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```
In [2]: import numpy as np
    from scipy.io import loadmat
    from sklearn.datasets import make_regression
    from sklearn.linear_model import LinearRegression

in_data = loadmat('face_emotion_data.mat')
    print([key for key in in_data])

X = in_data['X']
    y = in_data['y']

['__header__', '__version__', '__globals__', 'y', 'X']
```

a

Use the training data X and y and a least squares problem to train your classier weights.

```
In [3]: w = np.linalg.lstsq(X, y, rcond=None)[0]
    print("w = \n", w)

w =
        [[ 0.94366942]
        [ 0.21373778]
        [ 0.26641775]
        [-0.39221373]
        [-0.00538552]
        [-0.01764687]
        [-0.16632809]
        [-0.0822838]
        [-0.16644364]]
```

b

Suppose there is a new face with feature vectors $xi = [x1i \ x2i \ ... \ x9i]^T$ Compute for label $yi = xi^T @ w$. If yi > 0, then it will be classified as a happy face; it yi < 0, then it will be classified as an angry face.

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C

Feature realted to the first column of X seems to be most important, since its corresponding weight, w1, has the largest absolute value among all weights, meaning that the feature will have the largest effect on the value of its predicted label.

d

To design a classifier based on three of the nine features, choosing column 1, 4, and 3 can best represent the original matrix, since their respective weights have the highest 3 absolute values.

e

```
In [4]: # assessing performance using all 9 features.
        y head = X @ w
        counter = 128;
        for i in range(0, 128):
            if (y[i] > 0 and y_head[i] > 0) or (y[i] <= 0 and y_head[i] <= 0):</pre>
                counter-=1
        print("error rate using 9 features: ", counter/128)
        # assessing performance using only 3 features
        X2 = np.hstack([X[:, 0:1], X[:, 2:3], X[:, 3:4]])
        w2 = np.linalg.lstsq(X2, y, rcond=None)[0]
        y2 head = X2 @ w2
        counter = 128
        for i in range(0, 128):
            if (y[i] > 0 and y2 head[i] > 0) or (y[i] \le 0 and y2 head[i] \le 0
        ):
                counter-=1
        print("error rate using 3 features: ", counter/128)
```

error rate using 9 features: 0.0234375 error rate using 3 features: 0.0625

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```
In [5]: SETS = 8
        SAMPLE SIZE = 16
        \# [t*16 : (t+1)*16 - 1]
        miss_rate = np.array(np.ones(SETS))
        for t in range(0, SETS):
            X3 = np.delete(X, slice(t*16, (t+1)*16), 0)
            y3 = np.delete(y, slice(t*16, (t+1)*16), 0)
            w3 = np.linalg.lstsq(X3, y3, rcond=None)[0]
            y3 head = x3 @ w3
            counter = 0
            for i in range(0, 127-SAMPLE_SIZE):
                 if (y3[i] > 0 and y3_head[i] <= 0) or (y3[i] <= 0 and y3_head[</pre>
        i > 0:
                     counter+=1
            miss_rate[t] = counter / SAMPLE_SIZE
        print("error rate = ", np.average(miss_rate))
        error rate = 0.171875
In [ ]:
In [ ]:
```