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| **Faculty of Science and Technology**  **CISC3025 – Natural Language Processing** | | |
| **Project Task 2: Implementation of a Naïve-Bayes Text Classification Model and its Performance Evaluation in Reuters Dataset** | | |
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# Introduction

# Background

# Approaches, Designs and Methods

## 3.1 Python Packages

There are some python packages that are useful for fulfilling this project. Below shows a list of packages imported and the corresponding tasks they are used to perform.

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| **Table 1:** Python packages used in this project | |
| **Package Name** | **Usage** |
| json | Compile the .json source file into structural objects. |
| re | Substitute varieties of delimiters or useless symbols in natural language writings by a single space. |
| nltk | Construct the tokenizer for tokenizing a string into an array of words with a given delimiter. |
| pandas | Construct a DataFrame object to contain the word frequency matrix, indexed by vocabulary. |
| numpy | Some basic math tasks, like initializing an array filled with 0. |
| collections | Turn a word array (which may contain duplicates) into a dictionary of word-frequency pairs. |

## 3.2 Word Count in Different Classes

This corresponds to the Requirement 1 and 2. In this part, this report demonstrates the ideas and methods for information retrieval and data processing for counting frequencies of all the individual words in different classes.

### 3.2.1 Retrieve Information from train.json

By applying the internal package of json in Python, it is easy to extract the training data into a two-dimensional list in python. The first attribute of each instance, i.e., the training id, is ignored by intuition.

Traversing all the instances, the program accumulates the document number of each types by reading the second attribute of the instance. The third attribute is the actual sentence, which would be further tokenized into word arrays, accompanied by its class.

### 3.2.2 String Tokenization

The key task of this phase is to determine whether a string segment is a valid word. By design, the following table shows the abbreviated version of the disambiguating rules that drives the idea of tokenization.

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| **Table2:** Disambiguating rules to define a word | | | | |
| **Pattern** | **Examples** | **Validity** | **Interpretation** | **Correction** |
| In-segment dots | U.S. | Yes | Country name abbreviation; |  |
| Co. | Yes | Abbreviation for “cooperation” |  |
| 13.10 | Yes | Floating point numbers |  |
| In- segment Slashes | autumn/winter | No | Selections, i.e. autumn or winter. | ‘autumn’, ‘winter’ |
| 13-3/2 | Yes | Hybrid number. |  |
| In-segment Hyphens | government-to-government | Yes | Connected subwords forming a long word. |  |
| In-segment Commas | 2,365,000 | Yes | A large number separated by a comma. |  |
| “&lt;” and “>” | &lt;Banca> | No | Escape sign for “<”. | Banca |
| Ending with a punctuation mark | nations' | Yes | Possessive pronoun of the original noun plural. |  |
| policy. | No | Extra period. | policy |
| Brackets surrounded | (Bracket) | No |  | Bracket |
| Pure punctuation marks | ... | No | Abbreviation mark | *Empty Char* |
| -- | No | Extension mark | *Empty Char* |
| **…** | | | | |

The tokenization process is performed in sequence by two roles considering the ideas shown above. The first rule is made to avoid in-segment symbols that connects two disjoint words. For instance, the segment “said…Taiwan” should be separated into two disjoint words. Below shows the regular expression for replacing these symbols by a space.

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| **Table3:** Regular expression for the first rule | | |
| **Rule** | r'\"|\.\.+|\(|\)|\s--+\s|(?<=[A-Za-z])/|&[a-z]+;|>' | |
| **Patterns** | | **Interpretation** |
| \" | | Any double-quotation mark won’t be a part of a valid word. |
| \.\.+ | | Any continuous periods always separates two disjoint words. |
| \(|\) | | Any brackets won’t be a part of a valid word. |
| \s--+\s | | Any continuous hyphens always separates two disjoint words. |
| (?<=[A-Za-z])/ | | A slash only separates two disjoint words but doesn’t separate two numbers. |
| &[a-z]+;|> | | Remove the escape sign of “<”, as well as the actual sign of “>”. |

The second rule is made to normalize different delimiters. There are all kinds of delimiters in the natural language, like a comma followed by a space, or a period followed by a space. The second rule replaces these patterns by a single space, realizing a unification.

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| **Table4:** Regular expression for the second rule | |
| **Rule** | r'(?<![A-Z])([.,?!"]\s+)' |
| **Interpretation** | This rule basically listed many possible situations for a delimiter. Any punctuation mark followed by any number of spaces is likely to be a delimiter. However, this rule doesn’t apply for abbreviations like U.S. or U.K., so these cases are included using the ?<![A-Z] signs. |

Since all delimiters are unified to be arbitrary (mostly only one) number of spaces, it is very easy for a tokenizer to parse a sentence using the delimiter of “\s”. However, there are still space to improve, like there are still some words that contain some invalid words at the end. For instance, there is a word like “berry,”, having an extra comma. There were also invalid symbols like “--” presenting as a word string in the tokenization. Therefore, it is necessary to use the built-in rstrip() function to filter these invalid tokens.

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| **Code 1:** Python code for filtering invalid tokens |
| for word in \_cur\_token\_array:  word = word.rstrip(',?!"-') # Remove extra punc marks at the end  cur\_token\_array.append(word) if word != "-" or "" else None |

Even though these rules and methods can’t guarantee a 100-percent accuracy of tokenization, it is completely accurate enough for parsing the training data given.

After information retrieval and tokenizing, the data should be of the following form.

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| **Code2:** Data structure after processing |
| [  [‘acq’,[‘word1’,’word2’,’word3’,’word4’]],  [‘grain’,[‘word1’,’word2’,’word3’]],  [‘grain’,[‘word1’,’word2’,’word3’,’word4’,’word5’]],  [‘money-fx’,[‘word1’,’word2’]],  [‘acq’,[‘word1’,’word2’,’word3’,’word4’]],  …  ] |

The overall data structure of the training data retrieved from the json file is an array of arrays. An instance or element of this array is a tuple. The first element of the tuple is the class of the sentence. The second element of the tuple is the tokenized sentence, which is in the form of an array of tokens.

### 3.2.3 Instance-wise Word-Frequency Dictionary Construction

This part only regards the scope of an instance, i.e. a class-sentence tuple. The goal of this part is to merge multiple identical words in the sentence into a single key-value pair, where the key is the word string, and the value is the frequency of the word.

An instance is a string-list pair, where the list represents the tokenized version of the original sentence and the string is the class of the sentence. The Counter() function extracted from package collections is turns the list into a dictionary of word-frequency pairs.

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| **Table 5:** Construct word-frequency dictionary | |
| Instance before construction | [‘acq’,[‘the’,**’cake’**,’is’,’a’,’lying’,**’cake’**]],… |
| Instance after construction | [‘acq’,{‘the’:1,**‘cake’:2**,‘is’:1,‘a’:1,‘lying’:1}] |

The reason why converting original list into a dictionary is necessary is that the order of the words doesn’t matter much for the present tasks, yet merging word counts saves space and time for frequency statistics.

### 3.2.4 Vocabulary Construction

Unlike dictionary construction, the vocabulary construction regards the scope of all instances of the data. The goal of constructing a vocabulary is to preserve a unique index for all words disregarding their frequencies, making it easier to store statistic values into the correct place.

The vocabulary embraces every word that had ever been present in any of the documents, and only store them once. Hence, it is intuitive to consider the vocabulary as a set. By traversing all the instances, the vocabulary only inserts words it had never seen before into its storage. This is better when the instances are processed to merge identical words into one, saving the time for traversing. The built-in set() function is used to perform the construction. Below shows the algorithm for vocabulary construction.

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| **Algorithm 1:** Vocabulary construction | |
| 1 | **Procedure** ConstructVocab(testData); |
| 2 | Let vocab ← ∅; |
| 3 | **for** instance **in** testData **do** |
| 4 | **for** word **in** instance.tokenizedSentence **do** |
| 5 | vocab ← vocab ∪ {word}; |
| 6 | **Output** vocab. |

### 3.2.5 Data Summarization using DataFrame

It is observed that the size of vocabulary is around 43,000. For each individual word, we need to count its frequencies in five different classes. Therefore, it is more efficient to construct a Token Frequency Matrix.

The row indexes is the vocabulary, while the column indexes are five different classes. By traversing every instances of the train data, the program first get the class of the instance. It then adds the frequency value of every unique word in the dictionary into the matrix. Notice that the matrix cell is located by the word-class pair. For each instance, the insertion is performed only on one column of the matrix since there’s only one class in an instance.

Below shows one possibility of the token frequency matrix. The matrix is realized using the DataFrame object from the pandas package, which by default generates index in a random order.

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| --- | --- | --- | --- | --- | --- |
| **Table 6:** The token frequency matrix | | | | | |
| Index\Class | crude | grain | money-fx | acq | earn |
| prior | 4 | 7 | 1 | 27 | 501 |
| 30 | 33 | 47 | 34 | 133 | 300 |
| board | 6 | 24 | 12 | 343 | 192 |
| six | 32 | 22 | 106 | 81 | 286 |
| year | 0 | 0 | 0 | 0 | 526 |
| loss | 0 | 0 | 2 | 0 | 470 |
| may | 11 | 47 | 11 | 54 | 333 |

We want to then select 10,000 most frequent words as feature words, we need to sort this matrix. This matrix is then sorted using the sum of each column. Due to lack of functionalities of DataFrame, it is required to calculate the sum during matrix construction, and then slice out the last column storing the sum of each row after sorting. The algorithm below shows the full construction process.

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| **Algorithm 2.1:** Token Frequency Matrix construction | |
| 1 | **Procedure** ConstructTFMatrix(tokenizedDataFreq, vocab, classes); |
| 2 | Let TFM←new Matrix(row=vocab, col=classes); |
| 3 | **for** row **in** tokenizedDataFreq **do** |
| 4 | Let curClass ← tokenizedDataFreq.class; |
| 5 | Let curWordDict ← tokenizedDataFreq.wordDictionary; |
| 6 | **for** word, frequency **in** curWordDict **do** |
| 7 | TFM [word, curClass] += frequency; |
| 8 | TFM ←sortByRowSum(TFM, order=descending); |
| 9 | **Output** TFMatrix. |

## 3.3 Naïve-Bayes Probability Calculation & Model Implementation

This corresponds to the Requirement 3 and 4.

### 3.3.1 Naïve Bayes Algorithm Analysis

An essential goal of the Naïve Bayes algorithm is to predict a class for a sentence based on the current datastore. To be more specific, the below table demonstrates the inputs and outputs of Naïve Bayes Classification Algorithm.

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| **Table 7:** Inputs and outputs of Naïve Bayes Classification Algorithm |
| **Given:** |
| 1. A test document , whereare words of the document. |
| 2. A set of class , where are classes stored in the set. |
| 3. A set of documents , where are classes stored in the set. |
| 4. A mapping relation , i.e. a training data , where |
| **Compute:** |
| Target Class: |
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Therefore, we can break the task of sentence classification into two subtasks: First, calculate the prior probability of each class. Second, calculate for each document in the training dataset by calculating the posterior probabilities of each word in a specific document respectively and then multiplying them together. The second subtask can only hold if the assumption of independence, that is,

### 3.3.2 Class Prior Probability

The prior probability of a specific class *c* is the portion of documents that is labelled as class *c* in the training set. It is equal to the number of documents in labelled in class *c* divide by , the number of all documents.

Remark that the given training set is in the data structure of an array of tuples, where each tuple stores both the sentence itself and the class that this sentence is labelled to. To calculate , we should calculate both the numerator and denominator. To calculate the denominator is simple enough, just by calculating the size of the document set, that is, . To calculate the numerator, we should iterate through each instance of training set tuples, accumulating the occurrences of the class encountered. The below algorithm is a modified version of Algorithm 2.1 that also calculates the occurrence of each class. Note that the feature selection process is abbreviated for clarity.

|  |  |
| --- | --- |
| **Algorithm 2.2:** Token Frequency Matrix construction | |
| 1 | **Procedure** ConstructTFMatrix(tokenizedDataFreq, vocab, classes); |
| 2 | Let TFM ← new Matrix(row=vocab, col=classes); |
| 3 | Let classDocFreq ← zeros(1,5); |
| 4 | **for** row **in** featureDataFreq **do** |
| 5 | Let curClass ← tokenizedDataFreq.class; |
| 6 | Let curWordDict ← tokenizedDataFreq.wordDictionary; |
| 7 | **for** word, frequency **in** curWordDict **do** |
| 8 | TFM [word, curClass] += frequency; |
| 9 | classDocFreq[curClass] += 1 |
| 10 | TFM ← sortByRowSum(TFM, order=descending); |
| 11 | **Output** TFMatrix, classDocFreq. |

At this point, we’re able to successfully calculate the prior probability of all the classes in , finishing the first subtask.

### 3.3.3 Word Posterior Probability

The posterior probability of a word is . It is a conditional probability stating that, within the scope of all documents with label class , the portion of word compared to all the words in the documents.

Again, we need to find out the numerator and denominator in order to calculate this probability.

The calculation of this denominator is similar to the previous one, where the only difference is that it takes regard to not just the occurrence of document that belongs to this class, but also the number of words contained in the sentence in that instance. This is done by iterating through the Token-Frequency Matrix generated before.

The calculation of the numerator is just an altered version of calculating the denominator, only filtering the word that is equal to .

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| **Algorithm 2.3:** Token Frequency Matrix construction | |
| 1 | **Procedure** GetProbs(features, vocab, classes); |
|  | for instance in features do |
|  | curDataSet ← instance. |

## 3.4 Evaluation using F-Score

# Results

# Conclusion