

CS 613 – Homework 1

1) Problem 1

a. Weight-averaged entropy of feature 1:

$$\begin{aligned}P_{x=0,y=0} &= \frac{0}{3} = 0, P_{x=0,y=1} = \frac{3}{3} = 1 \\P_{x=1,y=0} &= \frac{3}{5}, P_{x=1,y=1} = \frac{2}{5} \\P_{x=2,y=0} &= \frac{2}{2} = 1, P_{x=2,y=1} = \frac{0}{2} = 0\end{aligned}$$

$$\begin{aligned}H_1 &= -(0)(\log_2(0)) - (1)(\log_2(1)) = 0 \\H_2 &= -\left(\frac{3}{5}\right)\log_2\left(\frac{3}{5}\right) - \left(\frac{2}{5}\right)\log_2\left(\frac{2}{5}\right) = 0.971 \\H_3 &= -(1)(\log_2(1)) - (0)(\log_2(0)) = 0\end{aligned}$$

$$E_{feature\ 1} = \sum_{i=1}^3 \frac{|C_i|}{N} H_i = \frac{3}{10}(0) + \frac{5}{10}(0.971) + \frac{2}{10}(0) = 0.515$$

b. Weight-averaged entropy of feature 2:

$$\begin{aligned}P_{x=0,y=0} &= \frac{3}{5}, P_{x=0,y=1} = \frac{2}{5} \\P_{x=1,y=0} &= \frac{2}{5}, P_{x=1,y=1} = \frac{3}{5} \\H_1 &= -\left(\frac{3}{5}\right)\log_2\left(\frac{3}{5}\right) - \left(\frac{2}{5}\right)\log_2\left(\frac{2}{5}\right) = 0.971 \\H_2 &= -\left(\frac{2}{5}\right)\log_2\left(\frac{2}{5}\right) - \left(\frac{3}{5}\right)\log_2\left(\frac{3}{5}\right) = 0.971\end{aligned}$$

$$E_{feature\ 2} = \sum_{i=1}^2 \frac{|C_i|}{N} H_i = \frac{5}{10}(0.971) + \frac{5}{10}(0.971) = 0.971$$

c. Feature 1 provides a more discriminating result i.e. better class separation as it gave a weight-averaged normalized entropy of approximately 0.51, lower than that of (and indicating it is less random than) Feature 2 which gave a weight-averaged entropy of approximately 0.97.

- d. Principal components of observed data X, found after mean-centering data, calculating covariance matrix of the mean-centered data, and then calculating the eigenvectors using `numpy.linalg.eig()` and ordered based on decreasing eigenvalue:

(rounded values)

1st Principal Component: [0.981, 0.196]

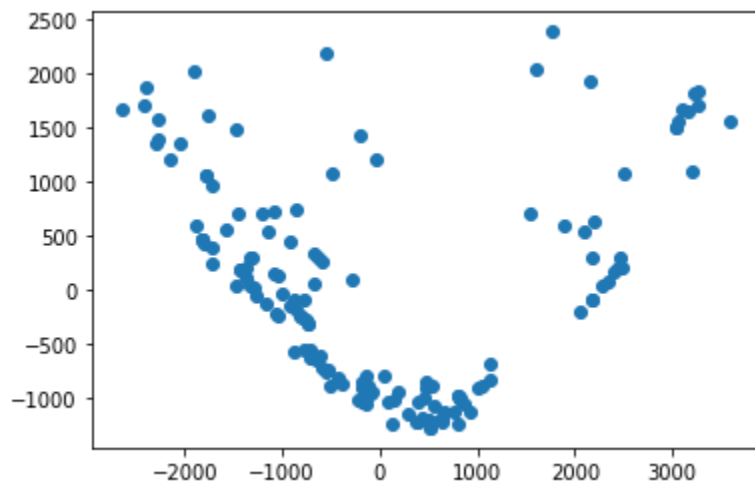
2nd Principal Component: [-0.196, 0.981]

- e. The "axes" formed by the principal components (orthogonal eigenvectors of the covariance matrix) form a transformed 2D coordinate system i.e. basis onto which points from the original matrix X could be projected. These axes point in the directions of most variance and in being orthogonal, reduce collinearity present in the original coordinate system.
- f. Projected data matrix onto 1st principal component (rounded values):

[-0.78, -0.98, 0.20, -0.98, 0.20, 0.00, 0.00, 0.20, 0.98, 1.18]

2) Problem 2

Results from reducing data to 2D using PCA and plotting via `matplotlib.pyplot.scatter()` – see `HW1_Problem2.py`



3) Problem 3 – see submitted video and `HW1_Problem3.py`