CSU44061 Week 2 Assignment

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1 A

(i) id:18–18-18

The data seems to have a sort of quadratic shape at the top with a clear distinction between the data. The data isn't evenly distributed, with the majority of data points belonging to the -1 class.

```
f = open("ass2.txt", "r")
start = True
data = {'x': [], 'y': [], 'z': []}
for i in f:
    if not start:
        i = i.rstrip('\n')
        vals = i.split(",")
        data['x'].append(float(vals[0]))
        data['y'].append(float(vals[1]))
        data['z'].append(int(vals[2]))
    else:
        start = False
df = pd.DataFrame(data)
df1 = df[df['z'] == -1]
df2 = df[df['z'] != -1]
```

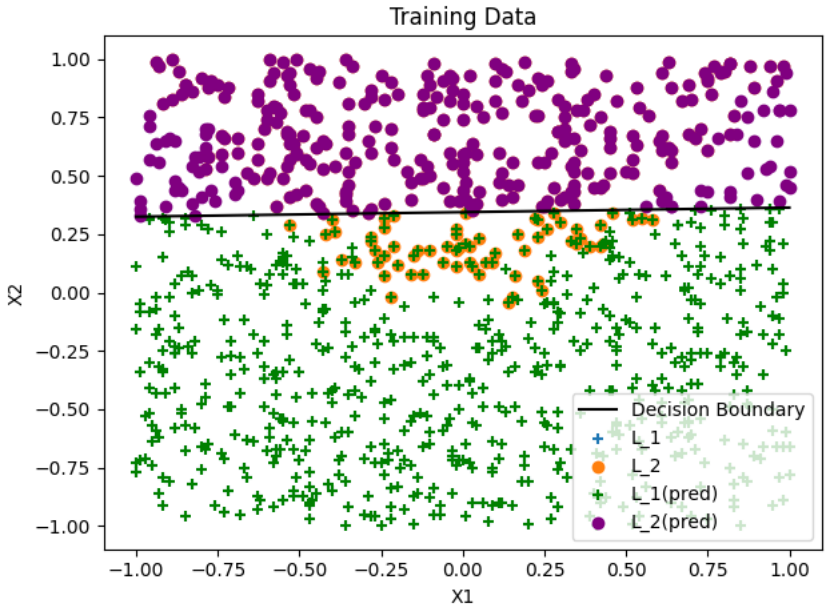
To derive the plot, I read in the data and placed it in a dataframe. From there I seperated the data into 2 seperate dataframes based on the value of the classification and plotted the graph with different markers for each frame.

(ii) $\theta_0 = -2.01562941, \theta_1 = -0.11408452$ $\theta_2 = 5.85191207$
From training the model, we can see that Z = +1 when $-2.01562941 - 0.11408452x_1 + 5.85191207x_2 > 0$ and Z = -1 when < 0.

```
def loger():
    df1 = df[df['z'] == -1]
    df2 = df[df['z'] != -1]
    x = df[['x', 'y']]
    model = LogisticRegression(penalty='none', solver='lbfgs')
```

```
model.fit(x, df['z'])
print(model.intercept_, model.coef_)
ys = model.predict(x)
```

I created a function to do the logistic regression, using some of the code we got in class. I called Scikit-Learn to get the Logistic Regression model and fitted the data that was already in the dataframe I created in part (i). From there I printed out the values reported to me by the model to get the parameter values.
(iii)



To obtain the decision boundary, I needed to get the correct value of x_2 given x_1. To achieve this, I just needed to solve the following equation:

$$x_2 = -(\theta_0 + \theta_1 * x_1)/\theta_2$$

which gave me the correct value of y as I have the other parameters from my model. I just picked values of x between 1 and -1 using linspace and then plotted the line through those points to generate my decision boundary. I split the predictions into 2 separate dataframes to plot them also.

```
ys = model.predict(x)
x['ys'] = ys
df3 = x[x['ys'] == -1]
df4 = x[x['ys'] != -1]

x_vals = np.linspace(-1, 1, 50)
y = -(model.intercept_ + model.coef_[0][0] * x_vals) / model.coef_[0][1]
```

(iv) The training data and the predictions made by the mode are accurate for the majority of cases. But as we can see in the above graph, the decision boundary is a straight line bisecting the classifications, instead of a more quadratic curve that we would expect. This causes us to have the errors in prediction like we can see towards the centre of the graph with the blue dots. Our data is clearly not linearly separable without doing some additional feature engineering.

2 B

(i)
I created an additional dataframe just containing the values of x1 and x2, then created a list of models to hold the different models I was about to generate. From there I created a list of C values in the range .001 - 1000 using np.geomspace that would increment each value of C logarithmically increasing. From there I used a for loop to iterate through my C values and created a model for each value of C and added each model to my list of models.

```
df1 = df[df['z'] == -1]
df2 = df[df['z'] != -1]
x = df[['x', 'y']]
models = []
c_vals = np.geomspace(.001, 1000, num=7)
print(c_vals)
for i in c_vals:
        model = LinearSVC(C=i)
```

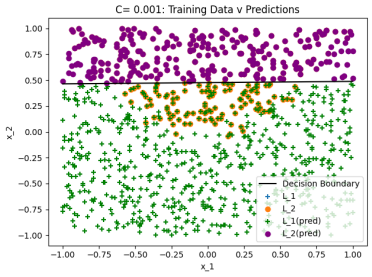
```
model.fit(x, df['z'])
models.append((model,i))
```

The values that were reported: From the table we can see our parameters changing as our values of C change also.

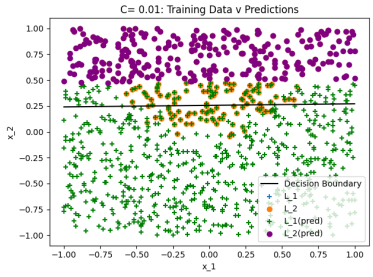
C	θ_0	θ_1	θ_2
0.001	-0.22455416	-0.005645851095120078	0.4719346941148196
0.01	-0.22455812	-0.00564579379445042	0.47193503867031295
0.1	-0.58606903	-0.04703557261644461	1.7321454214013863
1	-0.64422422	-0.04977653564180903	1.8907362329846127
10	-0.65199195	-0.050029482385095074	1.9116600091510394
100	-0.64589482	-0.03309475226557805	1.9442524392896159
1000	-0.96418217	0.37131381996648427	0.9543004068755857

Table 1: C values and parameters

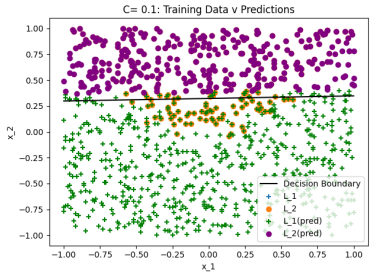
As our values of C change, we can see that the y intercept changes drastically, with it getting smaller as our value of C increases. The values in our table seem to diifer by much less as our c value increases in size, this could possibly be due to the SVM becoming more strict in terms of classification.
(ii) To calculate the decision boundary for each of these plots, I used the same approach as I used in part A(iii). I



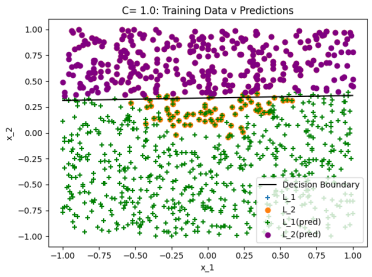
(a) C = 0.001



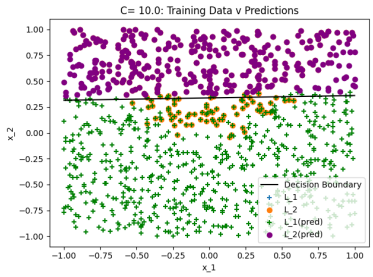
(b) C = 0.01



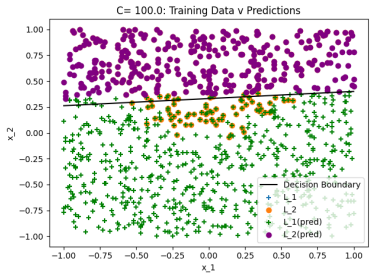
(c) C = 0.1



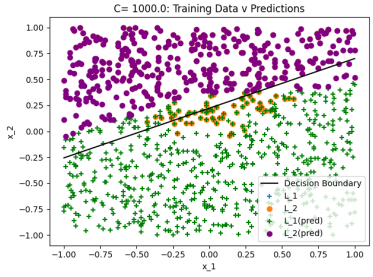
(d) C = 1



(e) C = 10



(f) C = 100



(g) C = 1000

used MatplotLib to generate all the graphs and a for loop to iterate through each of the models I had created to create each of the individual graphs.

```
for model in models:
    plt.clf()
    model[0].fit(x,df['z'])
    ys = model[0].predict(x)
    x['ys'] = ys
    df3 = x[x['ys'] == -1]
    df4 = x[x['ys'] != -1]
    x_vals = np.linspace(-1, 1, 50)
    y = -(model[0].intercept_ + model[0].coef_[0][0] * x_vals) / model[0].coef_[0][1]
```

(iii)
Changing the value of C influences the decision boundary by changing the slope and the intercept of the line generated.

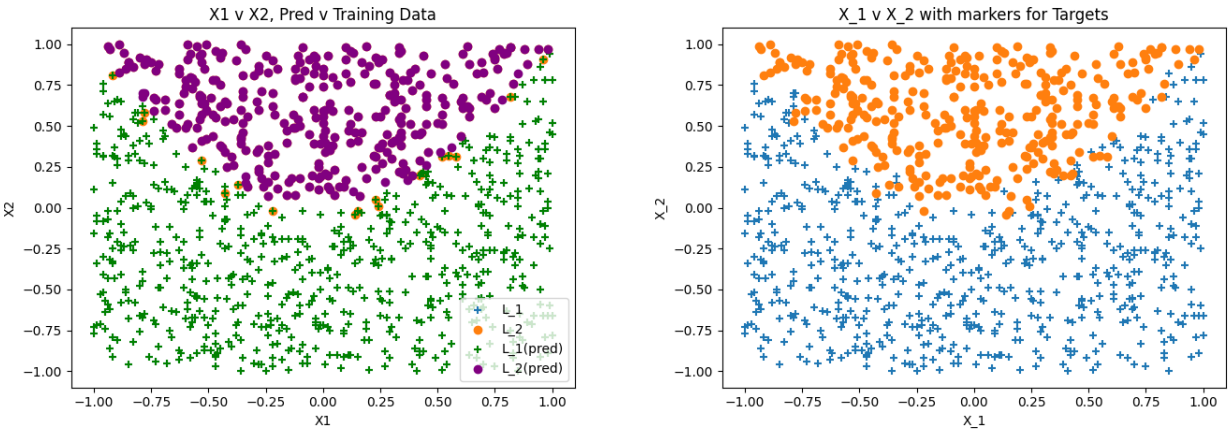
This happens as the model attempts prevent misclassifying the data. When we've low values of C like in graph 1 and 2, we misclassified a lot of the data and we can see that with the position of the decision boundary being much higher than in the other graphs. This happens as we've got a larger margin of error so it allows for more points to be misclassified. Low values of c can even cause misclassification of linearly separable data. For larger values of C, like for C=100, we've misclassified much less of the data, and this can be seen in how the slope of the line has changed, becoming much less horizontal. But we've still got to be careful not to use too large values of C, like C = 1000 as this can make the classifier much too conservative and influences the slope a lot as it tries to prevent misclassifying any of the data.

3 C

(i) To get the square of each of the features, I selected each of the individual rows with features and multiplied the value in each row by itself to get the square. I then added these values and the original values to a new dataframe called squared. Using this dataframe I fit a Logistic Regression classifier using scikit-learn. I then printed out the values of the parameters
The values reported to me by the model: $\theta_0 = 0.2388532 \theta_1 = -0.59851887$ $\theta_2 = 21.11277526$ $\theta_3 = -26.29209894$ $\theta_4 = 5.87851124$. These values give me the formula for some sort of quadratic line which would match the shape of the decision boundary I would plot for the data. In comparison to the linear equation I got earlier, the parameter values are rather different, with my intercept being much larger and my values for theta 1 and 2 being larger also.

```
plt.clf()
    df['x3'] = df['x']**2
    df['x4'] = df['y']**2
    df1 = df[df['z'] == -1]
    df2 = df[df['z'] != -1]
    x = df[['x', 'y']]
    square = df[['x', 'y', 'x3', 'x4']]
    model = LogisticRegression(penalty='none', solver='lbfgs')
    model.fit(square, df['z'])
    print(model.intercept_, model.coef_)
```

(ii) When we add the squared features to the dataset and add this data to our model, we can see our predictions



(a) Training vs Predictions

(b) Training data

become much more accurate for each classification of data. The decision boundary would be quadratic in shape roughly, so squaring the features gives us a quadratic model also. While the model isn't perfect, overall it fits the data much more accurately than our linear model.

```
ys = model.predict(square)
    x['ys'] = ys
    df3 = x[x['ys'] == -1]
    df4 = x[x['ys'] != -1]
```

(iii) For the baseline model, I used a predictor based of the ratio of the data. From the data I could see it's split roughly 70/30 so I let it predict one class 70% of the time and the other the rest of the time. I generated 999 numbers between 1 and 10 from there turned those numbers into a +1 or -1 depending on if it was bigger than 7 or not. I then appended the results to the dataframe.
From this, I then put the number of correct predictions over the number of points. I did this multiple times to get an average. On average, using this method, I got the correct class 58% of the time giving me an accuracy of 58%. In comparison, using the model, I got the correct class 97% of the time.
Using the random model as my baseline, I could see that the model I created using Logistic regression was significantly better than the baseline model I created. While I expected the random model to be more accurate than it is, due

to the fact it's generating a random number between 1 and 10 for it to be classified is probably why there's a higher error rate than just guessing the most prevalent class in the dataset.

```
v = np.random.randint(10,size=999)
    for i in range(len(v)):
        if v[i] >= 7:
            v[i] = -1
        else:
            v[i] = -1
    df['rand'] = v
    df5 = df[df['rand'] == -1]
    df6 = df[df['rand'] != -1]
    num = df[df['rand'] == df['z']]
    num2 = df[df['z'] == ys]
    print(len(num), len(num2))
```

4 Appendix: Code

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC

f = open("ass2.txt", "r")
start = True
data = {'x': [], 'y': [], 'z': []}
for i in f:
    if not start:
        i = i.rstrip('\n')
        vals = i.split(",")
        data['x'].append(float(vals[0]))
        data['y'].append(float(vals[1]))
        data['z'].append(int(vals[2]))
    else:
        start = False
df = pd.DataFrame(data)



def loger():
    df1 = df[df['z'] == -1]
    df2 = df[df['z'] != -1]
    x = df[['x', 'y']]
    model = LogisticRegression(penalty='none', solver='lbfgs')
    model.fit(x, df['z'])
    print(model.intercept_, model.coef_)
    ys = model.predict(x)
    x['ys'] = ys
    df3 = x[x['ys'] == -1]
    df4 = x[x['ys'] != -1]

    x_vals = np.linspace(-1, 1, 50)
    y = -(model.intercept_ + model.coef_[0][0] * x_vals) / model.coef_[0][1]
    plt.scatter(df1['x'], df1['y'], marker='+')
    plt.scatter(df2['x'], df2['y'], marker='o')
    plt.scatter(df3['x'], df3['y'], marker='+', color='green')
    plt.scatter(df4['x'], df4['y'], marker='o', color='purple')
    plt.plot(x_vals,y, color='black')
    plt.legend(["Decision Boundary","L_1", "L_2", "L_1(pred)", "L_2(pred)"])
    plt.title(f"Training Data")
    plt.xlabel('X1')
    plt.ylabel('X2')
    plt.show()
```

```
def svm():
    df1 = df[df['z'] == -1]
    df2 = df[df['z'] != -1]
    x = df[['x', 'y']]
    models = []
    c_vals = np.geomspace(.001, 1000, num=7)
    print(c_vals)
    for i in c_vals:
        model = LinearSVC(C=i)
        model.fit(x, df['z'])
        models.append((model,i))

    for model in models:
        plt.clf()
        model[0].fit(x,df['z'])
        ys = model[0].predict(x)
        x['ys'] = ys
        df3 = x[x['ys'] == -1]
        df4 = x[x['ys'] != -1]
        x_vals = np.linspace(-1, 1, 50)
        y = -(model[0].intercept_ + model[0].coef_[0][0] * x_vals) / model[0].coef_[0][1]
        plt.scatter(df1['x'], df1['y'], marker='+')
        plt.scatter(df2['x'], df2['y'], marker='o')
        plt.scatter(df3['x'], df3['y'], marker='+', color='green')
        plt.scatter(df4['x'], df4['y'], marker='o', color='purple')
        plt.plot(x_vals, y, color='black')
        plt.legend(["Decision Boundary", "L_1", "L_2", "L_1(pred)", "L_2(pred)" ])
        plt.title(f"C= {model[1]}: Training Data v Predictions")
        plt.xlabel("x_1")
        plt.ylabel("x_2")
        plt.show()
        plt.clf()

def squared():
    plt.clf()
    df['x3'] = df['x']**2
    df['x4'] = df['y']**2
    df1 = df[df['z'] == -1]
    df2 = df[df['z'] != -1]
    x = df[['x', 'y']]
    square = df[['x', 'y', 'x3', 'x4']]
    model = LogisticRegression(penalty='none', solver='lbfgs')
    model.fit(square, df['z'])
    print(model.intercept_, model.coef_)
    ys = model.predict(square)
    x['ys'] = ys
    df3 = x[x['ys'] == -1]
    df4 = x[x['ys'] != -1]
    plt.scatter(df1['x'], df1['y'], marker='+')
    plt.scatter(df2['x'], df2['y'], marker='o')
    plt.scatter(df3['x'], df3['y'], marker='+', color='green')
    plt.scatter(df4['x'], df4['y'], marker='o', color='purple')
    plt.legend(["L_1", "L_2", "L_1(pred)", "L_2(pred)"])
    plt.title(f"X1 v X2, Pred v Training Data")
    plt.xlabel('X1')
    plt.ylabel('X2')
    plt.show()

    v = np.random.randint(10,size=999)
    for i in range(len(v)):
        if v[i] >= 7:
            v[i] = -1
        else:
            v[i] = -1
    df['rand'] = v
    df5 = df[df['rand'] == -1]
```

```
df6 = df[df['rand'] != -1]
plt.clf()
plt.scatter(df1['x'], df1['y'], marker='+')
plt.scatter(df2['x'], df2['y'], marker='o')
plt.scatter(df5['x'], df5['y'], marker='+', color='green')
plt.scatter(df6['x'], df6['y'], marker='o', color='purple')
plt.show()
num = df[df['rand'] == df['z']]
num2 = df[df['z'] == ys]
print(len(num), len(num2))
```