



Proven Practices for Predictive Modeling

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Agenda

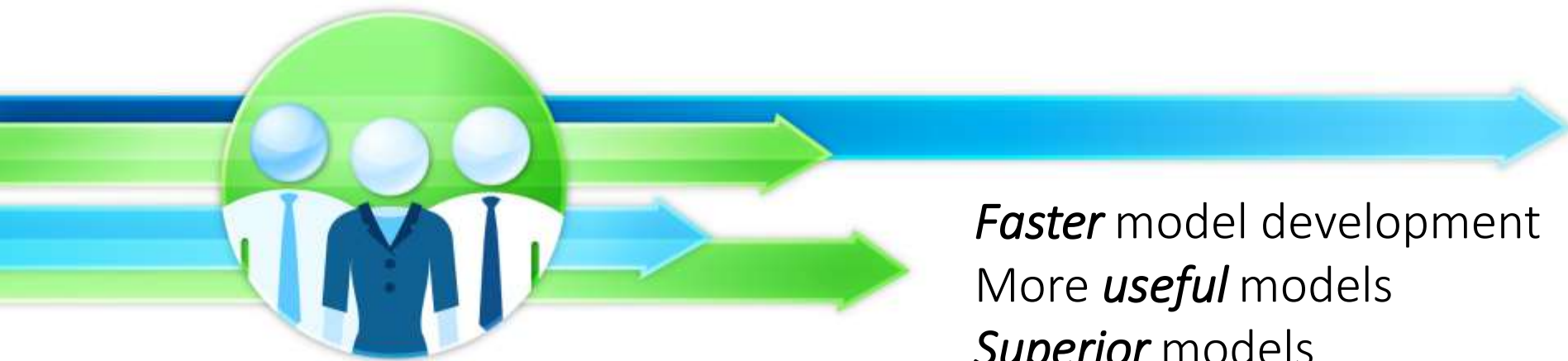
SAS Enterprise Miner & SAS Visual Data Mining and Machine Learning

Best practices for creating a predictive model

- Background and General Guidance
- Data Construction
- Model Development and Delivery



Best practices to help you meet and exceed your goals



Faster model development
More ***useful*** models
Superior models

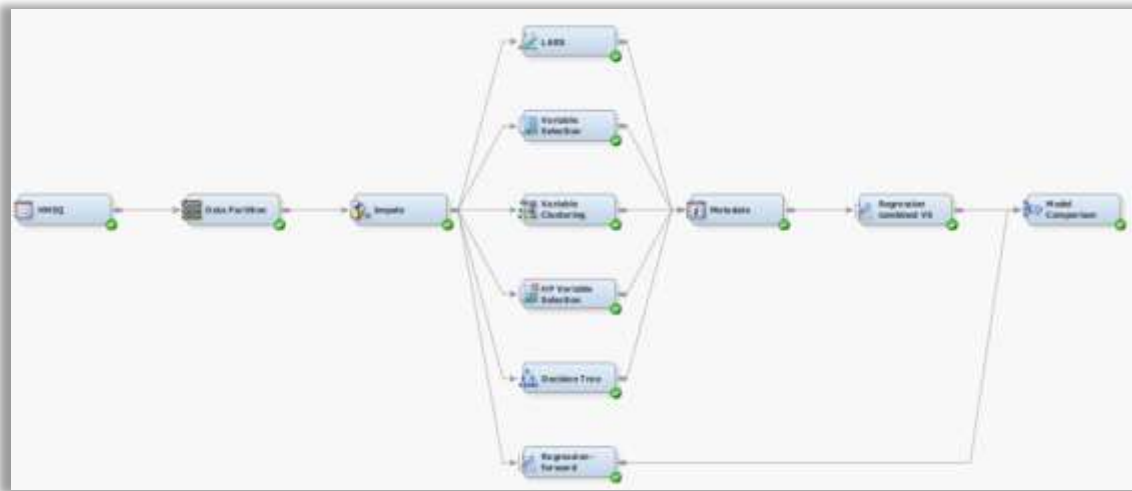
Disclaimers

- The choice of “Best Practices” is highly subjective.
- Certain suggested practices may not be suitable for a particular situation.
- It is the responsibility of a predictive modeler to critically evaluate methods and select the best method for a particular situation.
- This presentation represents the opinions of those who contributed.

SAS® Enterprise Miner™

Overview

Streamlines data mining process and allows you to create accurate predictive and descriptive analytical models in a drag-and-drop GUI.



[More info here](#)

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Integrated
data mining and
machine learning

1

Open platform with
access from SAS and
Open Source

2

Modern machine
learning algorithms

3

Cloud-ready and industrial
scalable analytics

4

SAS® Visual Data Mining and Machine Learning is an end-to-end machine learning solution on the most advanced analytics platform.



Background

Analytics Cycle and the Modeling Process

Why use Predictive Modeling?

To turn increasing amounts of raw data into useful information

Descriptive

Clustering (Segmentation)

grouping together similar people, things, events

- Transactions that are likely to be fraudulent, Customers that are likely to have similar behaviors.

Associations

affinity, or how frequently things occur together, and sometimes in what order

- Customers who purchase product A also purchase product B

Predictive Models

Classification models

predict class membership

- 0 or 1: 1 if person responded; 0 otherwise
- Low, Medium, High: a customer's likeliness to respond

Regression models

predict a number

- \$217.56 – Total profit, expense, cost for a customer
- 37 – The number of months before a customer churns

The Goal? Scoring!

- Scoring is the act of applying what we've learned from our predictive model to **new cases**.
- Keep this goal in mind and use it to help formulate the questions and the data needed for predictive modeling and scoring.



Example

Developing a Classification Model

- Models are developed using historical data in which the **behavior is observed or known**.



- Information about each subject, in this case an individual, is used as inputs to the model to see how well the model can distinguish between the people who exhibit the behavior and those who do not. For example, age, gender, previous behaviors, etc.

Why?

- Consider a group of subjects whose relevant behavior is unknown.
- The same information is available for each of these subjects (age, gender, etc.) as is available for the individuals with known behavior.
- We would like to know **which individuals are most likely to have the relevant behavior.**



How?

- The output of a predictive classification model is typically an equation. Models are applied to new cases to calculate the **predicted behavior** through a process called **scoring**.
- **Scoring**, using the equation, calculates each subject's *likelihood to have the relevant behavior*. (It also calculates the likelihood to *not* have the behavior.)





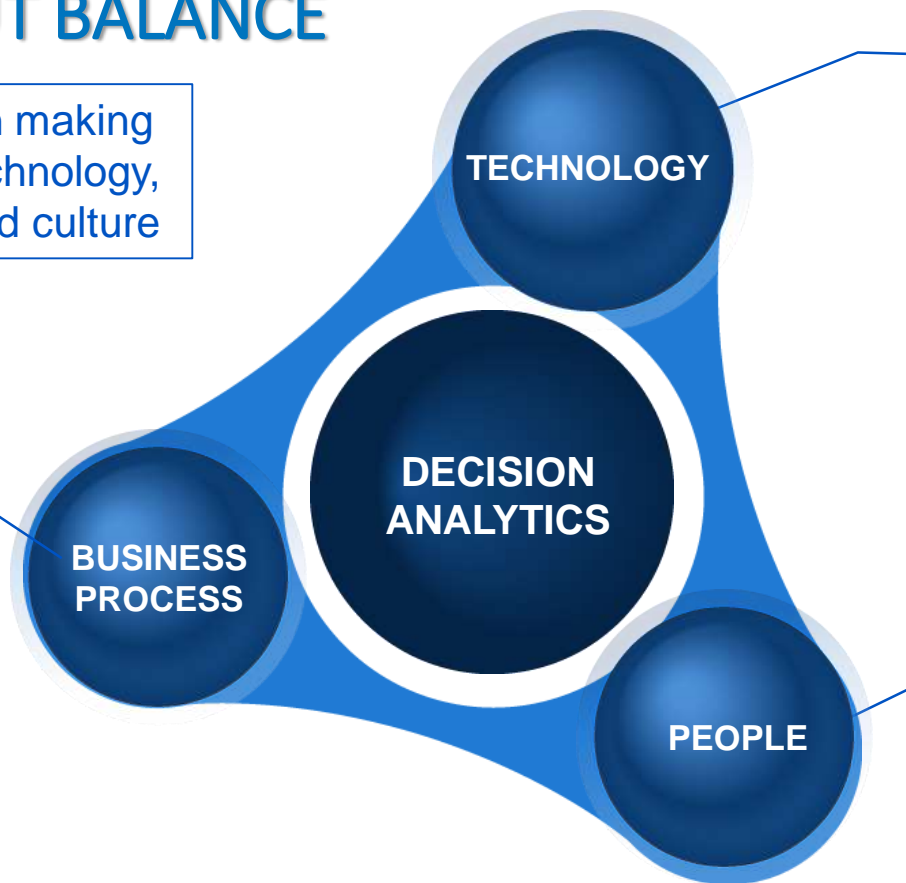
General Guidance

Analytics Cycle and the Modeling Process

ITS ALL ABOUT BALANCE

Fact-based decision making
requires the right technology,
talent, processes and culture

- Planning
- Project methodology
- Standards
- Continuous Process Improvement



- Reporting
- Dashboards
- Information management
- Problem-specific business solutions
- Predictive analytics
- Hardware

- Vision & Leadership
- Team composition
- Enterprise authority

Lifecycle Best Practice

Involve all the relevant people/roles

BUSINESS MANAGER



Domain Expert
Makes Decisions
Evaluates Processes & ROI

BUSINESS ANALYST



Data Exploration
Data Visualization
Report Creation

DATA MINER DATA SCIENTIST

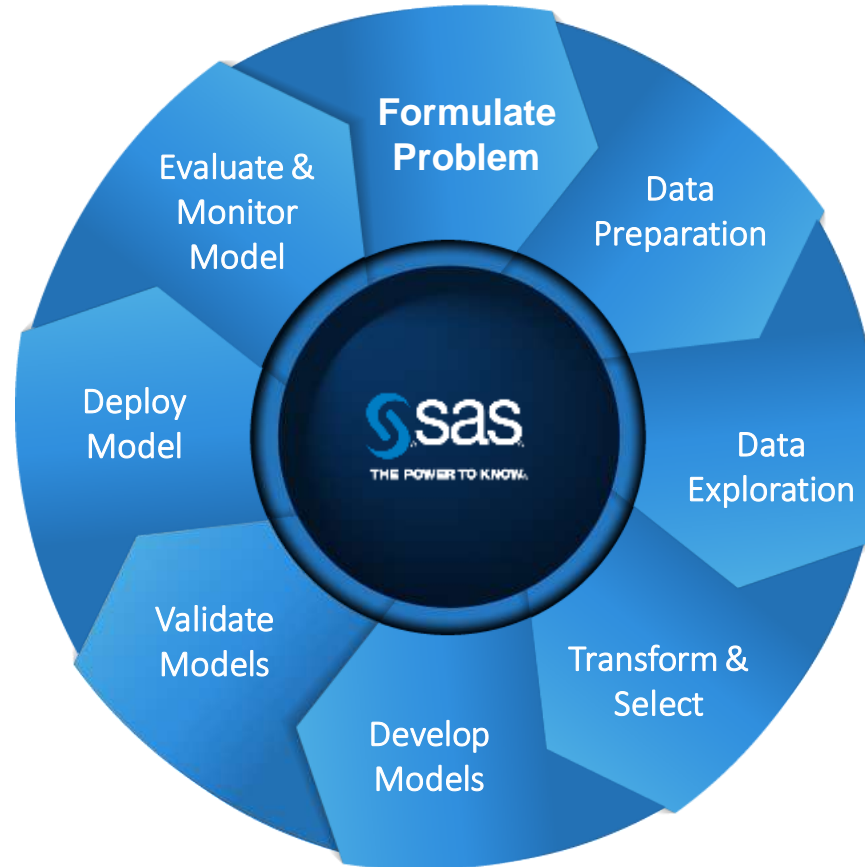


Exploratory Analysis
Descriptive Segmentation
Predictive Modeling
Model Validation &
Registration

IT/SYSTEMS MANAGEMENT



Model Validation
Model Deployment
Model Monitoring
Data Preparation



Use the Technology and Method the Fits the Job

Every tool and method has advantages and disadvantages.

Whenever possible, select the tool or method that balances *long-term* goals for the *entire* process.

Best Practice

Begin with the End in Mind



Begin with the End in Mind

- *What* is the overarching strategic objective/initiative?
- *How* will the model be used?
- *How* will it be put into production?
- *Who* will be affected by the use of the model?
- *Who* needs to be convinced of the value of the model?
- *When* will the model be used?



Best Practices

Business considerations before you model

- Thoroughly understand the business/marketing objectives
- Detail the precise (planned) usage for the output
- Define the target variable (the outcome being modeled / predicted)
- Formulate a theoretical model: $Y = f(X_1, X_2, \dots)$ ← fill-in the likely X's

The SAS Platform



Essential Data Tasks



- Collect and organize data
- Divide the data
- Address rare events
- Manage missing values
- Add unstructured data
- Extract features
- Handle extreme or unusual values
- Select useful inputs

Essential Discovery Tasks



- Select an algorithm
- Improve the model
- Optimize complexity of the model
- Regularize and tune hyperparameters of the model
- Build ensemble models
- Attempt other algorithms

Essential Deployment Tasks



- Assess models
- Compare models
- Score the champion model
- Monitor model performance over time
- Update the model as needed



Developing the Data

Best Practices

Optimizing Data



Determining Data
Selecting Target
Preparing Variables



Determining Data

Best Practices

Technical Considerations Before Modeling

- Brainstorm all potential input data elements
- Identify source systems, specific data fields, availability/priority/level-of-effort of data
- Finalize data to be collected

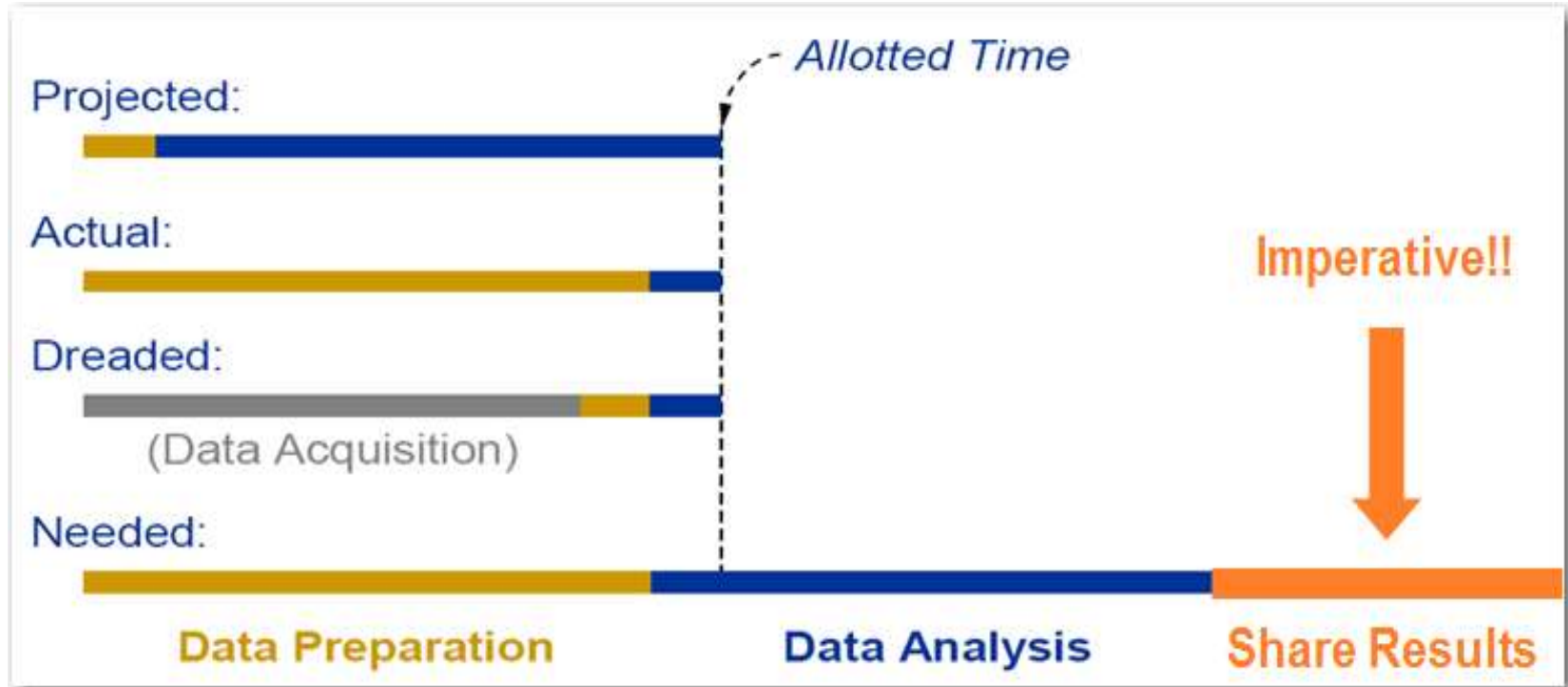
Best Practices

Technical Considerations Before Modeling

- Formulate structure and layout of modeling dataset to be built
- Devil-in-the-details: filters, timeframe of history, etc...
- Build modeling dataset

Best Practice

Allow sufficient time for all aspects





Sample

Sample

To Sample or Not?

- Sampling is a valuable tool that can be used to great effect.
- If computing resources are no object, it's possible to use all data.
- When resource constrained, try increasing sample sizes as model development progresses.
- When model is nearly finalized, try different seeds for samples to ensure model stability.



Sample

What About Oversampling?

- It depends.
- Frequently one needs to oversample in order to allow algorithm(s) to identify effect, especially with rare targets.
- Only oversample as much as you need to in order to obtain a model that makes sense from a business perspective. This is **highly subjective**.



Partitioning

Honest Assessment

SAMPLE

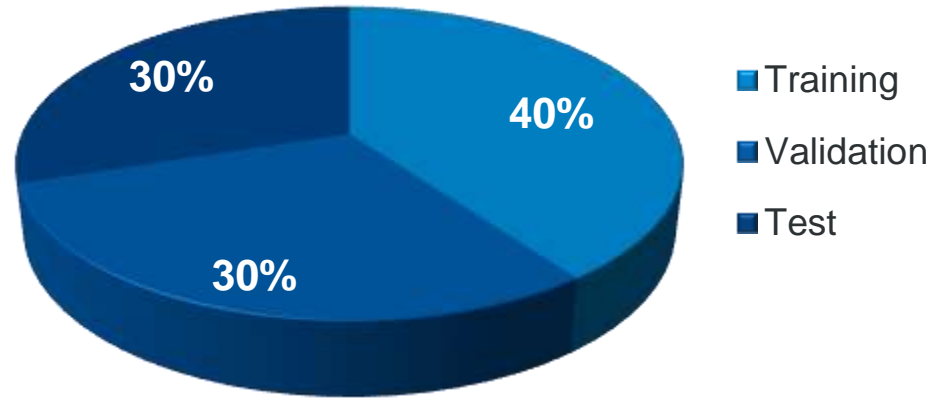
Data Partitioning

PARTITION	ROLE
Training	Used to fit the model
Validation	Used to validate the model and prevent over-fitting
Test	Used to provide unbiased estimate of model performance

Sample

SAMPLE: Data Partitioning

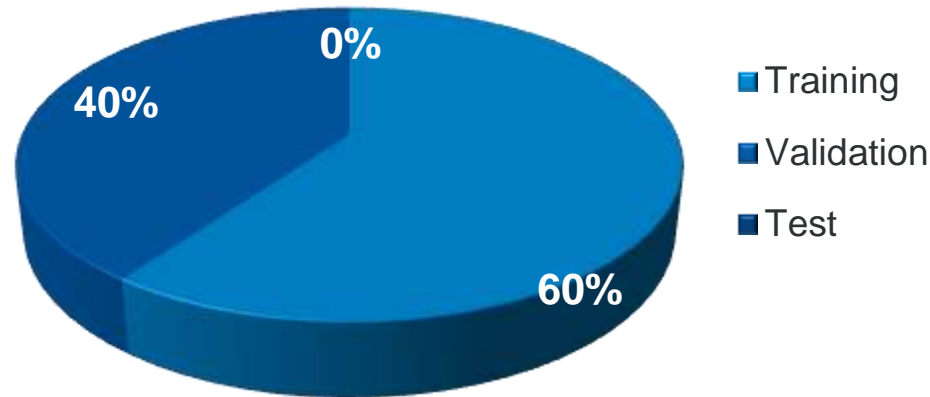
WHAT IS OPTIMAL PARTITION?



Best Practice

SAMPLE: Data Partitioning

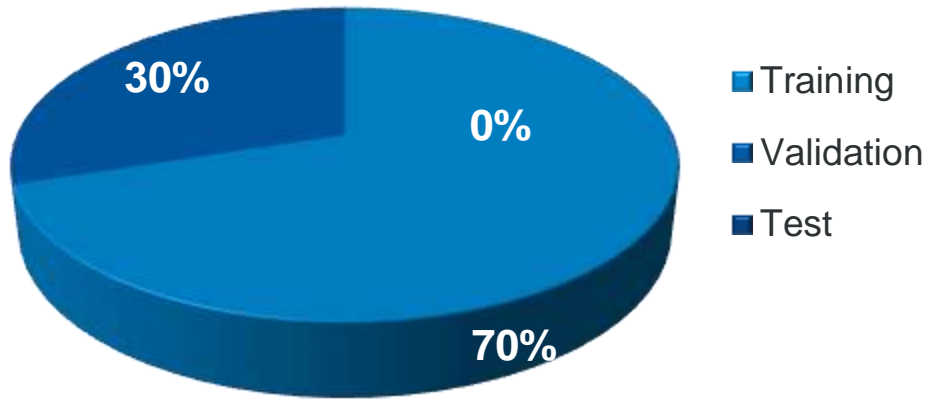
WHAT IS OPTIMAL PARTITION?



Best Practice

Sample: Data Partitioning

**WHAT IS OPTIMAL
PARTITION?**



Sample

Data Partitioning Considerations

- How much data is available?
- Is an unbiased measure of model performance required?
 - Should test data be in-sample or out-of-sample?
- How many test samples are needed? (e.g. different time periods, different geographies, etc.)
 - When should test data be used in the process?

Data Partitioning

- Percentages: frequently used percentages are 50/50/0, 60/40/0 and 70/30/0 with a completely separate Test partition.
- Do not bring Test data into process until model is complete. It should not influence modeling process, merely used to report performance.
- Multiple Test data can be used – consider how model will be deployed and create representative samples.



Selecting Target

Choosing your target



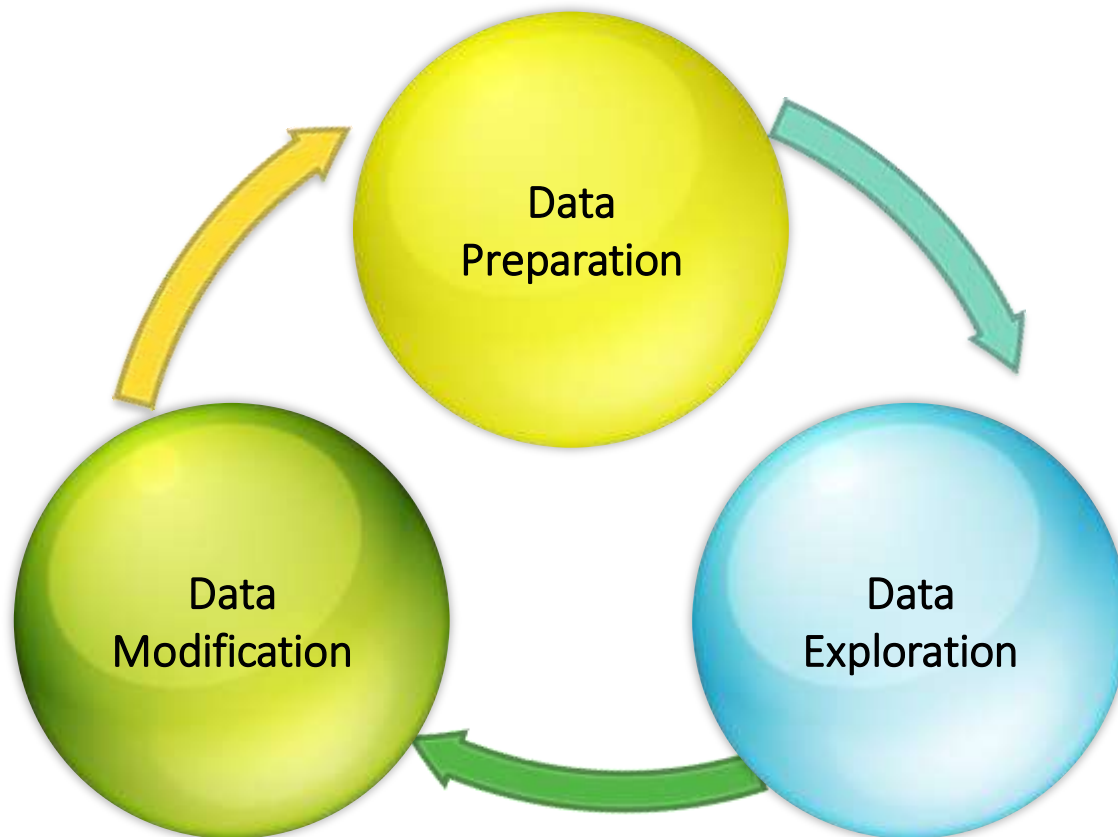
- Choosing the Target
- Response vs. Propensity
- Number of Models



Preparing Data

EXPLORE & MODIFY

Iterative Relationship with Data Preparation

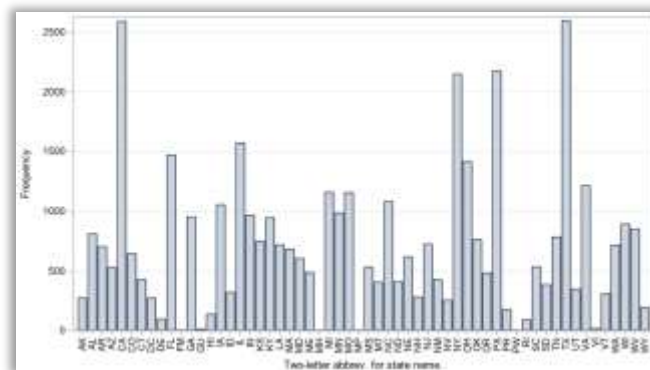
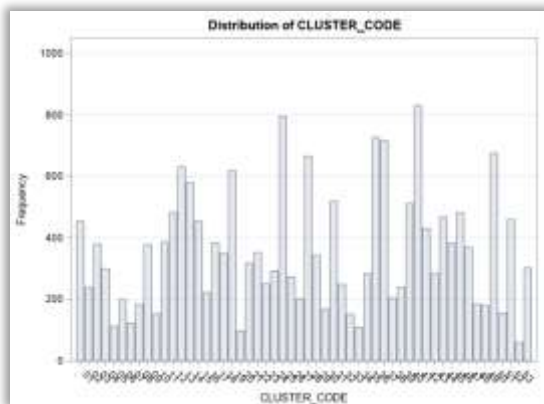
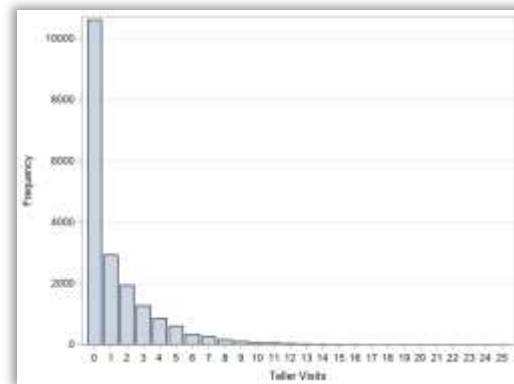
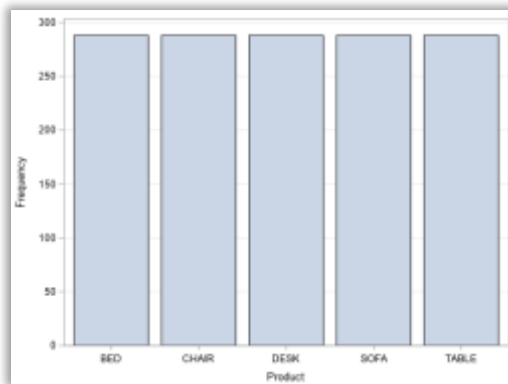




Explore & Modify: Getting the Most out of Data

- Once you have an analytics-ready table:
 - Examine *Categorical* Variables
 - Examine *Continuous* Variables
 - Explore *Missing* Values
 - *Cluster* Variables

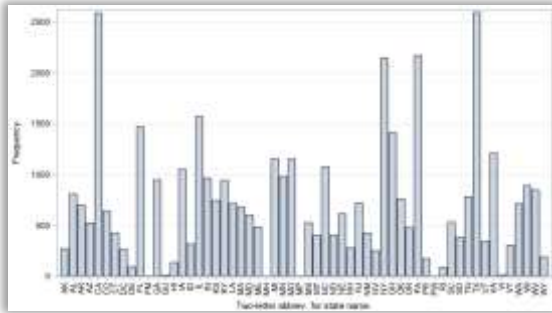
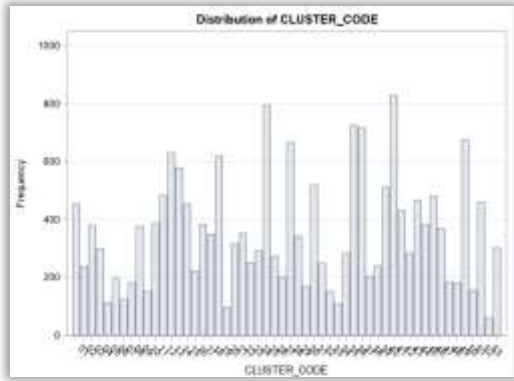
Explore & Modify Categorical Variables



Explore & Modify Categorical Variables

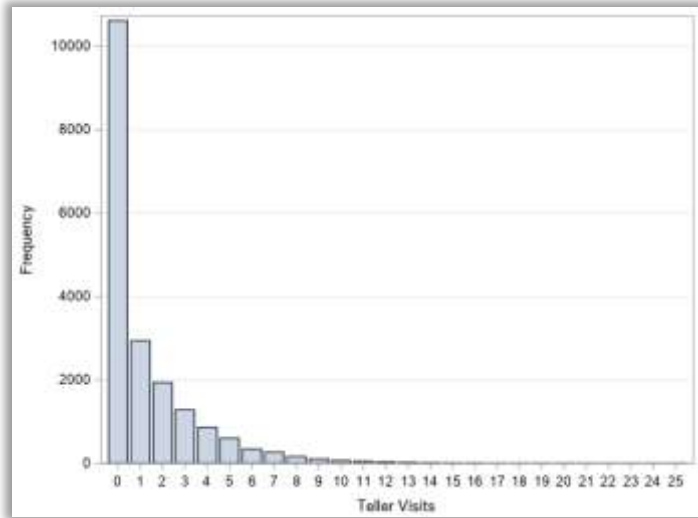
Too many overall values

- Is there a higher level of a hierarchy that could be used instead?
- Can this be represented by a group of variables with fewer values?
 - Example: **Zip Codes** alternatives
 - MSA or state
 - Geographic, demographic, economic status



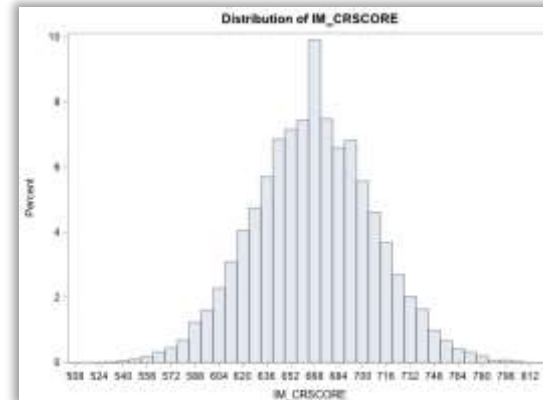
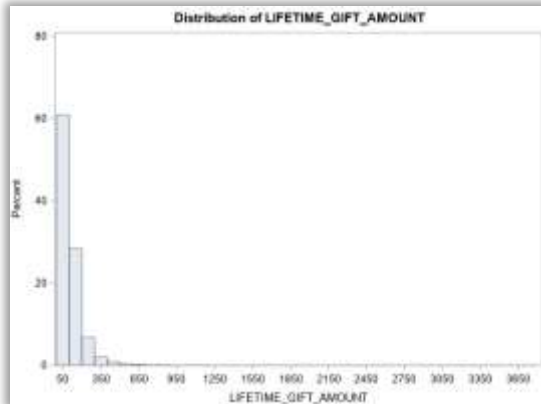
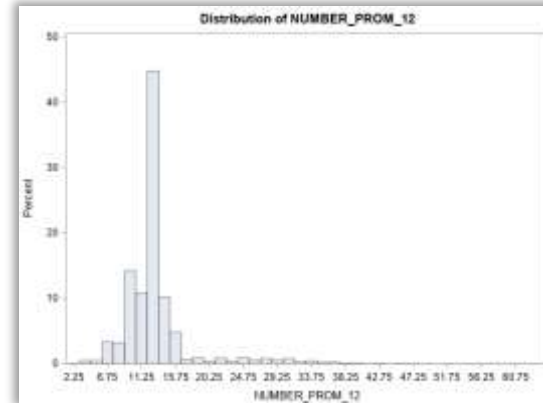
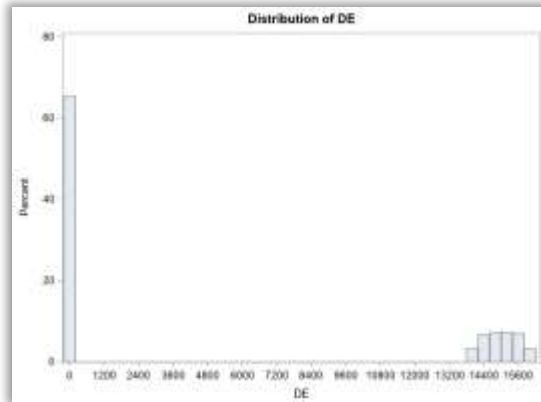
Explore & Modify Categorical Variables

Levels that rarely occur



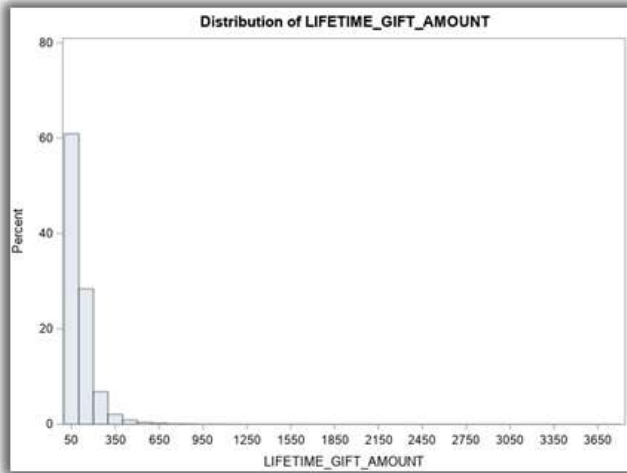
- Group infrequently occurring values together as “other”
- Judiciously combine a less frequently occurring level with a more frequent one where it makes business sense
- Consider a less granular level of a hierarchy

Explore & Modify Continuous Variables



Explore & Modify Continuous Variables

Extremely skewed predictors

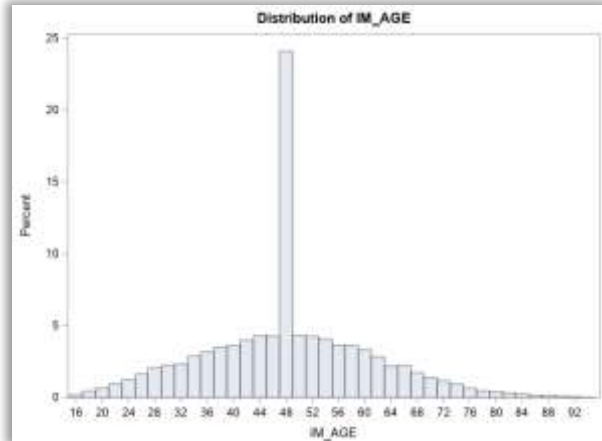
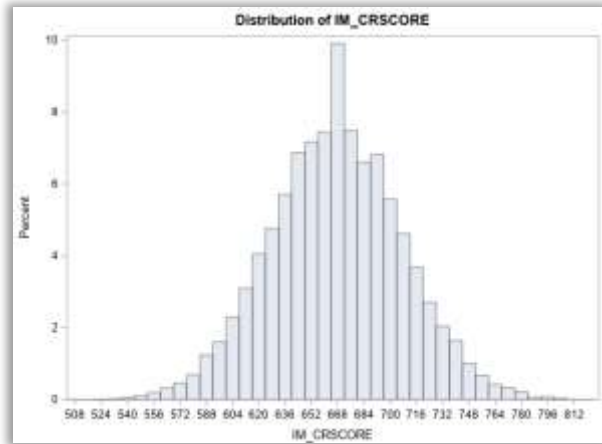


- Consider transformations that stabilize variance and generate more support across the range of values
- Consider binning transformation with appropriate number of bins to enable each portion of the ranges to be weighed appropriately

Explore & Modify Continuous Variables

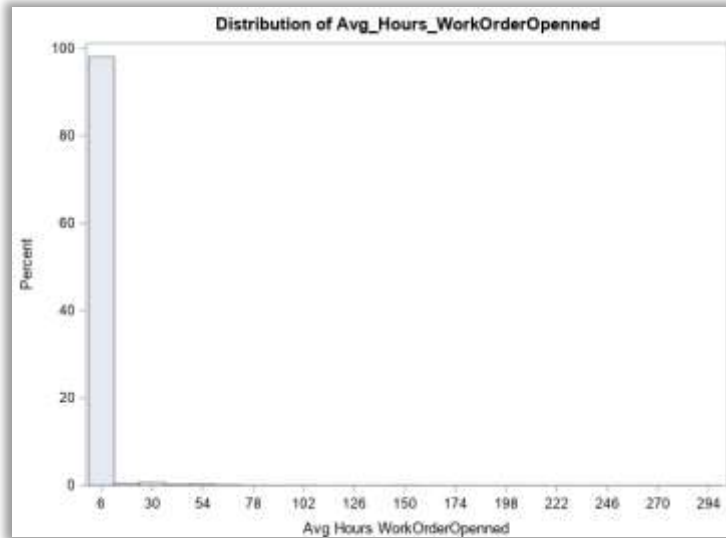
Spike and a Distribution

- Consider creating two variables from the original
 - Flag variable to indicate whether value is in the spike
 - Variable from the values of the predictors in the distribution
 - Set values at spike to missing and impute



Explore & Modify

Continuous Variables



One level that almost always occurs

- Consider a new variable that is a binned version
- Consider whether it's sufficient to create only a binary indicator

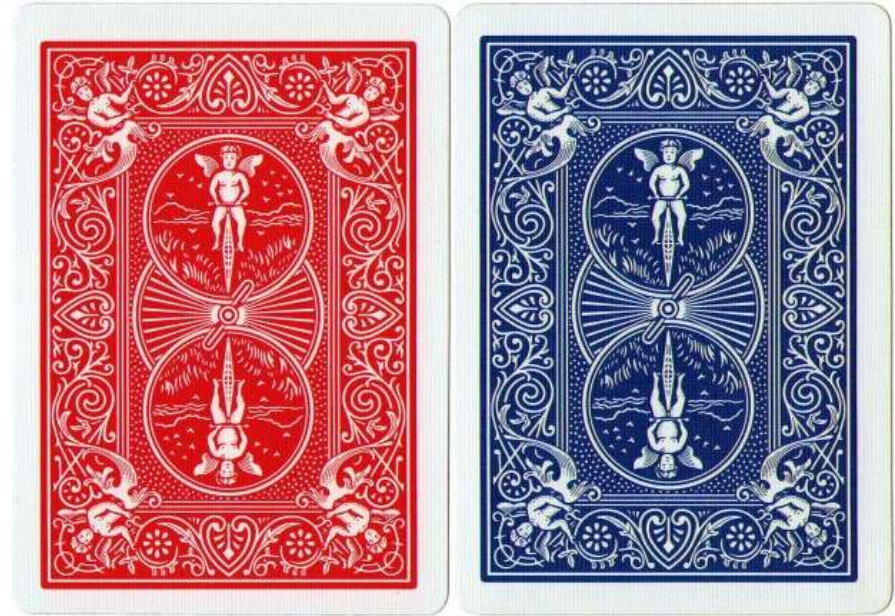
Explore & Modify

Missing Data

- *Why* is data missing?
- Are there *patterns* to the missing data within or across variables?
- *Imputation methods* to consider
- *Indicator variables*

Explore & Modify Variables for Clustering

- There is no single answer for clusters
- Design clusters and profiles around themes using smaller set of related variables





Selecting Variables

What?



Variable Selection or Variable Reduction

Variable selection is used to find a subset of the available inputs that accurately predict the output.

Why Variable Selection?

- Smaller Data
 - Speed/Performance
 - Decreased Computation Time
 - Decreased Scoring Effort
 - Cost
 - Data Collection
 - Data Cleaning
- Other Statistical Reasons
 - Interpretability
 - Multicollinearity & Irrational Coefficients
 - Missing Data
 - Redundancy
 - Predictive Power
 - Destabilize the parameter estimates
 - Increase the risk of over fitting
 - Noise



The principle of Occam's Razor states that among several plausible explanations for a phenomenon, the simplest is best.

Variable Selection

Concepts

Variable Selection

- Regression based
- Criterion Based
- Variable Screening
- Variable Clustering

Variable Combination

- Principal Components uncorrelated linear combinations of *all* input variables



Methods available

- Regression
- Decision Trees
 - Random Forest
- Variable Selection
 - Stat Explore (one level tree)
 - Variable Selection (Chi-Square & R-Square)
 - LARS/LASSO
 - High Performance Variable Selection
- Variable Clustering
- Principle Components
- Weight of Evidence (WOE)



Methods available

- Variable Selection
 - Unsupervised Selection (No Target)
 - Supervised Selection
 - Fast Supervised Selection
 - Linear Regression Selection
 - Decision Tree Selection
 - Forest Selection
 - Gradient Boosting Selection
- Variable Clustering

Summary of Data Preparation

Topic	Common Challenges	Suggested Best Practices
Data Collection	<ul style="list-style-type: none">• Biased data• Incomplete data• High-dimensional data• Sparsity	<ul style="list-style-type: none">• Take time to understand the business problem and its context• Enrich the data• Dimension reduction (Feature Extraction, Variable Clustering, and Variable Selection)• Change representation of data (Transformations node)

Summary of Data Preparation

Topic	Common Challenges	Suggested Best Practices
Messy Data	<ul style="list-style-type: none">• Value ranges as columns• Multiple variables in the same column• Variables in both rows and columns	<ul style="list-style-type: none">• Transform the data with SAS code (Code node)
Outliers	<ul style="list-style-type: none">• Out-of-range numeric values and unknown categorical values in score data	<ul style="list-style-type: none">• Discretization (Transformations node)• Winsorizing (Imputation node)

Summary of Data Preparation

Topic	Common Challenges	Suggested Best Practices
Sparse target variables	<ul style="list-style-type: none">• Low primary event occurrence rate• Overwhelming preponderance of zero or missing values in target	<ul style="list-style-type: none">• Proportional oversampling
Variables of disparate magnitudes	<ul style="list-style-type: none">• Misleading variable importance• Distance measure imbalance• Gradient dominance	<ul style="list-style-type: none">• Standardization (Transformations node)

Summary of Data Preparation

Topic	Common Challenges	Suggested Best Practices
High-cardinality variables	<ul style="list-style-type: none">• Overfitting• Unknown categorical values in holdout data	<ul style="list-style-type: none">• Binning (Transformations node)• Replacement (Replacement node)
Missing Data	<ul style="list-style-type: none">• Information loss• Bias	<ul style="list-style-type: none">• Binning (Transformations node)• Imputation (Imputation node)
Strong multicollinearity	<ul style="list-style-type: none">• Unstable parameter estimates	<ul style="list-style-type: none">• Dimension reduction (Feature Extraction, Variable Clustering, and Variable Selection nodes)

Best Practices

Optimizing Data



Determining Data
Selecting Target
Preparing Variables



Developing & Delivering the Model



Delivering the Model

- *Developing* Your Model
- *Choosing* a Model
- *Deploying* the Model



Developing the Model

MODEL

Model Development



- Regression
- Decision Trees
- Neural Networks
- Ensemble
- Random Forest
- Something Else?

BEST PRACTICE



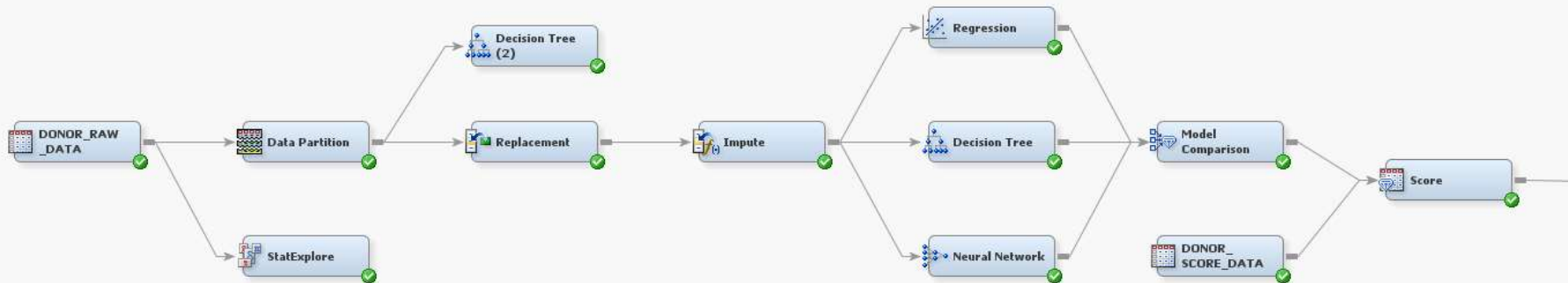
Model Development

Try various techniques and combinations of techniques.

Complete List of SAS Enterprise Miner nodes

SAMPLE	Append	Data Partition	File Import	Filter	Merge	Sample	Input Data			
EXPLORE	Association Cluster	Graph Explore	Variable Clustering	DMDb MultiPlot	Market Basket StatExplore	Link Analysis Path Analysis	Variable Selection	SOM/Kohonen		
MODIFY	Drop	Impute	Interactive Binning	Principal Components	Replacement	Rules Builder	Transform Variables			
MODEL	Decision Tree	AutoNeural Regression	Neural Network	Partial Least Squares	Dmine Regression	DM Neural Ensemble	Rule Induction	Gradient Boosting	LARS MBR	Two Stage Model Import
	Incremental Response	Survival Analysis	Credit Scoring*	TS Correlation	TS Data Prep	TS Dimension Reduction	TS Decomp.	TS Similarity	TS Exponential Smoothing	
	HP Explore HP Bayesian Network	HP Regression	HP Transform HP Impute	HP Variable Selection	HP Neural HP Forest	HP Decision Tree	HP Data Partition	HP GLM HP SVM	HP Cluster	HP Principal Components
ASSESS	Cutoff	Decisions	Model Comparison	Score	Segment Profile					
UTILITY	Control Point	End Groups Start Groups	Open Source Integration	Reporter	Score Code Export	Metadata	SAS Code Ext Demo	Save Data	Register Metadata	SAS Viya Code

SAS Enterprise Miner



SAS® Visual Data Mining and Machine Learning Capabilities

Analytics

Analytic Astore Scoring
Data Step
Data Transpose
DS2
Function Compiler
FedSQL
Frequency / Crosstab
Imputation
Model Assessment
Sampling and Partitioning
Sentiment Analysis
Sequencing/Pathing Analysis
Text Mining
Variable Binning
Variable Cardinality Analysis
Variable Clustering
Variable Selection
Variable Summary

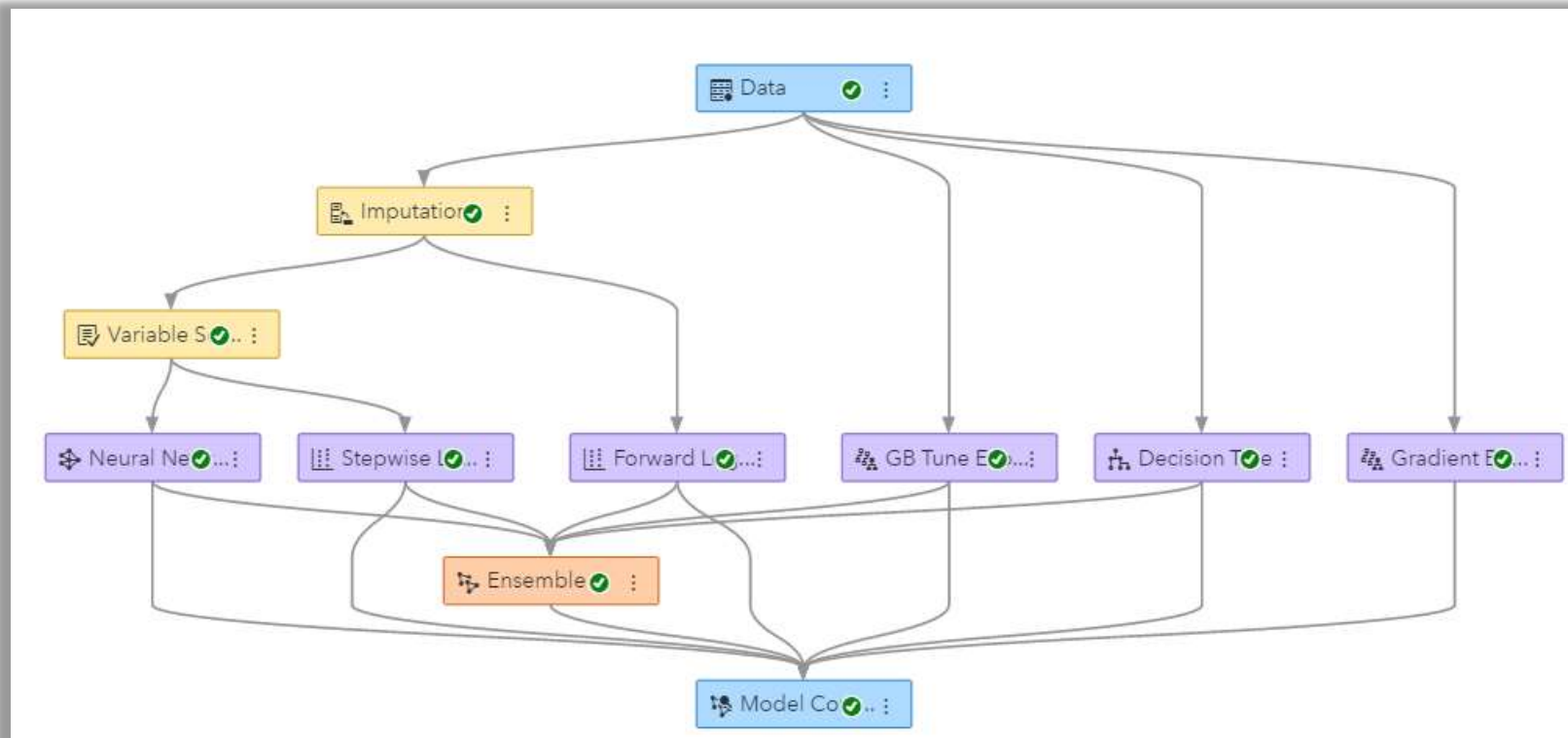
Statistics

Cox Proportional Hazards
Decision Trees
Design Matrix
General Additive Models
Generalized Linear Models
Independent Component Analysis
Clustering
K-means and K-modes
Linear Regression
Linear Mixed Models
Logistic Regression
Model-Based Clustering
Model Scoring
Nonlinear Regression
Ordinary Least Squares Regression
Partial Least Squares Regression
Pearson Correlation
Principal Component Analysis
Kernel Principal Comp. Analysis
Quantile Regression
Shewhart Control Chart Analysis

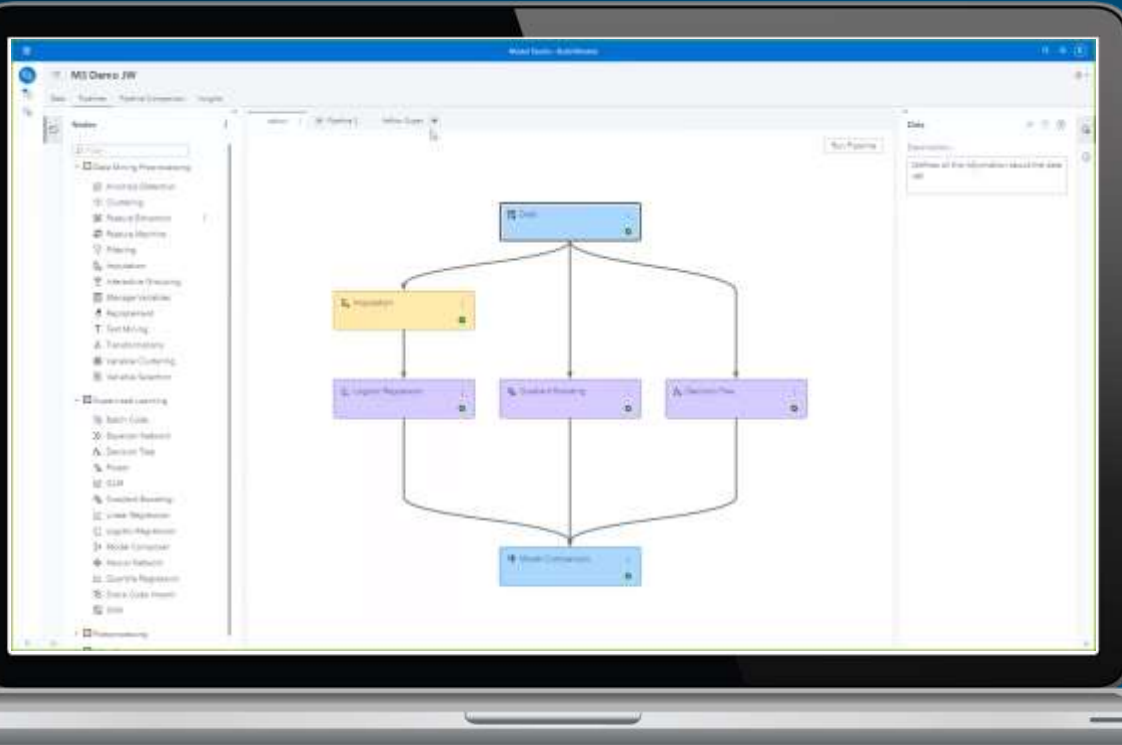
Machine Learning

Automated ML
Data Science Pilot
Model Composer
Audio Data Processing
Bayesian Networks
Boolean Rules
Cross Validation ML
Deep Learning
Convolutional NN
Deep Forward NN
Recurrent NN
Transfer Learning
Factorization Machine
Frequent Item Set Mining
Gaussian Mixture Model
Gaussian Process Regression
Gradient Boosting
Hyperparameter Auto-tuning
K Nearest Neighbor
Image Processing (*incl. Biomedical*)
Market Basket Analysis
Model Interpretability
LIME, ICE, PD, Shapley
Moving Windows PCA
Multitask Learning
Network Analytics
Neural Networks
Random and Isolation Forests
Recommendation Engine
Robust PCA
Semi-supervised Learning
Sparse Machine Learning
Support Vector Data Description
Support Vector Machine
t-distributed SNE
Text Parsing

SAS Visual Data Mining and Machine Learning



Automated Pipelines



- ✓ Repository of best practice pipelines
- ✓ Models by SAS or by end-user
- ✓ Dynamically reads thru data
- ✓ Fixes data quality issues w/ ML
- ✓ Performs Data transformations
- ✓ Recommends & builds models
- ✓ Optimizes across models
- ✓ Fully editable, no black-box



Choosing a Model

Model Selection

- Evaluate model metrics
- Consider business knowledge
- Recognize constraints

How do we choose?

Prediction Type	Validation Fit Statistic	Direction
Decisions	Misclassification	smallest
	Average Profit/Loss	largest/smallest
	Kolmogorov-Smirnov Statistic	largest
Rankings	ROC Index (concordance)	largest
	Gini Coefficient	largest
Estimates	Average Squared Error	smallest
	Schwarz's Bayesian Criterion	smallest
	Log-Likelihood	largest

Model Comparison Node



Property	Value
General	
Node ID	MdlComp
Imported Data	
Exported Data	
Notes	
Train	
Variables	
Assessment Reports	
Number of Bins	20
ROC Chart	Yes
Recompute	No
Model Selection	
Selection Data	Default
Selection Statistic	Default
Grid Selection Statistic	Default
Selection Table	Akaike's Information Criterion
Selection Depth	Average Squared Error
Score	
Selection Editor	Mean Squared Error
Report	
Selected Model	
Target	Captured Response
Model Node	Gain
Model Description	Gini Coefficient
Selection Criteria	Regression DT
Status	
	Valid: Misclassification Rate

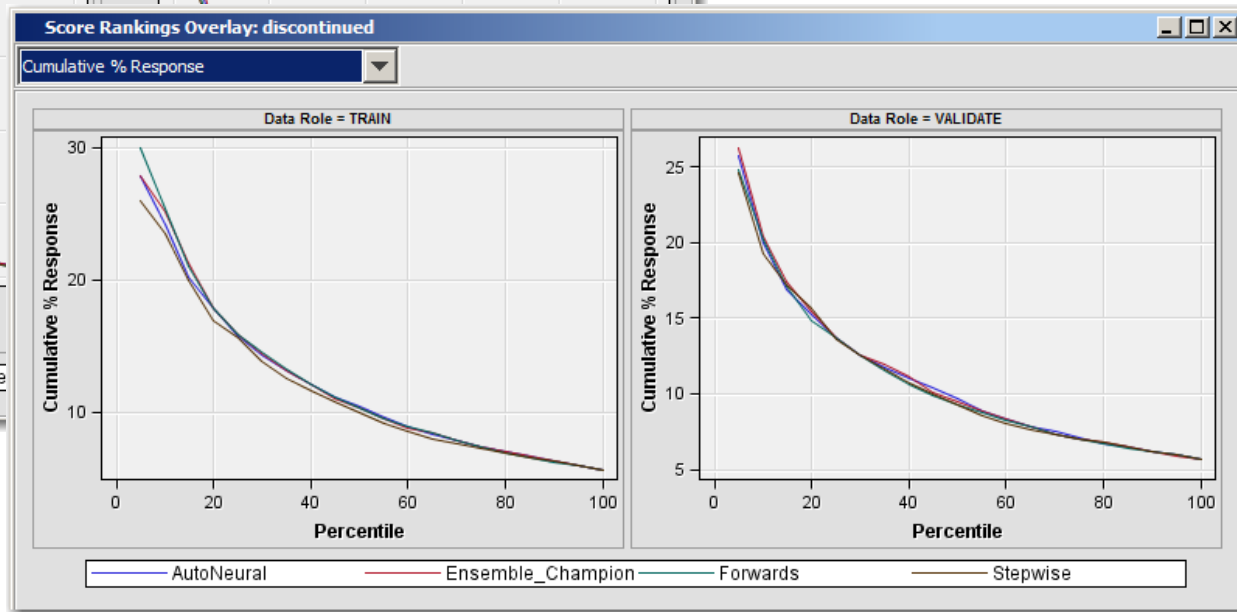
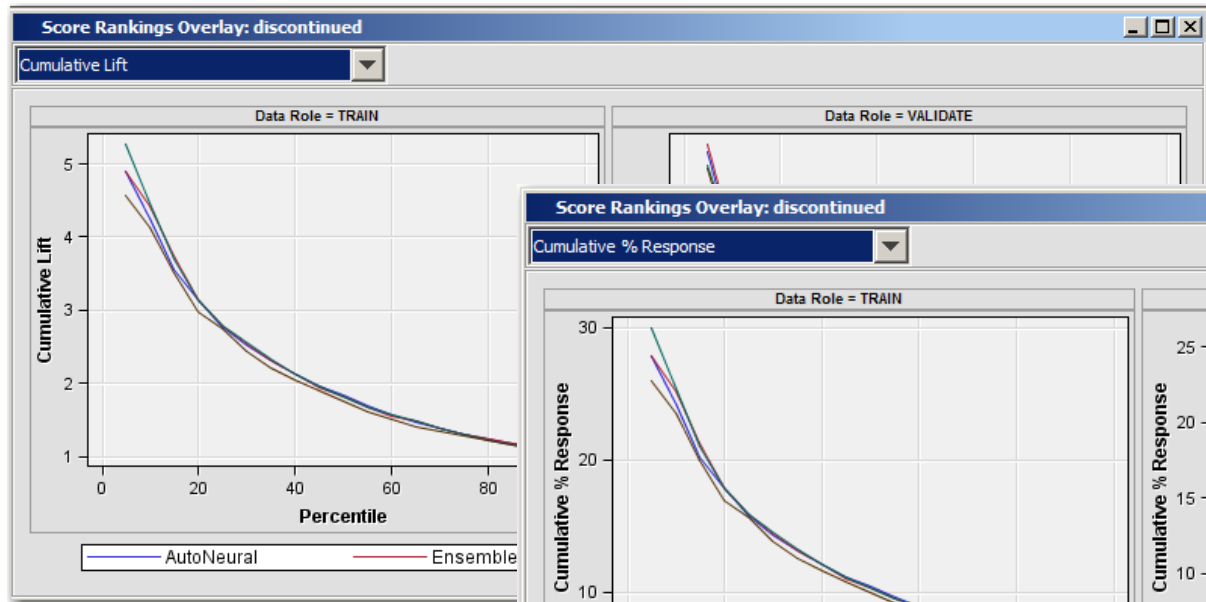
The [Model Comparison](#) node provides a common framework for comparing models and predictions from any of the modeling tools (such as Regression, Decision Tree, and Neural Network tools). The comparison is based on standard model fits statistics as well as potential expected and actual profits or losses that would result from implementing the model. The node produces the following charts that help to describe the usefulness of the model: lift, profit, return on investment, receiver operating curves, diagnostic charts, and threshold-based charts.

AIC	Captured Response
ASE	KS Statistic
MSE	Misclassification
ROC	Average Profit/Loss
Gain	Cumulative Lift
Lift	Cumulative Captured Response
Gini	Cumulative Percent Response

Available for training, validation
and test datasets

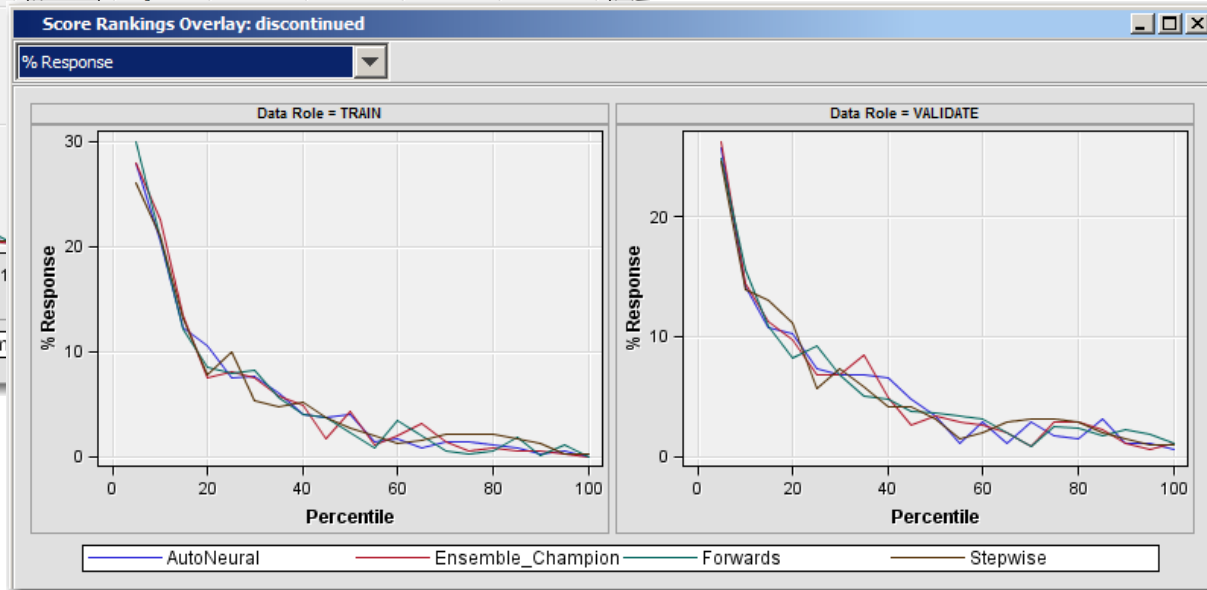
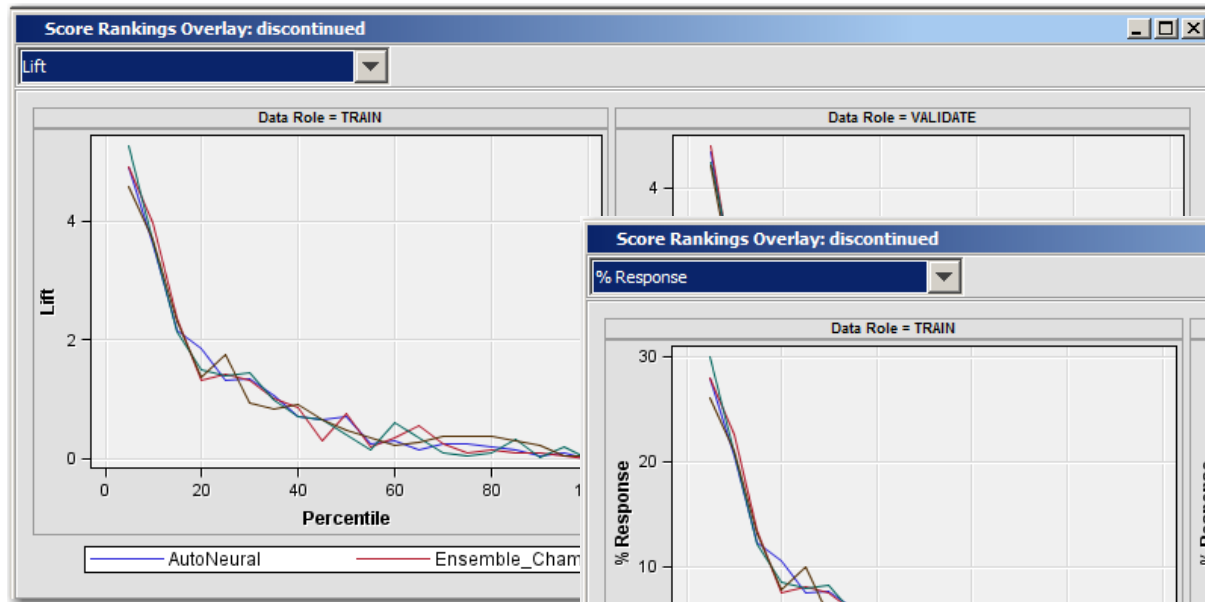
Assess

Cumulative charts



Assess

Non-Cumulative charts



SAS® Enterprise Miner™

Model Comparison Node

Selected Model	Predecessor or Node	Model Node	Model Description	Target Variable	Target Label	Selection Criterion: Valid: Misclassification Rate ▲	Train: Misclassification Rate	Valid: Lift	Train: Schwarz's Bayesian Criterion
Y	Reg4	Reg4	Regression DT	TARGET...	Donated ...	0.24944	0.24965	1.539784	15059.33
	HPDMFo...	HPDMFo...	HP Forest	TARGET...	Donated ...	0.249957	0.249797	1.429799	.
	HPReg4	HPReg4	HP Regression stepwise	TARGET...	Donated ...	0.250473	0.249428	1.546658	.
	Reg5	Reg5	Regression PC	TARGET...	Donated ...	0.250645	0.249133	1.443547	14993.11
	HPReg	HPReg	HP Reg - Backward	TARGET...	Donated ...	0.250817	0.249281	1.457295	.
	HPReg3	HPReg3	HP Reg forward	TARGET...	Donated ...	0.250989	0.247585	1.374807	.
	Reg2	Reg2	Regression Forward	TARGET...	Donated ...	0.251161	0.247585	1.361059	15075.82
	Reg3	Reg3	Regression Stepwise	TARGET...	Donated ...	0.251161	0.247585	1.361059	15075.82
	Reg	Reg	Regression Backward	TARGET...	Donated ...	0.251849	0.247732	1.361059	15075.56
	HPReg2	HPReg2	HP Reg Fast Backward	TARGET...	Donated ...	0.252193	0.248838	1.539784	.
	Reg8	Reg8	Regression 2 Poly	TARGET...	Donated ...	0.253226	0.246478	1.484792	15017.38
	Reg6	Reg6	Regression Full	TARGET...	Donated ...	0.253398	0.246773	1.622272	15639.84
	Reg9	Reg9	Reg 2-way Int 2 Poly	TARGET...	Donated ...	0.258214	0.241463	1.429799	16427.17
	Reg7	Reg7	Regression 2-way Interactions	TARGET...	Donated ...	0.295544	0.21211	1.127342	33523.52

Best Model



SAS Enterprise Miner assumes decision processing and selects the model with the lowest misclassification rate when there is a binary target.

Model Comparison Node

Model Comparison

Class selection statistic:

Kolmogorov-Smirnov statistic (KS)

Accuracy

Area under curve (C statistic)

Average squared error

Captured response

Cumulative captured response

Cumulative lift

F1 score

False discovery rate

False positive rate

Gain

Gini

Kolmogorov-Smirnov statistic (KS)

Accuracy

C statistic

Average Squared Error

Captured response

Cumulative captured response

Cumulative lift

Root average squared error

False Discover rate

False positive rate

Gain

Gini

KS Statistic

Lift

Misclassification

Multiclass log loss

ROC separation

F1 Score

Available for training, validation
and test datasets

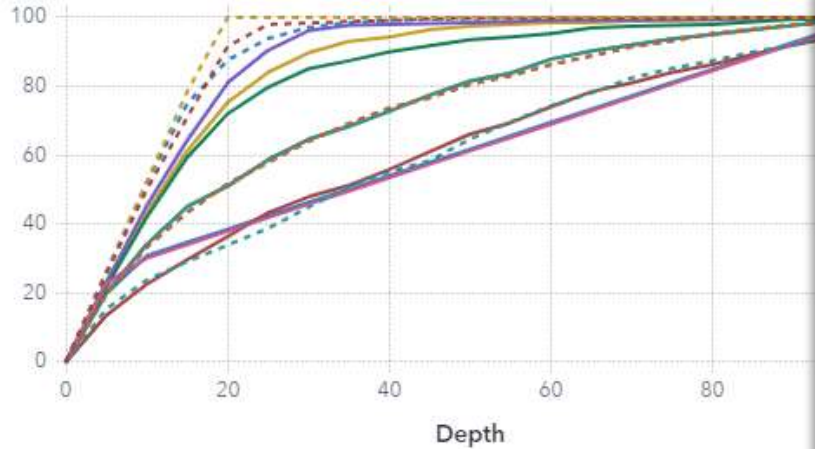
Assess Cumulative charts

Lift Reports

Cumulative Captured Response Percentage ▾



Cumulative Captured Response Percentage

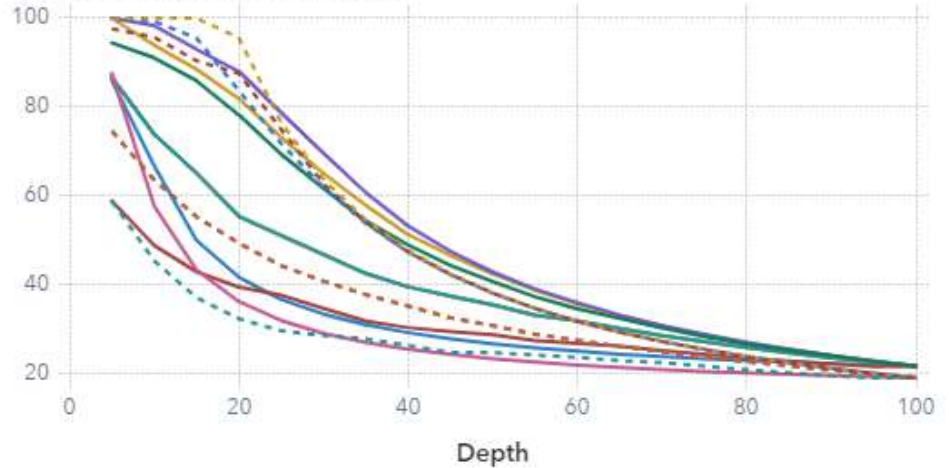


Lift Reports

Cumulative Response Percentage ▾

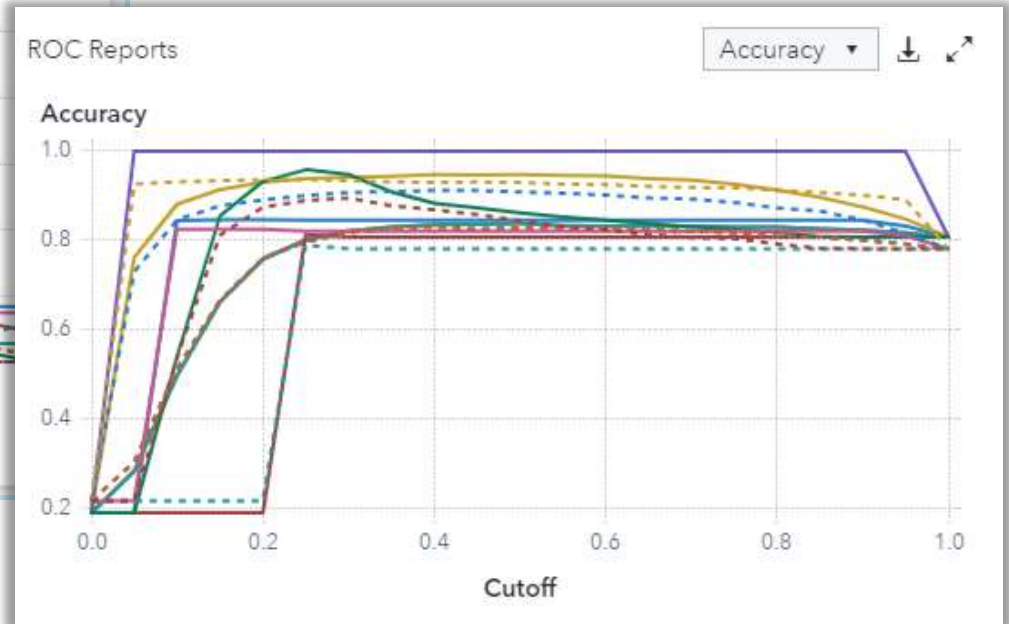
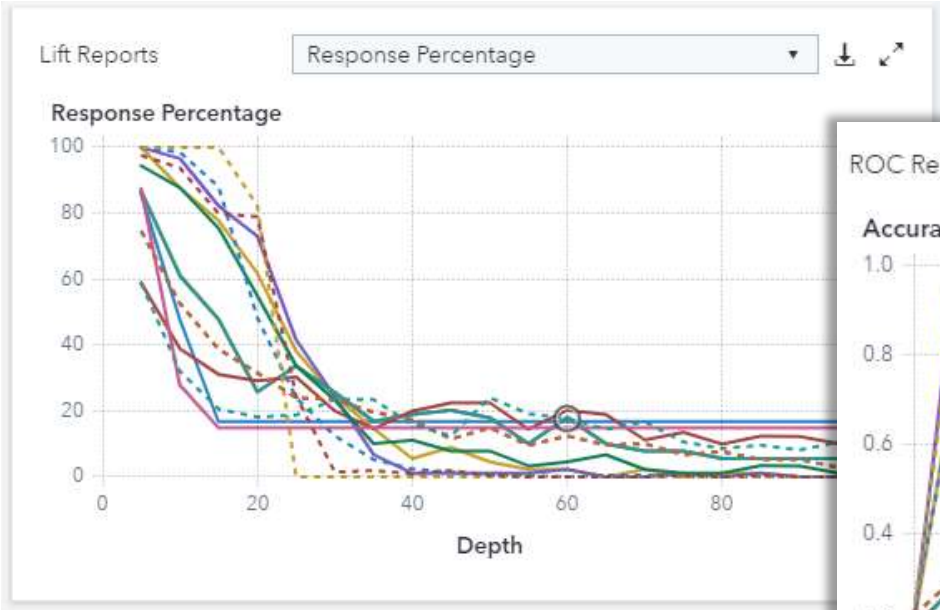


Cumulative Response Percentage



Assess

Non-cumulative charts




SAS® Visual Data Mining and Machine Learning

Model Comparison Node

Home Loan Default Demo > "Model Comparison" Results Close

Node Assessment

Model Comparison Download Refresh

Champion	Name	Algorithm Name	Misclassification Rate (Event)	Misclassification Rate
	GB Tune Explain	Gradient Boosting	0.0699	0.0699
	Gradient Boosting	Gradient Boosting	0.0912	0.0912
	Ensemble	Ensemble	0.1549	0.1549
	Forward Logistic Regression	Logistic Regression	0.1711	0.1711
	Stepwise Logistic Regression	Logistic Regression	0.1711	0.1711
	Decision Tree	Decision Tree	0.1784	0.1784
	Neural Network	Neural Network	0.2181	0.2181

Best
Model



Deploying the Model

Best Practices



Model Deployment

- Reporting Results
- Clean up and back up
- Monitor performance



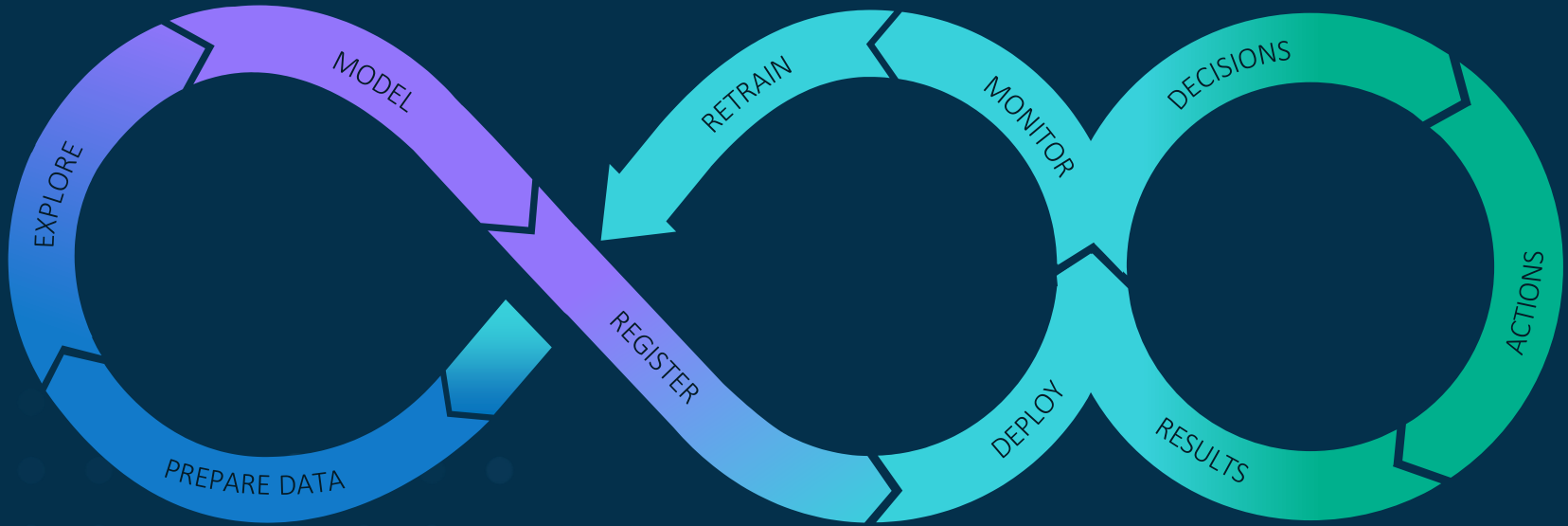
Best Practices



Model Deployment

- Incorporate and share knowledge
- Automate ETL (Extract, Transform, Load)
- Automate process

Analytics Operationalization with SAS



Format of Presentation

- Background & General Guidance
- Developing the Data
- Developing & Delivering the Model

Best Practice

Be analytically savvy and creative



It's both
science *and*
art!



Resources



Ready to Get on the Fast Track with Enterprise Miner?

Visit sas.com/learn-em

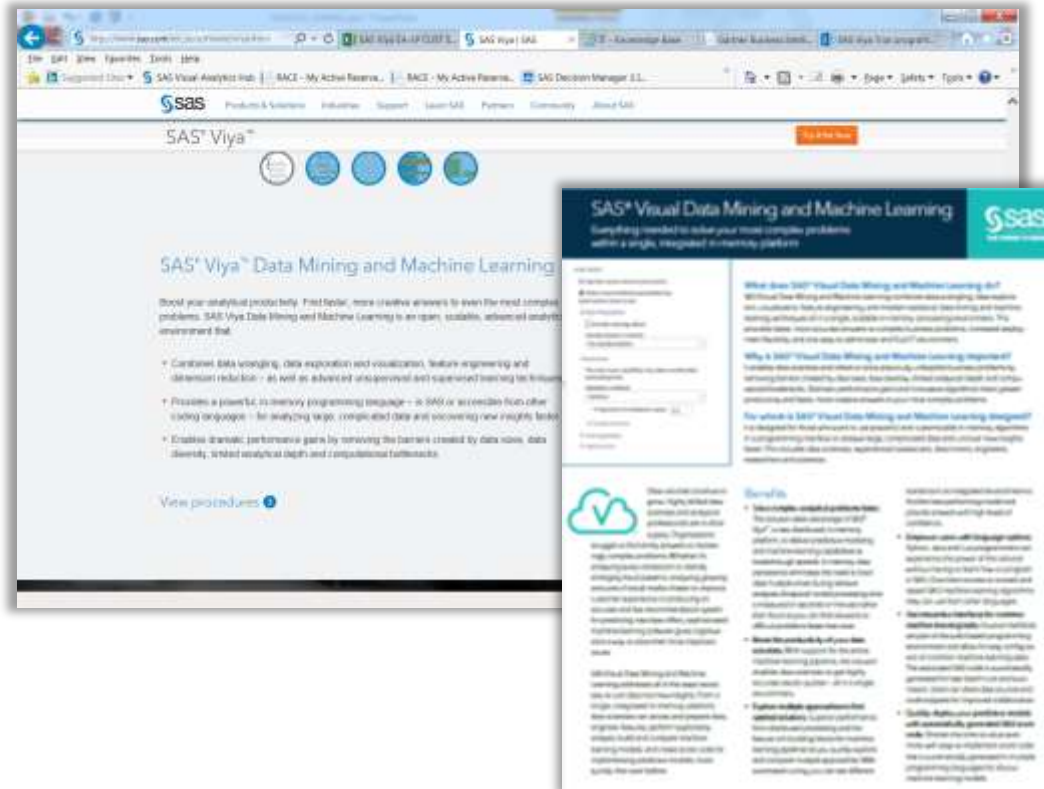
*and sign up to receive EM technical resources, tips & tricks
delivered directly from Brett Wujek, Sr. Data Scientist from SAS R&D*

SAS® Visual Data Mining and Machine Learning

Where to learn more?

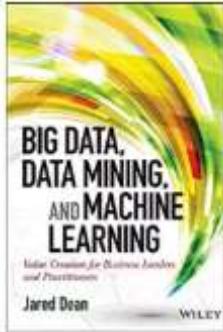
Key Resources

- [SAS VDMML Product Web Page](#)
- [Factsheet](#)
- [SAS Viya Brochure](#)
- [Documentation](#)
- [VDMML SAS Community](#)



Resources

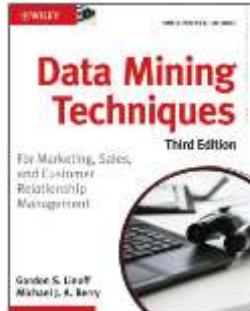
Suggested Reading



Big Data, Data Mining, and Machine Learning: Value Creation for Business Leaders and Practitioners

By Jared Dean

Available on [Amazon](#)



Data Mining Techniques: For Marketing, Sales, and Customer Relationship Management

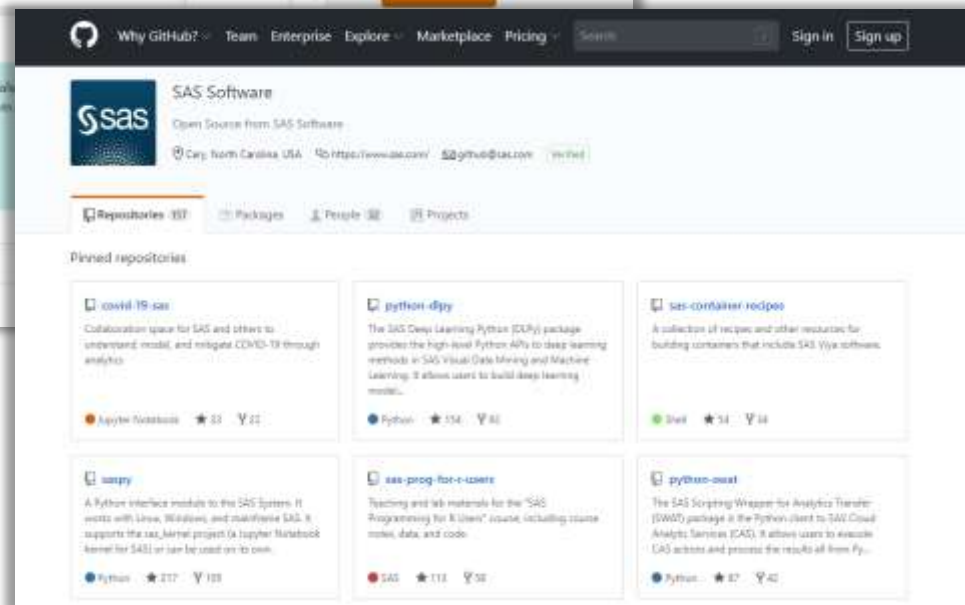
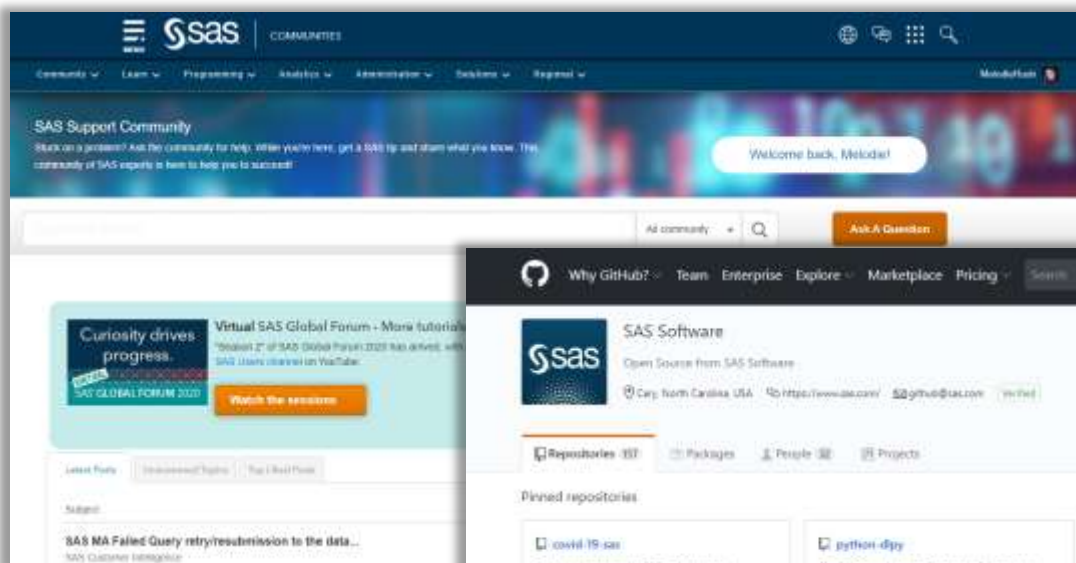
by Gordon S. Linoff and Michael J. A. Berry

Available on [Amazon](#)

Communities



[Communities.sas.com](https://communities.sas.com)
[Github.com/sassoftware](https://github.com/sassoftware)





Questions?

Thank you for your time and attention!

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