Binnr Quick Start Guide

Installation

```
if(!require(installr)) install.packages("installr")
if(!require(devtools)) install.packages("devtools")

installr::install.Rtools()

url <- "https://gitlab.ins.risk.regn.net/minneapolis-r-packages/"
devtools::install_git(paste0(url, "binnr.git"), build_vignettes=TRUE)
devtools::install_git(paste0(url, "binnrtools.git"), build_vignettes=TRUE)
devtools::install_git(paste0(url, "mkivtools.git"), build_vignettes=TRUE)
```

The freshest way to install binnr is from Gitlab. This requires two support packages that should be installed anyhow: installr & devtools.

Classing Variables

```
library(binnr)
library(mkivtools)
library(binnrtools)

register_mkiv("Z:/Resources/_MKIV/consumer-mkiv/mk_iv_5_2_3.sas")

d <- read.csv("mkiv_perf.csv", header=TRUE)
mod <- bin(d, d$depvar, exceptions=-1, mono=2, min.res=25, min.cnt=100)
Binning    : ==========|
Warning messages:
1: dropping variables with all NA values: nf_inq_adls_per_email, nf_email_name_addr_ver
2: Variable, account, has more than 20 levels -- Skipping
3: Variable, nf_fp_addrchangeecontraj, has more than 20 levels -- Skipping
```

The first step in any binnr development is to prepare the variables for modeling. The bin function processes a data.frame for downstream modeling and manipulation.

The resulting object is a Scorecard object. It stores everything about a model and provides methods for manipulating the Scorecard.

Correlated Predictors

```
cc <- mod$cluster(bag.fraction = 0.20)
clusters <- mod$get_clusters(cc, corr = 0.80)
> head(clusters)
                    variable sort_value Cluster
1 rv_L79_adls_per_apt_addr_c6 0.05604534       1
2    rv_L79_adls_per_apt_addr 0.05559702       1
3    nf_inq_ssns_per_sfd_addr 0.05299009       1
4  nf_inq_lnames_per_apt_addr 0.05073883       1
5    nf_inq_adls_per_apt_addr 0.05019285       1
6         nf_inq_per_apt_addr 0.04940860       1

drop_corr <- mod$prune_clusters(cc, corr=0.80, n=1)
mod$drop(drop_corr)
```

The Scorecard variables can be clustered into groups with related correlation coefficients.

We can subsequently view all of the variable cluster groups or prune the groups retaining a representative variable from each one. The retained variables have the highest information value within each cluster.

Fit Initial Model

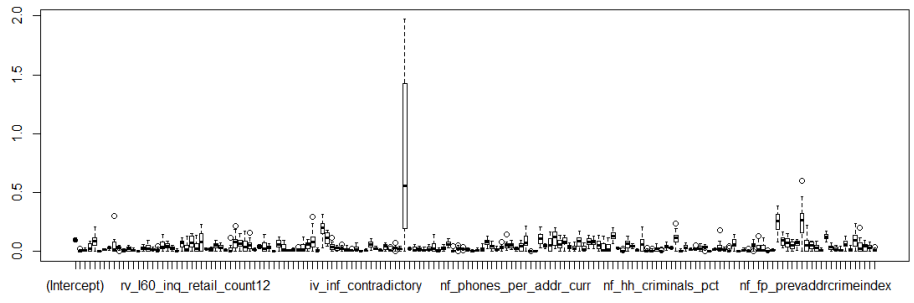
```
mod$fit("model 1", "initial model with all variables")
> mod
2 models
 |--    scratch              | 00.0 ks |
 |--    model 1              | 47.3 ks | initial model with all variables

mod$drop(mod$get_inmodel(invert = TRUE))
```

Dropping highly correlated variables is a good first step before fitting an initial model.

A good second step is repeatedly fitting the model on bootstrap samples to winnow the candidate set down even further.

Bootstrap Model Fits

```
pvals <- mod$pseudo_pvalues(20, bag.fraction = 1, replace = TRUE)
boxplot(t(pvals$coefs)
```



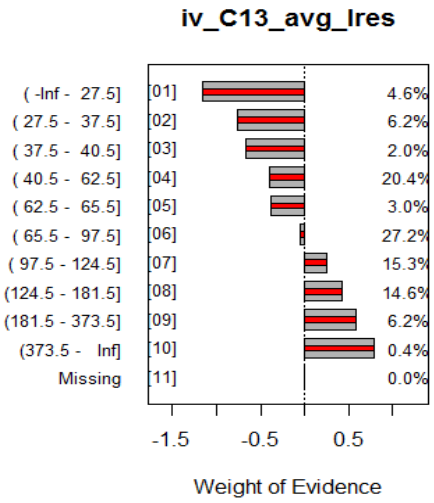
The boot strap sample results reveal variables that have high-variance coefficients or enter the model sporadically. For example, some variables only have non-zero coefficients in 1 out of 20 model runs and are clearly not reliable.

```
v <- apply(pvals$coefs, 1, var) # some coefs have high variance
high_var <- names(which(v > quantile(v, 0.95)))
high_pval <- names(which(pvals$pvalues > 0.10)) # some enter the model inconsistently

mod$drop(c(high_var, high_pval))
mod$fit("model 2", "after dropping high variance/pvalue vars")
> mod
2 models
 |--    scratch              | 00.0 ks |
 |--    model 1              | 47.3 ks | initial model with all variables
 |-- *  model 2              | 49.2 ks | after dropping high variance/pvalue vars
```

We can pass the names of these unreliable variables to the `drop` method and refit the model. The out-of-fold KS improved considerably. We now have a solid set of candidate variables to investigate through the `adjust` method shown below.

Adjust the Model Variables

```
mod$adjust()

iv_C13_avg_lres
                         N  #1   #0    %N    %1    %0  P(1)    WoE    IV   Pred
[01]  ( -Inf -  27.5]   460  10  450 0.046 0.015 0.048 0.022 -1.155 0.038 -1.155
[02]  ( 27.5 -  37.5]   623  20  603 0.062 0.030 0.065 0.032 -0.755 0.026 -0.755
[03]  ( 37.5 -  40.5]   201   7  194 0.020 0.011 0.021 0.035 -0.671 0.007 -0.671
[04]  ( 40.5 -  62.5]  2045  92 1953 0.204 0.140 0.209 0.045 -0.404 0.028 -0.404
[05]  ( 62.5 -  65.5]   303  14  289 0.030 0.021 0.031 0.046 -0.376 0.004 -0.376
[06]  ( 65.5 -  97.5]  2716 172 2544 0.272 0.261 0.272 0.063 -0.043 0.000 -0.043
[07]  ( 97.5 - 124.5]  1534 127 1407 0.153 0.193 0.151 0.083  0.246 0.010  0.246
[08]  (124.5 - 181.5]  1456 142 1314 0.146 0.215 0.141 0.098  0.426 0.032  0.426
[09]  (181.5 - 373.5]   625  70  555 0.062 0.106 0.059 0.112  0.581 0.027  0.581
[10]  (373.5 -   Inf]    37   5   32 0.004 0.008 0.003 0.135  0.795 0.003  0.795
[11]  Missing             0   0    0 0.000 0.000 0.000 0.000  0.000 0.000  0.000
Total                 10000 659 9341 1.000 1.000 1.000 0.000  0.000 0.176  0.000

 [In Model:  TRUE | Dropped: FALSE]

Enter command (Q to quit; h for help):
?
```



Bring up Variable Definition

```
*# iv_C13_avg_lres;
*@group: Length of Residence;
*@description: Average Length of residence;
    if not truedid
        then iv_C13_avg_lres = .;
    else iv_C13_avg_lres = min(avg_lres, 999);
```

If a MKIV is registered through the `mkivtools` library, typing a "?" during the interactive adjust session will pull up the model code the Rstudio Viewer pane.

Apply Bin Operations

Command	Definition
(Q)uit	Quit adjust function
(n)ext	Move to next variable
(p)revious	Move to previous variable
(g)oto	Goto variable; prompted to enter variable name
(m)ono	Change monotonicity when prompted
(e)xceptions	Change variable exceptions when prompted
(s)et equal	Set one WoE level equal to another when prompted
(u)ndo	Undo the last manipulation command
(r)eset	Reset the bin to its initial state
(d)rop/undrop	Flag the variable as dropped or un-dropped
!= <#>	Neutralize requested variable levels (WoE -> 0)
+ <#>	Expand requested level (one at a time)
- <#>	Collapse requested levels

The adjust method starts an interactive session where the modeler can enter commands to manipulate binned variables. Bins can be expanded, collapsed, and neutralized much like in Xeno.

Variables should be inspected for palatability and regulatory conformance. Once they are adjusted to satisfaction, the model is nearly finished.

Finalize Model

```
pvals <- mod$pseudo_pvalues(50, bag.fraction = 1, replace = TRUE)
high_pval <- names(which(pvals$pvalues > 0.10))
mod$drop(high_pval)
mod$fit("model 3", "Final Model", nfolds = 20)
```

A final round of bootstrap model fitting serves identify truly predictive from spurious variables.

```
> mod
4 models
 |--    scratch             | 00.0 ks |
 |--    model 1             | 47.3 ks | initial model with all variables
 |--    model 2             | 49.2 ks | after dropping high variance/pvalue vars
 |-- *  model 3             | 50.5 ks | Final Model
```

A combination of model adjustments and further winnowing increase the KS by another point.

Analyze Model Variables

```
s <- mod$summary(inmodel.only=TRUE) ## data.frame summarizing model variables

> mod$compare("model 2", "model 3")

mkiv_summary <- summarize_model_vars(mod)

> View(mkiv_summary$missing_groups)
> View(mkiv_summary$model_vars)
```

There are several functions for analyzing the final model. Univariate statistics can be reported using the `summary` method.

Different models can be compared using the `compare` method.

If a MKIV is registered, variable groups missing from the model can be easily identified and inspected.

Generate SAS Code

```
code <- mod$gen_code_sas(pfx = "mod1", method="neutral")
cat(code, file="my_binnr_model.sas", sep="\n")
```

```
/*** nf_fp_curraddrmurderindex ***/
if missing(nf_fp_curraddrmurderindex)
  then mod1_V01_w = 0;
else if nf_fp_curraddrmurderindex <= 1.5
  then mod1_V01_w = -0.902187998182727;
else if nf_fp_curraddrmurderindex <= 46.5
  then mod1_V01_w = -0.0974965223769837;
else if nf_fp_curraddrmurderindex <= 93.5
  then mod1_V01_w = -0.0879939778663614;
else if nf_fp_curraddrmurderindex <= 152.5
  then mod1_V01_w = 0.0817707163869025;
else mod1_V01_w = 0.142064000910119;
```

If I MKIV is registered, binnr will print the mkiv variable code in the generated SAS code.

Exporting Bivariates

```
lm <- export_classing(mod, sheet = "bivariates")
lm$open_workbook()
```

iv_C13_avg_lres	N	#1	#0	%N	%1	%0	P(1)	WoE	IV	Pred
(-Inf - 27.5]	460	10	450	4.60%	1.50%	4.80%	2.20%	-1.1550	0.0380	-1.1550
(27.5 - 37.5]	623	20	603	6.20%	3.00%	6.50%	3.20%	-0.7550	0.0260	-0.7550
(37.5 - 40.5]	201	7	194	2.00%	1.10%	2.10%	3.50%	-0.6710	0.0070	-0.6710
(40.5 - 62.5]	2,045	92	1,953	20.40%	14.00%	20.90%	4.50%	-0.4040	0.0280	-0.4040
(62.5 - 65.5]	303	14	289	3.00%	2.10%	3.10%	4.60%	-0.3760	0.0040	-0.3760
(65.5 - 97.5]	2,716	172	2,544	27.20%	26.10%	27.20%	6.30%	-0.0430	0.0000	-0.0430
(97.5 - 124.5]	1,534	127	1,407	15.30%	19.30%	15.10%	8.30%	0.2460	0.0100	0.2460
(124.5 - 181.5]	1,456	142	1,314	14.60%	21.50%	14.10%	9.80%	0.4260	0.0320	0.4260
(181.5 - 373.5]	625	70	555	6.20%	10.60%	5.90%	11.20%	0.5810	0.0270	0.5810
(373.5 - Inf]	37	5	32	0.40%	0.80%	0.30%	13.50%	0.7950	0.0030	0.7950
Missing	0	0	0	0.00%	0.00%	0.00%	0.00%	0.0000	0.0000	0.0000
Total	**10,000**	**659**	**9,341**	**100%**	**100%**	**100%**	**0%**	**0.0000**	**0.1760**	**0.0000**

Pretty bivariates can all be sent directly to Excel if the binnrtools package is loaded.

These functions can take a while to run.