Storage Solutions and Data Analytics: RDBM,

Hadoop and APIs in Neural Networks Contexts

Jose Maria Rico Leal  
*Master of Science in Data Analytics*  
sba23021@student.cct.ie

*Abstract*

*This study investigates the relationship between Big Data management tools such as Relational Database Management System (RDBMS), Hadoop, and APIs, and how they can be separately interlinked with advanced data analytics, specifically neural networks. The purpose of the study is to compare a RDBMS with Hadoop when processing a 1.6GB dataset, and then apply a Neural Network. To expand the scope, this study will also include the usage of APIs (Keras library) for implementing Neural Networks. This study was conducted using my personal laptop to load a 1.6GB dataset into a RDBMS and Spark. I utilized Jupyter Notebooks to interact with these two technologies, exploring computing times, roadblocks faced, and other insights. Following this, we applied the same Neural Network to predict if certain jobs are more popular based on gender. Another aspect of the study involves utilizing an API; for this, we are employing Keras and a Convolutional Neural Network (CNN). Our aim is to evaluate the performance of the CNN model in classifying movie reviews as positive or negative based on their sentiment. The research findings indicate that using RDBMS or Hadoop for data processing is not as quick and straightforward as using an API like Keras, where you simply import the data without the need to worry about how to push it into databases, this becomes clear when modelling data using NN via Jupyter Notebooks.*

Keywords: Relational Database Management System, Hadoop, API, Keras, Neural Network (NN), Convolutional Neural Network (CNN)

# Introduction

Relational Database Management Systems have been well-established since the late 1970s; at that time, the concept of Big Data was not the same as it is today. As technology rapidly advanced, the industry needed to process large amounts of data. To address this need, an open-source framework for writing and running distributed applications, called Hadoop, entered the scene (Lam, 2011). These two technologies, RDMS and Hadoop, are great; however, the implementation of both requires a high level of technical software skill. This is where APIs offer a solution to this problem, which the industry refers to as Machine Learning as a Service (MLaaS), e.g., Azure ML or AWS ML, just to mention a few (Atakan Cetinsoy et al., 2016).

The intention of this paper is to explore all three technologies—RDBMS, Hadoop, and APIs—to determine which one is the best fit for data extraction and processing in the context of Neural Networks implementation. This consideration is crucial, given that many individuals interested in Machine Learning are not software developers, and the need for a 'plug-in' to deploy their ML models is evident.

# Topic overview

The chosen topic is Big Data and Neural Networks, with NN being considered a type of Machine Learning (ML) process known as Deep Learning (Mishra and Gupta, 2017). The field of Big Data is constantly growing and encompasses a need for efficient data management and processing tools. Two well-known tools for handling and analyzing large datasets are Relational Database Management Systems (RDBMS) and Hadoop. However, the rampant advancement of Machine Learning and Neural Networks, the integration of these data management tools with advanced analytics technologies is the focus of this paper.

## Objectives

* Examine the current state of RDBMS, Hadoop, and APIs when used in modeling NN.
* Store a 1.6GB dataset in both an RDBMS (SQL) and Hadoop, and then retrieve the data into a Jupyter Notebook to model a neural network.
* Utilize an API (Keras) to model a neural network and compare its performance in conjunction with RDBMS and Hadoop.
* Discuss the rationale behind the selection of the NN model for both scenarios.

## Research question

How do Relational Database Management Systems (RDBMS) and Hadoop compare in terms of efficiency and effectiveness in processing large datasets for the application of neural networks, and how can APIs, particularly the Keras library, streamline the implementation of neural network models in data analytics (B Arnold, 2017).

# State of the art

## RDBMS

The current state of RDBMS has evolved substantially with enhancements in storage, speed, and scalability by using cloud-based solutions (Li et al., 2016). The future holds a shift for RDBMS transitioning to a NoSQL database (Candel, Sevilla Ruiz and García-Molina, 2022). To understand why NoSQL is taking over RDBMS, it is crucial to talk about: Schemas, where NoSQL uses dynamic instead of static schemas; the type of data to be stored, with NoSQL databases offering advantages for hierarchical data storage due to their flexible data models and scalability, while RDBMS are not that flexible; scalability, with NoSQL depending on horizontal scalability and RDBMS on vertical scalability; and other points where NoSQL surpasses RDBMS, including data warehouse, complexity, cloud, and big data handling, and output performance (Palanisamy and SuvithaVani, 2020).

## Hadhoop

In the era of Big Data, where we sometimes run out of storage and face difficulties on a single host due to the volume of data, Hadoop came into the scene to tackle this by offering computational capabilities over huge amounts of data (Holmes, A., 2012). The present and future look bright for Hadoop, as some of the major Big Data companies, such as *Google, Facebook, eBay, Twitter* and *Spotify,* rely on this technology (Neeta Awasthy and Nikhila Valivarthi, 2023).

## ML APIs

Machine Learning APIs have helped developers integrating data flows into complex algorithms without requiring deep expertise (Jordan & Mitchell, 2015). These APIs were once primarily used for basic tasks like picture and speech recognition, but they have since grown to include a variety of machine learning activities, such as predictive analytics and natural language processing (Halevy, Norvig, & Pereira, 2009). Today, they are essential to leading tech companies and cutting-edge industries, being ML accessible and customizable than in the past (Bughin, Seong, Manyika, Chui, & Joshi, 2018). Looking at the future ML APIs will remain as they have simplified model development across diverse environments (Sculley et al., 2015).

## Deep Learning Neural Networks

The development of Deep Learning Neural Networks (DLNNs) traces back to the 1950s. The method has improved since the introduction of Convolutional Neural Networks (CNNs) by LeCun et al. in the late 1980s, which showed how good deep architectures are for image processing (LeCun, Bengio, & Hinton, 2015). In 2012 this field achieved another milestone with AlexNet's success in the ImageNet challenge, showcasing DLNNs' potential in image recognition (Krizhevsky, Sutskever, & Hinton, 2012). The introduction of Transformer models by Vaswani et al. in 2017 marked another significant advancement, in natural language processing (Vaswani et al., 2017). Neural Networks have the future guaranteed as all points mentioned earlier RDMS and Hadoop store and process data for Neural Networks models.

## Research methodologies and key papers

## Topic Overview

* Objectives
* Research questions
* State of Art

# Literature review

## Selecting a Template (Heading 2)

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## Maintaining the Integrity of the Specifications

The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts.

# Implementation

This section aims to explain the demo work with all its components.

## Technical Setup

Hardware and software configuration of the host laptop and the VM.

* Laptop: HP 250 G8 PC.
  + Operating System (OS): Microsoft Windows 10 Pro.
  + Processor: 11th Gen Intel® Core™ i7-1165G7 @ 2.80GHz, 2803 Mhz, 4 cores, 8 logical processors.
  + RAM: 16GB.
  + Hard Disk Drive (HDD): 237GB.
* VirtualBox: Version 7.0.14.
  + OS: Ubuntu 22.04 LTS (Jammy Jellyfish) (64-bit).
  + Processor: Configured with 2 cores and 2 logical processors from the host's 11th Gen Intel® Core™ i7-1165G7 processor.
  + RAM: 4GB.
  + Memory (Disk Space): 100GB.

Essential software versions installed on VM:

* Hadoop: 3.3.6.
* Spark: 3.4.2.
* MySQL: 8.0.36.
* MySQL Workbench: 8.0.36.
* Jupyter Notebook: 6.4.8.

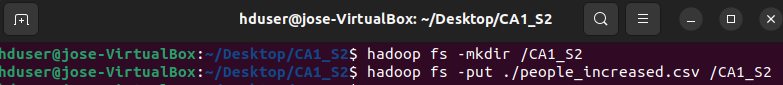
## Dataset

The dataset loaded into Hadoop and MySQL was sourced from the Datablist website (www.datablist.com, n.d.). It comprises nine columns and two hundred rows, containing personal data such as names, surnames, gender, job positions, etc. A significant consideration with this type of data is privacy; however, the data was randomly generated by the Python Faker package, as seen on the Datablist GitHub account (GitHub, 2023). This approach ensures GDPR compliance, carefully avoiding any conflict with it. Importantly, this dataset does not require a license for use, as this data is dummy generated for testing purposes.

## Data load

At first *people.csv* weighted 0.23 GB however for testing purposes it was increased to 1.6GB using *1.Increasing\_dataset\_size.ipynb* script. The dataset was duplicated seven times, resulting in *people\_increased.csv.* This choice is made with the intention of approaching Big Data. Although 1.6GB is not near what Big Data looks like nowadays, it is close to concept in terms of overwhelming most conventional applications. For instance, Excel CSV grid will crash automatically when attempting to open this file. Yes, we can use Notepad ++ to how the data looks but no more than that.

### Hadoop people\_increased.csv load: First step creating a new directory and moving the dataset into it:



1. Commands to create and move a dataset into Hadoop.

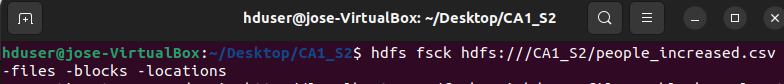
After a successful load Hadoop UI shows:

A screenshot of a computer

Description automatically generated

1. Hadoop UI, Utilities, Browse the file system, *CA1\_S2* directory.

Above figure shows a 1.52GB file that is replicated once with a block size of 128MB. To get a sense of how HDFS works we need to run the following command:



1. HDFS report health files command.

After running it, we see the file divided and stored across 13 blocks:

A computer screen shot of a program

Description automatically generated

1. Console output HDFS report health files command.

This means the HDFS has filled 12 blocks completely 128MB (134,217,728 bytes) in size, consistent with HDFS's default block size setting except the last one as is the remainder, with 20.24MB (21,234,682 bytes). This is common as the final block not using the default block size unless is a multiple of that block size.

### MySQL people\_increased.csv load: Before loading the file an schema and a table inside must be created:

A screenshot of a computer

Description automatically generated

1. MySQL workbench schema creation.

A screenshot of a computer

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1. MySQL table creation.

After successful schema and table creation, data will be loaded via *2.Importing\_1.6GB\_CSV\_to\_MySQL.ipynb* script.This approach was chosen because MySQL Workbench server import failed, displaying the error : *”Error Code: 2013. Lost connection to MySQL server during query”.* MySQL workbench appears to struggle with importing large CSV files into a schema. However, the script did with a time of 7 minutes and 28 seconds. Let us examine the size of the table:

A computer screen shot of a computer code

Description automatically generated

1. MySQL table size

### HDFS vs MySQL loading process: After this implementation step, it is clear that HDFS is quicker in terms loading time. It required just two commands and took only 5 to 10 seconds for the file to be integrated in the system whereas, MySQL took 7 minutes and 28 seconds. Furthermore, MySQL required the creation of a schema and table. A second advantage of HDFS is memory comsumption; from an intial 1.63GB csv file when loaded, it was reduced to 1.52GB, whereas MySQL, upon loading, increased to 1.87GB.

## Data from HDFS Modeled with a Neural Network

## Data from MySQL Modeled with a Neural Network

# Critical evaluation

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## Authors and Affiliations

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### For papers with less than six authors: To change the default, adjust the template as follows.

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#### Deletion: Delete the author and affiliation lines for the extra authors.

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Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

Component heads identify the different components of your paper and are not topically subordinate to each other. Examples include Acknowledgments and References and, for these, the correct style to use is “Heading 5”. Use “figure caption” for your Figure captions, and “table head” for your table title. Run-in heads, such as “Abstract”, will require you to apply a style (in this case, italic) in addition to the style provided by the drop down menu to differentiate the head from the text.

## Figures and Tables

#### Positioning Figures and Tables: Place figures an

1. Table Type Styles

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1. Sample of a Table footnote. (*Table footnote*)
2. Example of a figure caption. (*figure caption*)

# Future work

# Conclusions

##### Acknowledgment *(Heading 5)*

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