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Case study

FIA GLIB income commencement using credibility theory in a predictive analytics context

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Evolution of modeling for FIA GLIB income utilization

- Your company model – traditional approaches, from simple to complex
- Your company model – using predictive analytics
- Model based on industry data – using predictive analytics
- Your <u>improved</u> company model – using predictive analytics and industry blending in a credibility-based framework, <u>and quantifying the benefits</u>

Your company model – traditional approaches

(a) Once upon a time, very basic modeling of partial withdrawals and income

e.g. 3% of account value annually, consistent with aggregate historical company experience

Your company model – traditional approaches

(b) …evolved to split between base free partial withdrawals and GLIB income utilization

(i) Base: 2.5% of account value annually

(ii) GLIB: 4.6% of premium annually

Your company model – traditional approaches

(c) …then refined for GLIB income commencement timing options

(i) Base: 2.5% of account value annually

(ii) GLIB:

Year	Income
1	10% commence with 5% of premium
2-10	5% commence with 5% of premium
11	20% commence with 10% of premium
12-15	4% commence with 10% of premium
16+	9% never commence income

Your company model – traditional approaches

(d) …continued refinements, chopping into tiny cohorts with dubious credibility

Unwieldy, complex, and error-prone

Lacks a sense of range of outcomes, leading to unpredictability and endless “unlocking”

Is there a better way?

Your company model – using predictive analytics

Example: logistic regression model, which is a simple type of Generalized Linear Model

$$\ln\left(\frac{\mu}{1-\mu}\right) = \beta_0 + \sum \beta_i x_i$$

"Log of odds" of the behavior is a linear function of key factors

In this case study, the behavior is FIA GLIB income commencement

Your company model – using predictive analytics

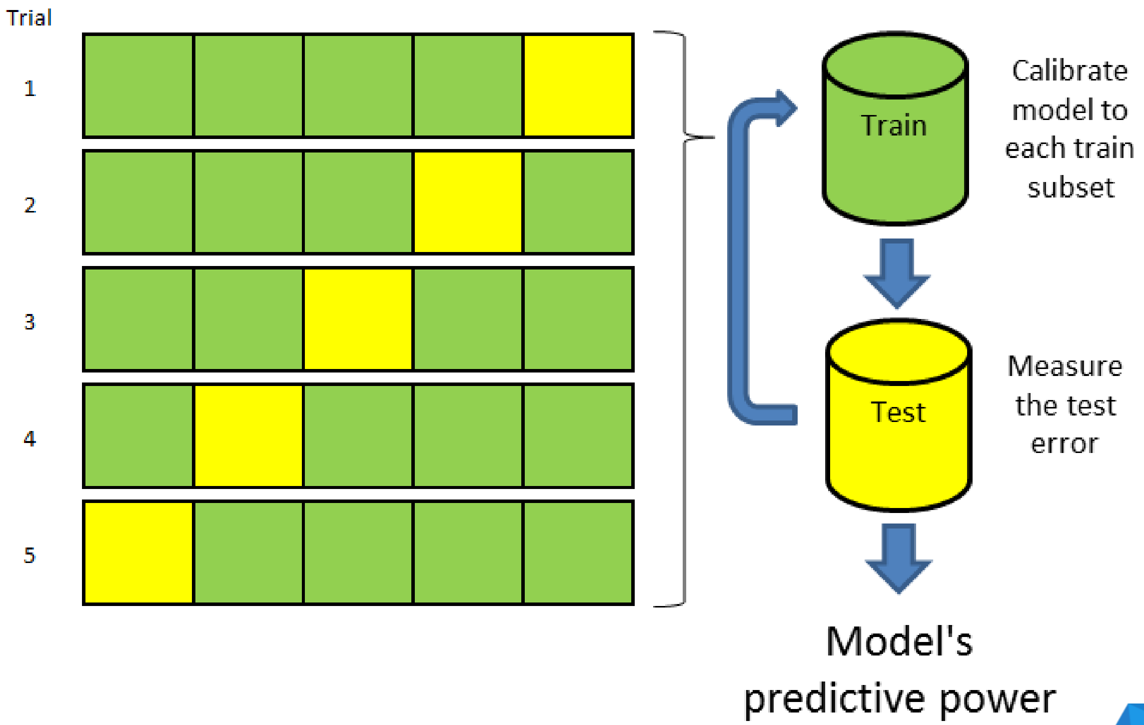
Use algorithms (R, Python, etc) to solve for the “best” model balancing goodness-of-fit, predictive power, and explainability

- Train candidate models on some of your data
- Test candidate models on the data that you held out
- Choose your model!

Refer to our presentation at the Equity-Based Insurance Guarantees Conference for details on experience data analysis, sampling techniques, goodness-of-fit metrics, bias-variance trade-off, predictive power metrics, and model selection

5-Fold Cross Validation

Measures the bias-variance trade-off



Your company model – using predictive analytics

i	X_i	B_i
0	Constant base	-5.0
1	Attained age 0-69	-2.0
2	Attained age 70-75	1.0
3	Attained age 76-79	0.5
4	Attained age 80+	0.1
5	Contract duration 1	0.8
6	Contract duration 2-10	0.3
7	Contract duration 11	1.4
8	Contract duration 12-15	0.2
9	Contract size $0-50k	-3.0
10	Contract size $50-150k	0.1
11	Contract size $150k+	0.5

Representative <u>large</u> company with $35 billion account value and 20k GLIB income commencements, but still only a fairly simple model is statistically justified

Average absolute value 5-fold cross-validation error is 0.80% (pretty good)

Using five years of data to predict the next year resulted in A/E of 47% (yikes!)

How would this result be viewed internally? What could have been done differently to get a better result?

Model based on industry data – using predictive analytics

What if we had more (relevant) data from across the industry?

What if we fed this data into the same algorithms?

We should be able to produce a more sophisticated model that is statistically justified, with better goodness-of-fit and predictive power

Model based on industry data – using predictive analytics

i	X_i	B_i
0-11	… as above for your company model	…numerical refinements
12	Qualified and attained age 70+	0.7
13	OTM 25%+	-0.2
14	OTM 0-25%	-0.1
15	ATM	0.0
16	ITM 0-25%	0.2
17	ITM 25%+	0.6
18	Frequency of withdrawals over last five years	1.4

Industry data with $100 billion account value and 110k GLIB income commencements

Average absolute value 5-fold cross-validation error is 0.60%

Using five years of data to predict the next year resulted in A/E of 101%

Looks like a great model of industry behavior. How can we use this to improve your company model?

Your improved company model – using predictive analytics and industry blending in a credibility-based framework

Apply credibility concepts at the factor level

Let the data speak

Following is an approach that we have developed that produces very good results

Process to Create Credibility-Blended Model

Create Industry Coefficients

Use industry model with all industry data to produce set of Coeff_Ind

Create Industry Credibilities

Z_Ind = 1 / (1 + SE_Ind / Coeff_Ind)

Create Company Coefficients

Use industry model with only company data to produce set of Coeff_Co

Create Company Credibilities

Z_Co_Prelim = 1 / (1 + SE_Co / Coeff_Co)

Adjust Company Credibilities

to the extent industry is not fully credible

Z_Co = min(1, Z_Co_Prelim / Z_Ind)

Credibility-Blended Coefficients

Coeff_Blended = Z_Co * Coeff_Co + (1 - Z_Co) * Coeff_Ind

Adjust Intercept to match Historical Industry

Use blended model with industry data but then solve for intercept needed to match historical industry data

Final Blended Model

Use Coeff_Blended but with intercept calculated above

Your improved company model – using predictive analytics and industry blending in a credibility-based framework

i	X_i	B_i
0-11	… as above for your original company model	…further numerical refinements
12	Qualified and attained age 70+	
13	OTM 25%+	
14	OTM 0-25%	
15	ATM	
16	ITM 0-25%	
17	ITM 25%+	
18	Frequency of withdrawals over last five years	

Average absolute value 5-fold cross-validation error is 0.62%
(improved from 0.80%)

Using five years of data to predict the next year resulted in A/E of 90%
(much improved from 47%)

Quantify the financial benefits (i.e. in your KPIs) of this improved model relative to the cost of acquiring the industry data

Our experience is that the financial benefits can be 1000x greater than the costs. Let’s discuss exactly how this can work for you.

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