



2022 CAS RPM

GBMs: The Real Impact of a Rate Change

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UNDERSTANDING CUSTOMER DEMAND

Agenda

- Understanding Customer Demand
- Model Form
- Applications

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What is insurance customer demand?

- Customer demand in insurance generally reflects the following:
 - Conversion of new policies
 - Renewals of existing policies
- To model the conversion of new policies, we build an acquisition model
- To model the renewals of existing policies, we build a retention model
- In addition to the models above, insurers might be interested in modeling mid-term cancellations on existing policies

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What impacts customer demand?

**Attributes &
Attitudes**

What is the customer like?

Influences

What you have done to the customer?

Environmental

What are the external influences?

**Status Changes
& Triggers**

What has changed and when?

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Why consider customer demand?

- Forecasting profitability
- Studying retention & acquisition
- Understanding the future mix of business

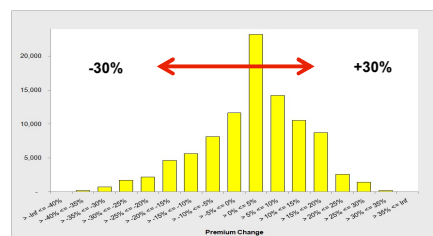
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Why consider customer demand?

Revenue Neutrality Example

- Revenue neutrality
 - Overall effect on premium volume is revenue neutral
 - Individual policies could still see large swings in rate

$$\frac{\sum_{\text{CurrentPolicies}} \text{ProposedPremium}}{\sum_{\text{CurrentPolicies}} \text{CurrentPremium}} = 1.000$$



- Disadvantage of this view of revenue neutrality is that it fails to consider the future shape of the book (need to reflect retention and conversion effects)
- Off-balance to achieve desired demand-weighted loss ratio

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How to model customer demand?

- Any modeling approach that produces a probability can be used to model customer demand
 - GLM
 - Decision trees
 - GBM
 - And so on...

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Modeling Customer Demand with a GLM

Advantages & Disadvantages

- Advantages
 - A known commodity
 - Relatively easy to interpret and explain
 - Response variable does not have to be normally distributed
- Disadvantages
 - Does not handle non-linear relationships well
 - Modeling interactions often requires manual adjustments

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MODEL FORM

Modeling Customer Demand with a GLM

Distribution Function

- Binomial
 - Basic functional form in decision modeling
 - Belongs to the exponential family of distributions
- Variance Function = $\mu(1-\mu)$

Higher variability associated with less certain probability outcomes

Extreme probabilities of success/failure related to low variability

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MODEL FORM

Modeling Customer Demand with a GLM

Link Function

- Logit link is canonical for the binomial distribution:

$$\frac{1}{1 + \frac{1}{\exp(X\beta)}}$$
- Properties of the logit link function:
- S-shape curve “traps” the predictive value to the probability range

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Modeling Customer Demand with a Gradient Boosted Machine (GBM)

Advantages & Disadvantages

- Advantages
 - Can handle non-linear relationships
 - Naturally models interactions without manual adjustments
 - Tends to produce better model fits
- Disadvantages
 - Not as common in the insurance industry
 - Can overfit the data without proper tuning
 - Large trees can be difficult to interpret

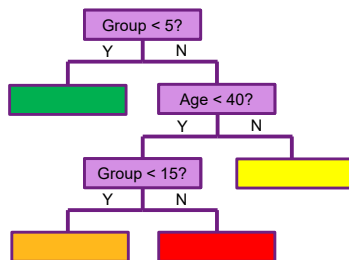
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How Does a GBM Work?

What is a GBM?

A tree

$$f_i(x)$$



A GBM

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

$$\lambda \begin{matrix} \text{tree} \\ \text{tree} \\ \text{tree} \\ \text{tree} \end{matrix} + \lambda \begin{matrix} \text{tree} \\ \text{tree} \\ \text{tree} \\ \text{tree} \end{matrix} + \lambda \begin{matrix} \text{tree} \\ \text{tree} \\ \text{tree} \\ \text{tree} \end{matrix} + \lambda \begin{matrix} \text{tree} \\ \text{tree} \\ \text{tree} \\ \text{tree} \end{matrix} +$$

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MODEL FORM

How Does a GBM Work?

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

```

graph TD
    A[Group < 5?] -- Y --> B[Green]
    A -- N --> C[Age < 40?]
    C -- Y --> D[Group < 15?]
    C -- N --> E[Yellow]
    D -- Y --> F[Orange]
    D -- N --> G[Red]
  
```

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MODEL FORM

How Does a GBM Work?

A Simple Example

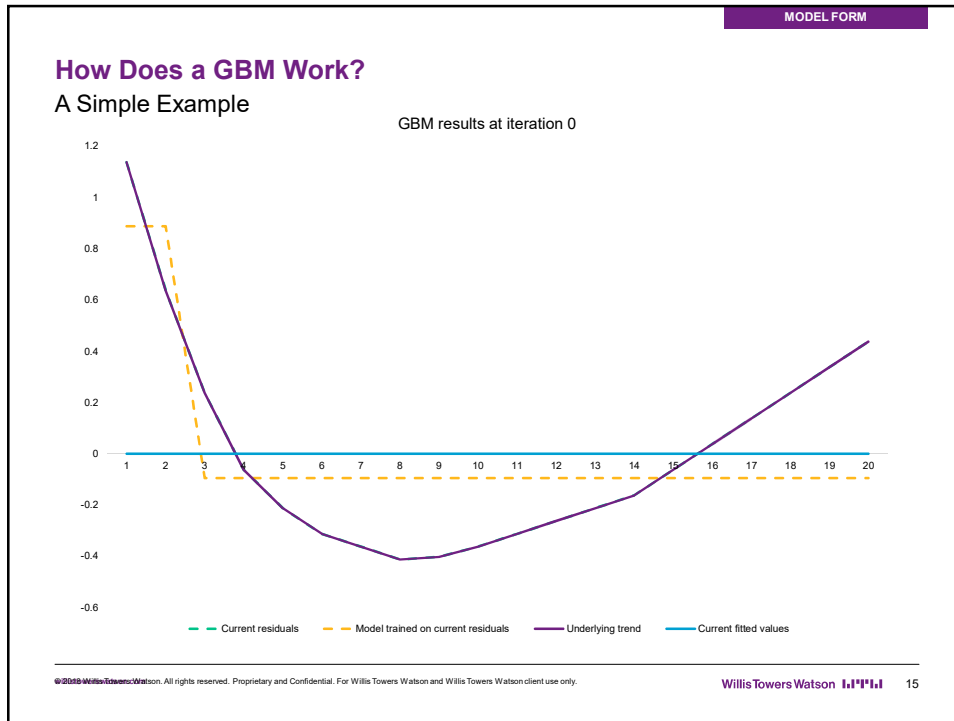
GBM results at iteration 0

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

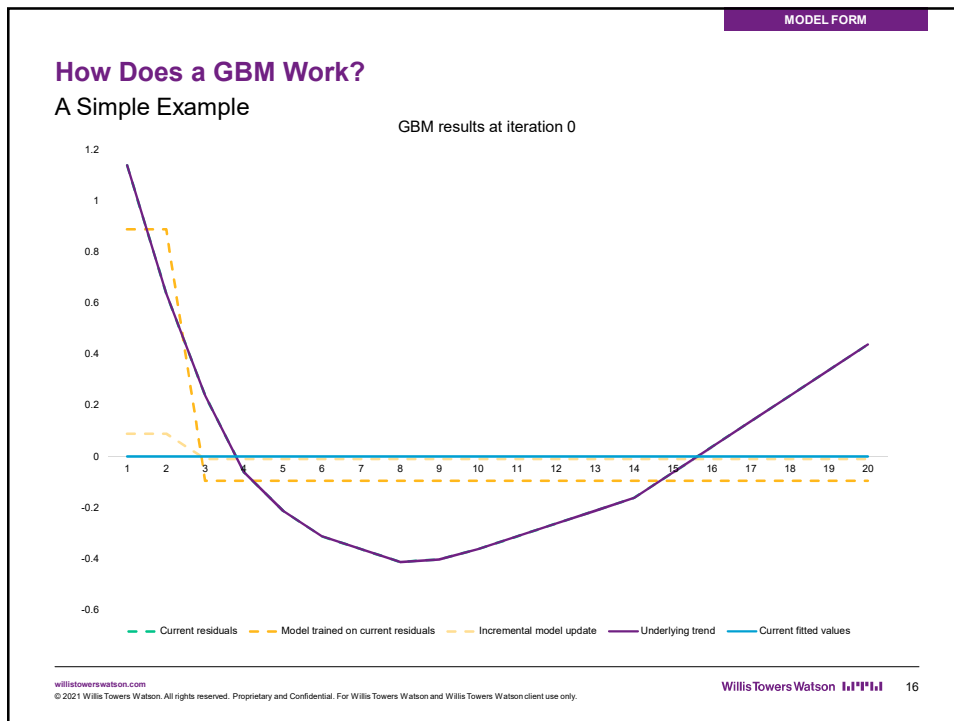
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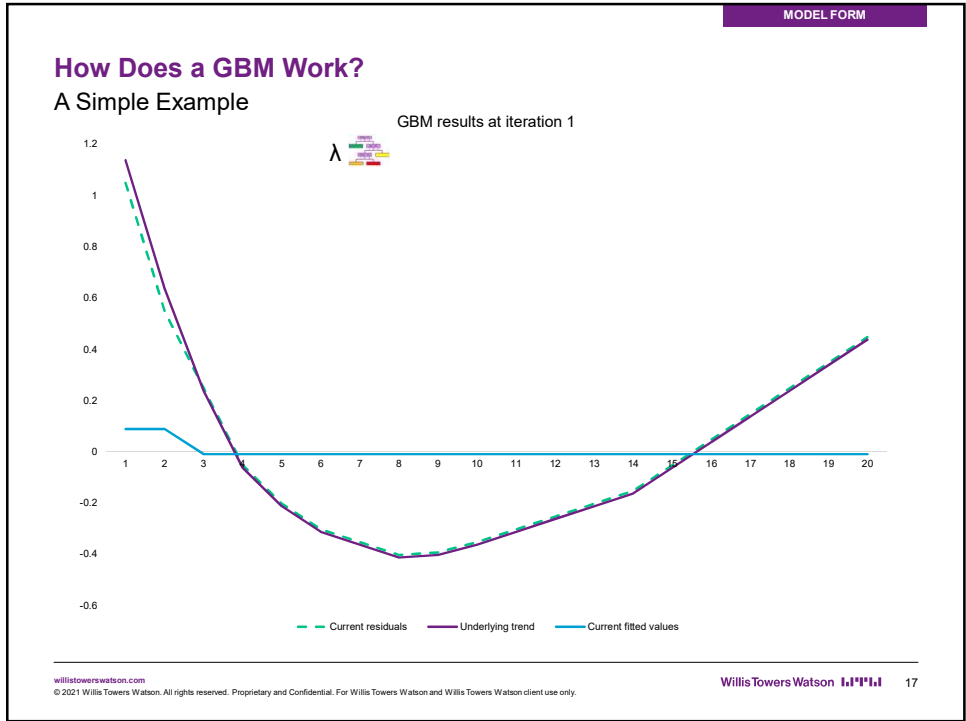
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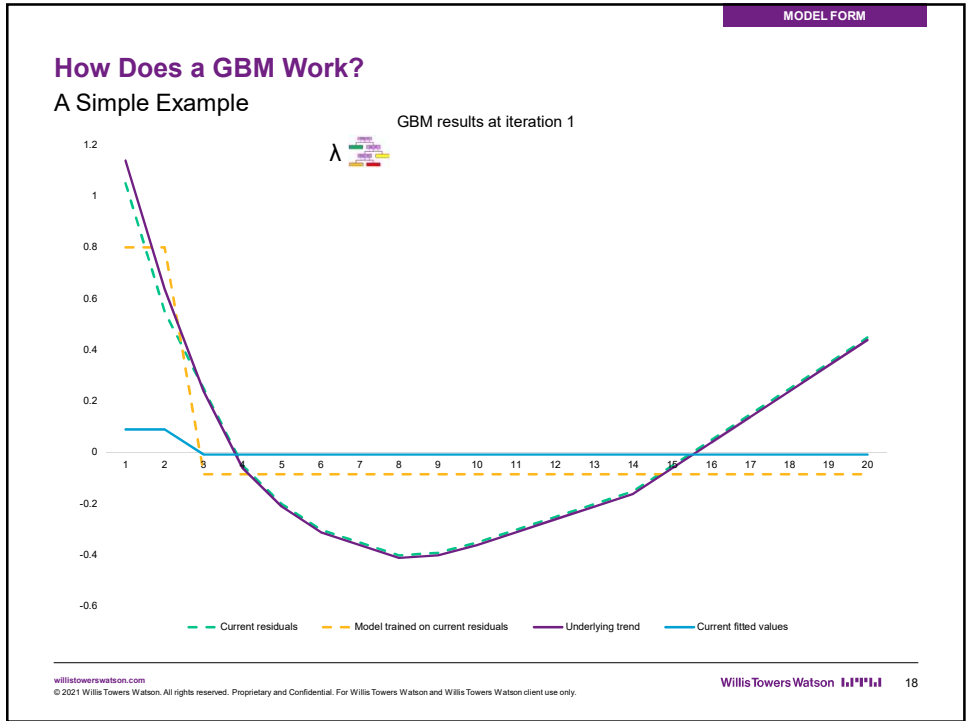
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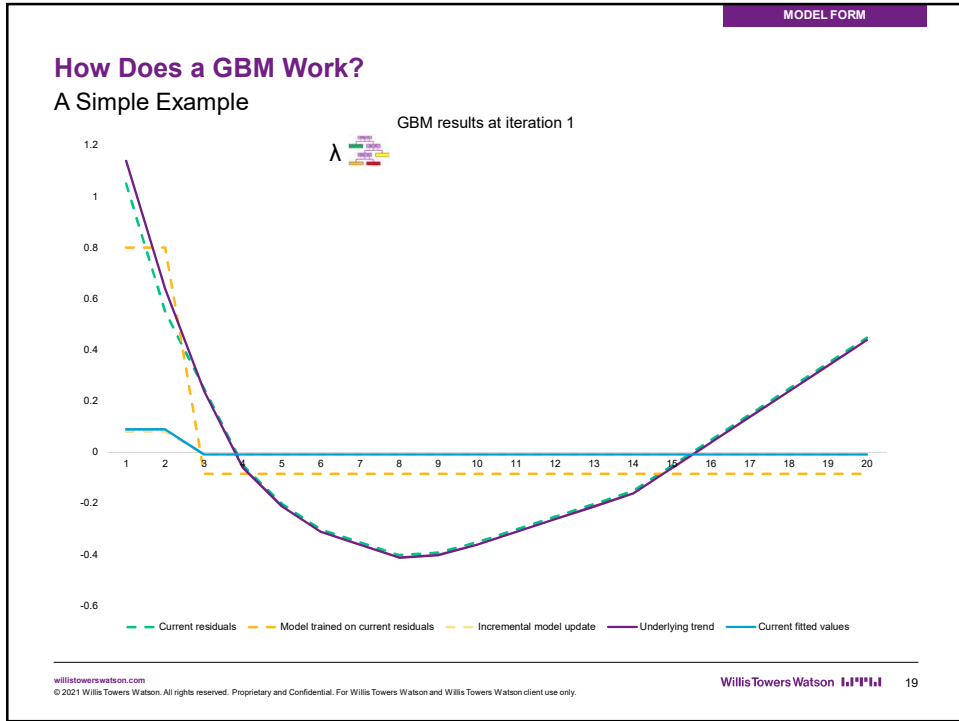
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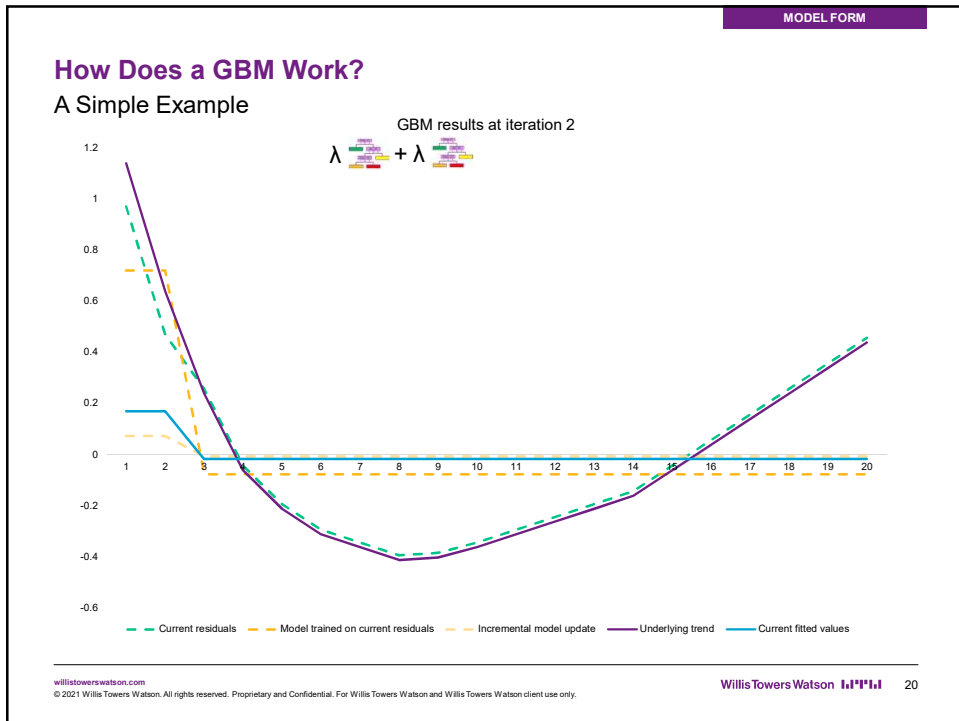
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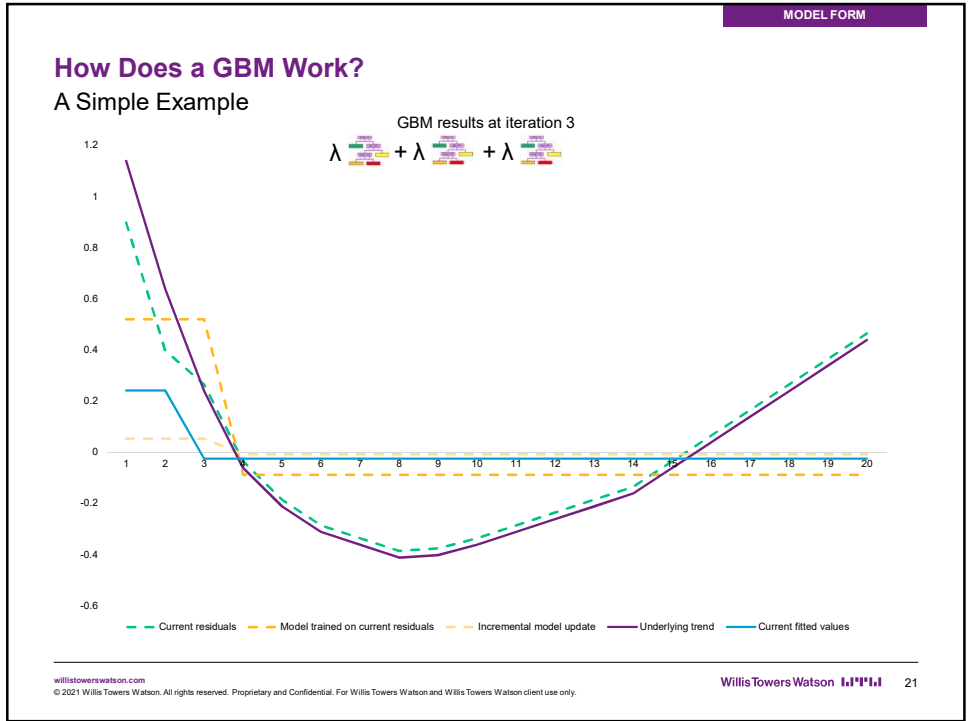
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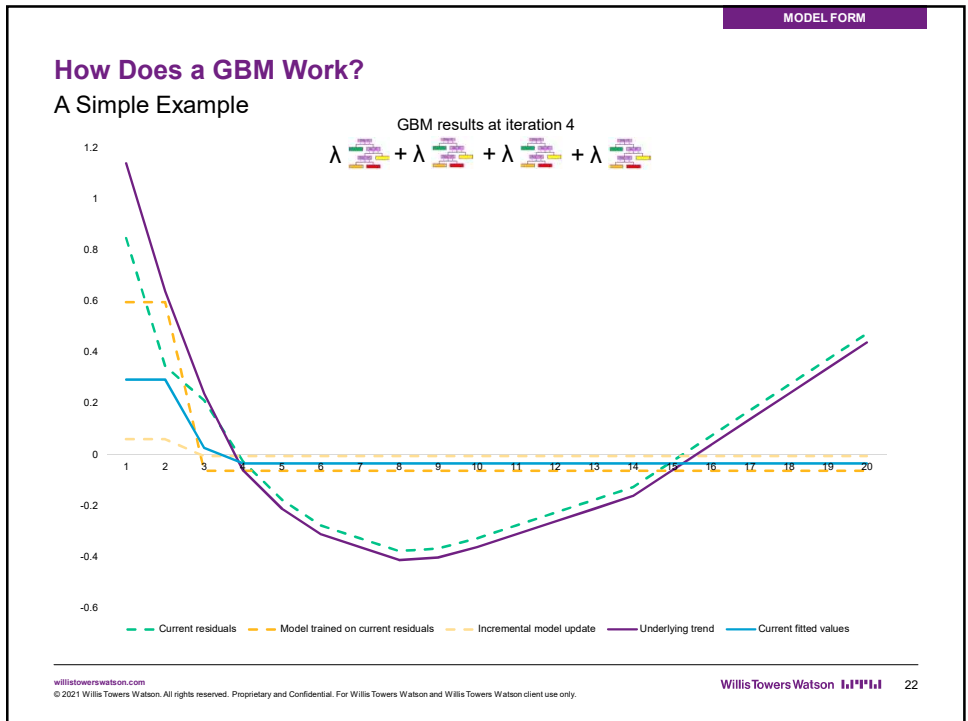
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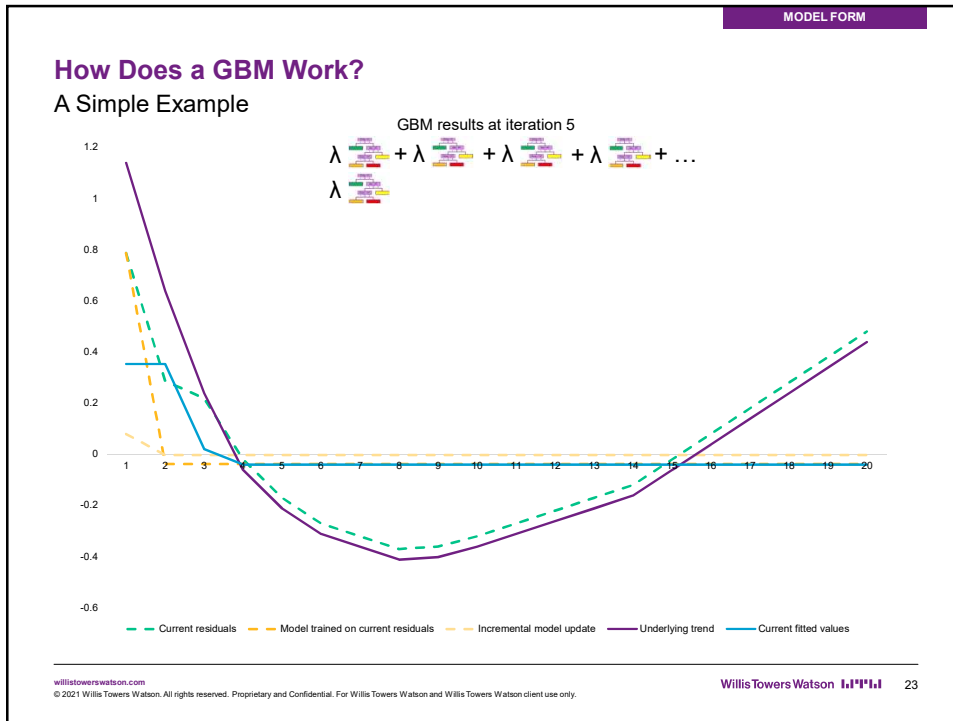
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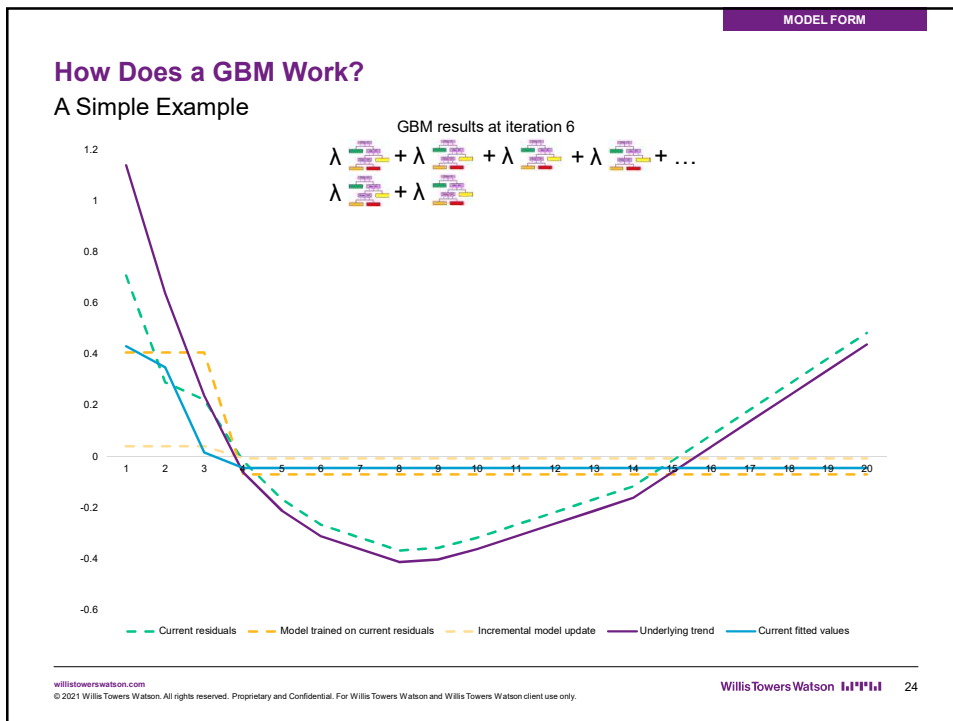
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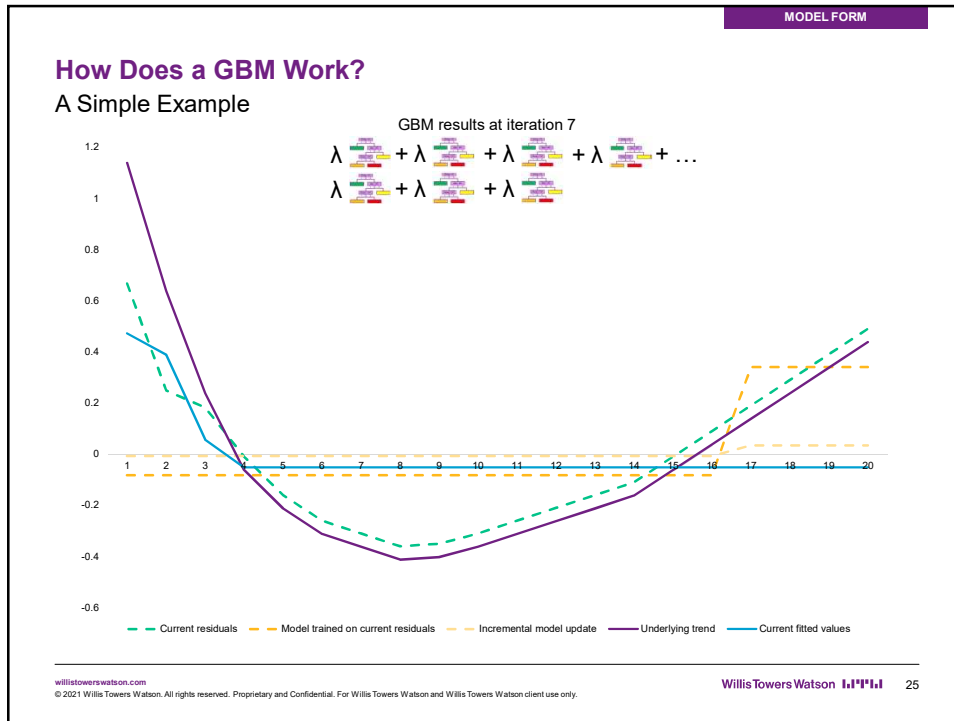
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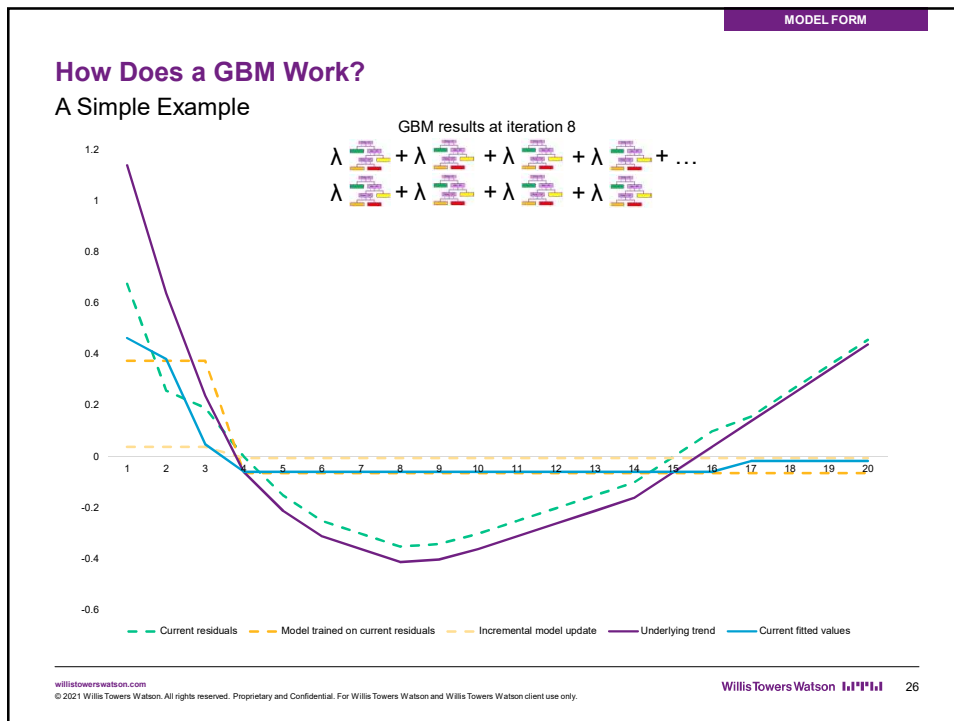
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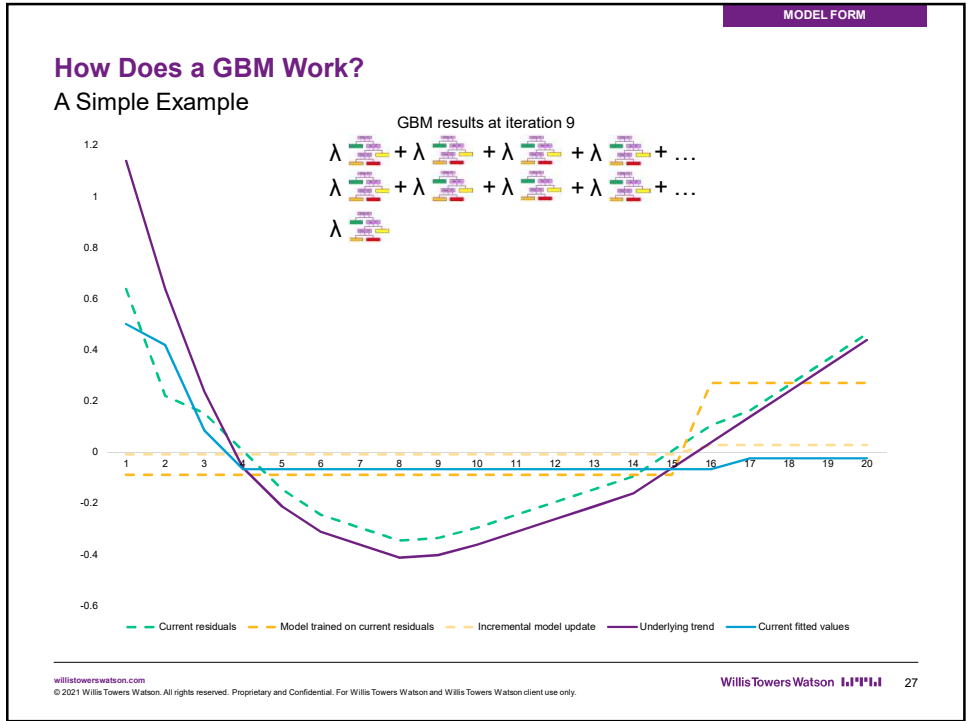
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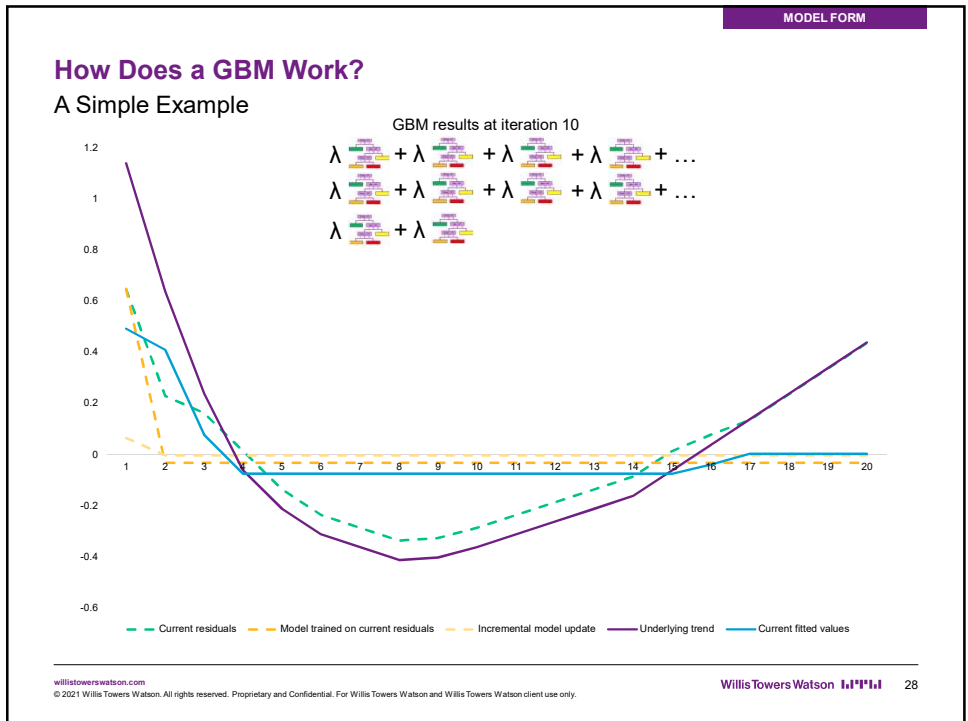
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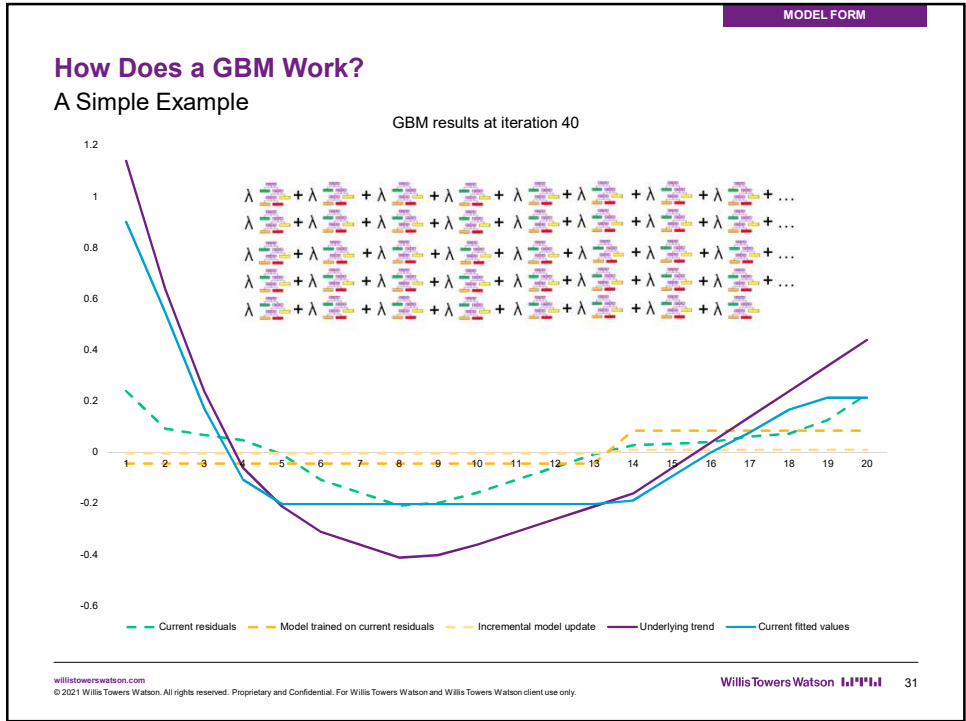
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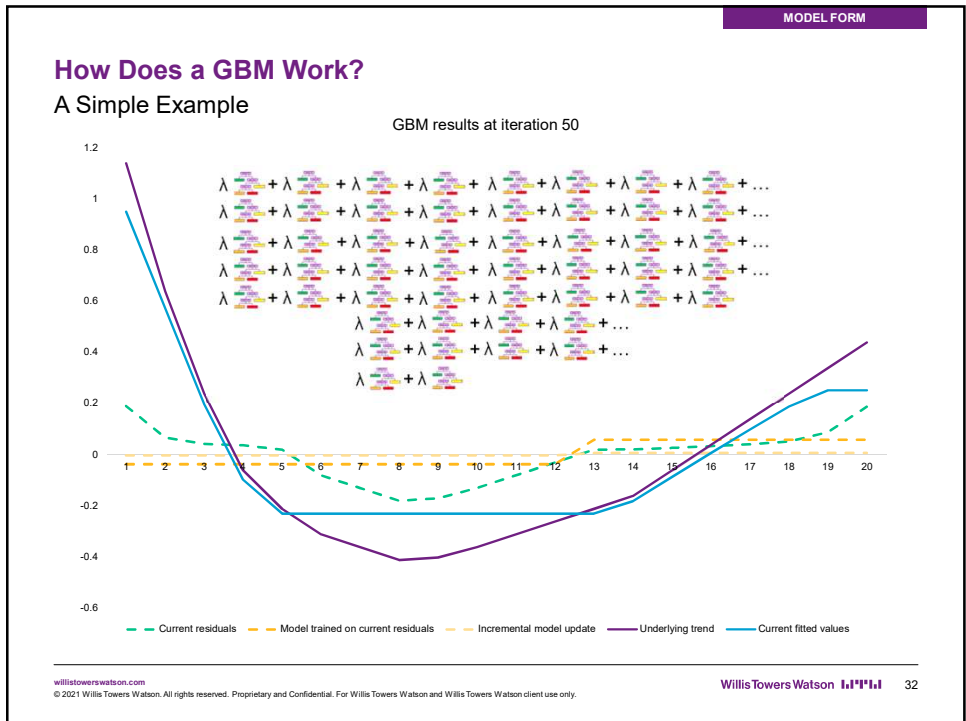
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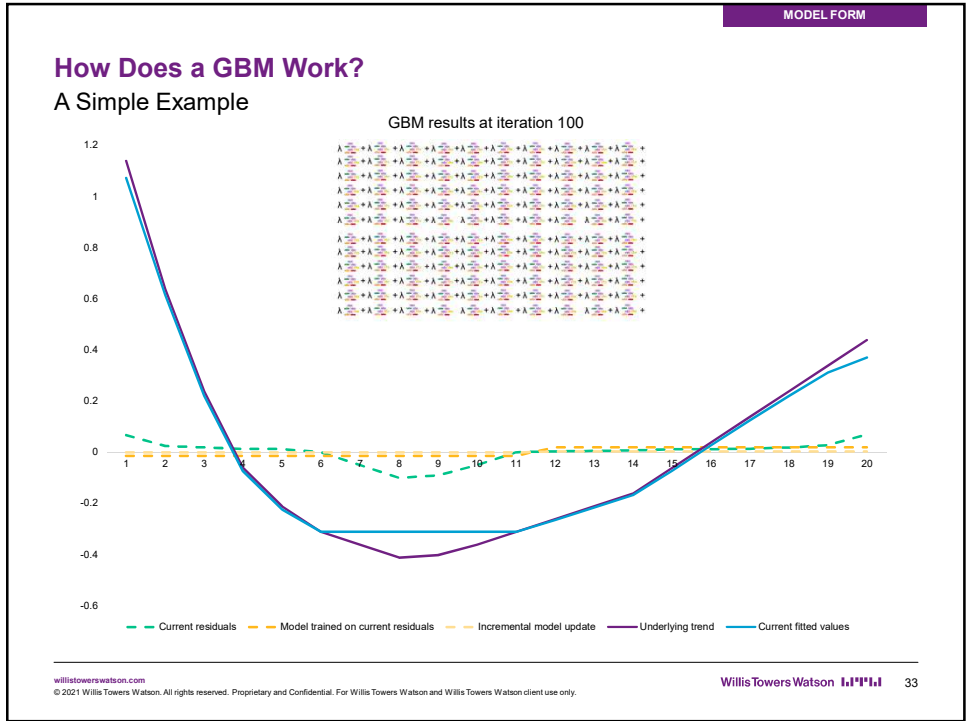
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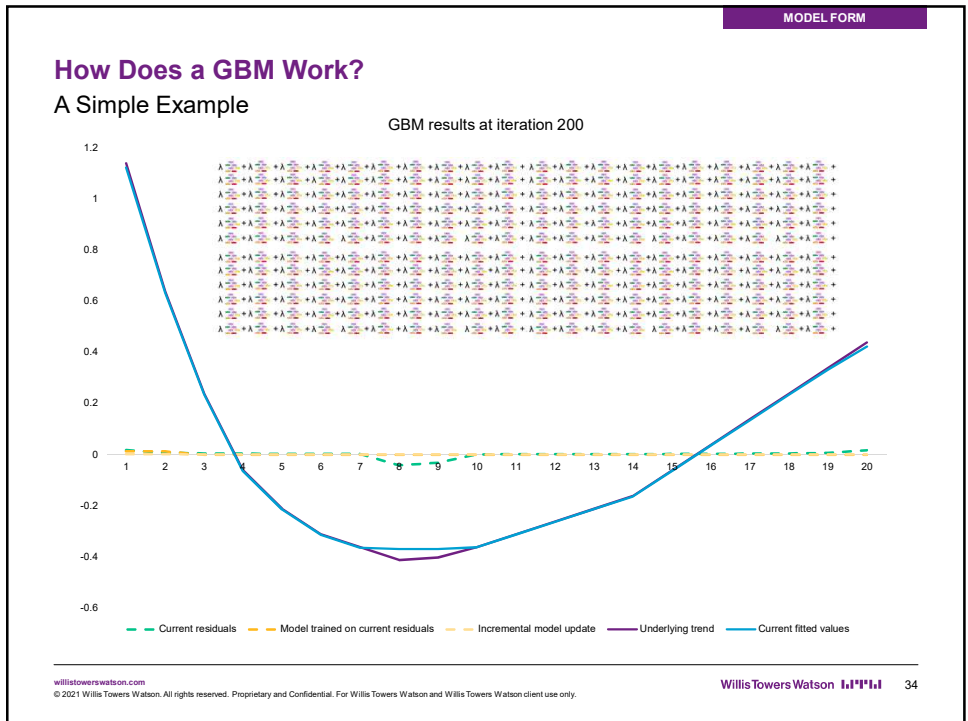
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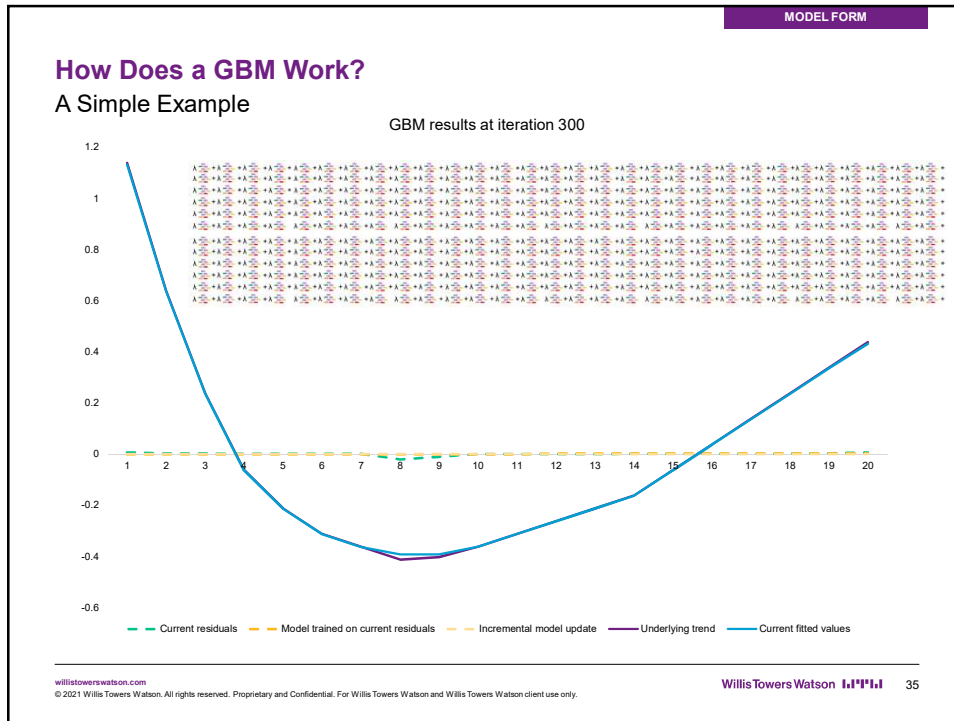
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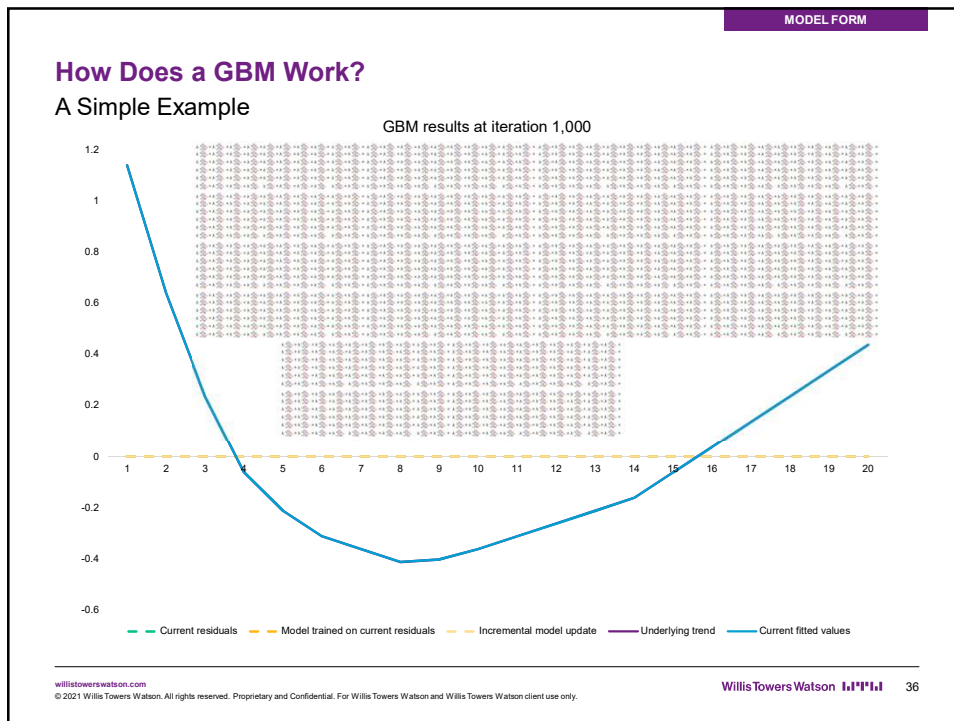
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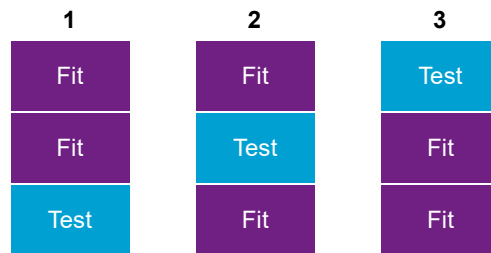


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How Does a GBM Work?

Calibrating the Assumptions

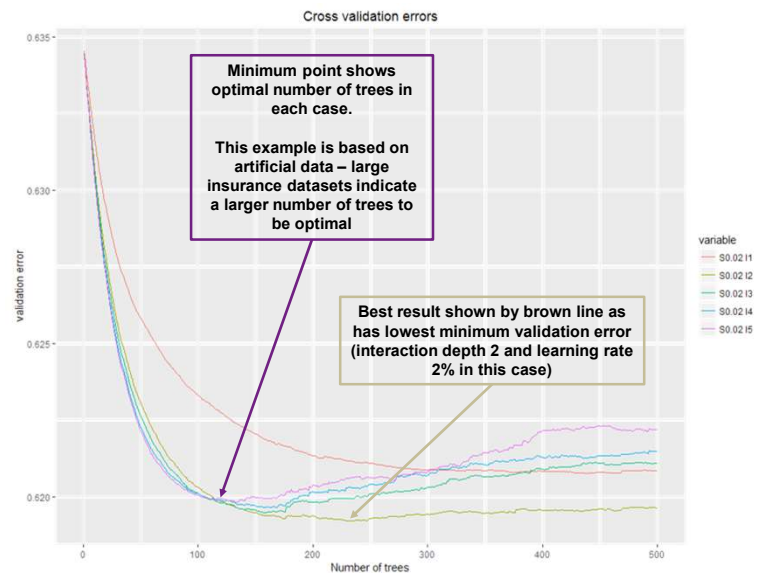
- n -fold cross validation used to develop the interaction depth and learning rate assumptions
 - Eg for 3-fold validation, split into 3, fit on purple, test on blue parts, take average



- 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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Application #1

Off-balancing (5% rate increase)

▪ Inforce Dataset

Inforce Policy	Current Premium	Proposed Premium	Expected Losses	Retention
1	974	1,023	682	0.88
2	958	1,006	680	0.89
3	950	998	684	0.90
4	968	1,016	707	0.91
5	986	1,035	730	0.92
6	955	1,003	716	0.93
7	965	1,013	733	0.94
8	963	1,011	742	0.95
9	973	1,022	759	0.96
10	961	1,009	807	0.97
Total	9,653	10,136	7,240	

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Application #1

Off-balancing (5% rate increase)

▪ Quote Dataset

Quote	Proposed Premium	Expected Losses	Conversion	Retention
1	1,044	835	0.20	0.80
2	1,048	891	0.22	0.82
3	1,063	914	0.24	0.85
4	1,079	950	0.26	0.88
5	1,095	986	0.28	0.92
Total	5,329	4,575		

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Application #1

Off-balancing (5% rate increase)

- Traditional view focuses on inforce dataset
 - Current loss ratio = $7,240/9,653 = 0.75$
 - Proposed loss ratio = $7,240/10,136 = 0.714$

- Alternative view focuses on inforce and quote datasets AND considers demand
 - Demand-weighted proposed premium on inforce dataset = $1,023(0.88) + \dots + 1,009(0.97) = 9,376$
 - Demand-weighted expected losses on inforce dataset = 6,707
 - Demand-weighted proposed premium on quote dataset = $1,044(0.20)(0.80) + \dots + 1,095(0.28)(0.92) = 1,102$
 - Demand-weighted expected loss on quote dataset = 952
 - Current loss ratio = $7,240/9,653 = 0.75$
 - Demand-weighted proposed loss ratio = $(6,707 + 952)/(9,376 + 1,102) = 0.731$

- **Key point: Traditional off-balance approach may lead to insufficient rate**

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Application #2

Multi-period Simulation

- Personal auto
- Renewal dataset & quote dataset
- Time Horizon – four periods, each lasting six months
- Quote growth rate – 5% each period
- Quotes do not enter simulation until new rates go into effect at the beginning of period 1
- Quote distribution constant over time
- Aging assumptions
 - Operators age by 1 every other period
 - Vehicles age by 1 every other period
- Current loss ratio is 75%
- Ignore trend
- Scenarios
 - 5% base rate decrease
 - 15% decrease operators aged 25-30 off-balanced to an overall 5%

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EXAMPLES

Application #2

Multi-period Simulation

Quotes							
	Period	Policies Offered	Policies Written	Conversion	Policies Retained	Retention	Profit Margin
Scenario 1	0	N/A	N/A	N/A	N/A	N/A	N/A
	1	20,000	5,493	27.5%	4,669	85.0%	1.9%
	2	21,000	5,767	27.5%	4,902	85.0%	1.9%
	3	22,050	6,058	27.5%	5,150	85.0%	1.9%
	4	23,153	6,360	27.5%	5,406	85.0%	1.9%
Scenario 2	0	N/A	N/A	N/A	N/A	N/A	N/A
	1	20,000	5,646	28.2%	4,743	84.0%	1.8%
	2	21,000	5,928	28.2%	4,980	84.0%	1.8%
	3	22,050	6,228	28.2%	5,231	84.0%	1.8%
	4	23,153	6,538	28.2%	5,492	84.0%	1.8%

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EXAMPLES

Application #2

Multi-period Simulation

Renewals					
	Period	Policies Offered	Policies Retained	Retention	Profit Margin
Scenario 1	0	50,000	44,000	88.0%	2.5%
	1	44,000	41,287	93.8%	2.4%
	2	45,956	44,162	96.1%	2.3%
	3	49,064	47,147	96.1%	2.2%
	4	52,296	49,315	94.3%	2.2%
Scenario 2	0	50,000	44,000	88.0%	2.5%
	1	44,000	41,287	93.8%	2.4%
	2	46,030	44,155	95.9%	2.5%
	3	49,135	47,121	95.9%	2.6%
	4	52,352	49,263	94.1%	2.7%

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Application #2

Multi-period Simulation

Quotes + Renewals							
	Period	Policies Offered	Policies Written	Policies Retained	Earned Premium	Profit Margin	Absolute Profit
Scenario 1	0	50,000	50,000	44,000	\$35,250,000	2.5%	\$881,250
	1	64,000	49,493	45,956	\$34,486,258	2.3%	\$810,152
	2	66,956	51,723	49,064	\$36,412,258	2.3%	\$822,930
	3	71,114	55,122	52,296	\$38,800,399	2.2%	\$842,146
	4	75,449	58,657	54,722	\$40,949,798	2.2%	\$888,759
Scenario 2	0	50,000	50,000	44,000	\$35,250,000	2.5%	\$881,250
	1	64,000	49,646	46,030	\$34,729,064	2.3%	\$812,026
	2	67,030	51,958	49,135	\$36,692,114	2.4%	\$891,271
	3	71,185	55,363	52,352	\$39,087,466	2.5%	\$985,029
	4	75,505	58,890	54,755	\$41,236,423	2.6%	\$1,076,159

- **Key point: A multi-period view is often needed to make the best rate decision**

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Conclusions

- GBMs provide a robust alternative to GLMs for modeling demand
- Traditional off-balance approach may lead to insufficient rate
- A multi-period view is often needed to make the best rate decision

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Thank You!



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