Introduction

La transition énergétique et la gestion de l'énergie représentent des enjeux sociétaux et actuels.

Par ailleurs, la transition numérique, les nouvelles technologies et la science des données constituent des leviers pour relever ces défis.

Aussi, je porte un fort intérêt pour tous ces domaines (science des données, énergie) ; et j'aimerais, par mon travail, participer à l'effort collectif pour les accélerer, les améliorer.

C'est pourquoi je réalise ce petit projet, en autonomie (pas dans le cadre de mes cours), d'exploration et d'analyse d'une base de données sur la production d'énergie solaire.

Références

J'ai trouvé le jeu de données sur kaggle : https://www.kaggle.com/datasets/stucom/solar-energy-power-generation-dataset

En plus d'utiliser les bases techniques et méthodologiques que j'ai pu acquérir en cours, j'essai également d'apprendre à l'aide de différentes ressources en ligne.

En voici certaines : https://www.youtube.com/watch?v=jCYjcEaNfzc&list=PLXf2gx1SC6EI2QYKjekXc4AvaReogmW8X

In [1]:
```
import numpy as np
import pandas as pd
import datetime as dt
import seaborn as sns
import matplotlib.pyplot as plt
```

Import and visualize the file

In [44]:
```
#Import and modify the data
FILE = "sol_pow_gen.csv"
data = pd.read_csv(FILE)

print(data.shape)

#As we dont have a column with standard date type values (Year, month, day an
#Double brackets here data[["Year", "Month", "Day"]] to make a data frame
data.insert(5, "datetime", pd.to_datetime(data[["Year", "Month", "Day"]]) + p

#The columns Year, Month, Day and First Hour are no longer needed and are rea
data = data.drop(["Year", "Month", "Day", "First Hour of Period"], axis=1)

#We want degrees celsius not F
data["Average Temperature (Day)"] = round((data["Average Temperature (Day)"]


data.head()
```

```
(2920, 16)
```

Out[44]:

	Day of Year	datetime	Is Daylight	Distance to Solar Noon	Average Temperature (Day)	Average Wind Direction (Day)	Average Wind Speed (Day)	Sky Cover	Visibility	Rel Hun
0	245	2008-09-01 01:00:00	False	0.859897	20.56	28	7.5	0	10.0	
1	245	2008-09-01 04:00:00	False	0.628535	20.56	28	7.5	0	10.0	
2	245	2008-09-01 07:00:00	True	0.397172	20.56	28	7.5	0	10.0	
3	245	2008-09-01 10:00:00	True	0.165810	20.56	28	7.5	0	10.0	
4	245	2008-09-01 13:00:00	True	0.065553	20.56	28	7.5	0	10.0	

In [45]:

```
#We can check that the data types are all convenient here
data.dtypes
```

Out[45]:

```
Day of Year                              int64
datetime                        datetime64[ns]
Is Daylight                               bool
Distance to Solar Noon                 float64
Average Temperature (Day)              float64
Average Wind Direction (Day)             int64
Average Wind Speed (Day)               float64
Sky Cover                                int64
Visibility                             float64
Relative Humidity                        int64
Average Wind Speed (Period)            float64
Average Barometric Pressure (Period)   float64
Power Generated                          int64
dtype: object
```

In [46]:

```
#Let's explore the data with .describe()
data.describe(datetime_is_numeric=True)
```

Out[46]:

	Day of Year	datetime	Distance to Solar Noon	Average Temperature (Day)	Average Wind Direction (Day)	Average Wind Speed (Day)	Sky C
count	2920.000000	2920	2920.000000	2920.000000	2920.000000	2920.000000	2920.00
mean	183.334247	2009-03-02 11:30:00	0.503294	14.704877	24.953425	10.096986	1.98
min	1.000000	2008-09-01 01:00:00	0.050401	5.560000	1.000000	1.100000	0.00
25%	92.000000	2008-12-01 06:15:00	0.243714	11.670000	25.000000	6.600000	1.00

	Day of Year	datetime	Distance to Solar Noon	Average Temperature (Day)	Average Wind Direction (Day)	Average Wind Speed (Day)	Sky C
50%	183.000000	2009-03-02 11:30:00	0.478957	15.000000	27.000000	10.000000	2.00
75%	275.000000	2009-06-01 16:45:00	0.739528	17.220000	29.000000	13.100000	3.00
max	366.000000	2009-08-31 22:00:00	1.141361	25.560000	36.000000	26.600000	4.00
std	105.769919	NaN	0.298024	3.800963	6.915178	4.838185	1.4

In [53]:
```
#Getting the full range of times
date_range = pd.date_range(start = "2008-09-01 01:00:00", end = "2009-08-31 2

#Checking if this corresponds to our data
assert (date_range == data["datetime"]).all()

#Checking if we have duplicates
data.duplicated().sum()

#Checking for missing value
data.isna().sum().sum()
```

Out[53]: 1

In [ ]:
```
#It would be interesting to see if the timeperiods with no daylight striclty
#As we can see there are none, so to train a model to predict the energy outp

data[(data["Is Daylight"] == False)&(data["Power Generated"] != 0)] #empty da
#(data[(data["Is Daylight"] == False)]["Power Generated"] != 0).any()


data_light = data[data["Is Daylight"] == True].drop("Is Daylight", axis=1)

data_light.head()
```

Out[ ]:

	Day of Year	datetime	Distance to Solar Noon	Average Temperature (Day)	Average Wind Direction (Day)	Average Wind Speed (Day)	Sky Cover	Visibility	Relative Humidity	Ave S (Pe
2	245	2008-09-01 07:00:00	0.397172	20.56	28	7.5	0	10.0	70	
3	245	2008-09-01 10:00:00	0.165810	20.56	28	7.5	0	10.0	33	
4	245	2008-09-01 13:00:00	0.065553	20.56	28	7.5	0	10.0	21	
5	245	2008-09-01 16:00:00	0.296915	20.56	28	7.5	0	10.0	20	

	Day of Year	datetime	Distance to Solar Noon	Average Temperature (Day)	Average Wind Direction (Day)	Average Wind Speed (Day)	Sky Cover	Visibility	Relative Humidity	Ave S (Pe
6	245	2008-09-01 19:00:00	0.528278	20.56	28	7.5	0	10.0	36	

In [105…
```
#As we can see, daylight doesn't guarantee energy production
data_light[data_light["Power Generated"] == 0]
```

Out[105…

	Day of Year	datetime	Distance to Solar Noon	Average Temperature (Day)	Average Wind Direction (Day)	Average Wind Speed (Day)	Sky Cover	Visibility	Relative Humidity
150	263	2008-09-19 19:00:00	0.567347	17.22	21	7.3	4	10.0	81
214	271	2008-09-27 19:00:00	0.586592	18.89	29	9.1	0	10.0	73
222	272	2008-09-28 19:00:00	0.589060	16.11	30	12.3	1	10.0	87
238	274	2008-09-30 19:00:00	0.594633	18.33	29	6.9	1	10.0	68
254	276	2008-10-02 19:00:00	0.598862	19.44	27	9.5	3	10.0	87
…	…	…	…	…	…	…	…	…	…
2521	194	2009-07-13 04:00:00	0.568156	21.11	28	10.6	1	10.0	86
2529	195	2009-07-14 04:00:00	0.568156	22.78	30	10.4	1	10.0	72
2635	208	2009-07-27 10:00:00	0.159251	16.11	29	14.2	1	10.0	70
2818	231	2009-08-19 07:00:00	0.387376	18.33	30	8.6	4	10.0	84
2898	241	2009-08-29 07:00:00	0.396178	23.33	29	12.4	1	10.0	66

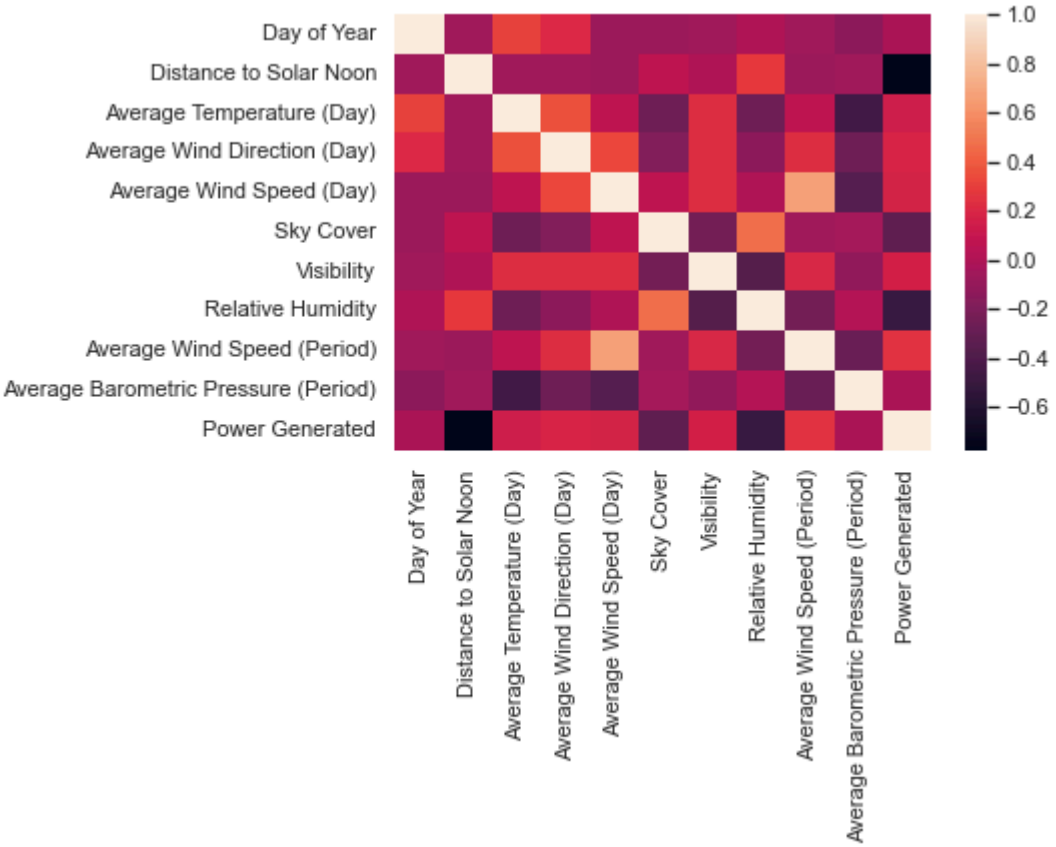
205 rows × 12 columns

In [ ]:
```
#Let's try and see if there are any correlated variables
corr_mat = data_light.corr()

sns.set_theme()
sns.heatmap(corr_mat)
```

```
#We are interested in the variables strongly correlated with the Power Genera
#As we can see, Distance to solar noon is strongly negatively correlated with
```

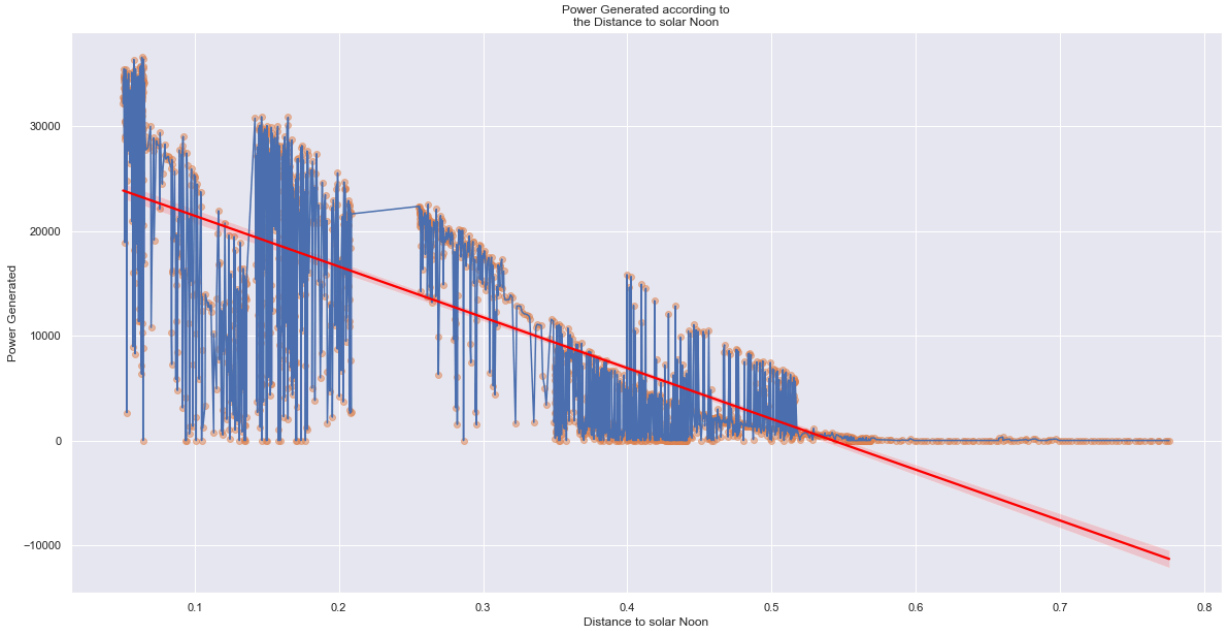
Out[ ]: <AxesSubplot:>



In [128…

```
#We can try and plot it to see if we can spot any trend
pow_gen = data_light.sort_values(by="Distance to Solar Noon")[["Power Generat
dist_sol = data_light.sort_values(by="Distance to Solar Noon")["Distance to S

plt.figure(figsize=(20, 10))
plt.plot(dist_sol, pow_gen)
sns.regplot(x=dist_sol, y=pow_gen, scatter_kws={'alpha':0.5}, line_kws={'colo
plt.title("Power Generated according to\nthe Distance to solar Noon")
plt.xlabel("Distance to solar Noon")
plt.ylabel("Power Generated")
plt.show()
```



In [ ]:

```
#Modèle demandé à ChatGPT, je vérifie s'il est pertinent (les lignes signalée
from statsmodels.tsa.arima.model import ARIMA

crop_data = data[0:len(data)-10]        #Vérification : on fait un jeu de don

# Définir l'ordre du modèle (AR, I, MA)
model = ARIMA(crop_data["Power Generated"], order=(2,1,2))
model_fit = model.fit()

# Prédire les prochaines valeurs
predictions = model_fit.forecast(steps=10)
print(predictions)
print(data[-10:]["Power Generated"])   #Vérification

#On constate que cette méthode n'est pas adaptée, ou bien il faudrait tester
```

```
/Users/matt/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/statesp
ace/sarimax.py:966: UserWarning: Non-stationary starting autoregressive param
eters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
/Users/matt/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/statesp
ace/sarimax.py:978: UserWarning: Non-invertible starting MA parameters found.
Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
2910     -488.798207
2911    -2702.367639
2912     5309.438869
2913    12590.991205
2914    13746.700673
2915    10655.147542
2916     7681.058415
2917     7110.494356
2918     8298.502918
2919     9510.280748
Name: predicted_mean, dtype: float64
2910      895
2911        0
2912        0
2913        0
2914      464
2915     6995
2916    29490
```

```
2917    17257
2918      677
2919        0
Name: Power Generated, dtype: int64
```