

mentation

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [2]: #california House Pricing dataset
from sklearn.datasets import fetch_california_housing
california_df=fetch_california_housing()
```

```
In [3]: california_df
```

```
Out[3]: {'data': array([[ 8.3252, 41., 6.98412698, ..., 2.55555556,
    37.88, -122.23, ],
    [ 8.3014, 21., 6.23813708, ..., 2.10984183,
    37.86, -122.22, ],
    [ 7.2574, 52., 8.28813559, ..., 2.80225989,
    37.85, -122.24, ],
    ...,
    [ 1.7, 17., 5.20554273, ..., 2.3256351,
    39.43, -121.22, ],
    [ 1.8672, 18., 5.32951289, ..., 2.12320917,
    39.43, -121.32, ],
    [ 2.3886, 16., 5.25471698, ..., 2.61698113,
    39.37, -121.24, ]]),
'target': array([4.526, 3.585, 3.521, ..., 0.923, 0.847, 0.894]),
'frame': None,
'target_names': ['MedHouseVal'],
'feature_names': ['MedInc',
'HouseAge',
'AveRooms',
'AveBedrms',
'Population',
'AveOccup',
'Latitude',
'Longitude'],
'DESCR': '.. _california_housing_dataset:\n\nCalifornia Housing dataset\n-----\n\n**Data Set Characteristics:**\n\n :Number of Instances: 20640\n\n :Number of Attributes: 8 numeric, predictive attributes and the target\n\n :Attribute Information:\n - MedInc median income in block group\n - HouseAge median house age in block group\n - AveRooms average number of rooms per household\n - AveBedrms average number of bedrooms per household\n - Population block group population\n - AveOccup average number of household members\n - Latitude block group latitude\n - Longitude block group longitude\n\n :Missing Attribute Values: None\n\nThis dataset was obtained from the StatLib repository.\nhttps://www.dcc.fc.up.pt/~ltorgo/Regression/cal_housing.html\nThe target variable is the median house value for California districts,\nexpressed in hundreds of thousands of dollars ($100,000).\n\nThis dataset was derived from the 1990 U.S. census, using one row per census\nblock group. A block group is the smallest geographical unit for which the U.S.\nCensus Bureau publishes sample data (a block group typically has a population\nof 600 to 3,000 people).\n\nA household is a group of people residing within a home. Since the average\nnumber of rooms and bedrooms in this dataset are provided per household, these\ncolumns may take surprisingly large values for block groups with few households\nand many empty houses, such as vacation resorts.\n\nIt can be downloaded/loaded using the\nfunc:`sklearn.datasets.fetch_california_housing` function.\n\n.. topic:: References\n - Pace, R. Kelley and Ronald Barry, Sparse Spatial Autoregressions,\n Statistics and Probability Letters, 33 (1997) 291-297\n'}
```

```
In [4]: #independent features
x=pd.DataFrame(california_df.data,columns=california_df.feature_names)
#dependent features
y=california_df.target
```

```
In [5]: x.head()
```

```
Out[5]:
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25

```
In [6]: #train tes split
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state=55)
```

```
In [7]: from sklearn.tree import DecisionTreeRegressor
regressor=DecisionTreeRegressor()
```

```
In [8]: regressor
```

```
Out[8]: ▼ DecisionTreeRegressor
DecisionTreeRegressor()
```

```
In [9]: regressor.fit(x_train,y_train)
```

```
Out[9]: ▼ DecisionTreeRegressor
DecisionTreeRegressor()
```

```
In [10]: y_pred=regressor.predict(x_test)
```

```
In [11]: y_pred
```

```
Out[11]: array([3.266 , 5.00001, 1.253 , ..., 3.382 , 5.00001, 2.425  ])
```

```
In [12]: from sklearn.metrics import r2_score
score=r2_score(y_pred,y_test)
```

```
In [13]: score
```

```
Out[13]: 0.6383580185781638
```

```
In [24]: #Hyperparameter Tunning
parameter={
    'criterion':['squared_error','friedman_mse','absolute_error','poisson'],
    'splitter':['best','random'],
    'max_depth':[1,2,3,4,5,6,7,8,9,10,11,12],
    'max_features':['auto','sqrt','log2']
}
regressor=DecisionTreeRegressor()
```

```
In [25]: from sklearn.model_selection import GridSearchCV
regressorcvcv=GridSearchCV(regressor,param_grid=parameter,cv=2,scoring='neg_mean_squared_e
```

```
In [26]: regressorcvcv.fit(x_train,y_train)
```

```

C:\Users\PRATHMESH\anaconda3\Lib\site-packages\sklearn\model_selection\_validation.py:425: FitFailedWarning:
192 fits failed out of a total of 576.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
-----
192 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\PRATHMESH\anaconda3\Lib\site-packages\sklearn\model_selection\_validation.py", line 729, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\PRATHMESH\anaconda3\Lib\site-packages\sklearn\base.py", line 1145, in wrapper
    estimator._validate_params()
  File "C:\Users\PRATHMESH\anaconda3\Lib\site-packages\sklearn\base.py", line 638, in _validate_params
    validate_parameter_constraints(
  File "C:\Users\PRATHMESH\anaconda3\Lib\site-packages\sklearn\utils\_param_validation.py", line 96, in validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' parameter of DecisionTreeRegressor must be an int in the range [1, inf), a float in the range (0.0, 1.0], a str among {'sqrt', 'log2'} or None. Got 'auto' instead.

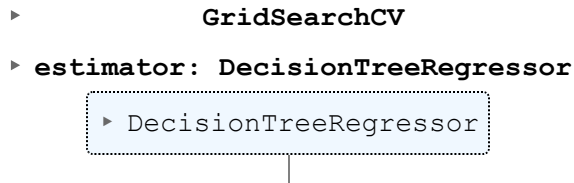
warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\Users\PRATHMESH\anaconda3\Lib\site-packages\sklearn\model_selection\_search.py:979: UserWarning: One or more of the test scores are non-finite: [          nan          nan -1.26756302 -1.26394246 -1.04933426 -1.20926412
          nan          nan -0.90941067 -1.3167412  -0.96336551 -1.13530629
          nan          nan -0.89765204 -1.22266281 -0.8194725  -1.16047002
          nan          nan -0.82936368 -1.11733375 -0.68385504 -1.23381367
          nan          nan -0.7363701  -1.21572025 -0.61947432 -1.00697387
          nan          nan -0.60765938 -0.93612642 -0.57998378 -0.79912332
          nan          nan -0.56383743 -0.96490213 -0.50648974 -0.69423087
          nan          nan -0.5226716  -1.03298827 -0.47912671 -0.62301724
          nan          nan -0.51532394 -0.82695573 -0.50062118 -0.75495578
          nan          nan -0.5253521  -0.82748909 -0.47730626 -0.72398682
          nan          nan -0.53681235 -0.76899792 -0.47982818 -0.61907425
          nan          nan -0.58574715 -0.76460975 -0.54330263 -0.57612351
          nan          nan -1.09848566 -1.32050716 -1.09230812 -1.32506352
          nan          nan -0.84916881 -1.31550982 -0.9733992  -1.09089511
          nan          nan -0.83984538 -1.11901026 -0.73728681 -1.22173646
          nan          nan -0.7112623  -1.06709855 -0.62350863 -1.24038936
          nan          nan -0.69986695 -1.0824697  -0.70425429 -1.08178152
          nan          nan -0.65733587 -0.84758118 -0.50822288 -1.15133402
          nan          nan -0.56332556 -0.93857039 -0.53851877 -0.78103823
          nan          nan -0.57726642 -0.85076399 -0.54419435 -0.91015114
          nan          nan -0.53224976 -0.91237414 -0.48621413 -0.69489859
          nan          nan -0.60668585 -0.74890955 -0.49877568 -0.69936659
          nan          nan -0.52346155 -0.71346275 -0.48675659 -0.68713075
          nan          nan -0.53682675 -0.63966064 -0.50952928 -0.62661578
          nan          nan -1.0834203  -1.40573407 -1.21775928 -1.40832607
          nan          nan -1.04068069 -1.37712915 -1.04123523 -1.04792463
          nan          nan -1.07322736 -1.2930419  -0.86015962 -1.14933021
          nan          nan -0.84261244 -1.32873543 -0.75674981 -1.25529111
          nan          nan -0.77235862 -1.14424401 -0.69981935 -1.01482663
          nan          nan -0.69664376 -0.85340288 -0.55511523 -1.02976664
          nan          nan -0.64551887 -0.7534348  -0.55527349 -1.03128405
          nan          nan -0.49724714 -0.97112672 -0.52791448 -0.77158749
          nan          nan -0.61669348 -0.76981406 -0.47918176 -0.80374554
          nan          nan -0.56045734 -0.70142825 -0.52209857 -0.78899667
          nan          nan -0.55020263 -0.62589042 -0.5140678  -0.62571661

```

```
nan      nan -0.54545787 -0.67977992 -0.48347056 -0.61019087
nan      nan -1.10574069 -1.08867572 -1.10729868 -1.1358576
nan      nan -1.02064393 -1.14348179 -0.97662094 -1.30591281
nan      nan -0.99126519 -1.23097528 -0.7358691  -1.01807956
nan      nan -0.84851862 -1.24147169 -0.6902697  -0.91379016
nan      nan -0.63992601 -1.1280495  -0.56223245 -1.01510721
nan      nan -0.7131085  -0.89136564 -0.58917554 -0.84099316
nan      nan -0.62476576 -0.90674482 -0.57322074 -1.03372151
nan      nan -0.52509904 -0.88353466 -0.5476596  -0.67147941
nan      nan -0.54545609 -0.75612919 -0.49888268 -0.71018014
nan      nan -0.54933827 -0.80467659 -0.51155163 -0.73590181
nan      nan -0.53302507 -0.81934364 -0.50334704 -0.68298238
nan      nan -0.53394173 -0.61603722 -0.55942379 -0.66299489]
```

```
warnings.warn(
```

Out[26]:



In [29]:

```
regressorcv.best_params_
```

Out[29]:

```
{'criterion': 'squared_error',
 'max_depth': 10,
 'max_features': 'log2',
 'splitter': 'best'}
```

In [30]:

```
y_pred=regressorcv.predict(x_test)
```

In [31]:

```
r2_score(y_pred,y_test)
```

Out[31]:

```
0.5894976592027634
```

In []: