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Scikit-learn/sklearn

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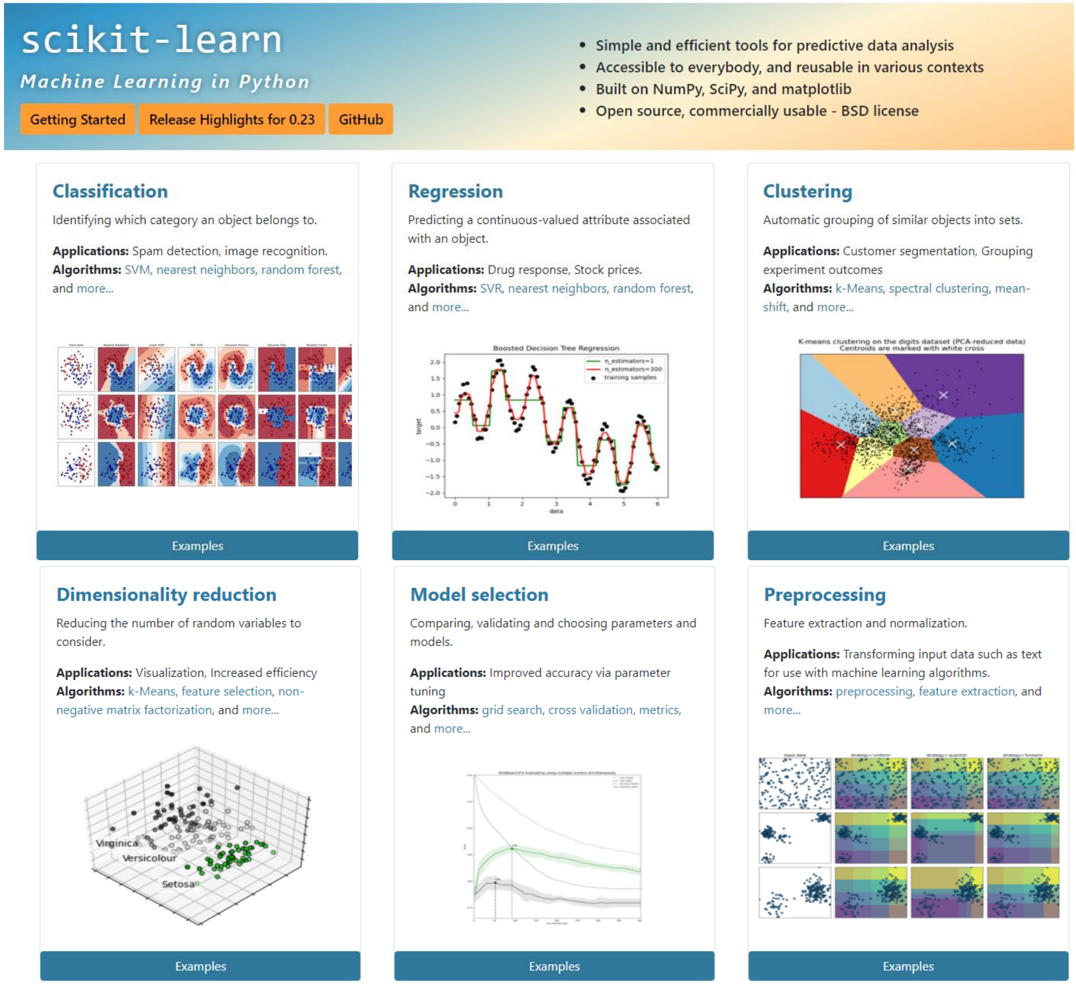
Topics

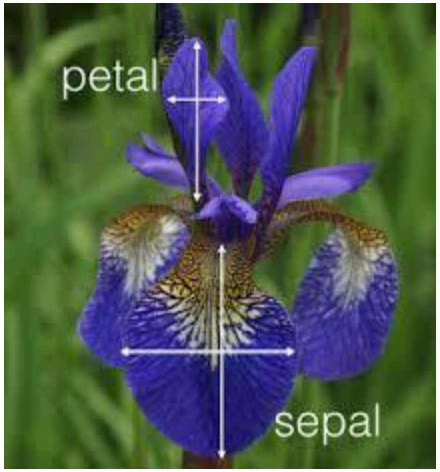
- Sklearn
- Iris classification in sklearn (binary classification)
- Plot of decision boundary
- Split data into training and testing
- A perceptron for multiclass classification
- Logistic regression classifier
- Logistic regression for IRIS dataset
- Separable and inseparable dataset
- Confusion matrix
- Multilayer neural network (MLP)
- MLP classifier in sklearn
- MLP classifier in Keras

Scikit-learn

- Is a Python machine learning library offering a vast collection of machine learning algorithms from data processing, model selection, model training, fine tune, and evaluation.
- **sci**Py Tool**kit** developed by Google.
- https://scikit-learn.org/stable/



Iris dataset classification



	A	B	C	D	E
1	Sepal Length	Sepal Width	Petal Length	Petal Width	Class
2	5.1	3.5	1.4	0.2	Iris-setosa
3	4.9	3	1.4	0.2	Iris-setosa
4	4.7	3.2	1.3	0.2	Iris-setosa
5	4.6	3.1	1.5	0.2	Iris-setosa
6	5	3.6	1.4	0.2	Iris-setosa
7	5.4	3.9	1.7	0.4	Iris-setosa
8	4.6	3.4	1.4	0.3	Iris-setosa
9	5	3.4	1.5	0.2	Iris-setosa
10	4.4	2.9	1.4	0.2	Iris-setosa
11	4.9	3.1	1.5	0.1	Iris-setosa
12	5.4	3.7	1.5	0.2	Iris-setosa
13	4.8	3.4	1.6	0.2	Iris-setosa
14	4.8	3	1.4	0.1	Iris-setosa
15	4.3	3	1.1	0.1	Iris-setosa
16	5.8	4	1.2	0.2	Iris-setosa
17	5.7	4.4	1.5	0.4	Iris-setosa
18	5.4	3.9	1.3	0.4	Iris-setosa
19	5.1	3.5	1.4	0.3	Iris-setosa
20	5.7	3.8	1.7	0.3	Iris-setosa
21	5.1	3.8	1.5	0.3	Iris-setosa
22	5.4	3.4	1.7	0.2	Iris-setosa
23	5.1	3.7	1.5	0.4	Iris-setosa
24	4.6	3.6	1	0.2	Iris-setosa
25	5.1	3.3	1.7	0.5	Iris-setosa

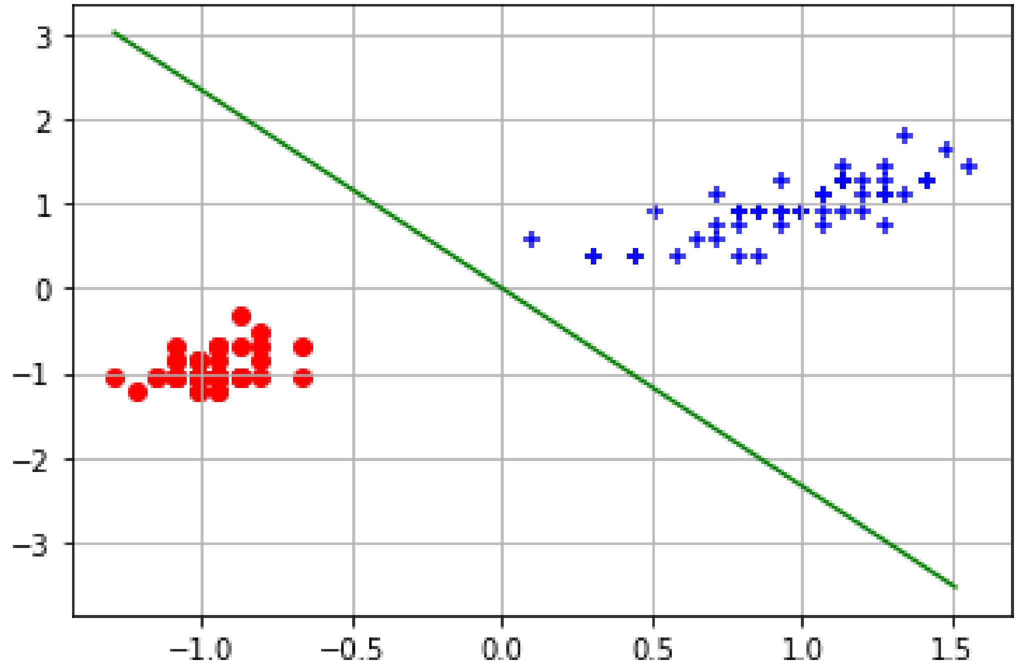
Implementation

```
# implement a perceptron to classifiy iris using Scikit-Learn
import numpy as np
from sklearn import datasets
import matplotlib.pyplot as plt
from sklearn.linear_model import Perceptron
from sklearn.preprocessing import StandardScaler
```

```
iris = datasets.load_iris()
x = iris.data[0:100,[2,3]]     # petal length and petal width
y = iris.target[0:100]

print(x[0:5,:])
print('Class labels:', np.unique(y))
labels = ['setosa', 'versicolor', 'virginica']

# standarization
sc = StandardScaler()
sc.fit(x)   # to estimate mean and standard deviation
xstd = sc.transform(x)
print(xstd[0:5,:])
```

```
# import a model
#!pip install ....
model = Perceptron(max_iter=100, eta0=0.01, random_state=1)
model.fit(xstd, y)
y_pred=model.predict(x)

print(model.coef_, model.intercept_)

error=np.mean((y-y_pred)**2)
print(error)
```

```
#plot decision line
plt.scatter(xstd[y==0,0],xstd[y==0,1], color='red', marker='o',label=labels[0])
plt.scatter(xstd[y==1,0],xstd[y==1,1], color='blue', marker='+',label=labels[1])

xx = np.arange(xstd[:,0].min(),xstd[:,0].max(),0.1)
yy = -model.coef_[0,0]/model.coef_[0,1] * xx - model.intercept_/model.coef_[0,1]
plt.plot(xx,yy,'g-')
plt.grid()
plt.show()
```

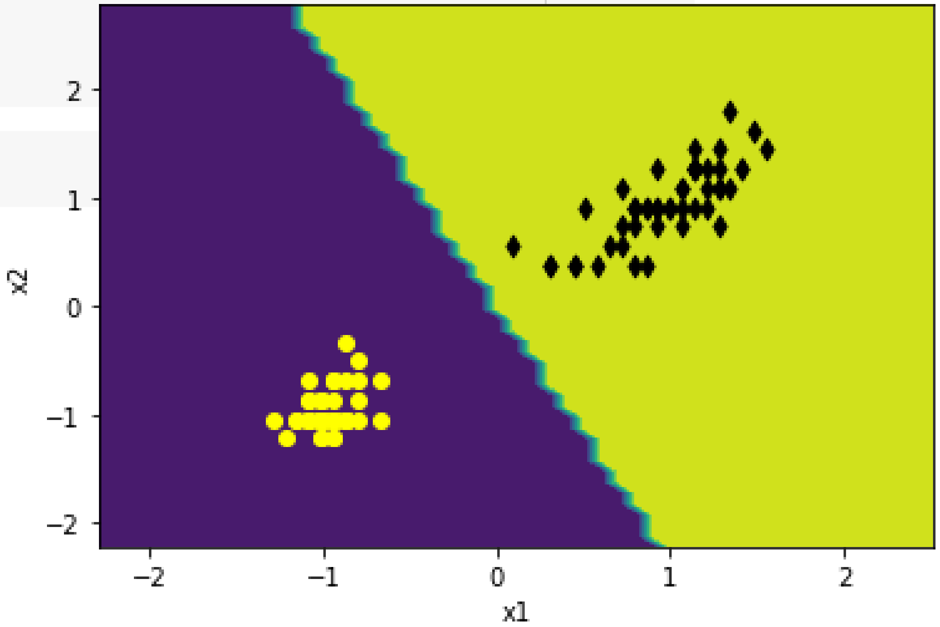


https://github.com/ibribr/ML/blob/master/perceptron_iris_scilkit.ipynb

Plot decision region

```
# Another way for plotting the decision line/region
def plot_decision_region(x, y):
  x1 = np.arange(x[:,0].min()-1, x[:,0].max()+1,0.1)
  x2 = np.arange(x[:,1].min()-1,x[:,1].max()+1, 0.1)

  xg1, xg2 = np.meshgrid(x1, x2)

  #print(xg2.flatten().T) # ravel()/flatten() returns a flattened one-dimensional array
  z = model.predict(np.array([xg1.ravel(), xg2.ravel()]).T)

  plt.contourf(xg1, xg2, z.reshape(xg1.shape))

  #plot the scatter plot of the dataset
  plt.scatter(x[y==0,0],x[y==0,1],color='yellow', marker='o' )
  plt.scatter(x[y==1,0],x[y==1,1],color='black', marker='d')
  plt.xlabel('x1')
  plt.ylabel('x2')
  plt.show()
```

```
plot_decision_region(x,y)
```

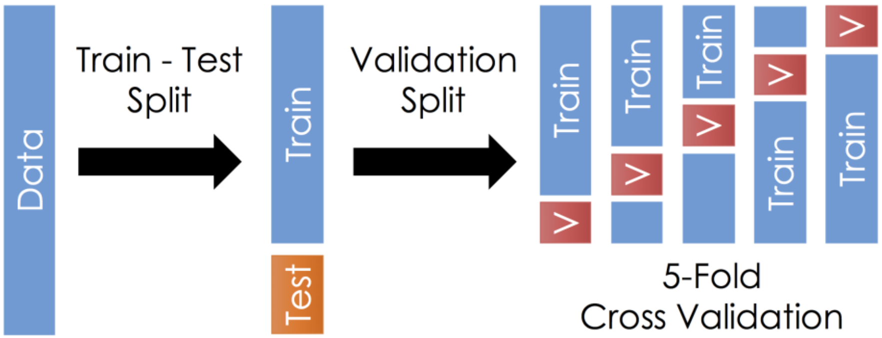


Splitting the dataset into training and testing sets

- It is important to evaluate the trained model performance on unseen data

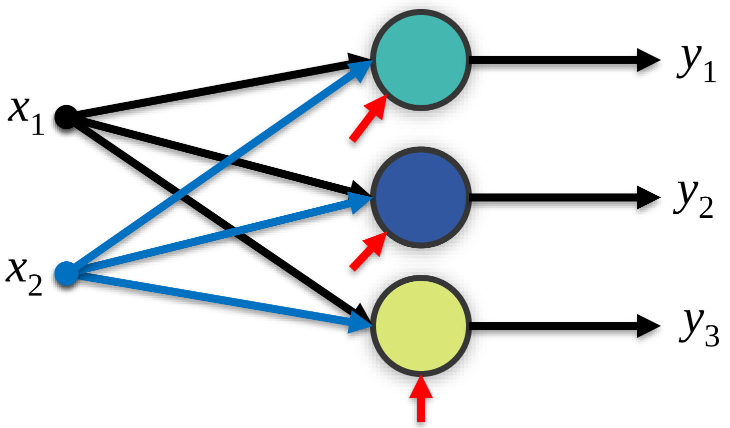
```
# split the dataset into training and testing sets using (train_test_split) function
# this function shuffels the training sets internally before splitting
from sklearn.model_selection import train_test_split

xtarin, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.3, random_state=1)
print(ytest)
print('proportion of class labels in train and test sets:\n',np.bincount(ytrain), np.bincount(ytest))
#stratify: to have the same proportional of class labels in both training and testing sets (balanced sets)
xtarin, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.3, random_state=1, stratify=y)
print('proportion of class labels in train and test sets:\n',np.bincount(ytrain), np.bincount(ytest))
```

```
[1 1 0 1 1 0 0 1 1 1 1 0 1 1 1 0 0 0 1 0 0 1 1 1 0 0 1 0 0 0]
proportion of class labels in train and test sets:
 [36 34] [14 16]
proportion of class labels in train and test sets:
 [35 35] [15 15]
```



Extending a perceptron for multiclass classification

- **Iris dataset:**
  - 2 input feature: [sepal length (cm), sepal width (cm), **petal length** (cm), and **petal width** (cm)]
  - 3 classes (**setosa**, **versicolor**, and **virginica**)



Weights		Bias
-0.00220757	-0.00237113	-0.002
0.00540865	-0.00210787	-0.002
0.00628849	0.00683785	-0.008

Implementation

```
# In this example we will use a perceptron from sklearn to classify three iris classes (setosa, versicolor, and virginica)
# upload python liberaries
import numpy as np
from sklearn import datasets
import matplotlib.pyplot as plt
```

```
# upload your iris datset
iris = datasets.load_iris()
# select two features
x = iris.data[:,[2,3]]   # petal length and petal width
y = iris.target
print(np.unique(y))
print(iris.target_names)
print(iris.feature_names)
```

```
[0 1 2]
['setosa' 'versicolor' 'virginica']
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
```

```
# standardize your feature vector
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
sc.fit(x)
xstd=sc.transform(x)
print(x[1:2,:], xstd[1:2,:])
```

```
[[1.4 0.2]] [[-1.34022653 -1.3154443 ]]
```

```
#split dataset into training and testing sets
from sklearn.model_selection import train_test_split
x = xstd
xtrain, xtest, ytrain, ytest = train_test_split(x,y,test_size=0.3, random_state=1,stratify=y)

print(np.bincount(ytrain), np.bincount(ytest))
```

```
[35 35 35] [15 15 15]
```

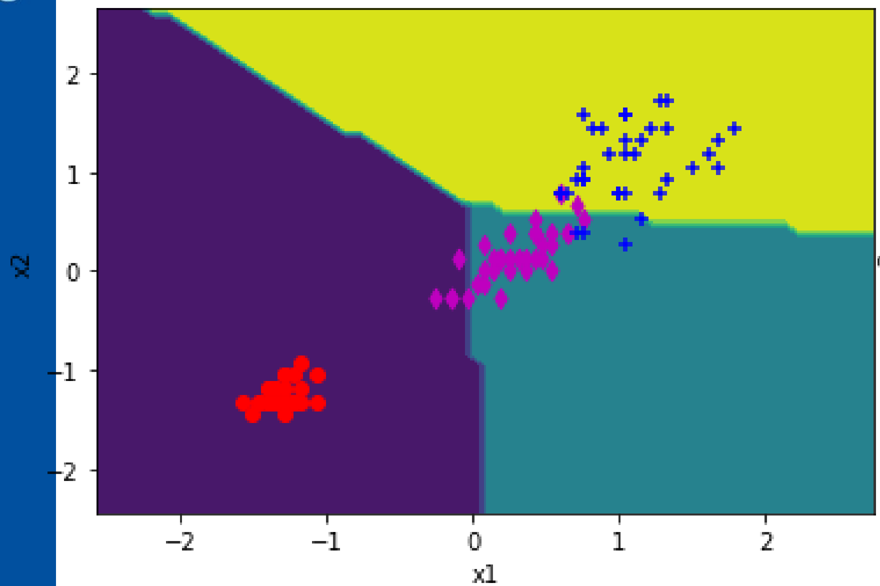
```python
# select a model for training
from sklearn.linear_model import Perceptron
model = Perceptron(max_iter=20, eta0=0.002, random_state=1)
model.fit(xtrain, ytrain)
ypred = model.predict(xtest)
missclassified = (ytest != ypred).sum()
print('missclassified samples = ', missclassified)
print('Model accuracy = ', (len(ytest)-missclassified)/len(ytest)*100)
print('Model accuracy = ', model.score(xtest, ytest)*100, '%')

print('weights: \n', model.coef_)
print('bias    : \n', model.intercept_)
```

```
missclassified samples =  2
Model accuracy =  95.55555555555556
Model accuracy =  95.55555555555556 %
weights:
 [[-0.00220757 -0.00237113]
 [ 0.00540865 -0.00210787]
 [ 0.00628849  0.00683785]]
bias    :
 [-0.002 -0.002 -0.008]
```

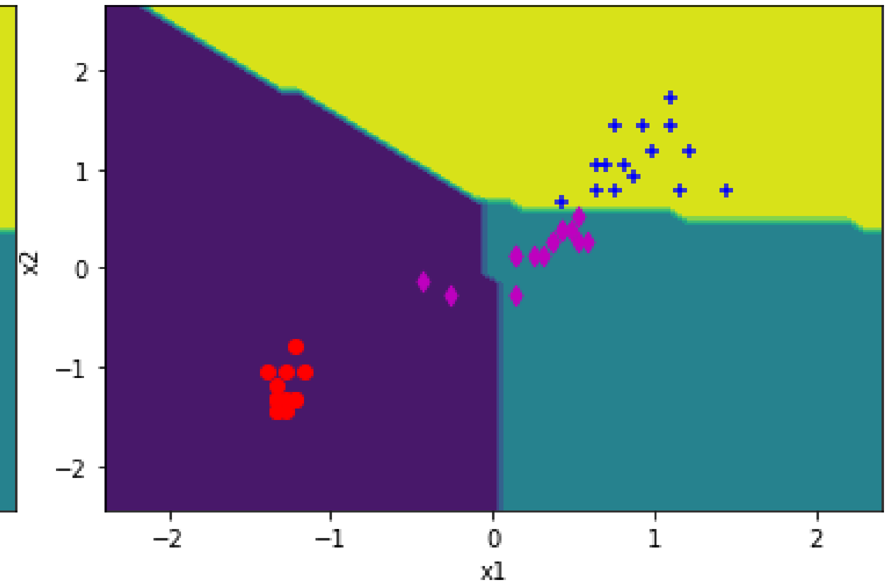
```python
# plot decision regions in 2D space
x1 = np.arange(x[:,0].min()-1, x[:,0].max()+1, 0.1)
x2 = np.arange(x[:,1].min()-1, x[:,1].max()+1, 0.1)
x1g, x2g = np.meshgrid(x1, x2)
z = model.predict(np.array([x1g.flatten(), x2g.flatten()]).T)
plt.contourf(x1g, x2g, z.reshape(x1g.shape))
plt.scatter(x[y==0,0],x[y==0,1],color='red', marker='o')
plt.scatter(x[y==1,0],x[y==1,1],color='m', marker='d')
plt.scatter(x[y==2,0],x[y==2,1],color='blue', marker='+')
plt.xlabel('x1')
plt.ylabel('x2')
plt.show()
```

Decision regions

TRAIN



TEST

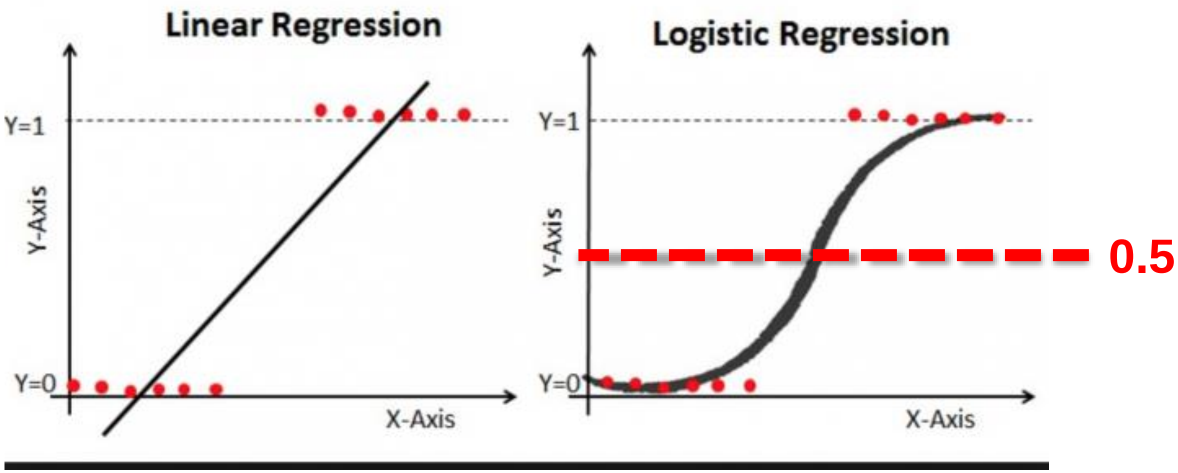


	Misclassified samples	Model accuracy
Train	11	89.52%
Test	2	95.55%

- Notes that a perceptron will never converge if the classes are not perfectly linearly separable.
- In iris dataset, there will be always at least one misclassified sample present in each epoch.

Modeling class probabilities via logistic regression

- Logistic regression is one of the most popular machine learning algorithms in industry.
- It is a classification model that performs very well for linearly separable binary classes (YES/NO, TRUE/FALSE) instead of predicting something continues.
- Instead of fitting a line to the data, logistic regression fits an ‘S’ shaped logistic function
- Although it gives the probability as a number between 0 and 1, it is usually used for classification using a threshold value.
- Examples: ham/spam email, fraudulent (yes/no) online transactions, etc.



Logistic regression

$$y \in \begin{cases} 1 & Positive\,Class\ (Yes/True) \\ 0 & Negative\,Class\ (No/False) \end{cases}$$

- It can also be extended into multiclass classification

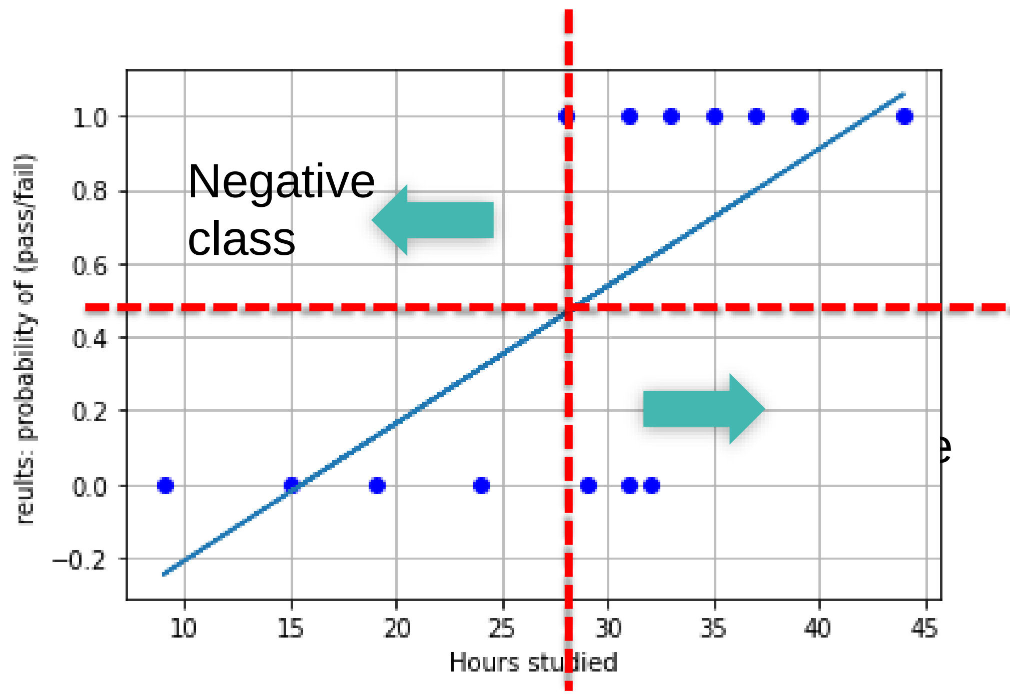
$$y \in \{0, 1, 2, 3\}$$

It is all about likelihood of an event: hours studied to pass example

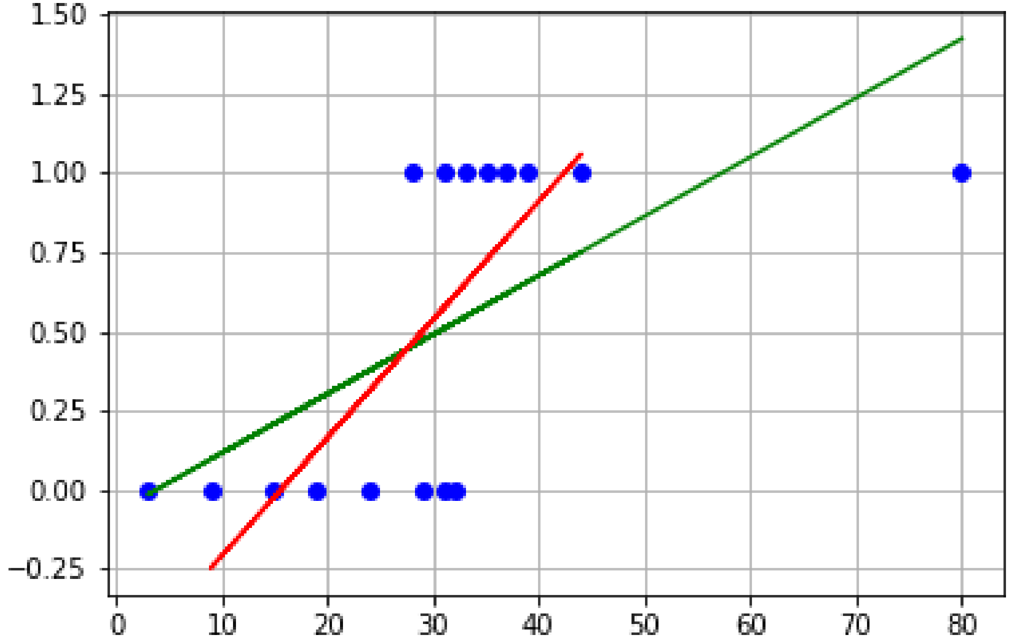
Hours studied	Exam result (1=pass, 0=fail)
29	0
15	0
33	1
28	1
39	1
44	1
31	1
19	0
9	0
24	0
32	0
31	0
37	1
35	1

- Can we fit a straight line?

```
m, b = np.polyfit(x, y, 1)
plt.plot(x, m*x+b)
plt.show()
```



Adding outliers



Fitting a logistic regression model: fit a sigmoid/logistic function

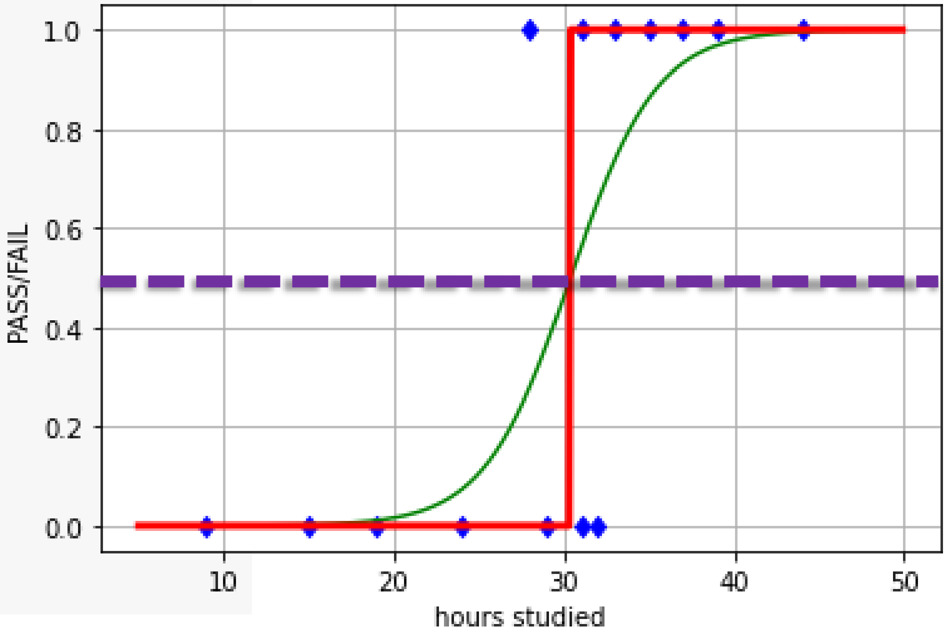
$$net = w^T x = wx + b = 0.4x - 12.05 \qquad g(net) = \frac{1}{1+e^{-net}} = \frac{e^{net}}{1+e^{net}}$$

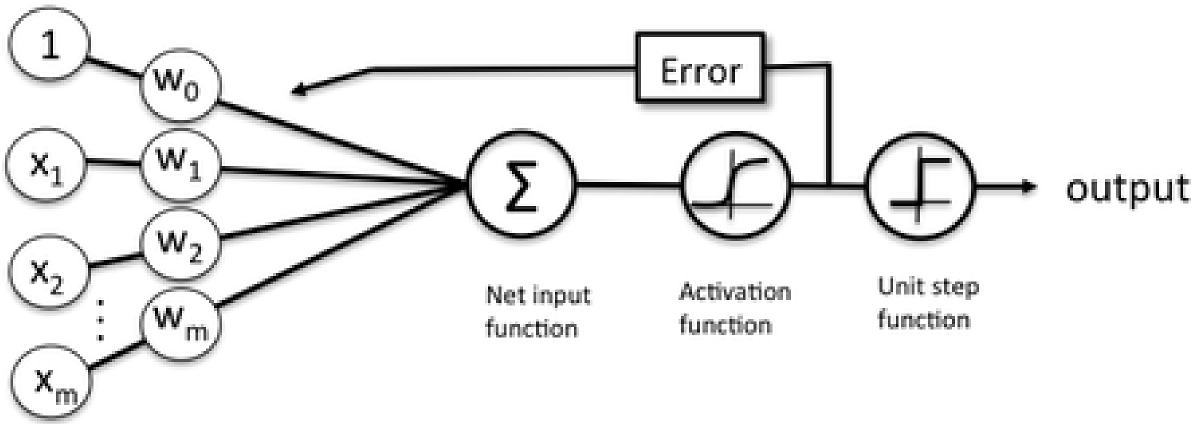
```
from sklearn.linear_model import LogisticRegression

# fit a logistic regression model
logreg = LogisticRegression()

# fit the model with data
logreg.fit(x.reshape(-1,1),y.reshape(-1,1))

print(logreg.coef_)
print(logreg.intercept_)

xx = np.arange(5, 50,0.1).reshape(-1,1)
y_pred = logreg.predict(xx)

def sig(x):
  return(np.exp(x)/(1+np.exp(x)))

net = logreg.intercept_ + logreg.coef_ * xx

plt.plot(x,y,'bd')
plt.plot(xx, sig(net), 'g-')
plt.plot(xx,y_pred,'r-',LineWidth=3.0)
plt.grid()

plt.show()
```

Hypothesis:

$$y = 1 \quad when \quad g(w^T x) \geq 0.5$$

$$y = 0 \quad when \quad g(w^T x) < 0.5$$

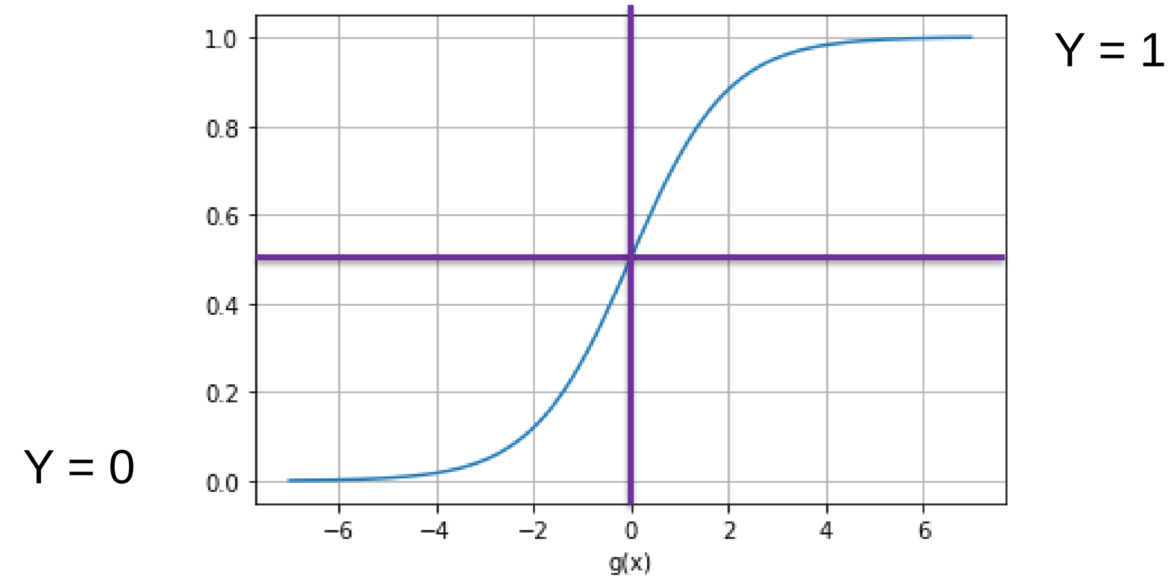




Schematic of a logistic regression classifier.

https://github.com/ibribr/ML/blob/master/logistic_regression.ipynb

Decision boundary



$$p(y=1)+p(y=0)=1$$

$$p(y=1)=1-p(y=0)$$

$$y=g(x)\rightarrow 1 \;\; as \;\; x\rightarrow\infty (1/(1+0)=1)$$

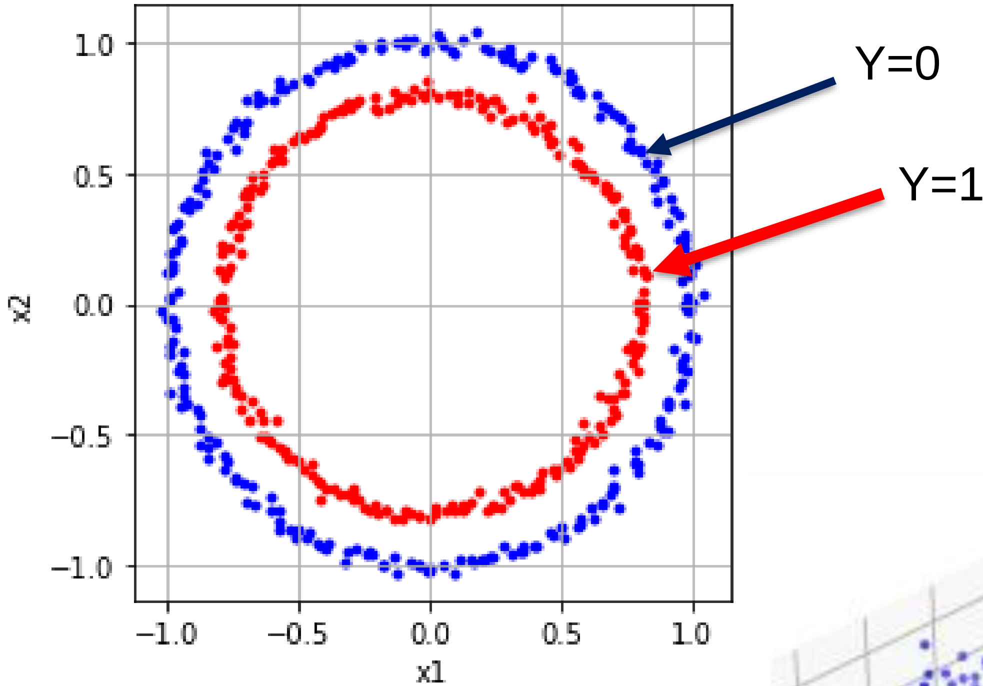
$$y=g(x)\rightarrow 0 \;\; as \;\; x\rightarrow -\infty \; (1/(1+\infty)=0)$$

Hypothesis:

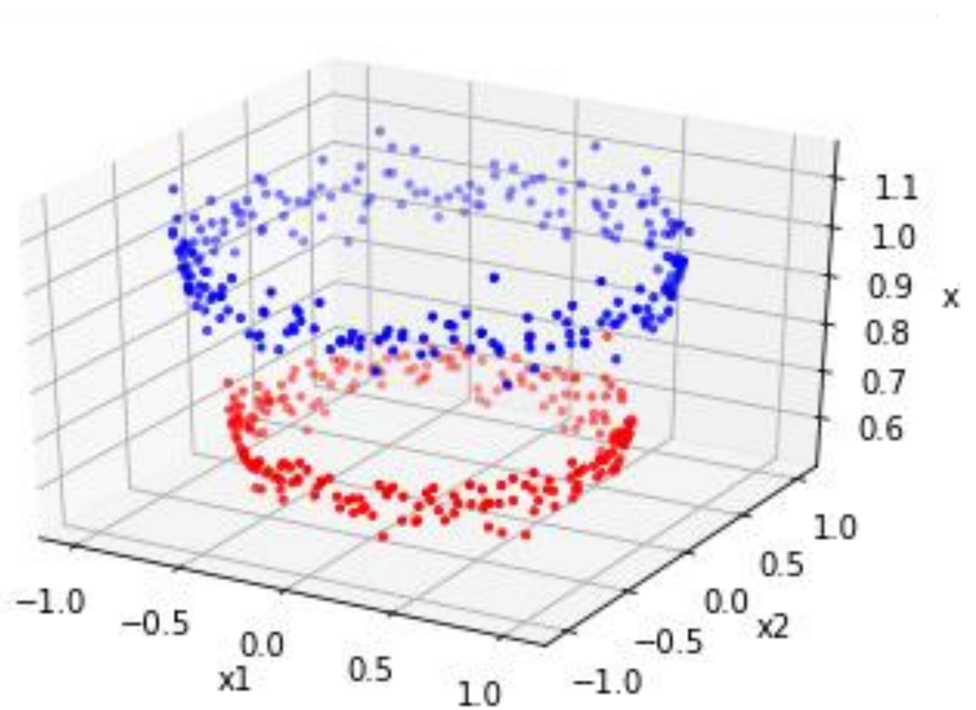
$$y=1 \quad when \quad g(w^T x)\geq 0.5 \rightarrow w^T x \geq 0$$

$$y=0 \quad when \quad g(w^T x)< 0.5 \rightarrow w^T x < 0$$

Linearly inseparable dataset



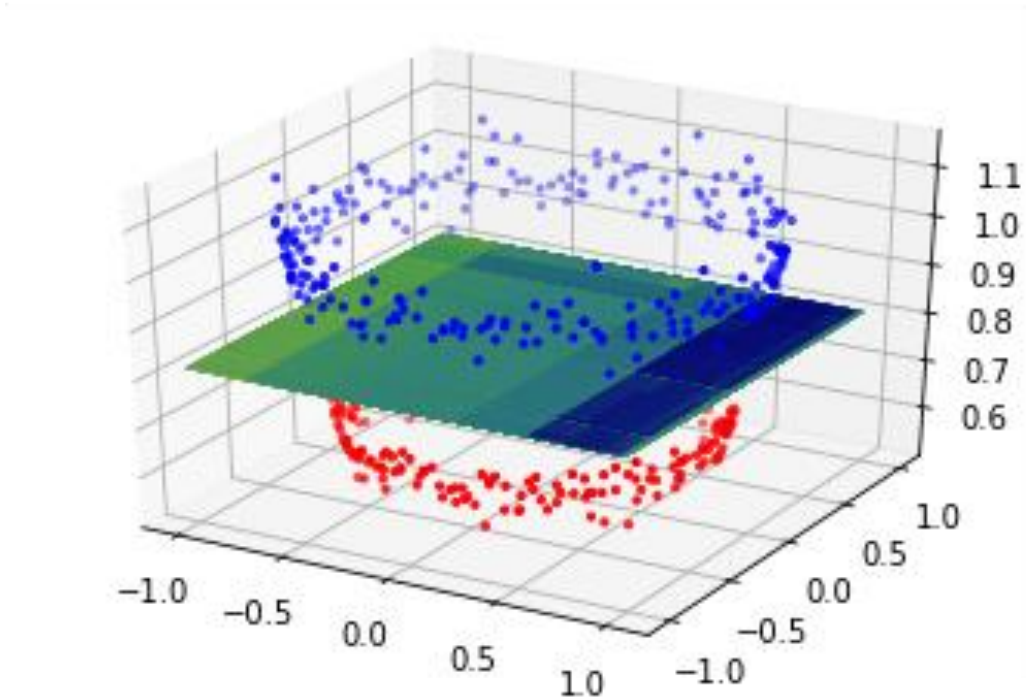
Adding a new dimension (feature) of higher order



$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$x_3 = x_1^2 + x_2^2$$

Fit a logistic regression model



$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$x_3 = x_1^2 + x_2^2$$

$$net = w_1 x_1 + w_2 x_2 + w_3 x_3 + b$$

https://github.com/ibribr/ML/blob/master/non_seprable_dataset.ipynb

Logistic regression: Iris example

```
# implement a perceptron to classifiy iris using Scikit-Learn
import numpy as np
from sklearn import datasets
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
```

```
iris = datasets.load_iris()
x = iris.data
y = iris.target

print(x[0:5,:])
print('Class labels:', np.unique(y))
labels = ['setosa', 'versicolor', 'virginica']

# standarization
sc = StandardScaler()
sc.fit(x)   # to estimate mean and standard deviation
x = sc.transform(x)
```

```
[[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]]
Class labels: [0 1 2]
```

```
# import a model
#!pip install ....
model = LogisticRegression(C=1, random_state=1)
model.fit(x, y)
y_pred=model.predict(x)

print(model.coef_, model.intercept_)

error=np.mean((y-y_pred)**2)
print(error)

print(np.sum(y!=y_pred))
```

```
[[-1.07404149  1.16006342 -1.93062866 -1.81168873]
 [ 0.58780051 -0.36182377 -0.36346274 -0.82619289]
 [ 0.48624098 -0.79823965  2.2940914   2.63788161]] [-0.20531681  2.07486525 -1.86954844]
0.02666666666666667
4
```

https://github.com/ibribr/ML/blob/master/logistic_regresion_iris.ipynb

Assignment

- Implement logistic regression
- Convert Adaline into a logistic regression
- Training set (m-examples)

$$\left\{(x^{(1)},y^{(1)}),(x^{(2)},y^{(2)}),\cdots,(x^{(m)},y^{(m)})\right\},\ y\in\{0,1\}$$

- Hypothesis:

$$\phi_w(x)=\frac{1}{1+e^{-net}}=\frac{1}{1+e^{-w^Tx}} \qquad (notes: net = w^Tx+b=w^Tx)$$

- Cost function:

$$J(w)=\frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}\left(\phi_w(x^{(i)})-y^{(i)}\right)^2=\frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}\left(\phi(net)-y^{(i)}\right)^2$$

$$\hat{y}=\begin{cases}1 & if \quad \phi(net)\geq 0.5\\ 0 & otherwise\end{cases}=\begin{cases}1 & if \quad net=w^Tx\geq 0\\ 0 & otherwise\end{cases}$$

$$J(\phi(net),y)=\begin{cases}-\log(\phi(net)) & if \quad y=1\\ -\log(1-\phi(net)) & if \quad y=0\end{cases}$$

$$J(\phi(net),y)=-y\log(\phi(net))-(1-y)\log(1-\phi(net))$$

- Update the weights:

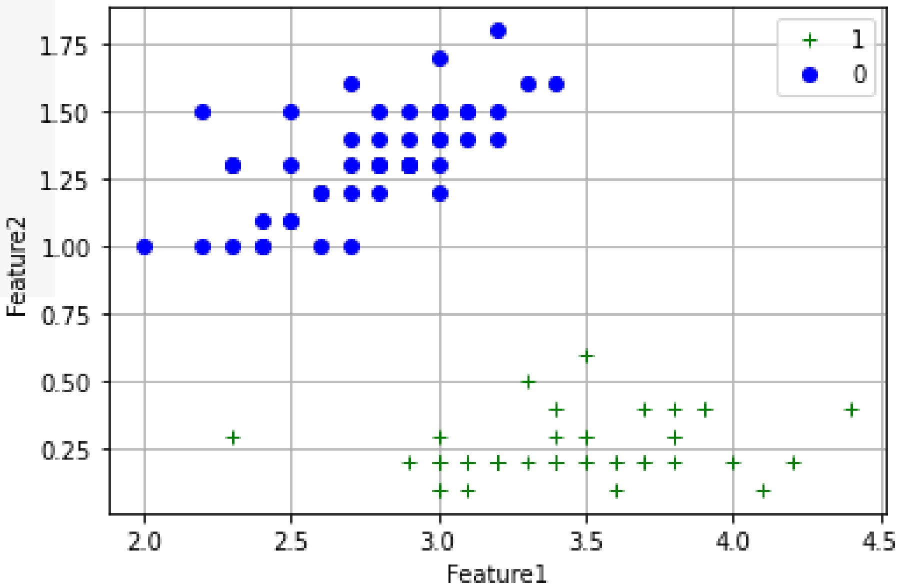
$$w_j=w_j+\Delta w_j$$

$$\Delta w_j=-\eta\frac{\partial J}{\partial w_j}=\frac{1}{m}\sum_{i=1}^{m}(y(i)-\phi(w^Tx_j^{(i)}))x_j^{(i)}$$

For Iris classification

```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
```

```python
iris = load_iris()
x = iris.data[1:100,[1,3]]
y = iris.target[1:100]
list(iris.target_names)
print(x.shape)

plt.plot(x[y==0,0],x[y==0,1],'g+',label='1')
plt.plot(x[y==1,0],x[y==1,1],'bo',label='0')
plt.legend(loc='upper right')
plt.xlabel('Feature1')
plt.ylabel('Feature2')
plt.grid()
plt.show()
```

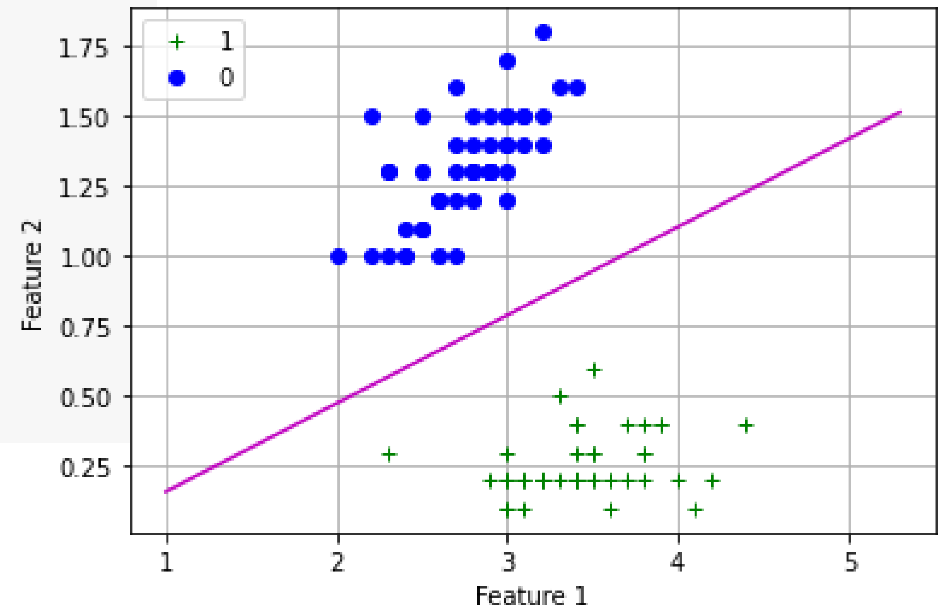


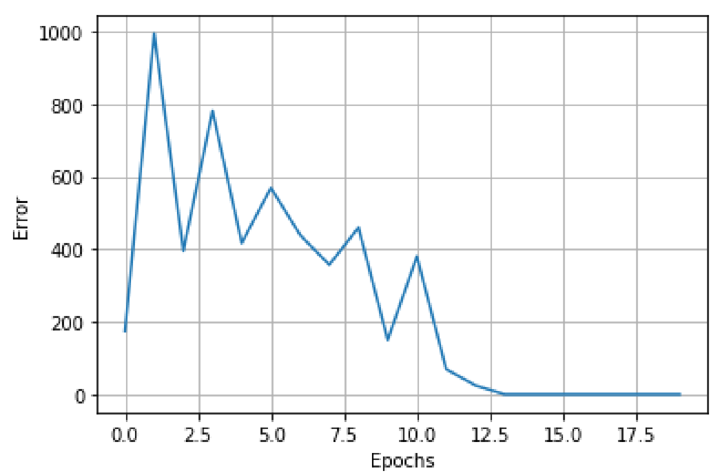
https://github.com/ibribr/ML/blob/master/logistic_regression_implementation.ipynb

A perceptron (/Adaline) with Gaussian activation function

```
# implement logistic regression classified
class logistic_regression(object):
  def __init__(self, epochs = 100, eta = 0.1, random_state=1):
    self.epochs = epochs
    self.eta = eta
    self.random_state = random_state

  def fit(self, x,y):
    np.random.RandomState(self.random_state)
    self.w_ = np.random.normal(loc = 0.0, scale = 1.0, size = x.shape[1]+1)
    print(self.w_)
    self.cost_ = []
    for i in range(self.epochs):
      net = np.dot(x,self.w_[1:])+self.w_[0]
      #print(net)
      #print(net.shape)
      output = 1./(1.+np.exp(-net))
      #print(output)
      error = (y-output)
      #print(np.dot(x.T,error))
      #print(x.T.dot(error))
      self.w_[1:]+=self.eta*np.dot(x.T,error)
      self.w_[0]+=self.eta*error.sum()
      #print(y.shape)
      #print(output.shape)
      #print(np.log(output))
      cost = error.mean()#
      cost=-np.dot(y, np.log(output))-np.dot((1-y), np.log(1-output))
      self.cost_.append(cost)
    return(self)

  def predict(self, x):
    net = np.dot(x,self.w_[1:])+self.w_[0]
    output = 1./(1.+np.exp(-net))
    return(np.where(output>=0.5,1,0))
```

```
model = logistic_regression(epochs=20, eta = 0.05)
model.fit(x,y)
y_pred = model.predict(x)
error=np.sum(np.abs(y-y_pred))
print(error)
# decision line
xx1 = np.arange(x[:,0].min()-1,x[:,0].max()+1,0.1)
xx2 = -(model.w_[1]*xx1+model.w_[0])/model.w_[2]

plt.plot(x[y_pred==0,0],x[y_pred==0,1],'g+',label='1')
plt.plot(x[y_pred==1,0],x[y_pred==1,1],'bo',label='0')
plt.legend(loc='upper left')
plt.plot(xx1, xx2, 'm-')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.grid()
plt.show()

plt.plot(range(len(model.cost_)), model.cost_)
plt.xlabel('Epochs')
plt.ylabel('Error')
plt.grid()
plt.show()
```





Confusion matrix

- A confusion matrix is a table that is often used to **describe the performance of a classification model** (or "classifier") on a set of test data for which the true values are known.

		Predicted Class		
		Positive	**Negative**	
Actual Class	**Positive**	True Positive (TP)	False Negative (FN) **Type II Error**	**Sensitivity** $\frac{TP}{(TP+FN)}$
	Negative	False Positive (FP) **Type I Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
		Precision $\frac{TP}{(TP+FP)}$	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

Basic terms of a confusion matrix (CM)

- True positives (TP): These are cases in which we predicted yes (they have the disease), and they do have the disease.
- True negatives (TN): We predicted no, and they don't have the disease.
- False positives (FP): We predicted yes, but they don't have the disease. (Also known as a "Type I error")
- False negatives (FN): We predicted no, but they do have the disease. (Also known as a "Type II error")
- Prediction error (ERR): the sum of all false predictions divided by the total number of predictions.
- Accuracy (ACC): the sum of correct (true) predictions divided by the total number of predictions.
- True positive rate (TPR)
- False positive rate (FPR)
- Precision (PRE):
- Recall (REC):

$$ERR = \frac{FP + FN}{FP + FN + TP + TN}$$

$$ACC = \frac{TP + TN}{FP + FN + TP + TN} = 1 - ERR$$

$$FPR = \frac{FP}{N} = \frac{FP}{FP + TN}, \quad TPR = \frac{TP}{P} = \frac{FP}{FN + TP}$$

$$PRE = \frac{TP}{TP + FP}, \quad REC = \frac{TP}{FN + TP}$$

Confusion matrix example

1) A binary classifier for medical testing to determine if a patient has certain disease or not (e.g. tumor diagnosis).
2) There are two possible predicted classes: "yes" and "no".

n=165	Predicted: NO	Predicted: YES	
Actual: NO	50	10	60
Actual: YES	5	100	105
	55	110	

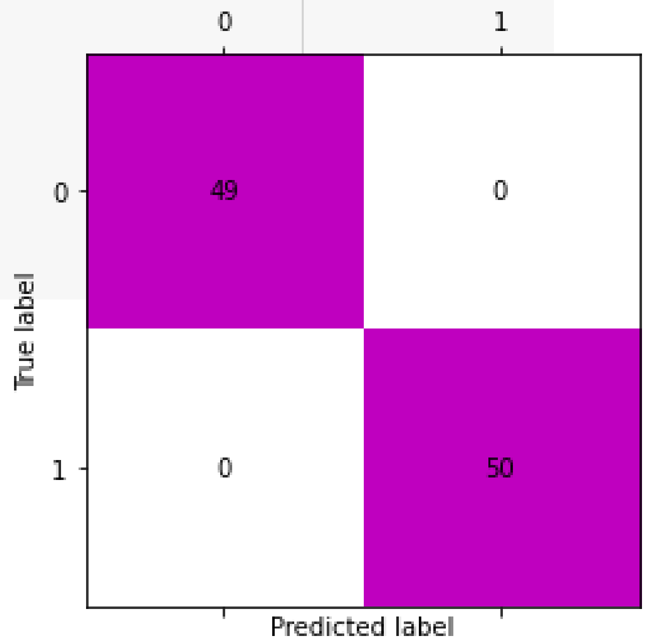
3) If we were predicting the presence of a disease, "**yes**" would mean a patient has the disease, and "**no**" would mean he/she doesn't have the disease.
4) The classifier made a total of **165** predictions (e.g., 165 patients were being tested for the presence of that disease).
5) Out of those 165 cases, the classifier predicted "**yes**" **110** times, and "**no**" **55** times.
6) In reality,105 patients in the sample have the disease, and 60 patients do not.

n=165	Predicted: NO	Predicted: YES	
Actual: NO	50	10	60
Actual: YES	5	100	105
	55	110	

- **Accuracy:** Overall, how often is the classifier correct?
  - (TP+TN)/total = (100+50)/165 = 0.91
- **Misclassification Rate:** Overall, how often is it wrong?
  - (FP+FN)/total = (10+5)/165 = 0.09
  - equivalent to 1 minus Accuracy
  - also known as "Error Rate"
- **True Positive Rate:** When it's actually yes, how often does it predict yes?
  - TP/actual yes = 100/105 = 0.95
  - also known as "Sensitivity" or "Recall"
- **False Positive Rate:** When it's actually no, how often does it predict yes?
  - FP/actual no = 10/60 = 0.17
- **True Negative Rate:** When it's actually no, how often does it predict no?
  - TN/actual no = 50/60 = 0.83
  - equivalent to 1 minus False Positive Rate
  - also known as "Specificity"
- **Precision:** When it predicts yes, how often is it correct?
  - TP/predicted yes = 100/110 = 0.91
- **Prevalence:** How often does the yes condition actually occur in our sample?
  - actual yes/total = 105/165 = 0.64

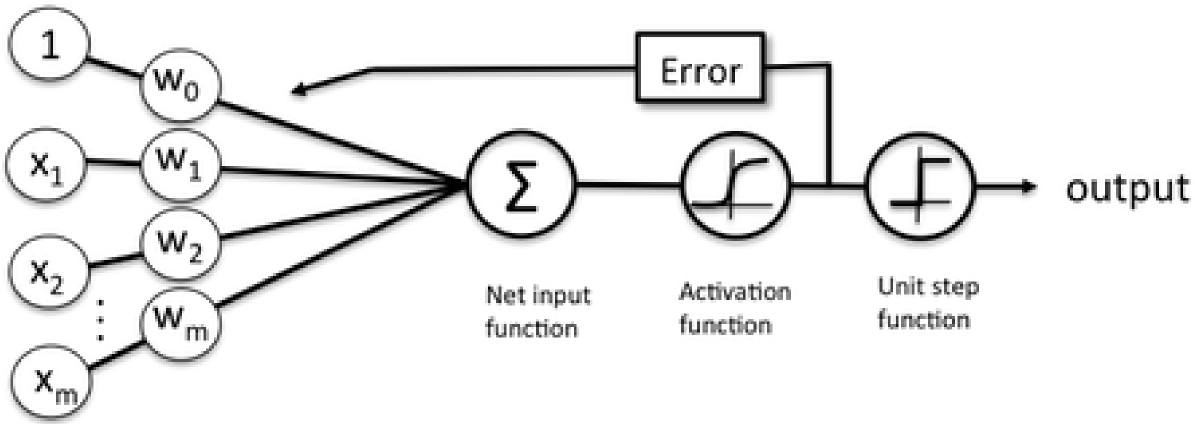
CM for iris

```
from matplotlib.colors import ListedColormap

cmap = ListedColormap(['W', 'Y', 'M'])
# Compute confusion matrix
y_true = y
class_names = iris.target_names
print(class_names[0:-1])

#cnf_matrix = confusion_matrix(y_true, y_pred, labels=[0, 1])  # 0 = 'setosa', 1 = 'versicolor'
cm = confusion_matrix(y, y_pred)  # y_true and y_pred - 0 = 'setosa', 1 = 'versicolor'
print(cm)

plt.figure()
plt.matshow(cm, cmap=cmap)
for i in range(cm.shape[0]):
  for j in range(cm.shape[1]):
    plt.text(x=j, y=i, s=cm[i,j], va='center', ha='center')
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.show()
```



https://github.com/ibribr/ML/blob/master/logistic_regression_implementation.ipynb

Recap: single-layer neural network



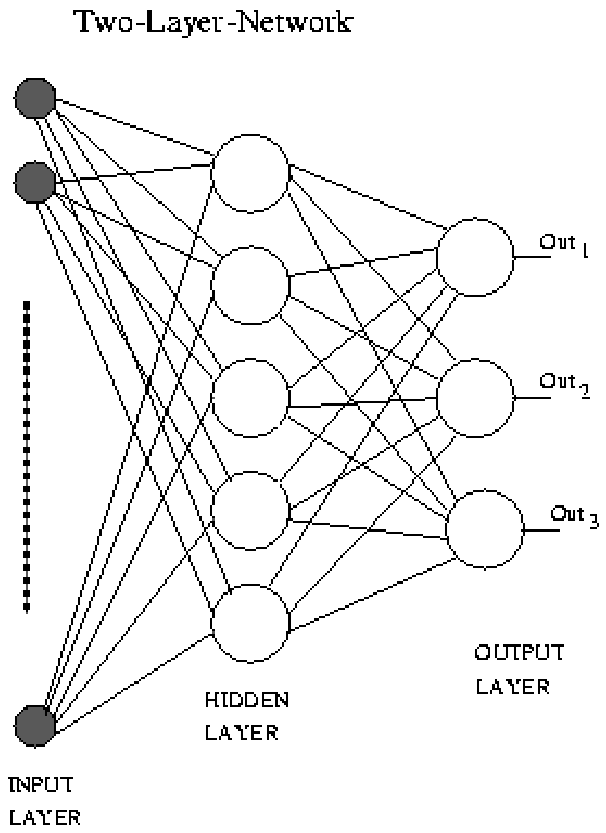
Schematic of a logistic regression classifier.

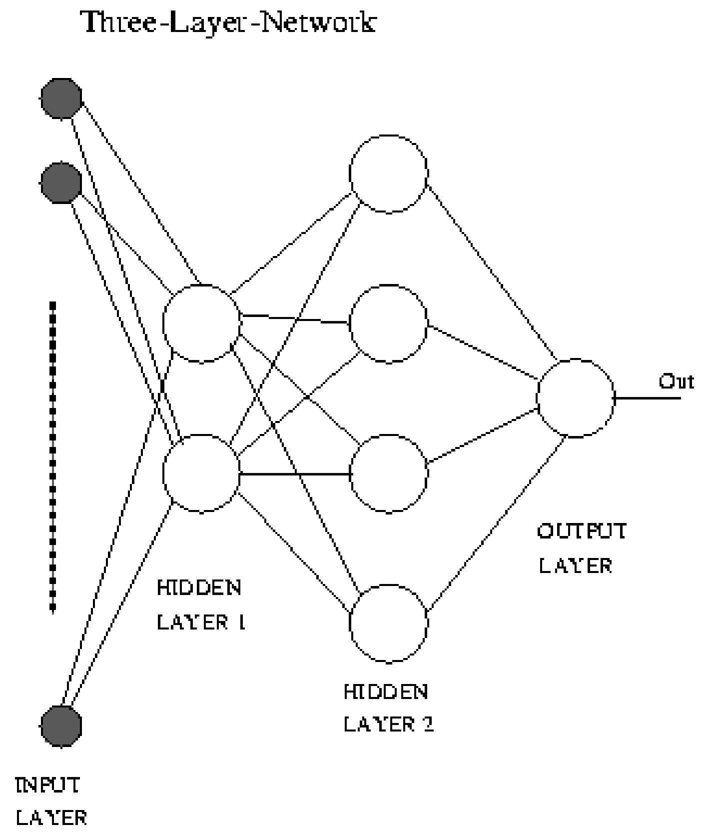
$$J(w) = \frac{1}{2}\sum_{i=1}^{m}(y(i) - \phi(w^T x_j^{(i)}))^2$$

$$w_j = w_j + \Delta w_j$$

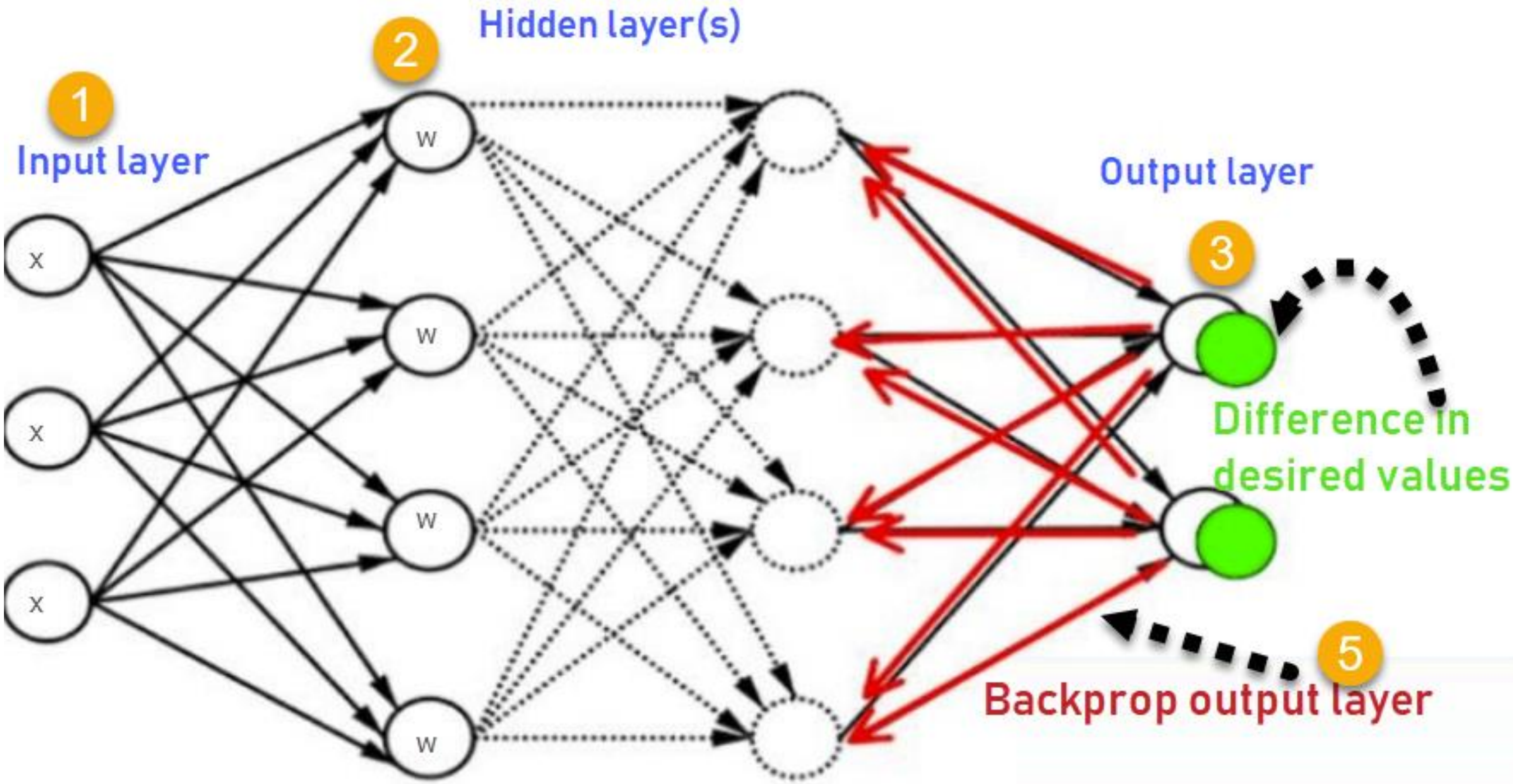
$$\Delta w_j = -\eta \frac{\partial J(w)}{\partial w_j} = \frac{1}{m}\sum_{i=1}^{m}(y(i) - \phi(w^T x_j^{(i)}))x_j^{(i)}$$

Multilayer neural network





How backpropagation works?



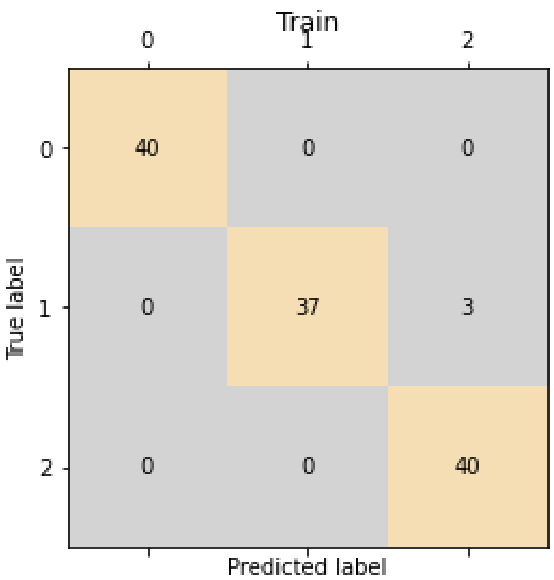
MLP in sklearn

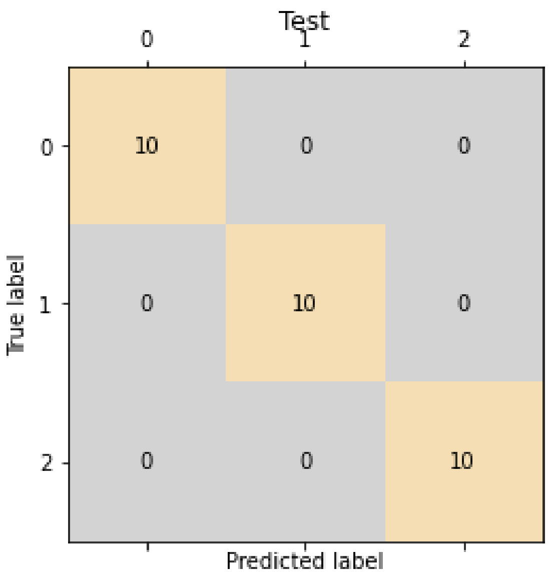
```
# MLP
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from matplotlib.colors import ListedColormap
```

```
iris = load_iris()
x = iris.data
y = iris.target
print(iris.target_names)

x_train, x_test, y_train, y_test = train_test_split(x, y, stratify=y,random_state=1,test_size=0.2)
np.bincount(y), np.bincount(y_train), np.bincount(y_test)
```

https://github.com/ibribr/ML/blob/master/MLP_sklearn.ipynb

```python
mlp =MLPClassifier(solver='sgd', random_state=0, hidden_layer_sizes=[5], alpha = 0.5,max_iter=1000)
# optimizer = 'lbfgs': quasi-Newton methods, 'sgd': stochastic gradient descent, and 'adam': stochastic gradient-based optimizer
mlp.fit(x_train, y_train)
y_pred = mlp.predict(x_test)
print(np.sum(y_test!=y_pred)/len(y_test)*100)

#confusion matrix
def cm(y_test, y_pred):
  cm = confusion_matrix(y_test, y_pred)
  cmap = ListedColormap(['lightgrey', 'silver', 'ghostwhite', 'lavender', 'wheat'])
  cm = confusion_matrix(y_test, y_pred)

  plt.figure()
  plt.matshow(cm, cmap=cmap)
  for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
      plt.text(x=j, y=i, s=cm[i,j], va='center', ha='center')
  plt.xlabel('Predicted label')
  plt.ylabel('True label')
  plt.show()

cm(y_test, mlp.predict(x_test))
cm(y_train, mlp.predict(x_train))
```





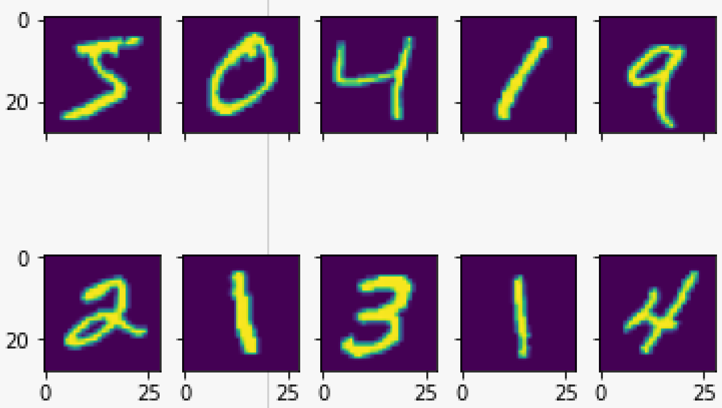
MLP for MNIST dataset

- The MNIST database of handwritten digits has a training set of 60,000 examples, and a test set of 10,000 examples.
- The digits have been size-normalized and centered in a fixed-size image.
- It is a good database for people who want to try learning techniques and pattern recognition methods on real-world data while spending minimal efforts on preprocessing and formatting.
- Each digit is 28x28 pixels gray image.

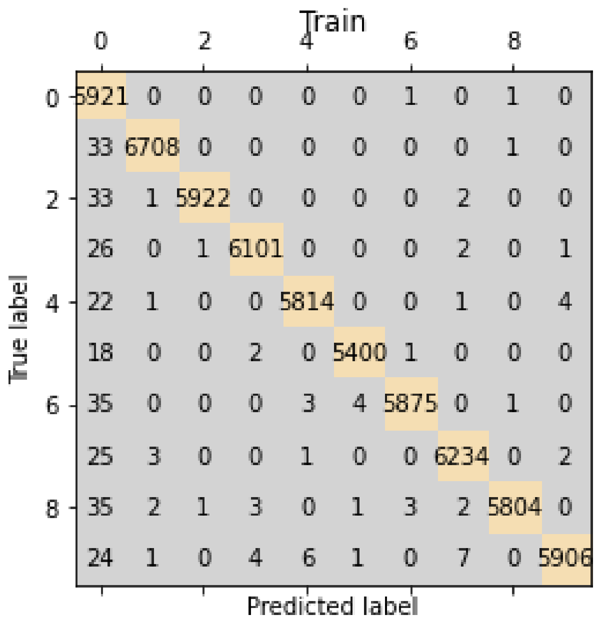
MLP Classifier

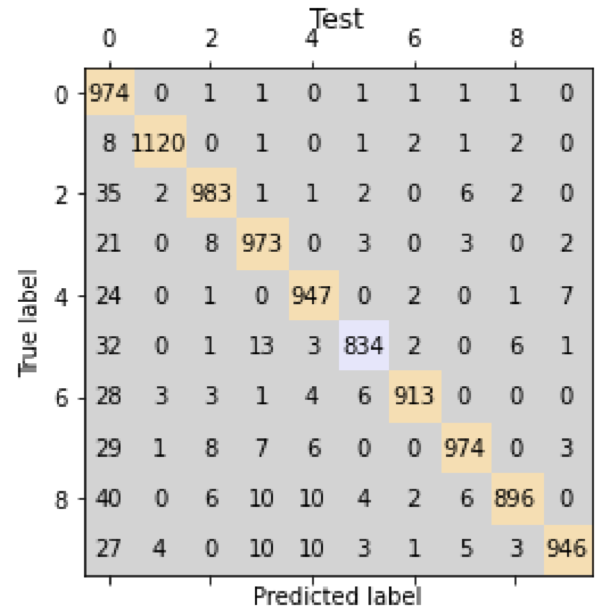
```
# MLP for MNIST
import numpy as np
import matplotlib.pyplot as plt
from keras.datasets import mnist
from keras.utils import to_categorical
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
from matplotlib.colors import ListedColormap
```

```
(x_train, y_train), (x_test, y_test)=mnist.load_data()  #60000 samples for training, 10000 samples for testing

print('train:', x_train.shape, y_train.shape)
print('Test set:', x_test.shape, y_test.shape)

# visualize some
fig, ax = plt.subplots(2,5,sharex=True,sharey=True)
ax = ax.flatten()
for i in range(10):
  ax[i].imshow(x_train[i,:])
plt.show()

# prepare the data for training
x_train = x_train.reshape(60000,28*28)
x_train = x_train.astype('float32')/255
x_test = x_test.reshape(10000,28*28)
x_test = x_test.astype('float32')/255
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
```



```
mlp = MLPClassifier(solver='sgd', activation='logistic',alpha=1e-4,hidden_layer_sizes=(100,30),
                    random_state=1, max_iter=100,verbose=True, learning_rate_init=.1, tol=1e-4)
mlp.fit(x_train, y_train)

print("Training set score: %f" % mlp.score(x_train, y_train))
print("Test set score: %f" % mlp.score(x_test, y_test))

y_pred = mlp.predict(x_test)

cmap = ListedColormap(['lightgrey', 'silver', 'ghostwhite', 'lavender', 'wheat'])

#confusion matrix
def cm(y_test, y_pred, title):
  cm = confusion_matrix(y_test, y_pred)

  plt.figure()
  plt.matshow(cm, cmap=cmap)

  for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
      plt.text(x=j, y=i, s=cm[i,j], va='center', ha='center')

  plt.title(title)
  plt.xlabel('Predicted label')
  plt.ylabel('True label')
  plt.show()

cm(y_train.argmax(1), mlp.predict(x_train).argmax(1), title='Train')
cm(y_test.argmax(1), mlp.predict(x_test).argmax(1), title='Test')
```





	Training	Testing
Accuracy	99.31	94.84

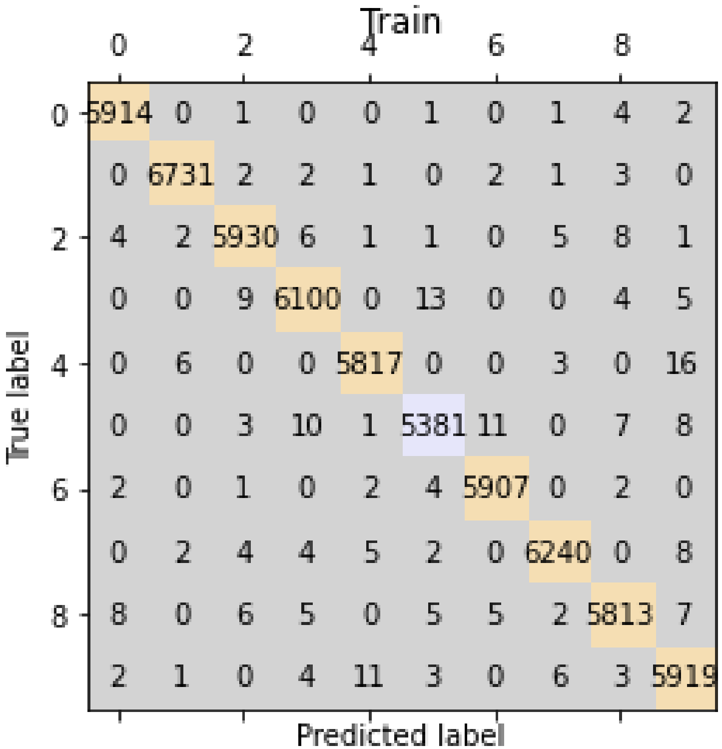
https://github.com/ibribr/ML/blob/master/MNIST_MLP.ipynb

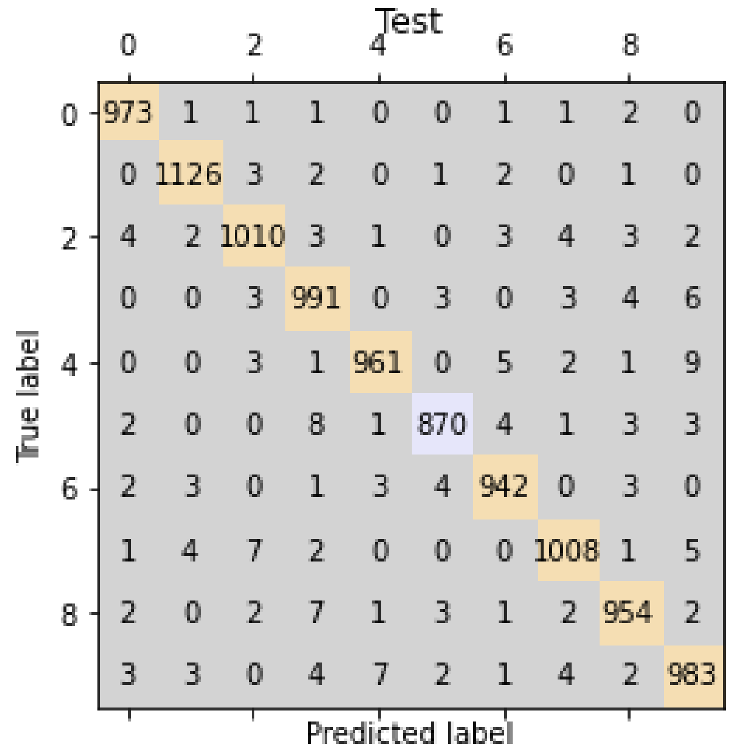
MNIST using Keras

```
# MLP for MNIST
import numpy as np
import matplotlib.pyplot as plt
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense
from keras.utils import to_categorical
from sklearn.metrics import confusion_matrix
```

```
# classification model
input_shape=x_train.shape[1]
num_classes = y_train.shape[1]
model = Sequential()
model.add(Dense(350, activation='relu', input_shape=(28*28,)))
model.add(Dense(50, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model.fit(x_train, y_train, epochs=100, batch_size=512, verbose=1, validation_split=0.2)

# Test the model after training
test_results = model.evaluate(x_test, y_test, verbose=1)

print(f'Test results \n - Loss    : {test_results[0]: 0.3f}  \n - Accuracy: {test_results[1]: 0.3f}')
```


https://github.com/ibribr/ML/blob/master/MNIST_keras.ipynb





	Loss	Accuracy
Categorical cross entropy	0.122	0.982

Saving and loading models

- Models take a long time to train.
- It is required to save trained models, so we do not have to train them every time.