PREDICTIVE MODELING: BASICS & BEYOND

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Agenda

1. Review of the Basics.
2. Data, Data Preparation and Algorithms.
3. Grouper Models.

   Break.
4. Uses of Predictive Models.
5. Types of predictive models.

   Break
6. Practical Example of Model Building.
7. Applications – case studies.

Introductions

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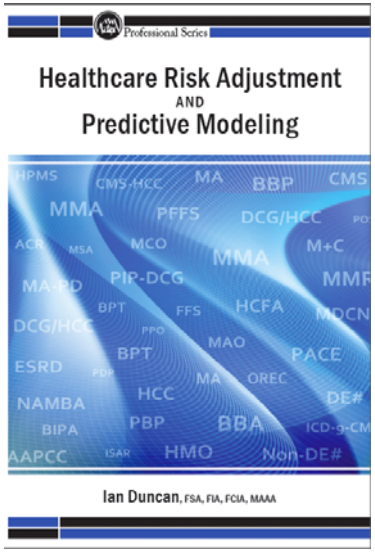


Predictive Modeling:
A Review of the Basics

Definition of Risk

- You can't understand risk adjustment or predictive modeling without understanding risk.
- At its most fundamental, risk is a combination of two factors: **loss** and **probability**.
- We define a **loss** as having occurred when an individual's post-occurrence state is less favorable than the pre-occurrence state. Financial Risk is a function of Loss Amount and Probability, but in healthcare, risk and loss are not restricted to financial quantities only. Therefore we use the following, more general, definition:

RISK = F (Loss; Probability)

Definition of Risk

RISK = F (Loss; Probability)

•Another way of saying this is that Risk is a function of Frequency (of occurrences) and Severity of the occurrence.

•In healthcare, we are interested in many different states. Most frequently actuaries are interested in Financial Loss, which occurs because an event imposes a cost on an individual (or employer or other interested party). To a clinician, however, a **loss** could be a loss of function, such as an inability to perform at a previous level or deterioration in an organ.

Definition of Predictive Modeling

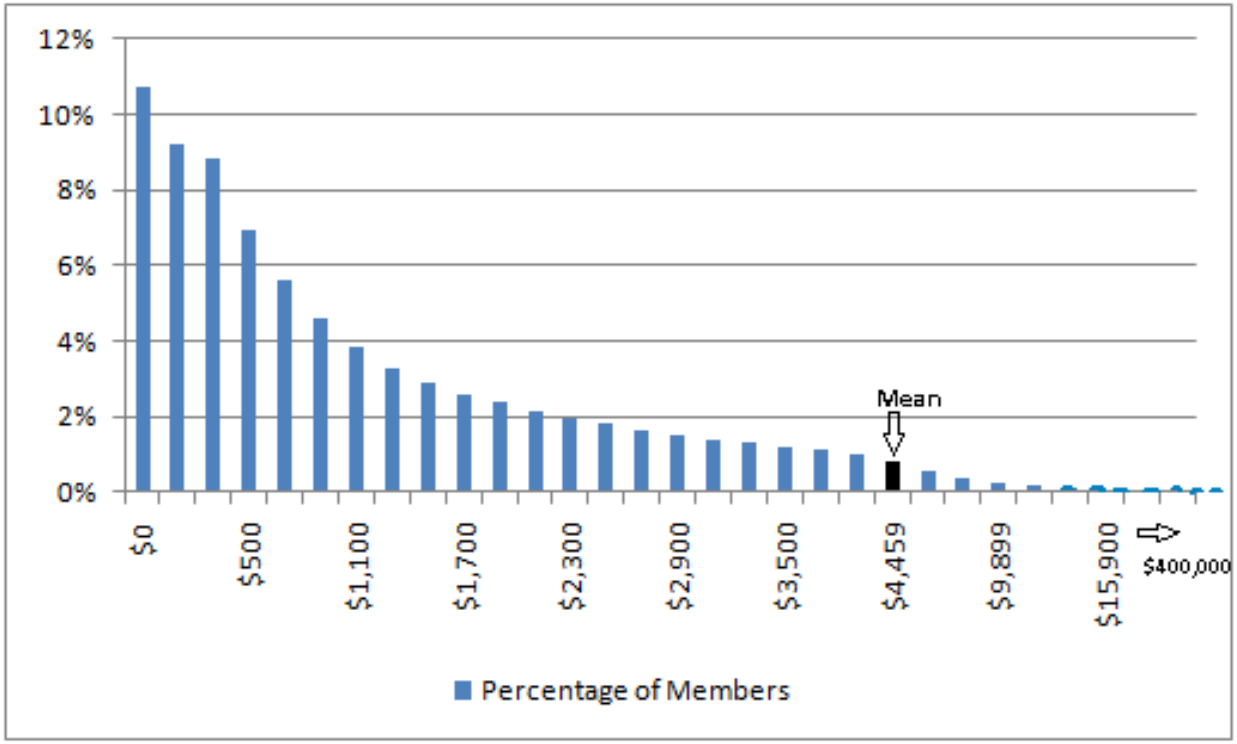
•Predictive Modeling is the process of estimating, predicting or stratifying members according to their relative risk.

- Prediction can be performed separately for Frequency (probability) and Severity (loss).

•Risk adjustment is a concept closely related to Predictive Modeling. One way to distinguish is in their uses: Predictive Modeling focuses on the *future;* while Risk Adjustment often applies to the *past*.

Typical Distribution of health cost

Health cost (Risk) is typically highly-skewed. The challenge is to predict the tail*.



* Distribution of allowed charges within the Solucia Consulting database (multi-million member national database).

Key Concept: Member Transition

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%

Key Concept: Member Transition

	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%				

Traditional (actuarial) Risk Prediction

Age/Sex: although *individuals* of the same age and sex represent a range of risk profiles and costs, *groups* of individuals of the same age and sex categories follow more predictable patterns of cost. The majority of non-Government healthcare is financed by employer groups.

Relative Cost PMPY 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

Typical Age/Sex Prediction (Manual Rating)

Age/Sex: Relative costs for different age/sex categories can be expressed as relative risk factors, enabling us to assess the "average" risk of an individual, or the overall (relative) risk of a population.

Relative Costs Using Age/Sex Factors					
	Male Risk Factor	**Male Number**	**Female Risk Factor**	**Female Number**	**Weighted Number**
< 19	0.46	4	0.44	12	7.12
20-29	0.42	12	0.88	19	22.00
30-39	0.56	24	1.09	21	36.33
40-49	0.82	30	1.18	24	52.92
50-59	1.41	15	1.57	12	39.99
60-64	2.08	3	2.05	1	8.29
Total	0.89	88	1.11	89	166.65
Total Membership					177.00
Relative age/sex factor					0.94

Accuracy of Traditional Risk Prediction

Traditional (Age/Sex) risk prediction is somewhat accurate at the population level. Larger group costs are more predictable than smaller groups.

Demographic Factors as Predictors of Future Health Costs								
		Age/Sex Factors		Factor Ratio			Difference** (Predicted-Actual)	
Employer	Number of lives	Baseline	Subsequent Year	Subsequent/ Average	Predicted Cost*	Actual Cost	$	%
1	73	1.37	1.42	138%	$4,853	$23,902	**($19,049)**	-392.5%
2	478	0.74	0.76	74%	$2,590	$2,693	**($102)**	-3.9%
3	37	0.86	0.87	84%	$2,965	$1,339	$1,626	54.8%
4	371	0.95	0.97	95%	$3,331	$3,325	$6	0.2%
5	186	1.00	1.03	100%	$3,516	$3,345	$170	4.8%
6	19	1.80	1.85	180%	$6,328	$10,711	**($4,383)**	-69.3%
7	359	0.95	0.97	94%	$3,315	$3,401	**($87)**	-2.6%
8	543	0.94	0.96	93%	$3,269	$3,667	**($398)**	-12.2%
9	26	1.60	1.64	159%	$5,595	$5,181	$414	7.4%
Average		1.00	1.03	1.00	$3,520	$3,520	$ -	0.0%
Sum of absolute Differences (9 sample groups only)							$26,235	

Prior Experience adds to accuracy

To account for the variance observed in small populations, actuaries typically incorporate prior cost into the prediction, which adds to the predictive accuracy. A "credibility weighting" is used. Here is a typical formula:

$$\text{Expected Cost} = \text{Prior Year Cost} \times \text{Trend} \times Z + \text{Book of Business Cost} \times (1 - Z)$$

where $Z = \left(\frac{N}{2000}\right)^{0.5}$ and N is the number of members in the group.

Combination of Age, Sex, and Prior Cost as a Predictor of Future Experience.							
			Cost PMPY			Difference vs. Actual	
Employer	No. of lives	Credibility Factor	Baseline	Subsequent Year Pre-dicted	Subsequent Year Actual	Difference	Difference (% of Actual)
1	73	0.19	$27,488	$9,908	$23,902	**($13,994)**	-141.2%
2	478	0.49	$1,027	$2,792	$2,693	$100	3.6%
3	37	0.14	$1,050	$2,724	$1,339	$1,385	50.9%
4	371	0.43	$2,493	$3,119	$3,325	**($205)**	-6.6%
5	186	0.30	$3,377	$3,617	$3,345	$271	7.5%
6	19	0.10	$11,352	$6,971	$10,711	**($3,739)**	-63.6%
7	359	0.42	$2,008	$2,880	$3,401	**($522)**	-18.1%
8	543	0.52	$2,598	$3,108	$3,667	**($559)**	-18.0%
9	26	0.11	$3,022	$5,350	$5,181	$169	3.2%
….	….	….	….	….	….	….	….
Average			$3,090	$3,520	$3,520	$ 0	0%
Sum of absolute Differences (9 sample groups only)						$20,944	

What does Clinical information tell us about risk?

Having information about a patient's condition, particularly chronic condition(s) is potentially useful for predicting risk.

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 and 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%

Risk Groupers predict relative risk

Commercial Risk Groupers are available that predict relative risk based on diagnoses. Particularly helpful for small groups.

Application of Condition Based Relative Risk						
			Cost PMPY		Difference (Predicted-Actual)	
Employer	Number of lives	Relative Risk Score	Predicted	Actual	$	%
1	73	8.02	$28,214	$23,902	$4,312	15.3%
2	478	0.93	$3,260	$2,693	$568	17.4%
3	37	0.47	$1,665	$1,339	$326	19.6%
4	371	0.94	$3,300	$3,325	**($25)**	-0.8%
5	186	1.01	$3,567	$3,345	$222	6.2%
6	19	4.14	$14,560	$10,711	$3,850	26.4%
7	359	0.84	$2,970	$3,401	**($432)**	-14.5%
8	543	0.80	$2,833	$3,667	**($834)**	-29.4%
9	26	1.03	$3,631	$5,181	**($1,550)**	-42.7%
Average			$ -	0.0%	$ -	0.0%
Sum of absolute Differences (9 sample groups only)					$12,118	

Condition and Risk 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.

Identification – example (Diabetes)

Diabetics can be identified in different ways:

Diagnosis type	Reliability	Practicality
Physician Referral/ Medical Records/EMRs	High	Low
Lab tests	High	Low
Claims	Medium	High
Prescription Drugs	Medium	High
Self-reported	Low/medium	Low

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

Identification – example (Diabetes)

Inpatient Hospital Claims – ICD-9 Claims Codes

ICD-9-CM CODE DIABETES	DESCRIPTION
250.xx	Diabetes mellitus
357.2	Polyneuropathy in diabetes
362.0, 362.0x	Diabetic retinopathy
366.41	Diabetic cataract
648.00-648.04	Diabetes mellitus (as other current condiition in mother classifiable elsewhere, but complicating pregnancy, childbirth or the puerperioum.

Diabetes – additional procedure codes

CODES DIABETES;	CODE TYPE	DESCRIPTION - ADDITIONAL
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

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**

Algorithm Development: Diabetes Example

Not all diabetics represent the same level of risk. Different diagnosis codes help identify levels of severity.

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

Algorithm Development: Diabetes Example

Relative Costs of Members with Different Diabetes Diagnoses			
Diagnosis Code ICD-9-CM	**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		$12,589	100%

Algorithm Development: Diabetes Example

Which leads to a possible relative risk severity structure for diabetes:

A Possible Code Grouping System for Diabetes			
Severity Level	**Diagnosis Codes Included**	**Average Cost**	**Relative Cost**
1	250; 250.0	$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%

Risk Groupers

Diagnoses found in claims 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; HCPS; V and G codes); Procedure (CPT); Diagnosis Group (DRG – Hospital); Drug type/dose/manufacturer (NDC; J codes); lab test (LOINC); Place of service, type of provider, etc. etc.

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

All people are not equally identifiable

An important issue with any claims-based identification algorithm is that you are *imputing,* rather than *observing* a diagnosis. Thus you are always at risk of including false positives, or excluding false negatives, from the analysis.

One consequence of using a grouper model is that you are at the mercy of the modeler's definition of diagnoses, and thus cannot control for false positives or negatives.

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%

All people are not equally identifiable (2)

A less-rigorous algorithm will identify more people with the condition (more than twice as many in the example above). But it runs the risk of sweeping in false positives. This table shows the likelihood re-qualifying with the condition in the following year:

Probability that a Member Identified with 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%

Algorithm Development: Diabetes Example

Example of an identification algorithm:

Example of a Definitional Algorithm			
Disease	**Type**	**Frequency**	**Codes**
Diabetes Mellitus	Hospital Admission or ER visit with diagnosis of diabetes in any position	At least one event in a 12-month period	ICD-9 codes 250, 357.2, 362.0, 366.41, 648.0
	Professional visits with a primary or secondary diagnosis of diabetes	At least 2 visits in a twelve month period	CPT Codes in range of 99200-99499 series E & M codes or 92 series for eye visits
	Outpatient Drugs: dispensed insulin, hypoglycemic, or anti-hyperglycemic prescription drug	One or more prescriptions in a twelve month period	Diabetes drugs (see HEDIS or similar list of drug codes).
EXCLUDE gestational diabetes.	Any (as above)	As above	648.8x

Sources of Algorithms

- NCQA – HEDIS.
- DMAA (Now CCA; Chronic definitions).
- Grouper Models.

Grouper Construction

Grouper/Risk-adjustment theory is based on 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. 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.

Commercial Groupers: SOA studies

There have been three Society of Actuaries studies of commercial risk grouper models published. All are available at www.soa.org.

Dunn DL, Rosenblatt A, Taira DA, et al. "A comparative Analysis of Methods of Health Risk Assessment." *Society of Actuaries (SOA Monograph M-HB96-1).* Oct 1996:1-88.

Cumming RB, Cameron BA, Derrick B, et al. "A Comparative Analysis of Claims-Based Methods of Health Risk Assessment for Commercial Populations". *Research study sponsored by Society of Actuaries.* 2002.

Winkelman R, Mehmud S. "A Comparative Analysis of Claims-Based Tools for Health Risk Assessment". *Society of Actuaries.* 2007 Apr:1-63. (available at: www.soa.org/files/pdf/ risk-assessmentc.pdf).

Commercial Groupers: SOA studies

The Society of Actuaries studies show:

1.Risk grouper modeling tools use *different algorithms* to group the source data. For example, the Symmetry models are built on episodes of care, DRGs are built on hospital episodes, while other models are built on diagnoses.

2.Similar performance among all leading risk groupers.

3.Accuracy of prediction has increased since the publication of the original study. In part, this is due to more accurate coding and the inclusion of more claims codes.

4.Risk groupers use *relatively limited data* sources (e.g. DCG and Rx Groups use ICD-9 and NDC codes but not lab results or HRA information).

5.Accuracy of **retrospective (concurrent)** models is now in the 30%-40% R^2 range. **Prospective** model accuracy is in the range of 20% to 25%.

A note about Prospective and Concurrent Models

Both have their place. Neither is perfect.

1.Concurrent models are also called Retrospective.

The concurrent model is used to reproduce **actual historical costs.** This type of model is used for assessing relative resource use and for determining compensation to providers for services rendered because it normalizes costs across different members. Normatively, the concurrent model provides an assessment of what costs *should* have been for members, given the health conditions with which they presented in the past year. It is also used in program evaluation, which is performed once all known conditions may be identified.

2.The Prospective model predicts what costs w*ill* be for a group of members in the future. The Prospective model is predicting the unknown, because the period over which the prediction is made lies in the future. The Concurrent model, by contrast, provides an estimate of normalized costs for services that have already occurred. For prospective prediction, members with no claims receive a relative risk score component based on age/sex alone.

A note about Prospective and Concurrent Models

Concurrent models have the advantage that they represent all the known information about the member in the completed year. However, when they are used to compensate providers (for example) for managing a group of members, there is a risk to the provider that if the provider does a good job and prevents the exacerbation of the member's condition, the member risk score (and therefore the provider's compensation) will be lower than it would be if the provider does not prevent the exacerbation.

Prospective models are often used to allocate revenue to different managed care plans. The drawback to this approach is that members' prospective risk scores are based on historical data, and do not take account of developing (incident) conditions that emerge during the year.

Commercially-available Risk Groupers

Commercially Available Grouper Models		
Developer	**Risk Grouper**	**Data Source**
CMS	Diagnostic Risk Groups (DRG) (There are a number of subsequent "refinements" to the original DRG model.	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 Medicaid Rx	Age/Sex, ICD -9 NDC
Verisk Sightlines™	DCG RxGroup	Age/Sex, ICD -9 Age/Sex, NDC
Symmetry/Ingenix	Episode Risk Groups (ERG) Pharmacy Risk Groups (PRG)	ICD – 9, NDC NDC
Symmetry/Ingenix	Episode Treatment Groups (ETG)	ICD – 9, NDC
Johns Hopkins	Adjusted Clinical Groups (ACG)	Age/Sex, ICD – 9

Grouper Algorithms

As an alternative to commercially-available risk groupers, analysts can develop their own models using common data mining techniques. Each method has its pros and cons:

There is a considerable amount of work involved in building algorithms from scratch, particularly when this has to be done for the entire spectrum of diseases. Adding drug or laboratory sources to the available data increases the complexity of development.

While the *development* of a model may be within the scope and resources of the analyst who is performing research, use of models for production purposes (for risk adjustment of payments to a health plan or provider groups for example) requires that a model be maintained to accommodate new codes. New medical codes are not published frequently, but new drug codes are released monthly, so a model that relies on drug codes will soon be out of date unless updated regularly.

Commercially-available clinical grouper models are used extensively for risk adjustment when a consistent model, accessible to many users, is required. Providers and plans, whose financial stability relies on payments from a payer, often require that payments be made according to a model that is available for review and validation.

Grouper Algorithms

An analyst that builds his own algorithm for risk prediction has control over several factors that are not controllable with commercial models:

Which codes, out of the large number of available codes to recognize. The numbers of codes and their redundancy (the same code will often be repeated numerous times in a member record) makes it essential to develop an aggregation or summarization scheme.

The level at which to recognize the condition. How many different levels of severity should be recognized?

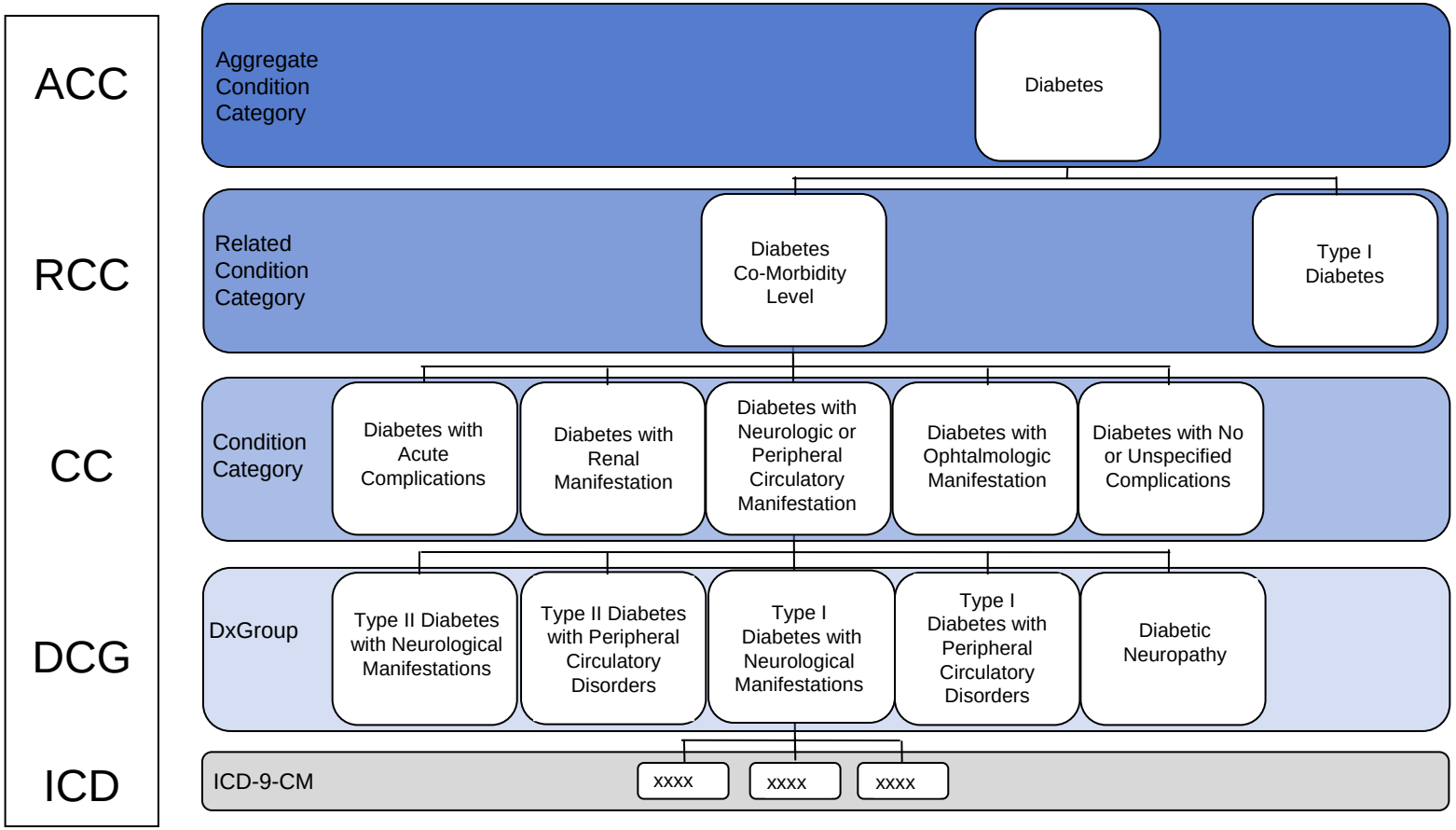
The impact of co-morbidities. Some conditions are often found together (for example heart disease with diabetes). The analyst will need to decide whether to maintain separate conditions and then combine where appropriate, or to create combinations of conditions.

The degree of certainty with which the diagnosis has been identified (confirmatory information). The accuracy of a diagnosis may differ based on who codes the diagnosis, for what purpose and how frequently a diagnosis code appears in the member record. The more frequently a diagnosis code appears, the more reliable the interpretation of the diagnosis. Similarly, the source of the code (hospital, physician, laboratory) will also affect the reliability of the diagnostic interpretation.

Data may come from different sources with a range of reliability and acquisition cost. A diagnosis in a medical record, assigned by a physician, will generally be highly reliable. Other types of data are not always available or as reliable.

Example of Grouper Construction

Grouper models are constructed in a similar fashion to that illustrated above. Below we show the hierarchical structure of the DxCG model for Diabetes:



Example of Grouper Construction

Grouper models are constructed in a similar fashion to that illustrated above. Below we show how the risk score is developed for a patient with diagnoses of Diabetes, HTN, CHF and Drug Dependence, illustrating the hierarchical and additive structure of the DxCG model:

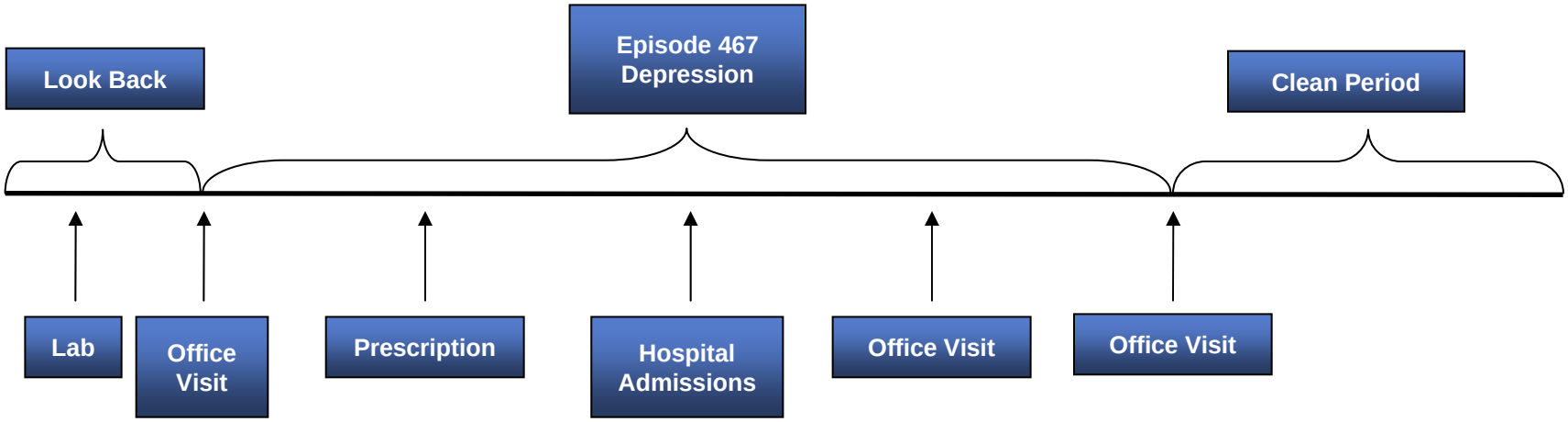
Example of Construction of a Relative Risk Score		
Condition Category	**Risk Score Contribution**	**Notes**
Diabetes with No or Unspecified Complications	0.0	Trumped by Diabetes with Renal Manifestation
Diabetes with Renal Manifestation	2.1	
Hypertension	0.0	Trumped by CHF
Congestive Heart Failure (CHF)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

Concurrent vs. Prospective Models

- An area that will receive more attention with Health Reform and Exchanges.
- There are two major types of Grouper models: concurrent and prospective. The concurrent model is used to reproduce actual historical costs. This type of model is used for assessing relative resource use and for determining compensation to providers for services rendered because it normalizes costs across different members. Normatively, the concurrent model provides an assessment of what costs *should* have been for members, given the conditions with which they presented in the past year.
- The Prospective model predicts what costs w*ill* be for a group of members in the future. The Prospective model is predicting the unknown, because the period over which the prediction is made lies in the future. The Concurrent model provides an estimate of normalized costs for services that have already occurred. For prospective prediction, members with no claims receive a relative risk score component based on age/sex alone.

Episode-based Groupers

An example of an episode Group: the Symmetry Grouper.



Episode-based Groupers

Application of the Symmetry Grouper. Risk Scores are developed similarly to DxCG.

Construction of Relative Risk Scores Using ETGs						
Example: Male Aged 58						
ETG	Severity Level	Description	ERG	Description	Retrospective Risk Weights	Prospective Risk Weights
163000	2	Diabetes	2.022	Diabetes w/significant complication/co-morbidity I	0.9874	1.2810
386800	1	Congestive Heart Failure	8.043	Ischemic heart disease, heart failure, cardiomyopathy III	2.2870	2.0065
238800	3	Mood Disorder, Depression	4.033	Mood disorder, depression w/ significant cc/cb	0.8200	0.7913
473800	3	Ulcer	11.022	Other moderate cost gastroenterology II	2.3972	0.6474
666700	1	Acne	17.011	Lower cost dermatology I	0.1409	0.1023
666700	1	Acne	17.011	Lower cost dermatology I		
Demographic risk: Male 55-64						0.7331
					6.6325	5.5616

One more very useful grouper…

Drug groupers group 100,000s NDC codes into manageable therapeutic classes

Example of Therapeutic Classes Within the GPI Structure					
Group	**Class**	**Sub Class**	**Group**	**Class**	**Sub Class**
GROUPS 1- 16 ANTI-INFECTIVE AGENTS					
01	00	00	***PENICILLINS***		
01	10	00		Penicillin G	
01	30	00		PENICILLINASE -RESISTANT PENICILLINS	
01	50	00		AMINO PENICILLINS/BROAD SPECTRUM PENICILLINS	
01	20	00		Ampicillins	
01	40	00		EXTENDED SPECTRUM PENICILLINS	
01	99	00		*Penicillin Combinations**	
01	99	50			*Penicillin-Arninoglycoside Combinations***
01	99	40			*Penicillin-NSAIA Combinations***
02	00	00	***CEPHALOSPORINS***		
02	10	00		*Cephalosporins -1st Generation**	
02	20	00		*Cephalosporins -2nd Generation**	
02	30	00		*Cephalosporins -3rd Generation**	
02	40	00		*Cephalosporins -4th Generation**	
02	99	00		*Cephalosporin Combinations**	
03	00	00	***MACROLIDE ANTIBIOTICS***		
03	10	00		*Erythromycins**	
03	10	99			*Erythromycin Combinations***
03	20	00		*Troleandomycin**	
03	30	00		*Lincomycins**	
03	40	00		*Azithromycin**	
03	50	00		*Clarithromycin**	
03	52	00		*Dirithromycin**	
Etc.	Etc.	Etc.			

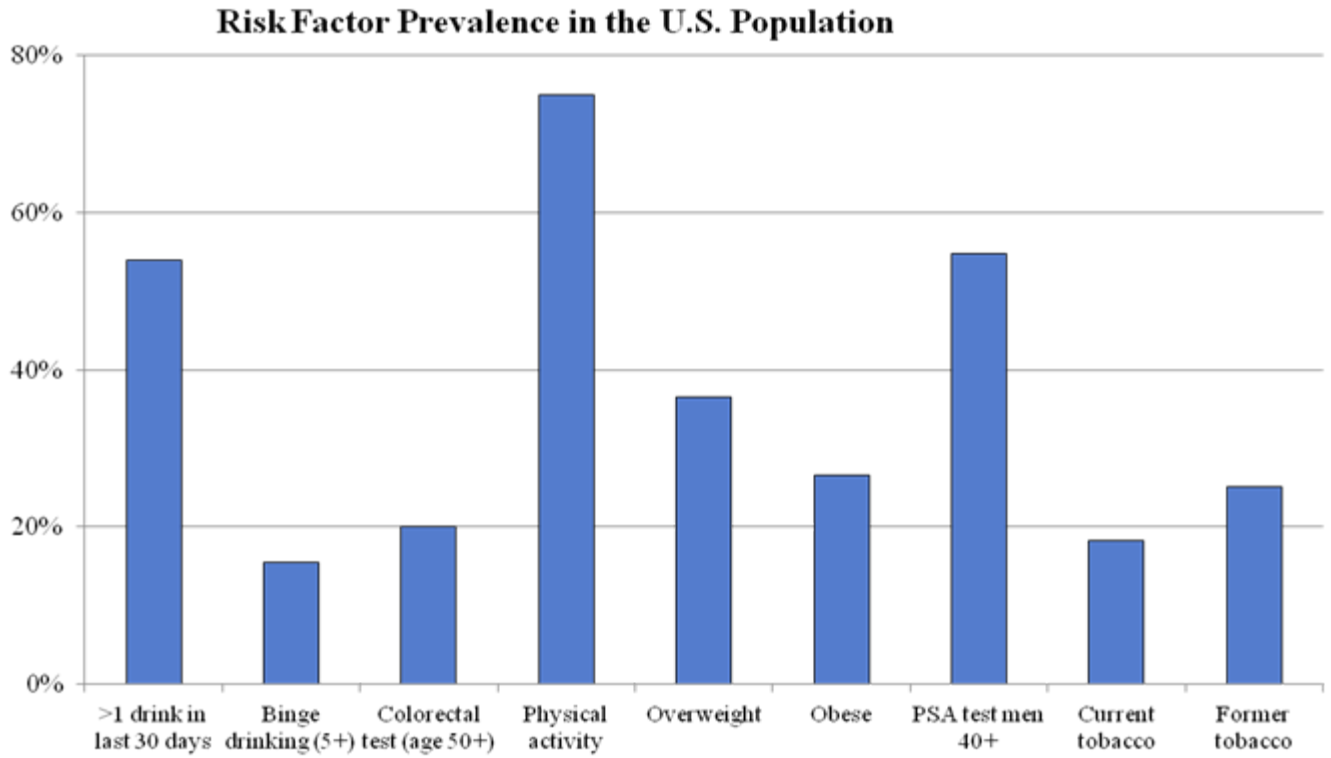
Rules-based vs. Statistical Models

We are often asked about rules-based models.

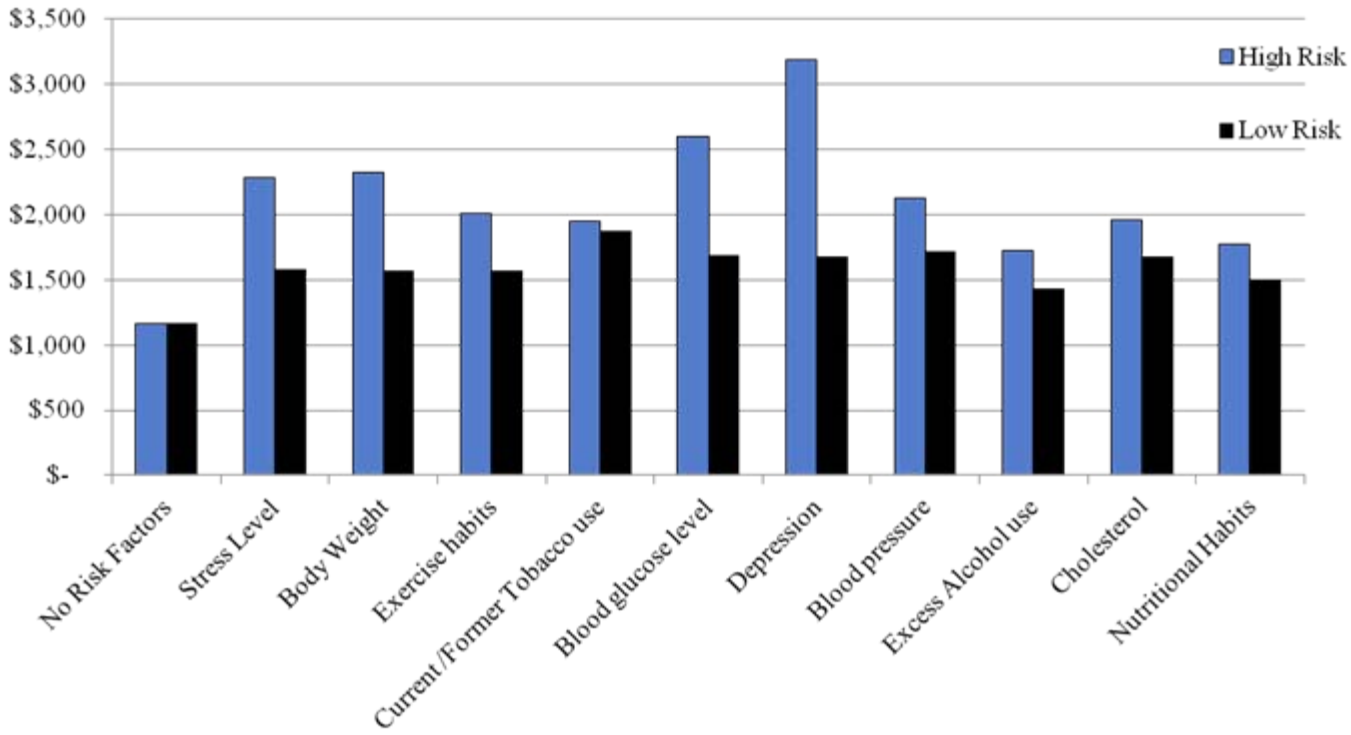
1. First, all models ultimately have to be converted to rules in an operational setting.
2. What most people mean by "rules-based models" is actually a "Delphi*" approach. For example, application of "Gaps-in-care" or clinical rules (e.g. ActiveHealth).
3. Rules-based models have their place in Medical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

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

Don’t overlook non-condition-based Risk

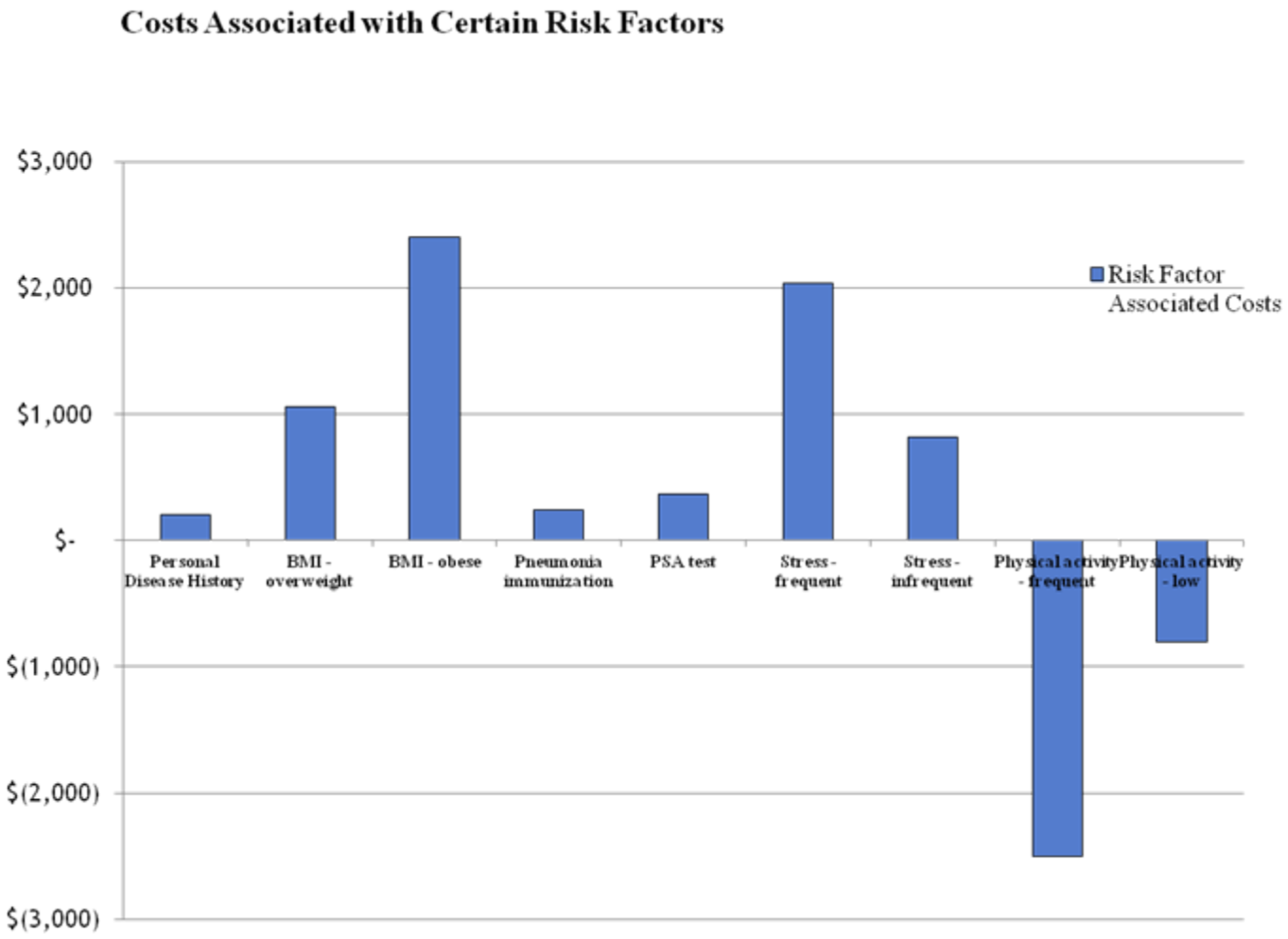


Non-condition-based Risk



Relationship Between Modifiable Health Risk Factors and Annual Health Insurance Claims

Non-condition-based Risk



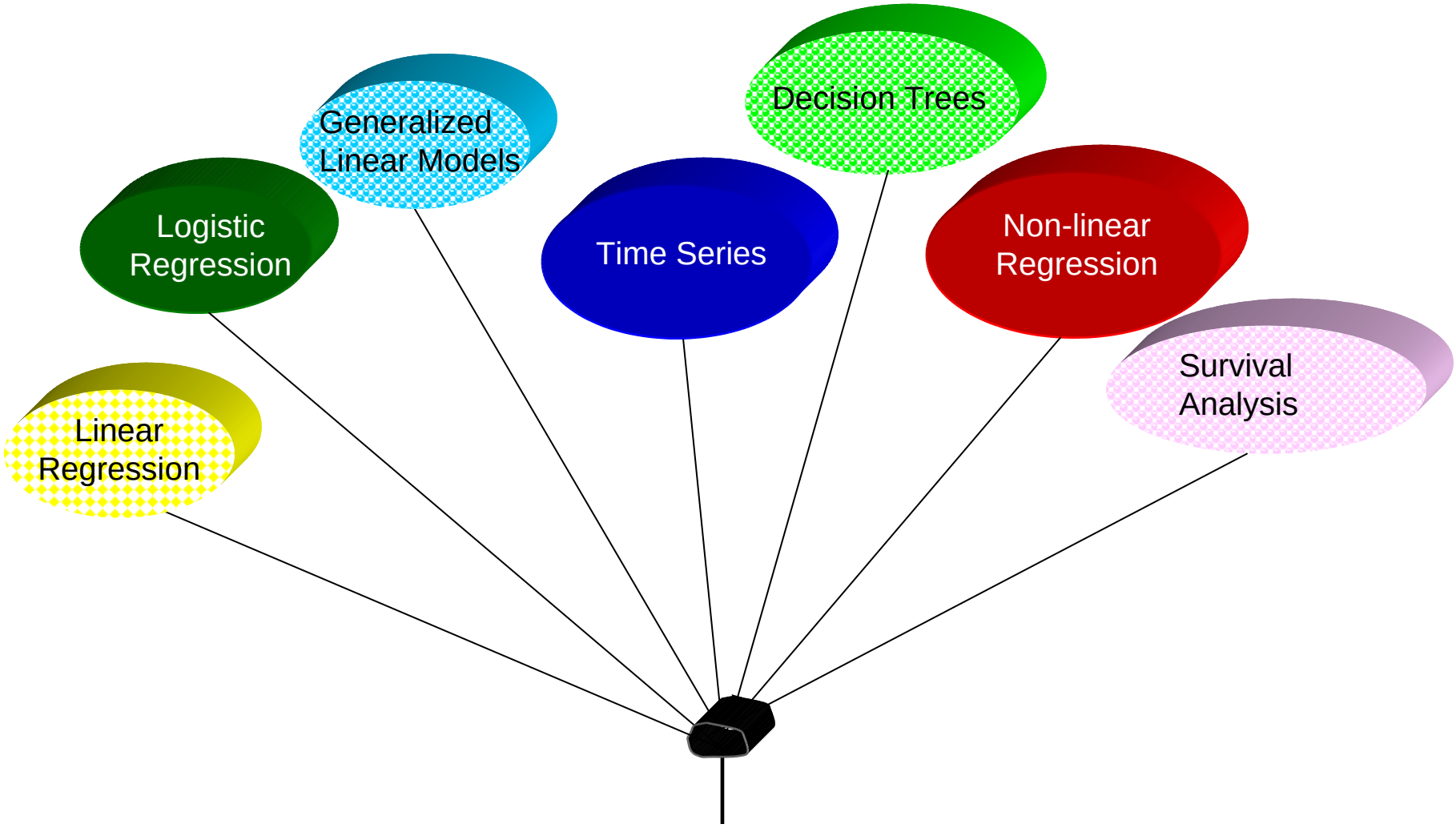
Developing your own model

There are pros and cons to using a commercially available model. There is no reason not to develop your won predictive or risk adjustment model. Chapters 7-12 of my book address different statistical models that are encountered in this work. Examples of statistical models used frequently:

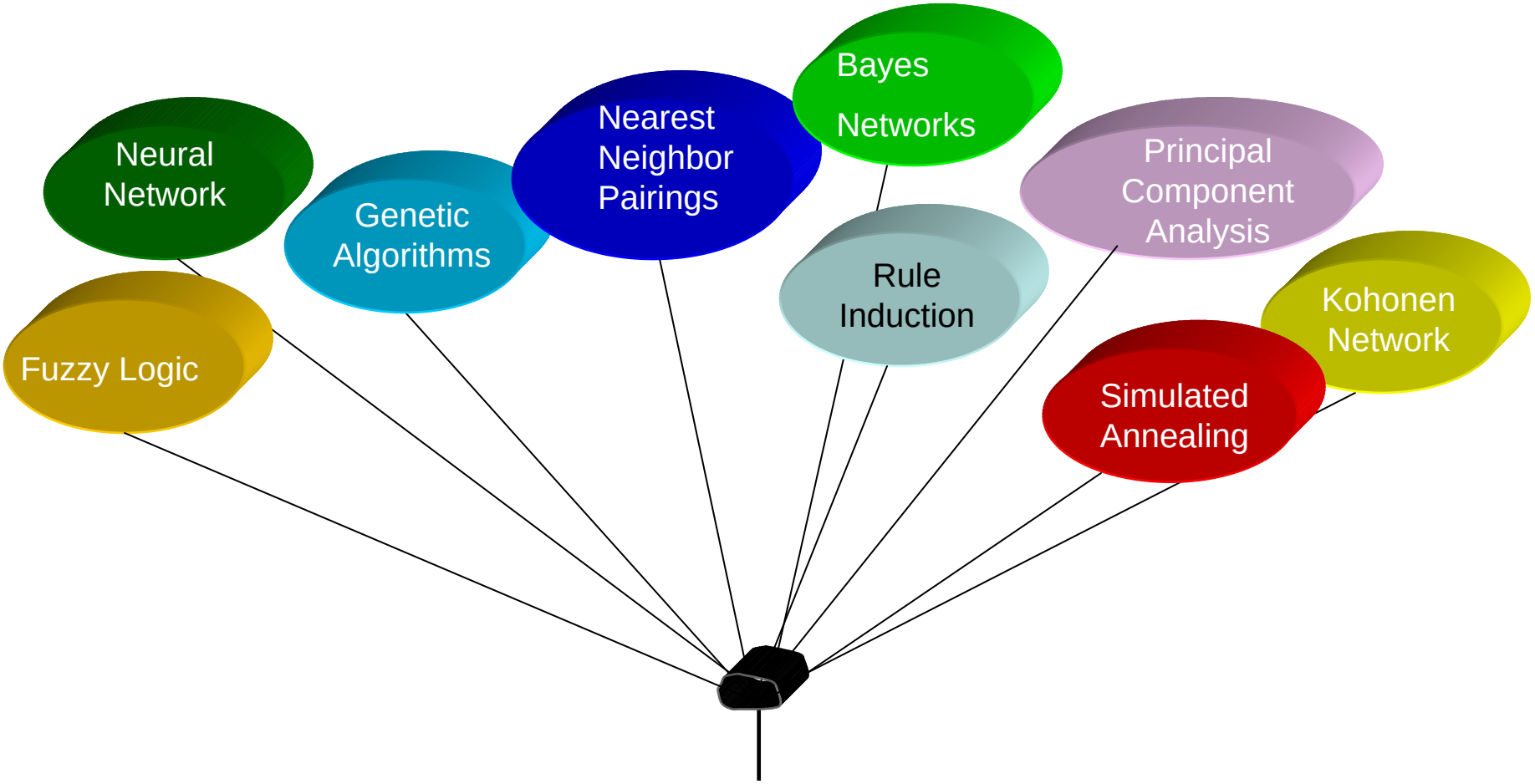
- Linear Regression. Advantage: everyone understands this.
- Generalized linear model and Logistic regression: more sophisticated models often used for healthcare data.
- Tree models: more difficult to apply operationally than regression models.
- Neural networks: black box.

There are a couple of others less frequently encountered.

Types of Statistical Models



Artificial Intelligence Models



Artificial Intelligence Models

- **Supervised learning (Predictive Modeling)**
  - Neural Network
  - Fuzzy Logic
  - Decision Trees (rule Induction)
  - K-Nearest Neighbor (KNN)
  - Etc.
- **Unsupervised Learning**
  - Association Rules (rule induction)
  - Principal components analysis (PCA)
  - Kohonen Networks, also known as Self-Organizing Maps (SOM)
  - Cluster Analysis, etc.

Optimization or Search Methods:

- Conjugate Gradient
- Genetic algorithm
- Simulated annealing
- Etc.

Some Quick Comments

1. Linear Regression remains popular because it is simple, effective and practitioners understand it.
2. Generalized Linear Models (GLM): in these models, the linear relationship between the dependent and independent variables (basis of Linear Models) is relaxed, so the relationship can be non-linear.
3. Logistic Regression is one frequently used example of GLM in which dependence may be discrete rather than continuous.
4. Time Series models are models that are fitted to moving data.
5. Decision Trees are a means of classifying a population using a series of structured, successive steps.
6. Non-linear regression: models relationships that are non-linear (often by transforming data).
7. Survival Analysis develops a “hazard rate” or the probability that an individual will experience the event at time t.

Practical Model Building

What is a Model??

- A model is a set of coefficients to be applied to production data in a live environment.

- With individual data, the result is often a predicted value or "score." For example, the likelihood that an individual will purchase something, or will experience a high-risk event (surrender; claim, etc.). (In practical applications, individual scores are rolled-up or averaged at the population level.)

- For underwriting, we can predict either cost or risk-score. For care management, the prediction could be cost or the likelihood of an event.

Background

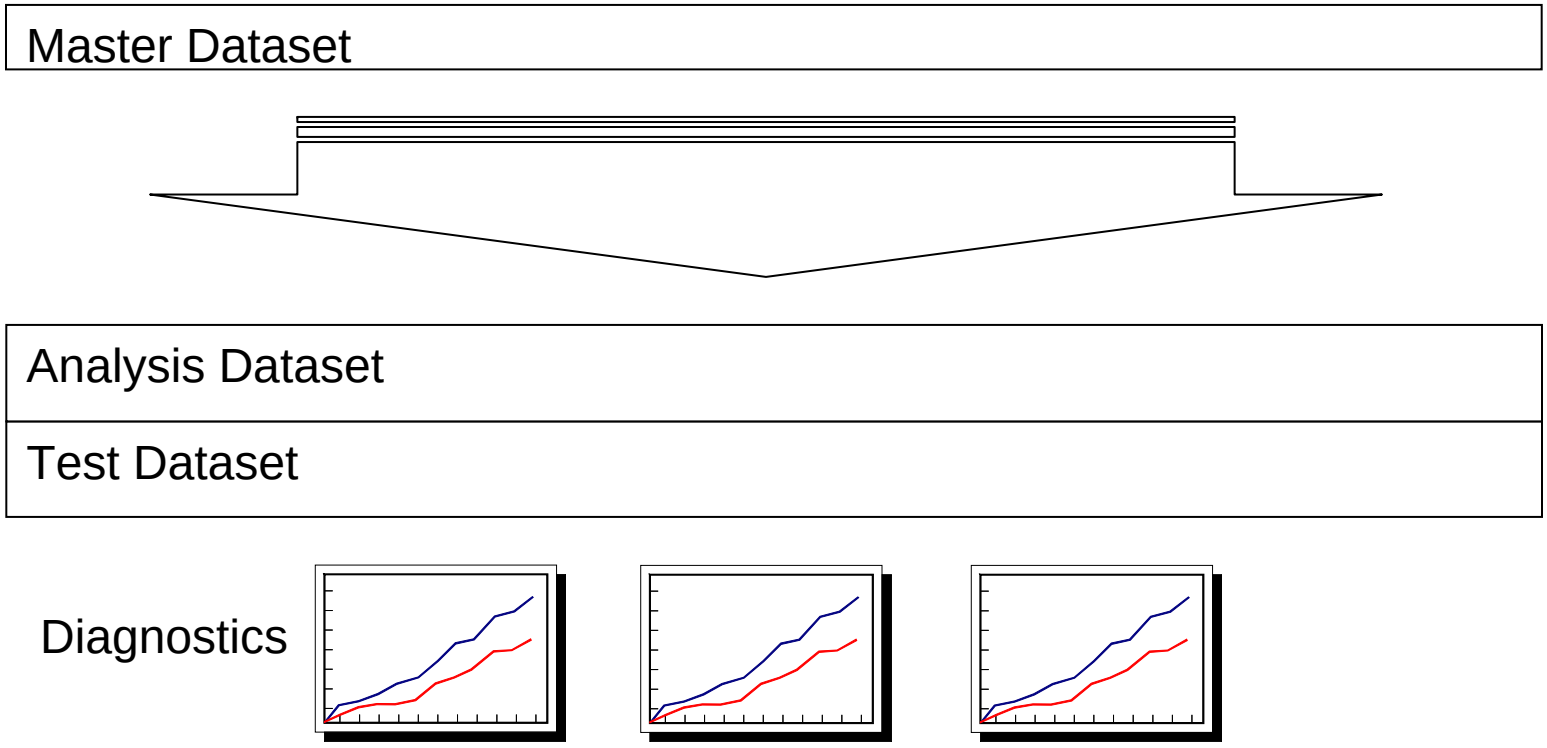
Available data for creating the risk score included the following:

- 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:

- The regression model was more intuitively understandable by end-users than other models; and
- With proper data selection and transformation, the regression was very effective, more so than the tree.

1. Split the dataset randomly into halves



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.

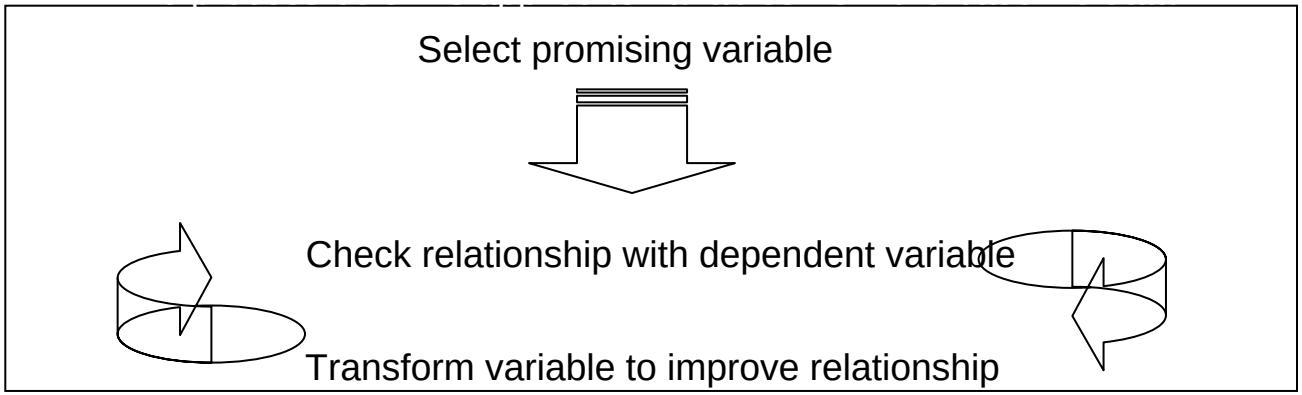
2. Build and Transform independent variables

- 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”.

3. Build dependent variable

- What are we trying to predict? Utilization? Cost? Likelihood of high cost?
- 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.
- So we could predict total cost (allowed charges) net of random costs and capitated expenses.
- Predicted cost can be converted to a risk-factor.

3. Build and transform Independent Variables

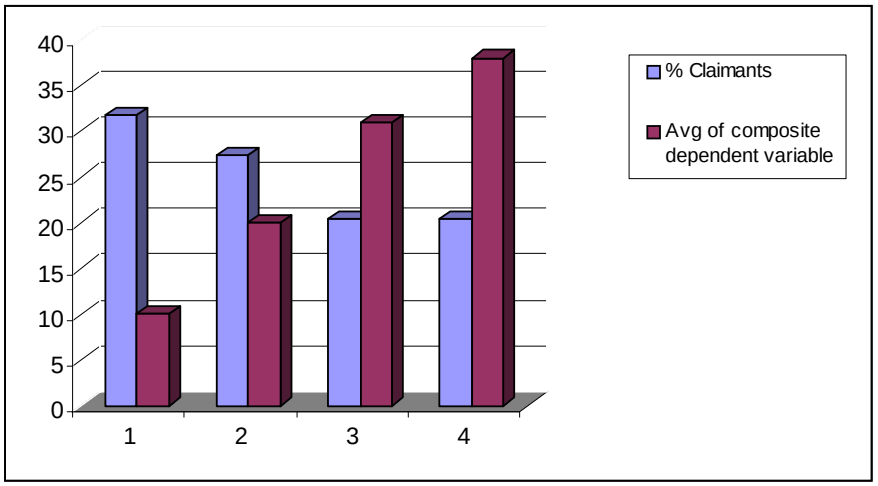


Typical transforms include.

- Truncating data ranges to minimized the effects of outliers.
- Converting values into binary flag variables.
- Altering the shape of the distribution with a log transform to compare orders of magnitude.
- Smoothing progression of independent 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 composite dependent variable.



Typical "transformed variable"

4. Select Independent Variables

- The following variables were most promising
- Age -Truncated at 15 and 80
- Baseline cost
- Number of comorbid conditions 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

4. Select Independent Variables (contd.)

- Scheduled drug prescriptions truncated at 5
- NClass
  - Rx-only generalization of the comorbidity 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
- Neuroleptic drug flag
- Digoxin flag
- Number of corticosteroid drug prescriptions truncated at 2

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 incremental 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 incremental 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

Scheduled drug prescription	358.1
NClass	414.5
MClass	157.5
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

- Examples of application of the female model

Female Regression Regression Formula

(Scheduled Drug *358.1) + (NClass*414.5) + (Cost*0.5) + (Diabetes*1818.9) + (MClass*157.5) -18.5

Claimant ID	Raw Value	Transformed Value	Predicted Value	Actual Value
Schedule Drugs				
1	3	2	$ 716.20	
2	2	2	$ 716.20	
3	0	1	$ 358.10	
NClass				
1	3	3	$ 1,243.50	
2	6	6	$ 2,487.00	
3	0	0.5	$ 207.25	
Cost				
1	423	2,000	$ 1,000.00	
2	5,244	6,000	$ 3,000.00	
3	1,854	2,000	$ 1,000.00	
Diabetes				
1	0	0	$ -	
2	0	0	$ -	
3	0	0	$ -	
MClass				
1	8	3	$ 472.50	
2	3	2	$ 315.00	
3	0	0.5	$ 78.75	
TOTAL				
1			$ 3,413.70	$ 4,026.00
2			$ 6,499.70	$ 5,243.00
3			$ 1,625.60	$ 1,053.00

Transform Function

Schedule Drugs			
Value Range	RV< 2	2 < RV < 5	RV >5
Transformed Value	1.0	2.0	3.0
NClass			
Value Range	RV < 2	2 < RV < 5	RV > 5
Transformed Value	0.5	3.0	6.0
Cost			
Value Range	RV < 5k	5k < RV < 10k	RV > 10k
Transformed Value	2,000	6,000	10,000
Diabetes			
Value Range	Yes	No	
Transformed Value	1.0	0.0	
MClass			
Value Range	RV < 1	1 < RV < 7	RV > 7
Transformed Value	0.5	2.0	3.0

Model Evaluation: Case Examples

In this section we will look at up to 5 different case studies, depending on time.

1. Underwriting model.
2. Underwriting (group disability).
3. Case management case identification.
4. Wellness Prediction using Risk Factors.
5. Health plan members with depression.

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).

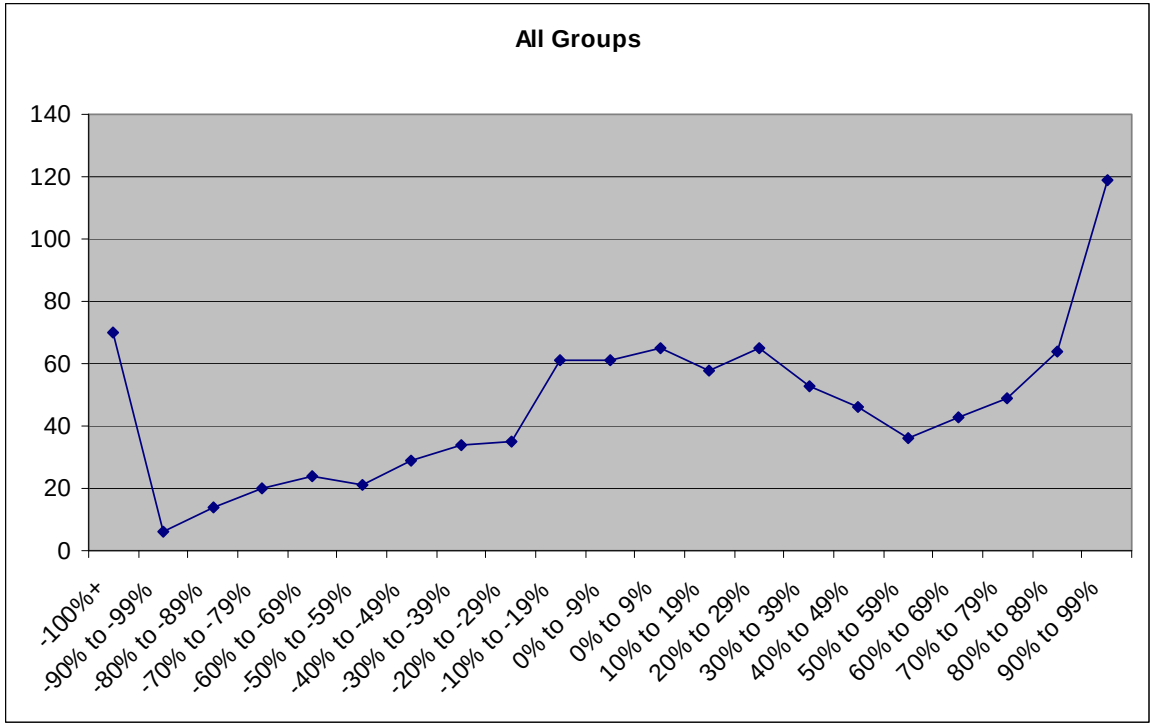
Client (excl. capitation)	Claims/ Member/ Year	PMPM
Medical + Rx	5.36	$ 82.38

Benchmark	Claims/ Member/ Year	PMPM
Medical	14.4	$ 176.00
Rx	7.7	$ 41.23
Medical + Rx	22.1	$ 217.23

Background – Case 1

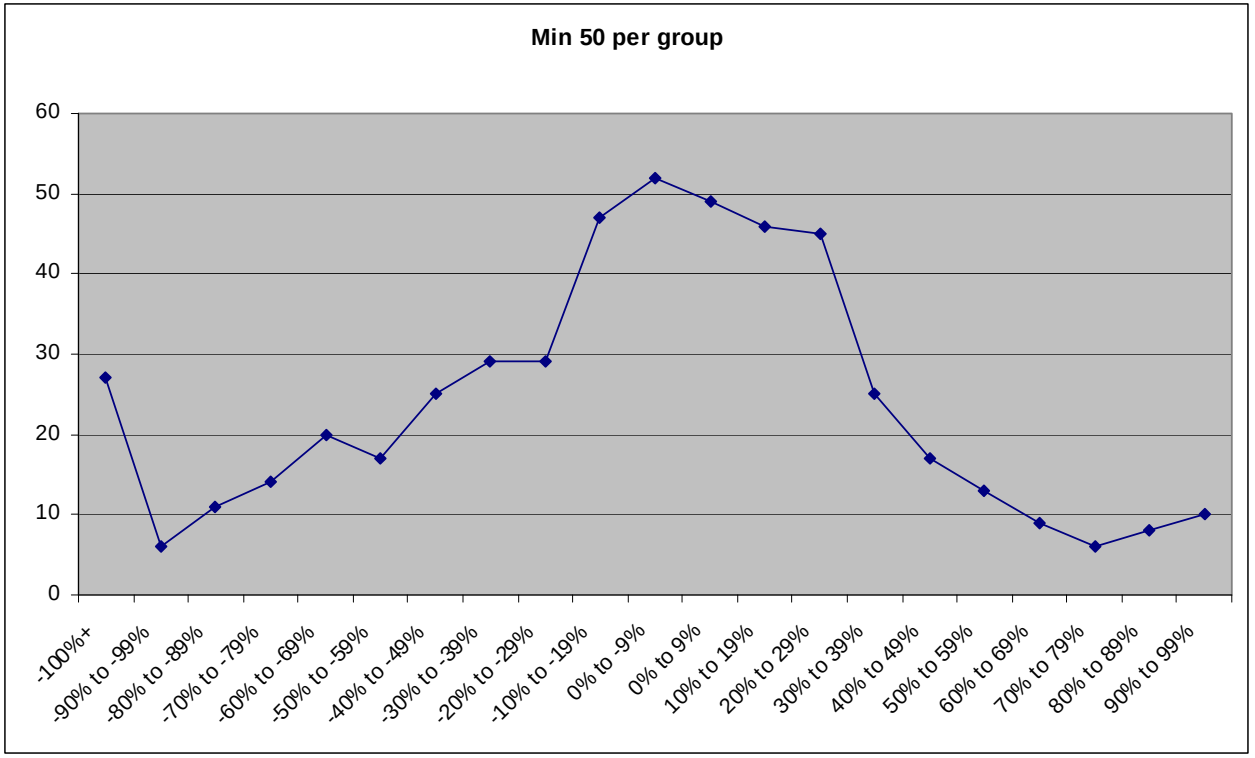
- Built models to predict cost in year 2 from year 1.
- Now for the hard part: evaluating the results.

How well does the model perform?



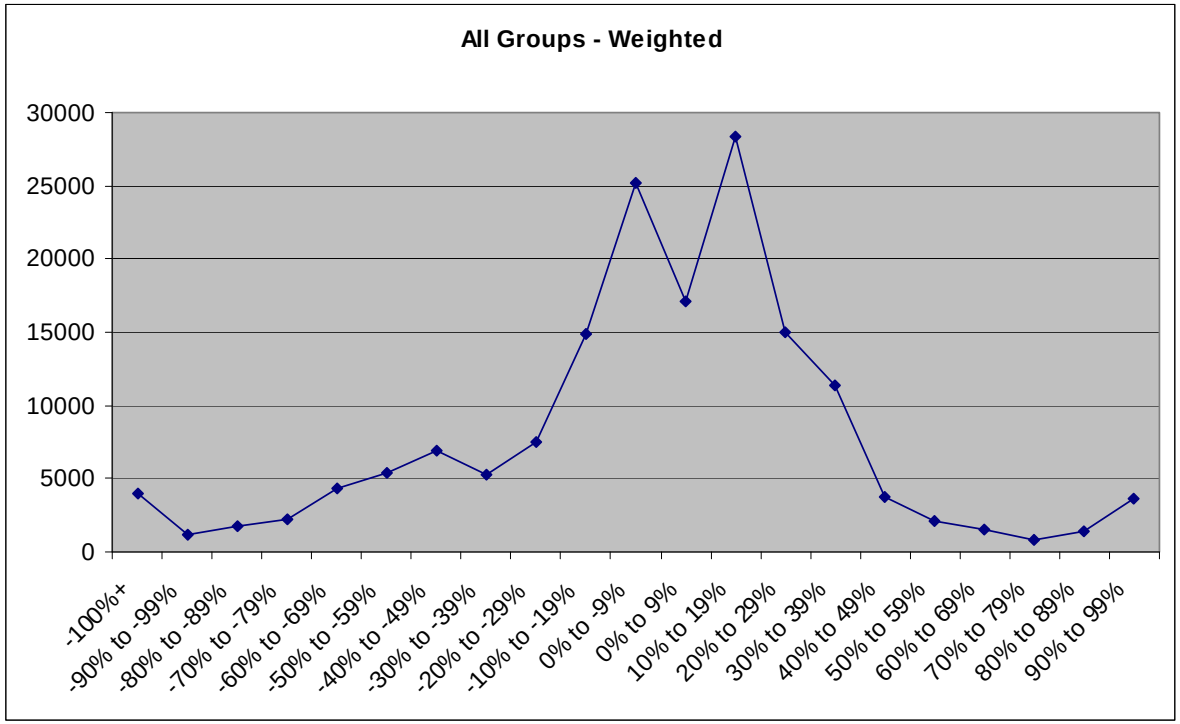
Analysis 1: all groups. This analysis shows that, at the group level, prediction is not particularly accurate, with a significant number of groups at the extremes of the distribution.

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.

- Conclusion: if you are going to do anything in this area, be sure you have good data.

Background – Case 2.

- Long-term Disability coverage.
- 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 (client specified use of Tree Models).
- 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

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	
5	(0.40)	680	1,678	20	0.02	
6	(0.27)	350	863	760	0.16	
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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	

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		
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		
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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)		
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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		
						6 red 13 green	11 nodes

Supporting Underwriting Decision-making

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

Supporting Underwriting Decision-making

Underwriting Decision	Total Profit	Average Profit per Case	Cases Written
Accept all cases as rated.	557.5	0.005	104,380
Accept all cases predicted to be profitable; reject all predicted unprofitable cases.	1,379.4	0.016	87,760

Supporting Underwriting Decision-making

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

Supporting Underwriting Decision-making

Underwriting Decision	Total Profit	Average Profit per Case	Cases Written
Accept all cases as rated.	557.5	0.005	104,380
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
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.	2,540.8	0.025	101,090

Example 3: evaluating a high-risk model

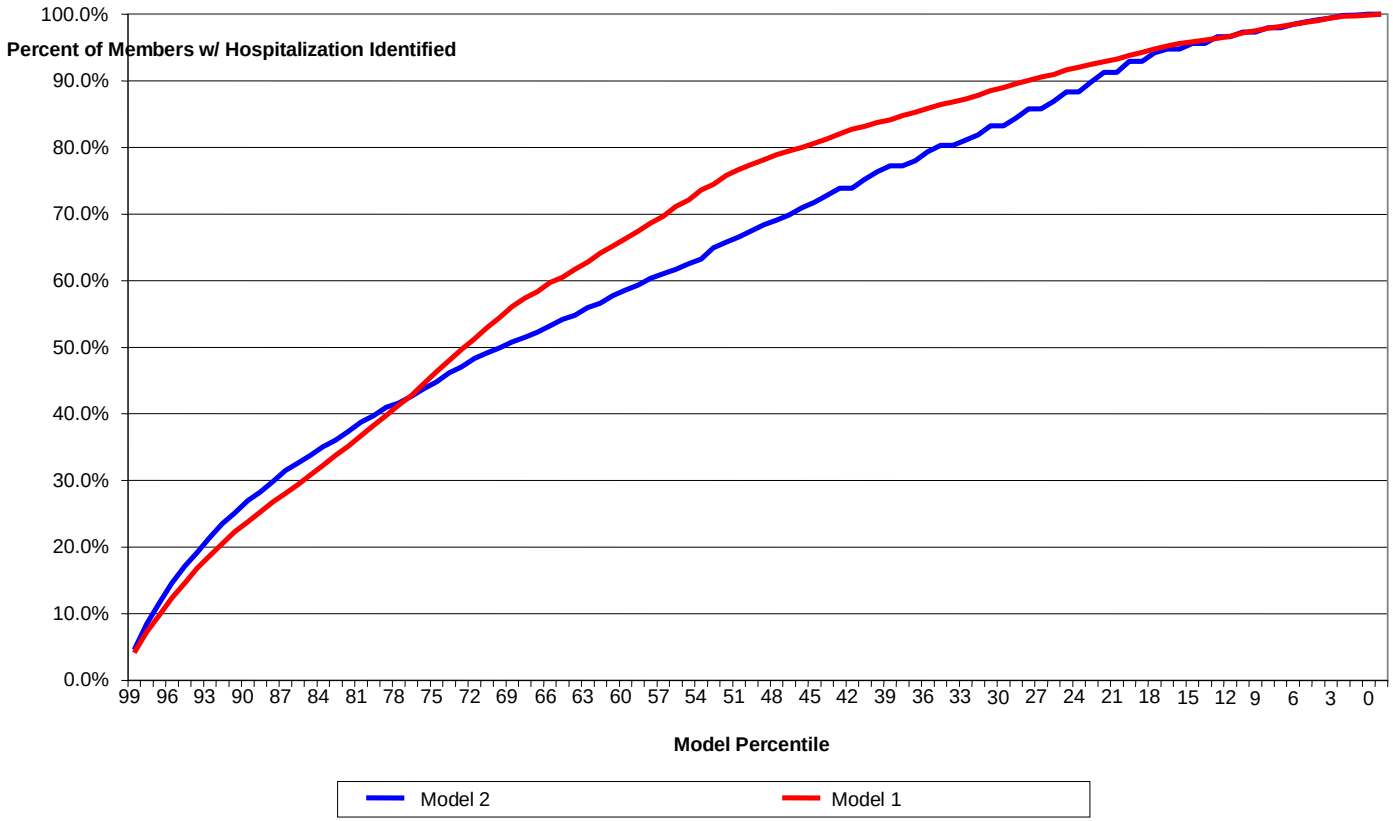
Background

- 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.

Analysis

- Two models: standard, off-the-shelf grouper model vs. a model developed specifically for predicting high-risk individuals for case management.
- 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.

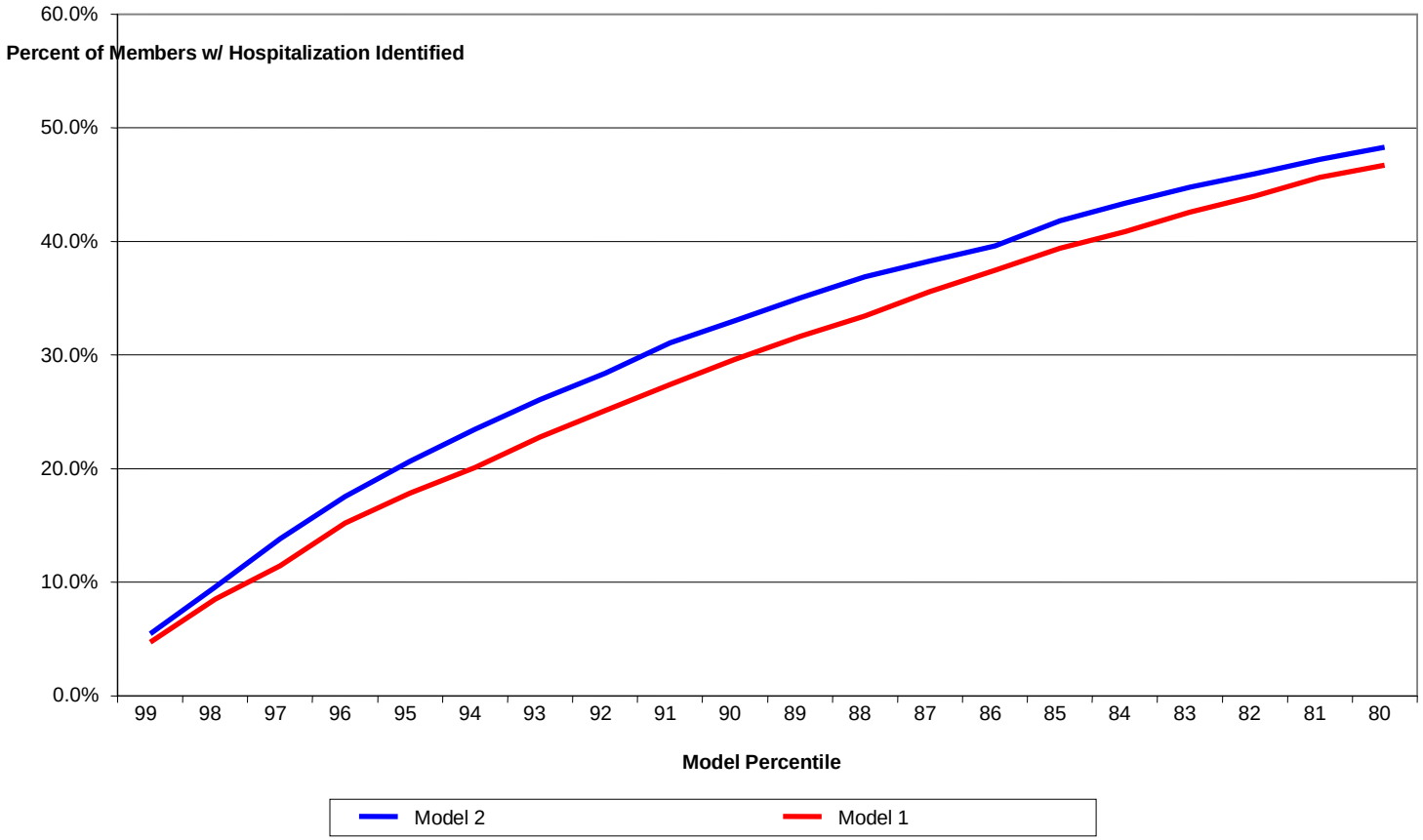
Lift Chart – Comparison between Two models



Analysis

- Looking at the results over a narrower range, they appear different.

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%	

Example 4: Constructing a Wellness Model

Solucia Wellness Model

- Data from a large health plan database (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

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)

Example 5: Model to predict severe depression

5. Depression Model

OBJECTIVES

- To develop a depression prediction model based on available data from the Solucia warehouse (primarily demographic and claims).
- Model objective is to identify those members of health plans who are likely to register a high score on the PHQ-9 survey when tested by the depression survey.
- To allow model users to apply the model to an entire unscreened population and to identify those that are predicted to have a high level of PHQ-9 score.

Study Population

- To develop the model we used a subset of members of our dataset for whom a PHQ-9 score exists.
- All the members for this analysis are members of a large regional health plan, enrolled between July 2004 and March 2008.
- In total, 838 members were enrolled in the plan and completed depression surveys between July 2004 and March 2008. A minority of members completed multiple surveys.
- Among those members with PHQ-9 scores, 460 members had scores of at least 10 on their first survey.
- To validate the model we used a subset of members from another large regional health plan , enrolled between July 2004 and March 2008.
- In total, 193 members were enrolled in the plan and completed depression surveys between July 2004 and March 2008.
- Among those members with PHQ-9 scores, 59 members had scores of at least 10 on their first survey.

Available Data

- Demographics: age, gender, zip code, ethnicity.
- Eligibility: coverage periods, benefit information.
- Medical claims: facility and professional.
- Pharmacy claims.
- PHQ-9 scores.

Model Development

Note that the purpose of the model is not to predict cost or utilization. The model simply predicts a binary outcome (presence/absence of a PHQ-9 score greater than or equal to 10).

- Depression status defined by PHQ-9 score >=10. Used first PHQ-9 survey for members with multiple surveys.
- Considered all claims incurred in the 12-month period prior to PHQ-9 survey date for independent variables.
- We added a “disease burden” or risk component by calculating a concurrent risk score using a standard Solucia model.

Descriptive Statistics

	PHQ-9 Score >=10 (N=460)	PHQ-9 Score <10 (N=378)	Total (N=838)
Average age	41.9	44.1	42.9
Female (%)	37.2%	37.0%	37.1%
Average depression outpatient claims	14.17	3.70	9.45
Proportion of members who had at least one depression outpatient claim	55.2%	20.6%	39.6%
Proportion of members who had at least two fills of anti-depressants	67.4%	39.9%	55.0%
Proportion of members who had at least one fill of anti-depressants	74.1%	47.4%	62.1%
Proportion of members who had at least one fill of pain drug	62.8%	49.2%	56.7%
Average Solucia concurrent risk score	1.03	0.87	0.96
Proportion of members who had at least one fatigue claim	13.7%	6.1%	10.0%
Average psychotherapy visits	67.0%	38.4%	54.1%
Proportion of males between 0 and 34 years old	15.9%	18.3%	16.9%

Predictive Modeling

Multivariate Logistic Models

- Forward selection.
- A split sample approach (50%/50%).
- Key validation statistics: Area under ROC curve, sensitivity, and specificity.
- Internal validation: Model performance based on validation sample.

Logistic Models

- Dependent Variable: PHQ-9 score is greater than or equal to 10.
- Independent variables:
  - Measures from claims and demographics, plus Solucia concurrent risk score.

	Development Group	Validation Group	Total
Members (n)	419	419	838
Members without depression claims	253	253	506
Members without anti-depressant scripts	167	151	318
Members without both claims and scripts	145	135	280
Members with PHQ-9 Score >=10	217	243	460

Model Development Summary

Parameters	Association	Odds Ratio
Intercept	Negative	0.39
Depression Outpatient Claims	Positive	1.03
Depression Inpatient Claims	Positive	1.59
Depression Drug 2fills Flag	Positive	2.16
Pain Drug Flag	Positive	1.13
Solucia Concurrent Risk Score	Positive	1.29
Fatigue Flag	Positive	2.43
Psychotherapy Visits	Positive	1.02
Schizophrenia	Positive	1.80
Age	Positive	1.01
Interaction between Concurrent Risk Score and Depression Outpatient Claims	Negative	0.99
Interaction between Concurrent Risk Score and Age	Negative	0.99

Model Development Summary (w/out Claims)

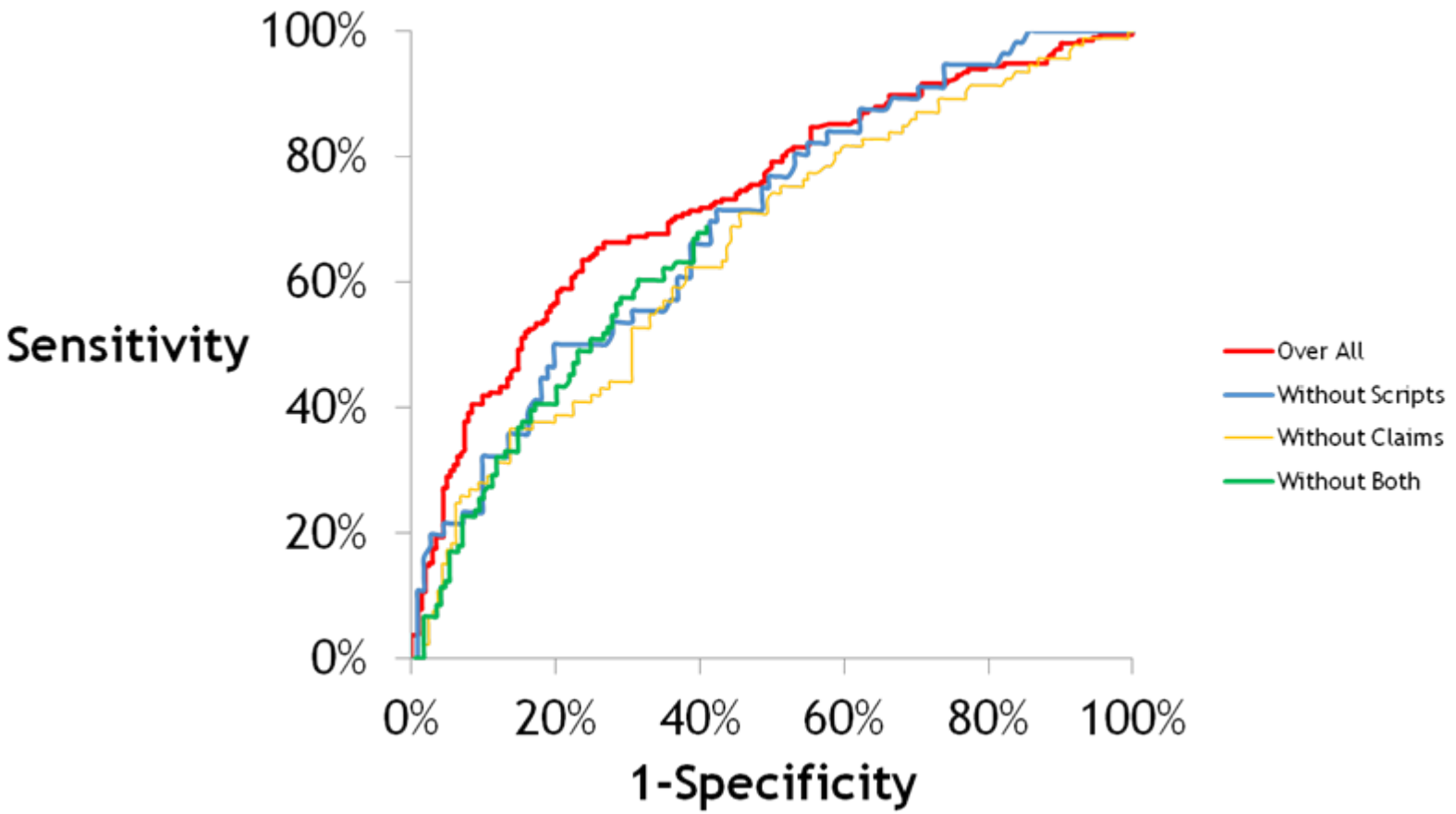
Parameters	Association	Odds Ratio
Intercept	Negative	0.33
Depression Drug 2 fills Flag	Positive	1.59
Solucia Concurrent Risk Score	Positive	2.60
Fatigue Flag	Positive	2.62
Psychotherapy Visits	Positive	1.02
Age	Positive	1.01
Interaction between Concurrent Risk Score and Age	Negative	0.97

Performance Assessment

- Receiver Operating Characteristic (ROC) curve:
  - Definition: A graphical representation of the trade off between the false negative and false positive rates for every possible cut off.
  - By tradition, the plot shows the false positive rate (1-specificity) on the X axis and the true positive rate (sensitivity or 1 - the false negative rate) on the Y axis.
  - Interpretation:
    - 0.90-1.00 = Excellent
    - 0.80-0.90 = Good
    - 0.70-0.80 = Fair
    - 0.60-0.70 = Poor
    - 0.50-0.60 = Fail

Model Evaluation: ROC Curve

	Overall	Without Scripts	Without Both	Without Claims
Area under the curve	0.737	0.695	0.686	0.655



Sensitivity and Specificity

		Condition (as determined by "Gold standard")		
		Positive	Negative	
Test outcome	Positive	True Positive	False Positive (Type I error, P-value)	→ Positive predictive value
	Negative	False Negative (Type II error)	True Negative	→ Negative predictive value
		↓ Sensitivity	↓ Specificity	

- Sensitivity: Maximizing the number of depressed patients correctly identified (correctly predicted depressed patients over total depressed patients)
- Specificity: Minimizing the number of false positives

$$\text{Sensitivity} = \frac{\text{Number of True Positives}}{\text{Number of True Positives} + \text{Number of False Negatives}}$$

$$\text{Specificity} = \frac{\text{Number of True Negatives}}{\text{Number of True Negatives} + \text{Number of False Positives}}$$

Sensitivity/Specificity (Contd.)

Solucia Depression Prediction Model

Cut Points	Probability	Sensitivity	False Negative	Specificity	False Positive
1	95%	4%	96%	100%	0%
2	74%	25%	75%	96%	4%
3	61%	45%	55%	86%	14%
4	50%	67%	33%	70%	30%
5	38%	74%	26%	55%	45%
6	34%	85%	15%	42%	58%
7	27%	100%	0%	4%	96%

As the sensitivity increases, the specificity drops, and vice-versa.

Using "Cutpoint 1 or 2" means that a very small proportion of the depressed patients will be identified.

Using "Cutpoint 6 or 7" means that almost all of the patients with depression will be identified as depressed, but so will many without depression.

Cutpoint 4 does a much better job of balancing the need to maximize the true positives and minimize the false positives.

Table for Cutpoint 4

		Actual (PHQ-9)		
		Y	N	Total
Predicted	Y	146	61	207
	N	71	141	212
	Total	217	202	419

PPV	=146/207	=71%
Specificity	=141/202	=70%
Sensitivity	=146/217	=67%
False Negative	=71/217	=33%
False Positive	=61/202	=30%

Sensitivity/Specificity (Contd.)

Sensitivity analyses for potential substitutes for high PHQ-9 score Indicator

Variable	Probability	Sensitivity	False Negative	Specificity	False Positive	Area Under ROC
Depression Claim Flag	64%	80%	20%	50%	50%	0.653
Depression Drug Flag	64%	74%	26%	55%	45%	0.646
Multivariate Logistic Model	50%	67%	33%	70%	30%	0.737

In these analyses, PHQ-9 score >=10 was used as a gold standard to test the sensitivity and specificity of applying those variables above to identify depressed patients.

The Multivariate model does a much better job of distinguishing depressed patients from non-depressed patients as demonstrated by substantially lower false negative rates.

Evaluation of Depression Claim Flag

		Actual (PHQ-9)		
		Y	N	Total
Predicted (Depression Claim)	Y	174	100	274
	N	43	102	145
	Total	217	202	419

PPV	=174/274	64%		
Specificity	=102/202	50%		
Sensitivity	=174/217	80%		
False Negative	=43/217	20%		
False Positive	=100/202	50%		

Depression Model Summary

- The claims-based model is effective in predicting high PHQ-9 score (score>=10) claimants:
  - Claims-based variables, especially those directly related to individuals' past depression history are significantly correlated with a high level of PHQ-9 score.
  - In general, demographic variables are not very predicative.
  - After controlling covariance, members are more likely to be depressed as age increases.
- The claims-based model can be applied to identifying high-risk depression candidates across the entire population:
  - Area under ROC curves is greater than 0.7, which indicates a fair predictive power.
  - We continue to try to obtain PHQ-9 score data from clients for whom we also have claims data. The increased sample size may further improve the predicative power of the model.

Selected references

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

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