Homework 1

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Metrics

Model A	Predicted dog	Predicted cat
Actual dog	30	20
Actual cat	10	40

T1

Accuracy = (TP + TN) / (TP + TN + FP + FN) = (30 + 40) / (30 + 20 + 10 + 40) = 0.7

T2

Precision = TP / (TP + FP) = 40 / (40 + 20) = 0.67 Recall = TP / (TP + FN) = 40 / (40 + 10) = 0.8 F1 = 2 * TP / (2*TP + FP + FN) = 2 * 40 / (2 * 40 + 20 + 10) = 0.73

T3

Accuracy = (TP + TN) / (TP + TN + FP + FN) = (30 + 40) / 100 = 0.7 Precision = TP / (TP + FP) = 30 / (30 + 10) = 0.75 Recall = TP / (TP + FN) = 30 / (30 + 20) = 0.6 F1 = 2 * TP / (2*TP + FP + FN) = 2 * 30 / (2 * 30 + 10 + 20) = 0.67

T4

Let x be the total population Actual dog = 0.2x Actual cat = 0.8x

Calculate the new values TP = 0.2x * 30 / (30 + 20) = 0.12x FN = 0.2x * 20 / (30 + 20) = 0.08x
FP = 0.8x * 10 / (10 + 40) = 0.16x TN = 0.8x * 40 / (10 + 40) = 0.64x

Precision = 0.12x / (0.12x + 0.16x) = 0.4285 Recall = 0.12x / (0.12x + 0.08x) = 0.6 F1 = 2 * 0.4285 * 0.6 / (0.4285 + 0.6) = 0.49995

OT1

Accuracy = (TP + TN) / (TP + TN + FP + FN) = 1 / (1 + (FP + FN) / (TP + TN)) F1 = 2TP / (2TP + FP + FN) = 1 / (1 + (FP + FN / (2TP)))

Case TN = TP: Accraucy = F1 Case TN > TP: Accraucy > F1 Case TN < TP: Accraucy < F1

Hello Clustering

T5

Round 1

Centriod 1 have assigned points (3, 3), (8, 8), (6, 6), (7, 7) The updated centriod = (6, 6)

Centriod 2 have assigned points (1, 2), (2, 2) The updated centriod = (1.5, 2)

Centriod 3 have assigned points (-3, -3), (2, -4), (-7, -7) The updated centriod = (-4, -4.67)

Round 2

Centriod 1 have assigned points (8, 8), (6, 6), (7, 7) The updated centriod = (7, 7)

Centriod 2 have assigned points (1, 2), (2, 2), (3, 3) The updated centriod = (2, 2.33)

Centriod 3 have assigned points (-3, -3), (2, -4), (-7, -7) The updated centriod = (-4, -4.67)

Round 3

Centriod 1 have assigned points (8, 8), (6, 6), (7, 7) The updated centriod = (7, 7)

Centriod 2 have assigned points (1, 2), (2, 2), (3, 3) The updated centriod = (2, 2.33)

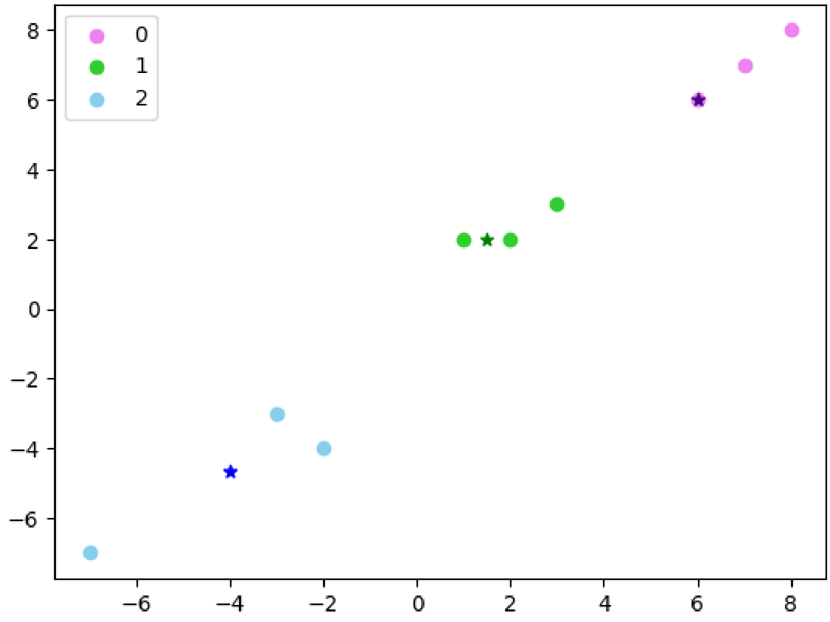
Centriod 3 have assigned points (-3, -3), (2, -4), (-7, -7) The updated centriod = (-4, -4.67)

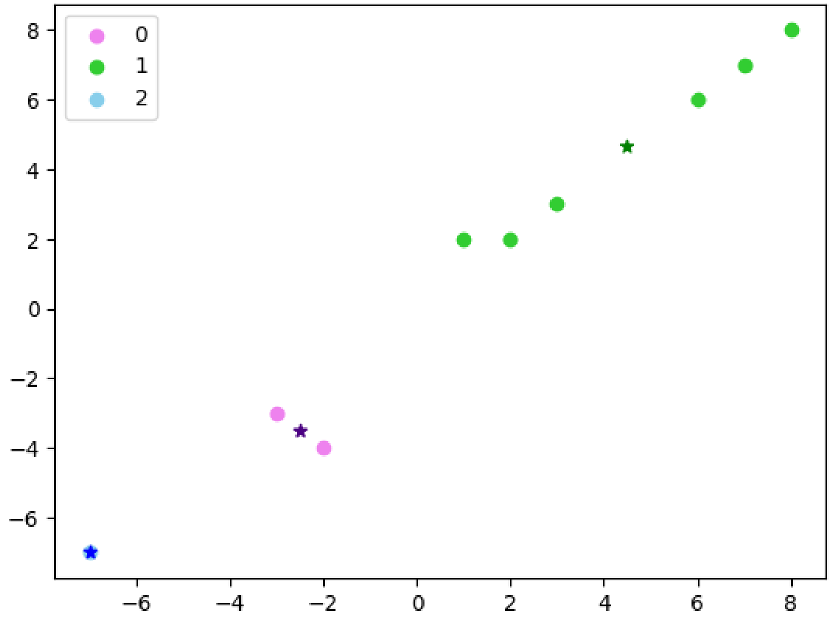
The centriods in round 3 do not change. So the centriods is (7, 7), (2, 2.33), (-4, -4.67)

T6

The centriods change to (-2.5, -3.5), (4.5, 4.67), (-7, -7)

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


class KMeans:
  def __init__(self, points, starting_centriods):
    self.points = points
    self.centriods = starting_centriods
    self.clusters = self.__find_clusters()
    self.iterations = 0

  def __find_clusters(self):
    centriods = self.centriods.copy()
    points = self.points.copy()
    clusters = [[] for _ in range(len(centriods))]
    for point in points.to_numpy():
      distances = []
      for centroid in centriods.to_numpy():
        distance = np.linalg.norm(point - centroid)
        distances.append(distance)
      clusters[np.argmin(distances)].append(point)
    self.clusters = clusters
    return clusters

  def __update_centriods(self):
    centriods = self.centriods.copy()
    clusters = self.clusters.copy()
    for i in range(len(clusters)):
      clustered_points = clusters[i]
      centriods.iloc[i] = np.mean(clustered_points, axis=0)
    return centriods

  def run(self):
    self.centriods = self.__update_centriods()
    self.clusters = self.__find_clusters()
    self.iterations += 1

  def plot(self):
    colors = ['violet', 'limegreen', 'skyblue']
    darken_colors = ['indigo', 'green', 'blue']
    for i in range(len(self.clusters)):
      clustered_points = np.array(self.clusters[i])
      plt.scatter(clustered_points[:, 0], clustered_points[:, 1], label=i, c=colors[i])
      plt.scatter(self.centriods['x'][i], self.centriods['y'][i], marker='*', c=darken_colors[i])
    plt.legend()
    plt.show()


x = np.array([1, 3, 2, 8, 6, 7, -3, -2, -7])
y = np.array([2, 3, 2, 8, 6, 7, -3, -4, -7])
dataframe_points = pd.DataFrame({'x': x, 'y': y})



starting_centriods = pd.DataFrame({
  'x': [3, 2, -3],
  'y': [3, 2, -3]
})
kMeans = KMeans(dataframe_points, starting_centriods)
kMeans.run()
kMeans.plot()

starting_centriods = pd.DataFrame({
  'x': [-3, 2, -7],
  'y': [-3, 2, -7]
})
kMeans = KMeans(dataframe_points, starting_centriods)
kMeans.run()
kMeans.plot()
```





T7

Judging from using my eyes, T5 is better because the grouping is more complete and is distributed equally.

The goodness of the starting point can be measured using various metrics such as Silhouette Score, Within-Cluter Sum of Square, Variance Ratio, etc.

OT2

K = 4 is the best for this data because of two reasons. First, I used my eyes to clearly see the grouping. Second, I used fraction of explained variance = 410.55 / 418.22 = 0.9816

My heart will go on

```
train_url = "http://s3.amazonaws.com/assets.datacamp.com/course/Kaggle/train.csv"
train = pd.read_csv(train_url) #training set
test_url = "http://s3.amazonaws.com/assets.datacamp.com/course/Kaggle/test.csv"
test = pd.read_csv(test_url) #test set

train['Age'] = train["Age"].median()
test['Age'] = test["Age"].median()
```

T8

Median of age = 28

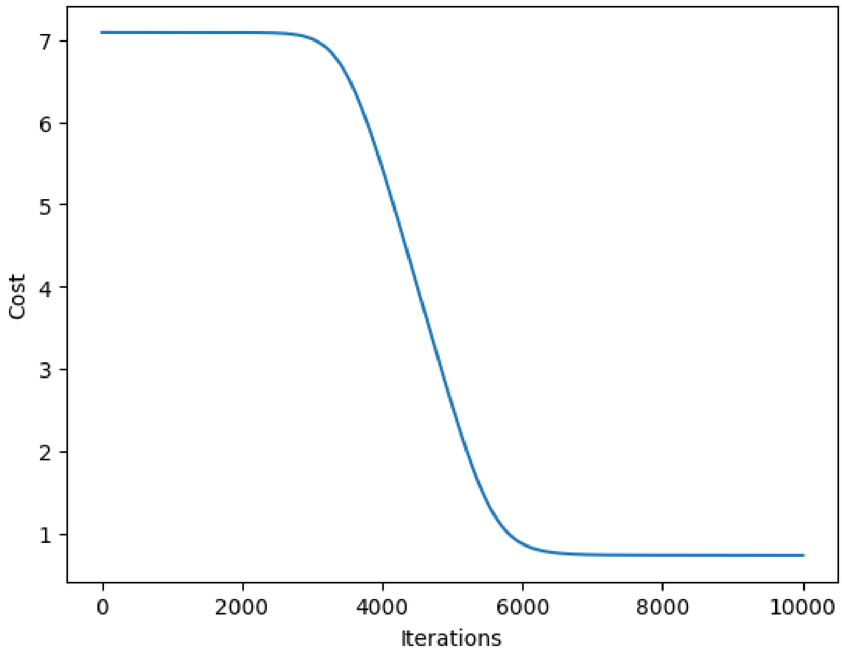
T9

```
embark_mode = train['Embarked'].mode()[0]
train["Embarked"] = train["Embarked"].fillna(embark_mode)
train.loc[train["Embarked"] == "S", "Embarked"] = 0
train.loc[train["Embarked"] == "C", "Embarked"] = 1
train.loc[train["Embarked"] == "Q", "Embarked"] = 2

sex_mode = train["Sex"].mode()[0]
train["Sex"] = train["Sex"].fillna(sex_mode)
train.loc[train["Sex"] == "male", "Sex"] = 0
train.loc[train["Sex"] == "female", "Sex"] = 1
```

T10

```
def sigmoid(x):
  return np.array(1/(1+np.exp(-x)))

def cost(theta, data, y):
  m = data.shape[0]
  predictions = np.array(sigmoid(np.dot(data, theta)))
  cost = -(1/m)*(np.dot(y, np.log(predictions.T+1e-5)) + np.dot((1-y), np.log(1-predictions.T+1e-5)))
  return cost

def gradient(theta, data, y):
  m = data.shape[0]
  predictions = sigmoid(np.dot(data, theta))
  error = predictions - y
  gradient = (1/m)*np.dot(data.T, error)
  return gradient

def gradient_descent(theta, data, y, alpha=0.00001, iteration=10000):
  cost_history = []
  for _ in range(iteration):
    cost_history.append(cost(theta, data, y))
    theta = theta - alpha*gradient(theta, data, y)
  return theta, cost_history

def predict(data, theta, raw):
  predictions = np.array(sigmoid(np.dot(data, theta)))
  predictions = np.where(predictions >  0.5, 1, predictions)
  predictions = np.where(predictions <= 0.5, 0, predictions)
  predictions = np.array(predictions, dtype = int)
  print("Survived", np.count_nonzero(predictions))
  result = pd.DataFrame({
    "PassengerId": raw["PassengerId"],
    "Survived": predictions
  })
  return result

def compare_prediction(actual, prediction):
  df = pd.DataFrame({
    "Actual": actual,
    "Prediction": prediction,
    "Compare": actual == prediction
  })
  return df["Compare"].sum()/len(actual)


embark_mode = test['Embarked'].mode()[0]
test["Embarked"] = test["Embarked"].fillna(embark_mode)
test.loc[test["Embarked"] == "S", "Embarked"] = 0
test.loc[test["Embarked"] == "C", "Embarked"] = 1
test.loc[test["Embarked"] == "Q", "Embarked"] = 2

sex_mode = test["Sex"].mode()[0]
test["Sex"] = test["Sex"].fillna(sex_mode)
test.loc[test["Sex"] == "male", "Sex"] = 0
test.loc[test["Sex"] == "female", "Sex"] = 1
```

```
train_df = copy.deepcopy(train)
test_df  = copy.deepcopy(test)

train_data = np.array(train_df[["Pclass","Sex","Age","Embarked"]].values, dtype = float)
test_data = np.array(test_df[["Pclass","Sex","Age","Embarked"]].values, dtype = float)

train_y = np.array(train_df[["Survived"]].values, dtype = float)
train_y = train_y.reshape(train_y.size)

features = train_data.shape[1]
theta = np.random.random(features)
alpha = 0.00001
theta, cost_history = gradient_descent(theta, train_data, train_y, alpha)
plt.plot(cost_history)
plt.ylabel('Cost')
plt.xlabel('Iterations')
plt.show()

print(theta)
```




```
[ 0.80519482  0.91257915 -0.10596363  0.67028044]
```

```
print("Train Survived", np.count_nonzero(train["Survived"]))
result = predict(train_data, theta, train_df)
print("Accuracy", compare_prediction(train_y, result["Survived"]))
result = predict(test_data, theta, test_df)
result.to_csv("submission_T10.csv", index = False)
```

```
Train Survived 342
Survived 236
Accuracy 0.5645342312008979
Survived 126
```

T11

submission_T10.csv **0.66507**

Complete · now

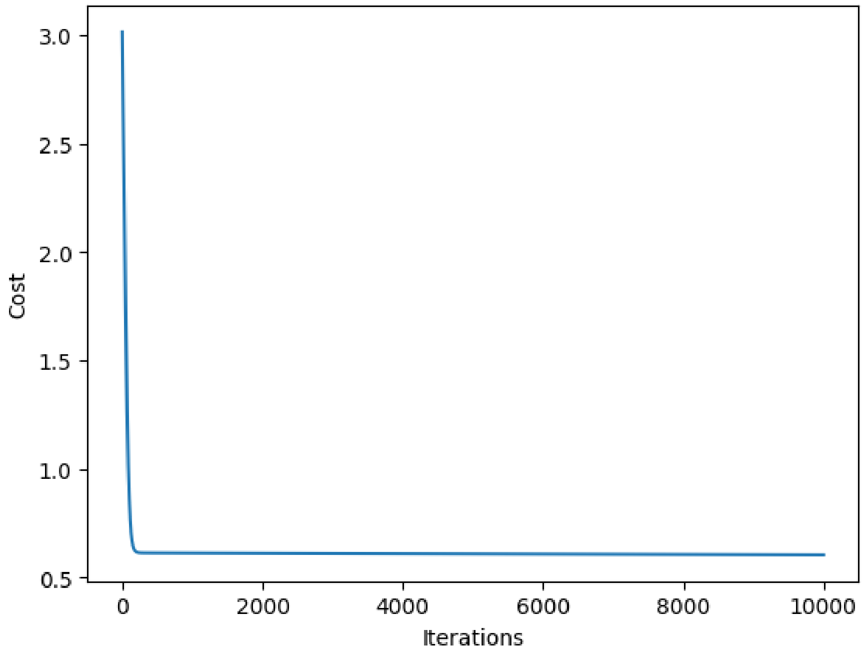
T12

[ ] ↳ *2 cells hidden*

T13

The accuracy also decreases to 0.62

```
train_df = copy.deepcopy(train)
test_df  = copy.deepcopy(test)

train_data = np.array(train_df[["Sex","Age"]].values, dtype = float)
test_data = np.array(test_df[["Sex","Age"]].values, dtype = float)

train_y = np.array(train_df[["Survived"]].values, dtype = float)
train_y = train_y.reshape(train_y.size)

features = train_data.shape[1]
theta = np.random.random(features)
alpha = 0.0001
iterations = 10000
theta, cost_history = gradient_descent(theta, train_data, train_y, alpha)
plt.plot(cost_history)
plt.ylabel('Cost')
plt.xlabel('Iterations')
plt.show()

print(theta)

print("Train Survived", np.count_nonzero(train["Survived"]))
result = predict(train_data, theta, train_df)
print("Accuracy", compare_prediction(train_y, result["Survived"]))
result = predict(test_data, theta, test_df)
result.to_csv("submission_T13.csv", index = False)
```




```
[ 0.57180945 -0.02437151]
Train Survived 342
Survived 0
Accuracy 0.6161616161616161
Survived 0
```

OT3

```
def linear_regression(X, y, learning_rate, num_iterations):
    theta = np.zeros(X.shape[1])

    for _ in range(num_iterations):
        predictions = X @ theta
        diff = y - predictions
        loss = X.T @ diff

        theta = theta + learning_rate / X.shape[0] * loss

    return theta
```

```
import numpy as np
import copy

train_df = copy.deepcopy(train)
test_df = copy.deepcopy(test)

train_data = np.array(train_df[["Pclass","Sex","Age","Embarked"]].values, dtype=float)
test_data = np.array(test_df[["Pclass","Sex","Age","Embarked"]].values, dtype=float)

train_y = np.array(train_df[["Survived"]].values, dtype=float)
train_y = train_y.reshape(train_y.size)

learning_rate = 0.001
num_iterations = 100000

theta = linear_regression(train_data, train_y, learning_rate, num_iterations)

print(theta)
theta_gradient_descent = theta
```

OT4

```
def linear_regression_matrix_inversion(data, y):
    X = data
    theta_matrix_inversion = np.linalg.inv(X.T @ X) @ X.T @ y
    return theta_matrix_inversion


train_df = copy.deepcopy(train)
test_df  = copy.deepcopy(test)


train_data = np.array(train_df[["Pclass","Sex","Age","Embarked"]].values, dtype = float)
test_data = np.array(test_df[["Pclass","Sex","Age","Embarked"]].values, dtype = float)

train_y = np.array(train_df[["Survived"]].values, dtype = float)
train_y = train_y.reshape(train_y.size)


theta = linear_regression_matrix_inversion(train_data, train_y)

print(theta)
theta_matrix_inversion = theta
```

```
[-0.16024524  0.5089065   0.01991192  0.0467863 ]
```

```
MSE = np.power(theta_gradient_descent - theta_matrix_inversion, 2).sum()
print(MSE)
```

```
4.8770433001680174e-20
```