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Факультет «Информатика и системы управления»
Кафедра ИУ5 «Системы обработки информации и управления»

Курс

«Технологии машинного обучения»

Отчет по лабораторной работе №4

«Разведочный анализ данных. Исследование и визуализация данных.»

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Лабораторная работа №4

Линейные модели, SVM и деревья 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:
    - одну из линейных моделей (линейную или полиномиальную регрессию при решении задачи регрессии, логистическую регрессию при решении задачи классификации);
    - SVM;
    - 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.

В качестве исходных данных возьмём датасет расхода топлива автомобилей в Канаде 2022 года В этой лабораторной работе будем решать задачу классификации Целевой признак - Cylinders

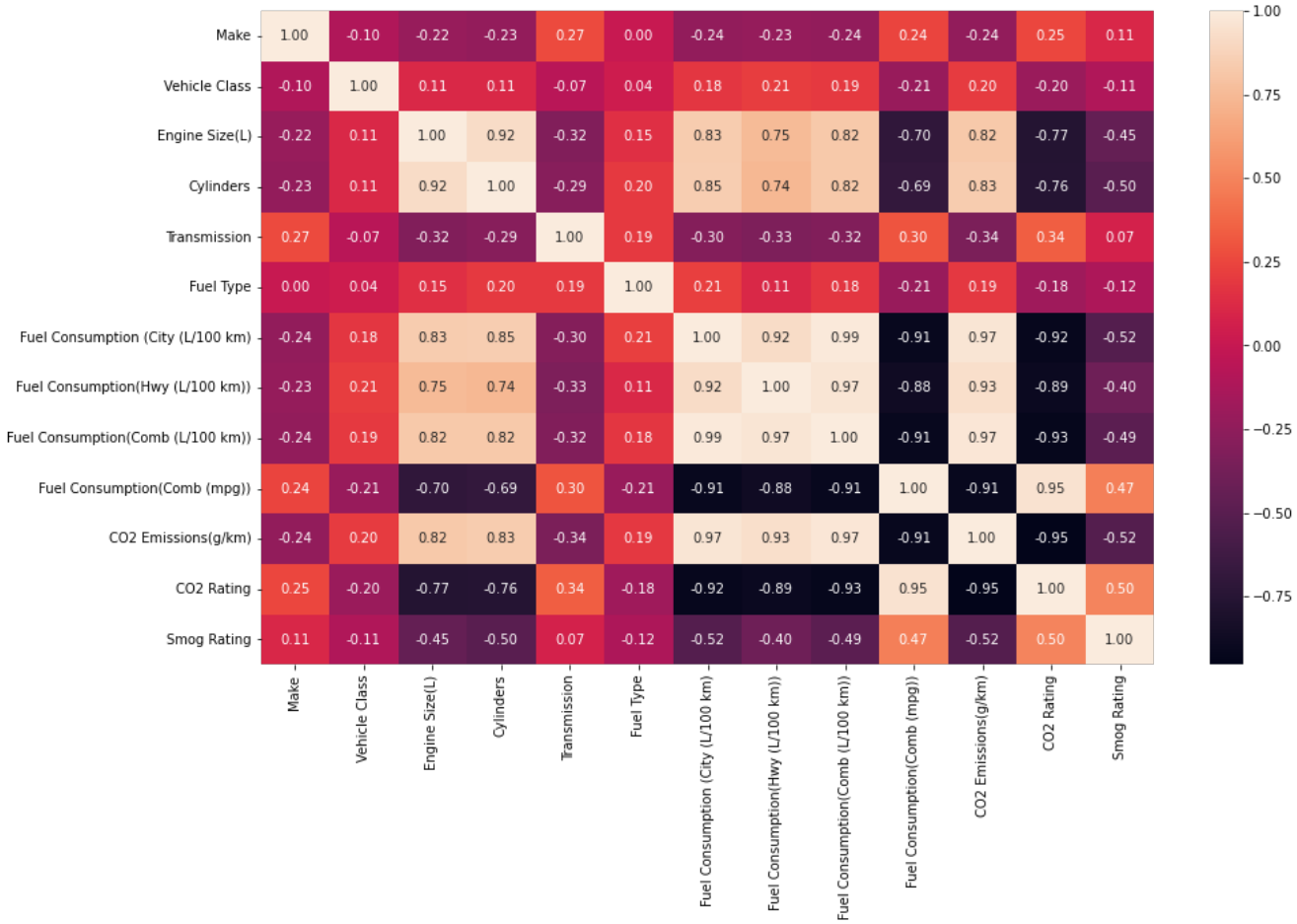
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from typing import Tuple
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.metrics import balanced_accuracy_score
from sklearn.tree import DecisionTreeClassifier
import graphviz
from sklearn.tree import export_graphviz
from sklearn import tree
from operator import itemgetter
data = pd.read_csv("Fuel.csv")
#Первые 5 записей датасета
data.head()
```

	Model Year	Make	Model	Vehicle Class	Engine Size(L)	Cylinders	Transmission	Fuel Type	Fue Consumptio (Cit (L/100 km
0	2022	Acura	ILX	Compact	2.4	4	AM8	Z	9.9
1	2022	Acura	MDX SH-AWD	SUV: Small	3.5	6	AS10	Z	12.6
2	2022	Acura	RDX SH-AWD	SUV: Small	2.0	4	AS10	Z	11.0
3	2022	Acura	RDX SH-AWD A-SPEC	SUV: Small	2.0	4	AS10	Z	11.3
4	2022	Acura	TLX SH-AWD	Compact	2.0	4	AS10	Z	11.2

```
#Проверка наличия пустых значений
data.isnull().sum()
Model Year                                0
Make                                      0
Model                                     0
Vehicle Class                             0
Engine Size(L)                            0
Cylinders                                 0
Transmission                              0
Fuel Type                                 0
Fuel Consumption (City (L/100 km)         0
Fuel Consumption(Hwy (L/100 km))          0
Fuel Consumption(Comb (L/100 km))         0
Fuel Consumption(Comb (mpg))              0
CO2 Emissions(g/km)                       0
CO2 Rating                                0
Smog Rating                               0
dtype: int64
#Размер исходного датасета
data.shape
(946, 15)
#Проверка типов
data.dtypes
Model Year                                int64
Make                                     object
```

```
Model                                    object
Vehicle Class                            object
Engine Size(L)                          float64
Cylinders                                 int64
Transmission                             object
Fuel Type                                object
Fuel Consumption (City (L/100 km)       float64
Fuel Consumption(Hwy (L/100 km))        float64
Fuel Consumption(Comb (L/100 km))       float64
Fuel Consumption(Comb (mpg))              int64
CO2 Emissions(g/km)                       int64
CO2 Rating                                int64
Smog Rating                               int64
dtype: object
```

```
#Удаление ненужных столбцов
data = data.drop(columns=["Model", "Model Year"], axis=1)
#Кодирование категориальных признаков
LE = LabelEncoder()
for column in ["Fuel Type","Make", "Vehicle Class",
"Transmission"]:
    data[column] = LE.fit_transform(data[column])
fig, ax = plt.subplots(figsize=(15,9))
sns.heatmap(data.corr(method='pearson'), ax=ax, annot=True,
fmt='.2f')
<AxesSubplot:>
```




```
#Выделяем записи, где присутствуют 4 или 6 цилиндров
```

```
#Для бинарной классификации
data = data.loc[data["Cylinders"].isin([4,6])]
data.shape
(699, 13)
xArray = data.drop("Cylinders", axis=1)
yArray = data["Cylinders"]
#Разделяем выборку для обучения модели
trainX, testX, trainY, testY = train_test_split(xArray, yArray,
test_size=0.2, random_state=1)
```

Линейная регрессия

```
#Обучение модели
LR = LogisticRegression()
LR.fit(trainX, trainY)
D:\Anaconda\lib\site-
packages\sklearn\linear_model\_logistic.py:763:
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()
#Предсказание целевого признака
predict = LR.predict(testX)
predict
array([6, 6, 4, 6, 6, 4, 6, 4, 4, 4, 4, 6, 6, 6, 4, 4, 6, 4, 4,
4, 4, 6,
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       4, 4, 6, 6, 4, 4, 4, 4, 6, 6, 6, 4, 4, 4, 4, 6, 4, 4, 6,
6, 6, 4,
       4, 4, 4, 4, 6, 6, 6, 4], dtype=int64)
#Вычисление вероятности попадания в той или иной класс
predictpr = LR.predict_proba(testX)
predictpr
array([[9.89144089e-02, 9.01085591e-01],
       [1.72492351e-02, 9.82750765e-01],
       [9.79594360e-01, 2.04056401e-02],
```

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       [1.22974875e-01, 8.77025125e-01],
       [9.17510420e-01, 8.24895804e-02]])
#Оценка качества модели
balanced_accuracy_score(testY, LR.predict(testX))
0.9724506578947368
```

SVM

```
#Обучение модели
svm = SVC(kernel='rbf', probability=True)
svm.fit(trainX, trainY)
SVC(probability=True)
#Предсказание целевого признака
svm.predict_proba(testX)
array([[0.21664647, 0.78335353],
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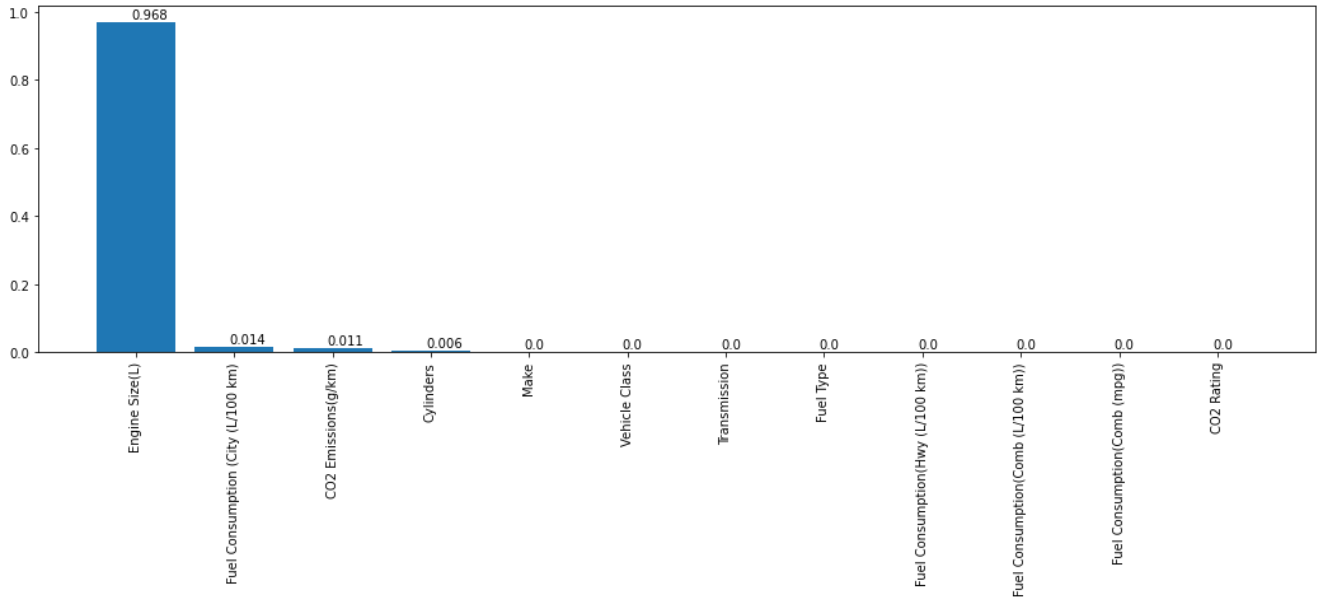
        [0.40290725, 0.59709275],
        [0.84436936, 0.15563064],
        [0.98831162, 0.01168838],
        [0.91828506, 0.08171494],
        [0.24174623, 0.75825377],
        [0.31564252, 0.68435748],
        [0.31581121, 0.68418879],
        [0.86035113, 0.13964887]])
#Оценка качества модели
balanced_accuracy_score(testY, svm.predict(testX))
0.8573190789473684
```

Деревья решений

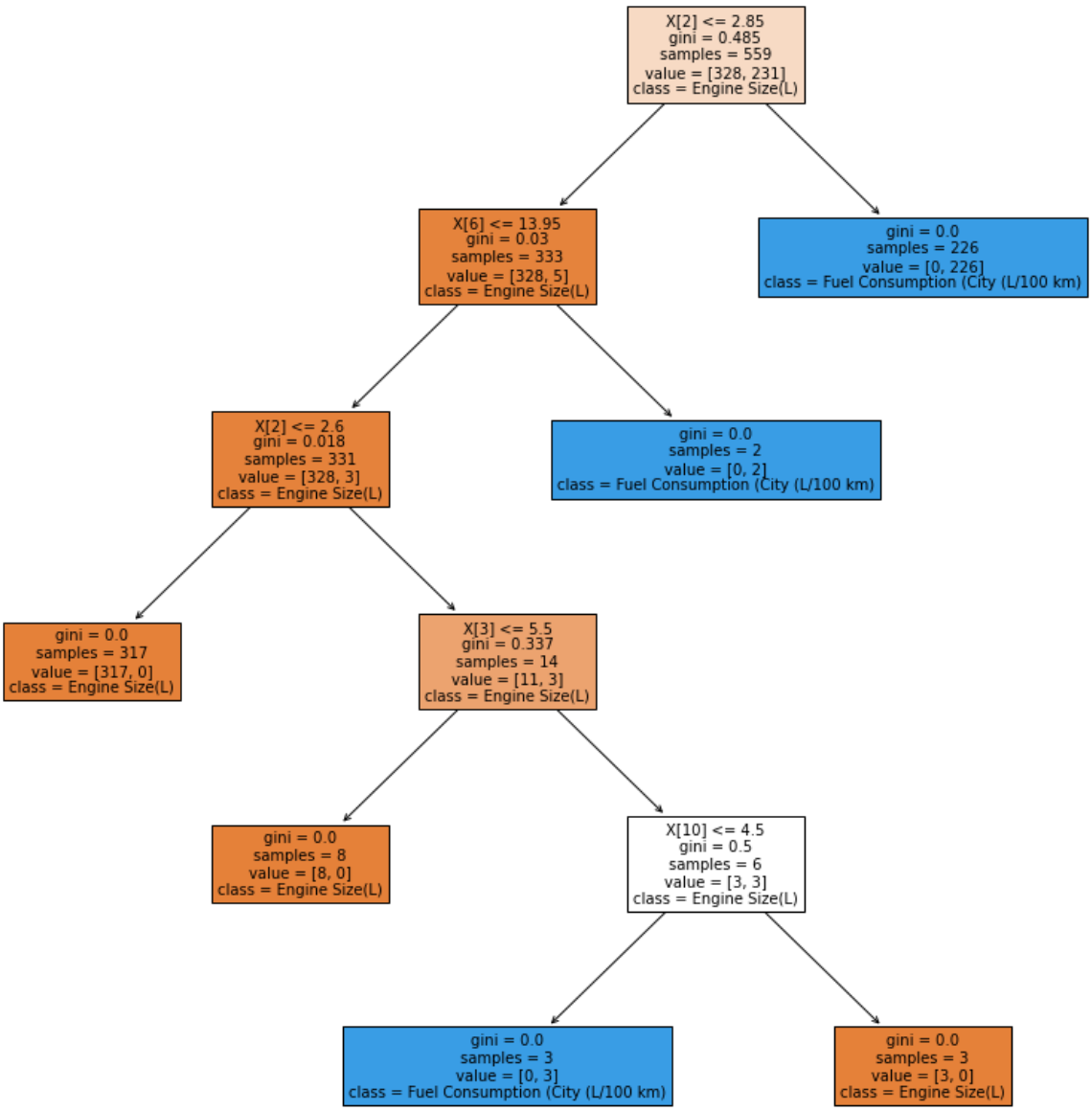
```
#Обучение модели
DeTree = DecisionTreeClassifier(random_state=1)
DeTree.fit(trainX, trainY)
DecisionTreeClassifier(random_state=1)
#Оценка качества модели
balanced_accuracy_score(testY, DeTree.predict(testX))
0.985608552631579
```

Как показала оценка качества модели, метод дерева решений работает наилучшим образом

```
#Функция построения графика для вывода признаков, наиболее
важных для определения целевого признака
def draw_feature_importances(tree_model, X_dataset,
figsize=(18,5)):
    """
    Вывод важности признаков в виде графика
    """
    # Сортировка значений важности признаков по убыванию
    list_to_sort = list(zip(X_dataset.columns.values,
tree_model.feature_importances_))
    sorted_list = sorted(list_to_sort, key=itemgetter(1),
reverse = True)
    # Названия признаков
    labels = [x for x,_ in sorted_list]
    # Важности признаков
    data = [x for _,x in sorted_list]
    # Вывод графика
    fig, ax = plt.subplots(figsize=figsize)
    ind = np.arange(len(labels))
    plt.bar(ind, data)
    plt.xticks(ind, labels, rotation='vertical')
    # Вывод значений
    for a,b in zip(ind, data):
        plt.text(a-0.05, b+0.01, str(round(b,3)))
    plt.show()
    return labels, data
diagram, _ = draw_feature_importances(DeTree, data)
```




```
#Визуальное отображение дерева решений
fig, ax = plt.subplots(figsize=(15, 15))
cn=['Engine Size(L)', 'Fuel Consumption (City (L/100 km)', 'CO2
Emissions(g/km', 'Cylinders' ]
tree.plot_tree(DeTree, fontsize=10,class_names=cn, filled=True)
plt.show()
```


X[2] <= 2.85
gini = 0.485
samples = 559
value = [328, 231]
class = Engine Size(L)
X[6] <= 13.95
gini = 0.03
samples = 333
value = [328, 5]
class = Engine Size(L)
gini = 0.0
samples = 226
value = [0, 226]
class = Fuel Consumption (City (L/100 km)
X[2] <= 2.6
gini = 0.018
samples = 331
value = [328, 3]
class = Engine Size(L)
gini = 0.0
samples = 2
value = [0, 2]
class = Fuel Consumption (City (L/100 km)
gini = 0.0
samples = 317
value = [317, 0]
class = Engine Size(L)
X[3] <= 5.5
gini = 0.337
samples = 14
value = [11, 3]
class = Engine Size(L)
gini = 0.0
samples = 8
value = [8, 0]
class = Engine Size(L)
X[10] <= 4.5
gini = 0.5
samples = 6
value = [3, 3]
class = Engine Size(L)
gini = 0.0
samples = 3
value = [0, 3]
class = Fuel Consumption (City (L/100 km)
gini = 0.0
samples = 3
value = [3, 0]
class = Engine Size(L)