CSU44061 Machine Learning - Week 2
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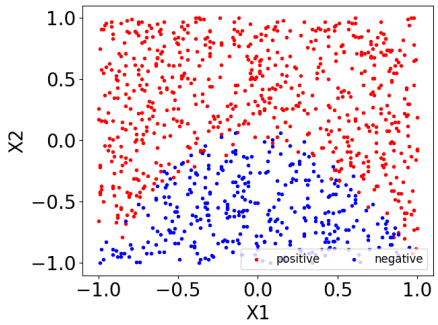
Dataset # id:9–9–9

Question a

Code for all questions provided in the appendix.

Part i

Using matplotlib with python to generate graphs, I plotted X2 against X1 (both features) and made the colour of the marker different based on the prediction. The red colour represents a positive prediction (+1) and the blue colour represents a negative prediction (-1)



Part ii

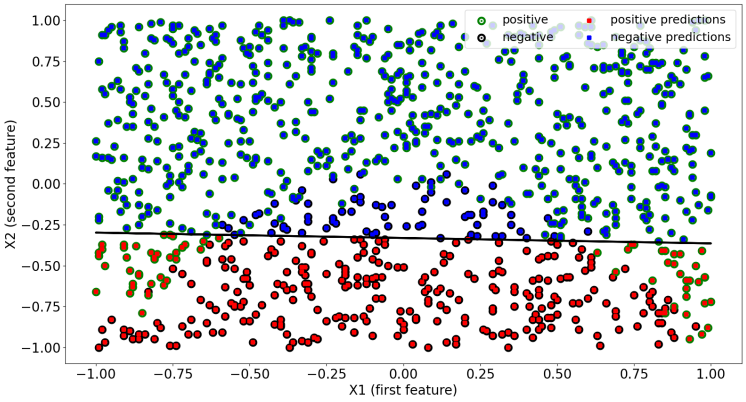
Using code provided in the appendix, I trained a logistic regression classifier which gave me the following model:

$$\theta_0 + \theta_1 x_1 + \theta_2 x_2 = -1.91100581 - 0.18987022 * x_1 - 5.76650534 * x_2$$

Part iii

The following plot plots X1 against X2, using the predictions and the actual y output from the dataset. The y output and predictions use different colours and markers to attempt to make this graph more readible.

We can clearly see that the predictions are quite rough and very inacurrate on the edges as well as the top of the slope.



As for the slope representing the classifier separation, I used the following equation. It is obtained by computing the sum of the linear function which uses θ_0 and θ_1 and dividing the result by the 3rd value of the model: θ_2.

$$y = -\frac{\theta_1 * x_1^i + \theta_0}{\theta_2}$$

Question b

Part i

Using code provided in the appendix, I trained a linear SVM classifier with 3 different C values. I obtained the following parameters:

C = 0.001

$$-0.21517665 - 0.00849777 * x_1 - 0.47908454 * x_2$$

C = 1

$$-0.61452025 - 0.06661916 * x_1 - 1.88463746 * x_2$$

C = 1000

$$-0.62224281 - 0.06807451 * x_1 - 1.90613439 * x_2$$

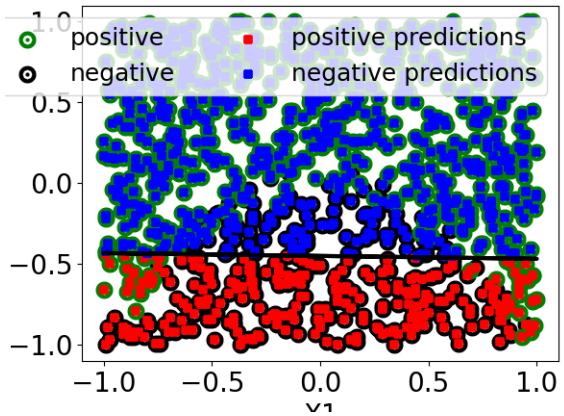
It is worth noting that using C = 1000 required a maximum amount of iterations when training the model to be much higher. I used a maximum of 100000 iterations for this algorithm.

Part ii

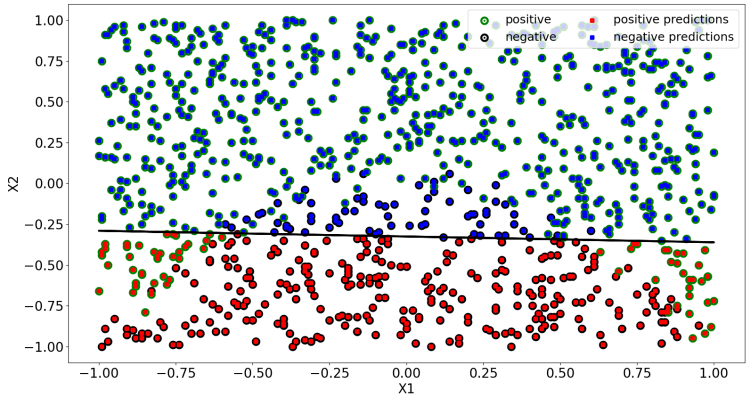
Using the same method for plotting as in the previous question, I plot the predictions on top of the actual values in order to try detect inconsistencies on the predictions. The separation line is also plotted using the same function as

explained in the previous question. Using the different values for C we obtain the following graphs:

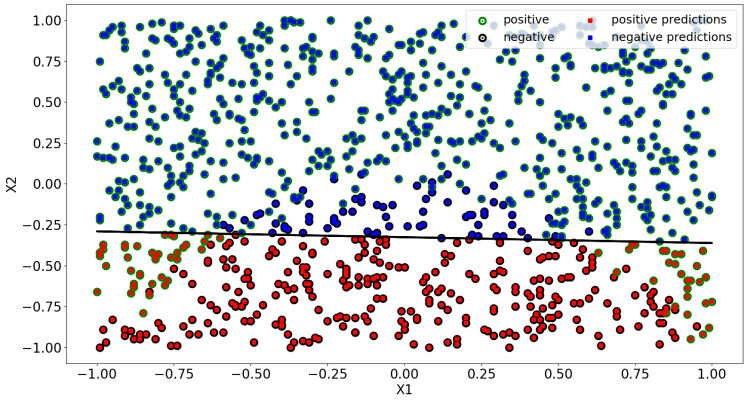
C = 0.001



C = 1



C = 1000



Part iii

A larger value for C will choose a smaller margin for the hyperplane separating our data. In this case this results in a higher intercept value and smaller coefficient. A smaller value for C will make the margin for data separation bigger, potentially resulting in more misclassifications.

Looking at the plot, a higher value for C makes the separating line for the predictions higher on the y axis (representing X2), thus prediciting more values as positive (y = 1).

A lower value for C makes the separating line lower on the y axis, thus predicting less values as positive (y = 1).

In our situation it seems that a larger value for C works best.

Question c

Part i

I created two additional features by squaring both features $X1$ and $X2$. This gives me a total of 4 features to use to train a logistic regression classifier. Using code provided in the appendix we get the following parameters:

$$\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2$$

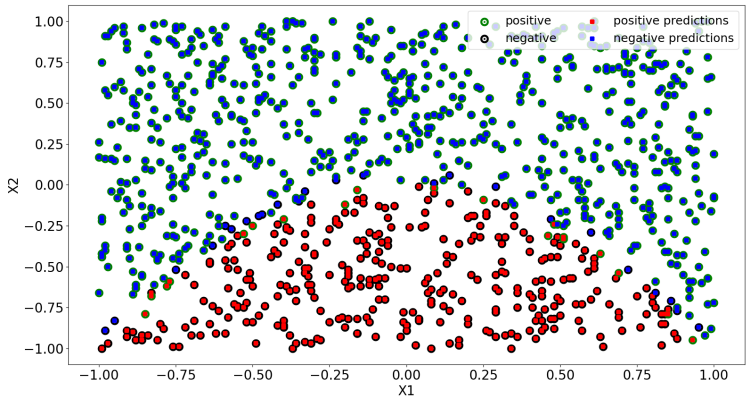
$$= 0.34532747 - 0.61211948 * x_1 - 20.55468232 * x_2 - 22.19408429 * x_1^2 + 2.27234931 * x_2^2$$

Part ii

Using the same system as with previous graphs, I plotted the predictions on top of the actual outputs values. This plot is X1 against X2, where actual outputs

and predictions are plotted with different colours and markers using a model with 4 features as described in the previous section.

We notice that predictions are much better than our previous models.



Part iii

base model accuracy score: 0.6643286573146293 trained model accuracy score: 0.9569138276553106 To obtain the baseline model, I compute the mean of all output values y. I keep the sign of the mean and that is the prediction. For my dataset this turned out to be -1. I then compute the percentage of accuracy of our predictions for both models against the actual outputs and we obtain the following values:

- Logistic Regression Classifier: 0.9569138276553106 (or 96% accuracy)
- Baseline Model: 0.6643286573146293 (or 66% accuracy)

We notice an increase of 30% in the accuracy of our model which is not negligible.

Appendix

Util methods:

```
import numpy as np
import pandas as pd

def get_data():
    # Read in data
    df = pd.read_csv("week2.csv", comment='#')
    X1 = df.iloc[:, 0]
    X2 = df.iloc[:, 1]
    X = np.column_stack((X1, X2))
    y = df.iloc[:, 2]
```

```
    ytrain = np.sign(y)
    return X1, X2, X, y, ytrain
```

Question A i:

```
import matplotlib.pyplot as plt
from util import get_data

# Read in data
X1, X2, X, y, ytrain = get_data()

# Plot the data
plt.rc('font', size=20)
plt.rcParams['figure.constrained_layout.use'] = True
neg = plt.scatter(X1[y < 0], X2[y < 0],
                  color='red', marker=".")
pos = plt.scatter(X1[y > 0], X2[y > 0],
                  color='blue', marker=".")
plt.xlabel("X1")
plt.ylabel("X2")
plt.legend((neg, pos), ["positive", "negative"],
           scatterpoints=1,
           loc='lower right',
           ncol=2,
           fontsize=12)
plt.show()
```

Question A ii and iii:

```
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
from util import get_data
import numpy as np

# Read in data
X1, X2, X, y, ytrain = get_data()

# Train the model
model = LogisticRegression(solver='lbfgs',
                           penalty="none")
model.fit(X, ytrain)

# Print model values
print("Logistic Regression Classifier")
print("intercept:", model.intercept_)
print("slope:", model.coef_)

# Predict values
```

```
ypred = np.sign(model.predict(X))

# Extract the slope to display from model coefs
line_bias = model.intercept_
line_w = model.coef_.T
points_y = [(line_w[0]*x+line_bias)/(-1*line_w[1])
                                        for x in X1]

# Plot the preditions
plt.rc('font', size=20)
pos = plt.scatter(X1[y > 0], X2[y > 0],
                  color='black', marker=".")
neg = plt.scatter(X1[y < 0], X2[y < 0],
                  color='green', marker=".")
pos_pred = plt.scatter(X1[ypred > 0], X2[ypred > 0],
                       color='red', marker="+")
neg_pred = plt.scatter(X1[ypred < 0], X2[ypred < 0],
                       color='blue', marker="+")
plt.rcParams['figure.constrained_layout.use'] = True
plt.xlabel("X1 (first feature)")
plt.ylabel("X2 (second feature)")
plt.plot(X1, points_y, color='black', linewidth=3)
plt.legend((neg, pos, pos_pred, neg_pred),
           ["positive", "negative",
           "positive predictions",
           "negative predictions"],
           scatterpoints=1,
           loc='upper right',
           ncol=2,
           fontsize=18)
plt.show()
```

Question b

```
from sklearn.svm import LinearSVC
import matplotlib.pyplot as plt
from util import get_data
import numpy as np

# Read in data
X1, X2, X, y, ytrain = get_data()

# Train Linear SVC for C=0.001, 1 and 1000
for C_val in [0.001, 1, 1000]:
    # max iter lower than 100 000
    #makes C=1000 not converge
    model = LinearSVC(C=C_val, max_iter=100000)
```

```
                    .fit(X, ytrain)
    print("C, intercept, slope",
          C_val, model.intercept_, model.coef_)

# Plot one of the 3 models
# (change C value to plot the other ones)
model = LinearSVC(C=0.001, max_iter=100000)
                .fit(X, ytrain)
line_bias = model.intercept_
line_w = model.coef_.T
points_y = [(line_w[0]*x+line_bias)
            / (-1*line_w[1]) for x in X1]

# Predict values
ypred = np.sign(model.predict(X))

# Plot the preditions
plt.rc('font', size=20)
pos = plt.scatter(X1[y > 0], X2[y > 0],
                  color='black', marker=".")
neg = plt.scatter(X1[y < 0], X2[y < 0],
                  color='green', marker=".")
pos_pred = plt.scatter(X1[ypred > 0], X2[ypred > 0],
                       color='red', marker="+")
neg_pred = plt.scatter(X1[ypred < 0], X2[ypred < 0],
                       color='blue', marker="+")
plt.rcParams['figure.constrained_layout.use'] = True
plt.xlabel("X1")
plt.ylabel("X2")
plt.plot(X1, points_y, color='black', linewidth=3)
plt.legend((neg, pos, pos_pred, neg_pred),
           ["positive", "negative",
           "positive predictions",
           "negative predictions"],
           scatterpoints=1,
           loc='upper right',
           ncol=2,
           fontsize=18)
plt.show()
```

Question c

```
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
from util import get_data
import numpy as np
```

```
import pandas as pd
from sklearn.preprocessing import PolynomialFeatures
from sklearn import metrics
import statistics

# Read in data
X1, X2, X, y, ytrain = get_data()

X1 = np.array(X1)
X2 = np.array(X2)
# Square both features
X1_square = X1.reshape(-1, 1)
X2_square = X2.reshape(-1, 1)
X1_square = np.square(X1)
X2_square = np.square(X2)
X = np.column_stack((X1, X2, X1_square, X2_square))

# Train our model
model = LogisticRegression(solver='lbfgs',
                           penalty="none")
model.fit(X, ytrain)

# Print model values
print("Logistic Regression Classifier")
print("intercept:", model.intercept_)
print("slope:", model.coef_)

# Predict values
ypred = np.sign(model.predict(X))

# Create a baseline model which predicts the most
# common value. Find the most common value by getting
# the sign of the mean.
baseline_model = np.sign(statistics.mean(y))
# generate an array of same size as y
# filled with out baseline predictions
y_baseline_pred = np.full((len(y), 1), baseline_model)

# Compute percentage of accurace for each predictions
accuracy_model = metrics.accuracy_score(y, ypred)
accuracy_base = metrics.accuracy_score
                                (y, y_baseline_pred)
# Print outputs
print("base model accuracy score: ",
    accuracy_base, " - trained model accuracy score: ",
    accuracy_model)
```

```
# Plot the preditions
plt.rc('font', size=20)
pos = plt.scatter(X1[y > 0], X2[y > 0],
                  color='black', marker=".")
neg = plt.scatter(X1[y < 0], X2[y < 0],
                  color='green', marker=".")
pos_pred = plt.scatter(X1[ypred > 0], X2[ypred > 0],
                       color='red', marker="+")
neg_pred = plt.scatter(X1[ypred < 0], X2[ypred < 0],
                       color='blue', marker="+")
plt.rcParams['figure.constrained_layout.use'] = True
plt.xlabel("X1")
plt.ylabel("X2")
plt.legend((neg, pos, pos_pred, neg_pred),
           ["positive", "negative",
           "positive predictions",
           "negative predictions"],
           scatterpoints=1,
           loc='upper right',
           ncol=2,
           fontsize=18)
plt.show()
```