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A Planner-centric Approach to Judgmental Forecasting

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A Planner-centric Approach to Judgmental Forecasting

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When reviewing a forecast, the planner must consider whether it needs an adjustment. If the answer is yes, they must next decide on the direction and size of the adjustment. Then, they must take an action – often simply to type in the judgmental quantity in a workbook and press enter. So how can a planner continuously make better quality adjustment decisions with minimum effort and maximum impact?

Recently *Foresight* discussed this topic in a special feature on Forecast Value Added (FVA). However, the discussion did not guide planners on how to modify their processes and systems to improve their forecasting practices. For this, *human-centric design*, based on user needs and user stories, is a good approach to develop processes and systems. And in this age of AI, we can add a layer of human-machine collaboration and learning to these design principles.

FOCUSING ADJUSTMENT EFFORTS

Before the planner makes an adjustment decision, we want to assure they only spend effort where it has the most impact. There is little need to adjust B and C products, or highly forecastable A products, as the business impact may be inconsequential. The Low Touch Forecast (LTF%) metric used at Kraft Heinz (*Foresight* Issue 71) shows the percentage of computer-based forecasts that were not manually adjusted (because the FVA shows minimal accuracy improvement or even degradation of forecast accuracy). This seems like a good incentive for the data science community to keep improving algorithms and thus shrinking the number of adjustments that need to be made. Our aim is to reduce effort and make an impact where it matters.

The *nudge*, as described by Jeff Baker (*Foresight* Issue 60), is an FVA idea where the planner can improve together with the machine. Grounded in behavioral economics, the nudge compels the planner to have a second thought about making an adjustment, and the size of that adjustment. These nudges can be activated once a machine learning (ML) classification detects that the judgment is likely to be non-value-adding, with classification based on, for example, override size, positive versus negative overrides, or any other factor that detects bias. The nudge can influence a planner's bias to make better quality adjustment decisions.

To support a planner in making a better-informed decision before the nudge, we can introduce ML explainability for a forecast that is being considered for adjustment. A LIME (Local Interpretable Model-agnostic Explanation) or a SHAP (Shapley Additive exPlanations) value can provide a planner with an automated explanation on what influencers drive the ML forecast. This type of decision-support information should be accessible during the whole judgmental process.

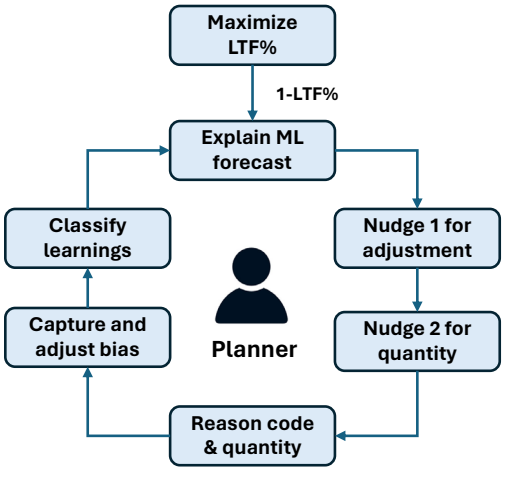
Evidence shows that combining forecasts tends to improve accuracy. Now new research by Brau and colleagues, "Demand Planning for the Digital Supply Chain: How to Integrate Human Judgment and Predictive Analytics" highlights that *integrative judgment learning* outperforms judgmental adjustment and other integration methods in the lab and, in most cases, in the field. This means a forecast where a human makes adjustments

is more accurate when afterwards the machine detects the bias in human adjustments and corrects the forecast accordingly.

A human will always have capabilities that a machine doesn't possess (intuition, understanding context, relationships, and emotional intelligence). Humans will also have access to data the machine doesn't have (such as a call from a supplier or customer). Despite the risk of ML algorithms having biases themselves, we can still engage ML to help reduce human bias, such as through a nudge. Capturing bias outcomes provides a wonderful opportunity for the planner to learn.

To continuously make better quality adjustment decisions, a planner needs to learn and improve. We can record reason codes during the planner's adjustment actions, along with relevant context like product and customer types, horizon and aggregation level, nudges the planner received, and ML-generated bias adjustments. These elements can provide a learning feedback loop to the planner as shown in **Figure 1**. Bias feedback can be provided on product type, nudge type, reason code, or any other classification recorded during the adjustment process. Explainability and nudges to the planner can be adjusted based on these new insights, creating a continuous improvement loop for the planner.

Figure 1. Guiding a Planner through Adjustments



LOOKING FORWARD

Let's design forecasting and FVA processes with the planner in the center, supported by the machine. Let the machine automate forecasts where possible and guide the planner during judgmental decision making, providing specific feedback on where the planner applies good or bad judgment.

There is great opportunity for the planner to learn, have some self-reflection, and improve within the forecast function – and maybe even outside of it. Improving the planner's judgment will leave ML to detect an ever-decreasing bias over time and see an increase of the LTF% metric across the product portfolio.

The technology to support the described model is available and not all that complicated – so adoption shouldn't be an issue. Planners and forecasters who don't adjust their mindset to accepting the role of the machine and this new type of collaboration will be left behind and self-select out of the planner role. We all have biases. Let's embrace them and learn from them!

Niels van Hove is a Client Engagement Principal at Aera Technology. He uses his 20-plus years of experience to help companies make more autonomous decisions and actions in their supply chain. See our "Forecaster in the Field" interview with Niels in the Summer 2016 issue.

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