CSEE5590/490: Big Data Programming

Increment 2

Project Title: Energy Demand Analysis in Spain

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Introduction:

Forecasting in energy markets is one exceedingly helpful tool in making the transition to a renewable-based electrical infrastructure (Rolnick et al, 2019). By improving forecasting, we can also increase the efficiency of a power grid and help reduce the usage of peak demand on power plants, which are generally less efficient than their counterparts. While the short-term results have the potential to improve 24-hour and hour-by-hour predictions, this work also has the potential predict energy prices for consumers.

Background:

The data is collected from the five largest cities in Spain: Madrid, Barcelona, Valencia, Seville, and Bilbao between the years of 2015 and 2019. This data has the ability to impact every community that uses an electrical grid. Not only is it advantageous at the individual level to be able to predict the cost of an electric bill, but it is also extremely helpful to be able to predict energy usage at a macro level as communities across the globe begin to make the transition to renewable energies in response to climate change. As stated in the introduction, forecasting in energy markets is an exceedingly helpful tool in making the transition to a renewable-based electrical infrastructure (Rolnick et al, 2019).

Goals and Objectives:

- Motivation:
 - Forecasting in energy markets is one exceedingly helpful tool in making the transition to a renewable-based electrical infrastructure, as stated in "Tackling Climate Change with Machine Learning" (see resources for link to paper). Our goal is to demonstrate this by leveraging Big Data analysis tools on a dataset that consists of energy usage and weather data for five large cities in Spain.
- Significance:
 - o Predict energy usage to increase efficiency of electrical production
 - o Predict energy price
 - o Locate areas that would benefit from renewable energies
- Objectives:
 - Predict energy usage based on the weather
 - o Predict energy prices by:
 - Time of day
 - Day of the week
 - Time of year
 - o Analyze the factors that affect the fluctuations in energy usage, as well as the sources of energy
- Features:

- o dt_iso (datetime index localized to CET)
- o generation biomass (in MW)
- o generation fossil brown coal/lignite (in MW)
- o generation fossil coal-derived gas (in MW)
- o generation fossil gas (in MW)
- generation fossil hard coal (in MW)
- o generation fossil oil (in MW)
- o generation fossil oil shale (in MW)

- generation fossil peat (in MW)
- o generation geothermal (in MW)
- o city_name
- o temp (in kelvin)
- o temp_min (in kelvin)
- o temp_max (in kelvin)
- o pressure (in hPa)
- o humidity (in %)
- o wind_speed (in m/s)
- wind_deg (wind direction)
- o rain_1h (rain in last hour in mm)

Dataset

Our dataset is comprised of two .csv files:

- o weather_features.csv contains information about the weather
- o energy_dataset.csv contains information about the production, price, and variation of energy resources

The two files can be joined by a timestamp. The dataset can be found on Kaggle with the heading "Hourly energy demand generation and weather". See resources for link.

Features Developed:

This section is dedicated to the features developed in this increment, and a guide to the files within the team repo.

HiveQL: (Wes)

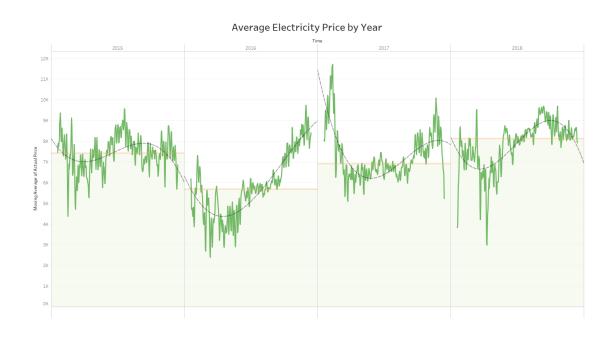
During a past class our professor mentioned using Graphs in this project and as soon as I heard that I knew I wanted to use Tableau to visualize some key aspects of the data, not only to learn more about it but to show key findings.

With the data already loaded from the previous Increment I took to asking some questions about the data and then visualizing the data to see what was interesting about it. Because we are dealing with trends of prices over time, that was a key aspect that I wanted to be able to visualize. Using Tableau I could add some extra visuals without having to calculate, such as trend lines for each particular year. Looking at the Average Electricity Price per Year Graph we can see there are clear lows and highs between the years, which will require some further investigation as to why those trends exist

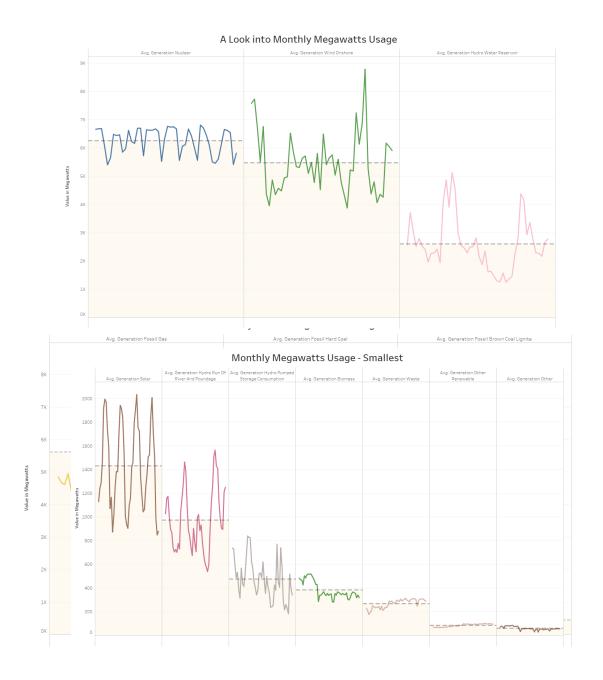
With a wide dataset, part of what I wanted to accomplish this Increment was to determine what columns had interesting and worthwhile data and what columns could be more or less ignored. By writing a large HiveQL query that included summary statistics over time, it would allow us to look for trends and determine which were worth investigating further. All separate Megawatts Usage graphs were trends I found interesting enough to highlight, and all others within the dataset I left ignored from the graphs and queries

Something I wanted to see was not only trends over months and years, but just over the course of a day. Specifically the average prices over different times of day. The Prices by Hour of Day Graph shows that there is a fluctuation of the cost throughout the course of the day. This is to be expected and the highs and lows also match times that make sense for what time most people will be working and most people will be sleeping

With the 5 different cities in the dataset I wanted to explore the quantitative difference between the locations and see if there was any interesting information that varied between them. Well, the answer was that there isn't, but this wasn't an unfortunate discovery it was a happy one! This

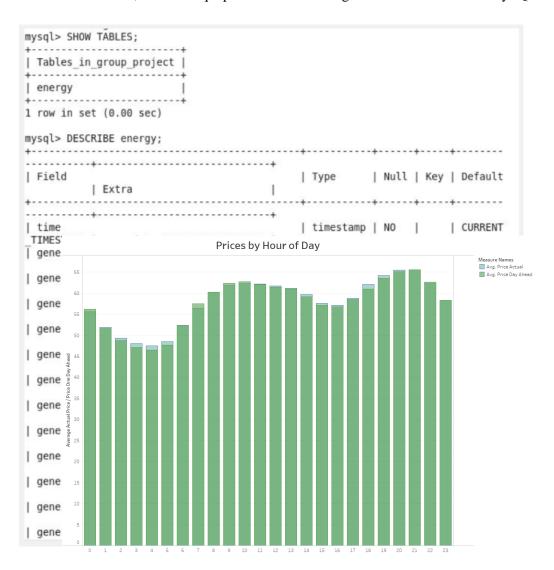


means that these prices were being fairly priced between all of the different locations within the region, meaning that the pricing is independent of location which was a good thing to learn.



Sqoop: (Shelby)

Within Cloudera, we used Sqoop to transfer the merged dataset from Hive to mySQL.



mySQL: (Claire)

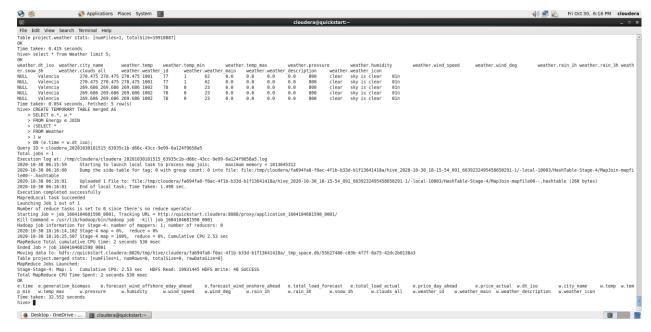
So Basically, my aim was to import our dataset into mysql and see what queries I can run to get information from this dataset. While working on this, I did realize most of the columns were hard for me to interpret what their values mean and how they were related to each other. That is one of the aspects I will have to focus on so it's easier for me to decide on what to get out of this data.

Importing dataset to mysql

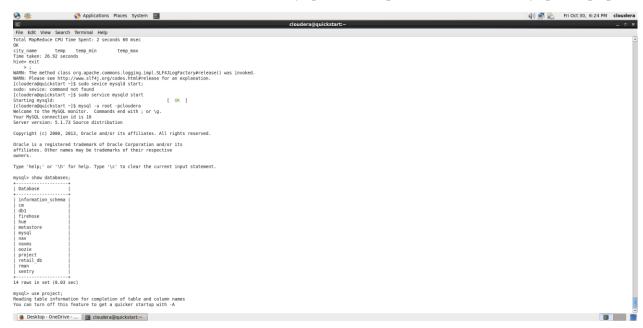
First I had to create a table in HIVE, import the dataset from hdfs to hive

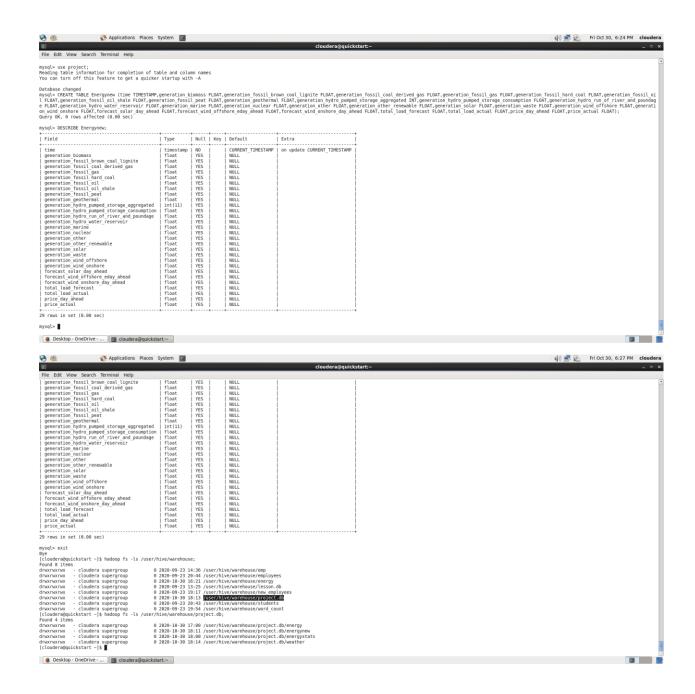






One thing I noticed was some of my columns returned NULL values and I tried fixing this by making sure ROW DELIMITERS was set but this didn't help at all. Secondly I had to create a table with similar columns in mysql so I can export data from hive to mysql via sqoop

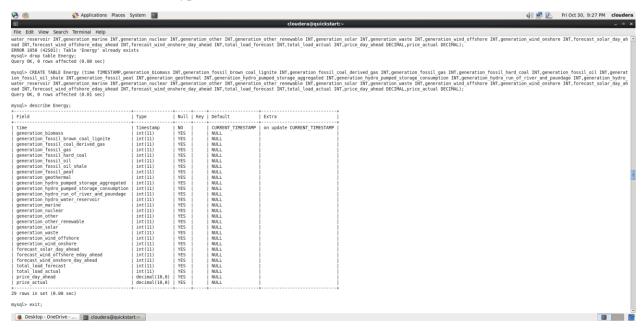




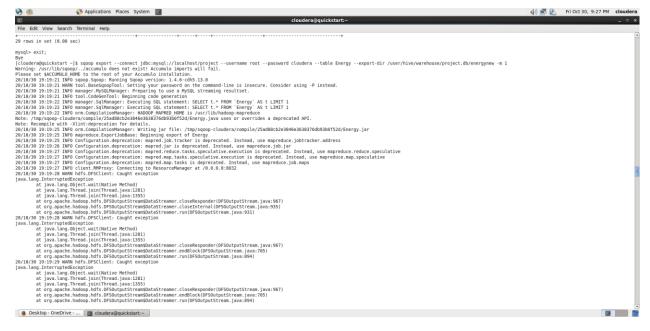
I succeeded to create a table in mysql which matched that in hive, Now the next step is to import the data from hive into mysql so I can run some queries



Unfortunately, this process kept failing, so I had to recreate my tables and made sure I used the correct datatypes.



That didn't work either.



For my future work with MySQL, I plan to:

- Find out why imported data in hive has NULL columns and fix
- Successfully move data into mysql and run queries to see relationships that exists amongst these columns

MapReduce: (Scott)

Starting with the basics in MapReduce I wanted to get some descriptive statistics for each column in our dataset. Fortunately, our dataset makes this easy since nearly all the columns are of the same type. Since I only have one datatype to worry about, I can get away with creating only one reducer to find the mean, min, and max. Each row is split up by column and written to the reducer with the field name as the key.

I wish to calculate a few more descriptive statistics, such as the median, quartiles, standard deviation, and variance but found them difficult to calculate due to the nature of MapReduce. I believe I can overcome a few of these limitations by using a secondary sort, changing the algorithm used to calculate the statistic or only calculating an approximation. In addition, I also want experiment with joining the weather dataset to start doing some complex grouping. A mapper-side join currently is not be possible without some preprocessing since the datasets are different lengths and some rows may be missing from the energy dataset.

```
💹 cloudera@quickstart:~/project/Energy_Demand_Analysis/MapReduce/output
[cloudera@quickstart output]$ cat job_output.log
20/10/30 04:27:44 INFO mapreduce.Job: map 0% reduce 0%
20/10/30 04:27:58 INFO mapreduce.Job: map 100% reduce 0%
20/10/30 04:28:17 INFO mapreduce.Job: map 100% reduce 100%
20/10/30 04:28:17 INFO mapreduce.Job: Job job_1604032870144_0008 completed successfully
20/10/30 04:28:17 INFO mapreduce.Job: Counters: 49
         File System Counters
                   FILE: Number of bytes read=28038648
                   FILE: Number of bytes written=56365263
                   FILE: Number of read operations=0
                   FILE: Number of large read operations=0
                   FILE: Number of write operations=0
                   HDFS: Number of bytes read=6062761
                   HDFS: Number of bytes written=2170
                   HDFS: Number of read operations=6
                   HDFS: Number of large read operations=0
                   HDFS: Number of write operations=2
         Job Counters
                   Launched reduce tasks=1
                   Data-local map tasks=1
                   Total time spent by all maps in occupied slots (ms)=10581
                   Total time spent by all reduces in occupied slots (ms)=15436
                   Total time spent by all map tasks (ms)=10581
                   Total time spent by all reduce tasks (ms)=15436
Total vcore-milliseconds taken by all map tasks=10581
                   Total vcore-milliseconds taken by all reduce tasks=15436
Total megabyte-milliseconds taken by all map tasks=10834944
Total megabyte-milliseconds taken by all reduce tasks=15806464
         Map-Reduce Framework
                   Map input records=35065
                   Map output records=911263
                   Map output bytes=26216116
                   Map output materialized bytes=28038648
                   Input split bytes=136
                   Combine input records=0
                   Combine output records=0
                   Reduce input groups=26
                   Reduce shuffle bytes=28038648
                   Reduce input records=911263
                   Reduce output records=26
                   Spilled Records=1822526
                   Shuffled Maps =1
                   Failed Shuffles=0
                   Merged Map outputs=1
                   GC time elapsed (ms)=221
                   CPU time spent (ms)=18370
                   Physical memory (bytes) snapshot=714465280
Virtual memory (bytes) snapshot=3139694592
Total committed heap usage (bytes)=643825664
                   BAD ID=0
                   CONNECTION=0
                   IO ERROR=0
                   WRONG_LENGTH=0
                  WRONG_MAP=0
WRONG REDUCE=0
         File Input Format Counters
                  Bytes Read=6062625
         File Output Format Counters
                   Bytes Written=2170
[cloudera@quickstart output]$
```

Cassandra: (Shelby)

Because joins aren't possible in Cassandra, it was necessary to keep the two tables separate. Furthermore, since Cassandra operates by a query-first approach, I created several tables within Cassandra such that each table was designed for a specific query. Though it did result it duplication of data, this design is good for high-load queries that usually happened in big data. The insights gleaned from these queries seemed rather unhelpful compared to the query capabilities of HQL and mySQL. Whereas HQL/mySQL can perform direct analysis on the data (such as calculating averages, join functions, etc.), it seems like there would have to be some secondary analysis step performed with any data returned from a Cassandra query.

'Cassandra Tables Creation.cql' – This file contains the script that was used to create and load data into five different Cassandra tables. Because the data is just text, the class used was SimpleStrategy. A replication factor of 3 was arbitrarily decided upon.

'Cassandra Queries.cql' – This file contains the queries used for each table. The result of the queries was stored into a unique txt file.

'Cassandra Results" – This folder contains the results of the five .cql queries used for each of the Cassandra tables, as well as screenshots of the successfully created tables.

```
cqlsh:group_project> DESCRIBE TABLES;
energy_by_price_actual temp_by_time_and_city energy_renewable_by_time
energy_fossil_by_time weather_by_time
```

dt_iso	temp	city_name	clouds_all	humidity	pressure	rain_1h	rain_3h	snow_3h	temp_max	temp_min	weather_description	weather_icon	weather_id	weather_main	wind_deg	wind_speed
2018-05-31 12:00:00.000000+0000	292.04001	Bilbao	75	68	1018	0	0	0	293.14999	291.14999	broken clouds	04d	803	clouds	40	2
2018-05-31 12:00:00.000000+0000	295.32999	Madrid	40	43	1018	0			297.14999	293.14999	scattered clouds	03d	802	clouds	220	2
2018-05-31 12:00:00.000000+0000	296.14999	Barcelona		57	1017	0			297.14999	295.14999	few clouds	02d	801	clouds	130	5
2018-05-31 12:00:00.000000+00000	298.32999	Seville		34	1017	0				297.14999	sky is clear	01d	800	clear	300	2
2018-05-31 12:00:00.000000+0000	299.14999	Valencia		39	1016	0			299.14999	299.14999	few clouds	02d	801	clouds	100	4
2016-12-20 20:00:00.0000000+00000	276.26001	Madrid		70	1024	0				274.14999	sky is clear	01n	800	clear	340	2
	280.51999	Bilbao	88	100	1026	0.3				279.14999	light rain	10n	500	rain	9	1
2016-12-20 20:00:00.000000+0000		Valencia		70	1021	0				282.14999	sky is clear	01n	800	clear	300	3
2016-12-20 20:00:00.000000+00000		Barcelona		87	1020	0.3	9				light intensity shower rain	09n	520	rain	9	0
	283.20999	Seville	0	93	1025	0	0	0		278.14999	sky is clear	01n	800	clear		0
2015-01-08 19:00:00.000000+0000		Madrid	0	65	978	0	0			269.29401	sky is clear	01n	800	clear		1
2015-01-08 19:00:00.000000+0000		Bilbao		88	1041	0	0			275.10599	broken clouds	04	803	clouds		1
2015-01-08 19:00:00.000000+0000		Valencia	0	83	1040	0	9	0		276.95001	sky is clear	01n	800	clear	294	1
2015-01-08 19:00:00.000000+0000		Seville	9	90	1046	0	Θ	0	278.944	278.944	sky is clear	01n	800	clear	54	3
2015-01-08 19:00:00.000000+0000		Barcelona	0	60	1036	0	0	0		283.45001	sky is clear	01n	800	clear		2
	293.95001	Bilbao		88	1021	0.3	ө	Θ		293.14999	light rain	10n	500	rain	290	1
2018-07-07 17:00:00.000000+0000		Barcelona		54	1018	0	0	0		298.14999	few clouds	02n	801	clouds	0	1
2018-07-07 17:00:00.000000+0000		Valencia	9	74	1018	9	9	θ		299.14999	sky is clear	01n	800	clear	120	1
	301.67001	Madrid	0	24	1017	0	0	0		300.14999	sky is clear	01n	800	clear	270	2
2018-07-07 17:00:00.000000+0000	302.32999	Seville	9	31	1014	9	9	0	304.14999	301.14999	sky is clear	01n	800	clear	230	4

Project Management:

- Work completed:
 - Description: We have analyzed our dataset using Hive, mySQL, MapReduce, and Cassandra, as well as created some preliminary data visualizations.
 - Contributions:
 - Claire: mySQL queries (20%)
 - Wes: Hive table creation, HQL queries, visualizations (30%)
 - Scott: MapReduce queries (25%)
 - Shelby: Sqoop transfer from Hive to mySQL, Cassandra analysis, report composition (25%)
- Work to be completed:
 - o Description: For our next increment, we will utilize Spark to gain more insights about our data.
 - o Concerns: IntelliJ/Scala can be finicky, and some members of our group are using PySpark instead. It will be a challenge to coordinate our efforts when our setups are not the same.

Assignment 2 Questions:

- Who:
 - This dataset is about the people who use energy in Spain, whose energy production and grid was sampled for this dataset. There is no identifiable information on the individual level, meaning that there is little personal risk with this dataset.
- What:
 - The energy usage and sources of energy production of the people of Spain are what is being recorded by the data set. This addresses all of our questions in Assignment 1.
- When:
 - This data was collected between 2015 2019, meaning that the data is recent and therefore relevant. It is cross-sectional since the data was collected from several cities in Spain. This dataset contains real-time data.
- Where:
 - The data is collected from the five largest cities in Spain: Madrid, Barcelona, Valencia, Seville, and Bilbao. It could possible be extrapolated that the energy usage would be similar in the surrounding European countries with similar populations and weather as these five cities, and it is certainly possible that larger generalizations about predicting energy usage could be used for non-European locations.
- Why:
 - The data was collected by ENTSOE, a public portal for Transmission Service Operator (TSO) data and is publicly available.

References:

"Tackling Climate Change with Machine Learning"

https://arxiv.org/abs/1906.05433

"Hourly energy demand generation and weather – Electrical demand, generation by type, prices and weather in Space"

 $\frac{https://www.kaggle.com/nicholasjhana/energy-consumption-generation-prices-and-weather?select=weather_features.csv$

"Chapter 4. The Cassandra Query Language"

https://www.oreilly.com/library/view/cassandra-the-definitive/9781491933657/ch04.html

"Defining Application Queries"

https://cassandra.apache.org/doc/latest/data modeling/data modeling queries.html

"LanguageManual Select"

https://cwiki.apache.org/confluence/display/Hive/LanguageManual+Select

MapReduce:

https://nestedsoftware.com/2018/03/27/calculating-standard-deviation-on-streaming-data-2531.23919.html

https://hadoop.apache.org/docs/r2.6.0/api/org/apache/hadoop/mapred/lib/ChainMapper.html

https://hadoop.apache.org/docs/r2.6.0/api/org/apache/hadoop/mapred/lib/ChainReducer.html

https://hadoop.apache.org/docs/r2.6.0/api/org/apache/hadoop/mapred/Mapper.html

https://hadoop.apache.org/docs/r2.6.0/api/org/apache/hadoop/mapred/Reducer.html

https://hadoop.apache.org/docs/r2.6.0/api/org/apache/hadoop/mapreduce/Job.html

https://hadoop.apache.org/docs/r2.6.0/api/org/apache/hadoop/io/package-summary.html