In [1]:
```
import pandas as pd
```

In [11]:
```
from sklearn.datasets import fetch_california_housing
```

In [9]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [13]:
```
df = fetch_california_housing()
```

In [14]:
```
df
```

Out[14]:
```
{'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: 2
0640\n\n    :Number of Attributes: 8 numeric, predictive attributes and the target
\n\n    :Attribute Information:\n        - MedInc        median income in block gr
oup\n        - HouseAge      median house age in block group\n        - AveRooms
average number of rooms per household\n        - AveBedrms     average number of b
edrooms per household\n        - Population    block group population\n        - A
veOccup      average number of household members\n        - Latitude      block gr
oup latitude\n        - Longitude     block group longitude\n\n    :Missing Attrib
ute Values: None\n\nThis dataset was obtained from the StatLib repository.\nhttp
s://www.dcc.fc.up.pt/~ltorgo/Regression/cal_housing.html\n\nThe target variable is
the median house value for California districts,\nexpressed in hundreds of thousan
ds of dollars ($100,000).\n\nThis dataset was derived from the 1990 U.S. census, u
sing one row per census\nblock group. A block group is the smallest geographical u
nit for which the U.S.\nCensus Bureau publishes sample data (a block group typical
ly has a population\nof 600 to 3,000 people).\n\nAn household is a group of people
residing within a home. Since the average\nnumber of rooms and bedrooms in this da
taset are provided per household, these\ncolumns may take surpinsingly large value
s for block groups with few households\nand many empty houses, such as vacation re
sorts.\n\nIt can be downloaded/loaded using the\n:func:`sklearn.datasets.fetch_cal
ifornia_housing` function.\n\n.. topic:: References\n\n    - Pace, R. Kelley and R
onald Barry, Sparse Spatial Autoregressions,\n      Statistics and Probability Let
ters, 33 (1997) 291-297\n'}
```

In [16]:
```
dataset = pd.DataFrame(df.data)
```

In [17]:
```
dataset
```

Out[17]:

	0	1	2	3	4	5	6	7
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
...	...	...	...	...	...	...	...	...
20635	1.5603	25.0	5.045455	1.133333	845.0	2.560606	39.48	-121.09
20636	2.5568	18.0	6.114035	1.315789	356.0	3.122807	39.49	-121.21
20637	1.7000	17.0	5.205543	1.120092	1007.0	2.325635	39.43	-121.22
20638	1.8672	18.0	5.329513	1.171920	741.0	2.123209	39.43	-121.32
20639	2.3886	16.0	5.254717	1.162264	1387.0	2.616981	39.37	-121.24

20640 rows × 8 columns

In [19]:
```
dataset.columns = df.feature_names
```

In [20]:
```
dataset.head()
```

Out[20]:

	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 [25]:
```
## devide the data in dependent and independent features
X = dataset
y = df.target
```

In [22]:
```
y
```

Out[22]:
```
array([4.526, 3.585, 3.521, ..., 0.923, 0.847, 0.894])
```

In [26]:
```
### train test isplat
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.30, random_state=42)
```

In [27]:
```
X_train
```

Out[27]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
7061	4.1312	35.0	5.882353	0.975490	1218.0	2.985294	33.93	-118.02
14689	2.8631	20.0	4.401210	1.076613	999.0	2.014113	32.79	-117.09
17323	4.2026	24.0	5.617544	0.989474	731.0	2.564912	34.59	-120.14
10056	3.1094	14.0	5.869565	1.094203	302.0	2.188406	39.26	-121.00
15750	3.3068	52.0	4.801205	1.066265	1526.0	2.298193	37.77	-122.45
...	...	...	...	...	...	...	...	...
11284	6.3700	35.0	6.129032	0.926267	658.0	3.032258	33.78	-117.96
11964	3.0500	33.0	6.868597	1.269488	1753.0	3.904232	34.02	-117.43
5390	2.9344	36.0	3.986717	1.079696	1756.0	3.332068	34.03	-118.38
860	5.7192	15.0	6.395349	1.067979	1777.0	3.178891	37.58	-121.96
15795	2.5755	52.0	3.402576	1.058776	2619.0	2.108696	37.77	-122.42

14448 rows × 8 columns

In [28]:
```
## standardizing the dataset
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

In [30]:
```
X_train = scaler.fit_transform(X_train)
```

In [31]:
```
X_test = scaler.transform(X_test)
```

In [32]:
```
X_train
```

Out[32]:
```
array([[ 0.13350629,  0.50935748,  0.18106017, ..., -0.01082519,
        -0.80568191,  0.78093406],
       [-0.53221805, -0.67987313, -0.42262953, ..., -0.08931585,
        -1.33947268,  1.24526986],
       [ 0.1709897 , -0.36274497,  0.07312833, ..., -0.04480037,
        -0.49664515, -0.27755183],
       ...,
       [-0.49478713,  0.58863952, -0.59156984, ...,  0.01720102,
        -0.75885816,  0.60119118],
       [ 0.96717102, -1.07628333,  0.39014889, ...,  0.00482125,
         0.90338501, -1.18625198],
       [-0.68320166,  1.85715216, -0.82965604, ..., -0.0816717 ,
         0.99235014, -1.41592345]])
```

In [33]:
```
scaler.inverse_transform(X_train)
```

Out[33]:
```
array([[   4.1312    ,   35.        ,    5.88235294, ...,    2.98529412,
          33.93      , -118.02      ],
       [   2.8631    ,   20.        ,    4.40120968, ...,    2.0141129 ,
          32.79      , -117.09      ],
       [   4.2026    ,   24.        ,    5.61754386, ...,    2.56491228,
          34.59      , -120.14      ],
       ...,
       [   2.9344    ,   36.        ,    3.98671727, ...,    3.33206831,
          34.03      , -118.38      ],
       [   5.7192    ,   15.        ,    6.39534884, ...,    3.17889088,
          37.58      , -121.96      ],
       [   2.5755    ,   52.        ,    3.40257649, ...,    2.10869565,
          37.77      , -122.42      ]])
```

In [36]:
```
from sklearn.linear_model import LinearRegression
##cross validtion
from sklearn.model_selection import cross_val_score
```

In [44]:
```
regression = LinearRegression()
regression.fit(X_train,y_train)
```

Out[44]:
```
▾ LinearRegression

LinearRegression()
```

In [40]:
```
mse  = cross_val_score(regression , X_train , y_train , scoring = 'neg_mean_squared
```

In [41]:
```
np.mean(mse)
```

Out[41]:
```
-0.5268253746355749
```

In [42]:
```
## prediction
```

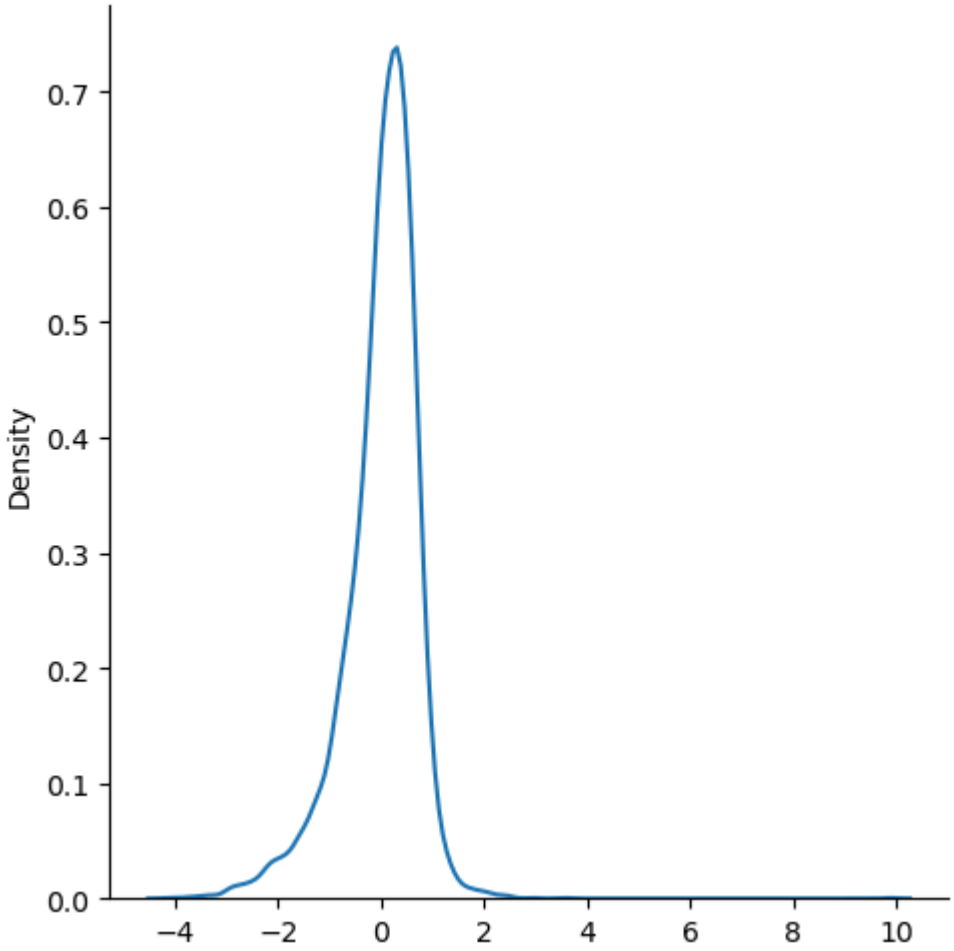
In [45]:
```
reg_pred = regression.predict(X_test)
```

In [46]:
```
reg_pred
```

Out[46]:
```
array([0.72604907, 1.76743383, 2.71092161, ..., 2.07465531, 1.57371395,
       1.82744133])
```

In [49]:
```
import seaborn as sns
sns.displot(reg_pred-y_test,kind  = 'kde')
```

Out[49]:
```
<seaborn.axisgrid.FacetGrid at 0x217d72a7af0>
```



In [50]:
```
from sklearn.metrics import r2_score
```

In [51]:
```
score = r2_score(reg_pred , y_test)
```

In [52]:
```
score
```

Out[52]:
```
0.3451339380943964
```

In [ ]:
```

```