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Кафедра «Системы обработки информации и управления»

Лабораторная работа №4-5
по дисциплине
«Технологии машинного обучения»
на тему

«Линейные модели, SVM и деревья решений. Ансамбли моделей машинного обучения.»

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1. Лабораторная №4

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;
    - SVM;
    - дерево решений.
5. Оцените качество моделей с помощью двух подходящих для задачи метрик. Сравните качество полученных моделей.

Дополнительные задания:

1. Проведите эксперименты с важностью признаков в дереве решений.
2. Визуализируйте дерево решений.

[1]:
```
from IPython.display import Image
from io import StringIO
import graphviz
import pydotplus

import numpy as np
import pandas as pd
import math

import seaborn as sns
sns.set(style="ticks")

import matplotlib.pyplot as plt
%matplotlib inline
```

[231]:
```
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR

from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
from sklearn.metrics import median_absolute_error

from sklearn.tree import export_graphviz
```

[3]:
```
class MetricLogger:
```

```
    def __init__(self):
        self.df = pd.DataFrame(
            {'metric': pd.Series([], dtype='str'),
            'alg': pd.Series([], dtype='str'),
            'value': pd.Series([], dtype='float')})

    def add(self, metric, alg, value):
        """

        """
        #
        self.df.drop(self.df[(self.df['metric']==metric)&(self.
↪df['alg']==alg)].index, inplace = True)
        #
        temp = [{'metric':metric, 'alg':alg, 'value':value}]
        self.df = self.df.append(temp, ignore_index=True)

    def get_data_for_metric(self, metric, ascending=True):
        """

        """
        temp_data = self.df[self.df['metric']==metric]
        temp_data_2 = temp_data.sort_values(by='value', ascending=ascending)
        return temp_data_2['alg'].values, temp_data_2['value'].values

    def plot(self, str_header, metric, ascending=True, figsize=(5, 5)):
        """

        """
        array_labels, array_metric = self.get_data_for_metric(metric,␣
↪ascending)
        fig, ax1 = plt.subplots(figsize=figsize)
        pos = np.arange(len(array_metric))
        rects = ax1.barh(pos, array_metric,
                         align='center',
                         height=0.5,
                         tick_label=array_labels)
        ax1.set_title(str_header)
        for a,b in zip(pos, array_metric):
            plt.text(0.2, a-0.1, str(round(b,3)), color='white')
        plt.show()
```

[188]:
```
data = pd.read_csv("SolarPrediction.csv")
```

1.1. Предобработка данных

[46]:
```
data.head()
```

[46]:
```
     UNIXTime                    Data      Time  Radiation  Temperature  \
0  1475229326  9/29/2016 12:00:00 AM  23:55:26       1.21           48
1  1475229023  9/29/2016 12:00:00 AM  23:50:23       1.21           48
2  1475228726  9/29/2016 12:00:00 AM  23:45:26       1.23           48
3  1475228421  9/29/2016 12:00:00 AM  23:40:21       1.21           48
4  1475228124  9/29/2016 12:00:00 AM  23:35:24       1.17           48

   Pressure  Humidity  WindDirection(Degrees)  Speed TimeSunRise TimeSunSet
0     30.46        59                  177.39   5.62    06:13:00   18:13:00
1     30.46        58                  176.78   3.37    06:13:00   18:13:00
2     30.46        57                  158.75   3.37    06:13:00   18:13:00
3     30.46        60                  137.71   3.37    06:13:00   18:13:00
4     30.46        62                  104.95   5.62    06:13:00   18:13:00
```

[6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32686 entries, 0 to 32685
Data columns (total 11 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   UNIXTime                32686 non-null  int64
 1   Data                    32686 non-null  object
 2   Time                    32686 non-null  object
 3   Radiation               32686 non-null  float64
 4   Temperature             32686 non-null  int64
 5   Pressure                32686 non-null  float64
 6   Humidity                32686 non-null  int64
 7   WindDirection(Degrees)  32686 non-null  float64
 8   Speed                   32686 non-null  float64
 9   TimeSunRise             32686 non-null  object
 10  TimeSunSet              32686 non-null  object
dtypes: float64(4), int64(3), object(4)
memory usage: 2.7+ MB
```

[7]:
```
data.describe()
```

[7]:
```
           UNIXTime     Radiation   Temperature      Pressure      Humidity  ␣
 ↪\
count  3.268600e+04  32686.000000  32686.000000  32686.000000  32686.000000
mean   1.478047e+09    207.124697     51.103255     30.422879     75.016307
std    3.005037e+06    315.916387      6.201157      0.054673     25.990219
min    1.472724e+09      1.110000     34.000000     30.190000      8.000000
25%    1.475546e+09      1.230000     46.000000     30.400000     56.000000
50%    1.478026e+09      2.660000     50.000000     30.430000     85.000000
75%    1.480480e+09    354.235000     55.000000     30.460000     97.000000
max    1.483265e+09   1601.260000     71.000000     30.560000    103.000000

       WindDirection(Degrees)         Speed
count            32686.000000  32686.000000
mean               143.489821      6.243869
```

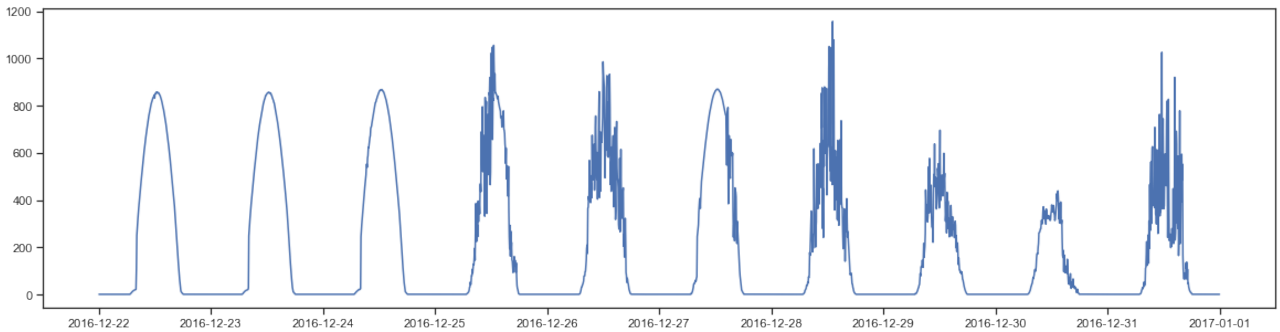
```
std          83.167500     3.490474
min           0.090000     0.000000
25%          82.227500     3.370000
50%         147.700000     5.620000
75%         179.310000     7.870000
max         359.950000    40.500000
```

Рассмотрим влияние времени на радиацию

[23]:
```
data['data_time'] = pd.to_datetime(data['Data'].str.split(' ', expand=True).
↪iloc[:,0] + ' '+ data['Time'])
```

[37]:
```
aux = data[data['data_time'] > pd.to_datetime('2016-12-22')]

fig, ax = plt.subplots(figsize=(20,5))
plt.plot(aux['data_time'], aux['Radiation'])
ax.set_title('           ')
```

[37]:
```
[<matplotlib.lines.Line2D at 0x7fd1d43b3f40>]
```



Заметны ежедневные колебания радиации в зависимости от времени суток, так что можем выделить только эту информацию.

[189]:
```
data["Time"] = data.Time.str.slice(stop=2).astype(int)
```

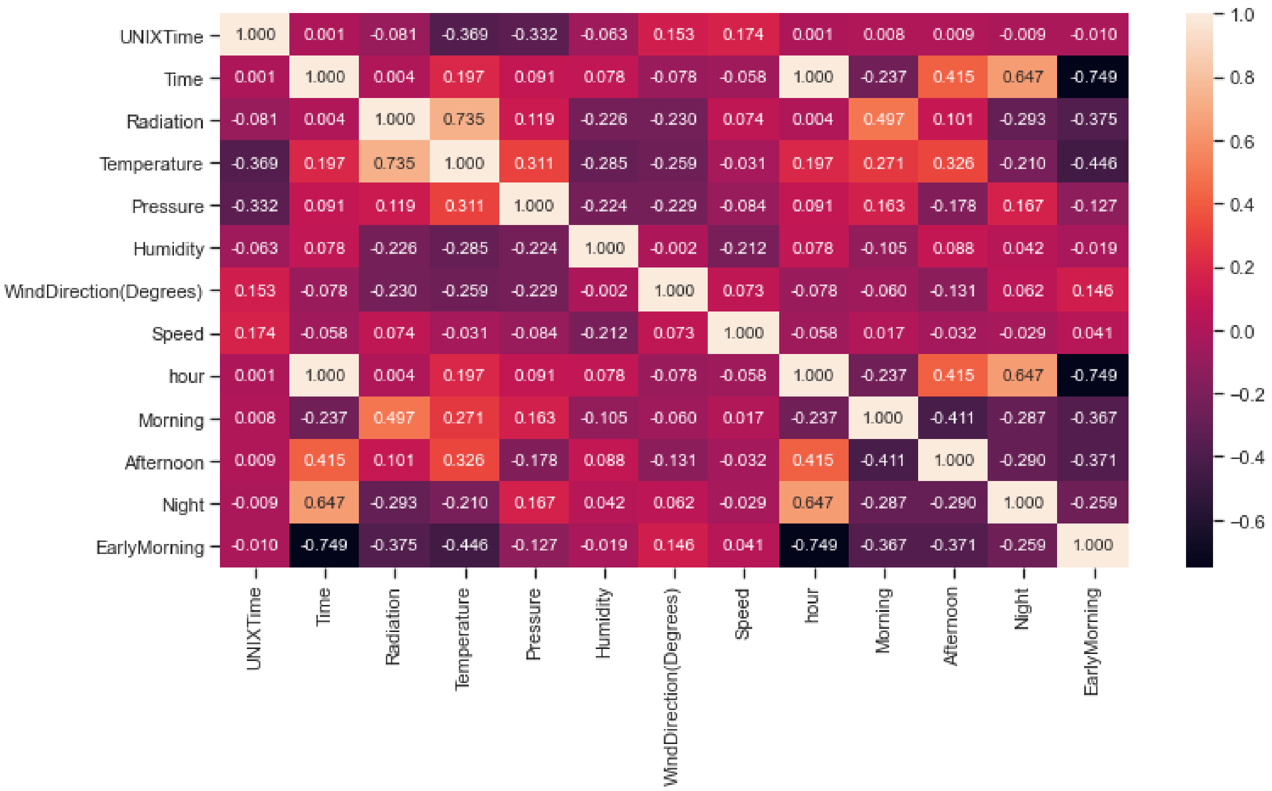
[190]:
```
data["Morning"] = (data["Time"] >= 6) & (data["Time"] <= 12)
data["Afternoon"] = (data["Time"] >= 13) & (data["Time"] <= 19)
data["Night"] = (data["Time"] >= 20) & (data["Time"] <= 23)
data["EarlyMorning"] = (data["Time"] >= 0) & (data["Time"] <= 5)
```

[191]:
```
from sklearn.preprocessing import LabelEncoder

lab_enc = LabelEncoder()
data['Morning'] = lab_enc.fit_transform(data['Morning'])
data['Afternoon'] = lab_enc.fit_transform(data['Afternoon'])
data['Night'] = lab_enc.fit_transform(data['Night'])
data['EarlyMorning'] = lab_enc.fit_transform(data['EarlyMorning'])
```

[59]:
```
corrmat = data.corr()
plt.figure(figsize=(12,6))
```

```
sns.heatmap(corrmat, annot=True, fmt='.3f')
```

[59]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd1d2fab0a0>



Учитывая информацию о корреляции признаков с целевым (радиацией), разделим выборку на обучающую и тестовую

[207]:
```
%%capture
y = data['Radiation']
X = data[['Temperature','Pressure', 'Humidity', 'WindDirection(Degrees)',␣
↪'Morning', 'Afternoon', 'Night', 'EarlyMorning']]
```

[193]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪random_state=23)
```

[115]:
```
metrics = MetricLogger()
```

1.2. Линейная модель

[73]:
```
model = LinearRegression()
model.fit(X_train, y_train)
```

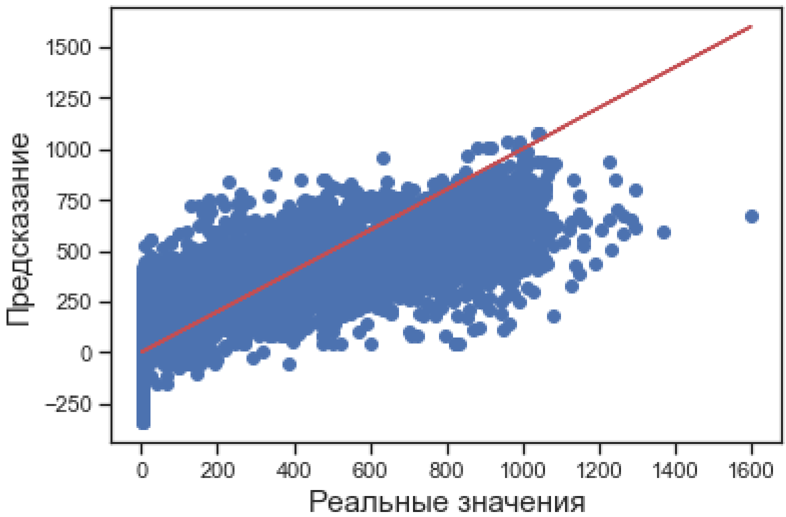
[73]: LinearRegression()

[116]:
```
y_pred_linear = model.predict(X_test)
```

```
RMSE = mean_squared_error(y_test, y_pred_linear, squared=False)
MAE = mean_absolute_error(y_test, y_pred_linear)
R2_Score = r2_score(y_test, y_pred_linear)
MedAE = median_absolute_error(y_test, y_pred_linear)

metrics.add('RMSE', 'Linear Regression', RMSE)
metrics.add('MAE', 'Linear Regression', MAE)
metrics.add('R2 Score', 'Linear Regression', R2_Score)
metrics.add('Median AE', 'Linear Regression', MedAE)

print('RMSE =', RMSE)
print('MAE =', MAE)
print('R2 Score =', R2_Score)
print ("Median AE =", MedAE) # 0 -
```

```
RMSE = 183.71440040226548
MAE = 139.74836818158906
R2 Score = 0.6628141270214678
Median AE = 108.58990730244786
```

[75]:
```
plt.scatter(y_test, y_pred_linear)
plt.plot(y_test, y_test, 'r')
plt.xlabel('          ', fontsize = 15)
plt.ylabel('       ', fontsize = 15)
plt.show()
```



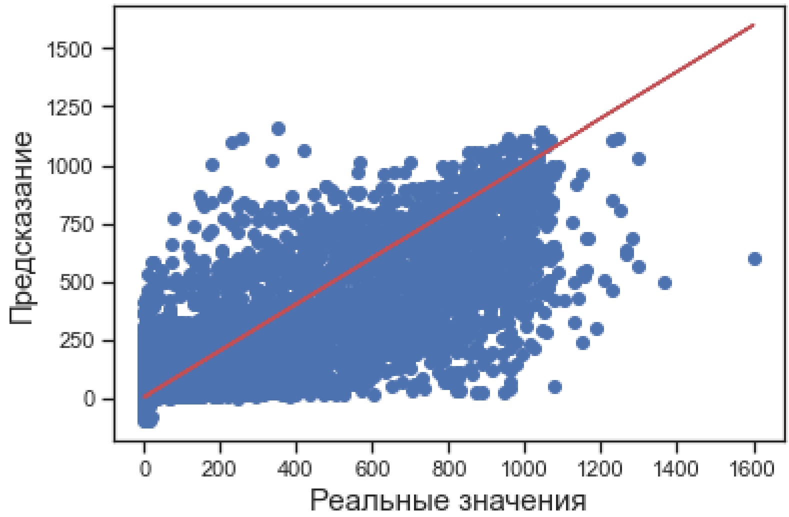
1.3. SVM

[79]:
```
svr = SVR(kernel='rbf', gamma=0.001, C=1000.0)
svr.fit(X_train, y_train)

y_pred_svr = svr.predict(X_test)
```

```
[117]: RMSE = mean_squared_error(y_test, y_pred_svr, squared=False)
MAE = mean_absolute_error(y_test, y_pred_svr)
R2_Score = r2_score(y_test, y_pred_svr)
MedAE = median_absolute_error(y_test, y_pred_svr)

metrics.add('RMSE', 'SVR', RMSE)
metrics.add('MAE', 'SVR', MAE)
metrics.add('R2 Score', 'SVR', R2_Score)
metrics.add('Median AE', 'SVR', MedAE)

print('RMSE =', RMSE)
print('MAE =', MAE)
print('R2 Score =', R2_Score)
print ("Median AE =", MedAE) # 0 -
```

```
RMSE = 170.86437326919935
MAE = 94.80425446802981
R2 Score = 0.7083338646042837
Median AE = 27.023257361608323
```

```
[87]: plt.scatter(y_test, y_pred_svr)
plt.plot(y_test, y_test, 'r')
plt.xlabel('          ', fontsize = 15)
plt.ylabel('      ', fontsize = 15)
plt.show()
```



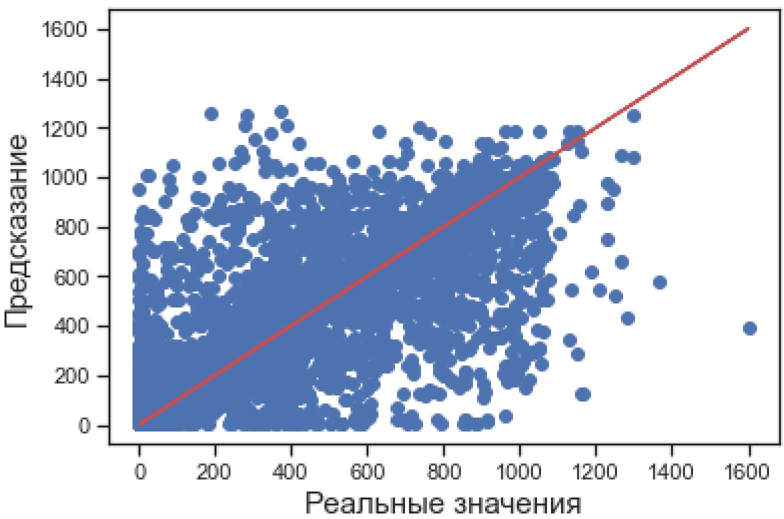
1.4. Дерево решений

```
[241]: tree = DecisionTreeRegressor(random_state=23)
tree.fit(X_train, y_train)

y_pred_tree = tree.predict(X_test)
```

[242]:
```
RMSE = mean_squared_error(y_test, y_pred_tree, squared=False)
MAE = mean_absolute_error(y_test, y_pred_tree)
R2_Score = r2_score(y_test, y_pred_tree)
MedAE = median_absolute_error(y_test, y_pred_tree)


metrics.add('RMSE', 'Decision Tree', RMSE)
metrics.add('MAE', 'Decision Tree', MAE)
metrics.add('R2 Score', 'Decision Tree', R2_Score)
metrics.add('Median AE', 'Decision Tree', MedAE)

print('RMSE =', RMSE)
print('MAE =', MAE)
print('R2 Score =', R2_Score) # 1 -
print ("Median AE =", MedAE) # 0 -
```

```
RMSE = 161.22134759760834
MAE = 70.68609243508645
R2 Score = 0.7403262406816951
Median AE = 1.5700000000000003
```

[88]:
```
plt.scatter(y_test, y_pred_tree)
plt.plot(y_test, y_test, 'r')
plt.xlabel('          ', fontsize = 15)
plt.ylabel('       ', fontsize = 15)
plt.show()
```



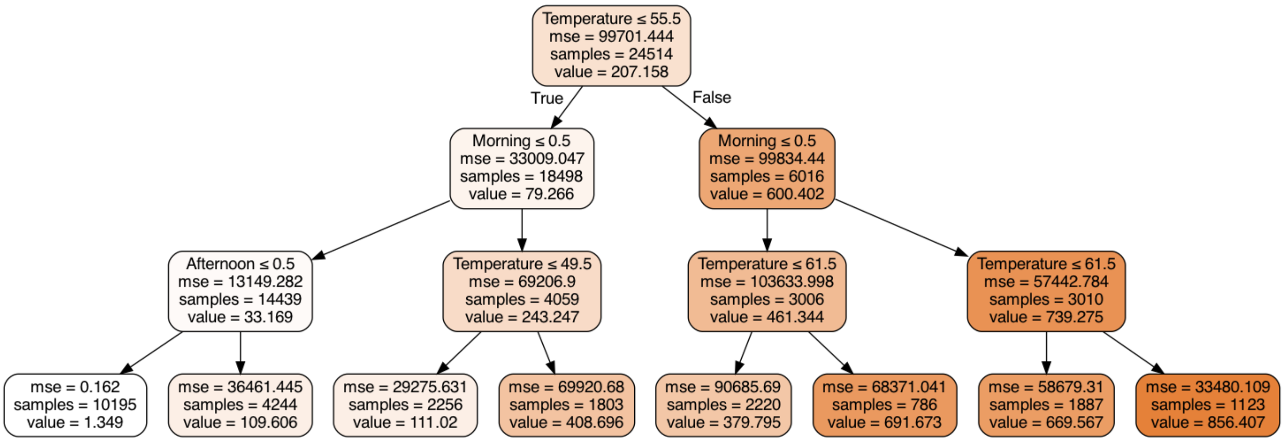
[214]:
```
features = ['Temperature','Pressure', 'Humidity', 'Morning', 'Afternoon',␣
 ↪'Night', 'EarlyMorning']
```

[234]:
```
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()
```

[240]:
```
Image(get_png_tree(tree, features), width='80%')
```

[240]:



[105]:
```
list(zip(features, reg.feature_importances_))
```

[105]:
```
[('Temperature', 0.6624176426693815),
 ('Pressure', 0.08179001615319866),
 ('Humidity', 0.13000493922461095),
 ('Morning', 0.11061342723451908),
 ('Afternoon', 0.015173786231224225),
 ('Night', 1.7539775096270733e-07),
 ('EarlyMorning', 1.3089314408436572e-08)]
```

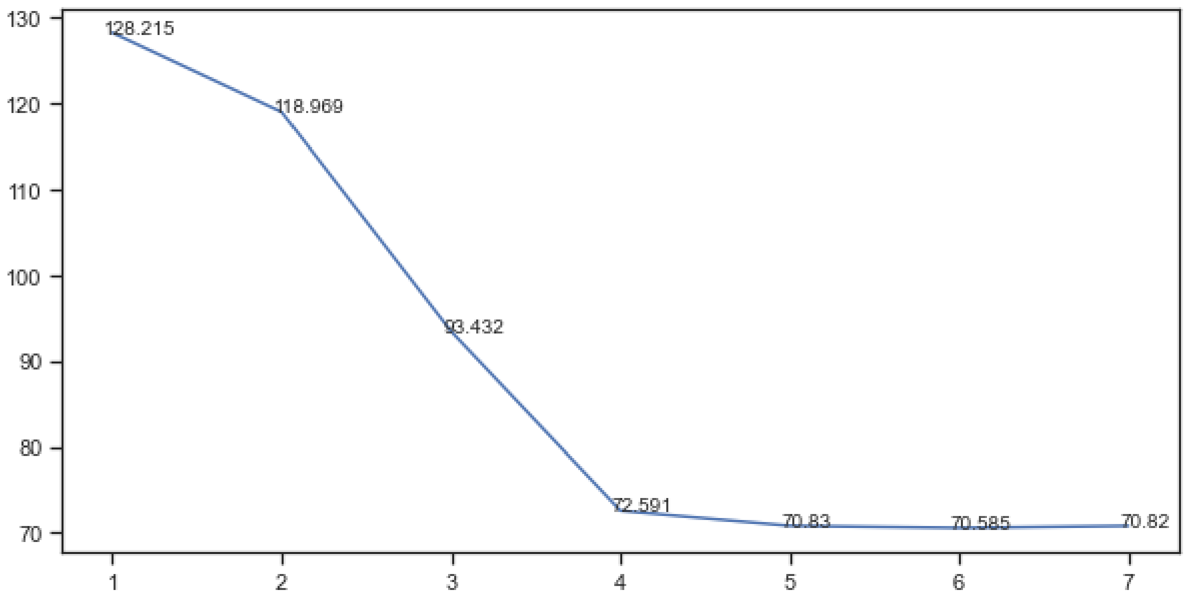
[106]:
```
from operator import itemgetter

list_to_sort = list(zip(features, reg.feature_importances_))
sorted_list = sorted(list_to_sort, key=itemgetter(1), reverse = True)
labels = [x for x,_ in sorted_list]
```

[107]:
```
labels
```

[107]:
```
['Temperature',
 'Humidity',
 'Morning',
 'Pressure',
 'Afternoon',
 'Night',
 'EarlyMorning']
```

[110]:
```
mae_list = []

reg = DecisionTreeRegressor(random_state = 42)
for i in range(1, len(labels)+1):
    reg.fit(X_train[labels[0:i]], y_train)
    y_pred_tree2 = reg.predict(X_test[labels[0:i]])

    temp_mae = mean_absolute_error(y_pred_tree2, y_test)
    mae_list.append(temp_mae)
```

[111]:
```
plt.subplots(figsize=(10,5))
plt.plot(range(1, len(labels)+1), mae_list)
for a,b in zip(range(1, len(labels)+1), mae_list):
    plt.text(a-0.05, b+0.01, str(round(b,3)))
plt.show()
```



[113]:
```
reg = DecisionTreeRegressor(random_state = 42)

reg.fit(X_train[labels[0:1]], y_train)
y_pred_tree2 = reg.predict(X_test[labels[0:1]])
```

[114]:
```
RMSE = mean_squared_error(y_test, y_pred_linear, squared=False)
MAE = mean_absolute_error(y_test, y_pred_linear)
R2_Score = r2_score(y_test, y_pred_linear)
MedAE = median_absolute_error(y_test, y_pred_linear)

print('RMSE =', RMSE)
print('MAE =', MAE)
print('R2 Score =', R2_Score) # 1 -
print ("Median AE =", MedAE) # 0 -
```

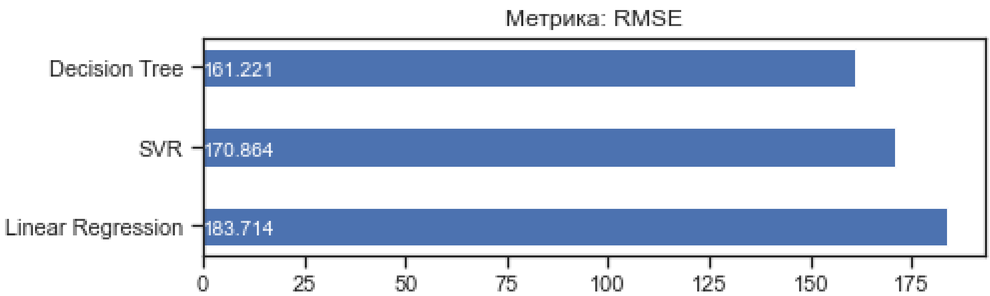
```
RMSE = 183.6450577090526
MAE = 139.7675386592176
R2 Score = 0.6630686194713111
Median AE = 108.23153722285949
```

1.5. Сравнение качества полученных моделей

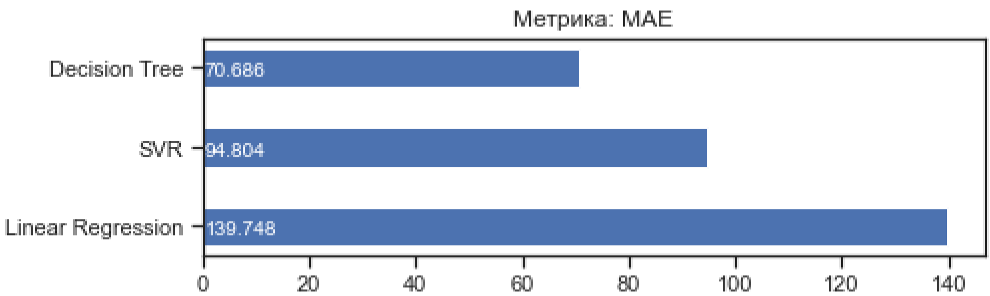
[119]:
```
clas_metrics = metrics.df['metric'].unique()
clas_metrics
```

[119]:
```
array(['RMSE', 'MAE', 'R2 Score', 'Median AE'], dtype=object)
```

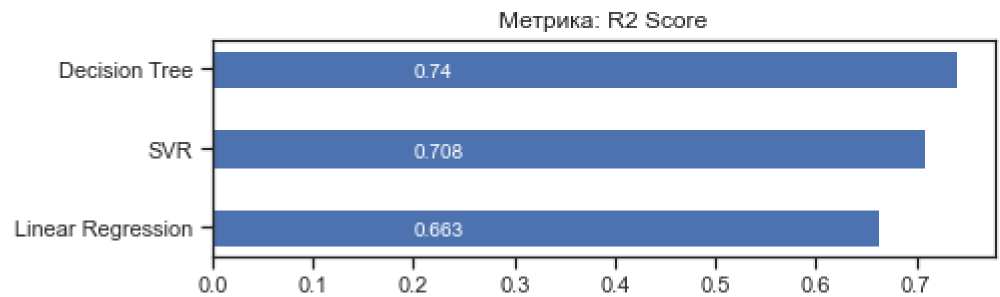
[122]:
```
metrics.plot('     : ' + 'RMSE', 'RMSE', ascending=False, figsize=(7, 2))
```



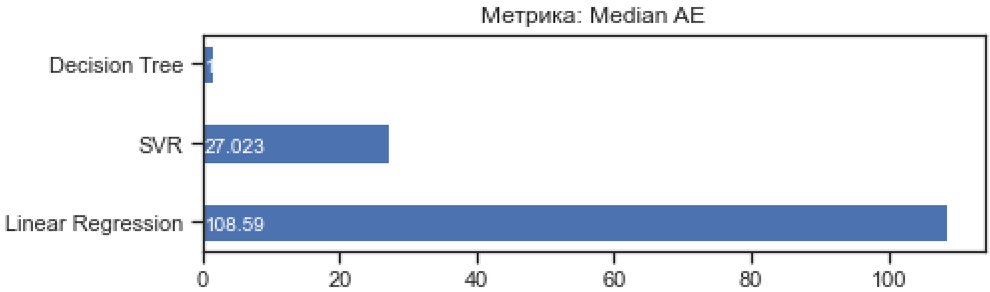
[123]:
```
metrics.plot('     : ' + 'MAE', 'MAE', ascending=False, figsize=(7, 2))
```



[124]:
```
metrics.plot('     : ' + 'R2 Score', 'R2 Score', ascending=True, figsize=(7,␣
↪2))
```



```
[125]: metrics.plot('     : ' + 'Median AE', 'Median AE', ascending=False,␣
        ↪figsize=(7, 2))
```




```
Decision Tree
```

2. Лабораторная №5

Задание:

```
1.              (   )                              .
2.                                                           .
3.            train_test_split                          .
4.                  .                                       .
                  .
```

2.1. Градиентный бустинг

```
[194]: from sklearn.ensemble import GradientBoostingRegressor
```

```
[195]: reg = GradientBoostingRegressor(random_state=0)
       reg.fit(X_train, y_train)
```

```
[195]: GradientBoostingRegressor(random_state=0)
```

```
[197]: gb_score = reg.score(X_test, y_test)     #R2
       gb_score
```

```
[197]: 0.7631290360315247
```

```
[143]: boost_prediction = rand_tree.predict(X_test)
```

```
[146]: print('mean absolute error =', mean_absolute_error(y_test,␣
        ↪boost_prediction))
```

```
mean absolute error = 65.7936654175928
```

2.2. Stacking and blending

[150]:
```
from heamy.estimator import Regressor
from heamy.pipeline import ModelsPipeline
from heamy.dataset import Dataset
```

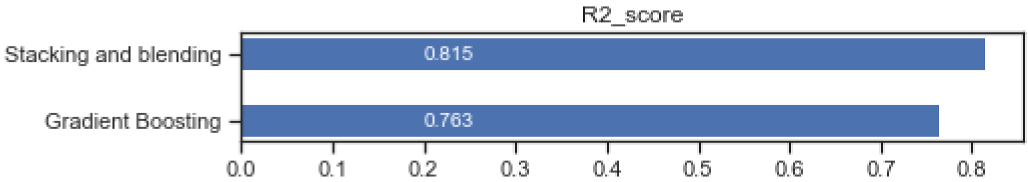
[151]:
```
dataset = Dataset(X_train, y_train, X_test)

#
model_tree = Regressor(dataset=dataset, estimator=DecisionTreeRegressor,␣
 ↪name='tree')
model_lr = Regressor(dataset=dataset, estimator=LinearRegression,␣
 ↪parameters={'normalize': True},name='lr')
model_svr = Regressor(dataset=dataset, estimator=SVR, parameters={'kernel':␣
 ↪'rbf', 'gamma': 0.001, 'C': 1000.0}, name = 'svr')

model_rf = Regressor(dataset=dataset, estimator=RandomForestRegressor,␣
 ↪parameters={'n_estimators': 50},name='rf')
```

[153]:
```
pipeline = ModelsPipeline(model_tree, model_lr, model_svr, model_rf)
stack_ds = pipeline.stack(k=10, seed=1)
#
stacker = Regressor(dataset=stack_ds, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=r2_score)
```

```
Metric: r2_score
Folds accuracy: [0.8218942037642474, 0.8291350275695792, 0.8102931798323086,
0.8082570039751233, 0.8280857545390783, 0.8128446419364532, 0.
 ↪8050669575457489,
0.8147181564716821, 0.8170559846925569, 0.802330567384455]
Mean accuracy: 0.8149681477711234
Standard Deviation: 0.00868510195703396
Variance: 7.543099600407513e-05
```

2.3. Сравнение качества полученных моделей

[205]:
```
array_labels = ['Gradient Boosting', 'Stacking and blending']
array_metric = [gb_score, 0.815]
fig, ax1 = plt.subplots(figsize=(7, 1))
pos = np.arange(len(array_metric))
rects = ax1.barh(pos, array_metric,
                         align='center',
                         height=0.5,
                         tick_label=array_labels)
ax1.set_title('R2_score')
for a,b in zip(pos, array_metric):
    plt.text(0.2, a-0.1, str(round(b,3)), color='white')
plt.show()
```


R2_score
Stacking and blending
Gradient Boosting
0.815
0.763
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8