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Факультет «Информатика и системы управления»

Кафедра «Системы обработки информации и управления»

Отчет по лабораторной работе №4

по теме «*Линейные модели, SVM и деревья решений.*»

по дисциплине «Технологии машинного обучения»

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Проверил:
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2024 г.

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.

Текст программы и экранные формы:

Ссылка на Colab:

https://colab.research.google.com/drive/1K3Y0OqCi1sOMr8TSNW6HMRAXVdSGxNLu?usp=sharing

Линейные модели, SVM и деревья решений.

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
%matplotlib inline
sns.set(style="ticks")
```

```
[ ] df = pd.read_csv('medical_insurance.csv', sep=",")
```

```
[ ] df
```

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520
...	...	...	...	...	...	...	...
2767	47	female	45.320	1	no	southeast	8569.86180
2768	21	female	34.600	0	no	southwest	2020.17700
2769	19	male	26.030	1	yes	northwest	16450.89470
2770	23	male	18.715	0	no	northwest	21595.38229
2771	54	male	31.600	0	no	southwest	9850.43200

2772 rows × 7 columns

```
[ ] df.shape
```

```
(2772, 7)
```

```
[ ] # ищем пропуски
    df.isna().sum()
```

```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

```
[ ] df.dtypes
```

```
age           int64
sex          object
bmi         float64
children      int64
smoker       object
region       object
charges     float64
dtype: object
```

```
[ ] categorical_cols=df.select_dtypes(include=object).columns.to_list()
    categorical_cols
```

```
['sex', 'smoker', 'region']
```

```
[ ] for cat in categorical_cols:
        print(f"column -- {cat}: {df[cat].unique()}")
```

```
column -- sex: ['female' 'male']
column -- smoker: ['yes' 'no']
column -- region: ['southwest' 'southeast' 'northwest' 'northeast']
```

```
[ ] from sklearn.preprocessing import LabelEncoder
```

```
[ ] for cat in categorical_cols:
        le = LabelEncoder()
        df[cat] = le.fit_transform(df[cat])
```

```
df
```

	age	sex	bmi	children	smoker	region	charges
0	19	0	27.900	0	1	3	16884.92400
1	18	1	33.770	1	0	2	1725.55230
2	28	1	33.000	3	0	2	4449.46200
3	33	1	22.705	0	0	1	21984.47061
4	32	1	28.880	0	0	1	3866.85520
...	...	...	...	...	...	...	...
2767	47	0	45.320	1	0	2	8569.86180
2768	21	0	34.600	0	0	3	2020.17700
2769	19	1	26.030	1	1	1	16450.89470
2770	23	1	18.715	0	0	1	21595.38229
2771	54	1	31.600	0	0	3	9850.43200

2772 rows × 7 columns

```
[ ] df.dtypes
```

```
age           int64
sex           int64
bmi         float64
children      int64
smoker        int64
region        int64
charges     float64
dtype: object
```

```
for cat in categorical_cols:
    print(f"column -- {cat}: {df[cat].unique()}")
```

```
column -- sex: [0 1]
column -- smoker: [1 0]
column -- region: [3 2 1 0]
```

```
X = df.drop('charges', axis=1)  # Замените 'целевая_переменная' на название вашей целевой переменной
y = df['charges']
```

```
# разделение на объекты-признаки и целевой признак
'''X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values'''
```

```
'X = df.iloc[:, :-1].values\ny = df.iloc[:, -1].values'
```

```
# Формирование обучающей и тестовой выборки
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
```

```
#Построим корреляционную матрицу
fig, ax = plt.subplots(figsize=(15,7))
sns.heatmap(df.corr(method='pearson'), ax=ax, annot=True, fmt='.2f')
```

```
<Axes: >
```


```
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error
```

```
[ ] import pandas as pd


    # Scaling the features
    scaler = StandardScaler()
    X_train_scale = scaler.fit_transform(X_train)
    X_test_scale = scaler.transform(X_test)

    # Converting the scaled arrays into DataFrames
    X_train = pd.DataFrame(X_train_scale, columns=X_train.columns)
    X_test = pd.DataFrame(X_test_scale, columns=X_test.columns)
```

```
[ ] def create_df(data,models, cols):
        index = []
        for model in models:
            model_name = type(model).__name__
            if model_name in index:
                model_name = str(type(model).__name__) + '_hyp'
            index.append(model_name)

        df = pd.DataFrame(data = data,
                         index = index)
        df.rename(columns=dict(zip(df.columns, cols)), inplace=True)
        return df

    def training(models, X=X_train, y=y_train):
        metric = {}
        train_model = []
        mses =[]
        maes =[]
        index =[]
        for model in models:
            #score = []  # Initialize score for each model
            model.fit(X, y)
            train_model.append(model)
            y_pred = model.predict(X)
            mse = mean_squared_error(y, y_pred)
            mses.append(mse)
            mae = mean_absolute_error(y, y_pred)
            maes.append(mae)

            #score.extend([mse, mae, r2])  # Use extend to add multiple elements to score
```

```python
        cols=['train_mse', 'train_mae']
        metric['mse'] = mses
        metric['mae'] = maes
        metric_df = create_df(data=metric,models= train_model, cols = cols)
        return metric_df, train_model

    def testing(models,X = X_test, y = y_test):
        mses =[]
        maes =[]
        index =[]
        metric = {}
        for model in models:
            #score = []  # Initialize score for each model
            y_pred = model.predict(X)
            mse = mean_squared_error(y, y_pred)
            mses.append(mse)
            mae = mean_absolute_error(y, y_pred)
            maes.append(mae)
            #score.extend([mse, mae, r2])  # Use extend to add multiple elements to score
        metric['mse'] = mses
        metric['mae'] = maes
        cols=['test_mse', 'test_mae']
        metric_df = create_df(data=metric,models= models, cols=cols)
        return metric_df
```

[ ]
```python
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR, NuSVR, LinearSVR
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, export_graphviz
lr = LinearRegression()
svr = SVR()
nu_svr = NuSVR()
l_svr = LinearSVR()
dtr = DecisionTreeRegressor(random_state=42)
```

[ ]
```python
pd.options.display.float_format = '{:.3f}'.format
models = [lr, svr, nu_svr, l_svr, dtr]
training_df, train_models = training(models)

training_df
```

```
training_df
```

	train_mse	train_mae
LinearRegression	36024723.554	4136.382
SVR	160158596.886	8287.505
NuSVR	150596955.951	8430.766
LinearSVR	270812656.312	11296.431
DecisionTreeRegressor	35245.921	5.639

```
test_df = testing(train_models)

test_df
```

	test_mse	test_mae
LinearRegression	39922479.354	4167.301
SVR	163569917.515	8297.132
NuSVR	155674257.450	8476.228
LinearSVR	266120424.066	10776.123
DecisionTreeRegressor	9660467.644	674.434

```
model = LinearRegression()
model.fit(X_train,y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
model.score(X_test,y_test)
```

```
0.7398864322395977
```

```
[ ] model.score(X_train,y_train)
```

```
0.753395406601626
```

```
[ ] models = [lr, svr, dtr]
```

```
[ ] for model in models:
        model.fit(X_train,y_train)
        print(f"train model -- {model}:  {model.score(X_train,y_train)}")
        print(f"train model -- {model}:  {model.score(X_test,y_test)}")
```

```
train model -- LinearRegression():  0.753395406601626
train model -- LinearRegression():  0.7398864322395977
train model -- SVR():  -0.09635388609299134
train model -- SVR():  -0.06573428081308741
train model -- DecisionTreeRegressor(random_state=42):  0.9997587266398212
train model -- DecisionTreeRegressor(random_state=42):  0.9370575488858102
```

```
[ ] from IPython.display import Image
    from io import StringIO
    import pydotplus
```

```
[ ] #!pip install pydotplus
```

```
[ ] def get_png_tree(tree_model_param, feature_names_param):
        dot_data = StringIO()
        export_graphviz(tree_model_param, out_file=dot_data, feature_names=feature_names_param,
                        filled=True, rounded=True, special_characters=True)
        graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
        return graph.create_png()
```

```
[ ] Image(get_png_tree(dtr, X.columns), height='70%')
```

```
dot: graph is too large for cairo-renderer bitmaps. Scaling by 0.237761 to fit
```

```
[ ] # Обучим дерево на всех признаках boston с ограничением глубины дерева
    short_tree = DecisionTreeRegressor(random_state=42, max_depth=3)
    short_tree.fit(X_train, y_train)
    short_tree
```

```
DecisionTreeRegressor
DecisionTreeRegressor(max_depth=3, random_state=42)
```

```
model = DecisionTreeRegressor(random_state=42, max_depth=13)
model.fit(X_train,y_train)
print(f"train model -- {model}:  {model.score(X_train,y_train)}")
print(f"train model -- {model}:  {model.score(X_test,y_test)}")
```

```
train model -- DecisionTreeRegressor(max_depth=13, random_state=42):  0.9955580733333849
train model -- DecisionTreeRegressor(max_depth=13, random_state=42):  0.9506082367868638
```

```
[ ] Image(get_png_tree(short_tree, X_train.columns), height='100%')
```

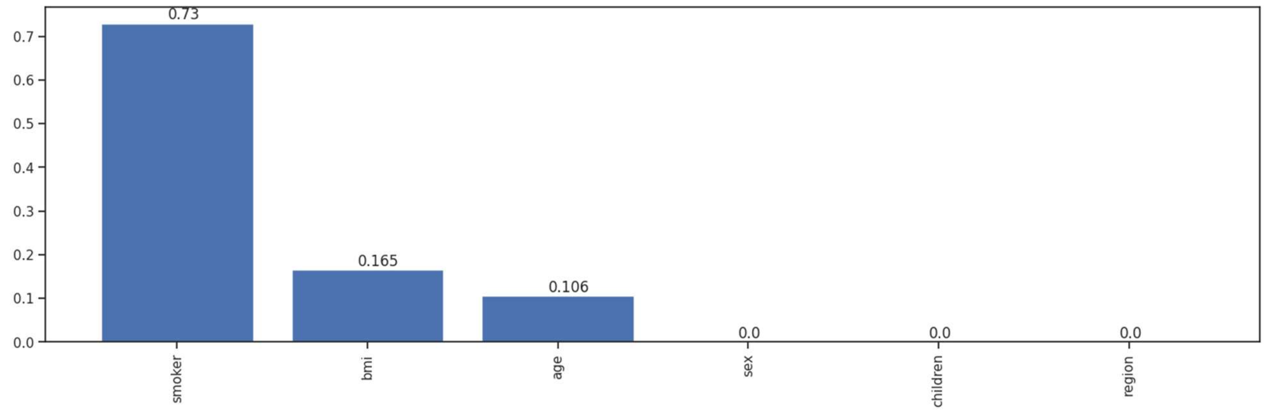
```
[ ] sum(short_tree.feature_importances_)
```

```
1.0
```

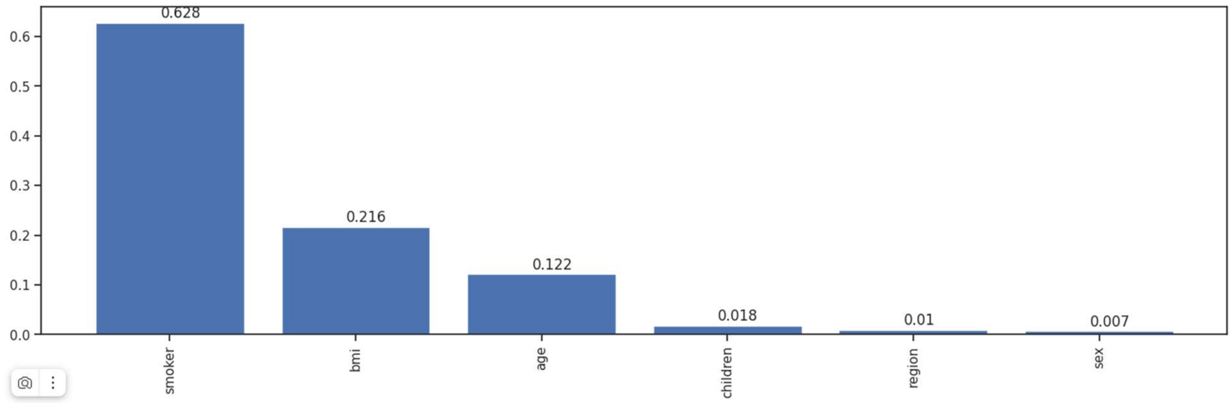
```
[ ] from operator import itemgetter

    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
```

```
[ ] tree_regr_fl, tree_regr_fd = draw_feature_importances(short_tree, df)
```



```python
tree_regr_fl, tree_regr_fd = draw_feature_importances(dtr, df)
```




```python
# Пересортируем признаки на основе важности
df_sorted = df[tree_regr_fl]
df_sorted.head()
```

	smoker	bmi	age	children	region	sex
0	1	27.900	19	0	3	0
1	0	33.770	18	1	2	1
2	0	33.000	28	3	2	1
3	0	22.705	33	0	1	1
4	0	28.880	32	0	1	1

```python
# Формирование обучающей и тестовой выборки
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
```

```python
# Scaling the features
scaler = StandardScaler()
X_train_scale = scaler.fit_transform(X_train)
X_test_scale = scaler.transform(X_test)

# Converting the scaled arrays into DataFrames
X_train = pd.DataFrame(X_train_scale, columns=X_train.columns)
X_test = pd.DataFrame(X_test_scale, columns=X_test.columns)
```

```python
#boston_tree_regr_fl[0:5]
```

```python
def create_df(data,models, cols):
    index = []
    for model in models:
        model_name = type(model).__name__
        if model_name in index:
            model_name = str(type(model).__name__) + '_hyp'
        index.append(model_name)

    df = pd.DataFrame(data = data,
                      index = index)
    df.rename(columns=dict(zip(df.columns, cols)), inplace=True)
    return df

def training(models, X=X_train, y=y_train):
    metric = {}
    train_model = []
    mses =[]
    maes =[]
    index =[]
    for model in models:
        #score = []  # Initialize score for each model
        model.fit(X, y)
        train_model.append(model)
        y_pred = model.predict(X)
        mse = mean_squared_error(y, y_pred)
        mses.append(mse)
        mae = mean_absolute_error(y, y_pred)
        maes.append(mae)
```

```
        #score.extend([mse, mae, r2])  # Use extend to add multiple elements to score

    cols=['train_mse', 'train_mae']
    metric['mse'] = mses
    metric['mae'] = maes
    metric_df = create_df(data=metric,models= train_model, cols = cols)
    return metric_df, train_model

def testing(models,X = X_test, y = y_test):
    mses =[]
    maes =[]
    index =[]
    metric = {}
    for model in models:
        #score = []  # Initialize score for each model
        y_pred = model.predict(X)
        mse = mean_squared_error(y, y_pred)
        mses.append(mse)
        mae = mean_absolute_error(y, y_pred)
        maes.append(mae)
        #score.extend([mse, mae, r2])  # Use extend to add multiple elements to score
    metric['mse'] = mses
    metric['mae'] = maes
    cols=['test_mse', 'test_mae']
    metric_df = create_df(data=metric,models= models, cols=cols)
    return metric_df
```

[ ]

[ ]

```
for i in range(2, 7):
    print(i)
    pd.options.display.float_format = '{:.3f}'.format
    models = [lr, svr, nu_svr, l_svr, dtr]
    training_df, train_models = training(models, X_train[tree_regr_fl[0:i]])

    print(training_df)
    test_df = testing(train_models, X_test[tree_regr_fl[0:i]])

    print(test_df)
```

```
2
```

```
2
                        train_mse  train_mae
LinearRegression       49059356.397   5351.355
SVR                   157594076.894   8264.909
NuSVR                 149067261.886   8360.161
LinearSVR             273532810.667  11437.626
DecisionTreeRegressor  16478625.531   2412.935
                         test_mse   test_mae
LinearRegression       55784083.121  5677.046
SVR                   161399671.497  8288.616
NuSVR                 154296455.547  8420.935
LinearSVR             269036873.409 10923.853
DecisionTreeRegressor  30984927.512  3655.173
3
                        train_mse  train_mae
LinearRegression       36503821.826   4180.217
SVR                   158408724.268   8174.710
NuSVR                 149064776.911   8371.329
LinearSVR             270955529.804  11320.017
DecisionTreeRegressor    501813.085     70.028
                         test_mse   test_mae
LinearRegression       40752860.565  4236.645
SVR                   161986397.117  8189.118
NuSVR                 154305470.272  8421.116
LinearSVR             266294918.260 10806.452
DecisionTreeRegressor   9928501.446   783.966
4
                        train_mse  train_mae
LinearRegression       36205128.272   4140.641
SVR                   159160688.989   8228.782
NuSVR                 149779434.476   8396.076
LinearSVR             270713896.818  11303.286
DecisionTreeRegressor     35518.493      6.653
                         test_mse   test_mae
LinearRegression       40094311.007  4168.989
SVR                   162647324.258  8240.572
NuSVR                 154892669.999  8441.856
LinearSVR             266026540.749 10786.902
DecisionTreeRegressor   8904850.282   691.917
```

```
5
                         train_mse   train_mae
LinearRegression       36025930.234   4136.844
SVR                   159763000.259   8263.772
NuSVR                 150254672.447   8416.289
LinearSVR             270653370.699  11299.001
DecisionTreeRegressor     35371.756      6.153
                          test_mse   test_mae
LinearRegression       39922583.826  4166.437
SVR                   163201081.364  8273.967
NuSVR                 155349167.070  8461.957
LinearSVR             266004939.704 10782.867
DecisionTreeRegressor  10326605.866   701.974
6
                         train_mse   train_mae
LinearRegression       36024723.554   4136.382
SVR                   160158596.886   8287.505
NuSVR                 150596955.951   8430.766
LinearSVR             270809927.877  11294.666
DecisionTreeRegressor     35245.921      5.639
                          test_mse   test_mae
LinearRegression       39922479.354  4167.301
SVR                   163569917.515  8297.132
NuSVR                 155674257.450  8476.228
LinearSVR             266125921.783 10774.577
DecisionTreeRegressor   7688325.884   564.445
```