Рубежный контроль №2

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Вариант 28

Тема: Методы построения моделей машинного обучения

Методы:

1. Линейная/логистическая регрессия
2. Случайный лес

Данные

https://www.kaggle.com/roysouravcu/forbes-billionaires-of-2021 (https://www.kaggle.com/roysouravcu/forbes-billionaires-of-2021)

B [1]:

```
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_predict
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from sklearn.metrics import mean_absolute_error as mae
from sklearn.metrics import mean_squared_error as mse
import numpy as np
```

B [2]:

```
df = pd.read_csv('archive.zip', compression='zip')
df.head(2)
```

Out[2]:

	Name	NetWorth	Country	Source	Rank	Age	Industry
0	Jeff Bezos	$177 B	United States	Amazon	1	57.0	Technology
1	Elon Musk	$151 B	United States	Tesla, SpaceX	2	49.0	Automotive

B [3]:

```
# проверка типов переменных
df.dtypes
```

Out[3]:

```
Name          object
NetWorth      object
Country       object
Source        object
Rank           int64
Age          float64
Industry      object
dtype: object
```

B [4]:

```
df.shape
```

Out[4]:

```
(2755, 7)
```

B [5]:

```
df.Source.nunique(), df.Rank.nunique(), df.Name.nunique(), df.Industry.nunique(), df.Countr
```

Out[5]:

```
(924, 245, 2752, 18, 70)
```

B [6]:

```
df.drop(['Source', 'Name'], axis=1, inplace=True)
```

B [7]:

```
f = lambda x: float(''.join([s for s in list(x) if (s.isnumeric() or s == '.')]))
df['NetWorth'] = df['NetWorth'].apply(f)
df.head(2)
```

Out[7]:

	NetWorth	Country	Rank	Age	Industry
0	177.0	United States	1	57.0	Technology
1	151.0	United States	2	49.0	Automotive

B [8]:

```
df.isna().sum()
```

Out[8]:

```
NetWorth     0
Country      0
Rank         0
Age         79
Industry     0
dtype: int64
```

B [9]:

```
df['Age'] = df['Age'].fillna(-1)
```

B [10]:

```
df.corr()
```

Out[10]:

	NetWorth	Rank	Age
NetWorth	1.000000	-0.475346	0.044209
Rank	-0.475346	1.000000	-0.089193
Age	0.044209	-0.089193	1.000000

B [11]:

```
df = pd.get_dummies(df, columns=['Industry'])
```

B [12]:

```
df.shape
```

Out[12]:

```
(2755, 22)
```

B [13]:

```
X = df.groupby('Country').mean()
X.head(1)
```

Out[13]:

Country	NetWorth	Rank	Age	Industry_Automotive	Industry_Construction & Engineering	Industry_Diversified
Algeria	4.8	589.0	77.0	0.0	0.0	0.0

1 rows × 21 columns

B [14]:

```
y = df.groupby('Country')['Rank'].count()
```

B [15]:

```
X1, X2 , y1, y2  = train_test_split(X,y, test_size= 0.5, shuffle=True)
X = X1.append(X2)
y = y1.append(y2)
X.head(1)
```

Out[15]:

Country	NetWorth	Rank	Age	Industry_Automotive	Industry_Construction & Engineering	Industry
Nigeria	7.5	401.666667	63.333333	0.0	0.0	

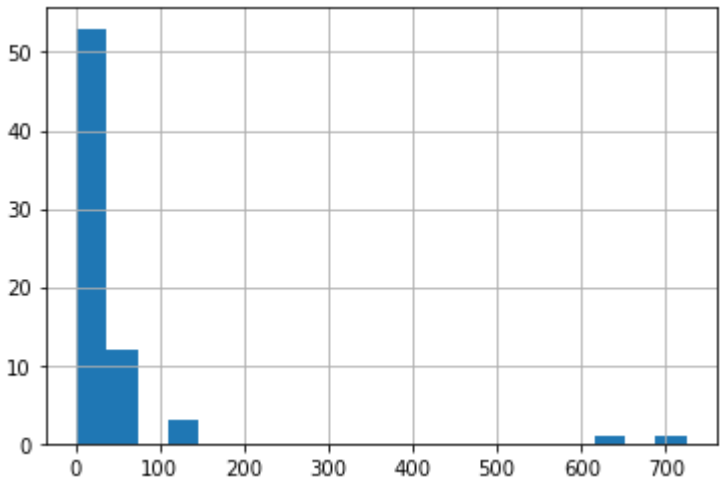
1 rows × 21 columns

B [16]:

```
y.hist(bins=20)
```

Out[16]:

```
<AxesSubplot:>
```

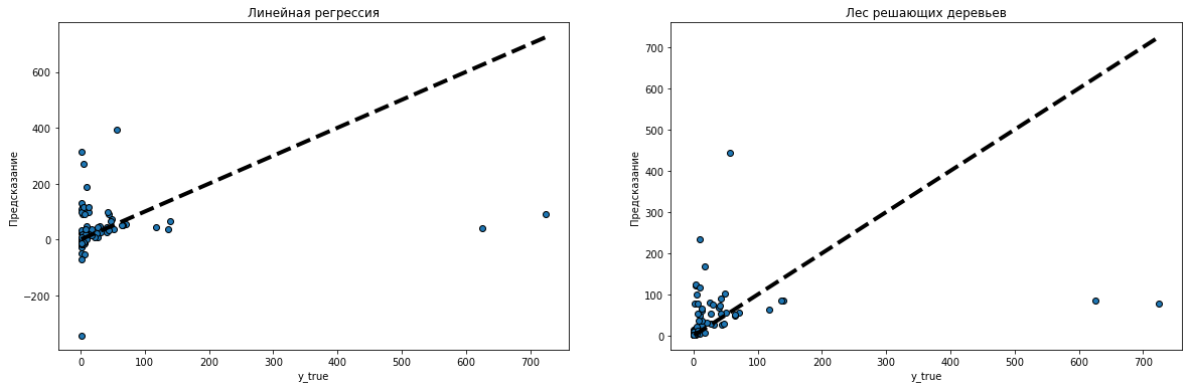


В [17]:

```
lr = make_pipeline(StandardScaler(), LinearRegression())
rf = RandomForestRegressor(n_estimators = 100, criterion='mae', random_state=12)

predicted_lr = cross_val_predict(lr, X, y, cv=7)
predicted_rf = cross_val_predict(rf, X, y, cv=7)

plt.figure(figsize=(20,6))
plt.subplot(121)
plt.scatter(y, predicted_lr, edgecolors=(0, 0, 0))
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'k--', lw=4)
plt.xlabel('y_true')
plt.ylabel('Предсказание')
plt.title('Линейная регрессия')

plt.subplot(122)
plt.scatter(y, predicted_rf, edgecolors=(0, 0, 0))
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'k--', lw=4)
plt.xlabel('y_true')
plt.ylabel('Предсказание')
plt.title('Лес решающих деревьев')
```

Out[17]:

```
Text(0.5, 1.0, 'Лес решающих деревьев')
```



В [18]:

```
maes, mses = [], []

for pred in [predicted_lr, predicted_rf]:
    maes.append(mae(y, pred))
    mses.append(mse(y, pred)**0.5)
```

B [19]:

```
# сравнение результатов работы
result = pd.DataFrame()
result['mean absolute error'] = maes
result['root mean squared error'] = mses
result.index = ['Линейная регрессия', 'Лес решающих деревьев']
result
```

Out[19]:

	mean absolute error	root mean squared error
Линейная регрессия	69.175750	138.121516
Лес решающих деревьев	50.030857	121.195944