

PRICING AND RESERVING LIFECYCLE

MACHINE LEARNING APPLICATIONS

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ABOUT OUR SPEAKER



Neil Covington

Global Head of General Insurance and
AI/ML Lead, FIS

With 30 years of industry experience, including serving as Chief Actuary and Head Actuary for multi-line, multinational businesses, Neil Covington's expertise covers the design, development and implementation of risk models.

With a knack for translating complex concepts to diverse audiences, Neil specializes in capital modelling, IFRS 17, reserving, pricing and AI/ML. At FIS, he is also responsible for global GI and AI/ML insurance solutions management and development, alongside pre-sales and professional services support.

FINTECH THE FINANCIAL WORLD IS BUILT ON

ECONOMIES RELY ON FIS

Trusted to move the world's money.

\$40T

was processed on our asset management technology in 2022. That's nearly half the world's total and 1.5x the GDP of the U.S.

FIS TODAY

BUSINESSES RUN ON FIS

Our business is powering business

95%

of the world's best banks use our technology

\$112B

Processed in transactions last year

80%

of the largest asset managers

200K+

Clients worldwide rely on our technology

\$9.8B

REVENUE

\$38.1B

MARKET CAP

INNOVATORS BUILD ON FIS

We are the innovator's innovator

50%

of the world's most innovative companies are clients or partners

100%

carbon neutrality and renewable energy by 2025

FIS INSURANCE RISK SUITE

TRUST

34+ years
10,000+ users
70+ countries

RELIABLE

4.73T managed Net
Written Premiums

COMPLETE

Life, Health, General and
Annuity

REDUCE

the total cost of owning
digital technology

GAIN

economies of scale with
outsourced services

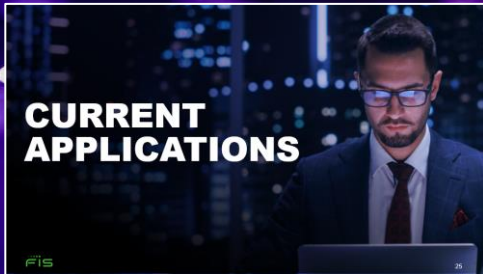
IMPROVE

efficiency and save money
on business processes



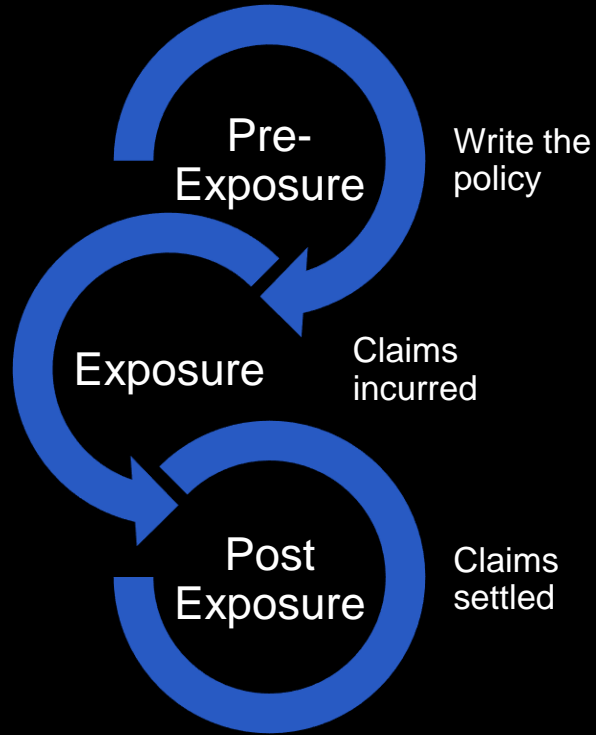
**GENERAL INSURERS,
WE HAVE YOU
COVERED....**

CONTENTS



POLICY LIFECYCLE

POLICY LIFECYCLE



POLICY LIFECYCLE



Pre-Exposure

Price
GLMs, GAMs
Frequency and severity all periods



Post Exposure Pre-Claim

IBNR
Paid, incurred, frequency, severity triangles
Frequency and severity this period



Post Exposure Post Claim

RBNS/Case, IBNER
Paid, incurred triangles
Severity this period, this claim

POLICY LIFECYCLE



Pre-Exposure

Pricing




Post Exposure
Pre-Claim

Reserving



Post Exposure
Post Claim

Reserving

A man in a blue shirt is shown in profile, looking towards a server rack in a data center. The background is filled with bokeh lights in shades of blue and yellow. The text "PREDICTIVE MODELLING FRAMEWORK" is overlaid in large, white, bold letters.

PREDICTIVE MODELLING FRAMEWORK

PREDICTIVE MODELLING

What is it?



Uses statistics to predict outcomes



Given predictor variables what is an outcome



Synonymous with machine learning



Often referred to as predictive analytics

**Predictive
modelling**

Uses a statistical model to predict a future event or outcome based on known data.

**Predictive
analytics**

Typically refers to analysing historical data about events to make predictions about the future.

PREDICTIVE MODELLING

Continuous – Regression



RISK COST



CLAIM
COST

PREDICTIVE MODELLING

Discrete – Classification



ACCEPT RISK



FRAUDULENT
CLAIM



MANAGE OR
PAY CLAIM

PREDICTIVE MODELLING FRAMEWORK

Question



Model-Building
and Testing

Uncertainty
Evaluation

PREDICTIVE MODELLING FRAMEWORK

Pre-exposure

Question

What is *the total* claim cost

Model-Building
and Testing

GLMs, GAMs

Uncertainty
Evaluation

Model testing, validation

PREDICTIVE MODELLING FRAMEWORK

Post exposure, pre and post claim

Question

What is *this* claim cost

Model-Building
and Testing

Triangles

Uncertainty
Evaluation

Residuals, actuals vs expected

A woman with dark hair and glasses is shown in profile, looking upwards and to the left. She is positioned in front of a large digital display. The display features a globe in the center, surrounded by various data visualizations including line graphs with red and green lines, and bar charts with yellow bars. The background is dark, suggesting a control room or data center environment.

MODEL PREDICTORS AND PREDICTIONS

MODEL PREDICTIONS

What affects the outcome?

Cause



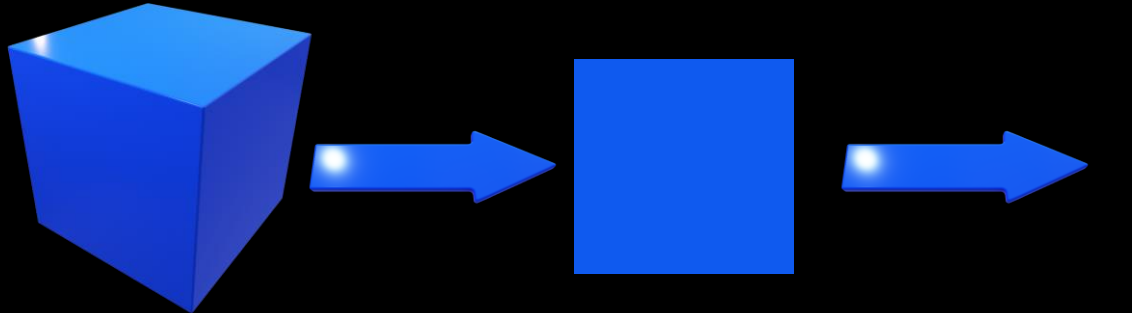
Effect



DIMENSIONALITY REDUCTION

What really matters?

- Transformation of data from a high-dimensional space into a low-dimensional space
- Low-dimensional representation retains some meaningful properties of the original data
- Converging to intrinsic dimensions
- Dimensions for shape or colour?
 - Shape requires all dimensions
 - Colour only requires one



DIMENSIONALITY REDUCTION

Features

Feature Selection

Find a subset of features

- Filter
- Wrapper
- Embedded (try it and see)
e.g. GLM factor regression

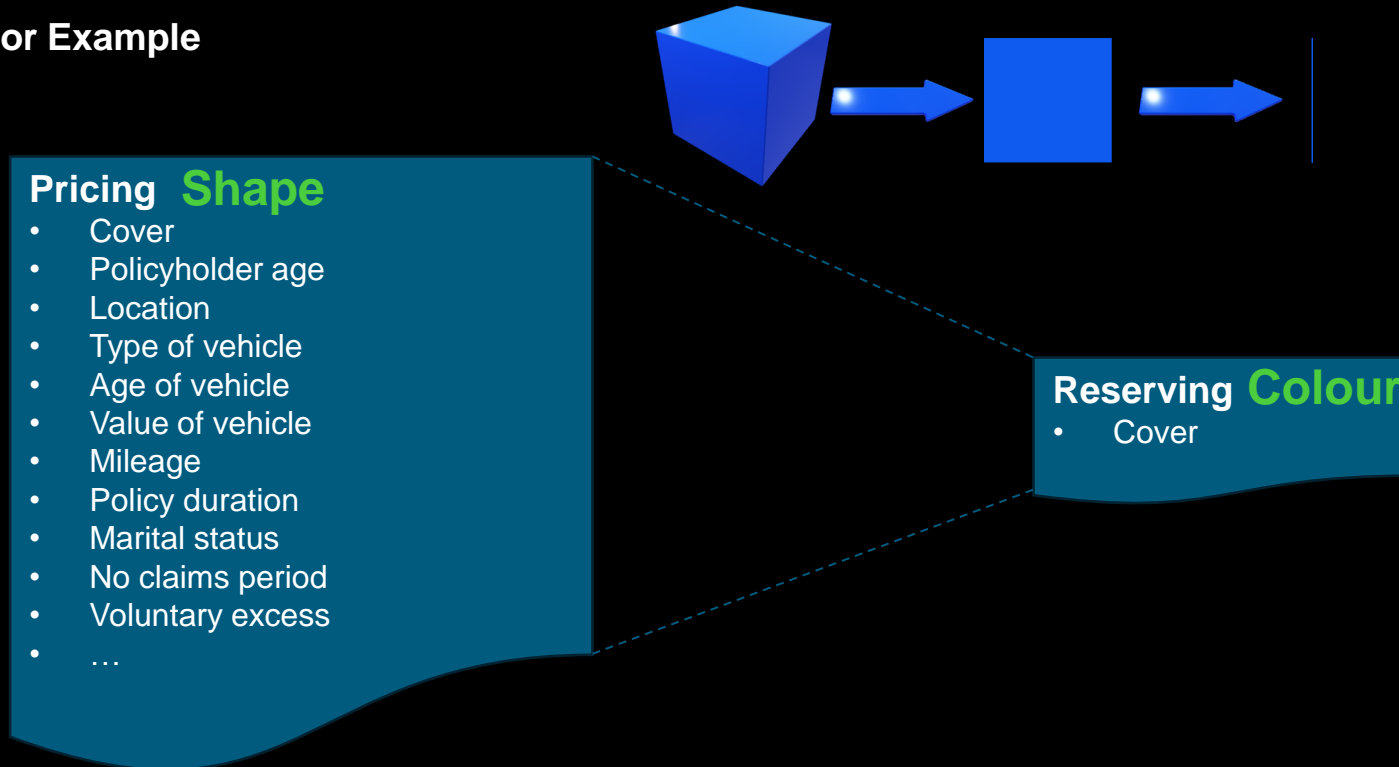
Feature Extraction

Transform the data

- Linear e.g. Principal Component Analysis
- Non-Linear e.g. Autoencoder, Clustering

MODEL PREDICTORS

Motor Example



MODEL TYPES

Forecast

- One of the most prominent predictive model types
- Predict future values based on historical data
- Manage metric value predictions by estimating the numeric value for new data based on learnings from historical data.

Classification

- Used to assign classes to data
- Generally easier and more cost-effective to implement than predicting continuous values
- Examples of these types of models include binary, multi-class and regression models

Outlier

- Used to identify anomalous data points that do not fit the pattern of the rest of the data
- For example, an outlier model might be used to identify incorrect credit card charges or other fraudulent numbers
- It would look at individual data points to determine whether they are incorrect compared to the rest of the data

Time Series

- Used to predict future events based on past data ordered in a sequence
- It is an econometric technique used to predict future values based on past values
- A time series model uses the trends, seasonality and cyclicity of a system, as well as other factors to forecast future behaviour

Clustering

- Used to identify groups of data points that are very similar to each other
- The clustering model is used to group similar items, which can help with tasks like customer segmentation and finding the best way to market products

MODEL TYPES – APPLICATIONS

Forecast

Pricing, Reserving

Classification

Underwriting decision, fraudulent claim, manage or pay claim

Outlier

Fraudulent claim, unusual claim

Time Series

Inflation, trends

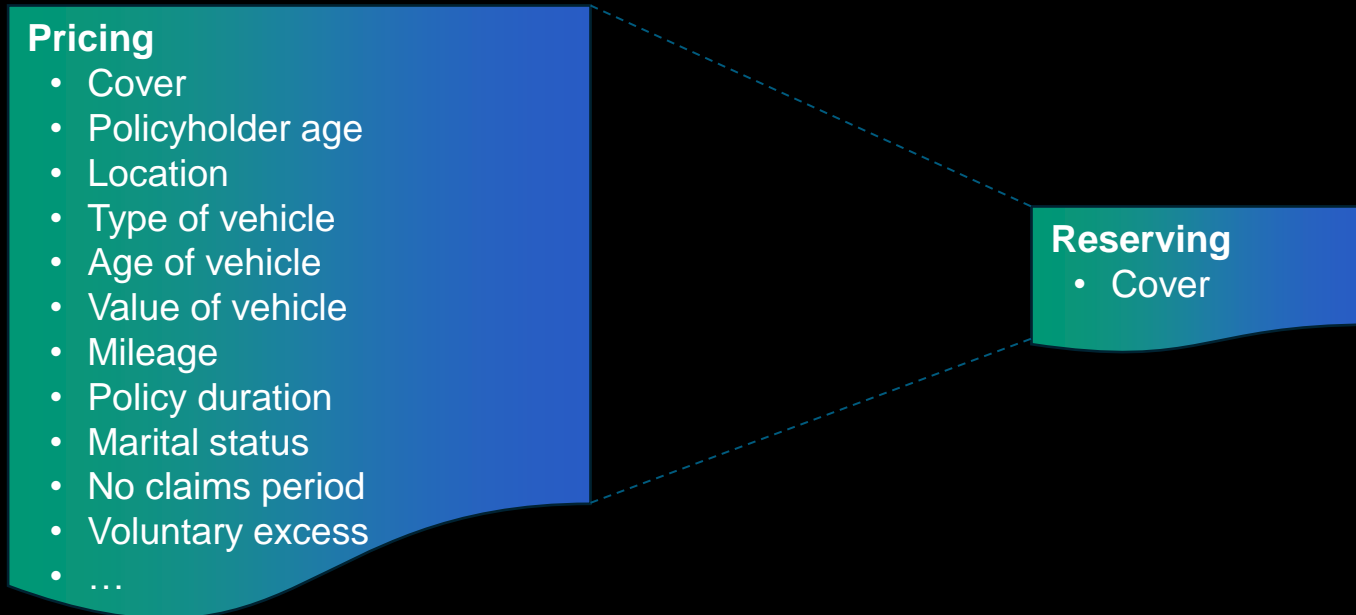
Clustering

Dimensionality reduction, model points

CURRENT APPLICATIONS

MODEL PREDICTORS

Motor Example



MODEL PREDICTORS

Motor Example

Pricing

- Cover
- Policyholder age
- Location
- Type of vehicle
- Age of vehicle
- Value of vehicle
- Mileage
- Policy duration
- Marital status
- No claims period
- Voluntary excess
- ...

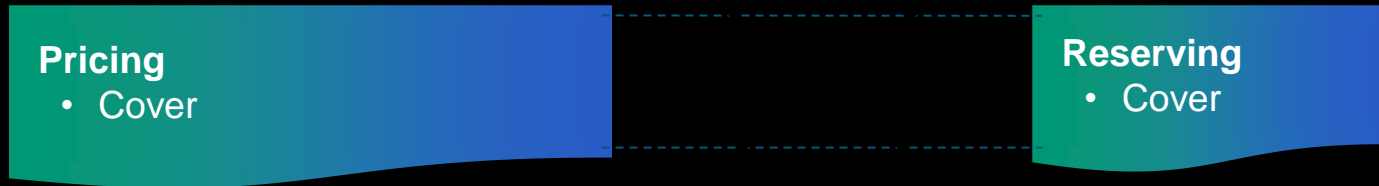


Reserving

- Cover
- Policyholder age
- Location
- Type of vehicle
- Age of vehicle
- Value of vehicle
- Mileage
- Policy duration
- Marital status
- No claims period
- Voluntary excess
- ...

MODEL PREDICTORS

Motor Example



MODEL TYPES

Motor Example

Pricing

- GLM
- GAM
- Other machine learning
 - Random Forest
 - Gradient Boosting
 - Etc.

Reserving

- Triangles

MODEL TYPES

Motor Example

Pricing

- GLM
- GAM
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Reserving

- Triangles
- GLM
- GAM
- Other machine learning
 - Random Forest
 - Gradient Boosting
 - Etc.

MODEL PREDICTORS

Motor Example

Training

• Overfitting?

- Models the training data too well
- Model learns the detail and noise in training data
- Negatively impacts the performance of the model on new data
- Noise or random fluctuations in training data picked up and learned as concepts by the model

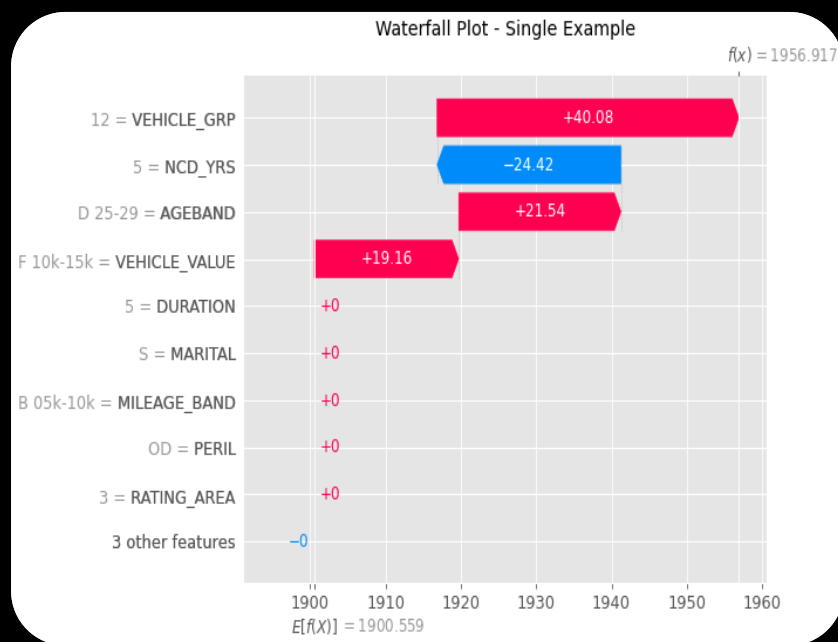
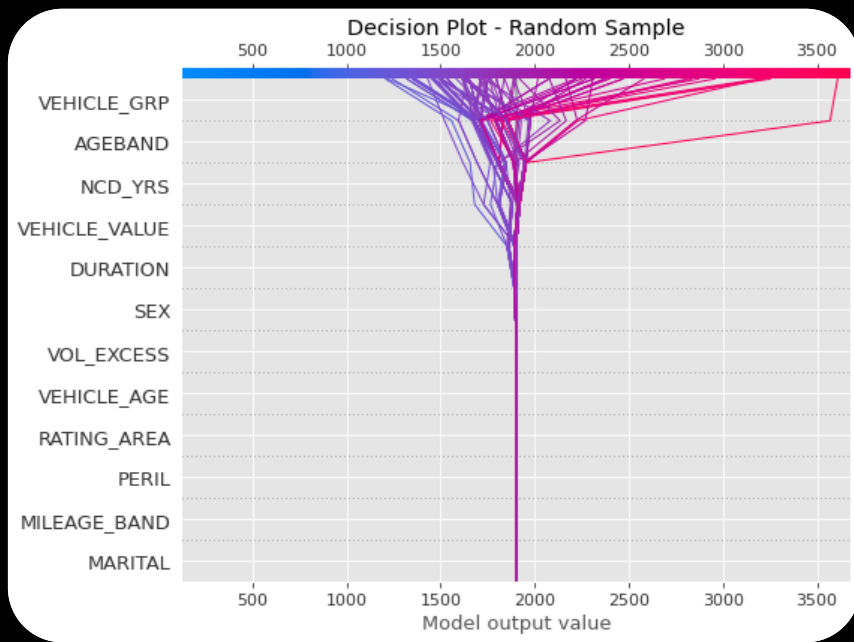
Reserving

• Underfitting?

- Model can neither model training data nor generalize to new data
- Not a suitable model

WHAT MATTERS

SHAP Values - Claim Severity, Gradient BOOST Model



WHAT MATTERS

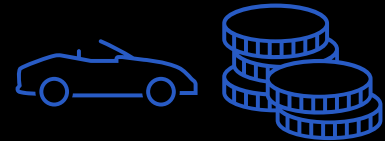
GLM Regression – Claim Severity

	AGEBAND	DURATION	MARITAL	MILEAGE_BAND	NCD_YRS	PERIL	RATING_AREA	SEX	VEHICLE_AGE	VEHICLE_GRP	VEHICLE_VALUE	VOL_EXCESS
GLM Backwards		x	x	x		x			x			x
GLM Forwards	✓			✓	✓		✓	✓		✓	✓	✓
GLM Bi-Directional	✓			✓	✓		✓	✓		✓	✓	✓

WHAT MATTERS

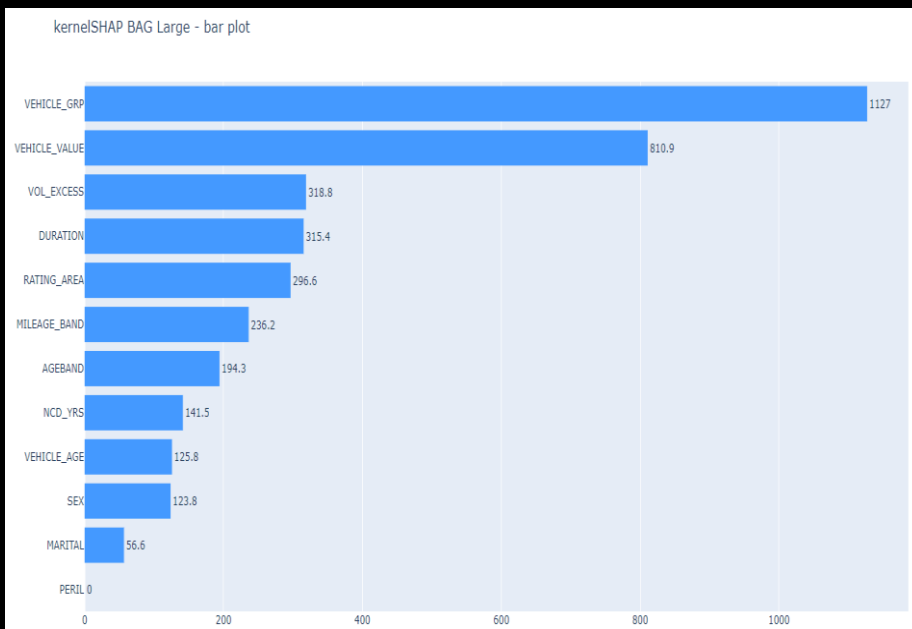
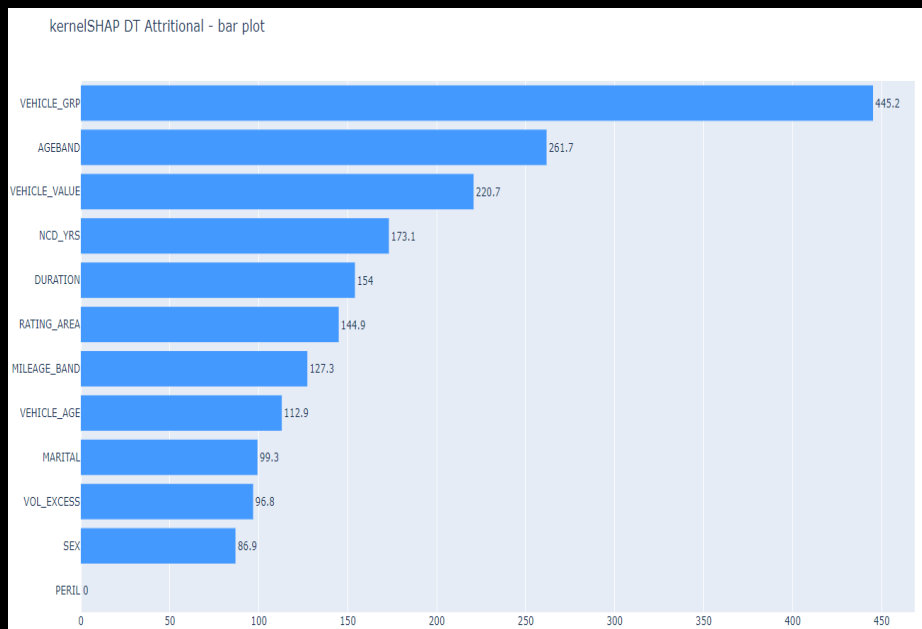
GLM Regression and Boosting – Claim Severity

	AGEBAND	DURATION	MARITAL	MILEAGE_BAND	NCD_YRS	PERIL	RATING_AREA	SEX	VEHICLE_AGE	VEHICLE_GRP	VEHICLE_VALUE	_EXCESS
GLM Backwards		x	x	x		x			x			x
GLM Forwards	✓			✓	✓		✓	✓		✓	✓	✓
GLM Bi-Directional	✓			✓	✓		✓	✓		✓	✓	✓
Gradient BOOST	✓				✓				✓		✓	



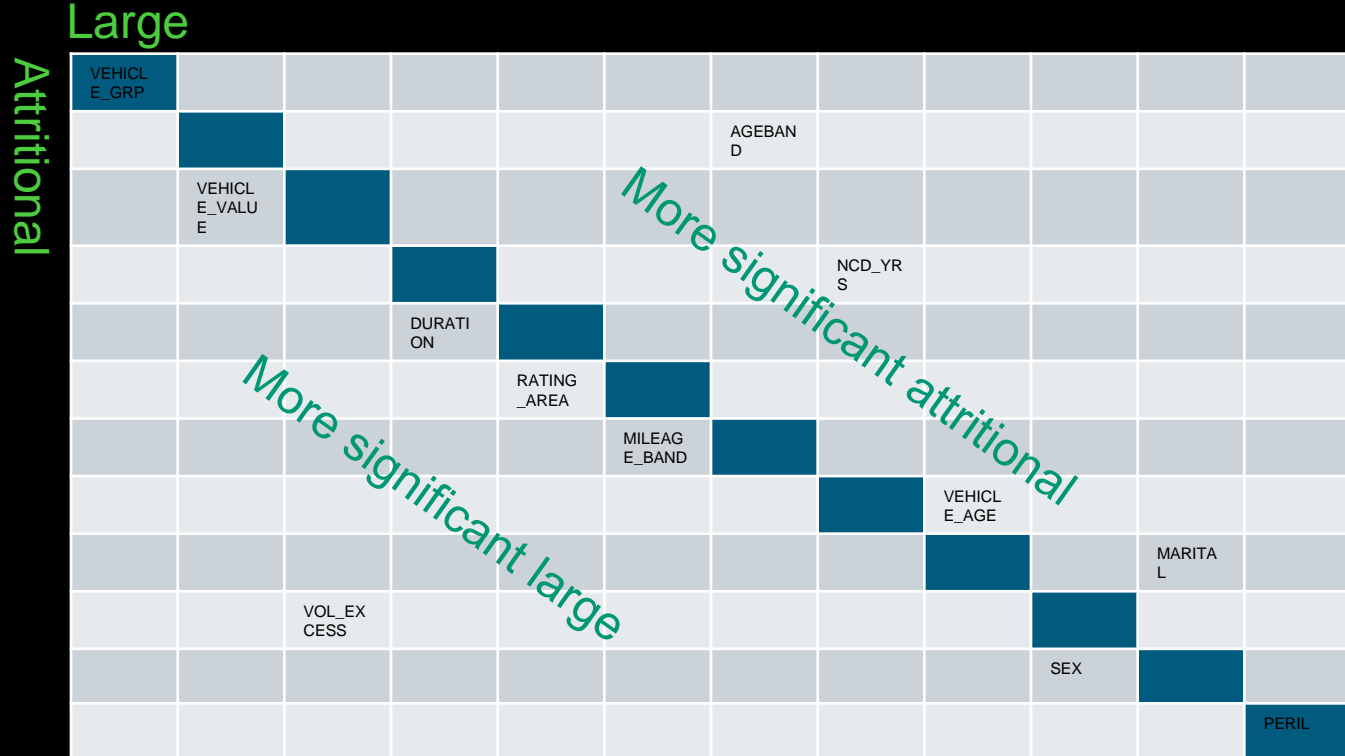
WHAT MATTERS

SHAP Values - Claim Severity, Attritional Large Split



WHAT MATTERS

SHAP Values - Claim Severity, Attritional Large Split



RESERVING

Why not using Machine Learning and more predictors

Triangles aggregate data for statistical significance
Not statistically significant enough if split?

Quality and availability of detailed claims data?

Claims development based on current paid and estimate levels

Investigating individual claim reserving methods

Triangles widely understood and accepted

Machine learning less explainable

PRICING

Why not using other Machine Learning algorithms



GLMs and GAMs more widely understood, accepted and programmable



Other machine learning algorithms less explainable

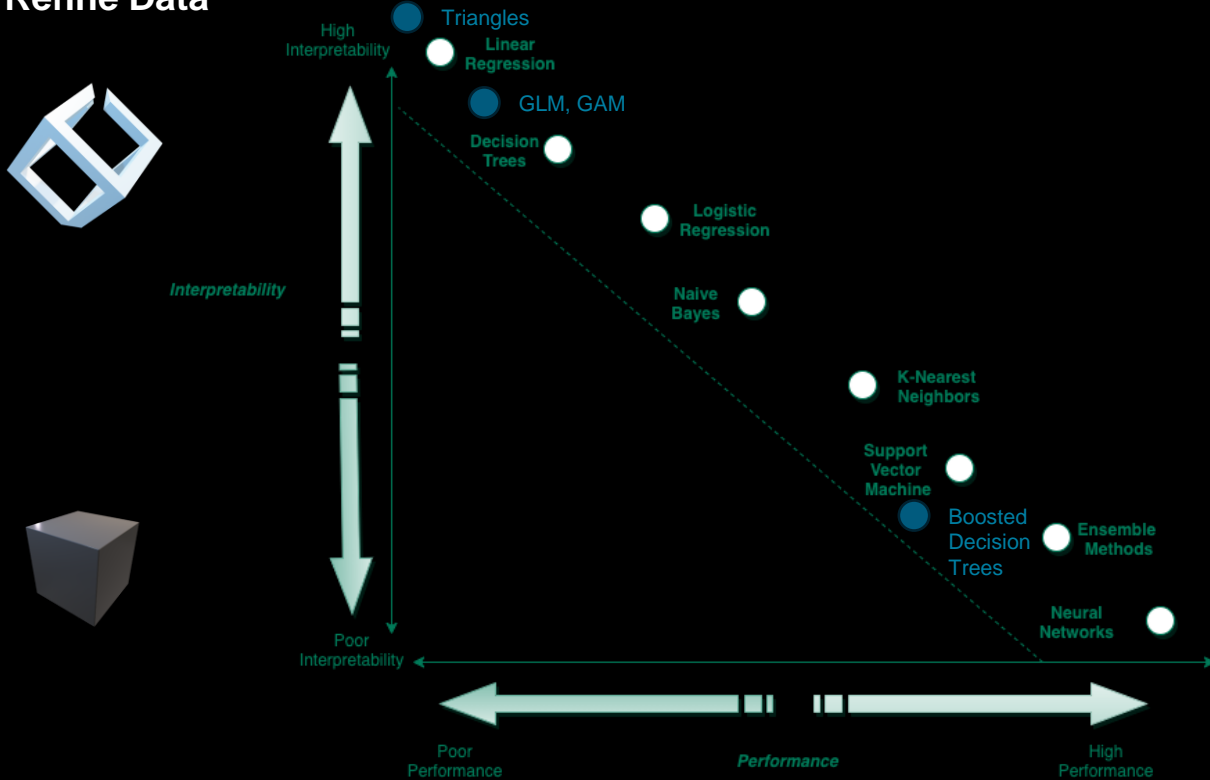
EXPLAINABILITY

**Interpretability
Vs
Performance**



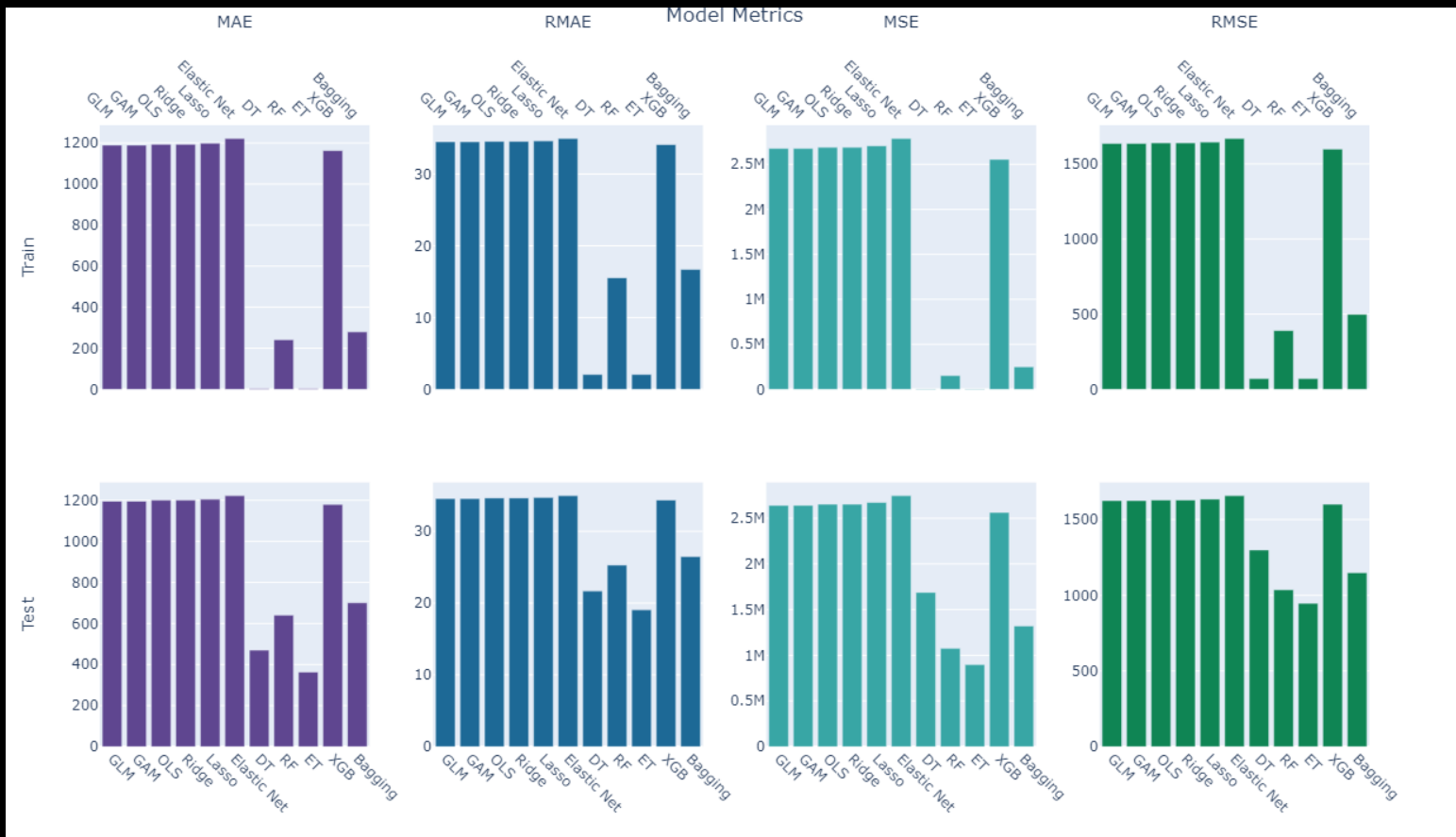
EXPLAINABILITY

Reduce and Refine Data



MODEL COMPARISON

Claim Severity





FEAR OF THE UNKNOWN OR BEING DIFFERENT?



THE FUTURE

WHAT'S IMPORTANT



NO ONE SIZE FITS ALL



**NEED TO HAVE ROBUST
SOLUTION TO BE ABLE
TO APPLY TECHNIQUES
TO OWN DATA**



**HAVE ALL TOOLS IN
ONE PLACE TO SEE AND
UNDERSTAND WHAT'S
GOING ON**



HYBRID MODELS

Reduce and Refine Data



Feature extraction
instead of feature
selection



Clustering to group
risks and claims for
applying models



Dimensionality
reduction or
expansion to identify
intrinsic dimensions
for each of pricing and
reserving

HYBRID MODELS

Explainability Options



Traditional learning with refined data e.g.

- GLM
- GAM
- Triangles



Advanced machine learning using explanatory techniques

- Local interpretation
- Global interpretation

HYBRID MODELS

Explainability Options



**CONSIDER
MULTIPLE
MODELS**



**COMPARE AND
CONTRAST**



**IDENTIFY
DRIVERS OF
DIFFERENCE**



SOLUTION PERSPECTIVE

INSURANCE RISK SUITE GI EDITION



Actuaries



Underwriters



Risk Managers

INSURANCE RISK SUITE GI EDITION



**Out of the box
functionality**

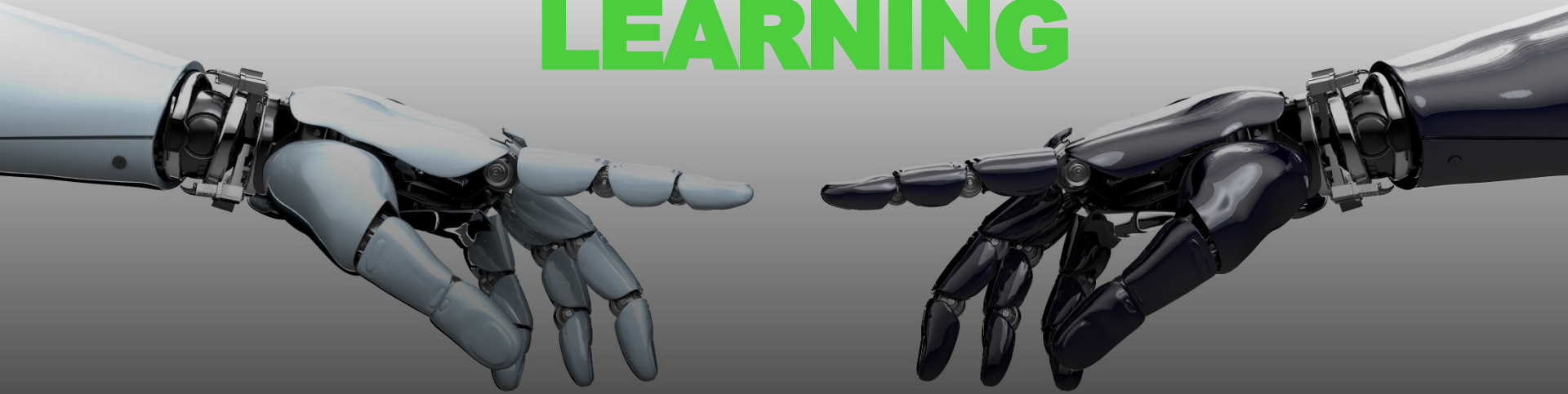


**Transparent
customisable
calculations**



**Rapid development
environment**

AI AND MACHINE LEARNING



Ask us what we are doing ...

**GI EDITION IS
READY ...
ARE YOU?**



**THANK YOU FOR
LISTENING**



**GI EDITION IS
READY ...
ARE YOU?**

Thank you for joining today's

**PRICING AND RESERVING
LIFECYCLE** session

Any questions?

Feel free to reach out to me:

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