Ансамбли моделей машинного обучения. Часть 2.

In [1]:

```
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats
from scipy.optimize import fmin_tnc
from IPython.display import Image
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score, classification_repor
t
from sklearn.metrics import confusion_matrix
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_squared_log_err
or, median_absolute_error, r2_score, root_mean_squared_error
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import SGDRegressor
from sklearn.linear_model import SGDClassifier
from sklearn import linear_model
from sklearn.ensemble import BaggingRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
import xgboost as xgb
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

In [2]:

```
mpg = pd.read_csv('C:\\MGTU\\6 semestr\\TMO\\auto-mpg.csv')
```

In [3]:

```
mpg.head()
```

Out[3]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino

In [4]:

```
mpg.dtypes
```

Out[4]:

```
mpg              float64
cylinders          int64
displacement     float64
horsepower        object
```

```
weight              int64
acceleration      float64
model year          int64
origin              int64
car name           object
dtype: object
```

In [5]:

```
mpg = mpg[mpg['horsepower'] != '?']
mpg['horsepower'] = mpg['horsepower'].astype(float)
```

In [6]:

```
mpg.dtypes
```

Out[6]:

```
mpg               float64
cylinders           int64
displacement      float64
horsepower        float64
weight              int64
acceleration      float64
model year          int64
origin              int64
car name           object
dtype: object
```

In [7]:

```
mpg = mpg.drop(columns=['car name'])
```

In [8]:

```
X = mpg.drop(columns=['mpg'])   # Признаки
y = mpg['mpg']   # Целевая переменная

# Разделение данных на обучающую и тестовую выборки
mpg_X_train, mpg_X_test, mpg_y_train, mpg_y_test = train_test_split(X, y, test_size=0.2,
random_state=1)
```

Стекинг

In [9]:

```
from sklearn.preprocessing import PolynomialFeatures
poly = PolynomialFeatures(degree=2)  # Задаем степень полинома
X_train_poly = poly.fit_transform(mpg_X_train)
X_test_poly = poly.transform(mpg_X_test)

# Создание и обучение модели линейной регрессии
model = LinearRegression()
model.fit(X_train_poly, mpg_y_train)

# Предсказание на тестовой выборке
y_pred = model.predict(X_test_poly)
```

In [10]:

```
root_mean_squared_error(mpg_y_test, y_pred)
```

Out[10]:

```
3.1367700997320496
```

In [11]:

```
# Качество отдельных моделей
def val_mae(model):
```

```
    model.fit(mpg_X_train, mpg_y_train)
    y_pred = model.predict(mpg_X_test)
    result = root_mean_squared_error(mpg_y_test, y_pred)
    print(model)
    print('RMSE={}'.format(result))
```

In [12]:

```
# Точность на отдельных моделях
for model in [
    LinearRegression(),
    DecisionTreeRegressor(),
    BaggingRegressor(n_estimators=1000)

]:
    val_mae(model)
    print('==========================')
    print()
```

```
LinearRegression()
RMSE=3.4667210313792913
==========================

DecisionTreeRegressor()
RMSE=3.431352097233665
==========================

BaggingRegressor(n_estimators=1000)
RMSE=3.14769333969485
==========================
```

In [13]:

```
from heamy.estimator import Regressor, Classifier
from heamy.pipeline import ModelsPipeline
from heamy.dataset import Dataset
# Используем библиотеку heamy
# набор данных
dataset = Dataset(mpg_X_train, mpg_y_train, mpg_X_test)
dataset_poly = Dataset(X_train_poly, mpg_y_train, X_test_poly)

# модели первого уровня
model_tree = Regressor(dataset=dataset, estimator=DecisionTreeRegressor, name='tree')
model_lr = Regressor(dataset=dataset, estimator=LinearRegression, parameters={},name='lr'
)
model_bg = Regressor(dataset=dataset, estimator=BaggingRegressor, parameters={'n_estimat
ors': 1000},name='bg')
model_pol = Regressor(dataset=dataset_poly, estimator=LinearRegression, parameters={},nam
e='pol')
```

In [14]:

```
# Эксперимент 1
# Первый уровень - две модели: дерево и линейная регрессия
# Второй уровень: линейная регрессия

pipeline = ModelsPipeline(model_tree, model_lr)
stack_ds = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=root_mean_squared_error)
```

```
Metric: root_mean_squared_error
Folds accuracy: [3.994079321735586, 1.705992063507044, 3.498820228195117, 2.7673139539681
8, 2.712828060377412, 3.4841399494608725, 3.25228287528604, 2.2873289517257005, 2.3492210
300648586, 3.1155478177581872]
Mean accuracy: 2.9167554252079
Standard Deviation: 0.6497375249314522
Variance: 0.4221588513040495
```

In [15]:

```
# Эксперимент 2
# Первый уровень - две модели: дерево и линейная регрессия
# Второй уровень: бэггинг

stacker = Regressor(dataset=stack_ds, estimator=BaggingRegressor)
results = stacker.validate(k=10,scorer=root_mean_squared_error)
```

```
Metric: root_mean_squared_error
Folds accuracy: [3.700301507985531, 2.029868376274678, 3.6541466172007935, 2.832069800488
4535, 2.158460472860975, 3.1404222029694076, 3.727705771997121, 3.023950631104092, 3.0233
23849139253, 3.589306699161434]
Mean accuracy: 3.0879555929181737
Standard Deviation: 0.584481559730816
Variance: 0.3416186936653674
```

In [16]:

```
# Эксперимент 3
# Первый уровень - три модели: дерево, линейная регрессия и бэггинг
# Второй уровень: линейная регрессия
pipeline = ModelsPipeline(model_tree, model_lr, model_bg)
stack_ds3 = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds3, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=root_mean_squared_error)
```

```
Metric: root_mean_squared_error
Folds accuracy: [3.6403189140413206, 1.6909385439581688, 3.1210478530807224, 2.4730654946
41954, 2.3501128326441725, 2.8243233216427135, 2.9219933081916283, 1.9200580654841277, 2.
0337059543181066, 2.8611198803670104]
Mean accuracy: 2.5836684168369923
Standard Deviation: 0.5710718005216499
Variance: 0.326123001351039
```

In [17]:

```
# Эксперимент 4
# Первый уровень - три модели: дерево, линейная регрессия и бэггинг
# Второй уровень: бэггинг
# Результат хуже чем в эксперименте 3
stacker = Regressor(dataset=stack_ds3, estimator=BaggingRegressor)
results = stacker.validate(k=10,scorer=root_mean_squared_error)
```

```
Metric: root_mean_squared_error
Folds accuracy: [4.190184587222859, 2.025479109988547, 3.2168151951891795, 2.804077675975
3334, 2.3644606559527235, 3.5579316209498533, 3.1367653361693395, 2.7487569037892436, 2.4
87028282392332, 3.3771962985159267]
Mean accuracy: 2.9908695666145335
Standard Deviation: 0.6044198778372512
Variance: 0.36532338872479764
```

In [18]:

```
# Эксперимент 5
# Первый уровень - три модели: дерево, полиномиальная регрессия и бэггинг
# Второй уровень: линейная регрессия
pipeline = ModelsPipeline(model_tree, model_pol, model_bg)
stack_ds3 = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds3, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=root_mean_squared_error)
```

```
Metric: root_mean_squared_error
Folds accuracy: [3.693460890209922, 1.7362629840497992, 2.925914053622691, 2.406480956733
7697, 2.1615832387448415, 2.7713155319395057, 3.0275702509290308, 1.8464204482106956, 1.9
708442676541493, 2.8133636162907356]
Mean accuracy: 2.5353216238385143
Standard Deviation: 0.587975570483654
Variance: 0.34571527148557835
```

In [19]:

```
# Эксперимент 6
# Первый уровень - 4 модели: дерево, линейная регрессия, полиномиальная регрессия и бэгги
нг
# Второй уровень: линейная регрессия
pipeline = ModelsPipeline(model_tree, model_lr, model_bg, model_pol)
stack_ds3 = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds3, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=root_mean_squared_error)
```

```
Metric: root_mean_squared_error
Folds accuracy: [3.6782230739738058, 1.7198164352717917, 2.9236976087077613, 2.3923579485
934496, 2.1831396493077877, 2.77189449053814, 3.0225977428745616, 1.8552063113789952, 1.9
744286618132019, 2.809894555135343]
Mean accuracy: 2.533125647759484
Standard Deviation: 0.5841646737497893
Variance: 0.3412483660571978
```

In [20]:

```
# Эксперимент 7
# Первый уровень - три модели: линейная регрессия, полиномиальная регрессия и бэггинг
# Второй уровень: линейная регрессия
pipeline = ModelsPipeline(model_lr, model_pol, model_bg)
stack_ds3 = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds3, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=root_mean_squared_error)
```

```
Metric: root_mean_squared_error
Folds accuracy: [3.6784309511228805, 1.685230022434641, 2.922802920212812, 2.390807263842
764, 2.1671003109396936, 2.7375956335473703, 3.014130519807417, 1.839176122515726, 1.9743
037453991856, 2.810312877055171]
Mean accuracy: 2.521989036687766
Standard Deviation: 0.5898595357207732
Variance: 0.3479342718807261
```

In [21]:

```
# Эксперимент 8
# Первый уровень - 2 модели: полиномиальная регрессия и бэггинг
# Второй уровень: линейная регрессия
pipeline = ModelsPipeline(model_pol, model_bg)
stack_ds3 = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds3, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=root_mean_squared_error)
```

```
Metric: root_mean_squared_error
Folds accuracy: [3.6929213456681556, 1.702684938698718, 2.925725511703319, 2.405297970060
379, 2.150195841123143, 2.7447476431147777, 3.0199722261563258, 1.8250286520144705, 1.968
6135646169518, 2.81285834277228]
Mean accuracy: 2.524804603592852
Standard Deviation: 0.5942477873268704
Variance: 0.3531304327428814
```

In [22]:

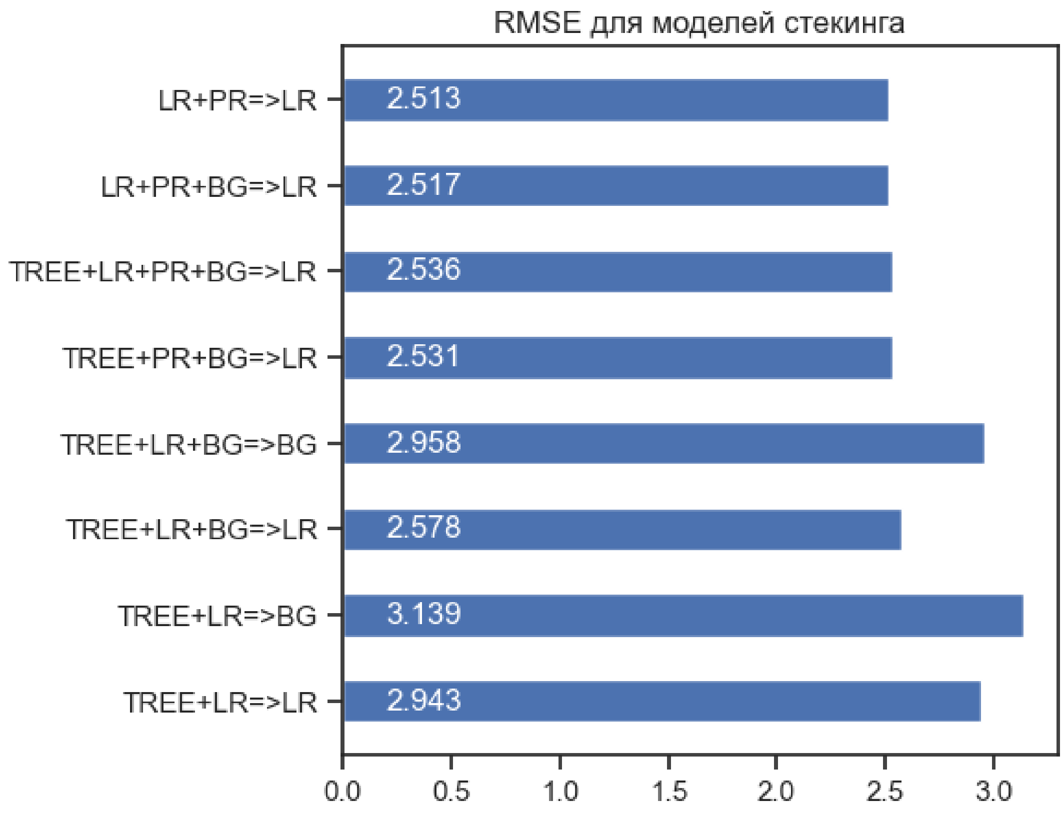
```
def vis_models_quality(array_metric, array_labels, str_header, figsize=(5, 5)):
    fig, ax1 = plt.subplots(figsize=figsize)
    pos = np.arange(len(array_metric))
    rects = ax1.barh(pos, array_metric,
                     align='center',
                     height=0.5,
                     tick_label=array_labels)
    ax1.set_title(str_header)
    for a,b in zip(pos, array_metric):
        plt.text(0.2, a-0.1, str(round(b,3)), color='white')
    plt.show()
```

In [35]:

```
# Результаты
array_labels = ['TREE+LR=>LR', 'TREE+LR=>BG', 'TREE+LR+BG=>LR', 'TREE+LR+BG=>BG', 'TREE+
PR+BG=>LR', 'TREE+LR+PR+BG=>LR','LR+PR+BG=>LR', 'BG+PR=>LR']
array_mae = [2.943373023221235, 3.13874388562688, 2.578048722056443, 2.95848390445565, 2
.5310358229314796, 2.53583835576526, 2.517015391925021, 2.51343770288313541]
```

In [24]:

```
vis_models_quality(array_mae, array_labels, 'RMSE для моделей стекинга')
```



Многослойный персептрон

In [25]:

```
from sklearn.neural_network import  MLPRegressor
```

In [26]:

```
mlp = MLPRegressor()
mlp.fit(mpg_X_train, mpg_y_train)
```

```
C:\Python311\Lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: Conv
ergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimizati
on hasn't converged yet.
  warnings.warn(
```

Out[26]:

▼ MLPRegressor i ?

```
MLPRegressor()
```

In [27]:

```
root_mean_squared_error(mpg_y_test, mlp.predict(mpg_X_test))
```

Out[27]:

```
3.684623254170565
```

In [28]:

```
import warnings
warnings.filterwarnings('ignore')
from time import time
i = 0
df = pd.DataFrame(columns = ['alpha','max_iter','test_rmse','train_time'])
for a in [0.00001,0.0001,0.001,0.01, 0.1, 1, 10]:
    for mi in [10,100,200,500,1000,2000]:
        for l in [10,20,50,100,200,500,1000]:
            st = time()
            mlp = MLPRegressor(alpha=a, max_iter=mi, hidden_layer_sizes=(l,))
            mlp.fit(mpg_X_train, mpg_y_train)
            end = time() - st

            rmse = root_mean_squared_error(mpg_y_test, mlp.predict(mpg_X_test))
            df.loc[i] = [a,mi,rmse,end]
            i=i+1
```

In [29]:

```
df.sort_values(by = 'test_rmse')
```

Out[29]:

	alpha	max_iter	test_rmse	train_time
80	0.00010	2000.0	3.215060	0.664493
191	0.10000	500.0	3.251294	0.672658
108	0.00100	500.0	3.252436	0.608567
114	0.00100	1000.0	3.329298	0.400934
159	0.01000	1000.0	3.334643	0.745109
...	...	...	...	...
210	1.00000	10.0	647.321807	0.007994
169	0.10000	10.0	699.505531	0.008001
1	0.00001	10.0	784.989586	0.008019
7	0.00001	100.0	1070.706551	0.056035
252	10.00000	10.0	1260.472276	0.008003

294 rows × 4 columns

In [30]:

```
from sklearn.model_selection import GridSearchCV
param_grid = {
    'alpha': [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10],
    'max_iter': [10, 100, 200, 500, 1000, 2000],
    'hidden_layer_sizes': [(10,), (20,), (50,), (100,), (200,), (500,), (1000,)]
}



# Создание модели
mlp = MLPRegressor()

# Настройка Grid Search
grid_search = GridSearchCV(estimator=mlp, param_grid=param_grid, scoring='neg_root_mean_
squared_error', cv=5, n_jobs=-1, verbose=2)

# Время начала поиска
start_time = time()

# Выполнение Grid Search
grid_search.fit(mpg_X_train, mpg_y_train)

# Время окончания поиска
```

```
end_time = time() - start_time

# Получение результатов
best_params = grid_search.best_params_
best_score = grid_search.best_score_

# Создание DataFrame с результатами
results = pd.DataFrame(grid_search.cv_results_)

print(f"Лучшие параметры: {best_params}")
print(f"Лучший RMSE: {-best_score}")
print(f"Время выполнения: {end_time} секунд")

# Предсказание и оценка на тестовых данных
best_model = grid_search.best_estimator_
test_rmse = root_mean_squared_error(mpg_y_test, best_model.predict(mpg_X_test))

print(f"RMSE на тестовых данных: {test_rmse}")
```

```
Fitting 5 folds for each of 294 candidates, totalling 1470 fits
Лучшие параметры: {'alpha': 0.001, 'hidden_layer_sizes': (500,), 'max_iter': 2000}
Лучший RMSE: 3.2641124909333152
Время выполнения: 103.81544375419617 секунд
RMSE на тестовых данных: 3.7211813370982614
```

МГУА

In [31]:

```
from gmdh import Combi, Multi, Mia, Ria
from sklearn.preprocessing import StandardScaler
# Стандартизация данных
scaler = StandardScaler()
X_train = scaler.fit_transform(mpg_X_train)
X_test = scaler.transform(mpg_X_test)
# Преобразование данных в тензоры NumPy
mpg_X_train = np.array(X_train)
mpg_y_train = np.array(mpg_y_train)
mpg_X_test = np.array(X_test)
mpg_y_test = np.array(mpg_y_test)

model = Ria()
model.fit(mpg_X_train, mpg_y_train)
y_pred = model.predict(mpg_X_test)
result = root_mean_squared_error(mpg_y_test, y_pred)
print(model)
print('RMSE={}'.format(result))
```

```
<gmdh.gmdh.Ria object at 0x000001E5F466DBD0>
RMSE=3.0558788306195948
```

In [32]:

```
def print_metrics(y_test, y_pred, squared=False):
    print(f"R^2: {r2_score(y_test, y_pred)}")
    crit_name = "MSE" if squared else "RMSE"
    print(f"{crit_name}: {mean_squared_error(y_test, y_pred, squared=squared)}")
    print(f"MAE: {mean_absolute_error(y_test, y_pred)}")
```

In [33]:

```
from gmdh import CriterionType
from gmdh import Criterion
from gmdh import Solver, PolynomialType
mpg_ria_model = Ria()
mpg_ria_model.fit(mpg_X_train, mpg_y_train, verbose=1, n_jobs=-1, test_size=0.53, limit=
0, k_best=1,
                  criterion = Criterion(criterion_type=CriterionType.STABILITY, solver =
Solver.ACCURATE), p_average = 3)
mpg_y_pred_ria = mpg_ria_model.predict(mpg_X_test)
```

```
print_metrics(mpg_y_test, mpg_y_pred_ria)
```

```
LEVEL 1  [========================] 100% [00m:00s] (21 combinations) error=2611.884785

LEVEL 2  [========================] 100% [00m:00s] (7 combinations) error=2321.174477

LEVEL 3  [========================] 100% [00m:00s] (7 combinations) error=2291.852059

LEVEL 4  [========================] 100% [00m:00s] (7 combinations) error=2266.391443

LEVEL 5  [========================] 100% [00m:00s] (7 combinations) error=2238.806791

LEVEL 6  [========================] 100% [00m:00s] (7 combinations) error=2197.496964

LEVEL 7  [========================] 100% [00m:00s] (7 combinations) error=2166.921487

LEVEL 8  [========================] 100% [00m:00s] (7 combinations) error=2158.990223

LEVEL 9  [========================] 100% [00m:00s] (7 combinations) error=2152.719748

LEVEL 10 [========================] 100% [00m:00s] (7 combinations) error=2151.236878

LEVEL 11 [========================] 100% [00m:00s] (7 combinations) error=2151.348313

R^2: 0.8713245652490978
RMSE: 2.986649277888555
MAE: 2.04648792970369
```

```
C:\Python311\Lib\site-packages\sklearn\metrics\_regression.py:483: FutureWarning: 'square
d' is deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean sq
uared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

In [34]:

```
from gmdh import SequentialCriterion
mpg_ria_model = Ria()
mpg_ria_model.fit(mpg_X_train, mpg_y_train, verbose=1, n_jobs=-1, test_size=0.52, limit=
0, k_best=1,
                  criterion = SequentialCriterion(criterion_type=CriterionType.SYM_REGUL
ARITY,
                                                  second_criterion_type=CriterionType.SYM_STABILITY, s
olver=Solver.ACCURATE))
mpg_y_pred_ria = mpg_ria_model.predict(mpg_X_test)
print_metrics(mpg_y_test, mpg_y_pred_ria)
```

```
LEVEL 1  [========================] 100% [00m:00s] (21 combinations) error=5209.485939

LEVEL 2  [========================] 100% [00m:00s] (7 combinations) error=4643.248172

LEVEL 3  [========================] 100% [00m:00s] (7 combinations) error=4590.687159

LEVEL 4  [========================] 100% [00m:00s] (7 combinations) error=4556.00767

LEVEL 5  [========================] 100% [00m:00s] (7 combinations) error=4508.576793

LEVEL 6  [========================] 100% [00m:00s] (7 combinations) error=4421.003715

LEVEL 7  [========================] 100% [00m:00s] (7 combinations) error=4367.013938

LEVEL 8  [========================] 100% [00m:00s] (7 combinations) error=4339.505272

LEVEL 9  [========================] 100% [00m:00s] (7 combinations) error=4331.713184

LEVEL 10 [========================] 100% [00m:00s] (7 combinations) error=4330.937627

LEVEL 11 [========================] 100% [00m:00s] (7 combinations) error=4331.288816

R^2: 0.8725742694435112
RMSE: 2.972110625621637
MAE: 2.0440419499147313
```

```
C:\Python311\Lib\site-packages\sklearn\metrics\_regression.py:483: FutureWarning: 'square
```

```
C:\Python311\Lib\site-packages\sklearn\metrics\_regression.py:483: FutureWarning: 'square
d' is deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean sq
uared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

In [ ]: