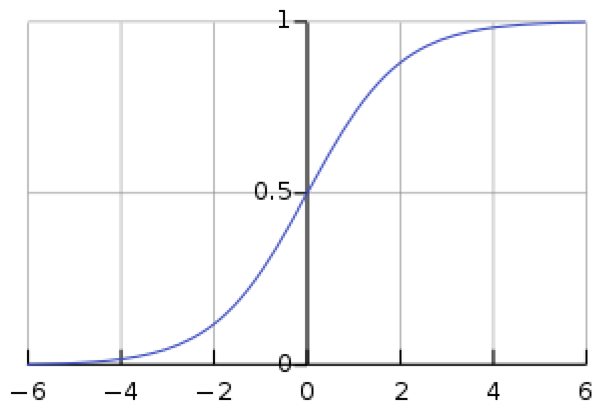
Good Afternoon Everyone

Logistic Regression

Decision Tree

Logistic Regression is a one type the classification algorithm

it works based on the probability it uses logistic function or Sigmoid Function



In [4]:

```
## Now we can apply logistic regression for IRIS dataset
from sklearn.datasets import load_iris
iris = load_iris()
iris.keys()
```

Out[4]:

```
dict_keys(['data', 'target', 'target_names', 'DESCR', 'feature_names'])
```

In [5]:
```
iris['data']
```

Out[5]:
```
array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2],
       [5.4, 3.9, 1.7, 0.4],
       [4.6, 3.4, 1.4, 0.3],
       [5. , 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3. , 1.4, 0.1],
       [4.3, 3. , 1.1, 0.1],
       [5.8, 4. , 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [5.7, 3.8, 1.7, 0.3],
```

In [6]:
```
iris['target_names']
```

Out[6]:
```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

In [7]:
```
iris['target']
```

Out[7]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

In [8]:

```
iris['DESCR']
```

Out[8]:

```
'Iris Plants Database\n====================\n\nNotes\n-----\nData Set Character
istics:\n    :Number of Instances: 150 (50 in each of three classes)\n    :Numb
er of Attributes: 4 numeric, predictive attributes and the class\n    :Attribut
e Information:\n        - sepal length in cm\n        - sepal width in cm\n
- petal length in cm\n        - petal width in cm\n        - class:\n
- Iris-Setosa\n                - Iris-Versicolour\n                - Iris-Virgi
nica\n    :Summary Statistics:\n\n    ============== ==== ==== ======= ===== ==
==================\n                    Min  Max   Mean    SD   Class Correlati
on\n    ============== ==== ==== ======= ===== ====================\n    sepal
length:   4.3  7.9   5.84   0.83    0.7826\n    sepal width:    2.0  4.4   3.05
0.43   -0.4194\n    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)\n
petal width:    0.1  2.5   1.20  0.76     0.9565  (high!)\n    ============== =
=== ==== ======= ===== ====================\n\n    :Missing Attribute Values: N
one\n    :Class Distribution: 33.3% for each of 3 classes.\n    :Creator: R.A.
Fisher\n    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)\n    :Date:
July, 1988\n\nThis is a copy of UCI ML iris datasets.\nhttp://archive.ics.uci.e
du/ml/datasets/Iris\n\nThe famous Iris database, first used by Sir R.A Fisher\n
\nThis is perhaps the best known database to be found in the\npattern recogniti
on literature.  Fisher\'s paper is a classic in the field and\nis referenced fr
equently to this day.  (See Duda & Hart, for example.)  The\ndata set contains
3 classes of 50 instances each, where each class refers to a\ntype of iris plan
t.  One class is linearly separable from the other 2; the\nlatter are NOT linea
rly separable from each other.\n\nReferences\n----------\n   - Fisher,R.A. "The
use of multiple measurements in taxonomic problems"\n     Annual Eugenics, 7, P
art II, 179-188 (1936); also in "Contributions to\n     Mathematical Statistic
s" (John Wiley, NY, 1950).\n   - Duda,R.O., & Hart,P.E. (1973) Pattern Classifi
cation and Scene Analysis.\n     (Q327.D83) John Wiley & Sons.  ISBN 0-471-2236
1-1.  See page 218.\n   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhoo
d: A New System\n     Structure and Classification Rule for Recognition in Part
ially Exposed\n     Environments".  IEEE Transactions on Pattern Analysis and M
achine\n     Intelligence, Vol. PAMI-2, No. 1, 67-71.\n   - Gates, G.W. (1972)
"The Reduced Nearest Neighbor Rule".  IEEE Transactions\n     on Information Th
eory, May 1972, 431-433.\n   - See also: 1988 MLC Proceedings, 54-64.  Cheesema
n et al"s AUTOCLASS II\n     conceptual clustering system finds 3 classes in th
e data.\n   - Many, many more ...\n'
```

In [9]:

```
iris['feature_names']
```

Out[9]:

```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

In [10]:

```
import pandas as pd
df = pd.DataFrame(iris['data'])
df
```

Out[10]:

	0	1	2	3
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
5	5.4	3.9	1.7	0.4
6	4.6	3.4	1.4	0.3
7	5.0	3.4	1.5	0.2
8	4.4	2.9	1.4	0.2
9	4.9	3.1	1.5	0.1
10	5.4	3.7	1.5	0.2
11	4.8	3.4	1.6	0.2
12	4.8	3.0	1.4	0.1
13	4.3	3.0	1.1	0.1
14	5.8	4.0	1.2	0.2
15	5.7	4.4	1.5	0.4
16	5.4	3.9	1.3	0.4
17	5.1	3.5	1.4	0.3
18	5.7	3.8	1.7	0.3
19	5.1	3.8	1.5	0.3
20	5.4	3.4	1.7	0.2
21	5.1	3.7	1.5	0.4
22	4.6	3.6	1.0	0.2
23	5.1	3.3	1.7	0.5
24	4.8	3.4	1.9	0.2
25	5.0	3.0	1.6	0.2
26	5.0	3.4	1.6	0.4
27	5.2	3.5	1.5	0.2
28	5.2	3.4	1.4	0.2
29	4.7	3.2	1.6	0.2
...	...	...	...	...
120	6.9	3.2	5.7	2.3
121	5.6	2.8	4.9	2.0

	0	1	2	3
122	7.7	2.8	6.7	2.0
123	6.3	2.7	4.9	1.8
124	6.7	3.3	5.7	2.1
125	7.2	3.2	6.0	1.8
126	6.2	2.8	4.8	1.8
127	6.1	3.0	4.9	1.8
128	6.4	2.8	5.6	2.1
129	7.2	3.0	5.8	1.6
130	7.4	2.8	6.1	1.9
131	7.9	3.8	6.4	2.0
132	6.4	2.8	5.6	2.2
133	6.3	2.8	5.1	1.5
134	6.1	2.6	5.6	1.4
135	7.7	3.0	6.1	2.3
136	6.3	3.4	5.6	2.4
137	6.4	3.1	5.5	1.8
138	6.0	3.0	4.8	1.8
139	6.9	3.1	5.4	2.1
140	6.7	3.1	5.6	2.4
141	6.9	3.1	5.1	2.3
142	5.8	2.7	5.1	1.9
143	6.8	3.2	5.9	2.3
144	6.7	3.3	5.7	2.5
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

In [11]:
```
df.columns = iris['feature_names']
```

In [12]:
```
df
```

Out[12]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
5	5.4	3.9	1.7	0.4
6	4.6	3.4	1.4	0.3
7	5.0	3.4	1.5	0.2
8	4.4	2.9	1.4	0.2
9	4.9	3.1	1.5	0.1
10	5.4	3.7	1.5	0.2
11	4.8	3.4	1.6	0.2
12	4.8	3.0	1.4	0.1
13	4.3	3.0	1.1	0.1
14	5.8	4.0	1.2	0.2
15	5.7	4.4	1.5	0.4
16	5.4	3.9	1.3	0.4
17	5.1	3.5	1.4	0.3
18	5.7	3.8	1.7	0.3
19	5.1	3.8	1.5	0.3
20	5.4	3.4	1.7	0.2
21	5.1	3.7	1.5	0.4
22	4.6	3.6	1.0	0.2
23	5.1	3.3	1.7	0.5
24	4.8	3.4	1.9	0.2
25	5.0	3.0	1.6	0.2
26	5.0	3.4	1.6	0.4
27	5.2	3.5	1.5	0.2
28	5.2	3.4	1.4	0.2
29	4.7	3.2	1.6	0.2
...	...	...	...	...
120	6.9	3.2	5.7	2.3
121	5.6	2.8	4.9	2.0
122	7.7	2.8	6.7	2.0

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
123	6.3	2.7	4.9	1.8
124	6.7	3.3	5.7	2.1
125	7.2	3.2	6.0	1.8
126	6.2	2.8	4.8	1.8
127	6.1	3.0	4.9	1.8
128	6.4	2.8	5.6	2.1
129	7.2	3.0	5.8	1.6
130	7.4	2.8	6.1	1.9
131	7.9	3.8	6.4	2.0
132	6.4	2.8	5.6	2.2
133	6.3	2.8	5.1	1.5
134	6.1	2.6	5.6	1.4
135	7.7	3.0	6.1	2.3
136	6.3	3.4	5.6	2.4
137	6.4	3.1	5.5	1.8
138	6.0	3.0	4.8	1.8
139	6.9	3.1	5.4	2.1
140	6.7	3.1	5.6	2.4
141	6.9	3.1	5.1	2.3
142	5.8	2.7	5.1	1.9
143	6.8	3.2	5.9	2.3
144	6.7	3.3	5.7	2.5
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

In [14]:
```
df['target'] = iris['target']
```

In [15]:
```
df
```

Out[15]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0
5	5.4	3.9	1.7	0.4	0
6	4.6	3.4	1.4	0.3	0
7	5.0	3.4	1.5	0.2	0
8	4.4	2.9	1.4	0.2	0
9	4.9	3.1	1.5	0.1	0
10	5.4	3.7	1.5	0.2	0
11	4.8	3.4	1.6	0.2	0
12	4.8	3.0	1.4	0.1	0
13	4.3	3.0	1.1	0.1	0
14	5.8	4.0	1.2	0.2	0
15	5.7	4.4	1.5	0.4	0
16	5.4	3.9	1.3	0.4	0
17	5.1	3.5	1.4	0.3	0
18	5.7	3.8	1.7	0.3	0
19	5.1	3.8	1.5	0.3	0
20	5.4	3.4	1.7	0.2	0
21	5.1	3.7	1.5	0.4	0
22	4.6	3.6	1.0	0.2	0
23	5.1	3.3	1.7	0.5	0
24	4.8	3.4	1.9	0.2	0
25	5.0	3.0	1.6	0.2	0
26	5.0	3.4	1.6	0.4	0
27	5.2	3.5	1.5	0.2	0
28	5.2	3.4	1.4	0.2	0
29	4.7	3.2	1.6	0.2	0
...	...	...	...	...	...
120	6.9	3.2	5.7	2.3	2
121	5.6	2.8	4.9	2.0	2
122	7.7	2.8	6.7	2.0	2

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
123	6.3	2.7	4.9	1.8	2
124	6.7	3.3	5.7	2.1	2
125	7.2	3.2	6.0	1.8	2
126	6.2	2.8	4.8	1.8	2
127	6.1	3.0	4.9	1.8	2
128	6.4	2.8	5.6	2.1	2
129	7.2	3.0	5.8	1.6	2
130	7.4	2.8	6.1	1.9	2
131	7.9	3.8	6.4	2.0	2
132	6.4	2.8	5.6	2.2	2
133	6.3	2.8	5.1	1.5	2
134	6.1	2.6	5.6	1.4	2
135	7.7	3.0	6.1	2.3	2
136	6.3	3.4	5.6	2.4	2
137	6.4	3.1	5.5	1.8	2
138	6.0	3.0	4.8	1.8	2
139	6.9	3.1	5.4	2.1	2
140	6.7	3.1	5.6	2.4	2
141	6.9	3.1	5.1	2.3	2
142	5.8	2.7	5.1	1.9	2
143	6.8	3.2	5.9	2.3	2
144	6.7	3.3	5.7	2.5	2
145	6.7	3.0	5.2	2.3	2
146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

150 rows × 5 columns

In [16]:
```
df.head()
```

Out[16]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0

In [17]:
```
df.tail()
```

Out[17]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
145	6.7	3.0	5.2	2.3	2
146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

In [18]:
```
df.sample(5)
```

Out[18]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
117	7.7	3.8	6.7	2.2	2
68	6.2	2.2	4.5	1.5	1
101	5.8	2.7	5.1	1.9	2
26	5.0	3.4	1.6	0.4	0
133	6.3	2.8	5.1	1.5	2

In [19]:
```
df['target']
```

Out[19]:
```
0      0
1      0
2      0
3      0
4      0
5      0
6      0
7      0
8      0
9      0
10     0
11     0
12     0
13     0
14     0
15     0
16     0
17     0
18     0
19     0
20     0
21     0
22     0
23     0
24     0
25     0
26     0
27     0
28     0
29     0
      ..
120    2
121    2
122    2
123    2
124    2
125    2
126    2
127    2
128    2
129    2
130    2
131    2
132    2
133    2
134    2
135    2
136    2
137    2
138    2
139    2
140    2
141    2
142    2
```

```
143    2
144    2
145    2
146    2
147    2
148    2
149    2
Name: target, Length: 150, dtype: int32
```

In [20]:
```
df['target'].unique()
```

Out[20]:
```
array([0, 1, 2], dtype=int64)
```

In [21]:
```
## No of sample in the dataset
df.shape
```

Out[21]:
```
(150, 5)
```

In [23]:
```
## is there  any missing values?
df.isna().sum()
```

Out[23]:
```
sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
target               0
dtype: int64
```

In [ ]:
```
## is there any invalid values
# 1.all featutres should contain only numbers
# 2.target only contains integers
```

In [24]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
sepal length (cm)    150 non-null float64
sepal width (cm)     150 non-null float64
petal length (cm)    150 non-null float64
petal width (cm)     150 non-null float64
target               150 non-null int32
dtypes: float64(4), int32(1)
memory usage: 5.4 KB
```

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

Out[25]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
sepal length (cm)	1.000000	-0.109369	0.871754	0.817954	0.782561
sepal width (cm)	-0.109369	1.000000	-0.420516	-0.356544	-0.419446
petal length (cm)	0.871754	-0.420516	1.000000	0.962757	0.949043
petal width (cm)	0.817954	-0.356544	0.962757	1.000000	0.956464
target	0.782561	-0.419446	0.949043	0.956464	1.000000

In [27]:
```
## sepal length (cm)petal length (cm)petal width (cm)
```

In [31]:
```
X = df[['sepal length (cm)','petal length (cm)','petal width (cm)']]
y = df['target']
```

In [35]:
```
from sklearn.linear_model import LogisticRegression
```

In [33]:
```
logisticObject = LogisticRegression()
logisticObject.fit(X,y)
```

Out[33]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

In [34]:
```
logisticObject.score(X,y)
```

Out[34]:
```
0.9466666666666667
```

In [36]:
```
## Error metrics
from sklearn.metrics import confusion_matrix
```

In [37]:
```
y_actual = ['cat','ant','cat','cat','ant','bird']
y_pred = ['ant','ant','cat','cat','ant','cat']
```

In [38]:
```
confusion_matrix(y_actual,y_pred,labels=['ant','bird','cat'])
```

Out[38]:
```
array([[2, 0, 0],
       [0, 0, 1],
       [1, 0, 2]], dtype=int64)
```

In [ ]:
```
#   left to right predicted values top to bottom actual values
```