Large Scale Sentiment Analysis of Tweets

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Abstract

Abstract, here is what an abstract is compared to an intro
https://www.discoverphds.com/blog/abstract-vs-introduction

1 Introduction

This project aims to apply distributed system concepts with real applications, such as NoSQL systems for big data, and demonstrate the power of distributed systems in extracting and analyzing the general sentiment expressed in a large data set of tweets, and detecting emotions and cyberbullying using pretrained Spark NLP DL classifiers. Emotions identified include: Joy, Surprise, Fear, Sadness while detecting Racism, Sexism or Neutral tweets.

2 Tools and Technologies

Given the large dataset, approximately 10 GB of scrapped tweets, we chose google cloud storage. Google Cloud Storage is a RESTful online file storage web service for storing and accessing data on a Google Cloud Platform infrastructure. The service combines the performance and scalability of the

cloud with advanced security and sharing capabilities, all at no cost to a user using less than 15 GB of cloud space for free.

Furthermore, Big Query was chosen to store the tweets as tabular data in datasets and tables. BigQuery is a data warehouse and a SQL Engine that enabled ease of data import due to it's compatibility with GCS. It's also an affordable big data warehouse, where the first Terabyte of data processed each month is free.

In order to process our data and draw insight, we chose Apache Spark, an open-source unified analytics engine for large-scale data processing. To run Apache Spark, we used Dataproc, given the fast, easy-to-use, and fully managed cloud service for running Apache Spark clusters in a simpler, more cost-efficient way. It helps you create clusters quickly, manage them easily, and save money by turning clusters off when you don't need them.

2.1 GCS

Some description about GCS

2.2 BigQuery

Some description about BigQuery

2.3 Dataproc and Spark

Some description about Dataproc and Spark. Mention cluster configuration, number of instances, type of instances, etc. Refer readers to our scripts for specifics.

3 Dataset

We relied heavily on the snscrape library[1] to scrape tweets. We filtered for tweets that were in the English language only. Approximately 1000000 tweets were scraped for each day between 2022-05-01 and 2022-07-12. The tweets were then saved in Google Cloud Storage.

4 Processing of Data

As mentioned in Section 2.3, we define the processing of the data as a Spark job. The steps involved in the job are illustrated in Figure 1 and will be further elaborated on in the subsequent sections. Our processing pipeline relies heavily on the Spark NLP library[2].

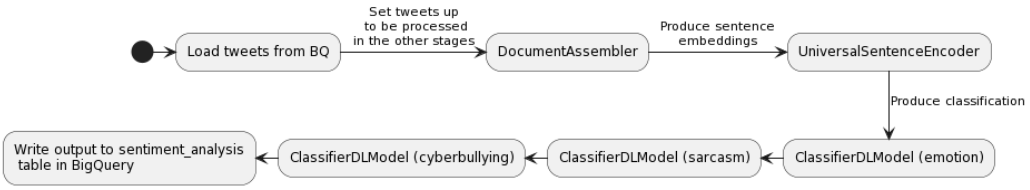

Figure 1: The processing pipeline

4.1 Data Ingestion

In order to use data stored in BigQuery as an input to our Spark job, we used the Spark BigQuery connector[3]. The Spark script reads from a table that contains all the tweets that were procured as described in Section 3.

Each run of the Spark job would typically be executed on 4-5 days' worth of tweets as we discovered that the Spark jobs had a tendency of failing when working with larger amounts of data. This was true even when the CPU

[1]Scraper for social networking services (SNS): https://github.com/JustAnotherArchivist/snscrape

[2]Spark NLP: State of the Art Natural Language Processing: https://nlp.johnsnowlabs.com

[3]Use the BigQuery connector with Spark: https://cloud.google.com/dataproc/docs/tutorials/bigquery-connector-spark-example

and memory utilization of the worker nodes were relatively healthy and thus should be further investigated.

4.2 Document Assembler

The first step of the pipeline is the `DocumentAssembler`[4]. This prepares the data into a format that is processable by Spark NLP and is essentially the entry point for every Spark NLP pipeline.

4.3 Generation of Sentence Embeddings

We generate sentence embeddings by leveraging a Universal Sentence Encoder[5] made available by Tensorflow. The output of this stage is a 512-dimensional vector that semantically captures the meaning of each tweet. This is the basis upon which the downstream classification algorithms build on.

4.4 Sentiment Classification

To actually use the embeddings described in the previous section, we utilise ClassifierDLModels[6] to classify the tweets. Each ClassifierDLModels essentially assigns a label to each tweet. To identify the emotion, presence of cyberbullying and presence of racism in each tweet, we use the `classifierdl_use_emotion`, `classifierdl_use_cyberbullying` and `classifierdl_use_sarcasm` pretrained models respectively (TODO: Better way of phrasing this?).

The emotion classifier produces the values `sadness`, `joy`, `love`, `anger`, `fear` and `surprise`. The cyberbullying classifier produces the values `neutral`, `racism` and `sexism`. The sarcasm classifier produces the values `sarcasm` and `normal`.

[4]https://nlp.johnsnowlabs.com/api/com/johnsnowlabs/nlp/DocumentAssembler
[5]https://www.tensorflow.org/hub/tutorials/semantic_similarity_with_tf_hub_universal_encoder?hl=en
[6]https://nlp.johnsnowlabs.com/api/com/johnsnowlabs/nlp/annotators/classifier/dl/ClassifierDLModel.html

4.5 Storing of Output

The output is then stored in a separate table in BigQuery. Note that the BigQuery Spark connector is once again used here, thus allowing the output of a Spark job to be appended directly to a BigQuery table.

5 Results

TODO: Some visualizations and the insights we obtained

6 Future Work

An idea that we originally had was to run an unsupervised clustering algorithm on the sentence embeddings produced in Section 4.3. The clustering algorithm that we had in mind was DBScan[1], with the objective of clustering tweets with similar topics. Unfortunately, we were not able to find a satisfactorily efficient implementation of the algorithm to employ with Spark. Due to the size of our dataset and the high number of dimensions of the embeddings, an efficient implementation was crucial to the success of this idea. Given that we had limited resources, we were forced to abandon this idea, however, it should be revisited in the future by implementing our own version of the DBScan algorithm.

7 Code

The code to reproduce our project may be found in our Github repository.[7]

[7] Github repository of the project: https://github.com/jamestjw/tweet_analysis_comp6231

8 Conclusion

We worked hard and achieved very little.

References

[1] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu. A density-based algorithm for discovering clusters in large spatial databases with noise. pages 226–231. AAAI Press, 1996.