

Machine Learning: Lab to Live Ben Wilson and Theeban Kuganesan, EY



Institute and Faculty of Actuaries

Agenda

- Setting the scene
- Typical 'Lab to Live' journey
- 'Lab to Live' challenges:
 - Common approval challenges
 - Pricing implementation considerations
 - Maintenance and review framework

Q&A

Setting the scene

You are tasked with updating the model which predicts propensity to renew an insurance policy as a function of the price charged.

Working in your sandbox "lab" environment, you prove that a machine learning approach based on a Gradient Boosting Machine gives a better solution across a range of measures.

Not only that, the process was fairly automated and you foresee efficiency savings in the team if it is rolled out.

Problem statement

How do you move from the POC in the sandbox 'lab' environment into "live" production?



Typical "lab to live" journey

	Stage 1: Proof of Concept	Stage 2: Pilot Implementation	Stage 3: Enterprise Implementation	Stage 4: Sustain & Enhance
Example	A one-off renewal POC model in a sandbox environment	Offline adjustments made to the renewal model for a subset of the portfolio	ML model is integrated with the price optimization framework and runs automatically	Process governs the ML model performance tracking, maintenance and updates
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Common approval challenges



Potential solutions:

- Redesign model governance process
 - Objective tests/check-box approach
 - Phased roll out to mitigate risk
- Robust model validation
 - Model diagnostics should include:

Variable Importance

Partial dependencies

Lift/gains chart

LIME (Local Interpretable Model-Agnostic Explanations)



Common approval challenges

"No human judgement"

"It will make the wrong decision" **Potential solutions:**

- Model Interventions:
 - Feature engineering
 - Feature shape
 - Feature
 selection/Regularization
 - Loss functions
 - Trend adjustments outside algorithm
- Model Comparison to GLM:
 - Segments with largest deltas
- Human Checkpoints/Triggers
 - Models operate within predefined thresholds



Common approval challenges



- Increased competition
 - Anti-selection
- Co-resourcing and shared development journey
 - Pricing team buy-in
 - Shared objectives
- Insurance domain knowledge
 - Data
 - Model validation
- Upskilling Pricing Actuaries
 - Translators
 - Team consolidation
- Shift focus to business applications



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Enterprise implementation considerations



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Maintenance and review framework



Hybrid Data Science team structure

"Fragmented" model

"Hybrid" models- lots of different potential configurations









Conclusions

- Many machine learning projects are stuck at POC or pilot stage
- Governance processes need to be redesigned and validation extended
- Know GDPR rules to mitigate risks and find opportunities
- Integrated data science teams help overcome cultural resistance
- Compatibility of pricing systems with ML techniques is constantly improving
- ML can be governed by automated processes, controlled by human checkpoints and triggers but equally so can traditional techniques





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