Data Science for water consumption forecasting and anomaly detection

Nouamane Arhachoui

In this notebook, you will find:

1. The way I have proceeded to predict the water consumption of a building based on its past data.
2. How to detect anomalies in order to alert people in the building.

In [1]:
```
import numpy as np
import pandas as pd
from sklearn.metrics import mean_squared_error, mean_absolute_error
from prophet import Prophet
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('fivethirtyeight')
```

1. Water consumption prediction

Step 1: understand the Dataset

In [2]:
```
data = pd.read_csv('water-consumption.csv', index_col='timestamp', parse_dates=True)
```

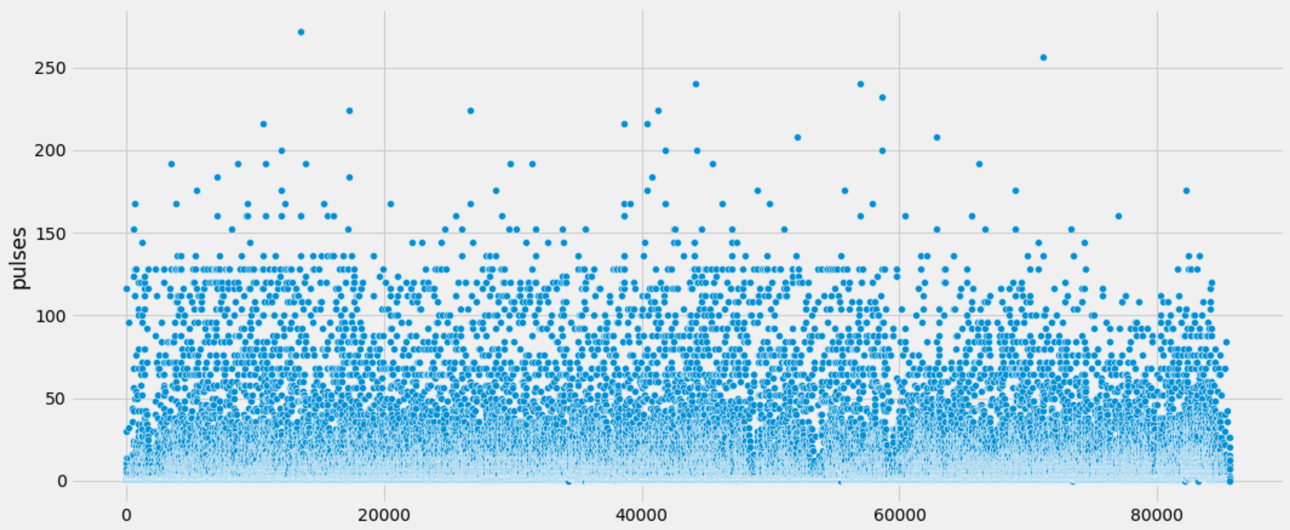
In [3]:
```
data
```

Out[3]:

	pulses
timestamp	
2019-12-25 11:10:17	0
2019-12-25 11:16:17	0
2019-12-25 11:22:17	0
2019-12-25 11:28:20	0
2019-12-25 11:34:20	0
...	...
2020-12-23 09:59:22	20
2020-12-23 10:05:22	9
2020-12-23 10:11:22	0
2020-12-23 10:17:22	12
2020-12-23 10:23:22	7

85592 rows × 1 columns

In [4]:
```
plt.figure(figsize=(16,7))
sns.scatterplot(x=np.arange(len(data.pulses)), y=data.pulses)
plt.show()
```



In [5]:
```
data.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
pulses	85592.0	7.16914	18.227112	0.0	0.0	0.0	5.0	272.0

First of all, looking at the scatter plot and the values above, I can notice that the pulses are measured aproximately every 6 minutes and that most of the time the pulse equals to zero.

By trying to do the prediction the first time, it was really bad because of this, so I decided to resample the dataset by considering the sum for each hour. Then, I've normalized the dataset in order to have values between 0 and 1 because, without doing this, the gaps between the maximum and most of the other values were very high.

In [6]:
```
data = data.resample('H').sum()
```

In [7]:
```
def normalize(x):
    return x/x.max()
```

In [8]:
```
data = data.apply(normalize)
```

In [9]:
```
data
```

Out[9]:

	pulses
timestamp	
2019-12-25 11:00:00	0.198680
2019-12-25 12:00:00	0.001466
2019-12-25 13:00:00	0.006598
2019-12-25 14:00:00	0.000000
2019-12-25 15:00:00	0.022727
...	...
2020-12-23 06:00:00	0.003666
2020-12-23 07:00:00	0.014663
2020-12-23 08:00:00	0.023460
2020-12-23 09:00:00	0.054985
2020-12-23 10:00:00	0.020528

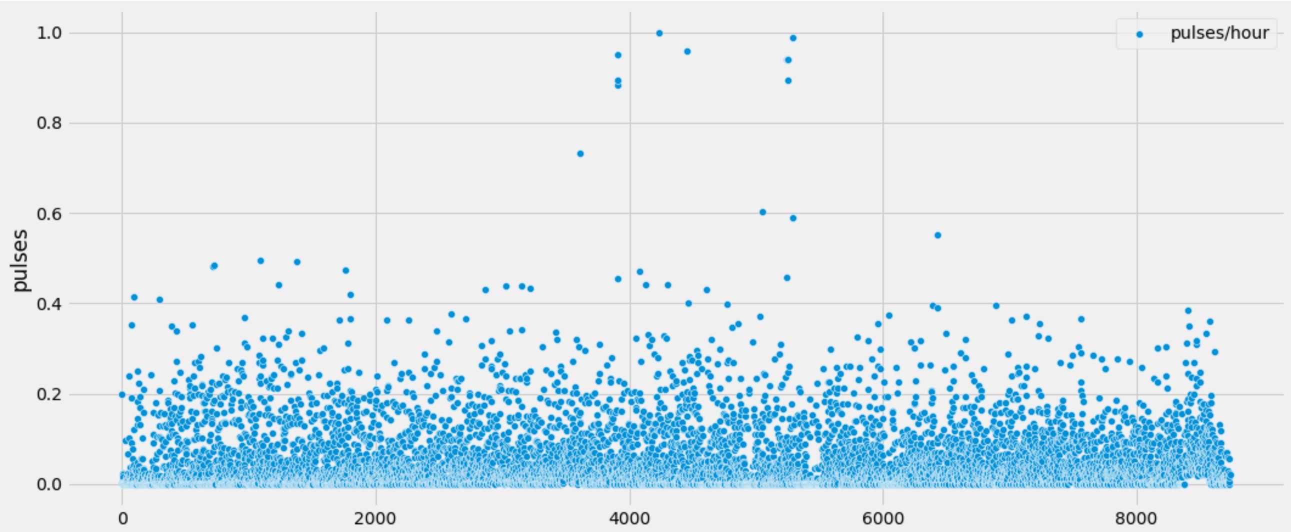
8736 rows × 1 columns

In [10]:
```
data.describe().T
```

Out[10]:

	count	mean	std	min	25%	50%	75%	max
pulses	8736.0	0.051496	0.075457	0.0	0.002199	0.024194	0.069648	1.0

In [11]:
```
plt.figure(figsize=(16,7))
sns.scatterplot(x=np.arange(len(data.pulses)), y=data.pulses, label='pulses/hour')
plt.show()
```



Above, you can see that there are not so many values greater that 0.7. We can wonder if those values show some anomalies. Maybe, the model will enlighten me.

Step 2: the model

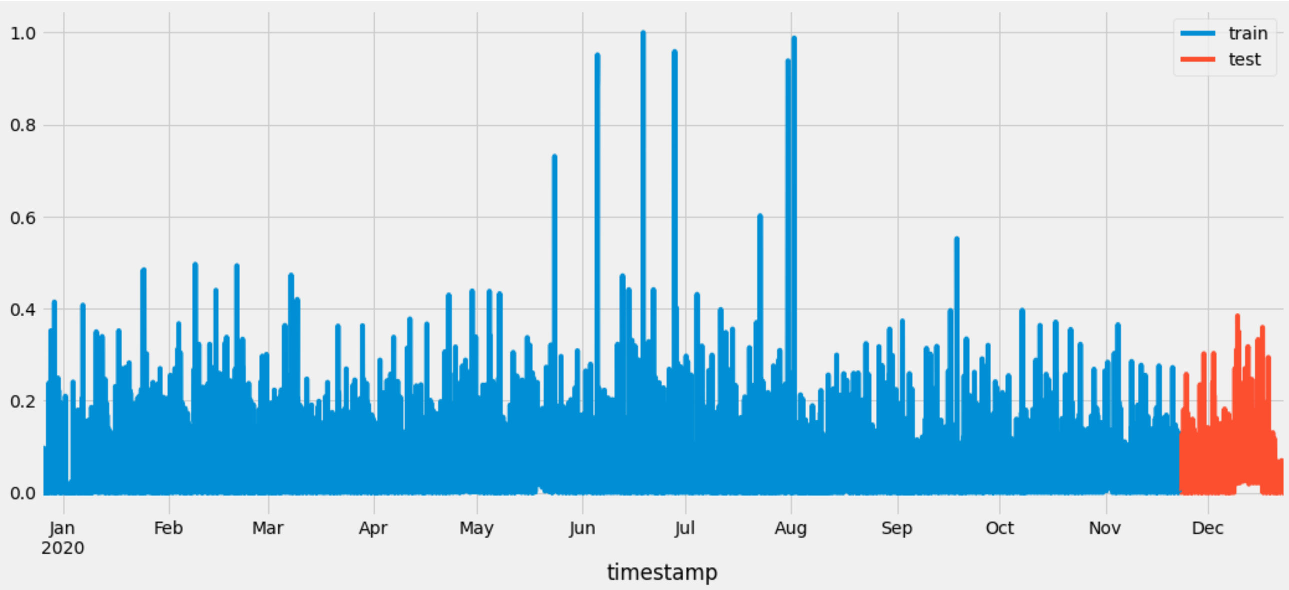
In this part, I chose to split the data exactly one month before the end. Next, I used the Prophet model from the prophet library to predict the future consumption.

In [12]:
```
split_date = '2020-11-23'
train = data.loc[data.index <= split_date].copy()
test = data.loc[data.index > split_date].copy()
```

In [13]:
```
join_train_test = train \
                    .rename(columns={'pulses': 'train'}) \
                    .join(test.rename(columns={'pulses': 'test'}), how='outer')
```

In [14]:
```
join_train_test.plot(figsize=(16,7))
```

Out[14]: <AxesSubplot:xlabel='timestamp'>



Below, I added some features to the dataset in order to understand it even more before defining and training the model. These new features are the hour, the day, the month, etc. I did this to see if there is some sort of periodicity.

In [15]:
```
def create_features(df, target='pulses'):

    df['date'] = df.index
    df['hour'] = df['date'].dt.hour
    df['dayofweek'] = df['date'].dt.dayofweek
    df['quarter'] = df['date'].dt.quarter
    df['month'] = df['date'].dt.month
    df['dayofmonth'] = df['date'].dt.day
    df.dropna(inplace=True)

    X = df[['hour', 'dayofweek','quarter','month','dayofmonth']]
    X.sort_index(inplace=True)

    if target:
        y = df[target]
        return X, y
    return X
```

In [16]:
```
X_train, y_train = create_features(train)
X_test, y_test = create_features(test)
X_y = pd.concat([X_train, y_train], axis=1)
X_y.head()
```

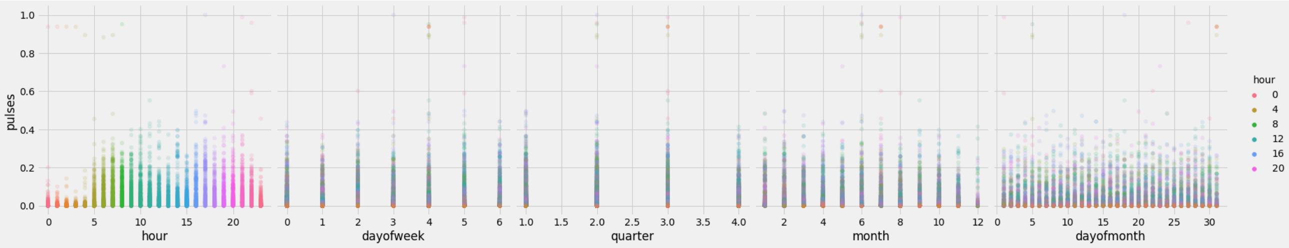
Out[16]:

	hour	dayofweek	quarter	month	dayofmonth	pulses
timestamp						
2019-12-25 11:00:00	11	2	4	12	25	0.198680
2019-12-25 12:00:00	12	2	4	12	25	0.001466
2019-12-25 13:00:00	13	2	4	12	25	0.006598
2019-12-25 14:00:00	14	2	4	12	25	0.000000
2019-12-25 15:00:00	15	2	4	12	25	0.022727

In [17]:
```
sns.pairplot(
    X_y,
    hue='hour',
    palette='husl',
    x_vars=['hour', 'dayofweek', 'quarter', 'month', 'dayofmonth'],
```

```python
    y_vars='pulses',
    height=5,
    plot_kws={'alpha':0.15, 'linewidth':0}  # The more matching values there are, the more opaque the points will be.
)
```

Out[17]: <seaborn.axisgrid.PairGrid at 0x7fa41a1716d0>



The pairplot function is very interesting to see if there is a correlation between the features and the number of pulses. In fact, I noticed that the consumption is often high at the same hour of the day (the morning and at the start of the evening) and it is low the night, which seems logic.

Next, I define the model and then train it. I tried many values for the hyperparameters but I noticed that it does not affect the error so much so I sticked to the default values.

In [18]:

```python
model = Prophet(yearly_seasonality=False) # yearly_seasonality=False because we have less that 1 year of data for training
model.fit(train.reset_index() \
              .rename(columns={'timestamp':'ds', 'pulses':'y'}))
```

Out[18]: <prophet.forecaster.Prophet at 0x7fa418fcabe0>

Step 3: Prediction

In [19]:

```python
test_pred = model.predict(df=test.reset_index() \
                                   .rename(columns={'timestamp':'ds'}))
```

In [20]:

```python
test_pred.head()
```

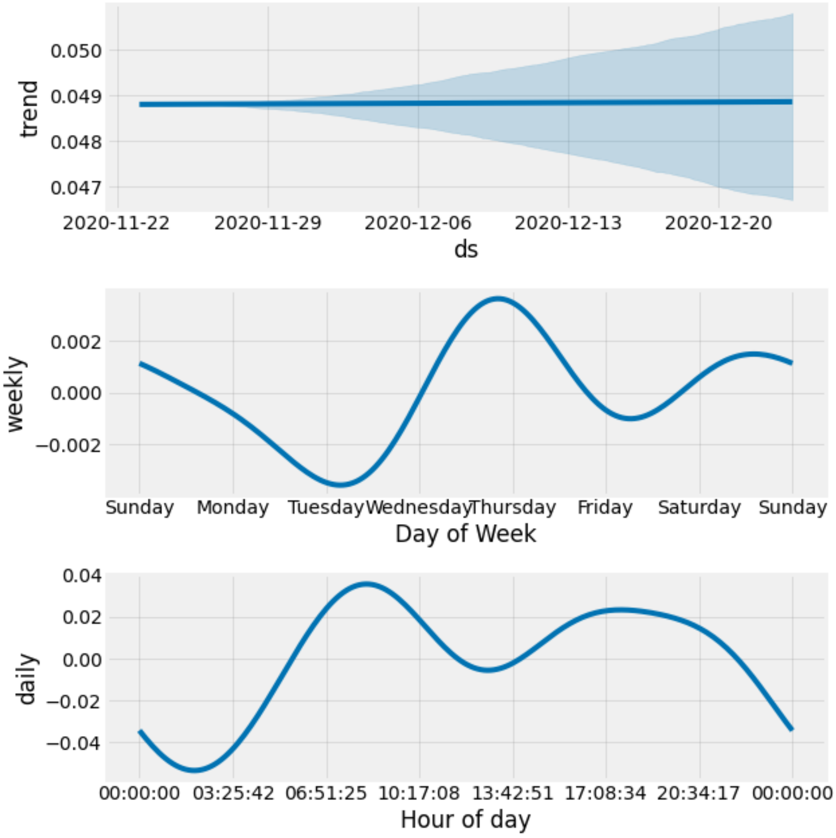
Out[20]:

	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additive_terms	additive_terms_lower	additive_terms_upper	daily	daily_lower
0	2020-11-23 01:00:00	0.048796	-0.088382	0.093848	0.048796	0.048796	-0.049163	-0.049163	-0.049163	-0.048249	-0.048249
1	2020-11-23 02:00:00	0.048797	-0.106115	0.087250	0.048797	0.048797	-0.054630	-0.054630	-0.054630	-0.053611	-0.053611
2	2020-11-23 03:00:00	0.048797	-0.092512	0.092739	0.048797	0.048797	-0.049647	-0.049647	-0.049647	-0.048520	-0.048520
3	2020-11-23 04:00:00	0.048797	-0.083092	0.104120	0.048797	0.048797	-0.035286	-0.035286	-0.035286	-0.034047	-0.034047
4	2020-11-23 05:00:00	0.048797	-0.064831	0.118038	0.048797	0.048797	-0.014941	-0.014941	-0.014941	-0.013589	-0.013589

The plot_compenents function, that I use below, allows me to confirm my guesses on the evolution of the number of pulses over time. We can see that there is also a weekly seasonality.

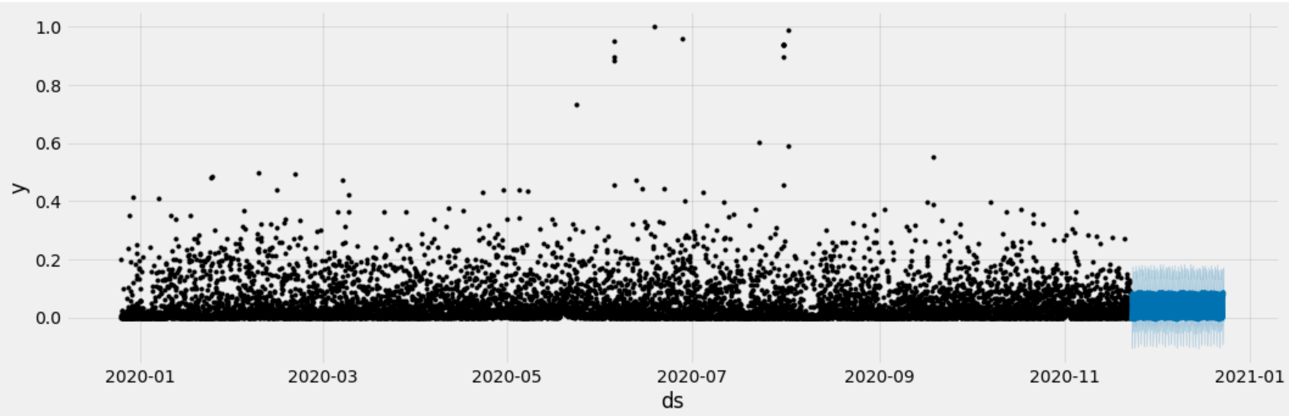
In [21]:

```python
fig = model.plot_components(test_pred)
```



Step 3: Visualizing and measuring the accuracy

In [22]:
```
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
fig = model.plot(test_pred, ax=ax)
plt.show()
```

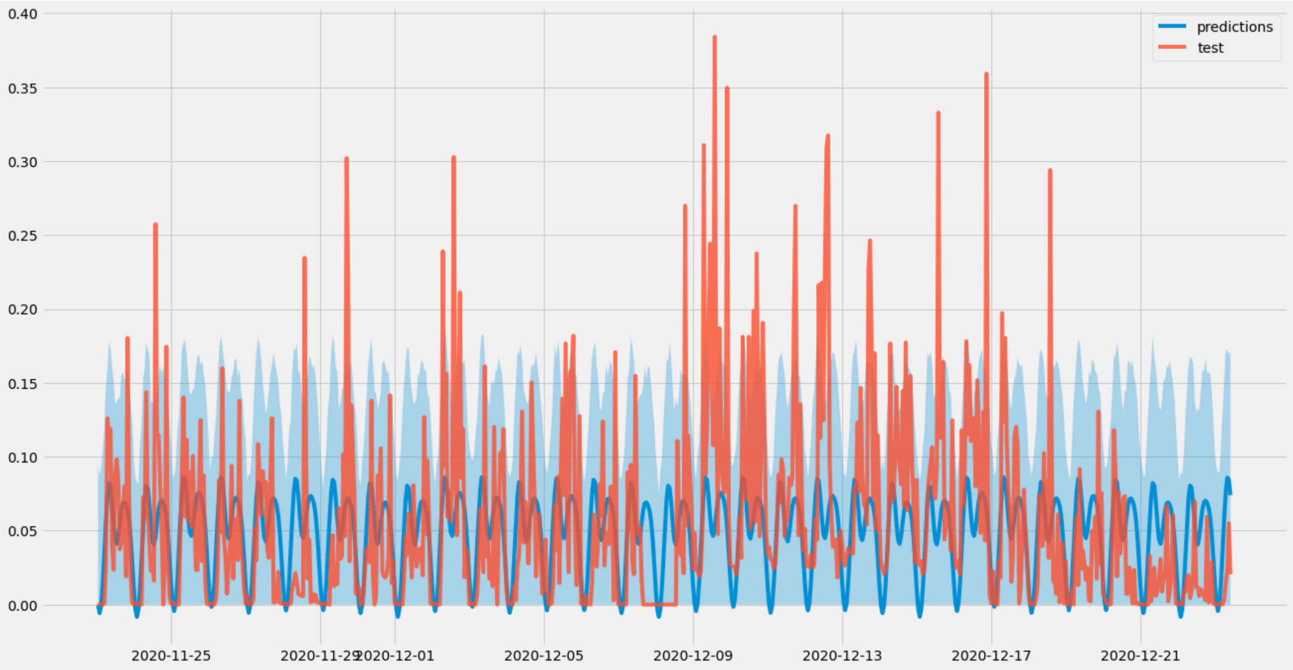


I did a zoom on the predicted part to better visualize it.

In [23]:
```
f, ax = plt.subplots(1)
f.set_figheight(11)
f.set_figwidth(20)

ax.plot(test_pred['ds'], test_pred['yhat'], label='predictions')
ax.plot(test.index, test['pulses'], label='test', alpha=0.8)
ax.fill_between(test_pred['ds'], test_pred['yhat_upper'], alpha=0.3)
ax.legend()
```

Out[23]:
```
<matplotlib.legend.Legend at 0x7fa406b25cd0>
```



In [24]:
```
mean_squared_error(y_true=test['pulses'], y_pred=test_pred['yhat'])
```

Out[24]:
```
0.0032895153895934107
```

In [25]:
```
mean_absolute_error(y_true=test['pulses'], y_pred=test_pred['yhat'])
```

Out[25]:
```
0.038522489263027833
```

2. How to detect an anomaly?

We know that most of the time, the pulse equals to 0. It means that we can detect when the pulse is not 0 for too long period and then conclude that there is a problem.

For example, we can see that between December 9th and December 17th the water consumption never equals zero. It means that there may be a leak somewhere in the building and people have to be notified.