The Impact of the Corona virus Pandemic on Consumer Sentiment Analysis: A Machine Learning Approach to Supply Chain Management

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Abstract

As a result of the COVID-19 pandemic, consumers and families have found it difficult to maintain a healthy and vibrant everyday life, excellence of living, and well-being. Poor daily living activities, according to early evidence, are connected to a higher risk of mortality and COVID-19 severity. The impact of the Corona virus pandemic on consumer attitudes, thoughts, and sentiments in their daily lives is investigated in this study. Sentiment analysis has been utilized to collect data from a range of clients, and the precision of our sentiment analysis projections has improved thanks to recent breakthroughs in machine learning algorithms. We'll use a range of rapid miner tools to perform sentiment analysis on "lifestyles" in this study.

The Supply Chain Management (SCM) concept aims to ensure that physical, financial, and information flows are efficiently exchanged amongst all supply chain components, both within intra-organizational and inter-organizational cooperation.

This perception is now a strategic mission for anyone who wants to meet their goals in terms of monetary competitiveness, delivery, and service excellence. This is even more difficult in a global economy marked by globalization of commerce, complication of trade flows, increased rivalry, and the emergence of new technologies. Needs for long-term improvement In our fast-paced and turbulent environment, characterized by massive data sharing, information technology use, and It's critical to have processes in place to connect with each supply chain partner.

Sentiment analysis is a technique for recognizing emotional states. We know that humans learn from their mistakes and that machines are programmed to follow human commands. But what if people could program machines using past data and put the output to work much faster? That's what machine learning is all about; it's not just about learning, but also about understanding. As a result, we'll learn how to use machine learning to perform sentiment analysis.

In this study, we'll use a variety of fast miner techniques to perform sentiment analysis on "lifestyles." According to a literature review on sentiment analysis, there are two methodologies that are important: semantic orientation and machine learning. Machine learning is a data analysis technology that automates the logical creation of a model, whereas semantic orientation of a view indicates whether the view is positive, negative, or neutral. In this work, we will do sentiment analysis on "lifestyles" using a number of quick mining methods. We try to classify a lifestyle's polarity as positive, negative, or neutral. According to a sentiment analysis literature survey, two approaches are crucial: semantic orientation and machine learning. Machine learning is a data analysis technique that automates the logical construction of a model, whereas semantic orientation of a view shows whether it is positive, negative, or neutral. Machine learning algorithms are utilized in two ways. The right number of centroids is calculated using K-means and X-means clustering to discover consumer sentiments.

Keywords : Machine Learning, Big Data, Sentiment Analysis, K-means Algorithm, X-means Algorithm , SCM, Intelligent decision making

Abbreviations: SA - Sentiment Analysis, OM - Opinion Mining, BD - Big Data , ML - Machine Learning, NLP - Natural Language Processing, OMSA - Opinion Mining and Sentiment Analysis, IDE -Integrated Development Environment, X-x- means , K - k-means algorithm, N - Negative, P - Positive

Introduction and Motivation :

Customers can leave comments on products, services, brands, or companies via social media sites. Customers commonly utilize social media sites like Twitter and Facebook to express their thoughts on a product or service. The quantity of user-generated social media Data from the media, particularly customer perceptions in the service and manufacturing industries, has experienced a meteoric rise. Companies can use social media data to acquire insights into customer opinions and, as a result, better predict consumer intents in supply chains. When it comes to managing distributed supply chain networks, traditional data sources can have significant drawbacks. As a result, social media data is an important source of real-time information for operating supply chain networks effectively. However, because to the massive nature of the data and the existence of irrelevant or garbage data, extracting valuable information from these social media data, such as stakeholder sentiment, emotion, or opinion, is not a simple AI process. These noisy data'should be vetted so that excellent data can be sorted out, especially in the context of supply chains, to reliably extract stakeholder sentiments.

We'll employ a range of rapid miner approaches to perform sentiment analysis on "lifestyles" in this research. According to a sentiment analysis literature survey, two approaches are crucial: semantic orientation and machine learning. Machine learning is a data analysis technique that automates the logical construction of a model, whereas semantic orientation of a view shows whether it is positive, negative, or neutral. We will use a variety of rapid mining algorithms to perform sentiment analysis on "lifestyles" in this project. We strive to categorise the polarity of a lifestyle as good, negative, or neutral. According to a literature review on sentiment analysis, two approaches are essential: semantic orientation and machine learning. Machine learning is a type of data analysis that automates the logical development of a model, whereas semantic orientation of a view indicates whether it is positive, negative, or neutral. There are two approaches to use machine learning algorithms. K-means and X-means clustering are used to determine the correct number of centroids to find the sentiments of consumers.

Over the past few months ,Covid-19 completely changed our lives. At the same time as the environment began to cure ,people were locked up at home due to induced lockdown. Major lifestyle changes were seen. Societies were inhabitants were taught social interaction was prohibited from it. Citizens begin to adapt, and now, a new way of living has emerged. We have realized it, there have been so many changes in our everyday lives because of coronavirus, that would have never happened.[1][2]

Social media and social capital:

There are many different definitions of social capital, but they all focus on two aspects: social networks and the resources embedded in them within each of those networks The primary idea behind social capital is that it is a resource that can be used to help .According to theory, networks of connections are a valuable resource for the purpose of social action The foundation of social capital theory is that the advantage that an actor, either individually or collectively, can gain from those social relationships and the resources they contain. The social attributes pertinent to social media in the framework of social capital theory are reach, engagement, and influence. The level of participation and involvement of a single individual in the network is measured by engagement. Time spent with a given individual, inter-contact times, and reciprocity of contacts can all be used to gauge engagement. Finally, influence refers to the amount of attention/mobilization that a person may elicit from other members of their network.

Social media and the supply chain:

Supply chains are complex socio-technical systems in which technical and social aspects coexist. The technical components are dominated by systems and address technological and supply chain structural challenges such logistics, information systems, and supply chain performance. Social variables, on the other hand, are human-centered and deal with social ties among supply chain participants. While formal processes established by businesses deal with technical factors, social elements such as reciprocity and mutual trust are related to the supply chain's social system. In the context of supply chains, both social and technical variables are equally essential. Because they are more closely rooted in the socio-cultural framework of the recipient culture, these soft constructs of supply chain management (SCM) are more prone to misalignment. Despite the fact that many scholars emphasize the need of trust and collaboration within supply chains, the social components of SCM have received little attention. Furthermore, since chances for supply chain performance improvement through breakthrough technical breakthroughs are diminishing, the focus on increasing supply chain performance by improving relationships among supply chain partners is growing. Exploring the connections between social media material and various supply chain functions can thus be a fruitful avenue of research.

Supply chain and social capital:

Several research have examined supply chain difficulties using social capital and social network theories. Bernardes (2010) researched aspects associated with the relational embeddedness of social capital and the function of supply management in the process, using a social network viewpoint. He confirmed that the relational embeddedness feature of social capital should be viewed as a significant antecedent to performance by using empirical data. While this study focused on the actors' network, our research focuses on the links that exist within the network, which is a premise of social capital theory. the theory of social capital,

Positive relational capital and its antecedents, supplier integration and supplier closeness, are linked to improved buyer performance, according to Lawson et al. (2008). They presented evidence that structural capital was also linked to improved buyer performance.

Sentiment analysis is the procedure of calculating, identifying and grouping views represented in a form of text, specifically in order to identify whether the author's behavior towards a particular task is positive, neutral or negative. Opinion Mining also refers to NLP (Natural Language Processing), biometrics, text analysis and computational linguistics in order to detect , extract and refer to subjective information. Sentiment analysis basically aims to identify the attitude of a writer with respect to a topic or the complete polarity to a document. The behavior may be a valuation or judgmental or affective state of the author or the emotional communication or interlocutor. It is the calculative study of users' opinions, views, behavior and emotions toward an object. Sentiment mining helps to gather positive, negative or neutral information about a product. Then, the highly counted opinions about a product are passed to the user. For promoting marketing, big companies and business magnets are making use of this opinion mining. Using given studies by Behdenna , et al[3][4][5], sentiment analysis is being performed at three levels i.e.:

Document level analysis: The task at this level is to determine the overall opinion of the document. Sentiment analysis at document level assumes that each document expresses opinions on a single entity.

Sentence level analysis: The task at this level is to determine if each sentence has expressed an opinion. This level distinguishes the objective sentences expressing factual information and subjective sentences expressing opinions. In this case, treatments are two fold; firstly identify if the sentence has expressed or not an opinion, then assess the polarity of opinion. But the main difficulty comes from the fact that objective sentences can carry an opinion.

· **Aspect level analysis**: This level performs a finer analysis and requires the use of natural language processing. In this level, opinion is characterized by a polarity and a target of opinion. In this case, treatments are twofold: first identify the entity and aspects of the entity in question, and then assess the opinion on each aspect

Literature Survey :

For the last two decades, digital data has been generated on a massive scale, which is defined as Big Data (BD). This phenomenon has changed the ways of managing and drawing conclusions from any size of data. Moreover, Artificial intelligence is shaping new techniques and methods of analysis considering BD. Sentiment Analysis (SA) or Opinion Mining (OM) has a positive potential in extracting value from data, thus it is widely studied for the last few years. Due to improved internet connectivity, the amount of data generated by users also increases. As a result, the challenge to handle this amount of data also increases. To handle such kinds of challenges, tools like machine learning (ML) can help organizations and individuals to handle and take advantage of the data generated by users.

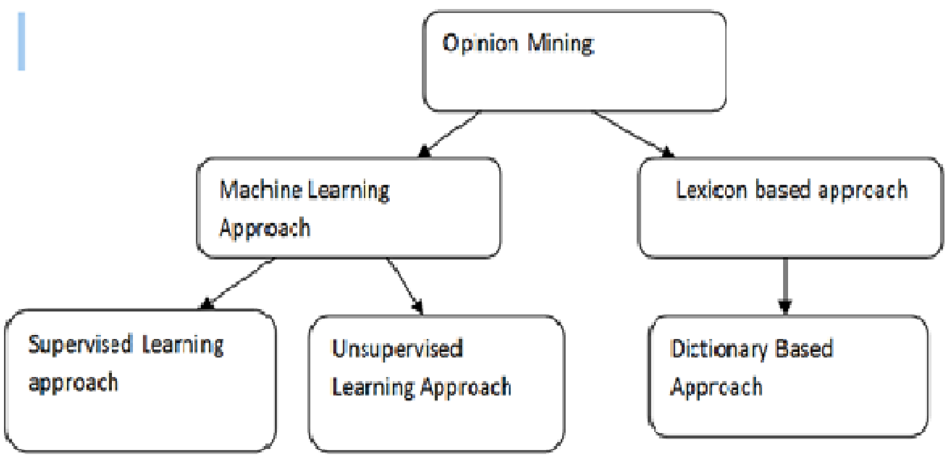

Fig 1 Opinion Mining Techniques

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A sentiment for each entity in a sentence is delivered in attribute level sentiment analysis. Sentiment analysis at the sentence level provides the overall sentiment of each and every sentence in a document. The overall sentiment of the entire document is offered in document level sentiment analysis. There are two strategies for sentiment analysis, according to a literature review i.e. semantic orientation and machine learning which are important. Machine learning is a data analysis technology that automates the logical creation of a model, whereas semantic orientation of a view indicates whether the view is positive, negative, or neutral. The techniques are shown in the following figure: (Opinion Mining Techniques)[2][3][4]

- Pseudocodes are learnt using descriptive examples as an input in the **supervised learning** approach of machine learning, where the desired output is already known. It's typically employed in situations where past data is used to forecast future data.

- There is no history data in the **unsupervised learning** method to machine learning. The goal is to look at the data and extract some helpful information from it..

CHALLENGES TO OPINION MINING

Opinion mining in interrogative questions may be difficult due to the lack of positive or negative sentiments in these sentences..

- It is not required that the statement contain sentiment words, but it must represent a positive or negative attitude..
- Opinion mining in spam sentences is difficult to predict as they are the sentences posted by the competitor organization in order to increase one's value. etc

In the field of research methodology, sentiment mining has grown highly popular. Although much study has been done, there are still several issues with sentiment mining that are related to unstructured data. As per the study of various published papers, it can be safely said, that supervised procedures produce far more accurate results than dictionary techniques.

Types of sentiment analysis [5][6]

1. Manual processing: The sentiment must be accurately interpreted by humans..

2. Keyword processing: Individual words are assigned as positivity or negativity, and the aggregate percentage score for the post is calculated.

3. Natural language processing (NLP): Also called text analytics, computational linguistics.

Keyword processing is inferior to NLP. NLP analyses language to determine its meaning. Vendors can use the information gleaned from sentiment analysis to better their marketing strategy. The researcher can use sentiment analysis to evaluate whether their audience is having positive or negative comments. The researcher can learn about the customer's ideas on their views by using sentiment analysis. The effectiveness of a viewpoint is not measured, but rather how well it is expressed in online reviews. Three methods can be used to assess sentiment analysis.

They are

- ✓ Machine learning approaches
- ✓ Lexicon based approaches
- ✓ Hybrid-based approaches.

The supervised learning model can be quickly taught, and the unsupervised model can easily categorize the data in the machine learning technique. The sentiment scores for each word can be simply calculated using the lexicon-based technique. The hybrid approach evaluates sentiment for noisy and less sensitive data by combining machine learning and lexicon-based approaches. The sentiment analysis can be divided into different categories as shown in Figure

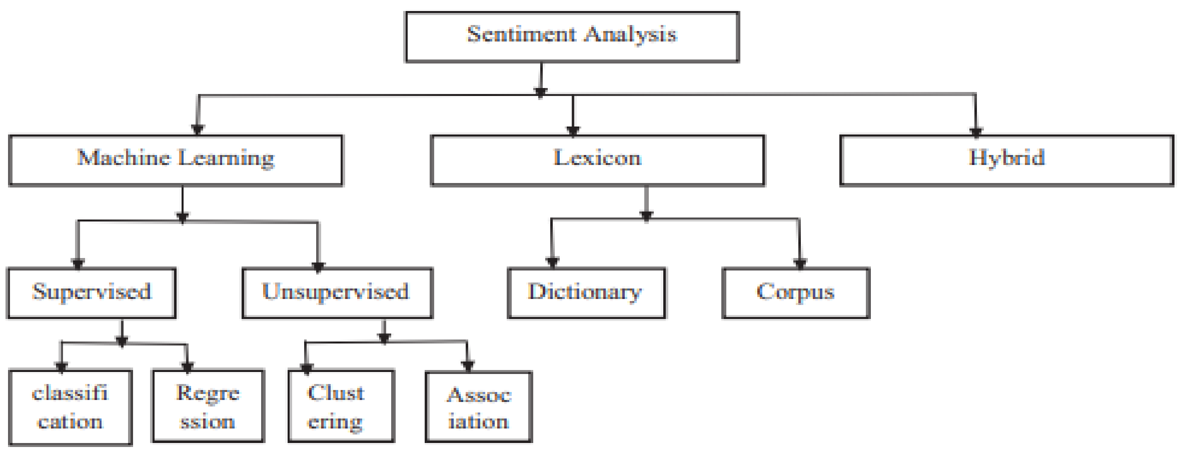


Fig 2: Categories of Sentiment Analysis

Sentiment analysis is concerned with discovering and presenting opinion trends in a clear and understandable manner. In an online review, the result of the sentiment analysis might be categorizing opinions such as positive, negative, or neutral regarding how covid-19 affected consumers' daily life. Bias analysis and emotion identification are two sub-streams of sentiment analysis[7].

We know that humans learn from their experiences and that machines follow human directions. But what if people could prepare machines from previous data and put output to work much more quickly? That is what machine learning is all about; it isn't only about learning, but also about comprehending. As a result, we will study the principles of machine learning.

So, let's use Shuchita as an example. She enjoys listening to songs and determines whether she likes or dislikes them based on tempo, variety, intensity, and the gender of the voice.

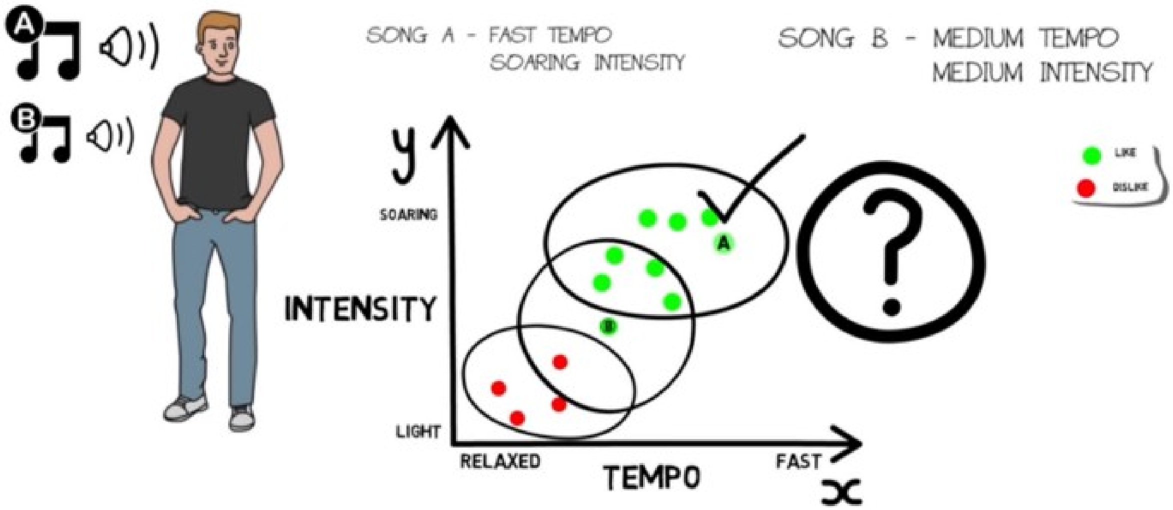


Fig 3.Tempo vs Intensity

- Here, Tempo is on the X axis ranging from relaxed to fast.
- Intensity is on the Y axis ranging from light to soaring.
- Chetan like songs with a quick tempo and high intensity, whereas he despises songs with a slow tempo and low intensity.
- So now that we know Chetan's preferences, let's see how he reacts to a new song. Let's call it song A. Song A has a quick tempo and soaring intensity, thus it belongs somewhere in the data chart. Can you anticipate where Chetan will like the song or not? Correct, Chetan likes the song. By looking at Chetan's previous choices, we can easily identify the unknown song right now.
- Chetan is listening to a new song, which we'll call song B. Song B is somewhere around here, with a medium tempo. And with a medium intensity that is neither relaxing, rapid, light, nor soaring, you can predict if Chetan likes it or not.
- It cannot be determined whether Chetan will enjoy or dislike this. We could simply identify song A, but when the option becomes hard, as in the case of song B, yes, and that's where machine learning comes in. Let's look at how, in the same example, if we draw a circle around song B, we see that there are three votes for like and one vote for dislike. If we go by the bulk of the words, we can assume that Chetan will most likely enjoy the music. That's all there is to it. This was also a fundamental machine learning algorithm, called K – nearest neighbors, so this is only one of many machine learning algorithms.

It's quite simple, right? But what happens when the choices become more complicated, as in the case of song B? Machine learning learns the data, builds the prediction model, and when new data points arrive, it can easily project for them. With more data, the model becomes better which results in higher accuracy. There are many ways in which the machine learns.[8][9]

- ✔ Supervised learning
- ✔ Unsupervised Learning
- ✔ Reinforcement Learning

Let's first quickly understand:

Supervised Learning:-

Assume a buddy offers you one million coins in three different currencies, each with a different weight, such as one rupee, one euro, and one dirham. For example, a rupee coin weighs 3 (three) grammes, a euro coin weighs 7 (seven) grammes, and a dirham coin weighs 4 (four) grammes.

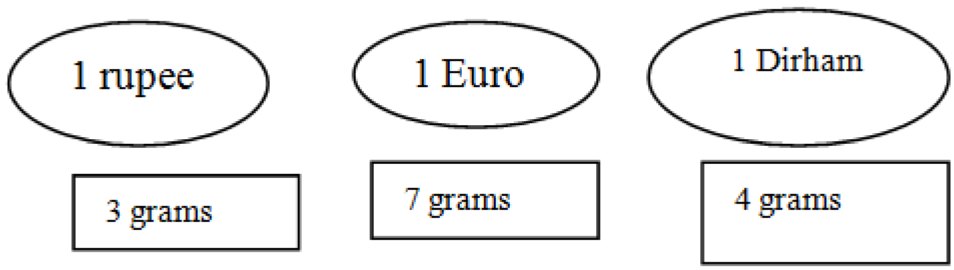


Fig 4. Supervised Learning

When you provide this data to the machine machine learning model, it learns which feature is connected with which label, and your weight becomes the feature of the coin, while currency becomes the label. It will learn, for example, that a coin weighing three grams is a one rupee coin. Let's give the machine a new coin, and your model will predict the currency based on the weight of the new coin. As a result, supervised learning employs labeled data to train the model; in this case, the machine was aware of the object's features as well as the labels associated with those features.

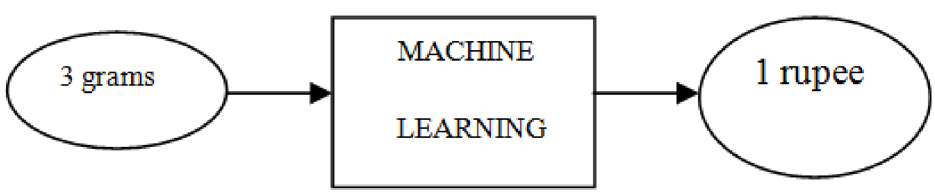


Fig 5 Supervised learning model

On this note let's see the difference with unsupervised learning

Unsupervised Learning:-

Unsupervised learning is a kind of machine learning in which models are trained on unlabeled data and then allowed to act on it without supervision.

Unsupervised learning aims to uncover a dataset's underlying structure, categorize data based on similarities, and display the dataset in a compact fashion.

Consider the following scenario: the unsupervised learning system is given an input dataset containing photographs of various cats and dogs. The algorithm is never trained on the given dataset, therefore it has no knowledge what the dataset's characteristics are. The unsupervised learning algorithm's goal is to recognise visual features on its own. This work will be completed by using an unsupervised learning method to cluster the image dataset into groups based on image similarities.

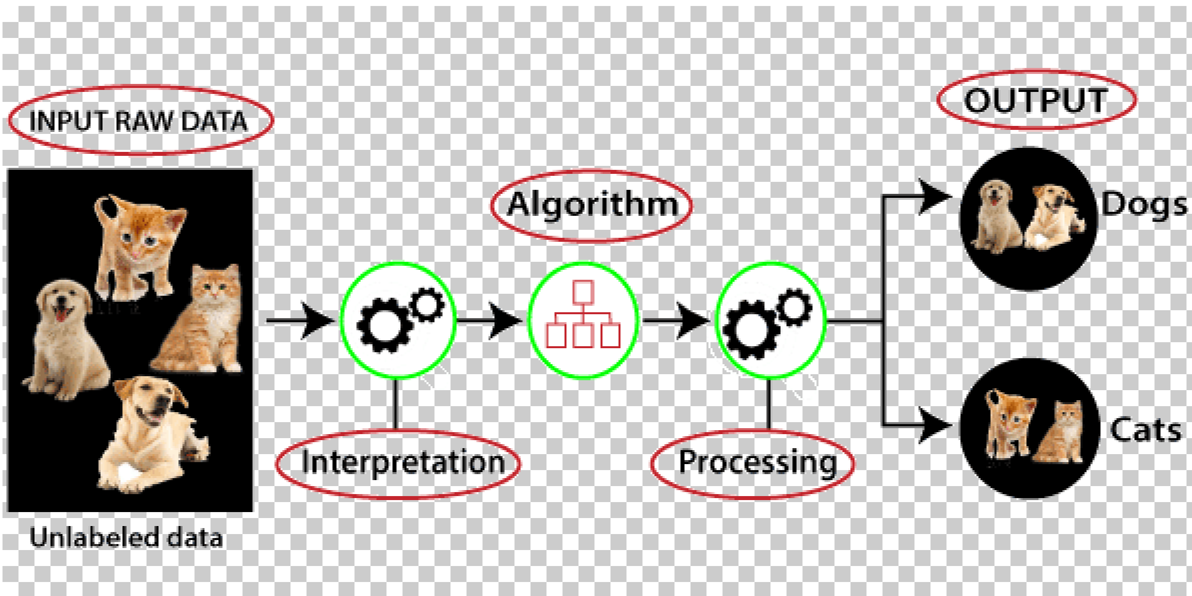


Fig 6. Unsupervised learning model

We've used unlabeled input data, which means it hasn't been categorized and no outputs have been provided. Now, the machine learning model is fed this unlabeled input data in order to train it. It will first analyse the raw data in order to uncover hidden patterns, and then use appropriate algorithms such as k-means clustering, Decision tree, and so on.

After applying the appropriate method, the algorithm splits the data objects into groups based on their similarities and differences.

Reinforcement learning:

Reinforced learning is reward-based learning or, to put it another way, it works on the *principle of feedback*. For example, let's say you give the system an image of a cat and ask it to identify it. The system incorrectly identifies it as a dog, so you give the machine negative feedback saying it's a cat's image. The machine will learn from the feedback.

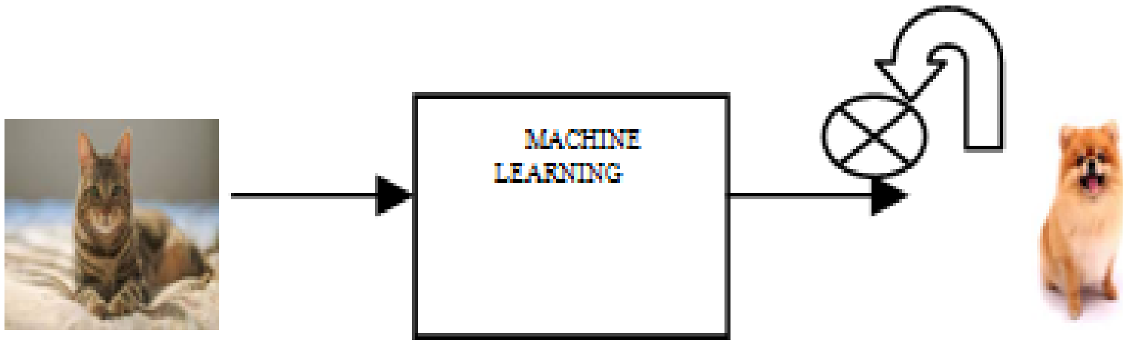


Fig 7 Reinforcement learning model

Finally, if it encounters another image of a cat, it will be able to accurately classify it, thanks to reinforcement learning.

Let's look at a flowchart to show how an input is provided to a machine learning model, which then produces an output based on the algorithm used.

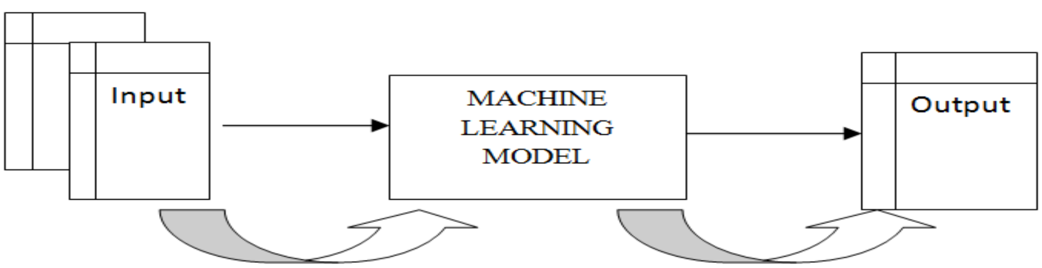


Fig 8 Flowchart of Machine learning model

If the output is correct, we use it as the final result; if not, we give the train model feedback and ask it to guess until it learns.

Don't you ever wonder how machine learning is possible in this day and age? That's because we now have access to enormous amounts of data. Everybody is online, either transacting or just surfing the web, generating a massive amount of data every minute, and that data, my friend, is the key to analysis. Also, computers' memory handling capabilities have greatly improved, allowing them to analyze vast amounts of data quickly, and yes, computers now have tremendous processing capacity, therefore machine learning has a wide range of applications. To name a few, machine learning is employed in:

- **Healthcare** :- To diagnostics are predicted for doctors review
- **Fraud Detection** :- In the finance sector
- **Sentiment Analysis** :- That the technology grants are doing on social media is another interesting application of machine learning
- **E-Commerce** **:-** Also to predict customer churning in the e-commerce sector

If you've ever booked a cab, you've probably seen a surge pricing message that states, "The far row field trip has been adjusted, continue booking yes please." I'm running late for work, so that's an interesting machine learning approach utilized by global cab giants OLA, UBER, and others to provide real-time differential pricing based on the following :-

- ✓ Demand
- ✓ Number of cars available
- ✓ Weather
- ✓ Rush hours etc.

So they employ the surge pricing approach to ensure that individuals who need a cab can obtain one, as well as predictive modeling to predict where demand would be strong, with the purpose of allowing drivers to meet demand and lowering the surge price.

“Hey Alexa, can you remind me to book a cab at 06:00PM today?”

Alexa: “Ok I will remind you”

There are many interesting everyday examples around us where machines are learning and are doing amazing jobs.

Conclusion of Sentiment Analysis:

Getting into your pockets Hopefully, your phones are still working; they do a lot for us, such as checking the weather and reminding us to set our alarm in case we don't wake up the next morning. But there's one thing our phones can't do yet: tell us how we're doing. "Alexa," "Siri," "How are you doing today?" These may seem ridiculous, but advances in sentiment analysis and machine learning are bringing our machines closer to answering these questions. Let me give you an example: "I loved that movie," and I asked you to rate it out of ten. Now, 0 represents negativity and 10 represents positivity. We all agreed that this is a very positive statement and gave it a score of about ten.

Let's try a different verb: "I enjoyed that movie"; it's still quite positive, but it's clearly lower on the scale; now let's try the opposite end of the spectrum: "I loathed that movie"; whoever started this certainly has a negative attitude toward the subject, and we'd probably give it a zero. Now, sentiment analysis is essentially teaching computers to extract the sentiments from human utterances using machine learning. Does this work now? What is machine learning? It is just a mathematical function that takes one or more integers and returns another. In machine learning, these functions are referred to as models.

These models are now commonly neural networks, which imitate the structures of our brains, and are used to collect inputs and their relationships in order to create models that predict future inputs.

Hypotheses and theories:

Members' social capital can influence supply chain performance while also providing a long-term source of competitive advantage. Furthermore, throughout the supply chain, social capital plays an important role in the formation and maintenance of buyer-supplier relationships and can be the primary source of value creation ,demonstrate how three types of social capital, namely structural, relational, and cognitive capital, might improve a supply chain partner's performance.

As a result, a partner's social capital can boost knowledge generation. This suggests that supply chain social capital might boost supply chain integration, which improves firm performance. For service supply chains, social capital also serves as a physical and informational resource. All of these studies have one thing in common: social capital can improve supply chain performance. Within a network, social profiles can be used to construct a collection of shared networks that can be further reinforced for the benefit of members. This can help to strengthen weak relationships and enable collective action. As a result, supply chain performance improves.

Social issues originating from concerns about product and human safety, welfare, and reputation can pose major supply chain operating risks, compromising the supply chain's reliability and performance. By effectively utilizing the social system of its core supply chain, a large firm can significantly increase its operating performance. They discovered that, rather of focusing heavily on formal governance and information technology (IT) systems, businesses can improve their operational performance in terms of cost and timeliness by using existing social systems. Product quality can be influenced by a company's social relationships. In conclusion, these studies emphasize the role of the social system, social issues, and social elements in supply chain performance.

The primary conclusion that can be drawn from this section of the research is that social media usage can have an impact on a product's market success. As a result,

Hypothesis 1 is proposed:

H1: The frequency with which supply chain members use social media is linked to supply chain performance.

Supply chain effectiveness is favorably connected with information sharing among supply chain partners on important supply chain operations such as point of sale, adaption of collaborative practices such as vendor controlled inventory, and collaborative planning, forecasting, and replenishment. Information sharing among members can also help members gain a competitive edge by increasing consumer value and lowering supply chain expenses. Information sharing among members can also help members gain a competitive edge by increasing consumer value and lowering supply chain expenses. One of the most important aspects that might improve channel-wide collaboration across the supply chain is information exchange. Through poor collaborative efforts, difficulty dealing with market volatility, inefficient decisions, and opportunistic conduct, asymmetric information amongst members can nullify value generation. These factors, alone or in combination, can have a major (negative) impact on supply chain performance.

Because of its scope, convenience of use, and rapid transmission of information, social media allows members to share real-time, easy, and high-quality information. As a result, we anticipate improved supply chain performance if supply chain partners share more information about supply chain management challenges on social media:

H2: The amount of information exchanged on social media by supply chain members about the changes in lifestyle is related to supply chain performance.

Collaboration allows partners to use their disparities in interests, concerns, and knowledge to their advantage. Online collaboration includes social media collaboration, which allows online groups to share, transmit, and reuse information, skills, and knowledge. In a supply chain setting, collaboration refers to the sharing of supply chain information such as product design, product development, manufacturing processes, logistics and distribution strategies, and other types of planning. Coordination, communication, relationship management, trust, and structure are all aspects of collaboration. Collaboration between supply chain partners can lead to increased efficiency, effectiveness, profitability, and better and longer-lasting ties between partners, all of which can improve supply chain performance.

Supply chain management is a set of ideas and efforts aimed at facilitating efficient collaboration between suppliers, producers, and customers, with the ultimate goal of attaining customer satisfaction. New internet technologies have enabled partners from various backgrounds and places to successfully collaborate to coordinate their actions and improve individual supply chain functions. Because they provide convenient ways of contact and information sharing, social media can dramatically augment these benefits. Formal and informal contacts, trust, motivation, and social links are all social variables that contribute to collaboration.

Individuals must be able to defend and evaluate their decision to share or obtain more helpful information, which is why trust is so important in information exchange and knowledge integration.

Members of virtual communities have been proven to need trust in order to share information with one another. From the standpoint of social networking, trust is a vital factor in determining the source and value of information for consumers, and hence has a significant impact on social media content. As a result, when social media users trust their social connections, they are more ready to rely on them because of the connections' perceived reliability and trustworthiness.

According to recent online studies, internet users have a higher level of generalized trust and have larger social networks. Although no clear proof exists, it is hypothesized that higher levels of trust and larger networks will also work in social media. Because sharing resources develops additional shared resources, trust within the network is critical. The foundation of social capital theory is the premise. As a result, there is a clear link between network trust/reciprocity and the availability of shared resources/social capital.

We hypothesize that higher levels of partner social media interactions related to trust will generate greater mutual trust and, as a result, lead to better supply chain performance: Social media usage has been found to be strongly associated with maintaining or strengthening existing offline relationships of communities.

H3: In social media, the level of trust among supply chain members is positively related to supply chain performance.

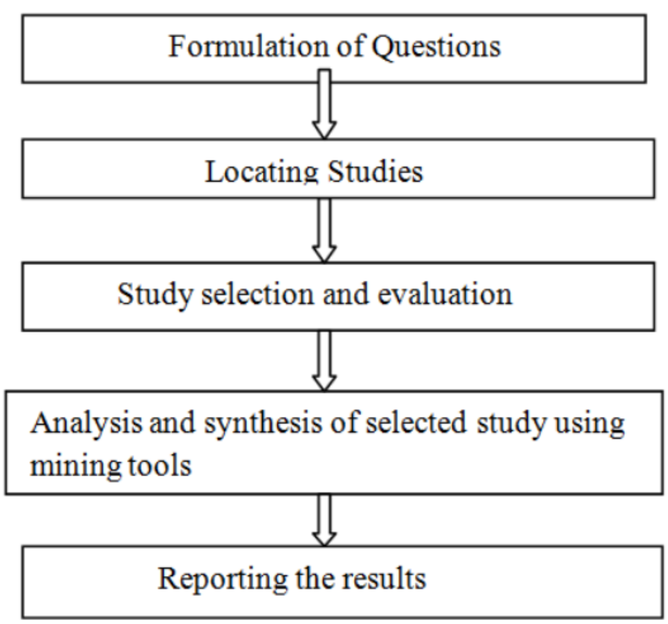
Supply chain integration is related to supply chain performance in a good way. Integration of supply chain functions such as design, purchasing, production, and distribution could be facilitated by increased trust and collaboration between partners.
While emotional commitment refers to a sense of belonging and attachment to a company, normative commitment relates to members' feelings of obligation to stay with a company and is based on broad cultural norms. Continuance commitment is thought to stem from a scarcity of viable alternatives. Normative commitment can improve coordination and integration, resulting in goals and ideals that are shared by all. Some of the most common reasons for utilising social networking sites are to identify with others, gain a sense of belonging, and gain insight into the lives of others. By providing many routes for relational feedback and peer approval, social media (specifically, several social networking sites) can assist in the development of personal identity.

In this way, social media can help users create affective and normative commitment, as well as trust, which will boost supply chain performance.

METHODOLOGY

The major purpose of this study is to gain a thorough understanding of the numerous opinion mining and sentiment analysis methodologies used in individual text analytics views. This study promotes the presence and use of applications in a variety of societal settings. The systematic literature review was used in the research. A systematic review begins with a well defined issue, then provides relevant studies, analyses their findings, and summarises the data using a clear approach. Systematic reviews differ from regular evaluations because of their explicit and deliberate methodology.[9]

It is just as vital as performing new research to combine evidence from the present literature to produce new understanding in existing studies. Rousseau et al. [13] argued that systematic reviews differ from traditional reviews in that they are comprehensive in nature, employ transparent and fair analysis, and apply certain criteria for understanding the findings that were previously presented in the literature. Furthermore, comprehensive literature reviews are primarily concerned with objectivity and reproducibility of findings [11][12]. The review process begins with formulating the questions, followed by a methodical, step-by-step approach, and the application of a repeatable method to answer these questions [11]. As a result, evidence derived from a systematic method to discovering, choosing, and evaluating data can have a major impact on the body of information gathered, but the primary aim of this technique is synthesizing the conclusions derived from this systematic procedure [10], [11]. [9] presented a five-step technique for the investigation, which is depicted in Figure 1. It entails locating, evaluating, synthesizing, deducing, and reporting evidence from the existing sentiment analysis and opinion mining literature in a systematic, unambiguous, and repeatable manner.



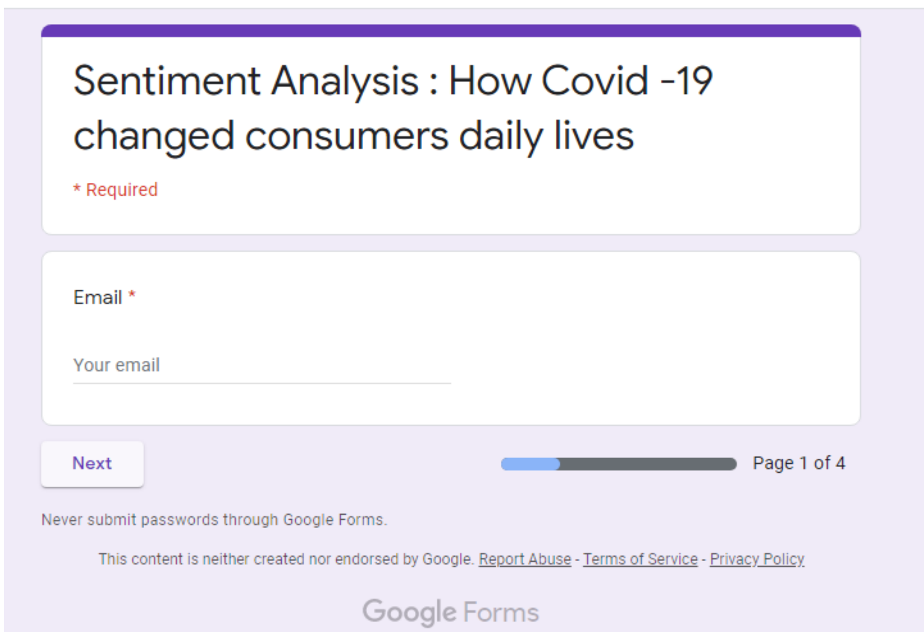
. Fig 9. Research methodology of systematic literature review

1. QUESTION FORMULATION:

The formation of a clear knowledge of your objectives should be the first step in conducting a thorough and comprehensive literature review [12]. As a result, in order to eliminate doubts in our study, we explicitly developed and considered research questions [13][14][15]. The goal of this study is to look into the methodological and application aspects of opinion mining and sentiment analysis, as well as to see if the intervention of opinion mining and sentiment analysis would be applicable to persons or to an entire organization.

https://forms.gle/Kp9vcxqBUXinjUyUA

The above link has the list of questionnaires of data collection of the current research topic.



Sentiment Analysis : How Covid -19 changed consumers daily lives

* Required

Email *

Your email

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Page 1 of 4

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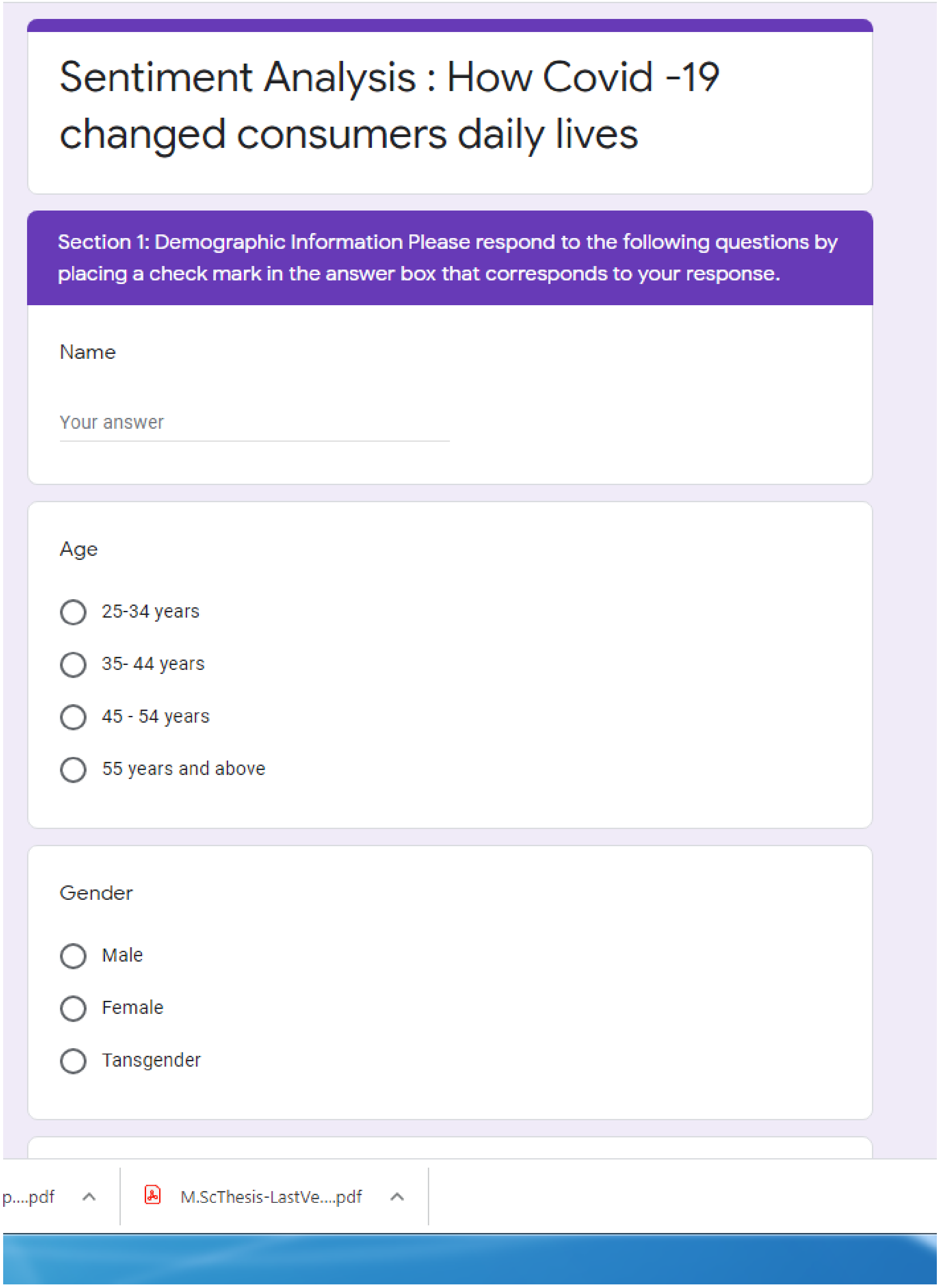

Sentiment Analysis : How Covid -19 changed consumers daily lives

Section 1: Demographic Information Please respond to the following questions by placing a check mark in the answer box that corresponds to your response.

Name

Your answer

Age

- 25-34 years
- 35- 44 years
- 45 - 54 years
- 55 years and above

Gender

- Male
- Female
- Tansgender

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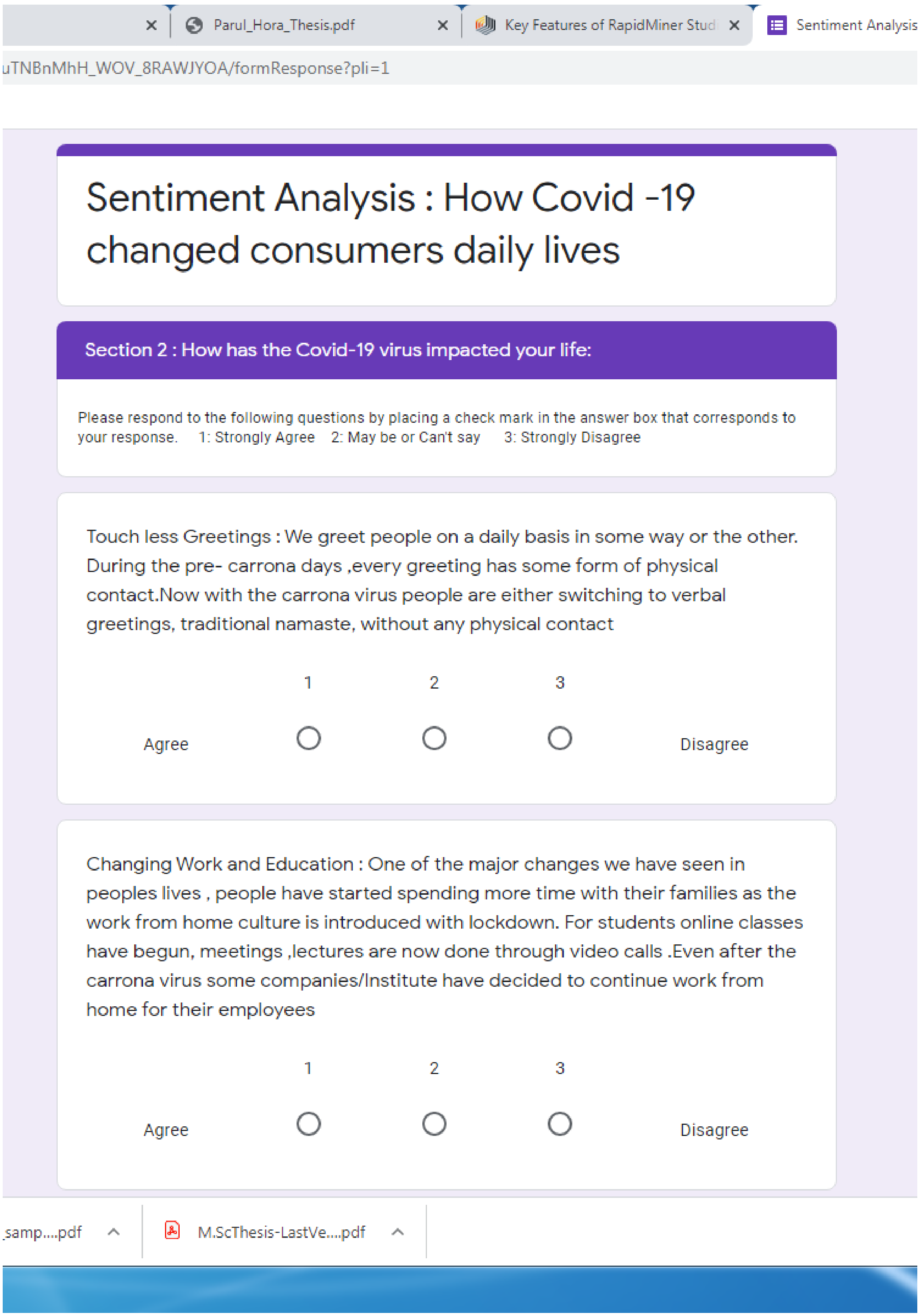

Parul_Hora_Thesis.pdf

Key Features of RapidMiner Stud

Sentiment Analysis

uTNBnMhH_WOV_8RAWJYOA/formResponse?pli=1

Sentiment Analysis : How Covid -19 changed consumers daily lives

Section 2 : How has the Covid-19 virus impacted your life:

Please respond to the following questions by placing a check mark in the answer box that corresponds to your response. 1: Strongly Agree 2: May be or Can't say 3: Strongly Disagree

Touch less Greetings : We greet people on a daily basis in some way or the other. During the pre- carrona days ,every greeting has some form of physical contact.Now with the carrona virus people are either switching to verbal greetings, traditional namaste, without any physical contact

	1	2	3	
Agree	○	○	○	Disagree

Changing Work and Education : One of the major changes we have seen in peoples lives , people have started spending more time with their families as the work from home culture is introduced with lockdown. For students online classes have begun, meetings ,lectures are now done through video calls .Even after the carrona virus some companies/Institute have decided to continue work from home for their employees

	1	2	3	
Agree	○	○	○	Disagree

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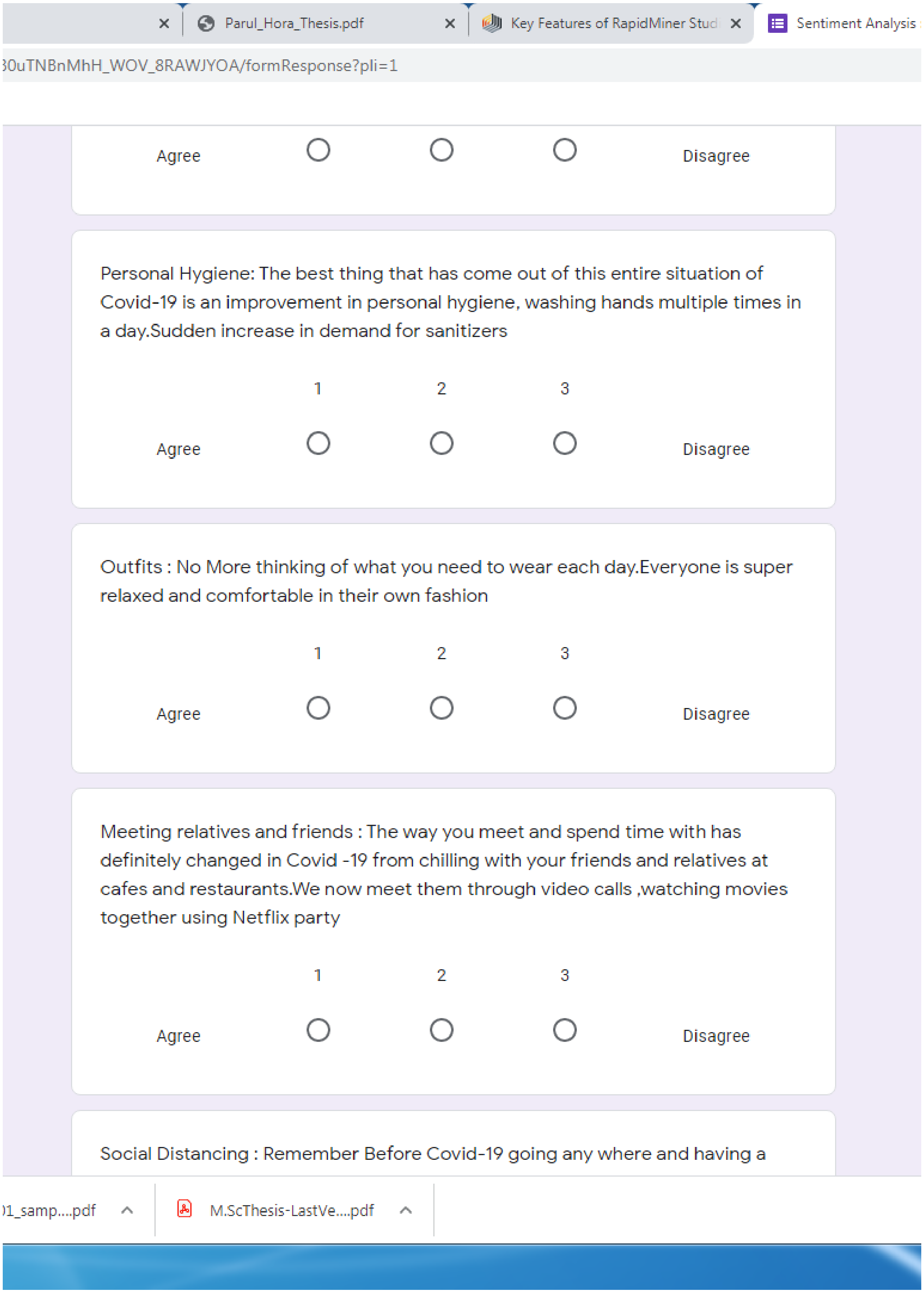

Parul_Hora_Thesis.pdf

Key Features of RapidMiner Stud

Sentiment Analysis

30uTNBnMhH_WOV_8RAWJYOA/formResponse?pli=1

Agree ○ ○ ○ Disagree

Personal Hygiene: The best thing that has come out of this entire situation of Covid-19 is an improvement in personal hygiene, washing hands multiple times in a day.Sudden increase in demand for sanitizers

	1	2	3	
Agree	○	○	○	Disagree

Outfits : No More thinking of what you need to wear each day.Everyone is super relaxed and comfortable in their own fashion

	1	2	3	
Agree	○	○	○	Disagree

Meeting relatives and friends : The way you meet and spend time with has definitely changed in Covid -19 from chilling with your friends and relatives at cafes and restaurants.We now meet them through video calls ,watching movies together using Netflix party

	1	2	3	
Agree	○	○	○	Disagree

Social Distancing : Remember Before Covid-19 going any where and having a

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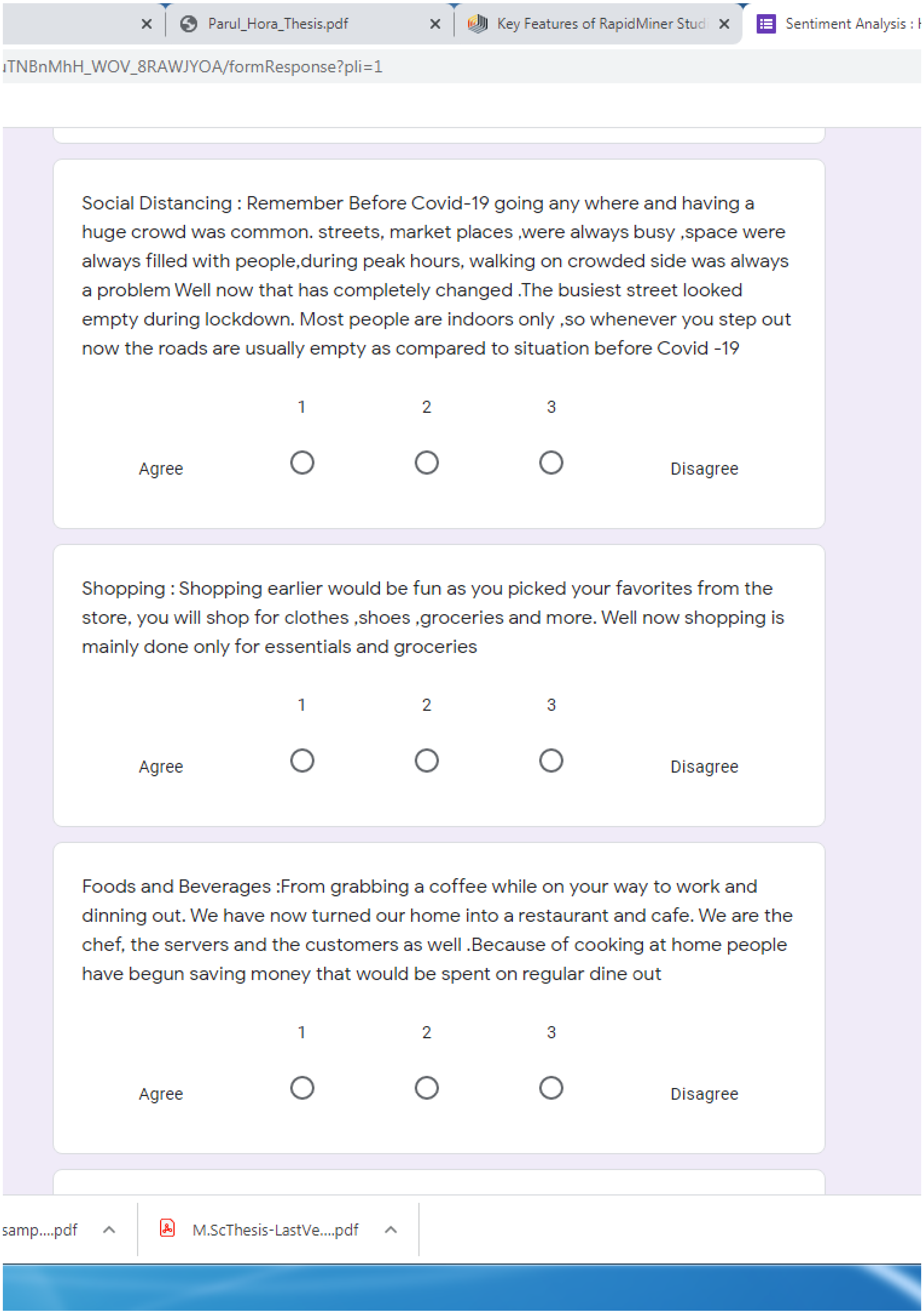
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Key Features of RapidMiner Stud
Sentiment Analysis : I
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Social Distancing : Remember Before Covid-19 going any where and having a huge crowd was common. streets, market places ,were always busy ,space were always filled with people,during peak hours, walking on crowded side was always a problem Well now that has completely changed .The busiest street looked empty during lockdown. Most people are indoors only ,so whenever you step out now the roads are usually empty as compared to situation before Covid -19

	1	2	3	
Agree	○	○	○	Disagree

Shopping : Shopping earlier would be fun as you picked your favorites from the store, you will shop for clothes ,shoes ,groceries and more. Well now shopping is mainly done only for essentials and groceries

	1	2	3	
Agree	○	○	○	Disagree

Foods and Beverages :From grabbing a coffee while on your way to work and dinning out. We have now turned our home into a restaurant and cafe. We are the chef, the servers and the customers as well .Because of cooking at home people have begun saving money that would be spent on regular dine out

	1	2	3	
Agree	○	○	○	Disagree

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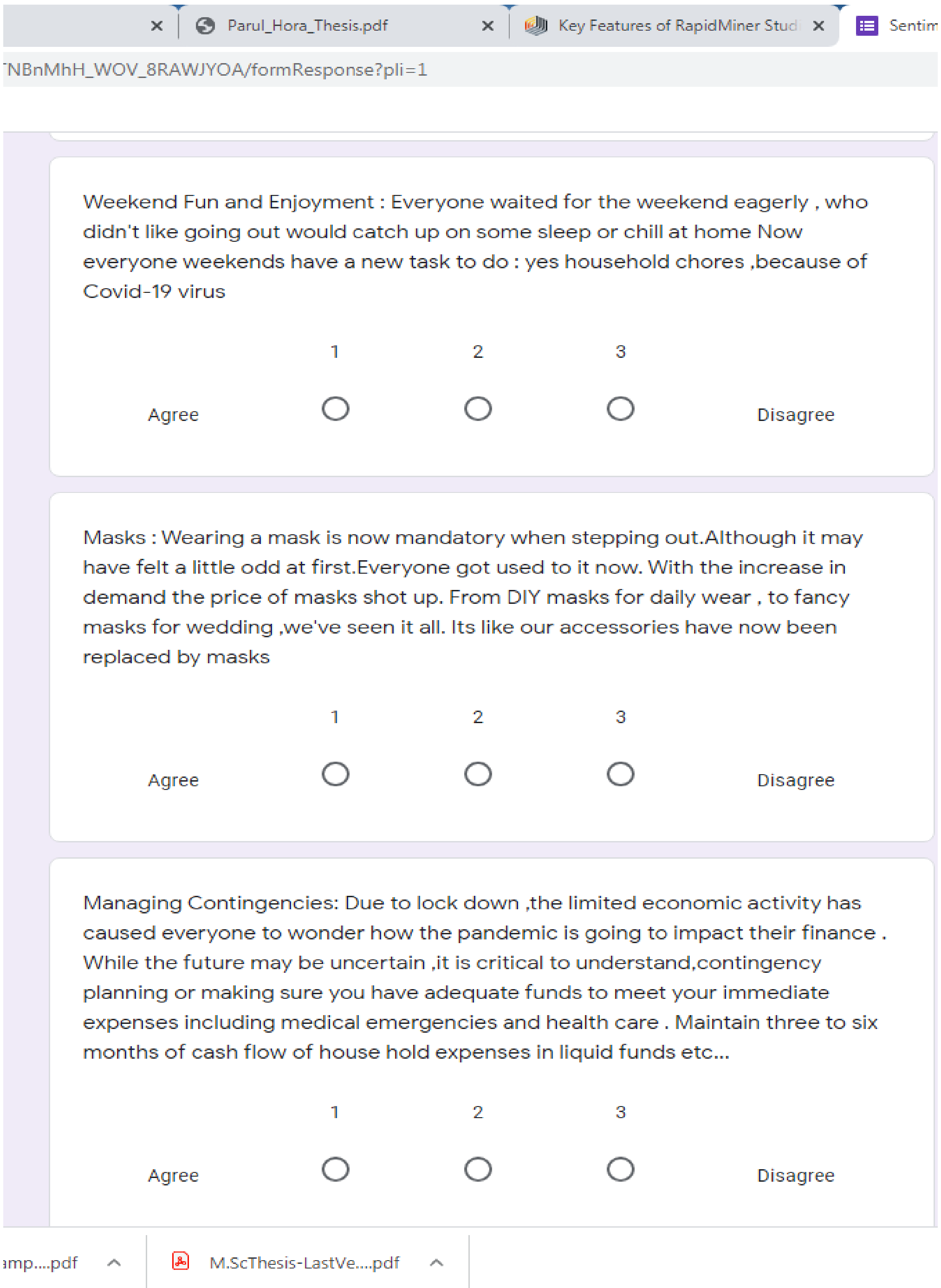

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Weekend Fun and Enjoyment : Everyone waited for the weekend eagerly , who didn't like going out would catch up on some sleep or chill at home Now everyone weekends have a new task to do : yes household chores ,because of Covid-19 virus

	1	2	3	
Agree	○	○	○	Disagree

Masks : Wearing a mask is now mandatory when stepping out.Although it may have felt a little odd at first.Everyone got used to it now. With the increase in demand the price of masks shot up. From DIY masks for daily wear , to fancy masks for wedding ,we've seen it all. Its like our accessories have now been replaced by masks

	1	2	3	
Agree	○	○	○	Disagree

Managing Contingencies: Due to lock down ,the limited economic activity has caused everyone to wonder how the pandemic is going to impact their finance . While the future may be uncertain ,it is critical to understand,contingency planning or making sure you have adequate funds to meet your immediate expenses including medical emergencies and health care . Maintain three to six months of cash flow of house hold expenses in liquid funds etc...

	1	2	3	
Agree	○	○	○	Disagree

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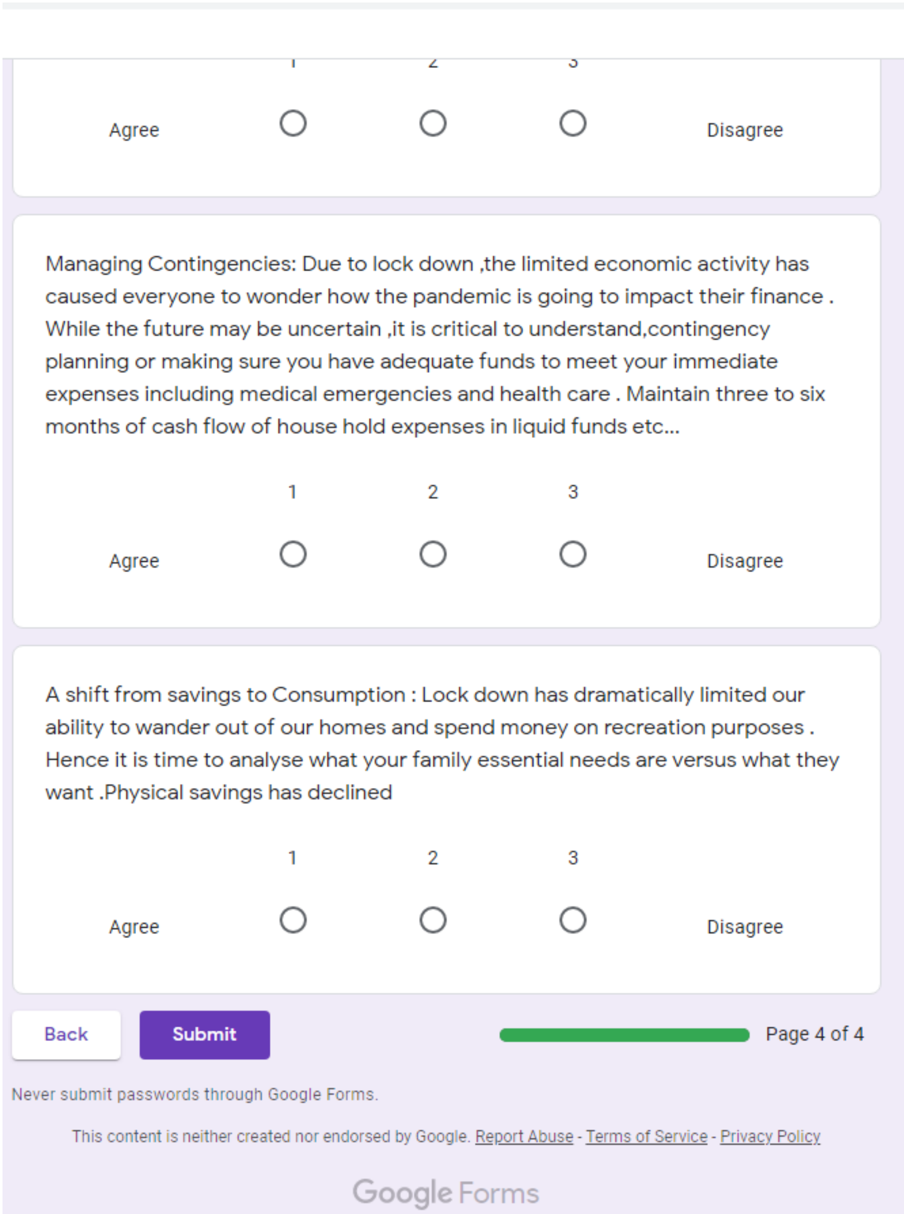

1 2 3

Agree ○ ○ ○ Disagree

Managing Contingencies: Due to lock down ,the limited economic activity has caused everyone to wonder how the pandemic is going to impact their finance . While the future may be uncertain ,it is critical to understand,contingency planning or making sure you have adequate funds to meet your immediate expenses including medical emergencies and health care . Maintain three to six months of cash flow of house hold expenses in liquid funds etc...

1 2 3

Agree ○ ○ ○ Disagree

A shift from savings to Consumption : Lock down has dramatically limited our ability to wander out of our homes and spend money on recreation purposes . Hence it is time to analyse what your family essential needs are versus what they want .Physical savings has declined

1 2 3

Agree ○ ○ ○ Disagree

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Fig 10 Screenshots of Question Formulated

B. LOCATING STUDIES

The goal of locating appropriate academic journal articles is to compile a list of all papers that are relevant to our research concerns. As a core database, I've compiled a collection of selected questionnaires. We employed alternative strings to find relevant papers because the study is based on opinion mining and sentiment analysis.[16][17]. However, in this study, the positive and negative emotions are highlighted using a tool.[18][19] **Rapid Miner 9.8.001** is a data science platform with analytics and artificial intelligence capabilities. Text mining is also included in this program.

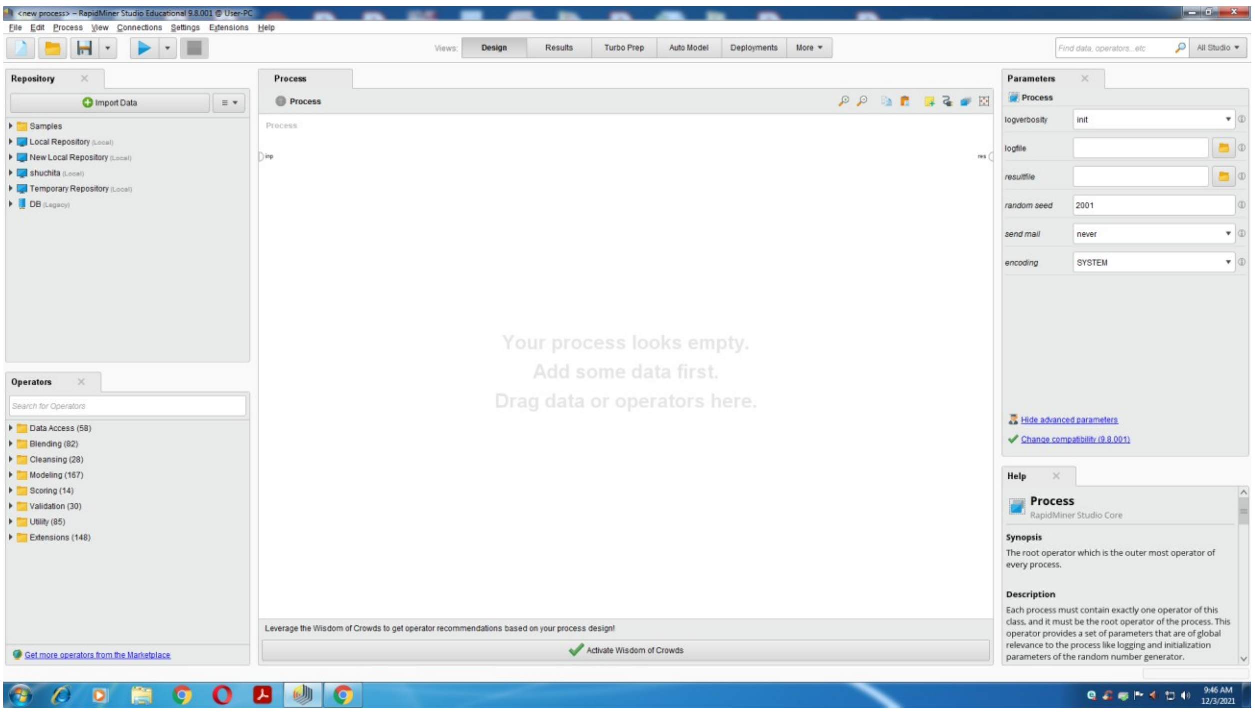


Fig 11 Rapid Miner studio Visual Workflow

RapidMiner Studio is a visual workflow builder for predictive analytics. For improved analysis, this blends machine learning and big data science. To construct the process diagram, you must first understand the quick miner studio. The IDE (Integrated Development Environment) includes a repository, Operators, Views, Global Search, Parameters, Help Panel, Functional Ports, and Process Panel, which includes standard tools like file and edit.

The advantages of Rapid Miner are detailed because it is a solid and powerful programme with several capabilities**.** Each component of the quick miner tool has a user-friendly environment interface that assists users in realising enormous productivity increases. It is a visual work-flow designer tool that is designed to provide users with a comfortable atmosphere. The user can construct, design, and deploy analytics processes, visual presentations, and models in this environment. Uncluttered, nonsensical, jumbled, expressions, and seemingly useless data were transformed into very valuable and visualizable data under the guidance of Rapid Miner tool operators. The system allows users to access data, maintain data that has been accessed, and load and assess data such as texts, photos, and audio files. Rapid Miner helps the user to organize data by structuring it. Rapid Miner was used to develop models and plans with a robust set of tools and functionalities, allowing the user to extricate or extract critical statistics and data. The user has complete access to data exploration and descriptive statistics such as graphics and visualization. This software is more powerful since it provides analytics for real-world data transformation settings, allowing users to master formatting and developing the best data set for user predictive analytics. [21] [22].

Explicit Features of the Rapid Miner tool is explained below: [21][22]

1. Visual Workflow Designer - A rich library of over 1500 machine learning algorithms, a drag-and-drop visual interface, pre-built templates, and proactive recommendations are all available.
2. Data Access and Management - Using SAS (Statistical Analysis System), ARFF (Attribute-Relation File Format), Stata (statistics and data science software), and URLs to access files..
3. Data Exploration - A label in column target variable.
4. Descriptive Statistics - Univariate statistics and plots, Distribution plots, Bivariate statistics and plots.
5. Graphs and Visualization - the visualization module was developed as a replacement for the well-known and outdated module - Plot View.
6. Data Prep - Turbo, often known as data prep, is a new module in Rapid Miner that helps analytics teams be more productive by speeding up time-consuming data prep operations.
7. Data Sampling - Depending on how the sample parameter is configured, the number of examples in the sample might be expressed as absolute, relative, or probability. In addition, the samples are generated at random.
8. Data Partitioning - The option is used to differentiate the number of subsets or partitions and the relative size of each partition in this partitioning. The partitions parameter is what it's called.
9. Data Replacement - The data replacement operator allows you to choose which attributes to utilize replacements for and to specify a regular expression to replace them with. The specified replacement is applied to the attribute values of chosen attributes that match this regular expression. It is possible for the replacement to be both empty and contain capturing groups.
10. Weighting and Selection - Select by Weights operator allows selecting attributes using the weights of the attribute.
11. Similarity Calculation - The determined similarity between each data to similarity and similarity to data is measured by a similarity calculated object. A similarity calculation or measure object can be generated using the Data to Similarity operation and vice versa.
12. Clustering - Clustering groups Examples together which are similar to each other. Clustering can be applied on unlabeled data and is an unsupervised machine learning approach because no Label Attribute is required.

13. Market Basket Analysis - Market Basket Analysis is a type of association analysis that is used to find intriguing relationships between variables in a set of data. The modelling of variable association is based on a set of objects that commonly appear together.
14. Bayesian Modeling - The Naive Bayes model is a low-variance, high-bias classifier. It has the ability to create a better model with a small amount of data. It is incredibly easy to use and comprehend. Text categorization, spam detection, sentiment analysis, and recommender systems are among the most common use cases.
15. Scoring - Rapidminer Time Scoring is an additional service to Rapid Miner. Scoring Agents are components that are developed for rapid scoring use cases through web services that are fulfilled by the components. It only uses a small amount of memory and responds quickly.
16. Automation and Process Control - It runs numerous processes at the same time. Long-term processes can operate in the background while other processes run in the foreground. Background process execution, automatic optimization, data preparation scripting, process logging, macros, process control, and process-based reporting are the core services.

C. STUDY SELECTION AND EVALUATION

We have limited our article selection to only peer-reviewed journals in order to ensure and preserve the paper's quality. Peer-reviewed journals have strict quality control, have gone through methodical, accurate processes, and have stringent publication standards, resulting in higher research output [2][3][22]. The examination and scanning of selected articles from the journal database began the procedure. The keywords "opinion mining" and "sentiment analysis" were used as the initial selection criteria.

The next step was to study the abstracts to see whether they were relevant to my research topic. Initially, it was read by a group of people, but in order to demonstrate its rigour, an independent consumer read the same amount of articles in order to increase its neutrality and strength. Intellectual outputs that did not fit with my study questions or appeared to be improper and non-substantive were eliminated. The publications included in the study are well-suited to the study's goal.

The chosen papers were then thoroughly analyzed and synthesized in order to respond to the research topics. I constructed a taxonomy for the preferred papers, which is shown in the following sections (dataset, methods, application, and major challenges)

DATASETS:

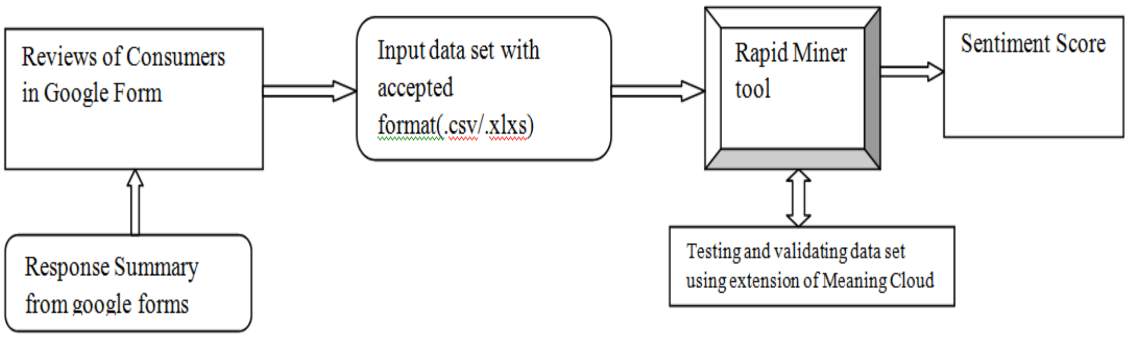
The sources of datasets were analyzed in greater depth using the constructed questionnaire, which had a total of 12 questions. The articles from Google are the primary source of information. Various consumers/people were invited to fill out a Google form, and roughly 1010 entries were captured in order to undertake big data analysis.

Row No.	id	Name	cluster	Age	text	sentiment(G...	Email Addre...	What is the ...	Touch less ...	Changing W...	Personal Hy...
1	1	?	cluster_2	?		Neutral	?	?	1	1	1
2	2	Shuchita Mud...	cluster_3	35- 44 years		Negative	shuchitamud...	Masters	1	1	1
3	3	Mrs.Chandra...	cluster_3	55 years and ...		Negative	mudgilchand...	Bachelors	1	1	1
4	4	RAVINDRA K...	cluster_2	35- 44 years		Neutral	ravindra.taks...	Masters	1	1	1
5	5	Shaheen	cluster_1	35- 44 years		Negative	shaheentwin...	Masters	2	1	1
6	6	Hemant Raj ...	cluster_1	25-34 years		Neutral	hemantmara...	Bachelors	2	1	1
7	7	Dhirendra Pa...	cluster_2	25-34 years		Neutral	dheerupatel4...	Masters	1	1	1
8	8	Bhaskaran	cluster_2	35- 44 years		Neutral	thetrendz343...	Masters	1	2	1
9	9	Shiv kumar ti...	cluster_2	25-34 years		Neutral	sshiv.tiwari22...	Masters	1	1	1
10	10	sharad	cluster_2	25-34 years		Neutral	sharadgosw...	Bachelors	1	1	1
11	11	Raghvendra	cluster_1	45 - 54 years		Neutral	sonuind21@...	Masters	1	2	1
12	12	Ankita	cluster_3	25-34 years		Negative	choubey.ankit...	Masters	1	1	1
13	13	Pallavi panday	cluster_3	25-34 years		Negative	pandaypallavi...	Bachelors	1	1	1
14	14	AMRENDRA ...	cluster_1	25-34 years		Neutral	cuteamarsah...	Bachelors	1	1	1
15	15	Mrs.Neera Sa...	cluster_3	55 years and ...		Negative	nrsaxena@ya...	Masters	1	1	1
16	16	Dr Vandana A...	cluster_1	45 - 54 years		Negative	vandanaaror...	Doctorate	1	1	1
17	17	Aakanksha J...	cluster_4	?		Negative	aakankshajai...	Masters	1	2	2
18	18	Priyanka Han...	cluster_4	35- 44 years		Negative	hansa.priyan...	Bachelors	2	1	2
19	19	shivani shar...	cluster_3	25-34 years		Negative	shivisharma1...	Masters	1	2	2
20	20	Anjleena Pan...	cluster_3	55 years and ...		Negative	anjurcp123@...	Masters	1	2	1
21	21	Shagun	cluster_4	25-34 years		Negative	dubeyshagun...	Doctorate	1	1	1
22	22	A k Singh	cluster_1	55 years and ...		Neutral	saisaudh@y...	Masters	1	1	1

ExampleSet (1,010 examples, 6 special attributes, 17 regular attributes)

Fig 12 Example Dataset

D. Method and Proposed framework :



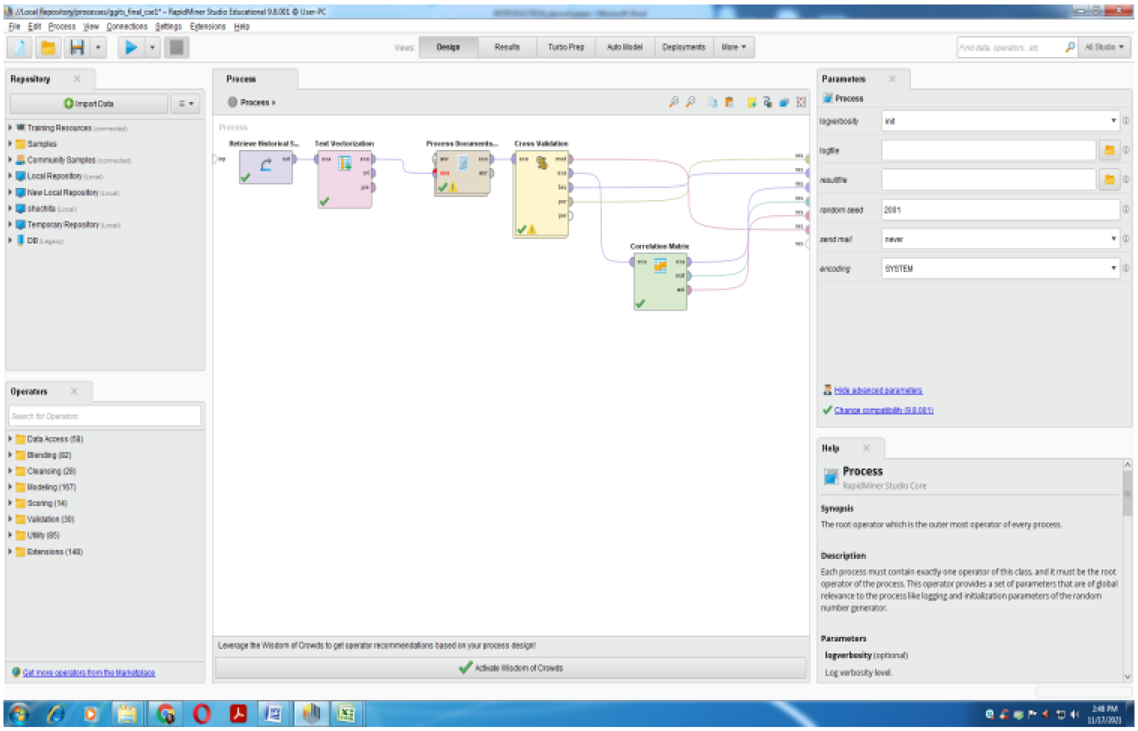
Methodology Diagram for Proposed Framework

Statistical text mining using rapid mining model, includes loading the data, Pre-processing the data, generating term-by-document matrix, building models and lastly applying the model on new data to predict the outcome. A process diagram also created for similarity-based methods and clustering techniques for measuring the similarity between the documents. The above figure explains the idea of proposed framework clearly. First, the data needed to be analysis are gathered from the various entries from Google form.. The review data are gathered in the acceptable Google form and then the response summary is downloaded in the excel sheet. The acceptable dataset is entered the tool to analysis based on the training data if the algorithms are depending on unsupervised learning.

Prior to that, the admissible data-set is processed using pre-processing procedures. Pre-processing entails transforming the given case into an accepted case, as well as Text Vectorization, document processing, and cross validation. Clustering, which can be performed on unlabeled data and is an unsupervised machine learning algorithm, is a building of the algorithm utilizing the k-means algorithm(Clustering groups Examples together that are similar to each other.). The output of the k-means algorithm is fed into X-Means, a clustering technique that uses a heuristic to calculate the optimal number of centroids. It starts with a small number of centroids and then iterates to see if adding more makes sense based on the data. The data model is created by combining the k-means technique and the X-Means algorithms for dataset cross validation. Finally, the Correlation matrix for sentiments is created, which determines the correlation between all attributes and may be used to generate a weights vector based on these correlations.

5. Experiment and Performance Analysis :

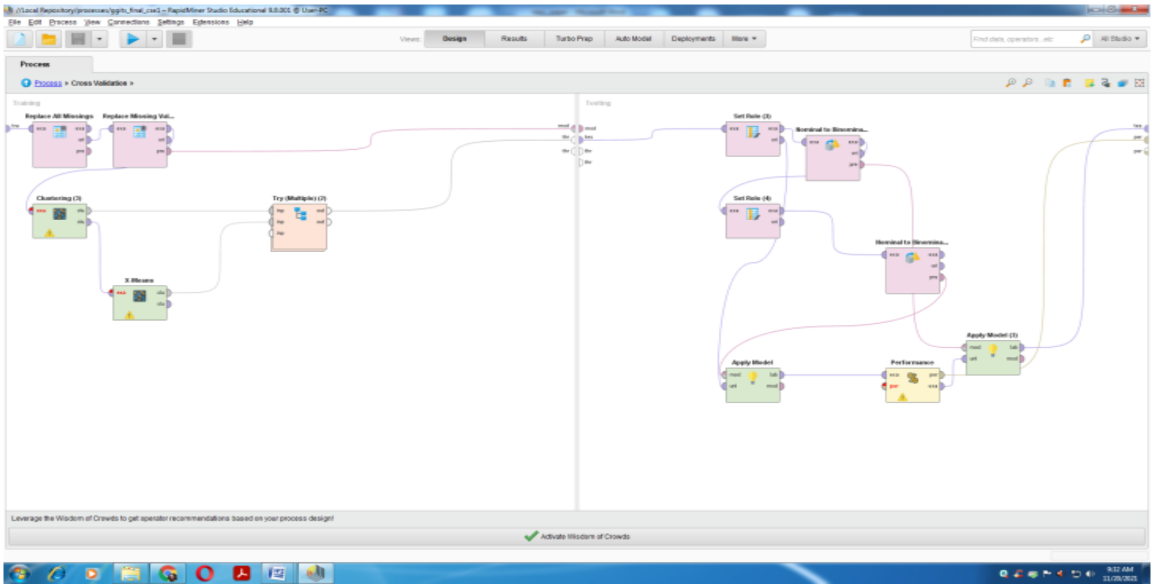
Rapid Miner is a fantastic application that includes text processing skills as well as a third-party Application Programming Interface (API) that is simple to connect to. The process diagram for sentiment analysis is depicted in the graphic below. Covid-19's impact on consumers' daily life



The sentiment analysis in Rapid Miner begins with the Retrieve Operator, which imports the excel sheet to be analyzed. This Operator has access to the Repository's stored data and can load it into the Process. This method of data retrieval also returns the Rapid Miner Object's Meta data. There are 1010 examples in the Example collection, each with three special features and 14 regular attributes.

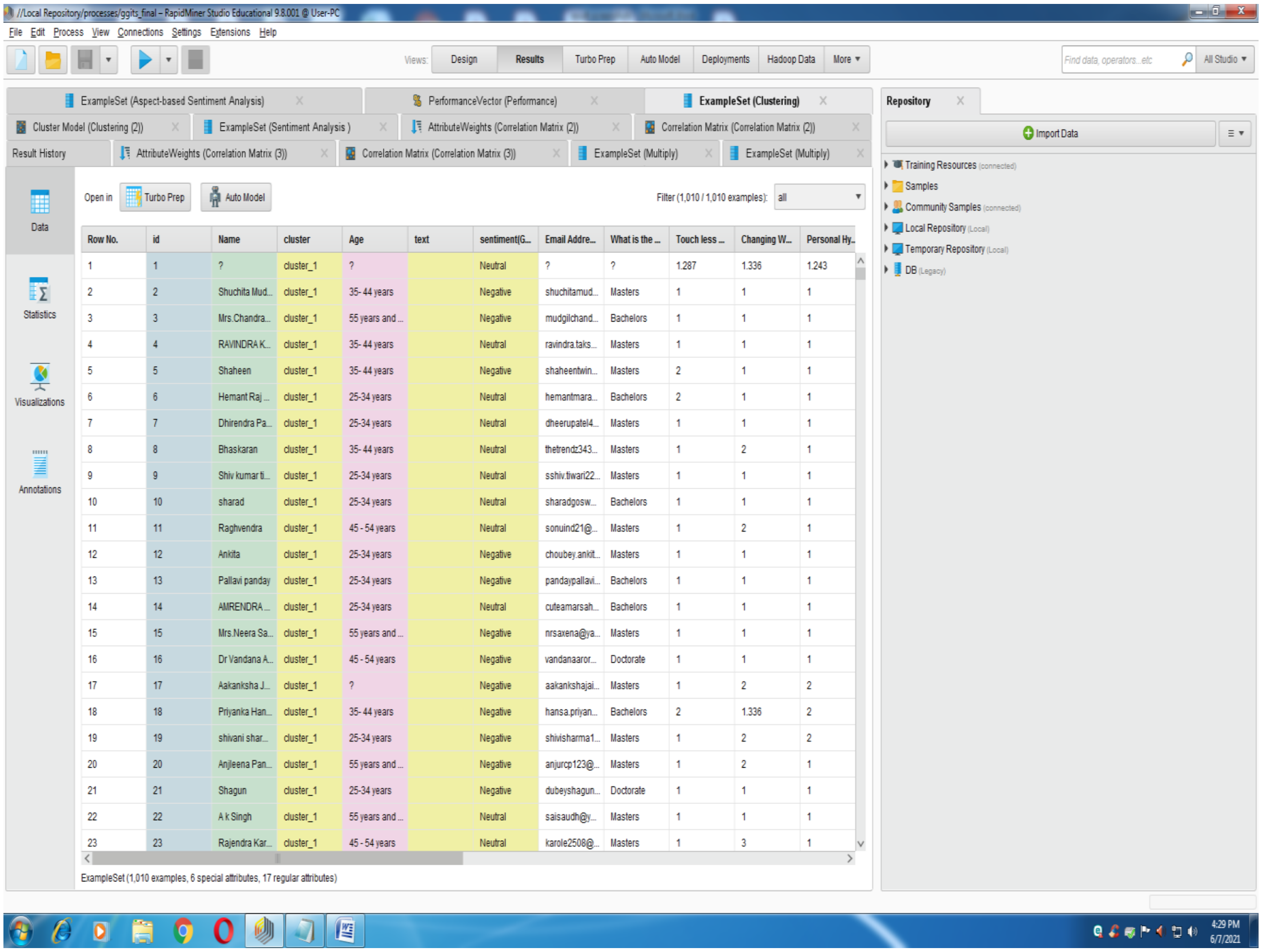
The next stage is to do text vectorization before extracting/generating word vectors from string attributes in process documents from data in order to perform cross validation to assess a learning model's statistical performance.

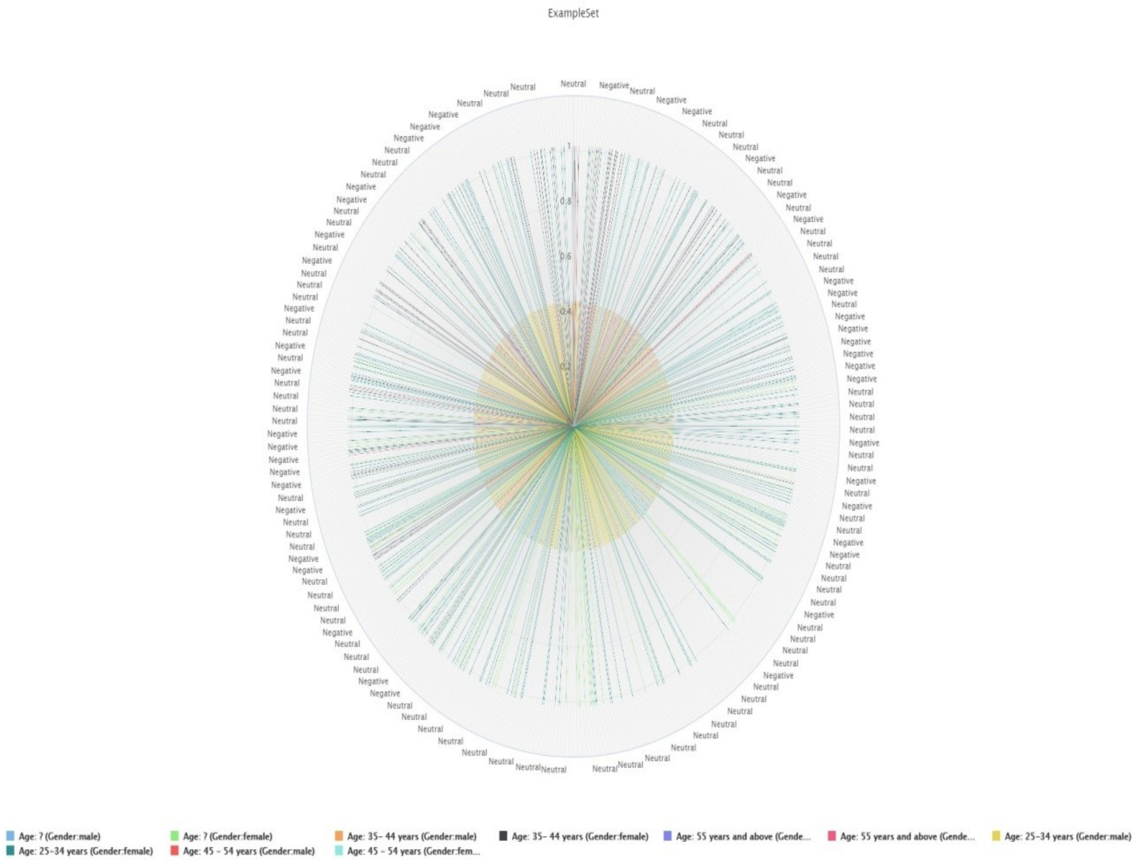
A nested Operator is the Cross Validation Operator. It has two subprocesses: one for training and the other for testing. A model is trained using the Training subprocess. In the Testing subprocess, the trained model is used. During the Testing phase, the model's performance is evaluated.



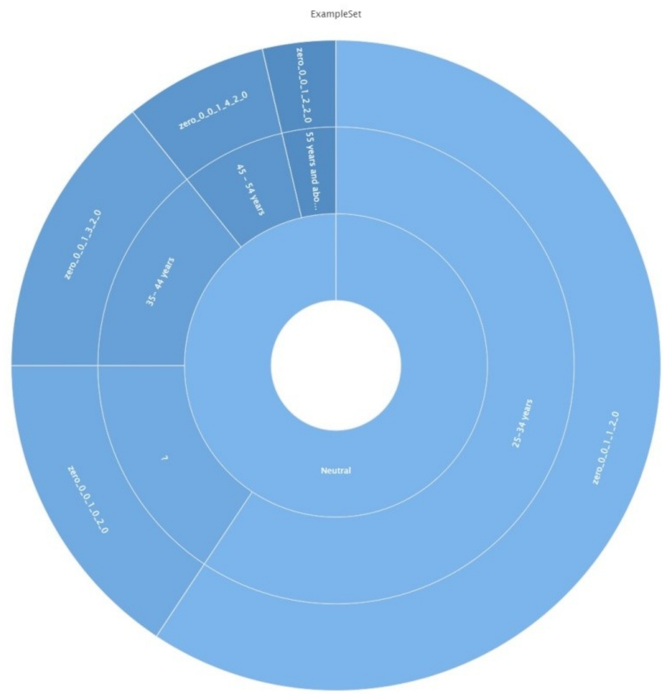
The k-means technique is used by this Operator to cluster data. Examples that are similar to each other are grouped together in a cluster. Clustering is an unsupervised machine learning approach that can be performed on unlabeled data because no Label Attribute is required. The k-means method creates a set of k clusters and assigns each Example to one of them. The clusters are made up of examples that are comparable. A distance measure between Examples is used to determine how similar they are. The position of the centre in the n-dimensional space of the n Attributes of the Example Set determines a cluster in the k-means algorithm. The centroid is the name given to this location. The **k-means algorithm** begins with a set of k points that serve as the centroid of k potential clusters. If determine good start values is set to true, these start points are either the positions of k randomly chosen Examples from the input Example Set, or they are decided by the k-means++ heuristic. All Examples are assigned to the cluster that is closest to them (nearest is defined by the measure type). The cluster centroids are then recalculated by averaging over all examples of a single cluster. The previous stages are repeated for fresh centroids until they no longer move or the maximum number of optimization steps is reached. The operation is done as many times as possible, with a different set of starting positions each time. The set of clusters with the shortest sum of squared distances between all Examples and their respective centroids is delivered. This output is now fed into the X-means operator. **X-Means** is a clustering algorithm that uses a heuristic to calculate the correct number of centroids. It starts with a small number of centroids and then iterates to see if adding more makes sense based on the data. Now the input of both K-means and X-means is given to **Try multiple**, this operator can be be used to try different processing variants for a given input.

The output of try operator id given as input to **set role operator,** An Attribute's role explains how other Operators interact with it. Regular is the default role; additional roles are categorized as special. The output of set role operator is given to apply model, the goal is to get a prediction on unseen data or to transform data by applying a preprocessing model. The Example Set upon which the model is applied, has to be compatible with the Attributes of the model. This means, that the Example Set has the same number, order, type and role of Attributes as the Example Set used to generate the model. Now the performance operator is a very simple operator. It takes an Example Set as input and returns a performance vector that has the count of attributes in the given Example Set and given as input to apply model to get a prediction on unseen data to estimate the statistical performance of a learning model.

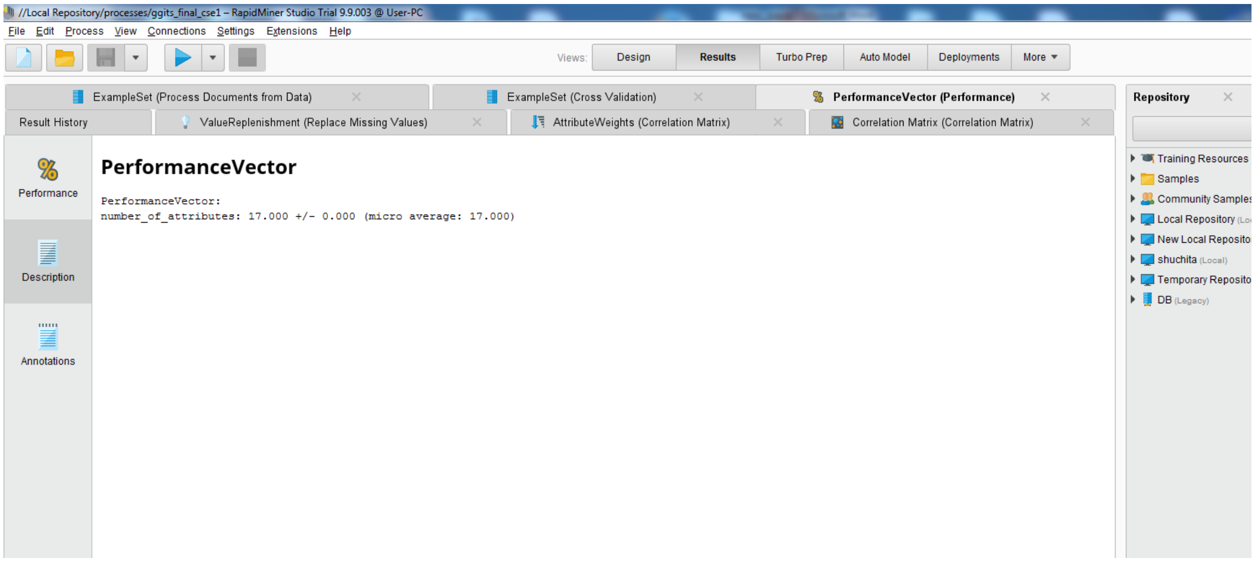



ExampleSet
Age: ? (Gender:male)
Age: ? (Gender:female)
Age: 35- 44 years (Gender:male)
Age: 35- 44 years (Gender:female)
Age: 55 years and above (Gende...
Age: 55 years and above (Gende...
Age: 25-34 years (Gender:male)
Age: 25-34 years (Gender:female)
Age: 45 - 54 years (Gender:male)
Age: 45 - 54 years (Gender:fem...

Now after the cross validation process is completed the port delivers the prediction model trained on the whole Example Set.

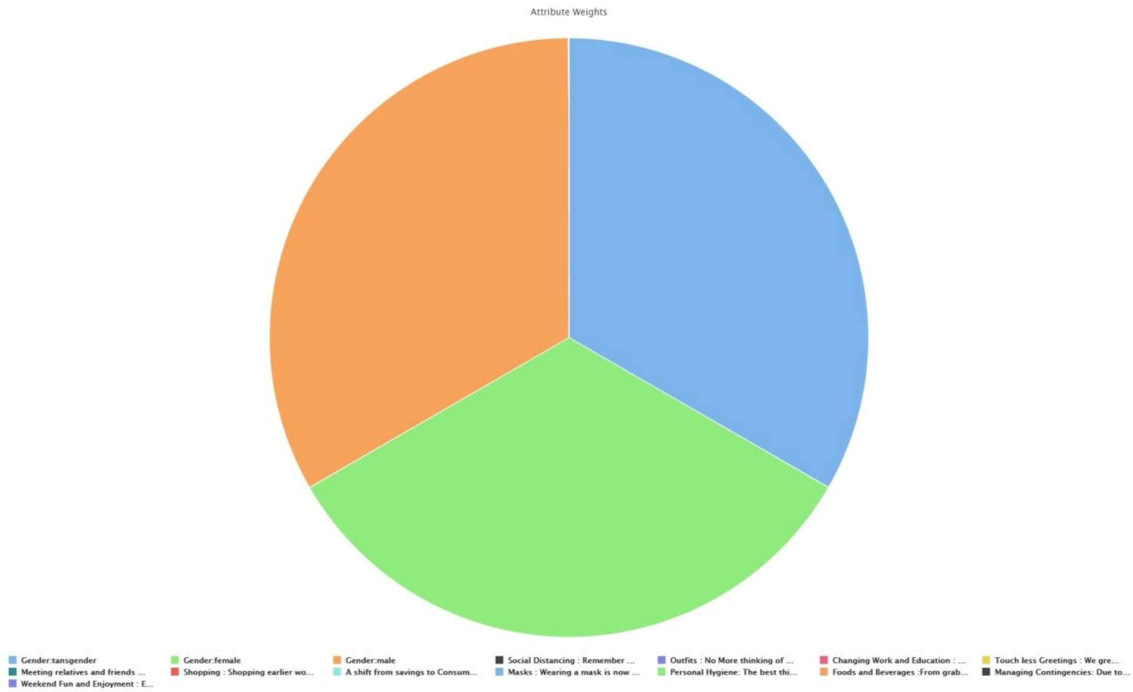


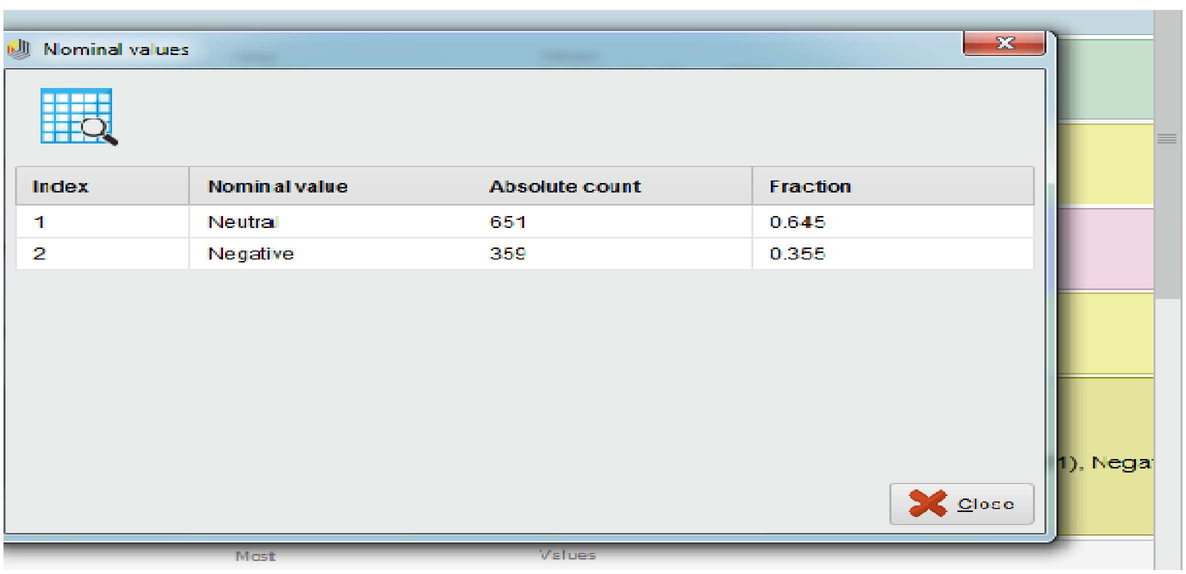
The performance output ports of the Cross Validation Operator deliver the average of the performances over the number of folds iterations.



The test result port delivers only an Example Set if the test set results port of the inner Testing sub process is connected.

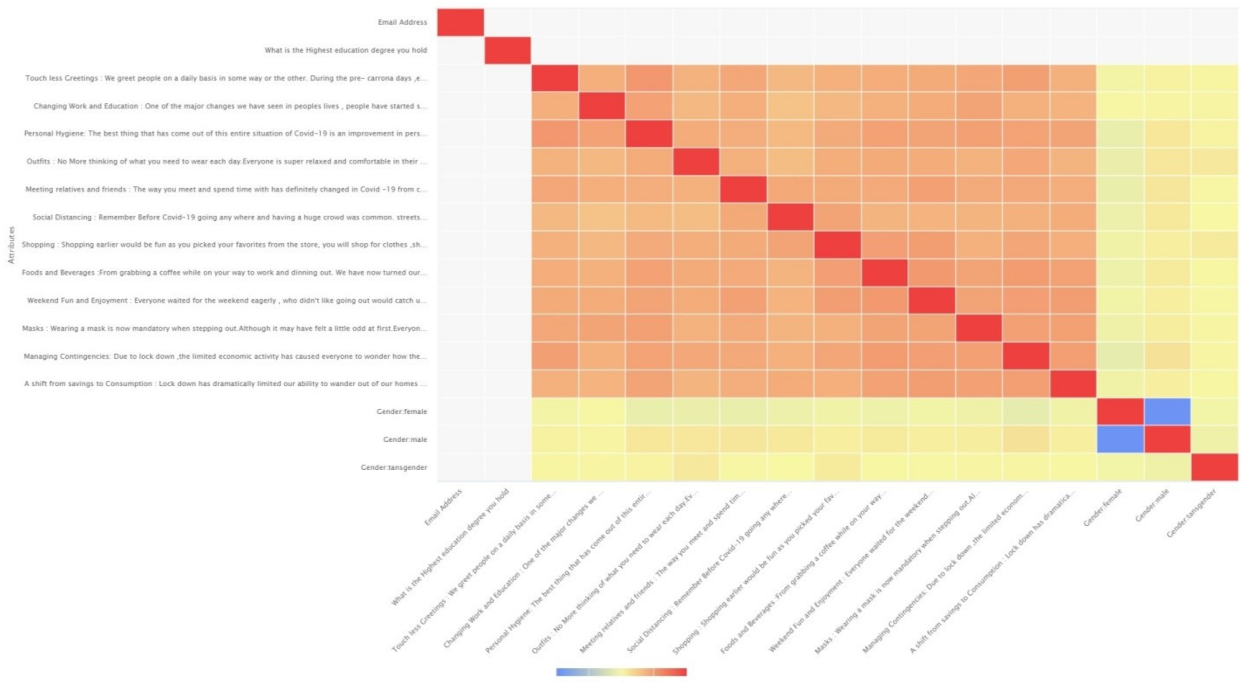
The example set port returns the same Example Set which has been given as input to the **Correlation matrix operator**





Index	Nominal value	Absolute count	Fraction
1	Neutral	651	0.645
2	Negative	359	0.355

The **Correlation matrix** is calculated for sentiments which determine correlation between all Attributes and it can produce a weights vector based on these correlations. Correlation is a statistical technique that can show whether and how strongly pairs of Attributes are related.



6. Discussion and Conclusion:

The major goal of this experiment was to determine an individual's attitudes during a covid19 circumstance. The polarity of unsupervised data was collected, and clustering was performed using k-means and the X means algorithm. The entire data obtained from Google forms responses was 1010 examples, which were imported into Rapid miner, which is one of the top programs with advanced features such as data exploration, sampling, replacement, partitioning, Bayesian modeling, clustering, and modeling assessment. The result of using the rapid miner tool with two different machine learning algorithms gives accuracy to consumer sentiments. The data set was 1010 example set with 6 special attributes and 22 regular attributes, The findings suggest that social media content could be useful for supply chain information sharing and collaboration, not just because it makes communication visible to others in the chain, but also because visibility gives members access to signals through which they can gather relevant information from other members . These findings also show that social media content can assist supply chain members in better identifying and collaborating with other chain members who have accurate and trustworthy relevant information. Supply chain managers can increase the accuracy of demand projections by assessing the quantity and sentiment of mentions for a certain question in terms of numbers and sentiment.

The goal of this study was to provide sentiments of consumer’s overview of the use of machine learning techniques in various supply chain domains. In this context, after a quick overview of commonly unsupervised machine learning approaches, the application of each to various aspects of the supply chain was discussed. Two alternative machine learning algorithms were presented in the section on supplier selection.

Although the paper's main purpose was met and the benefits of using machine learning to manage supply chains were discussed, there were significant caveats. For example, because the target audience of this paper was affected by the pandemic, providing details of ML algorithms was not possible, so only a general explanation and occasionally some flowcharts were provided to acquaint the consumers with the process of implementing and utilizing the power of ML algorithms in the Supply Chain Management area.

Supply chain analytics obtained from social media can improve network level collaboration, allowing for faster responses to shifts in demand and lifestyle, and thereby increasing chain profitability. The findings of the study did not support the hypothesis that a higher level of trust in content conversation on social media leads to improved supply chain performance. Our hypothesis was founded on the idea that the higher the level of trust supply chain members have in their network, the more likely they are to use social media to share information and collaborate. So the sentiment calculated for nominal values is ***maximum neutral with 651 absolute count and negative absolute count, and the rest is positive.*** The buzz on social media, as well as the thoughts, voices, and experiences of stakeholders, can serve as an early signal of possible demand, allowing businesses to build efficient supply chain strategies to meet it.

As a result, managers should exercise caution when employing various algorithms and assess the algorithm's applicability for the type of the data as well as its interpretability for the industry. Some sectors are still in the early phases of implementing machine learning techniques to improve their supply chain procedures. For example, there is a lot of ground to cover in the renewable energy supply chain, and there are a lot of interesting research topics to look forward to in this area in the future. In order to build and optimize Supply Chain, there is also a significant gap in harnessing the power of the mathematical optimizing model and machine learning, which can be addressed in future research projects. Furthermore, in future research investigations, the given framework can be tested utilizing structural equation modeling in a variety of industries. Despite AI's involvement over the past half-century and its recent growth in the SCM field, there is still a scarcity of study on specialized artificial intelligence subjects for various supply chain areas

More research has been done on the evaluation or evaluation of the various approaches of opinion mining and sentiment analysis in terms of applicability. The data sets retrieved from users' application databases thus include an aspect of human application, despite the fact that these correspond to the evaluation of the methodologies used. The financial, healthcare, hospitality and tourism industries and marketing-related activities continue to lead the applications. It's also worth noting that the use of opinion mining and sentiment analysis in politics and administration is still on the rise. Etc...

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