ML for Business Project

Well profitability estimation using bootstrapping

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Goal

- Develop a linear regression model for the OilyGiant mining company that would analyze oil well parameters in each of the three selected regions and predict the volume of reserves in the new wells for each region;
- Based on these predictions, pick the region with the highest total profit and the lowest risk of losses.

Data description

Features

- *id* — unique oil well identifier
- *f0, f1, f2* — three features of points (their specific meaning is unimportant, but the features themselves are significant)

Target

- *product* — volume of reserves in the oil well (thousand barrels).

Conditions:

- Only linear regression is suitable for model training (the rest are not sufficiently predictable).
- When exploring the region, a study of 500 points is carried with picking the best 200 points for the profit calculation.
- The budget for development of 200 oil wells is 100 USD million.
- One barrel of raw materials brings 4.5 USD of revenue The revenue from one unit of product is 4,500 dollars (volume of reserves is in thousand barrels).
- After the risk evaluation, keep only the regions with the risk of losses lower than 2.5%. From the ones that fit the criteria, the region with the highest average profit should be selected.

The data is synthetic: contract details and well characteristics are not disclosed.

Imports

In [148]:

```
import pandas as pd
import matplotlib
import numpy as np

from sklearn.preprocessing import StandardScaler as ss
from sklearn.model_selection import train_test_split

from sklearn.dummy import DummyRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

from scipy import stats as st

import matplotlib.pyplot as plt
%matplotlib inline

import sys
import warnings
if not sys.warnoptions:
       warnings.simplefilter("ignore")

pd.set_option('display.max_rows', None)

print("Setup Complete")
```

```
Setup Complete
```

Input data

In [149]:

```
try:
    df_0 = pd.read_csv('geo_data_0.csv')
    df_1 = pd.read_csv('geo_data_1.csv')
    df_2 = pd.read_csv('geo_data_2.csv')

except:
    df_0 = pd.read_csv('/datasets/geo_data_0.csv')
    df_1 = pd.read_csv('/datasets/geo_data_1.csv')
    df_2 = pd.read_csv('/datasets/geo_data_2.csv')
```

Descriptive statistics

In [150]:

```
df_0.head()
```

Out[150]:

	id	f0	f1	f2	product
0	txEyH	0.705745	-0.497823	1.221170	105.280062
1	2acmU	1.334711	-0.340164	4.365080	73.037750
2	409Wp	1.022732	0.151990	1.419926	85.265647
3	iJLyR	-0.032172	0.139033	2.978566	168.620776
4	Xdl7t	1.988431	0.155413	4.751769	154.036647

In [151]:

```
df_1.head()
```

Out[151]:

	id	f0	f1	f2	product
0	kBEdx	-15.001348	-8.276000	-0.005876	3.179103
1	62mP7	14.272088	-3.475083	0.999183	26.953261
2	vyE1P	6.263187	-5.948386	5.001160	134.766305
3	KcrkZ	-13.081196	-11.506057	4.999415	137.945408
4	AHL4O	12.702195	-8.147433	5.004363	134.766305

In [152]:

```
df_2.head()
```

Out[152]:

	id	f0	f1	f2	product
0	fwXo0	-1.146987	0.963328	-0.828965	27.758673
1	WJtFt	0.262778	0.269839	-2.530187	56.069697
2	ovLUW	0.194587	0.289035	-5.586433	62.871910
3	q6cA6	2.236060	-0.553760	0.930038	114.572842
4	WPMUX	-0.515993	1.716266	5.899011	149.600746

Notes for preprocessing:

- As we can see, the data has already been preprocessed, all features are numerical.

In [153]:

```
df_0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 5 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   id       100000 non-null  object 
 1   f0       100000 non-null  float64
 2   f1       100000 non-null  float64
 3   f2       100000 non-null  float64
 4   product  100000 non-null  float64
dtypes: float64(4), object(1)
memory usage: 3.8+ MB
```

In [154]:

```
df_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 5 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   id       100000 non-null  object 
 1   f0       100000 non-null  float64
 2   f1       100000 non-null  float64
 3   f2       100000 non-null  float64
 4   product  100000 non-null  float64
dtypes: float64(4), object(1)
memory usage: 3.8+ MB
```

In [155]:

```
df_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 5 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   id       100000 non-null  object 
 1   f0       100000 non-null  float64
 2   f1       100000 non-null  float64
 3   f2       100000 non-null  float64
 4   product  100000 non-null  float64
dtypes: float64(4), object(1)
memory usage: 3.8+ MB
```

Notes for preprocessing:

- no missing values found;
- data types seem fine.

In [156]:

```
df_0.describe()
```

Out[156]:

	f0	f1	f2	product
count	100000.000000	100000.000000	100000.000000	100000.000000
mean	0.500419	0.250143	2.502647	92.500000
std	0.871832	0.504433	3.248248	44.288691
min	-1.408605	-0.848218	-12.088328	0.000000
25%	-0.072580	-0.200881	0.287748	56.497507
50%	0.502360	0.250252	2.515969	91.849972
75%	1.073581	0.700646	4.715088	128.564089
max	2.362331	1.343769	16.003790	185.364347

In [157]:

```
df_1.describe()
```

Out[157]:

	f0	f1	f2	product
count	100000.000000	100000.000000	100000.000000	100000.000000
mean	1.141296	-4.796579	2.494541	68.825000
std	8.965932	5.119872	1.703572	45.944423
min	-31.609576	-26.358598	-0.018144	0.000000
25%	-6.298551	-8.267985	1.000021	26.953261
50%	1.153055	-4.813172	2.011479	57.085625
75%	8.621015	-1.332816	3.999904	107.813044
max	29.421755	18.734063	5.019721	137.945408

In [158]:

```
df_2.describe()
```

Out[158]:

	f0	f1	f2	product
count	100000.000000	100000.000000	100000.000000	100000.000000
mean	0.002023	-0.002081	2.495128	95.000000
std	1.732045	1.730417	3.473445	44.749921
min	-8.760004	-7.084020	-11.970335	0.000000
25%	-1.162288	-1.174820	0.130359	59.450441
50%	0.009424	-0.009482	2.484236	94.925613
75%	1.158535	1.163678	4.858794	130.595027
max	7.238262	7.844801	16.739402	190.029838

Notes for data preprocessing:

- features `f0`, `f1`, `f2` in all 3 data frames seem to be normally distributed as their mean and median values are close to each other. Maximum values are mostly within 3 std from the mean value.
- the target variable is continuous, so we will need to use a regression model for predictions. The targets' distributions are quite normal as well.

Developing a model for each region

In [159]:

```
def modeling(df):
    X = df.drop(['id','product'], axis=1)
    y = df['product']
    X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size = 0.25
, random_state=12345)

    sc = ss()
    X_train_scaled = sc.fit_transform(X_train)
    X_valid_scaled = sc.transform(X_valid)
    X_train = pd.DataFrame(data=X_train_scaled,
                        index=X_train.index,
                        columns=X_train.columns)
    X_valid = pd.DataFrame(data=X_valid_scaled,
                        index=X_valid.index,
                        columns=X_valid.columns)

    base_model = DummyRegressor(strategy='mean')
    base_model.fit(X_train, y_train)
    y_prelim_pred = base_model.predict(X_valid)
    rmse_baseline = round(mean_squared_error(y_valid,y_prelim_pred)** 0.5,2)

    model = LinearRegression()
    model.fit(X_train, y_train)
    predicted_valid = model.predict(X_valid)
    mse = mean_squared_error(y_valid, predicted_valid)
    rmse = round(mse ** 0.5, 2)
    predicted_valid_mean = round(predicted_valid.mean(),2)

    return model, rmse_baseline, rmse, predicted_valid_mean
```

In [160]:

```
model_0, rmse_baseline_0, rmse_0, predicted_valid_mean_0 = modeling(df_0)
model_1, rmse_baseline_1, rmse_1, predicted_valid_mean_1 = modeling(df_1)
model_2, rmse_baseline_2, rmse_2, predicted_valid_mean_2 = modeling(df_2)
```

In [161]:

```
models = pd.DataFrame({
    'Region': ['Region_0', 'Region_1', 'Region_2'],
    'Baseline RMSE': [rmse_baseline_0, rmse_baseline_1, rmse_baseline_2],
    'Model RMSE': [rmse_0, rmse_1, rmse_2],
    'Actual average volume': [round(df_0['product'].mean(),2), round(df_1['produ
ct'].mean(),2), round(df_2['product'].mean(),2)],
    'Predicted average volume': [predicted_valid_mean_0, predicted_valid_mean_1,
predicted_valid_mean_2]
})
models['% of error'] = round(models['Model RMSE'] / models['Predicted average vo
lume'], 2) * 100
models
```

Out[161]:

	Region	Baseline RMSE	Model RMSE	Actual average volume	Predicted average volume	% of error
0	Region_0	44.29	37.58	92.50	92.59	41.0
1	Region_1	46.02	0.89	68.83	68.73	1.0
2	Region_2	44.90	40.03	95.00	94.97	42.0

Each of the 3 models' RMSE is lower than the respective baseline RMSE, so the models are better than the average estimate but not much better, except for the model in Region 1: it shows an error of less than 1 thousand barrel. However, in this region the average predicted volume of reserves is much lower than in the other two regions.

It might be easier to see if we calculate the percentage by which the model is off compared to the average predicted volume of reserves (column `% of error`). The error is quite high (over 40%) in regions 0 and 2 and it is very low (only 1%) in region 1.

Overall, the actual and predicted volumes of reserves are very close in all 3 regions.

Profit calculations

Product predictions for each region

In [162]:

```
region_0_vals = pd.DataFrame()
region_0_vals['predicted']= model_0.predict(X_0)
region_0_vals['actual']= y_0.values

region_1_vals = pd.DataFrame()
region_1_vals['predicted']= model_1.predict(X_1)
region_1_vals['actual']= y_1.values

region_2_vals = pd.DataFrame()
region_2_vals['predicted']= model_2.predict(X_2)
region_2_vals['actual']= y_2.values
```

Minimum volume per well

First, let's calculate the volume of reserves sufficient for developing a new well without losses. Then we will compare the obtained value with the average volume of reserves in each region.

In [163]:

```
min_volume = round(100000000/(4500*200),2)
min_volume
```

Out[163]:

```
111.11
```

The budget for development of 200 oil wells is 100 USD million. One barrel of raw materials brings 4.5 USD of revenue The revenue from one unit of product is 4,500 dollars (volume of reserves is in thousand barrels).

Based on the above assumptions we have calculated that the minimum volume of reserves per well in the new region must be **111.11 thousand barrels** in order to break even.

Each of the 3 regions' **average** volume of predicted reserves is lower than this number. If we were to randomly take 200 wells in each region we would be at a loss, on average. To be able to make profit, let's select the most profitable wells in each region and see if the total reserves will cover the development cost.

Predicted profit calculation per region

In practice, instead of drilling all the wells in each region (and investing a lot of money in it), the company chooses 500 random wells, measure the features' values (`f0` , `f1` , `f2`) for each of them and then selects the best 200 wells for the profit calculation.

We will create a `RandomState()` instance from the `numpy.random module` which can be passed to the random_state argument of any function. It is important that with each new call, its state will change to random. This way we will get different subsamples.

Besides, subsamples should provide a selection of elements with replacement. That is, the same element can fall into a subsample several times. To do this, we will specify `replace=True` for the `sample()` function.

Profit calculator

First, let's create a helper function to calculate profit and then apply it to each region.

In [164]:

```
def profit_calculator(region_vals):
    state = np.random.RandomState(12345)
    developement_cost = 100000000

    profit_range = []
    for i in range(10000):
        subsample = region_vals.sample(n=500, replace=True, random_state=state).
sort_values('predicted', ascending=False).iloc[0:200,].actual
        revenue = subsample.sum() * 4500
        profit = revenue - developement_cost
        profit_range.append(profit)
    return profit_range
```

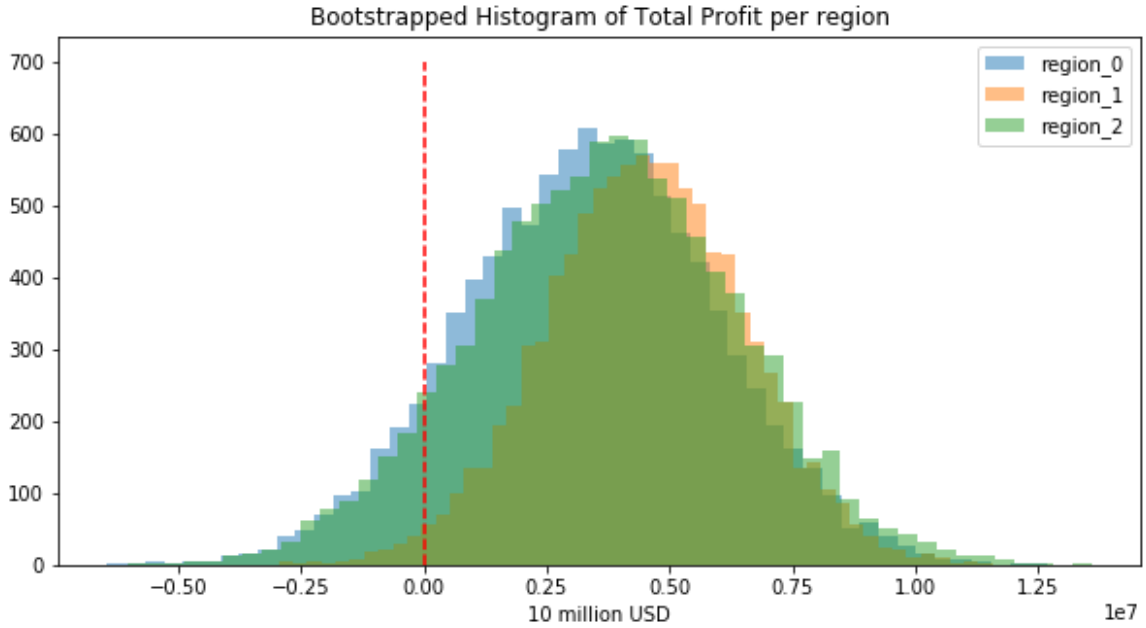
Profit distribution per region

In [165]:

```
profit_range_0 = pd.Series(profit_calculator(region_0_vals))
profit_range_1 = pd.Series(profit_calculator(region_1_vals))
profit_range_2 = pd.Series(profit_calculator(region_2_vals))
```

In [166]:

```
plt.figure(figsize=(10,5))
plt.hist(profit_range_0, alpha=0.5, bins=50, label='region_0')
plt.hist(profit_range_1, alpha=0.5, bins=50, label='region_1')
plt.hist(profit_range_2, alpha=0.5, bins=50, label='region_2')
plt.legend(loc='upper right')
plt.plot([0,0],[0,700],'r--')
plt.title('Bootstrapped Histogram of Total Profit per region')
plt.xlabel('10 million USD');
```



As we can see, The biggest part of the profit range for all 3 regions is above the break-even point. However, region 1 contains the most positive values. Based on that, we suggest that **Region 1** should be selected for development of oil wells. Next, we will perform risk assessment and make sure this conclusion holds.

Average profit per region

In [167]:

```
average_product_top_200_r0 = round((profit_range_0.mean()+100000000)/(200*4500),
2)
average_product_top_200_r1 = round((profit_range_1.mean()+100000000)/(200*4500),
2)
average_product_top_200_r2 = round((profit_range_2.mean()+100000000)/(200*4500),
2)
top_200 = pd.DataFrame(index=[0,1,2],
                       data={'Average product per best well, th barrel': [avera
ge_product_top_200_r0,average_product_top_200_r1, average_product_top_200_r2],
                       'Minimum volume': [111.11,111.11,111.11],
                       'Average profit per region, in 10 mln usd': [round(profi
t_range_0.mean()/10000000,2), round(profit_range_1.mean()/10000000,2), round(pro
fit_range_2.mean()/10000000,2)]
                      })
top_200.index.name = 'Region'
top_200
```

Out[167]:

Region	Average product per best well, th barrel	Minimum volume	Average profit per region, in 10 mln usd
0	114.85	111.11	0.34
1	116.11	111.11	0.45
2	115.22	111.11	0.37

The average volume of product in each region is higher than the minimum required level. Region 1 has the highest average target volume.

Risk assessment per region

The company's requirement for a new region is to have the risk of losses lower than 2.5%. First, let's estimate the 95% confidence interval (CI) that the profit will fall into a particular range.

In [168]:

```
def CI_calculator(lower, upper, profit_range):
    CI_lower = np.percentile(profit_range, lower)/10000000
    CI_upper = np.percentile(profit_range, upper)/10000000
    return CI_lower, CI_upper
```

In [169]:

```
lower_CI_r0, upper_CI_r0 = CI_calculator(2.5, 97.5, profit_range_0)
lower_CI_r1, upper_CI_r1 = CI_calculator(2.5, 97.5, profit_range_1)
lower_CI_r2, upper_CI_r2 = CI_calculator(2.5, 97.5, profit_range_2)
```

Now, let's calculate the risk of losses for each region.

In [170]:

```
risk_r0 = round((profit_range_0.sort_values(ascending=True) < 0).mean(),2)*100
risk_r0 = round((profit_range_1.sort_values(ascending=True) < 0).mean(),2)*100
risk_r0 = round((profit_range_2.sort_values(ascending=True) < 0).mean(),2)*100
```

In [171]:

```
CI = pd.DataFrame(index=[0,1,2],
                          data={'Lower border': [lower_CI_r0, lower_CI_r1, lower_C
I_r2],
                          'Upper border': [upper_CI_r0, upper_CI_r1, upper_CI_r2],
                          'CI,%': [95,95,95],
                          'Risk of losses, %': [risk_r0, risk_r1, risk_r2]
                         })
CI.index.name = 'Region'
CI
```

Out[171]:

Region	Lower border	Upper border	CI,%	Risk of losses, %
0	-0.176681	0.832282	95	9.0
1	0.048881	0.844417	95	1.0
2	-0.168624	0.890178	95	9.0

Based on the above table, risks of losses for regions 0 and 2 are much higher than the excepted 2.5%. Besides, with the 95% confidence we can expect the profit from Region 1 to be only positive, unlike for the two other regions.

These results confirm our previous conclusion: **Region 1 is the best candidate for the future development of oil wells because it has the highest total profit and the lowest risk of losses**.

Conclusion

In this project we have **developed a linear regression model for the OilyGiant mining company that analyzes oil well parameters in each of the three selected regions and predicts the volume of reserves in the new wells for each region. Based on these predictions, we have identified the region with the highest total profit and the lowest risk of losses**.

Steps:

1. First of all, we have familiarized ourselves with the data by performing the **descriptive statistics**. As the data was already preprocessed, we found no issues with it.
2. In the following section we have **developed a model for each region**. For that purpose we split the data into train and validation sets with the 75/25 proportion, respectively. Then we scaled it using the Standard Scaler method. Next, we calculated the baseline RMSE to be able to compare our models' score with a dummy regressor.

Each of the 3 models' RMSE turned out to be lower than the respective baseline RMSE, so the models are better than the average estimate but not much better, except for the model in Region 1: it has an error of less than 1 thousand barrel. However, in this region the average predicted volume of reserves was much lower than in the other two regions.

Then we calculated the percentage by which the model is off compared to the average predicted volume of reserves. The error is quite high (over 40%) in regions 0 and 2 and very low (only 1%) in region 1. Overall, the actual and predicted volumes of reserves are very close in all 3 regions.

1. Next step was **profit calculation**.

First, we calculated the volume of reserves sufficient for developing a new well without losses (a break-even point). The minimum volume of reserves per well in the new region must be 111.11 thousand barrels in order to break even.

Each of the 3 regions' average volume of predicted reserves is lower than this number. If we were to randomly take 200 wells in each region we would be at a loss, on average. To be able to make profit, let's select the most profitable wells in each region and see if the total reserves will cover the development cost.

In practice, instead of drilling all the wells in each region (and investing a lot of money in it), the company chooses 500 random wells, measure the features' values (`f0` , `f1` , `f2`) for each of them and then selects the best 200 wells for the profit calculation.

So we estimated the **profit distribution for the top 200 wells in each region**. For that we created 10000 samples of 500 random wells from our historic data using the bootstrapping technique. Next, we used our models to rank those wells and select 200 best ones in terms of the volume of product. Finally, we used the respective actual volume of product for each well and calculated the total profit for that sample. We obtained 10000 values for possible profit and plotted distribution based on that data.

The biggest part of the profit range for all 3 regions is above the break-even point. However, region 1 contains the most positive values. Based on that, we suggested that Region 1 should be selected for development of oil wells.

1. Next, we performed **risk assessment** to make sure this conclusion holds.

The company's requirement for a new region is to have the risk of losses lower than 2.5%. First, we estimated the 95% confidence interval (CI) that the profit will fall into a particular range. Then we calculated the risk of losses for each region.

The risks of losses for regions 0 and 2 are much higher than the excepted 2.5%. Besides, with the 95% confidence we can expect the profit from Region 1 to be only positive, unlike for the two other regions.

These results confirmed our previous conclusion:

Region 1 is the best candidate for the future development of oil wells because it has the highest total profit and the lowest risk of losses.