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AI Risk Management & The CRO of the Future

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To understand AI risk, we must understand human nature.

Actuaries made good risk managers, historically …

Underwriting Risk	Pricing Risk	Reserving Risk
Market Risk	Credit Risk	Financial Modelling
Financial Control	Regulatory Knowledge	(Traditional) Product Knowledge

… but the CRO of the future will require a new skillset

- Machine Learning
- Explainable AI and Black Box Algorithms
- Model Traceability, Stability & Reliability
- Model Risk Management & Governance
- Model Architecture & Hyperparameters
- Ethical AI
- Data & Consumer Protection
- Cybersecurity
- Legal & Compliance Skills

Zero risk appetite is the greatest risk of all

Audience Questions

1. What are the top five skills actuaries need to acquire to remain influential CROs and risk managers?
2. What are the top five skill / knowledge areas where actuaries should rely on other professionals (rather than upskill themselves)?
3. What are the biggest AI threats / opportunities within the insurance value chain?
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5. Where does the role of the CRO end and Head of Compliance begin?
6. How can the SAI help?

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AI Risk Management & The CRO of the Future: AI Regulation

David Purcell (he/him) – EY

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What does the EU AI Act say? (at a high level)

Applies to AI systems across all sectors which impact people in the EU, regardless of where they are developed or operated.

Entered into force on 01/08/2024 with a phased implementation ending on 31/12/2030.

Penalties for non-compliance are strict with fines ranging from a minimum of €7.5m to a minimum of €35m.

Risk-based classification with different compliance requirements (discussed more on the next page).

Must be considered in conjunction with other EU digital legislation, including GDPR.

Regulatory sandboxes have been introduced to foster innovation.

AI definition is broad and derived from the Organisation for Economic Co-operation and Development definition of AI.

Risk-based tiering

Classification	Description	Compliance Requirements	Some Use Cases (General)	Use Cases (Actuarial)
Prohibited AI systems	Use would pose an unacceptable risk to safety, security and fundamental rights of people.	Prohibited	• Social scoring • Emotional recognition in work • Predictive policing	• **To Be Seen**
High-risk AI systems	Permitted, subject to compliance with the EU AI Act.	Significant	• Safety of critical infrastructure, • Remote biometric recognition	• Life and Health Insurance Pricing • **To Be Seen**
Minimal risk AI systems	Permitted, subject to transparency and disclosure obligations.	Limited	• Chatbot, • Visual or audio deepfakes	• Microsoft Copilot
	Permitted, with no additional AI Act requirements.	Minimal	• Photo editing, • Spam filtering	

What are other jurisdictions doing?

A number of jurisdictions are implementing AI policies, including but not limited to, Canada, China, Japan, Korea, Singapore, the UK and the US.

Key trends seen in the international regulation of AI are:

- The **OECD principles** for AI are used widely for guiding policymakers
- **Risk-based** approach to AI
- Some policymakers are considering **sector-specific** AI policies. For example, Singapore have sector-specific policy for their financial sector.
- Consideration for how AI impacts **other policy areas** (e.g., data, cybersecurity, and digital content flows)
- Use of **sandboxes** to enable responsible testing of AI innovations
- There is growing momentum to understand and address risks of **powerful AI systems**

How does it impact the actuarial profession?

Knowledge of regulation, including updates, will be key

Actuaries have significant influence in insurance companies. If our opinions are driven, at least in part, by AI systems we need to consider the consequences of this.

As we will discuss in the next sections, a strong model risk management framework and an understanding of explainable AI will be key for actuaries to help provide clarity in a world with AI.

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Model Risk Management

Navigating Regulation & Building the CRO Skillset

Eilish Bouse (She/Her)

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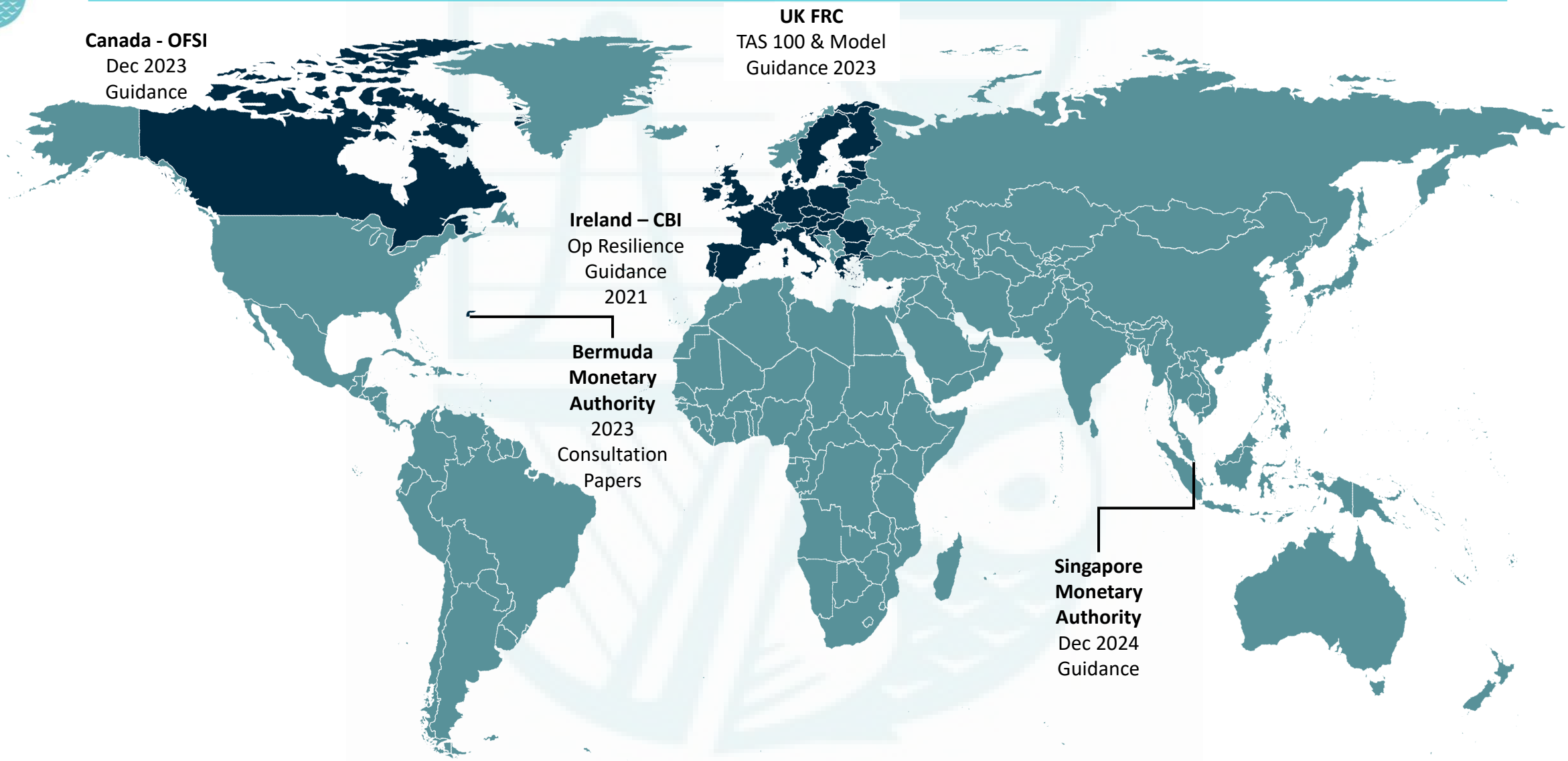
Regulatory Recap



Skills Required for Model Risk Management

What are the gaps for actuaries?

- Understanding of AI and ML techniques
- Setting model risk tolerances
- Managing complex models

Who can actuaries collaborate with to fill the skills gaps?

The Banking Sector

- More mature management of model risk
- Model development and model validation frameworks in place

Data Analysts / ML Experts

- Help gain an understanding in complex models, including AI and ML techniques

Three Lines of Defence

1. Day-to-Day Business Function
   Most familiar with the model environment
2. Risk Function
   Most familiar with developing risk frameworks
3. Internal Audit Function
   Should provide independent review of model risk management practices

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AI Risk Management & The CRO of the Future: What is Explainable AI?

Bence Zaupper (he/him) – Finalyse

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Explainability of AI models

What is model explainability?

- Our ability to understand, interpret, and trust how an AI model makes its predictions or decisions.

Insurance use cases of AI models:

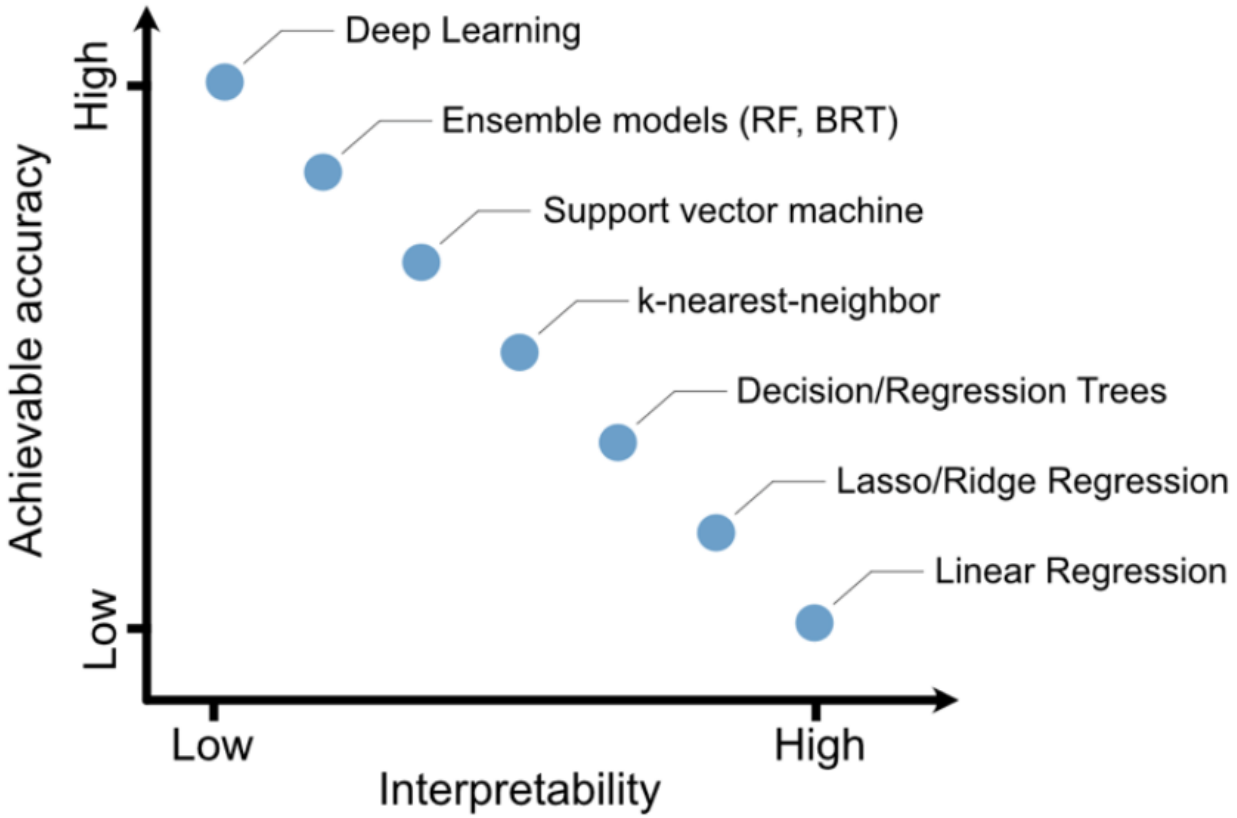
- Machine learning models in non-life pricing
- Fraud detection
- Lapse (churn) prediction
- Claims processing (e.g. categorisation, image processing)
- Extracting information from documents with NLP
- Chatbots

Explainability – why important?

Reasons why explainability is important	Examples
Accountability	If the model makes a wrong decision, it is important to find the root cause of the decision and who is responsible for it. This helps avoid similar failures in the future.
Trust	Trust is critical in high-risk domains (like insurance pricing). Before any complex models are used in production, stakeholders must understand what they do.
Compliance	As per GDPR, individuals have the right to explanation behind model decisions affecting them. Pricing models have to be explainable to the local regulator as well to assess fairness and compliance.
Performance	If you know how your model works it enables fine-tuning and optimisation.
Control	Understanding the decision-making process of your models helps uncover unknown vulnerabilities and flaws and enables correction of mistakes.

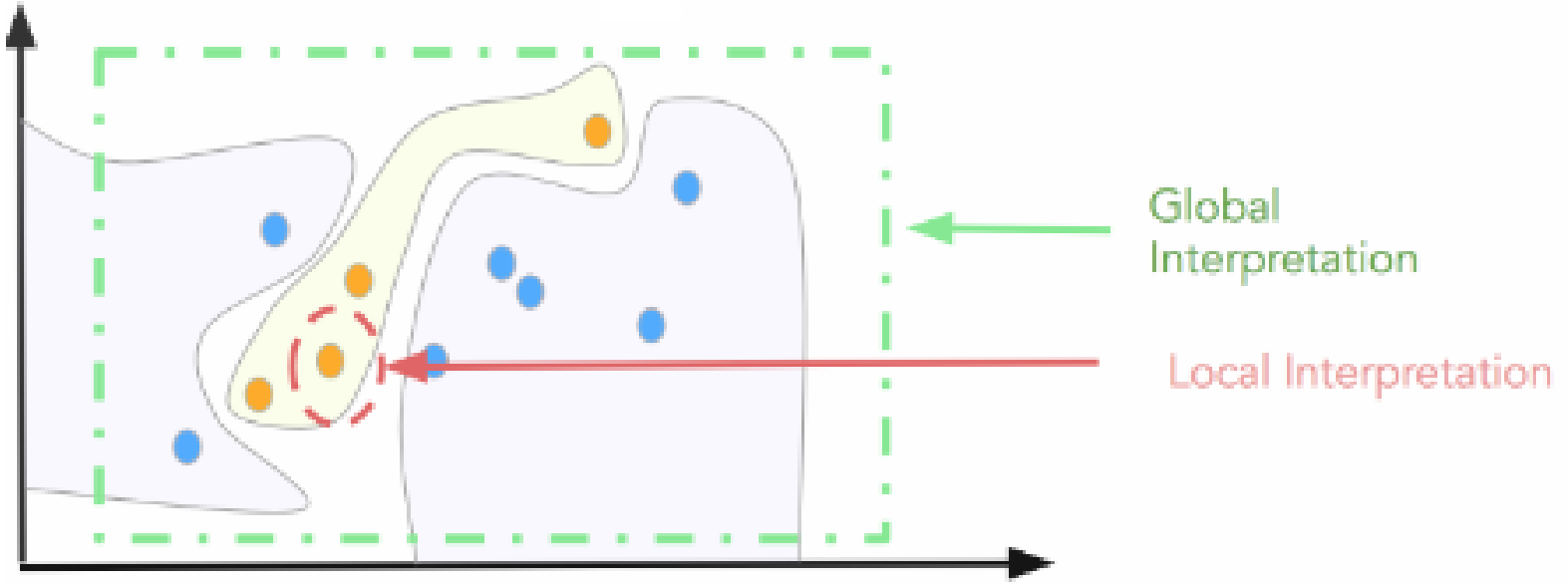
Interpretability vs performance

- Machine learning models may achieve higher level of accuracy
- Trade-off between interpretability and performance
- Methods to address loss in interpretability:
  - Use simple models – if accuracy close to complex ones
  - Interpretability by design (e.g. decision trees)
  - Surrogate models – approximate complex models by simple ones
  - Measure and visualise feature importance, dependence and interactions

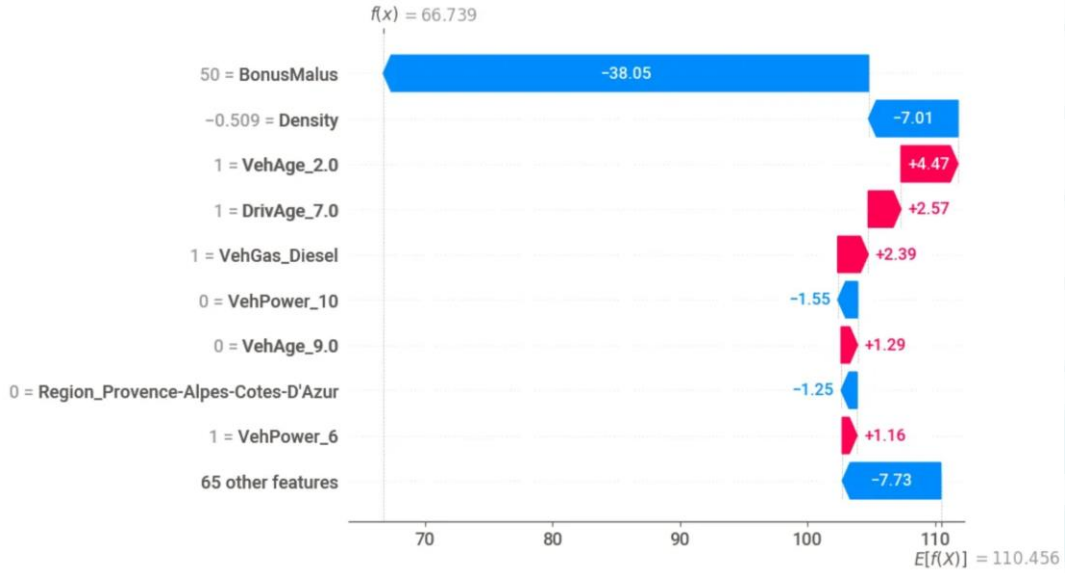


Explainability – global vs local

- Global explainability
  - Ability to explain interactions between the predictor and response variables based on the complete dataset
- Local explainability
  - Ability to explain interactions between the predictor and response variables with regards to a single prediction



SHAP – feature importance (local and global)

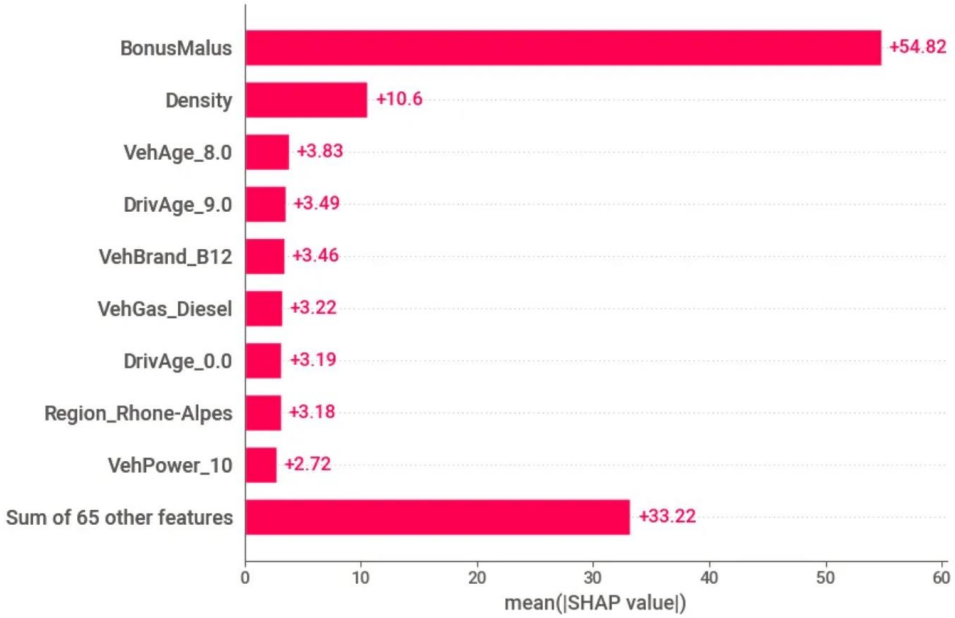


1. A baseline value is selected for each feature. It represents the starting point from which the contributions are measured.

2. For a specific prediction, subsets of features are considered, and their contributions are evaluated by comparing predictions with and without those features. This process takes into account all possible combinations of features.

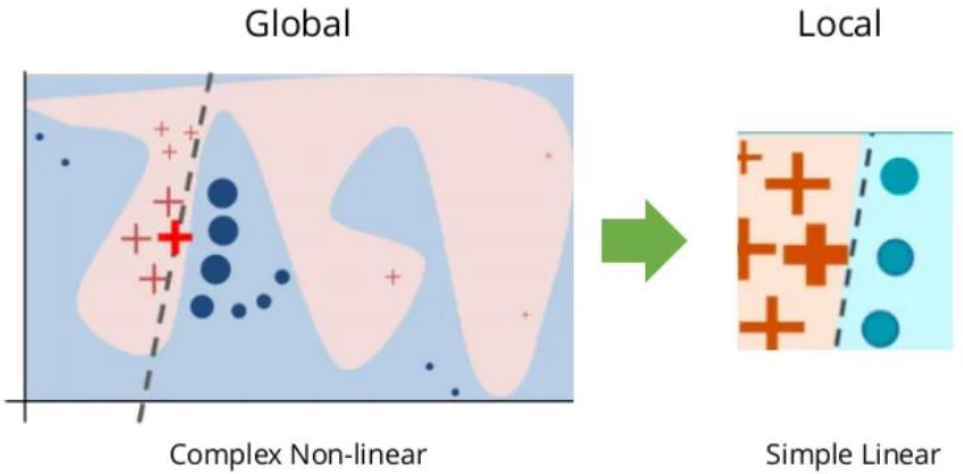
3. The contributions of each feature are averaged over all possible combinations, and the result is the SHAP value for that feature. Positive SHAP values indicate a feature's positive influence on the prediction, while negative values indicate a negative influence.

4. The sum of the SHAP values for all features, plus the model's average prediction, equals the final prediction for the instance under consideration.



Local explainability - LIME

- Intuition
  - Approximate non-linear function locally by linear function
    - Regression methods used to calculate as no analytical form available (e.g. derivative function)
  - Choice of random points and weights to be considered
    - Framework called OptiLime in Python addresses this and suggests solution



Skill required for risk professionals to assess explainability

Essential skills:

- Awareness of regulatory context and requirements (e.g. AI Act)
- Domain expertise to judge level of risk
- High level understanding of what AI models can (and cannot) do
- Ability to interpret explainable AI (XAI) metrics

Not required / essential for risk professionals:

- Technical knowledge of AI models and architecture
- Coding skills (e.g. implement XAI metrics in Python)

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Group Discussion

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