Подключение библиотек

In [1]:

```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
```

Смотрим на данные

In [2]:

```
df = pd.read_csv("2015.csv")
```

In [3]:

```
df.head()
```

Out[3]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Fr
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143	0
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	0
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	0
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	0
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	0

In [4]:

```
df.describe()
```

Out[4]:

	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom
count	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000
mean	79.493671	5.375734	0.047885	0.846137	0.991046	0.630259	0.428615
std	45.754363	1.145010	0.017146	0.403121	0.272369	0.247078	0.150693
min	1.000000	2.839000	0.018480	0.000000	0.000000	0.000000	0.000000
25%	40.250000	4.526000	0.037268	0.545808	0.856823	0.439185	0.328330
50%	79.500000	5.232500	0.043940	0.910245	1.029510	0.696705	0.435515
75%	118.750000	6.243750	0.052300	1.158448	1.214405	0.811013	0.549092
max	158.000000	7.587000	0.136930	1.690420	1.402230	1.025250	0.669730

Избавимся от ненужных столбцов.

In [5]:

```
df.Country.value_counts().sort_values()
```

Out[5]:

```
Ecuador                     1
France                      1
Afghanistan                 1
Nigeria                     1
Malaysia                    1
Qatar                       1
Libya                       1
Bahrain                     1
New Zealand                 1
Russia                      1
Denmark                     1
China                       1
Somaliland region           1
Dominican Republic          1
South Africa                1
Madagascar                  1
Chad                        1
Haiti                       1
Colombia                    1
Sudan                       1
Cyprus                      1
Mexico                      1
Switzerland                 1
Zimbabwe                    1
Lesotho                     1
India                       1
Turkey                      1
Vietnam                     1
Mauritius                   1
Philippines                 1
                           ..
Armenia                     1
Estonia                     1
Jordan                      1
Israel                      1
Bulgaria                    1
Kenya                       1
Sierra Leone                1
Kosovo                      1
Congo (Kinshasa)            1
Iceland                     1
Singapore                   1
Turkmenistan                1
Peru                        1
Botswana                    1
Ethiopia                    1
Czech Republic              1
Congo (Brazzaville)         1
Uruguay                     1
Egypt                       1
Cameroon                    1
Chile                       1
Algeria                     1
Luxembourg                  1
Oman                        1
```

```
Montenegro            1
Comoros               1
Sri Lanka             1
Nicaragua             1
Angola                1
Spain                 1
Name: Country, Length: 158, dtype: int64
```

Видим, что каждая страна представлена 1 раз, поэтому это больше тянет на индекс, чем на признак, выбрасываем.

In [6]:

```
df.corr()
```

Out[6]:

	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom
Happiness Rank	1.000000	-0.992105	0.158516	-0.785267	-0.733644	-0.735613	-0.556886
Happiness Score	-0.992105	1.000000	-0.177254	0.780966	0.740605	0.724200	0.568211
Standard Error	0.158516	-0.177254	1.000000	-0.217651	-0.120728	-0.310287	-0.129773
Economy (GDP per Capita)	-0.785267	0.780966	-0.217651	1.000000	0.645299	0.816478	0.370300
Family	-0.733644	0.740605	-0.120728	0.645299	1.000000	0.531104	0.441518
Health (Life Expectancy)	-0.735613	0.724200	-0.310287	0.816478	0.531104	1.000000	0.360477
Freedom	-0.556886	0.568211	-0.129773	0.370300	0.441518	0.360477	1.000000
Trust (Government Corruption)	-0.372315	0.395199	-0.178325	0.307885	0.205605	0.248335	0.493524
Generosity	-0.160142	0.180319	-0.088439	-0.010465	0.087513	0.108335	0.373916
Dystopia Residual	-0.521999	0.530474	0.083981	0.040059	0.148117	0.018979	0.062783

"Happiness Rank" сильно скореллировано с "Happiness Score".

In [7]:

```
dropped_happy = df.drop(["Standard Error", "Country", "Happiness Rank"], axis=1)
dropped_happy.head()
```

Out[7]:

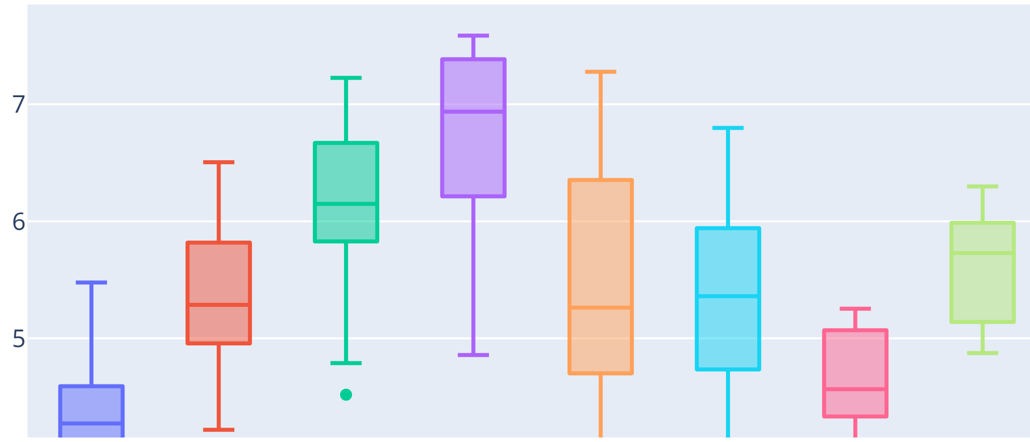
	Region	Happiness Score	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	Trust (Government Corruption)	Generosity
0	Western Europe	7.587	1.39651	1.34951	0.94143	0.66557	0.41978	0.29678
1	Western Europe	7.561	1.30232	1.40223	0.94784	0.62877	0.14145	0.43630
2	Western Europe	7.527	1.32548	1.36058	0.87464	0.64938	0.48357	0.34139
3	Western Europe	7.522	1.45900	1.33095	0.88521	0.66973	0.36503	0.34699
4	North America	7.427	1.32629	1.32261	0.90563	0.63297	0.32957	0.45811

In [8]:

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

# будем отображать графики прямо в jupyter'e
%matplotlib inline
import seaborn as sns
import matplotlib.pyplot as plt
#графики в svg выглядят более четкими
%config InlineBackend.figure_format = 'svg'

#увеличим дефолтный размер графиков
from pylab import rcParams
rcParams['figure.figsize'] = 8, 5
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
import plotly
import plotly.graph_objs as go
init_notebook_mode(connected=True)
```

In [9]:

```
data = []
for reg in df.Region.value_counts().index:
    data.append(
        go.Box(y=df[df.Region==reg]['Happiness Score'], name=reg)
    )

# визуализируем данные
iplot(data, show_link = False)
```



Видим, что регионы можно отранжировать по степени счастливости. Поэтому попробуем заменить регион медианным значением.

In [10]:

```
median = dropped_happy.groupby('Region')['Happiness Score'].median()
median
```

Out[10]:

```
Region
Australia and New Zealand          7.285
Central and Eastern Europe         5.286
Eastern Asia                       5.729
Latin America and Caribbean        6.149
Middle East and Northern Africa    5.262
North America                      7.273
Southeastern Asia                  5.360
Southern Asia                      4.565
Sub-Saharan Africa                 4.272
Western Europe                     6.937
Name: Happiness Score, dtype: float64
```

In [11]:

```
dropped_happy.Region = dropped_happy.Region.map(median)
```

In [12]:

```
dropped_happy.head()
```

Out[12]:

	Region	Happiness Score	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	Trust (Government Corruption)	Generosity	D F
0	6.937	7.587	1.39651	1.34951	0.94143	0.66557	0.41978	0.29678	
1	6.937	7.561	1.30232	1.40223	0.94784	0.62877	0.14145	0.43630	
2	6.937	7.527	1.32548	1.36058	0.87464	0.64938	0.48357	0.34139	
3	6.937	7.522	1.45900	1.33095	0.88521	0.66973	0.36503	0.34699	
4	7.273	7.427	1.32629	1.32261	0.90563	0.63297	0.32957	0.45811	

In [13]:

```
list(dropped_happy['Region'])
```

```
 4.272,
 4.272,
 4.272,
 4.272,
 4.272,
 4.272,
 4.272,
 4.272,
 5.36,
 4.272,
 4.272,
 4.272,
 4.272,
 4.272,
 4.272,
 4.272,
 4.565,
 4.272,
 4.272,
 5.2620000000000005
```

Обучим несколько моделей и сравним результат.

In [14]:

```
X = dropped_happy.drop("Happiness Score", axis = 1)
y = dropped_happy['Happiness Score']
```

In [15]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42, shuffle=
```

In [16]:

```
def evaluate(model):
    pred = model.predict(X_test)
    print("mse = ", mean_squared_error(y_test, pred))
    print("mae = ", mean_absolute_error(y_test, pred))
    print("r2  = ", r2_score(y_test, pred))
```

In [17]:

```
lr = LinearRegression()
lr.fit(X_train, y_train)
evaluate(lr)
```

```
mse =  7.824708779446114e-08
mae =  0.0002331973261068173
r2  =  0.999999941219971
```

In [18]:

```
coef = zip(X.columns, lr.coef_)
coef_df = pd.DataFrame(list(zip(X.columns, lr.coef_)), columns=['features', 'coeffi
coef_df
```

Out[18]:

	features	coefficients
0	Region	-0.000065
1	Economy (GDP per Capita)	1.000084
2	Family	1.000048
3	Health (Life Expectancy)	1.000121
4	Freedom	0.999803
5	Trust (Government Corruption)	0.999985
6	Generosity	0.999994
7	Dystopia Residual	1.000022

In [19]:

```
tree = DecisionTreeRegressor()
param_grid = {'criterion': ['mse', 'mae'] , 'max_depth': [5, 10, 30, 100], 'min_sam
search = GridSearchCV(tree, n_jobs=-1, param_grid=param_grid, cv=5)
search.fit(X_train, y_train)
```

Out[19]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=DecisionTreeRegressor(criterion='mse', max_dep
th=None,
                                             max_features=None,
                                             max_leaf_nodes=None,
                                             min_impurity_decrease=0.
0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf
=0.0,
                                             presort=False, random_st
ate=None,
                                             splitter='best'),
             iid='warn', n_jobs=-1,
             param_grid={'criterion': ['mse', 'mae'],
                         'max_depth': [5, 10, 30, 100],
                         'min_samples_leaf': [1, 2, 5, 10]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=
False,
             scoring=None, verbose=0)
```

In [20]:

```
evaluate(search.best_estimator_)
```

```
mse =  0.2684362135416667
mae =  0.42611458333333346
r2  =  0.798347915056061
```

In [21]:

```
rf = RandomForestRegressor()
rf.fit(X_train, y_train)
evaluate(rf)
```

```
mse =  0.12525464437499992
mae =  0.28086874999999983
r2  =  0.9059074040201739
```

In [22]:

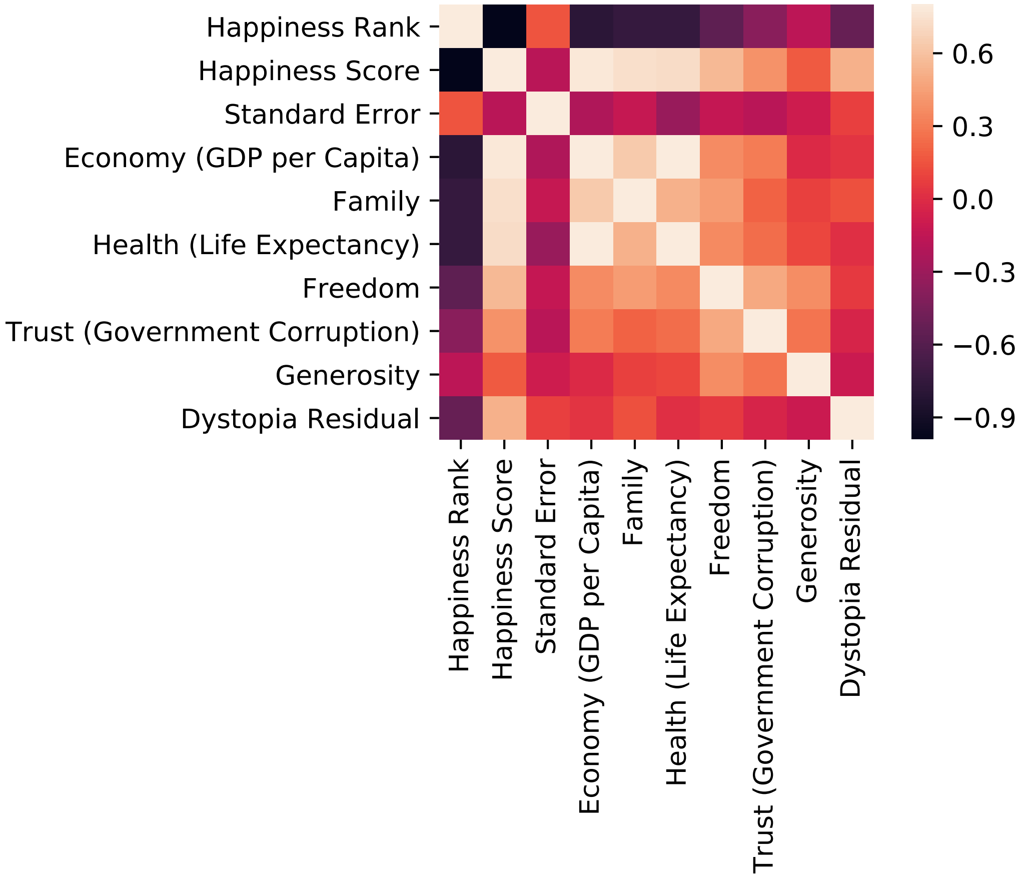
```
xgb = XGBRegressor()
xgb.fit(X_train, y_train)
evaluate(xgb)
```

```
mse =  0.08961095709448819
mae =  0.2373981233040491
r2  =  0.932683313873668
```

Вывод: видим, что лучше всего в этой задаче применить линейную регрессию.

In [23]:

```
import seaborn as sns

f, ax = plt.subplots(figsize=(5, 3))
sns.heatmap(df.corr(), vmax=.8, square=True);
```



Видим, что признаки довольно сильно скоррелированны и регуляризация может помочь.

In [24]:

```
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV

param_grid = {'alpha': [0, 0.005, 0.05, 0.1, 0.5, 1, 10]}
ridg = Lasso()
clf = GridSearchCV(ridg, param_grid=param_grid)
clf.fit(X, y)

pd.DataFrame(clf.cv_results_)
```

Out[24]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	params	split0_
0	0.005391	0.000216	0.003180	0.000025	0	{'alpha': 0}	
1	0.005244	0.000362	0.002966	0.000085	0.005	{'alpha': 0.005}	
2	0.004828	0.000073	0.002855	0.000030	0.05	{'alpha': 0.05}	
3	0.004817	0.000065	0.002838	0.000027	0.1	{'alpha': 0.1}	
4	0.004454	0.000420	0.002579	0.000246	0.5	{'alpha': 0.5}	
5	0.004786	0.000130	0.002839	0.000016	1	{'alpha': 1}	
6	0.004651	0.000327	0.002486	0.000181	10	{'alpha': 10}	

In [25]:

```
from sklearn.linear_model import Ridge

param_grid = {'alpha': [0, 0.005, 0.05, 0.1, 0.5, 1, 10]}
ridg = Ridge()
clf = GridSearchCV(ridg, param_grid=param_grid)
clf.fit(X, y)

pd.DataFrame(clf.cv_results_)
```

Out[25]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	params	split0
0	0.006075	0.001373	0.003133	0.000559	0	{'alpha': 0}	
1	0.003826	0.000109	0.002334	0.000072	0.005	{'alpha': 0.005}	
2	0.003905	0.000146	0.002344	0.000119	0.05	{'alpha': 0.05}	
3	0.004449	0.000501	0.002428	0.000289	0.1	{'alpha': 0.1}	
4	0.003730	0.000006	0.002258	0.000050	0.5	{'alpha': 0.5}	
5	0.003770	0.000046	0.002255	0.000041	1	{'alpha': 1}	
6	0.003787	0.000028	0.002291	0.000041	10	{'alpha': 10}	

Получили улучшение в третьем знаке после запятой, это того не стоило.