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:

    - одну из линейных моделей;
    - SVM;
    - дерево решений.
5. Оцените качество моделей с помощью трех подходящих для задачи метрик. Сравните качество полученных моделей.
6. Произведите для каждой модели подбор одного гиперпараметра с использованием GridSearchCV и кросс-валидации.
7. Повторите пункт 4 для найденных оптимальных значений гиперпараметров. Сравните качество полученных моделей с качеством моделей, полученных в пункте 4.

Дополнительные задания:

- Визуализируйте дерево решений.

1. Выбор набора данных (датасета) для решения задачи классификации или регресии.

In [463]:
```
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats
from sklearn.datasets import load_iris, load_boston
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassi
fier
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.linear_model import LinearRegression
from sklearn.linear_model import SGDRegressor
from sklearn.linear_model import SGDClassifier
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
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.preprocessing import MinMaxScaler
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR, Nu
SVR, LinearSVR
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegres
sor, export_graphviz
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import GridSearchCV
from sklearn.externals.six import StringIO
from IPython.display import Image
import pydotplus
import graphviz
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_absolute_error, median_absolute_er
ror, r2_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold, RepeatedKFold, LeavePOut
, ShuffleSplit, StratifiedKFold
from sklearn.model_selection import cross_val_score, train_test_spl
it
from sklearn.model_selection import learning_curve, validation_curv
e
from sklearn.neighbors import KNeighborsRegressor

from sklearn.tree import export_graphviz, plot_tree
# Enable inline plots
%matplotlib inline
sns.set(style="ticks")
```

In [142]:
```
data = pd.read_csv('data/vgsales.csv', sep=',')
data.head()
```

Out[142]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sale
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.7
1	2	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.8
2	3	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.85	12.88	3.7
3	4	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.75	11.01	3.2
4	5	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.2

In [143]:
```
data.shape
```

Out[143]:
```
(16598, 11)
```

In [144]:
```
data.isnull().sum()
```

Out[144]:
```
Rank              0
Name              0
Platform          0
Year            271
Genre             0
Publisher        58
NA_Sales          0
EU_Sales          0
JP_Sales          0
Other_Sales       0
Global_Sales      0
dtype: int64
```

In [145]:
```
data.dtypes
```

Out[145]:
```
Rank              int64
Name             object
Platform         object
Year            float64
Genre            object
Publisher        object
NA_Sales        float64
EU_Sales        float64
JP_Sales        float64
Other_Sales     float64
Global_Sales    float64
dtype: object
```

2. Заполнение пропусков и кодирование категориальных признаков

Заполнение пропусков

In [146]:
```
# Выберем числовые колонки с пропущенными значениями
# Цикл по колонкам датасета набора 1
num_cols = []
total_count = data.shape[0]
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'.format(col, dt, temp_null_count, temp_perc))
```

```
Колонка Year. Тип данных float64. Количество пустых значений 271, 1.63%.
```

In [147]:
```
# Фильтр по колонкам с пропущенными значениями  набора 1
data_num = data[num_cols].mean()
data_num
```

Out[147]:
```
Year    2006.406443
dtype: float64
```

In [148]:
```
data[num_cols] = data[num_cols].fillna(data[num_cols].mean())
```

In [149]:
```
# data = data.fillna(0)
data.isnull().sum()
```

Out[149]:
```
Rank             0
Name             0
Platform         0
Year             0
Genre            0
Publisher       58
NA_Sales         0
EU_Sales         0
JP_Sales         0
Other_Sales      0
Global_Sales     0
dtype: int64
```

In [150]:
```
data = data.fillna('')
data.isnull().sum()
```

Out[150]:
```
Rank            0
Name            0
Platform        0
Year            0
Genre           0
Publisher       0
NA_Sales        0
EU_Sales        0
JP_Sales        0
Other_Sales     0
Global_Sales    0
dtype: int64
```

In [151]:
```
data.dtypes
```

Out[151]:
```
Rank              int64
Name             object
Platform         object
Year            float64
Genre            object
Publisher        object
NA_Sales        float64
EU_Sales        float64
JP_Sales        float64
Other_Sales     float64
Global_Sales    float64
dtype: object
```

Кодирование категориальных признаков числовыми

In [152]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data['Name'] = le.fit_transform(data['Name'])
data['Platform'] = le.fit_transform(data['Platform'])
data['Genre'] = le.fit_transform(data['Genre'])
data['Publisher'] = le.fit_transform(data['Publisher'])
data.dtypes
```

Out[152]:
```
Rank              int64
Name              int64
Platform          int64
Year            float64
Genre             int64
Publisher         int64
NA_Sales        float64
EU_Sales        float64
JP_Sales        float64
Other_Sales     float64
Global_Sales    float64
dtype: object
```

In [153]:
```
data.head()
```

Out[153]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_
0	1	11007	26	2006.0	10	360	41.49	29.02	3.77	
1	2	9327	11	1985.0	4	360	29.08	3.58	6.81	
2	3	5573	26	2008.0	6	360	15.85	12.88	3.79	
3	4	11009	26	2009.0	10	360	15.75	11.01	3.28	
4	5	7346	5	1996.0	7	360	11.27	8.89	10.22	

3. Разделение выборки на обучающую и тестовую с использованием метода train_test_split.

X - признаки, У - целевые значения

In [ ]:
```

```

In [154]:
```
# # Масштабирование данных в диапазоне от 0 до 1
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data)
X_train_1, X_test_1, y_train_1, y_test_1 = train_test_split(
    sc1_data, data['Global_Sales'], test_size=0.26, random_state=1)

X_train_1.shape, X_test_1.shape
```

Out[154]:
```
((12282, 11), (4316, 11))
```

In [155]:
```
x_array = data['Rank'].values
y_array = data['Global_Sales'].values
```

In [156]:
```
X_train, X_test, y_train, y_test = train_test_split(x_array, y_arra
y,
test_size=0.26, random_state=1)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[156]:
```
((12282,), (4316,), (12282,), (4316,))
```

4. Обучение моделей

4.1. Линейная модель

Полином

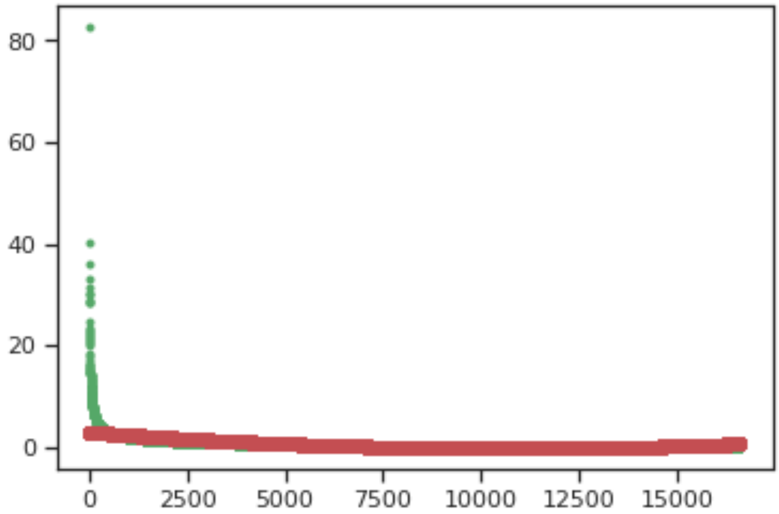
In [157]:
```
poly_model = Pipeline([('poly', PolynomialFeatures(degree=2)),
                       ('linear', LinearRegression(fit_intercept=Fa
lse))])

poly_model.fit(x_array.reshape(-1, 1), y_array)
```

Out[157]:
```
Pipeline(memory=None,
         steps=[('poly',
                 PolynomialFeatures(degree=2, include_bias=True,
                                    interaction_only=False, order=
'C')),
                ('linear',
                 LinearRegression(copy_X=True, fit_intercept=False
, n_jobs=None,
                                  normalize=False))],
         verbose=False)
```

In [158]:
```
poly_y_pred = poly_model.predict(x_array.reshape(-1, 1))
```

In [159]:
```
plt.plot(x_array, y_array, 'g.')
# plt.plot(x_array, y_array_regr, 'b', linewidth=2.0)
plt.plot(x_array, poly_y_pred, 'ro')
plt.show()
print('Степени полинома', poly_model.named_steps['linear'].coef_, p
oly_model.named_steps['linear'].intercept_)
poly_model.__repr__
```



```
Степени полинома [ 2.94125471e+00 -5.91307003e-04  2.72629824e-08]
0.0
```

Out[159]:
```
<bound method BaseEstimator.__repr__ of Pipeline(memory=None,
         steps=[('poly',
                 PolynomialFeatures(degree=2, include_bias=True,
                                    interaction_only=False, order=
'C')),
                ('linear',
                 LinearRegression(copy_X=True, fit_intercept=False
, n_jobs=None,
                                  normalize=False))],
         verbose=False)>
```

Оценка качества

In [160]:
```
def eval_model(y,predicted):
    mae = mean_absolute_error(y, predicted)
    mse = mean_squared_error(y, predicted)
    r2 = r2_score(y, predicted)
    print('MAE  ', mae)
    print('MSE  ', mse)
    print('R2   ', r2)
    return mae, mse, r2
```

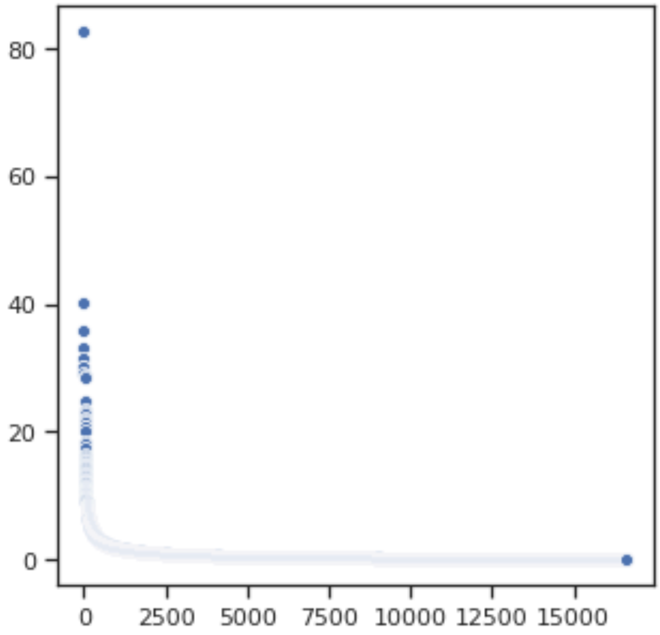
In [161]:
```
poly_mae, poly_mse, poly_r2 = eval_model(y_array, poly_y_pred)
```

```
MAE   0.4409386981151588
MSE   1.662735946164361
R2    0.31234111102885065
```

4.2. SVM

In [162]:
```
fig, ax = plt.subplots(figsize=(5,5))
sns.scatterplot(ax=ax, x=x_array, y=y_array)
```

Out[162]: <matplotlib.axes._subplots.AxesSubplot at 0x7febb0213910>



In [163]:
```
def plot_regr(clf):
    title = clf.__repr__
    clf.fit(x_array.reshape(-1, 1), y_array)
    y_array_pred = clf.predict(x_array.reshape(-1, 1))
```

SVR

In [283]:
```
svr_1 = SVR()
svr_1.fit(X_train_1, y_train_1)

y_pred_1 = svr_1.predict(X_test_1)
svr_1.__repr__
```

Out[283]:
```
<bound method BaseEstimator.__repr__ of SVR(C=1.0, cache_size=200,
coef0=0.0, degree=3, epsilon=0.1, gamma='scale',
    kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=
False)>
```

In [284]:
```
svr_1.get_params()
```

Out[284]:
```
{'C': 1.0,
 'cache_size': 200,
 'coef0': 0.0,
 'degree': 3,
 'epsilon': 0.1,
 'gamma': 'scale',
 'kernel': 'rbf',
 'max_iter': -1,
 'shrinking': True,
 'tol': 0.001,
 'verbose': False}
```

Оценка качества

In [166]:
```
svr_mae, svr_mse, r2 = eval_model(y_test_1, y_pred_1)
```

```
MAE   0.0804143007306765
MSE   0.18302966929993325
R2    0.9005914898410706
```

4.3. Дерево решений.

In [476]:
```
# Обучим дерево на всех признаках
tree_regr = DecisionTreeRegressor(random_state=1)
tree_regr.fit(X_train.reshape(-1,1), y_train.reshape(-1,1))
tree_regr
```

Out[476]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=No
ne,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_spli
t=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='depre
cated',
                      random_state=1, splitter='best')
```

In [477]:
```
plot_tree(tree_regr, filled=True);
```

In [170]:
```
tree_regr_predict = tree_regr.predict(X_test.reshape(-1,1))
tree_regr_predict.shape
```

Out[170]:
```
(4316,)
```

Оценка качества

In [171]:
```
tree_mae, tree_mse, tree_r2 = eval_model(y_test.reshape(-1,1), tree
_regr_predict)
```

```
MAE   0.0026807228915665697
MSE   0.0029771779425393865
R2    0.998383011754991
```

5. Оценка качества моделей с помощью трех подходящих для задачи метрик. Сравнение качества полученных моделей.

In [451]:
```
print('POLY')
print('mae: {}, mse: {}, r2: {}'.format(poly_mae, poly_mse, poly_r2
))
print()
print('SVR')
print('mae: {}, mse: {}, r2: {}'.format(svr_mae, svr_mse, svr_r2))
print()
print('TREE')
print('mae: {}, mse: {}, r2: {}'.format(tree_mae, tree_mse, tree_r2
))
```

```
POLY
mae: 0.4409386981151588, mse: 1.662735946164361, r2: 0.31234111102
885065

SVR
mae: 0.0804143007306765, mse: 0.18302966929993325, r2: 0.900591489
8410706

TREE
mae: 0.002680722891566597, mse: 0.0029771779425393865, r2: 0.9983
83011754991
```

6. Подбор одного гиперпараметра с использованием GridSearchCV и кросс-валидации.

6.1 Linear

In [322]:
```
PolynomialFeatures().get_params()
```

Out[322]:
```
{'degree': 2, 'include_bias': True, 'interaction_only': False, 'or
der': 'C'}
```

In [323]:
```
LinearRegression().get_params()
```

Out[323]:
```
{'copy_X': True, 'fit_intercept': True, 'n_jobs': None, 'normalize
': False}
```

In [ ]:
```

```

In [408]:
```
params = {
    'poly__degree': [ 1, 2, 3]
#     'linear__copy_X': [True, False]
}
```

In [409]:
```
poly_model = Pipeline([('poly', PolynomialFeatures()),
                       ('linear', LinearRegression(fit_intercept=Fa
lse))])
```

In [410]:
```
poly_model.get_params()
```

Out[410]:
```
{'memory': None,
 'steps': [('poly',
   PolynomialFeatures(degree=2, include_bias=True, interaction_onl
y=False,
                      order='C')),
  ('linear',
   LinearRegression(copy_X=True, fit_intercept=False, n_jobs=None,
normalize=False))],
 'verbose': False,
 'poly': PolynomialFeatures(degree=2, include_bias=True, interacti
on_only=False,
                    order='C'),
 'linear': LinearRegression(copy_X=True, fit_intercept=False, n_jo
bs=None, normalize=False),
 'poly__degree': 2,
 'poly__include_bias': True,
 'poly__interaction_only': False,
 'poly__order': 'C',
 'linear__copy_X': True,
 'linear__fit_intercept': False,
 'linear__n_jobs': None,
 'linear__normalize': False}
```

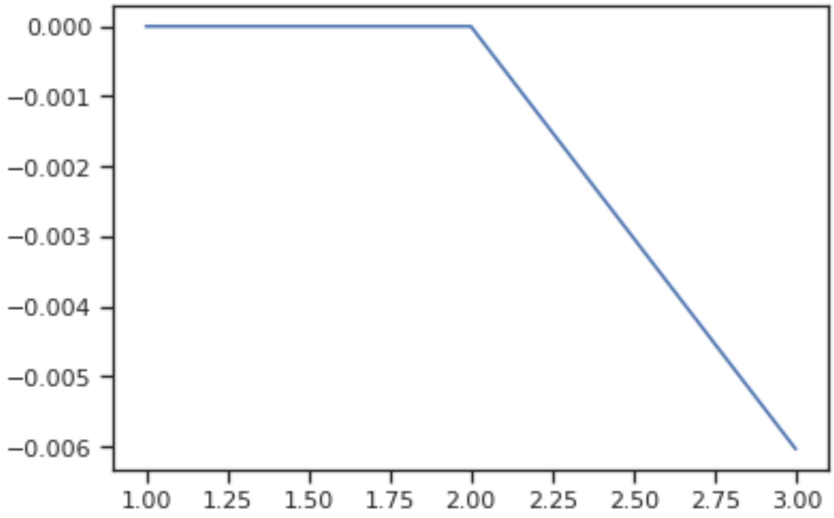
In [411]:
```
%%time
grid_1 = GridSearchCV(estimator=poly_model,
                    param_grid=params, scoring='neg_mean_absolute_e
rror', cv=3, n_jobs=-1)
grid_1.fit(data, data['Global_Sales'])
grid_1.estimator.get_params().keys()
```

```
CPU times: user 106 ms, sys: 12.1 ms, total: 118 ms
Wall time: 1.61 s
```

Out[411]:
```
dict_keys(['memory', 'steps', 'verbose', 'poly', 'linear', 'poly__
degree', 'poly__include_bias', 'poly__interaction_only', 'poly__or
der', 'linear__copy_X', 'linear__fit_intercept', 'linear__n_jobs',
'linear__normalize'])
```

In [412]:
```
-grid_1.best_score_, grid_1.best_params_
```
Out[412]:
```
(1.6394753926644193e-15, {'poly__degree': 1})
```

In [414]:
```
plt.plot(params['poly__degree'], grid_1.cv_results_["mean_test_scor
e"]);
```



6.2 SVR

In [218]:
```
SVR().get_params()
```
Out[218]:
```
{'C': 1.0,
 'cache_size': 200,
 'coef0': 0.0,
 'degree': 3,
 'epsilon': 0.1,
 'gamma': 'scale',
 'kernel': 'rbf',
 'max_iter': -1,
 'shrinking': True,
 'tol': 0.001,
 'verbose': False}
```

In [311]:
```
params = {
#     'degree': [ 1,2],
#     'C': [0.08, 0.09, 0.1]
    'epsilon' : [0.2, 0.3, 0.4, 0.5]
}
```

In [312]:
```
%%time
grid_1 = GridSearchCV(estimator=SVR(),
                      param_grid=params, scoring='neg_mean_absolute_e
rror', cv=3, n_jobs=-1)
grid_1.fit(data, data['Global_Sales'])
```

```
CPU times: user 3.13 s, sys: 11.8 ms, total: 3.14 s
Wall time: 11.5 s
```

Out[312]:
```
GridSearchCV(cv=3, error_score=nan,
             estimator=SVR(C=1.0, cache_size=200, coef0=0.0, degre
e=3,
                           epsilon=0.1, gamma='scale', kernel='rbf
',
                           max_iter=-1, shrinking=True, tol=0.001,
                           verbose=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'epsilon': [0.2, 0.3, 0.4, 0.5]},
             pre_dispatch='2*n_jobs', refit=True, return_train_sco
re=False,
             scoring='neg_mean_absolute_error', verbose=0)
```

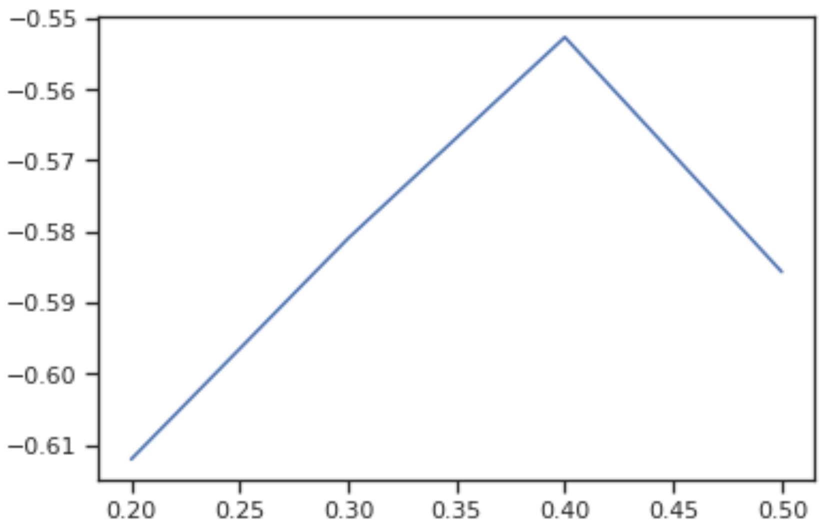
In [313]:
```
-grid_1.best_score_, grid_1.best_params_
```

Out[313]:
```
(0.55274376514688, {'epsilon': 0.4})
```

In [314]:
```
# plt.plot(params['C'], grid_1.cv_results_["mean_test_score"]);
```

In [315]:
```
# plt.plot(params['degree'], grid_1.cv_results_["mean_test_score"])
;
```

In [316]:
```
plt.plot(params['epsilon'], grid_1.cv_results_["mean_test_score"]);
```



In [317]:
```
# plt.plot(params['cache_size'], grid_1.cv_results_["mean_test_scor
e"]);
```

6.3 Decision tree

In [430]:
```
DecisionTreeRegressor(random_state=1).get_params()
```

Out[430]:
```
{'ccp_alpha': 0.0,
 'criterion': 'mse',
 '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': 'deprecated',
 'random_state': 1,
 'splitter': 'best'}
```

In [456]:
```
params = {
    'max_depth': [ 8, 9, 10,15],
#     'min_samples_leaf': [0.001, 0.002, 0.003],
#     'max_features': [0.6, 0.7, 0.8 ]
}
```

In [457]:
```
%%time
grid_1 = GridSearchCV(estimator=DecisionTreeRegressor(random_state=
1),
                    param_grid=params, scoring='neg_mean_absolute_e
rror', cv=3, n_jobs=-1)
grid_1.fit(data, data['Global_Sales'])
```

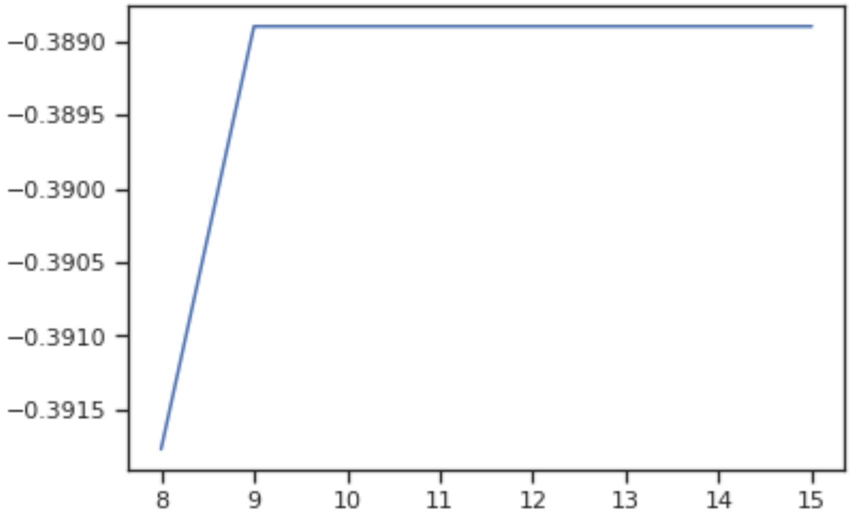
```
CPU times: user 179 ms, sys: 11.8 ms, total: 191 ms
Wall time: 511 ms
```

Out[457]:
```
GridSearchCV(cv=3, error_score=nan,
             estimator=DecisionTreeRegressor(ccp_alpha=0.0, criter
ion='mse',
                                             max_depth=None, max_f
eatures=None,
                                             max_leaf_nodes=None,
                                             min_impurity_decrease
=0.0,
                                             min_impurity_split=No
ne,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_l
eaf=0.0,
                                             presort='deprecated',
                                             random_state=1, split
ter='best'),
             iid='deprecated', n_jobs=-1,
             param_grid={'max_depth': [8, 9, 10, 15]}, pre_dispatc
h='2*n_jobs',
             refit=True, return_train_score=False,
             scoring='neg_mean_absolute_error', verbose=0)
```

In [458]:
```
-grid_1.best_score_, grid_1.best_params_
```

Out[458]:
```
(0.3888997849707991, {'max_depth': 9})
```

In [459]:
```
plt.plot(params['max_depth'], grid_1.cv_results_["mean_test_score"]
);
```



7. Повтор пункта 4 для найденных оптимальных значений гиперпараметров. Сравнение качества полученных моделей с качеством моделей, полученных в пункте 4.

7.1 Linear

In [415]:
```
poly_model = Pipeline([('poly', PolynomialFeatures(degree=1)),
                       ('linear', LinearRegression(fit_intercept=Fa
lse))])

poly_model.fit(x_array.reshape(-1, 1), y_array)
```

Out[415]:
```
Pipeline(memory=None,
         steps=[('poly',
                 PolynomialFeatures(degree=1, include_bias=True,
                                    interaction_only=False, order=
'C')),
                ('linear',
                 LinearRegression(copy_X=True, fit_intercept=False
, n_jobs=None,
                                  normalize=False))],
         verbose=False)
```

In [416]:
```
poly_y_pred_gs = poly_model.predict(x_array.reshape(-1, 1))
```

In [417]:
```
poly_mae_gs, poly_mse_gs, poly_r2_gs = eval_model(y_array, poly_y_p
red)
```
```
MAE  0.4409386981151588
MSE  1.662735946164361
R2   0.31234111102885065
```

Значения из 4 пункта

In [418]:
```
print('MAE ', poly_mae)
print('MSE ', poly_mse)
print('R2  ', poly_r2)
```
```
MAE  0.4409386981151588
MSE  1.662735946164361
R2   0.31234111102885065
```

In [419]:
```
print('MAE      ',poly_mae_gs - poly_mae)
print('MSE   ',poly_mse_gs - poly_mse)
print('R2       ', poly_r2_gs - poly_r2)
```
```
MAE      0.0
MSE   0.0
R2       0.0
```

При подборе параметров выяснилось, что на данный момент и так установлены оптимальные варианты, модель улучшить не удалось

7.2 SVR

In [420]:
```
svr_1 = SVR(epsilon=0.04)
svr_1.fit(X_train_1, y_train_1)

y_pred_1 = svr_1.predict(X_test_1)
```

In [421]:
```
svr_mae_gs, svr_mse_gs, svr_r2_gs = eval_model(y_test_1, y_pred_1)
```
```
MAE  0.052799879862795766
MSE  0.16717809629690494
R2   0.9092009205521336
```

Значения из 4 пункта

In [422]:
```
print('MAE ', svr_mae)
print('MSE ', svr_mse)
print('R2  ', svr_r2)
```

```
MAE  0.0804143007306765
MSE  0.18302966929993325
R2   0.9005914898410706
```

In [423]:
```
print('MAE      ',svr_mae_gs - svr_mae)
print('Med AE   ',svr_mse_gs - svr_mse)
print('R2       ', svr_r2_gs - svr_r2)
```

```
MAE      -0.027614420867880733
Med AE   -0.015851573003028308
R2       0.008609430711063015
```

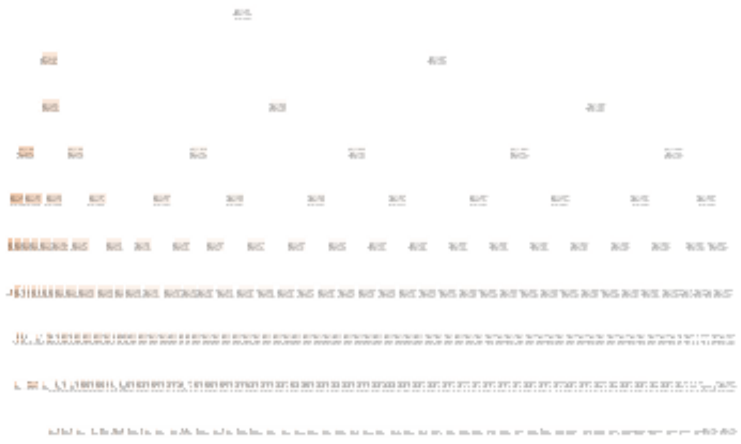
Модель улучшилась.

7.3 Decision tree

In [473]:
```
# Обучим дерево на всех признаках
tree_regr = DecisionTreeRegressor(random_state=1, max_depth=9)
tree_regr.fit(X_train.reshape(-1,1), y_train.reshape(-1,1))
tree_regr
```

Out[473]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=9,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_spli
t=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='depre
cated',
                      random_state=1, splitter='best')
```

In [475]:
```
plot_tree(tree_regr, filled=True);
```



In [444]:
```
tree_regr_predict = tree_regr.predict(X_test.reshape(-1,1))
tree_regr_predict.shape
```

Out[444]:
```
(4316,)
```

In [445]:
```
tree_mae_gs, tree_mse_gs, tree_r2_gs = eval_model(y_test.reshape(-1
,1), tree_regr_predict)
```

```
MAE  0.0038578393782797283
MSE  0.0029918576597652746
R2   0.9983750387917848
```

Из 4 пункта

In [446]:
```
print('MAE      ',tree_mae)
print('MSE   ',tree_mse)
print('R2       ', tree_r2)
```

```
MAE      0.0026807228915665697
MSE   0.0029771779425393865
R2       0.998383011754991
```

In [447]:
```
print('MAE      ',tree_mae_gs - tree_mae)
print('MSE   ',tree_mse_gs - tree_mse)
print('R2       ', tree_r2_gs - tree_r2)
```

```
MAE      0.0011771164867131587
MSE   1.4679717225888136e-05
R2       -7.97296320620422e-06
```

Видим, что точность незначительно отличается.

Еще раз сравним 3 модели:

In [450]:
```
print('POLY')
print('mae: {}, mse: {}, r2: {}'.format(poly_mae_gs, poly_mse_gs, poly_r2_gs))
print()
print('SVR')
print('mae: {}, mse: {}, r2: {}'.format(svr_mae_gs, svr_mse_gs, svr_r2_gs))
print()
print('TREE')
print('mae: {}, mse: {}, r2: {}'.format(tree_mae_gs, tree_mse_gs, tree_r2_gs))
```

```
POLY
mae: 0.4409386981151588, mse: 1.662735946164361, r2: 0.31234111102885065

SVR
mae: 0.052799879862795766, mse: 0.16717809629690494, r2: 0.9092009205521336

TREE
mae: 0.0038578393782797283, mse: 0.0029918576597652746, r2: 0.9983750387917848
```

Вывод:

Лучшую точность дает модель дерево решений, далее по точности следует метод SVR, а худшую точность дает линейная модель.

In [ ]:
```

```