# Лабораторная работа №5 по курсу «Методы машинного обучения» на тему «Линейные модели, SVM и деревья решений.»

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```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing, sym
from sklearn import model selection
from sklearn.model selection import train test split
from sklearn.linear model import BayesianRidge
from sklearn.tree import DecisionTreeClassifier,
DecisionTreeRegressor, export graphviz
from sklearn.metrics import r2 score
%matplotlib inline
sns.set(style="ticks")
import warnings
warnings.filterwarnings('ignore')
data = pd.read csv("advertising.csv")
data.head(2)
```

TV Radio Newspaper Sales 1 230.1 37.8 69.2 22.1 2 44.5 39.3 45.1 10.4

data.describe()

TVRadio Newspaper Sales count 200.000000 200.000000 200.000000 200.000000 mean 147.042500 23.264000 30.554000 14.022500 std 85.854236 14.846809 21.778621 5.217457 min 0.700000 0.000000 0.300000 1.600000 25% 74.375000 9.975000 12.750000 10.375000 50% 149.750000 22.900000 25.750000 12.900000 218.825000 36.525000 45.100000 17.400000 75% 296.400000 49.600000 114.000000 27.000000 max

### data.info()

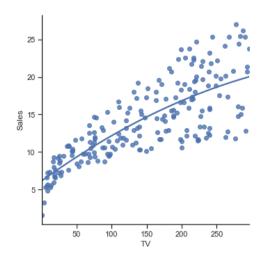
<class 'pandas.core.frame.DataFrame'>
Int64Index: 200 entries, 1 to 200
Data columns (total 4 columns):

#	Column	Non-Null Count	Dtype
0	TV	200 non-null	float64
1	Radio	200 non-null	float64
2	Newspaper	200 non-null	float64
3	Sales	200 non-null	float64

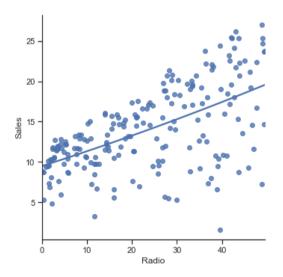
dtypes: float64(4)
memory usage: 7.8 KB

### data.columns

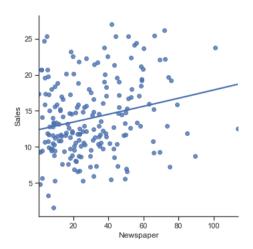
Index(['TV', 'Radio', 'Newspaper', 'Sales'], dtype='object')
sns.lmplot(x="TV", y="Sales", data=data, order=2, ci=None)
<seaborn.axisgrid.FacetGrid at 0x133706f10>



sns.lmplot(x="Radio", y="Sales", data=data, order=2, ci=None)
<seaborn.axisgrid.FacetGrid at 0x1357f9d90>



sns.lmplot(x="Newspaper", y="Sales", data=data, order=2, ci=None)
<seaborn.axisgrid.FacetGrid at 0x135878550>



```
data.corr()
```

```
TV Radio Newspaper Sales
TV 1.000000 0.054809 0.056648 0.782224
Radio 0.054809 1.000000 0.354104 0.576223
Newspaper 0.056648 0.354104 1.000000 0.228299
Sales 0.782224 0.576223 0.228299 1.000000
```

# Между TV и Sales есть корреляция 0.78

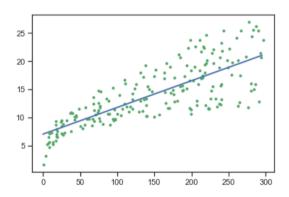
```
x = data["TV"].values
y = data["Sales"].values

reg = BayesianRidge(fit_intercept=True).fit(x.reshape(-1, 1),
y.reshape(-1, 1))
reg.coef_
reg.intercept_
7.054854152265513

def func(w, b, x):
    return w*x + b

x_t = list(range(0, 300, 5))
y_t = [func(reg.coef_[0], reg.intercept_, x) for x in x_t]
y_tt = reg.predict(x.reshape(-1, 1))

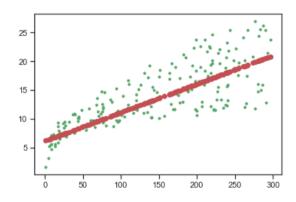
plt.plot(x, y, 'g.')
plt.plot(x_t, y_t, 'b', linewidth=2.0)
plt.show()
```



# Модель линейной регрессии дала неплохой результат

### **SVM**

```
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR,
NuSVR, LinearSVR
lin_SVR = LinearSVR(C=1.0, max_iter=10000)
lin_SVR.fit(x.reshape(-1, 1), y)
predict = lin_SVR.predict(x.reshape(-1, 1))
plt.plot(x, y, 'g.')
plt.plot(x, predict, 'ro')
[<matplotlib.lines.Line2D at 0x13e5a9b10>]
```



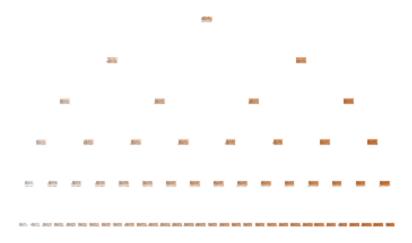
# Деревья решений

```
presort='deprecated'.
                                                                                                                                                                                                                                         random state=1, splitter='best')
dec predict = dec tree.predict(data)
from sklearn import tree
tree.plot tree(dec tree, filled=True)
 [Text(167.4, 199.32, 'X[3] \le 15.1 \times = 27.086 \times = 200 \times = 200
= 14.023'),
         Text(83.7, 163.079999999999999, 'X[3] \le 10.0 \times = 7.31 \times = 10.0 \times = 7.31 \times = 10.0 \times
 125 \text{ nvalue} = 10.67'),
          45 \cdot \text{nvalue} = 7.767'),
          Text(20.925, 90.6, 'X[0] \le 4.75 \times = 2.173 \times = 18 \times = 18
 5.872'),
         Text(10.4625, 54.3599999999999999, 'X[3] \le 2.4 \times = 0.64 \times = 0.64
2\nvalue = 2.4'),
         1.6'),
         Text(15.693750000000001, 18.11999999999976, 'mse = -0.0 \nsamples =
 1\nvalue = 3.2').
         Text(31.38750000000003, 54.3599999999999, 'X[3] <= 6.25 \times = 6.25
 0.669 \times 16 = 16 \times 16 = 6.306'
         5.443'),
         Text(36.61875, 18.1199999999999976, 'mse = 0.075 \nsamples = 9 \nvalue =
6.978'),
         Text(62.77500000000006, 90.6, 'X[3] \le 9.0 \times = 0.442 \times 
27\nvalue = 9.03'),
          Text(52.3125, 54.3599999999999999, 'X[3] \le 8.25 \times = 0.18 \times = 0.18
= 12 \setminus \text{nvalue} = 8.375'),
          Text(47.081250000000004, 18.119999999999976, 'mse = 0.052\nsamples =
 4 \neq 0.825'
          Text(57.54375, 18.119999999999976, 'mse = 0.017\nsamples = 8\nvalue =
8.65'),
         = 15 \nvalue = 9.553'),
         Text(68.00625000000001, 18.119999999999976, 'mse = 0.013\nsamples =
 7\nvalue = 9.386'),
          Text(78.46875, 18.1199999999999976, 'mse = 0.008\nsamples = 8\nvalue =
```

```
9.7').
  Text(125.5500000000001, 126.8399999999999, 'X[3] <= 12.55 \times = 12.55
2.031 \times = 80 \times = 12.302'
  Text(104.625, 90.6, 'X[3] \le 11.1 \times = 0.487 \times = 48 \times = 48
11.317'),
  Text(94.16250000000001, 54.359999999999985, 'X[3] <= 10.55 \nmse =
0.083 \text{ nsamples} = 19 \text{ nvalue} = 10.558'),
  Text(88.93125, 18.1199999999999976, 'mse = 0.024\nsamples = 9\nvalue =
10.3'),
  Text(99.39375, 18.1199999999999976, 'mse = 0.023 \nsamples = 10 \nvalue
= 10.79'),
  Text(115.0875, 54.3599999999999985, 'X[3] <= 11.85 \times = 11.85
0.127 \times = 29 \times = 11.814'
  Text(109.85625, 18.1199999999999976, 'mse = 0.034 \nsamples = 17 \nvalue
= 11.565'),
  Text(120.31875000000001, 18.119999999999976, 'mse = 0.047 \nsamples =
12 \cdot \text{nvalue} = 12.167'),
  Text(146.475, 90.6, 'X[3] \le 13.8 \times = 0.703 \times = 32 \times = 32
13.781'),
  Text(136.01250000000002, 54.3599999999999985, 'X[3] <= 13.05 \times = 10.05 \times =
0.091 \times 10^{-1} = 17 \times 10^{-1}
  Text(130.78125, 18.1199999999999976, 'mse = 0.014\nsamples = 9\nvalue
= 12.789'),
  Text(141.24375, 18.119999999999976, 'mse = 0.017 \nsamples = 8 \nvalue
= 13.338'),
  Text(156.9375, 54.359999999999985, 'X[3] \le 14.45 \times = 14.45
0.094 \times 15 = 15 \times 14.613'
  = 14.175'),
  Text(162.16875000000002, 18.11999999999976, 'mse = 0.026 \nsamples =
11 \setminus \text{nvalue} = 14.773'),
  Text(251.10000000000002, 163.0799999999999, 'X[3] <= 20.45 \nmse =
10.081 \times = 75 \times = 19.611'),
  = 47 \text{ nvalue} = 17.519'),
  Text(188.32500000000002, 90.6, 'X[3] \le 16.35 \times = 0.603 \times = 0.603
27\nvalue = 16.348'),
  0.084 \times 14 = 14 \times 15.657'
  Text(172.63125, 18.119999999999976, 'mse = 0.023\nsamples = 7\nvalue
```

```
= 15.4').
    Text(183.09375, 18.1199999999999976, 'mse = 0.013\nsamples = 7\nvalue
= 15.914').
    Text(198.7875, 54.3599999999999985, 'X[3] <= 17.05 \times = 17.05
0.095 \times = 13 \times = 17.092'
    Text(193.55625, 18.1199999999999976, 'mse = 0.026 \nsamples = 5 \nvalue
= 16.76').
    Text(204.01875, 18.1199999999999976, 'mse = 0.025\nsamples = 8\nvalue
= 17.3'),
    Text(230.175, 90.6, 'X[3] \le 19.1 \times = 0.505 \times = 20 \times = 20
19.1'),
    Text(219.7125, 54.3599999999999985, 'X[3] \le 18.7 \times = 18.7
0.162 \times = 10 \times = 18.5'
    Text(214.48125000000002, 18.119999999999976, 'mse = 0.043 \nsamples =
6\nvalue = 18.2'),
    Text(224.94375, 18.1199999999999976, 'mse = 0.002\nsamples = 4\nvalue
= 18.95'),
    Text(240.63750000000002, 54.359999999999985, 'X[3] <= 19.75 \nmse =
0.128 \times = 10 \times = 19.7'
    Text(235.40625, 18.1199999999999976, 'mse = 0.039\nsamples = 6\nvalue
= 19.45'),
    Text(245.86875, 18.1199999999999976, 'mse = 0.027 \nsamples = 4 \nvalue
= 20.075'),
    = 28 \text{ nvalue} = 23.121'),
    Text(272.0250000000003, 90.6, 'X[3] \le 21.75 \times = 0.581 \times = 0.581
16 \setminus \text{nvalue} = 21.744'),
    Text(261.5625, 54.3599999999999985, 'X[3] \le 21.0 \times = 21
0.149 \times = 8 \times = 21.088'),
    Text(256.33125, 18.1199999999999976, 'mse = 0.002\nsamples = 4\nvalue
= 20.725'),
    Text(266.79375, 18.119999999999976, 'mse = 0.032\nsamples = 4\nvalue
= 21.45'),
    Text(282.4875, 54.359999999999985, 'X[3] \le 22.5 \times = 24.5 \times = 22.5 \times = 22.
0.153 \times = 8 \times = 22.4'
    Text(277.25625, 18.1199999999999976, 'mse = 0.042\nsamples = 5\nvalue
= 22.16'),
    Text(287.71875, 18.119999999999976, 'mse = 0.08\nsamples = 3\nvalue =
22.8'),
    Text(313.875, 90.6, 'X[3] \le 25.05 \times = 0.984 \times = 12 \times = 12
```

```
= 24.958'),
  Text(303.4125, 54.35999999999985, 'X[3] <= 24.0\nmse =
0.133\nsamples = 6\nvalue = 24.1'),
  Text(298.18125000000003, 18.11999999999976, 'mse = 0.002\nsamples =
3\nvalue = 23.767'),
  Text(308.64375, 18.119999999999976, 'mse = 0.042\nsamples = 3\nvalue
= 24.433'),
  Text(324.33750000000003, 54.35999999999985, 'X[3] <= 25.85\nmse =
0.361\nsamples = 6\nvalue = 25.817'),
  Text(319.10625, 18.11999999999976, 'mse = 0.002\nsamples = 4\nvalue
= 25.425'),
  Text(329.56875, 18.119999999999976, 'mse = 0.16\nsamples = 2\nvalue =
26.6')]</pre>
```



# Метрики качества

from sklearn.metrics import mean\_absolute\_error, mean\_squared\_error,
mean\_squared\_log\_error, median\_absolute\_error, r2\_score

```
print("Метрики для линейной модели:\n")
print("Средняя абсолютная ошибка: ", mean_absolute_error(y, y_tt))
print("Средняя квадратичная ошибка: ", mean_squared_error(y, y_tt))
```

```
print("Коэффициент детерминации: ", r2 score(y, y tt))
print("\n\nMeтрики для SVM-модели:\n")
print("Средняя абсолютная ошибка: ", mean absolute error(y, predict))
print("Средняя квадратичная ошибка: ", mean squared error(y, predict))
print("Коэффициент детерминации: ", r2 score(y, predict))
print("\n\nMeтрики для Decision Tree:\n")
print("Средняя абсолютная ошибка: ", mean absolute error(y,
dec predict))
print("Средняя квадратичная ошибка: ", mean squared error(y,
dec predict))
print("Коэффициент детерминации: ", r2 score(y, dec predict))
Метрики для линейной модели:
Средняя абсолютная ошибка: 2.550919383216356
Средняя квадратичная ошибка: 10.512821002854928
Коэффициент детерминации: 0.6118688451058344
Метрики для SVM-модели:
Средняя абсолютная ошибка: 2.5708683334350892
Средняя квадратичная ошибка: 10.859652690875892
Коэффициент детерминации: 0.5990638916505333
Метрики для Decision Tree:
Средняя абсолютная ошибка: 0.14353164841694266
Средняя квадратичная ошибка: 0.03201810934980053
Коэффициент детерминации: 0.9988178980926156
Подбор гиперпараметров. Кросс-валидация
```

from sklearn.model selection import cross validate

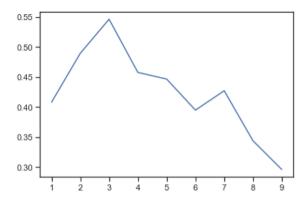
```
scoring = {'mean': 'neg mean absolute error', 'square':
'neg mean squared error', 'r2': 'r2'}
scores regr = cross validate(BayesianRidge(fit intercept=True).
                         x.reshape(-1, 1), v, cv=3, scoring=scoring)
scores regr
{'fit time': array([0.00085902, 0.00085711, 0.00055289]),
 'score time': array([0.00140524, 0.00080299, 0.00078702]),
 'test mean': array([-2.51215213, -2.46200408, -2.76711466]),
 'test square': array([-10.83437466. -9.33658309. -11.90833409]).
 'test r2': array([0.61497417, 0.65311667, 0.537153041)}
scores svm = cross validate(LinearSVR(C=1.0, max iter=10000),
                         x.reshape(-1, 1), y, cv=3, scoring=scoring)
scores svm
{'fit time': array([0.03139281, 0.02713585, 0.02338099]),
 'score time': array([0.00076604, 0.00061393, 0.00054908]),
 'test mean': array([-2.54098772, -2.37148251, -3.1291242 ]),
 'test square': array([-11.0231287 , -9.81978964, -15.84997398]),
 'test r2': array([0.60826634, 0.63516403, 0.38395142])}
scores dec = cross validate(DecisionTreeRegressor(random state=1,
max depth=3),
                         data, data["Sales"], cv=5, scoring=scoring)
scores dec
{'fit time': array([0.00271297, 0.0020709, 0.00206208, 0.00199294,
0.001951931),
 'score time': array([0.0018599 , 0.00148034, 0.00148678, 0.00142694,
0.0014143 1),
 'test mean': array([-0.72293478, -0.7307461 , -0.66116873,
-0.85487267, -0.915500491),
 'test square': array([-0.64975012, -0.70991464, -0.63349151,
-1.4104023 , -1.08449788]),
 'test r2': array([0.97486214, 0.97589358, 0.97175881, 0.95176776,
0.959388151)}
print("Метрики для линейной модели:\n")
print("Средняя абсолютная ошибка: ",
np.mean(scores regr['test mean']))
```

```
print("Средняя квадратичная ошибка: ".
np.mean(scores regr['test square']))
print("Коэффициент детерминации: ", np.mean(scores regr['test r2']))
print("\n\nMeтрики для SVM-модели:\n")
print("Средняя абсолютная ошибка: ", np.mean(scores svm['test mean']))
print("Средняя квадратичная ошибка: ",
np.mean(scores svm['test square']))
print("Коэффициент детерминации: ", np.mean(scores svm['test r2']))
print("\n\nMeтрики для Decision Tree:\n")
print("Средняя абсолютная ошибка: ", np.mean(scores dec['test mean']))
print("Средняя квадратичная ошибка: ",
np.mean(scores dec['test square']))
print("Коэффициент детерминации: ", np.mean(scores dec['test r2']))
Метрики для линейной модели:
Средняя абсолютная ошибка: -2.580423621885709
Средняя квадратичная ошибка: -10.693097277894969
Коэффициент детерминации: 0.601747959666948
Метрики для SVM-модели:
Средняя абсолютная ошибка: -2.6805314771806956
Средняя квадратичная ошибка: -12.23096410841425
Коэффициент детерминации: 0.5424605962417798
Метрики для Decision Tree:
Средняя абсолютная ошибка: -0.7770445553321956
Средняя квадратичная ошибка: -0.8976112886827845
Коэффициент детерминации: 0.9667340888852873
```

## Оптимизация с помощью решетчатого поиска

```
from sklearn.model selection import GridSearchCV
n range = np.array(range(1,10,1))
tuned parameters = [{'max depth': n range}]
tuned parameters
[{'max depth': array([1, 2, 3, 4, 5, 6, 7, 8, 9])}]
%%time
clf qs = GridSearchCV(DecisionTreeRegressor(), tuned parameters, cv=5,
scoring='r2')
clf qs.fit(x.reshape(-1, 1), y)
CPU times: user 48.9 ms, sys: 1.26 ms, total: 50.2 ms
Wall time: 49.2 ms
GridSearchCV(cv=5, error score=nan,
             estimator=DecisionTreeRegressor(ccp alpha=0.0,
criterion='mse',
                                             max depth=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='deprecated',
                                              random state=None,
                                             splitter='best'),
             iid='deprecated', n jobs=None,
             param grid=[{'max depth': array([1, 2, 3, 4, 5, 6, 7, 8,
```

```
91)}1,
             pre dispatch='2*n jobs', refit=True,
return train score=False,
             scoring='r2', verbose=0)
# Лучшая модель
clf qs.best estimator
DecisionTreeRegressor(ccp alpha=0.0, criterion='mse', max depth=3,
                      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='deprecated',
                      random state=None, splitter='best')
clf gs.best score
0.5464056968965096
clf qs.best params
{'max depth': 3}
plt.plot(n range, clf gs.cv results ['mean test score'])
[<matplotlib.lines.Line2D at 0x1365b10d0>]
```



### Оптимизация SVM

```
param grid = {'C': [0.1,1,10,100], 'epsilon': [0.1,0.2,0.3,0.4,
0.5, 0.6, 0.7, 0.8, 0.9, 1.01
grid = GridSearchCV(LinearSVR(),param grid,refit=True,verbose=2)
grid.fit(x.reshape(-1, 1),y)
Fitting 5 folds for each of 40 candidates, totalling 200 fits
[CV] C=0.1, epsilon=0.1 ......
[CV] C=0.1, epsilon=0.1 ......
[CV] ..... C=0.1, epsilon=0.1, total=
[CV] C=0.1, epsilon=0.1 ......
[CV] ..... C=0.1, epsilon=0.1, total=
[CV] C=0.1, epsilon=0.1 ......
[CV] ...... C=0.1, epsilon=0.1, total=
[CV] C=0.1, epsilon=0.1 ......
[CV] ...... C=0.1, epsilon=0.1, total=
[CV] C=0.1, epsilon=0.2 .....
[CV] ..... C=0.1, epsilon=0.2, total=
[CV] C=0.1, epsilon=0.2 ......
[CV] ...... C=0.1, epsilon=0.2, total=
[CV] C=0.1, epsilon=0.2 ......
[CV] ..... C=0.1, epsilon=0.2, total=
[CV] C=0.1, epsilon=0.2 .....
[CV] ..... C=0.1, epsilon=0.2, total=
[CV] C=0.1, epsilon=0.2 ......
[CV] ..... C=0.1, epsilon=0.2, total=
[CV] C=0.1, epsilon=0.3 ......
[CV] ...... C=0.1, epsilon=0.3, total=
[CV] C=0.1, epsilon=0.3 ......
[CV] ..... C=0.1, epsilon=0.3, total=
[CV] C=0.1, epsilon=0.3 ......
[CV] ...... C=0.1, epsilon=0.3, total=
[CV] C=0.1, epsilon=0.3 ......
[CV] ...... C=0.1, epsilon=0.3, total=
[CV] C=0.1, epsilon=0.3 ......
[CV] ..... C=0.1, epsilon=0.3, total=
```

```
[CV] C=0.1, epsilon=0.4 ......
[CV] ..... C=0.1, epsilon=0.4, total=
[CV] C=0.1, epsilon=0.4 ......
[CV] ..... C=0.1, epsilon=0.4, total=
[CV] C=0.1, epsilon=0.4 ......
[CV] ..... C=0.1, epsilon=0.4, total=
[CV] C=0.1, epsilon=0.4 .....
[CV] ..... C=0.1, epsilon=0.4, total=
[CV] C=0.1, epsilon=0.4 ......
[CV] ..... C=0.1, epsilon=0.4, total=
[CV] C=0.1, epsilon=0.5 ......
[CV] ...... C=0.1, epsilon=0.5, total=
[CV] C=0.1, epsilon=0.5 ......
[CV] ...... C=0.1, epsilon=0.5, total=
[CV] C=0.1, epsilon=0.5 ......
[CV] ...... C=0.1, epsilon=0.5, total=
[CV] C=0.1, epsilon=0.5 .....
[CV] ...... C=0.1, epsilon=0.5, total=
[CV] C=0.1, epsilon=0.5 ......
[CV] ...... C=0.1, epsilon=0.5, total=
[CV] C=0.1, epsilon=0.6 ......
[CV] ...... C=0.1, epsilon=0.6, total=
[CV] C=0.1, epsilon=0.6 ......
[CV] ..... C=0.1, epsilon=0.6, total=
[CV] C=0.1, epsilon=0.6 ......
[CV] ...... C=0.1, epsilon=0.6, total=
[CV] C=0.1, epsilon=0.6 ......
[CV] ..... C=0.1, epsilon=0.6, total=
[CV] C=0.1, epsilon=0.6 ......
[CV] ..... C=0.1, epsilon=0.6, total=
[CV] C=0.1, epsilon=0.7 ......
[CV] ..... C=0.1, epsilon=0.7, total=
[CV] C=0.1, epsilon=0.7 ......
[CV] ...... C=0.1, epsilon=0.7, total=
[CV] C=0.1, epsilon=0.7 ......
[CV] ...... C=0.1, epsilon=0.7, total=
[CV] C=0.1, epsilon=0.7 ......
```

```
[CV] ...... C=0.1, epsilon=0.7, total=
[CV] C=0.1, epsilon=0.7 ......
[CV] ..... C=0.1, epsilon=0.7, total=
[CV] C=0.1, epsilon=0.8 .....
[CV] ..... C=0.1, epsilon=0.8, total=
                                  0.0s
[CV] C=0.1, epsilon=0.8 ......
[CV] ..... C=0.1, epsilon=0.8, total=
[CV] C=0.1, epsilon=0.8 ......
[CV] ...... C=0.1, epsilon=0.8, total=
[CV] C=0.1, epsilon=0.8 ......
[CV] ...... C=0.1, epsilon=0.8, total=
[CV] C=0.1, epsilon=0.8 ......
[CV] ...... C=0.1, epsilon=0.8, total=
[CV] C=0.1, epsilon=0.9 ......
[CV] ..... C=0.1, epsilon=0.9, total=
[CV] C=0.1, epsilon=0.9 ......
[CV] ..... C=0.1, epsilon=0.9, total=
[CV] C=0.1, epsilon=0.9 ......
[CV] ..... C=0.1, epsilon=0.9, total=
[CV] C=0.1, epsilon=0.9 ......
[CV] ..... C=0.1, epsilon=0.9, total=
[CV] C=0.1, epsilon=0.9 ......
[CV] ..... C=0.1, epsilon=0.9, total=
[CV] C=0.1, epsilon=1.0 ......
[CV] ...... C=0.1, epsilon=1.0, total=
[CV] C=0.1, epsilon=1.0 ......
[CV] ..... C=0.1, epsilon=1.0, total=
                                  0.0s
[CV] C=0.1, epsilon=1.0 ......
[CV] ..... C=0.1, epsilon=1.0, total=
[CV] C=0.1, epsilon=1.0 ......
[CV] ..... C=0.1, epsilon=1.0, total=
[CV] C=0.1, epsilon=1.0 ......
[CV] ..... C=0.1, epsilon=1.0, total=
[CV] C=1, epsilon=0.1 .....
[CV] ..... C=1, epsilon=0.1, total=
[CV] C=1, epsilon=0.1 ......
```

```
[Parallel(n jobs=1)]: Using backend SeguentialBackend with 1
concurrent workers.
              1 out of
                    1 | elapsed:
[Parallel(n jobs=1)]: Done
                            0.0s
remaining:
       0.0s
[CV] ..... C=1, epsilon=0.1, total=
                                 0.0s
[CV] ..... C=1, epsilon=0.1, total=
[CV] C=1, epsilon=0.1 ......
[CV] ..... C=1, epsilon=0.1, total=
[CV] C=1, epsilon=0.1 .....
[CV] ..... C=1, epsilon=0.1, total=
                                 0.0s
[CV] C=1, epsilon=0.2 ......
[CV] ..... C=1, epsilon=0.2, total=
                                 0.0s
[CV] C=1, epsilon=0.2 ......
[CV] ..... C=1, epsilon=0.2, total=
[CV] C=1, epsilon=0.2 ......
[CV] ..... C=1, epsilon=0.2, total=
[CV] C=1, epsilon=0.2 ......
[CV] ..... C=1, epsilon=0.2, total=
[CV] C=1, epsilon=0.2 .....
[CV] ..... C=1, epsilon=0.2, total=
                                 0.0s
[CV] C=1, epsilon=0.3 ......
[CV] ..... C=1, epsilon=0.3, total=
[CV] C=1, epsilon=0.3 ......
[CV] ..... C=1, epsilon=0.3, total=
[CV] ..... C=1, epsilon=0.3, total=
[CV] C=1, epsilon=0.3 ......
[CV] ..... C=1, epsilon=0.3, total=
[CV] C=1, epsilon=0.3 ......
[CV] ..... C=1, epsilon=0.3, total=
[CV] C=1, epsilon=0.4 ......
```

[CV] ..... C=1, epsilon=0.4, total=

[CV] C=1, epsilon=0.4 ......

```
[CV] ..... C=1, epsilon=0.4, total=
[CV] C=1, epsilon=0.4 ......
[CV] ..... C=1, epsilon=0.4, total=
[CV] C=1, epsilon=0.4 ......
[CV] ..... C=1, epsilon=0.4, total=
                                0.0s
[CV] C=1, epsilon=0.4 ......
[CV] ..... C=1, epsilon=0.4, total=
[CV] C=1, epsilon=0.5 ......
[CV] ..... C=1, epsilon=0.5, total=
[CV] C=1, epsilon=0.5 ......
[CV] ..... C=1, epsilon=0.5, total=
[CV] C=1, epsilon=0.5 ......
[CV] ...... C=1, epsilon=0.5, total=
[CV] C=1, epsilon=0.5 ......
[CV] ..... C=1, epsilon=0.5, total=
[CV] C=1, epsilon=0.5 ......
[CV] ..... C=1, epsilon=0.5, total=
[CV] C=1, epsilon=0.6 ......
[CV] ..... C=1, epsilon=0.6, total=
[CV] C=1, epsilon=0.6 ......
[CV] ..... C=1, epsilon=0.6, total=
[CV] C=1, epsilon=0.6 ......
[CV] ..... C=1, epsilon=0.6, total=
[CV] C=1, epsilon=0.6 ......
[CV] ..... C=1, epsilon=0.6, total=
[CV] C=1, epsilon=0.6 ......
[CV] ..... C=1, epsilon=0.6, total=
                                0.0s
[CV] C=1, epsilon=0.7 .....
[CV] ..... C=1, epsilon=0.7, total=
[CV] C=1, epsilon=0.7 ......
[CV] ..... C=1, epsilon=0.7, total=
[CV] C=1, epsilon=0.7 ......
[CV] ..... C=1, epsilon=0.7, total=
                                0.0s
[CV] C=1, epsilon=0.7 ......
[CV] ..... C=1, epsilon=0.7, total=
                                0.0s
[CV] C=1, epsilon=0.7 ......
0.0s
```

```
[CV] C=1, epsilon=0.8 .....
CV1 ..... C=1, epsilon=0.8, total=
[CV] C=1, epsilon=0.8 .....
[CV] ..... C=1, epsilon=0.8, total=
[CV] C=1, epsilon=0.8 .....
[CV] ..... C=1, epsilon=0.8, total=
[CV] C=1, epsilon=0.8 .....
[CV] ..... C=1, epsilon=0.8, total=
[CV] C=1, epsilon=0.8 ......
[CV] ..... C=1, epsilon=0.8, total=
[CV] C=1, epsilon=0.9 ......
[CV] ...... C=1, epsilon=0.9, total=
[CV] C=1, epsilon=0.9 ......
[CV] ..... C=1, epsilon=0.9, total=
[CV] C=1, epsilon=0.9 ......
[CV] ..... C=1, epsilon=0.9, total=
[CV] C=1, epsilon=0.9 .....
[CV] ..... C=1, epsilon=0.9, total=
[CV] C=1, epsilon=0.9 ......
[CV] ..... C=1, epsilon=0.9, total=
[CV] C=1, epsilon=1.0 ......
[CV] ..... C=1, epsilon=1.0, total=
[CV] C=1, epsilon=1.0 ......
[CV] ..... C=1, epsilon=1.0, total=
[CV] C=1, epsilon=1.0 ......
[CV] ..... C=1, epsilon=1.0, total=
[CV] ..... C=1, epsilon=1.0, total=
[CV] C=1, epsilon=1.0 ......
[CV] ..... C=1, epsilon=1.0, total=
[CV] C=10, epsilon=0.1 ......
[CV] ..... C=10, epsilon=0.1, total=
[CV] C=10, epsilon=0.1 ......
[CV] ...... C=10, epsilon=0.1, total=
[CV] C=10, epsilon=0.1 ......
```

```
[CV] ..... C=10, epsilon=0.1, total=
[CV] C=10, epsilon=0.1 ......
[CV] C=10, epsilon=0.2 ......
0.0s
[CV] C=10, epsilon=0.2 ......
[CV] C=10, epsilon=0.2 ......
[CV] C=10, epsilon=0.2 ......
[CV] C=10, epsilon=0.2 .....
[CV] C=10, epsilon=0.3 ......
[CV] C=10, epsilon=0.3 ......
[CV] C=10, epsilon=0.3 ......
[CV] C=10, epsilon=0.3 ......
[CV] ..... C=10, epsilon=0.3, total=
[CV] C=10, epsilon=0.3 ......
[CV] C=10, epsilon=0.4 ......
[CV] C=10, epsilon=0.4 ......
[CV] ..... C=10, epsilon=0.4, total=
                  0.0s
[CV] C=10, epsilon=0.4 ......
[CV] C=10, epsilon=0.4 ......
[CV] C=10, epsilon=0.5 ......
0.0s
[CV] C=10, epsilon=0.5 ......
[CV] ..... C=10, epsilon=0.5, total=
                  0.0s
```

```
[CV] C=10, epsilon=0.5 ......
[CV] C=10, epsilon=0.5 .....
[CV] C=10, epsilon=0.5 ......
[CV] C=10, epsilon=0.6 ......
[CV] C=10, epsilon=0.7 .....
[CV] C=10, epsilon=0.7 ......
[CV] C=10, epsilon=0.7 ......
[CV] C=10, epsilon=0.7 ......
[CV] C=10, epsilon=0.7 ......
[CV] C=10, epsilon=0.8 ......
[CV] ..... C=10, epsilon=0.8, total=
[CV] C=10, epsilon=0.8 ......
[CV] C=10, epsilon=0.8 ......
[CV] ..... C=10, epsilon=0.8, total=
[CV] C=10, epsilon=0.8 ......
[CV] ...... C=10, epsilon=0.8, total=
[CV] C=10, epsilon=0.8 ......
[CV] C=10, epsilon=0.9 ......
```

```
[CV] ..... C=10, epsilon=0.9, total=
[CV] C=10, epsilon=0.9 ......
[CV] C=10, epsilon=0.9 ......
0.0s
[CV] C=10, epsilon=0.9 ......
[CV] C=10, epsilon=0.9 ......
[CV] C=10, epsilon=1.0 ......
[CV] C=100, epsilon=0.1 ......
[CV] ..... C=100, epsilon=0.1, total=
[CV] C=100, epsilon=0.1 ......
[CV] ...... C=100, epsilon=0.1, total=
[CV] C=100, epsilon=0.1 ......
[CV] ...... C=100, epsilon=0.1, total=
[CV] C=100, epsilon=0.1 ......
[CV] ...... C=100, epsilon=0.1, total=
                         0.0s
[CV] C=100, epsilon=0.1 ......
[CV] ...... C=100, epsilon=0.1, total=
[CV] C=100, epsilon=0.2 ......
[CV] ..... C=100, epsilon=0.2, total=
[CV] C=100, epsilon=0.2 ......
[CV] ...... C=100, epsilon=0.2, total=
[CV] C=100, epsilon=0.2 .....
[CV] ..... C=100, epsilon=0.2, total=
                         0.0s
[CV] C=100, epsilon=0.2 ......
[CV] ...... C=100, epsilon=0.2, total=
                         0.0s
```

```
[CV] C=100, epsilon=0.2 ......
[CV] ...... C=100, epsilon=0.2, total=
[CV] C=100, epsilon=0.3 ......
[CV] ...... C=100, epsilon=0.3, total=
[CV] C=100, epsilon=0.3 ......
[CV] ...... C=100, epsilon=0.3, total=
[CV] C=100, epsilon=0.3 .....
[CV] ...... C=100, epsilon=0.3, total=
[CV] C=100, epsilon=0.3 ......
[CV] ...... C=100, epsilon=0.3, total=
[CV] C=100, epsilon=0.3 ......
[CV] ...... C=100, epsilon=0.3, total=
[CV] C=100, epsilon=0.4 .....
[CV] ...... C=100, epsilon=0.4, total=
[CV] C=100, epsilon=0.4 .....
[CV] ...... C=100, epsilon=0.4, total=
[CV] C=100, epsilon=0.4 .....
[CV] ...... C=100, epsilon=0.4, total=
[CV] C=100, epsilon=0.4 ......
[CV] ...... C=100, epsilon=0.4, total=
[CV] C=100, epsilon=0.4 ......
[CV] ...... C=100, epsilon=0.4, total=
[CV] C=100, epsilon=0.5 ......
[CV] ...... C=100, epsilon=0.5, total=
[CV] C=100, epsilon=0.5 ......
[CV] ...... C=100, epsilon=0.5, total=
[CV] C=100, epsilon=0.5 ......
[CV] ..... C=100, epsilon=0.5, total=
[CV] C=100, epsilon=0.5 ......
[CV] ...... C=100, epsilon=0.5, total=
[CV] C=100, epsilon=0.5 ......
[CV] ...... C=100, epsilon=0.5, total=
[CV] C=100, epsilon=0.6 ......
[CV] ...... C=100, epsilon=0.6, total=
[CV] C=100, epsilon=0.6 ......
[CV] ..... C=100, epsilon=0.6, total=
[CV] C=100, epsilon=0.6 ......
```

```
[CV] ...... C=100, epsilon=0.6, total=
[CV] C=100, epsilon=0.6 ......
[CV] ...... C=100, epsilon=0.6, total=
[CV] C=100, epsilon=0.6 .....
[CV] ...... C=100, epsilon=0.6, total=
                                  0.0s
[CV] C=100, epsilon=0.7 .....
[CV] ..... C=100, epsilon=0.7, total=
[CV] C=100, epsilon=0.7 .....
[CV] ...... C=100, epsilon=0.7, total=
[CV] C=100, epsilon=0.7 ......
[CV] ...... C=100, epsilon=0.7, total=
[CV] C=100, epsilon=0.7 .....
[CV] ...... C=100, epsilon=0.7, total=
[CV] C=100, epsilon=0.7 .....
[CV] ..... C=100, epsilon=0.7, total=
[CV] C=100, epsilon=0.8 ......
[CV] ..... C=100, epsilon=0.8, total=
[CV] C=100, epsilon=0.8 ......
[CV] ...... C=100, epsilon=0.8, total=
[CV] C=100, epsilon=0.8 ......
[CV] ..... C=100, epsilon=0.8, total=
[CV] C=100, epsilon=0.8 ......
[CV] ...... C=100, epsilon=0.8, total=
[CV] C=100, epsilon=0.8 ......
[CV] ...... C=100, epsilon=0.8, total=
[CV] C=100, epsilon=0.9 ......
[CV] ...... C=100, epsilon=0.9, total=
[CV] C=100, epsilon=0.9 ......
[CV] ...... C=100, epsilon=0.9, total=
[CV] C=100, epsilon=0.9 ......
[CV] ..... C=100, epsilon=0.9, total=
[CV] C=100, epsilon=0.9 ......
[CV] ...... C=100, epsilon=0.9, total=
[CV] C=100, epsilon=0.9 .....
[CV] ..... C=100, epsilon=0.9, total=
[CV] C=100, epsilon=1.0 ......
[CV] ..... C=100, epsilon=1.0, total=
                                  0.0s
```

```
[CV] C=100, epsilon=1.0 ......
[CV] ..... C=100, epsilon=1.0, total=
CV1 C=100, epsilon=1.0 .....
[CV] ..... C=100, epsilon=1.0, total=
[CV] C=100, epsilon=1.0 .....
[CV] ..... C=100, epsilon=1.0, total=
                                                    0.0s
[CV] C=100, epsilon=1.0 .....
[CV] ..... C=100, epsilon=1.0, total=
                                                   0.0s
[Parallel(n jobs=1)]: Done 200 out of 200 | elapsed: 0.8s finished
GridSearchCV(cv=None, error score=nan,
          estimator=LinearSVR(C=1.0, dual=True, epsilon=0.0,
                          fit intercept=True,
intercept scaling=1.0,
                          loss='epsilon insensitive',
max iter=1000,
                          random state=None, tol=0.0001,
verbose=0),
          iid='deprecated', n jobs=None,
          param grid={'C': [0.1, 1, 10, 100],
                    'epsilon': [0.1, 0.2, 0.3, 0.4, 0.5, 0.6,
0.7, 0.8,
                             0.9, 1.01},
          pre dispatch='2*n jobs', refit=True,
return train score=False,
          scoring=None, verbose=2)
grid.best estimator
LinearSVR(C=10, dual=True, epsilon=1.0, fit intercept=True,
        intercept scaling=1.0, loss='epsilon insensitive',
max iter=1000,
       random state=None, tol=0.0001, verbose=0)
```

```
grid.best score
0.5440492644611755
grid.best params
{'C': 10, 'epsilon': 1.0}
parameters = {"alpha 1": np.logspace(-13, -5, 10),
              "alpha 2": np.logspace(-9, -3, 10),
              "lambda 1": np.logspace(-10, -5, 10),
              "lambda 2": np.logspace(-11,-4,10)}
grid regr = GridSearchCV(BayesianRidge(), parameters, cv=3, n jobs=-1)
grid regr.fit(x.reshape(-1, 1), y)
GridSearchCV(cv=3, error score=nan,
             estimator=BayesianRidge(alpha 1=1e-06, alpha 2=1e-06,
                                     alpha init=None,
compute score=False,
                                     copy X=True, fit intercept=True,
                                     lambda 1=1e-06, lambda 2=1e-06,
                                     lambda init=None, n iter=300,
                                     normalize=False, tol=0.001,
                                     verbose=False),
             iid='deprecated', n jobs=-1,
             param grid={'alpha 1': array([1.0000000e-13,
7.74263683e-13, 5.99484250e-...
                         'lambda 1': array([1.0000000e-10,
3.59381366e-10, 1.29154967e-09, 4.64158883e-09,
       1.66810054e-08, 5.99484250e-08, 2.15443469e-07, 7.74263683e-07,
       2.78255940e-06, 1.00000000e-05]),
                         'lambda 2': array([1.0000000e-11,
5.99484250e-11, 3.59381366e-10, 2.15443469e-09,
       1.29154967e-08, 7.74263683e-08, 4.64158883e-07, 2.78255940e-06,
       1.66810054e-05, 1.0000000e-04])},
             pre dispatch='2*n jobs', refit=True,
return train score=False,
             scoring=None, verbose=0)
grid regr.best estimator
```

```
BayesianRidge(alpha 1=1e-05, alpha 2=1e-09, alpha init=None,
              compute score=False, copy X=True, fit intercept=True,
              lambda 1=1e-10, lambda 2=0.0001, lambda init=None,
n iter=300,
              normalize=False, tol=0.001, verbose=False)
grid regr.best score
0.6017531508217578
grid regr.best params
{'alpha 1': 1e-05, 'alpha 2': 1e-09, 'lambda 1': 1e-10, 'lambda 2':
0.0001}
reg = BayesianRidge(fit intercept=True, alpha 1=1e-05, alpha 2=1e-09,
lambda 1=1e-10, lambda 2=0.0001).fit(x.reshape(-1, 1), y.reshape(-1,
1))
y tt = reg.predict(x.reshape(-1, 1))
lin SVR = LinearSVR(C=1.0, max iter=10000, epsilon=1.0)
lin SVR.fit(x.reshape(-1, 1), y)
predict = lin SVR.predict(x.reshape(-1, 1))
dec tree = DecisionTreeRegressor(random state=1, max depth=3)
dec tree.fit(data, data["Sales"])
dec predict = dec tree.predict(data)
print("Метрики для линейной модели:\n")
print("Средняя абсолютная ошибка: ", mean absolute error(y, y tt))
print("Средняя квадратичная ошибка: ", mean squared error(y, y tt))
print("Коэффициент детерминации: ", r2 score(y, y tt))
print("\n\nMeтрики для SVM-модели:\n")
print("Средняя абсолютная ошибка: ", mean absolute error(y, predict))
print("Средняя квадратичная ошибка: ", mean squared error(y, predict))
print("Коэффициент детерминации: ", r2 score(y, predict))
print("\n\nMeтрики для Decision Tree:\n")
print("Средняя абсолютная ошибка: ", mean absolute error(y,
```

```
dec_predict))
print("Средняя квадратичная ошибка: ", mean_squared_error(y, dec_predict))
print("Коэффициент детерминации: ", r2_score(y, dec_predict))
Метрики для линейной модели:
Средняя абсолютная ошибка: 2.5508292802546
Средняя квадратичная ошибка: 10.512794897173503
Коэффициент детерминации: 0.6118698089221382
Метрики для svm-модели:
Средняя абсолютная ошибка: 2.5996867264932724
Средняя квадратичная ошибка: 11.18839596468356
```

Метрики для Decision Tree:

Средняя абсолютная ошибка: 0.7095532407407409 Средняя квадратичная ошибка: 0.7222188657407407 Коэффициент детерминации: 0.9733358303760538

Коэффициент детерминации: 0.586926758668624

После подбора параметров модели показали лучший результат, чем без подбора.