

Python I - Group Assignment

IE MBD – Group B

Alan Haro, Jesús Fuster, Joao Ferris, Marilyn González,
Muriel Vergara, Sergio Ospina, Vignesh Viswanathan,
Zara Amer





Assignment Objectives

#01 /Concepts

- > Review and understand the **pandas concepts**

#02 /Exercise

- > Practice our **pandas coding skills** through a **practical exercise**

#03 /Group Work

- > Strengthen **abilities to work in group** in a coding context

#04 /Presentation Skills

- > Reinforce our **coding presentation skills**



We are working with an energy dataset



Date & Time

Specifies year, month, day, and hour of each data point



Energy Production

Hourly data of energy production (nuclear, gas, solar, hydro, coal, and wind) in Spain



Energy Demand

Hourly data of energy consumption in Spain



Spot Price

Hourly data for energy spot price in Spain



Q1 – Assigning strings to keys



ASK

Convert the **weekday column** in from a **number** to a **string**



Logic of approach

- 1) **Create dictionary** assigning **day name** to **corresponding integer** type key
- 2) **Map the dictionary** to get the **weekday names**



Conclusions

```
0 -----> Monday
1 -----> Tuesday
2 -----> Wednesday
3 -----> Thursday
4 -----> Friday
5 -----> Saturday
6 -----> Sunday
```



In [1]

```
energy_n["weekday"] = energy_n["weekday"].map(lambda x: weekday_name[x])
```

Q2 – Assigning strings to keys (2)



ASK

Convert **month column** from a **number to a string**



Logic of approach

- 1) **Create dictionary** assigning **month name** to **corresponding integer** type key
- 2) **Map the dictionary** to get the month names



Conclusions

```
0 -----> January
1 -----> February
2 -----> March
3 -----> April
4 -----> May
5 -----> June
6 -----> July
7 -----> August
8 -----> September
9 -----> October
10 -----> November
11 -----> December
```



In [2]

```
energy_n["month"] = energy_n["month"].map(lambda x: month_name[x])
```

Q3 – % unique days with at least 1 hr with $P < € 10$



ASK

Find **percentage of unique days** in the total period in which at **least one hour with a price $< €10$**



Logic of approach

- 1) Extract **unique dates** that **meet condition**
- 2) Find **total unique days**, then **required %**
- 3) Calculate **% of days** where **stock price $< €10$**



Conclusions

- 1) **16 days** with at least 1 hr with **stock price $< €10$**
- 2) **% of unique days** that meet condition: **4.38%**



```
In [3] print('percentage of unique days was', unique_days / total_days * 100, '%')
```

Q4 – # hours/month with P (<) & (>) Monthly P Avg



ASK

How many **hours per month**, in average, do we have a **price above** the **monthly average**? And **below**?



Logic of approach

- 1) **Group by month** to compute **monthly avg price**
- 2) Find for **how many hours** in **each month** the **spot price** is **above (below)** **monthly price avg.**



Conclusions

- 1) **11 / 12** months: more hours with **P above** **than** with P below monthly avg
- 2) Month with:
 - highest **# hours above -Mar** (66%)
 - highest **# hours below - Sep** (50%)



In [4]

```
energy_final = pd.merge (energy_hours_above_avg, energy_hours_below_avg, left_on =  
'month_year', right_on = 'month_year')
```



Q4 – # hours/month with P (<) & (>) Monthly P Avg

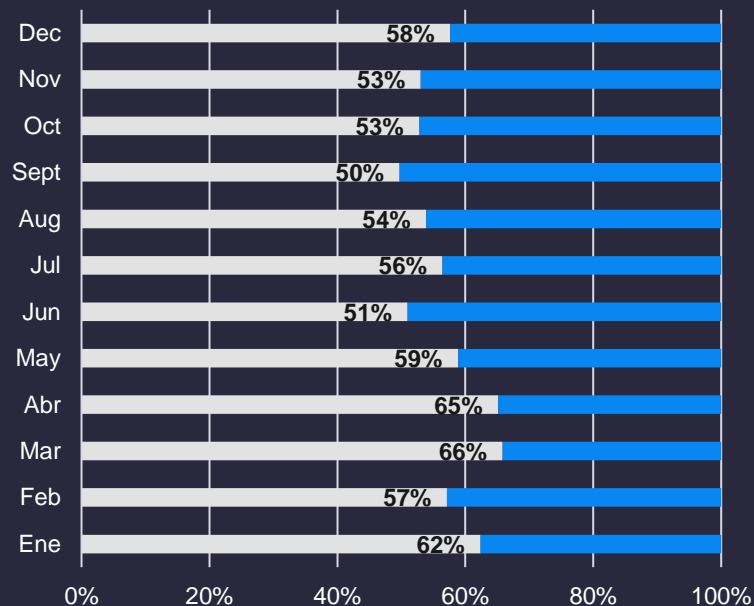
total hours above & below monthly price avg

	count_hours_above_avg	count_hours_below_avg
month_year		
2019-01	464	280
2019-02	384	288
2019-03	490	254
2019-04	469	251
2019-05	438	306
2019-06	367	353
2019-07	420	324
2019-08	401	343
2019-09	358	362
2019-10	393	351
2019-11	382	338
2019-12	415	305

% Hours above & below monthly price avg

■ Above Mean

■ Below Mean



Q5.1 – Gas generation vs Wind Generation



ASK

Is **gas generation** **higher or lower** than its **hr avg** when **wind generation > its hr avg**.



Logic of approach

- 1) Find **hr avg. of wind** and **gas production**
- 2) **Filter** using data points where **wind production > hr avg**
- 3) Find **data points: gas production higher / lower** than hr avg.



Conclusions

Higher 748 hrs

Lower 2864 hrs

% of higher gas generation 20.7 %



In [5]

```
energy_new.loc[:, 'H/L'] = np.where(energy_new.loc[:, 'gas'] > energy_new["gas_avg"], 'Higher', 'Lower')
```

Q5.2 – Spot Price vs Solar generation



ASK

Is the **spot_price** **higher or lower** than its **hr avg.** when **solar generation** is **above** its **hr avg**?



Logic of approach

- 1) Find **hr avg. of solar production** and of **spot_price**
- 2) **Filter** using data points were **solar production > hr avg**
- 3) Find **data points: spot_price higher / lower** than hr avg.



Conclusions

# Higher	1497 hrs
# Lower	1502 hrs
% of higher spot_price vs. hr mean	49.9 %



In [5]

```
energy_new.loc[:, 'H/L'] = np.where(energy_new.loc[:, 'spot_price'] > energy_new  
["spot_price_avg"], 'Higher', 'Lower')
```

Q5.3 – Gas generation vs Wind Generation



ASK

Is the **spot_price** **higher or lower** than its **monthly avg.** when **power_demand** is **above** its **monthly avg**?



Logic of approach

- 1) Find **monthly avg. of: power and spot_price**
- 2) **Filter** using data points where **power demands > monthly avg**
- 3) Find **data points: spot_price higher / lower** than hr avg.



Conclusions

# Higher	3521 hrs
# Lower	988 hrs
% of higher spot_price vs. monthly mean	78.1 %



```
In [5] energy_new.loc[:, 'H/L'] = np.where(energy_new.loc[:, 'spot_price'] > energy_new  
["spot_price_avg"], 'Higher', 'Lower')
```

Q6.1 – Avg. Contribution of each energy type



ASK

Finding the **average contribution** of **each energy type** during the whole period?



Logic of approach

- 1) **Sum** the **mean of each energy type**
- 2) **Divide energy sums by whole energy mean**



Conclusions



27%



12%



25%



5%



4%



26%

**In [6]**

```
energy_mean_per = energy_sums/sum_energy_mean
```

Q6.2 – Avg. Contribution of each energy type in \$ month



ASK

Finding the % **average contribution** of **each energy type** in most expensive month?



Logic of approach

- 1) We **index** the **month column** to **find** the **most expensive month**
- 2) Find **average usage** of **energy type** within **given month**



Conclusions

January 2019



25%



11%



16%



16%



2%



30%

In [6]

```
max_energy_sum = ((energy_sum.groupby(["month_year"])["power_demand"].sum()).idxmax())
```

Q6.3 – Avg. Contribution of each energy type in \$ month



ASK

Finding the % **average contribution** of **each energy type** in cheapest month?



Logic of approach

- 1) We **index** the **month column** to **find** the **cheapest month**
- 2) Find **average usage** of **energy type** within **given month**



Conclusions

December 2018



33%



18%



17%



10%



0%



21%

In [6]

```
min_energy_sum = ((energy_sum.groupby(["month_year"])["power_demand"].sum()).idxmin())
```

Q8 – Weekend vs. Weekdays



ASK

How **much expensive** in average is a **weekend** day compared to a **weekday**?



Logic of approach

- 1) **Categorize** data as **weekday** or **weekend**
- 2) **Filter** and **sum means** of weekdays and weekends
- 3) **Find difference** between both means



Conclusions

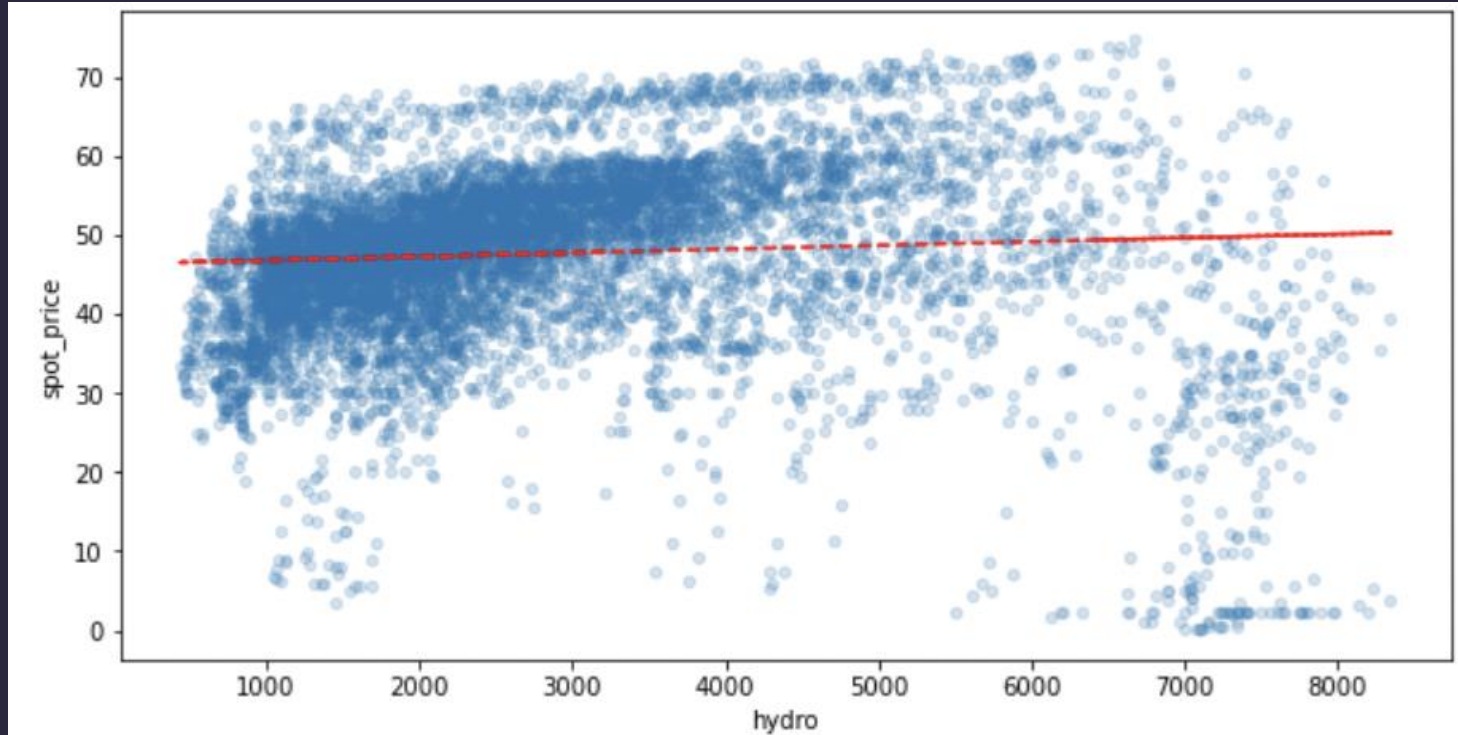
\$ Weekdays € 49.17

\$ Weekends € 44.04

Cost difference € -5.13

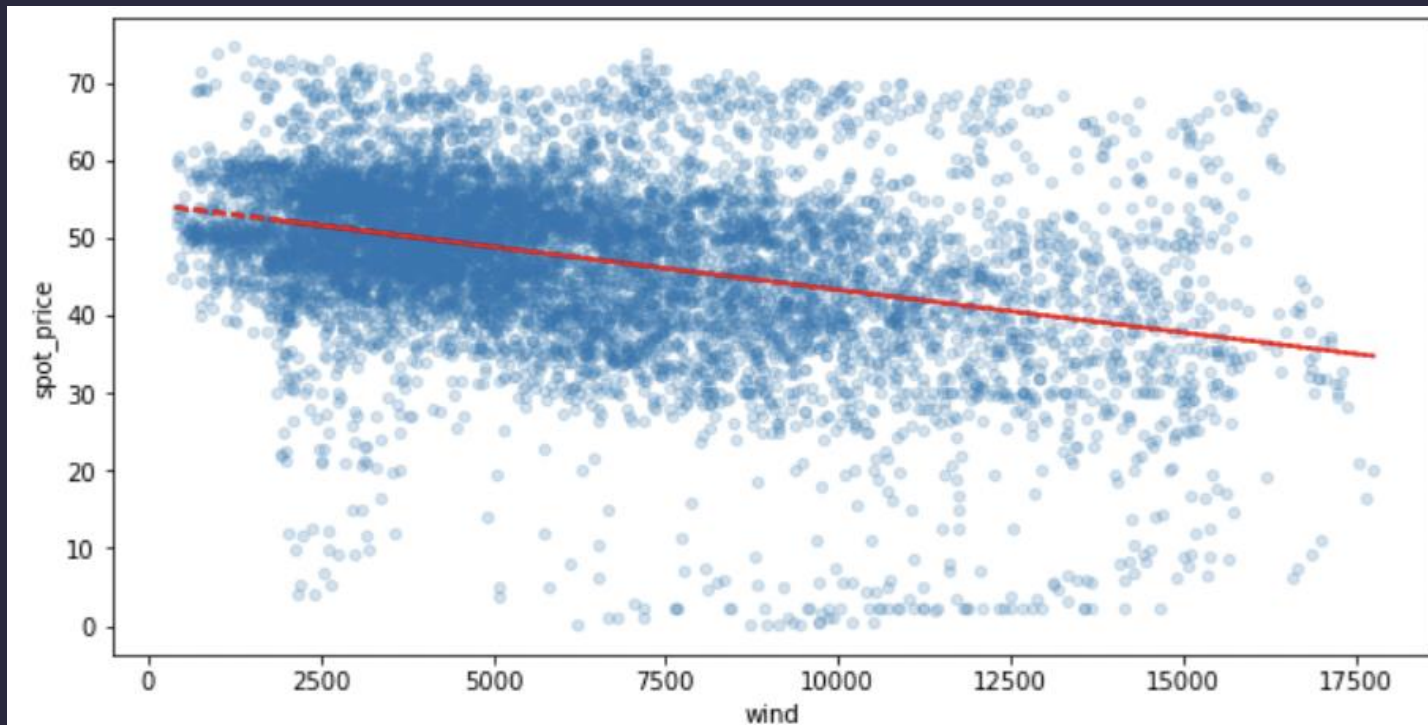
```
In [8] cost_difference = energy_weekend_filter_mean - energy_weekday_filter_mean
```

Q7.1 – Hydro Power vs Electricity Price



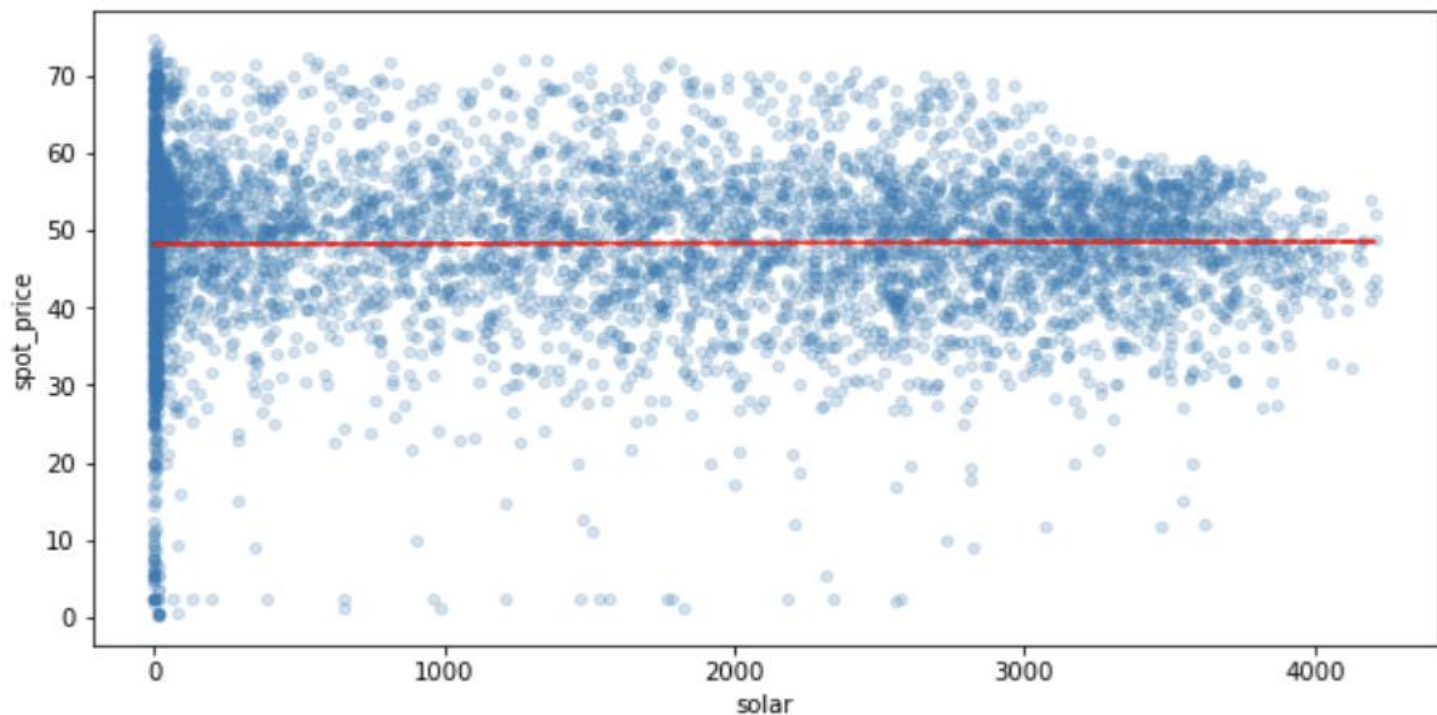
slope is = 0.04734649226076858

Q7.2 – Wind Power vs Electricity Price



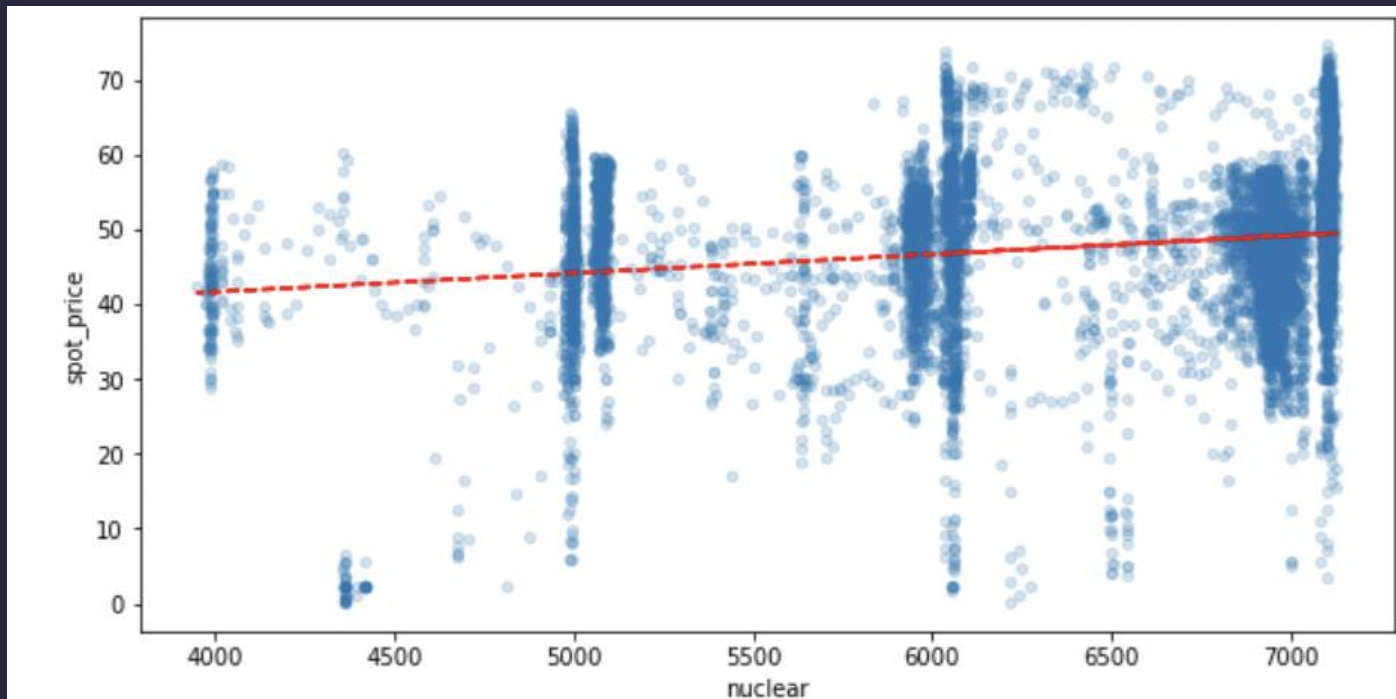
slope is = -0.11039973631887327

Q7.3 – Solar Power vs Electricity Price



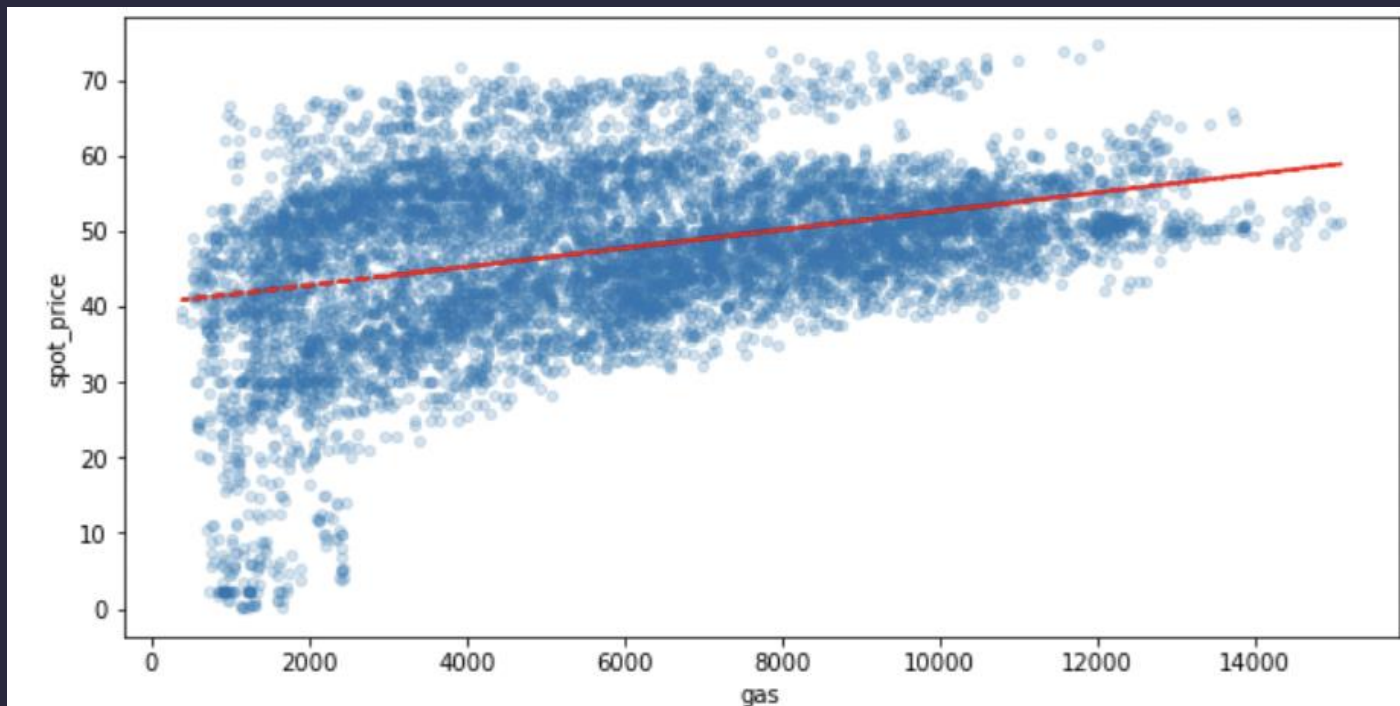
slope is = 0.007394602967425727

Q7.4 – Nuclear Power vs Electricity Price



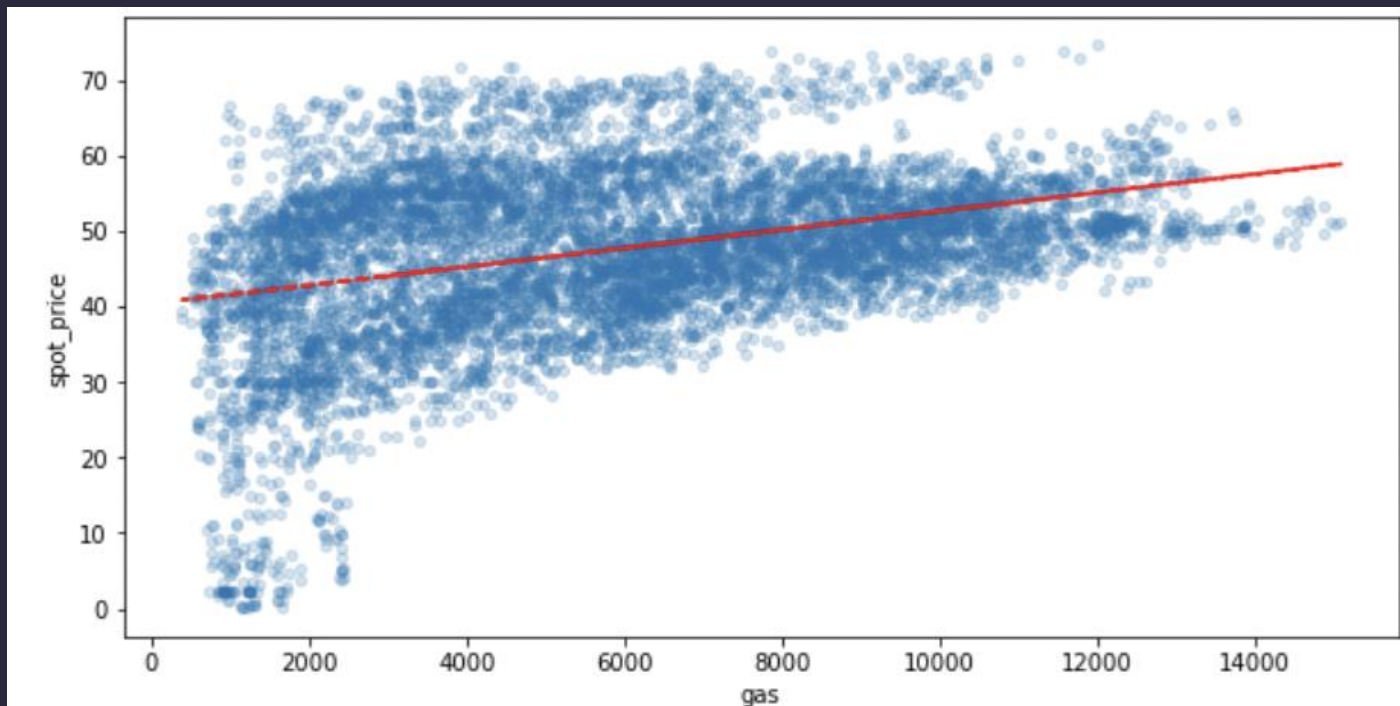
slope is = 0.25212678765476504

Q7.5 – Gas Power vs Electricity Price



slope is = 0.12298848041110276

Q7.6 – Coal Power vs Electricity Price



slope is = 0.12298848041110276



**Print (“WHOA! What a great
presentation from group B”)**

