Predictive analytics for life insurers – what how and why?

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Why is this interesting?

[1]

- We believe best results will be achieved by combining predictive analytics and the insurance domain expertise – Actuaries and Data Scientists must work together to realize the full potential of predictive modelling.
Why is this interesting?

[2]

- We will look at the general modelling framework and talk about issues which are specific to life insurance
Why is this interesting?

[3]

- We will look at a specific application – upselling by detecting underinsurance – and cover that from defining the idea to sharing and presenting the results.
Why Predictive Analytics

“Insurers say 60-80% of data they collect is 'not accessible’.” Atidot

- Contrasted to traditional actuarial methods, predictive tools have important advantages in the insurance field, in particular:
  - Few constraints on the volume of data and features used in the analysis
  - Lower requirement for clean data
  - Capture complex interactions
Standard predictive model for Insurance

Historical / Snapshot data
- Policy Admin System
- Premium Collection
- Customer Rel-ship Management

External data enhancement

One view of the client

Validation

Feature engineering

Actions

Results & Insights

The modeling Arena

Additional Tables

Business question

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### Feature Engineering - Examples

**How would we incorporate the sale date 24/11/2010?**

<table>
<thead>
<tr>
<th>Feature</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date (number)</td>
<td>Models long term trends</td>
</tr>
<tr>
<td>November</td>
<td>Month-specific sale features, year end targets</td>
</tr>
<tr>
<td>24th day of the month</td>
<td>Month end targets?</td>
</tr>
<tr>
<td>Monday</td>
<td>Significance of week days</td>
</tr>
<tr>
<td>Proximity to public holidays</td>
<td>Policyholder behavior</td>
</tr>
<tr>
<td>Proximity to financial / political events</td>
<td>Policyholder behavior</td>
</tr>
</tbody>
</table>

**Premium / Contribution information: Missing / Skipped premium**

- How many times did a policyholder miss a premium?
- How recent to the current date?
- How to combine the information – for example:

  \[
  \text{Missing\_Premium} = (\text{number of times missed in last 24 months}) \times \left(\frac{1}{\text{distance of last one}}\right)
  \]
Feature Engineering - Examples

“Free-Text” professions:

- Thousands of different occupations, not useful for analysis
- Used advanced clustering techniques to map to 10 groups
- Result: Occupation class is significant to lapsation
External data

- Most common – Demographic data based on address, for example: Median earnings, average household, homeowner vacancy, median age
- Lifestyle type data (subscriptions etc)
- Financial data (depending on product)
- Lifetime events will signal changing attitude to insurance:
  - house purchase
  - Job change
  - New family member
- Company data which is “external” to the book analyzed – for example from other operations (health, P&C?)

All data and (engineered) features can be useful and may lead to powerful insights –
Time spent here is usually well rewarded!

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Validation

- How do we know the model is “working”?
- Back-testing against historical data and against company assumptions:
  - Define “training” period (eg 2012-2016)
  - Defined “back testing” period (eg 2017)
- Check actual and own company assumptions against model results for 2017
- Continuous monitoring throughout
Insights into actions (persistency)

• Once model is validated, we get three useful outcomes:
  • Feature importance (Direct, Indirect, External)
  • Predictions on a per policy level – for example for proactive retention
  • Ability to predict target based on simulated input – strategic impact
Summary

• Predictive analytics can be a powerful tool in managing inforce business

• Results depend on availability of data. Frequency of client contact impact results. Use of external event data can substitute lacking internal data, but is more difficult / expensive to obtain.

• Feature engineering and augmentation are critical.

• We have not discussed feature correlation and masking but these are important issues which are tricky to handle

• Additional layers (eg profit) can be incorporated for simulations to help with strategic decisions

• Best results are achieved when predictive analytics are integrated to the business process
Part 2 – Upselling using underinsurance detection
Underinsurance in a predictive framework

- Business question
- Model definition
- External data
- Feature engineering
- Validation
- Communicating the results and turning insights to actions
Underinsurance: Business question

- Target: Identify individuals with insufficient life cover
- Sub target: Identify those individuals within existing policyholders
- How do we approach the problem?

*Life Insurance Need ~ Loss of Future Salary, dependents, assets and liabilities*

Can we approximate these details?

<table>
<thead>
<tr>
<th>Item</th>
<th>General population</th>
<th>Insurance data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Future Salary</td>
<td>Census – Income data</td>
<td>Disability insurance</td>
</tr>
<tr>
<td>Dependents</td>
<td>Census</td>
<td>List of beneficiaries</td>
</tr>
<tr>
<td>Assets and Liabilities</td>
<td>Population Surveys</td>
<td>? Other policies (mortgage, investment policies)</td>
</tr>
</tbody>
</table>
Underinsurance: Model definition

- Lets say insurance data is not available to discover underinsurance on a personal level – How do we define the problem?

- We assume that most people bought the right amount of cover and then set out to find those that bought too little - ‘people like you bought’

- In a predictive sense:
  - Target is face amount (or account value) of the policyholder
  - When the prediction is far from the actual amount:
    - A prediction error or
    - Potential for an underinsured person
Underinsurance: Connecting to external data

- Enhance the input to the model:
  - Premise: Residential address is indicative of life cover needs
  - Action: Link to demographic data based on address. Significant features include:
    - Median household income
    - Median household size
    - Monthly expenses for insurance
Underinsurance: Specificity of location data

Feature Importance (Zip code)
- Demographic data
- Distribution and other
- Product features
- Financial features
- Policy details

Feature Importance (ZIP code plus)
- Demographic data
- Distribution and other
- Policy details
- Financial features
- Product features

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Underinsurance: Connecting to external data

- Fine tune the output of the model:
  - Premise: A change of address is a trigger (‘life event’) for change in life cover needs
  - Action: Link to public data about address change

- Compliance with privacy laws, such as GDPR is paramount. Success of external data depends on volume, variety and relevance of the data and the specificity of personal details allowed under privacy laws.
Underinsurance: Validation: How good are we in identifying the ‘hottest’ leads?

- On a technical level, the standard train/test methodologies apply.
- However, who are the best leads, assuming the company has not performed similar exercises in the past?
  - Intuitively, the bigger the difference between the cover amount and the predicted coverage, the better the lead.
  - Check with other models and check variance of results (for example: variance of tree results around the mean for a random forest model)
  - Some policy owners purchased a second policy a while after the first:
    - Premise: These owners can be characterized and assist in identifying individuals with propensity to purchasing another policy
    - Action: ‘Purchase propensity’ sub model to assist in rating leads
- Blend results from the above
Underinsurance: Insights and Communicating within the insurer

- How do we communicate what we find?

- To Management:
  - simple explanation of what was done
  - Emphasize: This is not ‘magic’ - it is a statistical and not a ‘personal’ model, with clear advantages and disadvantages
  - High level insights to help with strategic decisions

- To Sales:
  - Simple explanation of method and caveats
  - List of potential leads and lead ‘propensity’ to buy
  - Simple ‘conversation starters’ based on model
Underinsurance – Management Communication (demo)
Underinsurance – Sales Communication (demo)

Coverage Breakdown:
- 148 Adequately Insured
- 35 Underinsured
- 25 Significantly Underinsured

New Leads Are Waiting for Your Call:
- Scott PARKER: 1 Policy, Current Life Cover: $250,000, Underinsured: $206,000
- Aaron ROSE: 1 Policy, Current Life Cover: $45,000, Underinsured: $42,000
- Amanda LYNCH: 1 Policy, Current Life Cover: $50,000, Underinsured: $58,000
- Jose BOYD: People with similar profiles purchasing this product and people with similar demographics (household size) buy more coverage.
- Norma SINGH: 1 Policy, Current Life Cover: $250,000, Underinsured: $100,000
- Eugene WALTERS: People with similar profiles purchasing this product and people with similar demographics (cigarette habit) buy more coverage.
- Theresa LEON: 1 Policy, Current Life Cover: $100,000, Underinsured: $117,000
- Gregory WONG: 1 Policy, Current Life Cover: $250,000, Underinsured: $86,000
- Benjamin STEWART: 1 Policy, Current Life Cover: $150,000, Underinsured: $121,000
- Kevin KELLEY: 1 Policy, Current Life Cover: $100,000, Underinsured: $86,000
- Peter RIOS: 1 Policy, Current Life Cover: $56,000, Underinsured: $50,000
- Anthony FLETCHER: 1 Policy, Current Life Cover: $250,000, Underinsured: $243,000
- Brandon LI: 1 Policy, Current Life Cover: $75,000, Underinsured: $77,000
- Ryan LUNA: 1 Policy, Current Life Cover: $102,000, Underinsured: $53,000
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