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Language detection

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Introduction

- A method that classifies text into a set of accessible languages.
- Plays a critical role in numerous NLP applications, such as autocorrection, machine translation, information retrieval, summarization, and question answering.
- Two approaches to language detection : computational and non-computational.
- Plays crucial role in natural language processing for sentiment analysis
- Useful in the development of chatbots and virtual assistants that can interact with users in multiple languages
- Helps linguists and historians identify the language of ancient manuscripts and documents

Source : Google

Problem Statement

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Implementing different classification models to predict the languages

Motivation

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- Is an important tool for facilitating communication and ensuring that content is appropriate and accessible to diverse audiences.

- Plays a crucial role in analyzing language usage and trends to provide insights into customer behavior, sentiment analysis.

- Companies operating globally use language detection to provide users with localized content and services.

- Can also be used for security purposes.

Scope

- Implementing different embedding methods
- Implementing numerous Machine learning models
- Implementing deep learning models
- Fine tuning mBERT
- Analyze and Compare

Datasets

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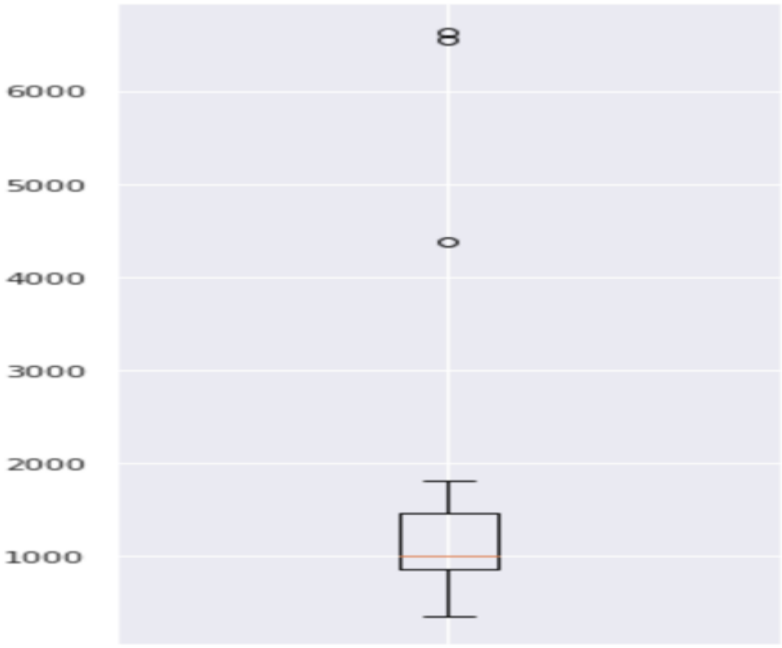
- Data-1(10267 records): https://www.kaggle.com/datasets/basilb2s/language-detection
- Data-2(21859 records): https://www.kaggle.com/code/martinkk5575/language-detection/data
- Data-3(12646 records): https://www.kaggle.com/datasets/lailaboullous/language-detection-dataset
- Data-4(10^7 records): https://www.kaggle.com/datasets/chazzer/big-language-detection-dataset?select=sentences.csv

Dataset Creation

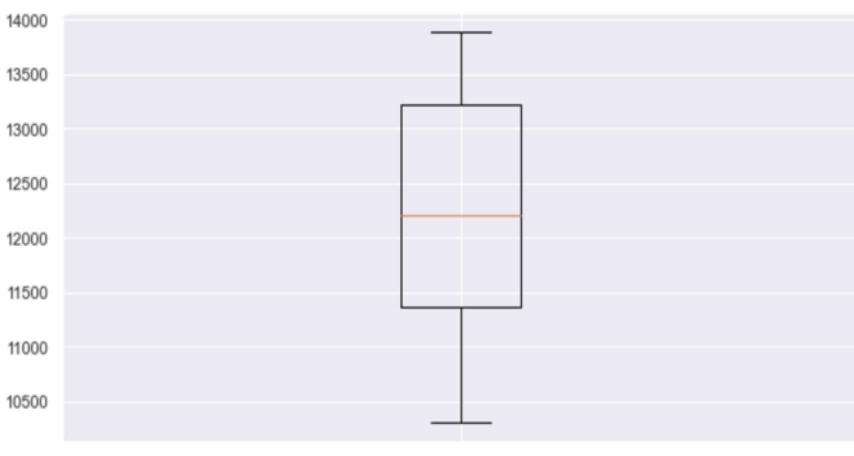
- We created two different datasets by merging the above four datasets.
- For Dataset-1, we started with combining Data-1, Data-2 and Data-3 resulting in approximately 45000 rows.
- To remove the outliers in above combined Dataset-1, we used the Data-4 and picked only languages whose sentences count is in between 4000-6000.
- We ended up generating Dataset-1 with around 2 lakh sentences.

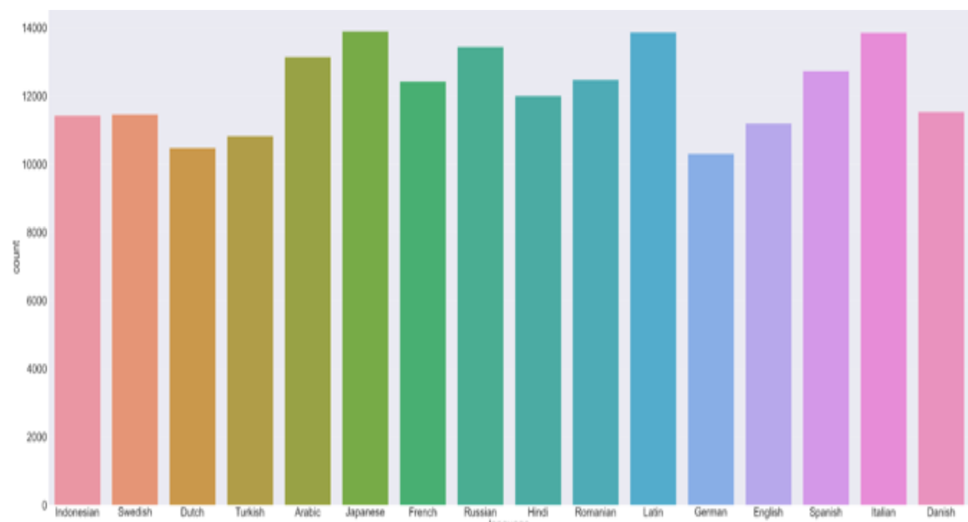


Dataset Creation

- The Dataset-2 is generated by combining Data-1, Data-2, Data-3 and few sentences from Data-4, to make each language in Dataset-2 to be between 10000 and 14000.

- Dataset-2 contains around 2 lakh rows.





Dataset Analysis

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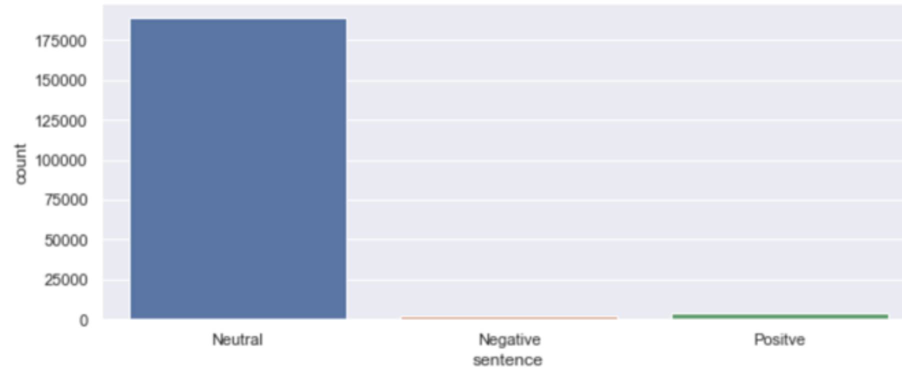
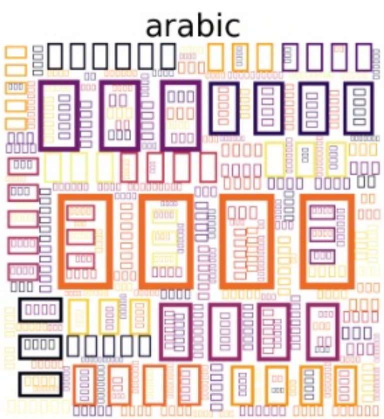
- Checked the sentiment of all the sentences, to make sure if we are using neutral sentences.
- Plotted the word cloud for different languages.





Methodology

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- **Text Preprocessing:**
  - Converted to lower case
  - Removed special characters
  - Removed of punctuation, htmls, email addresses.
  - Applied stemming
  - Removed stop words for each language separately.

- **Text vectorization:**
  - Bag-of-Words
  - TF-IDF vectorizer
  - transformer, Tokenizer
  - Word2Vec
  - N-gram analysis
  - DistilBERT-base-uncased
  - mBERT

Methodology

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- **Classification modeling:**
  - Naïve Bayes
  - Logistic Regression
  - Decision Tree
  - Random Forest
  - Ensemble
  - SVM
  - LSTM
  - BiLSTM
  - DISTILBERT

- **Training and Testing:**
  - Training – 80%
  - Testing – 20%

Results

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MODEL	ACCURACY
BoW + Naïve Bayes	87.1
BoW + Decision Trees	78.5
TF-IDF + Naïve Bayes	85
TF-IDF + Decision Trees	76
mBERT + Custom NN	72
LSTM + 1 Dense	87
LSTM + 2 Dense	86.7
Bi-LSTM + 2 Dense	85.6

Table 1: Dataset-1 Results

Results

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Model	Accuracy
Unigram(Word) + NB	82
Unigram(Word) + LR	88
Unigram(Word) + SVM	88
Unigram(Word) + RF	87
Bigram (Word) + NB	33
Bigram (Word) + LR	35
Bigram (Word) + SVM	35
Bigram (Word) + RF	35
Trigram (Word) + NB	13
Trigram (Word) + LR	15
Trigram (Word) + SVM	15
Trigram (Word) + RF	15
3 Char gram + NB	84
3 Char gram + LR	90.3
3 Char gram + SVM	91.5
3 Char gram + RF	89
4 Char gram + NB	74
4 Char gram + LR	82
4 Char gram + SVM	83
4 Char gram + RF	80
Word2Vec + LR	68.3
Char+Word+Pos+ NB	91.7
Char+Word+Pos + LR	92.3
Char+Word+Pos + RF	91
Char+Word+Pos + Ensemble	92.6
Fine-tuned DistilBERT	88.7
Fine-tuned mBERT	**93**

Table 2: Dataset-2 Results

Conclusion

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- We have experimented with various embedding techniques, machine learning and deep learning models.
- Observed that considering position along with character and word analysis plays a crucial role during embedding phase.
- Among all our implementations, the model with mBERT has given the best accuracy of **93%.**

Future Work

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- Improve the performance of low-resource language identifications.

- Develop a user interface to accept text or document as input and identify and parse the text to desired language.

- Explore domain specific language detection as language usage vary significantly depending on domain or industry.

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THANK YOU!