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Predictive Modeling



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Julie Chambers

Director Risk Research
London Life Insurance Company

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Question ...

Researcher investigating an individual's lifestyle discovers that personal credit scores correlates with risky behaviour



Question ...

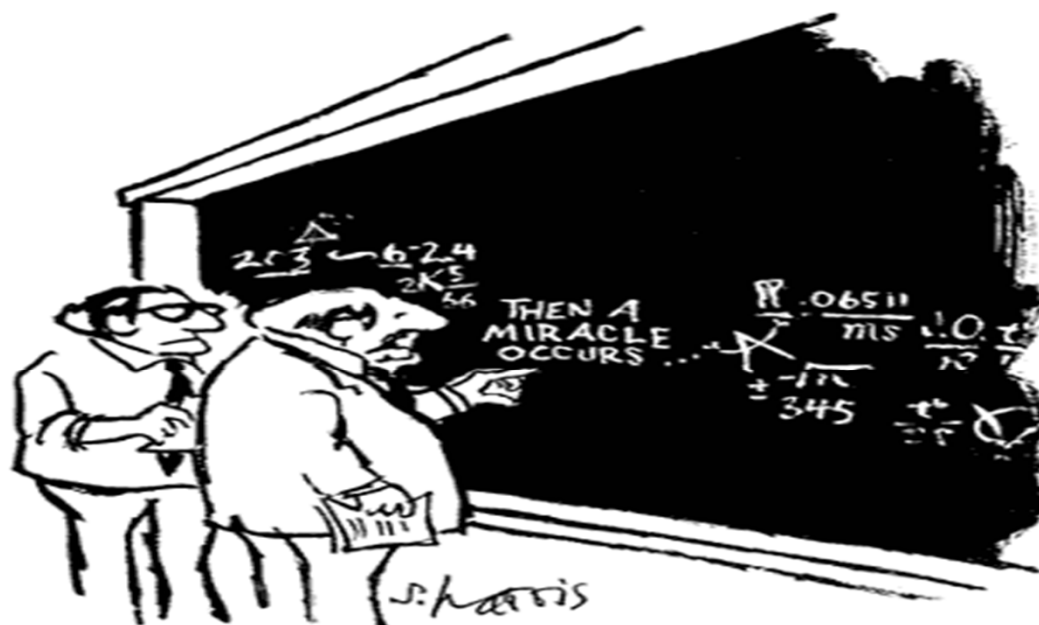
Researcher investigating an individual's lifestyle discovers that personal credit scores correlates with risky behaviour

Is this a predictive model?



Predictive Models Defined

- A **predictive model** is a mathematical algorithm that predicts a target variable from a number of factor variables



"I think you should be more explicit here in step two."

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Semantics

- Data Mining – Exploration and Discovery
 - Find “interesting” patterns in databases
 - Open-ended, “cast the net” wide
- Predictive Modeling – Apply Statistical Techniques
 - Quantify and synthesize relationships found during knowledge and discovery



Examples of Predictive Modeling



- The Netflix algorithm CineMatch determines which movies a customer is likely to enjoy based on:
 - The films themselves, which are arranged as groups of common movies
 - The customers' ratings, rented movies and current queue
 - The combined ratings of all Netflix users
- According to Netflix, half of Netflix users who rented CineMatch recommended movies gave them a five-star rating
- Netflix launched a contest with a \$1 million prize to the first person or team meet the accuracy goals for recommending movies based on users' personal preferences



Source: www.howstuffworks.com

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Examples of Predictive Modeling



To make matches, a computer:



1. Searches the CineMatch database for people who have rated the same movie - for example, "The Return of the Jedi"
2. Determines which of those people have also rated a second movie, such as "The Matrix"
3. Calculates the statistical likelihood that people who liked "Return of the Jedi" will also like "The Matrix"
4. Continues this process to establish a pattern of correlations between subscribers' ratings of many different films

Algorithms that keep the recommendation system running don't necessarily have anything to do with the plot or cast.

They are based on the other subscribers' rental and ratings histories.

Source: www.howstuffworks.com

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Examples of Predictive Modeling



- codenamed “Synapse” the Match algorithm, considers a variety of factors
- User’s stated preferences such as:
 - Age range
 - Hair colour
 - Body type
- The algorithm learns from the user’s actions on the site, it began “weighting” variables differently, according to how users behaved
 - For example, “if conservative users were actually looking at profiles of liberals, the algorithm would learn from that and recommend more liberal users to them”
 - For example, “if a woman says she doesn't want to date anyone older than 26, but often looks at profiles of thirty-somethings, Match will know she is in fact open to meeting older men.”
- Triangulation
 - Looks at the behaviour of similar users and factors this in too
- “It’s all about behaviour modeling. All that data goes into algorithms and affects who we put in front of you.”



Source: The Financial Times, “Inside Match.com, It’s all about the algorithm”

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Examples of Predictive Modeling



Santa Cruz's Predictive Policing Program

“police officers were directed to the parking structure by a computer program that had predicted that car burglaries were especially likely there that day”



- By analyzing and detecting patterns in years of past crime data, it generates projections about areas and windows of time that are high risk
- Projections are recalibrated daily as new crimes occur and are fed into the program

Source: Mercury News, Santa Cruz's predictive policing program becomes a model for departments nationwide, August 18, 2011

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Examples of Predictive Modeling



Fighting Medicare Fraud

“Centers for Medicare and Medicaid Services (CMS) is poised to begin using predictive modeling technology to fight Medicare fraud”



- Examine claims by beneficiary, provider, service origin and other patterns to identify potential problems
 - Similar to technology being used to detect fraud by credit card companies
- Create automatic alerts and “risk scores” for claims

Source: RACmonitor.com, “RAC Game Changer: Predictive Modeling”, June 22, 2011

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Examples of Predictive Modeling



How VISA Predicts Divorce



“Predicting people’s behaviour is becoming big business”

“Because people who are going through a divorce are more likely to miss payments, your domestic troubles are of great importance to a company that thrives on risk management”

- Credit card companies create psychological profiles of it’s cardholders that were built on alarming precise correlations
 - “if you show us what you buy, we can tell you who you are, maybe even better than you know yourself”

Source: The Daily Beast, “How Visa Predicts Divorce”

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Examples of Predictive Modeling



Harrah's Casino



“Analysis of gambling patterns ...showed that most customers have a “pain threshold” beyond which they will not bet. When losses reach that point, they may become disillusioned and leave the casino.”

- Harrah's calculates each individual's threshold and tracks their totals which are checked in real time against a loyalty index
 - This gives it the power to anticipate dissatisfaction and intervene before it happens

Source: www.information-age.com, “Nothing Left to Chance”, January 18, 2007

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Controversy ?????

- “There is a dark side to electronic records”
 - Hank George, Best’s Review, August 2010
- “Would you buy a life insurance policy from this machine?”
 - Wall Street Journal, March 12, 2011
- “Insurer’s test data profiles to identify risky clients”
 - Wall Street Journal, November 19, 2010
- “Useless Arithmetic: Ten Points to Ponder When Using Mathematical Models in Environmental Decision Making”
 - Public Administration Review, May/June 2008
- “What concerns me...with predictive modeling [is the idea that] we can predict what a criminal looks like, what a criminal is, and what a criminal might do ... [and that] predictive modeling leads to another area ...profiling.”
 - Excerpt from the New Mexico Independent, December 8, 2009



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Barry Senensky

President, Claim Analytics Inc.

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Agenda

- Introduction to Predictive Modeling
- The Past
- The Future



Introduction to Predictive Modeling

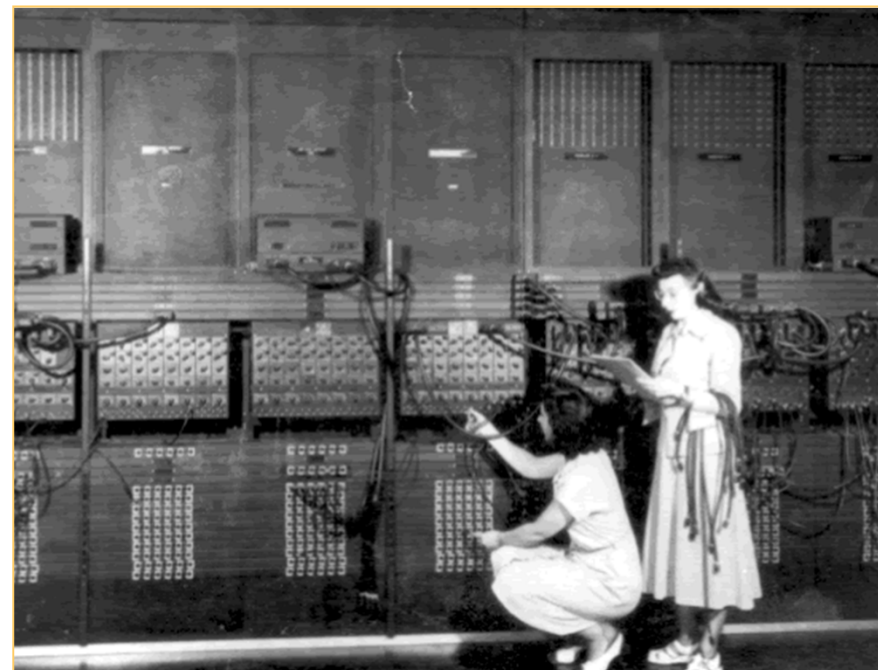
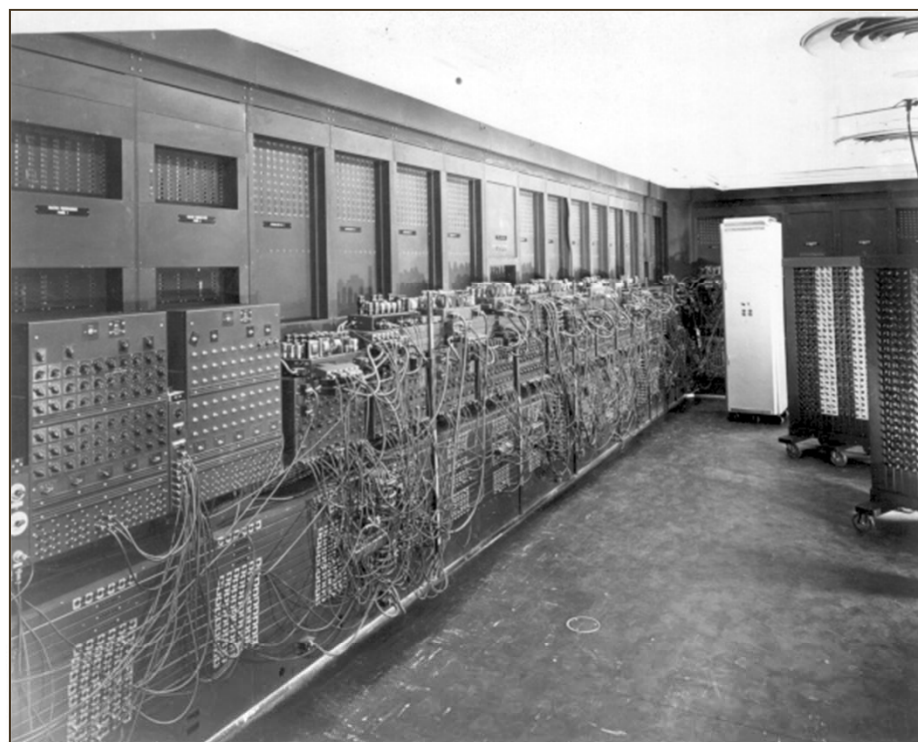
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Computer Performance

Measure	IBM 7094 c. 1967	Laptop c. 2009	Change
Processor Speed (MIPS)	0.25	2,800	11,000-fold increase
Main Memory	144 KB	4,000,000 KB	28,000-fold increase
Approx. Cost (\$2009)	\$12,000,000	\$1,000	12,000-fold decrease

What is Predictive Modeling



- **Analyze** historic data
- **Identify & quantify** relationships between predictive inputs and outcomes
- Apply learning to **predict outcomes** of new cases

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Two “ERA’s”

- Traditional
 - Around for 100+ years
 - Low usage of computer power
 - Relatively easy to understand
- Modern
 - Have been around 40+ years
 - Exploits power of computer processing
 - Can be “black boxes”



Modern Predictive Models



- Used extensively in industry
- Applications include
 - Credit Scores
 - Credit Card Fraud Detection
 - Mail sorting
 - Weather prediction
 - Hot dogs and Hamburgers

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Some Modern Predictive Modeling Methods



- Classification and Regression Trees
- Generalized Linear Models
- Neural Networks
- Genetic Algorithms
- Stochastic Gradient Boosted Trees
- Support Vector Machines

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Predictive Modeling and the Life Insurance Industry

“The Past”

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The Past-P&C Industry



- Progressive Insurance
- Incorporated Credit Ratings into auto pricing
- Huge competitive advantage
- Catalyst-others followed
- Now standard practice

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The Past-Life Insurance Industry



- Not too much!
- Some application for target marketing
- A few fraud applications
- Claim Analytics applications for claims management and group disability pricing
- Recent interest in mortality applications

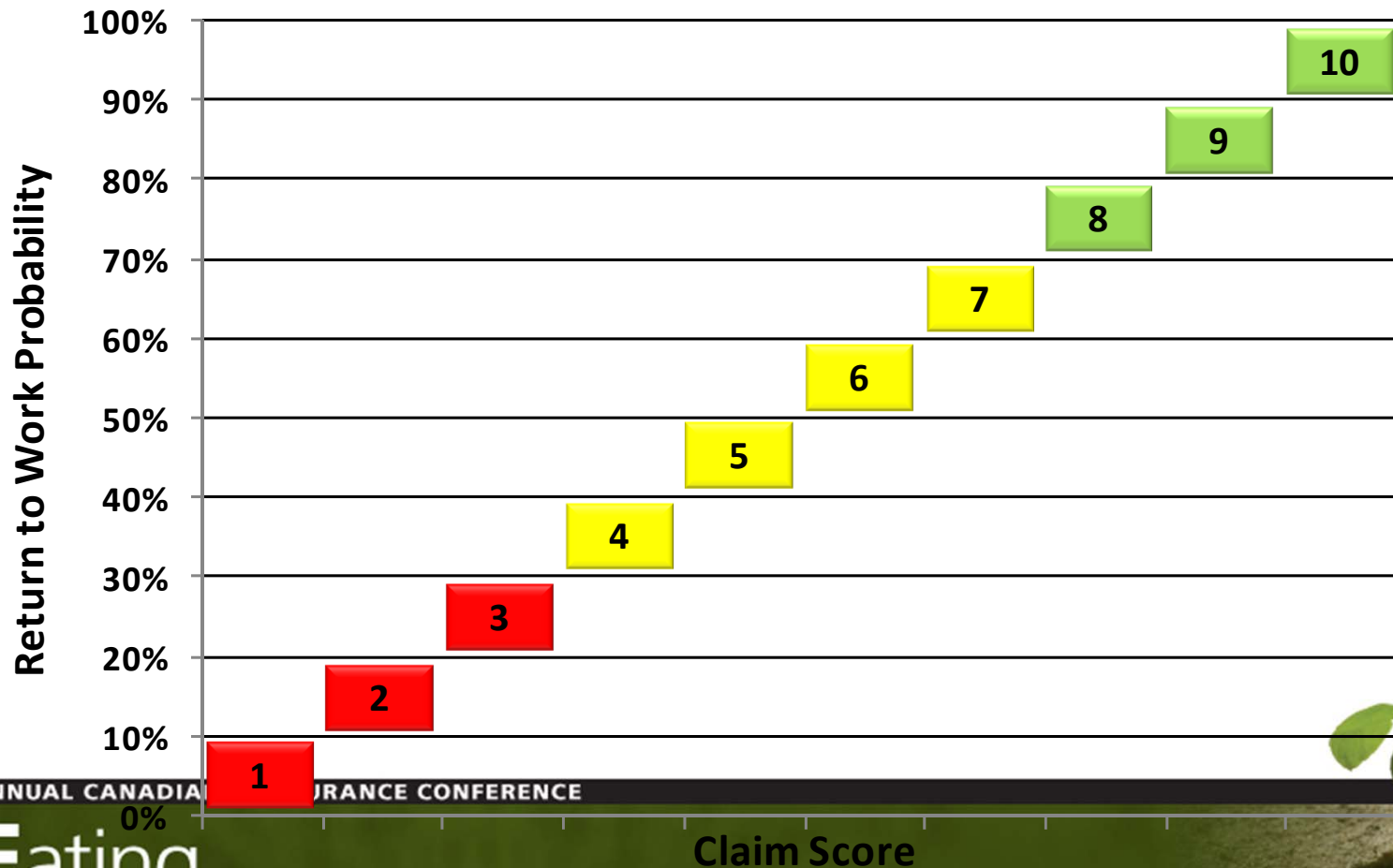
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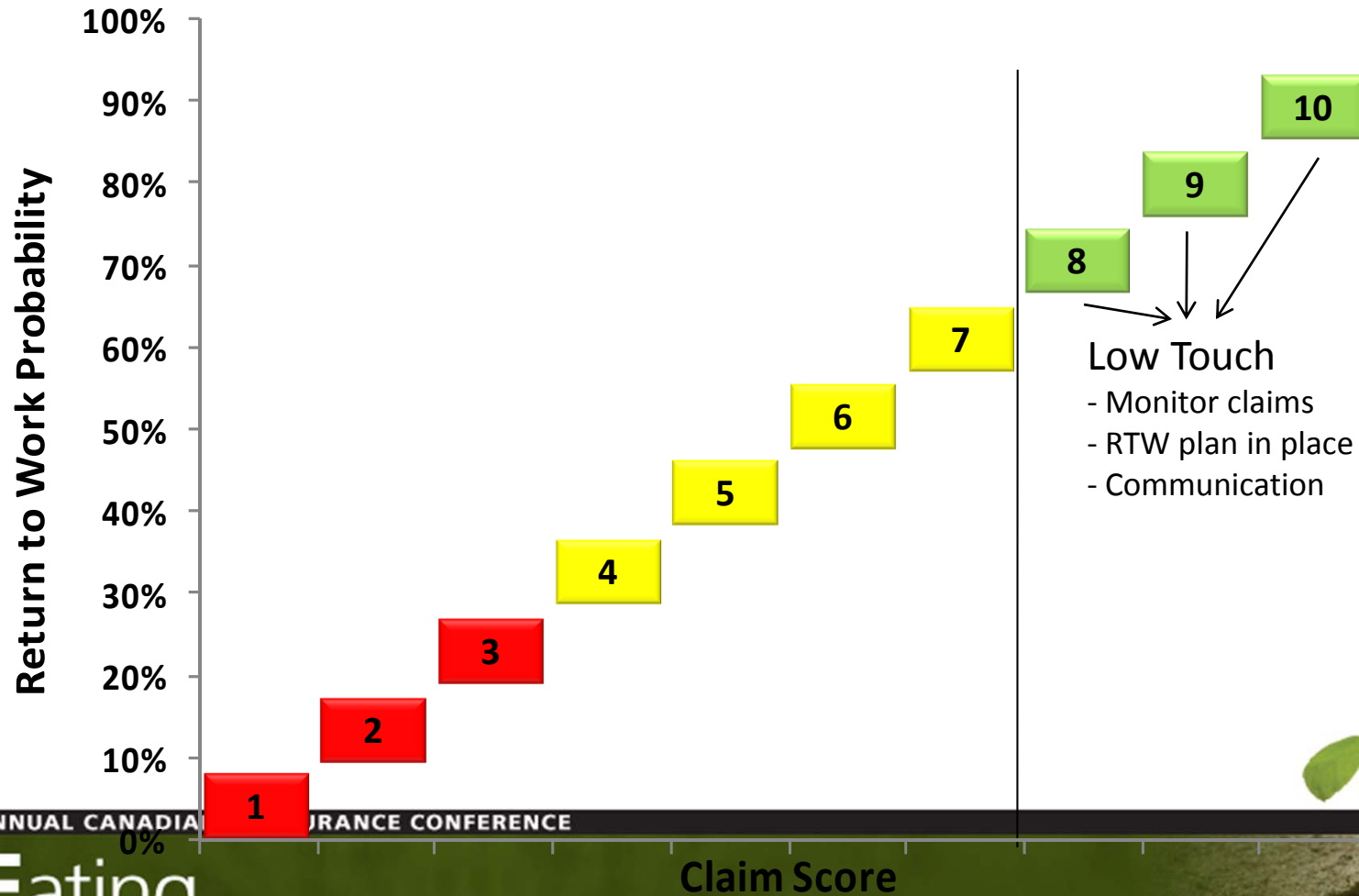
Claim Scores – Return to Work

Based on its specific attributes a claim is scored 1 to 10



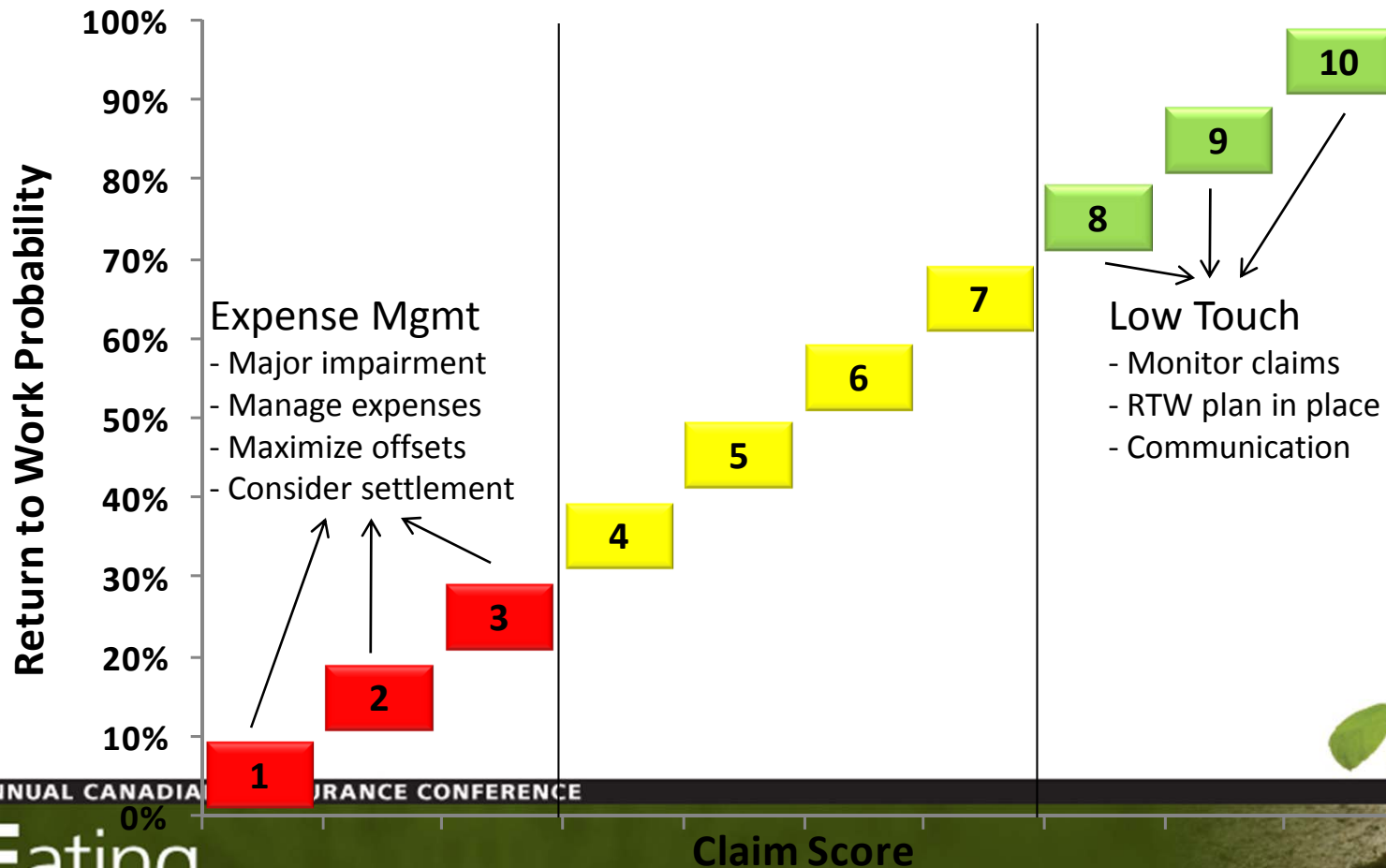
Claim Scores – Return to Work

Each claim receives the appropriate level and type of attention



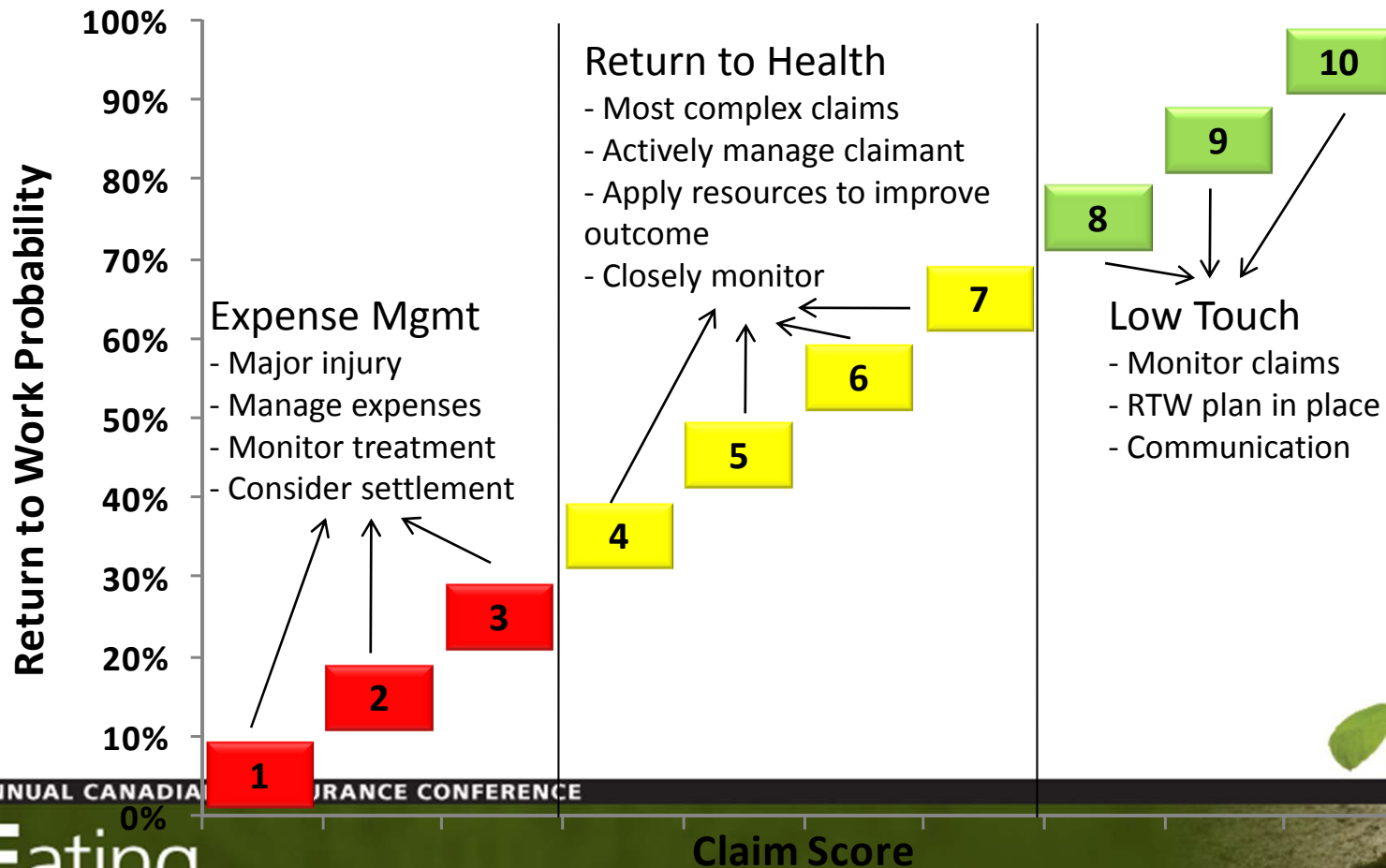
Claim Scores – Return to Work

Risk stratification provides early identification of at risk claims



Claim Scores – Return to Work

Scores facilitate claim triage – appropriate action for each claim



Recent Mortality Applications



1. Reproducing underwriting decisions
 - Relatively Straightforward to model
 - Automates underwriting function
 - Reduces costs but doesn't impact mortality

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Recent Mortality Applications



2. Predictive Scores based on lab analysis of fluids

- Produces additional variables to be considered in the underwriting process
- More complex to model as claim history needs to be known and reflected in models
- Impacts mortality but doesn't impact underwriting costs

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Recent Mortality Applications



3. Predictive Scores based on data on the insurance application

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Why haven't Life Insurance Companies embraced modern predictive models?



- Life Insurance Industry is conservative and slow to change
- Not a traditional actuarial tool

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Modern Predictive Modeling and the Life Insurance Industry

“The Future”

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The Future-Mortality



1. More and Better models available
2. Less reliance on fluids
3. Higher Limits on Simplified Underwriting
4. Use of Social Media Data/Web Scraping
5. Internet Selling
6. Direct development of mortality rates for each individual
7. More and Stricter Regulation

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The Future-General



1. Predictive modeling will become a tool of choice in the industry
2. Predictive models will be used extensively
 - Underwriting
 - Fraud Detection
 - Claims Management
 - Target Marketing
 - Experience Analysis

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The Future-General



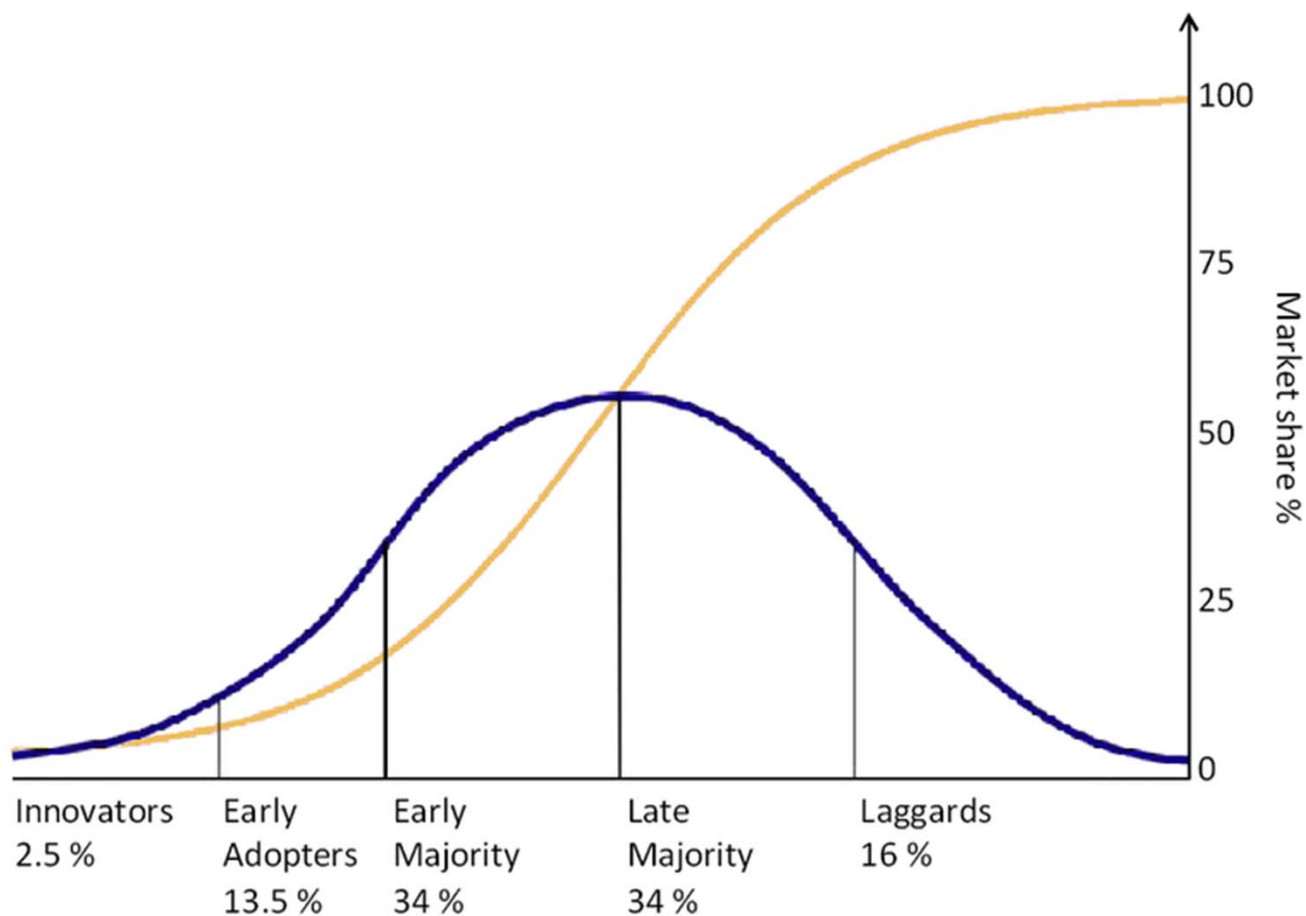
3. Rapid Innovation
4. New problems and issues
 - Use of data
 - Reliability of data
 - Measuring robustness of models

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Diffusion of Ideas



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More Information About Predictive Modeling

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Additional Predictive Modeling Resources



www.claimanalytics.com

- *Papers on insurance applications of predictive modeling*

Courses

- *Tools for Discovering Patterns in Data: A Survey of Modern Data Mining Algorithms*, John Elder of Elder Research, Inc. www.datamininglab.com
- *Statistical Learning and Data Mining II: Tools for Tall and Wide Data*, Trevor Hastie and Robert Tibshirani, both of Stanford University
www.stat.stanford.edu/~hastie/sldm.html

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Guizhou Hu, MD, PhD

Chief Scientific Officer, BioSignia Inc.

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Prediction Models in Life Underwriting



- Two kinds of prediction models
- Why use prediction models?
- An example:
Mortality Assessment Technology (MAT™)

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Two Kinds of Prediction Models

- Epidemiological research-based models
 - Based on biological associations
 - Smoking increased mortality
 - Framingham heart disease model
- Third party data-driven models
 - Based on any possible data correlation
 - People with yellow fingers (smokers tend to have yellow fingers) may have higher mortality
 - People with a gym membership may have lower mortality



Why Use Prediction Models?



- Improve mortality prediction by using epidemiological research-based models
 - Total/HDL ratio predicts risk better than total cholesterol alone
- Reduce underwriting costs by using third party data-driven models

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Example:

- Mortality Assessment Technology (MAT):
an epidemiological research-based
prediction model developed for life
insurance underwriting



How was MAT Developed ?

Scientific Research Literature



Synthesis Analysis

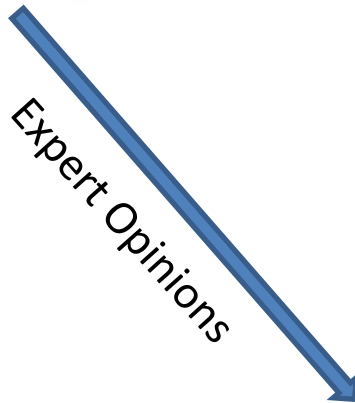



Meta Analysis

MAT

$$X = S^k \setminus A_i = B^k / \Gamma$$
$$v_j = \sum_{k=0}^{\infty} \frac{1}{(-2)^k (6k + j)^2}$$
$$v = (v_0, X), v_1, v_2, v_3, v_4, v_5) \in \mathbb{R}^6$$
$$m = (-1, 9, -9, -12, -3, 1) \in \mathbb{Z}^6$$
$$v \cdot m = 0$$
$$\Gamma = \left(\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ -\omega & 1 \end{pmatrix} \right) \quad 1 + \omega + \omega^2 = 0$$

Expert Opinions



Conventional
Underwriting
Rules &
Guidelines 



Features of MAT

- Based on epidemiological research
- Assess risk in totality, taking into account risk factors interactions
- Assess risk by age and gender



MAT Validations

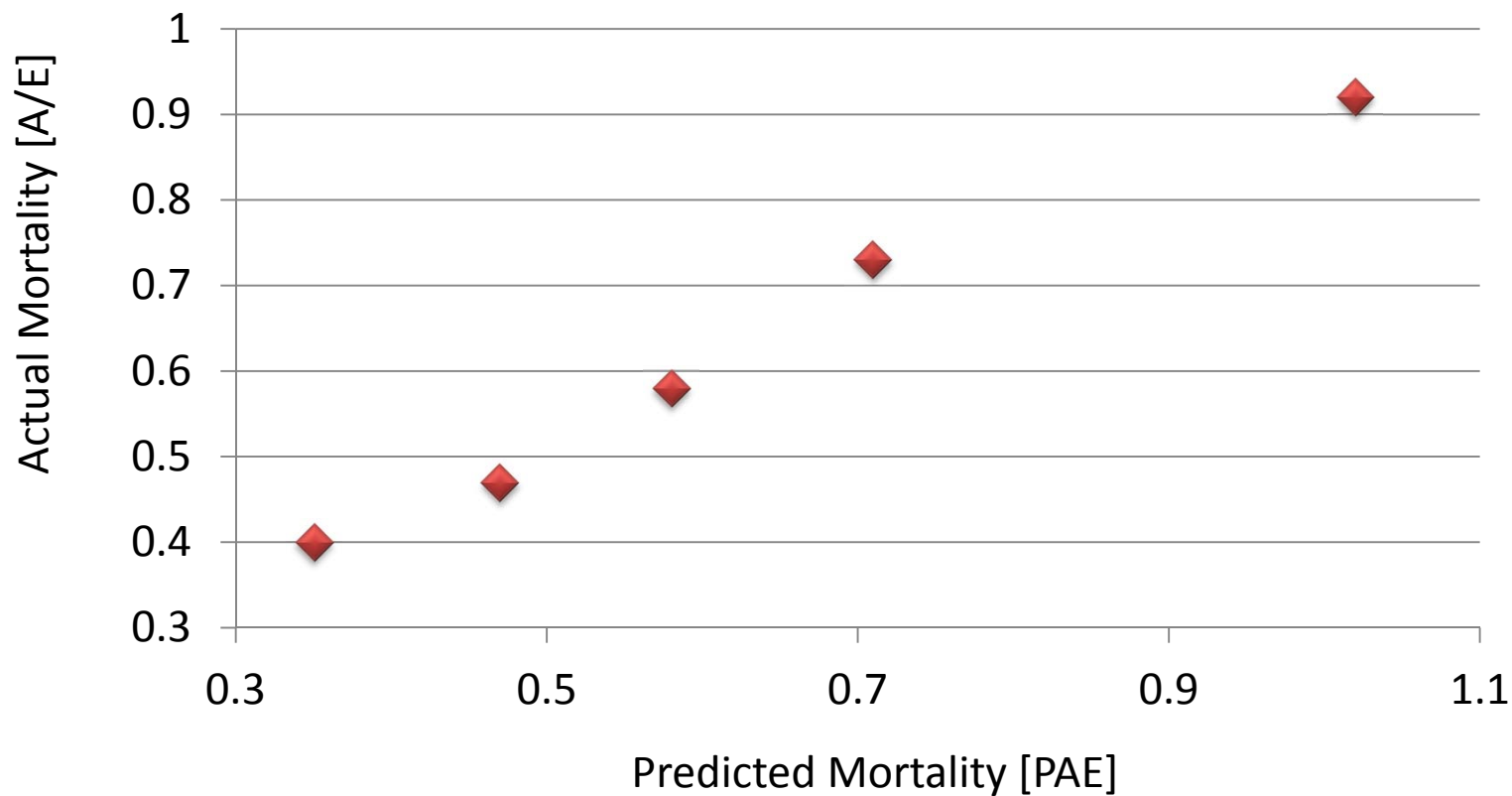
- Data: 311K historical issued policies (non smokers, standard and better) with 1.3 million policy-years of exposure and 837 death claims
- Test the Prediction: Use MAT score to rank order policies into 5 equally divided quintile groups, then compare predicted mortality with actual mortality
- Compare with conventional U/W: Use MAT score for risk classification while matching conventional U/W class distribution, then compare mortality
- Evaluate MAT advantage: simulate a competition between MAT and conventional U/W



Predicted vs. Actual Mortality



Correlation Coefficient=0.99



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MAT vs. Conventional U/W

Same distribution

	Conventional U/W		MAT	
	%	A/E	%	PAE
Super Preferred	39	0.53	39	0.44
Preferred	30	0.63	30	0.59
Standard	21	0.68	21	0.77
Residual	10	0.85	10	1.06

A/E: Actual vs. 2001 VBT Expected Mortality

Different mortality differentiation

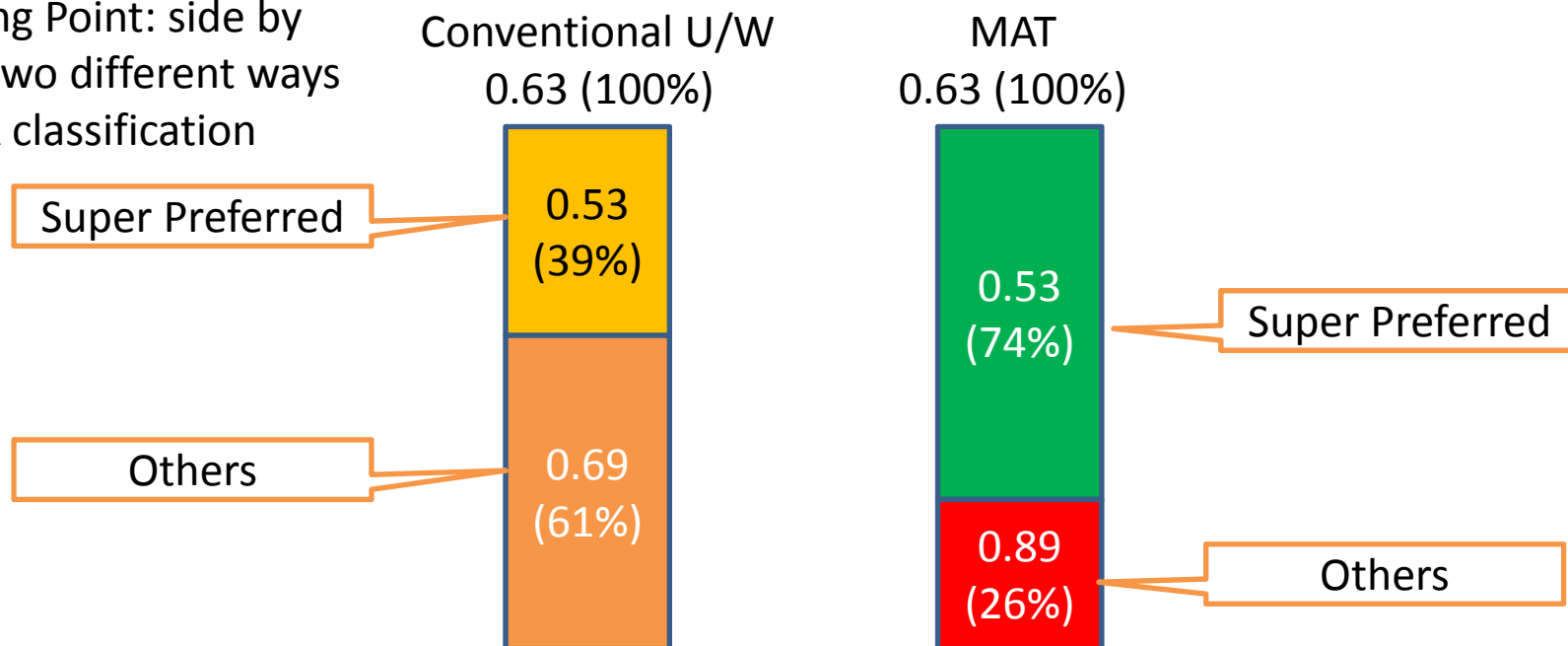
MAT improves mortality differentiation over Conventional U/W



Simulated Competition between Conventional U/W and MAT



Starting Point: side by side, two different ways of risk classification



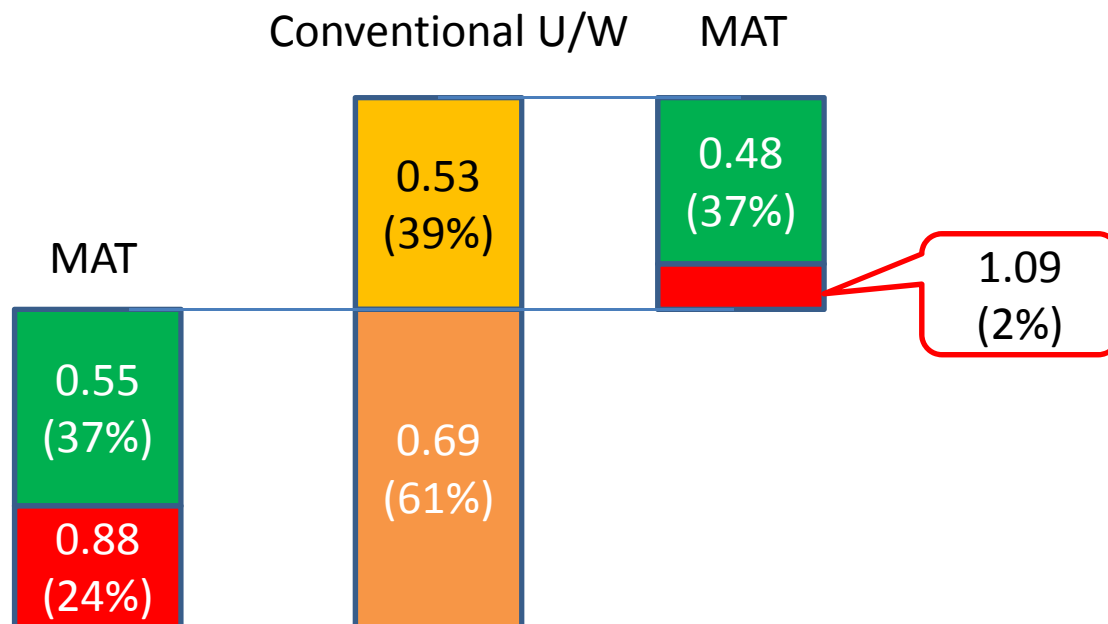
- Numbers in the graph are A/E ratio followed by % qualified
- For demonstration purposes, only two risk classifications were simulated
- MAT score cut-off points were set to match mortality of Super Preferred from Conventional U/W

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Detail Comparison

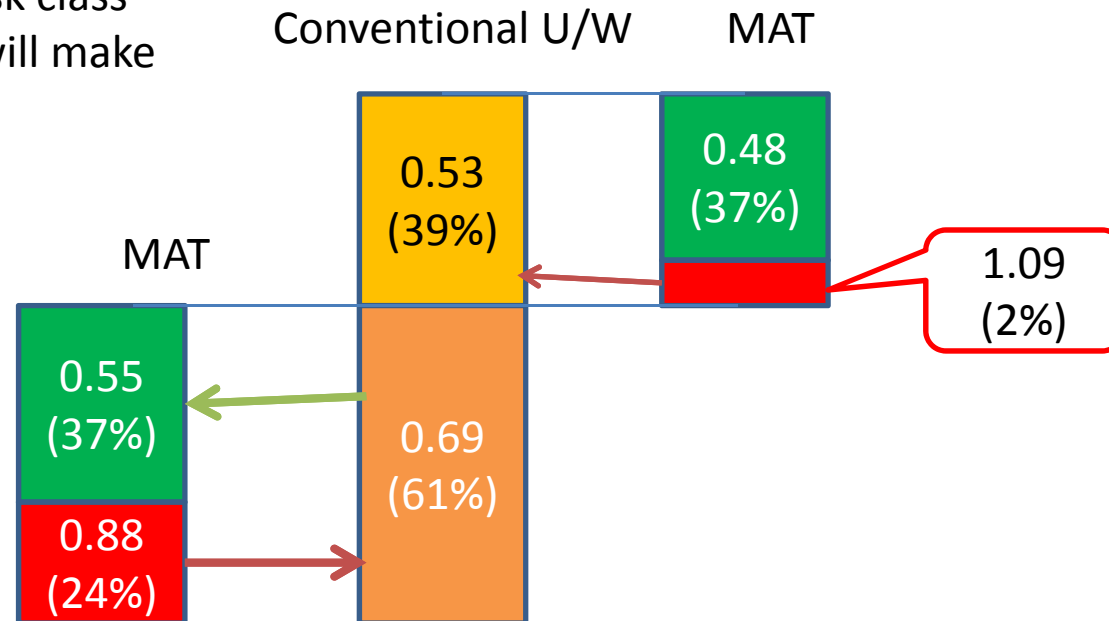


Lower risk by one classification may be regarded as higher risk by the other



Policy Movements

While MAT and conventional U/W give different risk class offer, some policies will make switch move



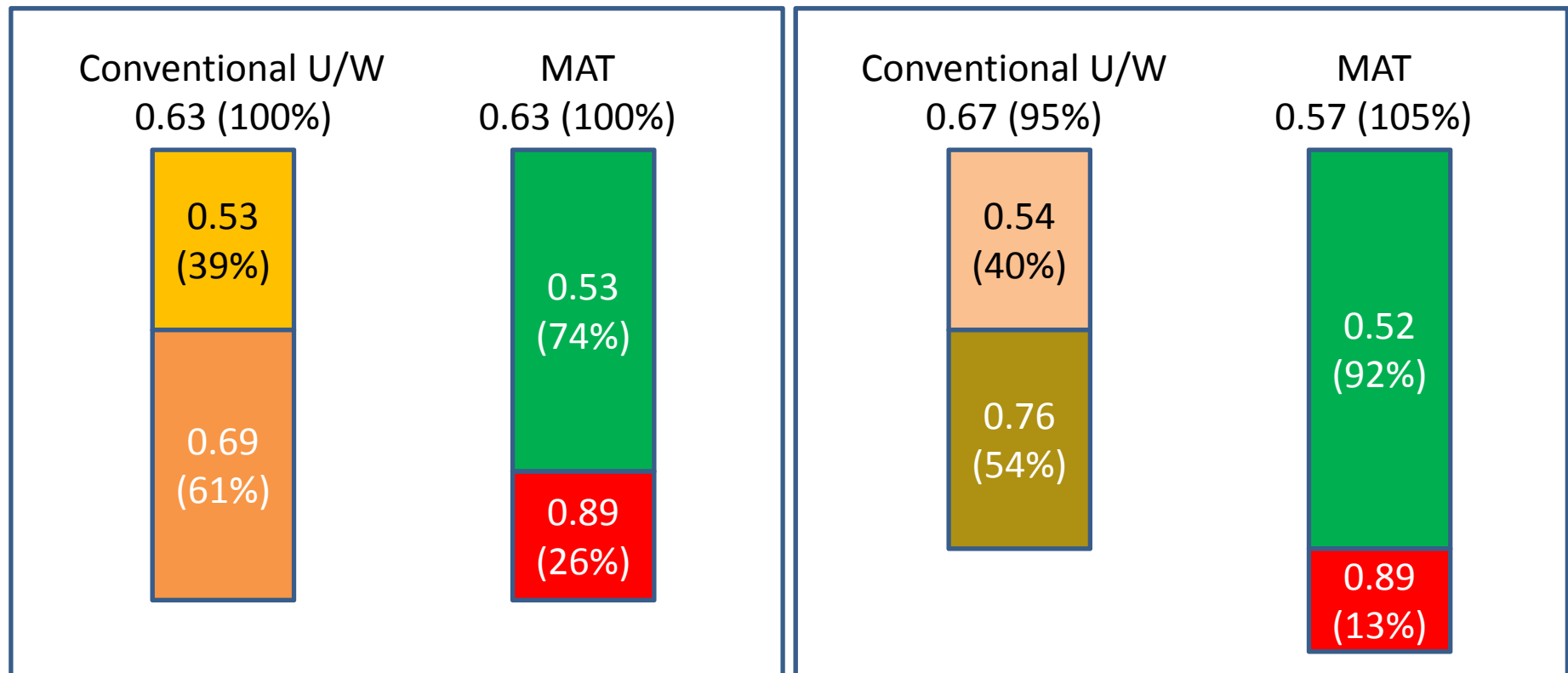
What happens if only half of the policies that can benefit from the switch actually move?



Simulated Competition

Start (before the move)

End (after the move)



Winner is MAT: Lower mortality, more policy



Summary

- Two kinds of prediction models
 - Epidemiological research-based models: improve mortality prediction
 - Third party data-driven models: reduce U/W costs
- Epidemiological research-based models help gain competitive advantage through improved mortality prediction



Any Questions?

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