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Feature Selection Approaches

> Finding the most important predictor variables (of features) that explains major part of variance of the response variable is key to identify and build high performing models.

Import Data

For illustrating the various methods, we will use the ‘Ozone’ data from ‘mlbench’ package, except for Information value method which is applicable for binary categorical response variables.

```
inputData <- read.csv("http://rstatistics.net/wp-content/uploads/2015/09/ozone1.csv", stringsAsFactors=F)
```

1. Random Forest Method

Random forest can be very effective to find a set of predictors that best explains the variance in the response variable.

```
library(party)
cf1 <- cforest(ozone_reading ~ . , data= inputData, control=cforest_unbiased(mtry=2,ntre
e=50)) # fit the random forest
varimp(cf1) # get variable importance, based on mean decrease in accuracy
#=>                Month           Day_of_month            Day_of_week
#=>          0.689167598            0.115937291           -0.004641633
#=>      pressure_height             Wind_speed               Humidity
#=>          5.519633507            0.125868789            3.474611356
#=>  Temperature_Sandburg   Temperature_ElMonte Inversion_base_height
#=>         12.878794481           14.175901506            4.276103121
#=>    Pressure_gradient Inversion_temperature             Visibility
#=>          3.234732558           11.738969777            2.283430842
varimp(cf1, conditional=TRUE)  # conditional=True, adjusts for correlations between pred
ictors
#=>                Month           Day_of_month            Day_of_week
#=>           0.08899435             0.19311805             0.02526252
#=>      pressure_height             Wind_speed               Humidity
#=>           0.35458493            -0.19089686             0.14617239
#=>  Temperature_Sandburg   Temperature_ElMonte Inversion_base_height
#=>           0.74640367             1.19786882             0.69662788
#=>    Pressure_gradient Inversion_temperature             Visibility
#=>           0.58295887             0.65507322             0.05380003
varimpAUC(cf1)  # more robust towards class imbalance.
#=>                Month           Day_of_month            Day_of_week
#=>           1.12821259            -0.04079495             0.07800158
#=>      pressure_height             Wind_speed               Humidity
#=>           5.85160593             0.11250973             3.32289714
#=>  Temperature_Sandburg   Temperature_ElMonte Inversion_base_height
#=>          11.97425093            13.66085973             3.70572939
#=>    Pressure_gradient Inversion_temperature             Visibility
#=>           3.05169171            11.48762432             2.04145930
```

2. Relative Importance

Using `calc.relimp` {relaimpo}, the relative importance of variables fed into a lm model can be determined as a relative percentage.

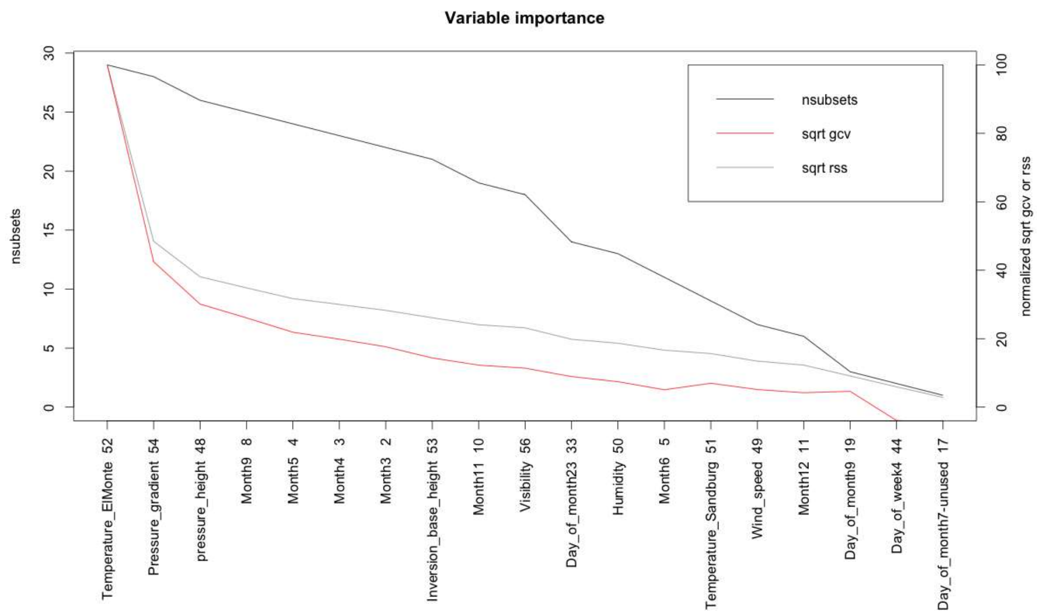
```
library(relaimpo)
lmMod <- lm(ozone_reading ~ . , data = inputData)  # fit lm() model
relImportance <- calc.relimp(lmMod, type = "lmg", rela = TRUE)  # calculate relative imp
ortance scaled to 100
sort(relImportance$lmg, decreasing=TRUE)  # relative importance
#=>   Temperature_ElMonte  Temperature_Sandburg Inversion_temperature
#=>          0.2297491560          0.2095385438          0.1692950876
#=>       pressure_height Inversion_base_height              Humidity
#=>          0.1104276154          0.1000912612          0.0833080699
#=>            Visibility     Pressure_gradient                 Month
#=>          0.0433277042          0.0320457048          0.0164342902
#=>            Wind_speed          Day_of_month           Day_of_week
#=>          0.0034984964          0.0016927799          0.0005912906
```

4. MARS

The earth package implements variable importance based on Generalized cross validation (GCV), number of subset models the variable occurs (nsubsets) and residual sum of squares (RSS).

```
library(earth)
marsModel <- earth(ozone_reading ~ ., data=inputData) # build model
ev <- evimp (marsModel) # estimate variable importance
#>                          nsubsets   gcv    rss
#> Temperature_ElMonte            29 100.0  100.0
#> Pressure_gradient              28  42.5   48.4
#> pressure_height                26  30.1   38.1
#> Month9                         25  26.1   34.8
#> Month5                         24  21.9   31.7
#> Month4                         23  19.9   30.0
#> Month3                         22  17.6   28.3
#> Inversion_base_height          21  14.4   26.1
#> Month11                        19  12.3   24.1
#> Visibility                     18  11.4   23.2
#> Day_of_month23                 14   8.9   19.8
#> Humidity                       13   7.4   18.7
#> Month6                         11   5.1   16.6
#> Temperature_Sandburg            9   7.0   15.6
#> Wind_speed                      7   5.1   13.4
#> Month12                         6   4.2   12.3
#> Day_of_month9                   3   4.6    9.1
#> Day_of_week4                    2  -3.9    5.9
#> Day_of_month7-unused            1  -4.7    2.8

plot(ev)
```



5. Step-wise Regression

If you have large number of predictors (> 15), split the inputData in chunks of 10 predictors with each chunk holding the `responseVar`.

```
base.mod <- lm(ozone_reading ~ 1 , data= inputData)  # base intercept only model
all.mod <- lm(ozone_reading ~ . , data= inputData) # full model with all predictors
stepMod <- step(base.mod, scope = list(lower = base.mod, upper = all.mod), direction = 
"both", trace = 0, steps = 1000)  # perform step-wise algorithm
shortlistedVars <- names(unlist(stepMod[[1]])) # get the shortlisted variable.
shortlistedVars <- shortlistedVars[!shortlistedVars %in% "(Intercept)"]  # remove interc
ept
print(shortlistedVars)
#=> [1] "Temperature_Sandburg"  "Humidity"              "Temperature_ElMonte"
#=> [4] "Month"                 "pressure_height"       "Inversion_base_height"
```

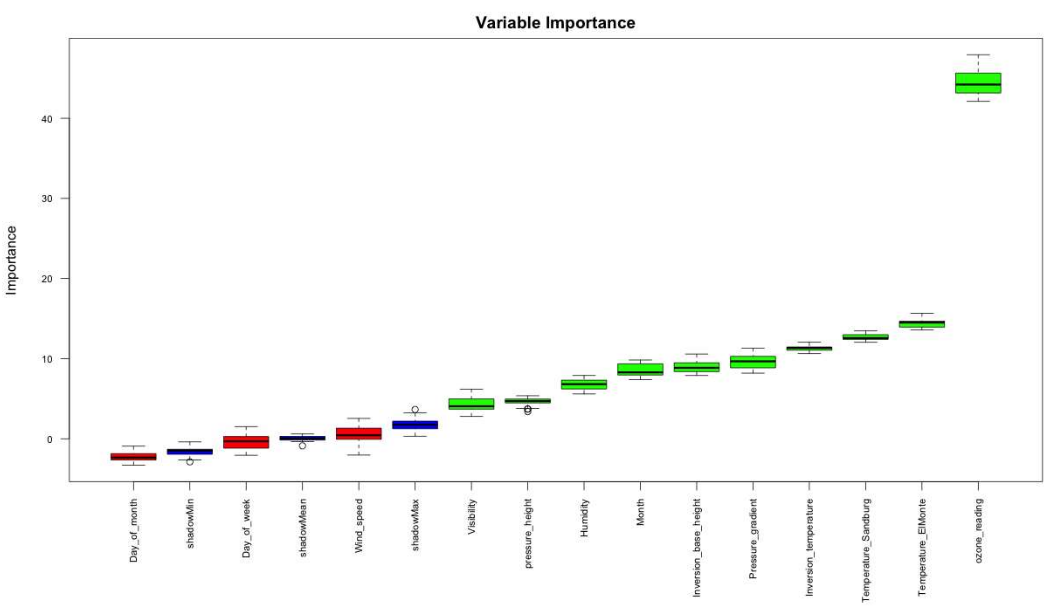
The output could includes levels within categorical variables, since 'stepwise' is a linear regression based technique, as seen above.

If you have a large number of predictor variables (100+), the above code may need to be placed in a loop that will run stepwise on sequential chunks of predictors. The shortlisted variables can be accumulated for further analysis towards the end of each iteration. This can be very effective method, if you want to (i) be highly selective about discarding valuable predictor variables. (ii) build multiple models on the response variable.

6. Boruta

The 'Boruta' method can be used to decide if a variable is important or not.

```
library(Boruta)
# Decide if a variable is important or not using Boruta
boruta_output <- Boruta(ozone_reading ~ ., data=na.omit(inputData), doTrace=2)  # perfor
m Boruta search
# Confirmed 10 attributes: Humidity, Inversion_base_height, Inversion_temperature, Mont
h, Pressure_gradient and 5 more.
# Rejected 3 attributes: Day_of_month, Day_of_week, Wind_speed.
boruta_signif <- names(boruta_output$finalDecision[boruta_output$finalDecision %in% c("C
onfirmed", "Tentative")])  # collect Confirmed and Tentative variables
print(boruta_signif)  # significant variables
#=> [1] "Month"                 "ozone_reading"         "pressure_height"
#=> [4] "Humidity"              "Temperature_Sandburg"  "Temperature_ElMonte"
#=> [7] "Inversion_base_height" "Pressure_gradient"     "Inversion_temperature"
#=> [10] "Visibility"
plot(boruta_output, cex.axis=.7, las=2, xlab="", main="Variable Importance")  # plot var
iable importance
```



7. Information value and Weight of evidence

The InformationValue package (https://cran.r-project.org/web/packages/InformationValue/vignettes/InformationValue.html) provides convenient functions to compute *weights of evidence* and *information value* for categorical variables.

Weights of Evidence (WOE) provides a method of recoding a categorical X variable to a continuous variable. For each category of a categorical variable, the **WOE** is calculated as:

$$WOE = ln\left(\frac{percentage\ good\ of\ all\ goods}{percentage\ bad\ of\ all\ bads}\right)$$

In above formula, 'goods' is same as 'ones' and 'bads' is same as 'zeros'.

Information Value (IV) is a measure of the predictive capability of a categorical `x` variable to accurately predict the goods and bads. For each category of `x`, information value is computed as:

$$InformationValue_{category} = \frac{percentage\ good\ of\ all\ goods - percentage\ bad\ of\ all\ bads}{WOE}$$

The total IV of a variable is the sum of IV's of its categories.

Example

Let me demonstrate how to create the weights of evidence for categorical variables using the `WOE` function in `InformationValue` pkg. For this we will use the `adult` data as imported below. The response variable in `adult` is the `ABOVE50K` which indicates if the yearly salary of the individual in that row exceeds $50K. We have a number of predictor variables originally, out of which few of them are categorical variables. On these categorical variables, we will derive the respective `WOE`s using the `InformationValue::WOE` function. Then, lets find out the `InformationValue:IV` of all categorical variables.

Install package from github

```
library(devtools)
install_github("selva86/InformationValue")
```

Import the data

```
library(InformationValue)
inputData <- read.csv("http://rstatistics.net/wp-content/uploads/2015/09/adult.csv")
head(inputData)
#=>   AGE         WORKCLASS FNLWGT  EDUCATION EDUCATIONNUM       MARITALSTATUS
#=> 1  39         State-gov  77516  Bachelors           13       Never-married
#=> 2  50  Self-emp-not-inc  83311  Bachelors           13  Married-civ-spouse
#=> 3  38           Private 215646    HS-grad            9            Divorced
#=> 4  53           Private 234721       11th            7  Married-civ-spouse
#=> 5  28           Private 338409  Bachelors           13  Married-civ-spouse
#=> 6  37           Private 284582    Masters           14  Married-civ-spouse
#            OCCUPATION   RELATIONSHIP   RACE     SEX CAPITALGAIN CAPITALLOSS
#=> 1       Adm-clerical  Not-in-family  White    Male        2174           0
#=> 2    Exec-managerial        Husband  White    Male           0           0
#=> 3  Handlers-cleaners  Not-in-family  White    Male           0           0
#=> 4  Handlers-cleaners        Husband  Black    Male           0           0
#=> 5     Prof-specialty           Wife  Black  Female           0           0
#=> 6    Exec-managerial           Wife  White  Female           0           0
#     HOURSPERWEEK  NATIVECOUNTRY ABOVE50K
#=> 1           40  United-States        0
#=> 2           13  United-States        0
#=> 3           40  United-States        0
#=> 4           40  United-States        0
#=> 5           40           Cuba        0
#=> 6           40  United-States        0
```

Calculate the Information Values

Below, the information value of each categorical variable is calculated using the `InformationValue::IV` and the strength of each variable is contained within the `howgood` attribute in the returned result. If you are want to dig further into the `IV` of individual categories within a categorical variable, the `InformationValue::WOETable` (https://cran.r-project.org/web/packages/InformationValue/vignettes/InformationValue.html#woetable) will be helpful.

```
factor_vars <- c ("WORKCLASS", "EDUCATION", "MARITALSTATUS", "OCCUPATION", "RELATIONSHI
P", "RACE", "SEX", "NATIVECOUNTRY")  # get all categorical variables
all_iv <- data.frame(VARS=factor_vars, IV=numeric(length(factor_vars)), STRENGTH=charact
er(length(factor_vars)), stringsAsFactors = F)  # init output dataframe
for (factor_var in factor_vars){
  all_iv[all_iv$VARS == factor_var, "IV"] <- InformationValue::IV(X=inputData[, factor_v
ar], Y=inputData$ABOVE50K)
  all_iv[all_iv$VARS == factor_var, "STRENGTH"] <- attr(InformationValue::IV(X=inputData
[, factor_var], Y=inputData$ABOVE50K), "howgood")
}

all_iv <- all_iv[order(-all_iv$IV), ]  # sort
#>          VARS         IV            STRENGTH
#>  RELATIONSHIP 1.53560810   Highly Predictive
#> MARITALSTATUS 1.33882907   Highly Predictive
#>    OCCUPATION 0.77622839   Highly Predictive
#>     EDUCATION 0.74105372   Highly Predictive
#>           SEX 0.30328938   Highly Predictive
#>     WORKCLASS 0.16338802   Highly Predictive
#> NATIVECOUNTRY 0.07939344 Somewhat Predictive
#>          RACE 0.06929987 Somewhat Predictive
```

Compute the weights of evidence (optional)

Optionally, we could create the weights of evidence for the factor variables and use it as continuous variables in place of the factors.

```
for(factor_var in factor_vars){
  inputData[[factor_var]] <- WOE(X=inputData[, factor_var], Y=inputData$ABOVE50K)
}
#>   AGE  WORKCLASS FNLWGT  EDUCATION EDUCATIONNUM MARITALSTATUS OCCUPATION
#> 1  39  0.1608547  77516  0.7974104           13    -1.8846680  -0.713645
#> 2  50  0.2254209  83311  0.7974104           13     0.9348331   1.084280
#> 3  38 -0.1278453 215646 -0.5201257            9    -1.0030638  -1.555142
#> 4  53 -0.1278453 234721 -1.7805021            7     0.9348331  -1.555142
#> 5  28 -0.1278453 338409  0.7974104           13     0.9348331   0.943671
#> 6  37 -0.1278453 284582  1.3690863           14     0.9348331   1.084280

#>   RELATIONSHIP        RACE        SEX CAPITALGAIN CAPITALLOSS HOURSPERWEEK
#> 1    -1.015318  0.08064715  0.3281187        2174           0           40
#> 2     0.941801  0.08064715  0.3281187           0           0           13
#> 3    -1.015318  0.08064715  0.3281187           0           0           40
#> 4     0.941801 -0.80794676  0.3281187           0           0           40
#> 5     1.048674 -0.80794676 -0.9480165           0           0           40
#> 6     1.048674  0.08064715 -0.9480165           0           0           40

#>   NATIVECOUNTRY ABOVE50K
#> 1    0.02538318        0
#> 2    0.02538318        0
#> 3    0.02538318        0
#> 4    0.02538318        0
#> 5    0.11671564        0
#> 6    0.02538318        0
```

The newly created woe variables can alternatively be in place of the original factor variables.
