

# FeatureEngineering

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## 1 Feature engineering

### 1.1 Milestone 2

#### 1.1.1 Dominik Pawlak, Przemysław Olender

```
[79]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib
import category_encoders as ce
import warnings
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from statistics import stdev
import xgboost as xgb
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
```

```
[80]: grades_df = pd.read_csv('school_grades_dataset.csv')

print(grades_df.shape)
grades_df.head()
```

(649, 33)

```
[80]:  school sex  age address famsize Pstatus  Medu  Fedu    Mjob    Fjob ... \
0      GP   F   18      U    GT3        A     4     4  at_home  teacher ...
1      GP   F   17      U    GT3        T     1     1  at_home   other ...
2      GP   F   15      U    LE3        T     1     1  at_home   other ...
3      GP   F   15      U    GT3        T     4     2  health  services ...
4      GP   F   16      U    GT3        T     3     3   other    other ...
```

	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G2	G3
0	4	3	4	1	1	3	4	0	11	11
1	5	3	3	1	1	3	2	9	11	11
2	4	3	2	2	3	3	6	12	13	12
3	3	2	2	1	1	5	0	14	14	14
4	4	3	2	1	2	5	0	11	13	13

[5 rows x 33 columns]

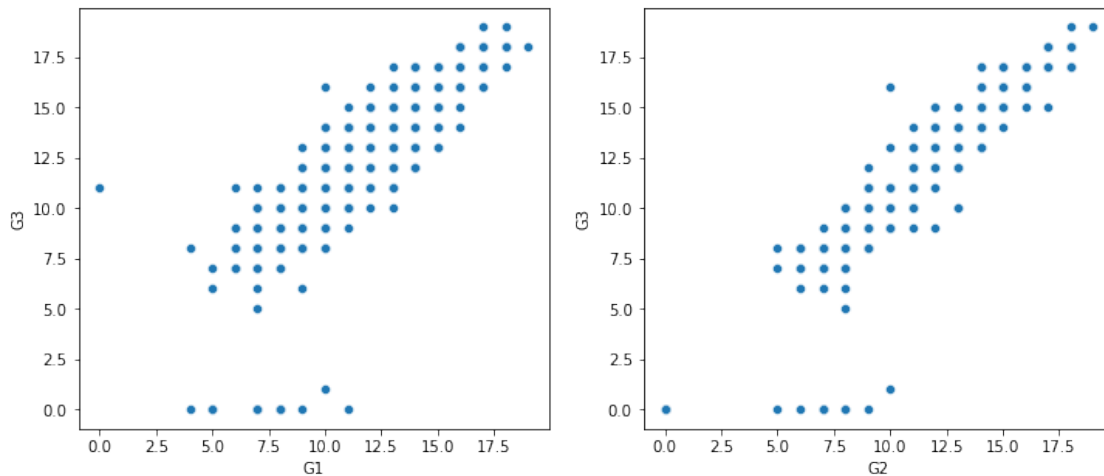
## 1.2 Regresja liniowa dla G1 i G2

```
[81]: fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (12, 5))

sns.scatterplot(data = grades_df, x = 'G1', y = 'G3', ax = ax1)
sns.scatterplot(data = grades_df, x = 'G2', y = 'G3', ax = ax2)

plt.show()

# liniowa zaleznosc miedzy G1, G2, i G3
```



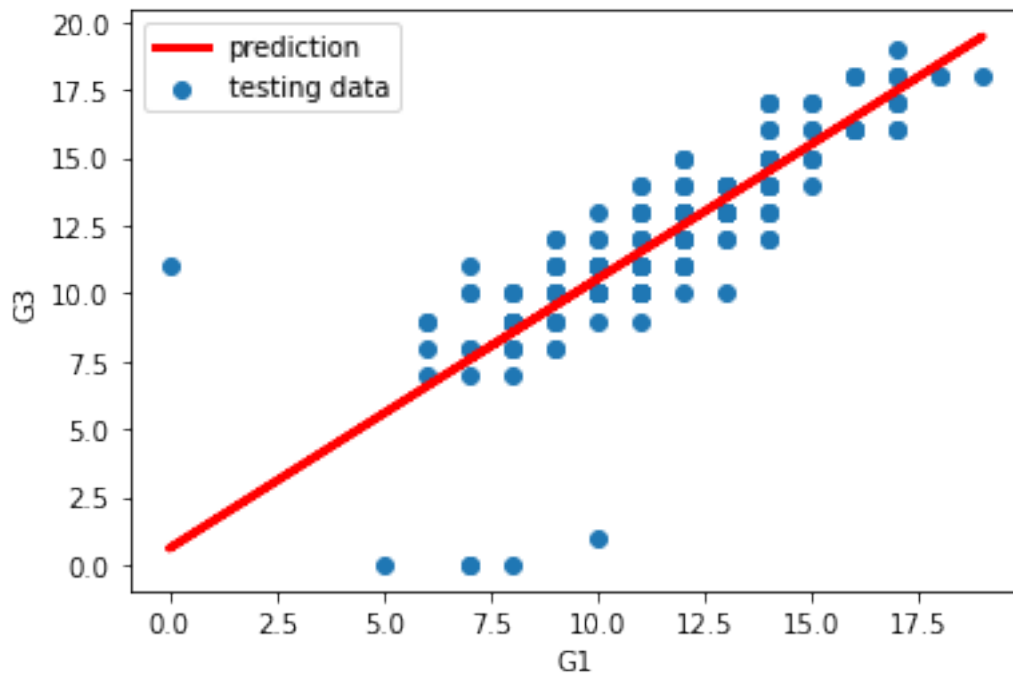
Sprawdźmy jak sprawdzi się prosty model regresji liniowej dla G1, G2 oraz G1 i G2 jednocześnie.

```
[82]: X1 = grades_df[['G1']]
Y = grades_df['G3']

model1 = LinearRegression()
X1_train, X1_test, Y1_train, Y1_test = train_test_split(X1, Y, test_size = 0.3,
    ↪random_state = 1)
model1.fit(X1_train, Y1_train)
```

```
Y1_test_predicted = model1.predict(X1_test)
```

```
[83]: plt.scatter(X1_test, Y1_test, label = 'testing data')
plt.plot(X1_test, Y1_test_predicted, label = 'prediction', linewidth = 3, color = 'red')
plt.xlabel('G1')
plt.ylabel('G3')
plt.legend(loc = 'upper left')
plt.show()
```



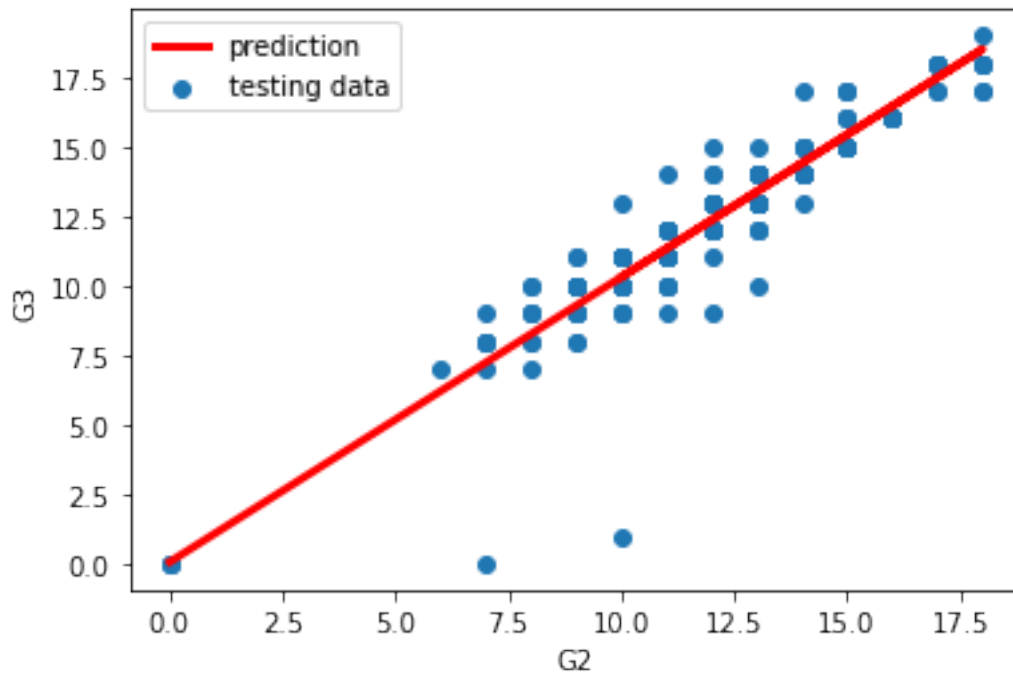
```
[84]: print(f'RMSE: {mean_squared_error(Y1_test, Y1_test_predicted, squared = False)}')
print(f'R-squared: {model1.score(X1_test, Y1_test)}')
```

RMSE: 1.8966454815676594

R-squared: 0.673962037596874

```
[85]: X2 = grades_df[['G2']]
model2 = LinearRegression()
X2_train, X2_test, Y2_train, Y2_test = train_test_split(X2, Y, test_size = 0.3, random_state = 1)
model2.fit(X2_train, Y2_train)
Y2_test_predicted = model2.predict(X2_test)
```

```
[86]: plt.scatter(X2_test, Y2_test, label = 'testing data')
plt.plot(X2_test, Y2_test_predicted, label = 'prediction', linewidth = 3, color='red')
plt.xlabel('G2')
plt.ylabel('G3')
plt.legend(loc = 'upper left')
plt.show()
```



```
[87]: print(f'RMSE: {mean_squared_error(Y2_test, Y2_test_predicted, squared = False)}')
print(f'R-squared: {model2.score(X2_test, Y2_test)}')
```

RMSE: 1.23850271285229  
R-squared: 0.8609760021107454

```
[88]: X3 = grades_df[['G1', 'G2']]
model3 = LinearRegression()
X3_train, X3_test, Y3_train, Y3_test = train_test_split(X3, Y, test_size = 0.3, random_state = 1)
model3.fit(X3_train, Y3_train)
Y3_test_predicted = model3.predict(X3_test)
```

```
[89]: print(f'RMSE: {mean_squared_error(Y3_test, Y3_test_predicted, squared = False)}')
```

```
print(f'R-squared: {model3.score(X3_test, Y3_test)}')
```

RMSE: 1.2238309021485727

R-squared: 0.8642503623493104

Najlepiej wypadła regresja oparta na G1 i G2, model oparty tylko na G2 jest minimalnie gorszy, najslabej prezentuje się model oparty na G1.

### 1.3 Przewidywanie G3 za pomocą innych zmiennych oraz bez G1 i G2

```
[90]: grades_df[grades_df['G3'] == 0]
```

```
[90]:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	\
163	GP	M	18	U	LE3	T	1	1	other	other	
440	MS	M	16	U	GT3	T	1	1	at_home	services	
519	MS	M	16	R	GT3	T	2	1	other	services	
563	MS	M	17	U	GT3	T	2	2	other	other	
567	MS	M	18	R	GT3	T	3	2	services	other	
583	MS	F	18	R	GT3	T	2	2	other	other	
586	MS	F	17	U	GT3	T	4	2	teacher	services	
597	MS	F	18	R	GT3	T	2	2	at_home	other	
603	MS	F	18	R	LE3	A	4	2	teacher	other	
605	MS	F	19	U	GT3	T	1	1	at_home	services	
610	MS	F	19	R	GT3	A	1	1	at_home	at_home	
626	MS	F	18	R	GT3	T	4	4	other	teacher	
637	MS	M	18	R	GT3	T	2	1	other	other	
639	MS	M	19	R	GT3	T	1	1	other	services	
640	MS	M	18	R	GT3	T	4	2	other	other	

	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G2	G3
163	...	2	3	5	2	5	4	0	11	9	0
440	...	5	4	5	4	5	3	0	7	0	0
519	...	5	2	1	1	1	2	0	8	7	0
563	...	1	2	1	2	3	5	0	7	0	0
567	...	2	3	1	2	2	5	0	4	0	0
583	...	5	5	5	1	1	3	0	8	6	0
586	...	5	5	5	1	3	5	0	8	8	0
597	...	4	3	3	1	1	4	0	9	0	0
603	...	5	3	1	1	1	5	0	5	0	0
605	...	5	5	5	2	3	2	0	5	0	0
610	...	3	5	4	1	4	1	0	8	0	0
626	...	3	2	2	4	2	5	0	7	5	0
637	...	4	4	3	1	3	5	0	7	7	0
639	...	4	3	2	1	3	5	0	5	8	0
640	...	5	4	3	4	3	3	0	7	7	0

[15 rows x 33 columns]

Cieżko jest nie zdobyć żadnego punktu na egzaminie, zakładamy, że te osoby nie podeszły i nie można przewidzieć ilości punktów, usuwamy rekordy z ramki.

```
[91]: grades_df = grades_df[grades_df['G3'] != 0]

grades_df.shape
```

```
[91]: (634, 33)
```

W naszej ramce mamy też dużo zmiennych kategorycznych, zakodujemy je, żeby usprawnić działanie modeli.

```
[92]: cat_cols = ['school', 'sex', 'address', 'famsize', 'Mjob', 'Fjob', 'reason', 'guardian', 'Pstatus', 'sex', 'school']
      bin_cols = ['famsup', 'activities', 'nursery', 'internet', 'romantic', 'higher', 'paid', 'schoolsup']

      grades_df_new = grades_df.drop(columns = cat_cols)
      grades_df_new = grades_df.drop(columns = bin_cols)

      for i in cat_cols:
          means = grades_df.groupby(i)['G3'].mean()
          grades_df_new[i] = grades_df[i].map(means)

      for i in bin_cols:
          encoder = ce.OrdinalEncoder(mapping = [{'col': i, 'mapping': {'yes': 1, 'no': 0}},])
          grades_df_new[i] = encoder.fit_transform(grades_df)[i]
```

Pogrupujemy rezultat G3 w przedział, aby nie trzeba było przewidywać dokładniej liczby - zadanie będzie prostsze.

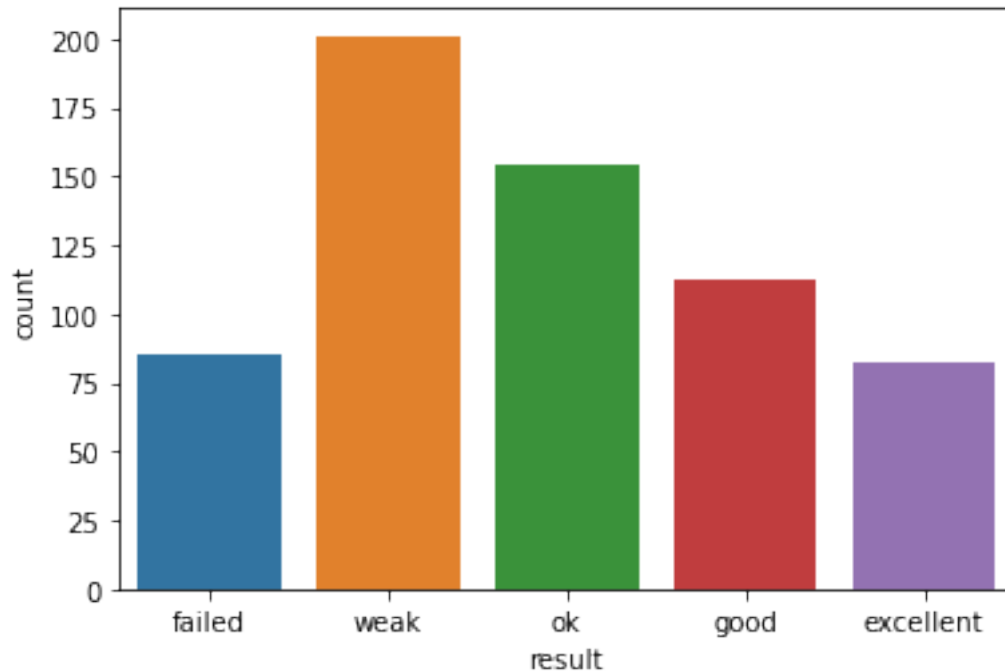
```
[93]: names = ['failed', 'weak', 'ok', 'good', 'excellent']

      grades_df_new['result'] = pd.cut(grades_df['G3'], bins=[-1, 9, 11, 13, 15, 21], labels = names)

      sns.countplot(grades_df_new['result'], order = names)
```

```
C:\Users\User\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

```
[93]: <AxesSubplot:xlabel='result', ylabel='count'>
```



```
[94]: # funkcja liczby accuracy dla 4 modeli i za pomocą xgboost wybiera
      ↪ najważniejsze cechy

def modelScores(X, X_train, X_test, y_train, y_test):

    importance = pd.DataFrame()
    importance['col'] = X.columns
    importance['xgb'] = 0

    model_xgb = xgb.XGBClassifier(
        max_depth=4
        ,learning_rate=0.2
        ,reg_lambda=1
        ,n_estimators=150
        ,subsample = 0.9
        ,colsample_bytree = 0.9)
    model_xgb.fit(X_train, y_train)

    importance['xgb'] = importance['xgb'] + model_xgb.feature_importances_ / 100
    importance = importance.sort_values(axis=0, ascending=False, by='xgb')

    print(importance.reset_index().drop('index', axis = 1))

    print(f'xgboost accuracy: {model_xgb.score(X_test,y_test)}')
```

```

modellLR = LogisticRegression(random_state=1, max_iter=100000)
modellLR.fit(X_train, y_train)
y_hat = modellLR.predict(X_test)
print(f'Logistic Regression accuracy: {accuracy_score(y_test, y_hat)}')

model_rf = RandomForestClassifier(n_estimators=188,
                                max_depth=5,
                                min_samples_split = 7,
                                max_features = len(X_train.columns),
                                random_state=0,
                                n_jobs = 15)

model_rf.fit(X_train, y_train)
print(f'RandomForestClassifier accuracy: {model_rf.score(X_test,y_test)}')

modell1 = DecisionTreeClassifier(random_state=1)
clf = BaggingClassifier(base_estimator=model_rf,
                        n_estimators=100, random_state=0)
clf.fit(X_train, y_train)
print(f'DecisionTreeClassifier accuracy: {clf.score(X_test,y_test)}')

return importance['col'].head(10)

```

```

[95]: X = grades_df_new.drop(['G3', 'result'], axis = 1)
      Y = grades_df_new['result']

      X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,
      ↪random_state=42)

```

```

[96]: cols = modelScores(X, X_train, X_test, y_train, y_test)

```

	col	xgb
0	G2	0.002208
1	G1	0.000905
2	higher	0.000437
3	paid	0.000432
4	schoolsup	0.000401
5	school	0.000306
6	famsize	0.000249
7	Pstatus	0.000247
8	freetime	0.000245
9	Dalc	0.000244
10	Walc	0.000242
11	Fjob	0.000241
12	Mjob	0.000236
13	health	0.000234
14	traveltime	0.000226
15	absences	0.000225



```

16         age  0.000218
17    failures 0.000217
18         reason 0.000216
19    studytime 0.000214
20    internet 0.000207
21         Fedu 0.000197
22    activities 0.000194
23        nursery 0.000194
24         goout 0.000181
25         Medu 0.000180
26         sex 0.000174
27    guardian 0.000159
28        famrel 0.000155
29        famsup 0.000146
30    romantic 0.000140
31    address 0.000131
xgboost accuarcy: 0.6596858638743456
Logistic Regression accuracy: 0.6492146596858639
RandomForestClassifier accuracy: 0.743455497382199
DecisionTreeClassifier accuracy: 0.7539267015706806

```

```

[97]: X = grades_df_new[cols]
      Y = grades_df_new['result']

      X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,
      ↪random_state=42)

      modelScores(X, X_train, X_test, y_train, y_test)

```

```

          col      xgb
0         G2  0.004274
1         G1  0.001353
2    schoolsup 0.000636
3         paid 0.000598
4        school 0.000589
5         Dalc 0.000565
6    famsize 0.000516
7        higher 0.000515
8    freetime 0.000510
9    Pstatus 0.000444
xgboost accuarcy: 0.6910994764397905
Logistic Regression accuracy: 0.6910994764397905
RandomForestClassifier accuracy: 0.7382198952879581
DecisionTreeClassifier accuracy: 0.743455497382199

```

```

[97]: 0         G2
      1         G1

```

```

4     schoolsup
3       paid
5       school
9       Dalc
6     famsize
2     higher
8     freetime
7     Pstatus
Name: col, dtype: object

```

```

[98]: X = grades_df_new.drop(['G3', 'result'], axis = 1)
      Y = grades_df_new['G3']

      X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,
      ↪random_state=42)

```

```

[99]: cols = modelScores(X, X_train, X_test, y_train, y_test)

```

	col	xgb
0	G2	0.001785
1	G1	0.000653
2	paid	0.000508
3	Pstatus	0.000445
4	higher	0.000393
5	Fedu	0.000322
6	failures	0.000314
7	school	0.000289
8	guardian	0.000284
9	Dalc	0.000273
10	schoolsup	0.000270
11	Mjob	0.000253
12	age	0.000250
13	famsize	0.000248
14	freetime	0.000240
15	Fjob	0.000240
16	goout	0.000238
17	studytime	0.000233
18	internet	0.000231
19	famrel	0.000224
20	traveltime	0.000222
21	Walc	0.000221
22	address	0.000220
23	health	0.000207
24	absences	0.000205
25	reason	0.000199
26	Medu	0.000199
27	romantic	0.000192

```

28         sex    0.000176
29  activities  0.000157
30    nursery   0.000156
31     famsup    0.000151
xgboost accuarcy: 0.3612565445026178
Logistic Regression accuracy: 0.3089005235602094
RandomForestClassifier accuracy: 0.450261780104712
DecisionTreeClassifier accuracy: 0.45549738219895286

```

```

[100]: X = grades_df_new[cols]
       Y = grades_df_new['G3']

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,
↳random_state=42)

modelScores(X, X_train, X_test, y_train, y_test)

```

```

      col      xgb
0      G2  0.003245
1    paid  0.001138
2      G1  0.001052
3  Pstatus  0.000766
4   higher  0.000672
5  failures  0.000659
6  guardian  0.000653
7     Dalc  0.000627
8     Fedu  0.000596
9   school  0.000592
xgboost accuarcy: 0.42408376963350786
Logistic Regression accuracy: 0.36649214659685864
RandomForestClassifier accuracy: 0.387434554973822
DecisionTreeClassifier accuracy: 0.4397905759162304

```

```

[100]: 0      G2
      2    paid
      1      G1
      3  Pstatus
      4   higher
      6  failures
      8  guardian
      9     Dalc
      5     Fedu
      7   school
      Name: col, dtype: object

```

Wyniki gorsze niż dla prostej regresji liniowej.

Stworzyliśmy prosty model opierający się a G1 i G2, spróbujmy teraz bez tych atrybutów.

```
[101]: grades_df_new = grades_df_new.drop(columns = ['G1', 'G2'])
```

Przewidywanie przedziału oceny za pomocą wszystkich kolumn:

```
[102]: X = grades_df_new.drop(['G3', 'result'], axis = 1)
Y = grades_df_new['result']

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,
↳random_state=42)
```

```
[103]: cols = modelScores(X, X_train, X_test, y_train, y_test)
```

	col	xgb
0	failures	0.000789
1	higher	0.000613
2	school	0.000549
3	schoolsup	0.000470
4	studytime	0.000403
5	paid	0.000360
6	internet	0.000339
7	Pstatus	0.000336
8	freetime	0.000331
9	Dalc	0.000326
10	absences	0.000324
11	Walc	0.000319
12	traveltime	0.000318
13	nursery	0.000315
14	sex	0.000313
15	Fedu	0.000312
16	Mjob	0.000303
17	Medu	0.000291
18	reason	0.000277
19	goout	0.000268
20	age	0.000262
21	famsup	0.000260
22	Fjob	0.000252
23	guardian	0.000250
24	famrel	0.000247
25	health	0.000244
26	romantic	0.000243
27	address	0.000232
28	activities	0.000232
29	famsize	0.000222

xgboost accuaracy: 0.3193717277486911  
Logistic Regression accuracy: 0.28272251308900526  
RandomForestClassifier accuracy: 0.31413612565445026  
DecisionTreeClassifier accuracy: 0.32460732984293195

Przewidywanie przedziału oceny za pomocą najważniejszych kolumn:

```
[104]: X = grades_df_new[cols]
Y = grades_df_new['result']

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,
↳random_state=42)
modelScores(X, X_train, X_test, y_train, y_test)
```

```
      col      xgb
0  failures 0.001669
1   higher 0.001527
2   school 0.001031
3 schoolsup 0.000964
4    paid  0.000941
5 studytime 0.000835
6  freetime 0.000795
7  internet 0.000780
8     Dalc  0.000775
9  Pstatus 0.000683
xgboost accuracy: 0.2879581151832461
Logistic Regression accuracy: 0.2931937172774869
RandomForestClassifier accuracy: 0.28272251308900526
DecisionTreeClassifier accuracy: 0.27225130890052357
```

```
[104]: 0    failures
1      higher
2      school
3 schoolsup
5      paid
4 studytime
8  freetime
6  internet
9      Dalc
7  Pstatus
Name: col, dtype: object
```

Przewidywanie dokładnej oceny za pomocą wszystkich kolumn:

```
[105]: X = grades_df_new.drop(['G3', 'result'], axis = 1)
Y = grades_df_new['G3']

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,
↳random_state=42)

cols = modelScores(X, X_train, X_test, y_train, y_test)
```

```
      col      xgb
```

0	failures	0.000595
1	school	0.000496
2	higher	0.000474
3	Pstatus	0.000407
4	paid	0.000399
5	schoolsup	0.000396
6	guardian	0.000391
7	studytime	0.000359
8	Dalc	0.000357
9	Fedu	0.000356
10	absences	0.000347
11	reason	0.000333
12	Mjob	0.000323
13	Fjob	0.000321
14	age	0.000318
15	address	0.000303
16	internet	0.000301
17	freetime	0.000295
18	goout	0.000294
19	traveltime	0.000293
20	sex	0.000279
21	Medu	0.000275
22	health	0.000274
23	activities	0.000271
24	famsup	0.000270
25	famsize	0.000270
26	famrel	0.000259
27	nursery	0.000259
28	Walc	0.000248
29	romantic	0.000235

xgboost accuracy: 0.18848167539267016

Logistic Regression accuracy: 0.17277486910994763

RandomForestClassifier accuracy: 0.17277486910994763

DecisionTreeClassifier accuracy: 0.18848167539267016

Przewidywanie dokładnej oceny za pomocą najważniejszych kolumn:

```
[106]: X = grades_df_new[cols]
Y = grades_df_new['G3']

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,
↳ random_state=42)

modelScores(X, X_train, X_test, y_train, y_test)
```

	col	xgb
0	failures	0.001404
1	higher	0.001228

```

2      paid  0.001070
3  schoolsup 0.001049
4      school 0.000984
5  guardian 0.000903
6    Pstatus 0.000872
7      Dalc  0.000855
8      Fedu  0.000836
9  studytime 0.000799
xgboost accuarcy: 0.1099476439790576
Logistic Regression accuracy: 0.17277486910994763
RandomForestClassifier accuracy: 0.13612565445026178
DecisionTreeClassifier accuracy: 0.16230366492146597

```

```

[106]: 0      failures
        2      higher
        4      paid
        5  schoolsup
        1      school
        6  guardian
        3    Pstatus
        8      Dalc
        9      Fedu
        7  studytime
Name: col, dtype: object

```