Deciphering Sentiments: Machine Learning Insights into Book Reviews

Capstone Project: CIND820

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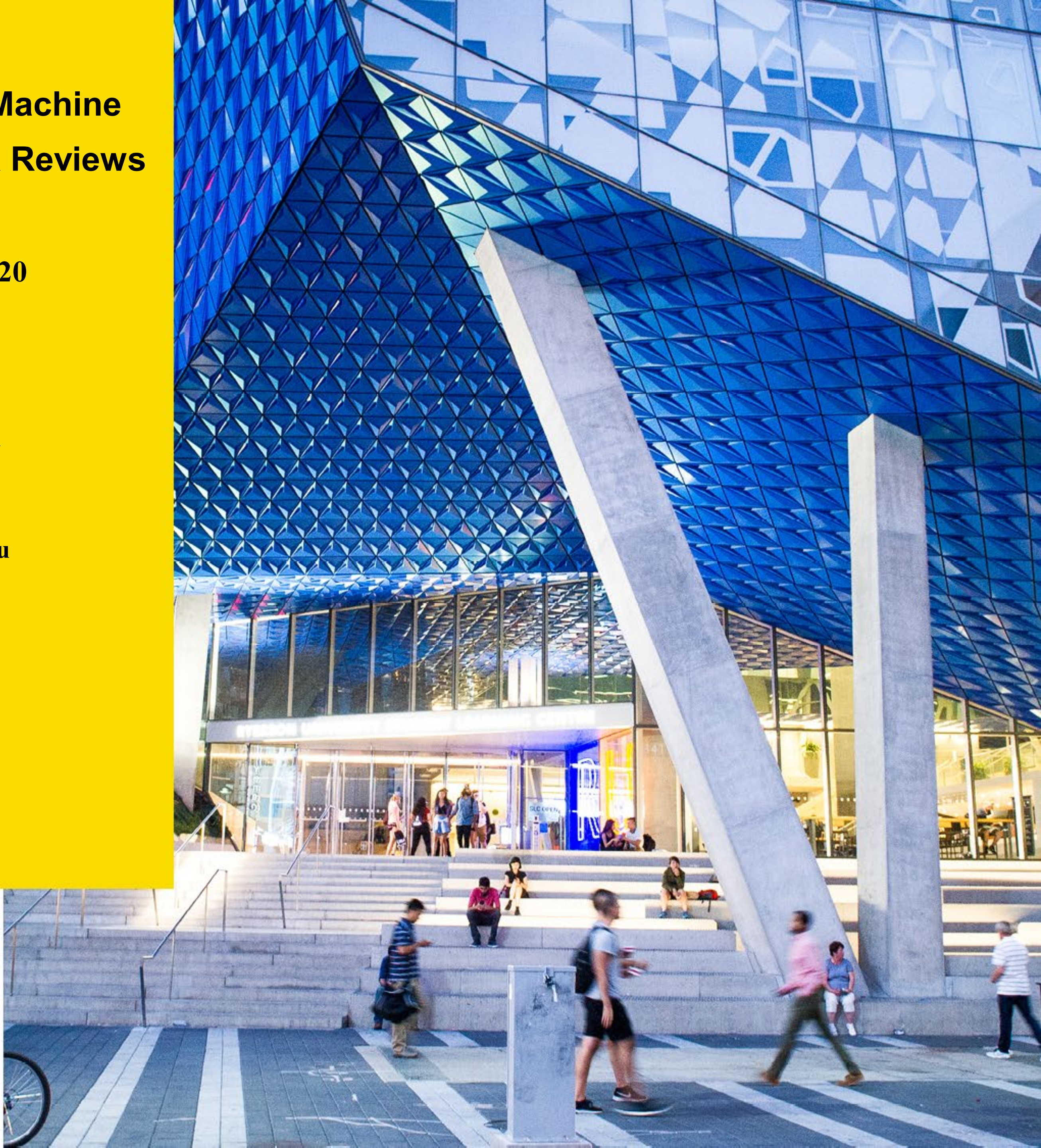

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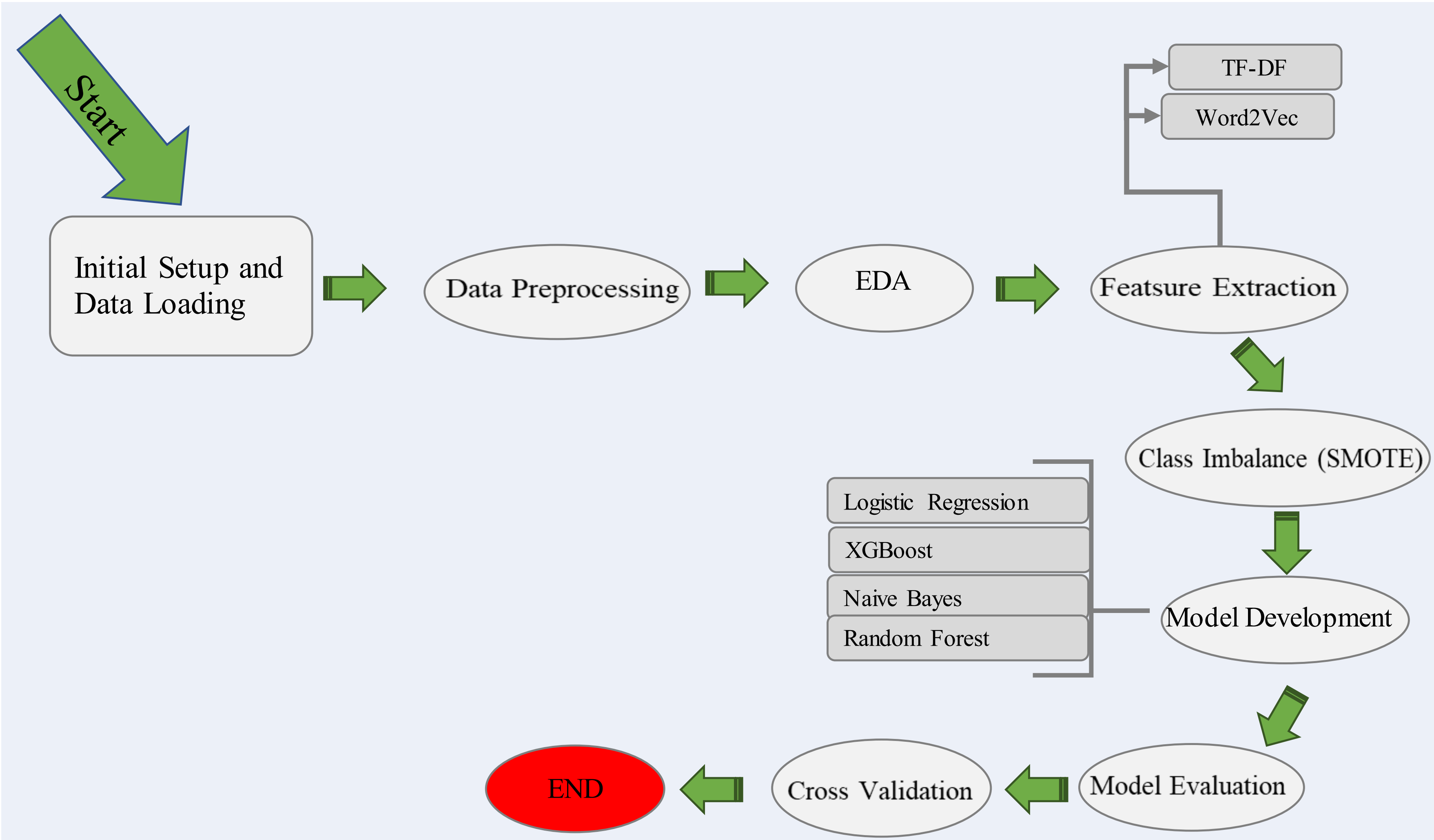
Project Objectives & Research Questions

- Objective: To understand sentiment distribution within book reviews, focusing on genre/author impact and feature extraction methods' efficacy.
- RQ1: What is the overall sentiment distribution in book reviews?
- RQ2: How do specific genres or authors influence sentiment tendencies?
- RQ3: How effective are TF-IDF and Word2Vec in enhancing sentiment analysis accuracy?

Methodology Overview

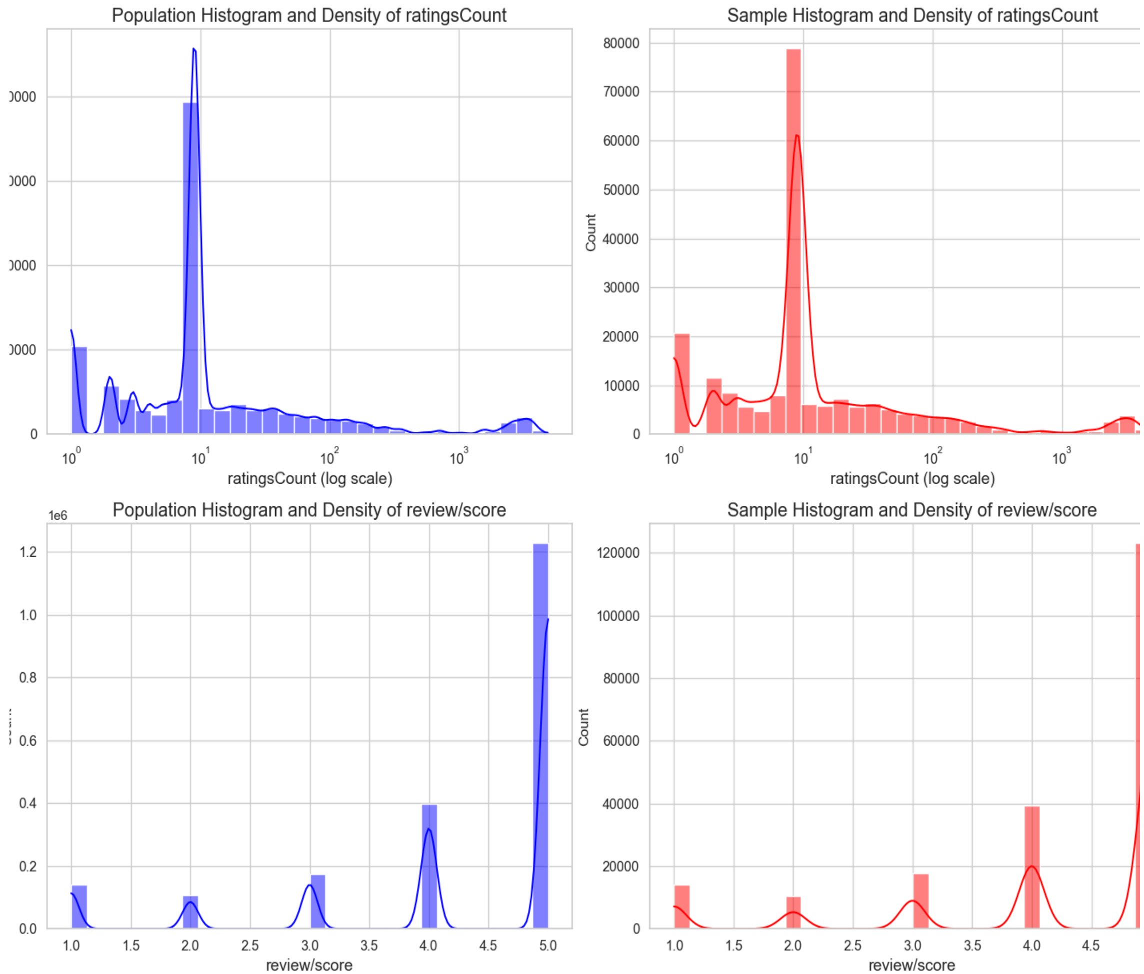


Data Description and Sampling Necessity

- **Dataset Overview**: Utilized two CSV files, each approximately 2.83 GB, encompassing 300,000 rows and 19 combined attributes after merging.
- **Sampling for Analysis**: Due to computational limits, a 10% stratified sample was extracted to maintain sentiment representation.
- **Core Attributes**: The research focused on eight key attributes including Title, Description, Authors, Categories, RatingsCount, Review/Score, Review/Summary, and Review/Text.
- **Statistical Summary**: RatingsCount ranged from 1 to 4,895 with most reviews scoring around 4.22, reflecting positive skewness.
- **Preprocessing Necessity**: Handled missing values, especially in RatingsCount, and removed duplicates to clean data for analysis.

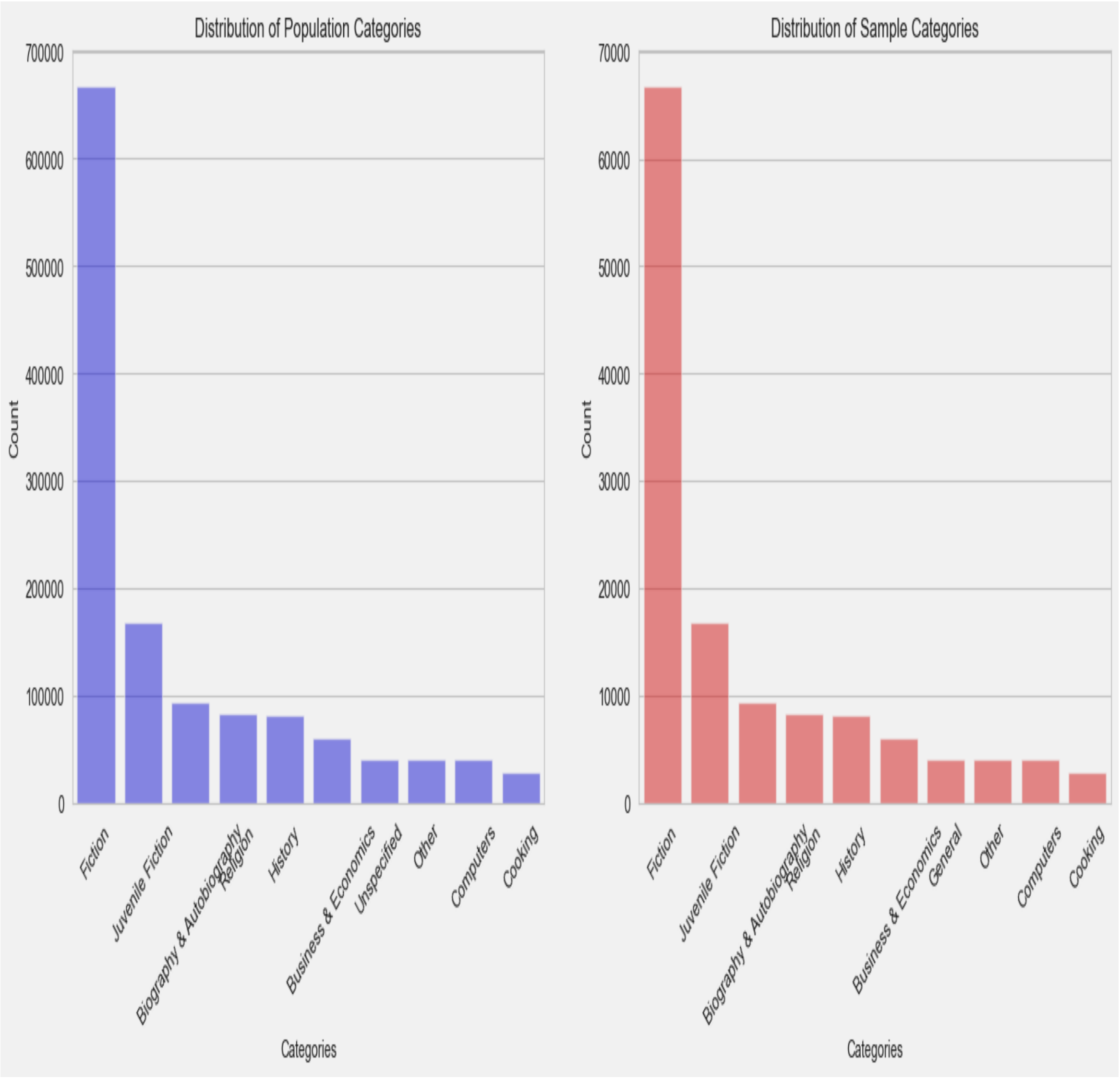
EDA

- The sample used for analysis mirrors the overall population, ensuring it's a valid representation for study.
- A logarithmic scale was used for the 'ratingsCount' to manage the wide range of data better.
- The sample and the population data showed a right skew in 'ratingsCount' and a left skew in 'review/score'.
- The density plots created for these attributes provide a clear visualization of the central trends.
- The sample’s consistency in distribution shapes and skewness confirms a robust sampling methodology which is critical for machine learning accuracy



EDA

- The sample matches the overall category distribution of the full dataset.
- Fiction is the most common category, well-represented in the sample.
- Smaller categories are proportionally included, showing a well-rounded sample.
- The sampling approach ensures an unbiased analysis, even with computational limit



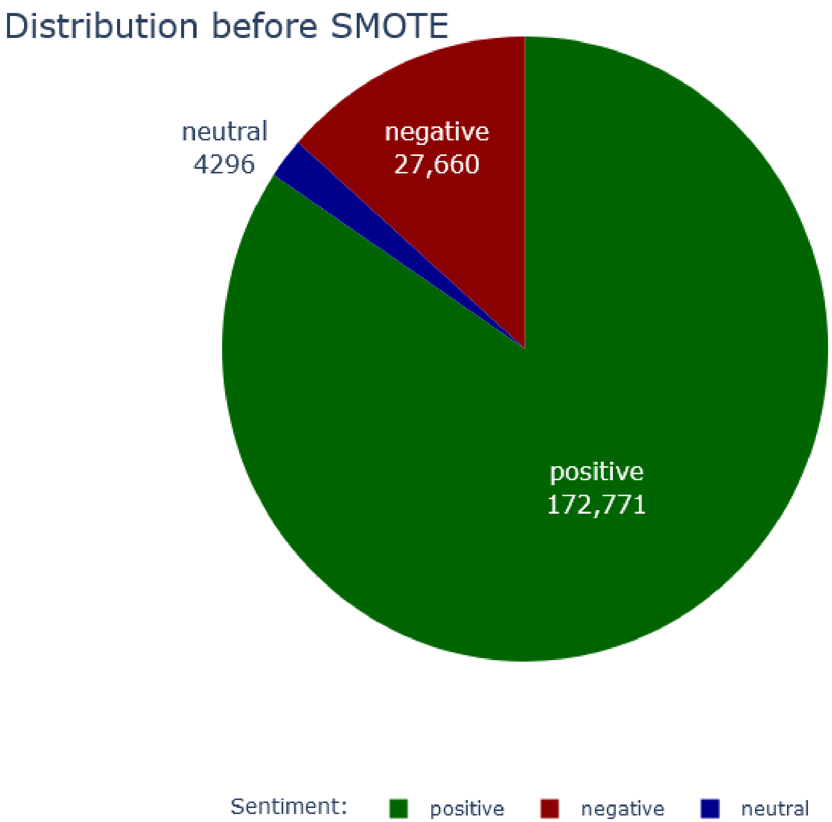
Feature Extraction Techniques

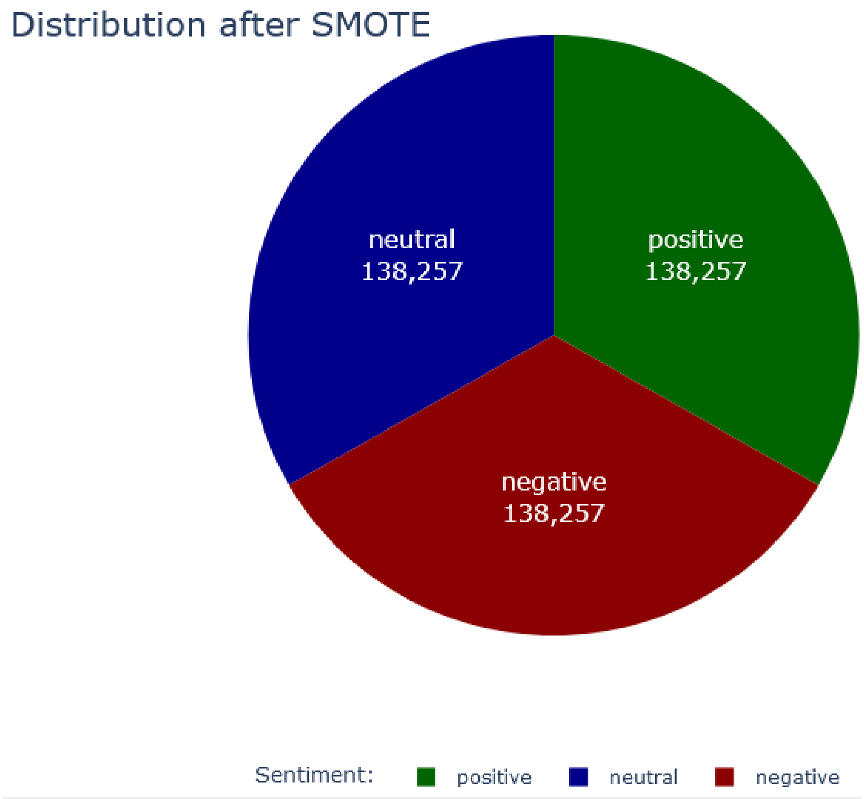
-Feature extraction transforms unstructured text into a structured form that machine learning models can process effectively.

-TF-IDF (Term Frequency-Inverse Document Frequency):
Highlights key terms critical to understanding sentiments within texts, aiding in the differentiation of sentiments by their importance relative to the whole document collection.

-Word2Vec: Goes beyond mere term frequency to capture contextual nuances and semantic relationships between words, thereby refining the sentiment classification process.

Class Imbalance





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Assessing Model Performance with TF-IDF and Word2Vec Features

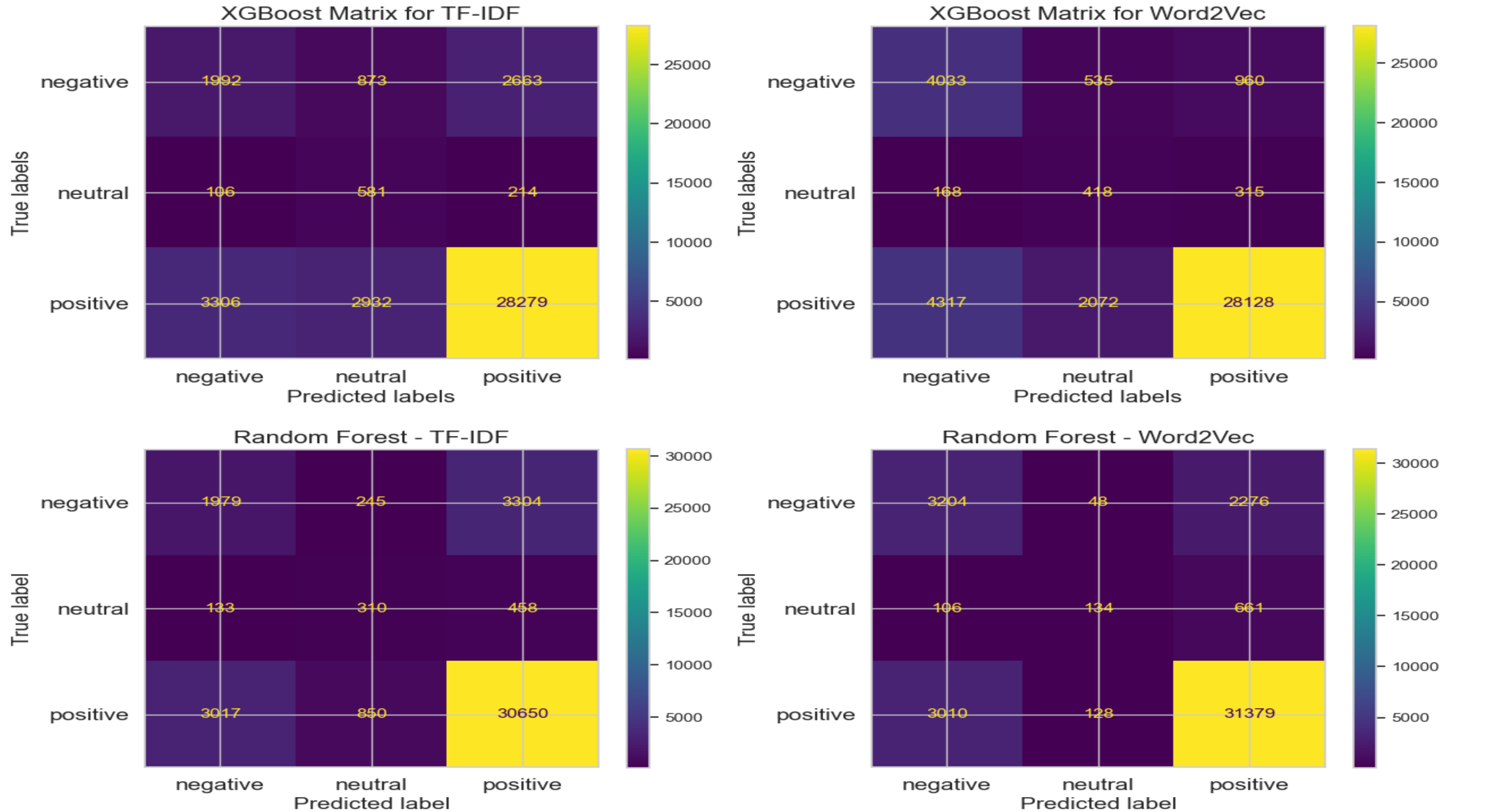
Table 1-Classification algorithms with TF-IDF

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.676476	0.83	0.68	0.73
Naive Bayes	0.59996	0.84	0.60	0.68
Random Forest	**0.804449**	0.81	0.80	0.81
XGBoost	0.75348	0.80	0.75	0.78

Table 2-Classification algorithms with Word2Vec

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.710716	0.88	0.71	0.77
Naive Bayes	0.499316	0.82	0.50	0.58
Random Forest	**0.847872**	0.85	0.85	0.85
XGBoost	0.796317	0.87	0.80	0.82

Model Comparison: Confusion Matrices for TF-IDF and Word2Vec



Confusion matrices reveal that Random Forest and XGBoost models, particularly with Word2Vec features, demonstrate higher accuracy and balanced classification across different sentiment classes.

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Cross Validation

Cross Validation Table 3

Algorithm	Mean Accuracy score	Standard Deviation
Random Forest TF-IDF	92.17%	2.38%
Random Fores Word2Vec	94.94%	0.37%
XGBoost TF-IDF	75.23%	0.35%
XGBoost Word2Vec	89.41%	0.10%

Conclusions

1. **Sentiment Distribution**: "Analysis revealed a predominantly positive sentiment across book reviews, with genre and authorship noticeably influencing sentiment tendencies."
2. **Feature Extraction Success**: "Both TF-IDF and Word2Vec significantly improved sentiment analysis accuracy. Word2Vec, in particular, was instrumental in enhancing model precision."
3. **Model Performance**: "Random Forest and XGBoost models, especially when using Word2Vec features, emerged as top performers in accurately classifying sentiments."

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Limitations & Recommendations

•**Limitations**: Our study faced computational constraints, limiting the depth of analysis. Processing slang and informal language also posed challenges due to the nuances of language use.

•**Recommendations**:

- Future research should leverage high-performance computing resources to expand dataset analysis capabilities."
- Incorporate advanced linguistic models and updated NLP techniques to improve accuracy in processing diverse language expressions.
- Explore sophisticated preprocessing and feature extraction methods, such as BERT or GPT, to further refine sentiment analysis insights.

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Thank You

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