**MSc in Data Analytics – Integrated Continuous Assessment**

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# Introduction

In the era of digital transformation, the ability to process and analyze large volumes of data, or “Big Data”, has become a critical success factor for businesses across various sectors. Through the application of advanced data processing techniques and forecasting models, this project strives to provide a comprehensive solution for handling Big Data and conducting robust time series analysis.

This document is structured as follows. Section 2 describes the tools used during this project in relation to data management. Section 3 focuses more on the actual data, its analysis and forecasting models. Conclusions for this work are then summarised in Section 4.

# Data processing and storage

## 2.1 Methods and tools

A dataset containing 1.6M observations has been provided for this project. The initial step has been choosing an appropriate database to store the data, process its content, and then store the processed data back in the database for further analysis and modelling. The outcome of the big data processing, along with modelling techniques, has been then summarised in an interactive dashboard. The diagram below represents the data phases, along with the tools used. Additional details on those steps are provided in the next section.

A diagram of a software company

Description automatically generated

Figure - Project Structure

Three Jupyter notebooks have been produced for this study and, as this is a data analysis project, modules like *pandas*, *matplotlib*, *sns* and other have been used for data manipulation and visualization.

Report’s notebooks, along with datasets and report can be found at

<https://github.com/sbs23006/MsC_BigData_AdvAnalytics/>

The report wordcount (including titles, references, and all sections excluding Appendix) is 3480.

## Data storage and processing

The initial step has been the evaluation of one SQL database (MySQL) and one noSQL (HBase). As the number of records is quite high, some benchmark tests have been run against those two databases to evaluate the best performance for this dataset. *Yahoo! Cloud Servicing Benchmark (YCSB)* framework has been used, being a widely recognized tool for evaluating the performances of different database management systems, including both SQL and NoSQL databases (Benchant.com, 2022).

### Database selection

Tests with different workload have been performed on both databases to evaluate their performance sensitivity to data size change. YCSB metrics have been collected for each and compared.

The first metric that has been analysed is runtime, that indicates the total execution time for the test operations. It was observed that MySQL runtime grows significantly as the size of the test data increases, making HBase more suitable for big data storage.

A graph showing a number of numbers

Description automatically generated with medium confidence

Figure - Runtime comparison between MySQL and HBase

The second metric compared has been throughput, that indicates the measure of how many units of information a system can process in a given amount of time. Also in this case, HBase results in being the best choice as it can process more units than MySQL per second.

A graph with a line and a red line

Description automatically generated

Figure - Throughput comparison between HBase and MySQL

Another important metric when looking at databases performances is latency, that is the total amount of time that it will take for the database to receive a request, process the underlying transaction, and return the correct response. Once again, HBase results in being quicker that MyQSL when inserting a bigger amount of data.

A graph showing the difference between latency and num operations

Description automatically generated

Figure - Latency comparison between HBase and MySQL

A NoSQL database is clearly the best choice for this project. Besides HBase, MongoDB has been also considered but, despite the great support from the open-source community, it required more configurations to be able to work with tools like Spark or pymongo to process the data in a Jupyter notebook. HBase has therefore been chosen due to its native integration with Apache Hadoop. Evidence of all those evaluations can be found in the accompanying Jupyter notebook *DB benchmark + Evaluation.ipynb*, as well as within the Big Data section in the file *DataProcessing.ipynb*.

### Data processing

The initial step has been preparing the initial csv file to be loaded into HBase using the built-in ImportTsv utility: this activity mainly consisted of creating a header first, and removing commas from the tweets text to avoid misinterpretation while loading the file into the database. HBase is an open-source, NoSQL, distributed big data store, it integrates seamlessly with Apache Hadoop and the Hadoop ecosystem and runs on top of the Hadoop Distributed File System (HDFS) (Amazon Web Services, Inc.), and for this reason it was very easy to store the csv in the database and then pre-process it with MapReduce jobs.

Due to the size of the data, MapReduce has been used to split the dataset into independent chunks which have then been processed by the map tasks in a completely parallel manner (hadoop.apache.org).

Most of the jobs consist of gaining insights from the data to be then displayed over a dashboard, while others are focused on text manipulation and sentiment extraction. Below is provided a small summary of those jobs, additional details can be found in the *hadoop\_jobs* project folder.

MapReduce jobs:

* Get the distribution of unique flags.
* Calculate how many tweets exist per date.
* Calculate distribution of tweets across moments of the day (morning, afternoon, evening, night)
* Get the number of tweets per user.
* Filter the data removing rows with empty values and not needed columns, as well as do text manipulation like removing punctuation and stopwords.
* A job has been created to test writing on HBase through Python libraries.
* Calculate the tweets sentiment using *vaderSentiment*

The output of this last job has been then stored in a new table in the database for further work in a Jupyter notebook.



Figure - HBase tables: original and processed tweets + ycsb test

### 2.2.3 Data extraction tool evaluation

The second part of the project consists of using this processed data to analysis and modeling techniques in a Jupyter notebook. Two extraction techniques have been evaluated to load the processed table for future work: python native with *happybase* library and Apache Spark.

Happybase is a developer-friendly Python library to interact with Apache HBase (happybase.readthedocs.io). It provides built-in APIs to read data from a database instance.

PySpark is the Python API for Apache Spark (https://domino.ai/data-science-dictionary/pyspark), an open source, distributed computing framework and set of libraries for real-time, large-scale data processing.

Both tools have been evaluated to read data from HBase. While Spark benefits from the HDFS integration to quickly ready the MapReduce output file, happybase resulted in being the best choice in terms of load performance and dataframe readiness (the df is already well formatted with the right headings). The table below summarizes the comparison, evidence of this work can be found in the Big Data section from the accompanying Jupyter notebook *DataProcessing.ipynb*.

|  |  |  |
| --- | --- | --- |
|  | Happybase | Spark |
| Read time | 2min 11s | 16.5s |
| Dataframe load time | 13.5s | 44.1s |
| Output dataframe | Ready to be analyzed | Some processing needed |

Table - Comparison between PySpark and Happybase

# Time series Forecasting

Once data has been pre-processed and sentiment assigned to each tweet, the next step of the project has been analyzing the dataset as a time series and evaluating forecasting models. This section will cover the initial analysis of the time series, the modeling evaluation as well as the final step of summarizing everything in an interactive dashboard.

## 3.1 Analysis

At the core of time-series data is time. Time-series data is a sequence of observations or data points captured in successive order. In the context of a DataFrame, time-series data has an ordered index type DatetimeIndex (Atwan, T.A. 2022).

Before starting any activity, some manipulation has been done on the dataframe loaded from HBase, such as removing unnecessary columns for the forecasting, set the date as index and converting it into a datetime format. Once data has been properly shaped into a time-series, it was observed from an initial plot that there were some missing timestamps.

A graph with blue lines

Description automatically generated

Figure - Sentiment plot of the initial 1.6M tweets

The initial timestamps were including, besides the date, the hour, minutes and seconds. If data is collected at a very high frequency, it might contain a lot of noise; Resampling to a lower frequency can help reduce it, but it can be also useful for handling missing values and and use methods to fill in those values with the lowest noise possible (Brownlee, J. 2016). Because of those reasons, the original time-series has been resampled to a daily frequency. The new time-series is now made of 81 observations with 33 missing values.

A graph with blue lines

Description automatically generated

Figure - Plot of daily sentiment

### 3. 1. 1. Dealing with missing values

Having 40% of missing data is quite significant and could potentially impact the reliability of the analysis. Different imputation techniques have been evaluated, keeping in mind that imputing missing data has implications such as introducing bias and noise, or distort the underlying relationships between variables.

## 3.2 Models

Blab la bla to be completed.

## 3.3 Dashboard

Bla Bla to be completed.

# Conclusion

Blab la to be completed.

# References

Benchant.com. (2022). Available at: https://benchant.com/blog/ycsb [Accessed 6 Nov. 2023].

Amazon Web Services, Inc. (n.d.). What is Apache HBase? | AWS. [online] Available at: https://aws.amazon.com/it/big-data/what-is-hbase/ [Accessed 6 Nov. 2023].

‌hadoop.apache.org. (n.d.). MapReduce Tutorial. [online] Available at: https://hadoop.apache.org/docs/r1.2.1/mapred\_tutorial.html#Overview [Accessed 6 Nov. 2023].

‌happybase.readthedocs.io. (n.d.). HappyBase — HappyBase 1.2.0 documentation. [online] Available at: https://happybase.readthedocs.io/en/latest/ [Accessed 6 Nov. 2023].

Atwan, T.A. (2022). TIME SERIES ANALYSIS WITH PYTHON COOKBOOK practical recipes for exploratory data analysis, data preparation, forecasting, and model evaluation. [S.l.]: PACKT PUBLISHING LIMITED.

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Brownlee, J. (2016). How To Resample and Interpolate Your Time Series Data With Python. [online] MachineLearningMastery.com. Available at: https://machinelearningmastery.com/resample-interpolate-time-series-data-python/ [Accessed 6 Nov. 2023].