# MACHINE LEARNING ALGORITHMS

## EXERCISE-1

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Completed Exercises – 1,2,3,4,5,6(All)

Solutions:

1. Code in Python
   PS: The entire python(jupyter notebook) code file is also attached.

```
In [2]: ###Question 1

        import numpy as np

        # Coordinates of the two points
        p1 = np.array([-2, 6])
        p2 = np.array([6, -2])

        # Slope of the line passing through p1 and p2
        slope = (p2[1] - p1[1]) / (p2[0] - p1[0])

        # Unit weight vector w perpendicular to line l
        w = np.array([-slope, 1]) / np.sqrt(slope**2 + 1)

        print("Unit weight vector w:", w)

        Unit weight vector w: [0.70710678 0.70710678]
```

The unit vector is: w = [0.70710678 0.70710678]

2.

```
In [4]: ###Question 2

# Define the two points on line l
p1 = np.array([-2, 6])
p2 = np.array([6, -2])

# Calculate the unit weight vector w perpendicular to line l
slope = (p2[1] - p1[1]) / (p2[0] - p1[0])
w = np.array([1, -1 / slope]) / np.linalg.norm(np.array([1, -1 / slope]))

# Load the data from Data.txt
data = np.loadtxt('C:/Users/chethankashyap/ML Data/Data.txt')

# Separate the data into C1 and C2 arrays
C1 = data[:100]
C2 = data[100:200]

# Calculate the dot product of w with each point in C1 and C2
C1_dot = np.dot(C1, w)
C2_dot = np.dot(C2, w)

# Calculate the threshold t
t = (np.min(C1_dot) + np.max(C2_dot)) / 2

# Classify the remaining 12 points based on their dot product with w
unknown_points = data[200:]
unknown_dot = np.dot(unknown_points, w)

C1_unknown = unknown_points[unknown_dot < t]
C2_unknown = unknown_points[unknown_dot > t]

print("Points in class C1:", C1_unknown)
print("Points in class C2:", C2_unknown)
```

The classified 12 points are:

```
Points in class C1: [[ 0.16026594 -1.06234105]
 [ 0.30104196  0.74522405]
 [ 0.46646615  0.32760407]
 [ 0.90292727  0.99105336]
 [-0.37900411  1.84875078]
 [-0.28377688 -3.37572261]]
Points in class C2: [[2.81614998 4.24887669]
 [4.72136853 6.2468573 ]
 [4.05926612 4.21292118]
 [5.43192756 4.80107228]
 [4.1210667  5.19128114]
 [4.94160501 6.32005915]]
```

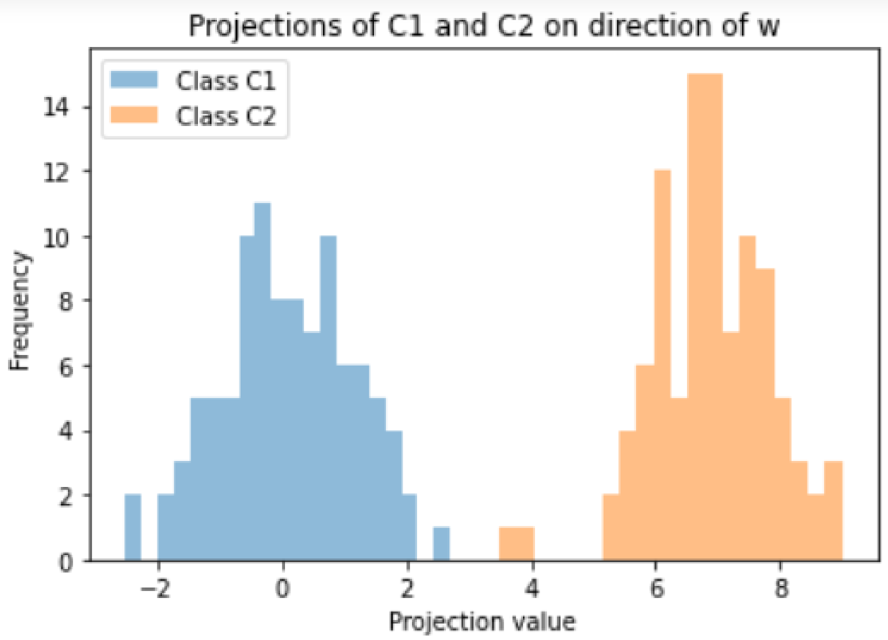
# 3.

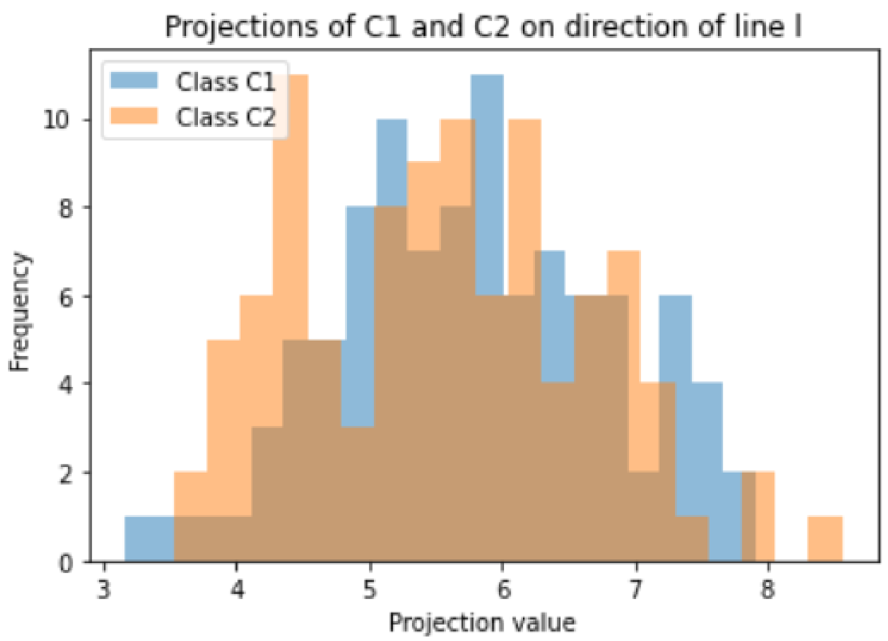
In [5]:
```
###Question 3

# Classify each point as belonging to C1 or C2 based on its dot product with w
C1_unknown_zero = data[200:][np.dot(data[200:], w) <= 0]
C2_unknown_zero = data[200:][np.dot(data[200:], w) > 0]

print("Points in class C1:", C1_unknown_zero)
print("Points in class C2:", C2_unknown_zero)
```

```
Points in class C1: [[ 0.16026594 -1.06234105]
 [-0.28377688 -3.37572261]]
Points in class C2: [[ 0.30104196  0.74522405]
 [ 0.46646615  0.32760407]
 [ 0.90292727  0.99105336]
 [-0.37900411  1.84875078]
 [ 2.81614998  4.24887669]
 [ 4.72136853  6.2468573 ]
 [ 4.05926612  4.21292118]
 [ 5.43192756  4.80107228]
 [ 4.1210667   5.19128114]
 [ 4.94160501  6.32005915]]
```

# 4.

In [7]:
```
###Question 4

import matplotlib.pyplot as plt

# Calculate the projections of C1 and C2 points on the directions of w and l
C1_w = np.dot(C1, w)
C2_w = np.dot(C2, w)
C1_l = np.dot(C1 - p1, p2 - p1) / np.linalg.norm(p2 - p1)
C2_l = np.dot(C2 - p1, p2 - p1) / np.linalg.norm(p2 - p1)

# Draw histograms for both directions
plt.hist(C1_w, bins=20, alpha=0.5, label='Class C1')
plt.hist(C2_w, bins=20, alpha=0.5, label='Class C2')
plt.legend(loc='upper left')
plt.title('Projections of C1 and C2 on direction of w')
plt.xlabel('Projection value')
plt.ylabel('Frequency')
plt.show()

plt.hist(C1_l, bins=20, alpha=0.5, label='Class C1')
plt.hist(C2_l, bins=20, alpha=0.5, label='Class C2')
plt.legend(loc='upper left')
plt.title('Projections of C1 and C2 on direction of line l')
plt.xlabel('Projection value')
plt.ylabel('Frequency')
plt.show()
```




From the graphs, We can interpret these results as follows:

1. For the direction of w, we can see that the projections of C1 and C2 are well separated, with C1 points having higher positive projections and C2 points having higher negative projections. This indicates that w is a good feature to use for distinguishing between the two classes.
2. For the direction of line l, we can see that there is some overlap between the projections of C1 and C2, especially in the middle range of projection values. This suggests that l may not be as effective as w for distinguishing between the two classes, although there is still some separation between the two classes at the extremes of the projection range

5.

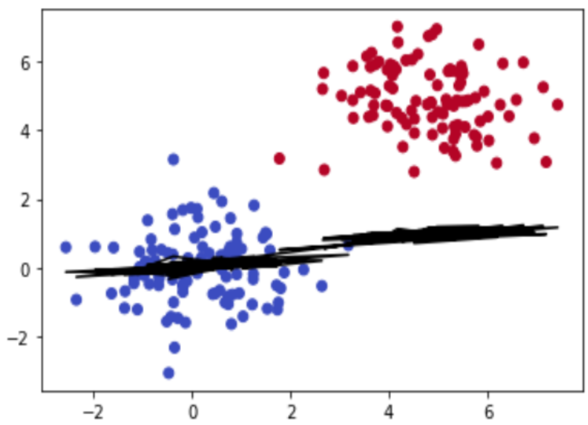
In [8]:
```
###Question 5

# Extract class C1 data
C1_data = data[:100]

# Calculate the mean distance of all points in C1 from the center point
mean_distance = np.mean(np.sqrt(np.sum(C1_data ** 2, axis=1)))

# Calculate the radius of the circular area
radius = mean_distance

# Loop through all points in C1 and count the number of points within the circular area
count = 0
for point in C1_data:
    distance = np.sqrt(np.sum(point ** 2))
    if distance <= radius:
        count += 1

# Calculate the probability that a point in C1 belongs to the circular area
probability = count / len(C1_data)

print("Probability:", probability)
```

```
Probability: 0.58
```

The probability for the event is 0.58.

6.

In [12]:
```
###Question 6

from sklearn.linear_model import LinearRegression

# Split the data into training and test sets
X_train = data[:200]
y_train = np.concatenate((np.zeros(100), np.ones(100)))

# Create the linear regression model and fit it to the training data
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

# Visualize the result
import matplotlib.pyplot as plt

plt.scatter(X_train[:,0], X_train[:,1], c=y_train, cmap='coolwarm')
plt.plot(X_train[:,0], lr_model.predict(X_train), color='black')
plt.show()
```



Upon inspection of the plot, we can see that a linear model may not be the best fit for this data as there are many points that do not appear to follow a linear trend. Additionally, there may be issues with overfitting or under fitting if we attempt to use this model on new data.