hw6

February 22, 2024

1 Homework 4

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[ ]:
```
import numpy as np
import pandas as pd
import platform
import os
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, roc_curve, auc
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import roc_curve, auc, accuracy_score
import matplotlib.pyplot as plt
```

1.1 Question 1

[ ]:
```
def loss_function(y, pred):
    y = 2 * y - 1  # Ensure y is in the form of -1 or 1
    # Use a numerically stable version of the logistic loss
    log_exp = np.log(1 + np.exp(-y * pred))
    # Handle large values explicitly to avoid overflow
    stable_log_exp = np.where(pred * y > 0, np.maximum(0, log_exp), log_exp +␣
 ↪pred * y)
    return np.sum(stable_log_exp)

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

def plot_roc_curve(y_true, y_score, label_prefix):
    fpr, tpr, _ = roc_curve(y_true, y_score)
    roc_auc = auc(fpr, tpr)

    plt.plot(fpr, tpr, label=f'{label_prefix} ROC curve (area = {roc_auc:.2f})')
```

```
old_settings = np.seterr(over='ignore')

data_direc = os.getcwd() + "/"
if platform.system() == "Windows":
    data_direc = data_direc.replace("/", "\\")
train = pd.read_csv(data_direc + "arcene_train.csv",header = None)
true_train_labels = pd.read_csv(data_direc + "arcene_train_labels.csv")
test = pd.read_csv(data_direc + "arcene_valid.csv",header = None)
test_labels = pd.read_csv(data_direc + "arcene_valid_labels.csv")

# Normalize the data
scaler = StandardScaler()
train = pd.DataFrame(scaler.fit_transform(train))
test = pd.DataFrame(scaler.transform(test))

# Define parameters
k_values = [10,30,100,300,600]
class_probabilities = np.zeros(len(true_train_labels)).reshape(-1, 1)

# Initialize lists to store results
train_losses = []
test_losses = []
train_errors = []
test_errors = []
best_lin_models = []
test_class_probabilities = np.zeros(test.shape[0]).reshape(-1, 1)
selected_features_indices = []
losses_per_k = []
train_prob_300 = None
test_prob_300 = None


train_labels = (true_train_labels + 1) / 2

for k in k_values:
    consecutive_count = 0
    train_losses_iter = []
    class_probabilities = np.zeros(len(true_train_labels)).reshape(-1, 1)
    active_features = set(range(train.shape[1]))
    temp_losses = []
    for _ in range(k):
        best_loss = float('inf')
        for feature_idx in active_features:
            # Fit univariate linear regressor
            X_feature = np.array(train.iloc[:, feature_idx]).reshape(-1, 1)
            exp_term = -1*np.array(class_probabilities)
```

```
            p = np.ones(len(train_labels)).reshape(-1,1) / (np.
↪ones(len(train_labels)).reshape(-1,1) + np.exp(exp_term))
            epsilon = 1e-6
            w = np.clip(p * (1 - p), epsilon, np.inf)
            z = (train_labels - p) / w

            temp_x = X_feature * w.reshape(-1, 1)  # Reshape w to match the␣
↪shape of X_feature
            lr = LinearRegression().fit(temp_x, z)
            pred = lr.predict(X_feature)
            pred = sigmoid(pred)

            # Calculate loss
            loss = loss_function(train_labels, pred)
            if loss < best_loss:
                best_loss_index = feature_idx
                #print("better :)")
                best_loss = loss
                best_predictor = lr

        temp_losses.append(best_loss)
        best_lin_models.append(lr)
        active_features.remove(best_loss_index)
        class_probabilities += best_predictor.predict(np.array(train.iloc[:,␣
↪best_loss_index]).reshape(-1,1))
        selected_features_indices.append(best_loss_index)
        train_losses_iter.append(loss_function(train_labels,␣
↪class_probabilities))  # Append the training loss at each iteration

        if len(temp_losses) >= 10 and all(x == temp_losses[-1] for x in␣
↪temp_losses[-10:]):
            print("The last ten values are the same. Breaking the loop.")
            break
    losses_per_k.append(temp_losses)


    train_losses.append(train_losses_iter)
    # Calculate training and test loss
    train_loss = loss_function(train_labels, class_probabilities)
    test_loss = loss_function(test_labels, class_probabilities)

    # Calculate training and test error
    train_pred = np.sign(class_probabilities)
    for model, feature_idx in zip(best_lin_models, selected_features_indices):
        current_test_predictions = model.predict(test.iloc[:, feature_idx].
↪values.reshape(-1,1))
```

```
        test_class_probabilities += current_test_predictions

    if k == 300:
        train_prob_300 = class_probabilities.copy()
        # Ensure test_class_probabilities are updated correctly in the loop
        test_prob_300 = test_class_probabilities.copy()


# Determine final predictions for the test set
    test_pred = np.sign(test_class_probabilities)
    train_pred = (train_pred +1)/2
    train_error = 1 - accuracy_score(train_labels, train_pred)
    test_error = 1 - accuracy_score(test_labels, test_pred)

    train_losses.append(train_losses_iter)  # Append the list of training␣
 ↪losses for this k to train_losses

    test_losses.append(test_loss)
    train_errors.append(train_error)
    test_errors.append(test_error)

# Plot training loss vs iteration number for k = 600
plt.plot(range(1, len(losses_per_k[-1])+1), losses_per_k[-1])
plt.xlabel('Iteration')
plt.ylabel('Training Loss')
plt.title('Training Loss vs Iteration Number for k = 600 with Early Stopping')
plt.show()

# Report misclassification errors on the training and test sets for all values␣
 ↪of k
error_table = pd.DataFrame({'k': k_values, 'Train Error': train_errors, 'Test␣
 ↪Error': test_errors})
print(error_table)

# Plot misclassification errors on the training and test sets vs k
plt.plot(k_values, train_errors, label='Train Error')
plt.plot(k_values, test_errors, label='Test Error')
plt.xlabel('Number of Boosting Iterations (k)')
plt.ylabel('Misclassification Error')
plt.title('Misclassification Error vs Number of Boosting Iterations')
plt.legend()
plt.show()

plt.figure(figsize=(10, 8))

if train_prob_300 is not None and test_prob_300 is not None:
    plt.figure(figsize=(10, 8))
```

```
    # Plot ROC curve for the training set
    plot_roc_curve(true_train_labels, train_prob_300, 'Train')
    # Plot ROC curve for the test set
    plot_roc_curve(test_labels, test_prob_300, 'Test')

    plt.plot([0, 1], [0, 1], 'k--', label='Random chance')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve for k=300 Iterations')
    plt.legend(loc="lower right")
    plt.show()


np.seterr(**old_settings)
```

```
The last ten values are the same. Breaking the loop.
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```
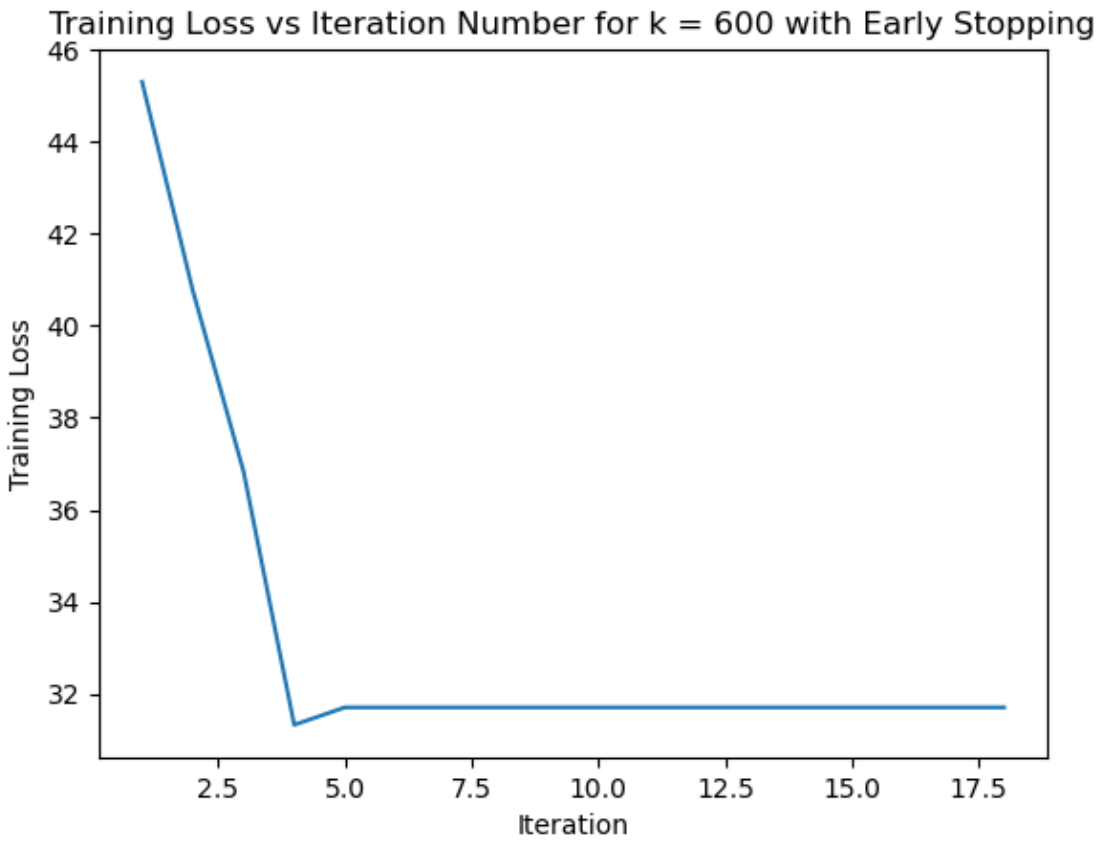
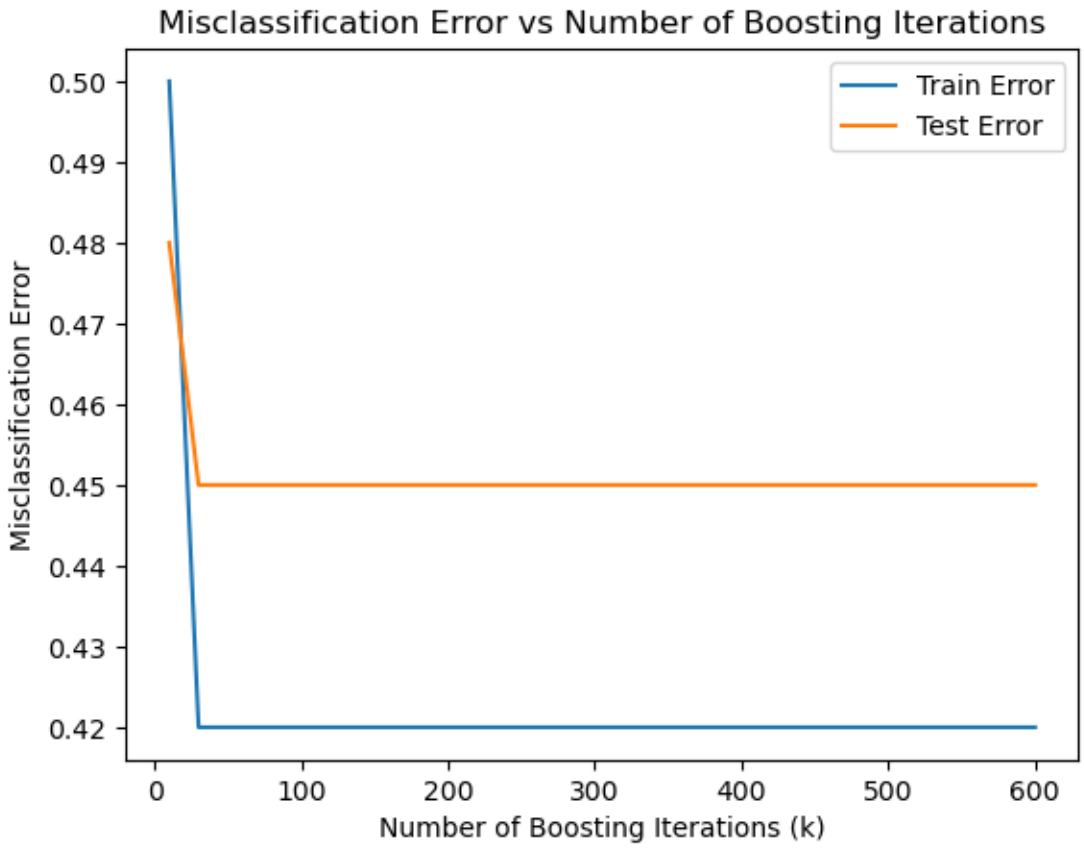
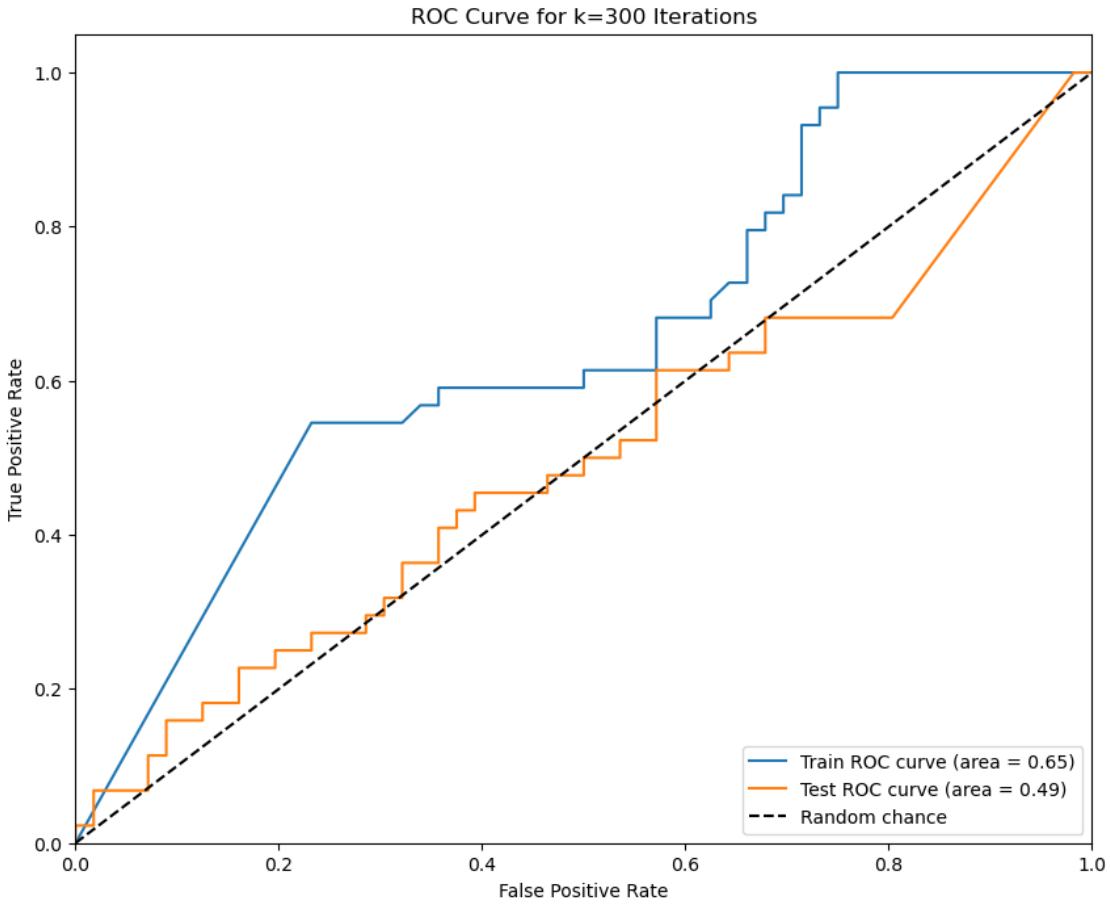



```
     k  Train Error  Test Error
0   10         0.50        0.48
1   30         0.42        0.45
2  100         0.42        0.45
3  300         0.42        0.45
4  600         0.42        0.45
```




```
<Figure size 1000x800 with 0 Axes>
```



[ ]: {'divide': 'warn', 'over': 'ignore', 'under': 'ignore', 'invalid': 'warn'}

1.2 Question 2

[ ]:
```
def loss_function(y, pred):
    y = 2 * y - 1  # Ensure y is in the form of -1 or 1
    # Use a numerically stable version of the logistic loss
    log_exp = np.log(1 + np.exp(-y * pred))
    # Handle large values explicitly to avoid overflow
    stable_log_exp = np.where(pred * y > 0, np.maximum(0, log_exp), log_exp +␣
 ↪pred * y)
    return np.sum(stable_log_exp)

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

def plot_roc_curve(y_true, y_score, label_prefix):
    fpr, tpr, _ = roc_curve(y_true, y_score)
```

```
    roc_auc = auc(fpr, tpr)

    plt.plot(fpr, tpr, label=f'{label_prefix} ROC curve (area = {roc_auc:.2f})')


data_direc = os.getcwd() + "/"
if platform.system() == "Windows":
    data_direc = data_direc.replace("/", "\\")
train = pd.read_csv(data_direc + "gisette_train.csv")
train_labels = pd.read_csv(data_direc + "gisette_train_labels.csv")
test = pd.read_csv(data_direc + "gisette_valid.csv")
test_labels = pd.read_csv(data_direc + "gisette_valid_labels.csv")
train = np.delete(train, 5000, axis=1)
test = np.delete(test, 5000, axis=1)

old_settings = np.seterr(over='ignore')

true_train_labels = train_labels

# Normalize the data
scaler = StandardScaler()
train = pd.DataFrame(scaler.fit_transform(train))
test = pd.DataFrame(scaler.transform(test))

# Define parameters
k_values = [10,30,100,300,600]
class_probabilities = np.zeros(len(true_train_labels)).reshape(-1, 1)

# Initialize lists to store results
train_losses = []
test_losses = []
train_errors = []
test_errors = []
best_lin_models = []
test_class_probabilities = np.zeros(test.shape[0]).reshape(-1, 1)
selected_features_indices = []
losses_per_k = []
train_prob_300 = None
test_prob_300 = None


for k in k_values:
    consecutive_count = 0
    train_losses_iter = []
    class_probabilities = np.zeros(len(true_train_labels)).reshape(-1, 1)
    active_features = set(range(train.shape[1]))
    temp_losses = []
```

```
  for _ in range(k):
      best_loss = float('inf')
      for feature_idx in active_features:
          # Fit univariate linear regressor
          X_feature = np.array(train.iloc[:, feature_idx]).reshape(-1, 1)
          exp_term = -1*np.array(class_probabilities)
          p = np.ones(len(train_labels)).reshape(-1,1) / (np.
↪ones(len(train_labels)).reshape(-1,1) + np.exp(exp_term))
          epsilon = 1e-6
          w = np.clip(p * (1 - p), epsilon, np.inf)
          z = (train_labels - p) / w

          temp_x = X_feature * w.reshape(-1, 1)  # Reshape w to match the␣
↪shape of X_feature
          lr = LinearRegression().fit(temp_x, z)
          pred = lr.predict(X_feature)
          pred = sigmoid(pred)

          # Calculate loss
          loss = loss_function(train_labels, pred)
          if loss < best_loss:
              best_loss_index = feature_idx
              #print("better :)")
              best_loss = loss
              best_predictor = lr

      temp_losses.append(best_loss)
      best_lin_models.append(lr)
      active_features.remove(best_loss_index)
      class_probabilities += best_predictor.predict(np.array(train.iloc[:,␣
↪best_loss_index]).reshape(-1,1))
      selected_features_indices.append(best_loss_index)
      train_losses_iter.append(loss_function(train_labels,␣
↪class_probabilities))  # Append the training loss at each iteration

      if len(temp_losses) >= 10 and all(x == temp_losses[-1] for x in␣
↪temp_losses[-10:]):
          print("The last ten values are the same. Breaking the loop.")
          break
  losses_per_k.append(temp_losses)


  train_losses.append(train_losses_iter)
  # Calculate training and test loss
  train_loss = loss_function(train_labels, class_probabilities)
```

```
    # Calculate training and test error
    train_pred = np.sign(class_probabilities)
    for model, feature_idx in zip(best_lin_models, selected_features_indices):
        current_test_predictions = model.predict(test.iloc[:, feature_idx].
 ↪values.reshape(-1,1))
        test_class_probabilities += current_test_predictions
    test_loss = loss_function(test_labels, test_class_probabilities)

    if k == 300:
        train_prob_300 = class_probabilities.copy()
        # Ensure test_class_probabilities are updated correctly in the loop
        test_prob_300 = test_class_probabilities.copy()


# Determine final predictions for the test set
    test_pred = np.sign(test_class_probabilities)
    train_pred = (train_pred +1)/2
    train_error = 1 - accuracy_score(train_labels, train_pred)
    test_error = 1 - accuracy_score(test_labels, test_pred)

    train_losses.append(train_losses_iter)  # Append the list of training␣
 ↪losses for this k to train_losses

    test_losses.append(test_loss)
    train_errors.append(train_error)
    test_errors.append(test_error)

# Plot training loss vs iteration number for k = 600
plt.plot(range(1, len(losses_per_k[-1])+1), losses_per_k[-1])
plt.xlabel('Iteration')
plt.ylabel('Training Loss')
plt.title('Training Loss vs Iteration Number for k = 600 with Early Stopping')
plt.show()

# Report misclassification errors on the training and test sets for all values␣
 ↪of k
error_table = pd.DataFrame({'k': k_values, 'Train Error': train_errors, 'Test␣
 ↪Error': test_errors})
print(error_table)

# Plot misclassification errors on the training and test sets vs k
plt.plot(k_values, train_errors, label='Train Error')
plt.plot(k_values, test_errors, label='Test Error')
plt.xlabel('Number of Boosting Iterations (k)')
plt.ylabel('Misclassification Error')
plt.title('Misclassification Error vs Number of Boosting Iterations')
plt.legend()
```

```
plt.show()

plt.figure(figsize=(10, 8))

if train_prob_300 is not None and test_prob_300 is not None:
    plt.figure(figsize=(10, 8))

    # Plot ROC curve for the training set
    plot_roc_curve(true_train_labels, train_prob_300, 'Train')
    # Plot ROC curve for the test set
    plot_roc_curve(test_labels, test_prob_300, 'Test')

    plt.plot([0, 1], [0, 1], 'k--', label='Random chance')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve for k=300 Iterations')
    plt.legend(loc="lower right")
    plt.show()


np.seterr(**old_settings)
```

```
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```
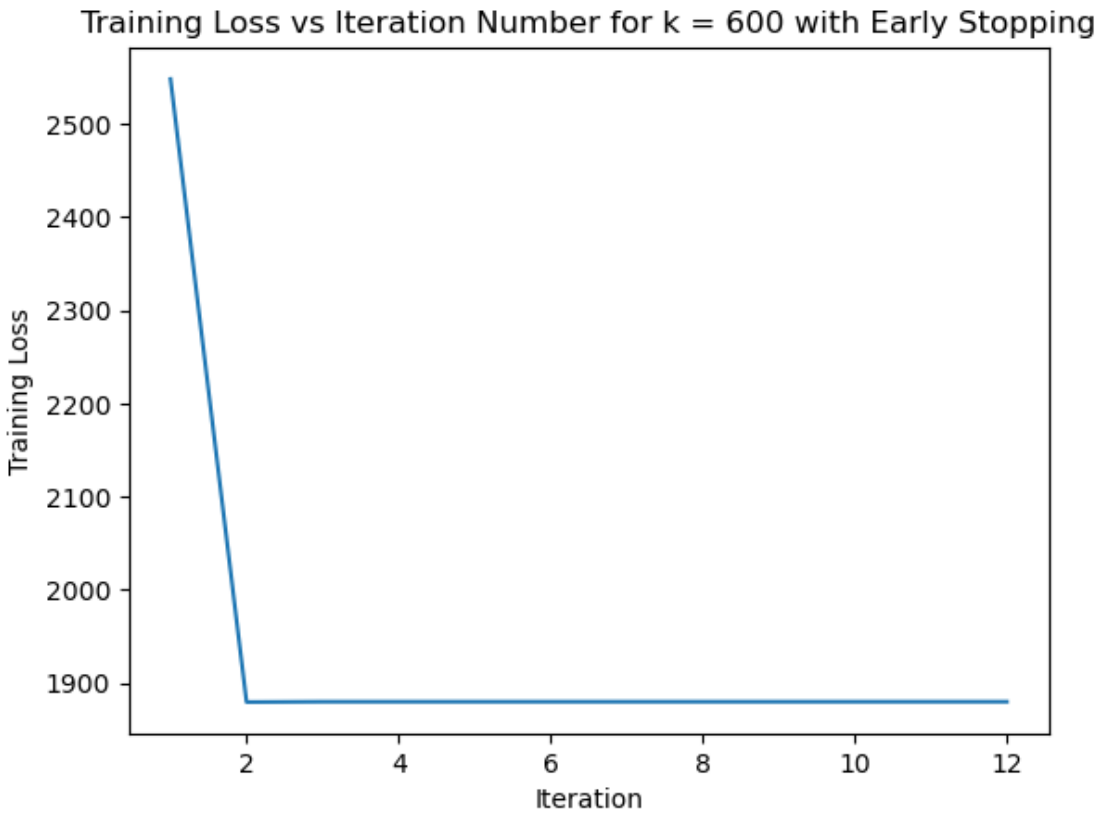
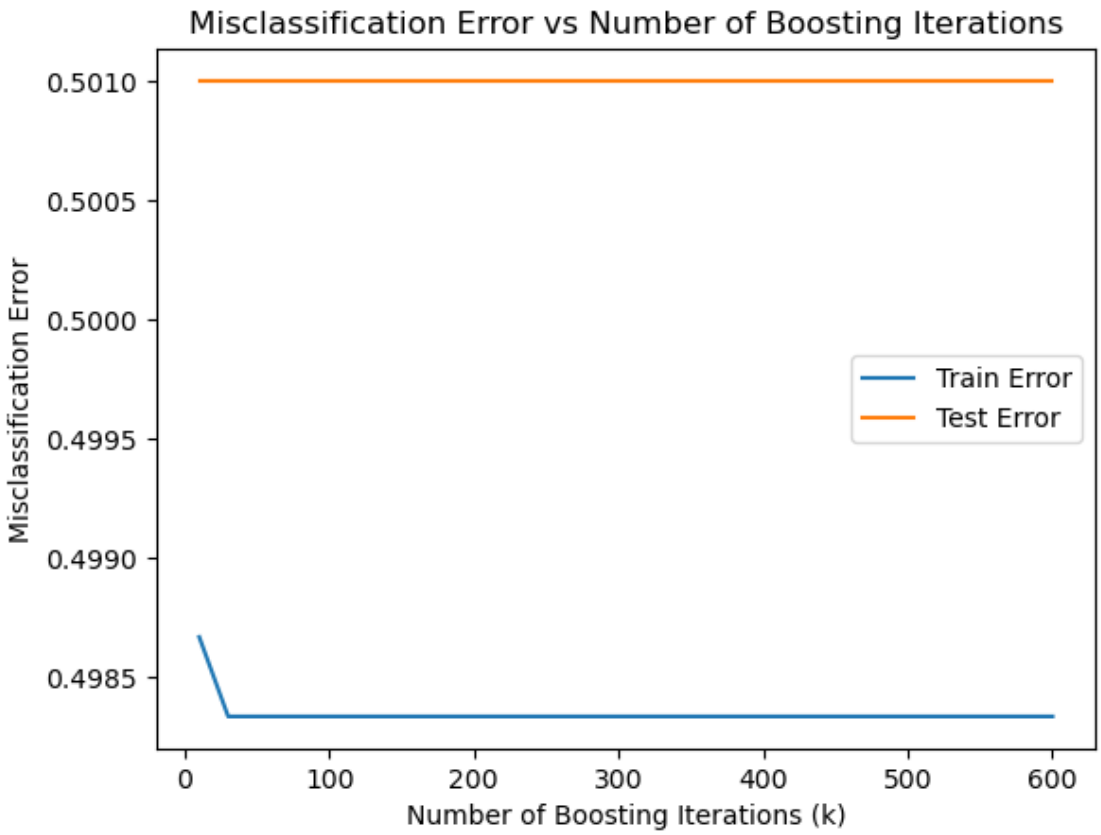
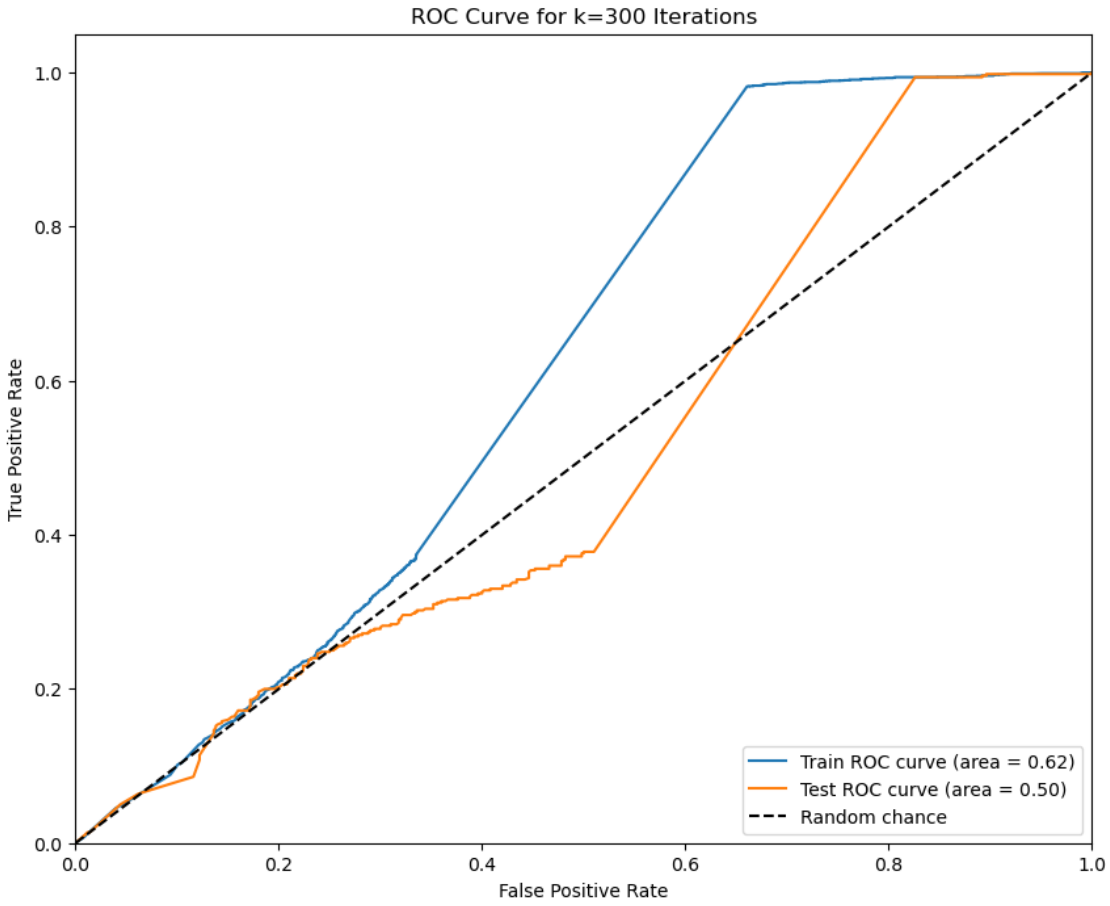



	k	Train Error	Test Error
0	10	0.498667	0.501
1	30	0.498333	0.501
2	100	0.498333	0.501
3	300	0.498333	0.501
4	600	0.498333	0.501




```
<Figure size 1000x800 with 0 Axes>
```



[ ]:
```
{'divide': 'warn', 'over': 'ignore', 'under': 'ignore', 'invalid': 'warn'}
```

1.3 Question 3

[ ]:
```
train = pd.read_csv(data_direc + "dexter_train.csv", header = None)
train_labels = pd.read_csv(data_direc + "dexter_train_labels.csv", header =␣
↪None)
test = pd.read_csv(data_direc + "dexter_valid.csv", header = None)
test_labels = pd.read_csv(data_direc + "dexter_valid_labels.csv", header = None)
true_train_labels = train_labels

old_settings = np.seterr(over='ignore')

train_labels = (true_train_labels + 1) / 2

# Normalize the data
scaler = StandardScaler()
train = pd.DataFrame(scaler.fit_transform(train))
```

```
test = pd.DataFrame(scaler.transform(test))

# Define parameters
k_values = [10,30,100,300,600]
class_probabilities = np.zeros(len(true_train_labels)).reshape(-1, 1)

# Initialize lists to store results
train_losses = []
test_losses = []
train_errors = []
test_errors = []
best_lin_models = []
test_class_probabilities = np.zeros(test.shape[0]).reshape(-1, 1)
selected_features_indices = []
losses_per_k = []
train_prob_300 = None
test_prob_300 = None


for k in k_values:
    consecutive_count = 0
    train_losses_iter = []
    class_probabilities = np.zeros(len(true_train_labels)).reshape(-1, 1)
    active_features = set(range(train.shape[1]))
    temp_losses = []
    for _ in range(k):
        best_loss = float('inf')
        for feature_idx in active_features:
            # Fit univariate linear regressor
            X_feature = np.array(train.iloc[:, feature_idx]).reshape(-1, 1)
            exp_term = -1*np.array(class_probabilities)
            p = np.ones(len(train_labels)).reshape(-1,1) / (np.
 ↪ones(len(train_labels)).reshape(-1,1) + np.exp(exp_term))
            epsilon = 1e-6
            w = np.clip(p * (1 - p), epsilon, np.inf)
            z = (train_labels - p) / w

            temp_x = X_feature * w.reshape(-1, 1)  # Reshape w to match the␣
 ↪shape of X_feature
            lr = LinearRegression().fit(temp_x, z)
            pred = lr.predict(X_feature)
            pred = sigmoid(pred)

            # Calculate loss
            loss = loss_function(train_labels, pred)
            if loss < best_loss:
                best_loss_index = feature_idx
```

```
                #print("better :)")
                best_loss = loss
                best_predictor = lr

        temp_losses.append(best_loss)
        best_lin_models.append(lr)
        active_features.remove(best_loss_index)
        class_probabilities += best_predictor.predict(np.array(train.iloc[:,␣
↪best_loss_index]).reshape(-1,1))
        selected_features_indices.append(best_loss_index)
        train_losses_iter.append(loss_function(train_labels,␣
↪class_probabilities))  # Append the training loss at each iteration

        if len(temp_losses) >= 10 and all(x == temp_losses[-1] for x in␣
↪temp_losses[-10:]):
            print("The last ten values are the same. Breaking the loop.")
            break
    losses_per_k.append(temp_losses)


    train_losses.append(train_losses_iter)
    # Calculate training and test loss
    train_loss = loss_function(train_labels, class_probabilities)


    # Calculate training and test error
    train_pred = np.sign(class_probabilities)
    for model, feature_idx in zip(best_lin_models, selected_features_indices):
        current_test_predictions = model.predict(test.iloc[:, feature_idx].
↪values.reshape(-1,1))
        test_class_probabilities += current_test_predictions
    test_loss = loss_function(test_labels, test_class_probabilities)

    if k == 300:
        train_prob_300 = class_probabilities.copy()
        # Ensure test_class_probabilities are updated correctly in the loop
        test_prob_300 = test_class_probabilities.copy()


# Determine final predictions for the test set
    test_pred = np.sign(test_class_probabilities)
    train_pred = (train_pred +1)/2
    train_error = 1 - accuracy_score(train_labels, train_pred)
    test_error = 1 - accuracy_score(test_labels, test_pred)

    train_losses.append(train_losses_iter)  # Append the list of training␣
↪losses for this k to train_losses
```

```
    test_losses.append(test_loss)
    train_errors.append(train_error)
    test_errors.append(test_error)

# Plot training loss vs iteration number for k = 600
plt.plot(range(1, len(losses_per_k[-1])+1), losses_per_k[-1])
plt.xlabel('Iteration')
plt.ylabel('Training Loss')
plt.title('Training Loss vs Iteration Number for k = 600 with Early Stopping')
plt.show()

# Report misclassification errors on the training and test sets for all values␣
 ↪of k
error_table = pd.DataFrame({'k': k_values, 'Train Error': train_errors, 'Test␣
 ↪Error': test_errors})
print(error_table)

# Plot misclassification errors on the training and test sets vs k
plt.plot(k_values, train_errors, label='Train Error')
plt.plot(k_values, test_errors, label='Test Error')
plt.xlabel('Number of Boosting Iterations (k)')
plt.ylabel('Misclassification Error')
plt.title('Misclassification Error vs Number of Boosting Iterations')
plt.legend()
plt.show()

plt.figure(figsize=(10, 8))

if train_prob_300 is not None and test_prob_300 is not None:
    plt.figure(figsize=(10, 8))

    # Plot ROC curve for the training set
    plot_roc_curve(true_train_labels, train_prob_300, 'Train')
    # Plot ROC curve for the test set
    plot_roc_curve(test_labels, test_prob_300, 'Test')

    plt.plot([0, 1], [0, 1], 'k--', label='Random chance')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve for k=300 Iterations')
    plt.legend(loc="lower right")
    plt.show()
```

```
np.seterr(**old_settings)
```

```
The last ten values are the same. Breaking the loop.
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```
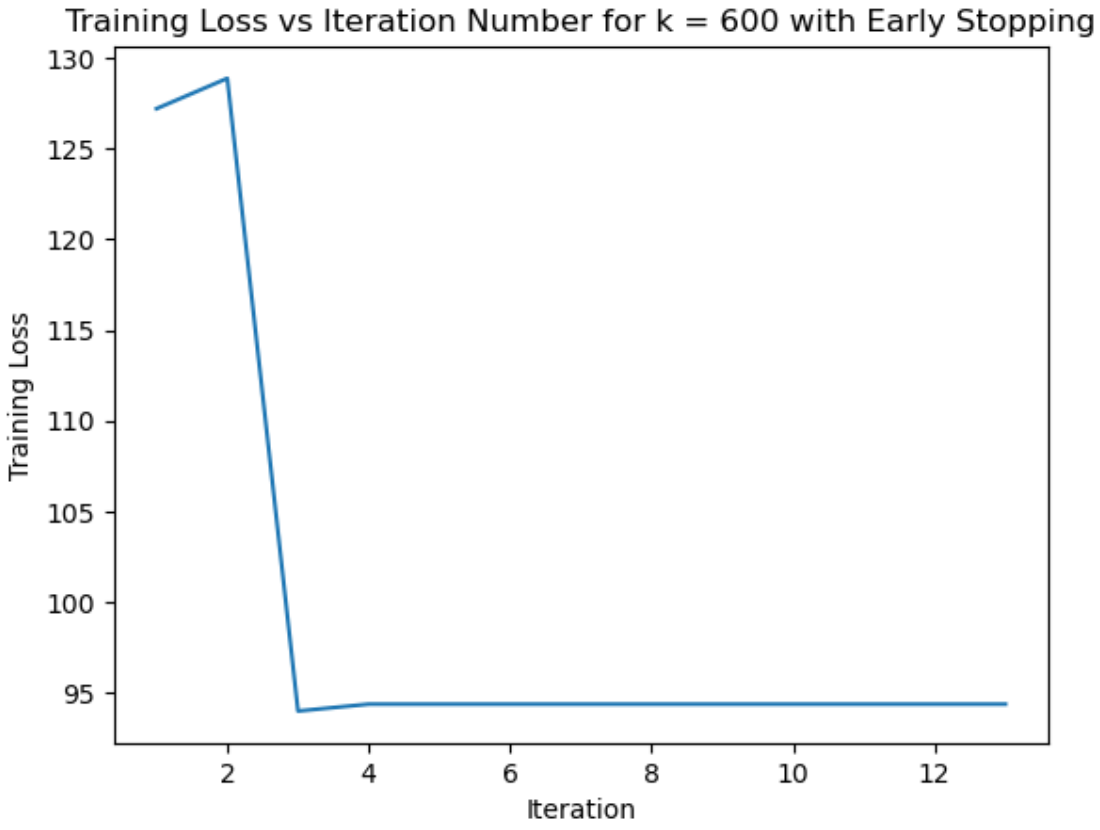
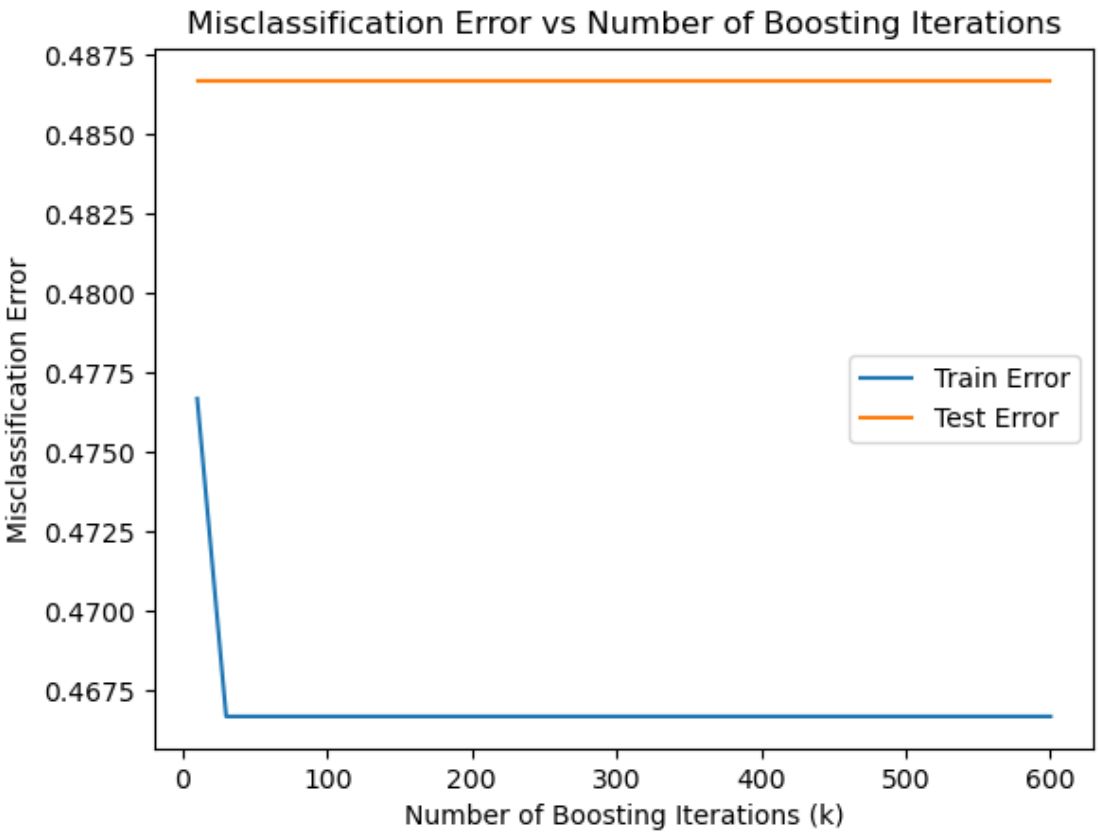
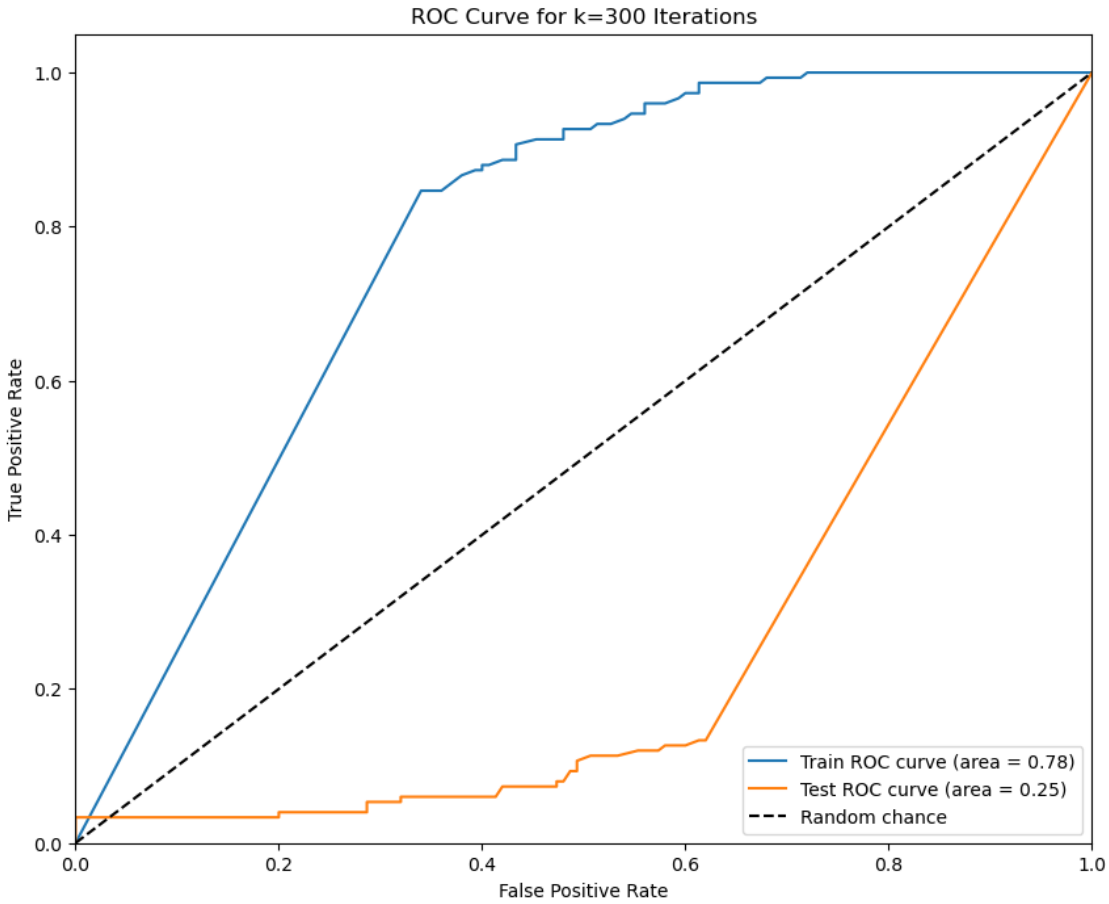



	k	Train Error	Test Error
0	10	0.476667	0.486667
1	30	0.466667	0.486667
2	100	0.466667	0.486667
3	300	0.466667	0.486667
4	600	0.466667	0.486667



<Figure size 1000x800 with 0 Axes>



[ ]: {'divide': 'warn', 'over': 'ignore', 'under': 'ignore', 'invalid': 'warn'}