# <u>BIG DATA CONCEPTS AND</u> <u>IMPLEMENTATION (rbhowmik)</u>

# 1. INTRODUCTION

For my project I have selected the Tétouan city power consumption dataset. It's a multivariate and time series dataset. The historical dataset contains every 10 minutes data from 2017-01-01 and 2017-12-3, collected from Supervisory Control and Data Acquisition system. The dataset used in this study is related to three different power distribution networks of Tétouan city which is in north Morocco. The entire dataset has 52417 data points including 9 attributes. The dataset has zone wise power consumption values, including humidity, temperature, wind speed and other attributes leading to the power consumption distribution in the zones. I would be analyzing zone was power consumption with respect to temperature and humidity, and feature engineer multiple columns to check the thresholds.

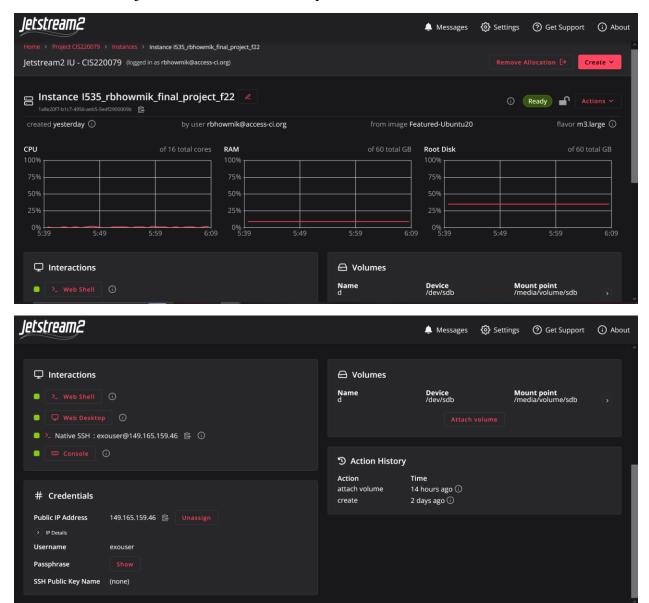
### 1. BACKGROUND

Power consumption is the most important use of resources in this world. Let it be in the field of manufacturing, IT, pharmaceutical etc., electricity consumption is the lifeline for all our day-to-day work. Predicting electricity power consumption is an important task which provides intelligence to utilities and helps them to improve their systems' performance in terms of productivity and effectiveness, and that's what make this data interesting, as it gives us a picture of the city of Tétouan and its power consumption, and how it varies based on temperature and humidity.

# 2. METHODS

# a. VIRTUAL MACHINE SETUP

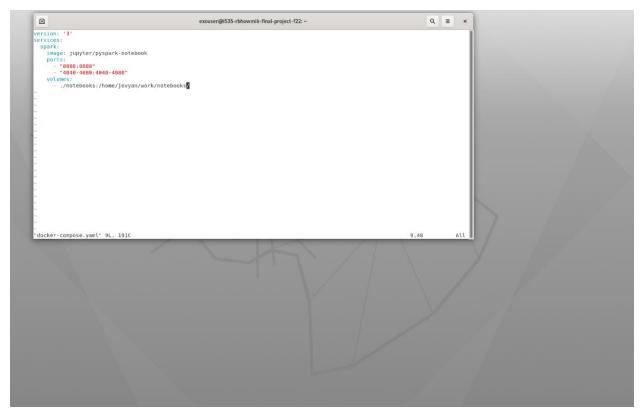
I created an ubuntu instance I535\_rbhowmik\_final\_project\_f22 under Project CIS220079 directory in Jetstream.



I chose the m3.large with 16cores CPU, 60GB disk, to analyze my dataset. I also additionally attached a 10GB volume disk. I triggered the web-desktop and performed the anaconda installation. I have also installed additional packages like pymongo, seaborn and charstudio.

# b.SPARK SETUP

Created a separate Spark folder in the instance having a docker engine running. Created a docker-compose.yaml file in the spark folder. In the docker-compose.yaml file I populated the below code for the pyspark to get instantiated.



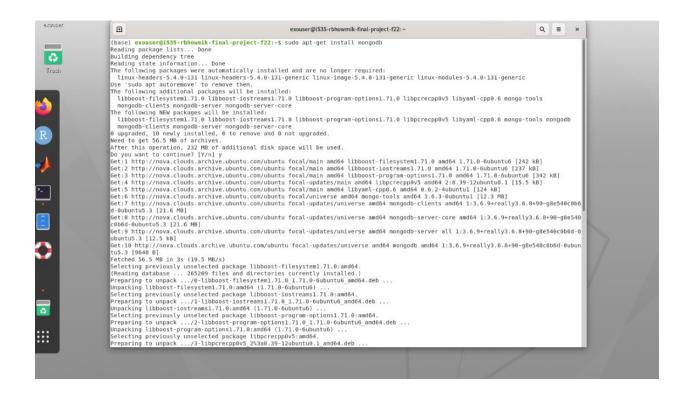
After running the sudo docker-compose command the pyspark notebook was triggered.

```
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| Complete | S277436c562: Pull complete | S277436c562: Pull complete | S277436c563: Pull complete | S277436c563: Pull complete | S274436c67: Pull complete | S274436c7: Pull complete | S274436c
```

# c. MONGODB SETUP

Before starting to analyze the dataset, the dataset is kept in a noSQL database i.e., MongoDB. So we installed the mongoDB using "sudo apt-get install mongodb".



After starting the mongoDB service, we checked the status using the "mongod" and "sudo systmectl status mongod", which was running.

Using the mongo shell I checked for databases available using "show dbs". I created the "i535\_final\_project" database dynamically in the code and created a collection "power consumption". Created user admin by using "use admin". After creating the user admin, I created my own account using db.createUser with user: rbhowmik, pwd: raj123 and roles:userAdminAnyDatabase.

I restarted mongodb to take the effect of new users and tested if it's opening with my credentials.

```
| International Control of Contro
```

# d. STEPS TAKEN TO ADDRESS THE PROBLEM

I installed MongoDB, Spark, and Anaconda to help me analyze the large dataset of Tétouan city power consumption. Using the parallel processing technique of PySpark i.e., Spark session, Spark Context and Spark SQL I garnered multiple insights from the data. I used transformations, filtering operations, string operations in my data. I generated new features for the data based on a particular threshold for the humidity and temperature features. I classified both the features as: low, medium, and high to classify zone wise power consumption and to check what is the count of humidity and temperature. I used MongoDB to store the data to store the data, so that it can be used to perform ETL in future. The reason for using NoSQL database because data might be unstructured in future, and we just generalized it for future use. Additionally, I implemented a Pipeline to perform one-hot encoding, vector assembler, string indexing and put a linear regression model (algorithm from SparkML library) to pass the pipeline to.

# 3. RESULTS

# Loading the data using MongoDB

#### Loading data into MongoDB

```
In [2]: import pymongo
import pandas as pd

In [3]: df = pd.read_csv('Tetuan City power consumption.csv')

In [4]: data = df.to_dict(orient="records")

In [3]: client_con = pymongo.MongoClient("mongodb://127.0.0.0:27017/")

In [5]: # Creating a Mongo DB "i335_final_project" using the MongoClient
db = client_con["i535_final_project"]

In [6]: # Creating a collections (table) in the db
table = db["power_consumption"]
```

Displaying the data and adding into the database

```
In [7]: # Data to be inserted into the mongo db
Out[7]: [{'DateTime': '1/1/2017 0:00',
               'Temperature': 6.559.
              'Humidity': 73.8,
              'Wind Speed': 0.083,
              'general diffuse flows': 0.051,
'diffuse flows': 0.119,
              'Zone 1 Power Consumption': 34055.6962,
            'Zone 2 Power Consumption': 16128.87538,
'Zone 3 Power Consumption': 20240.96386},
'DateTime': '1/1/2017 0:10',
'Tomestant': '1/1/2017 0:10',
               'Temperature': 6.414,
              'Humidity': 74.5,
              'Wind Speed': 0.083,
               'general diffuse flows': 0.07,
               'diffuse flows': 0.085,
              'Zone 1 Power Consumption': 29814.68354,
'Zone 2 Power Consumption': 19375.07599,
'Zone 3 Power Consumption': 20131.08434},
             {'DateTime': '1/1/2017 0:20',
In [8]: # Insert all the data into the database
           table.insert_many(data)
Out[8]: <pymongo.results.InsertManyResult at 0x7f968febfdc0>
```

### Checking one record and multiple records

```
In [9]: table.find one()
'Humidity': 73.8,
             'Wind Speed': 0.083,
             'general diffuse flows': 0.051,
'diffuse flows': 0.119,
             'Zone 1 Power Consumption': 34055.6962,
'Zone 2 Power Consumption': 16128.87538,
             'Zone 3 Power Consumption': 20240.96386}
In [14]: cnt = 0
            for i in table.find():
                while cnt < 5:
                     print(f'Row Number: {cnt}')
                     print(i)
                     print()
                break
            Row Number: 0
            {'_id': ObjectId('637977957c9505df93f08d94'), 'DateTime': '1/1/2017 0:00', 'Temperature': 6.559, 'Humidity': 73.8, 'Wind Speed
           ': 0.083, 'general diffuse flows': 0.051, 'diffuse flows': 0.119, 'Zone 1 Power Consumption': 34055.6962, 'Zone 2 Power Consumption': 16128.87538, 'Zone 3 Power Consumption': 20240.96386}
            Row Number: 1
           ('_id': ObjectId('637977957c9505df93f08d94'), 'DateTime': '1/1/2017 0:00', 'Temperature': 6.559, 'Humidity': 73.8, 'Wind Speed
': 0.083, 'general diffuse flows': 0.051, 'diffuse flows': 0.119, 'Zone 1 Power Consumption': 34055.6962, 'Zone 2 Power Consum
           ption': 16128.87538, 'Zone 3 Power Consumption': 20240.96386}
           {'_id': ObjectId('637977957c9505df93f08d94'), 'DateTime': '1/1/2017 0:00', 'Temperature': 6.559, 'Humidity': 73.8, 'Wind Speed': 0.083, 'general diffuse flows': 0.051, 'diffuse flows': 0.119, 'Zone 1 Power Consumption': 34055.6962, 'Zone 2 Power Consum
           ption': 16128.87538, 'Zone 3 Power Consumption': 20240.96386}
           general diffuse flows': 0.051, 'diffuse flows': 0.119, 'Zone 1 Power Consumption': 34055.6962, 'Zone 2 Power Consum
           ption': 16128.87538, 'Zone 3 Power Consumption': 20240.96386}
           ('_id': ObjectId('637977957c9505df93f08d94'), 'DateTime': '1/1/2017 0:00', 'Temperature': 6.559, 'Humidity': 73.8, 'Wind Speed ': 0.083, 'general diffuse flows': 0.051, 'diffuse flows': 0.119, 'Zone 1 Power Consumption': 34055.6962, 'Zone 2 Power Consumption': 16128.87538, 'Zone 3 Power Consumption': 20240.96386}
```

# Data cleaning with spark

- Changing the column names

### **Data cleaning using Spark**

```
## chaning column names

def withColumnRenamed(old:str, new: str): DataFrame

1 [40]: main_data = main_data.withColumnRenamed("Wind Speed","wind_speed")
    main_data = main_data.withColumnRenamed("general diffuse flows","general_diffuse_flows")
    main_data = main_data.withColumnRenamed("diffuse flows","diffuse_flows")
    main_data = main_data.withColumnRenamed("Zone 1 Power Consumption", "Zone_one_Power_Consumption")
    main_data = main_data.withColumnRenamed("Zone 2 Power Consumption", "Zone_two_Power_Consumption")
    main_data = main_data.withColumnRenamed("Zone 3 Power Consumption", "Zone_three_Power_Consumption")

1 [41]: main_data.createOrReplaceTempView('table')

1 [42]: main_data

Jt[42]: DataFrame[DateTime: string, Temperature: double, Humidity: double, wind_speed: double, general_diffuse_flows: double, diffuse_flows: double, Zone_one_Power_Consumption: double, Zone_three_Power_Consumption: double, Humidity_range: string, Temparature_range: string]
```

# Spark distributed processing

#### **Spark Context Initialization**

```
In [18]: from pyspark import SparkContext
          sc = SparkContext()
          Setting default log level to "WARN".
          To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
          22/11/20 20:43:42 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes w
          here applicable
In [19]: mongo_rdd = sc.textFile('Power_consumption.csv')
In [20]: mongo rdd.first()
Out[20]: 'DateTime,Temperature,Humidity,Wind Speed,general diffuse flows,diffuse flows,Zone 1 Power Consumption,Zone 2 Power Consumptio
          n, Zone 3 Power Consumption, Humidity_range, Temparature_range
In [21]: mongo_rdd.top(50)
Out[21]: ['DateTime,Temperature,Humidity,Wind Speed,general diffuse flows,diffuse flows,Zone 1 Power Consumption,Zone 2 Power Consumpti
         on, Zone 3 Power Consumption, Humidity_range, Temparature_range',
           9/9/2017 9:50,23.88,76.0,0.313,497.0,66.65,32724.95575,19788.77339,14920.69459,high_humidity,high_temperature'
           '9/9/2017 9:40,23.6,78.4,0.277,484.2,74.7,32419.11504,19511.85031,14779.48927,high_humidity,high_temperature'
            9/9/2017 9:30,23.29,80.6,0.283,329.2,75.6,31750.0885,19279.83368,14297.03779,high humidity,high temperature'
            9/9/2017 9:20,22.87,81.2,0.276,332.9,90.9,31291.32743,18778.37838,13955.79162,high humidity,high temperature
           9/9/2017 9:10,22.79,82.6,0.292,251.1,103.4,30628.67257,18636.17464,13861.65475,high_humidity,high_temperature
           '9/9/2017 9:00,22.58,83.1,0.286,278.4,110.4,29978.76106,18318.08732,13614.54545,high_humidity,high_temperature'
            '9/9/2017 8:50,22.37,84.0,0.257,232.9,94.5,29526.37168,17951.35135,13290.94995,high_humidity,high_temperature',
           '9/9/2017 8:40,21.99,84.2,0.289,156.0,95.4,28640.70796,17689.39709,13143.86108,high_humidity,high_temperature'
           '9/9/2017 8:30,21.7,84.2,0.271,110.6,83.2,28118.23009,17101.8711,12514.32074,high_numidity,high_temperature'
           '9/9/2017 8:20,21.28,84.5,0.283,81.2,62.83,27697.69912,16881.08108,12208.37589,high_humidity,high_temperature'
           '9/9/2017 8:10,20.95,84.2,0.285,74.1,59.08,27360.0,16375.88358,11961.2666,high_humidity,high_temperature',
'9/9/2017 8:00,20.65,84.1,0.285,62.89,46.47,26869.38053,16102.7027,11267.00715,high_humidity,high_temperature'
           '9/9/2017 7:50,20.35,84.1,0.309,54.36,41.05,26181.23894,15818.29522,11478.81512,high_humidity,high_temperature'
           '9/9/2017 7:40,20.13,84.5,0.283,42.39,31.48,25843.53982,15769.64657,11214.05516,high_humidity,high_temperature'
           '9/9/2017 7:30,19.93,84.7,0.352,27.04,19.94,25818.0531,15324.32432,11061.08274,high_humidity,medium_temperature'
            9/9/2017 7:20,19.81,85.2,0.359,16.34,11.97,25149.02655,15032.43243,11261.1236,high_humidity,medium_temperature'
           '9/9/2017 7:10,19.76,85.4,0.355,5.641,4.475,24543.71681,14744.28274,11166.98672,high_humidity,medium_temperature
            '9/9/2017 7:00,19.78,86.0,0.307,2.892,2.271,24002.12389,14545.94595,11108.15117,high_humidity,medium_temperature'
           '9/9/2017 6:50,19.68,86.2,0.352,1.078,0.896,23709.02655,14317.67152,10696.30235,high_humidity,medium_temperature'
            9/9/2017 6:40,19.68,86.4,0.301,0.263,0.211,23492.38938,14167.98337,10661.00102,high humidity,medium temperature',
            9/9/2017 6:30,19.85,87.2,0.328,0.102,0.126,23352.21239,14048.23285,10684.53524,high_humiditý,medium_temperature'
           9/9/2017 6:20,19.87,87.3,0.334,0.08,0.137,23460.53097,13902.2869,10643.35036,high_humidity,medium_temperature'
           9/9/2017 6:10,19.84,87.6,0.329,0.091,0.107,23466.90265,13891.06029,10690.41879,high humidity,medium temperature'
    In [22]: mongo_rdd.take(10)
    Out[22]: ['DateTime,Temperature,Humidity,Wind Speed,general diffuse flows,diffuse flows,Zone 1 Power Consumption,Zone 2 Power Consumpti
              on, Zone 3 Power Consumption, Humidity_range, Temparature_range
               1/1/2017 0:00,6.559,73.8,0.083,0.051,0.119,34055.6962,16128.87538,20240.96386,high_humidity,low_temperature',
               '1/1/2017 0:10,6.414,74.5,0.083,0.07,0.085,29814.68354,19375.07599,20131.08434,high_humidity,low_temperature',
'1/1/2017 0:20,6.313,74.5,0.08,0.062,0.1,29128.10127,19006.68693,19668.43373,high_humidity,low_temperature',
               '1/1/2017 0:30,6.121,75.0,0.083,0.091,0.096,28228.86076,18361.09422,18899.27711,high_humidity,low_temperature',
                '1/1/2017 0:40,5.921,75.7,0.081,0.048,0.085,27335.6962,17872.34043,18442.40964,high_humidity,low_temperature'
                1/1/2017 0:50,5.853,76.9,0.081,0.059,0.108,26624.81013,17416.41337,18130.12048,high_humidity,low_temperature
               '1/1/2017 1:00,5.641,77.7,0.08,0.048,0.096,25998.98734,16993.31307,17945.06024,high_humidity,low_temperature',
                '1/1/2017 1:10,5.496,78.2,0.085,0.055,0.093,25446.07595,16661.39818,17459.27711,high_humidity,low_temperature'
               '1/1/2017 1:20,5.678,78.1,0.081,0.066,0.141,24777.72152,16227.35562,17025.54217,high_humidity,low_temperature']
```

# Mapreduce jobs steps

```
In [23]: ## Mapreduce jobs
         mongo data rdd word counts = mongo rdd.flatMap(lambda line: line.split()).map(lambda m: (m[1:], 1)).reduceByKey(lambda x, y: x+y
In [24]: # mapreduce operations
         mongo_data_rdd_word_counts.collect()
          ':40,5.921,75.7,0.081,0.048,0.085,27335.6962,17872.34043,18442.40964,high_humidity,low_temperature',
          (':50,5.853,76.9,0.081,0.059,0.108,26624.81013,17416.41337,18130.12048,high_humidity,low_temperature',
          -',
(':10,5.496,78.2,0.085,0.055,0.093,25446.07595,16661.39818,17459.27711,high_humidity,low_temperature',
          (':20,5.678,78.1,0.081,0.066,0.141,24777.72152,16227.35562,17025.54217,high_humidity,low_temperature',
          (':30,5.491,77.3,0.082,0.062,0.111,24279.49367,15939.20973,16794.21687,high_humidity,low_temperature',
          (':40,5.516,77.5,0.081,0.051,0.108,23896.70886,15435.86626,16638.07229,high_humidity,low_temperature'
          (':50,5.471,76.7,0.083,0.059,0.126,23544.3038,15213.37386,16395.18072,high_humidity,low_temperature',
          (':10,4.968,78.8,0.084,0.07,0.134,22329.11392,14710.0304,15822.6506,high_humidity,low_temperature',
          (':30,4.897,79.1,0.083,0.07,0.096,21903.79747,14104.55927,15597.10843,high_humidity,low_temperature',
           1),
In [25]: # A few map reduce operations
        row = mongo_rdd.flatMap(lambda y:y.split(' '))
In [26]: row.collect()
          '1/1/2017
          '10:10,5.836,71.3,2.66,257.9,31.01,25920.0,15837.08207,14428.91566,high_humidity,low_temperature',
          '1/1/2017'
          '10:20,5.996,69.85,4.93,282.7,31.96,26393.92405,16059.57447,14671.80723,high_humidity,low_temperature',
          '10:30,6.22,68.81,4.924,307.0,32.42,26861.77215,16322.18845,15036.14458,high_humidity,low_temperature',
          '10:40,6.703,68.01,4.923,327.6,33.22,27511.89873,16774.46809,15267.46988,high_humidity,low_temperature',
          '1/1/2017'
          '11:00,7.54,64.21,4.916,371.1,33.43,28714.93671,17507.59878,15591.3253,high_humidity,low_temperature',
          '11:10,8.22,61.9,4.916,388.2,33.89,29043.03797,17478.41945,15816.86747,high_humidity,low_temperature',
          '1/1/2017'
          '11:20,9.49,59.3,2.451,401.3,34.4,29261.77215,17792.09726,15932.53012,medium_humidity,low_temperature',
```

# Creating new features from existing data

Humidity\_range and Temperature\_range are the two new attributes created from our power consumption dataset based on a threshold of humidity and temperature as shown in screenshot below.

```
In [11]: for i in data format.Humidity:
             if i < 40:
                 data_format.loc[data_format['Humidity']==i, "Humidity_range"]= "less_humidity"
              elif 40 < i <60:
                 data_format.loc[data_format['Humidity']==i, "Humidity_range"]= "medium_humidity"
                  data_format.loc[data_format['Humidity']==i, "Humidity_range"]= "high_humidity"
In [12]: data_format.Humidity_range.value_counts()
Out[12]: high_humidity
                            37717
          medium_humidity 11939
          less_humidity
         Name: Humidity_range, dtype: int64
In [13]: data_format['Temperature'].describe()
Out[13]: count 52416.000000
                    18.810024
         mean
                      3.247000
         25%
                    14.410000
                    18.780000
22.890000
         50%
                     40.010000
         Name: Temperature, dtype: float64
In [14]: for i in data_format.Temperature:
    if i < 10:</pre>
                 data_format.loc[data_format['Temperature']==i, "Temparature_range"]= "low_temperature"
              elif 10 < i <20:
                 data_format.loc[data_format['Temperature']==i, "Temparature_range"]= "medium_temperature"
                  data_format.loc[data_format['Temperature']==i, "Temparature_range"]= "high_temperature"
```

# **SPARK SESSION**

Showing the count of humidity range

#### **Spark Session Builder**

Plotting the humidity range

### Showing the count based on temperature range

### Plotting the temperature range

# **SPARK SQL**

 Selecting the Date, wind\_speed and diffusion flows based on humidity range and also printing the schema to show the datatypes of the attributes.

```
In [43]: spark.sql("SELECT DateTime,wind_speed, general_diffuse_flows FROM table WHERE Humidity_range == 'less_humidity'").show()
                 DateTime|wind_speed|general_diffuse_flows|
          |1/16/2017 15:20|
|1/16/2017 15:30|
                                  0.0831
                                  0.082
          1/16/2017 15:40
                                  0.085
                                                           332.8
          1/16/2017 15:50
           1/16/2017 16:00
                                  0.084
                                                           253.6
          |1/24/2017 12:10|
|1/24/2017 12:20|
                                  0.086
                                                           520.2
                                  0.089
                                                           532.1
          1/24/2017 12:30
                                  0.087
                                                           540.7
           1/24/2017 12:40
                                  0.089
                                                           546.5
           1/24/2017 12:50
                                  0.089
                                                           553.5
          11/24/2017 13:00
                                  0.091
                                                           559.0
          1/24/2017 13:10
                                  0.089
                                                           559.4
           1/24/2017 13:20
                                  0.092
                                                           560.4
          1/24/2017 13:30
                                   0.09
          1/24/2017 13:40
1/24/2017 13:50
                                  0.086
                                                           558.4
                                  0.091
                                                           555.6
          1/24/2017 14:00
                                  0.088
                                                           552.8
           1/24/2017 14:10
          1/24/2017 14:20
                                  0.087
                                                           534.8
          1/24/2017 14:30
                                  0.088
                                                           526.1
          only showing top 20 rows
In [44]: main_data.printSchema()
            |-- DateTime: string (nullable = true)
           |-- Temperature: double (nullable = true)
            -- Humidity: double (nullable = true)
            -- wind_speed: double (nullable = true)
            -- general_diffuse_flows: double (nullable = true)
|-- diffuse_flows: double (nullable = true)
            |-- Zone_one_Power_Consumption: double (nullable = true)
|-- Zone_two_Power_Consumption: double (nullable = true)
            -- Zone_three_Power_Consumption: double (nullable = true)
            -- Humidity_range: string (nullable = true)
           |-- Temparature_range: string (nullable = true)
```

### **BUILDING THE PIPELINE**

Using the one-hot encoder, string indexer and Vector Assembler. Splitting the data in training: 70% and testing: 30%

#### **Pipeline**

Calling the Linear regression model from pyspark.ml.regression package and fitting it into the Pipeline.

```
In [83]: from pyspark.ml.regression import LinearRegression
lr = LinearRegression(featuresCol = 'features', labelCol='Zone_one_Power_Consumption', maxIter=10, regParam=0.3, elasticNetParam=0.3

In [77]: from pyspark.ml import Pipeline
pipeline = Pipeline(stages=[consumption_string_index,consumption_encoder, temp_string_index, temp_encoder,vector_assembler,lr])
```

### Increasing the storage level of spark

```
In [79]: ##Increasing storage
         from pyspark import StorageLevel
         main_data.persist(StorageLevel.MEMORY_AND_DISK)
Out[79]: DataFrame[DateTime: string, Temperature: double, Humidity: double, wind_speed: double, general_diffuse_flows: double, diffuse_f
         lows: double, Zone_one_Power_Consumption: double, Zone_two_Power_Consumption: double, Zone_three_Power_Consumption: double, Hum
         idity_range: string, Temparature_range: string]
In [80]: ## persist on train data
         train_df.persist(StorageLevel.MEMORY_AND_DISK_2)
Out[80]: DataFrame[DateTime: string, Temperature: double, Humidity: double, wind_speed: double, general_diffuse_flows: double, diffuse_f
         lows: double, Zone_one_Power_Consumption: double, Zone_two_Power_Consumption: double, Zone_three_Power_Consumption: double, Hum
         idity_range: string, Temparature_range: string]
In [81]: ## Fitting into the pipeline
         model = pipeline.fit(train df)
         22/11/20 21:41:24 WARN RandomBlockReplicationPolicy: Expecting 1 replicas with only 0 peer/s.
         22/11/20 21:41:24 WARN BlockManager: Block rdd_111_1 replicated to only 0 peer(s) instead of 1 peers
         22/11/20 21:41:25 WARN RandomBlockReplicationPolicy: Expecting 1 replicas with only 0 peer/s.
         22/11/20 21:41:25 WARN BlockManager: Block rdd_111_0 replicated to only 0 peer(s) instead of 1 peers
In [85]: lr preds = model.transform(test df)
```

Prediction results and accuracy score

```
In [91]: lr_preds.select("prediction","Zone_one_Power_Consumption","features").show()
         +-----
                 prediction|Zone_one_Power_Consumption|
         29867.38501774147
                                     28228.86076 [6.121,75.0,0.083...
         29267.857992253554
                                            27335.6962 [5.921,75.7,0.081...
         25527.566468874382
                                          25275.94937 [5.124,73.7,0.076...
         25743.027123896234
                                               25920.0 | [5.836,71.3,2.66,...
                                           28714.93671 [7.54,64.21,4.916...
         27353.837927290442
                                           29261.77215 [9.49,59.3,2.451,...
         28524.423428672246
          30861.39611967553
                                           30258.22785 [15.57,58.06,0.07...
         30784.356380480596
                                           30404.05063 | [15.65,58.7,0.077...
         30375.312984203414
                                           30021.26582 | [15.79,56.66,0.07...
                                            29747.8481 [15.74,55.56,0.07...
           30057.61258644868
           29987.24830998185
                                           29571.64557 [15.64,57.26,0.07...
           29531.60925038769
                                           28885.06329 [15.39,57.6,0.075...
         29958.752650120743
                                           29097.72152 [15.47,58.23,0.07..
           30426.17605446363
                                            29723.5443 | [15.44,59.07,0.07...
                                           35793.41772 [15.11,59.53,0.07...
           36676.14467805445
           38449.39257826359
                                           39560.50633 [14.48,63.27,0.08...
           38673.47811033991
                                            39991.89873 [12.51,68.35,0.07...
         38923.246956238305
                                           40210.63291 [12.06,70.2,0.078...
          27296.58155992644
                                           24777.72152 | [5.678,78.1,0.081...
                                            23544.3038 [5.471,76.7,0.083...]
         26171.000304555437
         only showing top 20 rows
n [186]: pl = lr_preds.select("prediction","Zone_one_Power_Consumption","features").toPandas()
In [94]: from pyspark.ml.evaluation import RegressionEvaluator linear_evaluator = RegressionEvaluator(predictionCol="prediction", labelCol="Zone_one_Power_Consumption",metricName="r2")
In [96]: print("R_squared on test data = ",linear_evaluator.evaluate(lr_preds))
         R squared on test data = 0.8210994201793973
```

### AI FAIRNESS

AI fairness on our dataset to check for bias in the data using the bias\_variance\_decomposition library

Bias removal values before and after decomposition

```
In [159]: print('Average bias:',bias)
    Average bias: 9282674.22084863
In [156]: 1_mse, 1_bias, 1_var = bias_variance_decomp(lasso, X_train, y_train, X_test, y_test,loss='mse', num_rounds=500, random_seed=43)
In [158]: print('Average bias:',1_bias)
    Average bias: 9282667.116623234
```

# 4. **DISCUSSIONS**

Loaded the dataset Tétouan city power consumption into MongoDB, in "i535\_final\_project" database. Using spark context, we read the file in the spark rdd and performed few map-reduce jobs to check for word count. Using the groupby function of spark we grouped the humidity range and temperature range and found the count of high humidity is maximum, whereas the count of medium temperature is maximum. From **Fig.1** we can infer that the points where the color is darker humidity was more, and 38000 units of power was consumed when temperature hit maximum i.e., 40.

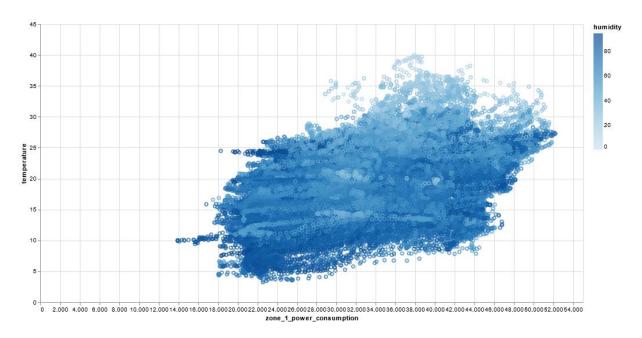


Fig.1: Zone one power consumption

From **Fig.2** we can see that humidity is high where temperature was low. And the points are darker when humidity is low and temperature is high and we can see that the power consumption is 36000 where humidity is 60.

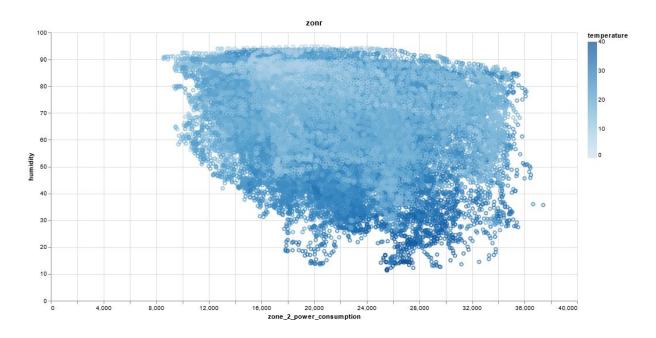


Fig.2: Zone two power consumption

Additionally, for zone two we can see the humidity range and their range of power consumption.

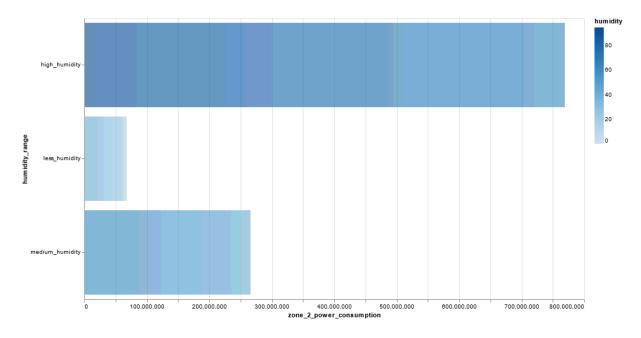
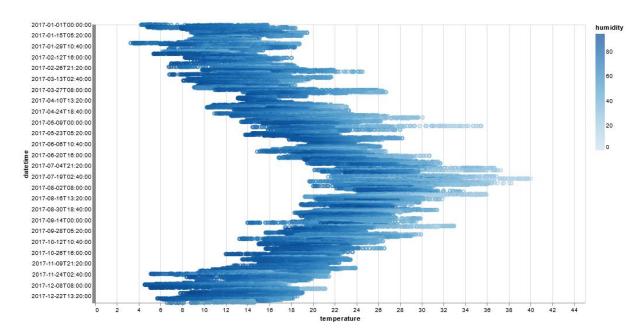


Fig.3 Zone two power consumption vs Humidity range

To see the temperature variations for a year we tried to verify the data and saw that in the month of January the temperature is low and it increases in June and July, and decreases as it approaches December. As it's a Time series data we can see a trend and a seasonality.



As the data didn't have any null values and the datatypes were proper, we went ahead and built a pipeline. We used the string indexer of pyspark to map our "humidity\_range" and "temperature\_range" columns, which are categorical column to map to ML column of label indices. Post that we used the one hot encoder to encode the categorical column and used the vector assembler on our final features. Following we defined a Linear Regression model and passed the model and features to our pipeline.

We predicted the values for zone one, and it gave us a good prediction result with r2 score of 82%.

As my data didn't have any privileged category or protected category, I removed the bias for the AI Fairness part. By using the "bias\_variance\_decomposition" of scikit learn library I removed the bias form the entire data. Using lasso regularization, the bias decrement is achieved.

### **BARRIERS/PROBLEM FACED**

I had a problem with my VM, where my VM was crashing. The stability was achieved by closing Firefox and restarting it. The MongoDB wasn't running, then I

restarted using my credentials, which worked fine. While working with my dataset, the SQL queries weren't working due to the spaces in the column names. Once I changed the column names using Spark, it worked fine. I visualized the data using Chart builder, which was very slow, but unfortunately there was no workaround it. So, visualizations took some time.

### **SKILLS FROM THIS COURSE**

Virtualization: I used Jetstream to create VM and finish my project in ubuntu.

**Ingest and Storage**: I used MongoDB as my storage to store my data.

**Processing and Analytics**: My analysis was Spark based. So, I used Spark RDD, Spark SQL, MapReduce operations and data preprocessing using Spark

Lifecycles and Pipelines: I created a Pipeline and fit my prediction model into it.

# 5. CONCLUSION

In this project I implemented a lot of things, right from storing data into a NoSQL database. I also created two features which gave us the range of humidity and temperature, based on which we saw the power consumption of all the three zones. I have predicted the power consumption of zone one and other prediction for zone two and three can be determined and based on natural occurrences of temperature and, wind speed, humidity etc. they can predict the overall power consumption which provides intelligence utilities and helps them to improve their systems' performance in terms of productivity and effectiveness.

### 6. REFERENCES

- [1] A Comparison Study of Machine Learning Methods for Energy Consumption Forecasting in Industry Mouad Bahij, M. Labbadi, M. Cherkaoui, Chakib Chatri, S. Lakrit
- [2] https://medium.com/analytics-vidhya/calculation-of-bias-variance-in-python-8f96463c8942
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[5] https://spark.apache.org/docs/3.1.1/api/python/reference/api/pyspark.SparkContext.html#pyspark.SparkContext