

# Latent Semantic Analysis and Sentiment Analysis

Nino Miljkovic

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## **OBJECTIVE**

To explore a large text-based dataset to uncover latent themes and analyze sentiments within the data.

## **DATASET**

### **Source:**

Public Domain dataset found at <https://www.kaggle.com/datasets/gpreda/bbc-news>

### **Dataset name:**

bbc\_news.csv

### **Description:**

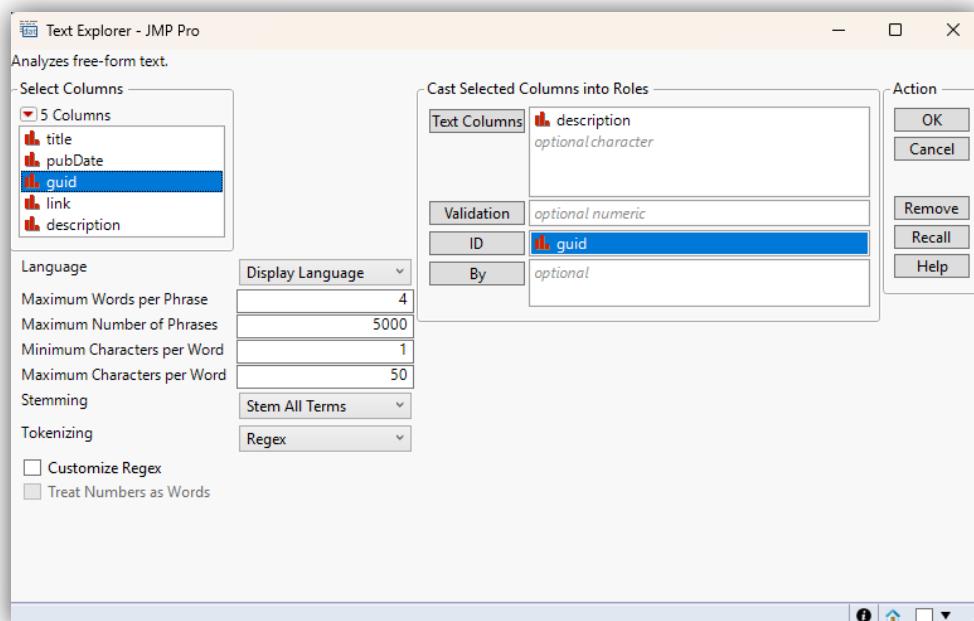
The BBC News dataset, created by a data scientist Gabriel Preda, is a publicly accessible and regularly updated collection of BBC news articles collected through their RSS feeds by utilizing requests\_html and Beautiful Soup.

The dataset is provided as a CSV file containing around 39,700 values, each representing a news article. Each of those entries is represented by a title, publication date, a unique identifier, the article link, and a brief description. By possessing rich unstructured textual data, this dataset is ideal for text mining projects, including LSA and sentiment analysis.

*The copy of the dataset is provided with this submission.*

## **ANALYSIS**

The first step was to download the CSV file and verify its content before loading it into JMP Pro. After the verification, the file was loaded into JMP Pro and the Preprocessing stage of the analysis could begin. The first step was to import the textual data into JMP Pro's Text Explorer.

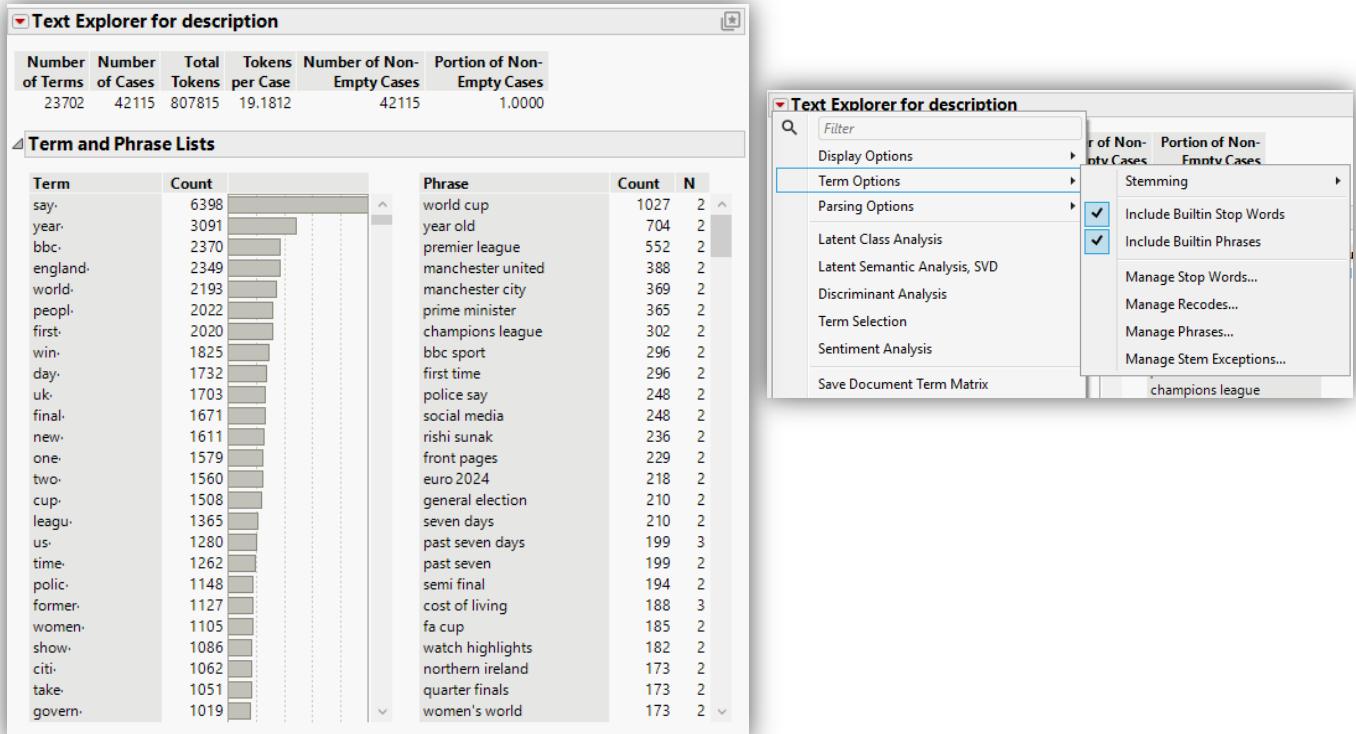


The *description* column containing the unstructured textual data was selected for “Text Columns”, while the unique identifier *guid* was selected for “ID”. *Stem All Terms* was selected as the stemming option.

After clicking OK, the following preprocessing steps were applied:

- **Tokenization:** Text was automatically tokenized by JMP into individual terms and phrases.
- **Stop Words Removal:** Common English stop words were automatically filtered out by JMP’s built-in stop word removal tool.
- **Stemming:** By choosing the *Stem All Terms* option, the words were reduced to their root forms (running → run) which helped consolidate similar terms.
- **Punctuation and Special Character Removal:** These were removed during the tokenization process.

*Lemmatization was not performed, as stemming provided sufficient dimensionality reduction for Latent Semantic Analysis (LSA) and sentiment classification tasks.*



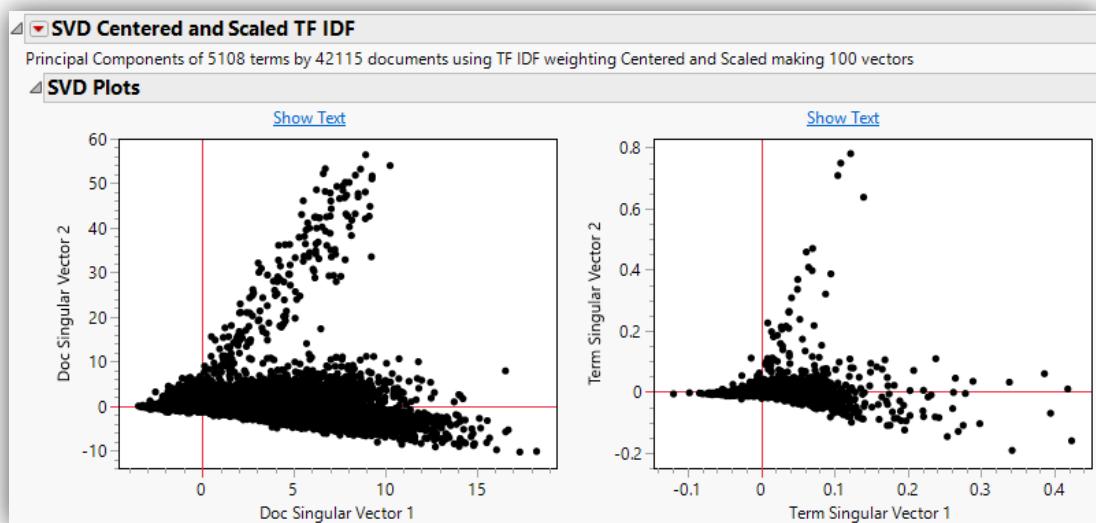
At this stage we are also provided with the List of Terms and Phrases that are most represented as indicated by their count. Terms like “say”, “year”, “bbc”, “england”, “world”, “peopl” and their variations are most common across documents, while “world cup”, “year old”, “premier league”, “manchester united”, “manchester city”, and “prime minister” dominate phrases, possibly indicating that the majority of articles cover themes of politics and sport.

Upon the completion of the preprocessing of the textual data, the next step was to conduct the **Latent Semantic Analysis (LSA)** in order to uncover the underlying themes in the textual data by using **Singular Value Decomposition (SVD)** on a term document matrix with TF-IDF weighting.

The screenshot shows the JMP Text Explorer interface for conducting LSA. On the left, a sidebar lists various analysis options, with "Latent Semantic Analysis, SVD" selected. A main panel displays a table of term counts and frequencies. To the right, a "Specifications" dialog box is open, containing settings for the SVD process:

- Maximum Number of Terms: 5108
- Minimum Term Frequency: 10
- Weighting: TF IDF
- Number of Singular Vectors: 100
- Centering and Scaling: Centered and Scaled

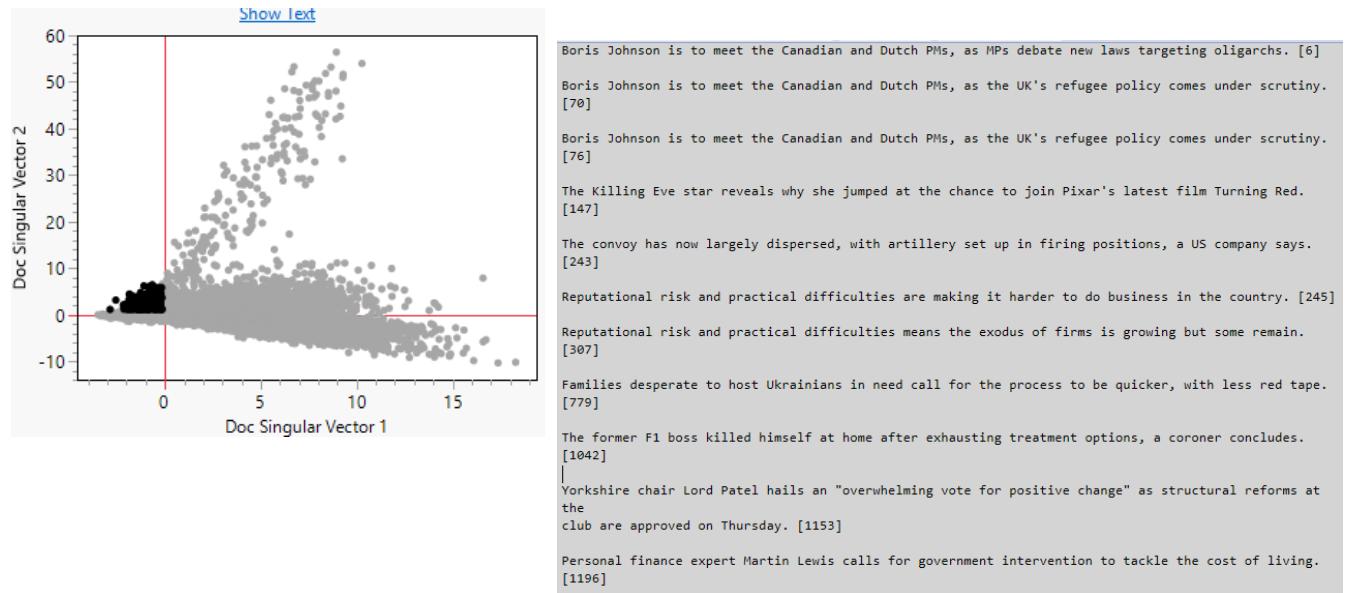
JMP was configured to use 100 singular vectors and the data was centered and scaled to highlight latent patterns. This resulted in two plots shown below.



The left plot (Doc Singular Vector 1 and 2) depicts documents clustered around similar themes, while the right plot (Term Singular Vector 1 and 2) visualizes distribution of terms alongside those same dimensions where densely clustered terms indicate shared context.

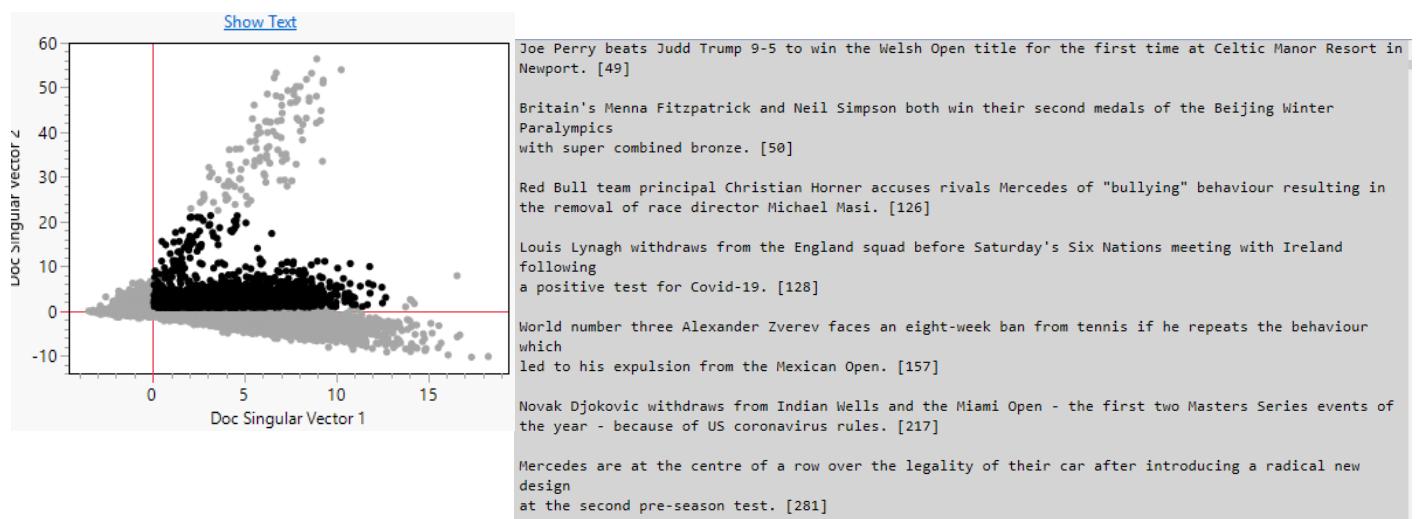
By reducing dimensionality SVD plots highlight distinct topic groups. These can be revealed by highlighting quadrants and using *Show Text* to examine the textual data.

### Top Left Quadrant of the Document Plot:

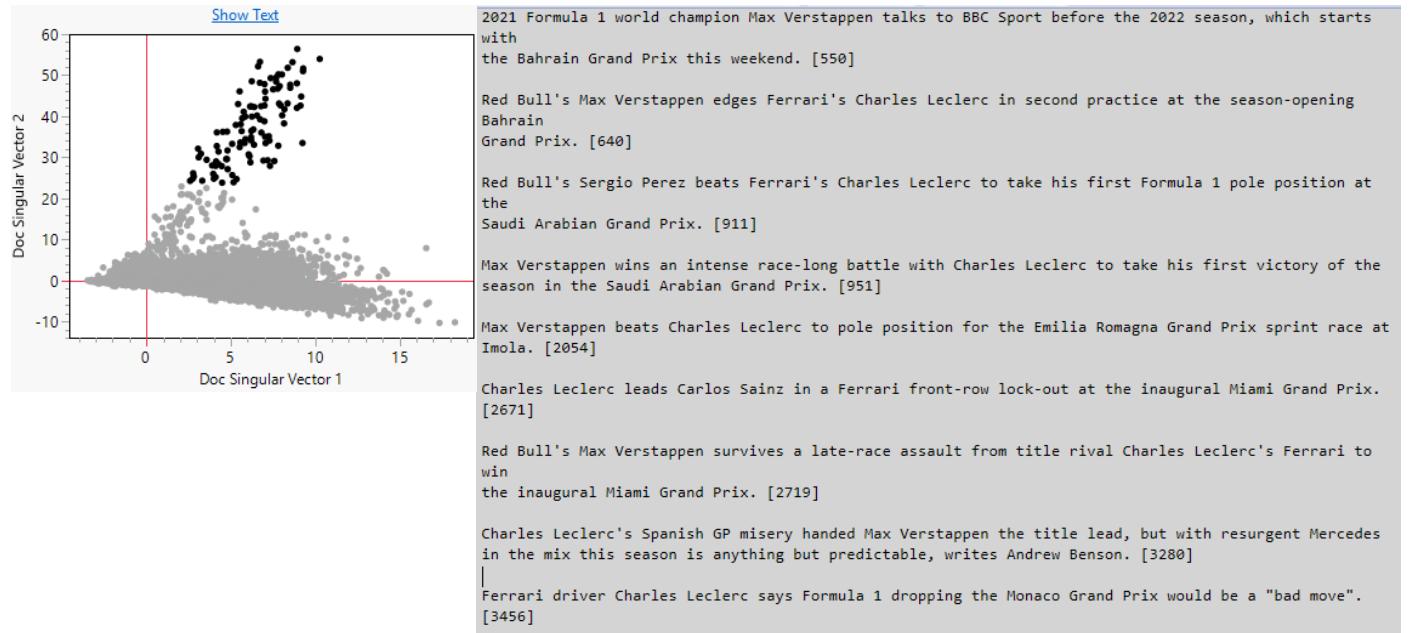


By analyzing this quadrant through *Show Text* function, we can observe that the articles that are clustered together in this section cover themes of global and local politics.

### Top Right Quadrant in the Document Plot:

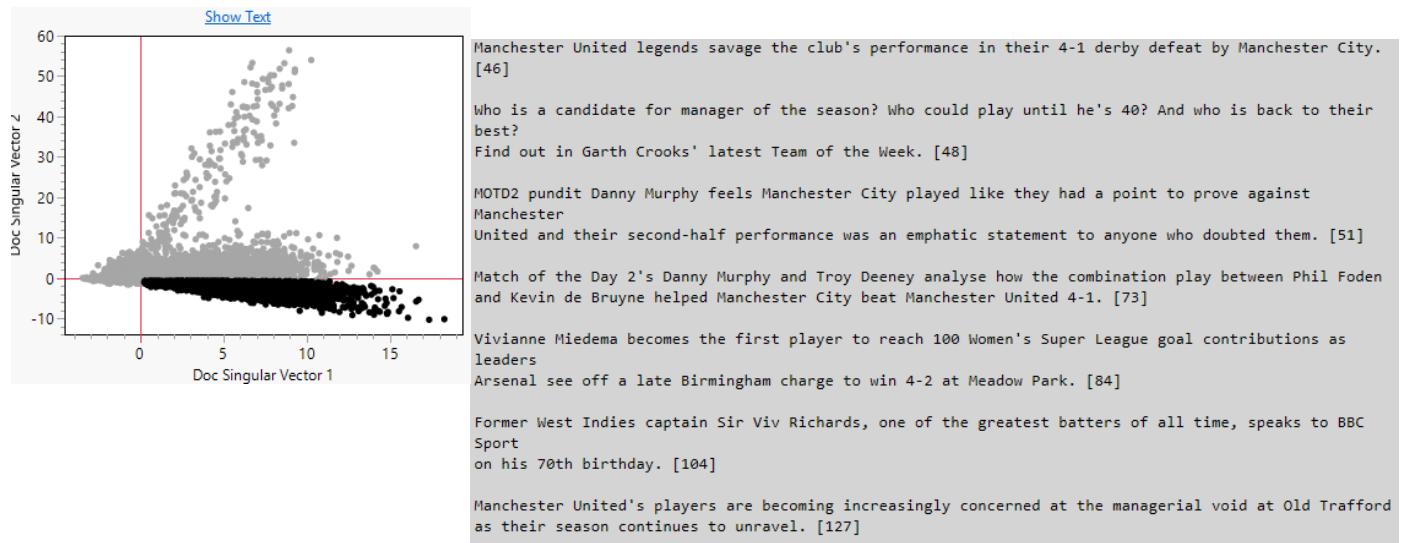


The articles that are present in this quadrant all cover different sports, like tennis, formula 1, paralympics, rugby and similar. However, if we shift the focus only on the upper cluster of data points like in the graph below:



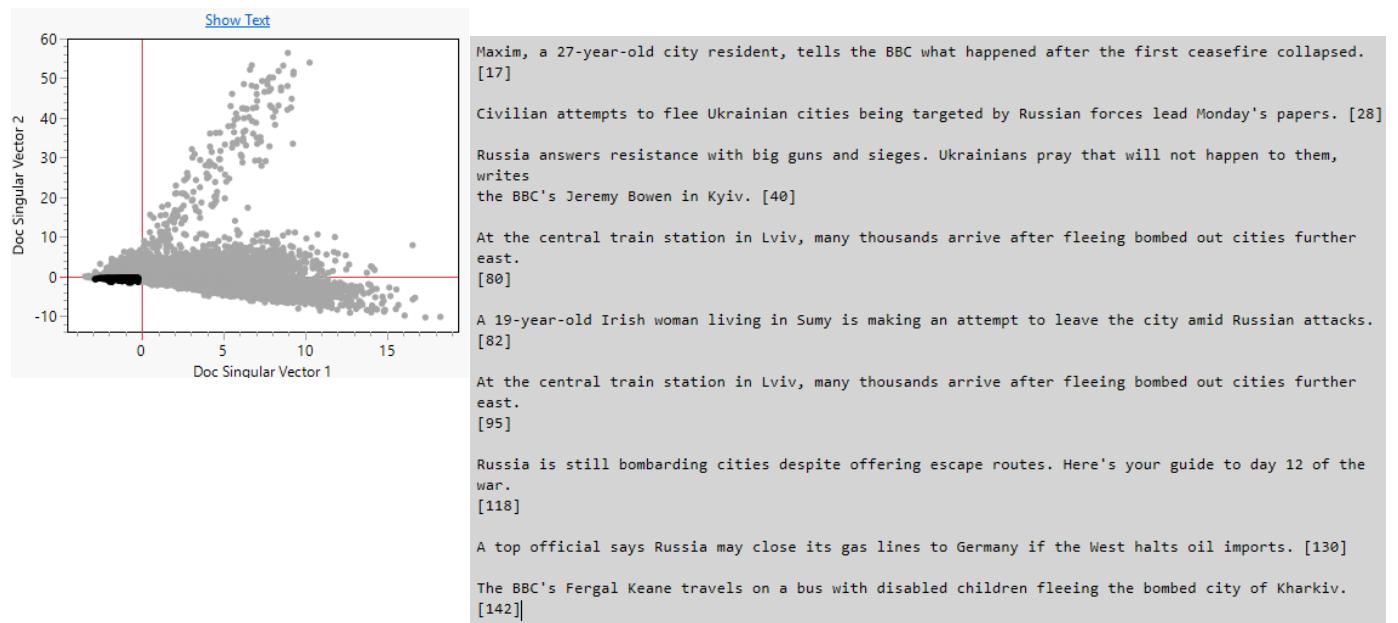
We will notice that those articles deal exclusively with Formula One racing.

### Bottom Right Quadrant in the Document Plot:



This quadrant contains articles that all share the same topic, which is football, predominantly the Premier League.

## Bottom Left Quadrant in the Document Plot:



The articles in this portion of the plot are clustered together due to their shared relationship of topics covering the war in Ukraine.

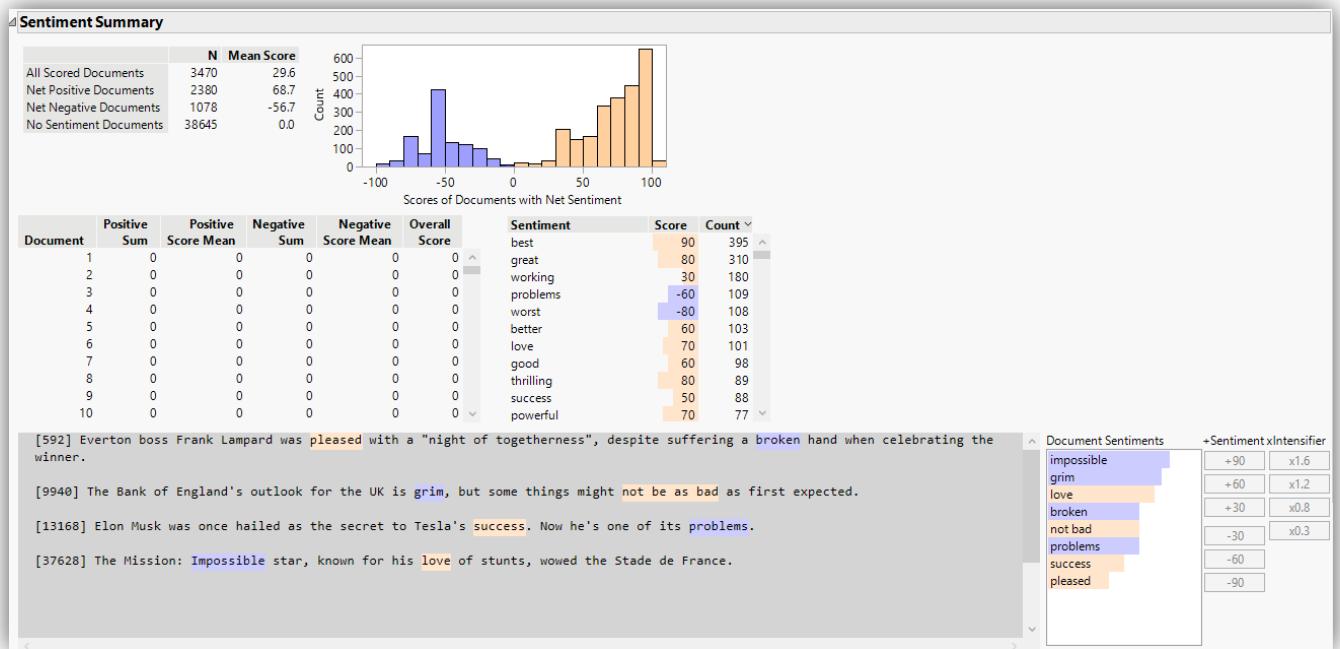
After examining the four quadrants in the SVD Document Plot, we can establish the **four major themes** in the BBC articles:

1. **Politics** (global and local)
2. **Sports** (all sports with a subgroup of articles sharing the theme of Formula One)
3. **Premier League** and other football news
4. **Conflict in Ukraine** and news related to it

The SVD Term Plot quadrants further depict these four themes by having terms related to those four themes clustered together in the corresponding quadrants.

By clearly revealing notable theme groups, Latent Semantic Analysis has helped reduce dimensionality and improve interpretability, thus setting the stage for the Sentiment Analysis.

**Sentiment Analysis** was conducted using JMP's built-in system that calculates net sentiment score for documents.



The number of all scored documents was 3,470, and of those 2,380 were classified as having net positive sentiment, while 1,078 were classified as having net negative sentiment. The rest either had a neutral or no detectable sentiment. The net positive mean was 68.7, while the negative mean was -56.7.

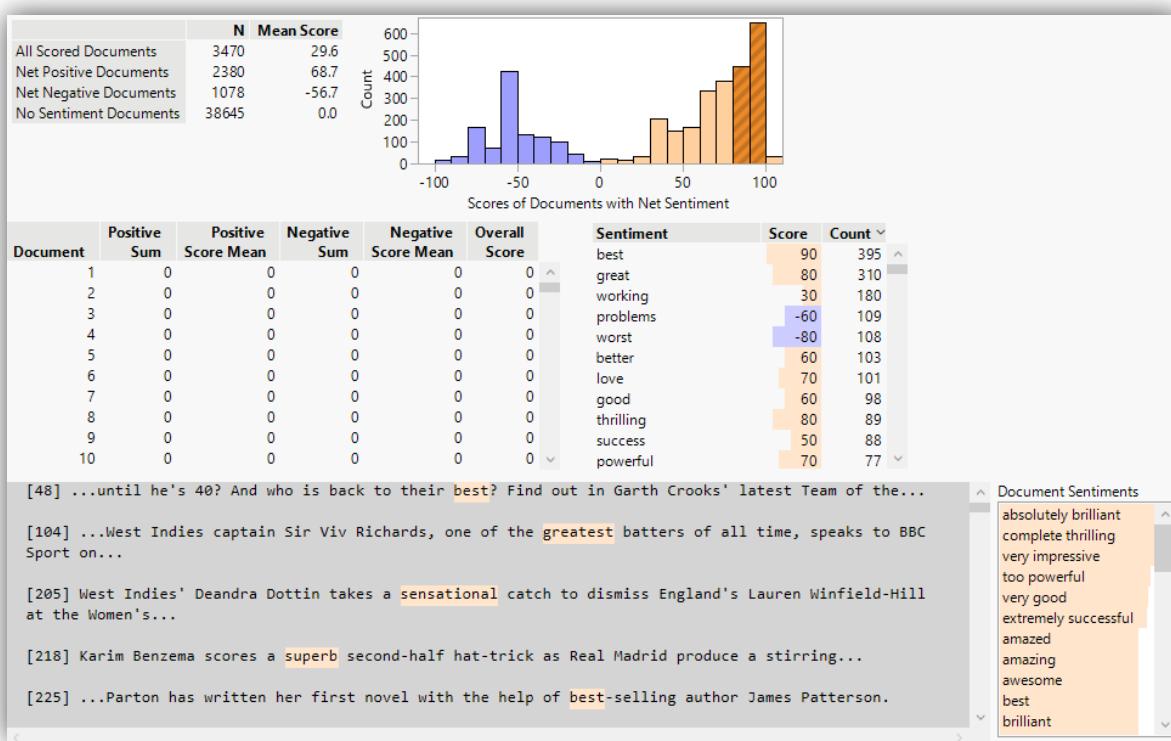
This is visually represented in the histogram that is showing a slight skew towards the net positive sentiment with the peak in +60 to +90 range. The negative sentiment peak was at -60.

The frequently occurring words reveal patterns of what kind of terms are most often related to positive and negative sentiments, as seen in this table:

Sentiment	Score	Count
best	90	395
great	80	310
working	30	180
problems	-60	109
worst	-80	108
better	60	103
love	70	101
good	60	98
thrilling	80	89
success	50	88
powerful	70	77

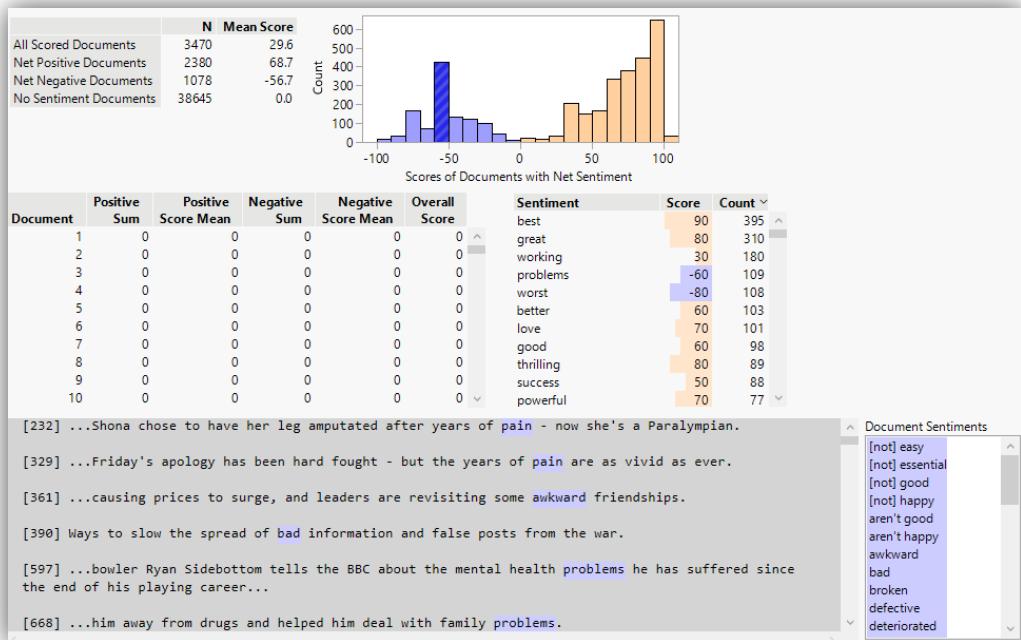
Words like “best”, “great”, “better”, “love” are the most frequently occurring positive terms, while the negative ones are “problems” and “worst”.

By selecting bins of the histogram, we can further investigate different portions of the plot by reviewing the terms and documents associated with them. First, the net positive peaks were chosen as shown in the plot below.



By reviewing the Document Sentiments, we can see the list of words associated with the positive context. Words like “absolutely brilliant”, “complete thrilling”, “very impressive”, “too powerful”, and so on. We can also see those words highlighted in the documents where they add a positive sentiment to the topic.

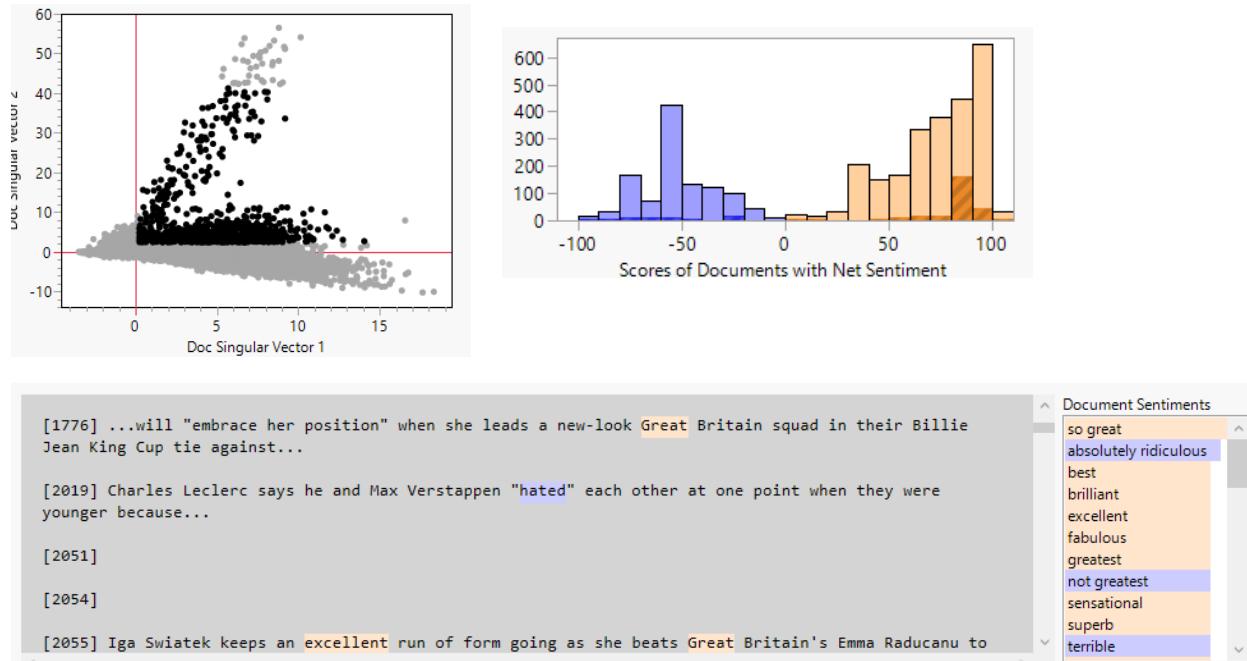
In the case of the net negative sentiment, we can see words that involve negation (“not”) and words generally associated with unpleasant feelings and emotions.



The documents shown highlight the words like “pain”, “awkward”, “bad”, and “problems”, which are adding a negative sentiment to the theme of the document.

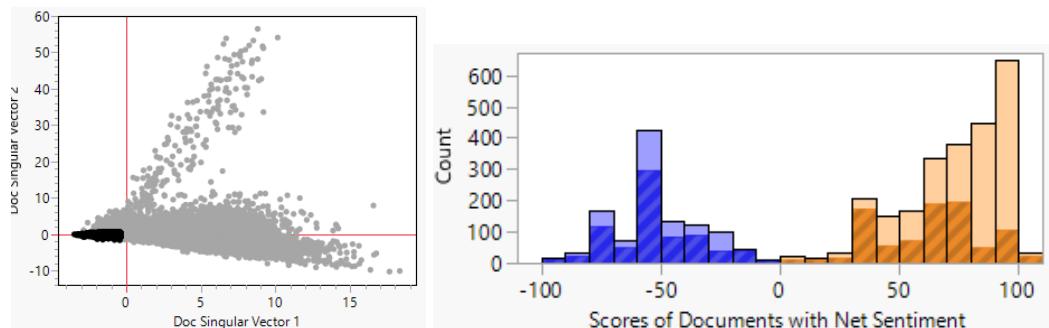
Furthermore, by selecting clusters in the SVD plots we can observe the shared sentiment of those particular themes. I will examine two clusters to reveal their overall sentiment.

### Cluster 1 (Sports):



The overall sentiment for news articles covering the topic of sports is a mostly positive one as shown in both the histogram and Document Sentiments. There are several terms usually associated with the negative sentiment but the overall context is positive.

### Cluster 2 (Conflict in Ukraine):



As expected, the news articles covering themes of war and crisis will dominate the negative sentiment portion of the histogram. The cluster in the bottom left quadrant makes up a huge majority of all the negative sentiment across all documents. There are, however, cases of positive sentiment as well, but we

can say that, overall, the topics surrounding the conflict in Ukraine share a more negative than a positive sentiment.

Overall **Sentiment Analysis** has provided a useful context for the latent themes uncovered in the **Latent Semantic Analysis**, and allowed us to have a richer interpretation of document clusters and their emotional tone.