

# Analytics in General Insurance

28 October 2021

**Predictive Modelling: Way forward -  
GLM with Actuarial Judgment or  
Machine Learning Models**



Institute of Actuaries of India

# Introductions



**Neil Chapman**

*Senior Director P&C UK,  
Global leader for Pricing Product Claim and  
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**Kylie Chen**

*Director P&C APAC,  
Pricing Product Claim and Underwriting leader  
for APAC*



**Sipika Tandon**

*Associate Director P&C India*

# Agenda



## Agenda

- Context of machine learning in pricing

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- Introduction to machine learning and comparison to GLMs
  - Tree-based methods
    - Decision trees
    - Random forests
    - Gradient boosting machines
  - Regression-based methods
    - Penalized regression

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- Pricing applications

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- How are insurers using machine learning?

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- Adoption and use of machine learning in India and APAC

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- Summary and Q&A

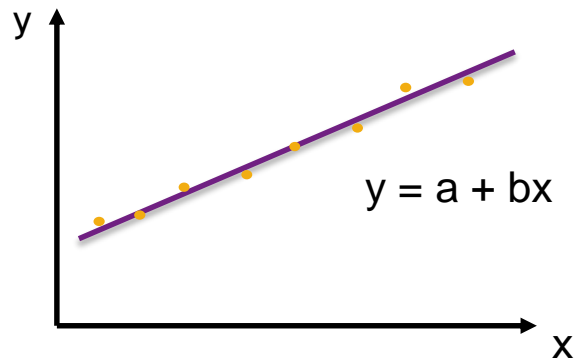
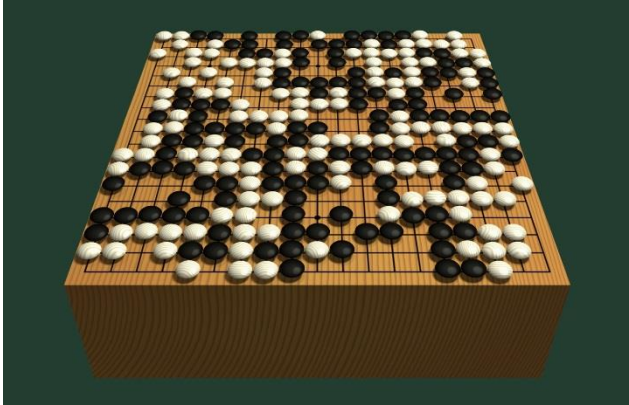
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**Objective:** to understand the advantages and disadvantages of machine learning, and how these could be used to enhance predictive modelling alongside actuarial judgement

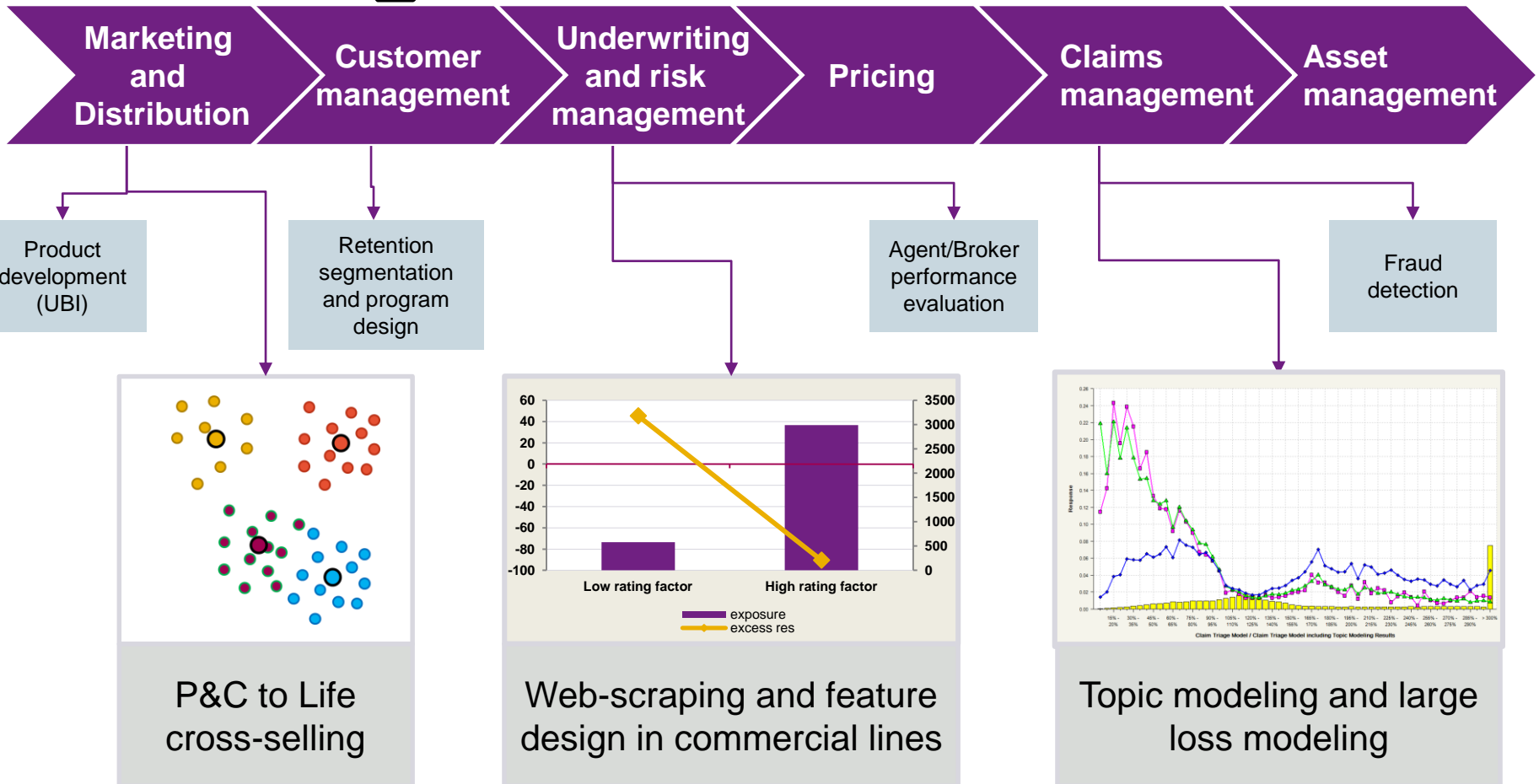


# Context of machine learning in pricing

# Who's interested in what?

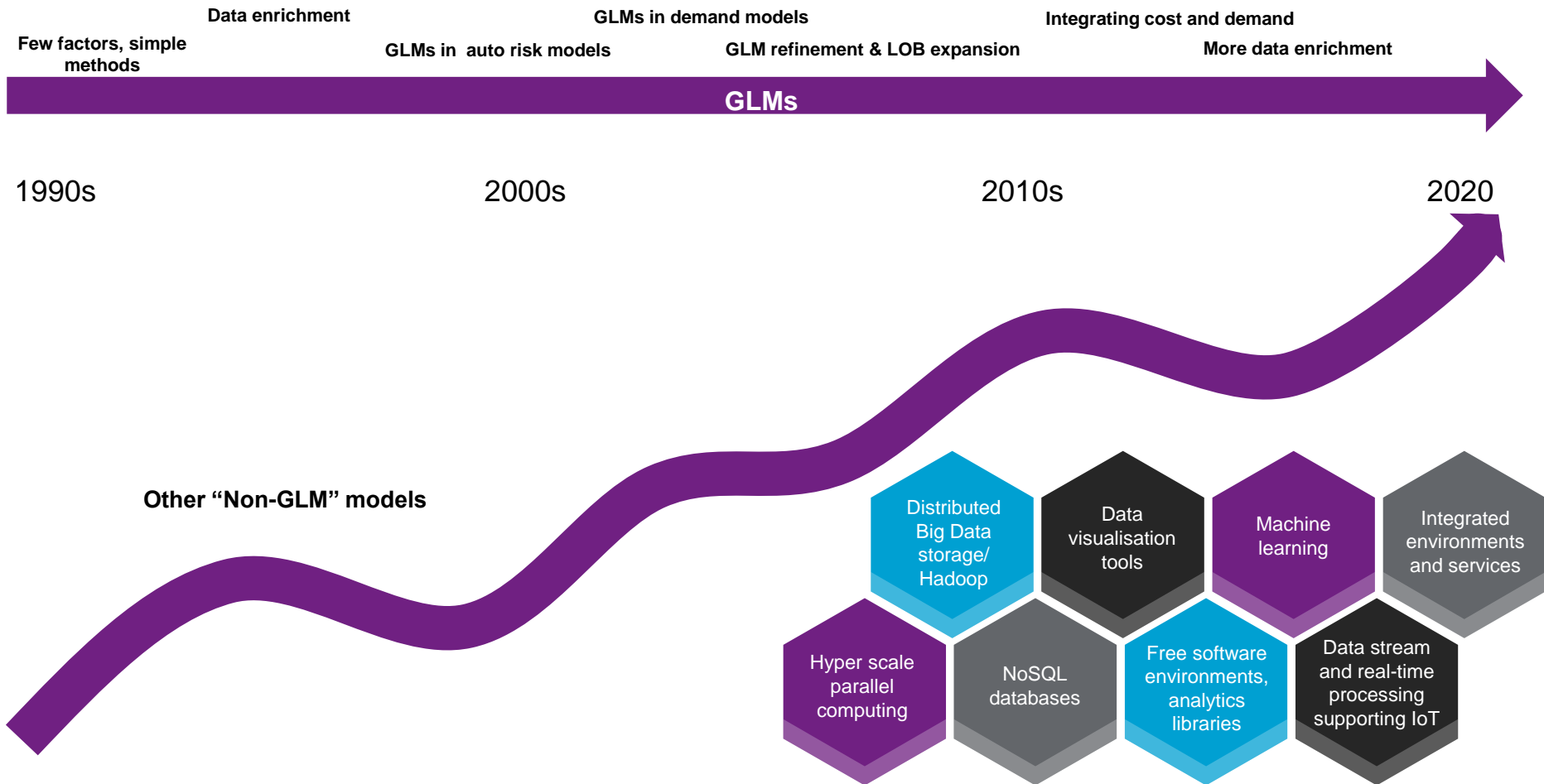


# Applications of machine learning in the insurance sector





# This is not new....



# What are these machine learning methods?

Ensembles

Classification  
Trees

"Earth"

Regression  
Trees

Gradient  
Boosting  
Machines

K-nearest  
Neighbors

Elastic Net

Neural  
Networks

Naïve Bayes

Random  
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Principal  
Components  
Analysis

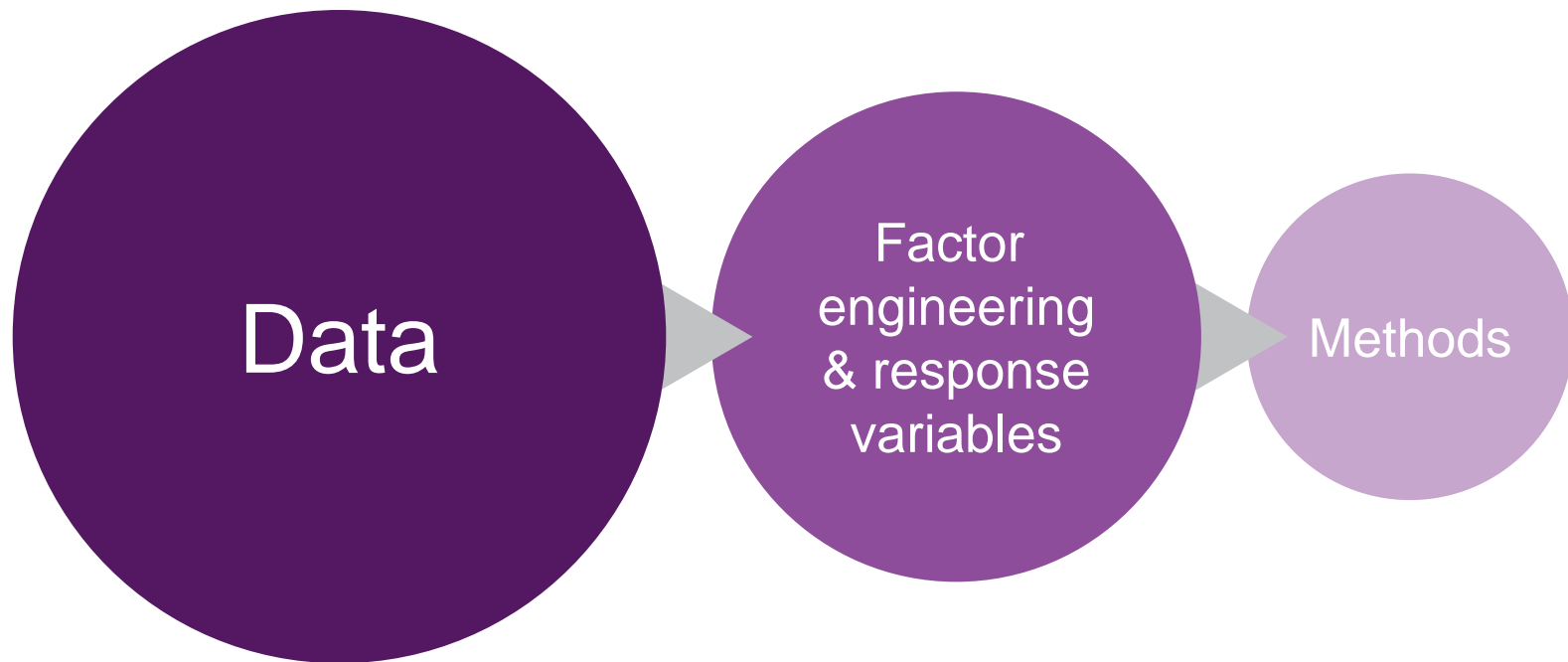
Lasso

Support Vector  
Machines

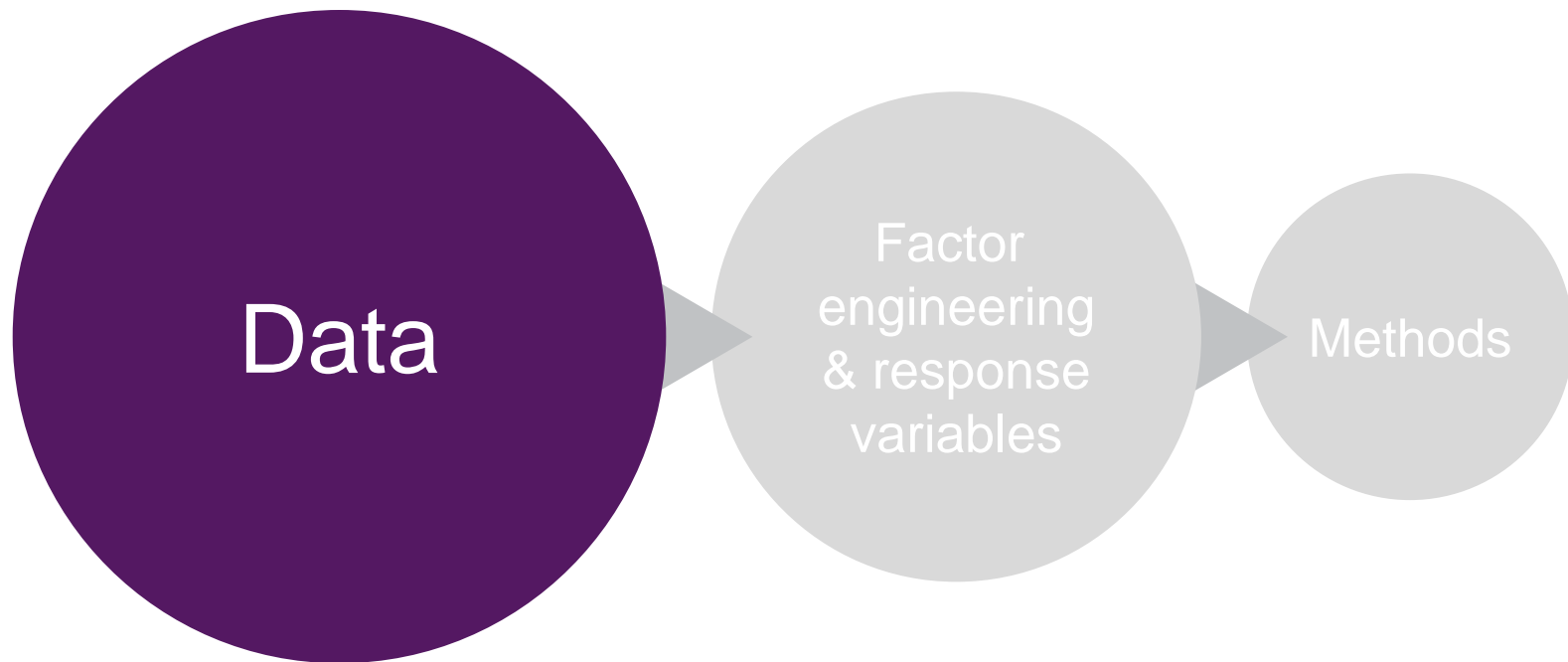
Ridge  
Regression



# Is it really all about the method?



# Is it really all about the method?



# Is it really all about the method?

Data



## Physical facticity

E.g., height, length, weight



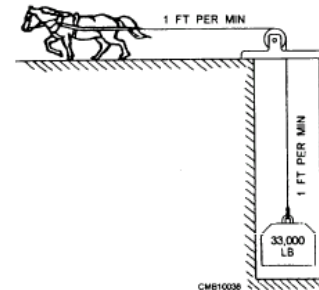
## Mechanical nature

E.g., engine size, fuel type



## Qualitative descriptors

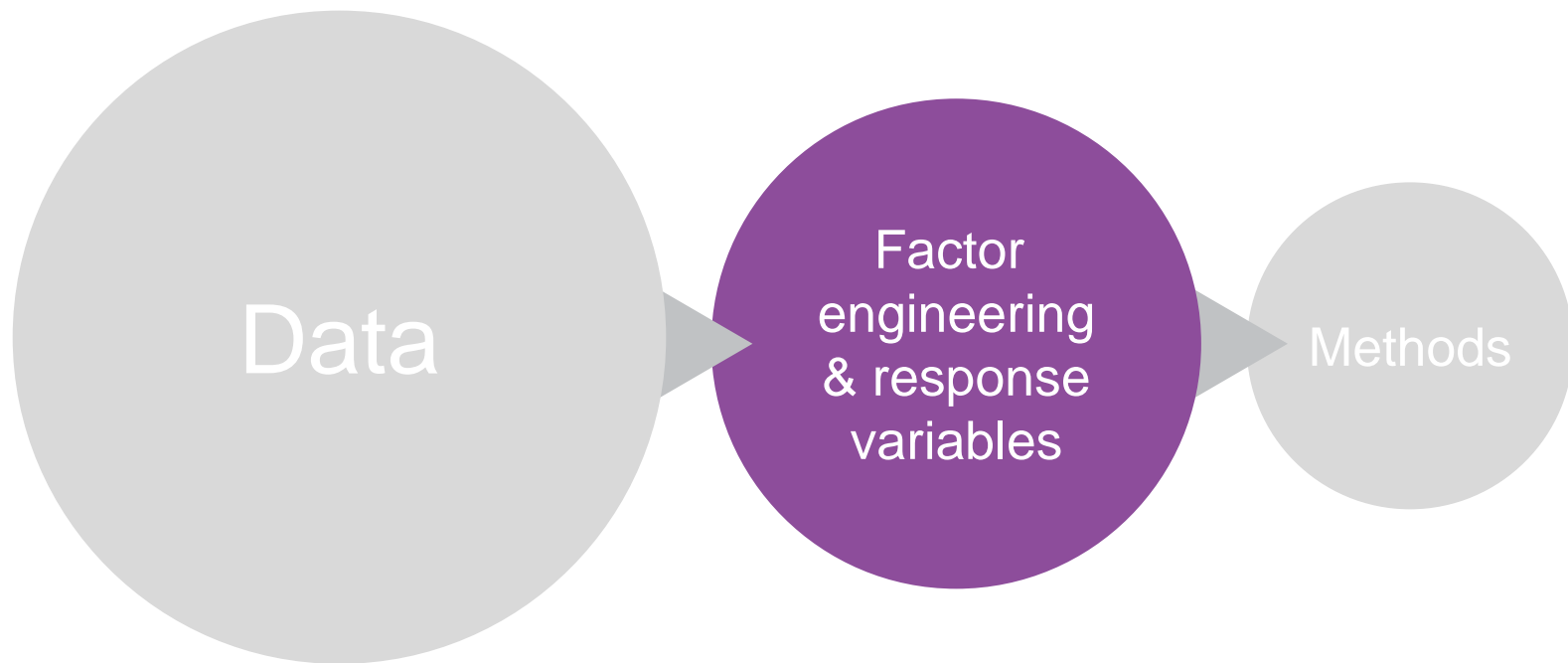
E.g., body type, model range



## Performance

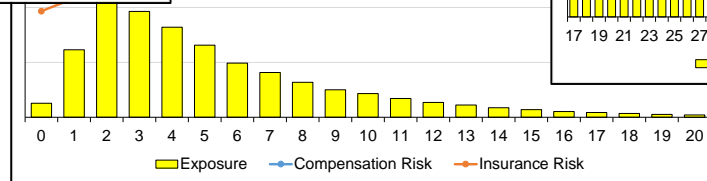
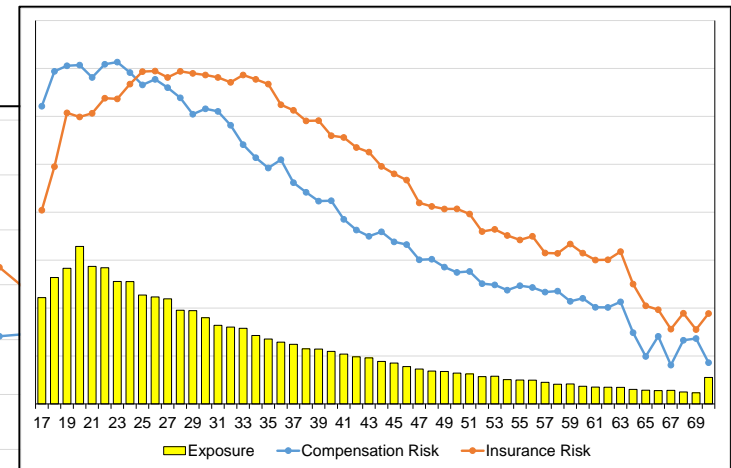
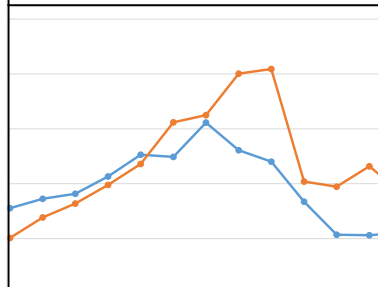
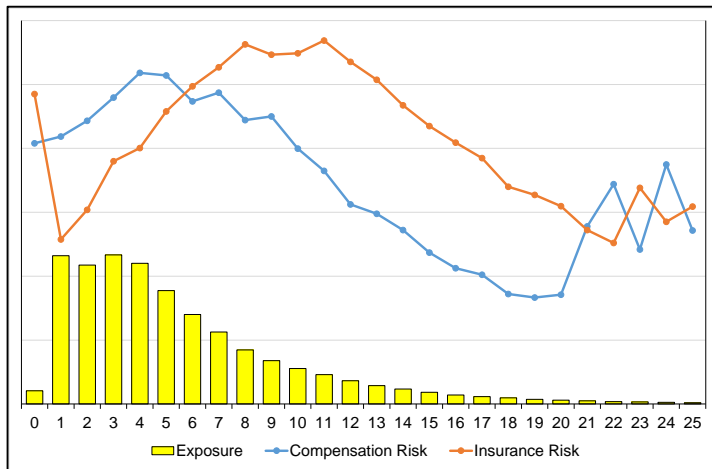
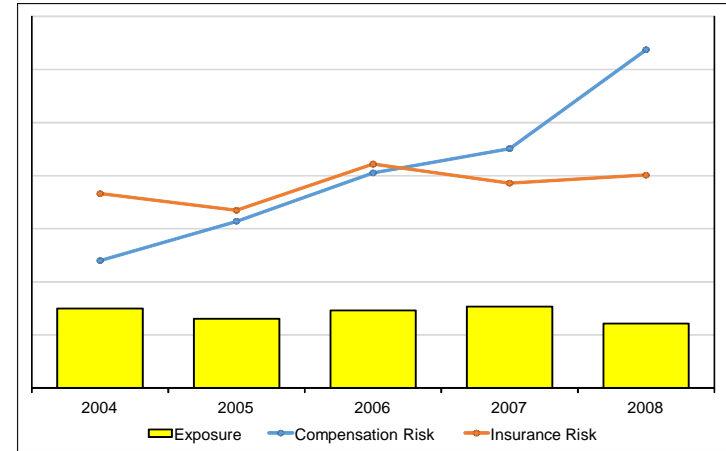
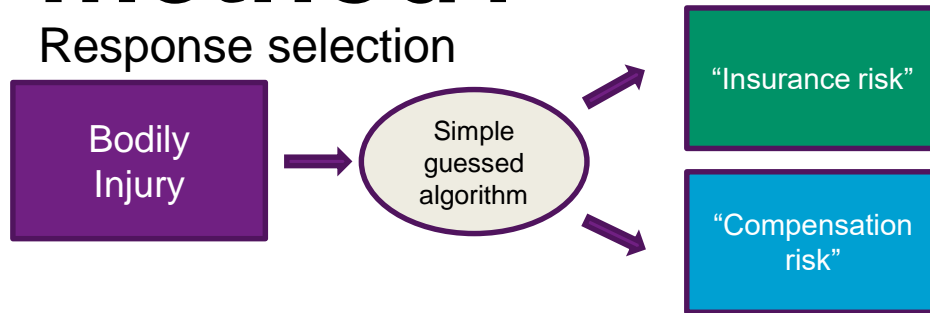
E.g., maximum speed, torque, BHP

# Is it really all about the method?

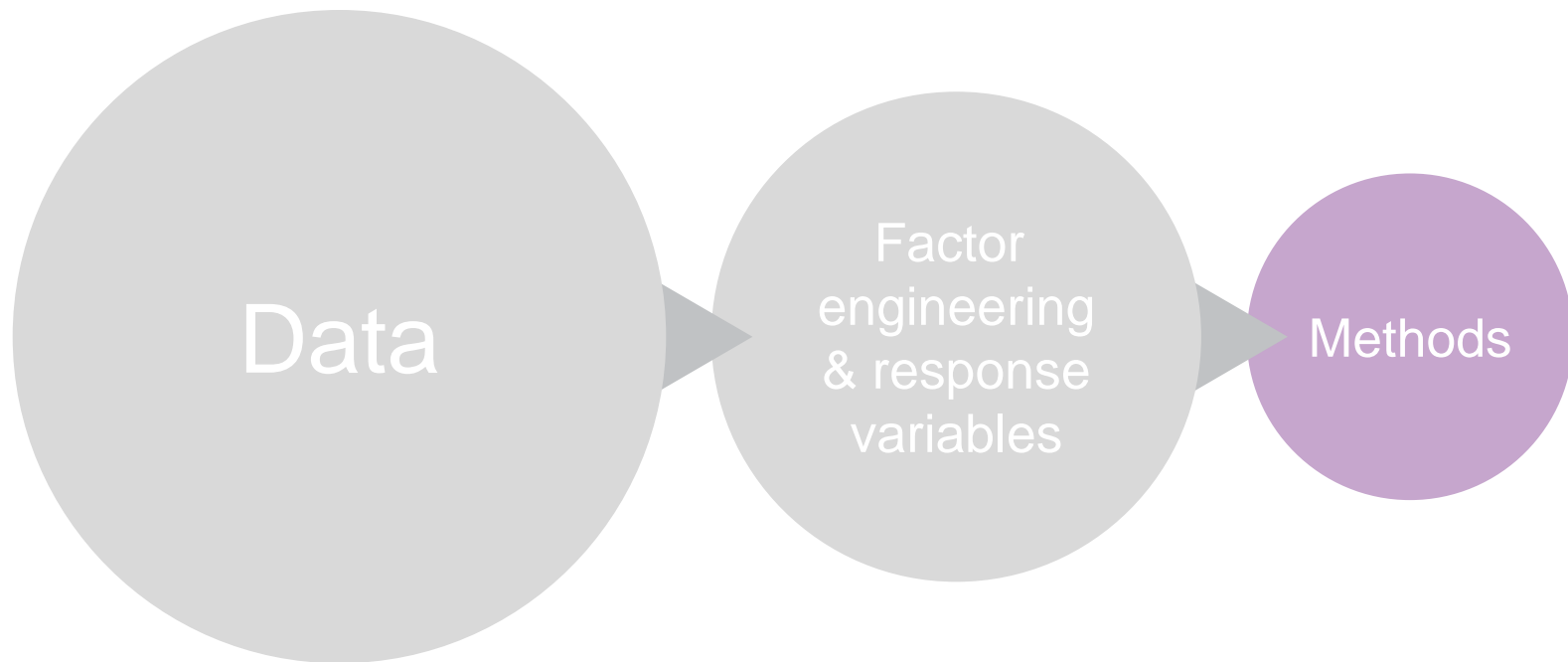


# Is it really all about the method?

Response selection



# Is it really all about the method?



# How do you know if a method works?



AIC

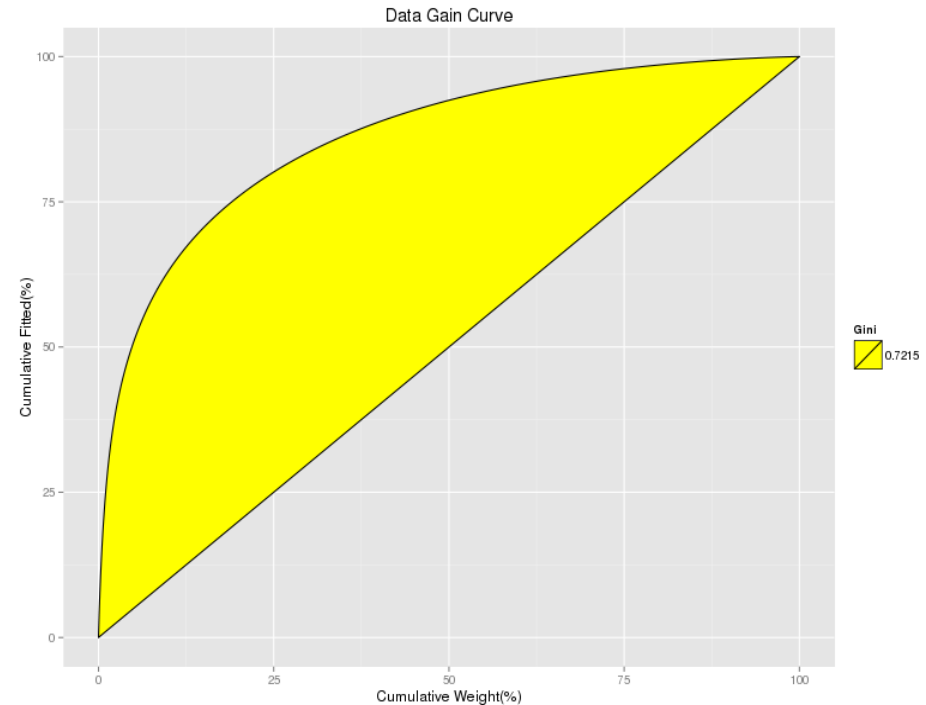
Gini

RMSE

MAE

Log  
loss

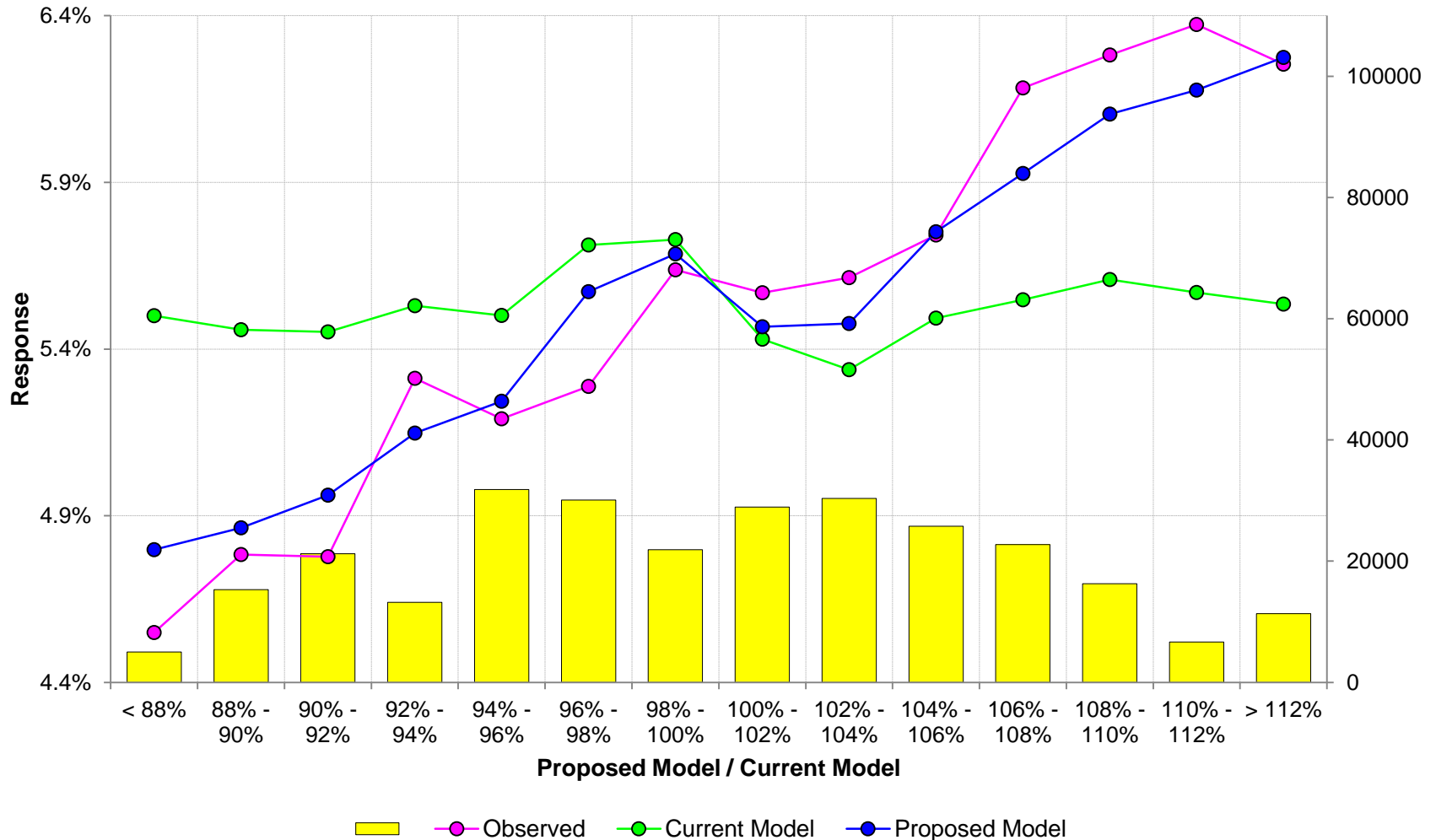
# How do you measure value?



- Rank hold out observations by their **fitted values** (high to low)
- Plot **cumulative response** by cumulative exposure
- A **better model** will explain a **higher proportion of the response** with a **lower proportion of exposure**
- ...and will give a **higher Gini coefficient** (yellow area)

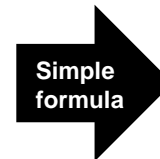
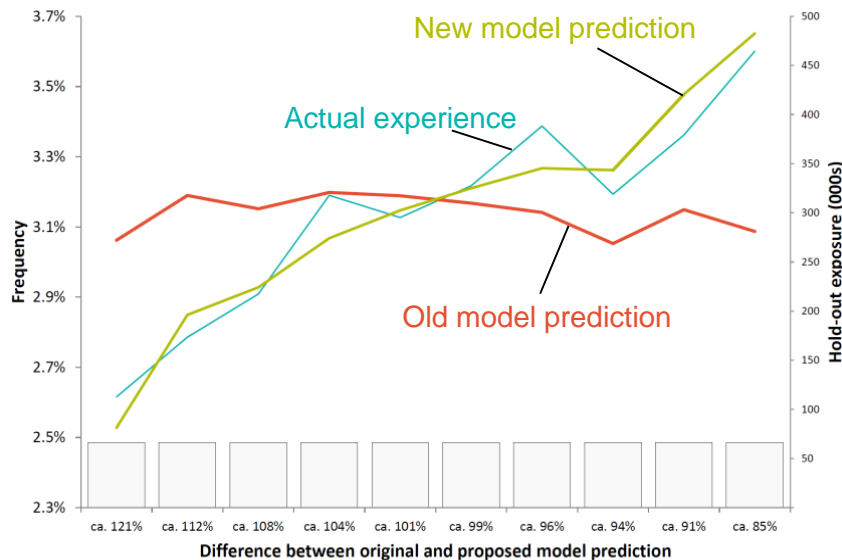


# Double lift chart



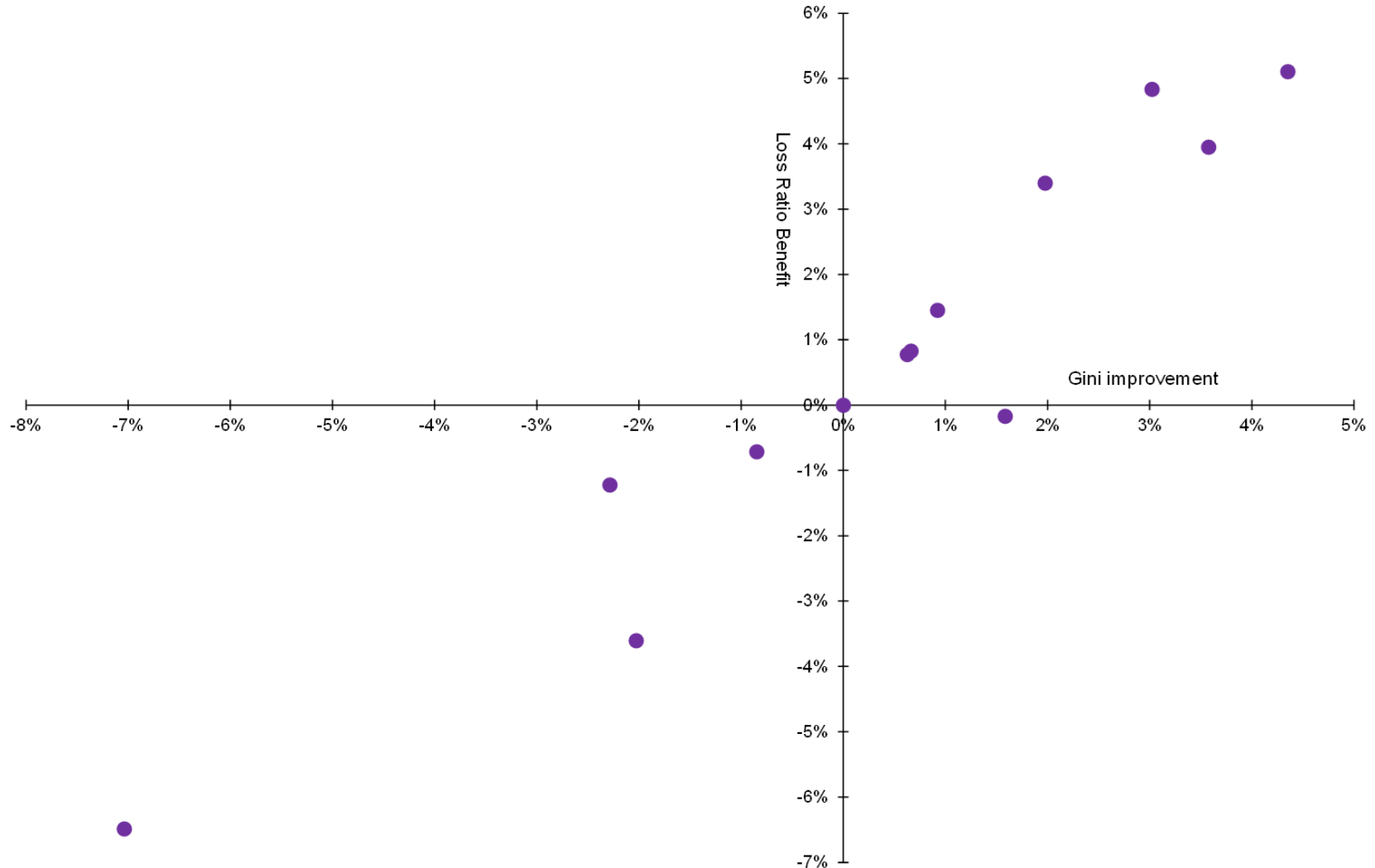
# Financial value estimate

- Errors in insurance pricing are not symmetrical
- Financial benefit can be estimated
- Consider **actual experience** in out of sample data for each percentile of old vs new model fitted values
- Estimate financial benefit that would have been attained
  - given an assumed elasticity
  - given business rules such as an assumed cap/floor approach



| Old/New | New premium | Expected volume | Actual claims | Increased profit     |             |
|---------|-------------|-----------------|---------------|----------------------|-------------|
| 121%    | $P_1$       | $V_1$           | $C_1$         | $X_1$                |             |
| ...     | $P_2$       | $V_2$           | $C_2$         | $X_2$                |             |
| ...     | ...         | ...             | ...           | ...                  |             |
| ...     | $P_{99}$    | $V_{99}$        | $C_{99}$      | $X_{99}$             |             |
| 85%     | $P_{100}$   | $V_{100}$       | $C_{100}$     | $X_{100}$            |             |
|         |             |                 |               | <b>Value created</b> | <b>\$ X</b> |

# Financial value vs Gini



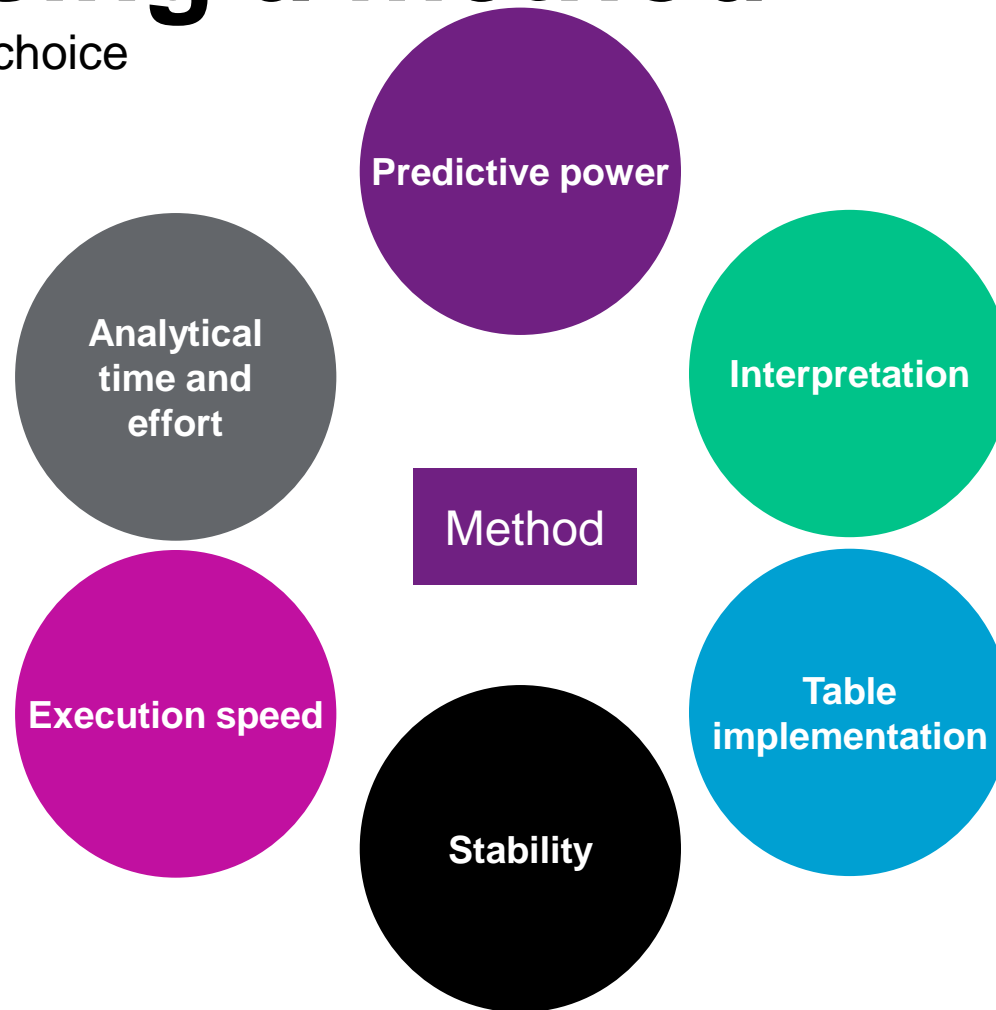
# Is there more to it...?

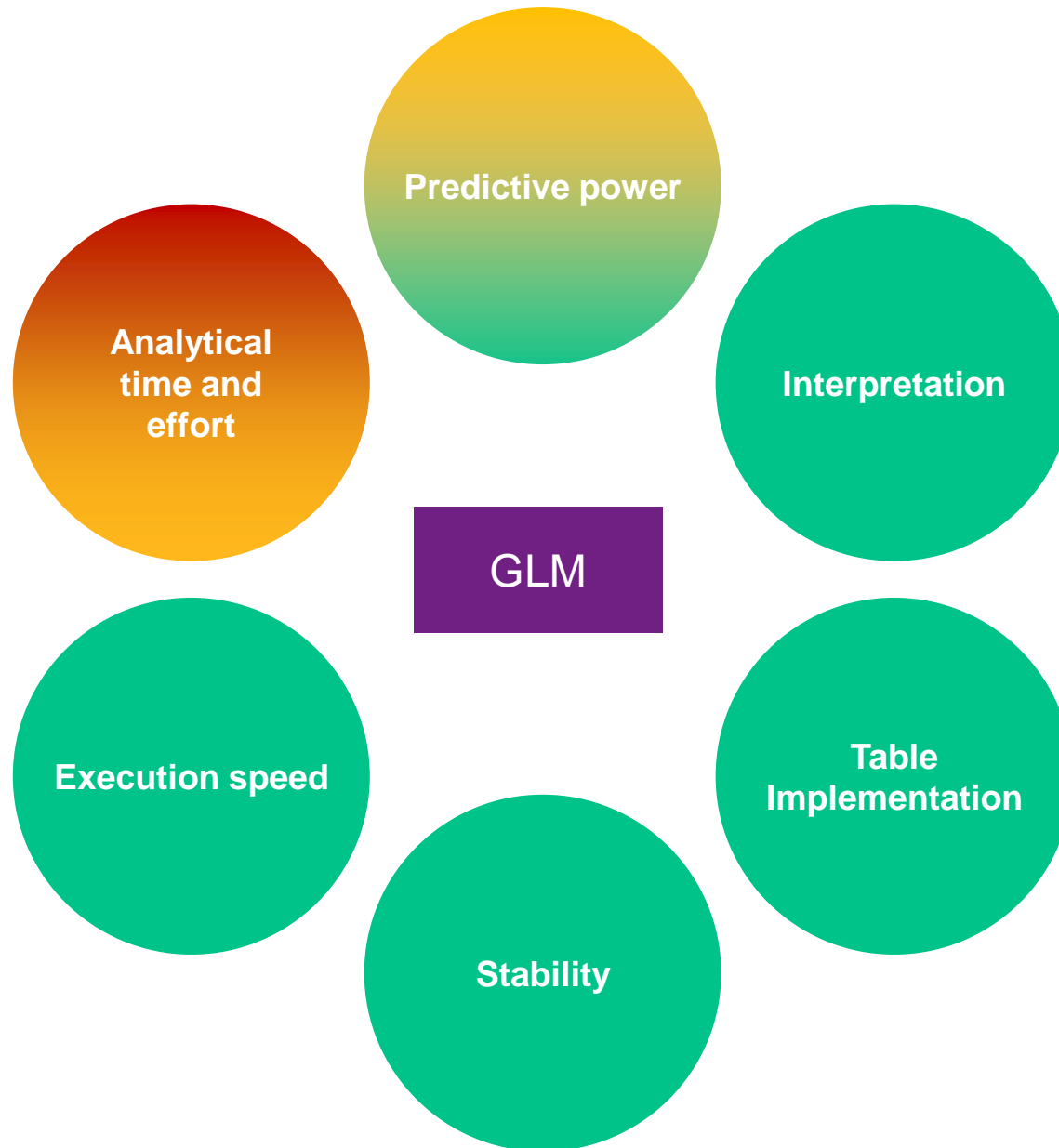


Predictive power

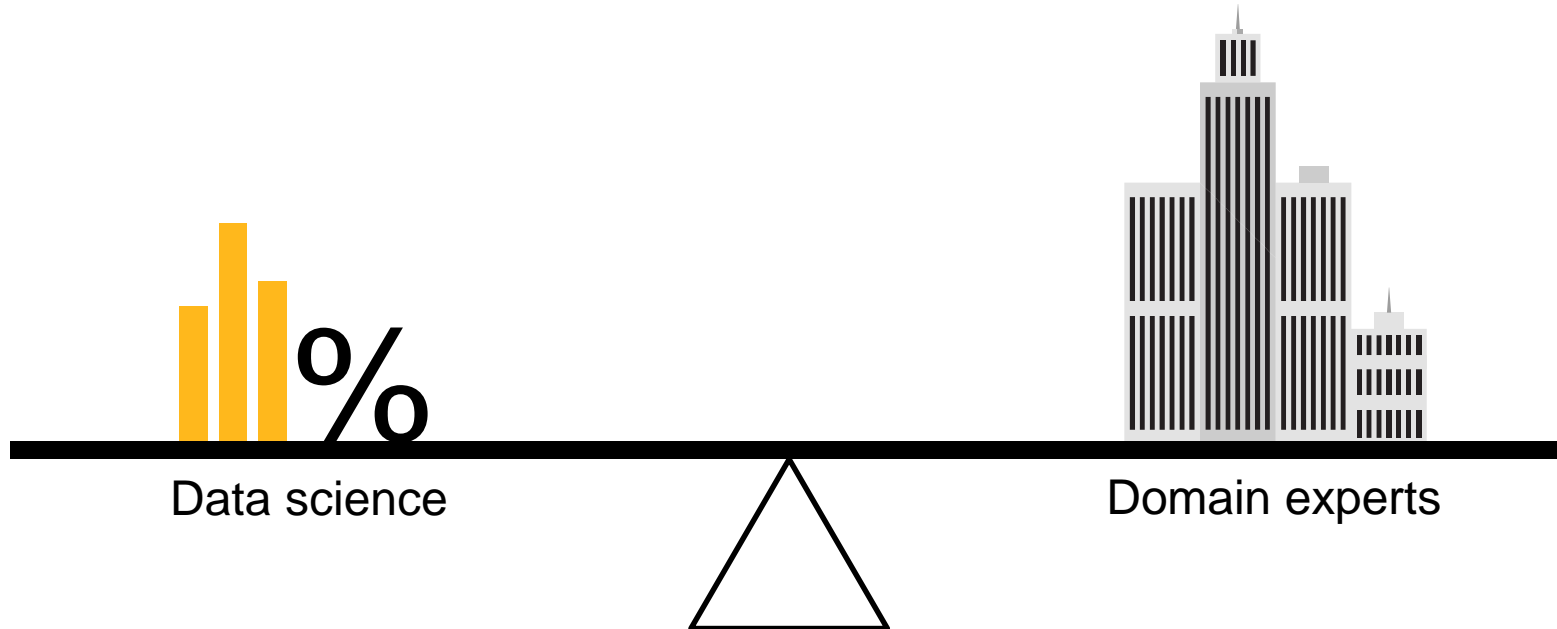
# Choosing a method

Dimensions of choice

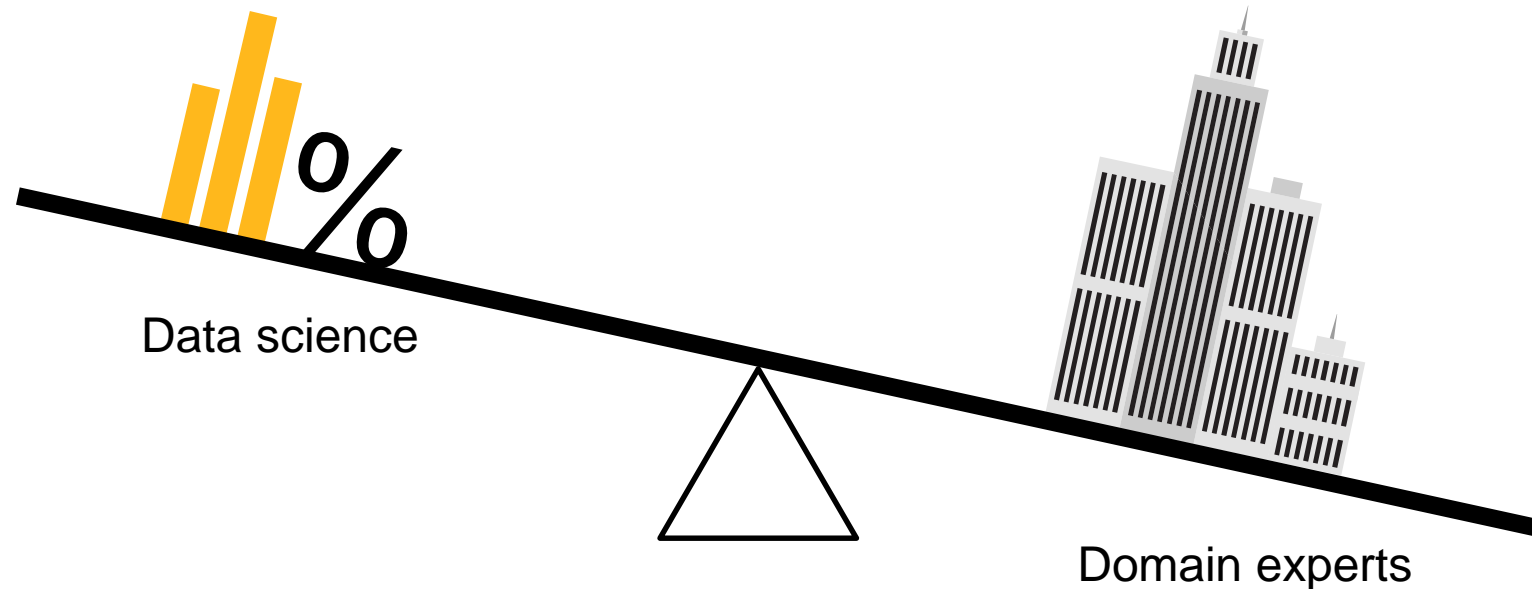




# What do you use where?



# It's domain expertise that helps decide

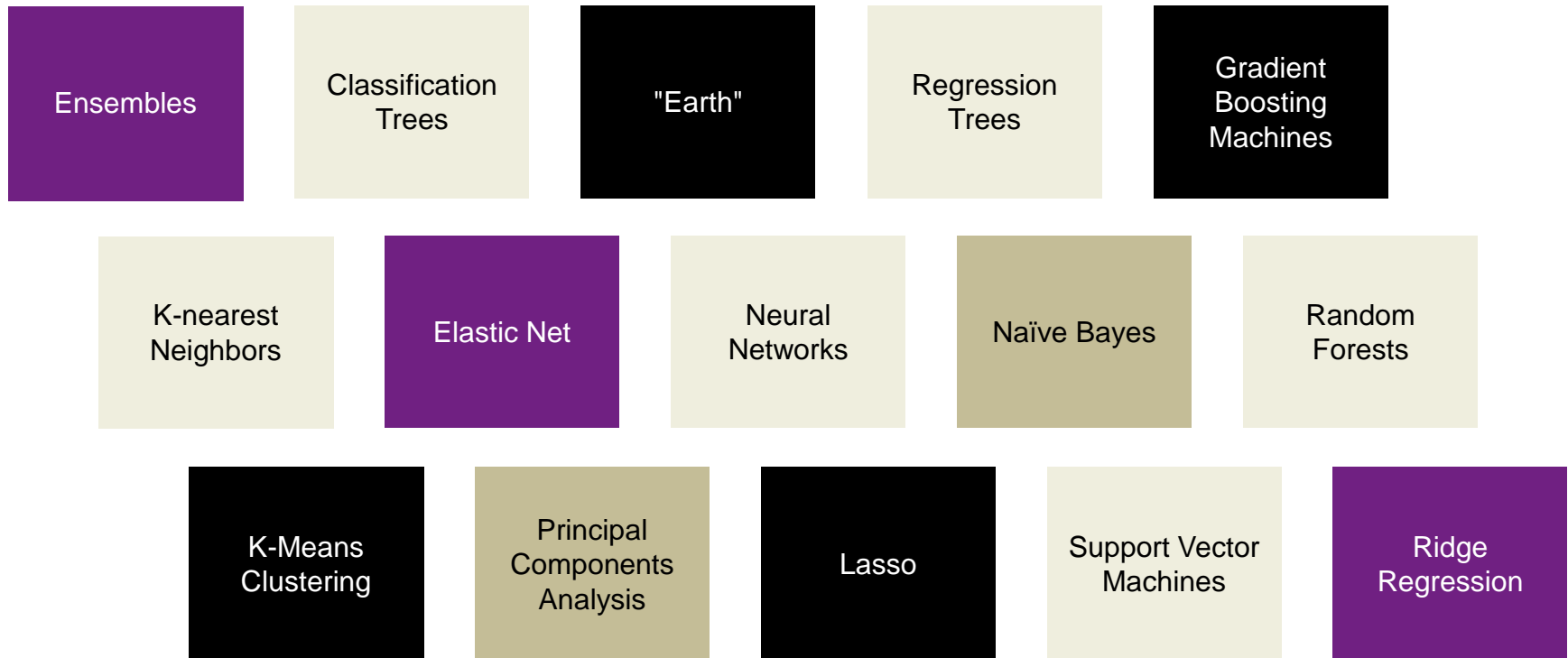




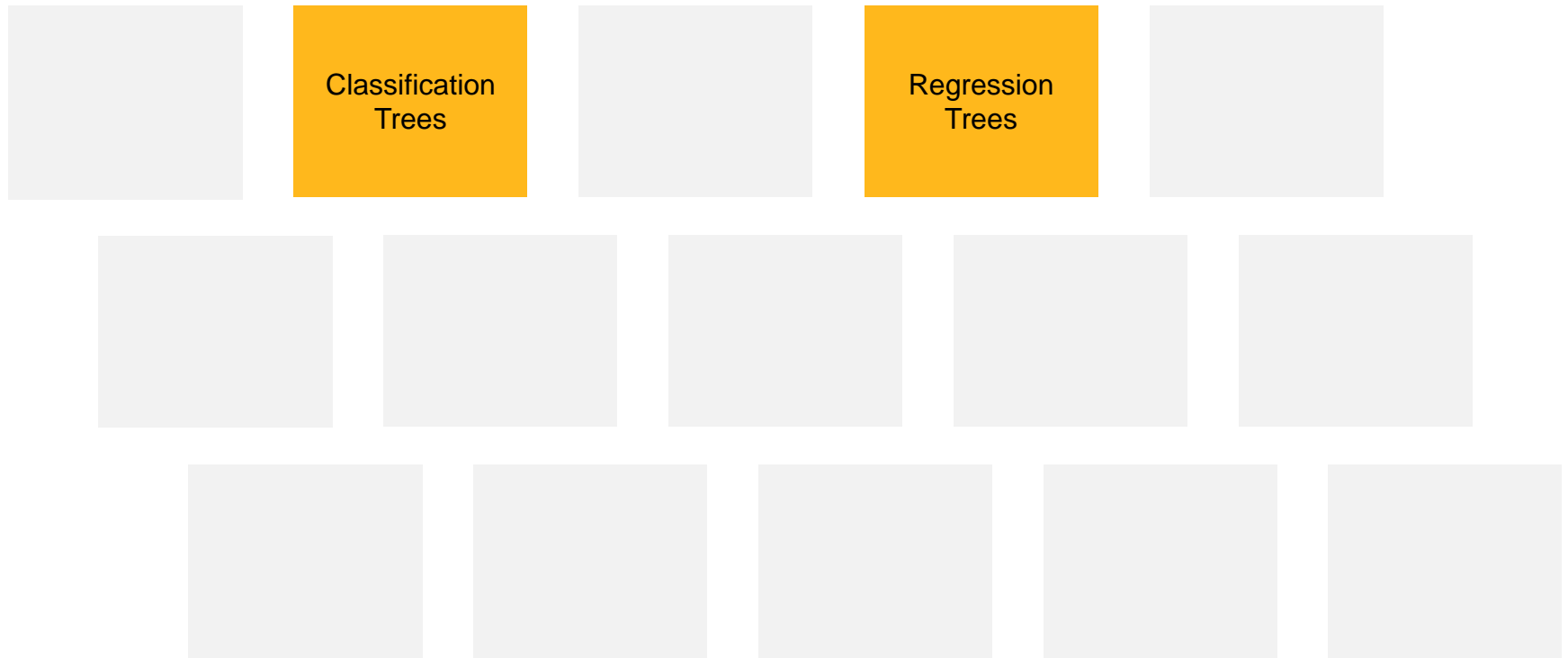


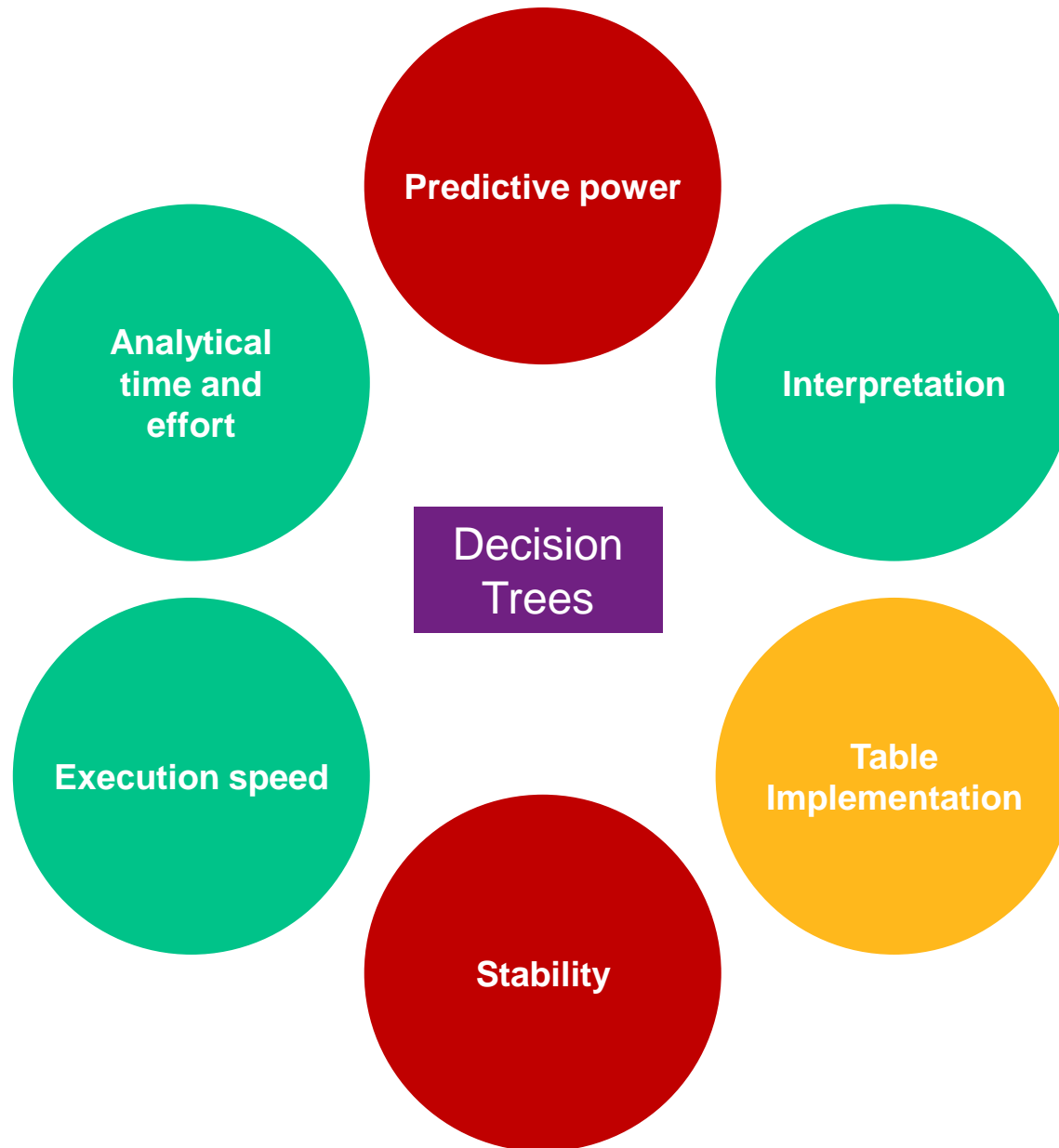
# Tree-based methods

# Some machine learning methods



# Focus on Trees





# Some machine learning methods

Ensembles

Classification  
Trees

"Earth"

Regression  
Trees

Gradient  
Boosting  
Machines

K-nearest  
Neighbors

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Principal  
Components  
Analysis

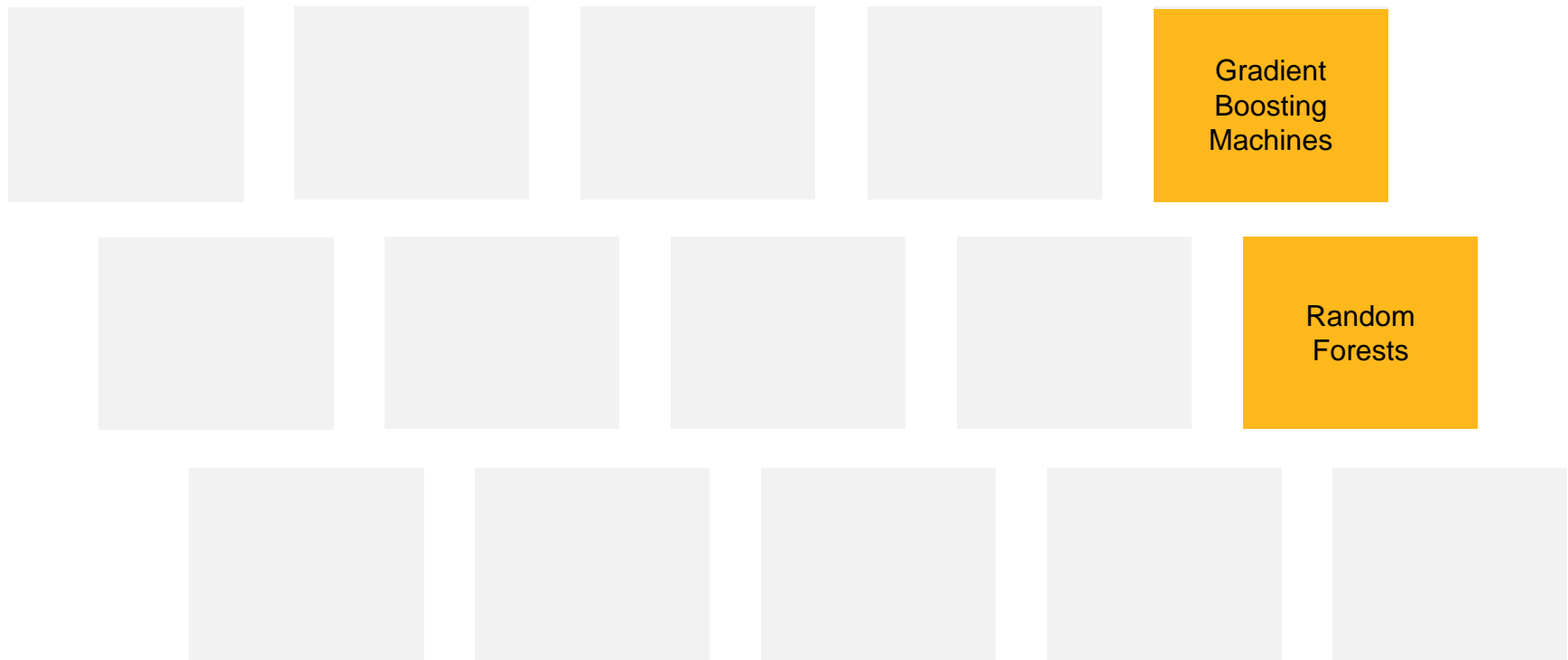
Lasso

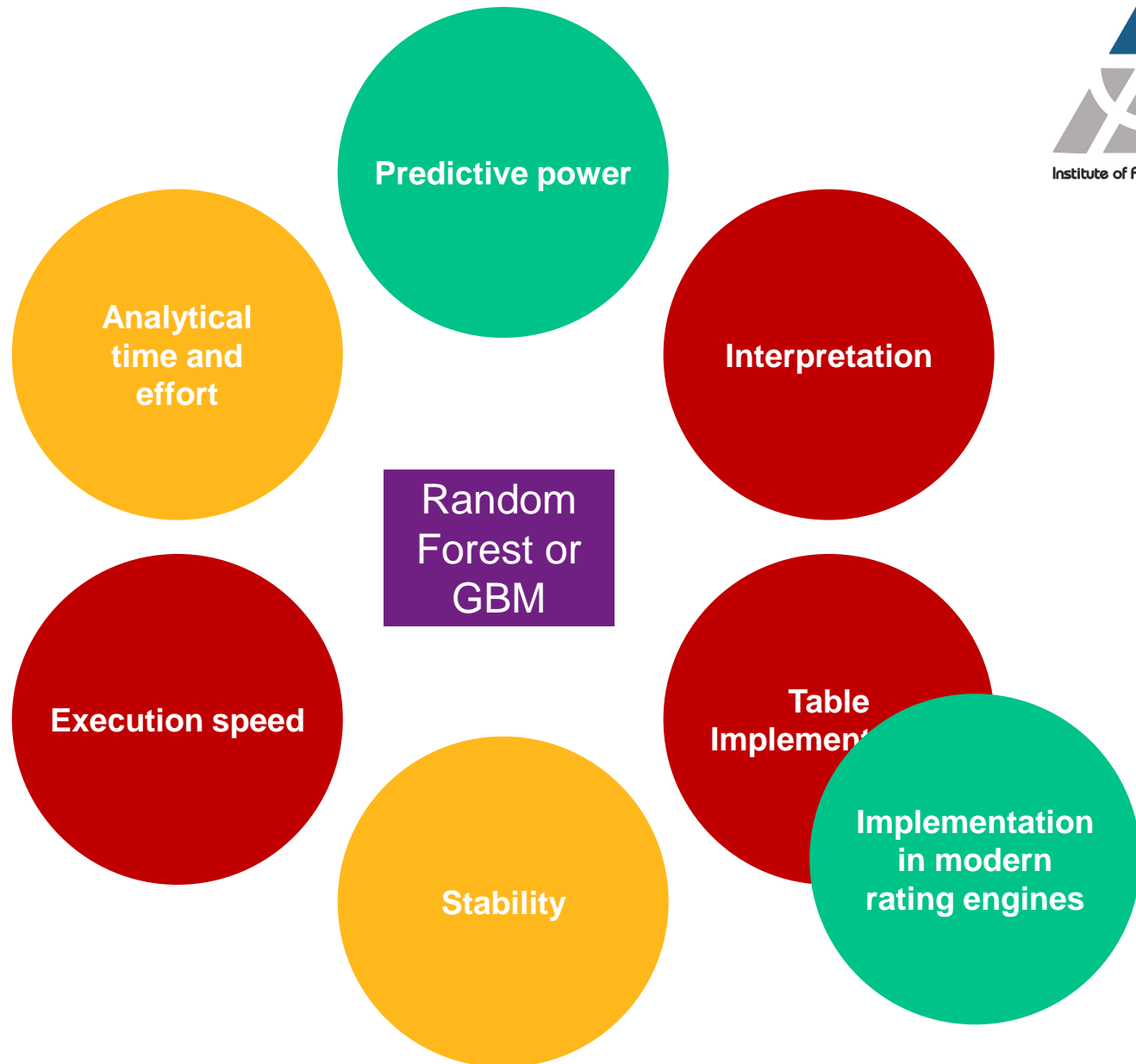
Support Vector  
Machines

Ridge  
Regression



# Focus on Random Forests & Gradient Boosting Machines







# Regression-based methods



# What are these machine learning methods?

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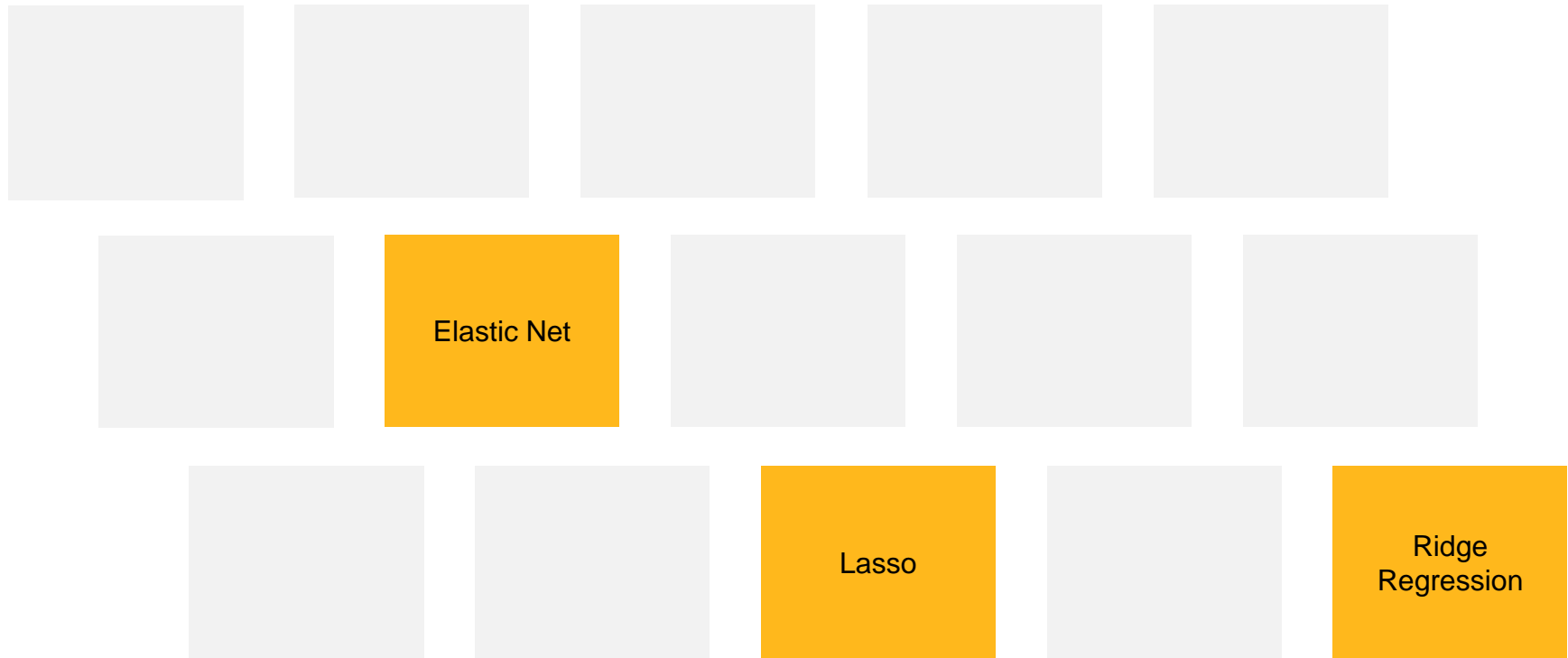
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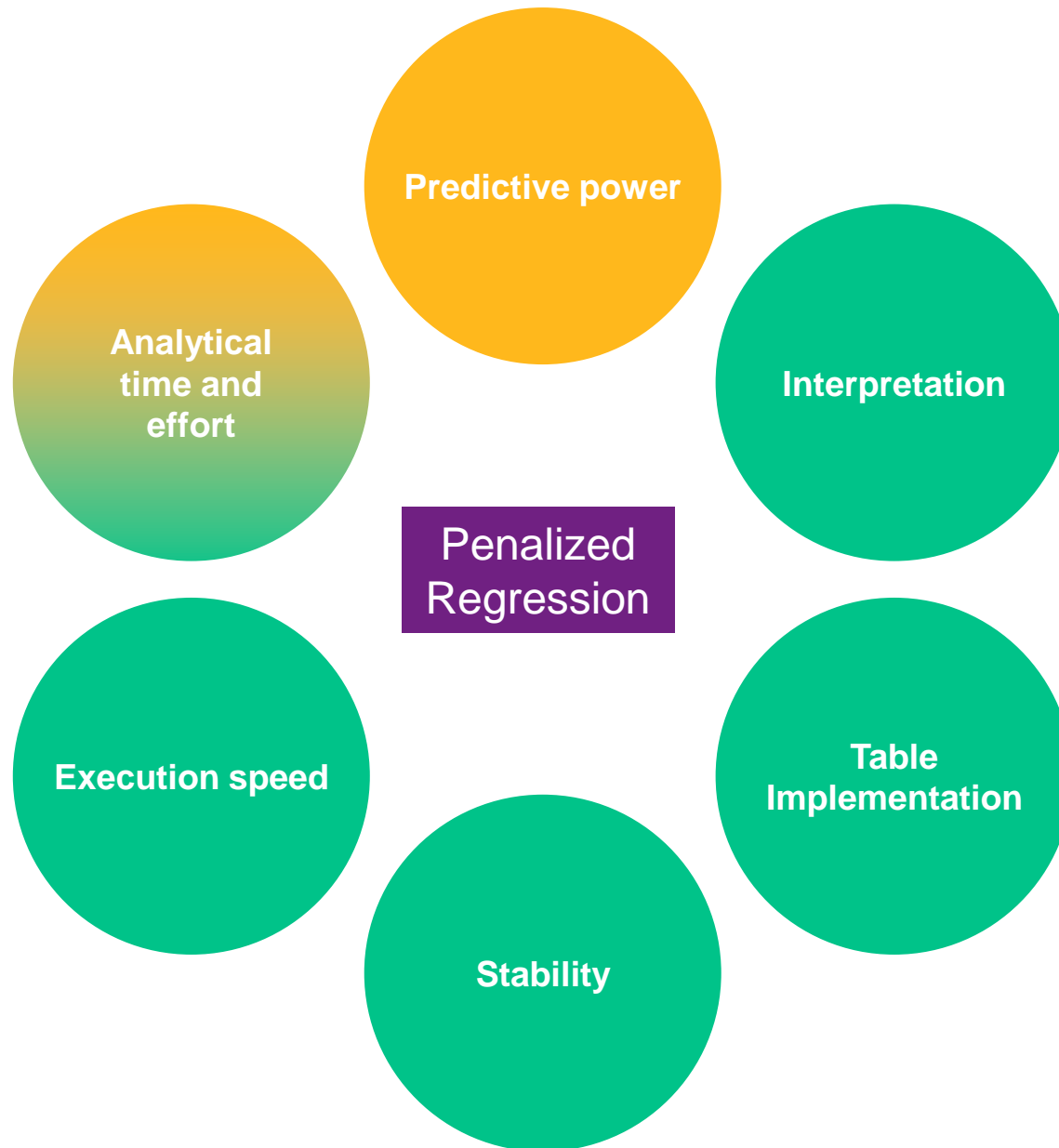
Lasso

Support Vector  
Machines

Ridge  
Regression

# Focus on Penalized Regression

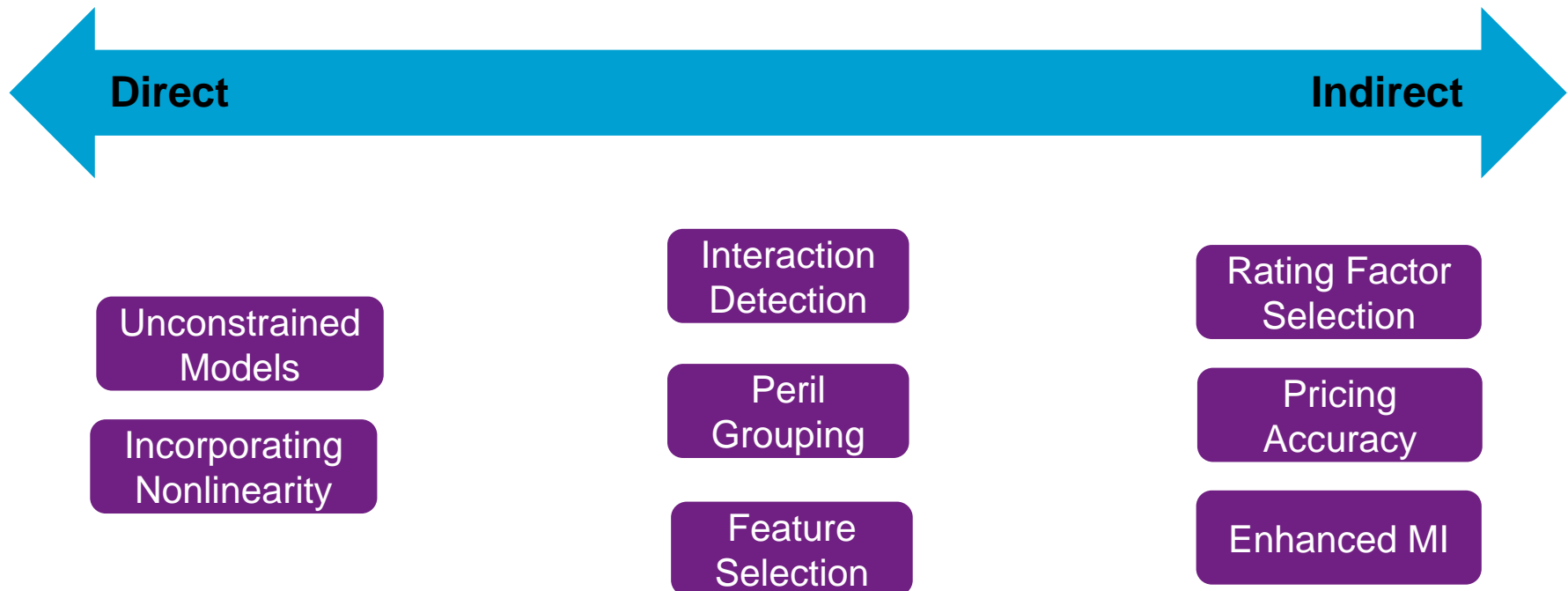






# Pricing applications

# Practical applications of machine learning methods in pricing





# How are insurers using machine learning?

## Insights from a North American survey

# How the North American market is doing with machine learning

## Top applications insurers plan to use two years from now for AI and machine learning



|   | Actual for 2017 | Expected for 2020 (in 2017) | Actual for 2020 | Expected for 2021 |
|---|-----------------|-----------------------------|-----------------|-------------------|
| Build risk models for better decision making                            | 13%             | 44%                         |                 |                   |
| Reduce time spent by humans   | 11%             | 49%                         |                 |                   |
| Better understand risk drivers  | 21%             | 44%                         |                 |                   |
| Identify cases that pose higher risk                                    | 11%             | 46%                         |                 |                   |
| Augment human-performed underwriting                                    | 7%              | 37%                         |                 |                   |
| Identify patterns of fraudulent claims                                  | 9%              | 39%                         |                 |                   |
| Identify bottlenecks in claim processes/Process claims more efficiently | 3%              | 30%                         |                 |                   |

# How the North American market is doing with machine learning

## Top applications insurers plan to use two years from now for AI and machine learning



|   | Actual for 2017 | Expected for 2020 (in 2017) | Actual for 2020 | Expected for 2021 |
|---|-----------------|-----------------------------|-----------------|-------------------|
| Build risk models for better decision making                            | 13%             | 44%                         | 26%             |                   |
| Reduce time spent by humans   | 11%             | 49%                         | 22%             |                   |
| Better understand risk drivers  | 21%             | 44%                         | 20%             |                   |
| Identify cases that pose higher risk                                    | 11%             | 46%                         | 14%             |                   |
| Augment human-performed underwriting                                    | 7%              | 37%                         | 7%              |                   |
| Identify patterns of fraudulent claims                                  | 9%              | 39%                         | 17%             |                   |
| Identify bottlenecks in claim processes/Process claims more efficiently | 3%              | 30%                         | 7%              |                   |



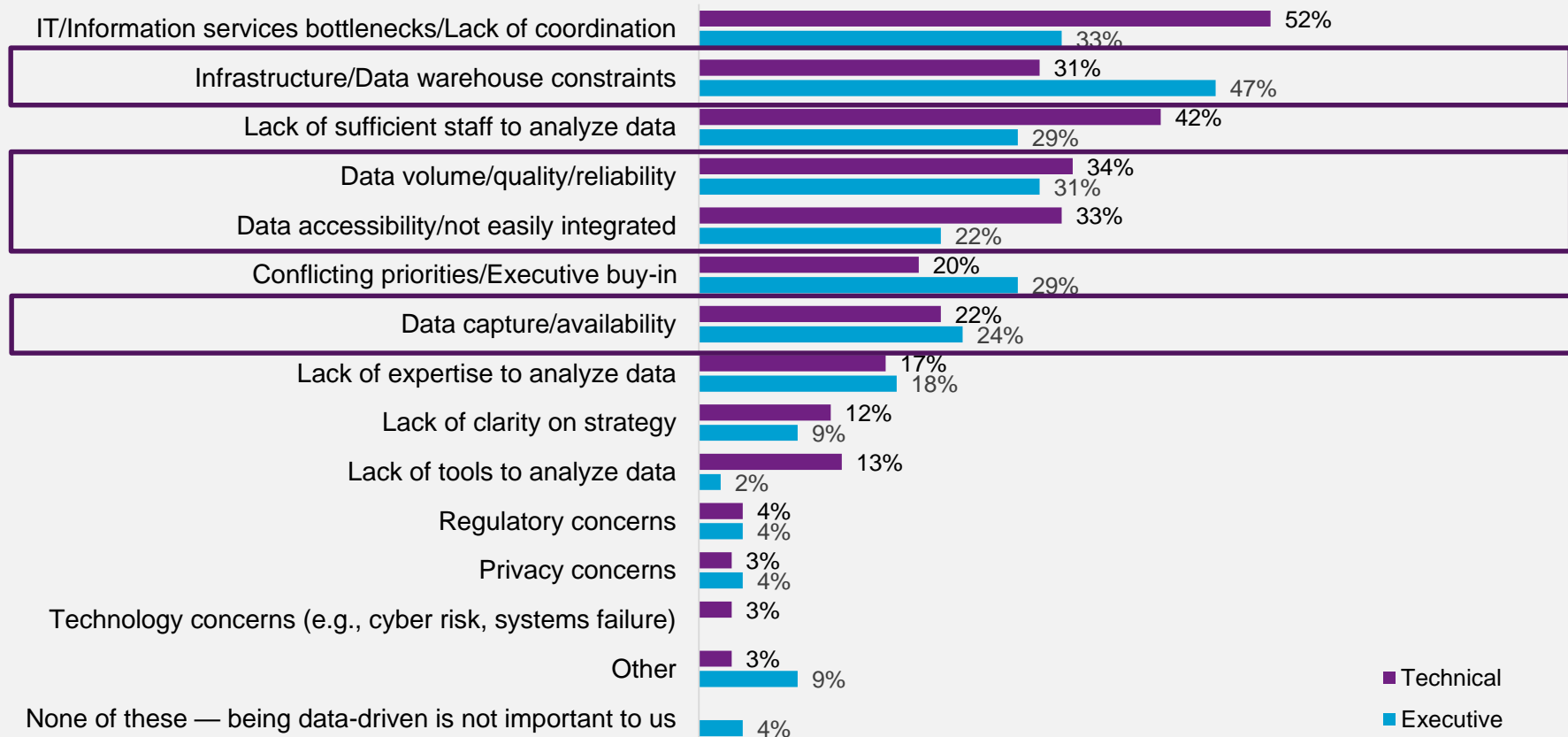
# How the North American market is doing with machine learning

## Top applications insurers plan to use two years from now for AI and machine learning



|   | Actual for 2017 | Expected for 2020 (in 2017) | Actual for 2020 | Expected for 2021 |
|---|-----------------|-----------------------------|-----------------|-------------------|
| Build risk models for better decision making                            | 13%             | 44%                         | 26%             | 60%               |
| Reduce time spent by humans   | 11%             | 49%                         | 22%             | 60%               |
| Better understand risk drivers  | 21%             | 44%                         | 20%             | 56%               |
| Identify cases that pose higher risk                                    | 11%             | 46%                         | 14%             | 50%               |
| Augment human-performed underwriting                                    | 7%              | 37%                         | 7%              | 47%               |
| Identify patterns of fraudulent claims                                  | 9%              | 39%                         | 17%             | 47%               |
| Identify bottlenecks in claim processes/Process claims more efficiently | 3%              | 30%                         | 7%              | 43%               |

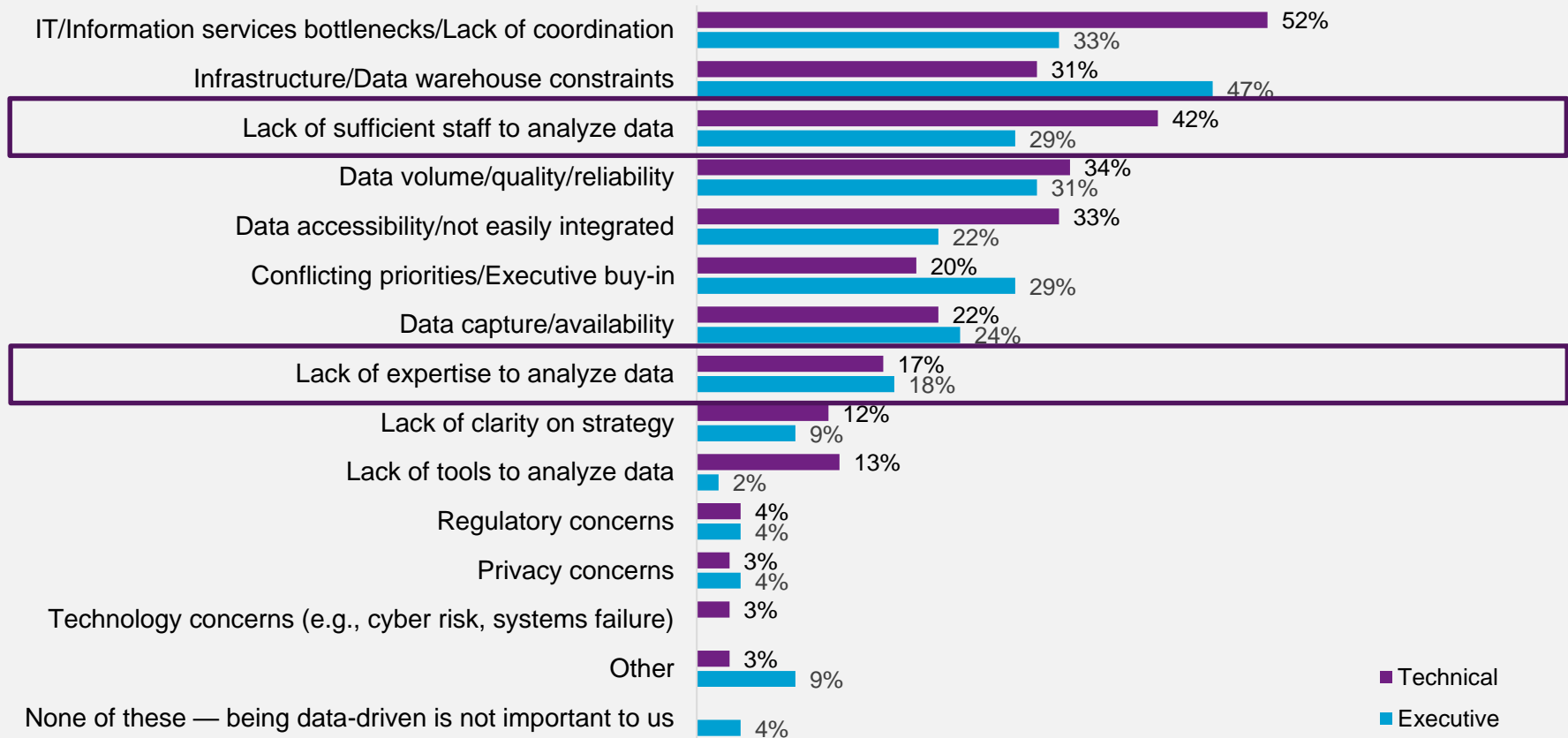
# What are the three biggest challenges preventing your company from becoming more data driven?



Base: Total respondents (technical n = 77, executive n = 45)



# What are the three biggest challenges preventing your company from becoming more data driven?

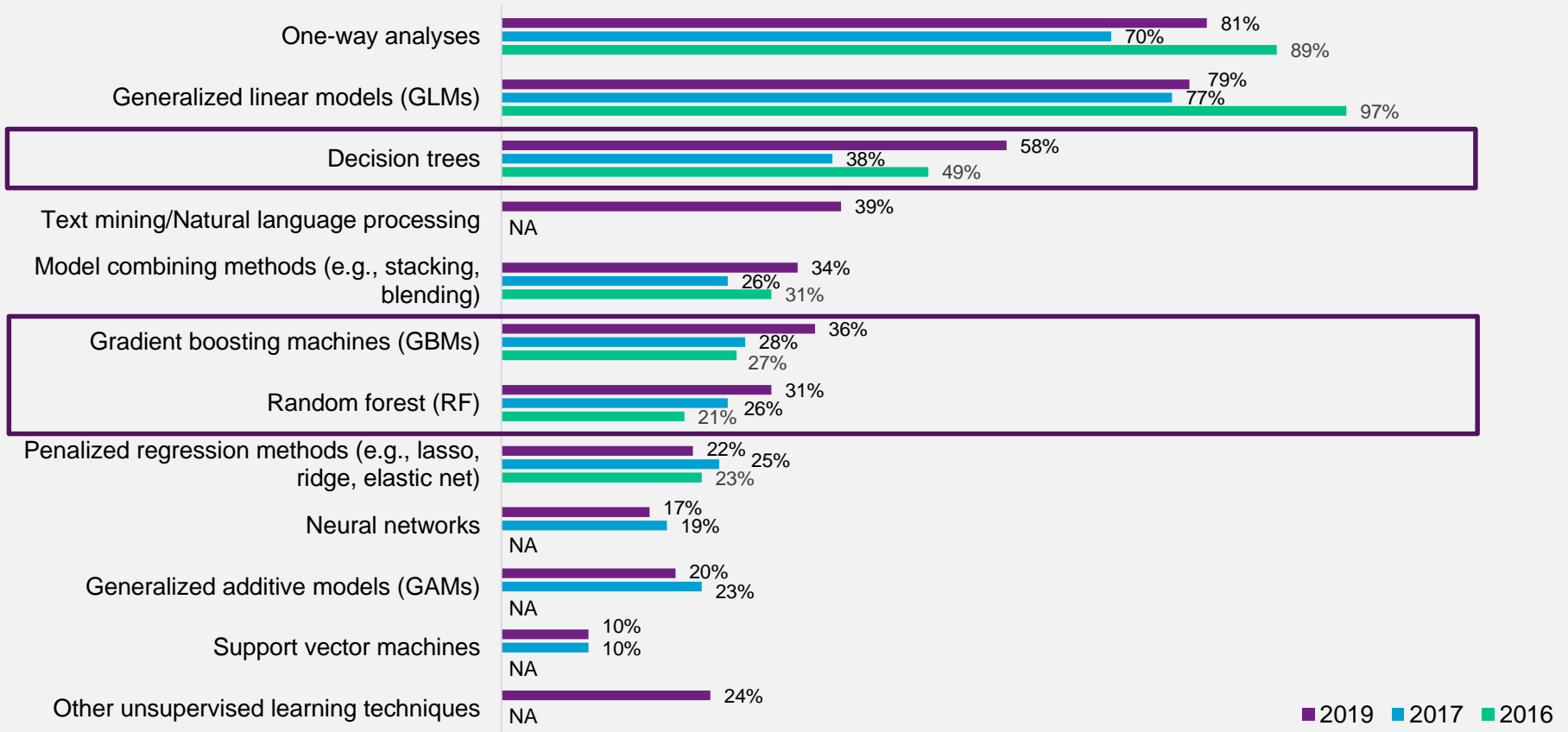


Base: Total respondents (technical n = 77, executive n = 45)



# How the North American market is doing with machine learning

## Methods used



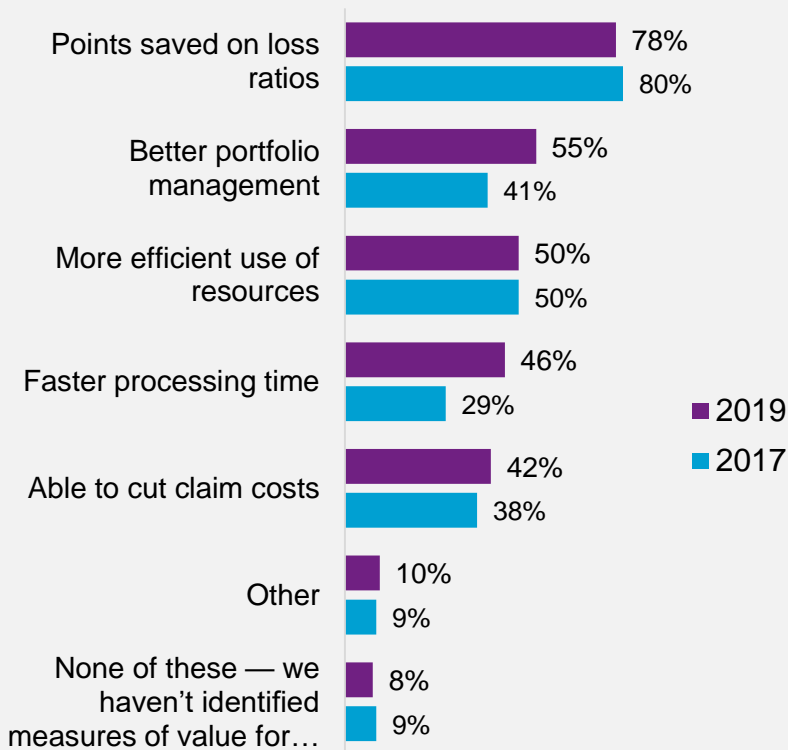
Base: Technical survey respondents using advanced analytics (n = 76 in 2020, n = 69 in 2017, n = 62 in 2016)



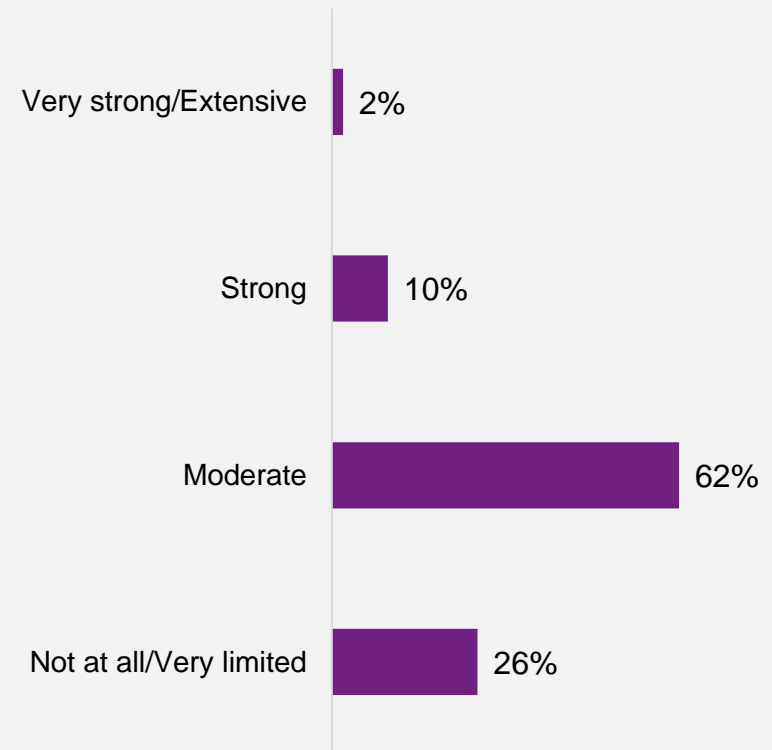
# How do you determine the value of your predictive models?

## How well understood are your predictive models by those who need to use them, outside of the modeling team?

Measures used to determine value of predictive models

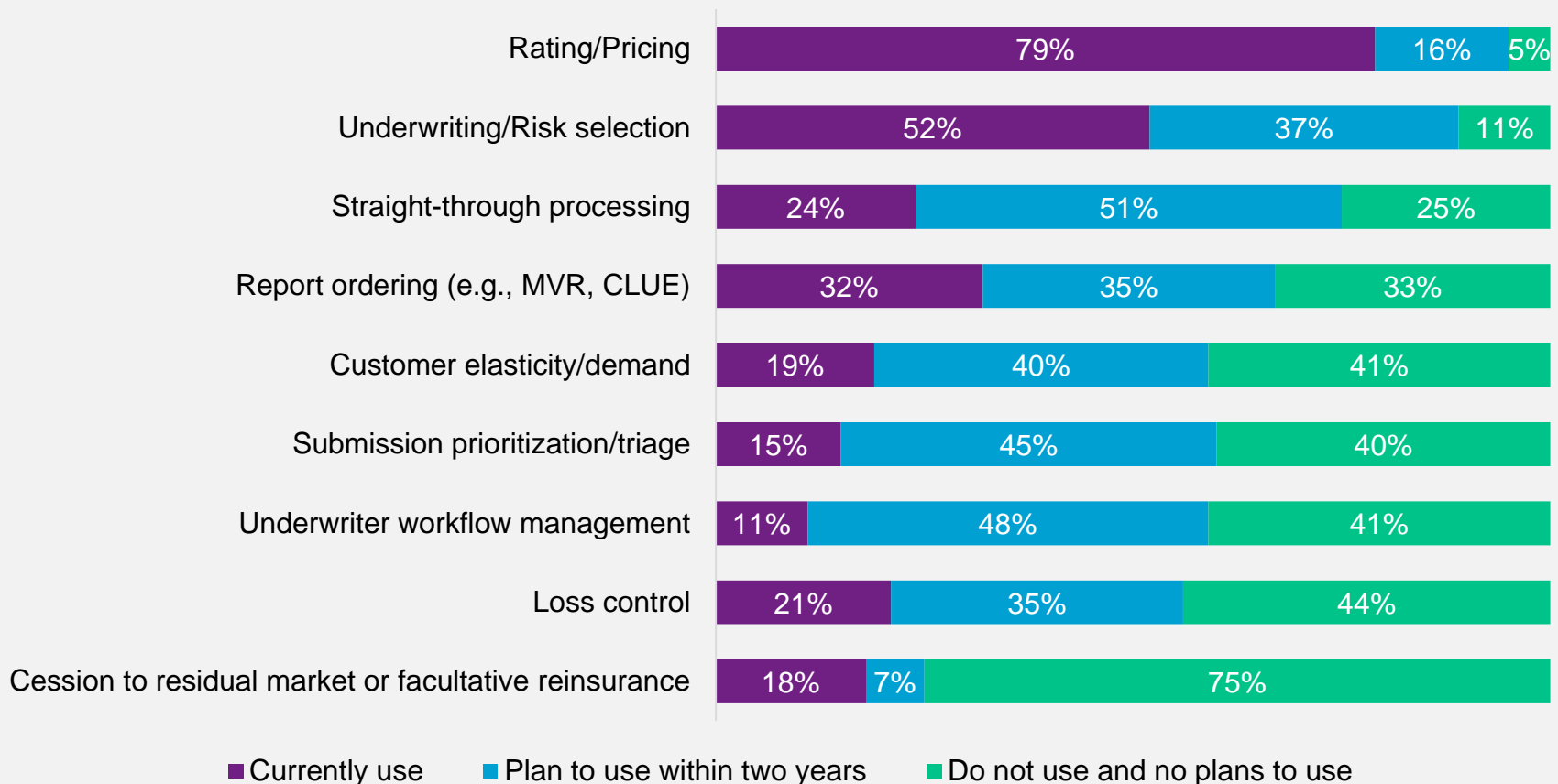


Level of understanding of predictive models outside of the modeling team



Base: Total respondents using advanced analytics (n = 113 in 2020, n = 56 in 2017)

# For which aspects of underwriting/pricing does your company group currently use or plan to use advanced analytics?



Base: Total respondents (n = 122)



# Adoption and use of machine learning in APAC and India

# Classification of Indian Market

## BEHIND THE MARKET

⑩ Few companies are still struggling with legacy issues and have old methods of carrying out core insurance work

## • AT MARKET

• Companies making limited use of AI/ML techniques for:

- 1. Actuarial
- 2. Claims Management/ Fraud Analytics
- 3. Underwriting
- 4. Sales

## ADVANCED

Companies using AI/ML techniques for:

1. Actuarial
2. Claims Management/ Fraud Analytics
3. Underwriting
4. Sales
5. Marketing
6. Customer Support
7. Human Resources



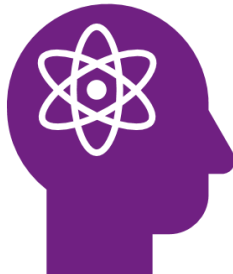
# GLM and ML in APAC



Adopting of GLM and Machine Learning in APAC

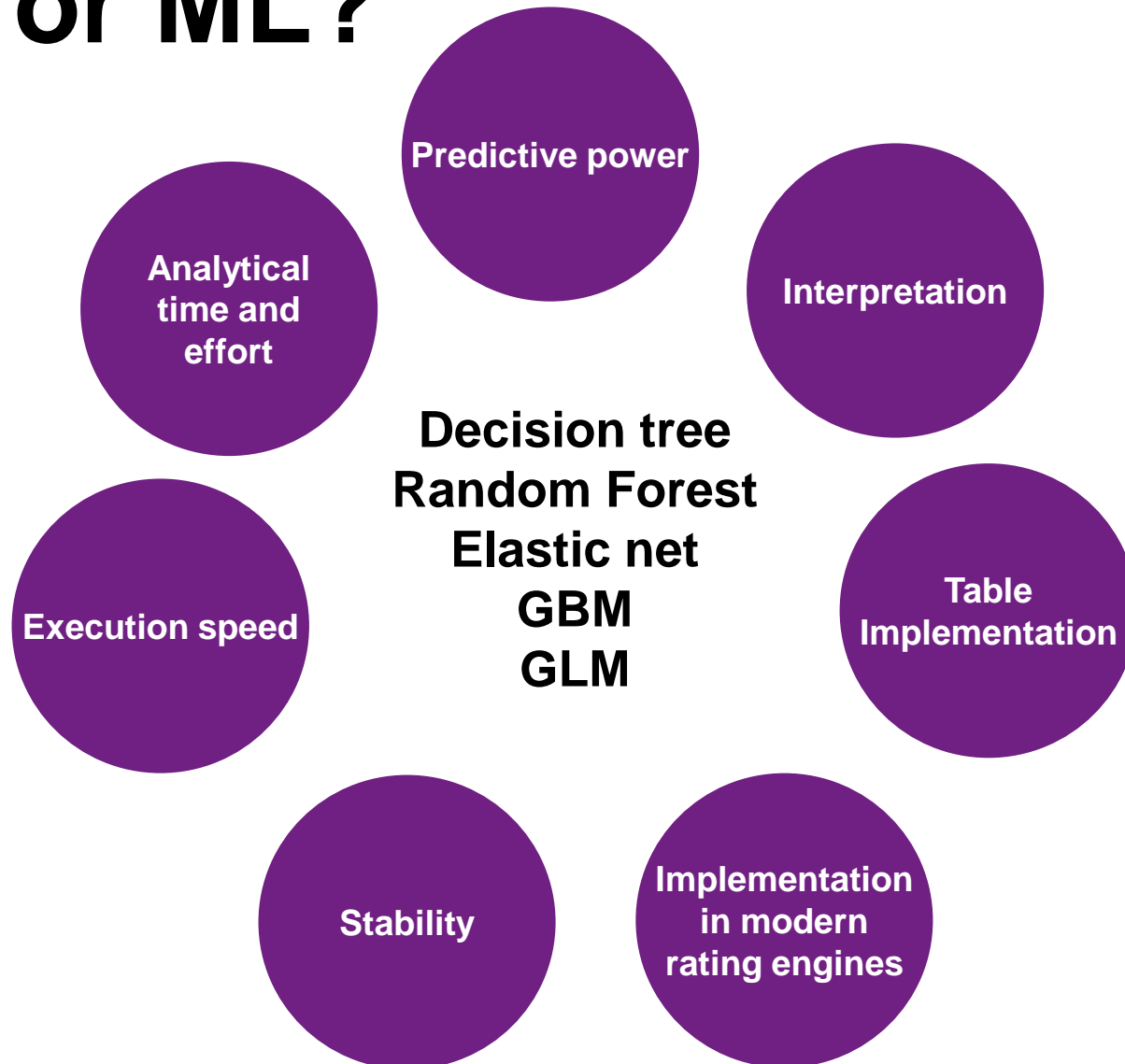


Education and skillsets



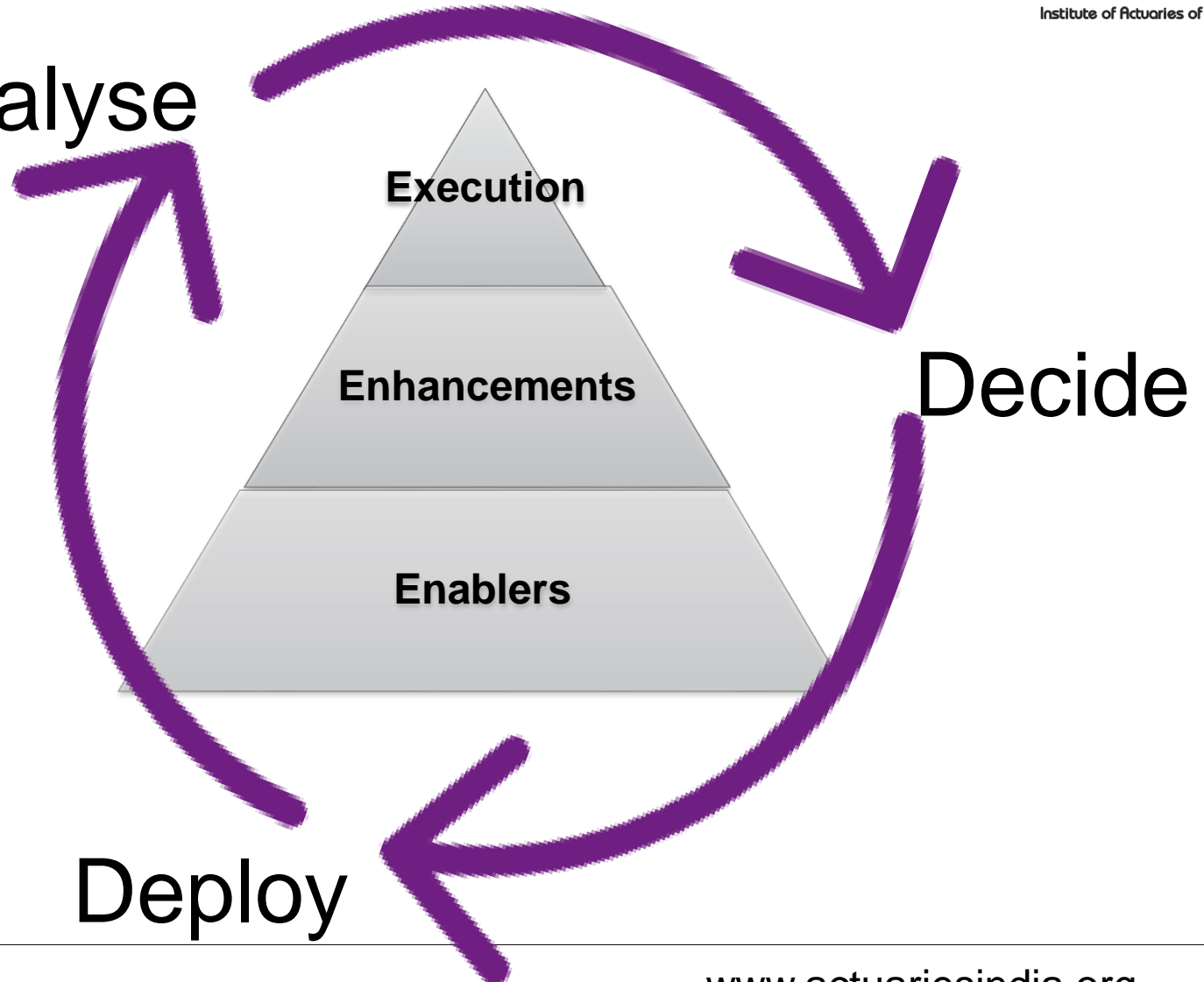
Actuary vs data scientist

# GLM or ML?



# Start your journey today

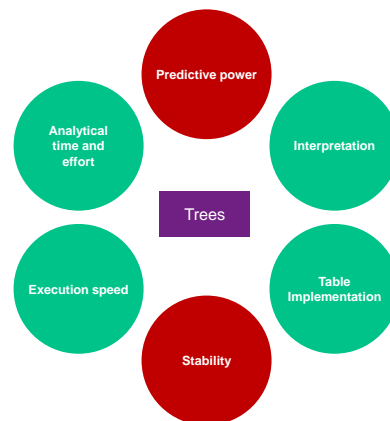
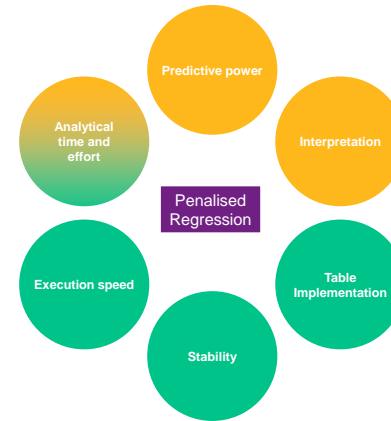
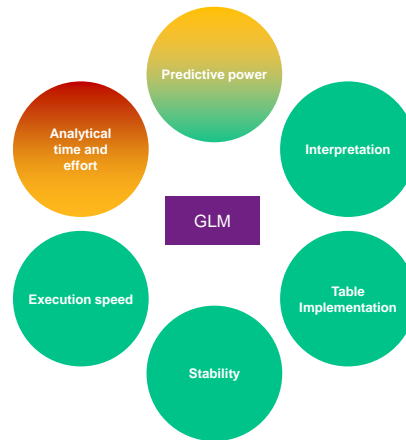
Analyse





# Summary and Q&A

# A more complete summary





# Machine Learning in Pricing

## Conclusions

- There are many forms of ML models
- New data and feature/response engineering generally add more value than new methods BUT we need to continuously explore which methods work on which problems
- Traditional measures of prediction value may not reflect applications in insurance
- And it's not all about predictive power anyway – other criteria are important
  
- GBMs and Random Forests can provide predictive lift benefits by capturing higher order effects ... BUT
  - Can you cope with not seeing the model and instead use broad diagnostics?
  - Effort is required to expose/understand higher order effects in an expeditious manner
  - How will business leaders and regulators respond to these methods?
  - Can you file and deploy results based on these models?



# Machine Learning in Pricing

## Conclusions

- Penalized regression can aid in factor selection decisions and may in fact be a good method in its own right – particularly when the modeler has less of a “feel” for the data
- Machine learning in pricing is not all about improving predictive power. Consider:
  - Fast investigation of new data
  - Quick assessment and response of emerging experience



# Machine Learning beyond Pricing

## Conclusions

- Machine Learning is becoming established within insurance analytics
- It opens up a broader set of problems to analytics, and offers a broader tool set for familiar problems
- There's opportunity to reveal actionable, first-order insights in applications to which analytics have not been deployed previously
- We expect use of Machine Learning to continue to grow- in Pricing and beyond



**Willis Towers Watson** 