Machine Learning Lab

Name : Aman Kumar Gupta

Roll No.: BTech/25013/18

Branch : CSE

Semester : 6

Candidate Elimination Algorithm

Terms Used:

1. **Concept learning**: Concept learning is basically learning task of the machine (Learn by Train data)
2. **General Hypothesis**: Not Specifying features to learn the machine.
3. **G** = {‘?’, ‘?’,’?’,’?’…} : Number of attributes
4. **Specific Hypothesis**: Specifying features to learn machine (Specific feature)
5. **S**= {‘pi’,’pi’,’pi’…} : Number of pi depends on number of attributes.
6. **Version Space**: It is intermediate of general hypothesis and Specific hypothesis. It not only just written one hypothesis but a set of all possible hypothesis based on training data-set.

Algorithm:

```
 Step1: Load Data set
 Step2: Initialize General Hypothesis  and Specific  Hypothesis.
 Step3: For each training example
 Step4: If example is positive example
          if attribute_value == hypothesis_value:
             Do nothing
          else:
             replace attribute value with '?' (Basically generalizing i
t)
 Step5: If example is Negative example
          Make generalize hypothesis more specific.
```

In [1]:
```
#import usful packages

import numpy as np
import pandas as pd
```

In [2]:
```
#read data set
df = pd.read_csv('data/ce.csv')
```

In [3]:
```
#preview dataset
df
```

Out[3]:

	sky	airtemp	humidity	wind	water	forcast	enjoysport
0	sunny	warm	normal	strong	warm	same	Yes
1	sunny	warm	high	strong	warm	same	Yes
2	rainy	cold	high	strong	warm	change	No
3	sunny	warm	high	strong	cool	change	Yes

In [4]:
```
#defining algorithm
def candidate_elimination(con,tar):
    for i,val in enumerate(tar):
        if val == 'Yes':
            specific_h = con[i].copy()
            break
    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specifi

    for i, val in enumerate(con):
        if tar[i] == "Yes":
            for j in range(len(specific_h)):
                if val[j]!= specific_h[j]:
                    specific_h[j] ='?'
                    general_h[j][j] ='?'

        if tar[i] == "No":
            for j in range(len(specific_h)):
                if val[j]!= specific_h[j]:
                    general_h[j][j] = specific_h[j]
                else:
                    general_h[j][j] = '?'
    return specific_h,general_h
```

In [5]:
```
#run algorithm
con = np.array(df)[:,:-1]
tar = np.array(df)[:,-1]

spe_h,gen_h = candidate_elimination(con,tar)
```

In [6]:
```
#print specific_h
spe_h
```

Out[6]:
```
array(['sunny', 'warm', '?', 'strong', '?', '?'], dtype=object)
```

In [7]:
```
#print gen_h
gen_h
```

Out[7]:
```
[['sunny', '?', '?', '?', '?', '?'],
 ['?', 'warm', '?', '?', '?', '?'],
 ['?', '?', '?', '?', '?', '?'],
 ['?', '?', '?', '?', '?', '?'],
 ['?', '?', '?', '?', '?', '?'],
 ['?', '?', '?', '?', '?', '?']]
```

Find-S algorithm:

Important Representation:

1. ? indicates that any value is acceptable for the attribute.
2. specify a single required value (e.g., Cold) for the attribute.
3. φ indicates that no value is acceptable.
4. The most general hypothesis is represented by: {?, ?, ?, ?, ?, ?}
5. The most specific hypothesis is represented by : {φ, φ, φ, φ, φ, φ}

Algorithm:

1. Initialize h to the most specific hypothesis in H
2. For each positive training instance x For each attribute constraint a, in h

```
If the constraint a, is satisfied by x
Then do nothing
Else replace a, in h by the next more general constraint that is sa
tisfied by x
```

3. Output hypothesis h

In [8]:
```
#import usful packages

import numpy as np
import pandas as pd
```

In [9]:
```
#read data set
df = pd.read_csv('data/fs.csv')
```

In [10]:
```
#preview dataset
df
```

Out[10]:

	Color	Toughness	Fungus	Appearance	Poisonous
0	Green	Hard	No	Wrinkled	Yes
1	Green	Hard	Yes	Smooth	No
2	Brown	Soft	No	Wrinkled	No
3	Orange	Hard	No	Wrinkled	Yes
4	Green	Hard	Yes	Wrinkled	Yes
5	Orange	Hard	No	Wrinkled	Yes

In [11]:
```
# find s algo
def find_s(con,tar):
    for i,val in enumerate(tar):
        if val == 'Yes':
            specific_h = con[i].copy()
            break

    for i,val in enumerate(con):
        if tar[i] == 'Yes':
            for j,feat in enumerate(val):
                if specific_h[j] != feat:
                    specific_h[j] = '?'
            print(specific_h)
    return specific_h
```

In [12]:
```
#run algorithm
con = np.array(df)[:,:-1]
tar = np.array(df)[:,-1]

gen_h = find_s(con,tar)
```

```
['Green' 'Hard' 'No' 'Wrinkled']
['?' 'Hard' 'No' 'Wrinkled']
['?' 'Hard' '?' 'Wrinkled']
['?' 'Hard' '?' 'Wrinkled']
```

In [13]:
```
#see result

gen_h
```

Out[13]:
```
array(['?', 'Hard', '?', 'Wrinkled'], dtype=object)
```

A. Simple Linear Analysis (From Scratch)

In [14]:
```
#import package
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [15]:
```
#read data
df = pd.read_csv('data/a.csv')
df.head()
```

Out[15]:

	X	Y
0	3.5	5.1
1	3.0	4.9
2	3.2	4.7
3	3.1	4.6
4	3.6	5.0

Suppose the required regression line equation is :

$$y = m.x + b$$

There are two equations called normal equation from which we can find `m` and `b` :

$$\Sigma XY = b.\Sigma X + m.\Sigma X^2 \quad \ldots\ldots\ldots (1)$$
$$\Sigma Y = n.b + m.\Sigma X \quad \ldots\ldots\ldots (2)$$

Or we can solve the two equation for m and b as:

$$m = \frac{n.\Sigma xy - \Sigma x.\Sigma y}{n.\Sigma x^2 - (\Sigma x)^2}$$
$$b = \overline{y} - m.\overline{x}$$

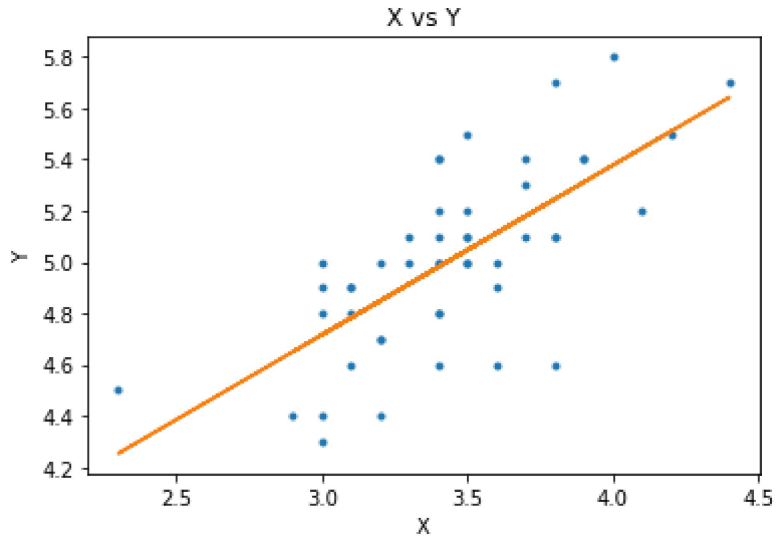
In [16]:
```
#Calculate m and b for y = mx+b
X = np.array(df['X'])
Y = np.array(df['Y'])

m = ((len(X)*sum(X*Y)) - sum(X)*sum(Y))/((len(X)*sum(X**2)) - (sum(X)**2))

b = np.mean(Y)- m*np.mean(X)
```

In [17]:
```
# append calculated y column in df
df['Y_h'] = m*X + b
```

In [18]:
```
#plot data points and y=mx+b line
plt.plot(df['X'],df['Y'],'.')
plt.plot(df['X'],df['Y_h'],'-')
plt.xlabel("X");
plt.ylabel("Y");
plt.title("X vs Y");
```



B. Multiple Linear Regression (From Scratch)

In [19]:
```
df1 = pd.read_csv("data/mlr.csv")
df1.head()
```

Out[19]:

	X1	X2	X3	X4	X5
0	6.8	225	0.442	0.672	9.2
1	6.3	180	0.435	0.797	11.7
2	6.4	190	0.456	0.761	15.8
3	6.2	180	0.416	0.651	8.6
4	6.9	205	0.449	0.900	23.2

Data Description

The following data (X1, X2, X3, X4, X5) are for each player.
X1 = height in feet
X2 = weight in pounds
X3 = percent of successful field goals (out of 100 attempted)
X4 = percent of successful free throws (out of 100 attempted)
X5 = average points scored per game

In [20]:
```
X = np.array(df1.drop('X5',axis = 1))
ones = np.ones((X.shape[0],1))
X = np.append(ones,X,axis = 1)
Y = np.array(df1['X5'])
```

$$y = b_0 + x_1 b_1 + x_2 b_2 + \cdots$$

$$Y = Xb$$

$$\mathbf{X} = \begin{bmatrix} 1 & X_1 & X_2 & \cdots \\ 1 & \cdots & \cdots & \cdot \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \cdots & \cdots & \cdots \end{bmatrix}$$

$$\mathbf{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} b_0 & b_1 & b_2 \cdots \end{bmatrix}$$

In [21]:
```
b = np.linalg.inv(X.T@X)@X.T@Y
b
```

Out[21]:
```
array([ 4.14870671e+00, -3.69049908e+00,  9.45845788e-03,  4.79401992e+01,
        1.13710193e+01])
```

In [22]:
```
Y_pred = X@b
Y_pred
```

Out[22]:
```
array([10.01235894, 12.51777389, 12.84069605, 10.3157912 , 12.38231366,
       12.18928646, 14.76231003, 12.2882684 , 11.06248103, 13.80102549,
       12.92521215, 13.24396498,  8.64006433, 12.60525851, 12.92430257,
       15.2545908 , 15.58138272,  5.09650334,  9.94940424, 12.49696124,
        9.05637536, 10.25083143,  8.06191203, 10.07255781, 14.74963484,
       12.07610898, 13.95300287,  8.71473239, 11.3419041 , 14.40707455,
       15.27283126, 10.4123043 , 13.64991307, 10.25083143,  8.97445925,
       14.70763753, 14.90726563, 13.253166  ,  7.32888666,  6.6597904 ,
        8.95334041,  5.83073166, 13.82675288, 16.36627839, 12.00928465,
       10.11871685, 17.63471509,  9.70871125,  8.95738083, 14.73644788,
       15.93275941, 12.25972646, 11.34188054, 10.03210379])
```

$$R^2 = \frac{\Sigma(\hat{Y} - \overline{Y})^2}{\Sigma(Y - \overline{Y})^2}$$

In [23]:
```
Y_mean = np.mean(Y)

R2 = (np.sum((Y_pred-Y_mean)**2))/(np.sum((Y-Y_mean)**2))
print(f"R^2 value is {R2}")
```

```
R^2 value is 0.22225063130014133
```

Linear Regression Using SKLearn

1. Read Data

In [24]:
```
df_3 = pd.read_csv("data/insurance.csv")
df_3.head()
```

Out[24]:

	age	sex	bmi	children	smoker	region	charges
0	19	0	27.900	0	1	3	16884.92400
1	18	1	33.770	1	0	2	1725.55230
2	28	1	33.000	3	0	2	4449.46200
3	33	1	22.705	0	0	1	21984.47061
4	32	1	28.880	0	0	1	3866.85520

In [25]:
```
df_3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 348 entries, 0 to 347
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       348 non-null    int64  
 1   sex       348 non-null    int64  
 2   bmi       348 non-null    float64
 3   children  348 non-null    int64  
 4   smoker    348 non-null    int64  
 5   region    348 non-null    int64  
 6   charges   348 non-null    float64
dtypes: float64(2), int64(5)
memory usage: 19.2 KB
```

2. Import Linear Regressor and Split Data Set

In [26]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
```

In [27]:
```
X = df_3.drop('charges', axis = 1)
Y = df_3['charges']
```

In [28]:
```
X_train,X_test,Y_train,Y_test = train_test_split(X,Y, test_size = 0.3)
```

3. Train Linear Regrression Model

In [29]:
```
lr_model = LinearRegression()
```

In [30]:
```
lr_model.fit(X_train,Y_train)
```

Out[30]:
```
LinearRegression()
```

4. Predict and check Model

In [31]:
```
loc = 10
x = X_test.iloc[loc]
y = Y_test.iloc[loc]
y_pred = lr_model.predict([x])
```

In [32]:
```
print(f'x = {x.values}\ny = {y}\nPredicted Value = {y_pred[0]}')
```

```
x = [53.    0.   22.61  3.    1.    0.  ]
y = 24873.3849
Predicted Value = 34055.77905142993
```

In [33]:
```
print(f'Score of Model = {lr_model.score(X_test,Y_test)}')
```

```
Score of Model = 0.6830254083167407
```

Locally Weight Regression (From Scretch)

In [34]:
```
# import useful module
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Algorithm

Locally weighted Regression is a non parametric Regression Algorithms in which we need data every time we calculate matrix.

Cost Function in Linear Regression :

$$\mathbf{costfn} = \Sigma(y_i - \theta x_i)^2$$

Cost Function for Locally Weighted Regression:

$$\mathbf{costfn} = \Sigma w_i(y_i - \theta x_i)^2$$

where x_i, y_i is the i^th example and w_i is weight.
Generally

$$w_i = e^{-\frac{(x_i - x)^2}{2\tau^2}}$$

by minimize `costfn` for θ and solving expression we get

$$\theta = (X^T W X)^{-1}(X^T W Y)$$

And prediction is $y = X\theta$.

In [35]:
```
def w_i(point,X,tau):
    m,n = X.shape
    w = np.mat(np.eye(m))

    for j in range(m):
        diff = X[j]-point
        w[j, j] = np.exp(diff * diff.T / (-2.0 * tau**2))
    return w
```

In [36]:
```
def theta(X,Y,point,tau):
    W = w_i(point,X,tau)
    th_x = X.T@W@X
    th_y = X.T@W@Y.T
    th = th_x.I@th_y
    return th
```

In [37]:
```
def predict(X,Y,tau):
    m,n = np.shape(X)
    ypred = np.zeros(m)

    for i in range(m):
        ypred[i] = X[i] * theta( X, Y, X[i],tau)
    return ypred
```

Part 1

Generate X and Y and apply

In [38]:
```
n = 100
xs = np.linspace(0, np.pi, n)
ys = 1 + np.sin(xs) + np.cos(xs**2) + np.random.normal(0, 0.1, n)
```

In [39]:
```
X = np.mat(xs)
Y = np.mat(ys)

#add 1 with each entry in X
m = X.shape[1]
one = np.ones((1,m))
X = np.hstack((one.T,X.T))

print(X[:5])
```

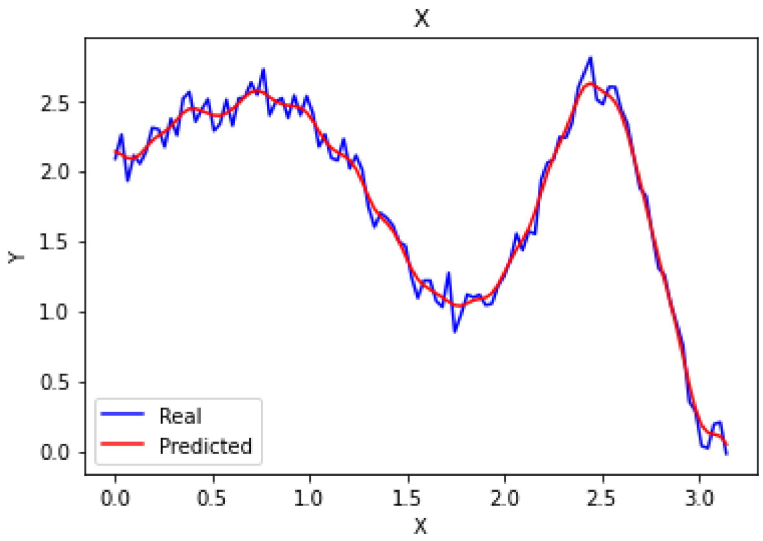
```
[[1.         0.        ]
 [1.         0.03173326]
 [1.         0.06346652]
 [1.         0.09519978]
 [1.         0.12693304]]
```

In [40]:
```
Y_prediction_05 = predict(X,Y,0.05)
```

In [41]:
```
X_l = xs
Y_l = ys
Y_p = Y_prediction_05

plt.plot(X_l,Y_l,'b-')
plt.plot(X_l,Y_p,'r-')
plt.xlabel('X')
plt.ylabel('Y')
plt.title('X')
plt.legend(['Real','Predicted'])
```

Out[41]: <matplotlib.legend.Legend at 0x19c43aae5e0>



Part 2

Use on DataSet

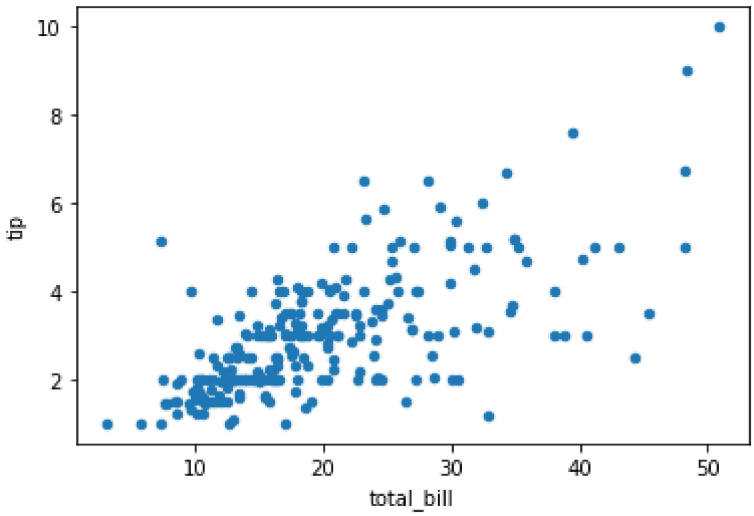
In [42]:
```
# Read Data and make DataFrame
df = pd.read_csv('data/tips.csv')
df.head()
```

Out[42]:

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

In [43]:
```
#plot total_bill vs tip
df.plot(x = 'total_bill',y = 'tip',kind = 'scatter')
```

Out[43]:
```
<AxesSubplot:xlabel='total_bill', ylabel='tip'>
```



In [44]:
```
# select columns regression
X = np.mat(df['total_bill'])
Y = np.mat(df['tip'])

#add 1 with each entry in X
m = X.shape[1]
one = np.ones((1,m))
X = np.hstack((one.T,X.T))

print(X[:5])
```

```
[[ 1.   16.99]
 [ 1.   10.34]
 [ 1.   21.01]
 [ 1.   23.68]
 [ 1.   24.59]]
```

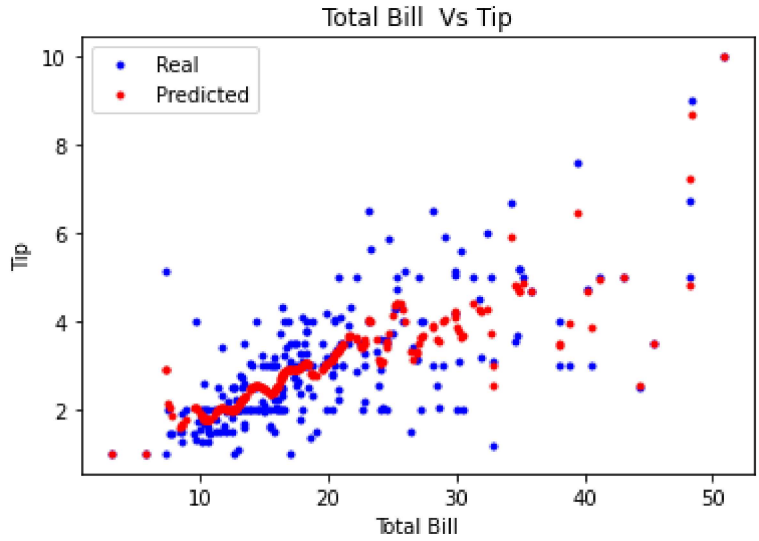
In [45]:
```
Y_prediction = predict(X,Y,0.4)
```

Plot the predicted result

In [46]:
```
X_l = df['total_bill']
Y_l = df['tip']
Y_p = Y_prediction

plt.plot(X_l,Y_l,'b.')
plt.plot(X_l,Y_p,'r.')
plt.xlabel('Total Bill')
plt.ylabel('Tip')
plt.title('Total Bill  Vs Tip')
plt.legend(['Real','Predicted'])
```

Out[46]: <matplotlib.legend.Legend at 0x19c43be4490>



Decision Tree

In [47]:
```
#import useful package
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix,accuracy_score
```

In [48]:
```
#read data
df = pd.read_csv('data/Iris.csv')
df.head()
```

Out[48]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

In [49]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             150 non-null    int64
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

In [50]:
```
#Splitting data in to train and test part

X = df.drop(['Species','Id'],axis=1)
class_name = list(df.Species.unique())
feat_name = list(X.columns)
Y = df.Species.apply(lambda x: class_name.index(x))
#Y = df.Species
```

In [51]:
```
x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size = 0.3)
```

Train Model :- ID3

Algorithm

```
ID3 (Examples, Target_Attribute, Attributes)
    Create a root node for the tree
    If all examples are positive, Return the single-node tree Root, with
label = +.
    If all examples are negative, Return the single-node tree Root, with
label = -.
    If number of predicting attributes is empty, then Return the single
 node tree Root,
    with label = most common value of the target attribute in the exampl
es.
    Otherwise Begin
        A ← The Attribute that best classifies examples.
        Decision Tree attribute for Root = A.
        For each possible value, vi, of A,
            Add a new tree branch below Root, corresponding to the test
 A = vi.
            Let Examples(vi) be the subset of examples that have the val
ue vi for A
            If Examples(vi) is empty
                Then below this new branch add a leaf node with label =
 most common target value in the examples
            Else below this new branch add the subtree ID3 (Examples(v
i), Target_Attribute, Attributes - {A})
    End
    Return Root
```

ID3 algorithm is based on entropy and information gain calculation.
Entropy is calculated as

$$\textbf{Entropy} = -\Sigma p(X) \log p(X)$$

Where `p(X)` is a Fraction of example in given class

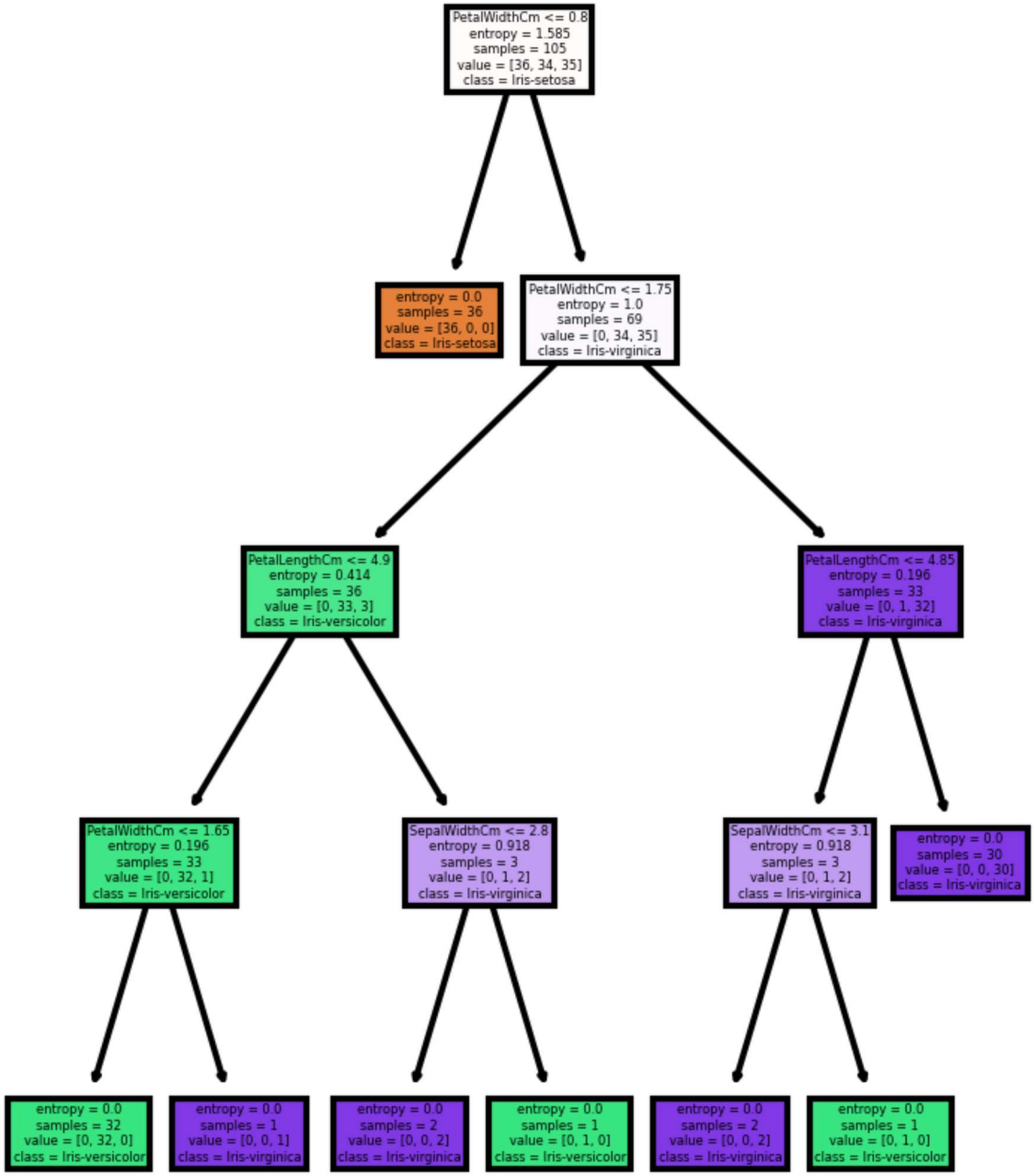
and information gain is calculated as-

$$\textbf{GAIN} = \textbf{Entropy(p)} - \Sigma \frac{n_i}{n} \textbf{Entropy(i)}$$

In [52]:
```
cd3 = DecisionTreeClassifier(criterion='entropy')
cd3.fit(x_train,y_train)
```

Out[52]:
```
DecisionTreeClassifier(criterion='entropy')
```

In [53]:
```
#plot tree
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (3,4), dpi=300)
plot_tree(cd3,
          feature_names = feat_name,
           class_names=class_name,
           filled = True);
```



In [54]:
```
#check accurecy
y_pred = cd3.predict(x_test)
print(f'Accuracy Score of model is : {accuracy_score(y_test,y_pred)}')
```

```
Accuracy Score of model is : 0.9555555555555556
```

In [55]:
```
print('Confusion Metrics :')
print(confusion_matrix(y_test,y_pred))
```

```
Confusion Metrics :
[[14  0  0]
 [ 0 15  1]
 [ 0  1 14]]
```

Train Model :- CART

Algorithm

```
Step 1: Start at the root node with all training instances
Step 2: Select an attribute on the basis of splitting criteria
Step 3: Partition instances according to selected attribute recursively
```

ID3 algorithm is based on GINI Impurity.
GINI is calculated as

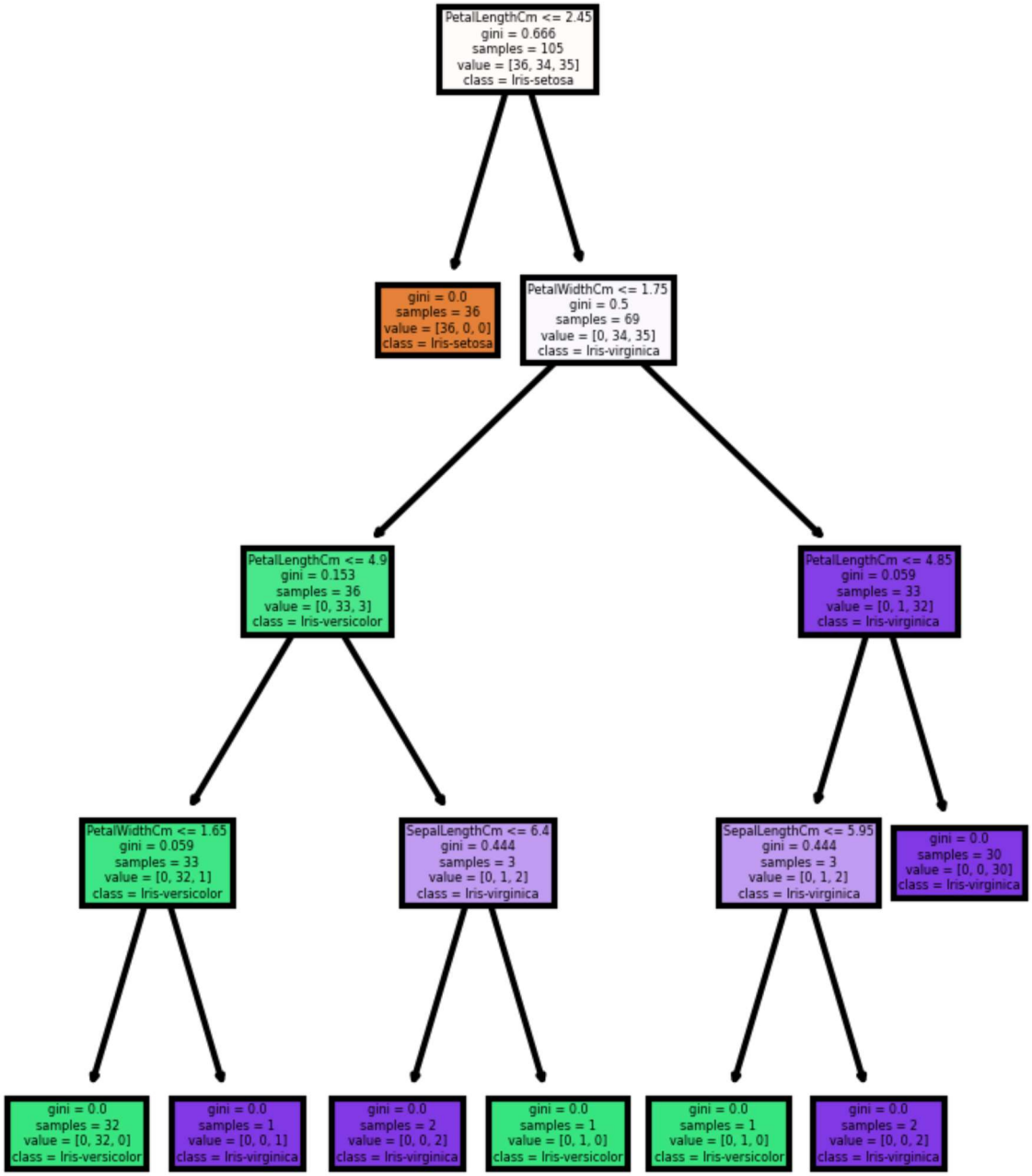
$$\mathbf{GINI} = 1 - \Sigma(p_i)^2$$

Where p_i is the probability that a tuple in `D` belongs to the class `C`

In [56]:
```
cart = DecisionTreeClassifier(criterion='gini')
cart.fit(x_train,y_train)
```

Out[56]:
```
DecisionTreeClassifier()
```

In [57]:
```
#plot tree
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (3,4), dpi=300)
plot_tree(cart,
          feature_names = feat_name,
           class_names=class_name,
           filled = True);
```



In [58]:
```
#check accurecy
y_pred = cart.predict(x_test)
print(f'Accuracy Score of model is : {accuracy_score(y_test,y_pred)}')
```

```
Accuracy Score of model is : 0.9555555555555556
```

In [59]:
```
print('Confusion Metrics :')
print(confusion_matrix(y_test,y_pred))
```

```
Confusion Metrics :
[[14  0  0]
 [ 0 15  1]
 [ 0  1 14]]
```

Logestic Regression

Logistic Regression is a Machine Learning algorithm which is used for the classification problems, it is a predictive analysis algorithm and based on the concept of probability.

For Logestic Regression Output Function :

$$\sigma(z) = \textbf{sigmoid}(z)$$

Where

$$z = \beta_0 + \beta_1 x + \cdots$$

And

$$sigmoid(z) = \frac{1}{1+e^{-z}} = \frac{1}{1+e^{-\beta_0+\beta_1 x+\cdots}}$$

$\sigma(z)$ gives values between 0 and 1.

and Cost Function is :

$$J(\theta) = -\frac{1}{m}\Sigma\left[y\log\sigma(z) + (1-y)\log\left(1-\sigma(z)\right)\right]$$

To minimise our cost Function we use `Gradient Descent` .

$$\theta_j := \theta_j - \alpha\sum_{i=1}^{m}(\sigma(x^{(i)}) - y^{(i)})x_j^{(i)}$$

In [60]:
```
#import useful package
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix,accuracy_score
```

In [61]:
```
df = pd.read_csv('data/Social_Network_Ads.csv')
df.head()
```

Out[61]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

In [62]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   User ID          400 non-null    int64
 1   Gender           400 non-null    object
 2   Age              400 non-null    int64
 3   EstimatedSalary  400 non-null    int64
 4   Purchased        400 non-null    int64
dtypes: int64(4), object(1)
memory usage: 15.8+ KB
```

In [63]:
```
#convert class feature in numerical
g_list = ['Male','Female']
df.Gender = df.Gender.apply(lambda x: g_list.index(x))
```

In [64]:
```
#Splitting Data in train and test
X = df.drop(['User ID','Purchased'],axis = 1)
Y = df['Purchased']

x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size = 0.3)
```

In [65]:
```
#Training Logestic Regression Model
LogReg = LogisticRegression()
LogReg.fit(X,Y)
```

Out[65]:
```
LogisticRegression()
```

In [66]:
```
print("Coefficient for Regression:")
print(*LogReg.coef_[0],sep = '\n')
```

```
Coefficient for Regression:
-9.322295567048426e-11
-2.1041517809748262e-09
-2.693014040541572e-06
```

In [67]:
```
#Test accurecy
y_pred = LogReg.predict(x_test)

print(f'Accurecy = {accuracy_score(y_test,y_pred)}')
```

```
Accurecy = 0.6666666666666666
```

Support vector machine

In the SVM algorithm, we are looking to maximize the margin between the data points and the hyperplane.

Cost Function :

$$C(x, y, f(x)) = \begin{cases} 0 & \text{if } y * f(x) \geq 1 \\ 1 - y * f(x) & \text{else} \end{cases}$$

We also add a regularization parameter in the cost function. The objective of the regularization parameter is to balance the margin maximization and loss. After adding the regularization parameter, the cost functions looks as below.

$$min_w \lambda ||w||^2 + \sum_{i=1}^{n} (1 - y_i \langle x_i, w \rangle)_+$$

Now that we have the loss function, we take partial derivatives with respect to the weights to find the gradients. Using the gradients, we can update our weights.

$$\frac{\delta}{\delta w_k} \lambda \|w\|^2 = 2\lambda w_k$$

When there is no misclassification, i.e our model correctly predicts the class of our data point, we only have to update the gradient from the regularization parameter.

$$\omega = \omega - \alpha \cdot (2\lambda\omega)$$

When there is a misclassification,we include the loss along with the regularization parameter to perform gradient update.

$$\omega = \omega - \alpha \cdot (y_i \cdot x_i - 2\lambda\omega)$$

---

1. Import Package and read Data

In [68]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix
from sklearn.svm import SVC
```

In [69]:
```
df = pd.read_csv("data/UniversalBank.csv")
```

In [70]:
```
df.head()
```

Out[70]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Personal Loan	Securities Accoun
0	1	25	1	49	91107	4	1.6	1	0	0	1
1	2	45	19	34	90089	3	1.5	1	0	0	1
2	3	39	15	11	94720	1	1.0	1	0	0	0
3	4	35	9	100	94112	1	2.7	2	0	0	0
4	5	35	8	45	91330	4	1.0	2	0	0	0

In [71]:
```
df = pd.get_dummies(df,drop_first=True, columns=['Family','Education'])
df.head()
```

Out[71]:

	ID	Age	Experience	Income	ZIP Code	CCAvg	Mortgage	Personal Loan	Securities Account	CD Account	Online
0	1	25	1	49	91107	1.6	0	0	1	0	0
1	2	45	19	34	90089	1.5	0	0	1	0	0
2	3	39	15	11	94720	1.0	0	0	0	0	0
3	4	35	9	100	94112	2.7	0	0	0	0	0
4	5	35	8	45	91330	1.0	0	0	0	0	0

In [72]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   ID                  5000 non-null   int64  
 1   Age                 5000 non-null   int64  
 2   Experience          5000 non-null   int64  
 3   Income              5000 non-null   int64  
 4   ZIP Code            5000 non-null   int64  
 5   CCAvg               5000 non-null   float64
 6   Mortgage            5000 non-null   int64  
 7   Personal Loan       5000 non-null   int64  
 8   Securities Account  5000 non-null   int64  
 9   CD Account          5000 non-null   int64  
 10  Online              5000 non-null   int64  
 11  CreditCard          5000 non-null   int64  
 12  Family_2            5000 non-null   uint8  
 13  Family_3            5000 non-null   uint8  
 14  Family_4            5000 non-null   uint8  
 15  Education_2         5000 non-null   uint8  
 16  Education_3         5000 non-null   uint8  
dtypes: float64(1), int64(11), uint8(5)
memory usage: 493.3 KB
```

2. Split Data in Training and Testing Set

In [73]:
```
X = df.drop(['ID','ZIP Code','CreditCard'],axis=1)
Y = df['CreditCard']
```

In [74]:
```
x_train,x_test,y_train,y_test = train_test_split(X,Y)
```

3. Create SVM model and train

In [75]:
```
svc_ = SVC(gamma='auto')
svc_.fit(x_train,y_train)
```

Out[75]:
```
SVC(gamma='auto')
```

In [76]:
```
svc_.predict([x_test.iloc[0]])
```

Out[76]:
```
array([0], dtype=int64)
```

4. Test Accuracy

In [77]:
```
y_pred = svc_.predict(x_test)
accuracy = accuracy_score(y_test,y_pred)
con_mat = confusion_matrix(y_test,y_pred)

print(f'Accuracy of Model is {accuracy} .')
print(f'Confusion Matrix :\n{con_mat}')
```

```
Accuracy of Model is 0.68 .
Confusion Matrix :
[[847  38]
 [362   3]]
```

K-Nearest Neighbors

Algorithm

1.Load the data
2.Initialize K to your chosen number of neighbors
3. For each example in the data
    1. Calculate the distance between the query example and the current example from the data.
    2. Add the distance and the index of the example to an ordered collection
4. Sort the ordered collection of distances and indices from smallest to largest (in ascending order) by the distances
5. Pick the first K entries from the sorted collection
6. Get the labels of the selected K entries
7. If regression, return the mean of the K labels
8. If classification, return the mode of the K labels

1. Import useful package

In [78]:
```
from sklearn.datasets import load_iris
from sklearn.metrics import confusion_matrix, accuracy_score, plot_confusion_matr
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
import pandas as pd
import numpy as np
import matplotlib.pyplot  as plt
```

2. Load dataset and make dataframe

In [79]:
```
df = load_iris()
```

In [80]:
```
data = np.append(df.data,df.target.reshape((150,1)),axis=1)
columns = list(df.feature_names)+['target']
dataframe = pd.DataFrame(data = data,columns=columns)
dataframe.head()
```

Out[80]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	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

3. Split data in Training and testing set

In [81]:
```
X = df.data
Y = df.target
```

In [82]:
```
x_train,x_test,y_train,y_test = train_test_split(X,Y)
```

4. Create Model and Train

In [83]:
```
knn = KNeighborsClassifier(n_neighbors=4)
```

In [84]:
```
knn.fit(x_train,y_train)
```

Out[84]:
```
KNeighborsClassifier(n_neighbors=4)
```

In [85]:
```
p = knn.predict([x_train[0]])
print(df.target_names[p])
```

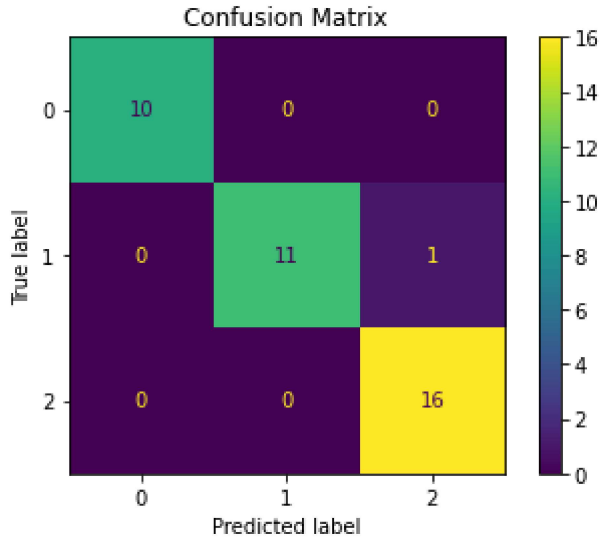
```
['virginica']
```

5. Accuracy and confusion matrix

In [86]:
```
y_p = knn.predict(x_test)
acc = accuracy_score(y_test,y_p)
con_mat = confusion_matrix(y_test,y_p)
print(f'Accuracy Score = {acc} .')
print(f'Confusion Matrix :\n{con_mat}')
```

```
Accuracy Score = 0.9736842105263158 .
Confusion Matrix :
[[10  0  0]
 [ 0 11  1]
 [ 0  0 16]]
```

In [87]:
```
plot_confusion_matrix(knn, x_test, y_test)
plt.title('Confusion Matrix')
plt.show()
```



Artificial Neural Network

Algorithms

1. Assign random weights to all the linkages to start the algorithm.
2. Using the inputs and the linkages find the activation rate of Hidden Nodes
3. Using the activation rate of Hidden nodes and linkages to output, find the activation rate of Output nodes.
4. Find the error rate at the output node and recalibrate all the linkages between hidden nodes and output nodes.
5. Using the weights and error found at output node, cascade down the error to hidden nodes.
6. Recalibrate the weights between hidden node and the input nodes.
7. Repeat the process till the convergence criterion is met.
8. Using the final linkage weights score the activation rate of the output nodes.

1. Import Package

In [31]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPRegressor
```

2. read data

In [23]:
```
df = pd.read_csv('data/hour_ride.csv')
df.head()
```

Out[23]:

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp
0	1	2011-01-01	1	0	1	0	0	6	0	1	0.24	0.2879
1	2	2011-01-01	1	0	1	1	0	6	0	1	0.22	0.2727
2	3	2011-01-01	1	0	1	2	0	6	0	1	0.22	0.2727
3	4	2011-01-01	1	0	1	3	0	6	0	1	0.24	0.2879
4	5	2011-01-01	1	0	1	4	0	6	0	1	0.24	0.2879

3. Make dummy variable

In [24]:
```
dummy_variables = ['season', 'weathersit', 'mnth', 'hr', 'weekday']
df = pd.get_dummies(df,columns=dummy_variables)
variables_to_drop = ['instant', 'dteday',  'atemp', 'workingday','casual', 'regis
df.drop(variables_to_drop,axis = 1,inplace=True)

df.head()
```

Out[24]:

	yr	holiday	temp	hum	windspeed	cnt	season_1	season_2	season_3	season_4	...	hr_21
0	0	0	0.24	0.81	0.0	16	1	0	0	0	...	0
1	0	0	0.22	0.80	0.0	40	1	0	0	0	...	0
2	0	0	0.22	0.80	0.0	32	1	0	0	0	...	0
3	0	0	0.24	0.75	0.0	13	1	0	0	0	...	0
4	0	0	0.24	0.75	0.0	1	1	0	0	0	...	0

5 rows × 57 columns

In [25]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17379 entries, 0 to 17378
Data columns (total 57 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   yr            17379 non-null  int64
 1   holiday       17379 non-null  int64
 2   temp          17379 non-null  float64
 3   hum           17379 non-null  float64
 4   windspeed     17379 non-null  float64
 5   cnt           17379 non-null  int64
 6   season_1      17379 non-null  uint8
 7   season_2      17379 non-null  uint8
 8   season_3      17379 non-null  uint8
 9   season_4      17379 non-null  uint8
 10  weathersit_1  17379 non-null  uint8
 11  weathersit_2  17379 non-null  uint8
 12  weathersit_3  17379 non-null  uint8
 13  weathersit_4  17379 non-null  uint8
 14  mnth_1        17379 non-null  uint8
 15  mnth_2        17379 non-null  uint8
 16  mnth_3        17379 non-null  uint8
 17  mnth_4        17379 non-null  uint8
 18  mnth_5        17379 non-null  uint8
 19  mnth_6        17379 non-null  uint8
 20  mnth_7        17379 non-null  uint8
 21  mnth_8        17379 non-null  uint8
 22  mnth_9        17379 non-null  uint8
 23  mnth_10       17379 non-null  uint8
 24  mnth_11       17379 non-null  uint8
 25  mnth_12       17379 non-null  uint8
 26  hr_0          17379 non-null  uint8
 27  hr_1          17379 non-null  uint8
 28  hr_2          17379 non-null  uint8
 29  hr_3          17379 non-null  uint8
 30  hr_4          17379 non-null  uint8
 31  hr_5          17379 non-null  uint8
 32  hr_6          17379 non-null  uint8
 33  hr_7          17379 non-null  uint8
 34  hr_8          17379 non-null  uint8
 35  hr_9          17379 non-null  uint8
 36  hr_10         17379 non-null  uint8
 37  hr_11         17379 non-null  uint8
 38  hr_12         17379 non-null  uint8
 39  hr_13         17379 non-null  uint8
 40  hr_14         17379 non-null  uint8
 41  hr_15         17379 non-null  uint8
 42  hr_16         17379 non-null  uint8
 43  hr_17         17379 non-null  uint8
 44  hr_18         17379 non-null  uint8
 45  hr_19         17379 non-null  uint8
 46  hr_20         17379 non-null  uint8
 47  hr_21         17379 non-null  uint8
 48  hr_22         17379 non-null  uint8
 49  hr_23         17379 non-null  uint8
```

```
 50  weekday_0     17379 non-null  uint8
 51  weekday_1     17379 non-null  uint8
 52  weekday_2     17379 non-null  uint8
 53  weekday_3     17379 non-null  uint8
 54  weekday_4     17379 non-null  uint8
 55  weekday_5     17379 non-null  uint8
 56  weekday_6     17379 non-null  uint8
dtypes: float64(3), int64(3), uint8(51)
memory usage: 1.6 MB
```

4. Split Data

In [29]:
```
target_fields = ['cnt' ]
X = df.drop(target_fields,axis=1)
Y = df[target_fields]
x_train,x_test,y_train,y_test = train_test_split(X,Y)
```

5. Set Hyperparameter and train Network

In [38]:
```
#Hyperparameter
learning_rate  = 0.1
max_iter = 100
hidden_layer_sizes = (200,100,50)
batch_size = 50
```

In [39]:
```
reg = MLPRegressor(hidden_layer_sizes=hidden_layer_sizes,
                   learning_rate_init=learning_rate,
                   max_iter=max_iter,
                   batch_size=batch_size)
reg.fit(x_train,y_train)
```

```
C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\utils\validation.py:72: Dat
aConversionWarning: A column-vector y was passed when a 1d array was expected.
Please change the shape of y to (n_samples, ), for example using ravel().
  return f(**kwargs)
```

Out[39]:
```
MLPRegressor(batch_size=50, hidden_layer_sizes=(200, 100, 50),
             learning_rate_init=0.1, max_iter=100)
```

6. Check Score

In [40]:
```
print(f'R^2 Score of Network : {reg.score(x_test,y_test)} .')
```

```
R^2 Score of Network : 0.9188769221513343 .
```

In [ ]: