SENTIMENT ANALYSIS: PERSPECTIVE OF AMAZON'S CUSTOMERS TOWARD THE BRAND

Course Name: Web and Social Media Analytics.

Course Code: ABM503D.

Submitted to: Dr. Nor Hasliza Md Saad.

Organized by: The Egyptian Legends Group.

Group Member Name	Metric Number	Academic E-mail
Mariem Ismail Ahmed Ismail	P-EM0128/22	mariem.ahmed0582@student.usm.my
Mennatallah Selim Mohamed El-Saieed	P-EM0389/22	mennaselim@student.usm.my
Ahmed Samir Ibrahim Ziada	P-EM0384/22	ahmedziada@student.usm.my
Islam Said El-Shafie	P-EM0377/22	islams.20100@student.usm.my

Semester 2

Academic Year 2021-2022

School of Management

Universiti Sains Malaysia

Table of contents.

List of Tables.

List of Figures.

1.0 Introduction.

The current world we live in is evolving and changing rapidly. Resources are either vanishing, submerging, or increasing. Big data is a source of data that can be structured, semi-structured, and unstructured. It is a resource that is widely enhanced by the era we are currently witnessing. It can affect our daily life, companies, and consumers themselves. One of the methods used to understand big data is called sentiment analysis.

(Keith Norambuena et al., 2019) Sentiment analysis is an area that has witnessed considerable evolvement over the last decade. It aims to identify and determine the emotions, opinions, feelings, among other things, of people on someone or something. Rosencrance (2020) said that sentiment analysis or text mining (opinion mining) is a subset of natural language processing (NLP), it uses machine learning to evaluate the emotional tone of the writer's text and categorize it into either positive, neutral or negative.

Considering the rapid growth of online shopping. (Rashid et al., 2021) Business ideas have refashioned and completely transformed by making it so easy for the customers to purchase anything they want with just one click of a mouse button. It is becoming even more famous because of its convenience. Amazon.com is a greatly known E-commerce website and is one that is used worldwide. In the start, it was known for its big book collection, but then, later on, it expanded to sell electronics, consumer products and home appliances. Currently, the brand is known for selling millions of products. More details about Amazon, it is visited each month by more than 197 million people because it has more than 12 million products and services therefore the probability of customer interaction on social media is high. Amazon is a multinational American technology company that focuses on cloud computing, e-commerce, artificial intelligence and digital streaming. It was started in 1995 by Jeff Bezos. It is a vast Internet-based enterprise that sells music, books, toys, movies, housewares, electronics and many other goods. It sells either directly or as a middleman between other retailers. It is expected to have its sales share increase to be 39.5% of the US. Retail e-commerce sales by the end of 2022.

Rashid et al., (2021) said that the growth of e-commerce gave importance to customer needs and opinions which in turn gave rise to an important aspect of online shopping known as 'User Reviews'. User reviews can be defined as customer opinions and suggestions towards a specific product or service. Those reviews make a contribution to other customers' decision making towards that same product or service. That review systems are considered the backbone of e-commerce. Therefore, sentiment analysis is a good approach for analyzing those reviews. By assessing the consumers' opinions and reactions towards a company's products and services, the outcomes will assist the company's decision-makers.

From all the available social media platforms. Twitter is quite suitable for data extraction .As it is a microblogging and social networking platform that encourages its audience to share tweets and engage with other users. Twitter was Released in 2006, by Jack Dorset. Twitter is very useful in generating a vast amount of sentiment data upon analysis up to 6000 tweets per second. This corresponds to over 350,000 tweets sent per minute, 500 million tweets per day, and around 200 billion tweets per year. Twitter was ranked as the ninth most visited website globally by 620 million unique accounts. It is also the world's 7th favorite social media platform.

1.1 Research Problem.

Living in the era of big data made it essential for companies to social listen to their customers' sentiments. Being able to know their customers' thoughts. Identifying which product to continue and which product to demolish. That would make companies' connections with their consumers grow stronger and would enhance customer loyalty.

However, there are lots of approaches to analyzing customer reviews. The massive size of data made it tricky to know which information is correct and which is false. Which machine learning approach to use and which tool to apply the chosen algorithm on.

That's why this paper was conducted. This study aims to derive customers' sentiment towards products and services. Then providing valuable consumer data that companies can use to measure their brand awareness and improve their products and services. The paper analyses the big data created by the social networking platforms using RapidMiner by applying the Vader algorithm. It is a simple rule-based algorithm used for sentiment analysis.

1.2 Research Objectives.

In order to analyze customers' sentiment, we need to determine the paper objectives. The following are what we aim to achieve.

1- To analyse Amazon's customers' reviews and classify the sentiments as either positive, negative or neutral.
2- To define the causes of negative sentiments and that will help in determining if the negative sentiments are directed towards Amazon itself or a specific product from it.

1.3 Research Questions.

We determined the following questions to reach our objectives.

1- What is the sentiment of Amazon's customers, is it a positive, neutral, or negative sentiment?

2- Are the words used in the negative sentiment of the customers directed towards amazon itself or a specific product?

2.0 Literature Review.

With the increase of users of social media platforms and the encouragement to share their opinions and reviews, the use of social media for conducting market research and analysing the users' feedback has increased. As a result, companies can improve their products and services, reduce marketing costs, create more engaging content, improve their revenues and enhance customers' satisfaction. That lead to a variety of researches discussing methods to analyse the users' reviews in the social media platforms efficiently.

Fang & Zhan (2015) aims to solve a fundamental problem facing sentiment analysis which is sentiment polarity categorization using a feature vector generation method based on datasets from Amazon that is publicly available and have ground truth. The frame was containing over 5.1 million product reviews, From February to April 2014. Based on 2 million machine-labelled sentences they formed 2 million feature vectors (1 million with positive labels and 1 million with negative labels) and they also found that the most significant enhancement model was the SVM model. (Fang & Zhan, 2015)

As the world became more digitalized and people rely more on online shopping, as a result, the importance of reviews becomes higher to the customer and also helps the seller to observe the pros and cons of their products. Therefore, the necessity of conducting sentiment analysis on the reviews has increased. The paper suggests implementing a supervised learning method on a large dataset from Amazon to analyze its accuracy using the bag of words approach to extract the features and for accuracy, the TF-IDF& Chi-square approach. After analyzing the data, they found out that the performance of the system was accurate enough to test case the reviews for products on Amazon and that classification of the reviews helps in improving the accuracy. (Haque et al., 2018)

Since social networking and microblogging sites are encouraging their users to share their feeling and opinions. In this paper they try to find the accuracy of the sentiment performed through RapidMiner using Naïve Bayes and k-NN algorithms about government schemes tweets from Twitter. Tweets were divided into two sets. The first one included 50 tweets in length. They concluded that Naïve Bayes is better than the K-NN method when the value of k is less than 25 and if k is 25 or more, they have the same accuracy. The second dataset consisted of 200 tweets length. Here, Naïve Bayes is preferred if the value of k is more than 5 but if the value of k is 5 they have the same accuracy. They also observed that both approaches fail to detect negative thoughts. (Singh Hanswal et al., 2019)

(Vyas & Uma, 2018) As analyzing customers' feedback has significant importance towards the improvement of organizations by helping in addressing their drawbacks. They compare the accuracy of twenty tools for analysis of text in terms of their applications and extension availability for sentiment analysis using RapidMiner in this experiment to extract sentiment from the tweets. They used SVM, Naïve Bayes and a Decision tree during the validation of training data and they found that the SVM model is better than other models with a 79.08% accuracy.

(Ijaz et al., 2020), this paper they try to Amazon is one of the biggest online retailers, so they use the reviews and ratings on it to analyze customers' sentiments towards the unlocked mobile phones using a generalized linear model, gradient boosted trees, Naïve Bayes, random forest, decision tree and support vector machine. They found that 4 algorithms when applied to the reviews the accuracy was 90.1% and 5 algorithms were on the items data file to analyze and count the rating, the gradient boosted tree was the best algorithm because its RMSE is 0.62 and accuracy is high then the other 4 algorithms.

As reviews can affect the customer's decision and since it is impossible to read all the reviews manually to analyze them. As a customer and also as a company it is very difficult to evaluate this number of reviews and ratings. Therefore, it was decided to analyze the reviews on a new corpus that includes reviews on digital cameras by RapidMiner using the SVM algorithm to evaluate how the classification of the sentiments is affected .They also used different weighting schemes (TFIDF, BO, TO) and different n-grams techniques (unigrams, trigrams and diagrams). They observed that the size of the corpus and the corpus domain affected the system performance and accuracy. They also found that the SVM algorithm is the best algorithm for sentiment classification. (Rushdi Saleh et al., 2011)

Alghamdi and Aljuhani (2019) said that the analysis of customers' feedback and classifying them into positive, neutral or negative have significant importance to the companies to improve their products and for potential buyers to make their decision. First, they convert the text to vector using a group of feature extraction techniques such as TF-IDF, bag-of-words, Glove, and word2vec. Then they compare the performance of different machine learning algorithms such as convolutional neural networks, stochastic gradient descent, naïve Bayes and logistic regression. Finally, they measure the accuracy using the accuracy and log loss function based on mobile phone reviews. They observed that the accuracy will increase if the size of 'n' in ngram increases and the Log loss value will decrease-IDF. The Bigram approach provided the best results with the unbalanced data. Trigram was better in balanced data, Also CNN with word2vec achieved the best accuracy for both balanced and unbalanced data. As the glove used a pre-trained model, they found that word2vec deep learning feature extraction provided better accuracy than Glove, they also observed that the length of a review has a significant effect to identify the polarity.

3.0 Methodology.

3.1 Data Structure.

In this study, 9833 raw tweets were collected from Twitter about Amazon. The datasets were collected in the 5^{th} of June 2022 around 5:57 pm. In the search word, the following keywords (amazon, e-commerce and online store) were used. While scrapping the data, it could contain audio, images, videos or even Gifs. As a result, the unneeded data will cost extra effort and time in the cleaning process because only text data is needed to conduct sentiment analysis and natural language processing (NLP). In order to avoid such hassle, the RapidMiner application was the chosen tool. Its usage is easy, and it can solve the issue of potential unnecessary data being obtained, as it is capable of extracting only the texts. Despite that, it is still necessary to walk through the cleaning process with operators before the sentiment analysis. we will use the VADER module to evaluate and analyze the text in order to determine whether a tweet is positive, negative or neutral. Then we will move forward into the word cloud to cut the extra words and return the main words, for example, the word "played" shall be "play". The step after that is to assess the frequency to get the top 20 repeated words in the documents and total. Finally applying the topic modeling using the standard tool in topic modeling, which is Latent Dirichlet Allocation (LDA) to identify topics in documents. The below figure is the process framework.

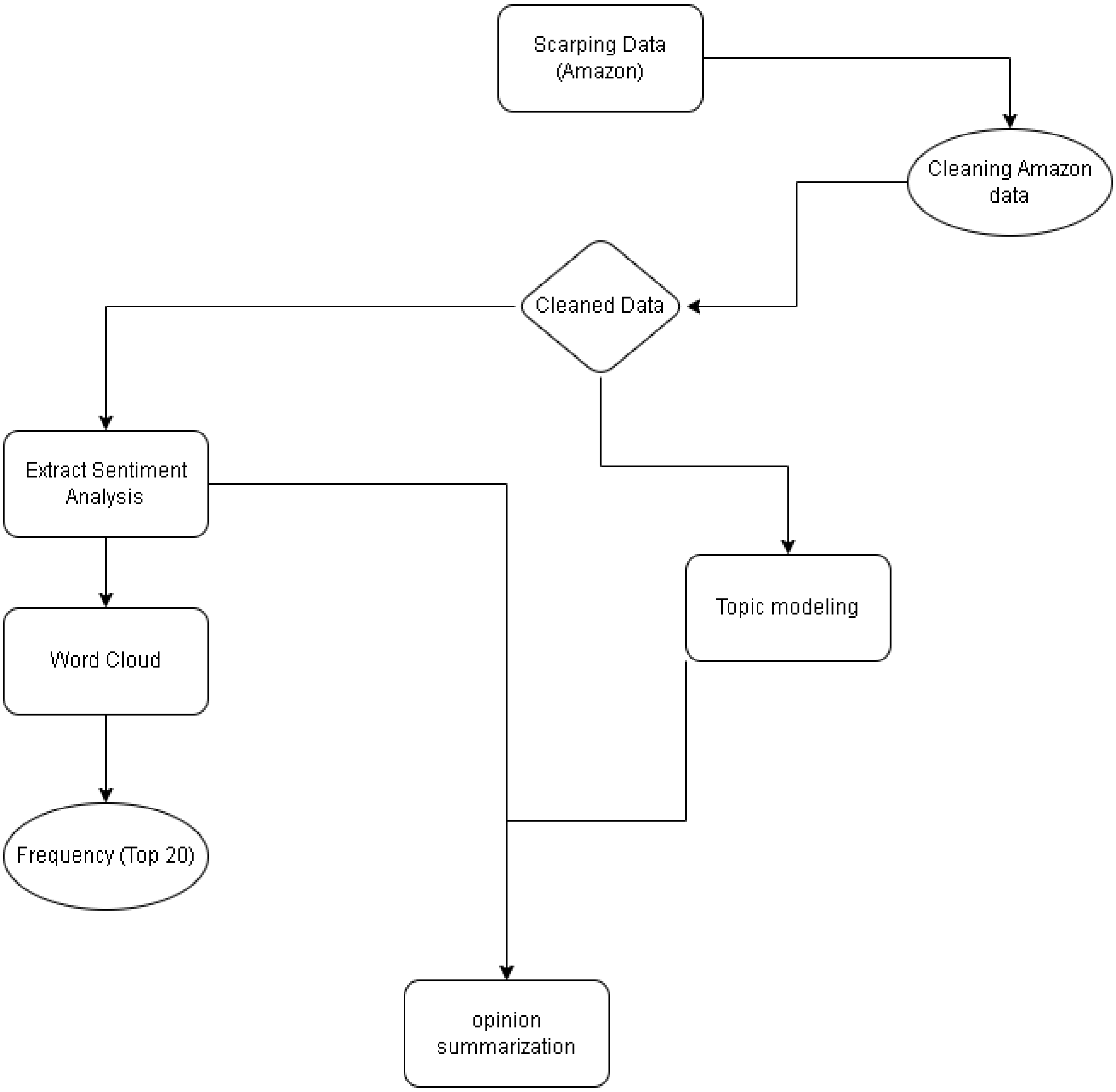


Figure 1

3.2 Sentiment Approaches in RapidMiner.

RapidMiner is the tool that will be used for this research. RapidMiner is a system that supports the design and documentation of a data mining process as a whole. It includes not just a nearly comprehensive collection of operators, but also structures that represent the process's control flow. In the Background of the program, The programing languages and machine learning algorithms are working, like the Naive Bayes algorithm. The user doesn't need to code or program at all, because it's just a drag and drop process, and it connects what has been dragged together as they appear as boxes, finally the user runs the process and the results will be shown easily. (Shoeb & Ahmed, 2017)

3.3 Research design.

Any company wants to know how its clients react towards its products or services that are provided. In the 21st century (The internet generation) anyone if they want to buy or subscribe to a specific service they will first check its reviews or ask on a trendy internet platform, like Facebook and Twitter to know more about it from people who used that service by going through their feedbacks,

This is a very powerful process that can help a company to find out about the problems their clients are facing, try to find solutions and develop the product or services they are providing through the results of sentiment analysis. People's opinions are very important. This study was conducted in order to assist in improving a company's performance. Therefore, the sentiment analysis in this project will be going through 6 processes and visualization.

3.3.1 Data collection.

In this phase, there's 9833 raw tweets collected from the limit of 10K about Amazon. It's the first step to getting the data to start analyzing it. Then save it into a ".xlsx" file and save the process.

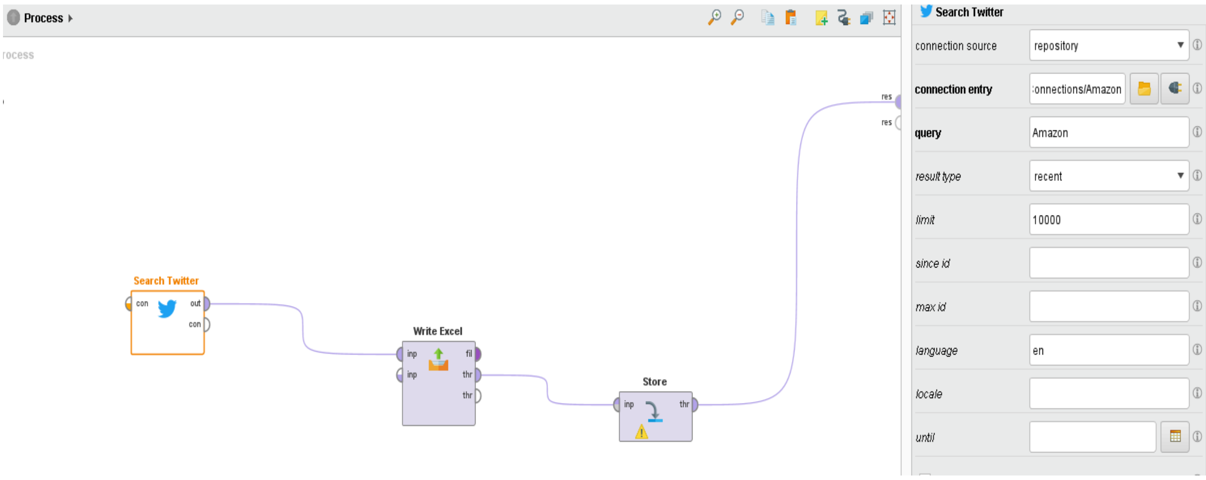


Figure 2

3.3.2 Cleaning Process.

1. The data that has been collected needs to go through the cleaning process by some of the operators. First, import the data into the process window.

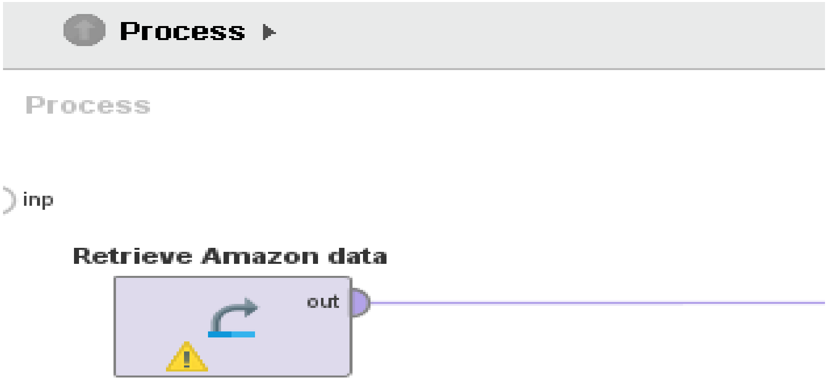


Figure 3

2. The following figure shows the “Select attribute” operator, it removes the unneeded columns. We used it and selected the single type attribute as we will only work on the Text column therefore we selected the Text attribute

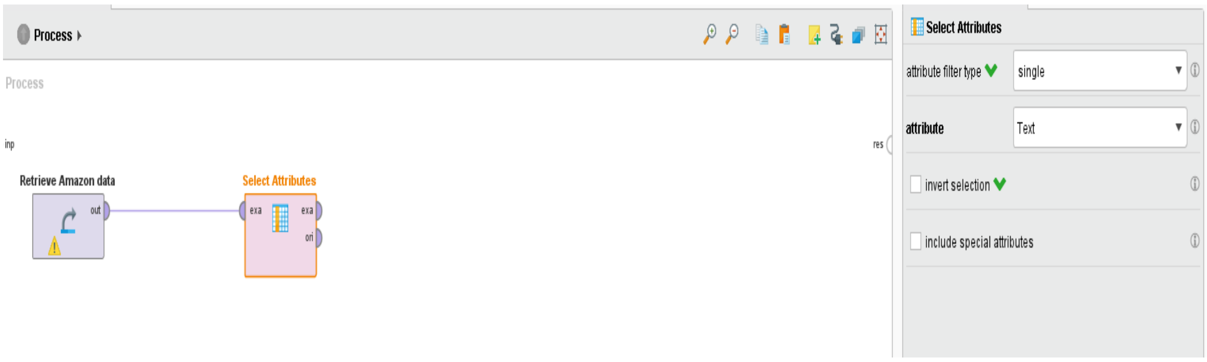


Figure 4

3. The next two figures are about the “Subprocess” operator. In it, we will apply five replace attributes/processes in order to remove (username, colon, hashtag, RT (retweets), URL) and replace all of those things with nothing (None).

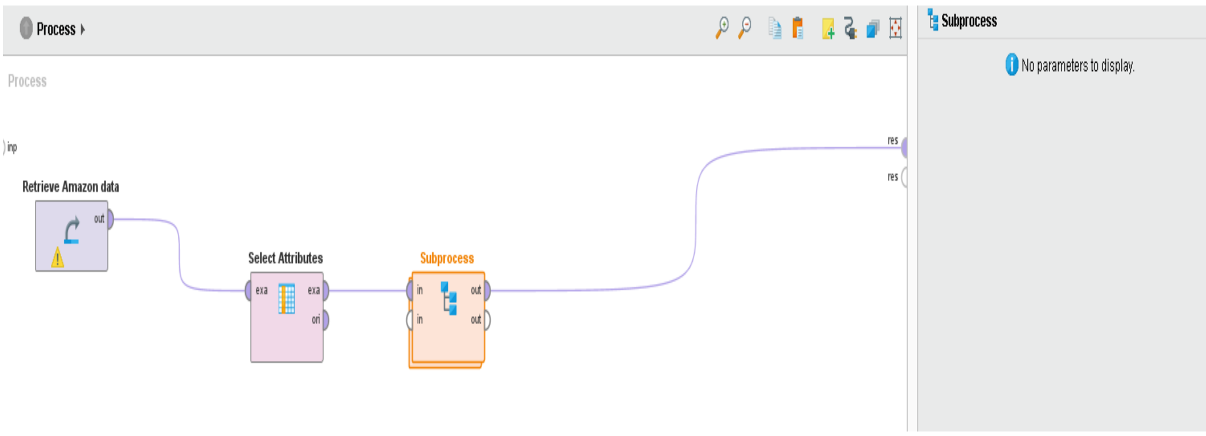


Figure 5

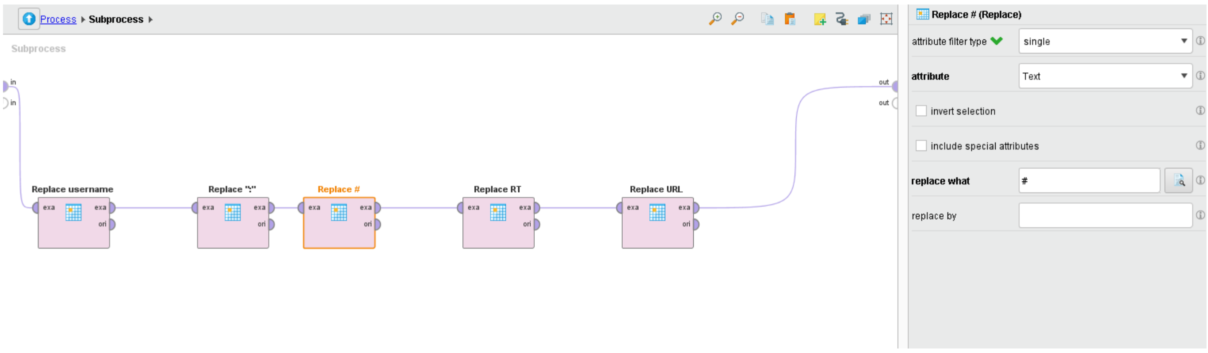


Figure 6

4. Since we need to remove the white spaces and the duplicates from the Text column (Data) will use as shown in the next figure: "Trim operator" for white spaces and the "Remove Duplicates" operator for the duplicates.

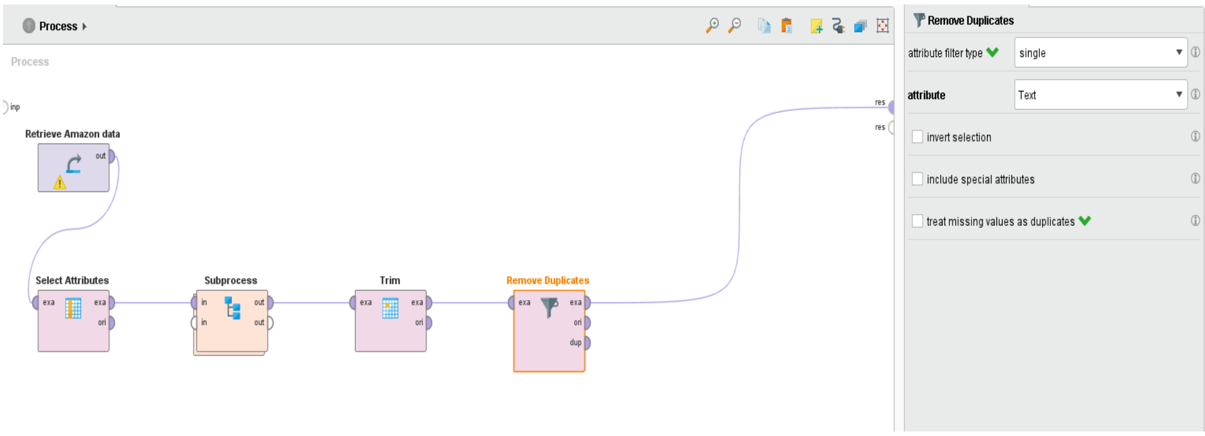


Figure 7

5. In the last cleaning process on the text column, it is expected that there will be rows with missing values. Therefore, we will handle this issue with the "Replace Missing Values" operator that turns values as None.

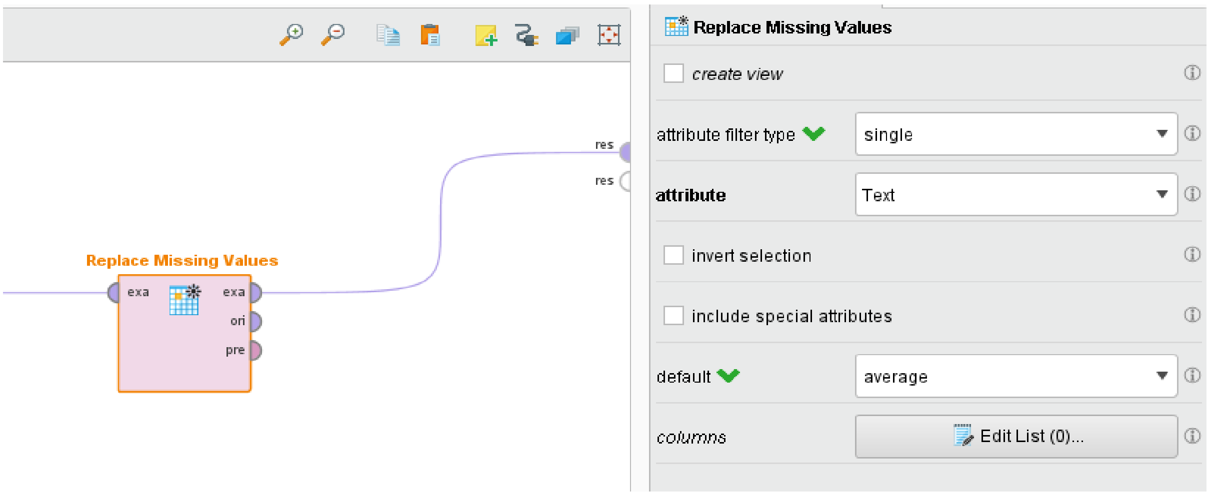


Figure 8

6. The final two operators we used in the cleaning process are used to save the result into a ".xlsx" file as we selected the path of the file in the computer, generated the name of the file and saved the process into the repository we created for this sentiment.

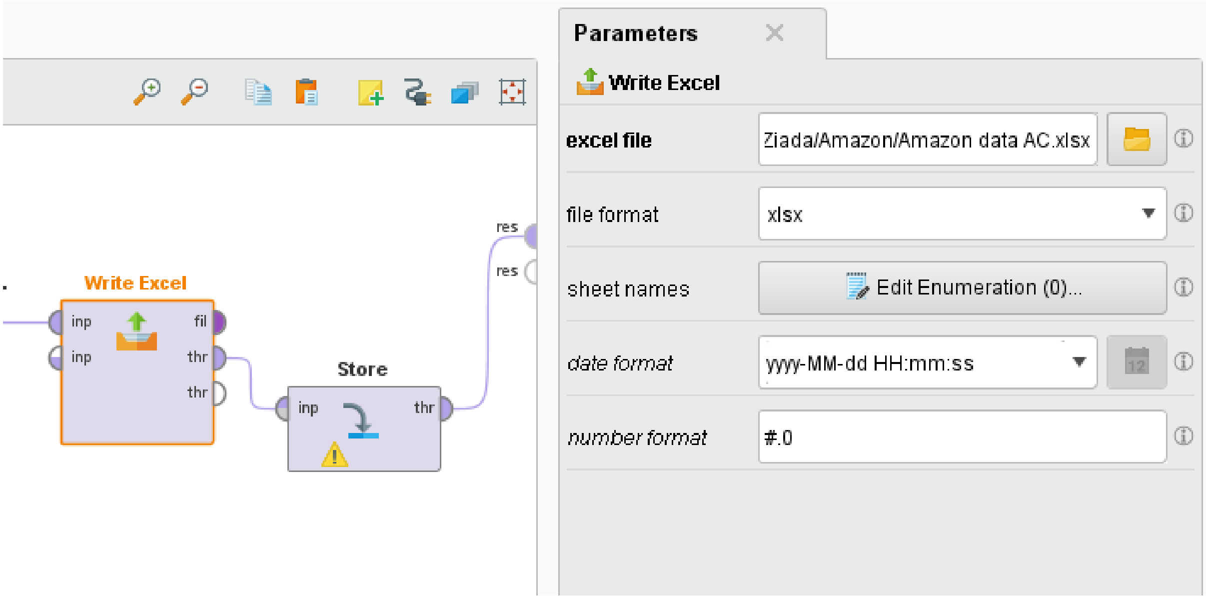


Figure 9

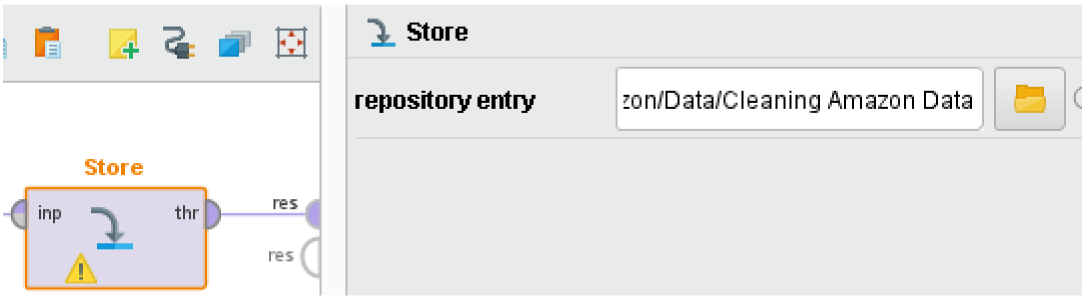


Figure 10

3.3.3 Sentiment Analysis.

After the cleaning process and the data is stored, we will retrieve the data and start implementing the model on it. By giving each text a score to determine whether it is either positive, negative or even neutral. We used a model called VADER that is used for sentiment analysis. Vader is very sensitive and can analyze emotions that is why we used it in the sentiment score. Vader will loop for every text and give each text a sentiment score and particularly the most used for the Vader model on the social media data and return good results. But we need to convert the Nominal to Text first. The maximum Vader score is +1 and the minimum is -1.

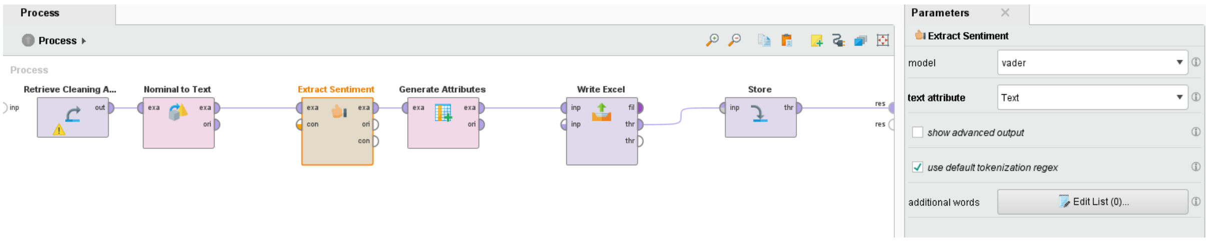


Figure 11

As shown in Extract sentiment we choose the Vader model and. In the "Generate Attribute" we write a function in the "Description function" to identify if the score is less than 0, it will return negative. If the score is equal to zero, it will return neutral. If the score is more than 0, it will return positive.

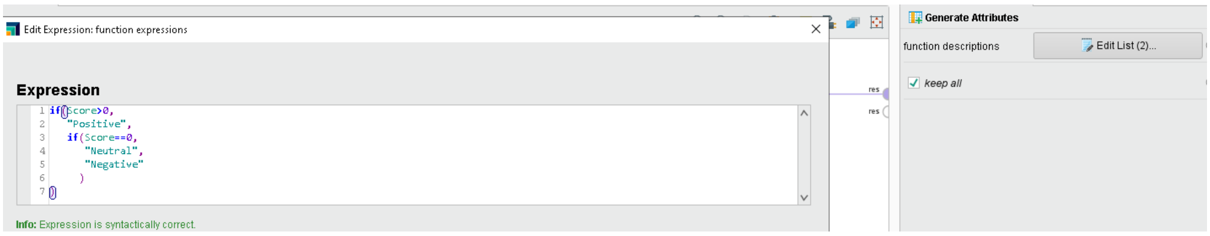


Figure 12

The output of the sentiment analysis is shown in the figure below:

Row No.	Id	Text	Score	Sentiment
1	1533477834...	Hi team hi I book slippers today was my deliver date but	-0.641	Negative
2	1533477831...	♠□◀▯♠♠♲♠♠▯♠♠♲ Day 28 SAVE AMAZON RAINFOREST ♠□◀▯♠♠♲♠♠▯...	1.026	Positive
3	1533477828...	Have a Smiling Sunday Guy!♥♥♥	0.513	Positive
4	1533477826...	(CA)EVGA X 3080 Ti FTW3 Ultra - $1557.99Link ATC As an Amazon Associate I earn from q...	0.179	Positive
5	1533477825...	(US)EVGA GeForce X 3070 FTW3 Ultra LHR - New - Other Seller - $689.06	0.179	Positive
6	1533477825...	Me having HBO Max, STARZ, Amazon Prime Video, Peacock, Netflix, Paramount+, Disney+, ...	1	Positive
7	1533477820...	Related I watched 'Yellowstone' on Amazon Prime recently and was really uncomfortable th...	-1.077	Negative
8	1533477817...	(CA)Sapphire Pulse AMD Radeon RX 6500 XT Gaming OC - $249.50Link ATC As an Amazo...	0.179	Positive
9	1533477816...	(CA)EVGA 3070 Ti FTW3 - $1007.99Link ATC As an Amazon Associate I earn from qualifyin...	0.179	Positive
10	1533477813...	Also, if you get emails from "Amazon" or "PayPal" saying your account has been used for XY...	0	Neutral
11	1533477812...	RECKONING WAVES - "Suspenseful!" →	0	Neutral
12	1533477811...	" is on the front line of the fight against the Bolsonaro government's attempt to destroy indig...	-1.051	Negative
13	1533477811...	Still the 1 DVD on Amazon among all movies and TV. Over 500 reviews and the average is 5...	0.179	Positive
14	1533477810...	(US)ASUS TUF X 3070 V2 OC LHR - $659.99	0.179	Positive
15	1533477807...	(CA)MSI Gaming X 3080 Ti X Trio - $1668.98Link ATC As an Amazon Associate I earn from ...	0.179	Positive
16	1533477805...	(CA)EVGA 3060 Ti XC - $744.59Link ATC As an Amazon Associate I earn from qualifying pur...	0.179	Positive
17	1533477804...	Amazon is selling duplicate products don't buy from Amazon.	0.359	Positive
18	1533477801...	My Son Started Working Yesterday. Over night shift at Amazon. He got off at 9am I call him to...	0.179	Positive

ExampleSet (6,702 examples, 2 special attributes, 2 regular attributes)

Table 1

Figure 13

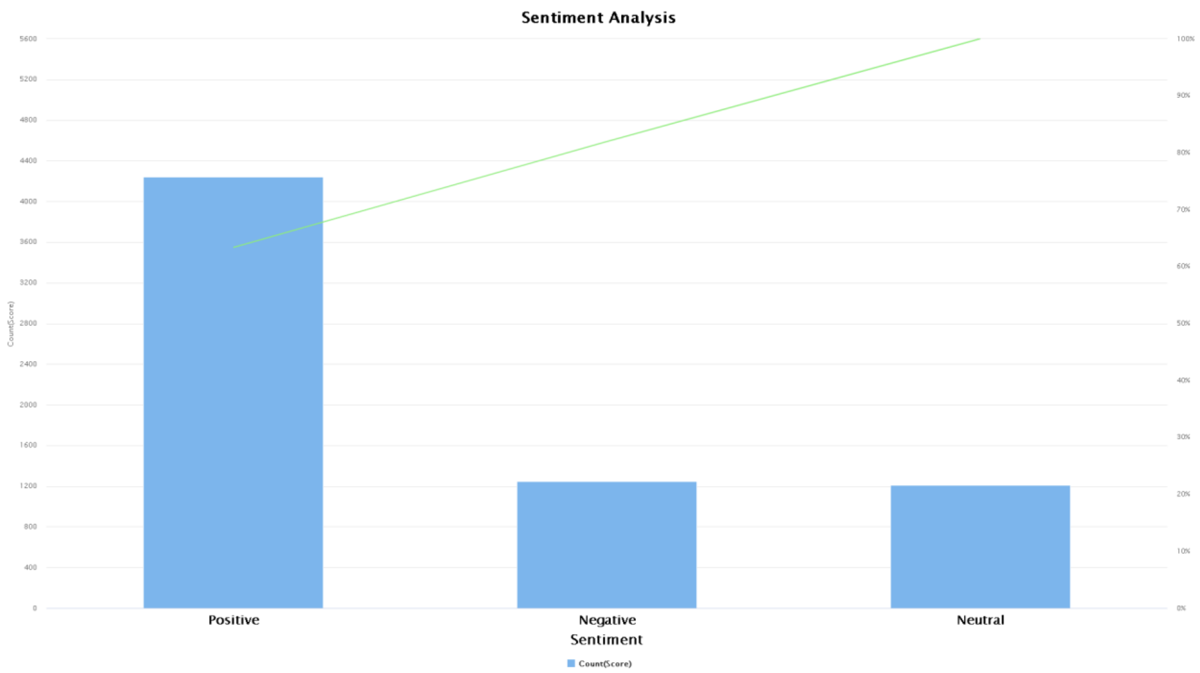


Figure 14

3.3.4 Word cloud.

After the sentiment analysis phase, we will go into the word cloud in the “Text attribute” by running a few processes so that it returns the most frequently appearing words and then trim the words. For example, the word should be “play” rather than “playing”, In addition, we will split the attribute we are working on (Text) into a sequence of tokens. Standardizing all the words by making them all lowercase, because it's case sensitive. Then removing English stop words such as that, this or is. After that, we will apply “WordList” to the data to convert the word list into a dataset.

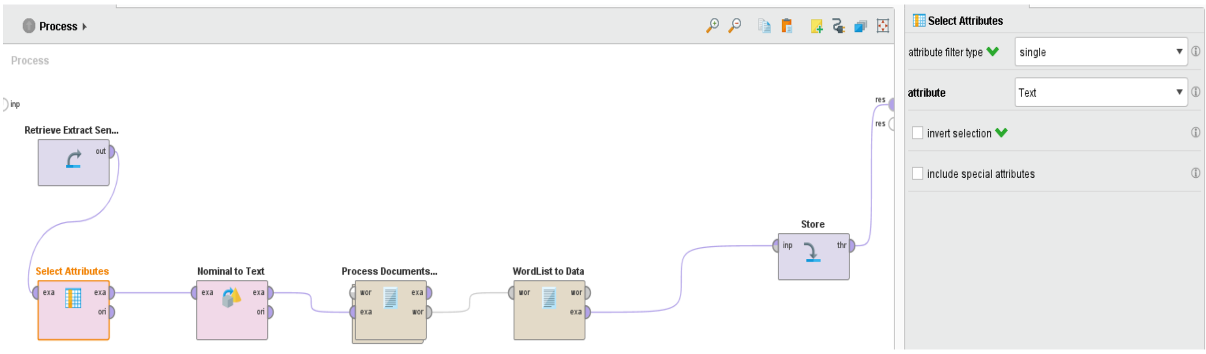


Figure 15

In the “Process Documents” operator, we used 5 operators:

1. Tokenize: split text into a sequence of tokens.
2. Transform Cases: standardize the text into a lower case.
3. Filter Stopwords (English): remove all the stop words in English language.
4. Stem (Porter): reduce the word length as much as possible in order to return the main word.
5. Filter Tokens (by Length): filter the tokens by the length.

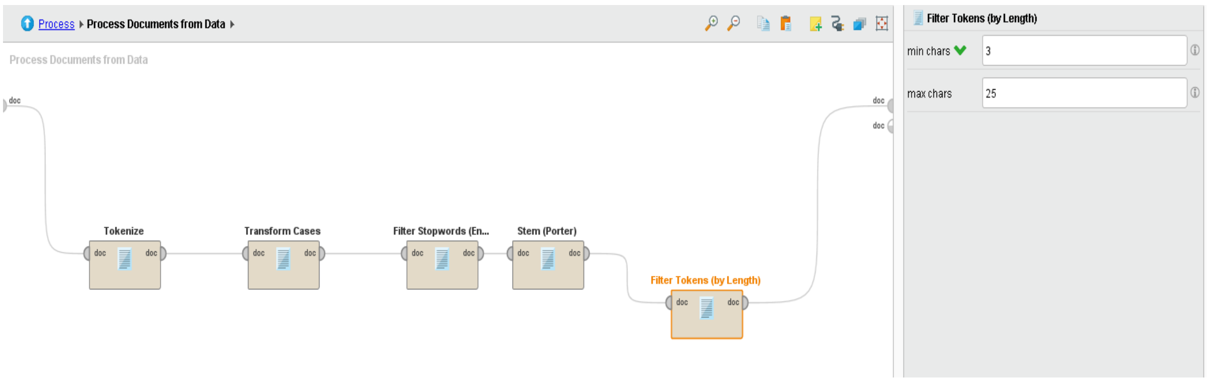


Figure 16

The output of word cloud is shown in the next figure:

Row No.	word	in documents	total
1	aaa	1	2
2	aam	1	1
3	aamslut	1	1
4	aapl	6	6
5	abandon	2	2
6	abask	1	1
7	abba	1	1
8	abbi	2	2
9	abbott	1	1
10	abbv	1	1
11	abbvi	1	1
12	abdel	1	1
13	abduct	1	1
14	abel	1	2
15	abella	1	1
16	abessm	1	1
17	abhidha	1	1
18	abil	4	4
19	abl	26	26
20	abo	1	1
21	abort	1	1
22	abou	1	1
23	abq	2	2
24	abras	1	1

ExampleSet (11,729 examples, 0 special attributes, 3 regular attributes)

Table 2

3.3.5 Frequency Analysis.

After the word cloud step, we will go through the Frequency. How many times does each word get repeated in the documents? Then we choose the top 20. First we get the “Retrieve data”, then the output of the word cloud process and finally sort the total attributes in the order of descending.

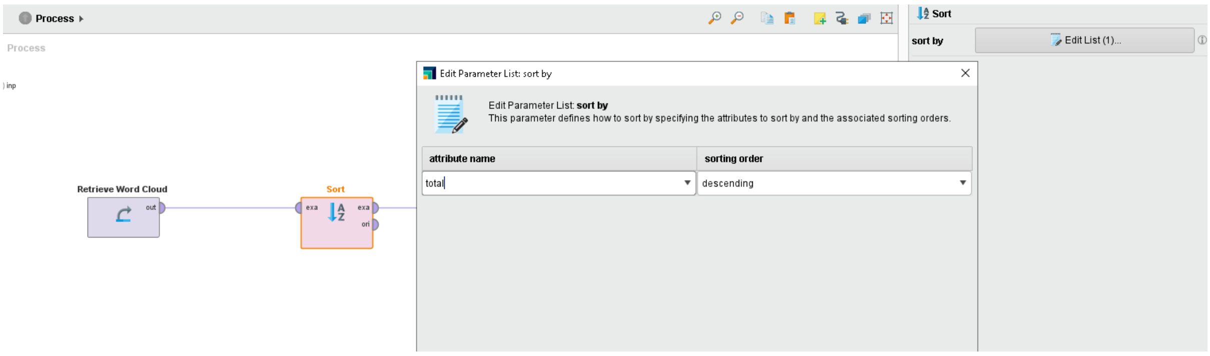


Figure 17

Choose “Filter Example Range” operator to select what range you want. We want to see the top 20 as shown in the below figure.

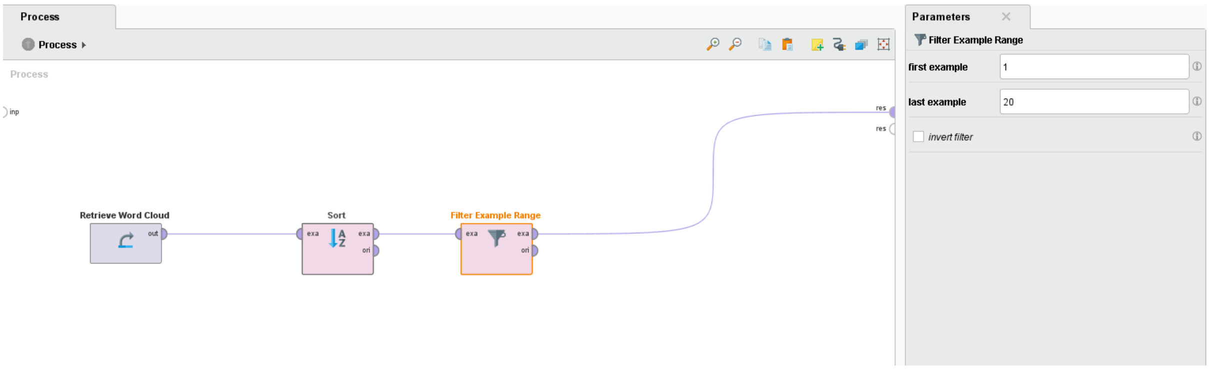


Figure 18

The output of the frequency for the top 20 most repeated words:

Row No.	word	in documents	total
1	amazon	2541	2748
2	book	869	1059
3	read	435	459
4	get	403	424
5	link	358	359
6	game	288	344
7	love	295	331
8	order	279	306
9	dai	267	289
10	purchas	281	289
11	bui	246	256
12	thank	246	251
13	atc	249	249
14	stori	234	247
15	free	229	246
16	deliv	141	245
17	year	217	229
18	click	224	225
19	earn	218	220
20	avail	214	217

Table 3

Figure 19

3.3.6 Topic Model.

First of all, the objective from topic modelling is to find the main topics that are not naturally obvious and can only be understood implicitly. Through analyzing the words in the source texts. The main criterion tool in topic modelling is Latent Dirichlet Allocation (LDA). It's a method that is used to analyze a massive set of documents. We used the "Retrieve data" after it being cleaned and selected the attribute that we will work on like usual (Text attribute) and finally converted the type from nominal to text.

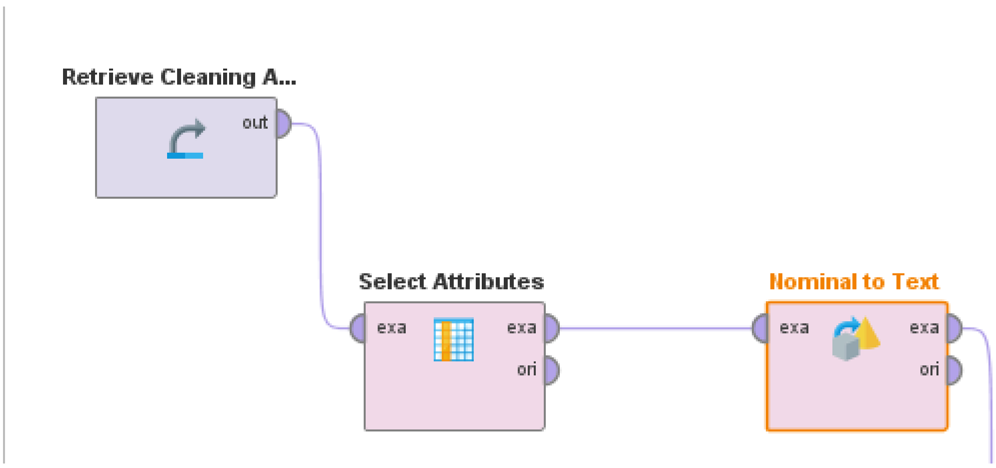


Figure 20

After that we will use a new operator called "Data to Documents" and its name explains itself as what it is doing is transforming the datasets into documents. Each example has its document being created.

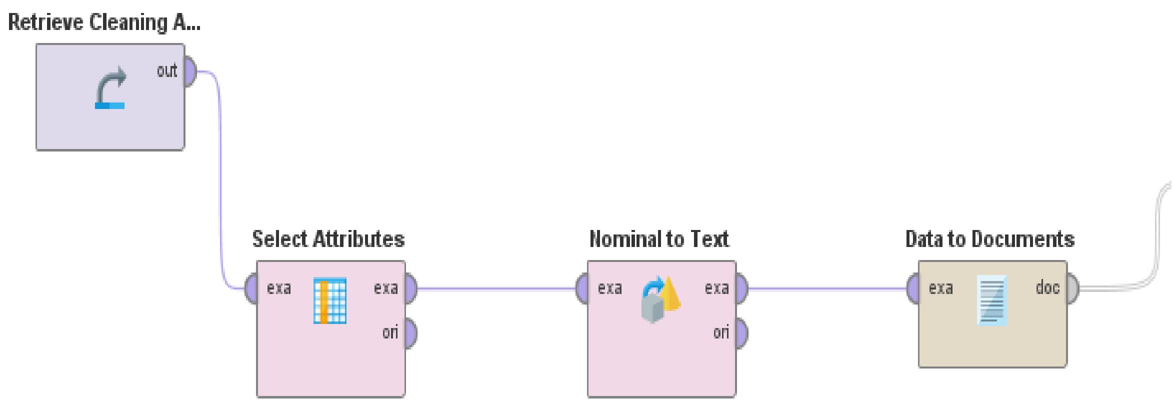


Figure 21

The next phase will be the "Loop Collection process". We will implement 5 processes inside the loop collection to do the same process for each loop.

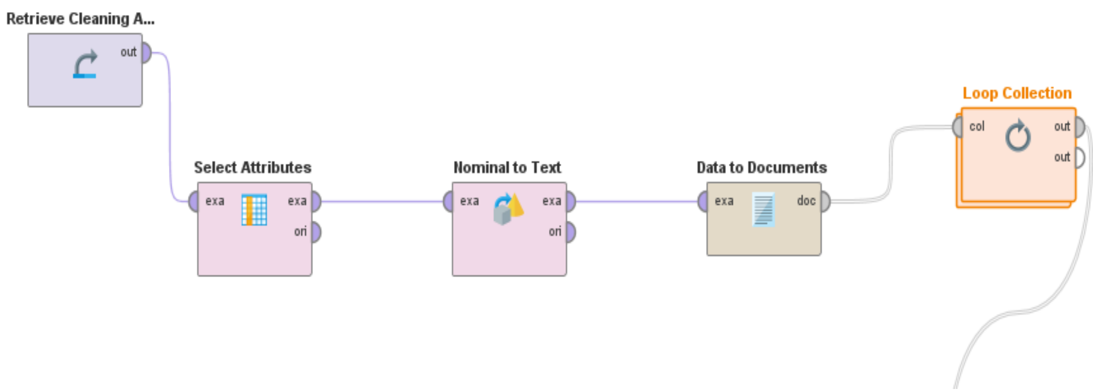


Figure 22

The 5 processes have been mentioned before and what they do exactly in the "Process Documents" operator. The 5 operators are (Tokenize, Transform Cases, Filter Stop words (English), Stem (Porter) and Filter Tokens (by Length).

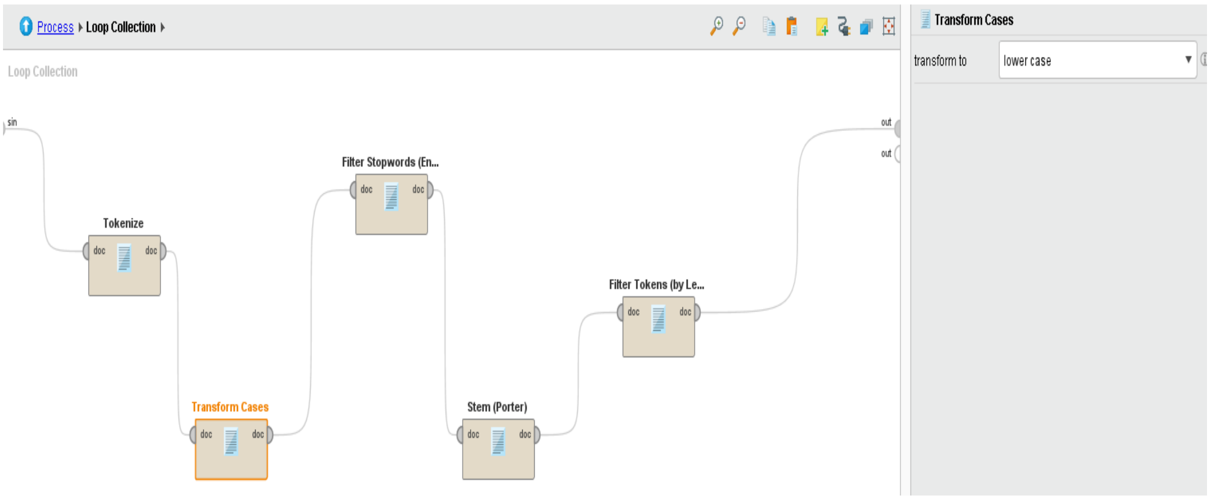


Figure 23

The last operator and final step will be implementing (LDA) tool by using the “Extract Topics” from Documents (LDA) operator. The output of LDA is classifying topics in documents.

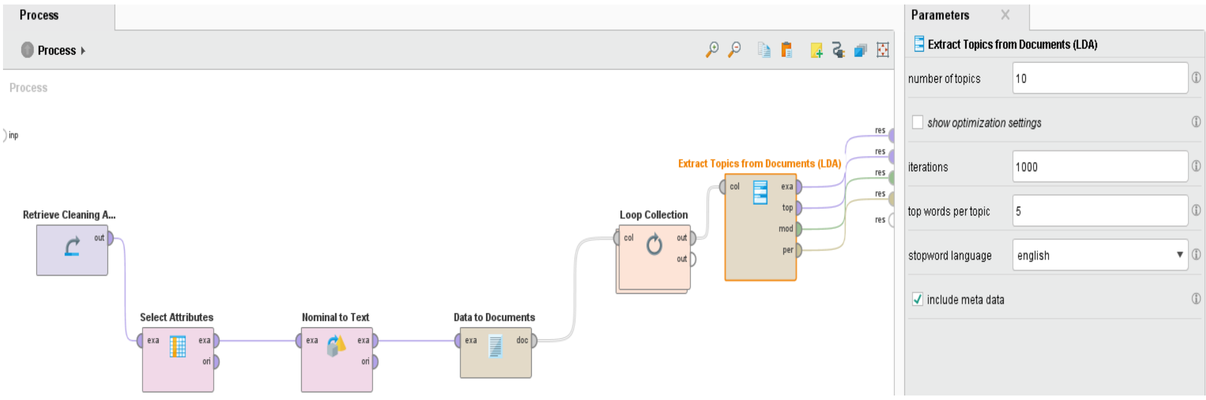


Figure 24

The output of topic modelling is shown in the next 3 figures:

LDAModel

```
LDA Model with 10 topics
alphaSum = 0.30711273966289904
beta = 0.07159056769613371
Topic 0 tokens=3659.0000        document_entropy=5.8817 w
  fish  word-length=4.0000      coherence=0.0000        u
  click word-length=5.0000      coherence=-0.1220       u
  amazon        word-length=6.0000      coherence=-0.5740
  aliexpress    word-length=10.0000     coherence=-0.4481
  daiwa word-length=5.0000      coherence=-0.8864       u
Topic 1 tokens=16538.0000       document_entropy=7.5341 w
  amazon        word-length=6.0000      coherence=0.0000
  prime word-length=5.0000      coherence=-2.0949       u
  get   word-length=3.0000      coherence=-2.4532       u
  order word-length=5.0000      coherence=-3.3501       u
  book  word-length=4.0000      coherence=-5.0846       u
Topic 2 tokens=5610.0000        document_entropy=6.1747 w
  amazon        word-length=6.0000      coherence=0.0000
  link  word-length=4.0000      coherence=-0.5895       u
  atc   word-length=3.0000      coherence=-0.6442       u
  game  word-length=4.0000      coherence=-1.0942       u
  purchas       word-length=7.0000      coherence=-1.0331
Topic 3 tokens=4567.0000        document_entropy=6.4696 w
  thank word-length=5.0000      coherence=0.0000        u
  help  word-length=4.0000      coherence=-1.8377       u
  teacher       word-length=7.0000      coherence=-1.7326
  year  word-length=4.0000      coherence=-2.1369       u
  grade word-length=5.0000      coherence=-1.9976       u
Topic 4 tokens=11345.0000       document_entropy=7.1222 w
  book  word-length=4.0000      coherence=0.0000        u
  read  word-length=4.0000      coherence=-1.5975       u
  kindl word-length=5.0000      coherence=-1.7901       u
  amazon        word-length=6.0000      coherence=-2.2995
  romanc        word-length=6.0000      coherence=-2.6534
Topic 5 tokens=2440.0000        document_entropy=5.3387 w
  deliv word-length=5.0000      coherence=0.0000        u
  amazon        word-length=6.0000      coherence=-0.0762
  order word-length=5.0000      coherence=-0.2806       u
  book  word-length=4.0000      coherence=-0.3279       u
  dai   word-length=3.0000      coherence=-0.3087       u
Topic 6 tokens=5422.0000        document_entropy=6.4928 w
  amazon        word-length=6.0000      coherence=0.0000
```

Figure 25

Row No.	topicId	word	weight
1	0	fish	210
2	0	click	120
3	0	amazon	101
4	0	aliexpress	80
5	0	daiwa	52
6	1	amazon	1337
7	1	prime	179
8	1	get	175
9	1	order	141
10	1	book	125
11	2	amazon	544
12	2	link	261
13	2	atc	249
14	2	game	232
15	2	purchas	219
16	3	thank	175
17	3	help	123
18	3	teacher	101
19	3	year	91
20	3	grade	87
21	4	book	447
22	4	read	219
23	4	kindl	173

ExampleSet (50 examples, 0 special attributes, 3 regular attributes)

Table 4

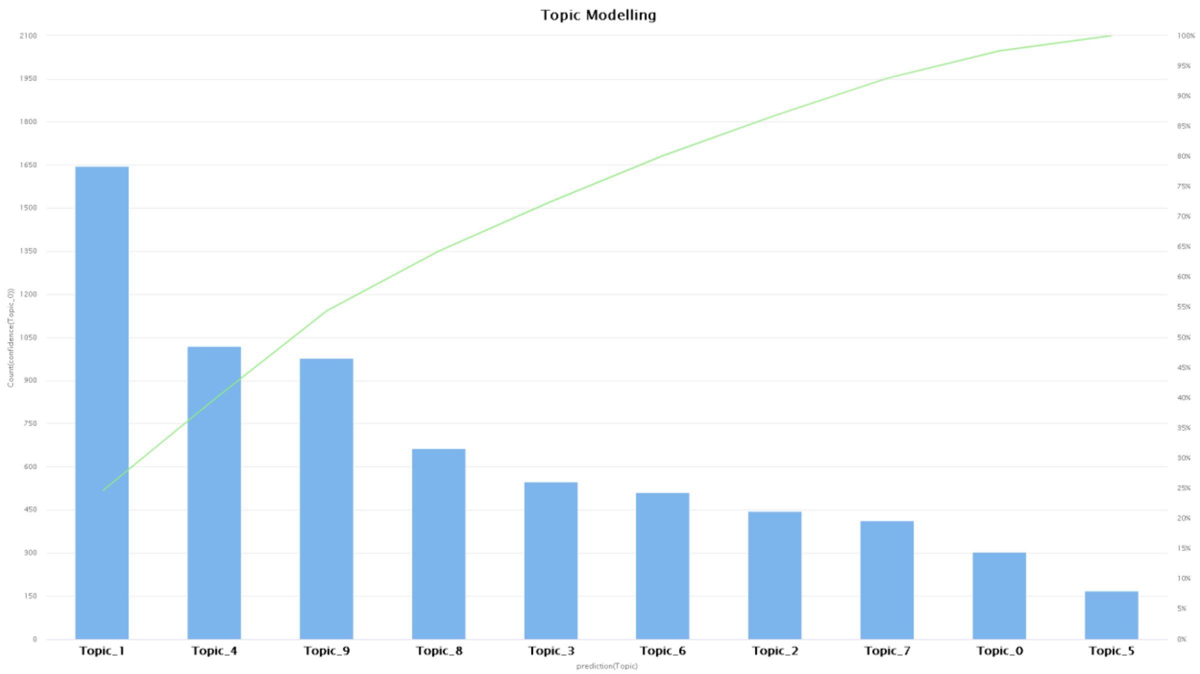


Figure 26

4.0 Findings.

We used around 9,883 raw tweets in this project. After the cleaning phase, it became 6,702 tweets. This is the number of tweets that were used to conduct sentiment analysis.
The tweets are divided into 3 categories: positive, negative, and neutral as shown in the figure. 13. It shows the percentages of each category from the total tweets used in the sentiment analysis. The results were:

- 63.3% (4,244 tweets) were positive tweets which is the highest portion,
- 18.6% (1,247 tweets) of negative tweets came in second place.
- 18.1% (1,211 tweets) were neutral tweets which is the lowest percentage.

Let's get into more detail to know the top 20 frequently repeated words that are used in the negative sentiments scores. As the below figure shows us the top three are:

- Amazon with a total of 494 times.
- book by 252 times.
- deliv (delivery) by 231 times.

which makes it safe to assume that a significant number of unsatisfied customers are not happy with amazon's book service and the delivery process.

Figure 27

Row No.	word	in documents	total
1	amazon	482	494
2	book	238	252
3	deliv	118	221
4	order	143	153
5	dai	134	145
6	peopl	133	135
7	bad	131	132
8	take	123	124
9	item	112	114
10	servic	114	114
11	futur	109	109
12	team	109	109
13	date	107	107
14	receiv	106	106
15	slipper	101	101
16	read	80	86
17	get	69	73
18	price	63	63
19	war	50	54
20	drop	51	52

Table 5

Regarding the positive sentiments let's see what the top 20 frequently repeated words that are used in the following figure. We can find out that the top 4 words are:

- Amazon with a massive number of 2220 times,
- Books by 679 times.
- link by 320 times.
- love by 320 times.

We can conclude that amazon's book service is very critical. Many customers evaluate that service. It is necessary to monitor this service carefully to know why people's feedbacks go between bad and well and try to figure out the problems and their solutions. The "link" word indicates a high visiting time for the website.

Figure 28

Row No.	word	in documents	total
1	amazon	2030	2220
2	book	514	679
3	link	320	320
4	love	285	320
5	read	294	311
6	get	287	303
7	game	228	271
8	thank	235	240
9	purchas	228	233
10	atc	229	229
11	free	209	225
12	associ	203	203
13	earn	202	202
14	qualifi	198	198
15	fish	73	186
16	stori	168	176
17	geforc	169	174
18	bui	161	170
19	gift	141	168
20	help	143	163

Table 6

On the other hand, the neutral sentiment top 20 words are presented in the below figure.

The tops 3 words are:

- book with 128 times.
- read with 62 times .
- bui with 58 times.

Figure 29

Row No.	word	in documents	total
1	book	117	128
2	read	61	62
3	bui	58	58
4	get	47	48
5	click	47	47
6	nowplai	41	41
7	year	40	41
8	outdoor	22	40
9	purchas	38	38
10	black	32	36
11	amazon	29	34
12	pack	33	34
13	seri	32	33
14	check	30	32
15	song	31	31
16	game	27	30
17	grade	30	30
18	world	26	28
19	deal	23	27
20	stori	24	26

Table 7

As it was shown, the positive sentiments are the highest percentage with 63.3% of total tweets that we got after the cleaning phase, which's an indicator that Amazon is doing fine but it needs improvement. Therefore, it is important to dig deeper into details to assist the improvements.

The amazon book service is the one with controversial feedback as it appeared in all three categories. On the other hand, some products have a good customer influence like in the positive sentiments word "game" which's a good category Amazon provides.

In the negative sentiments, there're also words like "price" which means that there are a good number of customers who are unsatisfied with the pricing. "Order, deliv (delivery), date, receive, drop, take, and reciv (receive)", all of those words are repeated in the negative sentiments and that indicates that there's an issue with the shipping, delivery, and return process.

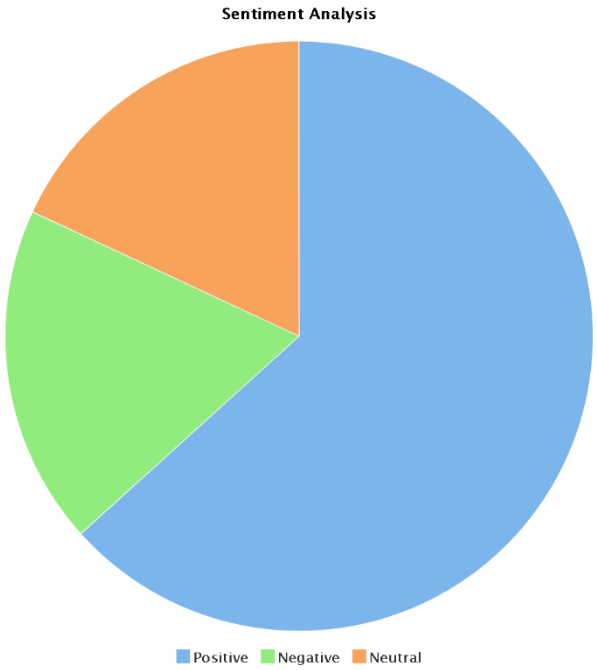
5.0 Discussion.

In this section, we will discuss the details of the finding of the sentiment analysis in our report whether positive, negative, or neutral which is shown in the findings section. Here we will also answer our research questions for this study which are:

1. What is the sentiment of Amazon's customers, is it a positive, neutral, or negative sentiment?
2. Are the words used in the negative sentiment of the customers directed towards amazon itself or a specific product?

5.1 Amazon Sentiment.

In The First Question: What is the sentiment of Amazon's customers, is it a positive, neutral, or negative sentiment?



In the previous figure 13, we detected that for most of the users of Twitter their sentiment through Tweets was positive sentiment with 63.3% (4,244 tweets) of the total tweets, in the second-place negative sentiment came with 18.6% (1,247 tweets) and in the third place, the neutral sentiment by 18.1% (1,211 tweets) from the total data used. The majority of tweets were positive because a lot of customers were giving a positive sentiment about amazon's website and are happy with Amazon services and recommended amazon to their followers. For example: "I LOVE, LOVE, LOVE ANGEL ON BOARD ON AMAZON!!! I was caught up from the beginning!!", "10 TV series on Amazon that will change your life + mindset", "So, I bought this from Amazon and I can't believe it- it's so cute!!!!", Loved it....want more." and "NowPlaying - Giving You The Best That I Got Tune In Amazon - Buy It", We found 21 total tokens and there were main words that refer to the positive sentiment like: "love", "thank" and "purchas" with 320, 240 and 233 respectively.

In the neutral, the outcome of the neutral sentiment resulted from the tweets that gave opinions that are neither positive nor negative with general expressions, For example: "New deal at Amazon", "the book is in my amazon cart", "Snowbound Romance by Lennart Thomsen 99cents KindleUnlimited kindlebook kindlebooks Romance Romantic in amazon" and "there's a book about it", these tweets don't give any specific expressions for the Lexicon Based Approach to classify and divide them into positive or negative.

The negative sentiment, 18.6% of the sentiment of the total tweets, which is a very small portion compared to the positive sentiment and approximately equal to the neutral sentiment, The examples of the negative tweets: "Hi team hi I book slippers today was my deliver date but Still i have not received Bad services .you people taking 5 days to deliver items Future I will not order anything from amazon", "Bad quality from Amazon!!!", "Secondly the Amazon customer support is worst available support.. they know just 2 words sorry and we will try. No actual support.. same item which was promised to deliver next day(today) 9am to 1Pm is not yet delivered.. pathetic support.." and "Amazon is the worst place to do online shopping. They have worst delivery network. Ordered a product on same day delivery, waited for 2 days , order canceled saying lost in transit. Same item ordered again waiting for 2 days breached deadline", from examples like that, the most frequent words were "deliv", "bad" and "servic" with 221, 132 and 114 respectively.

As shown in the next table, these are the top 10 listed words that have been chosen as a result of the findings section. It's important to make a word comparison in our paper to narrow down our focus on the results. So let's discuss that topic.

Positive Sentiment		Negative Sentiment	
Words	Total Occurrences	Words	Total Occurrences
amazon	2220	Amazon	494
Book	679	Book	252
Link	320	Deliv	221
Love	320	Order	153
Read	311	Dai	145
Get	303	peopl	135
game	271	Bad	132
thank	240	take	124
purchas	233	item	114
Atc	229	servic	114
Free	225	futur	109

Table 8

In table 8, we observed the top 10 occurrences of words in both positive and negative Tweets. The "amazon" word was the highest in the occurrences in both sentiments. However, it was mentioned in the positive sentiment more than the negative with 2220 occurrences. Most of the positive sentiment was because amazon's customers were satisfied with its services in selling the books, their delivery time and recommend their followers to purchase from Amazon. On the other hand, in the negative sentiment, the word amazon itself was mentioned because of the seller that did not provide the customers with a clear product description, or sold low quality products, for example: "This comes from the poor manufacturing quality" and other reasons but the most of the mentions were because of the sellers.

The next highest words in the positive sentiments were "book, link and love". the word love was mostly directed toward amazon book selling services such as "I just loved the book start to finish". Books and the word "link" were related to the recommendation for amazon such as "Recommend it to more than just science fiction lovers, but to anyone who enjoys a solidly great read".

In the second question: Are the words used in the negative sentiment of the customers directed towards amazon itself or a specific product?

Since Amazon is a retailer that connects the sellers with the customers, In the negative sentiment we found that most customers were complaining about the products that were delivered to them or about the bad quality products and even the overpricing. For example: “Am I seeing an Amazon seller who is overpricing their games..” and that was not caused by amazon’s services such as the delivery time, the quality of the product packaging, the delivery men's attitude or even by customer relationship services.

Based on our research we found that Amazon doesn’t ship to Cuba, Iran, North Korea, Sudan and Syria because of some issues. We also discovered that especially in North Korea, a lot of users give negative feedback about amazon on Twitter, worsening the company’s public opinion and discouraging other customers from buying from the brand and as a result decreasing its revenues.

5.2 Limitations.

The first limitation that constrained us in using RapidMiner in the sentiment analysis was that the majority of the operations involved the Lexicon-based Approach, particularly when using Vader. Vader is limited in its ability to process sarcastic sentences because it is used to analyze words rather than sentences. That means that the words used do not always mean what they are supposed to. Some users are employing this technique to launch attacks, defend, or simply express themselves.

For example: “Really, Sherlock? No! You are clever. " This sentence could be said When someone says something very obvious, another example: “That's just what I needed today!” this sentence may be said when something bad happens. Vader's approach can't analyze those sentences right and as a result return them to the positive sentiment category. As words like “clever” and “needed” have a high score in the Vader approach.

The Second Limitation was that RapidMiner has restrictions on scoring words where the maximum number of words that can be analyzed and displayed in a diagram or graph is 500 words, so it means that projects or data extractions with a huge number of words cannot be contained by RapidMiner or processed in a diagram. In order to analyze the gathered data, we have to analyze them with other tools and technologies or by using manual methods.

The third limitation was that RapidMiner has a restriction on the languages that can be tokenized, extracted, or simply processed using Vader. Even though RapidMiner said on their website that users could request the addition of additional languages by giving them access to dictionaries and other resources, it still takes a while for RapidMiner to extract some languages. For instance, RapidMiner can extract Chinese, but the majority of users encounter difficulties doing so and that requires the RapidMiner developer's assistance to ensure that the procedure can be carried out, this kind of restriction will complicate the extraction process.

The fourth and last limitation is that as RapidMiner is based on a Lexicon-based Approach, it means that it cannot learn and improve by itself to understand certain words. In most languages, some words have a complex meaning. In other cases, one word can have more than one meaning at the same time. For example, the word “nails” in the English language has two meanings which are nails that are used to join two pieces of wood together using a hammer or nails like fingernails. Another example: is called 'mononoaware' which means the awareness of the impermanence of all things and the gentle sadness at their passing in the Japanese Language, It’s hard for the Lexicon-based Approach that is used in the RapidMiner to recognize such words because of the lack of the training compared to other machine learning approaches that are trained to cluster and classify the words into positive, neutral and negative and determines the sentiment towards those words.

6.0 Conclusion.

Kumar and Sebastian (2012) stated that the proliferation of microblogging sites like Twitter provides an opportunity to implement techniques that mine for sentiments. In this paper, we choose Amazon as our scope of analysis. We presented a specific approach for sentiment analysis on Twitter data. To determine the sentiment, we extracted the opinion words regarding amazon in the tweets. The Vader module was used to analyze the data. The tool we used to apply our algorithm is called RapidMiner. After finishing the process, we concluded that amazon is doing relatively well with their customers and also discovered some of the causes of the setback and suggested recommendations for them. We can state that sentiment analysis is a double-edged sword that needs to be handled carefully to use it to its utmost benefit, otherwise if used wrong, it can turn the table on you with misinformation.

7.0 References.

1. Alghamdi, N. S., & Aljuhani, S. A. (2019). A Comparison of Sentiment Analysis Methods on Amazon Reviews of Mobile Phones. Article in International Journal of Advanced Computer Science and Applications, 10(6). https://doi.org/10.14569/IJACSA.2019.0100678
2. Fang, X., & Zhan, J. (2015). Sentiment analysis using product review data. Journal of Big Data, 2(1), 1–14. https://doi.org/10.1186/S40537-015-0015-2/FIGURES/9
3. Haque, T. U., Saber, N. N., & Shah, F. M. (2018). Sentiment analysis on large scale Amazon product reviews. 2018 IEEE International Conference on Innovative Research and Development, ICIRD 2018, 1–6. https://doi.org/10.1109/ICIRD.2018.8376299
4. Ijaz, F., Ali, Y., Akhtar, A., & Shafique, M. (2020). REVIEWS ANALYSIS OF UNLOCKED MOBILE PHONES IN AMAZON USING RAPID MINER.
5. Keith Norambuena, B., Lettura, E. F., & Villegas, C. M. (2019). Sentiment analysis and opinion mining applied to scientific paper reviews. Intelligent Data Analysis, 23(1), 191–214. https://doi.org/10.3233/ida-173807
6. Kumar, A., & Sebastian, T. M. (2012). Sentiment Analysis on Twitter.
7. Rashid, A., & Huang, C.-yu. (2021). Sentiment analysis on consumer reviews of Amazon Products. International Journal of Computer Theory and Engineering, 13(2), 35–41. https://doi.org/10.7763/ijcte.2021.v13.1287
8. Rosencrance, L. (2020, August 20). What is employee sentiment analysis and why is it important? SearchHRSoftware. Retrieved 2022, from https://www.techtarget.com/searchhrsoftware/definition/employee-sentiment-analysis
9. Rushdi Saleh, M., Martín-Valdivia, M. T., Montejo-Ráez, A., & Ureña-López, L. A. (2011). Experiments with SVM to classify opinions in different domains. Expert Systems with Applications, 38(12), 14799–14804. https://doi.org/10.1016/j.eswa.2011.05.070
10. Shoeb, M., & Ahmed, J. (2017). Sentiment analysis and classification of tweets using data mining. International Research Journal of Engineering and Technology (IRJET), 4(12).
11. Singh Hanswal, S., Pareek Sr Asst Professor, A., & Sharma Sr Asst Professor, A. (2019). Twitter Sentiment Analysis using Rapid Miner Tool. International Journal of Computer Applications, 177(16), 975–8887.

12. Vyas, V., & Uma, V. (2018). An extensive study of sentiment analysis tools and binary classification of tweets using rapid miner. Procedia Computer Science, 125, 329–335. https://doi.org/10.1016/j.procs.2017.12.044