Московский государственный технический университет им. Н. Э. Баумана

Курс «Технологии машинного обучения»

Отчёт по лабораторной работе №4

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Цель лабораторной работы: изучение линейных моделей, SVM и деревьев решений.

Задание:

1. Выберите набор данных (датасет) для решения задачи классификации или регрессии.
2. В случае необходимости проведите удаление или заполнение пропусков и кодирование категориальных признаков.
3. С использованием метода train_test_split разделите выборку на обучающую и тестовую.
4. Обучите следующие модели:
    a. одну из линейных моделей (линейную или полиномиальную регрессию при решении задачи регрессии, логистическую регрессию при решении задачи классификации);
    b. SVM;
    c. дерево решений.
5. Оцените качество моделей с помощью двух подходящих для задачи метрик. Сравните качество полученных моделей.
6. Постройте график, показывающий важность признаков в дереве решений.
7. Визуализируйте дерево решений или выведите правила дерева решений в текстовом виде.

Ход выполнения:

Практика

Датасет: https://github.com/ongaunjie1/credit-score-prediction

Загрузка и первичный анализ

```
[1] import numpy as np
    import pandas as pd
    import seaborn as sns
    import matplotlib.pyplot as plt
    %matplotlib inline
    sns.set(style="ticks")
```

```
[2] df0 = pd.read_csv("/dataset.csv")
    df0.info()
    df0.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14790 entries, 0 to 14789
Data columns (total 12 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   age                       14790 non-null  int64
 1   annual_income             14790 non-null  float64
 2   num_bank_acc              14790 non-null  int64
 3   num_credit_card           14790 non-null  int64
 4   interest_rate             14790 non-null  int64
 5   delay_from_due_date       14790 non-null  int64
 6   outstanding_debt          14790 non-null  float64
 7   credit_history_age        14790 non-null  float64
 8   installment_per_month     14790 non-null  float64
 9   monthly_balance           14790 non-null  float64
 10  payment_of_min_amount_Yes  14790 non-null  bool
 11  Predicted Credit Score    14790 non-null  int64
dtypes: bool(1), float64(5), int64(6)
memory usage: 1.3 MB
```

	age	annual_income	num_bank_acc	num_credit_card	interest_rate	delay_from_due_date	outstanding_debt	credit_history_age	installment_per_month	monthly_balance	payment_of_min_amount_Yes	P
0	23	19114.12	3	4	3	3	809.98	22.90	49.57	186.27	False	

Разделение на обучающую и тестовую выборки

```
[3] dfX = df0.drop(columns=["Predicted Credit Score"])
    dfY = df0["Predicted Credit Score"]
```

```
[4] print("\n=======X=======\n")
    dfX.info()
    dfX.head()

    print("\n=======Y=======\n")
    dfY.info()
    dfY.head()
```

```
=======X=======

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14790 entries, 0 to 14789
Data columns (total 11 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   age                       14790 non-null  int64
 1   annual_income             14790 non-null  float64
 2   num_bank_acc              14790 non-null  int64
 3   num_credit_card           14790 non-null  int64
 4   interest_rate             14790 non-null  int64
 5   delay_from_due_date       14790 non-null  int64
 6   outstanding_debt          14790 non-null  float64
 7   credit_history_age        14790 non-null  float64
 8   installment_per_month     14790 non-null  float64
 9   monthly_balance           14790 non-null  float64
 10  payment_of_min_amount_Yes  14790 non-null  bool
dtypes: bool(1), float64(5), int64(5)
memory usage: 1.1 MB

=======Y=======

<class 'pandas.core.series.Series'>
RangeIndex: 14790 entries, 0 to 14789
Series name: Predicted Credit Score
Non-Null Count  Dtype
--------------  -----
14790 non-null  int64
dtypes: int64(1)
```

```
memory usage: 1.1 MB

=======Y=======

<class 'pandas.core.series.Series'>
RangeIndex: 14790 entries, 0 to 14789
Series name: Predicted Credit Score
Non-Null Count  Dtype
--------------  -----
14790 non-null  int64
dtypes: int64(1)
memory usage: 115.7 KB
```

	Predicted Credit Score
0	2
1	2
2	2
3	2
4	1

dtype: int64

```
[5] from sklearn.model_selection import train_test_split
```

```
[6] xTrain, xTest, yTrain, yTest = train_test_split(
        dfX, dfY, test_size=0.2, random_state=1)
```

```
[7] print(xTrain.shape)
    print(xTest.shape)
    print(yTrain.shape)
    print(yTest.shape)
```

```
(11832, 11)
(2958, 11)
(11832,)
(2958,)
```

Линейная модель: логистическая регрессия

```
[10] from sklearn.linear_model import LogisticRegression
     logistic_regression_model = LogisticRegression()
     logistic_regression_model.fit(xTrain, yTrain)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
LogisticRegression()
```

SVM

```
[11] from sklearn.svm import SVC
     svm_model = SVC(kernel='rbf')
     svm_model.fit(xTrain, yTrain)
```

```
SVC()
```

Дерево решений

```
[13] from sklearn.tree import DecisionTreeClassifier
     decision_tree_model = DecisionTreeClassifier()
     decision_tree_model.fit(xTrain, yTrain)
```

```
DecisionTreeClassifier()
```

Оценка качества

```
[14] from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score, accuracy_score, precision_score, recall_score, f1_score
```

```
[21] # Logistic Regression
     y_pred_logistic_regression = logistic_regression_model.predict(xTest)

     logistic_regression_accuracy = accuracy_score(yTest, y_pred_logistic_regression)
     logistic_regression_precision = precision_score(yTest, y_pred_logistic_regression, average="weighted")
     logistic_regression_recall = recall_score(yTest, y_pred_logistic_regression, average="weighted")
     logistic_regression_f1 = f1_score(yTest, y_pred_logistic_regression, average="weighted")
```

```
[22] # SVM

     y_pred_svm = svm_model.predict(xTest)

     svm_accuracy = accuracy_score(yTest, y_pred_svm)
     svm_precision = precision_score(yTest, y_pred_svm, average='weighted')
     svm_recall = recall_score(yTest, y_pred_svm, average='weighted')
     svm_f1 = f1_score(yTest, y_pred_svm, average='weighted')
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
[23] # Decision Tree

     y_pred_decision_tree = decision_tree_model.predict(xTest)

     decision_tree_accuracy = accuracy_score(yTest, y_pred_decision_tree)
     decision_tree_precision = precision_score(yTest, y_pred_decision_tree, average='weighted')
     decision_tree_recall = recall_score(yTest, y_pred_decision_tree, average='weighted')
     decision_tree_f1 = f1_score(yTest, y_pred_decision_tree, average='weighted')
```

```
[24] from tabulate import tabulate

     data = [
         ['accuracy', round(logistic_regression_accuracy, 3), round(svm_accuracy, 3), round(decision_tree_accuracy, 3)],
         ['precision', round(logistic_regression_precision, 3), round(svm_precision, 3), round(decision_tree_precision, 3)],
         ['recall', round(logistic_regression_recall, 3), round(svm_recall, 3), round(decision_tree_recall, 3)],
         ['f1', round(logistic_regression_f1, 3), round(svm_f1, 3), round(decision_tree_f1, 3)]
```

```
[24] from tabulate import tabulate

     data = [
         ['accuracy', round(logistic_regression_accuracy, 3), round(svm_accuracy, 3), round(decision_tree_accuracy, 3)],
         ['precision', round(logistic_regression_precision, 3), round(svm_precision, 3), round(decision_tree_precision, 3)],
         ['recall', round(logistic_regression_recall, 3), round(svm_recall, 3), round(decision_tree_recall, 3)],
         ['f1', round(logistic_regression_f1, 3), round(svm_f1, 3), round(decision_tree_f1, 3)]
     ]

     headers = ['Метрика / модель', 'Logistic Regression', 'SVM', 'Decision tree']

     print(tabulate(data, headers=headers, tablefmt="grid"))
```

```
+--------------------+----------------------+-------+-----------------+
| Метрика / модель   |   Logistic Regression |   SVM |   Decision tree |
+====================+======================+=======+=================+
| accuracy           |                0.675 | 0.67  |           0.888 |
+--------------------+----------------------+-------+-----------------+
| precision          |                0.666 | 0.603 |           0.888 |
+--------------------+----------------------+-------+-----------------+
| recall             |                0.675 | 0.67  |           0.888 |
+--------------------+----------------------+-------+-----------------+
| f1                 |                0.638 | 0.629 |           0.888 |
+--------------------+----------------------+-------+-----------------+
```

График, показывающий важность признаков в дереве решений

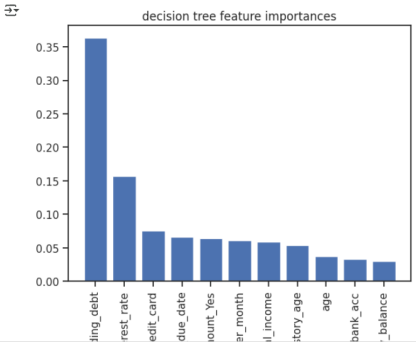
```
[25] import matplotlib.pyplot as plt
     import numpy as np
```

```
[27] feature_importances = decision_tree_model.feature_importances_

     indices = np.argsort(feature_importances)[::-1]

     names = [dfX.columns[i] for i in indices]

     plt.figure()
     plt.title("decision tree feature importances")
     plt.bar(range(dfX.shape[1]), feature_importances[indices])
     plt.xticks(range(dfX.shape[1]), names, rotation=90)
     plt.show()
```



Визуализация дерева решений

```
[32] from sklearn.tree import export_graphviz
     import graphviz
```

```
[33] export_graphviz(decision_tree_model, out_file='/tree.dot', feature_names=dfX.columns, class_names=True, filled=True, rounded=True)
```

```
[ ] # Вывод графа
    with open("/tree.dot") as f:
        dot_graph = f.read()

    graphviz.Source(dot_graph)
```

```
[35] from sklearn.tree import export_text
     import matplotlib.pyplot as plt
```

```
[37] tree_rules = export_text(decision_tree_model, feature_names=list(dfX.columns))
     print(tree_rules)
```

```
|--- outstanding_debt <= 1485.53
|   |--- interest_rate <= 20.50
|   |   |--- payment_of_min_amount_Yes <= 0.50
|   |   |   |--- num_credit_card <= 2.50
|   |   |   |   |--- delay_from_due_date <= 19.50
|   |   |   |   |   |--- credit_history_age <= 16.05
|   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |--- credit_history_age >  16.05
|   |   |   |   |   |   |--- num_bank_acc <= 6.00
|   |   |   |   |   |   |   |--- installment_per_month <= 31.26
|   |   |   |   |   |   |   |   |--- installment_per_month <= 30.14
|   |   |   |   |   |   |   |   |   |--- delay_from_due_date <= 13.50
|   |   |   |   |   |   |   |   |   |   |--- outstanding_debt <= 419.64
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |   |   |--- outstanding_debt >  419.64
|   |   |   |   |   |   |   |   |   |   |   |--- class: 2
|   |   |   |   |   |   |   |   |   |--- delay_from_due_date >  13.50
|   |   |   |   |   |   |   |   |   |   |--- outstanding_debt <= 767.70
|   |   |   |   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |   |   |   |--- outstanding_debt >  767.70
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
```