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Abstract

Text classification is one of the major tasks of AI in general, NLP in particular. Having five Gutenberg books, this report discusses the methodologies and models with different transformation techniques that have been applied to reach the best accuracy that the champion model achieves by correctly classifying unseen text to the corresponding book.

Introduction

Turning written material into useful information and insights is challenging because text is unstructured and not organized in a standardized way. The general goal is to produce categorizations and predictions from the text, compare the results, evaluate the benefits and limitations of different approaches. To achieve this, we will need to implement the approaches, determine the accuracy of each model, and select the most successful one. Python, with its many libraries, is well suited as a programming language for tackling such problems due to its text processing capabilities.

In our task, we perform these modern classifications techniques on some famous fiction novels which made us easily determine the style of each author later from his future writings thus leading to a big revolution in literature field.

Dataset

The Gutenberg dataset represents a corpus of over 60,000 book texts, their authors and titles. The data has been scraped from the Project Gutenberg website using a custom script to parse all bookshelves. we have taken five different samples of Gutenberg digital books that are of five different authors, that we think are of fiction novels. **The books are**

- The enhanced April.
- Middle March.
- Twenty years after.
- Great expectations.
- Aliece’s adventures.

Data Preparation:

After reading the books, we did some preprocessing methods:

- **Text cleaning** – converting text into lowercase and cleaning it by removing unsubstantial parts such as HTML tags, symbols, or sometimes numbers, ensures that words with less than 3 characters like "ye" are removed as they have no special meaning (Removing non-alphabetic characters)
- **Stop words removal** – excluding some common words that don't provide useful information.
- **Lemmatization and stemming** – simplifying words to their base or root form by following some rules from dictionaries, cutting off common prefixes and suffixes, and similar.
- **Tokenization** – when we separate cleaned text into smaller units, such as words, characters, or some combinations of them.
- **Data Partitioning** – partition each book into 200 documents, each document is a 100-word record.

	index	Author	title	label	100_Words
6	0	Elizabeth Von Arnim	The Enchanted April	a	went wilkins naturally mr wilkins wa blotted s...
134	4	Lewis Carroll	Alice's Adventures	e	literary archive foundation provide full refun...
22	4	Lewis Carroll	Alice's Adventures	e	would catch bad cold get dry soon ahem said mo...
71	1	George Eliot	Middlemarch	b	would hinder casaubon said knowing anything ma...
165	0	Elizabeth Von Arnim	The Enchanted April	a	air completest confidence anybody whose hair w...
...	...	...	...	...	...
72	0	Elizabeth Von Arnim	The Enchanted April	a	strained eye sight beginning san salvatore sup...
174	0	Elizabeth Von Arnim	The Enchanted April	a	rose expression appeared one anger anger fancy...
71	3	Charles Dickens	Great Expectations	d	looking file ought tell joe whole truth yet re...
158	0	Elizabeth Von Arnim	The Enchanted April	a	wa little place jutting great wall kind excres...
106	3	Charles Dickens	Great Expectations	d	misdealt wa natural knew wa lying wait wrong d...

942 rows × 5 columns

Feature engineering:

- **BOW**: one type of transformation that count of the total occurrences of most frequently used words, to convert the text into numbers so that the algorithm can deal with it.

Out[9]:

	aback	abandon	abandoned	abandonment	abb	abbey	abdicated	abear	abeyance	abhorrence	...	youngster	youth	youthful	youthfulness	zeal	zeal
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
937	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
938	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
939	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
940	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
941	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	

942 rows × 10892 columns

- **TF_IDF**: term frequency-inverse document frequency is a measure for estimating the importance of words in a document among a collection of documents.

Out[21]:

	aback	abandon	abandoned	abandonment	abb	abbey	abdicated	abear	abeyance	abhorrence	...	youngster	youth	youthful	youthfulness	zeal	zeal
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
937	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
938	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
939	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
940	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
941	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	

942 rows × 10892 columns

- **N-Gram**: may be used to create probabilistic language models called n-gram models, **which** predict the occurrence of a word based on its N – 1 previous word.

Out[30]:

	aback	aback constant	aback mr	aback said	abandon	abandon mazarin	abandon stream	abandon thus	abandoned	abandoned every	...	zigzag arrive	zigzag path	zigzag wa	zip	zip associated	zounds	zoun cri
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	1	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
937	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
938	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
939	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
940	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
941	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	

942 rows × 86554 columns

Classification:

For each technique of the above, these following models are trained and tested :

- SVM.
- Random Forest.
- Naïve Bayes.
- K-Nearest Neighbour.
- XG-Boost.
- (SGD)Stochastic Gradient Descent.

Testing accuracy						
	SVM	**Random forest**	**Naïve Bayes**	**K-NN**	**XG-Boost**	**SGD**
BOW	0.9788	0.9524	0.9841	0.8942	0.9471	0.9735
TF_IDF	0.9788	0.9683	0.9735	0.9577	0.9365	0.9788
N-gram	0.9683	0.9683	0.9841	0.8942	0.9471	0.9788

Cross-Validation accuracy						
	SVM	**Random forest**	**Naïve Bayes**	**K-NN**	**XG-Boost**	**SGD**
BOW	0.9894	0.9894	0.9947	0.9365	0.9577	0.9947
TF_IDF	0.9947	0.9788	0.9894	0.9683	0.9788	0.9947
N-gram	0.9894	0.9894	0.9947	0.9206	0.9630	0.9735

Champion model:

According to the previous tables of calculating the accuracy for both testing and validation,

The champion model is: Naïve Bayes based on (N-gram), which gives us the accuracy of 0.9841 (The same accuracy of Naïve Bayes based on BOW) , but the average variance of this model is lower (0.008 (N-gram) < 0.013(BOW)).

```
Cross Validation Accuracy :  [0.98245614 1.         0.98245614 0.98245614 1.         1.
 0.98214286 0.98214286 1.         1.        ]

Average Cross Validation Accuracy :  0.9911654135338346

Testing accuracy :  0.9841269841269841

Validation accuracy :  0.9947089947089947
```

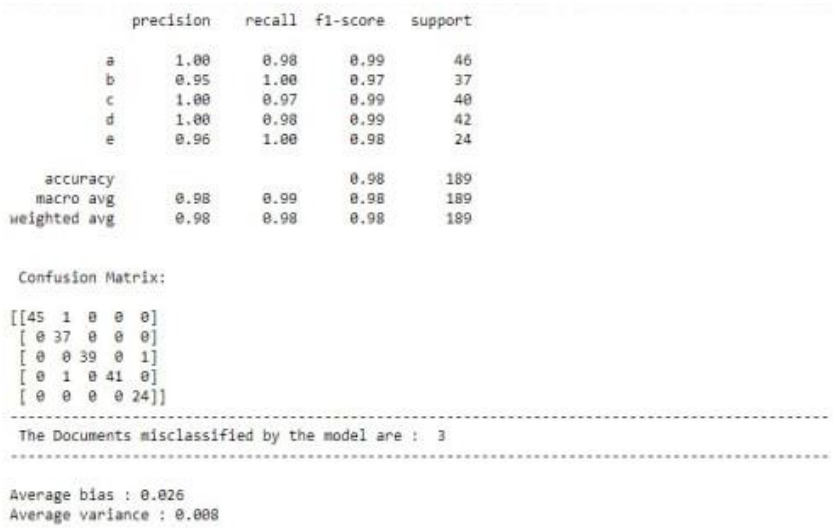
Error analysis:

Error analysis is an important step in improving the performance of text classification models. It involves analyzing the errors made by the model on the validation or test set and identifying the patterns or characteristics of the misclassified instances. Based on the analysis, we can identify the areas where the model needs improvement and take appropriate actions to address them.
Here are some common techniques We used in error analysis for our text classification problem:

- **Confusion matrix**: A confusion matrix can be used to visualize the number of true positives, true negatives, false positives, and false negatives. This can help identify which classes the model is struggling with and where it is making the most errors.

- **Precision, recall, and F1 score**: These metrics can be used to evaluate the performance of the model on a per-class basis. This can help identify which classes the model is struggling with and where it needs improvement.

- **Visualizing misclassified instances**: Misclassified instances can be visualized to identify patterns or characteristics that may be causing the errors.

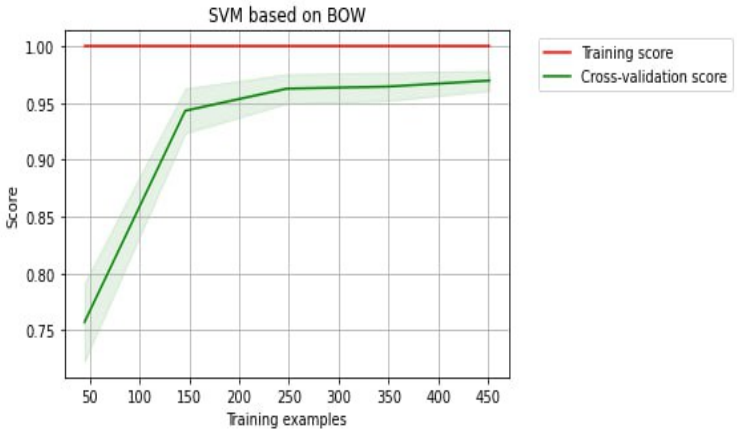


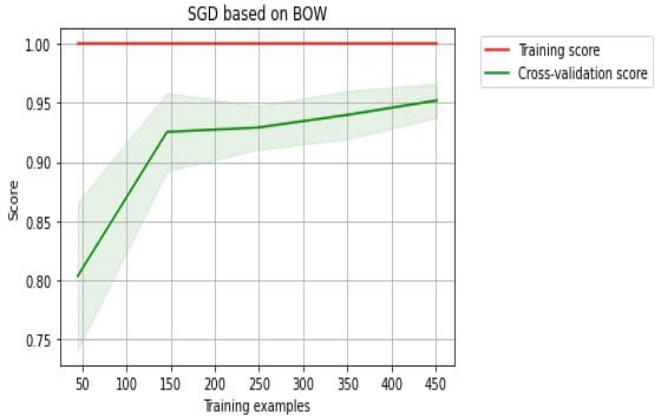
```
              precision    recall  f1-score   support

           a       1.00      0.98      0.99        46
           b       0.95      1.00      0.97        37
           c       1.00      0.97      0.99        40
           d       1.00      0.98      0.99        42
           e       0.96      1.00      0.98        24

    accuracy                           0.98       189
   macro avg       0.98      0.99      0.98       189
weighted avg       0.98      0.98      0.98       189

 Confusion Matrix:

[[45  1  0  0  0]
 [ 0 37  0  0  0]
 [ 0  0 39  0  1]
 [ 0  1  0 41  0]
 [ 0  0  0  0 24]]
--------------------------------------------------------------------------------
 The Documents misclassified by the model are :  3
--------------------------------------------------------------------------------

Average bias : 0.026
Average variance : 0.008
```

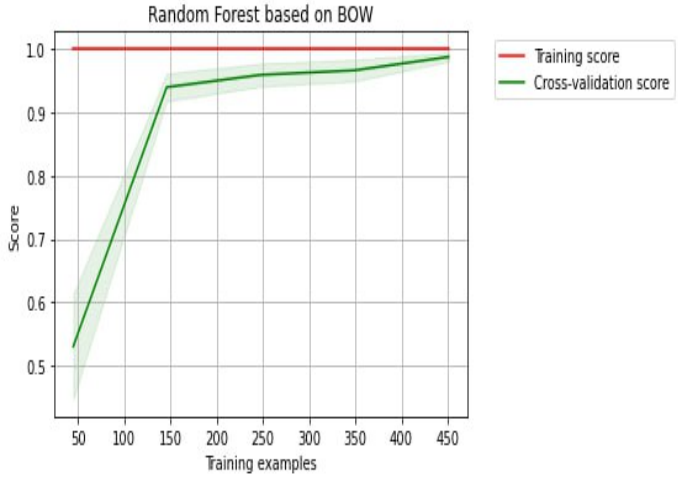
Testing results :

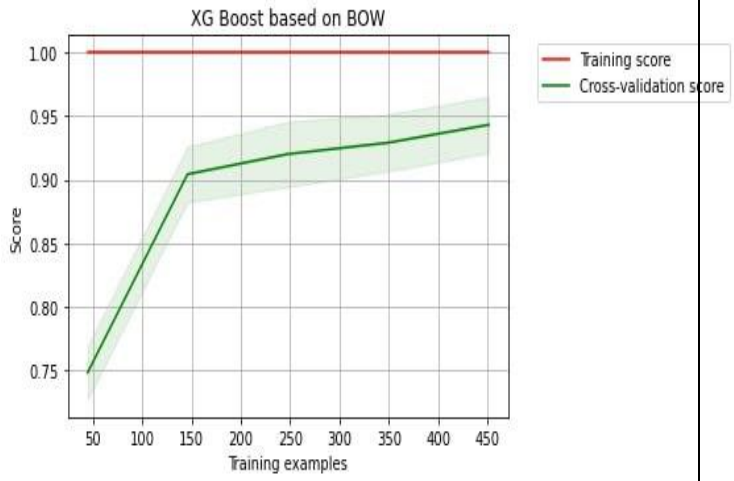
Learning curve: a learning curve is a plot of the model's performance as a function of the amount of training data. It is used to diagnose whether the model has a high bias or high variance. A high bias model is one that is too simple to capture the underlying patterns in the data, resulting in underfitting. A high variance model is one that is too complex and overfits the training data, resulting in poor generalization performance. A learning curve can help determine whether the model would benefit from more training data or if it is too complex and needs to be simplified.

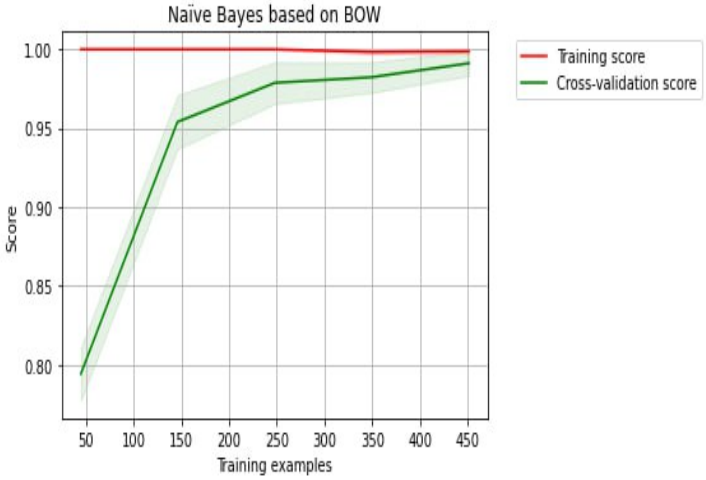
BOW:

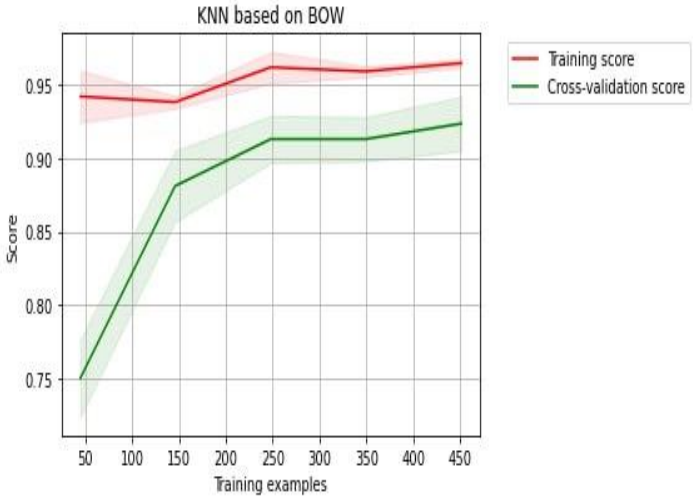

SVM based on BOW
Training score
Cross-validation score
Score
Training examples


SGD based on BOW
Training score
Cross-validation score
Score
Training examples

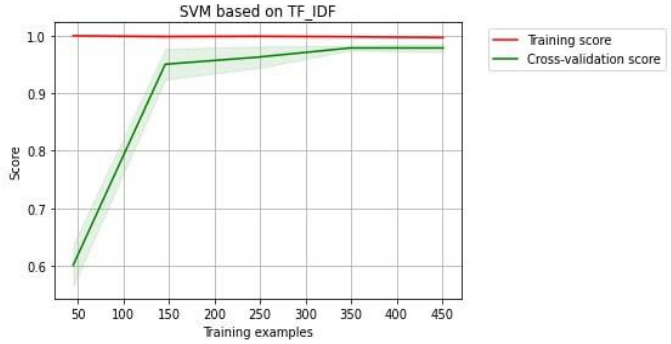

Random Forest based on BOW
Training score
Cross-validation score
Score
Training examples

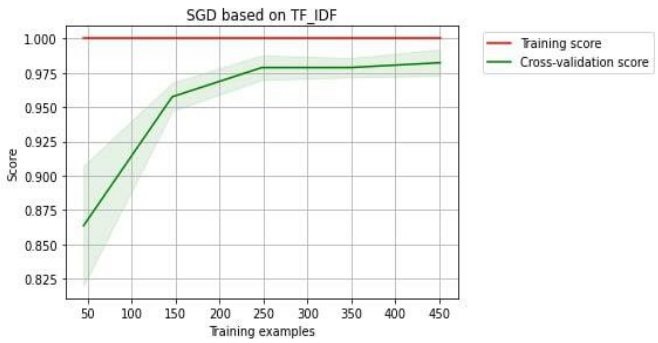

XG Boost based on BOW
Training score
Cross-validation score
Score
Training examples

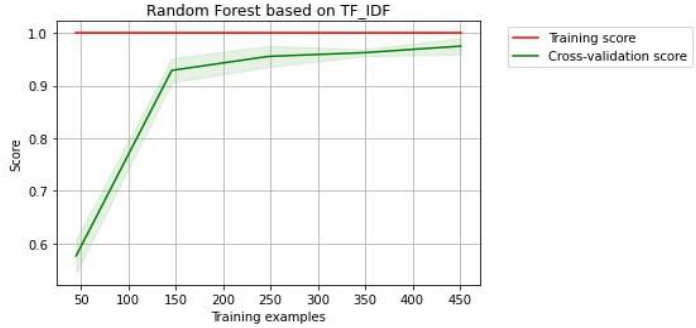

Naïve Bayes based on BOW
Training score
Cross-validation score
Score
Training examples

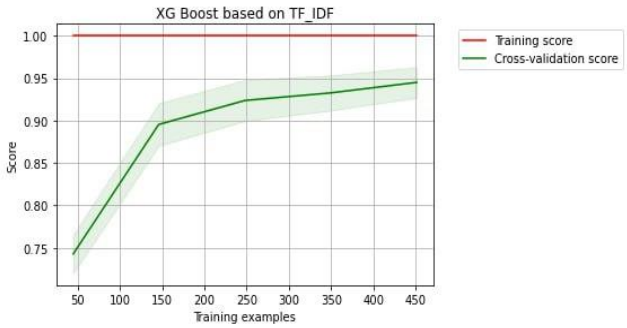

KNN based on BOW
Training score
Cross-validation score
Score
Training examples

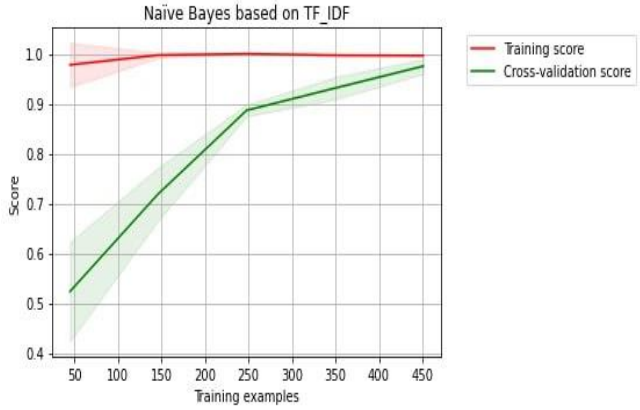
TF-IDF:

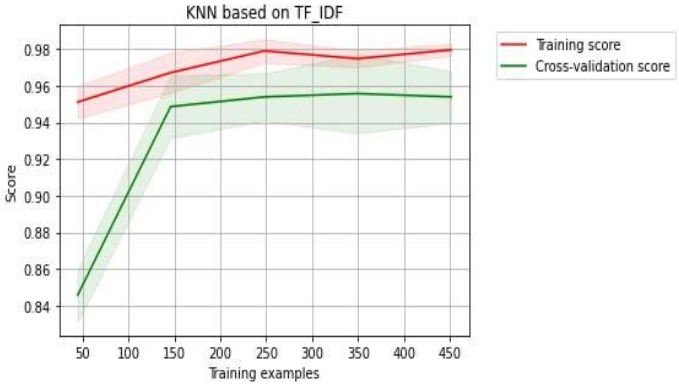

SVM based on TF_IDF
Training score
Cross-validation score
Score
Training examples


SGD based on TF_IDF
Training score
Cross-validation score
Score
Training examples

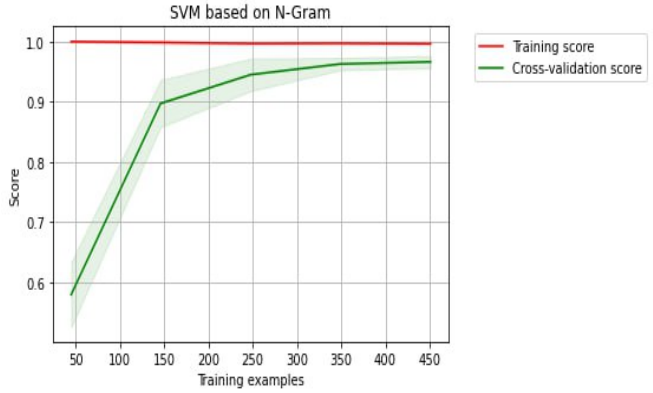

Random Forest based on TF_IDF
Training score
Cross-validation score
Score
Training examples

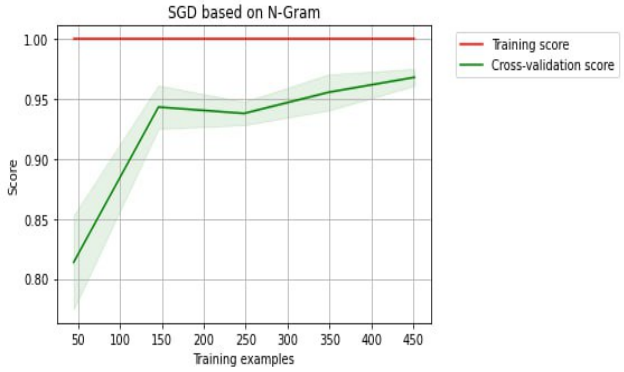

XG Boost based on TF_IDF
Training score
Cross-validation score
Score
Training examples

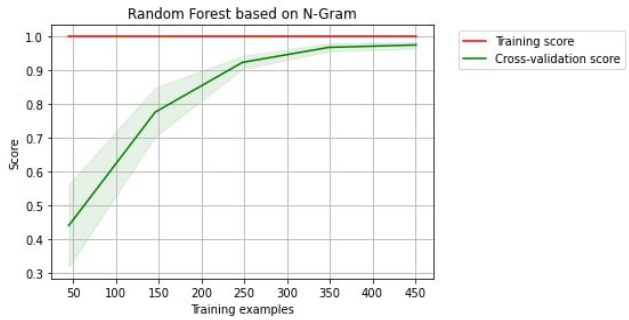

Naïve Bayes based on TF_IDF
Training score
Cross-validation score
Score
Training examples

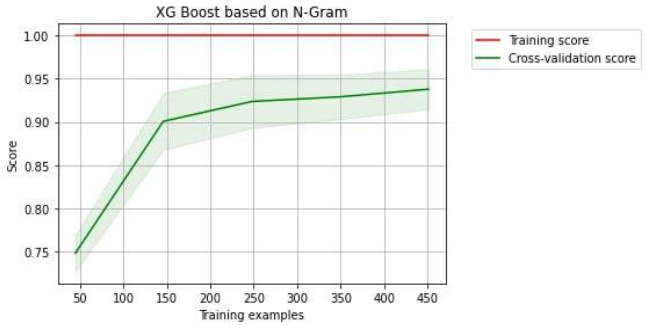

KNN based on TF_IDF
Training score
Cross-validation score
Score
Training examples

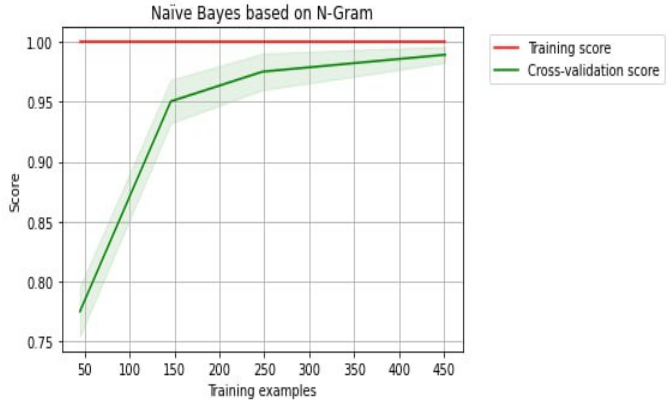
N-Gram:

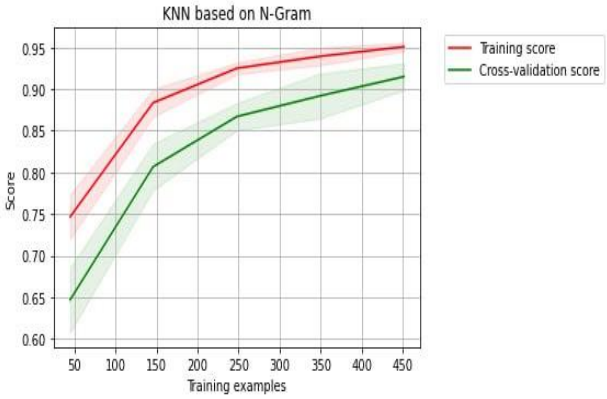

SVM based on N-Gram
Training score
Cross-validation score
Score
Training examples


SGD based on N-Gram
Training score
Cross-validation score
Score
Training examples


Random Forest based on N-Gram
Training score
Cross-validation score
Score
Training examples


XG Boost based on N-Gram
Training score
Cross-validation score
Score
Training examples


Naïve Bayes based on N-Gram
Training score
Cross-validation score
Score
Training examples


KNN based on N-Gram
Training score
Cross-validation score
Score
Training examples