I. DATA ACQUISITION (IMPORT)

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import OneHotEncoder
import scipy
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn import feature_selection
from sklearn.feature_selection import SelectKBest
import seaborn as sns
from sklearn import metrics
from sklearn.metrics import classification_report
```

```
tyre_data = pd.read_csv("/content/drive/MyDrive/Copia di tyres_train.csv")
#tyre_data = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/PoliMi colab/MIML_ML colab/tyres_train.csv")
```

```
tyre_data
```

	vulc	perc_nat_rubber	wiring_strength	weather	perc_imp	temperature	tread_type	tyre_se
0	17.990	26	1	0.16	0.01	-8.12	0	
1	20.704	36	1	0.30	0.01	-4.52	2	
2	19.156	34	1	0.30	0.01	-1.08	0	
3	16.802	35	1	0.19	0.02	7.44	1	
4	17.140	23	2	0.39	0.01	30.52	0	
...	...	...	...	...	...	...	...	
2995	17.818	29	2	0.39	0.01	7.28	1	
2996	17.076	30	1	0.22	0.00	-1.44	1	
2997	16.170	33	1	0.39	0.01	-3.44	1	
2998	18.872	37	0	0.03	0.00	-0.76	4	
2999	20.272	33	2	0.06	0.00	2.80	1	

3000 rows × 16 columns

Our target variable is "failure"

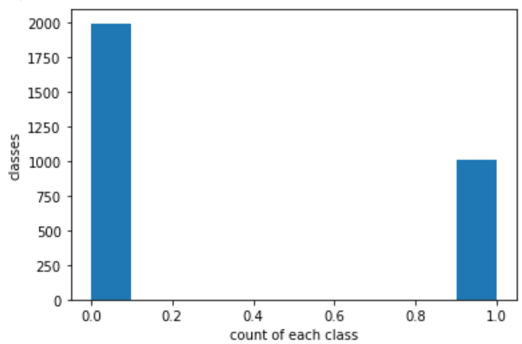
```
tyre_data['failure']
```

```
0       0
1       0
2       0
3       0
4       0
       ..
2995    1
2996    1
2997    0
2998    0
2999    0
Name: failure, Length: 3000, dtype: int64
```

```
# Number of successes and failures
print(tyre_data.groupby('failure').size())
```

```
# visual representation (histogram)
plt.hist(tyre_data['failure'])
plt.xlabel("count of each class")
plt.ylabel("classes")
plt.show()
```

```
failure
0    1992
1    1008
dtype: int64
```



we can see how the dataset is imbalanced

```
# copy of the dataset to work with (so we don't have to import again)
df = tyre_data.copy(deep=True);
df
```

	vulc	perc_nat_rubber	wiring_strength	weather	perc_imp	temperature	tread_type	tyre_season	elevation	month	tread_depth
0	17.990	26	1	0.16	0.01	-8.12	0	1	332.5	8	0
1	20.704	36	1	0.30	0.01	-4.52	2	0	328.0	11	1
2	19.156	34	1	0.30	0.01	-1.08	0	0	247.0	0	1
3	16.802	35	1	0.19	0.02	7.44	1	0	408.0	7	3
4	17.140	23	2	0.39	0.01	30.52	0	1	308.0	2	2
...	...	...	...	...	...	...	...	...	...	...	...
2995	17.818	29	2	0.39	0.01	7.28	1	1	287.5	10	1
2996	17.076	30	1	0.22	0.00	-1.44	1	1	152.5	6	1
2997	16.170	33	1	0.39	0.01	-3.44	1	0	235.0	8	3
2998	18.872	37	0	0.03	0.00	-0.76	4	0	290.0	11	0
2999	20.272	33	2	0.06	0.00	2.80	1	0	405.0	2	1

3000 rows × 16 columns

II. DATA PREPARATION

data: numerical and categorical attributes

```
numerical = ["vulc", "perc_nat_rubber", "weather", "perc_imp", "temperature", "elevation", "perc_exp_comp"]
categorical_original = ["tread_type", "tyre_season", "month", "tread_depth", "wiring_strength", "tyre_quality", "add_layers"]
```

1) Data validation

searching for and handling

- incompletenesses (NaN values)
- duplicate values

```
df.isna().any()
```

```
vulc               False
perc_nat_rubber    False
wiring_strength    False
weather            False
perc_imp           False
temperature        False
tread_type         False
tyre_season        False
elevation          False
month              False
tread_depth        False
tyre_quality       False
perc_exp_comp      False
diameter            True
add_layers         False
failure            False
dtype: bool
```

-> only diameter has NaN values

Lets explore it and deal with the missing data:

```
# count non nan and nan values

df['diameter'].isna().value_counts()
```

```
True     2110
False     890
Name: diameter, dtype: int64
```

-> we decide to remove the whole column of diameter because the majority of the observations are Nan values

```
# removing 'diameter' column

df = df.drop('diameter', axis=1)
```

```
np.isinf(df).any()
```

```
vulc               False
perc_nat_rubber    False
wiring_strength    False
weather            False
perc_imp           False
temperature        False
tread_type         False
tyre_season        False
elevation          False
month              False
tread_depth        False
tyre_quality       False
perc_exp_comp      False
add_layers         False
failure            False
dtype: bool
```

-> no infinite values

checking if there are duplicate rows

```
df[df.duplicated()]
```

vulc	perc_nat_rubber	wiring_strength	weather	perc_imp	temperature	tread_type	tyre_season	elevation	month	tread_depth	tyre_q

-> no duplicate rows

2) One-hot-encoding for categorical attributes

- now we are converting all the categorical attributes (there are 7 of them in our dataset)
- the one-hot encoding will create (k-1) binary columns for each categorical attribute and return a sparse matrix

```
ohe = OneHotEncoder(handle_unknown='ignore')
results = ohe.fit_transform(df[categorical_original])
dummy = pd.DataFrame.sparse.from_spmatrix(results)
dummy.columns = ohe.get_feature_names(df[categorical_original].columns)
dummy
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function get_feature_names is deprecated; get_fe
  warnings.warn(msg, category=FutureWarning)
```

	tread_type_0	tread_type_1	tread_type_2	tread_type_3	tread_type_4	tyre_season_0	tyre_season_1	month_0	month_1	month_2	...
0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...
1	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...
2	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	...
3	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...
4	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	...
...	...	...	...	...	...	...	...	...	...	...	...
2995	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...
2996	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...
2997	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...
2998	0.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	...
2999	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...

3000 rows × 31 columns

```
# removing extra columns
catlist = dummy.columns.tolist()
remlist = []
remlist += [catlist[-1]]
for i in range(0,len(catlist)-1):
  # print(catlist[i+1][:-2])
  if catlist[i][:-1] != catlist[i+1][:-1]:
    remlist += [catlist[i]]
remlist.remove('month_9')
remlist
```

```
['add_layers_2',
 'tread_type_4',
 'tyre_season_1',
 'month_11',
 'tread_depth_3',
 'wiring_strength_2',
 'tyre_quality_1']
```

```
dummy = dummy.drop(remlist,axis=1)
dummy
```

	tread_type_0	tread_type_1	tread_type_2	tread_type_3	tyre_season_0	month_0	month_1	month_2	month_3	month_4	...	month_9
0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
1	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0
2	1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	...	0.0
3	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0

```
df = pd.concat([df,dummy],axis=1)
for cat in categorical_original:
  df = df.drop(cat,axis=1)
df
```

	vulc	perc_nat_rubber	weather	perc_imp	temperature	elevation	perc_exp_comp	failure	tread_type_0	tread_type_1	...	month_
0	17.990	26	0.16	0.01	-8.12	332.5	5.13	0	1.0	0.0	...	0
1	20.704	36	0.30	0.01	-4.52	328.0	6.15	0	0.0	0.0	...	0
2	19.156	34	0.30	0.01	-1.08	247.0	6.36	0	1.0	0.0	...	0
3	16.802	35	0.19	0.02	7.44	408.0	6.62	0	0.0	1.0	...	0
4	17.140	23	0.39	0.01	30.52	308.0	6.15	0	1.0	0.0	...	0
...	...	...	...	...	...	...	...	...	...	...	...	
2995	17.818	29	0.39	0.01	7.28	287.5	5.68	1	0.0	1.0	...	0
2996	17.076	30	0.22	0.00	-1.44	152.5	5.81	1	0.0	1.0	...	0
2997	16.170	33	0.39	0.01	-3.44	235.0	5.57	0	0.0	1.0	...	0
2998	18.872	37	0.03	0.00	-0.76	290.0	5.89	0	0.0	0.0	...	0
2999	20.272	33	0.06	0.00	2.80	405.0	6.00	0	0.0	1.0	...	0

3000 rows × 32 columns

```
categorical = dummy.columns
categorical
```

```
Index(['tread_type_0', 'tread_type_1', 'tread_type_2', 'tread_type_3',
       'tyre_season_0', 'month_0', 'month_1', 'month_2', 'month_3', 'month_4',
       'month_5', 'month_6', 'month_7', 'month_8', 'month_9', 'month_10',
       'tread_depth_0', 'tread_depth_1', 'tread_depth_2', 'wiring_strength_0',
       'wiring_strength_1', 'tyre_quality_0', 'add_layers_0', 'add_layers_1'],
      dtype='object')
```

```
cols = df.columns.tolist()
cols.remove('failure')
cols.append('failure')
df = df[cols]
df
```

	vulc	perc_nat_rubber	weather	perc_imp	temperature	elevation	perc_exp_comp	tread_type_0	tread_type_1	tread_type_2	...	m
0	17.990	26	0.16	0.01	-8.12	332.5	5.13	1.0	0.0	0.0	...	
1	20.704	36	0.30	0.01	-4.52	328.0	6.15	0.0	0.0	1.0	...	
2997	16.170	33	0.39	0.01	-3.44	235.0	5.57	0.0	1.0	0.0	...	
2999	20.272	33	0.06	0.00	2.80	405.0	6.00	0.0	1.0	0.0	...	

II.A. DATA EXPLORATION

We conducted data exploration to get an idea of the distribution of the data in our dataset:

- if any feature is useful to predict the failure of the tyre
- if any feature has to be discarded or needs some transformation

So we proceeded with the univariate and bivariate analysis of numerical and categorical attributes separately.

1) Numerical

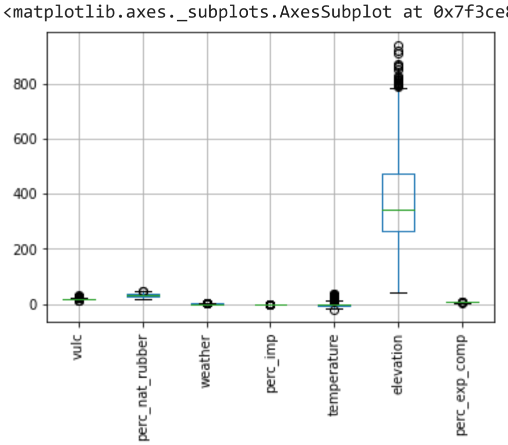
```
df[numerical].describe()
```

	vulc	perc_nat_rubber	weather	perc_imp	temperature	elevation	perc_exp_comp
count	3000.000000	3000.000000	3000.000000	3000.000000	3000.000000	3000.000000	3000.00000
mean	18.184712	31.249667	0.282987	0.014550	-2.375360	376.184000	5.79151
std	1.587193	4.933300	0.183252	0.014262	5.672184	151.149861	0.41032
min	12.312000	18.000000	0.030000	0.000000	-19.280000	41.500000	4.54000
25%	17.241500	28.000000	0.160000	0.010000	-6.960000	263.500000	5.48000
50%	17.834000	31.000000	0.210000	0.010000	-2.080000	342.000000	5.80000
75%	18.934000	35.000000	0.370000	0.020000	0.080000	471.625000	6.08000
max	29.932000	46.000000	0.930000	0.050000	37.000000	939.500000	7.21000

- UNIVARIATE analysis

```
df[numerical].boxplot(rot=90)
```

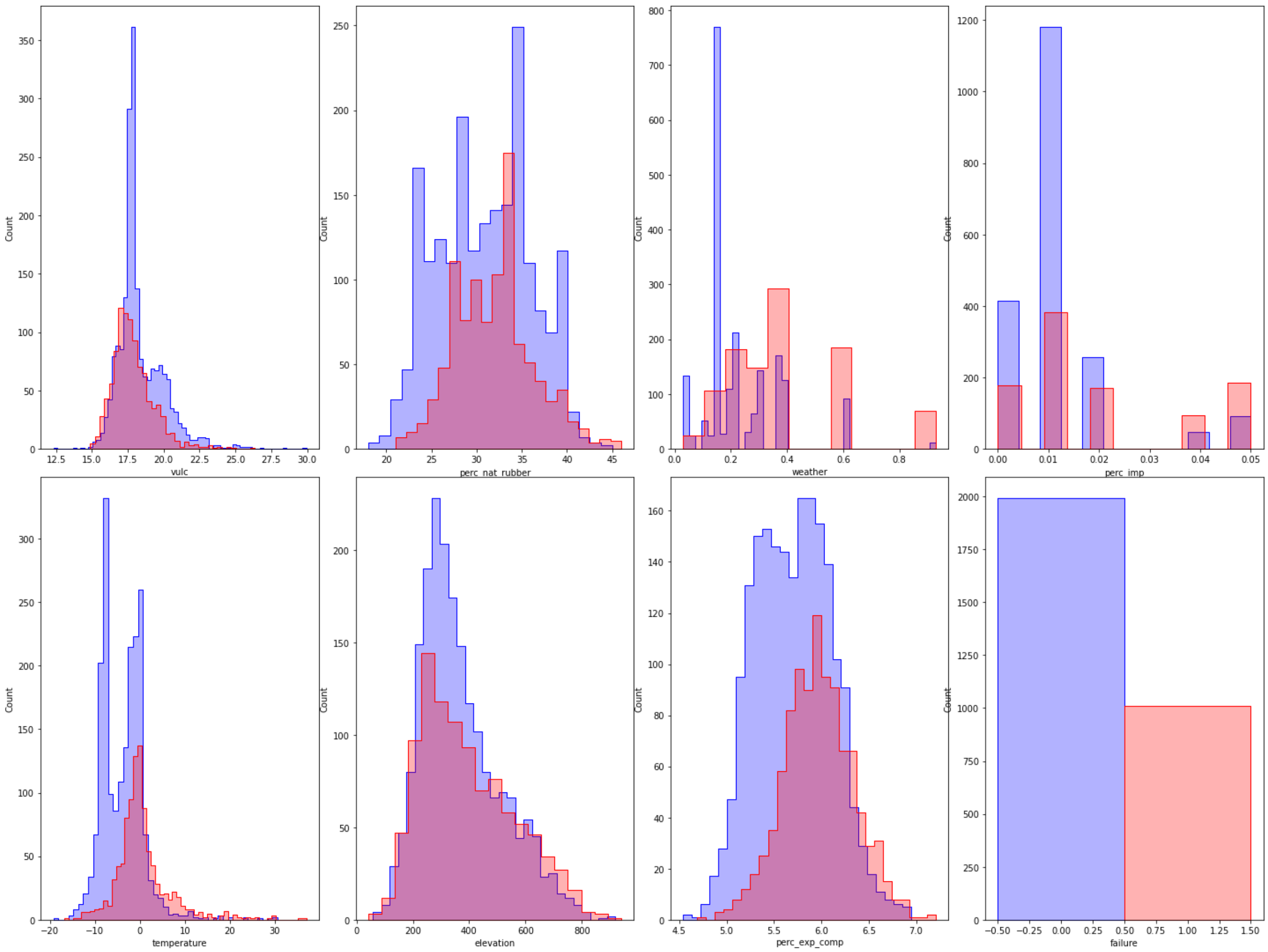
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3ce8fe1160>
```



We plot a histogram for each numerical attribute to compare the empirical density of the observations with target=0 (in blue) and those with target=1 (in red) if the two charts seem to overlap completely then the attribute is probably not useful for our case.

```
%matplotlib inline

X= pd.concat([df[numerical], df['failure']], axis=1)
X0 = X[X['failure']==0]
X1 = X[X['failure']==1]

fig, axes = plt.subplots(ncols=4, nrows=2, figsize=(20,15))
fig.tight_layout()

for i, ax in zip(range(X.columns.size), axes.flat):
```

```
    sns.histplot(X0.iloc[:,i], color="blue", element="step", ax=ax,  alpha=0.3)
    sns.histplot(X1.iloc[:,i], color="red", element="step", ax=ax,  alpha=0.3)
plt.show()
```



We can see from the graphs that in every case the blue and red histograms seem to be very similar

We might tend to conclude that these numerical attributes are not useful to discern the target value, so we want to perform some additional tests to asses whether the two distributions are different (red and blue)

In this case we performed chi-test (empirical distributions) and f-test (based on the analysis of variance)

note: since chi-test needs all non-negative inputs, we proceed by scaling the numerical attributes between 0 and 1

```
#MinMax scaling between 0 and 1

from sklearn.preprocessing import MinMaxScaler
mm_scaler =  MinMaxScaler(copy=False,feature_range=(0, 1))
mmScaled = mm_scaler.fit_transform(df[numerical])
mmscaled_df = pd.DataFrame(mmScaled)
mmscaled_df.columns = df[numerical].columns

mmscaled_df
```

	vulc	perc_nat_rubber	weather	perc_imp	temperature	elevation	perc_exp_comp
0	0.322247	0.285714	0.144444	0.2	0.198294	0.324053	0.220974
1	0.476277	0.642857	0.300000	0.2	0.262260	0.319042	0.602996
2	0.388422	0.571429	0.300000	0.2	0.323383	0.228842	0.681648
3	0.254824	0.607143	0.177778	0.4	0.474769	0.408129	0.779026
4	0.274007	0.178571	0.400000	0.2	0.884861	0.296771	0.602996
...	...	...	...	...	...	...	...
2995	0.312486	0.392857	0.400000	0.2	0.471926	0.273942	0.426966
2996	0.270375	0.428571	0.211111	0.0	0.316986	0.123608	0.475655
2997	0.218956	0.535714	0.400000	0.2	0.281450	0.215479	0.385768
2998	0.372304	0.678571	0.000000	0.0	0.329069	0.276726	0.505618

```
A=mmscaled_df

b=df['failure']

selector_chi=SelectKBest(feature_selection.chi2, k=5)
selector_f=SelectKBest(feature_selection.f_classif, k=5)

A_chi = pd.DataFrame(selector_chi.fit_transform(A, b),columns=A.columns[selector_chi.get_support()])
A_f = pd.DataFrame(selector_f.fit_transform(A, b),columns=A.columns[selector_f.get_support()])


# we are asking to provide to us the attributes that are the most likely to be different (so the best ones)

print(A.columns[selector_chi.get_support()])
print(A.columns[selector_f.get_support()])
```

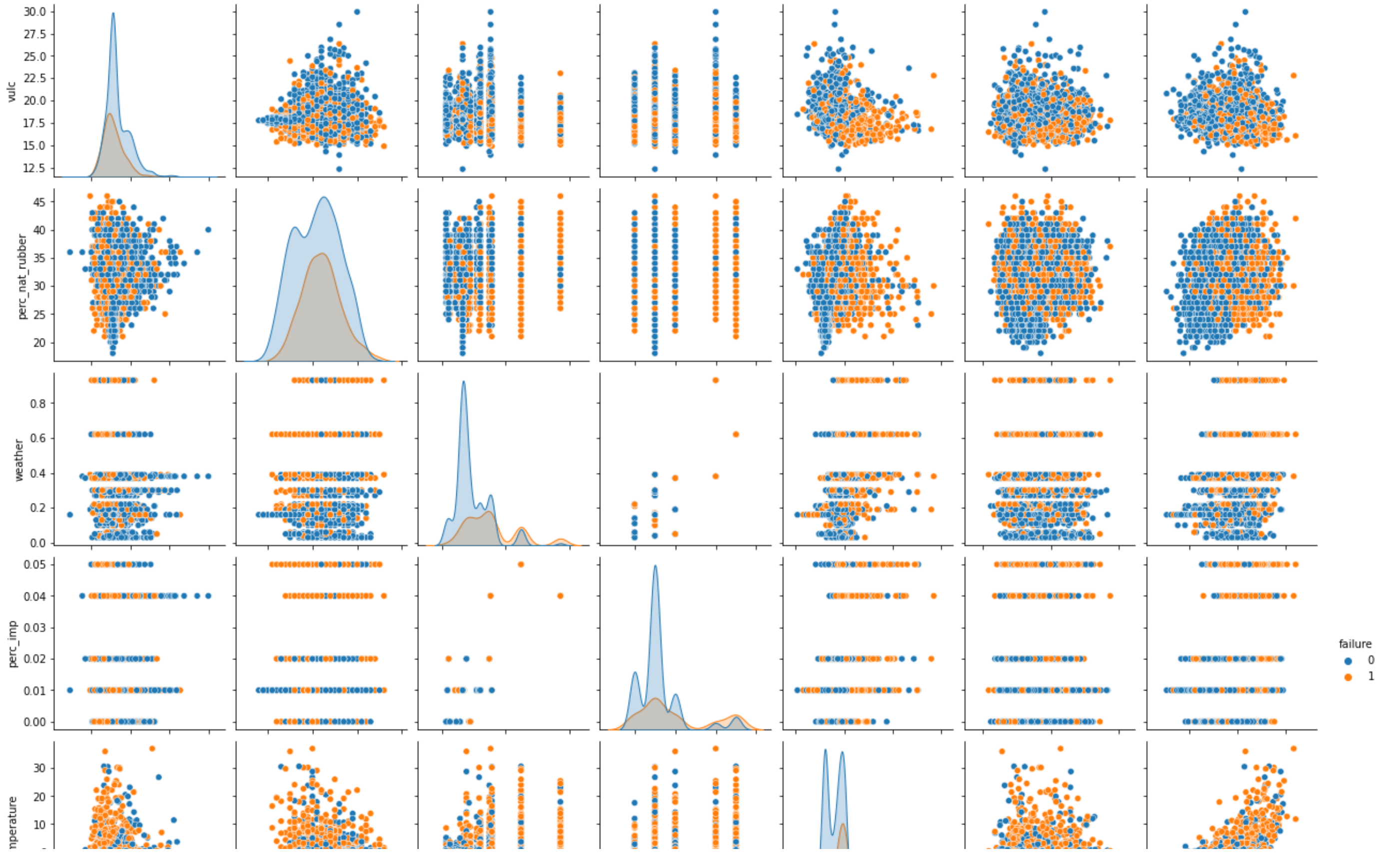
```
Index(['perc_nat_rubber', 'weather', 'perc_imp', 'temperature',
       'perc_exp_comp'],
      dtype='object')
Index(['vulc', 'weather', 'perc_imp', 'temperature', 'perc_exp_comp'], dtype='object')
```

In concusion, since from the tests we got that the red and blue distributions are actually different for all of the numerical attributes except 'elevation', we decided to remove the latter.

- BIVARIATE analysis

```
# we are conducting the analysis through a scatter plot

%matplotlib inline
sns.pairplot(X,hue='failure')
```

```
<seaborn.axisgrid.PairGrid at 0x7f3ce8bafb20>
```

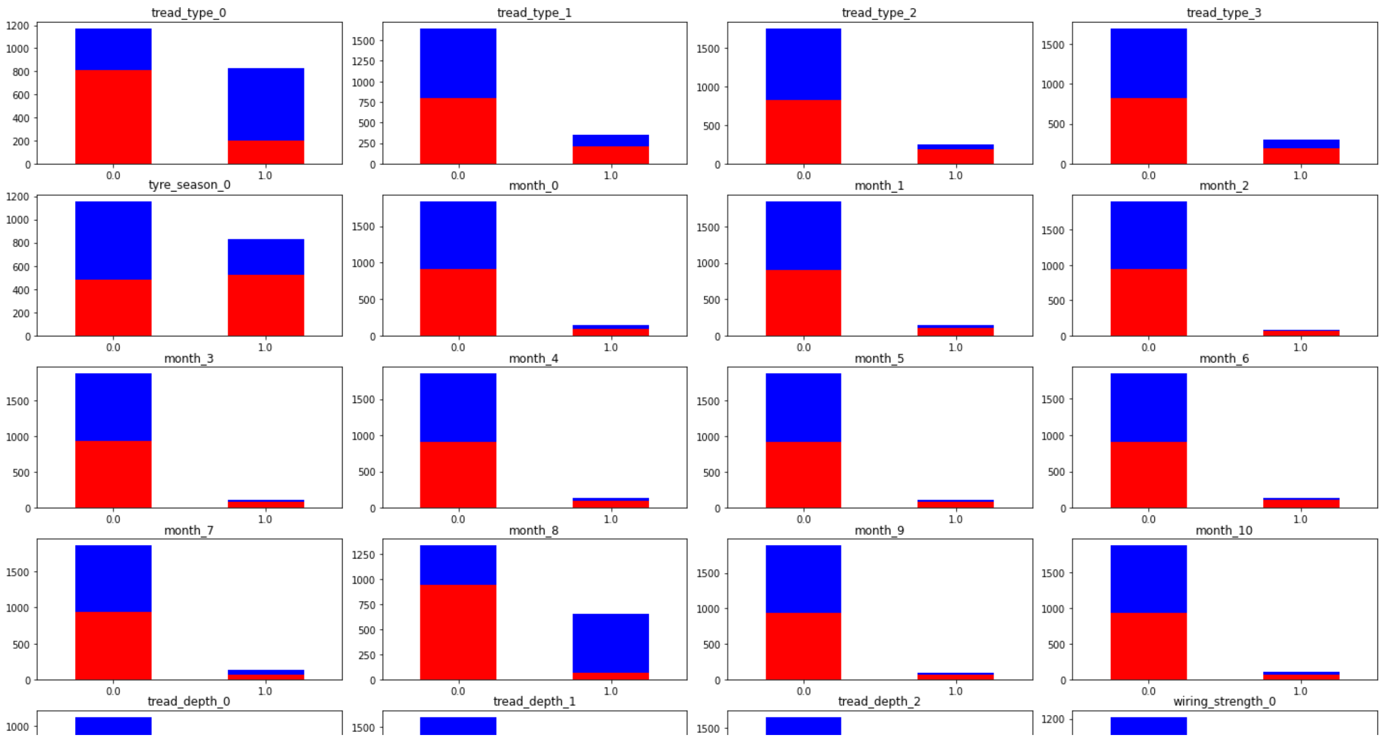


2) Categorical

UNIVARIATE GRAPHICAL ANALYSIS of categorical attributes

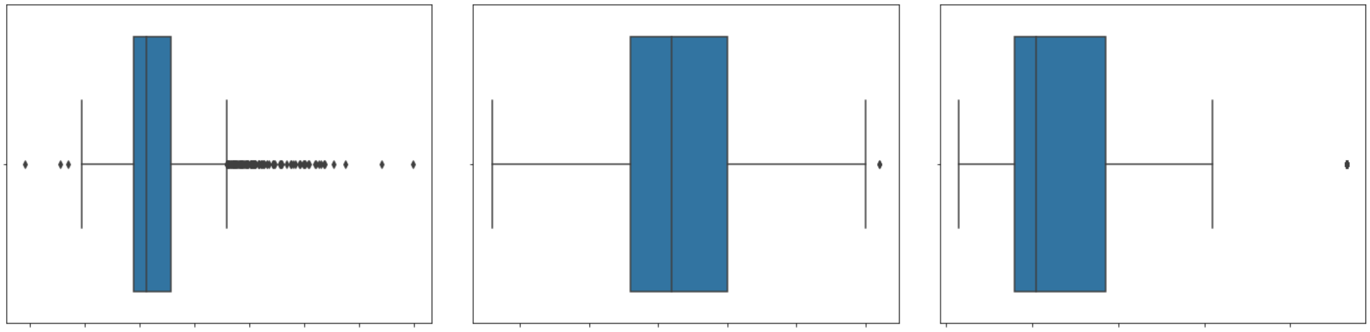
- we are plotting a vertical bar chart for each categorical attribute to compare the empirical distribution of the observations with target=0 (in blue) and those with target=1 (in red)

```
Y = pd.concat([df[categorical], df['failure']], axis=1)

Y0 = Y[Y['failure']==0]
Y1 = Y[Y['failure']==1]

fig, axes = plt.subplots(ncols=4, nrows=6, figsize=(20,15))
fig.tight_layout()

for i ,ax in zip(range(Y.columns.size), axes.flat):
  Y0.iloc[:,i].value_counts(sort=False).plot.bar(rot=0, color="blue", ax=ax).set_title(Y.columns[i])
  Y1.iloc[:,i].value_counts(sort=False).plot.bar(rot=0, color="red", ax=ax)
plt.show()
```



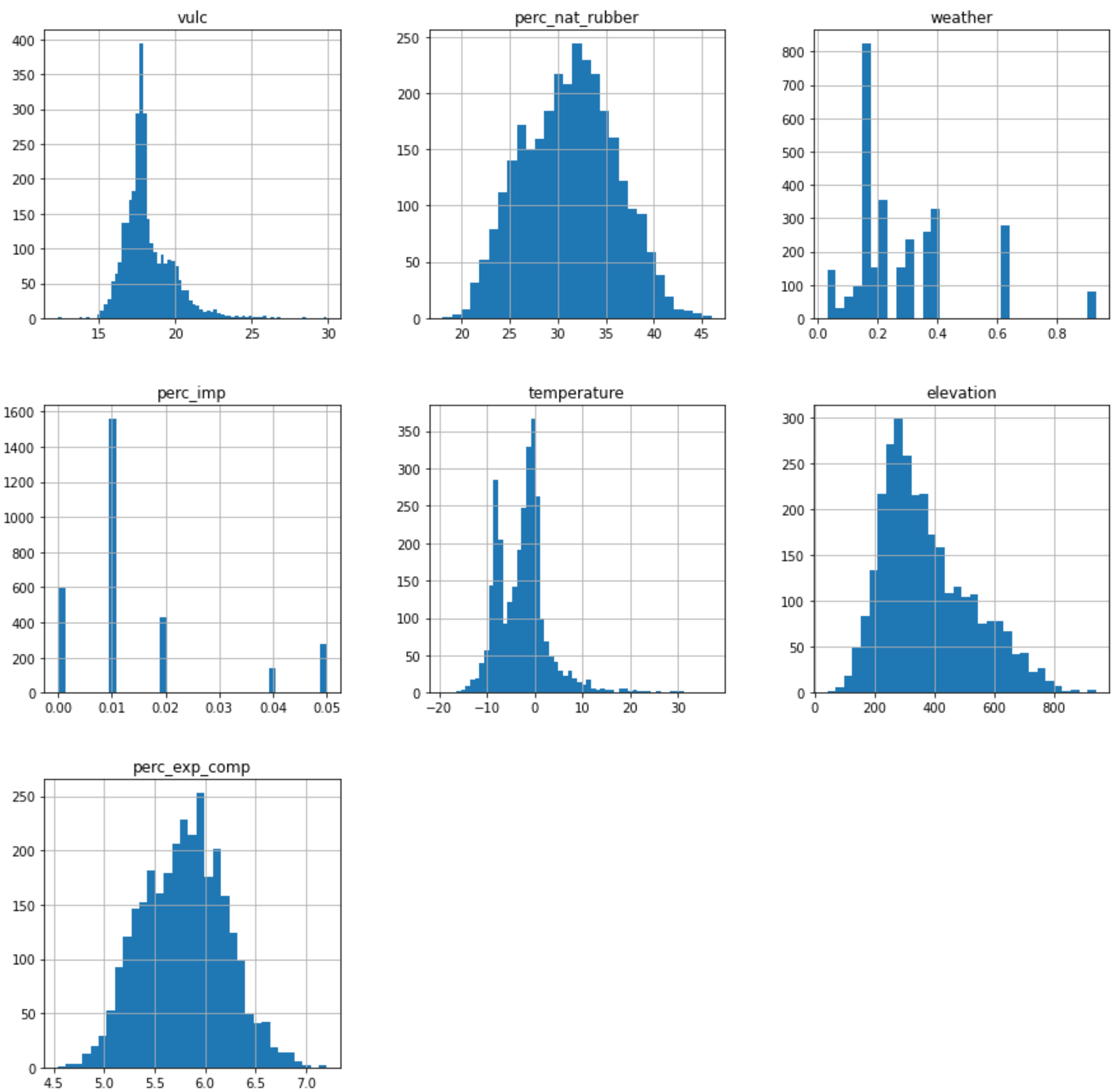
3) Outlier detection

```
%matplotlib inline

fig, axes = plt.subplots(ncols=3, nrows=3, figsize=(20,15))
fig.tight_layout()

for i, ax in zip(range(df[numerical].columns.size), axes.flat):
    sns.boxplot(x=df[numerical].iloc[:,i], ax=ax)
plt.show()
```



```
df[numerical].hist(bins='auto',figsize=(15,15))
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f3ce63d24f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3ce6f0e520>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3ce705abe0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f3ce6f08520>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3ce6ec7d00>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3ce6f5a700>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f3ce6f5af10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3ce6f728e0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3ce715cf10>]],
      dtype=object)
```



- boxplots indicated that outliers could be present, but after plotting the histograms, we notice that those "outlier" values are present in such a high number of observations that we wouldn't consider them outliers (for weather and perc_imp attributes)
- for other attributes, the "outliers" mostly follow the distribution shape so we didn't remove them

4) Correlation

We checked the correlation between all of the attributes and the target attribute ('failure') to assess which ones could be more relevant for predicting the target

```
df.corr().loc['failure']
```

```
vulc                -0.144981
perc_nat_rubber      0.103633
weather              0.401803
perc_imp             0.273367
temperature          0.364126
elevation            0.079229
perc_exp_comp        0.307221
tread_type_0        -0.217535
tread_type_1         0.038826
tread_type_2         0.083604
tread_type_3         0.045698
tyre_season_0        0.095066
month_0              0.040162
month_1              0.062862
month_2              0.039586
month_3              0.037830
month_4              0.051312
month_5              0.055764
month_6              0.055868
month_7             -0.003394
month_8             -0.287408
month_9              0.028791
month_10             0.026619
tread_depth_0       -0.226362
tread_depth_1        0.093872
tread_depth_2        0.073079
wiring_strength_0    0.030403
wiring_strength_1   -0.065282
tyre_quality_0       0.319223
add_layers_0         0.004087
add_layers_1        -0.020877
failure              1.000000
Name: failure, dtype: float64
```

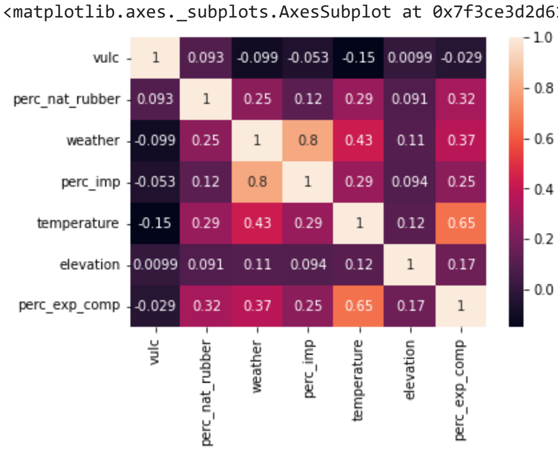
Since there are some attributes (month_7, add_layers_0) that have a correlation value very close to 0, we tried to train the model without them. Finally, we didn't get better scores so we kept all the attributes.

- Through a heat map, we then check the correation of each numerical attribute with the others

The idea is that if we find two attributes that have a very high correlation we could remove one of them because it would not bring additional information to the model.

```
sns.heatmap(df[numerical].corr(), annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3ce3d2d610>
```



From the analysis of the heat map we conclude that there are not any attributes that have a high enough correlation to remove one of them.

II.B. DATA PRE-PROCESSING

Like we mentioned in the data exploration, we decided to remove the columns of 'elevation', 'month_7', 'add_layers_0'

```
df2=df.drop(['elevation', 'month_7', 'add_layers_0'],axis=1)
df2
```

	vulc	perc_nat_rubber	weather	perc_imp	temperature	perc_exp_comp	tread_type_0	tread_type_1	tread_type_2	tread_type_3	..
0	17.990	26	0.16	0.01	-8.12	5.13	1.0	0.0	0.0	0.0	..
1	20.704	36	0.30	0.01	-4.52	6.15	0.0	0.0	1.0	0.0	..
2	19.156	34	0.30	0.01	-1.08	6.36	1.0	0.0	0.0	0.0	..
3	16.802	35	0.19	0.02	7.44	6.62	0.0	1.0	0.0	0.0	..
4	17.140	23	0.39	0.01	30.52	6.15	1.0	0.0	0.0	0.0	..
...	...	...	...	...	...	...	...	...	...	...	..
2995	17.818	29	0.39	0.01	7.28	5.68	0.0	1.0	0.0	0.0	..
2996	17.076	30	0.22	0.00	-1.44	5.81	0.0	1.0	0.0	0.0	..
2997	16.170	33	0.39	0.01	-3.44	5.57	0.0	1.0	0.0	0.0	..
2998	18.872	37	0.03	0.00	-0.76	5.89	0.0	0.0	0.0	0.0	..
2999	20.272	33	0.06	0.00	2.80	6.00	0.0	1.0	0.0	0.0	..

3000 rows × 29 columns

1) Splitting the data into train and test sets

```
X = df2.iloc[:,0:-1]
y = df2.iloc[:,-1]
```

We decided to use as training set the 75% of the original dataset, and the rest (25%) for the test set.

```
from sklearn.model_selection import train_test_split

#SPLIT DATA INTO TRAIN AND TEST SET
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size =0.25,
                                                    #shuffle is set True by default,
                                                    stratify=y, #preserve target proportions
                                                    random_state=123) #fix random seed for replicability

print(X_train.shape, X_test.shape)
```

```
(2250, 28) (750, 28)
```

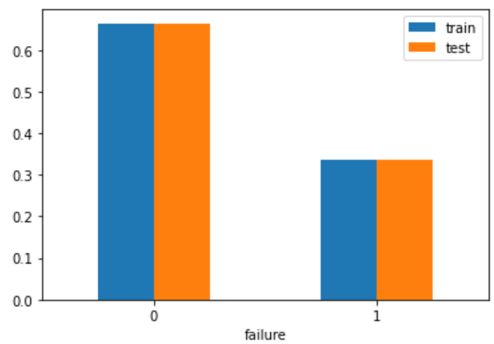
```
X_train
```

	vulc	perc_nat_rubber	weather	perc_imp	temperature	perc_exp_comp	tread_type_0	tread_type_1	tread_type_2	tread_type_3	..
1056	16.444	37	0.39	0.01	0.64	6.01	0.0	1.0	0.0	0.0	..
1492	17.754	22	0.16	0.01	-9.16	5.48	1.0	0.0	0.0	0.0	..
2443	18.400	29	0.16	0.01	-8.72	5.38	1.0	0.0	0.0	0.0	..
133	21.532	33	0.38	0.04	-5.08	6.01	0.0	0.0	0.0	1.0	..
1675	19.228	34	0.17	0.01	-2.36	5.72	0.0	0.0	0.0	0.0	..
1883	17.708	26	0.16	0.01	-8.12	5.18	1.0	0.0	0.0	0.0	..

We demonstrate how the distribution of the target variable is mantained after the spitting in train and test set.

```
y_train_dist=y_train.groupby(y_train.iloc[:]).size()/y_train.size
y_test_dist=y_test.groupby(y_test.iloc[:]).size()/y_test.size

train_test_dist = pd.DataFrame({'train': y_train_dist, 'test': y_test_dist})
ax = train_test_dist.plot.bar(rot=0) # rotation of the labels
train_test_dist
```

failure	train	test
0	0.664	0.664
1	0.336	0.336



2) Oversampling data

oversampling by duplicating rows

- we obtained better results with this method than with undersampling and oversampling with SMOTENC (synthetic data)

```
from collections import Counter
from imblearn.over_sampling import RandomOverSampler
# define oversampling strategy
oversample = RandomOverSampler(sampling_strategy='minority')
# fit and apply the transform
X_over, y_over = oversample.fit_resample(X_train, y_train)
# summarize class distribution
print(Counter(y_over))
```

```
Counter({0: 1494, 1: 1494})
/usr/local/lib/python3.8/dist-packages/sklearn/utils/validation.py:624: UserWarning: pandas.DataFrame with sparse columns found.It will
  warnings.warn(
```

III. MODEL

- we tried multiple models (Decision Tree, SVM, Random Forest, LGBM...) and Random Forest appears to be the best one

Random Forest

Random forests is an ensemble learning method for classification and other tasks that operates by constructing a multitude of decision trees at training time.

```
A = X_over
B = y_over

classifier= RandomForestClassifier()
parameters = {'n_estimators' : [50, 100, 200],
            'criterion' : ['entropy', 'gini'],
             'max_depth' : [2,4,8],
             'min_samples_split' : [1,2,4,5],
              'min_samples_leaf' : [1,2,4,5]
             }

gs = GridSearchCV(classifier, parameters, cv=3, scoring = 'f1', verbose=10, n_jobs=-1, refit=True)

gs.fit(A,B)
```

```
 0.73889674 0.7465186  0.74744875 0.74798319 0.7442404  0.74586902
        nan        nan        nan 0.74479721 0.74888678 0.74537111
 0.746199   0.74734313 0.74962308 0.7446887  0.744852   0.74631667
        nan        nan        nan 0.74138197 0.7462934  0.74685835
 0.74570401 0.74652294 0.74744538 0.74839492 0.74803604 0.74706113
        nan        nan        nan 0.74792059 0.74144245 0.74526289
 0.7465122  0.74535722 0.74463299 0.74701743 0.74630947 0.74420575
        nan        nan        nan 0.7578248  0.76070196 0.75842545
 0.75673478 0.765008   0.75726021 0.75335442 0.76003169 0.76356959
        nan        nan        nan 0.75955846 0.76055169 0.75928882
 0.75676739 0.7585377  0.75748249 0.76138392 0.7589412  0.76160097
        nan        nan        nan 0.75672883 0.76186477 0.75742235
 0.75688372 0.75971925 0.75372202 0.7568142  0.75643984 0.75762544
        nan        nan        nan 0.75654107 0.7557488  0.75794716
 0.75540922 0.76407308 0.75247888 0.75838744 0.75738493 0.75438366
        nan        nan        nan 0.80714322 0.81865004 0.81522064
 0.80407363 0.80636945 0.80902929 0.80370384 0.80069928 0.80188111
        nan        nan        nan 0.80093808 0.80253146 0.79968725
 0.7993893  0.80253534 0.80293822 0.80067736 0.8018957  0.79739472
        nan        nan        nan 0.79445164 0.7903729  0.79158391
 0.78371336 0.78987671 0.78949497 0.79267872 0.78737527 0.79023393
        nan        nan        nan 0.78687808 0.7876797  0.78298236
 0.78880686 0.78643085 0.79042924 0.78192336 0.78808737 0.7883682
        nan        nan        nan 0.74517799 0.74321551 0.74400493
 0.74665216 0.74660938 0.74336777 0.74757728 0.74645523 0.74707472
        nan        nan        nan 0.74559132 0.74639    0.75085881
 0.74729967 0.74620911 0.74796154 0.74742092 0.74755087 0.74605287
        nan        nan        nan 0.74329853 0.74592493 0.74842367
 0.7450318  0.74723349 0.74644301 0.74932034 0.74837648 0.74765496
        nan        nan        nan 0.74659376 0.74389573 0.7482543
 0.74660133 0.7465247  0.74513868 0.74583882 0.74396099 0.74574665
        nan        nan        nan 0.76348536 0.76015013 0.76023537
 0.75795764 0.7572126  0.75990654 0.75505517 0.75821105 0.76216739
        nan        nan        nan 0.76059449 0.76365903 0.76125062
 0.75612231 0.76112209 0.76172422 0.76263352 0.76548173 0.75799111
        nan        nan        nan 0.7583935  0.75837807 0.75643339
 0.75900649 0.76088071 0.76017393 0.75684657 0.76012096 0.75942479
        nan        nan        nan 0.76289807 0.75562149 0.75639672
 0.75789624 0.75606479 0.75913512 0.75495106 0.756532   0.75732625
        nan        nan        nan 0.8152132  0.81896141 0.81466237
 0.8006451  0.8147844  0.81116357 0.80006178 0.81347236 0.80308164
        nan        nan        nan 0.79965831 0.79891155 0.80537879
 0.8014407  0.803669   0.80276548 0.80109314 0.79917544 0.80288336
        nan        nan        nan 0.79205349 0.79232475 0.78684798
 0.78853633 0.79407041 0.78643265 0.79190516 0.79346651 0.79095228
        nan        nan        nan 0.78784682 0.78917932 0.78201208
 0.78767652 0.79021463 0.78654869 0.78716228 0.78734407 0.78836334]
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/sklearn/utils/validation.py:624: UserWarning: pandas.DataFrame with sparse columns found.It w
  warnings.warn(
GridSearchCV(cv=3, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'criterion': ['entropy', 'gini'],
                         'max_depth': [2, 4, 8],
                         'min_samples_leaf': [1, 2, 4, 5],
                         'min_samples_split': [1, 2, 4, 5],
                         'n_estimators': [50, 100, 200]},
             scoring='f1', verbose=10)
```

```
print('***GRIDSEARCH RESULTS***')
```

```
print("***GRIDSEARCH RESULTS***")

print("Best score: %f using %s" % (gs.best_score_, gs.best_params_))
means = gs.cv_results_['mean_test_score']
stds = gs.cv_results_['std_test_score']
params = gs.cv_results_['params']

for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
0.762898 (0.006438) with: {'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 50}
0.755621 (0.007958) with: {'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 100}
0.756397 (0.009598) with: {'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 200}
0.757896 (0.009571) with: {'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 4, 'n_estimators': 50}
0.756065 (0.009210) with: {'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 4, 'n_estimators': 100}
0.759135 (0.009775) with: {'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 4, 'n_estimators': 200}
0.754951 (0.010575) with: {'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 5, 'n_estimators': 50}
0.756532 (0.006079) with: {'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 5, 'n_estimators': 100}
0.757326 (0.010679) with: {'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 5, 'min_samples_split': 5, 'n_estimators': 200}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 1, 'n_estimators': 50}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 1, 'n_estimators': 100}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 1, 'n_estimators': 200}
0.815213 (0.007640) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}
0.818961 (0.006272) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}
0.814662 (0.005838) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
0.800645 (0.011943) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 4, 'n_estimators': 50}
0.814784 (0.010255) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 4, 'n_estimators': 100}
0.811164 (0.009113) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 4, 'n_estimators': 200}
0.800062 (0.008614) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 50}
0.813472 (0.013114) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 100}
0.803082 (0.004773) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 200}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 1, 'n_estimators': 50}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 1, 'n_estimators': 100}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 1, 'n_estimators': 200}
0.799658 (0.006270) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 50}
0.798912 (0.003798) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 100}
0.805379 (0.007338) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 200}
0.801441 (0.007816) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 4, 'n_estimators': 50}
0.803669 (0.007922) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 4, 'n_estimators': 100}
0.802765 (0.007637) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 4, 'n_estimators': 200}
0.801093 (0.004379) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 50}
0.799175 (0.007623) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 100}
0.802883 (0.007532) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 200}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 1, 'n_estimators': 50}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 1, 'n_estimators': 100}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 1, 'n_estimators': 200}
0.792053 (0.009501) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 2, 'n_estimators': 50}
0.792325 (0.007618) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 2, 'n_estimators': 100}
0.786848 (0.007367) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 2, 'n_estimators': 200}
0.788536 (0.005237) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 4, 'n_estimators': 50}
0.794070 (0.002926) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 4, 'n_estimators': 100}
0.786433 (0.010787) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 4, 'n_estimators': 200}
0.791905 (0.006682) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 5, 'n_estimators': 50}
0.793467 (0.003335) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 5, 'n_estimators': 100}
0.790952 (0.004939) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_split': 5, 'n_estimators': 200}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 1, 'n_estimators': 50}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 1, 'n_estimators': 100}
nan (nan) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 1, 'n_estimators': 200}
0.787847 (0.003316) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 50}
0.789179 (0.003987) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 100}
0.782012 (0.005355) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 200}
0.787677 (0.009869) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 4, 'n_estimators': 50}
0.790215 (0.011225) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 4, 'n_estimators': 100}
0.786549 (0.005943) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 4, 'n_estimators': 200}
0.787162 (0.006250) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 5, 'n_estimators': 50}
0.787344 (0.003332) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 5, 'n_estimators': 100}
0.788363 (0.007105) with: {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 5, 'min_samples_split': 5, 'n_estimators': 200}
```

```
#TESTING ON TEST SET
best_model = gs.best_estimator_
y_pred = best_model.predict(X_test)
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/utils/validation.py:624: UserWarning: pandas.DataFrame with sparse columns found.It will
  warnings.warn(
```

```
# PREDICTION ON THE TEST SET

print('***RESULTS ON TEST SET***')
print("precision: ", metrics.precision_score(y_test, y_pred)) # tp / (tp + fp)
```

```
print("recall: ", metrics.recall_score(y_test, y_pred)) # tp / (tp + fn)
print("f1_score: ", metrics.f1_score(y_test, y_pred)) #F1 = 2 * (precision * recall) / (precision + recall)
print("accuracy: ", metrics.accuracy_score(y_test, y_pred)) # (tp+tn)/m
```

```
***RESULTS ON TEST SET***
precision:  0.5580645161290323
recall:  0.6865079365079365
f1_score:  0.6156583629893239
accuracy:  0.712
```

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.72      0.77       498
           1       0.56      0.69      0.62       252

    accuracy                           0.71       750
   macro avg       0.69      0.71      0.69       750
weighted avg       0.73      0.71      0.72       750
```

As it is shown by the report, the f1-score that we obtained is around 0.63

IV. PREDICTION

Application of the trained model on unseen test dataset

```
tyre_test = pd.read_csv("/content/drive/MyDrive/Copia di tyres_test.csv")
#tyre_data = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/PoliMi colab/MIML_ML colab/tyres_train.csv")
```

```
tyre_test
```

	vulc	perc_nat_rubber	wiring_strength	weather	perc_imp	temperature	tread_type	tyre_season	elevation	month	tread_depth	t
0	17.180	30	1	0.21	0.00	-9.24	0	1	460.5	4	3	
1	17.744	24	1	0.16	0.01	-9.12	0	1	278.5	8	0	
2	16.930	34	0	0.27	0.01	3.64	2	0	733.5	11	2	
3	22.428	34	1	0.03	0.00	0.56	3	0	235.5	9	3	
4	16.818	29	1	0.06	0.00	-0.96	3	0	461.0	9	0	
...	...	...	...	...	...	...	...	...	...	...	...	
7979	20.060	31	1	0.29	0.01	0.40	4	1	361.5	6	2	
7980	17.718	21	1	0.16	0.01	-8.68	0	1	409.5	8	0	
7981	17.908	23	1	0.16	0.01	-6.92	0	1	266.0	8	0	
7982	17.916	28	1	0.16	0.01	-7.92	0	1	301.0	8	0	
7983	21.806	32	1	0.16	0.01	-6.48	1	1	313.0	5	0	

7984 rows × 15 columns

Data preparation

```
tyre_test.isna().any()
```

```
vulc               False
perc_nat_rubber    False
wiring_strength    False
weather            False
perc_imp           False
temperature        False
tread_type         False
tyre_season        False
elevation          False
month              False
```

```
tread_depth      False
tyre_quality     False
perc_exp_comp    False
diameter         False
add_layers       False
dtype: bool
```

```
tyre_test = tyre_test.drop('diameter', axis=1)
```

One-hot-encoding:

```
results_test = ohe.fit_transform(tyre_test[categorical_original])
dummy_test = pd.DataFrame.sparse.from_spmatrix(results_test)
dummy_test.columns = ohe.get_feature_names(tyre_test[categorical_original].columns)
dummy_test
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function get_feature_names is deprecated; get_fe
  warnings.warn(msg, category=FutureWarning)
```

	tread_type_0	tread_type_1	tread_type_2	tread_type_3	tread_type_4	tyre_season_0	tyre_season_1	month_0	month_1	month_2	...
0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...
1	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...
2	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...
3	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	...
4	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	...
...	...	...	...	...	...	...	...	...	...	...	...
7979	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	...
7980	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...
7981	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...
7982	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...
7983	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...

7984 rows × 31 columns

```
# removing extra columns
catlist = dummy_test.columns.tolist()
remlist = []
remlist += [catlist[-1]]
for i in range(0,len(catlist)-1):
  # print(catlist[i+1][:-2])
  if catlist[i][:-1] != catlist[i+1][:-1]:
    remlist += [catlist[i]]
remlist.remove('month_9')
remlist
```

```
['add_layers_2',
 'tread_type_4',
 'tyre_season_1',
 'month_11',
 'tread_depth_3',
 'wiring_strength_2',
 'tyre_quality_1']
```

```
dummy_test = dummy_test.drop(remlist,axis=1)
dummy_test
```

	tread_type_0	tread_type_1	tread_type_2	tread_type_3	tyre_season_0	month_0	month_1	month_2	month_3	month_4	...	month_9
0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	...	0.0
1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
2	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0
3	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	...	1.0
4	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	...	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...
7979	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
7980	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
7981	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0

```
tyre_test = pd.concat([tyre_test,dummy_test],axis=1)
for cat in categorical_original:
  tyre_test = tyre_test.drop(cat,axis=1)
tyre_test
```

	vulc	perc_nat_rubber	weather	perc_imp	temperature	elevation	perc_exp_comp	tread_type_0	tread_type_1	tread_type_2	...
0	17.180	30	0.21	0.00	-9.24	460.5	5.54	1.0	0.0	0.0	...
1	17.744	24	0.16	0.01	-9.12	278.5	5.01	1.0	0.0	0.0	...
2	16.930	34	0.27	0.01	3.64	733.5	6.41	0.0	0.0	1.0	...
3	22.428	34	0.03	0.00	0.56	235.5	5.95	0.0	0.0	0.0	...
4	16.818	29	0.06	0.00	-0.96	461.0	5.97	0.0	0.0	0.0	...
...	...	...	...	...	...	...	...	...	...	...	...
7979	20.060	31	0.29	0.01	0.40	361.5	5.89	0.0	0.0	0.0	...
7980	17.718	21	0.16	0.01	-8.68	409.5	5.56	1.0	0.0	0.0	...
7981	17.908	23	0.16	0.01	-6.92	266.0	5.20	1.0	0.0	0.0	...
7982	17.916	28	0.16	0.01	-7.92	301.0	5.76	1.0	0.0	0.0	...
7983	21.806	32	0.16	0.01	-6.48	313.0	5.26	0.0	1.0	0.0	...

7984 rows × 31 columns

```
tyre_test=tyre_test.drop(['elevation', 'month_7', 'add_layers_0'],axis=1)
tyre_test
```

	vulc	perc_nat_rubber	weather	perc_imp	temperature	perc_exp_comp	tread_type_0	tread_type_1	tread_type_2	tread_type_3	..
0	17.180	30	0.21	0.00	-9.24	5.54	1.0	0.0	0.0	0.0	..
1	17.744	24	0.16	0.01	-9.12	5.01	1.0	0.0	0.0	0.0	..
2	16.930	34	0.27	0.01	3.64	6.41	0.0	0.0	1.0	0.0	..
3	22.428	34	0.03	0.00	0.56	5.95	0.0	0.0	0.0	1.0	..
4	16.818	29	0.06	0.00	-0.96	5.97	0.0	0.0	0.0	1.0	..
...	...	...	...	...	...	...	...	...	...	...	..
7979	20.060	31	0.29	0.01	0.40	5.89	0.0	0.0	0.0	0.0	..
7980	17.718	21	0.16	0.01	-8.68	5.56	1.0	0.0	0.0	0.0	..
7981	17.908	23	0.16	0.01	-6.92	5.20	1.0	0.0	0.0	0.0	..
7982	17.916	28	0.16	0.01	-7.92	5.76	1.0	0.0	0.0	0.0	..
7983	21.806	32	0.16	0.01	-6.48	5.26	0.0	1.0	0.0	0.0	..

7984 rows × 28 columns

```
y_pred_test = best_model.predict(tyre_test)
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/utils/validation.py:624: UserWarning: pandas.DataFrame with sparse columns found.It will
  warnings.warn(
```

```
with open(r'output.txt','w') as textfile:
  [print(x,file=textfile) for x in y_pred_test]
```

V. ADDITIONAL NOTES

- Scaling

Initially we scaled the data because we tried to train different types of models, but we discarded this choice because our final model (Random Forest) does not require it and it did not improve the final result.

- PCA

We tried doing PCA of the dataset and then training the models with the principal components obtained, but this did not improve our final result.

we considered turning months into season to have less attributes, but we decided to leave them as they were originally

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