Maximizing Forecast Value Add Through Machine Learning and Behavioral Economics

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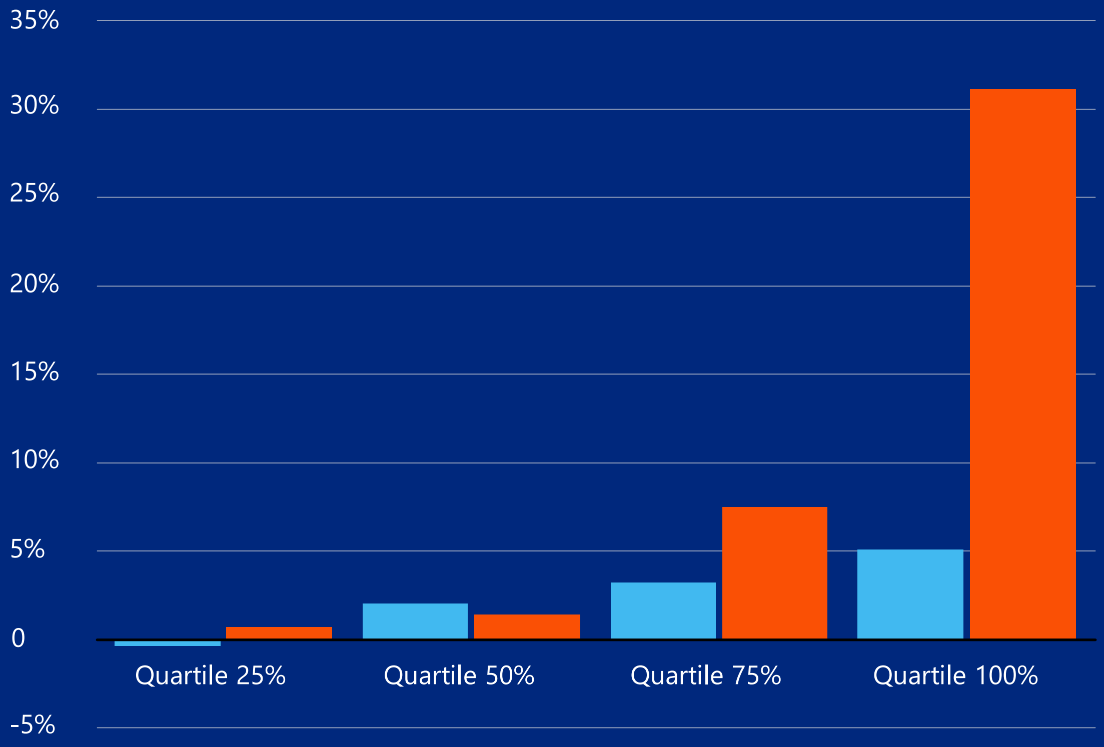
01

Background & Motivation

What's the motivation for adjusting forecasts?

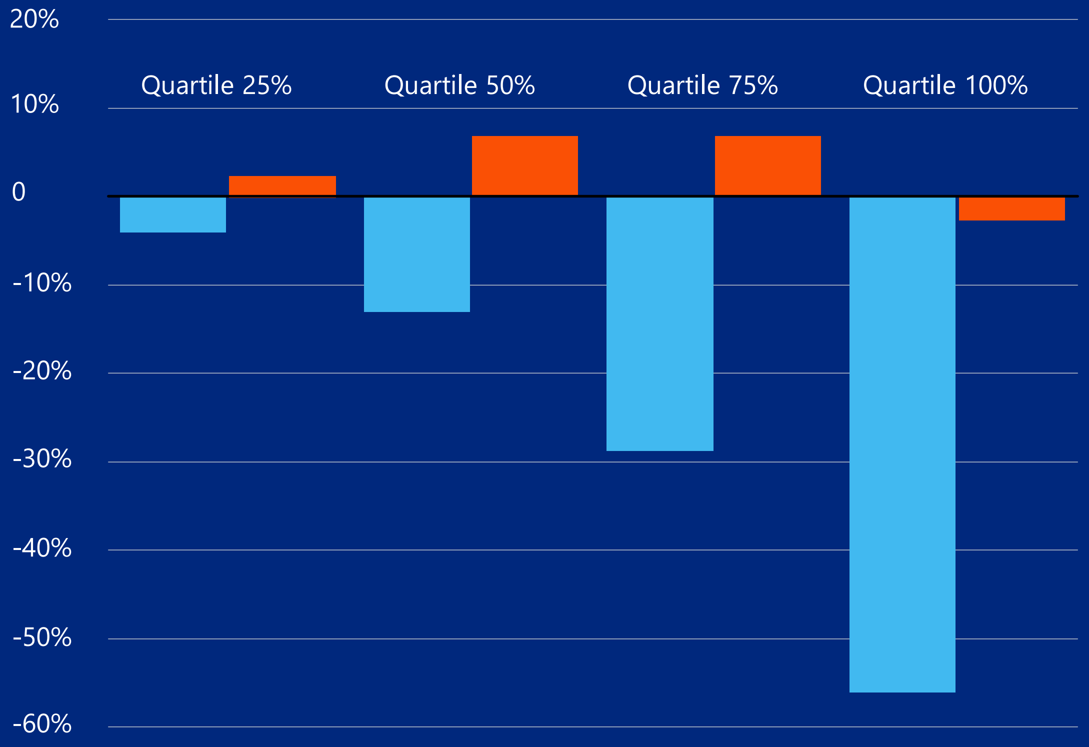
Positive info | Negative info

Improvement in accuracy by adjustment size group A-C



Sometimes we waste our time…

Improvement in accuracy by adjustment size group D1 & D2



Sometimes we destroy value…

Source: R. Fildes et al./International Journal Forecasting 25 (2009) 3-23

Unhealthy forecasting symptoms

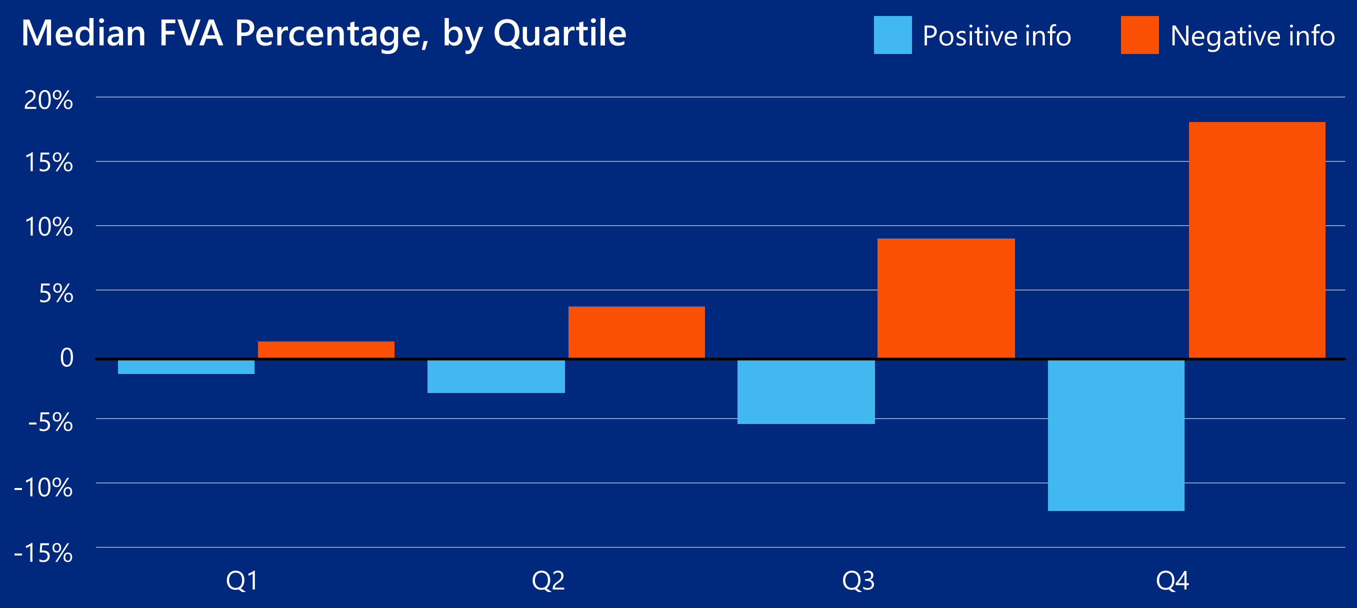
Excessive overrides

- Stat forecast trust issue?
- Looking busy issue?
- Wasted time

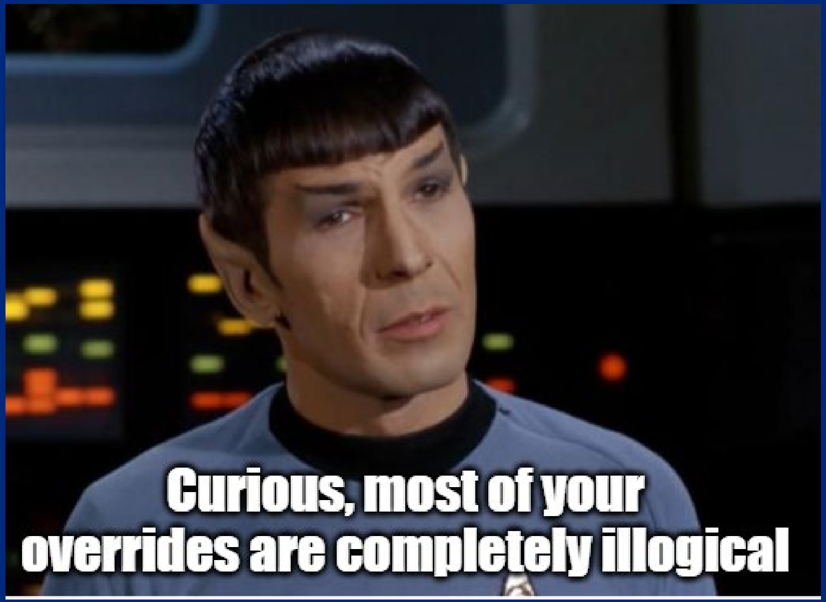
No value add

- Adding bias
- Hurting forecast accuracy
- Impacting the supply chain (service, inventory, cost, etc.)

Company	# of Forecasts	% with Override	% with FVA
A	Hundred	>95%	~40%
B	Thousand	>95%	~60%
C	Tens of Thousands	<15%	~60%



Where is the disconnect?



- Logically speaking, we should not enter overrides which:
  - Destroy value
  - Waster forecasting resources

02

Methodology & Results

Methodology

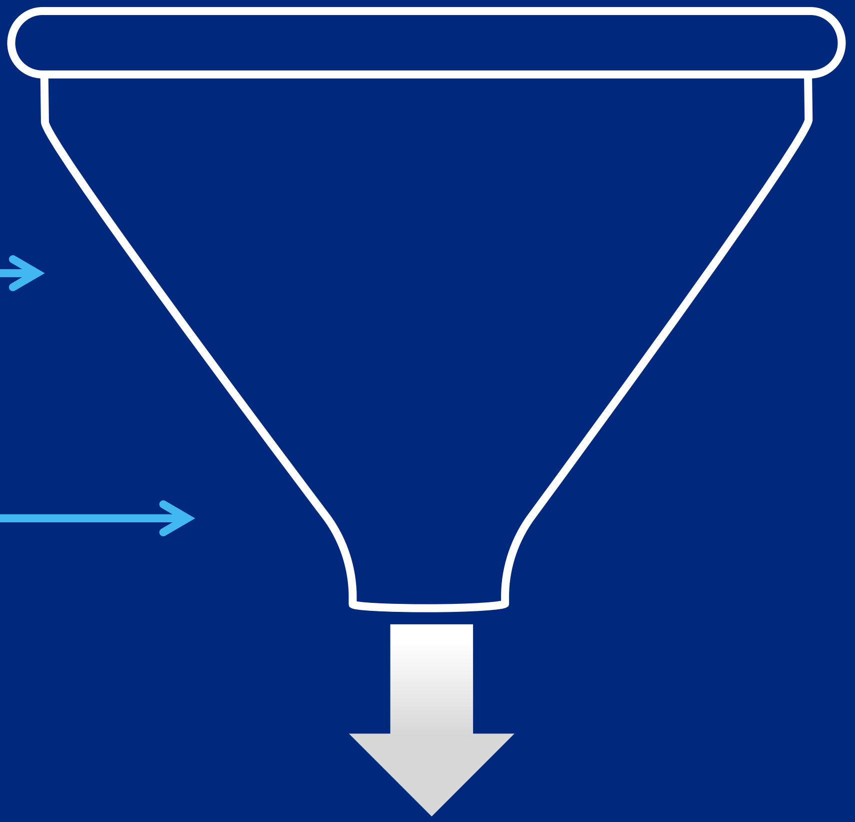
01 Collect time series triples data – actual demand, stat & override forecasts

02 Calculate FVA as response variable

03 Create predictor variables

- Override size
- Override direction
- In-sample forecast accuracy

04 Leverage machine learning classification techniques



Will override create value > FVA_{crit}?

Response Variable: Forecast Value Added

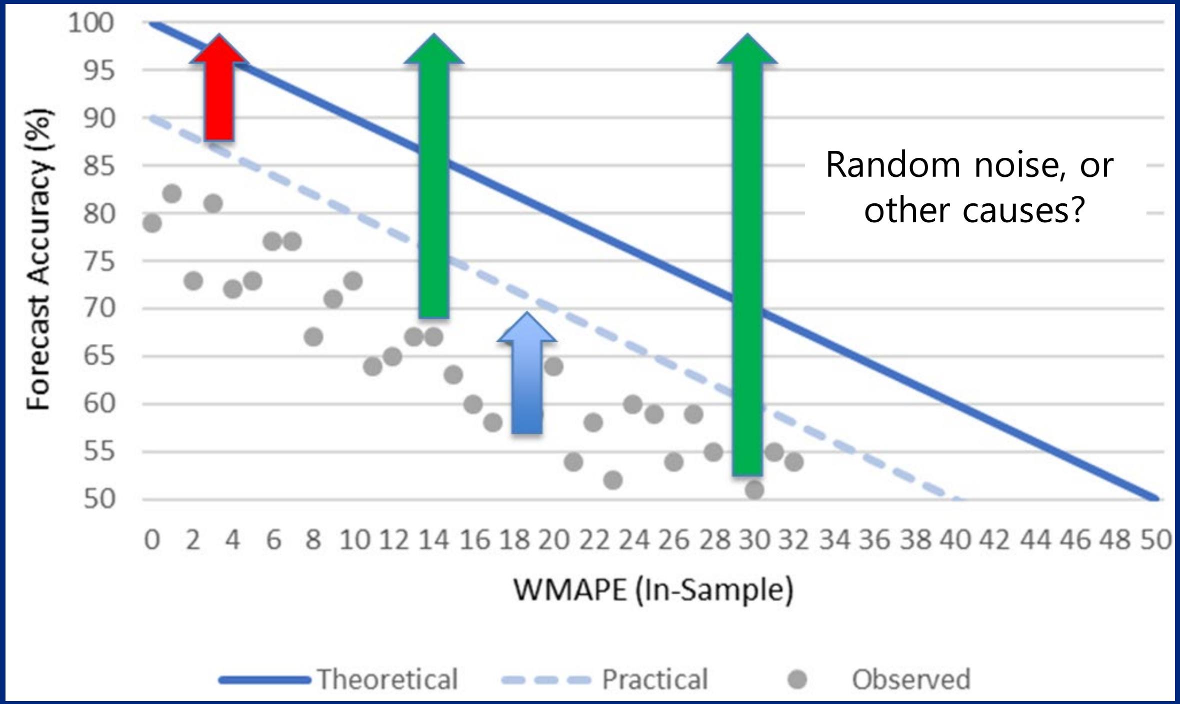
1. FVA measures the value added at each step of the forecasting process
   - Actual Demand
   - Statistical Forecast
   - Override Forecast
2. Classify overrides as value add or non value add to identify drivers of:
   - Wasted time
   - Value destruction
3. Introduce FVA_{crit} as a user-defined based threshold based on forecaster ROI requirement

	WMAPE	Value add vs. Naive	Value add vs. Stat
Naïve	48%		
Statistical	38%	10%	
Override	46%	2%	**(8%)**

Predictor 1: Statistical forecastability

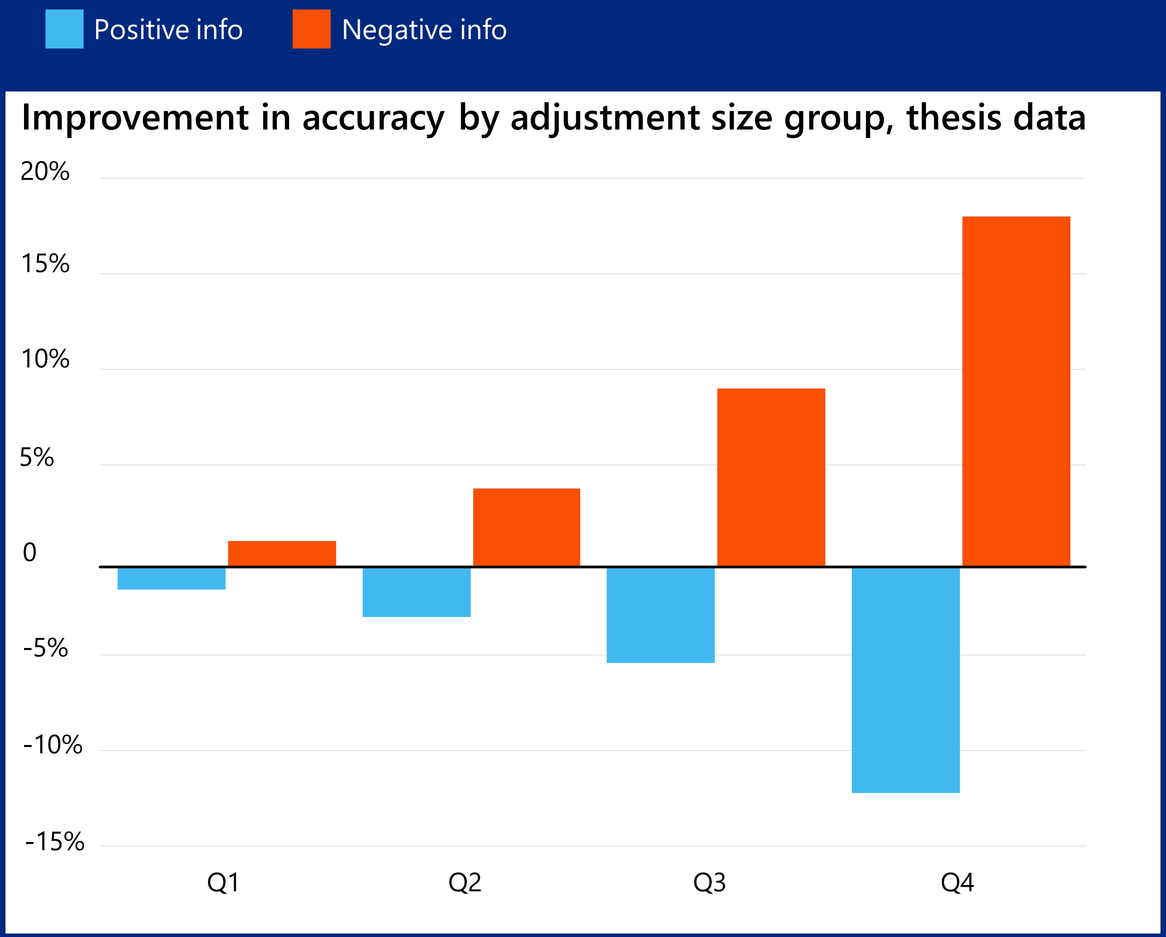
- Forecastability defined as in-sample WMAPE
  - Model to over-fit the data, which serves as upper limit to accuracy
- High forecastability
  - Model explains well; difficult to improve
  - Really need info about unusual event; even if correct override, is it worth it?
- Low forecastability
  - Model doesn't explain very well; easier to improve upon if additional information available

Forecast Accuracy vs. in-sample WMAPE



Predictor 2: Override direction

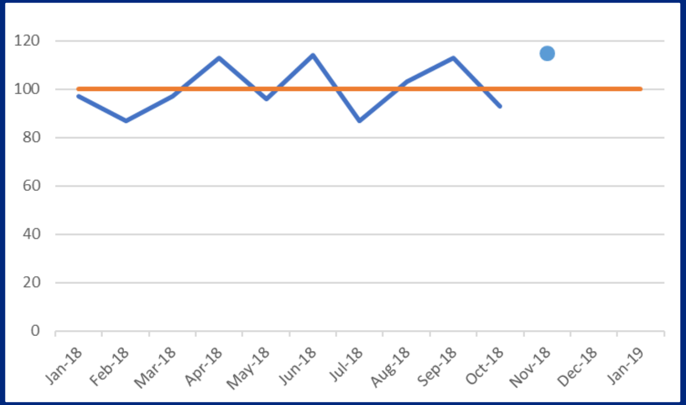
- Does direction matter?
  - No
  - Yes
  - Consultant’s answer
- Why?
  - Negative overrides typically add value
  - Positive overrides often don’t
    - Best case vs. most likely case
    - Match Annual Operating Plan
    - Maximize customer service
- Each company has unique “fingerprint”

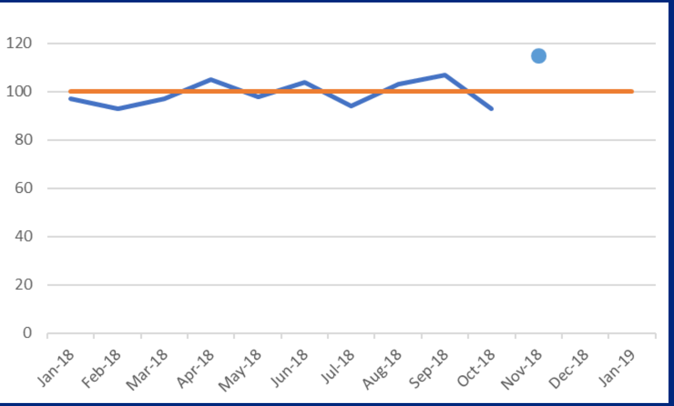


Predictor 3: Override size

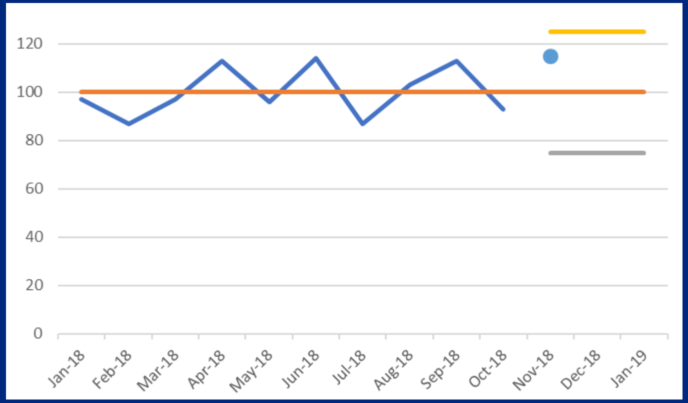
- Size indicates the magnitude of new information
- Based on percentage
  - Both are identical
- Based on variability
  - One is "noise"
  - One is "signal"
- Suggests the need to develop a signal-to-noise ratio metric

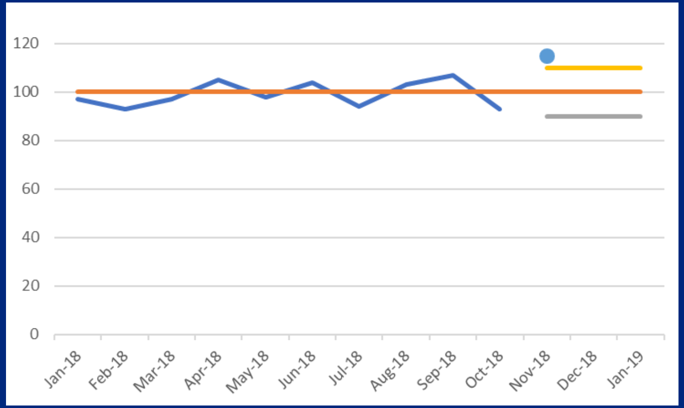
15% Override





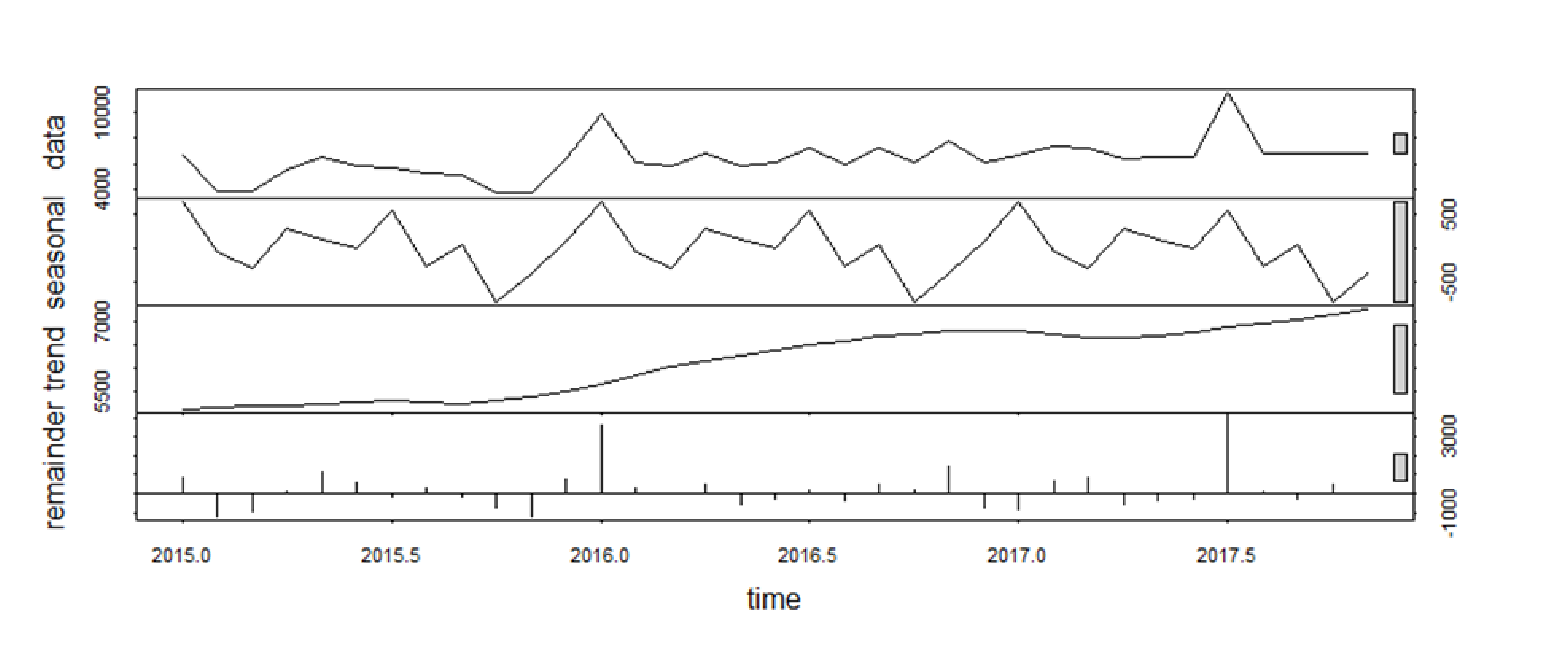
With confidence intervals





Predictor 3*: Dispersion-scaled overrides

- Use seasonal-trend decomposition of demand to extract residuals
- Calculate dispersion statistics on the residuals
  - Standard Deviation (sensitive)
  - Mean Absolute Deviation
  - Median Absolute Deviation (robust)
- Divide overrides by dispersion measures to create DSOs



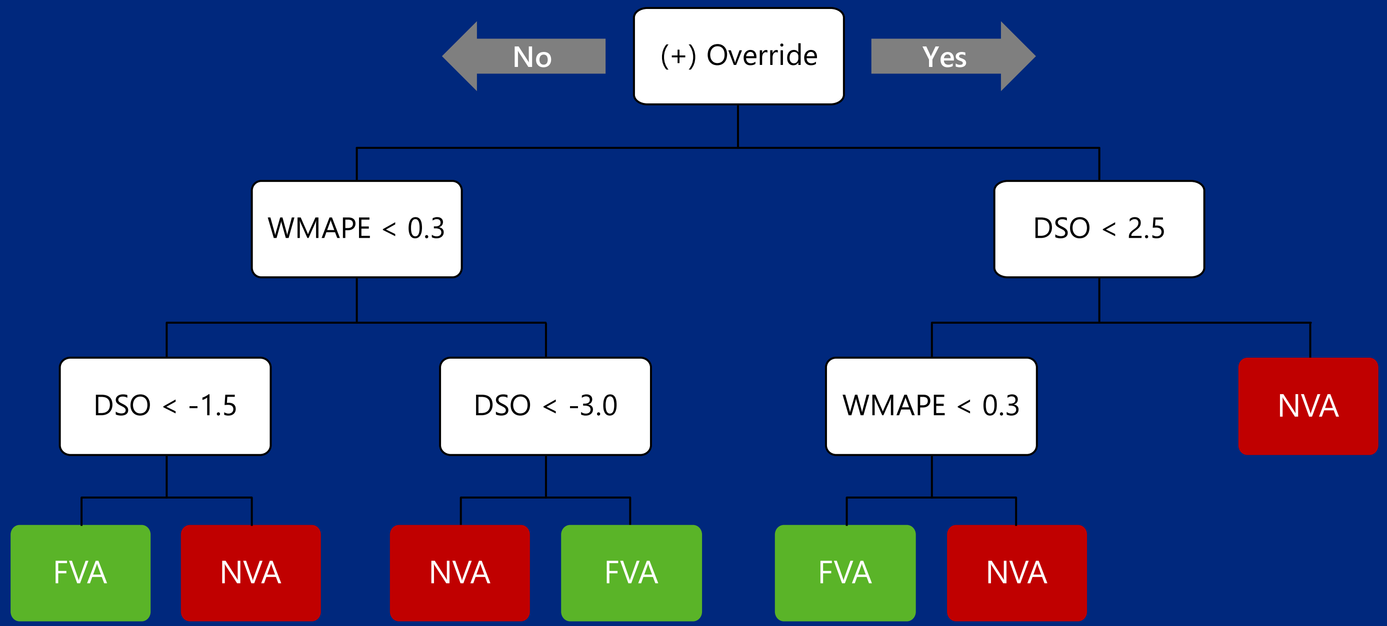
$$Dispersion\ Scaled\ Override_t = {(Override_t)}/{\sigma_{residuals}}$$

$$Dispersion\ Scaled\ Override_t = {(Override_t)}/{MAD_{residuals}}$$

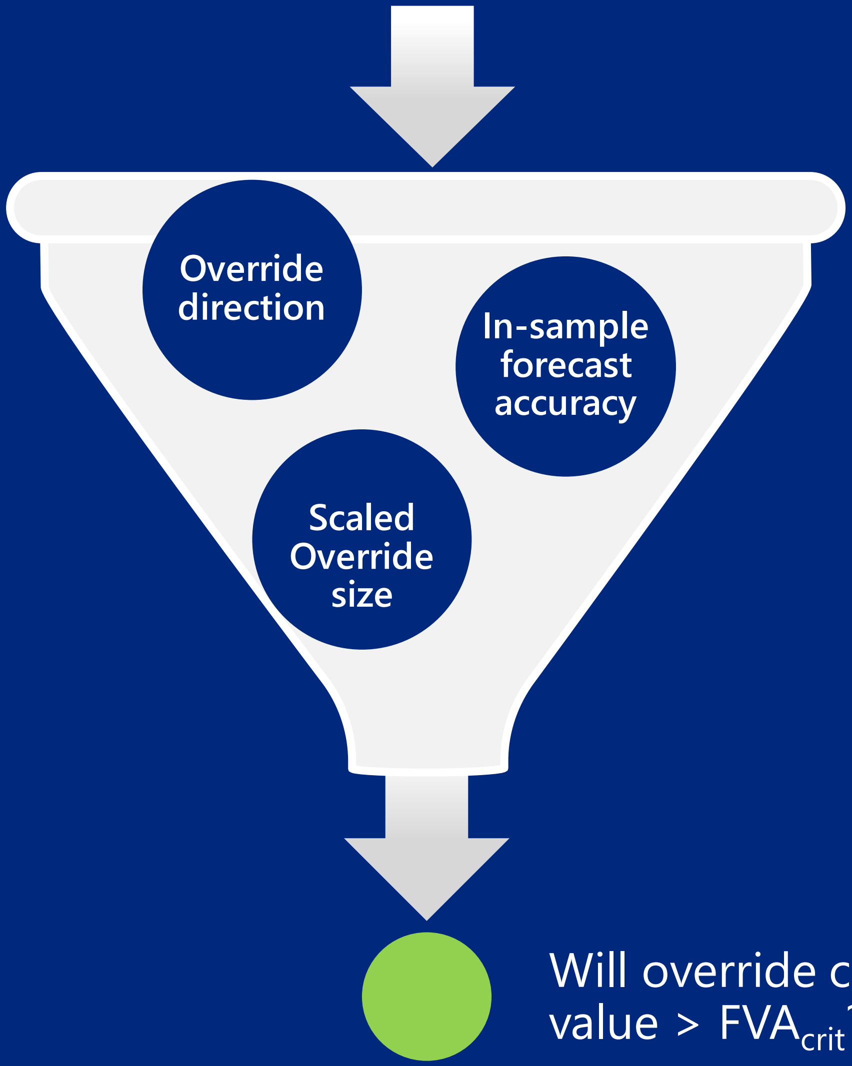
$$Dispersion\ Scaled\ Override_t = {(Override_t)}/{MdAD_{residuals}}$$

Machine learning classification techniques

- Classification tree
  - Visual, explainable to management
  - Most important variables at the top of the tree
- Random forest
  - Ensemble technique, black box
  - Variable importance plot
- Boosted tree
  - Over-samples misclassified records; black box
- Logistic regression
  - Probability values for variables



Results



Will override create value > FVA_{crit}?

Technique	Accuracy
Classification Tree	80 %
Random Forest	82 %
Boosted Tree	81 %
Logistic Regression	82 %

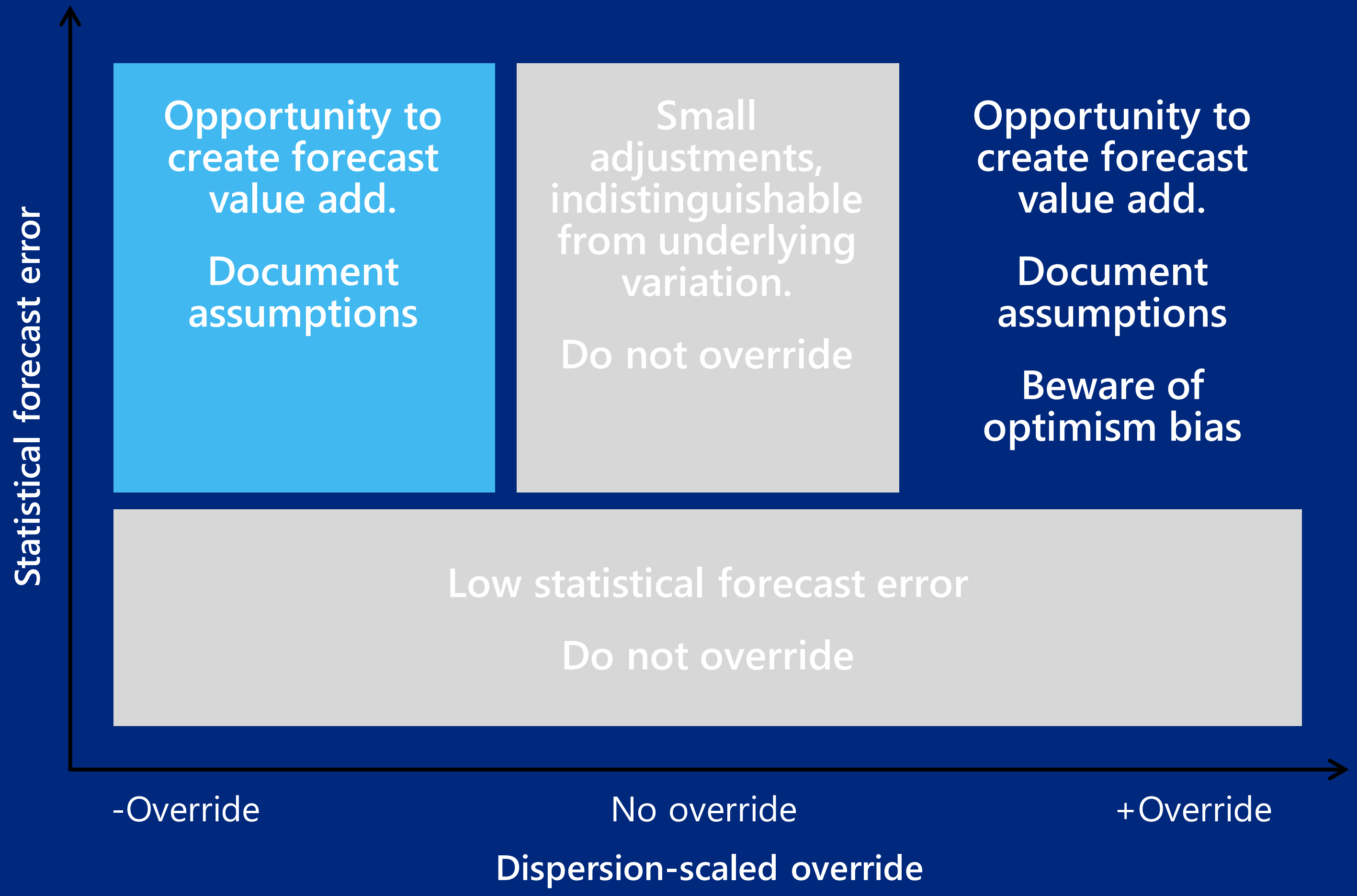
- Classification techniques may be used to predictive if an override will add value or not
- Methodology is robust enough to handle noisy data

03

Implications

Implications

- Can reduce or eliminate:
  - Small time-wasting overrides
  - Value destroying overrides
  - Bias
- “Work itself out of a job”
- What if every override added value?
  - Forecast accuracy increases will
  - Improve customer service
  - Decrease safety stock
  - Reduce SC expense



Can we Nudge our process?

Questions

- Is this **positive override** overly influenced budget goals, or sales best case optimism?
- Is this **small override** based on new information?
- Is this override of a **highly forecastable** product based on significant new information?
- Can you **explain this change** in an Exec Review?

Data

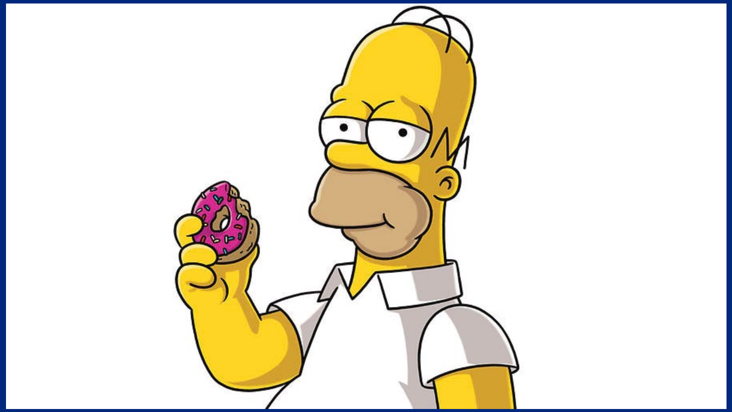
- Percent of forecasts overridden
- Percent positive vs. Percent negative
- Average override size (dispersion scaled signal-to-noise)
- Percent of forecast overrides which have added value

Source: *Nudge: Improving Decisions About Health, Wealth, and Happiness;* Richard Thaler and Cass Sunstein

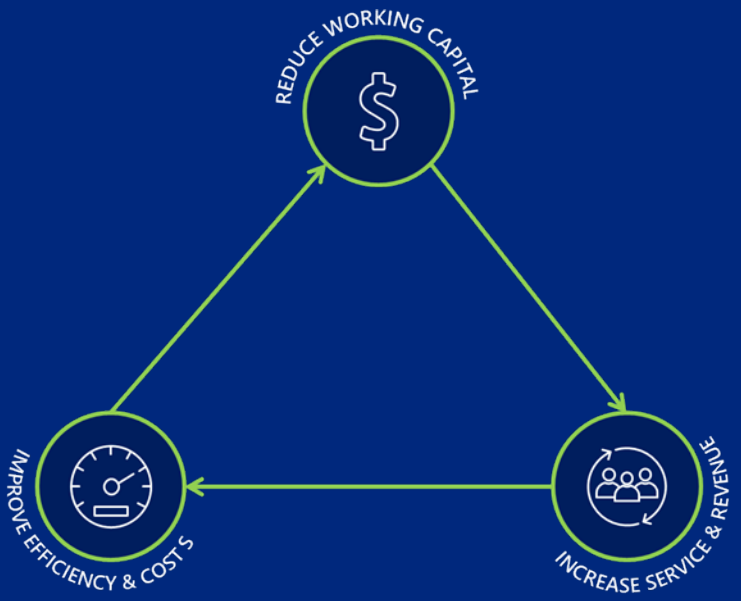
Summary

Machine Learning teaches us that we can predict if a particular override will create value, based on direction, forecastability, and DSO size

Behavior Economics teaches us that if we inform users on choices, we can nudge them into eliminating time-wasting and value-destroying overrides



Value Added Overrides will improve forecast accuracy, which positively impacts customer service, safety stock, and supply chain expense



Thank you!

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