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# C4: Pricing Workshop – Overview and Practical Applications of Machine Learning Methods in Pricing

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# C4: Pricing Workshop

## – Overview and Practical Applications of Machine Learning Methods in Pricing

## Agenda

**Context of machine learning in pricing**

- **Decision trees**
- **Random forests**
- **Gradient boosting machines**

**Practical applications of ML techniques**

**Conclusions**

**Q&A**

**Objective:**

to give you a working knowledge of some machine learning methods that may be used to improve GLM results and/or offer valuable insights in their own right in the field of P&C insurance pricing

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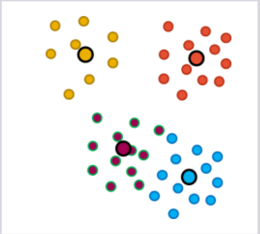
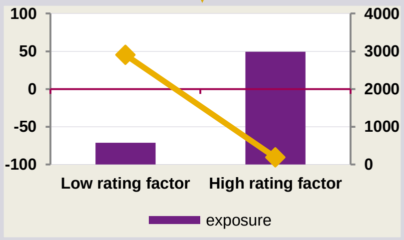
# Applications of machine learning in the insurance sector

Marketing and Distribution → Customer management → Underwriting and risk management → Pricing → Claims management → Asset management

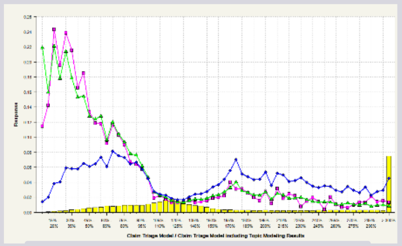
- Product development (UBI)
- Retention segmentation and program design
- Agent/Broker performance evaluation
- Fraud detection



P&C to Life cross-selling




Web-scraping and feature design in commercial lines



Topic modeling and large loss modeling

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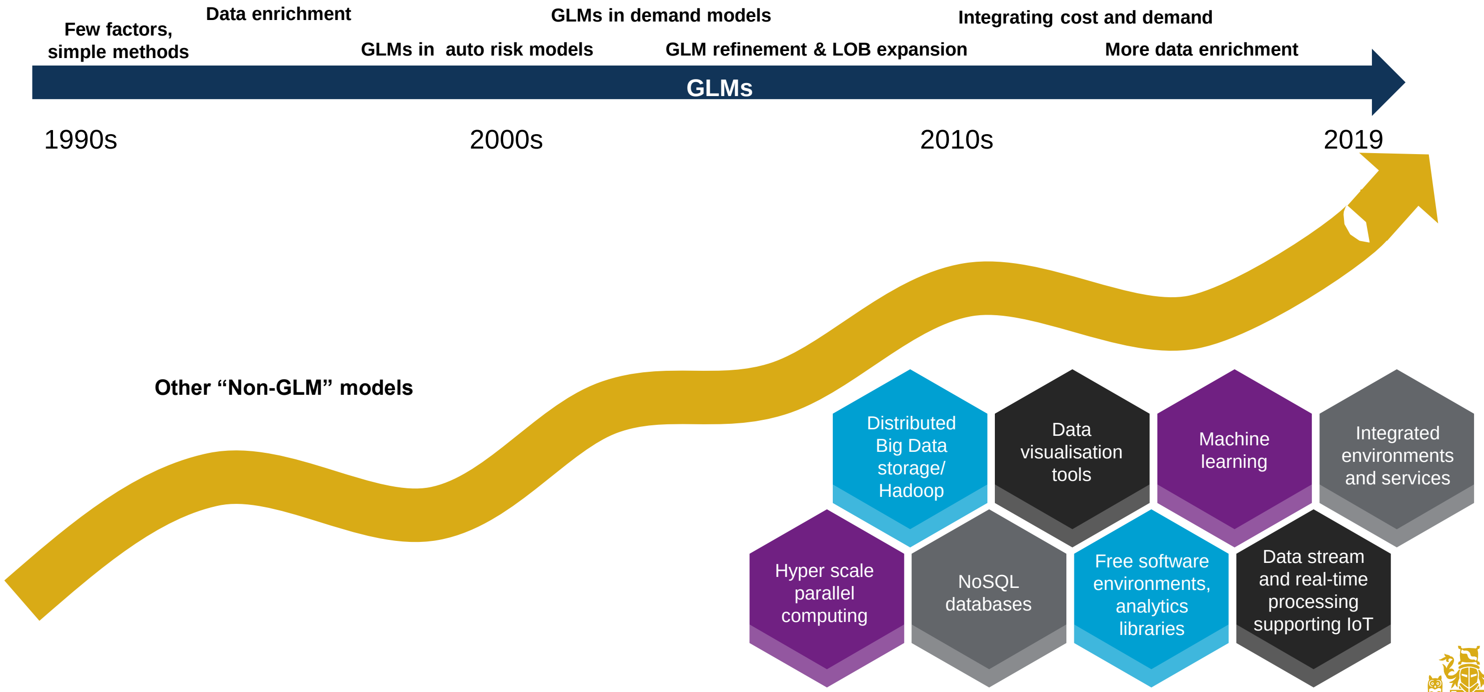
# This is not new….

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# What are these machine learning methods?

Ensembles

Classifications Trees

"Earth"

Regression Trees

Gradient Boosting Machines

K-nearest Neighbors

Elastic Net

Neural Networks

Naïve Bayes

Random Forests

K-Means Clustering

Principal Components Analysis

Lasso

Support Vector Machines

Ridge Regression

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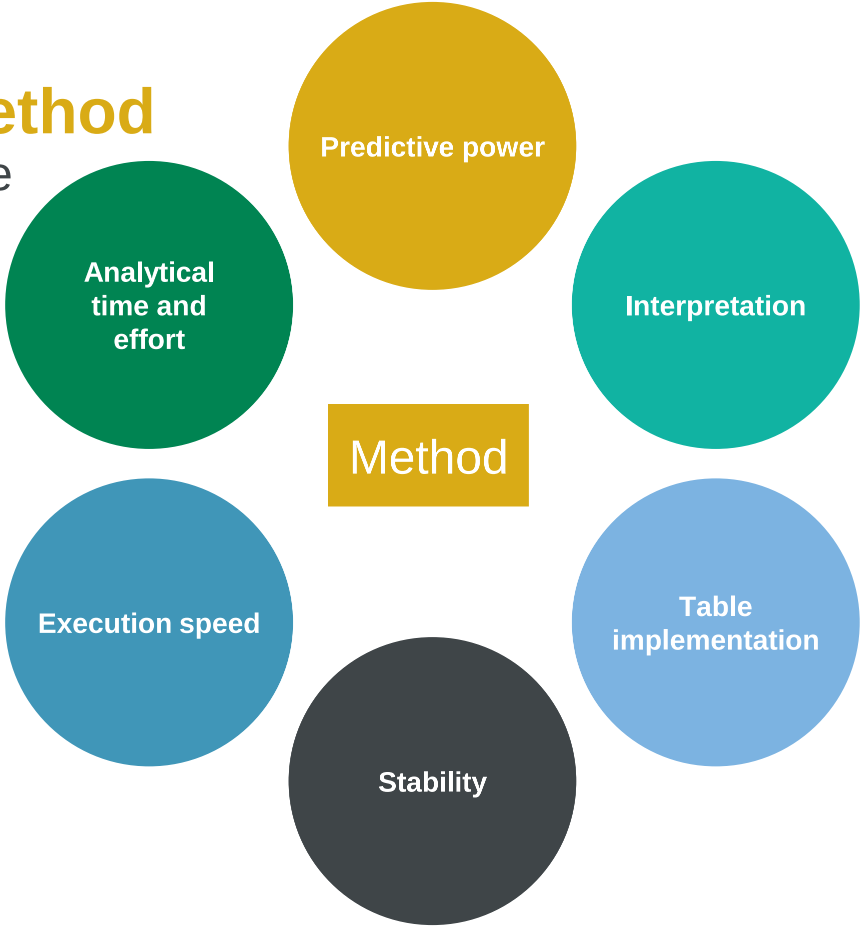
# Choosing a method
## Dimensions of choice

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# Focus on Trees

Ensembles

**Classifications Trees**

"Earth"

**Regression Trees**

Boosting

K-nearest Neighbours

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Neural Networks

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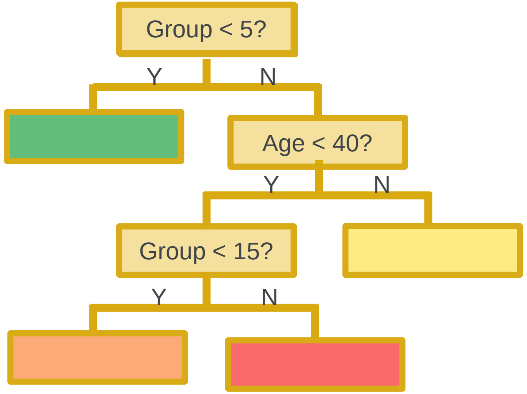
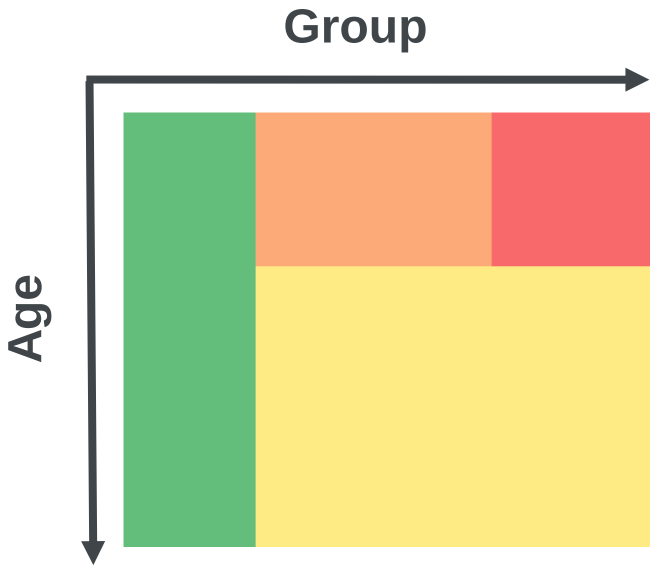
# Decision Trees

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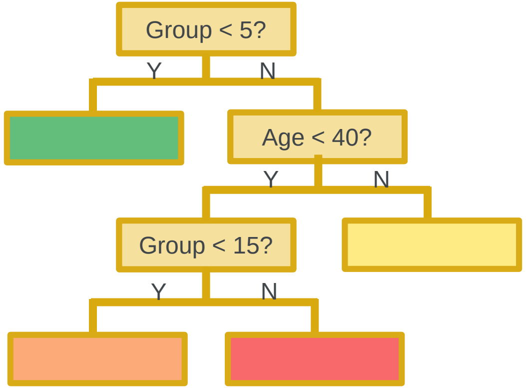
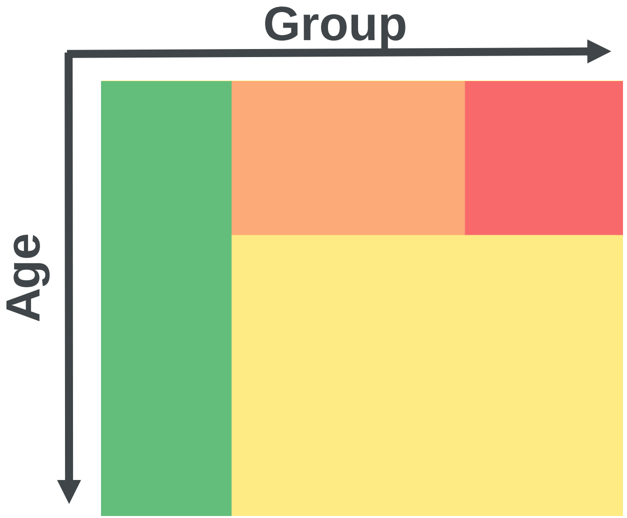
# Decision Trees

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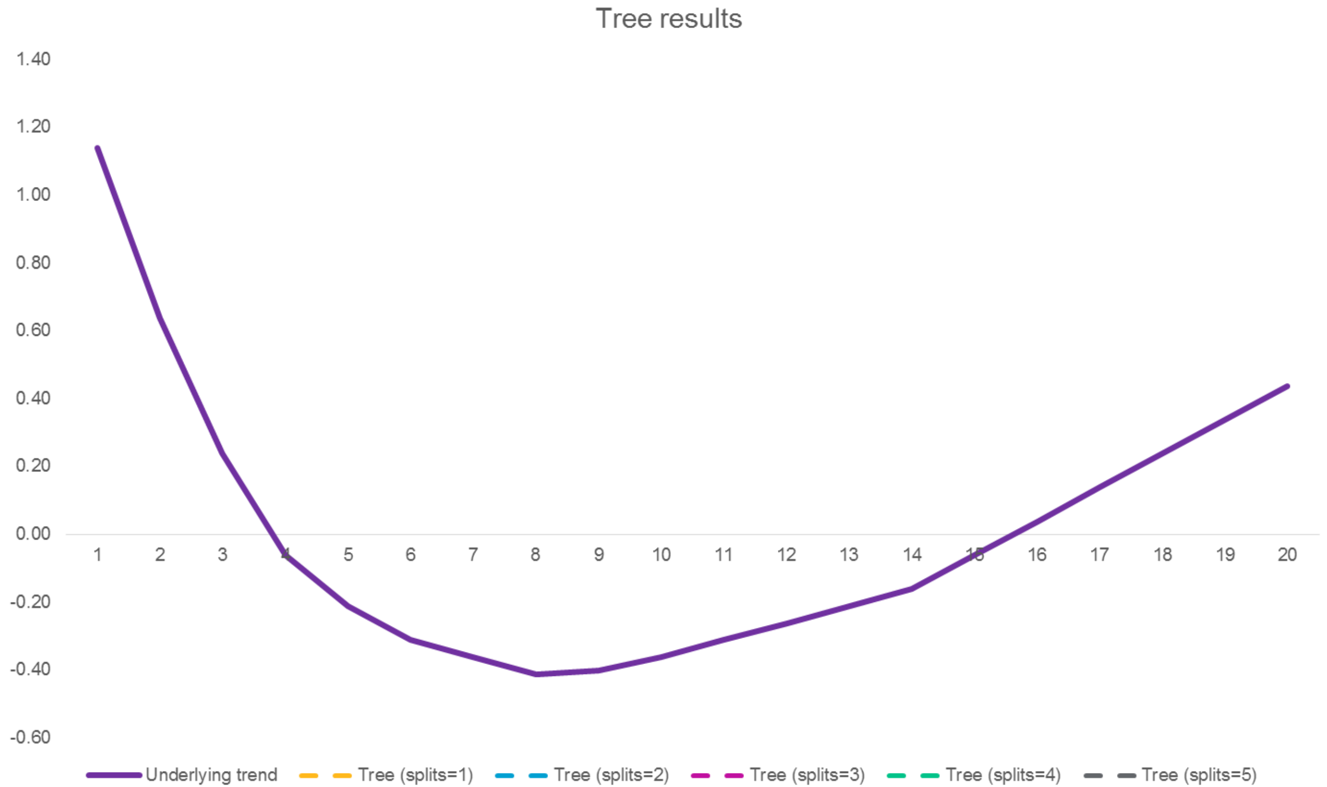
# A simple Tree example



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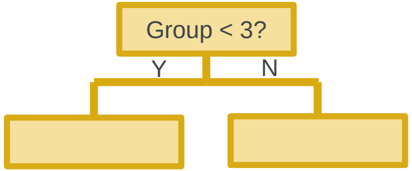


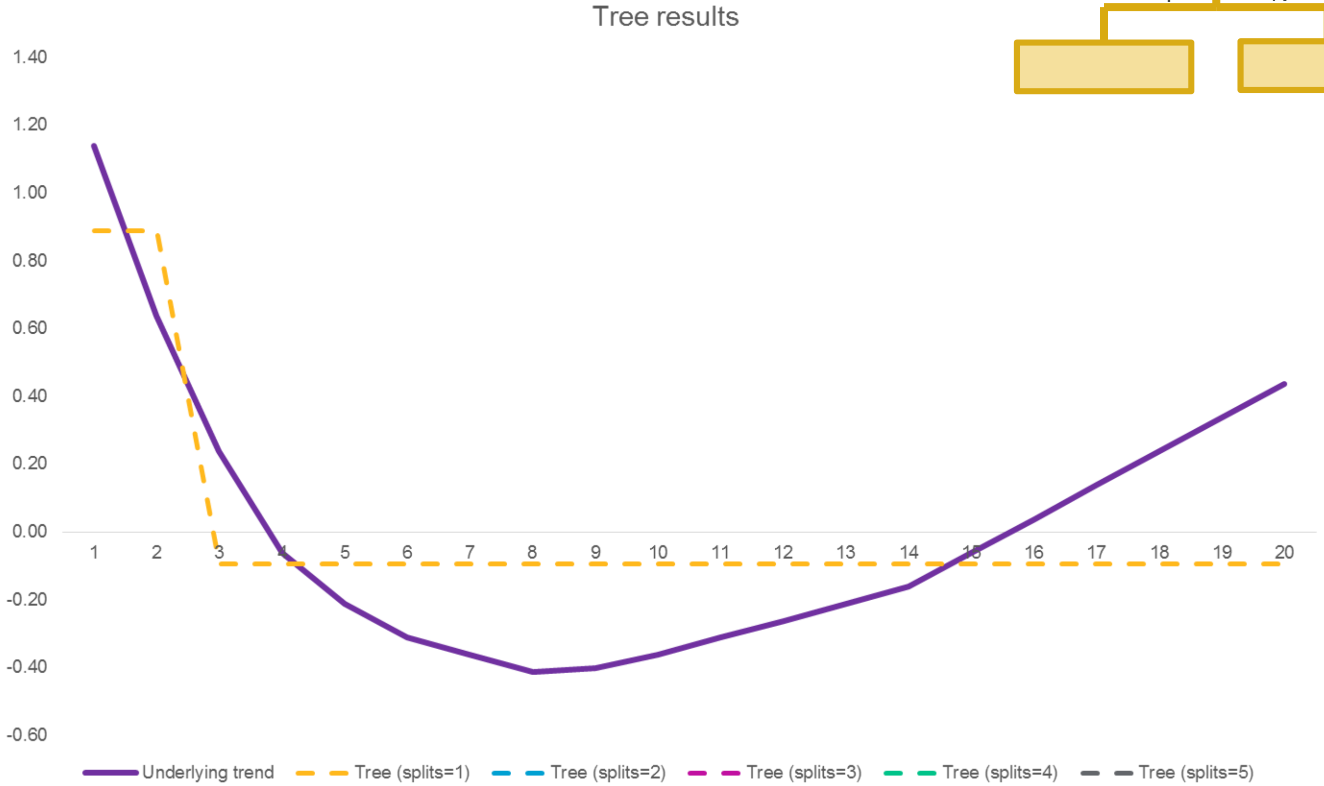

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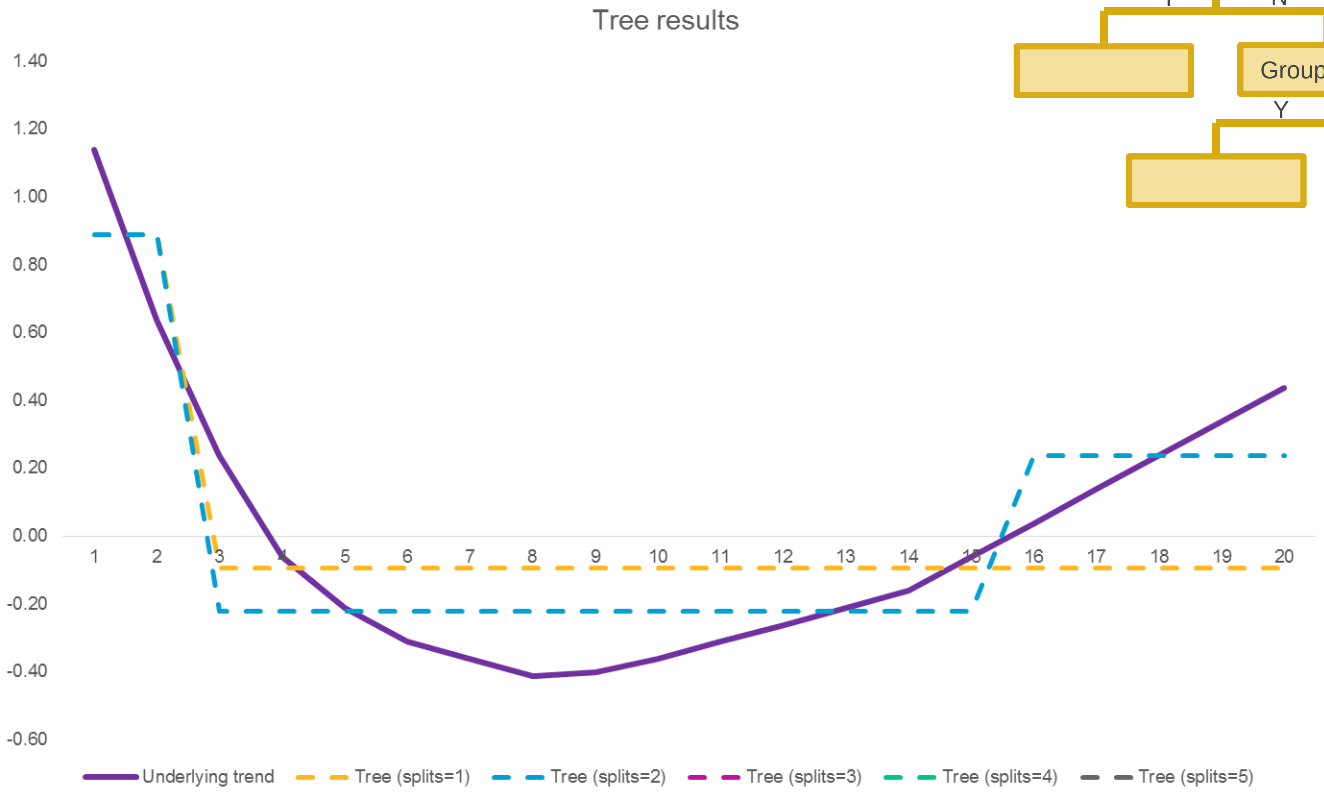


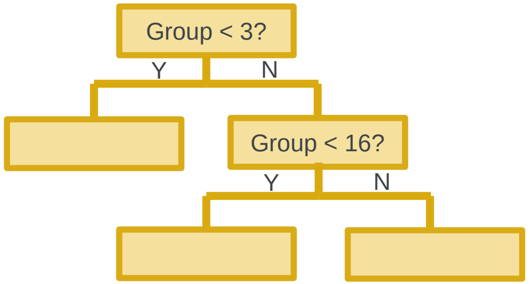

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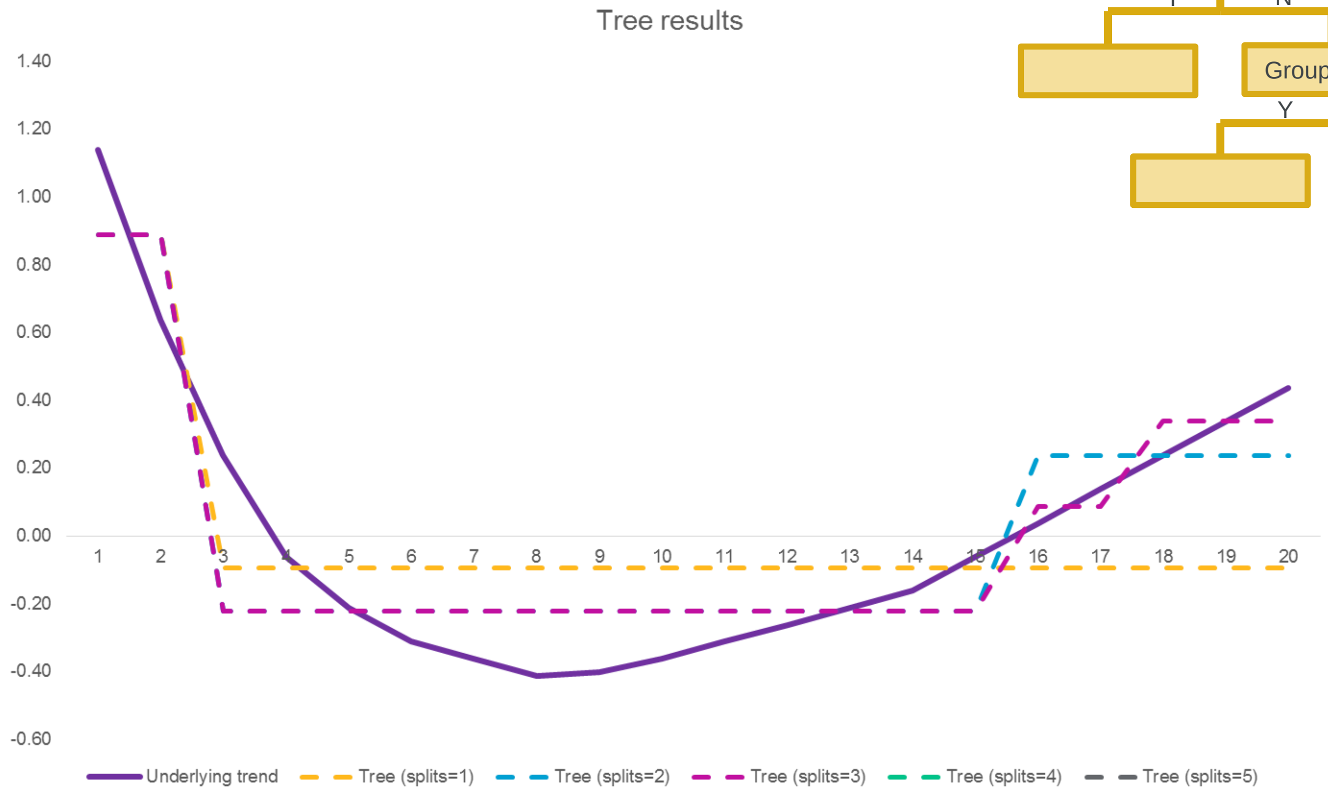


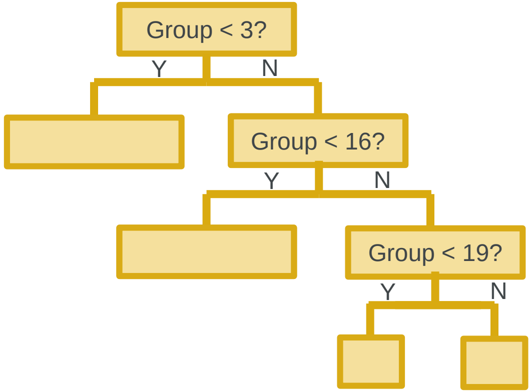


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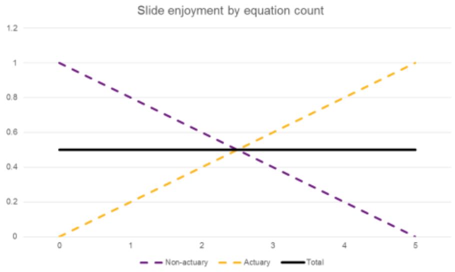
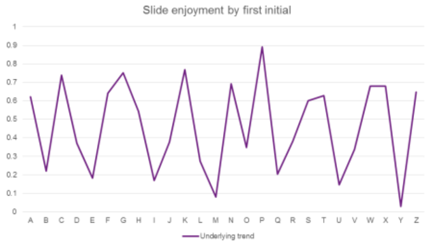
# Shortcomings of using trees

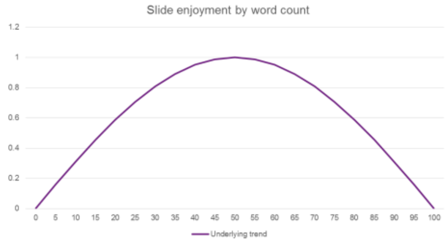
**They may miss interactions…**




**… they may struggle with categorical variables….**




**…and they can be bad at turning points**

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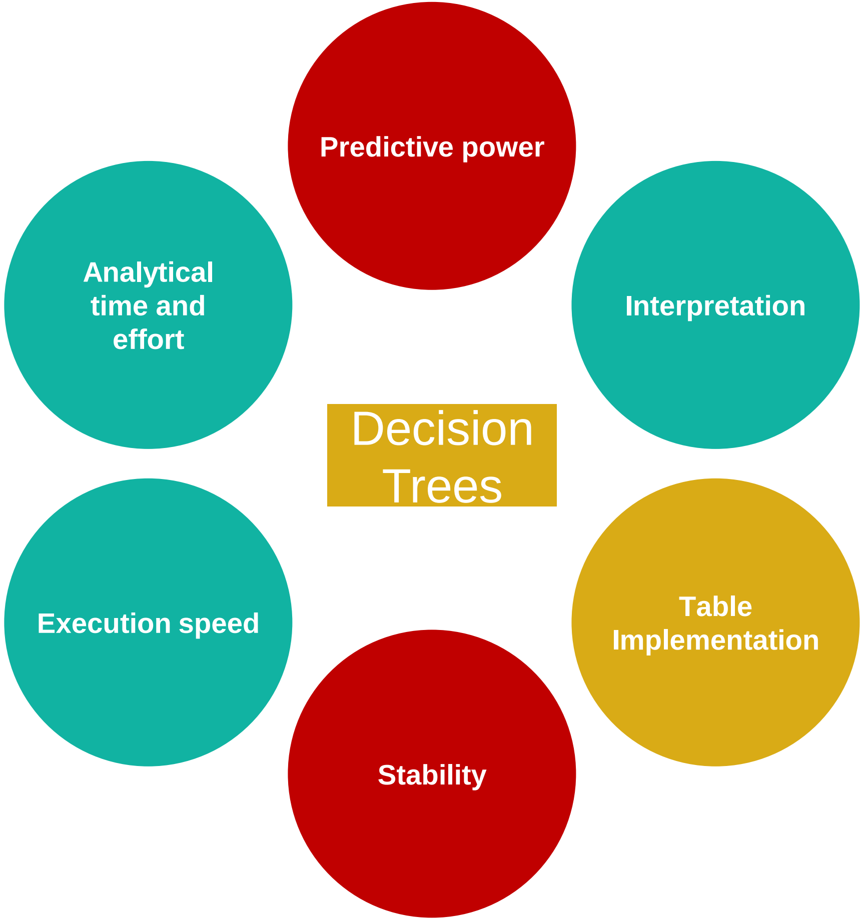


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# Focus on Random Forests

| | | | | |
|---|---|---|---|---|
| Ensembles | Classifications Trees | "Earth" | Regression Trees | Gradient Boosting Machines |
| K-nearest Neighbours | Elastic Net | Neural Networks | Naïve Bayes | **Random Forests** |
| K-Means Clustering | Principal Components Analysis | Lasso | Support Vector Machines | Ridge Regression |

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# Random Forests

- **Tree 1:** **Prediction 1** = **Signal 1** + **Noise 1**
- **Tree 2:** **Prediction 2** = **Signal 2** + **Noise 2**
- **Tree 3:** **Prediction 3** = **Signal 3** + **Noise 3**
- …
- **Tree 1000:** **Prediction 1000** = **Signal 1000** + **Noise 1000**

- **Random Forest:**
- **Prediction = AVERAGE(Tree Predictions)**
- = **AVERAGE(Tree Signal)** + **AVERAGE(Tree Noise)**

- **Average Noise → 0** if the trees are independent
- Independence of trees achieved by fitting each tree to:
  - Random subset of data (bootstrap sample)
  - Random subset of factors
- **Average Signal → Underlying trend**, provided trees are complex enough to represent it
- This is **bagging** (**b**ootstrap **agg**regation) – fit **lots** of independent models and take an average

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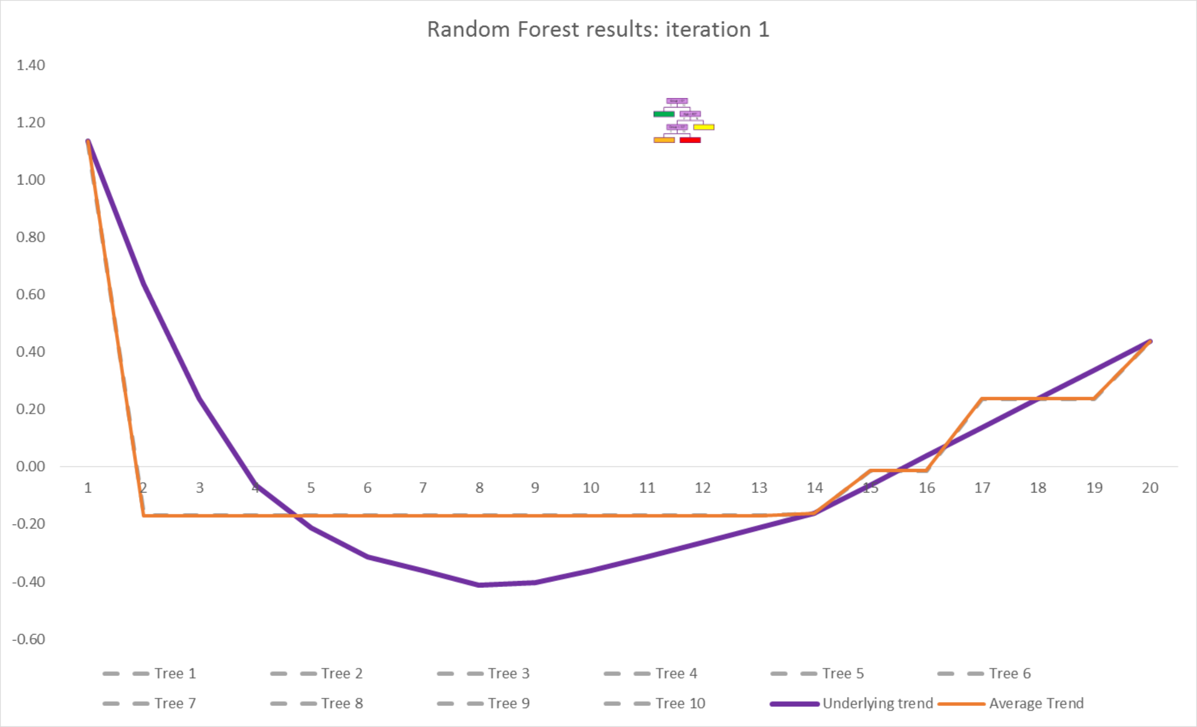
# A simple Random Forest example

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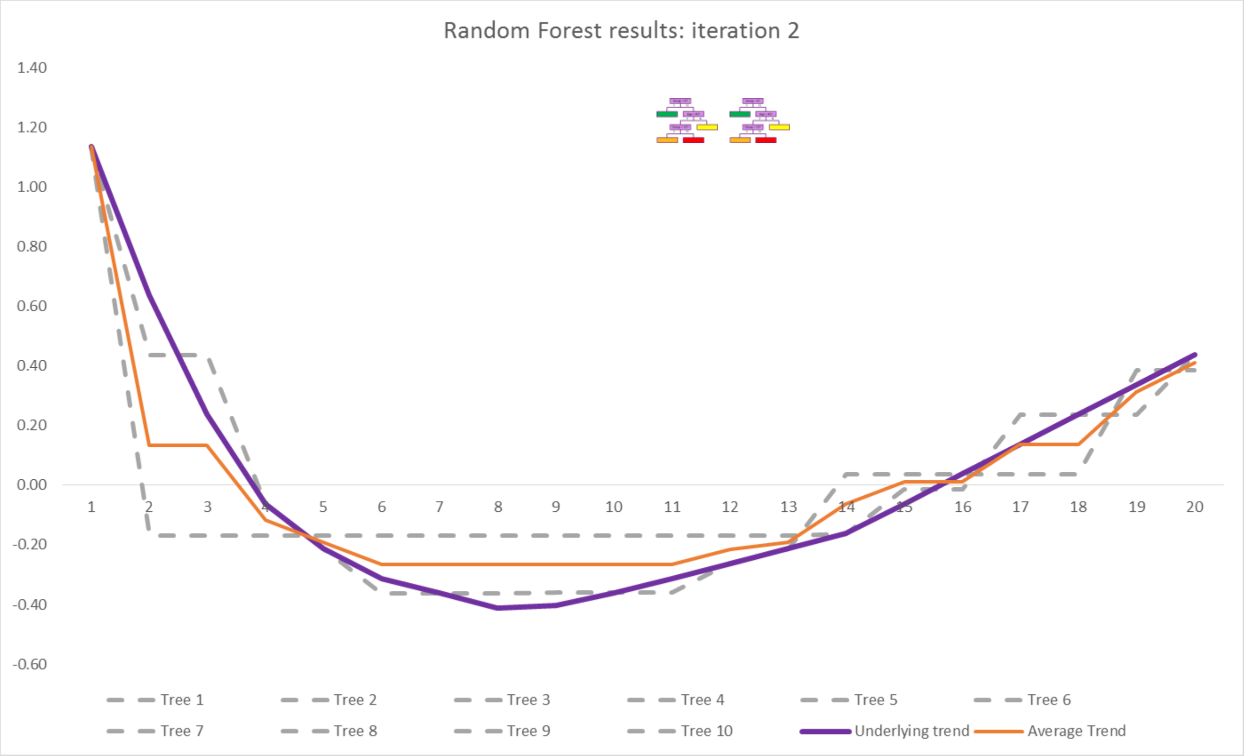
# A simple Random Forest example

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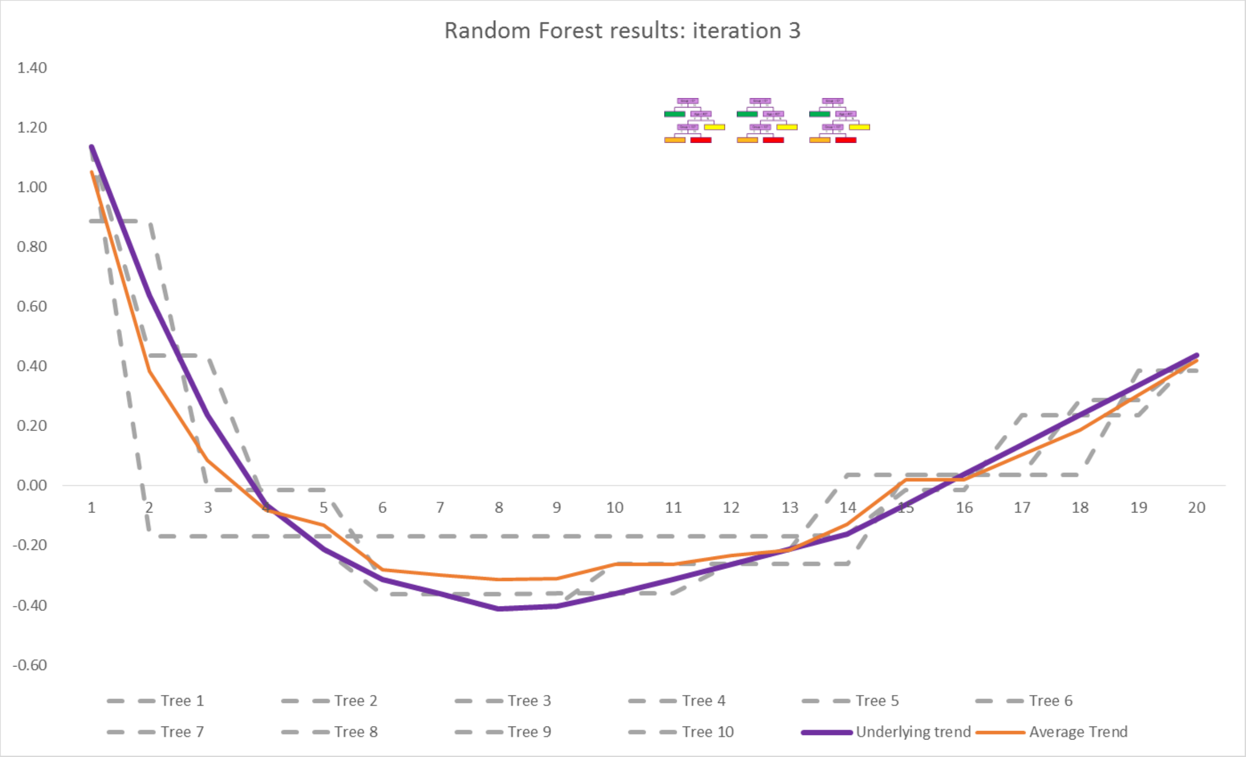
# A simple Random Forest example

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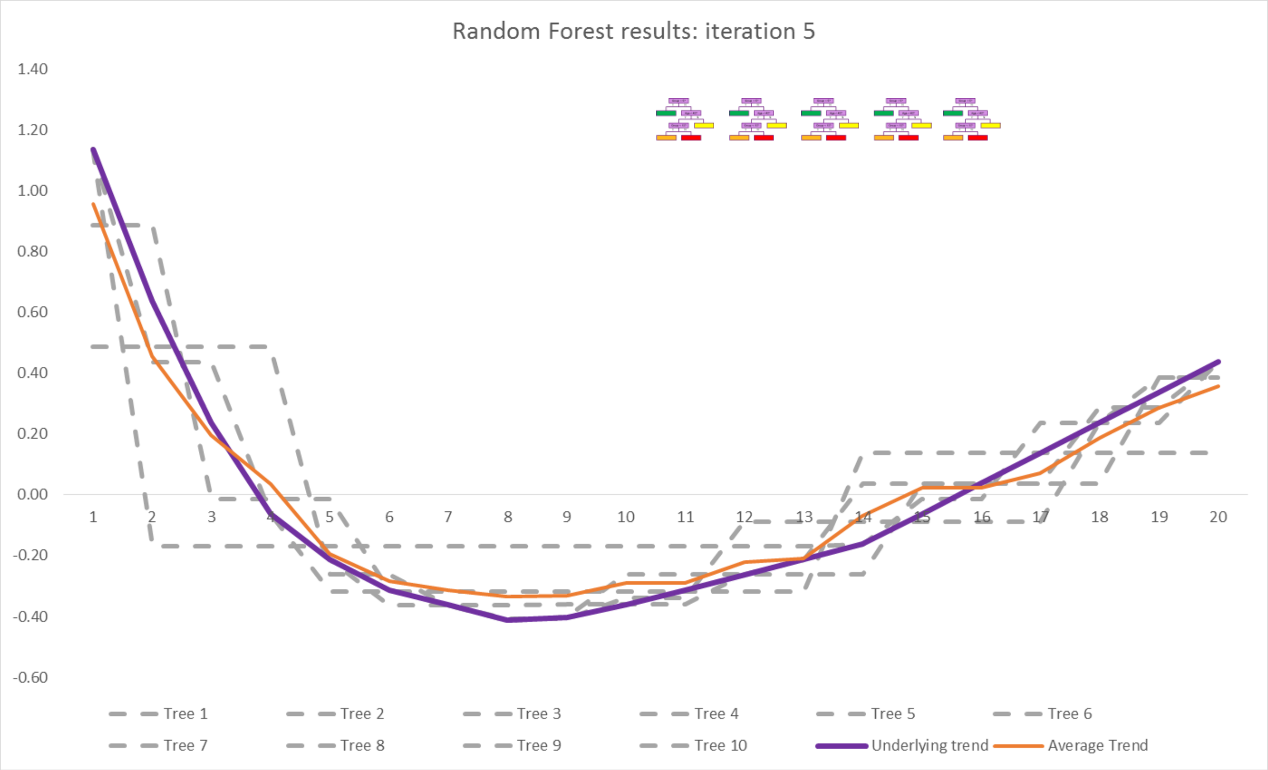
# A simple Random Forest example

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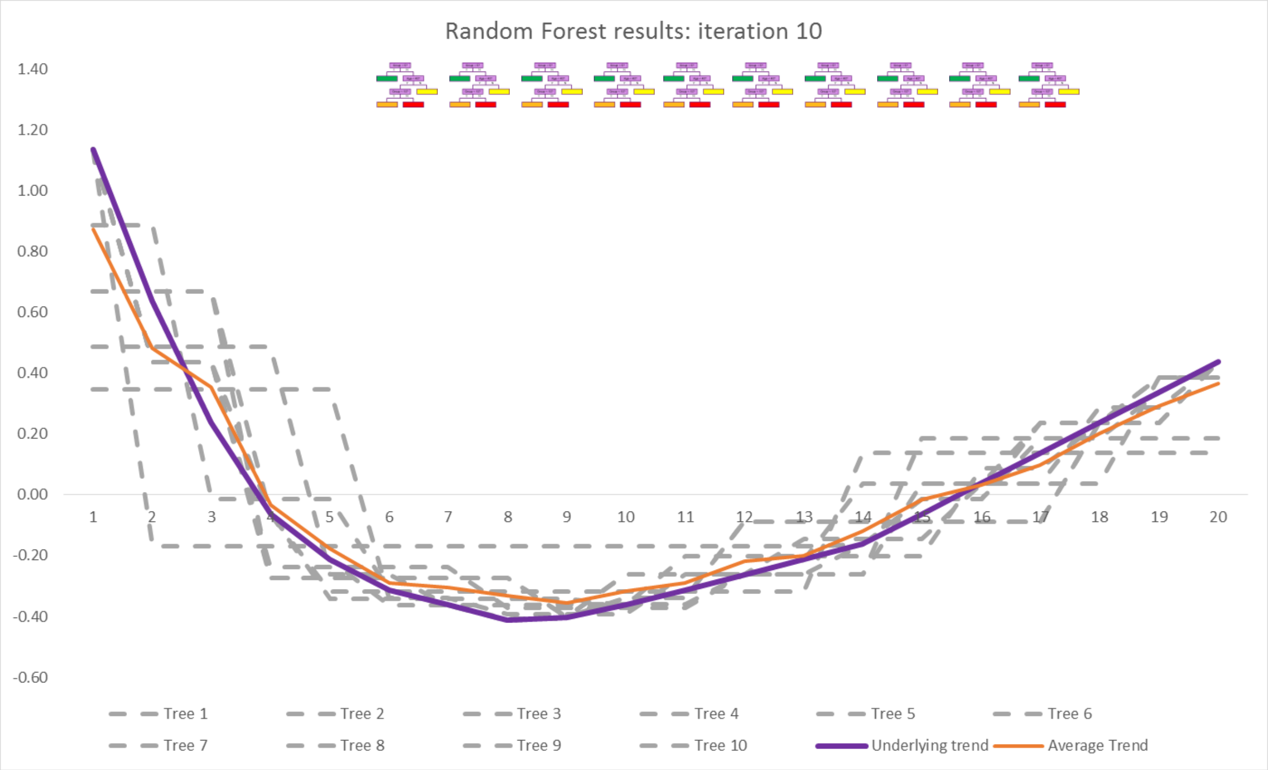
# A simple Random Forest example

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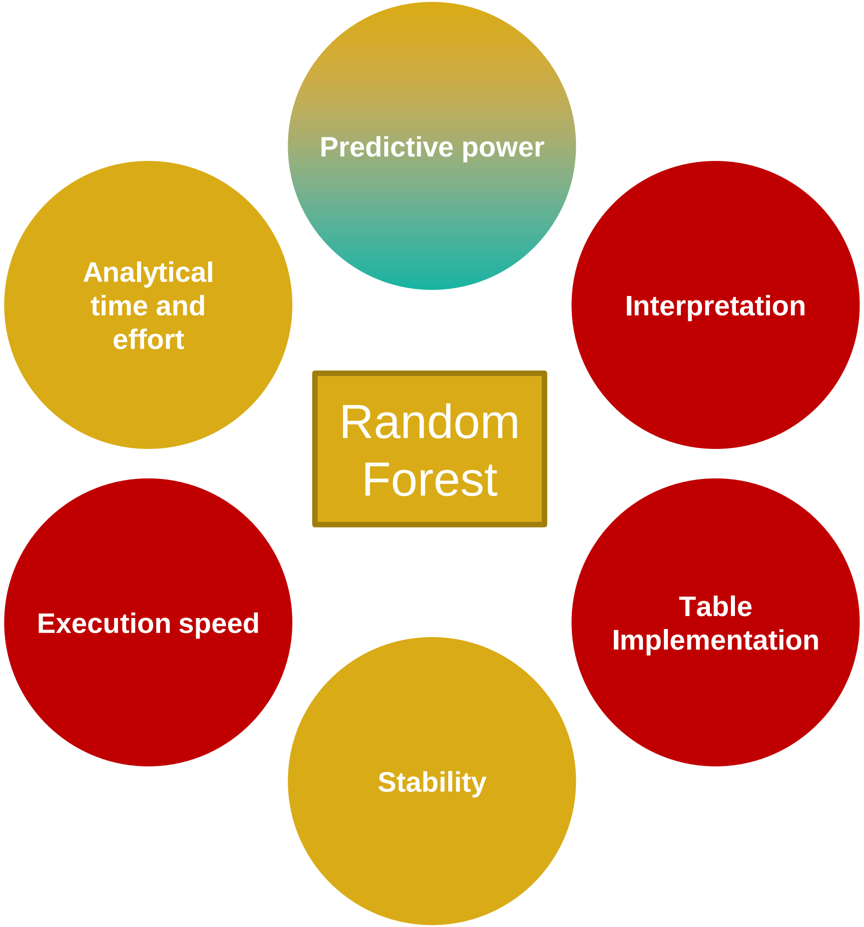
Predictive power
Analytical time and effort
Interpretation
Random Forest
Execution speed
Table Implementation
Stability

# Focus on Gradient Boosting Machines

Ensembles

Classifications Trees

"Earth"

Regression Trees

**Gradient Boosting Machines**

K-nearest Neighbours

Elastic Net

Neural Networks

Naïve Bayes

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Principal Components Analysis

Lasso

Support Vector Machines

Ridge Regression

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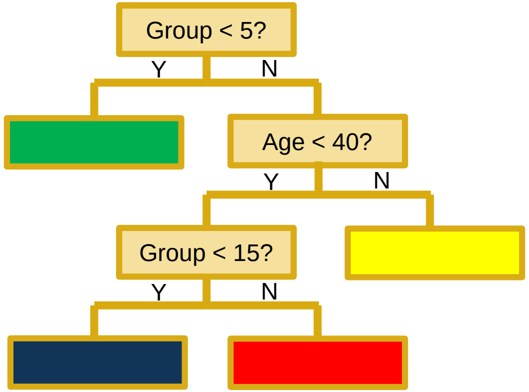
# Gradient Boosted Machine or "GBM"

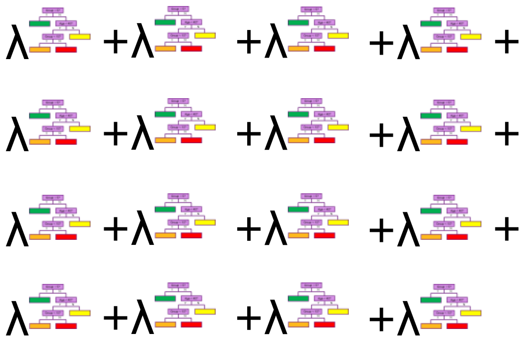
**A tree**

$f_i(x)$



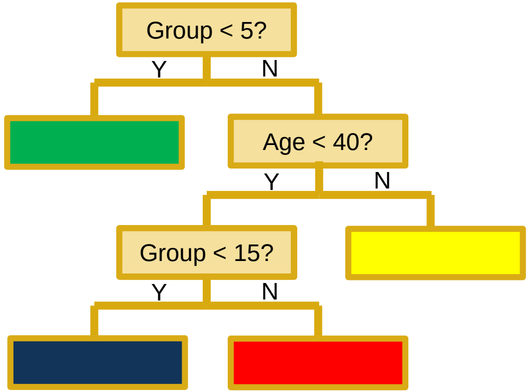

**A GBM**

$$f(x) = \lambda \sum_{n=1}^{N} f_n(x)$$



# Four main assumptions

- λ **Learning rate / "shrinkage"**
  - Amount by which the old model predictions are varied for the next model iteration
  - New model = Old + (Prediction x Learning rate)
- **Interaction depth**
  - Number of splits allowed on each tree (or the number of terminal nodes – 1)
- **N Number of trees** (iterations) allowed
- **Bag fraction**
  - Trees are fitted to a subset of the data (the bag fraction) on a randomized basis
  - Additional noise-reduction can be achieved by using a random subset of the available factors at each iteration

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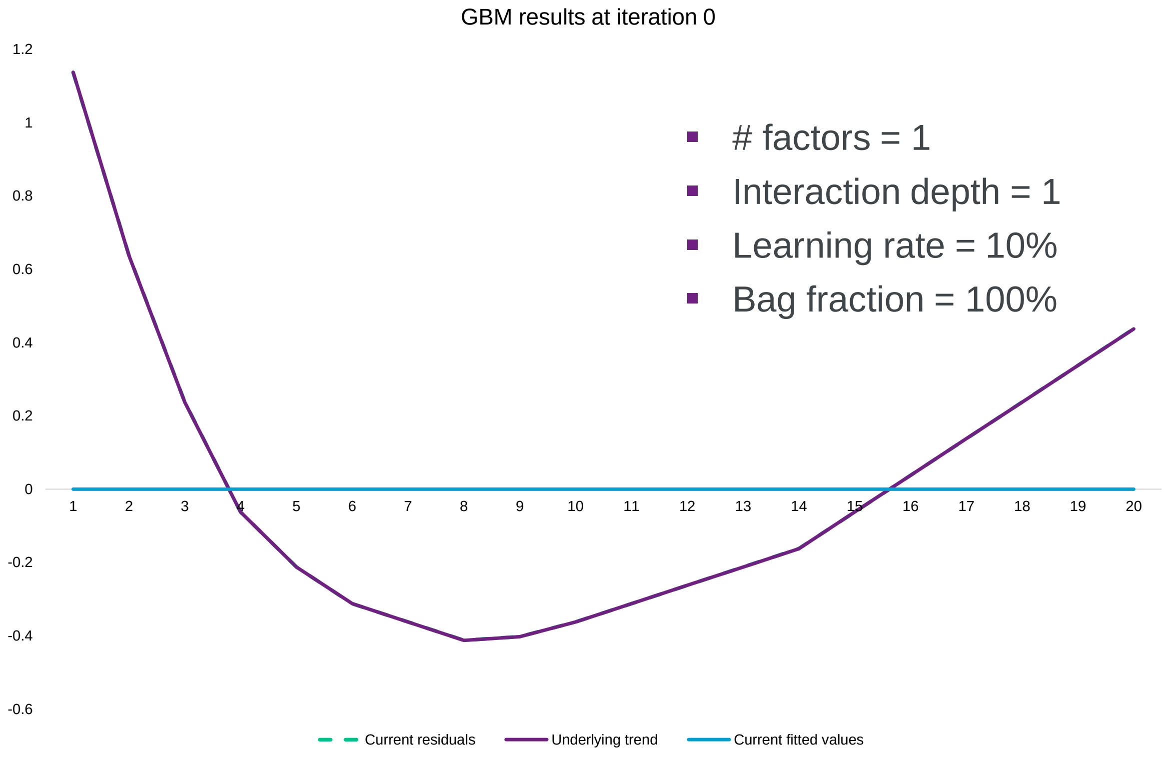
# A simple GBM example




- # factors = 1
- Interaction depth = 1
- Learning rate = 10%
- Bag fraction = 100%

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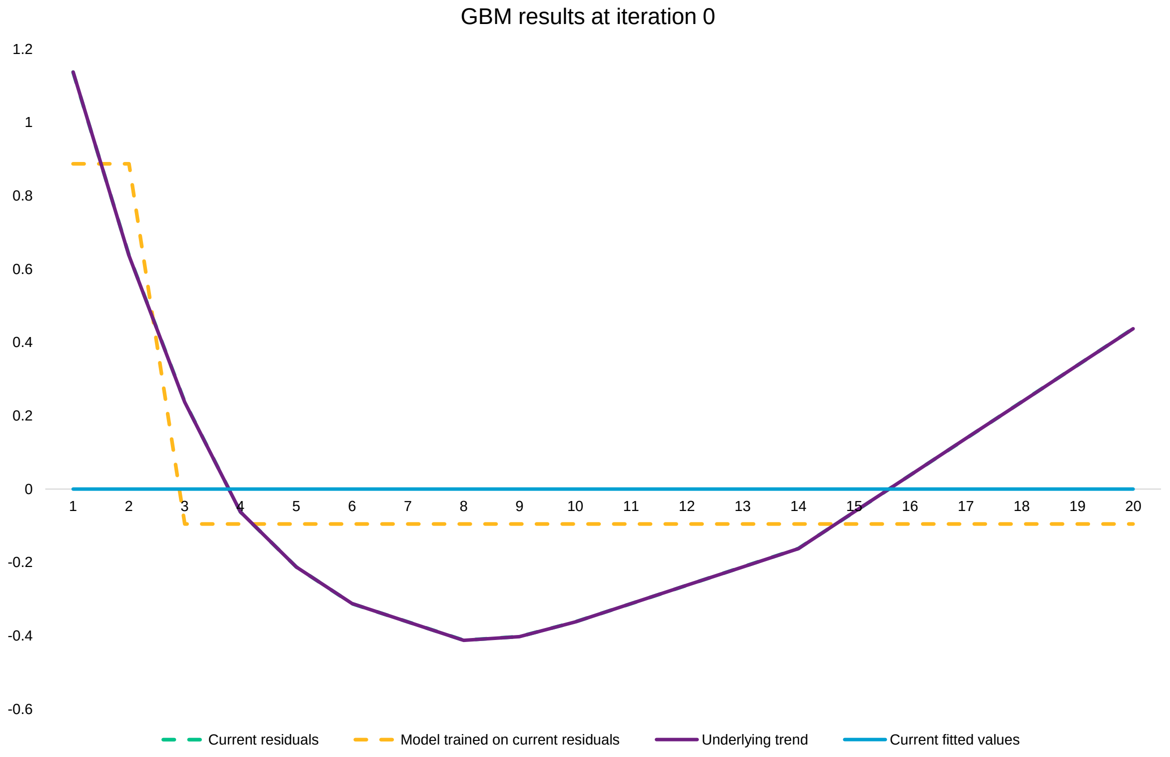
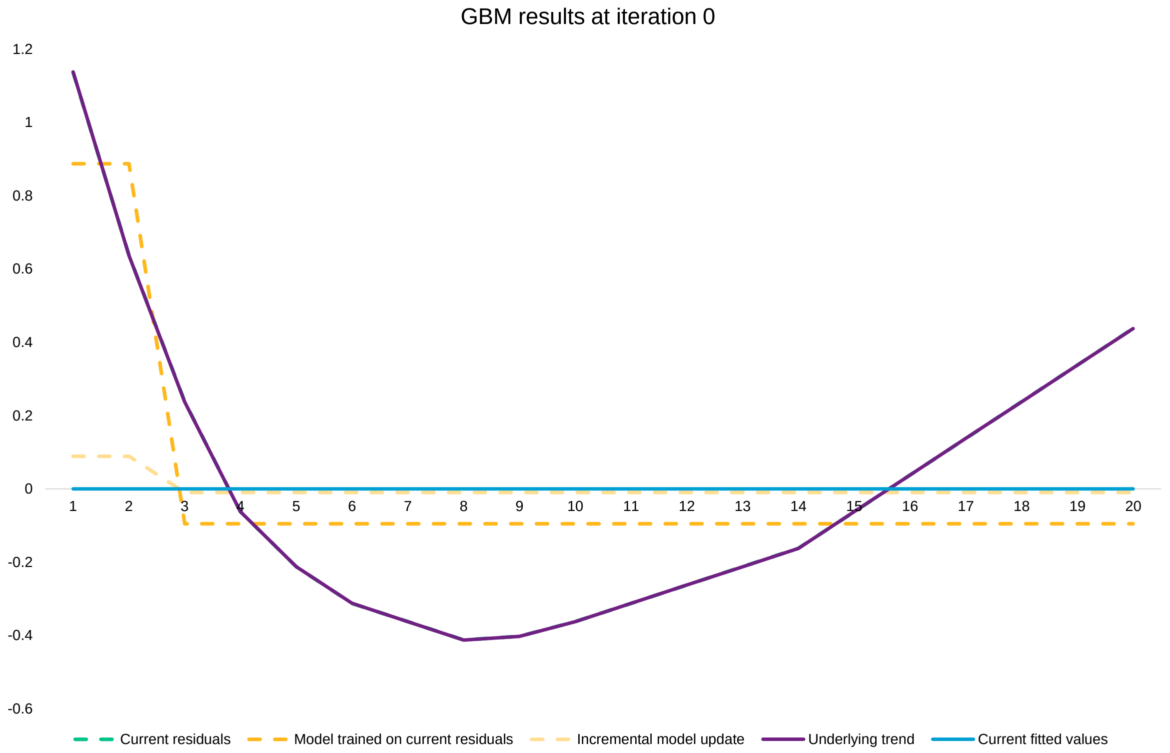
# A simple GBM example



# A simple GBM example



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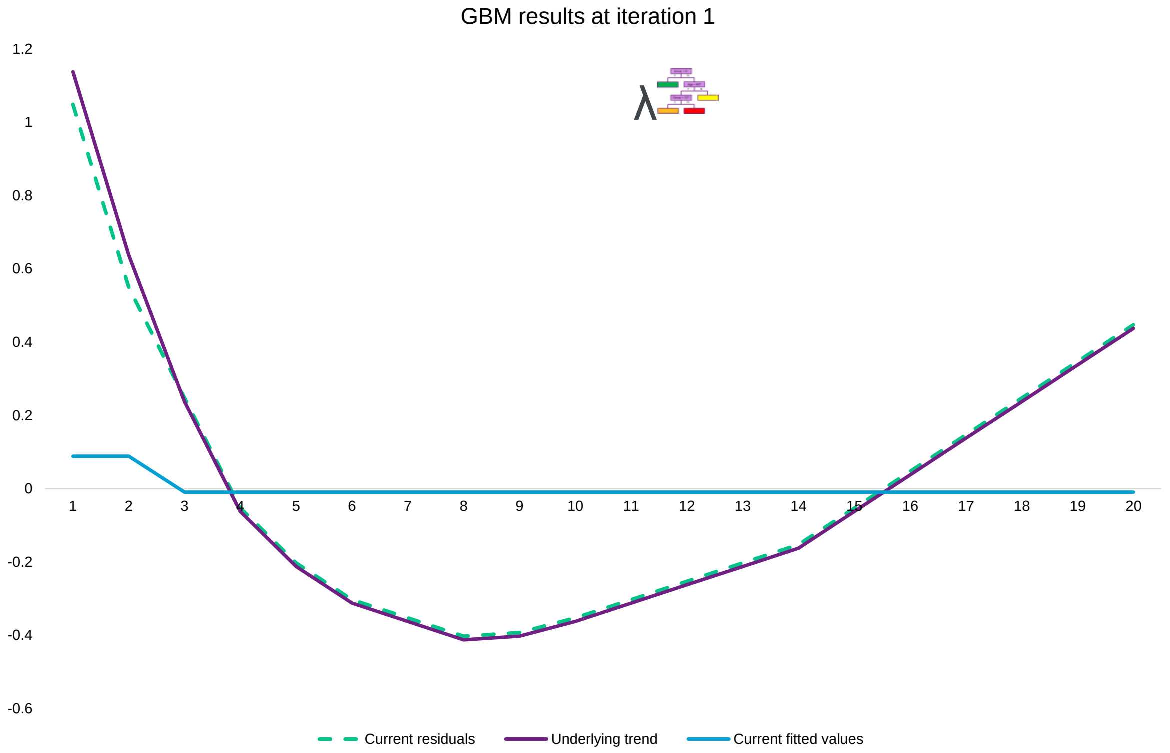

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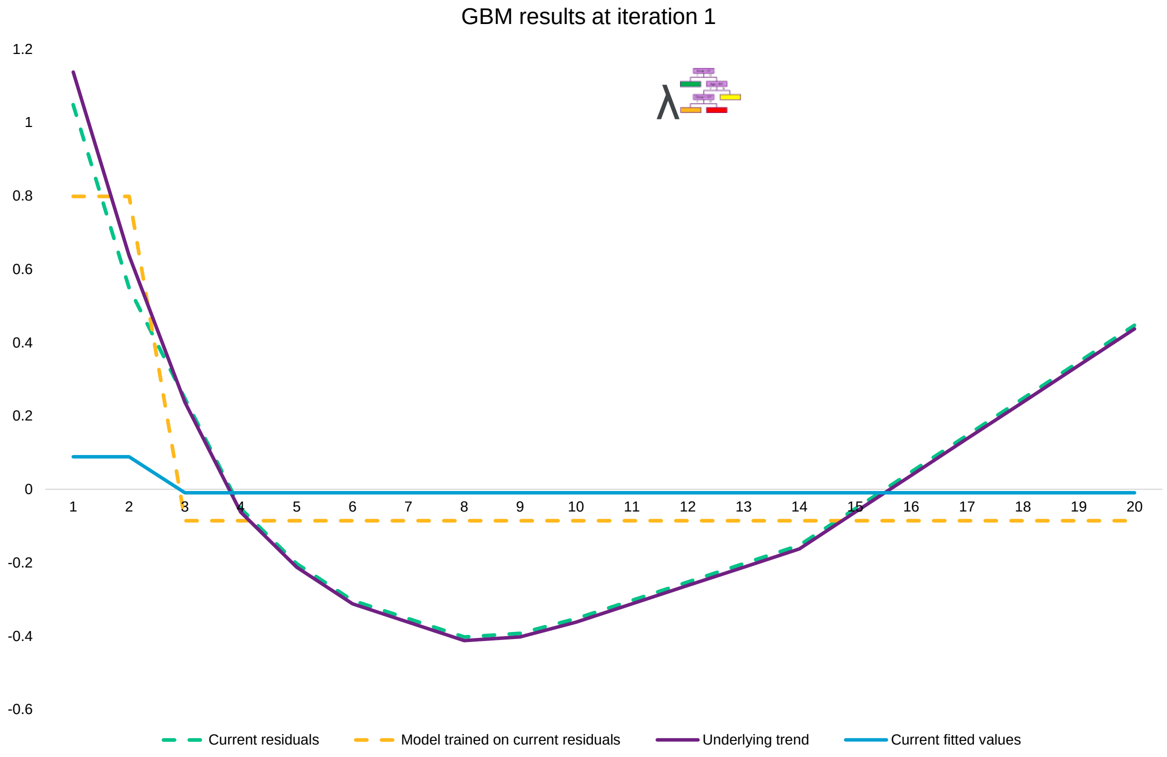


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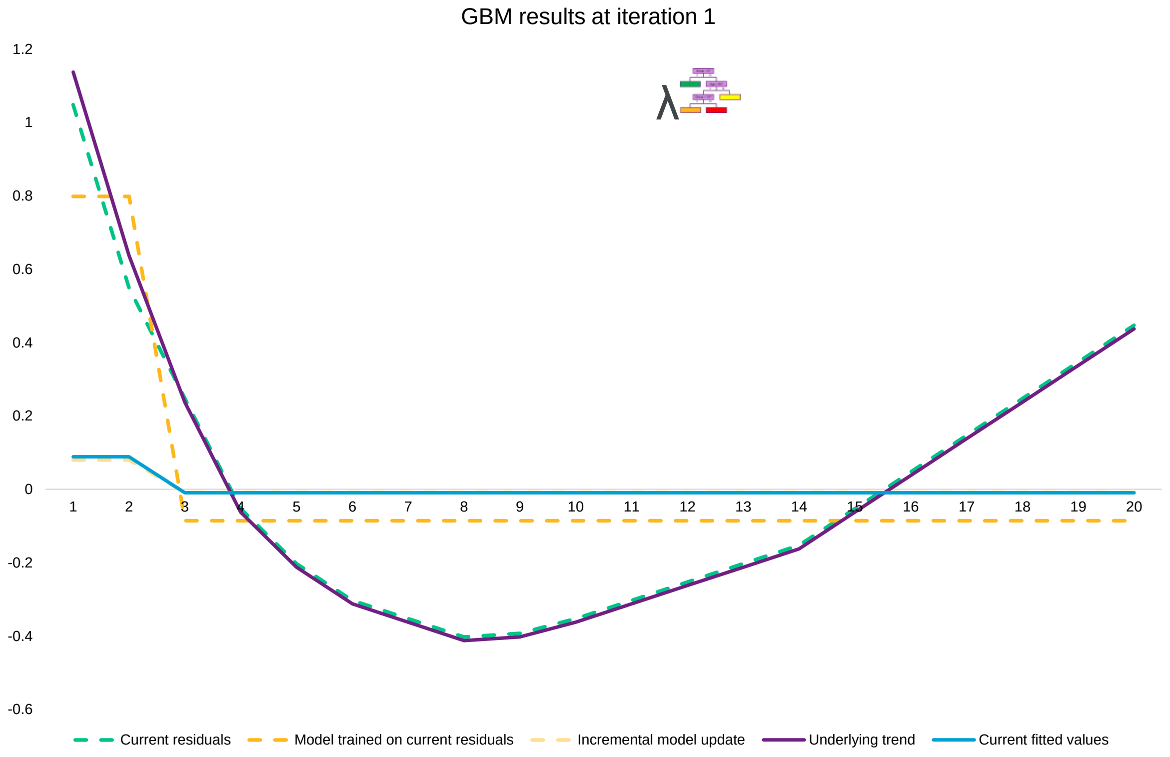
# A simple GBM example

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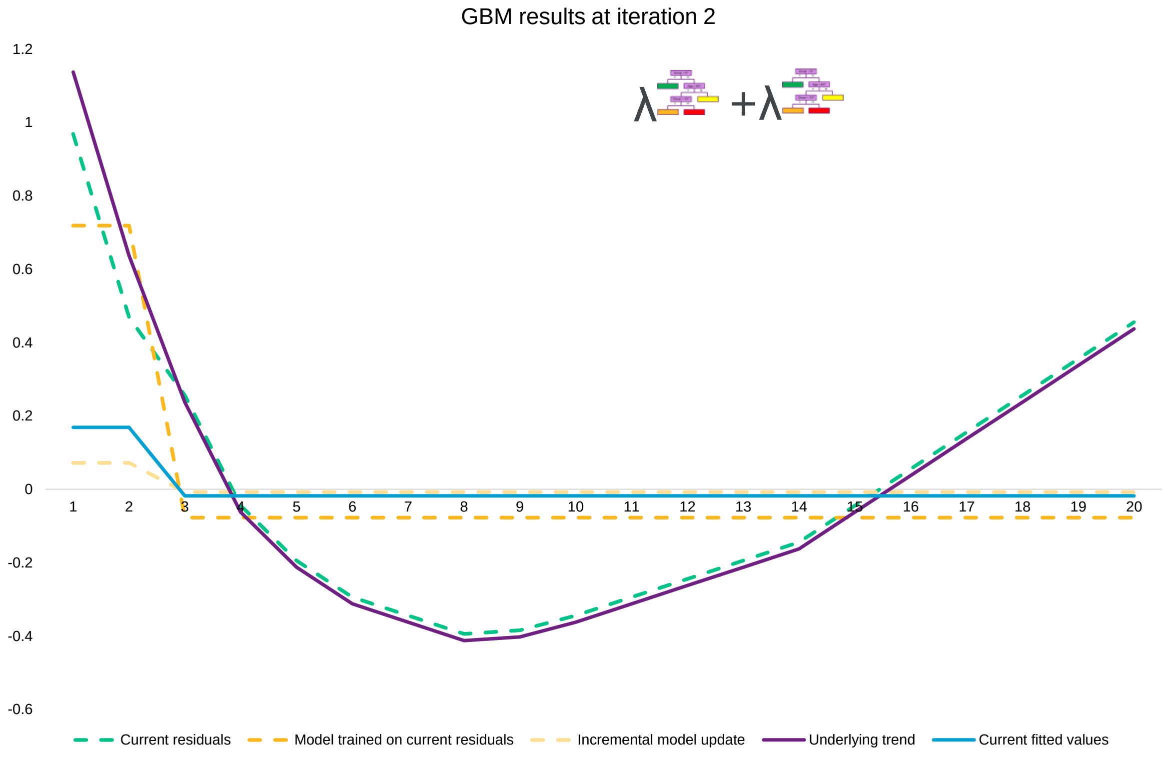

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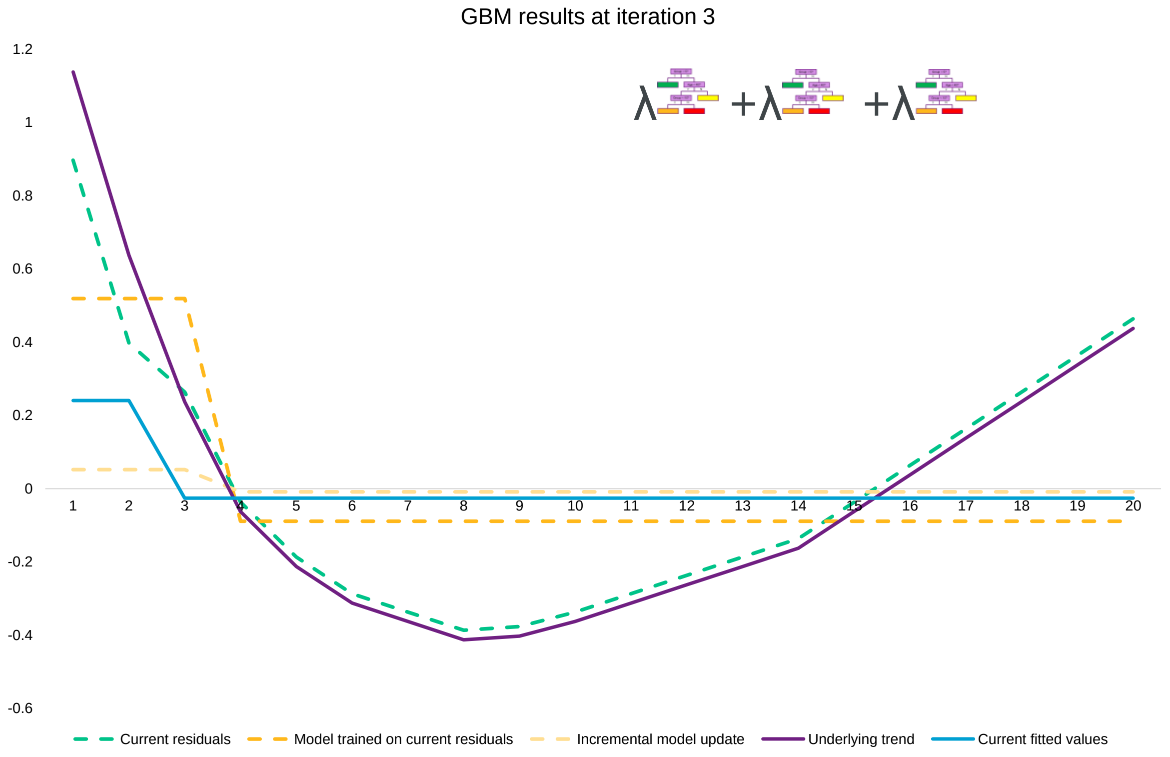

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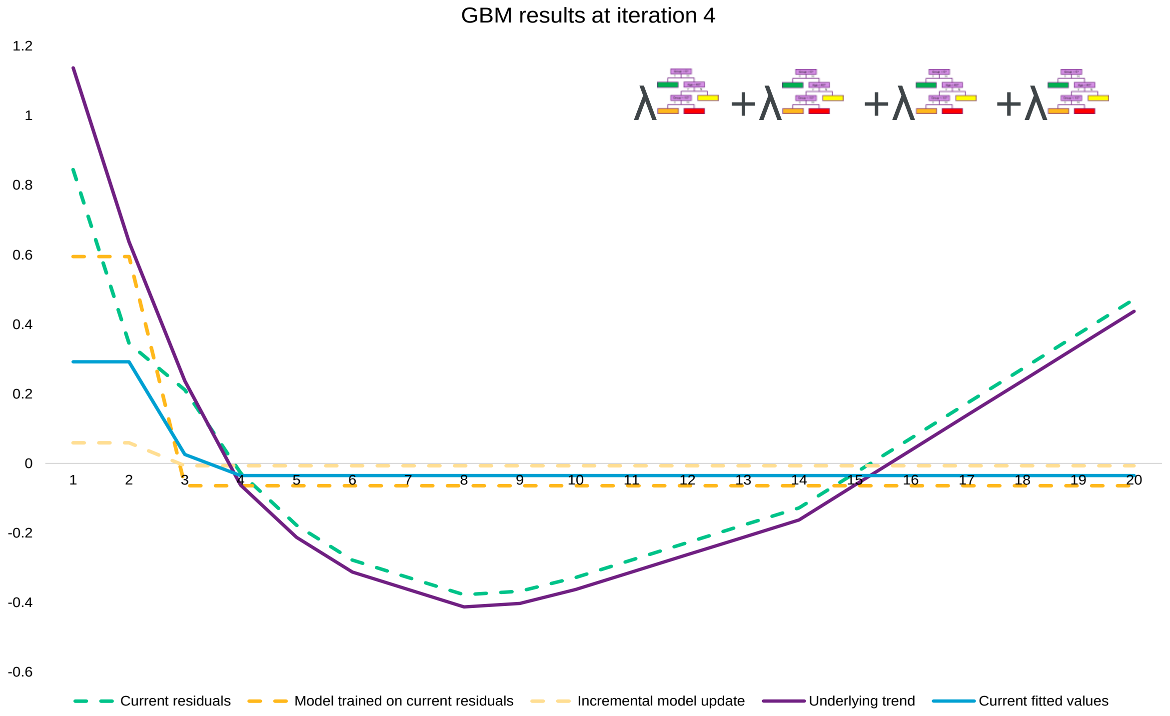

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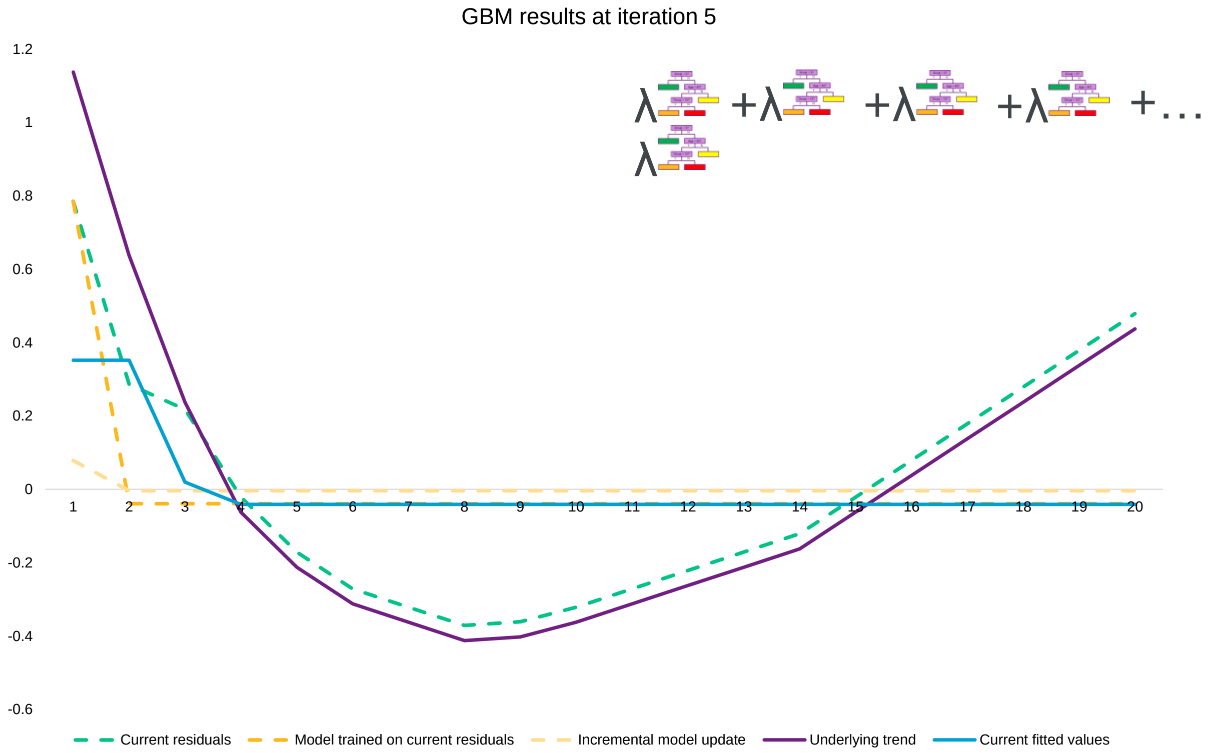

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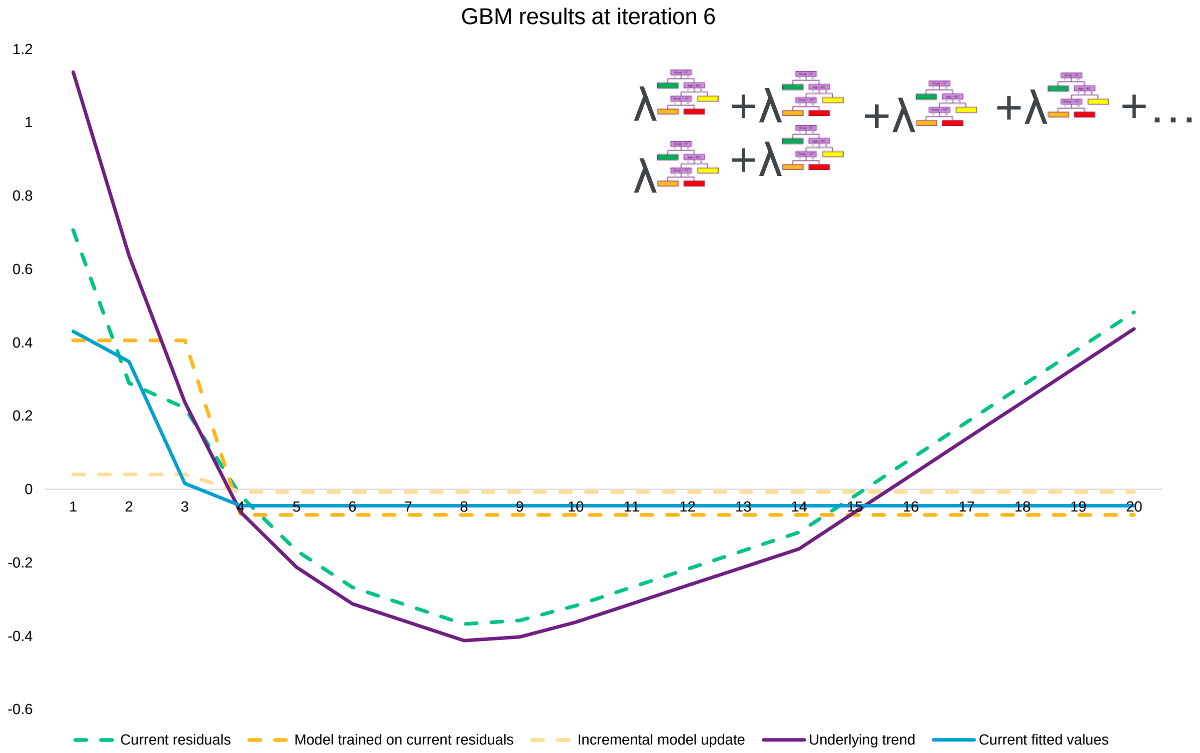


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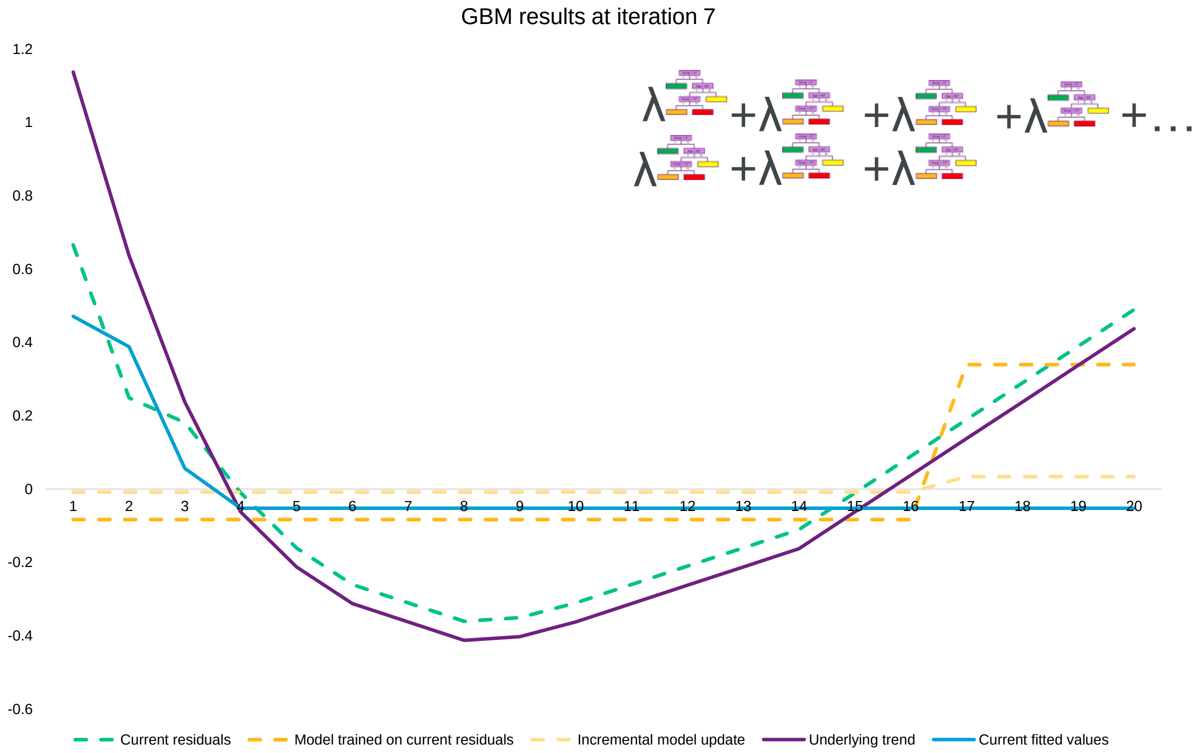


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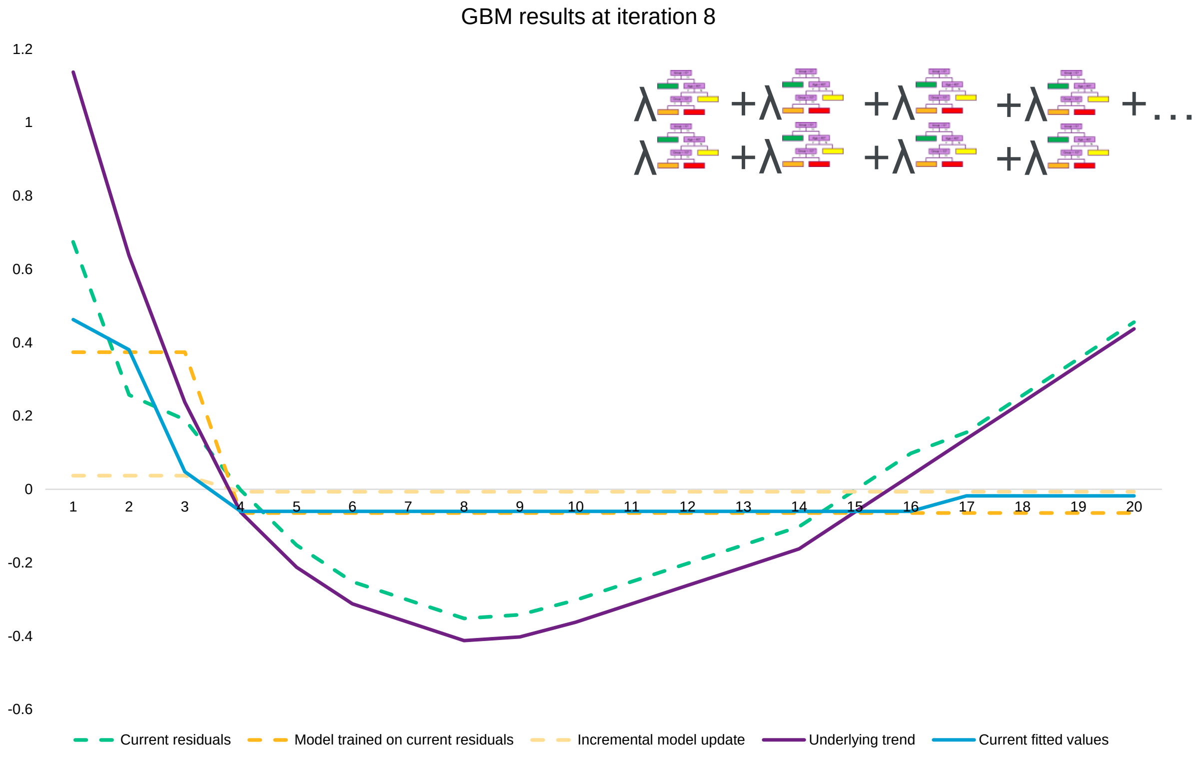


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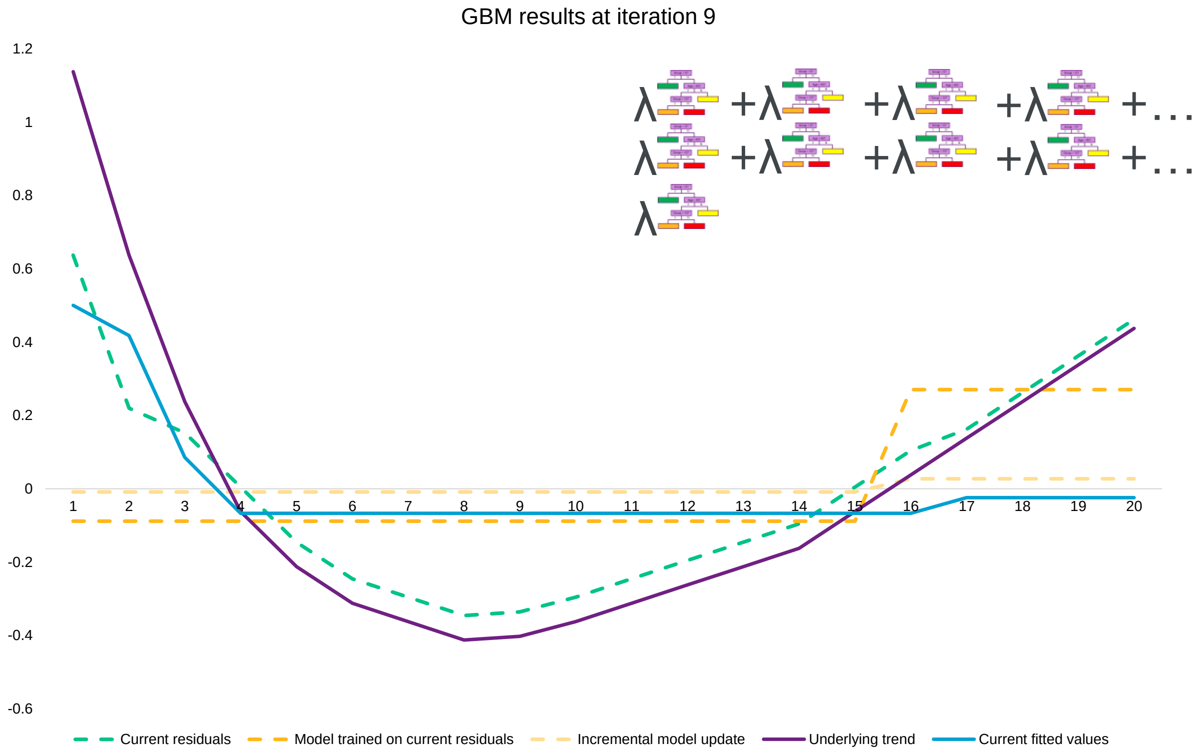

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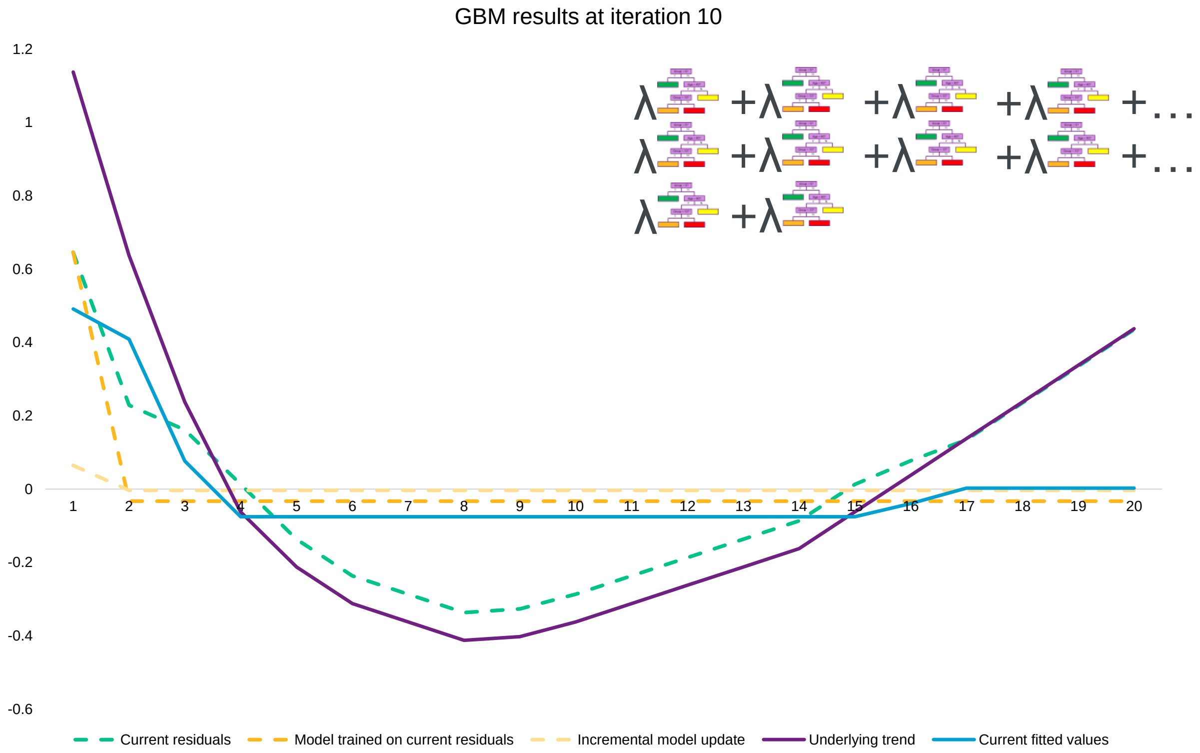


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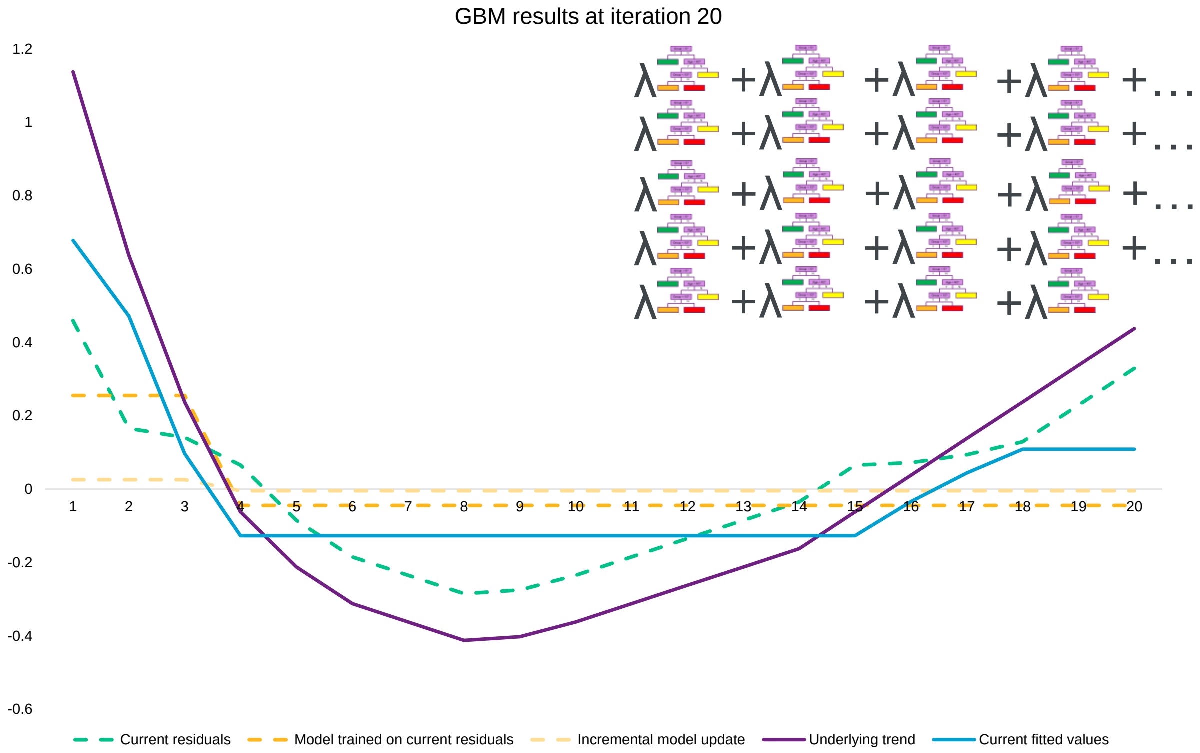


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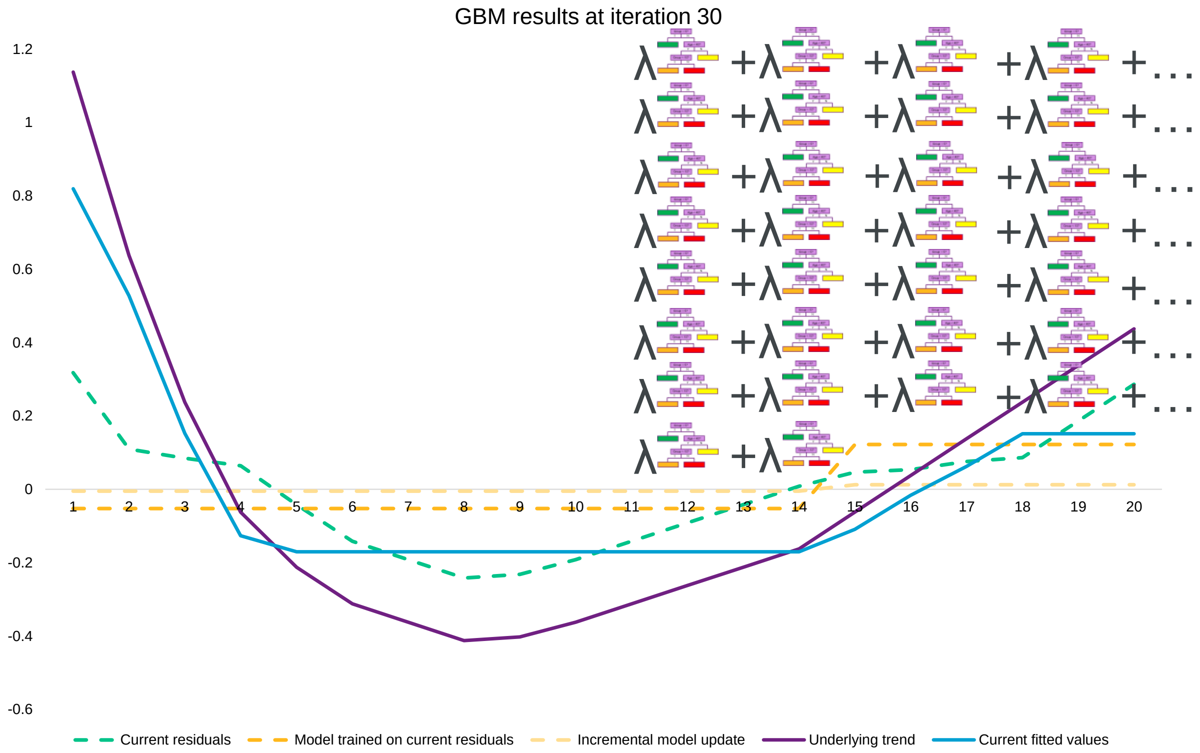


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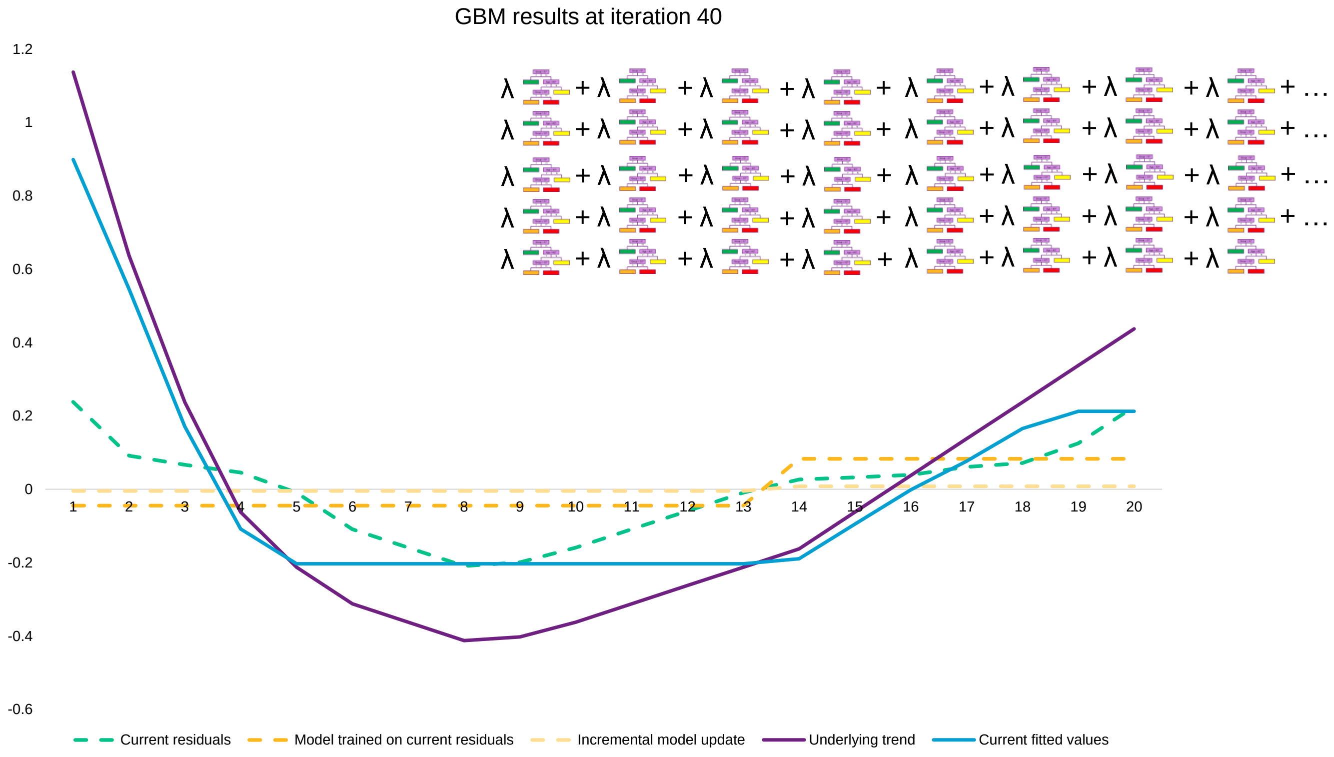


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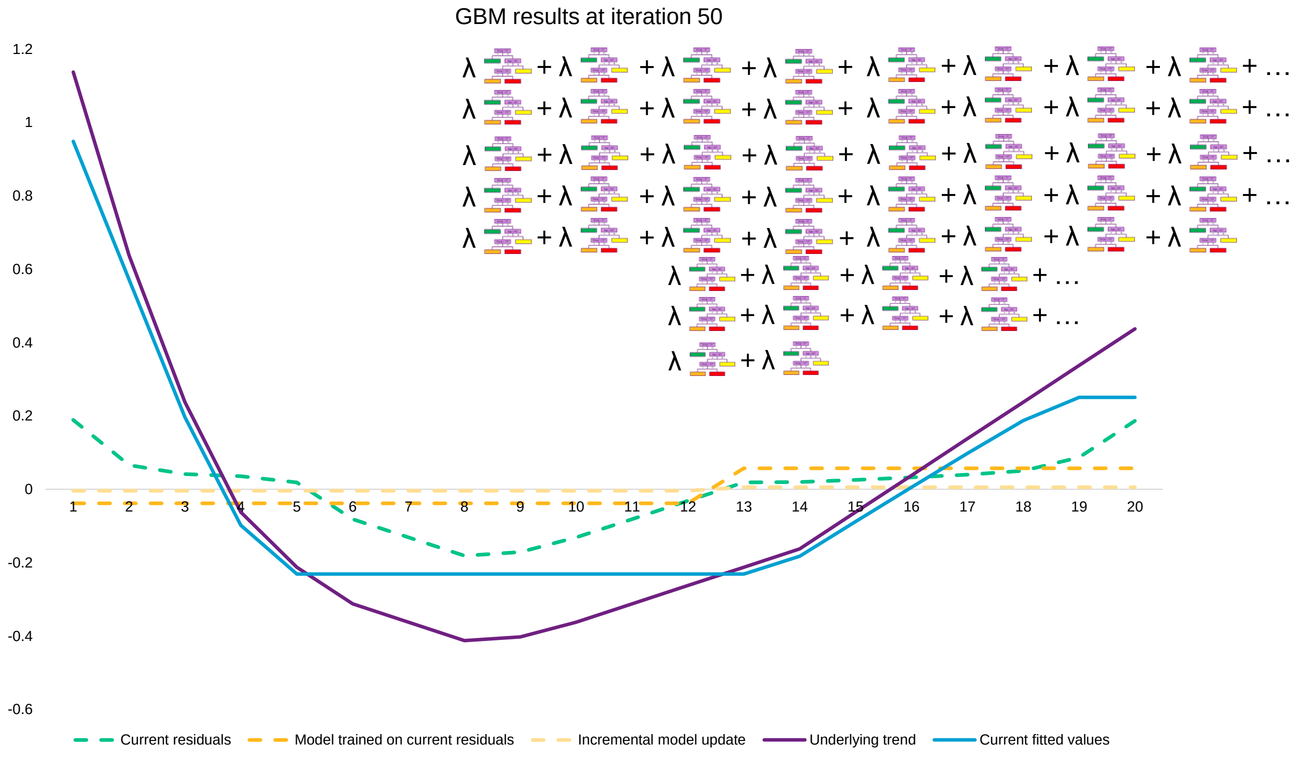


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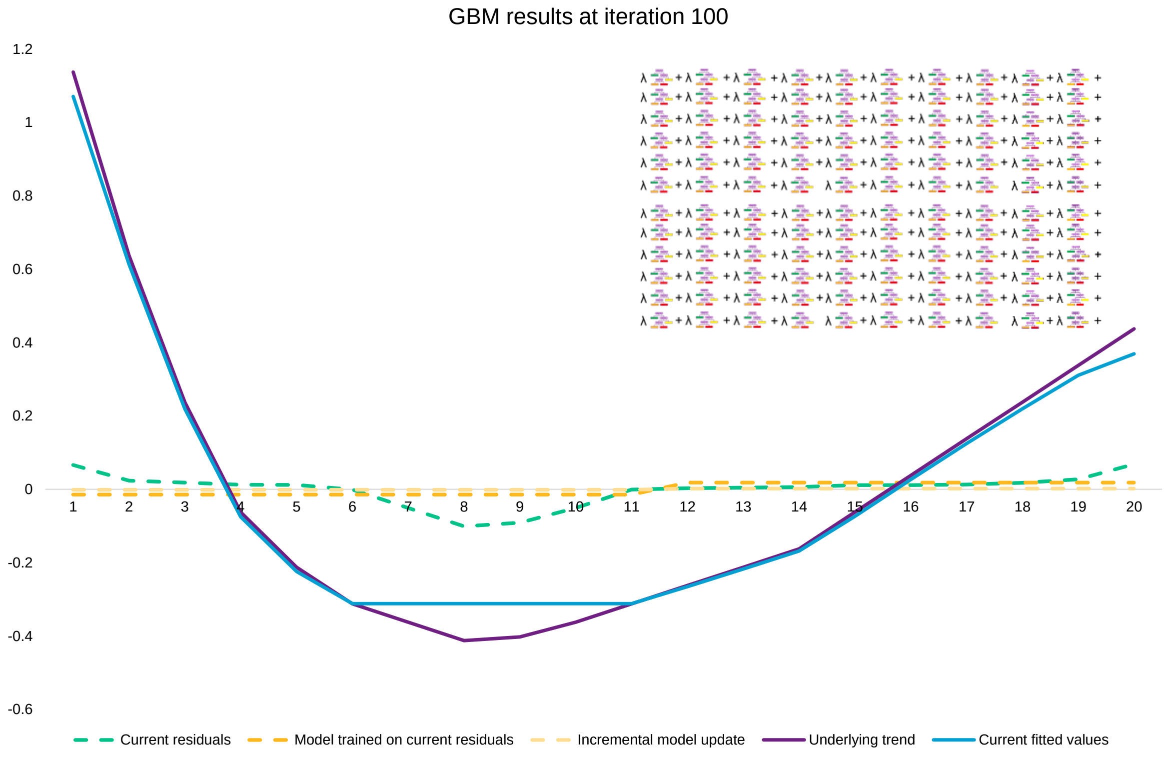

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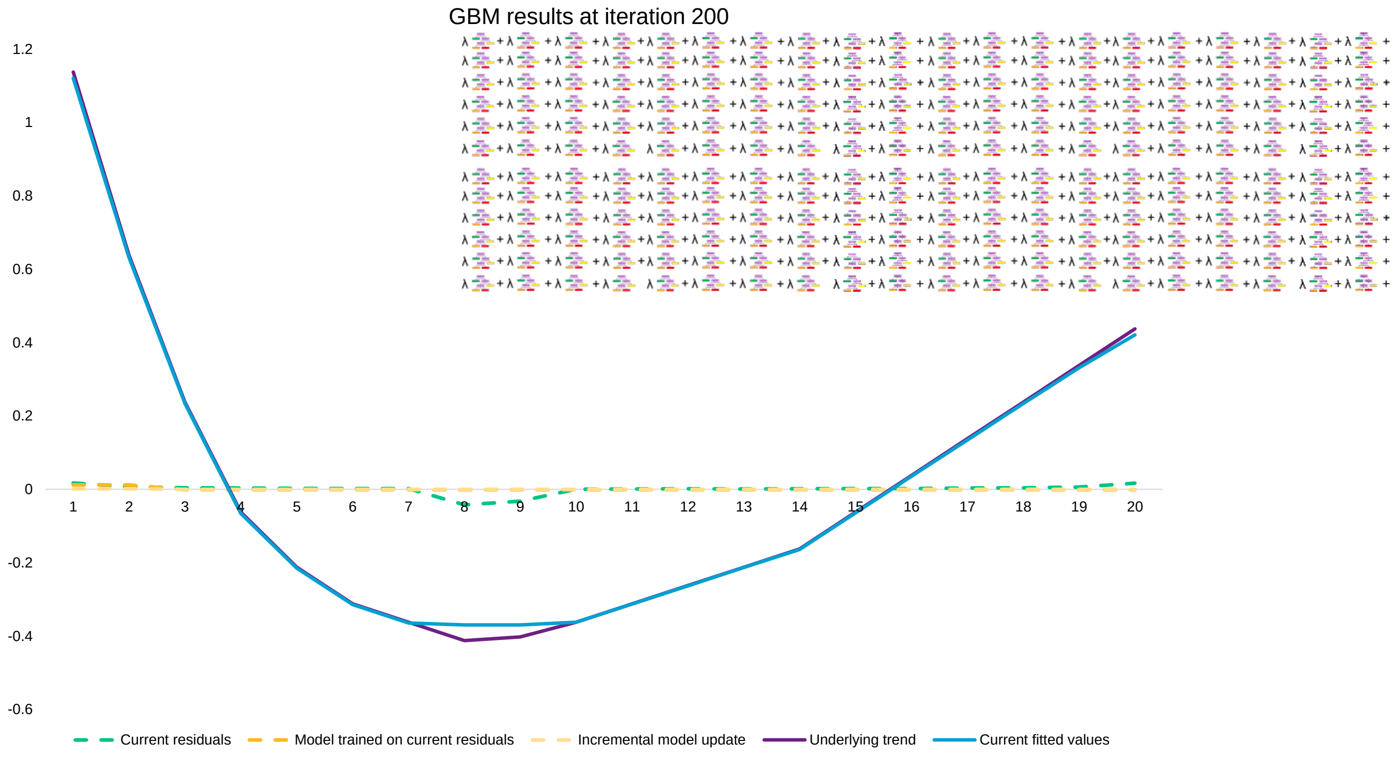

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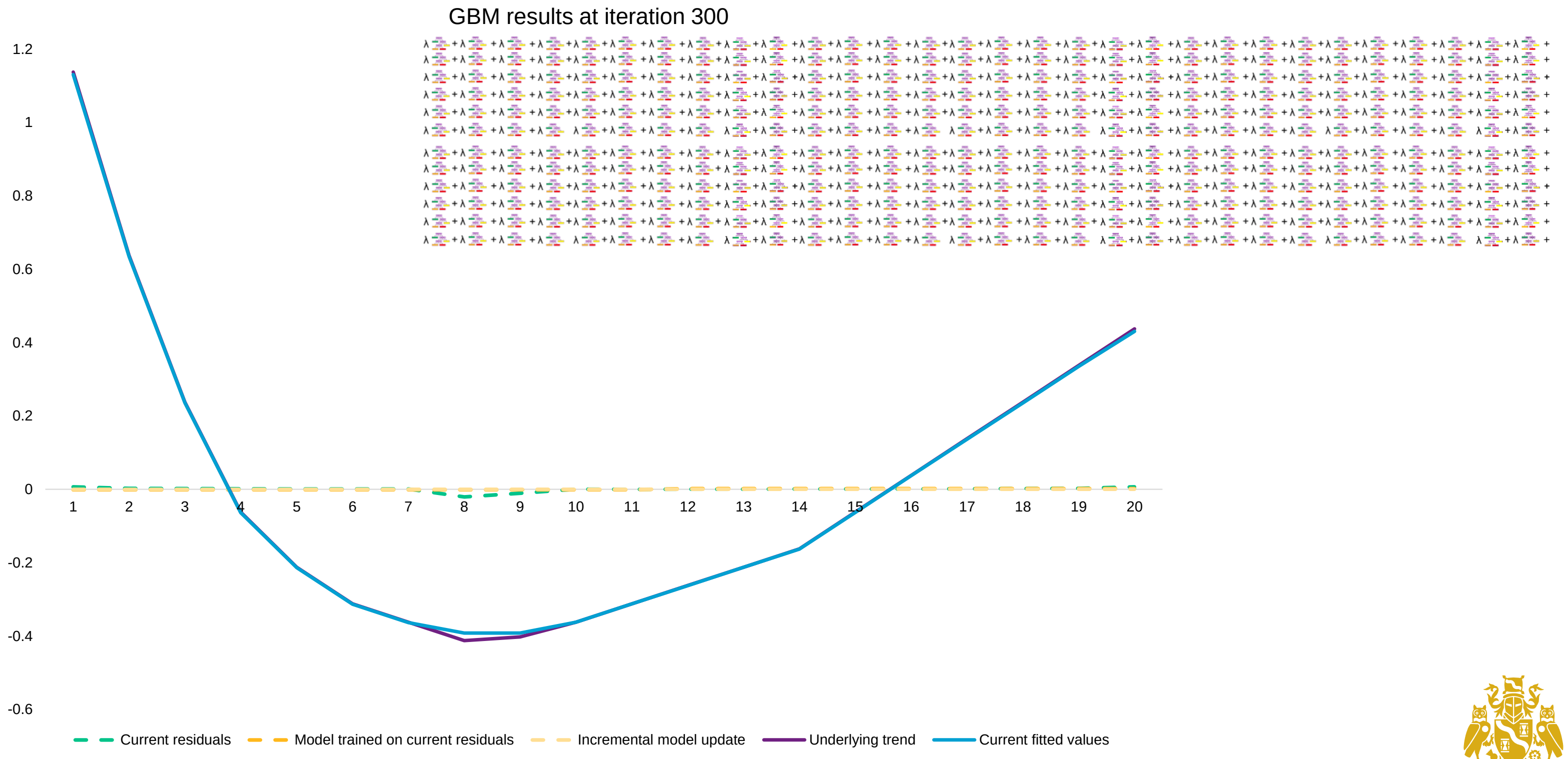


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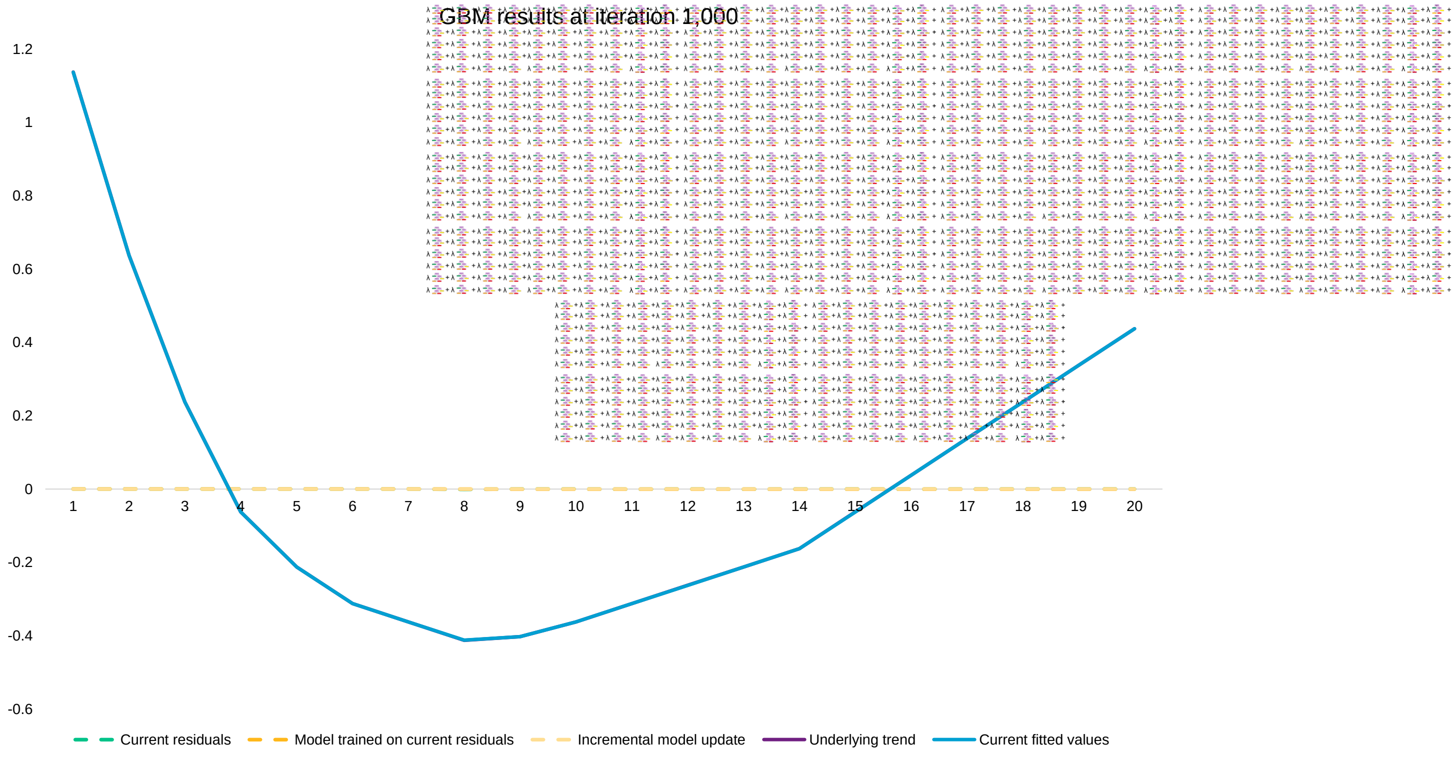
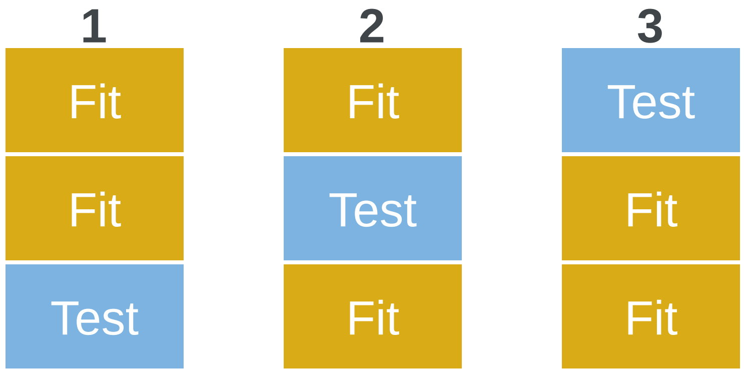
# A simple GBM example



# Calibrating the assumptions

- *n*-fold cross validation used to develop the interaction depth and learning rate assumptions
  - Eg for 3-fold validation, split into 3, fit on gold, test on blue parts, take average




- Resulting plots can be used to determine the optimal assumption choice
  - Including how many trees to run

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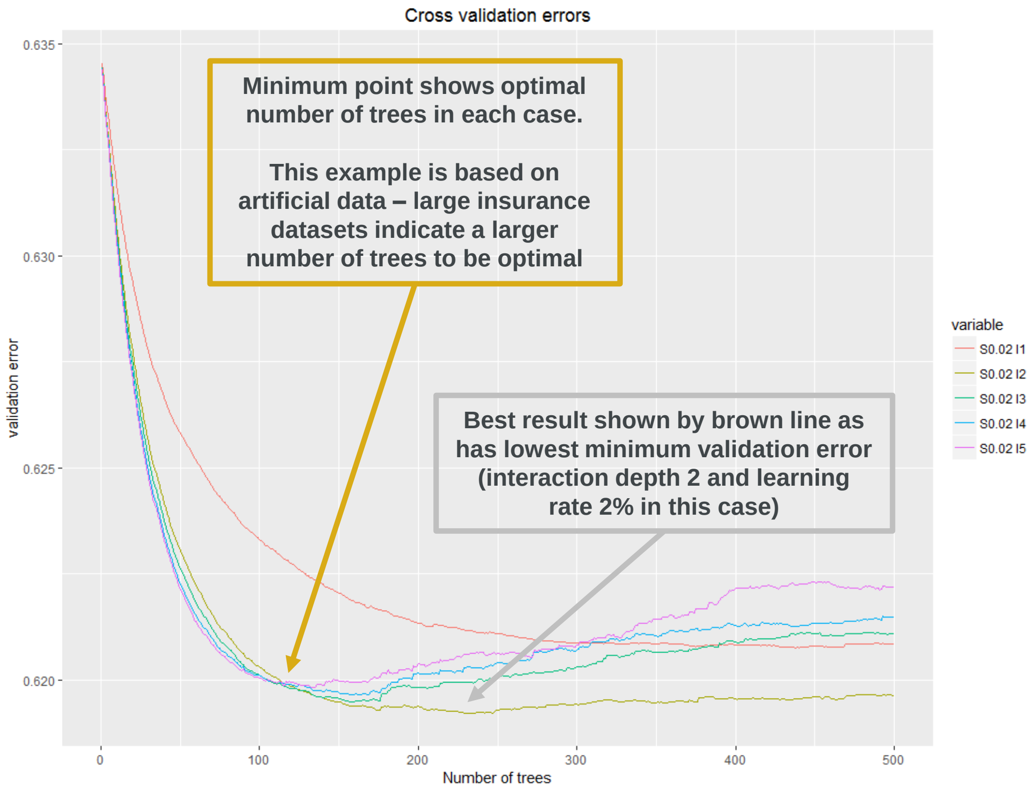
# Example 5-fold cross validation

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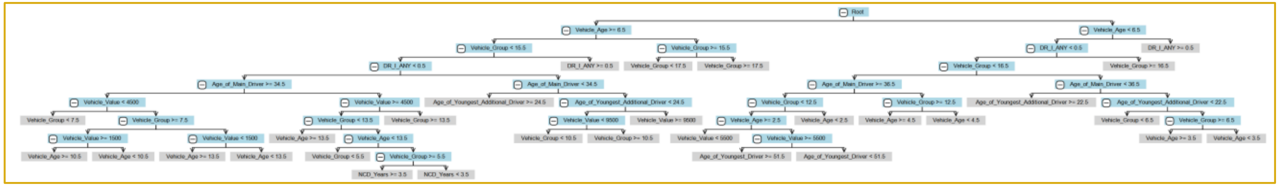
# What does a GBM look like?

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# What does a GBM look like?

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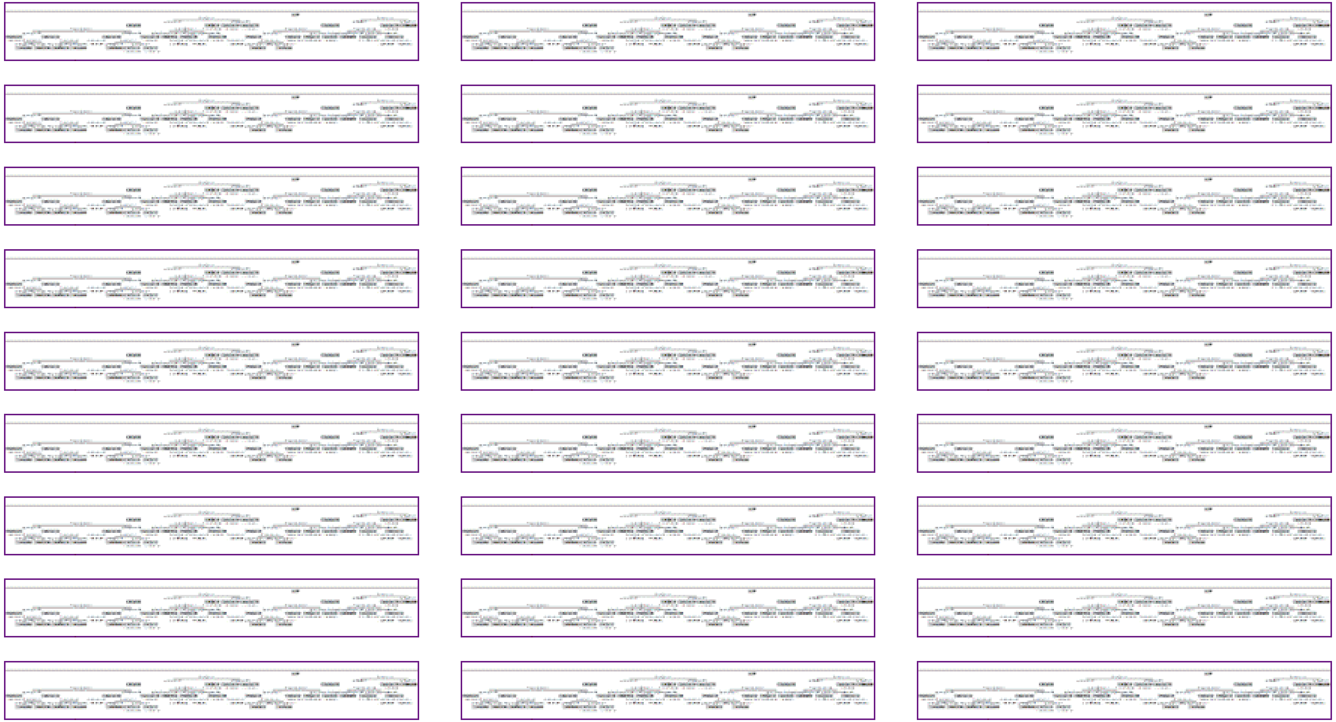

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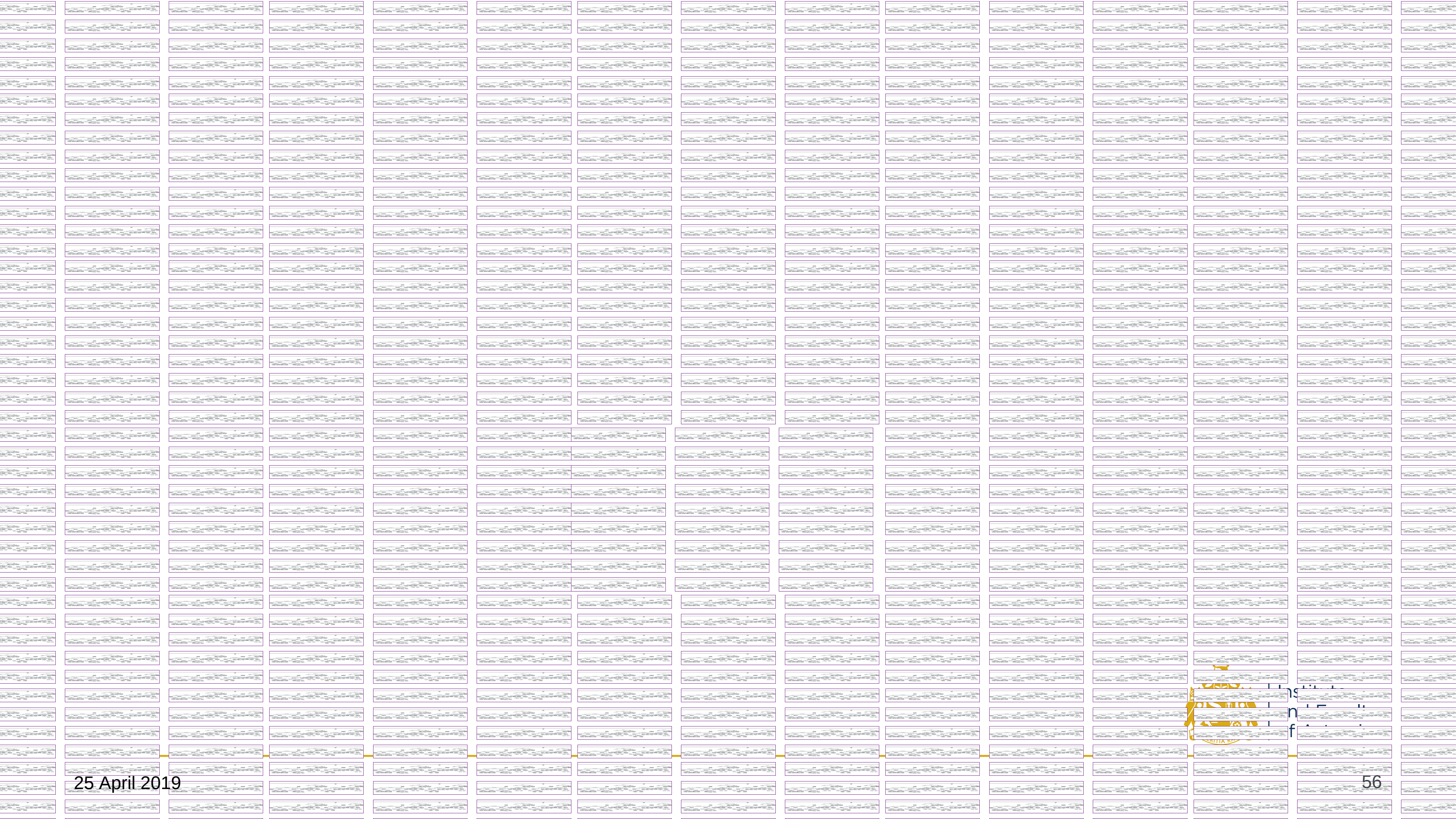
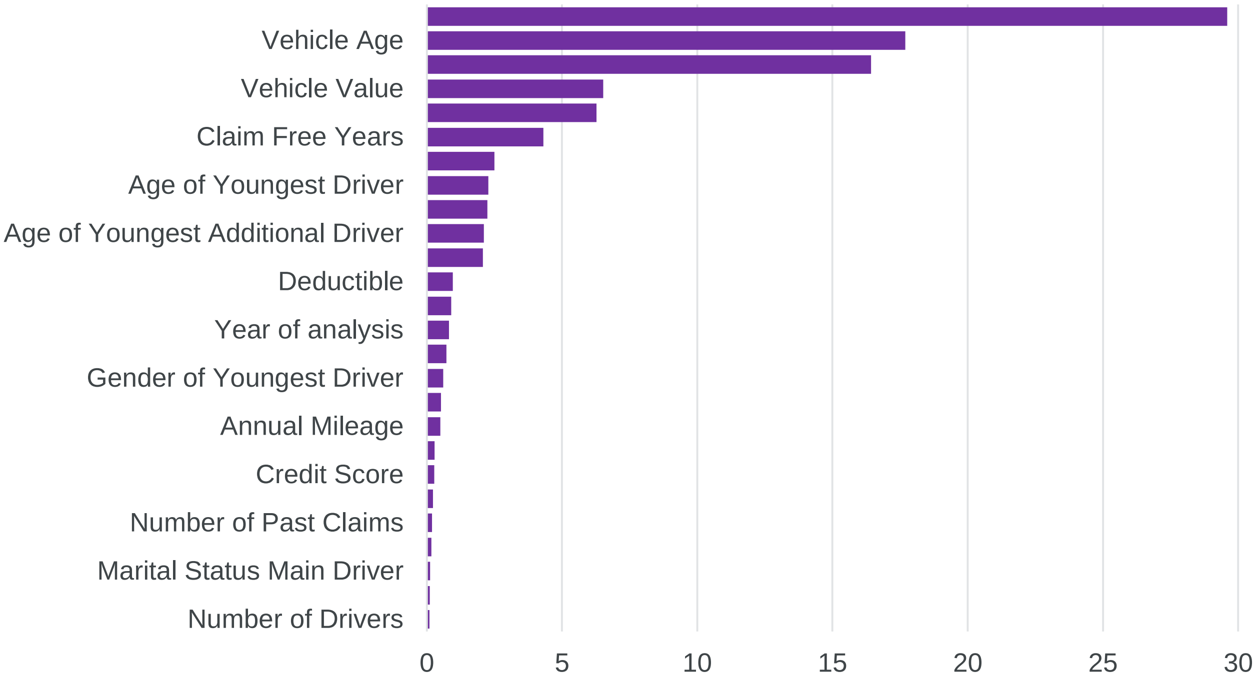


- Does it work?
- How does it work?

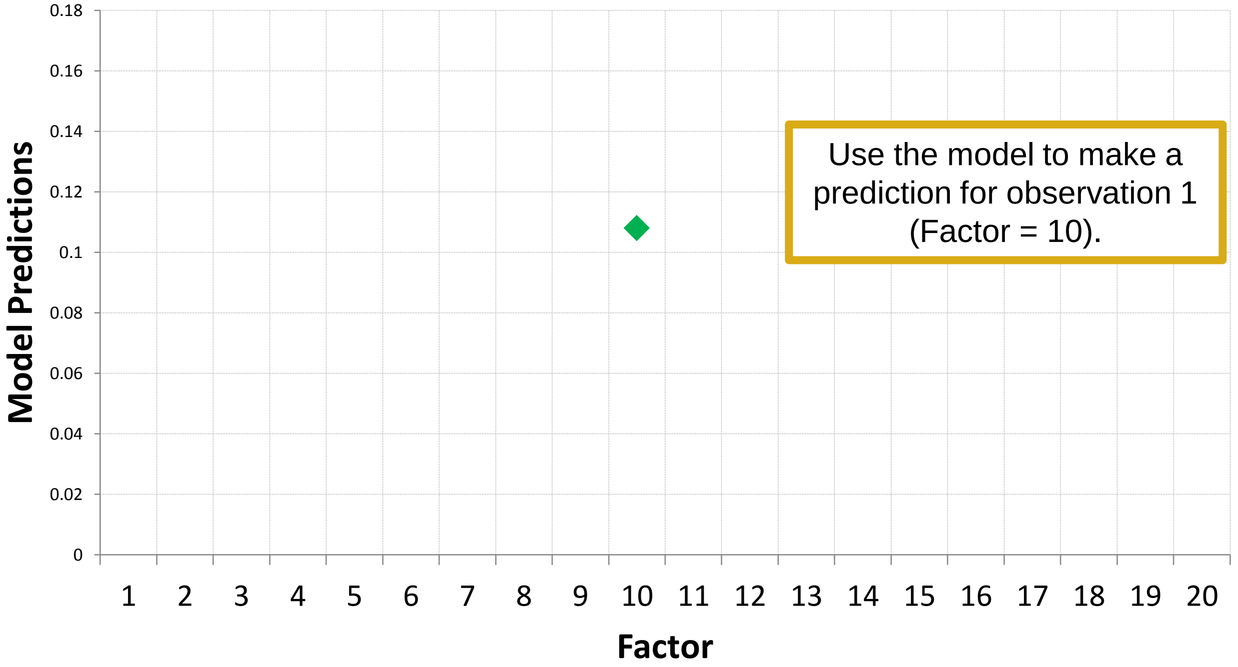
# Factor importance – relative influence

The relative influence of a factor can be measured as the total reduction in error attributable to splits by that factor, across all trees in the GBM



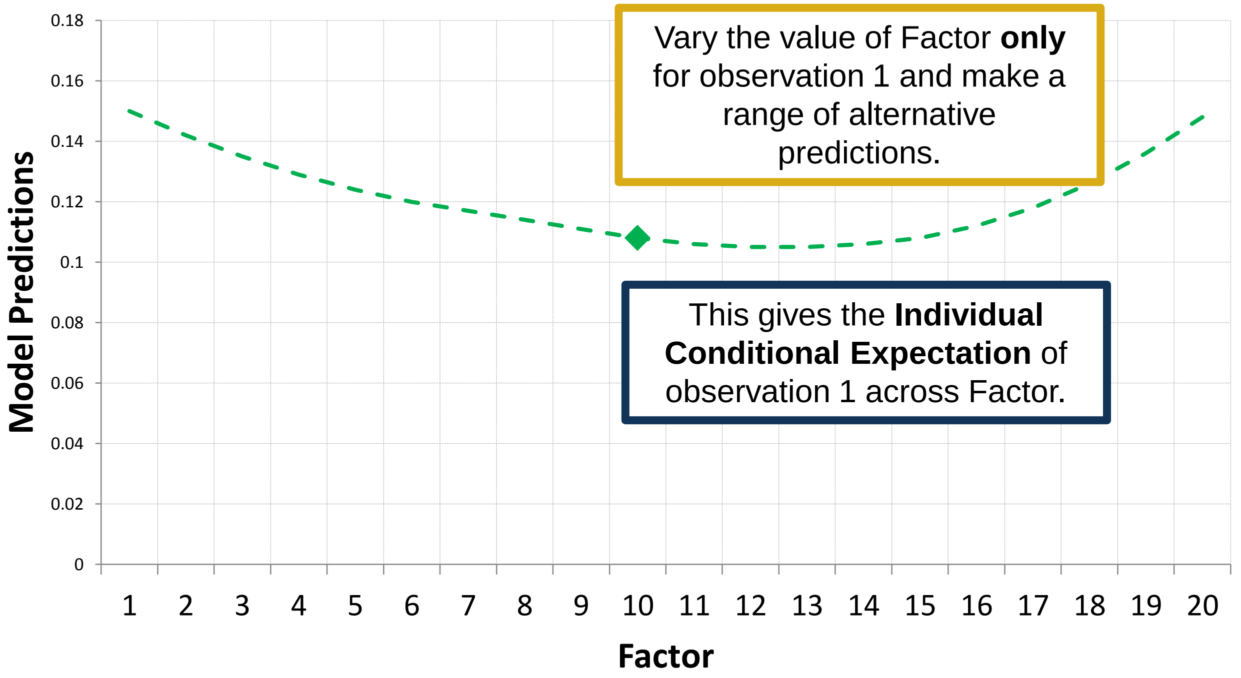
# Partial dependency plots

## Example



# Partial dependency plots

## Example

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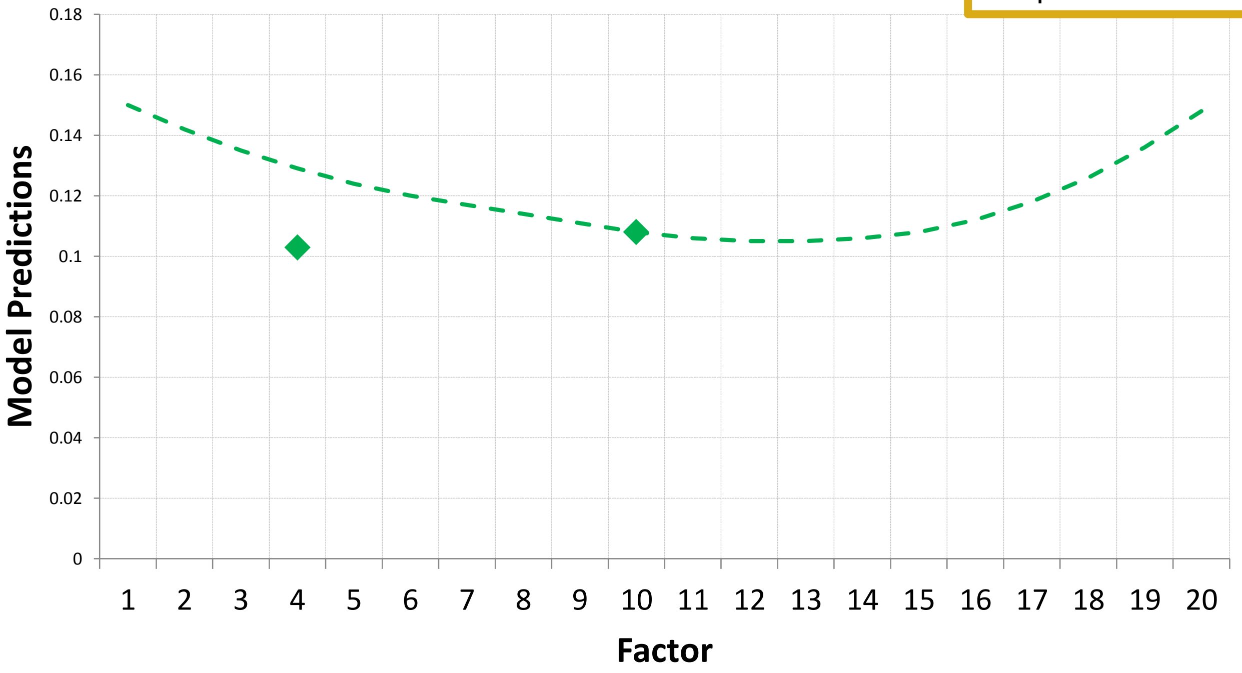
# Partial dependency plots

## Example

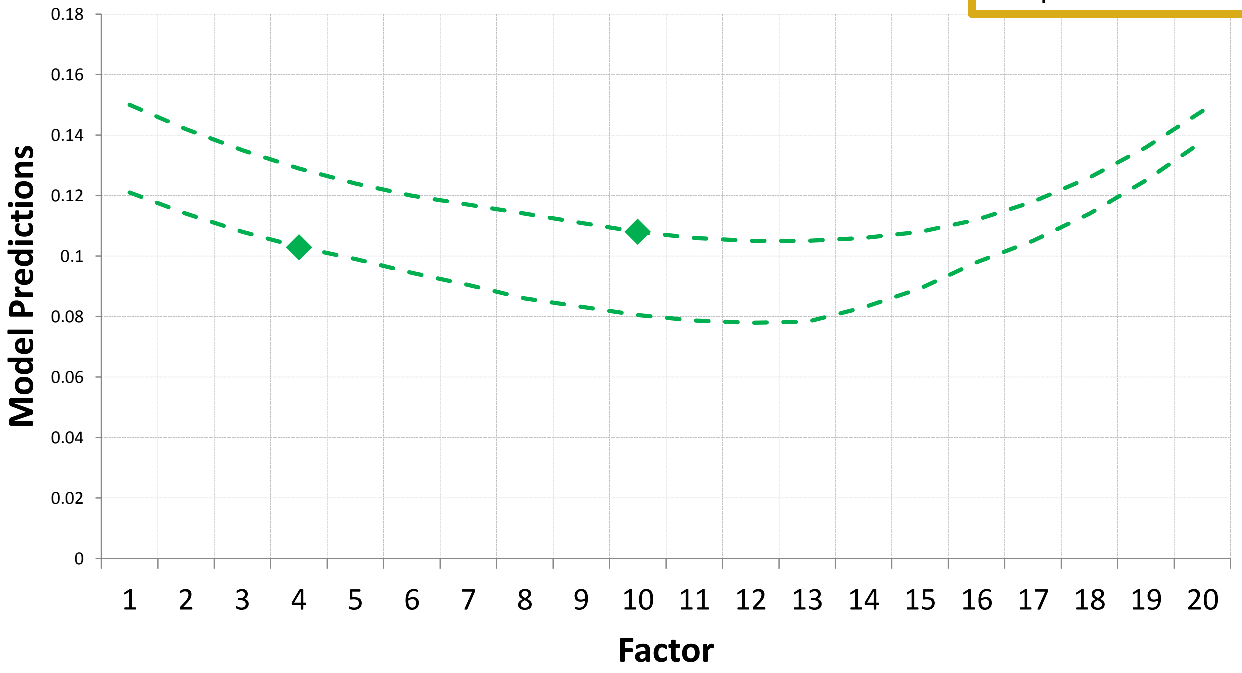
Repeat for all observations.



# Partial dependency plots

## Example

Repeat for all observations.

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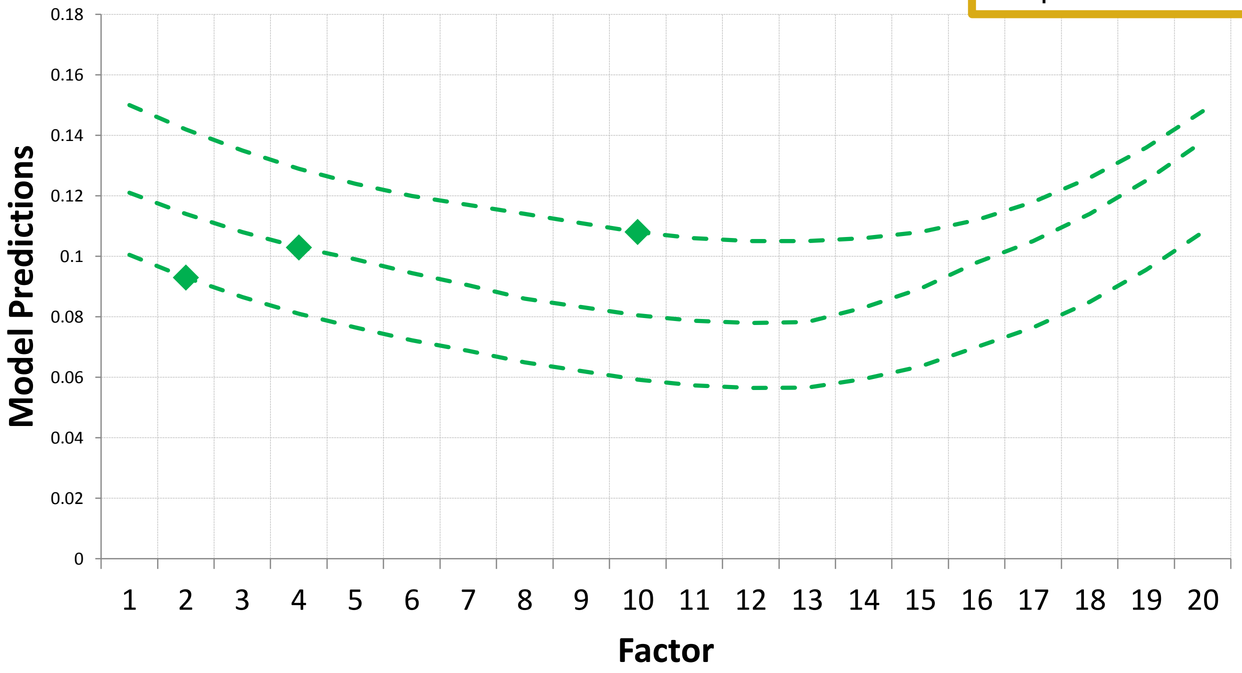
# Partial dependency plots

## Example

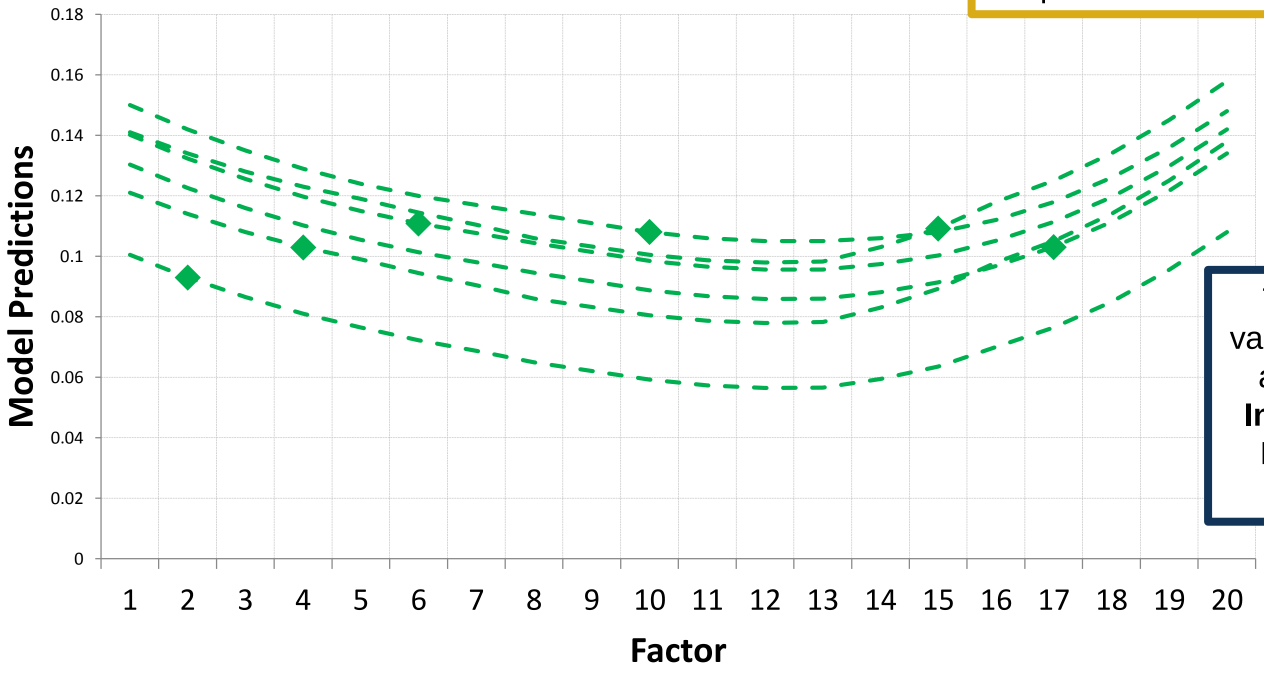
Repeat for all observations.



# Partial dependency plots

## Example

Repeat for all observations.




The full picture of the variation in predictions for all observations is the **Individual Conditional Expectation** (or **ICE**) plot.

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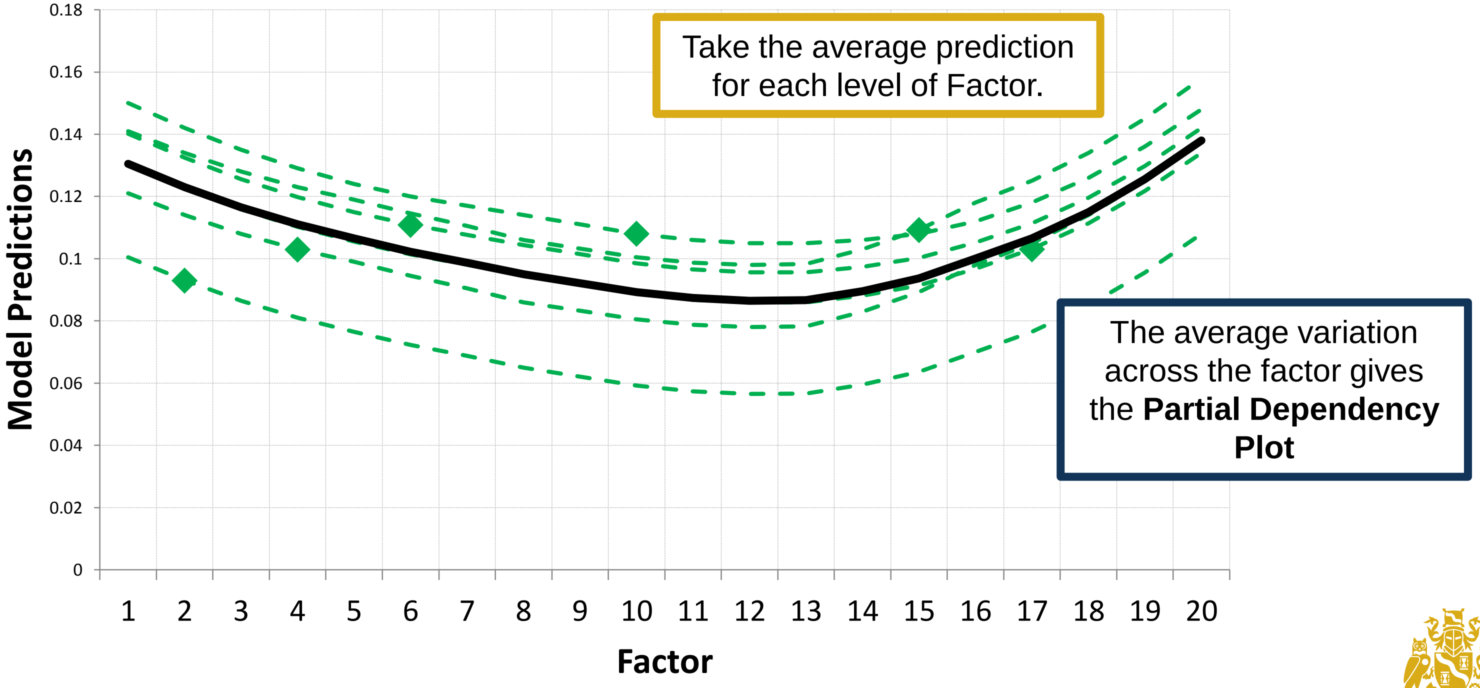
# Partial dependency plots

## Example

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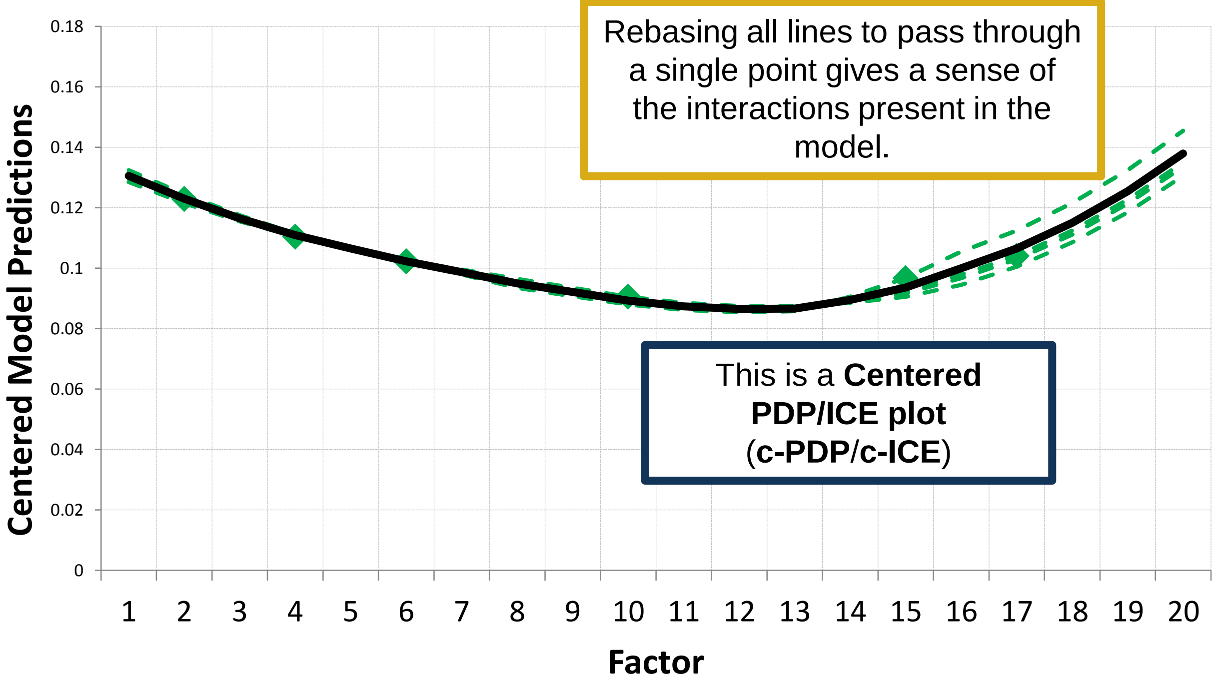
# Partial dependency plots

## Example

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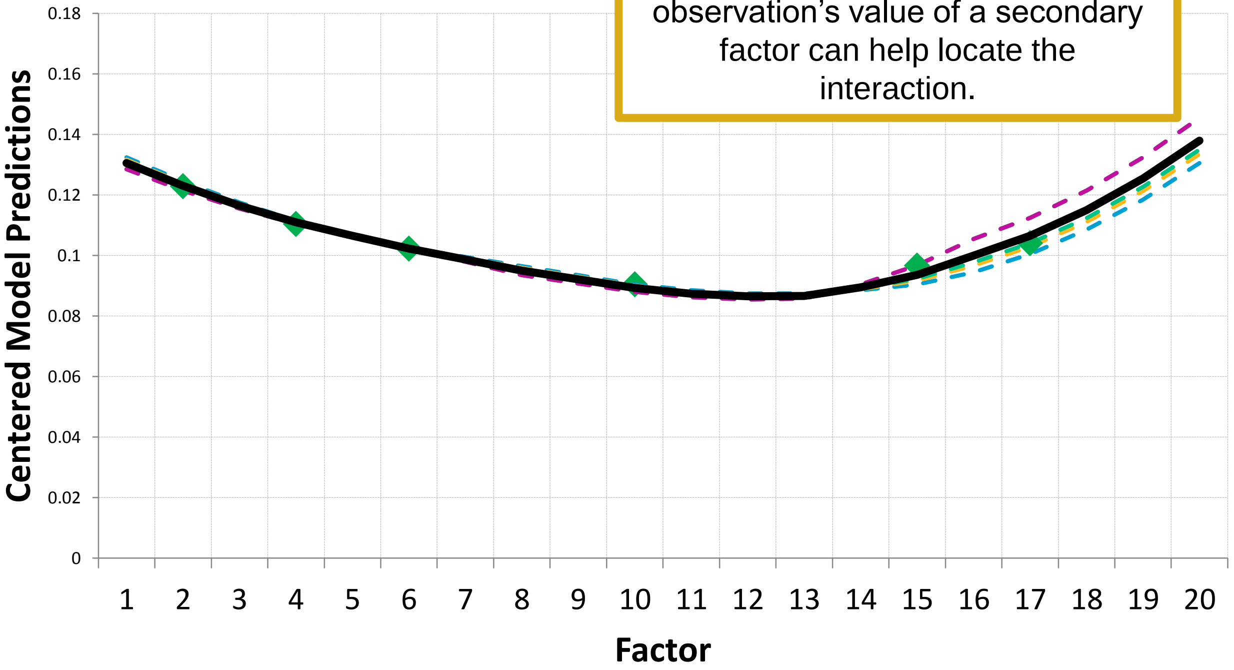
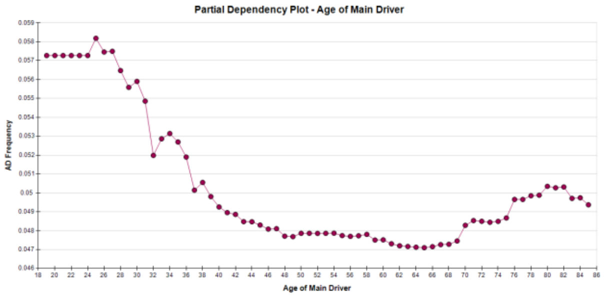
# Partial dependency plots

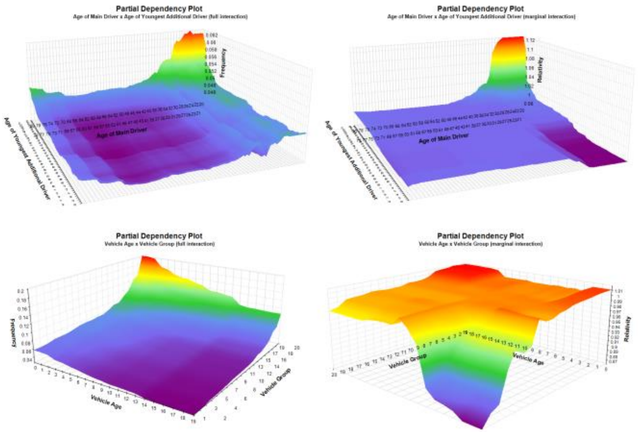
## Example

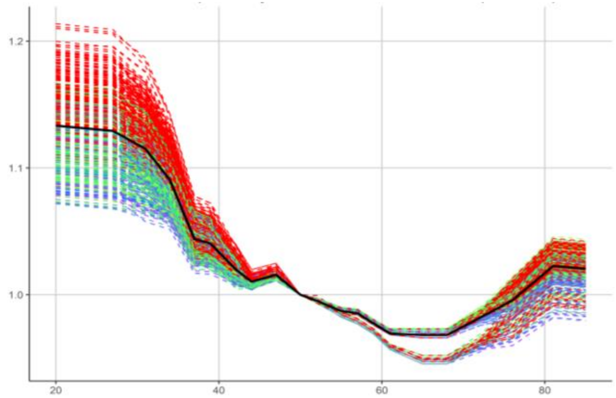
Colouring the c-ICE plots by each observation's value of a secondary factor can help locate the interaction.

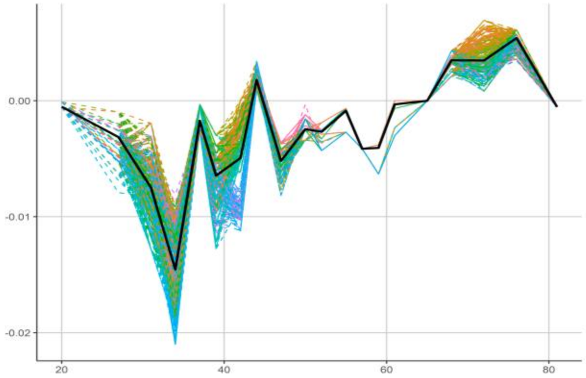


# Partial dependency plots etc

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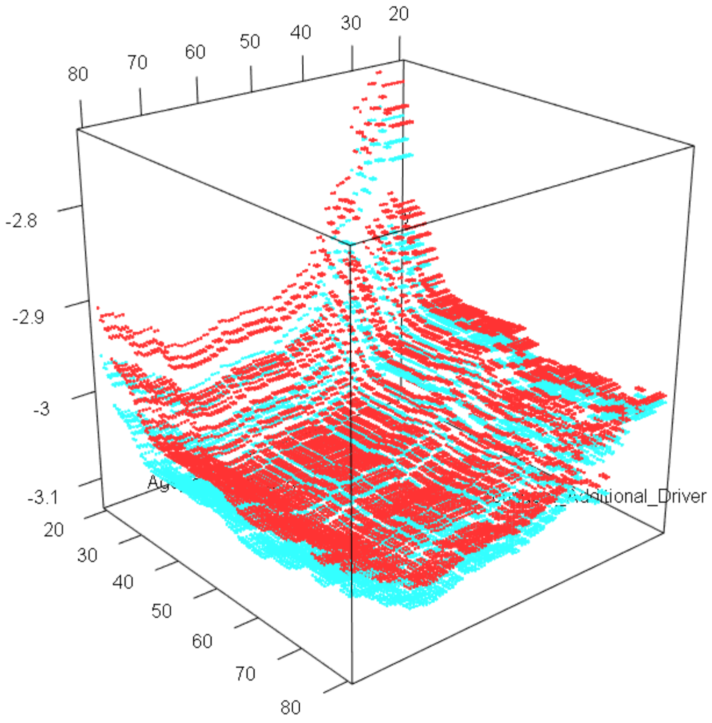
# Partial dependency plots




- Advantages
  - Qualitative description of properties of relationships
  - Most revealing of additive and multiplicative relationships
- Disadvantages
  - “GLM view of a non-GLM thing”
  - Interaction effects outside of the chosen subset may be obfuscated
  - eg if X1X2 is important and X2 is averaged out in the partial dependence plot, X1 may show as being heterogeneous, thus obfuscating the complexity of the modelled relationships

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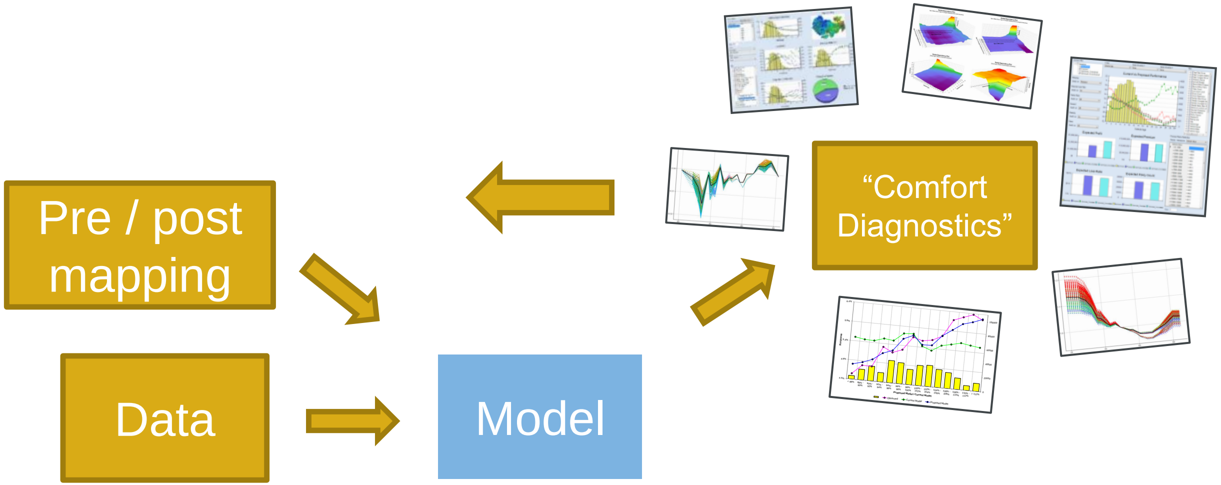
# Model build process




Deploy directly

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# Deploying GBMs

Model down into multiplicative tables via GLMs

| | Age | Exposure | Burning Cost |
|---|---|---|---|
| 1 | <=20 | 1,720 | 179 |
| 2 | 21-30 | 34,893 | 122 |
| 3 | 31-50 | 118,182 | 102 |
| 4 | 51+ | 127,054 | 70 |
| 5 | Age Total | 281,849 | 91 |

| | Vehicle Group | Exposure | Burning Cost |
|---|---|---|---|
| 1 | 1-10 | 164,107 | 77 |
| 2 | 11-14 | 84,859 | 101 |
| 3 | 15-18 | 28,952 | 116 |
| 4 | 19-20 | 3,931 | 272 |
| 5 | VG Total | 281,849 | 91 |

| | Gender | Exposure | Burning Cost |
|---|---|---|---|
| 1 | Male | 197,339 | 92 |
| 2 | Female | 84,510 | 87 |
| 3 | Gender Total | 281,849 | 91 |

**Analytical environ-ment**

**Next gen rating engine**

**Main Policy Admin System**

Deploy directly

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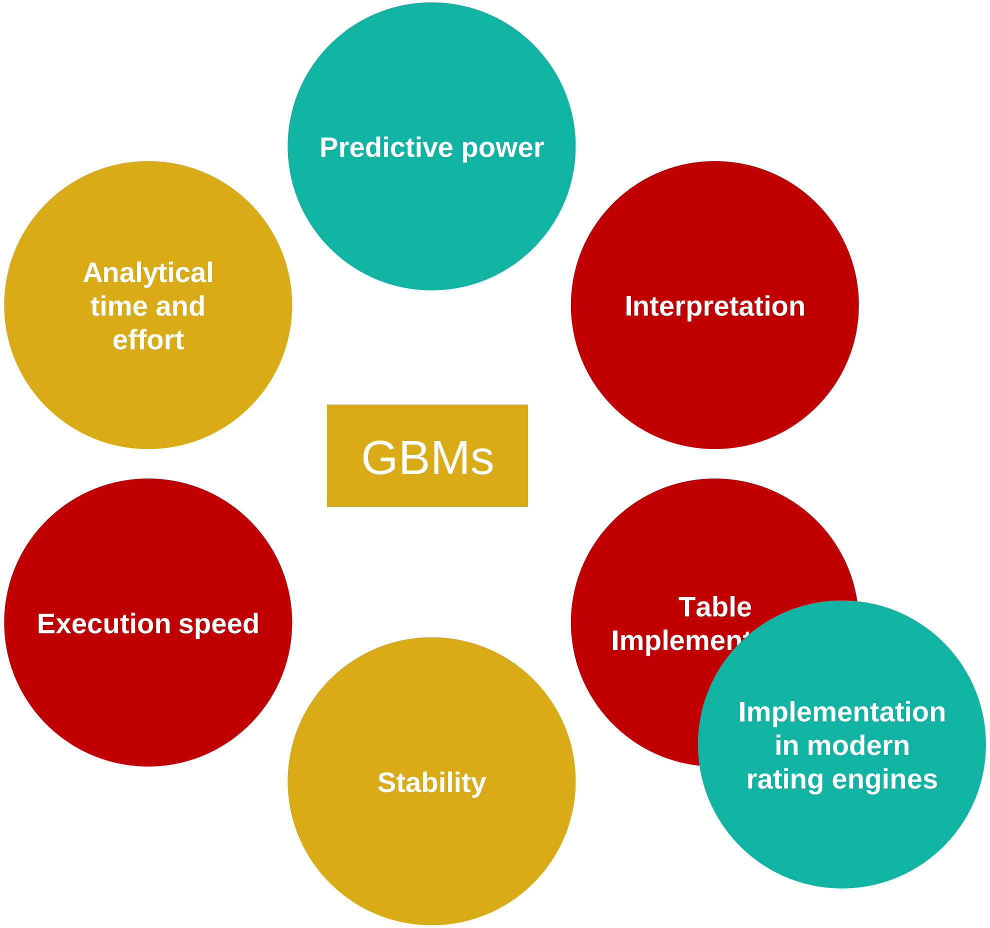
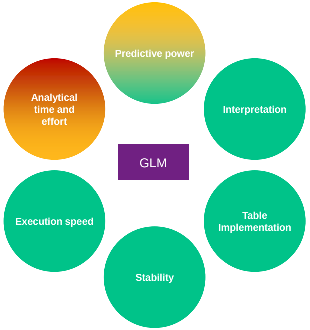
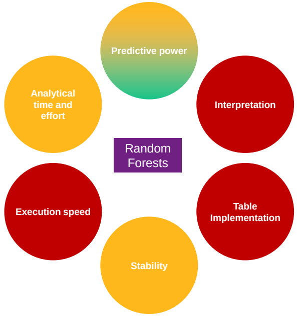
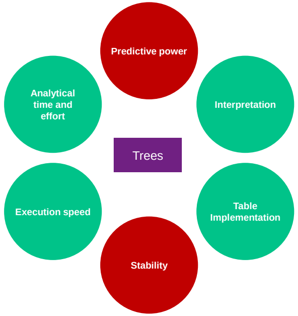
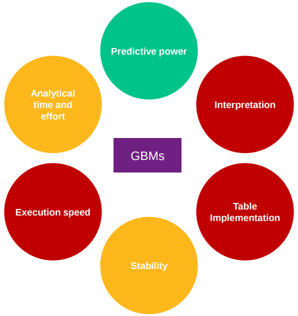

Predictive power
Analytical time and effort
Interpretation
GBMs
Execution speed
Table
Implement
Implementation in modern rating engines
Stability

# A summary…

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# 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 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 this method?
  - Do you have the software and hardware to fit to large dataset
  - Do you have a rating engine that can implement a GBM

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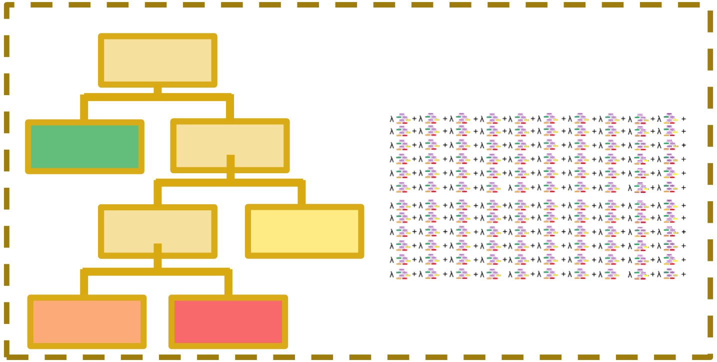
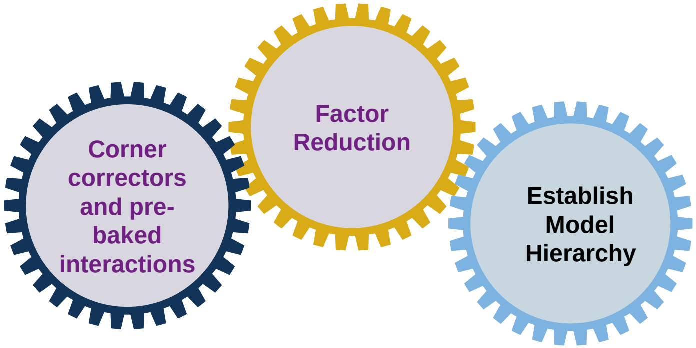
# Practical applications of tree based methods in pricing



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# Questions

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# Thank you