Московский государственный технический университет имени Н. Э. Баумана Кафедра «Системы обработки информации и управления»

Лабораторная работа №5 по курсу «Методы машинного обучения» на тему:

«Линейные модели, SVM и деревья решений»

Выполнил:

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Задание

- Выберите набор данных (датасет) для решения задачи классификации или регрессии.
- В случае необходимости проведите удаление или заполнение пропусков и кодирование категориальных признаков.
- С использованием метода train_test_split разделите выборку на обучающую и тестовую.
- Обучите следующие модели:
- одну из линейных моделей;
- SVM;
- дерево решений.
- Оцените качество моделей с помощью трех подходящих для задачи метрик. Сравните качество полученных моделей.
- Произведите для каждой модели подбор одного гиперпараметра с использованием GridSearchCV и кросс-валидации.
- Повторите пункт 4 для найденных оптимальных значений гиперпараметров. Сравните качество полученных моделей с качеством моделей, полученных в пункте 4.

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing, svm
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')
```

In [2]:

```
data = pd.read_csv("data/Admission_Predict_Ver1.1.csv")
```

In [3]:

```
data.head(2)
```

Out[3]:

| | Serial No. | GRE Score | TOEFL Score | University Rating | SOP | LOR | CGPA | Research | Chance of Admit |
|---|------------|-----------|-------------|----------------------|-----|-----|------|----------|--------------------|
| 0 | 1 | 337 | 118 | 4 | 4.5 | 4.5 | 9.65 | 1 | 0.92 |
| 1 | 2 | 324 | 107 | 4 | 4.0 | 4.5 | 8.87 | 1 | 0.76 |

In [4]:

```
data.describe()
```

Out[4]:

| | Serial No. | GRE Score | TOEFL Score | University Rating | SOP | LOR | CGPA | Research | Chance of Admit |
|-------|------------|------------|-------------|----------------------|------------|-----------|------------|------------|--------------------|
| count | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.00000 | 500.000000 | 500.000000 | 500.00000 |
| mean | 250.500000 | 316.472000 | 107.192000 | 3.114000 | 3.374000 | 3.48400 | 8.576440 | 0.560000 | 0.72174 |
| std | 144.481833 | 11.295148 | 6.081868 | 1.143512 | 0.991004 | 0.92545 | 0.604813 | 0.496884 | 0.14114 |
| min | 1.000000 | 290.000000 | 92.000000 | 1.000000 | 1.000000 | 1.00000 | 6.800000 | 0.000000 | 0.34000 |
| 25% | 125.750000 | 308.000000 | 103.000000 | 2.000000 | 2.500000 | 3.00000 | 8.127500 | 0.000000 | 0.63000 |
| 50% | 250.500000 | 317.000000 | 107.000000 | 3.000000 | 3.500000 | 3.50000 | 8.560000 | 1.000000 | 0.72000 |
| 75% | 375.250000 | 325.000000 | 112.000000 | 4.000000 | 4.000000 | 4.00000 | 9.040000 | 1.000000 | 0.82000 |
| max | 500.000000 | 340.000000 | 120.000000 | 5.000000 | 5.000000 | 5.00000 | 9.920000 | 1.000000 | 0.97000 |

```
In [5]:
```

data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
# Column
                    Non-Null Count Dtype
--- ----
                    -----
 0 Serial No.
                   500 non-null int64
 1 GRE Score
                   500 non-null int64
   TOEFL Score
                   500 non-null int64
 2
   University Rating 500 non-null
                                  int64
                                float64
                    500 non-null
 4
   SOP
                                float64
  LOR
                    500 non-null
```

8 Chance of Admit 500 dtypes: float64(4), int64(5)

memory usage: 35.3 KB

In [6]:

```
data.columns
```

CGPA

7 Research

Out[6]:

500 non-null float64

int64

float64

500 non-null 500 non-null

In [7]:

```
corr = data.corr()
data.corr()
```

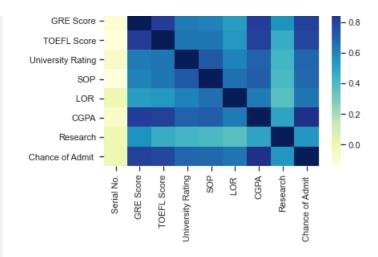
Out[7]:

| | Serial No. | GRE Score | TOEFL Score | University Rating | SOP | LOR | CGPA | Research | Chance of Admit |
|----------------------|------------|-----------|-------------|----------------------|-----------|-----------|-----------|-----------|--------------------|
| Serial No. | 1.000000 | -0.103839 | -0.141696 | -0.067641 | -0.137352 | -0.003694 | -0.074289 | -0.005332 | 0.008505 |
| GRE Score | -0.103839 | 1.000000 | 0.827200 | 0.635376 | 0.613498 | 0.524679 | 0.825878 | 0.563398 | 0.810351 |
| TOEFL Score | -0.141696 | 0.827200 | 1.000000 | 0.649799 | 0.644410 | 0.541563 | 0.810574 | 0.467012 | 0.792228 |
| University Rating | -0.067641 | 0.635376 | 0.649799 | 1.000000 | 0.728024 | 0.608651 | 0.705254 | 0.427047 | 0.690132 |
| SOP | -0.137352 | 0.613498 | 0.644410 | 0.728024 | 1.000000 | 0.663707 | 0.712154 | 0.408116 | 0.684137 |
| LOR | -0.003694 | 0.524679 | 0.541563 | 0.608651 | 0.663707 | 1.000000 | 0.637469 | 0.372526 | 0.645365 |
| CGPA | -0.074289 | 0.825878 | 0.810574 | 0.705254 | 0.712154 | 0.637469 | 1.000000 | 0.501311 | 0.882413 |
| Research | -0.005332 | 0.563398 | 0.467012 | 0.427047 | 0.408116 | 0.372526 | 0.501311 | 1.000000 | 0.545871 |
| Chance of Admit | 0.008505 | 0.810351 | 0.792228 | 0.690132 | 0.684137 | 0.645365 | 0.882413 | 0.545871 | 1.000000 |

In [8]:

Out[8]:

<matplotlib.axes._subplots.AxesSubplot at 0x17de383b588>



Между CGPA и Chance of Admit есть корреляция 0.88

In [10]:

```
x = data["CGPA"].values
y = data["Chance of Admit "].values

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

Out[10]:

-1.0433288693280354

In [12]:

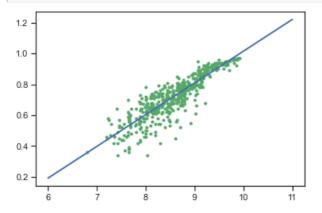
```
def func(w, b, x):
    return w*x + b
```

In [17]:

```
x_t = list(range(6, 12))
y_t = [func(reg.coef_[0], reg.intercept_, x) for x in x_t]
y_tt = reg.predict(x.reshape(-1, 1))
```

In [18]:

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



Модель линейной регрессии дала неплохой результат

SVM

```
In [19]:
```

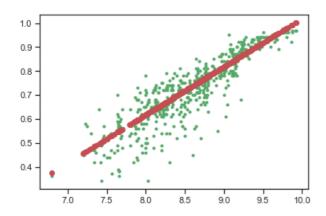
```
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR, NuSVR, LinearSVR
```

```
In [20]:
```

```
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')
```

Out[20]:

[<matplotlib.lines.Line2D at 0x17de5c3fb38>]



Деревья решений

```
In [27]:
```

```
dec_tree = DecisionTreeRegressor(random_state=1, max_depth=2)
dec_tree.fit(data, data["Chance of Admit "])
dec_tree
```

Out[27]:

DecisionTreeRegressor(max_depth=2, random_state=1)

In [28]:

```
dec_predict = dec_tree.predict(data)
```

In [29]:

```
from sklearn import tree
tree.plot_tree(dec_tree, filled=True)
```

Out[29]:

```
 [ \text{Text}(167.4, 181.2, 'X[8] <= 0.715 \mid \text{nmse} = 0.02 \mid \text{nsamples} = 500 \mid \text{nvalue} = 0.722'), \\  \text{Text}(83.7, 108.72, 'X[8] <= 0.575 \mid \text{nmse} = 0.008 \mid \text{nsamples} = 236 \mid \text{nvalue} = 0.601'), \\  \text{Text}(41.85, 36.2399999999998, 'mse = 0.004 \mid \text{nsamples} = 80 \mid \text{nvalue} = 0.495'), \\  \text{Text}(125.550000000000001, 36.2399999999998, 'mse = 0.002 \mid \text{nsamples} = 156 \mid \text{nvalue} = 0.656'), \\  \text{Text}(251.1000000000002, 108.72, 'X[8] <= 0.835 \mid \text{nmse} = 0.006 \mid \text{nsamples} = 264 \mid \text{nvalue} = 0.83'), \\  \text{Text}(209.25, 36.2399999999998, 'mse = 0.001 \mid \text{nsamples} = 144 \mid \text{nvalue} = 0.768'), \\  \text{Text}(292.95, 36.2399999999998, 'mse = 0.001 \mid \text{nsamples} = 120 \mid \text{nvalue} = 0.903')]
```

X[8] <= 0.715 mse = 0.02 samples = 500 value = 0.722

```
mse = 0.004 samples = 80 value = 0.495 mse = 0.001 samples = 156 value = 0.495 mse = 0.001 samples = 144 samples = 120 value = 0.768 value = 0.903
```

Метрики качества

```
In [30]:
```

```
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\nMетрики 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: 0.048356176421919375
Средняя квадратичная ошибка: 0.004400575179962326
Коэффициент детерминации: 0.77865169967127
Метрики для svм-модели:
Средняя абсолютная ошибка: 0.048000840719299075
Средняя квадратичная ошибка: 0.004531621770186015
Коэффициент детерминации: 0.7720600749804865
Метрики для Decision Tree:
Средняя абсолютная ошибка: 0.0349788333333333
Средняя квадратичная ошибка: 0.0017660232051282055
Коэффициент детерминации: 0.9111692861023747
```

Подбор гиперпараметров. Кросс-валидация

```
In [31]:
```

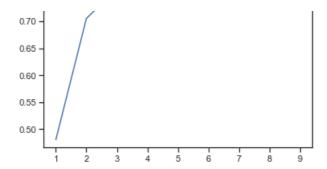
```
from sklearn.model_selection import cross_validate
In [32]:
scoring = {'mean': 'neg mean absolute error', 'square': 'neg mean squared error', 'r2': 'r2'}
```

```
scores_regr = cross_validate(BayesianRidge(fit_intercept=True),
                         x.reshape(-1, 1), y, cv=3, scoring=scoring)
scores regr
```

```
Out[33]:
{'fit_time': array([0.00099945, 0.00099969, 0.0019958 ]),
 'score_time': array([0.0019989 , 0.00200224, 0.00099802]),
 'test_mean': array([-0.06390867, -0.04166959, -0.0434577 ]),
 'test_square': array([-0.00805285, -0.00264878, -0.00341377]),
 'test_r2': array([0.69147165, 0.77100056, 0.83635644])}
In [34]:
scores svm = cross validate(LinearSVR(C=1.0, max iter=10000),
                          x.reshape(-1, 1), y, cv=3, scoring=scoring)
scores svm
Out[34]:
{'fit time': array([0.04097629, 0.0369761, 0.03497982]),
  'score_time': array([0.00100136, 0.00101209, 0.00099945]),
 'test_mean': array([-0.06527236, -0.03968679, -0.04267425]),
 'test_square': array([-0.00838947, -0.00241486, -0.00330504]),
 'test_r2': array([0.67857482, 0.79122418, 0.84156854])}
In [36]:
scores dec = cross validate(DecisionTreeRegressor(random state=1, max depth=3),
                          data, data["Chance of Admit "], cv=5, scoring=scoring)
scores_dec
Out[36]:
{'fit_time': array([0.00599432, 0.00499773, 0.00599909, 0.00599551, 0.00599694]),
 'score_time': array([0.00599647, 0.00499654, 0.0070045 , 0.00299644, 0.00499654]),
 'test mean': array([-0.01947024, -0.01658337, -0.01743311, -0.01960369, -0.01780489]),
 'test_square': array([-0.00070725, -0.00038489, -0.00040677, -0.00058168, -0.00045542]),
 'test r2': array([0.97674954, 0.97437313, 0.96746869, 0.96943965, 0.97486837])}
In [37]:
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: -0.049678655143161145
Средняя квадратичная ошибка: -0.004705132163926633
Коэффициент детерминации: 0.7662762176604807
Метрики для SVM-модели:
Средняя абсолютная ошибка: -0.04921113136081001
Средняя квадратичная ошибка: -0.0047031212018939636
Коэффициент детерминации: 0.7704558470118542
Метрики для Decision Tree:
Средняя абсолютная ошибка: -0.018179061248257487
Средняя квадратичная ошибка: -0.0005072017860681037
Коэффициент детерминации: 0.9725798741030808
```

Оптимизация с помощью решетчатого поиска

```
In [38]:
from sklearn.model_selection import GridSearchCV
In [39]:
n_range = np.array(range(1,10,1))
tuned_parameters = [{'max_depth': n_range}]
tuned_parameters
Out[39]:
[{'max_depth': array([1, 2, 3, 4, 5, 6, 7, 8, 9])}]
In [40]:
%%time
clf_gs = GridSearchCV(DecisionTreeRegressor(), tuned_parameters, cv=5, scoring='r2')
clf_gs.fit(x.reshape(-1, 1), y)
Wall time: 97 ms
Out[40]:
GridSearchCV(cv=5, estimator=DecisionTreeRegressor(),
             param_grid=[{'max_depth': array([1, 2, 3, 4, 5, 6, 7, 8, 9])}],
             scoring='r2')
In [41]:
# Лучшая модель
clf gs.best estimator
Out[41]:
DecisionTreeRegressor(max_depth=4)
In [42]:
clf_gs.best_score_
Out[42]:
0.7749073093532586
In [43]:
clf_gs.best_params_
Out[43]:
{'max_depth': 4}
In [44]:
plt.plot(n_range, clf_gs.cv_results_['mean_test_score'])
Out[44]:
[<matplotlib.lines.Line2D at 0x17de5da9ef0>]
```



Оптимизация SVM

```
In [45]:
```

```
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, 1.0]}
```

In [46]:

```
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, 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= 0.0s
[CV] C=0.1, epsilon=0.1 ......
[CV] ..... C=0.1, epsilon=0.1, total= 0.0s
[CV] C=0.1, epsilon=0.1 .....
[CV]
  ..... C=0.1, epsilon=0.1, total=
                                0.0s
[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= 0.0s
[CV] C=0.1, epsilon=0.2 ......
[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= 0.0s
[CV] C=0.1, epsilon=0.3 .....
[CV] ..... C=0.1, epsilon=0.3, total=
                                0.0s
[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= 0.0s
[CV] C=0.1, epsilon=0.3 .....
[CV] ..... C=0.1, epsilon=0.3, total= 0.0s
[CV] C=0.1, epsilon=0.4 ......
  ..... C=0.1, epsilon=0.4, total=
[CV]
                                0.0s
[CV] C=0.1, epsilon=0.4 ......
[CV] ..... C=0.1, epsilon=0.4, total=
[CV] ..... C=0.1, epsilon=0.4, total=
[CV] C=0.1, epsilon=0.4 ......
[CV] ...... C=0.1, epsilon=0.4, total= 0.0s
[CV] C=0.1, epsilon=0.4 .....
[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= 0.0s
[CV] C=0.1, epsilon=0.5 ......
[CV] ..... C=0.1, epsilon=0.5, total= 0.0s
[CV] C=0.1, epsilon=0.5 .....
[CV] ..... C=0.1, epsilon=0.5, total=
ICV1 C=0.1. epsilon=0.5
```

```
[CV] ..... C=0.1, epsilon=0.5, total= 0.0s
[CV] C=0.1, epsilon=0.6 ......
[CV] ..... C=0.1, epsilon=0.6, total= 0.0s
[CV] C=0.1, epsilon=0.6 ......
[CV] ..... C=0.1, epsilon=0.6, total= 0.0s
[CV] C=0.1, epsilon=0.6 ......
[CV] ..... C=0.1, epsilon=0.6, total= 0.0s
[CV] C=0.1, epsilon=0.6 ......
[CV] ..... C=0.1, epsilon=0.6, total=
                              0.0s
[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 ......
[CV] ...... C=0.1, epsilon=0.7, total= 0.0s
[CV] C=0.1, epsilon=0.7 .....
[CV] ...... C=0.1, epsilon=0.7, total= 0.0s
[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 ......
[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= 0.0s
[CV] C=0.1, epsilon=0.8 .....
[CV] ...... C=0.1, epsilon=0.8, total= 0.0s
[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 ......
[CV] ...... C=0.1, epsilon=0.9, total= 0.0s
[CV] C=0.1, epsilon=0.9 ......
[CV] ..... C=0.1, epsilon=0.9, total= 0.0s
[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= 0.0s
[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= 0.0s
[CV] C=1, epsilon=0.1 .....
[CV] C=1, epsilon=0.1 ......
[CV] C=1, epsilon=0.1 ......
[CV] ...... C=1, epsilon=0.1, total= 0.0s
[CV] C=1, epsilon=0.1 .....
[CV] ..... C=1, epsilon=0.1, total= 0.0s
[CV] ..... C=1, epsilon=0.1, total= 0.0s
[Parallel(n jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 0.0s remaining:
[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 .....
[CV] ...... C=1, epsilon=0.2, total= 0.0s
[CV] C=1, epsilon=0.2 ......
[CV] ..... C=1, epsilon=0.2, total= 0.0s
[CV] C=1, epsilon=0.2 .....
```

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| | C=1, epsiion=U.3 | | | |
|------|---|------|--------------|-------------|
| | C=1, epsilon=0.3 | | _ | |
| | C-1, epsiion-0.3 | | | |
| | C=1, epsilon=0.3 | | _ | |
| | · · · · · · · · · · · · · · · · · · · | | | |
| | C=1, epsilon=0.3 | | _ | |
| | , | | | |
| | C=1, epsilon=0.3 | | _ | |
| [CV] | ••••• | C=1, | epsilon=0.3, | total= 0.0s |
| | C=1, epsilon=0.4 | | | |
| | • | | _ | |
| | C=1, epsilon=0.4 | | | |
| | Q=1il0 4 | | - | |
| | C=1, epsilon=0.4 | | | |
| | C=1, epsilon=0.4 | | _ | |
| | • | | | |
| [CV] | C=1, epsilon=0.4 | | | |
| | ••••• | | - | |
| | C=1, epsilon=0.5 | | | |
| | 0.1 | | _ | |
| | C=1, epsilon=0.5 | | | |
| | C=1, epsilon=0.5 | | - | |
| | , | | | |
| [CV] | C=1, epsilon=0.5 | | | |
| | ••••• | | - | |
| | C=1, epsilon=0.5 | | | |
| | C=1, epsilon=0.6 | | - | |
| | C-1, epsiion-0.0 | | | |
| | C=1, epsilon=0.6 | | | |
| | • | | | |
| | C=1, epsilon=0.6 | | | |
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| | C=1, epsilon=0.6 | | | |
| | C=1, epsilon=0.6 | | | |
| | | | | |
| [CV] | C=1, epsilon=0.7 | | | |
| | ••••• | | _ | |
| | C=1, epsilon=0.7 | | | |
| | C=1, epsilon=0.7 | | | |
| | C-1, epsiion-0./ | | | |
| | C=1, epsilon=0.7 | | _ | |
| | | | | |
| | C=1, epsilon=0.7 | | | |
| | | | | |
| | C=1, epsilon=0.8 | | | |
| | C=1, epsilon=0.8 | | | |
| | | | | |
| | C=1, epsilon=0.8 | | | |
| [CV] | | C=1, | epsilon=0.8, | total= 0.0s |
| | C=1, epsilon=0.8 | | | |
| | G-1 | | | |
| | C=1, epsilon=0.8 | | | |
| | C=1, epsilon=0.9 | | _ | |
| | C-1, epsiion-0.9 | | | |
| | C=1, epsilon=0.9 | | | |
| | ••••• | | | |
| | C=1, epsilon=0.9 | | | |
| | C-1 ongilon-0 0 | | _ | |
| | C=1, epsilon=0.9 | | | |
| | C=1, epsilon=0.9 | | _ | |
| | · · · · · · · · · · · · · · · · · · · | | | |
| | C=1, epsilon=1.0 | | | |
| [CV] | | C=1, | epsilon=1.0, | total= 0.0s |
| | C=1, epsilon=1.0 | | | |
| | C-1 ongilon-1 0 | | _ | |
| | C=1, epsilon=1.0 | | | |
| | C=1, epsilon=1.0 | | | |
| | - | ~ 1 | 171 ^ | 1 - 1 - 3 |

| | C=1, epsilon=1.0, total= U.Us C=1, epsilon=1.0 |
|--------|---|
| | C=1, epsilon=1.0, total= 0.0s |
| | C=10, epsilon=0.1 |
| | C=10, epsilon=0.1, total= 0.0s |
| | C=10, epsilon=0.1 |
| | C=10, epsilon=0.1, total= 0.0s C=10, epsilon=0.1 |
| | |
| | C=10, epsilon=0.1 |
| | C=10, epsilon=0.1, total= 0.0s |
| | C=10, epsilon=0.1 C=10, epsilon=0.1, total= 0.0s |
| | C=10, epsilon=0.2 |
| | C=10, epsilon=0.2, total= 0.0s |
| | C=10, epsilon=0.2 |
| | C=10, epsilon=0.2 |
| | |
| | C=10, epsilon=0.2 |
| | C=10, epsilon=0.2, total= 0.0s C=10, epsilon=0.2 |
| | |
| | C=10, epsilon=0.3 |
| | C=10, epsilon=0.3, total= 0.0s C=10, epsilon=0.3 |
| | C=10, epsilon=0.3, total= 0.0s |
| | C=10, epsilon=0.3 |
| | C=10, epsilon=0.3, total= 0.0s |
| | C=10, epsilon=0.3 |
| | C=10, epsilon=0.3 |
| | C=10, epsilon=0.3, total= 0.0s |
| | C=10, epsilon=0.4 |
| | C=10, epsilon=0.4 |
| [CV] | |
| | C=10, epsilon=0.4 |
| | C=10, epsilon=0.4, total= 0.0s C=10, epsilon=0.4 |
| | |
| | C=10, epsilon=0.4 |
| | C=10, epsilon=0.4, total= 0.0s C=10, epsilon=0.5 |
| | |
| [CV] | C=10, epsilon=0.5 |
| | C=10, epsilon=0.5, total= 0.0s |
| | C=10, epsilon=0.5 C=10, epsilon=0.5, total= 0.0s |
| [CV] | C=10, epsilon=0.5 |
| | |
| | C=10, epsilon=0.5 |
| | C=10, epsilon=0.6 |
| | |
| | C=10, epsilon=0.6 |
| | C=10, epsilon=0.6 |
| | C=10, epsilon=0.6, total= 0.0s |
| | C=10, epsilon=0.6 |
| | C=10, epsilon=0.6 |
| | C=10, epsilon=0.6, total= 0.0s |
| | C=10, epsilon=0.7 C=10, epsilon=0.7, total= 0.0s |
| | C=10, epsilon=0.7 |
| [CV] | |
| | C=10, epsilon=0.7 |
| | C=10, epsilon=0.7, total= 0.0s C=10, epsilon=0.7 |
| | C=10, epsilon=0.7, total= 0.0s |
| [CV] | C=10, epsilon=0.7 |
| | C=10, epsilon=0.7, total= 0.0s C=10, epsilon=0.8 |
| | C=10, epsilon=0.8 |
| [CV] | C=10, epsilon=0.8 |
| [CV] | C=10, epsilon=0.8, total= 0.0s |
| | |

| | CV] | C=10, epsilon=0.8 |
|--|------|---------------------------------------|
| C=10, epsilon=0.8, total= 0.00 | | |
| | _ | |
| | CV] | C=10, epsilon=0.8 |
| | | |
| C=10, epsilon=0.9 | | |
| | | |
| | | |
| C=10, epsilon=0.9, total= 0.0; | _ | |
| | - | • |
| | CV j | C=10, epsilon=0.9 |
| C=10, epsilon=1.0, total= 0.0; | | |
| | - | , <u>.</u> |
| | | |
| | | |
| C=10, epsilon=1.0, total= 0.0; VN | - | · · |
| | | |
| | CV] | C=10, epsilon=1.0 |
| C=100, epsilon=0.1, total= 0.0; C=100, epsilon=0.1, total= 0.0; C=100, epsilon=0.1 C=100, epsilon=0.1, total= 0.0; C=100, epsilon=0.2, total= 0.0; C=100, epsilon=0.3, total= 0.0; C=100, epsilon=0.4, total= 0.0; C=100, epsilon=0.5, total= 0.0; C=100 | | |
| C=100, epsilon=0.1, total= 0.0; C=100, epsilon=0.1, total= 0.0; C=100, epsilon=0.1 C=100, epsilon=0.1, total= 0.0; C=100, epsilon=0.2, total= 0.0; C=100, epsilon=0.3, total= 0.0; C=100, epsilon=0.4, total= 0.0; C=100, epsilon=0.5, total= 0.0; C=100, epsilon=0. | _ | |
| | :V] | C=100, epsilon=0.1 |
| C=100, epsilon=0.1, total= 0.00 C=100, epsilon=0.1 C=100, epsilon=0.1, total= 0.00 C=100, epsilon=0.1 C=100, epsilon=0.1, total= 0.00 C=100, epsilon=0.2 C=100, epsilon=0.2, total= 0.00 C=100, epsilon=0.3 C=100, epsilon=0.3, total= 0.00 C=100, epsilon=0.4 C=100, epsilon=0.4, total= 0.00 C=100, epsilon=0.5 C=100, epsilon=0.5, total= | | |
| C=100, epsilon=0.1, total= 0.0; C=100, epsilon=0.1, total= 0.0; C=100, epsilon=0.1 C=100, epsilon=0.1, total= 0.0; C=100, epsilon=0.2 C=100, epsilon=0.2, total= 0.0; C=100, epsilon=0.2, total= 0.0; C=100, epsilon=0.3 C=100, epsilon=0.3, total= 0.0; C=100, epsilon=0.4, total= 0.0; C=100, epsilon=0.5, total= 0.0; C=100, | ZV] | |
| | | |
| C=100, epsilon=0.2 C=100, epsilon=0.2, total= 0.00 C=100, epsilon=0.3 C=100, epsilon=0.3, total= 0.00 C=100, epsilon=0.4 C=100, epsilon=0.4, total= 0.00 C=100, epsilon=0.5 C=100, epsilon=0.5, total= 0.00 C=100, epsilon=0.5 C=100, epsilon=0. | | _ |
| C=100, epsilon=0.2, total= 0.0s C=100, epsilon=0.2 | | |
| V] C=100, epsilon=0.2 V] | - | · · · · · · · · · · · · · · · · · · · |
| C=100, epsilon=0.2 C=100, epsilon=0.2, total= 0.0s C=100, epsilon=0.2 C=100, epsilon=0.2, total= 0.0s C=100, epsilon=0.2 C=100, epsilon=0.2, total= 0.0s C=100, epsilon=0.3 C=100, epsilon=0.3, total= 0.0s C=100, epsilon=0.4 C=100, epsilon=0.4, total= 0.0s C=100, epsilon=0.5 C=100, epsilon=0.5, total= 0.0s C=100, epsilon=0.5 C=100, epsilon=0. | :V] | C=100, epsilon=0.2 |
| V] | | |
| V] | V] | |
| V] C=100, epsilon=0.2 V] | _ | |
| TV C=100, epsilon=0.3 | CV] | C=100, epsilon=0.2 |
| C=100, epsilon=0.3, total= 0.0s C=100, epsilon=0.4, total= 0.0s C=100, epsilon=0.5, total= 0.0 | - | • • |
| C=100, epsilon=0.3, total= 0.0s CV] C=100, epsilon=0.3 CV] | | |
| C=100, epsilon=0.3 C=100, epsilon=0.3, total= 0.0s C=100, epsilon=0.3, total= 0.0s C=100, epsilon=0.3, total= 0.0s C=100, epsilon=0.3 C=100, epsilon=0.3, total= 0.0s C=100, epsilon=0.3, total= 0.0s C=100, epsilon=0.4, total= 0.0s C=100, epsilon=0.5, total= 0.0s | | |
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| C=100, epsilon=0.3, total= 0.0s CV] C=100, epsilon=0.3 CV] C=100, epsilon=0.4 CV] C=100, epsilon=0.5 CV] C=100, epsilon=0.5, total= 0.0s CV] C=100, epsilon=0.5 CV] C=100, epsilon=0.5, total= 0.0s | | |
| CV C=100, epsilon=0.3 C=100, epsilon=0.3, total= 0.0s C=100, epsilon=0.4 C=100, epsilon=0.4, total= 0.0s C=100, epsilon=0.5 C=100, epsilon=0.5, total= 0.0s C=100, epsilon=0.5, total= 0.0s C=100, epsilon=0.5 C=100, epsilon=0.5, total= 0.0s C=100, epsilon=0.5, total=0.0s C=100, epsilon=0.5, total=0.0s C=100, epsilon=0.5 | _ | |
| V] C=100, epsilon=0.4 V] | v] | C=100, epsilon=0.3 |
| V] | - | |
| V] | - | · · · |
| V] C=100, epsilon=0.4 V] | - | · • |
| V] C=100, epsilon=0.4, total= 0.0s V] C=100, epsilon=0.5, total= 0.0s | | |
| C=100, epsilon=0.4, total= 0.0s V C=100, epsilon=0.4 V C=100, epsilon=0.5 V C=100, epsilon=0.5 V C=100, epsilon=0.5 C=100, epsilon= | v] | |
| V] C=100, epsilon=0.4 C=100, epsilon=0.4, total= 0.0s V] C=100, epsilon=0.5 C=100, epsilon=0.5, total= 0.0s | - | · · · |
| V] C=100, epsilon=0.5 C=100, epsilon=0.5, total= 0.0s | V] | C=100, epsilon=0.4 |
| V] | - | · · · · · · · · · · · · · · · · · · · |
| 7] C=100, epsilon=0.5 | | |
| V] C=100, epsilon=0.5 | V] | C=100, epsilon=0.5 |
| V] C=100, epsilon=0.5, total= 0.09 V] C=100, epsilon=0.5 | | |
| | v j | |
| C=100 onciton=0 b. +o+a!=-0.06 | | C=100, epsilon=0.5 |
| V] C=100, epsilon=0.5 | - | |
| V] C=100, epsilon=0.5, total= 0.0s | | |

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[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=0.6 .....
[CV] ...... C=100, epsilon=0.6, total= 0.0s
[CV] C=100, epsilon=0.7 ......
[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= 0.0s
[CV] C=100, epsilon=0.7 .....
[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= 0.0s
[CV] C=100, epsilon=0.8 ......
[CV] ..... C=100, epsilon=0.8, total=
                                0.0s
[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= 0.0s
[CV] C=100, epsilon=0.9 .....
[CV] ..... C=100, epsilon=0.9, total= 0.0s
[CV] C=100, epsilon=0.9 ......
[CV] ..... C=100, epsilon=0.9, total= 0.0s
[CV] C=100, epsilon=0.9 .....
[CV] ...... C=100, epsilon=0.9, total= 0.0s
[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= 0.0s
[CV] C=100, epsilon=1.0 ......
[CV] C=100, epsilon=1.0 .....
[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 ......
[CV] ..... C=100, epsilon=1.0, total= 0.0s
[Parallel(n jobs=1)]: Done 200 out of 200 | elapsed:
                            0.7s finished
Out[46]:
GridSearchCV(estimator=LinearSVR(),
      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, 1.0]},
      verbose=2)
In [47]:
grid.best estimator
Out[47]:
LinearSVR(C=10, epsilon=0.1)
In [48]:
grid.best score
Out[48]:
```

```
0.6827159871789266
In [49]:
grid.best_params_
Out[49]:
{'C': 10, 'epsilon': 0.1}
In [50]:
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)
Out[50]:
GridSearchCV(cv=3, estimator=BayesianRidge(), n_jobs=-1,
             param_grid={'alpha_1': array([1.00000000e-13, 7.74263683e-13, 5.99484250e-12, 4.641588
83e-11,
       3.59381366e-10, 2.78255940e-09, 2.15443469e-08, 1.66810054e-07,
       1.29154967e-06, 1.00000000e-05]),
                         'alpha 2': array([1.00000000e-09, 4.64158883e-09, 2.15443469e-08,
1.0000000e-07,
       4.64158883e-07, 2.15443469e-06, 1.000000...
       2.15443469e-04, 1.00000000e-03]),
                         '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([1.00000000e-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])})
In [51]:
grid_regr.best_estimator_
Out[51]:
BayesianRidge(alpha 1=1e-13, alpha 2=0.001, lambda 1=1e-05, lambda 2=1e-11)
In [52]:
grid regr.best score
Out[52]:
0.7662762307971316
In [53]:
grid regr.best params
Out[53]:
{'alpha 1': 1e-13, 'alpha 2': 0.001, 'lambda 1': 1e-05, 'lambda 2': 1e-11}
In [55]:
reg = BayesianRidge(fit intercept=True, alpha 1=1e-05, alpha 2=1e-09, lambda 1=1e-10, lambda 2=0.00
01).fit(x.reshape(-1, 1), y.reshape(-1, 1))
y_tt = reg.predict(x.reshape(-1, 1))
```

lin SVR = T.inearSVR(C=1 0 may iter=10000 engilon=1 0)

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TIUTAN - HIHEOTDAN (C-T.O. MOV TOET-TOOOO' EBSTION-T.O.)
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["Chance of Admit "])
dec_predict = dec_tree.predict(data)
In [190]:
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 s∨м-модели:
Средняя абсолютная ошибка: 2.5996867264932724
Средняя квадратичная ошибка: 11.18839596468356
Коэффициент детерминации: 0.586926758668624
Метрики для Decision Tree:
Средняя абсолютная ошибка: 0.7095532407407409
Средняя квадратичная ошибка: 0.7222188657407407
Коэффициент детерминации: 0.9733358303760538
```

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