LIST 2 - MACHINE LEARNING

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EXERCISE 1 - ADABOOST

```
# Core
import pandas as pd
import numpy as np
from scipy.stats import skew

# Visual
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = [15, 7.5]
import plotly.express as px
import seaborn as sns

# Scikit
import sklearn
from sklearn.linear_model import LinearRegression, Ridge, RidgeCV, ElasticNet, Lass
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor, AdaBoostRegre

# Core
import seaborn as sns
import pandas as pd
import numpy as np
from math import log,exp

# Visual
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10, 5)
import graphviz

from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.ensemble import AdaBoostClassifier

import io
```

```
#Importing the dataset:
from google.colab import files
uploaded = files.upload()
df = pd.read_csv(io.BytesIO(uploaded['train.csv']))
df.head()
```

Choose Files No file chosen Upload widget is only available when the cell has been executec

```
Saving train.csv to train.csv
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	Lan
0	1	60	RL	65.0	8450	Pave	NaN	Reg	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	

5 rows × 81 columns

```
#Dividing into train, test and validation:
#train, test = train_test_split(df, test_size = 0.3, random_state = 7)
#train, val = train_test_split(train, test_size = 0.3, random_state = 7)
```

```
#creating all data with all of them to threat the whole base as one:
#all_data = pd.concat((train.loc[:,'MSSubClass':'SaleCondition'],
 #                     val.loc[:,'MSSubClass':'SaleCondition'],
  #                    test.loc[:,'MSSubClass':'SaleCondition']))
```

(A) Creating a function

```
#The following code it is what we first thought of doing. But it went wrong...

#Using a basic treatment to create the matrix:

#train["SalePrice"] = np.log1p(train["SalePrice"])
#numeric_feats = all_data.dtypes[all_data.dtypes != "object"].index
#all_data = pd.get_dummies(all_data)
#all_data = all_data.fillna(all_data.mean())

#Creating matrixes
#X_train = all_data[:train.shape[0]]
#X_test = all_data[train.shape[0]:]
#y_train = train.SalePrice
#y_test = test.SalePrice
```

```
#Defining accuracy measures:
#def mape(Y_actual, Y_Predicted):
#    mape = np.mean(np.abs( Y_actual - Y_Predicted)/Y_actual)*100
#    mape = round(mape,2)
#    return mape
```

```
#all_n_estimators = [10, 50, 100, 250, 500, 1000, 5000]
#max_depth = (n_depth)
```

```
#mape_list = []
#n estimators list = []

#the first function that failed:
#for n_estimators in all_n_estimators:
#    print('n_estimators', n_estimators )

#    ADA = AdaBoostRegressor(
#        n_estimators=n_estimators
#    ).fit(X_train, y_train)

#    pred = ADA.predict(X_test)

#    accuracy = mape(y_test, np.exp(pred))

#    mape_list.append(accuracy)
#    n_estimators_list.append(n_estimators)

# results = pd.DataFrame({
#   'n_estimators': n_estimators_list,
#    'MAPE': mape_list
#})
```

```
# Our actual option:
## The idea was based on: https://towardsdatascience.com/adaboost-from-scratch-37a9
df2 = df #for exercise 1.3
df3 = df #for exercise 1.4

#Listing explanatory features

#listing the features used on the adaboost code:
features = ['OverallQual', 'GrLivArea', 'GarageCars']
features_y = ['OverallQual', 'GrLivArea', 'GarageCars', 'SalePrice']
df = df[features_y]
```

```
## Changing the problem for a classification one

df['SalePrice'] = pd.qcut(df['SalePrice'],q = 2, labels = [-1, 1])
df.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: SettingWithCop
A value is trying to be set on a copy of a slice from a DataFrame.
```

1 (A) and (B)

```
#Steps of the fuctions:

##Computing error

def compute_error (y, y_pred, w_i):
    return (sum(w_i* (np.not_equal(y, y_pred)).astype(int)))/sum(w_i)

## Weights of weak classifiers

def compute_alpha(error):
    return np.log((1-error) / error)

##Update weights after boosting interaction

def update_weights(w_i, alpha, y, y_pred):
    return w_i* np.exp(alpha * (np.not_equal(y, y_pred)).astype(int))
```

```
# Define AdaBoost for classification:
class AdaBoost:

    def __init__(self):
        self.alphas = []
        self.G_M = []
        self.M = None
        self.training_errors = []
        self.prediction_errors = []

    def fit(self, X, y, M = 100):
        '''
        Fit model. Arguments:
        X: independent variables - array-like matrix
        y: target variable - array-like vector
        M: number of boosting rounds. Default is 100 - integer
        '''

        # Clear before calling
        self.alphas = []
        self.training_errors = []
        self.M = M

        # Iterate over M weak classifiers
        for m in range(0, M):

            # Set weights for current boosting iteration
            if m == 0:
                w_i = np.ones(len(y)) * 1 / len(y)  # At m = 0, weights are all the
            else:
                # (d) Update w_i
```

```
                w_i = update_weights(w_i, alpha_m, y, y_pred)

            # (a) Fit weak classifier and predict labels
            G_m = DecisionTreeClassifier(max_depth = 1)     # Stump: Two terminal-n
            G_m.fit(X, y, sample_weight = w_i)
            y_pred = G_m.predict(X)

            self.G_M.append(G_m) # Save to list of weak classifiers

            # (b) Compute error
            error_m = compute_error(y, y_pred, w_i)
            self.training_errors.append(error_m)

            # (c) Compute alpha
            alpha_m = compute_alpha(error_m)
            self.alphas.append(alpha_m)

        assert len(self.G_M) == len(self.alphas)

    def predict(self, X):

        weak_preds = pd.DataFrame(index = range(len(X)), columns = range(self.M))

        for m in range(self.M):
            y_pred_m = self.G_M[m].predict(X) * self.alphas[m]
            weak_preds.iloc[:,m] = y_pred_m

        y_pred = (1 * np.sign(weak_preds.T.sum())).astype(int)

        return y_pred


#the code was based on: https://towardsdatascience.com/adaboost-from-scratch-37a936
```

```
## Dividing into train and test:
train, test = train_test_split(df, test_size=0.3, random_state=7)

X_train = df[:train.shape[0]]
X_test = df[train.shape[0]:]
y_train = train.SalePrice
y_test = test.SalePrice
```

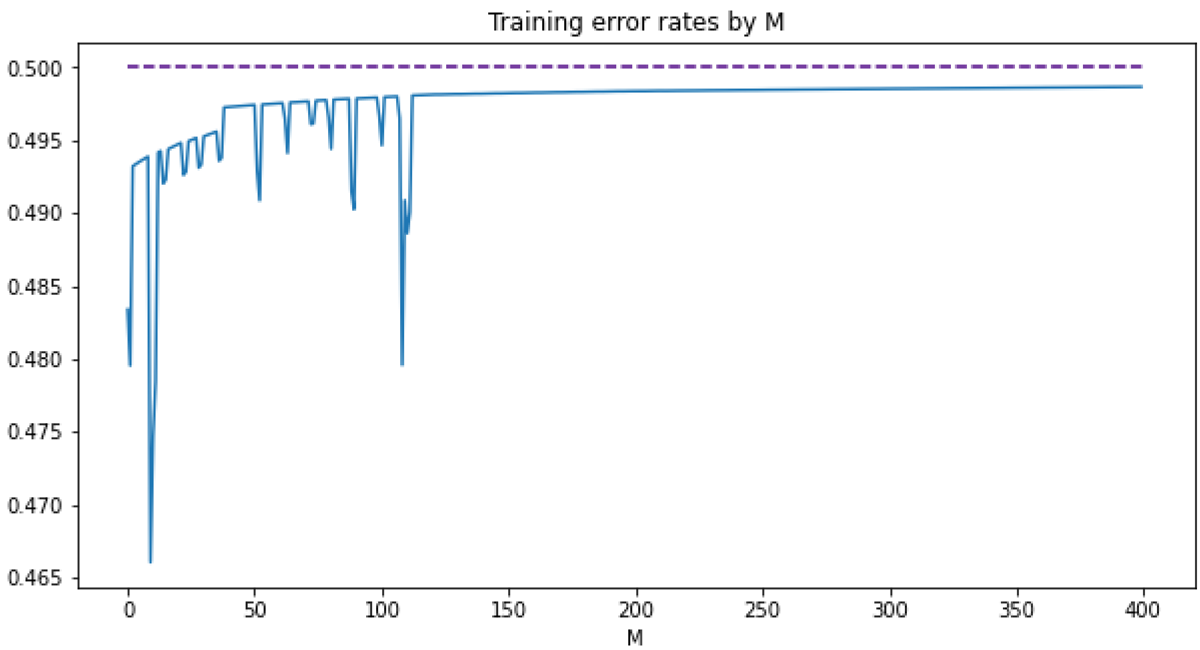
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_auc_score

def mape(Y_actual, Y_Predicted):
    mape = np.mean(np.abs( Y_actual - Y_Predicted)/Y_actual)*100
    mape = mape.round(2)
    return mape

# Predict

ab = AdaBoost()
```

```
ab.fit(X_train, y_train, M = 400)

# Predict on test set
y_pred = ab.predict(X_test)
print('The ROC-AUC score of the model is:', round(roc_auc_score(y_test, y_pred), 4))
```

```
The ROC-AUC score of the model is: 0.5084
```

1(C)

```
plt.figure(figsize=(10,5))
plt.plot(ab.training_errors)
plt.title('Training error rates by M')
plt.hlines(0.5, 0, 400, colors = 'indigo', linestyles='dashed')
plt.xlabel('M')
plt.show()
```



2(A) Adding max depth:

```
class AdaBoost:

    def __init__(self):
        self.alphas = []
        self.G_M = []
        self.M = None
        self.training_errors = []
        self.prediction_errors = []
        self.depth = []     #to include max depth, we will create a self.depth here

    def fit(self, X, y, depth = 1, M = 100):
        '''
        Fit model. Arguments:
        X: independent variables - array-like matrix
```

```
        y: target variable - array-like vector
        Depth: Max depth with default 1.
        M: number of boosting rounds. Default is 100 - integer
        '''

        # Clear before calling
        self.alphas = []
        self.training_errors = []
        self.M = M

        # Iterate over M weak classifiers
        for m in range(0, M):

            # Set weights for current boosting iteration
            if m == 0:
                w_i = np.ones(len(y)) * 1 / len(y)
            else:
                # (d) Update w_i
                w_i = update_weights(w_i, alpha_m, y, y_pred)

            # (a) Fit weak classifier and predict labels
            G_m = DecisionTreeClassifier(max_depth = depth)
            G_m.fit(X, y, sample_weight = w_i)
            y_pred = G_m.predict(X)

            self.G_M.append(G_m)

            # (b) Compute error
            error_m = compute_error(y, y_pred, w_i)
            self.training_errors.append(error_m)

            # (c) Compute alpha
            alpha_m = compute_alpha(error_m)
            self.alphas.append(alpha_m)

        assert len(self.G_M) == len(self.alphas)

    def predict(self, X):

        weak_preds = pd.DataFrame(index = range(len(X)), columns = range(self.M))

        for m in range(self.M):
            y_pred_m = self.G_M[m].predict(X) * self.alphas[m]
            weak_preds.iloc[:,m] = y_pred_m

        y_pred = (1 * np.sign(weak_preds.T.sum())).astype(int)

        return y_pred
```

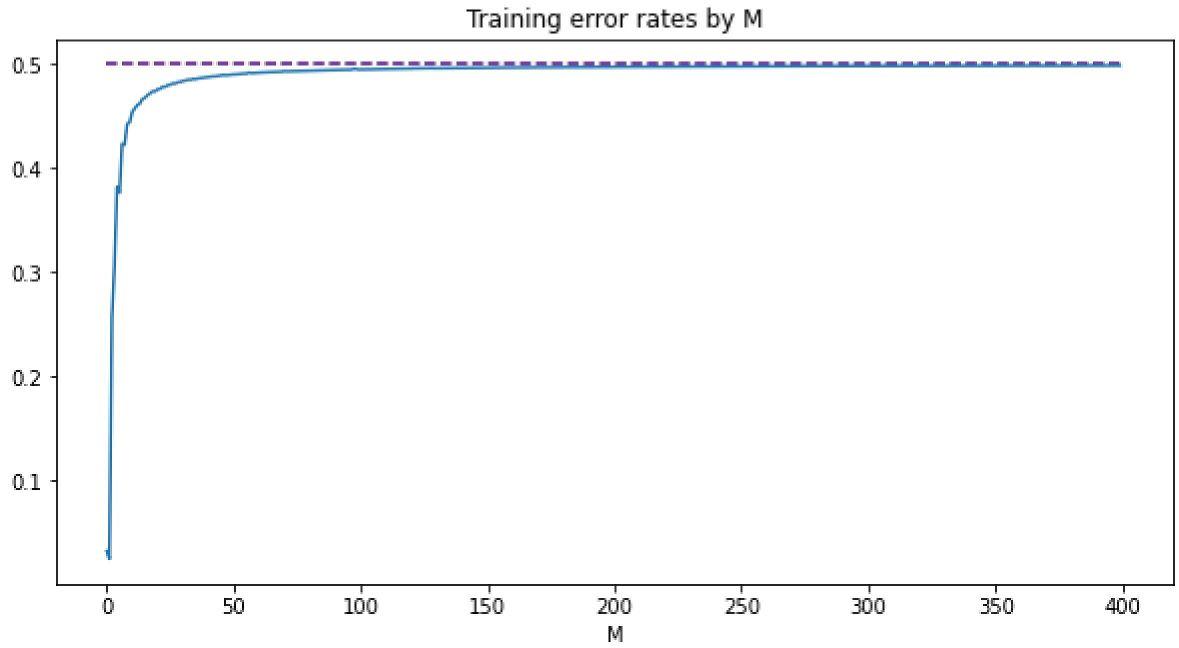
```
# Predict

ab = AdaBoost()
ab.fit(X_train, y_train, depth = 50, M = 400)
```

```
y_pred = ab.predict(X_test)
print('The ROC-AUC score of the model is:', round(roc_auc_score(y_test, y_pred), 4)
```

```
The ROC-AUC score of the model is: 0.497
```

(B) Plotting it:

```
plt.figure(figsize=(10,5))
plt.plot(ab.training_errors)
plt.title('Training error rates by M')
plt.hlines(0.5, 0, 400, colors = 'indigo', linestyles='dashed')
plt.xlabel('M')
plt.show()
```



The graph above shows us that the training error rates increase significaantly between 0 and 50 M.

(3) Modifying the function to allow a 3-value classification:

Here, we first tried to change the function where the alpha is replaced by an "i," which equals 3 — trying to make the classification be three objects (which clearly went wrong).

```
#class AdaBoost:

 #   def __init__(self):
#       self.i = []
#    self.G_M = []
#       self.M = None
#        self.training_errors = []
#        self.prediction_errors = []
```

```
#        self.depth = []

#    def fit(self, X, y, i = 3, depth = 1, M = 100): #change alpha to "i" that is =
      #        '''
 #      Fit model. Arguments:
 #       i: 3
 #       X: independent variables - array-like matrix
 #       y: target variable - array-like vector
 #       Depth: Max depth with default 1.
 #       M: number of boosting rounds. Default is 100 - integer
 #       '''

        # Clear before calling
  #      self.i = []
  #      self.training_errors = []
  #      self.M = M

        # Iterate over M weak classifiers
#        for m in range(0, M):

            # Set weights for current boosting iteration
#            if m == 0:
#                w_i = np.ones(len(y)) * 1 / len(y)
#            else:
               # (d) Update w_i
#                w_i = update_weights(w_i, alpha_m, y, y_pred)

            # (a) Fit weak classifier and predict labels
#            G_m = DecisionTreeClassifier(max_depth = depth)
#            G_m.fit(X, y, sample_weight = w_i)
#            y_pred = G_m.predict(X)

#            self.G_M.append(G_m)

            # (b) Compute error
 #           error_m = compute_error(y, y_pred, w_i)
#            self.training_errors.append(error_m)

#        assert len(self.G_M) == len(self.i)

#    def predict(self, X):

#        weak_preds = pd.DataFrame(index = range(len(X)), columns = range(self.M))

 #       for m in range(self.M):
 #           y_pred_m = self.G_M[m].predict(X) * self.i[m]
 #           weak_preds.iloc[:,m] = y_pred_m

 #       y_pred = (1 * np.sign(weak_preds.T.sum())).astype(int)

 #       return y_pred
```

```
#ab = AdaBoost()
#ab.fit(X_train, y_train, i, depth = 100, M = 400)
```

```
#y_pred = ab.predict(X_test)
#print('The ROC-AUC score of the model is:', round(roc_auc_score(y_test, y_pred), 4
```

So, we tried again, but changing other part of our code:

```
df2 = df2[features_y]
df2['SalePrice'] = pd.qcut(df2['SalePrice'], q = 3, labels = [1, 2, 3]) #here we tr
df2.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: SettingWithCop
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
```

	OverallQual	GrLivArea	GarageCars	SalePrice
0	7	1710	2	3
1	6	1262	2	2
2	7	1786	2	3
3	7	1717	3	2
4	8	2198	3	3

```
#and here we use the same code from before:
class AdaBoost:

    def __init__(self):
        self.alphas = []
        self.G_M = []
        self.M = None
        self.training_errors = []
        self.prediction_errors = []
        self.depth = []     #to include max depth, we will create a self.depth here

    def fit(self, X, y, depth = 1, M = 100):
        '''
        Fit model. Arguments:
        X: independent variables - array-like matrix
        y: target variable - array-like vector
        Depth: Max depth with default 1.
        M: number of boosting rounds. Default is 100 - integer
        '''

        # Clear before calling
        self.alphas = []
        self.training_errors = []
        self.M = M
```

```
        # Iterate over M weak classifiers
        for m in range(0, M):

            # Set weights for current boosting iteration
            if m == 0:
                w_i = np.ones(len(y)) * 1 / len(y)
            else:
                # (d) Update w_i
                w_i = update_weights(w_i, alpha_m, y, y_pred)

            # (a) Fit weak classifier and predict labels
            G_m = DecisionTreeClassifier(max_depth = depth)
            G_m.fit(X, y, sample_weight = w_i)
            y_pred = G_m.predict(X)

            self.G_M.append(G_m)

            # (b) Compute error
            error_m = compute_error(y, y_pred, w_i)
            self.training_errors.append(error_m)

            # (c) Compute alpha
            alpha_m = compute_alpha(error_m)
            self.alphas.append(alpha_m)

        assert len(self.G_M) == len(self.alphas)

    def predict(self, X):

        weak_preds = pd.DataFrame(index = range(len(X)), columns = range(self.M))

        for m in range(self.M):
            y_pred_m = self.G_M[m].predict(X) * self.alphas[m]
            weak_preds.iloc[:,m] = y_pred_m

        y_pred = (1 * np.sign(weak_preds.T.sum())).astype(int)

        return y_pred
```

```
# Predict

ab = AdaBoost()
ab.fit(X_train, y_train, depth = 50, M = 200)
y_pred = ab.predict(X_test)
print('The ROC-AUC score of the model is:', round(roc_auc_score(y_test, y_pred), 4)
```

```
The ROC-AUC score of the model is: 0.4925
```

4. Make it work with regressions:

```
from sklearn.tree import DecisionTreeRegressor
class AdaBoost:
```

```
    def __init__(self):
        self.alphas = []
        self.G_M = []
        self.M = None
        self.training_errors = []
        self.prediction_errors = []
        self.depth = None

    def fit(self, X, y, depth = 1, M = 100):
        '''
        Fit model. Arguments:
        X: independent variables - array-like matrix
        y: target variable - array-like vector
        Depth: Max depth with default 1.
        M: number of boosting rounds. Default is 100 - integer
        '''

        # Clear before calling
        self.alphas = []
        self.training_errors = []
        self.M = M

        # Iterate over M weak classifiers
        for m in range(0, M):

            # Set weights for current boosting iteration
            if m == 0:
                w_i = np.ones(len(y)) * 1 / len(y)
            else:
                # (d) Update w_i
                w_i = update_weights(w_i, alpha_m, y, y_pred)

            # (a) Fit weak classifier and predict labels
            G_m = DecisionTreeRegressor()  #we change it here!
            G_m.fit(X, y, sample_weight = w_i)
            y_pred = G_m.predict(X)

            self.G_M.append(G_m)

            # (b) Compute error
            error_m = compute_error(y, y_pred, w_i)
            self.training_errors.append(error_m)

            # (c) Compute alpha
            alpha_m = compute_alpha(error_m)
            self.alphas.append(alpha_m)

        assert len(self.G_M) == len(self.alphas)

    def predict(self, X):

        weak_preds = pd.DataFrame(index = range(len(X)), columns = range(self.M))

        for m in range(self.M):
            y_pred_m = self.G_M[m].predict(X) * self.alphas[m]
```

```
            weak_preds.iloc[:,m] = y_pred_m

        y_pred = (1 * np.sign(weak_preds.T.sum())).astype(int)

        return y_pred
```

```
df3 = df3[features_y]
```

```
train, test = train_test_split(df3, test_size=0.3, random_state=1)
X_train = train.drop('SalePrice', 1)
X_test = test.drop('SalePrice', 1)
y_train = train['SalePrice'].astype(int)
y_test = test[ 'SalePrice'].astype(int)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: FutureWarning:

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: FutureWarning:
  This is separate from the ipykernel package so we can avoid doing imports ur
```

```
ab = AdaBoost()
ab.fit(X_train, y_train, M = 400)
y_pred = ab.predict(X_test)
```

EXERCISE 2

I. Download data

```
from google.colab import files
uploaded = files.upload()
sloan_survey = pd.read_csv(io.BytesIO(uploaded['sloan_survey.csv']))
sloan_survey.head()
```

Choose Files No file chosen Upload widget is only available when the cell has been executec

```
Saving sloan_survey.csv to sloan_survey.csv
```

	objid	ra	dec	u	g	r	i	z
0	1.237650e+18	183.531326	0.089693	19.47406	17.04240	15.94699	15.50342	15.22531
1	1.237650e+18	183.598370	0.135285	18.66280	17.21449	16.67637	16.48922	16.39150
2	1.237650e+18	183.680207	0.126185	19.38298	18.19169	17.47428	17.08732	16.80125
3	1.237650e+18	183.870529	0.049911	17.76536	16.60272	16.16116	15.98233	15.90438
4	1.237650e+18	183.883288	0.102557	17.55025	16.26342	16.43869	16.55492	16.61326

II. First look

```
# Reordering the columns to see our dependent variable in the beginning
cols_to_order = ['class']
new_columns = cols_to_order + (sloan_survey.columns.drop(cols_to_order).tolist())
sloan_survey = sloan_survey[new_columns]
sloan_survey.head()
```

	class	objid	ra	dec	u	g	r	i
0	STAR	1.237650e+18	183.531326	0.089693	19.47406	17.04240	15.94699	15.50342
1	STAR	1.237650e+18	183.598370	0.135285	18.66280	17.21449	16.67637	16.48922
2	GALAXY	1.237650e+18	183.680207	0.126185	19.38298	18.19169	17.47428	17.08732
3	STAR	1.237650e+18	183.870529	0.049911	17.76536	16.60272	16.16116	15.98233
4	STAR	1.237650e+18	183.883288	0.102557	17.55025	16.26342	16.43869	16.55492

```
sloan_survey.info()
type(sloan_survey)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 18 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   class      10000 non-null  object 
 1   objid      10000 non-null  float64
 2   ra         10000 non-null  float64
 3   dec        10000 non-null  float64
 4   u          10000 non-null  float64
 5   g          10000 non-null  float64
 6   r          10000 non-null  float64
 7   i          10000 non-null  float64
 8   z          10000 non-null  float64
 9   run        10000 non-null  int64  
 10  rerun      10000 non-null  int64  
 11  camcol     10000 non-null  int64  
 12  field      10000 non-null  int64  
 13  specobjid  10000 non-null  float64
 14  redshift   10000 non-null  float64
 15  plate      10000 non-null  int64  
 16  mjd        10000 non-null  int64  
 17  fiberid    10000 non-null  int64  
dtypes: float64(10), int64(7), object(1)
memory usage: 1.4+ MB
pandas.core.frame.DataFrame
```

```
# Lets first take a look at the shape of our data
# Our database has 1000 observations and 18 variables/collumns

sloan_survey.shape
```

```
(10000, 18)
```

```
sloan_survey.describe()
```

	objid	ra	dec	u	g	
count	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.0000
mean	1.237650e+18	175.529987	14.836148	18.619355	17.371931	16.8409
std	1.577039e+05	47.783439	25.212207	0.828656	0.945457	1.0677
min	1.237650e+18	8.235100	-5.382632	12.988970	12.799550	12.4316
25%	1.237650e+18	157.370946	-0.539035	18.178035	16.815100	16.1733
50%	1.237650e+18	180.394514	0.404166	18.853095	17.495135	16.8587
75%	1.237650e+18	201.547279	35.649397	19.259232	18.010145	17.5126
max	1.237650e+18	260.884382	68.542265	19.599900	19.918970	24.8020

III. Selecting relevant variables based on df documentation:

```
sloan_survey = sloan_survey.drop(columns=['objid', 'run','rerun','camcol','specobji
#objid and specobjid are just different forms of identification - we do not need th
#the Camera column (camcol), the Rerun Number (rerun), and the Run number (run) are
```

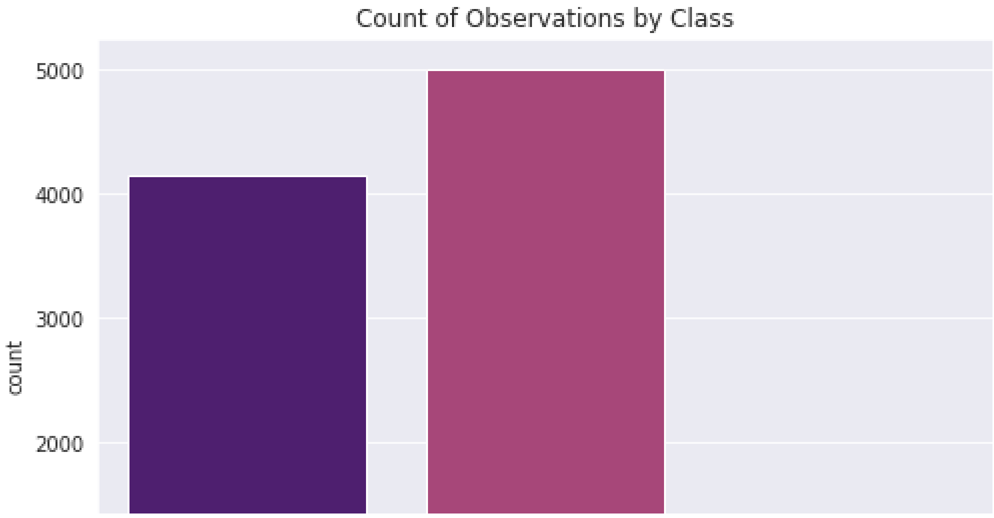
IV. Data Visualization: Univariate and Bivariate Analysis

(based on: https://www.kaggle.com/code/sanchitvj/sdss-dr16-data-analysis/notebook)

Dependent Variable - Class

```
sns.set_style('darkgrid')
plt.figure(figsize = (8, 6))
plt.title('Count of Observations by Class')
sns.countplot(sloan_survey['class'], palette = 'magma')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarnir
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f9230859690>
```



The figure above shows that our interest variable is unbalanced, since we have much more observations from GALAXY and STAR classes.

How our dependent varibale relates to "redshift".

Obs: Redshift - how much light of that celestial body is captured by the telescope.

```
fig, (ax1, ax2, ax3) = plt.subplots(ncols = 3, figsize = (24, 6))
sns.distplot(sloan_survey[sloan_survey['class'] == 'STAR'].redshift, ax = ax1, bins
sns.distplot(sloan_survey[sloan_survey['class'] == 'GALAXY'].redshift, ax = ax2, bi
sns.distplot(sloan_survey[sloan_survey['class'] == 'QSO'].redshift, ax = ax3, bins
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWa
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWa
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWa
```

Correlation Matrix


```
corr = sloan_survey.corr()
plt.figure(figsize = (10, 8))
sns.heatmap(corr, annot = True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f922e072e90>
```

V. Data Visualization: Univariate and Bivariate Analysis

Encoding Dependent Variable

To be able to run the models, we will make an encoding of the dependent variable. From "object" let's change it to "int64".

```
sloan_survey["class"].unique()
```

```
array(['STAR', 'GALAXY', 'QSO'], dtype=object)
```

```
sloan_survey['class'].value_counts()
```

```
GALAXY    4998
STAR      4152
QSO        850
Name: class, dtype: int64
```

```
sloan_survey.rename(columns = {'class':'Class'}, inplace = True)
```

```
sloan_survey.Class = sloan_survey.replace(
    {"Class": {'STAR': 1,
               'GALAXY': 2,
               'QSO': 3,
              }}
                  ).Class
sloan_survey
```

	Class	ra	dec	u	g	r	i	z	f
0	1	183.531326	0.089693	19.47406	17.04240	15.94699	15.50342	15.22531	
1	1	183.598370	0.135285	18.66280	17.21449	16.67637	16.48922	16.39150	
2	2	183.680207	0.126185	19.38298	18.19169	17.47428	17.08732	16.80125	
3	1	183.870529	0.049911	17.76536	16.60272	16.16116	15.98233	15.90438	
4	1	183.883288	0.102557	17.55025	16.26342	16.43869	16.55492	16.61326	
...	...	...	...	...	...	...	...	...	
9995	2	131.316413	51.539547	18.81777	17.47053	16.91508	16.68305	16.50570	
9996	2	131.306083	51.671341	18.27255	17.43849	17.07692	16.71661	16.69897	
9997	1	131.552562	51.666986	18.75818	17.77784	17.51872	17.43302	17.42048	
9998	2	131.477151	51.753068	18.88287	17.91068	17.53152	17.36284	17.13988	
9999	2	131.665012	51.805307	19.27586	17.37829	16.30542	15.83548	15.50588	

10000 rows × 13 columns

```
sloan_survey.info()
type(sloan_survey)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Class      10000 non-null  int64  
 1   ra         10000 non-null  float64
 2   dec        10000 non-null  float64
```

```
 3   u         10000 non-null  float64
 4   g         10000 non-null  float64
 5   r         10000 non-null  float64
 6   i         10000 non-null  float64
 7   z         10000 non-null  float64
 8   field     10000 non-null  int64
 9   redshift  10000 non-null  float64
 10  plate     10000 non-null  int64
 11  mjd       10000 non-null  int64
 12  fiberid   10000 non-null  int64
dtypes: float64(8), int64(5)
memory usage: 1015.8 KB
pandas.core.frame.DataFrame
```

Selecting Features by applying Principal Component Analysis (PCA)

As we saw in the correlation map, features u, g, r, i, z are highly correlated. So we will use PCA to reduce from five resources to three and have better accuracy.

```
from sklearn.decomposition import PCA
#(based on: https://www.kaggle.com/code/sanchitvj/sdss-dr16-data-analysis/notebook)
pca = PCA(n_components = 3)
df_pca = pca.fit_transform(sloan_survey[['u', 'g', 'r', 'i', 'z']])

sloan_survey  = pd.concat((sloan_survey, pd.DataFrame(df_pca)), axis = 1)
sloan_survey .rename({0:'F1', 1:'F2', 2:'F3'}, axis = 1, inplace = True)
sloan_survey .drop(['u', 'g', 'r', 'i', 'z'], axis = 1, inplace = True)
sloan_survey
```

	Class	ra	dec	field	redshift	plate	mjd	fiberid	F
0	1	183.531326	0.089693	267	-0.000009	3306	54922	491	-1.5072
1	1	183.598370	0.135285	267	-0.000055	323	51615	541	-0.1957
2	2	183.680207	0.126185	268	0.123111	287	52023	513	1.2976
3	1	183.870529	0.049911	269	-0.000111	3306	54922	510	-1.4461
4	1	183.883288	0.102557	269	0.000590	3306	54922	512	-0.8492
...	...	...	...	...	...	...	...	...	
9995	2	131.316413	51.539547	161	0.027583	447	51877	246	0.2229
9996	2	131.306083	51.671341	162	0.117772	447	51877	228	0.2591
9997	1	131.552562	51.666986	162	-0.000402	7303	57013	622	1.4807
9998	2	131.477151	51.753068	163	0.014019	447	51877	229	1.3920
9999	2	131.665012	51.805307	163	0.118417	447	51877	233	-0.9362

10000 rows × 11 columns

Spliting our df

```
train_df, test_df = train_test_split(sloan_survey, test_size = 0.3, random_state =
#train_df, val_df = train_test_split(train_df, test_size = 0.3, random_state = 7)
    #here we decided to not create the validation because after we will use only Gr
```

```
# Checking for the size of our new datasets and if our splitting code worked

# This step is important to see if the matrix that we will build to test the models
# is correct

# Train dataset shape
train_df.shape
```

```
(7000, 11)
```

```
# Validation dataset shape
#val_df.shape
```

```
# Test dataset shape
test_df.shape
```

```
(3000, 11)
```

```
# Now, we will concat these dataframes in one (df) so we can apply all the transfor
# at the same time to all the dataframes

df = pd.concat((train_df.loc[:,'ra':'F3'],
             #   val_df.loc[:,'ra':'F3'],
                test_df.loc[:,'ra':'F3']))
```

```
# Checking if everything went well when concating the data

df.shape
```

```
(10000, 10)
```

Selecionar o conjunto de informações relevantes

```
X_train = df[:train_df.shape[0]]
#X_val = df[:val_df.shape[0]]
X_test = df[:test_df.shape[0]]
y_train = train_df.Class
#y_val = val_df.Class
y_test = test_df.Class
```

B) Running Models

- Decision Trees
- Random Forest
- AdaBoost

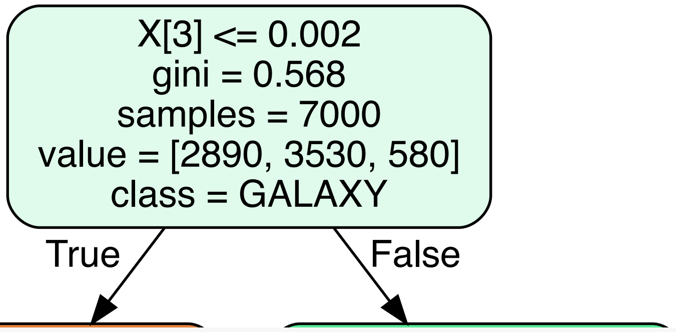
DECISION TREES

```
!pip install sklearn
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-w
Requirement already satisfied: sklearn in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: numpy>=1.14.6 in /usr/local/lib/python3.7/dist-
```

```
# DECISION TREES

#Scikit
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor, AdaBoostRegre
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn import metrics
from sklearn.tree import _tree

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

```
# NAIVE 1: Decision tree with depth = 1

dtc = tree.DecisionTreeClassifier(max_depth = 1)
dtc_noprune = tree.DecisionTreeClassifier()

dtc.fit(X_train, y_train)
dtc_noprune.fit(X_train, y_train)

dot_data = tree.export_graphviz(dtc, out_file=None,
                     class_names = ['STAR', 'GALAXY', 'QSO'],
                     filled=True, rounded=True)

graph = graphviz.Source(dot_data)
graph
```




```
y_pred_dtc = dtc.predict(X_test)
cm_dtc = confusion_matrix(y_test, y_pred_dtc)
print("Accuracy", metrics.accuracy_score(y_test, y_pred_dtc))
```

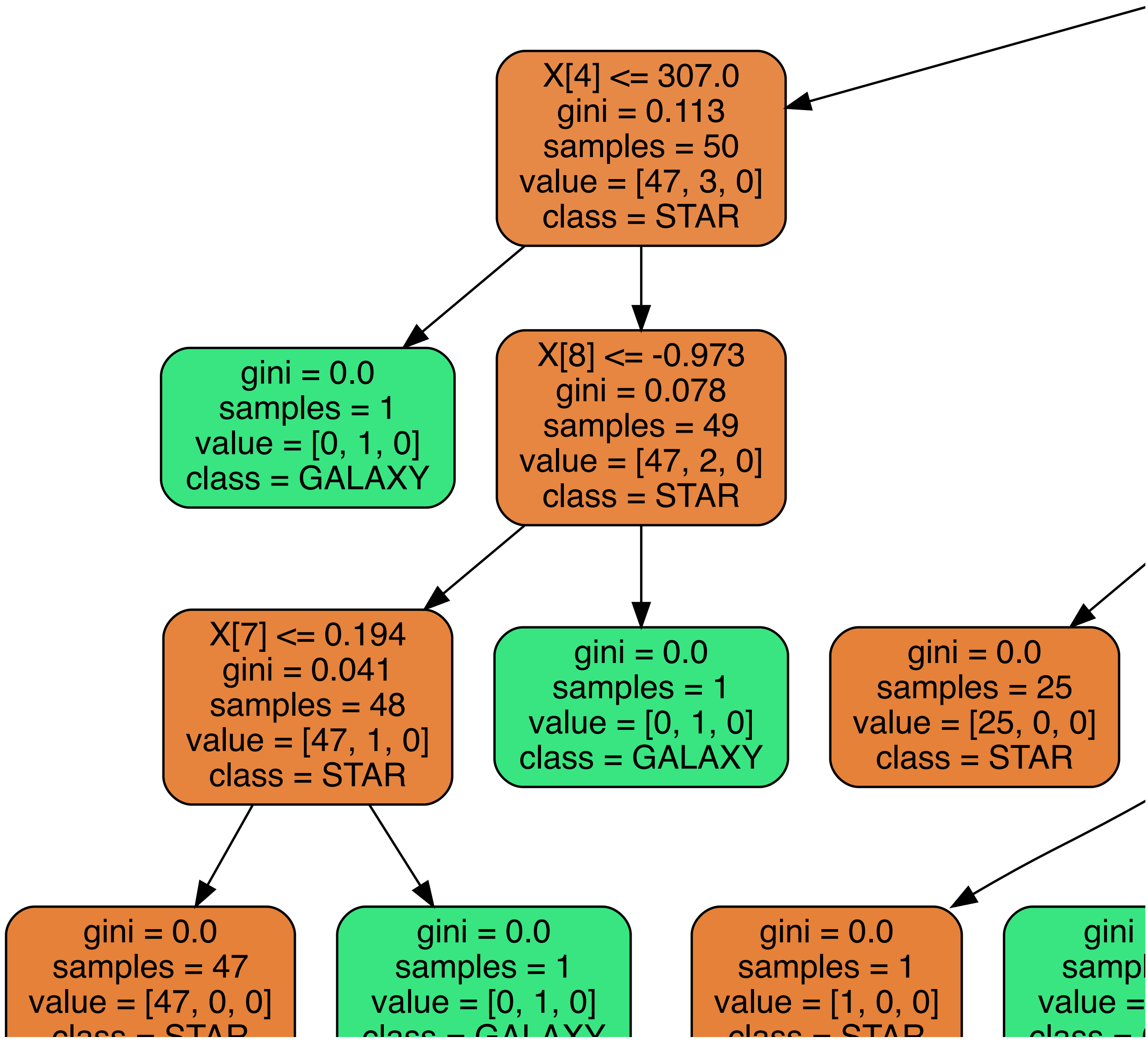
```
Accuracy 0.458
```

```
#we tried to compute like this, but we failed:

#all_n_estimators = [50, 100, 250]
#all_max_depth = [1,2,3, 5,10, 25, 50]
#accuracy_list = []
#n_estimators_list = []
#max_depth_list = []

#for n_estimators in all_n_estimators:
 #   for max_depth in all_max_depth:
  #      print('n_estimators', n_estimators,
   #            'max_depth', max_depth )

    #    DTR = DecisionTreeRegressor(
     #       n_estimators=n_estimators,
      #      max_depth=max_depth
       #     ).fit(X_train, y_train)

        #pred = DTR.predict(X_val)

        #accuracy = metrics.accuracy_score(y_val, np.exp(pred))

        #accuracy_list.append(accuracy)
        #n_estimators_list.append(n_estimators)
        #max_depth_list.append(max_depth)
```

```
#results = pd.DataFrame({
#    'n_estimators': n_estimators_list,
#    'max_depth': max_depth_list,
#    'accuracy': accuracy_list
#})

#results
```

```
# Model: Decision tree with depth = 10
```

```
dtc = tree.DecisionTreeClassifier(max_depth = 100)
dtc_noprune = tree.DecisionTreeClassifier()

dtc.fit(X_train, y_train)
dtc_noprune.fit(X_train, y_train)

dot_data = tree.export_graphviz(dtc, out_file=None,
                     class_names = ['STAR', 'GALAXY', 'QSO'],
                     filled=True, rounded=True)

graph = graphviz.Source(dot_data)
graph
```


X[4] <= 307.0
gini = 0.113
samples = 50
value = [47, 3, 0]
class = STAR
gini = 0.0
samples = 1
value = [0, 1, 0]
class = GALAXY
X[8] <= -0.973
gini = 0.078
samples = 49
value = [47, 2, 0]
class = STAR
X[7] <= 0.194
gini = 0.041
samples = 48
value = [47, 1, 0]
class = STAR
gini = 0.0
samples = 1
value = [0, 1, 0]
class = GALAXY
gini = 0.0
samples = 25
value = [25, 0, 0]
class = STAR
gini = 0.0
samples = 47
value = [47, 0, 0]
gini = 0.0
samples = 1
value = [0, 1, 0]
gini = 0.0
samples = 1
value = [1, 0, 0]


```
y_pred_dtc = dtc.predict(X_test)
cm_dtc = confusion_matrix(y_test, y_pred_dtc)
print("Accuracy", metrics.accuracy_score(y_test, y_pred_dtc))
```

```
Accuracy 0.424
```

```
# based on https://www.kaggle.com/code/pruthviacharya1/decision-tree-classifier-wit

from sklearn.model_selection import GridSearchCV
#Finding the best parameters

#Seperating the target variable "class" from the set of the dataset
X = sloan_survey.drop('Class',axis=1)
y = sloan_survey['Class']

parameters_list = {'max_depth':np.arange(1,11),'min_samples_leaf':np.arange(2,10)},
all_decision_trees = GridSearchCV(DecisionTreeClassifier(),parameters_list)
all_decision_trees.fit(X,y)

#Using the best parameters
y_pred = all_decision_trees.predict(X_test)
print(accuracy_score(y_test,y_pred))
```

```
0.4236666666666667
```

Our naive model has performed better than depth = 10.

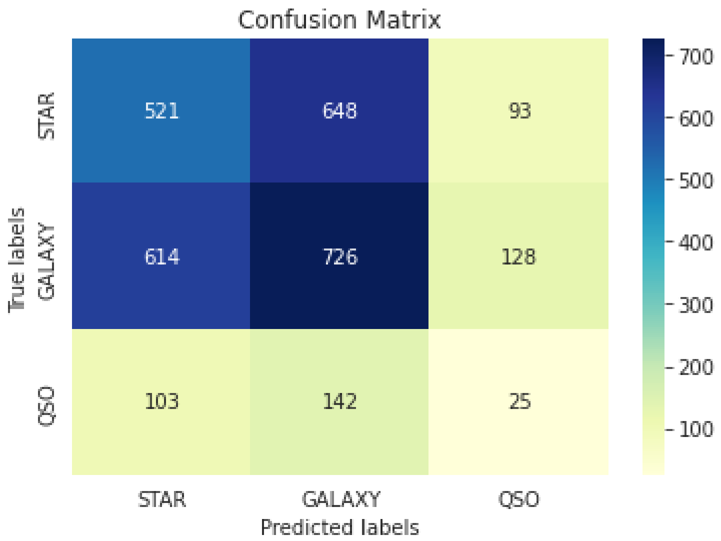
RANDOM FOREST

```
# From: https://www.geeksforgeeks.org/random-forest-classifier-using-scikit-learn/

from sklearn.ensemble import RandomForestClassifier

clf = RandomForestClassifier(n_estimators = 100)
#testar para estimadores diferentes, alem de 100

# Training the model on the training dataset
# fit function is used to train the model using the training sets as parameters
clf.fit(X_train, y_train)

# performing predictions on the test dataset
```

```
y_pred_rf = clf.predict(X_test)

# using metrics module for accuracy calculation
print("Accuracy", metrics.accuracy_score(y_test, y_pred_rf))

# confusion matrix
cm_rf = confusion_matrix(y_test, y_pred_rf)
```

```
Accuracy 0.424
```

```
# Now, lets check our Confusion Matrix for Random Forest

labels = ['STAR', 'GALAXY', 'QSO']

ax= plt.subplot()
sns.heatmap(cm_rf, annot=True, fmt='g', ax=ax, cmap="YlGnBu");
# labels, title and ticks
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(labels); ax.yaxis.set_ticklabels(labels);
```




```
# Optimizing hyperparameters:

from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(random_state = 42)
from pprint import pprint
# Look at parameters used by our current forest
print('Parameters currently in use:\n')
pprint(rf.get_params())
```

```
Parameters currently in use:

{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'squared_error',
 'max_depth': None,
```

```
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

```
from sklearn.model_selection import RandomizedSearchCV

# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]

# Number of features to consider at every split
max_features = ['auto', 'sqrt']

# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]
max_depth.append(None)

# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]

# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]

# Method of selecting samples for training each tree
bootstrap = [True, False]

# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}

pprint(random_grid)
```

```
{'bootstrap': [True, False],
 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None],
 'max_features': ['auto', 'sqrt'],
 'min_samples_leaf': [1, 2, 4],
 'min_samples_split': [2, 5, 10],
 'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000]}
```

```
# Use the random grid to search for best hyperparameters

# First create the base model to tune
```

```
##rf = RandomForestRegressor()

# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores


##rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid,

# Fit the random search model

##rf_random.fit(X_train, y_train)
```

```
#rf_random.best_params_

#our best model was:
```

ADABOOST

```
from sklearn.ensemble import AdaBoostClassifier
```

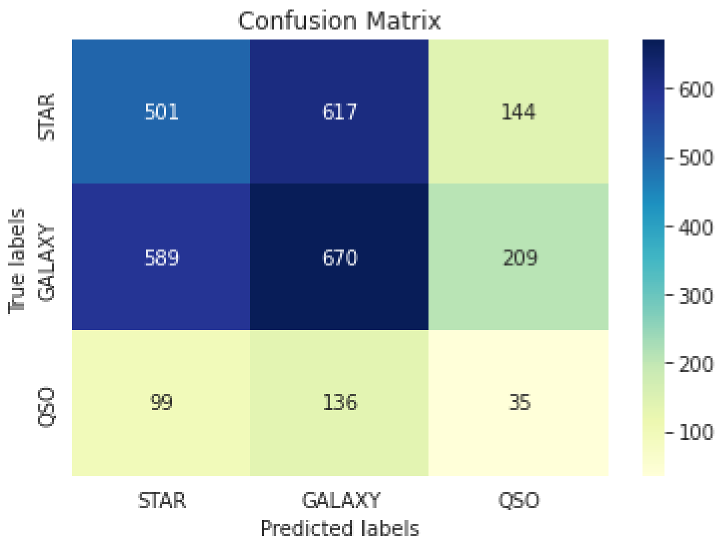
```
# From:https://www.datacamp.com/tutorial/adaboost-classifier-python

# Create adaboost classifer object
abc = AdaBoostClassifier(n_estimators=50,
                         learning_rate=1)
# Train Adaboost Classifer
model = abc.fit(X_train, y_train)

#Predict the response for test dataset
y_pred_adb = model.predict(X_test)
```

```
# Computing model accuracy
print("Accuracy:",metrics.accuracy_score(y_test, y_pred_adb))
```

```
Accuracy: 0.402
```

```
# Confusion Matrix
cm_adb = confusion_matrix(y_test, y_pred_adb)
```

```
#Now, lets check our Confusion Matrix for AdaBoost

labels = ['STAR', 'GALAXY', 'QSO']
ax= plt.subplot()
sns.heatmap(cm_adb, annot=True, fmt='g', ax=ax, cmap="YlGnBu");
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(labels); ax.yaxis.set_ticklabels(labels);
```




```
#Using grid search to optimize hyperparameters:
#based on: https://machinelearningmastery.com/adaboost-ensemble-in-python/


from sklearn.datasets import make_classification
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import AdaBoostClassifier
```

```
# define the model with default hyperparameters
model = AdaBoostClassifier()

# define the grid of values to search
grid = dict()
grid['n_estimators'] = [10, 50, 100, 500]
grid['learning_rate'] = [0.0001, 0.001, 0.01, 0.1, 1.0]
```

```
# define the evaluation procedure
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

# define the grid search procedure
grid_search = GridSearchCV(estimator=model, param_grid=grid, n_jobs=-1, cv=cv, scor

# execute the grid search
grid_result = grid_search.fit(X_train, y_train)

# summarize the best score and configuration
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
```

```
Best: 0.920333 using {'learning_rate': 0.01, 'n_estimators': 500}
```

```
# summarize all scores that were evaluated
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
```

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

```
0.914286 (0.001952) with: {'learning_rate': 0.0001, 'n_estimators': 10}
0.914286 (0.001952) with: {'learning_rate': 0.0001, 'n_estimators': 50}
0.914286 (0.001952) with: {'learning_rate': 0.0001, 'n_estimators': 100}
0.914286 (0.001952) with: {'learning_rate': 0.0001, 'n_estimators': 500}
0.914286 (0.001952) with: {'learning_rate': 0.001, 'n_estimators': 10}
0.914286 (0.001952) with: {'learning_rate': 0.001, 'n_estimators': 50}
0.914286 (0.001952) with: {'learning_rate': 0.001, 'n_estimators': 100}
0.914286 (0.001952) with: {'learning_rate': 0.001, 'n_estimators': 500}
0.914286 (0.001952) with: {'learning_rate': 0.01, 'n_estimators': 10}
0.914333 (0.001898) with: {'learning_rate': 0.01, 'n_estimators': 50}
0.914429 (0.001704) with: {'learning_rate': 0.01, 'n_estimators': 100}
0.920333 (0.011715) with: {'learning_rate': 0.01, 'n_estimators': 500}
0.914476 (0.001720) with: {'learning_rate': 0.1, 'n_estimators': 10}
0.919571 (0.011067) with: {'learning_rate': 0.1, 'n_estimators': 50}
0.919667 (0.007699) with: {'learning_rate': 0.1, 'n_estimators': 100}
0.911905 (0.015546) with: {'learning_rate': 0.1, 'n_estimators': 500}
0.900333 (0.041069) with: {'learning_rate': 1.0, 'n_estimators': 10}
0.900810 (0.042291) with: {'learning_rate': 1.0, 'n_estimators': 50}
0.889429 (0.070791) with: {'learning_rate': 1.0, 'n_estimators': 100}
0.902000 (0.028114) with: {'learning_rate': 1.0, 'n_estimators': 500}
```

Best model for Adaboost:

0.914286 (0.001952) with: {'learning_rate': 0.0001, 'n_estimators': 10}

GRADIENT BOOSTING

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn import metrics
```

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train_scale = scaler.fit_transform(X_train)
X_test_scale = scaler.transform(X_test)
```

```
from sklearn.model_selection import train_test_split
X_train_sub, X_test_sub, y_train_sub, y_test_sub = train_test_split(X_train_scale,
```

```
learning_rates = [0.05, 0.1, 0.25, 0.5, 0.75, 1]
for learning_rate in learning_rates:
    gb = GradientBoostingClassifier(n_estimators=20, learning_rate = learning_rate,
    gb.fit(X_train_sub, y_train_sub)
    print("Learning rate: ", learning_rate)
    print("Accuracy score (training): {0:.3f}".format(gb.score(X_train_sub, y_train
    print("Accuracy score (validation): {0:.3f}".format(gb.score(X_test_sub, y_test
```

```
Learning rate:  0.05
Accuracy score (training): 0.967
Accuracy score (validation): 0.965
Learning rate:  0.1
Accuracy score (training): 0.981
Accuracy score (validation): 0.982
Learning rate:  0.25
Accuracy score (training): 0.990
Accuracy score (validation): 0.988
Learning rate:  0.5
Accuracy score (training): 0.994
Accuracy score (validation): 0.989
Learning rate:  0.75
Accuracy score (training): 0.834
Accuracy score (validation): 0.821
Learning rate:  1
Accuracy score (training): 0.991
Accuracy score (validation): 0.986
```

Best model for Gradient Boosting:

Learning rate: 0.5

Accuracy score (training): 0.994

Accuracy score (test): 0.989

Feature Importance

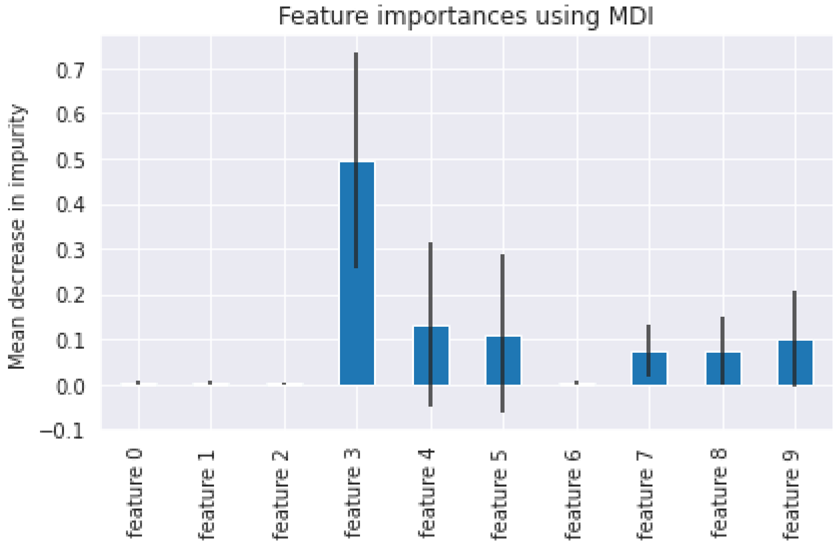
```
import time

from sklearn.ensemble import RandomForestClassifier

feature_names = [f"feature {i}" for i in range(df.shape[1])]
forest = RandomForestClassifier(random_state=0)
forest.fit(X_train, y_train)
from sklearn.inspection import permutation_importance
```

```
start_time = time.time()
importances = forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in forest.estimators_], axis=0)
elapsed_time = time.time() - start_time

print(f"Elapsed time to compute the importances: {elapsed_time:.3f} seconds")
```

```
Elapsed time to compute the importances: 0.014 seconds
```

```
import pandas as pd

forest_importances = pd.Series(importances, index=feature_names)

fig, ax = plt.subplots()
```

```
forest_importances.plot.bar(yerr=std, ax=ax)
ax.set_title("Feature importances using MDI")
ax.set_ylabel("Mean decrease in impurity")
fig.tight_layout()
```




```
from sklearn.inspection import permutation_importance

start_time = time.time()
result = permutation_importance(
forest, X_test, y_test, n_repeats=10, random_state=42, n_jobs=2)
elapsed_time = time.time() - start_time
print(f"Elapsed time to compute the importances: {elapsed_time:.3f} seconds")

forest_importances = pd.Series(result.importances_mean, index=feature_names)
```

```
Elapsed time to compute the importances: 2.714 seconds
```

```
fig, ax = plt.subplots()
forest_importances.plot.bar(yerr=result.importances_std, ax=ax)
ax.set_title("Feature importances using permutation on full model")
ax.set_ylabel("Mean accuracy decrease")
fig.tight_layout()
plt.show()
```

Feature importances using permutation on full model

```
df.info()
type(df)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 2317 to 3582
Data columns (total 10 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   ra        10000 non-null  float64
 1   dec       10000 non-null  float64
 2   field     10000 non-null  int64
 3   redshift  10000 non-null  float64
 4   plate     10000 non-null  int64
 5   mjd       10000 non-null  int64
 6   fiberid   10000 non-null  int64
 7   F1        10000 non-null  float64
 8   F2        10000 non-null  float64
 9   F3        10000 non-null  float64
dtypes: float64(6), int64(4)
memory usage: 859.4 KB
pandas.core.frame.DataFrame
```

OUR CHOSEN MODEL:

GRADIENT BOOSTING

Learning rate: 0.5

Accuracy score (training): 0.994

Accuracy score (test): 0.989

Features more important were redshift, mjd, and F9.

EXERCICIO 3 - DATA VISUALIZATION DASHBOARD

```
from google.colab import files
uploaded = files.upload()
equipment = pd.read_csv(io.BytesIO(uploaded['russia_losses_equipment.csv']))
equipment.head()
```

Choose Files No file chosen Upload widget is only available when the cell has been executec

```
Saving russia_losses_equipment.csv to russia_losses_equipment.csv
```

	date	day	aircraft	helicopter	tank	APC	field artillery	MRL	military auto	fuel tank
0	2022-02-25	2	10	7	80	516	49	4	100.0	60.0
1	2022-02-26	3	27	26	146	706	49	4	130.0	60.0

```
from google.colab import files
uploaded = files.upload()
personnel = pd.read_csv(io.BytesIO(uploaded['russia_losses_personnel.csv']))
personnel.head()
```

Choose Files No file chosen Upload widget is only available when the cell has been executec

```
Saving russia_losses_personnel.csv to russia_losses_personnel.csv
```

	date	day	personnel	personnel*	POW
0	2022-02-25	2	2800	about	0
1	2022-02-26	3	4300	about	0
2	2022-02-27	4	4500	about	0
3	2022-02-28	5	5300	about	0
4	2022-03-01	6	5710	about	200

GENERAL INFORMATION

```
# Shape equipment
equipment.shape
```

```
(102, 18)
```

```
# Shape personnel
personnel.shape
```

```
(102, 5)
```

Since both dfs regards the same event, we will merge both informations

```
df = equipment.merge(personnel,how='left',left_on=["date","day"],right_on=["date","
```

```
df
```

	date	day	aircraft	helicopter	tank	APC	field artillery	MRL	military auto	fuel tank
0	2022-02-25	2	10	7	80	516	49	4	100.0	60.(
1	2022-02-26	3	27	26	146	706	49	4	130.0	60.(
2	2022-02-27	4	27	26	150	706	50	4	130.0	60.(
3	2022-02-28	5	29	29	150	816	74	21	291.0	60.(
4	2022-03-01	6	29	29	198	846	77	24	305.0	60.(
...	...	...	...	...	...	...	...	...	...	..
97	2022-06-02	99	210	175	1363	3354	661	207	NaN	NaN
98	2022-06-03	100	210	175	1367	3366	675	207	NaN	NaN
99	2022-06-04	101	210	175	1376	3379	680	207	NaN	NaN
100	2022-06-05	102	210	175	1381	3392	686	207	NaN	NaN
101	2022-06-06	103	211	176	1386	3400	690	207	NaN	NaN

102 rows × 21 columns

DATA PREP

Inspired on: https://www.kaggle.com/code/tomasborges/2022-russian-invasion-of-ukraine-eda-forecast

```
# Lest first check for missing values in our dataset, visualizing the percentage
# of NaN in each variable.

total = df.isnull().sum().sort_values(ascending=False)
percent = (df.isnull().sum()/df.isnull().count()*100).sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data.head(20)
```

	Total	Percent
greatest losses direction	89	87.254902
mobile SRBM system	66	64.705882
cruise missiles	65	63.725490
vehicles and fuel tanks	65	63.725490
military auto	37	36.274510
fuel tank	37	36.274510
special equipment	19	18.627451
date	0	0.000000
anti-aircraft warfare	0	0.000000
personnel*	0	0.000000
personnel	0	0.000000
drone	0	0.000000
naval ship	0	0.000000
day	0	0.000000
MRL	0	0.000000
field artillery	0	0.000000

```
# Drop variables with over 60% of missing values
df.drop(labels= ['personnel*','greatest losses direction','mobile SRBM system','cru
```

```
#The equipment data has missing values we need to treat
#the personnel data has a column with little to no value: 'personnel*'

#changing 'date' type to datetime for our timeseries study
df['date'] = pd.to_datetime(df['date'])


#fill na (missing values)
df.fillna(value=0, inplace=True)
```

SOME BASIC FEATURE ENGINEERING

Incremental Personel Loss

Since we have personnel losses are cumulative, we are adding a column with daily/incremental personnel losses

```
df['incremental_personnel_loss'] = df['personnel'].diff(periods=1)
```

```
#setting day 1
df['incremental_personnel_loss'] = df['incremental_personnel_loss'].replace(df['inc
```

Week and Month Variables

```
df['month'] = df['day']//30
df['week'] = df['day']//7
```

```
print(df["month"].unique()) # 4 months
print(df["week"].unique()) # 15 weeks
```

```
[0 1 2 3]
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14]
```

VISUALIZATIONS

Attempt 1: Dashboard \ We were not abble to run the code for our dashboard visualization. In the last code chuck we received an Error Message saying "syntax error" in the following line: col1, col2= st.columns(2).

```
#pip install streamlit
```

```
#import time
#import numpy as np
#import pandas as pd
#import plotly.express as px
#import streamlit as st
```

```
#st.set_page_config(
#    page_title = 'Russian-Ukranian War Dashboard',
#    page_icon = '🇺🇦',
#    layout = 'wide'
#)
```

```
# dashboard title

#st.title("Russian-Ukranian War Dashboard - 2022")
```

```
# top-level filters
#month_filter = st.selectbox("Select the Month", pd.unique(df["month"]))
```

```
# creating a single-element container.
#placeholder = st.empty()

# dataframe filter (here we would be able to filter/visualize data by month)
```

```
#df = df[df['month']==month_filter]
```

```
# Code for the dashboard itself:

#for month in range(15):
#    while True:

#        df['personnel)new'] = df['personnel'] * np.random.choice(range(1,5))
#        df['POW_new'] = df['POW'] * np.random.choice(range(1,5))

    # creating KPIs
#    avg_personnel = np.mean(df['personnel'])

#    count_pow = int(df[(df["POW"]=='POW')]['POW'].count() + np.random.choice(range

#    count_artillery = int(df[(df["field artillery"]=='field artillery')]['field ar


#   with placeholder.container():
        # create three columns
#        kpi1, kpi2= st.columns(2)

        # fill in those three columns with respective metrics or KPIs
#        kpi1.metric(label="Avarege Personnel", value=round(avg_personnel), delta=
#        kpi2.metric(label="Count of Prisioners of War", value= int(POW, delta= - 1


    # create two columns for charts

#    col1, col2= st.columns(2)
#        with col1:
#            st.markdown("Total Count of Personnel Losses by Week")
#            fig = px.bar(data_frame=df, y = 'personnel', x = 'week')
#            st.write(col1)
#        with col2:
#            st.markdown("Total Count of Personnel Losses by Week")
#            fig2 = px.bar(data_frame=df, y = 'military auto', x = 'week')
#            st.write(fig_c2)

#    st.markdown("### Detailed Data View")
#    st.dataframe(df)

#    time.sleep(1)
```

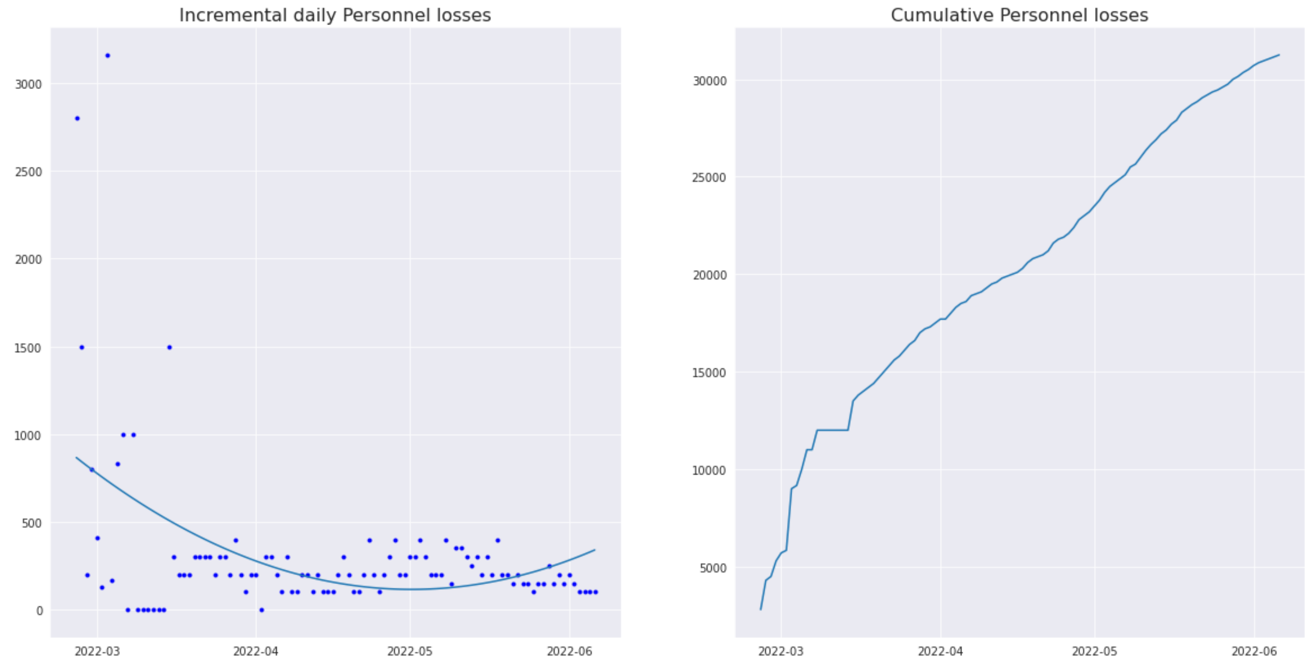
TO OVERCOME OUR PROBLEM WITH THE DASHBOARD WE WILL RELY ON A BASIC VISUALIZATION ANALYSIS.

```
import matplotlib.dates as mdates
```

```
from scipy.stats import pearsonr
```

```
fig, axes = plt.subplots(1, 2, figsize=(20, 10))

axes[0].plot(df['date'], df['incremental_personnel_loss'], "b.")
axes[1].plot(df['date'], df['personnel'])

for ax in axes:
    ax.xaxis.set_minor_locator(mdates.DayLocator(bymonthday=[25], interval=1, tz=No
    ax.xaxis.set_major_locator(mdates.MonthLocator())
    ax.grid(True)


#adding a trendline to personnel losses
z = np.polyfit(mdates.date2num(df['date']), df['incremental_personnel_loss'], 3)
p = np.poly1d(z)
axes[0].plot(mdates.date2num(df['date']),p(mdates.date2num(df['date'])))

axes[0].set_title('Incremental daily Personnel losses', fontsize = 16)
axes[1].set_title('Cumulative Personnel losses', fontsize = 16)
```

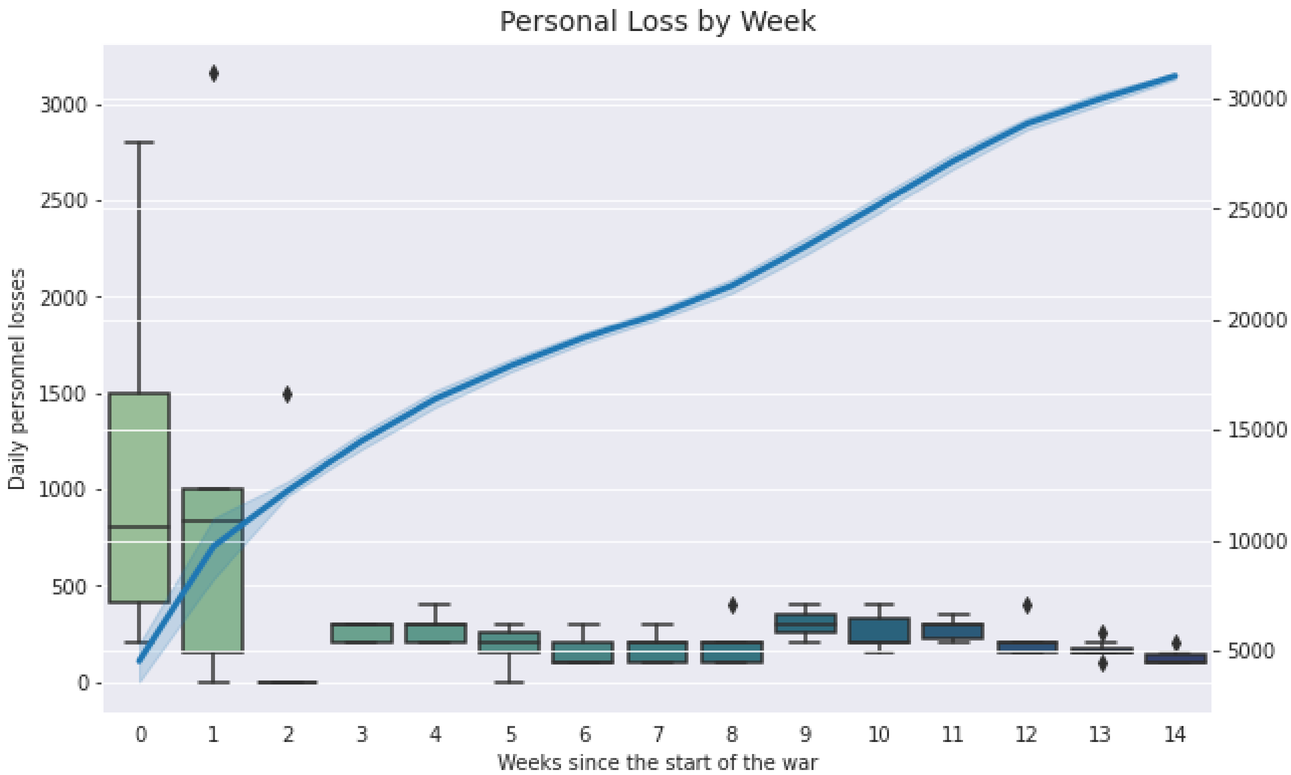
```
Text(0.5, 1.0, 'Cumulative Personnel losses')
```



Graphs one and two shwo that there is a signifficant increase in deaths in the first half of the war. After hiting a cummulative loss of 12000, there is a stabilization of fatalities.

PERSONNEL LOSS BY WEEK

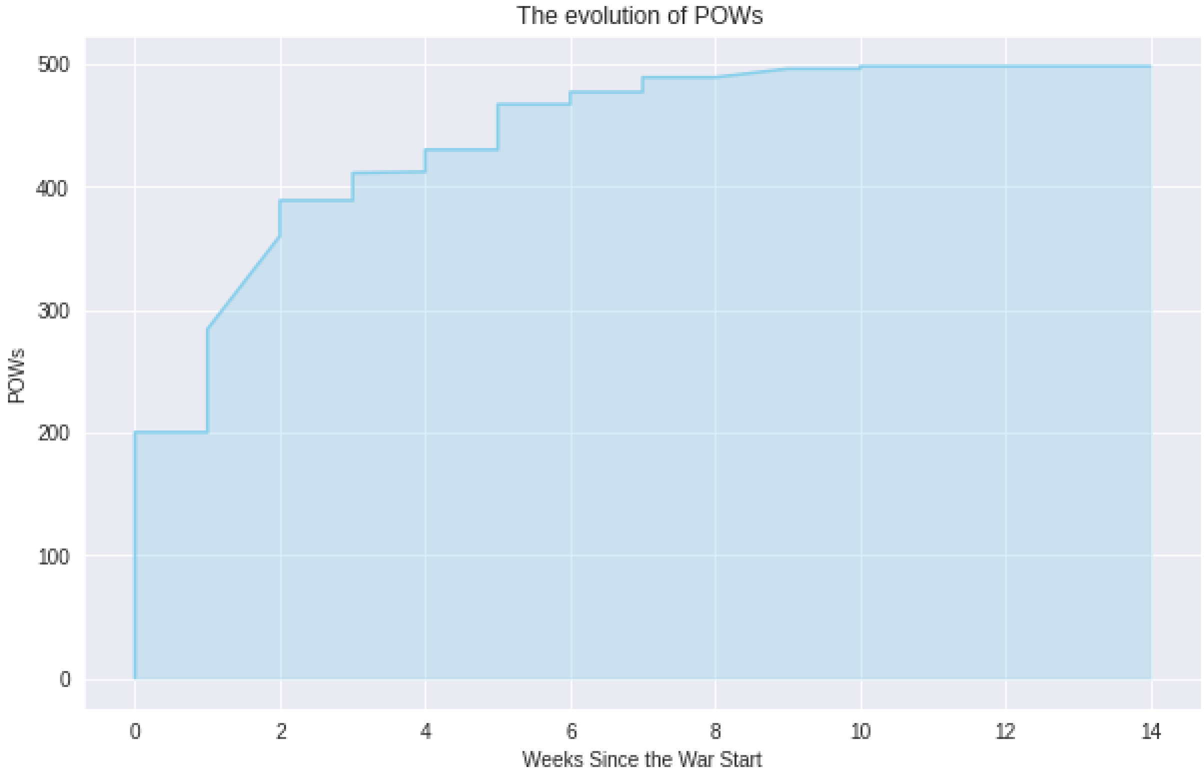
```
fig,ax1 = plt.subplots(figsize= (10,10*0.618))


bp = sns.boxplot(data = df,
                     x = "week",
                     y = "incremental_personnel_loss",
                     palette="crest",
                     ax = ax1)

ax2 = ax1.twinx()

lp = sns.lineplot(data = df,
                     x = "week",
                     y = "personnel",
                     linewidth = 3,
                     ax=ax2)
ax1.set(xlabel='Weeks since the start of the war', ylabel='Daily personnel losses')
ax2.set(ylabel='')
ax1.set_title("Personal Loss by Week", fontsize = 14);
```



As we have argued on the first and second figures, there was a significant ammount of fatalities in the first two weeks of war. More precisely, only on the second week russia lost over 3000 people.

PRISIONERS OF WAR (POW)

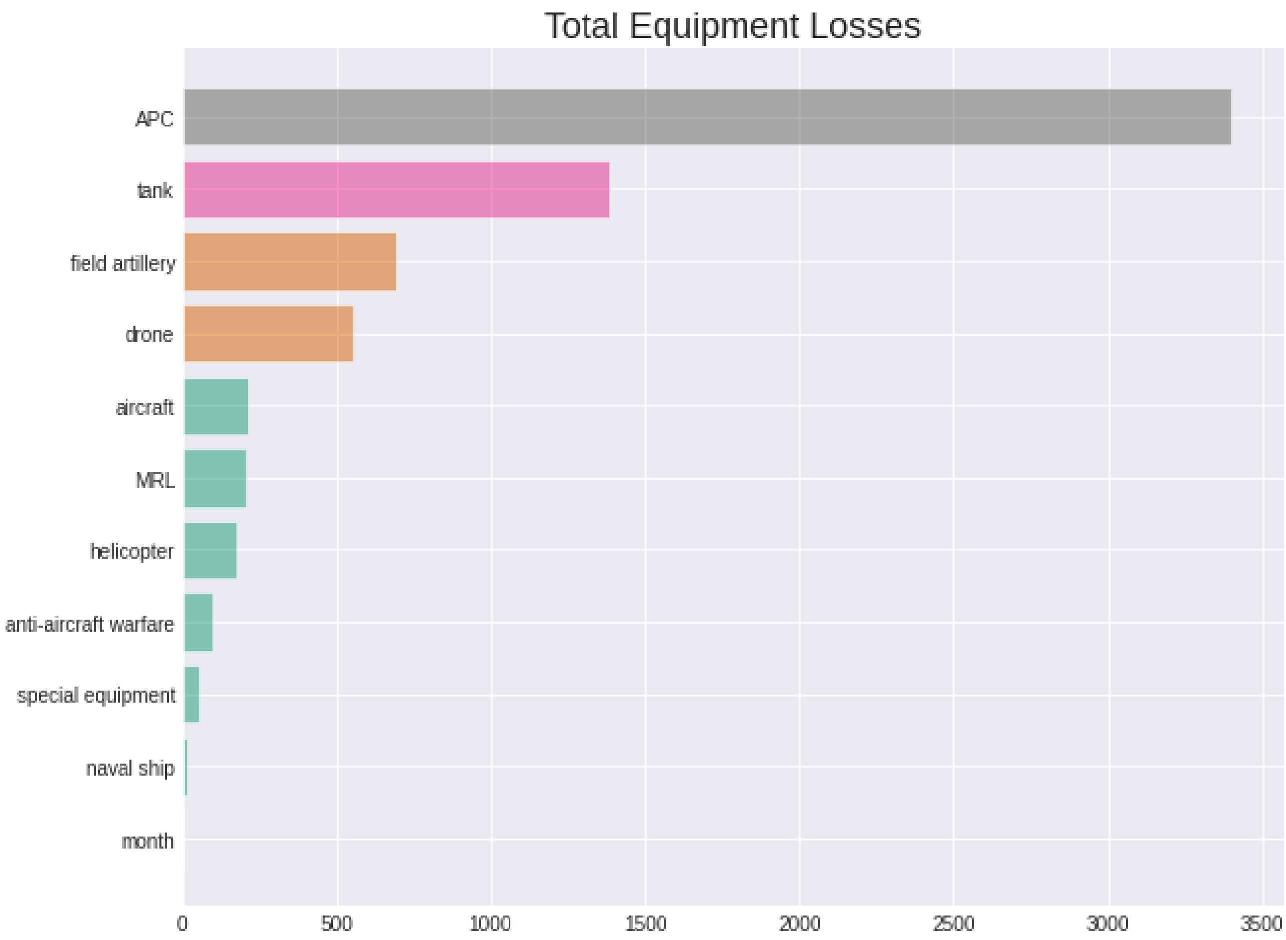
```
fig,ax = plt.subplots(figsize= (10,10*0.618))

# Change the style of plot
plt.style.use('seaborn-darkgrid')

# Make the same graph
ax.fill_between(df["week"], df["POW"], color="skyblue", alpha=0.3)
ax.plot(df["week"], df["POW"], color="skyblue")

#getting correlation with personnel losses
corr, _ = pearsonr(df["POW"], df['personnel'])
Pearsons_correlation = 'Pearsons correlation: %.3f' % corr

# Add titles
plt.title(f"The evolution of POWs ", fontsize=12)
plt.xlabel("Weeks Since the War Start")
plt.ylabel("POWs")

# Show the graph
plt.show()
```



Prisioners of war tendencies also behaves similarly to personnel losses with a Pearsons Correlation of 0.825. As most POWs were captured in the first 4 weeks of the war and most losses happened on the first couple of weeks.

EQUIPMENT LOSSES

```
ig,ax = plt.subplots(figsize= (10,8))

#getting the proper df with columns sorted by the last row, we also drop the column
df_bar = df.loc[:, ~df.columns.isin(['date', 'day', 'week', 'personnel', 'POW', 'in

#It's important to properly capture the data we want before plotting
x = df_bar.columns.values

#we want an array and not index, also we removed irrelevant columns
y = df_bar.tail(1).squeeze().values

#we get the values of the last day to give us the most recent losses

#adding a color map
my_cmap = plt.get_cmap("Dark2")
rescale = lambda y: (y - np.min(y)) / (np.max(y) - np.min(y))

#plotting
ax.barh(x, y, align = 'center', alpha=0.5, color = my_cmap(rescale(y)))
ax.set_title('Total Equipment Losses', fontsize=18)

plt.show()
```

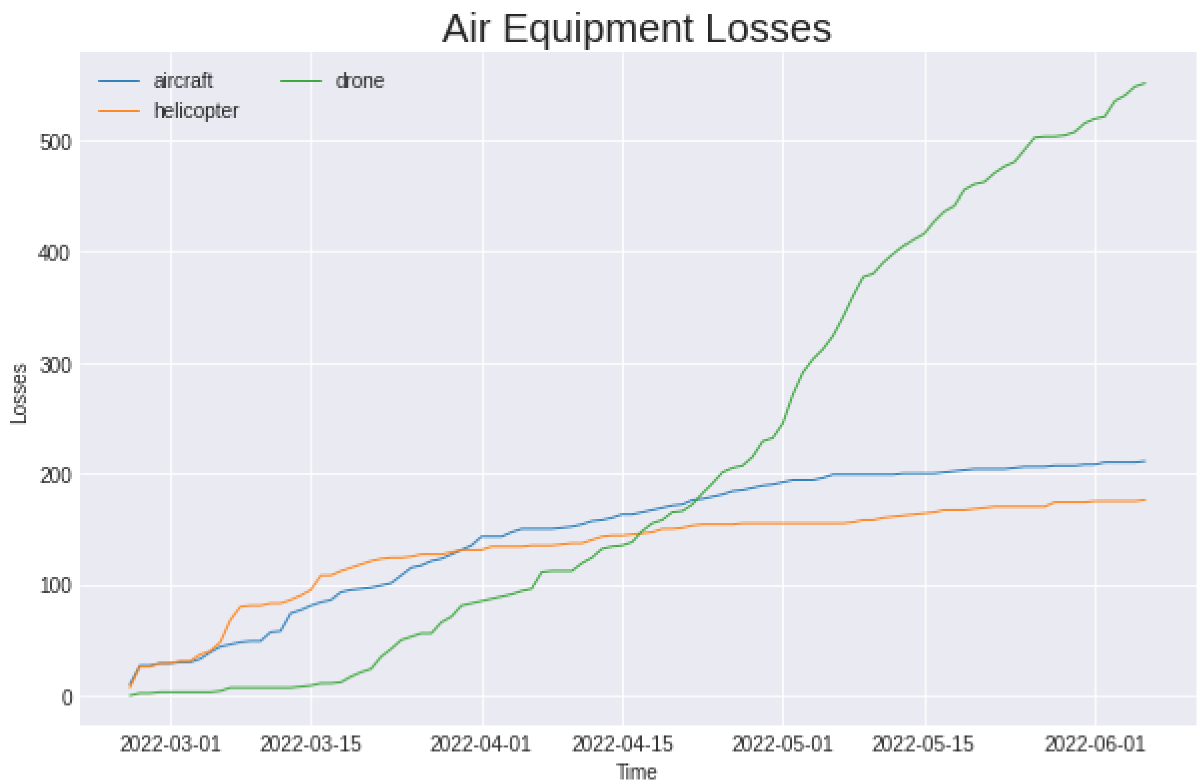


If we analyse the equiment losses, Armored Personnel Carrier (APC) is the item which has been more affected. We believe this happens because the total count of APC that belongs to the

Russian Army is greater than naval ships or aircrafts, for example. In this sense, a better metric would be to compare the propostional loss, considering the losses relation to the total count of a given equipment.

AIR EQUIPMENT LOSSES

```
# Plot multiple lines
fig, ax = plt.subplots(figsize= (10,10*0.618))

num=0
for column in df[['aircraft', 'helicopter', 'drone']]:
    num+=1
    plt.plot(df['date'], df[column], marker='', linewidth=1, alpha=0.9, label=colum

# Add legend
plt.legend(loc=2, ncol=2)

# Add titles
plt.title("Air Equipment Losses", fontsize=20)
plt.xlabel("Time")
plt.ylabel("Losses")

# Show the graph
plt.show()
```



We believe in two hypothesis about drones being the most lost air equipment:

- H_1: we proportionally have more drone than other air equipments.
- H_2: Drones are easier targets to hit.

Unfortunately, since our data regards only losses, we cannot test any of the hypothesis.