Institute and Faculty of Actuaries

Enhancing the Commercial Insurance Value Chain with AI and Analytics

Bijal Patel, Betty Zhu, Karol Gawlowski & Bruno Bécha

IFoA GIRO Conference 2024

Presenters

Introduction

Bijal Patel

Betty Zhu

Bruno Bécha

Karol Gawlowski

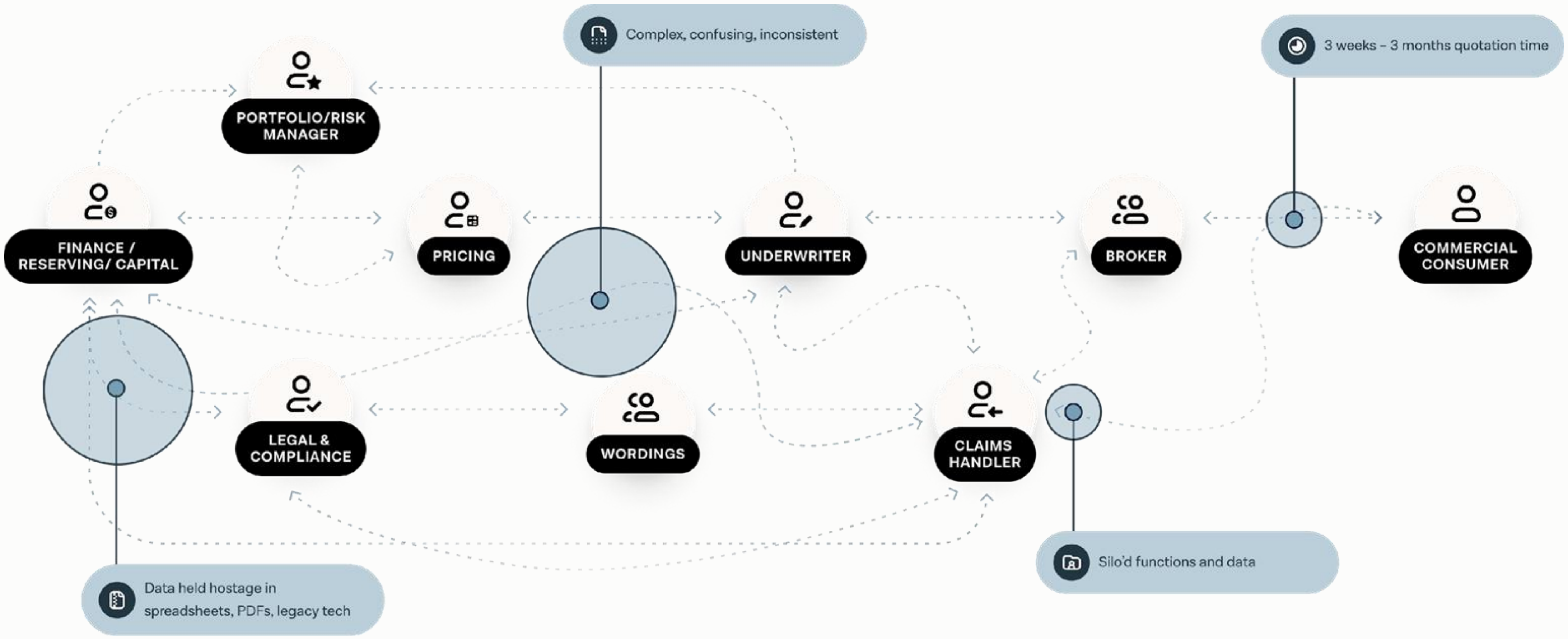
Agenda

1 — 2 — 3 — 4

1. Commercial Insurance Value Chain
2. What is AI?
3. Latest Innovations & Use Cases
4. Q&A

Commercial Insurance Value Chain

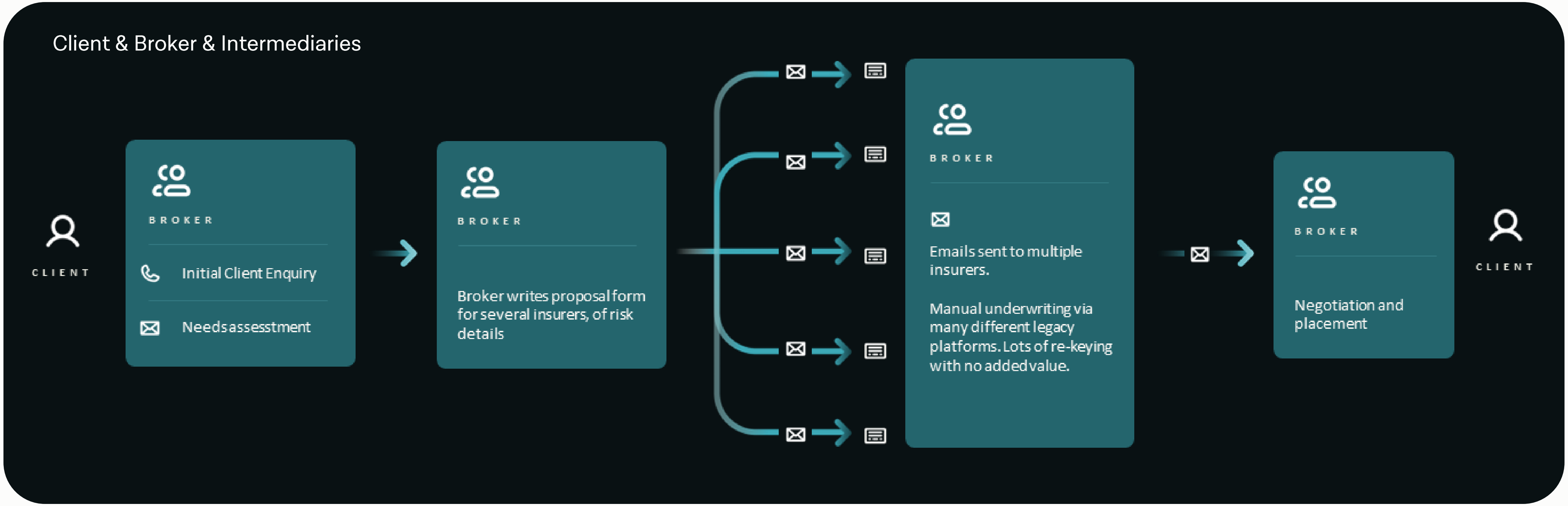
The commercial insurance value chain is manual, inefficient, expensive, complex, inconsistent



Traditional Operating Models

Problem Statements and Targets for Innovation

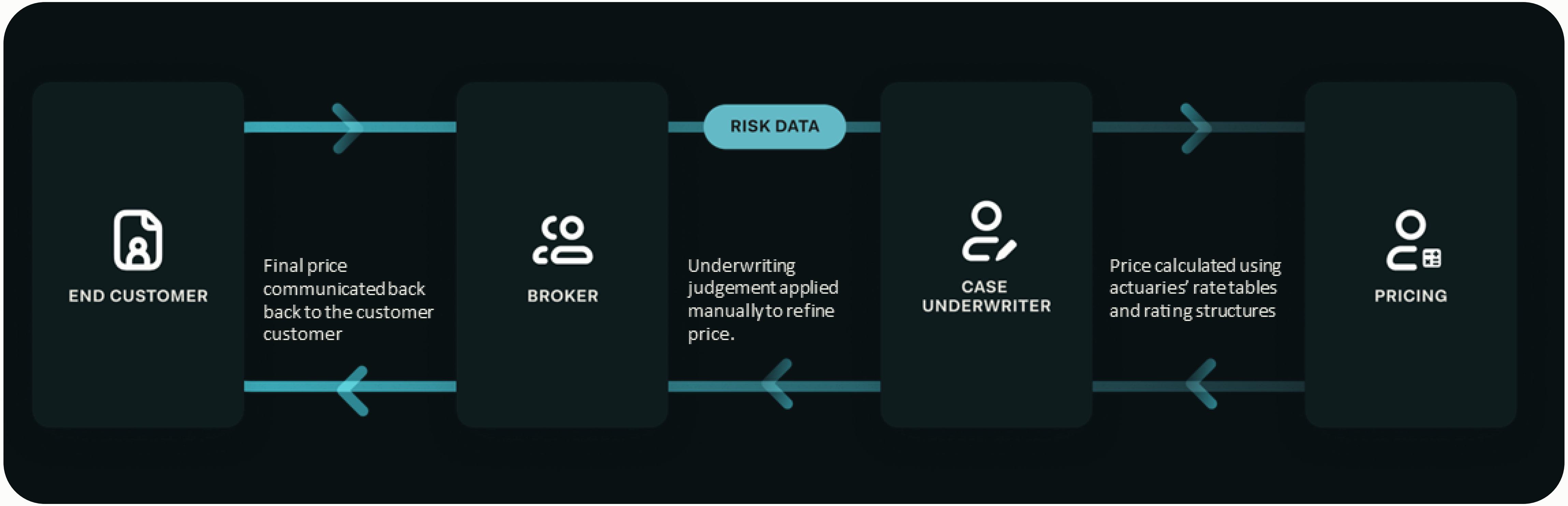
Traditional Broking



Traditional Operating Models

Problem Statements and Targets for Innovation

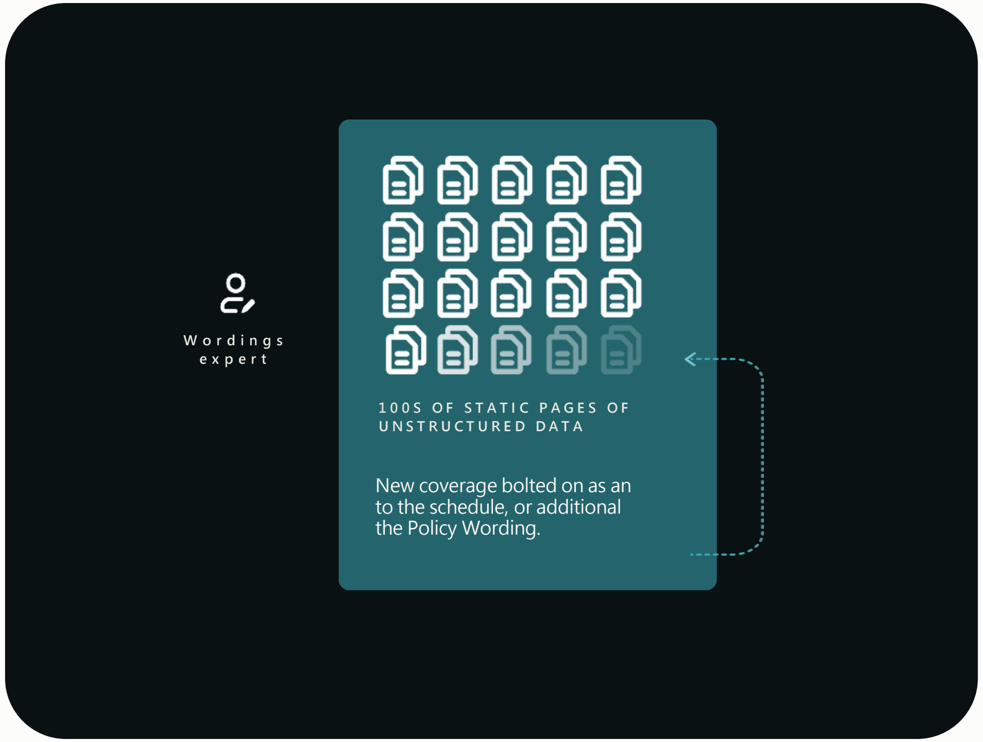
Traditional Underwriting



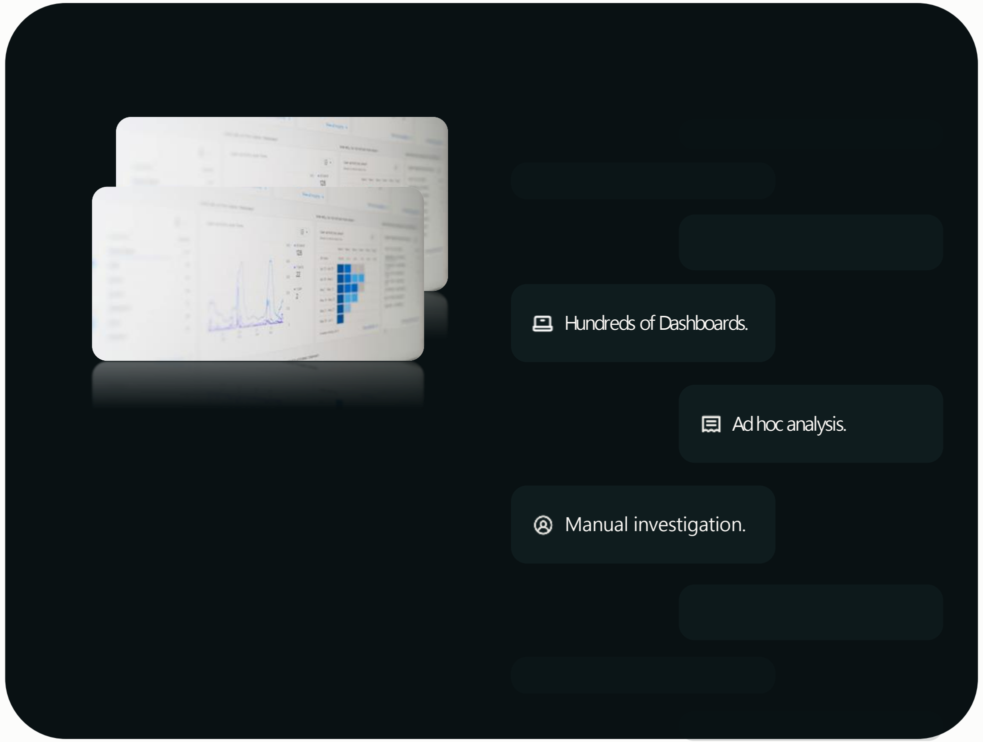
Traditional Operating Models

Problem Statements and Targets for Innovation

Product Development & Policy Wording Iteration



Portfolio Management



Traditional Operating Models

Problem Statements and Targets for Innovation

Traditional Reserving

RESERVING
Data Collection

→

RESERVING
Data Cleansing and and Prep

→

RESERVIN
Initial Reserve Estimations

→

RESERVING
Reviews and signs off off

Infrequent - 4x a year

Traditional Claims Handling

FNOL
Initial contact by policyholder

→

DATA COLLECTION
Claim registration and and data collection

→

VERIFICATIO
N
Coverage verification verification

→

ASSESSMEN
T
Claims extent of loss

→

SETTLEMENT
Settlement, & Closure

What is AI?

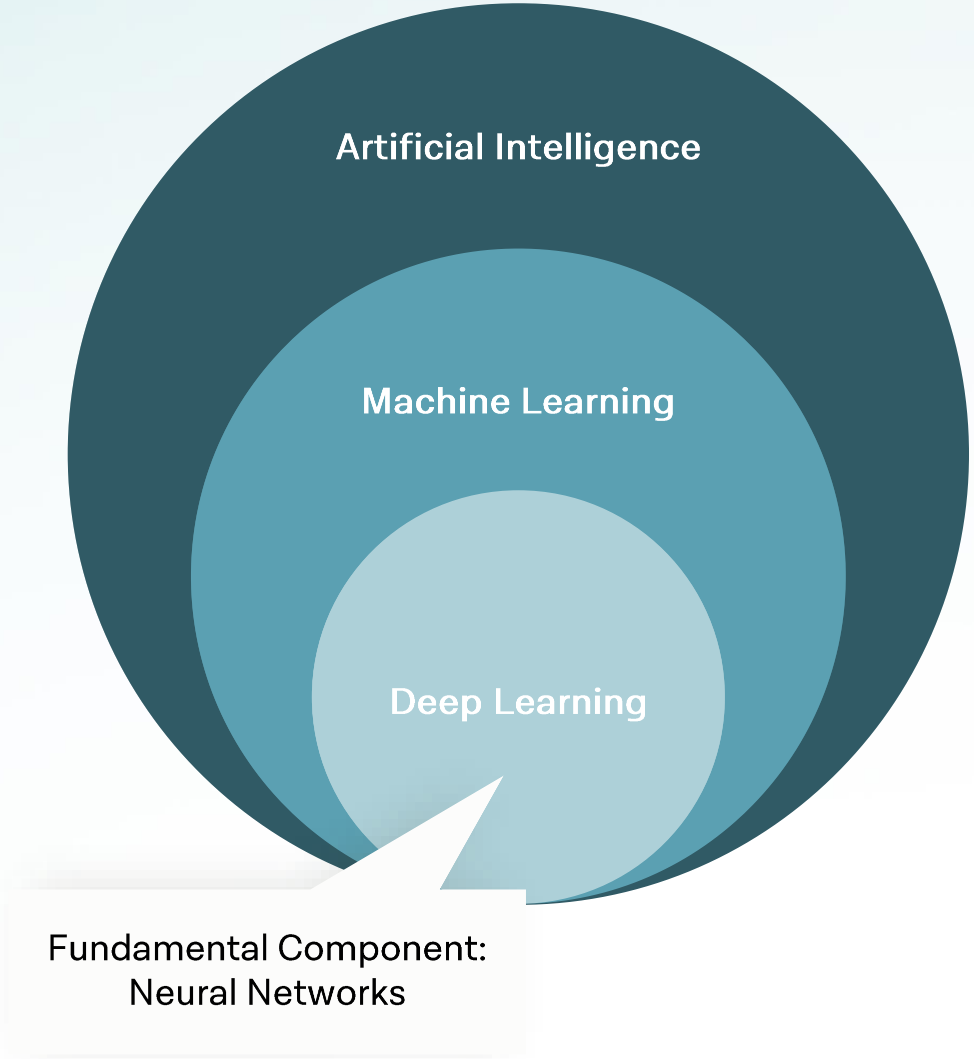
Definitions & Issues to tackle

Poll – AI

Which part of the insurance process would you most like AI to improve?

a. Customizing policies to fit customer's unique needs and offering real-time customer support and answering questions.
b. Streamlining the claims process for faster payouts.
c. Detecting fraud and preventing issues before they occur.
d. Handling everything! So we can lie on a beach, get paid, and chill—life goals!

The AI Landscape



Two fundamental approaches: the *"D&G"*

D Discriminative AI (‘traditional’ AI)

- Categorizes data by identifying patterns and learning the boundaries between different classes
- Handle typical classification and regression tasks
- Example popular model forms: KNNs, GBMs, Neural Networks (e.g., CNNs)

G Generative AI (GenAI)

- Learn to generate ***new*** contents based on training data by capturing the underlying distribution of training data
- Often leveraging Deep Learning models (Neural Networks) as the foundation

Common AI pain points

D

Discriminative AI (‘traditional’ AI)

- Not explainable
- Can easily lead to overfitting
- Usually required large labeled data
- …

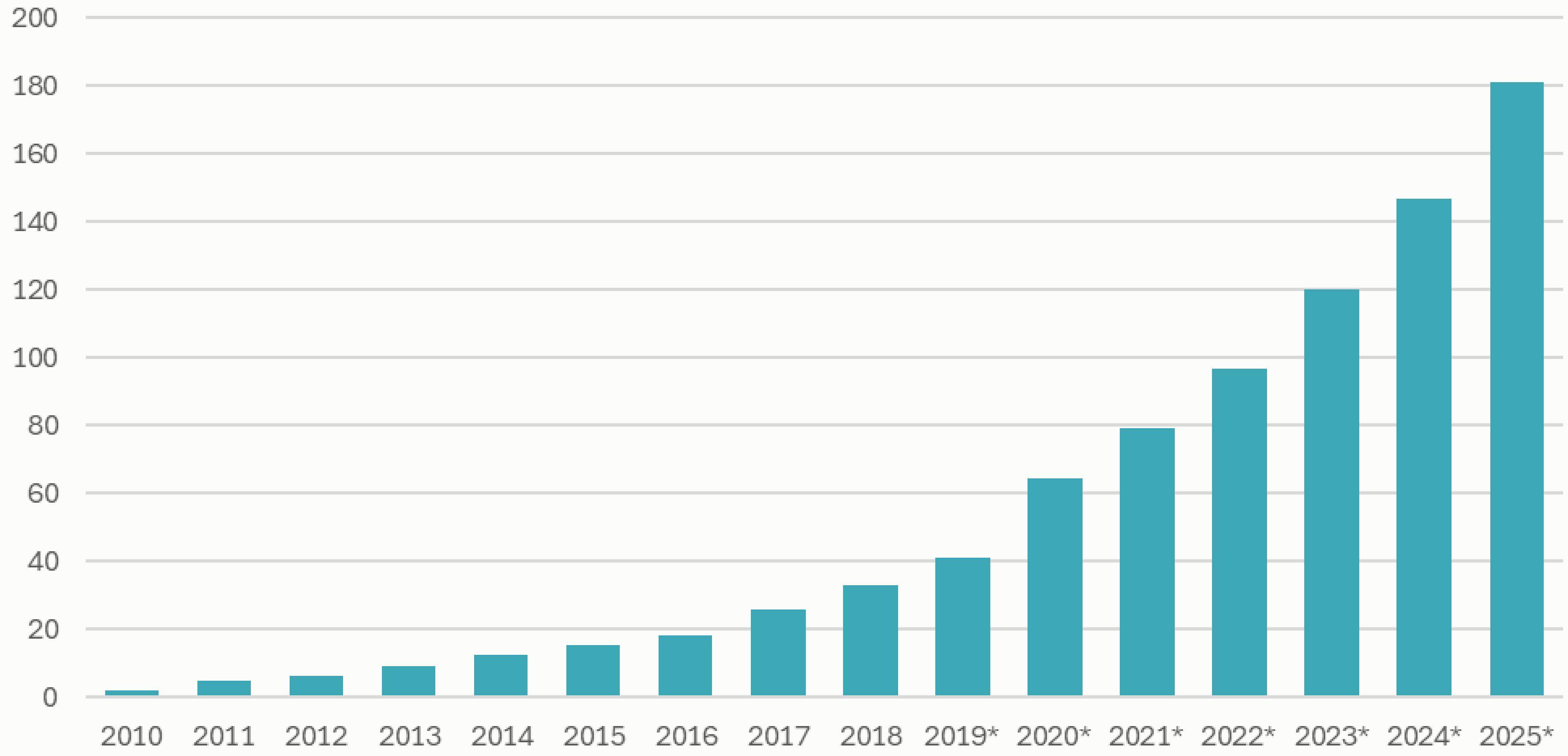
G

Generative AI (GenAI)

- Hallucinations
- Data Privacy Concerns
- …

The latest methods

D



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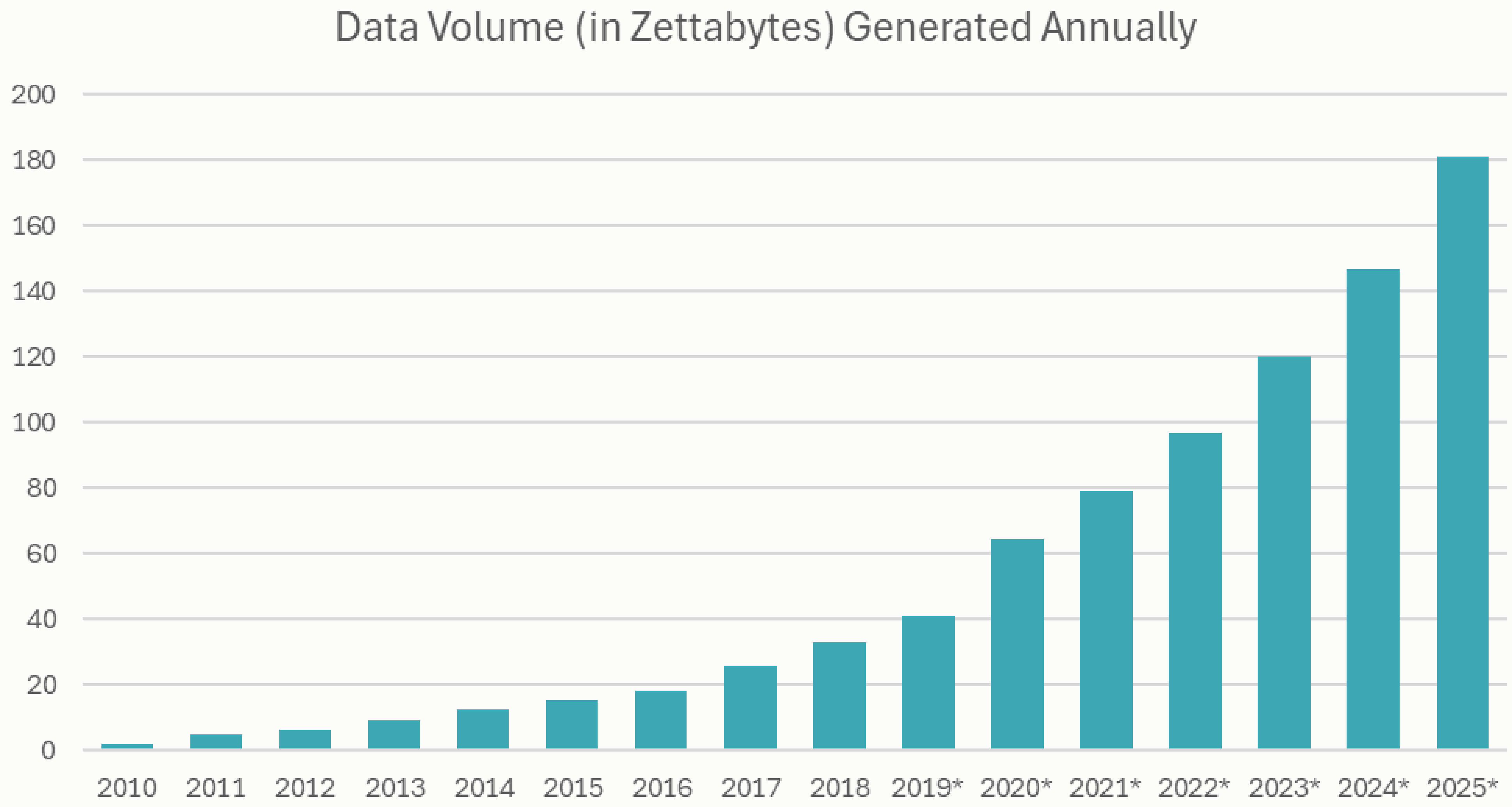
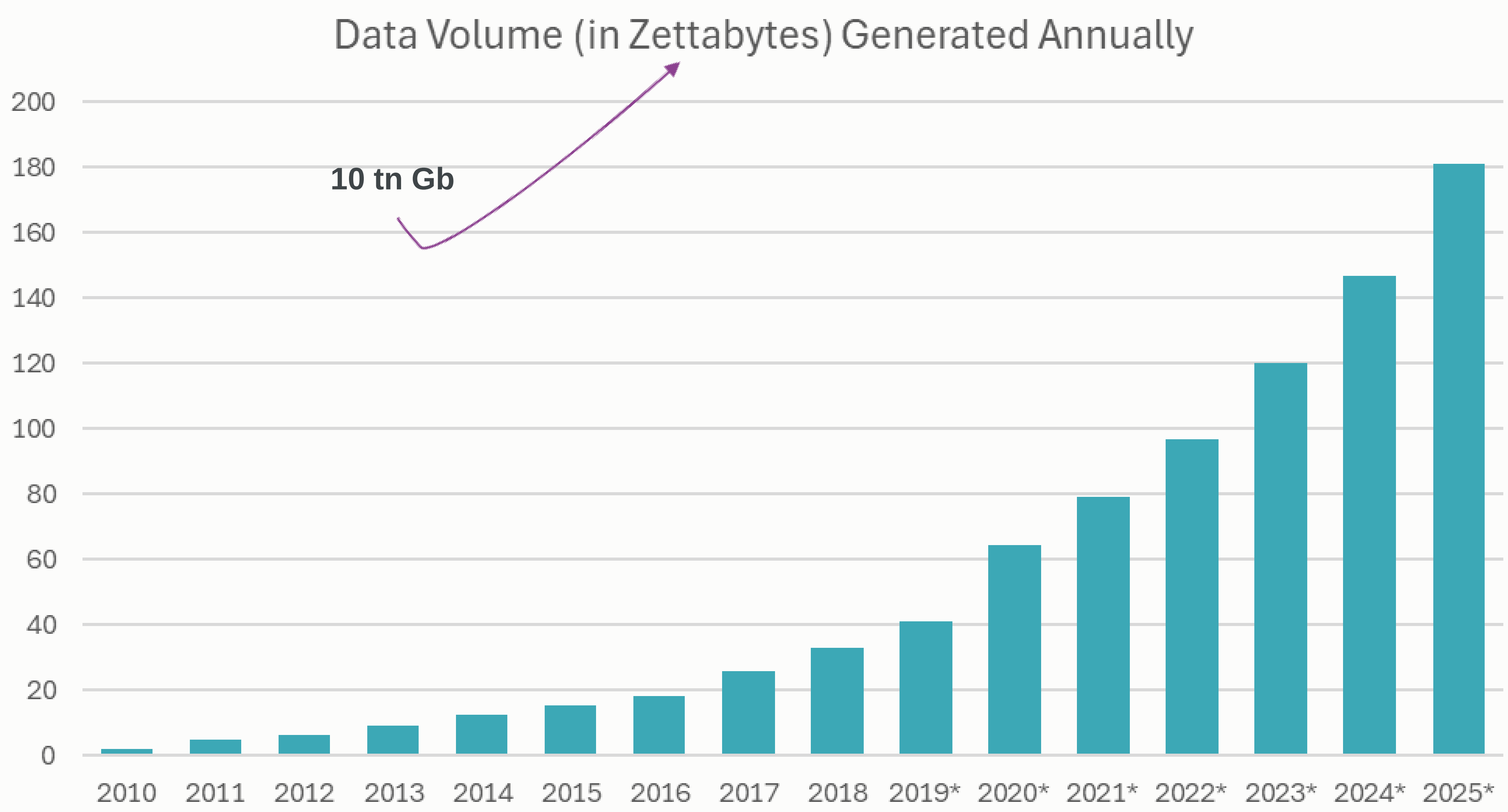


https://www.statista.com/statistics/871513/worldwide-data-created/



https://www.statista.com/statistics/871513/worldwide-data-created/

Challenges and Opportunities

Data Integration Complexity
(Managing diverse, growing datasets)

Legacy Systems Limitations
(Adapting outdated infrastructure)

Skills Gap
(Upskilling in ML and coding)

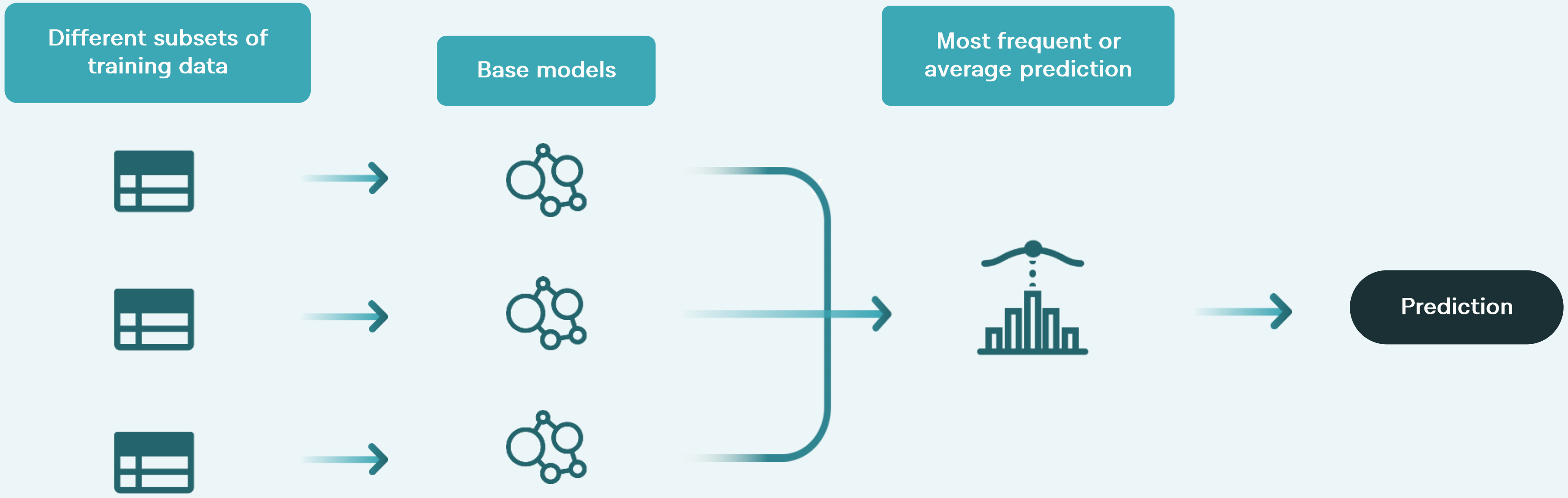
Enhanced Risk Insights
(Leverage advanced data analytics)

Innovative Pricing Models
(Precision through ML techniques)

Collaboration with Data Scientists
(Cross-disciplinary growth potential)

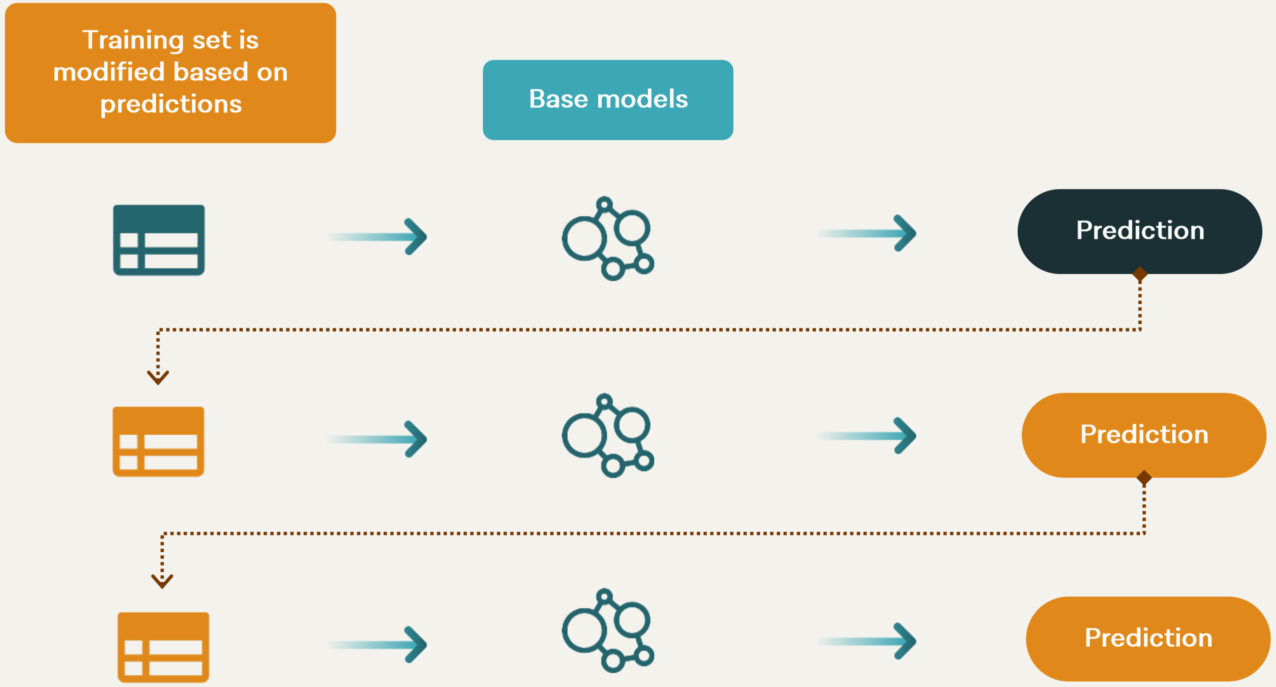
Ensembles

Bagging



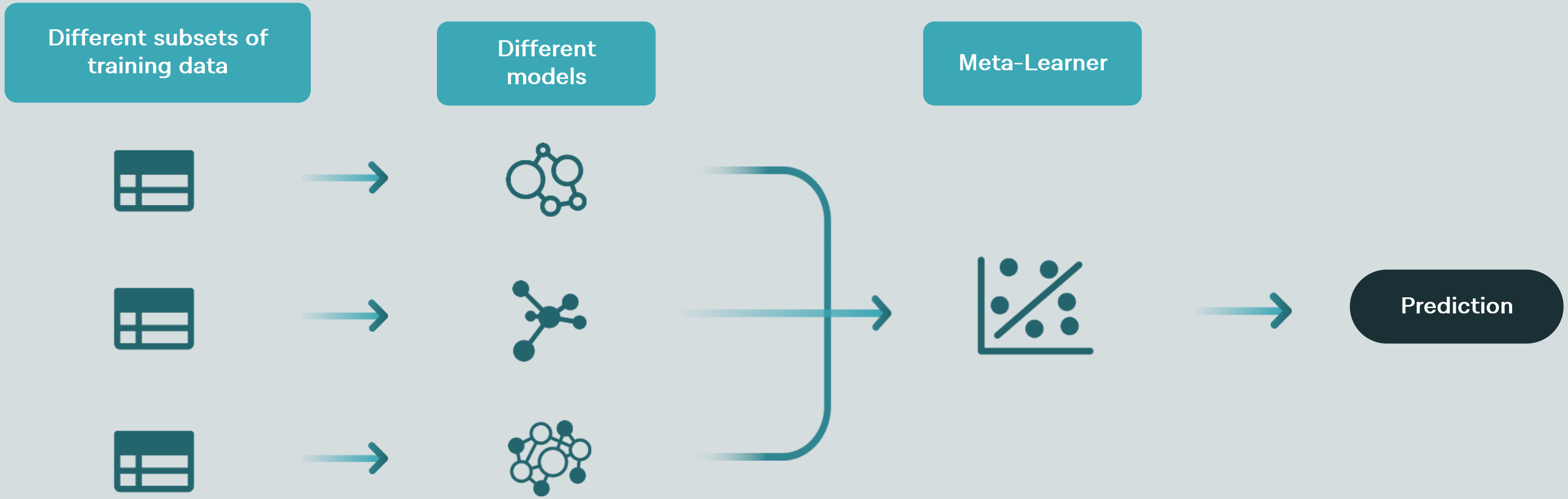
Ensembles

Boosting



Ensembles

Stacking



Ensembles – GLM/XGB

$$pred = pred_{glm} + pred_{xgb}$$

v

$$pred = pred_{glm} * pred_{xgb}$$

github.com/actuarial-data-science/CourseDeepLearningWithActuarialApplications/blob/master/1_glm/1_glm.pdf

Ensembles – GLM/XGB

$$pred = pred_{glm} + pred_{xgb}$$

$$pred = pred_{glm} * pred_{xgb}$$

Pinball Score shows improvement over a homogenous model

$$\mathrm{D}^2 = 1 - \frac{D_{model}}{D_{null}}$$

github.com/actuarial-data-science/CourseDeepLearningWithActuarialApplications/blob/master/1_glm/1_glm.pdf

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$$\mathrm{D}^2 = 1 - \frac{D_{model}}{D_{null}}$$

Model benchmarking – D^2

CV	GLM	S GLM	XGB
CV1	3.6%	8.1%	12.3%
CV2	3.2%	7.0%	11.6%
CV3	3.8%	8.1%	13.0%
CV4	3.5%	7.9%	12.7%
CV5	3.4%	7.6%	11.5%
Mean 〚D〛^2	**3.5%**	**7.8%**	**12.2%**

Folds: 3 to train; 1 to evaluate; 1 to test

github.com/actuarial-data-science/CourseDeepLearningWithActuarialApplications/blob/master/1_glm/1_glm.pdf

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Model benchmarking – D^2

CV	GLM	S GLM	XGB	GLM + XGB	GLM x XGB
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CV4	3.5%	7.9%	12.7%	9.8%	11.6%
CV5	3.4%	7.6%	11.5%	8.5%	11.1%
Mean 〖D〗^2	**3.5%**	**7.8%**	**12.2%**	**9.4%**	**11.6%**

Folds: 3 to train; 1 to evaluate; 1 to test

Ensembles – GLM/XGB

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CV4	3.5%	7.9%	12.7%	9.8%	11.6%	9.1%	11.7%
CV5	3.4%	7.6%	11.5%	8.5%	11.1%	8.4%	11.1%
Mean 〖D〗^2	**3.5%**	**7.8%**	**12.2%**	**9.4%**	**11.6%**	**9.3%**	**11.5%**

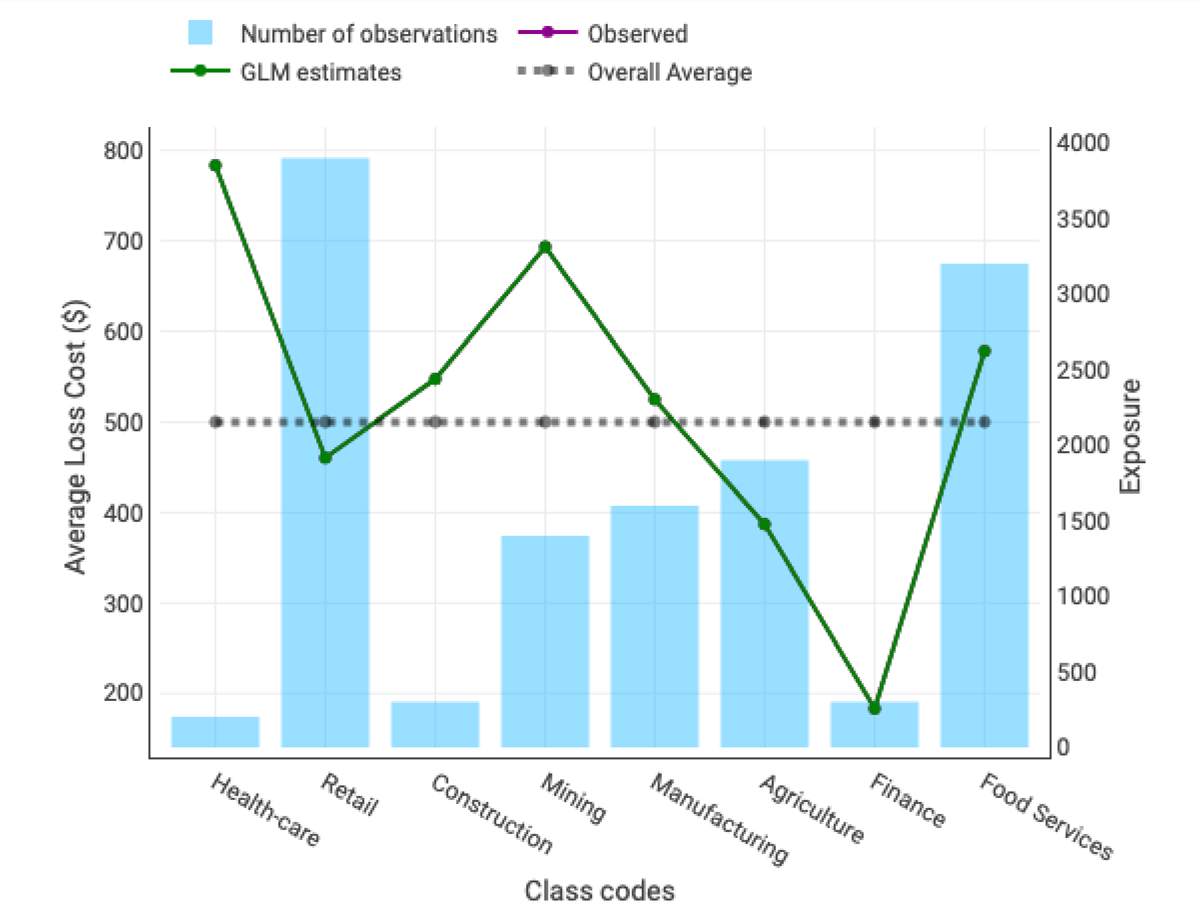
Folds: 3 to train; 1 to evaluate; 1 to test

github.com/actuarial-data-science/CourseDeepLearningWithActuarialApplications/blob/master/1_glm/1_glm.pdf

Another way to leverage AI in a transparent way: penalised regressions

- Automate model creation to achieve gains in speed & performance
- Retain upsides of coefficient-based structure:
    - auditability
    - editability
    - ease of operational deployment

What are penalised regressions?



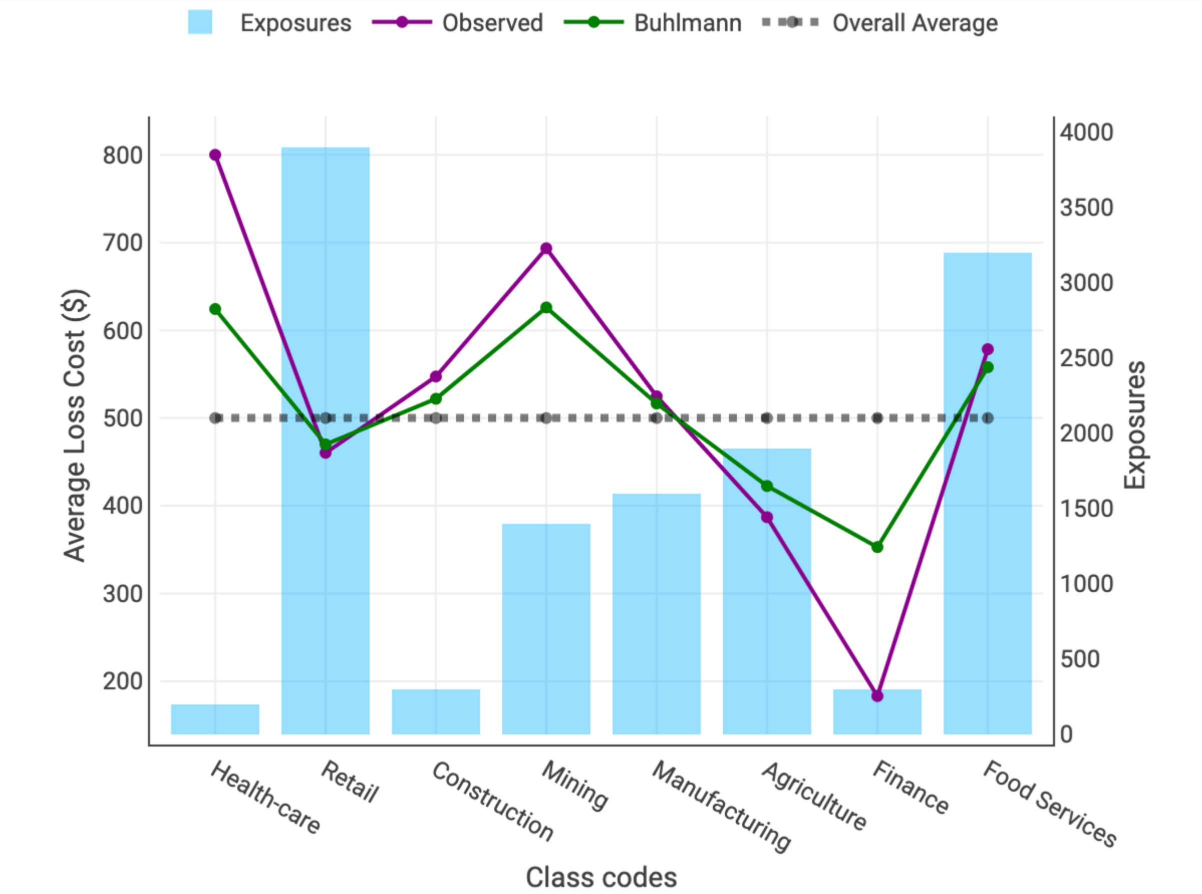
Standard GLM fit:

$$\beta^* = \text{ArgMax LogLikelihood}(\text{Obs}, \beta)$$

Full Credibility is given to the data

Estimates on low exposure segments can be volatile

What are penalised regressions?



Standard GLM fit:

$$\beta^* = \text{ArgMax LogLikelihood}(\text{Obs}, \beta) + \text{constraints}$$

- Partial Credibility given to the data
- More robust estimates
- Different types of constraints yield different types of estimates and behaviours

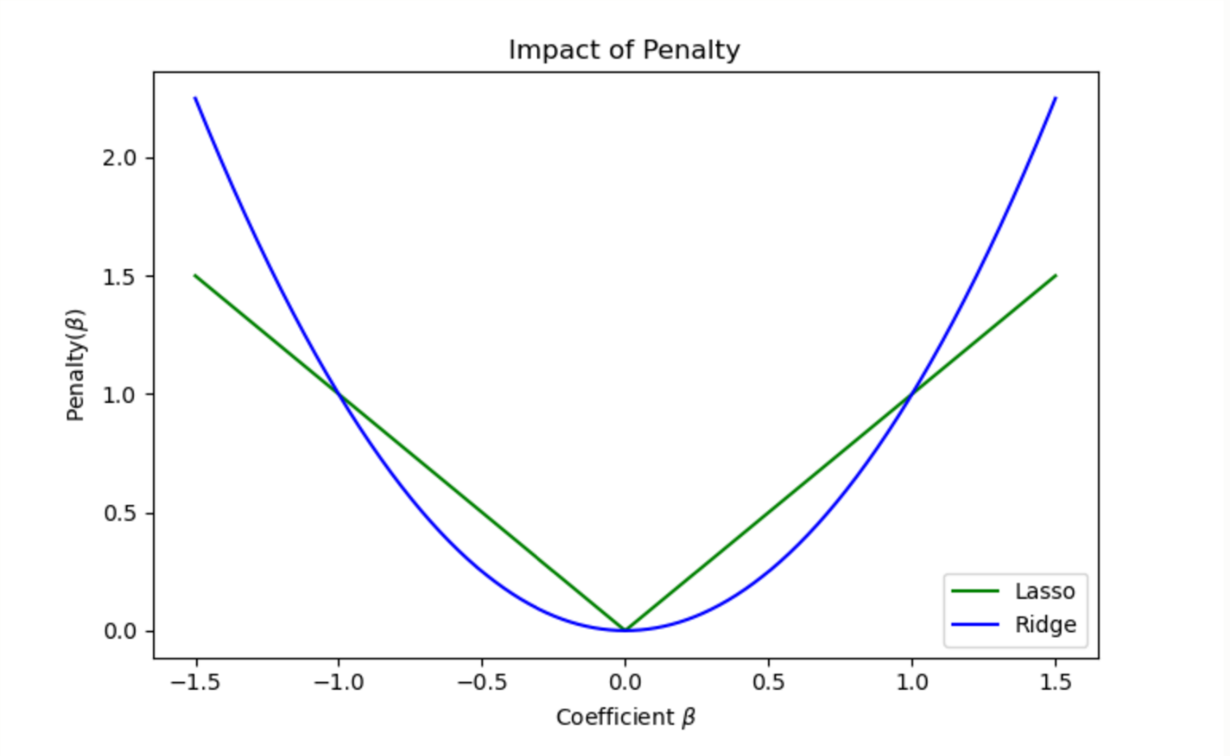
Penalisation regressions' loss functions

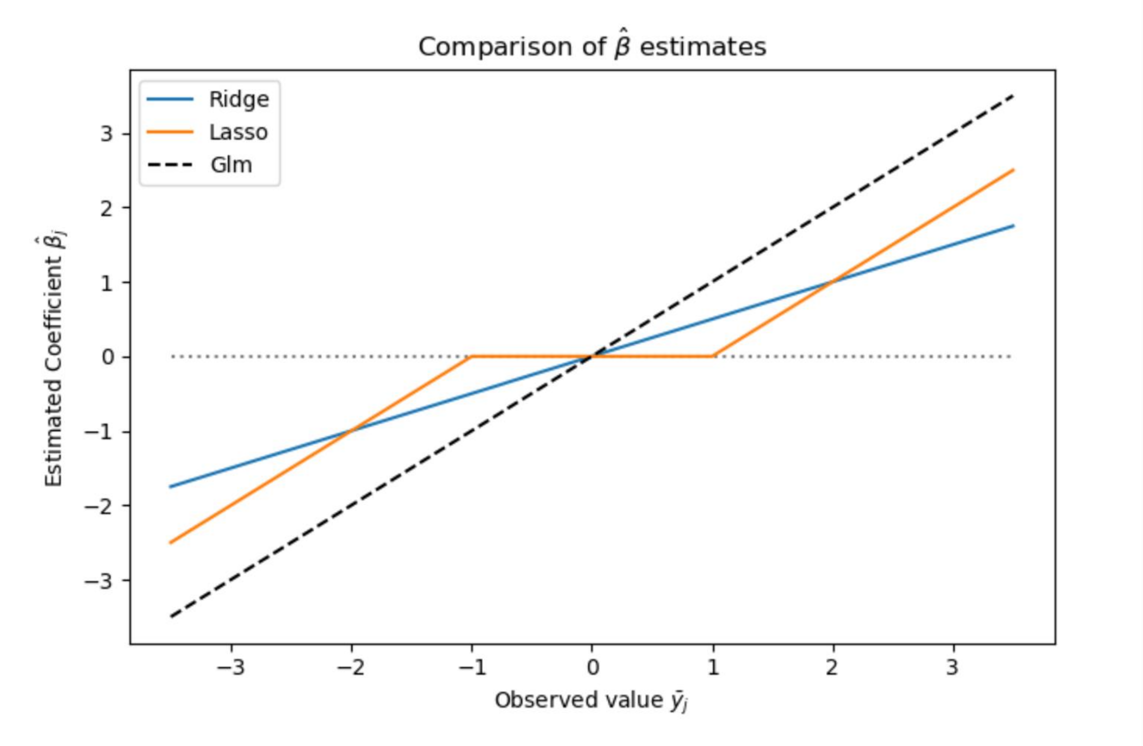
$$\beta^* = \text{ArgMax}\left(LL(Obs, \beta_i) - \lambda f(\beta_i)\right)$$

rewards fit close to the observations

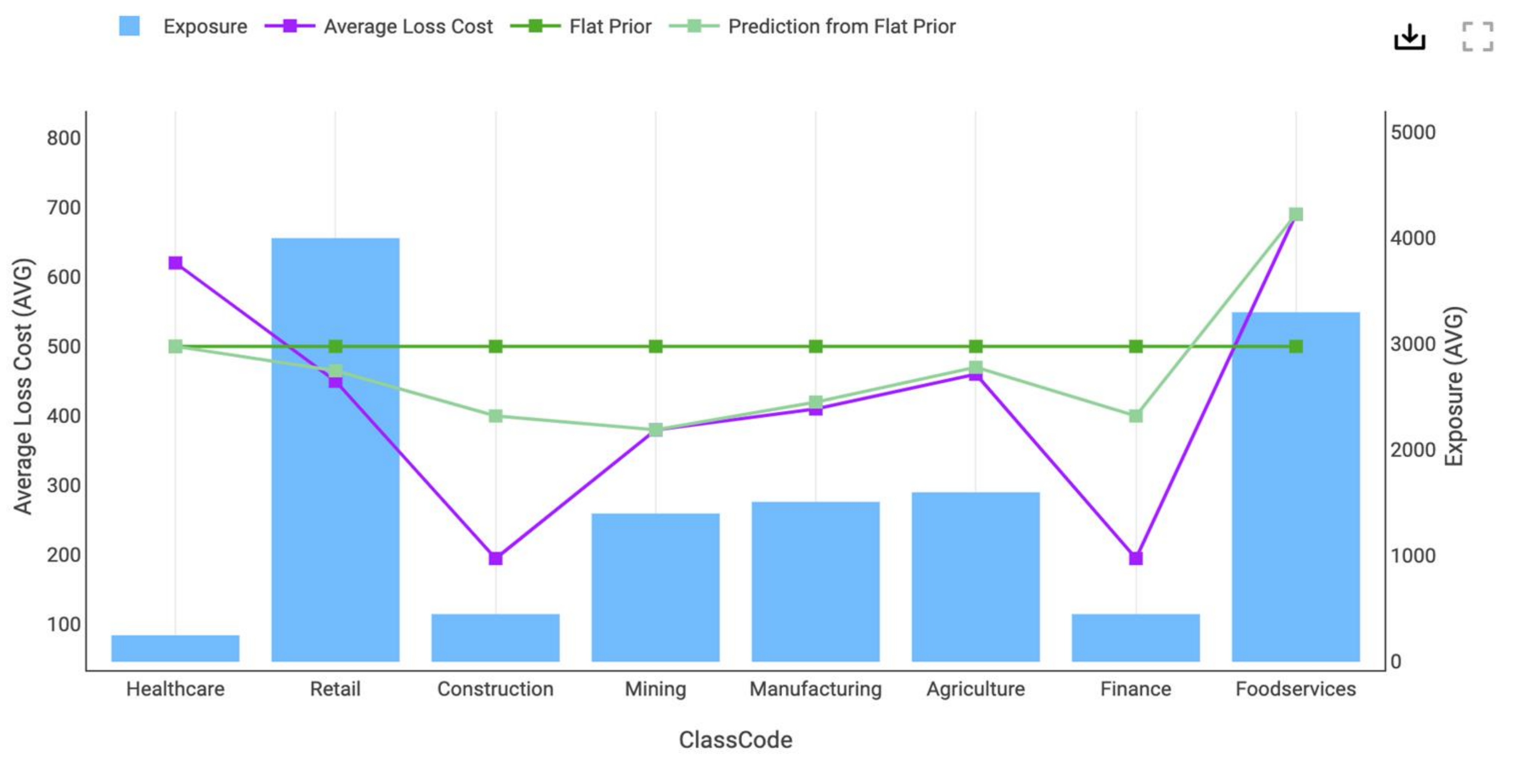
cost associated to the use of the betas

Usual penalty terms

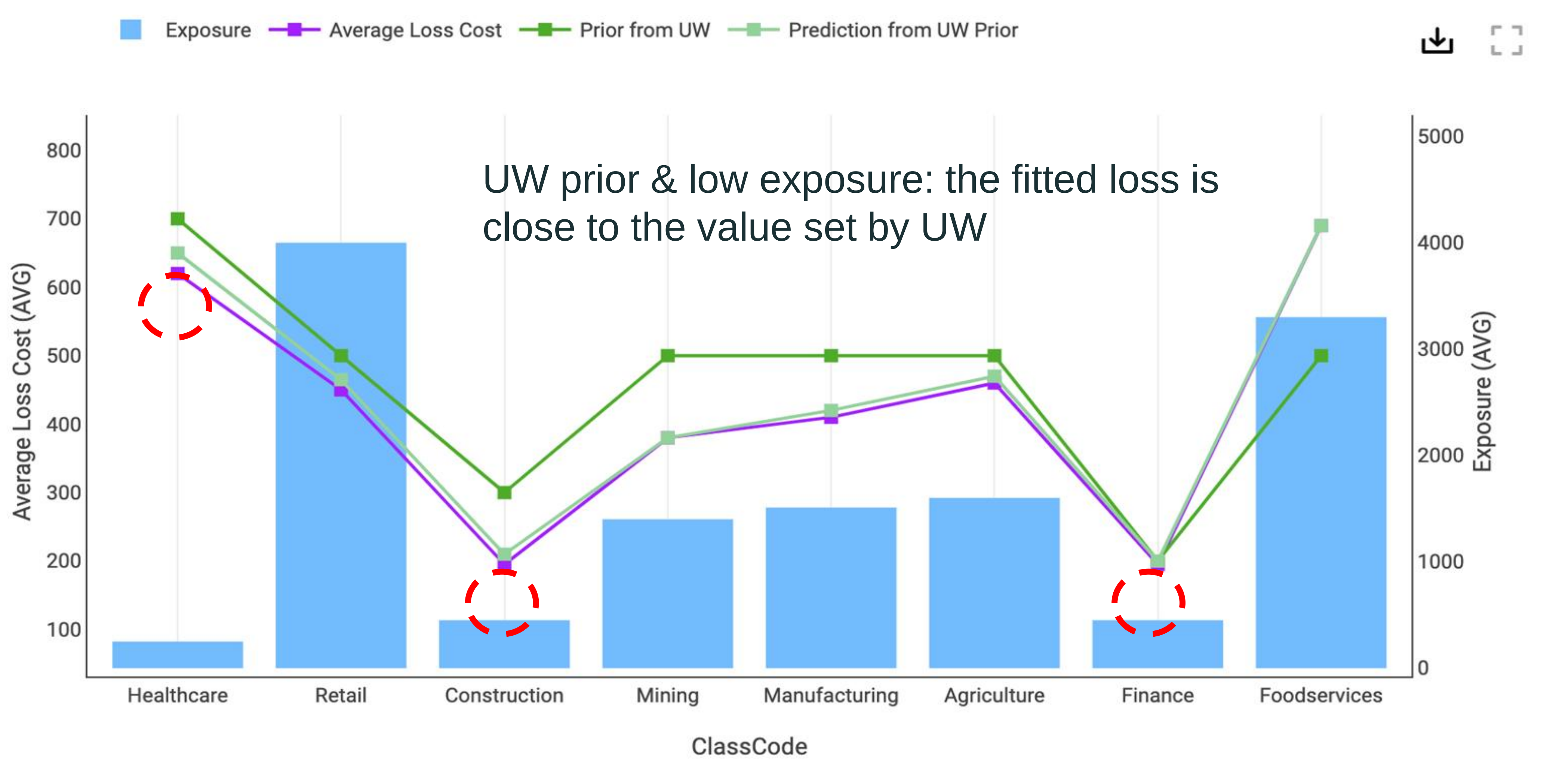




Penalisation against a prior



Penalisation against a prior



Properties of penalised regressions

Penalisation can natively deal with:

- Fitting with credibility (shrinkage)
- Variable selection (LASSO shrinkage)
- Dealing with correlations (shrinkage)
- Capturing non-linearities (LASSO on derivative)
- Interactions & Zoning (Regularisation can be extended to more than one dimension)
- Stacking models (penalisation against a prior - input or model)

For Commercial Lines

Penalisation methods help tackling common challenges in Commercial Lines:

- Small & Sparse datasets
- Need for manual adjustments into the models
- Use of model in production is straightforward

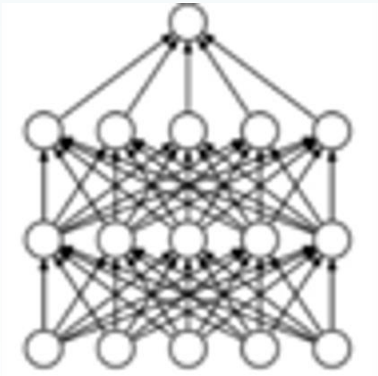
Generative AI methods

GenAI - specific category of foundation model called Large Language Models (LLMs)

Prompts

"Draw me a picture of multiple actuaries sitting in the room and watching the presentation Enhancing the Commercial Insurance Value Chain with AI and analytics"

LLMs



Completions

Here is the image depicting multiple actuaries in a room watching the presentation titled "Enhancing the Commercial Insurance Value Chain with AI and Analytics." The setting captures the professional and collaborative atmosphere you described.

- Ability to ingest and work with different types of data: Text, images, audio, visual, etc.
- Inputs and outputs can both be of different modalities (e.g. text-to-image)
- Inputs and outputs can accept multiple modalities at the same time (e.g. a mix images and text)

Large Language Models (LLMs) Traditional Approach:

Pre-trained vs Fine-tuning vs In-Context Learning

Pre-training:

- Foundation for the different NLP tasks, gives model an understanding of language
- Self-supervised: by learning from vast amounts of text data generating labels from the data itself
- Keywords: Next Token Prediction, Masked Token Prediction, Entailment

Fine-tuning:

- Supervised Fine-Tuning (SFT): Training the pre-trained LLMs on datasets with labels for specific tasks
- Reinforcement Learning (RL): Aligns model to a specific task using a reward model
- Keywords: Supervised Fine-Tuning (SFT), Reinforcement Learning Human Feedback (RLHF), Direct Preference Optimization (DPO)

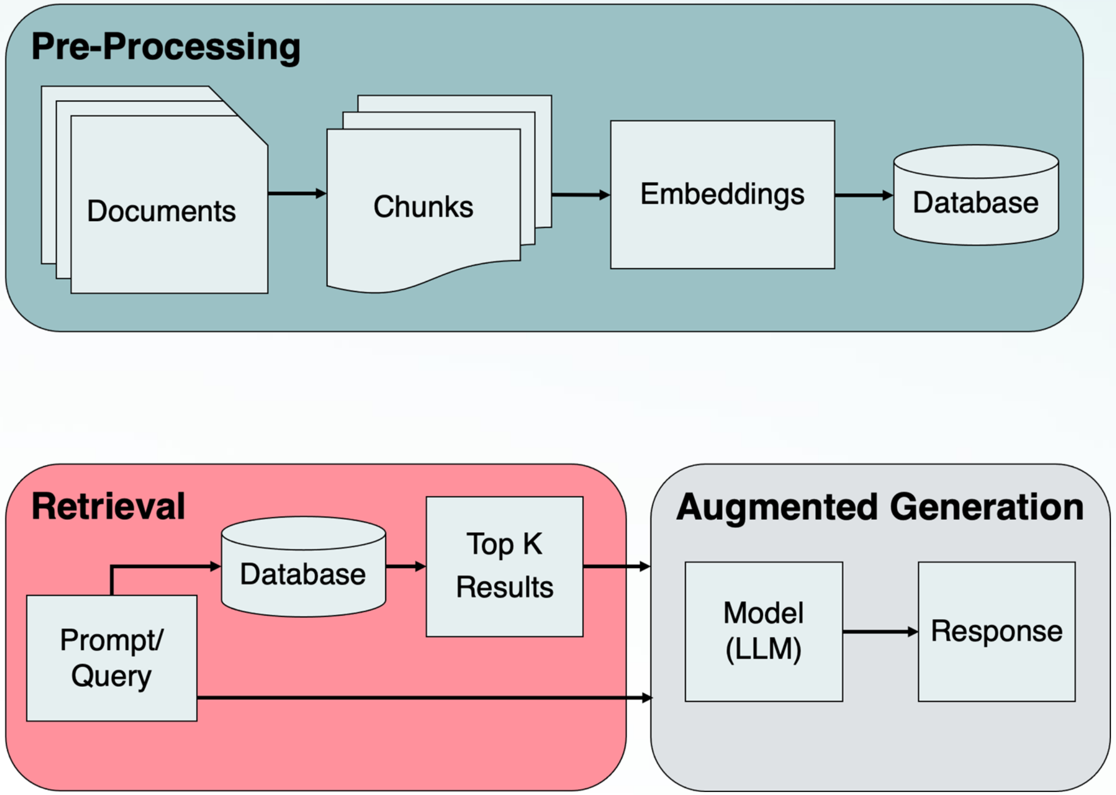
In-Context Learning:

- Let the model learn the task through the prompt (context) without any weight updates
- Prompt Engineering: Incorporating examples in prompts and/or task-specific instructions
- Keywords: k-shot learning, 0-shot learning, few-shot learning, soft prompting/prompt tuning

Large Language Models (LLMs)

Alternative - Retrieval Augmented Generations (RAG)

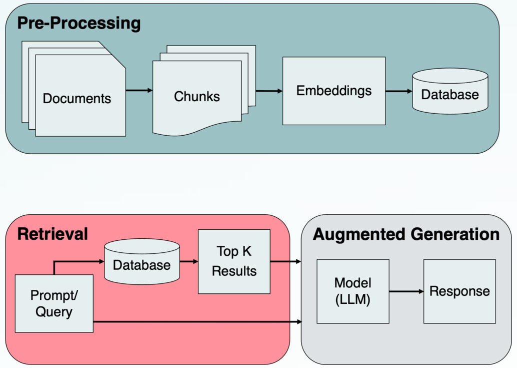
- **Mechanism:**
  - 'Retrieval-Augment': LLM first retrieves content from a collection of information (e.g. relevant documents or data) that is relevant to the user's query
  - After the retrieval-augment process, prompt will then contain three parts to feed into LLM for a more accurate response:
    - — The instruction guiding model to retrieved content
    - — The retrieved content
    - — The user question (original prompt)
- **Reduce hallucinations:**
  - Grounding their responses in verifiable retrieved information rather than internalized information it learned during training only
  - Provide more up to date responses and information or know when to say 'I don't know' rather than making up answers



Large Language Models (LLMs)

RAG end-to-end process

RAG Pipeline → Evaluation → Consider Fine-Tuning LLMs? → Deployment and Monitoring

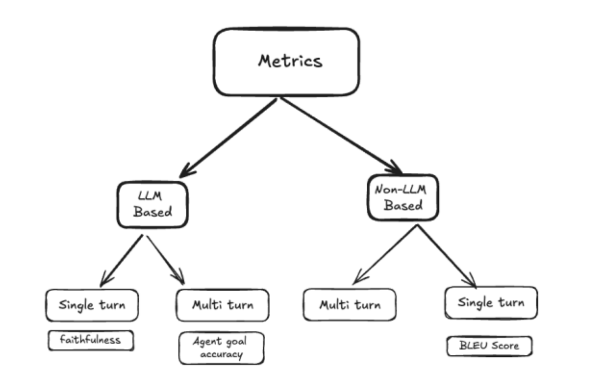


LangChain

Suited for applications requiring complex interaction and content generation

LlamaIndex

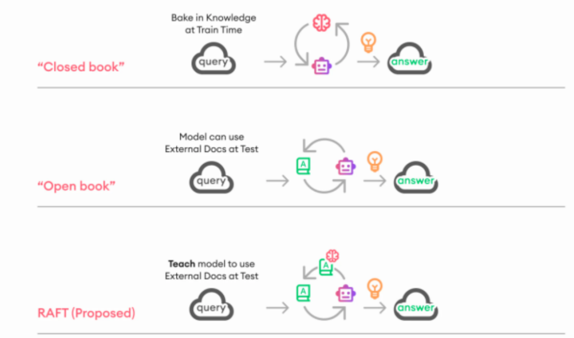
Optimized for search and retrieval tasks



Source: ragas

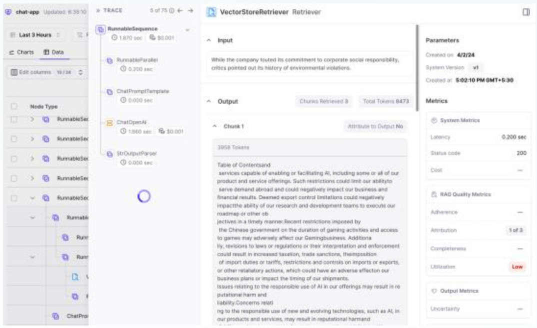
Example package:

- ragas,
- tonic-validate,
- llama_index.evaluation
- ....



Source: RAFT: Adapting Language Model to Domain Specific RAG

'RAFT' - Retrieval-Augmented Fine-Tuning



Source: Galileo

The future Commercial Insurance Landscape using these techniques

Rethinking the traditional data extraction process?

- Often, after receiving the policy proposal form, which is always in pdf format, underwriters have to manually type the information into the system, this can easily lead to **human errors** and this **process is cumbersome and manual.**

- Alternatively, can leverage GenAI for possible automations:

    - RAG pipeline:
        - Convert the pdfs into images and save them in private storage - one image represents one page
        - In the example below, LlamaIndex was used since it's optimized for simple retrieval tasks
        - Underlying LLMs: GPT-4o for multimodality
        - Design prompts carefully for each question for retrieval
        - For complex information retrieval, such as charts, better retrieval results can be achieved by cropping the target tables from the image with necessary transformation adjustment
        - Information will be then retrieved from the images, and the entire process provides greater control on data privacy
    - Evaluation
    - Fine-tuning LLMs? - not needed in this case
    - Deployment and Monitoring

PROFESSIONAL INDEMNITY INSURANCE
PROPERTY PROFESSIONALS AND CHARTERED SURVEYORS (EXCLUDING MARINE AND ENGINEERING), QUANTITY SURVEYORS, AUCTIONEERS, VALUERS AND ESTATE AGENTS PROPOSAL FORM

A FULL POLICY WORDING IS AVAILABLE ON REQUEST

Please complete and tick boxes as appropriate. If there is insufficient space to provide answers to the proposal form questions, please use the ADDITIONAL INFORMATION section at the end of the form.

In this proposal we use the term 'Principal' to mean any sole principal, partner, director or member of a Limited Liability Partnership.

Reference to 'Proposer' 'You' or 'Your' in this proposal shall include all names included under question 1 who will be the Insured in the insurance policy.

Please ensure that **all** relevant sections of the Proposal are completed.

1. a. Name under which business is conducted: ('You')

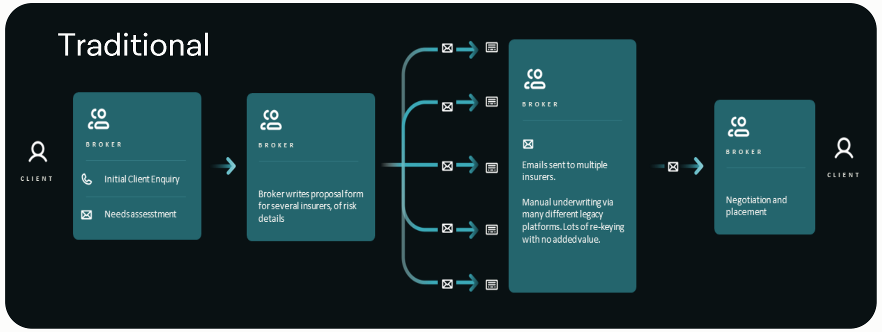
   Tuhao Zhu

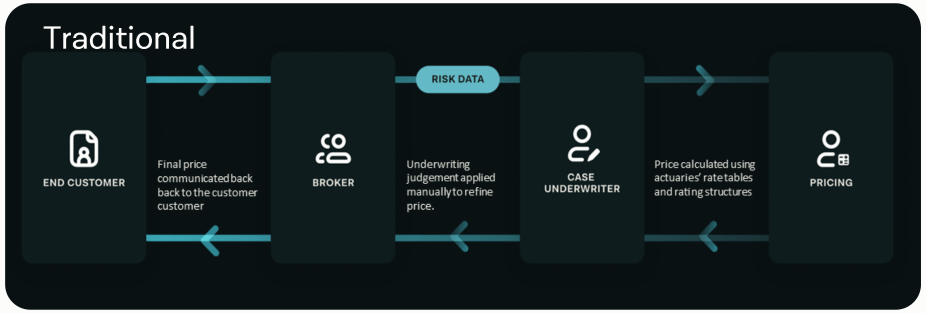
   b. Are you 'Regulated by RICS'? Yes ✔ No ☐

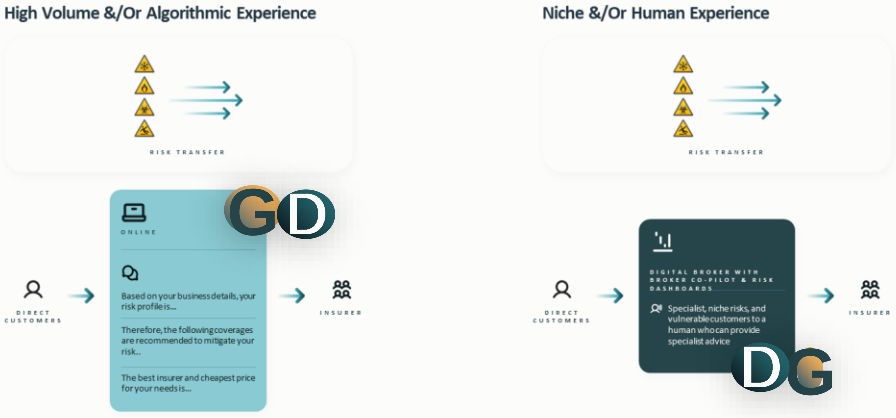
2. Addresses of all of your offices & percentage of total fees in each

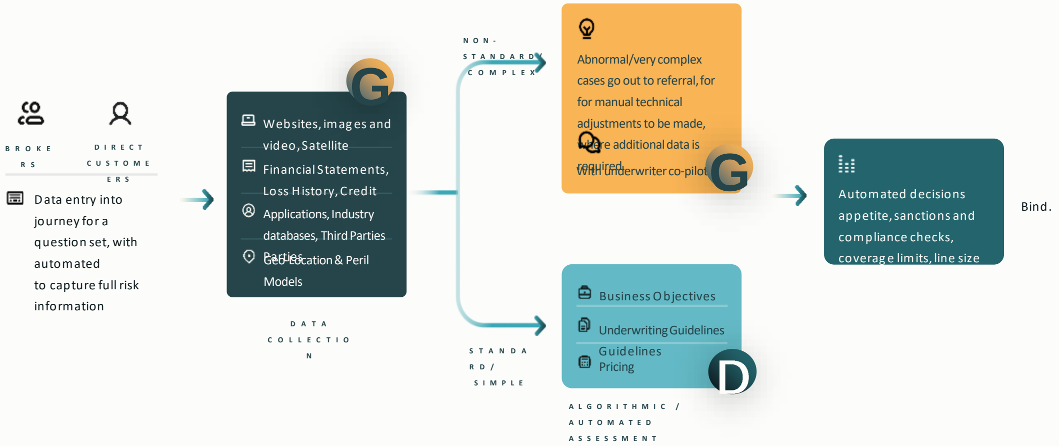
   Wembley Park, Wembley

Future of Broking & Underwriting





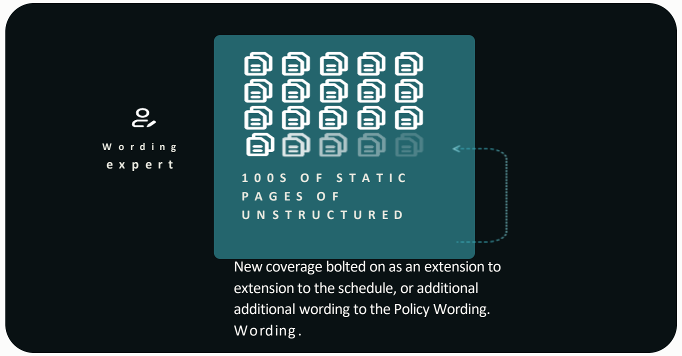


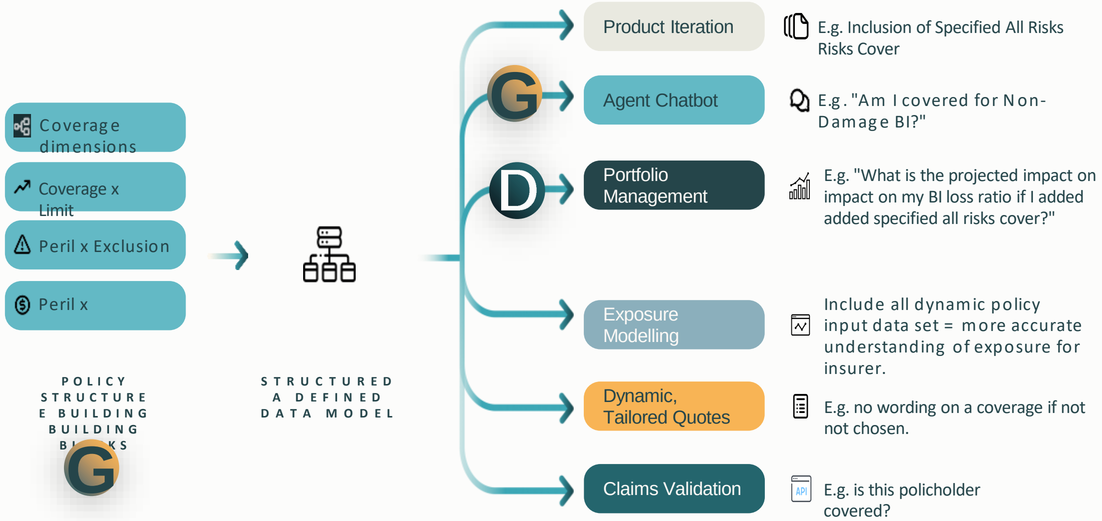


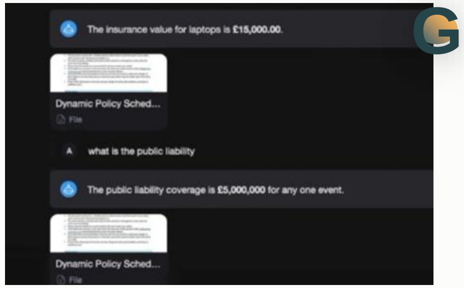
Future of Wordings

Enhanced Product Innovation, Portfolio Management, Claims Validation and Exposure Modelling

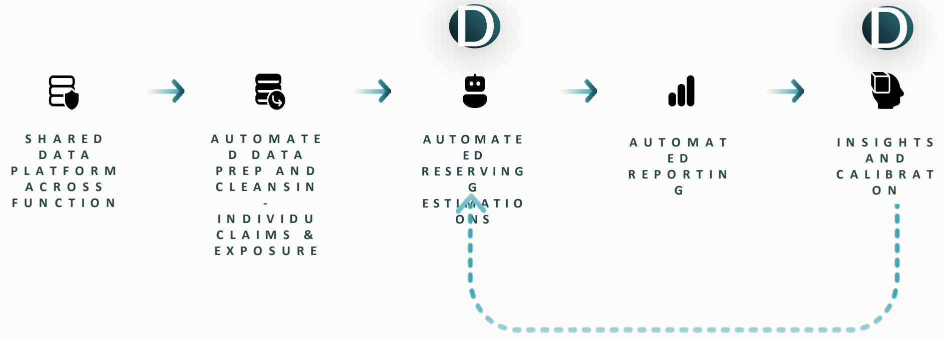
Traditional







Future of Reserving



Future of Portfolio Management

Summary

Main Issues in CLines

Lack of clean, standardised data available

Inefficient and manual processes

Expensive

Legacy systems

Silo'd functions and data

Heterogenous data

AI Techniques

Discriminative AI

- categorizes data by identifying patterns and learning boundaries between classes for tasks like classification and regression.

Generative AI

- generates new content by capturing the underlying distribution of training data, often using deep learning models as a foundation.

Opportunity

Enhancing **data capture**, and **analyse large amounts of data at speed**.

Reducing re-keying.

Automating traditionally manual processes.

Shifts focus to **insights** rather than process delivery.

New practice areas for actuaries and data scientists.

Poll – post presentation

Which area of commercial insurance do you think will see the most transformative impact from AI and analytics in the next five years?

a. Broking
b. Underwriting
c. Product Development & Policy Wording Iteration, and Portfolio Management
d. Reserving

Q&A

Thank you.

Questions & Comments

Expressions of individual views by members of the Institute and Faculty of Actuaries and its staff are encouraged. The views expressed in this presentation are those of the presenter.