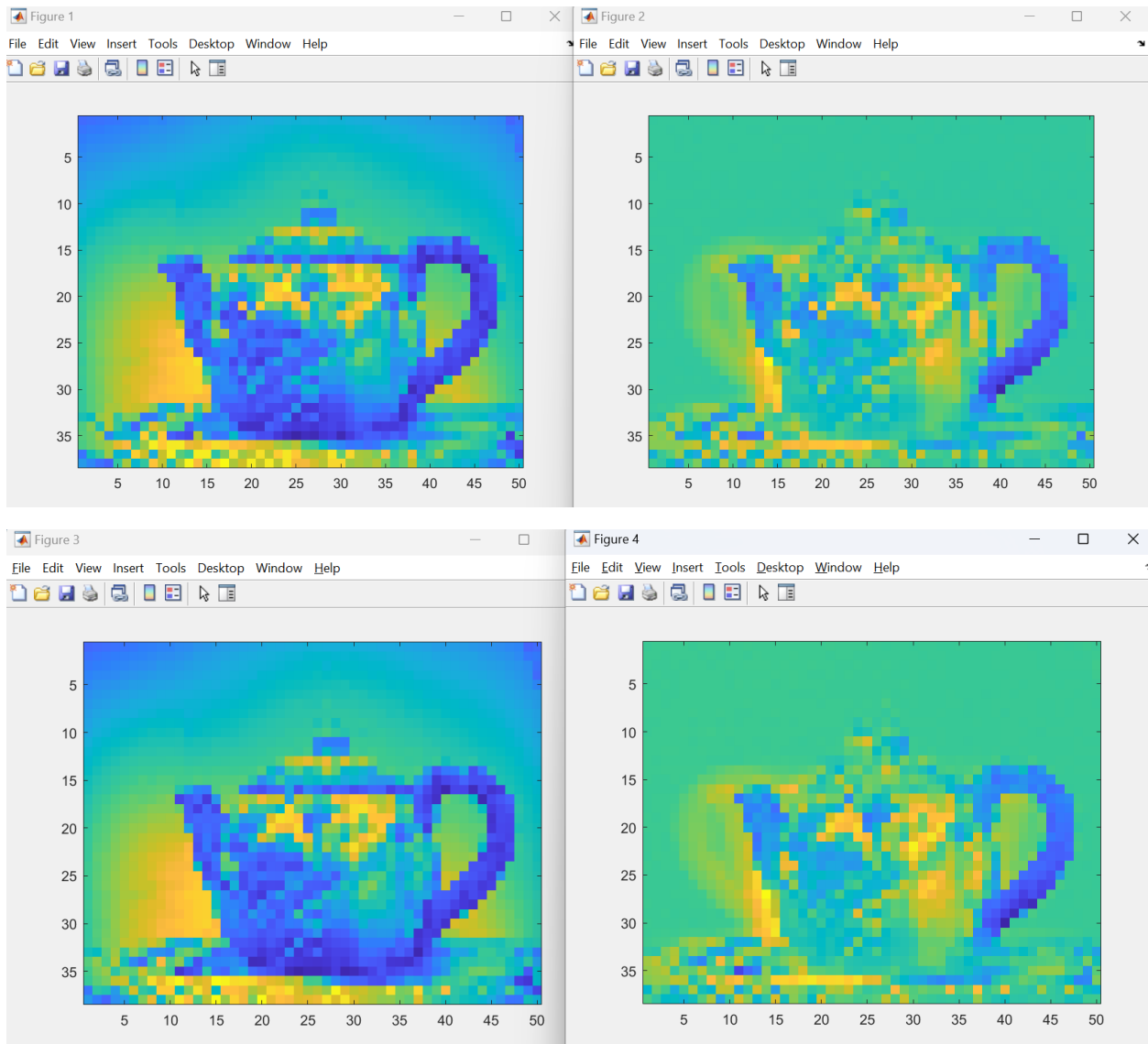
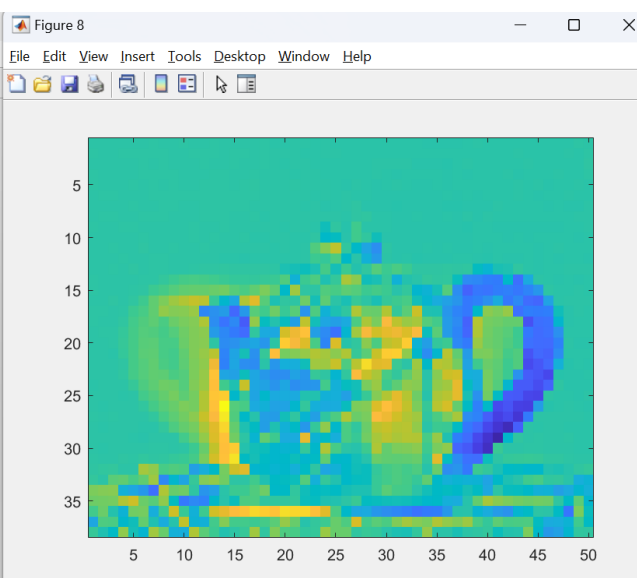
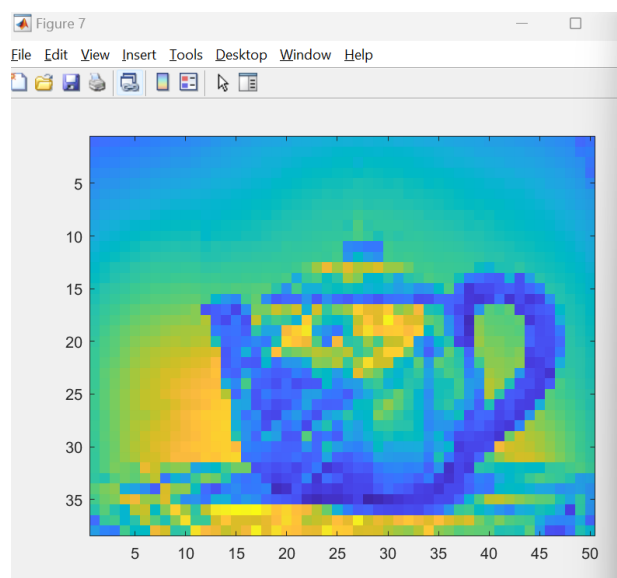
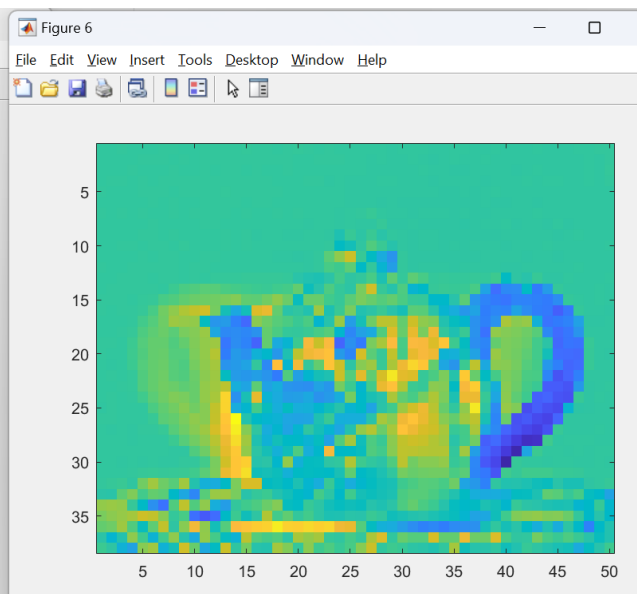
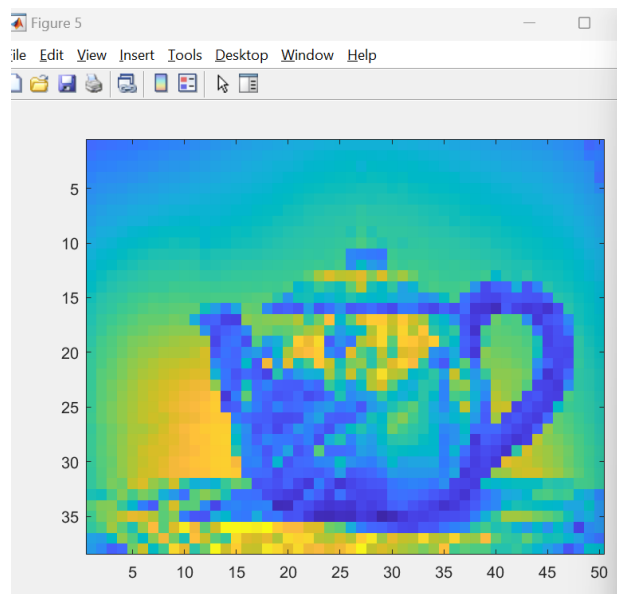


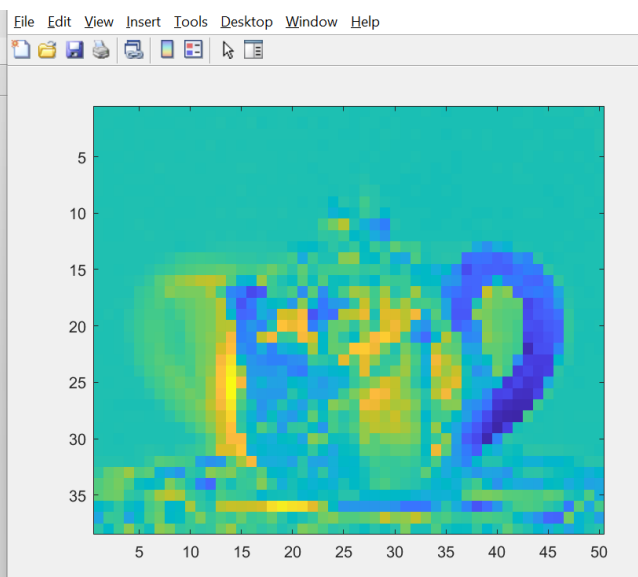
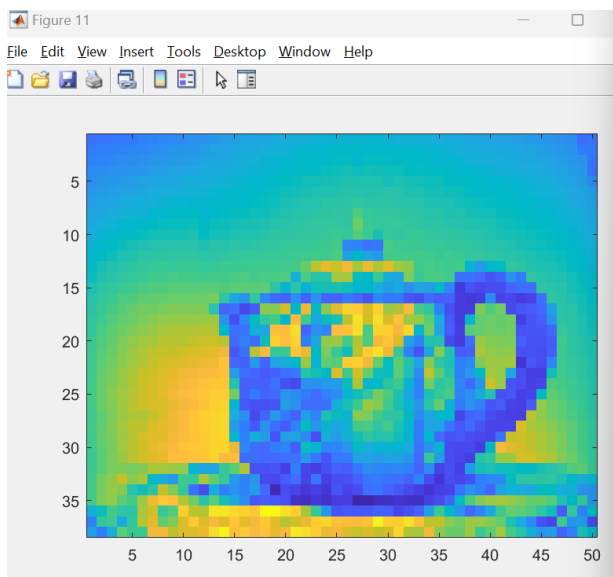
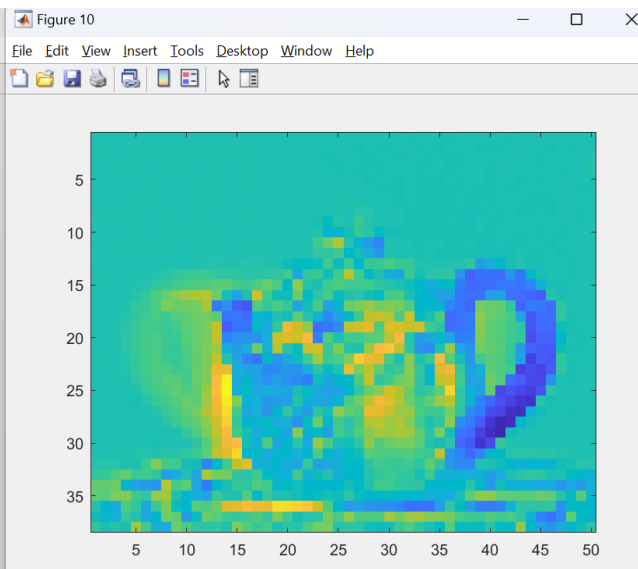
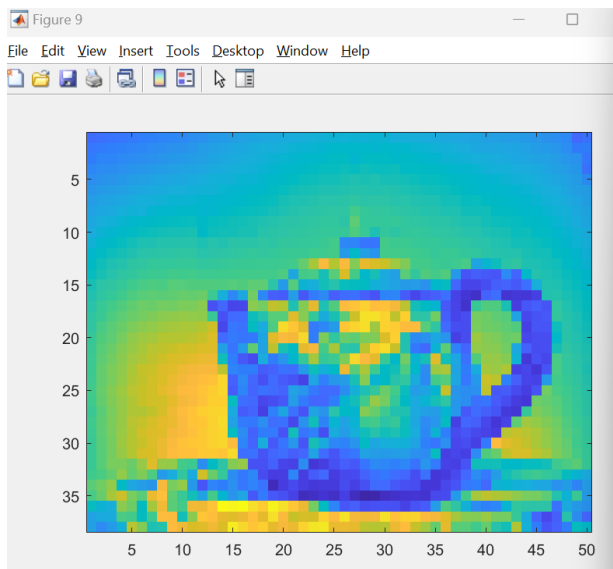
HW4

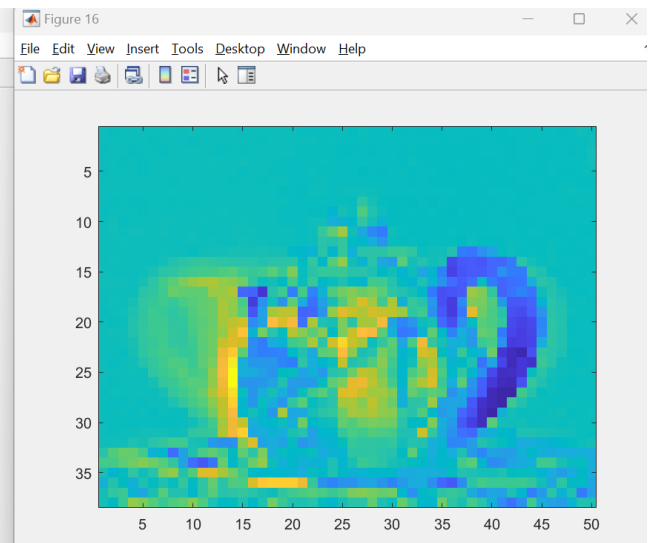
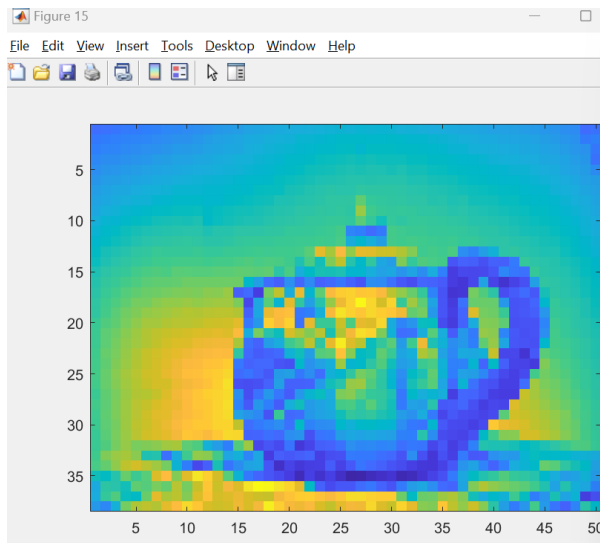
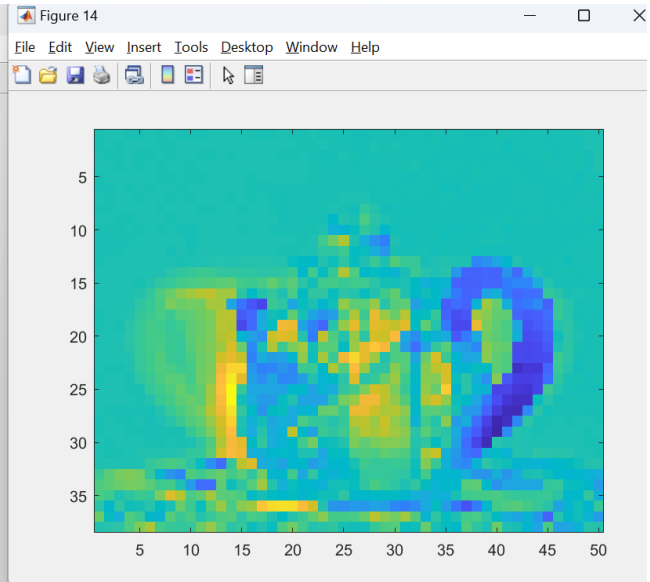
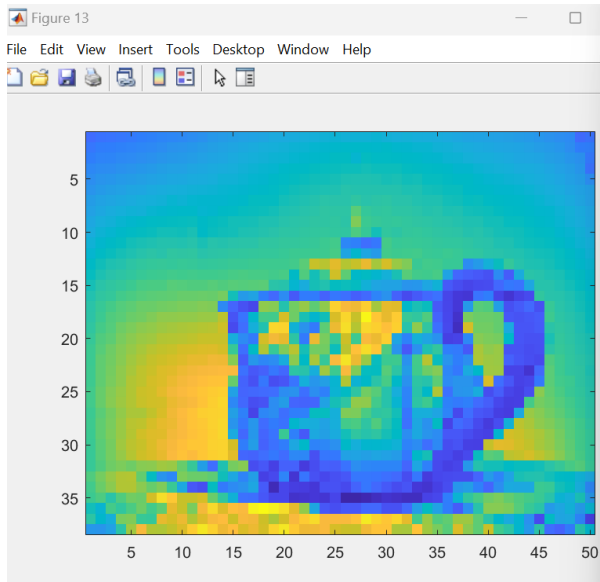
Q1

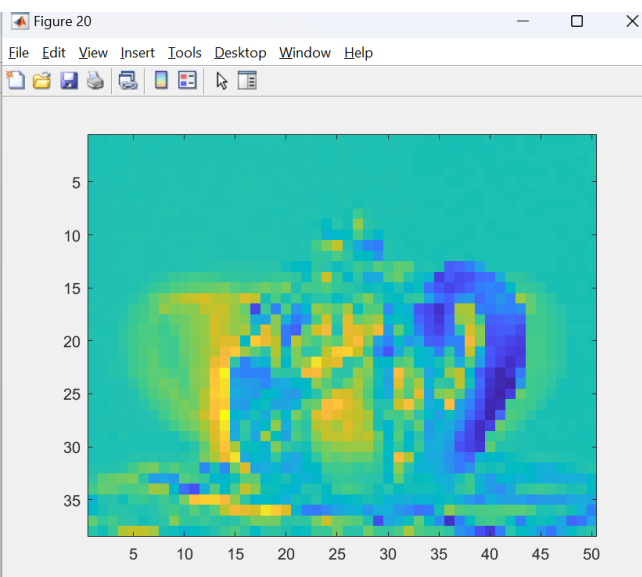
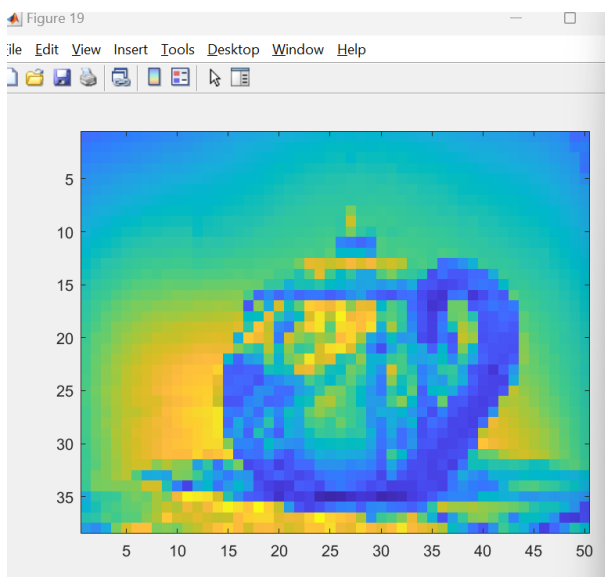
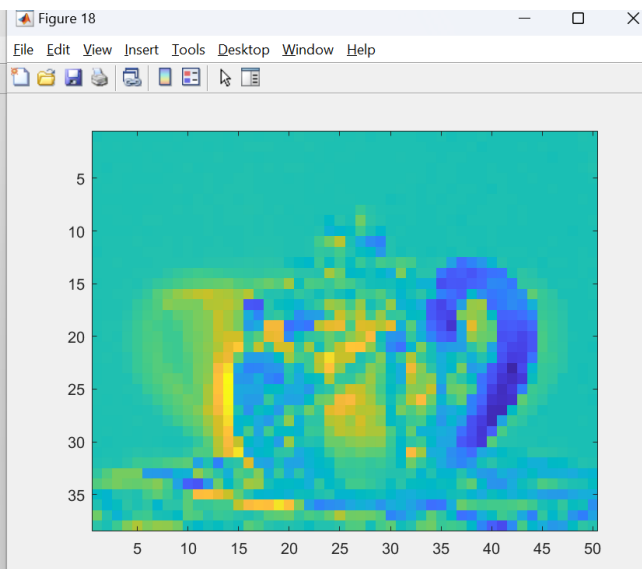
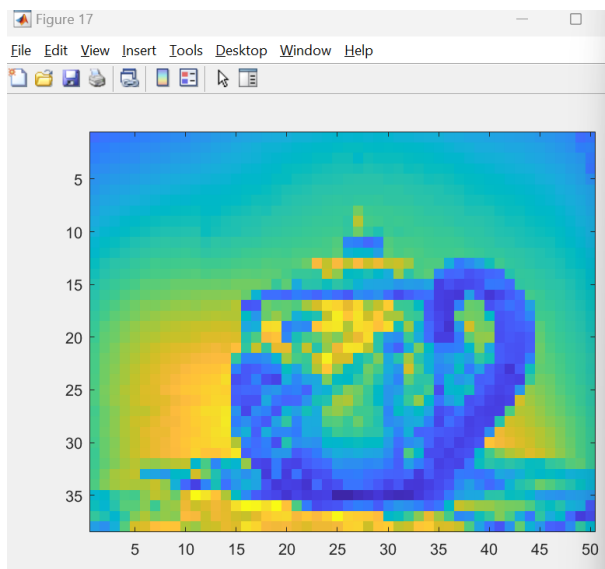
After observing the following 10 sets of pictures (the original one on the left, the generated one on the right), it can be concluded that PCA reduced the dimensions of the original data by keeping the most relevant and effective features.











Q2

X : draw Apple E_1 : Box 1 E_2 : Box 2

$$P(E_1|X) = \frac{P(X|E_1)P(E_1)}{P(X)} = \frac{P(X|E_1)P(E_1)}{P(X|E_1)P(E_1) + P(X|E_2)P(E_2)}$$
$$= \frac{\frac{8}{12} \cdot \frac{1}{2}}{\frac{8}{12} \cdot \frac{1}{2} + \frac{10}{12} \cdot \frac{1}{2}} = \frac{4}{9}$$

Q3

$$\begin{aligned}
 P(y|\theta) &= \alpha^y (1-\alpha)^{1-y} \\
 \sum_{i=1}^N \log P(y_i|\alpha) &= \sum_{i=1}^N \log \alpha^{y_i} (1-\alpha)^{1-y_i} \\
 \Rightarrow \frac{\partial}{\partial \alpha} \sum_{i=1}^N \log \alpha^{y_i} (1-\alpha)^{1-y_i} &= 0 \\
 \frac{\partial}{\partial \alpha} \sum_{i=1}^N y_i \log \alpha + (1-y_i) \log (1-\alpha) &= 0 \\
 \frac{\partial}{\partial \alpha} \sum_{i \in \text{class 1}} \log \alpha + \sum_{i \in \text{class 0}} \log (1-\alpha) &= 0 \\
 \sum_{i \in \text{class 1}} \frac{1}{\alpha} + \sum_{i \in \text{class 0}} \frac{-1}{1-\alpha} &= 0 \\
 \downarrow \\
 N_1 \frac{1}{\alpha} - N_0 \frac{1}{1-\alpha} &= 0 \\
 N_1 (1-\alpha) - N_0 \alpha &= 0 \\
 N_1 - \alpha (N_1 + N_0) &= 0 \\
 \boxed{\alpha = \frac{N_1}{N_1 + N_0}}
 \end{aligned}$$

$$\begin{aligned}
 \sum_{i=1}^N \log P(\vec{x}_i | \vec{\mu}, \Sigma) &= \sum_{i=1}^N \log \frac{1}{(2\pi)^{D/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2} (\vec{x}_i - \vec{\mu})^T \Sigma^{-1} (\vec{x}_i - \vec{\mu})\right) \\
 \rightarrow \text{Max over } \mu & \\
 \frac{\partial}{\partial \mu} \left(\sum_{i=1}^N \log \frac{1}{(2\pi)^{D/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2} (\vec{x}_i - \vec{\mu})^T \Sigma^{-1} (\vec{x}_i - \vec{\mu})\right) \right) &= 0 \\
 \sum_{i=1}^N (\vec{x}_i - \vec{\mu}) \Sigma^{-1} &= \vec{0} \\
 \boxed{\vec{\mu} = \frac{1}{N} \sum_{i=1}^N \vec{x}_i}
 \end{aligned}$$

$$l = \sum_{i=1}^N -\frac{D}{2} \log 2\pi - \frac{1}{2} \log |\Sigma| - \frac{1}{2} (\vec{x}_i - \vec{\mu})^T \Sigma^{-1} (\vec{x}_i - \vec{\mu})$$

$$= -\frac{ND}{2} \log 2\pi + \frac{N}{2} \log |\Sigma| - \frac{1}{2} \sum_{i=1}^N \text{tr} [(\vec{x}_i - \vec{\mu})^T \Sigma^{-1} (\vec{x}_i - \vec{\mu})]$$

$$= -\frac{ND}{2} \log 2\pi + \frac{N}{2} \log A - \frac{1}{2} \sum_{i=1}^N \text{tr} [(\vec{x}_i - \vec{\mu}) (\vec{x}_i - \vec{\mu})^T A]$$

$$\frac{\partial l}{\partial A} = -0 + \frac{N}{2} (A^{-1})^T - \frac{1}{2} \sum_{i=1}^N [(\vec{x}_i - \vec{\mu}) (\vec{x}_i - \vec{\mu})^T]^T$$

$$= \frac{N}{2} \Sigma - \frac{1}{2} \sum_{i=1}^N (\vec{x}_i - \vec{\mu}) (\vec{x}_i - \vec{\mu})^T \Rightarrow 0$$

$$\Sigma = \frac{1}{N} \sum_{i=1}^N (\vec{x}_i - \vec{\mu}) (\vec{x}_i - \vec{\mu})^T$$

$$Y = \arg \max_{\hat{Y} \in \{0,1\}} P(\hat{Y}|x)$$

$$\Rightarrow Y = \arg \max_{\hat{Y} \in \{0,1\}} P(x|\hat{Y}) P(\hat{Y})$$

$$P(x|\hat{Y}) = \frac{1}{(2\pi)^{d/2} |\Sigma_Y|^{1/2}} \exp\left(-\frac{1}{2} (x - \mu_Y)^T \Sigma_Y^{-1} (x - \mu_Y)\right)$$

$$\Rightarrow Y = \arg \max_{\hat{Y} \in \{0,1\}} \left(-\frac{1}{2} (x - \mu_Y)^T \Sigma_Y^{-1} (x - \mu_Y) + \log P(\hat{Y}) - \frac{d}{2} \log(2\pi) - \frac{1}{2} \log(\Sigma_Y) \right)$$

$$\text{assume } \Sigma_0 = \Sigma_1 = \Sigma$$

$$\Rightarrow \cancel{Y = \arg \max_{\hat{Y} \in \{0,1\}}}$$

$$\Rightarrow Y = \arg \min_{\hat{Y} \in \{0,1\}} \left((x - \mu_Y)^T \Sigma^{-1} (x - \mu_Y) - 2 \log P(\hat{Y}) \right)$$

$$Y = \arg \min_{\hat{Y} \in \{0,1\}} \left(x^T \Sigma^{-1} x - 2 x^T \Sigma^{-1} \mu_Y + \mu_Y^T \Sigma^{-1} \mu_Y - 2 \log P(\hat{Y}) \right)$$

$$\Rightarrow Y = \arg \max \left(x^T \Sigma^{-1} \mu_Y - \frac{1}{2} \mu_Y^T \Sigma^{-1} \mu_Y + \log P(\hat{Y}) \right)$$

$$\text{Define } w_0 = \Sigma^{-1} \mu_0 - \frac{1}{2} \mu_0^T \Sigma^{-1} \mu_0 + \log P(0)$$

$$w_1 = \Sigma^{-1} \mu_1 - \frac{1}{2} \mu_1^T \Sigma^{-1} \mu_1 + \log P(1)$$

$$\Rightarrow Y = \arg \max x^T w_Y$$

$(w_0 - w_1)^T x = 0$ decision boundary, it's linear.

$$\log P(X|Y=0) = -\frac{d}{2} \log(2\pi) - \frac{1}{2} \log |\Sigma_0| - \frac{1}{2} (X - \mu_0)^T \Sigma_0^{-1} (X - \mu_0)$$

$$\Rightarrow -\frac{d}{2} \log(2\pi) - \frac{1}{2} \log \Sigma_0 - \frac{1}{2} (X - \mu_0)^T \Sigma_0^{-1} (X - \mu_0) + \log P(Y=0) =$$

$$-\frac{d}{2} \log(2\pi) - \frac{1}{2} \log \Sigma_1 - \frac{1}{2} (X - \mu_1)^T \Sigma_1^{-1} (X - \mu_1) + \log P(Y=1)$$

$$\Rightarrow \frac{1}{2} \log(\Sigma_0/\Sigma_1) - \frac{1}{2} (X^T \Sigma_0^{-1} X - X^T \Sigma_1^{-1} X - 2X^T \Sigma_0^{-1} \mu_0 + 2X^T \Sigma_1^{-1} \mu_1 + \mu_0^T \Sigma_0^{-1} \mu_0$$

$$- \mu_1^T \Sigma_1^{-1} \mu_1) + \log(P(Y=0)/P(Y=1)) = 0$$

This is a quadratic equation in X , therefore the decision boundary is quadratic.