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Predictive Modeling: Basics and Beyond

June 2009

Agenda

1. What is Predictive Modeling?
2. Types of predictive models.
3. Data and Data Preparation.
4. Applications – case studies.

Introductions

Ian Duncan FSA FIA FCIA MAAA. President, Solucia Consulting, A SCIOinspire Company.

Actuarial Consulting company founded in 1998. A leader in managed care, disease management and predictive modeling applications.

4 healthcare actuaries; 4 PhDs; healthcare analytics team.

<u>Four main business segments:</u>

- Disease and Care Management consulting (operations; ROI; outcomes; predictive modeling).
- Actuarial Consulting (start-up health insurers in NY and IN; state Medicaid plans; Massachusetts Healthcare Connector Board Member).
- Wellness and Care Management Operations Support Services (analytics, data management, risk assessment, outreach, fulfillment).
- Analytics and Reporting Software Applications.

Strong research foundation: we have always supported a strong research function to inform our recommendations.

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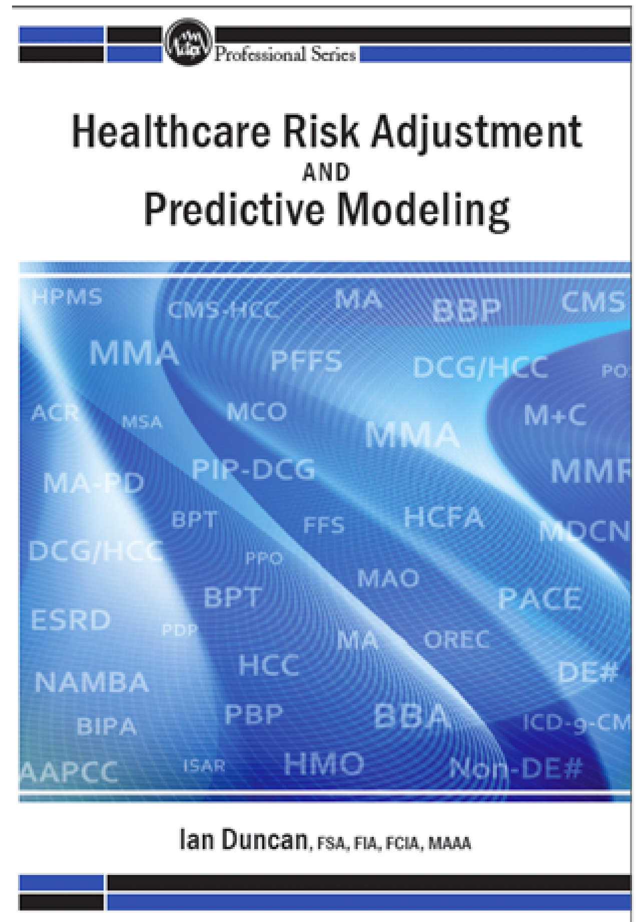
Introductions

Author of several books and peer-reviewed studies in healthcare management and predictive modeling.

Published 2008

Due end-2010



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Predictive Modeling:
A Review of the Basics

Definition of Predictive Modeling

"Predictive modeling is a set of tools used to stratify a population according to its risk of nearly any outcome…ideally, patients are risk-stratified to identify opportunities for intervention <u>before</u> the occurrence of adverse outcomes that result in increased medical costs."

Cousins MS, Shickle LM, Bander JA. An introduction to predictive modeling for disease management risk stratification. Disease Management 2002;5:157-167.

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Predictive Modeling is about *Risk*

RISK = F (Loss Amount; Probability of Occurrence)

- Predictive modeling is about searching for high probability occurrences.
- The fact that member costs are predictable makes Predictive Modeling Possible.

In the next 2 slides we shall see examples of member costs over time.

Member costs over time

MEMBERSHIP

	Baseline Year	Sequent Year		
Baseline Year Cost Group	Baseline Percentage Membership	LOW <$2,000	MODERATE $2,000-$24,999	HIGH $25,000+
LOW <$2,000	69.5%	57.4%		
			11.7%	
				0.4%
MODERATE $2,000-$24,999	28.7%	9.9%		
			17.7%	
				1.1%
HIGH $25,000+	1.8%	0.2%		
			0.9%	
				0.6%
TOTAL	100.0%	67.6%	30.3%	2.2%

Member costs over time

	Baseline Year	Sequent Year PMPY CLAIMS			Baseline Year	Sequent Year CLAIMS TREND		
Baseline Year Cost Group	Mean Per Capita Cost	LOW <$2,000	MODERATE $2,000-$24,999	HIGH $25,000+	Mean Per Capita Cost Trend	LOW <$2,000	MODERATE $2,000-$24,999	HIGH $25,000+
LOW <$2,000	$510.37	$453.24			11.5%	7.4%		
			$5,282.58				17.6%	
				$56,166.54				6.9%
MODERATE $2,000-$24,999	$6,157.06	$888.30			57.2%	2.5%		
			$6,803.91				34.1%	
				$49,701.87				15.8%
HIGH $25,000+	$55,197.12	$907.47			31.3%	0.1%		
			$10,435.51				2.7%	
				$73,164.49				13.0%
TOTAL		$518.72	$6,325.46	$57,754.19	100.0%	10.0%	54.4%	35.6%
AVERAGE	$3,090.36			$3,520.09				
TREND				13.9%				

Actuaries have known this for a long time

- Absent other information, Age/Sex are predictive.

Relative cost by age/sex

	Male	Female	Total
<19	$1,429	$1,351	$1,390
20-29	$1,311	$2,734	$2,017
30-39	$1,737	$3,367	$2,566
40-49	$2,547	$3,641	$3,116
50-59	$4,368	$4,842	$4,609
60-64	$6,415	$6,346	$6,381
Total	$2,754	$3,420	$3,090

Adding Medical Condition Improves Prediction

Condition-based vs. standardized costs

Member	Age	Sex	Condition	Actual Cost (annual)	Standardized cost (age/sex)	Condition-based cost/ Standardized cost (%)
1	25	M	None	$863	$1,311	66%
2	55	F	None	$2,864	$4,842	59%
3	45	M	Diabetes	$5,024	$2,547	197%
4	55	F	Diabetes	$6,991	$4,842	144%
5	40	M	Diabetes + Heart conditions	$23,479	$2,547	922%
6	40	M	Heart condition	$18,185	$2,547	714%
7	40	F	Breast Cancer and other conditions	$28,904	$3,641	794%
8	60	F	Breast Cancer and other conditions	$15,935	$6,346	251%
9	50	M	Lung Cancer and other conditions	$41,709	$4,368	955%

Identification – how?

- At the heart of predictive modeling!
  - Who?
  - What common characteristics?
  - What are the implications of those characteristics?
- There are many different algorithms for identifying member conditions. THERE IS NO SINGLE AGREED FORMULA.
- Condition identification often requires careful balancing of sensitivity and specificity.

A word about codes and groupers

Codes are the “raw material” of predictive modeling.

Codes are required for payment, so they tend to be reasonably accurate - providers have a vested interest in their accuracy.

Codes define important variables like Diagnosis (ICD-9 or 10); Procedure (CPT); Diagnosis Group (DRG – Hospital); Drug type/dose/manufacturer (NDC); lab test (LOINC); Place of service, type of provider, etc. etc.

“Grouper” models sort-through the raw material and consolidate it into manageable like categories.

Identification – example (Diabetes)

Diabetics can be identified in different ways:

Data source	Reliability	Practicality
Physician Referral/chart	High	Low
Enrollment	High	High
Claims	Medium	High
Prescription Drugs	Medium	High
Laboratory Values	High	Low
Self-reported	Low/medium	Low

Medical and Drug Claims are often the most practical method of identifying candidates for predictive modeling.

Identification – example (Diabetes)

Diagnosis Code	Code Description
ICD-9-CM Diagnosis 250.0	Diabetes mellitus without mention of complication
ICD-9-CM Diagnosis 250.1	Diabetes with ketoacidosis (complication resulting from severe insulin deficiency)
ICD-9-CM Diagnosis 250.2	Diabetes with hyperosmolarity (hyperglycemia (high blood sugar levels) and dehydration)
ICD-9-CM Diagnosis 250.3	Diabetes with other coma
ICD-9-CM Diagnosis 250.4	Diabetes with renal manifestations (kidney disease and kidney function impairment)
ICD-9-CM Diagnosis 250.5	Diabetes with ophthalmic manifestations
ICD-9-CM Diagnosis 250.6	Diabetes with neurological manifestations (nerve damage as a result of hyperglycemia)
ICD-9-CM Diagnosis 250.7	Diabetes with peripheral circulatory disorders
ICD-9-CM Diagnosis 250.8	Diabetes with other specified manifestations
ICD-9-CM Diagnosis 250.9	Diabetes with unspecified complication

Diabetes – additional codes

CODES	CODE TYPE	DESCRIPTION - ADDITIONAL
DIABETES;		
G0108, G0109	HCPCS	Diabetic outpatient self-management training services, individual or group
J1815	HCPCS	Insulin injection, per 5 units
67227	CPT4	Destruction of extensive or progressive retinopathy, (e.g. diabetic retinopathy) one or more sessions, cryotherapy, diathermy
67228	CPT4	Destruction of extensiive or progressive retinopathy, one or more sessions, photocoagulation (laser or xenon arc).
996.57	ICD-9-CM	Mechanical complications, due to insulin pump
V45.85	ICD-9-CM	Insulin pump status
V53.91	ICD-9-CM	Fitting/adjustment of insulin pump, insulin pump titration
V65.46	ICD-9-CM	Encounter for insulin pump training

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Diabetes – Relative Severity

Relative costs of Members with Different Diabetes Diagnoses

Diagnosis	Description	Average cost PMPY	Relative cost
250	A diabetes diagnosis without a fourth digit (i.e. 250 only).	$13,258	105%
250.0	Diabetes mellitus without mention of complication	$10,641	85%
250.1	Diabetes with ketoacidosis (complication resulting from severe insulin deficiency)	$16,823	134%
250.2	Diabetes with hyperosmolarity (hyperglycemia (high blood sugar levels) and dehydration)	$26,225	208%
250.3	Diabetes with other coma	$19,447	154%
250.4	Diabetes with renal manifestations (kidney disease and kidney function impairment)	$24,494	195%
250.5	Diabetes with ophthalmic manifestations	$11,834	94%
250.6	Diabetes with neurological manifestations (nerve damage as a result of hyperglycemia)	$17,511	139%
250.7	Diabetes with peripheral circulatory disorders	$19,376	154%
250.8	Diabetes with other specified manifestations	$31,323	249%
250.9	Diabetes with unspecified complication	$13,495	107%
357.2	Polyneuropathy in Diabetes	$19,799	157%
362	Other retinal disorders	$13,412	107%
366.41	Diabetic Cataract	$13,755	109%
648	Diabetes mellitus of mother complicating pregnancy childbirth or the puerperium unspecified as to episode of care	$12,099	96%
TOTAL	All Diabetes Diagnoses	$12,589	100%

Diabetes – Possible Grouping System

Different codes are mapped to groups for ease of analysis

Severity level	Diagnosis Codes Included	Average Cost	Relative Cost
1	250	$10,664	85%
2	250.5; 250.9; 362; 366.41; 648	$12,492	99%
3	250.1; 250.3; 250.6; 250.7; 357.2	$18,267	145%
4	250.2; 250.4	$24,621	196%
5	250.8	$31,323	249%
	TOTAL (All diabetes codes)	$12,589	100%

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Diabetes – drug codes

Insulin or Oral Hypoglycemic Agents are often used to identify members. A simple example follows; for more detail, see the HEDIS code-set.

This approach is probably fine for Diabetes, but may not work for other conditions where off-label use is prevalent.

Insulin	
2710*	Insulin**

OralAntiDiabetics	
2720*	Sulfonylureas**
2723*	Antidiabetic - Amino Acid Derivatives**
2725*	Biguanides**
2728*	Meglitinide Analogues**
2730*	Diabetic Other**
2740*	ReductaseInhibitors**
2750*	Alpha-Glucosidase Inhibitors**
2760*	Insulin Sensitizing Agents**
2799*	Antiadiabetic Combinations**

More about Grouper Models

Grouper models address several problems inherent in identification from claims (medical and/or drug):

•What "recipe" or algorithm to apply?
•How to keep the algorithm up-to-date?
•How to achieve consistency among users (important, for example, in physician reimbursement or program assessment).

They also have draw-backs:
•Someone else's definitions;
•Lack of transparency;
•You can't control sensitivity/specificity trade-off.

Grouper Models – example (DCGs)

Summary of DxCG Grouping Levels		
DxCG Grouping Level	Number of Groups	Application
Aggregated Condition Categories (ACC)	31	Population profiling, reporting
Related Condition Categories (RCC)	117	Population profiling, reporting
Condition Categories (CC)	394	Clinical screening, reporting
Hierarchical Condition Categories (HCC)	293	Making predictions, clinical screening, reporting
DxGroups	1,010	Clinical screening, reporting
ICD-9 diagnostic codes	15,000+	Coding and reimbursement

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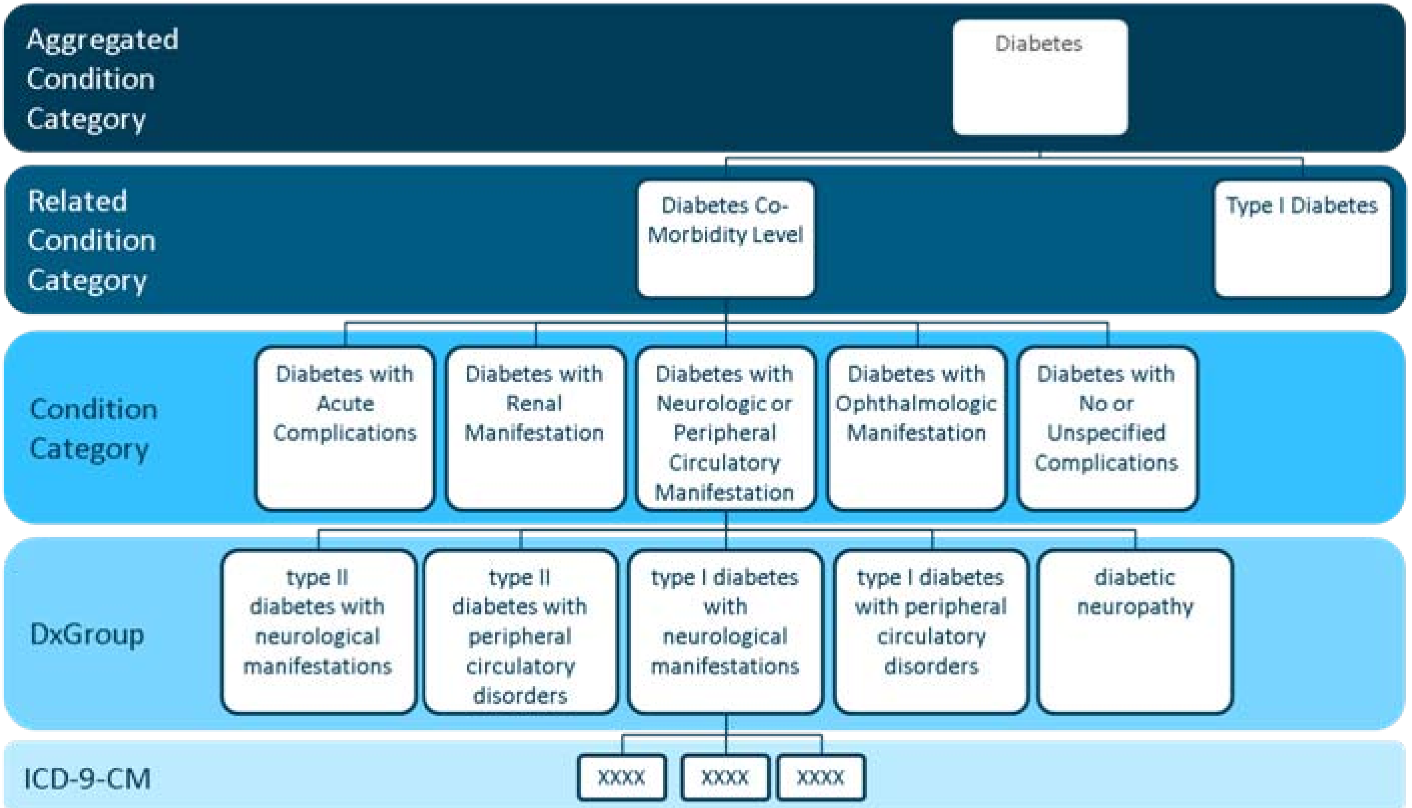
Grouper Models – example (DCGs)

Example of DxCG Hierarchy for Diabetes



- For Risk Scoring, each Group and Condition Category becomes an independent variable in a multiple regression equation that results in a weight for that condition;
- Weights correlate with average resource utilization for that condition;
- Some are “trumped” by others (more severe);
- Scores can range from ≅ 0.0 (for young people without diagnoses) to numbers in the 40’s and 50’s (for multiple co-morbid patients).

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Construction of a model*

* From Ian Duncan: “Healthcare Risk Adjustment and Predictive Modeling” (Actex, forthcoming)

Condition Category	Risk Score Contribution	Notes
Diabetes with No or Unspecified Complications	0.0	Trumped by Diabetes with Renal Manifestation
Diabetes with Renal Manifestation	2.1	
Hypertension	0.0	Trumped by CHF
Congestive Heart Failure (CHF)	1.5	
Drug Dependence	0.6	
Age-Sex	0.4	
Total Risk Score	**4.6**	

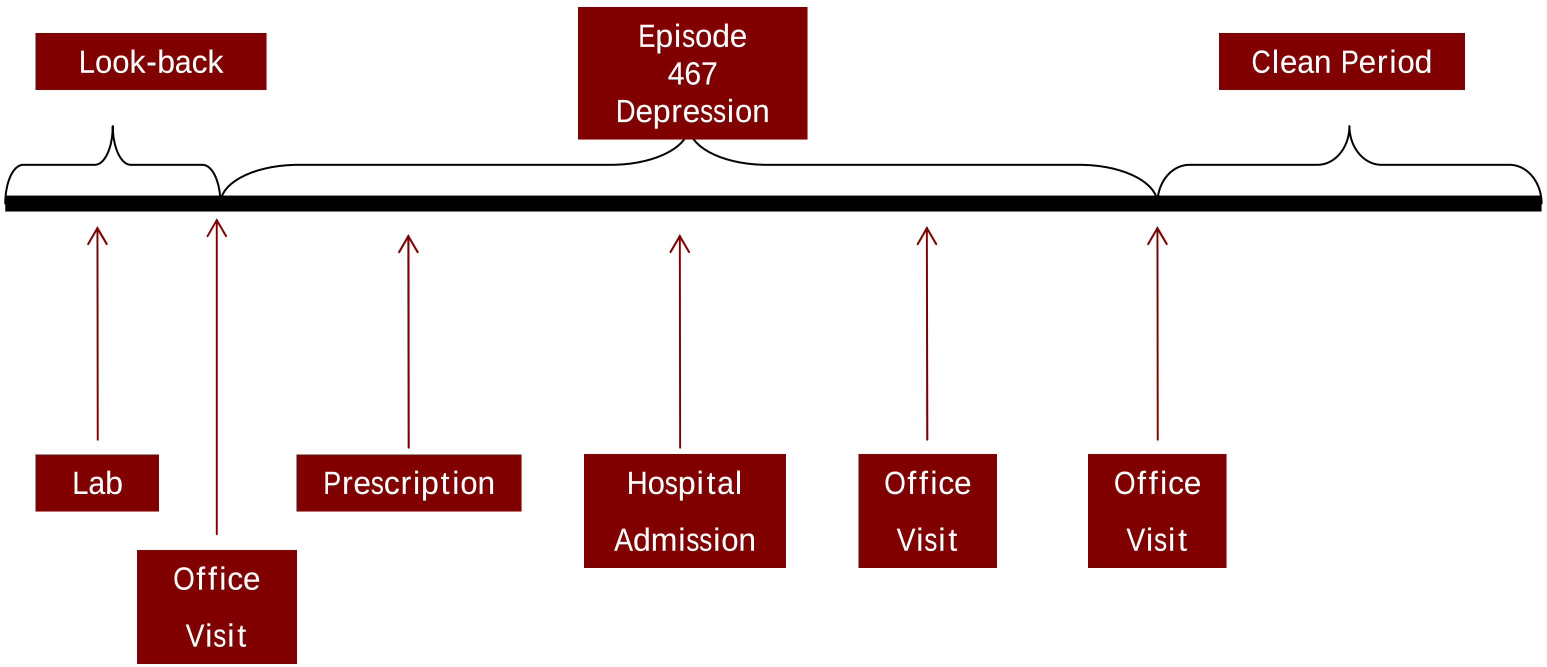
A different approach to grouping

Grouping by Episode

Services related to the underlying diagnosis are grouped

Different diagnosis related groups have different cost weights.

Complete/Incomplete groups



Construction of a model

Grouper/Risk-adjustment theory is that there is a high correlation between risk scores and actual dollars (resources used).

The Society of Actuaries has published three studies that test this correlation. They are available from the SOA and are well worth reading. (See bibliography.) They explain some of the theory of risk-adjusters and their evaluation, as well as showing the correlation between $'s and Risk Scores for a number of commercial models.

Note 1: the SOA tests both *Concurrent* (retrospective) and *Prospective* models. Concurrent model correlations tend to be higher.

Note 2: there are some issues with models that you should be aware of:

- They tend to be less accurate at the "extremes" (members with high or low risk scores);
- We have observed an inverse correlation between risk-score and $'s across a wide range of members.

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All people are not equally identifiable

Prevalence of chronic conditions identified using different claims algorithms

	Number of claiming events in the year			
Condition	4 or more	3 or more	2 or more	1 or more
Asthma	2.4%	2.9%	3.9%	6.1%
Cardiovascular disease	0.8%	1.2%	1.7%	2.8%
Heart Failure	0.2%	0.2%	0.3%	0.6%
Pulmonary Disease	0.2%	0.3%	0.5%	1.0%
Diabetes	3.3%	3.7%	4.1%	4.9%
All	6.3%	7.4%	9.2%	13.1%

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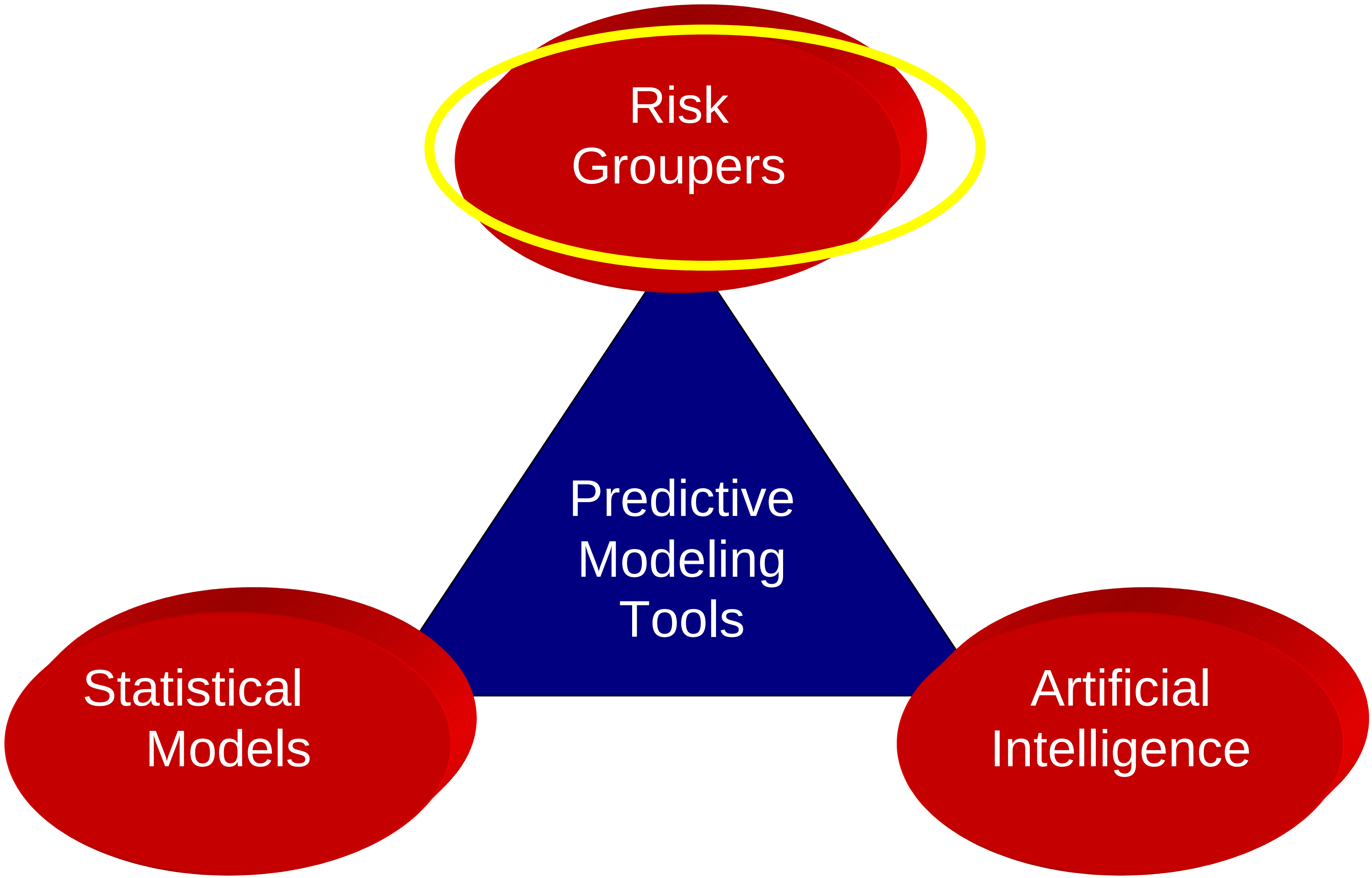
The Problem of False Positives

Probability that a Member identified with a chronic condition in Year 1 will be identified with that condition in Year 2.

All Chronic Conditions

No. Claiming Events in Year 2	Number of claiming Events in Year 1			
	4 or more	3 or more	2 or more	1 or more
4 or more	59.7%	26.3%	15.7%	7.2%
3 or more	65.8%	35.9%	22.9%	10.6%
2 or more	72.0%	47.9%	34.3%	17.2%
1 or more	78.0%	62.3%	49.9%	30.9%
Do not re-qualify	22.0%	37.7%	50.1%	69.1%

Types of Predictive Modeling Tools



Risk Groupers

What are the different types of risk groupers?

SOA Risk Grouper Study

Commercially available Grouper models

Company	Risk Grouper	Data Source
CMS	Diagnostic Risk Groups (DRG) (There are a number of subsequent "refinements" to the original DRG model as well)	Hospital claims only
CMS	HCCs	Age/Sex, ICD -9
3M	Clinical Risk Groups (CRG)	All Claims (inpatient, ambulatory and drug)
IHCIS/Ingenix	Impact Pro	Age/Sex, ICD-9 NDC, Lab
UC San Diego	Chronic disability payment system	Age/Sex, ICD -9
	Medicaid Rx	NDC
Verisk Sightlines™	DCG	Age/Sex, ICD -9
	RxGroup	Age/Sex, NDC
Symmetry/Ingenix	Episode Risk Groups (ERG)	ICD – 9, NDC
	Pharmacy Risk Groups (PRG)	NDC
Symmetry/Ingenix	Episode Treatment Groups (ETG)	ICD – 9, NDC
Johns Hopkins	Adjusted Clinical Groups (ACG)	Age/Sex, ICD – 9

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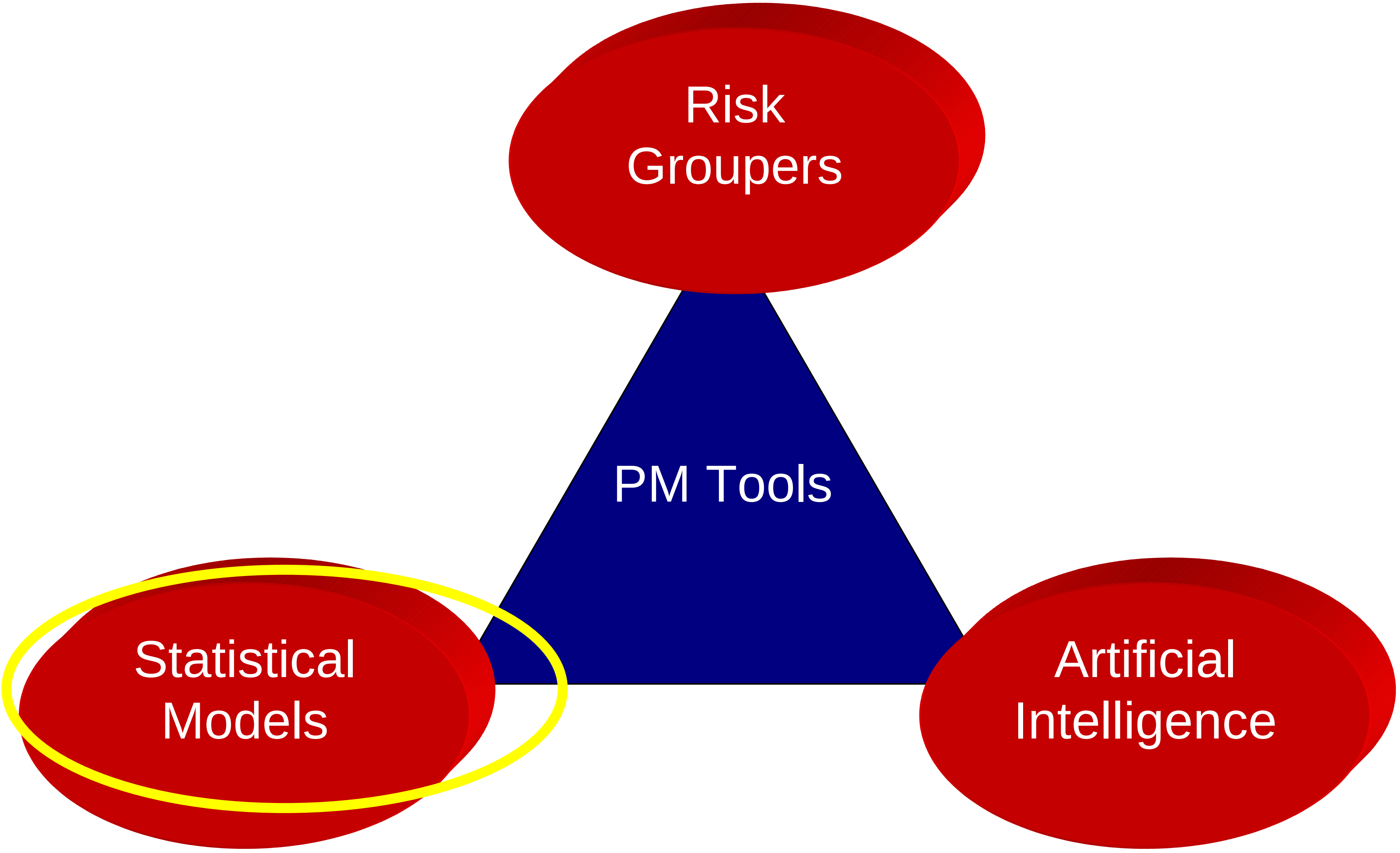
Risk Grouper Summary

1. Similar performance among all leading risk groupers*.
2. Risk grouper modeling tools use *different algorithms* to group the source data.
3. Risk groupers use *relatively limited data* sources (e.g. DCG and Rx Group use ICD-9 and NDC codes but not lab results or HRA information)
4. Most Risk Grouper based Predictive Models combine also use statistical analysis.

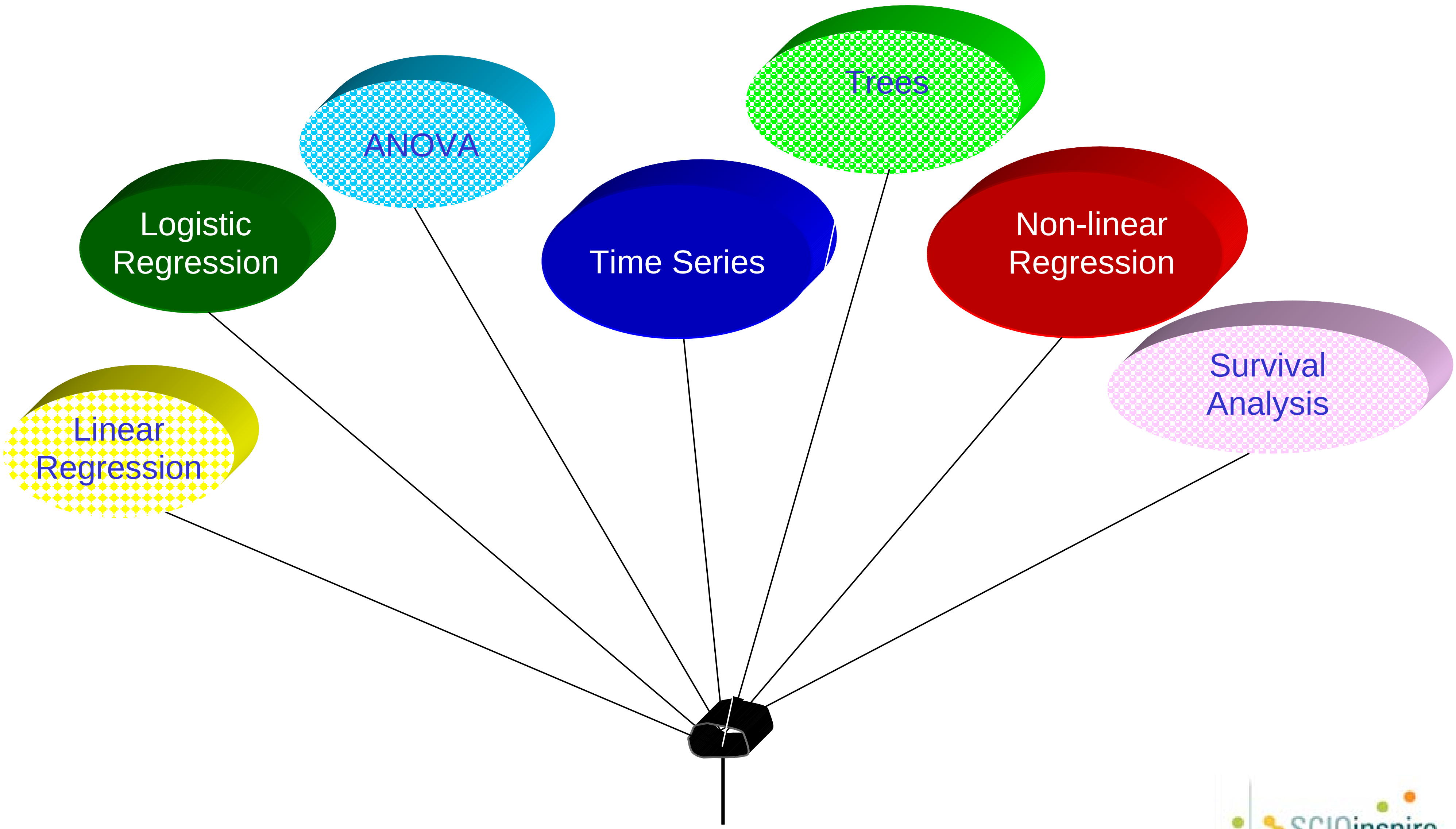
* See SOA study (Winkelman et al) published 2007.   Available from SOA (www.soa.org)

Types of Predictive Modeling Tools

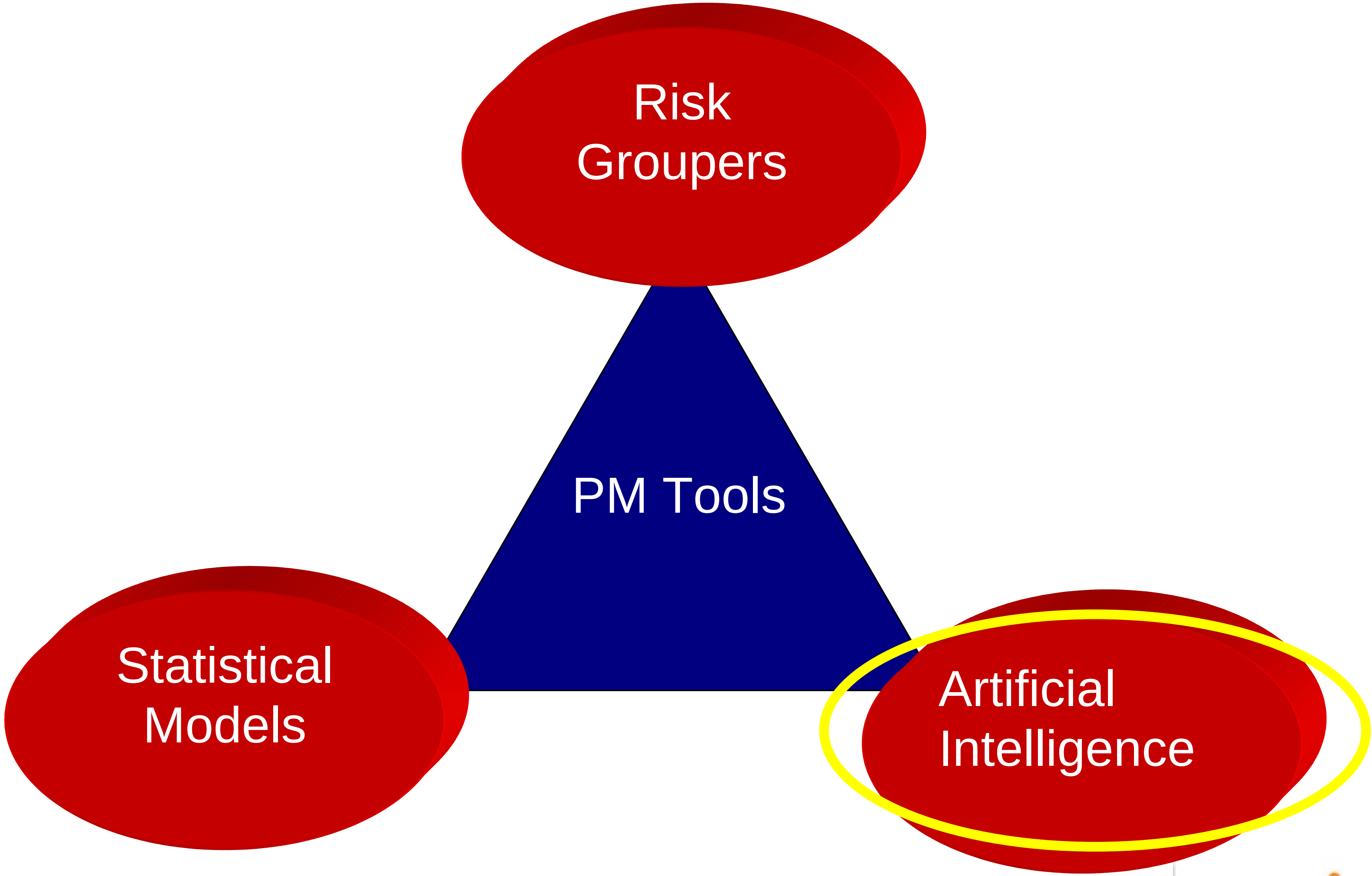


What are the different types of statistical models?

Types of Statistical Models



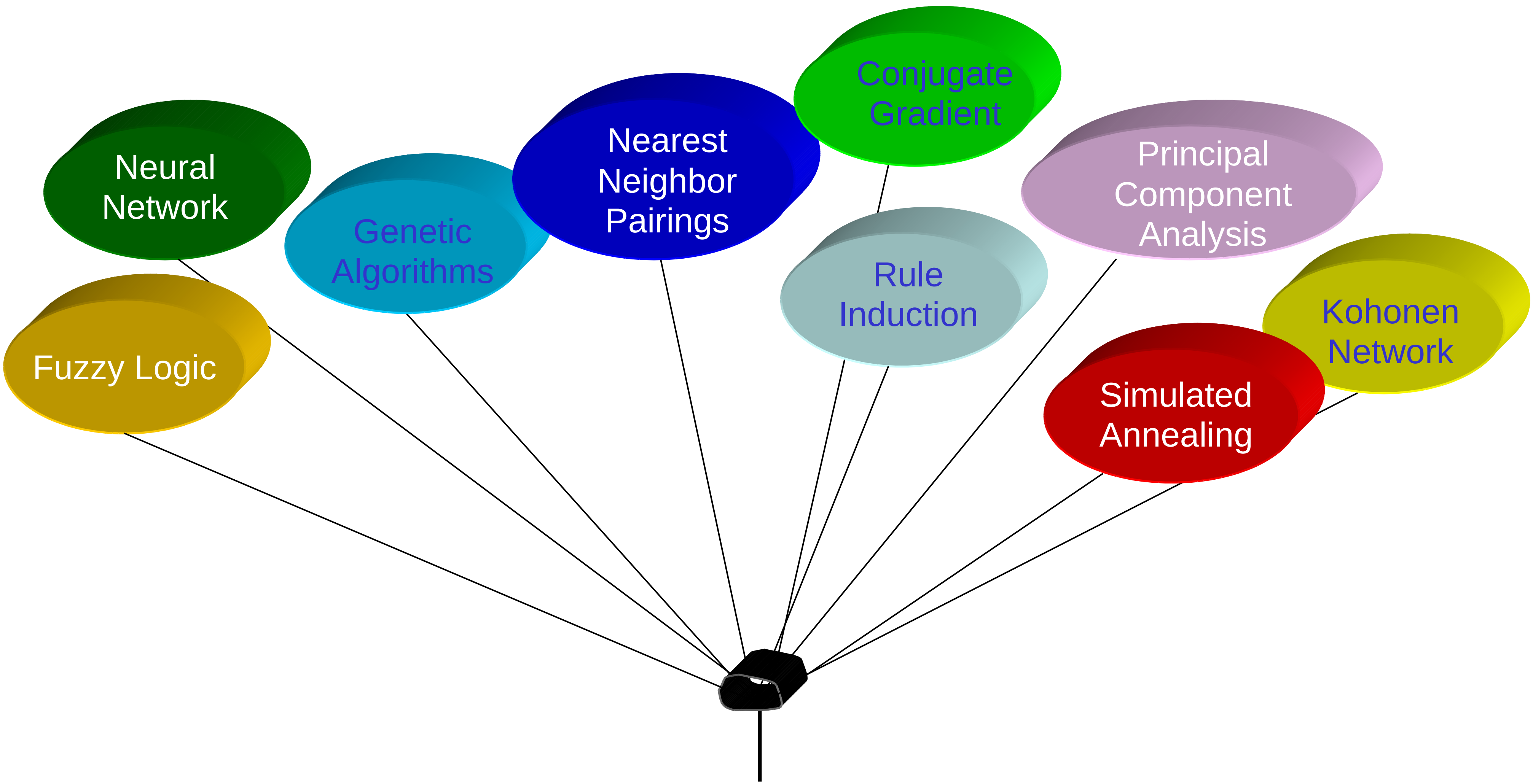
Types of Predictive Modeling Tools



Artificial Intelligence Models

What are the different types of artificial intelligence models?

Artificial Intelligence Models



In Summary

1. Leading predictive modeling tools have similar performance.
2. Selecting a predictive modeling tool should be based on your specific objectives - one size doesn't fit all.
3. A good predictive model for medical management should be linked to the intervention (e.g. impactibility).
4. "Mixed" models can increase the power of a single model.

For those of you interested in developing your own models, my new book comes with a test dataset that you can use for model development. And there are software applications in the public domain to support modeling (for example R; see Comprehensive R Archive Network (CRAN at http://cran.r-project.org/).

Rules-based vs. Predictive Models

We are often asked about rules-based models.

1. First, all models ultimately have to be converted to rules in an operational setting.
2. What most people mean by "rules-based models" is actually a "Delphi*" approach.   For example, application of "Gaps-in-care" or clinical rules (e.g. ActiveHealth or Resolution Health).
3. Rules-based models have their place in Medical Management. One challenge, however, is risk-ranking identified targets, particularly when combined with statistical models.

* Meaning that experts determine the risk factors, rather than statistics.

Practical Example of Model-Building

What is a “model?”

A model is an abstraction of the real world which attempts to capture the salient features of complex human behaviors in simple mathematical and statistical terms. A model is a set of coefficients that can be applied within a production (data) environment to generate a prediction of some outcome. The model coefficients, applied to each member’s independent variable values, will generate values of a dependent variable, which may be a relative risk score (as with the commercial grouper models such as ACGs, DCGs, and ERGs) or the likelihood of an event occurring, or even a predicted cost.

Background

Start with a clear statement of the problem:

Remember this Table from earlier?

MEMBERSHIP				
	Baseline Year	Sequent Year		
Baseline Year Cost Group	Baseline Percentage Membership	LOW <$2,000	MODERATE $2,000-$24,999	HIGH $25,000+
LOW <$2,000	69.5%	57.4%		
			11.7%	
				0.4%
MODERATE $2,000-$24,999	28.7%	9.9%		
			17.7%	
				1.1%
HIGH $25,000+	1.8%	0.2%		
			0.9%	
				0.6%
TOTAL	100.0%	67.6%	30.3%	2.2%

We would like to develop a model to identify those members of a population who are currently low cost but who are at risk of becoming high cost utilizers of medical resources.

Background

Available data for creating the model included the following:

- Eligibility/demographics
- Rx claims
- Medical claims

For this project, several data mining techniques were considered: neural net, CHAID decision tree, and regression. The regression was chosen for the following reasons:

- With proper data selection and transformation, the regression was very effective, more so than the tree.
- The results are easily understood by all stake-holders (everyone understands Regression!).

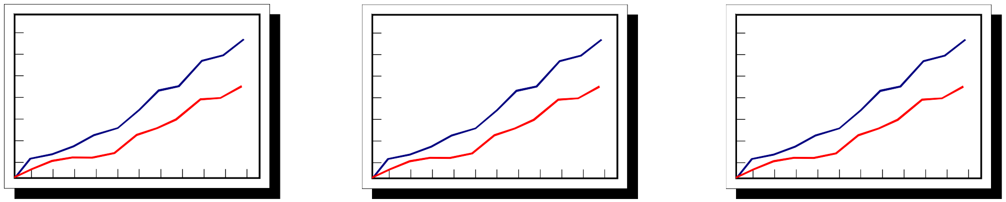
1. Split the dataset randomly into halves

Master Dataset

Analysis Dataset

Test Dataset

Diagnostics



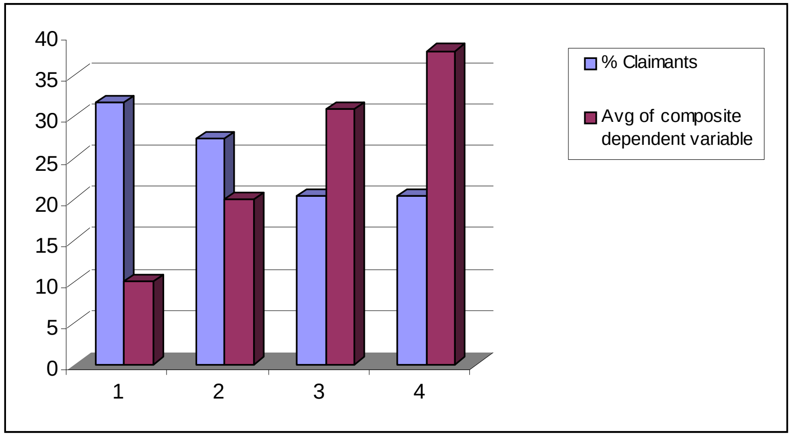
Put half of the claimants into an analysis dataset and half into a test dataset. This is to prevent over-fitting. The scoring will be constructed on the analysis dataset and tested on the test dataset. Diagnostic reports are run on each dataset and compared to each other to ensure that the compositions of the datasets are essentially similar. Reports are run on age, sex, cost, as well as disease and Rx markers.

2. Build and Transform independent variables

- In any data-mining project, the output is only as good as the input.
- Most of the time and resources in a data mining project are actually used for variable preparation and evaluation, rather than generation of the actual “recipe”.
- In our test dataset (provided with the forthcoming book) we provide a number of independent variables, as well as “derived” flags, for example:
  - Age group;
  - Condition Categories (using the HCC Grouper);
  - Urban/Rural residence;
  - No. Admissions;
  - Etc.
- Of course, the analyst should consider the needs of the project and create his/her own variables.

3. Build and transform Independent Variables

- A simple way to look at variables
- Convert to a discrete variable. Some variables such as number of prescriptions are already discrete. Real-valued variables, such as cost variables, can be grouped into ranges
- Each value or range should have a significant portion of the patients.
- Values or ranges should have an ascending or descending relationship with average value of the dependent variable.



Typical "transformed" variable

3. Dependent variable

- A key step is the choice of dependent variable. What is the best choice?
- A likely candidate is total patient cost in the predictive period. But total cost has disadvantages
  - It includes costs such as injury or maternity that are not generally predictable.
  - It includes costs that are steady and predictable, independent of health status (capitated expenses).
  - It may be affected by plan design or contracts.
- We generally predict total cost (allowed charges) net of random costs and capitated expenses.
- For this project, we decide to predict cost.

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4. Select Independent Variables

- The following variables were most promising
- Age -Truncated at 15 and 80
- Baseline cost
- Number of comorbid condition truncated at 5
- MClass
  - Medical claims-only generalization of the comorbidity variable.
  - Composite variable that counts the number of distinct ICD9 ranges for which the claimant has medical claims.
  - Ranges are defined to separate general disease/condition categories.
- Number of prescriptions truncated at 10.

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4. Select Independent Variables (contd.)

- Scheduled drug prescriptions truncated at 5
- NClass
  - Rx-only generalization of the co-morbidity variable.
  - Composite variable that counts the number of distinct categories distinct ICD9 ranges for which the claimant has claims.
  - Ranges are defined using GPI codes to separate general disease/condition categories.
- Ace inhibitor flag
- Anticoagulants flag
- Diuretics flag
- Number of corticosteroid drug prescriptions truncated at 2

Neuroleptic drug flag

Digoxin flag

5. Run Stepwise Linear Regression

An ordinary linear regression is simply a formula for determining a best-possible linear equation describing a dependent variable as a function of the independent variables. But this pre-supposes the selection of a best-possible set of independent variables. How is this best-possible set of independent variables chosen?

One method is a stepwise regression. This is an algorithm that determines both a set of variables and a regression. Variables are selected in order according to their contribution to incremental R^2.

5. Run Stepwise Linear Regression (continued)

Stepwise Algorithm

1. Run a single-variable regression for each independent variable. Select the variable that results in the greatest value of R^2. This is "Variable 1."
2. Run a two-variable regression for each remaining independent variable. In each regression, the other independent variable is Variable 1. Select the remaining variable that results in the greatest <u>incremental</u> value of R^2. This is "Variable 2."
3. Run a three-variable regression for each remaining independent variable. In each regression, the other two independent variables are Variables 1 and 2. Select the remaining variable that results in the greatest <u>incremental</u> value of R^2. This is "Variable 3."

……

n. Stop the process when the incremental value of R^2 is below some pre-defined threshold.

6. Results - Examples

- Stepwise linear regressions were run using the "promising" independent variables as inputs and the composite dependent variable as an output.
- Separate regressions were run for each patient sex.
- Sample Regressions

Female: Cost =

Scheduled drug prescription	358.1
NClass	414.5
MClass	57.5
Baseline cost	0.5
Diabetes Dx	1,818.9
Intercept	(18.5)

Why are some variables selected while others are omitted? The stepwise algorithm favors variables that are relatively uncorrelated with previously-selected variables. The variables in the selections here are all relatively independent of each other.

6. Results - Examples

Application of a Regression-based model to Three Sample Members

Female Regression Formula

	Model Coefficients	Member Values: Member 1	Member 2	Member 3
Scheduled Drug	358.1	3	2	0
NClass	414.5	3	6	0
Prior Cost	0.5	$ 2,000	$ 6,000	$ 2,000
Diabetes	1,818.9	0	1	0
MClass	57.5	8	3	0
Intercept	-18.5	1	1	1
Predicted Cost		$ 3,759.30	$ 8,176.10	$ 981.50
Actual Cost		$ 4,026.00	$ 5,243.00	$ 1,053.00

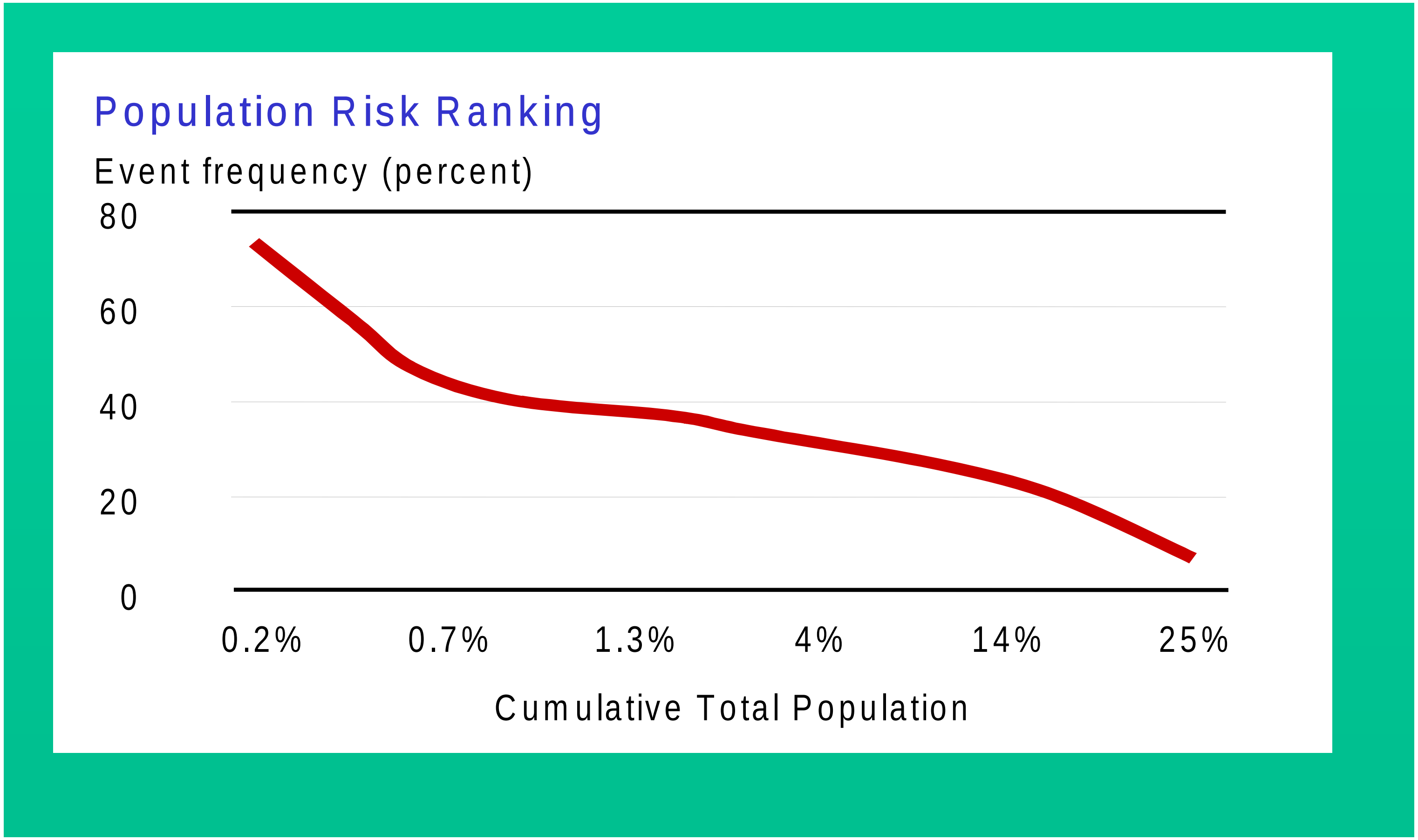
PM is <u>NOT</u> always about *Cost Prediction*.....

.....it IS about resource allocation.

- Where/how should you allocate resources?
- Who is *intervenable* or *impactable*?
- What can you expect for outcomes?
- How can you manage the key drivers of the economic model for better outcomes?

Decreasing Cost / Decreasing Opportunity

One output of the predictive model is a relative risk (or probability) ranking for the entire population.



Important Concept: this chart represents *Predicted,* not *Actual* Cost.

The Economic Model and Program Planning

- As the Population Risk Ranking slide shows, all people do not represent equal opportunity.
- The difference in opportunity means that programs need to be well planned.
- It also gives you an opportunity to test the accuracy of different models.

Economic Model: Simple example

- 30,000 eligible members (ee/dep)
- 1,500 – 2,000 with chronic conditions
- 20% “high risk” – 300 to 400
- 60% are reachable and enroll: 180 - 240
- Admissions/high-risk member/year: 0.65
- “Change behavior” of 25% of these:

  - reduced admissions: 29 to 39 annually

  - cost: $8,000/admission

- Gross Savings: $232,000 to $312,000

  - $0.64 to $0.87 pmpm.

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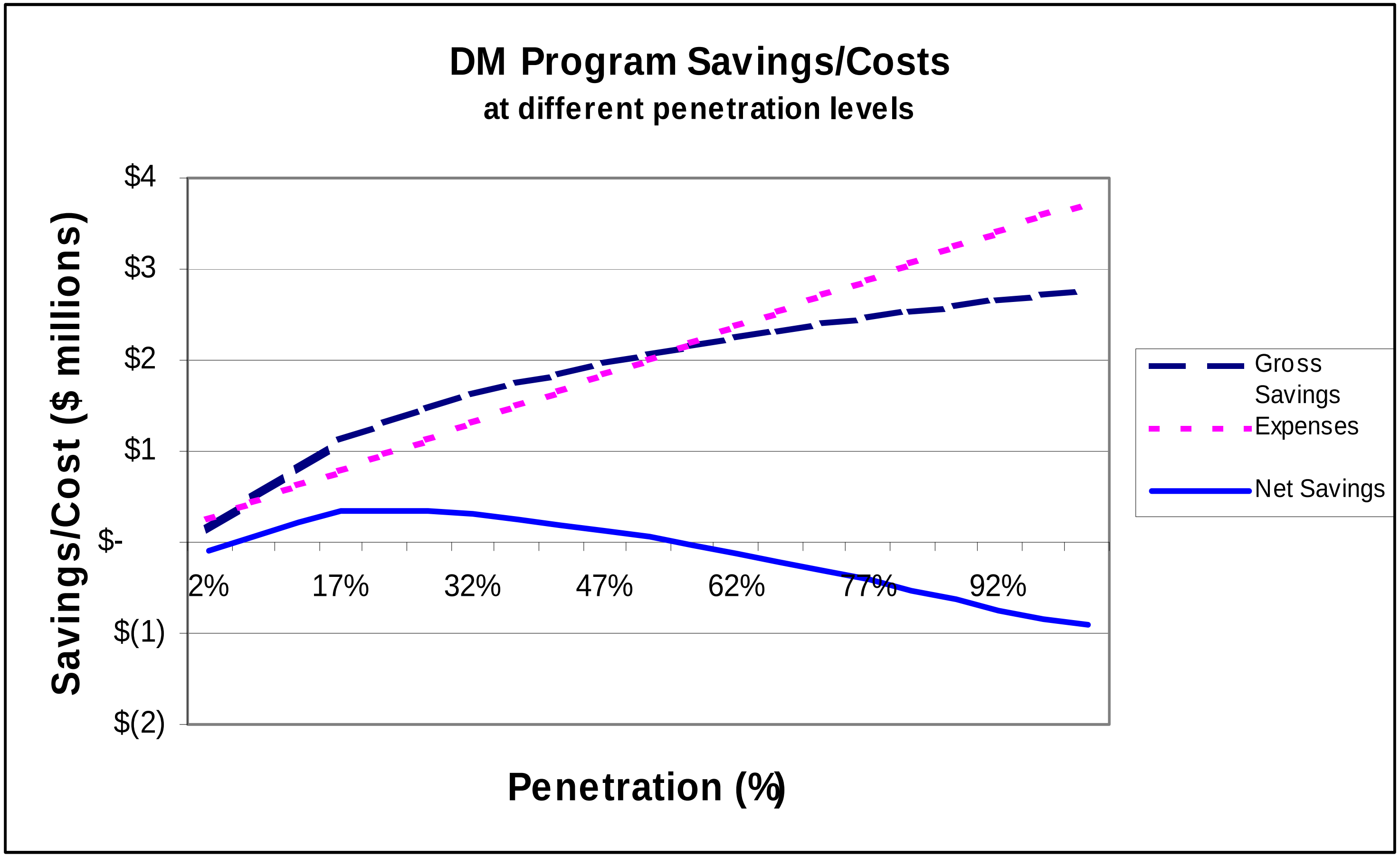
Key drivers of the economic model

- Prevalence within the population (numbers)
- Ability to Risk Rank the Population
- Data quality
- Reach/engage ability
- Cost/benefit of interventions
- Timeliness
- Resource productivity
- Random variability in outcomes

Understanding the Economics



Evaluation – Case Examples

Background – Case 1

- Large client.
- Several years of data provided for modeling.
- Never able to become comfortable with data which did not perform well according to our benchmark statistics ($/claimant; $ pmpm; number of claims per member).

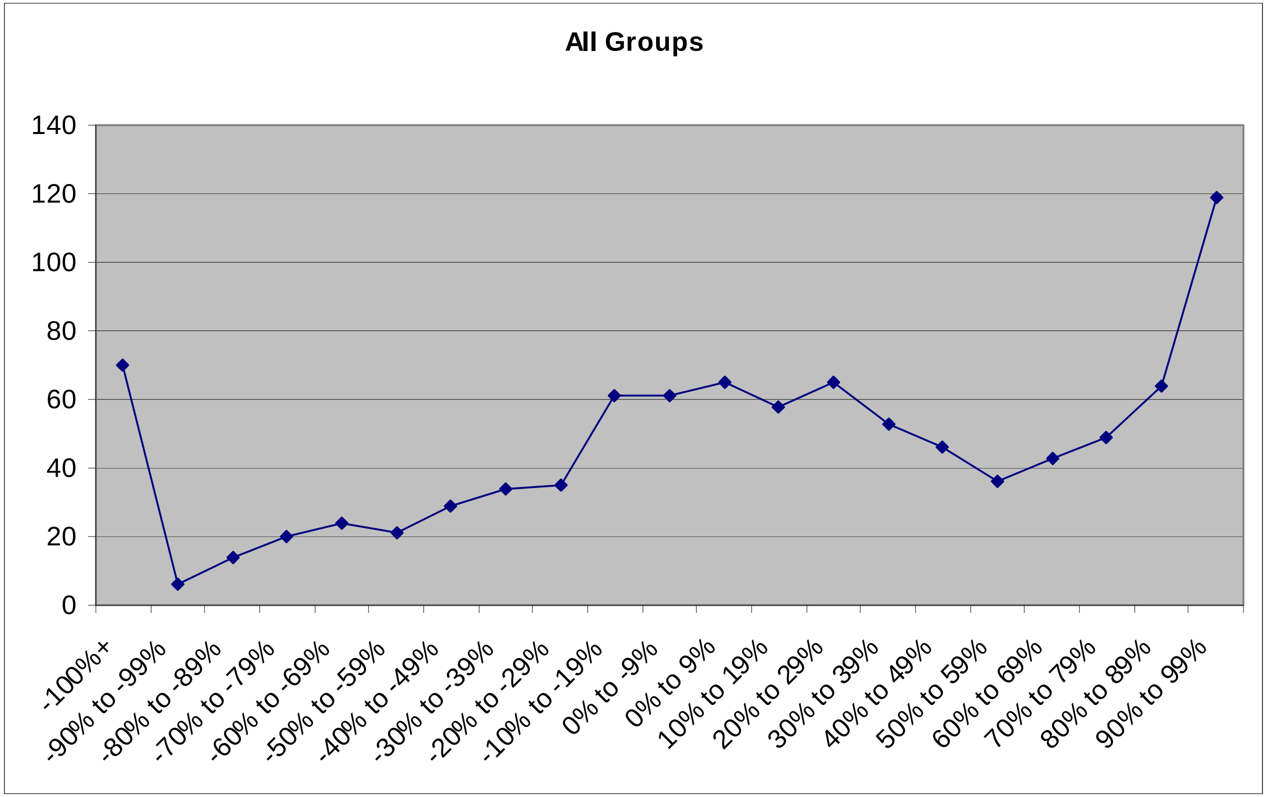
BENCHMARK DATA		(Commercial only)	pmpm	Claims/ member/ year
		Medical Only	$ 70.40	14.40
		Rx Only	$ 16.49	7.70
		TOTAL	$ 86.89	22.10

CLIENT DATA		(Commercial; excludes Capitation)	pmpm	Claims/ member/ year
		Medical + Rx	$ 32.95	5.36
		TOTAL	$ 32.95	5.36

Background – Case 1

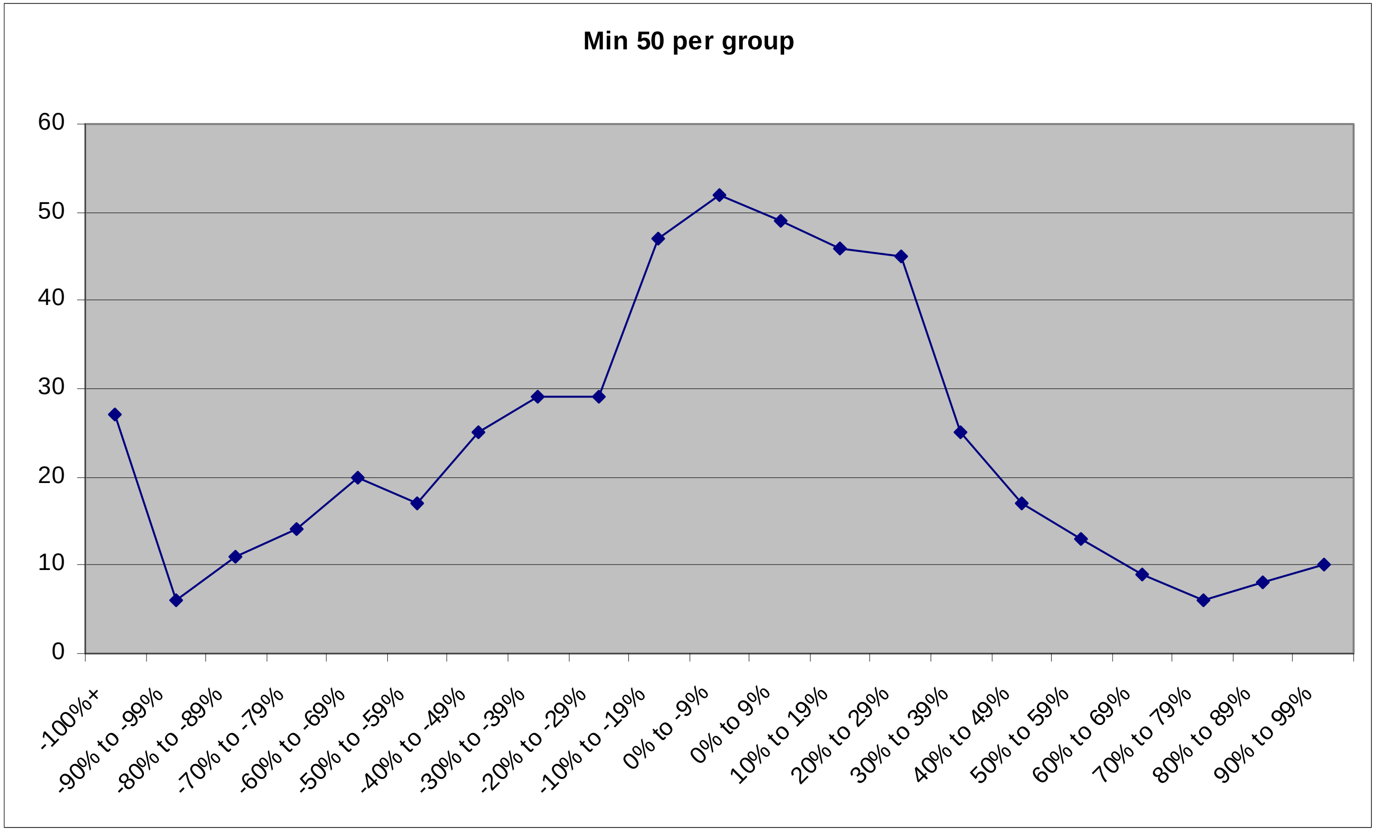
- Built models to predict cost in year 2 from year 1.
- Now for the hard part: evaluating the results.

How well does the model perform?



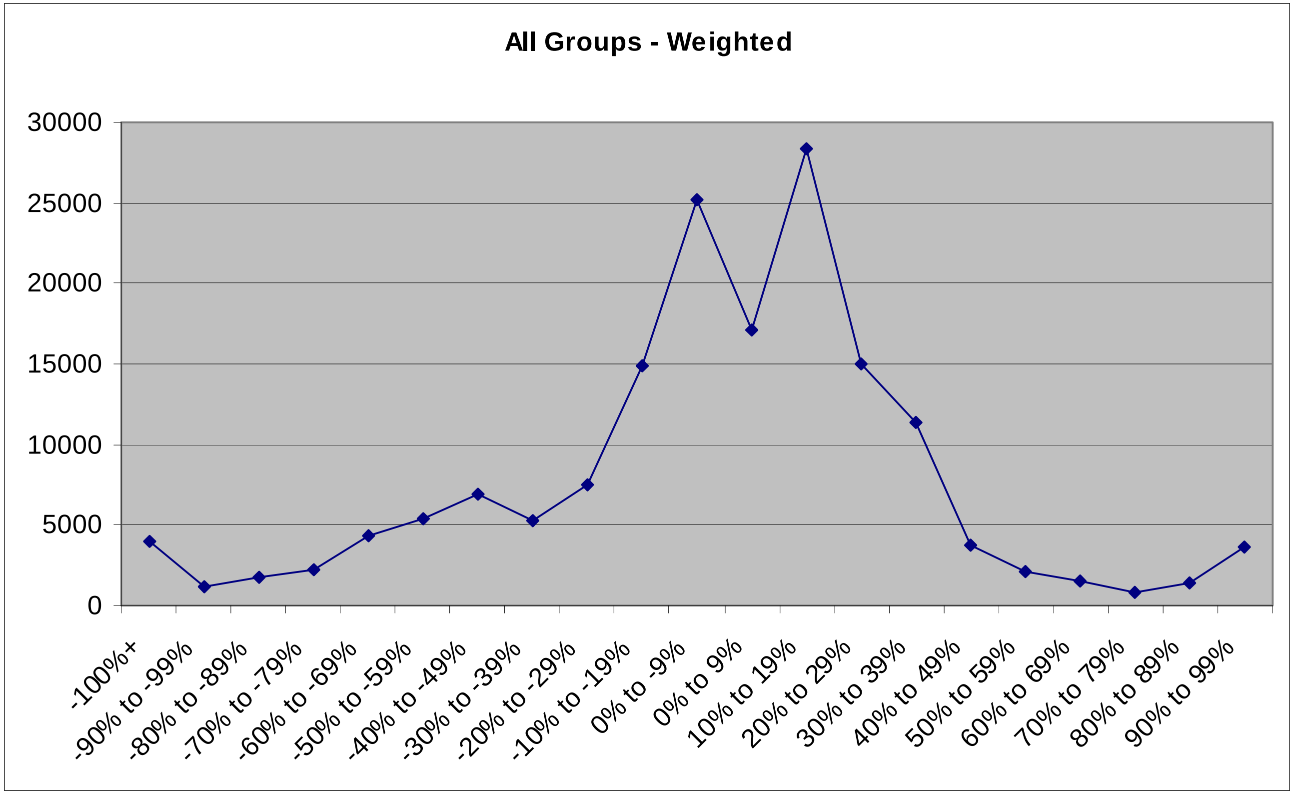
Analysis 1: all groups. This analysis shows that, at the group level, prediction is not particularly accurate, with a significant number of groups at the extremes of the distribution.

How well does the model perform?



Analysis 2: Omitting small groups (under 50 lives) significantly improves the actual/ predicted outcomes.

How well does the model perform?



Analysis 3: Weighting the results by the number of lives in the group shows that most predictions lie within +/- 30% of the actual.

Conclusion

- Significant data issues were identified and not resolved.
- This was a large group carrier who had many groups “re-classified” during the period. They were unable to provide good data that “matched” re-classified groups to their previous numbers.

- Conclusions:

This case study Illustrates 2 things:

- The importance of data evaluation (and if necessary, correction).
- Evaluation of a model is more than simply looking at the statistics (R^2, etc.). The implications of the model for the business problem must also be evaluated.

Background – Case 2.

- Client uses a manual rate basis for rating small cases. Client believes that case selection/ assignment may result in case assignment to rating classes that is not optimal.

- A predictive model may add further accuracy to the class assignment process and enable more accurate rating and underwriting to be done.

Background

- A number of different tree models were built (at client's request).
- Technically, an optimal model was chosen.

Problem: how to convince Underwriting that:

- Adding the predictive model to the underwriting process produces more accurate results; and
- They need to change their processes to incorporate the predictive model.

Some data

Node	PREDICTED Average Profit	PREDICTED Number in Node	PREDICTED Number in Node (Adjusted)	ACTUAL Number in node	ACTUAL Average Profit
1	(3.03)	70	173	170	(0.60)
2	0.19	860	2,122	2,430	0.07
3	(0.20)	2,080	5,131	6,090	(0.06)
4	0.09	910	2,245	2,580	0.10
5	(0.40)	680	1,678	20	0.02
6	(0.27)	350	863	760	0.16
7	0.11	650	1,604	1,810	0.04
8	0.53	190	469	470	(0.01)
9	(0.13)	1,150	2,837	2,910	0.03
10	0.27	1,360	3,355	3,740	0.04
11	0.38	1,560	3,849	3,920	(0.07)
12	0.08	320	789	830	0.08
13	0.06	12,250	30,221	29,520	0.02
14	0.27	2,400	5,921	6,410	0.21
15	(1.07)	540	1,332	1,320	(0.03)
16	0.07	10,070	24,843	24,950	(0.08)
17	(0.33)	1,400	3,454	3,250	(0.10)
18	0.11	4,460	11,003	11,100	0.08
19	(0.13)	1,010	2,492	2,100	(0.11)
		42,310	104,380	104,380	0.005

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How well does the model perform?

Node	PREDICTED Average Profit	PREDICTED Number in Node	PREDICTED Number in Node (Adjusted)	ACTUAL Number in node	ACTUAL Average Profit	Directionally Correct (+ or -)
1	(3.03)	70	173	170	(0.60)	
2	0.19	860	2,122	2,430	0.07	
3	(0.20)	2,080	5,131	6,090	(0.06)	
4	0.09	910	2,245	2,580	0.10	
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		42,310	104,380	104,380	0.005	

6 red
13 green

How well does the model perform?

Node	PREDICTED Average Profit	PREDICTED Number in Node	PREDICTED Number in Node (Adjusted)	ACTUAL Number in node	ACTUAL Average Profit	Directionally Correct (+ or -)	Predicted to be Profitable
1	(3.03)	70	173	170	(0.60)		
2	0.19	860	2,122	2,430	0.07		
3	(0.20)	2,080	5,131	6,090	(0.06)		
4	0.09	910	2,245	2,580	0.10		
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		42,310	104,380	104,380	0.005	6 red 13 green	11 nodes

Underwriting Decision-making

Underwriting Decision	Total Profit	Average Profit per Case	Cases Written
Accept all cases as rated.	557.5	0.005	104,380

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Accept all cases predicted to be profitable; reject all predicted unprofitable cases.	1,379.4	0.016	87,760
Accept all cases predicted to be profitable; rate all cases predicted to be unprofitable +10%.	2,219.5	0.021	104,380

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Accept all cases for which the directional prediction is correct.	2,543.5	0.026	100,620

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Accept all cases for which the directional prediction is correct.	2,543.5	0.026	100,620
Accept all cases for which the directional prediction is correct; rate predicted unprofitable cases by +10%	3,836.5	0.038	100,620

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Accept all cases for which the directional prediction is correct; rate predicted unprofitable cases by +10%	3,836.5	0.038	100,620
Accept all cases for which the directional prediction is correct.	2,540.8	0.025	101,090

Example 3: evaluating a high-risk model

Background

- Large health plan client seeking a model to improve case identification for case management.
- Considered two commercially-available models:
    - Version 1: vendor's typical predictive model based on conditions only. Model is more typically used for risk-adjustment (producing equivalent populations).
    - Version 2: vendor's high-risk predictive model that predicts the probability of a member having an event in the next 6-12 months.
- Client initially rejected model 2 as not adding sufficient value compared with model 1. (Vendor's pricing strategy was to charge additional fees for model 2) based on cumulative predictions.

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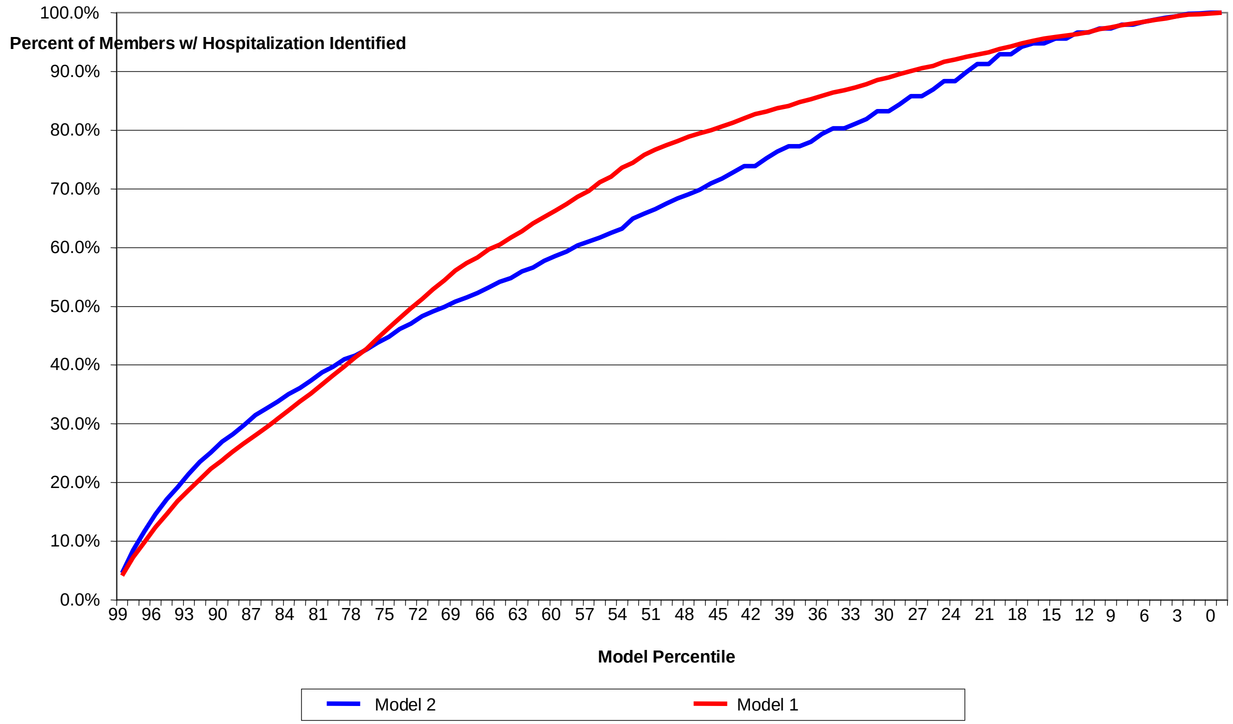
Analysis

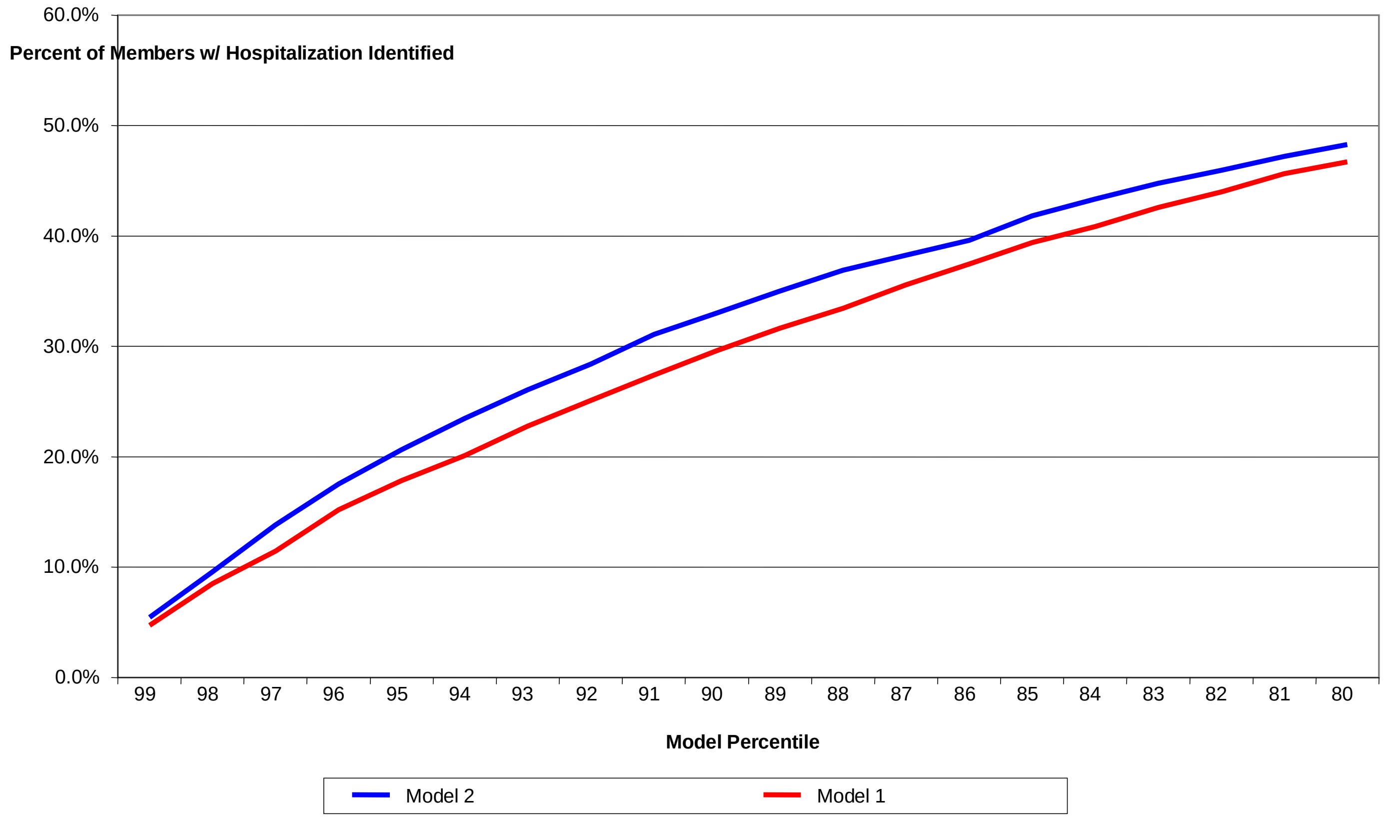
Lift Chart – Comparison between Two models



- Looked at over a narrower range, however, the results appear different.

Analysis

Lift Chart – Comparison between Two models



Analysis

Decile		Decile Admissions					
From	To	Population	Expected	Actual	Predicted Frequency	Actual Frequency	Predictive ratio
100%	90%	1,690	808	694	47.8%	41.1%	85.9%
90%	80%	1,699	268	321	15.8%	18.9%	119.6%
80%	70%	1,657	152	247	9.2%	14.9%	162.0%
70%	60%	1,673	107	191	6.4%	11.4%	178.4%
60%	50%	1,681	82	168	4.9%	10.0%	204.0%
50%	40%	1,760	67	165	3.8%	9.4%	246.7%
40%	30%	1,667	50	118	3.0%	7.1%	236.0%
30%	20%	1,729	38	92	2.2%	5.3%	241.9%
20%	10%	1,624	26	68	1.6%	4.2%	261.7%
10%	0%	1,708	91	37	5.3%	2.2%	40.9%
		16,888	1,690	2,101	100%	124.4%	

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Example 4: Provider Evaluation

Example 1: Normalized resources

Remember the "Scores" we introduced earlier?

PROVIDER GROUP XXX

Member Group ID	Condition(s)	# members	Score	Risk Total	Expected Cost	Actual Cost
1080	CHF	2	19.9	39.8	$ 43,780	$ 50,000
532	Cancer 1	20	8.7	174.2	$ 191,620	$ 150,000
796	Cancer 2 + Chronic condition	10	16.0	159.7	$ 175,670	$ 160,000
531	Cancer 2 + No chronic condition	15	9.0	135.3	$ 148,830	$ 170,000
1221	Multiple chronic conditions	6	4.8	28.8	$ 31,680	$ 50,000
710	Acute + Chronic Conditions	10	11.1	110.9	$ 121,990	$ 125,000
882	Diabetes	7	3.7	25.7	$ 28,270	$ 28,000
967	Cardiac	4	6.1	24.5	$ 26,950	$ 30,000
881	Asthma	8	3.0	24.1	$ 26,510	$ 40,000
		82		723.0	$ 795,300	$ 803,000

Example 2: Provider profiling

Different approaches: provider panel resource prediction (example 1) OR Episode Risk projection

Example of Provider Efficiency Measurement using Episodes

Episode	Severity Level	No. of Episodes	Actual Cost per Episode	Expected Cost per Episode	Total Actual Costs	Total Expected Costs	Ratio
Diabetes	1	45	$ 4,825	$ 4,200	$ 217,125	$ 189,000	1.15
Diabetes	2	75	$ 3,125	$ 2,800	$ 234,375	$ 210,000	1.12
Diabetes	3	125	$ 2,129	$ 2,000	$ 266,125	$ 250,000	1.06
Diabetes	4	165	$ 1,112	$ 1,150	$ 183,480	$ 189,750	0.97
Diabetes	All	410	$ 2,198	$ 2,046	$ 901,105	$ 838,750	1.07

Example 3: Program Evaluation

Typical Program Evaluation Methodology (e.g. DMAA)

Estimated Savings due to reduced PMPY =

Baseline Cost PMPY x Cost Trend	$6,000 * 1.12 =	$	6,720
Minus Actual Cost		$	6,300
Equals Reduced Cost PMPY		$	420
Multiplied by Actual Member Years			20,000
Estimated Savings		$	8,400,000

Trend can be biased by changes in population risk-profile over time; adjustment for change in average risk will correct for this.

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Example 3: Program Evaluation (contd.)

In the prior calculation, Non-Chronic trend experience is used to adjust the baseline (chronic) population cost. However, if the risk profile of the non-chronic population changes between the baseline and program years, an adjustment is appropriate. For example:

- Baseline average Risk: 1.240
- Program Year averge Risk: 1.302
- Risk profile trend: 5%

Non-chronic Cost Trend: 1.12
Adjusted for change in risk profile: 1.12/1.05 = 1.067

Adjusted Savings Calculation:

Baseline Cost PMPY x Cost Trend	$6,000 * 1.067 =	$ 6,400
Minus Actual Cost		$ 6,300
Equals Reduced Cost PMPY		$ 100
Multiplied by Actual Member Years		20,000
Estimated Savings		$ 2,000,000

Example 5: A wellness predictive model

Solucia Wellness Model

- Using data from a large health plan (multi-million lives; both self-reported data and health claims) we developed a risk-factor model that relates claims dollars to risk factors;
- Multiple regression model;
- 15 different risk factors;
- Multiple categorical responses.

Solucia Wellness Model

Attribute	Variable	Values	Cost Impact
	Intercept	1	190
Personal Disease History 1	Chronic Obstructive Pulmonary Disease (COPD), Congestive Heart Failure (CHF), Coronary Heart Disease (CHD), Peripheral Vascular Disease (PVD) and Stroke	0 (No)	-
		1 (Yes)	10,553
Health Screenings	Have you had a SIGMOIDOSCOPY within the last 5 years? (tube inserted in rectum to check for lower intestine problems)	0 (No)	-
		1 (Yes)	2,045
Weight Management	Body Mass Index	26 (Min)	3,069
		40 (No Value)	4,722
		45 (Max)	5,312
Health Screenings	Influenza (flu) within the last 12 months?	0 (No)	-
		1 (Yes)	1,176
Personal Disease History 2	Have you never been diagnosed with any of the following: list of 27 major conditions	0 (No)	-
		1 (Yes)	(1,220)
Personal Disease History 3	TIA (mini-stroke lasting less than 24 hrs), Heart Attack, Angina, Breast Cancer, Emphysema	0 (No)	-
		1 (Yes)	2,589
Immunizations	Pneumonia	0 (No)	-
		1 (Yes)	1,118
Physical Activity 1	Moderate-intensity physical activity - minutes per day	0 (Min, No Value)	-
		20 (Max)	(915)
Stress and Well-Being	In the last month, how often have you been angered because of things that happened that were outside your control?	0 (Never, Almost Never, Sometimes, Fairly Often)	-
		1 (Very Often, No Value)	1,632

Solucia Wellness Model (contd.)

Skin Protection	Please rate how confident you are that you can have your skin checked by a doctor once a year?	1 (Not at all confident)	(224)
		2 (Not confident)	(447)
		3 (Fairly confident)	(671)
		4 (Confident)	(894)
		5 (Very Confident)	(1,118)
		7 (No Value)	(1,565)
Women's health 1	Are you currently on hormone replacement therapy (Estrogen Therapy, Premarin) or planning to start?	0 (No)	-
		1 (Yes)	999
Women's health 2	Select the appropriate answer regarding pregnancy status/plan	1 (NotPlanning (I am planning on becoming pregnant in the next 6 months.))	590
		2 (No Value)	1,181
		3 (Planning (I am planning on becoming pregnant in the next 6 months.))	1,771
		4 (Pregnant (I am currently pregnant))	2,361
Physical Activity 2	HIGH intensity activities? (hours per week)	0 (Min, No Value)	-
		3 (Max)	(917)
Nutrition	On a typical day, how many servings do you eat of whole grain or enriched bread, cereal, rice, and pasta?	0 (None, No Value)	-
		1 (OneThree, FourFive)	(868)
		2 (SixPlus)	(1,736)
Tobacco	Please rate how confident you are that you can keep from smoking cigarettes when you feel you need a lift.	1 (Not at all confident)	(294)
		1.5 (No Value)	(441)
		2 (Not confident)	(588)
		3 (Fairly confident)	(883)
		4 (Confident)	(1,177)

Discussion

Selected references

This is not an exhaustive bibliography. It is only a starting point for explorations.

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Further Questions?

iduncan@soluciaconsulting.com

Solucia Consulting, A SCIOinspire Company
220 Farmington Avenue, Suite 4
Farmington, CT 06032

860-676-8808

www.soluciaconsulting.com