Skewness

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_boston
```

In [2]:

```
boston=load_boston()
```

In [3]:

```
#Boston Housing dataset
X=boston['data']
Y=boston['target']
col=boston['feature_names']
df=pd.DataFrame(X,columns=col)
df['Price']=Y
df.head()
```

Out[3]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Price
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2

In [4]:

```
col
```

Out[4]:

```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

We will check for skewness in every feature of our housing dataset

In [5]:

```
m=list(df.columns)
```

In [6]:

```
m
```

Out[6]:

```
['CRIM',
 'ZN',
 'INDUS',
 'CHAS',
 'NOX',
 'RM',
 'AGE',
 'DIS',
```

```
 'RAD',
 'TAX',
 'PTRATIO',
 'B',
 'LSTAT',
 'Price']
```

In [7]:

```
skewness_dict={}
for i in m:
    n=df[i].skew()
    skewness_dict.update({i:n})
```

In [8]:

```
skewness_dict
```

Out[8]:

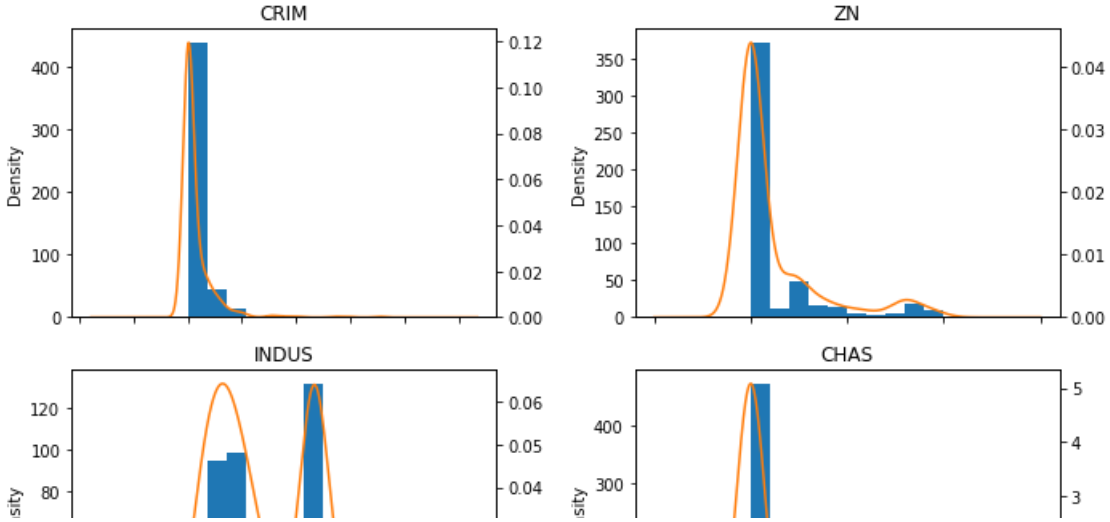
```
{'CRIM': 5.223148798243851,
 'ZN': 2.2256663227354307,
 'INDUS': 0.29502156787351164,
 'CHAS': 3.405904172058746,
 'NOX': 0.7293079225348787,
 'RM': 0.40361213328874385,
 'AGE': -0.5989626398812962,
 'DIS': 1.0117805793009007,
 'RAD': 1.0048146482182057,
 'TAX': 0.669955941795016,
 'PTRATIO': -0.8023249268537809,
 'B': -2.8903737121414492,
 'LSTAT': 0.9064600935915367,
 'Price': 1.1080984082549072}
```

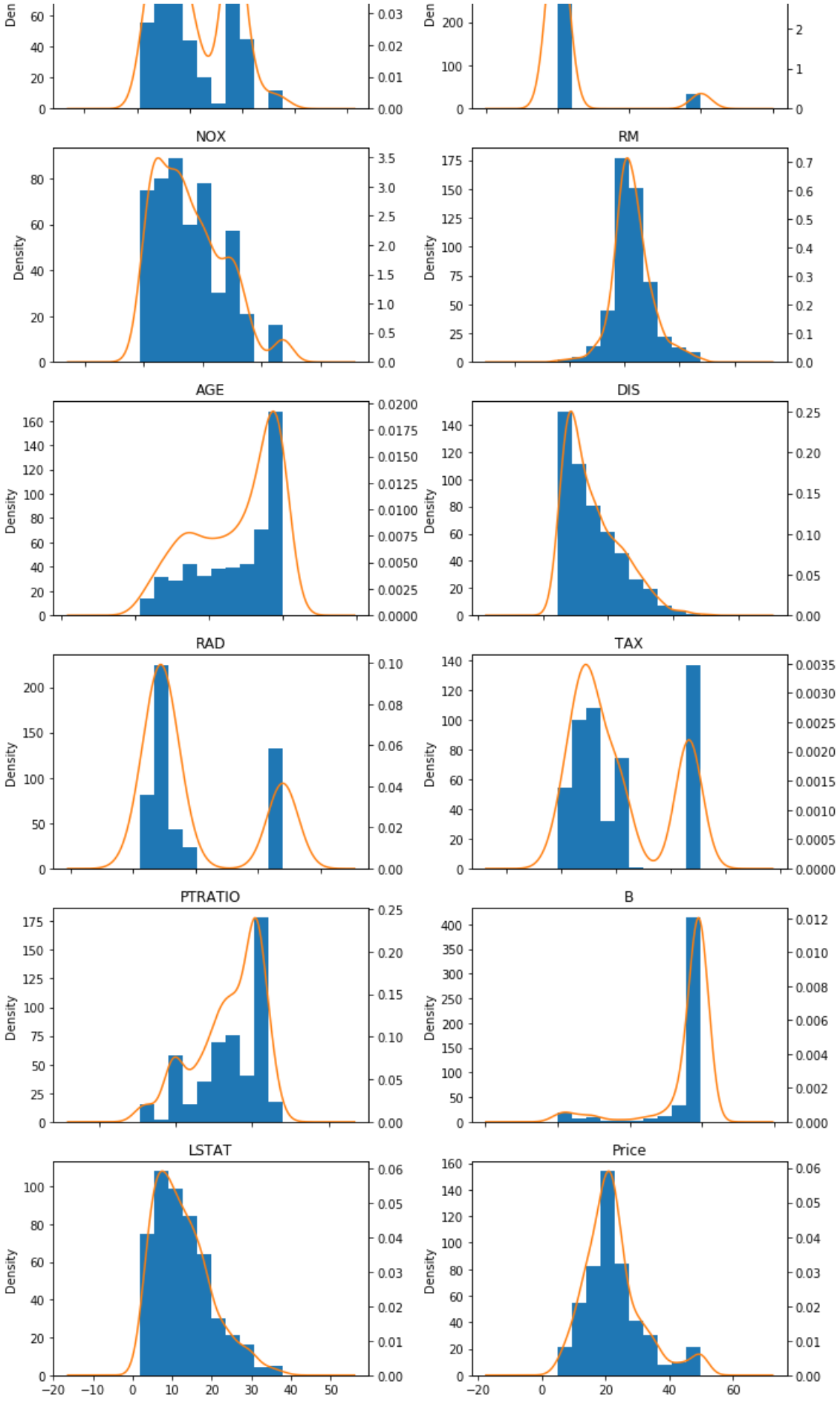
So above dict give us the information that in our housing dataset feature "CRIM","ZN" and "CHAS" are positively skewed. Feature "B" is negatively skewed.

In [9]:

```
k = len(df.columns)
n = 2
m = (k - 1) // n + 1
fig, axes = plt.subplots(m, n, figsize=(n * 5, m * 3))
for i, (name, col) in enumerate(df.iteritems()):
    r, c = i // n, i % n
    ax = axes[r, c]
    col.hist(ax=ax)
    ax2 = col.plot.kde(ax=ax, secondary_y=True, title=name)
    ax2.set_ylim(0)

fig.tight_layout()
```





1. Log Transformation

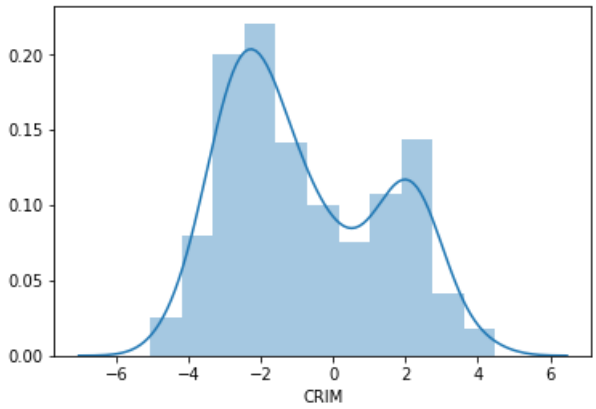
In [10]:

```
print("Skewness before log transformation "+str(df['CRIM'].skew()))
print("**************************************************************************")
crim_log=np.log(df['CRIM'])
print("Skewness after log transformation "+str(crim_log.skew()))
print("**************************************************************************")
#Plot after transformation
sns.distplot(crim_log)
```

```
Skewness before log transformation 5.223148798243851
**************************************************************************
Skewness after log transformation 0.4059344988496048
**************************************************************************
```

Out[10]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2466d0184e0>
```



So above transformation shows us the that skewness for feature CRIM has drastically gone down.

2. Sqaure root transform

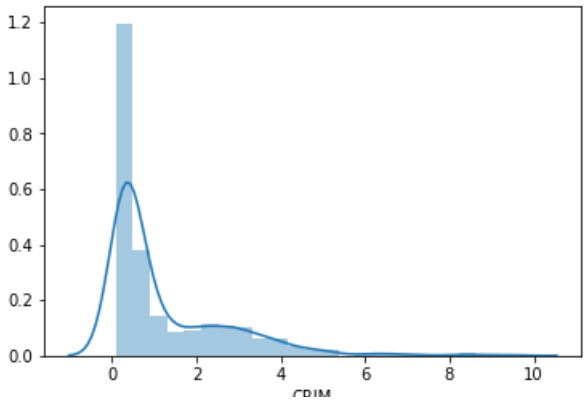
In [11]:

```
crim_sqrt=np.sqrt(df['CRIM'])
print("Skewness before log transformation "+str(df['CRIM'].skew()))
print("**************************************************************************")
print("Skewness after square root transformation "+str(crim_sqrt.skew()))
print("**************************************************************************")
sns.distplot(crim_sqrt)
```

```
Skewness before log transformation 5.223148798243851
**************************************************************************
Skewness after square root transformation 2.024382103123676
**************************************************************************
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2466d03beb8>
```



Sqaure root transformation has not much impacted our feature values but still the skewness is lowered to a reasonable level

3.BoxCox Transformation

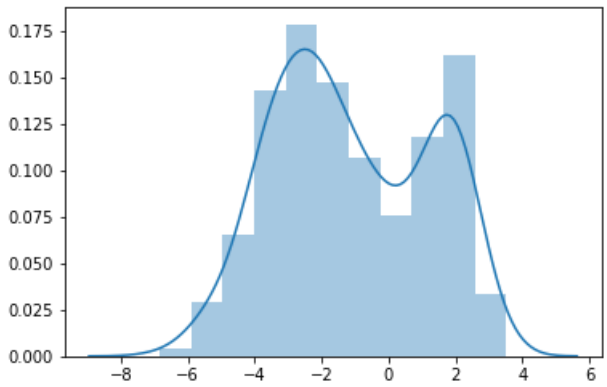
In [12]:

```
from scipy import stats
crim_boxcox=stats.boxcox(df['CRIM'])[0]
print("Skewness before log transformation "+str(df['CRIM'].skew()))
print("**************************************************************************")
print("Skewness after square root transformation "+str(pd.Series(crim_boxcox).skew()))
print("**************************************************************************")
sns.distplot(crim_boxcox)
```

```
Skewness before log transformation 5.223148798243851
**************************************************************************
Skewness after square root transformation 0.09364916787825833
**************************************************************************
```

Out[12]:

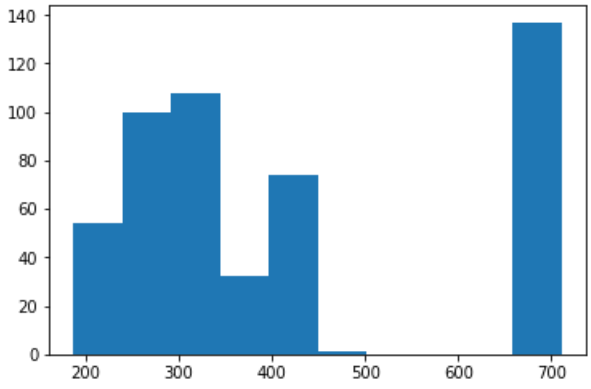
```
<matplotlib.axes._subplots.AxesSubplot at 0x2466d606978>
```



Normalization

In [13]:

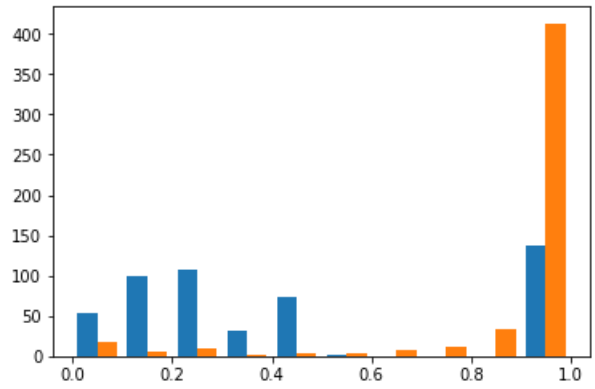
```
import matplotlib.pyplot as plt
plt.hist(df['TAX'])
plt.show()
```



So this feature of our dataframe has lot big numbers compare to our other features will normalize this feature now

In [14]:

```
from sklearn.preprocessing import MinMaxScaler
scaling=MinMaxScaler()
tax_normalize=scaling.fit_transform(df[['TAX','B']])
plt.hist(tax_normalize)
plt.show()
```



In [15]:

```
tax_normalize
```

Out[15]:

```
array([[0.20801527, 1.        ],
       [0.10496183, 1.        ],
       [0.10496183, 0.98973725],
       ...,
       [0.16412214, 1.        ],
       [0.16412214, 0.99130062],
       [0.16412214, 1.        ]])
```

Standardization(Z-score normalization)

In [16]:

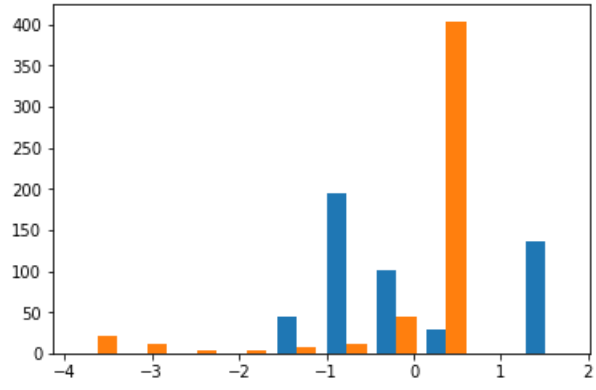
```
from sklearn.preprocessing import StandardScaler
```

In [17]:

```
scaling=StandardScaler()
```

In [18]:

```
tax_standard=scaling.fit_transform(df[['TAX','B']])
plt.hist(tax_standard)
plt.show()
```



In [19]:

```
tax_standard
```

Out[19]:

```
array([[-0.66660821,  0.44105193],
       [-0.98732948,  0.44105193],
       [-0.98732948,  0.39642699],
       ...,
       [-0.80321172,  0.44105193],
       [-0.80321172,  0.4032249 ],
       [-0.80321172,  0.44105193]])
```