Sarcasm Detector Natural Language Processing



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CONTENT



INTRODUCTION

Project is about detecting sarcasm in text, which is tricky because sarcasm can be subtle. The goal is to build a model that can spot sarcastic comments, especially in social media posts.

THEORETICAL PART

We look at the basics of natural language processing and machine learning, and how they can help us understand sarcasm in text.

PRACTICAL PART

We clean the data and build a machine learning model using Python to tell sarcastic sentences apart from regular ones.



The model was tested on real data and demonstrated a strong ability to detect sarcasm, providing valuable insights for future enhancements.



SUMMARY

This project shows how NLP and machine learning can work together to detect sarcasm, and points to ways we could improve in the future.

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Natural Language Processino

network approaches.

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Abstract

Detecting sarcasm in text is one of the more difficult challenges in Natural Language Processing. In this project, we aimed to develop and compare several machine learning and deep learning models for sarcasm detection, using a balanced dataset from Kaggle.

Our workflow included data exploration,

preprocessing, feature extraction, model training, and evaluation. Transformer-based models, such as RoBERTa, demonstrated significantly better performance than traditional and recurrent neural

Introduction

Aim

The main goal of our project is to design and evaluate different models capable of identifying sarcasm in text data, thereby enhancing the automated understanding of nuanced human language in digital communication.

Scope

This project covers several stages: acquiring a public sarcasm detection dataset, performing text preprocessing, building models using supervised learning, neural networks, and transformer-based methods, and finally evaluating these models using appropriate performance metrics.

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Methodology

We implemented this project in Python using Jupyter Notebook. The libraries we used include Pandas, NLTK, Scikit-learn, TensorFlow/Keras, and Hugging Face Transformers. The workflow involved data cleaning, feature extraction, model training, and thorough evaluation using crossvalidation and classification metrics.

I. Theoretical Part



Supervised Learning Algorithms

We applied two supervised algorithms:

- linear patterns.



Neural Network Models

78 %

Transformer-Based Models

RoBERTa (A Robustly Optimized BERT Pretraining Approach): A state-of-the-art pretrained transformer model that excels in understanding the context and nuances of natural language.

Logistic Regression: A simple, interpretable linear classifier with fast training time.
Gradient Boosting: An ensemble learning technique that combines multiple weak learners to build a more accurate and robust model, especially for handling non-

LSTM (Long Short-Term Memory): A type of recurrent neural network effective for sequential data and capable of capturing long-term dependencies in text.
GRU (Gated Recurrent Unit): A simplified variant of LSTM, offering similar advantages with fewer parameters and faster training.



We used a dataset sourced from Kaggle, containing approximately 1.3 million text samples labeled as sarcastic or non-sarcastic. The data was provided in CSV format and was already balanced between both classes.

Data Preprocessing

Text preprocessing included several steps: Removing URLs, punctuation, numbers, and stopwords Applying tokenization and lemmatization Conducting exploratory analysis to understand class distribution and text characteristics

Model Implementation

 Logistic Regression with TF-**IDF** vectorization

Gradient Boosting Classifier

An example:

from sklearn.pipeline import Pipeline from sklearn.feature extraction.text import TfidfVectorizer from sklearn.linear model import LogisticRegression

pipeline = Pipeline([('tfidf', TfidfVectorizer(max features=10000, ngram range=(1,2))), ('clf', LogisticRegression(max iter=100))]) pipeline.fit(X train, y train)

- LSTM and GRU neural networks using TensorFlow/Keras RoBERTa transformer model using
- Hugging Face Transformers



Model Evaluation



These metrics help us understand how accurately the model detects sarcasm and balances between false positives and false negatives.



Summary

GOALS ACHIEVED

sarcasm in text.

BEST MODEL

Transformer-based models (especially RoBERTa) gave the best results.

OTHER MODELS

FUTURE WORK

- overfitting issues
- Use larger datasets

Successfully applied NLP methods to detect

• LSTM / GRU: Promising, but slow training and

• Traditional ML: Simple, but solid baseline

• Fine-tune transformer hyperparameters • Try newer models like GPT or LLaMA

