Let's take a look into what happens in RDA

$$\boxed{\begin{aligned} \Sigma_0^{RDA} &= (1-\alpha)\cdot\Sigma_p + \alpha\cdot\hat{\Sigma}_0 \\ \Sigma_1^{RDA} &= (1-\alpha)\cdot\Sigma_p + \alpha\cdot\hat{\Sigma}_1 \end{aligned}} \Bigg\}$$

A compromise between LDA (when $\alpha=0$) and QDA (when $\alpha=1$)

This is the way to estimate covariance matrices in RDA

Therefore the only difference will be –

$$\frac{P\left(C=1 \,\middle|\, X=\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right)}{P\left(C=0 \,\middle|\, X=\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right)} = \frac{\sqrt{\left|\Sigma_0^{RDA}\right|}}{\sqrt{\left|\Sigma_1^{RDA}\right|}} e^{\frac{1}{2}\begin{bmatrix} x_1 - \hat{\mu}_1^{X_1} \\ x_2 - \hat{\mu}_1^{X_2} \end{bmatrix} {\Sigma_1^{RDA}}^{-1} \begin{bmatrix} x_1 - \hat{\mu}_0^{X_1} \\ x_2 - \hat{\mu}_0^{X_2} \end{bmatrix}}$$

$$-\frac{1}{2}\begin{bmatrix} x_1 - \hat{\mu}_0^{X_1} \\ x_2 - \hat{\mu}_0^{X_2} \end{bmatrix} \Sigma_0^{RDA-1} \begin{bmatrix} x_1 - \hat{\mu}_0^{X_1} \\ x_2 - \hat{\mu}_0^{X_2} \end{bmatrix}$$