Lessons Learned from the Pricing Game

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Today's Speakers

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Agenda

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Our consulting model builds on Munich Re's strengths

Focus segments and core competences

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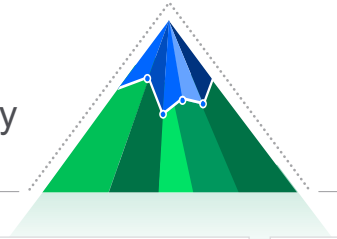
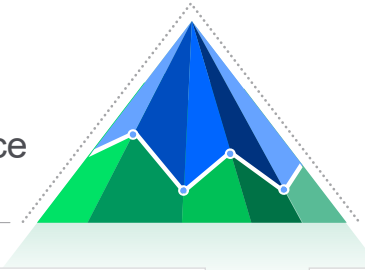
Value Proposition

Risk Advisory



Portfolio Performance



Clients

- Primary Insurers
- MGAs
- Bank Assurers
- Verticals

Solutions

- Business Advisory
- Products
- Pricing
- Data Analytics
- Claims
- Customer Experience

Funda-mentals

Data

- Data as asset
- Bench-marking
- Int. Best Practices

Expertise

- PI Domain Knowledge
- Analytical Capabilities
- Broad MR Expertise

Technology

- Automation
- Platforms
- Strategic Partnerships

Pricing Tribe: one team across four continents

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Pricing Game – Motor insurance market simulation

Overview

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The insurance pricing game

A market simulation completion

Participation

- 1800+ participants
- 45+ countries
- 80% work in actuarial industries

Submissions

- 10,000+ code submissions (R, Python)
- Avg. 100 submissions/day for 3 months

Global reach

- 2 leading universities
- 21 national actuarial institutions
  - Providing access to 80,000 actuaries
- 2 major re-insurers

AIcrowd

Motor insurance market simulation

Prizes $12,000 (USD)

Imperial College London

Singapore Actuarial Society

Actuaries Institute

UQÀM

Institute and Faculty of Actuaries

IAA AAI ASTIN Non-Life Insurance

CAS

01	World Experts	Yes	185919.311	0.161
02	glep	Yes	90108.871	0.190
03	edwin_graham	Yes	87058.322	0.162
04	michael_borde…	Yes	66778.702	0.111
05	jocelyn	Yes	52332.963	0.168
06	guillaume_bs	Yes	22756.903	0.278
07	tk230147	Yes	12730.821	0.027

Introduction

Short description of the game (1/2)

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AIcrowd

- Platform for streamlining your AI workflow
- Enables data science experts and enthusiasts to collaboratively solve real-world problems through challenges
- Covers a variety of different topics: Alzheimer's Detection, Hockey Puck Detection, Music Demixing Challenge

Goal of the pricing game

- Act as insurance company and build a pricing model
- Compete against other players for profit
- Cheapest-wins market
- Price contracts for incoming policies for the 5th year
- "Realistic" game design

	Company 1	Company 2	Claim amount
Policy 1	120	90	100
Policy 2	30	25	10
Policy 3	10	15	0
Policy 4	5	10	0
Total revenue	15	115	
Most profit	0	110	Total loss
Total profit	15	5	

Introduction

Short description of the game (2/2)

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Rules

- Non-negative training profit: models must be profitable on the training data
- Participation rule: Model must win at least 1 policy in 5% of the markets it is placed in
- Weekly market feedback

Weekly Leaderboards

RMSE Leaderboards computed in 4 stages

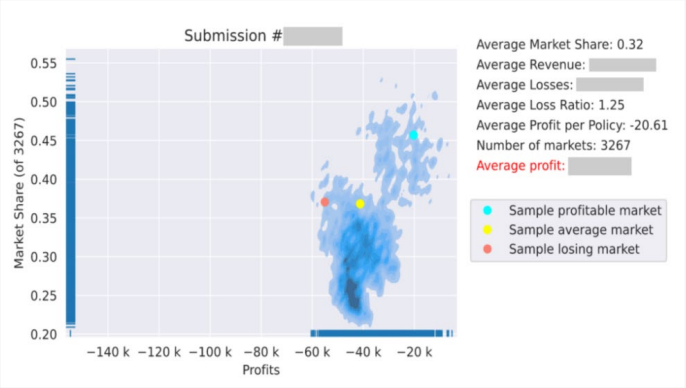
- Year 1 with access to data from year 1
- Year 2 with access to data from years 1–2
- …

→ Use the past to inform the present

Competitive Profit Leaderboard

- Measures average profit in a market of size 10
- Many runs to ensure stable results

→ Profit rank for your model



Competitive Profit (Final metric)

- Model is placed in a market size of 10 with 9 other models picked from the top **10%** of the profit ranking
- Many runs of different random markets

Methodologies

Techniques used by other competitors

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CHALLENGES

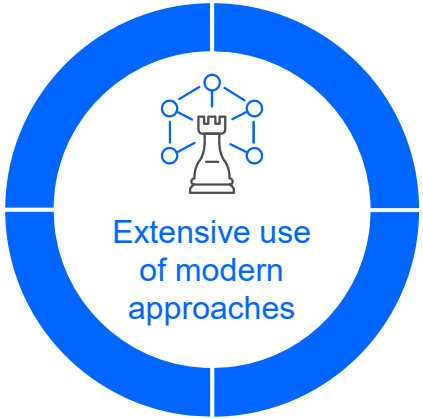
Changing evaluation data

Limited amount of attempts

No access to competitors' premiums

- Feature engineering
- Market simulation
- Target encoding

- Large claim detection model
- Meta models built on base models (GLM, GBM, NN)
- Heavy loadings for risky policies



- Extensive use of GBMs
- Being competitive on every segment

- Stacking GLM with random forest
- Classification models to steer the loading

Methodologies

Our journey and approach (1/2)

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Starting point

- Focusing on pure pricing and the RMSE leaderboard
- Simple feature engineering
- Starting with vanilla GAMs

Improving technical pricing

- Switching from Tweedie to GAM for frequency and severity
- Adding interactions by assumptions
- Comparing with a GBM for frequency and severity
- Using vh_make_model variable with PCA
- Detecting Large Claims and avoiding to insure policies with those claims in the past
- Using AutoML to provide proposals for interactions

→ Lead to improvement on RMSE Leaderboard

Week	1–5	6	7	8	9	10
Profit rank	NA	126	24	95	82	63
Method		GAM	Tweedie (AutoML influenced)	Tweedie (AutoML influenced)	GBM	GAM (AutoML influenced)
Market share		0.55	0.048	0.27	0.051	0.012

Pricing Strategy

Dividing Premium into 4 segments and adding different fixed + variable loadings

Methodologies

Our journey and approach (2/2)

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Final week: What to do?

Findings

- Market share is difficult to steer
- Higher market share might lead to less profit
- Our XGBoost isn‘t performing robustly
- Data and environment is changing heavily from week to week
- Forum: People are trying to avoid „risky policies“ → Can we use that?
- Pricing Strategy is more important than the pricing model

Final approach

- Using a robust GAM for frequency and severity with AutoML suggested interactions
- Opportunity in risky policies: Cancelling the large loss detection
- Trying to aim for a low but not extremely low market share

Average Market Share	0.027
Average Revenue	211038.0
Average Loss	198308.0
Average Loss Ratio	0.944
Average Profit per Policy	5.0
Number of Markets	365
Average Profit	**12730.82**

Lessons Learned

Market Expectations vs. Reality

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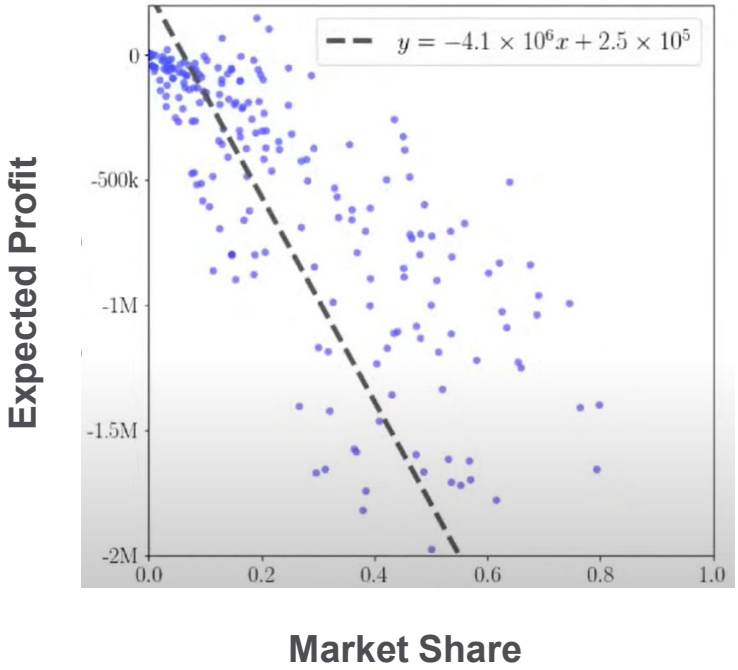


Market Share & Profitability

We quickly learned that **high market share isn't necessarily desirable**. However, some market share is needed to place well:

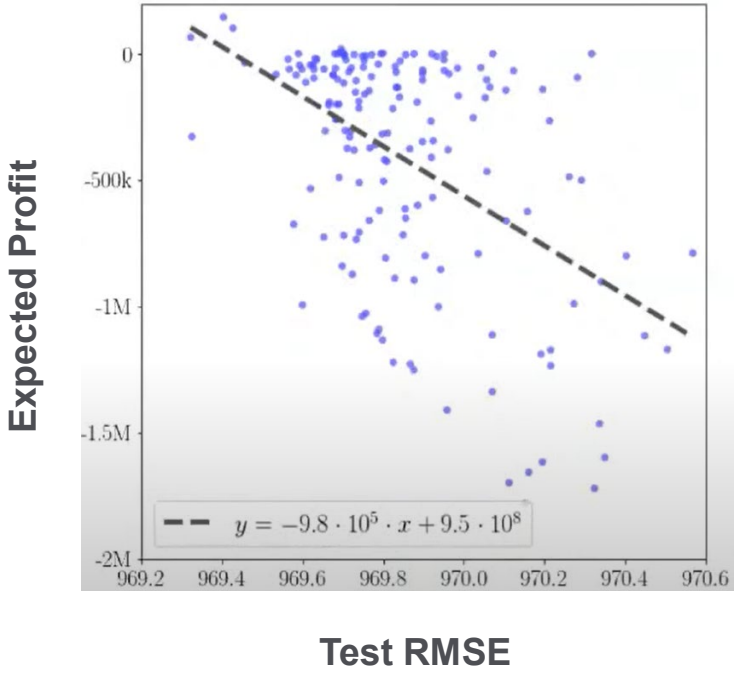
Final Leaderboard

Place	Profit	Market Share
1	$186k	16%
2	$90k	19%
3	$87k	16%
4	$67k	11%
5	$52k	17%
6	$23k	28%
7	$13k	3%
8	$11k	7%
9	$6k	0.1%
10	$1k	0.6%

Image source: shared by organiser

Lessons Learned

Profits, Model Accuracy and the Winner‘s Curse



The Winner’s Curse

- The most dramatic result of the pricing game was that, on average, **almost every team lost money**
- This is an expected result in a blind auction with a pure cheapest-wins criteria

Model Accuracy = RMSE

- Root Mean Squared Error (RMSE) is a measure of accuracy of the pricing model
- More accurate models (lower RMSE) correlate with better profitability
- But having an accurate state-of-the-art pricing model is a **necessary but not sufficient** condition for winning on profitability

Image source: shared by organiser

Learnings and Outlook

Pricing Game 2.0?

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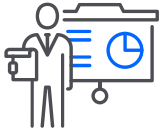
Results of the Pricing Game

Current and expected (academic) studies

- Impact of AI in market competition
- Pricing Strategy Vs Claim estimation
- Model Complexity Vs Market profit
- ...



Pricing Game 2.0

Ideas for a second pricing game with some adaptions

- More insights on how competitors are building their models
- Players can get bankrupt
- Adding a reinsurance component
  - Shock events
- Change from vanilla motor setting to more “exotic” insurance (e.g., pets)
- Adding more external data

Check our website to stay up to date

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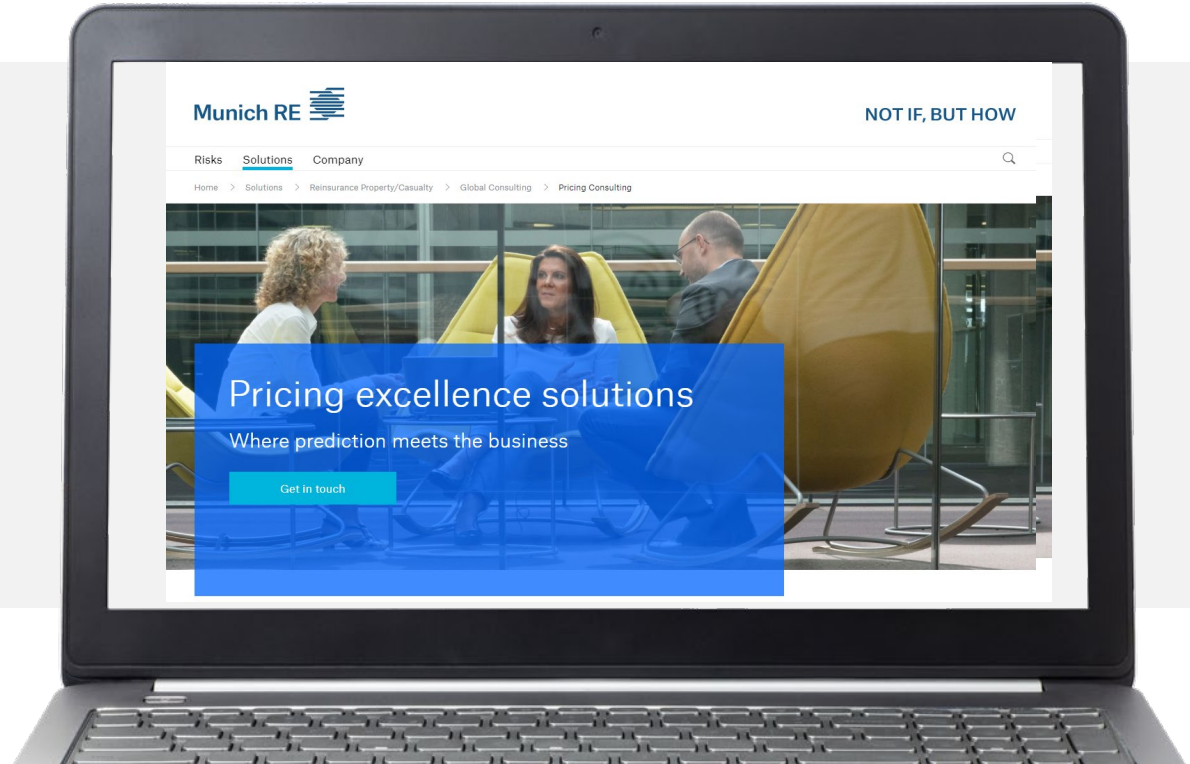

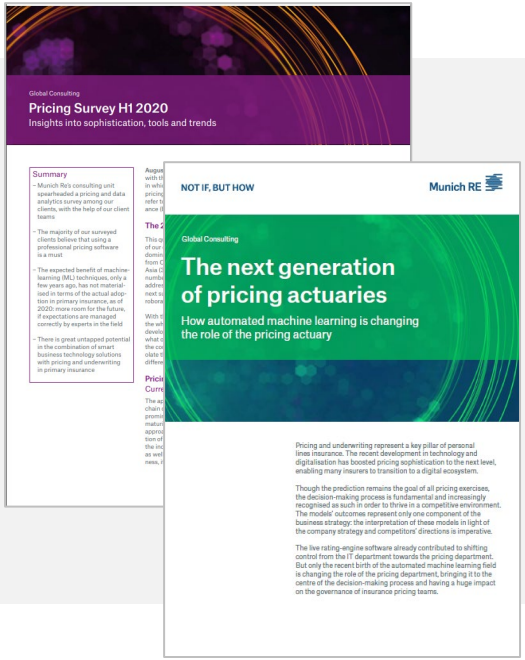

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Thank you for your attention

23 November 2021

Thibault Imbert – Till Kischkat – Lukas Linder

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Appendix

Introduction

”Realistic” Game Design

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Reality

- Estimating risk based on historical data
- Competing with others for profit in live market
- Consequences for bad market performance

Pricing game parallel

- RMSE leaderboard on consistent data
- Profit leaderboard on disjoint data
- Two round profit metric to filter bad models

Introduction

Data provided

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Data

- 100k real historical car insurance policies over 5 years in the recent past
- Majority concerns third-party liability but also other types of car insurance are present
- Training data: 60k policies with 4 years of history
- Final test data: 100k policies for the 5th year
- History of some policies are present in the training data, others will be entirely new

Claim frequency	Average severity
10%	1118.75

Variables

Id_policy	
Year	
Pol_no_claims_discount	7 policy
Pol_coverage	
Pol_duration	
Pol_sit_duration	
Pol_pay_frequency	
Pol_payd	
Pol_usage	
Drv_sex1	7 driver
Drv_age1	
Drv_age_lic1	
Drv_drv2	
Drv_sex2	
Drv_age2	
Drv_age_lic2	
Vh_make_model	7 vehicle
Vh_age	
vh_fuel	
Vh_type	
Vh_speed	
Vh_value	
Vh_weight	
Population	2 external data
Town_surface_area	
Claim_amount	