

IDS 572

HW 4

Predicting Automobile Pricing using Neural Network

Ajay Pawar (676955899) Darshan Radadiya (656230601) Priyanshi Patel (650927804)

- (1) After your EDA, what factors do you think influence a customer's decision to buy a car? What are the objectives of the model that Farid plans to build?

While purchasing a car, customers tend to look at how **old** the car is, reading on the odometer (KMs driven), then comes the features the customer is looking for: these can vary from cruise control, navigation systems, radio, ABS, and Airbags. Farid plans to build a predicting model with an accurate MSRP recommendation for new cars. For this, he decided to proceed with **Linear Regression and Feed-forward Neural Networks**, as neural networks have higher accuracy than the linear regression model.

- (2) Construct a neural network model. Validate and interpret the model using a different number of hidden neurons.

```
9- #Required Libraries
10- {r}
11- library(readxl)
12- library(caret)
13- library(neuralnet)
14- library(nnet)
15- library(NeuralNetTools)
16-
17-
18- #Read data
19- {r}
20- hw4Data <- read_excel("HW4_Data.xlsx", sheet = "draft")
21-
22-
23- #Normalize Values
24- {r}
25- hw4Data$Price = (hw4Data$Price - min(hw4Data$Price))/(max(hw4Data$Price) - min(hw4Data$Price))
26- hw4Data$KM = (hw4Data$KM - min(hw4Data$KM))/(max(hw4Data$KM) - min(hw4Data$KM))
27-
28-
29- #Make Train and Test Data
```

First, we imported necessary libraries such as readxl for importing the dataset, caret for creating confusion matrix, neuralnet/nnet/NeuralNetTools for creating Neural Network model(NN).

After examining the dataset, we found Colour & Fuel fields as Categorical, so we encoded them as factors.

For creating a price value ranging between 0 to 1, we performed normalization using min max scaling as seen on line 25/26. We decided to use Age, KP and HP as primary variables to construct neural and linear model.

```

29 #Make Train and Test Data
30 ```{r}
31 set.seed(1234)
32 ind <- sample(2, nrow(hw4Data), replace = T, prob = c(0.6, 0.4))
33 print(ind)
34 train <- hw4Data[ind == 1, ]
35 test <- hw4Data[ind == 2, ]
36 ```
37
38 #Neural Network Model with hidden Layer as 10
39 ```{r}
40 pnnModel <- nnet(train$Price ~ Age + HP + KM,
41                 data = train,
42                 linout = FALSE,
43                 size = 10,
44                 decay = 0.01,
45                 maxit = 1000)
46 summary(pnnModel)
47 pnnModel$wts
48 pnnModel$fitted.values
49 plotnet(pnnModel)
50 ```

```

We used 10 hidden neurons for constructing the Neural Network using nnet and 1000 iterations.

```

70
71 #Method for Calculating Precision, Recall, FalsePositive, FalseNegative, and Error
72 ```{r}
73 errMat = function(CM){
74   TN = CM[1,1]
75   TP = CM[2,2]
76   FN = CM[1,2]
77   FP = CM[2,1]
78   recall = (TP)/(TP+FN)
79   precision = (TP)/(TP+FP)
80   falsePositiveRate = (FP)/(FP+TN)
81   falseNegativeRate = (FN)/(FN+TP)
82   error = (FP+FN)/(TP+TN+FP+FN)
83   modelPerf <- list("precision" = precision,
84                    "recall" = recall,
85                    "falsepositiverate" = falsePositiveRate,
86                    "falsenegativerate" = falseNegativeRate,
87                    "error" = error)
88   return(modelPerf)
89 }
90 ```
91

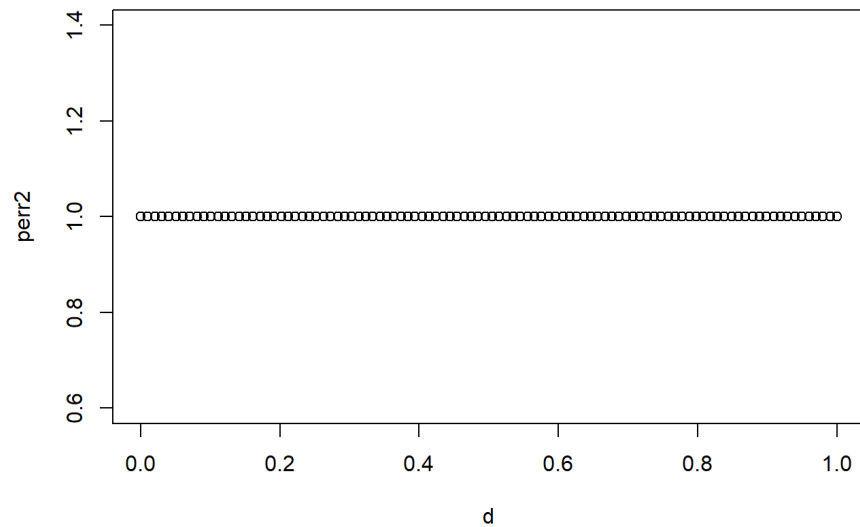
```

We created a function for calculating the confusion matrix using formulas for precision, false positive, false negative and error. Moreover, calculated decay parameter on the training dataset

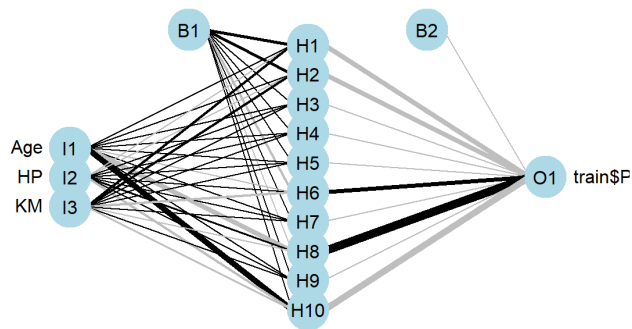
```

99 #Decay Parameter on Training data
100 ```{r}
101 set.seed(156)
102 indx <- sample(2, nrow(train), replace = T, prob = c(0.5, 0.5))
103 train2 <- train[indx == 1, ]
104 validation <- train[indx == 2, ]
105 perr2 <- vector("numeric", 100)
106 d <- seq(0.0001, 1, length.out=100)
107 k = 1
108 for(i in d) {
109   mymodel2 <- nnet(train2$Price ~ Age + HP + KM, data = train2, decay = i, size = 10, maxit = 1000)
110   pred.class2 <- predict(mymodel2, newdata = validation)
111   perr2[k] <- mean(pred.class2 != validation$Price)
112   k <- k + 1
113 }
114 plot(d, perr2)
115 ```

```



Plot for 10 Hidden neurons was:



Neural model using 15 hidden neurons:

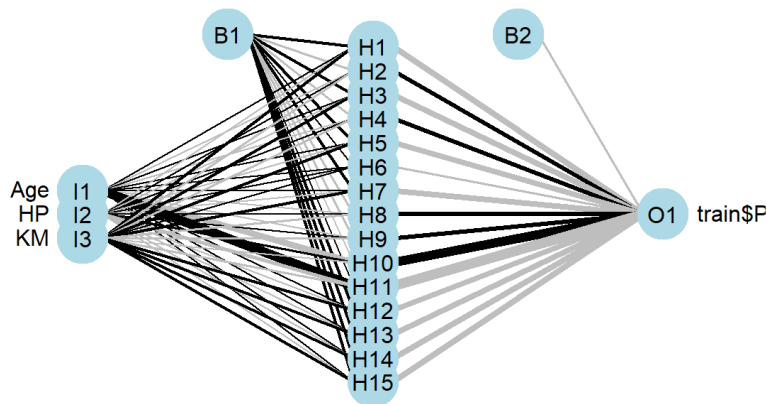
```

117- #Neural Network with hidden layers 15
118- {r}
119- pnnModel15 <- nnet(train$Price ~ Age + HP + KM,
120-                   data = train,
121-                   linout = FALSE,
122-                   size = 15,
123-                   decay = 0.01,
124-                   maxit = 1000)
125- summary(pnnModel15)
126- pnnModel15$wts
127- pnnModel15$fitted.values
128- plotnet(pnnModel15)
129- {r}
130-
131- #Prediction for NN Model with hidden neurons 15
132- {r}
133- pnnPred15 = predict(pnnModel15, test)
134- pnnPred15
135- pnnPred15 <- ifelse(pnnPred15 > 0.36, 1, 0)
136- tblCM15 <- cbind(test$Price, pnnPred15)
137- tblCM15
138- tblCM15 <- as.data.frame(tblCM15)

```

We initially used 10 hidden neurons to find 85% accuracy with error rate of 16.75%, later to find 100% accuracy with error rate of 8.3% using 15 hidden neurons.

Plot for 15 Hidden Neurons was:



(3) Compare your neural network models with linear regression models. Which one is better?

```

Source Visual
155 lmmod <- lm(Price ~ Age + KM + HP, data = train)
156 summary(lmmod)
157 #The coefficient Age, KM, and HP can explain 79% of the Variation in Price
158 coefficients(lmmod)
159 confint(lmmod, level = 0.95)
160 residuals(lmmod)
161 ...
162
163 # Checking Performance on Test Data
164 ...{r}
165 predL <- predict(lmmod, newdata = test)
166 predL
167 test$Price
168 predL <- ifelse(predL > 0.33, 1, 0)
169 tblCMLR <- cbind(test$Price, predL)
170 tblCMLR
171 tblCMLR <- as.data.frame(tblCMLR)
172 colnames(tblCMLR) <- c('Actual', 'Pred')
173 tblCMLR
174
175 pconfusionMatrixLR <- table(tblCMLR)
176 pconfusionMatrixLR
177
1:1 HW4 Final R Markdown

```

We constructed a Linear Regression model using the same variables Age, KM and HP which explained 79% of variation in Price. Also, a precision of 100% with error rate of 17%.

(4) Make a decision and offer your recommendations.

Conclusion and Recommendation:

Model	Hidden Neurons	Precision	Recall	Error Rate (%)
Neural Network	10	0.85	0.75	16.7
	15	1	0.87	8.3

Model	Precision	Recall	Error (%)
Linear Regression	1	0.77	17

- For long term marketing and deciding one computer system for determining the prices, we recommend using **Neural Network model over Linear Regression model** for this dataset.
- We also suggest starting to construct the neural network with more than 10 hidden neurons as we observed better accuracy with it.
- Although we found 100% precision on Linear Regression model (which we also observed in Neural network with 15 neurons) the error rate was 17% compared to 8% with Neural Network.