Basic imports and function ceil

```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller #to see if timeseries is stationary
import numpy as np
import statsmodels.formula.api as smf
import statsmodels.api as sm
import datetime
```

```
# Fonction pour majorer ou minorer un nombre à l'entier le plus proche

def my_ceil(predictions):
  for i in range(len(predictions)):
    if predictions[i]%1<=0.5:
      predictions[i] = int(predictions[i])
    else:
      predictions[i] = int(predictions[i]) + 1
  return predictions
```

```
import io
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving test_input.csv to test_input.csv
Saving train_input.csv to train_input.csv
Saving train_output.csv to train_output.csv
```

Dataset Exploration

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import datetime
```

```
%%capture
train_input= pd.read_csv('https://raw.githubusercontent.com/nisrineha/Challenge_data_well_being_at_work/master/datasets/train_input.csv')
train_output= pd.read_csv('https://raw.githubusercontent.com/nisrineha/Challenge_data_well_being_at_work/master/datasets/train_output.csv')
train= train_input
train['Score']= train_output.Score
train.head()
for i in range(len(train['Date'])):
  train['Date'][i] = datetime.datetime.strptime(train['Date'][i], '%Y-%m-%d %H:%M:%S')
```

```
print(train.shape)
print(train.head())

```

```
(8000, 8)
   ID                 Date  Temperature  Humidity  Humex    CO2  Bright  Score
0   0  2017-08-31 23:30:00         22.7      56.0   25.7  534.0     1.0    4.0
1   1  2017-09-01 00:30:00         22.8      55.0   25.7  506.0     1.0    4.0
2   2  2017-09-01 01:30:00         22.9      55.0   25.9  577.0     1.0    4.0
3   3  2017-09-01 02:30:00         23.0      55.0   26.1  630.0     1.0    2.0
4   4  2017-09-01 03:30:00         23.0      55.0   26.1  643.0     1.0    3.0
```

Verifying if any na value in our dataframe, the result of this query shows us that there is none.

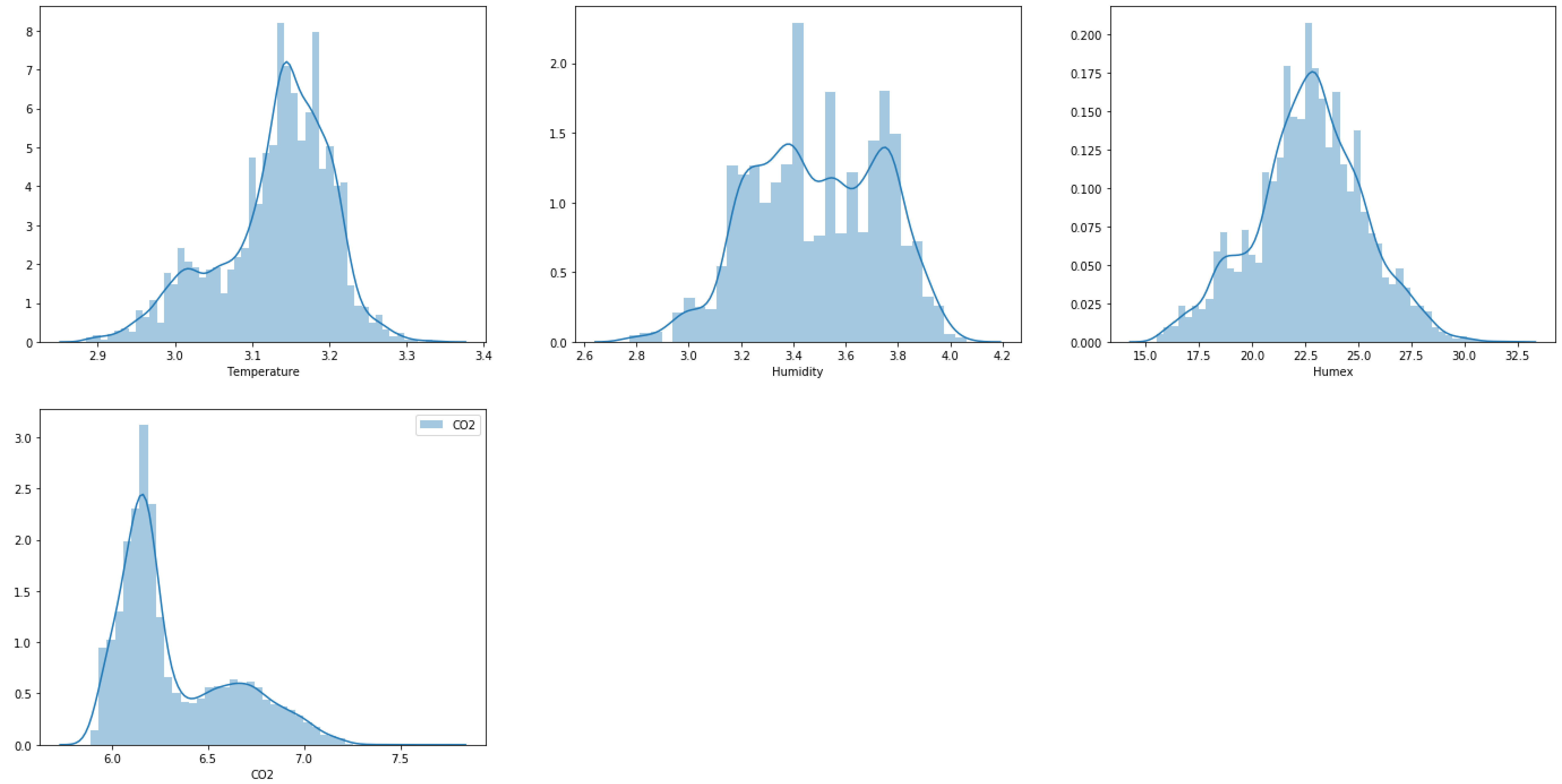
```
train.isnull().values.any()
```

```
False
```

Distribution of different features:

```
plt.figure("Distribution Plots")
fig = plt.figure(figsize = (24,12))
plt.subplot(2, 3,  1)
sns.distplot(np.log(train.Temperature), label = 'Temperature')
plt.subplot(2, 3, 2)
sns.distplot(np.log(train.Humidity), label = 'Humidity')
plt.subplot(2, 3, 3)
sns.distplot(train.Humex, label = 'Humex')
plt.subplot(2, 3, 4)
sns.distplot(np.log(train.CO2), label = 'CO2')
# sns.distplot(well_BE.month, label = 'month')
plt.legend()
plt.show()
```

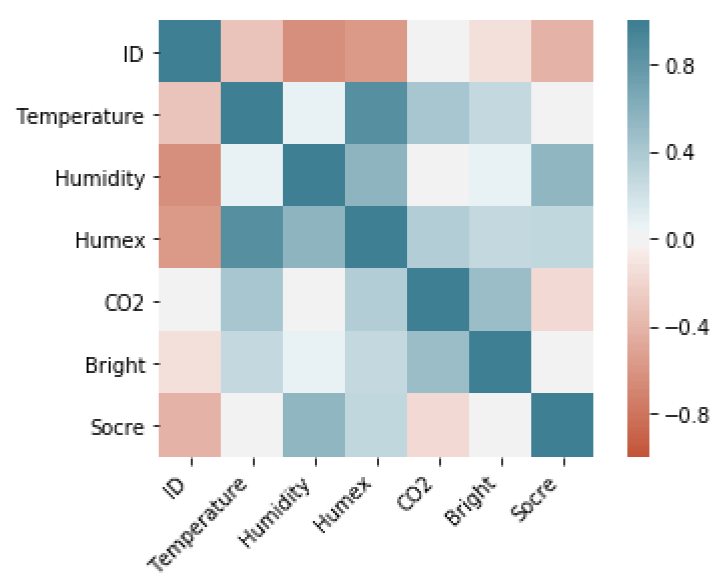
```
<Figure size 432x288 with 0 Axes>
```



We have the only varibale who has a normal distribution is the Humex variable which represents the air qualtiy

Matrice de correlation

```
corr = train.corr()
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200),
    square=True
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```




```
corr
```

	ID	Temperature	Humidity	Humex	CO2	Bright	Socre
ID	1.000000	-0.306515	-0.630485	-0.571340	0.006029	-0.131696	-0.416685
Temperature	-0.306515	1.000000	0.071968	0.861334	0.426742	0.275884	0.028900
Humidity	-0.630485	0.071968	1.000000	0.566265	0.015807	0.075624	0.541904
Humex	-0.571340	0.861334	0.566265	1.000000	0.361522	0.268284	0.287406
CO2	0.006029	0.426742	0.015807	0.361522	1.000000	0.486382	-0.172919
Bright	-0.131696	0.275884	0.075624	0.268284	0.486382	1.000000	-0.024523
Socre	-0.416685	0.028900	0.541904	0.287406	-0.172919	-0.024523	1.000000

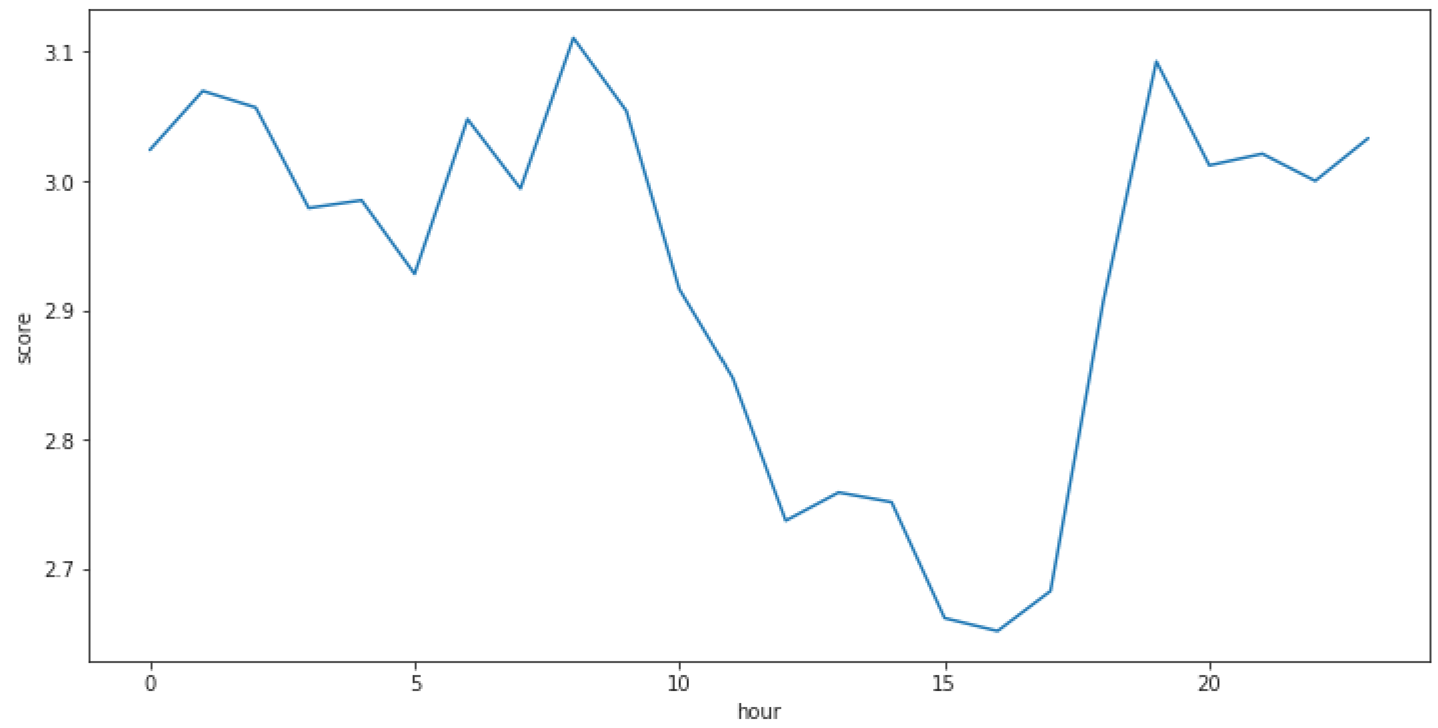
Again, there is only one variable **Humidty** which is hihgly correlated with our traget variable **score**

Relation between our target variable and the variable Date

```
series = pd.Series(np.array(train.Score), index=train.Date)
groupHour = series.groupby(series.index.hour).mean()
groupHour = pd.DataFrame({'hour':groupHour.index, 'score':groupHour.values})

# plt.plot(groupHour.hour, groupHour.score)
fig, ax = plt.subplots(1,1, figsize = (12,6))
#sns.barplot(x = 'hour', y = 'score', data = groupHour)

sns.lineplot(x = 'hour', y = 'score', data = groupHour)
sns.set_style("ticks", {"xtick.major.size": 16, "ytick.major.size": 8})
```

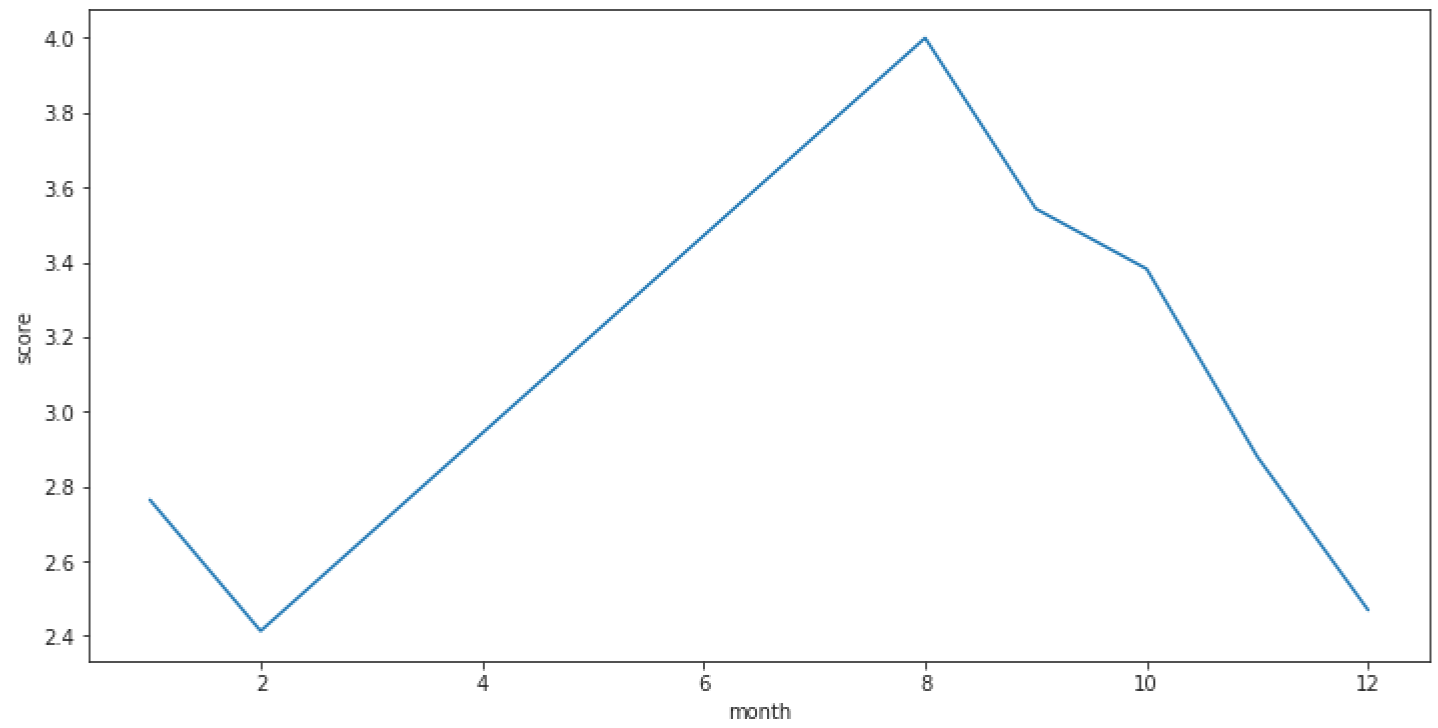


From the graph before which reprensents the score in function of day hours, the confort subjectif drop at 9:00 Am and raise again at 19:00, maybe people are working at this hours and they are less confortable.

```
series = pd.Series(np.array(train.Score), index=train.Date)
groupHour = series.groupby(series.index.month).mean()
groupHour = pd.DataFrame({'month':groupHour.index, 'score':groupHour.values})

fig, ax = plt.subplots(1,1, figsize = (12,6))
#sns.barplot(x = 'month', y = 'score', data = groupHour)
sns.lineplot(x = 'month', y = 'score', data = groupHour)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9581d19ba8>
```

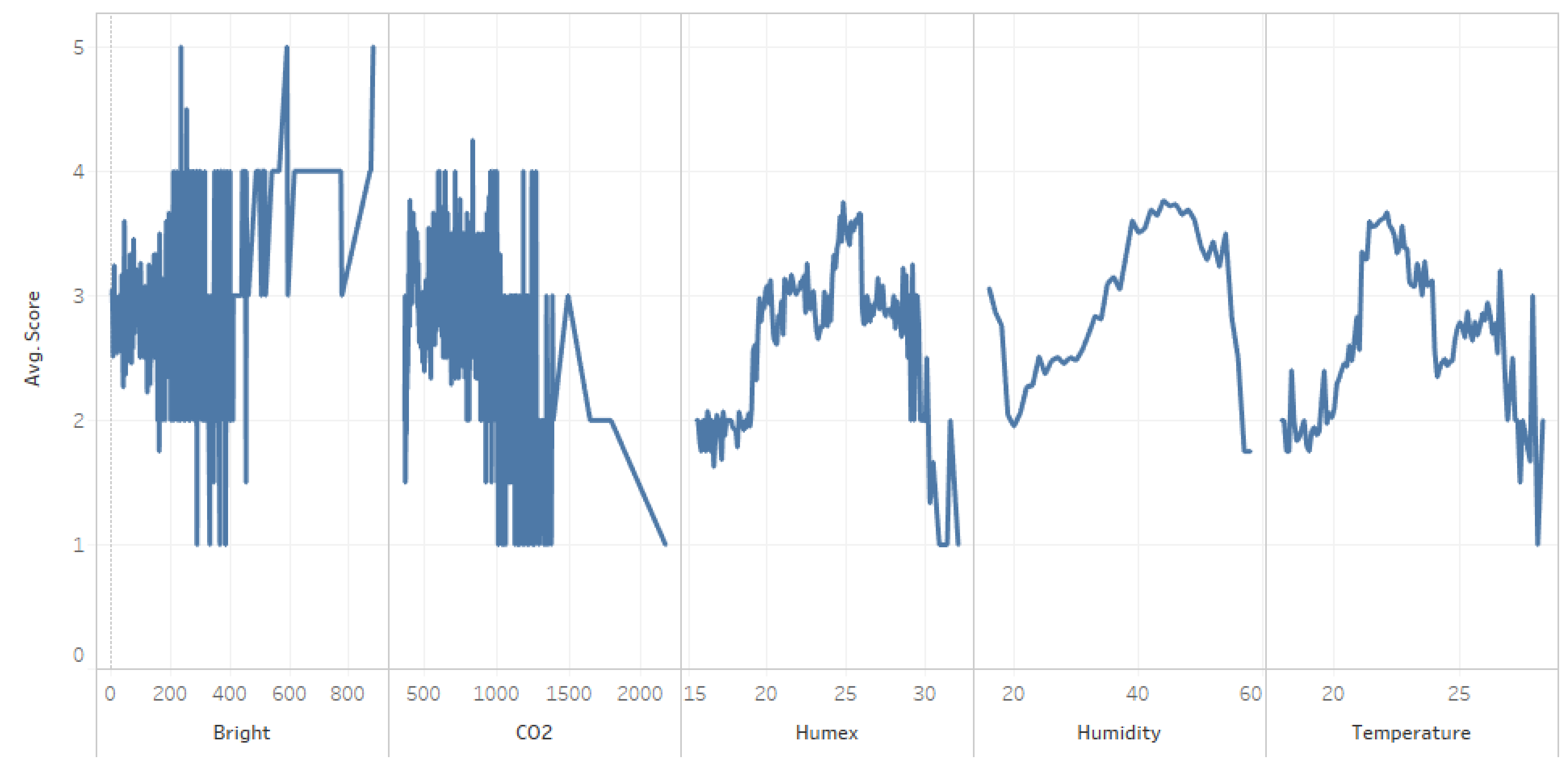


We did a variation of the score in function of months, but it is insignificant, since we have only few months in our dataset

Tableau software

In order to have a better idea about our dataset we used the software Tableau

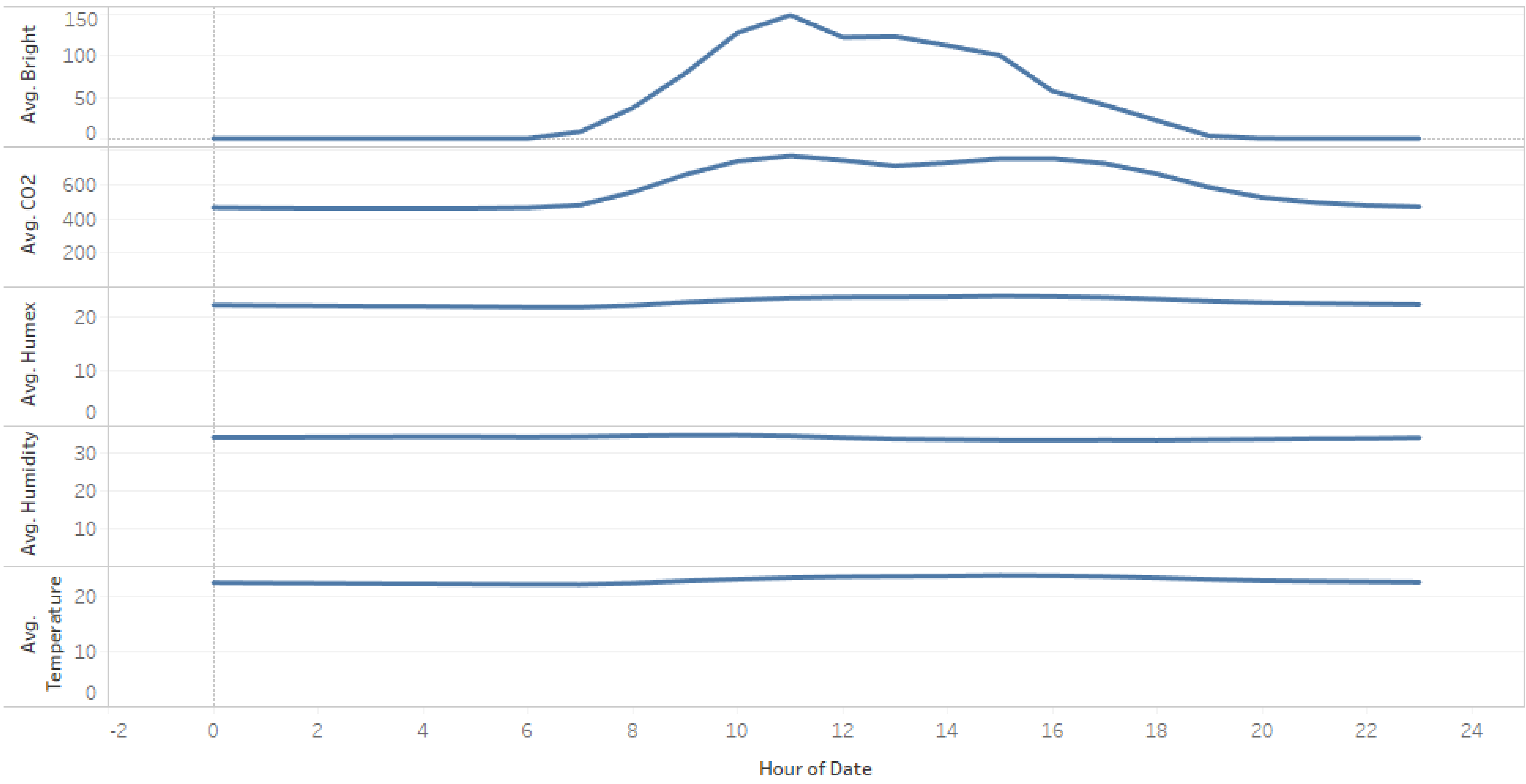
```
from IPython.core.display import Image, display
display(Image('/content/score(autresvariables).PNG'))
```



The graph shows us that there is no apprent relation between our traget and features

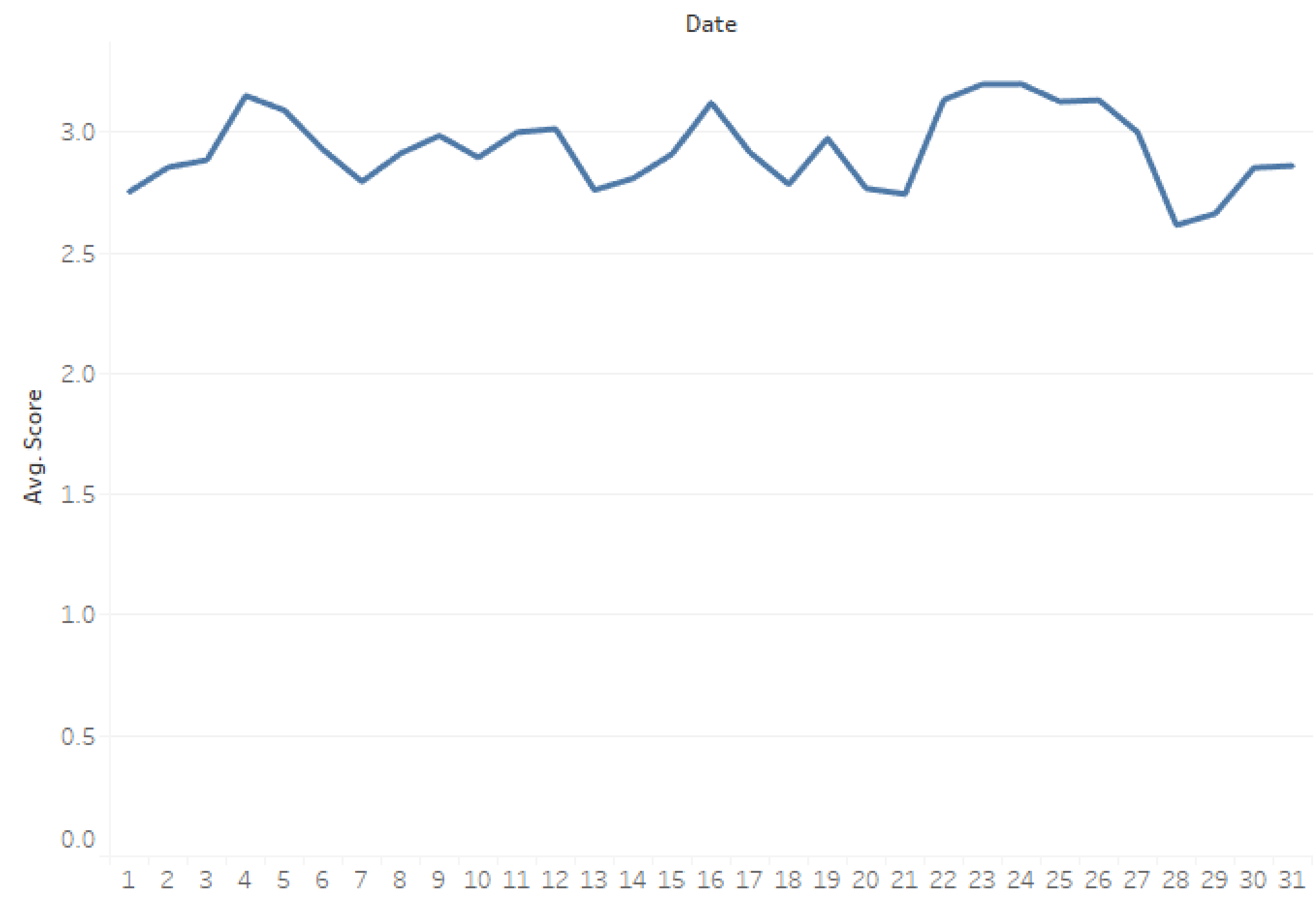
```
display(Image('/content/variable(hours).PNG'))

```



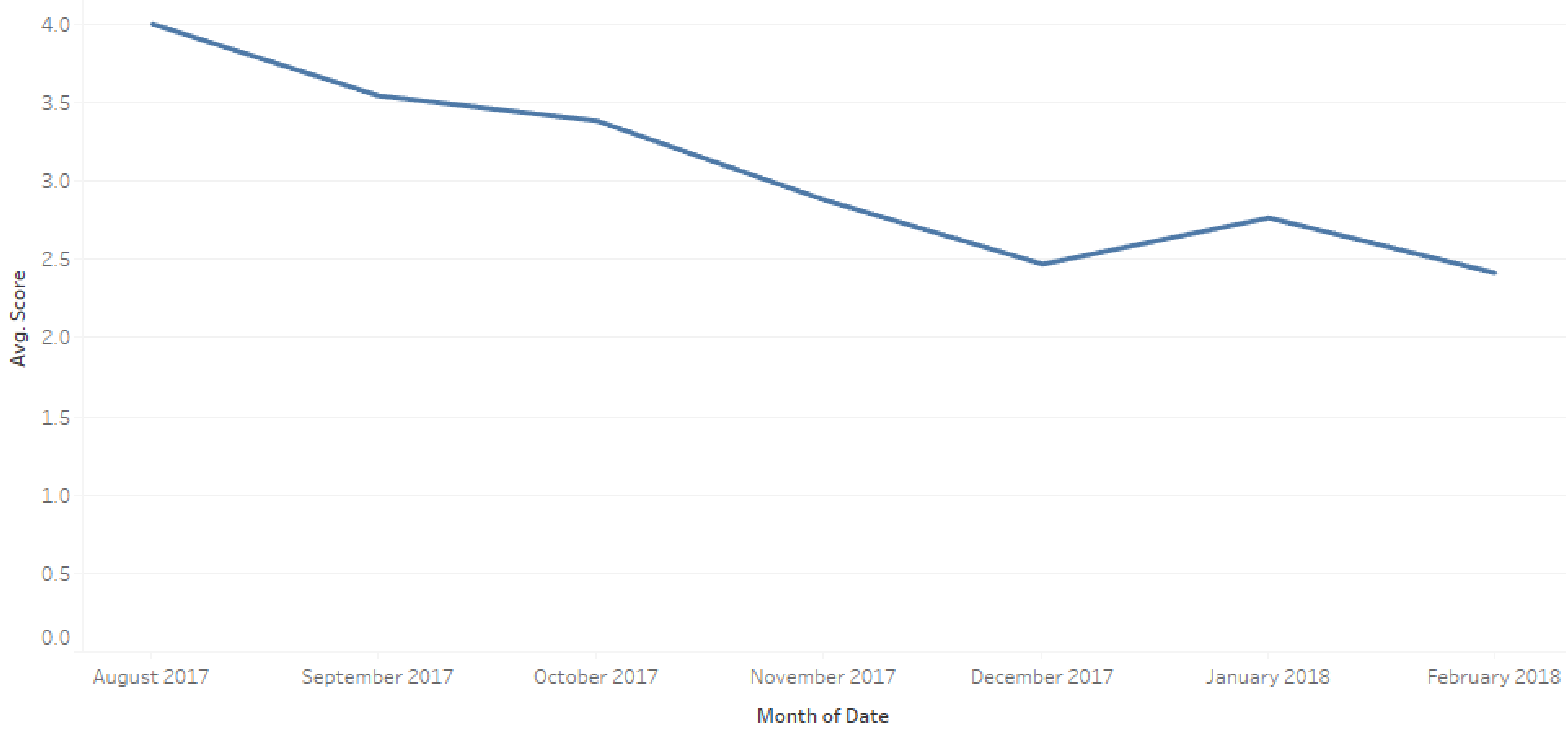
The graph shows us that except the bright and CO2, the other features are constant during the day.

```
display(Image('/content/score(day).PNG'))
```



this graph shows us that there is no apparent seasonality concerning the score and the time.

```
display(Image('/content/score(month).PNG'))
```



This graph shows us that the score is dropping from August to Decemeber and maybe of the season from summer to winter.

Conclusion

After exploring of our data, in the next section we will preprocess the data for modelisation.

Preprocessing phase

Train data

Import train data

```
wellB_in = pd.read_csv(io.BytesIO(uploaded['train_input.csv']))
wellB_out = pd.read_csv(io.BytesIO(uploaded['train_output.csv']))
well_B = wellB_in
```

```
# Convert Date column from String to Date
for i in range(len(well_B['Date'])):
  well_B['Date'][i] = datetime.datetime.strptime(well_B['Date'][i], '%Y-%m-%d %H:%M:%S')

train_ID = well_B.ID
train_Date = well_B.Date

well_B = well_B.drop(['ID','Date'], axis = 1)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  import sys
```

Add weekdays to columns as dummies

```
well_B['weekday'] = train_Date

# Add weekday column to data
for i in range(len(well_B.weekday)):
  well_B.weekday[i] = well_B.weekday[i].weekday()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """
```

```
dummy_weekday = pd.get_dummies(well_B['weekday'])
dummy_weekday.columns = ['lundi','mardi','mercredi','jeudi','vendredi','samedi','dimanche']

# dummy_weekday.rename(columns = {'0':'lundi','1':'mardi','2':'mercredi','3':'jeudi','4':'vendredi','5':'samedi','6':'dimanche'})
# dummy_weekday.head()

well_B = pd.concat([well_B,dummy_weekday], axis=1)
```

```
# Drop Weekday column with categorical values
well_B = well_B.drop('weekday', axis = 1)
```

Add hours to columns as dummy variables

```
well_B['hour'] = train_Date

for i in range(len(well_B.hour)):
  well_B.hour[i] = well_B.hour[i].hour

dummy_hour = pd.get_dummies(well_B['hour'])
dummy_hour.columns = ['midnight','AM1','AM2','AM3','AM4','AM5','AM6','AM7','AM8','AM9','AM10','AM11','midday','PM1','PM2','PM3','PM4','PM5','PM6','PM7','PM8','PM9','PM10','PM11']

well_B = pd.concat([well_B,dummy_hour], axis = 1)

well_B = well_B.drop('hour', axis = 1)


well_B.head()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
```

	Temperature	Humidity	Humex	CO2	Bright	lundi	mardi	mercredi	jeudi	vendredi	samedi	dimanche	midnight	AM1	AM2	AM3	AM4	AM5	AM6	AM7	AM8	AM9	AM10	AM11	midday	PM1	PM2
0	22.7	56.0	25.7	534.0	1.0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	22.8	55.0	25.7	506.0	1.0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	22.9	55.0	25.9	577.0	1.0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
3	23.0	55.0	26.1	630.0	1.0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
4	23.0	55.0	26.1	643.0	1.0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0

```
# Add objective variable to data
well_B['Score'] = wellB_out.Score
```

Test Data

Import test data

```
well_Btest = pd.read_csv(io.BytesIO(uploaded['test_input.csv']))

# Convert Date column from String to Date
for i in range(len(well_Btest['Date'])):
  well_Btest['Date'][i] = datetime.datetime.strptime(well_Btest['Date'][i], '%Y-%m-%d %H:%M:%S')

test_ID = well_Btest.ID
test_Date = well_Btest.Date

well_Btest = well_Btest.drop(['ID','Date'], axis = 1)
# well_Btest_ = well_Btest
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """
```

Add weekdays to columns as dummies

```
well_Btest['weekday'] = test_Date

# Add weekday column to data
for i in range(len(well_Btest.weekday)):
```

```
  well_Btest.weekday[i] = well_Btest.weekday[i].weekday()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """
```

```
dummy_weekday = pd.get_dummies(well_Btest['weekday'])
dummy_weekday.columns = ['lundi','mardi','mercredi','jeudi','vendredi','samedi','dimanche']

# dummy_weekday.rename(columns = {'0':'lundi','1':'mardi','2':'mercredi','3':'jeudi','4':'vendredi','5':'samedi','6':'dimanche'})
# dummy_weekday.head()

well_Btest = pd.concat([well_Btest,dummy_weekday], axis=1)
```

```
# Drop Weekday column with categorical values
well_Btest = well_Btest.drop('weekday', axis = 1)
```

Add hours to columns as dummy variables

```
well_Btest['hour'] = test_Date

for i in range(len(well_Btest.hour)):
  well_Btest.hour[i] = well_Btest.hour[i].hour

dummy_hour = pd.get_dummies(well_Btest['hour'])
dummy_hour.columns = ['midnight','AM1','AM2','AM3','AM4','AM5','AM6','AM7','AM8','AM9','AM10','AM11','midday','PM1','PM2','PM3','PM4','PM5','PM6','PM7','PM8','PM9','PM10','PM11']

well_Btest = pd.concat([well_Btest,dummy_hour], axis = 1)

well_Btest = well_Btest.drop('hour', axis = 1)

well_Btest.head()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
```

	Temperature	Humidity	Humex	CO2	Bright	lundi	mardi	mercredi	jeudi	vendredi	samedi	dimanche	midnight	AM1	AM2	AM3	AM4	AM5	AM6	AM7	AM8	AM9	AM10	AM11	midday	PM1	PM2
0	20.1	26.0	17.9	377.0	1.0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	20.2	26.0	18.0	374.0	1.0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	20.1	26.0	17.9	379.0	1.0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	20.1	26.0	17.9	380.0	1.0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	20.0	26.0	17.8	379.0	1.0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

K-fold Cross validation: regression and classification

Imports and functions

```
from sklearn.model_selection import KFold # import KFold
from sklearn.metrics import accuracy_score #To calculate accuracy
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
```

```
kf = KFold(n_splits = 7)
```

```
def cross_validation_XG_classifier(model):
  accuracy = []
  for train_index, test_index in kf.split(well_B):
    # print("TRAIN:", train_index, "TEST:", test_index)
    #train part
    X_train = np.array(well_B.drop('Score', axis = 1))[train_index]
    y_train = np.array(well_B.Score)[train_index]
    #test part
    X_test = np.array(well_B.drop('Score', axis = 1))[test_index]
    y_test = np.array(well_B.Score)[test_index]

    # Define the scaler
    # scaler = StandardScaler().fit(X_train)

    # X_train = scaler.transform(X_train)
    # X_test = scaler.transform(X_test)

    # rgr_time = RandomForestClassifier(n_estimators = 400, random_state = 0, max_depth=20)
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    y_pred = my_ceil(np.array(y_pred))

    accuracy.append(accuracy_score(y_pred, y_test))
    # print("The score of the " + str(cpt) + " is " + str(accuracy_score(y_pred, y_test)))
    # cpt = cpt+1

  return np.average(accuracy)

# Converts floats to integers for classification
def my_ceil(predictions):
  for i in range(len(predictions)):

    if predictions[i]%1 <= +0.5:
      predictions[i] = int(predictions[i])
    else:
      predictions[i] = int(predictions[i]) + 1
  return predictions


def cross_validation_Lregressor(formula):
  accuracy = []
```

```
    for train_index, test_index in kf.split(well_B):
      # print("TRAIN:", train_index, "TEST:", test_index)
      #train part
      train = well_B.iloc[train_index]
      #test part
      test = well_B.iloc[test_index]

      # Define the scaler
      # scaler = StandardScaler().fit(X_train)

      # X_train = scaler.transform(X_train)
      # X_test = scaler.transform(X_test)

      model_lr = formula
      result_lr = smf.ols(model_lr, data = train).fit()

      y_pred = np.array(result_lr.predict(test))

      y_pred = my_ceil(y_pred)

      accuracy.append(accuracy_score(y_pred, test.Score))
      # print("The score of the " + str(cpt) + " is " + str(accuracy_score(y_pred, y_test)))
      # cpt = cpt+1

    return np.average(accuracy)
```

Regression

Linear regression

```
import statsmodels.formula.api as smf
import statsmodels.api as sm
```

First model

```
model_lr = 'Score ~ Temperature + Humidity + Humex + CO2 + Bright'
result_lr = smf.ols(model_lr, data = well_B).fit()
print(result_lr.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Score   R-squared:                       0.380
Model:                            OLS   Adj. R-squared:                  0.380
Method:                 Least Squares   F-statistic:                     979.6
Date:                Thu, 19 Dec 2019   Prob (F-statistic):               0.00
Time:                        18:09:19   Log-Likelihood:                -8541.0
No. Observations:                8000   AIC:                         1.709e+04
Df Residuals:                    7994   BIC:                         1.714e+04
Df Model:                           5
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept     -18.7846      0.790    -23.779      0.000     -20.333     -17.236
Temperature     2.0279      0.080     25.209      0.000       1.870       2.186
Humidity        0.2986      0.010     30.564      0.000       0.279       0.318
Humex          -1.5151      0.061    -24.712      0.000      -1.635      -1.395
CO2            -0.0010   4.75e-05    -20.754      0.000      -0.001      -0.001
Bright          0.0004      0.000      3.234      0.001       0.000       0.001
==============================================================================
Omnibus:                       10.461   Durbin-Watson:                   1.163
Prob(Omnibus):                  0.005   Jarque-Bera (JB):               10.717
Skew:                          -0.070   Prob(JB):                      0.00471
Kurtosis:                       3.112   Cond. No.                     6.32e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.32e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
cross_validation_Lregressor(model_lr)
```

```
0.5186297859877849
```

Second model

```
model_lr_1 = 'Score ~ Temperature + Humidity + Humex + CO2 + Bright + lundi + mardi + mercredi + jeudi + vendredi + samedi + dimanche'
result_lr_1 = smf.ols(model_lr_1, data = well_B).fit()
print(result_lr_1.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  Score   R-squared:                       0.386
Model:                            OLS   Adj. R-squared:                  0.385
Method:                 Least Squares   F-statistic:                     456.1
Date:                Thu, 19 Dec 2019   Prob (F-statistic):               0.00
Time:                        18:09:27   Log-Likelihood:                -8503.0
No. Observations:                8000   AIC:                         1.703e+04
Df Residuals:                    7988   BIC:                         1.711e+04
Df Model:                          11                                         
Covariance Type:            nonrobust                                         
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept     -16.2137      0.691    -23.456      0.000     -17.569     -14.859
Temperature     2.0151      0.080     25.098      0.000       1.858       2.172
Humidity        0.2984      0.010     30.612      0.000       0.279       0.317
Humex          -1.5116      0.061    -24.714      0.000      -1.631      -1.392
CO2            -0.0010   5.11e-05    -20.223      0.000      -0.001      -0.001
Bright          0.0003      0.000      2.857      0.004       0.000       0.001
lundi          -2.3511      0.101    -23.205      0.000      -2.550      -2.152
mardi          -2.3638      0.102    -23.267      0.000      -2.563      -2.165
mercredi       -2.2852      0.101    -22.581      0.000      -2.484      -2.087
jeudi          -2.2261      0.101    -22.046      0.000      -2.424      -2.028
vendredi       -2.2103      0.101    -21.947      0.000      -2.408      -2.013
samedi         -2.3632      0.100    -23.712      0.000      -2.559      -2.168
dimanche       -2.4141      0.099    -24.280      0.000      -2.609      -2.219
==============================================================================
Omnibus:                       11.224   Durbin-Watson:                   1.174
Prob(Omnibus):                  0.004   Jarque-Bera (JB):               11.583
Skew:                          -0.071   Prob(JB):                      0.00305
Kurtosis:                       3.121   Cond. No.                     1.25e+18
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.99e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

```
cross_validation_Lregressor(model_lr_1)
```

```
0.5176292543116874
```

Third model

```
allcolumns = '+'.join(well_B.columns[:len(well_B.columns)-1])
allcolumns
model_lr_2 = 'Score ~'+ allcolumns
model_lr_2
result_lr_2 = smf.ols(model_lr_2, data = well_B).fit()
print(result_lr_2.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  Score   R-squared:                       0.393
Model:                            OLS   Adj. R-squared:                  0.391
Method:                 Least Squares   F-statistic:                     151.9
Date:                Thu, 19 Dec 2019   Prob (F-statistic):               0.00
Time:                        18:22:00   Log-Likelihood:                -8452.9
No. Observations:                8000   AIC:                         1.698e+04
Df Residuals:                    7965   BIC:                         1.722e+04
Df Model:                          34                                         
Covariance Type:            nonrobust                                         
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept     -15.5752      0.665    -23.410      0.000     -16.879     -14.271
Temperature     2.0095      0.080     25.025      0.000       1.852       2.167
Humidity        0.2977      0.010     30.458      0.000       0.279       0.317
Humex          -1.5074      0.061    -24.603      0.000      -1.628      -1.387
CO2            -0.0011   5.94e-05    -18.148      0.000      -0.001      -0.001
Bright          0.0004      0.000      2.615      0.009    9.34e-05       0.001
lundi          -2.2590      0.098    -23.131      0.000      -2.450      -2.068
mardi          -2.2672      0.098    -23.161      0.000      -2.459      -2.075
mercredi       -2.1918      0.098    -22.478      0.000      -2.383      -2.001
jeudi          -2.1334      0.097    -21.931      0.000      -2.324      -1.943
vendredi       -2.1180      0.097    -21.827      0.000      -2.308      -1.928
samedi         -2.2777      0.096    -23.638      0.000      -2.467      -2.089
dimanche       -2.3282      0.096    -24.211      0.000      -2.517      -2.140
midnight       -0.6755      0.047    -14.256      0.000      -0.768      -0.583
AM1            -0.6304      0.048    -13.258      0.000      -0.724      -0.537
AM2            -0.6536      0.048    -13.746      0.000      -0.747      -0.560
AM3            -0.7399      0.048    -15.499      0.000      -0.834      -0.646
AM4            -0.7341      0.048    -15.395      0.000      -0.828      -0.641
AM5            -0.7869      0.048    -16.510      0.000      -0.880      -0.693
AM6            -0.6627      0.048    -13.885      0.000      -0.756      -0.569
AM7            -0.7093      0.048    -14.903      0.000      -0.803      -0.616
AM8            -0.5489      0.047    -11.606      0.000      -0.642      -0.456
AM9            -0.5267      0.048    -11.027      0.000      -0.620      -0.433
AM10           -0.5867      0.049    -11.989      0.000      -0.683      -0.491
AM11           -0.6063      0.050    -12.225      0.000      -0.704      -0.509
midday         -0.7021      0.048    -14.506      0.000      -0.797      -0.607
PM1            -0.7001      0.048    -14.522      0.000      -0.795      -0.606
PM2            -0.6717      0.048    -14.028      0.000      -0.766      -0.578
PM3            -0.7147      0.048    -14.998      0.000      -0.808      -0.621
PM4            -0.7004      0.047    -14.880      0.000      -0.793      -0.608
PM5            -0.7102      0.047    -15.104      0.000      -0.802      -0.618
PM6            -0.5424      0.047    -11.616      0.000      -0.634      -0.451
PM7            -0.4362      0.046     -9.392      0.000      -0.527      -0.345
PM8            -0.5937      0.047    -12.663      0.000      -0.686      -0.502
PM9            -0.6194      0.047    -13.197      0.000      -0.711      -0.527
PM10           -0.6652      0.047    -14.116      0.000      -0.758      -0.573
PM11           -0.6582      0.047    -13.884      0.000      -0.751      -0.565
==============================================================================
Omnibus:                       13.195   Durbin-Watson:                   1.185
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               13.656
Skew:                          -0.078   Prob(JB):                      0.00108
Kurtosis:                       3.129   Cond. No.                     2.99e+18
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 3.49e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

```
cross_validation_Lregressor(model_lr_2)
```

```
0.5175061304727452
```

XGboost

```
import xgboost
```

```
model_xg = xgboost.XGBRegressor(objective ='reg:squarederror', colsample_bytree = 0.3, learning_rate = 0.05,
                          alpha = 10,base_score= 0.4, booster='gbtree', n_estimators = 150)
```

```
cross_validation_XG_classifier(model_xg)
```

```
0.7156269433045913
```

Classification

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from google.colab import files
```

```
def my_ceil(predictions):
  for i in range(len(predictions)):
    if predictions[i]%1<=0.5:
      predictions[i] = int(predictions[i])
    else:
      predictions[i] = int(predictions[i]) + 1
  return predictions

#Export function
def export( data_test, predictions):
  result_ = pd.DataFrame({'ID': data_test.ID, 'Score': my_ceil(predictions)})
  result_.to_csv('results_.csv', index = False)

  files.download('results_.csv')

```

Upload preprocessed dataset train and test

```
test = pd.read_csv('https://raw.githubusercontent.com/nisrineha/Challenge_data_well_being_at_work/master/datasets/data_test_processed.csv')
train = pd.read_csv('https://raw.githubusercontent.com/nisrineha/Challenge_data_well_being_at_work/master/datasets/data_train_processed.csv')
test_with_ID = pd.read_csv('https://raw.githubusercontent.com/nisrineha/Challenge_data_well_being_at_work/master/datasets/test_input.csv')
test_with_date= pd.read_csv('https://raw.githubusercontent.com/nisrineha/Challenge_data_well_being_at_work/master/datasets/train_input.csv')
```

```
test_with_date.head()

```

	ID	Date	Temperature	Humidity	Humex	CO2	Bright
0	0	2017-08-31 23:30:00	22.7	56.0	25.7	534.0	1.0
1	1	2017-09-01 00:30:00	22.8	55.0	25.7	506.0	1.0
2	2	2017-09-01 01:30:00	22.9	55.0	25.9	577.0	1.0
3	3	2017-09-01 02:30:00	23.0	55.0	26.1	630.0	1.0
4	4	2017-09-01 03:30:00	23.0	55.0	26.1	643.0	1.0

Creation of features and the target variable Score

```
y= train['Score']
train1= train
train1= train1.drop('Score', axis= 1)
X= train1
train1.head()
```

Spliting of the data

```
X_train, X_test, y_train, y_test= train_test_split(X, y , test_size= 0.2, random_state= 42)
```

Pipeline method

Implement of pipeline method using different transformer: numeric and categorial

```
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder

#SimpleImputer fill any missing values
#Scaler numeric transformer

numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())])

#One hot encoder to transform categorial values into integers.

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='constant', fill_value='missing')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))])
```

Transform the categorical features and numeric on train dataset and test

```
#Select les columns numeric
#Select les columns categoric


integer_features = list(X.columns[X.dtypes == 'int64'])
continuous_features = list(X.columns[X.dtypes == 'float64'])
categorical_features = list(X.columns[X.dtypes == 'object'])
numeric_features = integer_features + continuous_features


```

```
from sklearn.compose import ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)])

integer_features_test = list(test.columns[test.dtypes == 'int64'])
continuous_features_test = list(test.columns[test.dtypes == 'float64'])
categorical_features_test = list(test.columns[test.dtypes == 'object'])
numeric_features = integer_features + continuous_features


from sklearn.compose import ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)])
```

Model selection

In this section, we chose different classifier from sklearn, to get the best classifier for our dataset, we calculate the score thanks to the splitting of the dataset that we did before.

```
from sklearn.metrics import accuracy_score, log_loss
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC, NuSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
classifiers = [
    KNeighborsClassifier(3),
    SVC(kernel="rbf", C=0.025, probability=True),
    DecisionTreeClassifier(),
    RandomForestClassifier(),
    AdaBoostClassifier(),
    GradientBoostingClassifier(),
    LinearDiscriminantAnalysis(),
    QuadraticDiscriminantAnalysis()
    ]
pipes= []
for classifier in classifiers:
    pipe = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', classifier)])
    pipe.fit(X_train, y_train)
    pipes.append(pipe)
    print(classifier)
    print("model score: %.3f" % pipe.score(X_test, y_test))

```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=3, p=2,
                     weights='uniform')
model score: 0.587
SVC(C=0.025, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='rbf', max_iter=-1, probability=True, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
model score: 0.439
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
model score: 0.601
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=10,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
model score: 0.677
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None, learning_rate=1.0,
                   n_estimators=50, random_state=None)
model score: 0.565
GradientBoostingClassifier(criterion='friedman_mse', init=None,
                           learning_rate=0.1, loss='deviance', max_depth=3,
                           max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_split=None,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimators=100,
                           n_iter_no_change=None, presort='auto',
                           random_state=None, subsample=1.0, tol=0.0001,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
model score: 0.750
LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
                           solver='svd', store_covariance=False, tol=0.0001)
model score: 0.562
QuadraticDiscriminantAnalysis(priors=None, reg_param=0.0,
                              store_covariance=False, tol=0.0001)
model score: 0.138
/usr/local/lib/python3.6/dist-packages/sklearn/discriminant_analysis.py:388: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
/usr/local/lib/python3.6/dist-packages/sklearn/discriminant_analysis.py:693: UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
```

From the results above, we observe that the best classifiers are **GradientBoostingClassifier** and **RandomForestClassifier**

we chose GradientBoostingClassifier for submission, we had our best score which is **0,6990**

```
x = test
y_pred= pipes[-3].predict(x)
export(test_with_ID, y_pred)
```

Using pipeline in GridSearch

```
param_grid = {
    'classifier__n_estimators': [ 200, 300,  400, 500],
```

```
    'classifier__n_estimators' : [200, 300, 400, 500],
    'classifier__max_features': ['auto', 'sqrt', 'log2'],
    'classifier__max_depth' : [10, 20, 25, 30],
    'classifier__criterion' :['gini', 'entropy']}
from sklearn.model_selection import GridSearchCV
CV = GridSearchCV(rf, param_grid, n_jobs= 1)

CV.fit(X_train, y_train)
print(CV.best_params_)
print(CV.best_score_)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_split.py:1978: FutureWarning: The default value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to sile
  warnings.warn(CV_WARNING, FutureWarning)
{'classifier__criterion': 'entropy', 'classifier__max_depth': 10, 'classifier__max_features': 'auto', 'classifier__n_estimators': 400}
0.71359375
```

we had from our grid search our best max depth and number of estimators for our randomforset model.

```
#Fitting the classifier
from sklearn.ensemble import RandomForestClassifier
rf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', RandomForestClassifier(n_estimators= 400, max_depth=20))])
```

```
rf.fit(X_train, y_train )

pipe = Pipeline(steps=[('preprocessor', preprocessor),
                  ('classifier',RandomForestClassifier(n_estimators= 400, max_depth=20) )])
pipe.fit(X_train, y_train)
print(classifier)
print("model score: %.3f" % pipe.score(X_test, y_test))
x = test
y_pred= pipe.predict(x)
export(test_with_ID, y_pred)
```

```
QuadraticDiscriminantAnalysis(priors=None, reg_param=0.0,
                              store_covariance=False, tol=0.0001)
model score: 0.734
```

We submitted our results, but we had a score less than the one when we implemented **GradientBoostingClassifier**

Random forest model

```
rf_time = RandomForestClassifier(n_estimators = 400, random_state = 0, max_depth=20)
```

```
cross_validation_XG_classifier(rf_time)
```

```
0.706623909314313
```

K nearest neighbor

```
neigh_time = KNeighborsClassifier(n_neighbors=5)
```

```
cross_validation_XG_classifier(neigh_time)
```

```
0.48610790989129854
```

Gradient Boosting Classification

```
from sklearn.ensemble import GradientBoostingClassifier
```

```
gbC_time = GradientBoostingClassifier()
```

```
cross_validation_XG_classifier(gbC_time)
```

```
0.6976108065300944
```

Basic deep learning model

```
# Import `Sequential` from `keras.models`
from keras.models import Sequential

# Import `Dense` from `keras.layers`
from keras.layers import Dense

# Initialize the constructor
model = Sequential()

# Add an input layer
model.add(Dense(12, activation='softmax', input_shape=(36,)))

# Add one hidden layer
model.add(Dense(12, activation='relu'))

# # Add one hidden layer
# model.add(Dense(12, activation='relu'))

# Add an output layer
model.add(Dense(output_dim = 5, activation = 'softmax'))
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:19: UserWarning: Update your `Dense` call to the Keras 2 API: `Dense(activation="relu", units=5)`
```

```
def dummies_categ(y):
  cat = []
  for i in range(len(y)):
    ind = np.argmax(y_pred[i]) + 1
    cat.append(ind)
  return cat
```

```
accuracy = []
for train_index, test_index in kf.split(well_B):
  # print("TRAIN:", train_index, "TEST:", test_index)
  #train part
  X_train = np.array(well_B.drop('Score', axis = 1))[train_index]
```

```
    y_train = np.array(well_B.Score)[train_index]

    y_train = pd.get_dummies(y_train)
    #test part
    X_test = np.array(well_B.drop('Score', axis = 1))[test_index]
    y_test = np.array(well_B.Score)[test_index]

    y_test = pd.get_dummies(y_test)


    # Define the scaler
    scaler = StandardScaler().fit(X_train)

    X_train = scaler.transform(X_train)
    X_test = scaler.transform(X_test)

    model.compile(loss='binary_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])

    model.fit(X_train, y_train,epochs=2, batch_size=1, verbose=1)

    y_pred = model.predict(X_test)

    y_pred = dummies_categ(y_pred)
    y_test = np.array(well_B.Score)[test_index]
    # print(y_pred)
    accuracy.append(accuracy_score(y_pred, y_test))
    # print("The score of the " + str(cpt) + " is " + str(accuracy_score(y_pred, y_test)))
    # cpt = cpt+1

np.average(accuracy)
```

```
Epoch 1/2
6857/6857 [==============================] - 12s 2ms/step - loss: 0.5317 - acc: 0.8609
Epoch 2/2
6857/6857 [==============================] - 11s 2ms/step - loss: 0.5344 - acc: 0.8626
Epoch 1/2
6857/6857 [==============================] - 12s 2ms/step - loss: 0.5495 - acc: 0.8596
Epoch 2/2
6857/6857 [==============================] - 10s 2ms/step - loss: 0.5380 - acc: 0.8617
Epoch 1/2
6857/6857 [==============================] - 12s 2ms/step - loss: 0.5503 - acc: 0.8602
Epoch 2/2
6857/6857 [==============================] - 11s 2ms/step - loss: 0.5311 - acc: 0.8629
Epoch 1/2
6857/6857 [==============================] - 12s 2ms/step - loss: 0.5359 - acc: 0.8615
Epoch 2/2
6857/6857 [==============================] - 11s 2ms/step - loss: 0.5310 - acc: 0.8646
Epoch 1/2
6857/6857 [==============================] - 13s 2ms/step - loss: 0.5457 - acc: 0.8645
Epoch 2/2
6857/6857 [==============================] - 11s 2ms/step - loss: 0.5314 - acc: 0.8665
Epoch 1/2
6857/6857 [==============================] - 13s 2ms/step - loss: 0.5260 - acc: 0.8682
Epoch 2/2
6857/6857 [==============================] - 11s 2ms/step - loss: 0.5188 - acc: 0.8701
Epoch 1/2
6858/6858 [==============================] - 13s 2ms/step - loss: 0.5262 - acc: 0.8665
Epoch 2/2
6858/6858 [==============================] - 11s 2ms/step - loss: 0.5191 - acc: 0.8684
0.6390032025331335
```