Comparative Analysis of Machine Learning Algorithms for Fake News Detection

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Introduction

- In the IoT era, no less than twenty billion devices are connected to the Internet, and the dissemination of information also has become inexpensive, hassle free.
- Moreover, the internet has made it easy to post content without any restrictions.
- The propagation of news (both, legitimate and fake) is inevitable.
- Several research groups have delved into this problem.
- Very few of them have made use of Linguistic properties of the English (natural) language.

Dataset - FakeNewsCorpus

- This dataset contains 9,408,908 labelled news articles. These articles have been scraped from a curated list of 1001 domains from http://www.opensources.co/.
- This corpus is aimed toward training algorithms for detecting fake news.Includes
  - news articles related to a number of ‘tags’, like fake, reliable, satire, bias, etc.
- 60,000 articles were selected randomly from the corpus.
  - Articles had their ‘tag’ attribute either equal to ‘fake’ or ‘reliable’.
- During random sampling from the corpus, it was ensured that articles belonging to both the categories, were represented equally.

Features

- Word Embeddings
  - The text is being represented using word embeddings (Mikolov et al. 2013a). We have used a pre-trained Google word2vec model (Mikolov et al. 2013b) to get the vectorized representations (of dimensions) for the words.
  - represent the text, the mean of Word Embeddings are taken into account.
- Syllable Count - Returns a count of the number of syllables in a particular text.
- Sentence Count - Returns a count of the number of sentences in a particular text.
- Flesch-Kincaid Readability Tests - Represents the ease with which a particular text can be read. It provides the following metrics :-
  - Flesch-Kincaid Grade Level
  - Flesch Reading Ease

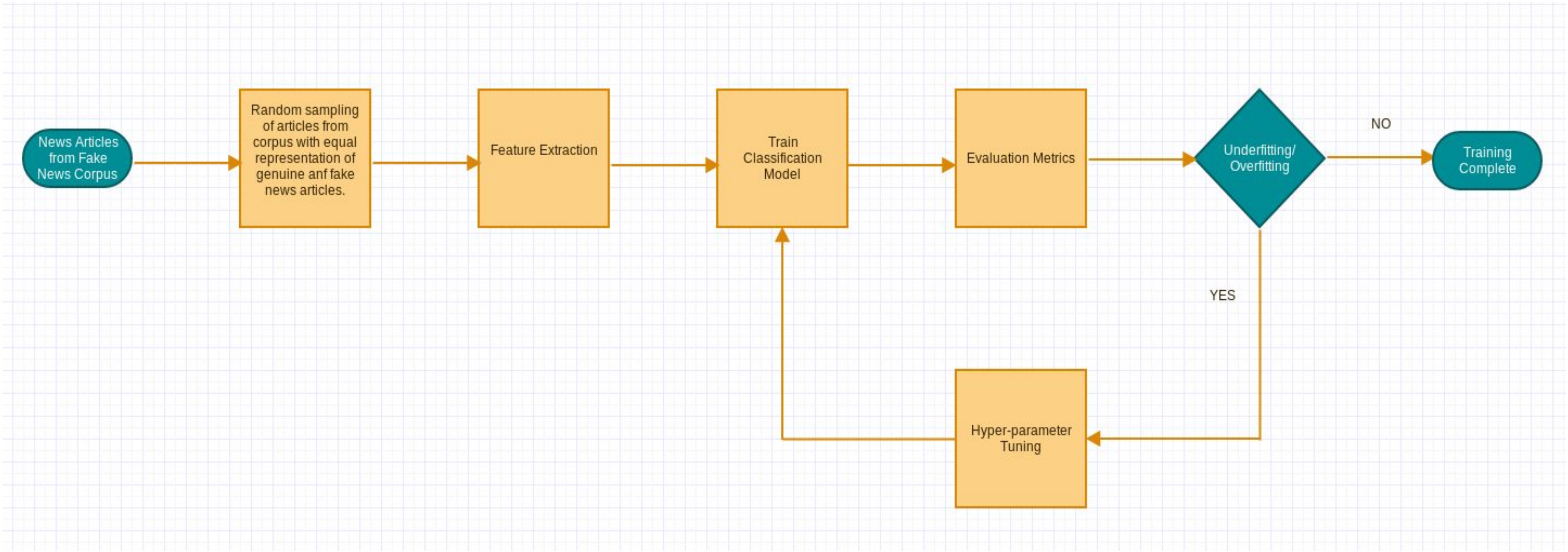
Features Contd.

- Gunning-Fog Index
  - Produces an estimate of the number of years of formal education required by a person to understand a given text <u>on the first reading</u>.
  - Different from Flesch - Kincaid Grade Level.
- Automated Readability Index
  - Gauges the understandability of a text. Given by (Eltorai et al. 2015)
- SMOG Grade
  - Stands for ‘Simple Measure of Gobbledygook’.
  - Returns a measure of readability similar to the Gunning Fog Index that estimates the years of education needed to understand a piece of writing.
- Linsear Write Score
  - This score is designed to calculate the readability of technical writing.

Features Contd.

- Dale Chall Readability Score
  - Provides a numeric gauge of the difficulty of comprehension that readers face while reading a given text.
  - Formula given by (Dubay 2004)
- Coleman-Liau Index
  - Used to gauge the understandability of a text.
  - Given by (Karmakar and Zhu 2010).
- Part-of-Speech (POS) Tagging
  - We restrict the POS features to <u>Nouns, Adjectives, Verbs and Adverbs</u> since they are most informative and generic unlike other parts of speech, such as Conjunctions and Prepositions.

Workflow


News Articles from Fake News Corpus
Random sampling of articles from corpus with equal representation of genuine anf fake news articles.
Feature Extraction
Train Classification Model
Evaluation Metrics
Underfitting/ Overfitting
NO
Training Complete
YES
Hyper-parameter Tuning

Models Compared

- Logistic Regression
- Random Forest
- Support Vector Machines
- Artificial Neural Network
- LSTM (Long Short-Term Memory)
  - Allows us to implicitly capture temporal structure in the sentence.
- Bi-directional LSTM (Long Short-Term Memory)
  - Provides capacity to process of sentence in both forward and backward direction.

Models Compared

- GRU (Gated Recurrent Unit)
  - Another instance from family of RNNs with comparable performance to LSTMs but with lesser parameters.
- Bi-directional GRU (Gated Recurrent Unit)
  - To provide bi-directional information processing capacity

- Our work demonstrates a comparative analysis of the results obtained by setting the dimensions of word embeddings as 50, 100 and 200.

Results

Table 1: Evaluation Metrics of Classification Algorithms

Algorithm	Accuracy	Sensitivity	Specificity	Precision
Logistic Regression	0.9444	0.9397	0.9492	0.9493
Random Forest	0.9481	0.9302	0.9659	0.9645
SVM	0.8947	0.8836	0.9045	0.9026
ANN	0.9574	0.8636	0.9454	0.9416
LSTM(50-D)	0.9721	0.9866	0.9574	0.9587
Bi-LSTM(50-D)	0.9796	0.9895	0.9774	0.9777
LSTM(100-D)	0.9723	0.9682	0.97627	0.97620
Bi-LSTM(100-D)	0.9765	0.9875	0.9654	0.9663
LSTM(200-D)	0.9669	0.9945	0.9388	0.9429
Bi-LSTM(200-D)	0.9828	0.9945	0.9388	0.9429
GRU(50-D)	0.9312	0.9895	0.9249	0.9347
Bi-GRU(50-D)	0.9290	0.9857	0.9380	0.9355
GRU(100-D)	0.9225	0.9790	0.9372	0.9343
Bi-GRU(100-D)	0.9232	0.9744	0.9315	0.9389
GRU(200-D)	0.9222	0.9667	0.9318	0.9451
Bi-GRU(200-D)	0.9258	0.9704	0.9446	0.9457

Conclusion

- In this paper, we proposed a deep learning solution to the problem and have presented a comparative analysis of how standard machine learning algorithms fare against recurrent neural networks.
- We observed that Bi-LSTM performed better than other algorithms with reasonable performance gains as can be deduced from the values of evaluation metrics obtained.