

Actuarial

Data Analytics / Predictive Modeling Seminar Part 2

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16th Annual Intercompany Long Term Care Insurance Conference



- Introduction
- Overview of Seminar
- “Traditional” Experience Study
- “Traditional” vs. “Predictive Modeling”
- Types of Predictive Modeling



Welcome to the first ever

ILTCI Predictive Modeling Seminar

Three part series providing an in depth introduction to predictive modeling

Agenda

Sunday; Part 1: Background

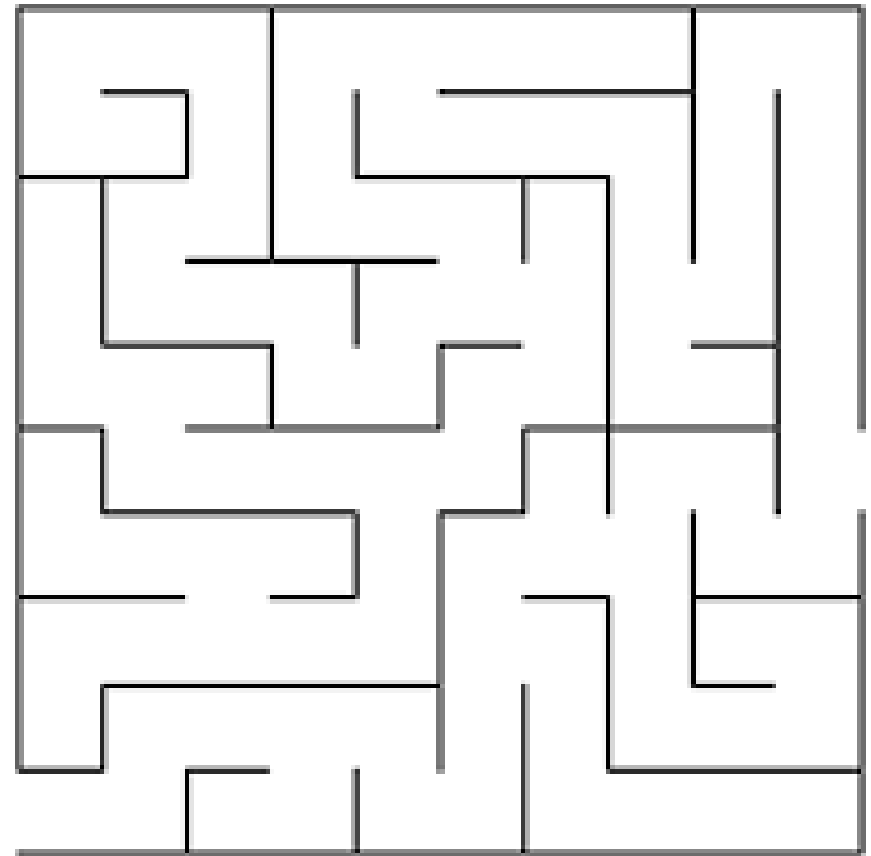
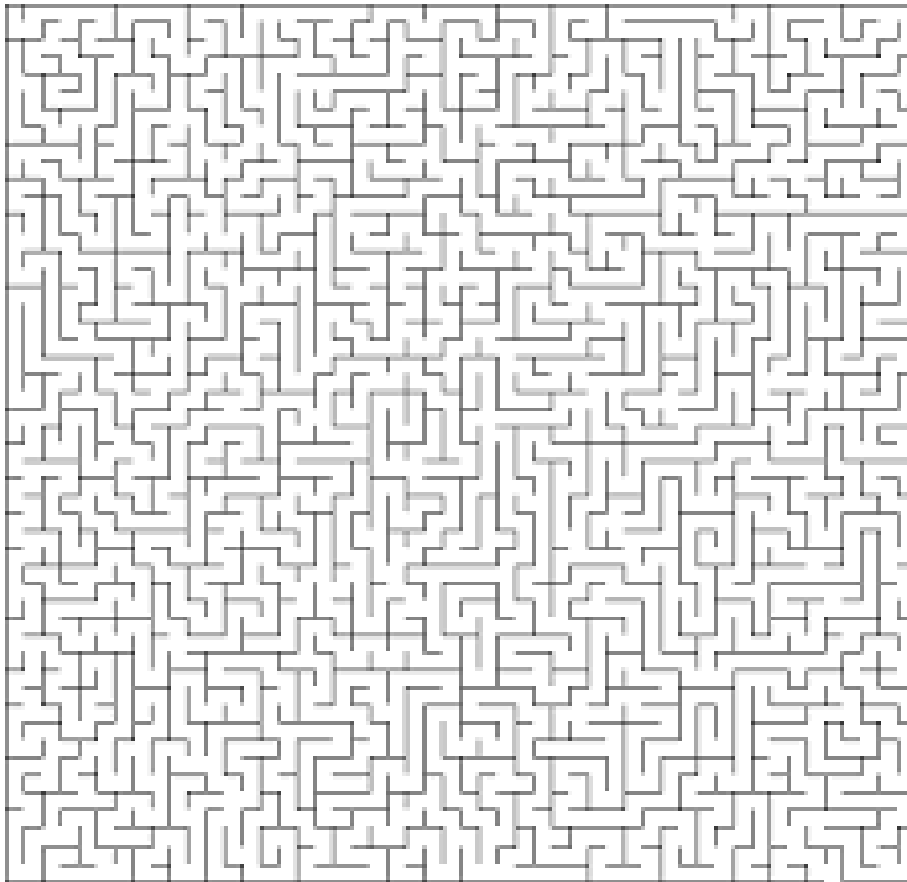
Monday; Part 2: Conference session

Wednesday; Part 3: Hands on experience

Overview of Seminar



Goal of this Session



Traditional Experience Study



Determine goal

- What are we measuring?
- Why are we measuring?

Data and reasonability review

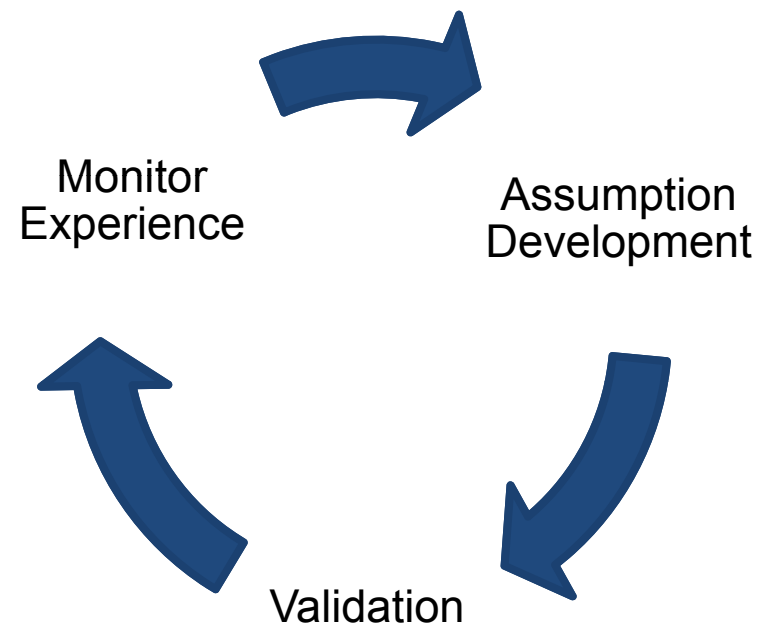
- Quality review
- Completeness
- General patterns and relationships

Develop assumptions

- Iterations
- Analysis of change

Validation

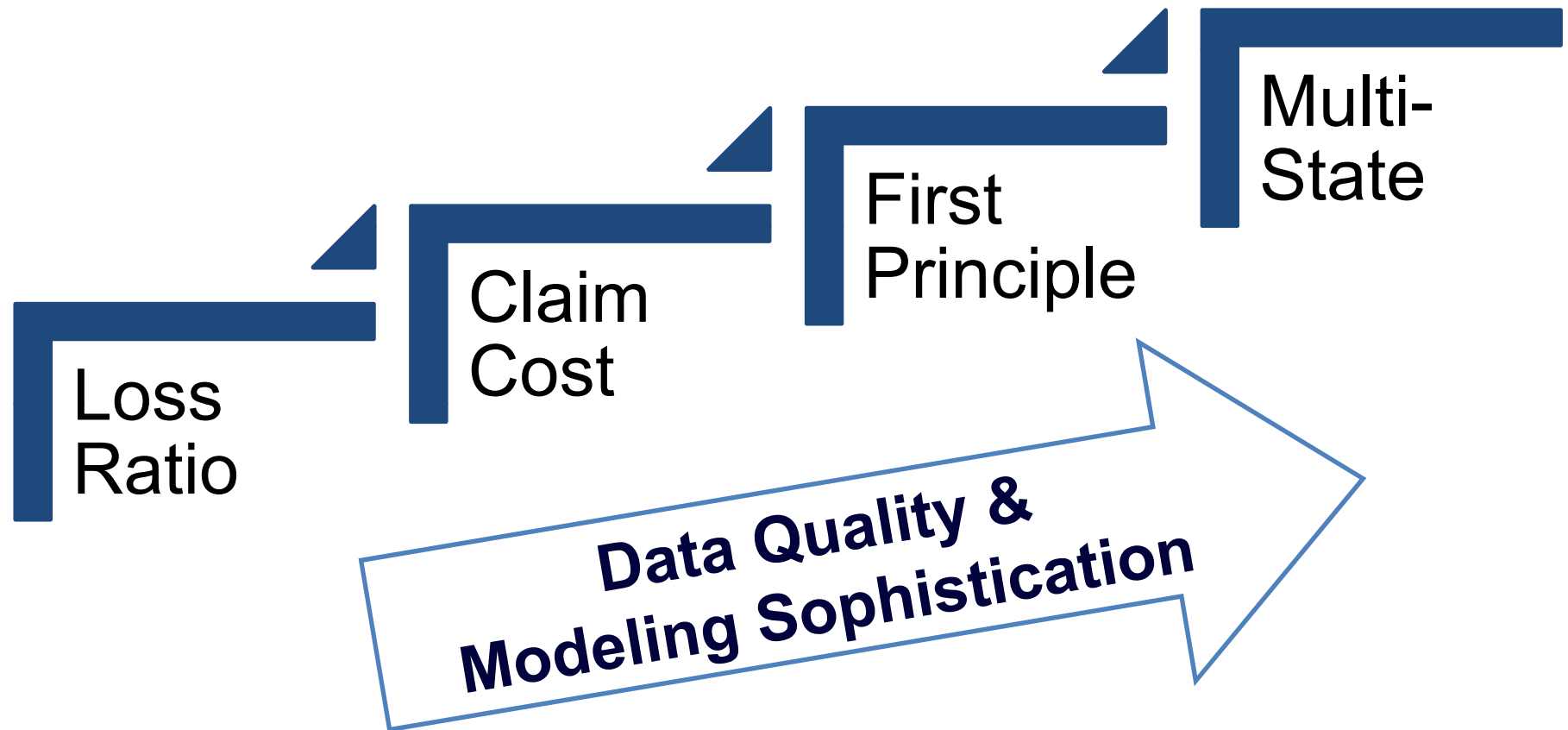
- Tests
- Business review



Traditional Experience Study



Determine goal





Data and reasonability review

- Summary of business (demographics)
- Completeness
- Financial reconciliation
- Volume of information
- Granular cell checks or audits



Assumption development / review

- Source of information
 - Company data
 - Industry data
 - Population data
 - Actuarial judgment
- Methodology & analysis toolset
- Degree of rigor



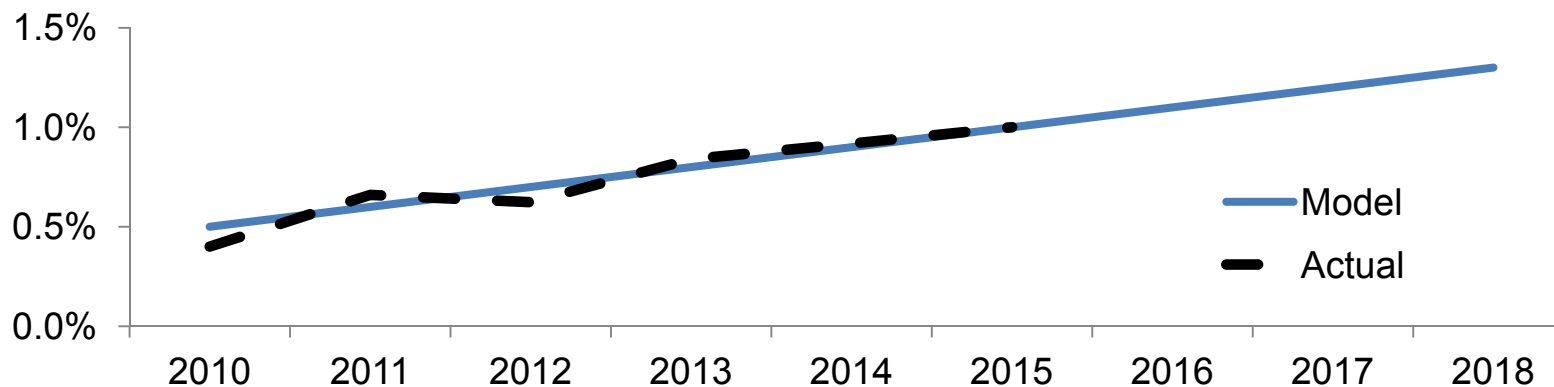
Assumption development / review

- Example – Incidence – Develop from data
- One approach
 - Develop ultimate attained age curve
 - Adjust for policyholder and benefit characteristic
 - Test to ensure fit...
 - Repeat.. test to ensure fit
 - Repeat.. test to ensure fit



Validation of Assumptions

- Reasonability
- Tests
 - Actual to expected analyses
 - Retrospective adequacy
 - Dynamic validation to projection
 - Key metric review
- Comparison to prior





Advantages

Easy to understand

Transparent

Flexible

Disadvantages

Interdependencies /
Iterative

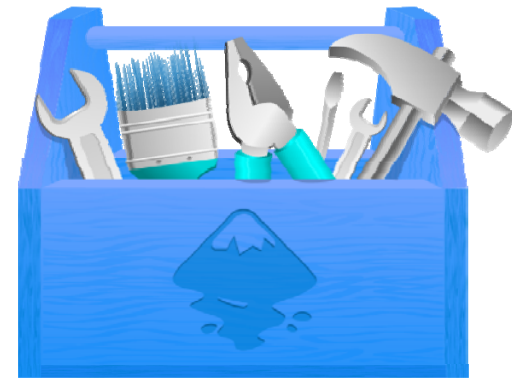
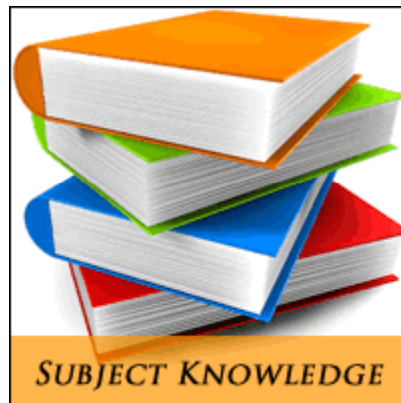
Data grouping

Time consuming

Traditional vs Predictive Modeling



- What inhibits a traditional modeler from using predictive modeling





- Will PM help with the following questions:
 - Will it tell me what I don't know?
 - Would PM tell me what to assume in places we don't have data?
 - How should we handle an RPU?
 - Will it tell me what to assume for cost of care in 40 years?

Easy Answer: NO



What is Predictive Modeling?

- We have a series of historical observations showing how input variables x (independent variables) are related to responses y (dependent variables) by some process



- A predictive model is some function of the independent variables that mimics this process
- Predictive Modeling is the process of developing a predictive model



What is Predictive Modeling?

- There are two goals in fitting a predictive model
 - Prediction: to be able to predict responses for future input variables x
 - Information: to understand the process that associates response variables with input variables
- Note: Just the same as the goal of developing an assumption!!!



How is Predictive Modeling different from Traditional Analysis?

- Traditional Analysis assumes a model structure, and compares Actual vs Expected (according to the model) on a one-way or a two-way basis. The model is iteratively modified (independent variables added or parameters changed) to improve the fit on this basis
- Predictive Modeling doesn't force parameters to take certain values*
- Predictive Modeling uses statistics** to determine which independent variables should be included, and what parameters they should take

*But it can

**And potentially other tests



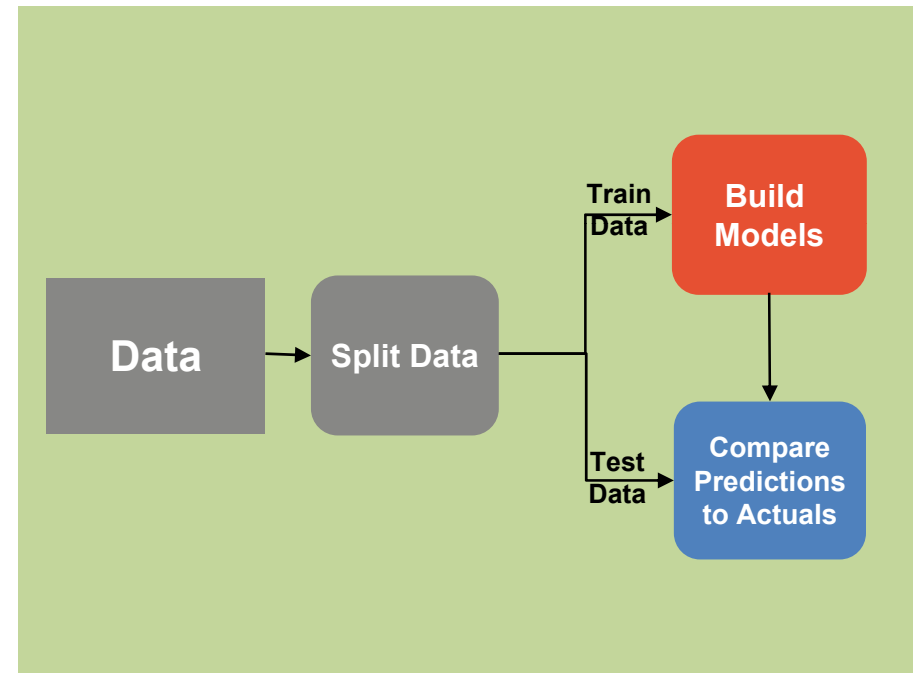
- Why do Predictive Modeling?
- Remember our goals in fitting a predictive model
 - Prediction: to be able to predict responses for future input variables x
 - Information: to understand the process that associates response variables with input variables
- Predictive models can give
 - Better predictions of responses
 - A better understanding of the process

Traditional vs Predictive Modeling



Better predictions?

- How do we show this?
- When modeling, we split the available data into two sets, training and testing
- We fit models on the training data
- Apply both of these models to the testing data

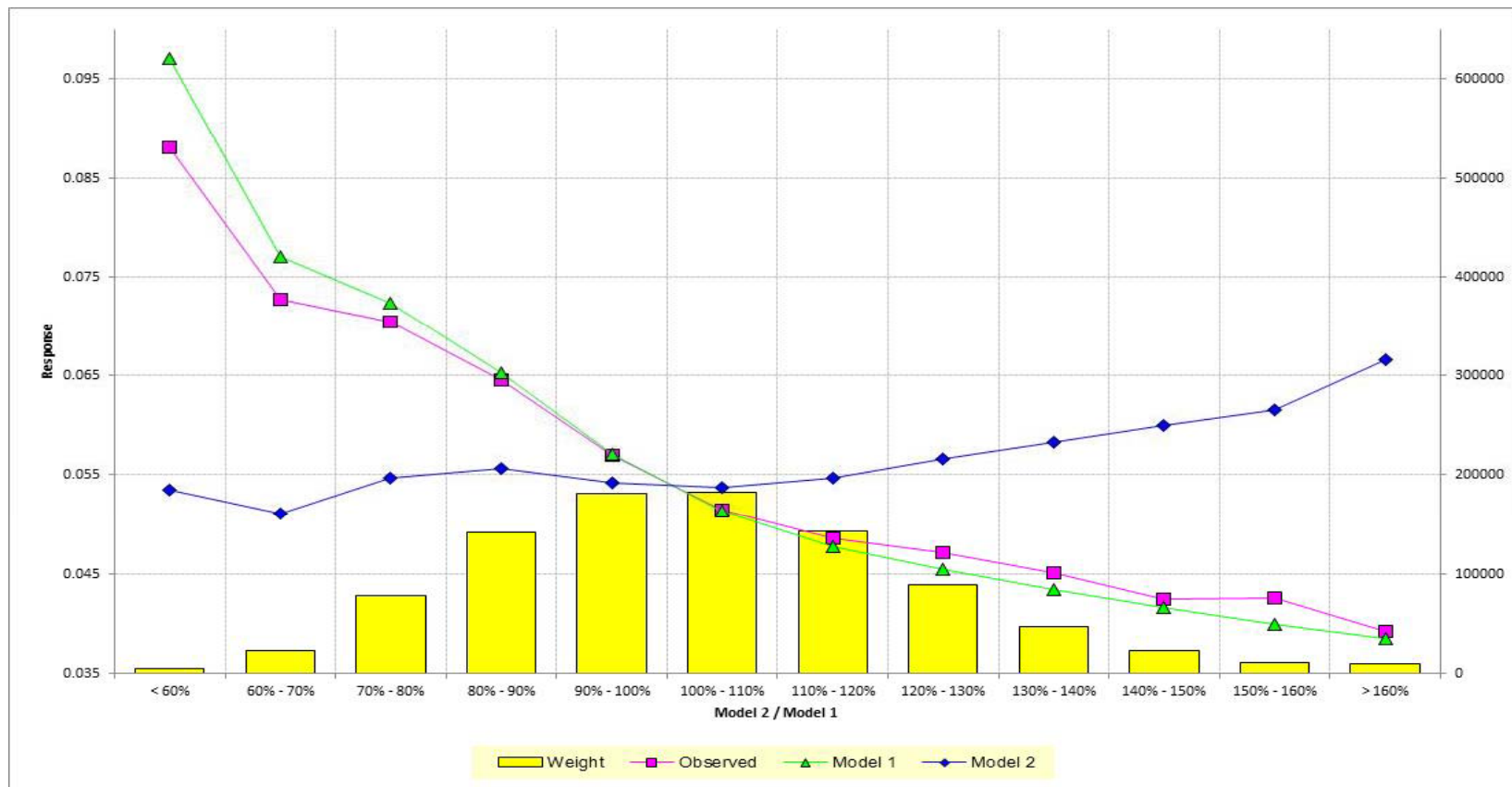


Traditional vs Predictive Modeling



Better predictions?

- We can see which of the models gave predictions closer to the observed response





Better understanding of the process?

- Predictive modeling tells us
 - Which factors need to be in a model according to some combination of criteria
 - The true effect of each independent variable included in the model (which can be different from the actual oneway effect, or the ratio of the actual to expected effects on a oneway basis, as it takes into account correlations between variables)
- (Arguably) not all predictive modeling methods will give a better understanding of the process (black box)



There are many types of predictive model

- Regression
- Decision Trees
- Neural Networks
- Genetic Algorithms
- Support Vector Machines
- K-nearest Neighbors



Many of these have different varieties. For example, Regression includes

- Ordinary Linear Regression
- Generalized Linear Models (GLM)
- Ridge regression
- Lasso
- Elastic Net



Regression

- The expected value of independent variable Y for a given combination of levels of dependent variables X is a function of X
- Fitting this kind of model involves determining the structure of the model function and solving for the parameters
- Outcome is a list of model parameters that have to be combined in some way (e.g. multiplicatively)

Types of Predictive Model



Regression

- Example output of a Regression model (a GLM)

Base	0.0004								
Gender		Incurred Age		Duration		Marital Status		Premium Class	
Female	1.0000	35-	0.1171	1	1.0000	Married	1.0000	Preferred	0.8682
Male	0.7560	36	0.1326	2	1.4224	Single	2.1227	Standard	1.0000
		37	0.1484	3	1.8732			Substandard	1.1006
		38	0.1641	4	2.3096				
		39	0.1796	5	2.6933				
		40	0.1947	6	2.9984				
		41	0.2092	7	3.2136				
		42	0.2231	8	3.3414				
		---	---	---	---				
Base	Gender	Incurred Age	Duration	Marital Status	Premium Class	Expected Mortality (per '000)			
	Male	51	5	Single	Preferred				
0.0004	0.7560	0.3293	2.6933	2.1227	0.8682	0.4775			
		51	0.3293	17	2.7583				
		52	0.3425	18	2.6561				
		53	0.3570	19	2.5474				



Regression

- Example: they can allow us to make statements like (all else being equal)
 - Incidence is 10% higher in single than married people
 - Duration impacts on incidence in a certain way
- **Pros:**
 - Flexible, easy to interpret and to explain
 - The result is a formula (which can be turned into a table)
- **Cons:** do not give good results if data is highly nonlinear (to some extent this can be overcome)



Generalized Linear Model (GLM)

- Has three components
 - An error distribution coming from the exponential family
 - A linear predictor function of dependent variables
 - A link function, which relates the linear predictor to the expected value of the response
- Parameters typically found by minimizing $L = \text{negative log likelihood}$ for model structure
- Model structure developed by experiment (can be automated to some extent)
 - Factors are added, removed, combined and simplified, and statistics related to the fit of the model are studied
 - Not dissimilar to development of assumptions by traditional method, but aided by statistics



Generalized Linear Model (GLM)

- Widely used in P&C insurance for the reasons given previously (flexible, easy to interpret and to explain)
- GLMs will be used in the workshop after the conference to fit a model of incidence



Penalized Regression

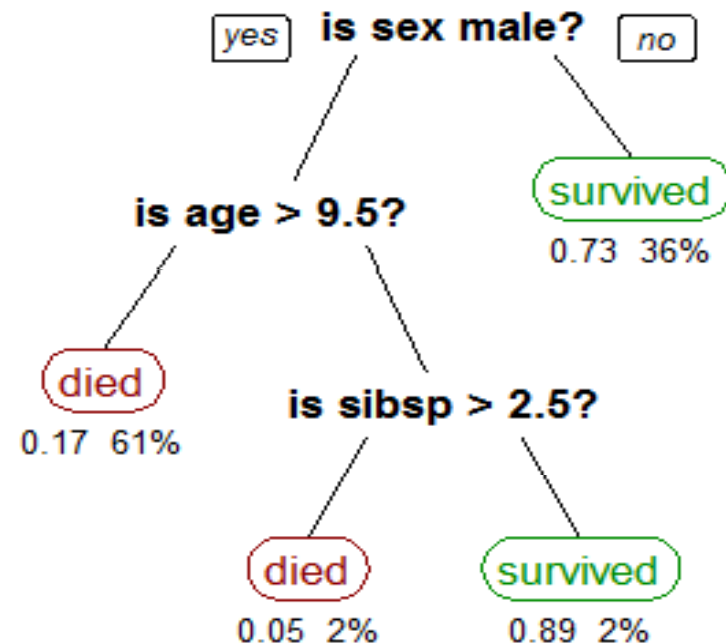
- Same model form as GLM, but parameters β are estimated differently
- Function minimized to find parameters is $L + \lambda \cdot \text{Penalty}(\beta)$
 - $\lambda = 0$ means GLM
 - $\lambda = \text{infinity}$ makes all parameters 0
 - Necessary to choose “best” value of λ
- Ridge Regression and Lasso have different penalty functions which lead to different properties
 - For example, Lasso is useful for understanding variable importance, useful when number of variables is large
- Elastic Net combines the penalty functions of Ridge Regression and Lasso



Decision Trees

- Determines a series of rules based on values of the independent variables that segment the data
- The process is recursive
- It stops when no further splitting will improve results, or some stopping condition is satisfied

Passengers of the Titanic





Decision Trees

Pros

- Outcome is a set of rules applying to different segments (easy to interpret, explain, and order)
- Good for identifying high-dimensional features of data, as in the Titanic example (and these features can be used as variables in other modeling techniques)

Cons

- Highly dependent on the data, and therefore doesn't give predictions as good as some other techniques



Generalizations of Decision Trees

- To overcome this issue, generalizations of Decision Trees exist, such as
 - Random Forests
 - Gradient Boosted Trees
- These are examples of ensemble methods, which use combinations of different underlying models



Random Forests

- Roughly speaking, this involves
 - Taking a large number of random samples of the data (with replacement)
 - Fitting a simple tree on each sample
 - The model is an average of these trees



•The idea is that the combination of simple trees avoids overfitting to the data, and is more predictive than the single tree



- Output is a complex set of rules
- They can give very good predictions, but interpreting the model can be complicated (some people would argue with this statement)



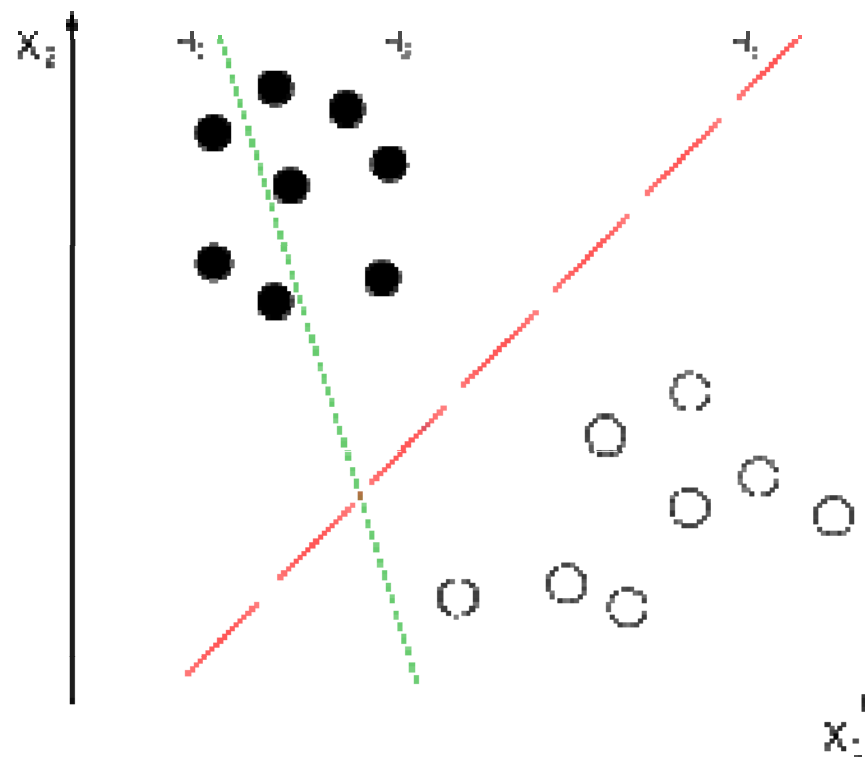
Gradient Boosted Trees

- Roughly speaking, this involves
 - Fit a simple tree on a random sample of the data
 - On another random sample
 - Calculate predictions according to previous tree
 - Calculate model residuals
 - Fit another simple tree on the residuals
 - Repeat the process
- Output is a complex combination of sets of rules
- They can give very good predictions, but interpreting the model can be complicated (some people would argue with this statement)



Support Vector Machines

- Hyperplanes in high-dimensional space separate observations into different groups by
- Each different group gets a different prediction

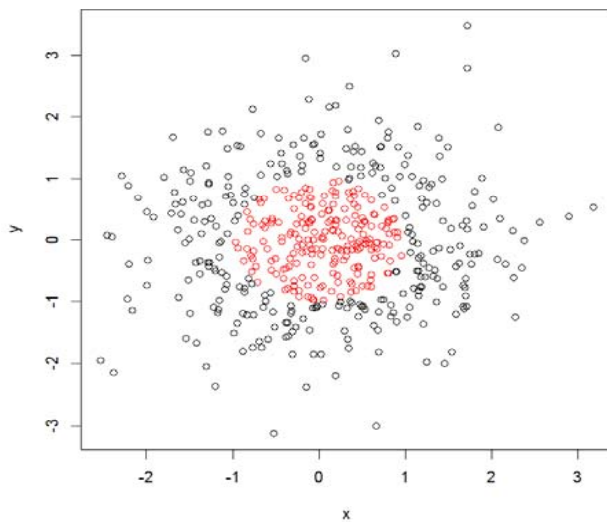




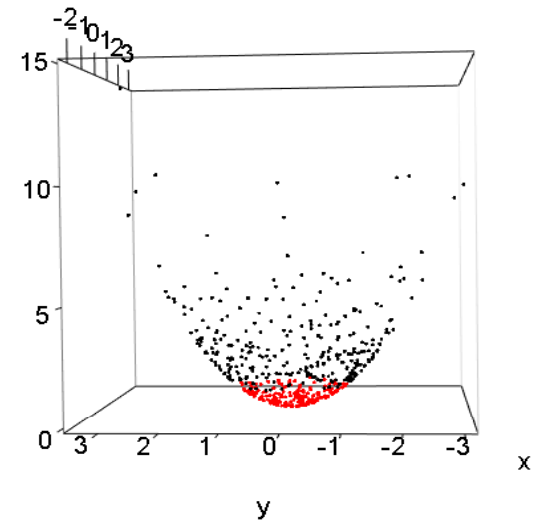
Support Vector Machines

- Modeling involves implicitly transforming data to aid search for hyperplanes, as below (red means low risk, black means high risk)

Original feature space



After transformation

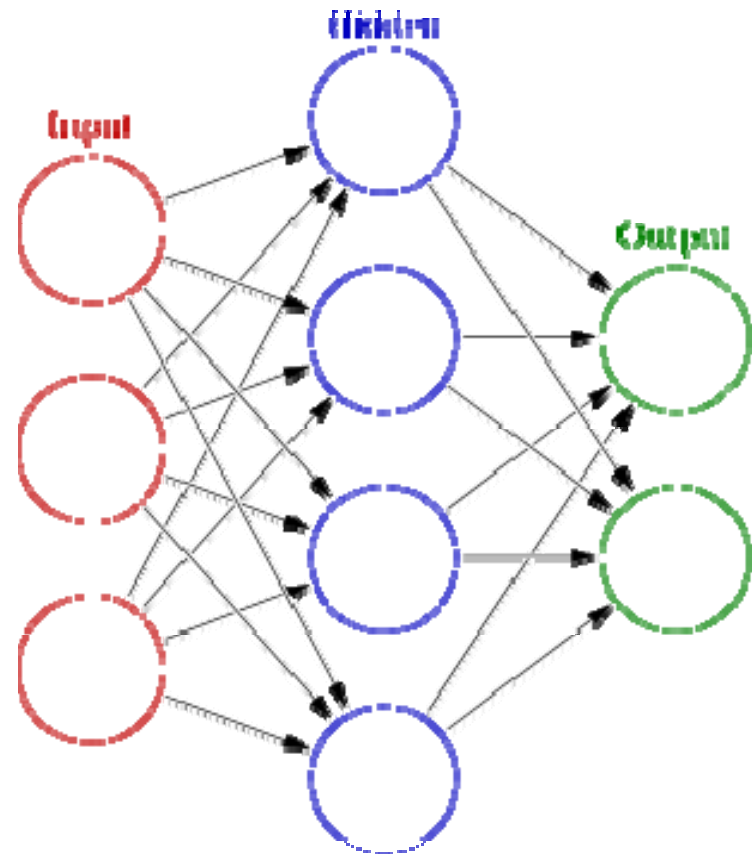


- Problem becomes more difficult as more dimensions are added



Neural Networks

- Inspired by biological neural networks (e.g. the brain)
- Predicted values calculated in stages by passing through a network of layers
- Value of a node given by a weighted sum of values in the layer before, transformed by a non-linear activation function
- Number/size of hidden layers chosen during modeling
- Weights estimated to minimize a loss function (e.g., negative log-likelihood)
- Can give very good predictions, but interpretation can be complicated (some people would argue with this statement)





- The goals of Predictive Modeling are the same as traditional assumption setting
 - Making predictions of future outcomes
 - Understanding the process
- Predictive Modeling can give demonstrably better results than traditional techniques
- There are many predictive modeling techniques
- Predictive Modeling is not necessarily a Black Box



- Possible Long Term Care Applications
 - Traditional actuarial assumption development
 - Incidence
 - Length of stay
 - Utilization
 - Lapse
 - Mortality (active vs disabled)
 - Could we determine other uses?



- Possible Long Term Care Applications
 - Underwriting
 - Can we quantify the most critical aspects of the UW process?
 - Could we determine better early knockout questions?
 - Could we determine who qualifies using less questions?
 - Claim intake
 - Can we quantify the most critical data collection to pay a claim?
 - Could we determine the right claims to manage closely?



Questions?