

2018 Predictive Analytics Symposium

Session 03: B/I - Behavioral Simulation in Actuarial Models

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Behavioral Simulation in Actuarial Models

Who are we?

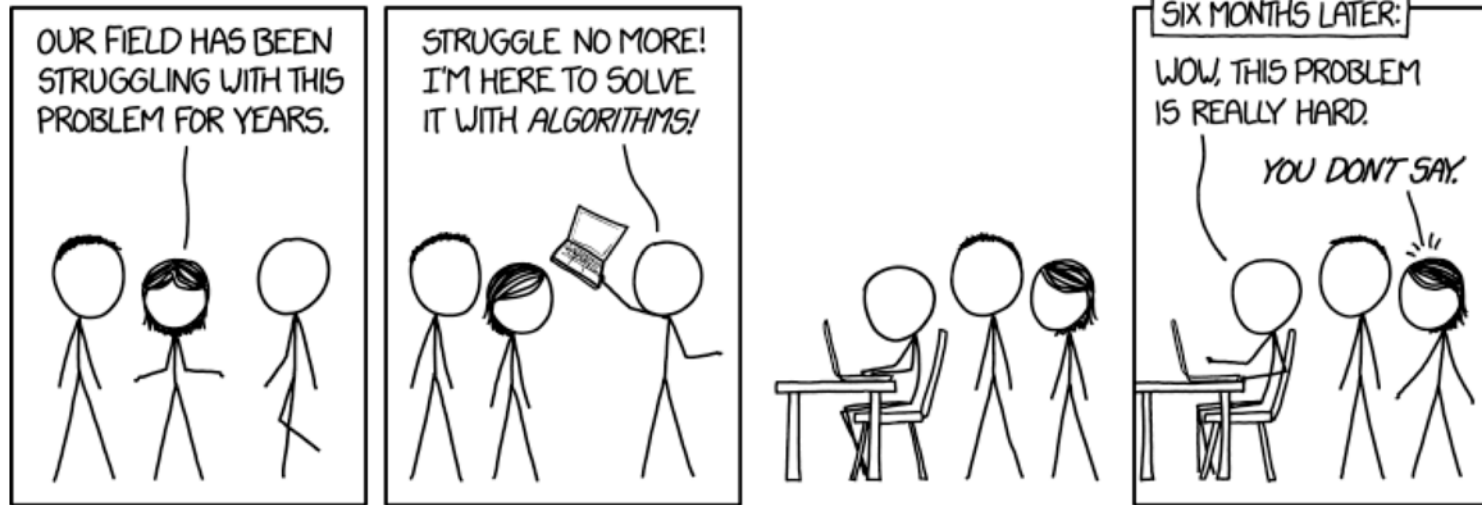


Julia is the lead for Actuarial Engineering and Advanced Modeling at Haven Life, an online life insurance agency backed by MassMutual. At Haven Life, Julia is focused on integrating and applying data science and other analytics models to drive innovation in actuarial technology. Prior to joining Haven Life, Julia worked as an actuary at AXA US, where she focused on the development of agent based models of annuity policyholder behavior.



Ada is a Data Scientist at MassMutual. Prior to joining MassMutual, Ada was a principal analyst at Liberty Mutual Insurance, working on pricing models and initiatives for personal insurance products. She is passionate about utilizing data science to drive business insights and enable data-driven decision making. Ada holds a Ph.D. in Biostatistics from UMass Amherst, with a focus on the development of statistical methods and machine learning algorithms for big data with time-to event outcomes. Outside of work, Ada loves Japanese cuisine and traveling with loved ones.

Goals for the day



It's stochastic!
It's fantastic!

Monte Carlo simulation for insurance

q_x



live

die

Uses of Stochastic Simulation



Markets

- Ubiquitous and well established
- Tool to forecast uncertain values
- Measures sensitivity to markets



Actuarial Assumptions

- Emerging; gaining acceptance
- Works well with predictive model based assumptions

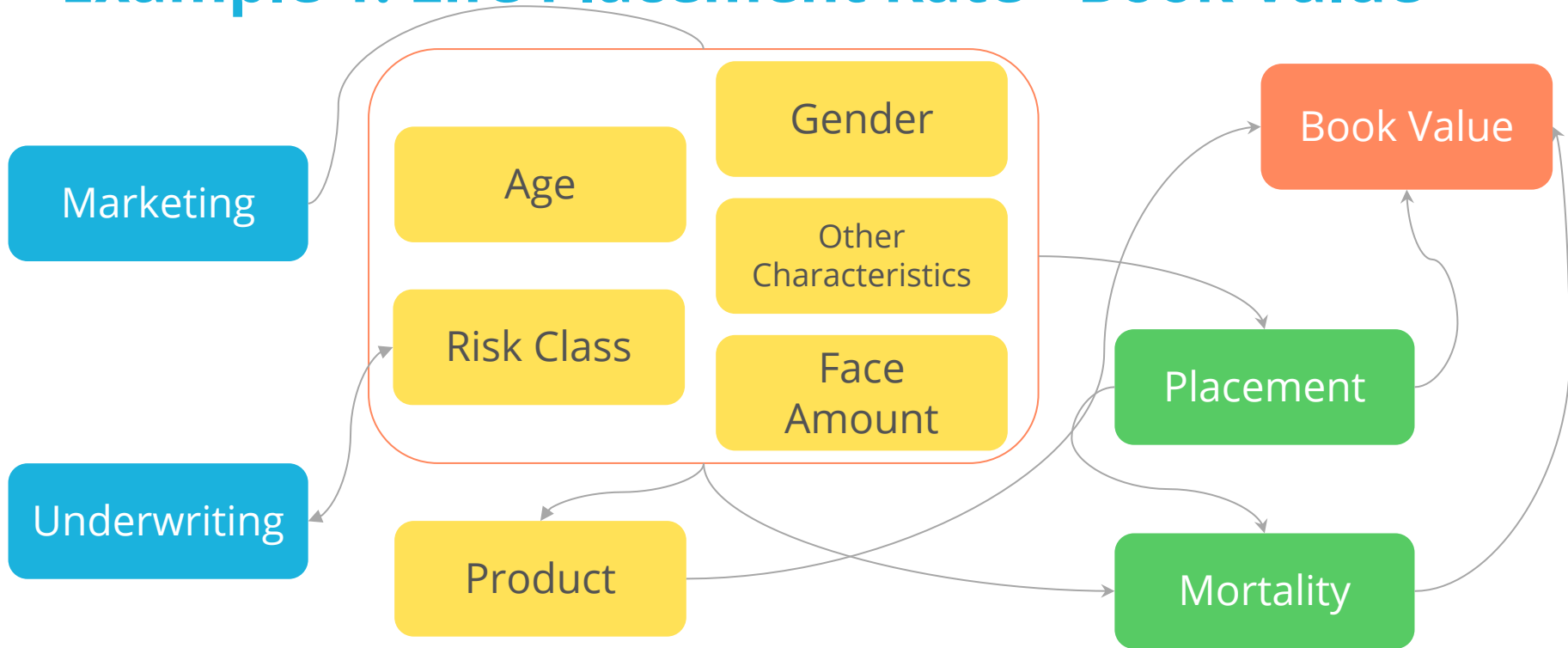


Systems

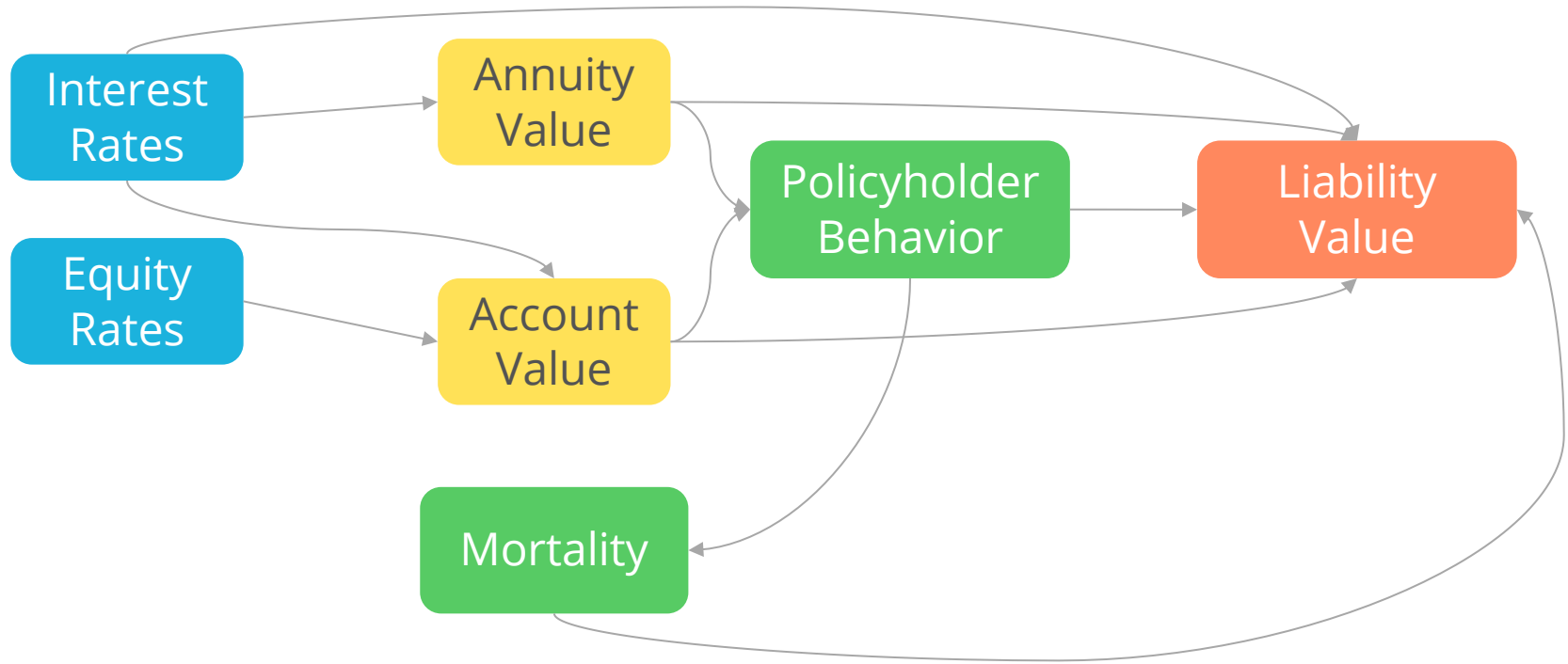
- Relatively new to insurance
- Great tool to attack complexity due to assumption interactions

**Why would you want to
use simulation?**

Example 1: Life Placement Rate - Book Value



Example 2: Variable Annuity Hedging



The nuts and bolts of probabilistic models

What is a Probabilistic Model?

- Example – we want to simulate new entrants to our life insurance block of business.
 - We want to choose the sex, issue age, face amount, policy type, smoking, and risk class.
 - We encode choosing each combination with a probability
e.g. $P(\text{Male, Issue Age 20, 100,000 Face, Term, Non-Smoking, Preferred}) = p$
 - This is the joint probability distribution

Probabilistic Model - Example

- To get the joint probability we would need to realize a probability for every combination of values:
 - Sex – 2 choices: male/female
 - Issue Age – 35 choices: Age 20-55
 - Face – 10 choices: 300K to 3M with 300K increment
 - Policy Type – 3 choices: whole life, 10-yr term, 20-yr term
 - Smoking - 2 choices: Nonsmoker/smoker
 - Risk Class – 10 choices: rank list 1-10
- To define the joint probability we would need to define
 $4,200 = 2 * 35 * 10 * 3 * 2 * 10$
- $2.38 * 10^{-5} = 1 / 4,200$ – uniform probability

Probabilistic Model - Problems

- Joint probability with K binary input variables would require a joint with 2^K probabilities defined.
 - Difficult for a modeler to define.
 - Uniform probability is $1 / 2^K$ – very small for even modest K !
 - Can become numerically unstable/impossible to realize
 - For $K > 32$, a 32-bit computer system would not be able to represent a probability that small.

Probabilistic Model - Solution

Split the joint into the product of conditional and marginal probabilities.

- $P(A = a, B = b) = P(A = a | B = b) * P(B = b)$
- $P(A = a, B = b, C = c) = P(C = c | A = a, B = b) * P(A = a, B = b)$
 - For example, A is policy type, B is issued age, C is face amount

For a marginal probability of one variable X, it can be expressed as a table of size of X.

Conditional probability of $X | Y, Z$ needs to be expressed in multiple tables of size X. The number of tables is the size of Y multiplied by the size of Z

Can cut down the number of tables if X and Y or X and Z are independent

- $P(A = a, B = b) = P(A = a) * P(B = b)$ if A and B are independent of each other

Probabilistic Model - Example

Sex: marginal is 50/50 male/female.

Issue Age: independent of sex and is uniform distributed

Product Types:

- 1) 90% of people 45 and older get whole life, 5% get 20 year term, 5% get 10 year term;
- 2) People under 45 have uniform probability of all product types ($\frac{1}{3}$ whole life, $\frac{1}{3}$ 10 year term, $\frac{1}{3}$ 20-yr term)

Face Amount:

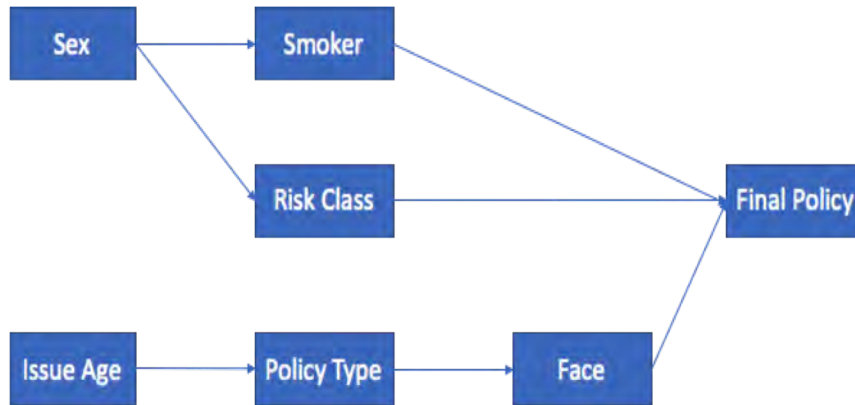
- 1) Whole Life policies have 70% probability of 10 million, remaining are uniform.
- 2) Term policies have a uniform probability of face amount.

Smoker: Males are 60/40 likely to be smokers/nonsmokers. Females are 50/50.

Risk Class:

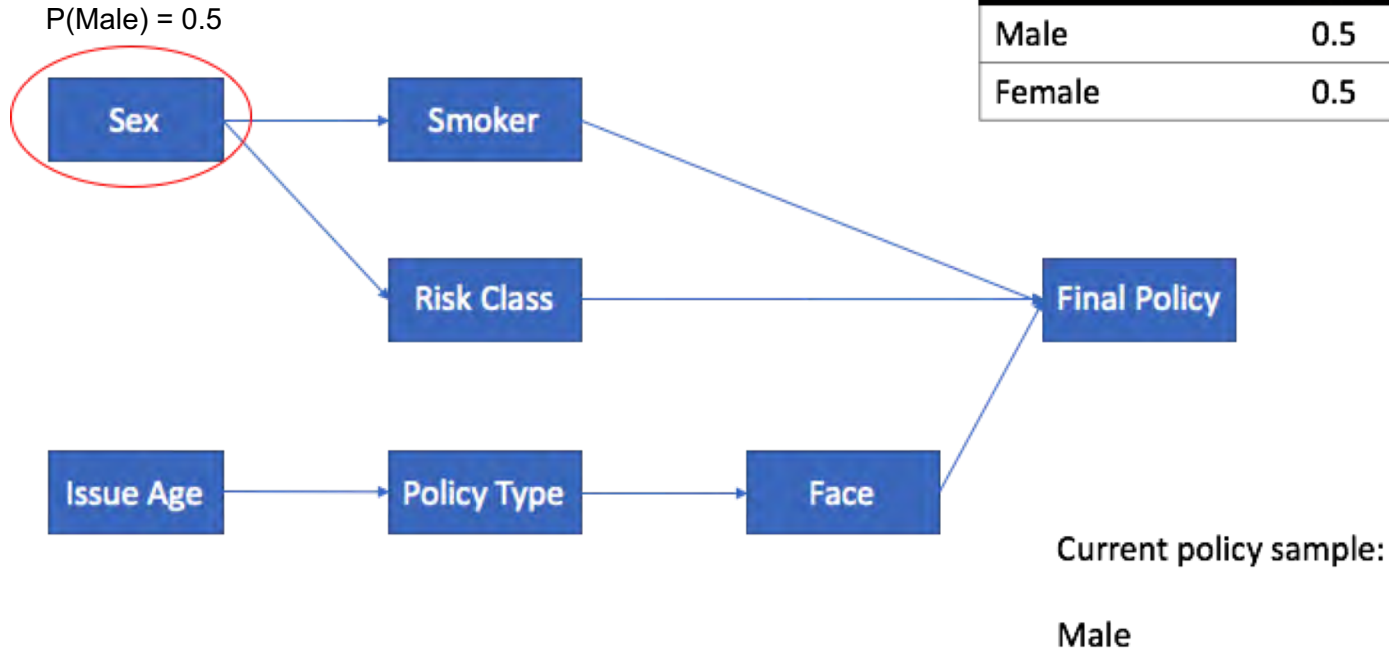
- 1) Males have a 30% probability of being the highest risk class, uniform remaining.
- 2) Females are uniform on risk class

Probabilistic Model - Example

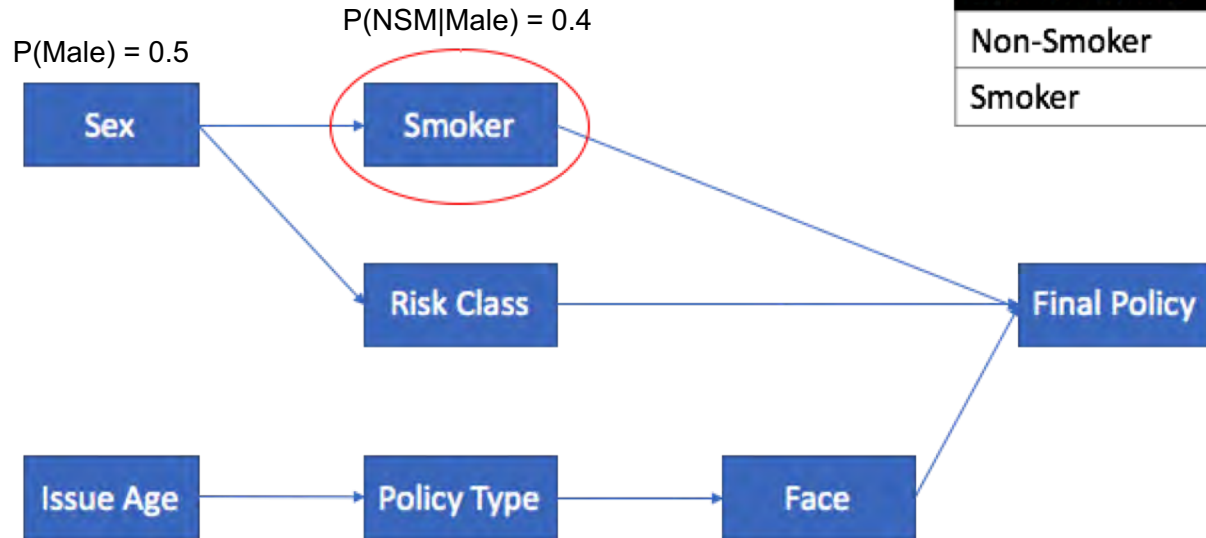


- This is a **probabilistic graphical model**.
- A **directed edge** represents an immediate dependence on the conditional probability.
- Issue Age, Policy type, and face amount are in a line, but the probability distribution of policy type only depends immediately on issue age and face amount only depends immediately on policy type.
- A node encodes a marginal probability distribution if there are no edges directed into it or a conditional probability distribution conditioned on the prior nodes that directly lead into the node.

Probabilistic Model - Example



Probabilistic Model - Example

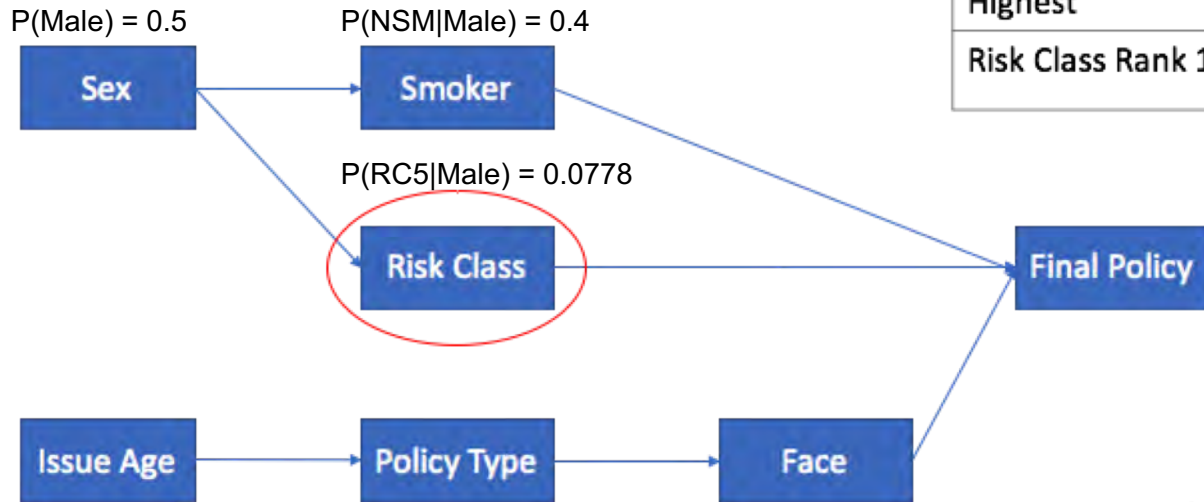


Smoker Status	Probability
Non-Smoker	0.4
Smoker	0.6

Current policy sample:

Male, Non-smoker

Probabilistic Model - Example

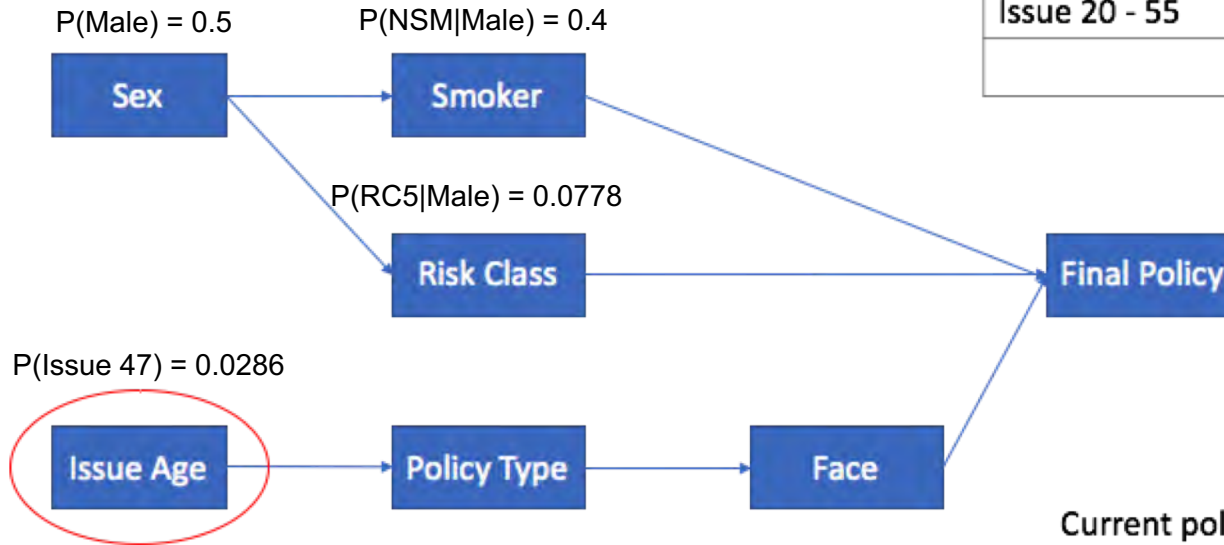


Risk Class	Probability
Highest	0.3
Risk Class Rank 1-9	0.0778

Current policy sample:

Male, Non-smoker, Rank 5 Risk

Probabilistic Model - Example

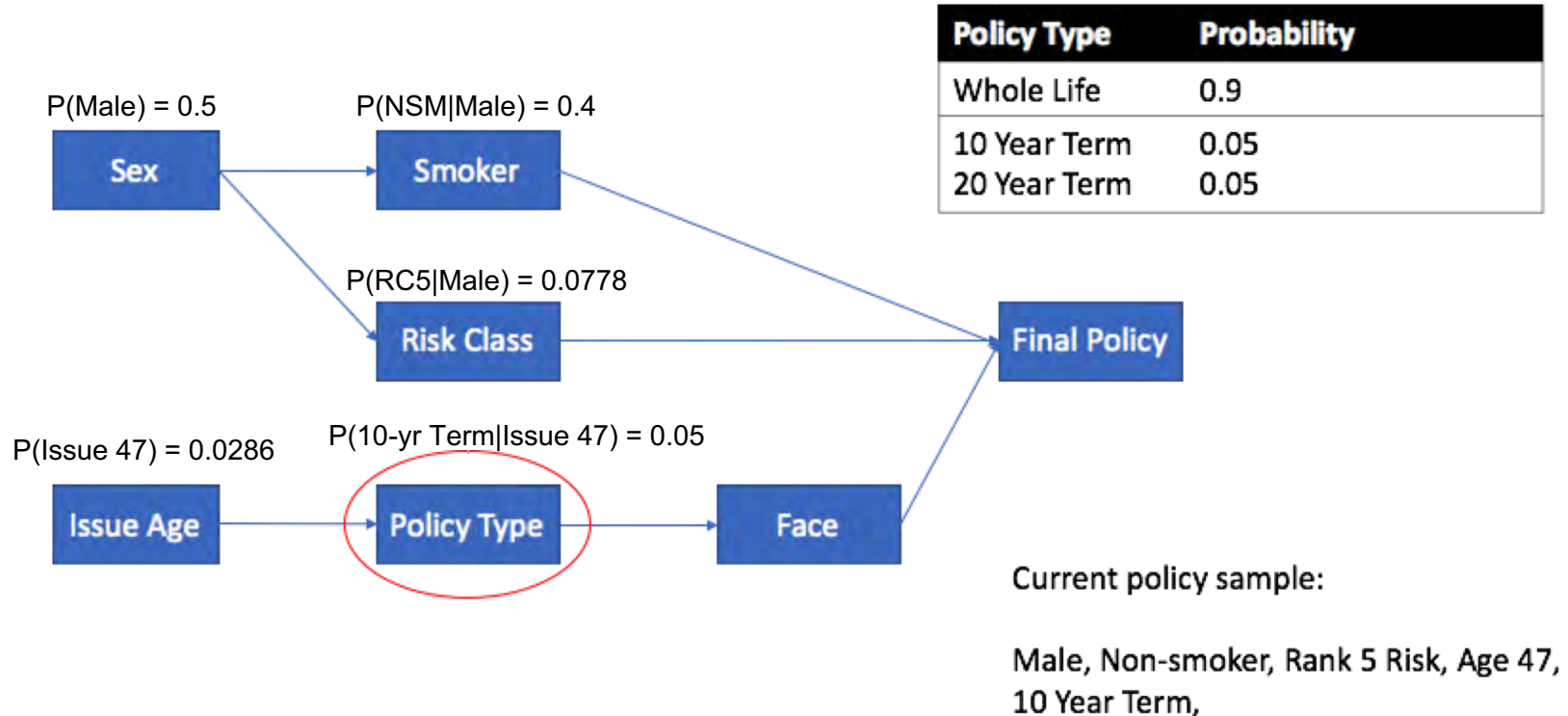


Issue Age	Probability
Issue 20 - 55	0.0286

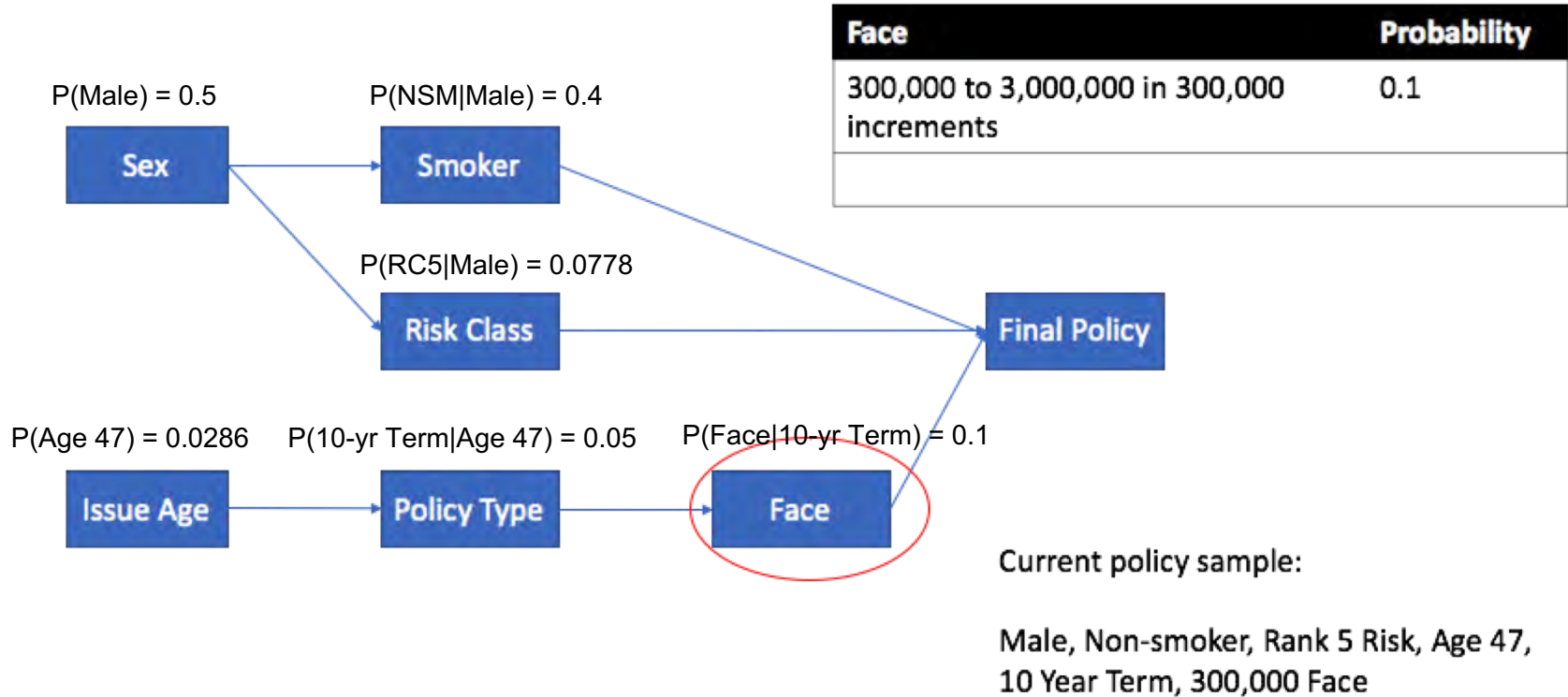
Current policy sample:

Male, Non-smoker, Rank 5 Risk, Age 47

Probabilistic Model - Example



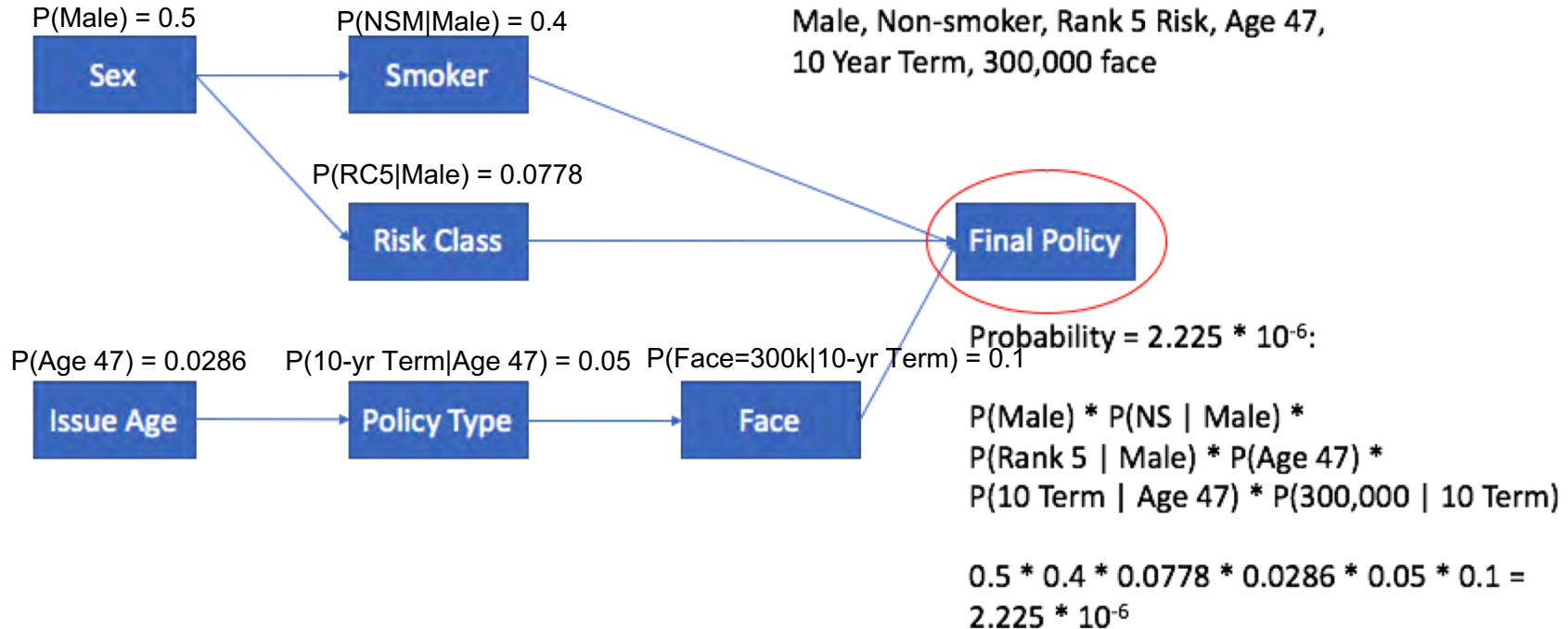
Probabilistic Model - Example



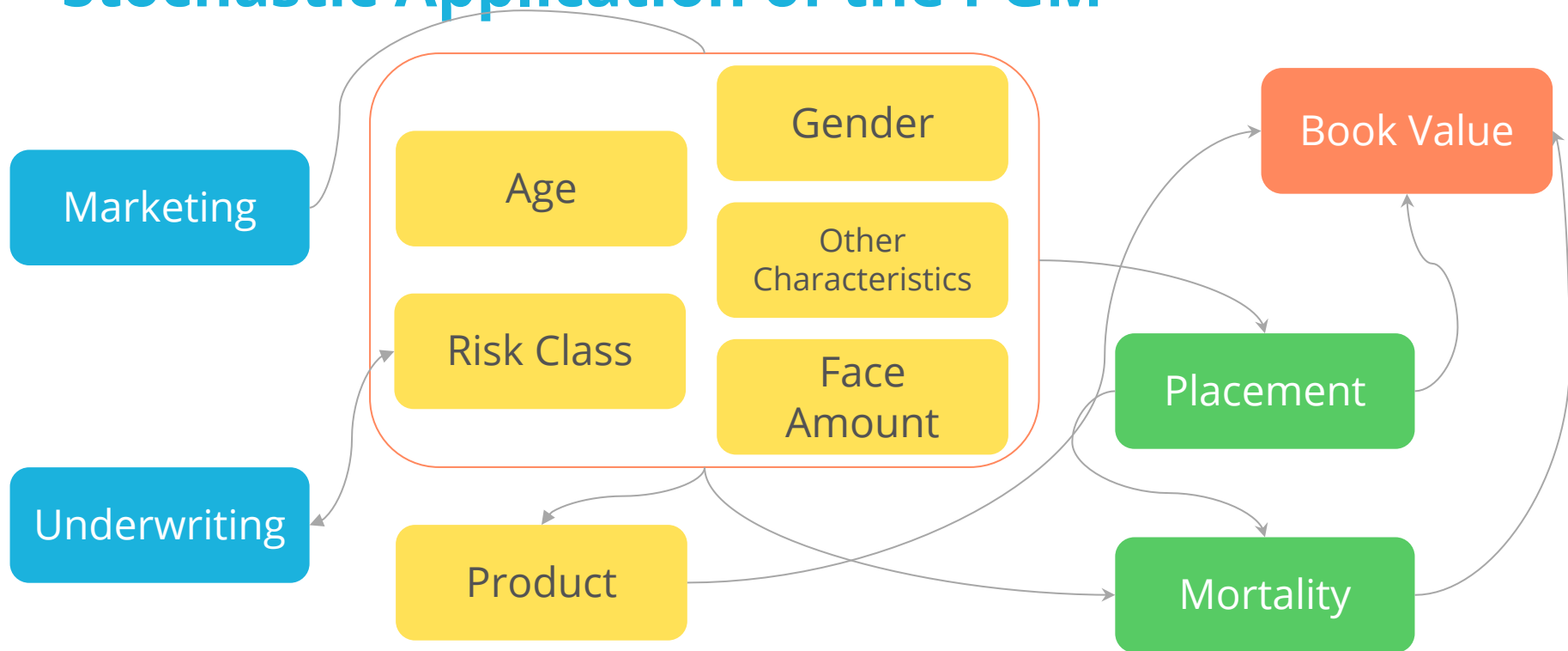
Probabilistic Model - Example

Final Policy:

Male, Non-smoker, Rank 5 Risk, Age 47,
10 Year Term, 300,000 face



Stochastic Application of the PGM

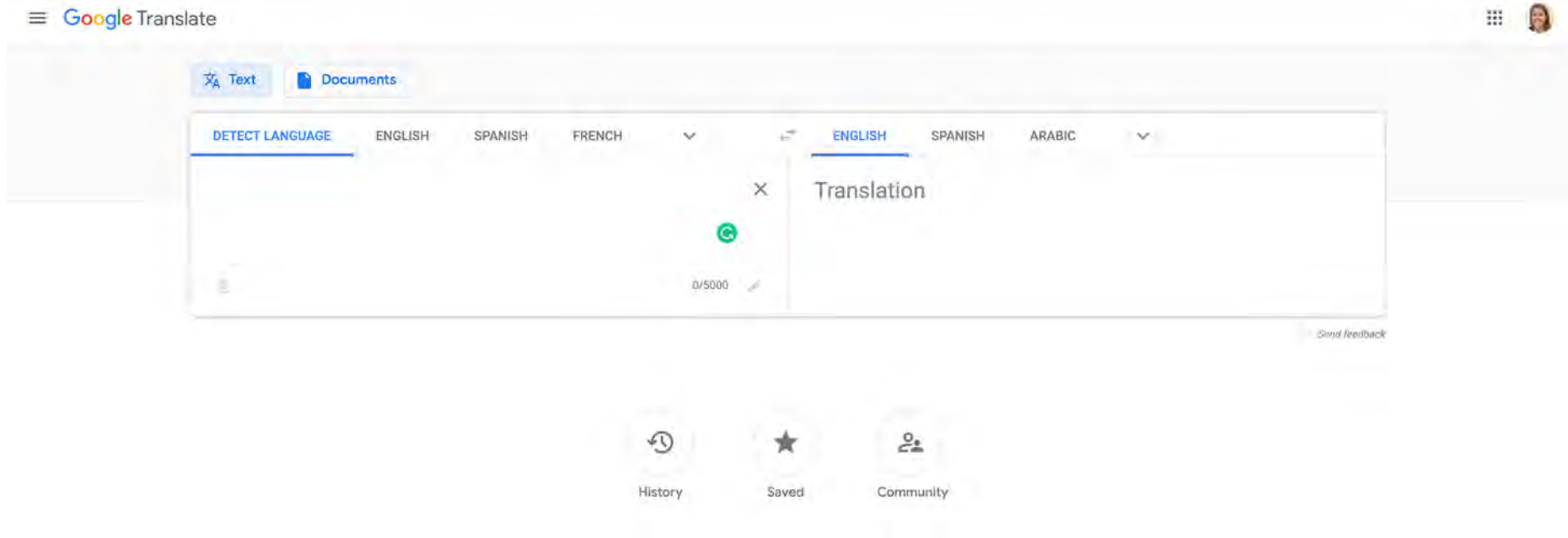


Challenges of the stochastic approach

Transparency



Interpretability



Lots of power, lots of data



