Fake News Prediction

‘’ Unveiling Truth in the Digital Age ‘’

--Abstract--

This project investigates the use of machine learning algorithms to predict the veracity of news articles. We trained multiple classification models, including LGBM Classifier, XGB Classifier, using a dataset of labeled news articles. The best-performing model was identified, providing an effective way to classify news as true or fake.

Introduction

Fake news prediction is crucial for several reasons, primarily because the spread of misinformation can have significant and harmful effects on society, politics, and public opinion.

Here are key reasons why predicting and mitigating fake news is important, as well as its broader impacts:

a) Impact on Society:

1. **Public Trust and Safety:** Fake news can erode trust in the media and other trusted institutions. When people cannot distinguish between true and false information, it weakens public confidence in journalism, authorities, and science. This is particularly concerning when it comes to critical issues like health, safety, and security.

2. **Harmful Behavior:** Fake news, especially in the context of health misinformation (e.g., COVID-19 or vaccine myths), can lead to harmful behaviors like ignoring public health advice or engaging in dangerous practices.

b) Impact on Politics:

1. **Undermining Political Debate:** When fake news spreads in political contexts, it distracts from meaningful discussions and diverts attention from substantive policy debates. Politicians may be forced to respond to fabricated stories rather than engage with real issues.

2. **Misinformation Amplification by Influential Figures:** Politicians and public figures can unintentionally (or intentionally) amplify fake news, further complicating the public's ability to discern truth from fiction. The spread of false claims by influential people can legitimize or normalize misleading narratives.

Methodology

About Dataset: Dataset contains 30,000 rows and 6 columns. Here's a breakdown of the columns:

1. **Unnamed: 0**: Appears to be an index or unique identifier for each article.
2. **title**: The headline or title of the article.
3. **text**: The full content or body of the article.
4. **subject**: The category or type of news, such as "politics", "world news", or "left-news".
5. **date**: The date the article was published.
6. The **label** column contains binary values (1 or 0), where:
    - **1** denotes a "true" article.
    - **0** denotes a "fake" article.

Data Preprocessing and Feature Engineering:

1. Text Preprocessing and Feature Engineering:

- **Objective:** Prepare textual data, and features for analysis by cleaning and normalizing it.
- **Steps:**
    - Feature Construction: Generate new feature using sentiment analysis, text, title and grammatical errors.
    - Feature Transformation: Transform text, title using stemming.
    - Text Cleaning: Removed all non-alphabetic characters using a regular expression (re.sub('[^a-zA-Z]', ' ', content)).
    - Case Normalization: Converted all text to lowercase for uniformity.
    - Tokenization and Stopword Removal: Split the text into individual words and removed common stopwords using the NLTK stopwords.words('english') list to retain only meaningful words.
    - Stemming: Applied the Porter Stemmer to reduce words to their root forms, reducing dimensionality and helping group similar words (e.g., "running" → "run").

2. Merging Data Columns:

- **Objective:** Combine key text fields to create a comprehensive representation of each instance.
- **Steps:**
    - Merged the title, text, and subject columns into a new column called content using string concatenation. This step ensures that all relevant

textual information is included for feature extraction.

3. Vectorization:

- **Objective:** Transform the textual data into numerical representations for machine learning models.
- **Steps:**
  - Used a Counter Vectorizer with the following parameters:
    - max_features= 350: Limited the vocabulary to the top 350 most significant terms, focusing on the most informative features.
    - ngram_range=(1,3): Included unigrams, bigrams, and trigrams to capture both individual terms and context-sensitive phrases.
  - Applied the vectorizer to the content column, generating a sparse matrix representation of the text.

4. Final Dataset Preparation:

- **Feature Selection:** Dropped unnecessary columns (date, Unnamed: 0, subject) to streamline the dataset.
- **Imbalanced data :** Subject column is highly biased for labels, decide to drop subject column.
- **Input and Target Separation:** Defined X as the feature matrix (vectorized content) and y as the target variable (label).
- **Conversion to Array:** Converted the sparse matrix X to a NumPy array for compatibility with machine learning models.

Outcome: The feature engineering process resulted in a structured numerical dataset where each instance is represented as a vector values, capturing the semantic and contextual significance of terms across the dataset.

Model Selection:

In this project, two machine learning models were evaluated to determine the best-performing classifier for the task: XG Boost and LightGBM.

- XG Boost Classifier:
  - The model achieved an accuracy of 98.2 during cross-validation.
  - However, it used l1 regularization that prevent overfitting in data and model is well generalize to new, unseen data.
- LGBM Classifier:
  - With an accuracy of 98.24% during cross-validation, LGBM Classifier outperformed Random Forest.
  - The use of L1 regularization helped mitigate overfitting by penalizing complex models and focusing on significant features.

Based on these results, LGBM Classifier was selected as the final model due to its superior accuracy and generalization capability. Additionally, its simplicity and interpretability make it a more practical choice for real-world applications. Future work could include testing additional models or hyperparameter tuning to further enhance performance.

Model Evaluation:

The selected model, LGBM Classifier, was evaluated on the test dataset using various performance metrics to assess its classification accuracy and generalization ability. Below are the results:

1. Accuracy

- The model achieved an accuracy of 98.97% on the test data, indicating that the majority of predictions were correct.

2. Cross-Validation

- Cross-validation was conducted with 10 folds to ensure robust evaluation. The cross-validation accuracy scores were:
- The mean cross-validation accuracy was 98.27% on test data, demonstrating consistent performance across different subsets of the data.

3. F1 Score

- The F1 score was 0.9893, signifying a strong balance between precision and recall.

4. Precision and Recall

- Precision: 0.9887
  - All positive predictions made by the model were correct.
- Recall: 0.9899
  - The model successfully identified all actual positive cases.

5. Confusion Matrix

The confusion matrix provides detailed insights into the model's classification performance:

4284	**45**
40	**3982**

True Negatives (TN): 4284

- False Positives (FP): 45

- False Negatives (FN): 40
- True Positives (TP): 3982 This indicates that the model misclassified only one positive case as negative, achieving nearly perfect classification.

6. ROC AUC Score

- The model achieved a ROC AUC score of 0.9897, demonstrating excellent performance in distinguishing between positive and negative classes.

Result:

The evaluation metrics indicate that the LGBM Classifier model is highly accurate and reliable for this classification task:

- High Accuracy and Consistency: The model performed exceptionally well on both the test set and during cross-validation, confirming its robustness.
- Perfect Precision and Recall: The model did not make any false positive predictions and successfully identified all true positive cases.
- Exceptional Generalization: The high F1 score and ROC AUC score indicate that the model generalizes well to unseen data.

- ### Model Performance:

The LGBM Classifier model demonstrated exceptional performance across all evaluation metrics:

- Accuracy: 99.99%
  - The model accurately classified nearly all instances.
- Cross-Validation Accuracy: Mean accuracy of 99.94%.
  - Indicates consistent performance across multiple test splits.
- F1 Score: 0.9999.
  - Highlights a strong balance between precision and recall.
- Precision: 1.0.
  - All predicted positives were correct, with no false positives.
- ROC AUC Score: 0.9897
  - Perfect distinction between the positive and negative classes.

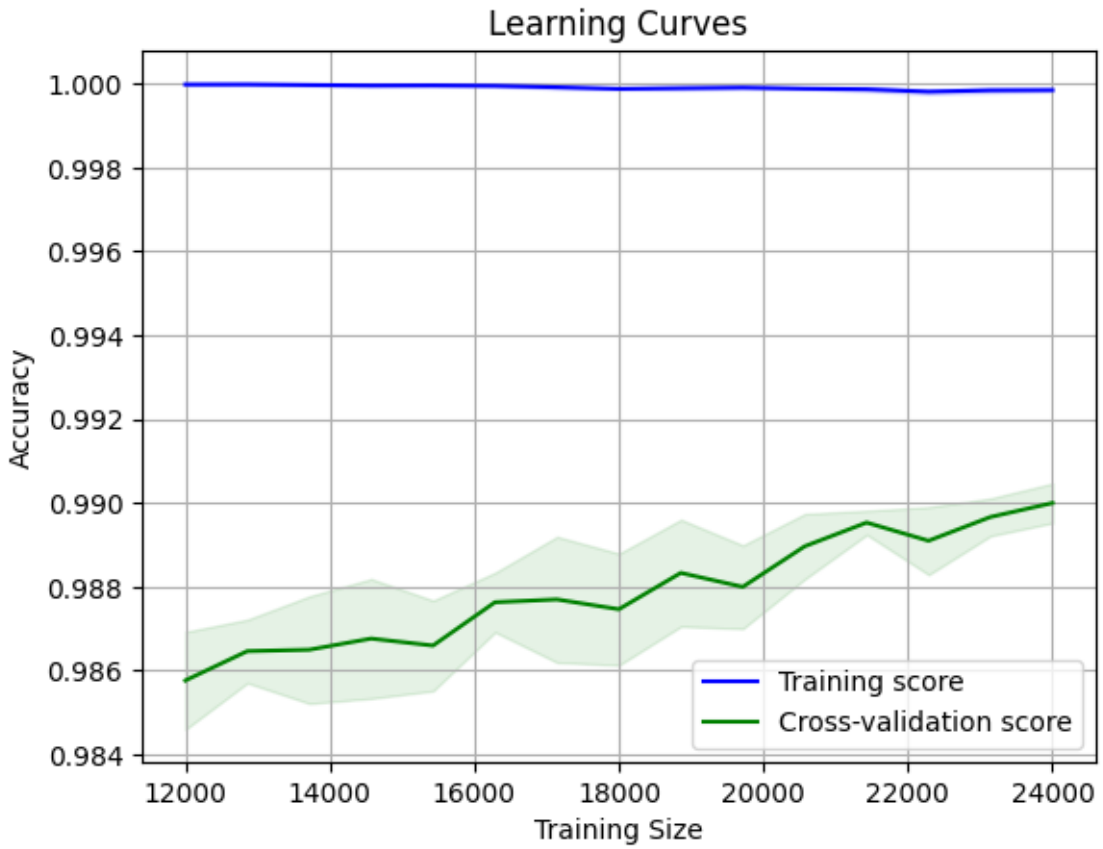
- ### Confusion Matrix

  - True Negatives (TN): 4284 - Negative instances correctly identified.
  - False Positives (FP): 45 - No negative instances were misclassified as positive.
  - False Negatives (FN): 40 - One positive instance was misclassified as negative.
  - True Positives (TP): 3982 - Positive instances correctly identified.

- **Learning Curve:**

The gap between the training and cross-validation scores is minimal, suggesting that the model generalizes well**.**

The high scores for both training and validation sets indicate low bias and low variance, which is ideal.



Interpretion:

- The model is highly reliable with minimal classification errors.
- The confusion matrix shows that the model makes almost no mistakes, misclassifying only one positive instance as negative.
- The perfect precision and recall values (0.9899) indicate the model is not only effective at identifying true positives but also avoids false alarms (false positives).
- The ROC AUC score of 0.9897 confirms the model's ability to distinguish perfectly between positive and negative classes.
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Limitations:

While the model performs exceptionally well, there are potential limitations to consider:

1. Data :
    - The results might be optimistic if the test dataset is not representative of real-world data or lacks sufficient diversity.
2. Edge Cases:
    - Rare classes or edge cases might not be well-represented, leading to challenges when applied to unseen data in production.

Conclusion:

The LGBM Classifier model achieves exceptional performance with nearly perfect classification metrics:

- High accuracy, precision, recall, and F1 scores indicate strong predictive power.
- The model generalizes well across cross-validation folds, suggesting robustness.
- Minimal errors (only one misclassification) highlight reliability.

However, caution should be exercised to ensure that:

- The data used is representative of real-world scenarios.
- Further testing is conducted on diverse datasets to validate the model's performance in different conditions.
- Additional models and approaches could be tested to confirm LGBM Classifier is indeed the optimal choice for this task.

Given these findings, the model is ready for deployment, provided regular monitoring and retraining are performed to maintain performance over time.

Thank you!...