Reduce maintenance cost through predictive techniques

Background

Company (3D Technologies) has a fleet of devices transmitting daily aggregated telemetry attributes. Predictive maintenance techniques are designed to help determine the condition of in-service equipment in order to predict when maintenance should be performed. This approach promises cost savings over routine or time-based preventive maintenance, because tasks are performed only when warranted.

Goal

You are tasked with building a predictive model using machine learning to predict the probability of a device failure. When building this model, be sure to minimize false positives and false negatives. The column you are trying to predict is called failure with binary value 0 for non-failure and 1 for failure.

Data

Download link: http://aws-proserve-data-science.s3.amazonaws.com/device_failure.csv (http://aws-proserve-data-science.s3.amazonaws.com/device_failure.csv)

columns : date -> YYYY-MM-DD format device -> device did failure ->non-failure is 0, failure is 1 attribute1 - attribute9 - > daily aggregated telemetry

1. Data exploration

In [1]:

```
# get the data from the source
!wget http://aws-proserve-data-science.s3.amazonaws.com/device_failure.csv
```

```
--2020-06-07 11:54:55--  http://aws-proserve-data-science.s3.amazon
aws.com/device_failure.csv
Resolving aws-proserve-data-science.s3.amazonaws.com (aws-proserve-
data-science.s3.amazonaws.com)... 52.218.249.82
Connecting to aws-proserve-data-science.s3.amazonaws.com (aws-prose
rve-data-science.s3.amazonaws.com)|52.218.249.82|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 6856222 (6,5M) [text/csv]
Saving to: ‘device_failure.csv.14’

device_failure.csv. 100%[===================>]   6,54M  2,05MB/s
in 3,2s

2020-06-07 11:54:59 (2,05 MB/s) - ‘device_failure.csv.14’ saved [68
56222/6856222]
```

In [2]:

```
import pandas as pd
import numpy as np
device_df =  pd.read_csv('device_failure.csv', encoding = "ISO-8859-1")
device_df.head(4)

device_df.head()
```

Out[2]:

	date	device	failure	attribute1	attribute2	attribute3	attribute4	attribute5	attribut
0	2015-01-01	S1F01085	0	215630672	56	0	52	6	4074
1	2015-01-01	S1F0166B	0	61370680	0	3	0	6	4031
2	2015-01-01	S1F01E6Y	0	173295968	0	0	0	12	2373
3	2015-01-01	S1F01JE0	0	79694024	0	0	0	6	4101
4	2015-01-01	S1F01R2B	0	135970480	0	0	0	15	3131

In [3]:

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize = (15,20))
ax = fig.gca()
attributes = ['attribute1', 'attribute2', 'attribute3',
       'attribute4', 'attribute5', 'attribute6', 'attribute7', 'attribute8',
       'attribute9']

device_df.hist(attributes, ax = ax)
```

```
/home/leo/.local/lib/python3.6/site-packages/ipykernel_launcher.py:
8: UserWarning: To output multiple subplots, the figure containing
the passed axes is being cleared
```

Out[3]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fc3ea9a
09b0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc3e71c
eb00>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc3e718
5d68>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fc3e713
c400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc3e70e
e668>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc3e712
18d0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fc3e70d
3b38>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc3e708
9d68>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc3e7ab
bb00>]],
      dtype=object)
```


attribute1
0 2000 4000 6000 8000 10000 12000
0.0 0.5 1.0 1.5 2.0 2.5
1e8
attribute2
0 20000 40000 60000 80000 100000 120000
0 20000 40000 60000
attribute3
0 20000 40000 60000 80000 100000 120000
0 5000 10000 15000 20000 25000
attribute4
0 20000 40000 60000 80000 100000 120000
0 500 1000 1500
attribute5
0 10000 20000 30000 40000 50000 60000 70000
0 20 40 60 80 100
attribute6
0 10000 20000 30000 40000 50000 60000
0 200000 400000 600000
attribute7
0 20000 40000 60000 80000 100000 120000
0 200 400 600 800
attribute8
0 20000 40000 60000 80000 100000 120000
0 200 400 600 800
attribute9
0 20000 40000 60000 80000 100000 120000
0 5000 10000 15000

In [4]:

```
print('failure mean ', device_df['failure'].mean())
for atribute_name in   [ 'attribute2', 'attribute3',
       'attribute4',  'attribute7', 'attribute8',
       'attribute9'] :

    print('Failure mean for the 100 largest of {}: {} '.format( atribute_name, d
evice_df.loc[device_df[atribute_name].nlargest(200).index]['failure'].mean() ))
```

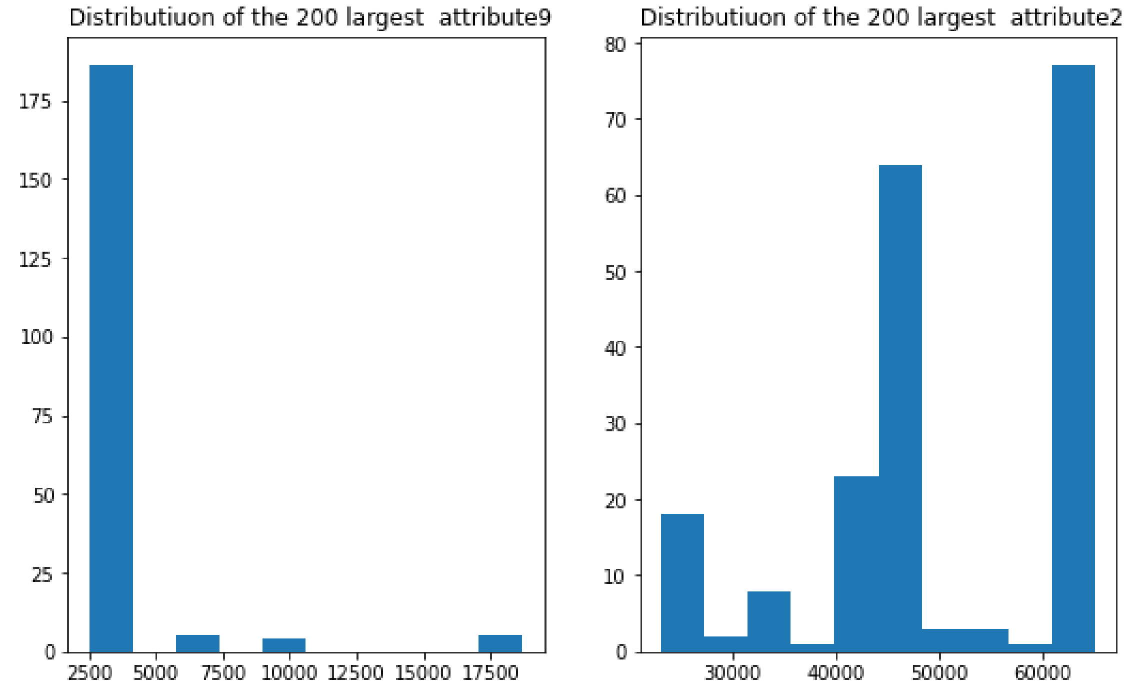
```
failure mean  0.0008514466560637462
Failure mean for the 100 largest of attribute2: 0.025
Failure mean for the 100 largest of attribute3: 0.0
Failure mean for the 100 largest of attribute4: 0.025
Failure mean for the 100 largest of attribute7: 0.08
Failure mean for the 100 largest of attribute8: 0.08
Failure mean for the 100 largest of attribute9: 0.0
```

In [5]:

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(10, 6))
axes[0].hist(device_df['attribute9'].nlargest(200))
axes.flat[0].set( title=' Distributiuon of the 200 largest  attribute9')

axes[1].hist(device_df['attribute2'].nlargest(200))
axes.flat[1].set( title=' Distributiuon of the 200 largest  attribute2')
```

Out[5]:

```
[Text(0.5, 1.0, ' Distributiuon of the 200 largest  attribute2')]
```

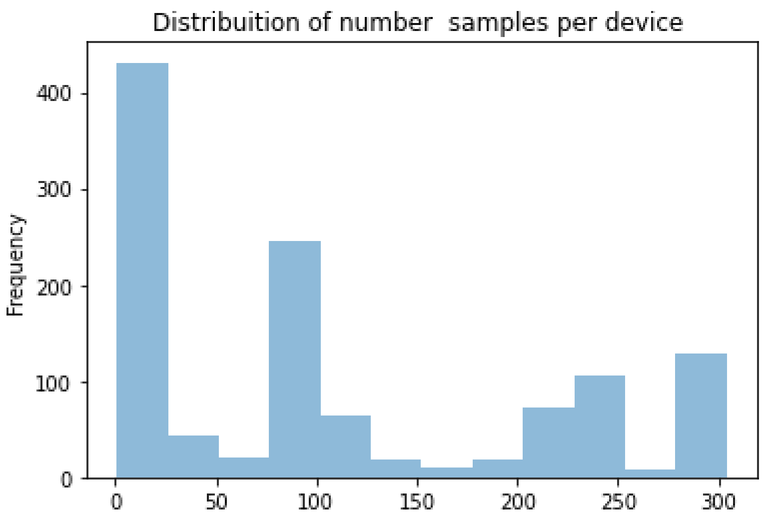


The outliers of the attributes 4, 7and 8 are strongly corelated to the failure, and these values can mean that something is wrong with the device

In [6]:

```
print('Number of failure: {}   Number of  not failure: {} |rate {:.0f}'.format(d
evice_df[device_df['failure'] ==1 ].shape[0], device_df[device_df['failure'] ==0
].shape[0],
                                                                                (d
evice_df[device_df['failure'] ==0 ].shape[0] / device_df[device_df['failure'] ==
1 ].shape[0]  )  ))


print('Number of devices : ', len(device_df.device.unique()))
device_failure = device_df[device_df['failure'] ==1 ]
print('Number of devices failure : ', len(device_failure.device.unique()))
histdevice = device_df.device.value_counts()
ax = histdevice.plot.hist(bins=12, alpha=0.5, title = "Distribuition of number
 samples per device ")


print('Devices  with less than 10 samples ')
print(histdevice[histdevice < 10].head())
```

```
Number of failure: 106   Number of  not failure: 124388 |rate 1173
Number of devices :  1169
Number of devices failure :  106
Devices  with less than 10 samples
W1F0PNA5    9
Z1F1AG5N    9
Z1F0M7QD    9
S1F0QZXV    9
S1F0TNYF    7
Name: device, dtype: int64
```



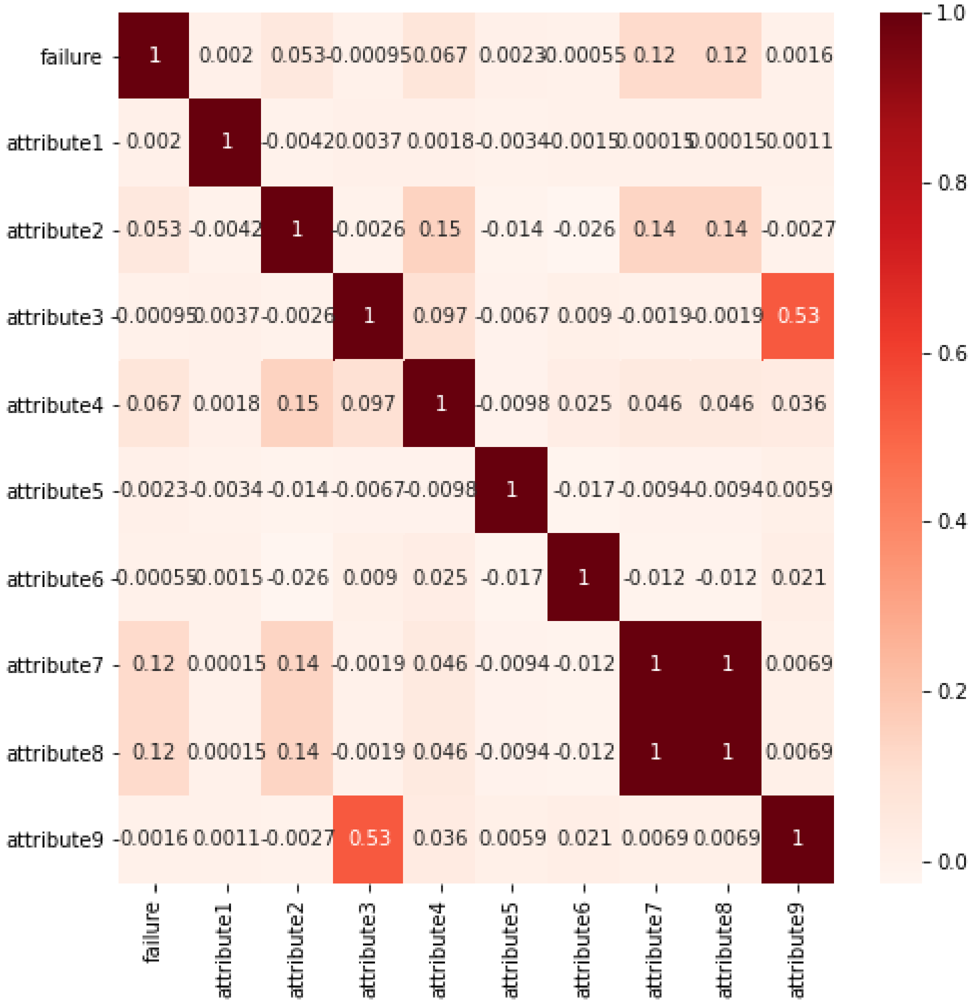
In [ ]:

In [7]:

```
import seaborn as sns
plt.figure(figsize=(8,8))
notascoora = device_df.corr()
sns.heatmap(notascoora, annot=True, cmap=plt.cm.Reds)
print('Correlation Matrix')
plt.show()
```

```
/home/leo/.local/lib/python3.6/site-packages/statsmodels/tools/_tes
ting.py:19: FutureWarning: pandas.util.testing is deprecated. Use t
he functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

```
Correlation Matrix
```



In [8]:

```
device_df[device_df['attribute7']  !=device_df['attribute8'] ]
```

Out[8]:

date	device	failure	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	att

Data explore conclusions

- The dataset is time series about failure of multiple devices.
- The two classes in the dataset failure and not failure is extremely unbalanced, for each failure there are 1173 not failure.
- The number of samples per device is incostant
- The values of the Attribute7 and attribute8 are the same.
- The outliers of the attributes 4, 7 and 8 are strongly corelated to the failure, and these values could indicatethat something is wrong with the device.

Feature engineering

Lag features aproche

The Lag feature is a classic technique for time series prediction problems. The simplest approach is add previous features (t-1), (t-2) .. to each sample in time (t).

In [9]:

```
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
device_df =  pd.read_csv('device_failure.csv', encoding = "ISO-8859-1")

# number of lags fetures in the windows
number_lags = 7

device_df["date"] = pd.to_datetime(device_df["date"])
device_df["day_week"] = device_df['date'].dt.dayofweek

# since attribute8 = attribute7, one of them can be discarded
device_df = device_df.drop(['attribute8'], axis=1)

device_names = device_df.device.unique().tolist()
```

In [ ]:

```

```

In [10]:

```
# add lgs features to each row to create a device's data set
def get_device_dataste(device_name, device_df):
    device_df =  device_df[device_df['device'] ==   device_name]

    column_names =['attribute1', 'attribute2', 'attribute3', 'attribute4', 'attr
ibute5', 'attribute6', 'attribute7',  'attribute9']

    for column_name in column_names:
        for i in range(1, number_lags +1):
            coluna_lag = column_name+'_'+ str((i) )
            device_df[coluna_lag] = device_df[column_name].shift(i)


    device_df['failure_f'] = device_df['failure'].shift(-1)
    device_df.drop(device_df.tail(1).index,inplace=True)

    # discart the fists columns
    if device_df.shape[0]  < number_lags +1 :
        device_df  = device_df.tail(1)
    else:
        device_df  = device_df.tail( device_df.shape[0] - number_lags )
    device_df.fillna(0)
    device_df = device_df.drop(['date', 'device', 'failure'], axis=1)
    return device_df



device_data = get_device_dataste(device_names[0], device_df)
for device_name in device_names[1:]:
    data_temp = get_device_dataste(device_name, device_df)
    device_data = pd.concat([device_data, data_temp])
```

In [ ]:

```

```

In [11]:

```
#  Let's check the correlation in
import seaborn as sns
import matplotlib.pyplot as plt

def print_correlation(lag):
    column_names =[ 'failure_f']
    for i in range(1, 10):
        if i != 8 :
            column_name = 'attribute' + str(i)
            if lag > 0 :
                column_name = column_name + '_' + str(lag)
            column_names.append(column_name)

    device_data_one_lag =  device_data[column_names]
    ## calcula matriz de correlacao


    coora = device_data_one_lag.corr()
    return coora




coora= print_correlation(0)
print("Failure  coorelation of features with no lag ")
coora.head(1)
```

Failure coorelation of features with no lag

Out[11]:

	failure_f	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attribute
failure_f	1.0	0.001272	0.047923	-0.001178	0.067709	0.001946	-0.001089	0.11408

In [12]:

```
coora= print_correlation(3)
print("Failure  coorelation of features with 3  lags")
coora.head(1)
```

Failure coorelation of features with 3 lags

Out[12]:

	failure_f	attribute1_3	attribute2_3	attribute3_3	attribute4_3	attribute5_3	attribut
failure_f	1.0	-0.001459	0.036124	-0.001311	0.055209	0.001846	-0.00

In [13]:

```
split_rate =0.2
device_data_f = device_data[device_data['failure_f'] ==1]
print(device_data_f.shape)

device_data__not_f = device_data[device_data['failure_f'] ==0]
print(device_data__not_f.shape)

print(' Unbalance data rate {:.2f}  !!'.format( device_data__not_f.shape[0]/ dev
ice_data_f.shape[0]))

from sklearn.model_selection import train_test_split
train_failure, test_failure = train_test_split(device_data_f, test_size=split_ra
te)
train_not_failure, test_not_failure = train_test_split(device_data__not_f, test_
size=split_rate)


failure_train_size =  train_failure.shape[0] * 4
failure_train_size
```

```
(106, 66)
(116193, 66)
 Unbalance data rate 1096.16  !!
```

Out[13]:

```
336
```

In [ ]:

```

```

Resampling

A widely adopted technique for dealing with highly unbalanced datasets is called resampling. It consists of removing samples from the majority class (under-sampling) and / or adding more examples from the minority class (over-sampling). Since, the rate of imbalance in our dataset is hight we adopted the two techniques together. Under-sampling the class of 'no failure' and over-sampling the 'failure' class As there are few points of failure, we adopt an integer as over-sampling rate in order to use the same weight for each point of failure during the training.

In [14]:

```
train_not_failure = train_not_failure.sample(n=failure_train_size, random_state=
1)
train_failure = train_failure.sample(n=failure_train_size, random_state=1, repla
ce=True)

final_train = pd.concat([train_failure, train_not_failure])
final_test = pd.concat([test_failure, test_not_failure])
print(final_train.shape)
print(final_test.shape)
print("Nuber of falures in the dataset test: ",  test_failure.shape[0])
```

```
(672, 66)
(23261, 66)
Nuber of falures in the dataset test:  22
```

Resolvers

Classifier candidates

```
1. Linerar Algorithms  ->  SVD is efficient and Versatile.
2. Neuron network - LSTM is a good candidate to solve time series problem
s, whenever I didn't  achieve goods results using this technique, probabi
lity because the dataset has few points of failure.
3. Decision Tree - could be too simple for the problem. *
4.  Ensemble methods appears to be more apropriеted,  Randow florest and
 GradientBoosting are good options.
```

- in order to keep the document concise,the LSTM code is not in this notebook

In [ ]:

In [15]:

```
## useful functions

import seaborn as sn
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import f1_score


#transfom the pandasFrame to x, y for train
def getDataset(df):
    df= df.dropna()
    label = df['failure_f'].values
    X = df.drop(['failure_f'], axis = 1)
    Xmatrix = X.values
    return Xmatrix, label

x_train, label_train = getDataset(final_train)
x_test,  label_test = getDataset(final_test)



def printAcuracyDetail(classificador, x, true_label ):
    predicted_label = classificador.predict(x)
    confu = confusion_matrix(true_label, predicted_label)
    TP = confu[1][1]
    TN = confu[0][0]
    FP = confu[0][1]
    FN = confu[1][0]


    accuracy =  accuracy_score(true_label, predicted_label)
    falures  = np.count_nonzero(true_label == 1)
    not_falures  = np.count_nonzero(true_label == 0)
    # https://en.wikipedia.org/wiki/Precision_and_recall
    # true positive rate = TP / (TP  + FN)
    # False positive rate = FP / (FP  + TN)
    # False Negative Rate = FN ( FN + TP)
    # True Negative Rate = TN/ (TN +FP )
    TP_rate = TP / (TP  + FN)
    FP_rate = FP / (FP  + TN)
    FN_rate = FN / (FN +TP )
    TN_rate = TN / ( TN +FP )

    print('         -Total acuracy {:.3f}%'.format( accuracy* 100 ))
    print('         -True  positives  {} | True positive rate   {:.3f}%'.format(
TP, TP_rate * 100  ))
    print('         -False positives  {} | False positive rate  {:.3f}%'.format(
FP, FP_rate * 100 ))
    print('         -True  negatives  {} | True negatives rate  {:.3f}% '.format
(TN, TN_rate* 100 ))
    print('         -False negatives  {} | False negatives rate {:.3f}% '.format
(FN, FN_rate* 100 ))


def getF1Acuracy(classificador, x, y_true ):
    y_pret_treino = classificador.predict(x)
```

```
    f1_s = f1_score(y_true, y_pret_treino, average='macro')
    return f1_s
```

In [16]:

```
from sklearn import svm
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import NuSVC

#svm_classificlf = svm.SVC()
svm_classificlf = svm.SVC(kernel='rbf')
#svm_classificlf = make_pipeline(StandardScaler(), NuSVC())

svm_classificlf.fit(x_train, label_train)

trainf1=  getF1Acuracy( svm_classificlf, x_train, label_train)



print("     train Acuracy {:.2f} testes Acuracy {:.2f}    ".format(svm_classificl
f.score(x_train, label_train) , svm_classificlf.score(x_test, label_test)) )
print("     train F1-Score {:.2f} teste F1-Score {:.2f} ".format(getF1Acuracy( s
vm_classificlf, x_train, label_train) , getF1Acuracy( svm_classificlf, x_test, l
abel_test)) )



print("\n     Results for the train dataset  ")
printAcuracyDetail(svm_classificlf,x_train , label_train )
print("\n     Results for the test dataset  ")
printAcuracyDetail(svm_classificlf,x_test , label_test )
```

```
     train Acuracy 0.69 testes Acuracy 0.68
     train F1-Score 0.69 teste F1-Score 0.41

     Results for the train dataset
         -Total acuracy 69.008%
         -True  positives  217 | True positive rate   67.812%
         -False positives  100 | False positive rate  29.851%
         -True  negatives  235 | True negatives rate  70.149%
         -False negatives  103 | False negatives rate 32.188%

     Results for the test dataset
         -Total acuracy 68.331%
         -True  positives  8 | True positive rate   36.364%
         -False positives  7329 | False positive rate  31.638%
         -True  negatives  15836 | True negatives rate  68.362%
         -False negatives  14 | False negatives rate 63.636%
```

In [17]:

```
from sklearn import ensemble
from sklearn import datasets
from sklearn.utils import shuffle
from sklearn.metrics import mean_squared_error
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
# funcap para calcula f1-dcore
from sklearn.metrics import f1_score

def boostingGridResolve(X_train, y_train, X_test, y_test):

    parameters = {
        "learning_rate": [ 0.05, 0.1],
            "max_depth":[ 2, 4, 6],
        "subsample":[0.4 ],
        "n_estimators":[  10, 15]
    }

    clf = GridSearchCV(GradientBoostingClassifier(), parameters, cv=4, n_jobs=-1
)
    clf.fit(X_train, y_train)
    trainf1=  getF1Acuracy( clf, X_train, y_train)
    trainf1_teste=  getF1Acuracy( clf, X_test, y_test)

    print("     train Acuracy {:.2f} testes Acuracy {:.2f}    ".format(clf.score(
X_train, y_train) , clf.score(X_test, y_test)) )
    print("     train F1-Score {:.2f} teste F1-Score {:.2f} ".format(getF1Acurac
y( clf, X_train, y_train) , getF1Acuracy( clf, X_test, y_test)) )
    print("best_params_",   clf.best_params_)

    return clf , trainf1



GB_Classifier ,trainf1 =  boostingGridResolve(x_train, label_train,x_test, label
_test  )

print("\n     Results for the train dataset  ")
printAcuracyDetail(GB_Classifier,x_train , label_train )
print("\n     Results for the test dataset  ")
printAcuracyDetail(GB_Classifier,x_test , label_test )
```

```
     train Acuracy 0.98 testes Acuracy 0.93
     train F1-Score 0.98 teste F1-Score 0.49
best_params_ {'learning_rate': 0.1, 'max_depth': 6, 'n_estimators':
15, 'subsample': 0.4}

     Results for the train dataset
         -Total acuracy 98.015%
         -True  positives  310 | True positive rate   96.875%
         -False positives  3 | False positive rate  0.896%
         -True  negatives  332 | True negatives rate  99.104%
         -False negatives  10 | False negatives rate 3.125%

     Results for the test dataset
         -Total acuracy 93.022%
         -True  positives  17 | True positive rate   77.273%
         -False positives  1613 | False positive rate  6.963%
         -True  negatives  21552 | True negatives rate  93.037%
         -False negatives  5 | False negatives rate 22.727%
```

-Total acuracy 91.134% -True positives 17 | True positive rate 80.952% -False positives 2052 | False positive rate 8.857% -True negatives 21117 | True negatives rate 91.143% -False negatives 4 | False negatives rate 19.048% 100,

In [24]:

```
from sklearn import ensemble
from sklearn import datasets
from sklearn.utils import shuffle
from sklearn.metrics import mean_squared_error
from sklearn.ensemble import RandomForestRegressor

def randonForestResolve(X_train, y_train, X_test, y_test ):
    from sklearn.model_selection import GridSearchCV


    # Set the parameters by cross-validation
    parameters = {'n_estimators': [   100, 150],
                  'max_depth': [ 5, 10],
                  'min_samples_split': [0.1, 0.4],
                  'min_samples_leaf': [1, 3]
                 }


    clf = GridSearchCV(ensemble.RandomForestClassifier(), parameters, cv=5,  n_j
obs=-1, verbose=1)


    clf.fit(X_train, y_train)


    print("     train Acuracy {:.2f} testes Acuracy {:.2f}   ".format(clf.score(
X_train, y_train) , clf.score(X_test, y_test)) )
    print("     train F1-Score {:.2f} teste F1-Score {:.2f} ".format(getF1Acurac
y( clf, X_train, y_train) , getF1Acuracy( clf, X_test, y_test)) )
    print("best_params_",   clf.best_params_)



    return clf

rf_classificatior =  randonForestResolve(x_train, label_train,x_test, label_test
)
print("\n     Results for the train dataset  ")
printAcuracyDetail(rf_classificatior,x_train , label_train )
print("\n     Results for the test dataset  ")
printAcuracyDetail(rf_classificatior,x_test , label_test )
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    1.3s
[Parallel(n_jobs=-1)]: Done  80 out of  80 | elapsed:    2.8s finis
hed

     train Acuracy 0.90 testes Acuracy 0.91
     train F1-Score 0.90 teste F1-Score 0.49
best_params_ {'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_
split': 0.1, 'n_estimators': 150}

     Results for the train dataset
         -Total acuracy 89.618%
         -True  positives  280 | True positive rate   87.500%
         -False positives  28 | False positive rate  8.358%
         -True  negatives  307 | True negatives rate  91.642%
         -False negatives  40 | False negatives rate 12.500%

     Results for the test dataset
         -Total acuracy 91.120%
         -True  positives  18 | True positive rate   81.818%
         -False positives  2055 | False positive rate  8.871%
         -True  negatives  21110 | True negatives rate  91.129%
         -False negatives  4 | False negatives rate 18.182%
```

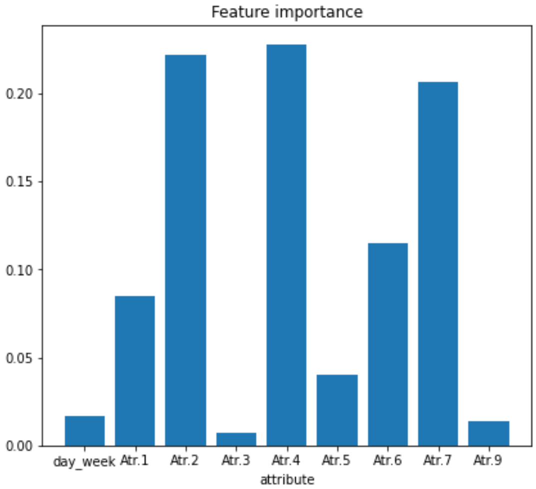
In [19]:

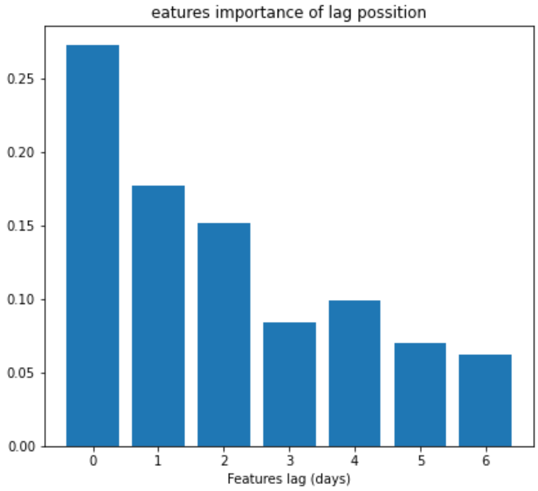
```
# get the importance of the featureregarding all lags

basecolumns = ['attribute1', 'attribute2', 'attribute3', 'attribute4', 'attribut
e5',  'attribute6', 'attribute7',  'attribute9']
colunmsList = device_data_f.columns.tolist()
rf_classificatior.best_estimator_.feature_importances_

def getColum_importance(base_feature):
    indexes = [colunmsList.index(base_feature)];
    column_importances = rf_classificatior.best_estimator_.feature_importances_[
colunmsList.index(base_feature)]
    for i in range (1, number_lags):
        column_importances += rf_classificatior.best_estimator_.feature_importan
ces_[colunmsList.index(base_feature + '_' + str(i))]

    return column_importances

columns_importance = []
columns_importance.append( rf_classificatior.best_estimator_.feature_importances
_[colunmsList.index('day_week')])

for basecolumn in basecolumns:
    columns_importance.append( getColum_importance(basecolumn))


# get the importance of all fature regaring a especific lag

basecolumns = ['attribute1', 'attribute2', 'attribute3', 'attribute4', 'attribut
e5',  'attribute6', 'attribute7',  'attribute9']
colunmsList = device_data_f.columns.tolist()
rf_classificatior.best_estimator_.feature_importances_

def getlag_importance(lag):
    if lag > 0 :
        suffix = '_' + str(lag )
    else:
        suffix =''

    lag_importance =  0
    for basecolumn in basecolumns:
        lag_importance += rf_classificatior.best_estimator_.feature_importances_
[colunmsList.index(basecolumn + suffix)]


    return lag_importance


lags_importance = []
for lag in range(0, number_lags):
    lags_importance.append( getlag_importance(lag))



fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15, 6))
axes[0].bar(['day_week', 'Atr.1','Atr.2','Atr.3','Atr.4','Atr.5','Atr.6','Atr.7'
,'Atr.9'] , columns_importance)
axes.flat[0].set(xlabel='attribute', title='Feature importance')

axes[1].bar(range(0,number_lags), lags_importance)
```

```
axes.flat[1].set(xlabel='Features lag (days)', title='eatures importance of lag
 possition')
```

Out[19]:

```
[Text(0.5, 0, 'Features lag (days)'),
 Text(0.5, 1.0, 'eatures importance of lag possition')]
```





In [ ]:

In [ ]:

Results

The folowing table compares the metrics of the The GradientBoosting and RandomForest Algorithms for the test dataset

	suporte vector machine	GradientBoosting	RandomForest
Acuracy	68%	93%	91%
True positive rate	36%	77%	82%
False positive rate	32 %	6.9 %	8.8 %
False negative rate	64%	22.7%	18.2%

Conclusions

- The data set is extremely unbalanced, with incostant number of samples per device and few samples of failure.
- The LSTM approche didn't achived good results.
- In order to use shallow classifiers two feature engineering have been aplyed: lag features and resampling .
- Sinse the dataset has few samples of failures (22 in test dataset) and the split process is randomic, the accuracy has a variation of 10% from one training to another
- The results show that GradientBoosting performed similarly to RandonForest, with a small advantage for RandonForest which is more stable and presents better results for the test dataset. Below the final results achieved by the randonForestResolve model:
    - Acuracy 91 %
    - True positives rate 82%
    - False positives rate 8.8%
    - False negatives rate 18.2%

In [ ]:

```

```