Загрузка данных

In [230]:

```
from IPython.display import Image
#import graphviz
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from sklearn.datasets import load_iris, load_wine, load_boston
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, export_graphviz
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean absolute error
import matplotlib.pyplot as plt
%matplotlib inline
from IPython.display import Image
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.datasets import load_iris, load_boston
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.model_selection import KFold, RepeatedKFold, LeaveOneOut, LeavePOut, ShuffleSplit, StratifiedKFold
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score, classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_squared_log_error, median_absolute_error, r2_score
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.model_selection import learning_curve, validation_curve
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

In [185]:

wine = load_wine()

In [196]:

df_wine = pd.DataFrame(wine.data,columns=wine.feature_names)
df_wine['target'] = pd.Series(wine.target)
df_wine.head()

Out[196]:

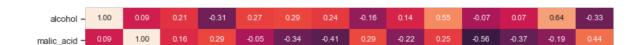
	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	proanthocyanins	color_intensity	hue	oc
0	14.23	1.71	2.43	15.6	127.0	2.80	3.06	0.28	2.29	5.64	1.04	
1	13.20	1.78	2.14	11.2	100.0	2.65	2.76	0.26	1.28	4.38	1.05	
2	13.16	2.36	2.67	18.6	101.0	2.80	3.24	0.30	2.81	5.68	1.03	
3	14.37	1.95	2.50	16.8	113.0	3.85	3.49	0.24	2.18	7.80	0.86	
4	13.24	2.59	2.87	21.0	118.0	2.80	2.69	0.39	1.82	4.32	1.04	
4												F

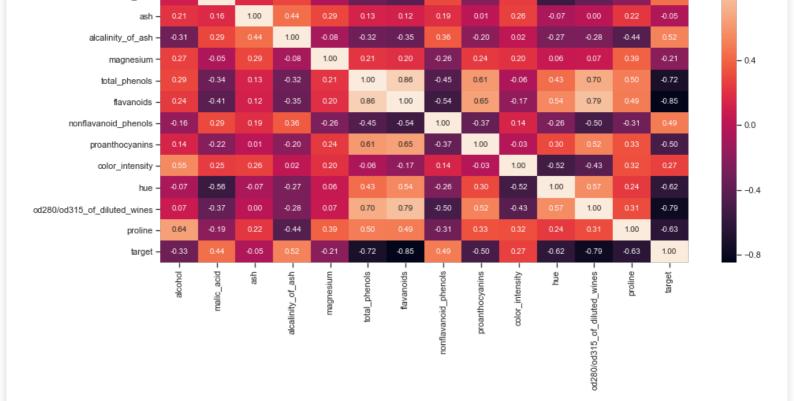
In [198]:

fig, ax = plt.subplots(figsize=(15,7))
sns.heatmap(df_wine.corr(method='pearson'), ax=ax, annot=True, fmt='.2f')

Out[198]:

<matplotlib.axes._subplots.AxesSubplot at 0x1868fa06cc0>





Деревья решений

In [187]:

```
wine_tree_cl = DecisionTreeClassifier(random_state=1)
wine_tree_cl.fit(wine_x_ds, wine.target)
wine_tree_cl
```

Out[187]:

DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None, max_features=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, presort=False, random_state=1, splitter='best')

In [188]:

wine.target

Out[188]:

In [189]:

```
list(zip(wine_x_ds.columns.values, wine_tree_cl.feature_importances_))
```

Out[189]:

```
[('alcohol', 0.012570564071187309),
('malic_acid', 0.014223159778821876),
('ash', 0.0),
('alcalinity_of_ash', 0.0),
('magnesium', 0.0534597951279922),
('total_phenols', 0.0),
('flavanoids', 0.16704836491408806),
('nonflavanoid_phenols', 0.0),
```

```
('proanthocyanins', 0.0),
('color_intensity', 0.0),
('hue', 0.058185091460406506),
('od280/od315_of_diluted_wines', 0.3120425747831769),
('proline', 0.38247044986432716)]
In [190]:
sum(wine_tree_cl.feature_importances_)
Out[190]:
1.0
In [191]:
wine_X_train, wine_X_test, wine_y_train, wine_y_test = train_test_split(
  wine_x_ds, wine.target, test_size=0.5, random_state=1)
wine_X_train.shape, wine_X_test.shape
Out[191]:
((89, 13), (89, 13))
In [192]:
wine_tree_cl_feat_1 = DecisionTreeClassifier(random_state=1).fit(wine_X_train, wine_y_train)
wine_y_test_predict = wine_tree_cl_feat_1.predict(wine_X_test)
wine_y_test_predict.shape
Out[192]:
(89,)
In [193]:
print_accuracy_score_for_classes(wine_y_test, wine_y_test_predict)
Метка Accuracy
0 0.8181818181818182
 0.8823529411764706
2 0.95454545454546
In [194]:
mean_absolute_error(wine_y_test, wine_y_test_predict)
Out[194]:
0.12359550561797752
In [195]:
median_absolute_error(wine_y_test, wine_y_test_predict)
Out[195]:
0.0
Линейная зависимость
In [212]:
wine_X_train, wine_X_test, wine_y_train, wine_y_test = train_test_split(
  wine.data, wine.target, test_size=0.5, random_state=1)
wine_X_train.shape, wine_X_test.shape
Out[212]:
```

((89, 13), (89, 13))

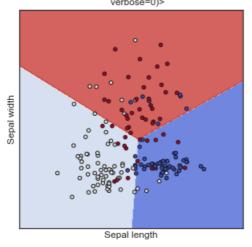
```
In [214]:
reg1 = LinearRegression().fit(wine_X_train, wine_y_train)
(b1, reg1.coef_), (b0, reg1.intercept_)
Out[214]:
((0.20884722950068055,
 array([-0.14363533, 0.01736955, -0.12304724, 0.04618784, -0.00180479,
      0.21048533, -0.37095489, -0.47875276, -0.10163014, 0.09471474,
     -0.37481097, -0.19107785, -0.00077269])),
(-1.0715116629341392, 3.881691199237158))
In [215]:
wine_y_test_predict = reg1.predict(wine_X_test)
In [218]:
mean_absolute_error(wine_y_test, wine_y_test_predict)
Out[218]:
0.23201284251888057
In [219]:
median_absolute_error(wine_y_test, wine_y_test_predict)
Out[219]:
0.2123153564338245
Метод опорных векторов
In [220]:
# Используем датасет iris с двумя первыми признакам
wine_X = wine.data[:, :2]
wine_y = wine.target
In [227]:
def make_meshgrid(x, y, h=.02):
   """Create a mesh of points to plot in
  Parameters
  x: data to base x-axis meshgrid on
  y: data to base y-axis meshgrid on
  h: stepsize for meshgrid, optional
  Returns
  xx, yy : ndarray
  x_{min}, x_{max} = x.min() - 1, x.max() + 1
  y_{min}, y_{max} = y.min() - 1, y.max() + 1
  xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
              np.arange(y_min, y_max, h))
  return xx, yy
def plot_contours(ax, clf, xx, yy, **params):
    ""Plot the decision boundaries for a classifier.
  Parameters
  ax: matplotlib axes object
  clf: a classifier
  xx: meshgrid ndarray
  yy: meshgrid ndarray
  params: dictionary of params to pass to contourf, optional
```

```
Z = \text{cli.predict}(\text{np.c}_[xx.ravel(), yy.ravel()])
  Z = Z.reshape(xx.shape)
  #Можно проверить все ли метки классов предсказываются
  print(np.unique(Z))
  out = ax.contourf(xx, yy, Z, **params)
  return out
def plot_cl(clf):
  title = clf.__repr_
  clf.fit(wine_X, wine_y)
  fig, ax = plt.subplots(figsize=(5,5))
  X0, X1 = wine_X[:, 0], wine_X[:, 1]
  xx, yy = make\_meshgrid(X0, X1)
  plot_contours(ax, clf, xx, yy, cmap=plt.cm.coolwarm, alpha=0.8)
  ax.scatter(X0, X1, c=wine_y, cmap=plt.cm.coolwarm, s=20, edgecolors='k')
  ax.set_xlim(xx.min(), xx.max())
  ax.set_ylim(yy.min(), yy.max())
  ax.set_xlabel('Sepal length')
  ax.set_ylabel('Sepal width')
  ax.set_xticks(())
  ax.set yticks(())
  ax.set_title(title)
  plt.show()
```

In [228]:

```
plot_cl(LinearSVC(C=1.0, max_iter=10000))
```

[0 1 2]



Подбор гиперпараметров

In [236]:

```
scores = cross_val_score(LinearRegression(),
wine.data, wine.target, cv=3)
scores
```

Out[236]:

array([-73.46648267, 0. , -6.64995487])

In [238]:

C:\Users\cveto\Anaconda3\lib\site-packages\sklearn\svm\base.py:931: ConvergenceWarning: Liblinear failed to converge, increase the number of ite rations.

"the number of iterations.", ConvergenceWarning)

C:\Users\cveto\Anaconda3\lib\site-packages\sklearn\svm\base.py:931: ConvergenceWarning: Liblinear failed to converge, increase the number of ite rations.

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the number of iterations. , Convergencewarning) C:\Users\cveto\Anaconda3\lib\site-packages\sklearn\svm\base.py:931: ConvergenceWarning: Liblinear failed to converge, increase the number of ite rations "the number of iterations.", ConvergenceWarning) Out[238]: array([0.93333333, 0.93333333, 0.96551724]) In [239]: scores = cross_val_score(DecisionTreeClassifier(random_state=1), wine.data, wine.target, cv=3) scores Out[239]: array([0.85 , 0.83333333, 0.9137931]) In [246]: $n_range = np.array(range(5,55,5))$ tuned_parameters = [{'DecisionTreeClassifier': n_range}] tuned_parameters Out[246]: [{'DecisionTreeClassifier': array([5, 10, 15, 20, 25, 30, 35, 40, 45, 50])}] In [274]: $tree_para = \{ \criterion': [\criterion': [$ clf_gs = GridSearchCV(DecisionTreeClassifier(random_state=1), tree_para, cv = 20, scoring='accuracy') clf_gs.fit(wine_X_train, wine_y_train) C:\Users\cveto\Anaconda3\lib\site-packages\sklearn\model_selection_search.py:841: DeprecationWarning: The default of the `iid` parameter will ch ange from True to False in version 0.22 and will be removed in 0.24. This will change numeric results when test-set sizes are unequal. DeprecationWarning) Out[274]: GridSearchCV(cv=20, error_score='raise-deprecating', estimator=DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None, max_features=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, presort=False, random_state=1, splitter='best'), fit_params=None, iid='warn', n_jobs=None, param_grid={'criterion': ['gini', 'entropy'], 'max_depth': [4, 5, 6, 7, 8, 9, 10, 11, 12, 15, 20, 30, 40, 50, 70, 90]}, pre_dispatch='2*n_jobs', refit=True, return_train_score='warn', scoring='accuracy', verbose=0) In [275]: clf_gs.best_estimator_ Out[275]: DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=4, max_features=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, presort=False, random_state=1, splitter='best') In [276]: clf_gs.best_score_

Out[276]:

In [277]

0.9213483146067416

```
#Параметры для дерева решений
clf gs.best params
Out[277]:
{'criterion': 'entropy', 'max_depth': 4}
In [282]:
model = LinearRegression()
parameters = {'fit_intercept':[True,False], 'normalize':[True,False], 'copy_X':[True, False]}
grid = GridSearchCV(model,parameters, cv=None)
grid.fit(wine X train, wine y train)
C:\Users\cveto\Anaconda3\lib\site-packages\sklearn\model selection\ split.py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in version 0.22.
 warnings.warn(CV_WARNING, FutureWarning)
C:\Users\cveto\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:841: DeprecationWarning: The default of the `iid` parameter will ch
ange from True to False in version 0.22 and will be removed in 0.24. This will change numeric results when test-set sizes are unequal.
 DeprecationWarning)
Out[282]:
GridSearchCV(cv=None, error_score='raise-deprecating',
   estimator=LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
     normalize=False),
   fit_params=None, iid='warn', n_jobs=None,
   param grid={'fit intercept': [True, False], 'normalize': [True, False], 'copy X': [True, False]},
   pre dispatch='2*n jobs', refit=True, return train score='warn',
   scoring=None, verbose=0)
In [283]:
#Параметры для линейной регрессии
grid.best_params_
Out[283]:
{'copy_X': True, 'fit_intercept': True, 'normalize': False}
In [285]:
param_grid = {'C':[1,10,100,1000],'gamma':[1,0.1,0.001,0.0001], 'kernel':['linear','rbf']}
grid = GridSearchCV(SVC(),param_grid,refit = True, verbose=2)
grid.fit(wine X train, wine y train)
C:\Users\cveto\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in version 0.22.
 warnings.warn(CV WARNING, FutureWarning)
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 0.1s remaining: 0.0s
Fitting 3 folds for each of 32 candidates, totalling 96 fits
[CV] C=1, gamma=1, kernel=linear .....
[CV] ...... C=1, gamma=1, kernel=linear, total= 0.1s
[CV] C=1, gamma=1, kernel=linear .....
[CV] ...... C=1, gamma=1, kernel=linear, total= 0.0s
[CV] C=1, gamma=1, kernel=linear .....
[CV] ...... C=1, gamma=1, kernel=linear, total= 0.1s
[CV] C=1, gamma=1, kernel=rbf .....
[CV] ...... C=1, gamma=1, kernel=rbf, total= 0.0s
[CV] C=1, gamma=1, kernel=rbf .....
[CV] ...... C=1, gamma=1, kernel=rbf, total= 0.0s
[CV] C=1, gamma=1, kernel=rbf .....
[CV] ...... C=1, gamma=1, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.1, kernel=linear .....
[CV] ...... C=1, gamma=0.1, kernel=linear, total= 0.0s
[CV] C=1, gamma=0.1, kernel=linear .....
[CV] ...... C=1, gamma=0.1, kernel=linear, total= 0.0s
[CV] C=1, gamma=0.1, kernel=linear .....
[CV] ...... C=1, gamma=0.1, kernel=linear, total= 0.1s
[CV] C=1, gamma=0.1, kernel=rbf .....
[CV] ...... C=1, gamma=0.1, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.1, kernel=rbf .....
[CV] ...... C=1, gamma=0.1, kernel=rbf, total= 0.0s
```

1 aamma_0 1 kornol_rbf

[0]	0-1, gainina-0.1, komoi-101
[CV]	C=1, gamma=0.1, kernel=rbf, total= 0.0s
[CV]	C=1, gamma=0.001, kernel=linear
[CV]	C=1, gamma=0.001, kernel=linear, total= 0.0s
[CV]	C=1, gamma=0.001, kernel=linear
[CV]	C=1, gamma=0.001, kernel=linear, total= 0.0s
	C=1, gamma=0.001, kernel=linear
	C=1, gamma=0.001, kernel=linear, total= 0.1s
	C=1, gamma=0.001, kernel=rbf
	C=1, gamma=0.001, kernel=rbf, total= 0.0s
	C=1, gamma=0.001, kernel=rbf
	C=1, gamma=0.001, kernel=rbf, total= 0.0s
	C=1, gamma=0.001, kernel=rbf
	C=1, gamma=0.001, kernel=rbf, total= 0.0s
	C=1, gamma=0.0001, kernel=linear
	C=1, gamma=0.0001, kernel=linear, total= 0.0s
	C=1, gamma=0.0001, kernel=linear
	C=1, gamma=0.0001, kernel=linear
	C=1, gamma=0.0001, kernel=rbf
	C=1, gamma=0.0001, kernel=rbf
	C=1, gamma=0.0001, kernel=rbf
	C=10, gamma=1, kernel=linear
	C=10, gamma=1, kernel=linear
	C=10, gamma=1, kernel=linear
	C=10, gamma=1, kernel=rbf
	C=10, gamma=1, kernel=rbf
	C=10, gamma=1, kernel=rbf, total= 0.0s
[CV]	C=10, gamma=1, kernel=rbf
[CV]	C=10, gamma=1, kernel=rbf, total= 0.0s
	C=10, gamma=0.1, kernel=linear
	C=10, gamma=0.1, kernel=linear
	C=10, gamma=0.1, kernel=linear, total= 0.0s
	C=10, gamma=0.1, kernel=linear
	C=10, gamma=0.1, kernel=rbf
	C=10, gamma=0.1, kernel=rbf
	C=10, gamma=0.1, kernel=rbf
	C=10, gamma=0.001, kernel=linear, total= 0.0s
	C=10, gamma=0.001, kernel=linear
	C=10, gamma=0.001, kernel=linear
	C=10, gamma=0.001, kernel=rbf
[CV]	C=10, gamma=0.001, kernel=rbf
[CV]	
[CV]	C=10, gamma=0.001, kernel=rbf
[CV]	C=10, gamma=0.001, kernel=rbf, total= 0.0s
	C=10, gamma=0.0001, kernel=linear
	C=10, gamma=0.0001, kernel=linear, total= 0.0s
	C=10, gamma=0.0001, kernel=linear
	C=10, gamma=0.0001, kernel=linear
	C=10, gamma=0.0001, kernel=rbf
	C=10, gamma=0.0001, kernel=rbf
	C=10, gamma=0.0001, kernel=rbf, total= 0.08
	C=100, gamma=1, kernel=linear
	C=100, gamma=1, kernel=linear
	C=100, gamma=1, kernel=linear, total= 0.0s
	C=100, gamma=1, kernel=linear
	C=100, gamma=1, kernel=linear, total= 0.1s
[CV]	C=100, gamma=1, kernel=rbf
[CV]	C=100, gamma=1, kernel=rbf, total= 0.0s
	C=100, gamma=1, kernel=rbf

[CV]	C=100, gamma=1, kernel=rbf, total= 0.0s
	C=100, gamma=1, kernel=rbf
[CV]	C=100, gamma=0.1, kernel=linear, total= 0.0s
	C=100, gamma=0.1, kernel=linear
[CV]	C=100, gamma=0.1, kernel=linear
	C=100, gamma=0.1, kernel=rbf
[CV]	C=100, gamma=0.1, kernel=rbf
[CV]	C=100, gamma=0.1, kernel=rbf, total= 0.0s
	C=100, gamma=0.001, kernel=linear
	C=100, gamma=0.001, kernel=linear
[CV]	C=100, gamma=0.001, kernel=linear, total= 0.1s
[CV]	C=100, gamma=0.001, kernel=rbf
	C=100, gamma=0.001, kernel=rbf, total= 0.0s C=100, gamma=0.001, kernel=rbf
[CV]	C=100, gamma=0.001, kernel=rbf, total= 0.0s
	C=100, gamma=0.001, kernel=rbf
[CV]	C=100, gamma=0.0001, kernel=linear
	C=100, gamma=0.0001, kernel=linear
[CV]	C=100, gamma=0.0001, kernel=rbf, total= 0.0s
	C=100, gamma=0.0001, kernel=rbf
[CV]	C=100, gamma=0.0001, kernel=rbf
[CV]	C=1000, gamma=1, kernel=linear, total= 0.0s
	C=1000, gamma=1, kernel=linear
[CV]	C=1000, gamma=1, kernel=linear
[CV]	C=1000, gamma=1, kernel=linear, total= 0.1s C=1000, gamma=1, kernel=rbf
[CV]	C=1000, gamma=1, kernel=rbf, total= 0.0s
	C=1000, gamma=1, kernel=rbf
[CV]	C=1000, gamma=1, kernel=rbf
	C=1000, gamma=0.1, kernel=linear
[CV]	C=1000, gamma=0.1, kernel=linear, total= 0.0s C=1000, gamma=0.1, kernel=linear
	C=1000, gamma=0.1, kernel=rbf
[CV]	C=1000, gamma=0.1, kernel=rbf
[CV]	
	C=1000, gamma=0.001, kernel=linear
[CV]	C=1000, gamma=0.001, kernel=linear
[CV]	
	C=1000, gamma=0.001, kernel=rbf
[CV]	C=1000, gamma=0.001, kernel=rbf
[CV]	C=1000, gamma=0.001, kernel=rbf, total= 0.0s
[CV]	C=1000, gamma=0.0001, kernel=linear
[CV]	
	C=1000, gamma=0.0001, kernel=linear
[CV]	C=1000, gamma=0.0001, kernel=rbf
[CV]	C=1000_gamma=0_0001_kernel=rbf_total=_0.0s

[Parallel(n_jobs=1)]: Done 96 out of 96 | elapsed: 7.3s finished

C:\Users\cveto\Anaconda3\lib\site-packages\sklearn\model_selection_search.py:841: DeprecationWarning: The default of the `iid` parameter will change from True to False in version 0.22 and will be removed in 0.24. This will change numeric results when test-set sizes are unequal. DeprecationWarning)

Out[285]:

GridSearchCV(cv='warn', error_score='raise-deprecating',
 estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
 decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
 kernel='rbf', max_iter=-1, probability=False, random_state=None,
 shrinking=True, tol=0.001, verbose=False),
 fit_params=None, iid='warn', n_jobs=None,
 param_grid={'C': [1, 10, 100, 1000], 'gamma': [1, 0.1, 0.001, 0.0001], 'kernel': ['linear', 'rbf']},
 pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
 scoring=None, verbose=2)

In [286]:

grid.best_params_

Out[286]:

{'C': 1, 'gamma': 1, 'kernel': 'linear'}

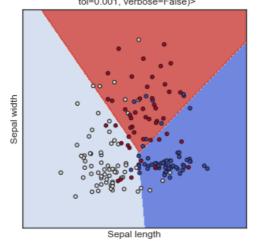
Повторение для найденных оптимальных значений гиперпараметров

In [288]:

plot_cl(SVC(C=1.0, gamma = 1, kernel = 'linear'))

[0 1 2]

<bound method BaseEstimator.__repr__ of SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0, decision_function_shape='ovr', degree=3, gamma=1, kernel='linear', max_iter=-1, probability=False, random_state=None, shrinking=True, tol=0.001, verbose=False)>



In [291]:

reg1 = LinearRegression(copy_X = **True**, fit_intercept = **True**, normalize = **False**).fit(wine_X_train, wine_y_train) (b1, reg1.coef_), (b0, reg1.intercept_)



Out[291]:

((0.20884722950068055, array([-0.14363533, 0.0

array([-0.14363533, 0.01736955, -0.12304724, 0.04618784, -0.00180479, 0.21048533, -0.37095489, -0.47875276, -0.10163014, 0.09471474,

-0.37481097, -0.19107785, -0.00077269])),

(-1.0715116629341392, 3.881691199237158))

```
In [295]:
wine_y_test_predict = reg1.predict(wine_X_test)
In [296]:
mean_absolute_error(wine_y_test, wine_y_test_predict)
Out[296]:
0.23201284251888057
In [297]:
median_absolute_error(wine_y_test, wine_y_test_predict)
Out[297]:
0.2123153564338245
In [294]:
wine_tree_cl = DecisionTreeClassifier(criterion = 'entropy', max_depth = 4)
wine_tree_cl.fit(wine_x_ds, wine.target)
wine_tree_cl
Out[294]:
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=4,
       max_features=None, max_leaf_nodes=None,
       min_impurity_decrease=0.0, min_impurity_split=None,
       min_samples_leaf=1, min_samples_split=2,
       min_weight_fraction_leaf=0.0, presort=False, random_state=None,
       splitter='best')
In [298]:
wine_y_test_predict = wine_tree_cl.predict(wine_X_test)
In [299]:
print_accuracy_score_for_classes(wine_y_test, wine_y_test_predict)
Метка Accuracy
0 1.0
1 1.0
2 1.0
In [300]:
mean_absolute_error(wine_y_test, wine_y_test_predict)
Out[300]:
0.0
In [301]:
median_absolute_error(wine_y_test, wine_y_test_predict)
Out[301]:
0.0
In []:
```



Министерство науки и высшего образования Российской Федерации Федеральное государственное бюджетное образовательное учреждение высшего образования

«Московский государственный технический университет имени Н.Э. Баумана (национальный исследовательский университет)» (МГТУ им. Н.Э. Баумана)

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

Лабораторная работа №5 по дисциплине «Технология машинного обучения» на тему:

Линейные модели, SVM и деревья решений.

Выполнил: студент группы № ИУ5-62 Чернышев Павел подпись, дата

Проверил: Ю.Е. Гапанюк подпись, дата

Задание:

- 1. Выберите набор данных (датасет) для решения задачи классификации или регресии.
- 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 1) одну из линейных моделей, 2) SVM и 3) дерево решений. Оцените качество моделей с помощью трех подходящих для задачи метрик. Сравните качество полученных моделей.
- 5. Произведите для каждой модели подбор одного гиперпараметра с использованием GridSearchCV и кросс-валидации.
- 6. Повторите пункт 4 для найденных оптимальных значений гиперпараметров. Сравните качество полученных моделей с качеством моделей, полученных в пункте 4.