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```
In [20]: import numpy as np
         from scipy.io import loadmat
         import matplotlib.pyplot as plt
         in_data = loadmat('face_emotion_data.mat')
         print([key for key in in data]) # -- use this line to see the keys in the di
         \# m(faces) \times n(features) = y
         ['__header__', '__version__', '__globals__', 'y', 'X']
In [21]: #1a)
         # Using the formula: w = (X^T X)^(-1) X^T y
         X transpose = X.transpose()
         w = np.linalq.inv(X.transpose()@ X) @ X.transpose() @ y
Out[21]: array([[ 0.94366942],
                [ 0.21373778],
                [0.26641775]
                [-0.39221373],
                 [-0.00538552],
                [-0.01764687],
                [-0.16632809].
                [-0.0822838]
                [-0.16644364]]
In [22]: #1b)
         # Each weight corresponds to one of the 9 features the model takes
         # when we solve y=X^Tw, each weight will be applied to its associated measur
In [23]: #1c)
         #The features that seem to be most important are the ones who have the higher
         #all the features have been normalized, they are on the same scale. Features
In [24]: #1d)
         selected\_columns = [0, 2, 3]
         x_slice = X[:, selected_columns]
         w2 = np.linalg.inv(x_slice.transpose()@ x_slice) @ x_slice.transpose() @ y
         #If we are minimizing the features we want to use we should include the ones
         #the three expressed above
Out[24]: array([[ 0.94366942],
                [ 0.21373778],
                [ 0.26641775],
                [-0.39221373],
                 [-0.00538552],
                [-0.01764687],
                [-0.16632809],
                [-0.0822838]
                [-0.16644364]]
```

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In [36]: #1e)
          y_hat1 = np.sign(X@w)
          y hat2 = np.sign(x slice@w2)
          error_vec1 = [0 \text{ if } i[0] == i[1] \text{ else } 1 \text{ for } i \text{ in } np.hstack((y_hat1, y))]
          error_vec2 = [0 \text{ if } i[0] == i[1] \text{ else } 1 \text{ for } i \text{ in } np.hstack((y_hat2, y))]
          print("Percent error for 9 features: {}%. Percent error for 3 features: {}%.
          Percent error for 9 features: 2.34%. Percent error for 3 features: 6.25%.
In [42]: #1d)
          num_subsets = 8
          subset_size = len(X) // num_subsets
          error rates = []
          #8folds cross validation
          for fold in range(num subsets):
              start_index = fold * subset_size
              end index = (fold + 1) * subset size
              X_train = np.concatenate((X[:start_index], X[end_index:]), axis=0)
              y train = np.concatenate((y[:start index], y[end index:]), axis=0)
              X_holdout = X[start_index:end_index]
              y_holdout = y[start_index:end_index]
              predictions = X holdout @ w
              misclassifications = np.sum(np.sign(predictions) != y_holdout)
              error rate = misclassifications / len(X holdout)
              error_rates.append(error_rate)
          average error rate = np.mean(error rates)
          print("Average Error Rate: {}%.".format(round(average_error_rate*100, 2)) )
          Average Error Rate: 2.34%.
 In []:
```