Predictive Analytics in Strategy and Decisions – A Tour Around the Globe

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About Earnix

EARNIX

Earnix is the Global Leader in the field of Integrated Customer Analytics, providing state-of-the-art Pricing Management Software Solutions for Financial Institutions

Used by Financial Institutions as an Enterprise Software analytical application across different business functions for various business lines

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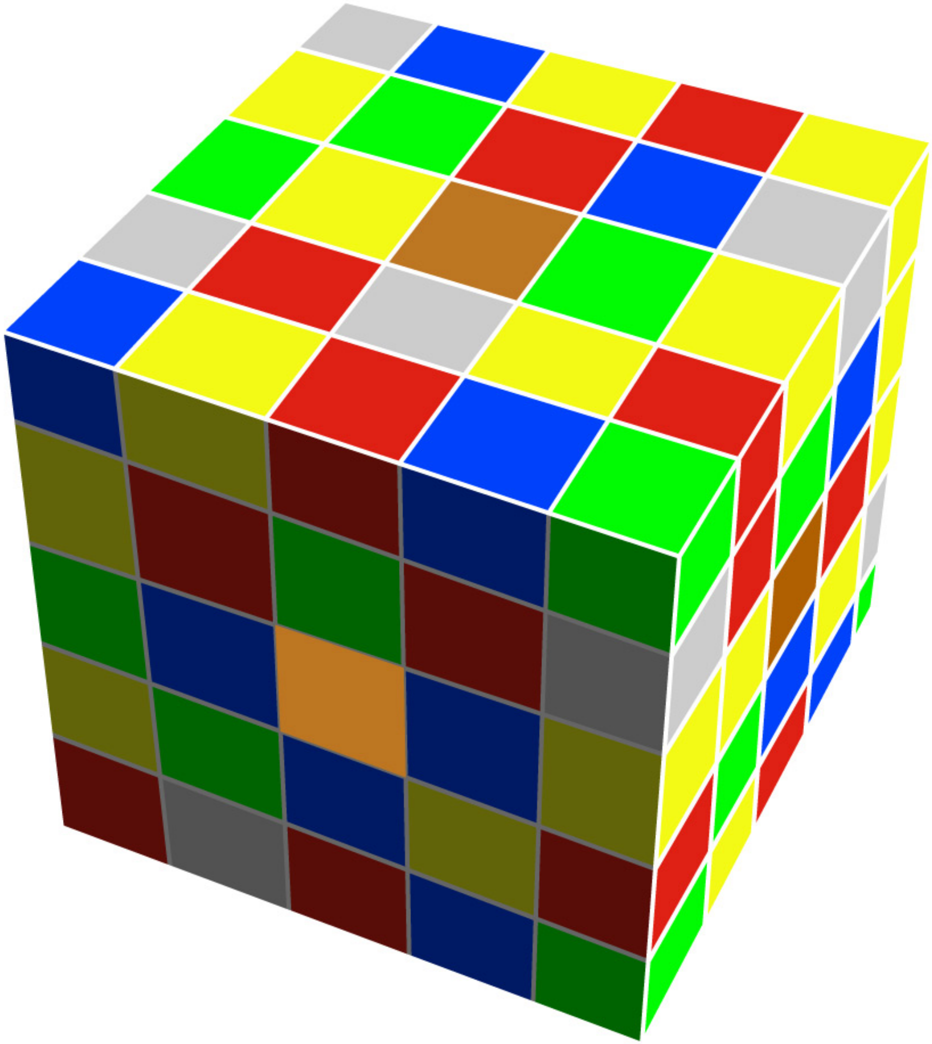
Software Company, with strong Professional Services Division

Over 70 Customers in more than 20 countries

Global Presence- Offices in USA, UK, Israel & India

Cube Illusion



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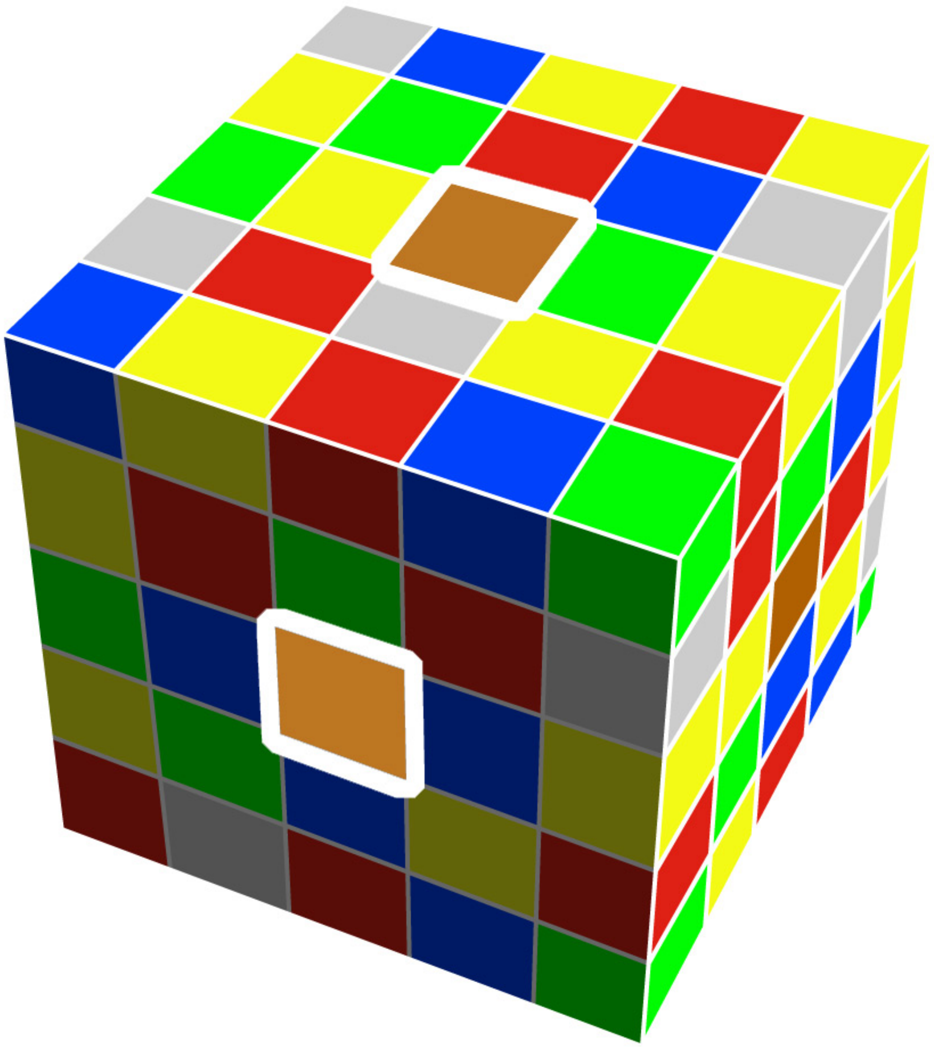

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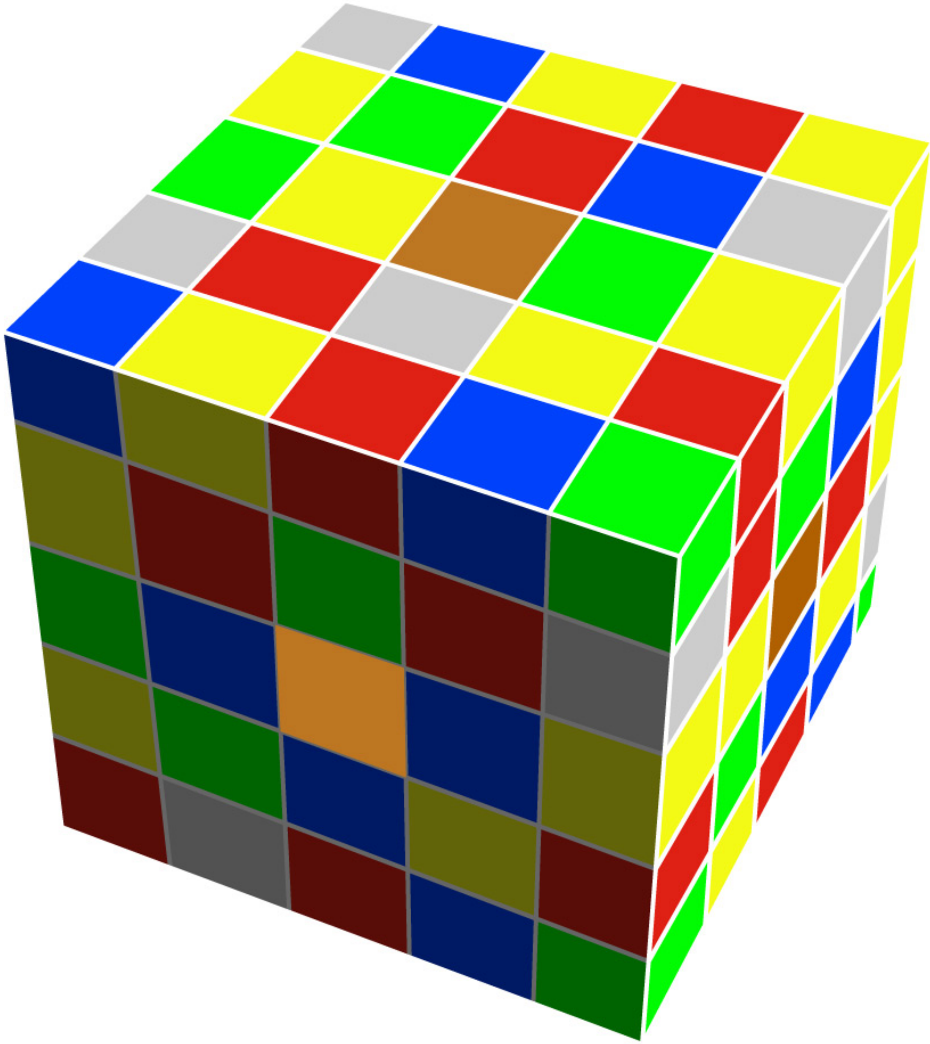

Presentation Outline

- Personal stories
- Customer journey & decision sequence
- Insurance Trivia time - what do you know about the international insurance community?
- Applications:
  - Customer Life Time Value for Underwriting
  - Proactive management of renewal calls
  - Pricing under the presence of strong independent agents
  - Credibility
  - Marketing optimization - optimal allocation
- Q&A

My Personal Stories and what does it have to do with Analytics?

Poll Question

How much was I asked to pay as a new business customer the following year?

- $700
- $625
- $450
- $550

Customer journey & decision sequence

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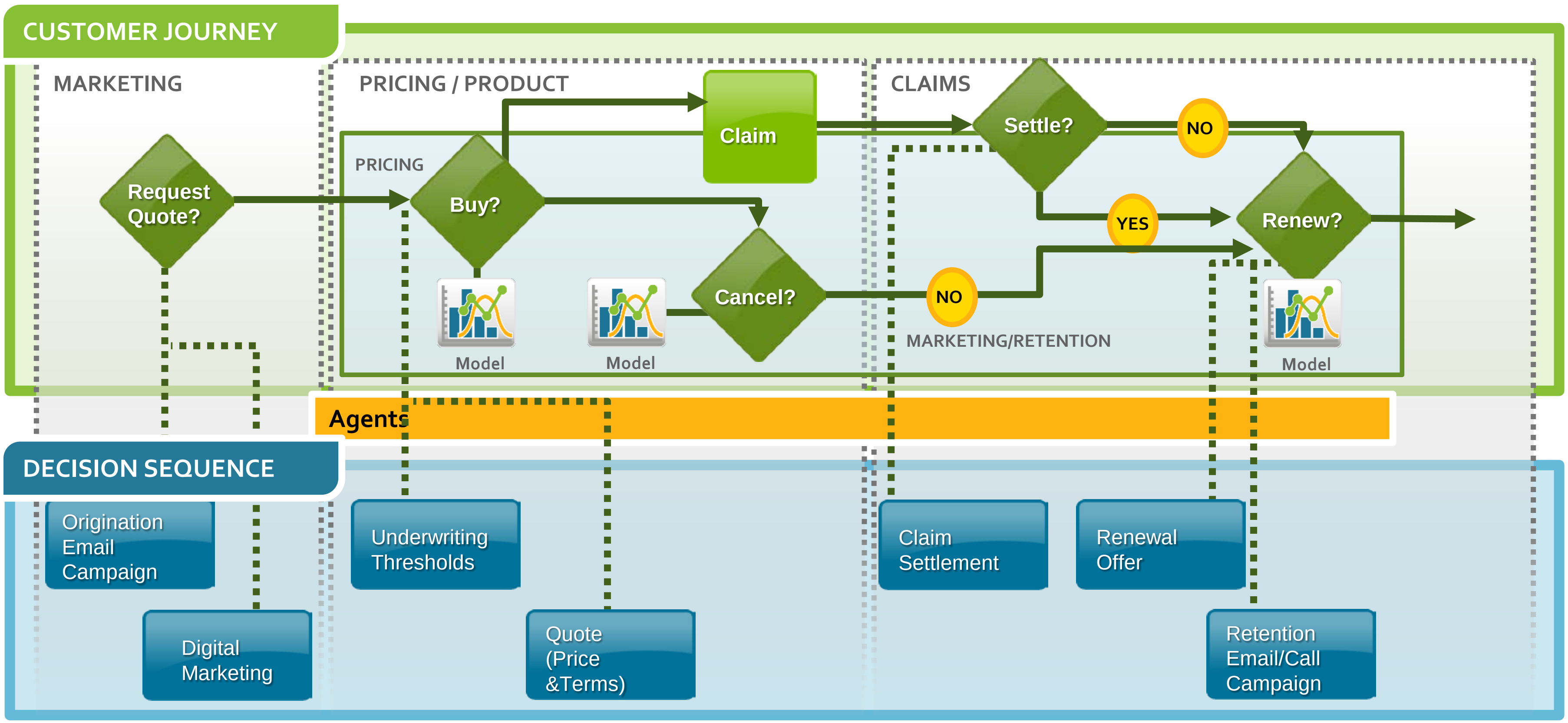

Poll Question

In which of the following countries one can’t use GLM for Risk Pricing?

- Denmark
- Italy
- South Korea
- Singapore

Poll Question

Gender-neutral pricing in auto insurance industry is applicable in:

- UK
- EU
- France
- Turkey

Poll Question

Which of the following 2 countries are most similar in terms of their Auto Insurance Renewal rates?

- Denmark, UK
- Italy, USA
- UK, Turkey
- Spain, USA

Poll Question

In which of the following countries most auto insurance policies are renewed on January 1st?

- UK
- France
- Germany
- Spain

Poll Question

Which of the following global insurance companies also operates in Israel?

- Generali
- Axa
- Zurich
- AIG

Poll Question

PZU is the largest insurance company in:

- Italy
- Greece
- UK
- Poland

Customer Life Time Value Application for Underwriting

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Pricing at a client level – Customer Life Time Value (CLTV)

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Key points to consider

- Renewal dates of auto & home policies don't always match
- Does CLTV means coming up with one price for all the insurance products at a given time?
  - Do we need to define a bundled price or price each product separately?
- What should we include within the CLTV?
  - Current products and their possible evolution or also future products?
- What do we do about "aging" of models or other key variables?
  - Can we rely on averages , deterministic or stochastic processes?
- Can we rely on historical processes & data to reflect the future?
  - Can the 20 years old of 5-10 years ago represent the 20 years old of today?

Poll Question

For how many of the following functions /activities you currently use an LTV metric?

Pricing, Underwriting, Claims, Next Best Offer/action, Retention, Marketing, Acquisition

- 0
- 1
- 2
- 3
- 4
- 5+

Poll Question

If you currently use an LTV metric for more than one function/activity, do you use the same metric across all functions?

- No, each function has its own definition
- No, some functions share the same definition
- Yes, we use the same definitions across all functions
- Not applicable

Customer Life Time Value Application for Underwriting

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- Build multiple propensity models, including conversion, mid-term cancellation, additional product take up, retention models, etc. to correctly reflect CLTV
- Use it in conjunction with risk models to better understand the attractiveness of each prospect and to guide underwriting decisions.
  - Can use refined segmentation of risk beyond what is being used for pricing (e.g. refined geographical segmentation)
- Underwriting decisions are based on information known only at the time the underwriting decision is made.
  - Scoring models will be developed linking current customer profile & risk characteristics to their potential CLTV

Customer Life Time Value Application for Underwriting

- Implementation for Renewals:
  - For each customer will be able to calculate in advance of the renewal the CLTV score. We can then sort the customers by their CLTV and set a threshold for underwriting decision.
  - Depending on company objectives and constraints, different thresholds can be set for different customer segments or geographies.
  - The company could simulate the effect of changes to the thresholds on the company's KPIs
  - The CLTV score should be updated periodically based on life events and updates to the customer profile or changes to the risk models

Customer Life Time Value Application for Underwriting

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- Implementation for New Business:
  - Can leverage real time capabilities to compute CLTV score:
    - Compare to a desired threshold and make a real time underwriting decision.
    - The threshold can be assigned dynamically and changed frequently based on business objectives and needs.
  - Alternatively, can apply scoring models to recent new business quote data:
    - Sort the data by the CLTV score and then set a threshold for underwriting. Assign a 1 for those that should have been underwritten and a 0 for those that should have been rejected.
    - Use decision trees to reverse engineer the underwriting decision and set underwriting guidelines

Proactive Management of Renewal Calls

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Proactive Management of Renewal Calls
Explaining The Concept

- Does calling people prior to renewal help?
- How do I determine who to call and how to prioritize my calling list?

Proactive Management of Renewal Calls
Explaining The Concept

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Problem

- Companies derive most of their revenue from renewals
- Furthermore, renewal customers are usually more profitable. Therefore, companies put significant effort into trying to maximize renewals
- Often, dedicated retention teams call customers to secure the renewals
- However, not all customers respond positively to such calls
- Furthermore, resources are limited and so calling all people on the renewal list can be wasteful and costly
- One might mistakenly think that the company should first call those with the lowest probability of renewing

Proactive Management of Renewal Calls
Explaining The Concept

Solution

- Given the rich database at their disposal, and based on historical experience, companies can estimate the marginal contribution of calling renewing customers
- Simple economic logic suggests that whenever the marginal contribution of a call exceeds the cost of making the call, then the call should take place
- However, when resources are limited and the company can only call a subset of customers, the call list needs to be prioritized based on a ranking of the marginal contribution of the call
- The marginal contribution of a renewal call is the outcome of the multiplication of the following factors
  - Probability of response
  - Given response, probability of conversation taking place
  - Given conversation, increase (decrease) in renewal probability
  - Value of renewal (one-year profit (revenue)) or over a number of years — LTV)

Pricing under the presence of strong independent agents

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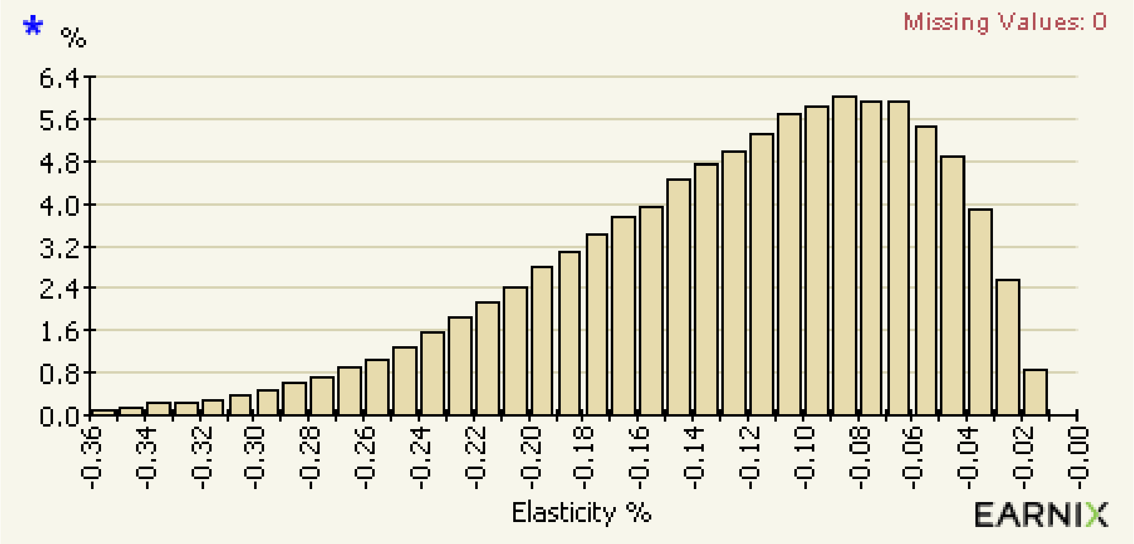
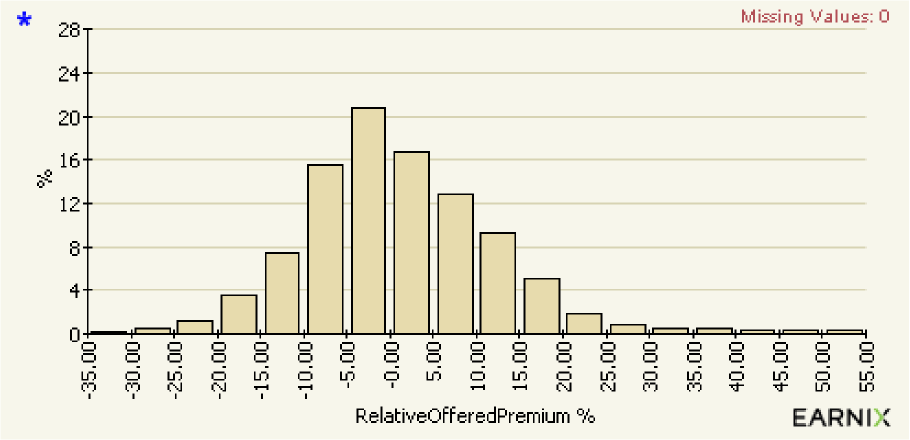
General

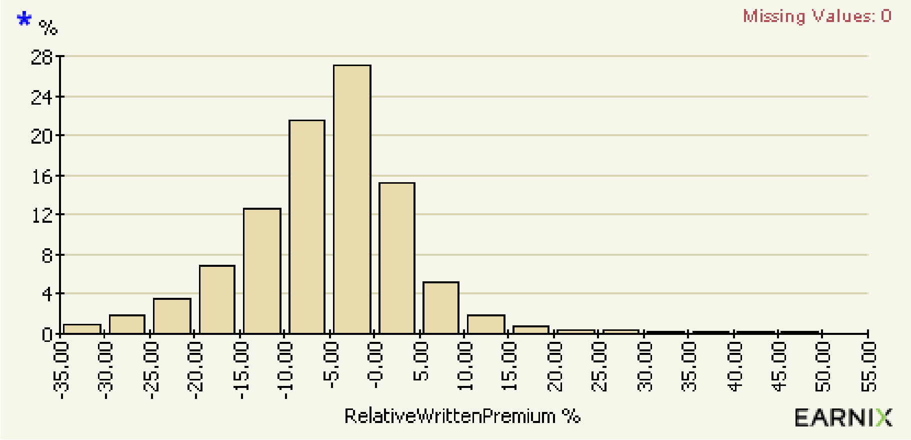
- Major player in the Italian market
- Due to market changes, new business premiums reduced extensively, and the market became more competitive
- Renewal process goes through very strong agents, which results in low elasticity than originally assumed (relative to the original offered price)
- Lack in a random price variation



The Business Environment

- The agents are effectively cancelling most of the price increases
- On the offering stage 50% of the customers are receiving high relative prices. On the written stage the percentage decreases to less than 25%.
- It means that the flexibility to increase prices is in the agent hands





Pricing Scenarios Considered

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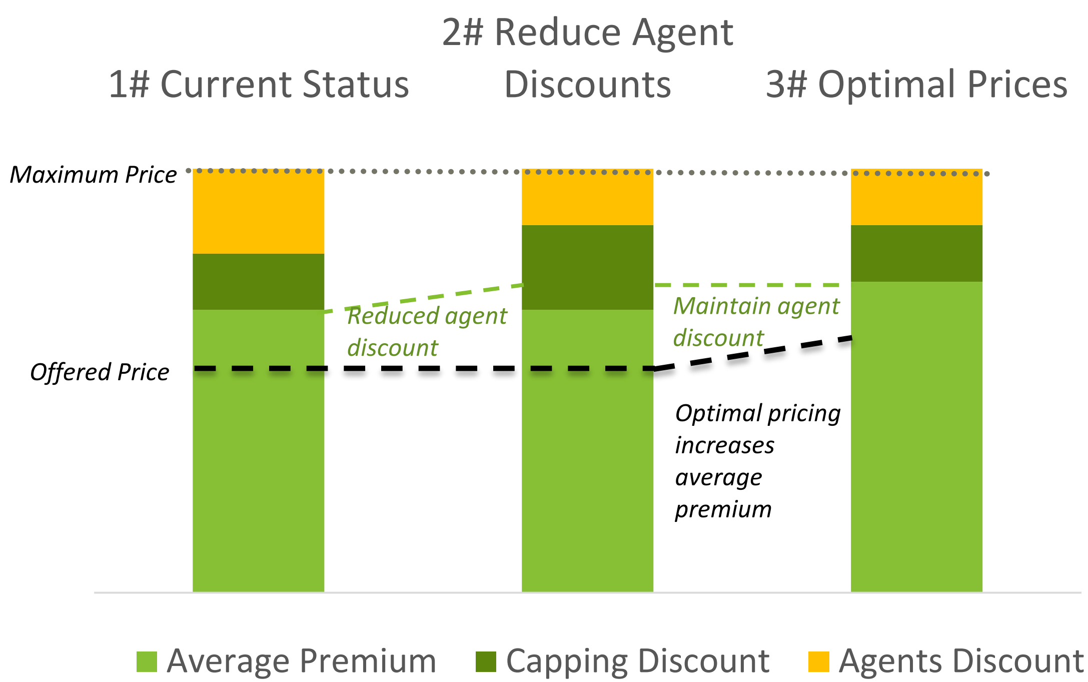
- Option #1: Increase Tariff (1.6% uplift for Tariff+5% and 1.9% uplift for Tariff+10%)
- Option #2: Optimization with low uplift (~0.6%). In parallel, to make a price test.
- Option #3: reduce agents flexibility to give discounts. Discounts will be given directly to customers in an optimal way (~1.6% uplift)



Credibility Blend Modelling

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Background

- Motor fleet pricing is a combination of technical pricing and underwriter's judgment. The general trend in the world is toward a more automated process, in order to allocate more of the underwriter’s time to capture risk elements that statistical pricing models cannot assess.
- if we want to blend a pricing component that derives from standard GLMs with a pricing component that relies on fleet-history information only, what weight should we give to each of these components? Credibility theory can help us answer this question.
- We focus on risk modeling in the framework of credibility theory and propose different methods for computing risks at the fleet level. Our proposals are all based on the Bühlmann—Straub model, and they differ in their ways of estimating the credibility factor.

Background - Credibility

- When estimating risk models in order to price fleet businesses, there are two extreme approaches:
  - An estimate based on data about the past experience of the individual fleet only can be chosen, on the grounds that all information needed for pricing rests in the history of that fleet only, or
  - Risk for the fleet is considered just as the composition of the individual risks for the single vehicles in the fleet, which are estimated with traditional Generalized Linear Models, on the grounds that vehicle-level information is what ultimately matters for determining risk, and the fleet is nothing but a collection of single vehicles.
- Credibility blending suggests using a combination of these methods. In particular, a linear combination of the two. The basic formula for calculating a credibility-weighted estimate is:

$$\textit{Credibility prediction} = Z * (\textit{Fleet Past Experience prediction}) + (1 - Z) * (\textit{GLM prediction}),$$
$$\textit{where } 0 \leq Z \leq 1.$$

- Z is a parameter that represents the weight given to the first approach, the one that uses only data from the individual fleet to make predictions.

Background- Bühlmann—Straub Credibility

- The classical approach to calculate the credibility factor is the following:

$$Claim\ frequency_{ij} = Z_{ij} * EXPER_{ij} + (1 - Z_{ij})^{*} EXPOS_{ij}$$

- For fleet j and vehicle type i, let n_{ij} be the number of vehicles of type i in fleet j. We have:
  - EXPOSij Exposure pricing. is the summation over the n_{ij} vehicles of the predicted frequency based on a GLM that uses data on all vehicles.
  - EXPERij Experience pricing is the weighted average claim frequency for the vehicle type i in fleet j.

$$Z_{ij} = \frac{n_{ij}}{n_{ij} + \frac{\varphi_i}{\lambda_i}}$$

- The two parameters in the above formula are the following:
  - φ- variation in claims frequency for vehicle type i of the individual fleet (from year to year)
  - λ- variation of average frequency for vehicle type i between fleets.
  - We will refer to the ratio (φ/λ) using simplified notation, $\boldsymbol{k}$.

Data and Testing

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- Evaluating credibility methods using only the GLM modeling dataset.
  - We randomly split the data into 3 groups: In sample 1 (25%), in sample 2 (25%) and out of sample (50%).
  - GLM model was re estimated based on Sample 1 (with the same model structure)
  - We proposed three methods listed below are based on 50% in-sample data randomly selected from the entire population. After estimation we checked the credibility blending against the 50% out-sample population.
- We evaluate the following methods:
  - Model 1: Non-parametric Empirical Estimation for the Buhlmann-Straub Model - We estimated the two parameters of the Bühlmann-Straub Model (φ and λ) directly form the data using sample means
  - Model 2: Finding K that will minimize the in-sample error.
  - Model 3: GLM with Random effect – we used fleet indicator as a random effect

Model 2: Minimizing the Error Term

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- In this method we estimated the parameter k for each vehicle type, by choosing the value of k that minimizes the credibility blending projection error. This was done in the following steps five:
- We estimated the parameters of the GLM regression using the In-sample 1 data.
- We computed the predicted frequency (using the two models of Exposure and Experience pricing) for all vehicles in dataset In-sample 2:
- Exposure pricing - For every fleet j in In-sample 2 we calculated the predicted claims frequency – $\hat{Y}_j^{GLM}$ – based on the parameters estimated by the GLM on In-sample 1 data.
- Experience pricing - For every fleet j in In-sample 2 we predicted the claim frequency – $\hat{Y}_j^{Experience}$ – based on the average frequency for that fleet in In-sample 1
- Actual frequency - For every fleet j in In-sample 2 we calculated the actual claim frequency - Y_j^{Actual}
- We excluded from the analysis fleets without exposure in both “in-sample” datasets.
- Using the Gauss-Newton method, we found the optimal k^∗ that minimizes the in-sample error, i.e. the following sum of squared errors:

$$\sum_{j=1,\dots,J}\left\{\mathrm{Y}_{\mathrm{j}}^{\mathrm{Actual}}-\left[\left(\frac{N^{IS\_1}}{N^{IS\_1}+k}\right)\hat{\mathrm{Y}}_{\mathrm{j}}^{Experience}+\left(1-\frac{N^{IS\_1}}{N^{IS\_1}+k}\right)\hat{\mathrm{Y}}_{\mathrm{j}}^{\mathrm{GLM}}\right]\right\}^2$$

N^{IS_1} - Number of vehicles in the fleet in “In-sample 1”

Model 3: Random Effect Model

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- We use the original risk models and add a fleet random effect. b_j is the fleet effect and it is modeled as deviation of the fleet j from the fixed effect part.
- We consider the following model. Let Y_{ij} be the claim frequency for vehicle k in fleet j. We assume that this is a random variable following a Poisson distribution with parameter λ_{kj}:

$$Y_{kj} \sim \mathrm{Pois}(\lambda_{kj}) \qquad \log\lambda_{kj} = \beta_0 + \sum_{\mathrm{p}=1}^{P} \beta_k x_{kjp} + b_j + \log(\mathrm{exposure}_{kj}), \quad b_j \sim \mathrm{N}(0, \tau^2)$$

- We estimated this Generalized Linear Mixed Model (GLMM), using In-sample 1 data, and computed $Y\grave{}\_ij$ $\hat{}GLMM$ for each fleet in the In-sample 2 dataset using these parameter estimates. We then calculated for every fleet the implied credibility factor Z_j in using the formula:

$$\hat{Y}_j^{GLMM} = Z_j \cdot \hat{Y}_{\mathrm{j}}^{Experience} + \left(1 - Z_j\right) \cdot \hat{Y}_j^{GLM}.$$

- Solving for Z_j, we obtained

$$Z_j = \frac{\hat{Y}_j^{GLMM} - \hat{Y}_j^{GLM}}{\hat{Y}_{\mathrm{j}}^{Experience} - \hat{Y}_j^{GLM}}$$

- The parameter *k* was found by reverse engineering the implied *Z* values computed with the above formula. We used a non-linear regression to fit the Bühlmann—Straub relationship between *Z*, *n*, and *k* for all fleets:

$$Z_j = \frac{n_j}{n_j + k}$$

Results Comparison (1)

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- In order to evaluate each model predictive power we scored the “out sample” data and calculate the weighted prediction error according to the following formula:

- $Weighted\ Prediction\ Error = \sum_{Fleets} \left\{ (N^{OS})^2 * \left(Y_j^{OS} - Y_j^{Model} \right)^2 \right\} / \sum_{Fleets} N^{OS}$

Model	Weighted Prediction Error
Model 3A- With Claims segmentation	0.22025
Model 3B- With Claims segmentation	0.22025
Model 3A	0.22035
Model 3B	0.22035
Model 2	0.22061
Original GLM	0.29919
In Sample data	0.33124

- The credibility models improves the GLM predictions significantly, about 25% reduction in weighted prediction error.

- There is no significant difference between the three modelling approaches

- When the credibility calculation is segmented, fleets without past claims have a lower credibility factor (higher k), i.e. more weight is given to the GLM.
  - Model 3A was estimated of fleets with more then 10 vehicles while model 3B was estimated based on all fleets using different algorithm.

Results Comparison (2)

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	Fleet Size Group				
	<10	10 ≤ N < 50	50 ≤ N <100	100 ≤ N <500	>500
# of Fleets	6,928	2,927	291	165	21
# of Vehicles	26,950	57,158	19,656	29,258	34,132
Model 2	1.75E-01	2.03E-01	1.64E-01	2.10E-01	3.28E-01
Model 3A	1.76E-01	2.04E-01	1.64E-01	2.07E-01	3.28E-01
Model 3A- With Claims segmentation	1.75E-01	2.03E-01	1.64E-01	2.08E-01	3.28E-01
Model 3B	1.76E-01	2.04E-01	1.64E-01	2.07E-01	3.28E-01
Model 3B- With Claims segmentation	1.75E-01	2.03E-01	1.64E-01	2.08E-01	3.28E-01
Original GLM	1.77E-01	2.11E-01	1.81E-01	2.74E-01	6.33E-01
In Sample data	3.18E-01	3.85E-01	2.56E-01	2.85E-01	3.35E-01
Relative differane	0.817%	3.817%	9.656%	24.551%	48.264%

When segmenting the analysis by fleet size, we can clearly notice that:

1. Blending results improve (compare to GLM model) as fleet size increase
2. Model 2 gives the better results for smaller fleets
3. Experience Pricing (labelled “In sample data”) gives better results for larger fleets (>500).
4. There is no significant difference between the modeling approaches

Marketing Optimization - Optimal Allocation

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Offer optimization

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- Customer decision is not only around price. It is also based on other product characteristics (e.g. terms & brand) which can be controlled and optimized.
- Better performance can be achieved by optimizing what is offered to which customer (optimal treatment).
- Build response models to campaigns/offers/actions and perform optimization to decide which offer/treatment should be given to which customer.

Marketing spend optimization

- Is pricing aligned with the expected leads resulting from the planned marketing strategy?
- Is the marketing spend enough to generate required business? Is it targeting the right populations?
- Create a framework that combines marketing and pricing to create optimal synchronized strategies.

Allocation- Which Offer j to Offer Customer i

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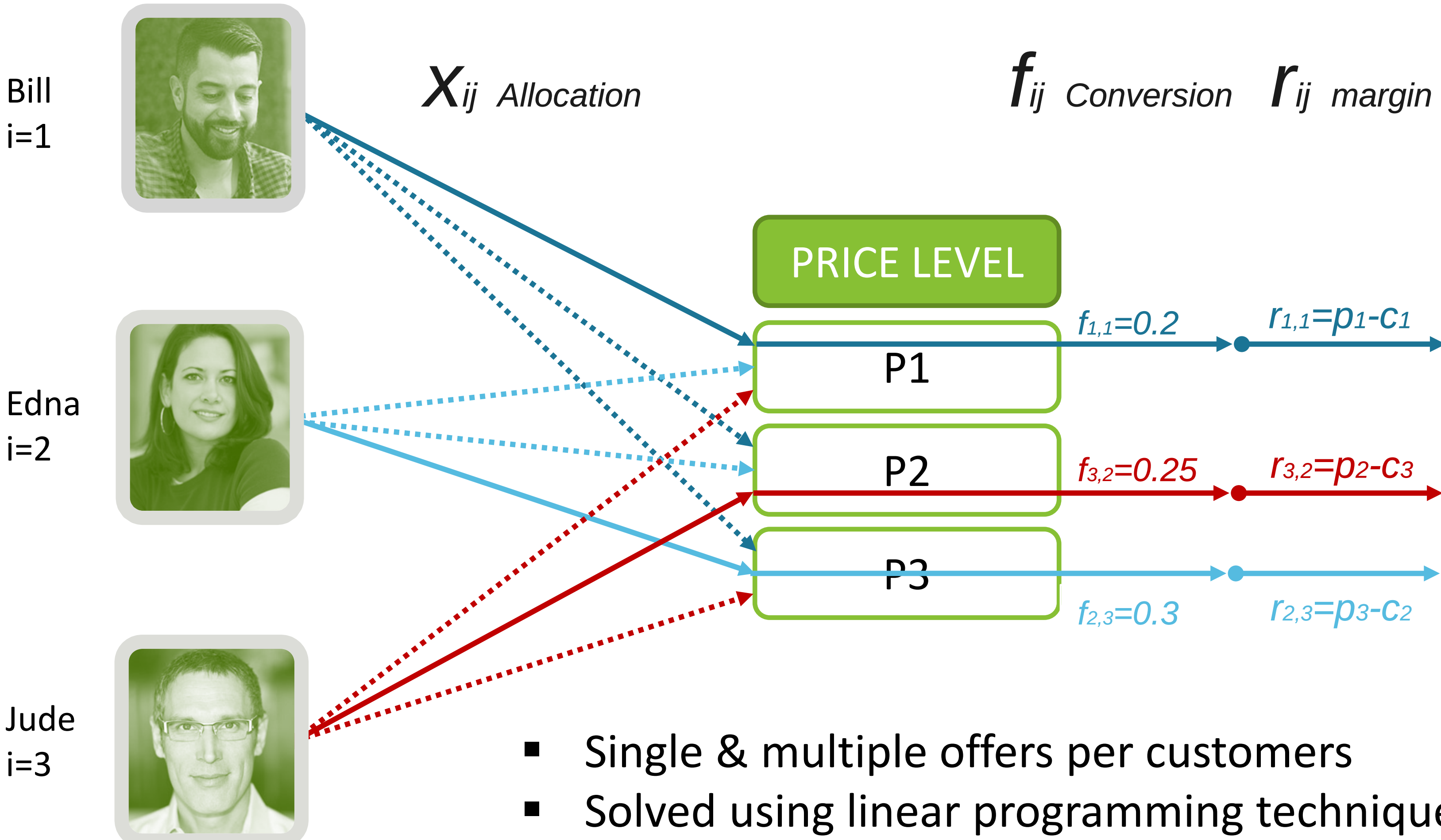
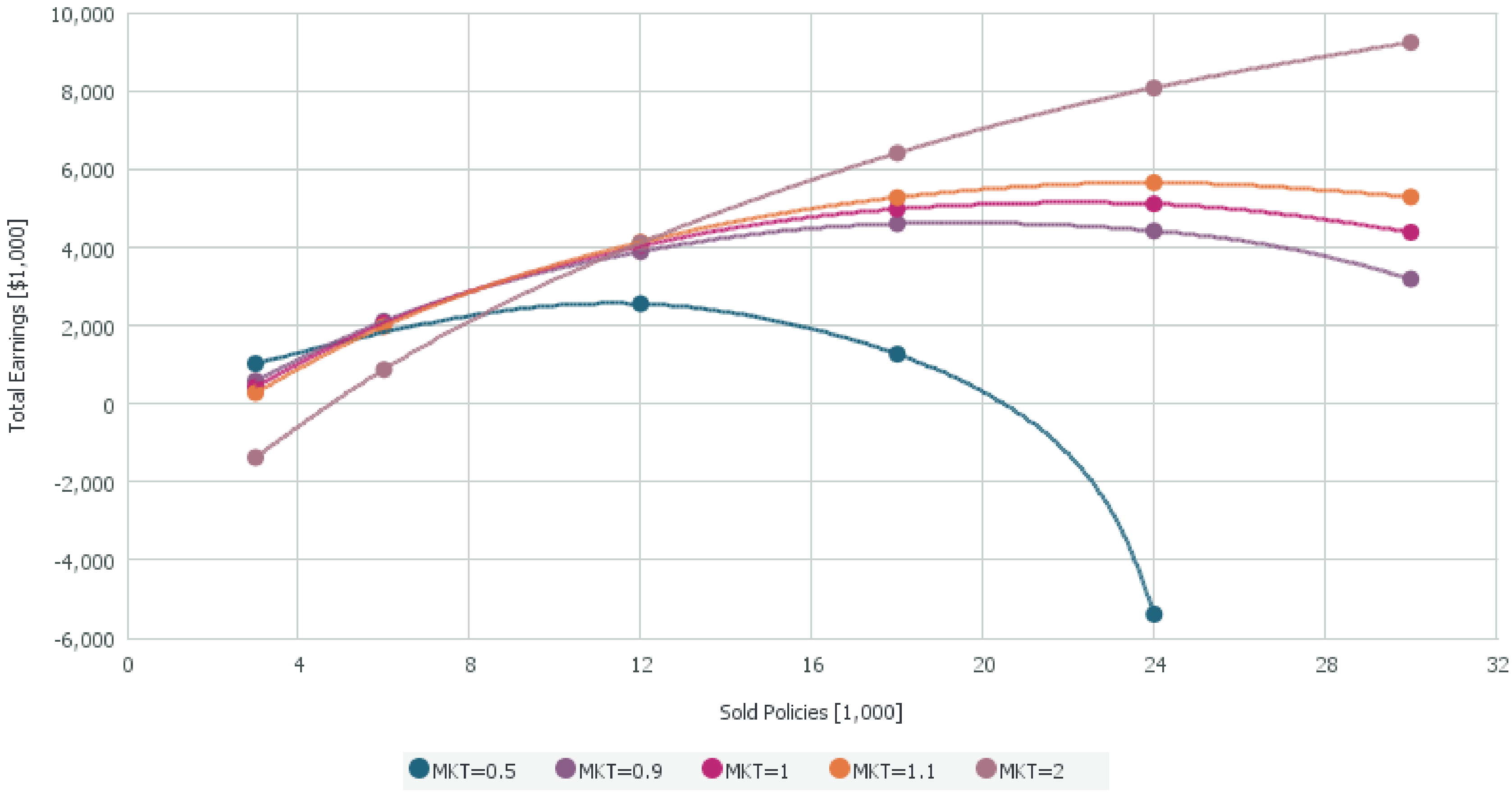


- Single & multiple offers per customers
- Solved using linear programming techniques

Acquisition Marketing Strategy Use Case



Thank you

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