Задача 14

Используя данные о школьниках, выявить степень их алкогольной зависимости. В данных, взятых с UCI 'Students' (исходная выборка изъята из UCI, но осталась в других источниках), содержится информация о 30 признаках для каждого школьника, включая социальные и гендерные, а также указана материальная обеспеченность и количество свободного времени. Выбрать на свой взгляд наиболее весомые признаки и предсказать степень употребления алкоголя по выходным или будним по шкале от 0 до 5.

Данные: [https://github.com/amanchoudhary/student-alcohol-consumption-prediction (https://github.com/amanchoudhary/student-alcohol-consumption-prediction)](https://github.com/amanchoudhary/student-alcohol-consumption-prediction)

In [41]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.preprocessing import OneHotEncoder, scale
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, accuracy_score
import seaborn as sns
```

In [42]:
```python
data = pd.read_csv('data.csv')
data.head(3)
```

Out[42]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	famrel	freetime	goout	Dalc	Walc
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	4	3	4	1	1
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	5	3	3	1	1
2	GP	F	15	U	LE3	T	1	1	at_home	other	...	4	3	2	2	3

3 rows × 33 columns

Описание признаков:

feature	description
school	student's school (binary: 'GP' - Gabriel Pereira or 'MS' - Mousinho da Silveira)
sex	student's sex (binary: 'F' - female or 'M' - male)
age	student's age (numeric: from 15 to 22)
address	student's home address type (binary: 'U' - urban or 'R' - rural)
famsize	family size (binary: 'LE3' - less or equal to 3 or 'GT3' - greater than 3)
Pstatus	parent's cohabitation status (binary: 'T' - living together or 'A' - apart)
Medu	mother's education (numeric: 0 - none, 1 - primary education (4th grade), 2 – 5th to 9th grade, 3 – secondary education or 4 – higher education)
Fedu	father's education (numeric: 0 - none, 1 - primary education (4th grade), 2 – 5th to 9th grade, 3 – secondary education or 4 – higher education)
Mjob	mother's job (nominal: 'teacher', 'health' care related, civil 'services' (e.g. administrative or police), 'at_home' or 'other')
Fjob	father's job (nominal: 'teacher', 'health' care related, civil 'services' (e.g. administrative or police), 'at_home' or 'other')
reason	reason to choose this school (nominal: close to 'home', school 'reputation', 'course' preference or 'other')
guardian	student's guardian (nominal: 'mother', 'father' or 'other'
traveltime	home to school travel time (numeric: 1 - <15 min., 2 - 15 to 30 min., 3 - 30 min. to 1 hour, or 4 - >1 hour)
studytime	weekly study time (numeric: 1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours)
failures	number of past class failures (numeric: n if 1<=n<3, else 4)

feature	description
schoolsup	extra educational support (binary: yes or no)
famsup	family educational support (binary: yes or no)
paid	extra paid classes within the course subject (Math or Portuguese) (binary: yes or no)
activities	extra-curricular activities (binary: yes or no)
nursery	attended nursery school (binary: yes or no)
higher	wants to take higher education (binary: yes or no)
internet	Internet access at home (binary: yes or no)
romantic	with a romantic relationship (binary: yes or no)
famrel	quality of family relationships (numeric: from 1 - very bad to 5 - excellent)
freetime	free time after school (numeric: from 1 - very low to 5 - very high)
goout	going out with friends (numeric: from 1 - very low to 5 - very high)
Dalc	workday alcohol consumption (numeric: from 1 - very low to 5 - very high)
Walc	weekend alcohol consumption (numeric: from 1 - very low to 5 - very high)
health	current health status (numeric: from 1 - very bad to 5 - very good)
absences	number of school absences (numeric: from 0 to 93)

Подготовим данные: заменим категориальные признаки на бинарные (one-hot encoding), разделим входные признаки и те, которые мы должны предсказать.

In [43]:

```
data.replace({'yes': 1, 'no': 0}, inplace=True)
data['school'].replace({'GP': 1, 'MS': 0}, inplace=True)
data['sex'].replace({'F': 1, 'M': 0}, inplace=True)
data['address'].replace({'R': 1, 'U': 0}, inplace=True)
data['famsize'].replace({'GT3': 1, 'LE3': 0}, inplace=True)
data['Pstatus'].replace({'A': 1, 'T': 0}, inplace=True)
data = data.rename(columns={'school': 'GP_school',
            'sex': 'is_female',
            'address': 'address_is_rural',
            'famsize': 'big_family',
            'Pstatus': 'parents_live_apart'})
data.head(3)
```

Out[43]:

	GP_school	is_female	age	address_is_rural	big_family	parents_live_apart	Medu	Fedu	Mjob	Fjob	...	famrel
0	1	1	18	0	1	1	4	4	at_home	teacher	...	4
1	1	1	17	0	1	0	1	1	at_home	other	...	5
2	1	1	15	0	0	0	1	1	at_home	other	...	4

3 rows × 33 columns

In [44]:

```
enc = OneHotEncoder(sparse=False)
categorial = ['Mjob', 'Fjob', 'reason', 'guardian']
enc.fit(data[categorial])
enc.get_feature_names()
encoded = pd.DataFrame(
    enc.transform(data[categorial]),
    columns=enc.get_feature_names())
encoded.drop([f'x{i}_other' for i in range(4)], axis=1, inplace=True)
data.drop(categorial, axis=1, inplace=True)
data = data.join(encoded)
data = data.astype('float64')
data.head(3)
```

Out[44]:

	GP_school	is_female	age	address_is_rural	big_family	parents_live_apart	Medu	Fedu	traveltime	studytime	...	x0
0	1.0	1.0	18.0	0.0	1.0	1.0	4.0	4.0	2.0	2.0	...	
1	1.0	1.0	17.0	0.0	1.0	0.0	1.0	1.0	1.0	2.0	...	
2	1.0	1.0	15.0	0.0	0.0	0.0	1.0	1.0	1.0	2.0	...	

3 rows × 42 columns

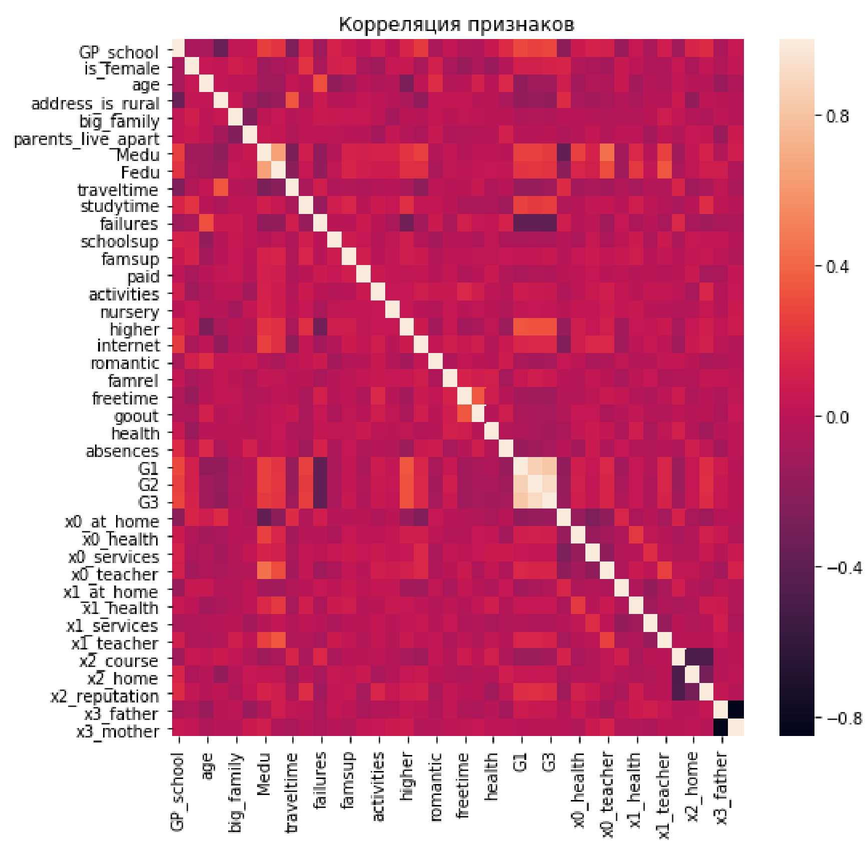
In [39]:

```
y_Dalc = data['Dalc']
y_Walc = data['Walc']
data.drop(['Dalc', 'Walc'], axis=1, inplace=True)
```

Теперь посмотрим, какие признаки кореллируют и уберём лишние.

In [40]:

```
plt.figure(figsize=(8,8))
sns.heatmap(data.corr())
t = plt.title("Корреляция признаков")
```



Итак, из признаков с оценками (`G1, G2, G3`) оставим только `G3` , а `Fedu` и `Medu` усредним.

In [34]:
```
data['parents_education'] = (data['Fedu'] + data['Medu'])/2
data.drop(['Fedu', 'Medu', 'G1', 'G2'], axis=1, inplace=True)
data = pd.DataFrame(scale(data), columns=data.columns)
data.head(3)
```

Out[34]:

	GP_school	is_female	age	address_is_rural	big_family	parents_live_apart	traveltime	studytime	failures	sch
0	0.730944	0.833377	1.031695	-0.660182	0.648175	2.666927	0.576718	0.083653	-0.374305	2.9
1	0.730944	0.833377	0.210137	-0.660182	0.648175	-0.374963	-0.760032	0.083653	-0.374305	-0.3
2	0.730944	0.833377	-1.432980	-0.660182	-1.542792	-0.374963	-0.760032	0.083653	-0.374305	2.9

3 rows × 37 columns

In [8]:
```
X_train, X_test, y_train, y_test = train_test_split(data, y_Dalc,
                                                    test_size=0.3,
                                                    random_state=22)
```

Будем рассматривать задачу регрессии (хотя фактически нас просят предсказать 5 классов, но на них есть порядок). В ответе округлим предсказания до ближайшего целого от 1 до 5.

In [9]:
```
lr = LinearRegression(fit_intercept=True)
lr.fit(X_train, y_train)
y_pred = lr.predict(X_train)
print('Train')
print('no round:', mean_squared_error(y_pred, y_train))
print('rounded:', mean_squared_error(y_pred.round(), y_train))
print('accuracy:', accuracy_score(np.minimum(np.round(y_pred), 5), y_train))

print('Test')
y_test_pred = lr.predict(X_test)
print('no round:', mean_squared_error(y_test_pred, y_test))
print('rounded:', mean_squared_error(y_test_pred.round(), y_test))
print('accuracy:', accuracy_score(np.minimum(np.round(y_test_pred), 5), y_test))
```

```
Train
no round: 0.5958400507521732
rounded: 0.7092511013215859
accuracy: 0.579295154185022
Test
no round: 0.8545655788660281
rounded: 1.005128205128205
accuracy: 0.5128205128205128
```

Выше мы использовали все доступные признаки. Теперь попробуем установить оптимальное число признаков, пользуясь критерием Стьюдента для гипотезы о незначимости каждого из признаков. Отсортируем признаки в порядке возрастания pvalue и будем последовательно добавлять следующие по значимости.

In [18]:
```
from statsmodels.regression.linear_model import OLS
results = OLS(y_train, X_train, hasconst=True).fit(use_t=True)
feature_importance = results.pvalues.to_dict()
sorted_features = sorted(feature_importance, key=feature_importance.get)
features = len(sorted_features)
```

In [11]:
```
mse_results = []
accuracy_results = []
mse_results_round = []
for k in range(1, features + 1):
    lr = LinearRegression(fit_intercept=True)
    reduced_features = sorted_features[:k]
    X_train_reduced = X_train[reduced_features]
    X_test_reduced = X_test[reduced_features]
    lr.fit(X_train_reduced, y_train)

    y_pred = lr.predict(X_train_reduced)
    y_test_pred = lr.predict(X_test_reduced)
    y_pred_rounded = np.minimum(np.round(y_pred), 5)
    y_test_pred_rounded = np.minimum(np.round(y_test_pred), 5)
    mse_results.append((mean_squared_error(y_pred, y_train),
                       mean_squared_error(y_test_pred, y_test)))
    mse_results_round.append((mean_squared_error(y_pred_rounded, y_train),
                       mean_squared_error(y_test_pred_rounded, y_test)))
    accuracy_results.append((accuracy_score(y_pred_rounded, y_train),
                       accuracy_score(y_test_pred_rounded, y_test)))
```

In [12]:
```
mse_results_train = np.array(mse_results_round).T[0]
mse_results_test = np.array(mse_results_round).T[1]
acc_results_train = np.array(accuracy_results).T[0]
acc_results_test = np.array(accuracy_results).T[1]
```

Посчитаем дисперсию ошибки при взятии разных подвыборок в качестве тестовой.

In [13]:
```
indices = np.arange(data.shape[0])
indices_shuffled = []
test_size = int(np.round(0.3 * data.shape[0]))
partitions_size = 100
mse_data = np.zeros((partitions_size, features))
accuracy_data = np.zeros((partitions_size, features))
mse_test_data = np.zeros((partitions_size, features))
accuracy_test_data = np.zeros((partitions_size, features))
for i in range(partitions_size):
    indices_shuffled = np.random.permutation(indices)
    X_train = data.iloc[indices_shuffled[test_size:]]
    X_test = data.iloc[indices_shuffled[:test_size]]
    y_train = y_Dalc[indices_shuffled[test_size:]]
    y_test = y_Dalc[indices_shuffled[:test_size]]
    for k in range(1, features + 1):
        lr = LinearRegression(fit_intercept=True)
        reduced_features = sorted_features[:k]
        X_train_reduced = X_train[reduced_features]
        X_test_reduced = X_test[reduced_features]
        lr.fit(X_train_reduced, y_train)
        y_pred = lr.predict(X_train_reduced)
        y_test_pred = lr.predict(X_test_reduced)
        y_pred_rounded = np.minimum(np.round(y_pred), 5)
        y_test_pred_rounded = np.minimum(np.round(y_test_pred), 5)
        mse_data[i][k-1] = mean_squared_error(y_pred_rounded, y_train)
        accuracy_data[i][k-1] = accuracy_score(y_pred_rounded, y_train)
        mse_test_data[i][k-1] = mean_squared_error(y_test_pred_rounded, y_test)
        accuracy_test_data[i][k-1] = accuracy_score(y_test_pred_rounded, y_test)
```

In [ ]:
```

```

Посмотрим на среднюю дисперсию при разном количестве признаков (более наглядно покажем на графике)

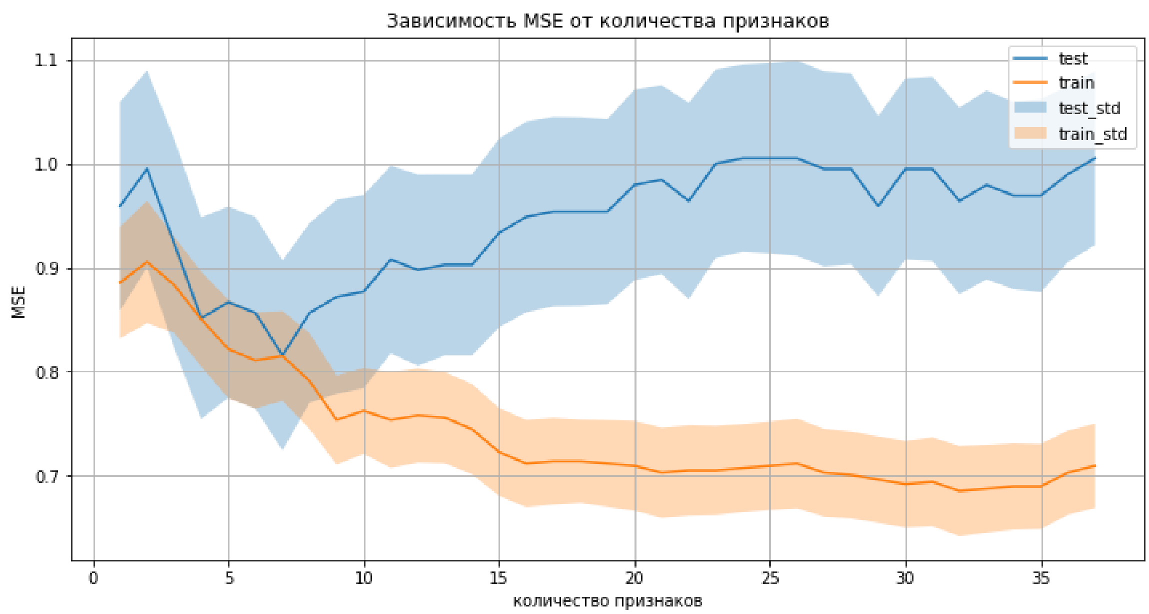
In [14]:
```
mse_std = np.std(mse_data, axis=0)
mse_test_std = np.std(mse_test_data, axis=0)
acc_std = np.std(accuracy_data, axis=0)
acc_test_std = np.std(accuracy_test_data, axis=0)
print('MSE')
print('train:', mse_std.mean())
print('test:', mse_test_std.mean())
print('Accuracy')
print('train:', acc_std.mean())
print('test:', acc_test_std.mean())
```

```
MSE
train: 0.043711321156705604
test: 0.0911881493949942
Accuracy
train: 0.021003891011671237
test: 0.035083109815568746
```

Построим график зависимости ошибки от количества признаков, указав на нём и дисперсию тоже.

In [15]:
```
plt.figure(figsize=(12, 6))
plt.plot(np.arange(1, features + 1), mse_results_test, label='test')
plt.fill_between(np.arange(1, features + 1),
                 mse_results_test - mse_test_std,
                 mse_results_test + mse_test_std,
                 alpha = 0.3, label='test_std')

plt.plot(np.arange(1, features + 1), mse_results_train, label='train')
plt.fill_between(np.arange(1, features + 1),
                 mse_results_train - mse_std,
                 mse_results_train + mse_std,
                 alpha = 0.3, label='train_std')
plt.legend()
plt.grid()
plt.ylabel('MSE')
plt.xlabel('количество признаков')
t = plt.title('Зависимость MSE от количества признаков')
plt.savefig('graph.jpg')
```

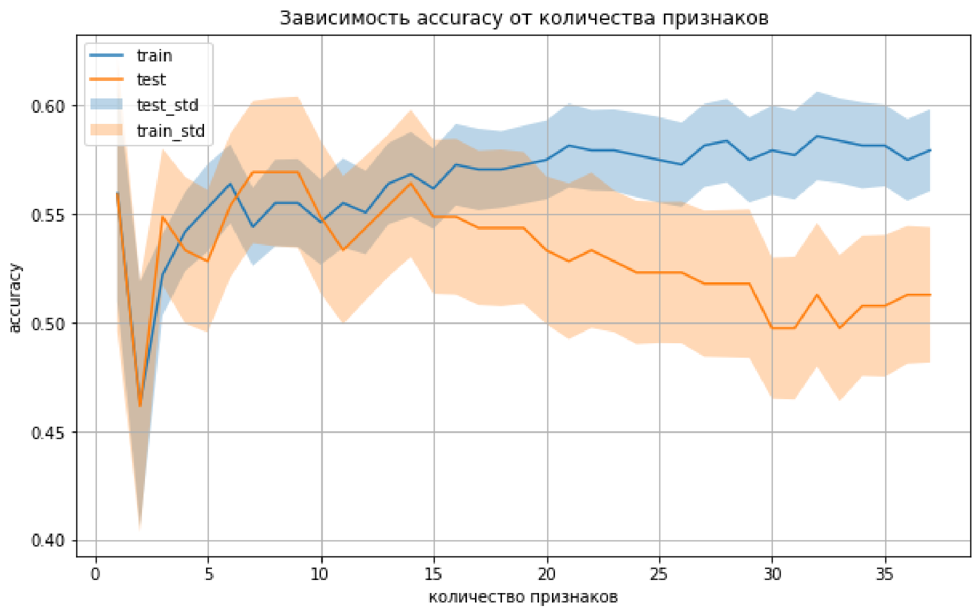


Таким образом, мы видим, что уже после 8 признаков ошибка на контрольной выборке начинает расти.

In [ ]:

Accuracy менее важная для нас метрика, но убедимся, что на ней 8 признаков тоже являются одним из оптимальных выборов:

In [16]:
```
plt.figure(figsize=(10, 6))
plt.plot(np.arange(1, features + 1), np.array(accuracy_results).T[0],
        label='train')
plt.plot(np.arange(1, features + 1), np.array(accuracy_results).T[1],
        label='test')
plt.fill_between(np.arange(1, features + 1),
                 acc_results_train - acc_std,
                 acc_results_train + acc_std,
                 alpha = 0.3, label='test_std')
plt.fill_between(np.arange(1, features + 1),
                 acc_results_test - acc_test_std,
                 acc_results_test + acc_test_std,
                 alpha = 0.3, label='train_std')
plt.legend()
plt.grid()
plt.ylabel('accuracy')
plt.xlabel('количество признаков')
t = plt.title('Зависимость accuracy от количества признаков')
```



In [ ]:
```

```