School of Computer Science and Engineering (SCOPE)

B. Tech (CSE)

SOCIAL MEDIA USER'S SENTIMENT ANALYSIS

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A Report on the Course Project

SOCIAL MEDIA USER'S SENTIMENT ANALYSIS

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Project Title: Social media User's sentiment Analysis

1. Introduction

1.1 Background

Social media platforms allow businesses to engage with the customers through their social media accounts. Customers comment on their product experience, recent launches and the services the business provides. So manually reading the entire data is not an efficient manner so we thought to automate the process and perform better results.

1.2 Problem Statement

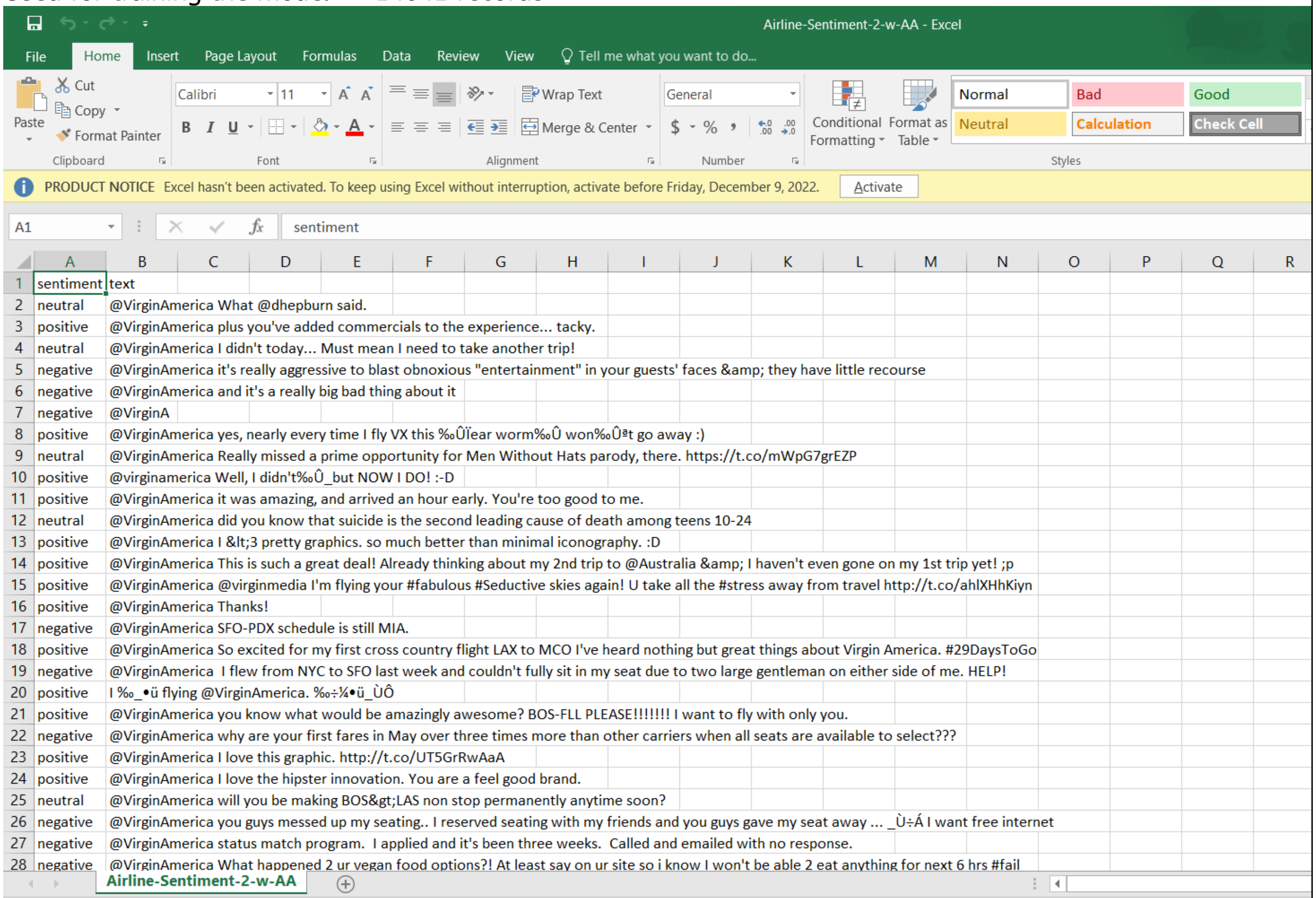
There is so much data available on platforms that it's difficult for the brands to prioritize the mentions or tweets to respond to first. The total polarity detection of the whole customer comments is also difficult so in this project will try to analyze the tweets using twitter API and classify the comments as positive, negative and neutral based on the ML models available.

1.3 Novelty

Implementation of sentiment analysis from scratch rather than using built-in libraries and many people worked on twitter API calls and sentiment analysis separately but only few analysis on the combined. We cannot get whole implementation of the twitter sentiment analysis from scratch with using libraries for sentiment analysis.

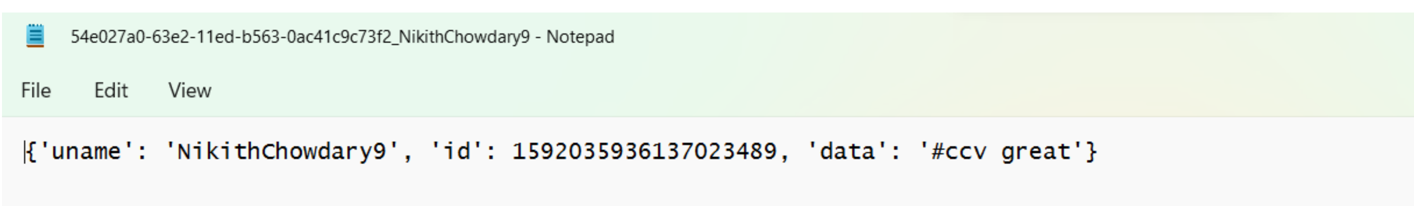
1.4 Dataset

Used for training the model -- 14641 records



	A	B
1	sentiment	text
2	neutral	@VirginAmerica What @dhepburn said.
3	positive	@VirginAmerica plus you've added commercials to the experience... tacky.
4	neutral	@VirginAmerica I didn't today... Must mean I need to take another trip!
5	negative	@VirginAmerica it's really aggressive to blast obnoxious "entertainment" in your guests' faces & they have little recourse
6	negative	@VirginAmerica and it's a really big bad thing about it
7	negative	@VirginA
8	positive	@VirginAmerica yes, nearly every time I fly VX this ‰ÛÏear worm‰Û won‰Ûªt go away :)
9	neutral	@VirginAmerica Really missed a prime opportunity for Men Without Hats parody, there. https://t.co/mWpG7grEZP
10	positive	@virginamerica Well, I didn't‰Û_but NOW I DO! :-D
11	positive	@VirginAmerica it was amazing, and arrived an hour early. You're too good to me.
12	neutral	@VirginAmerica did you know that suicide is the second leading cause of death among teens 10-24
13	positive	@VirginAmerica I <3 pretty graphics. so much better than minimal iconography. :D
14	positive	@VirginAmerica This is such a great deal! Already thinking about my 2nd trip to @Australia & I haven't even gone on my 1st trip yet! ;p
15	positive	@VirginAmerica @virginmedia I'm flying your #fabulous #Seductive skies again! U take all the #stress away from travel http://t.co/ahlXHhKiyn
16	positive	@VirginAmerica Thanks!
17	negative	@VirginAmerica SFO-PDX schedule is still MIA.
18	positive	@VirginAmerica So excited for my first cross country flight LAX to MCO I've heard nothing but great things about Virgin America. #29DaysToGo
19	negative	@VirginAmerica I flew from NYC to SFO last week and couldn't fully sit in my seat due to two large gentleman on either side of me. HELP!
20	positive	I ‰_•ü flying @VirginAmerica. ‰÷¼•ü_ÙÔ
21	positive	@VirginAmerica you know what would be amazingly awesome? BOS-FLL PLEASE!!!!!!! I want to fly with only you.
22	negative	@VirginAmerica why are your first fares in May over three times more than other carriers when all seats are available to select???
23	positive	@VirginAmerica I love this graphic. http://t.co/UT5GrRwAaA
24	positive	@VirginAmerica I love the hipster innovation. You are a feel good brand.
25	neutral	@VirginAmerica will you be making BOS>LAS non stop permanently anytime soon?
26	negative	@VirginAmerica you guys messed up my seating.. I reserved seating with my friends and you guys gave my seat away ... _Ù÷Á I want free internet
27	negative	@VirginAmerica status match program. I applied and it's been three weeks. Called and emailed with no response.
28	negative	@VirginAmerica What happened 2 ur vegan food options?! At least say on ur site so i know I won't be able 2 eat anything for next 6 hrs #fail

Live twitter data format



{'uname': 'NikithChowdary9', 'id': 1592035936137023489, 'data': '#ccv great'}

2. Related Works

2.1 Literature Survey and Comparative Statement

Title	Abstract	Findings	Citation
Sentiment Analysis Using Language Models: A Study	In this paper, they focused on DNN based language models to classify them into positive, negative and neutral emotions. Further, these models were analysed and evaluated using Twitter US Airline sentiment dataset.	Here, they conducted experiments to evaluate bi-LSTM, BERT, Roberta and Electra models on tweet dataset which concluded that language modelling is well-suited for finding facets of a natural language.	S. Kumawat, I. Yadav, N. Pahal and D. Goel, "Sentiment Analysis Using Language Models: A Study," 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2021, pp. 984-988, doi: 10.1109/Confluence51648.2021.9377043.
A Quantitative Performance Evaluation of Machine Learning Algorithms for Analysing Sentiments Of Emoticons	Twitter is important source of data for companies to evaluate their product using the reviews provided by the users. But generally, a tweet can consist of only 280 characters. So, people started using emoticons. So, this paper mainly focused on evaluating existing twitter sentiment analysis algorithms in their capability to analyse these emojis.	Based on the experiments conducted here, it is concluded that Logistic regression performed best in finding both the texts without and with emoticons. Here they only considered emoticons formed from punctuation marks. In future, studies related to image emoticons will be studied.	G. Aditi, U. Sharma, S. Kumar and J. S. Jadon, "A Quantitative Performance Evaluation of Machine Learning Algorithms for Analysing Sentiments Of Emoticons," 2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2022, pp. 606-611, doi: 10.1109/Confluence52989.2022.9734201.
A Novel Stock Price Prediction Scheme from Twitter Data by using Weighted Sentiment Analysis	As the stock market changes from time to time, combining both sentiment analysis and machine learning will help the user with accurate prediction. The main aim is to give the user an overview of the selected stock's potential based on the tweets related to market indicators and pricing.	In this paper, stock prices were analysed using sentiment analysis so that user can know whether to sell or buy the selected stock based on different factors like likes, re-tweets gained over particular tweets on the twitter.	N. Korivi, K. S. Naveen, G. C. Keerthi and V. M. Manikandan, "A Novel Stock Price Prediction Scheme from Twitter Data by using Weighted Sentiment Analysis," 2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2022, pp. 623-628, doi: 10.1109/Confluence52989.2022.9734139.
Impact Of Covid-19 On Education Using Twitter Data	This paper focused on using twitter sentiment analysis to know how people felt during pandemic. They used Tableau software to classify the countries with more concerned tweets	Through analysing all the tweets based on word clouds and hashtags related to different sectors especially education, the authors were able to understand how	A. Makode, A. Chakraborty, A. Darekar and P. Bist, "Impact of Covid-19 On Education Using Twitter Data," 2021 16th International Workshop on Semantic and Social Media Adaptation & Personalization (SMAP), 2021, pp. 1-6, doi:

	and word cloud to map these concerns.	widely did covid-19 effected people all around the world.	10.1109/SMAP53521.2021.9610821.
US presidential election 2020 prediction based on Twitter data using lexicon-based sentiment analysis	In this paper, they used lexicon-based sentiment analysis to predict the outcome of the US presidential election and compared the results with actual results of the polls. The model used in this research is VADER sentiment analysis. The data is obtained from twitter i.e. one week before the elections were held.	It was concluded that the Twitter sentiment analysis data with the VADER model can predict the results of the United States presidential election. The results obtained are not the same as the original data but it showed Joe Biden's victory over Donald trump. More Data collection and updation can overcome the difference seen in the results obtained from both cases.	D. K. Nugroho, "US presidential election 2020 prediction based on Twitter data using lexicon-based sentiment analysis," 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2021, pp. 136-141, doi: 10.1109/Confluence51648.2021.9377201.
Sentiment Knowledge Discovery in Twitter Using Core-NLP Library	The tweets data-set is very large which cannot be handled by traditional methods and techniques. Hadoop is capable of handling such large datasets. So, here they used Hadoop and big-data to analyse the input text and classify them into different tables and classified using a training model from Stanford Core-NLP.	So, proposed system showed better outcomes in comparision to existing systems as they used Hadoop for handling such large data and Core-NLP for language processing. The proposed system implements a hybrid approach which increased accuracy and efficiency of sentiment classification.	N. Kaur and A. Solanki, "Sentiment Knowledge Discovery in Twitter Using Core-NLP Library," 2018 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2018, pp. 574-580, doi: 10.1109/CONFLUENCE.2018.8442439.
Scaling Archived Social Media Data Analysis Using a Hadoop Cloud	In this paper, they used COSMOS platform for twitter sentiment analysis and demonstrated it on OpenNebula cloud with Map-reduce based analysis using Hadoop. The data set that has been collected consisted of several million tweets analysed over two types of cloud infrastructure i.e. deployment using single cluster and also using multiple virtual machines.	The results obtained showed the benefits on using Virtual nodes rather than using a sequential version. This particular paper focused on use of text data-using other types of content, such as images having a different performance profile. The variability of Cloud environment used here showed that the deployment policy is essential to ensure that predictable	J. Conejero, P. Burnap, O. Rana and J. Morgan, "Scaling Archived Social Media Data Analysis Using a Hadoop Cloud," 2013 IEEE Sixth International Conference on Cloud Computing, 2013, pp. 685-692, doi: 10.1109/CLOUD.2013.120.

		performance can be achieved-an aspect that cannot be controlled when deploying over public Clouds. Hadoop deployment showed that we can scale content analysis of Tweets to the extent where we can calculate approximately five days worth of Tweets in around 3 minutes, as opposed to > 10 minutes on a single machine.	
A Comprehensive Survey on Effective Feature Selection Approaches for Text Sentiment Classification Process	This paper aimed on studying selection process involved in choosing optimal features for sentimental analysis. The sentiment classification of the text includes different Feature Selection approaches such as Bag-of-Words (BoW), lexicon-based methods, and Term Frequency-Inverse Document Frequency (TF-IDF)	The study analysed that the adoption of efficient feature selection technique provides a meaningful output from different features that are gathered through web pages, emails, blogs, social networking platforms, online campaigns, online newsletters, corporate documents, and product reviews.	A. K. Rajpoot, P. Nand and A. I. Abidi, "A Comprehensive Survey on Effective Feature Selection Approaches for Text Sentiment Classification Process," 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2021, pp. 971-977, doi: 10.1109/Confluence51648.2021.9377117.
Unstructured Data Analysis on Big Data Using Map Reduce	The method proposed in this paper will process the data in small chunks in distributed clusters and aggregate all the data to get the final data. In Hadoop framework, Map-reduce performs filtering and aggregation. This method is enhanced using sentimental analysis that is implemented with natural language processing by clustering data into emoticon clusters.	The results from the experiment showed that the proposed method increases the performance of complexity analysis as the unstructured data has been structured using Hadoop and Map-reduce technique. They also tried to Implement the work done by map-reduce in distributed mode in which they used some N number of slaves for a single master.	Subramaniyaswamy V, Vijayakumar V, Logesh R, Indragandhi V. Unstructured Data Analysis on Big Data Using Map Reduce. Procedia Computer Science [Internet]. 2015 Jan 1 [cited 2022 Sep 27]; 50:456–65.
Microblogging Sentiment Analysis	In this paper, the authors experimented on analysing public moods on some events in micro-blogging.	The evaluations from experiments conducted concluded that there is a strong correlation	L. Zhang, Y. Jia, B. Zhou and Y. Han, "Microblogging Sentiment Analysis Using Emotional Vector," 2012 Second International

Using Emotional Vector	Here they used emotional vector that studies internet emotional words using the proposed algorithm for sentiment-analysis.	between tragic events and public moods. So, using emotional vector in this case does a great job in analysis.	Conference on Cloud and Green Computing, 2012, pp. 430-433, doi: 10.1109/CGC.2012.29.
Analysis and Visualization of Twitter Data using R	In this paper, they developed an application using twitter data and analysed the data collected using R-tool. The data consists of tweets, online reviews, and e-commerce transaction details.	Here, they utilised the features of R for sentiment analysis and as an outcome, the built an application to analyse these aspects which is then deployed on cloud platform.	A. Sharma and R. Rana, "Analysis and Visualization of Twitter Data using R," 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC), 2020, pp. 455-459, doi: 10.1109/PDGC50313.2020.9315740.
An English-Japanese Twitter-Based Analysis of Disaster Sentiment during Typhoons and Earthquakes	In this paper, the authors proposed a sentiment analysis-based method that helps the residents of cities like Tokyo to predict natural disasters like earthquakes and typhoons. They collected tweets both in Japanese and English and developed machine learning algorithms using SVM and XG-boost for sentiment analysis. the polarity (how much it aligns to a positive or negative sentiment) of each tweet is calculated using VADER and pre-trained BERT algorithms for the English and Japanese datasets, respectively.	For classification of English typhoon tweets, SVM showed higher accuracy while XGBoost is better for the earthquake dataset. On the other hand, classification of Japanese typhoon dataset can achieve higher accuracy with XGBoost while SVM for the earthquake dataset. The outcomes helps in predicting the probability of natural disasters.	B. J. Detera, A. Kodaka, N. Kohtake, A. Nishino and K. Onda, "An English-Japanese Twitter-Based Analysis of Disaster Sentiment during Typhoons and Earthquakes," 2021 IEEE International Symposium on Systems Engineering (ISSE), 2021, pp. 1-8, doi: 10.1109/ISSE51541.2021.9582473.
Comparative Analysis of Customer Sentiments on Competing Brands using Hybrid Model Approach	In this paper, they used sentiment analysis to know user thoughts on new releases of two brands vivo and oppo. Each tweet is then classified using Lexicon Based Sentiment analysis and the Naive Bayes algorithms aiming better accuracy. The results are used for comparision and later development of new models.	Comparision was carried out for features like camera, display, on-screen fingerprint sensor etc. As a result, vivo had more positives sentiments than that of oppo which will help users to buy their products. This can also help brands to know their weaknesses and use them in improving for upcoming models.	N. Srivats Athindran, S. Manikandaraj and R. Kamaleshwar, "Comparative Analysis of Customer Sentiments on Competing Brands using Hybrid Model Approach," 2018 3rd International Conference on Inventive Computation Technologies (ICICT), 2018, pp. 348-353, doi: 10.1109/ICICT43934.2018.9034283.

Social and Sensor Data Fusion in the Cloud	This paper tried to combine social and sensor data in the cloud. They built a travel recommendation system using information from platforms like twitter. To handle these large data, they used various cloud-serving systems, such as Hadoop, HBase, and GSN.	They analysed and filtered the data which turned out to be effective and scalable for the fusion approach.	S. R. Yerva, J. Saltarin, H. Jeung and K. Aberer, "Social and Sensor Data Fusion in the Cloud," 2012 IEEE 13th International Conference on Mobile Data Management, 2012, pp. 276-277, doi: 10.1109/MDM.2012.52.
Smart Monitoring and Controlling of Government Policies Using Social-Media and Cloud Computing	E-governance policies are currently being influenced by cloud-based policies, as the value of IT infrastructure availability is being recognized to its fullest potential by the primary user- who are the government advisors. A suitable approach is being presented by the paper in question here, which is a combinational approach of the capabilities of cloud computing and social media analytics - public involvement is the pre-eminent factor which helps in the effective monitoring and controlling of government policies. The data used has been collected from Twitter. The experiment has been performed on compute optimized Amazon EC2 instances (c4 type)- which contains 2 processors and 8GB RAM.	The system which had been proposed has provided some encouraging results. Taking an example, when implemented on the Goods and Service Tax (GST) Policy implemented by the government of India, the resource utilization (and consequently, the execution time) of the compute-optimized instances increased as the primary data (i.e. tweets from Twitter) increased.	Singh, P.; Dwivedi, Y.K.; Kahlon, K.S.; Sawhney, R.S.; Alalwan, A.A.; Rana, N.P.. Information Systems Frontiers, 1 April 2020, 22(2):315-337 Language: English. Springer DOI: 10.1007/s10796-019-09916-y
Sentiment Analysis on Top Five Cloud Service Providers in the Market	→In this paper, they used Twitter to collect cloud customers' opinions on the services provided by cloud.	→ **Positive polarity** among five cloud service providers Microsoft azure – 72 %, Amazon – 71.5%, sales force-64%, IBM cloud – 55.5% → **Negative polarity** IBM-9.5%, Amazon-5.50%, Google cloud -5.50%, Sales force-6% and Microsoft Azure -4.5% →**Neutral polarity** Google cloud - 51 % and IBM Cloud - 35%, Sales force - 24%,	A. Koneru, N. B. Naga Sai Rajani Bhavani, K. Purushottama Rao, G. Sai Prakash, I. Pavan Kumar and V. Venkat Kumar, "Sentiment Analysis on Top Five Cloud Service Providers in the Market," 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI), 2018, pp. 293-297, doi: 10.1109/ICOEI.2018.8553970.

	→On this basis, the **naive bayes algorithm** is used to assess the popularity of Cloud Service Providers. →They compared cloud service providers such as Microsoft Azure, Salesforce, Amazon, IBM Cloud, and Google Cloud Platform.	Amazon - 23% Microsoft Azure - 23.5% As a result, Microsoft Azure received more positive feedback than other providers.	
A Survey of Sentiment Analysis from Social Media Data	This article provides a multifaceted look at the rise of sentiment analysis in the spotlight as a result of the internet's sudden explosion of data. This article also discusses the process of capturing data from social media over time, as well as similarity detection based on similar choices of social network users.	→ The accuracy of sentiment mining was **84.29%**, with the Nave Bayes classifier identifying optimistic and pessimistic tweets and the maximum entropy classifier identifying unbiased and inappropriate tweets. →VADER is a simple rule-based sentiment analysis method that achieves **96%** accuracy when compared to other methods.	K. Chakraborty, S. Bhattacharyya and R. Bag, "A Survey of Sentiment Analysis from Social Media Data," in IEEE Transactions on Computational Social Systems, vol. 7, no. 2, pp. 450-464, April 2020, doi: 10.1109/TCSS.2019.2956957.

Sentiment analysis and classification based on textual reviews	In order to increase the classification accuracy on the dataset of Movies reviews, a new algorithm called Sentiment Fuzzy Classification algorithm with parts of speech tags is used in this paper. Due to the difficulty of sentiment analysis using multi-theme documents and the low classification accuracy.	→It determines whether an opinion document (movie review) is positive or negative or neural sentiment. →**Accuracy**=(TP+TN)/(TP+TN+FP+FN) Where, False Positives (FP), False Negatives (FN), True Positives (TP), and True Negatives (TN) are terms used to compare the classes that an item actually belongs to with the labels that a classifier has assigned to it.	K. Mouthami, K. N. Devi and V. M. Bhaskaran, "Sentiment analysis and classification based on textual reviews," 2013 International Conference on Information Communication and Embedded Systems (ICICES), 2013, pp. 271-276, doi: 10.1109/ICICES.2013.6508366.
Sentiment analysis in twitter using machine learning techniques	In this paper, they attempt to use Machine Learning to analyse Twitter posts about electronic products such as mobile phones and laptop computers. They have introduced a new feature vector for categorising tweets as positive or negative by extracting people's opinions	The first step is to extract and add twitter-specific features to the feature vector. Following that, these features are removed from tweets, and feature extraction is performed again as if it were on normal text. The classifiers Nave Bayes, SVM, Maximum Entropy, and Ensemble are used, and their accuracy for the new feature vector is nearly identical.	M. S. Neethu and R. Rajasree, "Sentiment analysis in twitter using machine learning techniques," 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), 2013, pp. 1-5, doi: 10.1109/ICCCNT.2013.6726818.

	about products.		
Sentiment analysis of Twitter data using data mining	This paper describes a method for analysing user sentiments using data mining classifiers and compares the effectiveness of individual classifiers versus an ensemble of classifiers for sentiment analysis.	In this experiment, the k-nearest neighbour (IBK) classifier outperforms all three classifiers: Random Forest, Basnet, and Naive Baysein. Random Forest also has a high level of prediction accuracy.	A. P. Jain and V. D. Katkar, "Sentiments analysis of Twitter data using data mining," 2015 International Conference on Information Processing (ICIP), 2015, pp. 807-810, doi: 10.1109/INFOP.2015.7489492.
A twitter sentiment analysis for cloud providers: A case study of Azure vs. AWS	In order to analyse the opinions and reviews of their customers, the authors of this paper used the sentiment analysis of two of the top cloud service providers, namely Amazon and Microsoft Azure. To do that, two datasets are extracted from tweets that either contained the names of organisations or cloud names.	According to the results of the classification of emotions, Microsoft Azure performs better in the "joy" category than Amazon, and Amazon has a higher percentage of "sadness" than Microsoft Azure.	L. M. Qaisi and I. Aljarah, "A twitter sentiment analysis for cloud providers: A case study of Azure vs. AWS," 2016 7th International Conference on Computer Science and Information Technology (CSIT), 2016, pp. 1-6, doi: 10.1109/CSIT.2016.7549473.
Election result prediction	In this paper, they propose a two-stage	When naive Bayes and SVM classification techniques are compared, it is discovered that	J. Ramteke, S. Shah, D. Godhia and A. Shaikh, "Election result prediction using Twitter sentiment analysis,"

using Twitter sentiment analysis	framework for creating training data from mined Twitter data without compromising features or contextual relevance. Using our two-stage framework, they also proposed a scalable machine learning model for predicting election results.	SVM is more accurate than naive Bayes in this particular training dataset.	2016 International Conference on Inventive Computation Technologies (ICICT), 2016, pp. 1-5, doi: 10.1109/INVENTIVE.2016.7823280.
Machine learning tool for exploring sentiment analysis on twitter data	In this paper, the methodology developed an algorithm based on sentimental analysis using customer review classification, which dealt with dataset preparation, data clustering based on specific domains, feature vector extraction using n-gram models and tf-idf vectors, synonym extraction, and sentiment analysis.	The developed tool is 1.5 times faster than traditional database to Hadoop cluster and has a near 80% accuracy, which aids the user in computing, analysing, and interpreting interaction and associations between people, topics, and ideas.	Biradar SH, Gorabal JV, Gupta G. Machine learning tool for exploring sentiment analysis on twitter data. Materials Today: Proceedings [Internet]. 2022 Jan 1 [cited 2022 Sep 27];56(Part 4):1927–34.

Consumers' Sentiment Analysis of Popular Phone Brands and Operating System Preference Using Twitter Data: A Feasibility Study	They demonstrated the potential of sentiment analysis of Twitter data to gauge users' reactions to popular smart phone brands and their underlying operating systems in this paper. They have used Lexicon Based Sentiment Analysis Approach. It is the approach of using opinion words (the lexicon) to determine opinion orientations.	Sentiment analysis is performed for five smart phone brands to assess consumers' overall opinion on social media for these brands, as well as their battery life, screen quality, and underlying operating systems. Furthermore, the variation of results based on data collected during the week, weekends, different days of the week, and different geographic regions.	D. Arora, K. F. Li and S. W. Neville, "Consumers' Sentiment Analysis of Popular Phone Brands and Operating System Preference Using Twitter Data: A Feasibility Study," 2015 IEEE 29th International Conference on Advanced Information Networking and Applications, 2015, pp. 680-686, doi: 10.1109/AINA.2015.253.
Naive Bayes Algorithm for Sentiment Analysis on Twitter	The sentiment analysis is performed using algorithms implemented in the Python environment, which is also used for statistical data analysis, and a web user interface has been developed for the overall data output. Then the sentiment	→Algorithm used here is Naive Bayes, using Python, for the Data retrieval and Data analytics which gives the statistical analysis of the data in a graphical representation. → Using naive bayes, the output showed the number of positive and negative reviews from the used dataset.	A. K, K. P, L. Celestine S and V. V Kumar, "Naive Bayes Algorithm for Sentiment Analysis on Twitter," 2021 International Conference on System, Computation, Automation and Networking (ICSCAN), 2021, pp. 1-4, doi: 10.1109/ICSCAN53069.2021.9526473.

	algorithm is applied step by step to gather the positive and negative in the tweets of applied section.		
A Novel Approach to Predict the Real Time Sentimental Analysis by Naive Bayes & RNN Algorithm during the COVID Pandemic in UAE	This research work focuses on the issue for which the use of specific apps in the UAE such as zoom, totok, and botim for internet calling has been identified because this is the only way of connecting with the outside world. To conduct this analysis, tweets from December to July were converted to text and analysed using two algorithms: Naive Bayes Classifier (NBC) and Recurrent Neural Networks (RNN).	→According to the sentimental analysis, 630 tweets were positive, and people in the UAE feel secure, satisfied, and internet calling is very useful for them in the prospect of work, education, and so on. Only 48 tweets had a negative impact, while 155 tweets had an impact that was both positive and negative and was said to be natural. →The study discovered that NB (84%) is more accurate, user friendly, and takes less time to perform the analysis than RNN (79%).	A. Radaideh, F. Dweiri and M. Obaidat, "A Novel Approach to Predict the Real Time Sentimental Analysis by Naive Bayes & RNN Algorithm during the COVID Pandemic in UAE," 2020 International Conference on Communications, Computing, Cybersecurity, and Informatics (CCCI), 2020, pp. 1-5, doi: 10.1109/CCCI49893.2020.9256587.
Serverless Architecture - A Revolution in Cloud Computing	Serverless computing is an execution model in which the cloud service	The principle of serverless computing when deployed in non-cloud systems lead to a new computing technology known 'deviceless edge computing'.	R. A. P. Rajan, "Serverless Architecture - A Revolution in Cloud Computing," 2018 Tenth International Conference on Advanced Computing (ICoAC), 2018,

	provider dynamically manages the allocation of compute resources of the server. This research paper presents a comprehensive study on serverless computing architecture and also extends an experimentation of the working principle of serverless computing reference model adapted by AWS Lambda.	Because serverless computing is still in its infancy, a number of technical difficulties and challenges remain unresolved, such as smooth scaling with a tolerance for network hiccups and secure resource provisioning.	pp. 88-93, doi: 10.1109/ICoAC44903.2018.8939081.
Implementation and Analysis of a Serverless Shared Drive with AWS Lambda	This paper describes the design and implementation of a shared drive web application using AWS Lambda. The application is tested to compare response times for cold and warm requests, the impact on load balancing, memory reservation performance, and resource	AWS Lambda executes the Lambda function on user's behalf, it takes care of provisioning and managing resources needed to run the Lambda function. The cold start phenomenon was monitored by sending 10 sequential calls to the video-transcode function with a time interval of 1 minute each. And it was observed that Lambda platform is able to keep the infrastructure warm for about 60 minutes after which it may experience an initialization overhead.	S. Gandhi, A. Gore, S. Nimbarte and J. Abraham, "Implementation and Analysis of a Serverless Shared Drive with AWS Lambda," 2018 4th International Conference for Convergence in Technology (I2CT), 2018, pp. 1-6, doi: 10.1109/I2CT42659.2018.9058237.

	retention behaviour.		
FaasRS: Remote Sensing Image Processing System on Serverless Platform	FaasRS, a framework for processing remote sensing images on a serverless platform, is presented in this paper. FaasRS is built on AWS Lambda, exposes only simple APIs for image operations, and creates DAG for the user's algorithm. FaasRS divides the task by dividing the image into small tiles based on geospatial region and assigning one tile to each Lambda worker. We also make optimizations based on the DAG algorithm to reduce redundant operations. In our evaluation, FaasRS demonstrates good performance and scalability.	→ In comparison to Spark and Ray, FaasRS performs significantly better in various types of RS processing jobs. → In the comparisons with similar system built on Spark and Ray, FaasRS shows 84% and 206% performance improvements respectively.	G. Yang, J. Liu, M. Qu, S. Wang, D. Ye and H. Zhong, "FaasRS: Remote Sensing Image Processing System on Serverless Platform," 2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC), 2021, pp. 258-267, doi: 10.1109/COMPSAC51774.2021.00044.

A framework and a performance assessment for serverless MapReduce on AWS Lambda	This article describes a high-performance serverless architecture for running MapReduce jobs on AWS Lambda with Amazon S3 as the storage backend. And studied the suitability of AWS Lambda as a platform for the execution of High Throughput Computing jobs.	The results show that AWS Lambda provides a convenient computing platform for general-purpose applications that fit within the service's constraints (15 minutes of maximum execution time, 3008 MB of RAM, and 512 MB of disc space), but it has inhomogeneous performance behaviour that may limit adoption for tightly coupled computing jobs.	V. Giménez-Alventosa, Germán Moltó, Miguel Caballer, A framework and a performance assessment for serverless MapReduce on AWS Lambda, Future Generation Computer Systems, Volume 97, 2019, Pages 259-274, ISSN 0167-739X,
Serverless computing for container-based architectures	This paper describes a framework and methodology for developing Serverless Container-aware ARchitectures (SCAR). SCAR can be used to create highly parallel event-driven serverless apps that run on customised runtime environments defined as Docker images on top of AWS Lambda.	The results show that, by means of SCAR, AWS Lambda becomes a convenient platform for High Throughput Computing, especially for highly-parallel bursty workloads of short stateless jobs.	Alfonso Pérez, Germán Moltó, Miguel Caballer, Amanda Calatrava, Serverless computing for container-based architectures, Future Generation Computer Systems, Volume 83, 2018, Pages 50-59, ISSN 0167-739X,

2.2 Proposed System Overview

The real-time twitter data is fetched using twitter API and then its streamed into a EC2 based on hash tag used in the tweet. Then it's stored in a S3 bucket and whenever a data is stored into the S3 it triggers a serverless architecture which will lead to sentiment analysis using ML model and the result is traversed back to lambda and then using queuing service retweet and store the processed results in a Relational database.

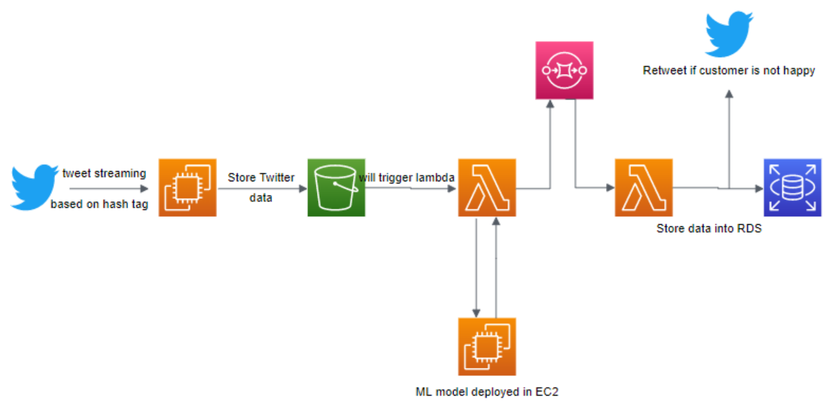
2.3 Challenges

> Processing the requests without server using serverless architecture like lambda.
> using auto ML model.

2.4 Assumptions

> Hashtag to perform the sentiment analysis is assumed prior.

2.5 Architecture Specifications



2.6 Hardware Requirements

Laptop or system to access the AWS console

2.7 Software Requirements

Amazon Web services (AWS)
Python language

3. System Design

Designing an auto ML model for sentiment analysis

Functional Requirements:

1) storing the twitter data
2) Analyzing the data and classifying it.
3) Retweeting accordingly.
4) Storing the analyzed data.

Non-functional Requirements:

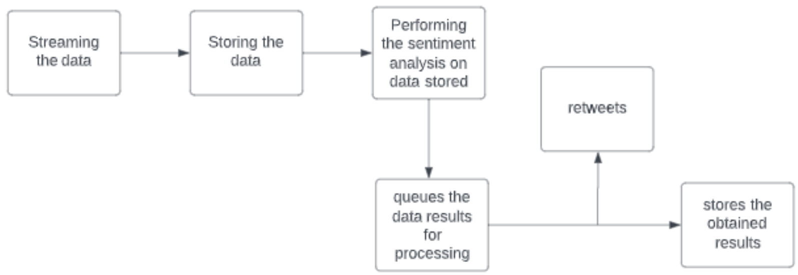
1) scalability
2) Availability

Components:

1) streaming the data

2) storing the data
3) triggering the ML model
4) processing the results obtained
5) storing them and retweeting.

3.1 High-Level Design



3.2 Low-Level Design

Streaming the data:
Using twitter API access, the data is based on #hashtag using python language and EC2 instance

Storing the data:
The data streamed is stored using S3 bucket.

Process the data:
The S3 bucket triggers the lambda which then calls the ML model deployed in EC2 and performs the analysis.

Queues the data results:
Using simple Queuing service, the results are queued for further storage and reply and then trigger lambda.

Stores the obtained results:
Stores the results obtained in RDB for further use.

4. System Implementation

4.1 Algorithms

Bag Of Words (BOW):
Counts the no of times a word repeated in the documents so that the text is converted into numbers for machine understanding

Ex: This movie is nice I like bad

1	1	1	1	0	0	0
1	1	0	0	1	1	0
1	1	1	0	0	0	1

1st movie review vector == [1,1,1,1,0,0,0]

Term Frequency (TF) and Inverse Document Frequency (IDF):
TF = no. of time word occurs in the text/ (Total no of words in text)
IDF = log (Total no. of documents / (No. of documents the particular word is present)) ------- value of a word will be more if it occurs rarely in a document.
------Tells the uniqueness or rareness of the word across the documents.

Stop Words: this, and, is, for, an etc.

Stemming and Lemmatization:

Stemming	Lemmatization
Output word has no meaning	Output word has meaning
It takes less time as it removed just the common end words.	It takes long time as it searches for The meaningful root word.
we can use when the meaning of word is not much imp as spam detection.	meaning is imp as sentiment analysis.

Word Tokenization:

sequence of words is broken down into pieces as words

4.2 Mathematical Models

SVC Model:

SVC, or Support Vector Classifier, is a supervised machine learning algorithm typically used for classification tasks. SVC works by mapping data points to a high-dimensional space and then finding the optimal hyperplane that divides the data into two classes.

LR Model:

Logistic regression is a supervised learning classification algorithm used to predict the probability of a target variable. Generally, logistic regression means binary logistic regression having binary target variables, but there can be two more categories of target variables that can be predicted by it.

4.3 Module Development (CODE):

C:\Users\rishitha\Downloads\tweet_search.py - Notepad++

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lambdafunction.py | tweet_search.py

```python
import tweepy
import configparser
import pandas as pd
import boto3
from datetime import date
import uuid
api_key='obTNcyKepNLY4bavYTWwvVcWo'
api_key_secret='HZ20KH52ygvpJBiB2X0YMPyNVq6yOqmaxnUhypUBpIC6sQJm53'
access_token='1289116007684923393-WVCJjdHGulDa18DZznjmuojsa2NhI8'
access_token_secret='23cFtLmTwms9KTVN9Ni25rf9P9Mh8upcAblwnHPUAJPEv'
s3 = boto3.client('s3')
# authentication
auth = tweepy.OAuthHandler(api_key, api_key_secret)
auth.set_access_token(access_token, access_token_secret)
api = tweepy.API(auth)
# search tweets
keywords = '#CCV'
limit=100
tweets = tweepy.Cursor(api.search_tweets, q=keywords, count=100, tweet_mode='extended').items(limit)
# create DataFrame
columns = ['User', 'Tweet']
data = []

for tweet in tweets:
    values = {"uname":tweet.user.screen_name,"id":tweet.id,"data":tweet.full_text}
    today = date.today()
    today = today.strftime("%Y/%m/%d")
    u_id=uuid.uuid1()
    key_name= today+'/'+ str(u_id)+'_'+tweet.user.screen_name+'.json'
    s3.put_object(Body=str(values), Bucket='ccv-s3', Key=key_name)
    data.append([tweet.user.screen_name, tweet.full_text])
df = pd.DataFrame(data, columns=columns)
print(df)
```

Python file | length : 1,187 lines : 33 | Ln : 33 Col : 2 Pos : 1,180 | Windows (CR LF) | UTF-8 | INS

C:\Users\rishitha\Downloads\tweet_stream.py - Notepad++

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lambdafunction.py | tweet_search.py | tweet_stream.py

```python
import tweepy
import configparser
import pandas as pd
import boto3
from datetime import date
import uuid
api_key='obTNcyKepNLY4bavYTWwvVcWo'
api_key_secret='HZ20KH52ygvpJBiB2X0YMPyNVq6yOqmaxnUhypUBpIC6sQJm53'
access_token='1289116007684923393-WVCJjdHGulDa18DZznjmuojsa2NhI8'
access_token_secret='23cFtLmTwms9KTVN9Ni25rf9P9Mh8upcAblwnHPUAJPEv'
s3 = boto3.client('s3')
# authentication
auth = tweepy.OAuthHandler(api_key, api_key_secret)
auth.set_access_token(access_token, access_token_secret)
api = tweepy.API(auth)
class Linstener(tweepy.Stream):
    tweets = []
    limit = 1
    def on_status(self, status):
        self.tweets.append(status)

        values = {"uname":status.user.screen_name,"id":status.id,"data":status.text}
        today = date.today()
        today = today.strftime("%Y/%m/%d")
        u_id=uuid.uuid1()
        key_name= today+'/'+ str(u_id)+'_'+status.user.screen_name+'.json'
        s3.put_object(Body=str(values), Bucket='ccv-s3', Key=key_name)

        # print(status.user.screen_name + ": " + status.text)

        if len(self.tweets) == self.limit:
            self.disconnect()
```

Python file   length : 1,678   lines : 58   Ln : 18   Col : 14   Pos : 595   Windows (CR LF)   UTF-8   INS

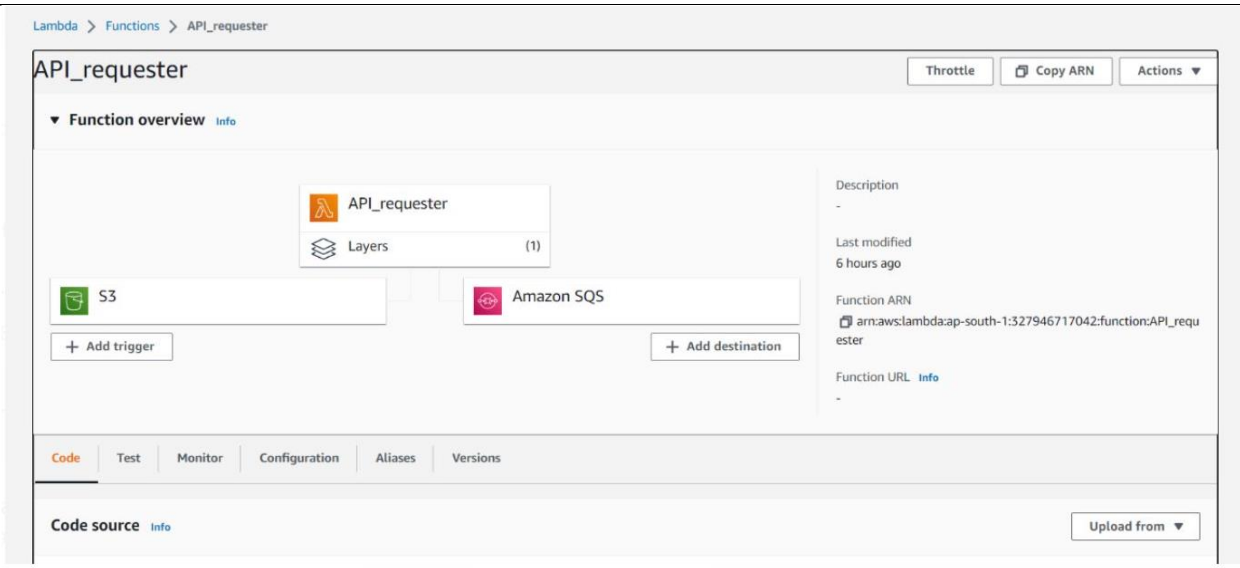
C:\Users\rishitha\Downloads\predict_sentiment.py - Notepad++

File Edit Search View Encoding Language Settings Tools Macro Run Plugins Window ?

lambdafunction.py | tweet_search.py | tweet_stream.py | predict_sentiment.py

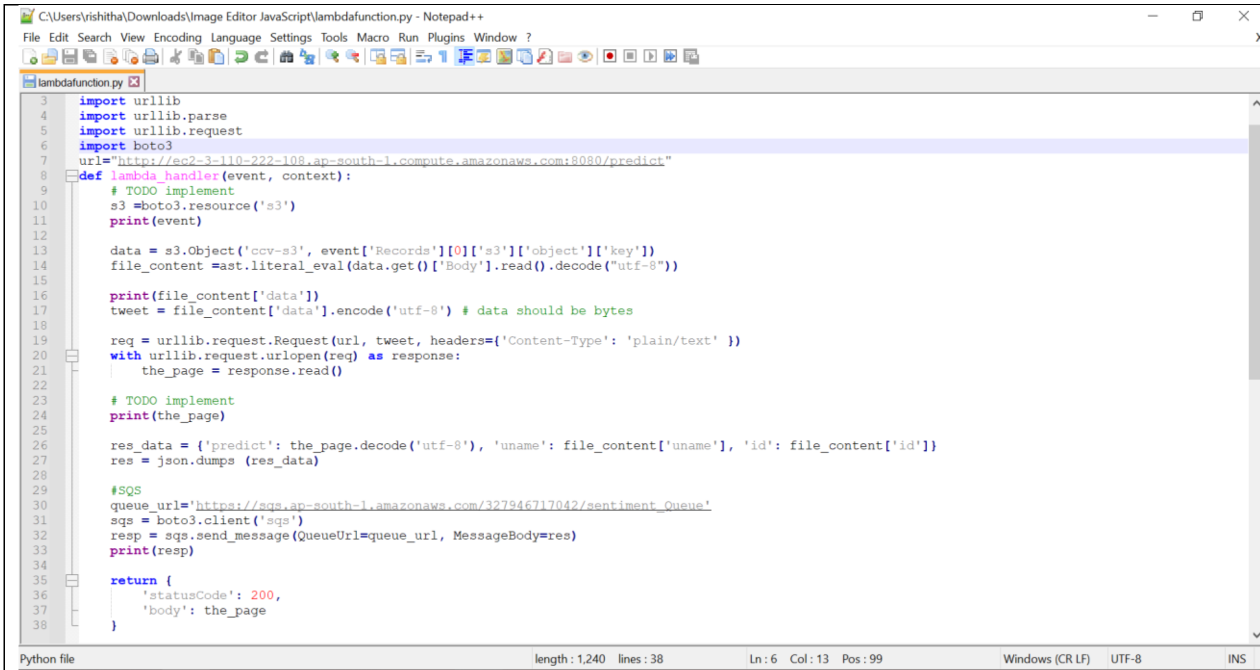
```python
import pandas as pd
import re
import nltk
import pickle
from nltk.corpus import stopwords
stop_words= stopwords.words('english')
emojis = {':)': 'smile', ':-)': 'smile', ';d': 'wink', ':-E': 'vampire', ':(': 'sad',
':-(': 'sad', ':-<': 'sad', ':P': 'raspberry', ':O': 'surprised', ':-@': 'shocked', '@': 'shocked',
   ':-$': 'confused', ':\\': 'annoyed', ':#': 'mute', ':X': 'mute', ':^)': 'smile', ':-&': 'confused',
   '$_$': 'greedy', '@@': 'eyeroll', ':-!': 'confused', ':-D': 'smile', ':-0':'yell', 'O.o': 'confused','<(-_-)>' : 'robot',
   'd[-_-]b': 'dj', ":'-)": 'sadsmile', ';)': 'wink', ';-)': 'wink', 'O:-)': 'angel',
   'O*-)': 'angel', '(:-D': 'gossip', '=^.^=': 'cat'}
def clean_data(data):
    data = str(data).lower()
    data = re.sub(r"@\S+ ", r'', data)
    for emoji in emojis.keys():
        data = data.replace(emoji, emojis[emoji])
    data = re. sub("\s+", ' ', data)
    data = re. sub("\n", ' ', data)
    letters = re. sub ("[^a-zA-Z]", " ", data)
    return letters
def stops_words (words):
    filter_words = []
    for w in words:
        if w not in stop_words:
            filter_words.append(w)
    return filter_words
def load_model():
    vector_file = open(r"C:\Users\welcome\Downloads\tfvectoriser.pickle",'rb')
    vector = pickle.load(vector_file)
    vector_file.close()
    model_file = open(r"C:\Users\welcome\Downloads\ LogisticRegression.pickle",'rb')
    model = pickle.load(model_file)
    model_file.close()

    return vector,model
```

Python file   length : 2,093   lines : 73   Ln : 25   Col : 32   Pos : 1,132   Windows (CR LF)   UTF-8   INS



lambda_function

```python
import json
import ast
import urllib
import urllib.parse
import urllib.request
import boto3

url="http://ec2-3-110-222-108.ap-south-1.compute.amazonaws.com:8080/predict"


def lambda_handler(event, context):
    # TODO implement
    s3 =boto3.resource('s3')
    print(event)

    data = s3.Object('ccv-s3', event['Records'][0]['s3']['object']['key'])
    file_content =ast.literal_eval(data.get()['Body'].read().decode("utf-8"))

    print(file_content['data'])
    tweet = file_content['data'].encode('utf-8') # data should be bytes

    req = urllib.request.Request(url, tweet, headers={'Content-Type': 'plain/text' })
    with urllib.request.urlopen(req) as response:
        the_page = response.read()

    # TODO implement
    print(the_page)

    res_data = {'predict': the_page.decode('utf-8'), 'uname': file_content['uname'], 'id': file_content['id']}
    res = json.dumps (res_data)

    #SQS
    queue_url='https://sqs.ap-south-1.amazonaws.com/327946717042/sentiment_Queue'
    sqs = boto3.client('sqs')
    resp = sqs.send_message(QueueUrl=queue_url, MessageBody=res)
    print(resp)

```



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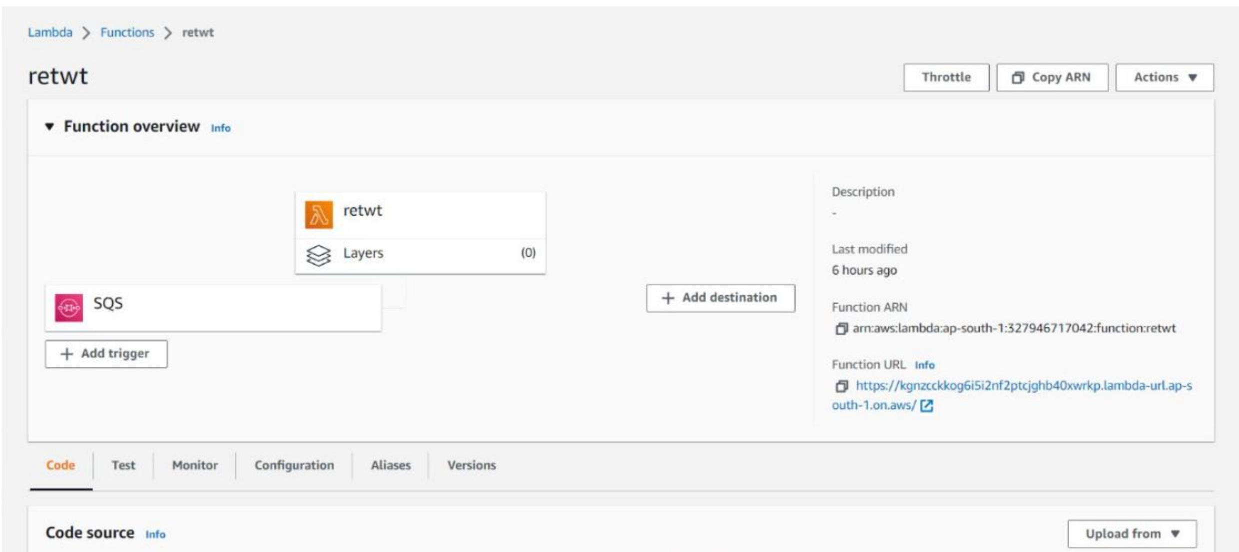
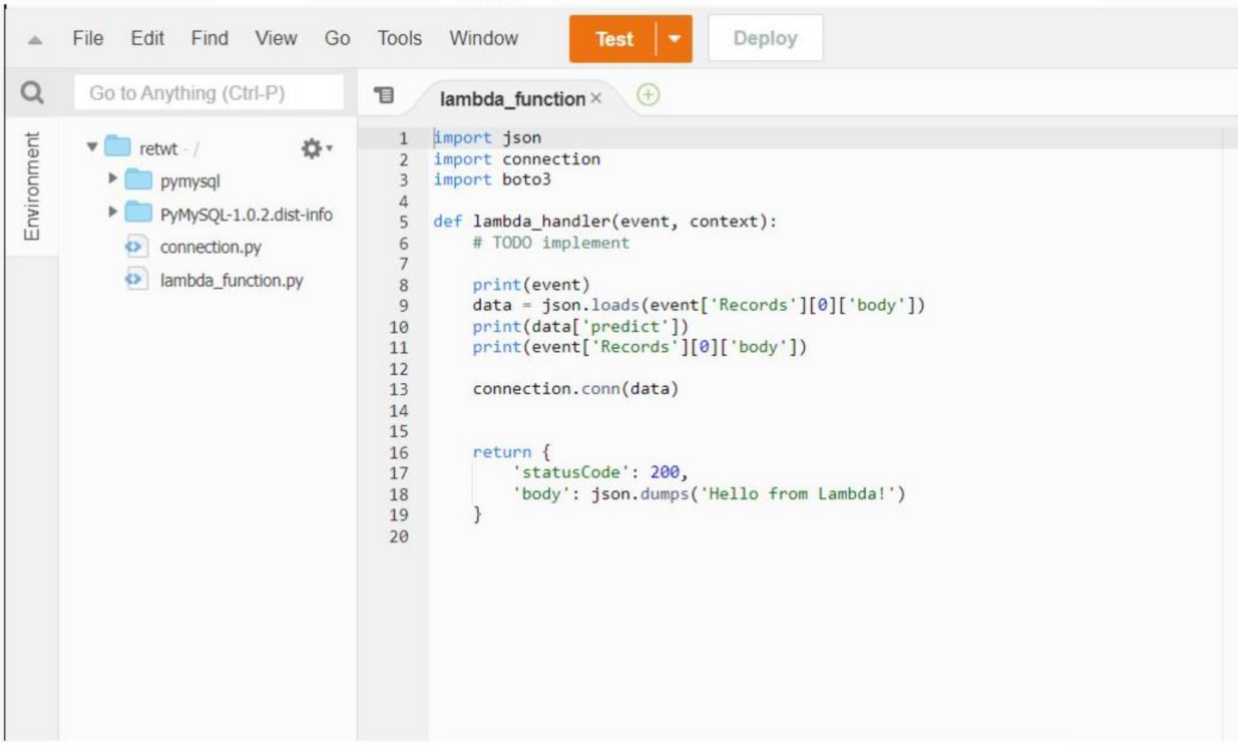
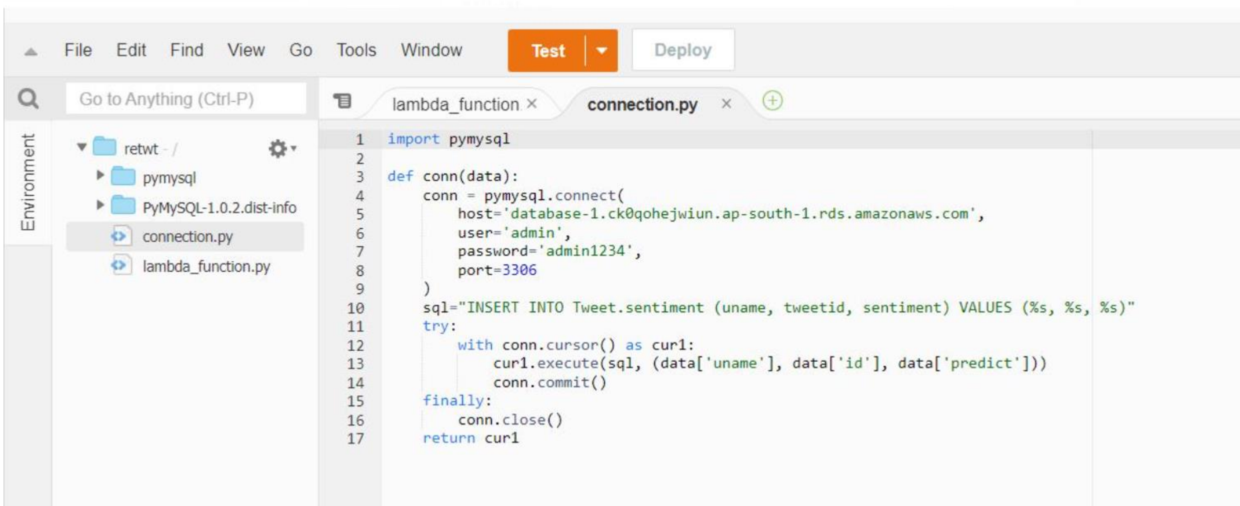
lambdafunction.py

```python
import urllib
import urllib.parse
import urllib.request
import boto3
url="http://ec2-3-110-222-108.ap-south-1.compute.amazonaws.com:8080/predict"
def lambda_handler(event, context):
    # TODO implement
    s3 =boto3.resource('s3')
    print(event)

    data = s3.Object('ccv-s3', event['Records'][0]['s3']['object']['key'])
    file_content =ast.literal_eval(data.get()['Body'].read().decode("utf-8"))

    print(file_content['data'])
    tweet = file_content['data'].encode('utf-8') # data should be bytes

    req = urllib.request.Request(url, tweet, headers={'Content-Type': 'plain/text' })
    with urllib.request.urlopen(req) as response:
        the_page = response.read()

    # TODO implement
    print(the_page)

    res_data = {'predict': the_page.decode('utf-8'), 'uname': file_content['uname'], 'id': file_content['id']}
    res = json.dumps (res_data)

    #SQS
    queue_url='https://sqs.ap-south-1.amazonaws.com/327946717042/sentiment_Queue'
    sqs = boto3.client('sqs')
    resp = sqs.send_message(QueueUrl=queue_url, MessageBody=res)
    print(resp)

    return {
        'statusCode': 200,
        'body': the_page
    }
```

Python file length : 1,240 lines : 38 Ln : 6 Col : 13 Pos : 99 Windows (CR LF) UTF-8 INS







RDBMS Design

Creation of DB and table for storing data:

```sql
CREATE DATABASE Tweet;

USE Tweet;

CREATE TABLE sentiment (
 uname varchar(30),
 tweetid varchar(45) primary key ,
 sentiment varchar(45)
)
```

Desc of table:

	Field	Type	Null	Key	Default	Extra
▶	uname	varchar(30)	YES		NULL	
	tweetid	varchar(45)	NO	PRI	NULL	
	sentiment	varchar(45)	YES		NULL	

5. Results and Discussion

5.1 Implementation Results

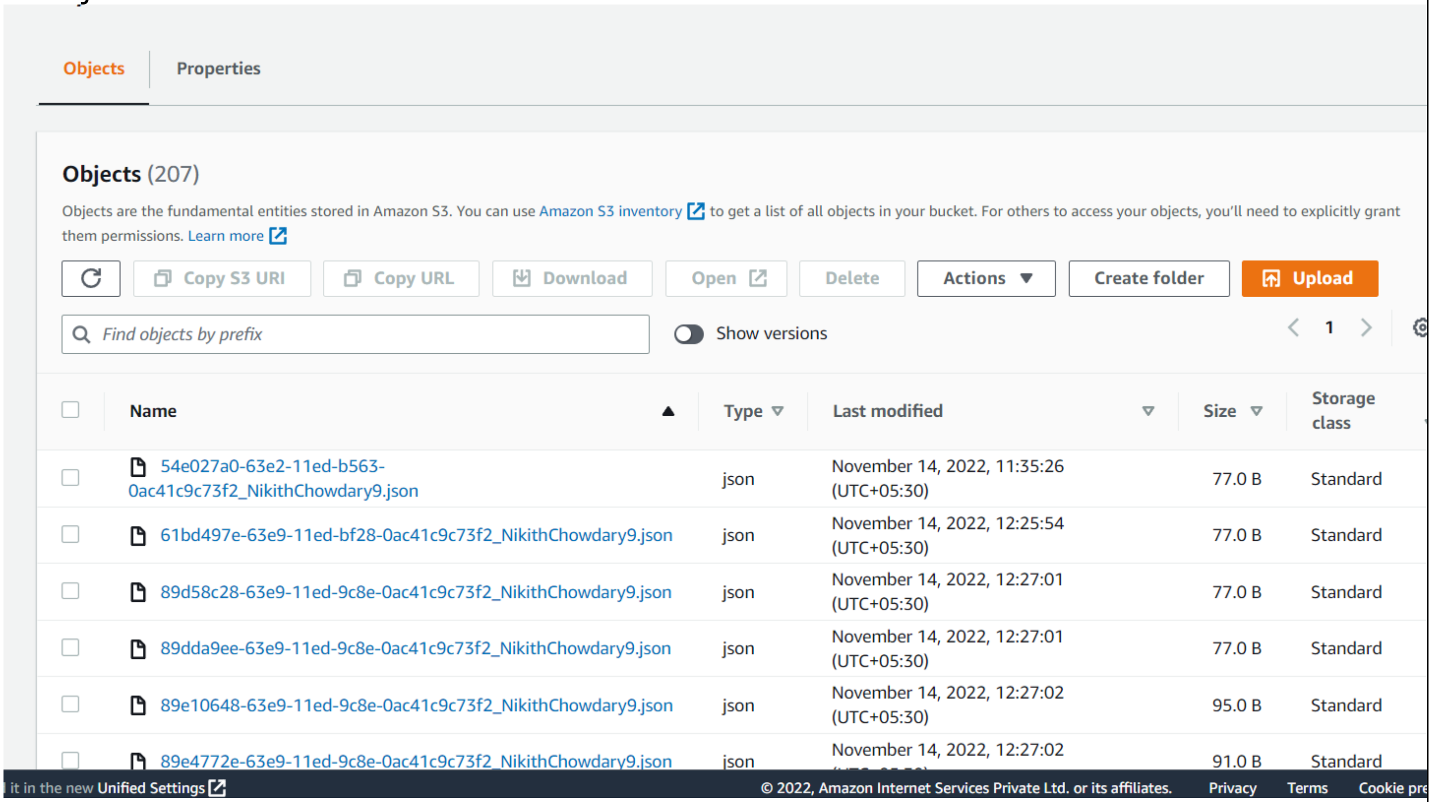
Live tweet Data

```
Stream connection closed by Twitter
              User                Tweet
0  NikithChowdary9  #ccv its not great

In [5]:
```

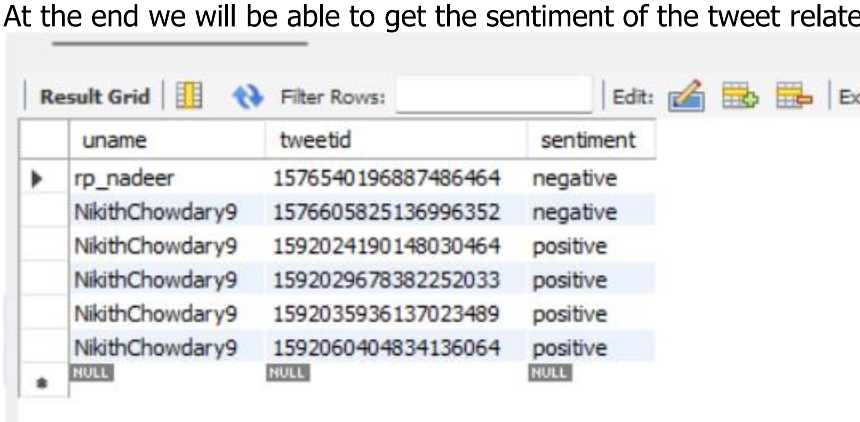
Tweet-Search data (terminal output)

```
               User                                              Tweet
0       nogood1111  テレグラムいただければ連絡差し上げます。\n\n#クローンカード\n#現物クレカ\n#口座売...
1     bitmancard2424  釣ったカード現金化\n手数料15%一律。\n\n振込手数料等全て込み\n\nよろしくお願いし...
2    NikithChowdary9                              #ccv Its a good class
3    NikithChowdary9                               #ccv its interesting
4    NikithChowdary9                                         #ccv worst
..              ...                                                ...
95  socialstudiestx  RT @WalterDGreason: Thank you and welcome to e...
96           dbc___  RT @WalterDGreason: It took me a few days to r...
97       StarkMinds  RT @WalterDGreason: It took me a few days to r...
98   WalterDGreason  RT @esgarchitect: Useful thread. \nCounter con...
99   UnfitChristian  RT @WalterDGreason: It took me a few days to r...

[100 rows x 2 columns]
```

S3 Objects



At the end we will be able to get the sentiment of the tweet related to the #CCV hashtag



uname	tweetid	sentiment
rp_nadeer	1576540196887486464	negative
NikithChowdary9	1576605825136996352	negative
NikithChowdary9	1592024190148030464	positive
NikithChowdary9	1592029678382252033	positive
NikithChowdary9	1592035936137023489	positive
NikithChowdary9	1592060404834136064	positive
NULL	NULL	NULL

5.2 Metrics

Metrics used for evaluation of the results is accuracy score of the predicted model that is airlines dataset but also the live data is used to manually read the tweets and verify whether the results.

5.3 Results in table/Graph/Data (No screenshots, only text form of data in table), Graph should be drawn using Excel tool

5.4 Mapping the results with problem statement and existing systems

Now the model can directly analyse the tweets and classify them into positive, negative and neutral statements without any human involvement by this we were able to solve the problem of the sentiment analysis for huge social media data.

5.5 Discussions

6. Conclusion and Future Developments

So now we can able to perform sentiment analysis on tweets based on hashtags and we can be able to handle it to any scale because we are using AWS services. For future developments we can retweet based on the actual data rather than the sentiment of the data.

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Any other related information you want to add.