

Predictive analytics for life insurers – what how and why?

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Atidot

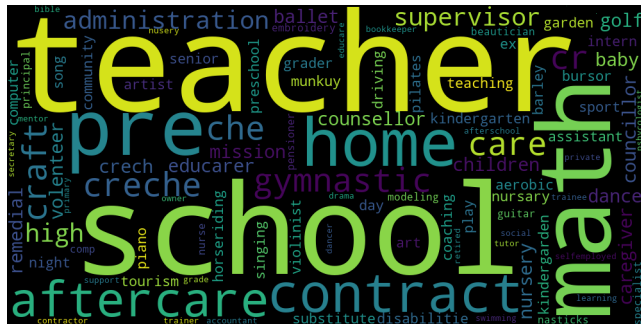
08 November 2018



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

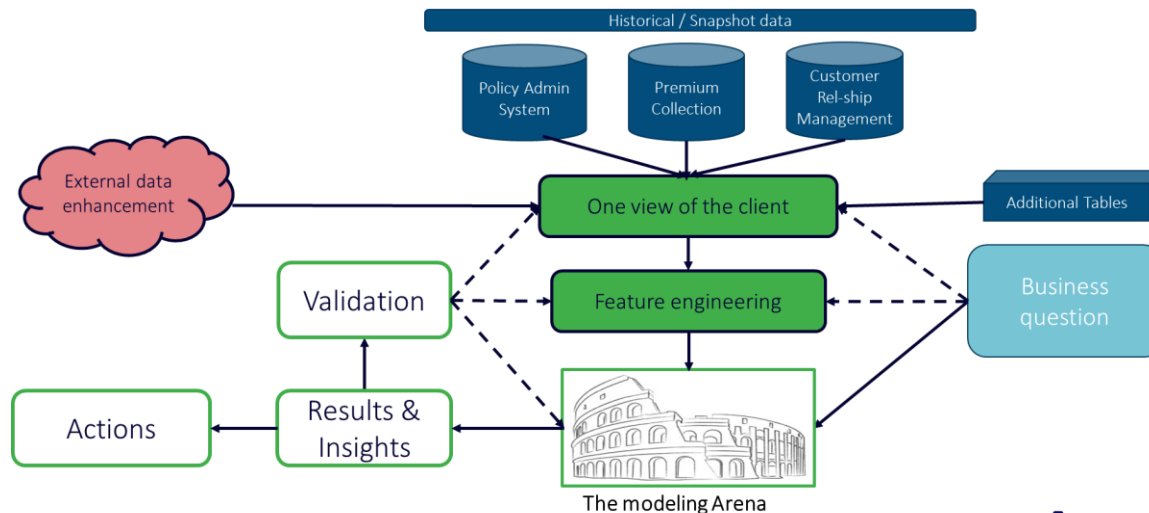


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Why is this interesting?

[2]

- We will look at the general modelling framework and talk about issues which are specific to life insurance

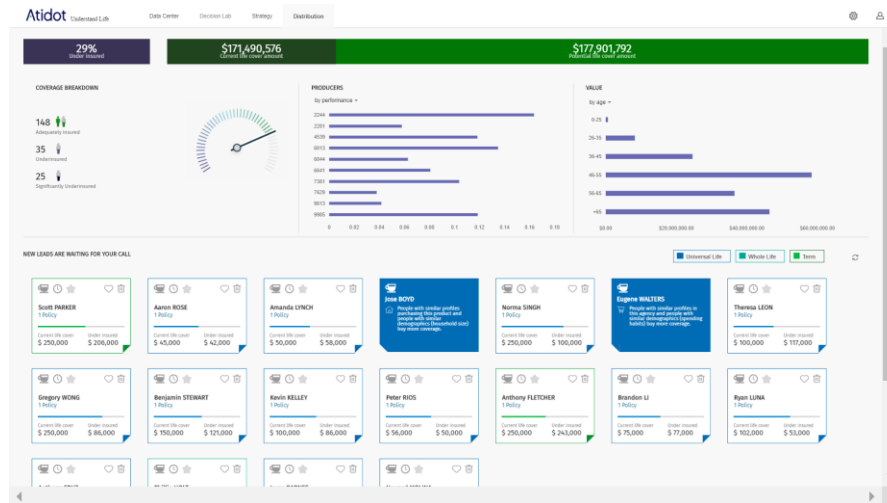


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Why is this interesting?

[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



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Why Predictive Analytics

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



**New
forms
of data**



**New
types
of model**

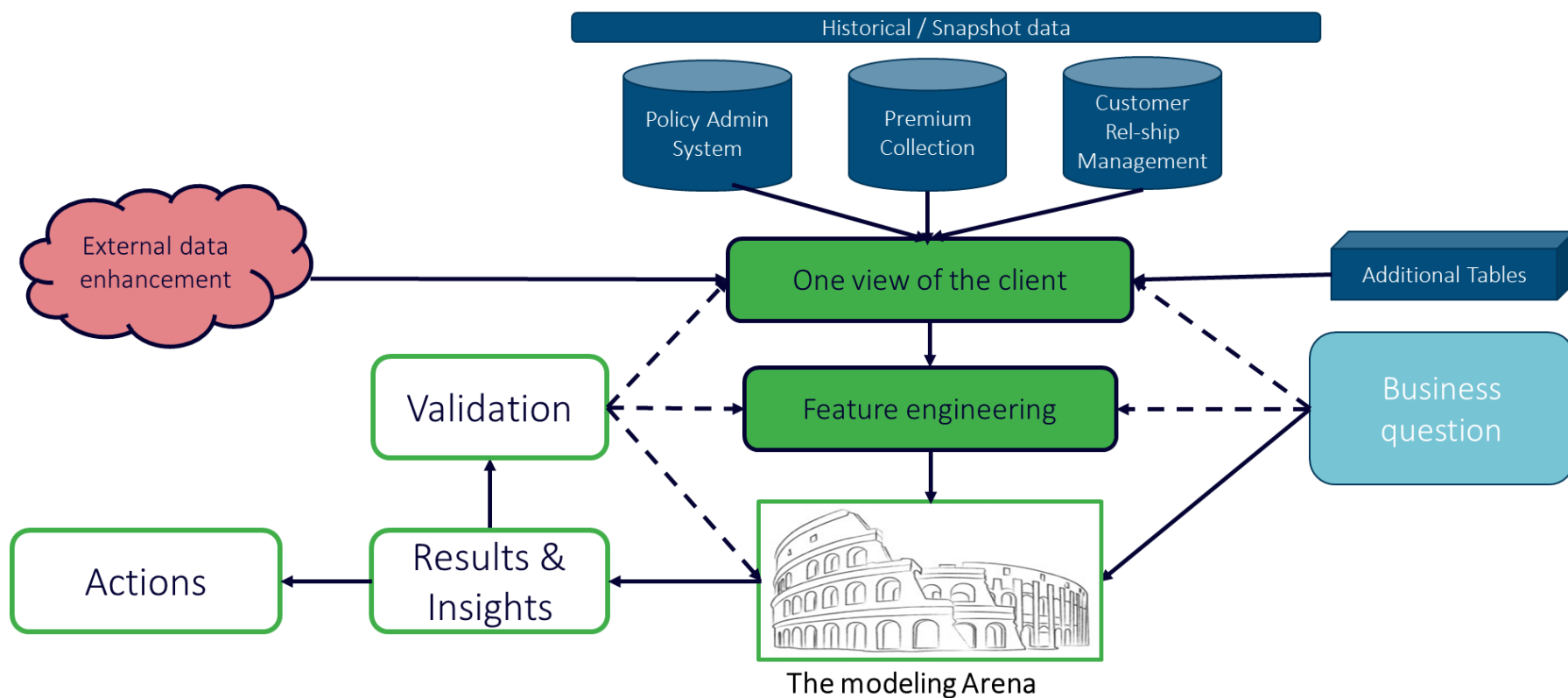


**New
forms
of
analysis**

- 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

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Standard predictive model for Insurance



Feature Engineering - Examples

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

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

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:

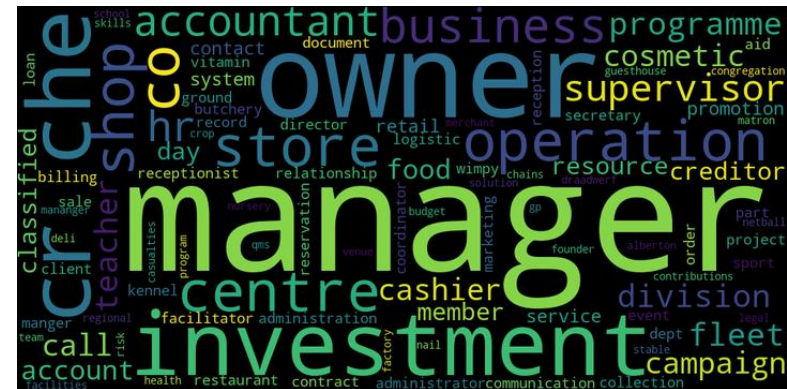
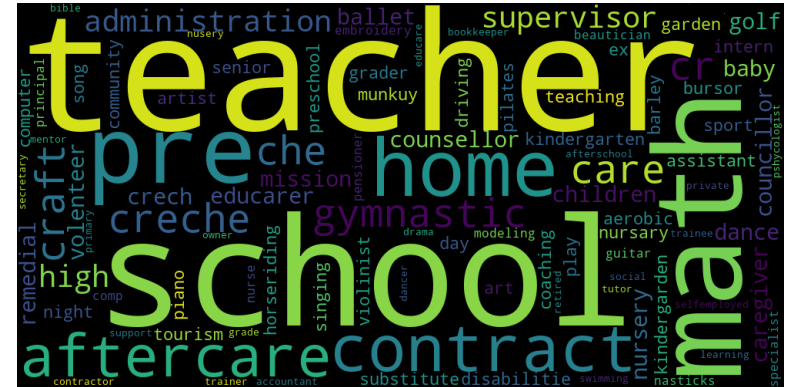
Missing_Premium = (number of times missed in last 24 months) * (1 / distance of last one)



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



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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?)

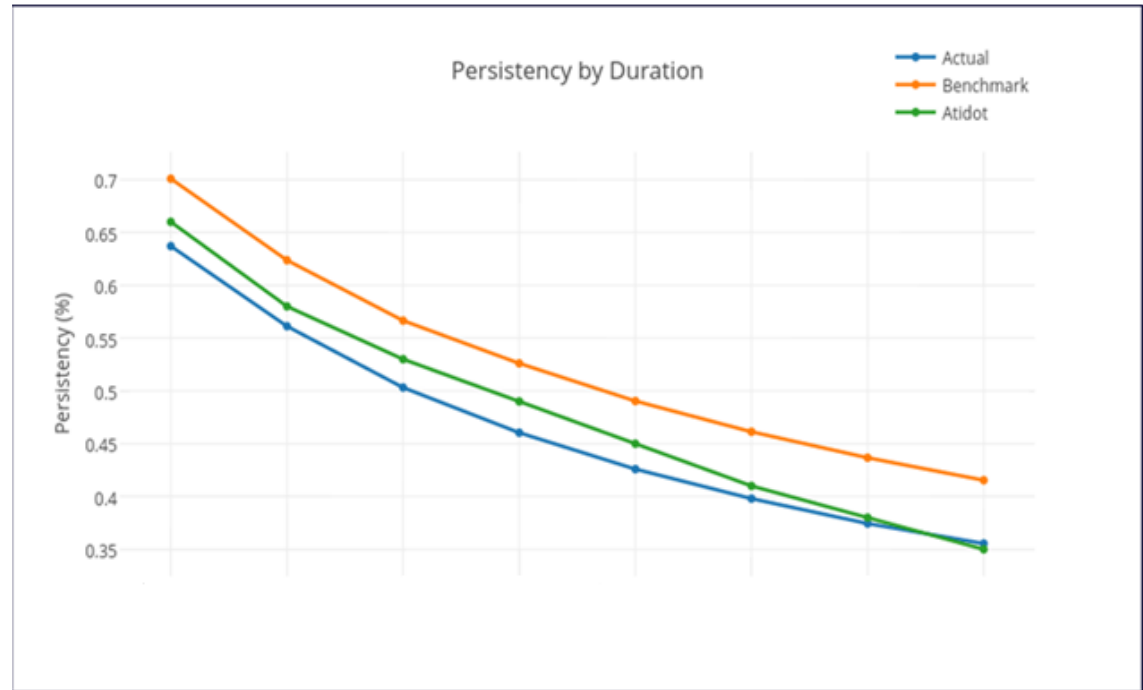
All data and (engineered) features can be useful and may lead to powerful insights –

Time spent here is usually well rewarded!

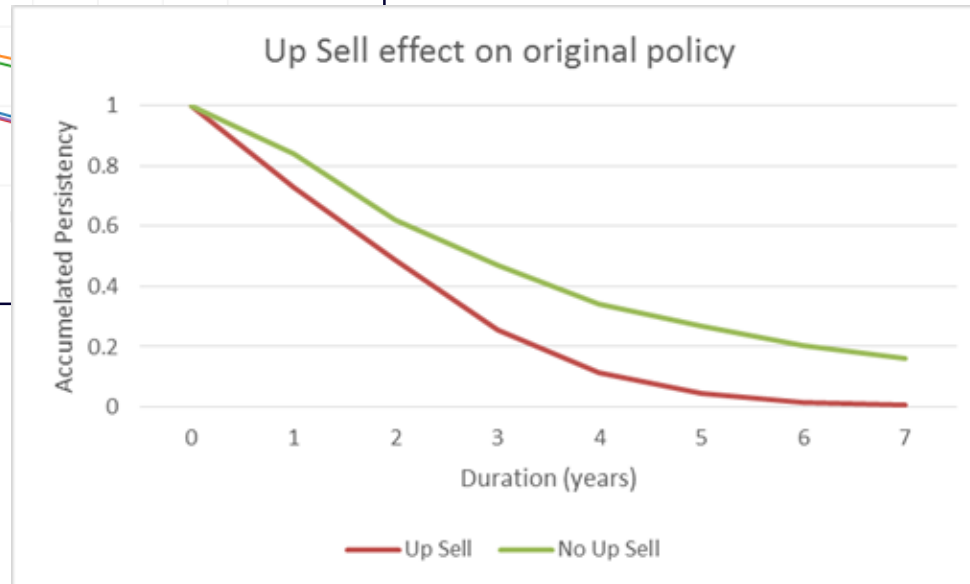
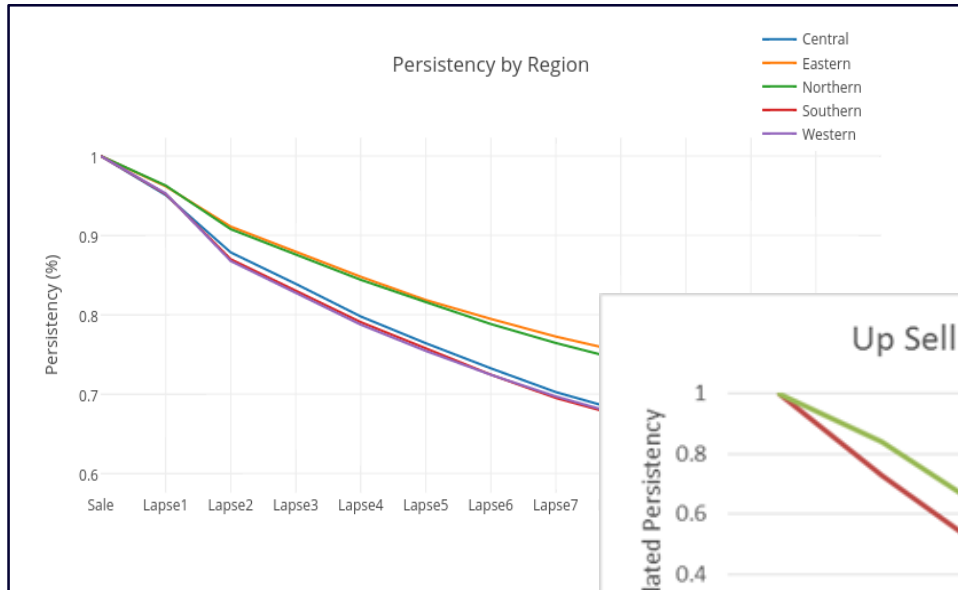


Validation

- 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



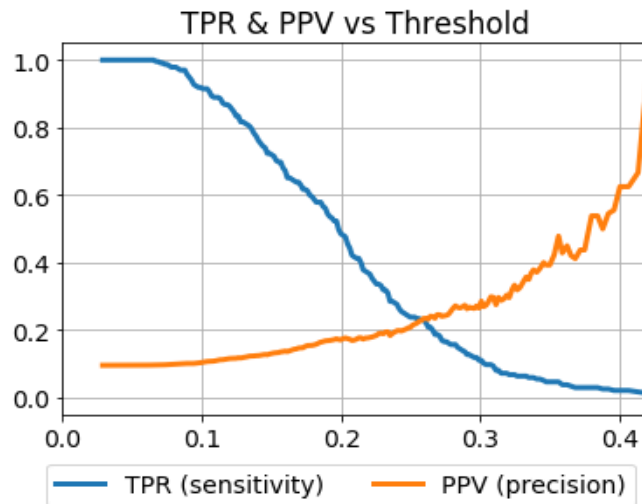
Insights



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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 ?

Item	General population	Insurance data
Future Salary	Census – Income data	Disability insurance
Dependents	Census	List of beneficiaries
Assets and Liabilities	Population Surveys	? Other policies (mortgage, investment policies)

Underinsurance : Model definition

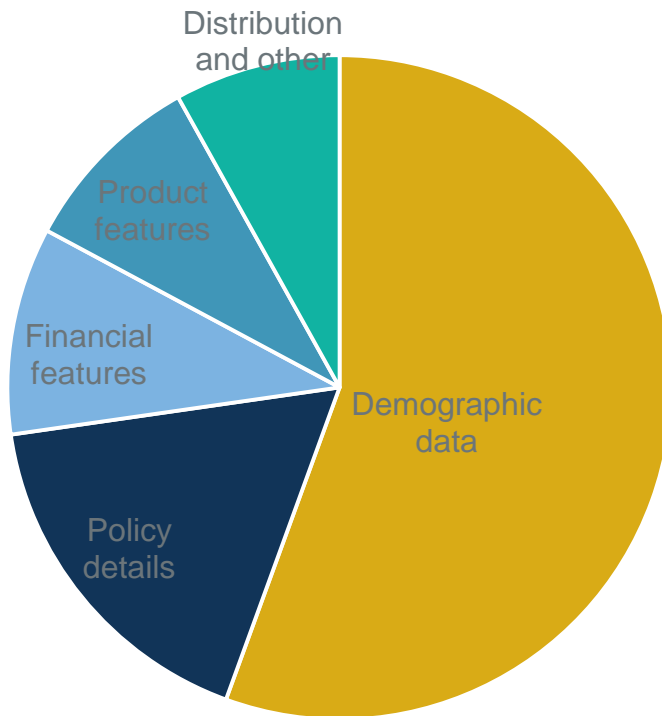
- Lets say insurance data is not available to discover underinsurance on a personal level – How do we define the problem?
- We assume that most people bought the right amount of cover and then set out to find those that bought too little - ‘people like you bought ’
- In a predictive sense:
 - Target 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

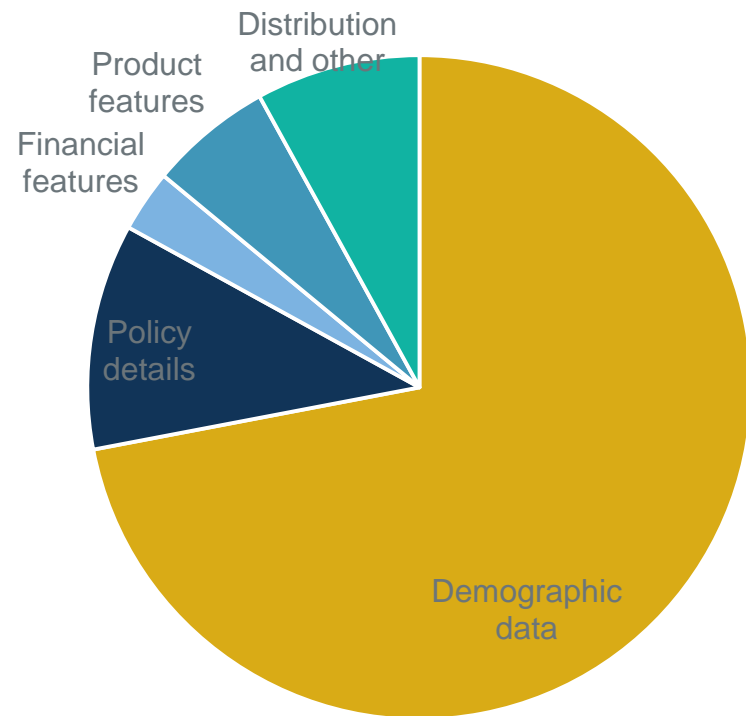
- Enhance the input to the model:
 - Premise: Residential address is indicative of life cover needs
 - Action: Link to demographic data based on address. Significant features include:
 - Median household income
 - Median household size
 - Monthly expenses for insurance

Underinsurance: Specificity of location data

Feature Importance (Zip code)



Feature Importance (ZIP code plus)



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)

Atidot Understand Life

Data Center

Decision Lab

Strategy

Distribution

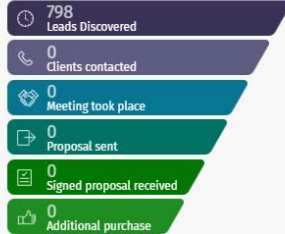


32%
Under insured

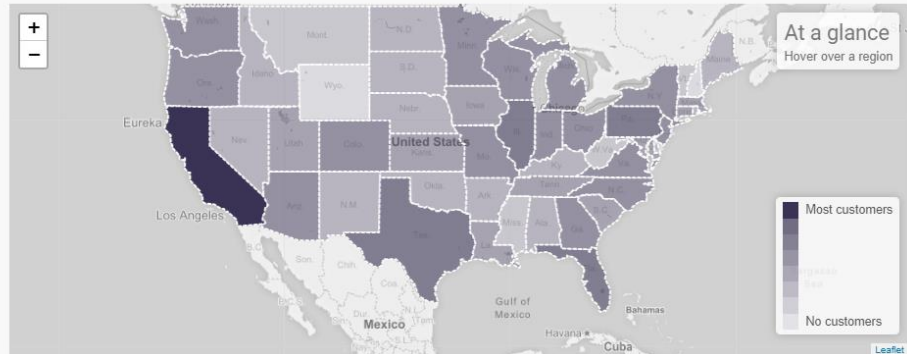
\$1,750,804,736
Current life cover amount

\$1,828,055,424
Potential life cover amount

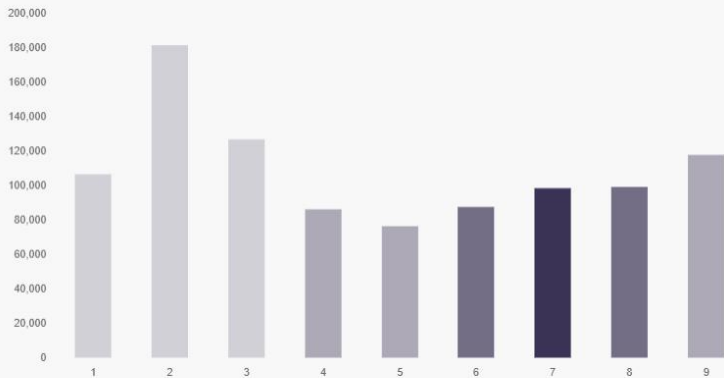
SALES STATUS BREAKDOWN



UNDER INSURANCE HEATMAP



UNDER INSURANCE BY SOCIOECONOMIC STATUS



COVERAGE BREAKDOWN

1691 Adequately Insured

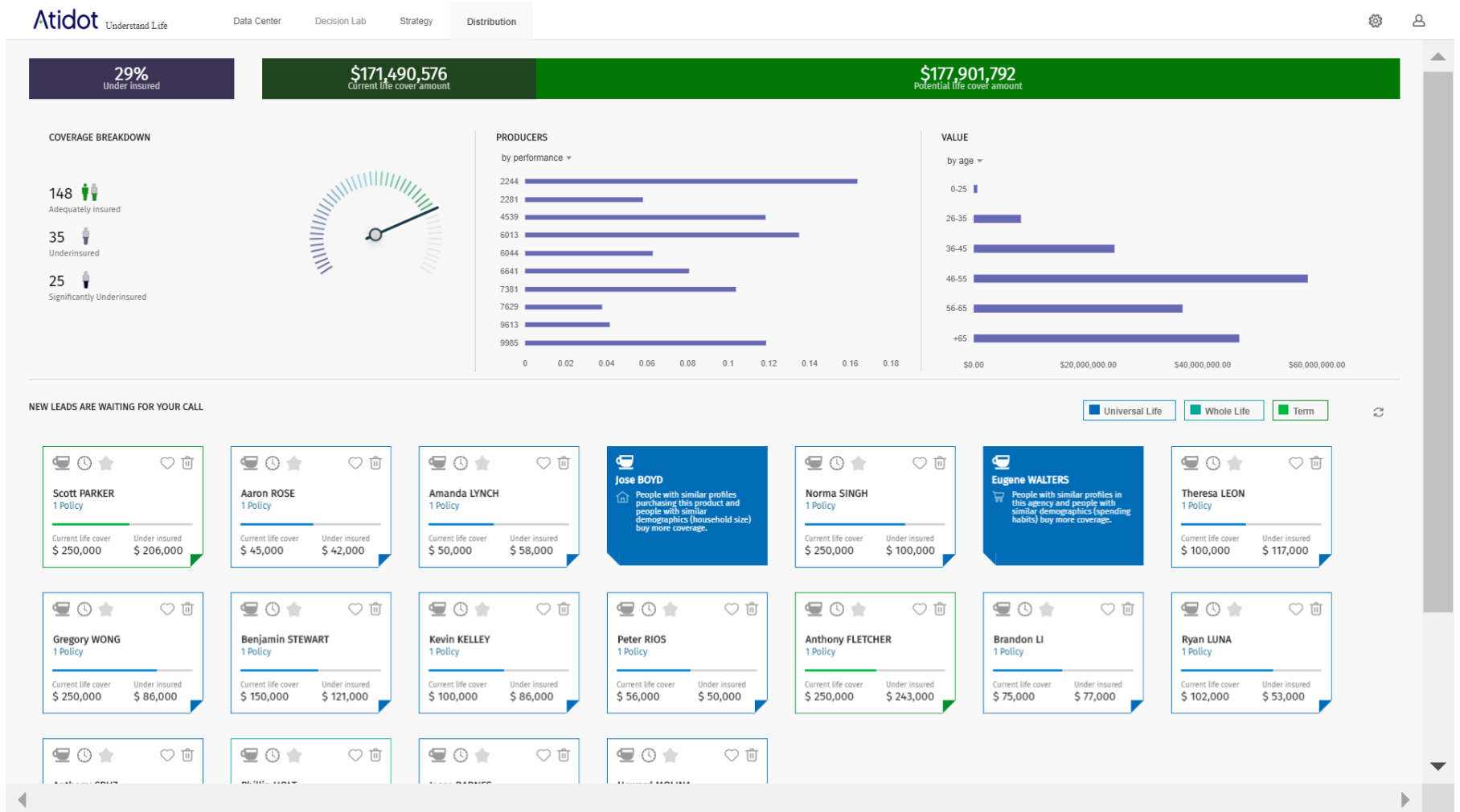
476 Underinsured

322 Significantly Underinsured



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Underinsurance – Sales Communication (demo)



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Questions



Comments

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