Classifier_Mystery_Machine

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[31]:
```
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sn
%matplotlib inline
```

1 Importing and cleaning the data set

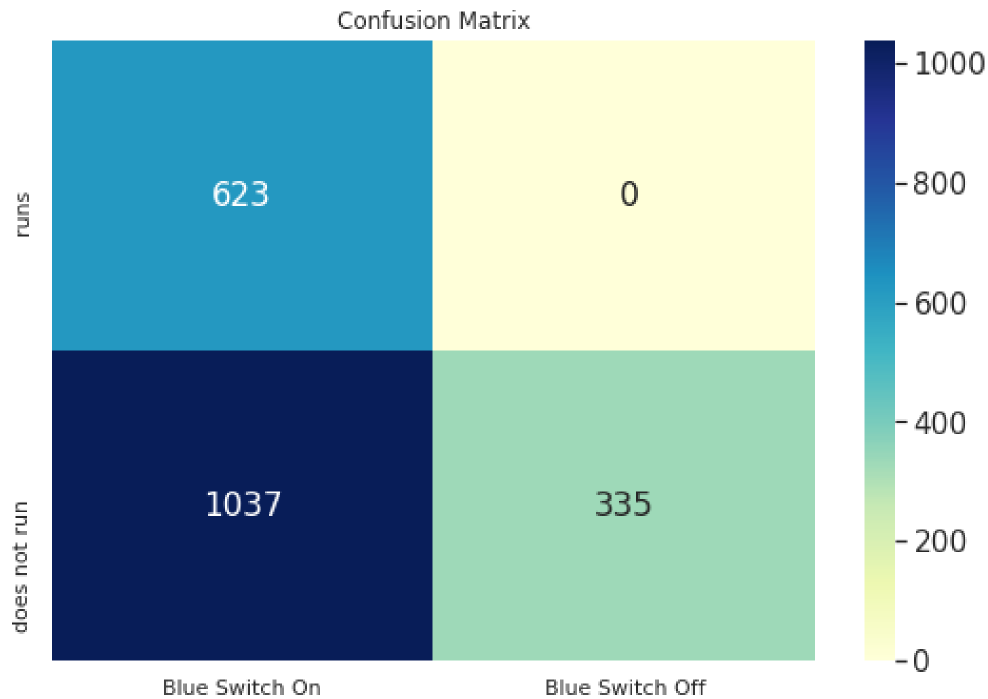
[2]:
```
data_train_db = pd.read_csv('data_train_db.csv')
data_test_db = pd.read_csv('data_test_db.csv')
```

[3]:
```
#It seems like there are some data points which have much higher standard␣
 ↪deviation than most. Lets just remove those.
def clean_dataset(data):
    to_drop= []
    for k in range(data.shape[0]):
        if data[k,:].std()>12:
            to_drop.append(k)
    return np.delete(data, to_drop, axis = 0)

data_train = data_train_db.values
columns=data_train_db.columns

data_train = clean_dataset(data_train)
df_train=pd.DataFrame(data_train,columns=columns)
```

2 Looking for patterns in the data set

[4]:
```
runs_switchon = np.count_nonzero((data_train[:,0]==1)*(data_train[:,1]==1))
runs_switchoff = np.count_nonzero((data_train[:,0]==1)*(data_train[:,1]==0))
runsnot_switchon = np.count_nonzero((data_train[:,0]==0)*(data_train[:,1]==1))
runsnot_switchoff = np.count_nonzero((data_train[:,0]==0)*(data_train[:,1]==0))
```

```
conf_matrix = [[runs_switchon, runs_switchoff], [runsnot_switchon,␣
 ↪runsnot_switchoff]]

sn.set(color_codes=True)
plt.figure(1, figsize=(9, 6))

plt.title("Confusion Matrix")

sn.set(font_scale=1.4)
ax = sn.heatmap(conf_matrix, annot=True, cmap="YlGnBu",fmt='2')

ax.set_yticklabels(['runs', 'does not run'])
ax.set_xticklabels(['Blue Switch On', 'Blue Switch Off'])
plt.show()
```



Hence if the **Blue Switch On** is off=0 the machine does not run.

Next we look at variable witch are highly (positively or negatively) corrolated (pearson) with "Running" for easily spotted deppendencies:

[5]:
```
#S is the list of variables sorted by how highly (positively or negatively)␣
 ↪corrolated they are with "Running"
s = np.argsort(np.abs(np.array(df_train.corr()['Running'])))[::-1]
S=columns[s]
```

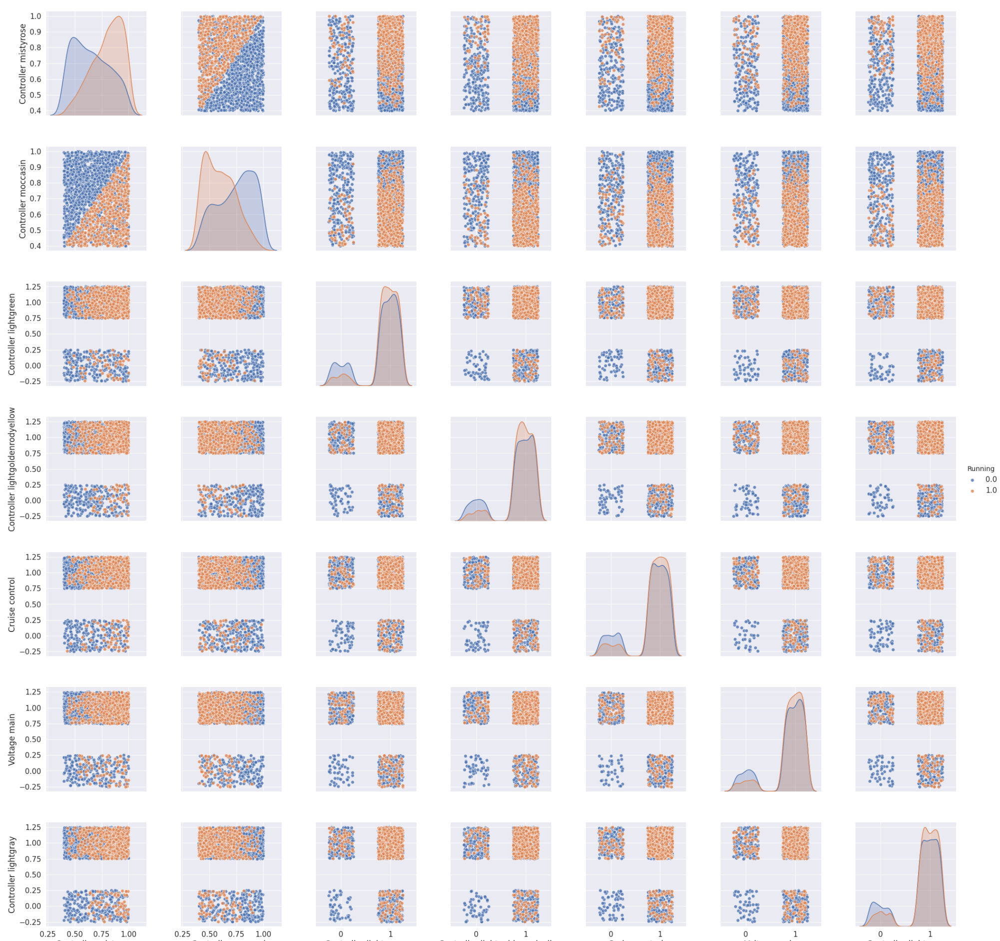
```
#Since we already know how "Running" and "Blue Switch On" corrolate with␣
↪"Running" we delete those
S = S.drop(["Running","Blue Switch On"])
```

Since some of the variables are binary scatterplots will only be informative if we add some sort of jitter:

[6]:
```
df_train_jitter=df_train.copy()
#CB is a list of binary variables
CB=[c for c in columns if len(np.unique(df_train[c]))<20]
CB=CB[2:]#We ignore the "Running" and "Blue Swich On"
for c in CB:
    df_train_jitter[c]+=np.random.uniform(-1/4,1/4,len(df_train_jitter))
```

Now we plot the plot the interaction of the variables most correlated with “Running”

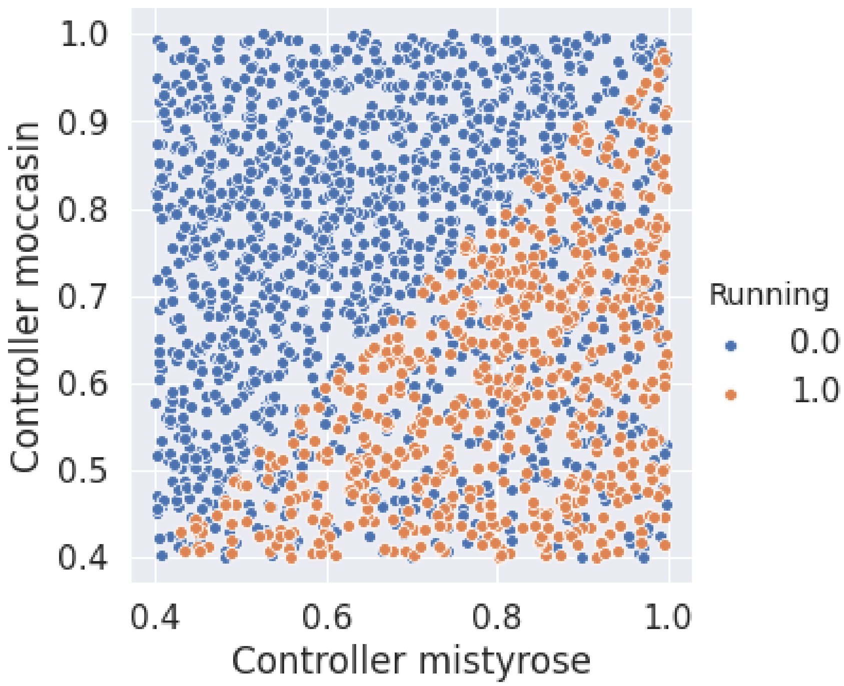
[7]:
```
A=sn.pairplot(df_train_jitter,y_vars=S[0:7],x_vars=S[0:
↪7],hue="Running",plot_kws={"s":50,'alpha':0.8},height=4)
plt.show()
```



We spot two things:

1) If **Controller moccasin > Controller mistyrose** the machine does not work.

[8]:
```
sn.pairplot(df_train,y_vars="Controller moccasin",x_vars="Controller␣
↪mistyrose",hue="Running",plot_kws={"s": 35},height=5)
plt.show()
```

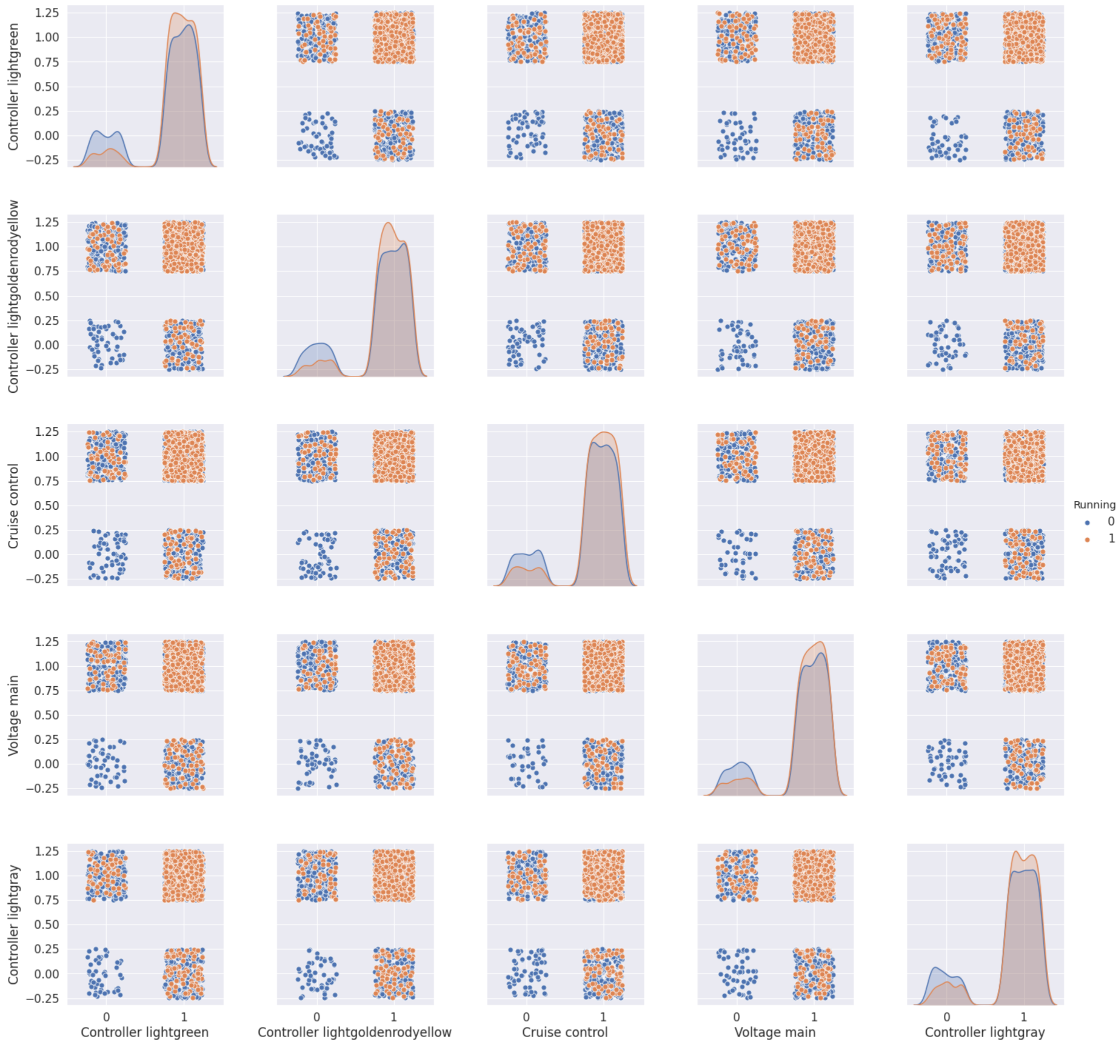


[9]:
```
errors=0
for i in range(1000):
    if df_train["Controller mistyrose"][i]<=df_train["Controller moccasin"][i]␣
↪and df_train["Running"][i]==1:
        errors+=1
print("When we test this assumtion we get", errors, "errors :)")
```

```
When we test this assumtion we get 0 errors :)
```

2) The second thing we notice is that in the graphic below there are never any orange points in the lower left squares, hence we assume that if at least **two of the plotted variables are 0** the machine does not run.

[10]:
```
A=sn.pairplot(df_train_jitter,y_vars=S[2:7],x_vars=S[2:
↪7],hue="Running",plot_kws={"s": 50,'alpha':1},height=4,hue_order=[0,1])
plt.show()
```



[11]:
```
errors=0
for i in range(len(df_train)):
    if np.sum(df_train[S[2:7]],axis=1)[i]<=3:
        if df_train['Running'][i]:
            errors+=1
print("When we test this assumtion we get", errors, "errors :)")
```

```
When we test this assumtion we get 0 errors :)
```

3 Filter out cases where the result has already been determined

Lets filter out the cases where the **Blue Switch On=0**, **Controller moccasin > Controller mistyrose** or **two of the above varibles are 0 at the same time** since we already know that the machine will not run in these cases

[12]:
```
df_train0 = df_train[df_train["Blue Switch On"]!=0]
df_train1 = df_train0[df_train0["Controller moccasin"]<df_train0["Controller␣
↪mistyrose"]]
df_train2 = df_train1[np.sum(df_train1[['Controller lightgreen', 'Controller␣
↪lightgoldenrodyellow','Cruise control', 'Voltage main', 'Controller␣
↪lightgray']],axis=1)>3]
```

Lets check how many times the machine runs or not runs in our filtered dataset

[13]:
```
np.unique(df_train2["Running"],return_counts=True)
```

[13]:
```
(array([0., 1.]), array([ 68, 623]))
```

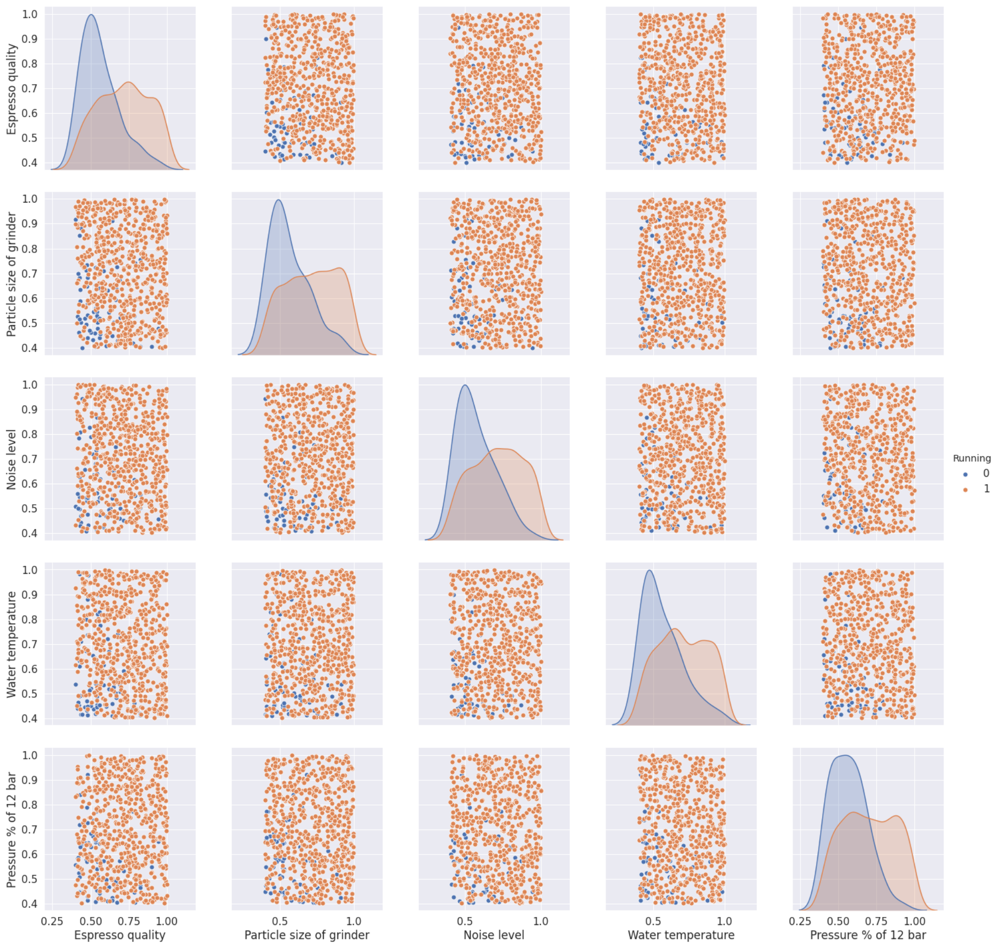
Wow only 68 fail cases not accounted for!

Lets repeat the previous procedure:

4 Looking for patterns in the remaining data set

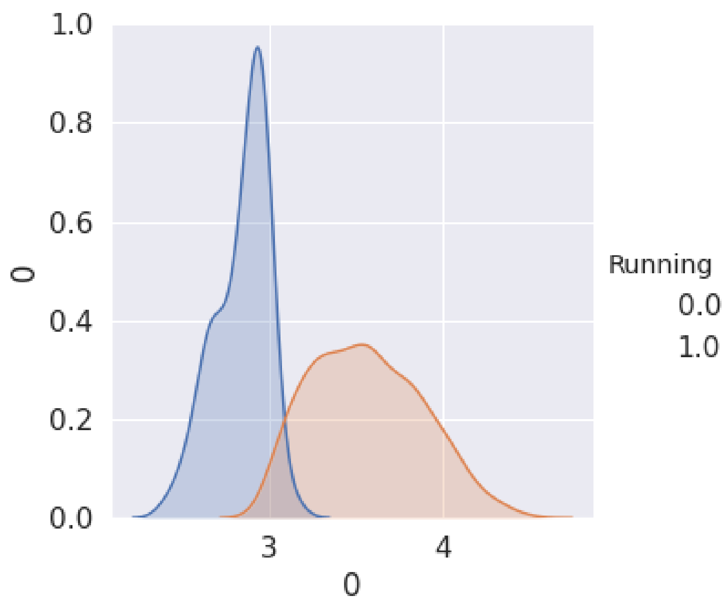
[14]:
```
#S is the list of variables sorted by how highly (positively or negatively)␣
↪corrolated they are with "Running"
s = np.argsort(np.abs(np.array(df_train2.corr()['Running'])))[::-1]
S=columns[s]

#We delete "Running", "Blue Swich On" and the other binarie variables we already␣
↪used
S = S.drop(['Running','Blue Switch On','Controller mistyrose', 'Controller␣
↪moccasin', 'Controller lightgreen','Controller lightgoldenrodyellow', 'Cruise␣
↪control'])
```

[15]:
```
A=sn.pairplot(df_train2,y_vars=S[:5],x_vars=S[:5],hue="Running",plot_kws={"s":␣
↪50},height=4,hue_order=[0,1])
plt.show()
```



None of these are great classifiers but we suspect that the sum might be

[16]:
```
df_train2_sum=pd.concat([df_train2["Running"],np.sum(df_train2[['Espresso quality', 'Particle size of grinder', 'Noise level','Water temperature','Pressure % of 12 bar']],axis=1)],axis=1)
sn.pairplot(df_train2_sum,y_vars=0,x_vars=0,hue="Running",plot_kws={"s":35},height=5)
plt.show()
```



3 looks like a good threshhold (it's better then it looks since the plot smoothes out the curves)

Lets look at how it holds up:

[29]:
```
errors=0
for i in range(len(df_train2)):
    if np.array(np.sum(df_train2[['Espresso quality', 'Particle size of␣
↪grinder', 'Noise level','Water temperature', 'Pressure % of 12␣
↪bar']],axis=1))[i]<3:
        if np.array(df_train2['Running'])[i]:
            #print("False Negative")
            errors+=1
    else:
        if not np.array(df_train2['Running'])[i]:
            #print("False Positive")
            errors+=1
print("When we test this assumtion we get", errors, "errors :)")
```

```
When we test this assumtion we get 2 errors :)
```

This looks great choosing 3 as a threshold gives a classifier that only makes 2 mistakes when classifing the remaining 691 samples

Let's formulate this classifier as a function:

[18]:
```
def mycls(data,p=False):
    #determine if x is an outlier but maybee also useless since in the test set␣
↪all outliers are also mapped to not Running which makes somewhat sense
```

```
    #check if "Blue Switch On"==1
    if data["Blue Switch On"]==0:
        if p:
            print("Blue Switch On")
        return 0

    #check if Controller moccasin > Controller mistyrose
    if data["Controller moccasin"] > data["Controller mistyrose"]:
        if p:
            print("Controller moccasin > Controller mistyrose")
        return 0

    #check  two of the varibles ['Controller lightgreen', 'Controller␣
↪lightgoldenrodyellow',
    #'Cruise control', 'Voltage main', 'Controller lightgray'] are 0 at the same␣
↪time
    if np.sum(data[['Controller lightgreen', 'Controller␣
↪lightgoldenrodyellow','Cruise control', 'Voltage main', 'Controller␣
↪lightgray']])<=3:
        if p:
            print("two varibles are 0 at the same time")
        return 0


    #check if sum(['Espresso quality', 'Particle size of grinder', 'Noise level',
    #               'Water temperature', 'Pressure % of 12 bar'])>3
    if np.sum(data[['Espresso quality', 'Particle size of grinder', 'Noise␣
↪level', 'Water temperature', 'Pressure % of 12 bar']])<3:
        if p:
            print("np.sum(data[['Espresso quality', 'Particle size of grinder',␣
↪'Noise level','Water temperature', 'Pressure % of 12 bar']])<3")
        return 0

    return 1
```

[19]:
```
err=0
for x in df_train.T:
    if  df_train.T[x]['Running']!=mycls(df_train.T[x]):
        err+=1
print(err)
```

2

[26]:
```
#By the way these are the all the indices of the used variables
c=[0,1,70,71,72,73,74,80,81,82,83,84,98,99]
```

5 Looking at Outliers:

[21]:
```
def problems_dataset(data):
    to_drop= []
    for k in range(data.shape[0]):
        if data[k,:].std()>12:
            to_drop.append(k)
    return to_drop# np.delete(data, to_drop, axis = 0)
```

[22]:
```
problemtrain=problems_dataset(np.array(data_train_db))
problemtest=problems_dataset(np.array(data_test_db))
problemtrain,problemtest
```

[22]:
```
([17, 372, 644, 881, 928], [168, 190, 216, 229, 253, 262, 461, 462, 475, 491])
```

[23]:
```
qwertz=pd.DataFrame(np.array(data_train_db)[problemtrain],columns=columns)
qwertz["Running"]
```

[23]:
```
0    0.0
1    0.0
2    0.0
3    0.0
4    0.0
Name: Running, dtype: float64
```

This could let us assume that the machine does not run for outliers, especially since the classifier *mycls* gives a false positve on the sample:

[24]:
```
for x in qwertz.T:
    print(mycls(qwertz.T[x]),end=", ")
```

```
0, 0, 0, 1, 0,
```

But since *mycls* classifies all outliers in the testset as not running anyhow, we will not have to code that assumtion into the classifier:

[25]:
```
for x in problemtest:
    print(mycls(data_test_db.T[x]),end=", ")
```

```
0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
```