SCORECARD VARIABLE GROUPING AND SELECTION

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Process Flow

Data Collection
- Variable Selection
- Sample Size
- Sample / Performance Window

Data Cleaning
- Eliminate Duplicates
- Examine / Remove Outliers

Variable Grouping and Selection
- Weights of Evidence (WOE)
- Information Value (IV)
- Gini Criterion

Initial Scorecard Creation
- Logistic Regression
- Accuracy
- Threshold
- Assessment

Reject Inference
- Remove bias resulting from exclusion of rejects

Final Scorecard Creation
- Final Model Assessment

VARIABLE GROUPING

Variable Grouping and Selection

- Scorecards end up with only just groups within a variable.
- Objectives:
  1. Eliminate weak characteristics (variables) or those that do not conform to good business logic.
  2. Group the strongest characteristics' attribute levels in order to produce a model in scorecard format.
- Function/package "smbinning" in R.
- Package "scorecard" or "OptBinning" in Python.
- PROC BINNING in SAS VIYA.

Variable	Level
MISS	$x < 24$
MISS	$24 \leq x < 36$
MISS	$36 \leq x < 48$
MISS	$x \geq 48$
HOME	OWN
HOME	RENT

Why Grouping (Binning)?

- Goal is to help simplify analysis through grouping:
  - Useful for understanding relationships – no worries about explaining coefficients.
  - Modeling nonlinearities – similar to decision trees.
    (NO MORE LOGISTIC REGRESSION LINEARITY ASSUMPTION!)
  - Dealing with outliers – contained in the smallest / largest group.
  - Missing values typically in own group.

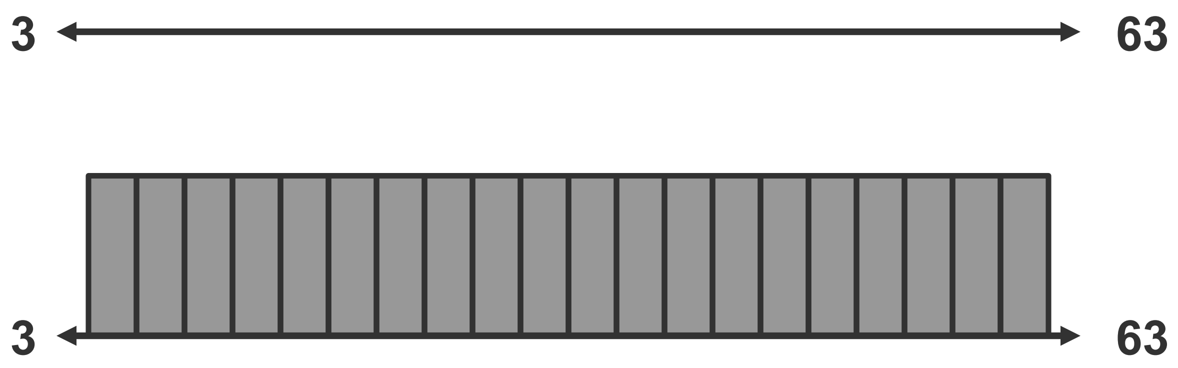
Initial Characteristic Analysis – SAS

- Need a starting point for the grouping / binning.
  - Quantiles are most popular technique.
- Pre-bin the interval variables into a number of user-specified quantiles / buckets for fine detailed groupings.
- Aggregate the fine detailed groupings into a smaller number to produce coarse groupings.
  - Chi-squared tests to combine groups.

Initial Characteristic Analysis – SAS

3 ⟷ **63**

Initial Characteristic Analysis – SAS



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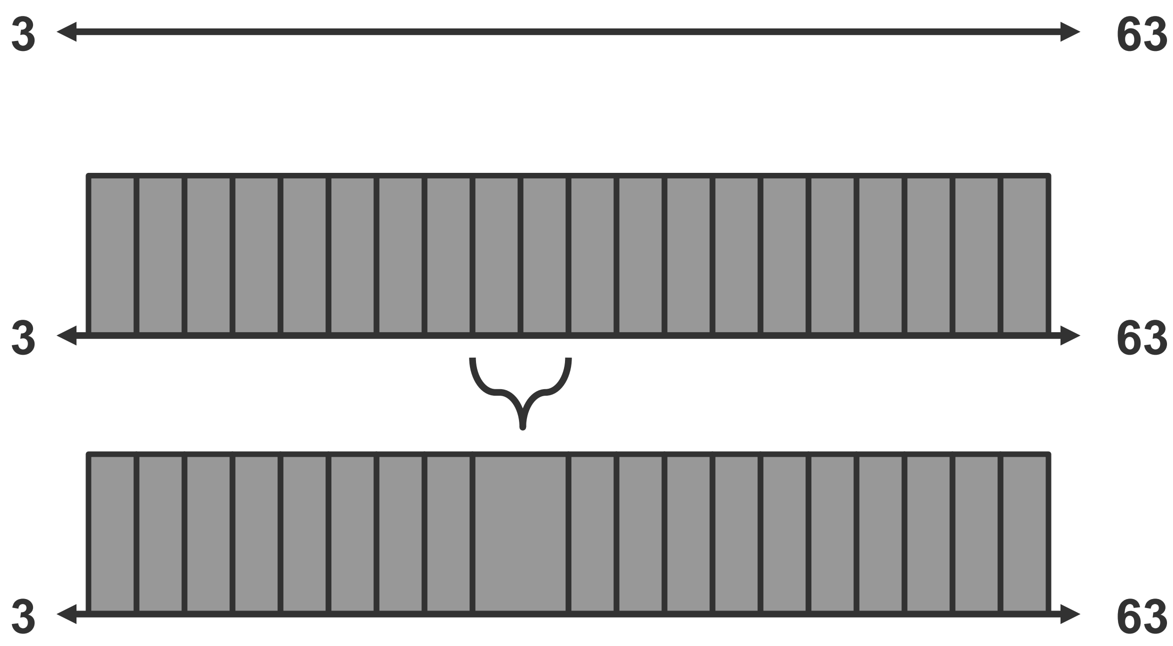
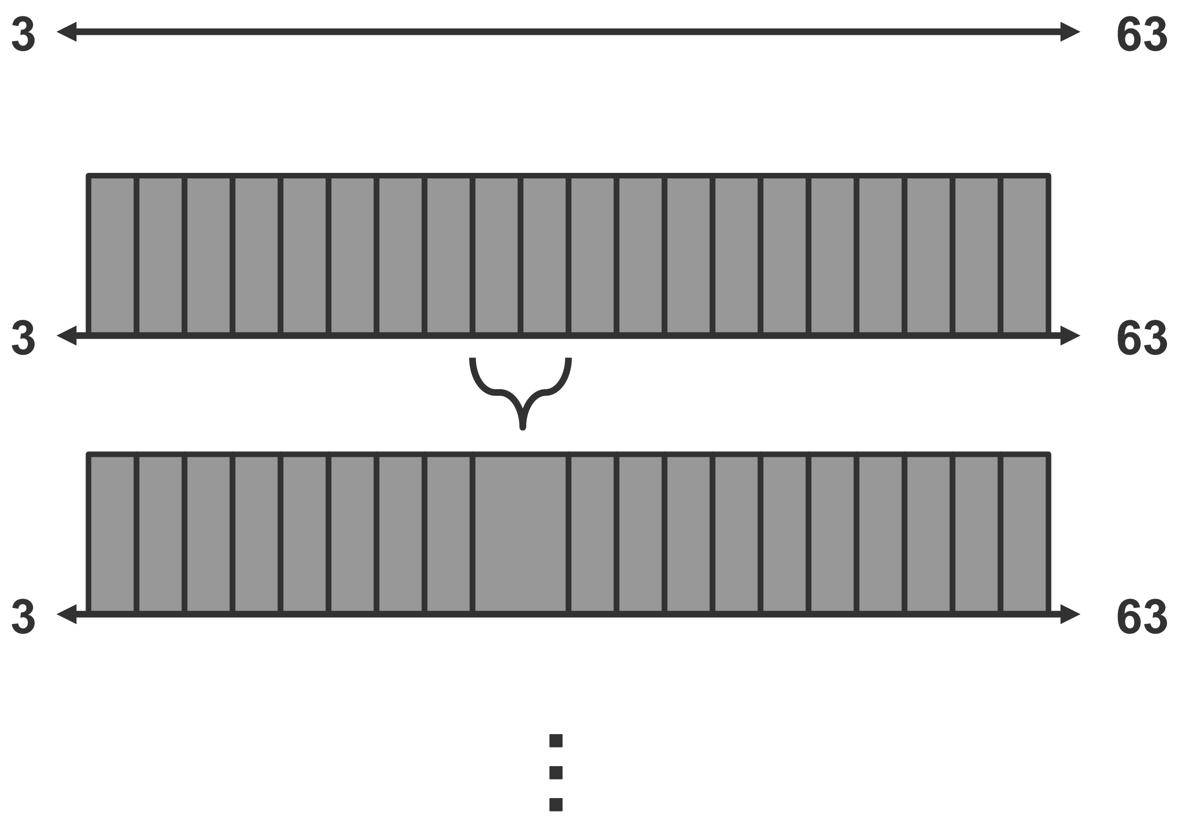
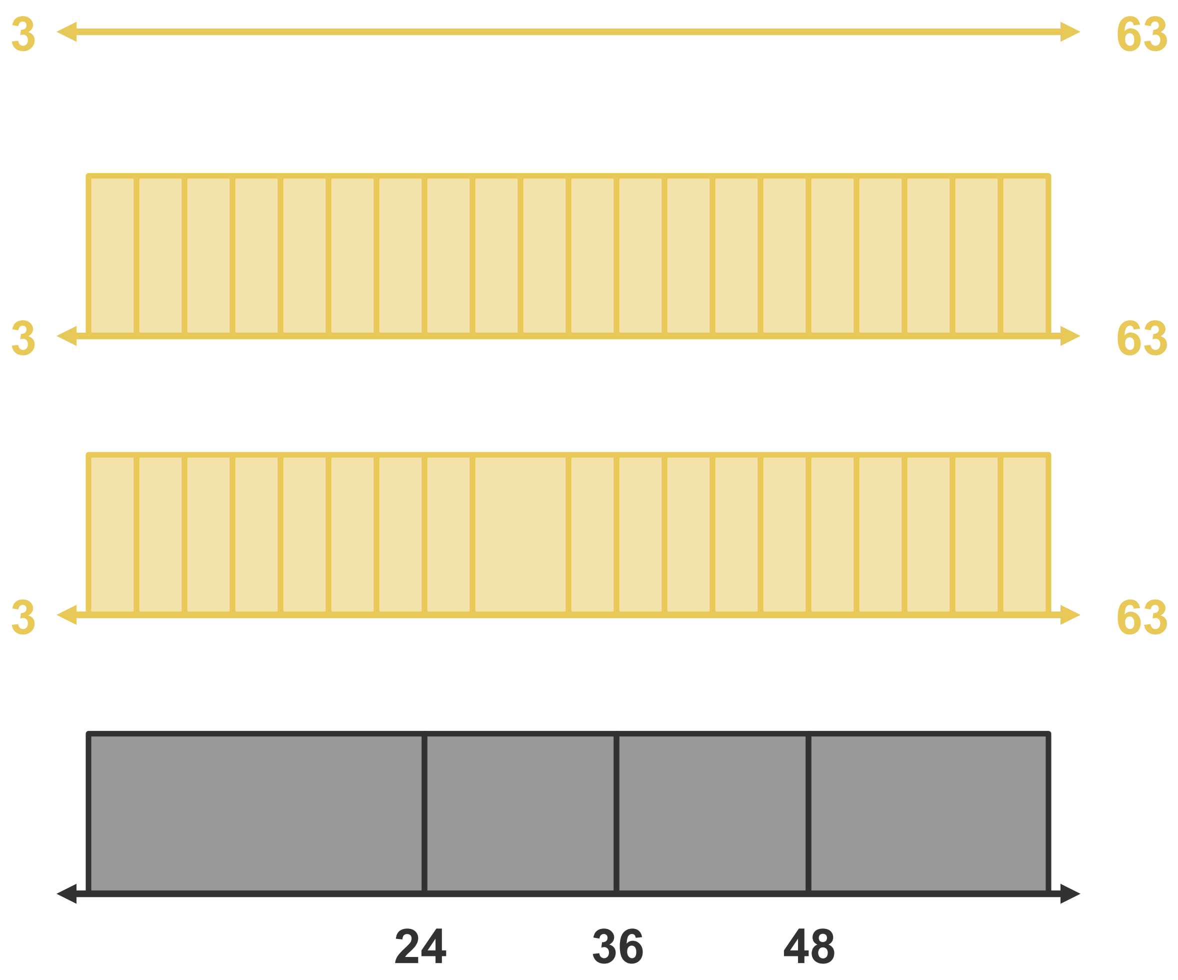


Initial Characteristic Analysis – SAS



Initial Characteristic Analysis – SAS



Initial Characteristic Analysis – R

- The package (and function) “smbinning” uses a different approach than SAS.

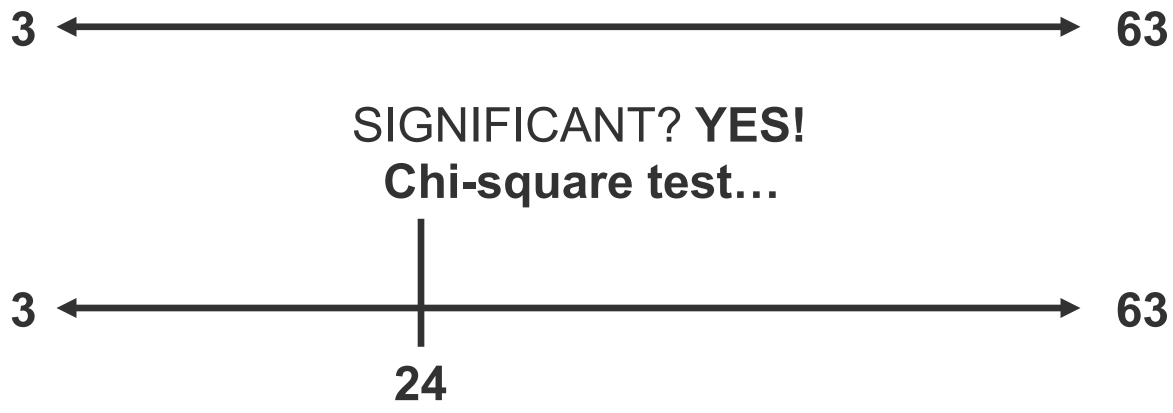
- Conditional Inference Trees:
  - CART methods have inherent bias – variables with more levels → more likely to be split on if split on Gini and Entropy.
  - CIT method adds extra statistical step before splits occur – statistical tests of significance.
  - What is **MOST** significant variable? → What is the best split (Chi-square) on **THIS** variable? → **REPEAT**.

Initial Characteristic Analysis – R

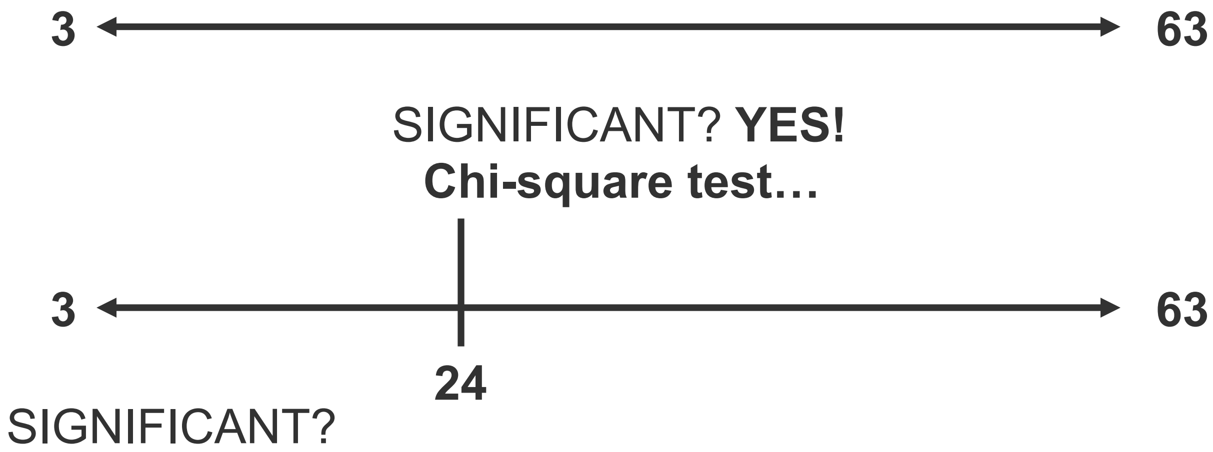
3 ⟷ **63**

SIGNIFICANT?

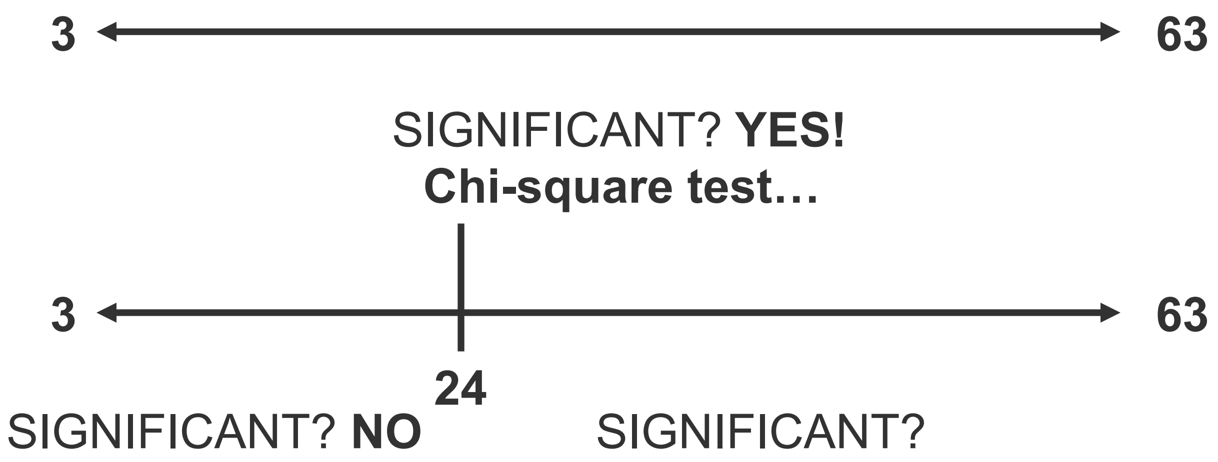
Initial Characteristic Analysis – R



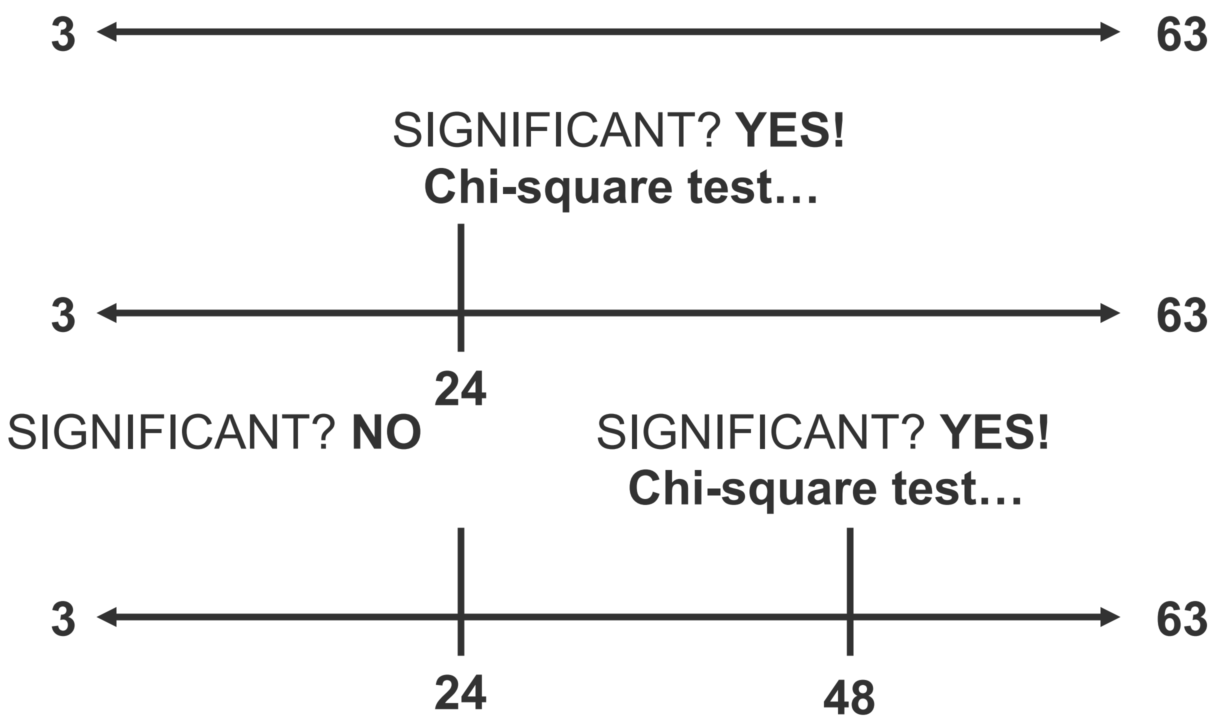
Initial Characteristic Analysis – R



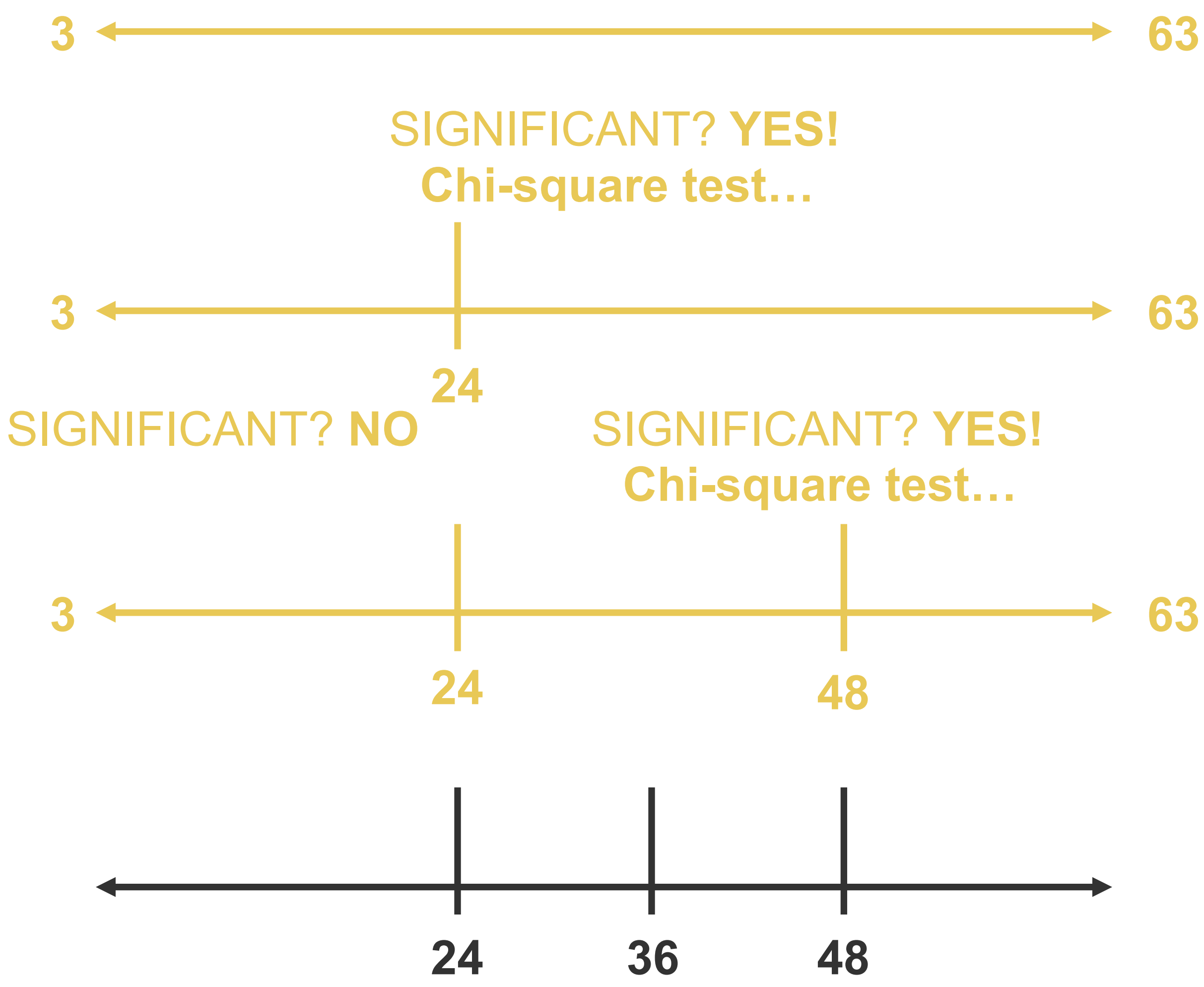
Initial Characteristic Analysis – R



Initial Characteristic Analysis – R



Initial Characteristic Analysis – R



Initial Characteristic Analysis

- Cut-offs may be rough from decision tree combining.
- **Optional to override** automatically generated groups to conform to business rules.
- Overrides may make groups suboptimal.

Group Definition
Missing
< $35,200
$35,200 - $60,000
$60,000 - $85,000
$85,000 - $110,000
$110,000 - $142,530
> $142,530

Initial Characteristic Analysis

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- Overrides may make groups suboptimal.

Group Definition	Override
Missing	Missing
< $35,200	< $35,000
$35,200 - $60,000	$35,000 - $60,000
$60,000 - $85,000	$60,000 - $85,000
$85,000 - $110,000	$85,000 - $110,000
$110,000 - $142,530	$110,000 - $140,000
> $142,530	> $140,000

Initial Characteristic Analysis

- Cut-offs may be rough from decision tree combining.
- **Optional to override** automatically generated groups to conform to business rules.
- Overrides may make groups suboptimal.

Group Definition	Override
Missing	Missing
< $35,200	**< $35,000**
$35,200 - $60,000	**$35,000** - $60,000
$60,000 - $85,000	$60,000 - $85,000
$85,000 - $110,000	$85,000 - $110,000
$110,000 - $142,530	$110,000 - **$140,000**
> $142,530	**> $140,000**

Initial Characteristic Analysis

- Calculate and examine the key assessment metrics:
  - **Weight of Evidence** (WOE) – how well attributes discriminate for each given characteristic
  - **Information Value** (IV) – evaluate a characteristic's overall predictive power
  - **Gini Statistic** – alternate to IV for selecting characteristics for final model.

WEIGHT OF EVIDENCE

Weight of Evidence (WOE)

- WOE measures the strength of the attributes of a characteristic in **separating good and bad accounts**.
- WOE is based on comparing the proportion of goods to bads at each attribute level (levels of the predictor variable).

$$WOE_i = \log\left(\frac{Dist.Good_i}{Dist.Bad_i}\right)$$

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$$WOE_i = \log\left(\frac{Dist.Good_i}{Dist.Bad_i}\right)$$

$$Dist.Good_i = \frac{Number\ Good\ in\ group\ i}{Total\ Number\ Good}$$

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- WOE is based on comparing the proportion of goods to bads at each attribute level (levels of the predictor variable).

$$WOE_i = \log\left(\frac{Dist.Good_i}{Dist.Bad_i}\right)$$

$$Dist.Bad_i = \frac{Number\ Bad\ in\ group\ i}{Total\ Number\ Bad}$$

Weight of Evidence (WOE)

- What are we looking for?
  - Looking for “big” differences in WOE between groups.
  - Monotonic changes within an attribute for **interval variables** (not always required).

- Why monotonic increases?
  - Oscillation back and forth of positive to negative values of WOE typically sign of variable that has trouble separating good vs. bad.
  - Not always required **if makes business sense** – credit card utilization for example.

WOE – Example

WOE for Bureau Score				
Group	Values	Event Count	Non-event Count	WOE
1	< 603	111	112	
2	604 – 662	378	678	
3	663 – 699	185	754	
4	700 – 717	74	440	
5	718 – 765	75	824	
6	> 765	15	498	
7	MISSING	80	153	
Total		**918**	**3,459**	

WOE – Example

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$$Dist.Good_1 = \frac{112}{3459}$$

$$= 0.032$$

WOE – Example

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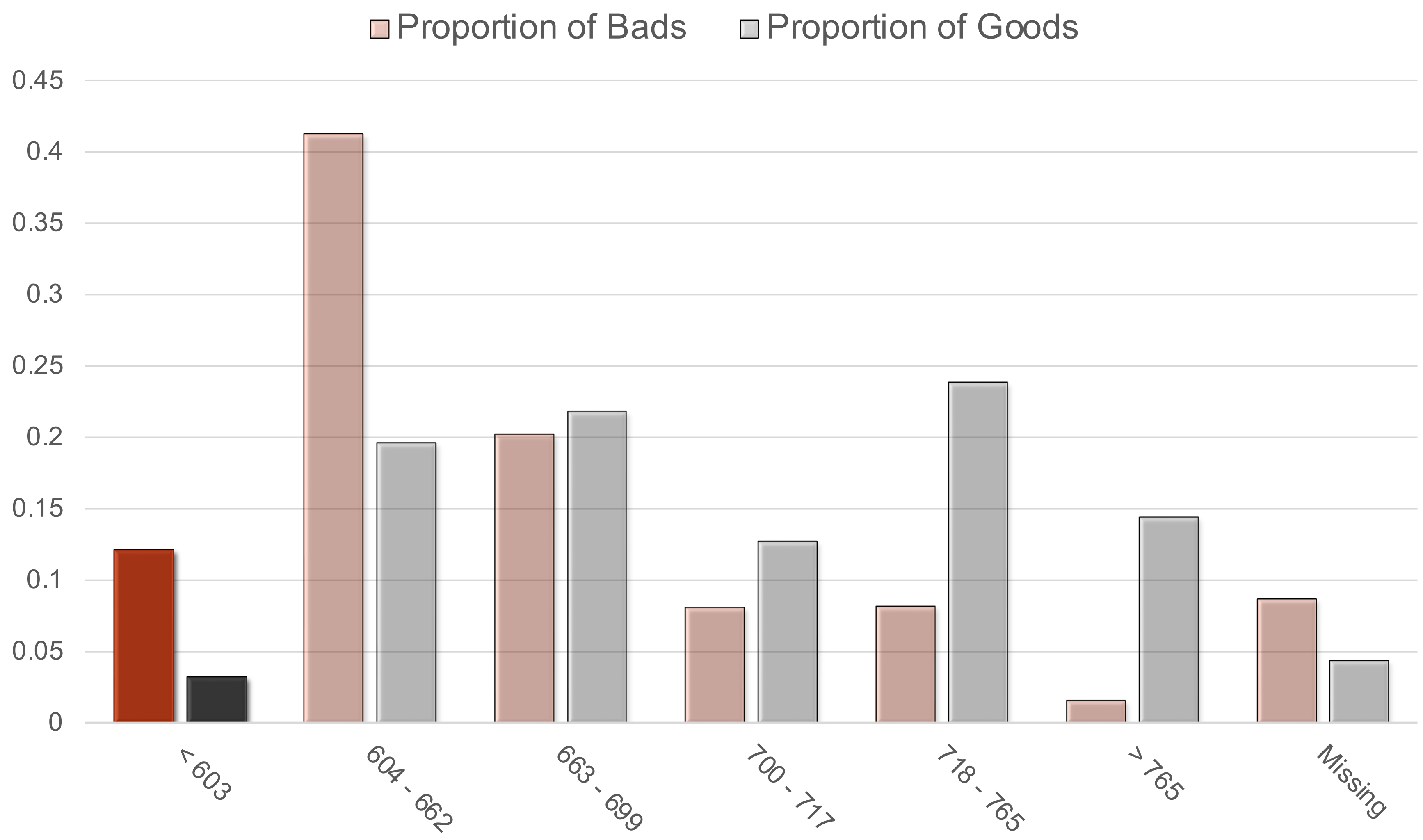
$$Dist.Good_1 = \frac{112}{3459}$$

$$= 0.032$$

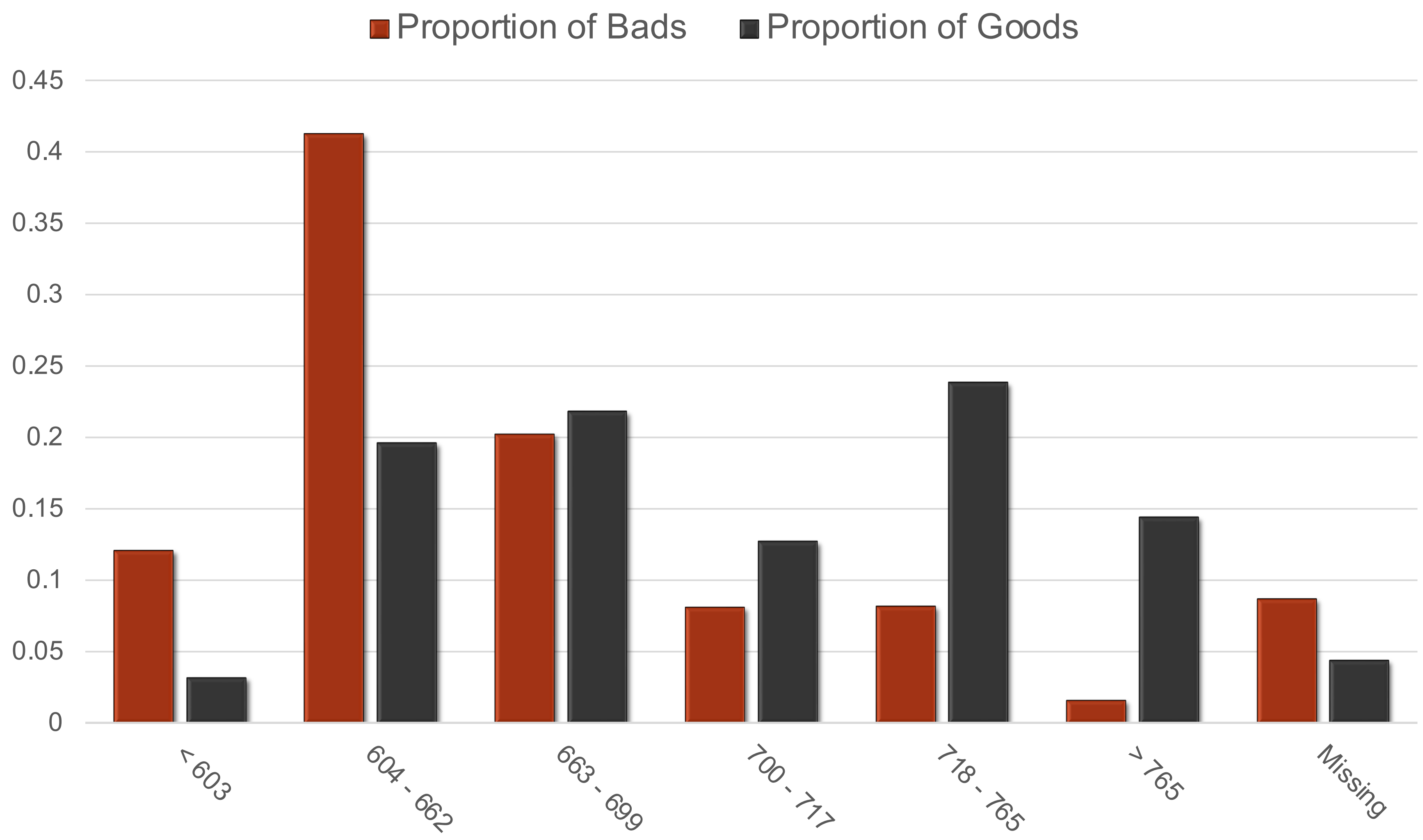
$$Dist.Bad_1 = \frac{111}{918}$$

$$= 0.121$$

WOE – Example


Proportion of Bads
Proportion of Goods
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
< 603
604 - 662
663 - 699
700 - 717
718 - 765
> 765
Missing

WOE – Example


Proportion of Bads
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0.45
0.4
0.35
0.3
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< 603
604 - 662
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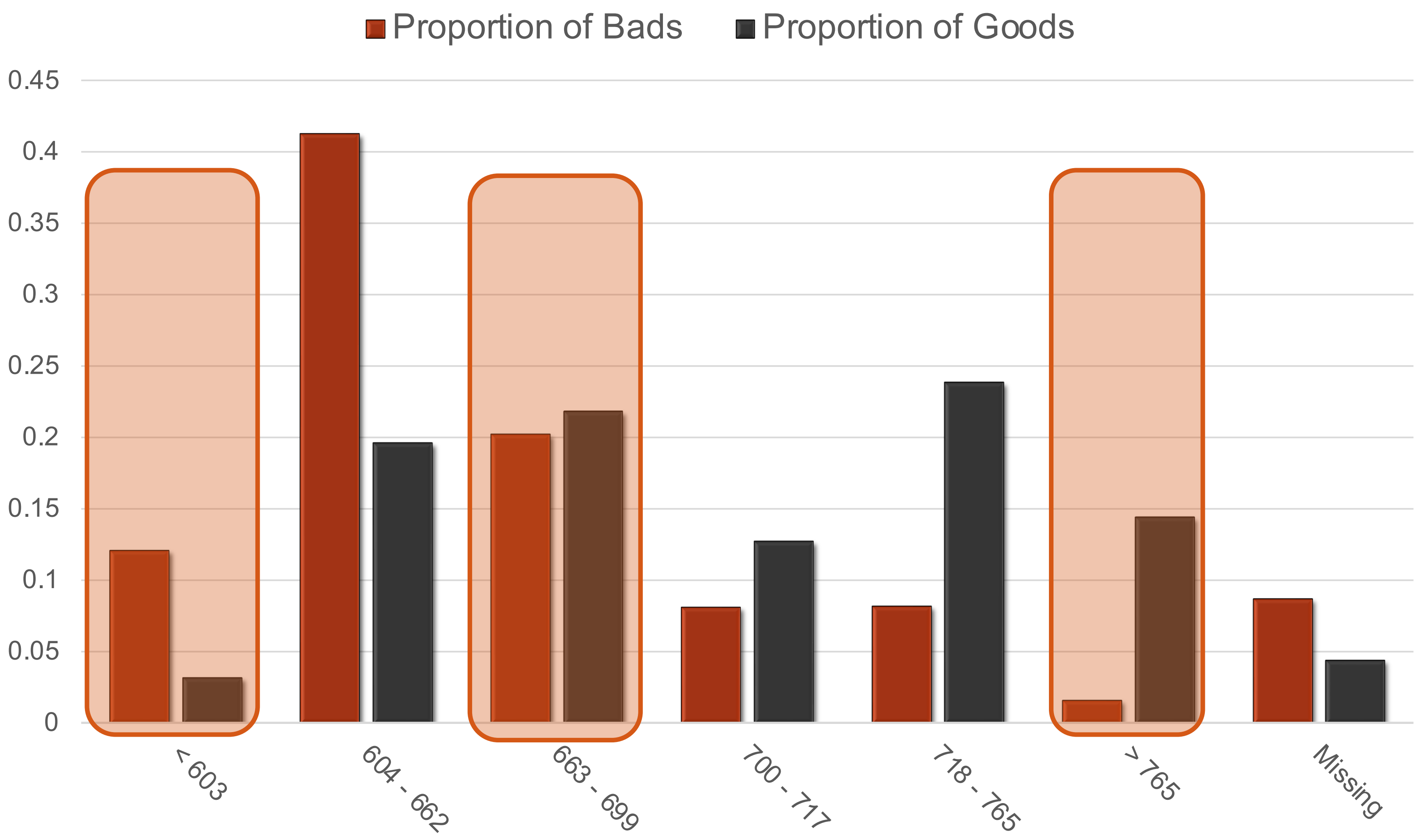
700 - 717
718 - 765
> 765
Missing

WOE – Example



Proportion of Bads
Proportion of Goods
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
< 603
604 - 662
663 - 699
700 - 717
718 - 765
> 765
Missing

WOE – Example

WOE for Bureau Score				
Group	Values	Event Count	Non-event Count	WOE
1	< 603	111	112	**-1.32**
2	604 – 662	378	678	
3	663 – 699	185	754	
4	700 – 717	74	440	
5	718 – 765	75	824	
6	> 765	15	498	
7	MISSING	80	153	
Total		**918**	**3,459**	

$$Dist.Good_1 = \frac{112}{3459}$$

$$= 0.032$$

$$Dist.Bad_1 = \frac{111}{918}$$

$$= 0.121$$

$$WOE_1 = \log\left(\frac{0.032}{0.121}\right)$$

$$= -1.32$$

WOE – Example

WOE for Bureau Score				
Group	Values	Event Count	Non-event Count	WOE
1	< 603	111	112	**-1.32**
2	604 – 662	378	678	**-0.74**
3	663 – 699	185	754	**0.08**
4	700 – 717	74	440	**0.46**
5	718 – 765	75	824	**1.07**
6	> 765	15	498	**2.18**
7	MISSING	80	153	**-0.68**
Total		**918**	**3,459**	

Weight of Evidence (WOE)

- WOE measures the strength of the attributes of a characteristic in **separating good and bad accounts**.

$$WOE_i = \log\left(\frac{Dist.Good_i}{Dist.Bad_i}\right)$$

- WOE approximately zero implies what?

Weight of Evidence (WOE)

- WOE measures the strength of the attributes of a characteristic in **separating good and bad accounts**.

$$WOE_i = \log\left(\frac{Dist.Good_i}{Dist.Bad_i}\right)$$

- WOE approximately zero implies % good approximately equal to % bad so group doesn’t separate good vs. bad well.

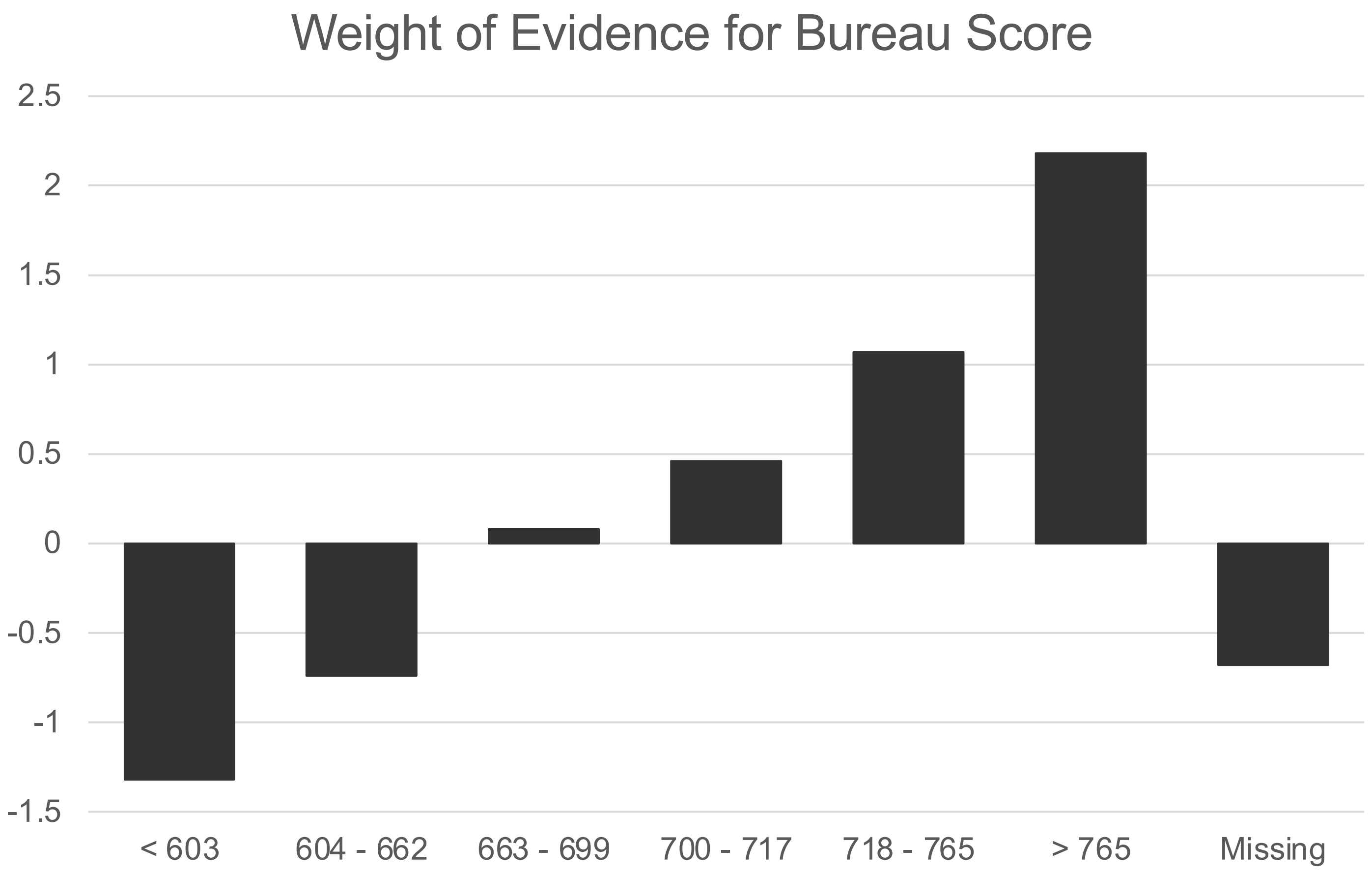
Weight of Evidence (WOE)

- WOE measures the strength of the attributes of a characteristic in **separating good and bad accounts**.

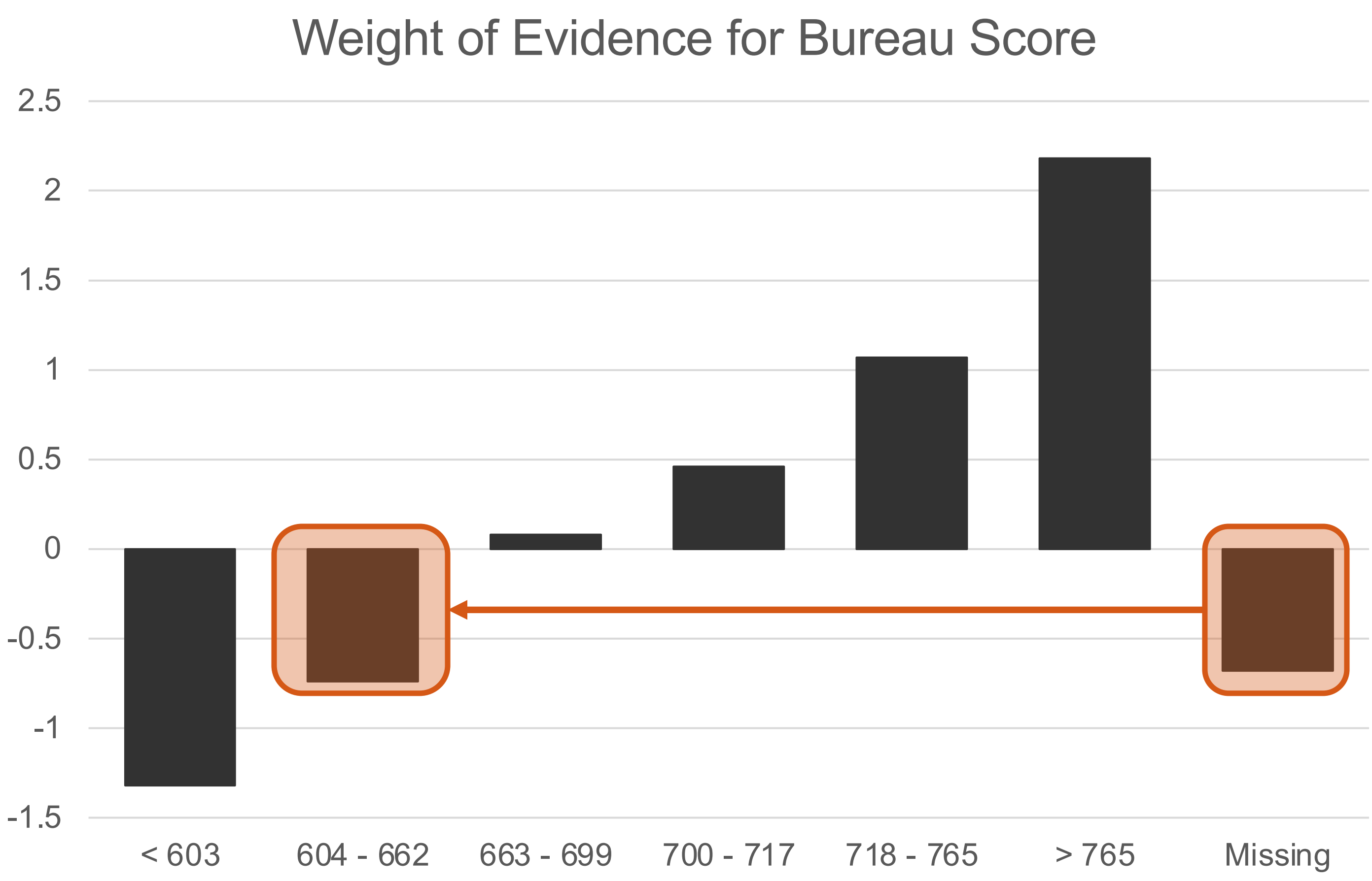
$$WOE_i = \log\left(\frac{Dist.Good_i}{Dist.Bad_i}\right)$$

- WOE approximately zero implies % good approximately equal to % bad so group doesn't separate good vs. bad well.
- WOE positive implies group identifies people who are good.
- WOE negative implies group identifies people who are bad.

WOE – Example


Weight of Evidence for Bureau Score
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
< 603
604 - 662
663 - 699
700 - 717
718 - 765
> 765
Missing

WOE – Example


Weight of Evidence for Bureau Score
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
< 603
604 - 662
663 - 699
700 - 717
718 - 765
> 765
Missing

WOE – R

```
result <- smbinning(df = train, y = "good", x = "bureau_score")
result$ivtable
```

```
##   Cutpoint CntRec CntGood CntBad CntCumRec CntCumGood CntCumBad PctRec
## 1   <= 603    223     112    111       223        112       111 0.0509
## 2   <= 662   1056     678    378      1279        790       489 0.2413
## 3   <= 699    939     754    185      2218       1544       674 0.2145
## 4   <= 717    514     440     74      2732       1984       748 0.1174
## 5   <= 765    899     824     75      3631       2808       823 0.2054
## 6    > 765    513     498     15      4144       3306       838 0.1172
## 7  Missing    233     153     80      4377       3459       918 0.0532
## 8    Total   4377    3459    918        NA         NA        NA 1.0000

##   GoodRate BadRate    Odds LnOdds     WoE     IV
## 1   0.5022  0.4978  1.0090 0.0090 -1.3176 0.1167
## 2   0.6420  0.3580  1.7937 0.5843 -0.7423 0.1602
## 3   0.8030  0.1970  4.0757 1.4050  0.0785 0.0013
## 4   0.8560  0.1440  5.9459 1.7827  0.4562 0.0213
## 5   0.9166  0.0834 10.9867 2.3967  1.0701 0.1675
## 6   0.9708  0.0292 33.2000 3.5025  2.1760 0.2777
## 7   0.6567  0.3433  1.9125 0.6484 -0.6781 0.0291
## 8   0.7903  0.2097  3.7680 1.3265  0.0000 0.7738
```

WOE – R

```
result$cut

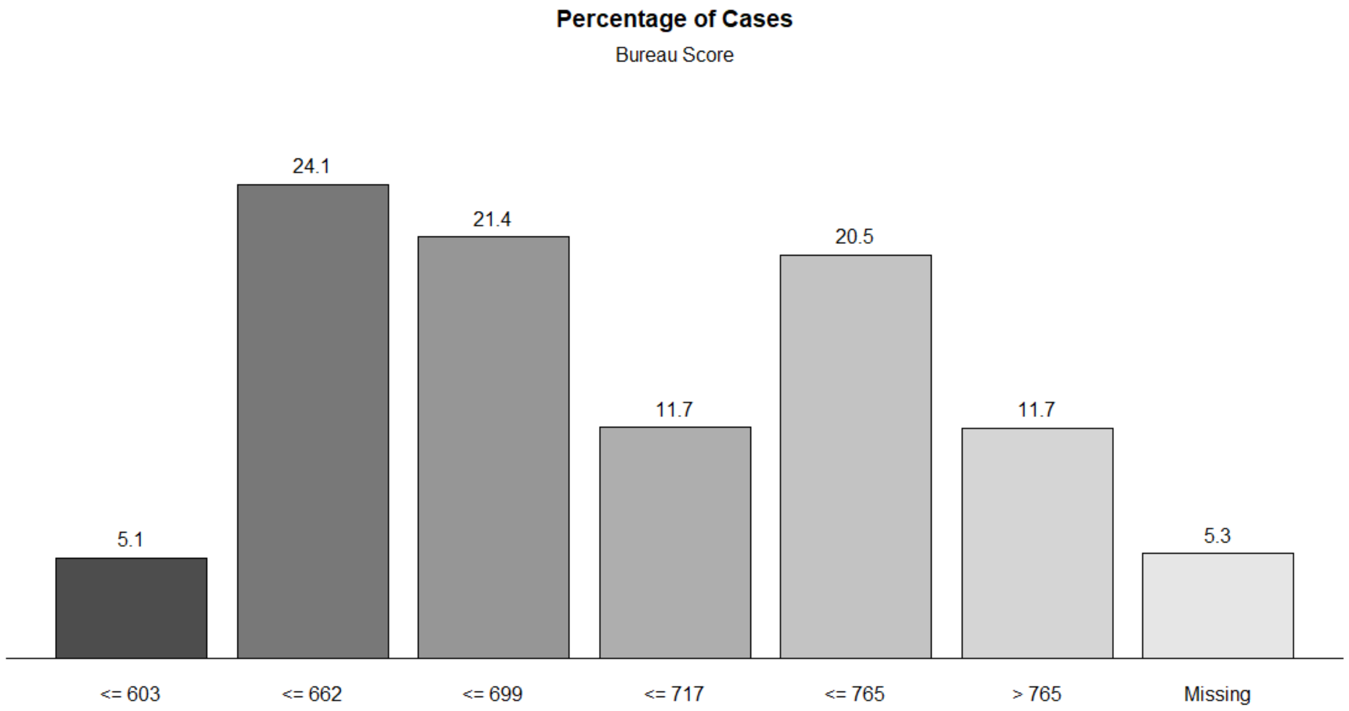
## [1] 603 662 699 717 765

result$iv

## [1] 0.7738
```

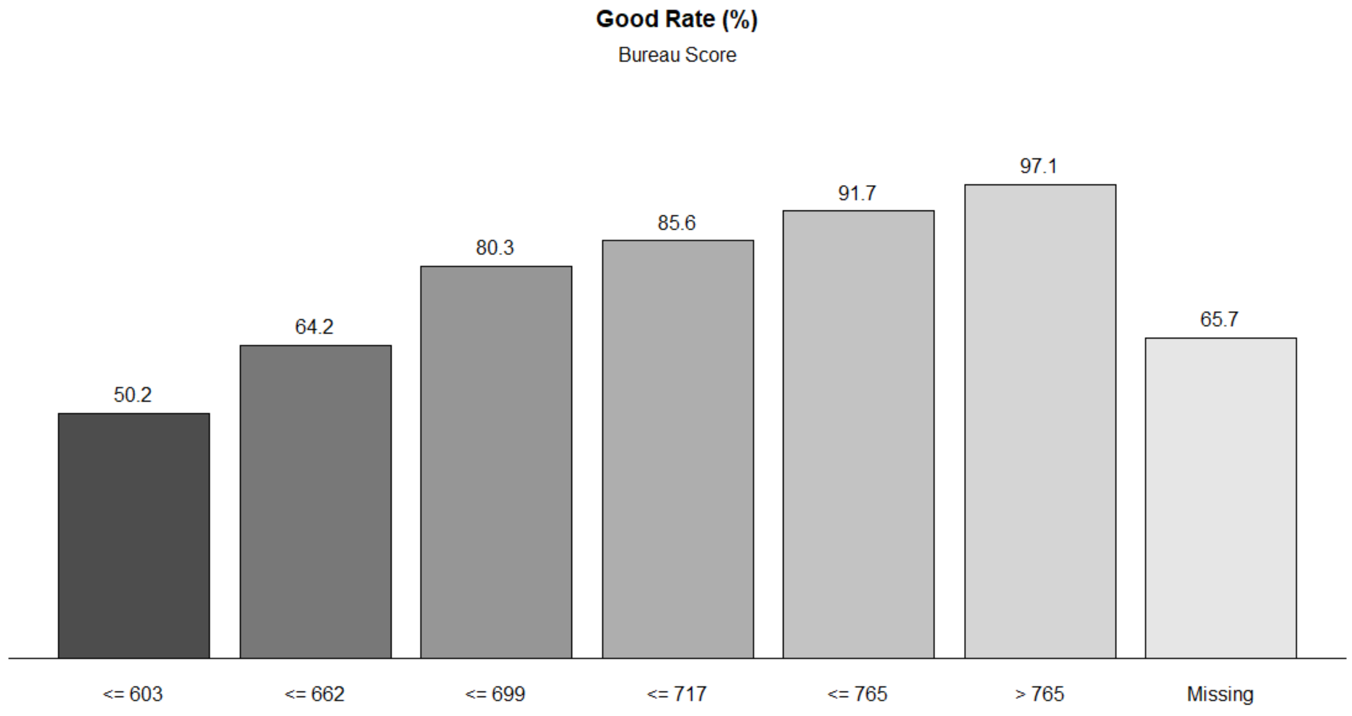
WOE – R

```
smbinning.plot(result, option = "dist", sub = "Bureau Score")
```



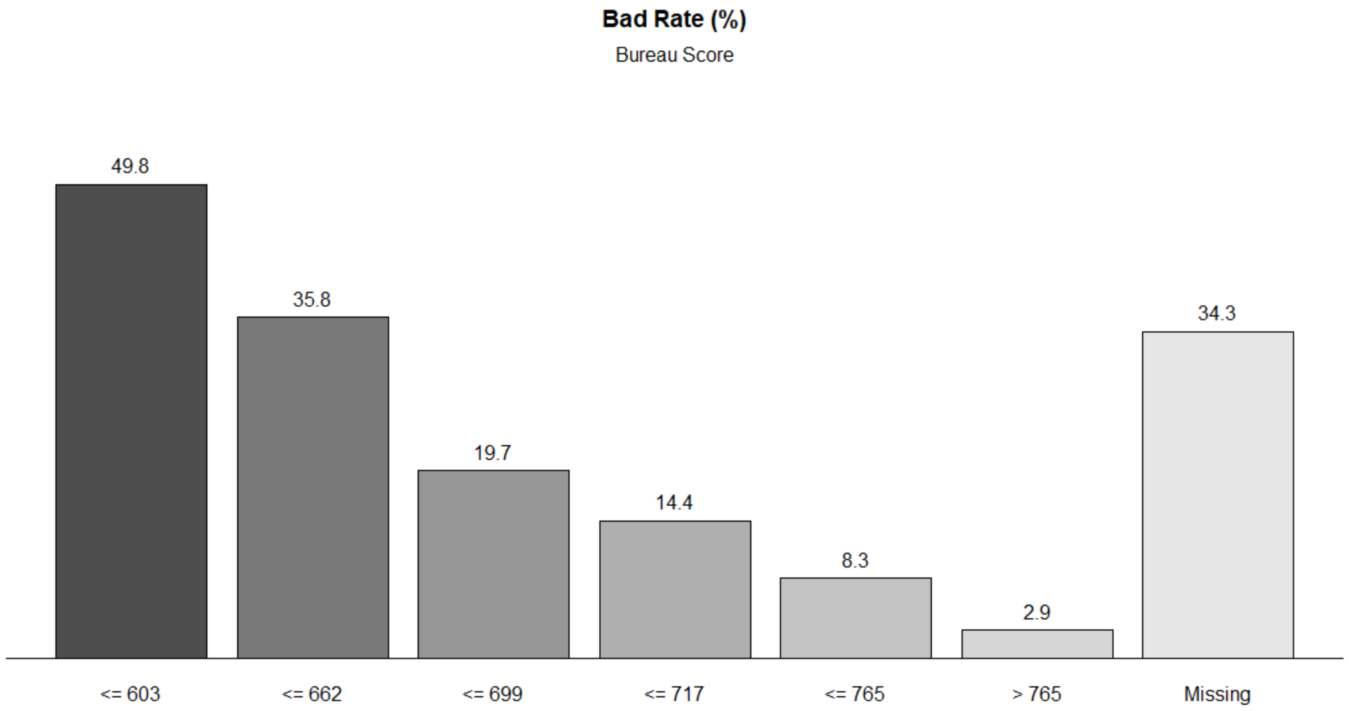
WOE – R

```
smbinning.plot(result, option = "goodrate", sub = "Bureau Score")
```



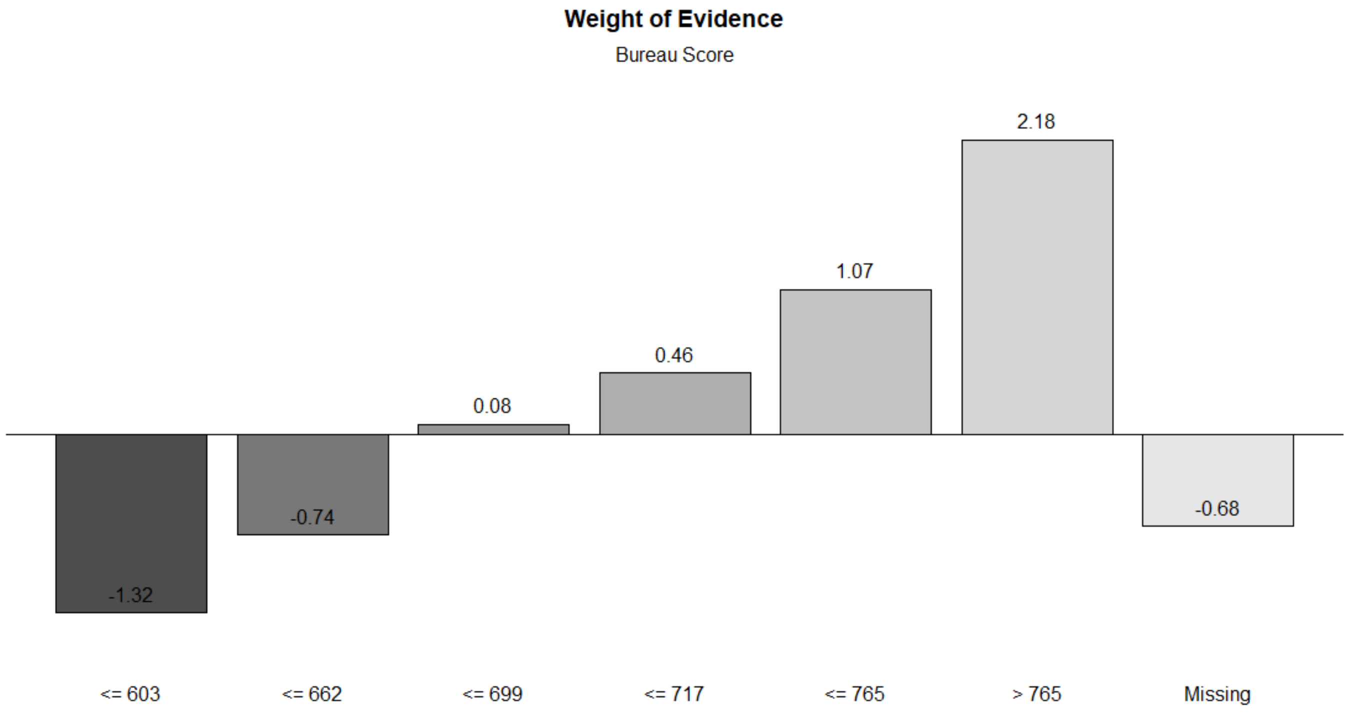
WOE – R

```
smbinning.plot(result, option = "badrate", sub = "Bureau Score")
```



WOE – R

```
smbinning.plot(result, option = "WoE", sub = "Bureau Score")
```



WOE – R

```
result <- smbinning.factor(df = train, y = "good", x = "purpose")
result$ivtable
```

```
##    Cutpoint CntRec CntGood CntBad CntCumRec CntCumGood CntCumBad PctRec
## 1 = 'LEASE'   1466    1149    317      1466       1149       317 0.3349
## 2  = 'LOAN'   2911    2310    601      4377       3459       918 0.6651
## 3   Missing      0       0      0      4377       3459       918 0.0000
## 4     Total   4377    3459    918        NA         NA        NA 1.0000

##   GoodRate BadRate   Odds LnOdds     WoE     IV
## 1   0.7838  0.2162 3.6246 1.2877 -0.0388 0.0005
## 2   0.7935  0.2065 3.8436 1.3464  0.0199 0.0003
## 3      NaN     NaN    NaN    NaN     NaN    NaN
## 4   0.7903  0.2097 3.7680 1.3265  0.0000 0.0008
```

Separation Issues Remain

- Quasi-complete separation still a problem:

	Non-Event	Event	WOE
A	28	7	**-0.032**
B	16	0	∞
C	94	11	**0.728**
D	23	21	**-1.327**
Total	**161**	**39**	

Adjusted WOE

- Adjust the WOE calculation to account for possible quasi-complete separation:

$$Adjusted\ WOE_i = \log\left(\frac{Dist.Good_i + \eta_1}{Dist.Bad_i + \eta_2}\right)$$

- The η_1 and η_2 parameters are smoothing parameters that correct for potential overfitting and also protect against quasi-complete separation.
- Most software just sets $\eta_1 = \eta_2$ and has one parameter.

Adjusted WOE ($\eta_1 = \eta_2 = 0.005$)

- Quasi-complete separation no longer a problem:

	Non-Event	Event	WOE
A	28	7	**-0.031**
B	16	0	**3.039**
C	94	11	**0.719**
D	23	21	**-1.302**
Total	**161**	**39**	

Smoothed WOE (SWOE)

- SAS has recently proposed a slightly different smoothed version of the WOE calculation to account for possible quasi-complete separation:

$$SWOE_i = \log\left(\frac{\#Bad_i + (Overall\ Prop.Bad)\times c}{\#Good_i + (Overall\ Prop.Good)\times c}\right)$$

- This is just a smoothing parameter put in a slightly different place in the WOE calculation based on more Bayesian inference techniques.
- Haven’t seen it really used elsewhere.

INFORMATION VALUE

Information Value (IV)

- How big is a “big” difference when looking across groups for WOE?
- IV measures the ability of the characteristic to separate goods vs. bads.

$$IV = \sum_{i=1}^{L} (Dist.Good_i - Dist.Bad_i) \times \log\left(\frac{Dist.Good_i}{Dist.Bad_i}\right)$$

Information Value (IV)

- How big is a “big” difference when looking across groups for WOE?
- IV measures the ability of the characteristic to separate goods vs. bads.

$$IV = \sum_{i=1}^{L} (Dist.Good_i - Dist.Bad_i) \times \boxed{\log\left(\frac{Dist.Good_i}{Dist.Bad_i}\right)}$$

Weight of Evidence!

Information Value (IV)

- How big is a “big” difference when looking across groups for WOE?
- IV measures the ability of the characteristic to separate goods vs. bads.

$$IV = \sum_{i=1}^{L} (Dist.Good_i - Dist.Bad_i) \times \log\left(\frac{Dist.Good_i}{Dist.Bad_i}\right)$$

- Used to select characteristics with strong predictive value.

Information Value (IV)

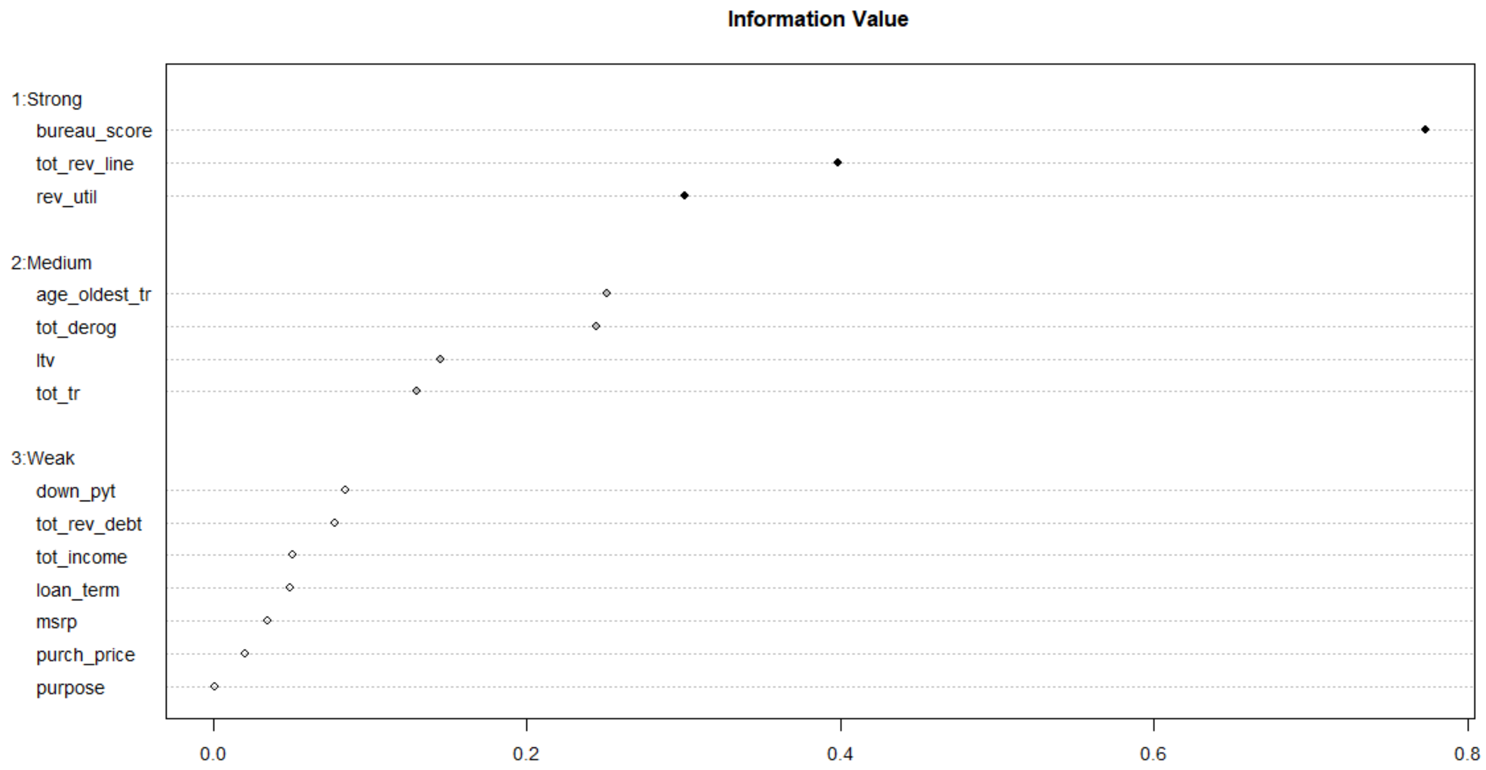
- Characteristics of IV:
  - $IV \geq 0$
  - Bigger is Better!

- Rules of Thumb:
  - IV < 0.02 – Not predictive
  - 0.02 < IV < 0.1 – Weak predictor
  - 0.1 < IV < 0.25 – Medium predictor
  - 0.25 < IV – Strong predictor

Information Value (IV) – R

```
iv_summary <- smbinning.sumiv(df = train, y = "good")

smbinning.sumiv.plot(iv_summary)
```



Information Value (IV) – R

```
iv_summary

##               Char     IV              Process
## 12  bureau_score 0.7738    Numeric binning OK
## 10  tot_rev_line 0.3987    Numeric binning OK
## 11      rev_util 0.3007    Numeric binning OK
## 6  age_oldest_tr 0.2512    Numeric binning OK
## 4      tot_derog 0.2443    Numeric binning OK
## 19           ltv 0.1454    Numeric binning OK
## 5         tot_tr 0.1304    Numeric binning OK
## 15      down_pyt 0.0848    Numeric binning OK
## 9   tot_rev_debt 0.0782    Numeric binning OK
## 20    tot_income 0.0512    Numeric binning OK
## 17     loan_term 0.0496    Numeric binning OK
## 14          msrp 0.0353    Numeric binning OK
## 13   purch_price 0.0204    Numeric binning OK
## 16       purpose 0.0008     Factor binning OK
## 1     bankruptcy     NA    Uniques values < 5
## 2            bad     NA    Uniques values < 5
## 3         app_id     NA No significant splits
## 7    tot_open_tr     NA No significant splits
## 8     tot_rev_tr     NA No significant splits
## 18      loan_amt     NA No significant splits
## 21      used_ind     NA    Uniques values < 5
## 22        weight     NA    Uniques values < 5
```

Information Value (IV) – R

```
iv_summary

##                Char     IV                 Process
## 12  bureau_score 0.7738     Numeric binning OK
## 10  tot_rev_line 0.3987     Numeric binning OK
## 11      rev_util 0.3007     Numeric binning OK
## 6  age_oldest_tr 0.2512     Numeric binning OK
## 4      tot_derog 0.2443     Numeric binning OK
## 19           ltv 0.1454     Numeric binning OK
## 5         tot_tr 0.1304     Numeric binning OK
## 15      down_pyt 0.0848     Numeric binning OK
## 9   tot_rev_debt 0.0782     Numeric binning OK
## 20    tot_income 0.0512     Numeric binning OK
## 17     loan_term 0.0496     Numeric binning OK
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## 13   purch_price 0.0204     Numeric binning OK
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## 1     bankruptcy     NA     Uniques values < 5
## 2            bad     NA     Uniques values < 5
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## 18      loan_amt     NA No significant splits
## 21      used_ind     NA     Uniques values < 5
## 22        weight     NA     Uniques values < 5
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Information Value (IV) – R

```
iv_summary

##              Char     IV               Process
## 12  bureau_score 0.7738    Numeric binning OK
## 10  tot_rev_line 0.3987    Numeric binning OK
## 11      rev_util 0.3007    Numeric binning OK
## 6   age_oldest_tr 0.2512    Numeric binning OK
## 4      tot_derog 0.2443    Numeric binning OK
## 19           ltv 0.1454    Numeric binning OK
## 5         tot_tr 0.1304    Numeric binning OK
## 15      down_pyt 0.0848    Numeric binning OK
## 9   tot_rev_debt 0.0782    Numeric binning OK
## 20    tot_income 0.0512    Numeric binning OK
## 17     loan_term 0.0496    Numeric binning OK
## 14          msrp 0.0353    Numeric binning OK
## 13   purch_price 0.0204    Numeric binning OK
## 16       purpose 0.0008     Factor binning OK
## 1      bankruptcy     NA    Uniques values < 5
## 2             bad     NA    Uniques values < 5
## 3          app_id     NA No significant splits
## 7     tot_open_tr     NA No significant splits
## 8      tot_rev_tr     NA No significant splits
## 18      loan_amt     NA No significant splits
## 21      used_ind     NA    Uniques values < 5
## 22        weight     NA    Uniques values < 5
```

Information Value (IV) – R

```
iv_summary

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## 12  bureau_score 0.7738    Numeric binning OK
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```

Information Value (IV)

- Characteristics of IV:
  - $IV \geq 0$
  - Bigger is Better!

- Rules of Thumb:
  - IV < 0.02 – Not predictive
  - 0.02 < IV < 0.1 – Weak predictor
  - 0.1 < IV < 0.25 – Medium predictor
  - 0.25 < IV < 0.5 – Strong predictor
  - IV > 0.5 – Over-predicting?

Information Value (IV)

- Rules of Thumb:
  - IV < 0.02 – Not predictive
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  - 0.1 < IV < 0.25 – Medium predictor
  - 0.25 < IV < 0.5 – Strong predictor
  - IV > 0.5 – Over-predicting?
- Over-predicting Example:
  - All previous mortgage decisions have been made only on bureau score so of course bureau score is highly predictive – becomes only significant variable!
  - Create two models – one with bureau score, one without bureau score and **ensemble**.

GINI STATISTIC

Gini Statistic

- **Gini statistic** is optional technique that tries to answer the same question as Information Value – which variables are strong enough to enter the scorecard model?
- IV is more in line with WOE calculation and used more often.
- Characteristics:
  - Range is 0 to 100.
  - Bigger is Better.

Gini Statistic Calculation

- More complicated technique for trying to evaluate how characteristics separate good from bad.
- Majority of the time Gini and IV agree, but could be different on the borderline cases.
- Calculation:
  - Sort *L* groups of variable by descending order of the proportion of all events.

$$Gini = \left(1 - \frac{\left(2\sum_{i=2}^{L}\left(n_{i,E} \times \sum_{i=1}^{i-1} n_{i,NE}\right) + \sum_{i=1}^{L}\left(n_{i,E} \times n_{i,NE}\right)\right)}{N_E \times N_{NE}}\right) \times 100$$

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Number of events in group *i*

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Number of non-events in group *i*

Gini Statistic Calculation

- More complicated technique for trying to evaluate how characteristics separate good from bad.
- Majority of the time Gini and IV agree, but could be different on the borderline cases.
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$$Gini = \left(1 - \frac{\left(2\sum_{i=2}^{L}\left(n_{i,E} \times \sum_{i=1}^{i-1} n_{i,NE}\right) + \sum_{i=1}^{L}\left(n_{i,E} \times n_{i,NE}\right)\right)}{N_E \times N_{NE}}\right) \times 100$$

Total number of events and non-events

PROC BINNING IN SAS VIYA

WOE – SAS Viya

```
proc binning data = public.train method = tree(initbin = 100
               maxnbins = 10);
   target bad / level = int;
   input bureau_score / level = int;
   ods output BinDetails = bincuts VarTransInfo = bincount;
run;
```

WOE – SAS Viya

Bin Details										
Variable	Bin ID	Lower Bound	Upper Bound	Bin Width	N Levels	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
bureau_score										

WOE – SAS Viya

Transformation Information					
Variable	**N**	**N Miss**	**N Bins**	**Importance**	**Relative Importance**
bureau_score					

WOE – SAS Viya

```
data _null_;
   set bincount;
   call symput('numbin', Nbins - 1);
run;

proc sql;
   select Max
      into :cuts separated by ' '
      from bincuts(firstobs = 2 obs = &numbin);
quit;

proc binning data = public.train numbin = &numbin
             method=cutpts(&cuts) woe;
   target bad / event = '1';
   input bureau_score / level = int;
run;
```

WOE – SAS Viya

Bin Details							
Variable	Bin ID	Lower Bound	Upper Bound	Bin Width	Number of Observations	Mean	Standard Deviation
bureau_score							

WOE – SAS Viya

Bin Details						
Variable	**Bin ID**	**Minimum**	**Maximum**	**Event Count**	**Weight of Evidence**	**Information Value**
bureau_score						

WOE – SAS Viya

Variable Information Value	
Variable	**Information Value**
bureau_score	

WOE – SAS Viya

```
proc tabulate data=public.train out=facwoe;
   class bad purpose;
   table purpose, bad*colpctn / rts=10;
run;

proc transpose data = facwoe out = facwoe2(rename=
                                   (col1 = bad0 col2 = bad1));
   var PctN_10;
   by purpose;
run;

data facwoe2;
   set facwoe2;
   WOE = log(bad1/bad0);
run;
```

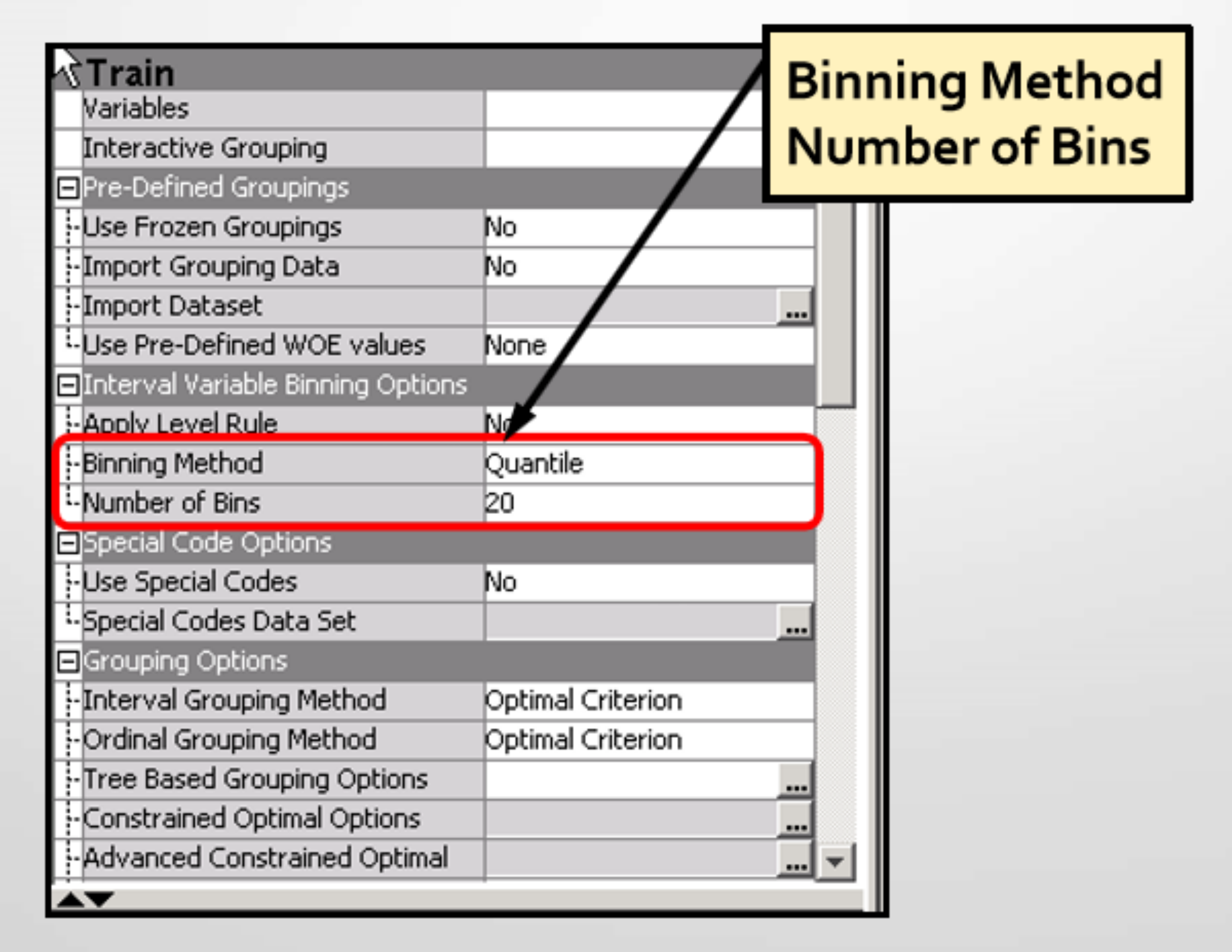
WOE – SAS Viya

	bad	
	0	1
	ColPctN	ColPctN
purpose		
LEASE		
LOAN		

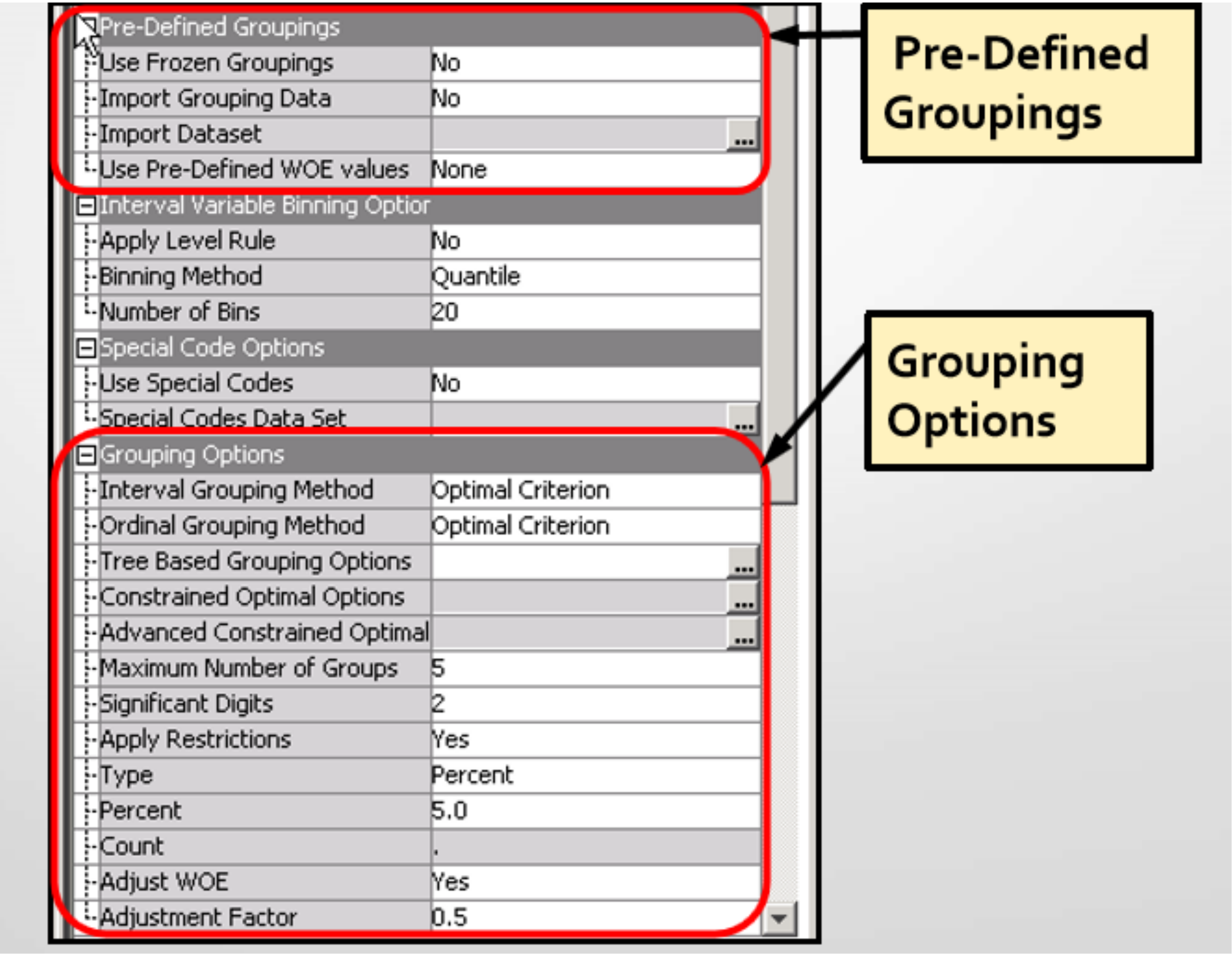
Obs	purpose	_NAME_	bad0	bad1	WOE
1					
2					

INTERACTIVE GROUPING NODE IN SAS EM

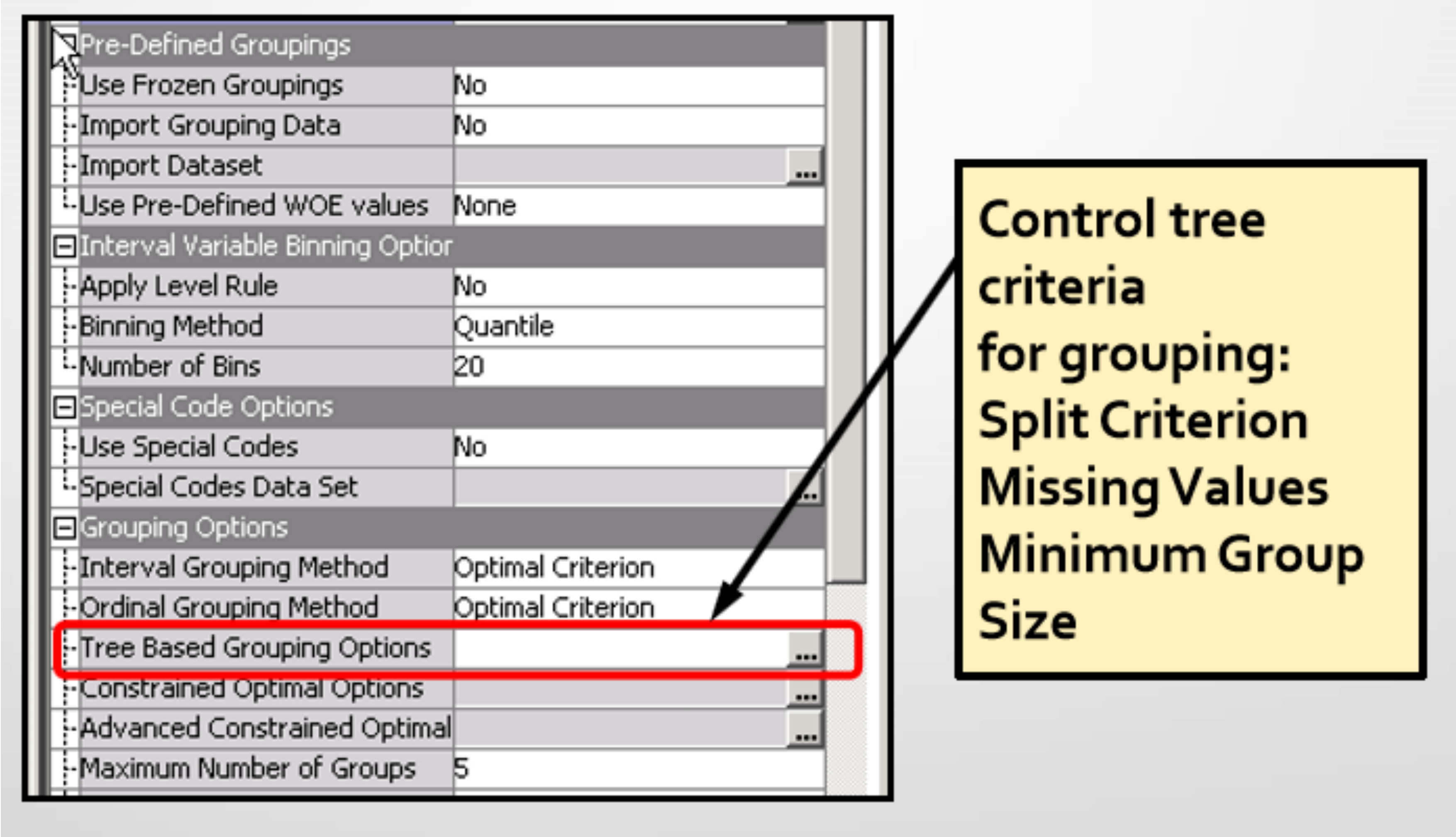
Pre-Binning of the Interval Variables



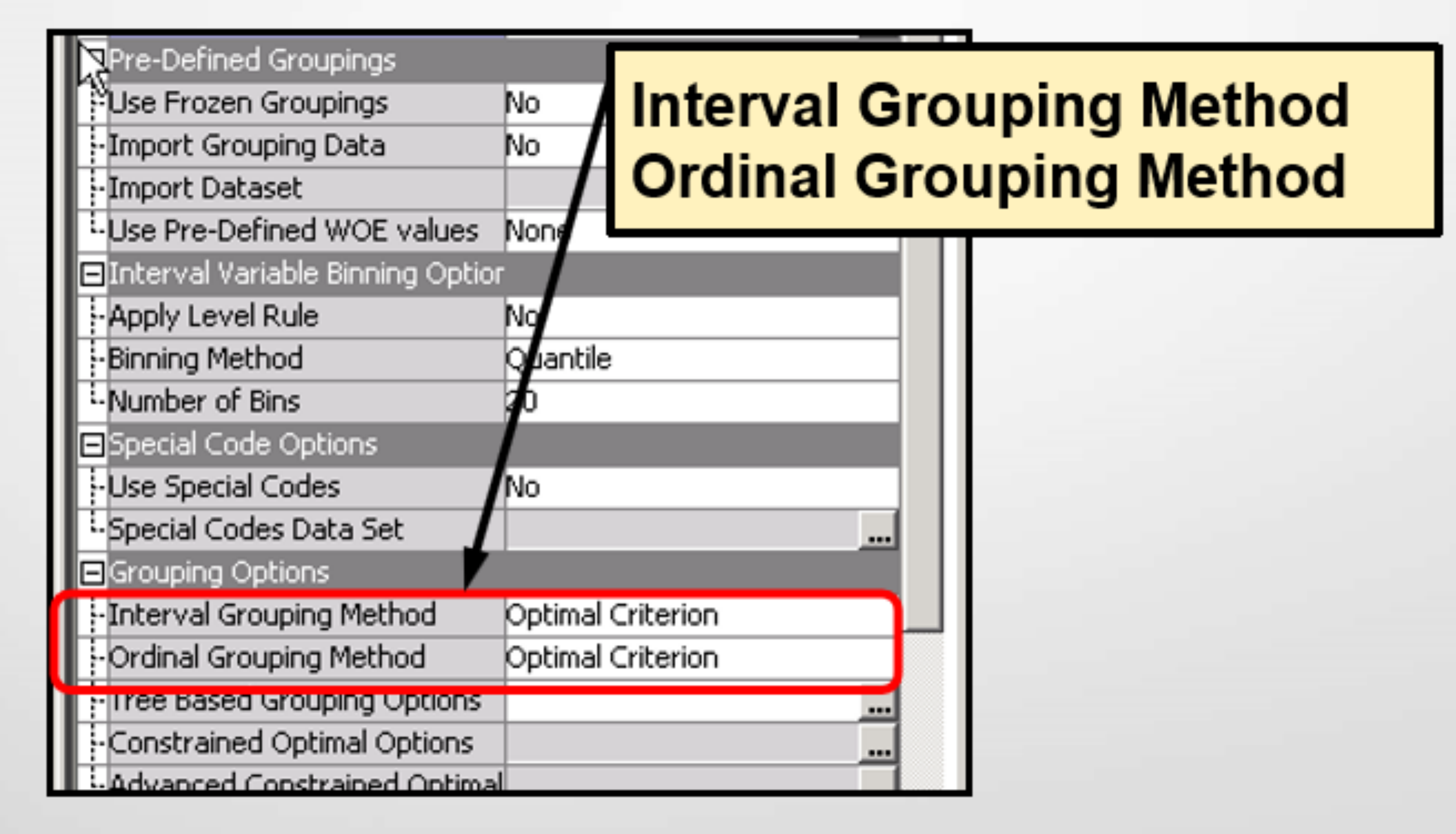
Grouping Options



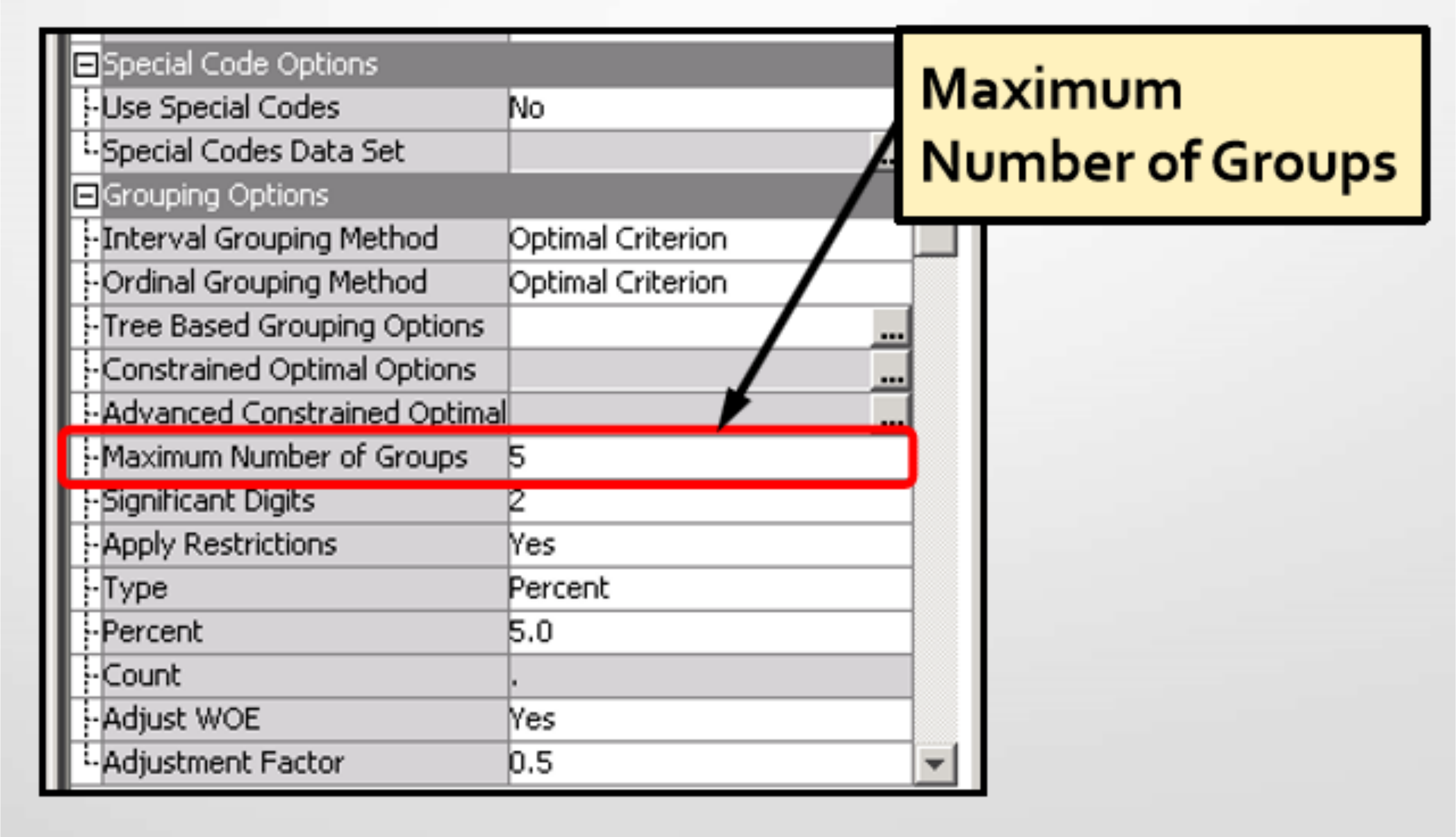
Grouping Options: Tree Criteria



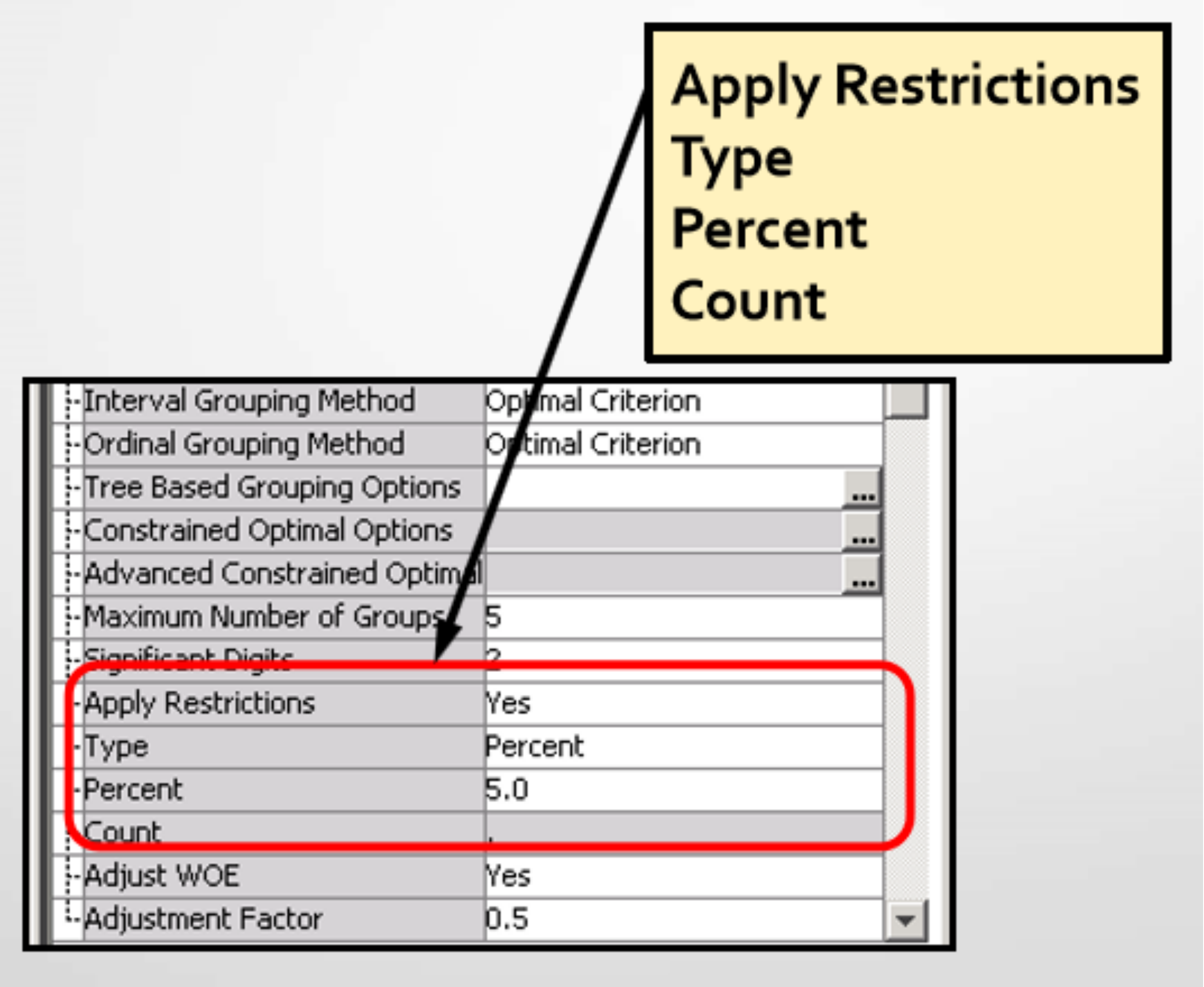
Grouping Options: Interval vs. Ordinal



Grouping Options: Number of Groups



Grouping Options: Stopping Rules



Grouping Options: WOE Adjustments