Overview and Practical Application of Machine Learning Methods in Pricing

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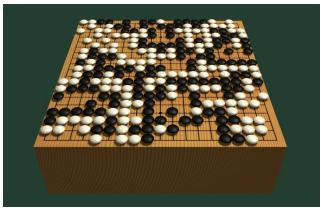
Introduction

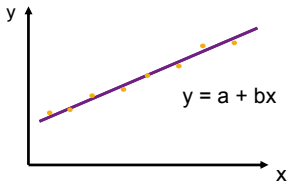
What I promised to do…

"We take a look at the common machine learning methods in use today and try to extract the value from the hype around this field"

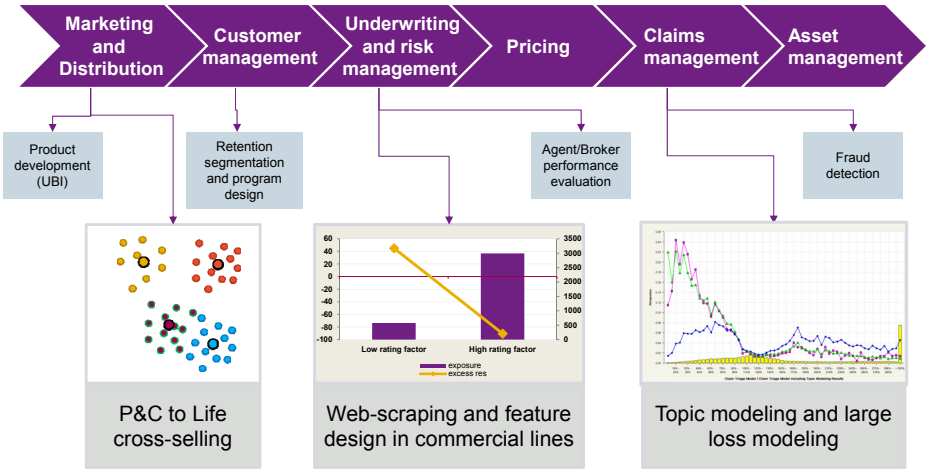
- What is needed to make them work?
- What are the strengths and weaknesses of these methods?
- Where does the role of the pricing actuary and the actuarial profession fit in?

Who's interested in what?





Applications of machine learning in the insurance sector



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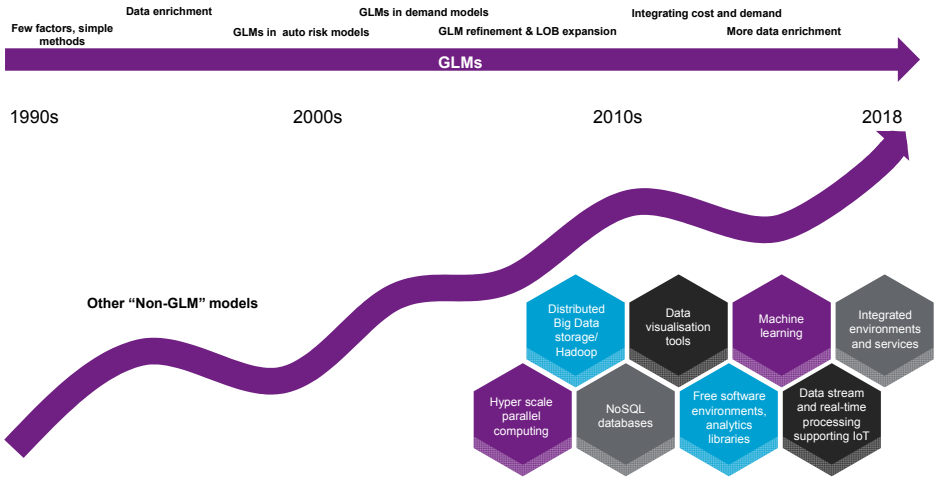
This is not new….



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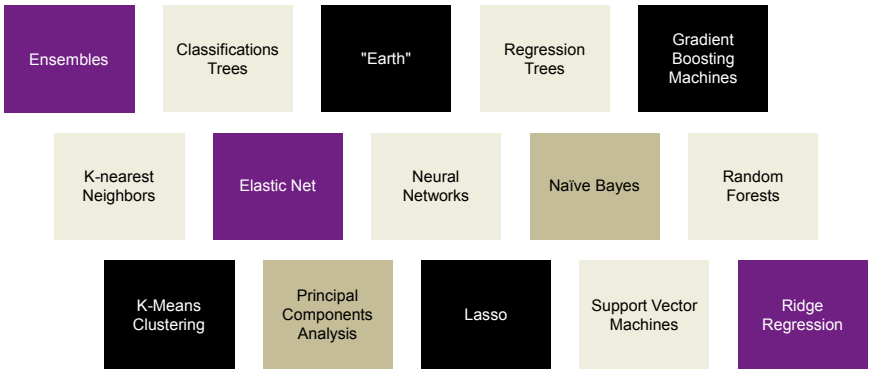
What are these machine learning methods?



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How do you know if a method works?

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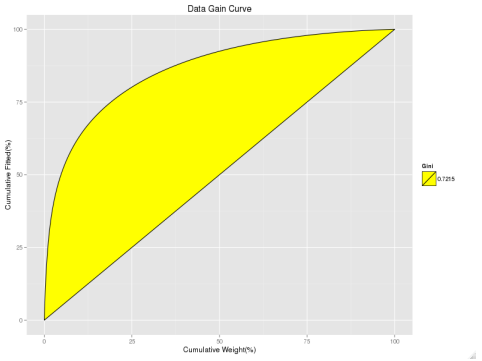
How do you measure value?



- 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)

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But…

- Think of a model…
- Multiply it by 123
- Square it
- Add 74½ billion

- …and you get the same Gini coefficient!

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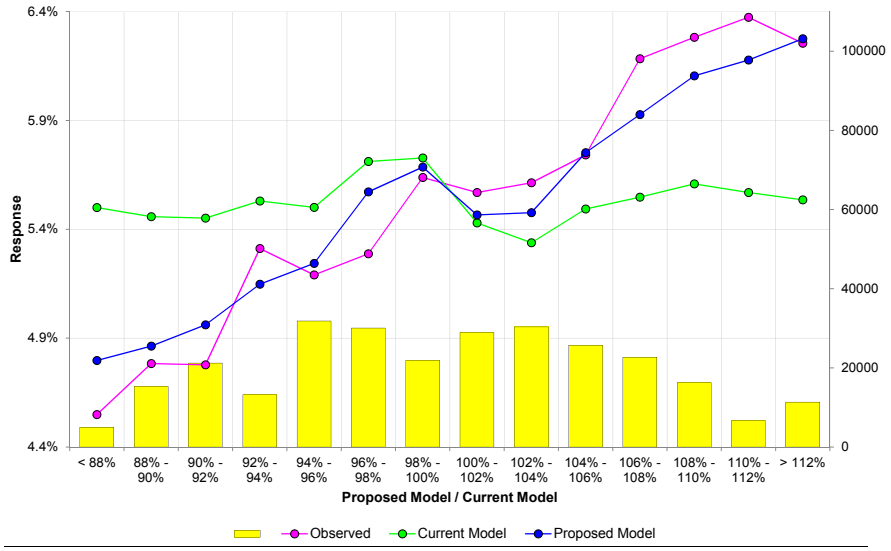
Double lift chart



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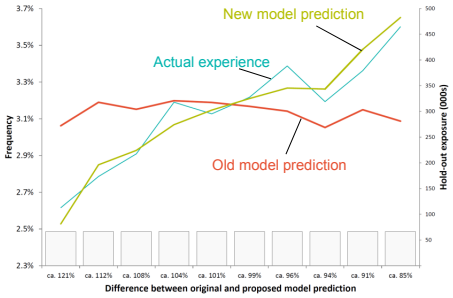
Financial value estimate

- 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



Simple formula

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}
			Value created	$ X

2.1% on loss ratio…

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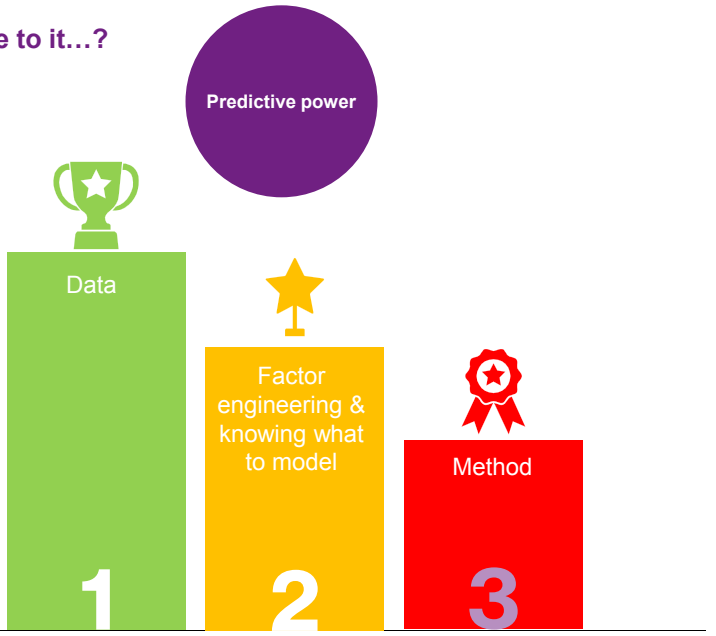
Is there more to it…?



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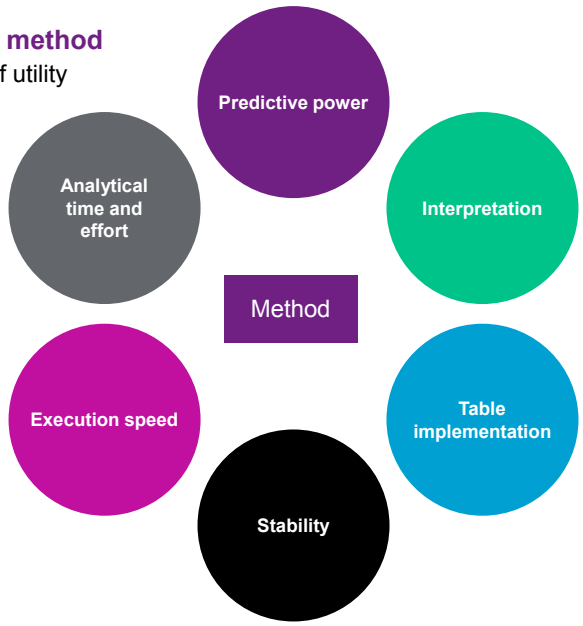
Choosing a method

Dimensions of utility



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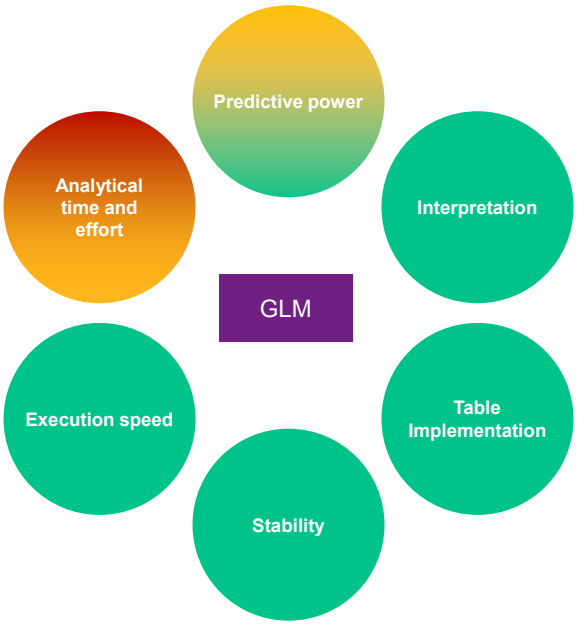

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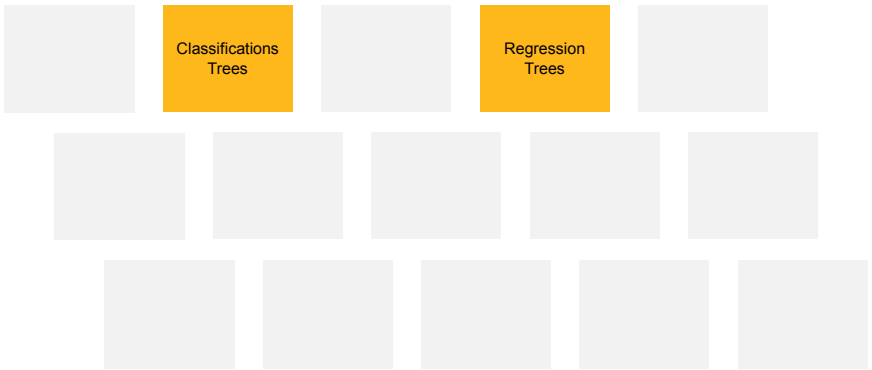
Focus on Trees



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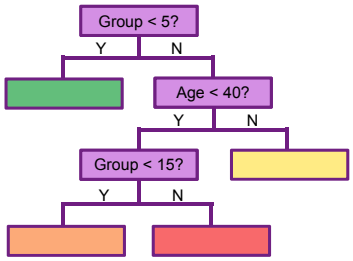
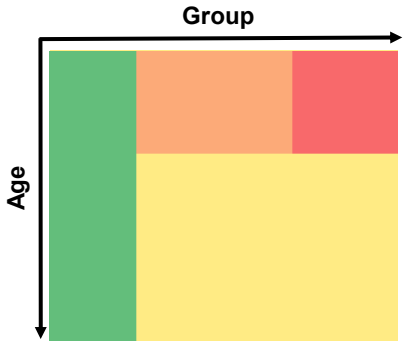
Decision Trees





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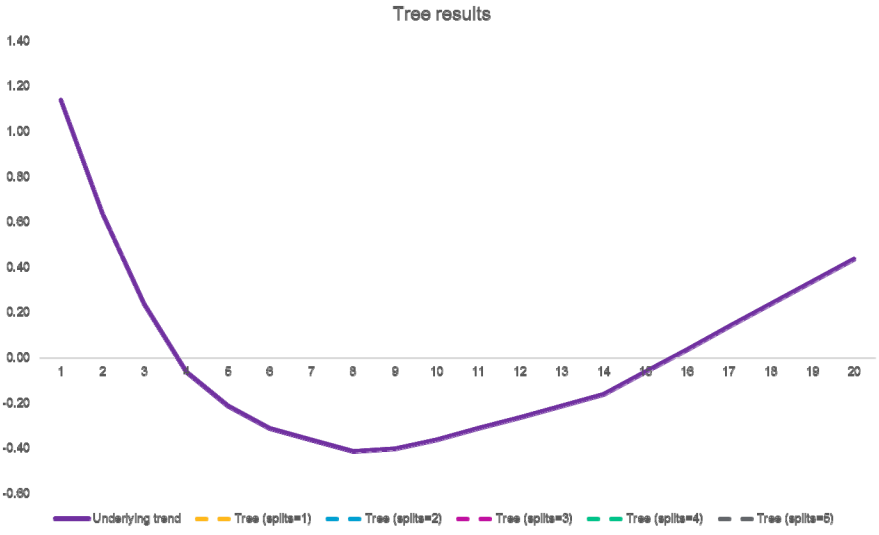
A simple Tree example



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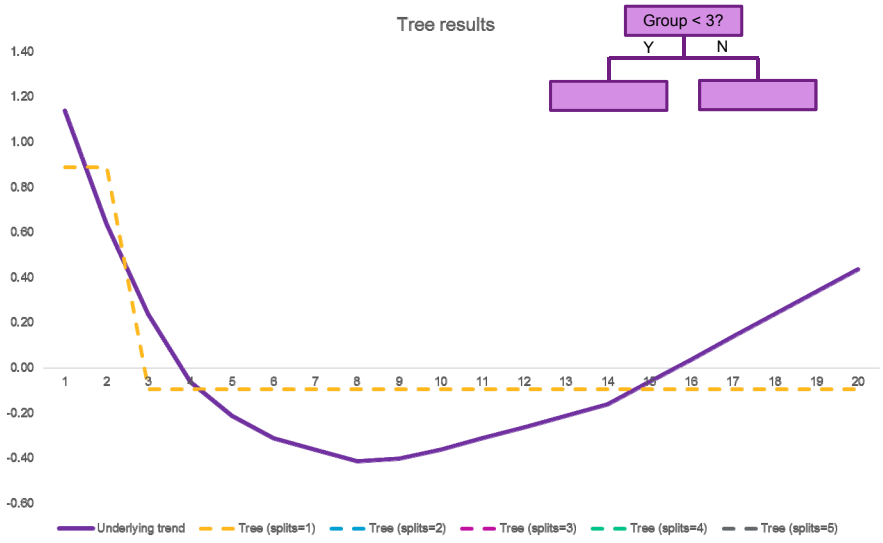

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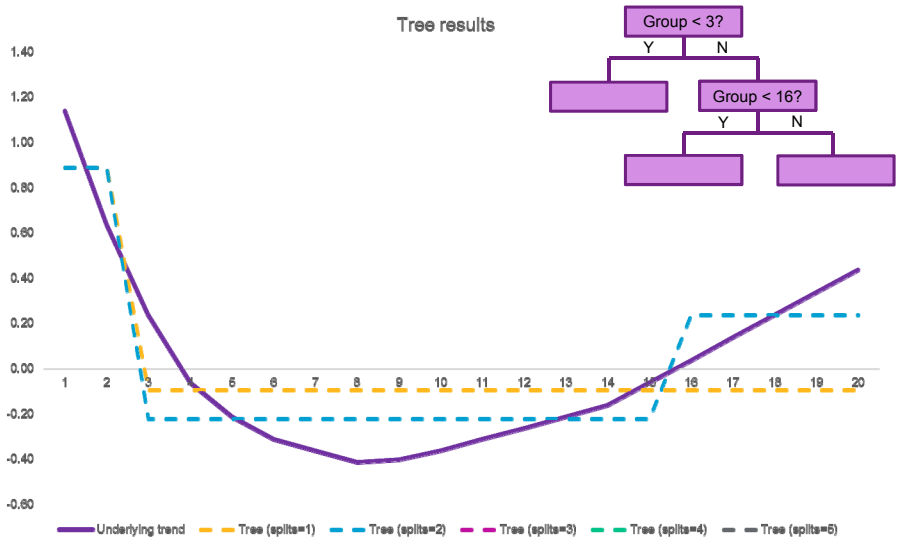

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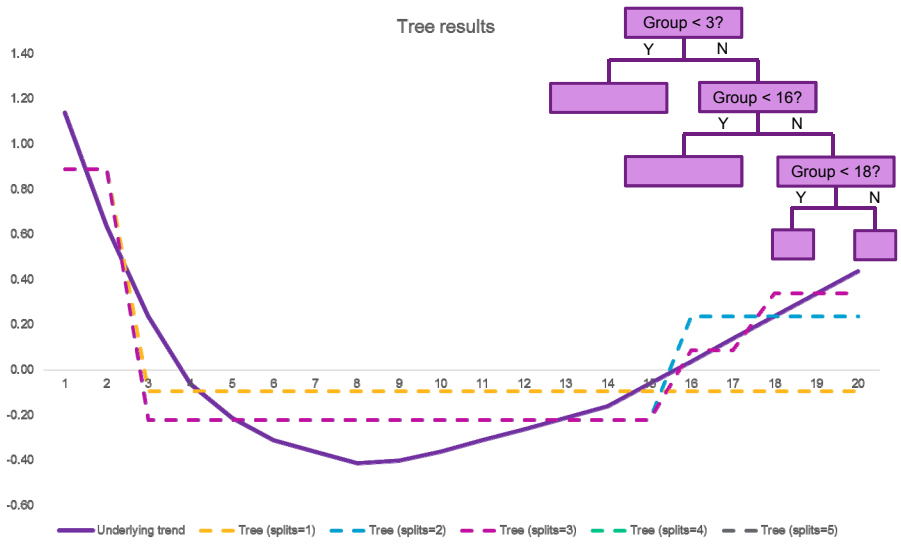

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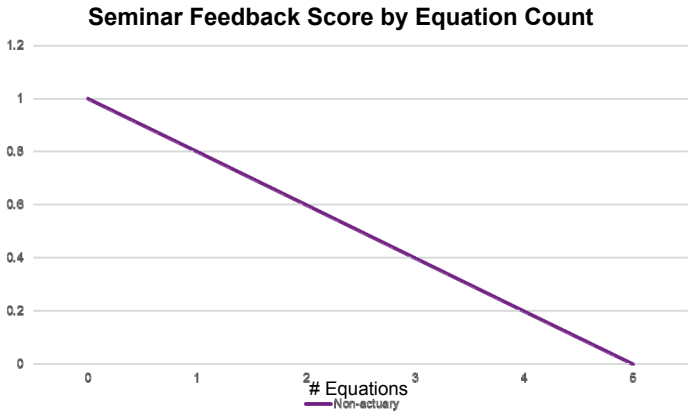
Trees are greedy

Let's build a simple model:



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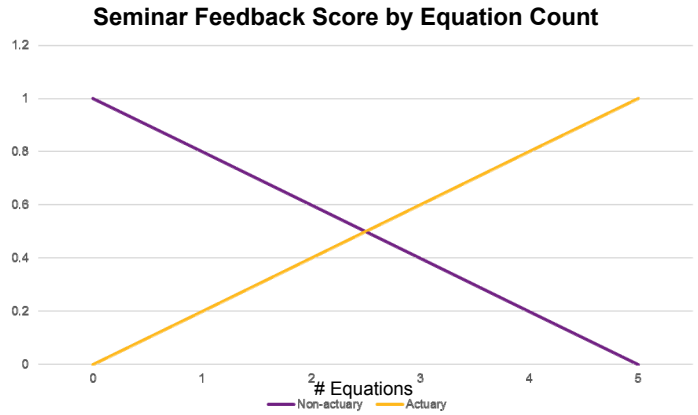

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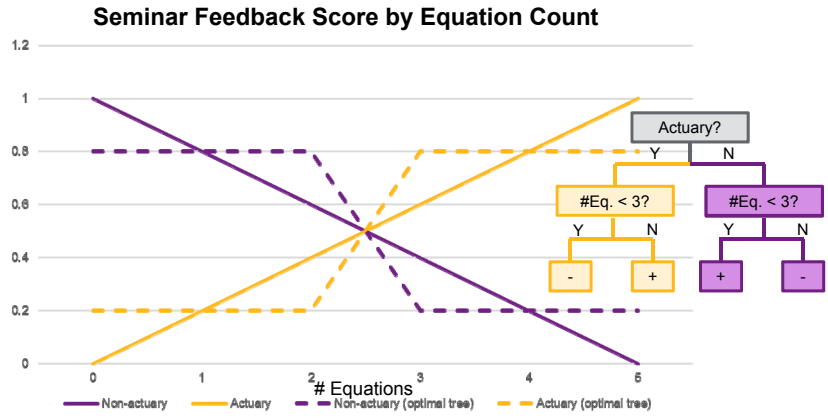

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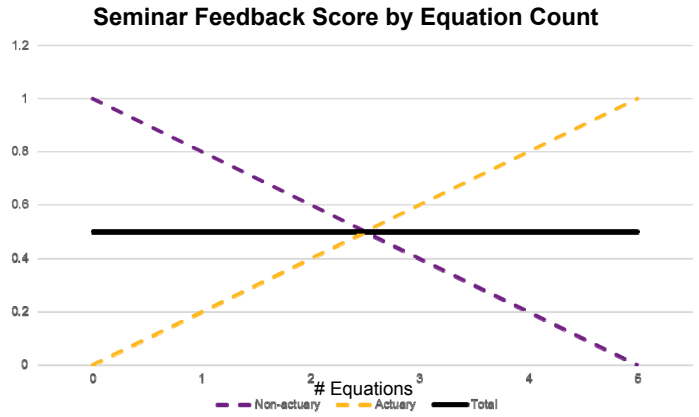
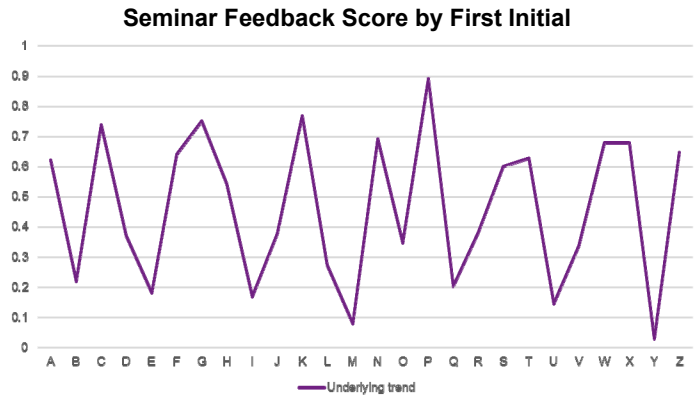


Trees are bad at categorical variables



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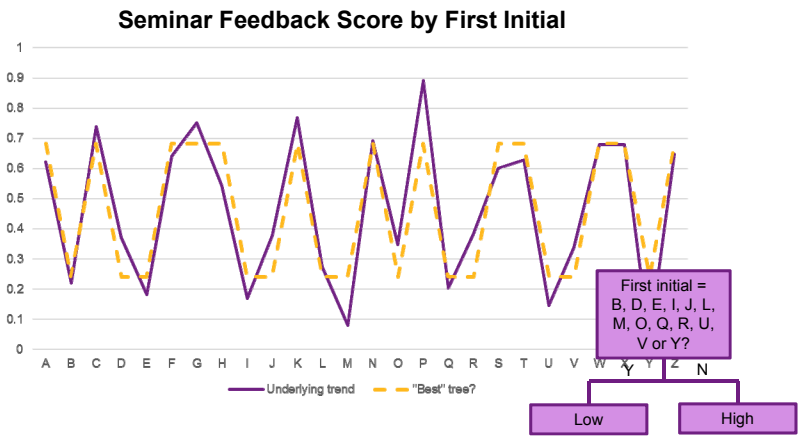

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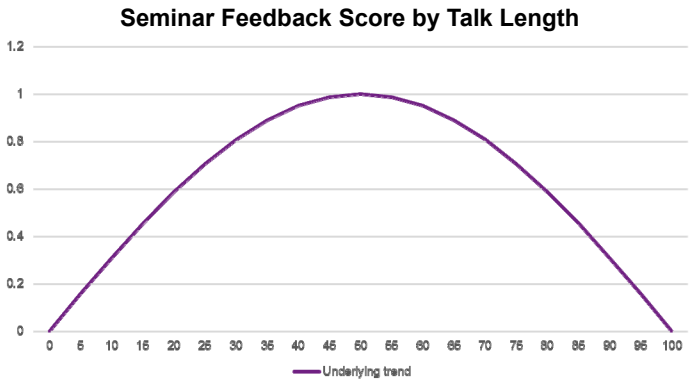
Trees are bad at turning points



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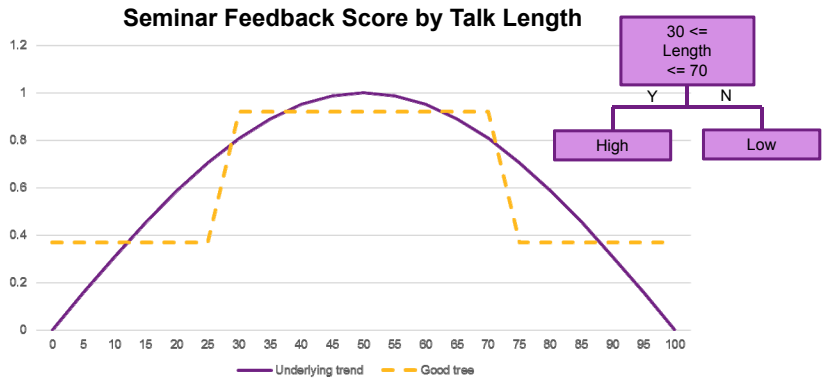
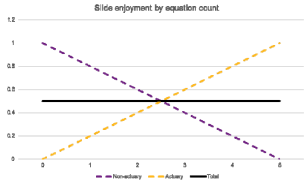


Shortcomings of using trees

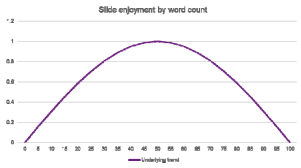
Summary

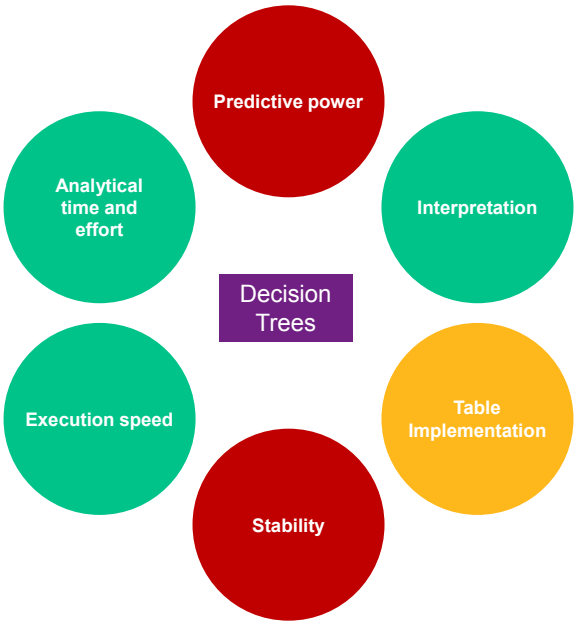
They may miss interactions…



… they may struggles with categorical variables….

…and they can be bad at turning points





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Some 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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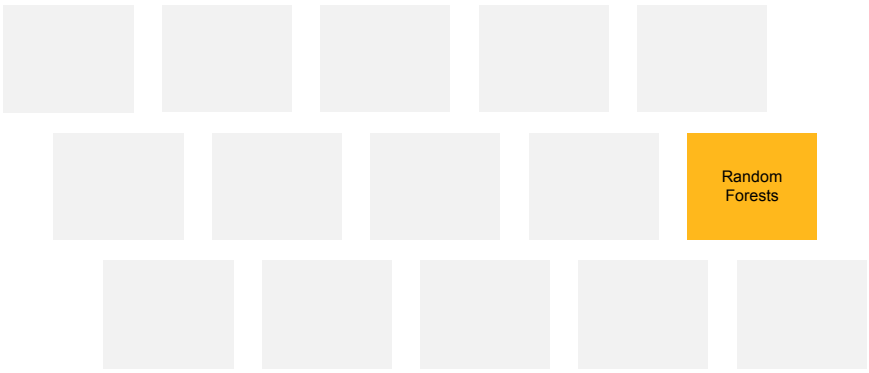
Focus on Random Forests



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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 **ag**gregation) – fit **lots** of independent models and take an average

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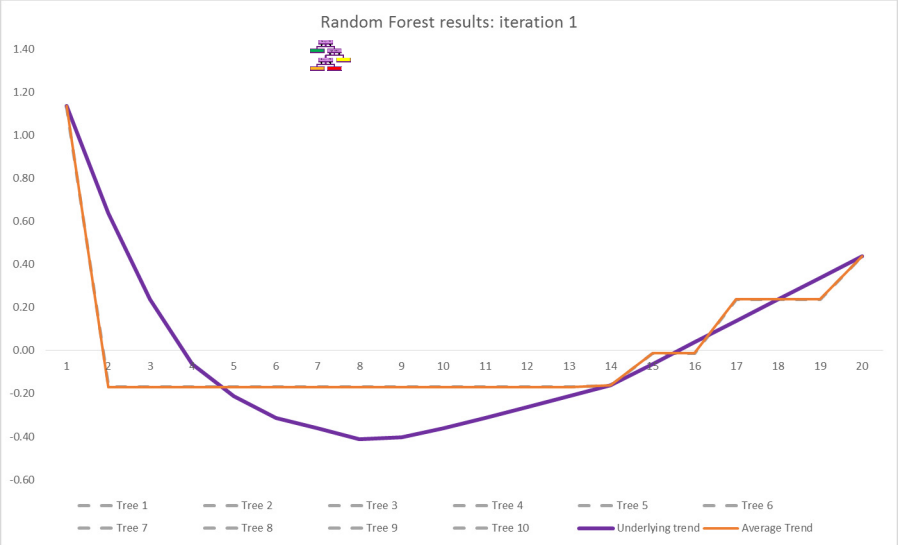
A simple Random Forest example



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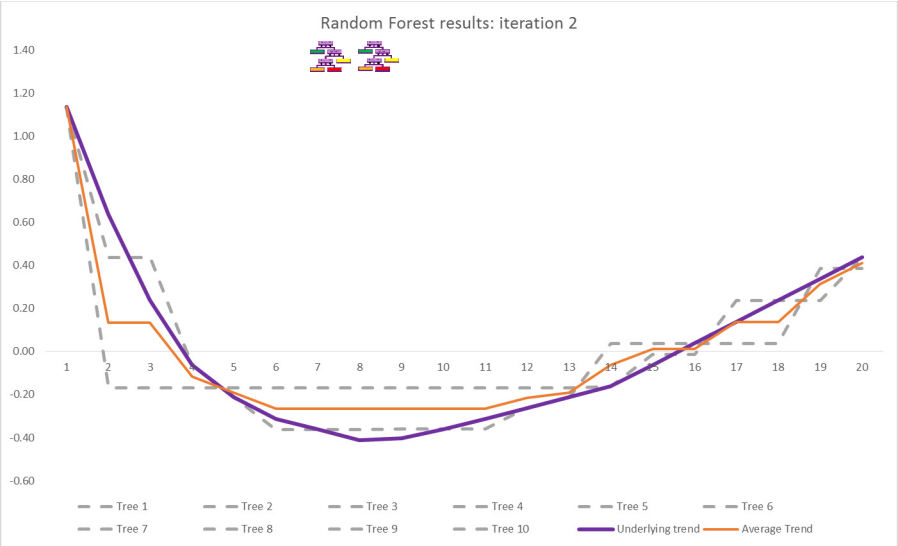

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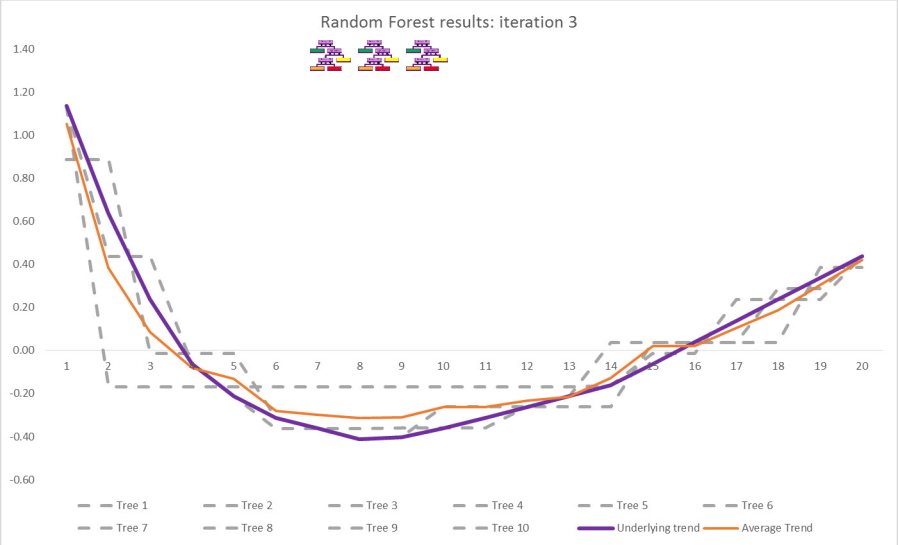

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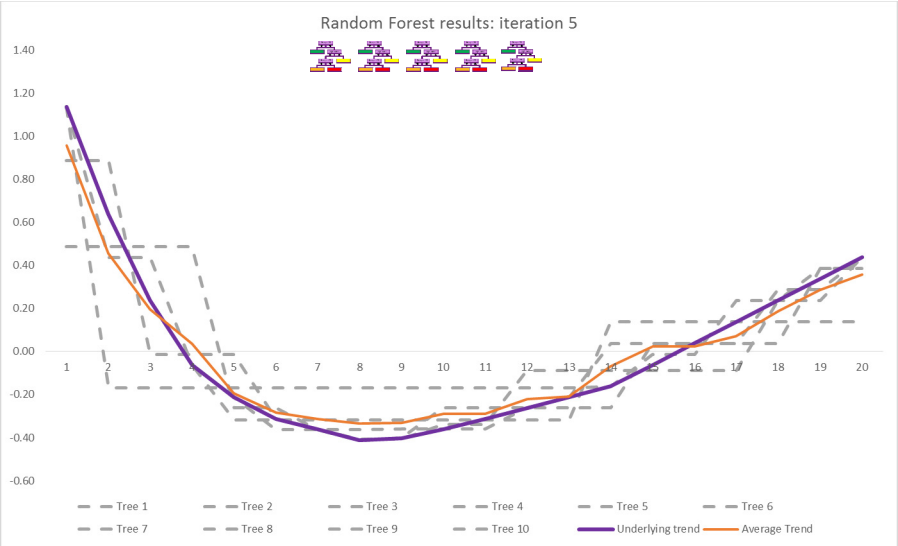

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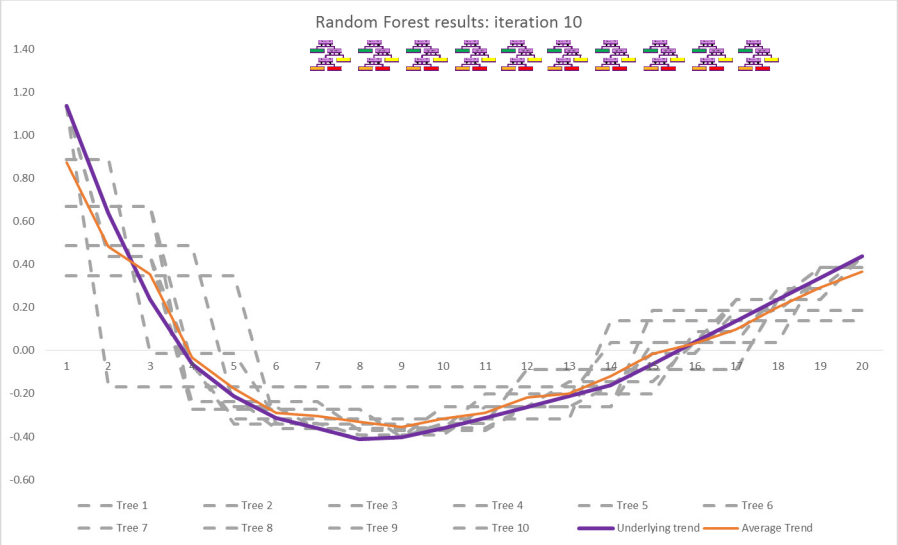

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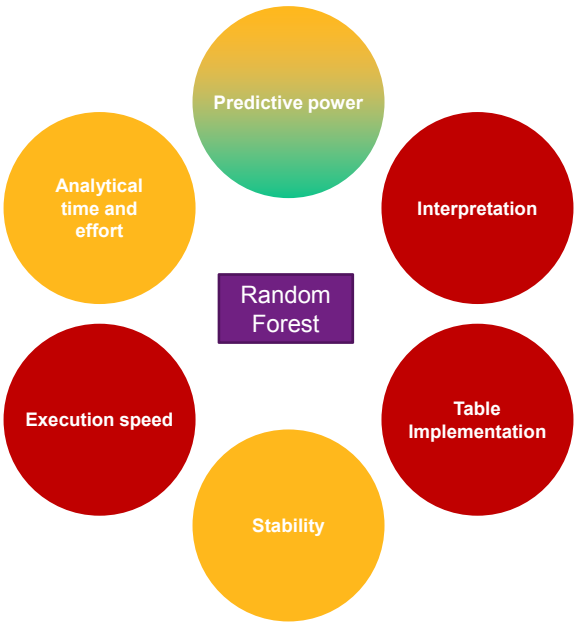

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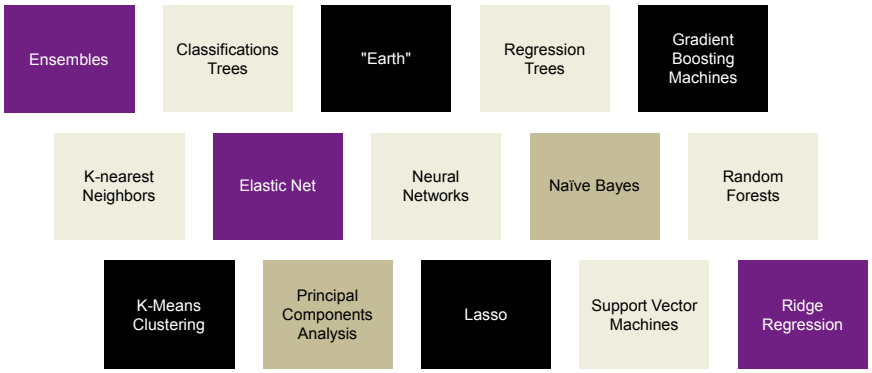
Some machine learning methods



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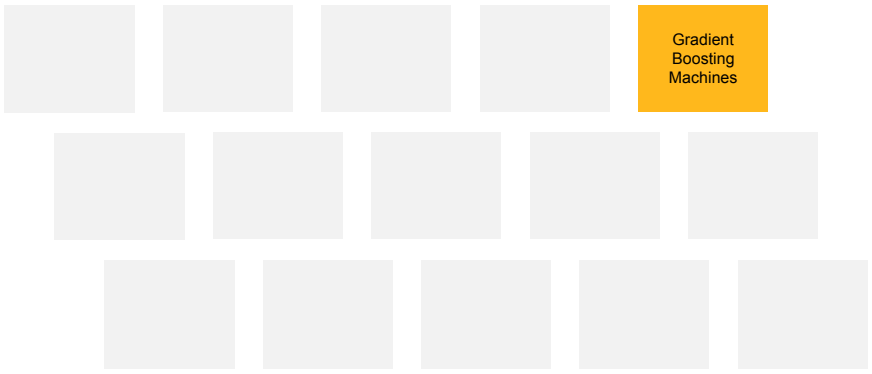
Focus on Gradient Boosting Machines



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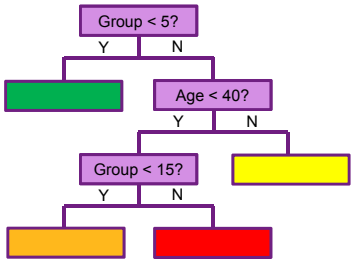
Gradient Boosting Machine or "GBM"

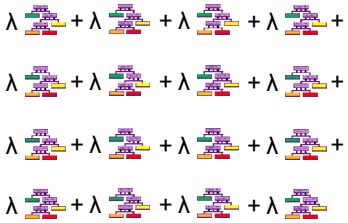
A tree

$f_i(x)$



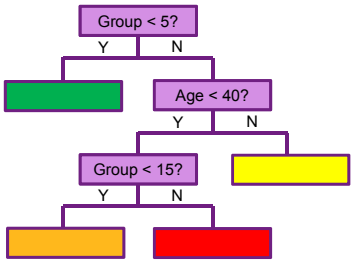
A GBM

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

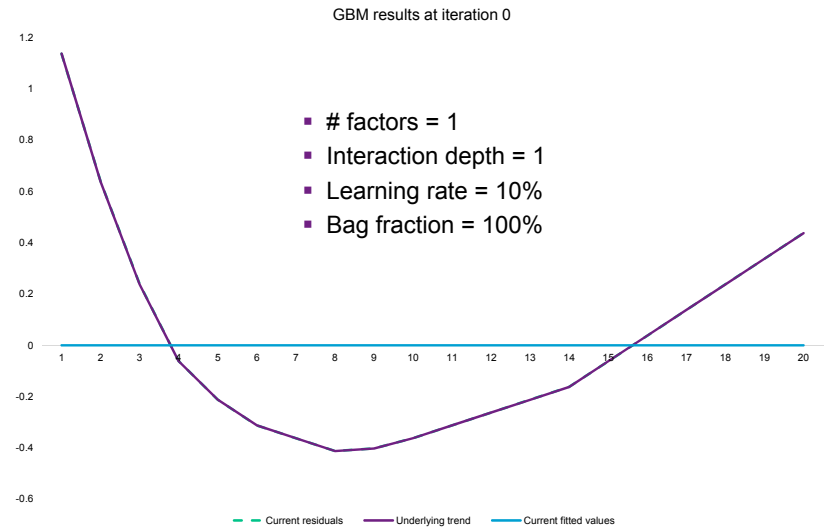


Four main assumptions

- 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



A simple GBM example



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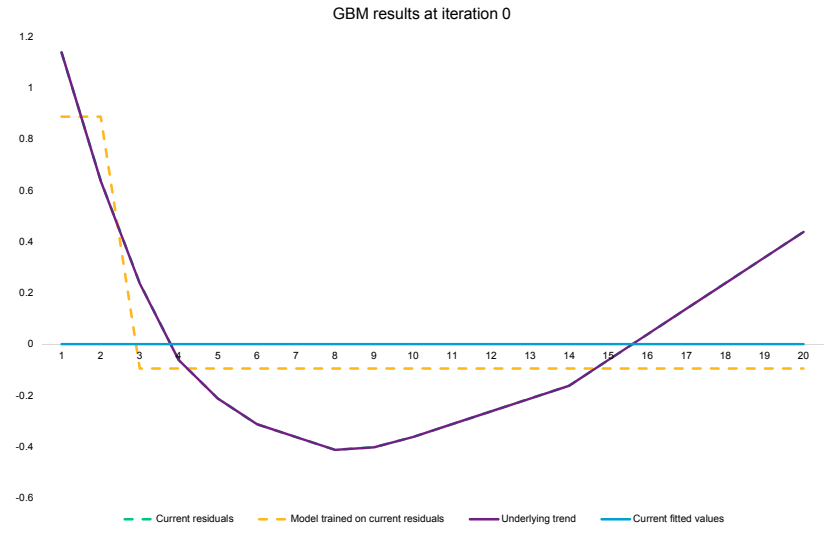

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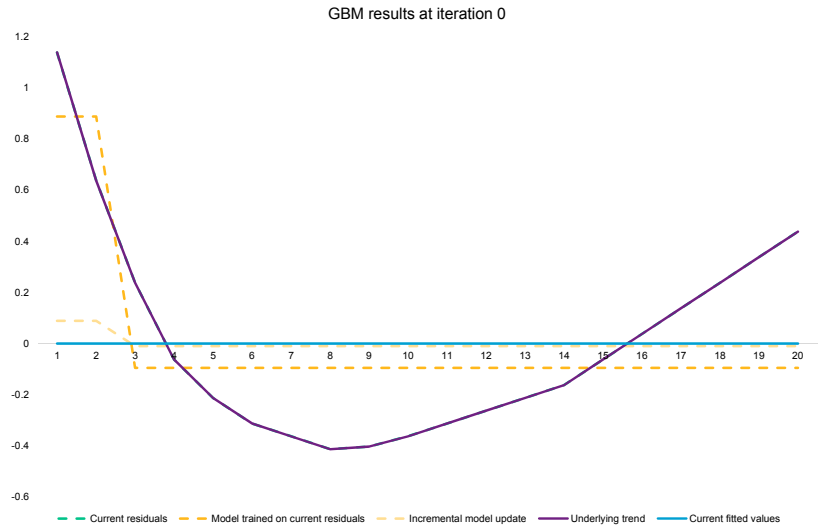

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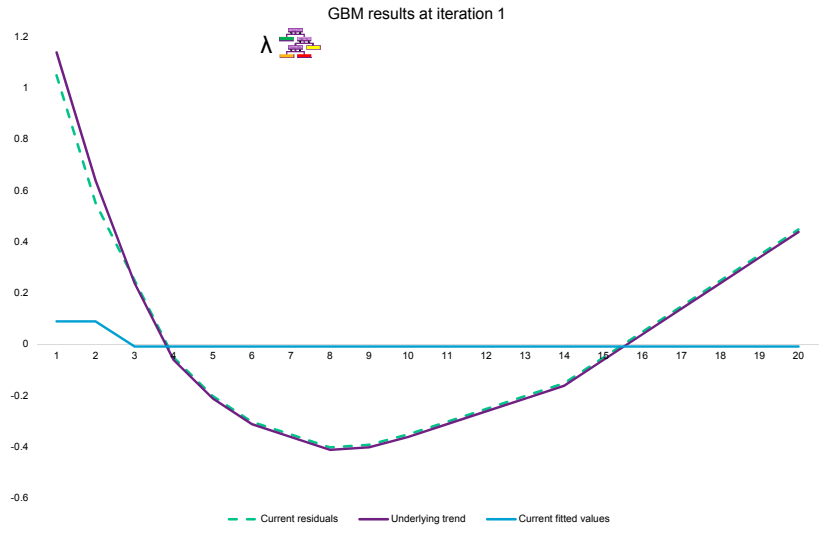

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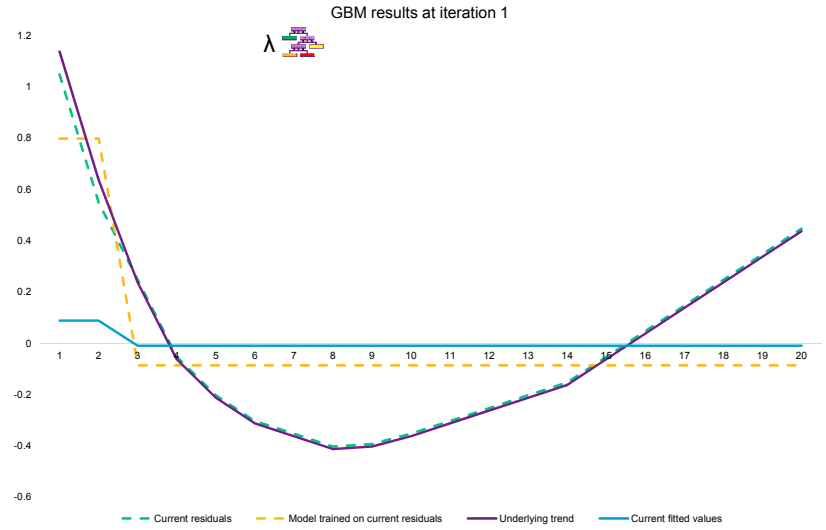

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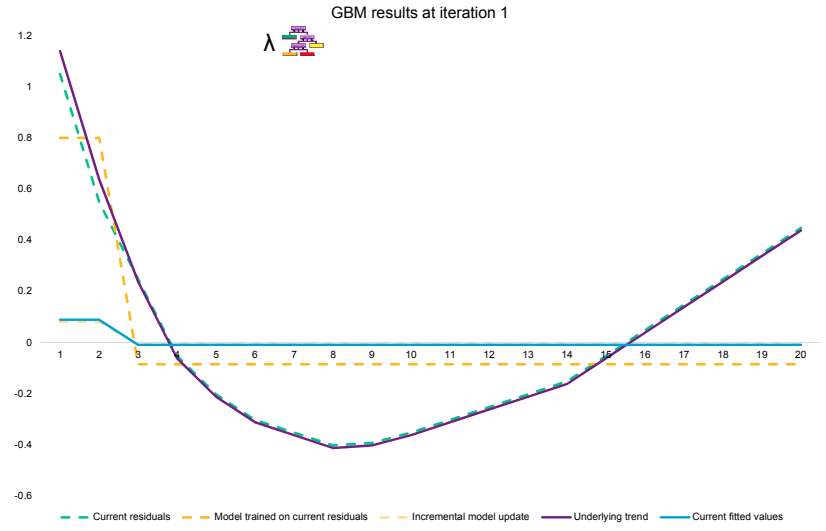
A simple GBM example

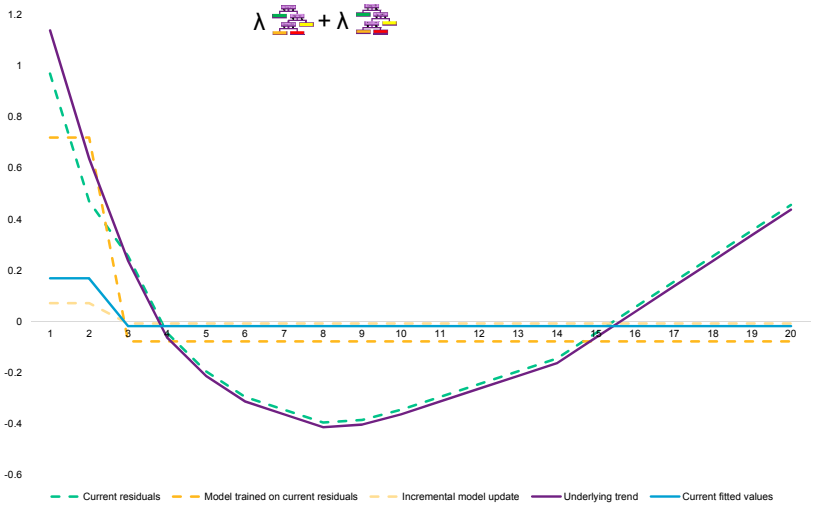


Willis Towers Watson

A simple GBM example

GBM results at iteration 2

λ + λ



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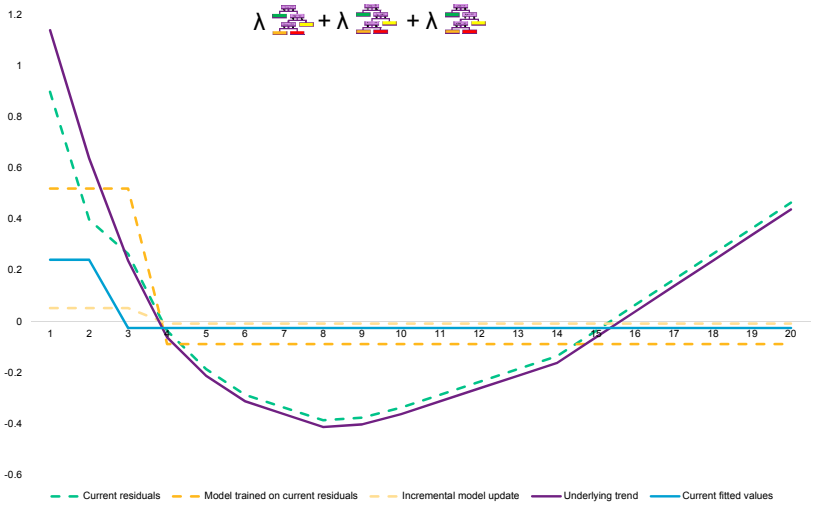
A simple GBM example

GBM results at iteration 3

λ + λ + λ



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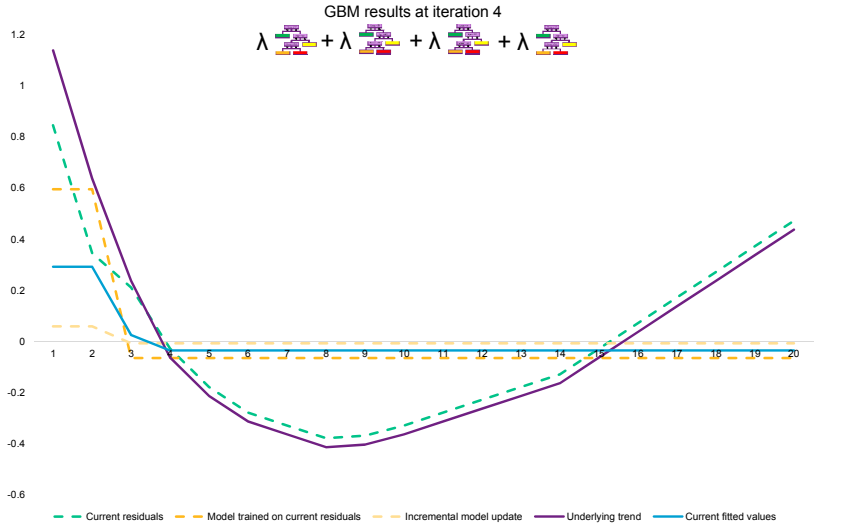

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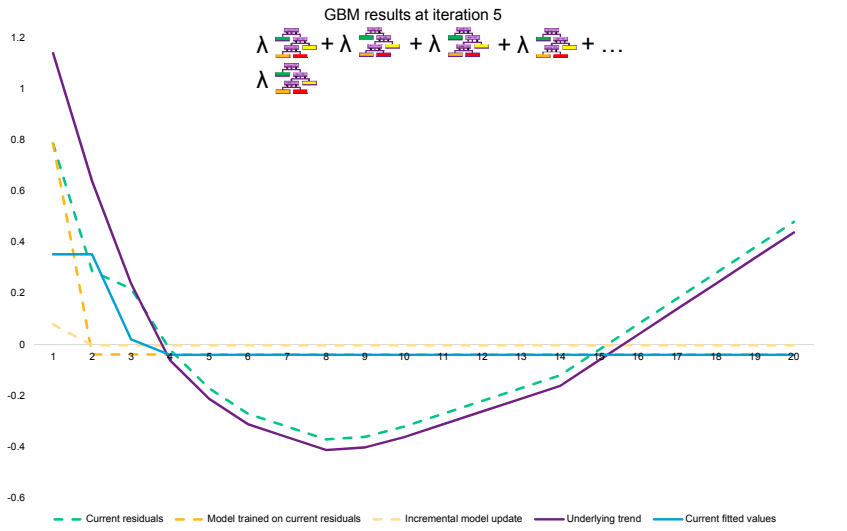

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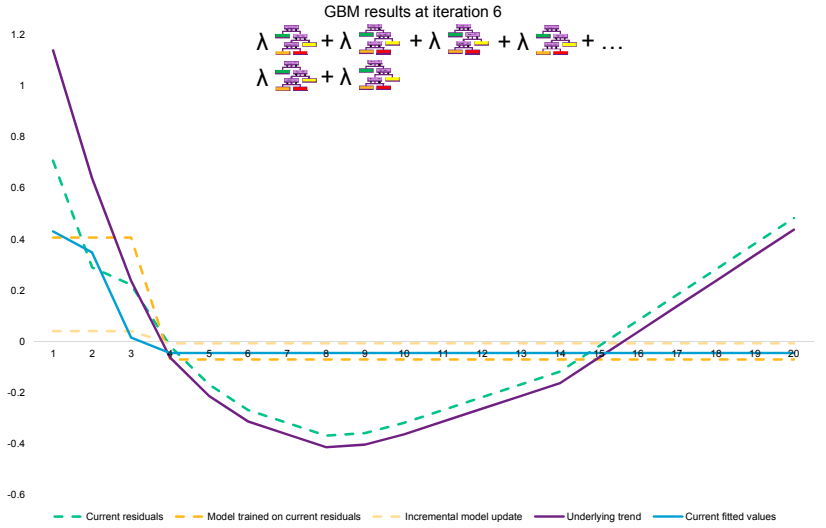

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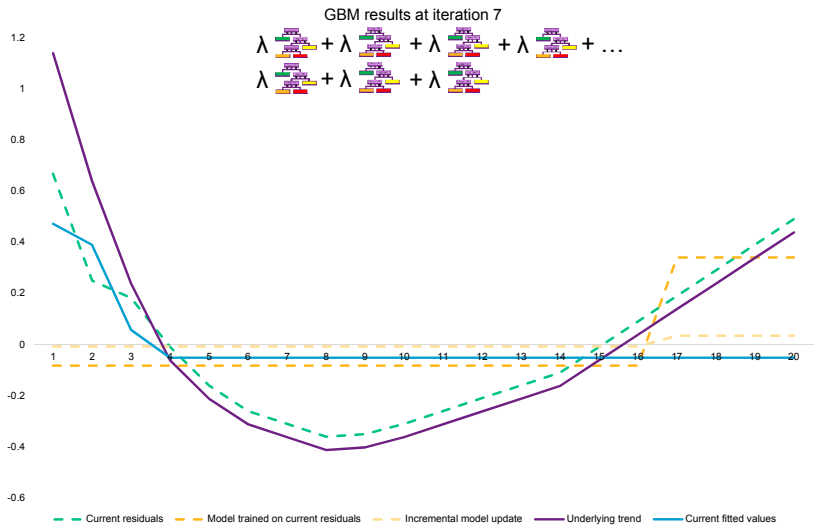

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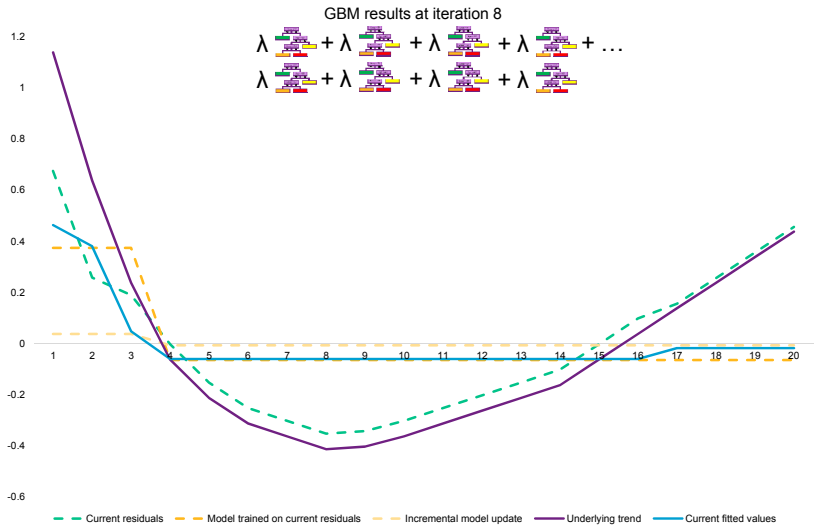

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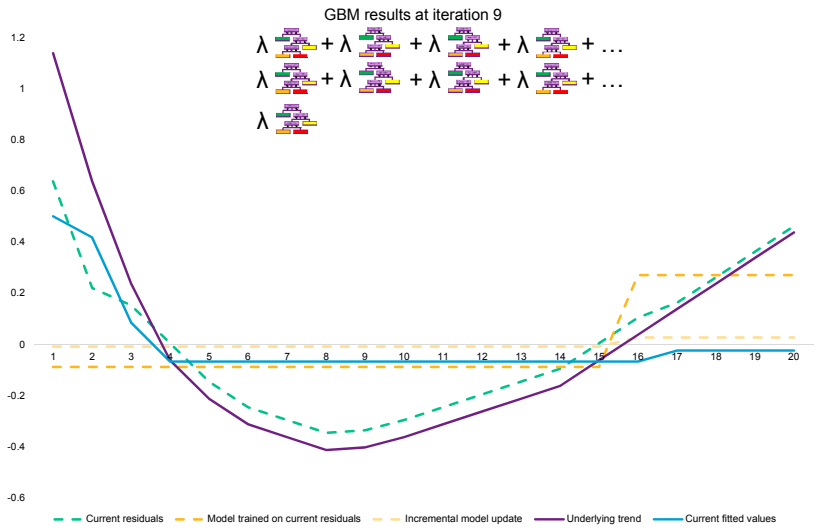

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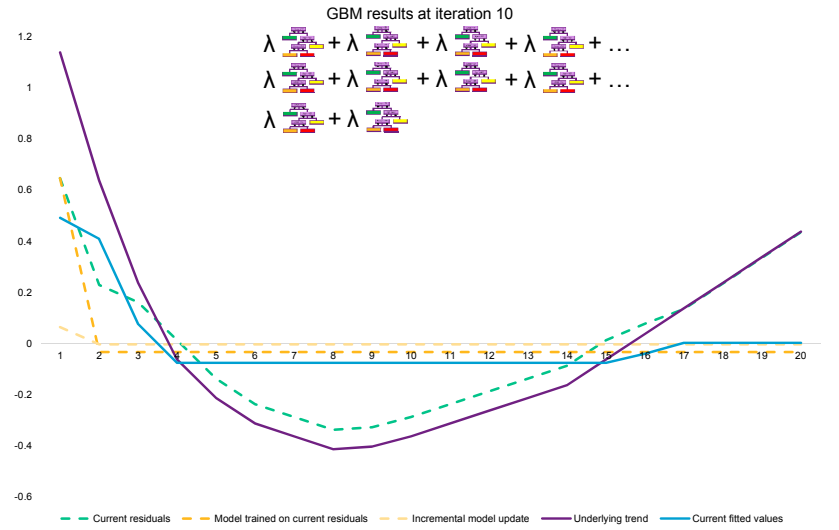
A simple GBM example



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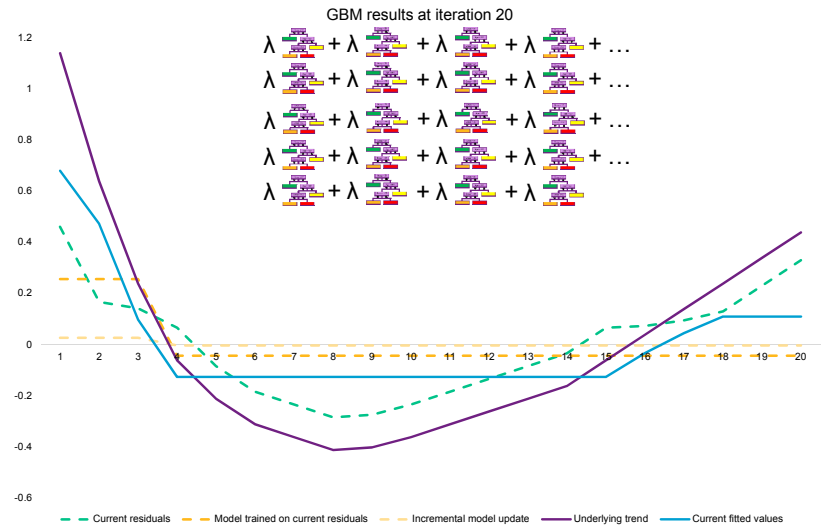
A simple GBM example



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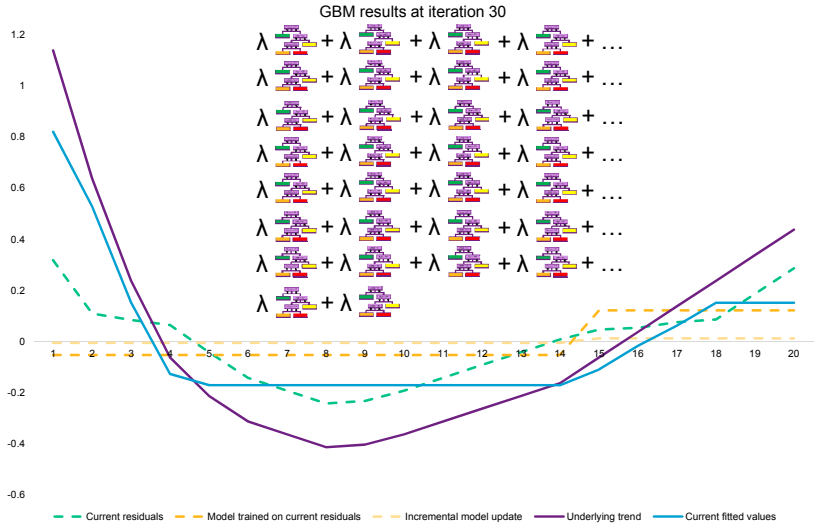

Willis Towers Watson

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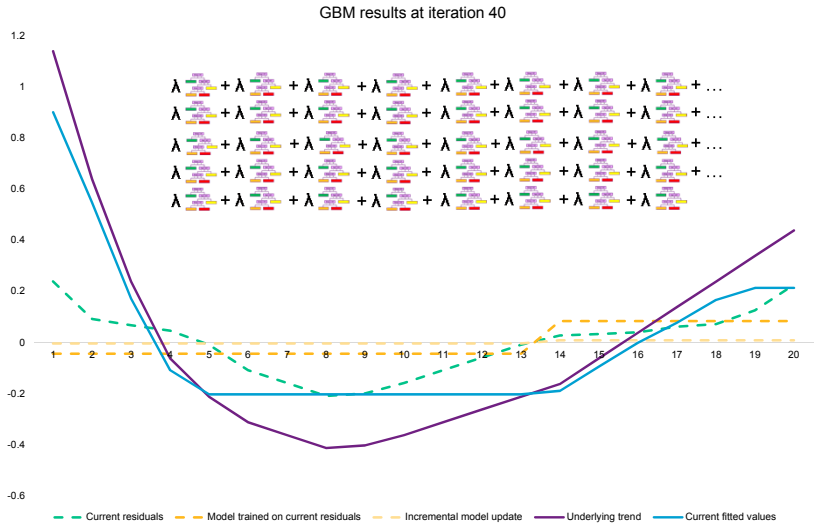

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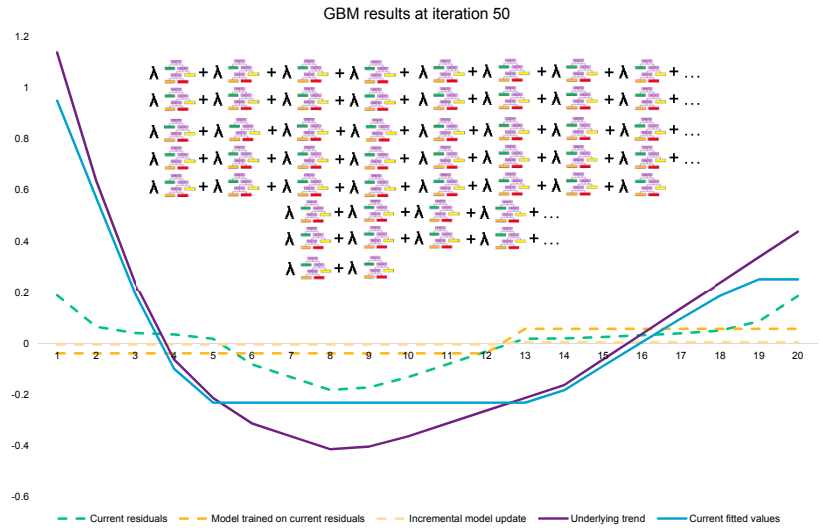
A simple GBM example



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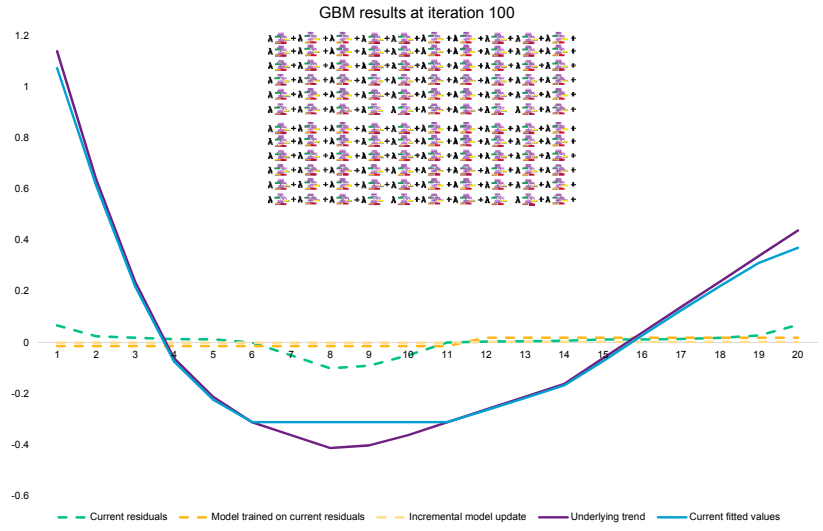

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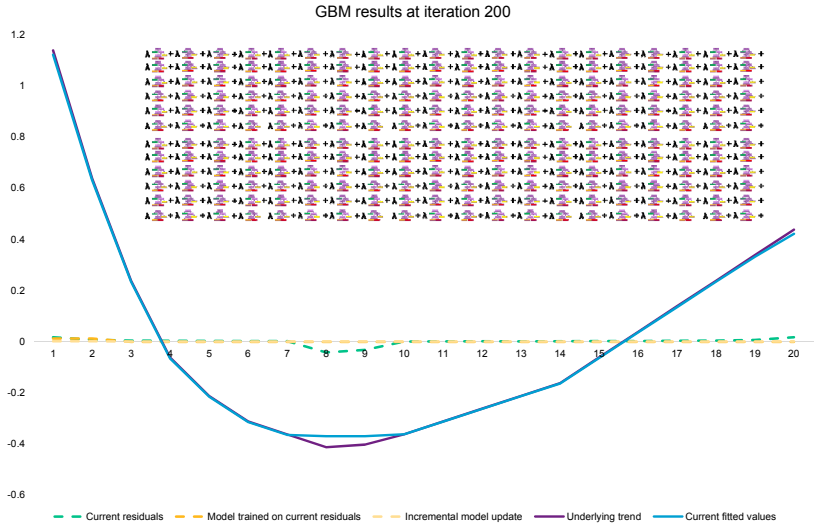
A simple GBM example



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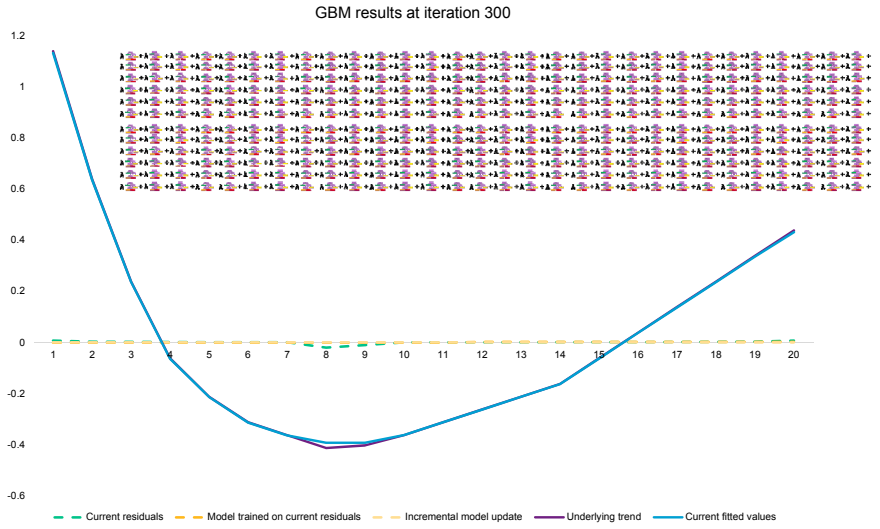
A simple GBM example



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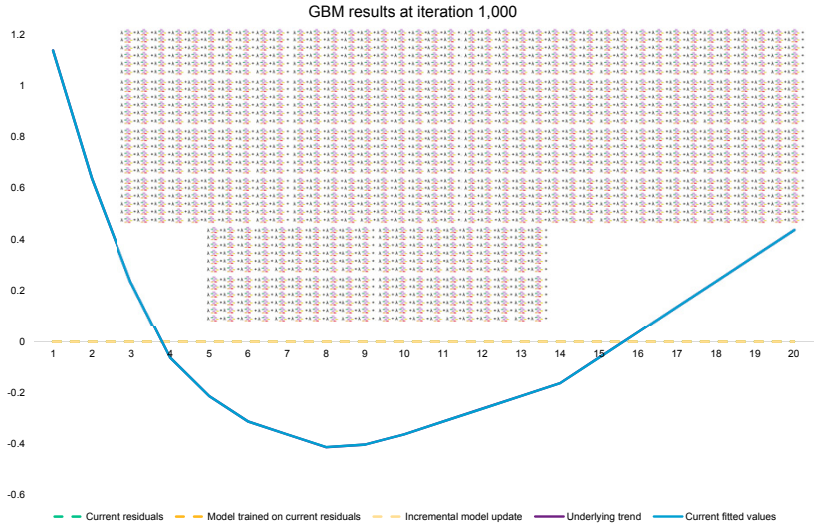
A simple GBM example



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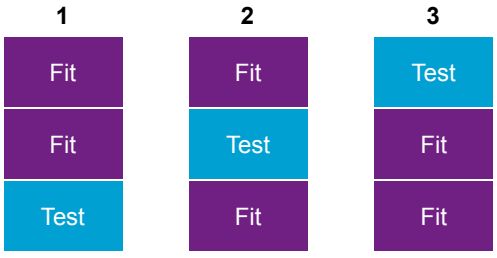
Calibrating the assumptions

- *n*-fold cross validation used to develop the interaction depth and learning rate assumptions
  - Eg for 3-fold validation, split into 3, fit on purple, 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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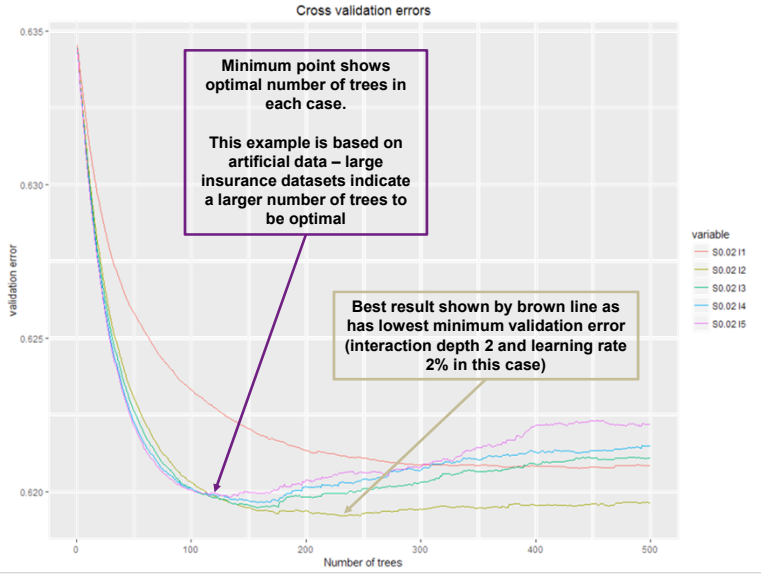
Example 5-fold cross validation



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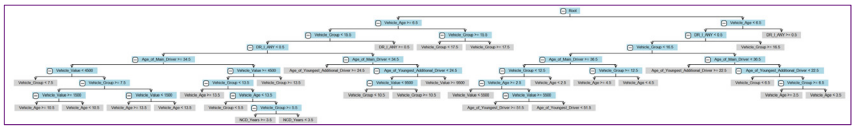
What does a GBM look like?



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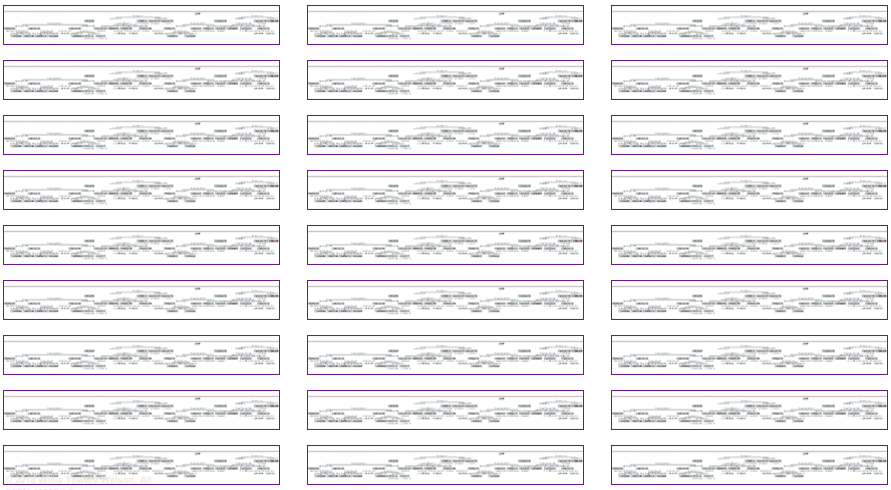
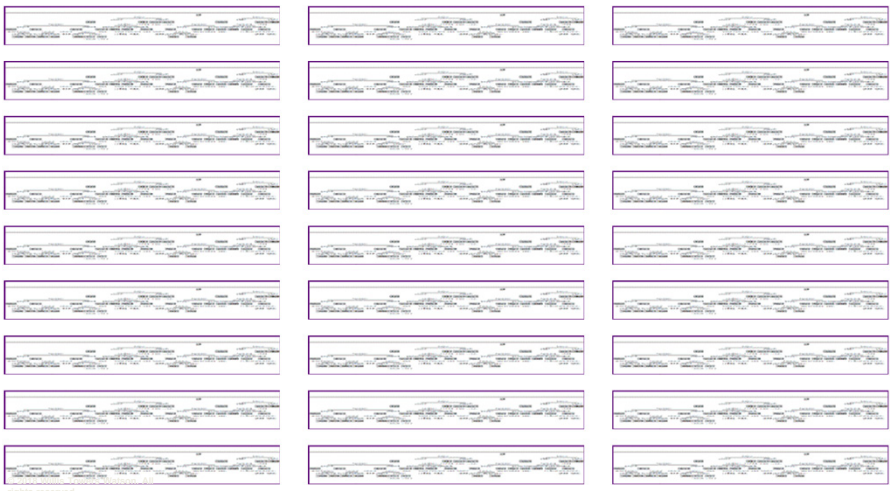
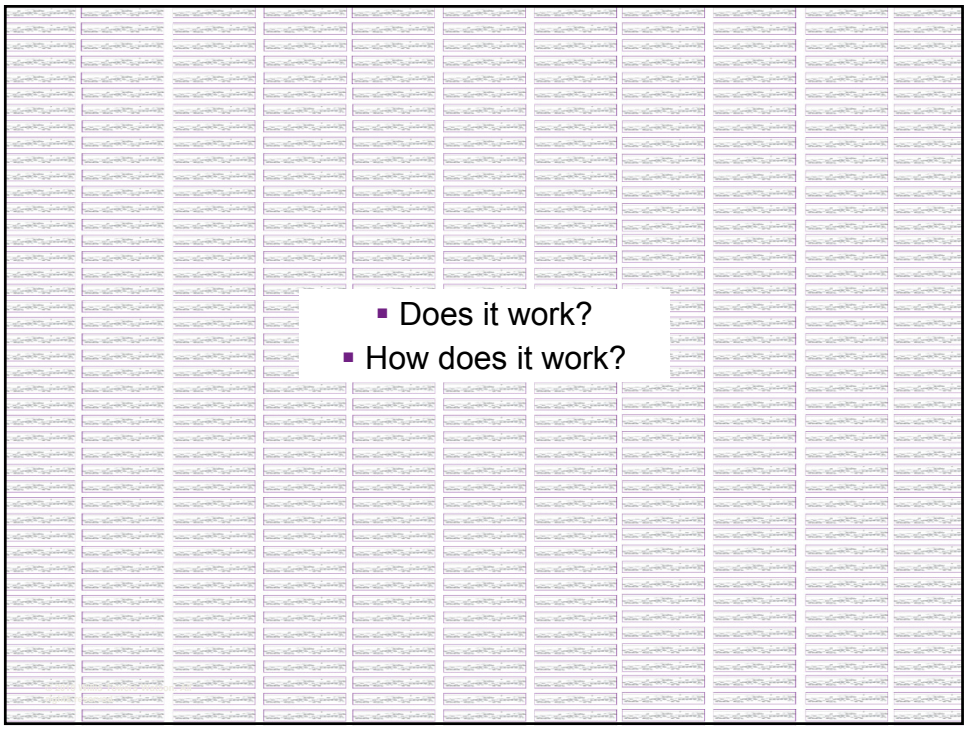


What does a GBM look like?




Does it work?
How does it work?

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
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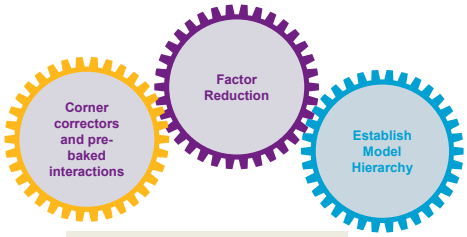

Use insights to guide GLM

Deploy directly

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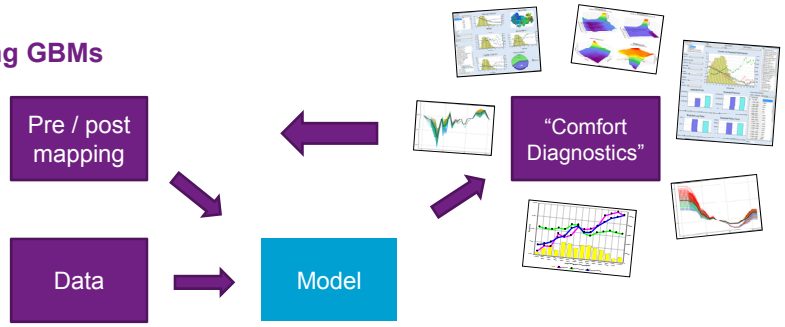
Deploying GBMs



Deploy directly

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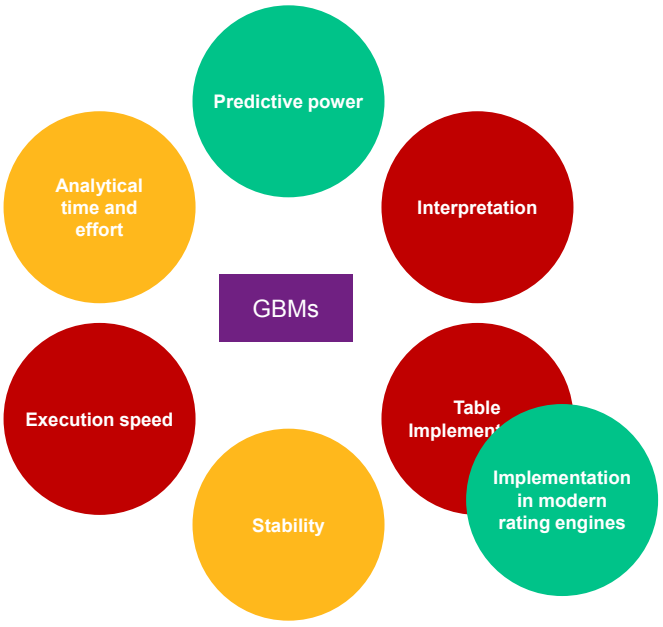

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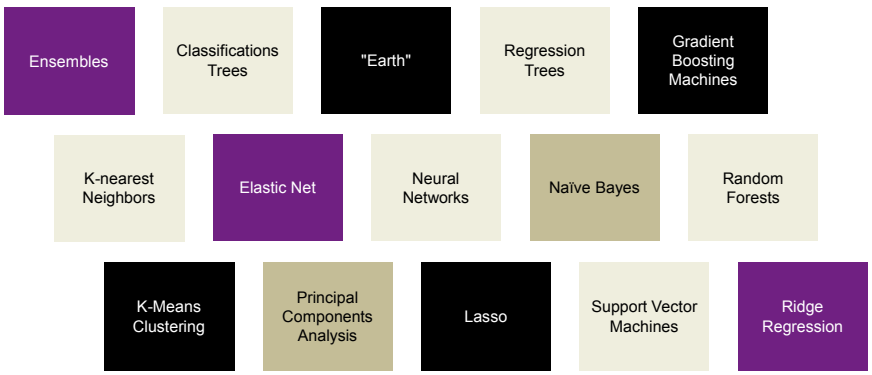
Some machine learning methods



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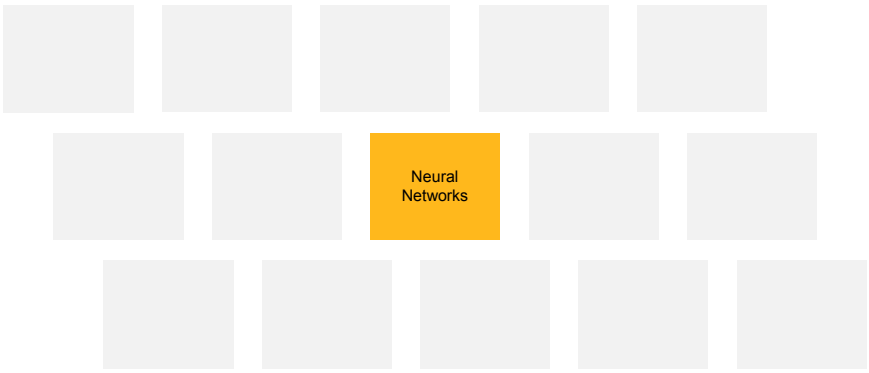
Focus on Neural Networks



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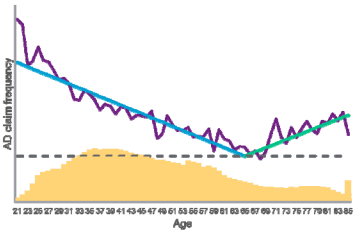
Where is the value?



Which policyholder is more likely to make a claim?

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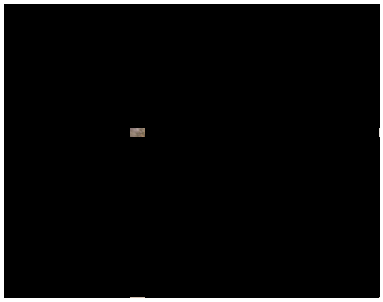
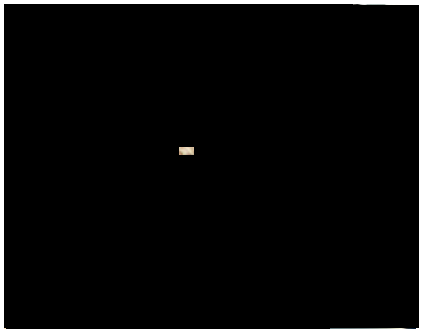
Where is the value?



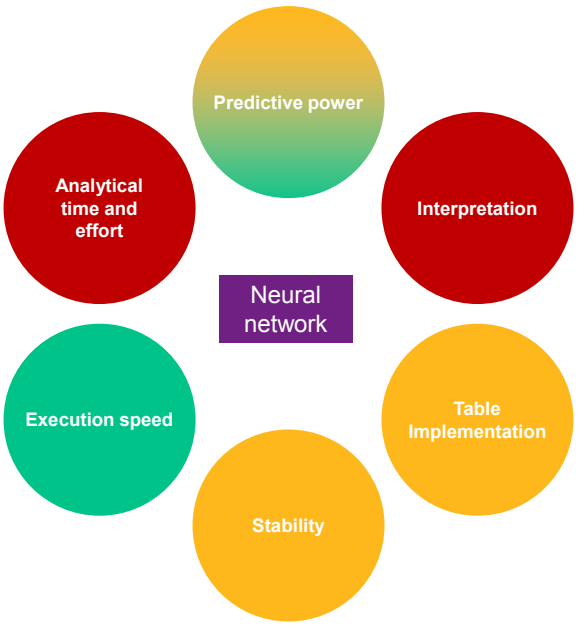
Which picture is more likely to be of a cat?



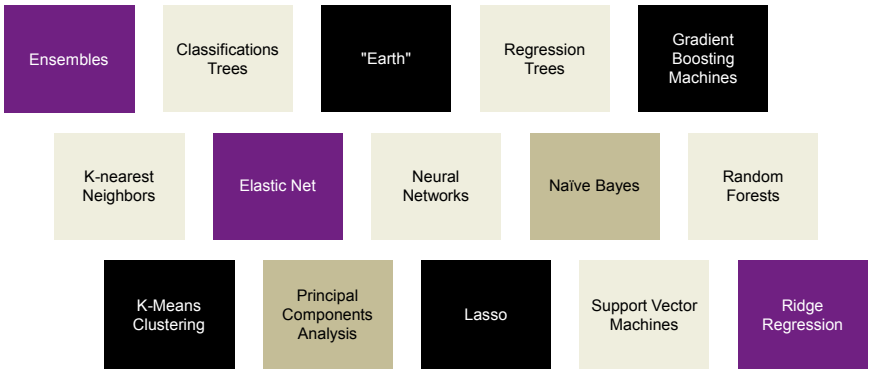
Where is the value?

Which picture is more likely to be of a cat?

Neural networks



Some machine learning methods



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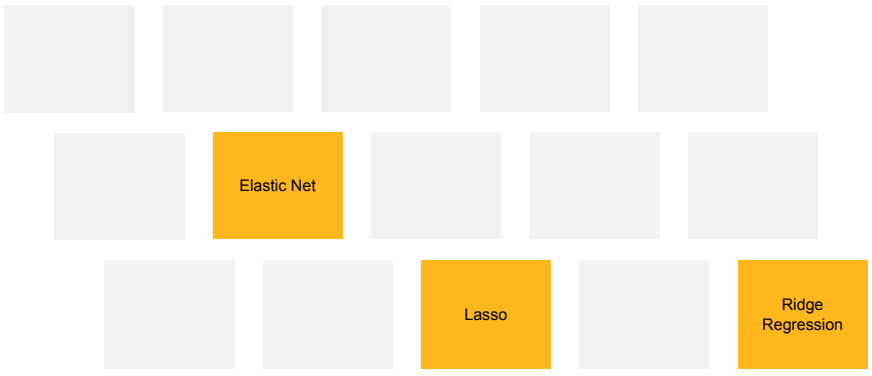
Focus on Penalized Regression



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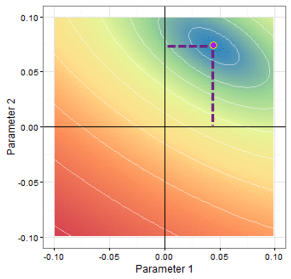
Penalized Regression

GLM

f(x) = g^{-1}(**X**.β) where β estimated by minimizing $L(\beta|X,y)$



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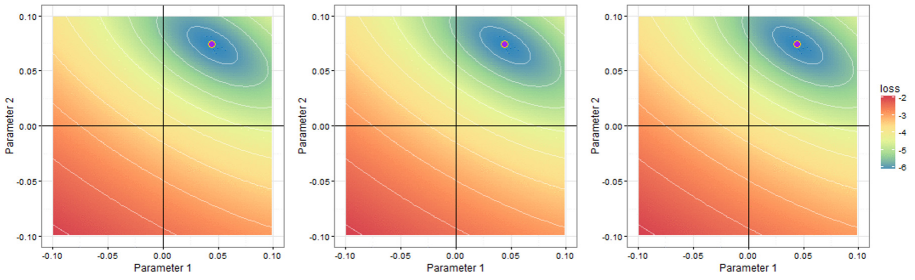
Penalized Regression

GLM **Lasso** **Ridge**

f(x) = g^{-1}(**X**.β) where β estimated by minimizing $L(\beta|X,y) + \lambda_1 \sum_i |\beta_i| + \lambda_2 \sum_i \beta_i^2$

Elastic Net

Ridge $\sum_i \beta_i^2$ **Elastic Net** **Lasso $\sum_i |\beta_i|$**



Heavily penalize large parameters, but does not reduce parameters to zero

Mix of the two

Penalty reduces insignificant parameter values to zero - useful for variable selection

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Penalized Regression

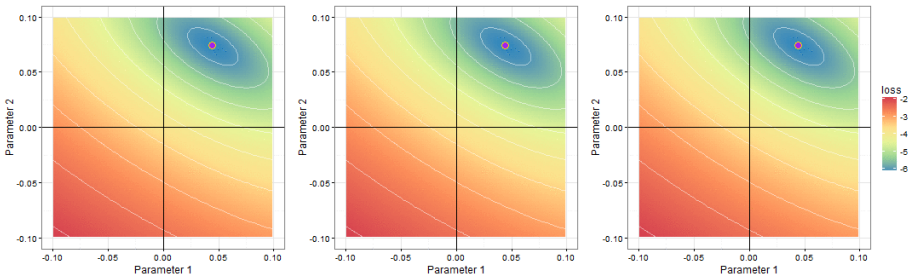
f(x) = g^{-1}(**X**.β) where β estimated by minimizing

GLM Lasso Ridge

$$L(\beta|X,y) + \lambda_1 \sum_i |\beta_i| + \lambda_2 \sum_i \beta_i^2$$

Elastic Net

Ridge $\sum_i \beta_i^2$ | **Elastic Net** | **Lasso $\sum_i |\beta_i|$**



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Deploying Penalized Regression

Same as GLMs!

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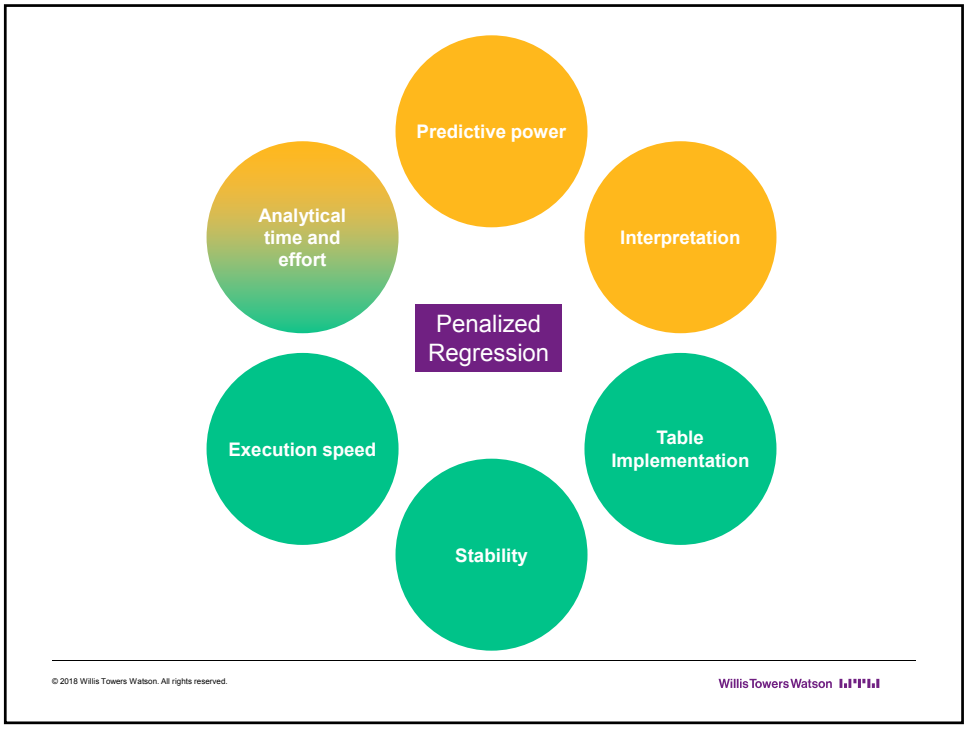

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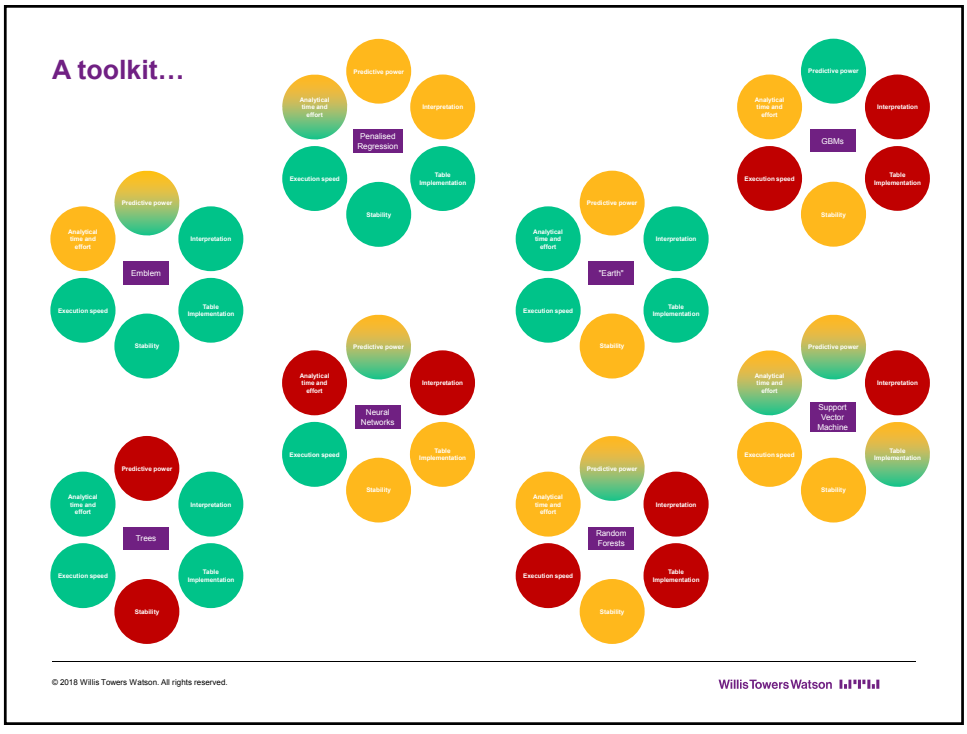

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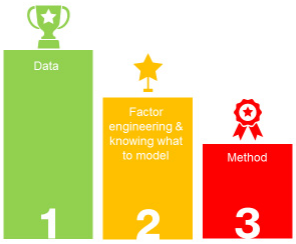
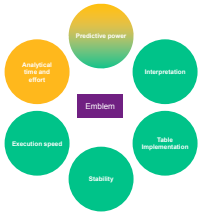
Conclusions





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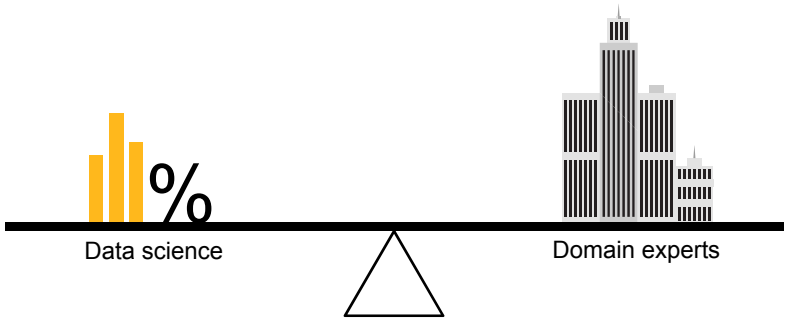
What do you use where?



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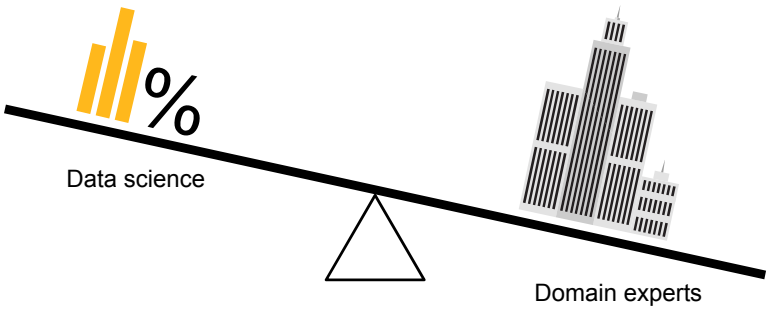
It's domain expertise that helps decide



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Issues for the Profession(s)

Role of the actuary

- Domain expertise matters (at least currently)
- Easier for an actuary to pick up machine learning than for a data scientist to understand insurance?
- Siloed teams don't work
- Familiarity and the right vernacular can help
- Scope of involvement?
  Pricing ✓ Reserving ✓ Claims analytics ✓
  Customer management ? Marketing ???

Training

- CAS, SOA ahead? (eg CSPA)
- IFoA playing catch up
- Is it too late?

Regulatory issues

- TAS: Judgement - what judgement?
- GDPR
- UK Government Select Committee (Science and Technology)

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Questions and Discussion

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