Intuit Quickbooks Upgrade Campaign Analysis

Project Workflow

** Define business object*

** Data Quality Report (missing data, outliers, data errors)*

** Data Exploratory Analysis*

** Model Generation*

** Model Evaluation*

** Result Visulization*

1. Define business object

Increase Profit

Intuit Quickbooks has mailed 801821 customers an offer to upgrade to the latest version of the Quickbooks software in the wave-1 mailing, and 38487 users responded. Now, the company wants to mail this offer again to customers who did not repsond to the wave-1 mailing.

Each mail piece costs 1.41$ and the margin from each responder, excluding the mailing cost ,is 60$. “intuit75k.rds” file contains data on 75,000 (small) businesses that were selected randomly from the 801,821 that were sent the wave-1 mailing. In order to **acheive greater profit** through the wave-2 mailing, this project will use the available data to predict which businesses that did not respond to the wave-1 mailing, are most likely to respond to the wave-2 mailing.

Load Libraries

```
library(tidyverse)
library(radiant.data)
library(radiant)
library(readr)
library(glmnet)
library(caret)
library(pROC)
```

Loading the data

```
intuit75k <- readr::read_rds(file.path(radiant.data::find_dropbox(), "MGTA455-2019/data/intuit75k.rds"))
```

2. Data Quality Report

Data Description

Variable	Type	Description
id	integer	Small business customer ID
zip	character	5-Digit ZIP Code (00000 = unknown, 99999 = international ZIPs).
zip_bins	integer	Zip-code bins (20 approximately equal sized bins from lowest to highest zip code number)
sex	factor	"Female", "Male", or "Unknown."
bizflag	integer	Business Flag. Address contains a Business name (1=yes, 0=no or unknown).
numords	integer	Number of orders from Intuit Direct in the previous 36 months
dollars	numeric	Total $ ordered from Intuit Direct in the previous 36 months
last	integer	Time (in months) since last order from Intuit Direct in the previous 36 months
sincepurch	integer	Time (in months) since original (not upgrade) Quickbooks purchase
version1	integer	Is 1 if the customer's current Quickbooks is version 1, 0 if version 2
owntaxprod	integer	Is 1 if the customer purchased tax software, 0 otherwise
upgraded	integer	Is 1 if customer upgraded from Quickbooks version 1 to version 2
res1	factor	Response to wave-1 mailing ("Yes" if responded else "No")
training	integer	70/30 split, 1 for training sample, 0 for validation sample

Data Type Transformation

```
intuit75k$zip_bins <- as.factor(intuit75k$zip_bins)
intuit75k$bizflag <- as.factor(intuit75k$bizflag)
intuit75k$version1 <- as.factor(intuit75k$version1)
intuit75k$owntaxprod <- as.factor(intuit75k$owntaxprod)
intuit75k$upgraded<- as.factor(intuit75k$upgraded)

categorical_variable <- intuit75k %>% select_if(is.factor)
numerical_variable <- intuit75k %>% select_if(is.numeric)
```

Data Summary - Numeric Variable

```
records_have_value = sapply(numerical_variable, function(x) sum(!is.na(x)))
populated = records_have_value/75000
unique_values = sapply(numerical_variable,n_distinct)
numer_of_zero_values = sapply(numerical_variable,function(x) sum(x==0))
mean = sapply(numerical_variable,mean)
std = sapply(numerical_variable,sd)
min = sapply(numerical_variable,min)
max = sapply(numerical_variable,max)
numeric_data_summary <- data.frame(records_have_value,populated,unique_values,numer_of_ze
ro_values,mean,std,min,max)
numeric_data_summary
```

```
           records_have_value populated unique_values numer_of_zero_values        mean
        std min   max
id                      75000         1         75000                    0 37500.50000 21
650.7794317   1 75000
numords                 75000         1             5                    0     2.07628
  1.2413549   1     5
dollars                 75000         1          1147                    0    93.08713
```

```
 81.2059002   1  1149
last                  75000         1            36                    0    15.83843
  9.5390573   1    36
sincepurch            75000         1            36                    0    15.65717
 10.0263119   1    36
training              75000         1             2                22500     0.70000
  0.4582606   0     1
```

Data Summary - Categorical Variable

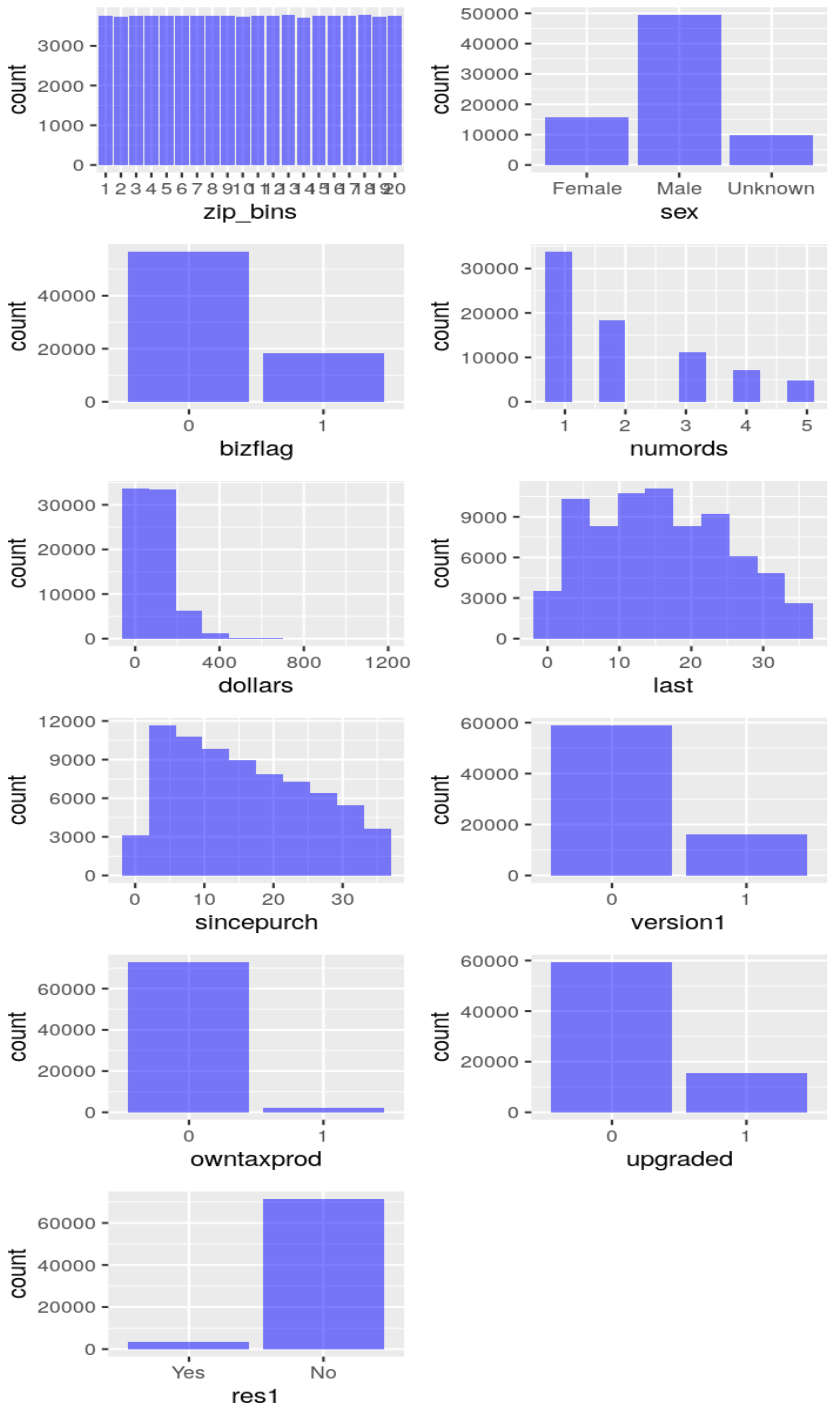
```
records_have_value = sapply(categorical_variable, function(x) sum(!is.na(x)))
populated = records_have_value/75000
unique_values = sapply(categorical_variable,n_distinct)
calculate_mode <- function(x) {
  uniqx <- unique(na.omit(x))
  uniqx[which.max(tabulate(match(x, uniqx)))]
}

most_common_values = sapply(categorical_variable,calculate_mode)
categorical_data_summary <- data.frame(records_have_value,populated,unique_values,most_co
mmon_values)
categorical_data_summary
```

```
          records_have_value populated unique_values most_common_values
zip_bins               75000         1            20                 13
sex                    75000         1             3               Male
bizflag                75000         1             2                  0
version1               75000         1             2                  0
owntaxprod             75000         1             2                  0
upgraded               75000         1             2                  0
res1                   75000         1             2                 No
```

3. Conduct EDA

Distributions of Variables

```
visualize(
  intuit75k,
  xvar = c(
    "zip_bins","sex", "bizflag", "numords", "dollars", "last", "sincepurch",
    "version1", "owntaxprod", "upgraded", "res1"
  ),
  type = "dist",
  custom = FALSE
)
```



Association between metric variables and response to wave-1

```
result <- compare_means(
  intuit75k,
  var1 = "res1",
  var2 = "numords"
)
summary(result, show = FALSE)

Pairwise mean comparisons (t-test)
Data      : intuit75k
Variables : res1, numords
Samples   : independent
```

```
Confidence: 0.95
Adjustment: None

 res1  mean      n    sd    se    me
  Yes 2.593  3,601 1.429 0.024 0.047
   No 2.050 71,399 1.225 0.005 0.009

 Null hyp.  Alt. hyp.             diff  p.value
 Yes = No   Yes not equal to No   0.543 < .001  ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
result <- compare_means(
  intuit75k,
  var1 = "res1",
  var2 = "dollars"
)
summary(result, show = FALSE)
```

```
Pairwise mean comparisons (t-test)
Data      : intuit75k
Variables : res1, dollars
Samples   : independent
Confidence: 0.95
Adjustment: None

 res1    mean      n      sd    se    me
  Yes 117.631  3,601 102.827 1.714 3.360
   No  91.849 71,399  79.762 0.299 0.585

 Null hyp.  Alt. hyp.             diff   p.value
 Yes = No   Yes not equal to No   25.781 < .001  ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
result <- compare_means(
  intuit75k,
  var1 = "res1",
  var2 = "last"
)
summary(result, show = FALSE)
```

```
Pairwise mean comparisons (t-test)
Data      : intuit75k
Variables : res1, last
Samples   : independent
Confidence: 0.95
Adjustment: None

 res1   mean      n    sd    se    me
  Yes 12.033  3,601 8.937 0.149 0.292
   No 16.030 71,399 9.528 0.036 0.070

 Null hyp.  Alt. hyp.             diff   p.value
 Yes = No   Yes not equal to No   -3.998 < .001  ***
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
result <- compare_means(
  intuit75k,
  var1 = "res1",
  var2 = "sincepurch"
)
summary(result, show = FALSE)
```

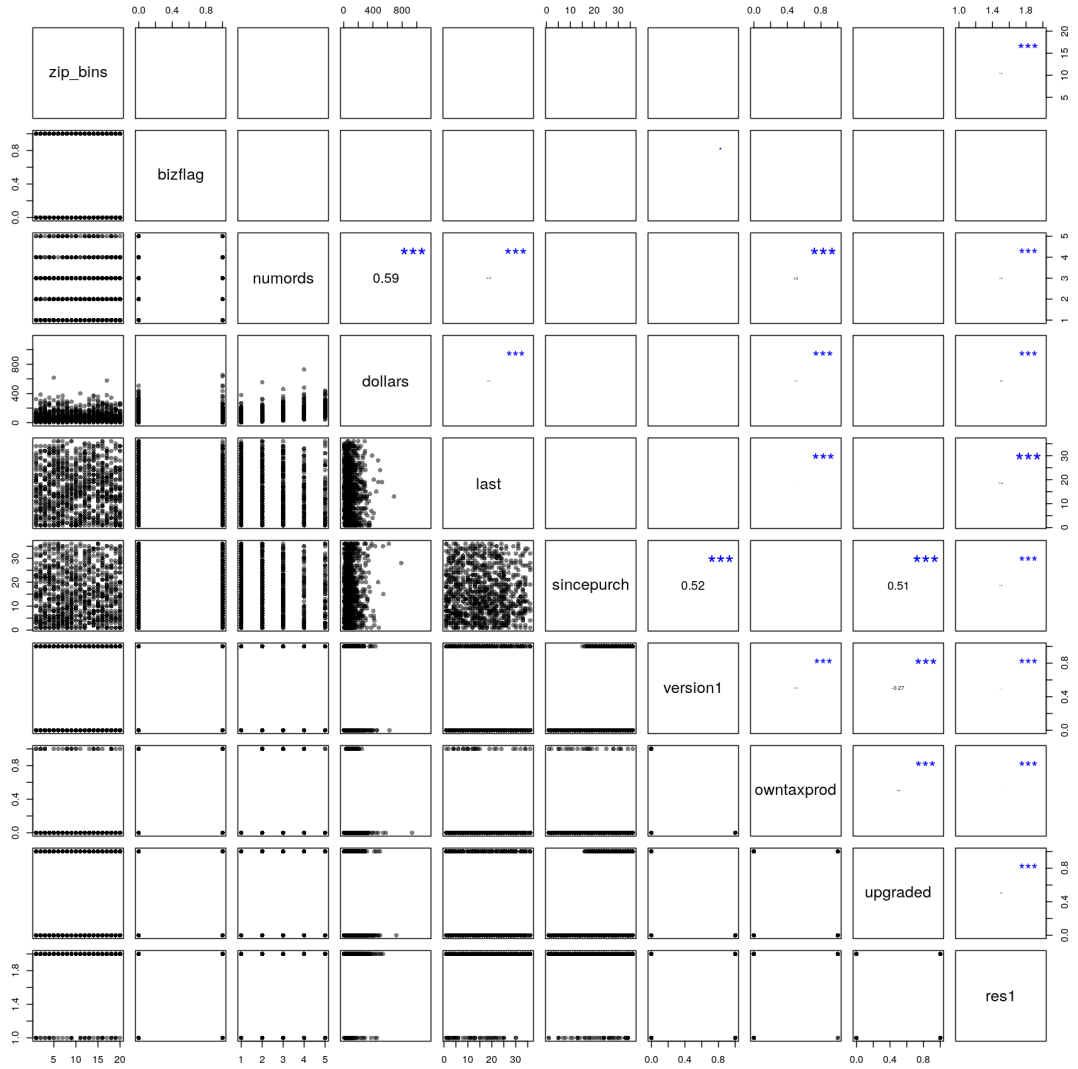
```
Pairwise mean comparisons (t-test)
Data      : intuit75k
Variables : res1, sincepurch
Samples   : independent
Confidence: 0.95
Adjustment: None

 res1   mean      n    sd    se    me
  Yes 19.180  3,601 9.936 0.166 0.325
   No 15.480 71,399 9.998 0.037 0.073

 Null hyp.  Alt. hyp.             diff p.value
 Yes = No   Yes not equal to No   3.7  < .001  ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Correlation between variables

```
result <- correlation(
  intuit75k,
  vars = c(
    "zip_bins", "bizflag", "numords", "dollars", "last", "sincepurch",
    "version1", "owntaxprod", "upgraded", "res1"
  )
)
summary(result, covar = TRUE)
```

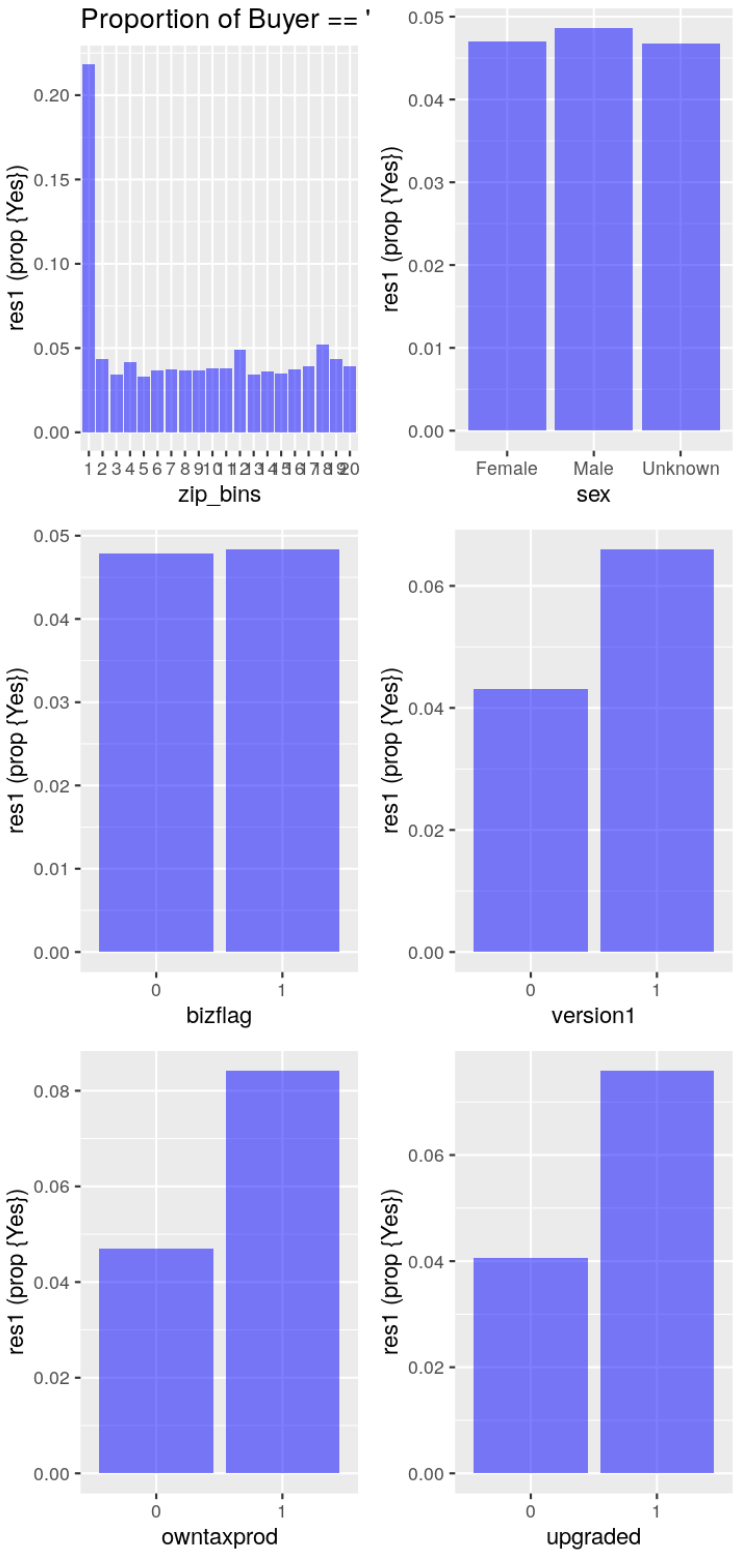
```
Correlation
Data     : intuit75k
Method   : pearson
Variables: zip_bins, bizflag, numords, dollars, last, sincepurch, version1, owntaxprod, u
pgraded, res1
Null hyp.: variables x and y are not correlated
Alt. hyp.: variables x and y are correlated

Correlation matrix:
           zip_bins bizflag numords dollars last  sincepurch version1 owntaxprod upgraded
bizflag     0.00
numords     0.01     0.00
dollars     0.01     0.00    0.59
last       -0.00    -0.00   -0.13   -0.07
sincepurch -0.00    -0.01    0.00    0.00   -0.00
version1   -0.00    -0.01    0.01    0.00    0.00  0.52
owntaxprod  0.00     0.00    0.12    0.07   -0.02 -0.00      -0.08
upgraded   -0.00    -0.00   -0.00   -0.00   -0.00  0.51      -0.27     0.09
```

```
res1        0.06    -0.00   -0.09   -0.07    0.09 -0.08      -0.04    -0.03      -0.07

p.values:
           zip_bins bizflag numords dollars last sincepurch version1 owntaxprod upgraded
bizflag    0.74
numords    0.16     0.96
dollars    0.11     0.58    0.00
last       0.47     0.91    0.00    0.00
sincepurch 0.65     0.15    0.63    0.82    0.75
version1   0.38     0.10    0.12    0.54    0.58 0.00
owntaxprod 0.57     0.21    0.00    0.00    0.00 0.75       0.00
upgraded   0.97     0.40    0.45    0.70    0.96 0.00       0.00     0.00
res1       0.00     0.83    0.00    0.00    0.00 0.00       0.00     0.00       0.00

Covariance matrix:
           zip_bins bizflag numords dollars last   sincepurch version1 owntaxprod upgrade
d
bizflag      0.00

numords      0.04     0.00

dollars      2.73     0.07   59.04

last        -0.15    -0.00   -1.54  -57.83

sincepurch  -0.10    -0.02    0.02    0.66   -0.11

version1    -0.01    -0.00    0.00    0.07    0.01   2.16

owntaxprod   0.00     0.00    0.02    1.02   -0.03  -0.00      -0.01

upgraded    -0.00    -0.00   -0.00   -0.05   -0.00   2.08      -0.04     0.01

res1         0.08    -0.00   -0.02   -1.18    0.18  -0.17      -0.00    -0.00      -0.01


plot(result, nrobs = 1000)
```



Association between categorical variables and response to wave-1

```
visualize(
  intuit75k,
  xvar = c(
   "zip_bins", "sex", "bizflag",  "version1", "owntaxprod", "upgraded"
  ),
  yvar = "res1",
  type = "bar",
  fun = "prop",
  labs = list(title = "Proportion of Buyer == 'Yes'"),
  custom = FALSE
)
```



According to the EDA part above, I noticed that the response rate in zip_bins = 1 is much higher than that of other zip_bins, therefore, I decided to further investigate what is going on in the first zip bin.

Which zip code is skewing bin 1 so high for proportion of buyers?

```
intuit75k %>%
  filter(res1 == "Yes" & zip_bins == "1") %>%
  count(zip) %>%
  arrange(desc(n)) %>%
  slice(1:10)
```

```
# A tibble: 10 x 2
   zip       n
   <chr> <int>
 1 00801   688
 2 00804    64
 3 00000     5
 4 01923     4
 5 01890     3
 6 01504     2
 7 01752     2
 8 01754     2
 9 01863     2
10 01950     2
```

What do some of the response rates look like for the common zip codes that included in dataset?

```
intuit75k %>%
  group_by(zip) %>%
  summarize(total = sum(n()),
            num_resp = sum(res1 == "Yes"),
            no_resp = total - num_resp,
          resp_rate = num_resp / total) %>%
  arrange(desc(total)) %>%
  slice(1:10)
```

```
# A tibble: 10 x 5
   zip   total num_resp no_resp resp_rate
   <chr> <int>    <int>   <int>     <dbl>
 1 00801  1668      688     980    0.412
 2 99999   648       19     629    0.0293
 3 00804   186       64     122    0.344
 4 00000   137        5     132    0.0365
 5 92714    64        7      57    0.109
 6 94087    63        3      60    0.0476
 7 10021    59        1      58    0.0169
 8 10022    59        5      54    0.0847
 9 94025    56        3      53    0.0536
10 94596    55        4      51    0.0727
```

From the analysis above, it is obvious that the response rate in zip-code 00801 and 00804 is way higher than that of other zip-codes, therefore, creating features to denote this might be helpful to model building. Hence, I create a new variable to demonstrate this called `zip_801` and `zip_804`.

```
intuit75k <- mutate(intuit75k, zip_801 = ifelse(zip == "00801" , 1, 0), zip_804 = ifelse(
zip == "00804" , 1, 0))
```

4. Model Generation

Define Train/Test Data

```
training <- intuit75k %>% filter(training == 1)
testing <- intuit75k %>% filter(training == 0)
```

Models:

Estimate a logistic regression model with all original variables

```
resultl1 <- logistic(
  training,
  rvar = "res1",
  evar = c(
    "zip_bins", "sex", "bizflag", "numords", "dollars", "last",
    "sincepurch", "version1", "owntaxprod", "upgraded"
  ),
  lev = "Yes"
)
summary(resultl1, sum_check = "odds")
```

```
Logistic regression (GLM)
Data                 : training
Response variable    : res1
Level                : Yes in res1
Explanatory variables: zip_bins, sex, bizflag, numords, dollars, last, sincepurch, versio
n1, owntaxprod, upgraded
Null hyp.: there is no effect of x on res1
Alt. hyp.: there is an effect of x on res1

                OR coefficient std.error z.value p.value
 (Intercept)            -3.761     0.211 -17.815  < .001 ***
 zip_bins|2  0.148      -1.910     0.110 -17.297  < .001 ***
 zip_bins|3  0.118      -2.141     0.121 -17.710  < .001 ***
 zip_bins|4  0.136      -1.996     0.112 -17.811  < .001 ***
 zip_bins|5  0.116      -2.152     0.120 -17.894  < .001 ***
 zip_bins|6  0.126      -2.068     0.115 -18.043  < .001 ***
 zip_bins|7  0.121      -2.110     0.117 -17.970  < .001 ***
 zip_bins|8  0.131      -2.034     0.114 -17.844  < .001 ***
 zip_bins|9  0.124      -2.086     0.117 -17.856  < .001 ***
 zip_bins|10 0.121      -2.110     0.118 -17.919  < .001 ***
 zip_bins|11 0.128      -2.053     0.116 -17.642  < .001 ***
 zip_bins|12 0.172      -1.763     0.104 -16.871  < .001 ***
 zip_bins|13 0.113      -2.177     0.121 -17.940  < .001 ***
 zip_bins|14 0.131      -2.031     0.115 -17.718  < .001 ***
 zip_bins|15 0.118      -2.135     0.119 -17.892  < .001 ***
 zip_bins|16 0.130      -2.042     0.114 -17.896  < .001 ***
 zip_bins|17 0.130      -2.038     0.114 -17.848  < .001 ***
 zip_bins|18 0.183      -1.698     0.101 -16.745  < .001 ***
 zip_bins|19 0.143      -1.947     0.111 -17.500  < .001 ***
 zip_bins|20 0.124      -2.084     0.116 -17.973  < .001 ***
 sex|Male    0.975      -0.025     0.053  -0.472   0.637
 sex|Unknown 0.964      -0.037     0.076  -0.485   0.628
 bizflag     1.036       0.036     0.049   0.728   0.466
 numords     1.259       0.230     0.019  12.047  < .001 ***
 dollars     1.001       0.001     0.000   4.009  < .001 ***
 last        0.957      -0.044     0.002 -18.064  < .001 ***
 sincepurch  1.002       0.002     0.004   0.467   0.641
 version1    2.113       0.748     0.087   8.583  < .001 ***
 owntaxprod  1.356       0.304     0.103   2.959   0.003 **
 upgraded    2.616       0.962     0.086  11.201  < .001 ***
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Pseudo R-squared: 0.114
Log-likelihood: -8899.946, AIC: 17859.893, BIC: 18125.95
Chi-squared: 2289.751 df(29), p.value < .001
Nr obs: 52,500

            odds ratio  2.5% 97.5%
zip_bins|2       0.148 0.119 0.184
zip_bins|3       0.118 0.093 0.149
zip_bins|4       0.136 0.109 0.169
zip_bins|5       0.116 0.092 0.147
zip_bins|6       0.126 0.101 0.158
zip_bins|7       0.121 0.096 0.153
zip_bins|8       0.131 0.105 0.163
zip_bins|9       0.124 0.099 0.156
zip_bins|10      0.121 0.096 0.153
zip_bins|11      0.128 0.102 0.161
zip_bins|12      0.172 0.140 0.211
zip_bins|13      0.113 0.089 0.144
zip_bins|14      0.131 0.105 0.164
zip_bins|15      0.118 0.094 0.149
zip_bins|16      0.130 0.104 0.162
zip_bins|17      0.130 0.104 0.163
zip_bins|18      0.183 0.150 0.223
zip_bins|19      0.143 0.115 0.178
zip_bins|20      0.124 0.099 0.156
sex|Male         0.975 0.879 1.082
sex|Unknown      0.964 0.831 1.118
bizflag          1.036 0.941 1.141
numords          1.259 1.212 1.307
dollars          1.001 1.001 1.002
last             0.957 0.953 0.962
sincepurch       1.002 0.994 1.010
version1         2.113 1.781 2.506
owntaxprod       1.356 1.108 1.659
upgraded         2.616 2.211 3.096
```

Estimate a logistic regression model with new feature zip_801 and zip_804

```
resultl2 <- logistic(
  training,
  rvar = "res1",
  evar = c(
          "zip_bins","sex", "bizflag", "numords", "dollars", "last",
    "sincepurch", "version1", "owntaxprod", "upgraded","zip_801","zip_804"
  ),
  lev = "Yes",
)
summary(resultl2, sum_check = "odds")

Logistic regression (GLM)
Data                 : training
Response variable    : res1
```

```
Level                : Yes in res1
Explanatory variables: zip_bins, sex, bizflag, numords, dollars, last, sincepurch, versio
n1, owntaxprod, upgraded, zip_801, zip_804
Null hyp.: there is no effect of x on res1
Alt. hyp.: there is an effect of x on res1

                OR coefficient std.error z.value p.value
 (Intercept)             -6.119     0.261 -23.403  < .001 ***
 zip_bins|2   1.300       0.262     0.180   1.457   0.145
 zip_bins|3   1.031       0.031     0.187   0.165   0.869
 zip_bins|4   1.189       0.173     0.181   0.956   0.339
 zip_bins|5   1.020       0.020     0.186   0.109   0.913
 zip_bins|6   1.107       0.102     0.183   0.557   0.578
 zip_bins|7   1.063       0.061     0.184   0.331   0.741
 zip_bins|8   1.147       0.137     0.182   0.751   0.453
 zip_bins|9   1.088       0.085     0.184   0.461   0.645
 zip_bins|10  1.063       0.062     0.185   0.334   0.739
 zip_bins|11  1.126       0.119     0.184   0.646   0.518
 zip_bins|12  1.505       0.409     0.176   2.319   0.020 *
 zip_bins|13  0.995      -0.005     0.187  -0.024   0.981
 zip_bins|14  1.150       0.140     0.183   0.765   0.444
 zip_bins|15  1.037       0.036     0.186   0.195   0.845
 zip_bins|16  1.137       0.129     0.182   0.706   0.480
 zip_bins|17  1.141       0.132     0.182   0.723   0.470
 zip_bins|18  1.606       0.474     0.175   2.714   0.007 **
 zip_bins|19  1.251       0.224     0.181   1.242   0.214
 zip_bins|20  1.090       0.086     0.183   0.471   0.638
 sex|Male     0.988      -0.012     0.054  -0.223   0.823
 sex|Unknown  0.957      -0.044     0.077  -0.572   0.568
 bizflag      1.047       0.046     0.050   0.917   0.359
 numords      1.281       0.248     0.019  12.707  < .001 ***
 dollars      1.001       0.001     0.000   4.145  < .001 ***
 last         0.956      -0.045     0.002 -18.299  < .001 ***
 sincepurch   1.002       0.002     0.004   0.519   0.604
 version1     2.184       0.781     0.089   8.759  < .001 ***
 owntaxprod   1.384       0.325     0.105   3.112   0.002 **
 upgraded     2.749       1.011     0.088  11.511  < .001 ***
 zip_801|1   25.333       3.232     0.164  19.746  < .001 ***
 zip_804|1   18.398       2.912     0.249  11.709  < .001 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Pseudo R-squared: 0.148
Log-likelihood: -8560.817, AIC: 17185.633, BIC: 17469.428
Chi-squared: 2968.011 df(31), p.value < .001
Nr obs: 52,500

            odds ratio   2.5%  97.5%
zip_bins|2       1.300  0.914  1.850
zip_bins|3       1.031  0.715  1.487
zip_bins|4       1.189  0.834  1.695
zip_bins|5       1.020  0.708  1.470
zip_bins|6       1.107  0.774  1.583
zip_bins|7       1.063  0.741  1.526
zip_bins|8       1.147  0.802  1.639
```

```
zip_bins|9       1.088  0.759  1.561
zip_bins|10      1.063  0.741  1.527
zip_bins|11      1.126  0.786  1.614
zip_bins|12      1.505  1.065  2.127
zip_bins|13      0.995  0.690  1.436
zip_bins|14      1.150  0.804  1.645
zip_bins|15      1.037  0.721  1.492
zip_bins|16      1.137  0.796  1.626
zip_bins|17      1.141  0.798  1.631
zip_bins|18      1.606  1.141  2.262
zip_bins|19      1.251  0.879  1.783
zip_bins|20      1.090  0.761  1.562
sex|Male         0.988  0.888  1.099
sex|Unknown      0.957  0.822  1.114
bizflag          1.047  0.949  1.155
numords          1.281  1.233  1.331
dollars          1.001  1.001  1.002
last             0.956  0.951  0.960
sincepurch       1.002  0.994  1.010
version1         2.184  1.834  2.601
owntaxprod       1.384  1.128  1.699
upgraded         2.749  2.314  3.266
zip_801|1       25.333 18.381 34.915
zip_804|1       18.398 11.300 29.956
```

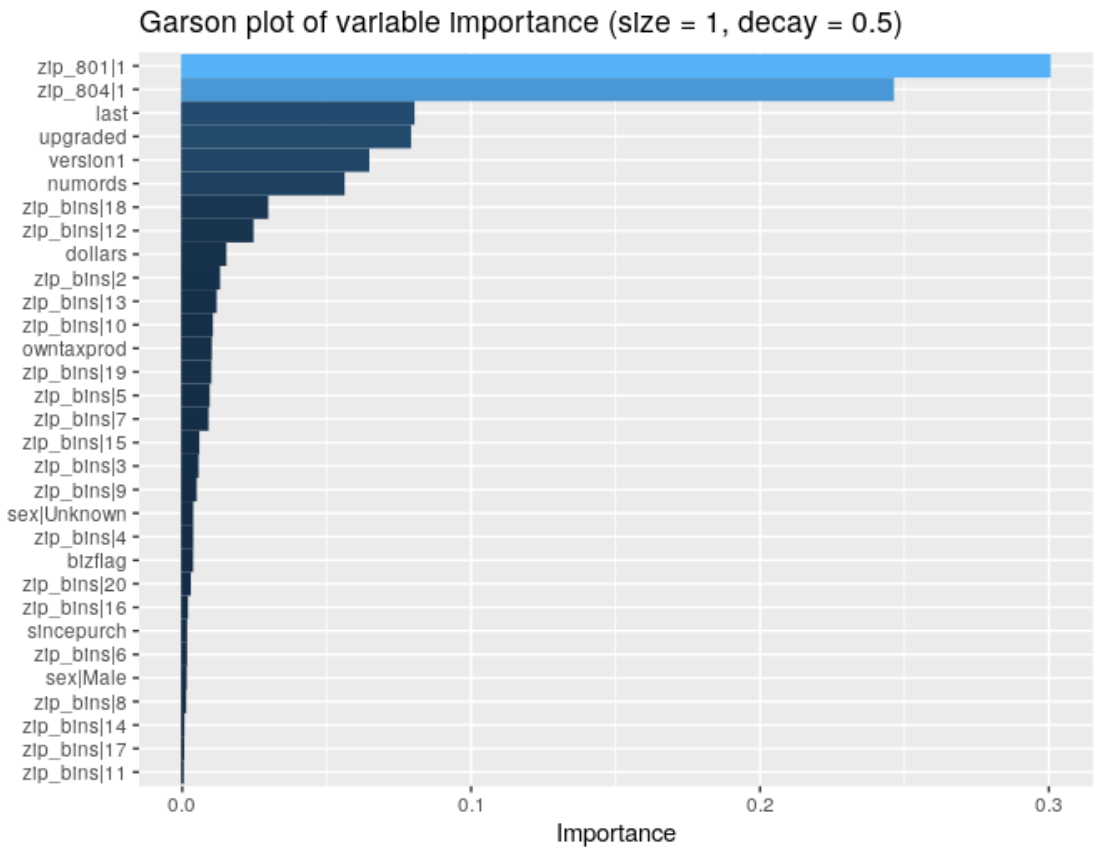
Estimate a Neural Network model with all variables with one hidden layer

```
resultn1 <- nn(
  training,
  rvar = "res1",
  evar = c(
     "zip_bins","sex", "bizflag", "numords", "dollars", "last",
    "sincepurch", "version1", "owntaxprod", "upgraded","zip_801","zip_804"
  ),
  lev = "Yes",
  seed = 1234
)
summary(resultn1, prn = TRUE)
```

```
Neural Network
Activation function  : Logistic (classification)
Data                 : training
Response variable    : res1
Level                : Yes in res1
Explanatory variables: zip_bins, sex, bizflag, numords, dollars, last, sincepurch, versio
n1, owntaxprod, upgraded, zip_801, zip_804
Network size         : 1
Parameter decay      : 0.5
Seed                 : 1234
Network              : 31-1-1 with 34 weights
Nr obs               : 52,500
Weights              :
    b->h1  i1->h1  i2->h1  i3->h1  i4->h1  i5->h1  i6->h1  i7->h1  i8->h1  i9->h1 i10->h1
 i11->h1
     0.93   -0.11    0.05   -0.03    0.08    0.01    0.08    0.01    0.04    0.09    0.00
```

```
   -0.21
  i12->h1 i13->h1 i14->h1 i15->h1 i16->h1 i17->h1 i18->h1 i19->h1 i20->h1 i21->h1 i22->h1
 i23->h1
     0.10    0.00    0.05   -0.01    0.00   -0.26   -0.08    0.02   -0.01    0.03   -0.03
   -0.49
  i24->h1 i25->h1 i26->h1 i27->h1 i28->h1 i29->h1 i30->h1 i31->h1
    -0.13    0.70   -0.01   -0.56   -0.09   -0.69   -2.61   -2.14
   b->o h1->o
   0.60 -5.84
```

```
plot(resultn1, plots = "garson", custom = FALSE)
```



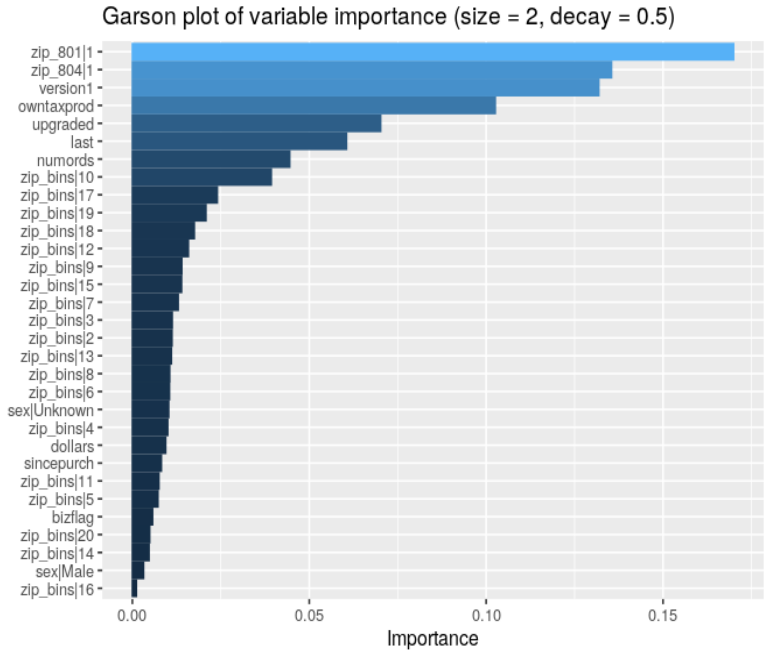
Estimate a Neural Network model with all variables with two hidden layers

```
resultn2 <- nn(
  training,
  rvar = "res1",
  evar = c(
     "zip_bins","sex", "bizflag", "numords", "dollars", "last",
    "sincepurch", "version1", "owntaxprod", "upgraded","zip_801","zip_804"
  ),
  lev = "Yes",
  size = 2,
  seed = 1234
)
summary(resultn2, prn = TRUE)
```

```
Neural Network
Activation function  : Logistic (classification)
```

```
Data                  : training
Response variable     : res1
Level                 : Yes in res1
Explanatory variables: zip_bins, sex, bizflag, numords, dollars, last, sincepurch, versio
n1, owntaxprod, upgraded, zip_801, zip_804
Network size          : 2
Parameter decay       : 0.5
Seed                  : 1234
Network               : 31-2-1 with 67 weights
Nr obs                : 52,500
Weights               :
    b->h1  i1->h1  i2->h1  i3->h1  i4->h1  i5->h1  i6->h1  i7->h1  i8->h1  i9->h1 i10->h1
 i11->h1
    -1.00   -0.34    0.34   -0.18    0.02   -0.18   -0.13   -0.15   -0.21   -0.62    0.19
   -0.30
  i12->h1 i13->h1 i14->h1 i15->h1 i16->h1 i17->h1 i18->h1 i19->h1 i20->h1 i21->h1 i22->h1
 i23->h1
     0.13    0.10    0.38   -0.01   -0.45   -0.25    0.36    0.15    0.06    0.23   -0.14
   -1.01
  i24->h1 i25->h1 i26->h1 i27->h1 i28->h1 i29->h1 i30->h1 i31->h1
    -0.12    1.33   -0.19    1.94    1.90   -1.37   -1.99   -1.33
    b->h2  i1->h2  i2->h2  i3->h2  i4->h2  i5->h2  i6->h2  i7->h2  i8->h2  i9->h2 i10->h2
 i11->h2
     1.30   -0.02    0.01    0.12    0.17    0.13    0.23    0.15    0.19    0.52   -0.04
   -0.17
  i12->h2 i13->h2 i14->h2 i15->h2 i16->h2 i17->h2 i18->h2 i19->h2 i20->h2 i21->h2 i22->h2
 i23->h2
     0.18    0.04   -0.05    0.02    0.26   -0.26   -0.25   -0.01   -0.03   -0.08    0.04
   -0.34
  i24->h2 i25->h2 i26->h2 i27->h2 i28->h2 i29->h2 i30->h2 i31->h2
    -0.15    0.50    0.06   -1.86   -1.13   -0.72   -2.81   -2.45
   b->o h1->o h2->o
   0.99 -3.12 -4.65
```

```
plot(resultn2, plots = "garson", custom = FALSE)
```



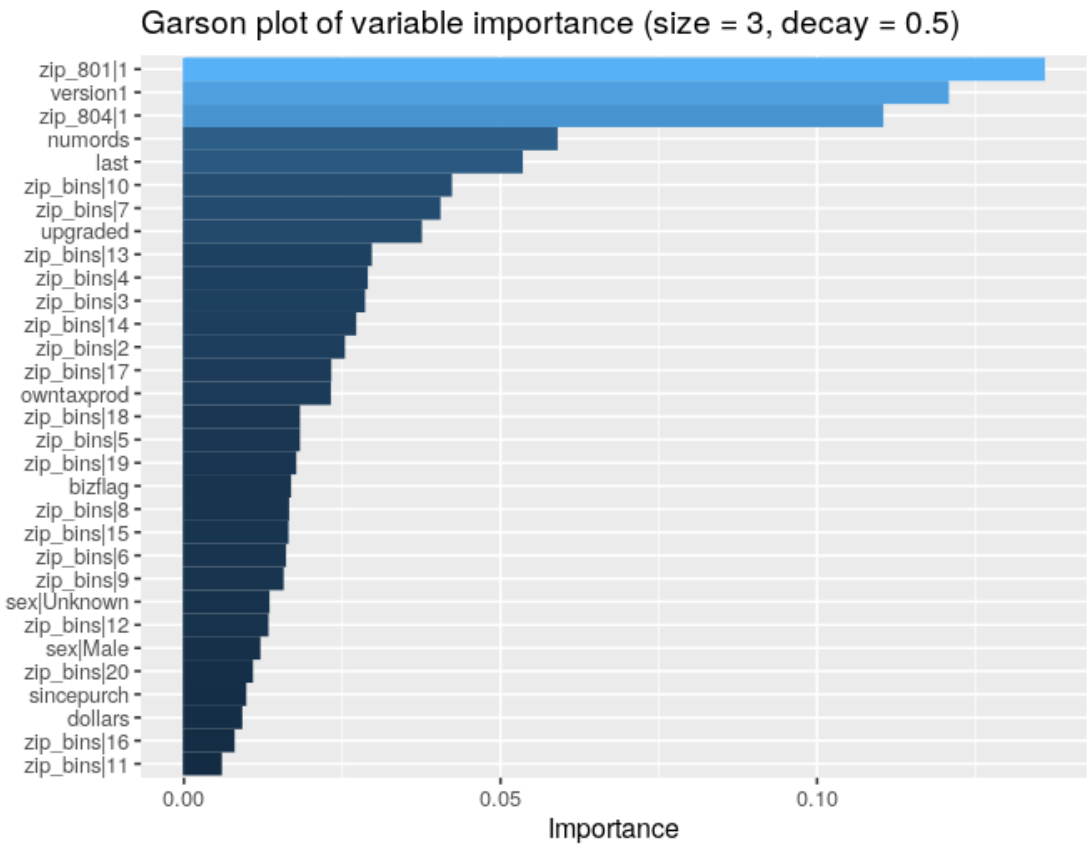
Estimate a Neural Network model with all variables with three hidden layers

```
resultn3 <- nn(
  training,
  rvar = "res1",
  evar = c(
     "zip_bins","sex", "bizflag", "numords", "dollars", "last",
    "sincepurch", "version1", "owntaxprod", "upgraded","zip_801","zip_804"
  ),
  lev = "Yes",
  size = 3,
  seed = 1234
)
summary(resultn3, prn = TRUE)
```

```
Neural Network
Activation function  : Logistic (classification)
Data                 : training
Response variable    : res1
Level                : Yes in res1
Explanatory variables: zip_bins, sex, bizflag, numords, dollars, last, sincepurch, versio
n1, owntaxprod, upgraded, zip_801, zip_804
Network size         : 3
Parameter decay      : 0.5
Seed                 : 1234
Network              : 31-3-1 with 100 weights
Nr obs               : 52,500
Weights              :
    b->h1  i1->h1  i2->h1  i3->h1  i4->h1  i5->h1  i6->h1  i7->h1  i8->h1  i9->h1 i10->h1
 i11->h1
    1.44   -0.43    0.15    0.53   -0.03   -0.33    0.85    0.25    0.30    0.90   -0.11
   -0.44
  i12->h1 i13->h1 i14->h1 i15->h1 i16->h1 i17->h1 i18->h1 i19->h1 i20->h1 i21->h1 i22->h1
 i23->h1
    0.17    0.36   -0.22   -0.12    0.38   -0.15    0.24   -0.12    0.23    0.06    0.28
   -1.00
  i24->h1 i25->h1 i26->h1 i27->h1 i28->h1 i29->h1 i30->h1 i31->h1
    -0.11    0.49    0.14   -0.93    0.35   -0.05   -2.49   -2.23
    b->h2  i1->h2  i2->h2  i3->h2  i4->h2  i5->h2  i6->h2  i7->h2  i8->h2  i9->h2 i10->h2
 i11->h2
    -1.15   -0.28    0.56   -0.24    0.49   -0.01   -0.67    0.07   -0.26   -0.40    0.10
   -0.09
  i12->h2 i13->h2 i14->h2 i15->h2 i16->h2 i17->h2 i18->h2 i19->h2 i20->h2 i21->h2 i22->h2
 i23->h2
    0.60    0.20    0.27   -0.06   -0.55   -0.27   -0.25   -0.10   -0.07    0.26   -0.19
   -0.87
  i24->h2 i25->h2 i26->h2 i27->h2 i28->h2 i29->h2 i30->h2 i31->h2
    0.05    1.61   -0.01    2.07   -0.06   -0.56   -1.55   -0.67
    b->h3  i1->h3  i2->h3  i3->h3  i4->h3  i5->h3  i6->h3  i7->h3  i8->h3  i9->h3 i10->h3
 i11->h3
    -0.31    0.31   -0.41   -0.39   -0.19    0.30   -0.15   -0.33   -0.09   -0.42    0.03
    0.02
  i12->h3 i13->h3 i14->h3 i15->h3 i16->h3 i17->h3 i18->h3 i19->h3 i20->h3 i21->h3 i22->h3
 i23->h3
    -0.40   -0.51    0.17    0.12   -0.03   -0.29   -0.21    0.20   -0.18   -0.20   -0.20
```

```
    0.52
  i24->h3 i25->h3 i26->h3 i27->h3 i28->h3 i29->h3 i30->h3 i31->h3
    -0.20   -0.08   -0.22   -1.76   -0.49   -0.83   -1.47   -1.56
   b->o h1->o h2->o h3->o
   1.70 -3.64 -3.16 -3.41
```

```
plot(resultn3, plots = "garson", custom = FALSE)
```

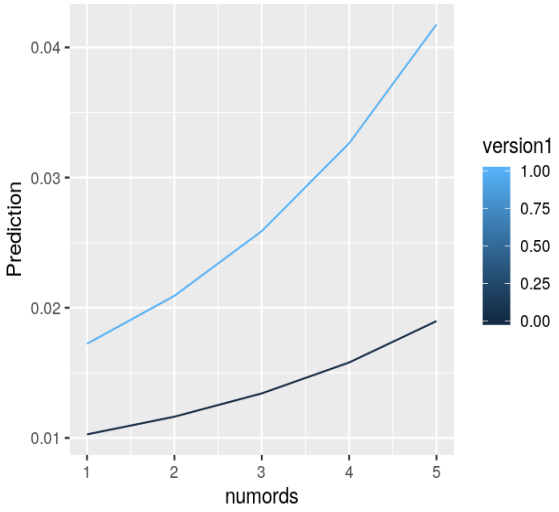


From the three garson plots above, we can noticed that the importance of variable version1 changed a lot from neural network model with one hidden layer to the model with three hidden layers, which shows that there are non-linearity or interaction effects between version1 and the response variable. Next,let us go deeper into the effect of version1 on res1.

Explore Interaction Effects

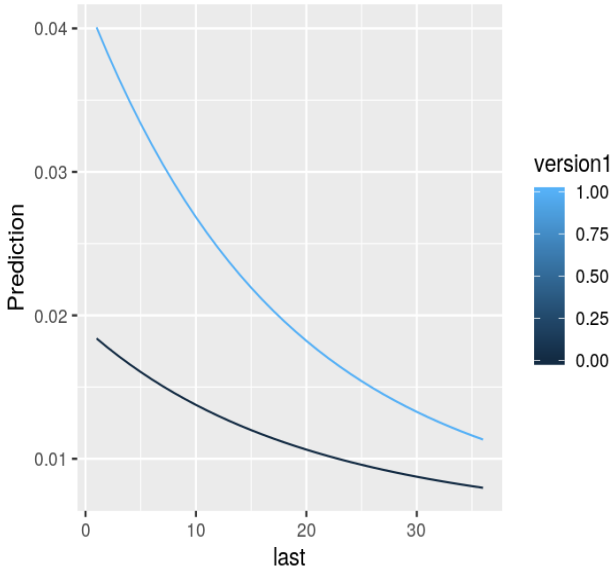
Explore the effect of version1 on response rate under different number of orders while holding all other variables constant.

```
pred <- predict(resultn1, pred_cmd = "numords = 1:5,version1 = c(0,1)")
plot(pred, xvar = "numords",color = "version1")
```



It is shown in the above chart that there the effect of version1 on res1 is influenced by the value of numords, which suggests that there is interaction between version1 and numords.

```
pred <- predict(resultn1, pred_cmd = "last = 1:36,version1 = c(0,1)")
plot(pred, xvar = "last",color = "version1")
```



It is shown in the above chart that there the effect of version1 on res1 is influenced by the value of last, which suggests that there is interaction between version1 and last.

Add Interaction Effect to Logistic Model

```
resultl3 <- logistic(
  training,
  rvar = "res1",
  evar = c(
     "zip_bins","sex", "bizflag", "numords", "dollars", "last",
    "sincepurch", "version1", "owntaxprod", "upgraded","zip_801","zip_804"
  ),
  lev = "Yes",
  int = c("version1:numords","version1:last")
```

```
)

summary(resultl3)

Logistic regression (GLM)
Data                 : training
Response variable    : res1
Level                : Yes in res1
Explanatory variables: zip_bins, sex, bizflag, numords, dollars, last, sincepurch, versio
n1, owntaxprod, upgraded, zip_801, zip_804
Null hyp.: there is no effect of x on res1
Alt. hyp.: there is an effect of x on res1

                     OR coefficient std.error z.value p.value
 (Intercept)                 -5.689     0.301 -18.904  < .001 ***
 zip_bins|2       1.296       0.259     0.181   1.436   0.151
 zip_bins|3       1.034       0.034     0.187   0.181   0.857
 zip_bins|4       1.180       0.166     0.182   0.912   0.362
 zip_bins|5       1.015       0.015     0.187   0.078   0.938
 zip_bins|6       1.099       0.094     0.183   0.514   0.607
 zip_bins|7       1.055       0.053     0.185   0.287   0.774
 zip_bins|8       1.118       0.111     0.183   0.608   0.543
 zip_bins|9       1.074       0.072     0.185   0.388   0.698
 zip_bins|10      1.060       0.058     0.185   0.314   0.753
 zip_bins|11      1.122       0.116     0.184   0.627   0.531
 zip_bins|12      1.504       0.408     0.177   2.307   0.021 *
 zip_bins|13      0.985      -0.015     0.188  -0.081   0.936
 zip_bins|14      1.129       0.122     0.183   0.664   0.507
 zip_bins|15      1.019       0.019     0.186   0.102   0.919
 zip_bins|16      1.123       0.116     0.183   0.633   0.527
 zip_bins|17      1.119       0.112     0.183   0.614   0.539
 zip_bins|18      1.604       0.472     0.175   2.695   0.007 **
 zip_bins|19      1.243       0.217     0.181   1.201   0.230
 zip_bins|20      1.087       0.083     0.184   0.451   0.652
 sex|Male         0.992      -0.008     0.055  -0.154   0.878
 sex|Unknown      0.964      -0.037     0.078  -0.471   0.638
 bizflag          1.048       0.046     0.050   0.923   0.356
 numords          0.832      -0.184     0.050  -3.682  < .001 ***
 dollars          1.001       0.001     0.000   4.208  < .001 ***
 last             1.007       0.007     0.008   0.864   0.388
 sincepurch       1.002       0.002     0.004   0.531   0.595
 version1         1.474       0.388     0.151   2.572   0.010 *
 owntaxprod       1.496       0.403     0.105   3.849  < .001 ***
 upgraded         2.719       1.000     0.088  11.371  < .001 ***
 zip_801|1       25.908       3.255     0.164  19.832  < .001 ***
 zip_804|1       18.400       2.912     0.250  11.661  < .001 ***
 numords:version1  1.397      0.334     0.035   9.442  < .001 ***
 last:version1     0.959     -0.042     0.006  -7.089  < .001 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Pseudo R-squared: 0.156
Log-likelihood: -8479.762, AIC: 17027.524, BIC: 17329.055
Chi-squared: 3130.12 df(33), p.value < .001
Nr obs: 52,500
```

Prediction Using Different Models

Set the break even rate

```
mail_cost <- 1.41
margin_sales <- 60
breakeven <- mail_cost / margin_sales
```

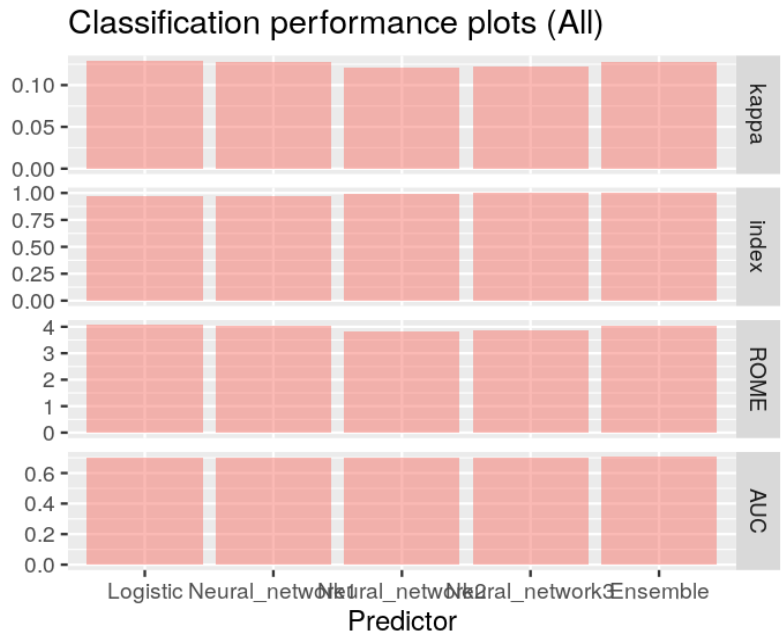
Prediction

```
## Logistic Model
predl3 <- predict(resultl3, pred_data = testing)
testing <- store(testing, predl3, name = "purch_probl3")

## Neural Network Model
predn1 <- predict(resultn1, pred_data = testing)
testing <- store(testing, predn1, name = "purch_probn1")
predn2 <- predict(resultn2, pred_data = testing)
testing <- store(testing, predn2, name = "purch_probn2")
predn3 <- predict(resultn3, pred_data = testing)
testing <- store(testing, predn3, name = "purch_probn3")

## Ensemble Logistic and Neural Network Model
testing$purch_ensemble <- (testing$purch_probl3 + testing$purch_probn1 + testing$purch_pr
obn2 + testing$purch_probn3)/4

## Create Mailto Variable)
testing <- testing %>%
  mutate(mailto_logit = purch_probl3/2 > breakeven,
         mailto_n1 = purch_probn1/2 > breakeven,
         mailto_n2 = purch_probn2/2 > breakeven,
         mailto_n3 = purch_probn3/2 > breakeven,
         mailto_ensemble = purch_ensemble/2 > breakeven)
```

5. Model Comparison

```
prediction_result <- tibble::tibble(
  Logistic = as.integer(testing$mailto_logit),
  Neural_network1 = as.integer(testing$mailto_n1),
  Neural_network2 = as.integer(testing$mailto_n2),
  Neural_network3 = as.integer(testing$mailto_n3),
  Ensemble = as.integer(testing$mailto_ensemble),
  res1 = testing$res1)

compare_result <- confusion(
  prediction_result,
  pred = c("Logistic","Neural_network1","Neural_network2","Neural_network3","Ensemble"),
  rvar = "res1",
  lev = "Yes",
  cost = 1.41,
  margin = 60
```

```
)
summary(compare_result)

Confusion matrix
Data       : prediction_result
Results for: All
Predictors : Logistic, Neural_network1, Neural_network2, Neural_network3, Ensemble
Response   : res1
Level      : Yes in res1
Cost:Margin: 1.41 : 60

 Type       Predictor  TP    FP     TN  FN  total   TPR   TNR precision Fscore
  All        Logistic 712 5,268 16,129 391 22,500 0.646 0.754     0.119  0.201
  All Neural_network1 718 5,365 16,032 385 22,500 0.651 0.749     0.118  0.200
  All Neural_network2 740 5,774 15,623 363 22,500 0.671 0.730     0.114  0.194
  All Neural_network3 741 5,733 15,664 362 22,500 0.672 0.732     0.114  0.196
  All        Ensemble 737 5,514 15,883 366 22,500 0.668 0.742     0.118  0.200

 Type       Predictor accuracy kappa profit index  ROME contact   AUC
  All        Logistic    0.748 0.129 34,288 0.968 4.067   0.266 0.700
  All Neural_network1    0.744 0.127 34,503 0.974 4.023   0.270 0.700
  All Neural_network2    0.727 0.121 35,215 0.995 3.834   0.290 0.701
  All Neural_network3    0.729 0.122 35,332 0.998 3.871   0.288 0.702
  All        Ensemble    0.739 0.128 35,406 1.000 4.017   0.278 0.705

plot(compare_result, custom = FALSE)
```

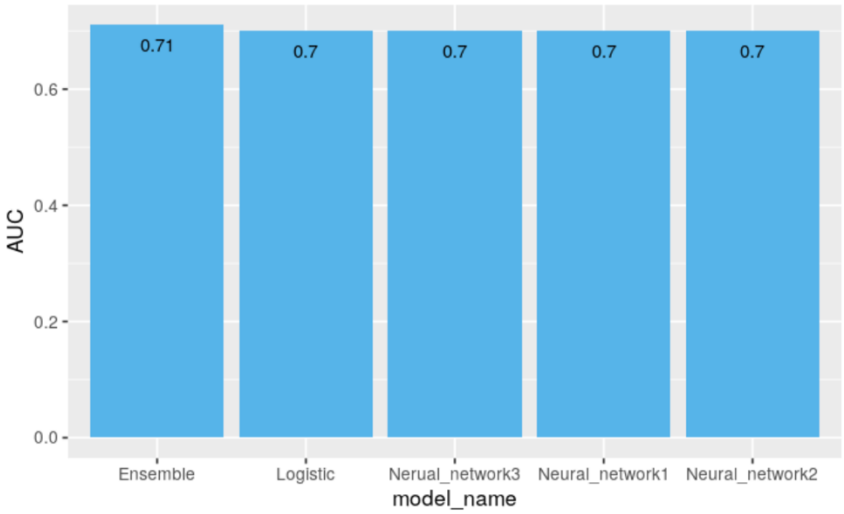


6. Result Visualization

Visualize AUC Comparison

```
visualize(
  compare_result$dataset,
  xvar = "Predictor",
  yvar = "AUC",
```

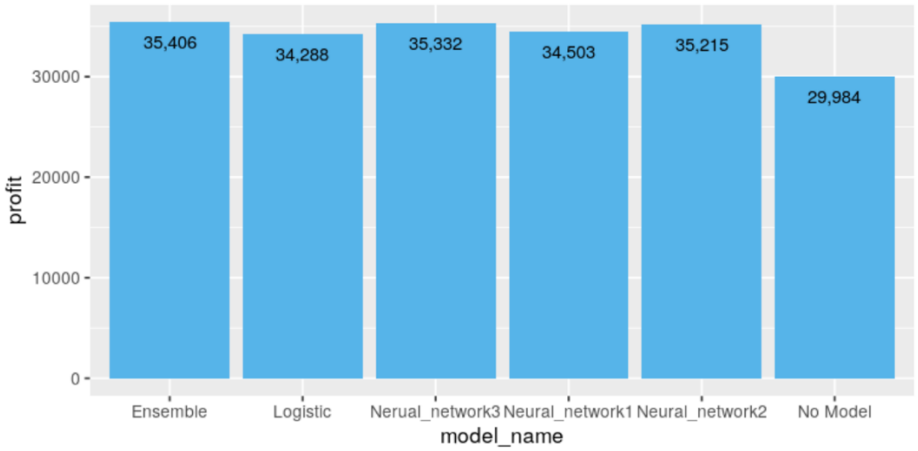
```
  type = "bar",
  labs = list(title = "AUC", x = ""),
  custom = TRUE
) +
  geom_text(aes(label = format_nr(AUC, dec = 2)), vjust = 2)
```



Visualize Profit Comparison

Benchmark Profit

```
benchmark_profit <- sum(testing$res1 == "Yes")*margin_sales - 22500 * mail_cost

visualize(
  compare_result$dataset,
  xvar = "Predictor",
  yvar = "profit",
  type = "bar",
  labs = list(title = "Profit", x = ""),
  custom = TRUE
) +
  geom_text(aes(label = format_nr(profit, dec = 0)), vjust = 2)
```



Conclusion:

1. Increased the R-square value of Logistic Regression by adding two new variables **zip_801** and **zip_804**. When starting out, I performed basic exploratory analysis to observe correlations and associations contained in the data. As seen above, I noted that the response rate of two zip codes, 00801 and 00804, in Wave 1 was high relative to the other zip codes. Therefore, I decided to target these two zip codes in Wave 2, and create two variables zip_801 and zip_804.

2. Increased the R-square value of Logistic Regression by adding two **interaction effects**. I attempted to find interactions between the variables through the performance of the Neural Network. And I found that there are interaction effects between version1 and last and numords.

3. Compared and evaluated different models based upon the profit and Area-Under-the-Curve (AUC). These results can be seen above, the **ensemble** model performed the best in terms of both profit and AUC value.

4. Increased upsell campaign profits by **18%** (35406 – 29984)/35406 by using the created ensemble model to develop email campaign strategies