CS550 - Machine Learning and Business Intelligence

Machine Learning - Text Classification

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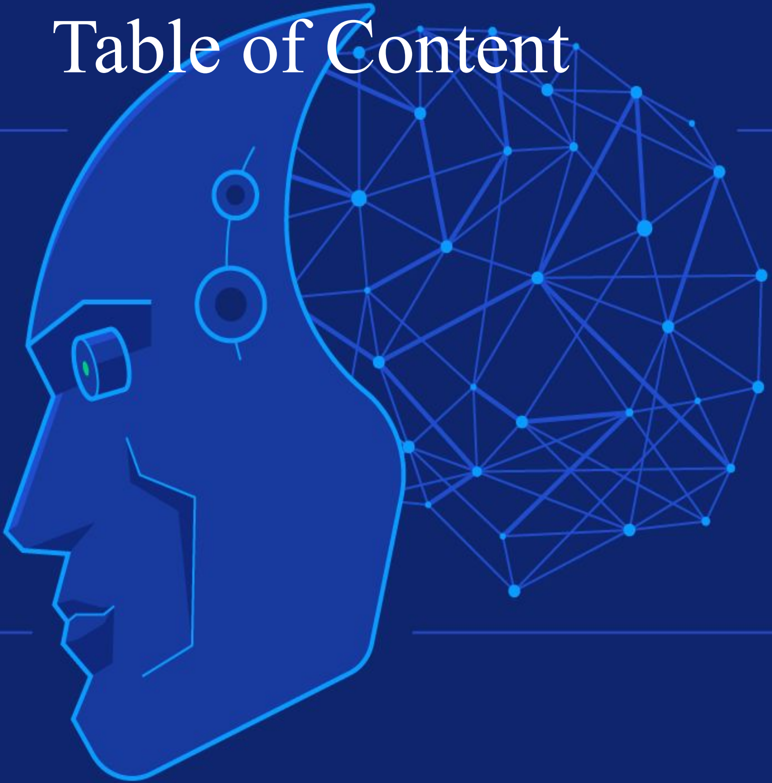


1. Introduction

A text classifier is a type of machine learning model that learns to classify text data into different categories or classes. The goal of a text classifier is to automatically analyze and understand the content of text data and classify it into predefined categories based on its content.

Text classifiers are widely used in many applications such as sentiment analysis, spam detection, topic categorization, and language identification. They work by using algorithms that analyze the features of the text data, such as the frequency of certain words, the presence of specific patterns or keywords, and the context in which the text appears. The model then uses this information to make predictions about the category or class that the text belongs to.

2. Types of Text Classifiers

There are various types of text classifiers, including rule-based classifiers, Naive Bayes classifiers, decision tree classifiers, support vector machines (SVM), and neural network classifiers. Each type has its own strengths and weaknesses, and the choice of classifier depends on the specific task and the nature of the text data being analyzed.

Overall, text classifiers are a powerful tool for automatically analyzing and categorizing large volumes of text data, which can help businesses and organizations make better decisions and improve their operations.

3. Manual Calculation

	Doc	Words	Author
Training	1	W1 W2 W3 W4 W5	C (Christopher Marlowe)
	2	W1 W1 W4 W3	C (Christopher Marlowe)
	3	W1 W2 W5	C (Christopher Marlowe)
	4	W5 W6 W1 W2 W3	W (William Stanley)
	5	W4 W5 W6	W (William Stanley)
	6	W4 W6 W3	F (Francis Bacon)
	7	W2 W2 W4 W3 W5 W5	F (Francis Bacon)
Test	8 (Hamlet)	W1 W4 W6 W5 W3	?

We have the training data and need to calculate the probabilities of each before testing the Text Classifier to identify the true author of Hamlet.

3. Manual Calculation

P(C): The probability of class C = 3/7

P(W): The probability of class W = 2/7

P(F): The probability of class F = 2/7

P(W1|C): The probability that the word "W1" appears on the 3 class C documents
= (count (W1, C) + 1) / (count(C)+|V|) = (4+1) / (12+6) = 5/18

P(W1|W) : The probability that the word "W1" appears on the 3 class W documents
= (count (W1, W) + 1) / (count(W)+|V|) = (1+1) / (8+6) = 2/14 = 1/7

P(W1|F): The probability that the word "W1" appears on the 2 class F documents
= (count(W1, F) + 1) / (count(F)+|V|) = (0+1) / (9+6) = 1/15

P(W3|C) : The probability that the word "W3" appears on the 3 class C documents
= (count(W3, C) + 1) / (count(C)+|V|) = (2+1) / (12+6) = 3/18 = 1/6

3. Manual Calculation

P(W3|W) : The probability that the word "W3" appears on the 3 class W documents
= (count(W3, W) + 1) / (count(W)+|V|) = (1+1) / (8+6) = 2/14 = 1/7

P(W3|F) : The probability that the word "W3" appears on the 2 class F documents
= (count(W3, F) + 1) / (count(F)+|V|) = (2+1) / (9+6) = 3/15 = 1/5

P(W4|C) : The probability that the word "W4" appears on the 3 class C documents
= (count(W4, C) + 1) / (count(C)+|V|) = (2+1) / (12+6) = 3/18 = 1/6

P(W4|W) : The probability that the word "W4" appears on the 3 class W documents
= (count(W4, W) + 1) / (count(W)+|V|) = (1+1) / (8+6) = 2/14 = 1/7

P(W4|F) : The probability that the word "W4" appears on the 2 class F documents
= (count(W4, F) + 1) / (count(F)+|V|) = (2+1) / (9+6) = 3/15

P(W5|C): The probability that the word "W5" appears on the 3 class C documents
= (count(W5, C) + 1) / (count(C)+|V|) = (2+1) / (12+6) = 3/18 = 1/6

3. Manual Calculation

P(W5|F): The probability that the word "W5" appears on the 2 class F documents
= (count(W5, F) + 1) / (count(F)+|V|) = (2+1) / (9+6) = 3/15

P(W6|C): The probability that the word "W6" appears on the 3 class C documents
= (count(W6, C) + 1) / (count(C)+|V|) = (0+1) / (12+6) = 1/18

P(W6|W): The probability that the word "W6" appears on the 2 class W documents
= (count(W6, W) + 1) / (count(W)+|V|) = (2+1) / (8+6) = 3/14

P(W6|F) : The probability that the word "W6" appears on the 2 class F documents
= (count(W6, F) + 1) / (count(F)+|V|) = (1+1) / (9+6) = 2/15

3. Manual Calculation

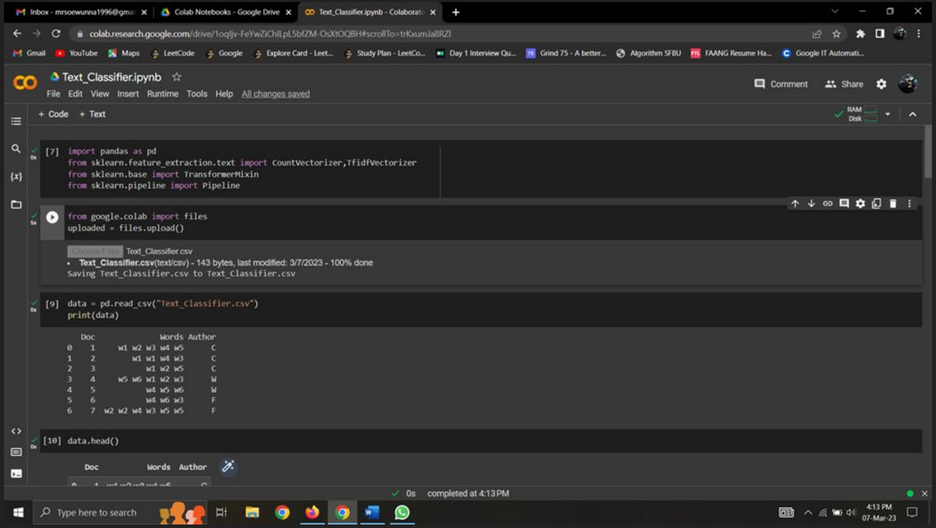
P(C|d8) : P(C) * P(W1|C) * P(W4|C)* P(W6|C) * P(W5|C) * P(W3|C)
= ((3/7) * (5/18) * (1/6) * (1/18) * (1/6) * (1/6)
= 0.00003061924 , approx. 0.00004

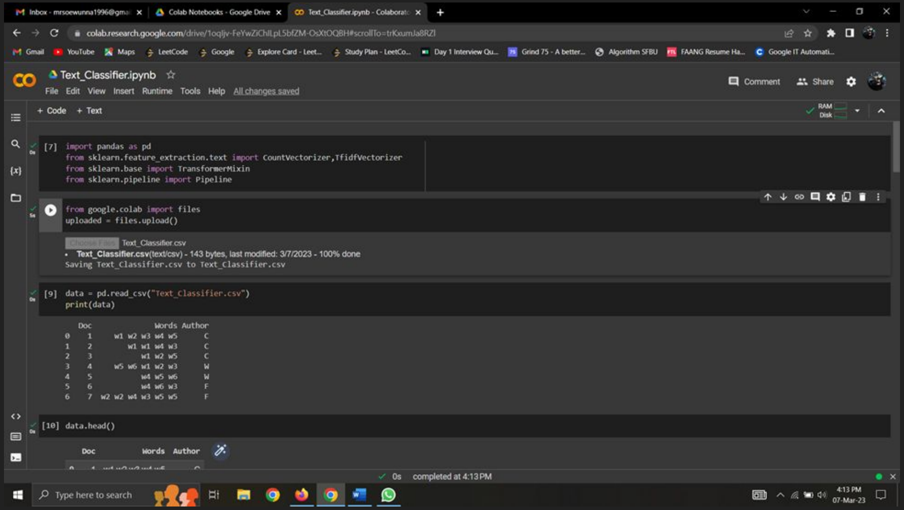
P(W|d8) = P(W) * P(W1|W) * P(W4|W)* P(W6|W) * P(W5|W) * P(W3|W)
= (2/7* 2/14 * 2/14 * 3/14 * 3/14 * 2/14)
= 0.00002824936, approx. 0.00003

P(F|d8) = P(F) * P(W1|F) * P(W4|F)* P(W6|F) * P(W5|F) * P(W3|F)
= ((2/7) * (1/15) * (3/15) * (2/15) * (3/15) * (3/15))
= 0.00002031746, approx. 0.00002

The probability calculations show that Document 8 should be in Class C because it has the highest probability calculation.

4. Implementation of Code





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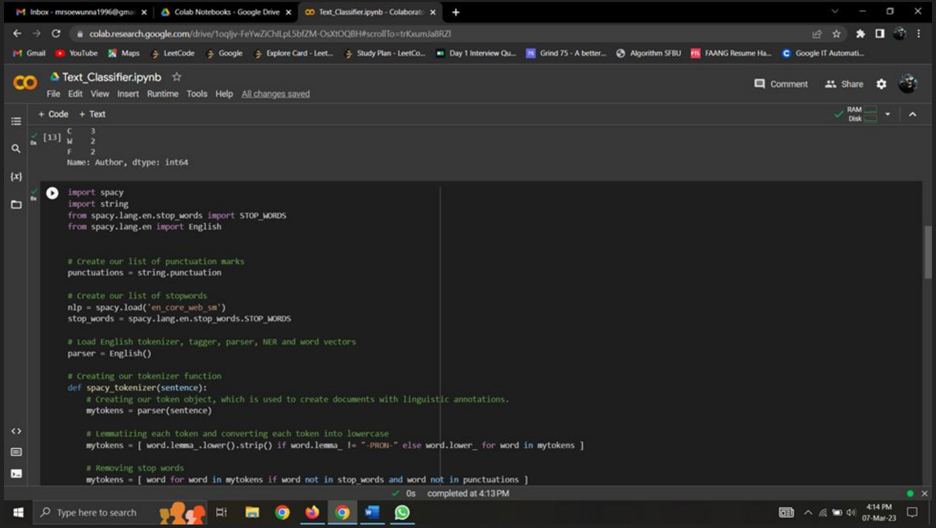

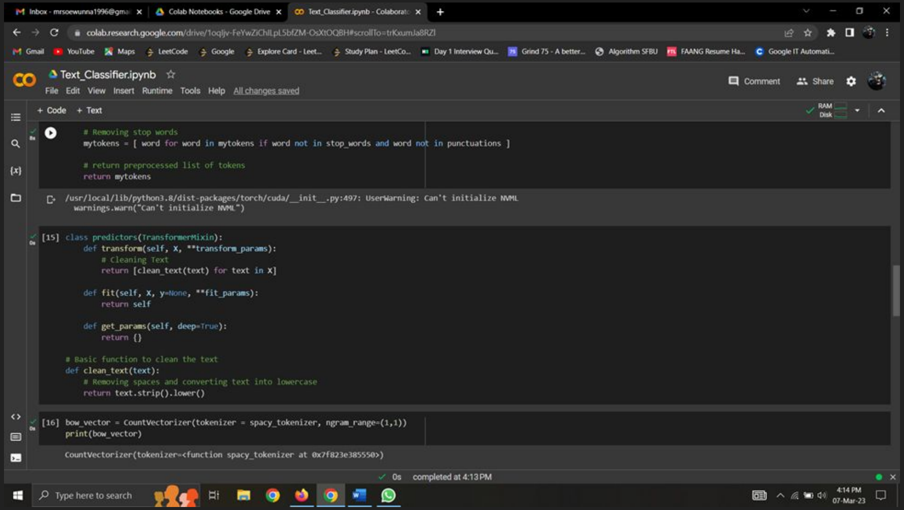

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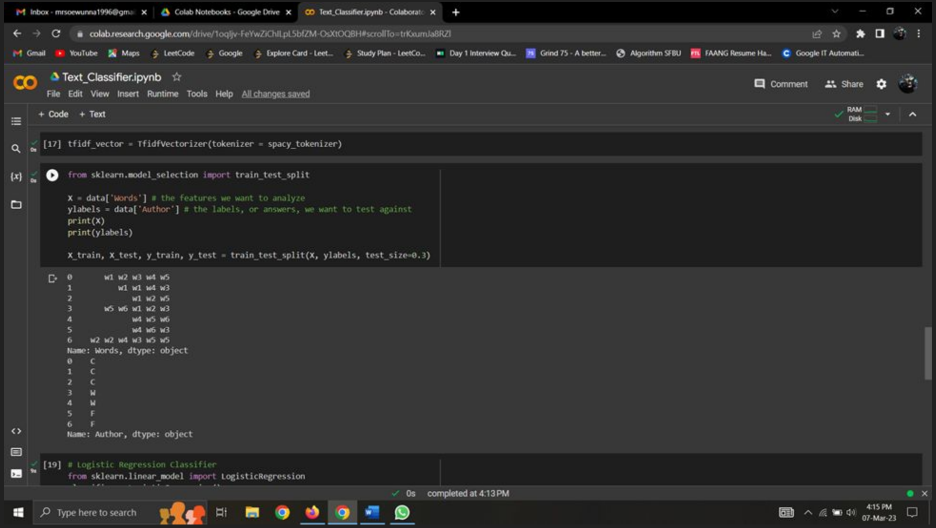

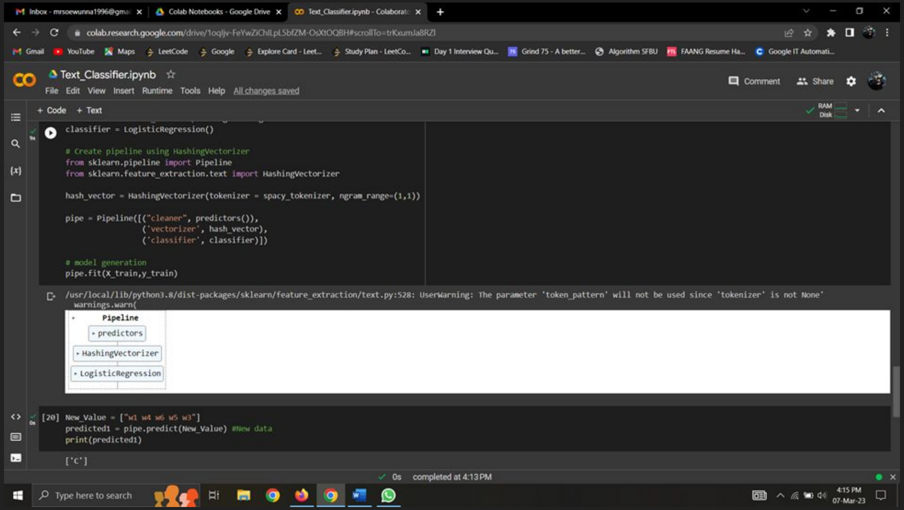

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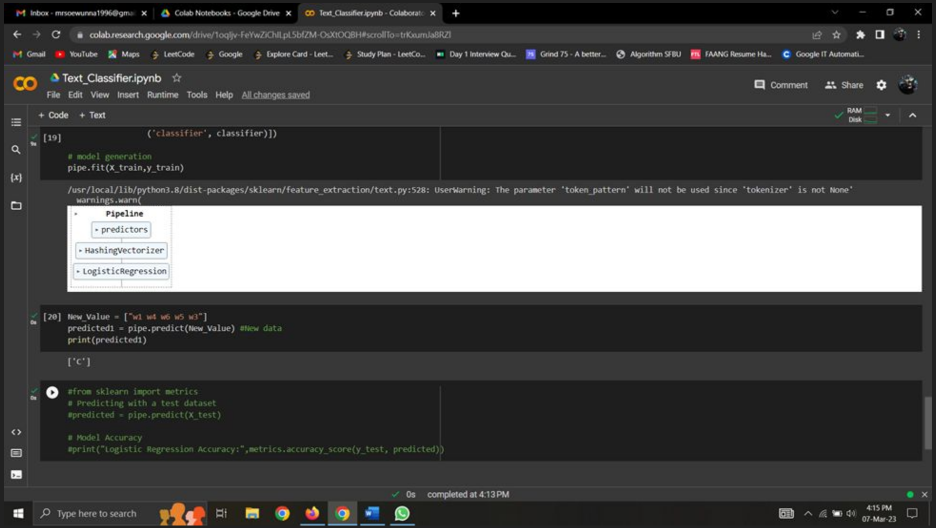

Final Result is Class 'C'.

5. Conclusion

In conclusion, text classifiers are an essential component of modern machine learning systems. They enable the automatic analysis and categorization of large volumes of text data, which can be used for various applications such as sentiment analysis, spam detection, topic categorization, and language identification.

Text classifiers have become increasingly important in today's data-driven world, where organizations generate and collect vast amounts of text data. With the help of text classifiers, businesses can extract valuable insights from this data and make better-informed decisions.

6. References

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