Credit Risk Model Building Steps

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Disclaimer

- This presentation is just the class notes. The best way to treat this is as a high-level summary;
- The actual session went more in-depth and contained other information.
- Most of this material was written as informal notes, not intended for publication
- Prerequisites:
  - Basic knowledge of Credit Risk and Predictive modeling
  - Practical Business Analytics Using SAS: A Hands-on Guide http://www.amazon.com/Practical-Business-Analytics-Using-Hands/dp/1484200446

Credit Risk Model Building Steps

- Objective
- Exclusions
- Observation point and/or window
- Performance window
- Bad definition
- Segmentation
- Variable selection
- Regression Line
- Model validation
- Model recalibration

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Initial Discussions

- Do we need a model? What type of model?

  Issue, portfolio size, performance, growth plans, competitive and economic environment

- Can we build a model?

  Data availability and integrity, legal/regulatory environment

- Can we implement a model?

  Project management and system development resources

- Can we use the model in a strategy?

  What decision can we make differently by using score

- Can we prioritize the model in regional plan?

  Evaluate the capacity of regional plan and the necessity of the model

Initial Discussions

Project Objectives

- Business Issue and Size of Problem/Driver for Score Development, Potential Strategic Score Uses, Estimated Project Impact (NCL, collection expenses, revenue, others)

Business Overview

- Products, Target Market, Economic Environment, Cultural Influences, Product Features and MIS, Collection and Other Policies, Existing Scores

Data Availability and Implementation Restrictions

- Data Files and Systems, File Layouts and Data Dictionaries

Scope of Score

- **Customer Score vs Account Score**
  - Often in the use of the day to day operation the business prefer to have a customer view not an account view. Why ?
- **Scope of the score**
  - Be clear about the objective of the score. Information about the scope of the score and the product business operation should be collected during project initiation.
- For ECM and collections scores all the customer accounts data is used during development. Why? and why only for ECM and collections

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Exclusions

- What are exclusions?
- Why we need to apply exclusions?
- Exclusions are discussed with the business prior to start project design. During project design the impact of each exclusion is measured and additional exclusion could be proposed
- Observation Exclusions
- Performance exclusions

Exclusions.....examples

- Possible Observation Period Exclusions
  - Fraud cases
  - Credit policy deviations that can include age, income, loan amount, debt burden, tenure etc.
  - Credit Policy Fatal Criteria
  - Test Accounts (what are these?)

- Possible Performance Exclusions
  - Fraud Cases
  - Deceased customers
  - Indeterminate

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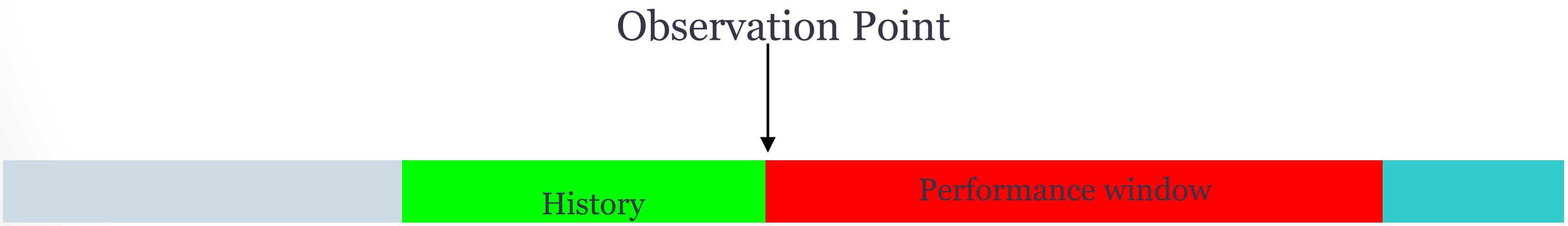
Observation Point

- Observation Point :Time period used to define the modeling population/ sample.
  - The period needs to be representative of the current/future scoring environment.
  - Only variables showing applicant/account behavior or characteristics at time of observation or prior to that can be used in model development. Why?

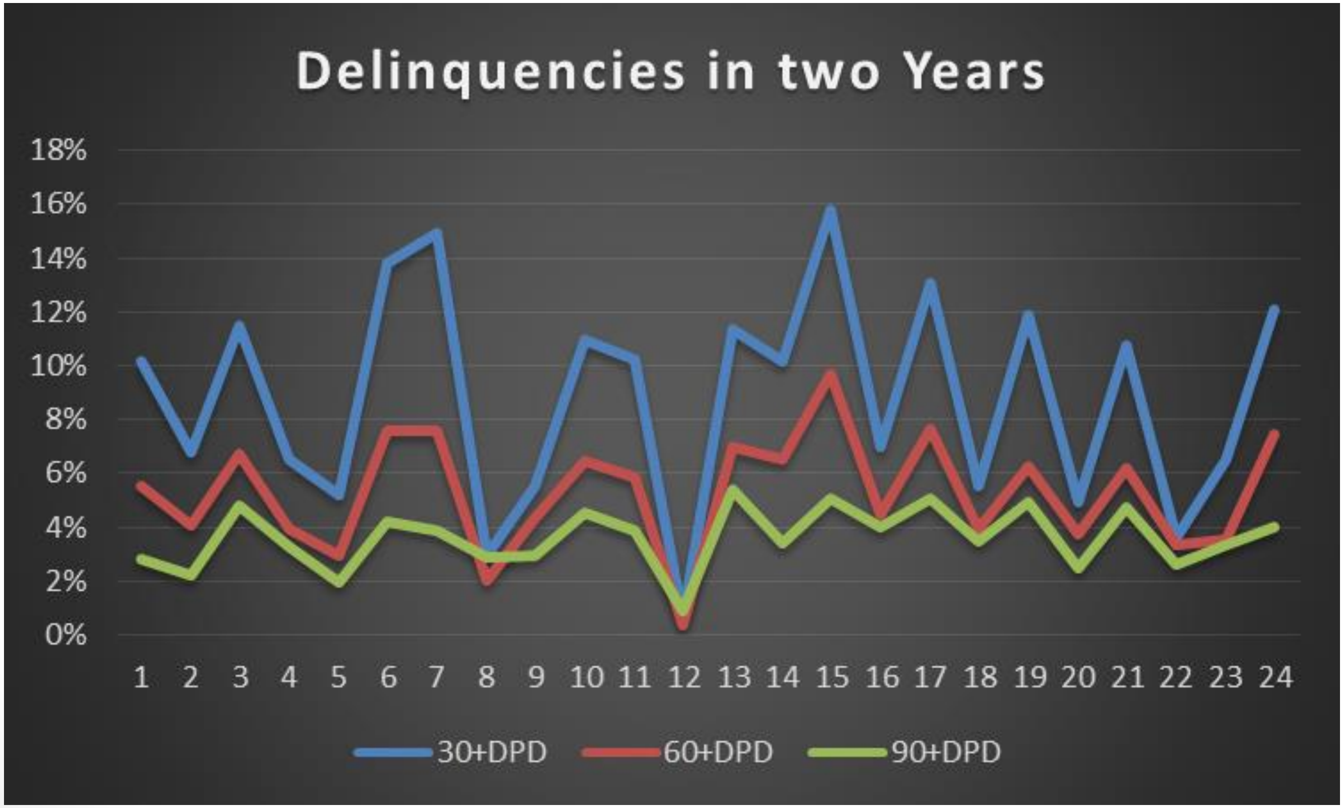


Performance window

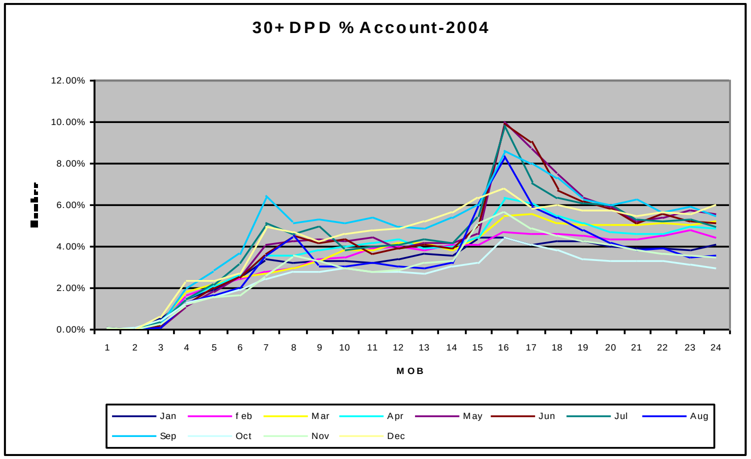
- What is performance window?
- Key factors in choosing Performance period are :
  - Window should be long enough to ensure accounts have sufficient time for their performance to mature
  - Sufficient number of goods and bads are there
- Choosing optimal performance window could be done using **Vintage Analysis**.

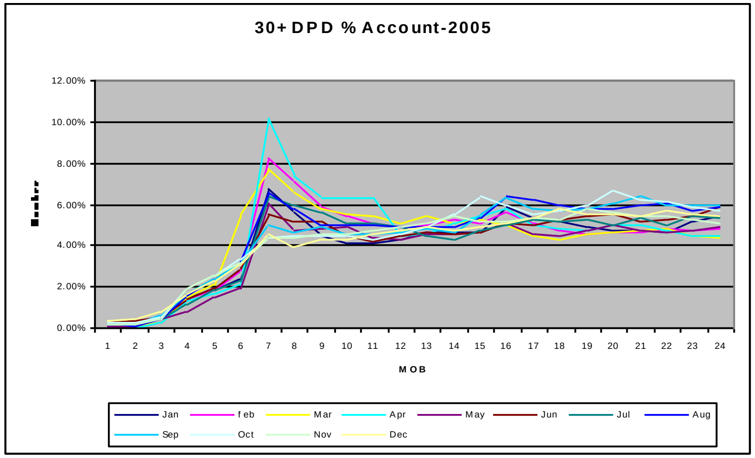
Vintage Analysis to decide Performance window

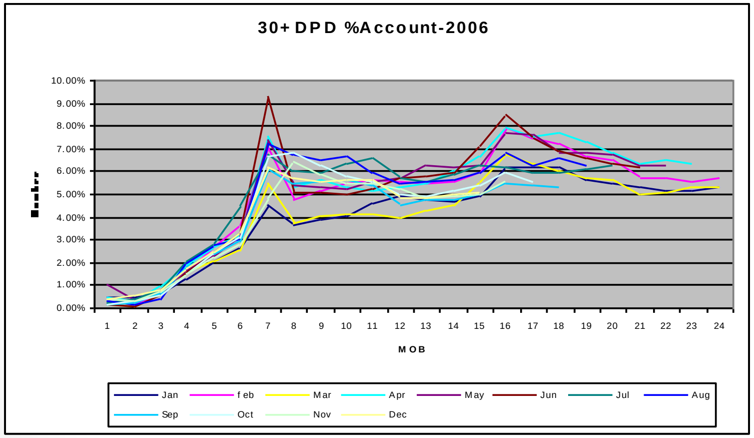
- Minimum number of months required to capture the default
- How much time does it take to get defaulted
- Look at the previous delinquencies for the accounts

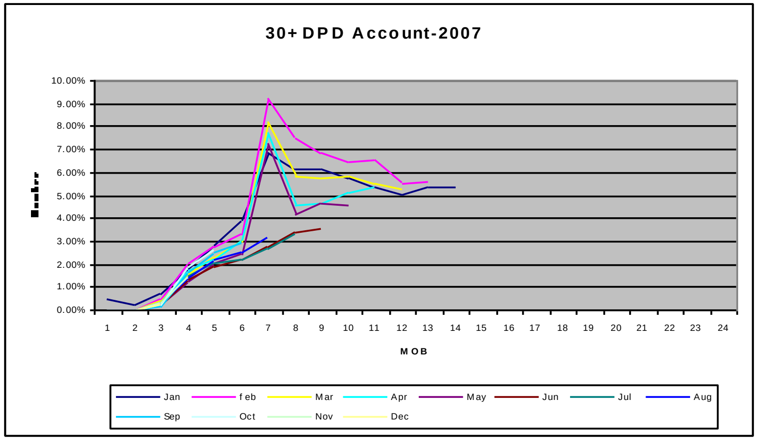


30+ DPD % Account By Vintage and MOB



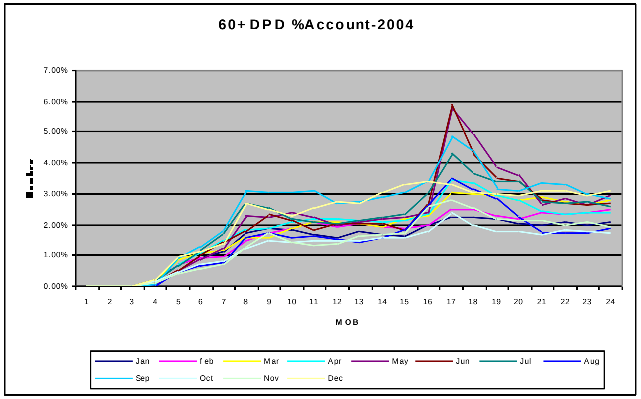


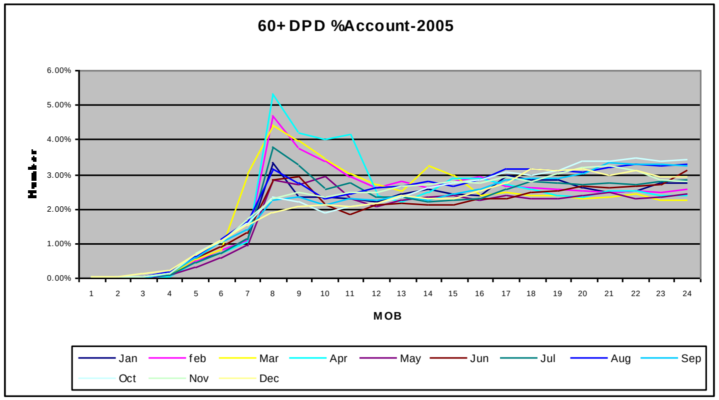


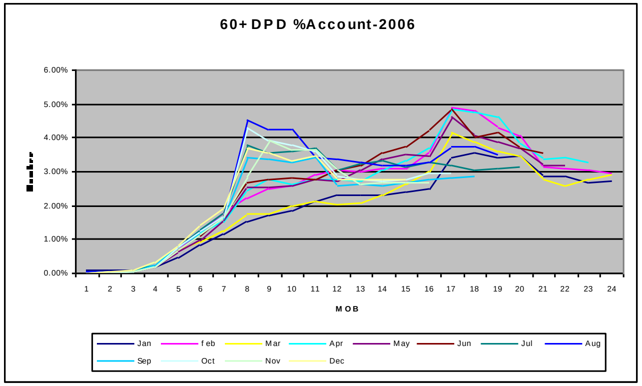


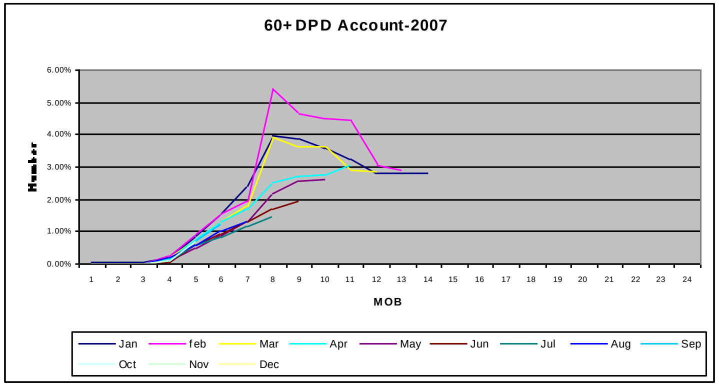
- 30+ DPD Count is getting stabilized at MOB 18

60+ DPD % Account By Vintage and MOB



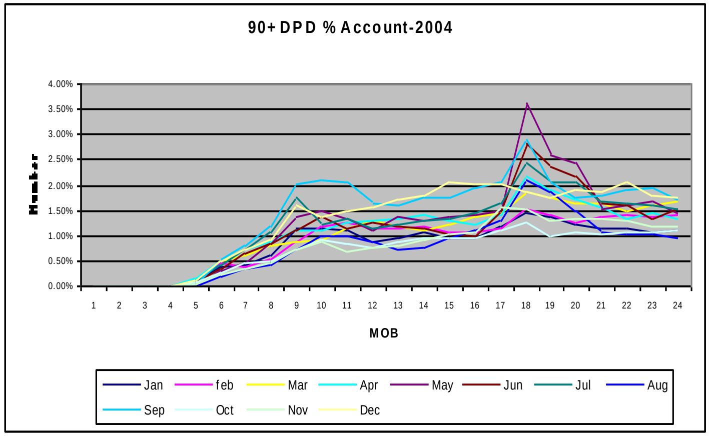


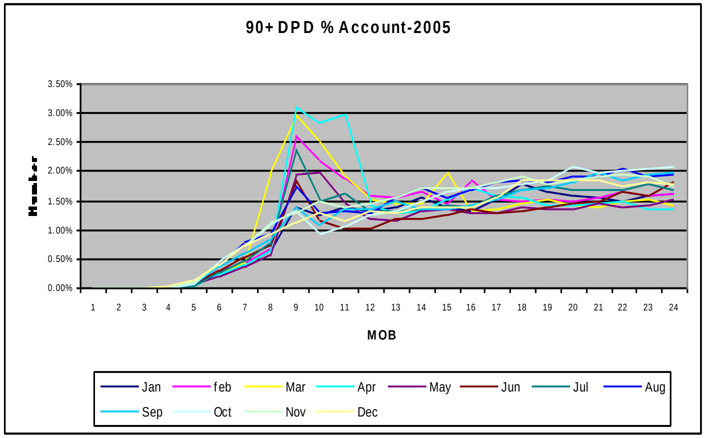


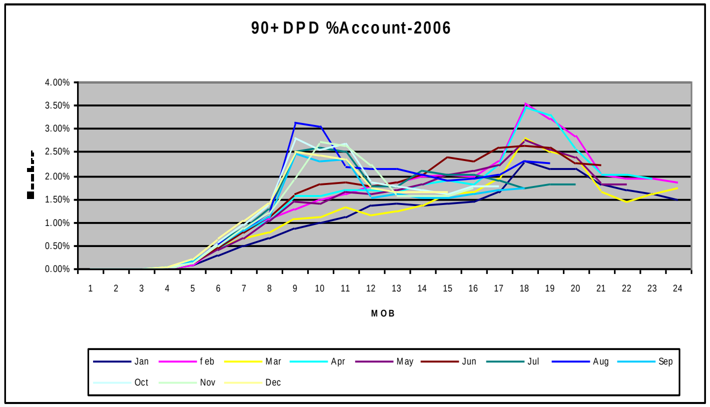


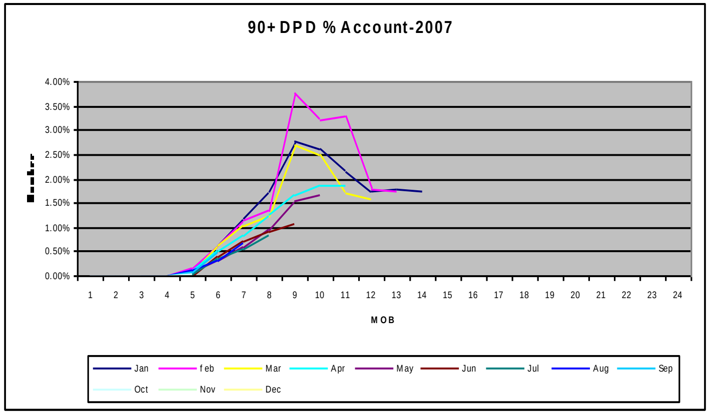
60+ DPD is getting stabilized at MOB 18

90+ DPD Count By Vintage and MOB









- 90+ DPD is getting stabilized at MOB 18

Vintage analysis-Conclusion

- For Counts , the peak is occurring at 7 MOB for 30+, at 8 MOB for 60+ and 9 MOB for 90+.
- For Counts, there are peaks at 16, 28, 40 MOB for 30+. Similarly, these peaks occur for 60+ and 90+ at 17, 29, 41 MOB and 18 , 30, 42 MOB respectively.
- Peak delinquency followed by stable delinquency rates occur within the first 18 months of performance.
- So the performance window is 18 months

Lab: Vintage Analysis

- Download Credit Risk Vintage Data
- Draw 30+ DPD, 60+ DPD, 90+DPD graphs
- Write your observations
- What is the peak month with respect to delinquencies?
- Decide the performance window

Model Building steps

- Objective
- Exclusions
- Observation point and/or window
- Performance window
- **Bad definition**
- Segmentation
- Variable selection
- Regression Line
- Model validation
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‘Bad’ Definition

- Bankruptcy is the only form of bad?
- Can 160+ delinquent be bad?
- A customer or a loan is bad when, due to lack of repayment, the customer or loan must to be charged off.
- Typically, the concern is to catch the “MOST BAD” account in the shortest performance window.

‘Bad’ Definition

- So what should we use as “BAD”?
  - Ask the business how they define bad as they need to be comfortable with the definition.
  - Perform some analysis to confirm that the business’ perception of bad is accurate:
    - Roll rate analysis and waterfall analysis
    - Re-write and re-aging analysis

Bad definition

Start of the performance window

No Due	90,000
30 days due	40,000
60 days due	20,000
90 days due	10,000
120 days due	6,000
150 days due	2,000
.80 days due -B	1,000

	End- After 18 Months							
	No Due	30 days due	60 days due	90 days due	120 days due	150 days due	180 days due -BK	
No Due	78,300	4,500	3,150	1,800	1,350	630	270	90,000
30 days due	30,800	4,000	2,200	1,200	1,000	480	320	40,000
60 days due	13,400	3,000	2,100	400	300	140	660	20,000
90 days due	3,700	2,500	1,350	200	950	770	530	10,000
120 days due	1,620	480	300	120	420	1,842	1,218	6,000
150 days due	340	100	70	40	30	514	906	2,000
180 days due -BK	30	20	10	5	3	4	928	1,000

Calculation of Bad

	End- After 18 Months								
	No Due	30 days due	60 days due	90 days due	120 days due	150 days due	180 days due -BK	Rollback	Roll Forward
No Due	87.0%	5.0%	3.5%	2.0%	1.5%	0.7%	0.3%	0	13.0%
30 days due	77.0%	10.0%	5.5%	3.0%	2.5%	1.2%	0.8%	77.0%	13.0%
60 days due	67.0%	15.0%	10.5%	2.0%	1.5%	0.7%	3.3%	82%	7.5%
90 days due	37.0%	25.0%	13.5%	2.0%	9.5%	7.7%	5.3%	76%	22.5%
120 days due	27.0%	8.0%	5.0%	2.0%	7.0%	30.7%	20.3%	42%	51.0%
150 days due	17.0%	5.0%	3.5%	2.0%	1.5%	25.7%	45.3%	29%	45.3%
180 days due -BK	3.0%	2.0%	1.0%	0.5%	0.3%	0.4%	92.8%	7%	0.0%

- How many people are 120+ dpd at the start of the year?
- How may people out them jumped below 120+ bucket (current/ 30+/60+/90+) how may people are above 120+ (150+/180+)
- From the Flow Rate Analysis we can segment the population in 2 segments.

Bad Definition- Example

Performance at the end of 12th MOB				Performance at the end of 18th MOB																	
	Count	%	Cum%	Current	%	Current due	%	X-DPD	%	30-59 DPD	%	60-89 DPD	%	90-119 DPD	%	120-149 DPD	%	150-179 DPD	%	180+DPD	%
Current	26637	46.36%	46.36%	20364	76.45%	3806	14.29%	1821	6.84%	333	1.25%	150	0.56%	74	0.28%	45	0.17%	44	0.17%		0.00%
Current due	20402	35.50%	81.86%	4683	22.95%	12632	61.92%	2330	11.42%	425	2.08%	161	0.79%	84	0.41%	51	0.25%	36	0.18%		0.00%
X-DPD	6544	11.39%	93.25%	2003	30.61%	1831	27.98%	1554	23.75%	531	8.11%	250	3.82%	149	2.28%	96	1.47%	66	1.01%	64	0.98%
30-59 DPD	1255	2.18%	95.43%	335	26.69%	183	14.58%	183	14.58%	149	11.87%	107	8.53%	83	6.61%	59	4.70%	54	4.30%	102	8.13%
60-89 DPD	601	1.05%	96.48%	162	26.96%	35	5.82%	62	10.32%	40	6.66%	41	6.82%	30	4.99%	38	6.32%	48	7.99%	145	24.13%
90-119 DPD	383	0.67%	97.14%	117	30.55%	14	3.66%	15	3.92%	14	3.66%	14	3.66%	27	7.05%	27	7.05%	26	6.79%	129	33.68%
120-149 DPD	357	0.62%	97.77%	96	26.89%	8	2.24%	12	3.36%	7	1.96%	8	2.24%	14	3.92%	30	8.40%	17	4.76%	165	46.22%
150-179 DPD	308	0.54%	98.30%	49	15.91%	1	0.32%	14	4.55%	7	2.27%	6	1.95%	13	4.22%	9	2.92%	56	18.18%	153	49.68%
180+DPD	976	1.70%	100.00%	44	4.51%	4	0.41%	33	3.38%	11	1.13%	6	0.61%	4	0.41%	18	1.84%	24	2.46%	832	85.25%

- How many people are 90+ dpd at the start of the year?
- How may people out them jumped below 90+ bucket (current/ 30+/60+) how may people are above 90+ (120+/150+/180+)
- From the Flow Rate Analysis we can segment the population in 3 segments.
- **Good**: Current, Current due, X-DPD at the end of 12 month
- **Indeterminate**: 30-59 DPD at the end of 12 month
- **Bad**:60+DPD at the end of 12 month

Indeterminate

- Example:
  - BAD: 90 or worse in the performance window
  - Indeterminate: 30+ but never worse in the performance window
  - Good: not bad or indeterminate

- In general, It is not advised to have a indeterminate group bigger than 20% of the total sample.
- Observations flagged as indeterminate are excluded from the modeling sample (performance exclusion). Why?
- Defining an indeterminate population can help to show a higher KS (exclude grey keep only black and white).

Lab: Bad definition

- Download 'bad_definition.xls'
- How many accounts are we studying in this example?
- How may accounts are current?
- How many of these are 90+ dpd at the start
- Interpret the water fall analysis
- What can be bad definition
- Give definition for good & Indeterminate
- How do you decide indeterminate?

Model Building steps

- Objective
- Exclusions
- Observation point and/or window
- Performance window
- Bad definition
- **Segmentation**
- Variable selection
- Regression Line
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Segmentation

"One size does not fit all"

- "Separating good from bad" - Is this the objective of segmentation?
- Not directly, but segmentation allows different scorecards to be built for each population, which in turn leads to better separation of goods from the bads better than a single scorecard could, thus improving overall accuracy.

Segmentation Variables

- **Product types** (since usually different product variations are targeted at different sub-sections of the population)
  - Platinum / Silver / Gold Credit Cards
  - Store Cards / Bank Cards
  - Secured / Unsecured Loans
  - New vs. Refinanced Auto Loans
  - Fixed Rate / Adjustable Rate Mortgages
  - Fixed / Revolving Home Equity Line of Credit
- **Length / tenure** of close ended product (esp. applicable for installment products)
- **Month on Book on Bureau (Thin / Thick File)**
- **Clean / Dirty File**
- **Different portfolios**
  - Consumer / Commercial
  - Oil / Financial Institutions / Business / Professional Institutions
  - Existing Customers / Former Customers / New Customers
- **Demographics**
  - Regional / Age / Income / Lifestyle attributes
- **Channel**
  - Prescreen mailing / Telemarketing / Email campaign
- **Type of Customer**
  - New / Former / Existing

When to segment?

- When it will improve the score's ability to separate goods from bads
- When population is made up of distinct subpopulations
- When there is a business need to do so
- When segmented scorecards perform significantly better than single scorecard
- When incremental cost of using multiple scorecards is significantly less
- When the interactive variable approach is not feasible

"The gain from segmentation should be substantial before a developer opts for it"

Types of segmentation

1.Strategic

- A lender strategically targeting a certain group of customers
- eg. Borrowers who are already in the books of the lender on a different line of credit

2.Operational

- Availability of different data sources for different customer segments
- eg. Origination through bank branch or third party origination

3.Statistical

- Some characteristics affecting the outcome variable differently for some population
- eg. Effect of serious delinquency on a thin-file vs thick-file applicant

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What is variable selection?

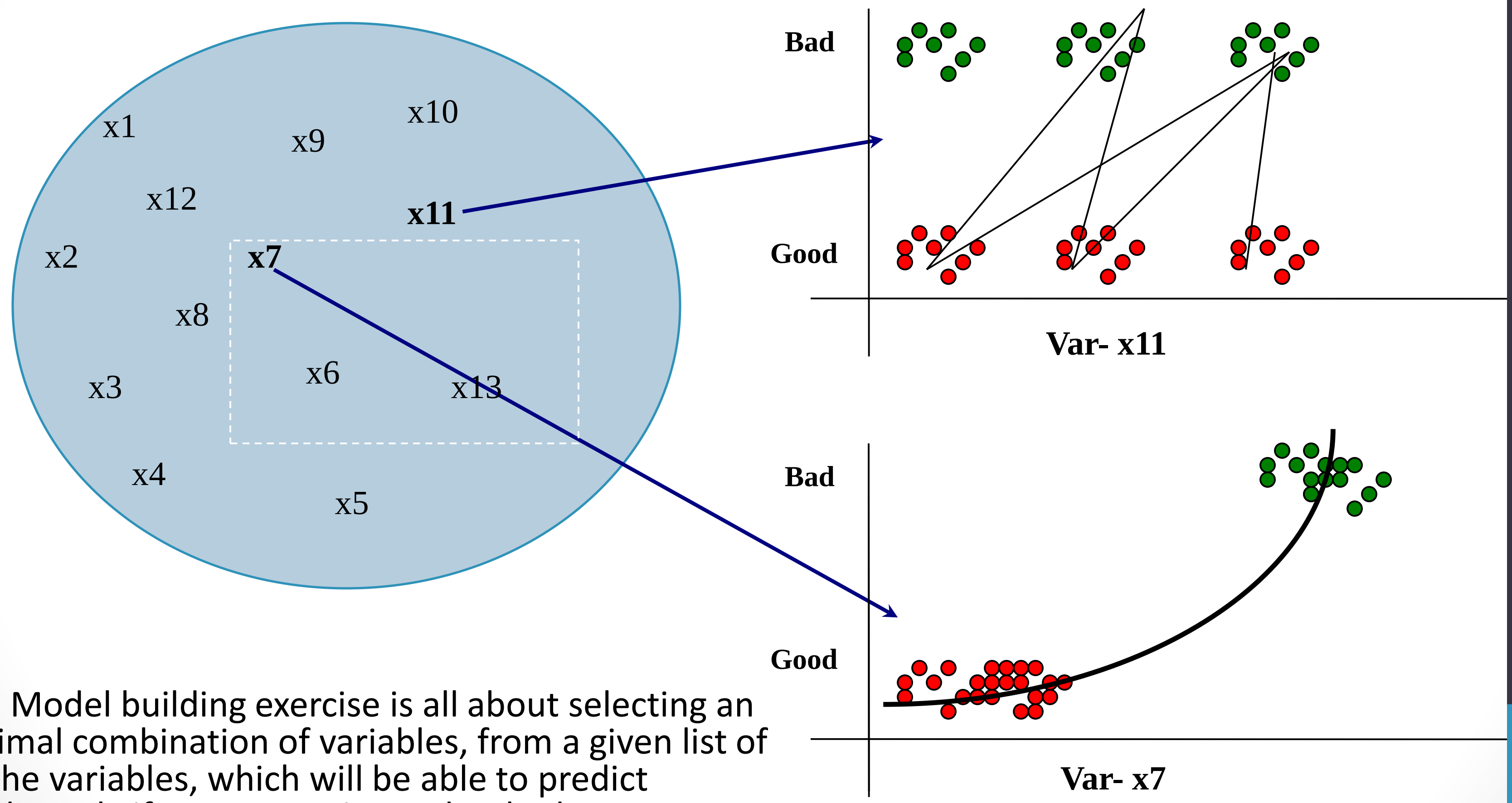
- We have historical data of 10,000 customers. There are two variables income class, distance from bank
- What is the difference between these two variables?
- Which one is important ?

Income	Good	Bad
Very High	1990	10
High	1960	40
Medium	1900	100
Low	1850	150
Very Low	1300	700
	9000	**1000**

Distance	Good	Bad
Very far	1800	200
Far	1800	200
Medium	1800	200
Not far	1800	200
Very near	1800	200
	9000	**1000**

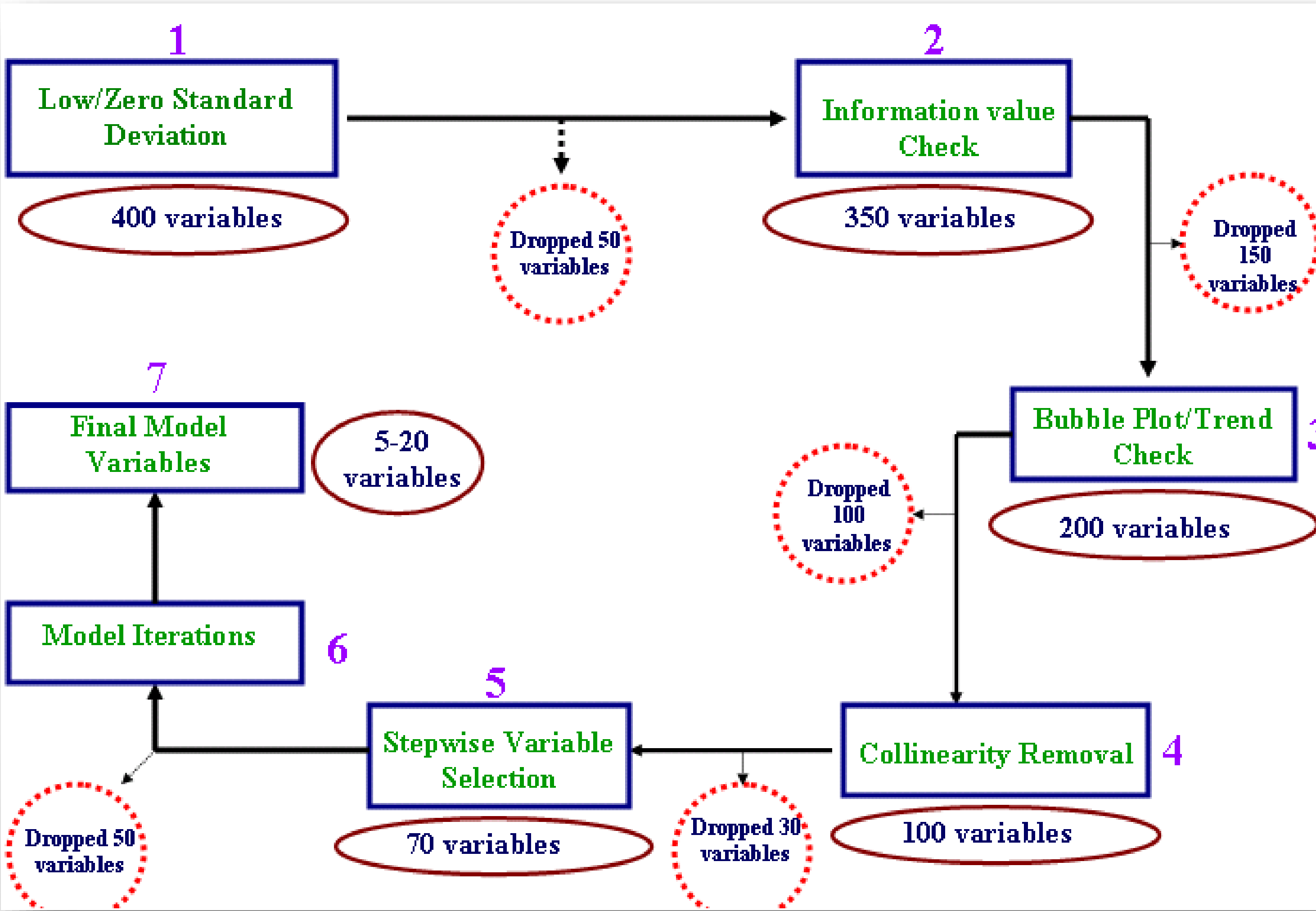
- As income increase what happens to number of bad?
- As distance increases what happens to number of bad?

Which variable to select?

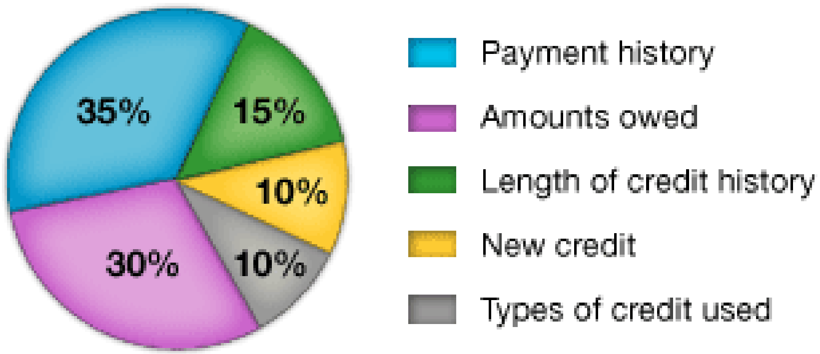


The Model building exercise is all about selecting an optimal combination of variables, from a given list of all the variables, which will be able to predict moderately if an account is good or bad.

Steps in Variable Selection/Elimination



Types of variables



Payment History

- **Account payment** information on specific types of accounts (credit cards, retail accounts, installment loans, finance company accounts, mortgage, etc.)
- Presence of adverse public records (bankruptcy, judgements, suits, liens, wage attachments, etc.), collection items, and/or delinquency (past due items)
- Severity of delinquency (how long past due)
- Amount past due on delinquent accounts or collection items
- Time since (recency of) past due items (delinquency), adverse public records (if any), or collection items (if any)
- Number of past due items on file
- Number of accounts paid as agreed

List of variables

Amounts Owed

- Amount owing on accounts
- Amount owing on specific types of accounts
- Lack of a specific type of balance, in some cases
- Number of accounts with balances
- Proportion of credit lines used (proportion of balances to total credit limits on certain types of revolving accounts)
- Proportion of installment loan amounts still owing (proportion of balance to original loan amount on certain types of installment loans)

List of variables

Length of Credit History

- Time since accounts opened
- Time since accounts opened, by specific type of account
- Time since account activity

New Credit

- Number of recently opened accounts, and proportion of accounts that are recently opened, by type of account
- Number of recent credit inquiries
- Time since recent account opening(s), by type of account
- Time since credit inquiry(s)
- Re-establishment of positive credit history following past payment problems

Types of Credit Used

- Number of (presence, prevalence, and recent information on) various types of accounts (credit cards, retail accounts, installment loans, mortgage, consumer finance accounts, etc.)

Variable Selection-Drop inconsistent variables

- Before going to different statistical methods of variable selection, we remove inconsistent variables from data.
  - Variables with all missing or high percentages (as > 90%) of missing should be discarded.
  - Variables with single value (or standard deviations as 0) should be discarded. (Any other examples?)
  - Variables with infinite variance, unique to each account(mobile number etc.,)

Variable Selection-Information Value

Income	Good	Bad
Very High	1990	10
High	1960	40
Medium	1900	100
Low	1850	150
Very Low	1300	700
	9000	**1000**

Distance	Good	Bad
Very far	1800	200
Far	1800	200
Medium	1800	200
Not far	1800	200
Very near	1800	200
	9000	**1000**

- Which variable to keep and which one to drop in above examples?
- How to quantify this effect?
- Measuring the trend using a mathematical formula?

Information Value-Example

Utilization %	# of Good	# of Bad	%Good [x]	%Bad [Y]	%Good / %Bad	X -Y	WOE = Log (X/Y)	IV
< 5	1850	150	29%	5%	6.31	0.25	0.80	0.20
5-30	1600	400	25%	12%	2.05	0.13	0.31	0.04
31 - 60	1200	600	19%	18%	1.02	0.00	0.01	0.00
60 - 90	900	900	14%	28%	0.51	(0.14)	-0.29	0.04
>= 91	800	1200	13%	37%	0.34	(0.24)	-0.47	0.11
Total	**6350**	**3250**						**0.39**

- The relative risk of the attribute is determined by its "Weight of Evidence."

Demo : Calculation of IV

Utilization	Good	Bad
0%	4,948	9,870
10%	6,400	8,956
20%	7,203	7,869
30%	8,679	7,045
40%	9,345	6,800
50%	10,983	5,934
60%	11,673	5,021
70%	13,457	4,356
80%	14,000	3,004
90%	14,689	2,890

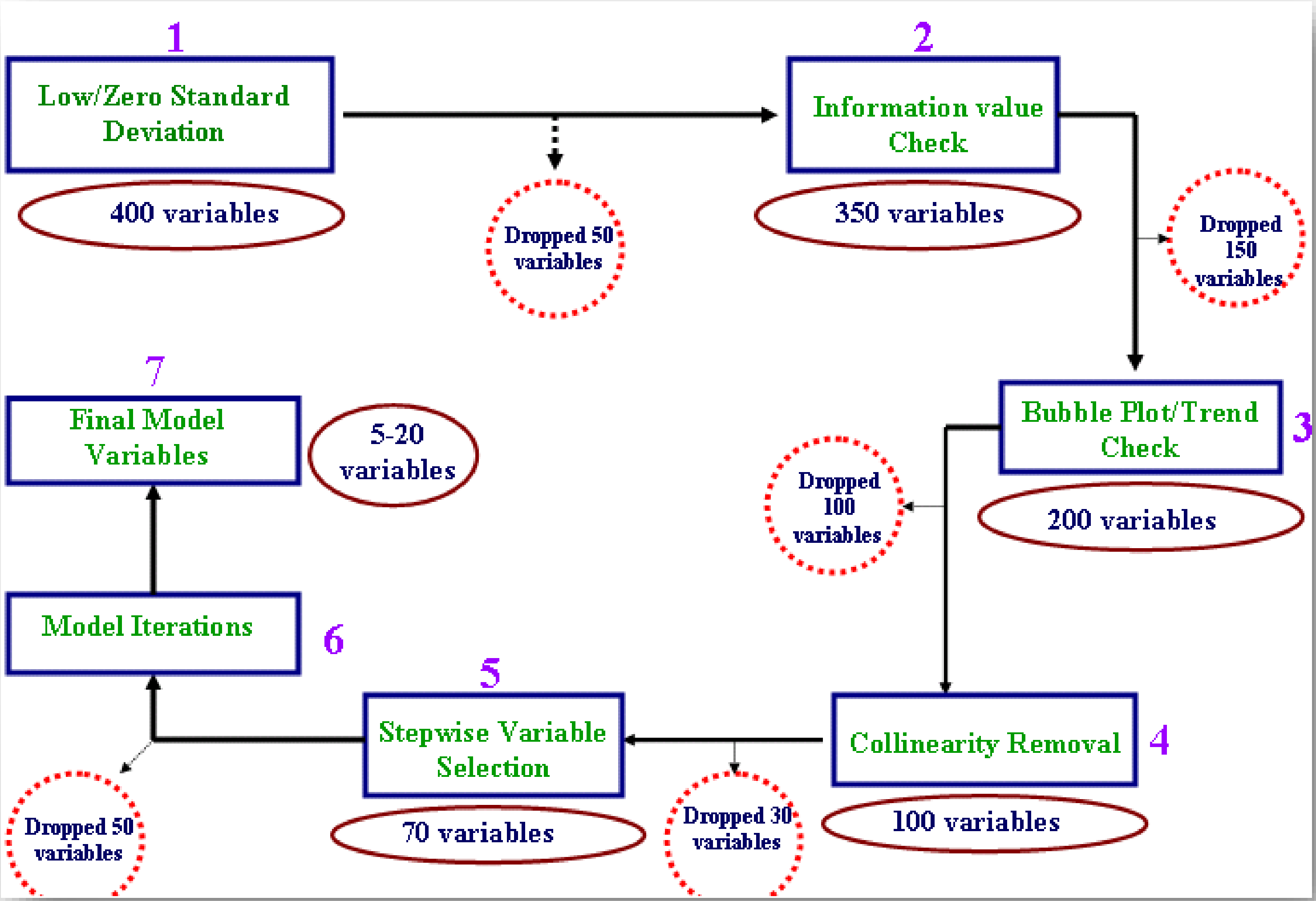
Rules of Thumb for selecting variable with the help of IV

- IF IV < 0.01 => very weak, discard the variable;
- ELSE IF IV < 0.1 => weak, variable can be included ;
- ELSE IF IV < 0.3 => medium, should be included;
- ELSE IF IV < 0.5 => strong, must be included
- ELSE IF >= 0.5 => the characteristic may be over-predicting, meaning that it is in some form trivially related to the good/bad information, check for the variable

Lab: WOE & IV

- Download Information value data
- Find IV of the variable “Number of enquiries”
- As number of enquiries increase what happens to bad rate?
- Find IV for “number of cards”
- As number of cards increase what happens to bad rate?

Steps in Variable Selection/Elimination

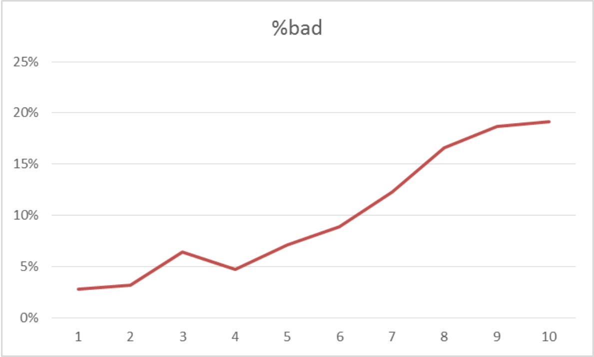


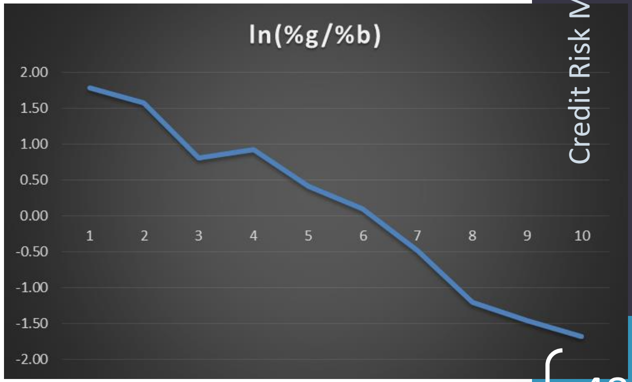
Bi-variate Trend Analysis

- After short listing variables based on information value, we perform trend analysis to check if the variables we want to include in the model having proper tend or not.
- Bivariate Trend Analysis is an analysis to check the trend of a variable with respect to the bad rates (i.e. what is the trend of bad-rate if the value of the variable increases) and accordingly include / exclude variables in the model
- What is the need of bivariate analysis?
- To identify the variable where, IV is high but variable is good for nothing

Log odd graph

Num_Enq	Good	Bad	%good	%bad	%g-%b	%g/%b	ln(%g/%b)	IV
0	6400	150	17%	3%	14%	5.97	1.79	0.25
1	5800	169	15%	3%	12%	4.80	1.57	0.19
2	5445	340	14%	6%	8%	2.24	0.81	0.06
3	4500	250	12%	5%	7%	2.52	0.92	0.07
4	4070	375	11%	7%	4%	1.52	0.42	0.02
5	3726	470	10%	9%	1%	1.11	0.10	0.00
6	2879	650	8%	12%	-5%	0.62	-0.48	0.02
7	1893	876	5%	17%	-12%	0.30	-1.20	0.14
8	1636	987	4%	19%	-14%	0.23	-1.46	0.21
9	1354	1008	4%	19%	-16%	0.19	-1.67	0.26
	37703	**5275**						**1.22**





Demo: Bivariate graph

- Number of dependents

Lab: Bivariate graph

- Draw log odds graph for Number of enquiries
- Draw log odds graph for Number of cards

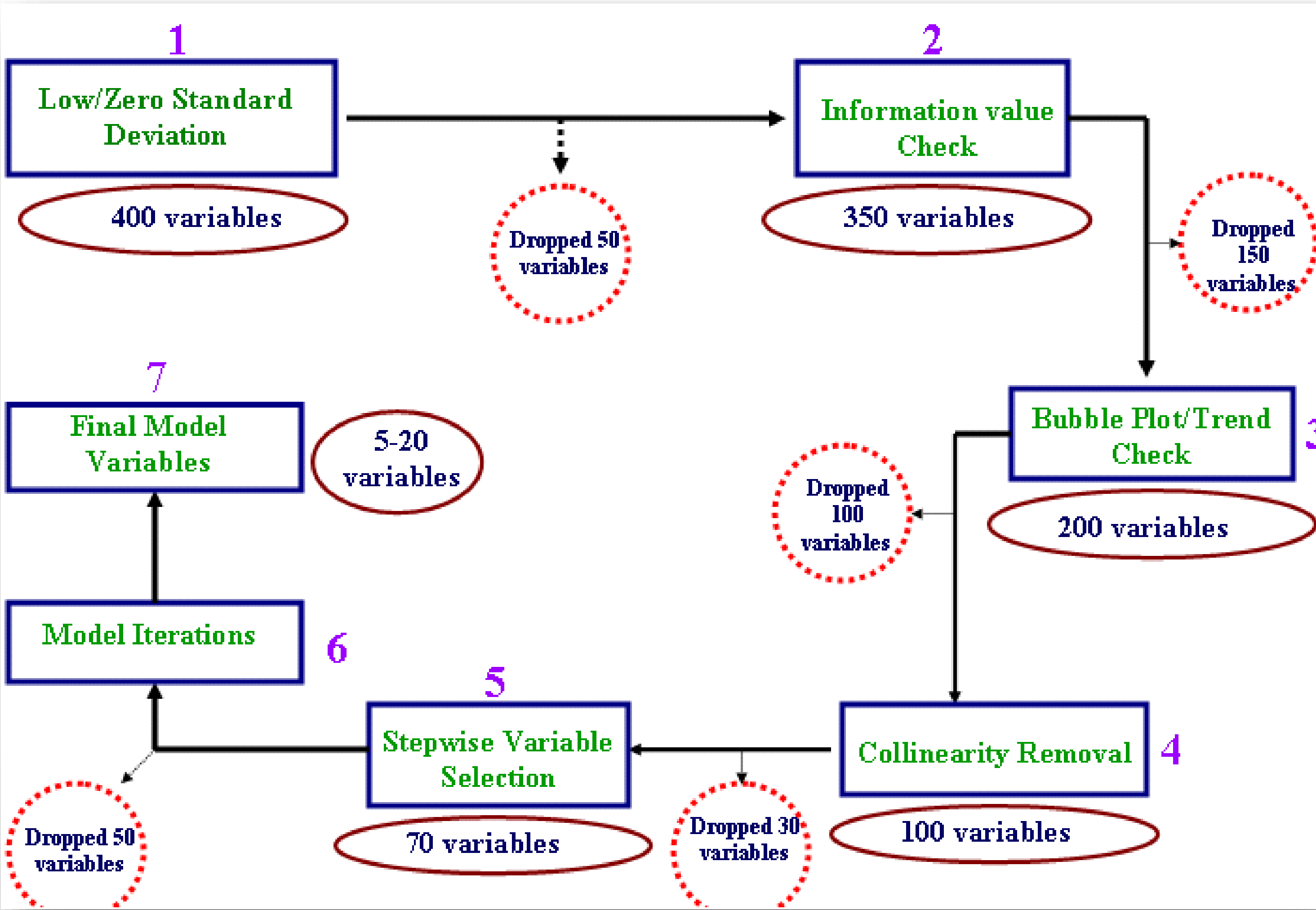
Rules of Thumb for selecting variable with the help of trend chart

- **Include Variable in the model if trend plot shows**
  - the trend following business intuition
- **Exclude Variable from the model if plot shows**
  - opposite trend from business point of view.
  - no trend / completely random plot. As no trend implies with the increase in the variables value, there is no / random change in good (and hence log(odds)) and hence the variable cannot be used to discriminate good from bad. Hence variable should be dropped.
- **Include variable with some adjustment if plot shows**
  - If a variable has a appropriate trend for most of the values and erratic in the extreme values; do capping / flooring and include the variable in the model if after capping / flooring the variable has a correct trend.
  - monotonic but non-linear trend; such that after some transformation e.g. Log transform, exponential transformation etc. the variable follows a proper linear trend

Lab: Bi-variate Trend Analysis

- Download Information value data
- Find IV of the variable “Number of enquiries”
- Draw bivariate chart
- Find IV for “number of cards”
- Draw the bivariate chart
- As number of cards increase what happens to bad rate?
- Can we keep both variables in the model? Which one to keep? Which one to drop?
- Draw bivariate chart for utilization

Steps in Variable Selection/Elimination



Stepwise Regression

- Forward selection
- Backward elimination
- Stepwise Regression

Forward selection

1. Start with a null model
2. Add one variable at a time, record adj R-Square(or AIC). See if there is any significant increment in the adj R-square(or AIC)
   - If there is significant increment then retain the variables
   - If there is no significant increment then drop the variable
3. Repeat step-2 for all the variables

Backward elimination

1. Start with the full model with k variables
2. Remove variables one at a time, record adj R-Square(or AIC). See if there is any significant dip in adj R-square(or AIC)
   - If there is significant dip then retain the variables
   - If there is no significant dip then drop the variable
3. Repeat step-2 for all the variables

Stepwise regression

- Combination of FS & BE
- Start with null model
  - Repeat:
    - one step of FS
    - one step of BE
- Stop when no improvement in Adj R-square or AIC is possible

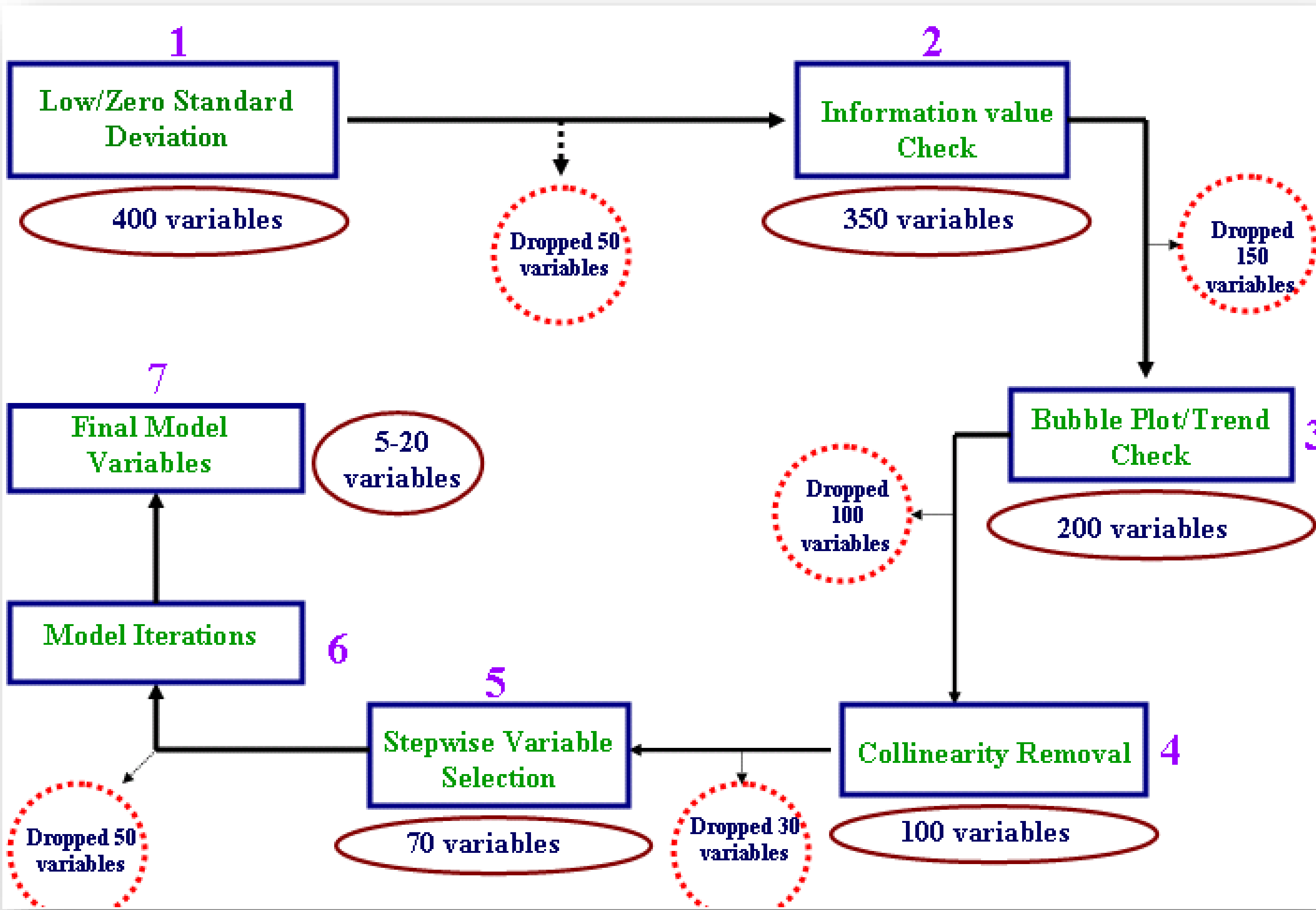
Demo: Stepwise regression

- Contact center Customer satisfaction data
- C-Sat vs. Communication, Resolution,Attitude, Handling Time score

Lab: Stepwise Regression

- Import 8.3 Stepwise Regression_fraud.csv
- Print the contents
- Build a logistic regression line to predict the fraud
- Use stepwise regression to select/eliminate variables

Steps in Variable Selection/Elimination



Model Building steps

- Objective
- Exclusions
- Observation point and/or window
- Performance window
- Bad definition
- Segmentation
- Variable selection
- **Regression Line**
- Model validation
- Model recalibration

Regression Line

- Logistic regression line
- Good/Bad on list of variables

Demo regression line

```
proc logistic data=mylib.Sample_cc descending;
model
SeriousDlqin2yrs=
util
age1
DebtRatio1
MonthlyIncome1
num_loans
depend
/ selection=stepwise ;
output out = mylib.lect_logit p=prob ;
run;
```

Model Building steps

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What is the need of model validation?

Mar-2012

Population
- 100,000 applications for loan

Scorecard
- We build a model to decide the score

Approval
- We approved and rejected applications based on the score

Mar-2013

Population
- 125,000 applications for loan

Scorecard
- ?

Approval
- ?

What is the need of model validation?

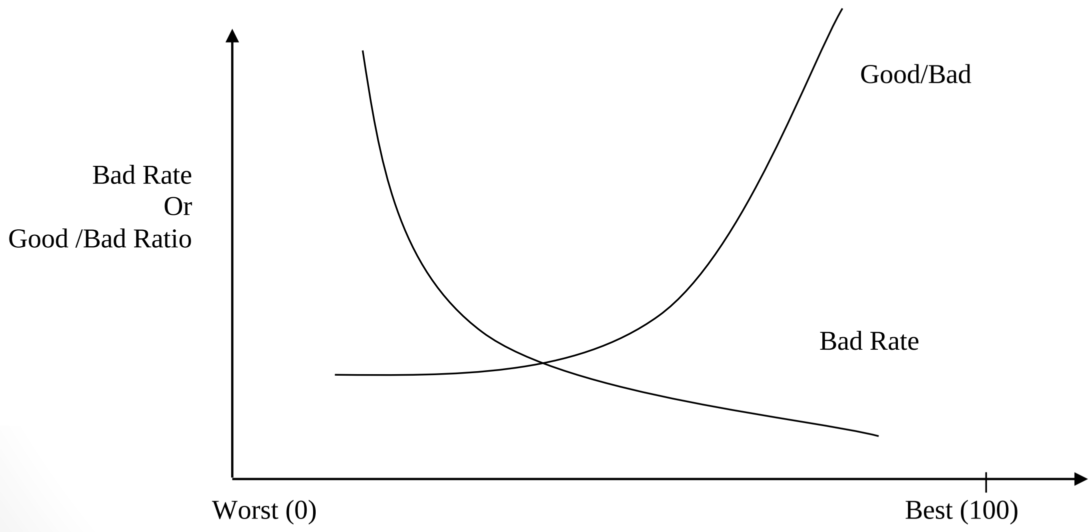
- To make sure that the old model is still working
- To see whether the model lost any separation power and quantify it
- To check whether the underlined population changed significantly or not
- To use the same model on the similar population and product
- *Above all, it is mandatory: Guidelines set by the Office of the Comptroller of the Currency (OCC)*

How to validate the model

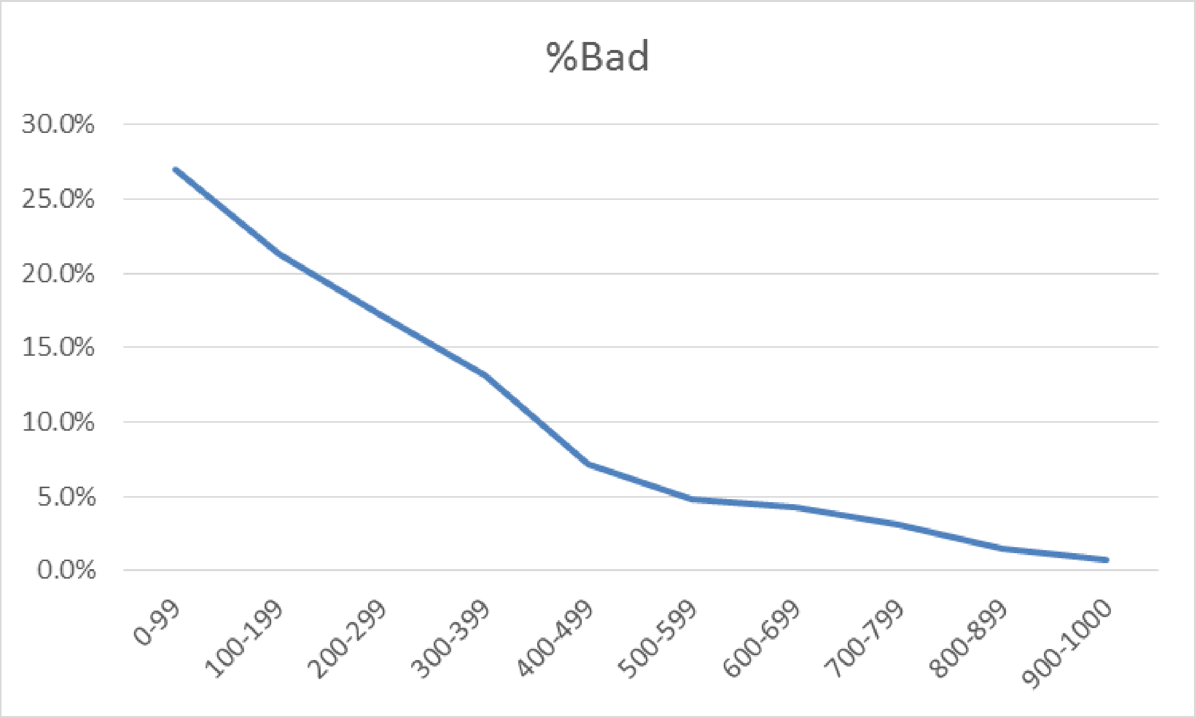
- As the score increases, bad rate should decrease and good rate should increase – Rank ordering
- There should be a maximum separation between good and bad – KS Statistic
- Make sure that the population hasn't changed much - PSI

Rank Ordering

- If the bad rate is a monotonically decreasing function, the model is said to rank order. The model is said to rank order if the
  - Bad Rate is monotonically decreasing **OR**
  - Odds Ratio (Good/Bad) is monotonically increasing,



Demo Rank ordering

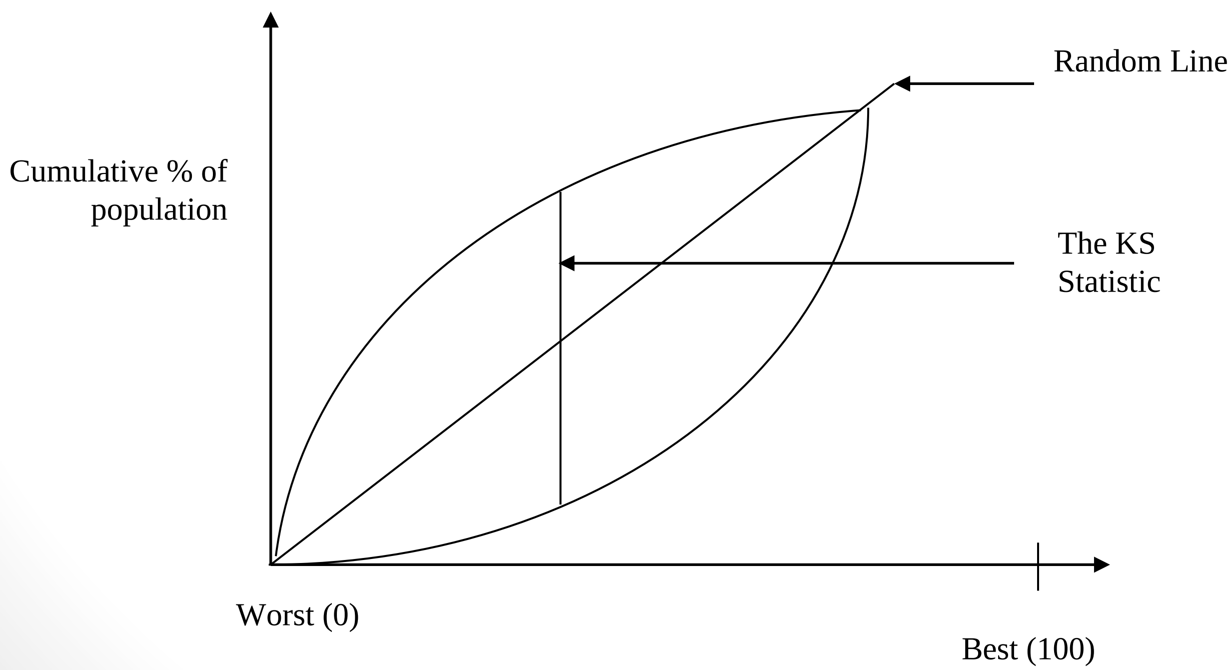


Lab: Rank Ordering

- Draw a rank ordering graph for %bad for scorecard2
- Draw a rank ordering graph for %good for scorecard2

KS

- Measures maximal separation of cumulative good and bad distributions
- KS= (cumulative% Bad – Cumulative %Good)*100
- Closer to random line model losses its power. KS<20 at model development then it is a Bad Model
- KS is like checking the rank ordering of good and bad in single shot



KS Table

Score	Good	Bad	%Good	%Bad	Cum(%Good)	Cum(%bad)	Ks
0-99	135	4700	0.6%	24.6%	0.6%	24.6%	24
100-199	189	3500	0.9%	18.3%	1.5%	43.0%	41
200-299	1267	3600	6.0%	18.9%	7.6%	61.8%	54
300-399	469	2785	2.2%	14.6%	9.8%	76.4%	67
400-499	1780	1504	8.5%	7.9%	18.2%	84.3%	66
500-599	1245	1006	5.9%	5.3%	24.2%	89.5%	65
600-699	2689	890	12.8%	4.7%	36.9%	94.2%	57
700-799	3457	640	16.4%	3.4%	53.4%	97.6%	44
800-899	4215	320	20.0%	1.7%	73.4%	99.2%	26
900-1000	5600	146	26.6%	0.8%	100.0%	100.0%	-
	21046	19091					**67**

- KS= max(cumulative% Bad – Cumulative %Good)*100
- Higher the KS, better the separation power.

Lab: KS Calculation

Score	Good	Bad
0-99	1135	5700
100-199	1689	4500
200-299	1267	3600
300-399	1469	2785
400-499	1780	1504
500-599	1245	1006
600-699	2689	3913
700-799	3457	4491
800-899	4215	2046
900-1000	5600	1957
	24546	31502

PSI

- We built a model on population A, we want to use it on population B
- Population stability report compare distributions of recent applicants to a standard population distribution(development sample)
- The comparison is done in order to see if there is any shift in in the distribution of new applicants.
- PSI = Σj [(A - B) * ln (A / B)]
  - Where, A = % of observations in group j in development sample, and B = % of observations in group j in validation sample

PSI Table

Score	Dev	Recent	%A	%B	%A-%B	Ln(%A/%B)	PSI
0-99	4229	5234	8.6%	10.7%	-2.1%	-22.1%	0.00
100-199	4360	4557	8.9%	9.3%	-0.5%	-5.2%	0.00
200-299	6245	4255	12.7%	8.7%	4.0%	37.6%	0.01
300-399	4771	4325	9.7%	8.9%	0.8%	9.1%	0.00
400-499	4747	5789	9.7%	11.9%	-2.2%	-20.6%	0.00
500-599	4577	6546	9.3%	13.4%	-4.1%	-36.5%	0.01
600-699	4899	4980	10.0%	10.2%	-0.2%	-2.4%	0.00
700-799	4337	4421	8.8%	9.1%	-0.2%	-2.7%	0.00
800-899	4515	4311	9.2%	8.8%	0.3%	3.9%	0.00
900-1000	6500	4399	13.2%	9.0%	4.2%	38.3%	0.02
	49180	48817					**5.7%**

- PSI = Σj [(A - B) * ln (A / B)]
- Higher the PSI, higher the population shift

Lab: PSI calculation

- Download Model Validation data
- Draw rank ordering graph for model-1 and model-2. What is your inference?
- Calculate KS for model-1 and model-2.
- Which one of these two models have higher separation power
- Find the PSI for scorecard-1 & scorecard-2
- Which one can be used for 2013 population?

Triggers for Model validation

- There is red flag if:
  - For ECM, KS<20 and for application/acquisition KS<15 at the time of model validation
  - KS drops more than 25% (or more than 10 points in absolute) from development of model to validation
  - KS drops more than 15% (or more than 5 points in absolute) from previous validation
- If KS Drop is significant and rank ordering is also not perfect then we go for re development or re estimation of the model

Model Building steps

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- Model validation
- **Model recalibration**

Model recalibration

- Re-estimation or Re-development?
- Decided by using Character analysis
- Find the PSI for each variable in the final model
  - If the population remained unchanged with respect to al variables then simply re-estimate the coefficients.
  - What if the population changed drastically with respect to a variable?

Income	Dev Sample	Recent(2013)	%A	%B	%A-%B	Ln(%A/%B)	CI(Income)
0-1499	4229	3678	9.5%	3.8%	5.7%	91.0%	0.05
1500-4600	5900	7800	13.2%	8.1%	5.1%	49.1%	0.03
4601- 5900	7923	9848	17.8%	10.2%	7.5%	55.3%	0.04
5901-8000	10240	14078	23.0%	14.6%	8.4%	45.2%	0.04
8001-12000	6900	18905	15.5%	19.6%	-4.1%	-23.7%	0.01
12001-20000	5400	17000	12.1%	17.7%	-5.5%	-37.6%	0.02
>20001	3981	25000	8.9%	26.0%	-17.0%	-106.7%	0.18
	44573	96309					**36.9%**

Lab: Character Analysis

- Find the distribution shift with respect to variable “Number of loans”
- Is the population changed with respect to this variable?

Thank You