Fake News Detection Using Ranking Neural Networks

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ABSTRACT

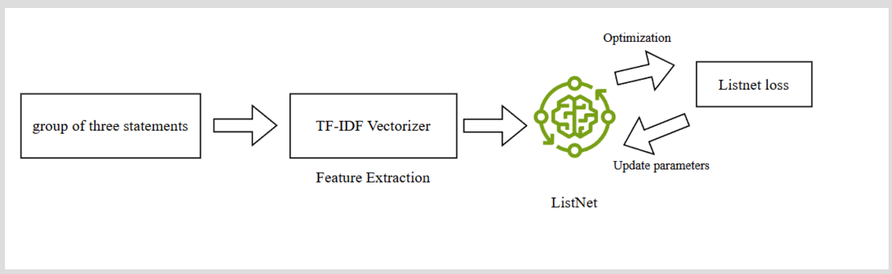
Traditional fake news detection predominantly relies on binary classification, which categorizes news as either "True" or "False." However, such an approach often oversimplifies the inherent nuances and varying degrees of credibility found in real-world information. This research proposes an alternative methodology by framing fake news detection as a Learning to Rank (LTR) problem. Using the ListNet algorithm **[1]**, the model is trained to process news items in triplets (sets of three) to effectively learn and predict their relative scores. This transition from binary classification to relative ranking allows for a more granular assessment of information. The experimental results demonstrate that the proposed model successfully generates ranking scores that accurately reflect the hierarchy of credibility among news articles.

INTRODUCTION

In the current era of rapid technological advancement, particularly the proliferation of social media platforms, the volume of accessible information has reached unprecedented levels. Consequently, the public is increasingly exposed to disinformation and 'fake news' at a frequency far greater than in previous decades. While significant research has been dedicated to the field of fake news detection, the majority of existing literature primarily treats the problem as a binary classification. However, veracity in information often exists on a spectrum rather than a dichotomy. This research, therefore, proposes an alternative approach by focusing on Learning to Rank (LTR) **[2]**. By prioritizing information based on relative reliability, this work aims to provide a more nuanced and practical framework for evaluating information credibility in complex digital environments.

METHODOLOGY

Data Pre-processing (from Politifact Dataset)



Triplet Construction

Group statement items into sets of three (triplets) to capture relative credibility relationships.

Feature Extraction: TF-IDF Vetorizer

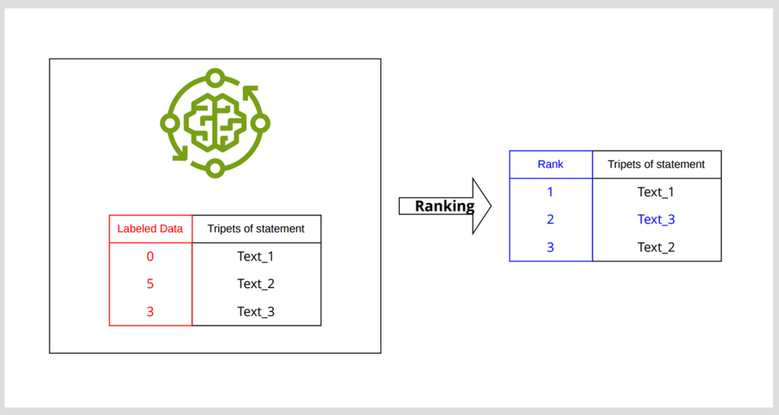
Convert statements into numerical vectors using TF-IDF (5,000 features).

ListNet Architecture

A Multi-Layer Perceptron (MLP) model optimized with a Listnet loss function.

Learning Process

The model learns by comparing the probability distribution of predicted scores against the actual labels **(0-5 veracity levels)**



RESULT

Global test: NDCG(Normalized Discounted Cumulative Gain)

NDCG is a position-aware metric that evaluates ranking effectiveness by penalizing relevant items placed lower in the list **[3]**.
It specifically measures the model's ability to prioritize the most truthful news at the top of the rankings, where a value closer to 1 indicates near-perfect ranking precision.

Round	NDCG@5
Round 1	0.3139
Round 2	0.5995
Round 3	0.7876
Round 4	0.6245
Round 5	0.8059
Average	0.6263 ± 0.1770

The model significantly learns the credibility standards of news across multiple levels (6 levels), achieving an average NDCG@5 of 0.6263. This demonstrates that the Listwise learning approach is highly effective in filtering the 'most truthful' news into the top rankings, performing substantially better than random selection.

Local test

Base line: the model achieved a perfect ranking accuracy of 50.20% for triplets. This performance is three times higher than the random probability baseline of 16.67%.
Majority vote: the test results indicate that the model exhibits high decision stability. Despite varying the comparison pairs with different news.

CONCLUSION & FUTURE WORKS

The ListNet model effectively ranks news veracity with a 0.6263 NDCG@5, significantly outperforming random baselines in unseen triplet tests and demonstrating high decision stability via majority voting. To further enhance performance, future work will transition from TF-IDF to transformer-based architectures like BERT **[4]** to better capture deep semantic contexts. Additionally, expanding the dataset and fine-tuning hyperparameters could reduce performance variance and improve overall ranking robustness.

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