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Загрузка датасета

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import PolynomialFeatures, MinMaxScaler,
StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error,
mean_absolute_error
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from heamy.estimator import Regressor
from heamy.pipeline import ModelsPipeline
from heamy.dataset import Dataset
from sklearn.neural_network import MLPRegressor
from gmdhpy import gmdh
from warnings import simplefilter

simplefilter('ignore')

data = pd.read_csv('cars_price_2_processed.csv')
data.head()
```

```
   Unnamed: 0  Year  Kilometers_Driven  Mileage  Engine   Power  Seats
Price  \
0           0  2010              72000    26.60     998   58.16    5.0
1.75
1           1  2015              41000    19.67    1582  126.20    5.0
12.50
2           2  2011              46000    18.20    1199   88.70    5.0
4.50
3           3  2012              87000    20.77    1248   88.76    7.0
6.00
4           4  2013              40670    15.20    1968  140.80    5.0
17.74

   Location_Ahmedabad  Location_Bangalore  ...  Fuel_Type_CNG  \
0                   0                   0  ...              1
1                   0                   0  ...              0
2                   0                   0  ...              0
3                   0                   0  ...              0
4                   0                   0  ...              0

   Fuel_Type_Diesel  Fuel_Type_LPG  Fuel_Type_Petrol
```

```
Transmission_Automatic  \
0                   0              0                   0
0
1                   1              0                   0
0
2                   0              0                   1
0
3                   1              0                   0
0
4                   1              0                   0
1

   Transmission_Manual  Owner_Type_First  Owner_Type_Fourth & Above  \
0                    1                 1                          0
1                    1                 1                          0
2                    1                 1                          0
3                    1                 1                          0
4                    0                 0                          0

   Owner_Type_Second  Owner_Type_Third
0                  0                 0
1                  0                 0
2                  0                 0
3                  0                 0
4                  1                 0

[5 rows x 29 columns]
```

Корреляционный анализ

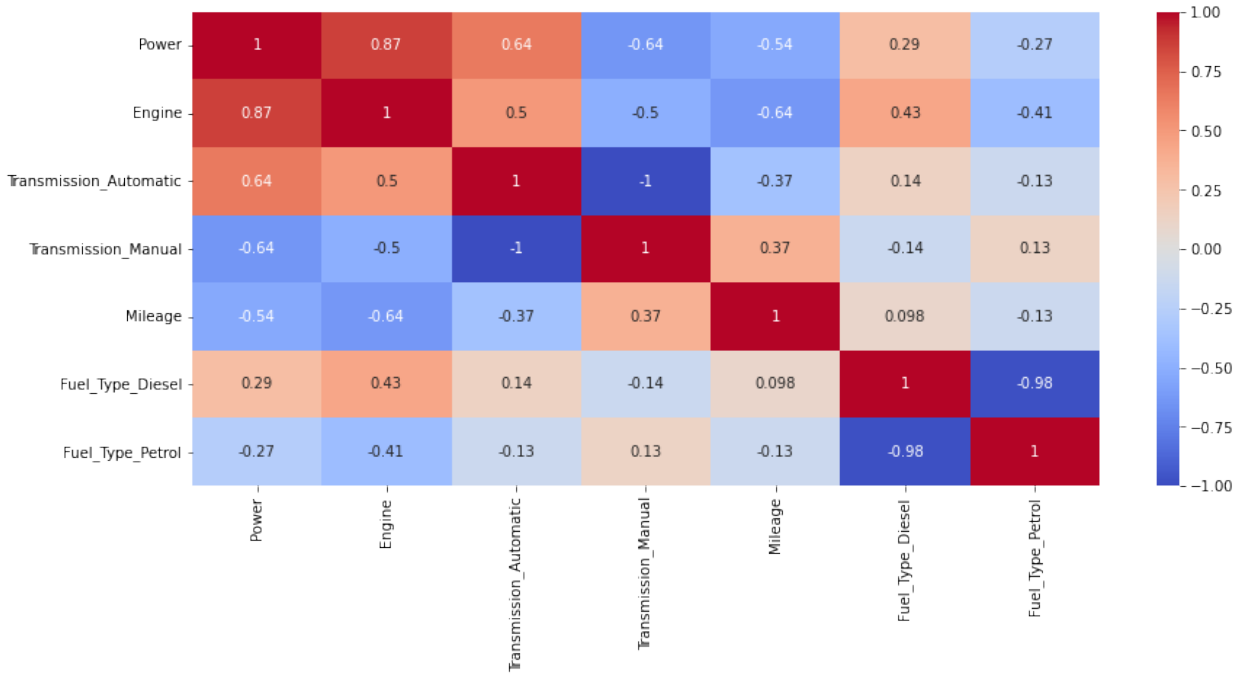
```
print('Признаки, имеющие максимальную по модулю корреляцию с ценой
автомобиля')
best_params = data.corr()
['Price'].map(abs).sort_values(ascending=False)[1:]
best_params = best_params[best_params.values > 0.3]
best_params
```

```
Признаки, имеющие максимальную по модулю корреляцию с ценой автомобиля

Power                     0.772843
Engine                    0.658047
Transmission_Automatic    0.585623
Transmission_Manual       0.585623
Mileage                   0.341652
Fuel_Type_Diesel          0.321035
Fuel_Type_Petrol          0.309363
Name: Price, dtype: float64
```

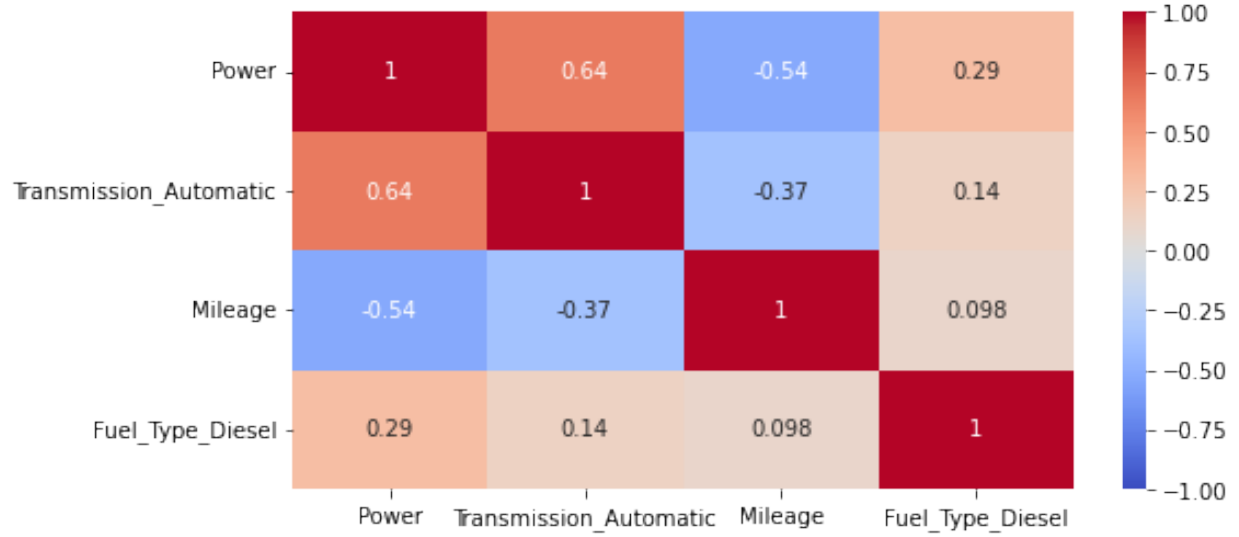
```
plt.figure(figsize=(14, 6))
sns.heatmap(data[best_params.index].corr(), vmin=-1, vmax=1,
```

```
cmap='coolwarm', annot=True)
plt.show()
```




```
best_params = best_params.drop(['Engine', 'Transmission_Manual',
'Fuel_Type_Petrol'])

plt.figure(figsize=(8, 4))
sns.heatmap(data[best_params.index].corr(), vmin=-1, vmax=1,
cmap='coolwarm', annot=True)
plt.show()
```



Разделение выборки на обучающую и тестовую

```
y = data['Price']
X = data[best_params.index]
x_train, x_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=3)
```

Масштабирование данных

```
scaler = StandardScaler().fit(x_train)
x_train_scaled = pd.DataFrame(scaler.transform(x_train),
columns=x_train.columns)
x_test_scaled = pd.DataFrame(scaler.transform(x_test),
columns=x_train.columns)
```

Метрики

```
def print_metrics(y_test, y_pred):
    print(f"R^2: {r2_score(y_test, y_pred)}") #коэф детерминации, чем
выше, тем лушче
    print(f"MSE: {mean_squared_error(y_test, y_pred)}")
    print(f"MAE: {mean_absolute_error(y_test, y_pred)}")
```

Модель №1: Случайный лес

```
print_metrics(y_test,
RandomForestRegressor(random_state=17).fit(x_train,
y_train).predict(x_test))
```

```
R^2: 0.8169695703110462
MSE: 21.368523550280464
MAE: 2.2272108897882124
```

Подбор гиперпараметров

```
rf = RandomForestRegressor(random_state=17)
params = {'n_estimators': [100, 1000], 'criterion': ['squared_error',
'absolute_error', 'poisson'],
          'max_features': ['auto', 'sqrt'], 'min_samples_leaf': [1, 3,
5]}
grid_cv = GridSearchCV(estimator=rf, cv=5, param_grid=params, n_jobs=-
1, scoring='neg_mean_absolute_error') #Поиск оптимального ГП
grid_cv.fit(x_train, y_train)
print(grid_cv.best_params_)
```

```
{'criterion': 'absolute_error', 'max_features': 'sqrt',
'min_samples_leaf': 1, 'n_estimators': 100}
```

criterion - качество разделения max_features - макс. кол-во признаков для лучшего разделения (для каждого разделение sqrt от общего числа) min_samples_leaf - мин. число образцов в листе n_estimators - кол-во деревьев в лесу

```
best_rf = grid_cv.best_estimator_
best_rf.fit(x_train, y_train)
y_pred_rf = best_rf.predict(x_test)
print_metrics(y_test, y_pred_rf)
```

```
R^2: 0.8208117147424516
MSE: 20.919959047068673
MAE: 2.1854572077185015
```

Модель №2: Градиентный бустинг

```
print_metrics(y_test,
GradientBoostingRegressor(random_state=17).fit(x_train,
y_train).predict(x_test))
```

```
R^2: 0.7712549309952805
MSE: 26.705637976944956
MAE: 2.8692068306824234
```

Подбор гиперпараметров

```
gb = GradientBoostingRegressor(random_state=17)
params = {'loss': ['squared_error', 'absolute_error', 'huber'],
'n_estimators': [10, 50, 100, 200],
          'criterion': ['friedman_mse', 'squared_error', 'mse',
'mae'], 'min_samples_leaf': [1, 3, 5]}
grid_cv = GridSearchCV(estimator=gb, cv=5, param_grid=params, n_jobs=-
1, scoring='r2')
grid_cv.fit(x_train, y_train)
print(grid_cv.best_params_)
```

```
{'criterion': 'friedman_mse', 'loss': 'huber', 'min_samples_leaf': 3,
'n_estimators': 200}
```

```
best_gb = grid_cv.best_estimator_
best_gb.fit(x_train, y_train)
y_pred_gb = best_gb.predict(x_test)
print_metrics(y_test, y_pred_gb)
```

```
R^2: 0.7750617066966918
MSE: 26.26120271902374
MAE: 2.66518306958836
```

Модель №3: Стекинг

```
dataset = Dataset(x_train, y_train, x_test)
```

```
# Создаем экземпляры трех различных моделей
model_lr = Regressor(dataset=dataset, estimator=LinearRegression,
name='lr')
model_rf = Regressor(dataset=dataset, estimator=RandomForestRegressor,

                     parameters={'criterion': 'absolute_error',
'n_estimators': 1000, 'random_state': 17}, name='rf')
model_gb = Regressor(dataset=dataset,
estimator=GradientBoostingRegressor,
                     parameters={'loss': 'huber', 'random_state': 17},
name='rf')

pipeline = ModelsPipeline(model_lr, model_rf)
stack_ds = pipeline.stack(k=10, seed=1)
stacker = Regressor(dataset=stack_ds,
estimator=GradientBoostingRegressor)
results = stacker.validate(k=10, scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [2.118518079925378, 2.366942214889117,
2.654642030745365, 2.4726790895523836, 2.343767119086641,
2.341834955257515, 2.82948363821963, 2.09283849153532,
2.8587044048057866, 2.3338125113348562]
Mean accuracy: 2.441322253535199
Standard Deviation: 0.2516971648119532
Variance: 0.06335146277437553
```

```
y_pred_stack = stacker.predict()
print_metrics(y_test, y_pred_stack)
```

```
R^2: 0.7840610516996481
MSE: 25.21054291365927
MAE: 2.3494797099849425
```

Модель №4: Многослойный персептрон

```
print_metrics(y_test, MLPRegressor(random_state=17).fit(x_train,
y_train).predict(x_test))
```

```
R^2: 0.6461253526988189
MSE: 41.31432542421033
MAE: 3.6332677362127788
```

Подбор гиперпараметров

```
mlp = MLPRegressor(random_state=17)
params = {'solver': ['lbfgs', 'sgd', 'adam'], 'hidden_layer_sizes':
[(100,), (50, 30,), (100, 40,)],
          'alpha': [1e-4, 3e-4, 5e-4], 'max_iter': [500, 1000]}
grid_cv = GridSearchCV(estimator=mlp, cv=5, param_grid=params,
```

```
n_jobs=-1, scoring='r2')
grid_cv.fit(x_train, y_train)
print(grid_cv.best_params_)
```

```
{'alpha': 0.0001, 'hidden_layer_sizes': (100, 40), 'max_iter': 1000,
'solver': 'lbfgs'}
```

```
best_mlp = grid_cv.best_estimator_
best_mlp.fit(x_train, y_train)
y_pred_mlp = best_mlp.predict(x_test)
print_metrics(y_test, y_pred_mlp)
```

```
R^2: 0.6795190063389385
MSE: 37.415667286044616
MAE: 3.4568890196314794
```

Модель №5: Метод группового учёта аргументов

```
gm = gmdh.Regressor(n_jobs=-1)
gm.fit(np.array(x_train_scaled), np.array(y_train))
y_pred_gm = gm.predict(np.array(x_test_scaled))
print()
print_metrics(y_test, y_pred_gm)
```

```
train layer0 in 0.02 sec
train layer1 in 0.05 sec
train layer2 in 0.05 sec
train layer3 in 0.05 sec

R^2: 0.6866573748606544
MSE: 36.58227364693177
MAE: 3.3962429053289607
```

Сравнение моделей

```
print("Случайный лес")
print_metrics(y_test, y_pred_rf)

print("\nГрадиентный бустинг")
print_metrics(y_test, y_pred_gb)

print("\nСтекинг")
print_metrics(y_test, y_pred_stack)

print("\nМногослойный персептрон")
print_metrics(y_test, y_pred_mlp)

print("\nМетод группового учёта аргументов")
print_metrics(y_test, y_pred_gm)
```

```
Случайный лес
R^2: 0.8208117147424516
MSE: 20.919959047068673
MAE: 2.1854572077185015

Градиентный бустинг
R^2: 0.7750617066966918
MSE: 26.26120271902374
MAE: 2.66518306958836

Стекинг
R^2: 0.7840610516996481
MSE: 25.21054291365927
MAE: 2.3494797099849425

Многослойный персептрон
R^2: 0.6795190063389385
MSE: 37.415667286044616
MAE: 3.4568890196314794

Метод группового учёта аргументов
R^2: 0.6866573748606544
MSE: 36.58227364693177
MAE: 3.3962429053289607
```