



# Linear Classifier

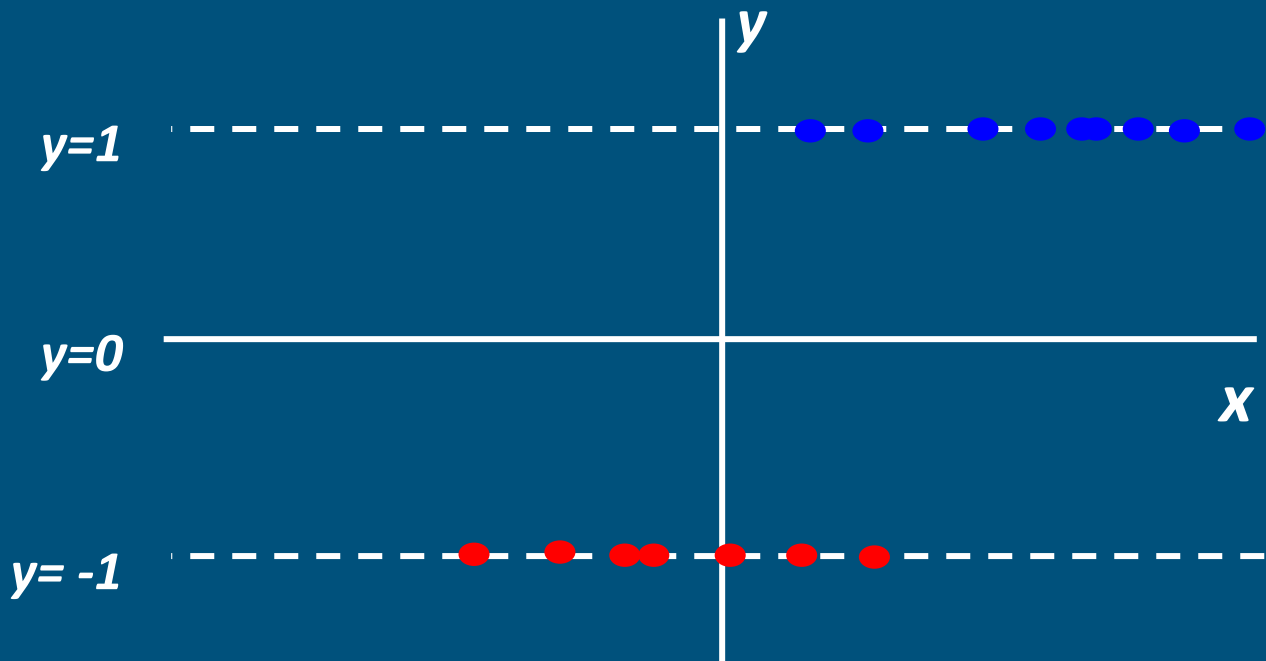


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# Linear Classifier for Binary class

- Let's simplify the data by assuming:
  - $x$  is a scalar. (a single feature)
  - There are only two classes,  $y=+1$  and  $y=-1$

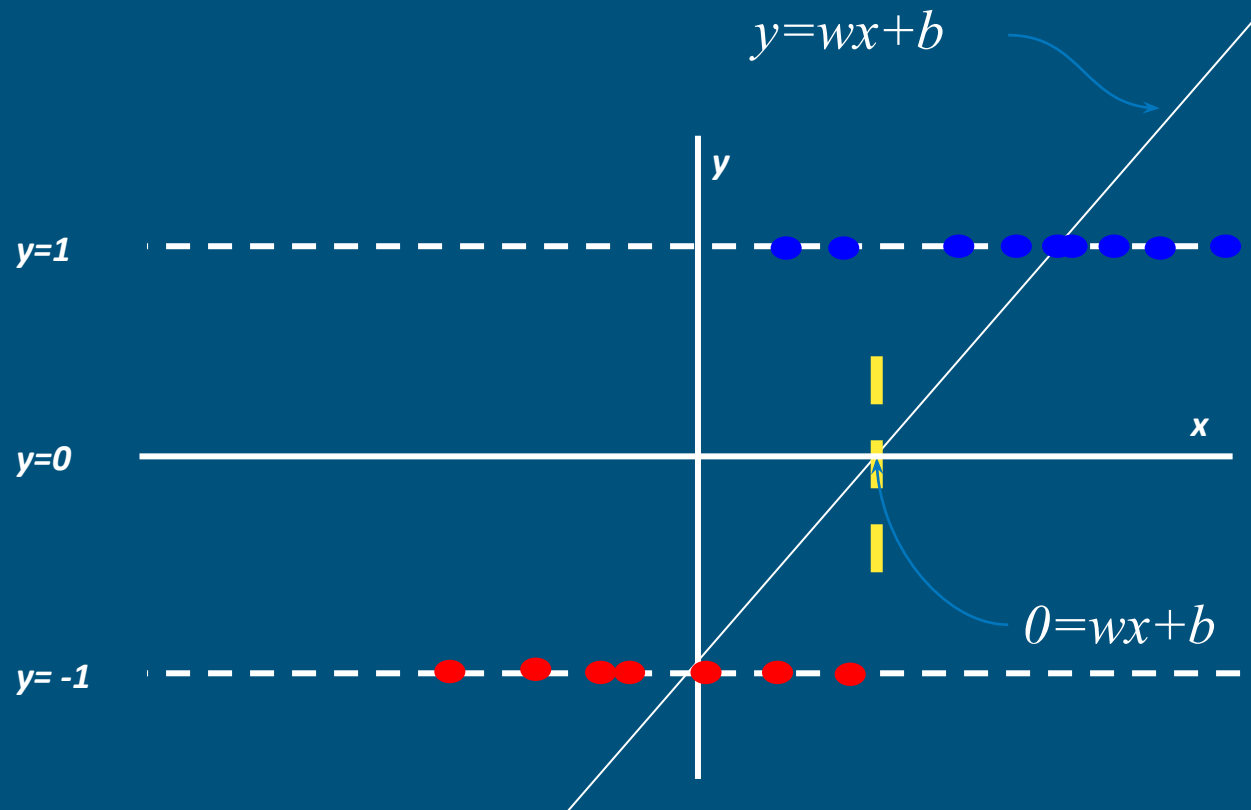


# Linear Classifier

$$y = \textit{sign}(wx + b) = \textit{sign}(H(x))$$

$$\textit{sign}(x) = +1 \quad \textit{if} \quad x \geq 0$$

$$-1 \quad \textit{if} \quad x < 0$$



Linear regression model is a line (a single IV)  
Classification boundary is a point (1D) but not line (2D)

# Example

Binary class data

x	y
2	+1
3	+1
4	+1
5	+1
6	+1
-2	-1
-3	-1
-4	-1
-5	-1
-6	-1

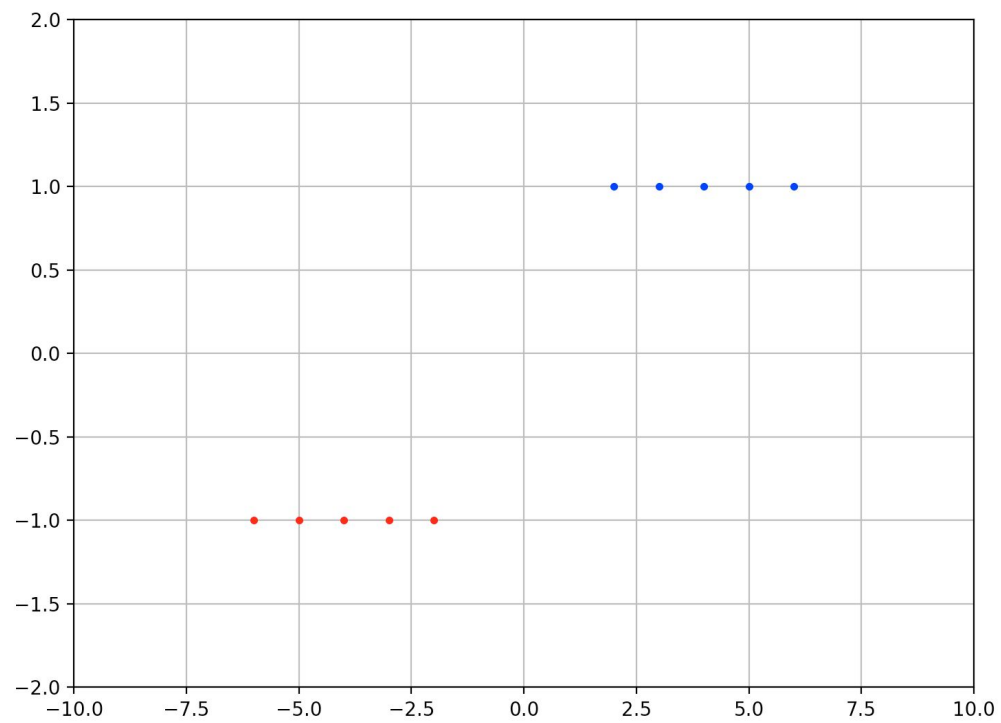
# plot

---

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

trainx = np.array([2, 3, 4, 5, 6, -2, -3, -4, -5, -6])
trainy = np.array([1, 1, 1, 1, 1, -1, -1, -1, -1, -1])

plt.plot(trainx[0:5], trainy[0:5], 'bo', markersize=3)
plt.plot(trainx[5:], trainy[5:], 'ro', markersize=3)
plt.axis([-10, 10, -2, 2])
plt.grid(True)
plt.show()
```





# Estimate $w$ and $b$

---

```
1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # data
5 trainx = np.array([2, 3, 4, 5, 6, -2, -3, -4, -5, -6])
6 trainy = np.array([1, 1, 1, 1, 1, -1, -1, -1, -1, -1])
7 # plot
8 plt.plot(trainx[0:5], trainy[0:5], 'bo', markersize=3)
9 plt.plot(trainx[5:], trainy[5:], 'ro', markersize=3)
10 xl = np.linspace(-10, 10, 100)
11 plt.axis([-10, 10, -2, 2])
12 # initialization
13 w, b = 0, 0
14 # learning rate
15 alpha = 0.05
16 # GD
17 for i in range(10):
18     w = w - alpha * (1/len(trainx)) * sum((w * trainx + b - trainy) * trainx)
19     b = b - alpha * (1/len(trainx)) * sum(w * trainx + b - trainy)
20     print("w = %f, b = %f" % (w, b))
21 # plot
22 plt.plot(xl, w * xl + b)
23 plt.grid(True)
24 plt.show()
```



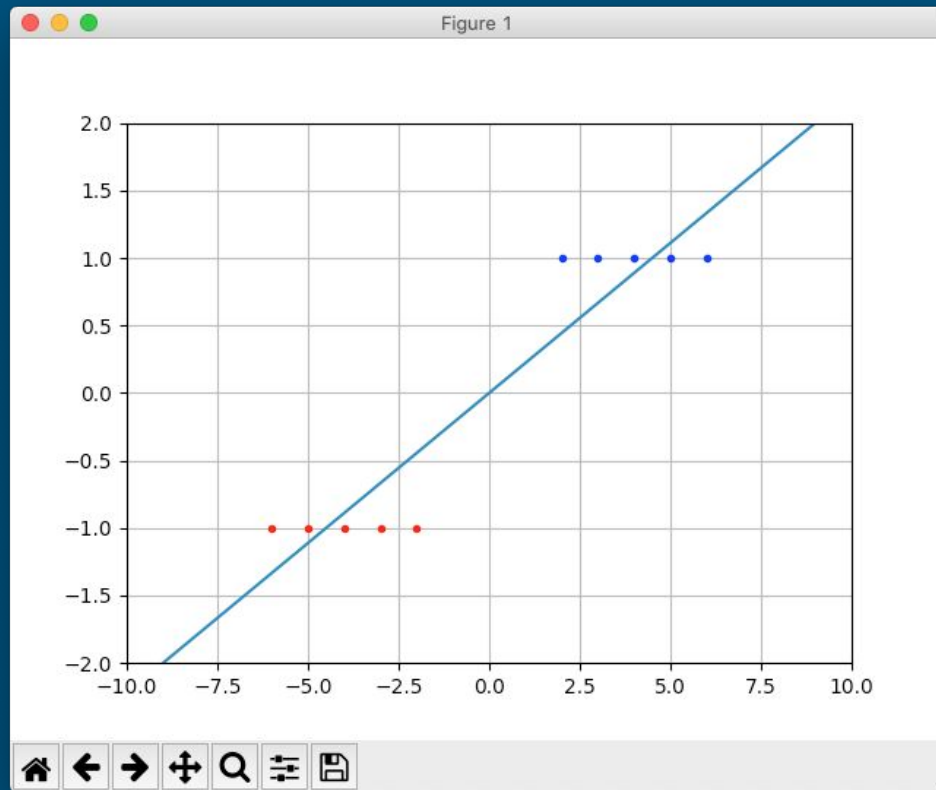
# Estimate $w$ and $b$

---

```
Run: linear_classifier_gd x
/Users/dkim/PycharmProjects/CSCI4352/venv/bin/python /Users/dkim/PycharmProjects/CSCI4352/linear_classifier_gd.py
0: w = 0.200000, b = 0.000000
1: w = 0.220000, b = 0.000000
2: w = 0.222000, b = 0.000000
3: w = 0.222200, b = 0.000000
4: w = 0.222220, b = 0.000000
5: w = 0.222222, b = 0.000000
6: w = 0.222222, b = 0.000000
7: w = 0.222222, b = 0.000000
8: w = 0.222222, b = 0.000000
9: w = 0.222222, b = 0.000000
```

# Plot

- $w = 0.2222222$
- $b = 0$



# Test



```

import numpy as np

def hypothesis(_w, _x, _b):
    return _w * _x + _b

# train data
trainx = np.array([2, 3, 4, 5, 6, -2, -3, -4, -5, -6])
trainy = np.array([1, 1, 1, 1, 1, -1, -1, -1, -1, -1])
# test data
testx = np.array([-4.4, 0.9, -2.5, -0.7, 2.4, 5.2])
testy = np.array([-1, 1, -1, -1, 1, 1])

# initialization
w, b = 0, 0
# learning rate
alpha = 0.05
# GD
for i in range(10):
    w = w - alpha * (1/len(trainx)) * sum((w * trainx + b - trainy) * trainx)
    b = b - alpha * (1/len(trainx)) * sum(w * trainx + b - trainy)
    print("w = %f, b = %f" % (w, b))

# test
print("Accuracy:", sum(np.sign(hypothesis(w, testx, b)) == testy)/len(testx))

```

# Accuracy

---

```
w = 0.222222, b = 0.000000
```

```
Accuracy: 1.0
```

# Multiple Linear Classifier for binary class data

---

# Without using matrix





```

import numpy as np

def hypothesis(w1, x1, w2, x2, w3, x3, b):
    return w1 * x1 + w2 * x2 + w3 * x3 + b

# data
trainX = np.array([[1.5, 2.7, 1.3],
                   [2.4, 1.7, 2.1],
                   [2.5, 1.3, 2.2],
                   [8.5, 5.3, 4.8],
                   [4.9, 6.4, 5.7],
                   [7.2, 7.1, 7.4]])
trainy = np.array([1, 1, 1, -1, -1, -1])
testX = np.array([[2.4, 2.5, 0.7],
                  [5.9, 4.4, 5.2]])
testy = np.array([1, -1])

# initialization
w1, w2, w3, b = 0, 0, 0, 0

# learning rate
alpha = 0.05

# GD
for i in range(100):
    w1 = w1 - alpha * (1 / len(trainX)) * sum((trainX[:, 0] * w1 + trainX[:, 1] * w2 + trainX[:, 2] * w3 + b - trainy) * trainX[:, 0])
    w2 = w2 - alpha * (1 / len(trainX)) * sum((trainX[:, 0] * w1 + trainX[:, 1] * w2 + trainX[:, 2] * w3 + b - trainy) * trainX[:, 1])
    w3 = w3 - alpha * (1 / len(trainX)) * sum((trainX[:, 0] * w1 + trainX[:, 1] * w2 + trainX[:, 2] * w3 + b - trainy) * trainX[:, 2])
    b = b - alpha * (1 / len(trainX)) * sum(trainX[:, 0] * w1 + trainX[:, 1] * w2 + trainX[:, 2] * w3 + b - trainy)

print("w1 = %f, w2 = %f, w3 = %f, b = %f" % (w1, w2, w3, b))

# test (accuracy)
print(sum(np.sign(hypothesis(w1, testX[:, 0], w2, testX[:, 1], w3, testX[:, 2], b)) == testy)/len(testX))

```

```
w1 = -0.123876, w2 = -0.244516, w3 = 0.046912, b = 1.244646  
1.0
```

# Using matrix

---

# Linear Classifier (Multi-dimension)

```
1 import numpy as np
2
3
4 def hypothesis(X, w, b):
5     return np.dot(X, w)+b
6
7 # data
8 trainX = np.array([[1.5, 2.7, 1.3],
9                    [2.4, 1.7, 2.1],
10                   [2.5, 1.3, 2.2],
11                   [8.5, 5.3, 4.8],
12                   [4.9, 6.4, 5.7],
13                   [7.2, 7.1, 7.4]])
14 trainy = np.array([1, 1, 1, -1, -1, -1])
15 testX = np.array([[2.4, 2.5, 0.7],
16                  [5.9, 4.4, 5.2],
17                  [0.2, 0.5, 0.6],
18                  [4.3, 4.5, 5.5]])
19 testy = np.array([1, -1, 1, -1])
20 # initialization
21 w = np.zeros(np.size(trainX, 1))
22 b = 0
23 # learning rate
24 alpha = 0.01
25 # GD
26 for i in range(2000):
27     w = w - alpha * (1 / len(trainX)) * np.dot(np.transpose(np.dot(trainX, w)+b - trainy), trainX)
28     b = b - alpha * (1 / len(trainX)) * sum(np.dot(trainX, w)+b - trainy)
29     print(w, b)
30 # test (accuracy)
31 print(sum(np.sign(hypothesis(testX, w, b)) == testy)/len(testX))
```

# Linear Classifier (Multi-dimension)

---

```
/Users/dkim/PycharmProjects/CSCI4352/venv/bin/python /Users/dkim/PycharmProjects/CSCI4352/linear_classifier_gd_test_data_multivariable_matrix.py  
[-0.15005405 -0.28097513  0.00386677] 1.8027770609918465  
1.0
```

```
Process finished with exit code 0
```

# Lab

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- Implement a linear classifier with Iris data.  
(<https://archive.ics.uci.edu/ml/datasets/iris>)
- Step 1: Use **only the first 100 samples** (**only two classes**) to make it binary class data.
- Step 2: Shuffle and split the data into train and test (test size is 0.2)
- Step 3: Repeat Step 2 for 100 times, then calculate accuracy on average.