device-failure-final-notebook

May 16, 2023

1 Implémentation :

Réalisé par Ilyas El Amrani, Mohamed El Jaouhari, Afaf Matouk & Mouna Guerrab. Dans cette partie, nous allons chargé nos données, les analyser , les transformer pour pouvoir construire notre modèle, par la suite nous allons utiliser les prédiction de notre modèle pour générer nos KPIs, qui seront affichés par la suite à l'aide de MS Power BI.

[136]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

2 Chargement des données

[137]:
```python
df = pd.read_csv('predictive_maintenance_dataset.csv')
df.head()
```

[137]:
```
       date    device  failure    metric1  metric2  metric3  metric4  metric5  \
0  1/1/2015  S1F01085        0  215630672       55        0       52        6
1  1/1/2015  S1F0166B        0   61370680        0        3        0        6
2  1/1/2015  S1F01E6Y        0  173295968        0        0        0       12
3  1/1/2015  S1F01JE0        0   79694024        0        0        0        6
4  1/1/2015  S1F01R2B        0  135970480        0        0        0       15

   metric6  metric7  metric8  metric9
0   407438        0        0        7
1   403174        0        0        0
2   237394        0        0        0
3   410186        0        0        0
4   313173        0        0        3
```

[138]:
```python
import pandas_profiling
pandas_profiling.ProfileReport(df)
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
```

```
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

[138]:

[139]:
```
df.failure.value_counts()
```

[139]:
```
0    124388
1       106
Name: failure, dtype: int64
```

Donc on dispose de 124494 enregistrement, dont 106 représentent une panne.

3 Data Engineering

[140]:
```
df.date = pd.to_datetime(df.date)

#Création de la colonne activedays pour pouvoir mesurer de combien de jours la␣
↪machine est elle active durant cette année.
df['activedays']=df.date-df.date[0]

#Création de la colonne 'month', le mois.
df['month']=df['date'].dt.month
#Création de la colonne 'week_day', le jour de la semaine (0 est Dimanche)
df['week_day']=df.date.dt.weekday
df['week_day'].replace(0,7,inplace=True)
df.head()
```

[140]:
```
         date    device  failure    metric1  metric2  metric3  metric4  \
0 2015-01-01  S1F01085        0  215630672       55        0       52
1 2015-01-01  S1F0166B        0   61370680        0        3        0
2 2015-01-01  S1F01E6Y        0  173295968        0        0        0
3 2015-01-01  S1F01JE0        0   79694024        0        0        0
4 2015-01-01  S1F01R2B        0  135970480        0        0        0

   metric5  metric6  metric7  metric8  metric9 activedays  month  week_day
0        6   407438        0        0        7     0 days      1         3
1        6   403174        0        0        0     0 days      1         3
2       12   237394        0        0        0     0 days      1         3
3        6   410186        0        0        0     0 days      1         3
4       15   313173        0        0        3     0 days      1         3
```

[141]:
```
#Données par mois
df.groupby('month').agg({'device':lambda x: x.nunique()})
```

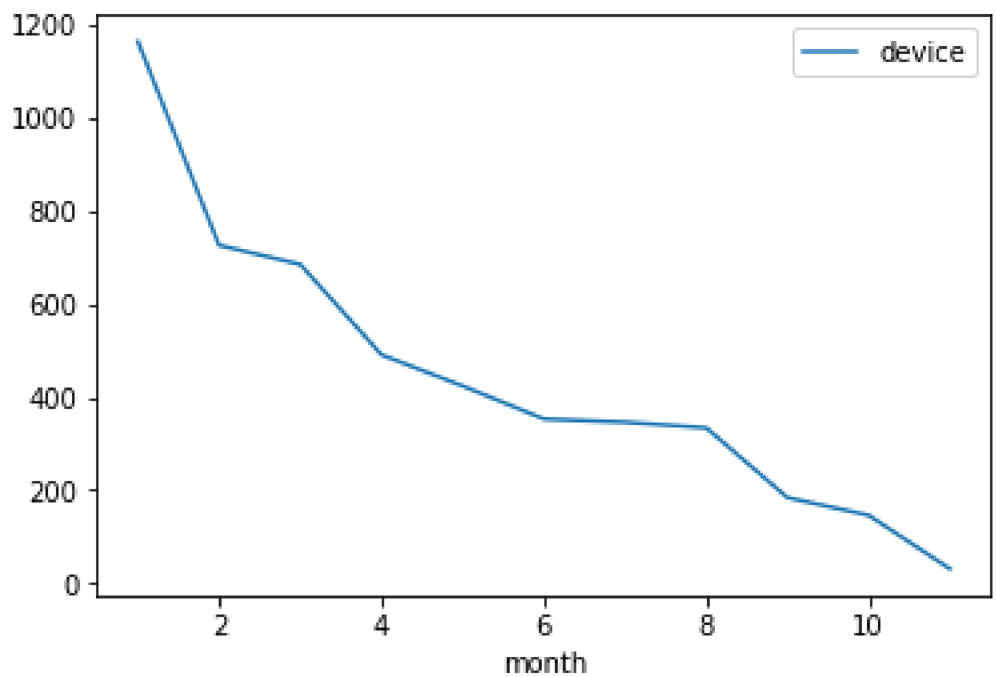
[141]:

```
       device
month
1        1164
2         726
3         685
4         491
5         424
6         353
7         346
8         334
9         184
10        146
11         31
```

On remarque que la quantité des données diminue d'un mois à l'autre d'une manière très rapide.

[142]:

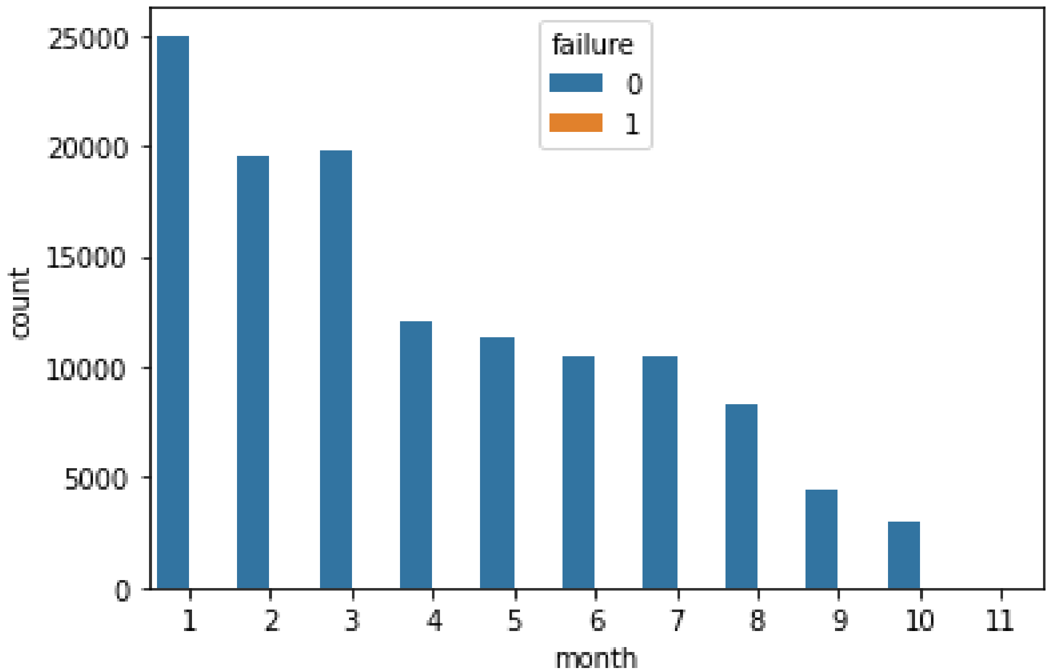
```
#machines par mois
df.groupby('month').agg({'device':lambda x: x.nunique()}).plot()
plt.show()
```



La même remarque sur le nombre des machines, qui diminue d'un mois à l'autre.

[143]:

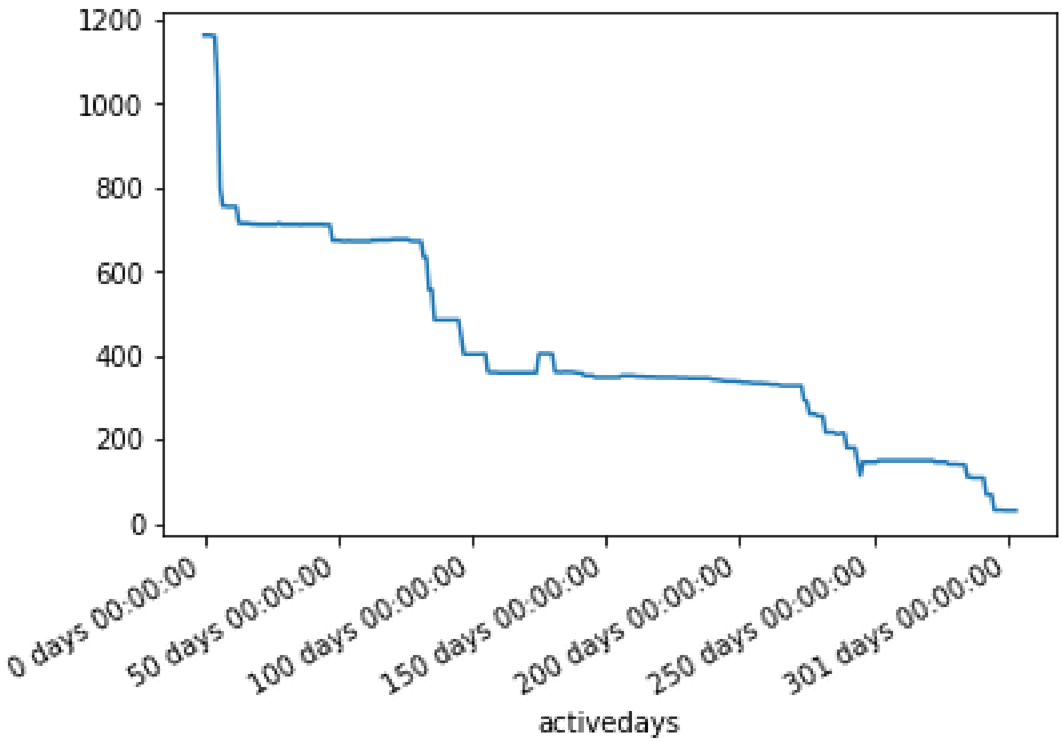
```
#Nombre de pannes et de fonctionnement normal par mois
ax = sns.countplot(x="month", hue="failure", data=df)
plt.show()
```



[144]:
```
#Date maxmiale et minimale
max(df.date), min(df.date)
```

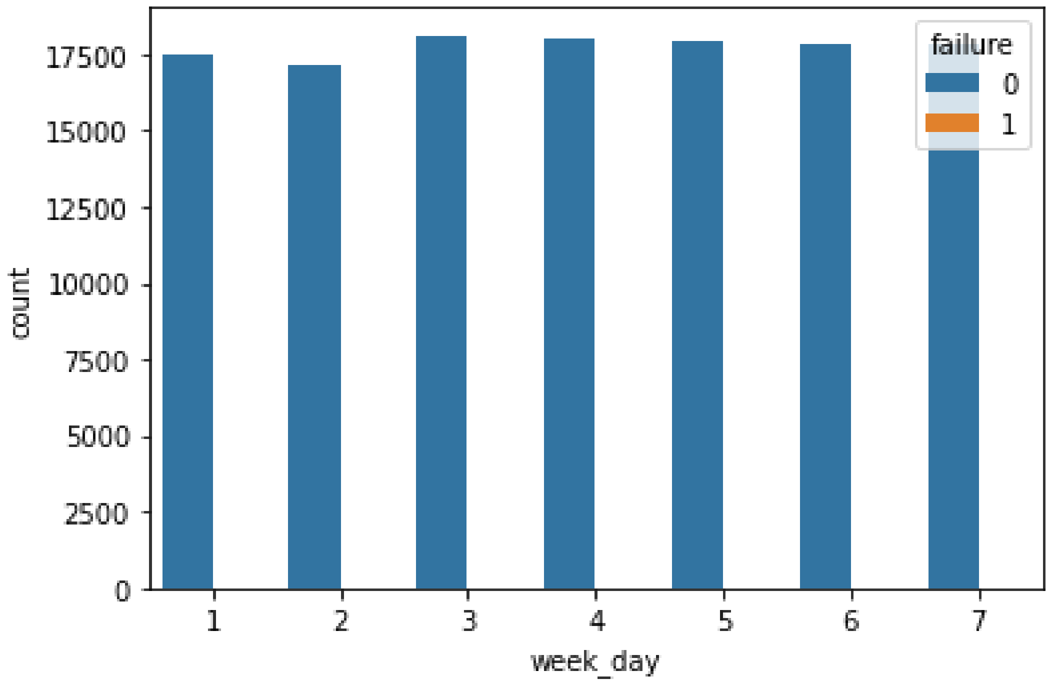
[144]: (Timestamp('2015-11-02 00:00:00'), Timestamp('2015-01-01 00:00:00'))

[145]:
```
#Nombre de machines par journées d'activités
df.groupby('activedays')['device'].count().plot()
plt.show()
```



On déduit qu'un nombre très grand de machines ne diposent pas de donnés plus que de 50 jours.

[146]:
```
#Nombre de fonctionnement normale vs pannes par jour de semaine
ax = sns.countplot(x='week_day',hue='failure',data=df)
plt.show()
```



Le nombre de pannes est relativement très bas.

[147]:
```
df_date = df.groupby('device').agg({'date':max})
df_date.date.to_dict()
#Création de la date maximale, c'est à dire la dernière date dont laquelle
df['max_date']=df.device.map(df_date.date.to_dict())
df.head()
```

[147]:
```
         date    device  failure    metric1  metric2  metric3  metric4  \
0 2015-01-01  S1F01085        0  215630672       55        0       52
1 2015-01-01  S1F0166B        0   61370680        0        3        0
2 2015-01-01  S1F01E6Y        0  173295968        0        0        0
3 2015-01-01  S1F01JE0        0   79694024        0        0        0
4 2015-01-01  S1F01R2B        0  135970480        0        0        0

   metric5  metric6  metric7  metric8  metric9 activedays  month  week_day  \
0        6   407438        0        0        7     0 days      1         3
1        6   403174        0        0        0     0 days      1         3
2       12   237394        0        0        0     0 days      1         3
3        6   410186        0        0        0     0 days      1         3
4       15   313173        0        0        3     0 days      1         3

    max_date
0 2015-01-06
1 2015-01-06
```

```
2 2015-02-17
3 2015-01-06
4 2015-08-24
```

[148]:
```
#Date maximale d'enregistrement de données par machine
df1 = df.groupby('device').agg({'date':max})
df1.head()
```

[148]:
```
                date
device
S1F01085 2015-01-06
S1F013BB 2015-05-11
S1F0166B 2015-01-06
S1F01E6Y 2015-02-17
S1F01JE0 2015-01-06
```

[149]:
```
# Nous allons maintenant essayer de créer une variable qui mesure si notre␣
↪machine a tombé en panne précédemment ou pas
df1=df1.reset_index()

df=df.reset_index(drop=True)

df2= pd.merge(df1,df,how='left',on=['device','date'])

df2.head()
```

[149]:
```
     device       date  failure    metric1  metric2  metric3  metric4  \
0  S1F01085 2015-01-06        0  128832128       56        0       52
1  S1F013BB 2015-05-11        0  115676688        0        0        0
2  S1F0166B 2015-01-06        0    7441792        0        3        0
3  S1F01E6Y 2015-02-17        0  147350000        0        0        0
4  S1F01JE0 2015-01-06        0  185424928        0        0        0

   metric5  metric6  metric7  metric8  metric9 activedays  month  week_day  \
0        6   409404        0        0        7     5 days      1         1
1        5   689161        0        0        0   130 days      5         7
2        6   404786        0        0        0     5 days      1         1
3       12   259491        0        0        0    47 days      2         1
4        6   412151        0        0        0     5 days      1         1

    max_date
0 2015-01-06
1 2015-05-11
2 2015-01-06
3 2015-02-17
4 2015-01-06
```

[150]:
```
df2['failure_before']=0
df2.head()
```

[150]:
```
     device        date  failure    metric1  metric2  metric3  metric4  \
0  S1F01085 2015-01-06        0  128832128       56        0       52
1  S1F013BB 2015-05-11        0  115676688        0        0        0
2  S1F0166B 2015-01-06        0    7441792        0        3        0
3  S1F01E6Y 2015-02-17        0  147350000        0        0        0
4  S1F01JE0 2015-01-06        0  185424928        0        0        0

   metric5  metric6  metric7  metric8  metric9 activedays  month  week_day  \
0        6   409404        0        0        7     5 days      1         1
1        5   689161        0        0        0   130 days      5         7
2        6   404786        0        0        0     5 days      1         1
3       12   259491        0        0        0    47 days      2         1
4        6   412151        0        0        0     5 days      1         1

    max_date  failure_before
0 2015-01-06               0
1 2015-05-11               0
2 2015-01-06               0
3 2015-02-17               0
4 2015-01-06               0
```

[151]:
```
#On sait, d'après l'analyse précédante que ces machines on eu déjà une panne
df2.loc[df2.device == 'S1F136J0','failure_before'] = 1
df2.loc[df2.device == 'W1F0KCP2','failure_before'] = 1
df2.loc[df2.device == 'W1F0M35B','failure_before'] = 1
df2.loc[df2.device == 'S1F0GPFZ','failure_before'] = 1
df2.loc[df2.device == 'W1F11ZG9','failure_before'] = 1
```

4 Data Transformation

[152]:
```
cat_ftrs = ['metric3','metric4', 'metric5', 'metric7', 'metric9']
for col in cat_ftrs:
    df2[col]=df2[col].astype('object')
```

[153]:
```
#Conversion des activesdays vers le type entier
def str_to_num(str):
    return str.split(' ')[0]
df2.activedays = df2.activedays.astype('str')
df2.activedays=df2.activedays.apply(str_to_num)
df2.activedays = df2.activedays.astype('int')
df2.head()
```

[153]:
```
    device        date  failure    metric1  metric2 metric3 metric4 metric5  \
0  S1F01085 2015-01-06        0  128832128       56       0      52       6
1  S1F013BB 2015-05-11        0  115676688        0       0       0       5
2  S1F0166B 2015-01-06        0    7441792        0       3       0       6
3  S1F01E6Y 2015-02-17        0  147350000        0       0       0      12
4  S1F01JE0 2015-01-06        0  185424928        0       0       0       6

   metric6 metric7  metric8 metric9  activedays  month  week_day   max_date  \
0   409404       0        0       7           5      1         1 2015-01-06
1   689161       0        0       0         130      5         7 2015-05-11
2   404786       0        0       0           5      1         1 2015-01-06
3   259491       0        0       0          47      2         1 2015-02-17
4   412151       0        0       0           5      1         1 2015-01-06

   failure_before
0               0
1               0
2               0
3               0
4               0
```

[154]:
```python
# converstion du mois et de jour de la semaine en type catégorique
for col in ['month','week_day']:
    df2[col]=df2[col].astype('object')
```

[155]:
```python
# la colonne metric8 est metric7 sont semblables
df2.drop('metric8',axis=1,inplace=True)
```

5 Pipeline

[156]:
```python
df_pipeline = df2.copy()
df_pipeline.head()
```

[156]:
```
    device        date  failure    metric1  metric2 metric3 metric4 metric5  \
0  S1F01085 2015-01-06        0  128832128       56       0      52       6
1  S1F013BB 2015-05-11        0  115676688        0       0       0       5
2  S1F0166B 2015-01-06        0    7441792        0       3       0       6
3  S1F01E6Y 2015-02-17        0  147350000        0       0       0      12
4  S1F01JE0 2015-01-06        0  185424928        0       0       0       6

   metric6 metric7 metric9  activedays month week_day   max_date  \
0   409404       0       7           5     1        1 2015-01-06
1   689161       0       0         130     5        7 2015-05-11
2   404786       0       0           5     1        1 2015-01-06
3   259491       0       0          47     2        1 2015-02-17
4   412151       0       0           5     1        1 2015-01-06
```

```
   failure_before
0               0
1               0
2               0
3               0
4               0
```

[157]:
```
len(['metric1', 'metric2', 'metric3', 'metric4', 'metric5', 'metric6',
       'metric7', 'metric9', 'activedays', 'failure_before','device_S1F0',␣
 ↪'device_S1F1',
       'device_W1F0', 'device_W1F1', 'device_Z1F0', 'device_Z1F1',
       'device_Z1F2', 'month_1' , 'month_2', 'month_3', 'month_4', 'month_5',␣
 ↪'month_6',
       'month_7', 'month_8', 'month_9', 'month_10', 'month_11','week_day_1',␣
 ↪'week_day_2',
       'week_day_3', 'week_day_4', 'week_day_5', 'week_day_6', 'week_day_7'])
```

[157]: 35

[158]:
```
from datetime import datetime
def pipeline(base,array,scaler):

    # notre vecteur d'entrée
    """
    [date d'aujourd'hui ,device name,
    'metric1', 'metric2', 'metric3', 'metric4', 'metric5', 'metric6',␣
 ↪'metric7', 'metric9']
    """
    # our output array
    length = len(['metric1', 'metric2', 'metric3', 'metric4', 'metric5',␣
 ↪'metric6',
       'metric7', 'metric9', 'activedays', 'failure_before','device_S1F0',␣
 ↪'device_S1F1',
       'device_W1F0', 'device_W1F1', 'device_Z1F0', 'device_Z1F1',
       'device_Z1F2', 'month_1' , 'month_2', 'month_3', 'month_4', 'month_5',␣
 ↪'month_6',
       'month_7', 'month_8', 'month_9', 'month_10', 'month_11','week_day_1',␣
 ↪'week_day_2',
       'week_day_3', 'week_day_4', 'week_day_5', 'week_day_6', 'week_day_7'])

    output_array = [0 for i in range(length)]

    # notre vecteur de sortie
    match array[1][:4] :
        case "S1F0" : output_array[10] = 1
```

```
        case "S1F1" : output_array[11] = 1
        case "W1F0" : output_array[12] = 1
        case "W1F1" : output_array[13] = 1
        case "Z1F0" : output_array[14] = 1
        case "Z1F1" : output_array[15] = 1
        case "Z1F2" : output_array[16] = 1

    # prenons le mois et le jour
    temp = array[0]
    array[0] = datetime.strptime(array[0], "%Y-%m-%d")
    month = array[0].month
    #print(f"month = {month}")
    day = array[0].weekday() +1 # LUNDI = 0 donc on ajoute 1 pour avoir lundi =1
    #print(f"day = {day}")


    # insertion des jours
    match day :
        case 1 : output_array[28] = 1
        case 2 : output_array[29] = 1
        case 3 : output_array[30] = 1
        case 4 : output_array[31] = 1
        case 5 : output_array[32] = 1
        case 6 : output_array[33] = 1
        case 7 : output_array[34] = 1

    # insertions des mois
    match month :
        case 1 : output_array[17] = 1
        case 2 : output_array[18] = 1
        case 3 : output_array[19] = 1
        case 4 : output_array[20] = 1
        case 5 : output_array[21] = 1
        case 6 : output_array[22] = 1
        case 7 : output_array[23] = 1
        case 8 : output_array[24] = 1
        case 9 : output_array[25] = 1
        case 10 : output_array[26] = 1
        case 11 : output_array[27] = 1

    # Trouvons combien de jour la machine était actif
    for i in base.device :
        if array[1] == i:
        # conversion de la colonne des dates en type date
            time = base[base.device == array[1]].date.values
            time = np.datetime_as_string(time, unit='D')[0]
            time = datetime.strptime(time,"%Y-%m-%d")
```

```
            output_array[8] = time.day
            # ajout des jours entre aujourd'hui et mois 10 (en supposant que␣
↪notre modèle va prédire à partir de 01/10/2015)
            new_days = datetime.strptime(temp, "%Y-%m-%d") - datetime.
↪strptime('2015-10-01', "%Y-%m-%d")
            output_array[8] = output_array[8] + new_days.days
            break


    # on mentionne si la machine a déjà tombé en panne précedement ou non
    failures = base.groupby('device').agg({'failure_before':lambda x: np.
↪sum(x)})
    for i in failures.index :
        if i == array[1] :
            output_array[9] = failures.loc[i].failure_before

    # normalisation des données
    array = np.array(array)
    output_array = np.array(output_array,np.float64)
    val = scaler.transform(array[2:].reshape(1, -1))
    output_array[:8] = val.flatten()

    return output_array.reshape(1, -1)
```

6 Essai de pipeline

[ ]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler() # objet pour normaliser les données
```

[159]:
```
df_train = df2.copy()
```

[160]:
```
num_ftrs␣
↪=['metric1','metric2','metric3','metric4','metric5','metric6','metric7','metric9']
df_train[num_ftrs]=scaler.fit_transform(df_train[num_ftrs]) # entrainement de␣
↪l'objet sur les données d'entrainement numérique
df_train.head()
```

[160]:
```
     device        date  failure   metric1   metric2   metric3   metric4  \
0  S1F01085 2015-01-06        0  0.094795 -0.136309 -0.042339  0.534665
1  S1F013BB 2015-05-11        0 -0.092146 -0.145660 -0.042339 -0.124295
2  S1F0166B 2015-01-06        0 -1.630184 -0.145660 -0.038274 -0.124295
3  S1F01E6Y 2015-02-17        0  0.357937 -0.145660 -0.042339 -0.124295
4  S1F01JE0 2015-01-06        0  0.898989 -0.145660 -0.042339 -0.124295

    metric5   metric6   metric7   metric9  activedays month week_day  \
```

```
0 -0.521389  1.333502 -0.101656 -0.047396           5      1         1
1 -0.602290  4.008798 -0.101656 -0.050645         130      5         7
2 -0.521389  1.289341 -0.101656 -0.050645           5      1         1
3 -0.035987 -0.100105 -0.101656 -0.050645          47      2         1
4 -0.521389  1.359772 -0.101656 -0.050645           5      1         1

    max_date  failure_before
0 2015-01-06               0
1 2015-05-11               0
2 2015-01-06               0
3 2015-02-17               0
4 2015-01-06               0
```

[161]:
```python
# on supprime les 2 colonne liée à la date
df_train.drop(['date','max_date'],axis=1,inplace=True)
```

[162]:
```python
# on dive les machines en 6 catégorie, machine de type : S1F0, S1F1, W1F0 ,␣
↪W1F1 , Z1F0 , Z1F1
Id = df_train.device.values.tolist()
Id1 = []
for i in Id:
    i = i[:4]
    Id1.append(i)

df_train.device=Id1
df_train.head()
```

[162]:
```
  device  failure   metric1   metric2   metric3   metric4   metric5   metric6  \
0   S1F0        0  0.094795 -0.136309 -0.042339  0.534665 -0.521389  1.333502
1   S1F0        0 -0.092146 -0.145660 -0.042339 -0.124295 -0.602290  4.008798
2   S1F0        0 -1.630184 -0.145660 -0.038274 -0.124295 -0.521389  1.289341
3   S1F0        0  0.357937 -0.145660 -0.042339 -0.124295 -0.035987 -0.100105
4   S1F0        0  0.898989 -0.145660 -0.042339 -0.124295 -0.521389  1.359772

    metric7   metric9  activedays month week_day  failure_before
0 -0.101656 -0.047396           5     1        1               0
1 -0.101656 -0.050645         130     5        7               0
2 -0.101656 -0.050645           5     1        1               0
3 -0.101656 -0.050645          47     2        1               0
4 -0.101656 -0.050645           5     1        1               0
```

[163]:
```python
df_train = pd.get_dummies(df_train) # à fin d'obtenir les mois et le jours␣
↪divisées
```

```
C:\Users\pc\AppData\Local\Temp\ipykernel_10212\3739043471.py:1: FutureWarning:
In a future version, the Index constructor will not infer numeric dtypes when
passed object-dtype sequences (matching Series behavior)
```

```
  df_train = pd.get_dummies(df_train)
C:\Users\pc\AppData\Local\Temp\ipykernel_10212\3739043471.py:1: FutureWarning:
In a future version, the Index constructor will not infer numeric dtypes when
passed object-dtype sequences (matching Series behavior)
  df_train = pd.get_dummies(df_train)
```

[164]:
```
df_train.head()
```

[164]:
```
   failure   metric1   metric2   metric3   metric4   metric5   metric6  \
0        0  0.094795 -0.136309 -0.042339  0.534665 -0.521389  1.333502
1        0 -0.092146 -0.145660 -0.042339 -0.124295 -0.602290  4.008798
2        0 -1.630184 -0.145660 -0.038274 -0.124295 -0.521389  1.289341
3        0  0.357937 -0.145660 -0.042339 -0.124295 -0.035987 -0.100105
4        0  0.898989 -0.145660 -0.042339 -0.124295 -0.521389  1.359772

    metric7   metric9  activedays  …  month_9  month_10  month_11  \
0 -0.101656 -0.047396           5  …        0         0         0
1 -0.101656 -0.050645         130  …        0         0         0
2 -0.101656 -0.050645           5  …        0         0         0
3 -0.101656 -0.050645          47  …        0         0         0
4 -0.101656 -0.050645           5  …        0         0         0

   week_day_1  week_day_2  week_day_3  week_day_4  week_day_5  week_day_6  \
0           1           0           0           0           0           0
1           0           0           0           0           0           0
2           1           0           0           0           0           0
3           1           0           0           0           0           0
4           1           0           0           0           0           0

   week_day_7
0           0
1           1
2           0
3           0
4           0

[5 rows x 36 columns]
```

[167]:
```
# Posons notre X comme les entrée, et Y notre sortie
X = df_train.drop('failure',axis=1)
Y = df_train.failure
```

[170]:
```
indexes_train = df_pipeline[df_pipeline.date < "2015-10-01"].index
X.iloc[indexes_train].head()
```

[170]:
```
    metric1   metric2   metric3   metric4   metric5   metric6   metric7  \
0  0.094795 -0.136309 -0.042339  0.534665 -0.521389  1.333502 -0.101656
```

```
1 -0.092146 -0.145660 -0.042339 -0.124295 -0.602290  4.008798 -0.101656
2 -1.630184 -0.145660 -0.038274 -0.124295 -0.521389  1.289341 -0.101656
3  0.357937 -0.145660 -0.042339 -0.124295 -0.035987 -0.100105 -0.101656
4  0.898989 -0.145660 -0.042339 -0.124295 -0.521389  1.359772 -0.101656

    metric9  activedays  failure_before  …  month_9  month_10  month_11  \
0 -0.047396           5               0  …        0         0         0
1 -0.050645         130               0  …        0         0         0
2 -0.050645           5               0  …        0         0         0
3 -0.050645          47               0  …        0         0         0
4 -0.050645           5               0  …        0         0         0

   week_day_1  week_day_2  week_day_3  week_day_4  week_day_5  week_day_6  \
0           1           0           0           0           0           0
1           0           0           0           0           0           0
2           1           0           0           0           0           0
3           1           0           0           0           0           0
4           1           0           0           0           0           0

   week_day_7
0           0
1           1
2           0
3           0
4           0

[5 rows x 35 columns]
```

[171]:

```
indexes_test = df_pipeline[df_pipeline.date >= "2015-10-01"].index
X.iloc[indexes_test].head()
```

[171]:

```
     metric1   metric2   metric3   metric4   metric5   metric6   metric7  \
60 -0.037285 -0.145660 -0.042339 -0.124295 -0.359588  1.431379 -0.101656
61  1.384632 -0.145660 -0.042339 -0.124295 -0.602290  0.882199 -0.101656
72  0.191214  0.400737 -0.042339 -0.048261 -0.359588  1.453268 -0.101656
79  1.183773 -0.145660 -0.042339  0.027773 -0.116887  0.797338 -0.101656
81  0.535810 -0.145660 -0.042339  0.040445 -0.116887  0.738315  0.630489

     metric9  activedays  failure_before  …  month_9  month_10  month_11  \
60 -0.049717         291               0  …        0         1         0
61 -0.050645         286               0  …        0         1         0
72 -0.050645         284               0  …        0         1         0
79 -0.050645         305               0  …        0         0         1
81 -0.050645         305               0  …        0         0         1

    week_day_1  week_day_2  week_day_3  week_day_4  week_day_5  week_day_6  \
60           0           0           0           0           0           0
```

```
61            0            1            0            0            0            0
72            0            0            0            0            0            0
79            0            0            0            0            0            0
81            0            0            0            0            0            0

    week_day_7
60            1
61            0
72            1
79            1
81            1

[5 rows x 35 columns]
```

[172]:
```
# division des données en données d'entraienement, et autre de tests
x_train , y_train , x_test , y_test = X.iloc[indexes_train] , Y.
 ↪iloc[indexes_train] , X.iloc[indexes_test] , Y.iloc[indexes_test]
```

6.0.1 Modèle Machine Learning : K-Nearest Neighbors

[173]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
```

[174]:
```
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(x_train, y_train)

y_pred = knn.predict(x_test)

print(f"{metrics.accuracy_score(y_test, y_pred)*100} %")
```

```
97.94520547945206 %
```

6.0.2 partie test du pipeline

[175]:
```
l = ["2015-01-06","S1F01085",128832128,56,0,52,6,409404,0,7]
out = pipeline(df2,l,scaler)
```

```
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
ra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\base.py:439:
UserWarning: X does not have valid feature names, but StandardScaler was fitted
with feature names
  warnings.warn(
```

[176]:
```
y_pred = knn.predict(out)
y_pred
```

```
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
```

```
ra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\base.py:439:
UserWarning: X does not have valid feature names, but KNeighborsClassifier was
fitted with feature names
  warnings.warn(
```

[176]:
```
array([0], dtype=int64)
```

Construction du modèle de prédiction et son utilisation

D'après ce qu'on a vu dans la phase d'analyse, il est claire que la construction d'un modèle fiable avec ces données sera presque impossible, vu le faible nombre d'occurance des pannes, ainsi qu'il ne sera pas très util pour une tel entreprise, ainsi que les metriques ont un type différent pour chaque type de machines, nous allons construit un modèle qui permet de prédire le nombre de pannes par mois et donc pourvoir faire des maintenances prédictives et préventives, pour le faire nous allons au début générer des données en se basant sur les données précédantes.

Sélectionnons un type de machines précis:

[177]:
```
for device in ['device_S1F0', 'device_S1F1', 'device_W1F0',␣
↪'device_W1F1','device_Z1F0', 'device_Z1F1', 'device_Z1F2']:
    print(f'{device} : {df_train[df_train[device]==1].shape}')
```

```
device_S1F0 : (391, 36)
device_S1F1 : (139, 36)
device_W1F0 : (282, 36)
device_W1F1 : (138, 36)
device_Z1F0 : (149, 36)
device_Z1F1 : (67, 36)
device_Z1F2 : (3, 36)
```

On choisi les machines de type S1F0 puisque on dispose de beaucoup de données sur eux, On élemine les colonnes non nécessaires :

[178]:
```
df_train.columns
```

[178]:
```
Index(['failure', 'metric1', 'metric2', 'metric3', 'metric4', 'metric5',
       'metric6', 'metric7', 'metric9', 'activedays', 'failure_before',
       'device_S1F0', 'device_S1F1', 'device_W1F0', 'device_W1F1',
       'device_Z1F0', 'device_Z1F1', 'device_Z1F2', 'month_1', 'month_2',
       'month_3', 'month_4', 'month_5', 'month_6', 'month_7', 'month_8',
       'month_9', 'month_10', 'month_11', 'week_day_1', 'week_day_2',
       'week_day_3', 'week_day_4', 'week_day_5', 'week_day_6', 'week_day_7'],
      dtype='object')
```

[179]:
```
df_train1 = df_train[df_train['device_S1F0']==1].copy()
df_train1.drop(['device_S1F0', 'device_S1F1', 'device_W1F0', 'device_W1F1',
       'device_Z1F0', 'device_Z1F1', 'device_Z1F2','activedays',␣
↪'failure_before','month_1', 'month_2',
       'month_3', 'month_4', 'month_5', 'month_6', 'month_7', 'month_8',
       'month_9', 'month_10', 'month_11','week_day_1', 'week_day_2',
```

```
      'week_day_3', 'week_day_4', 'week_day_5', 'week_day_6',␣
 ↪'week_day_7'],inplace=True, axis=1)
df_train1.head()
```

[179]:
```
   failure   metric1   metric2   metric3   metric4   metric5   metric6  \
0        0  0.094795 -0.136309 -0.042339  0.534665 -0.521389  1.333502
1        0 -0.092146 -0.145660 -0.042339 -0.124295 -0.602290  4.008798
2        0 -1.630184 -0.145660 -0.038274 -0.124295 -0.521389  1.289341
3        0  0.357937 -0.145660 -0.042339 -0.124295 -0.035987 -0.100105
4        0  0.898989 -0.145660 -0.042339 -0.124295 -0.521389  1.359772

    metric7   metric9
0 -0.101656 -0.047396
1 -0.101656 -0.050645
2 -0.101656 -0.050645
3 -0.101656 -0.050645
4 -0.101656 -0.050645
```

Créons le générateur de données avec une distribution par défaut de type Gamma:

[180]:
```python
from sdv.tabular import GaussianCopula
gen = GaussianCopula(default_distribution='gamma')
gen.fit(df_train1)
```

```
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
ra8p0\LocalCache\local-packages\Python310\site-
packages\rdt\transformers\numerical.py:100: UserWarning: No rounding scheme
detected for column 'metric1'. Data will not be rounded.
  warnings.warn(
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
ra8p0\LocalCache\local-packages\Python310\site-
packages\rdt\transformers\numerical.py:100: UserWarning: No rounding scheme
detected for column 'metric2'. Data will not be rounded.
  warnings.warn(
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
ra8p0\LocalCache\local-packages\Python310\site-
packages\rdt\transformers\numerical.py:100: UserWarning: No rounding scheme
detected for column 'metric3'. Data will not be rounded.
  warnings.warn(
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
ra8p0\LocalCache\local-packages\Python310\site-
packages\rdt\transformers\numerical.py:100: UserWarning: No rounding scheme
detected for column 'metric4'. Data will not be rounded.
  warnings.warn(
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
ra8p0\LocalCache\local-packages\Python310\site-
packages\rdt\transformers\numerical.py:100: UserWarning: No rounding scheme
detected for column 'metric5'. Data will not be rounded.
```

```
  warnings.warn(
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
ra8p0\LocalCache\local-packages\Python310\site-
packages\rdt\transformers\numerical.py:100: UserWarning: No rounding scheme
detected for column 'metric6'. Data will not be rounded.
  warnings.warn(
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
ra8p0\LocalCache\local-packages\Python310\site-
packages\rdt\transformers\numerical.py:100: UserWarning: No rounding scheme
detected for column 'metric7'. Data will not be rounded.
  warnings.warn(
C:\Users\pc\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kf
ra8p0\LocalCache\local-packages\Python310\site-
packages\rdt\transformers\numerical.py:100: UserWarning: No rounding scheme
detected for column 'metric9'. Data will not be rounded.
  warnings.warn(
```

[181]:
```
newdata = gen.sample(500)
newdata.head()
```

[181]:
```
   failure   metric1   metric2   metric3   metric4   metric5   metric6  \
0        0  1.720853 -0.145369 -0.042339 -0.124183 -0.767231  0.792990
1        0 -0.278253  0.453380 -0.042339 -0.088611 -0.844873  0.155796
2        0 -0.707268 -0.136342 -0.040956 -0.124120 -0.785259  0.337097
3        0 -1.594126 -0.145649 -0.042339 -0.124295 -0.775799  0.602567
4        0 -0.516563  0.142044 -0.042339 -0.123259 -0.843607 -1.153715

    metric7   metric9
0 -0.101656 -0.050645
1 -0.101656 -0.050645
2 -0.101656  0.137425
3 -0.101656 -0.050645
4 -0.101656 -0.050645
```

[182]:
```
newdata.failure.value_counts()
```

[182]:
```
0    368
1    132
Name: failure, dtype: int64
```

Nous allons générer les données pour les mois, supposons qu'on a un enregistrement par jour: Générons pour le mois de Janvier en premier par example:

[183]:
```
jan_data = gen.sample(31)
jan_data["date"] = pd.to_datetime([f'2015-01-{f"0{d}" if d<10 else d}' for d in␣
 ↪range(1,32)])
jan_data.head()
```

[183]:
```
   failure   metric1   metric2   metric3   metric4   metric5   metric6  \
0        0 -1.198970  1.186175 -0.042339 -0.124295 -0.809015 -0.708721
1        1  1.720853  0.060647 -0.042339  1.045583 -0.777851  0.660444
2        1  1.311306  3.477940 -0.042304 -0.069260 -0.844650  0.473681
3        0 -0.684862 -0.145660 -0.042334 -0.124295 -0.843849 -0.473397
4        1 -1.735933  0.045323 -0.042339  3.867599 -0.842477 -0.442049

    metric7   metric9       date
0 -0.101656 -0.050062 2015-01-01
1  1.287553 -0.050645 2015-01-02
2  2.883124 -0.050645 2015-01-03
3 -0.101656 -0.049923 2015-01-04
4 -0.101656  0.355978 2015-01-05
```

[184]:
```
jan_data.failure.value_counts()
```

[184]:
```
0    21
1    10
Name: failure, dtype: int64
```

En fait de même avec le reste des mois:

[185]:
```
months_data = [jan_data]
m=2
for maxDays in [28,31,30,31,30,31,31,30,31,30,31]:
    temp_data = gen.sample(maxDays)
    temp_data["date"] = pd.to_datetime([f'2015-{f"0{m}" if m<10 else␣
 ↪m}-{f"0{d}" if d<10 else d}' for d in range(1,maxDays+1)])
    m+=1
    months_data.append(temp_data)
newdata = pd.concat(months_data,axis=0)
newdata.to_csv("./GENDATA/device_S1F0/orgendata.csv")
newdata.head()
```

[185]:
```
   failure   metric1   metric2   metric3   metric4   metric5   metric6  \
0        0 -1.198970  1.186175 -0.042339 -0.124295 -0.809015 -0.708721
1        1  1.720853  0.060647 -0.042339  1.045583 -0.777851  0.660444
2        1  1.311306  3.477940 -0.042304 -0.069260 -0.844650  0.473681
3        0 -0.684862 -0.145660 -0.042334 -0.124295 -0.843849 -0.473397
4        1 -1.735933  0.045323 -0.042339  3.867599 -0.842477 -0.442049

    metric7   metric9       date
0 -0.101656 -0.050062 2015-01-01
1  1.287553 -0.050645 2015-01-02
2  2.883124 -0.050645 2015-01-03
3 -0.101656 -0.049923 2015-01-04
4 -0.101656  0.355978 2015-01-05
```

Nous allons réviser les statistiques sur nos données :

[186]:
```
newdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 365 entries, 0 to 30
Data columns (total 10 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   failure   365 non-null    int64
 1   metric1   365 non-null    float64
 2   metric2   365 non-null    float64
 3   metric3   365 non-null    float64
 4   metric4   365 non-null    float64
 5   metric5   365 non-null    float64
 6   metric6   365 non-null    float64
 7   metric7   365 non-null    float64
 8   metric9   365 non-null    float64
 9   date      365 non-null    datetime64[ns]
dtypes: datetime64[ns](1), float64(8), int64(1)
memory usage: 31.4 KB
```

[187]:
```
newdata.describe()
```

[187]:

	failure	metric1	metric2	metric3	metric4	metric5	\
count	365.000000	365.000000	365.000000	365.000000	365.000000	365.000000	
mean	0.246575	-0.027347	0.302854	0.334128	0.187600	-0.589764	
std	0.431609	0.977673	1.464467	2.397107	1.046383	0.598720	
min	0.000000	-1.735933	-0.145660	-0.042339	-0.124295	-0.844991	
25%	0.000000	-0.777581	-0.145660	-0.042339	-0.124295	-0.843635	
50%	0.000000	-0.040309	-0.143984	-0.042339	-0.124239	-0.814631	
75%	0.000000	0.693936	-0.030287	-0.042339	-0.105799	-0.642766	
max	1.000000	1.720853	10.674075	33.739714	7.267167	4.378624	

	metric6	metric7	metric9
count	365.000000	365.000000	365.000000
mean	0.167197	0.131756	-0.004383
std	0.802130	1.040476	0.229635
min	-1.934834	-0.101656	-0.050645
25%	-0.421912	-0.101656	-0.050645
50%	0.120148	-0.101656	-0.050645
75%	0.612296	-0.099223	-0.050369
max	4.008798	9.599273	2.621107

[188]:
```
newdata.failure.value_counts()
```

[188]:
```
0    275
1     90
Name: failure, dtype: int64
```

Nous allons recréer des colonnes importantes pour la suite :

[189]:
```
newdata['activedays']=newdata.date-newdata.date.iloc[0]
def str_to_num(str):
    return str.split(' ')[0]

newdata.activedays = newdata.activedays.astype('str')

newdata.activedays=newdata.activedays.apply(str_to_num)
newdata.activedays = newdata.activedays.astype('int')

newdata['month']=newdata['date'].dt.month
newdata['week_day']=newdata.date.dt.weekday
newdata['week_day'].replace(0,7,inplace=True)

newdata.head()
```

[189]:
```
   failure   metric1   metric2   metric3   metric4   metric5   metric6  \
0        0 -1.198970  1.186175 -0.042339 -0.124295 -0.809015 -0.708721
1        1  1.720853  0.060647 -0.042339  1.045583 -0.777851  0.660444
2        1  1.311306  3.477940 -0.042304 -0.069260 -0.844650  0.473681
3        0 -0.684862 -0.145660 -0.042334 -0.124295 -0.843849 -0.473397
4        1 -1.735933  0.045323 -0.042339  3.867599 -0.842477 -0.442049

    metric7   metric9       date  activedays  month  week_day
0 -0.101656 -0.050062 2015-01-01           0      1         3
1  1.287553 -0.050645 2015-01-02           1      1         4
2  2.883124 -0.050645 2015-01-03           2      1         5
3 -0.101656 -0.049923 2015-01-04           3      1         6
4 -0.101656  0.355978 2015-01-05           4      1         7
```

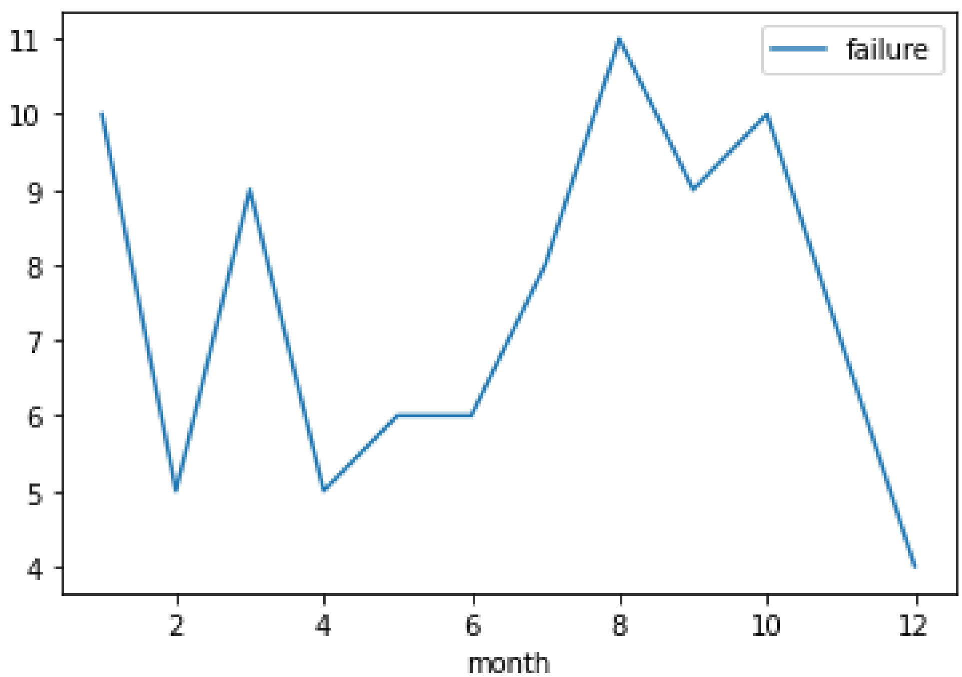
[190]:
```
newdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 365 entries, 0 to 30
Data columns (total 13 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   failure     365 non-null    int64
 1   metric1     365 non-null    float64
 2   metric2     365 non-null    float64
 3   metric3     365 non-null    float64
 4   metric4     365 non-null    float64
 5   metric5     365 non-null    float64
```

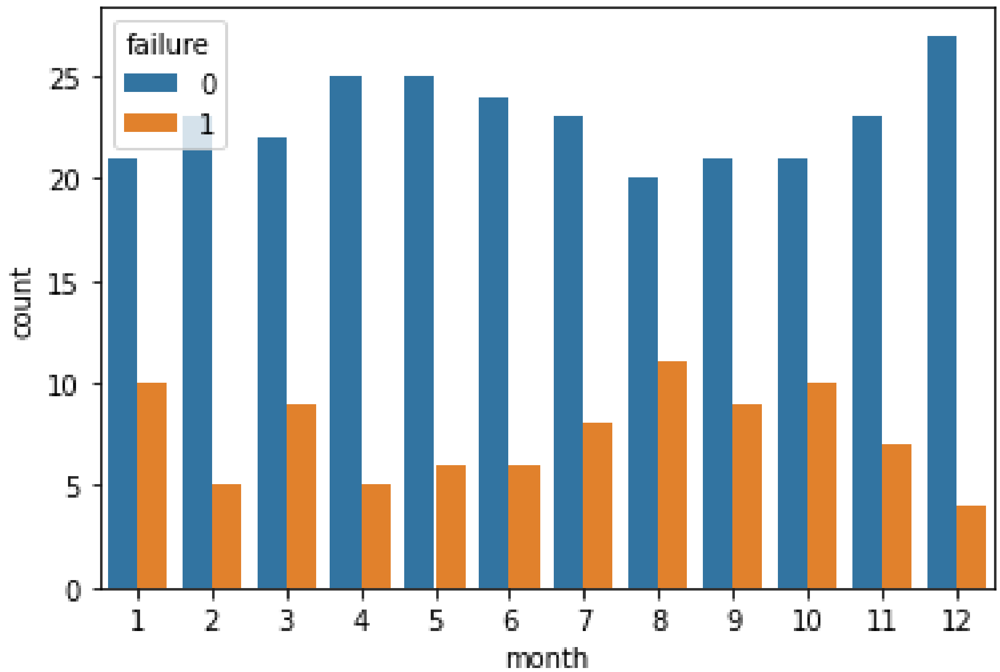
```
 6   metric6     365 non-null    float64
 7   metric7     365 non-null    float64
 8   metric9     365 non-null    float64
 9   date        365 non-null    datetime64[ns]
 10  activedays  365 non-null    int32
 11  month       365 non-null    int64
 12  week_day    365 non-null    int64
dtypes: datetime64[ns](1), float64(8), int32(1), int64(3)
memory usage: 38.5 KB
```

Voyons voir si nous avons arriver à équilibrer un peu nos données :

[191]:
```
newdata.groupby('month').agg({'failure':lambda x: x.sum()}).plot()
plt.show()
```



[192]:
```
ax = sns.countplot(x="month", hue="failure", data=newdata)
plt.show()
```



Les données sont distribués maintenant d'une bonne manière qui rend notre modèle important.

[193]:
```
newdata.to_csv("./GENDATA/device_S1F0/traindata.csv")
```

[194]:
```
newdata.describe()
```

[194]:
```
         failure    metric1    metric2    metric3    metric4    metric5  \
count 365.000000 365.000000 365.000000 365.000000 365.000000 365.000000
mean    0.246575  -0.027347   0.302854   0.334128   0.187600  -0.589764
std     0.431609   0.977673   1.464467   2.397107   1.046383   0.598720
min     0.000000  -1.735933  -0.145660  -0.042339  -0.124295  -0.844991
25%     0.000000  -0.777581  -0.145660  -0.042339  -0.124295  -0.843635
50%     0.000000  -0.040309  -0.143984  -0.042339  -0.124239  -0.814631
75%     0.000000   0.693936  -0.030287  -0.042339  -0.105799  -0.642766
max     1.000000   1.720853  10.674075  33.739714   7.267167   4.378624

         metric6    metric7    metric9 activedays      month   week_day
count 365.000000 365.000000 365.000000 365.000000 365.000000 365.000000
mean    0.167197   0.131756  -0.004383 182.000000   6.526027   3.997260
std     0.802130   1.040476   0.229635 105.510663   3.452584   2.000685
min    -1.934834  -0.101656  -0.050645   0.000000   1.000000   1.000000
25%    -0.421912  -0.101656  -0.050645  91.000000   4.000000   2.000000
50%     0.120148  -0.101656  -0.050645 182.000000   7.000000   4.000000
75%     0.612296  -0.099223  -0.050369 273.000000  10.000000   6.000000
max     4.008798   9.599273   2.621107 364.000000  12.000000   7.000000
```

Essaions de contruire notre modèle :

[232]:
```
X=newdata.drop(["failure","date","month","week_day"],axis=1)
Y=newdata.failure

from sklearn.neighbors import KNeighborsClassifier

clf = KNeighborsClassifier(1)
clf.fit(X,Y)
```

[232]:
```
KNeighborsClassifier(n_neighbors=1)
```

Générons des données pour l'année (2016):

[233]:
```
nmonths_data = []
m=1
for maxDays in [31,28,31,30,31,30,31,31,30,31,30,31]:
    temp_data = gen.sample(maxDays)
    temp_data["date"] = pd.to_datetime([f'2016-{f"0{m}" if m<10 else␣
 ↪m}-{f"0{d}" if d<10 else d}' for d in range(1,maxDays+1) ])
    m+=1
    nmonths_data.append(temp_data)
validdata = pd.concat(nmonths_data,axis=0)
validdata.to_csv("./GENDATA/device_S1F0/orgenvaldata.csv")
validdata.failure.value_counts()
```

[233]:
```
0    262
1    103
Name: failure, dtype: int64
```

[234]:
```
validdata['activedays']=validdata.date-validdata.date.iloc[0]

validdata.activedays = validdata.activedays.astype('str')
validdata.activedays=validdata.activedays.apply(str_to_num)
validdata.activedays = validdata.activedays.astype('int')

validdata['month']=validdata['date'].dt.month
validdata['week_day']=validdata.date.dt.weekday
validdata['week_day'].replace(0,7,inplace=True)
vmonths = validdata['month']
y_true = validdata['failure']
validdata.drop(['failure','date',"month","week_day"],axis=1,inplace=True)

validdata.head()
```

[234]:
```
    metric1   metric2   metric3   metric4   metric5   metric6   metric7  \
0 -1.593395 -0.145660 -0.042339 -0.124295 -0.844991 -0.508731 -0.101656
1 -0.237287 -0.145643 -0.042261 -0.124065 -0.836441  0.506254 -0.101656
```

```
2  0.912668 -0.145324 -0.042339  1.104955 -0.844776  0.322832 -0.101656
3  0.201851 -0.069080 -0.042338 -0.047424 -0.836333  0.876492 -0.101279
4 -1.735933 -0.145578 -0.042295 -0.124288 -0.621529 -0.103020 -0.101656

    metric9  activedays
0 -0.050645           0
1 -0.050645           1
2 -0.050645           2
3 -0.050645           3
4 -0.050641           4
```

Prédiction et extraction des données :

[235]:
```
y_pred = clf.predict(validdata)
from sklearn.metrics import f1_score,accuracy_score,recall_score,precision_score
print(f1_score(y_true,y_pred),accuracy_score(y_true,y_pred),recall_score(y_true,y_pred),precis
 ↪= ' -- ')
pd.DataFrame(y_pred).value_counts()
```

```
0.30434782608695654 -- 0.6493150684931507 -- 0.27184466019417475 --
0.345679012345679
```

[235]:
```
0    284
1     81
dtype: int64
```

[236]:
```
validdata['failure']=y_pred
validdata['date']=pd.read_csv("./GENDATA/device_S1F0/orgenvaldata.csv").date.
 ↪astype('datetime64[ns]')
validdata.to_csv("./GENDATA/device_S1F0/valdata.csv")
validdata['month']=vmonths
validdata['realFail']=y_true
validdata=validdata.groupby('month').agg('sum').loc[:,['failure','realFail']]

validdata.to_csv('results.csv')
validdata.head()
```

```
C:\Users\pc\AppData\Local\Temp\ipykernel_10212\264768352.py:6: FutureWarning:
The default value of numeric_only in DataFrameGroupBy.sum is deprecated. In a
future version, numeric_only will default to False. Either specify numeric_only
or select only columns which should be valid for the function.
  validdata=validdata.groupby('month').agg('sum').loc[:,['failure','realFail']]
```

[236]:
```
       failure  realFail
month
1            6        11
2            6         9
3            4         6
```

4	4	9
5	6	11