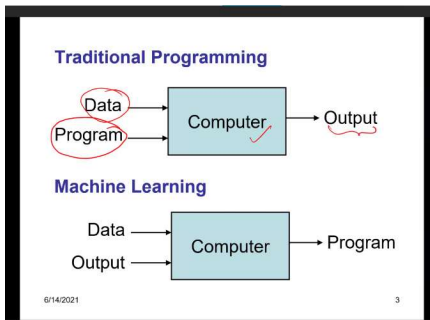


Supervised algorithm

- Basic linear regression
 - Least square method
 - Gradient descent method
- Multiple linear regression
 - Image processing
- ❖ Un supervised
 - K means clustered
 - Swiggy, realestate, making them into groups and assigning nearest members;
 - Image processing, image compression;
 - K nearest member
- ❖ NEURAL NETWORK
 - Back propa
 - CNN
 - RNN
- ❖ Image processing
- ❖ GANS

14-06-2021

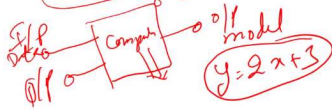
- ❖ Introduction to machine learning and linear regression
 - Automating Automation;
 - Getting computers to program themselves
 - Writing software is the bottleneck
 - Let the data do the work instead



-
- ❖ What is ML
 - Branch of AI

$x = [1, 2, 3, 4, 5]$

$y = [5, 7, 9, 11, 13]$



Introduction to Machine Learning

Based on the amount of rainfall, how much would be the crop yield?



Crop Field



Based on Rainfall

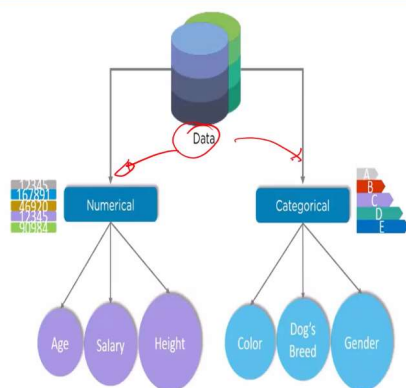


Predict crop yield

6/14/2021

8

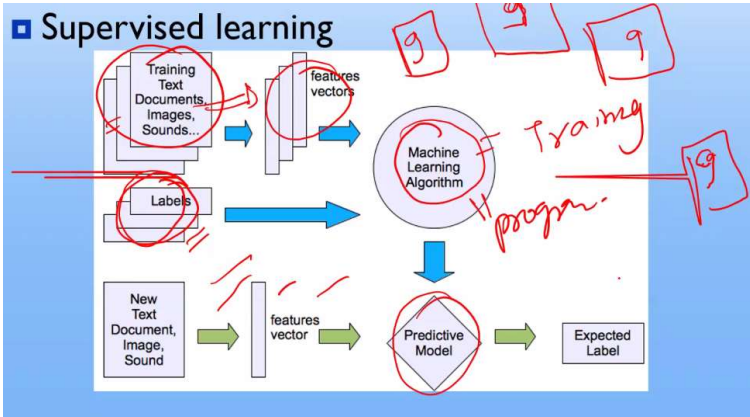
Numerical and Categorical Values



6/14/2021

- ❖ Machine learning algo
 - Supervised

- Input
 - Featured vectors
 - ◆ Training text
 - ◆ Documents
 - ◆ Images
 - ◆ Sounds
 - ◆ Etc
 - Labels



- Regression (estimation of relation between the variables)
 - Real-estate cost, runs based on previous performance, etc.
 - We use least square for checking;

Classification	Regression
Two or more labels Ex: spam or not spam, Obese or not obese, etc Methods: logistic regression	Continuous quantity Ex: weather prediction COST PREDICTION Grade prediction Methods: linear regression

Regression equation

$Y' = B_0 + B_1 X$ $Y' = 26.77 + 0.64X$	$B_1 = \Sigma xy / \Sigma x^2$ $B_1 = 470 / 730$ $B_1 = 0.64$	$B_0 = \bar{Y} - B_1 * \bar{X}$ $B_0 = 77 - 0.64 * 78$ $B_0 = 26.77$
---	---	--

Raw data		Deviation scores					
X	Y	x	y	x ²	y ²	xy	
95	85	17	8	289	64	136	
85	95	7	18	49	324	126	
80	70	2	-7	4	49	-14	
70	65	-8	-12	64	144	96	
60	70	-18	-7	324	49	126	
Sum	390		385		730	630	470
Mean	78		77				

6/14/202170

- Coefficient of determination-R²
 - Ranges from 0-1
 - Near to 0 don't use regression
 - Else use regression
 - C of Determination is related to C of correlation($r_{xy} = \frac{\sum xy}{\sqrt{(\sum x^2 * \sum y^2)}}$)

Problem	Solution
<p>X = math aptitude score</p> <p>Y = statistics grade</p> <p>If X = 75, find Y'</p>	<p>$Y' = 26.77 + 0.64 * X$</p> <p>$Y' = 26.77 + 0.64 * 75$</p> <p>$Y' = 74.8$</p>

- Avoid extrapolation 😞 (only between the min and max of our input to be predicted)

Coding part:

- Basic code

```
import numpy as np
import matplotlib.pyplot as plt

x=np.array([95,85,80,70,60])
y=np.array([85,95,70,65,70])
#x is independent and y is dependent variable,
# we are storing those data in the array

n=np.size(x);
m_x,m_y=np.mean(x),np.mean(y)#mean
```

```

ss_xy=np.sum(x*y)-n*(m_x*m_y)#
ss_xx=np.sum(x*x)-n*m_x*m_x

b0_1=ss_xy/ss_xx# slope
b0_0=m_y-b0_1*m_x#intercept

np.append(x,70)#to predict the value of 70,
np.append(y,b0_0+b0_1*70)#predicted value
y_pred=b0_0+b0_1*x#list of predicted values
print("intercept:",b0_0)
print("slope: ",b0_1)
plt.scatter(x,y)#plotting the actual values on graph
plt.plot(x,y_pred,color='r',markers='o')#plotting the predicted values on graph
from sklearn.metrics import r2_score
r2=r2_score(y,y_pred)#greater the score(coefficient of determination) better the prediction

print("r2 =",r2)
r=r2**0.5
print("r=",r)

```



- Weather prediction

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
dataset=pd.read_csv("C:/Users/rajar/Documents/.summercoding/ML/to
train/weather/weather.csv")dataset.plot(x='MinTemp',y='MaxTemp',style='o')
plt.title('min temp vs max temp')
plt.xlabel('MinTemp')
plt.ylabel('MaxTemp')
plt.plot()
plt.show()

X=dataset['MinTemp'].values.reshape(-1,1)
y=dataset['MaxTemp'].values.reshape(-1,1)

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=0)

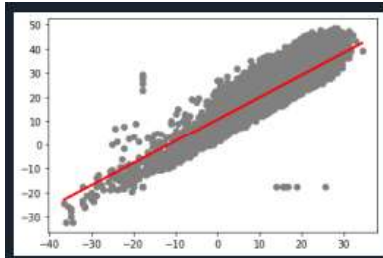
regressor=LinearRegression()
regressor.fit(X_train,y_train)

print(regressor.intercept_)
print(regressor.coef_)
y_pred=regressor.predict(X_test)
df=pd.DataFrame({'Actual':y_test.flatten(), 'predicted ':y_pred.flatten()})
print(df);
plt.scatter(X_test,y_test,color='gray')
plt.plot(X_test,y_pred,color='red',linewidth=2)
plt.show()

from sklearn.metrics import r2_score
r2=r2_score(y_test,y_pred)

```

```
print("r2 score ",r2)
print("the regression eqation : y=10.6619*x+0.92")
```



```
Ln.py )
[10.66185201]
[[0.92033997]]

   Actual    predicted
0      28.88889    33.670351
1      31.11111    30.091251
2      27.22222    26.512151
3      28.88889    31.113851
4      23.33333    15.774852
...      ...      ...
23803    32.77778    32.136451
23804    32.22222    29.068651
23805    31.11111    32.647751
23806    31.11111    30.602551
23807    36.66667    31.625151

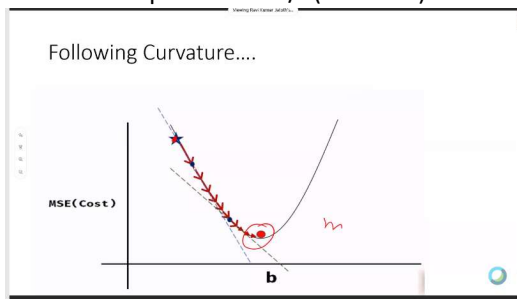
[23808 rows x 2 columns]
r2 score  0.7670218843587764
the regression eqation : y=10.6619*x+0.92
```

- Corona data is having very random values,
- We cannot apply this linear regression when the data is not linear;
- We can apply this to predict our grades even we calculate the grades using BELL CURVE, we can predict efficiently with previous data;

14-06-2021

➤ Graient Descent method: best fit for given data based on MSE

- MSE:mean square error= $\frac{1}{n}(\sum D^2)$



- The problem arises when t_i is dependent on 2 variables,
 - We take partial derivatives of that surface

Example: find the partial derivatives of $f(x,y,z) = x^4 - 3xyz$ using "curly dee" notation

$$f(x,y,z) = x^4 - 3xyz$$

$$\rightarrow \frac{\partial f}{\partial x} = 4x^3 - 3yz$$

$$\rightarrow \frac{\partial f}{\partial y} = -3xz$$

$$\rightarrow \frac{\partial f}{\partial z} = -3xy$$

$$mse = \frac{1}{n} \sum_{i=1}^n (y_i - (mx_i + b))^2$$

$$\frac{\partial}{\partial m} = \frac{2}{n} \sum_{i=1}^n -x_i (y_i - (mx_i + b))$$

$$\frac{\partial}{\partial b} = \frac{2}{n} \sum_{i=1}^n -(y_i - (mx_i + b))$$

Gradient Descent

The simplest algorithm in the world (almost). Goal:

minimize $f(x)$

Just iterate

$$x_{t+1} = x_t - \eta_t \nabla f(x_t)$$

where η_t is stepsize.

```
import numpy as np

def gradient_descent(x,y):
    m_curr = b_curr = 0
    iterations = 1000
    n = len(x)
    learning_rate = 0.001

    for i in range(iterations):
        y_predicted = m_curr * x + b_curr
        md = -(2/n)*sum(x*(y-y_predicted))
        bd = -(2/n)*sum(y-y_predicted)
        m_curr = m_curr - learning_rate * md
        b_curr = b_curr - learning_rate * bd
        print ("m {}, b {}, iteration {}".format(m_curr,b_curr,i))

x = np.array([1,2,3,4,5])
y = np.array([5,7,9,11,13])
```

$x = [1, 2, 3, 4, 5]$
 $y = [5, 7, 9, 11, 13]$

```
import numpy as np

def gradient_descent(x,y):
    m_curr = b_curr = 0
    iterations = 10
    n = len(x)
    learning_rate = 0.01

    for i in range(iterations):
        y_predicted = m_curr * x + b_curr
        cost = (1/n) * sum([val**2 for val in (y-y_predicted)])
        md = -(2/n)*sum(x*(y-y_predicted))
        bd = -(2/n)*sum(y-y_predicted)
        m_curr = m_curr - learning_rate * md
        b_curr = b_curr - learning_rate * bd
        print ("m {}, b {}, cost {} iteration {}".format(m_curr,b_curr,cost, i))

x = np.array([1,2,3,4,5])
y = np.array([5,7,9,11,13])
```

Run gradient_descent

```
m 0.62, b 0.18, cost 89.0 iteration 0
m 1.0929, b 0.3192, cost 58.400774999999999 iteration 1
m 1.453232, b 0.42724799999999996, cost 30.831949440000002 iteration 2
m 1.7278860800000002, b 0.51150911999999999, cost 18.347751350784 iteration 3
m 1.9370605952000002, b 0.57760577279999999, cost 11.070010749324897 iteration 4
m 2.096250917888, b 0.62983002163199999, cost 6.82635152519786 iteration 5
m 2.2172859146547204, b 0.6714583661260799, cost 4.350826141683065 iteration 6
m 2.309195511463117, b 0.7049920439242751, cost 2.9056952040975976 iteration 7
m 2.3788729763057748, b 0.7323404723580026, cost 2.0610450731046615 iteration 8
m 2.431580493177024, b 0.7549612843324961, cost 1.566423003130599 iteration 9
```

Process finished with exit code 0

◆ Basic code

```
import numpy as np
import matplotlib.pyplot as plt
x=np.array([1,2,3,4,5])
y=np.array([5,7,9,11,13])
m_curr=float(0)
b_curr=float(0)
lr=0.02#learning_rate
n=len(x)
itr=200#no of iterations
plt.scatter(x,y)
cost=[] #difference of actual and predicted
for i in range(itr):#iterating itr times
    y_pred=m_curr*x+b_curr
    #prediction in every iteration
```



```

cost_tmp=(1/n)*sum([val**2 for val in (y-y_pred)])
#calculating difference
cost.append(cost_tmp)

dm=-(2/n)*sum(x*(y-y_pred))
db=-(2/n)*sum(y-y_pred)
m_curr=m_curr-lr*dm
b_curr=b_curr-lr*db

#print("m {},b {}, cost {}, iteration {}".format(m_curr,b_curr,cost_tmp,i))
plt.plot(x,y_pred)

from sklearn.metrics import r2_score
r2=r2_score(y, y_pred)
print("r2 =",r2)
plt.show()
plt.figure
index=np.arange(200)
plt.scatter(index,cost)
plt.show

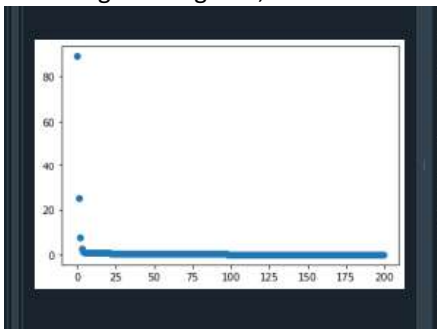
```

```

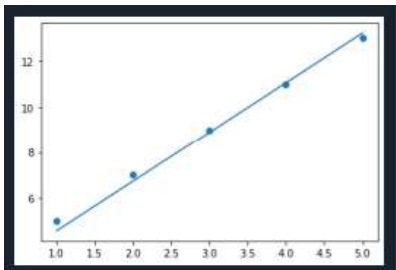
Documents/.summercoding/ML/
gradee.py')
r2 = 0.9921117798784067

```

- ◆ # can increase it by increasing iterations and decreasing learning rate;



- ◆ #cost array , decreases as increase in iterations,



- ◆ #final prediction line

Article

A Prediction Algorithm for Paddy Leaf Chlorophyll Using Colour Model Incorporate Multiple Linear Regression

Sattarpoom Thaiparnit^a and Mahasak Ketcham^{b,*}

^aDepartment of Information Technology Management, King Mongkut's University of Technology North Bangkok, 1518 Pibulsongkram Road, Bangsue, Bangkok 10800, Thailand
E-mail: ^asattarpoom@hotmail.com, ^bmahasak.k@it.kmutnb.ac.th (Corresponding author)

➤ Multiple linear regression

- Home prices => area bedrooms age price
 - $\text{Price} = m_1 * \text{area} + m_2 * \text{bedrooms} + m_3 * \text{age} + b$
- Fuel economy=vehicle,engine displacement,horsepower,type of transmission
- Overfitting decreases the correlation
- Multi collinearity increases correlation
-

Correlation: milesTraveled(x1), numDeliveries(x2), gasPrice(x3), travelTime(y)

	milesTraveled (x1)	numDeliveries (x2)	gasPrice (x3)
numDeliveries (x2)	0.956 0.000		
gasPrice (x3)	0.356 0.313	0.498 0.143	
travelTime (y)	0.928 0.000	0.916 0.000	0.267 0.455

Cell Contents: Pearson correlation
P-Value

Handwritten notes: "Correlation Coefficient" circled in red, and "Correlation" written in red above the first column of data.

- Company profit using label and one hot encoders to separate the sates

-*- coding: utf-8 -*-

"""

Created on Tue Jun 15 11:18:42 2021

@author: Mr.BeHappy

"""

```
import pandas as pd;
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import OneHotEncoder
```

```
companies=pd.read_csv('C:/Users/rajar/Documents/.summercoding/ML/to
train/profit prediction/1000_companies.csv')
```

Article

A Prediction Algorithm Using Colour Model I Regression

Sattarpoom Thaiparnit^a and Mahasak Ketcham^{b,*}

^aDepartment of Information Technology Management, King Mongkut's University of Technology North Bangkok, 1518 Pibulsongkram Road, Bangkok, 10800, Thailand
E-mail: ^asattarpoom@hotmail.com, ^bmahasak.k@it.kmutnb.ac.th (Corresponding author)

Commented [RR1]:

Commented [RR2]: Examples

```

data=companies
companies.head()
x=companies['R&D Spend'].values.reshape(-1,1)
y=companies['State'].values.reshape(-1,1)
from sklearn.preprocessing import LabelEncoder
from sklearn.compose import ColumnTransformer
le=LabelEncoder()
data.State=le.fit_transform(data.State)
columnTransformer =
ColumnTransformer([(['encoder',OneHotEncoder(),[3])],remainder='passthroug
h')]

```

```

data = np.array(columnTransformer.fit_transform(data), dtype = np.float64)

```

```

#extracting features
X=data[:, :-1]
#extracting targets
Y=data[:, -1]
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test =
train_test_split(X,Y,test_size=0.3,random_state=0)

```

```

lin_reg=LinearRegression()
lin_reg.fit(X_train,y_train)
y_pred=lin_reg.predict(X_test)
print("coeff:",lin_reg.coef_)
print("intercept:",lin_reg.intercept_)
from sklearn.metrics import r2_score
score=r2_score(y_pred,y_test)
print('prediction accuracy:',score)
import statsmodels.api as sm
X = sm.add_constant(X)
model= sm.OLS(Y, X).fit()
model.summary()

```

```

coeff: [ 4.46921768e+02 -3.42694235e+02 -1.04227533e+02  5.26047095e-01
 9.78530820e-01  9.80946128e-02]
intercept: -66123.76082364793
prediction accuracy: 0.9239867538223704

```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared:                0.950
Model:                  OLS    Adj. R-squared:           0.950
Method:                 Least Squares    F-statistic:       3769.
Date:                   Sat, 19 Jun 2021    Prob (F-statistic): 0.00
Time:                   15:42:36    Log-Likelihood:    -10588.
No. Observations:      1000    AIC:                2.119e+04
Df Residuals:          994    BIC:                2.122e+04
Df Model:              5
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-5.263e+04	2977.655	-17.674	0.000	-5.85e+04	-4.68e+04
x1	-1.743e+04	1087.818	-16.019	0.000	-1.96e+04	-1.53e+04
x2	-1.787e+04	1083.657	-16.492	0.000	-2e+04	-1.57e+04
x3	-1.733e+04	1074.779	-16.122	0.000	-1.94e+04	-1.52e+04
x4	0.5531	0.035	15.892	0.000	0.485	0.621
x5	1.0262	0.031	33.014	0.000	0.965	1.087
x6	0.0811	0.017	4.814	0.000	0.048	0.114

```

=====
Omnibus:                1577.782    Durbin-Watson:        1.690
Prob(Omnibus):          0.000    Jarque-Bera (JB):     1032877.856
Skew:                   9.327    Prob(JB):              0.00
Kurtosis:               159.336    Cond. No.              2.53e+18
=====

```

- IRIS dataset, predicting the species;

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

leaves=pd.read_csv('C:/Users/rajar/Documents/.summercoding/ML/to
train\iris/Iris.csv')
data=leaves
leaves.head()
from sklearn.preprocessing import LabelEncoder,OneHotEncoder
from sklearn.compose import ColumnTransformer

le=LabelEncoder()
data['Species']=le.fit_transform(data['Species']);
columnTransformer=ColumnTransformer([(['encoder',OneHotEncoder(),[4])],re
mainder='passthrough')

data=np.array(columnTransformer.fit_transform(data), dtype = np.float64)

X=data[:, :-1]
Y=data[:, -1]
#extracting targets

```

```

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test
train_test_split(X,Y,test_size=0.3,random_state=0)

```

=

```

lin_reg=LinearRegression()
lin_reg.fit(X_train,y_train)
y_pred=lin_reg.predict(X_test)
print("coeff:",lin_reg.coef_)
print("intercept:",lin_reg.intercept_)
from sklearn.metrics import r2_score
score=r2_score(y_pred,y_test)
print('prediction accuracy:',score)
import statsmodels.api as sm
X = sm.add_constant(X)
model= sm.OLS(Y, X).fit()
model.summary()

```

```

In [67]: runcell(0, 'C:/Users/rajar/Documents/.summercoding/ML/to train/iris/untitled
coeff: [-0.48089423  0.06162781  0.41926642 -0.1030543  0.21940979  0.27963455]
intercept: 0.07655739532205819
prediction accuracy: 0.9326560643682853

```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared:                0.954
Model:                  OLS    Adj. R-squared:           0.953
Method:                 Least Squares    F-statistic:       599.5
Date:                   Sat, 19 Jun 2021    Prob (F-statistic):  1.79e-94
Time:                   15:45:58    Log-Likelihood:      59.398
No. Observations:       150    AIC:                  -106.8
Df Residuals:           144    BIC:                  -88.73
Df Model:                5
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0632	0.123	0.515	0.607	-0.179	0.305
x1	-0.5509	0.097	-5.666	0.000	-0.743	-0.359
x2	0.1073	0.051	2.106	0.037	0.007	0.208
x3	0.5068	0.090	5.639	0.000	0.329	0.684
x4	-0.0948	0.045	-2.129	0.035	-0.183	-0.007
x5	0.2497	0.048	5.248	0.000	0.156	0.344
x6	0.2409	0.049	4.947	0.000	0.145	0.337

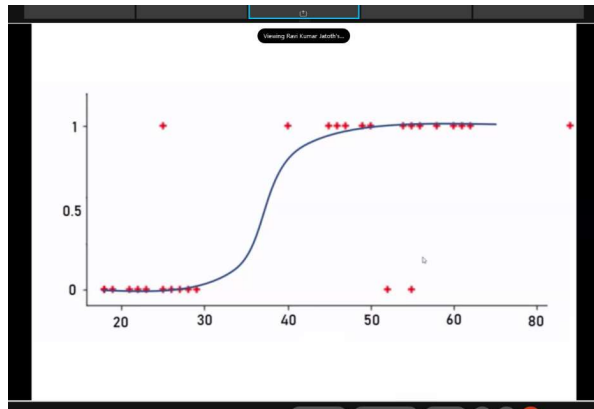
```

=====
Omnibus:                 5.957    Durbin-Watson:           1.840
Prob(Omnibus):            0.051    Jarque-Bera (JB):         8.404
Skew:                     -0.159    Prob(JB):                 0.0150
Kurtosis:                 4.115    Cond. No.                 2.77e+16
=====

```

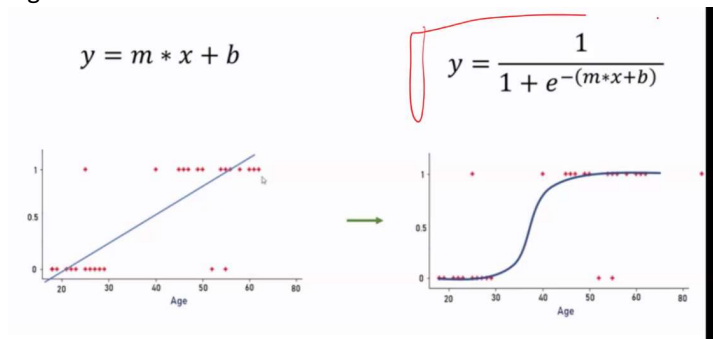
❖ 18-06

- Intro to logical regression
- LOGISTIC REGRESSION
- Rat obesity :



#sigmoid curve;

Sigmoid function



Odds= ratio of favour and not in favour; p/1-p

- For generalisation we take log,,
- Log of odds= $\lg(p/1-p)$

(I) Linear Regression

- (a) Simple Linear Regression $Y = b_0 + b_1 x$
- (b) Multiple " " $Y = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_n x_n$

Annotations: In the simple linear regression equation, b_0 is labeled 'Intercept' and b_1 is labeled 'Slope'.

$$f(x) = \frac{1}{1 + e^{-(b_0 + b_1 x_1 + b_2 x_2 + \dots)}}$$

$$f(x) = \frac{1}{1 + e^{-(b_0 + b_1 x_1 + b_2 x_2 + \dots)}}$$

Annotations: b_0, b_1, b_2, \dots are labeled 'weight vector'. Below the equation, a handwritten note shows '0.3' with an arrow pointing to 'class-1' and another arrow pointing to 'class-0'.

- If f is >0.5 then odds are in favour else not in favour;

$$f(x) = \frac{1}{1 + e^{-(b_0 + b_1 x_1 + b_2 x_2)}}$$

$f(x)$ = probability $(x_1, x_2) \rightarrow$ Class-0
Class-1

$P(y=1|x;w) = f(x)$

$P(y=0|x;w) = 1 - f(x)$

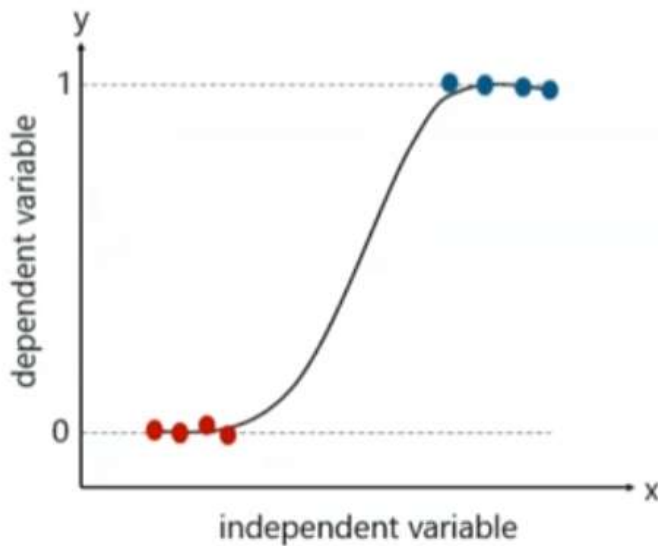
$P(y|x;w) = (f(x))^y (1-f(x))^{(1-y)}$

m - Independent training samples

$$\sum_{i=1}^m P(y^i | x^i; w) = \sum_{i=1}^m \left[(f(x^i))^{y^i} (1-f(x^i))^{(1-y^i)} \right]$$

= $L(b)$

We get a sigmoid curve;



◆ Basic code on advertising

```
# -*- coding: utf-8 -*-
"""
```

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"""
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```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```

from sklearn.model_selection import train_test_split
from math import exp
data=pd.read_csv('C:/Users/rajar/Documents/.summercoding/ML/to
train/socialnetworkadd/Social_Network_Ads.csv')
data.head()
plt.scatter(data['Age'], data['Purchased'])
plt.show()
X_train, X_test, y_train, y_test = train_test_split(data['Age'],
data['Purchased'], test_size=0.20)

def normalize(X):
    return X - X.mean()
def predict(X, b0, b1):
    return np.array([1 / (1 + exp(-1*b0 + -1*b1*x)) for x in X])

def logistic_regression(X, Y):
    X = normalize(X)
    b0 = 0
    b1 = 0
    L = 0.01
    epochs = 500
    for epoch in range(epochs):
        y_pred = predict(X, b0, b1)
        D_b0 = -2* sum((Y - y_pred) * y_pred * (1 - y_pred)) # Derivative
of loss wrt b0
        D_b1 = -2* sum(X * (Y - y_pred) * y_pred * (1 - y_pred)) #
Derivative of loss wrt b1
        b0 = b0 - L * D_b0
        b1 = b1 - L * D_b1
    return b0, b1

# Training the model
b0, b1 = logistic_regression(X_train, y_train)
X_test_norm = normalize(X_test)
y_pred = predict(X_test_norm, b0, b1)

y_pred = [0.9 if p >= 0.5 else 0.1 for p in y_pred]
plt.clf()
plt.scatter(X_test, y_test)
plt.scatter(X_test, y_pred, c="red")
# plt.plot(X_test, y_pred, c="red", linestyle='-', marker='o') # Only if
values are sorted

```

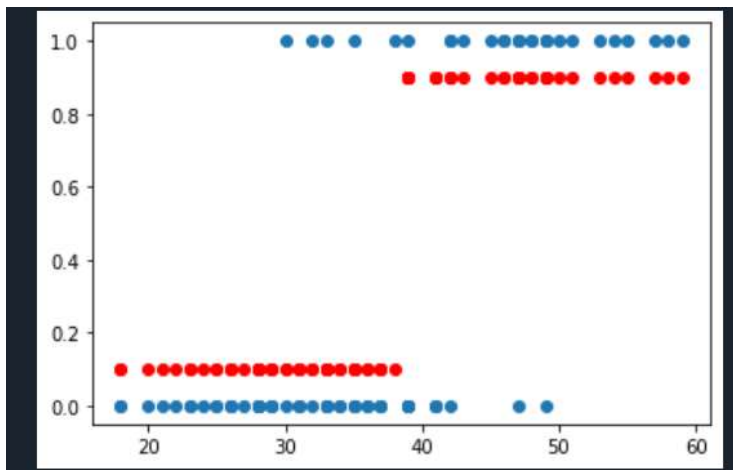


```
plt.show()
```

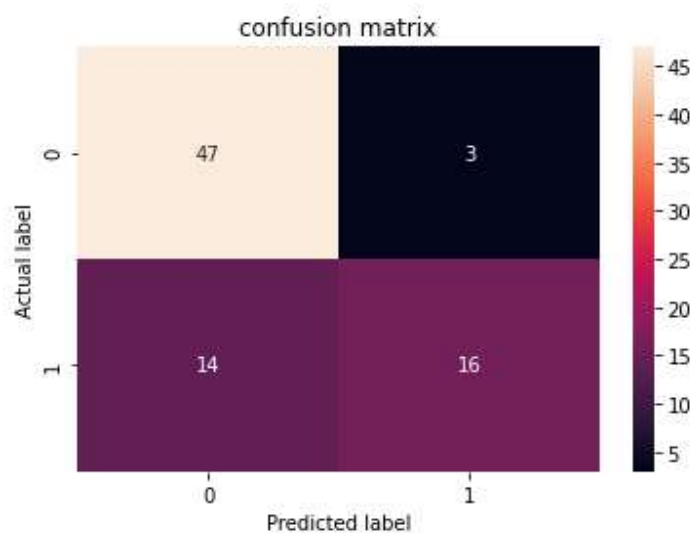
```
from sklearn import metrics
```

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import seaborn as sns
```

```
y_pred = [1 if p >= 0.5 else 0 for p in y_pred]  
conf_matrix=metrics.confusion_matrix(y_test,y_pred)  
print(conf_matrix)  
sns.heatmap(conf_matrix,annot=True)  
plt.title('confusion matrix')  
plt.ylabel('Actual label')  
plt.xlabel('Predicted label')  
print("Accuracy:", metrics.accuracy_score(y_test,y_pred))
```



```
[[47  3]  
 [14 16]]  
Accuracy: 0.7875
```



➤ Obese vs non obese

- Code

import numpy as np

import matplotlib.pyplot as plt

from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import train_test_split

import pandas as pd

from sklearn import metrics

import seaborn as sns

data=

pd.read_csv('C:/Users/rajar/Documents/.summercoding/ML/to
train/diabetis/diabetes.csv')

dd=pd.DataFrame({'hi':data['Pregnancies']],index=data['Glucose'])

dd.describe()

X=data.iloc[:, :-1]

y=data.iloc[:, -1]

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,ran
dom_state=1)

logreg=LogisticRegression()

logreg.fit(X_train,y_train)

y_pred=logreg.predict(X_test)

df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})

print(df)

```
conf_matrix=metrics.confusion_matrix(y_test,y_pred)
print(conf_matrix)
sns.heatmap(conf_matrix,annot=True)
plt.title('confusion matrix')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
print("Accuracy:", metrics.accuracy_score(y_test,y_pred))
```

```
684      0      0
643      0      0

[154 rows x 2 columns]
[[89 10]
 [24 31]]
Accuracy: 0.7792207792207793
```

