Project - Predictive Maintenance

September 15, 2018

1 A predictive maintenance project in the solar industry

```
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```

1.1 1 - Context of problematic

In the solar industry to make a photovoltaic panel, one of the crucial steps is the cutting of silicon ingots into wafers.

For this, diamond wire saws are used. These equipment are very efficient but also subject to drift manufacturing. Quality monitoring is therefore imperative. #### In our context, important and regular drifts were observed. This is why a predictive maintenance prediction project was set up to reduce the impact of these production anomalies.

The aim was to predict when a drift would occur in order to realize an action of maintenance to prevent the anomaly (for example change the wire of the saw or recalibrate settings...).

1.2 2 - Presentation of data

For this project, we had a datadet with a dozen of variables. Each hour for each day (the factory was working on unceasing full time shift - 24 hours a day), when a cut is performed on a silicium ingot, a log file is produced with many useful informations.

Here are the most useful variables which be used for this project :

In [40]:
```
import pandas as pd
import numpy as np

path = './/Data'
fileName = 'Data_Maintenance.csv'

filePath = '//'.join([path,fileName])

data_maintenance = pd.read_csv(filePath,delimiter=';')
```

In [41]: data_maintenance.head(5)

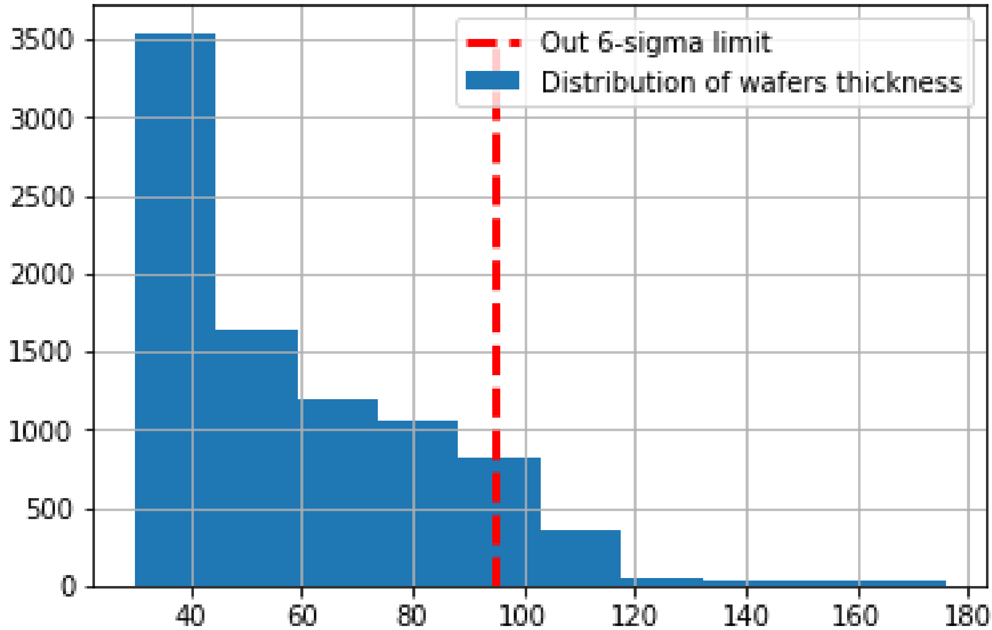
Out[41]:

```
         Date   Time          DateTime  TTV  Thickness  SawGroove  SawEdge  \
0  01/01/2017  00:00  01/01/2017 00:00   30        250        120        1
1  01/01/2017  01:00  01/01/2017 01:00   30        251        121        0
2  01/01/2017  02:00  01/01/2017 02:00   30        251        120        0
3  01/01/2017  03:00  01/01/2017 03:00   31        251        119        2
4  01/01/2017  04:00  01/01/2017 04:00   32        251        124        1

   SawStep LastEmptying  OutSixSigma  WafersProduction SiliciumType
0        0   01/01/2017            0              1000         Mono
1        0   01/01/2017            0              3000         Mono
2        0   01/01/2017            0              5000         Mono
3        0   01/01/2017            0              6000         Mono
4        0   01/01/2017            0              7000         Mono
```

Let's take a look at the data :

In [12]:

```
import matplotlib.pyplot as plt
import seaborn as sns

data_maintenance.TTV.hist(label="Distribution of wafers thickness")
plt.plot([95, 95], [0, 3500],
         color='red',
         linestyle='--',
         linewidth=3,
         label="Out 6-sigma limit")

plt.legend(loc='upper right');
plt.show()
```



As we can see, mostly 15% of the production is out 6-sigma limit. It's a lot and it's a quite waste of ressources since the wafers which doesn't respond to quality criteria are thrown away.

That's why this project of predictive maintenance has for first goal to prevent this drift of non quality production, because the cost of these anomalies are pretty heavy for the firm.

1.3 3 - Study of hypothesis

At first, before beginning the step of modeling, we have to check the following hypothesis :

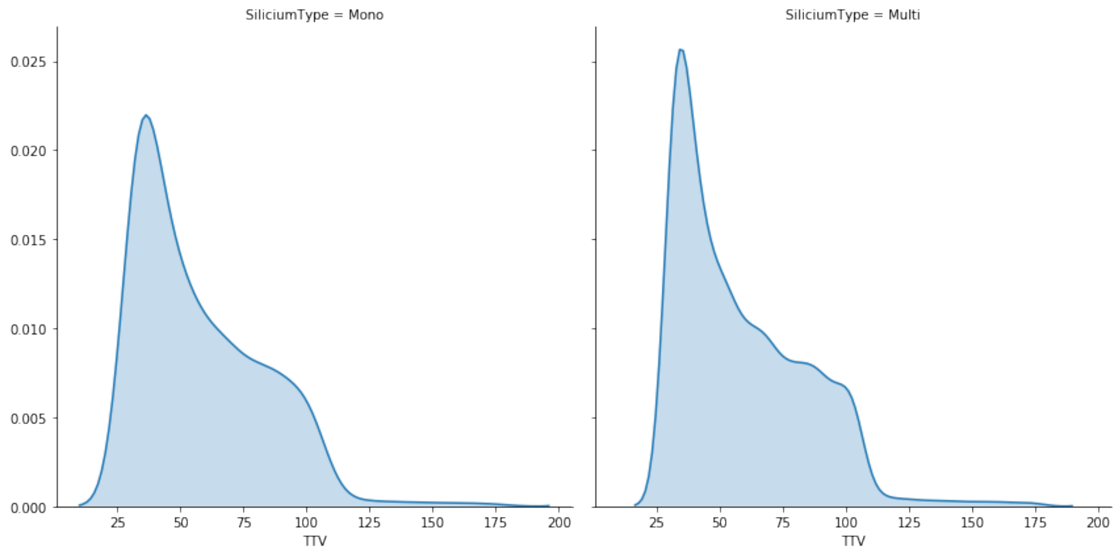
A - Hypothesis of normality of data
B - Hypothesis of stationnary time serie
C - Hypothesis of event without memory (Markov process)

1.3.1 A - Hypothesis of normality of data

The purpose of the verification of this hypothesis is to know if parametric methods can be used for our learning model.

```
In [14]: g = sns.FacetGrid(data_maintenance,
                           col="SiliciumType",
                           size=6)

         g.map(sns.kdeplot,
               "TTV",
               shade=True)
```

```
plt.xlabel('TTV')
plt.show()
```

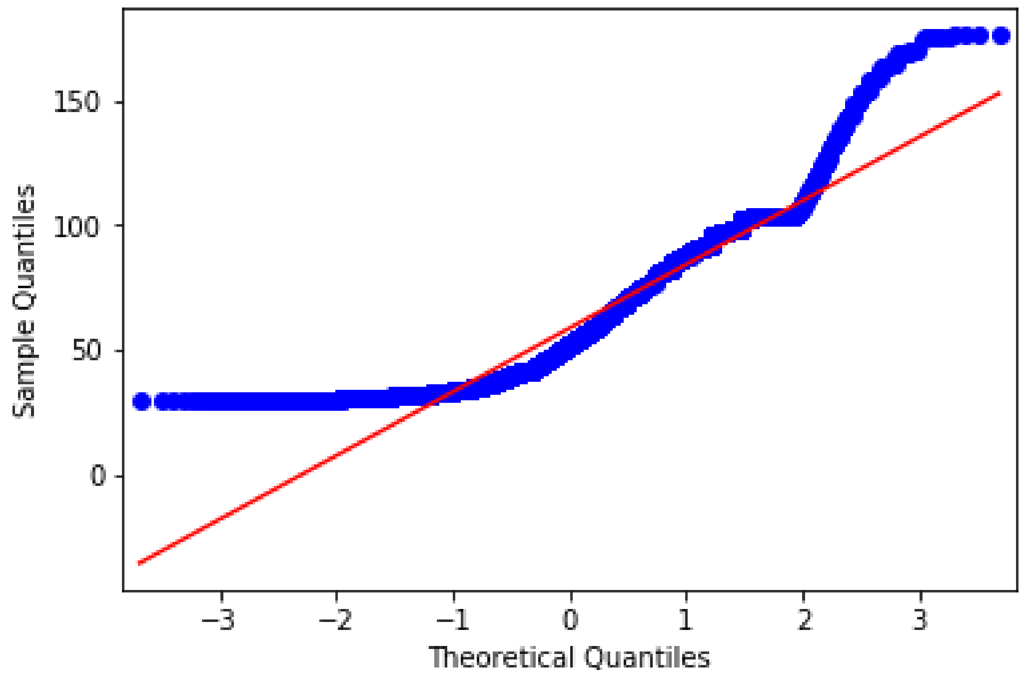


A first visual look would suggest that the parameter observed doesn't follow a gaussian distribution (low Skewness and non symetric Kurtosis).

We could check also with a QQ plot test (using percentile cumul) :

```
In [15]: import scipy
         from statsmodels.graphics.gofplots import qqplot
         from scipy.stats import shapiro
         from scipy.stats import anderson
         from statsmodels.tsa.stattools import adfuller
         from statsmodels.tsa.stattools import kpss

         from statsmodels.tsa.arima_model import ARIMA

         qqplot(data_maintenance.TTV, line='s')
         plt.show()
```

```
C:\Users\monne\Anaconda3\lib\site-packages\statsmodels\compat\pandas.py:56: FutureWarning: The
  from pandas.core import datetools
```



It seems that the distribution is not a gaussian one...

To be sure, we could compute a statiscal test and we will use the following ones : Shapiro Test
D'Agostino Test
Anderson Test

```
In [17]: stats,p_value = shapiro(data_maintenance.TTV)
         print('Stats = {} - p-value = {}'.format(stats,p_value))
```

```
Stats = 0.8932368159294128 - p-value = 0.0


C:\Users\monne\Anaconda3\lib\site-packages\scipy\stats\morestats.py:1310: UserWarning: p-value
  warnings.warn("p-value may not be accurate for N > 5000.")
```

```
In [18]: # D'Agostino and Pearson's Test
         print(scipy.stats.normaltest(data_maintenance.TTV))
```

```
NormaltestResult(statistic=1268.5132451261297, pvalue=3.514379931470798e-276)
```

```
In [28]: # Anderson's Test
         result = anderson(data_maintenance.TTV)
         print('Statistic: %.3f' % result.statistic)
```

```
    for i in range(len(result.critical_values)):
        sl, cv = result.significance_level[i], result.critical_values[i]

        if result.statistic < result.critical_values[i]:
            print('%.3f: %.3f, data looks normal (fail to reject H0)' % (sl, cv))
        else:
            print('Critical value of {}%  : {} --> data doesn\'t look normal (reject H0)'
```

```
Statistic: 259.087
Critical value of 15.0%  : 0.576 --> data doesn't look normal (reject H0)
Critical value of 10.0%  : 0.656 --> data doesn't look normal (reject H0)
Critical value of 5.0%  : 0.787 --> data doesn't look normal (reject H0)
Critical value of 2.0%  : 0.918 --> data doesn't look normal (reject H0)
Critical value of 1.0%  : 1.092 --> data doesn't look normal (reject H0)
```

1.4 B - Hypothesis of stationnary time serie

A first look on the distribution of one of the parameter (the BOW measure which is globally the same as the TTV criteria) would indicate that fluctuations are following a time serie, as we could read on the below picture :

Let's check this assumption :

```
<li>Transform the data</li>
<li>Test of Ad Fuller</li>
<li>ARIMA performing</li>
```

1.4.1 Transform the data :

At first, we have to group the data on the variable Date in order to be able to compute the analysis on a daily basis.

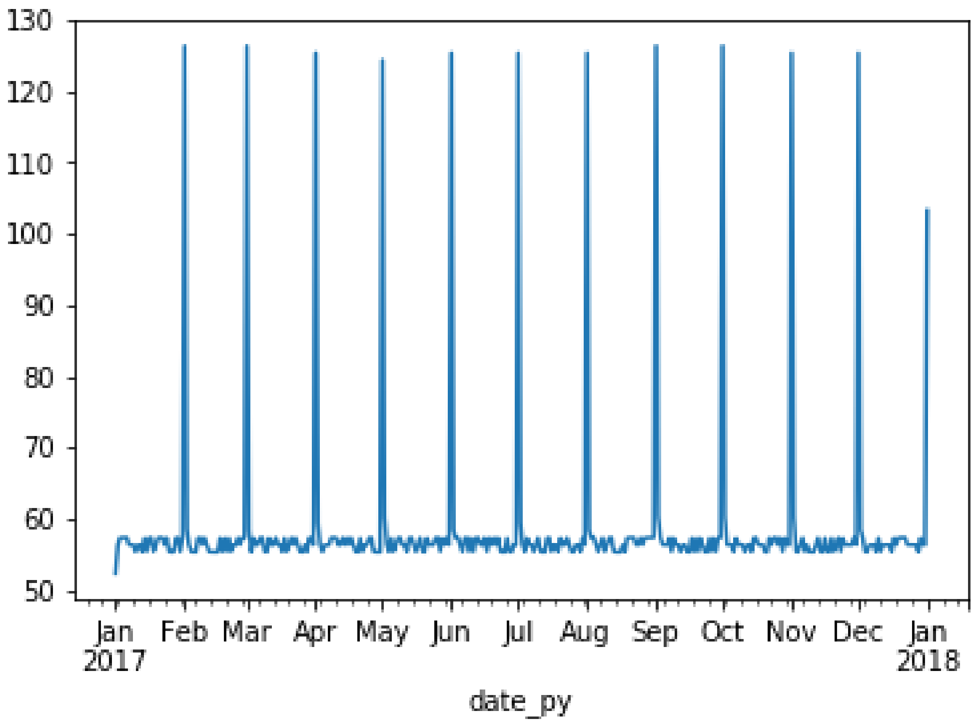
```
In [30]: data_maintenance['year'] = data_maintenance['Date'].apply(lambda x:x[len(x)-4:])
         data_maintenance['month'] = data_maintenance['Date'].apply(lambda x:x[len(x)-7:len(x)-
         data_maintenance['day'] = data_maintenance['Date'].apply(lambda x:x[:2])

         data_maintenance['date_py'] = pd.to_datetime(data_maintenance[['year','month','day']]

         grouped = data_maintenance.groupby('date_py')
         mean_TTV = grouped['TTV'].agg(np.mean)
         print(mean_TTV.head(5))
```

```
date_py
2017-01-01    52.333333
2017-01-02    56.291667
2017-01-03    57.291667
2017-01-04    57.333333
2017-01-05    57.333333
```

```
Name: TTV, dtype: float64
```

The dataset is now regrouped by the date of the day (we keep the mean of each variable)

```
In [32]: mean_TTV.plot()
         plt.show()
```



The graphical visualisation could let think that we are facing a stationnary time series use case...

Stationnary, because there is no trend, the variance doesn't grow with the date and there is not sign of covariance with the time axis...

1.4.2 Augmented Dickey Fuller Test

```
In [33]: print('--'*20)
         print('Augmented Dickey Fuller Test')

         results = adfuller(mean_TTV,
                            autolag='AIC')

         test_statistics,p_value = results[0],results[1]
```

```
print('valeur du test : {} - Valeur de la p-value : {}'.format(test_statistics,
                                                                  p_value))

for key,value in results[4].items():
    print('Critical value à {} % : {}'.format(key,value))
print('--'*20)
if p_value < 0.05:
    print('Reject H0 : the serie of fluctuations of TTV is stationnary...')
else:
    print('Fail to reject H0 : the serie of fluctuations of TTV is not stationnary...
```

```
----------------------------------------
Augmented Dickey Fuller Test
valeur du test : -18.501751389268442 - Valeur de la p-value : 2.1201245071674424e-30
Critical value à 1% % : -3.4483935212959844
Critical value à 5% % : -2.8694912343676497
Critical value à 10% % : -2.571005879151811
----------------------------------------
Reject H0 : the serie of fluctuations of TTV is stationnary...
```

1.4.3 Kwiatkowski-Phillips-Schmidt-Shin Test

In [34]:
```
print('--'*20)
print('Kwiatkowski-Phillips-Schmidt-Shin Test')


results = kpss(mean_TTV,
                   regression='c')

test_statistics,p_value = results[0],results[1]

print('valeur du test : {} - Valeur de la p-value : {}'.format(test_statistics,
                                                                  p_value))

for key,value in results[3].items():
    print('Critical value à {} % : {}'.format(key,value))
print('--'*20)
if p_value > 0.05:
    print('Fail to reject H0 : the serie of fluctuations of TTV is stationnary...')
else:
    print('Reject H0 : the serie of fluctuations of TTV is not stationnary...')
```

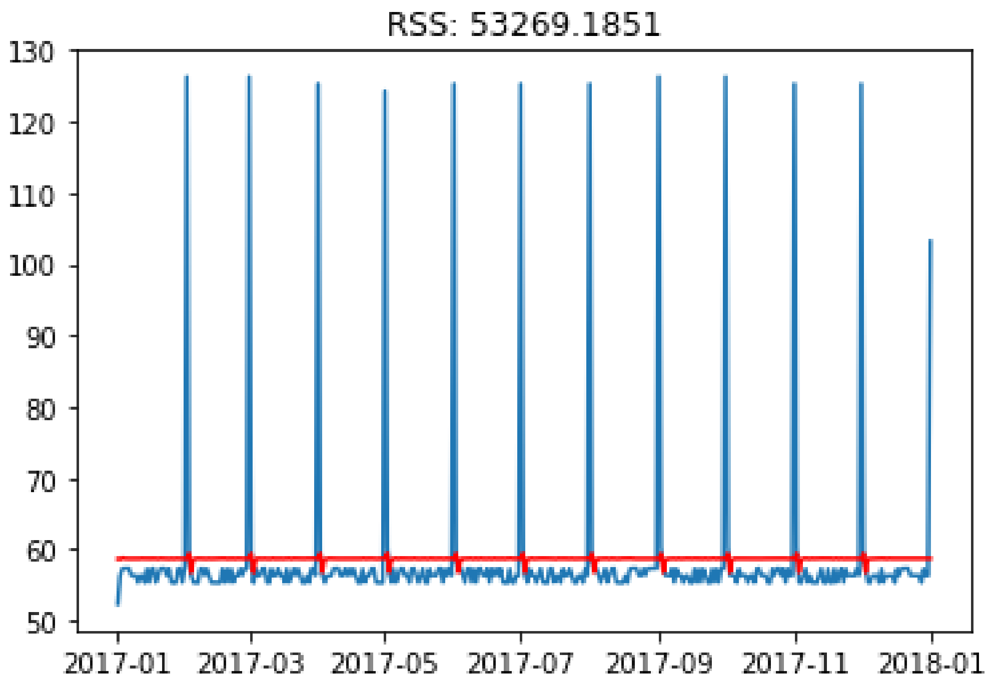
```
----------------------------------------
Kwiatkowski-Phillips-Schmidt-Shin Test
valeur du test : 0.036624491810607694 - Valeur de la p-value : 0.1
```

```
Critical value à 10% % : 0.347
Critical value à 5% % : 0.463
Critical value à 2.5% % : 0.574
Critical value à 1% % : 0.739
----------------------------------------
Fail to reject H0 : the serie of fluctuations of TTV is stationnary...


C:\Users\monne\Anaconda3\lib\site-packages\statsmodels\tsa\stattools.py:1260: InterpolationWarn
  warn("p-value is greater than the indicated p-value", InterpolationWarning)
```

1.4.4 ARIMA performing

```
In [35]: # Forecast with ARIMA model
         model = ARIMA(mean_TTV, order=(2,0, 0))
         results_ARIMA = model.fit()

         plt.plot(mean_TTV)
         plt.plot(results_ARIMA.fittedvalues, color='red')
         plt.title('RSS: %.4f'% sum((results_ARIMA.fittedvalues-mean_TTV)**2))
```

```
Out[35]: Text(0.5,1,'RSS: 53269.1851')
```



The ARIMA model seems specifically poor on this case.

```
<li> The predictions (in red) is not aligned on the time series.</li>
<li> And the RSS score is pretty high... but why ???</li>
```

After a lot of research and discussion with the process engineers, it seems that data are not correlated with date or time, but with the number of wafers produced.

If nothing is produced while a month, all parameters will remain stable and no drift will be observed. So, our data are not a stationnary time serie use case...

It's a bit tricky since results of tests and visual graphics insinuate the opposite, but this is an effect of an hidden correlation between the date and the cumul of number of wafers produced during the interval...

1.4.5 C - Hypothesis of event without memory (Markov process)

If events observed were without memory, no links would be notified with a past parameter. But on the below visualisation, we could see that fluctutations seem correlated with the past cumul of wafers :

Futhermore, we have observed that drifts are sometimes concomitant with operations of emptying on the saw equipment (oil lubricant). It seems that probability of drift occurence is proportional with the past delay of the last action of emptying performed on the saw equipment : #### So, we can deduct that we are not facing a Markov process use case...

2 4 - Modeling and learning

A - Design the features
B - Select the features
C - Build the model

2.0.1 A - Design the features

in connection with the observations made previously, we will create 4 new features :

A feature to indicate if it is a day when an emptying action is performed
A feature to calculate the number of wafers produced since the last day of emptying
A feaure to count the number of days since the last action of emptying
A dummy feature for coding the type of silicium material (has an impact on the saw wire att

In [43]:
```
is_emptying =list()
cumul_wafers = list()
day_since_emptying = list()
cumul_ant=0

for index,row in data_maintenance.iterrows():
    if row['Date'][:2]=='01':
        is_emptying.append(1)
        cumul_wafers.append(0)
        cumul_ant=row['WafersProduction']
        day=int(row['LastEmptying'][:2])
        day_since_emptying.append(0)
```

```
            else:
                is_emptying.append(0)
                cumul_wafers.append(row['WafersProduction']-cumul_ant)
                day_since_emptying.append(np.abs(int(row['Date'][:2])-day))

        data_maintenance['day of emptying']  = is_emptying
        data_maintenance['cumul of wafers']  = cumul_wafers
        data_maintenance['day since emptying']  = day_since_emptying
        data_maintenance['Is Mono'] = data_maintenance['SiliciumType'].apply(lambda x: 1 if x=
```

```
In [47]: data_maintenance[['Date','day of emptying','cumul of wafers','LastEmptying','day since
```

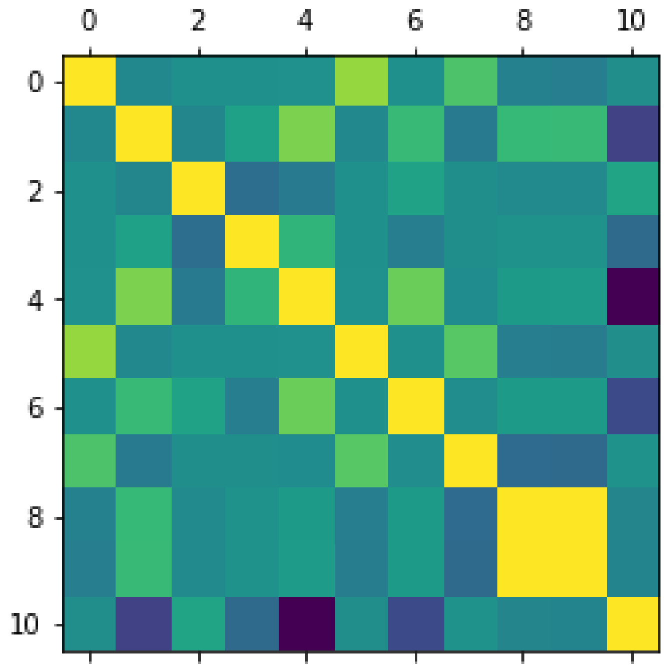
```
Out[47]:             Date  day of emptying  cumul of wafers LastEmptying  \
         8761  01/01/2018                1                0   01/01/2018
         8762  01/01/2018                1                0   01/01/2018
         8763  01/01/2018                1                0   01/01/2018

               day since emptying  Is Mono
         8761                   0        0
         8762                   0        0
         8763                   0        0
```

2.0.2 B - Select the features

At first, we are checking the correlation between variables since models are sometimes sensitive to it :

```
In [48]: plt.matshow(data_maintenance.corr())
```

```
Out[48]: <matplotlib.image.AxesImage at 0x19eb99787b8>
```




```
In [52]: for col in data_maintenance.corr().columns:
             conditions = (data_maintenance.corr()[col]>0.6) & (data_maintenance.corr()[col]<1
             if len(data_maintenance.corr()[conditions][col])>0:
                 columns_correlated = data_maintenance.corr()[conditions][col]
                 print('--'*20)
                 print(col)
                 print('--'*20)
                 print(columns_correlated)
```

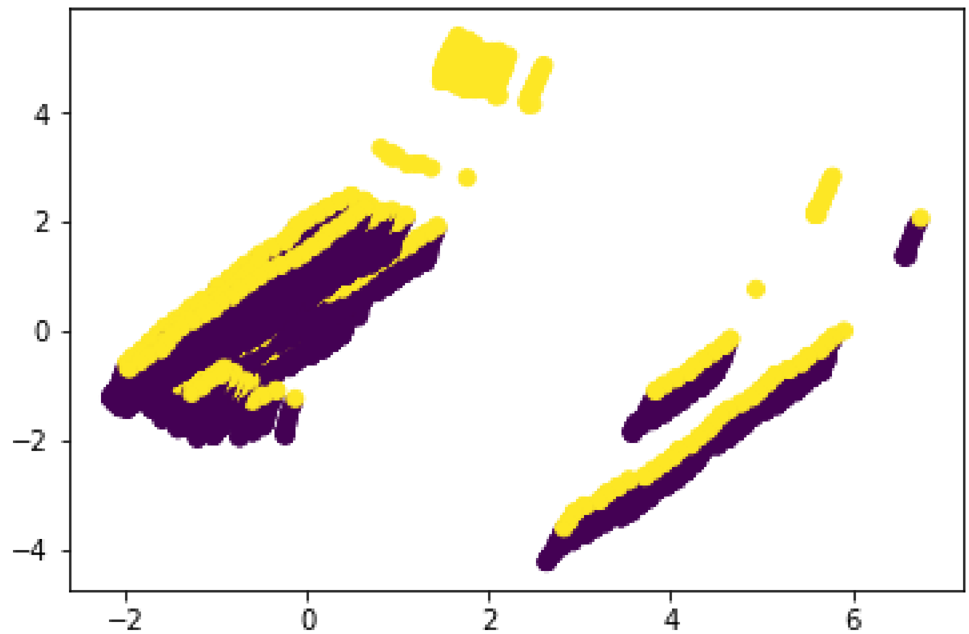
```
----------------------------------------
TTV
----------------------------------------
OutSixSigma    0.682667
Name: TTV, dtype: float64
----------------------------------------
Thickness
----------------------------------------
SawStep    0.604948
Name: Thickness, dtype: float64
----------------------------------------
SawStep
----------------------------------------
Thickness    0.604948
Name: SawStep, dtype: float64
----------------------------------------
```

```
OutSixSigma
----------------------------------------
TTV    0.682667
Name: OutSixSigma, dtype: float64
----------------------------------------
cumul of wafers
----------------------------------------
day since emptying    0.999174
Name: cumul of wafers, dtype: float64
----------------------------------------
day since emptying
----------------------------------------
cumul of wafers    0.999174
Name: day since emptying, dtype: float64
```

Then we are trying to detect the variables which explain the most of variability in the dataset with a PCA :

```
In [53]: from sklearn.preprocessing import StandardScaler

         features = data_maintenance.corr().columns.tolist()
         features.remove('OutSixSigma')
         target = 'OutSixSigma'

         X = data_maintenance.loc[:,features]
         y = data_maintenance.loc[:,target]

         X = StandardScaler().fit_transform(X)

         from sklearn.decomposition import PCA

         pca = PCA(n_components=4)
         principal_components = pca.fit_transform(X)

         principalDf = pd.DataFrame(data = principal_components,
                                    columns = ['PCI' + str(i) for i in range(4)])

         plt.scatter(principalDf.iloc[:,0],
                     principalDf.iloc[:,1],
                     c=y,
                     label=y.unique())

         print('Variances explained by axes : {}'.format(pca.explained_variance_ratio_))

         plt.show()
```

```
Variances explained by axes : [ 0.31732599  0.21365304  0.13912937  0.12088666]
```




```
In [54]: sortedFeatures_axe1 = [i[0] for i in sorted(zip(features,pca.components_[0]),
                                                   key=lambda l:l[1],reverse=True)]

         sortedFeatures_axe2 = [i[0] for i in sorted(zip(features,pca.components_[1]),
                                                   key=lambda l:l[1],reverse=True)]

         sortedFeatures_axe3 = [i[0] for i in sorted(zip(features,pca.components_[2]),
                                                   key=lambda l:l[1],reverse=True)]

         sortedFeatures_axe4 = [i[0] for i in sorted(zip(features,pca.components_[3]),
                                                   key=lambda l:l[1],reverse=True)]

         print(sortedFeatures_axe1[:1])
         print(sortedFeatures_axe2[:1])
         print(sortedFeatures_axe3[:1])
         print(sortedFeatures_axe4[:1])
```

```
['Is Mono']
['day of emptying']
['SawGroove']
['TTV']
```

Then we have our features which will carry the most of variability for our future learning model.

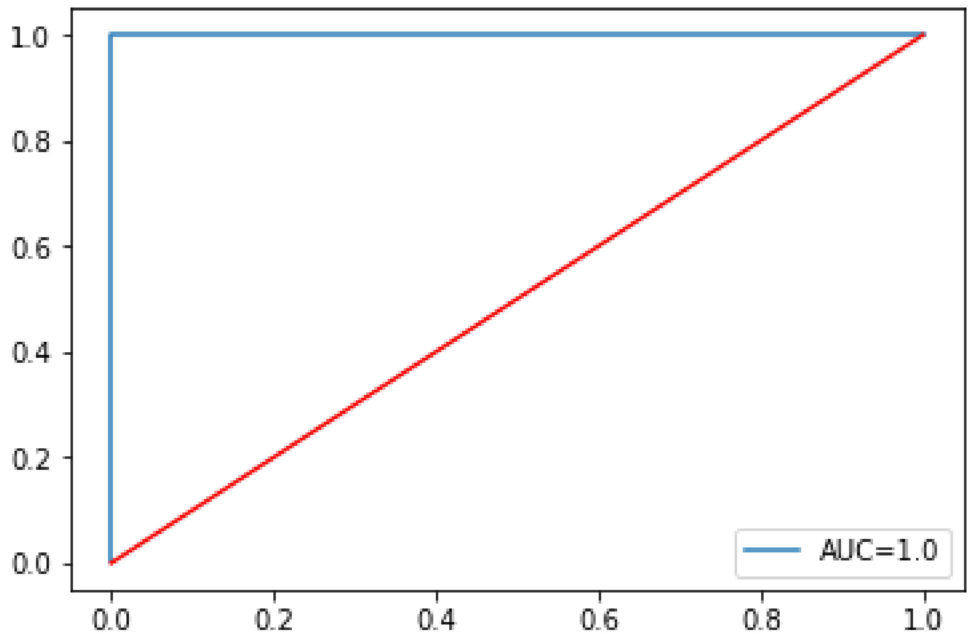
As we can see on the plan projection above, our data are segmented by the type of silicium and the proximity of the day of emptying.

It seems that the day of emptying has an impact on the target feature ("OutOf6Sigma") since points in yellow on the plan, are systemtically above the others (when the axis vertical is carried by the "day of emptying" feature).

2.0.3 C - Build the model

```
In [55]: from sklearn.model_selection import train_test_split

         train_features, test_features, train_target, test_target = train_test_split(X,
                                                                                      y,
                                                                                      test_size
                                                                                      stratify=y


         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import auc,roc_curve

         model_regression = LogisticRegression()
         model_regression.fit(train_features,train_target)
         predictions = model_regression.predict(test_features)
         probalities = model_regression.predict_proba(test_features)

         accuracy = predictions == test_target

         true_positives = (predictions==1) & (test_target==1)
         false_positives = (predictions==1) & (test_target==0)
         true_negatives = (predictions==0) & (test_target==0)
         false_negatives = (predictions==0) & (test_target==1)

         sensitivity = np.sum(true_positives) / (np.sum(true_positives)+np.sum(false_negatives

         specificity = np.sum(true_negatives) / (np.sum(true_negatives) + np.sum(false_positiv

         print('Sensibility of predictions is about : {}'.format(sensitivity))
         print('Specificity of predictions is about : {}'.format(specificity))

         fpr, tpr, thresholds = roc_curve(test_target, probalities[:,1], pos_label=1)
         auc = auc(fpr,tpr)

         print('Perimeter of AUC curb : {}'.format(auc))

         plt.plot(fpr,tpr,label='AUC={}'.format(auc))
         plt.plot([0,1],[0,1],color='red')
         plt.legend(loc='lower right')
         plt.show()
```

```
Sensibility of predictions is about : 1.0
Specificity of predictions is about : 1.0
Perimeter of AUC curb : 1.0
```



The score of accuracy seems perfect... too perfect. When performing this logistic regression, we made a rookie mistake. We keep features which contain information on the future... the measure of thickness or TTV are not known when the cut is peformed... these values are measured a fews hours later by a specific equipment. It a bias...

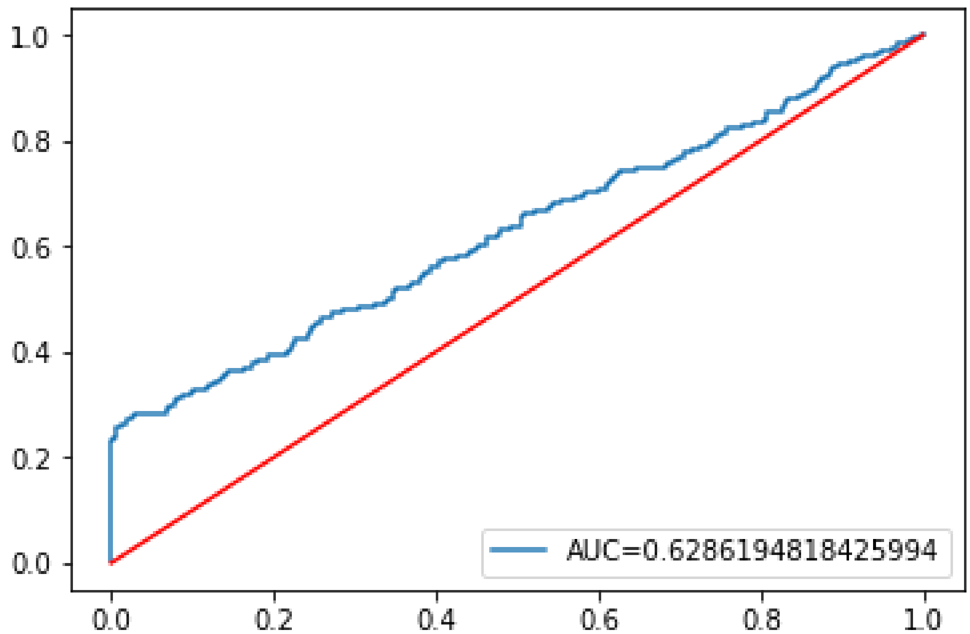
When the predicition will be performed, no information about thickness of the wafer will be available.That's why we have toremove these features to build our model :

```
In [59]: X_reduced = ['cumul of wafers',
                      'day since emptying',
                      'Is Mono',
                      'day of emptying',
                      'WafersProduction']


         X = data_maintenance.loc[:,X_reduced]
         y = data_maintenance.loc[:,target]

         X = StandardScaler().fit_transform(X)

         train_features, test_features, train_target, test_target = train_test_split(X,
```

```
y,
test_size=
stratify=y
```

```
from sklearn.metrics import auc,roc_curve

penalty = {
    0:10,
    1:1
}

model_regression = LogisticRegression(class_weight=penalty)

model_regression.fit(train_features,train_target)
predictions = model_regression.predict(test_features)
probalities = model_regression.predict_proba(test_features)

accuracy = predictions == test_target

true_positives = (predictions==1) & (test_target==1)
false_positives = (predictions==1) & (test_target==0)
true_negatives = (predictions==0) & (test_target==0)
false_negatives = (predictions==0) & (test_target==1)

sensitivity = np.sum(true_positives) / (np.sum(true_positives)+np.sum(false_negatives)

specificity = np.sum(true_negatives) / (np.sum(true_negatives) + np.sum(false_positiv

print('Sensibility of predictions is about : {}'.format(sensitivity))
print('Specificity of predictions is about : {}'.format(specificity))

fprs, tprs, thresholds = roc_curve(test_target, probalities[:,1], pos_label=1)
aucs = auc(fprs,tprs)

print('Perimeter of AUC curb : {}'.format(aucs))

plt.plot(fprs,tprs,label='AUC={}'.format(aucs))
plt.plot([0,1],[0,1],color='red')
plt.legend(loc='lower right')
plt.show()
```

```
Sensibility of predictions is about : 0.20491803278688525
Specificity of predictions is about : 1.0
Perimeter of AUC curb : 0.6286194818425994
```



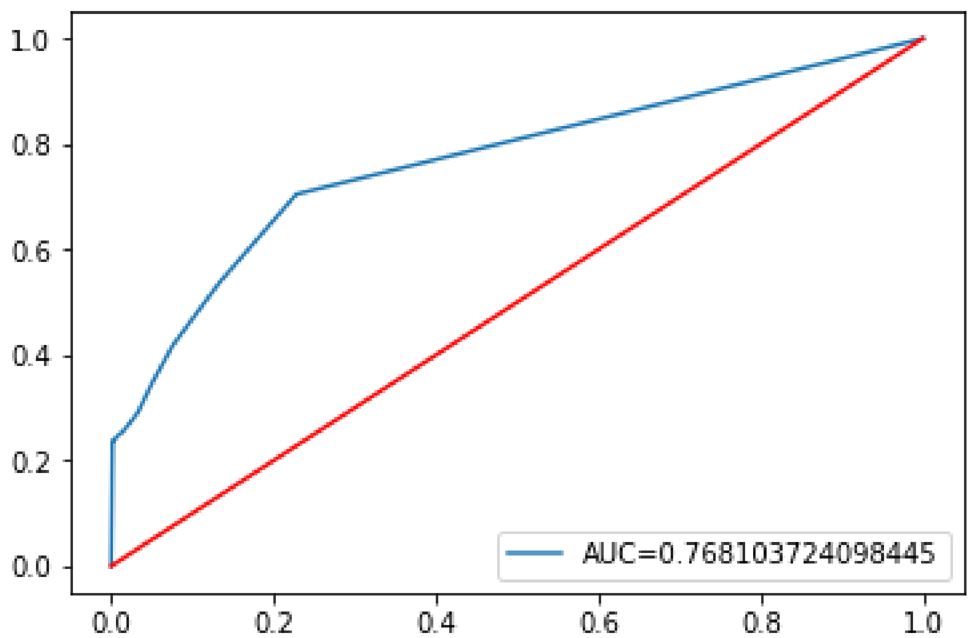
Right now, the accuracy of the model is less impressive. The cuts with drifts 'out of 6 sigma specifications' are very poorly predicted (about 20%) The only good point is that the model never made a prediction of non drift which was false. But, this is not sufficient and we have to try better model than logistic regression...

We will now perform an ensemblist model called "Random Forest". Ensemblist since many instances of decision trees are running to compute a accurate prediction on the binary target.

```
In [64]: from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import auc,roc_curve

         rf = RandomForestClassifier(n_estimators=10,
                                     random_state=1,
                                     class_weight='balanced')

         rf.fit(train_features,train_target)
         predictions = rf.predict(test_features)
         probalities = rf.predict_proba(test_features)

         accuracy = predictions == test_target

         true_positives = (predictions==1) & (test_target==1)
         false_positives = (predictions==1) & (test_target==0)
         true_negatives = (predictions==0) & (test_target==0)
         false_negatives = (predictions==0) & (test_target==1)
```

```
sensitivity = np.sum(true_positives) / (np.sum(true_positives)+np.sum(false_negatives

specificity = np.sum(true_negatives) / (np.sum(true_negatives) + np.sum(false_positive

print('Sensibility of predictions is about : {}'.format(sensitivity))
print('Specificity of predictions is about : {}'.format(specificity))

fprs, tprs, thresholds = roc_curve(test_target, probalities[:,1], pos_label=1)
aucs = auc(fprs,tprs)

print('Perimeter of AUC curb : {}'.format(aucs))

plt.plot(fprs,tprs,label='AUC={}'.format(aucs))
plt.plot([0,1],[0,1],color='red')
plt.legend(loc='lower right')
plt.show()
```

```
Sensibility of predictions is about : 0.27049180327868855
Specificity of predictions is about : 0.9774011299435028
Perimeter of AUC curb : 0.768103724098445
```



The reults are better so we can attempt a first move with this model...

2.1 5 - Results and operation

In production, an input of values of the features are sent to the model before the ingot been cut in the saw equipment. If the model predict a drift, an operation of preventive maintenance (change of diamant cutwire for example is then performed in order to prevent the drift or the anomaly. And the ingot is cut into wafers...

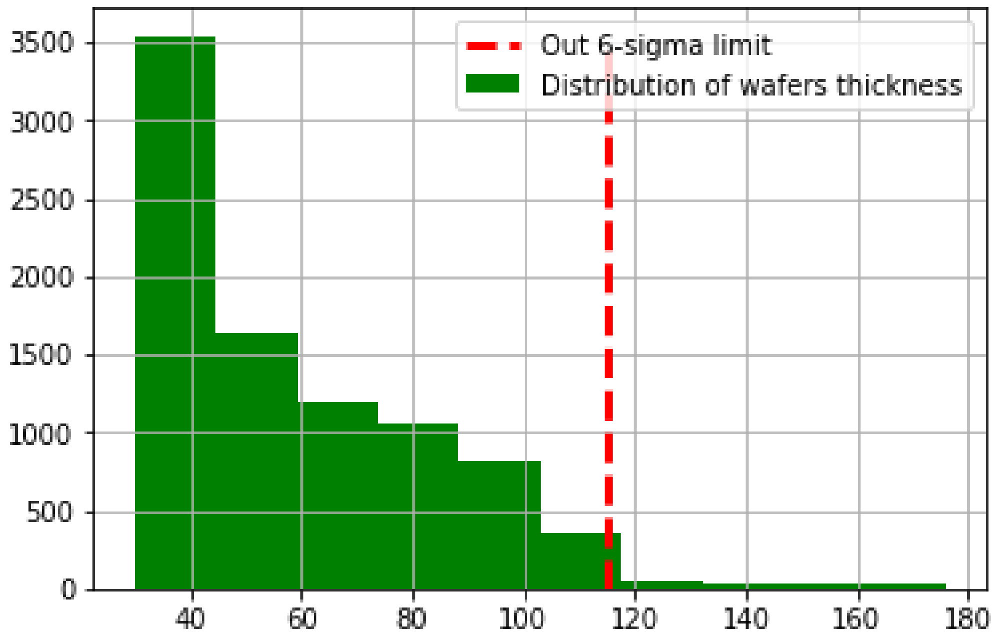
In [67]:
```
def prediction_maintenance(cumul_wafers,days_since_emptying,is_mono,days_of_emptying,W

    data = [cumul_wafers,
            days_since_emptying,
            is_mono,
            days_of_emptying,
            WaferProduction]

    data_res = np.asarray(data).reshape(1,-1)

    #data = StandardScaler().fit_transform(data_res)
    data = data_res
    prevision = rf.predict(data)
    prevision_proba = rf.predict_proba(data)

    if prevision:
        print('With the data given in input, we can predict that a maintenance action
    else :
        print('With the data given in input, no need at the moment for a maintenance a

    print('Probalities of need of action maintenance {}%'.format(prevision_proba[:,1]*

    return prevision_proba

#
print('--'*20)
### day 1
cumul_wafers = 10
days_since_emptying = 1
is_mono = 0
days_of_emptying= 0
WaferProduction= 0

prediction = prediction_maintenance(cumul_wafers,days_since_emptying,is_mono,days_of_e
print('--'*20)

### day 24
cumul_wafers = 879000
days_since_emptying = 24
is_mono = 1
days_of_emptying= 0
WaferProduction= 8790000
```

```
prediction = prediction_maintenance(cumul_wafers,days_since_emptying,is_mono,days_of_e
print('--'*20)
```

```
----------------------------------------
With the data given in input, we can predict that a maintenance action is necesary !!!
Probalities of need of action maintenance [ 70.]%
----------------------------------------
With the data given in input, no need at the moment for a maintenance action...
Probalities of need of action maintenance [ 30.]%
----------------------------------------
```

The model is perfectibe but it gives some interesting results. For example, the ratio of non quality on wafers cut dropped at 5% when it culminates at 15% before the predictive model.

```
In [69]: data_maintenance.TTV.hist(label="Distribution of wafers thickness",color="green")
         plt.plot([115, 115], [0, 3500],
                  color='red',
                  linestyle='--',
                  linewidth=3,
                  label="Out 6-sigma limit")

         plt.legend(loc='upper right');
         plt.show()
```



Then, this project was a good example of a smart use of data science for accurate prediction of action maintenance... A first step towards industry 4.0 for solar manufacturing !!!