IFOA eXplainable AI Workstream - SHAP

1. Intro to case study

1.1 Motivation

The aim of this document is to supply the reader of name of the article in The Actuary Magazine, with a practical, comprehensive example of applying SHAP to explain models' predictions. K. Gawlowski, D. Liew and C. Richard.

1.2 Intro to dataset

The dataset can be downloaded from: freMTPL2freq

Originally it was accessible through CASdatasets R package. Excerpt from the original documentation:

Description

In the two datasets freMTPL2freq, freMTPL2sev, risk features are collected for 677,991 motor third-part liability policies (observed mostly on one year). In addition, we have claim numbers by policy as well as the corresponding claim amounts. freMTPL2freq contains the risk features and the claim number while freMTPL2sev contains the claim amount and the corresponding policy ID.

Format

IDpol The policy ID (used to link with the claims dataset).
ClaimNb Number of claims during the exposure period.
Exposure The period of exposure for a policy, in years.
VehPower The power of the car (ordered values).
VehAge The vehicle age, in years.
DrivAge The driver age, in years (in France, people can drive a car at 18).
BonusMalus Bonus/malus, between 50 and 350: <100 means bonus, >100 means malus in France.
VehBrand The car brand (unknown categories).
VehGas The car gas, Diesel or regular.
Area The density value of the city community where the car driver lives in: from "A" for rural area to "F" for urban centre.
Density The density of inhabitants (number of inhabitants per square-kilometer) of the city where the car driver lives in.
Region The policy region in France (based on the 1970-2015 classification)

```r
if(FALSE){
  data_input = read.csv2("data/freMTPL2freq.csv",sep = ",") %>%
    as_tibble() %>%
    mutate(VehPower  = factor(VehPower, order = TRUE,levels = 4:15),
           across(c(Area,Region,VehBrand,VehGas),factor)) %>%
    rowwise() %>%
    mutate(ClaimNb = as.integer(min(ClaimNb,4)),
           VehAge = as.integer(min(VehAge,20)),
           DrivAge = as.integer(min(DrivAge,90)),
           Exposure = as.numeric(min(Exposure,1)),
           Density = log(Density)) %>%
    ungroup()
}
```

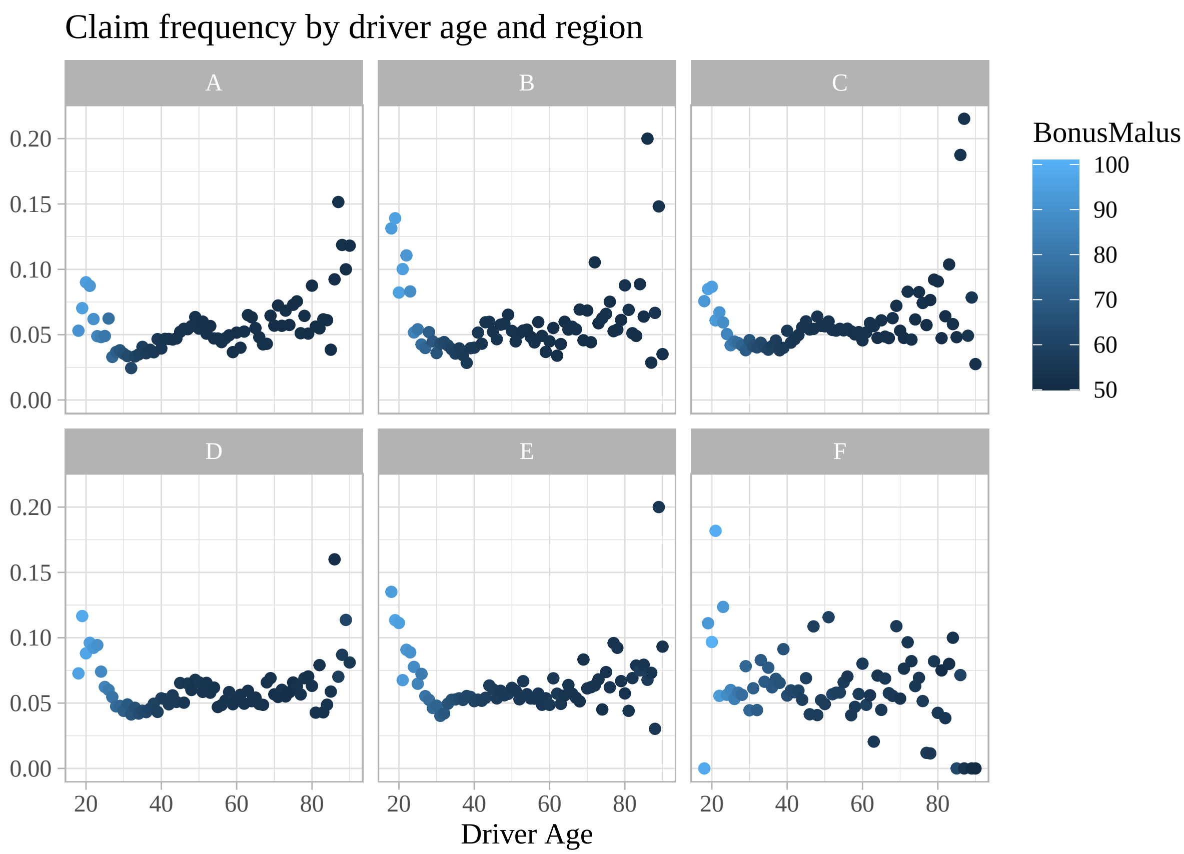
1.3 Preprocessing and Basic summary statistics

ClaimNb	Area	VehPower	VehAge	DrivAge	BonusMalus	VehBrand	VehGas	Density	Region
1	D	5	0	55	50	B12	Regular	7.104144	R82
1	D	5	0	55	50	B12	Regular	7.104144	R82
1	B	6	2	52	50	B12	Diesel	3.988984	R22
1	B	7	0	46	50	B12	Diesel	4.330733	R72
1	B	7	0	46	50	B12	Diesel	4.330733	R72
1	E	6	2	38	50	B12	Regular	8.007367	R31

1.4 EDA

```r
data_input %>%
  group_by(DrivAge,Area) %>%
  summarise(Freq = mean(ClaimNb),
            BonusMalus = mean(BonusMalus)) %>%
  ggplot(aes(x = DrivAge, y=Freq, color = BonusMalus))+
  facet_wrap(~Area)+
  geom_point()+
  ggtitle("Claim frequency by driver age and region")+
  xlab("Driver Age")+
  ylab("")+
  theme_light()+
  theme(text=element_text(family="serif"),
        legend.justification = c("right", "top"))
```

```
## `summarise()` has grouped output by 'DrivAge'. You can override using the `.groups` argument.
```



2. models - fitting, output comparison

In this section we build the three models (NN, XGB, GLM) and assess their performance. The objects holding the models are pulled from the Prep_RMD folder for convenience. The code used to generate them however is supplied below in each respective section.

We examine the models' outputs using a hold out test dataset and applying a custom model_evalulation function. It lets us view: the obtained MSE or Poisson loss; prediction statistics grouped by the actual claim number and raw predictions. model_evalulation is standardized to accept all three of the models considered in the exercise. Further details alNong with the source code can be found in section 4.1

Poisson deviance loss is not symmetrical around the actual value we compare the prediction against. It puts more emphasis on differentiating between zero and non-zero claims instances than say observations with 1 and 2 claims (see 4. Additional Information).

2.1 NN

```
# notrun
if(FALSE){

# don't enter next epoch if there are no significant performance gains
early_stop = callback_early_stopping(monitor = "val_loss", patience = 3)
```

```r
# Neural network structure
Neural_Net = keras_model_sequential(input_shape = c(ncol(train))) %>%
  layer_dense(units = 64, activation = 'relu') %>%
  layer_dense(units = 64, activation = 'relu') %>%
  layer_dense(units = 32, activation = 'relu') %>%
  layer_dense(units = 1, activation = 'relu')

# Fitting the model
Neural_Net %>%
  compile(
    loss = "poisson",
    optimizer = optimizer_rmsprop()
  ) %>%
  fit(
    callbacks = list(early_stop),
    train %>% as.matrix(),
    (data[sample_TTS,"ClaimNb"]/data_input$Exposure[sample_TTS]) %>% as.matrix(),
    batch_size = 2^13,
    epochs = 10,
    validation_split = 0.1,
    shuffle = TRUE ,
    sample_weight = data_input$Exposure[sample_TTS] %>% as.matrix()
  )


eval_list$Neural_Net = model_evaluation(Neural_Net,
                                         cbind(test,data[-sample_TTS,"ClaimNb"]),
                                         type = "NN",
                                         ClaimNBadj = FALSE)


}

summary(Neural_Net)
```

```
## Model: "sequential_13"
## ________________________________________________________________________________
## Layer (type)                        Output Shape                    Param #
## ================================================================================
## dense_56 (Dense)                    (None, 64)                      3712
## ________________________________________________________________________________
## dense_55 (Dense)                    (None, 64)                      4160
## ________________________________________________________________________________
## dense_54 (Dense)                    (None, 32)                      2080
## ________________________________________________________________________________
## dense_53 (Dense)                    (None, 1)                       33
## ================================================================================
## Total params: 9,985
## Trainable params: 9,985
## Non-trainable params: 0
## ________________________________________________________________________________
```

```
knitr::kable(eval_list$Neural_Net$Evaluation)
```

Evaluation

absolute_error	mean_squared_error	Poisson_Loss	Poisson_Deviance_Loss
0.136935	0.0613371	NaN	Inf

```
knitr::kable(eval_list$Neural_Net$AvE)
```

Actual vs Expected

Actual	count	mean_pred	sd_pred	min	max	Q1	Q2	Q3	IQR	Negative_Pred
0	96495	0.0947969	0.0782287	0.0000000	1.0163970	0.0504009	0.0737341	0.1110968	0.8231724	0
1	4924	0.1381341	0.1312485	0.0000000	0.9781889	0.0608504	0.0896462	0.1632747	1.1425395	0
2	271	0.1591628	0.1453359	0.0063936	0.7340175	0.0670954	0.1037881	0.1973480	1.2549857	0
3	9	0.2424376	0.2363870	0.0623032	0.7751731	0.0975339	0.1390310	0.2256630	0.9215861	0
4	3	0.1224184	0.0358691	0.0832797	0.1537231	0.1067661	0.1302524	0.1419877	0.2704109	0

2.2 XGB

```
# notrun
if(FALSE){

  XGB_validation = 1:10000

  dtrain = xgb.DMatrix(data = train[-XGB_validation,] %>% as.matrix(),
                       label = data[sample_TTS,]$ClaimNb[-XGB_validation])

  dvalid = xgb.DMatrix(data = train[XGB_validation,] %>% as.matrix(),
                       label = data[sample_TTS,]$ClaimNb[XGB_validation])

  watchlist <- list(train=dtrain, test=dvalid)

  m5_xgb <-
    xgboost(
      # data = data[sample_TTS,] %>% select(-ClaimNb) %>% ,
      # label = data[sample_TTS,]$ClaimNb ,

      # data = train[-XGB_validation,] %>% as.matrix() ,
      # label = data[sample_TTS,]$ClaimNb[-XGB_validation],
      data = dtrain,

      nrounds = 200,
```

```
      weight = (data[sample_TTS,"ClaimNb"]+1) %>% as.matrix(),
      objective = "reg:squarederror",
      early_stopping_rounds = 3,
      max_depth = 8,
      eta = .3,
      verbose = 2,
      watchlist = watchlist
    )

# eval_list$xgb5 = model_evalulation(model = m5_xgb,
#                                    data = data.frame(test,
#                                                      ClaimNb = data[-sample_TTS,"ClaimNb"]),
#                                    type = "XGB")

}
```

text

```
# eval_list$xgb5$Evaluation
```

Evaluation

```
# eval_list$xgb5$AvE
```

Actual vs Expected

2.3 GLM

```
if(TRUE){

  GLM = glm(formula = ClaimNb/Exposure ~ Area + VehPower + VehAge + DrivAge + BonusMalus + VehBrand + Ve
            family = poisson(link = log),
            weights = Exposure,
            data = data_input[sample_TTS,] %>% select(-IDpol))  %>% suppressWarnings()

  # eval_list$GLM = model_evalulation(GLM,
  #                                    data_input[-sample_TTS,],
  #                                    type = "GLM")
}

GLM
```

Model fitting

```
##
## Call:  glm(formula = ClaimNb/Exposure ~ Area + VehPower + VehAge + DrivAge +
##     BonusMalus + VehBrand + VehGas + Density + Region, family = poisson(link = log),
##     data = data_input[sample_TTS, ] %>% select(-IDpol), weights = Exposure)
##
## Coefficients:
##   (Intercept)          AreaB          AreaC          AreaD          AreaE
##    -4.0114467      0.0161407      0.0005032      0.0339460      0.0184801
##         AreaF     VehPower.L     VehPower.Q     VehPower.C     VehPower^4
##    -0.0737318     -0.0502667     -0.1834956     -0.0409452     -0.0923431
##    VehPower^5     VehPower^6     VehPower^7     VehPower^8     VehPower^9
##     0.0140356     -0.2462388     -0.1482789      0.0890247      0.0124442
##   VehPower^10    VehPower^11         VehAge        DrivAge     BonusMalus
##    -0.0867967      0.1070066     -0.0404711      0.0063530      0.0225429
##   VehBrandB10    VehBrandB11    VehBrandB12    VehBrandB13    VehBrandB14
##     0.0173827      0.1143393      0.1727967      0.0193933     -0.0694485
##    VehBrandB2     VehBrandB3     VehBrandB4     VehBrandB5     VehBrandB6
##    -0.0132280     -0.0146900     -0.0223253      0.0444672     -0.0211478
## VehGasRegular        Density      RegionR21      RegionR22      RegionR23
##     0.0668401      0.0378664      0.1720110      0.0322257     -0.0821447
##     RegionR24      RegionR25      RegionR26      RegionR31      RegionR41
##     0.0738775      0.0304650     -0.0142948     -0.1117022     -0.2737856
##     RegionR42      RegionR43      RegionR52      RegionR53      RegionR54
##    -0.0228858     -0.0797646     -0.0230057      0.0716439     -0.0464823
##     RegionR72      RegionR73      RegionR74      RegionR82      RegionR83
##    -0.0833502     -0.0988507      0.1921085      0.0682227     -0.2679160
##     RegionR91      RegionR93      RegionR94
##    -0.0254702      0.0077099      0.1421034
##
## Degrees of Freedom: 576310 Total (i.e. Null);  576258 Residual
## Null Deviance:      190400
## Residual Deviance: 184100    AIC: Inf
```

```
knitr::kable(eval_list$GLM$Evaluation)
```

Evaluation

absolute_error	mean_squared_error
0.1493149	0.0619182

```
knitr::kable(eval_list$GLM$AvE)
```

Actual vs Expected

Actual	count	mean_pred	sd_pred	min	max	Q1	Q2	Q3	IQR	Negative_Pred
0	96495	0.1069912	0.0578541	0.0229774	3.3806627	0.0727551	0.0944196	0.1231715	0.5339618	0
1	4924	0.1222439	0.0749855	0.0339334	1.5036456	0.0792482	0.1034518	0.1393970	0.5814184	0
2	271	0.1494231	0.1327753	0.0417043	1.1820897	0.0876160	0.1158915	0.1575540	0.6034782	0
3	9	0.2146224	0.1718711	0.0546831	0.6001221	0.1115296	0.1547464	0.2442311	0.8575420	0
4	3	0.1131345	0.0739114	0.0580050	0.1971213	0.0711411	0.0842772	0.1406992	0.8253498	0

2.4 Model comparison

```
# NULL
```

3. XAI

Note that the current implementation of SHAP is insensitive to One-Hot Encoding, meaning that explanation of an instance might contain a non-zero contribution for both VehGas=Diesel AND VehGas!=Regular at the same time. This is caused by the lack of interface in the SHAP function to indicate the range of OHE variables. This and other issues will be fixed in my implementation of Kernel-SHAP, purely in R - to be published soon.

Currently to apply SHAP in R, one has to access a Python environment (through reticulate package) that has SHAP package installed. Here, DALEX package is used as a wrapper for SHAP.

For the full code producing graphs below go to: scripts/Prep_SHAP_Graphs.R, where you will find a wrapper for the original plotting function, to allow for selecting only the most significant variables. It will prove helpful in case the models use a large number of variables and/or including OHE.

3.1 Model - level SHAP

The code below is an example of how to call DALEX and SHAP in R. Here we estimate the SHAP values on a subset of 1000 observations. SHAP for the XGB and GLM are produced analogously.

```
if(FALSE){
  explainer = list()
  residuals = list()
  SHAP = list()

  row_subset = sample(1:nrow(test),1000)

  explainer$Neural_Net = explain(
    model = Neural_Net,
    data = test[row_subset,],
    y = (data[-sample_TTS,"ClaimNb"] %>% as.matrix())[row_subset],
    predict_function = predict_wrapper,
    label = "Neural_Net"
  )

  SHAP$Neural_Net_1 = shap(explainer$Neural_Net,
                          new_observation = test[678,],
                          method = "KernelSHAP"
  )

  SHAP$Neural_Net_1_plot = CustomSHAPplot(dalex_output = SHAP$Neural_Net_1)
}
```

3.2 Individual SHAP

Neural Network Individual SHAP value plots for observations: * with 1 claim and low error for NN; * an instance with 0 claims and very high error * An instance with 2 claims

For this observation ClaimNb = 1, we can see (as in most cases) that the BonusMalus variable along with vehicle age and brand/gas type have the most impact on the final prediction.

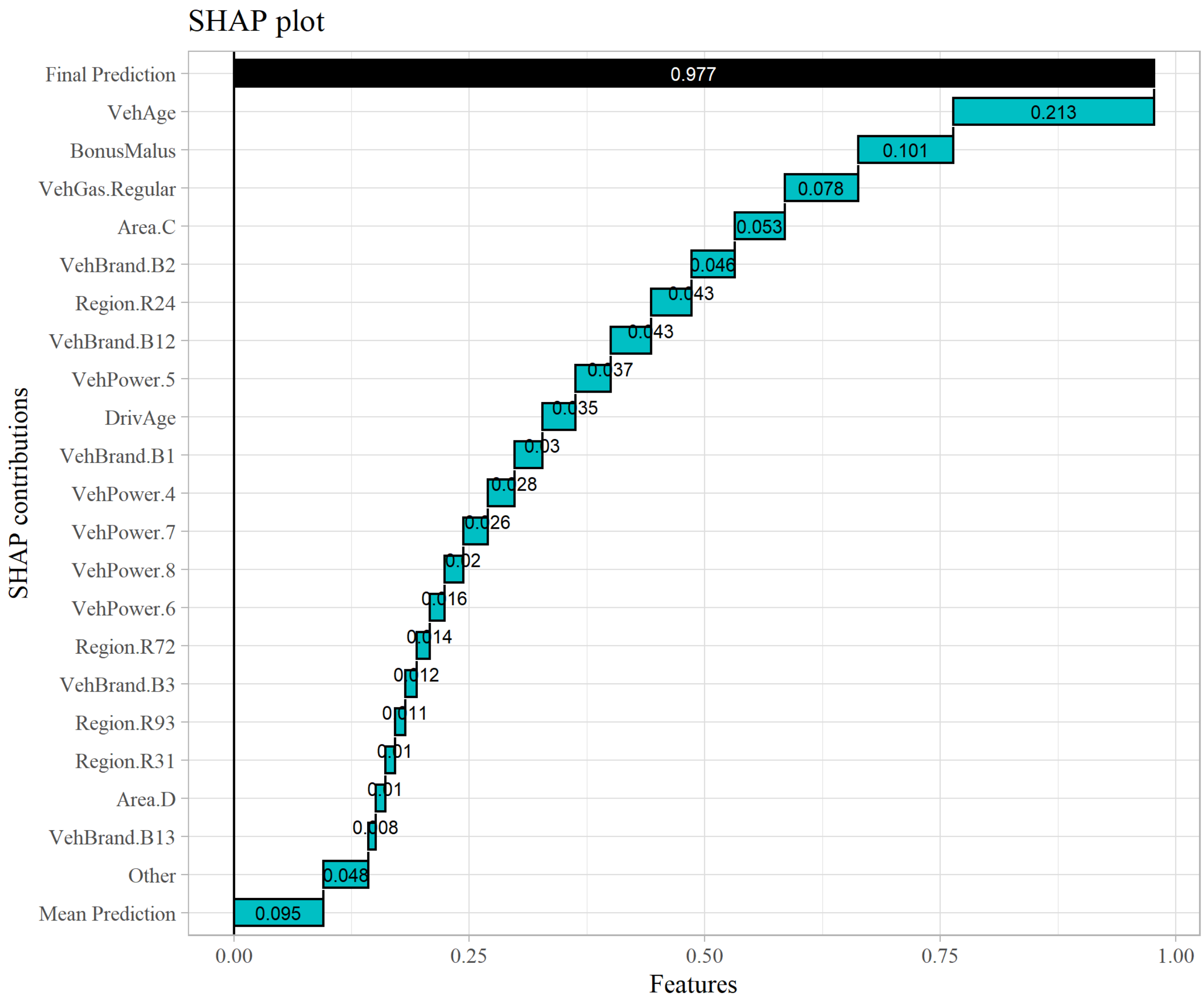


Figure 1: Individual SHAP

This instance, in reality has ClaimNb of 0 and Networks prediction for it, has the highest error from all observations with actual ClaimNb=1. Interestingly, if it wasn't for the BonusMalus value in case of this instance, the model could have output a much lower prediction. This could be confirmed using an ICE (Individual Conditional Expectation) plot for this observation.

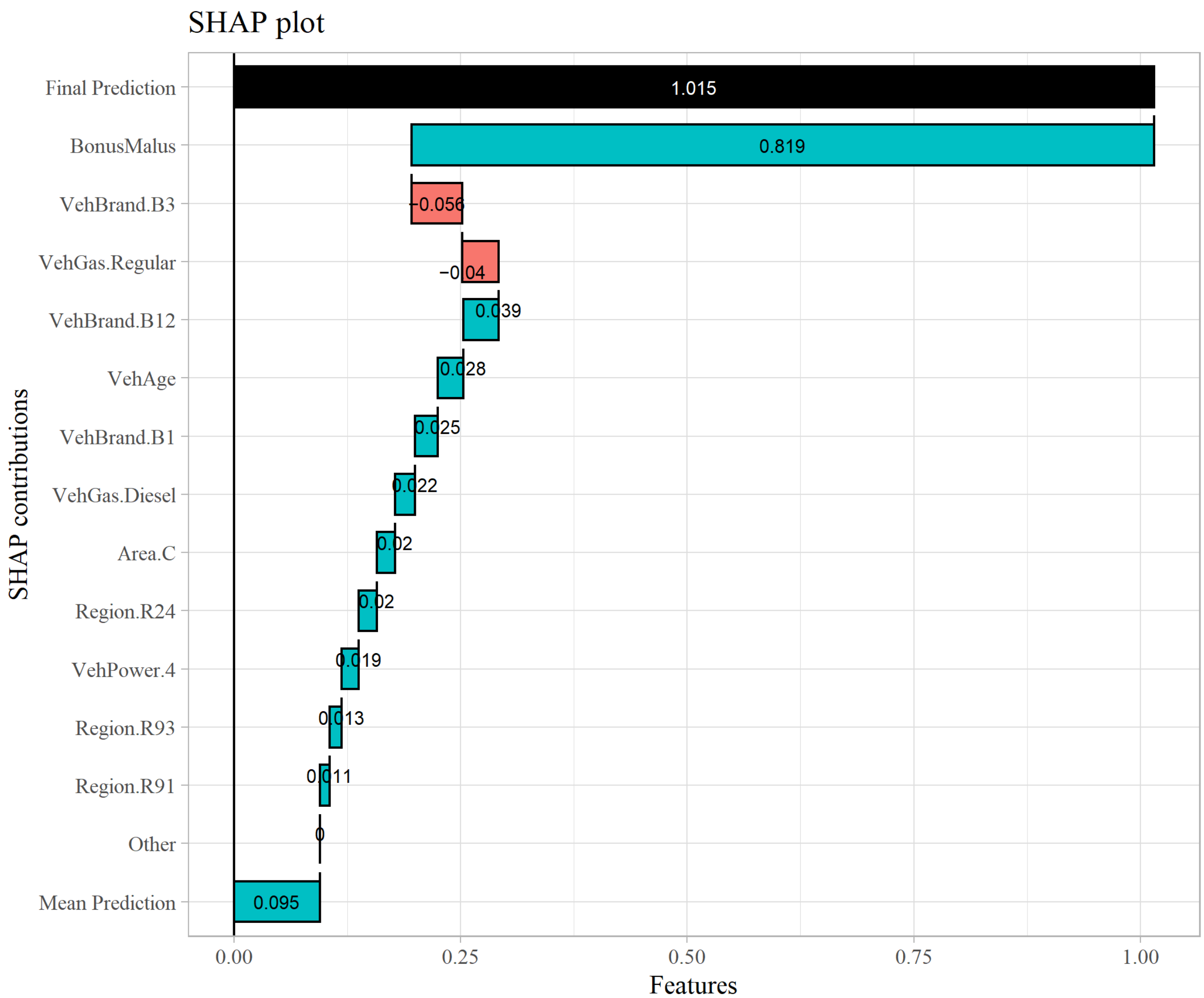


Figure 2: Individual SHAP

In case of this observation, the actual number of claims=2, and here again BonusMalus plays a siginficant role in the final prediction.

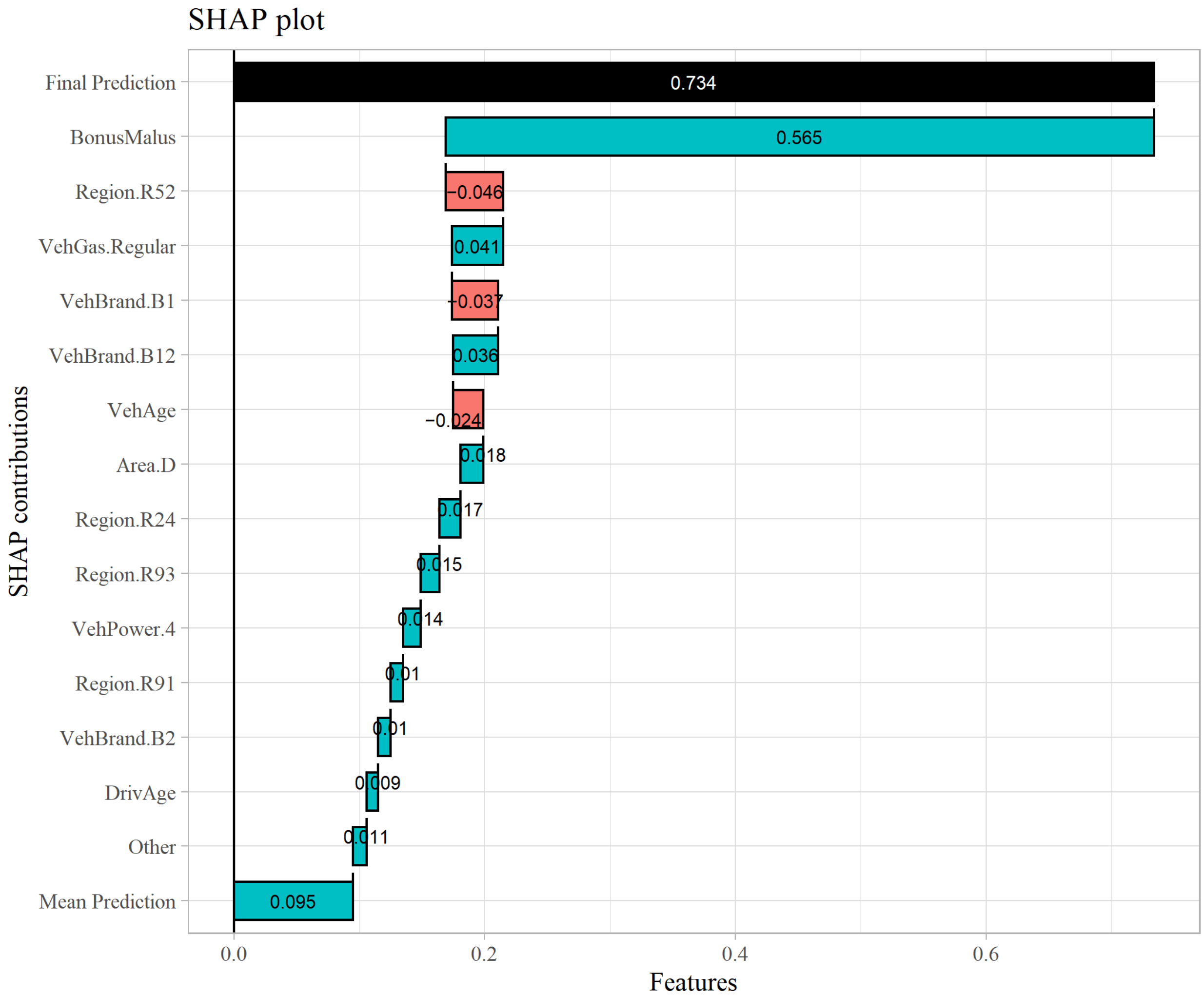


Figure 3: Individual SHAP

XGB Individual SHAP value plots for observations: * with 1 claim and low error for NN; * an instance with 0 claims and very high error * An instance with 2 claims

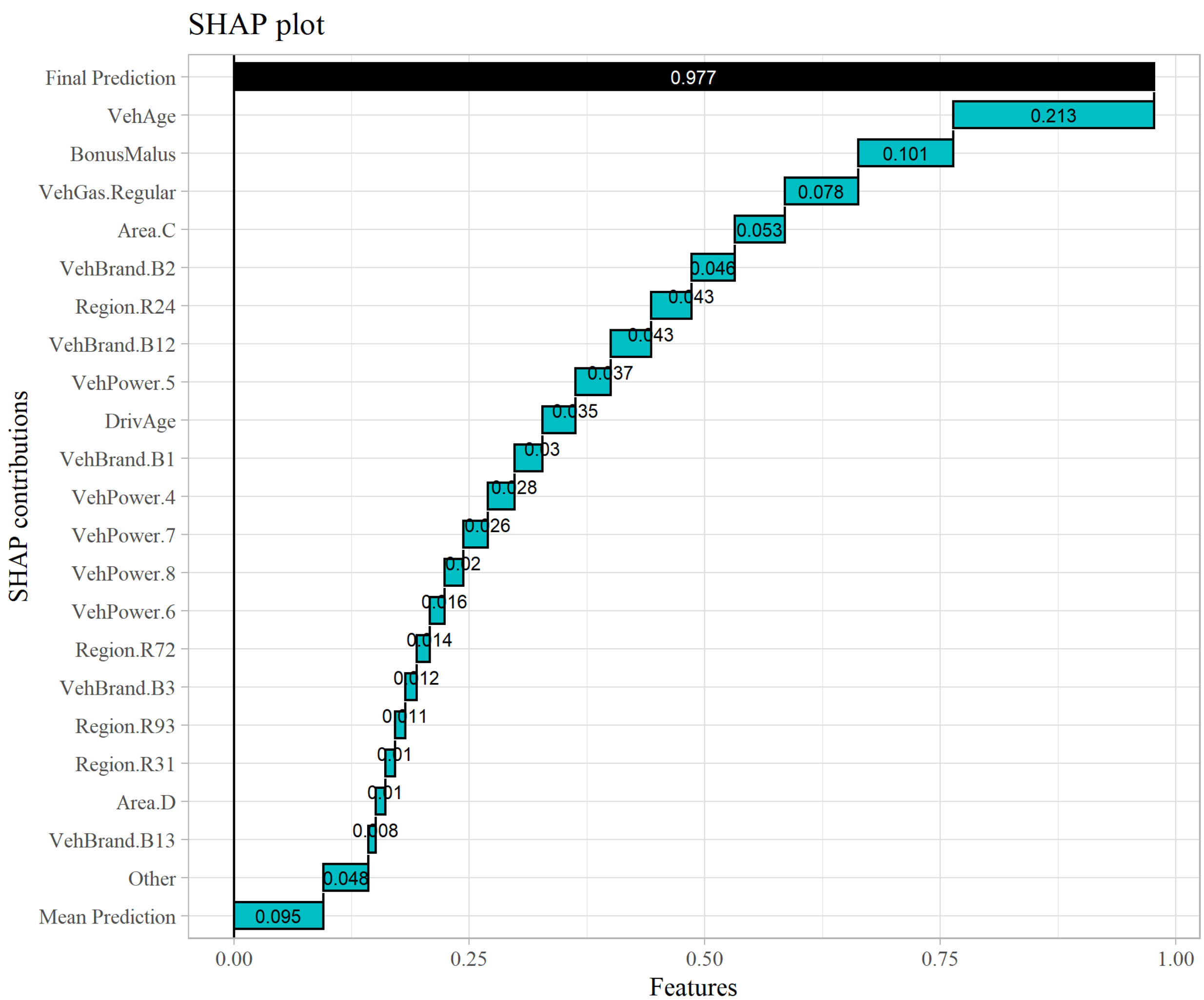


Figure 4: Individual SHAP

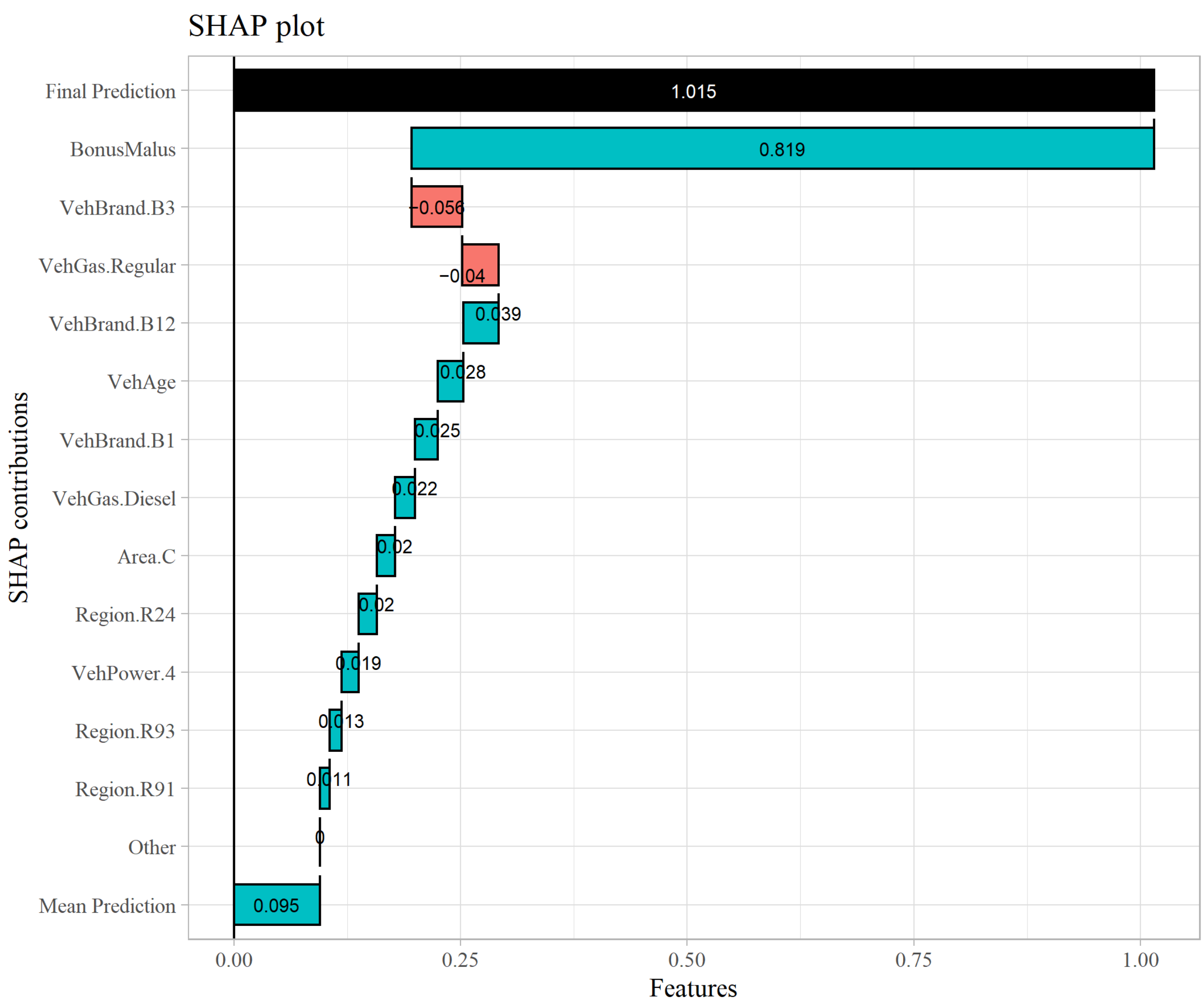


Figure 5: Individual SHAP

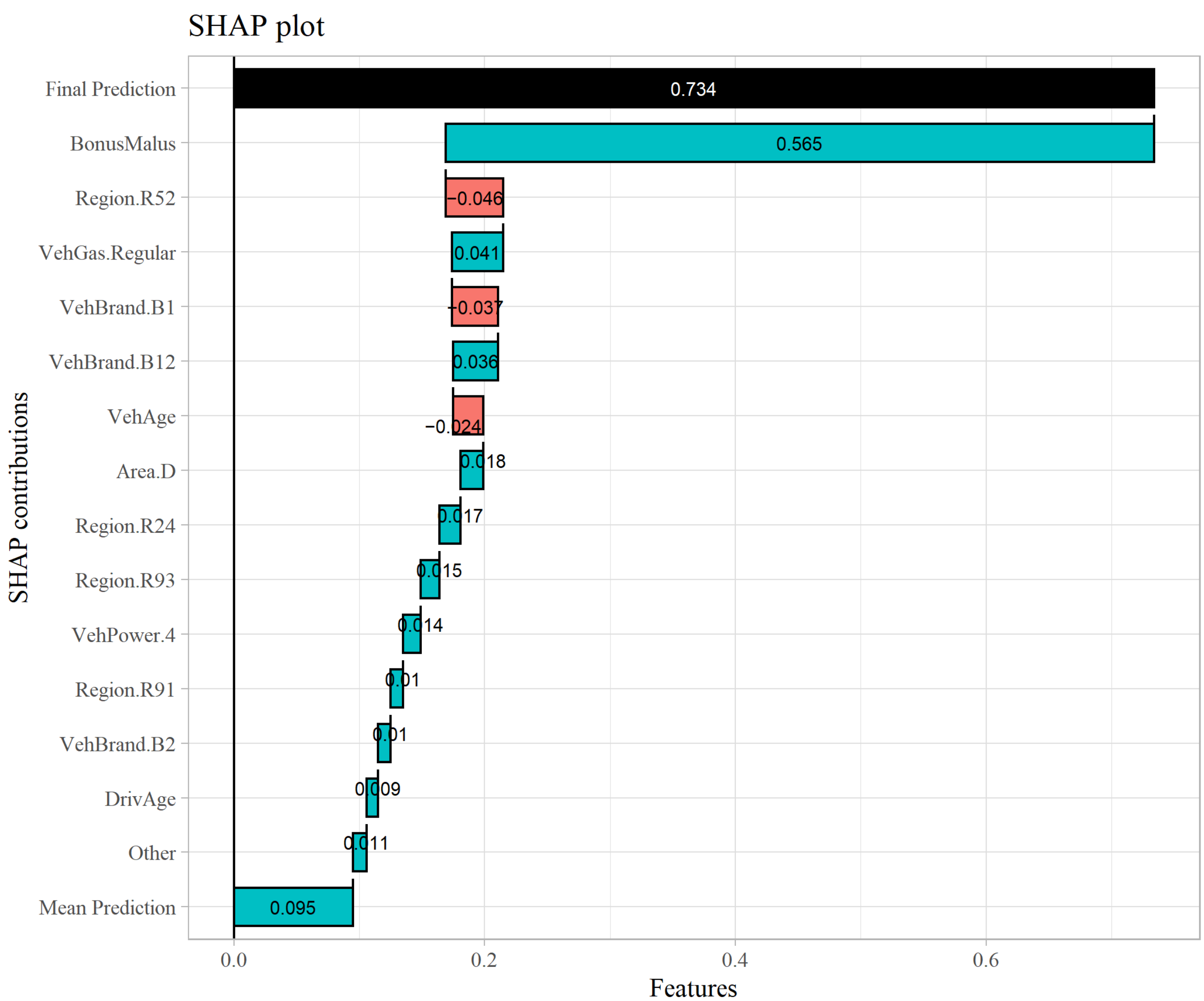


Figure 6: Individual SHAP

GLM Individual SHAP value plots for observations: * with 1 claim and low error for NN; * an instance with 0 claims and very high error * An instance with 2 claims

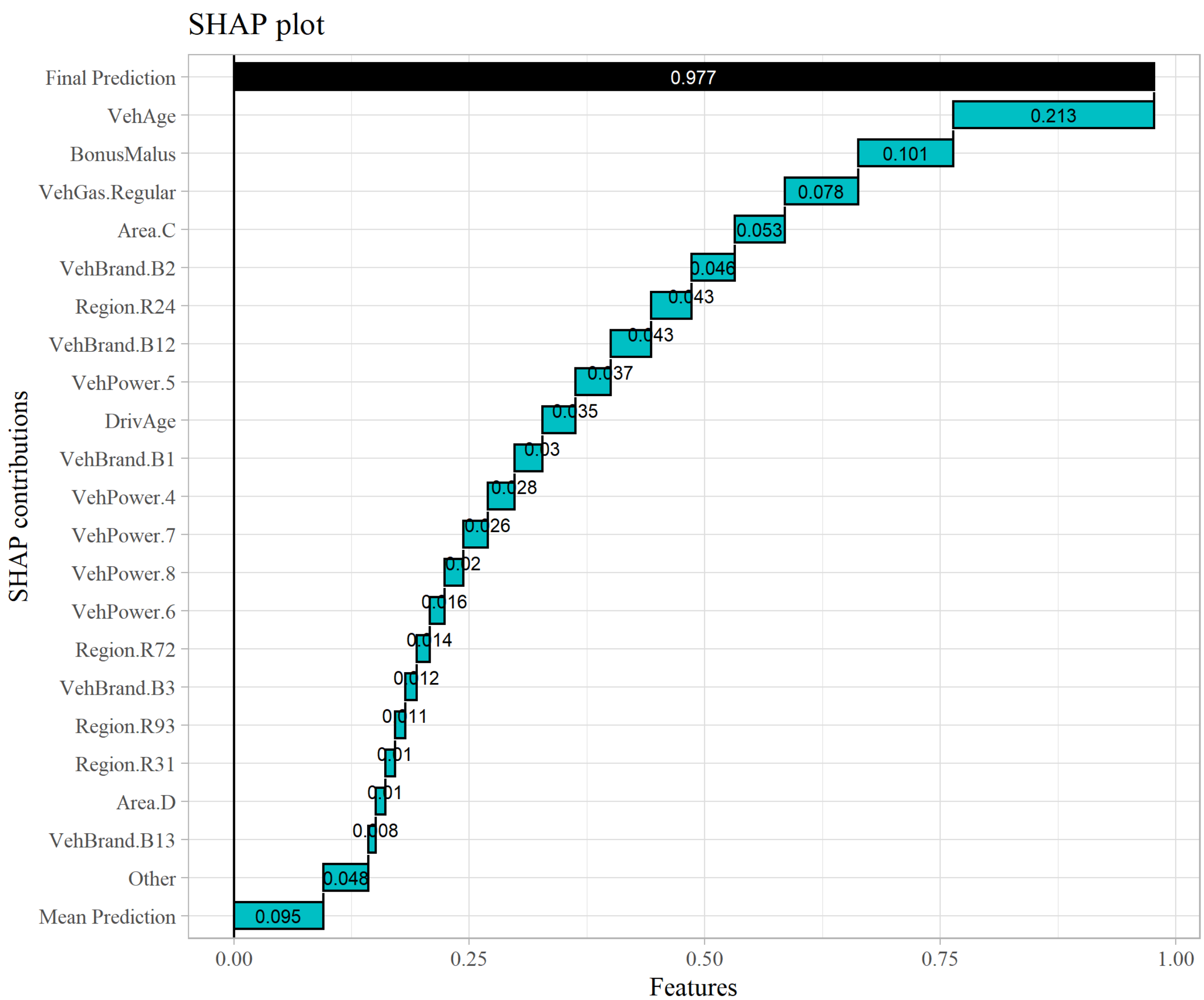


Figure 7: Individual SHAP

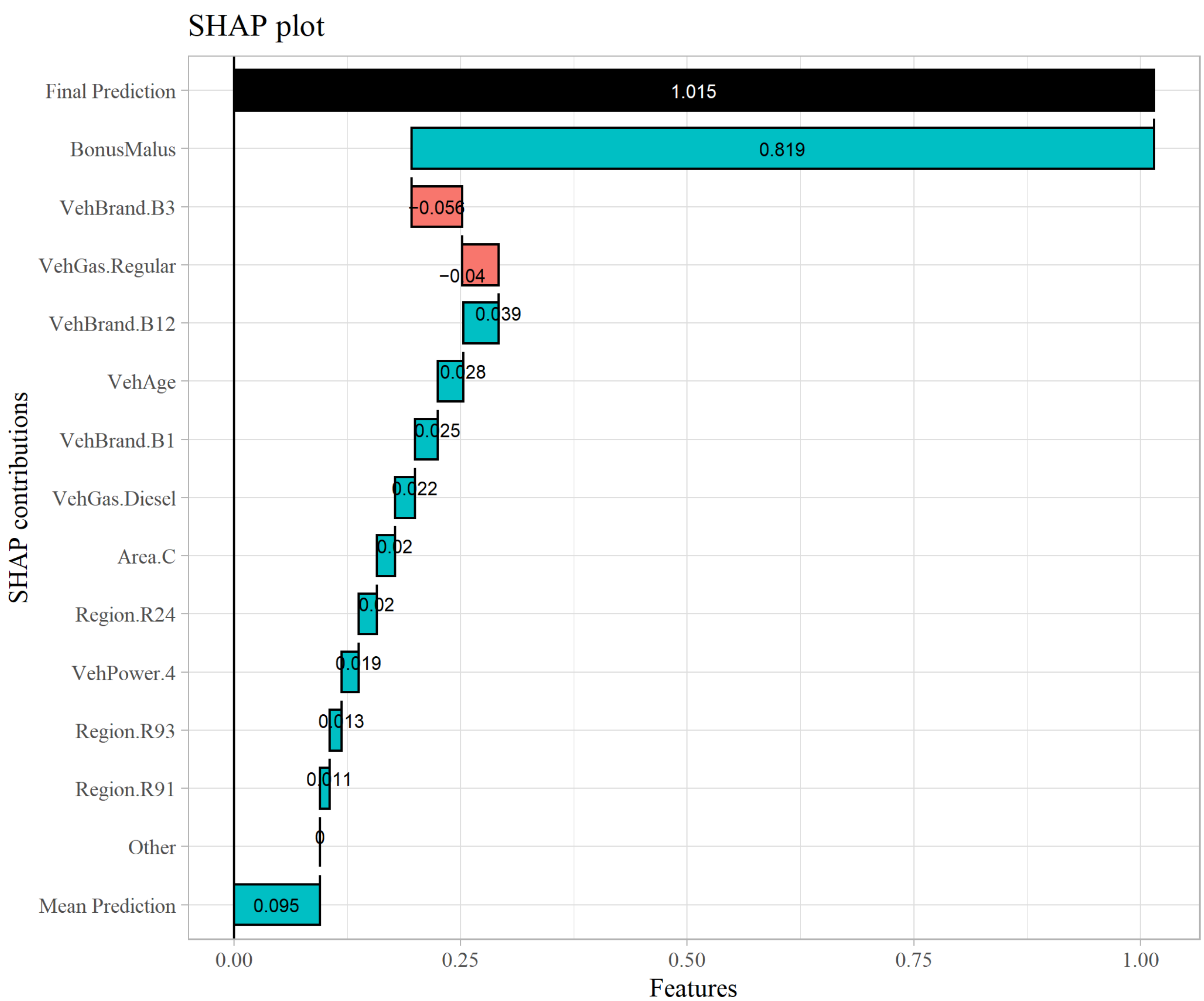


Figure 8: Individual SHAP

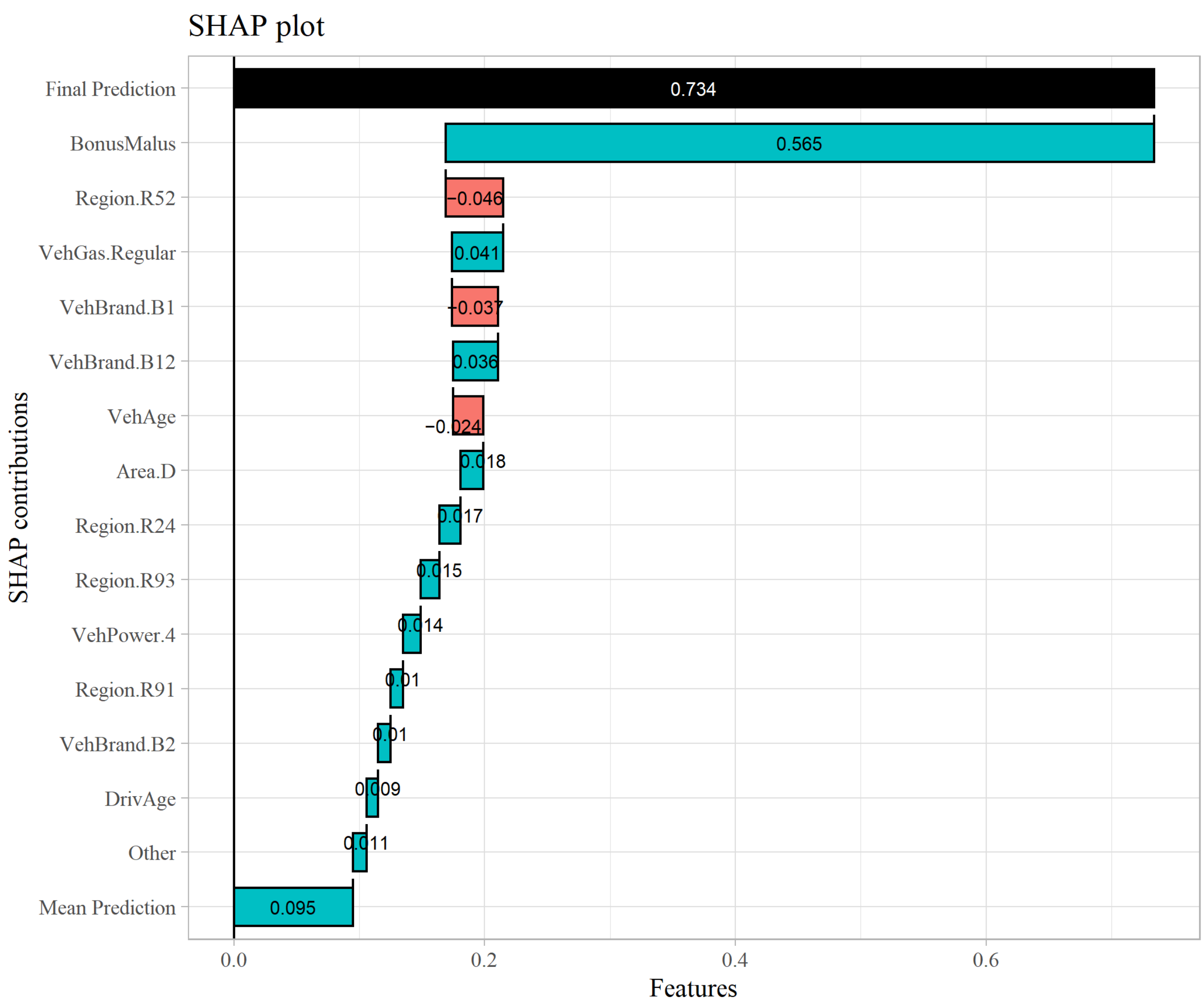


Figure 9: Individual SHAP

4. Additional Information

4.1 model_evaluation utility function

Utility function for analysing model performance.

Input:
model: KERAS Neural Network, XGBoost, GLM
type: specify the type of model can be done automatically
data: named dataframe to assess models' performance on
ClaimNBadj: When passing a NN with poisson loss, an adjustment has to be made to the Claim Number

Output:
list(Evaluation = Evaluation, Predictions = Predictions, AvE = AvE, Sorted_by_MSE = Sorted_by_MSE))

```
if (FALSE){

  model_evaluation = function(model,
                              data = test,
                              type = "NN",
                              ClaimNBadj = FALSE){
    if (type=="NN"){

      if( ClaimNBadj==TRUE){

        # rescaled Predictions
        Predictions = data.frame(Predicted = (model %>% predict(data %>% select(-ClaimNb) %>% as.matrix
                                 Actual = data$ClaimNb)
      }else{

        Predictions = data.frame(Predicted = (model %>% predict(data %>% select(-ClaimNb) %>% as.matrix
                                 Actual = data$ClaimNb)
      }

    }else if(type=="GLM"){

      Predictions = data.frame(Predicted = predict(model,newdata = data %>% select(-ClaimNb,-Exposure,-
                               Actual = data$ClaimNb)

    }else if(type == "XGB"){

      Predictions = data.frame(Predicted = predict(model,newdata = data %>% select(-ClaimNb) %>% as.mat
                               Actual = data$ClaimNb)
    }

    Evaluation = data.frame(
      absolute_error = mean(abs(as.matrix(Predictions$Predicted - data$ClaimNb))),
      mean_squared_error = mean(as.matrix((Predictions$Predicted - data$ClaimNb)^2)),
      Poisson_Loss = PoissonLoss(Predictions$Predicted,data$ClaimNb),
      Poisson_Deviance_Loss = PoissonDevianceLoss(Predictions$Predicted,data$ClaimNb)
    )


    AvE = Predictions %>% mutate(Actual = as.factor(Actual)) %>%
```

```
      group_by(Actual) %>%
      summarise(count = n(),
                mean_pred = mean(Predicted),
                sd_pred = sd(Predicted),
                min = min(Predicted),
                max = max(Predicted),
                Q1 = quantile(Predicted,probs = 0.25),
                Q2 = quantile(Predicted,probs = 0.5),
                Q3 = quantile(Predicted,probs = 0.75),
                IQR = (Q3-Q1)/Q2,
                Negative_Pred = sum(Predicted<0))


    Sorted_by_MSE = data %>% mutate(Predictions = Predictions$Predicted,
                                    SquaredError = (Predictions - ClaimNb)^2) %>%
      arrange(-SquaredError)

    return(list(Evaluation = Evaluation,
                Predictions = Predictions,
                AvE = AvE,
                Sorted_by_MSE = Sorted_by_MSE))
  }

  # for DALEX and SHAP explainer objects
  predict_wrapper=function(model,new_data){
    return(model %>% predict(new_data %>% as.matrix()))
  }

  predict_wrapper_GLM=function(model,new_data){
    return(predict(model,newdata = new_data,type="response"))
  }

}
```

4.2

Data wrangling was not the main intention of this exercise, thus the dataset in Prep_RMD/XAI_data.rda has been already processed. The script below takes the raw freMTPL data as in the source and transforms it to our needs.

```
if (FALSE){

  data_input=read.csv2("data/freMTPL2freq.csv",sep = ",") %>%
    as_tibble() %>%
    mutate(VehPower  = factor(VehPower, order = TRUE,levels = 4:15),
           across(c(Area,Region,VehBrand,VehGas),factor)) %>%
    rowwise() %>%
    mutate(ClaimNb = as.integer(min(ClaimNb,4)),
           VehAge = as.integer(min(VehAge,20)),
           DrivAge = as.integer(min(DrivAge,90)),
           Exposure = as.numeric(min(Exposure,1)),
           Density = log(Density)) %>%
    ungroup()
```

```
  # remove ID's
  data = data_input %>% select(-c(IDpol,Exposure))

  # train/test split
  sample_TTS = sample(x = 1:nrow(data),size = round(0.85 * nrow(data)),replace = FALSE)

  train = data[sample_TTS,] %>% as.data.frame()
  test = data[-sample_TTS,] %>% as.data.frame()

  # Normalization of numeric variables
  data_prep = function(data){

    Normalized = apply(data %>% select(-ClaimNb) %>% select_if(Negate(is.factor)),
                       2,
                       FUN = function(x){return((x-min(x))/(max(x)-min(x)))}) %>%
      as_tibble()

    data = data %>% select_if(is.factor) %>% cbind(Normalized)

    data$VehPower = factor(data$VehPower, order = FALSE)

    # OHE of factor variables
    OHE = dummyVars("~.", data = data %>% select_if(is.factor)) %>%
      predict(newdata = data %>% select_if(is.factor)) %>%
      as_tibble()

    data = data %>% select_if(Negate(is.factor)) %>% cbind(OHE) %>% as_tibble()

    return(data)
  }

  # data prep separately for train and test
  train = data_prep(train)
  test = data_prep(test)

}
```

4.3

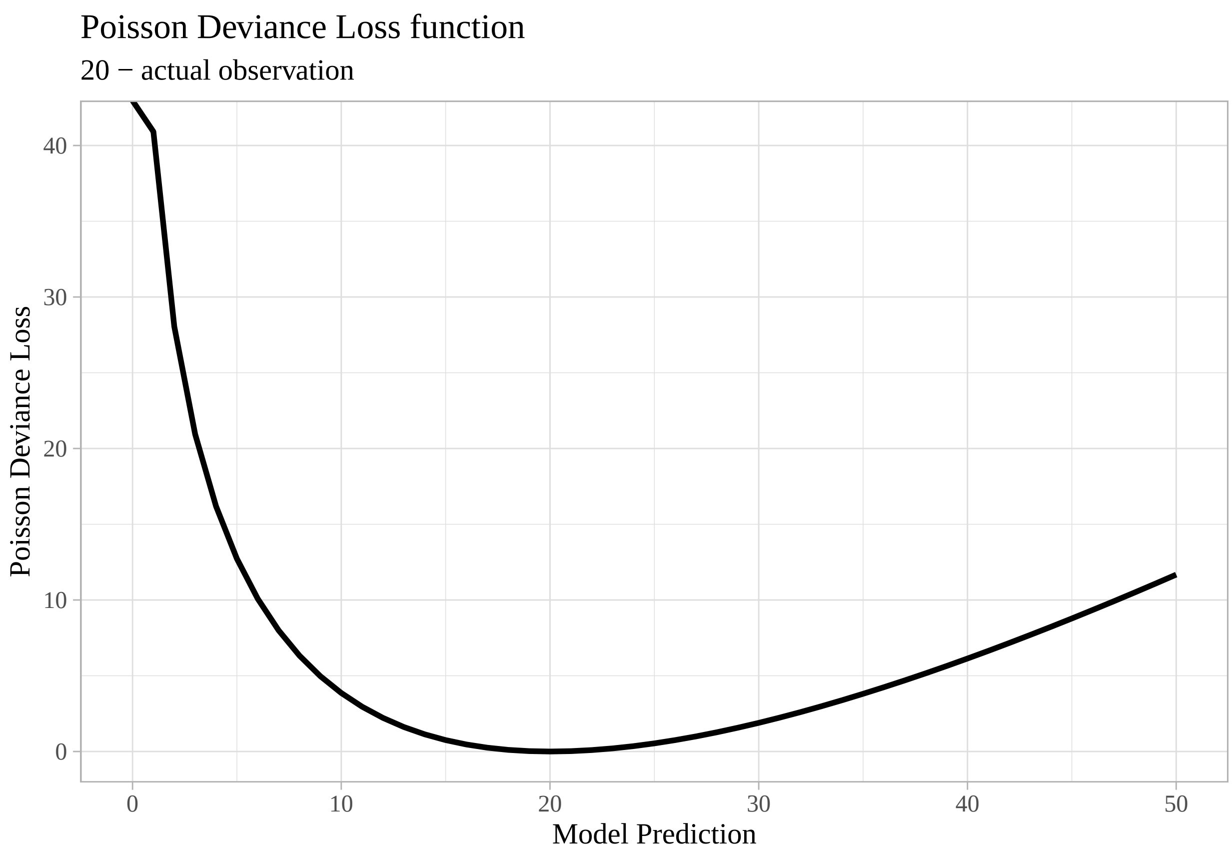
text

```
if (FALSE){

  # Customized and corrected SHAP plot
  CustomSHAPplot=function(dalex_output,
                          epsilon = 0.007){

    colnames(dalex_output) = str_replace_all(colnames(dalex_output),
                                             pattern = "_",
                                             replacement = "")

    dalex_output = dalex_output %>% as_tibble()
```

```
    avg_pred = dalex_output$yhatmean
    total_pred = dalex_output$yhat
    other_pred = sum(dalex_output$attribution[abs(dalex_output$attribution)<=epsilon])

    plot_data = rbind(data.frame(values = c(avg_pred[1],other_pred),
                                 labels = c("Mean Prediction","Other")),
                      dalex_output %>%
                        as_tibble() %>%
                        filter(abs(attribution) > epsilon) %>%
                        mutate(attribution = attribution) %>%
                        transmute(values = attribution,
                                  labels = vname) %>%
                        arrange(abs(values))) %>%
      mutate(values = round(values,3))

    plt = plot_data %>%
      waterfall(fill_by_sign = TRUE,
                calc_total = TRUE,
                total_axis_text = "Final Prediction")+
      coord_flip()+
      ggtitle("SHAP plot")+
      xlab("SHAP contributions")+
      ylab("Features")+
      theme_light()+
      theme(text=element_text(family="serif"),
            legend.justification = c("right", "top"))

    return(plt)
  }


}
```

4.4 Poisson Deviance Loss

```
data.frame(predicted = 0:50,
           actual = 20) %>%
  mutate(PDL = actual*log(actual / predicted) - (actual - predicted)) %>%
  ggplot(aes(x = predicted, y = PDL))+
  geom_line(size = 1)+
  ggtitle("Poisson Deviance Loss function",
          subtitle = "20 - actual observation")+
  xlab("Model Prediction")+
  ylab("Poisson Deviance Loss")+
  theme_light()+
  theme(text=element_text(family="serif"),
        legend.justification = c("right", "top"))
```



4.5 Session information

Hardware, R and Python configuration

```
sessionInfo()
```

```
## R version 4.0.4 (2021-02-15)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 10 x64 (build 19044)
##
## Matrix products: default
##
## locale:
## [1] LC_COLLATE=English_United States.1252
## [2] LC_CTYPE=English_United States.1252
## [3] LC_MONETARY=English_United States.1252
## [4] LC_NUMERIC=C
## [5] LC_TIME=English_United States.1252
## system code page: 1250
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] xgboost_1.5.0.2  skimr_2.1.3      keras_2.7.0      tensorflow_2.7.0
```

```
##  [5] reticulate_1.18  shapper_0.1.3    DALEX_2.2.0      caret_6.0-86
##  [9] lattice_0.20-41  forcats_0.5.1    stringr_1.4.0    dplyr_1.0.7
## [13] purrr_0.3.4      readr_1.4.0      tidyr_1.1.4      tibble_3.1.6
## [17] ggplot2_3.3.5    tidyverse_1.3.1
##
## loaded via a namespace (and not attached):
##  [1] nlme_3.1-152        fs_1.5.0             lubridate_1.7.10
##  [4] httr_1.4.2          repr_1.1.3           tools_4.0.4
##  [7] backports_1.2.1     utf8_1.2.1           R6_2.5.0
## [10] rpart_4.1-15        DBI_1.1.1            colorspace_2.0-0
## [13] nnet_7.3-15         withr_2.4.1          tidyselect_1.1.0
## [16] compiler_4.0.4      cli_3.1.0            rvest_1.0.0
## [19] xml2_1.3.2          labeling_0.4.2       scales_1.1.1
## [22] tfruns_1.5.0        rappdirs_0.3.3       digest_0.6.27
## [25] rmarkdown_2.7       base64enc_0.1-3      pkgconfig_2.0.3
## [28] htmltools_0.5.1.1   highr_0.8            dbplyr_2.1.1
## [31] rlang_0.4.10        readxl_1.3.1         rstudioapi_0.13
## [34] farver_2.1.0        generics_0.1.0       jsonlite_1.7.2
## [37] ModelMetrics_1.2.2.2 magrittr_2.0.1      Matrix_1.3-2
## [40] Rcpp_1.0.6          munsell_0.5.0        fansi_0.4.2
## [43] lifecycle_1.0.0     stringi_1.5.3        whisker_0.4
## [46] pROC_1.17.0.1       yaml_2.2.1           MASS_7.3-53
## [49] plyr_1.8.6          recipes_0.1.17       grid_4.0.4
## [52] crayon_1.4.1        haven_2.3.1          splines_4.0.4
## [55] hms_1.0.0           zeallot_0.1.0        knitr_1.31
## [58] pillar_1.6.4        reshape2_1.4.4       codetools_0.2-18
## [61] stats4_4.0.4        reprex_2.0.0         glue_1.4.2
## [64] evaluate_0.14       data.table_1.14.0    modelr_0.1.8
## [67] vctrs_0.3.8         foreach_1.5.1        cellranger_1.1.0
## [70] gtable_0.3.0        assertthat_0.2.1     xfun_0.22
## [73] gower_0.2.2         prodlim_2019.11.13   broom_0.7.10
## [76] class_7.3-18        survival_3.2-7       timeDate_3043.102
## [79] iterators_1.0.13    lava_1.6.9           ellipsis_0.3.2
## [82] ipred_0.9-12
```

Py: version: 3.8.5 (default, Sep 3 2020, 21:29:08) [MSC v.1916 64 bit (AMD64)] Architecture: 64bit numpy_version: 1.19.2