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**ECE 4150 – Spring 2024**

**Apache Spark project on AWS EC2**

# A) Purpose

The objective of this project is to learn how to integrate Spark into AWS EC2 and leverage various Spark operations on extensive datasets. The power of Spark will be demonstrated on the simple website we built for this project.

In addition to Spark, we also use Matplotlib to visually represent the data manipulated by Spark. With Spark and Matplotlib, we are able to construct an intuitive analytics website, providing users with deeper insights into the dataset under examination.

# B) Architecture and Process Flow

A diagram of a computer

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The users choose the details of the information they want to see on the frontend. When they click “submit”, the frontend triggers the corresponding Flask route in the backend to use Spark to manipulate, filter, and collect the appropriate data from the dataset. Then, the backend uses the collected data to sketch bar charts using Matplotlib, saves the plot as a ‘.png’ image, and send the image to the frontend.

# C) Project Walkthrough

**1) Choose a dataset**

To demonstrate how efficiently Spark works with large datasets, we must first choose a suitable dataset for the project.

The dataset we chose is a csv file that contains data about the Mortality Number and Rate for 187 countries between 1970 and 2010. The dataset has 58906 rows and 6 columns, which offers a lot of information for me to work with using Spark. Below is the first few rows of the dataset:

A screenshot of a computer

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and more...

**2) Choose an appropriate AWS EC2 instance**  
We opted for Ubuntu 20.04 as the OS image for the EC2 instance because it is no-cost and user-friendly. For streamlined development and testing of our application, we chose to run Spark in local mode. Additionally, setting up Flask locally for this project is straightforward.

Since Spark operates locally, we want it to use all CPU cores for parallel processing to ensure swift data filtering, collection, sketching, and presentation on the website for users. To achieve this, selecting an EC2 instance type that offers multiple CPU cores becomes a must. Hence, we decided on the t3.xlarge type, which boasts up to 4 cores and is very cost-effective (only $0.3328/h for Ubuntu OS).

We also allowed all inbound and outbound traffic for this EC2 instance.

**3) Install Anaconda and PySpark:**

After successfully launching the EC2 instance, the next step involves installing Anaconda and PySpark on it. While closely following the provided instructions, we made a few modifications to suit our preferences.

Initially, we installed Anaconda by executing two commands:

* wget <http://repo.continuum.io/archive/Anaconda3-4.1.1-Linux-x86_64.sh>
* bash Anaconda3-4.1.1-Linux-x86\_64.sh

Following this, we agreed to the Anaconda license terms and opted for installation at the present location. To complete the Anaconda installation, we ran the command “source .bashrc”.

Subsequently, we proceeded to install JRE using:

* sudo apt-get update
* sudo apt-get install default-jre

Additionally, we installed Scala with the command “sudo apt-get intall scala”. Py4J was installed using the following commands:

* export PATH=$PATH:$HOME/anaconda/bin
* conda install pip
* pip install py4j

Moving forward, we installed Spark/Hadoop by downloading the package and extracting its contents:

* wget <http://archive.apache.org/dist/spark/spark-2.0.0/spark-2.0.0-bin-hadoop2.7.tgz>
* sudo tar –zxvf spark-2.0.0-bin-hadoop2.7.tgz

Upon installing Spark/Hadoop, we configured Python to recognize Spark:

* export SPARK\_HOME=‘/home/ubuntu/spark-2.0.0-bin-hadoop2.7’
* export PATH=$SPARK\_HOME:$PATH
* export PYTHONPATH=$SPARK\_HOME/python:$PYTHONPATH

Finally, we installed PySpark with the command:

* pip install pyspark –no-cache-dir

These steps ensured the successful setup of Anaconda, PySpark, and related dependencies on the EC2 instance, paving the way for further development and analysis tasks. Now, let’s move on to the coding portion of the project.

**4) Import necessary modules and configure Spark session and data frame:**

To implement Flask backend with Spark and Matplotlib, we must import the appropriate modules at the beginning.

from flask import Flask, render\_template, redirect, session, request

from pyspark.sql import SparkSession, functions

import matplotlib

matplotlib.use('Agg') # Agg is non-interactive backend and compatible for flask frontend

import matplotlib.pyplot as plt

import io

import base64

We also must configure Spark Session as well. As mentioned earlier, we want Spark to run locally using as many available CPU cores as possible to suit its needs.

spark = SparkSession \

    .builder \

    .master("local[\*]") \

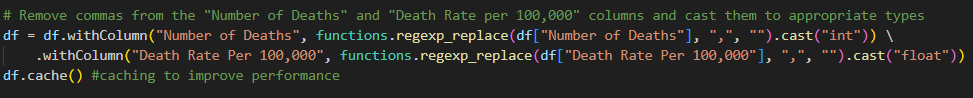
    .appName("Mortality Analysis") \

    .getOrCreate()

Then, we created a global DataFrame object **df** in PySpark, which is a distributed collection of data organized into named columns. This DataFrame **df** is created by reading the “mortality\_age.csv” file into Spark. we also specified that the first row of the file contains column headers, and the columns are separated by commas.

df = spark.read.csv("file:///home/ubuntu/data/mortality\_age.csv", header=True, sep=",")

we then perform some data cleaning and manipulation operations on **df**. Specifically, we remove commas from the “Number of Deaths” and “Death Rate per 100,000” columns and casts them to appropriate types. This is necessary because Spark cannot recognize numerical data if it contains comma in it. Also, **df** will be regularly used on multiple pages of the website, so we cache it to memory to avoid redundant computations and enhance performance.



**5) Homepage**

A screenshot of a computer

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This is the default Homepage of the website. The user has two options to interact with the dataset: “One Country” and “All Countries”. If the user clicks on “Close Webpage”, the backend will safely close the Spark Session and redirect the user to “Google.com”.

# ROUTES

@app.route('/', methods=['GET'])

def homepage():

    prepopulate\_data()

    return render\_template('home.html')

When the user reaches this route, the backend runs the “prepopulate\_data()” function to check if the Flask sessions “country\_codes” and “age\_group” are None. If the two sessions are None, then the backend will assign a suitable list to each session. We will use these two session to populate the dropdown in “oneAnalysis” and “allAnalysis” pages later.

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Now, let’s examine how the list for session “country\_codes” is created. From the DataFrame **df**, Spark selects the distinct values of the “Country Code” column, then sorts them in ascending order, converts the result to a resilient distributed dataset (RDD), flattens the RDD, and finally collects the elements into a list. This list is then assigned to the Flask session “country\_codes” for later usage.

We can see the same Spark operations to create the list for session “age\_group”. From **df**, Spark chooses the distinct values of the “Age Group” column, orders them in ascending order, converts the result to an RDD and flattens it, and collects the elements into a list. This list is assigned to Flask session “age\_group” for later usage as well.

A screenshot of a computer

Description automatically generated**6) One Country (oneAnalysis) page:**

After clicking on “One Country” button on homepage, the user is directed to this page. There will be 3 dropdowns for them to choose their desire values from. Their chosen values will be used as a filter for the DataFrame, and 2 corresponding plots will be created based on the filtered data.

A screen shot of a computer program

Description automatically generatedHere’s the Flask route for this page:

A computer screen with text on it

Description automatically generated

Looking at render\_template() function calls of the code above, we find that the Flask sessions “country\_codes” and “age\_group” are sent to the frontend. They are used to populate the dropdowns “Country Code” and “Age Group” we see on the webpage.

We programmed the “Submit” button to be clickable only when 3 values from 3 dropdowns are selected by the user. When the user clicks the “Submit”, a “POST” method will be triggered, and the backend jumps inside the ‘if’ block.

Now, let’s see what happens inside the ‘if’ block. First, the selected values from the dropdowns “Country Code”, “Age Group”, and “Gender” are used to filter the DataFrame **df**, which results in the filtered DataFrame **df\_filtered.**

Then, Spark groups the rows of **df\_filtered** by the “Year” column and aggregates the “Number of Deaths” column within each group, summing up the total number of deaths for each year. As a result, the DataFrame **df\_grouped\_1** is produced and it has two columns “Year” and “Total Deaths”.

A black background with colorful text

Description automatically generatedSimilarly, to produce **df\_grouped\_2**, Spark groups the rows of **df\_filtered** by the “Year” column and aggregates the “Death Rate Per 100,000” column within each group, summing up the total death rate per 100000 for each year. The DataFrame **df\_grouped\_2** has two columns “Year” and “Death Rate”.

Then, Spark collects the data from both **df\_grouped\_1** and **df\_grouped\_2** before assigning them to “data\_1” and “data\_2” respectively.

# Collect data from data frame

data\_1 = df\_grouped\_1.collect()

data\_2 = df\_grouped\_2.collect()

“data\_1” and “data\_2” are lists of dictionaries, where each dictionary represents a row from the DataFrames **df\_grouped\_1** and **df\_grouped\_2** respectively. In “data\_1” and “data\_2”, each row contains one dictionary. For example, we can visualize “data\_1” and “data\_2” as below:

data\_1 = [ data\_2 = [

{“Year”: 1970, “Total Deaths”: 23000}, {“Year”: 1970, “Death Rate”: 10.0},

{“Year”: 1980, “Total Deaths”: 50000}, {“Year”: 1980, “Death Rate”: 20.0},

... ...

] ]

(this is just an example, not real data)

After the “Submit” button is clicked, Spark filters and gathers data as shown above. Those data are used to sketch two plots in the backend – “Number of Deaths vs Year” and “Death Rate vs Year”.

To sketch the plots, we need values for x-axes and y-axes. Since both plots have the same type of x-axis (Year), we only need 1 list of values for both plots’ x-axes. We need a list of “Total Deaths” values for the 1st plot while we need a list of “Death Rate” values for the 2nd plot. We can get those list of values from the list of dictionaries “data\_1” and “data\_2” earlier.

x\_vals = [row["Year"] for row in data\_1]

y1\_vals = [row["Total Deaths"] for row in data\_1]

y2\_vals = [row["Death Rate"] for row in data\_2]

After we get all the values for x-axes and y-axes, now we can plot the two plots, save them in ‘.png’ format, and send them to frontend in render\_template() function call.

A computer screen shot of text

Description automatically generated

A graph of number of men and women

Description automatically generatedIf the user chooses “AUS” for Country Code dropdown, “35-39 years” for Age Group dropdown, and “Male” for Gender dropdown, below is what he/she will see on the webpage:

A graph of a number of years

Description automatically generated

**7) All Countries (allAnalysis) page:**

A screenshot of a computer

Description automatically generated

After clicking on “All Countries” button on homepage, the user reaches this page. There are 3 dropdowns for them to choose their desire values from. Their chosen values will be used as a filter for the DataFrame, and 2 corresponding plots will be created based on the filtered data.

The plots for this page shows the data for all 187 countries throughout the years, not just one specific country. The “Submit” button is disabled until all the user chooses 3 values from 3 dropdowns.

A screen shot of a computer program

Description automatically generatedHere’s the Flask route that handles this page:

A screen shot of a computer code

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A screen shot of a computer code

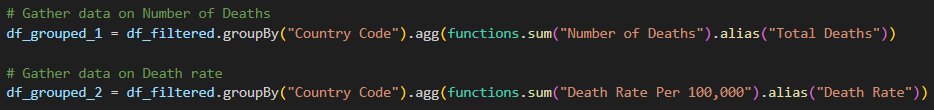
Description automatically generated

In the render\_template() function calls, we see that the Flask sessions “age\_group” is sent to the frontend as an argument. It’s used to populate the dropdowns “Age Group” we see on the webpage.

After the user choses items from all 3 dropdowns, they can click the “Submit” button, which triggers a “POST” response and the backend jumps inside the ‘if’ block. Now, let’s examine what happens inside the ‘if’ block.

First of all, Spark uses the selected values from the dropdowns “Age Group”, “Gender”, and “Year” to filter the DataFrame **df**, which results in the filtered DataFrame **df\_filtered.**

Then, Spark groups the rows of **df\_filtered** by the “Country Code” column and aggregates the “Number of Deaths” column in each group, summing up the total number of deaths for each country code. Consequently, the DataFrame **df\_grouped\_1** is produced and it has two columns “Country Code” and “Total Deaths”.

Similarly, to create **df\_grouped\_2**, Spark groups the rows of **df\_filtered** by the “Country Code” column and aggregates the “Death Rate Per 100,000” column in each group, summing up the total death rate per 100000 for each year. The DataFrame **df\_grouped\_2** has two columns “Country Code” and “Death Rate”.

Then, Spark collects the data from both **df\_grouped\_1** and **df\_grouped\_2** before assigning them to “data\_1” and “data\_2” respectively.

data\_1 = df\_grouped\_1.collect()

data\_2 = df\_grouped\_2.collect()

“data\_1” and “data\_2” are lists of dictionaries, where each dictionary represents a row from the DataFrames **df\_grouped\_1** and **df\_grouped\_2** respectively. In “data\_1” and “data\_2”, each row contains one dictionary. For example, we can visualize “data\_1” and “data\_2” as below:

data\_1 = [ data\_2 = [

{“Country Code”: AFG, “Total Deaths”: 45000}, {“Country Code”: AFG, “Death Rate”: 20.0},

{“Country Code”: AUS, “Total Deaths”: 30000}, {“Country Code”: AUS, “Death Rate”: 15.0},

... ...

] ]

(this is just an example, not real data)

After the user clicks on “Submit” button, Spark manipulates data as shown above. Those data help sketch two plots in the backend – “Number of Deaths vs Countries” and “Death Rate vs Countries”.

To sketch the plots, we require values for x-axes and y-axes. Since both plots have the same type of x-axis (Country Code), we only need 1 list of values for both plots’ x-axes. We need a list of “Total Deaths” values for the 1st plot while we need a list of “Death Rate” values for the 2nd plot. We can get those list of values from the list of dictionaries “data\_1” and “data\_2” earlier.

x\_vals = [row["Country Code"] for row in data\_1]

y1\_vals = [row["Total Deaths"] for row in data\_1]

y2\_vals = [row["Death Rate"] for row in data\_2]

For these 2 plots, the x-values are vertically displayed on top of each bar, not under the x-axes.

A screen shot of a computer code

Description automatically generatedAlso, the distances between x-values and their associated bars will be different to make sure the x-values do not overlap one another. Then, after the backend sketches the plots, it saves them in “.png” format and sends them to frontend in the render\_template() call.

A computer screen shot of colorful text

Description automatically generated

A graph showing numbers and a number of people

Description automatically generated with medium confidenceIf the user chooses “15-19 years” for Age Group dropdown, “Female” for Gender dropdown, and “1990” for Year dropdown, below is what he/she will see on the webpage:

A graph of blue lines

Description automatically generated

Note: The plots and country codes on top of the bars are much bigger and easier to view on the actual webpage. These are just small screenshots of the plots. Also, the user can conveniently scroll left, right, up, and down to see the plots from different angles on the real webpage.

# D) Conclusion

Apache Spark is a powerful distributed computing system that is used for big data processing and analytics. Throughout this project, we gained valuable insights into Spark’s ability at efficiently handling large datasets, alongside its seamless integration with AWS EC2 and Matplotlib to build a good visualization website.

At the beginning of this project, we learned how to choose an optimal instance type of AWS EC2 so that Spark can have enough resources to operate quickly on a large dataset. We also learned how to install and set up Spark on AWS EC2 virtual server so that it can run without errors.

During the development stages, we learned how to filter, manipulate, and use the data to craft insightful visualizations on the frontend. We also get familiar with the structures of Spark-produced DataFrames in order to use them effectively. Additionally, we tried our best to Optimize Spark’s performance by caching the DataFrame and maximizing CPU cure utilization.

If you would like to see the complete code for the Flask backend and the frontend, please refer to the zipped file. Thank you!