

R-project1

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Installing packages

```
install.packages(c("neuralnet", "keras", "tensorflow"), dependancies = T)
```

```
## Installing packages into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)

## Warning in download.file(url, destfile, method, mode = "wb", ...): cannot open
## URL
## 'http://rspm/default/__linux__/focal/latest/src/contrib/keras_2.15.0.tar.gz':
## HTTP status was '504 Gateway Timeout'

## Error in download.file(url, destfile, method, mode = "wb", ...) :
##   cannot open URL 'http://rspm/default/__linux__/focal/latest/src/contrib/keras_2.15.0.tar.gz'

## Warning in download.packages(pkgs, destdir = tmpd, available = available, :
## download of package 'keras' failed
```

```
library(neuralnet)
install.packages("tidyverse")
```

```
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
```

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr    1.5.1
## v ggplot2    3.5.1      v tibble     3.2.1
## v lubridate  1.9.3      v tidyr      1.3.1
## v purrr      1.0.2
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

```
## x dplyr::compute() masks neuralnet::compute()
```

```
## x dplyr::filter()  masks stats::filter()
```

```
## x dplyr::lag()     masks stats::lag()
```

```
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

Data analysis

```
iris <- iris %>%mutate_if(is.character, as.factor)
head(iris)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
```

```
## 1      5.1      3.5      1.4      0.2 setosa
## 2      4.9      3.0      1.4      0.2 setosa
## 3      4.7      3.2      1.3      0.2 setosa
## 4      4.6      3.1      1.5      0.2 setosa
## 5      5.0      3.6      1.4      0.2 setosa
## 6      5.4      3.9      1.7      0.4 setosa
```

```
summary(iris)
```

```
## Sepal.Length Sepal.Width Petal.Length Petal.Width
## Min. :4.300 Min. :2.000 Min. :1.000 Min. :0.100
## 1st Qu.:5.100 1st Qu.:2.800 1st Qu.:1.600 1st Qu.:0.300
## Median :5.800 Median :3.000 Median :4.350 Median :1.300
## Mean :5.843 Mean :3.057 Mean :3.758 Mean :1.199
## 3rd Qu.:6.400 3rd Qu.:3.300 3rd Qu.:5.100 3rd Qu.:1.800
## Max. :7.900 Max. :4.400 Max. :6.900 Max. :2.500
## Species
## setosa :50
## versicolor:50
## virginica :50
##
##
##
```

Train and test split

```
set.seed(254)
data_rows <- floor(0.80 * nrow(iris))
train_indices <- sample(c(1:nrow(iris)), data_rows)
head(train_indices)
```

```
## [1] 55 37 146 70 45 124
```

```
train_data <- iris[train_indices,]
head(train_data)
```

```
## Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 55      6.5      2.8      4.6      1.5 versicolor
## 37      5.5      3.5      1.3      0.2 setosa
## 146     6.7      3.0      5.2      2.3 virginica
## 70      5.6      2.5      3.9      1.1 versicolor
## 45      5.1      3.8      1.9      0.4 setosa
## 124     6.3      2.7      4.9      1.8 virginica
```

```
test_data <- iris[-train_indices, ]
head(test_data)
```

```
## Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1      5.1      3.5      1.4      0.2 setosa
## 15     5.8      4.0      1.2      0.2 setosa
## 16     5.7      4.4      1.5      0.4 setosa
## 21     5.4      3.4      1.7      0.2 setosa
## 22     5.1      3.7      1.5      0.4 setosa
## 26     5.0      3.0      1.6      0.2 setosa
```

Two hidden layers with 4 and 2 neurons

```
model <- neuralnet(Species ~ Sepal.Length + Sepal.Width + Petal.Length +  
Petal.Width, data = train_data, hidden = c(4,2), linear.output = FALSE)  
# Print the model summary  
head(model)
```

```
## $call  
## neuralnet(formula = Species ~ Sepal.Length + Sepal.Width + Petal.Length +  
##       Petal.Width, data = train_data, hidden = c(4, 2), linear.output = FALSE)  
##  
## $response  
##       versicolor setosa virginica  
## 1          FALSE  TRUE      FALSE  
## 2           TRUE FALSE      FALSE  
## 3          FALSE FALSE      TRUE  
## 4          FALSE  TRUE      FALSE  
## 5           TRUE FALSE      FALSE  
## 6          FALSE FALSE      TRUE  
## 7           TRUE FALSE      FALSE  
## 8          FALSE  TRUE      FALSE  
## 9          FALSE FALSE      TRUE  
## 10          TRUE FALSE      FALSE  
## 11          FALSE  TRUE      FALSE  
## 12          TRUE FALSE      FALSE  
## 13          FALSE FALSE      TRUE  
## 14          FALSE FALSE      TRUE  
## 15          FALSE FALSE      TRUE  
## 16          FALSE FALSE      TRUE  
## 17          FALSE  TRUE      FALSE  
## 18          FALSE FALSE      TRUE  
## 19          FALSE FALSE      TRUE  
## 20          TRUE FALSE      FALSE  
## 21          FALSE FALSE      TRUE  
## 22          FALSE FALSE      TRUE  
## 23          FALSE  TRUE      FALSE  
## 24          FALSE FALSE      TRUE  
## 25          FALSE FALSE      TRUE  
## 26          FALSE FALSE      TRUE  
## 27          FALSE  TRUE      FALSE  
## 28          FALSE FALSE      TRUE  
## 29          TRUE FALSE      FALSE  
## 30          FALSE  TRUE      FALSE  
## 31          FALSE  TRUE      FALSE  
## 32          FALSE  TRUE      FALSE  
## 33          FALSE  TRUE      FALSE  
## 34          TRUE FALSE      FALSE  
## 35          TRUE FALSE      FALSE  
## 36          FALSE  TRUE      FALSE  
## 37          FALSE FALSE      TRUE  
## 38          FALSE FALSE      TRUE  
## 39          FALSE FALSE      TRUE  
## 40          TRUE FALSE      FALSE  
## 41          TRUE FALSE      FALSE
```

## 42	FALSE	TRUE	FALSE
## 43	TRUE	FALSE	FALSE
## 44	FALSE	TRUE	FALSE
## 45	TRUE	FALSE	FALSE
## 46	TRUE	FALSE	FALSE
## 47	TRUE	FALSE	FALSE
## 48	FALSE	TRUE	FALSE
## 49	TRUE	FALSE	FALSE
## 50	FALSE	TRUE	FALSE
## 51	FALSE	FALSE	TRUE
## 52	FALSE	FALSE	TRUE
## 53	FALSE	TRUE	FALSE
## 54	FALSE	FALSE	TRUE
## 55	FALSE	TRUE	FALSE
## 56	FALSE	FALSE	TRUE
## 57	TRUE	FALSE	FALSE
## 58	TRUE	FALSE	FALSE
## 59	TRUE	FALSE	FALSE
## 60	FALSE	TRUE	FALSE
## 61	FALSE	TRUE	FALSE
## 62	FALSE	TRUE	FALSE
## 63	TRUE	FALSE	FALSE
## 64	FALSE	FALSE	TRUE
## 65	TRUE	FALSE	FALSE
## 66	FALSE	FALSE	TRUE
## 67	FALSE	TRUE	FALSE
## 68	TRUE	FALSE	FALSE
## 69	TRUE	FALSE	FALSE
## 70	FALSE	TRUE	FALSE
## 71	FALSE	TRUE	FALSE
## 72	TRUE	FALSE	FALSE
## 73	FALSE	FALSE	TRUE
## 74	TRUE	FALSE	FALSE
## 75	FALSE	FALSE	TRUE
## 76	FALSE	FALSE	TRUE
## 77	FALSE	FALSE	TRUE
## 78	TRUE	FALSE	FALSE
## 79	TRUE	FALSE	FALSE
## 80	FALSE	TRUE	FALSE
## 81	FALSE	TRUE	FALSE
## 82	TRUE	FALSE	FALSE
## 83	TRUE	FALSE	FALSE
## 84	FALSE	TRUE	FALSE
## 85	FALSE	FALSE	TRUE
## 86	FALSE	FALSE	TRUE
## 87	TRUE	FALSE	FALSE
## 88	TRUE	FALSE	FALSE
## 89	FALSE	FALSE	TRUE
## 90	FALSE	TRUE	FALSE
## 91	TRUE	FALSE	FALSE
## 92	TRUE	FALSE	FALSE
## 93	FALSE	TRUE	FALSE
## 94	FALSE	TRUE	FALSE
## 95	TRUE	FALSE	FALSE

```

## 96      FALSE  TRUE    FALSE
## 97      FALSE FALSE    TRUE
## 98      FALSE  TRUE    FALSE
## 99      FALSE  TRUE    FALSE
## 100     FALSE FALSE    TRUE
## 101     FALSE  TRUE    FALSE
## 102     FALSE  TRUE    FALSE
## 103     FALSE  TRUE    FALSE
## 104     FALSE FALSE    TRUE
## 105      TRUE FALSE    FALSE
## 106      TRUE FALSE    FALSE
## 107      TRUE FALSE    FALSE
## 108     FALSE FALSE    TRUE
## 109     FALSE FALSE    TRUE
## 110      TRUE FALSE    FALSE
## 111     FALSE FALSE    TRUE
## 112      TRUE FALSE    FALSE
## 113     FALSE  TRUE    FALSE
## 114     FALSE  TRUE    FALSE
## 115     FALSE  TRUE    FALSE
## 116     FALSE  TRUE    FALSE
## 117      TRUE FALSE    FALSE
## 118     FALSE  TRUE    FALSE
## 119     FALSE FALSE    TRUE
## 120     FALSE FALSE    TRUE

```

```
##
```

```
## $covariate
```

```

##      Sepal.Length Sepal.Width Petal.Length Petal.Width
## 55             6.5         2.8         4.6         1.5
## 37             5.5         3.5         1.3         0.2
## 146            6.7         3.0         5.2         2.3
## 70             5.6         2.5         3.9         1.1
## 45             5.1         3.8         1.9         0.4
## 124            6.3         2.7         4.9         1.8
## 20             5.1         3.8         1.5         0.3
## 76             6.6         3.0         4.4         1.4
## 144            6.8         3.2         5.9         2.3
## 3             4.7         3.2         1.3         0.2
## 88            6.3         2.3         4.4         1.3
## 10            4.9         3.1         1.5         0.1
## 136            7.7         3.0         6.1         2.3
## 126            7.2         3.2         6.0         1.8
## 102            5.8         2.7         5.1         1.9
## 125            6.7         3.3         5.7         2.1
## 64             6.1         2.9         4.7         1.4
## 111            6.5         3.2         5.1         2.0
## 122            5.6         2.8         4.9         2.0
## 32             5.4         3.4         1.5         0.4
## 147            6.3         2.5         5.0         1.9
## 123            7.7         2.8         6.7         2.0
## 95             5.6         2.7         4.2         1.3
## 101            6.3         3.3         6.0         2.5
## 149            6.2         3.4         5.4         2.3
## 143            5.8         2.7         5.1         1.9

```

## 94	5.0	2.3	3.3	1.0
## 150	5.9	3.0	5.1	1.8
## 11	5.4	3.7	1.5	0.2
## 83	5.8	2.7	3.9	1.2
## 54	5.5	2.3	4.0	1.3
## 57	6.3	3.3	4.7	1.6
## 61	5.0	2.0	3.5	1.0
## 48	4.6	3.2	1.4	0.2
## 29	5.2	3.4	1.4	0.2
## 69	6.2	2.2	4.5	1.5
## 130	7.2	3.0	5.8	1.6
## 115	5.8	2.8	5.1	2.4
## 145	6.7	3.3	5.7	2.5
## 17	5.4	3.9	1.3	0.4
## 50	5.0	3.3	1.4	0.2
## 96	5.7	3.0	4.2	1.2
## 35	4.9	3.1	1.5	0.2
## 93	5.8	2.6	4.0	1.2
## 49	5.3	3.7	1.5	0.2
## 12	4.8	3.4	1.6	0.2
## 14	4.3	3.0	1.1	0.1
## 60	5.2	2.7	3.9	1.4
## 18	5.1	3.5	1.4	0.3
## 97	5.7	2.9	4.2	1.3
## 109	6.7	2.5	5.8	1.8
## 134	6.3	2.8	5.1	1.5
## 62	5.9	3.0	4.2	1.5
## 113	6.8	3.0	5.5	2.1
## 75	6.4	2.9	4.3	1.3
## 119	7.7	2.6	6.9	2.3
## 41	5.0	3.5	1.3	0.3
## 27	5.0	3.4	1.6	0.4
## 25	4.8	3.4	1.9	0.2
## 89	5.6	3.0	4.1	1.3
## 100	5.7	2.8	4.1	1.3
## 91	5.5	2.6	4.4	1.2
## 19	5.7	3.8	1.7	0.3
## 137	6.3	3.4	5.6	2.4
## 46	4.8	3.0	1.4	0.3
## 103	7.1	3.0	5.9	2.1
## 85	5.4	3.0	4.5	1.5
## 6	5.4	3.9	1.7	0.4
## 44	5.0	3.5	1.6	0.6
## 86	6.0	3.4	4.5	1.6
## 71	5.9	3.2	4.8	1.8
## 36	5.0	3.2	1.2	0.2
## 104	6.3	2.9	5.6	1.8
## 42	4.5	2.3	1.3	0.3
## 139	6.0	3.0	4.8	1.8
## 118	7.7	3.8	6.7	2.2
## 106	7.6	3.0	6.6	2.1
## 9	4.4	2.9	1.4	0.2
## 43	4.4	3.2	1.3	0.2
## 84	6.0	2.7	5.1	1.6

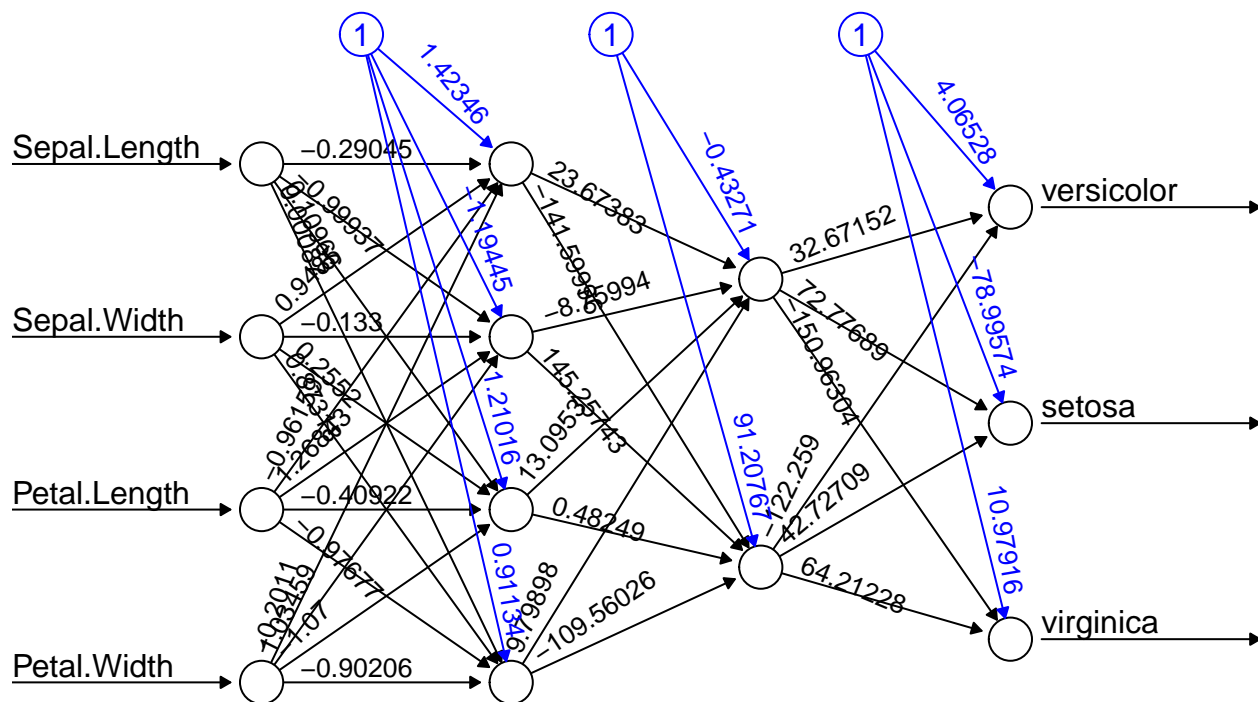
```

## 66          6.7          3.1          4.4          1.4
## 39          4.4          3.0          1.3          0.2
## 7           4.6          3.4          1.4          0.3
## 72          6.1          2.8          4.0          1.3
## 117         6.5          3.0          5.5          1.8
## 108         7.3          2.9          6.3          1.8
## 4           4.6          3.1          1.5          0.2
## 38          4.9          3.6          1.4          0.1
## 138         6.4          3.1          5.5          1.8
## 65          5.6          2.9          3.6          1.3
## 5           5.0          3.6          1.4          0.2
## 2           4.9          3.0          1.4          0.2
## 87          6.7          3.1          4.7          1.5
## 82          5.5          2.4          3.7          1.0
## 40          5.1          3.4          1.5          0.2
## 77          6.8          2.8          4.8          1.4
## 128         6.1          3.0          4.9          1.8
## 67          5.6          3.0          4.5          1.5
## 92          6.1          3.0          4.6          1.4
## 131         7.4          2.8          6.1          1.9
## 74          6.1          2.8          4.7          1.2
## 56          5.7          2.8          4.5          1.3
## 59          6.6          2.9          4.6          1.3
## 120         6.0          2.2          5.0          1.5
## 23          4.6          3.6          1.0          0.2
## 13          4.8          3.0          1.4          0.1
## 33          5.2          4.1          1.5          0.1
## 107         4.9          2.5          4.5          1.7
## 127         6.2          2.8          4.8          1.8
## 24          5.1          3.3          1.7          0.5
## 116         6.4          3.2          5.3          2.3
## 34          5.5          4.2          1.4          0.2
## 68          5.8          2.7          4.1          1.0
## 58          4.9          2.4          3.3          1.0
## 73          6.3          2.5          4.9          1.5
## 80          5.7          2.6          3.5          1.0
## 8           5.0          3.4          1.5          0.2
## 99          5.1          2.5          3.0          1.1
## 121         6.9          3.2          5.7          2.3
## 133         6.4          2.8          5.6          2.2
##
## $model.list
## $model.list$response
## [1] "versicolor" "setosa"      "virginica"
##
## $model.list$variables
## [1] "Sepal.Length" "Sepal.Width"  "Petal.Length" "Petal.Width"
##
##
## $err.fct
## function (x, y)
## {
##     1/2 * (y - x)^2
## }

```

```
## <bytecode: 0x5ff345bcfe58>
## <environment: 0x5ff345bcd720>
## attr(,"type")
## [1] "sse"
##
## $act.fct
## function (x)
## {
##     1/(1 + exp(-x))
## }
## <bytecode: 0x5ff345bd4408>
## <environment: 0x5ff345bd0f40>
## attr(,"type")
## [1] "logistic"
```

```
plot(model, rep = 'best')
```



Error: 1.00188 Steps: 6171

```
pred <- predict(model, test_data)
pred
```

```
##           [,1]      [,2]      [,3]
## 1  1.000000e+00  1.987582e-03  1.606099e-61
## 15 1.000000e+00  1.987582e-03  1.606099e-61
## 16 1.000000e+00  1.987582e-03  1.606099e-61
## 21 1.000000e+00  1.987582e-03  1.606099e-61
## 22 1.000000e+00  1.987582e-03  1.606099e-61
## 26 1.000000e+00  1.987582e-03  1.606099e-61
## 28 1.000000e+00  1.987582e-03  1.606099e-61
## 30 1.000000e+00  1.987582e-03  1.606099e-61
## 31 1.000000e+00  1.987582e-03  1.606099e-61
```



```
## 47 1.000000e+00 1.987582e-03 1.606099e-61
## 51 5.976903e-38 1.000000e+00 2.953469e-33
## 52 5.723452e-38 1.000000e+00 3.608146e-33
## 53 1.384220e-38 1.000000e+00 2.544987e-30
## 63 6.966252e-38 1.000000e+00 1.455306e-33
## 78 5.834333e-43 9.999693e-01 4.187287e-10
## 79 1.736209e-38 1.000000e+00 8.933657e-31
## 81 7.119429e-38 1.000000e+00 1.316157e-33
## 90 6.249596e-38 1.000000e+00 2.403280e-33
## 98 6.688873e-38 1.000000e+00 1.755865e-33
## 105 5.423696e-52 2.476923e-16 1.000000e+00
## 110 5.316714e-52 2.369408e-16 1.000000e+00
## 112 1.893062e-51 4.010254e-15 1.000000e+00
## 114 9.329015e-52 8.290613e-16 1.000000e+00
## 129 6.037474e-52 3.145041e-16 1.000000e+00
## 132 1.404842e-51 2.063591e-15 1.000000e+00
## 135 2.891381e-51 1.030162e-14 1.000000e+00
## 140 3.342740e-51 1.423096e-14 1.000000e+00
## 141 5.820653e-52 2.898980e-16 1.000000e+00
## 142 1.001202e-50 1.638601e-13 1.000000e+00
## 148 7.647401e-51 8.991549e-14 1.000000e+00
```

Three hidden layers with 5, 6 and 3 neurons

```
model2 <- neuralnet(Species ~ Sepal.Length + Sepal.Width + Petal.Length + Petal.Width, data = train_data,
# Print the model summary
head(model2)
```

```
## $call
## neuralnet(formula = Species ~ Sepal.Length + Sepal.Width + Petal.Length +
##      Petal.Width, data = train_data, hidden = c(5, 6, 3), linear.output = FALSE)
##
## $response
##      versicolor setosa virginica
## 1      FALSE    TRUE     FALSE
## 2      TRUE    FALSE     FALSE
## 3      FALSE    FALSE     TRUE
## 4      FALSE    TRUE     FALSE
## 5      TRUE    FALSE     FALSE
## 6      FALSE    FALSE     TRUE
## 7      TRUE    FALSE     FALSE
## 8      FALSE    TRUE     FALSE
## 9      FALSE    FALSE     TRUE
## 10     TRUE    FALSE     FALSE
## 11     FALSE    TRUE     FALSE
## 12     TRUE    FALSE     FALSE
## 13     FALSE    FALSE     TRUE
## 14     FALSE    FALSE     TRUE
## 15     FALSE    FALSE     TRUE
## 16     FALSE    FALSE     TRUE
## 17     FALSE    TRUE     FALSE
## 18     FALSE    FALSE     TRUE
## 19     FALSE    FALSE     TRUE
```

## 20	TRUE	FALSE	FALSE
## 21	FALSE	FALSE	TRUE
## 22	FALSE	FALSE	TRUE
## 23	FALSE	TRUE	FALSE
## 24	FALSE	FALSE	TRUE
## 25	FALSE	FALSE	TRUE
## 26	FALSE	FALSE	TRUE
## 27	FALSE	TRUE	FALSE
## 28	FALSE	FALSE	TRUE
## 29	TRUE	FALSE	FALSE
## 30	FALSE	TRUE	FALSE
## 31	FALSE	TRUE	FALSE
## 32	FALSE	TRUE	FALSE
## 33	FALSE	TRUE	FALSE
## 34	TRUE	FALSE	FALSE
## 35	TRUE	FALSE	FALSE
## 36	FALSE	TRUE	FALSE
## 37	FALSE	FALSE	TRUE
## 38	FALSE	FALSE	TRUE
## 39	FALSE	FALSE	TRUE
## 40	TRUE	FALSE	FALSE
## 41	TRUE	FALSE	FALSE
## 42	FALSE	TRUE	FALSE
## 43	TRUE	FALSE	FALSE
## 44	FALSE	TRUE	FALSE
## 45	TRUE	FALSE	FALSE
## 46	TRUE	FALSE	FALSE
## 47	TRUE	FALSE	FALSE
## 48	FALSE	TRUE	FALSE
## 49	TRUE	FALSE	FALSE
## 50	FALSE	TRUE	FALSE
## 51	FALSE	FALSE	TRUE
## 52	FALSE	FALSE	TRUE
## 53	FALSE	TRUE	FALSE
## 54	FALSE	FALSE	TRUE
## 55	FALSE	TRUE	FALSE
## 56	FALSE	FALSE	TRUE
## 57	TRUE	FALSE	FALSE
## 58	TRUE	FALSE	FALSE
## 59	TRUE	FALSE	FALSE
## 60	FALSE	TRUE	FALSE
## 61	FALSE	TRUE	FALSE
## 62	FALSE	TRUE	FALSE
## 63	TRUE	FALSE	FALSE
## 64	FALSE	FALSE	TRUE
## 65	TRUE	FALSE	FALSE
## 66	FALSE	FALSE	TRUE
## 67	FALSE	TRUE	FALSE
## 68	TRUE	FALSE	FALSE
## 69	TRUE	FALSE	FALSE
## 70	FALSE	TRUE	FALSE
## 71	FALSE	TRUE	FALSE
## 72	TRUE	FALSE	FALSE
## 73	FALSE	FALSE	TRUE

```

## 74      TRUE FALSE FALSE
## 75      FALSE FALSE TRUE
## 76      FALSE FALSE TRUE
## 77      FALSE FALSE TRUE
## 78      TRUE FALSE FALSE
## 79      TRUE FALSE FALSE
## 80      FALSE TRUE FALSE
## 81      FALSE TRUE FALSE
## 82      TRUE FALSE FALSE
## 83      TRUE FALSE FALSE
## 84      FALSE TRUE FALSE
## 85      FALSE FALSE TRUE
## 86      FALSE FALSE TRUE
## 87      TRUE FALSE FALSE
## 88      TRUE FALSE FALSE
## 89      FALSE FALSE TRUE
## 90      FALSE TRUE FALSE
## 91      TRUE FALSE FALSE
## 92      TRUE FALSE FALSE
## 93      FALSE TRUE FALSE
## 94      FALSE TRUE FALSE
## 95      TRUE FALSE FALSE
## 96      FALSE TRUE FALSE
## 97      FALSE FALSE TRUE
## 98      FALSE TRUE FALSE
## 99      FALSE TRUE FALSE
## 100     FALSE FALSE TRUE
## 101     FALSE TRUE FALSE
## 102     FALSE TRUE FALSE
## 103     FALSE TRUE FALSE
## 104     FALSE FALSE TRUE
## 105     TRUE FALSE FALSE
## 106     TRUE FALSE FALSE
## 107     TRUE FALSE FALSE
## 108     FALSE FALSE TRUE
## 109     FALSE FALSE TRUE
## 110     TRUE FALSE FALSE
## 111     FALSE FALSE TRUE
## 112     TRUE FALSE FALSE
## 113     FALSE TRUE FALSE
## 114     FALSE TRUE FALSE
## 115     FALSE TRUE FALSE
## 116     FALSE TRUE FALSE
## 117     TRUE FALSE FALSE
## 118     FALSE TRUE FALSE
## 119     FALSE FALSE TRUE
## 120     FALSE FALSE TRUE
##
## $covariate
##      Sepal.Length Sepal.Width Petal.Length Petal.Width
## 55              6.5          2.8          4.6          1.5
## 37              5.5          3.5          1.3          0.2
## 146             6.7          3.0          5.2          2.3
## 70              5.6          2.5          3.9          1.1

```

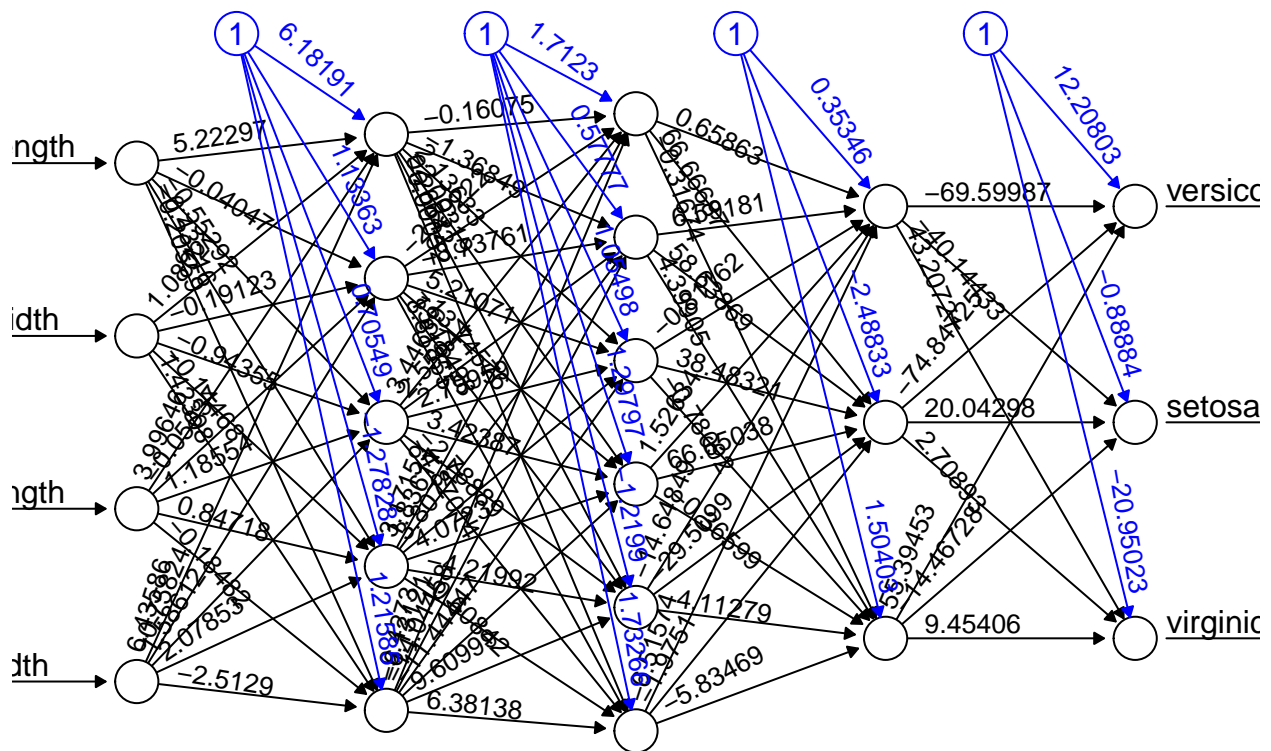
## 45	5.1	3.8	1.9	0.4
## 124	6.3	2.7	4.9	1.8
## 20	5.1	3.8	1.5	0.3
## 76	6.6	3.0	4.4	1.4
## 144	6.8	3.2	5.9	2.3
## 3	4.7	3.2	1.3	0.2
## 88	6.3	2.3	4.4	1.3
## 10	4.9	3.1	1.5	0.1
## 136	7.7	3.0	6.1	2.3
## 126	7.2	3.2	6.0	1.8
## 102	5.8	2.7	5.1	1.9
## 125	6.7	3.3	5.7	2.1
## 64	6.1	2.9	4.7	1.4
## 111	6.5	3.2	5.1	2.0
## 122	5.6	2.8	4.9	2.0
## 32	5.4	3.4	1.5	0.4
## 147	6.3	2.5	5.0	1.9
## 123	7.7	2.8	6.7	2.0
## 95	5.6	2.7	4.2	1.3
## 101	6.3	3.3	6.0	2.5
## 149	6.2	3.4	5.4	2.3
## 143	5.8	2.7	5.1	1.9
## 94	5.0	2.3	3.3	1.0
## 150	5.9	3.0	5.1	1.8
## 11	5.4	3.7	1.5	0.2
## 83	5.8	2.7	3.9	1.2
## 54	5.5	2.3	4.0	1.3
## 57	6.3	3.3	4.7	1.6
## 61	5.0	2.0	3.5	1.0
## 48	4.6	3.2	1.4	0.2
## 29	5.2	3.4	1.4	0.2
## 69	6.2	2.2	4.5	1.5
## 130	7.2	3.0	5.8	1.6
## 115	5.8	2.8	5.1	2.4
## 145	6.7	3.3	5.7	2.5
## 17	5.4	3.9	1.3	0.4
## 50	5.0	3.3	1.4	0.2
## 96	5.7	3.0	4.2	1.2
## 35	4.9	3.1	1.5	0.2
## 93	5.8	2.6	4.0	1.2
## 49	5.3	3.7	1.5	0.2
## 12	4.8	3.4	1.6	0.2
## 14	4.3	3.0	1.1	0.1
## 60	5.2	2.7	3.9	1.4
## 18	5.1	3.5	1.4	0.3
## 97	5.7	2.9	4.2	1.3
## 109	6.7	2.5	5.8	1.8
## 134	6.3	2.8	5.1	1.5
## 62	5.9	3.0	4.2	1.5
## 113	6.8	3.0	5.5	2.1
## 75	6.4	2.9	4.3	1.3
## 119	7.7	2.6	6.9	2.3
## 41	5.0	3.5	1.3	0.3
## 27	5.0	3.4	1.6	0.4

## 25	4.8	3.4	1.9	0.2
## 89	5.6	3.0	4.1	1.3
## 100	5.7	2.8	4.1	1.3
## 91	5.5	2.6	4.4	1.2
## 19	5.7	3.8	1.7	0.3
## 137	6.3	3.4	5.6	2.4
## 46	4.8	3.0	1.4	0.3
## 103	7.1	3.0	5.9	2.1
## 85	5.4	3.0	4.5	1.5
## 6	5.4	3.9	1.7	0.4
## 44	5.0	3.5	1.6	0.6
## 86	6.0	3.4	4.5	1.6
## 71	5.9	3.2	4.8	1.8
## 36	5.0	3.2	1.2	0.2
## 104	6.3	2.9	5.6	1.8
## 42	4.5	2.3	1.3	0.3
## 139	6.0	3.0	4.8	1.8
## 118	7.7	3.8	6.7	2.2
## 106	7.6	3.0	6.6	2.1
## 9	4.4	2.9	1.4	0.2
## 43	4.4	3.2	1.3	0.2
## 84	6.0	2.7	5.1	1.6
## 66	6.7	3.1	4.4	1.4
## 39	4.4	3.0	1.3	0.2
## 7	4.6	3.4	1.4	0.3
## 72	6.1	2.8	4.0	1.3
## 117	6.5	3.0	5.5	1.8
## 108	7.3	2.9	6.3	1.8
## 4	4.6	3.1	1.5	0.2
## 38	4.9	3.6	1.4	0.1
## 138	6.4	3.1	5.5	1.8
## 65	5.6	2.9	3.6	1.3
## 5	5.0	3.6	1.4	0.2
## 2	4.9	3.0	1.4	0.2
## 87	6.7	3.1	4.7	1.5
## 82	5.5	2.4	3.7	1.0
## 40	5.1	3.4	1.5	0.2
## 77	6.8	2.8	4.8	1.4
## 128	6.1	3.0	4.9	1.8
## 67	5.6	3.0	4.5	1.5
## 92	6.1	3.0	4.6	1.4
## 131	7.4	2.8	6.1	1.9
## 74	6.1	2.8	4.7	1.2
## 56	5.7	2.8	4.5	1.3
## 59	6.6	2.9	4.6	1.3
## 120	6.0	2.2	5.0	1.5
## 23	4.6	3.6	1.0	0.2
## 13	4.8	3.0	1.4	0.1
## 33	5.2	4.1	1.5	0.1
## 107	4.9	2.5	4.5	1.7
## 127	6.2	2.8	4.8	1.8
## 24	5.1	3.3	1.7	0.5
## 116	6.4	3.2	5.3	2.3
## 34	5.5	4.2	1.4	0.2

```

## 68          5.8          2.7          4.1          1.0
## 58          4.9          2.4          3.3          1.0
## 73          6.3          2.5          4.9          1.5
## 80          5.7          2.6          3.5          1.0
## 8           5.0          3.4          1.5          0.2
## 99          5.1          2.5          3.0          1.1
## 121         6.9          3.2          5.7          2.3
## 133         6.4          2.8          5.6          2.2
##
## $model.list
## $model.list$response
## [1] "versicolor" "setosa"      "virginica"
##
## $model.list$variables
## [1] "Sepal.Length" "Sepal.Width"  "Petal.Length" "Petal.Width"
##
##
## $err.fct
## function (x, y)
## {
##     1/2 * (y - x)^2
## }
## <bytecode: 0x5ff345bcfe58>
## <environment: 0x5ff34718e230>
## attr("type")
## [1] "sse"
##
## $act.fct
## function (x)
## {
##     1/(1 + exp(-x))
## }
## <bytecode: 0x5ff345bd4408>
## <environment: 0x5ff34718e6c8>
## attr("type")
## [1] "logistic"
plot(model2, rep = 'best')

```



Error: 1.00033 Steps: 755

```
pred2 <- predict(model2, test_data)
pred2
```

```
##           [,1]      [,2]      [,3]
## 1  1.000000e+00  6.509956e-04  5.385772e-08
## 15 1.000000e+00  6.506519e-04  5.387632e-08
## 16 1.000000e+00  6.504240e-04  5.388867e-08
## 21 1.000000e+00  6.510956e-04  5.385231e-08
## 22 1.000000e+00  6.508797e-04  5.386399e-08
## 26 1.000000e+00  6.515860e-04  5.382580e-08
## 28 1.000000e+00  6.510035e-04  5.385729e-08
## 30 1.000000e+00  6.514384e-04  5.383378e-08
## 31 1.000000e+00  6.515227e-04  5.382923e-08
## 47 1.000000e+00  6.508780e-04  5.386408e-08
## 51 1.504749e-23  9.999999e-01  6.693563e-08
## 52 4.326990e-24  1.000000e+00  5.411274e-08
## 53 1.756766e-24  1.000000e+00  4.665115e-08
## 63 3.673640e-22  9.999998e-01  1.154726e-07
## 78 1.603627e-29  2.902124e-01  7.257712e-01
## 79 2.267233e-24  1.000000e+00  4.862220e-08
## 81 3.948668e-22  9.999998e-01  1.169041e-07
## 90 2.145250e-23  9.999999e-01  7.111211e-08
## 98 8.937235e-23  9.999999e-01  9.072088e-08
## 105 3.066205e-35  8.900533e-16  1.000000e+00
## 110 7.804991e-35  6.578841e-16  1.000000e+00
## 112 5.407094e-37  4.365852e-15  1.000000e+00
## 114 3.033160e-36  2.063718e-15  1.000000e+00
## 129 1.641648e-35  1.101249e-15  1.000000e+00
```

```
## 132 5.574065e-38 1.600095e-14 1.000000e+00
## 135 4.238644e-23 9.999998e-01 1.367487e-07
## 140 7.385844e-36 1.463866e-15 1.000000e+00
## 141 6.528433e-35 6.959737e-16 1.000000e+00
## 142 3.516115e-35 8.496172e-16 1.000000e+00
## 148 7.505262e-37 3.726516e-15 1.000000e+00
```

5 hidden layers with 9, 21, 7, 8, 5, neurons

```
model3 <- neuralnet(Species ~ Sepal.Length + Sepal.Width + Petal.Length + Petal.Width, data = train_data,
# Print the model summary
head(model3)
```

```
## $call
## neuralnet(formula = Species ~ Sepal.Length + Sepal.Width + Petal.Length +
##     Petal.Width, data = train_data, hidden = c(9, 21, 7, 8, 5),
##     linear.output = FALSE)
##
## $response
##      versicolor setosa virginica
## 1      FALSE    TRUE     FALSE
## 2       TRUE   FALSE     FALSE
## 3      FALSE   FALSE      TRUE
## 4      FALSE    TRUE     FALSE
## 5       TRUE   FALSE     FALSE
## 6      FALSE   FALSE      TRUE
## 7       TRUE   FALSE     FALSE
## 8      FALSE    TRUE     FALSE
## 9      FALSE   FALSE      TRUE
## 10      TRUE   FALSE     FALSE
## 11      FALSE    TRUE     FALSE
## 12      TRUE   FALSE     FALSE
## 13      FALSE   FALSE      TRUE
## 14      FALSE   FALSE      TRUE
## 15      FALSE   FALSE      TRUE
## 16      FALSE   FALSE      TRUE
## 17      FALSE    TRUE     FALSE
## 18      FALSE   FALSE      TRUE
## 19      FALSE   FALSE      TRUE
## 20      TRUE   FALSE     FALSE
## 21      FALSE   FALSE      TRUE
## 22      FALSE   FALSE      TRUE
## 23      FALSE    TRUE     FALSE
## 24      FALSE   FALSE      TRUE
## 25      FALSE   FALSE      TRUE
## 26      FALSE   FALSE      TRUE
## 27      FALSE    TRUE     FALSE
## 28      FALSE   FALSE      TRUE
## 29      TRUE   FALSE     FALSE
## 30      FALSE    TRUE     FALSE
## 31      FALSE    TRUE     FALSE
## 32      FALSE    TRUE     FALSE
## 33      FALSE    TRUE     FALSE
```


## 34	TRUE	FALSE	FALSE
## 35	TRUE	FALSE	FALSE
## 36	FALSE	TRUE	FALSE
## 37	FALSE	FALSE	TRUE
## 38	FALSE	FALSE	TRUE
## 39	FALSE	FALSE	TRUE
## 40	TRUE	FALSE	FALSE
## 41	TRUE	FALSE	FALSE
## 42	FALSE	TRUE	FALSE
## 43	TRUE	FALSE	FALSE
## 44	FALSE	TRUE	FALSE
## 45	TRUE	FALSE	FALSE
## 46	TRUE	FALSE	FALSE
## 47	TRUE	FALSE	FALSE
## 48	FALSE	TRUE	FALSE
## 49	TRUE	FALSE	FALSE
## 50	FALSE	TRUE	FALSE
## 51	FALSE	FALSE	TRUE
## 52	FALSE	FALSE	TRUE
## 53	FALSE	TRUE	FALSE
## 54	FALSE	FALSE	TRUE
## 55	FALSE	TRUE	FALSE
## 56	FALSE	FALSE	TRUE
## 57	TRUE	FALSE	FALSE
## 58	TRUE	FALSE	FALSE
## 59	TRUE	FALSE	FALSE
## 60	FALSE	TRUE	FALSE
## 61	FALSE	TRUE	FALSE
## 62	FALSE	TRUE	FALSE
## 63	TRUE	FALSE	FALSE
## 64	FALSE	FALSE	TRUE
## 65	TRUE	FALSE	FALSE
## 66	FALSE	FALSE	TRUE
## 67	FALSE	TRUE	FALSE
## 68	TRUE	FALSE	FALSE
## 69	TRUE	FALSE	FALSE
## 70	FALSE	TRUE	FALSE
## 71	FALSE	TRUE	FALSE
## 72	TRUE	FALSE	FALSE
## 73	FALSE	FALSE	TRUE
## 74	TRUE	FALSE	FALSE
## 75	FALSE	FALSE	TRUE
## 76	FALSE	FALSE	TRUE
## 77	FALSE	FALSE	TRUE
## 78	TRUE	FALSE	FALSE
## 79	TRUE	FALSE	FALSE
## 80	FALSE	TRUE	FALSE
## 81	FALSE	TRUE	FALSE
## 82	TRUE	FALSE	FALSE
## 83	TRUE	FALSE	FALSE
## 84	FALSE	TRUE	FALSE
## 85	FALSE	FALSE	TRUE
## 86	FALSE	FALSE	TRUE
## 87	TRUE	FALSE	FALSE

```

## 88      TRUE FALSE FALSE
## 89      FALSE FALSE TRUE
## 90      FALSE TRUE FALSE
## 91      TRUE FALSE FALSE
## 92      TRUE FALSE FALSE
## 93      FALSE TRUE FALSE
## 94      FALSE TRUE FALSE
## 95      TRUE FALSE FALSE
## 96      FALSE TRUE FALSE
## 97      FALSE FALSE TRUE
## 98      FALSE TRUE FALSE
## 99      FALSE TRUE FALSE
## 100     FALSE FALSE TRUE
## 101     FALSE TRUE FALSE
## 102     FALSE TRUE FALSE
## 103     FALSE TRUE FALSE
## 104     FALSE FALSE TRUE
## 105     TRUE FALSE FALSE
## 106     TRUE FALSE FALSE
## 107     TRUE FALSE FALSE
## 108     FALSE FALSE TRUE
## 109     FALSE FALSE TRUE
## 110     TRUE FALSE FALSE
## 111     FALSE FALSE TRUE
## 112     TRUE FALSE FALSE
## 113     FALSE TRUE FALSE
## 114     FALSE TRUE FALSE
## 115     FALSE TRUE FALSE
## 116     FALSE TRUE FALSE
## 117     TRUE FALSE FALSE
## 118     FALSE TRUE FALSE
## 119     FALSE FALSE TRUE
## 120     FALSE FALSE TRUE

```

```
##
```

```
## $covariate
```

```

##      Sepal.Length Sepal.Width Petal.Length Petal.Width
## 55           6.5         2.8         4.6         1.5
## 37           5.5         3.5         1.3         0.2
## 146          6.7         3.0         5.2         2.3
## 70           5.6         2.5         3.9         1.1
## 45           5.1         3.8         1.9         0.4
## 124          6.3         2.7         4.9         1.8
## 20           5.1         3.8         1.5         0.3
## 76           6.6         3.0         4.4         1.4
## 144          6.8         3.2         5.9         2.3
## 3           4.7         3.2         1.3         0.2
## 88           6.3         2.3         4.4         1.3
## 10           4.9         3.1         1.5         0.1
## 136          7.7         3.0         6.1         2.3
## 126          7.2         3.2         6.0         1.8
## 102          5.8         2.7         5.1         1.9
## 125          6.7         3.3         5.7         2.1
## 64           6.1         2.9         4.7         1.4
## 111          6.5         3.2         5.1         2.0

```

## 122	5.6	2.8	4.9	2.0
## 32	5.4	3.4	1.5	0.4
## 147	6.3	2.5	5.0	1.9
## 123	7.7	2.8	6.7	2.0
## 95	5.6	2.7	4.2	1.3
## 101	6.3	3.3	6.0	2.5
## 149	6.2	3.4	5.4	2.3
## 143	5.8	2.7	5.1	1.9
## 94	5.0	2.3	3.3	1.0
## 150	5.9	3.0	5.1	1.8
## 11	5.4	3.7	1.5	0.2
## 83	5.8	2.7	3.9	1.2
## 54	5.5	2.3	4.0	1.3
## 57	6.3	3.3	4.7	1.6
## 61	5.0	2.0	3.5	1.0
## 48	4.6	3.2	1.4	0.2
## 29	5.2	3.4	1.4	0.2
## 69	6.2	2.2	4.5	1.5
## 130	7.2	3.0	5.8	1.6
## 115	5.8	2.8	5.1	2.4
## 145	6.7	3.3	5.7	2.5
## 17	5.4	3.9	1.3	0.4
## 50	5.0	3.3	1.4	0.2
## 96	5.7	3.0	4.2	1.2
## 35	4.9	3.1	1.5	0.2
## 93	5.8	2.6	4.0	1.2
## 49	5.3	3.7	1.5	0.2
## 12	4.8	3.4	1.6	0.2
## 14	4.3	3.0	1.1	0.1
## 60	5.2	2.7	3.9	1.4
## 18	5.1	3.5	1.4	0.3
## 97	5.7	2.9	4.2	1.3
## 109	6.7	2.5	5.8	1.8
## 134	6.3	2.8	5.1	1.5
## 62	5.9	3.0	4.2	1.5
## 113	6.8	3.0	5.5	2.1
## 75	6.4	2.9	4.3	1.3
## 119	7.7	2.6	6.9	2.3
## 41	5.0	3.5	1.3	0.3
## 27	5.0	3.4	1.6	0.4
## 25	4.8	3.4	1.9	0.2
## 89	5.6	3.0	4.1	1.3
## 100	5.7	2.8	4.1	1.3
## 91	5.5	2.6	4.4	1.2
## 19	5.7	3.8	1.7	0.3
## 137	6.3	3.4	5.6	2.4
## 46	4.8	3.0	1.4	0.3
## 103	7.1	3.0	5.9	2.1
## 85	5.4	3.0	4.5	1.5
## 6	5.4	3.9	1.7	0.4
## 44	5.0	3.5	1.6	0.6
## 86	6.0	3.4	4.5	1.6
## 71	5.9	3.2	4.8	1.8
## 36	5.0	3.2	1.2	0.2

## 104	6.3	2.9	5.6	1.8
## 42	4.5	2.3	1.3	0.3
## 139	6.0	3.0	4.8	1.8
## 118	7.7	3.8	6.7	2.2
## 106	7.6	3.0	6.6	2.1
## 9	4.4	2.9	1.4	0.2
## 43	4.4	3.2	1.3	0.2
## 84	6.0	2.7	5.1	1.6
## 66	6.7	3.1	4.4	1.4
## 39	4.4	3.0	1.3	0.2
## 7	4.6	3.4	1.4	0.3
## 72	6.1	2.8	4.0	1.3
## 117	6.5	3.0	5.5	1.8
## 108	7.3	2.9	6.3	1.8
## 4	4.6	3.1	1.5	0.2
## 38	4.9	3.6	1.4	0.1
## 138	6.4	3.1	5.5	1.8
## 65	5.6	2.9	3.6	1.3
## 5	5.0	3.6	1.4	0.2
## 2	4.9	3.0	1.4	0.2
## 87	6.7	3.1	4.7	1.5
## 82	5.5	2.4	3.7	1.0
## 40	5.1	3.4	1.5	0.2
## 77	6.8	2.8	4.8	1.4
## 128	6.1	3.0	4.9	1.8
## 67	5.6	3.0	4.5	1.5
## 92	6.1	3.0	4.6	1.4
## 131	7.4	2.8	6.1	1.9
## 74	6.1	2.8	4.7	1.2
## 56	5.7	2.8	4.5	1.3
## 59	6.6	2.9	4.6	1.3
## 120	6.0	2.2	5.0	1.5
## 23	4.6	3.6	1.0	0.2
## 13	4.8	3.0	1.4	0.1
## 33	5.2	4.1	1.5	0.1
## 107	4.9	2.5	4.5	1.7
## 127	6.2	2.8	4.8	1.8
## 24	5.1	3.3	1.7	0.5
## 116	6.4	3.2	5.3	2.3
## 34	5.5	4.2	1.4	0.2
## 68	5.8	2.7	4.1	1.0
## 58	4.9	2.4	3.3	1.0
## 73	6.3	2.5	4.9	1.5
## 80	5.7	2.6	3.5	1.0
## 8	5.0	3.4	1.5	0.2
## 99	5.1	2.5	3.0	1.1
## 121	6.9	3.2	5.7	2.3
## 133	6.4	2.8	5.6	2.2
##				
## \$model.list				
## \$model.list\$response				
## [1] "versicolor" "setosa" "virginica"				
##				
## \$model.list\$variables				


```
##           [,1]           [,2]           [,3]
## 1  1.000000e+00 1.028022e-03 1.462620e-03
## 15 1.000000e+00 7.860659e-04 2.017514e-03
## 16 1.000000e+00 1.140339e-03 1.288727e-03
## 21 1.000000e+00 1.014266e-03 1.487406e-03
## 22 1.000000e+00 1.057409e-03 1.413358e-03
## 26 1.000000e+00 1.129845e-03 1.306104e-03
## 28 1.000000e+00 1.025629e-03 1.466899e-03
## 30 1.000000e+00 1.568671e-03 8.730074e-04
## 31 1.000000e+00 1.300101e-03 1.099737e-03
## 47 9.999999e-01 1.843991e-03 7.145405e-04
## 51 1.816741e-09 1.000000e+00 1.858058e-11
## 52 2.675986e-09 1.000000e+00 1.901935e-11
## 53 3.868879e-10 1.000000e+00 3.138251e-11
## 63 1.548027e-09 1.000000e+00 1.893558e-11
## 78 3.149818e-12 9.999999e-01 5.536016e-08
## 79 4.296081e-10 1.000000e+00 4.720082e-11
## 81 2.671509e-09 1.000000e+00 1.761258e-11
## 90 1.892870e-09 1.000000e+00 2.189381e-11
## 98 2.333083e-09 1.000000e+00 1.826905e-11
## 105 4.725142e-08 7.108446e-14 1.000000e+00
## 110 4.278356e-08 8.474517e-14 1.000000e+00
## 112 6.502609e-09 2.064138e-12 1.000000e+00
## 114 2.903561e-08 1.772877e-13 1.000000e+00
## 129 3.804260e-08 1.028013e-13 1.000000e+00
## 132 1.085491e-09 2.696868e-11 1.000000e+00
## 135 6.584627e-09 1.649298e-12 1.000000e+00
## 140 1.351686e-09 3.931129e-11 1.000000e+00
## 141 4.132222e-08 9.921267e-14 1.000000e+00
## 142 2.712914e-10 2.035726e-09 9.999999e-01
## 148 1.371238e-09 5.056537e-11 1.000000e+00
```

Model Evaluation

prediction dataframe

create a table to display the actual and the predicted

```
evaluate_model <- function(pred, test_data) {
  labels <- c("setosa", "versicolor", "virginica")
  prediction_label <- data.frame(max.col(pred)) %>%
    mutate(pred = labels[max.col(pred)]) %>%
    select(2) %>%
    unlist()
  confusion_matrix <- table(test_data$Species, prediction_label)
  check <- as.numeric(test_data$Species) == max.col(pred)
  check
  accuracy <- (sum(check) / nrow(test_data)) * 100
  list(confusion_matrix = confusion_matrix, accuracy = accuracy)
}
```

Evaluate the model with two hidden layers

```
evaluation1 <- evaluate_model(pred, test_data)
print("Evaluation of Model 1:")
```

```
## [1] "Evaluation of Model 1:"
```

```
print(evaluation1$confusion_matrix)
```

```
##           prediction_label
##           setosa versicolor virginica
##  setosa           10           0           0
##  versicolor        0           9           0
##  virginica         0           0          11
```

```
print(paste("Accuracy:", evaluation1$accuracy))
```

```
## [1] "Accuracy: 100"
```

Evaluate the model with three hidden layers

```
evaluation2 <- evaluate_model(pred2, test_data)
print("Evaluation of Model 2:")
```

```
## [1] "Evaluation of Model 2:"
```

```
print(evaluation2$confusion_matrix)
```

```
##           prediction_label
##           setosa versicolor virginica
##  setosa           10           0           0
##  versicolor        0           8           1
##  virginica         0           1          10
```

```
print(paste("Accuracy:", evaluation2$accuracy))
```

```
## [1] "Accuracy: 93.3333333333333"
```

Evaluate the model with 5 hidden layers

```
evaluation3 <- evaluate_model(pred3, test_data)
print("Evaluation of Model 3:")
```

```
## [1] "Evaluation of Model 3:"
```

```
print(evaluation3$confusion_matrix)
```

```
##           prediction_label
##           setosa versicolor virginica
##  setosa           10           0           0
##  versicolor        0           9           0
##  virginica         0           0          11
```

```
print(paste("Accuracy:", evaluation3$accuracy))
```

```
## [1] "Accuracy: 100"
```

Tabular report

Number of Hidden Layers	Accuracy(%)
2	100
3	93.333333
5	100

analysis is Based on the accuracy scores from your models, the model with three hidden layers achieved an accuracy of 93.33%, indicating that it correctly classified most instances but made a few errors. The confusion matrix shows that this model misclassified one instance of “virginica” as “versicolor.” On the other hand, the model with five hidden layers achieved a perfect accuracy of 100%, correctly classifying all instances without any errors. This suggests that the model with five hidden layers was able to capture the patterns in the data more effectively than the one with three hidden layers. This result indicates that for the Iris dataset, increasing the complexity of the model to five hidden layers can enhance performance, eliminating misclassifications present in the simpler model.