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Overview of Predictive Models in the US
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Gary Nidds, FSA, MAAA

Munich Re America HealthCare

a division of MR America, Inc

Agenda

This session will provide a general view on the various uses of predictive models. Criteria typically used to select a model are also discussed, including complexity, accuracy and cost. A few examples will be used to demonstrate various uses.

First, what is a Medical Predictive Modeling and Risk Assessment?

Predictive models are used to assess the clinical risk level of an individual or group of individuals relative to a benchmark population mean.

Risk Adjustment refers to the process of adjusting the premium payment, provider reimbursement or health plan payment to reflect the results of the Risk Assessment or Predictive modeling.

Predictive Models can be used for purposes other than Risk Adjustments such as trend analysis, underwriting and medical management.

Benefits and uses of predictive modeling

- Identify candidates for disease and care management efforts
- Determine provider reimbursment levels based on riskiness of population
- Improve underwriting, pricing and risk selection
- Physician profiling
- Refine loss ratio estimates by policy duration
- Pay for Performance (P4P)
- Determining lasers, value for on-going claims
- Risk Equalization calculations
- Reinsurance excess of loss pricing
- Trend analysis

Options Available to Access Predictive Models

- Build your own
- Purchase an available model (DxCG, ACG, Ingenix, CPDS, D2Hawkeye)
    - Models are becomming customized for specific use
    - Engine may be from another company
- Rent or lease (e.g. Web based access to model)

Typical Model Structures

<u>Types of Models</u>

- Mathematical models (regression analysis, ai, claims only)
- Clinical models
    - Medical based, ICD-9/10, CPT codes (high predictive value)
    - Pharmacy based (less accurate, but timely and easy to get data)
    - Self reported data (surveys, questionaires, nurse coaching)
- Many models use a combination of the above “all encounter models“
    - Combination of clinical data and prior costs has highest R-squared

Example of Model Development

Typical Risk Adjuster Algorithm

-Model uses regression analysis to categorize diagnosis by predicted cost

-10,000 ICD-9/10 codes grouped into 200 condition categories. Drug and procedure information could be used to improve accuracy of grouping.

-The 200 conditions are combined with age/sex and prior year’s cost to arrive at 70 hierarchal cost categories.

-- A score of “1” could mean an expected cost of say 40% of the “expected”

-A score of “70” could be 100 times the mean cost

Criteria used to Select a Model

<u>Choosing a Model</u>

- Predictive power, R^2 or MAPE (generally not a distinguishing factor)
- Availability and timing of data (Rx vs medical, inpatient, history)
- Use of the model (DM versus UW). Is risk score multiplicative?
- Simplicity of use and output. Easy to explain
- Interface and knowledge of user
- Reinsurance vs insurance (accuracy varies by claim size)
- Sensitivity to data quality
- Cost, resource commitment to implementation and maintain
- Ability to provider or user gaming and manipulation

Predictive Models - SOA Published Results

Table I.1 - R-Squared and MAPE for Prospective Nonlagged - Offered vs. Optimized (Recalibrated, with Prior Cost, 250k Claim Truncation)						
			Offered Models		Optimized Models w/Prior Cost	
Risk Adjuster Tool	**Developer**	**Inputs**	**R-2[1]**	**MAPE %[2]**	**R-2**	**MAPE %**
ACG	Johns Hopkins	Diag	19.20%	89.90%	23.00%	86.20%
CDPS	Kronick / UCSD	Diag	14.90%	95.30%	24.60%	85.60%
Clinical Risk Groups	3M	Diag	17.50%	90.90%	20.50%	86.60%
DxCG DCG	DxCG	Diag	20.60%	87.50%	26.50%	82.50%
DxCG RxGroups	DxCG	Rx	20.40%	85.30%	27.10%	80.70%
Ingenix PRG	Ingenix	Rx	20.50%	85.80%	27.40%	80.90%
MedicaidRx	Gilmer / UCSD	Rx	15.80%	89.60%	26.30%	81.90%
Impact Pro	Ingenix	Med+Rx+Use	24.40%	81.80%	27.20%	80.60%
Ingenix ERG	Ingenix	Med+Rx	19.70%	86.40%	26.50%	81.20%
ACG - w/ Prior Cost	Johns Hopkins	Diag+$Rx	22.40%	85.60%	25.40%	82.10%
DxCG UW Model	DxCG	Diag+$Total	27.40%	80.40%	29.10%	78.30%
Service Vendor						
MEDai	MEDai	All	N/A	N/A	32.10%	75.20%
(1) R-2 is R-square, a measure of predictive accuracy. R-squared = 1-(Sum(Actual-Predicted))/(Sum(Actual-Average of Actual))						
(2) MAPE is Mean Absolute Prediction Error, another measure of predictive accuracy. MAPE = (Sum(Actual-Predicted))/Sample Size						

Source: A Comparative Analysis of Claims-Based Tools for Health Risk Assessment, The Society of Actuaries, SOA.com, April 23rd 2007 written by Ross Winkelman and Syed Mehmud of the Denver office of Milliman, Inc. (Mr. Winkelman has since joined Wakely Consulting)

Predictive Modeling Case Study 1
Small Group Medical Insurance Example

-US portfolio of Small Group Employers (2-50 lives)

-Program manager currently applies traditional underwriting methodology to price new and renewal business, using:

- Prior loss ratio experience
- Changes in UW manual (age, sex, location, network ,trend, etc)

- 3 underwriting tiers generated “the good, the bad and the ugly“
- Rate changes upon renewal based solely on UW tier
- Adverse selection was observed, hence a need for refined underwriting

Predictive Modeling Case Study 1
Considerations

Considerations:

- Above-average risk may not need higher-than-average renewal increase
- Statutory rating limitations may not allow for full application of risk adjustment
- Need to redefine “average” risk score to match underwriting methodology
- **Needs to be viewed as a supplement or enhancement to current process, not replacement.**
    - Can’t disregard manual “underwriting” process
    - <u>Makes it an easier internal sale</u>

Predictive Modeling Case Study 1
Solution…

- Used actual block of small group business, including actual underwriting decisions.

- Historical (Yr 1) clinical information available at time of underwriting was run through predictive model, DxCG

-Risk score for each employer group was calculated

- Actual (Yr 2) experience compared against risk score premium and against historical premium

Predictive Modeling Case Study 1

Current UW process using three tiers

Average Employees per Employer:	6
Year 1 Premium PEPM:	$300
Annual Trend:	10.0%
Target Loss Ratio:	60.0%

Renewal Tier	Employer Groups	Year 1 Premium	Year 1 Loss Ratio	Target Rate Increase	Year 2 Premium	Year 2 Loss Ratio	Renewal Persistency
Good	1500	32,400,000	40.0%	-26.7%	19,440,000	53.0%	60.0%
Bad	800	17,280,000	70.0%	28.3%	12,096,000	63.0%	70.0%
Ugly	300	6,480,000	175.0%	220.8%	5,184,000	122.0%	80.0%
Total	2600	56,160,000	64.8%	18.8%	36,720,000	66.0%	

Note: for illustration only

Predictive Modeling Case Study 1
Underwriting Classes with Model Output

Predictive Modeling Approach:

▪Expand 3 tier traditional breakdown to a 3 by 3 matrix including risk score

	Actual Yr2 Loss Ratios by DxCG Risk Classification			
Current Class	Class 1	Class 2	Class 3	TOTAL
Good	54%	41%	73%	53%
Bad	40%	75%	102%	63%
Ugly	85%	89%	186%	122%
TOTAL	50%	75%	126%	66%

Note: for illustration only

Predictive Modeling Case Study 1

Result:

- More refined rate assignment by underwriting tier and risk score (9 bands instead of 3)
- Improved isolation of best and worst cases. These are the cases worth investigating further
- Gives underwriter a sanity check on traditional underwriting process
- Identifies individuals with poor prognosis and likely very high costs
  - Laser or price separately
  - Contact for DM or CM

Predictive Modeling Case Study 2
Duration, Individual Insurance Block Analysis

Situation

-Block of Individual business

-Fully underwritten on entry, guaranteed renewable

- Adverse selection at renewal as healthy individuals are priced out

Solution

-Run lives through DxCG model and stratify by risk score

-Assume propensity to lapse a function of risk score and rate increase

-Balance rate changes for the class by risk score, policy duration and lapse

Predictive Modeling Case Study 2
Duration Analysis – Risk Scores by Policy Age

Risk Score by Duration
Individual Medical Insurance Policies

	Risk	Risk Score for those who…	
Duration	Score	Terminated	Renewed
Months 1-6	0.63	0.53	0.75
Months 7-12	0.89	0.60	0.99
Year 2	0.95	0.71	1.03
Year 3	1.05	0.83	1.12
Year 4	1.15	0.75	1.15
Year 5	1.22	0.92	1.20
Year 6	1.19	0.81	1.19

Note: for illustration only

Predictive Modeling Case Study 2
Risk Scores by Product, Deductible and Network

Risk Score by Product Type
Individual Medical Insurance Policies

Plan	Benefits	Deductible	Network	Risk Score
Health Logic	Moderate	Medium	PPO Weak	1.016
Health Next	Rich	Low	PPO Weak	1.260
Health Vantage	Rich	Low	PPO Weak	1.129
Spectra One	Moderate	High	PPO	0.773
Star Care	Moderate	High	PPO	0.841
Star Care 2	Rich	High	PPO	0.822
HSA Plus	Rich	Very High	PPO Strong	0.750

Note: for illustration only

Predictive Modeling Case Study 3
Reinsurance Example

Excess of Loss Pricing

- Individual “Discrete” distribution – calculate Expected Claims above certain retention levels
- Individual “Parametric” distribution – predict individual mean and variance
- Risk “buckets” – Put individuals in buckets using predictive model risk scores

Predictive Modeling Case Study 3
Reinsurance Example

Excess of Loss Pricing Example

Reinsurance Retention	Expected Annual Costs Above Retention			Multiple of "Healthy" Costs	
	Healthy RS = 1.00	CHF Only RS = 4.85	Diabetes & CHF RS = 24.29	CHF Only	Diabetes & CHF
-	1,778	8,630	43,195	4.85	24.29
10,000	281	4,488	34,050	15.99	121.32
25,000	99	2,719	24,760	27.49	250.31
50,000	36	1,598	16,059	44.03	442.54
100,000	11	804	8,302	73.57	759.44

Note: for illustration only

Thank you for your attention.

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