very expensive to perform.

Pseudo code

Input: Training data S, regularization parameters λ, learning rate η, initialization σ
Output: Model parameters $\Theta = (w_0, \mathbf{w}, \mathbf{V})$
$w_0 \leftarrow 0$; $\mathbf{w} \leftarrow (0, \ldots, 0)$; $\mathbf{V} \sim \mathcal{N}(0, \sigma)$;
repeat
  for $(x, y) \in S$ **do**
    $w_0 \leftarrow w_0 - \eta(\frac{\partial}{\partial w_0} l(y(\mathbf{x} \mid \Theta), y) + 2\lambda^0 w_0)$;
    for $i \in \{1, \ldots, p\} \wedge x_i \neq 0$ **do**
      $w_i \leftarrow w_i - \eta(\frac{\partial}{\partial w_i} l(y(x \mid \Theta), y) + 2\lambda_\pi^w w_i)$;
      for $f \in \{1, \ldots, k\}$ **do**
        $v_{i,f} \leftarrow v_{i,f} - \eta(\frac{\partial}{\partial v_{i,f}} l(y(x \mid \Theta), y) + 2\lambda_{f,\pi(i)}^v v_{i,f})$;
      end
    end
  end
until *stopping criterion is not met*;

Comparative Study of Algorithms

After the comparative study of algorithms, have found that logistic Regression algorithm results with high F1 compare to other algorithms.

Table 5.1: Comparison of Algorithms

Model	Accuracy
Naïve Bayes	75%
SVM	73%
Logistic Regression	76%
Random Forest	71%
Stochastic Gradient Descent	85%

Chapter 6

TESTING

Software testing is conducted to provide stakeholders with information about the quality of the software product or service under test. Software testing can also provide an objective, independent view of the software to allow the business to appreciate and understand the risks of software implementation. It involves the execution of a software component or system component to evaluate one or more properties of interest (a program or application), with the intent of finding software bugs (errors or other defects), and verifying that the software product is fit for use.

Introduction

A system based on machine learning is primarily been associated with building models that could do numerical or class-related predictions. This is unlike conventional software development, which is associated with both development and "testing" the software. The usage of the word "testing " in relation to Machine Learning models is primarily used for testing the model performance in terms of accuracy/precision of the model. It can be noted that the word, "testing" means different for conventional software development and Machine Learning models development.

Machine Learning models would also need to be tested as conventional software development from the quality assurance perspective. Techniques such as Blackbox and white box testing would, thus, apply to Machine Learning models as well for performing quality control checks on Machine Learning models.

What is Black Box Testing?

Blackbox testing is testing the functionality of an application without knowing the details of its implementation including internal program structure, data structures, etc. Test cases for Blackbox testing are created based on the requirement specifications. Therefore, it is also called as specification-based testing. The following figure 6.1 represents the Blackbox testing.

When applied to Machine Learning models, Blackbox testing would mean testing Machine Learning models without knowing the internal details such as features of the Machine Learning model, the algorithm used to create the model etc. The challenge, however, is to identify the test oracle which could verify the test outcome against the expected values known beforehand. This is discussed in the following section.

Testing

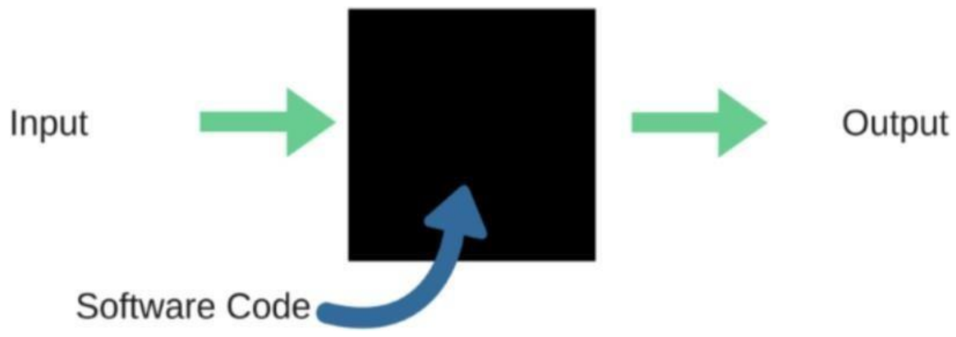


Figure 6.1: Blackbox testing

Normally in a machine learning process, data is divided into training and test sets; the training set is then used to train the model and the test set is used to evaluate the performance of a model. However, this approach may lead to variance problems. In simpler words, a variance problem refers to the scenario where our accuracy obtained on one test is very different to accuracy obtained on another test set using the same algorithm.

The solution to this problem is to use K-Fold Cross-Validation for performance evaluation where K is any number. The process of K-Fold Cross-Validation is straightforward. You divide the data into K folds. Out of the K folds, K-1 sets are used for training while the remaining set is used for testing. The algorithm is trained and tested K times, each time a new set is used as testing set while remaining sets are used for training. Finally, the result of the K-Fold Cross-Validation is the average of the results obtained on each set.

Testing Techniques for Machine Learning Model

The following represents some of the techniques which could be used to perform Blackbox testing on Machine Learning models:

- Model performance
- Metamorphic testing
- Dual coding
- Coverage guided fuzzing
- Comparison with simplified, linear models

- K-Fold Cross validation

Unit testing

For unit testing the different modules of the project were tested for their functionality. The model was trained using the same set of features using five different machine learning algorithms. The algorithms used were Naive-bayes, Logistic Regression, Linear SVM, Stochastic gradient decent and Random forest classifiers from sklearn. Each of the extracted features were used in all of the classifiers. Once fitting the model, compared the f1 score and checked the confusion matrix. After fitting all the classifiers, 2 best performing models were selected as candidate models for fake news classification.

Additionally, there are top 50 features extracted from term-frequency tfidf vectorizer to see what words are most and important in each of the classes.

Table 6.1: Unit testing

Test case	Description	Expected output	Obtained output	Result
1	Calculate accuracy of each model	F1 score and AUC ROC score for classifiers	Each classifiers F1 score and AUC score	Pass
2	To increase the accuracy of classifiers	Models with higher accuracy	Logistic Regression classifiers accuracy is increased	Partial
3	Accuracy of context verification for body and headline	At least 80%	Approximately 85%	Pass

Integration Testing

The final model was incorporated into a UI, and all the different units were integrated to function with the help of the UI. The System was then tested as a whole that is Black Box testing was performed by using test articles as input. The model predicted the truthfulness of the test input with an average accuracy of 87%.

Table 6.2: Integration Testing

Test Case	Description	Expected output	Obtained output	Result
1	To check if the best model was selected	Model with highest F1and auc roc score	Logistic Regress which had high F1 and Auc Roc score	Pass

System Testing

System testing is testing conducted on a complete integrated system to evaluate the system's compliance with its specified requirements. System testing is performed on the entire system in the context of either functional requirement specifications (FRS) or system requirement specification (SRS), or both. System testing tests not only the design, but also the behavior and even the believed expectations of the customer. It is also intended to test up to and beyond the bounds defined in the software or hardware requirements specification.

Table 6.3: System Testing

Test Case	Description	Expected output	Obtained output	Result
1	To predict the truthness prob of news articles	Prediction with accuracy more than 90%	Final model with accuracy 87%	Pass

Learning Curves

- Logistic Regression

  Following figure 6.2 represents the learning curve of Logistic Regression

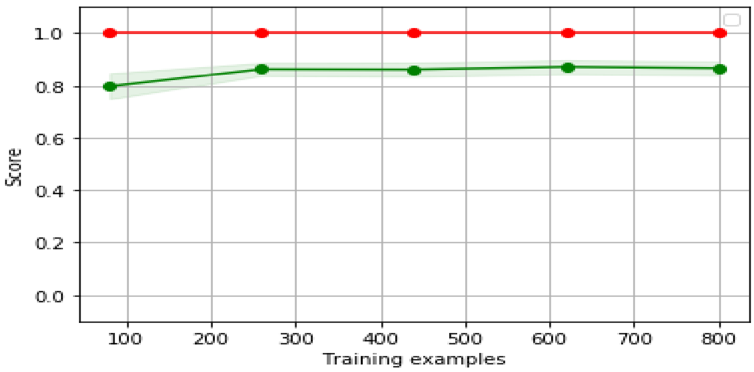


Figure 6.2: Logistic Regression

- Naïve Bayes

Following figure 6.3 represents the learning curve of Naïve Bayes classifier

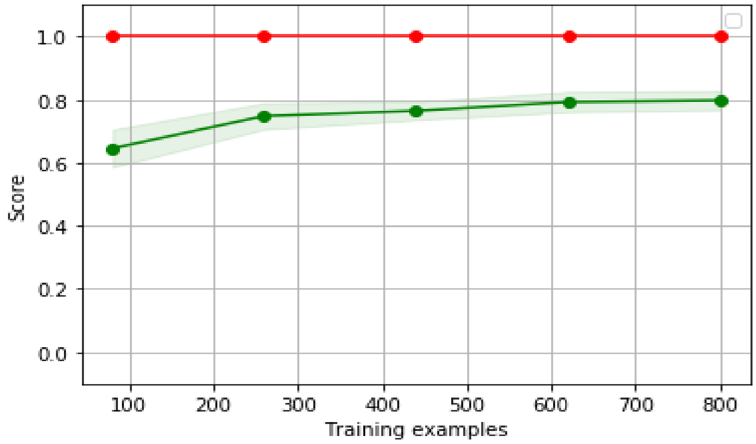


Figure 6.3: Naïve Bayes

- Random Forrest

Following figure 6.4 represents the learning curve of Random Forrect classifier.

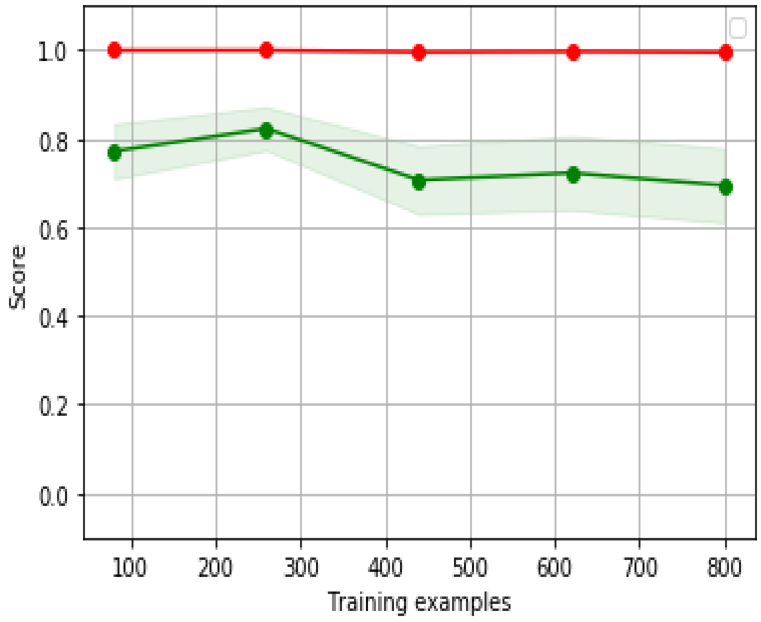


Figure 6.4: Random Forest

- Stochastic Gradient Descent

Following figure 6.5 represents the learning curve of Stochastic Gradient Descent

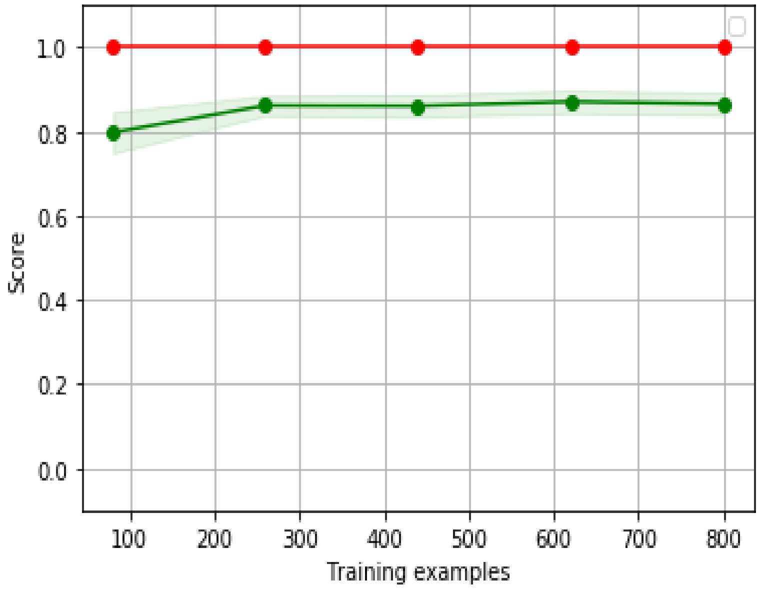
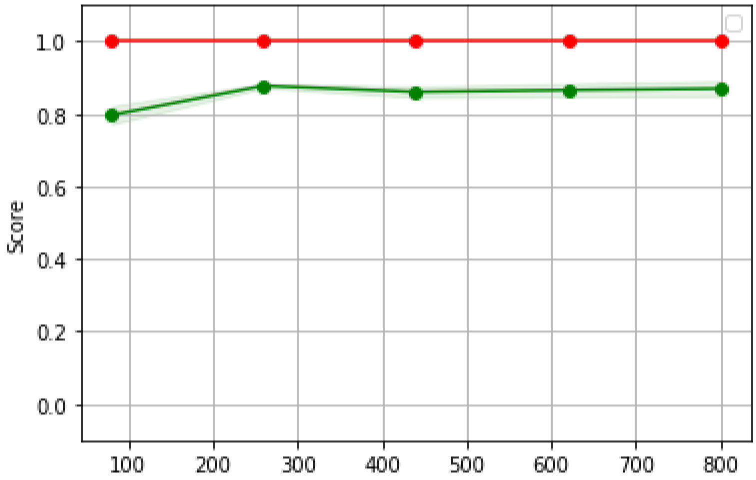


Figure 6.5: Stochastic Gradient Descent

- Support Vector Machine

Following figure 6.6 represents the learning curve of Support Vector Machine



Training example

Figure 6.6 Support Vector Machine

Chapter 7

DISCUSSION OF RESULTS

The outcomes of test results for a variety of user interactions with the application are discussed in the following section of the chapter.

Login Page

Shows the prompt to enter the login information.

Figure 7.1: Login Page

Real News Page

If the entered news URL is correct then real news page will be appeared.

Figure 7.2: Real News Page

Fake News Page

If the entered URL news is fake then Fake News page will be appeared.

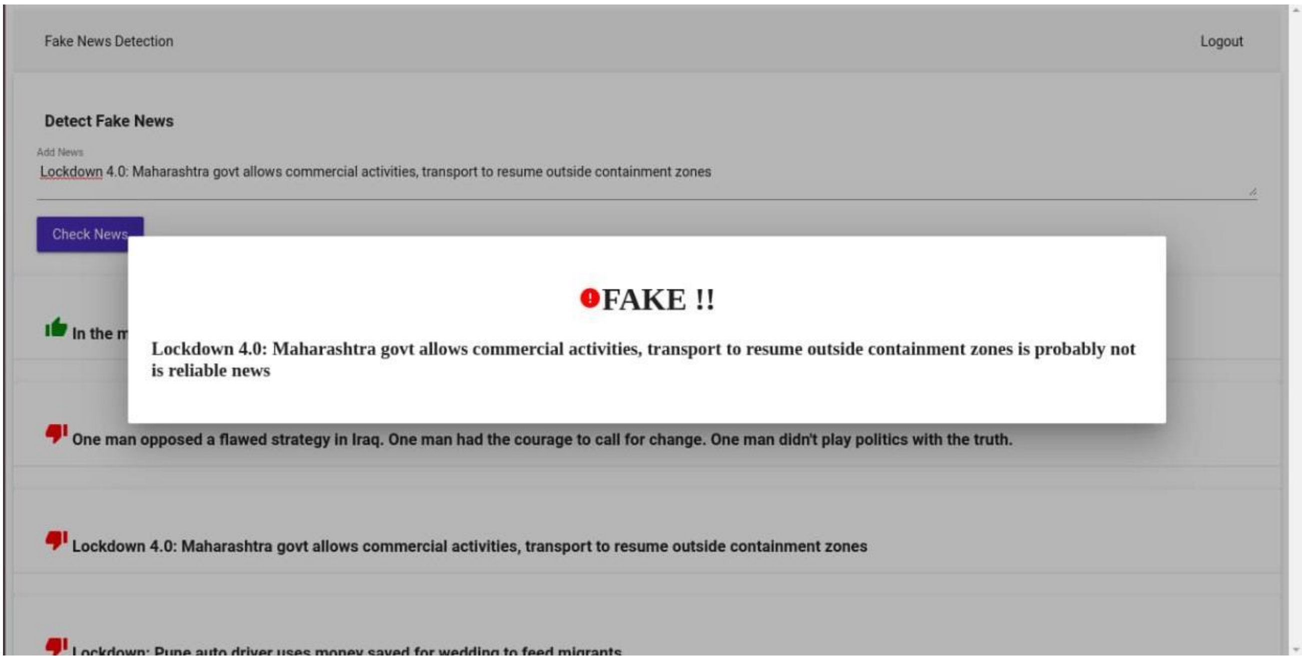


Figure 7.3: Fake News Page

Register new user

New user can register by providing user name password and suitable description.

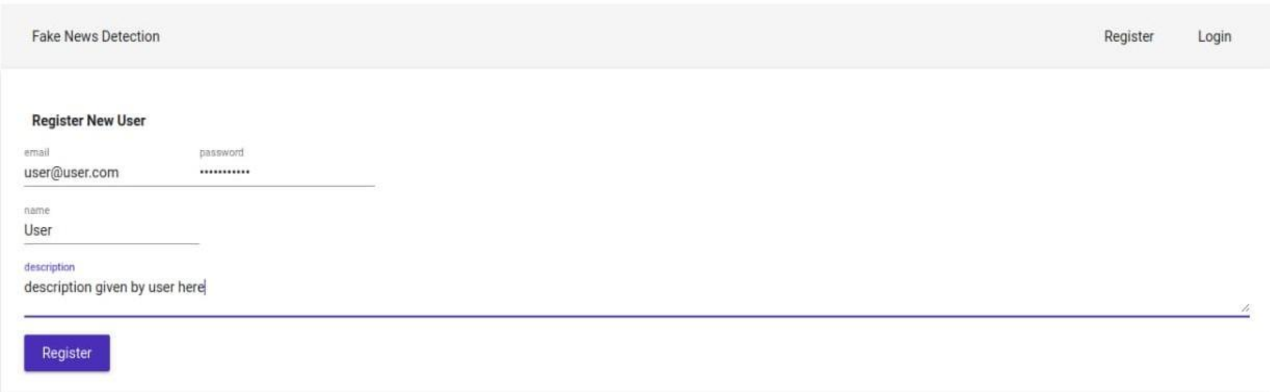


Figure 7.4: Register new user

Detect Fake News Page

Enter News to check if it is fake or real .

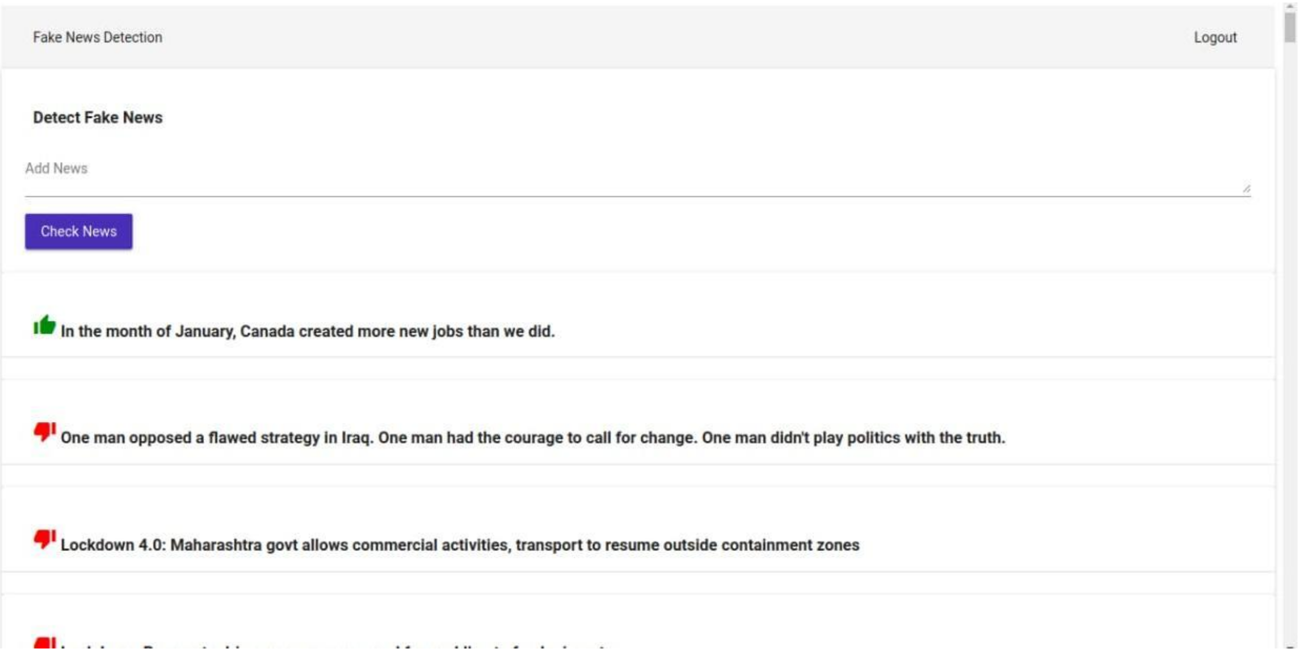


Figure 7.3: Detect Fake News Page

Chapter 8

CONCLUSION AND FUTURE WORK

The System developed was successful in detecting fake news with a high accuracy. The system can be adapted for different media bases , as long as it has a good dataset that the system can use to train with. For the current Dataset Logistic Regression had the best f1 score. GridSearchCV method improves the accuracy of the model for logistic regression about ten percent by selecting the optimal parameters. The optimal parameters for count vectorizer are no lowercasing, two- word phrases not single words, and to only use words that appear at least three times in the article. Context verification adds a significant amount of accuracy to the system.

Context verification can be used in future work to add new features such as stance detection to classify propaganda or articles that are biased. The System can be expanded to incorporate stance detection. The developed system does not consider the qualities like word ordering and context. There is a high probability that two articles that are similar in their word count will be completely different in their meaning. Future work would be focused on using the linguistic cues of the articles to identify fake news in all it’s forms such as click bait, sponsored content, false rumors and so on.

REFERENCES

[1] H. Allcott and M. Gentzkow, *Social media and fake news in the 2016 election*, in National Bureau of Economic Research, Working Paper 23089, January 2017.

[2] S. Feng, R. Banerjee, and Y. Choi, *Syntactic stylometry for deception detection*, Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers - Volume 2, ser. ACL '12. Stroudsburg, PA, USA: Association for Computational Linguistics, 2012, pp. 171–175.

[3] Y. Chen, N. J. Conroy, and V. L. Rubin, *News in an online world: The need for an automatic crap detector*, in Proceedings of the 78th ASIS&T Annual Meeting: Information Science with Impact: Research in and for the Community

[4] Gupta, P. Kumaraguru, C. Castillo, and P. Meier, *Tweetcred: Realtime credibility assessment of content on twitter*, in International Conference on Social Informatics.

[5] V. W. Feng and G. Hirst, *Detecting deceptive opinions with profile compatibility*, in Proceedings of the Sixth International Joint Conference on Natural Language Processing, 2013, pp. 338–346.

[6] D. M. Markowitz and J. T. Hancock, *Linguistic traces of a scientific fraud: The case of diederik stapel*, PloS one, vol. 9, no. 8, p. e105937, 2014.

[7] D. Pisarevskaya, *Deception detection in news reports in the Russian language: Lexics and discourse*, in Proceedings of the 2017 EMNLP Workshop: Natural Language Processing meets Journalism, 2017.

[8] V. L. Rubin, Y. Chen, and N. J. Conroy, *Deception detection for news: Three types of fakes*, in Proceedings of the 78th ASIS&T Annual Meeting: Information Science with Impact: Research in and for the Community, 2015

[9] K. Shu, A. Sliva, S. Wang, J. Tang, and H. Liu, *Fake news detection on social media: A data mining perspective.* Natural Language Processing meets Journalism, 2016.

[10] Seyed Ali Miraftabzadeh, Paul Rad, Kim-Kwang Raymond Cho, *Detecting deceptive opinions with profile compatibility*, 2014

[11] https://opencv.org/

[12] https://keras.io/

[13] https://www.python.org/

[14] https://www.tensorflow.org/

[15] https://www.stackoverflow.com/

[16] https://www.quora.com/

[17] https://github.com/

[18] https://www.w3schools.com/

[19] https://www.pyimagesearch.com/

[20] https://flask.pocoo.org/