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Why isn't machine learning more transparent in personal lines pricing?

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Agenda

- Introduction to transparent machine learning
- Challenges & opportunities
- What does the solution look like?
- Q&A

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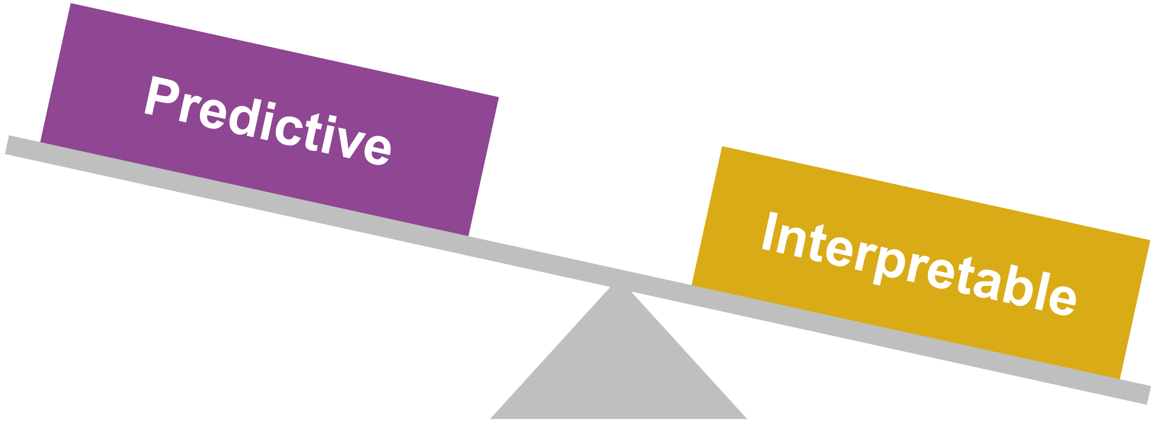
What is transparent machine learning?

What are we trying to achieve?



- Accuracy
- Justifiability
- Portfolio management
- Cost of implementation
- Stability
- Time to value

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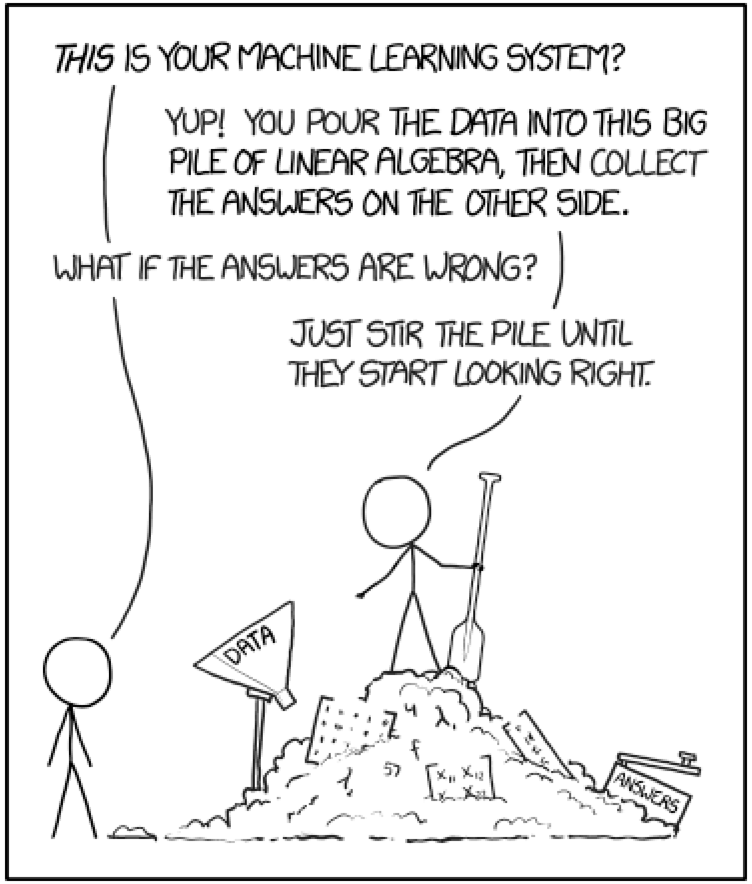
Why should we care about interpretability?



Source: https://xkcd.com/1838/

External

- Regulatory compliance
- Ethical standards
- Policyholder retention

Internal

- Domain knowledge
- Robust models
- Management approval
- Informed decisions
- Debugging

Qualities of Interpretations

Comprehensibility: How well do humans understand the explanations?

Fidelity: How well does the explanation approximate the prediction of the black box model?

Stability: How similar are the explanations for similar instances?

Selective: Focus on the most important few features

Constrastive: Why was this prediction made *instead of* another prediction?

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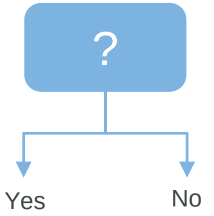
Challenges and opportunities

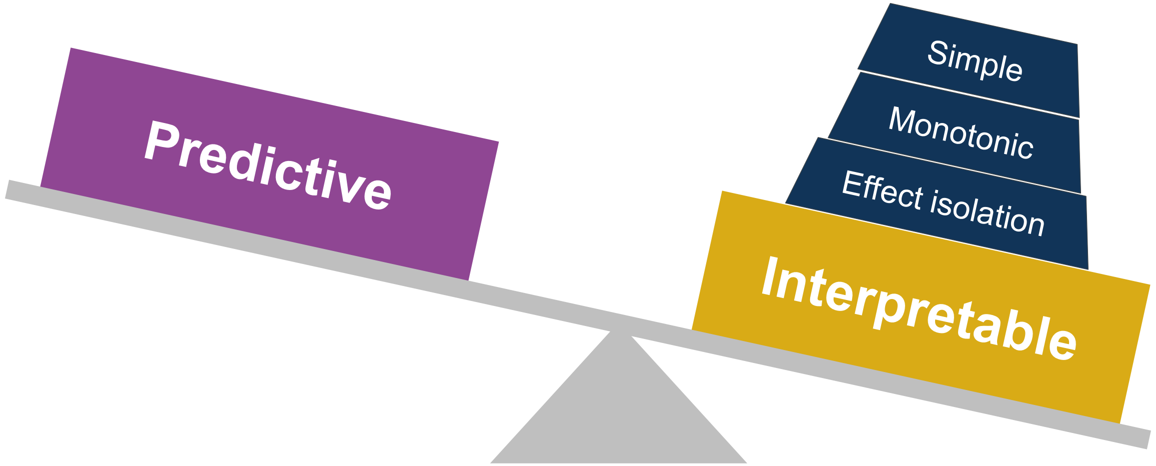
Why are the more predictive models not interpretable?

GLMs

$$g(Y) = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n$$

Decision trees





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What does it mean to interpret a model?

“extraction of relevant knowledge from a machine-learning model concerning relationships either contained in data or learned by the model”

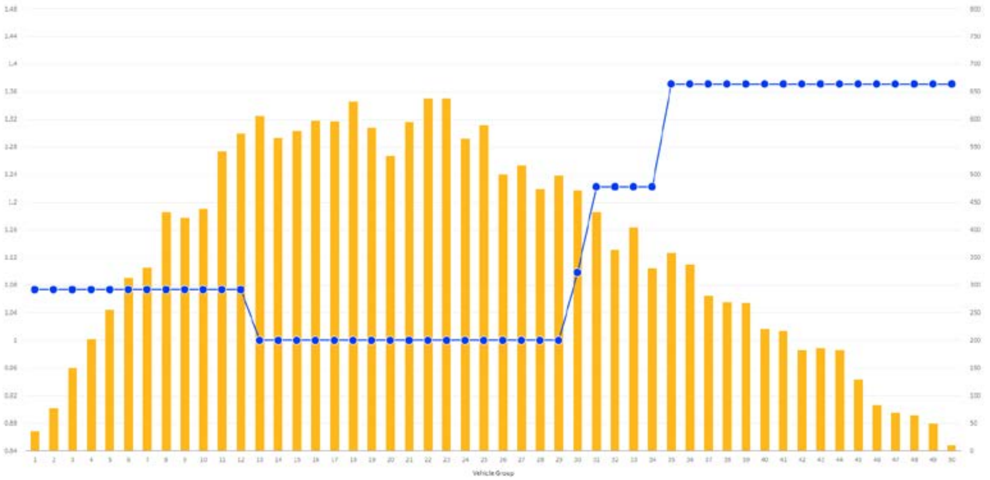
Source: Murdoch, W. J., Singh, C., Kumbier, K., Abbasi-Asl, R., & Yu, B. “Definitions, methods, and applications in interpretable machine learning.” Proceedings of the National Academy of Sciences, 116(44), 22071-22080. (2019)

Inherently interpretable model

Price = 50 + Age * 0.1 + License Length * 0.5

Approximate explanation for complex models

On average the model has learned the following relationship between vehicle age and claims Frequency:



Types of Interpretations - global and local approximations

Global

"How does the trained model make predictions?"

- Which features are generally important?
- What relationship does each feature have with the target?
- What interactions exist?

"Why did the model make a certain prediction for an observation?"

- How does this observation compare to a typical observation?
- Which features set this observation apart?
- What contribution did each feature have in determining the prediction for this observation?
- Locally, an otherwise complex model may behave more agreeably (i.e., linearly)

Local

Example: Feature Importance

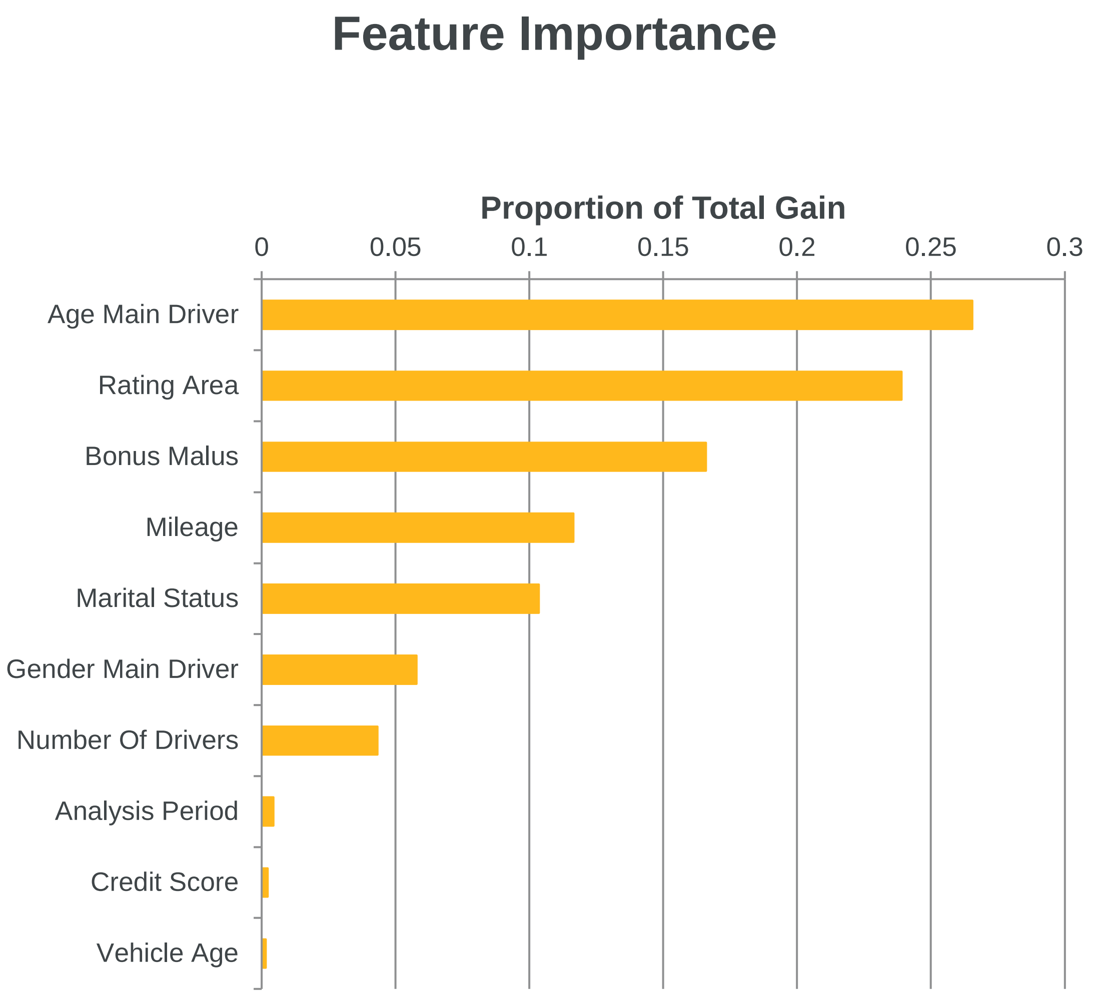
Answers global questions:

“which features are generally important”

But…

Doesn’t tell us about the relationship between features and the target

Doesn’t distinguish interaction and main effects



Example: Shapley Values

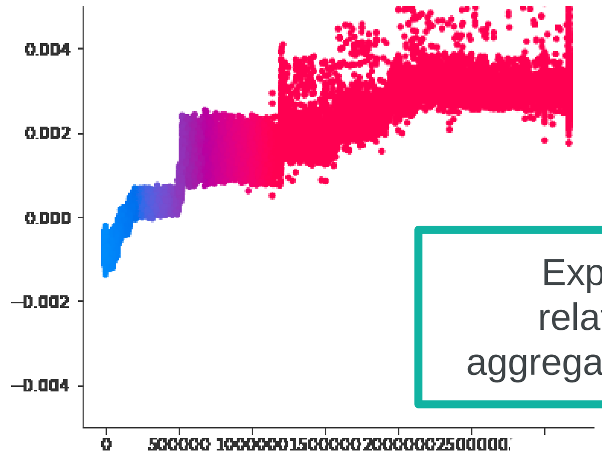
Answers local *and* global questions:

"How did each variable contribute to this prediction?"

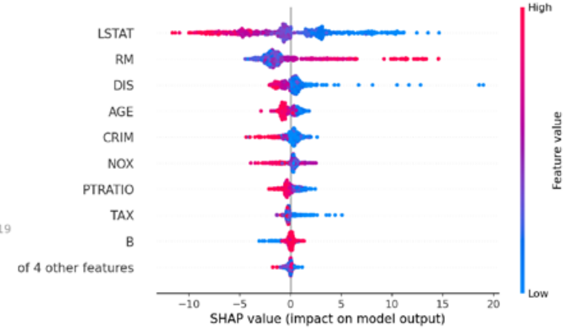
"What relationship does each feature have with the target?"

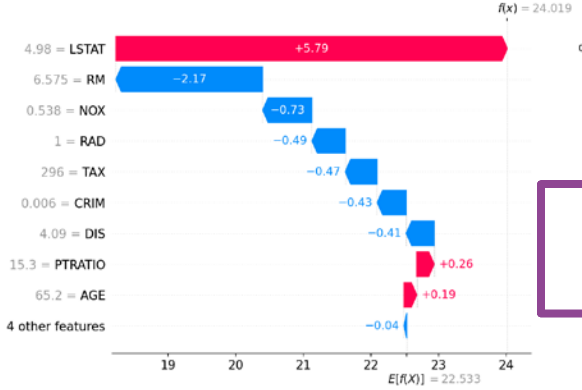
But…

Computationally intensive



Explains global relationships by aggregating local values





Attributes predictions to individual variables

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Broader challenges

Model stability

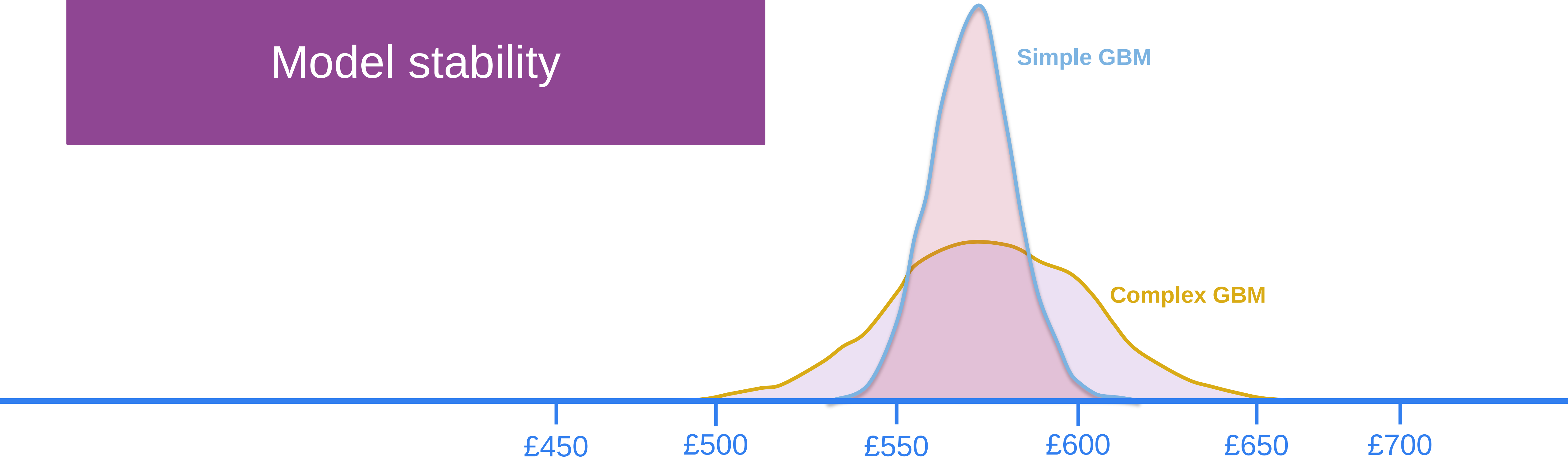
Deployment

Potential knowledge gap owing to legislation

Return on Data Science investments

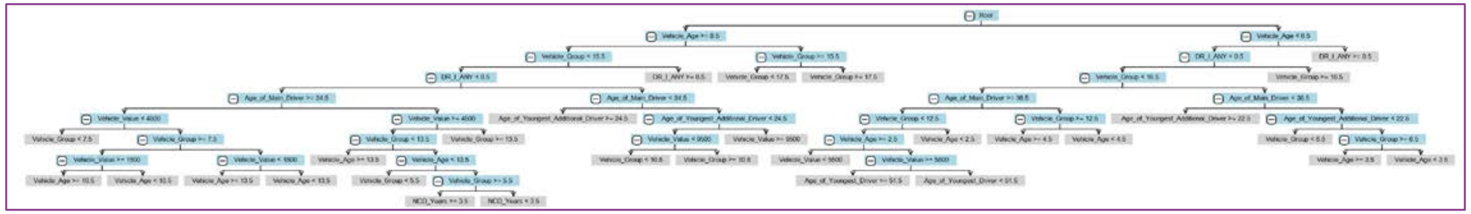
Broader challenges

Model stability



Broader challenges

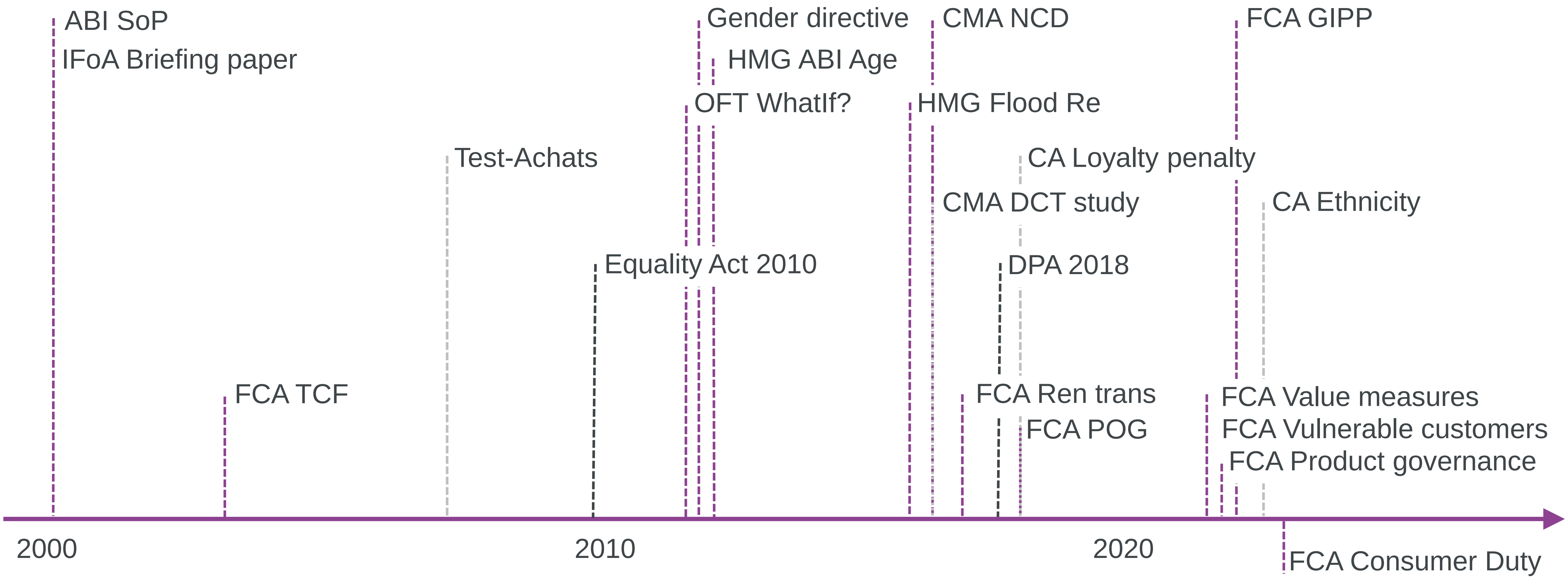
Deployment



Broader challenges

Potential knowledge gap owing to legislation

Timeline of increasing regulatory demands leading up to the FCA's new Consumer Duty rules



Broader challenges

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Return on Data Science investments

What are the opportunities?

- Use of insights across functions
- Better customer experience
- Lower cost to respond to new regulations
- Greater value from insight-driven modelling activities

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What does a solution look like?

So how do we achieve model transparency?

- Use an inherently interpretable model
- Use approximations to provide explanations for a complex model
- Constrain or adapt an algorithm for a complex model to incorporate built-in interpretability, or enhance its other qualities

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So how do we achieve model transparency?

Interpretability techniques vs. Interpretable models

- Interpretability techniques have a variety of weaknesses
  - Inability to distinguish main effects and interaction effects
  - Unrealistic assumptions
  - Approximations of the true effects
  - Computation time/resource
- Two potential alternatives:
  - Try to improve existing interpretable models (GLMs, ENs)
  - Adapt complex models to incorporate built-in interpretability

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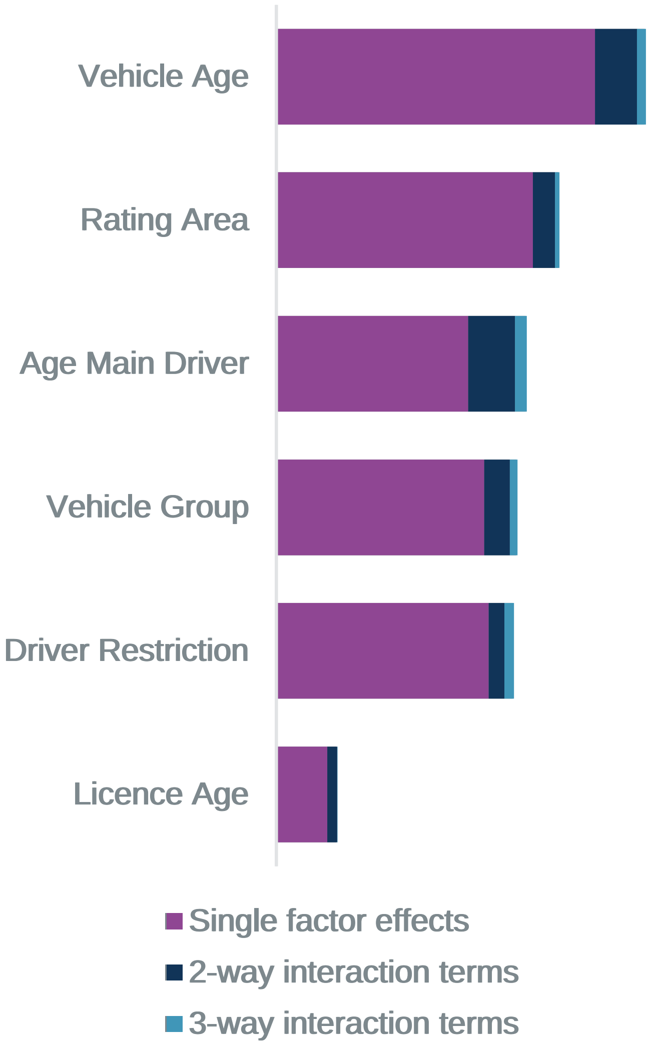
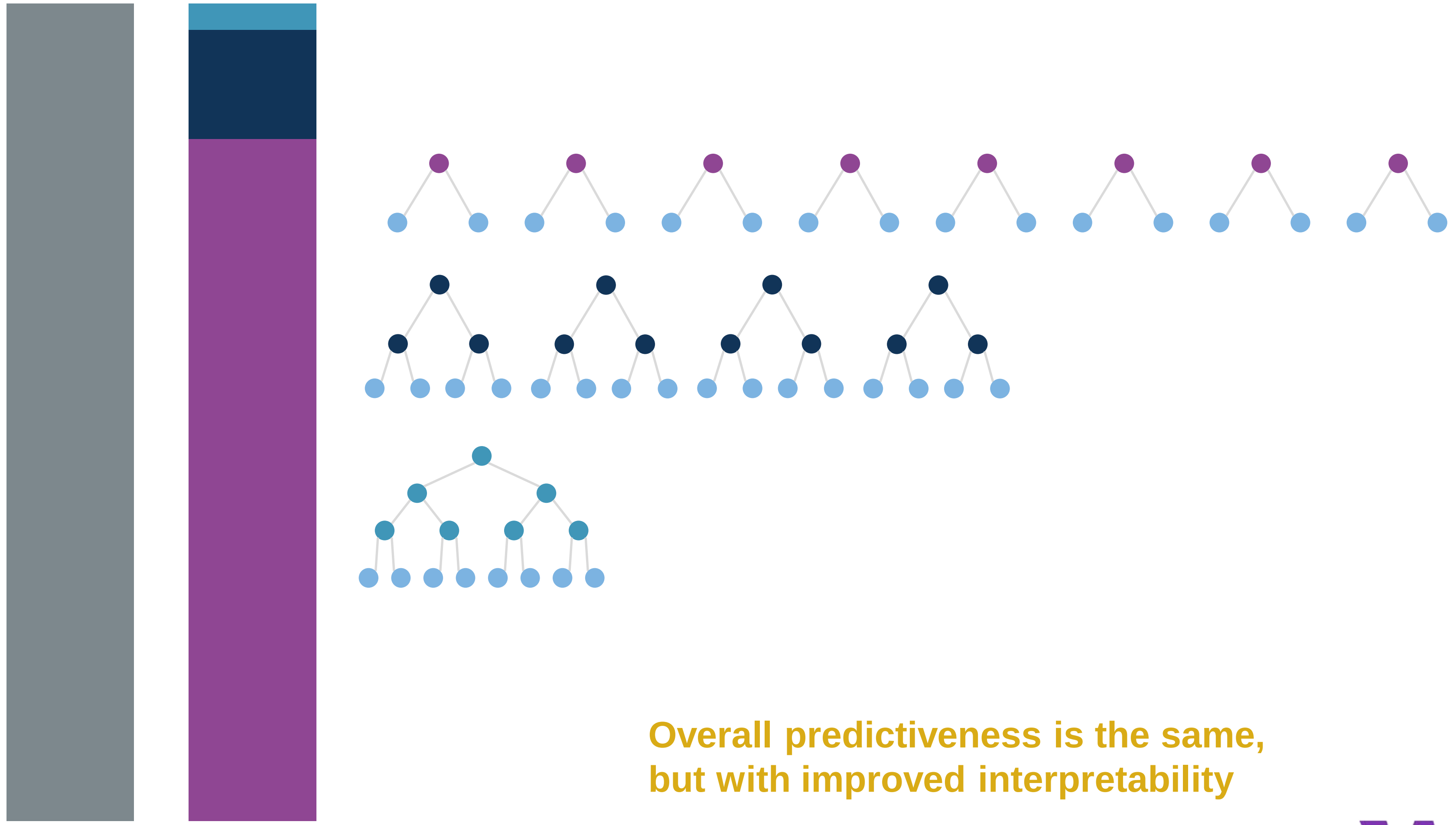
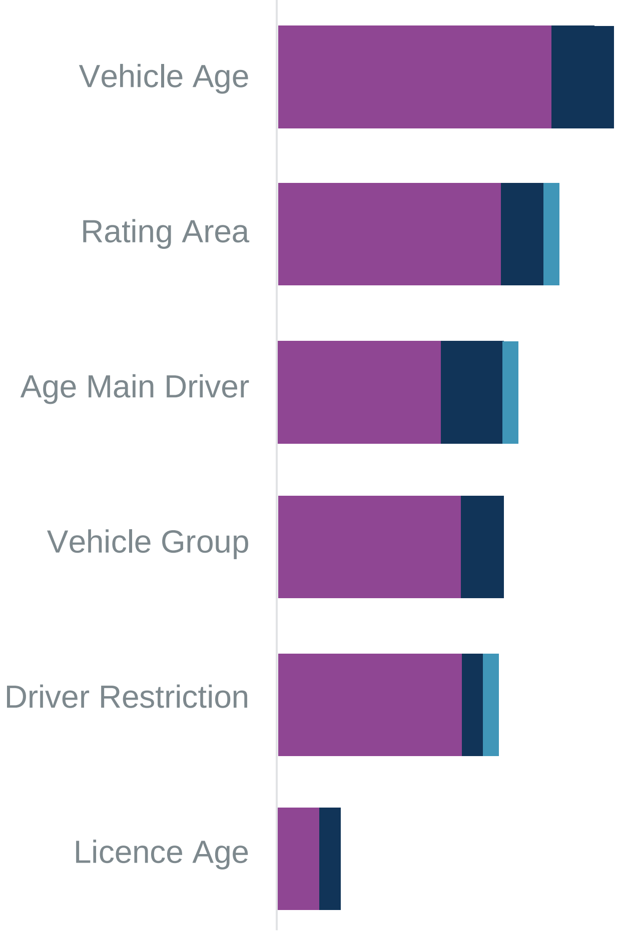
Example: Adapting an algorithm



Example: Adapting an algorithm





Overall predictiveness is the same, but with improved interpretability

Assessment of methods for insurance pricing

	Method						
Considerations:	GLM	Penalized Regression	Trees	Random Forests	GBMs	Layered GBMs	Neural Networks
Predictive power							
Interpretation							
Implementation							
Stability							
Execution speed							
Analytical time/effort							

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Beyond a better predictive model

Skills, Processes & Culture

- Understanding business context is key
- Ensure there is a “human in the loop”
- Consider what is being incentivised

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Build vs Buy

- ✓ Tailored to your particular needs
- ✓ Don’t pay for any features you don’t need
- ✓ You can adapt and enhance as you see fit
- ✓ Short term cost may be attractive

- × Risk in delivery and implementation
- × Commonly underestimate the costs
- × Not a core strategic area
- × Key-person risk
- × Long-term development and support often underfunded

- ✓ Often a proven solution
- ✓ Solution will be developed and maintained over time
- ✓ Commercial support available
- ✓ This is a core strategic area for the provider

- × The solution, whilst often customisable is not being built for your specific needs
- × The solution may appear expensive on a short-term basis
- × Less control on future development.
- × Risk the supplier could move away from this area or go out of business

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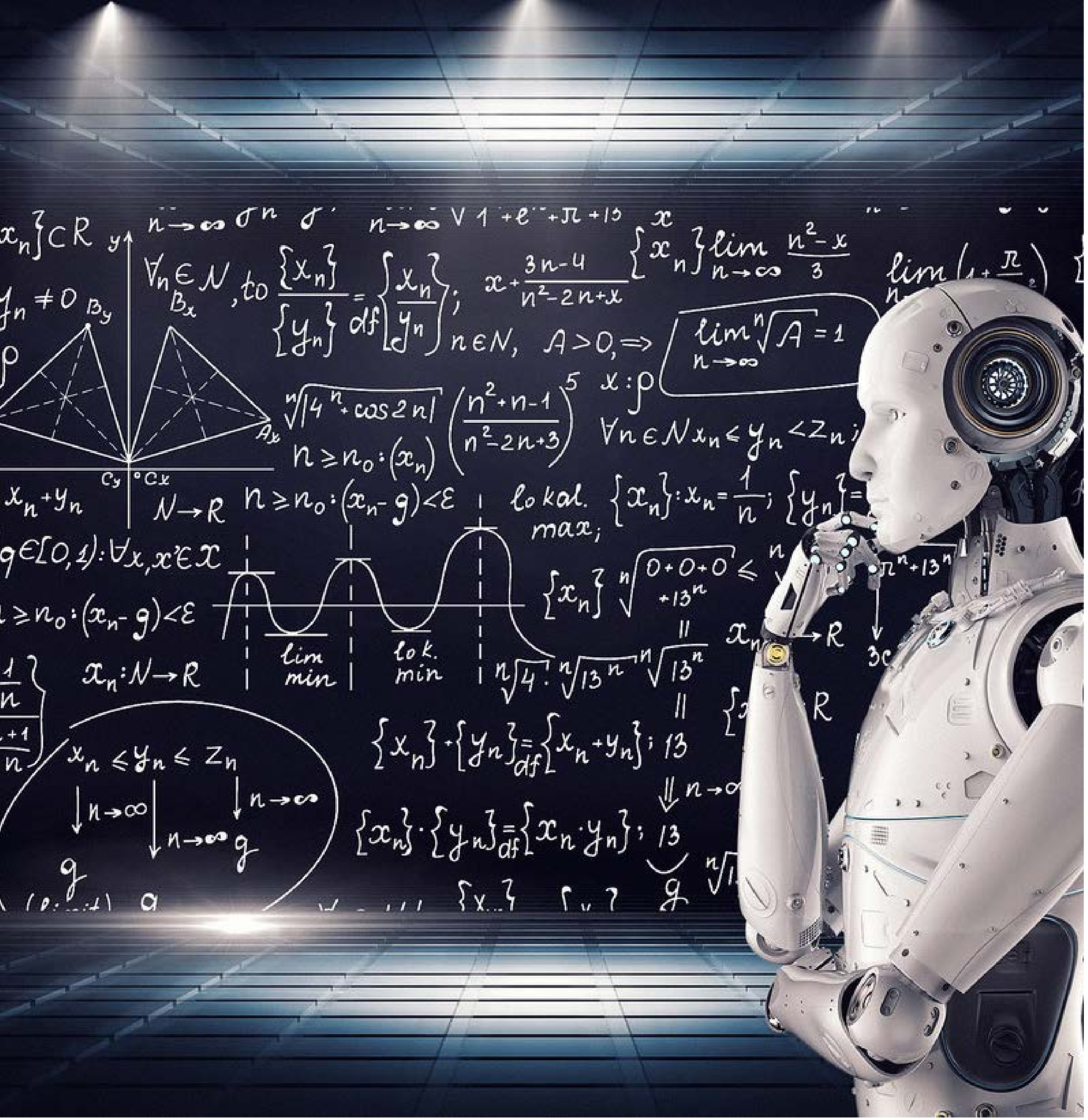
Conclusions



Conclusions

- Transparency is important
- There are challenges in achieving transparency
- Implementation is dependent on model specifics but also wider considerations

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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.

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Thank you