# Text Mining Monetary Policy Statements

**A Primer**

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# 1 Introduction

Dealing with text is typically not considered as important in training of economics and social sciences training for data analysis. This is in direct contrast with how often it has to be dealt with prior to more common analysis, or how interesting it might be to have text be the focus of analysis Text Analysis in R. This document and corresponding workshop will aim to provide a sense of the things one can do with text, and the sorts of analyses that might be useful. Moreover, in era of ML, AI and NLP, text analysis is becoming more and more important as human may miss some important information and computer-based approaches can process and summarise text more efficiently than humans. Also, textual analysis may extract meaning from text missed by human readers, who may overlook certain patterns because they do not conform to prior beliefs and expectations (Herasymova, 2022). There are many studies which have done in detail textual analysis of central bank statements Shapiro and Wilson (2021). I have mainly followed Benchimol, Kazinnik, and Saadon (2022) guidelines in this paper.

With this motivation, we apply textual analysis to monetary policy statements by the State Bank of Pakistan (SBP) which is aimed at understanding the monetary policy stance of the central bank. The monetary policy statement (MPS) is a document that is released by the central bank to communicate its monetary policy stance to the public. The MPS is released after the Monetary Policy Committee (MPC) meeting, which is usually held every two months. The MPS contains information on the current state of the economy, the central bank's assessment of the economy, and the central bank's monetary policy stance. The MPS is an important document for the public, as it provides information on the central bank's monetary policy stance, which can have implications for the economy.

The primary objective of these statements is to inform and guide economic analysts and other stakeholders involved in advising traders within the financial markets. They provide insights into recent economic developments and anticipate future trends, thereby facilitating informed decision-making. Therefore, it becomes all the important to analyse how effectively SBP communicates through its policy statements. In assessing the effectiveness of these MPS, we employ textual analysis techniques. Unstructured data, often rich in textual content, encompasses a wide array of sources such as news articles, social media posts, Twitter feeds, transcriptions from videos, and formal documents. Its abundance offers fresh opportunities and simultaneous challenges for researchers and research institutions alike. In this paper, I explore various methodologies for text analysis and propose a systematic approach to leverage text mining techniques. Furthermore, I examine potential empirical applications of these methods.

This paper focuses on the primer of extracting information from unstructured data, and the potential applications of text mining in the context of monetary policy statements. Quantitative analysis of text data is a rapidly growing field, and the methods and techniques used in this paper are not exhaustive. These methods are in extensive use in political science, sociology, linguistics and information security but are not in wide use in economics and finance in Pakistan. Nevertheless, there is a growing interest in the use of text mining in economics and finance, and this paper aims to provide a starting point for researchers interested in text mining and its applications in economics and finance. Recent advances in open source software and the availability of large text datasets have made it easier for researchers to apply text mining techniques to their research. As text data is usually unstructured, therefore, it is important that a reproducible and systematic approach is used to extract information from text data. This paper/tutorial aims to provide a systematic approach to text mining, and to demonstrate the potential applications of text mining in the context of monetary policy statements. Monetary policy and fiscal policy are two of the most important tools that governments and central banks use to manage the economy. Monetary policy refers to the actions taken by the central bank to influence the money supply and interest rates in the economy. The central bank uses monetary policy to achieve its objectives, such as price stability, full employment, and economic growth. The central bank uses a variety of tools to implement monetary policy, such as open market operations, discount rate changes, and reserve requirement changes. The central bank communicates its monetary policy stance to the public through monetary policy statements. Therefore, it is important to analyze these statements to understand the central bank's monetary policy stance. Text mining techniques can be used to extract information from monetary policy statements, and to analyze the central bank's monetary policy stance. This paper/tutorial aims to provide a systematic approach to text mining, and to demonstrate the potential applications of text mining in the context of monetary policy statements.

Monetary policy statements are an important source of information for researchers, as they provide information on the central bank's monetary policy stance, which can have implications for the economy. I have extracted monetary policy statements from the State Bank of Pakistan (SBP) website, and used text mining techniques to extract information from these statements.

The paper is organized as follows. Section 2 provides an overview of text mining and its applications in economics and finance. Section 3 provides a systematic approach to text mining, and Section 4 provides an overview of the potential applications of text mining in the context of monetary policy statements. Section 5 concludes the paper.

## 2 Theoretical Background

The principal goal of text mining is to capture and analyze all possible meanings embeded in text. Text mining transform unstructured data into structured data, and to extract information from text data. Text mining is a rapidly growing field, and has applications in a wide range of fields, such as information retrieval, natural language processing, and data mining. Text mining techniques can be used to analyze the content of text data, and to identify patterns and trends in the text data. Text mining techniques can be used to analyze the sentiment of text data, and to identify the sentiment of the text data. Text mining techniques can also be used to classify text data, and to categorize the text data. Text mining techniques can be used to extract information from text data, and to analyze the text data. Text mining techniques can be used to analyze the content of text data, and to identify patterns and trends in the text data. Text mining techniques can also be used to summarize the content of text data, and to extract information from the text data. Text mining techniques can be used to analyze the sentiment of text data, and to identify the sentiment of the text data. Text mining techniques can also be used to classify text data, and to categorize the text data. Text mining techniques can be used to extract information from text data, and to analyze the text data. Text mining techniques can be used to analyze the content of text data, and to identify patterns and trends in the text data. Text mining techniques can also be used to summarize the content of text data, and to extract information from the text data. Text mining techniques can be used to analyze the sentiment of text data, and to identify the sentiment of the text data. Text mining techniques can also be used to classify text data, and to categorize the text data. Text mining techniques can be used to extract information from text data, and to analyze the text data. Text mining techniques can be used to analyze the content of text data, and to identify patterns and trends in the text data. Text mining techniques can also be used to summarize the content of text data, and to extract information from the text data. Text mining techniques can be used to analyze the sentiment of text data, and to identify the sentiment of the text data. Text mining techniques can also be used to classify text data, and to categorize the text data.

## 3 Data

I apply topic, sentiment, and linguistic analysis to the Monetary Policy Statements (MPS) of the State Bank of Pakistan from 2005-2024 to capture the focus, tone, and clarity of monetary policy communications. Almost 19 years data of monetary policy statements is extracted from the SBP website. There are total 81 MPS documents from 2005 to 2024 I have used in this analysis. There are few statements which have very different structures, therefore are not included. Reason for excluding these statement is usually MPS is 2 to 3 pages but these occasional statements spread over 30 pages, so not included to have 95% documents of same structure. Couple of statements are missing from the website. The data is in PDF format and I have used the `pdftools` package to extract the text from the PDF files. The text is then cleaned and pre-processed to remove any unwanted characters and symbols. The text is then tokenized and converted to a document term matrix. The document term matrix is then used to analyze the text data. `tm` package is used to clean and preprocess the text data, and to create the document term matrix. `tidyverse` and `tidytext` packages are used to analyze and visualize the text data. I have used `tm` package to store data as corpus. There are other forms of data storage in R such as `tibble` and `dataframe` but I have used `tm` package to store data as corpus.`tm` package is used to clean and preprocess the text data, and to create the document term matrix.

```
<<SimpleCorpus>>
Metadata:  corpus specific: 1, document level (indexed): 0
Content:  documents: 1
```

```
                                MONETARY POLICY COMMITTEE\n                    ST
```

```
 [1] "01012018.txt" "02032023.txt" "04042023.txt" "05102012.txt" "07072022.txt"
 [6] "07082022.txt" "08032022.txt" "08062012.txt" "08102011.txt" "09042016.txt"
[11] "10102022.txt" "12042013.txt" "12062023.txt" "12092015.txt" "12122023.txt"
[16] "13042012.txt" "13112013.txt" "14072018.txt" "14092023.txt" "14122012.txt"
[21] "14122021.txt" "15032014.txt" "15052020.txt" "15112014.txt" "16042020.txt"
[26] "16072019.txt" "16092019.txt" "17032020.txt" "17052014.txt" "19032021.txt"
[31] "19112021.txt" "20052017.txt" "20052019.txt" "20092014.txt" "20092021.txt"
[36] "21032015.txt" "21052011.txt" "21052016.txt" "21062013.txt" "21092020.txt"
[41] "21112015.txt" "22012021.txt" "22072017.txt" "22082022.txt" "22112019.txt"
[46] "23012023.txt" "23052015.txt" "23052022.txt" "23112020.txt" "24012022.txt"
[51] "24032020.txt" "24052010.txt" "24092016.txt" "24112009.txt" "24112017.txt"
[56] "25032017.txt" "25052018.txt" "25062020.txt" "25112022.txt" "26032011.txt"
[61] "26062023.txt" "26112017.txt" "27032010.txt" "27072021.txt" "28012017.txt"
[66] "28012020.txt" "28052021.txt" "29012024.txt" "29032019.txt" "29092010.txt"
[71] "29092017.txt" "29092018.txt" "29112010.txt" "30012016.txt" "30032018.txt"
[76] "30072016.txt" "30102023.txt" "30112011.txt" "30112018.txt" "31012019.txt"
[81] "31072023.txt"
```

### 3.1 Cleaning and Preprocessing

The text data is cleaned and preprocessed to remove any unwanted characters and symbols. The text data is then tokenized and converted to a document term matrix. The document term matrix is then used to analyze the text data. 'tm' package is used to clean and preprocess the text data, and to create the document term matrix. All the tokens not necessarily carry meaningful information. Text cleaning (or text preprocessing) makes an unstructured set of texts uniform across and within and eliminates idiosyncratic characters or meaningless terms.6 Text cleaning can be loosely divided into a set of steps as shown below. Numbers can also be removed from the text data using `tm_map(corpus, removeNumbers)`. Therefore, it is important to remove the stop words from the text data. Stop words are the most common words in a language, such as 'the', 'is', 'at', 'which', and 'on'. These words do not carry much meaning, and can be removed from the text data. The `tm` package is used to remove the stop words from the text data. However, before removing stopwords, all words are converted to `lowercase` to make the text uniform. `corpus <- tm_map(corpus, tolower`

```
<<SimpleCorpus>>
Metadata:  corpus specific: 1, document level (indexed): 0
Content:  documents: 1
```

```
 MONETARY POLICY COMMITTEE STATE BANK OF PAKISTAN Monetary Policy Statement January Pakistans
```

Below is the text left from corpus after removing the stop words.

> monetary policy committee monetary policy statement ’s economic growth track achieve highest level last eleven years average headline inflation remains within forecast range core inflation continued increase fiscal deficit h fy expected fall close last ’s percent visible improvement export growth remittances marginally higher however largely due high level imports current account deficit remains pressure exchange rate adjustment expected help ease pressure external front progress real sector indicates agriculture sector set perform better second row production major kharif crops except maize surpassed level fy similarly large scale manufacturing lsm recorded healthy broad based growth percent.

One final step is to stem the words. Stemming is the process of reducing words to their root form. For example, the words ‘running’, ‘runs’, and ‘ran’ are all reduced to the root form ‘run’. The `tm` package is used to stem the words in the text data.

Once we have cleaned and preprocessed the text data, we can convert the text data to a document term matrix (dtm)

Now we create a matrix with term frequencies

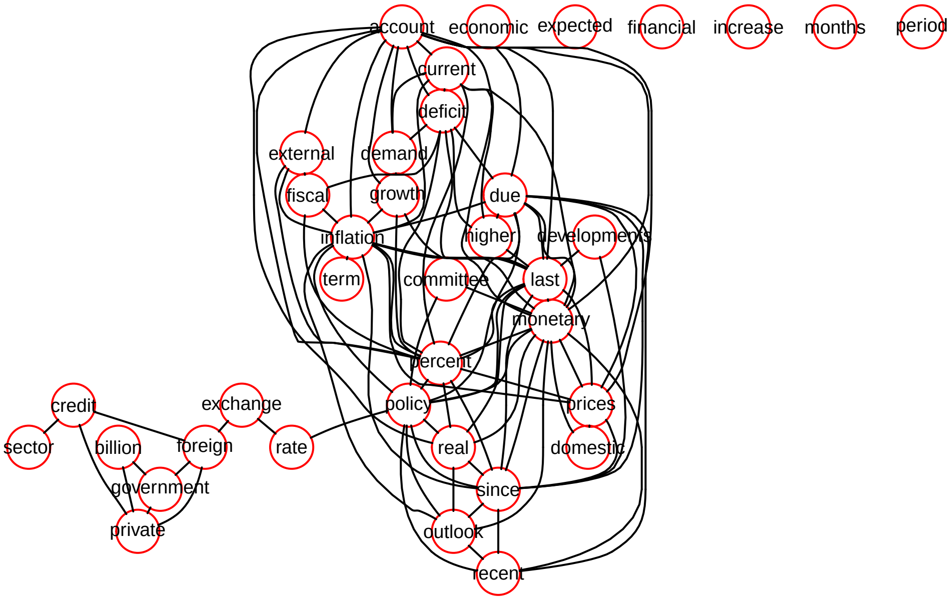
```
accordingly     account    accounts     achieve    activity      adjust 
         12         331          26          35         137           4 

     twelve     defense     emerged    notified recalibrate       serve 
          1           1           1           1           1           1 

[1] 81 12

 decided expected     rate  deficit  account  current 
      85      286      306      330      331      387 

   sector  monetary    growth    policy inflation   percent 
      415       511       520       604       897       905 

 [1] "account"   "current"   "deficit"   "expected"  "growth"    "inflation"
 [7] "monetary"  "percent"   "policy"    "rate"      "sector"   
 [1] "account"   "current"   "deficit"   "expected"  "growth"    "inflation"
 [7] "monetary"  "percent"   "policy"    "rate"      "sector"
```

```
 [1] "account"   "current"   "deficit"   "growth"    "inflation" "monetary"
 [7] "percent"   "policy"    "rate"      "sector"
```

```
[1] "growth"    "inflation" "monetary"  "percent"   "policy"
```

```
[1] "inflation" "percent"
```

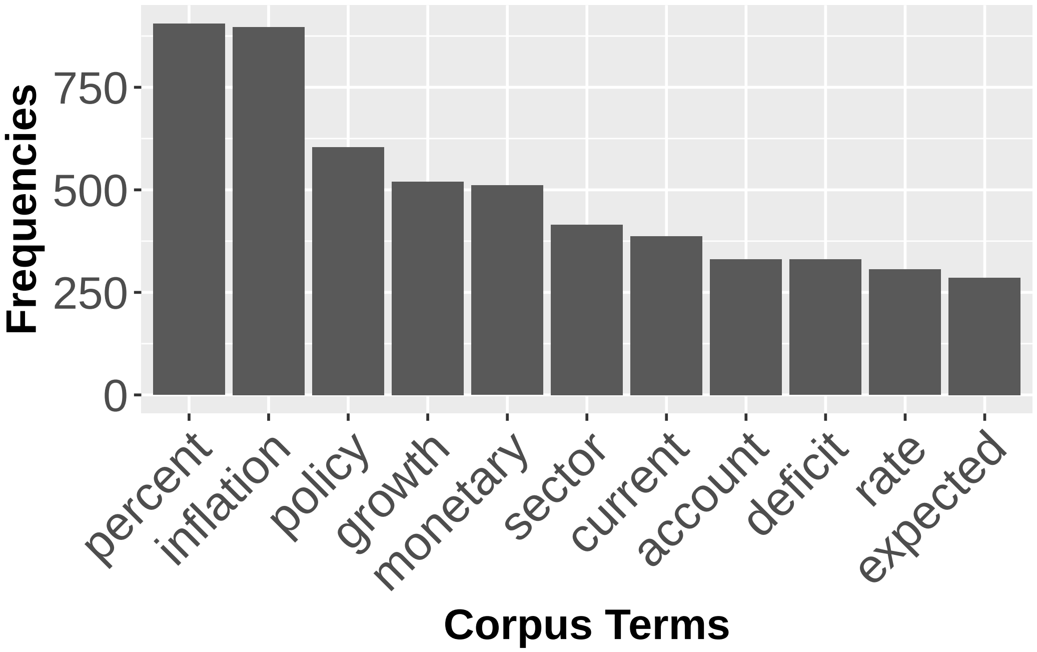
## 4 Plotting data

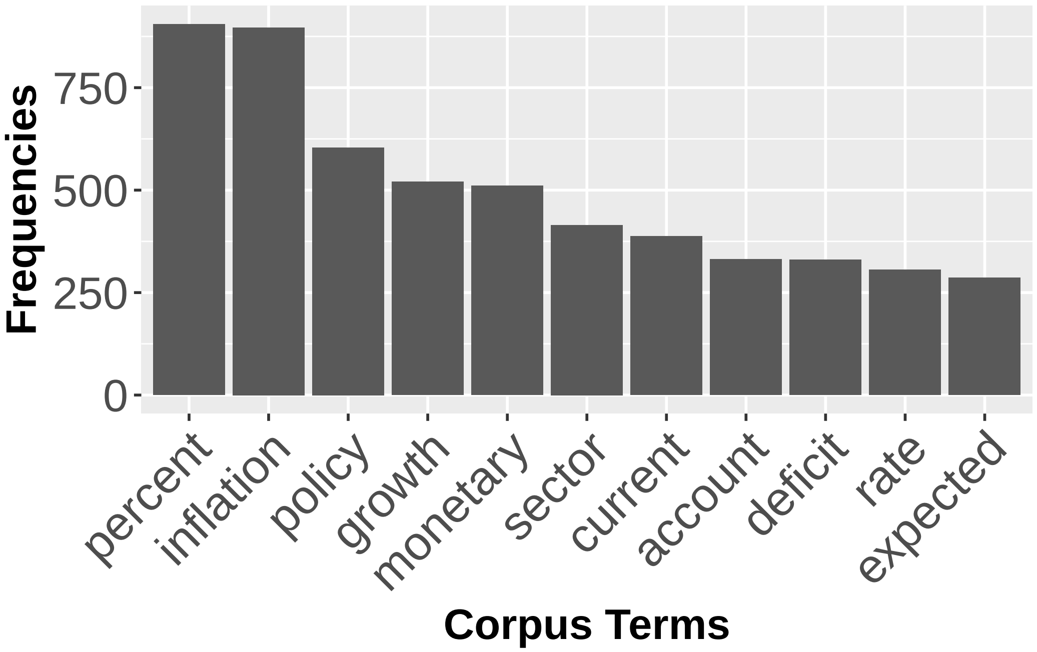


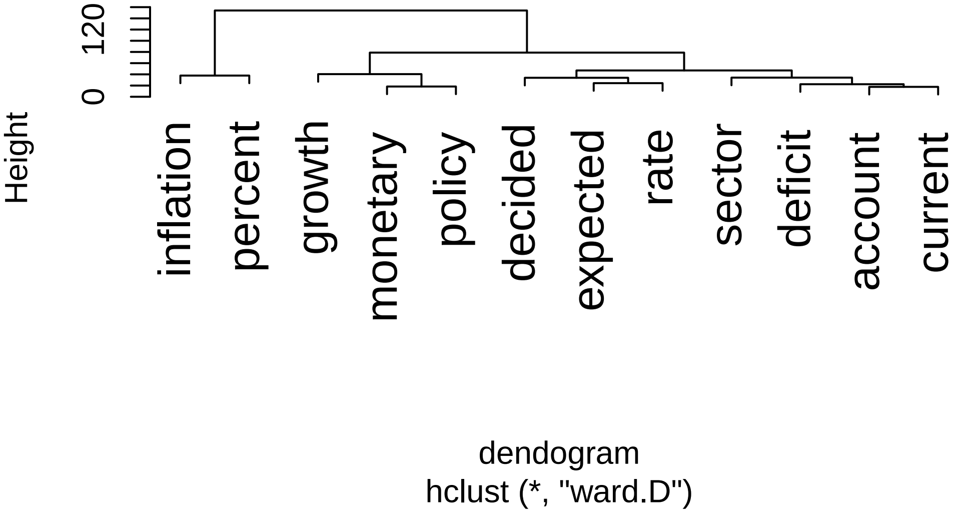
```
  percent inflation    policy    growth  monetary    sector   current   account
      905       897       604       520       511       415       387       331
  deficit      rate  expected   decided
      330       306       286        85
```

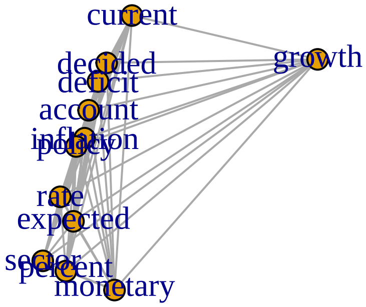
```
               word freq
percent     percent  905
inflation inflation  897
```

```
policy        policy  604
growth        growth  520
monetary    monetary  511
sector        sector  415
current      current  387
account      account  331
deficit      deficit  330
rate            rate  306
```



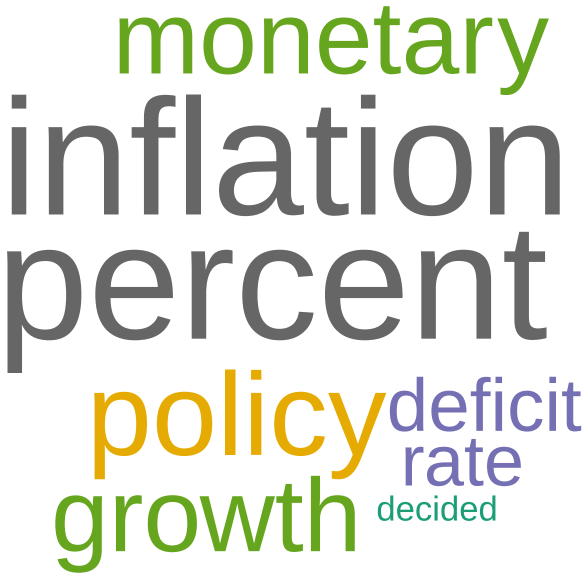

Frequencies
750
500
250
0
percent
inflation
policy
growth
monetary
sector
current
account
deficit
rate
expected
Corpus Terms

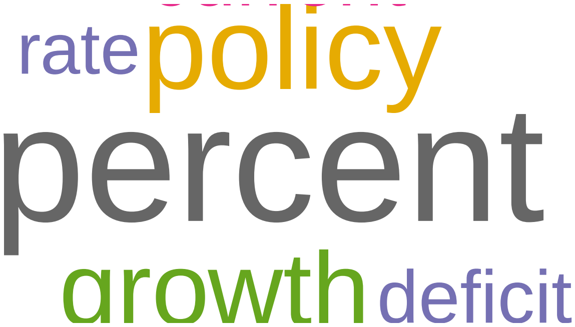

120
0
Height
inflation
percent
growth
monetary
policy
decided
expected
rate
sector
deficit
account
current
dendogram
hclust (*, "ward.D")

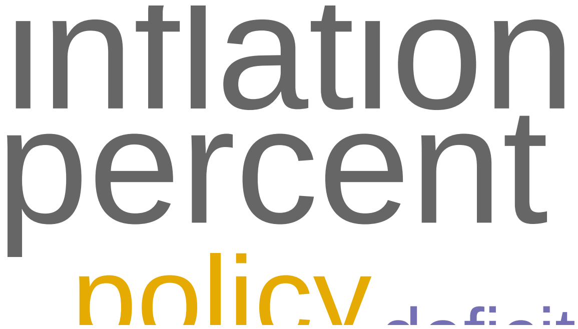


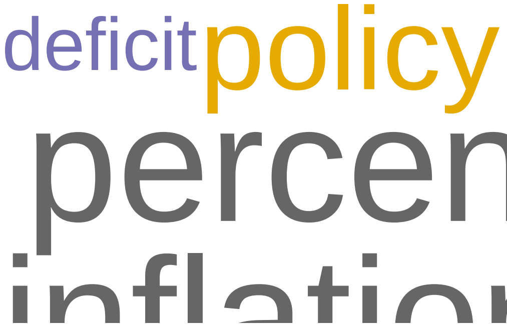
## 5 Word Cloud

The `wordcloud` package is used to visualize the text data. The word cloud is a visual representation of the frequency of words in the text data. The size of the word in the word cloud is proportional to the frequency of the word in the text data. The `wordcloud` package is used to create the word cloud. The word cloud is created using the document term matrix. The word cloud is used to identify the most frequent words in the text data.


monetary
inflation
percent
policy
deficit
rate
growth
decided


rate
policy
percent
growth
deficit


inflation
percent
policy
deficit


deficit
policy
percent
inflation

growth
percent
policy

policy
percent
inflation

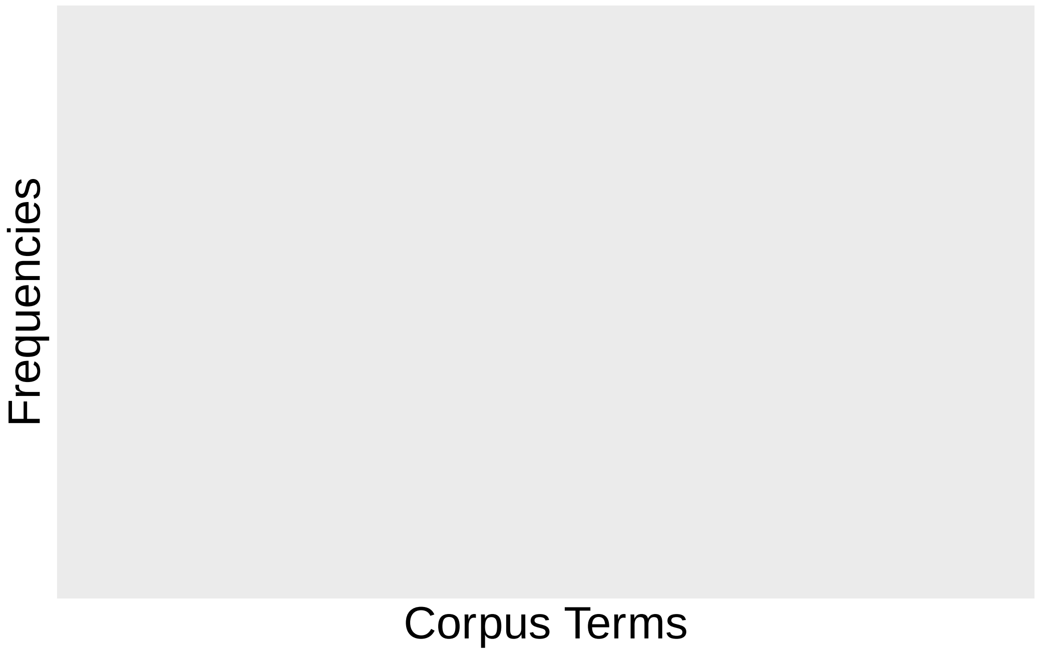
## 5.1 Weighting Scheme

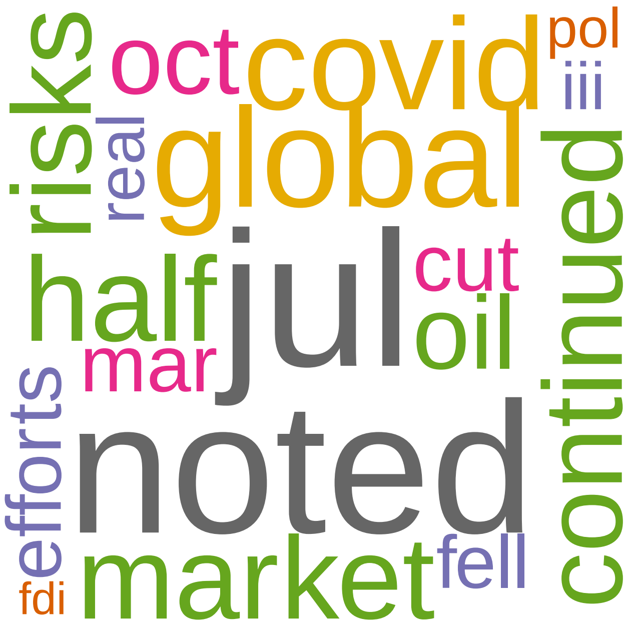
Another weighting scheme - term frequency/inverse document frequency is given here to create word clouds. The term frequency/inverse document frequency is a statistical measure used to evaluate the importance of a word in a document relative to a collection of documents.

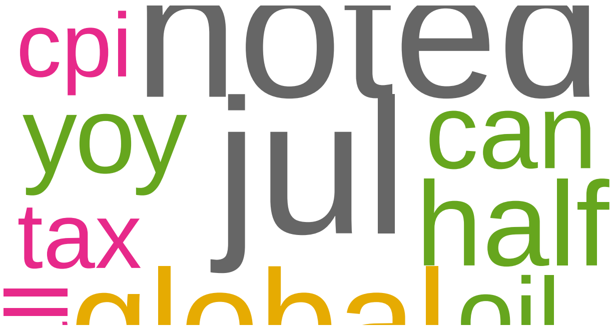
```
[1]   81 1160
```

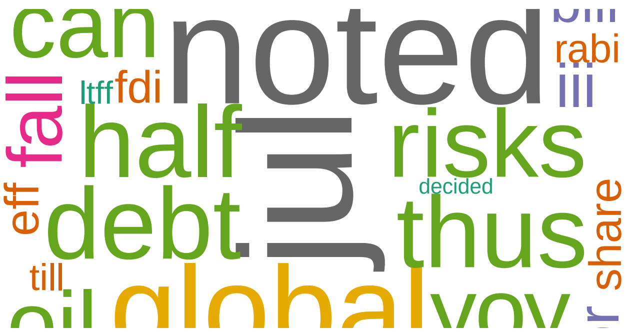
```
        jul       noted  borrowings coronavirus   committee      global 
  0.2841889   0.2759655   0.2673504   0.2441497   0.2295718   0.2025230 
    meeting    recovery       covid      floods      system     economy 
  0.1977287   0.1942000   0.1863952   0.1823993   0.1822402   0.1697131 
       half      market       month        debt     banking       views 
  0.1683789   0.1666185   0.1665209   0.1658002   0.1652578   0.1650299 
       thus    improved 
  0.1646712   0.1616948 
```

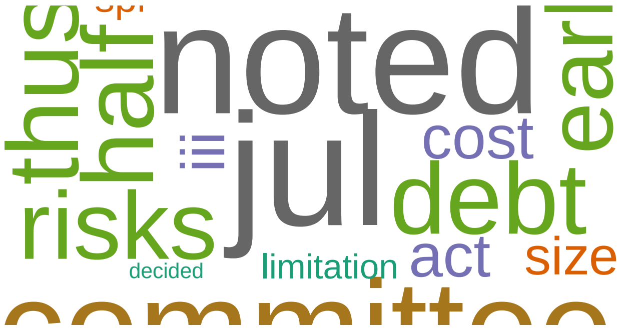
```
                   word      freq
jul                 jul 0.2841889
noted             noted 0.2759655
borrowings   borrowings 0.2673504
coronavirus coronavirus 0.2441497
committee     committee 0.2295718
global           global 0.2025230
```

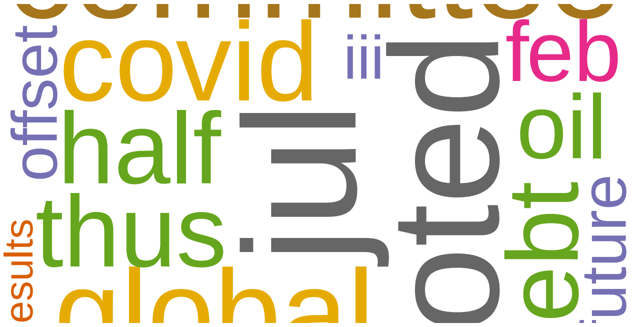

Frequencies
Corpus Terms


risks
oct
covid
pol
iii
real
global
continued
half
jul
cut
oil
mar
efforts
noted
market
fell
fdi


cpi
noted
yoy
jul
can
tax
half
global
oil


can
noted
rabi
iii
ltff
fdi
fall
half
risks
jul
decided
eff
debt
thus
share
till
oil
global
yoy





Document term matrix is a matrix that contains the frequency of words in the text data. The rows of the matrix represent the documents, and the columns represent the words. The matrix contains the frequency of each word in each document. The document term matrix is used to analyze the text data, and to identify patterns and trends in the text data. The `tm` package is used to create the document term matrix. After cleaning and preprocessing the text data, the text data is tokenized and converted to a document term matrix. The document term matrix is then used to analyze the text data. The goal of dtm is two fold. The first is to present the topic of each document by the frequency of semantically significant and unique terms, and second, to position the corpus for future data analysis. The term frequency-inverse document frequency (tf-idf) is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in information retrieval and text mining. The tf-idf value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general. The `tm` package is used to create the document term matrix.

Why is frequency of each word is important? Simple frequency of each word is inappropiate because it can overstate the importance of small words that happen to be frequent. The term frequency-inverse document frequency (tf-idf) is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in information retrieval and text mining. The tf-idf value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general. tf-idf is defined as follows:

tf(t)= (Number of times term t appears in a document) / (Total number of terms in the document)

A more appropriate way to calaculate word frequencies is to employ the tf-idf weighting scheme. The tf-idf value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general.

ifd(t)= log_e(Total number of documents / Number of documents with term t in it)

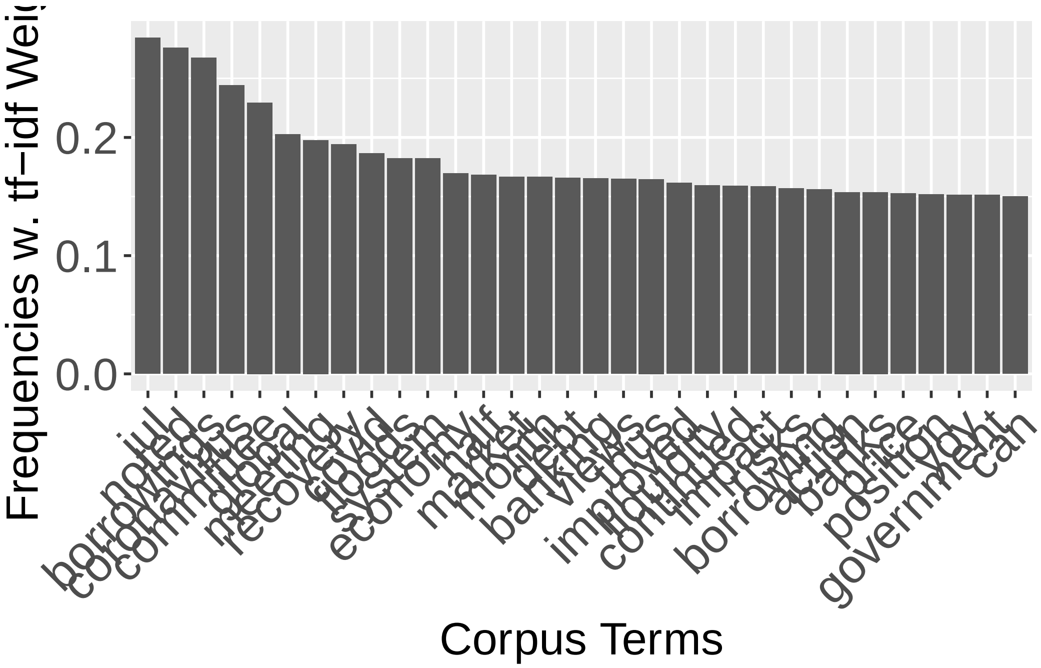
Conjugating the two gives the tf-idf score for each word in each document. $-\ (\ )=\ (\ )\times\ (\ )$

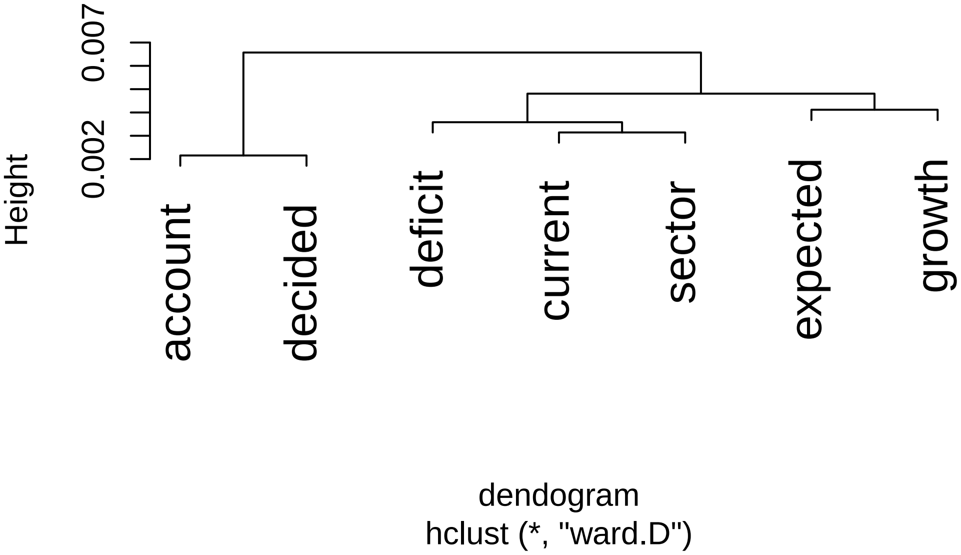
## 5.2 Tidytext data table

Now I shall use `tidytext` with the help of unnest_tokens to convert one word per row.

```
                    word      freq
jul                  jul 0.2841889
noted              noted 0.2759655
borrowings    borrowings 0.2673504
coronavirus  coronavirus 0.2441497
committee      committee 0.2295718
global            global 0.2025230
```

```
meeting          meeting 0.1977287
recovery        recovery 0.1942000
covid              covid 0.1863952
floods            floods 0.1823993
```





```
null device
          1

pdf
  2
```

# 6 Exploratory Data Analysis

With conversion to dtm, exploratory data analysis is performed to identify patterns and trends in the text data.

## 6.1 Word counting

Dictionary-based text analysis is popular approach mainly because its easy to implement and interpret. The dictionary-based approach is based on the idea that the frequency of certain words in a text can be used to infer the sentiment of the text. However, sentiment words from one discipline to another might be different. For example, words used in psychology to express positive sentiments might be different from words used in economics. Therefore, it is important to use a dictionary that is specific to the discipline. The `tidytext` package is used to count the frequency of words in the text data. The `get_sentiments` function is used to get the sentiment words from the dictionary. In this document, I am using Loughran and McDonald dictionary to count the frequency of positive and negative words in the text data.

It is important to be careful in use of words to be positive or negative. For example, the word 'increase' is generally considered to be positive, but in the context of inflation, it is considered to be negative. Similarly the word 'decrease' is generally considered to be negative, but in the context of inflation, it is considered to be positive. Another example is `tight` and `loose` monetary policy. The word `tight` is generally considered to be positive, but in the context of monetary policy, it is considered to be negative. Similarly, the word `loose` is generally considered to be negative, but in the context of monetary policy, it is considered to be positive. Therefore, it is important to be careful in use of words to be positive or negative.

Next we use the `match` function that compares the terms in both dictionary and the text data. The `match` function returns the position of the first match. If there is no match, the `match` function returns `NA`. The `match` function is used to count the frequency of positive and negative words in the text data.

We then assign a value of 1 to the positive and negative matches. The `ifelse` function is used to assign a value of 1 to the positive and negative, and measure the overall sentiment for each document $i$ by the following formula: $Score_i = \frac{Positive_i - Negative_i}{Positive_i + Negative} \in [-1, 1]$

A document is considered to be positive if the score is greater than 0, and negative if the score is less than 0.

### 6.2 Relative frequency

The relative frequency of positive and negative words is calculated by dividing the frequency of positive and negative words by the total number of words in the text.

### 6.3 Semantic analysis

The semantic analysis is performed to identify the semantic orientation of the text data. The semantic orientation is the degree to which a word is positive or negative. The semantic orientation is calculated by dividing the frequency of positive words by the frequency of negative words. The semantic orientation is calculated for each document in the text data.

## 7 Topic models

Topic modeling is a type of statistical model for discovering the abstract "topics" that occur in a collection of documents. Topic modeling is a frequently used text-mining tool for discovery of hidden semantic structures in a text body. Intuitively, given that a document is about a particular topic, one would expect particular words to appear in the document more or less frequently: "dog" and "bone" will appear more often in documents about dogs, "cat" and "meow" will appear in documents about cats, and "the" and "is" will appear equally in both. A document typically concerns multiple topics in different proportions; thus, in a document that is 10% about cats and 90% about dogs, there would probably be about 9 times more dog words than cat words. The "topics" produced by topic modeling techniques are clusters of similar words. A topic model captures this intuition in a mathematical framework, which allows examining a set of documents and discovering, based on the statistics of the words in each, what the topics might be and what each document's balance of topics is.

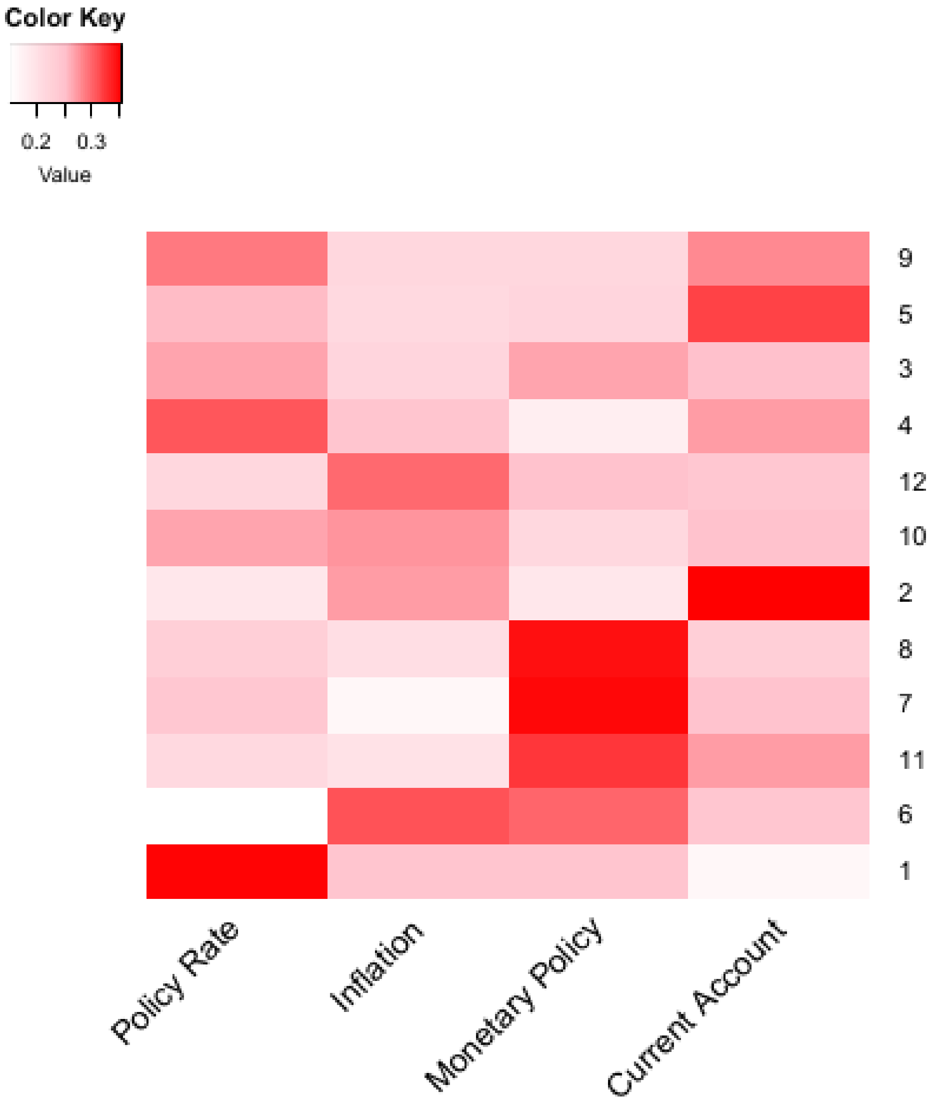
```
             [,1]
01012018.txt    1
02032023.txt    4
04042023.txt    1
05102012.txt    1
07072022.txt    4
07082022.txt    2
08032022.txt    3
08062012.txt    3
08102011.txt    1
09042016.txt    2
```

```
      Topic 1     Topic 2    Topic 3     Topic 4
 [1,] "growth"    "policy"   "percent"   "inflation"
 [2,] "percent"   "rate"     "current"   "monetary"
 [3,] "sector"    "expected" "account"   "percent"
 [4,] "policy"    "monetary" "deficit"   "decided"
 [5,] "expected"  "decided"  "policy"    "policy"
 [6,] "inflation" "percent"  "decided"   "rate"
 [7,] "account"   "sector"   "expected"  "current"
 [8,] "current"   "account"  "growth"    "deficit"
 [9,] "decided"   "current"  "inflation" "account"
[10,] "deficit"   "deficit"  "monetary"  "expected"
[11,] "monetary"  "growth"   "rate"      "growth"
```

### 7.1 Heatmap

The heatmap is used to visualize the frequency of positive and negative words in the text data. The `heatmap` function is used to create the heatmap. The `heatmap` function takes the frequency of positive and negative words as input and creates the heatmap. The `heatmap` function is used to create the heatmap. The `heatmap` function takes the frequency of positive and negative words as input and creates the heatmap.

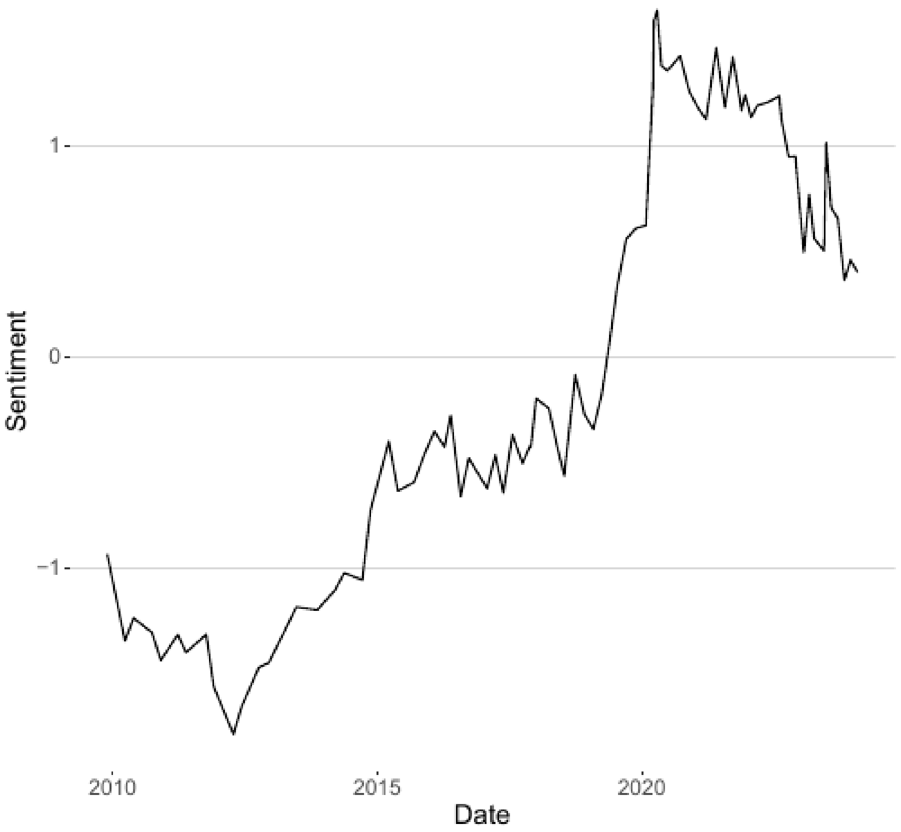
```
pdf
  2
```



## 7.2 Wordfish

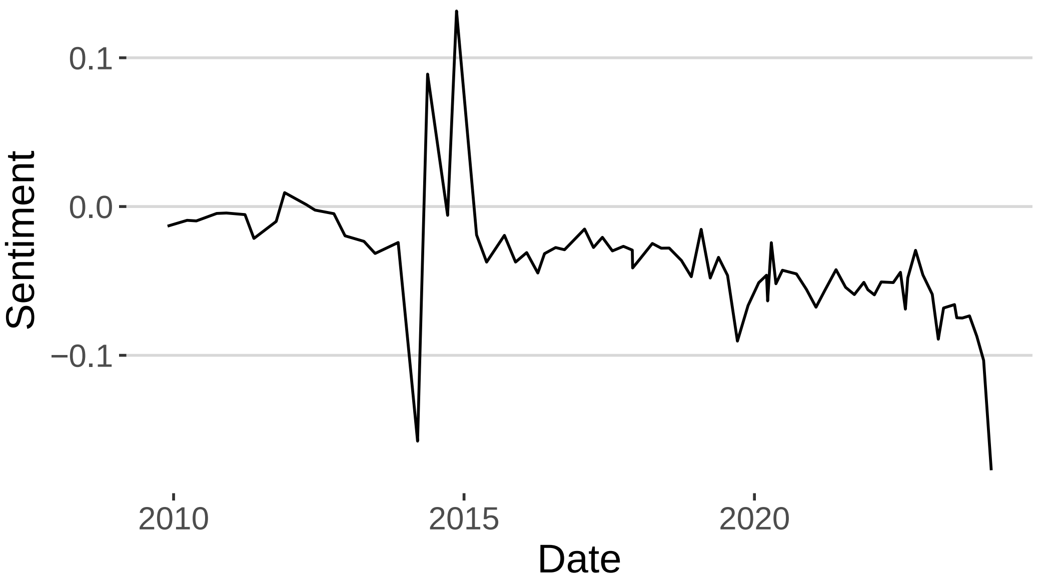
## 7.3 Plotting Wordfish Score

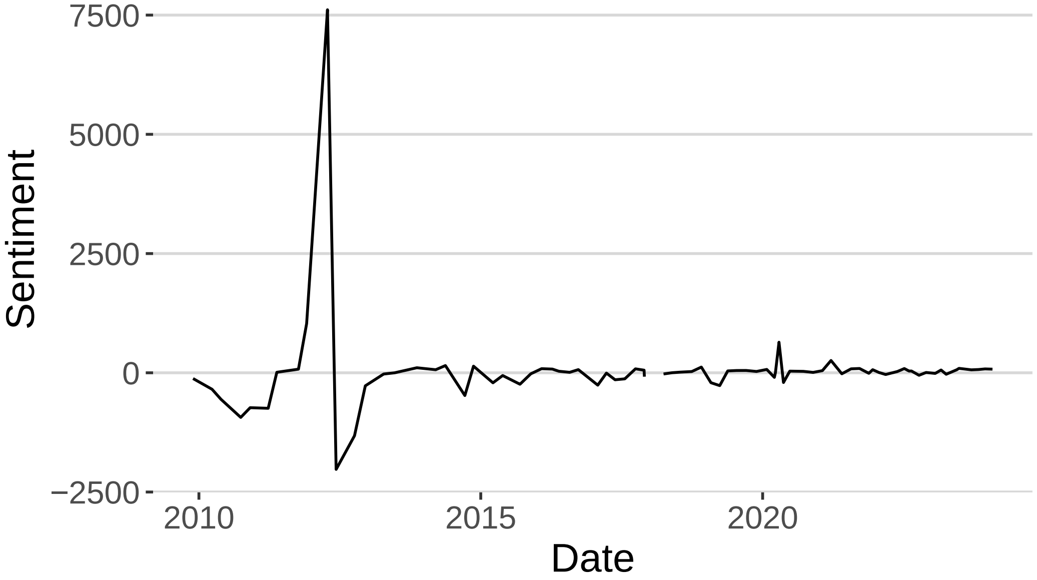
```
pdf
  2
```



```
   monetary      policy   committee   statement   pakistans    economic
-0.31834700 -0.26834445 -0.70253373  0.01884639  0.01165021 -0.19203767
     growth       track     achieve     highest
 0.01485533  0.01884639  0.01596416  0.01165021
```

### 7.4 Plotting Wordscores Score





# 8 Conclusion

I hope that this document will be useful for researchers and practitioners who are interested in text mining and sentiment analysis. I have demonstrated how to use the R programming language to perform text data analysis based on monetary policy statements. The code provided in this document can be used as a starting point for further research and analysis. The R programming language is a powerful tool for text mining and sentiment analysis, and it is widely used in the academic and business communities. I hope that this document will help to promote the use of R in the field of text mining and sentiment analysis. This reproducible document will also serve the purpose of how to automate the process of text data analysis and sentiment analysis. I also demonstrate that R langugage has made it easy to perform text data analysis and sentiment analysis and has become a powerful tool for text mining and sentiment analysis, and it is widely used in the academic and business communities. My initial findings suggest that SBP policy has nuetral tone and it is not biased towards hawkish or dovish. However, the sentiment analysis is based on the text data and it is important to consider the context and the content of the text data.

Benchimol, Jonathan, Sophia Kazinnik, and Yossi Saadon. 2022. "Text Mining Methodologies with R: An Application to Central Bank Texts." *Machine Learning with Applications* 8 (June): 100286. https://doi.org/10.1016/j.mlwa.2022.100286.

Shapiro, Adam Hale, and Daniel J Wilson. 2021. "Taking the Fed at Its Word: A New Approach to Estimating Central Bank Objectives Using Text Analysis." *The Review of Economic Studies* 89 (5): 2768–2805. https://doi.org/10.1093/restud/rdab094.