Visualizing and Optimizing a Retailer's Demand Forecasts

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ABSTRACT

This case study provides a way to visualize and explain product forecasts to merchant decision-makers. Often in data science and merchandising decision-support a team of technical team members (e.g., data scientists, analytics consultants, etc.) develop predictive models and provide analytics to help facilitate the decision-maker in performing their job. Analyses are often supported with statistical and business performance metrics to help level-set the decision-maker on how reliable the analytics they are receiving is. Being able to allocate products where they are most in demand stands to increase efficiency, decrease costs associated with logistics, gain customer loyalty, and give the firm a competitive advantage. We show how our tool helps explain the demand forecasting process to merchants, provides effective visuals to see how the forecast was derived, as well as visuals to support if the forecast makes sense compared to common decision-maker queries sent to decision-facilitators.

INTRODUCTION

In competitive industries where not having a product immediately available often means losing a sale to a competitor next door, being able to accurately forecast and interpret what consumer demands is to be is vital for success. An inextricable part of this demand forecasting, and all business intelligence related activities overall, is the visualization and communication of information derived from data.

When it comes to inventory management, companies have a hard time facilitating decisions due to insufficient communication between decision-facilitators and decision-makers. Having lack of visuals can lead to wrong inventories and poor customer satisfaction. Rather than focus on common statistical metrics that might not resonate with the decision-maker we design and develop a visual tool in Tableau that allows a bi-directional engagement amongst these stakeholders to show how the forecast for any product was obtained, how it relates to similar products and in similar locations, as well as other less obvious ways to group these forecasts and compare to what has occurred in the past.

Data gives meaningful information by way of relational connections, and knowledge is derived from the appropriate collection of information. Knowledge is the key factor for decision-makers. The figure shows the relationship between these concepts.

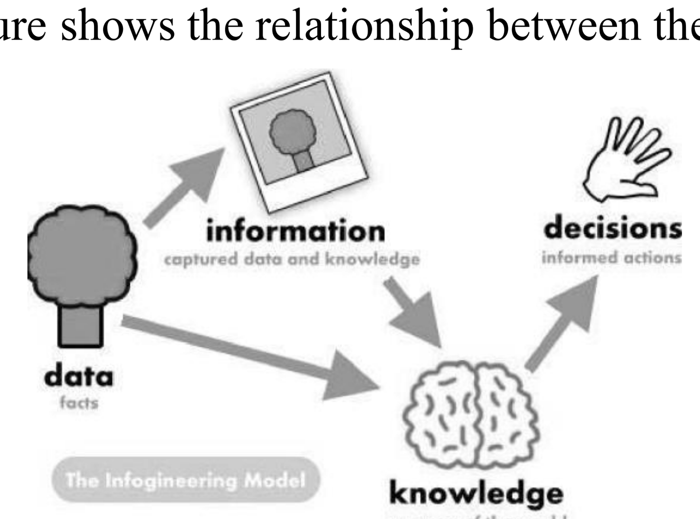


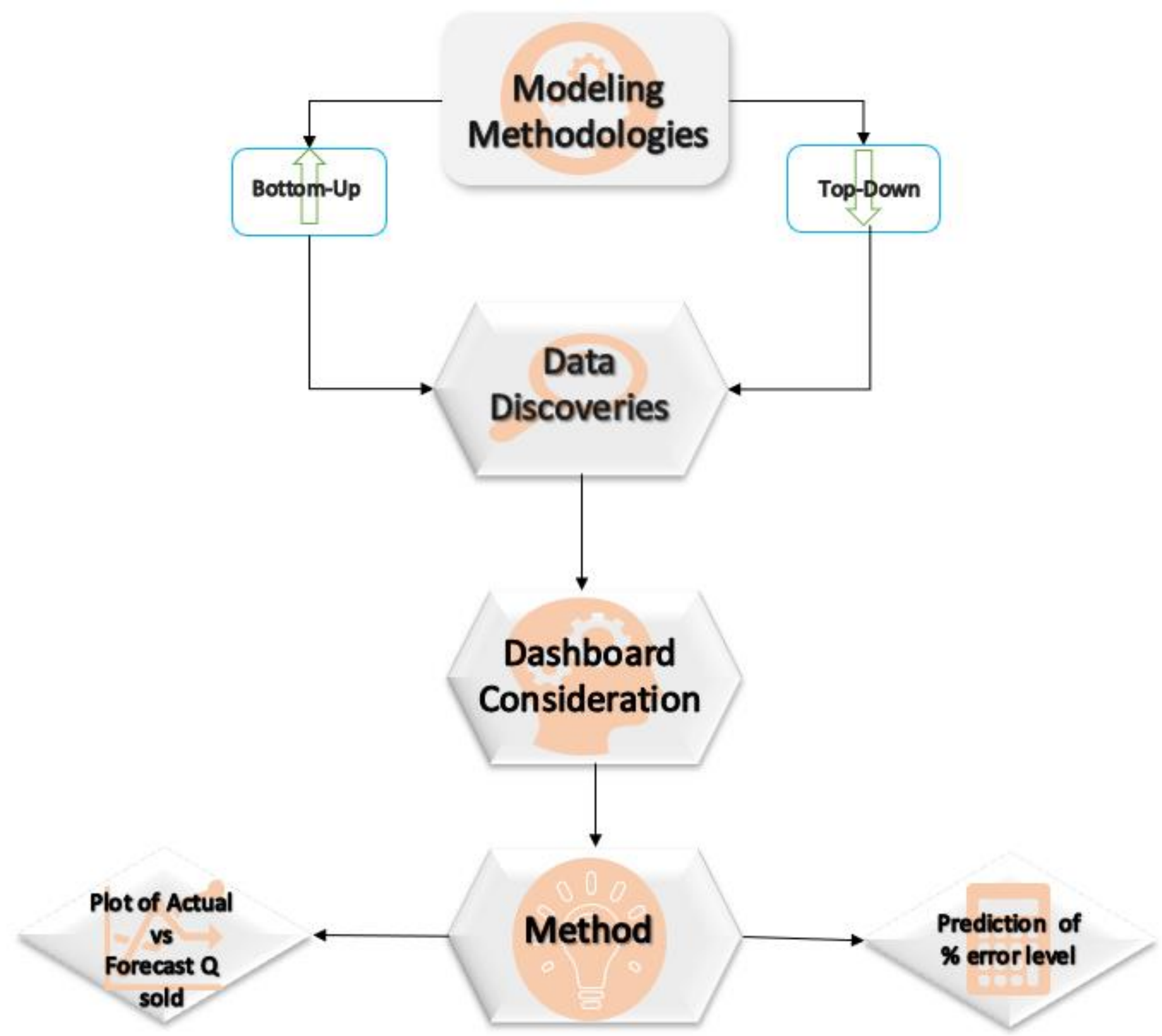
Fig1. Data Information, Knowledge and Decisions

RESEARCH QUESTIONS

This analytical research is carried out to answer the following questions:

- How do we effectively visualize why certain product forecasts more accurate than others?
- How can a post-model forecast correction algorithm improve the accuracy of certain forecasts?

METHODOLOGY



Bottom-Up
- prediction model when given historical sales data becomes more accurate

Top-Down
- prediction model for low quantity product giving more generalized and accurate prediction

Data Discoveries
- Identify significant variables affecting predictions model

Dashboard Creation
- Product groups which are over/under predicted
- Using Tableau dashboard as visualization tool

STATISTICAL RESULTS

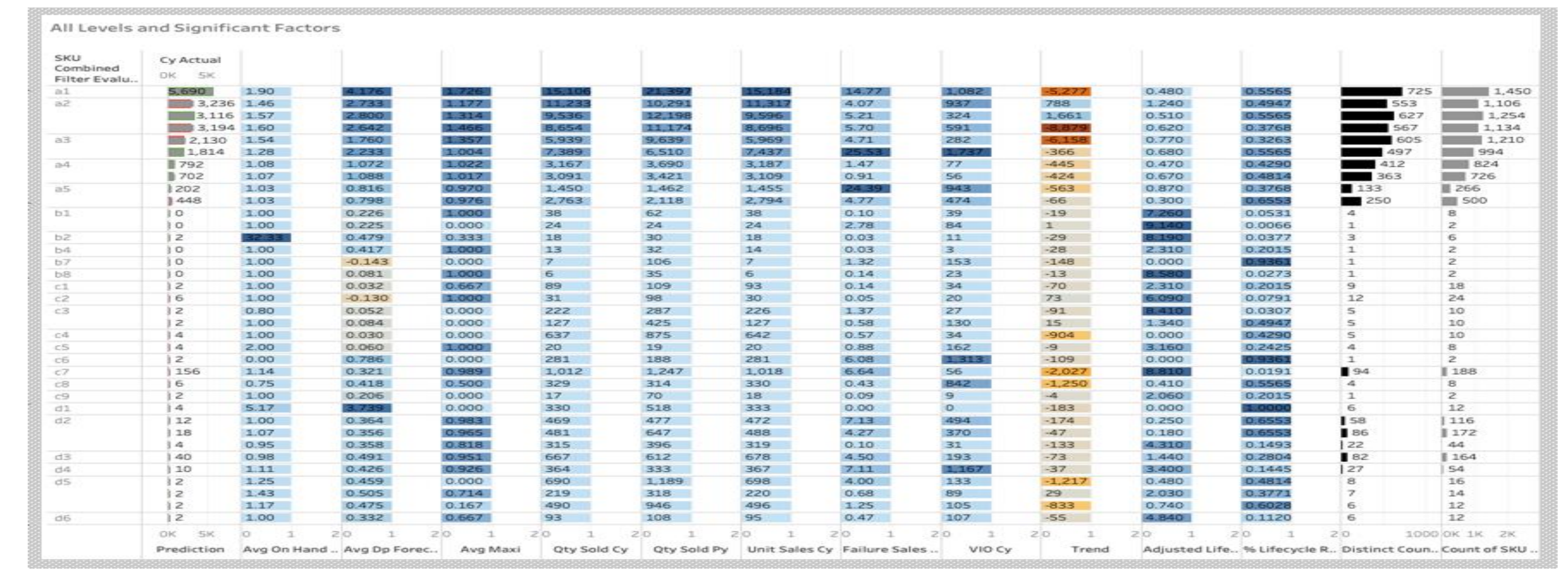


Fig 3. Cross Model Dashboard showing Grouped Highest & Lowest % Error by Model

Fig 4. Cross Model Dashboard showing Product Selection comparison using filters

- For the cross-model dashboard in Fig3, we combined the highest and lowest % errors for both models (Top-Down & Bottom-Up) as a selected Product and then determine from the distribution and how they vary in relation to each other, which levels are influenced by which significant variable factors.
- Products can also be selected to compare in a number of ways using filters or by selection on Scatter Plot as shown in Fig4. This shows how each products compare in terms of our Variables of interest with the % of Error levels.

CONCLUSIONS

- Our cross-model dashboard was used by the team to identify significant factors of prediction for the Highest and Lowest % Error Products within both the Top Down and Bottom-Up Models.
- Additionally, the dashboard is intended to be deployed to Data Science team members in order to compare selected products of interest to these % Error levels, as well as identify the likely significant factors for the selected products over or underprediction.

ACKNOWLEDGEMENTS

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