Untitled4

April 20, 2021

[1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import math
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import linear_model
from sklearn.model_selection import GridSearchCV
from sklearn import svm
from sklearn.neural_network import MLPClassifier
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_squared_error
import warnings
warnings.filterwarnings('ignore')
from category_encoders import OneHotEncoder
```

0.1 Przygotowanie danych

[2]:
```
data=pd.DataFrame(pd.read_json('https://api.apispreadsheets.com/api/dataset/
 ↪school-grades/',orient='split'))
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 649 entries, 0 to 648
Data columns (total 33 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   school      649 non-null    object
 1   sex         649 non-null    object
 2   age         649 non-null    int64
 3   address     649 non-null    object
 4   famsize     649 non-null    object
 5   Pstatus     649 non-null    object
 6   Medu        649 non-null    int64
 7   Fedu        649 non-null    int64
 8   Mjob        649 non-null    object
```

```
 9   Fjob        649 non-null    object
 10  reason      649 non-null    object
 11  guardian    649 non-null    object
 12  traveltime  649 non-null    int64
 13  studytime   649 non-null    int64
 14  failures    649 non-null    int64
 15  schoolsup   649 non-null    object
 16  famsup      649 non-null    object
 17  paid        649 non-null    object
 18  activities  649 non-null    object
 19  nursery     649 non-null    object
 20  higher      649 non-null    object
 21  internet    649 non-null    object
 22  romantic    649 non-null    object
 23  famrel      649 non-null    int64
 24  freetime    649 non-null    int64
 25  goout       649 non-null    int64
 26  Dalc        649 non-null    int64
 27  Walc        649 non-null    int64
 28  health      649 non-null    int64
 29  absences    649 non-null    int64
 30  G1          649 non-null    int64
 31  G2          649 non-null    int64
 32  G3          649 non-null    int64
dtypes: int64(16), object(17)
memory usage: 167.4+ KB
```

0.2 Inżynieria cech

0.2.1 Kodowanie kategoryczne i dodanie kolumny "Czy dostał 0 pkt"

Chcąc lepiej przewidywać wyniki postanowiliśmy inaczej potraktować osoby z zerowym wynikiem. Nasz plan jest taki, aby najpierw przewidywać czy osoba dostanie 0 pkt, a następnie, jeśli z przewidywania wyjdzie że nie powinna dostać 0 pkt, przewidujemy jej wynik.

[3]:
```
data['schoolsup'].describe()
```

[3]:
```
count     649
unique      2
top        no
freq      581
Name: schoolsup, dtype: object
```

Wyrzucamy również kolumne dotyczącą edukacji ojca, gdyż z EDA wyszło nam że jest ona mocno skorelowana z edukacją matki. Postanowiliśmy wyrzucić jedną z tych cech.

[4]:
```
data = data.drop(labels = "Fedu", axis = 1)
data = data.drop(labels = "Fjob", axis = 1)
```

```
ce_one_hot = OneHotEncoder(cols = ("Mjob", "sex", "school",'famsize',
                                   "address", "Pstatus", "reason",
                                   "guardian", "schoolsup",'famsup', 'paid',
                                   'activities', 'nursery', 'higher',␣
 ↪'internet', 'romantic' ))
df = ce_one_hot.fit_transform(data)
```

[5]:
```
a=df.shape[1]-3
df_G=df.iloc[:,:a]

a=df.shape[1]-1
df=df.iloc[:,:a]
data['is_zero']=np.where(data['G3']==0,0,1)

df.head()
```

[5]:

	school_1	school_2	sex_1	sex_2	age	address_1	address_2	famsize_1	\
0	1	0	1	0	18	1	0	1	
1	1	0	1	0	17	1	0	1	
2	1	0	1	0	15	1	0	0	
3	1	0	1	0	15	1	0	1	
4	1	0	1	0	16	1	0	1	

	famsize_2	Pstatus_1	…	romantic_2	famrel	freetime	goout	Dalc	Walc	\
0	0	1	…	0	4	3	4	1	1	
1	0	0	…	0	5	3	3	1	1	
2	1	0	…	0	4	3	2	2	3	
3	0	0	…	1	3	2	2	1	1	
4	0	0	…	0	4	3	2	1	2	

	health	absences	G1	G2
0	3	4	0	11
1	3	2	9	11
2	3	6	12	13
3	5	0	14	14
4	5	0	11	13

[5 rows x 52 columns]

0.3 Modele

[6]:
```
## Funkcja pomocnicza do testowania modeli

def models_score(model_params, x_train, y_train, x_test, y_test):
    results=[]
    for name, param in model_params.items():
```

```
        ␣
↪classifier=GridSearchCV(param['model'],param['params'],cv=6,return_train_score=False)
        classifier.fit(x_train,  y_train)
        model_performance = np.sqrt(mean_squared_error(classifier.
↪predict(x_test),y_test, squared=True))
        results.append({
            'model': name,
            'best_score': classifier.best_score_,
            'best_params': classifier.best_params_,
            'RMSE': model_performance
        })
    return results

def draw_hists(model, x_test, y_test):
    fig, ax =plt.subplots(1,2, sharey=True, figsize=(12,6))
    sns.histplot(clf.predict(x_test), ax=ax[0])
    sns.histplot(y_test, ax=ax[1])
    ax[0].set_title('Rozkład przewidywany')
    ax[1].set_title('Rozkład rzeczywisty')
    fig.show()
```

0.3.1 Regrasja bez podziału na uczniów, którzy dostali 0pkt

[7]:
```
x_train, x_test, y_train, y_test = train_test_split(df, data["G3"],test_size=0.
↪3, random_state=0)
x_train_G, x_test_G, y_train_G, y_test_G = train_test_split(df_G,␣
↪data["G3"],test_size=0.3, random_state=0)

model_params1={
    'linear_regression':{
        'model': linear_model.LinearRegression(),
        'params': {}
    },
    'lasso':{
        'model': linear_model.Lasso(random_state=15),
        'params':{
            'alpha':[0.1,1,0],
            'normalize':['True','False']
        }
    },
    'svm':{
            'model': svm.SVC(gamma='auto', tol=1e-1, cache_size=2000,␣
↪max_iter=1500),
            'params': {
                'C': [0.001, 0.01, 0.1, 1, 3, 10, 30],
                'kernel': ['linear', 'rbf']
            }
```

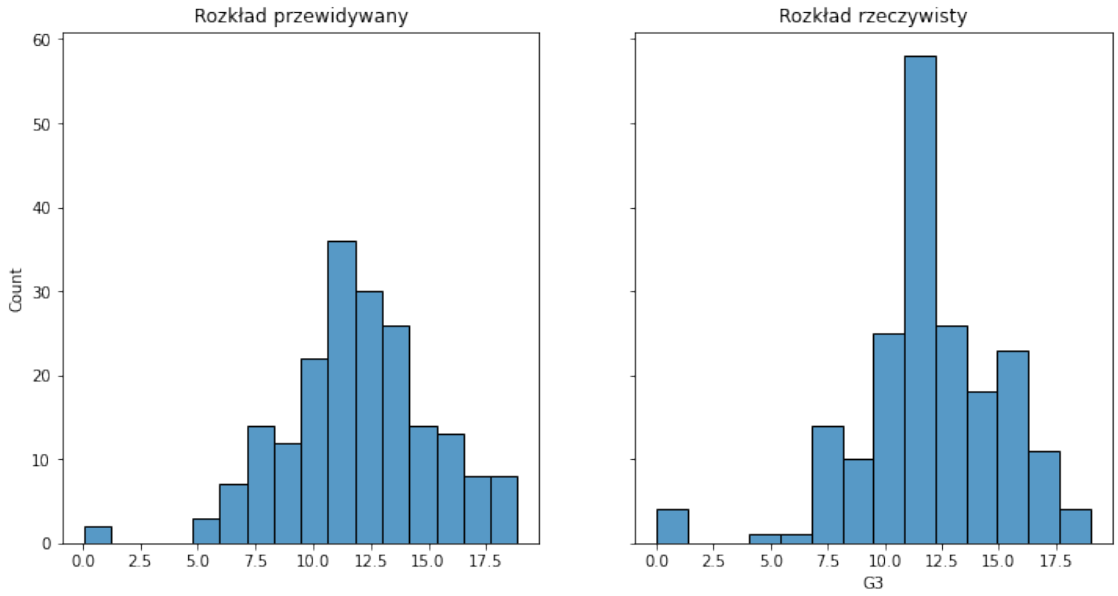
```
    }
}
```

Wyniki z G1 i G2

[8]:
```
results= models_score(model_params1, x_train, y_train, x_test, y_test)
results
```

[8]:
```
[{'model': 'linear_regression',
  'best_score': 0.826048271365063,
  'best_params': {},
  'RMSE': 1.3448902385469212},
 {'model': 'lasso',
  'best_score': 0.8260792371131339,
  'best_params': {'alpha': 0, 'normalize': 'True'},
  'RMSE': 1.3384449713763498},
 {'model': 'svm',
  'best_score': 0.4163157894736842,
  'best_params': {'C': 0.1, 'kernel': 'linear'},
  'RMSE': 1.6235447132424274}]
```

[9]:
```
clf = linear_model.Lasso(alpha=0, normalize = True).fit(x_train, y_train)
draw_hists(clf, x_test, y_test)
```

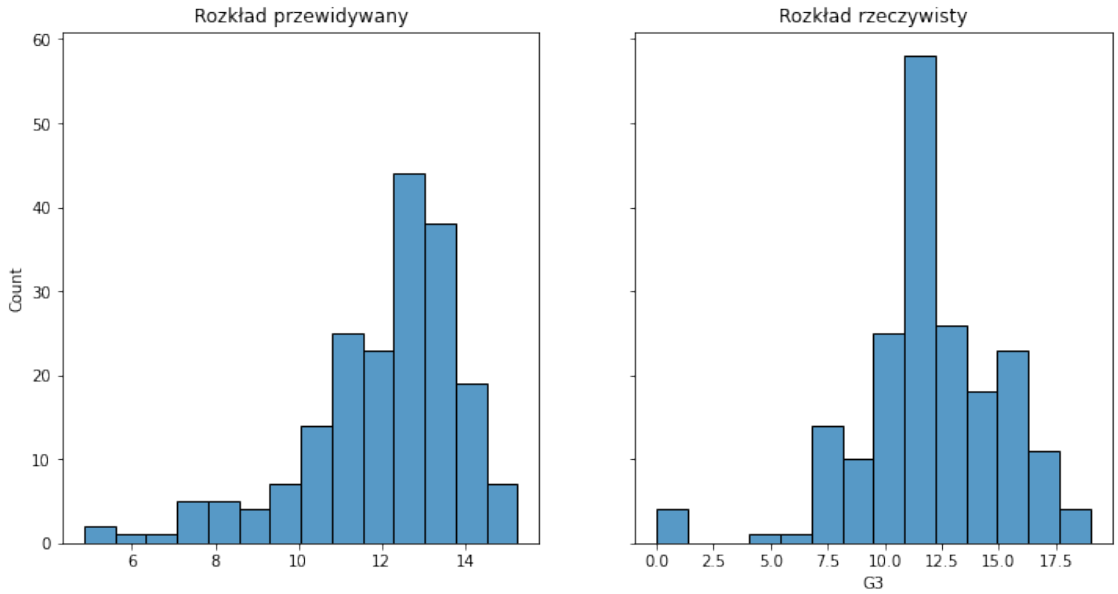


Wyniki bez G1 i G2

[10]:
```
results= models_score(model_params1, x_train_G, y_train_G, x_test_G, y_test_G)
results
```

[10]:
```
[{'model': 'linear_regression',
  'best_score': 0.21248193055614717,
  'best_params': {},
  'RMSE': 2.658618691346799},
 {'model': 'lasso',
  'best_score': 0.21121308154841392,
  'best_params': {'alpha': 0, 'normalize': 'True'},
  'RMSE': 2.649300622572791},
 {'model': 'svm',
  'best_score': 0.21160818713450294,
  'best_params': {'C': 3, 'kernel': 'rbf'},
  'RMSE': 3.550370150438994}]
```

[11]:
```
clf = linear_model.Lasso(alpha=0, normalize = True).fit(x_train_G, y_train_G)
draw_hists(clf, x_test_G, y_test_G)
```



0.3.2 Klasyfikacja uczniów z zerowym wynikiem

[12]:
```
x_train2, x_test2, y_train2, y_test2 = train_test_split(df,␣
↪data["is_zero"],test_size=0.3, random_state=13)
```

[13]:
```
from sklearn.linear_model import LogisticRegression

model_params2={
    'random_forest':{
        'model': RandomForestClassifier(random_state=15),
        'params': {
```

```
            'n_estimators':[1,3,8,13],
            'min_samples_split': [3,5,10,20]
        }
    },
    'logistic_regession':{
        'model': LogisticRegression(random_state=15, solver='liblinear'),
        'params':{
            'C':[1,5,10],
            'penalty':['l1','l2','elasticnet']
        }
    },
    'svm':{
            'model': svm.SVC(gamma='auto', tol=1e-1, cache_size=2000,␣
 ↪max_iter=1500),
            'params': {
                'C': [0.001, 0.01, 0.1, 1, 3, 10, 30],
                'kernel': ['linear', 'rbf']
            }
    }
}
```

[14]:
```
results_isZero= models_score(model_params2, x_train2, y_train2, x_test2,␣
 ↪y_test2)
results_isZero
```

[14]:
```
[{'model': 'random_forest',
  'best_score': 0.9846198830409355,
  'best_params': {'min_samples_split': 3, 'n_estimators': 8},
  'RMSE': 0.10127393670836667},
 {'model': 'logistic_regession',
  'best_score': 0.9823976608187134,
  'best_params': {'C': 1, 'penalty': 'l1'},
  'RMSE': 0.0},
 {'model': 'svm',
  'best_score': 0.9868128654970759,
  'best_params': {'C': 0.01, 'kernel': 'linear'},
  'RMSE': 0.10127393670836667}]
```

0.3.3 Regrasja tylko dla uczniów, którzy nie dostali zero punktów

[15]:
```
only_good_data=df.loc[data.is_zero==1]
data2=data.loc[data.is_zero==1]
x_train3, x_test3, y_train3, y_test3 = train_test_split(only_good_data,␣
 ↪data2["G3"],test_size=0.3, random_state=0)
```

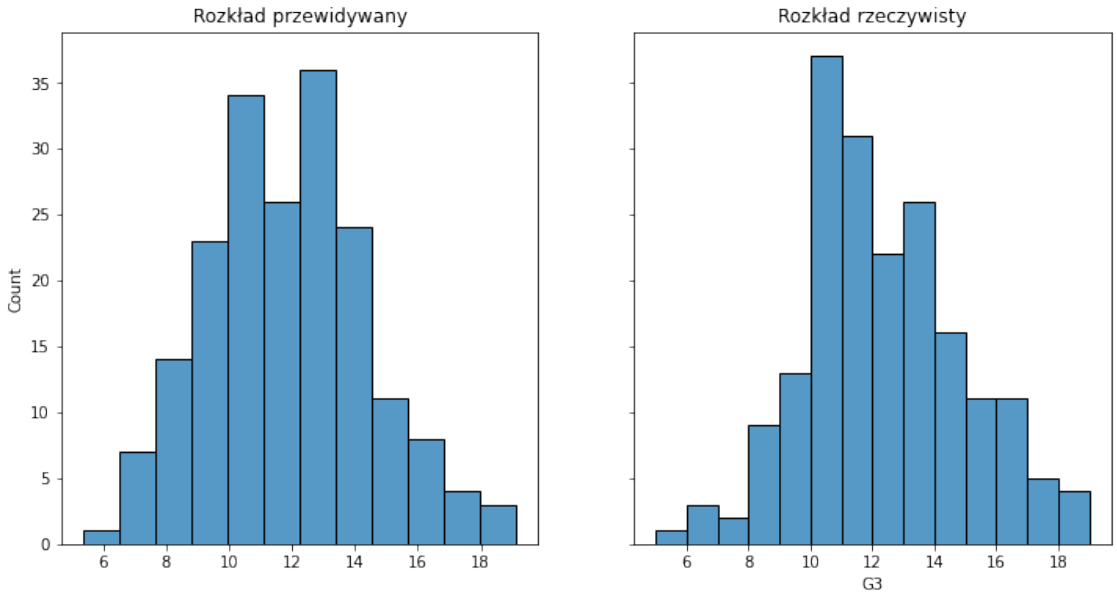
[16]:
```
model_params3={
    'linear_regression':{
```

```
        'model': linear_model.LinearRegression(),
        'params': {}
    },
    'lasso':{
        'model': linear_model.Lasso(random_state=15),
        'params':{
            'alpha':[0.1,1,0],
            'normalize':['True','False']
        }
    }
}
```

[17]:
```
results3= models_score(model_params3, x_train3, y_train3, x_test3, y_test3)
results3
```

[17]:
```
[{'model': 'linear_regression',
  'best_score': 0.8660971870949128,
  'best_params': {},
  'RMSE': 0.9344239094562881},
 {'model': 'lasso',
  'best_score': 0.8655754653074229,
  'best_params': {'alpha': 0, 'normalize': 'True'},
  'RMSE': 0.9344510773077692}]
```

[18]:
```
clf = linear_model.LinearRegression().fit(x_train3, y_train3)
draw_hists(clf, x_test3, y_test3)
```



1 Model z kubełkami

[19]:
```
data_bins = data.drop(labels = "is_zero", axis = 1)
```

[20]:
```
## Podział na kubełki
def divade(x, n):
    return (x//n) * n

df_bins = data_bins["G3"].apply(lambda x: divade(x, 4))

x_train4, x_test4, y_train4, y_test4 = train_test_split(df, df_bins,test_size=0.
↪3, random_state=0)
```

[21]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.neural_network import MLPClassifier

model_params4={
    'random_forest':{
        'model': RandomForestClassifier(random_state=15),
        'params': {
            'n_estimators':[1,3,8,13],
            'min_samples_split': [3,5,10,20]
        }
    },
    'logistic_regession':{
        'model': LogisticRegression(random_state=15, solver='liblinear'),
        'params':{
            'C':[1,5,10],
            'penalty':['l1','l2','elasticnet']
        }
    },
    'svm':{
            'model': svm.SVC(gamma='auto', tol=1e-1, cache_size=2000,␣
↪max_iter=1500),
            'params': {
                'C': [0.001, 0.01, 0.1, 1, 3, 10, 30],
                'kernel': ['linear', 'rbf']
            }
    }
}
```

[22]:
```
results4= models_score(model_params4, x_train4, y_train4, x_test4, y_test4)
results4
```

[22]:
```
[{'model': 'random_forest',
  'best_score': 0.8392397660818715,
  'best_params': {'min_samples_split': 3, 'n_estimators': 13},
```

```
 'RMSE': 1.900067475185134},
{'model': 'logistic_regession',
 'best_score': 0.7291520467836258,
 'best_params': {'C': 5, 'penalty': 'l1'},
 'RMSE': 2.2002330878853815},
{'model': 'svm',
 'best_score': 0.85453216374269,
 'best_params': {'C': 0.01, 'kernel': 'linear'},
 'RMSE': 1.718675697694639}]
```

[23]:
```
clf = svm.SVC(gamma='auto', tol=1e-1, cache_size=2000, max_iter=1500, C = 5,␣
↪kernel = 'linear').fit(x_train4, y_train4)
draw_hists(clf, x_test4, y_test4)
```