In [ ]:

```
%pip install matplotlib numpy pandas
```

```
Requirement already satisfied: matplotlib in e:\practice\pattern_2024\venv\lib\site-packag
es (3.8.2)
Requirement already satisfied: numpy in e:\practice\pattern_2024\venv\lib\site-packages
(1.26.3)
Requirement already satisfied: pandas in e:\practice\pattern_2024\venv\lib\site-packages
(2.1.4)
Requirement already satisfied: kiwisolver>=1.3.1 in e:\practice\pattern_2024\venv\lib\site
-packages (from matplotlib) (1.4.5)
Requirement already satisfied: python-dateutil>=2.7 in e:\practice\pattern_2024\venv\lib\s
ite-packages (from matplotlib) (2.8.2)
Requirement already satisfied: pyparsing>=2.3.1 in e:\practice\pattern_2024\venv\lib\site-
packages (from matplotlib) (3.1.1)
Requirement already satisfied: fonttools>=4.22.0 in e:\practice\pattern_2024\venv\lib\site
-packages (from matplotlib) (4.47.2)
Requirement already satisfied: packaging>=20.0 in e:\practice\pattern_2024\venv\lib\site-p
ackages (from matplotlib) (23.2)
Requirement already satisfied: cycler>=0.10 in e:\practice\pattern_2024\venv\lib\site-pack
ages (from matplotlib) (0.12.1)
Requirement already satisfied: pillow>=8 in e:\practice\pattern_2024\venv\lib\site-package
s (from matplotlib) (10.2.0)
Requirement already satisfied: contourpy>=1.0.1 in e:\practice\pattern_2024\venv\lib\site-
packages (from matplotlib) (1.2.0)
Requirement already satisfied: pytz>=2020.1 in e:\practice\pattern_2024\venv\lib\site-pack
ages (from pandas) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in e:\practice\pattern_2024\venv\lib\site-pa
ckages (from pandas) (2023.4)
Requirement already satisfied: six>=1.5 in e:\practice\pattern_2024\venv\lib\site-packages
(from python-dateutil>=2.7->matplotlib) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

```
[notice] A new release of pip is available: 23.0.1 -> 23.3.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

In [ ]:

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

In [ ]:

```
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
```

In [ ]:

```
print(train.head())
print(train.tail())
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
     PassengerId  Survived  Pclass                                      Name  \
886          887         0       2                     Montvila, Rev. Juozas
887          888         1       1              Graham, Miss. Margaret Edith
888          889         0       3  Johnston, Miss. Catherine Helen "Carrie"
889          890         1       1                     Behr, Mr. Karl Howell
890          891         0       3                       Dooley, Mr. Patrick

        Sex   Age  SibSp  Parch      Ticket   Fare Cabin Embarked
886    male  27.0      0      0      211536  13.00   NaN        S
887  female  19.0      0      0      112053  30.00   B42        S
888  female   NaN      1      2  W./C. 6607  23.45   NaN        S
889    male  26.0      0      0      111369  30.00  C148        C
890    male  32.0      0      0      370376   7.75   NaN        Q
```

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

Out[ ]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

T8

In [ ]:
```
# T8
median_age = train["Age"].median()

print(f"Median of age is {median_age}")

train["Age"] = train["Age"].fillna(train["Age"].median())
```

```
Median of age is 28.0
```

T9

In [ ]:
```python
# T9
train["Embarked"] = train["Embarked"].fillna(train["Embarked"].mode()[0])

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

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

T10

In [ ]:
```python
features = np.array(train[["Pclass", "Sex", "Age", "Embarked"]].values, dtype=float)
results = np.array(train["Survived"].values, dtype=float)
features, results
```

Out[ ]:
```
(array([[ 3.,  0., 22.,  0.],
        [ 1.,  1., 38.,  1.],
        [ 3.,  1., 26.,  0.],
        ...,
        [ 3.,  1., 28.,  0.],
        [ 1.,  0., 26.,  1.],
        [ 3.,  0., 32.,  2.]]),
 array([0., 1., 1., 1., 0., 0., 0., 0., 1., 1., 1., 1., 0., 0., 0., 1., 0.,
        1., 0., 1., 0., 1., 1., 1., 0., 1., 0., 0., 1., 0., 0., 1., 1., 0.,
        0., 0., 1., 0., 0., 1., 0., 0., 0., 1., 1., 0., 0., 1., 0., 0., 0.,
        0., 1., 1., 0., 1., 1., 0., 1., 0., 0., 1., 0., 0., 0., 1., 1., 0.,
        1., 0., 0., 0., 0., 0., 1., 0., 0., 0., 1., 1., 0., 1., 1., 0., 1.,
        1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 1., 1., 0., 0., 0.,
        0., 0., 0., 0., 1., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 1., 0., 1., 0., 1., 1., 0., 0., 0., 0., 1., 0., 0.,
        1., 0., 0., 0., 0., 1., 1., 0., 0., 0., 1., 0., 0., 0., 0., 1., 0.,
        0., 0., 0., 1., 0., 0., 0., 0., 1., 0., 0., 0., 1., 1., 0., 0., 0.,
        0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 1., 0., 1.,
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        0., 0., 0., 1., 0., 1., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 1.,
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        0., 1., 1., 1., 1., 1., 1., 1., 0., 0., 0., 1., 0., 1., 0., 1., 1.,
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        0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 1., 0., 1., 0., 0., 1.,
        0., 0., 1., 1., 0., 0., 1., 1., 0., 0., 0., 1., 0., 0., 1., 1., 0.,
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        0., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 1., 1., 0.,
        0., 0., 1., 1., 1., 1., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 1., 1., 0., 1., 0., 0., 0., 1., 1., 1., 1., 1., 0.,
        0., 0., 1., 0., 0., 1., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 1.,
        0., 0., 0., 1., 0., 1., 1., 1., 1., 0., 0., 0., 1., 0., 0., 1., 1.,
        0., 0., 1., 0., 1., 0., 0., 1., 1., 0., 0., 0., 1., 1., 0., 0., 0.,
        0., 0., 0., 1., 0., 1., 0.]))
```
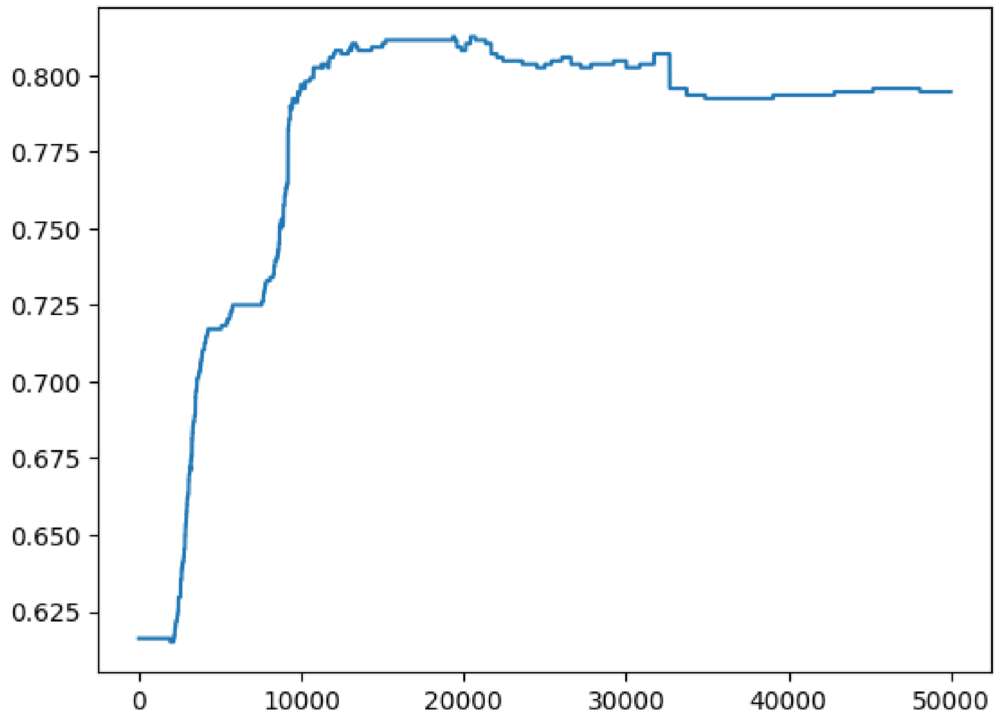

In [ ]:
```python
learning_rate = 1e-6


def calculate_logistic(h):
    return 1 / (1 + np.exp(-h))
```

```python
def get_next_theta(theta, x, y):
    error = y - calculate_logistic(np.dot(x, theta))

    diff_theta = x.T.dot(error) * learning_rate

    return diff_theta


def classifier(theta, x):
    solution = calculate_logistic(np.dot(x, theta))

    classifier_result = solution >= 0.5

    solution[classifier_result == True] = 1
    solution[classifier_result == False] = 0

    return solution


def measurement(predicts, actual):
    diff = predicts - actual
    correct = diff == 0

    return np.sum(correct) / actual.shape


def train_logistic_regression(features, results):
    iterations = int(1e4)
    features_with_one = np.insert(features, 0, 1, axis=1)

    starting_theta = np.zeros(features_with_one.shape[1])
    theta = np.copy(starting_theta)
    accuracy_list = []

    for _ in range(iterations):
        theta += get_next_theta(theta, features_with_one, results)
        accuracy = measurement(
            np.array(train["Survived"]), classifier(theta, features_with_one)
        )[0]
        accuracy_list.append(accuracy)

    print(theta)
    print("Training Accuracy:", accuracy_list[-1])

    plt.plot(accuracy_list)
    plt.show()

    return theta
```

In [ ]:
```python
theta = train_logistic_regression(features, results)
```

```
[ 0.60877697 -0.77117063  2.1963073  -0.01308992  0.34021432]
Training Accuracy: 0.7946127946127947
```



In [ ]:
```
# Clean test data
test["Embarked"] = test["Embarked"].fillna(test["Embarked"].mode()[0])

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

test.loc[test["Sex"] == "male", "Sex"] = 0
test.loc[test["Sex"] == "female", "Sex"] = 1
```

T11

In [ ]:
```
# T11
test_features = np.array(test[["Pclass", "Sex", "Age", "Embarked"]].values, dtype=float)
test_features = np.insert(test_features, 0, 1, axis=1)

test_result = classifier(theta, test_features)
test_id = test[["PassengerId"]]

df = pd.DataFrame()

df["PassengerId"] = test_id
df["Survived"] = np.array(test_result, dtype=int)

df.to_csv("titanic_result.csv", index=False)
```

× **Submission Details**

titanic_result.csv
Complete · 2m ago

Score: 0.66985

UPLOADED FILES

titanic_result.csv (3 KiB)

DESCRIPTION

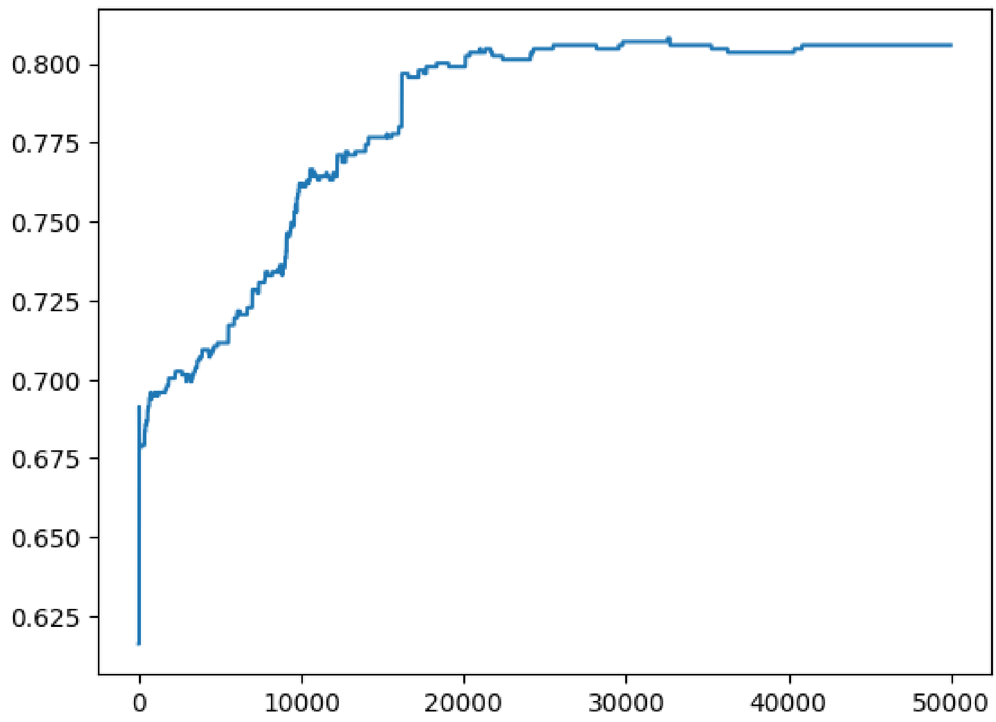
Logistic Regression with Gradient Descend V3

44 / 500

T12

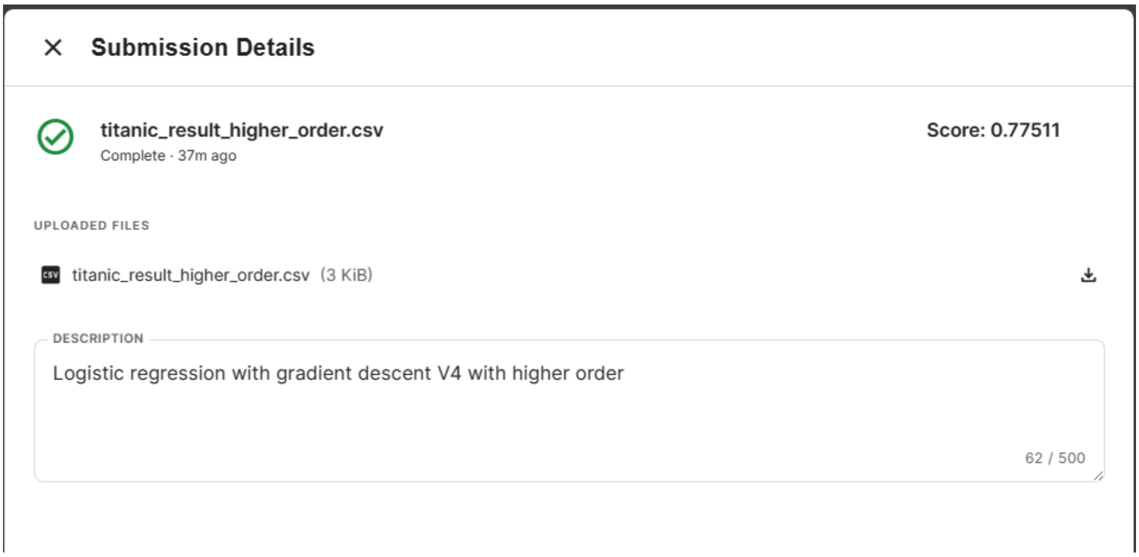
```
In [ ]: features_with_higher_order = np.insert(features, 0, features[:, 0] ** 2, axis=1)
        features_with_higher_order = np.insert(
            features_with_higher_order, 0, features[:, 0] * features[:, 2], axis=1
        )

        theta_higher_order = train_logistic_regression(features_with_higher_order, results)
```

```
[ 0.27778632 -0.01063309 -0.23897882  0.22627652  2.13072319 -0.00735009
  0.36545214]
Training Accuracy: 0.8058361391694725
```




```
In [ ]: test_features = np.array(test[["Pclass", "Sex", "Age", "Embarked"]].values, dtype=float)

        test_features_higher_order = np.insert(
            test_features, 0, test_features[:, 0] ** 2, axis=1
        )
```

```
test_features_higher_order = np.insert(
    test_features_higher_order, 0, test_features[:, 0] * test_features[:, 2], axis=1
)
test_features_higher_order = np.insert(test_features_higher_order, 0, 1, axis=1)

test_result = classifier(theta_higher_order, test_features_higher_order)
test_id = test[["PassengerId"]]

df = pd.DataFrame()

df["PassengerId"] = test_id
df["Survived"] = np.array(test_result, dtype=int)

df.to_csv("titanic_result_higher_order.csv", index=False)
```



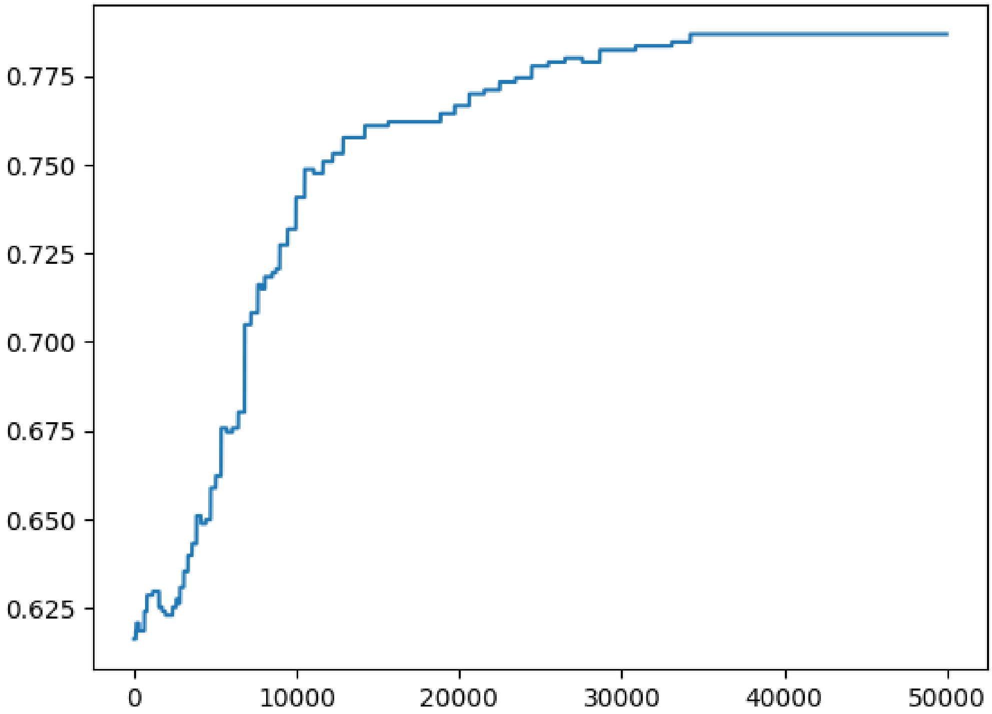
We see that there are little accuracy difference which higher order feature gives more accuracy than normal feature

T13

In [ ]:

```
reduced_features = np.array(train[["Sex", "Age"]].values, dtype=float)

theta_reduced = train_logistic_regression(reduced_features, results)
```

```
[-0.68387827  2.04999267 -0.0178297 ]
Training Accuracy: 0.7867564534231201
```



In [ ]:
```
test_features_reduced = np.array(test[["Sex", "Age"]].values, dtype=float)
test_features_reduced = np.insert(test_features_reduced, 0, 1, axis=1)

test_result = classifier(theta_reduced, test_features_reduced)
test_id = test[["PassengerId"]]

df = pd.DataFrame()

df["PassengerId"] = test_id
df["Survived"] = np.array(test_result, dtype=int)

df.to_csv("titanic_result_reduced.csv", index=False)
```

Submission Details

titanic_result_reduced.csv
Complete · 28m ago

Score: 0.77272

UPLOADED FILES

titanic_result_reduced.csv (3 KiB)

DESCRIPTION

Logistic regression with gradient descent V4 + Reduced features to age, sex

75 / 500

Overall result from reduced features give less accuracy than normal feature or features which has higher order

OT3

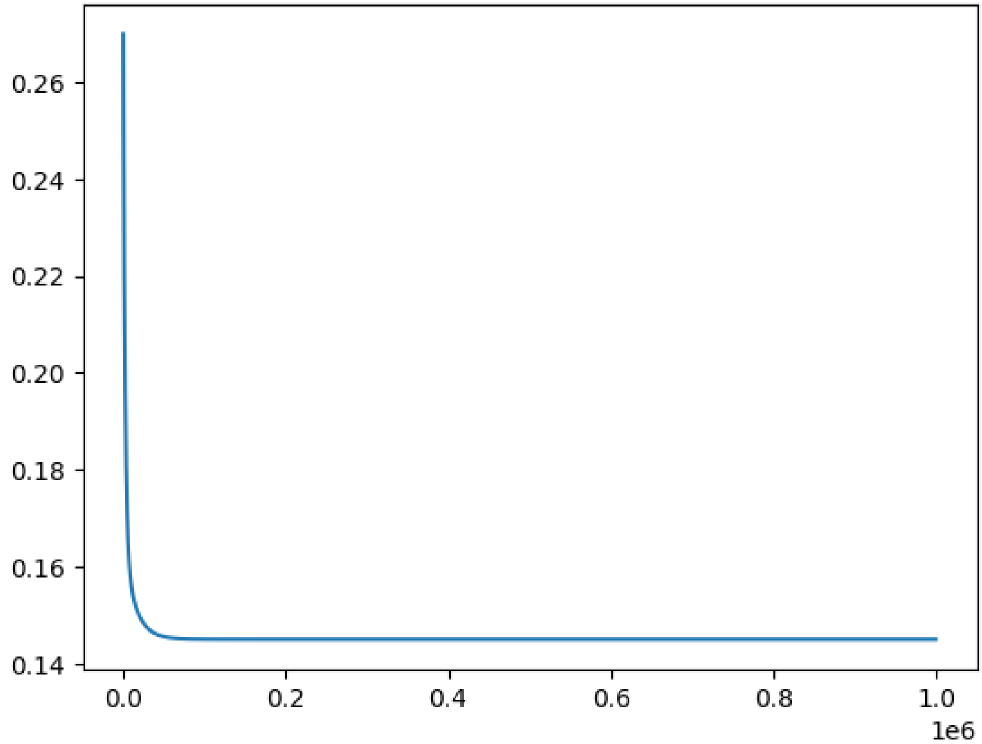
In [ ]:
```
# OT3
learning_rate = 1e-6
```

```python
def measurement(results, actual):
    size = results.shape[0]
    return np.sum((results - actual) ** 2) / size


def get_next_theta(theta, x, y):
    diff_theta = x.T.dot(y - x.dot(theta)) * learning_rate

    return diff_theta


def train_linear_regression(features, results):
    iterations = int(1e6)
    features_with_one = np.insert(features, 0, 1, axis=1)

    starting_theta = np.zeros(features_with_one.shape[1])
    theta = np.copy(starting_theta)

    accuracy_list = []

    for _ in range(iterations):
        diff_theta = get_next_theta(theta, features_with_one, results)
        theta += diff_theta
        accuracy = measurement(
            np.array(train["Survived"]), np.dot(features_with_one, theta)
        )
        accuracy_list.append(accuracy)

    plt.plot(accuracy_list)
    plt.show()

    print("Mean Square Error:", accuracy_list[-1])
    return theta
```

In [ ]:

```python
linear_theta = train_linear_regression(features, results)
linear_theta
```

```
Mean Square Error: 0.1449257376613481
```



Out[ ]:

```
array([ 0.77654442, -0.18843944,  0.49086711, -0.00505436,  0.04911346])
```

Result

- Mean Square Error: 0.1449257376613481
- Parameter: [0.77654442, -0.18843944, 0.49086711, -0.00505436, 0.04911346]

OT4

In [ ]:
```
# OT4

features_copy = np.insert(features, 0, 1, axis=1)

inverse_props = np.linalg.inv(np.matmul(features_copy.transpose(), features_copy))
linear_reg_theta = np.matmul(
    np.matmul(inverse_props, features_copy.transpose()), results
)

loss = measurement(np.array(train["Survived"]), np.dot(features_copy, linear_reg_theta))

print("Mean Square Error:", loss)
print("Parameter:", linear_reg_theta)
```

```
Mean Square Error: 0.14492573766134811
Parameter: [ 0.77654442 -0.18843944  0.49086711 -0.00505436  0.04911346]
```

Result

- Mean Square Error: 0.14492573766134811
- Parameter: [0.77654442 -0.18843944 0.49086711 -0.00505436 0.04911346]

which gives the same MSE and parameter value as in OT3