IMPORT LIBRARY

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.linear_model import LogisticRegression


from fasteda import fast_eda
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import r2_score,mean_absolute_error
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn
warnings.filterwarnings('ignore')


sns.set_context('notebook')
sns.set_style('white')
```

Load The dataset

In [2]:
```
iris_sklearn = load_iris()
```

In [3]:
```
# Extract the data and target labels as numpy array

iris_npy = np.concatenate([iris_sklearn['data'], np.atleast_2d(iris_sklearn['target']).T], axis = 1)
```

In [4]:
```
# defines columns names

col_names = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width', 'target']
```

In [5]:
```
# convert numpy array onto pandas dataframe with columns names

iris = pd.DataFrame(iris_npy, columns = col_names)
```

In [6]:
```
# description

print(iris_sklearn['DESCR'])
```

```
.. _iris_dataset:

Iris plants dataset
--------------------

**Data Set Characteristics:**

:Number of Instances: 150 (50 in each of three classes)
:Number of Attributes: 4 numeric, predictive attributes and the class
:Attribute Information:
    - sepal length in cm
    - sepal width in cm
    - petal length in cm
    - petal width in cm
    - class:
            - Iris-Setosa
            - Iris-Versicolour
            - Iris-Virginica

:Summary Statistics:

============== ==== ==== ======= ===== ====================
                Min  Max   Mean    SD   Class Correlation
============== ==== ==== ======= ===== ====================
sepal length:   4.3  7.9   5.84   0.83    0.7826
sepal width:    2.0  4.4   3.05   0.43   -0.4194
petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)
============== ==== ==== ======= ===== ====================

:Missing Attribute Values: None
:Class Distribution: 33.3% for each of 3 classes.
:Creator: R.A. Fisher
:Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
:Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is taken
from Fisher's paper. Note that it's the same as in R, but not as in the UCI
Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the
pattern recognition literature.  Fisher's paper is a classic in the field and
is referenced frequently to this day.  (See Duda & Hart, for example.)  The
```

```
data set contains 3 classes of 50 instances each, where each class refers to a
type of iris plant.  One class is linearly separable from the other 2; the
latter are NOT linearly separable from each other.

|details-start|
**References**
|details-split|

- Fisher, R.A. "The use of multiple measurements in taxonomic problems"
  Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
  Mathematical Statistics" (John Wiley, NY, 1950).
- Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.
  (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
- Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
  Structure and Classification Rule for Recognition in Partially Exposed
  Environments".  IEEE Transactions on Pattern Analysis and Machine
  Intelligence, Vol. PAMI-2, No. 1, 67-71.
- Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions
  on Information Theory, May 1972, 431-433.
- See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
  conceptual clustering system finds 3 classes in the data.
- Many, many more ...

|details-end|
```

GET ATTRIBUTE INFORMATION

In [7]:
```
iris.head()
```

Out[7]:

	sepal_length	sepal_width	petal_length	petal_width	target
0	5.1	3.5	1.4	0.2	0.0
1	4.9	3.0	1.4	0.2	0.0
2	4.7	3.2	1.3	0.2	0.0
3	4.6	3.1	1.5	0.2	0.0
4	5.0	3.6	1.4	0.2	0.0

In [8]:
```
iris.tail()
```

Out[8]:

	sepal_length	sepal_width	petal_length	petal_width	target
145	6.7	3.0	5.2	2.3	2.0
146	6.3	2.5	5.0	1.9	2.0
147	6.5	3.0	5.2	2.0	2.0
148	6.2	3.4	5.4	2.3	2.0
149	5.9	3.0	5.1	1.8	2.0

In [9]:
```
iris.columns
```

Out[9]:
```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width', 'target'], dtype='object')
```

In [10]:
```
iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   target        150 non-null    float64
dtypes: float64(5)
memory usage: 6.0 KB
```

In [11]:
```
iris.shape
```

Out[11]:
```
(150, 5)
```

In [12]:
```
class_names = dict(zip(list(map(float,range(len(iris_sklearn['target_names'])))), iris_sklearn['target_names'
print(class_names)
```

```
{0.0: 'setosa', 1.0: 'versicolor', 2.0: 'virginica'}
```

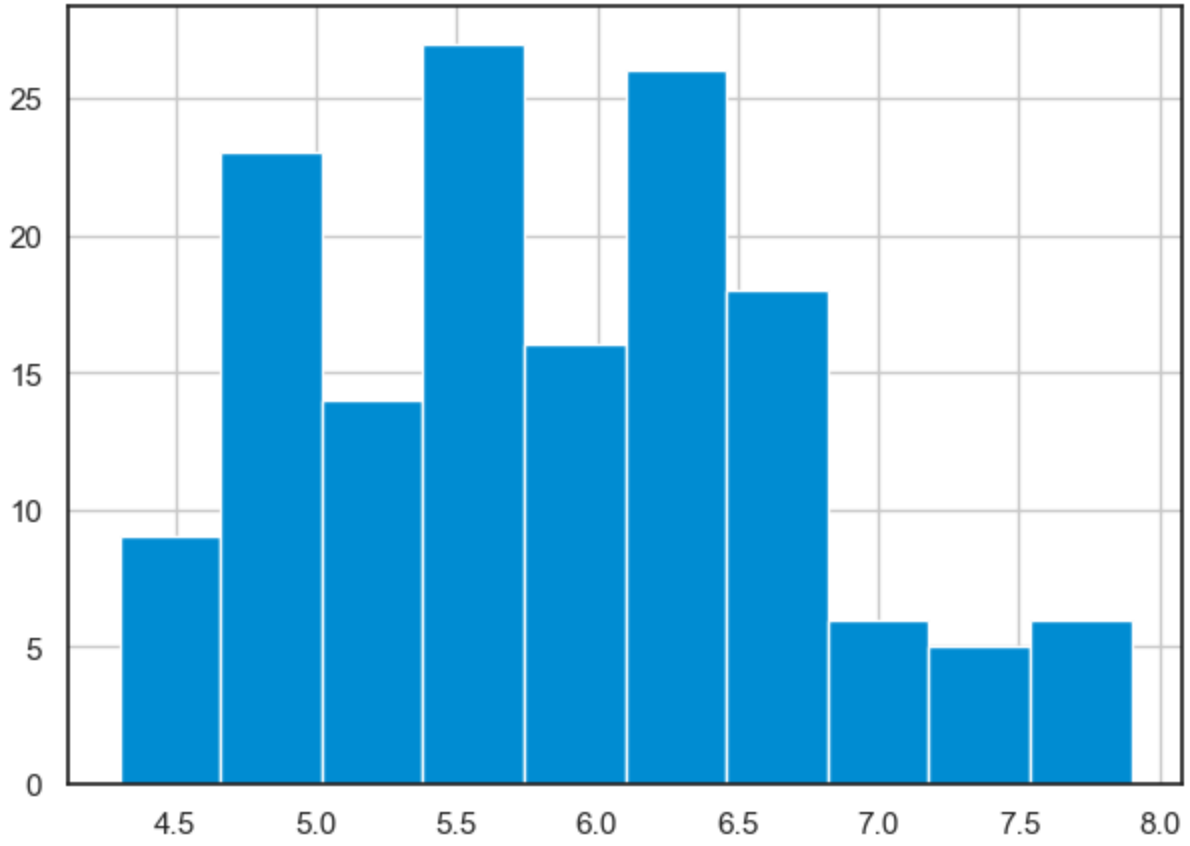
In [13]:
```
iris['target'].sample(10)
```

Out[13]:
```
31     0.0
81     1.0
0      0.0
115    2.0
106    2.0
117    2.0
82     1.0
18     0.0
91     1.0
114    2.0
Name: target, dtype: float64
```

Overview of Python libraries for visual data analysis

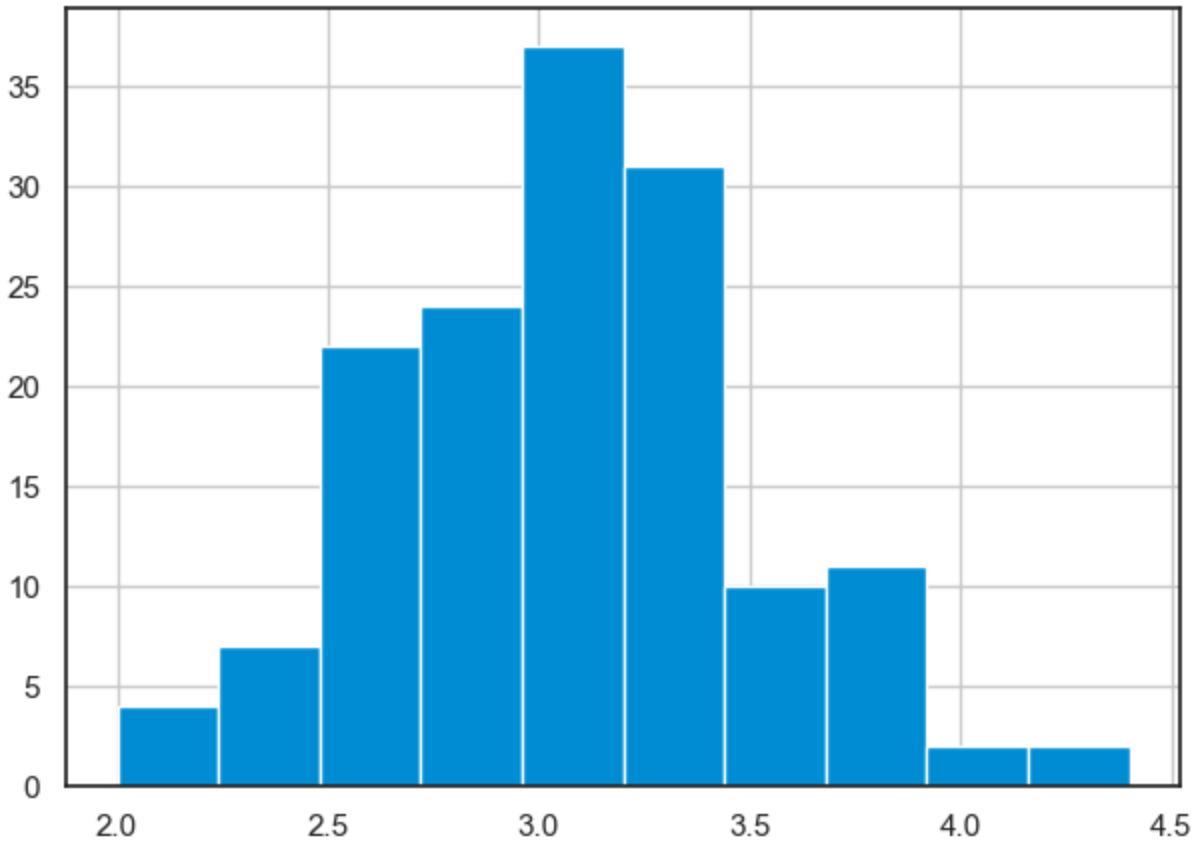
In [14]:
```
iris['sepal_length'].hist()
```

Out[14]: <Axes: >



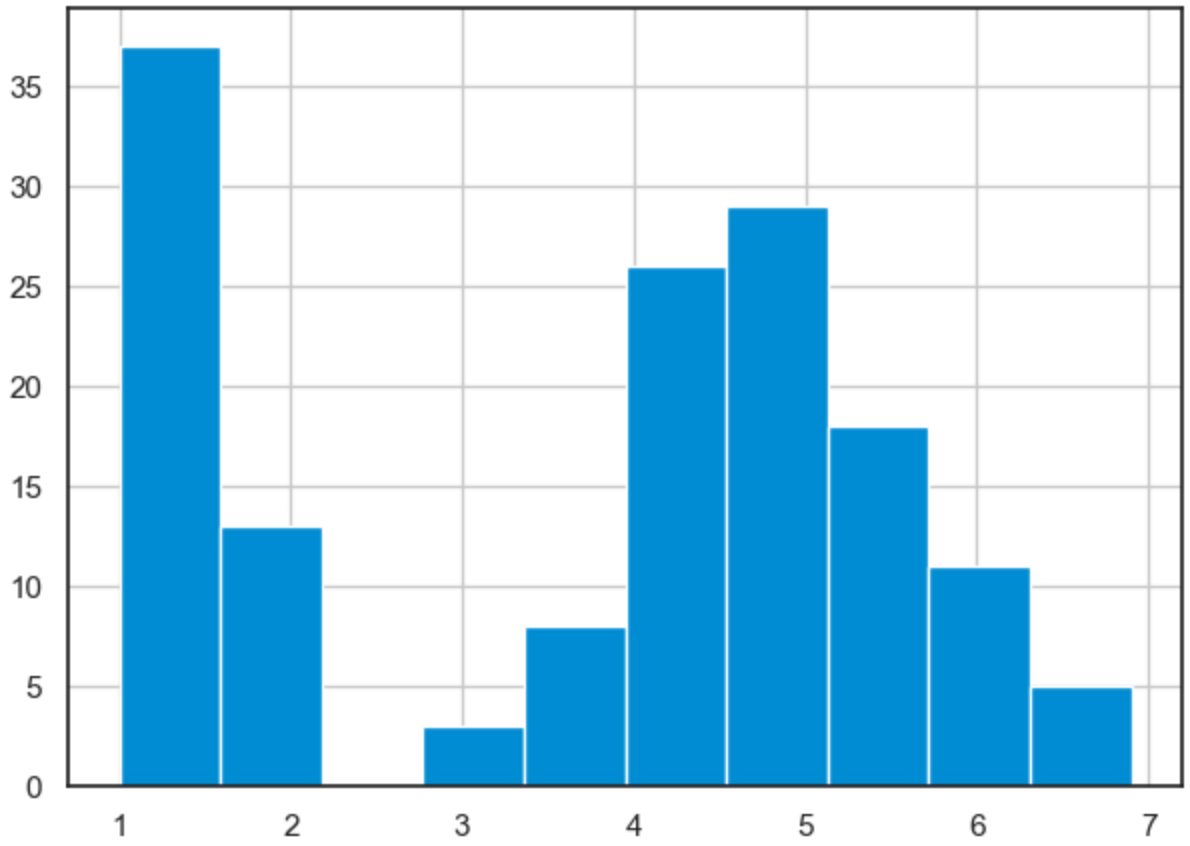
In [15]:
```
iris['sepal_width'].hist()
```

Out[15]: <Axes: >



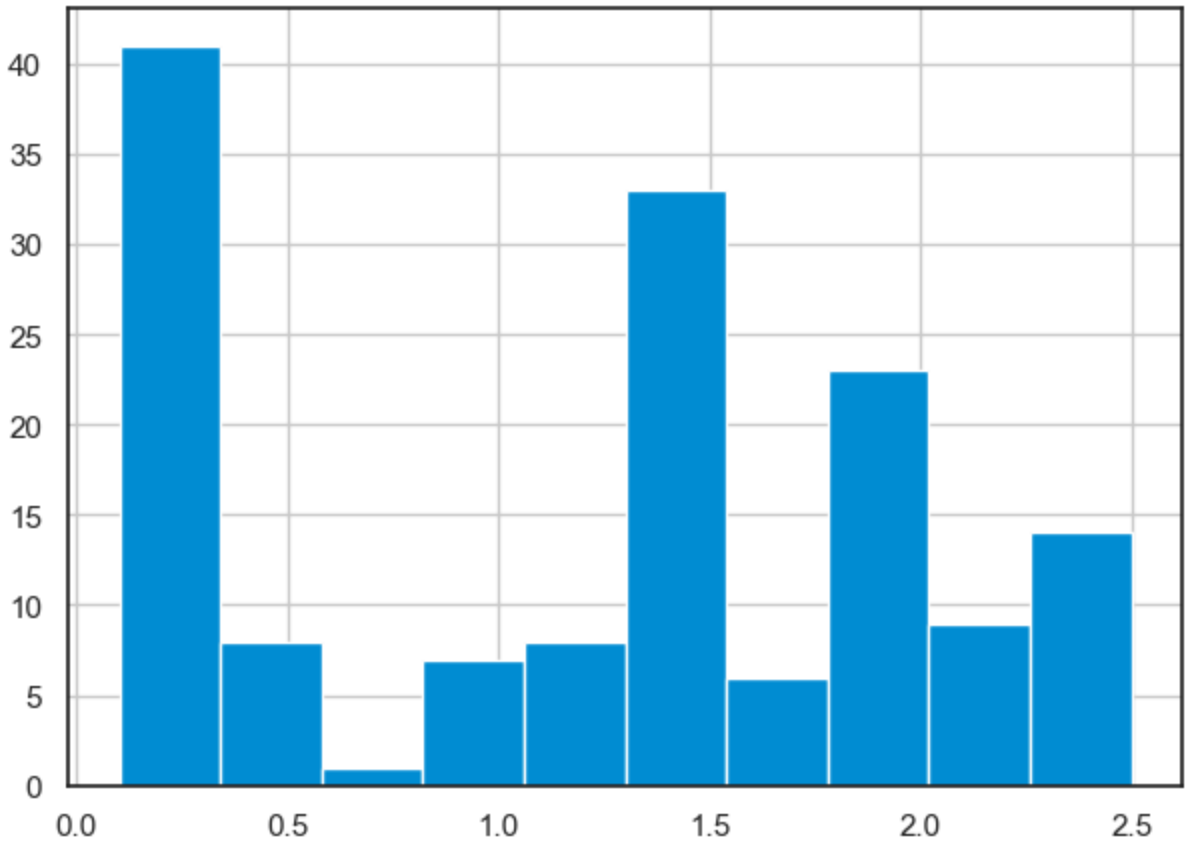
In [16]:
```
iris['petal_length'].hist()
```

Out[16]: <Axes: >



In [17]:
```
iris['petal_width'].hist()
```

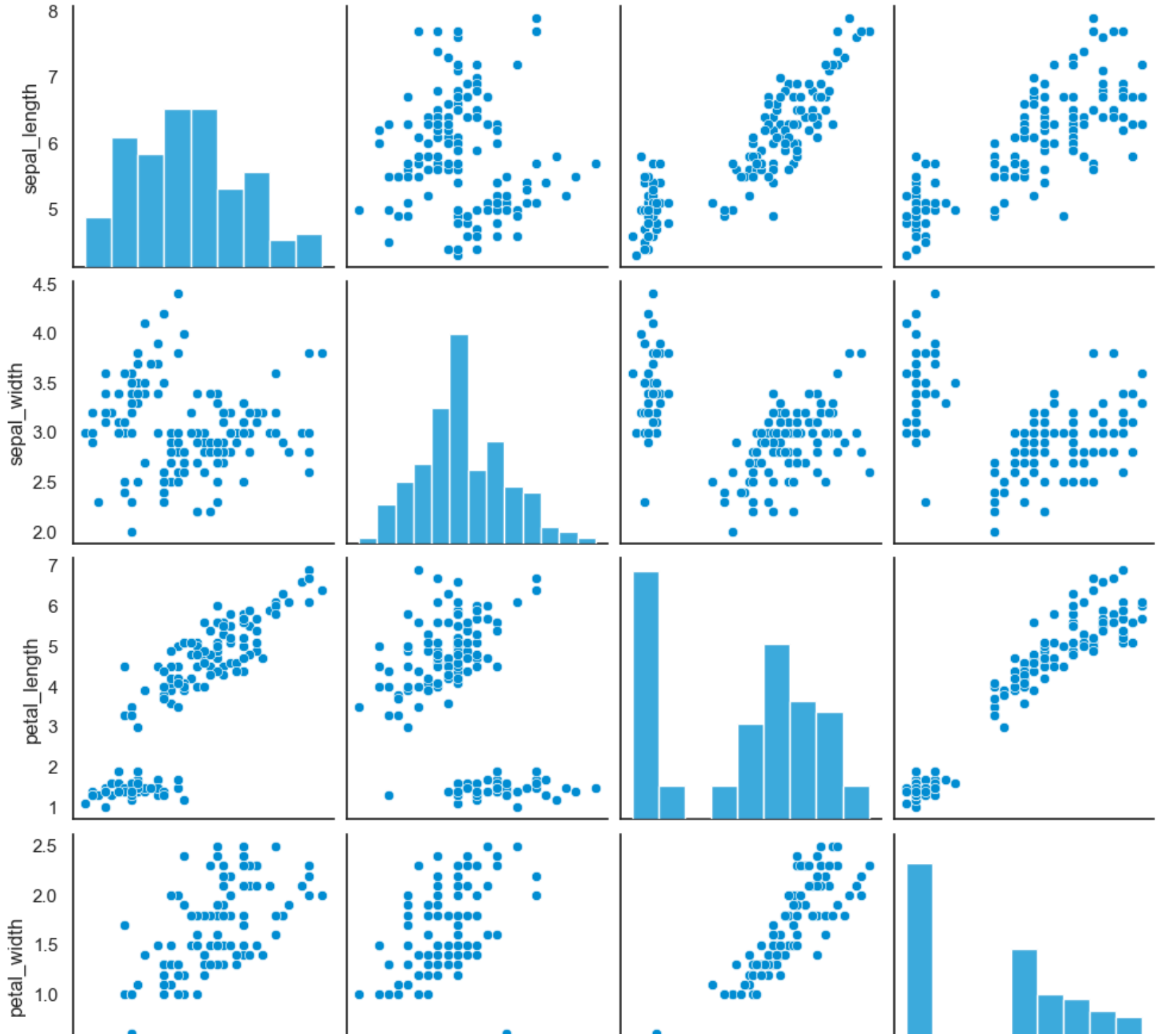
Out[17]: <Axes: >

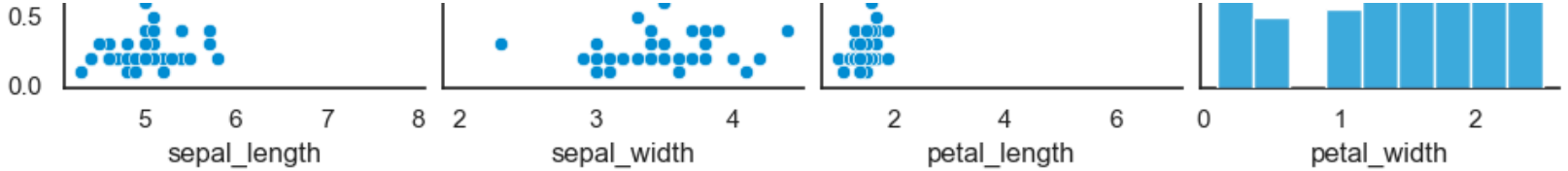


Seaborn

In [18]:
```
sns.pairplot(iris[['sepal_length','sepal_width','petal_length','petal_width']])
```

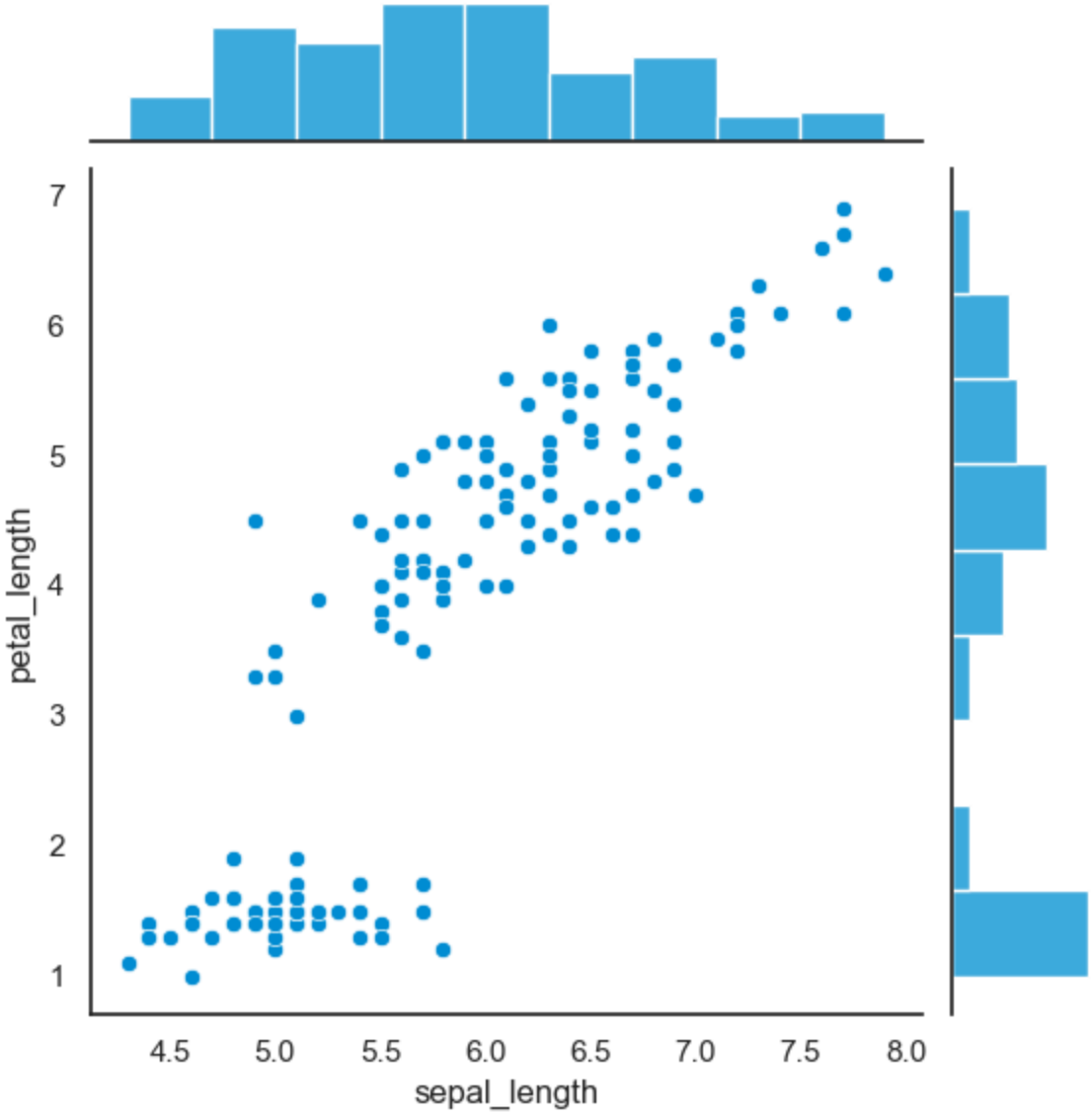
Out[18]:
```
<seaborn.axisgrid.PairGrid at 0x224003f28f0>
```


sepal_length
sepal_width
petal_length
petal_width
8
7
6
5
4.5
4.0
3.5
3.0
2.5
2.0
7
6
5
4
3
2
1
2.5
2.0
1.5
1.0

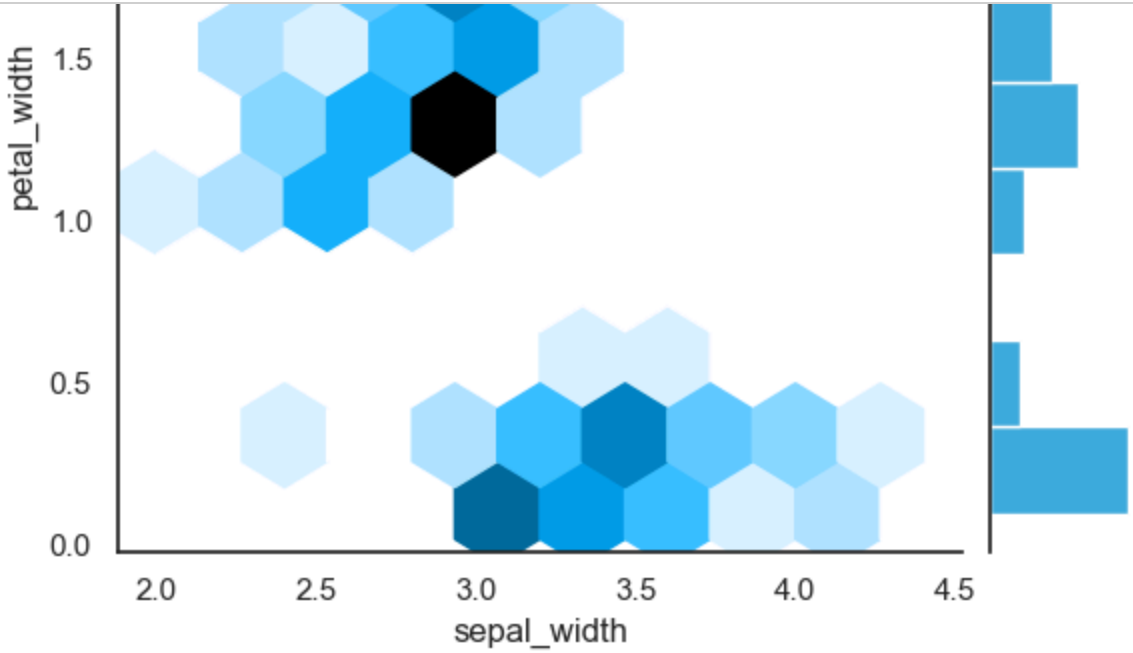

0.5
0.0
5
6
7
8
sepal_length
2
3
4
sepal_width
2
4
6
petal_length
0
1
2
petal_width

In [19]:
```
sns.jointplot(x='sepal_length',y='petal_length',kind='scatter' ,data=iris)
```

Out[19]:
```
<seaborn.axisgrid.JointGrid at 0x224021a65f0>
```



In [20]:
```
sns.jointplot(x='sepal_width',y='petal_width',kind='hex',data=iris)
```



Perform EDA on the iris data set

In [21]:
```
fast_eda(iris, target='target')
```

Describe DataFrame:

	count	mean	median	std	min	25%	50%	75%	max	skewness	kurtosis
sepal_length	150	5.843	5.8	**0.828**	4.3	5.1	5.8	6.4	7.9	**0.311753**	**-0.573568**
sepal_width	150	**3.057**	**3**	0.436	**2**	**2.8**	**3**	**3.3**	**4.4**	**0.315767**	**0.180976**
petal_length	150	**3.758**	**4.35**	1.765	1	**1.6**	**4.35**	**5.1**	6.9	**-0.272128**	**-1.395536**
petal_width	150	1.199	1.3	0.762	0.1	0.3	1.3	1.8	2.5	**-0.101934**	**-1.336067**
target	150	1	1	**0.819**	0	0	1	2	2		**-1.500000**

DataFrame Correlation:

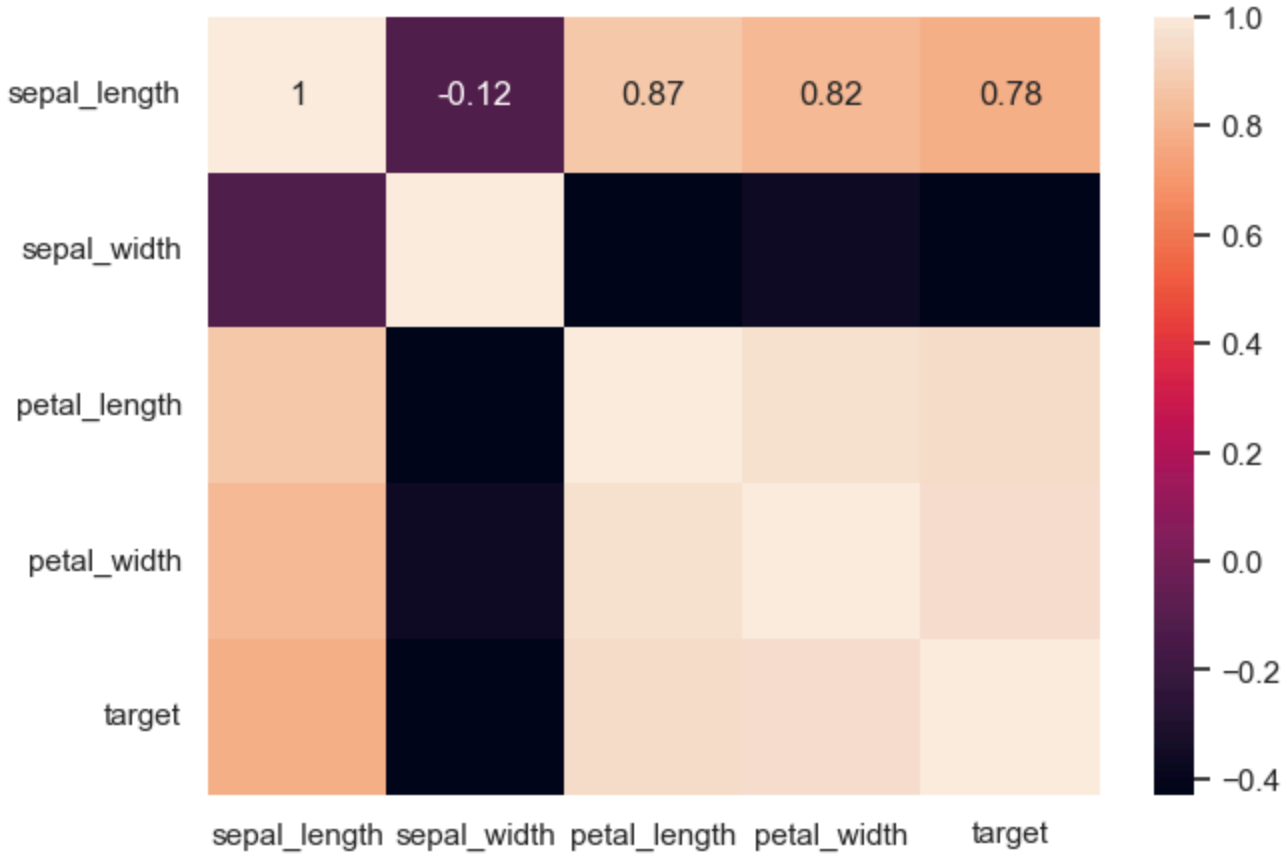
In [22]:
```
iris.corr()
```

Out[22]:

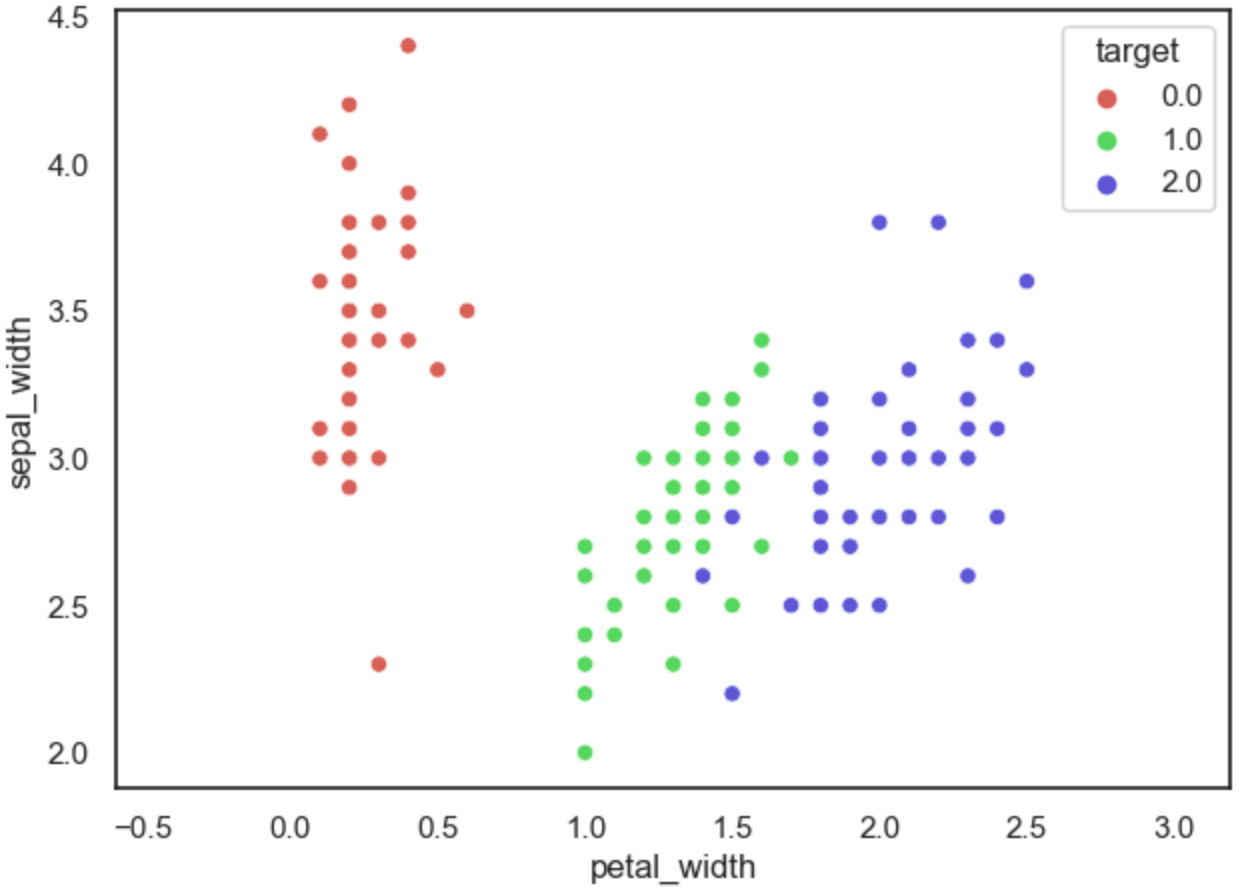
	sepal_length	sepal_width	petal_length	petal_width	target
sepal_length	1.000000	-0.117570	0.871754	0.817941	0.782561
sepal_width	-0.117570	1.000000	-0.428440	-0.366126	-0.426658
petal_length	0.871754	-0.428440	1.000000	0.962865	0.949035
petal_width	0.817941	-0.366126	0.962865	1.000000	0.956547
target	0.782561	-0.426658	0.949035	0.956547	1.000000

In [23]:
```
sns.heatmap(iris.corr(), annot=True)
```

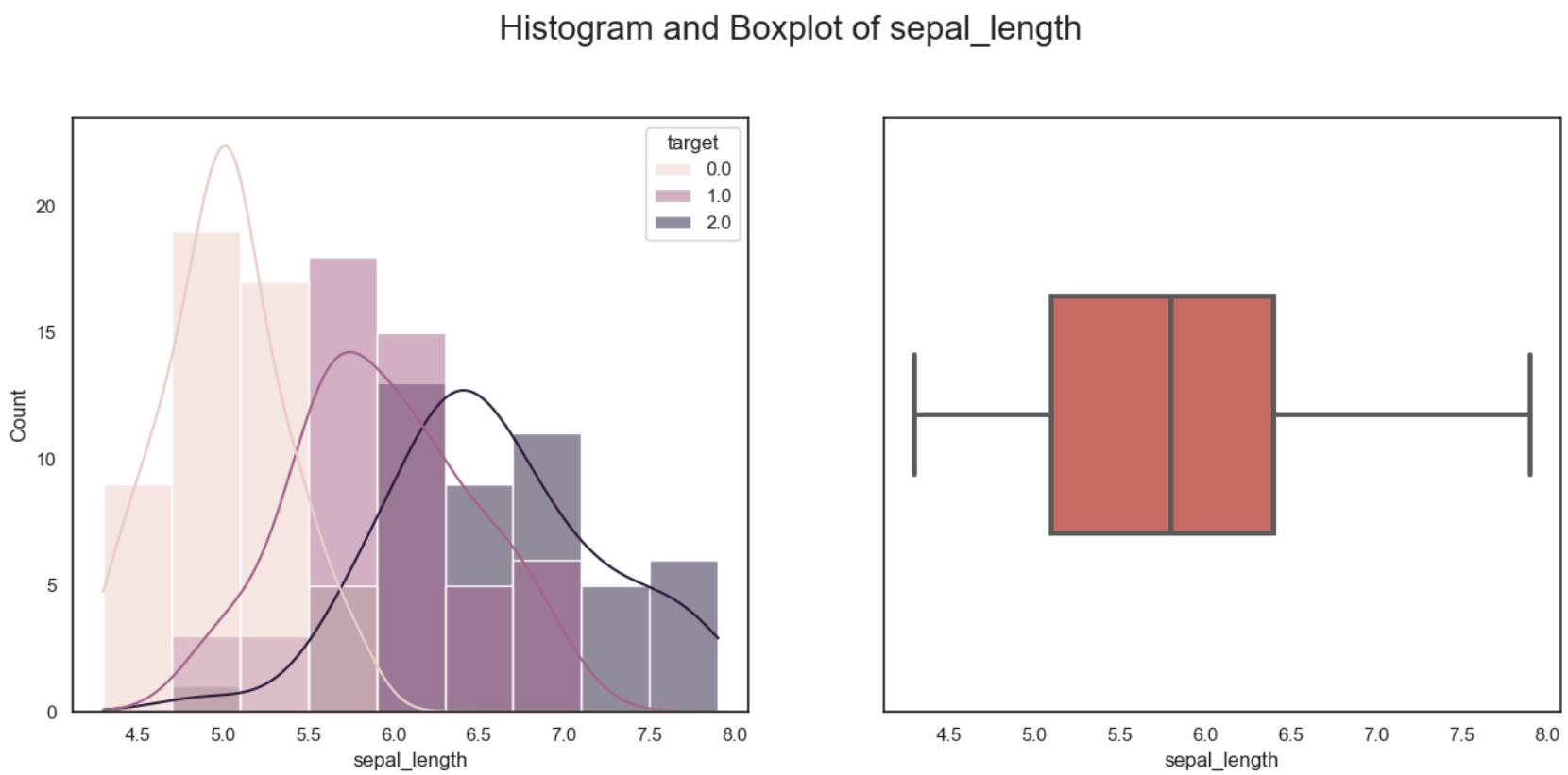
Out[23]: <Axes: >



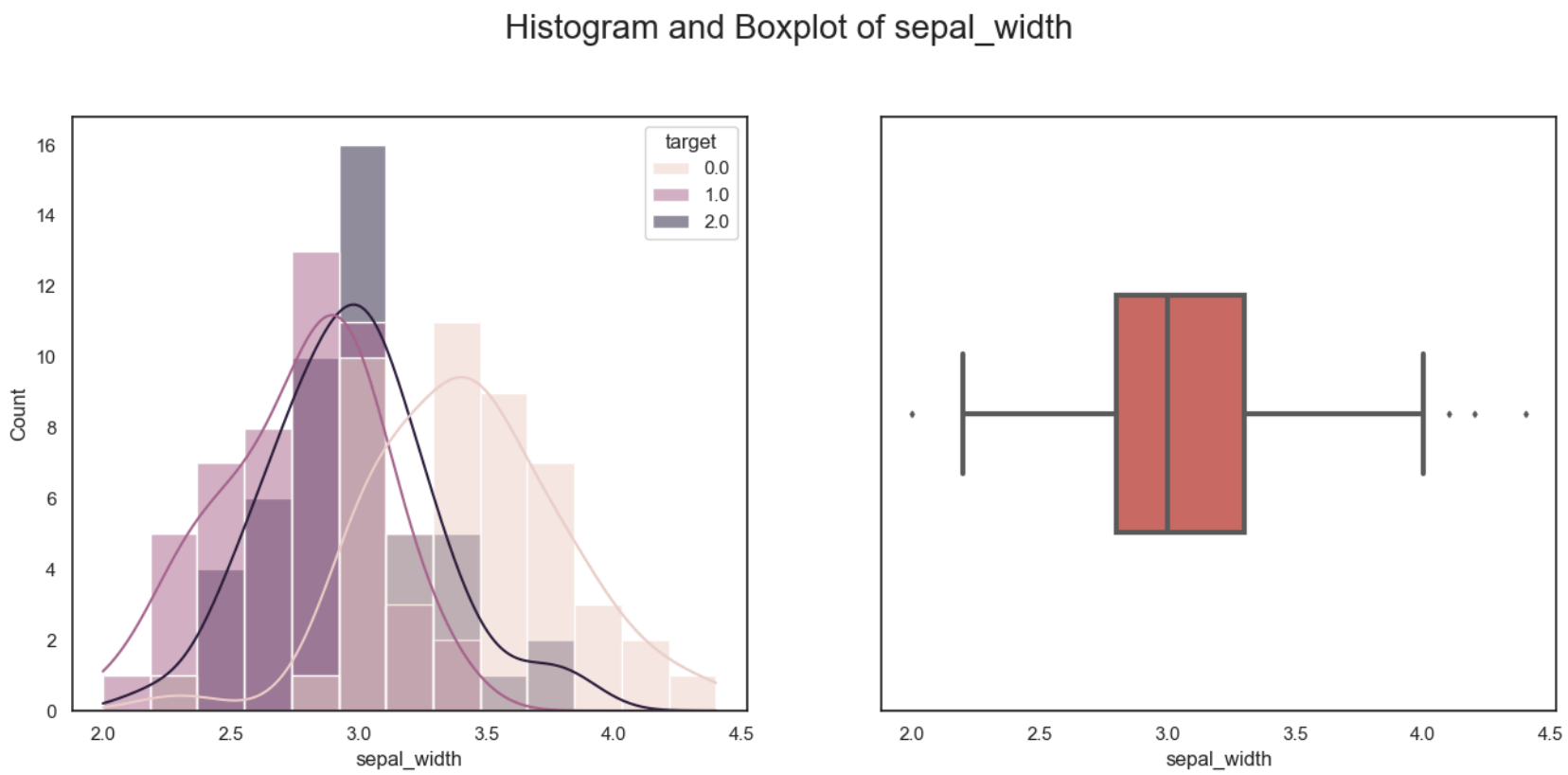
In [24]:
```
plt.axis('equal')
sns.scatterplot(iris, x = 'petal_width', y='sepal_width', hue='target' , palette=sns.color_palette("hls", iri
plt.show()
```



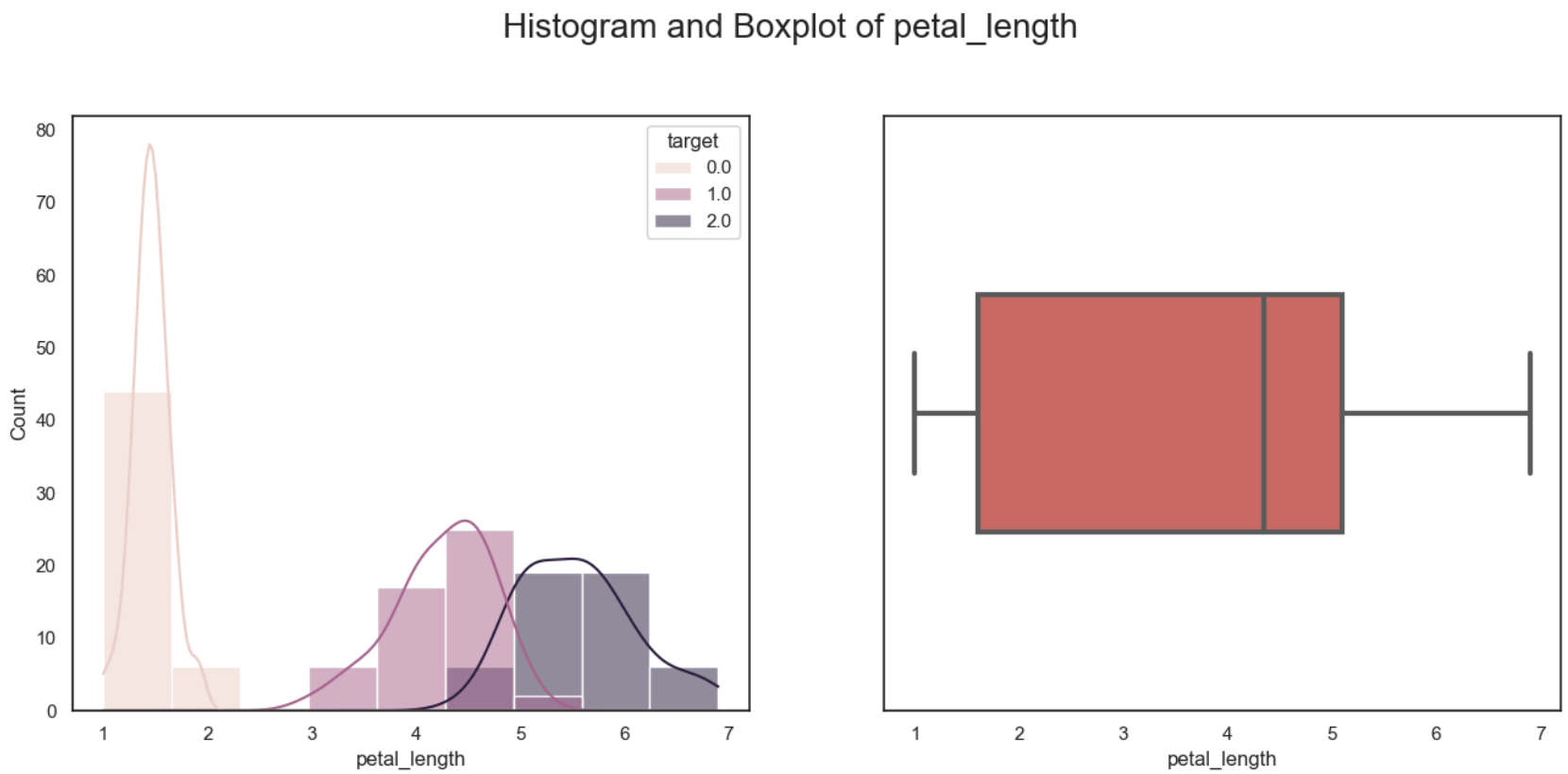
In [25]:
```
for idx, col in enumerate(['sepal_length']):
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (14, 6))
    sns.histplot(iris, x = iris[col], kde = True,
                 color = sns.color_palette("hls", iris['target'].nunique()), ax = ax1, hue = 'target')
    sns.boxplot(x = iris[col], width = 0.4, linewidth = 3, fliersize = 2.5,
                color = sns.color_palette("hls", iris['target'].nunique())[idx], ax = ax2)
    fig.suptitle(f"Histogram and Boxplot of {col}", size = 20, y = 1.02)
    plt.show()
```



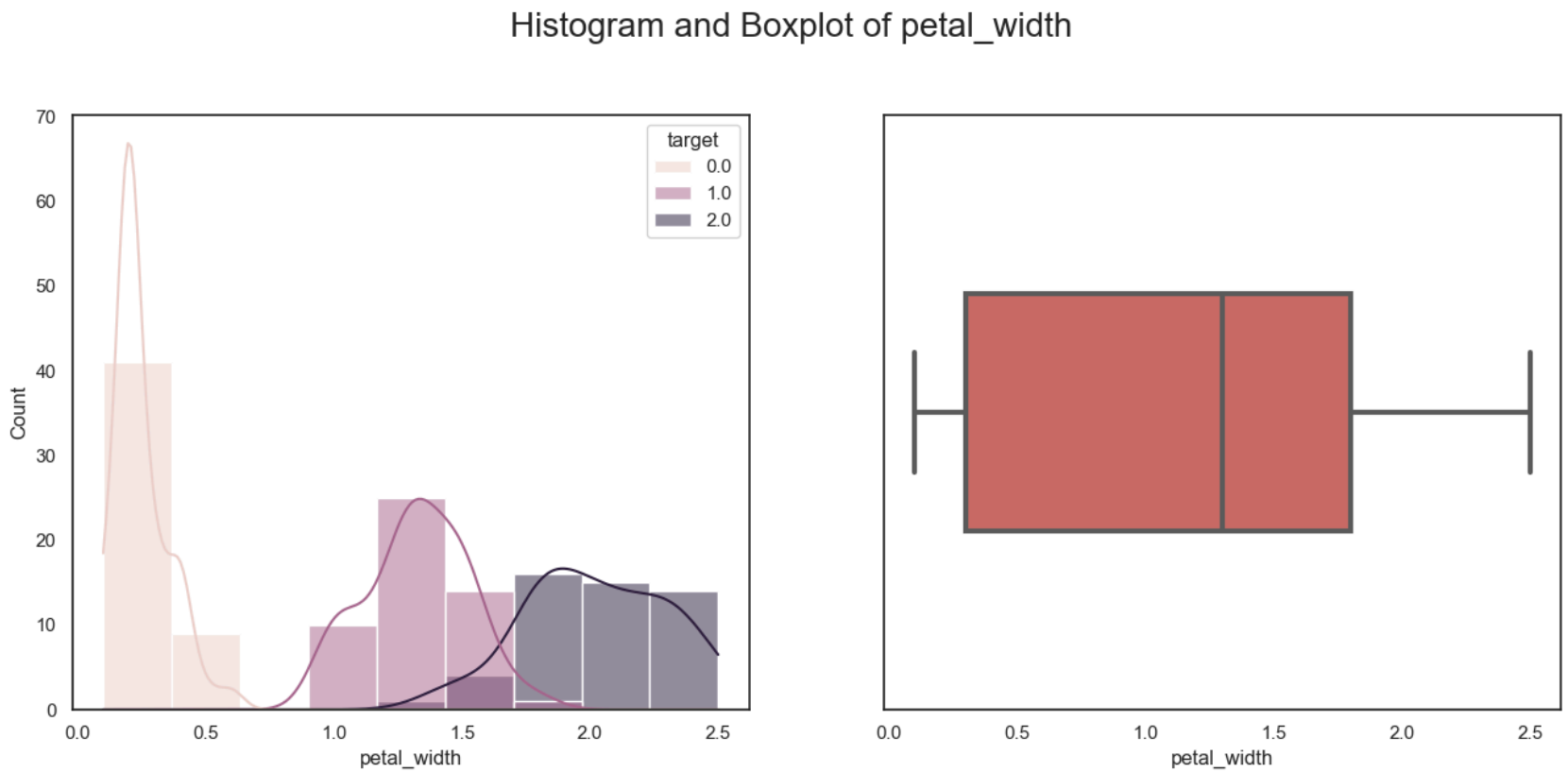
In [26]:
```
for idx, col in enumerate(['sepal_width']):
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (14, 6))
    sns.histplot(iris, x = iris[col], kde = True,
                 color = sns.color_palette("hls", iris['target'].nunique()), ax = ax1, hue = 'target')
    sns.boxplot(x = iris[col], width = 0.4, linewidth = 3, fliersize = 2.5,
                color = sns.color_palette("hls", iris['target'].nunique())[idx], ax = ax2)
    fig.suptitle(f"Histogram and Boxplot of {col}", size = 20, y = 1.02)
    plt.show()
```



In [27]:
```
for idx, col in enumerate(['petal_length']):
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (14, 6))
    sns.histplot(iris, x = iris[col], kde = True,
                 color = sns.color_palette("hls", iris['target'].nunique()), ax = ax1, hue = 'target')
    sns.boxplot(x = iris[col], width = 0.4, linewidth = 3, fliersize = 2.5,
                color = sns.color_palette("hls", iris['target'].nunique())[idx], ax = ax2)
    fig.suptitle(f"Histogram and Boxplot of {col}", size = 20, y = 1.02)
    plt.show()
```

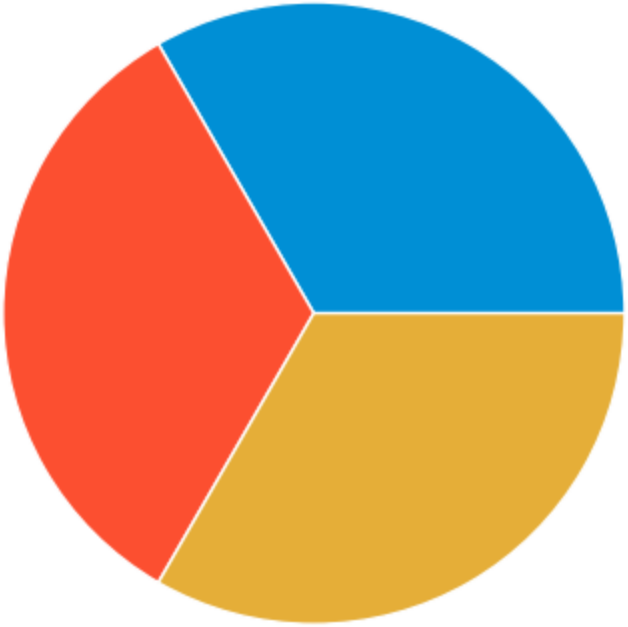


In [28]:
```
for idx, col in enumerate(['petal_width']):
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (14, 6))
    sns.histplot(iris, x = iris[col], kde = True,
                 color = sns.color_palette("hls", iris['target'].nunique()), ax = ax1, hue = 'target')
    sns.boxplot(x = iris[col], width = 0.4, linewidth = 3, fliersize = 2.5,
                color = sns.color_palette("hls", iris['target'].nunique())[idx], ax = ax2)
    fig.suptitle(f"Histogram and Boxplot of {col}", size = 20, y = 1.02)
    plt.show()
```



In [29]:
```
vc = iris['target'].value_counts()

_ = plt.pie(vc)
```

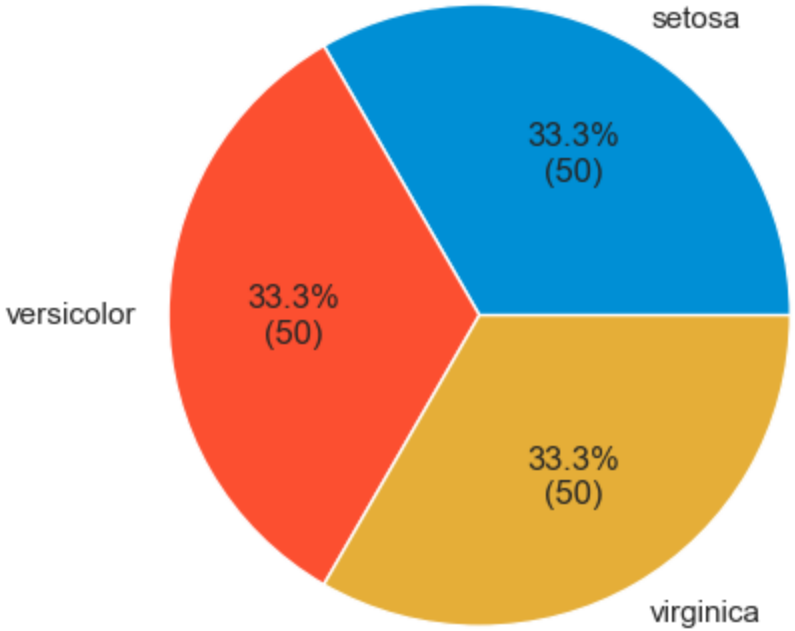


In [30]:
```
# Inspired by:
#https://stackoverflow.com/questions/73616867/pie-chart-from-count-of-values-showing-the-percentage/73617021#

# Define a function to format value counts into percentages
def autopct_format(values):
        def my_format(pct):
            total = sum(values)
            val = int(round(pct*total/100.0))
            return '{:.1f}%\n({v:d})'.format(pct, v=val)
        return my_format

# Get value counts
vc = iris['target'].value_counts()

# Draw a pie chart using value counts and the `autopct_format` format
_ = plt.pie(vc, labels = vc.rename(class_names).index, autopct=autopct_format(vc))
```



Training a Model

In [31]:
```
from sklearn.model_selection import train_test_split

X =iris.drop(columns=['target'])
y =iris['target']
```

In [32]:
```
X_train, X_test, y_train, y_test =train_test_split(X, y, test_size= 0.30)
```

LOGISTIC REGRESSION

In [33]:
```
model = LogisticRegression()
```

In [34]:
```
model.fit(X_train, y_train)
```

Out[34]:
```
LogisticRegression
LogisticRegression()
```

In [35]:
```
# model
y_pred = model.predict(X_test)
print('R2 Score:', r2_score(y_test,y_pred)*100)
```

```
R2 Score: 90.75342465753424
```

In [36]:
```
model.predict([[6.9, 4.5, 6.4, 2.0]])
```

Out[36]:
```
array([2.])
```

KNN

In [37]:
```
model = KNeighborsRegressor()
```

In [38]:
```
model.fit(X_train, y_train)
```

Out[38]:
```
KNeighborsRegressor
KNeighborsRegressor()
```
(https://scikit-learn.org/1.4/modules/generated/sklearn.neighbors.KNeighborsRegressor.html)

In [39]:
```
y_pred = model.predict(X_test)
```

In [40]:
```
print('R2 Score:', r2_score(y_test,y_pred)*100)
```

```
R2 Score: 94.69863013698631
```

Decision Tree Algorithms

In [41]:
```
model=DecisionTreeRegressor()
```

In [42]:
```
model.fit(X_train,y_train)
y_pred = model.predict(X_test)
```

In [43]:
```
print('R2 Score:', r2_score(y_test,y_pred)*100)
```

```
R2 Score: 90.75342465753424
```