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Teaser

Where do 90% of ML/AI models get deployed?

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Where do 90% of ML/AI models get deployed?

(Allegedly, and may be outdated)

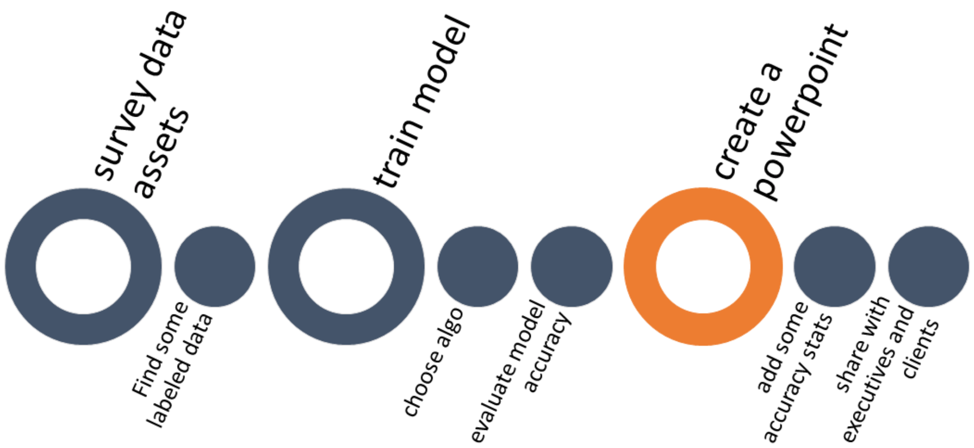
https://towardsdatascience.com/why-90-percent-of-all-machine-learning-models-never-make-it-into-production-ce7e250d5a4a

Where do 90% of ML/AI models get deployed?

ML in production: expectation

1. Collect data
2. Train model
3. Deploy model
4. 

Reality



Many models don't get deployed for…

Things Outside Model Performance Metrics

Business Sponsorship

Good Model = Good Product?

From Model to Product:
Implement ML Effectively for Insurance Underwriting

11.05.2024 at RE•WORK

Langyi Tian
Senior Data Scientist

From Model to Product: Implement ML Effectively for Insurance Underwriting

Agenda

1. Teaser: Are Our Models Getting Implemented?
2. Introduction: Model is Part of a Product
3. Case Study: Implementing GBMs for Insurance Underwriting

Introduction

About Me

Langyi Tian

- Senior Data Scientist, Homesite Insurance
- Background in finance and social science
- Columbia '19, CUHK ‘18

Homesite

- Based in Boston, MA. Part of American Family Group
- P&C, auto, commercial

Analytics Tools & Modeling

- Mixed manpower of actuaries, DS, and engineers
- Rating tools, dashboards, rating models, etc.

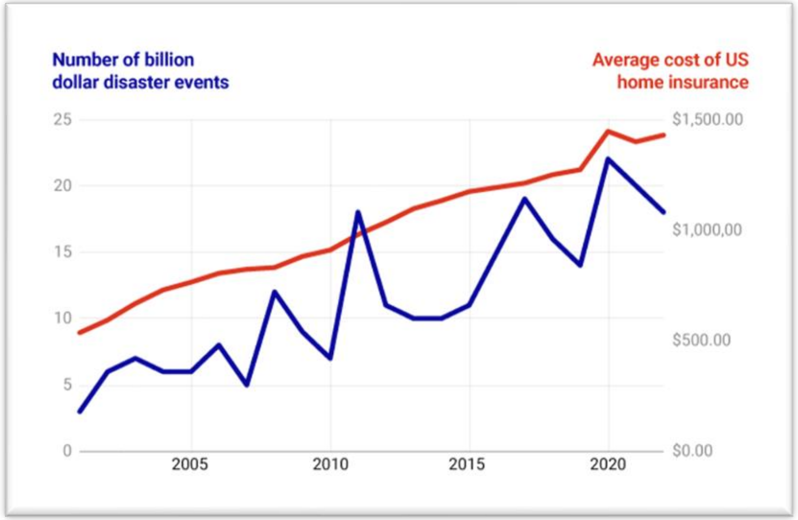
ML/AI in Insurance

Use cases

- **Pricing**
- **Inspection**
- **Customer Service**
- **Retention**

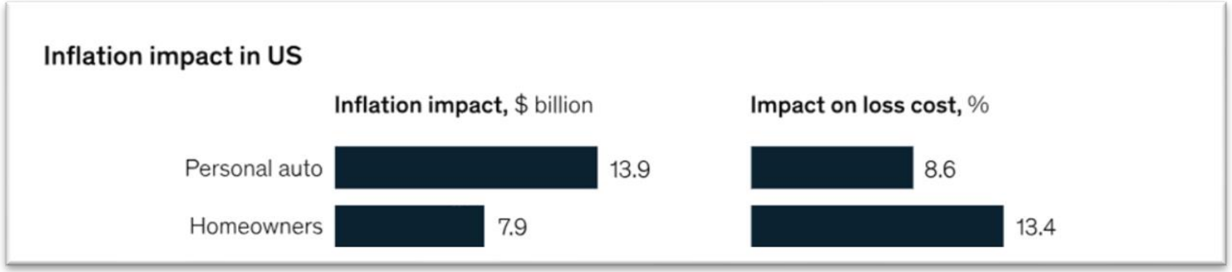
… And

Underwriting



- Targeting **unpriceable** high risks at far right tail
- More crucial to **profitability**
  - Increasing inflation
  - Frequent extreme weather events

…



Model is Part of a Product

Requirements

Predictive
Predicts risk better than alternatives (e.g. actuarial analysis)

Regulatable
Transparent and explainable for regulator considerations

Business Oriented
Flexible to adapt to market, easy to implement, transparent UX

Stakeholders

Workflow

Data Science
Collect data and build model

Regulator
Approve

IT
Implement

Product/Analysts
Monitoring and modifying

Agent/Customer
Interact

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Case Study: Implementing GBMs for Underwriting

Overview

Before

Approach:
- Automated underwriting
- Univariate/bivariate underwriting rules.

Result:
Declining **over 30%** Homeowners quotes

Issue:
Particularly bad for a **partner-based** company

After

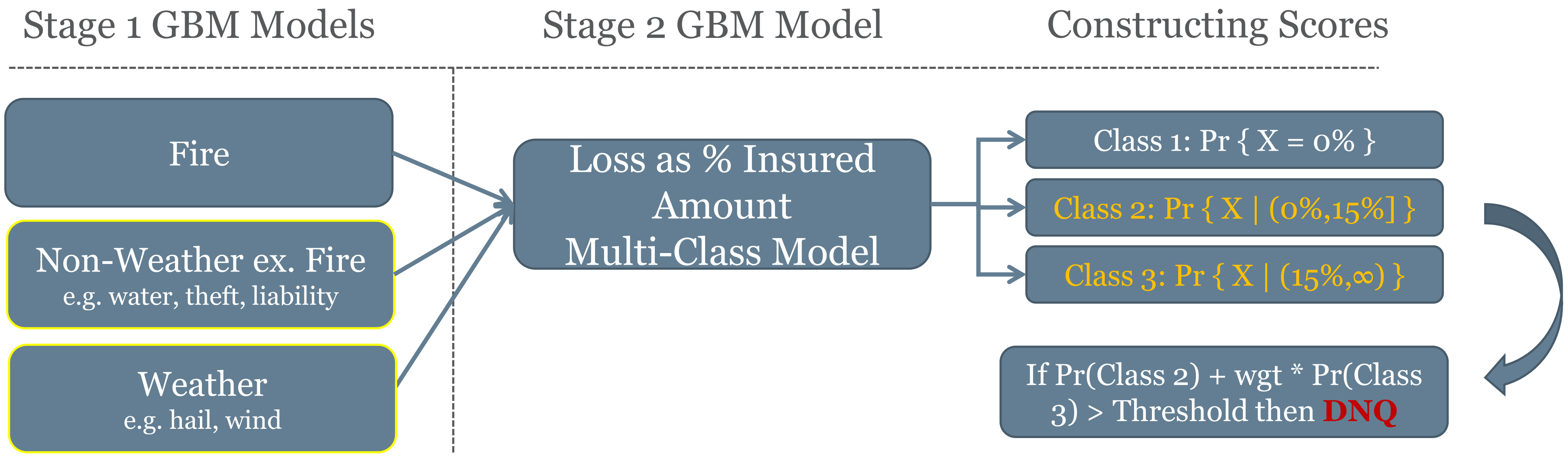
Goal:
Decline less without sacrificing profit

Approach:
- A **2-stage** Gradient Boosting Machine (GBM) model
- **More predictors**
- Custom built IT solution to **AWS microservice**
- Additional **control table** for fine tuning DNQ
- Dashboard for **monitoring/simulating** DNQ results

Result:
- Drop in DNQ (Do Not Quote) rate by **more than 10%**
- **No significant loss difference**

Modeling Technique

Balancing Technical/Business Needs



Two-stage Design:

- Stage 1 treat **distinct causes of loss**
- Stage 2 targets **small segments of less profitable business** with optimized weights

Gradient Boosting Machine (GBM):

- Moderately **explainable** with sample trees and variable importance plots
- GLM, GBM, XGB tested. Marginal difference in performance.

Modeling Technique

Ensure Consistency in Input/Output

Common Predictors

- Property-Related
  e.g. Replacement Cost
- Personal
  e.g. Age of Customer
- Credit Score
- Insured Limits

Geographical Predictors

- Historical Industry Losses
- Catastrophe Losses

Business Requirement

- Univariate UW rules
  - Prior Claims
  - Flat Roof
  - Wood Stove

  ...

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Implementation

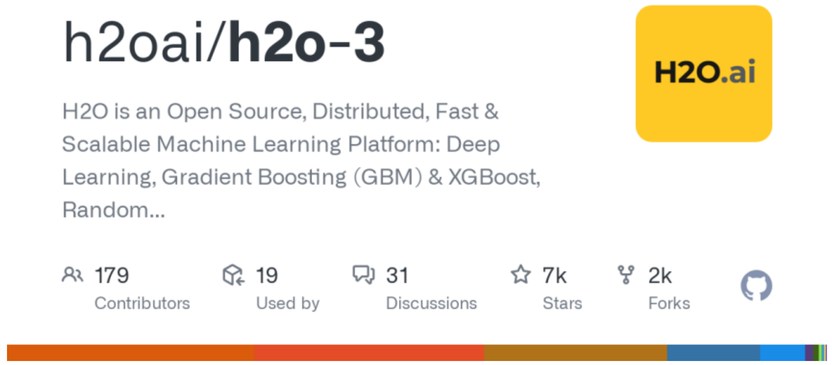
Faster Modeling & Easier for IT

Before:

- 500+ trees, all custom coded and QA-ed by IT
- **Unnecessary cost** from development, test and maintenance

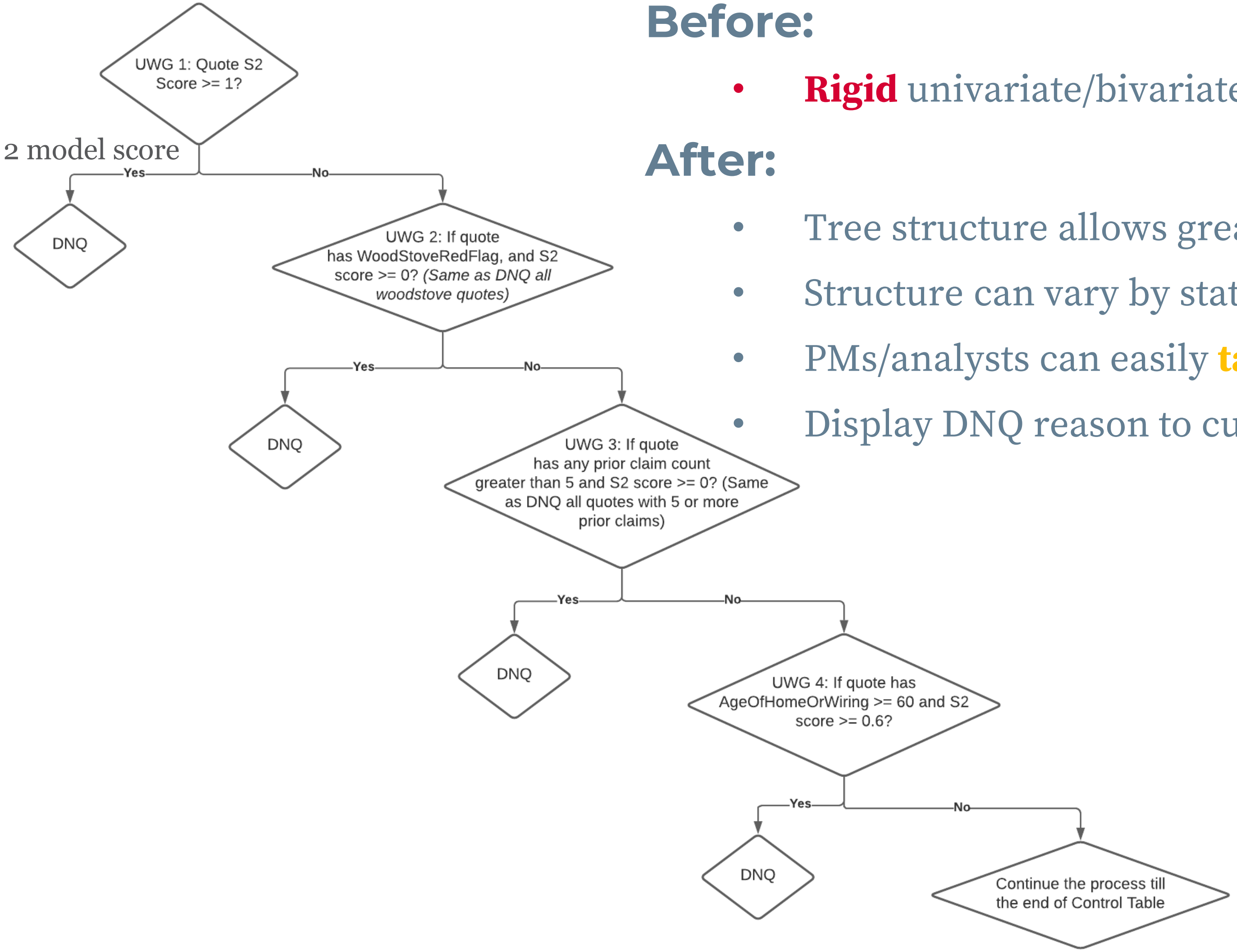
After:

- Train in H2O AutoML (Many alternatives such as VertexAI, DataRobot, SageMaker)
- Output models as Java objects for IT. Deployed as AWS microservice
- **Shorter time to market** with rapid implementation



Control Table

Additional Layer of Control for Business Needs



*S2 Score = Stage 2 model score

Before:

- **Rigid** univariate/bivariate underwriting rules

After:

- Tree structure allows greater flexibility with more levels available
- Structure can vary by state
- PMs/analysts can easily **target poor performing segments**
- Display DNQ reason to customers for **better UX**

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Dashboard

More Transparency for Product Managers

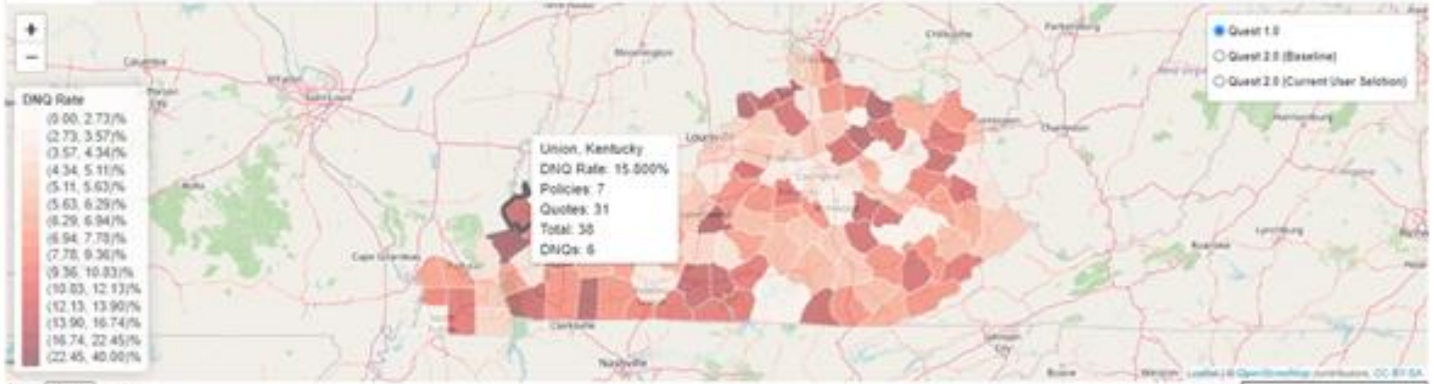
- Simulate DNQ changes from adjusting thresholds/control table with real data
- PMs can make **informed decisions** for underwriting adjustments

Step 4: Check summary tables and maps, then save the final control table.

Choose Partner for DNQ Map Results:

GEICO

DNQ Rate | DNQ Rate Differential



Show 10 entries

Search:

	FIPS_Code	County	Curr_DNQ_Rate	Base_DNQ_Rate	Sel_DNQ_Rate	Policies	Quotes	Total
1	21001	Adair	11.9048%	4.7619%	4.7619%	3	39	42
2	21003	Allen	11.2903%	8.0645%	8.0645%	6	56	62
3	21005	Anderson	3.4884%	0.0000%	0.0000%	17	69	86
4	21007	Ballard	7.3171%	14.6341%	14.6341%	7	34	41
5	21009	Barren	15.1515%	7.0707%	7.0707%	10	89	99
6	21011	Bath	2.6316%	5.2632%	5.2632%	3	35	38
7	21013	Bell	6.6667%	9.3333%	9.3333%	2	73	75
8	21015	Boone	5.1071%	4.4481%	4.4481%	98	509	607
9	21017	Bourbon	13.8462%	9.2308%	9.2308%	5	60	65
10	21019	Boyd	5.4726%	4.4776%	4.4776%	17	184	201

Showing 1 to 10 of 120 entries

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Download

Summary

From Model to Product: Implement ML Effectively for Insurance Underwriting

Balance Technical & Business Needs

Consistency in Input / Output

Faster & Easier Implementation

Enable Flexibility Outside Model

Tools for Monitoring / Making Informed Decisions

Any questions?

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