Homework1

January 9, 2026

0.1 K-Means

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

class KMeans:
    def __init__(self, init):
        self.data = np.array([(1, 2), (3, 3), (2, 2), (8, 8), (6, 6), (7, 7),␣
↪(-3, -3), (-2, -4), (-7, -7)])
        self.init = init
        self.old_centroids = []
        self.new_centroids = init.copy()
        self.group = {}

    def cluster(self, display=True):
        i = 0
        while (self.new_centroids != self.old_centroids):
            self.old_centroids = self.new_centroids

            centroids = np.array(self.old_centroids)
            self.group = {}
            for each_data in self.data:
                # Vectorization Optimized
                point = np.array(each_data)
                dist = np.sqrt(np.sum((centroids - point) ** 2, axis=1))
                group_of_each_data = np.argmin(dist)

                if (group_of_each_data not in self.group):
                    self.group[group_of_each_data] = []
                self.group[group_of_each_data].append(each_data)

                # Traditional Way
                # min_distance = 1e9
                # group_of_each_data = -1
                # for i in range(len(self.old_centroids)):
                #     current_distance = ( (self.old_centroids[i][0] -␣
↪each_data[0]) ** 2 + (self.old_centroids[i][1] - each_data[1]) ** 2 ) ** 0.5
```

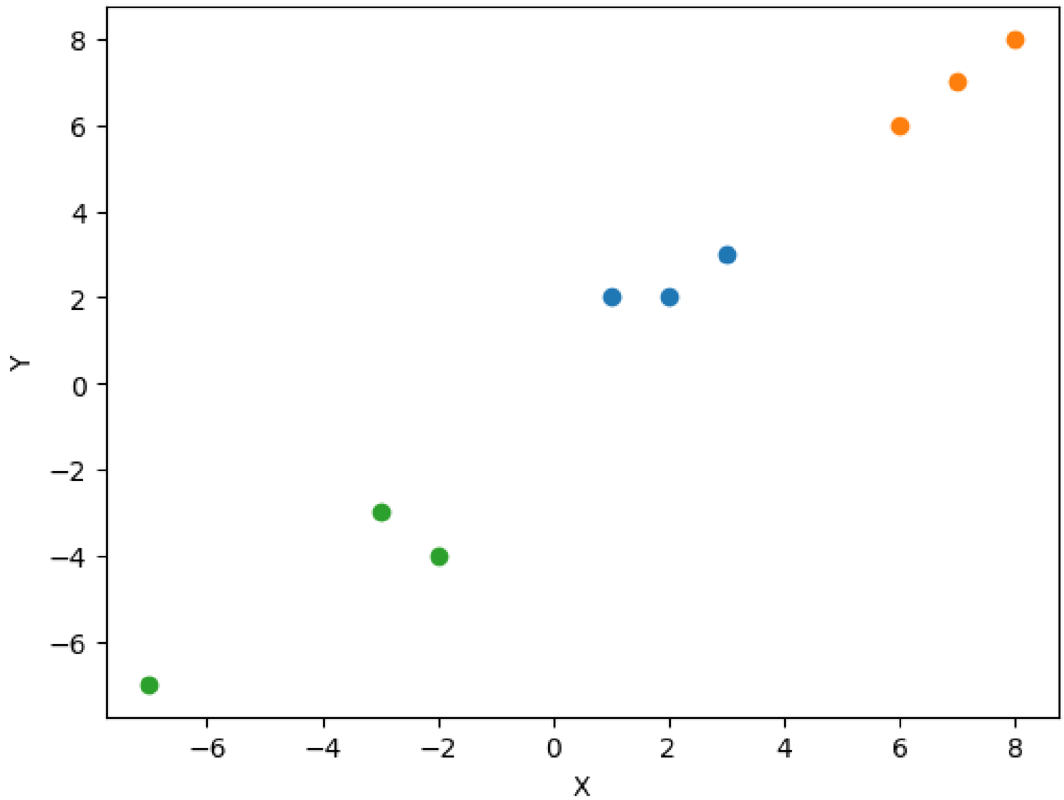
```
                #     if (current_distance < min_distance):
                #         group_of_each_data = i
                #         min_distance = current_distance

                # if (group_of_each_data not in self.group):
                #     self.group[group_of_each_data] = []

                # self.group[group_of_each_data].append(each_data)

            self.new_centroids = []
            for each in self.group.keys():
                centroid_x = sum(t[0] for t in self.group[each]) / len(self.
↪group[each])
                centroid_y = sum(t[1] for t in self.group[each]) / len(self.
↪group[each])
                self.new_centroids.append((centroid_x, centroid_y))

            i += 1

            if (display):
                print(f"--- Round {i} ---")
                print(f"Centroids: {self.new_centroids}")

        if (display):
            for cluster_id, points in self.group.items():
                xs, ys = zip(*points)
                plt.scatter(xs, ys, label=f"Cluster {cluster_id}")

            plt.xlabel("X")
            plt.ylabel("Y")
            plt.show()
```

0.1.1 T5. starting points are (3,3), (2,2), and (-3,-3).

[2]:
```
init_t5 = [(3, 3), (2, 2), (-3, -3)]

km_t5 = KMeans(init_t5)
km_t5.cluster()
```

```
--- Round 1 ---
Centroids: [(np.float64(1.5), np.float64(2.0)), (np.float64(6.0),
np.float64(6.0)), (np.float64(-4.0), np.float64(-4.666666666666667))]
--- Round 2 ---
Centroids: [(np.float64(2.0), np.float64(2.3333333333333335)), (np.float64(7.0),
np.float64(7.0)), (np.float64(-4.0), np.float64(-4.666666666666667))]
--- Round 3 ---
Centroids: [(np.float64(2.0), np.float64(2.3333333333333335)), (np.float64(7.0),
```

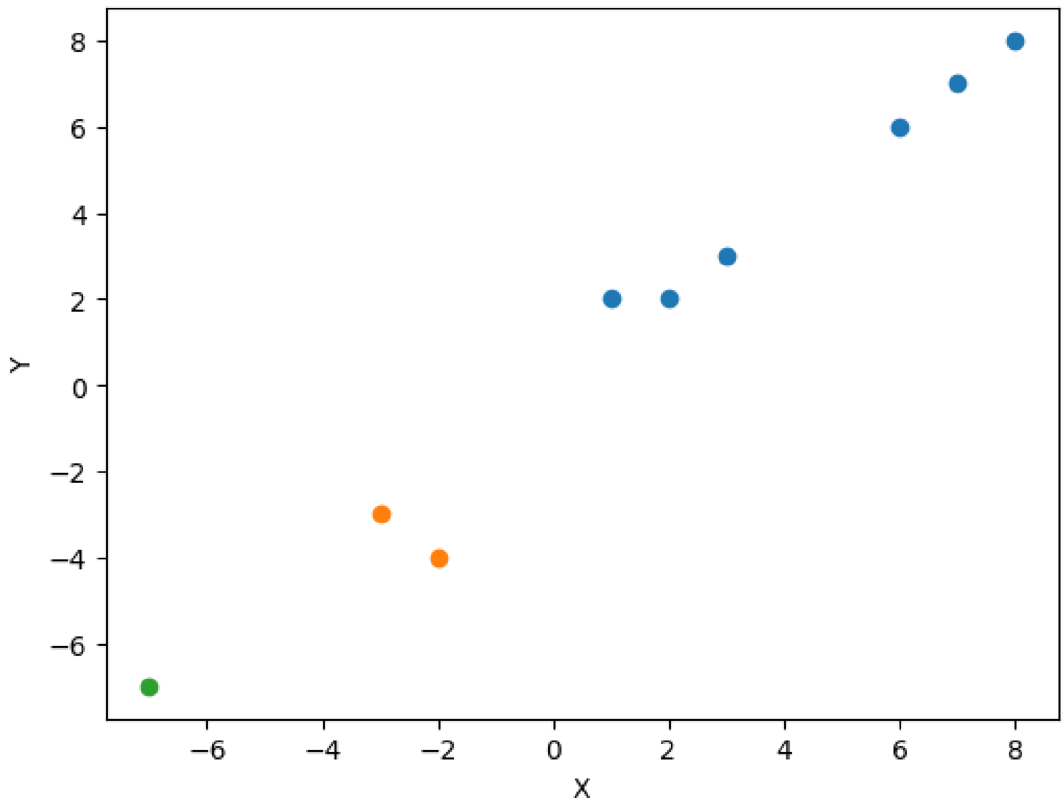
```
np.float64(7.0)), (np.float64(-4.0), np.float64(-4.666666666666667))]
```



0.1.2 T6. starting points are (-3,-3), (2,2), and (-7,-7),

[3]:
```
init_t6 = [(-3, -3), (2, 2), (-7, -7)]

km_t6 = KMeans(init_t6)
km_t6.cluster()
```

```
--- Round 1 ---
Centroids: [(np.float64(4.5), np.float64(4.666666666666667)), (np.float64(-2.5),
np.float64(-3.5)), (np.float64(-7.0), np.float64(-7.0))]
--- Round 2 ---
Centroids: [(np.float64(4.5), np.float64(4.666666666666667)), (np.float64(-2.5),
np.float64(-3.5)), (np.float64(-7.0), np.float64(-7.0))]
```



0.1.3 T7. Between the two starting set of points in the previous two questions, which one do you think is better? How would you measure the 'goodness' quality of a set of starting points?

0.1.4 In general, it is important to try different sets of starting points when doing k-means.

```
For me, the better one is the first one. The 'goodness' may measure with the variance in the g
```

0.1.5 OT2. What would be the best K for this question? Describe your reasoning.

```
For me, it's 4 because the distance between (-7, -7) to (-3, -3) and (-2, -4) is too large to
```

0.2 Regression

[4]:
```
train_url = "http://s3.amazonaws.com/assets.datacamp.com/course/Kaggle/train.
  ↪csv"
train = pd.read_csv(train_url)

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

[5]:
```
train.describe()
```

[5]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

0.2.1 T8. Median of the training datasets?

[6]:
```
train["Age"].median()
```

[6]:
```
np.float64(28.0)
```

28

0.2.2 T9. Mode of Embarked

[7]:
```
train["Embarked"].mode().iloc[0]
```

[7]:
```
'S'
```

"S" which is 0

0.2.3 T10.

[8]:
```
test
```

[8]:
```
     PassengerId  Pclass                                          Name  \
0            892       3                              Kelly, Mr. James
1            893       3              Wilkes, Mrs. James (Ellen Needs)
2            894       2                     Myles, Mr. Thomas Francis
3            895       3                              Wirz, Mr. Albert
4            896       3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)
..           …     …                                           …
```

```
413         1305       3                        Spector, Mr. Woolf
414         1306       1              Oliva y Ocana, Dona. Fermina
415         1307       3              Saether, Mr. Simon Sivertsen
416         1308       3                       Ware, Mr. Frederick
417         1309       3                  Peter, Master. Michael J

        Sex   Age  SibSp  Parch              Ticket      Fare Cabin Embarked
0      male  34.5      0      0              330911    7.8292   NaN        Q
1    female  47.0      1      0              363272    7.0000   NaN        S
2      male  62.0      0      0              240276    9.6875   NaN        Q
3      male  27.0      0      0              315154    8.6625   NaN        S
4    female  22.0      1      1             3101298   12.2875   NaN        S
..      …    …     …     …                 …      …    …       …
413    male   NaN      0      0           A.5. 3236    8.0500   NaN        S
414  female  39.0      0      0            PC 17758  108.9000  C105        C
415    male  38.5      0      0  SOTON/O.Q. 3101262    7.2500   NaN        S
416    male   NaN      0      0              359309    8.0500   NaN        S
417    male   NaN      1      1                2668   22.3583   NaN        C

[418 rows x 11 columns]
```

[9]:
```python
import pandas as pd
import numpy as np
import os

class LogisticRegression:
    def __init__(self, train, test, feature_cols, target_col, learning_rate=0.
 ↪001, iters=100000, threshold=0.5):
        self.train = train
        self.test = test
        self.feature_cols = feature_cols
        self.target_col = target_col
        self.learning_rate = learning_rate
        self.iters = iters
        self.threshold = threshold
        self.theta = np.zeros((len(self.feature_cols), 1)) # column vector

    def fit(self):
        self.process()
        x = np.array(self.train[self.feature_cols].values)
        y = np.array(self.train[self.target_col].values).reshape(-1, 1)
        for i in range(self.iters):
            self.theta += self.learning_rate / x.shape[0] * (x.T @ (y - self.
 ↪h(x @ self.theta)))

        print(f"trained with learning rate: {self.learning_rate} and iterations:
 ↪ {self.iters}")
```

```
    def predict(self, title="submission", directory="submission"):
        self.test["Survived"] = self.h(np.array(self.test[self.feature_cols].
↪values) @ self.theta)
        self.test.loc[self.test["Survived"] < self.threshold, "Survived"] = 0
        self.test.loc[self.test["Survived"] >= self.threshold, "Survived"] = 1
        self.test["Survived"] = self.test["Survived"].astype(int)

        os.makedirs(directory, exist_ok=True)
        self.test[["PassengerId", "Survived"]].to_csv(f"{directory}/{title}.
↪csv", index=False)
        print(f"Saved to {directory}/{title}.csv")

    def params(self):
        print(self.theta)

    def h(self, x):
        return 1 / (1 + np.exp(-x))

    def process(self):
        self.train["Age"] = self.train["Age"].fillna(self.train["Age"].median())
        self.test["Age"] = self.test["Age"].fillna(self.train["Age"].median())

        self.train.loc[self.train["Embarked"] == "S", "Embarked"] = 0
        self.train.loc[self.train["Embarked"] == "C", "Embarked"] = 1
        self.train.loc[self.train["Embarked"] == "Q", "Embarked"] = 2

        self.test.loc[self.test["Embarked"] == "S", "Embarked"] = 0
        self.test.loc[self.test["Embarked"] == "C", "Embarked"] = 1
        self.test.loc[self.test["Embarked"] == "Q", "Embarked"] = 2

        self.train["Embarked"] = self.train["Embarked"].fillna(self.
↪train["Embarked"].mode().iloc[0])
        self.test["Embarked"] = self.test["Embarked"].fillna(self.
↪train["Embarked"].mode().iloc[0])

        self.train.loc[self.train["Sex"] == "male", "Sex"] = 0
        self.train.loc[self.train["Sex"] == "female", "Sex"] = 1

        self.test.loc[self.test["Sex"] == "male", "Sex"] = 0
        self.test.loc[self.test["Sex"] == "female", "Sex"] = 1
        # print(self.test[self.feature_cols].dtypes)

        self.train[self.feature_cols] = self.train[self.feature_cols].
↪astype(float)
        self.test[self.feature_cols] = self.test[self.feature_cols].
↪astype(float)
```

[10]:
```
lr = LogisticRegression(train, test, ["Pclass","Sex","Age","Embarked"],␣
↪"Survived",iters=100000)
lr.fit()
lr.params()
lr.predict(title="T10_100k_iters")
```

```
C:\Users\chyut\AppData\Local\Temp\ipykernel_22544\3690440150.py:53:
FutureWarning: Downcasting object dtype arrays on .fillna, .ffill, .bfill is
deprecated and will change in a future version. Call
result.infer_objects(copy=False) instead. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  self.train["Embarked"] =
self.train["Embarked"].fillna(self.train["Embarked"].mode().iloc[0])
C:\Users\chyut\AppData\Local\Temp\ipykernel_22544\3690440150.py:54:
FutureWarning: Downcasting object dtype arrays on .fillna, .ffill, .bfill is
deprecated and will change in a future version. Call
result.infer_objects(copy=False) instead. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  self.test["Embarked"] =
self.test["Embarked"].fillna(self.train["Embarked"].mode().iloc[0])
```

```
trained with learning rate: 0.001 and iterations: 100000
[[-0.70281072]
 [ 2.59431049]
 [-0.00447441]
 [ 0.35126993]]
Saved to submission/T10_100k_iters.csv
```

[11]:
```
lr = LogisticRegression(train, test, ["Pclass","Sex","Age","Embarked"],␣
↪"Survived",iters=2000000)
lr.fit()
lr.params()
lr.predict(title="T10_2m_iters")
```

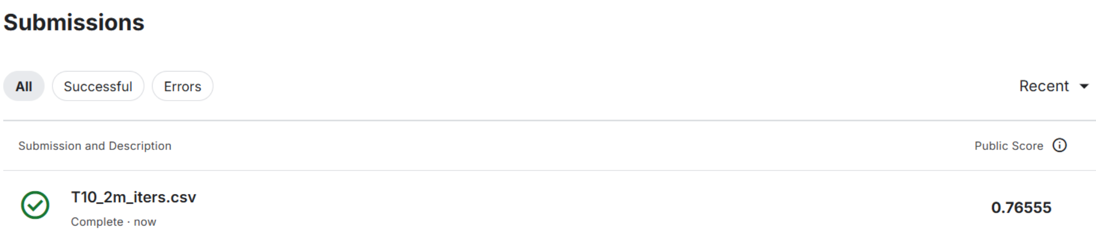
```
trained with learning rate: 0.001 and iterations: 2000000
[[-0.71333809]
 [ 2.65049353]
 [-0.00447566]
 [ 0.35092113]]
Saved to submission/T10_2m_iters.csv
```

[12]:
```
print(pd.read_csv("submission/T10_2m_iters.csv").set_index("PassengerId"))
```

```
             Survived
PassengerId
892                 0
893                 1
894                 0
895                 0
```

```
896                     1
...                   ...
1305                    0
1306                    1
1307                    0
1308                    0
1309                    0

[418 rows x 1 columns]
```

0.2.4 T11.



0.2.5 T12.

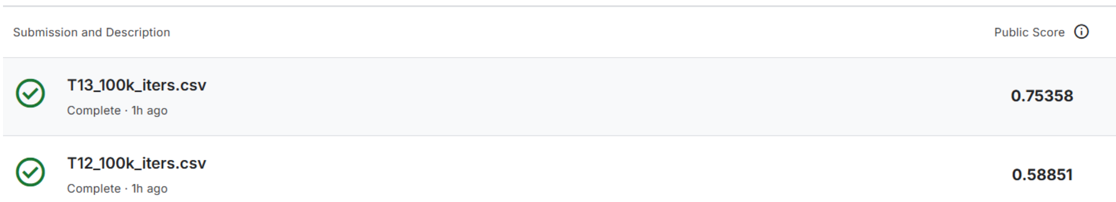
[13]:
```
train_high = train.copy()
train_high["Embarked**2"] = train_high["Embarked"] ** 2
train_high["Age*Pclass"] = train_high["Age"] * train_high["Pclass"]
train_high["Age**2"] = train_high["Age"] ** 2
train_high["Age*Sex"] = train_high["Age"] * train_high["Sex"]

test_high = test.copy()
test_high["Embarked**2"] = test_high["Embarked"] ** 2
test_high["Age*Pclass"] = test_high["Age"] * test_high["Pclass"]
test_high["Age**2"] = test_high["Age"] ** 2
test_high["Age*Sex"] = test_high["Age"] * test_high["Sex"]
```

[14]:
```
lr = LogisticRegression(train_high, test_high,
 ↪["Pclass","Sex","Age","Embarked", "Embarked**2", "Age*Pclass", "Age**2",
 ↪"Age*Sex"], "Survived",iters=100000)
lr.fit()
lr.params()
lr.predict(title="T12_100k_iters")
```

```
C:\Users\chyut\AppData\Local\Temp\ipykernel_22544\3690440150.py:39:
RuntimeWarning: overflow encountered in exp
  return 1 / (1 + np.exp(-x))
```

```
trained with learning rate: 0.001 and iterations: 100000
[[-0.52522612]
 [-2.49243163]
 [ 2.86031408]
```

```
 [ 0.8270162 ]
 [ 0.7425793 ]
 [-1.47554321]
 [ 0.01012895]
 [ 7.54272117]]
Saved to submission/T12_100k_iters.csv
```

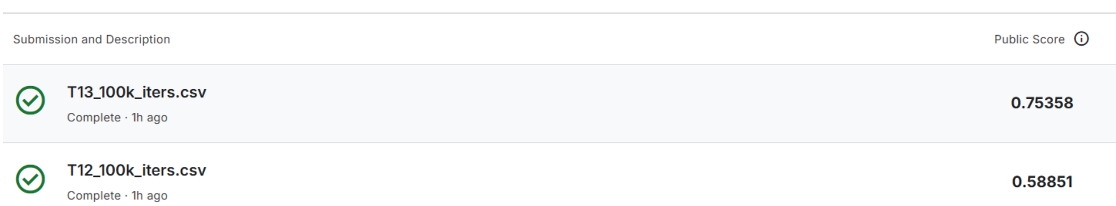


Submission and Description	Public Score
T13_100k_iters.csv Complete · 1h ago	0.75358
T12_100k_iters.csv Complete · 1h ago	0.58851

0.2.6 T13.

[15]:
```python
lr = LogisticRegression(train_high, test_high, ["Age", "Sex"], "Survived",iters=100000)
lr.fit()
lr.params()
lr.predict(title="T13_100k_iters")
```

```
trained with learning rate: 0.001 and iterations: 100000
[[-0.04000972]
 [ 2.21648735]]
Saved to submission/T13_100k_iters.csv
```



Submission and Description	Public Score
T13_100k_iters.csv Complete · 1h ago	0.75358
T12_100k_iters.csv Complete · 1h ago	0.58851

0.2.7 OT3.

[16]:
```python
import pandas as pd
import numpy as np
import os

class LinearRegression:
    def __init__(self, train, test, feature_cols, target_col, learning_rate=0.001, iters=100000, threshold=0.5):
        self.train = train
        self.test = test
        self.feature_cols = feature_cols
        self.target_col = target_col
        self.learning_rate = learning_rate
```

```
        self.iters = iters
        self.threshold = threshold
        self.theta = np.zeros((len(self.feature_cols), 1)) # column vector

    def fit(self):
        self.process()
        x = np.array(self.train[self.feature_cols].values)
        y = np.array(self.train[self.target_col].values).reshape(-1, 1)
        for i in range(self.iters):
            self.theta += self.learning_rate / x.shape[0] * (x.T @ (y - (x @␣
↪self.theta)))

        print(f"trained with learning rate: {self.learning_rate} and iterations:
↪ {self.iters}")

    def params(self):
        print(self.theta)
        return self.theta

    def process(self):
        self.train["Age"] = self.train["Age"].fillna(self.train["Age"].median())
        self.test["Age"] = self.test["Age"].fillna(self.train["Age"].median())

        self.train.loc[self.train["Embarked"] == "S", "Embarked"] = 0
        self.train.loc[self.train["Embarked"] == "C", "Embarked"] = 1
        self.train.loc[self.train["Embarked"] == "Q", "Embarked"] = 2

        self.test.loc[self.test["Embarked"] == "S", "Embarked"] = 0
        self.test.loc[self.test["Embarked"] == "C", "Embarked"] = 1
        self.test.loc[self.test["Embarked"] == "Q", "Embarked"] = 2

        self.train["Embarked"] = self.train["Embarked"].fillna(self.
↪train["Embarked"].mode().iloc[0])
        self.test["Embarked"] = self.test["Embarked"].fillna(self.
↪train["Embarked"].mode().iloc[0])

        self.train.loc[self.train["Sex"] == "male", "Sex"] = 0
        self.train.loc[self.train["Sex"] == "female", "Sex"] = 1

        self.test.loc[self.test["Sex"] == "male", "Sex"] = 0
        self.test.loc[self.test["Sex"] == "female", "Sex"] = 1
        # print(self.test[self.feature_cols].dtypes)

        self.train[self.feature_cols] = self.train[self.feature_cols].
↪astype(float)
        self.test[self.feature_cols] = self.test[self.feature_cols].
↪astype(float)
```

[17]:
```
lr = LinearRegression(train, test, ["Pclass","Sex","Age","Embarked"],␣
↪"Survived",iters=1000000)
lr.fit()
theta_ot3 = lr.params()
```

```
trained with learning rate: 0.001 and iterations: 1000000
[[-0.01411427]
 [ 0.60420619]
 [ 0.00501483]
 [ 0.06116326]]
```

0.2.8 OT4.

[18]:
```
x = np.array(train[["Pclass","Sex","Age","Embarked"]])
y = np.array(train["Survived"]).reshape((-1, 1))
theta_ot4 = np.linalg.inv(x.T @ x) @ (x.T @ y)
theta_ot4
```

[18]:
```
array([[-0.01411427],
       [ 0.60420619],
       [ 0.00501483],
       [ 0.06116326]])
```

[19]:
```
mse = np.sum((theta_ot3 - theta_ot4) ** 2) / theta_ot3.shape[1]
mse
```

[19]:
```
np.float64(5.471194131828056e-26)
```