

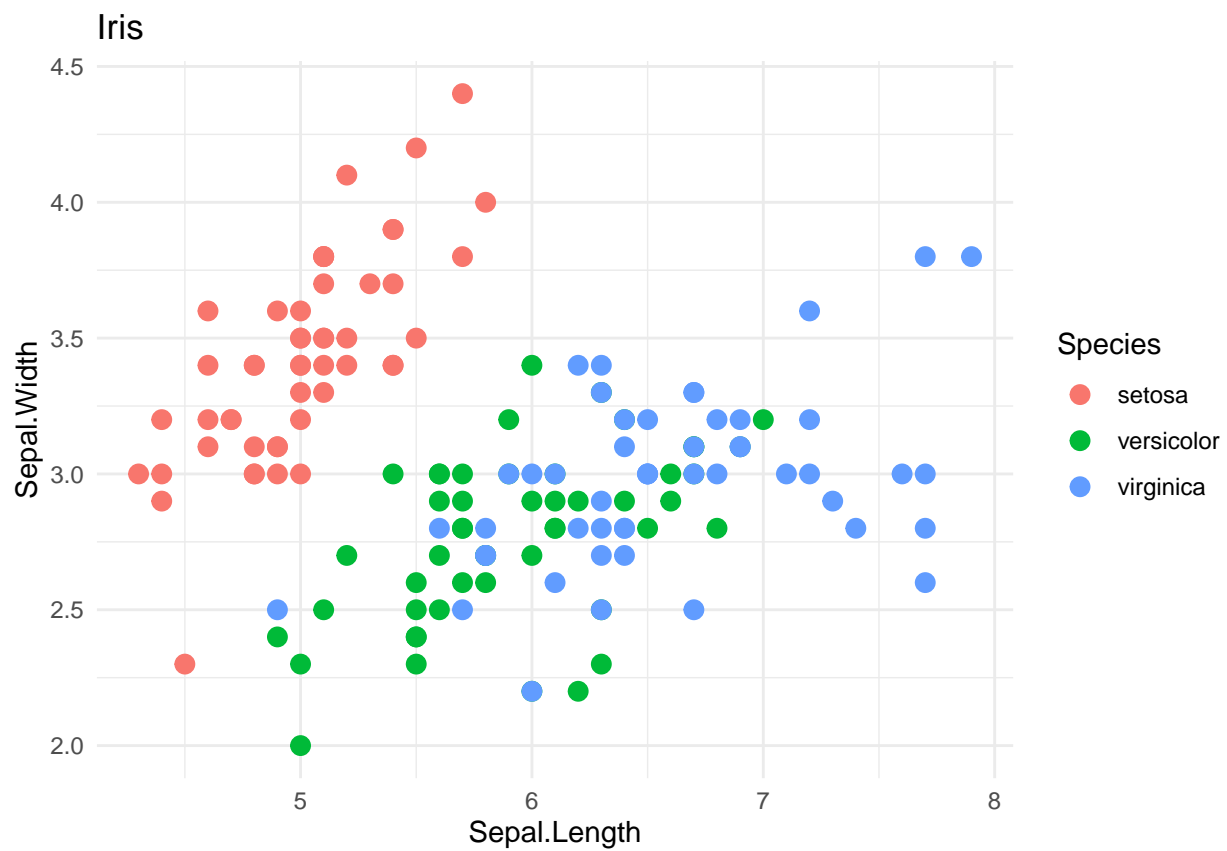
Assignment 1

Martynas Lukosevicius

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Assignment 1

1.



It is not easy to classify by LDA because as we can see from scatter plot versicolor overlay virginica. I expect that misclassification rate will be high because part of the virginica data will be predicted as versicolor and vice versa

2.

a)

Setosa: mean - $\begin{bmatrix} 5.006 \\ 3.428 \end{bmatrix}$, covariance - $\begin{bmatrix} 0.124 & 0.099 \\ 0.099 & 0.144 \end{bmatrix}$, $\pi_{setosa} = 0.3333333$

Virginica: mean - $\begin{bmatrix} 6.588 \\ 2.974 \end{bmatrix}$, covariance - $\begin{bmatrix} 0.404 & 0.094 \\ 0.094 & 0.104 \end{bmatrix}$, $\pi_{virginica} = 0.3333333$

Versicolor: mean - $\begin{bmatrix} 5.936 \\ 2.77 \end{bmatrix}$, covariance - $\begin{bmatrix} 0.266 & 0.085 \\ 0.085 & 0.098 \end{bmatrix}$, $\pi_{versicolor} = 0.3333333$

b)

Pooled covariance - $\begin{bmatrix} 0.219 & 0.09 \\ 0.09 & 0.114 \end{bmatrix}$

c)

Probabilistic model for LDA:

$$P(y = C_i | X, w) \propto P(X | Y = C_i, w) P(Y = C_i | w)$$

$$P(X | Y = C_i, w) \sim N(\mu_i, \Sigma)$$

$$P(Y = C_i | w) = \pi_i$$

$$P(y = C_i | X, w) \propto \exp[(\Sigma^{-1} \mu_i)^T X - \frac{1}{2} \mu_i^T \Sigma^{-1} \mu_i + \log(\pi_i)] = \exp[w_i X + w_{0i}]$$

Where $w_i = (\Sigma^{-1} \mu_i)^T$ and $w_{0i} = -\frac{1}{2} \mu_i^T \Sigma^{-1} \mu_i + \log(\pi_i)$

d)

discriminant function $\delta_k(x) = x^T \Sigma^{-1} \mu_k - \frac{1}{2} \mu_k^T \Sigma^{-1} \mu_k + \log(\pi_k)$

```
discrim <- function(x,a){
  constant <- (-1/2) * t(a$mean) %*% solve(pcov) %*% a$mean + log(a$prior)
  nonconstant <- t(x) %*% solve(pcov) %*% a$mean
  return(nonconstant+constant)
}
```

e)

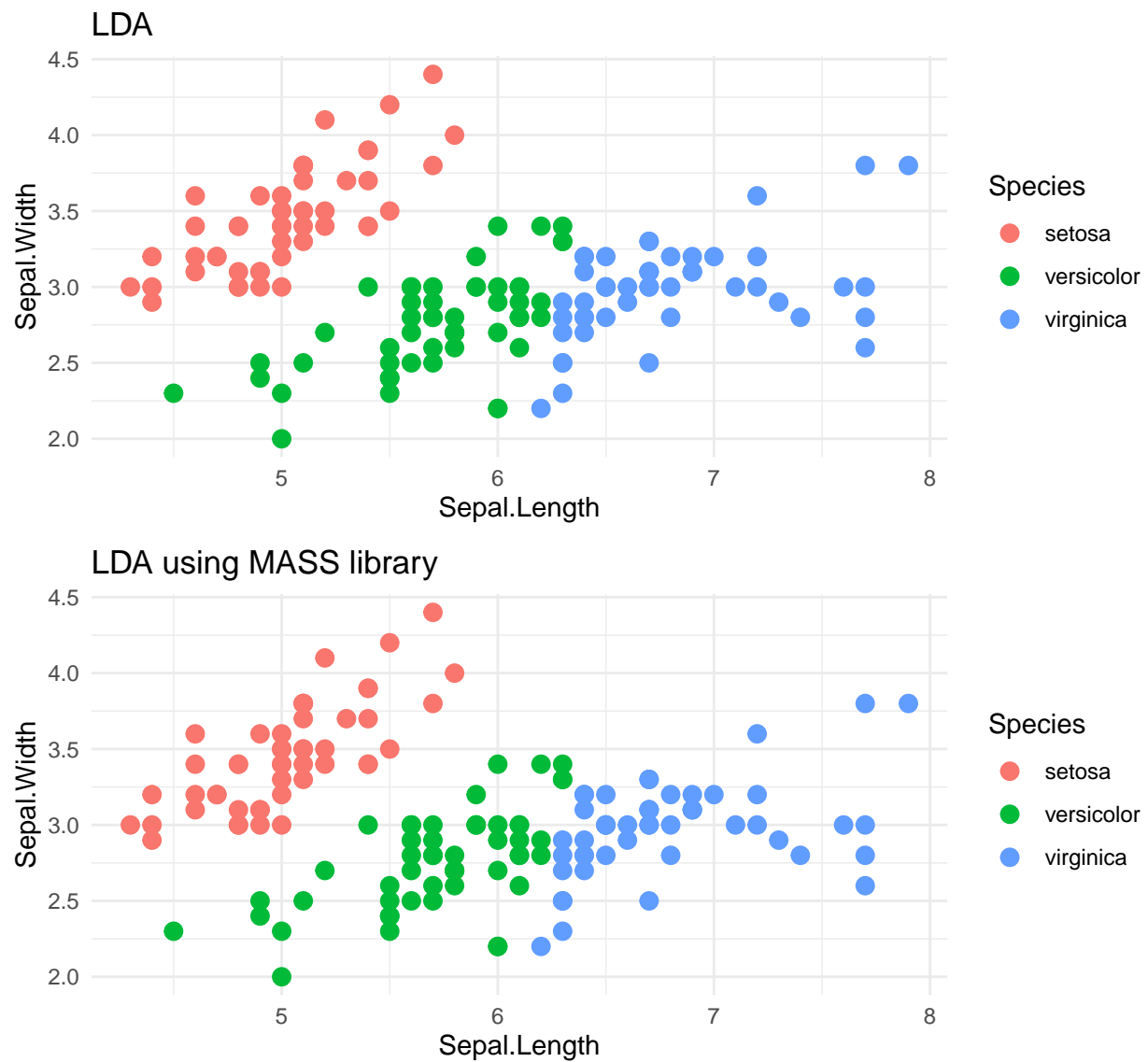
$$(w_i - w_k)x + (w_{0i} - w_{0k}) = 0$$

decision boundaries:

- Setosa - Versicolor: $\begin{pmatrix} -7.6573989 \\ 11.8556978 \end{pmatrix} x + (5.1528216) = 0$
- Virginica - Versicolor: $\begin{pmatrix} 2.5620509 \\ -0.2908121 \end{pmatrix} x + (-15.2083507) = 0$
- Setosa - Versicolor: $\begin{pmatrix} -10.2194498 \\ 12.1465099 \end{pmatrix} x + (20.3611723) = 0$

LDA assume that $\Sigma_i = \Sigma$, However it is not the case in this situation

3.

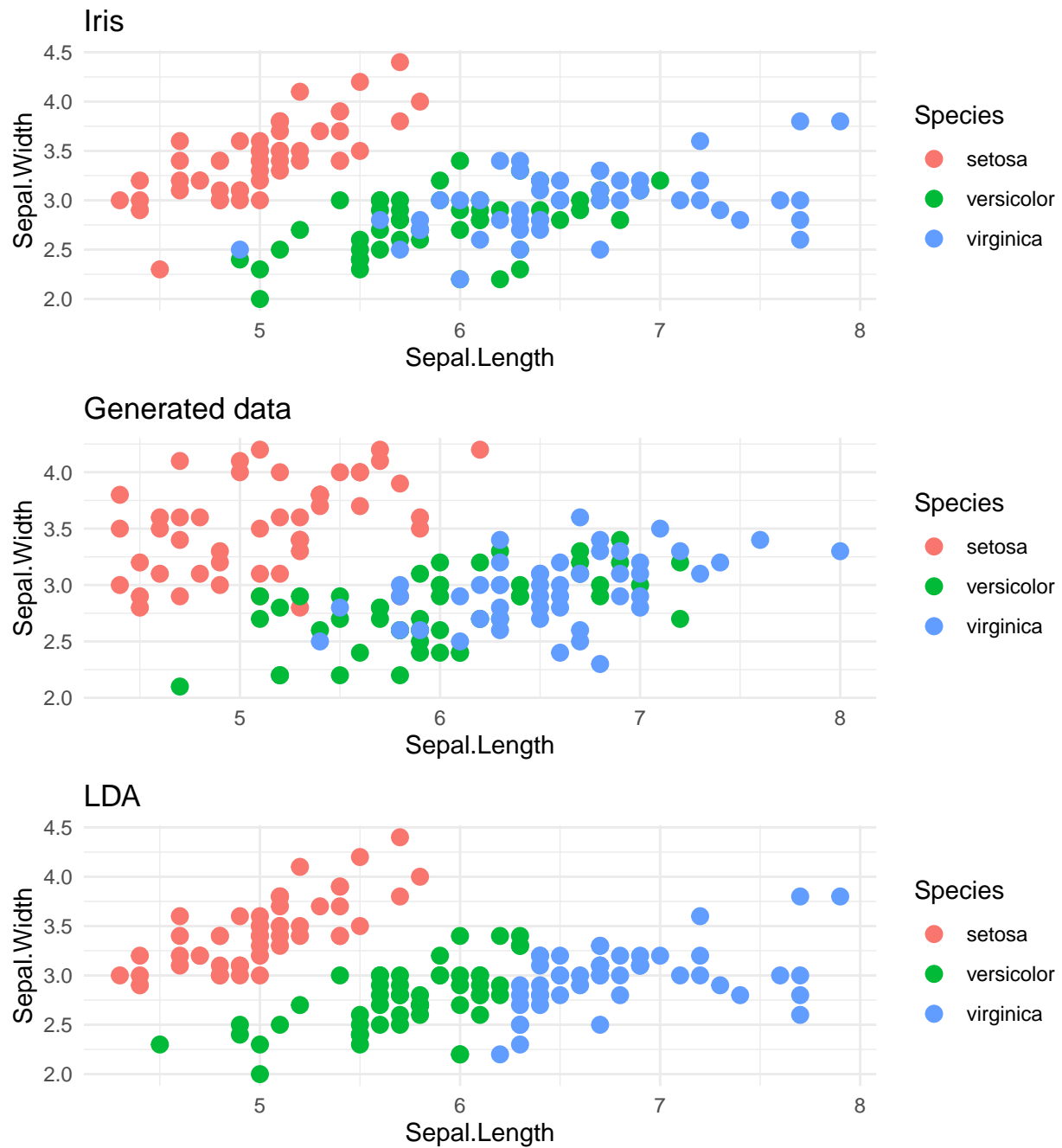


Missclassification rate of LDA: 0.2

Missclassification rate of LDA using MASS library: 0.2

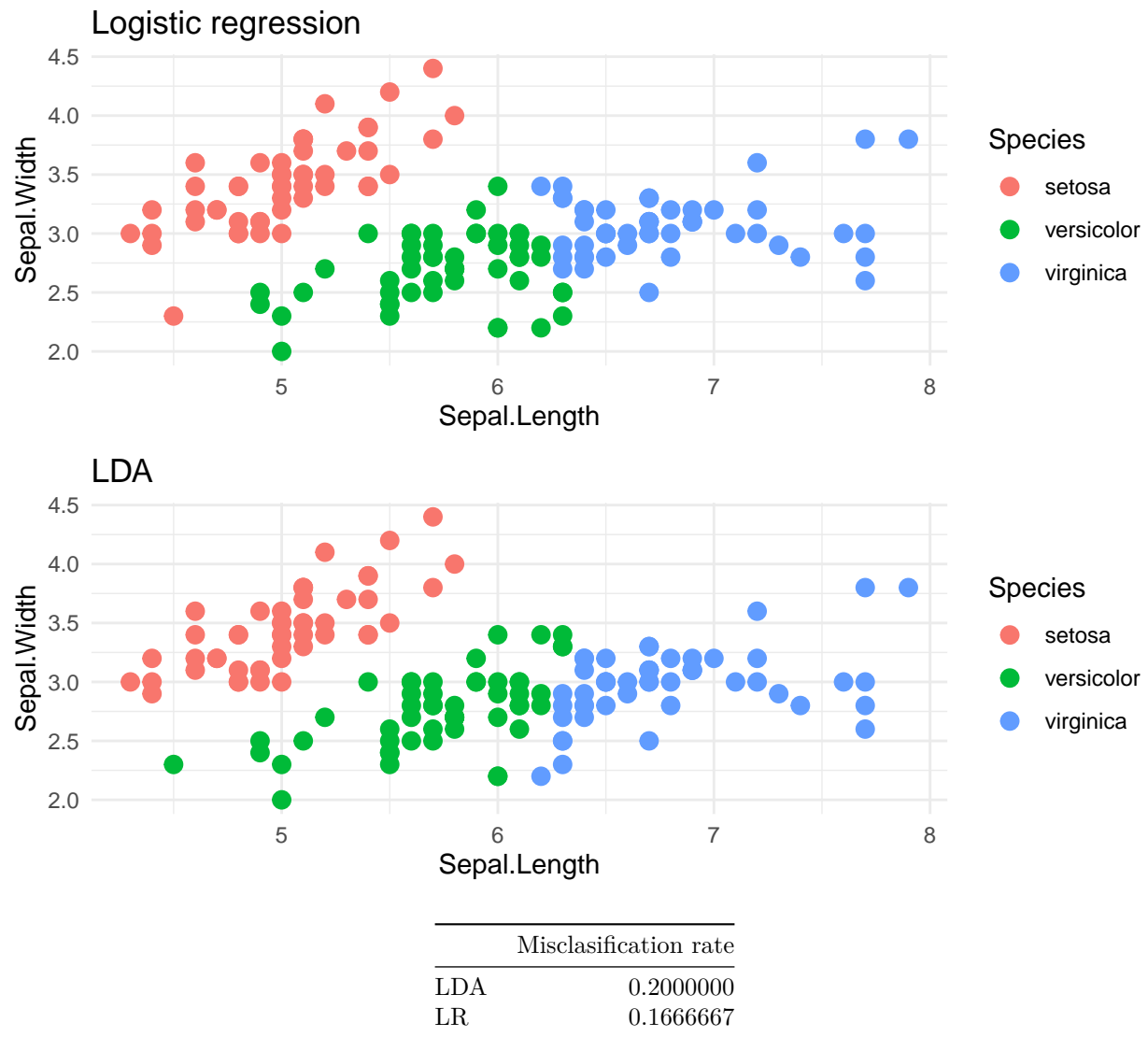
Test errors are the same, Classification methods are identical so and the results are identical

4.



From Plots we can see generated data is spread equally, it is because of LDA assumption that covariances are equal. We can also notice that LDA can not distinguish classes when data overlay.

5.



From misclassification rate we can see that logistic regression performed slightly better than LRA.