



# Forecasting in the AI Era: Advantages, Challenges, and the Shift in the Forecaster's Role

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# Outline



TRENDS IN THE ROLE OF  
THE FORECASTER



AI IN RETAIL AND CPG  
DEMAND FORECASTING



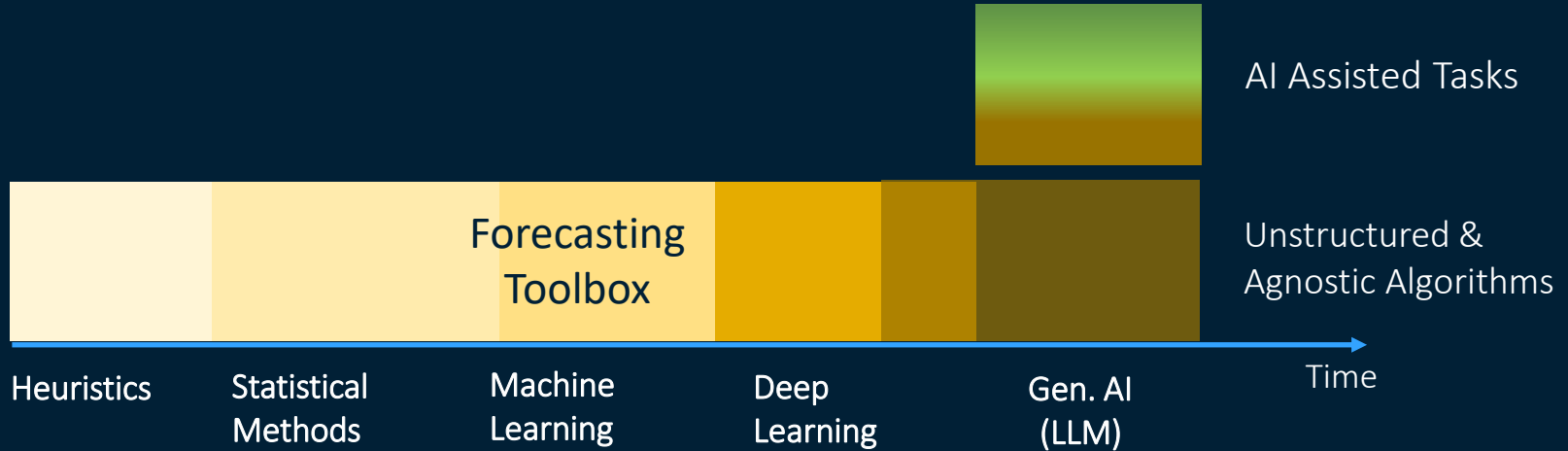
PRACTICAL  
CONSIDERATIONS &  
WAYS FORWARD

# Trends in the Role of the Forecaster

The Emergence of AI

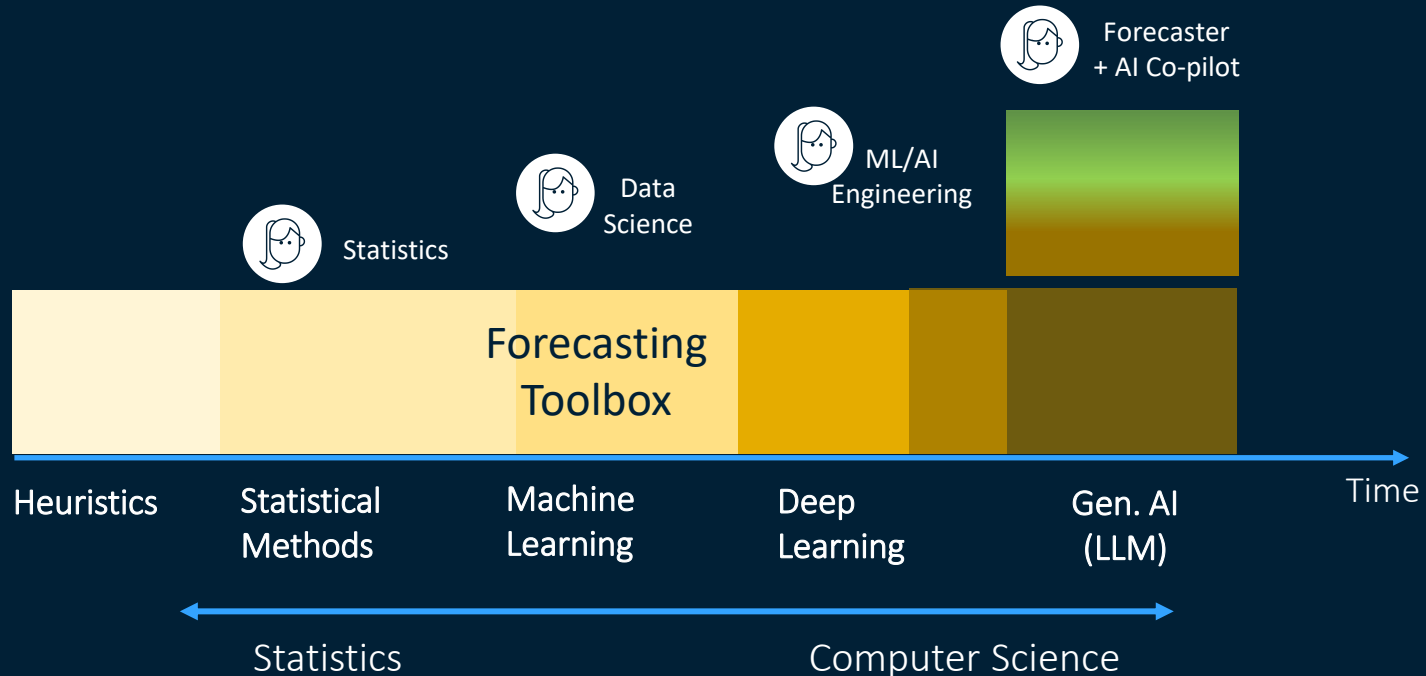
# The Emergence of AI in Forecasting

## Beyond the Toolbox



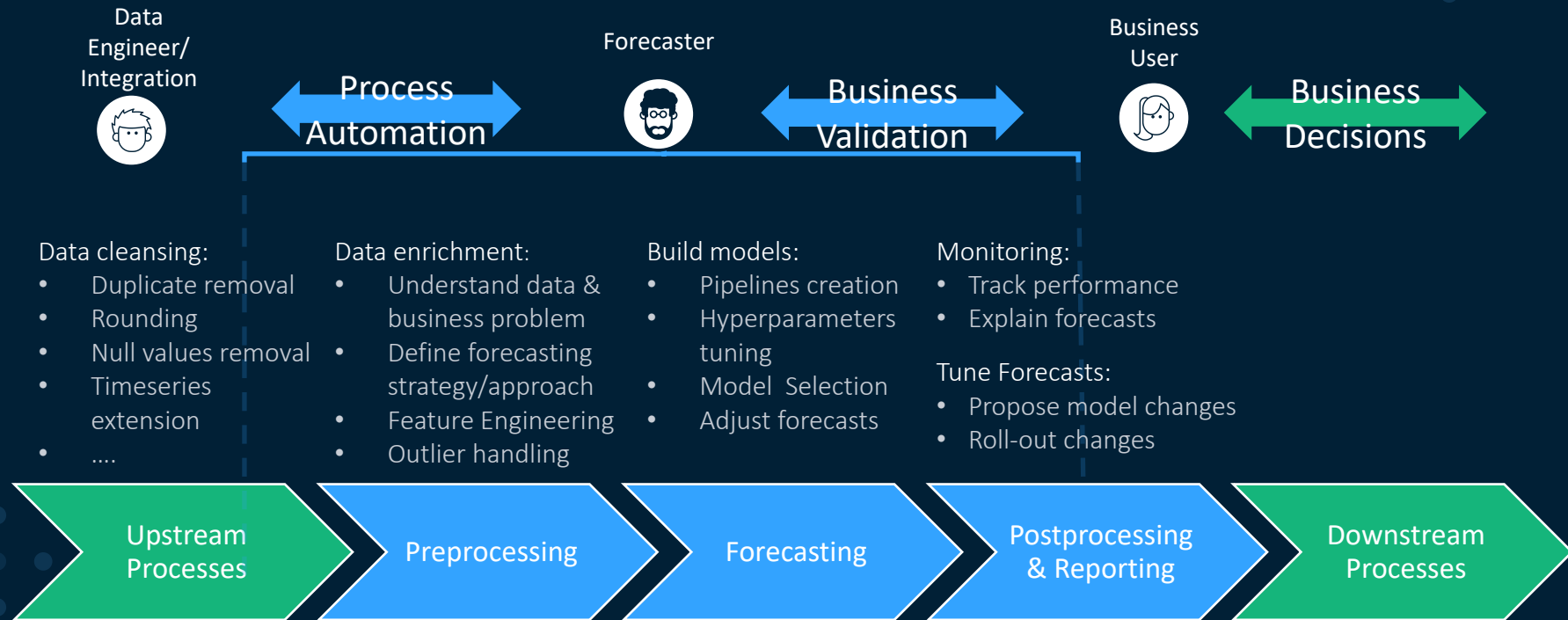
# Trends in the Role of the Forecaster

## The Shift in the Skills of the Forecaster



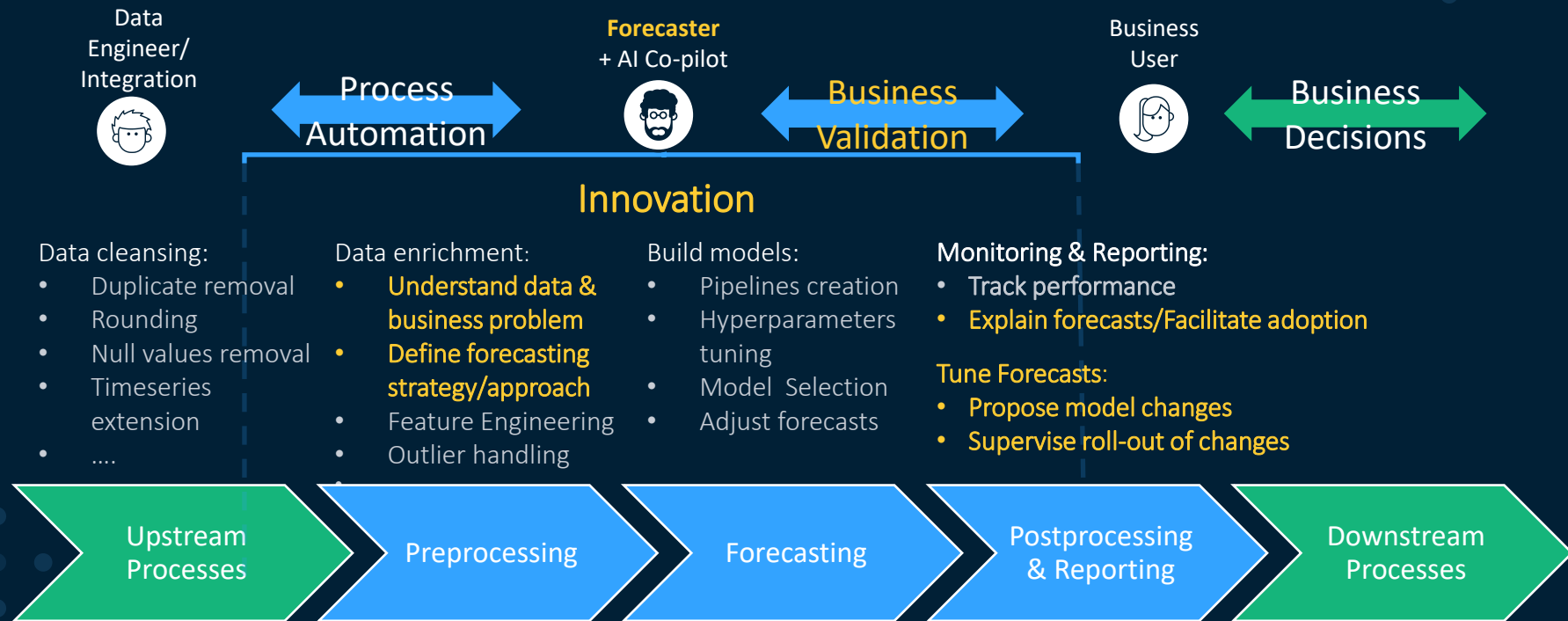
# The Role of the Forecaster Today

More than just Model Building



# Trends in the Forecaster's Role

## Skills that Will Grow in Importance



# Some Experiences From the Field

AI in Retail and CPG Demand Forecasting



# Retail and CPG Demand Forecasting

## Main Challenges



### LIMITED HISTORY

Products are becoming more and more short lived.



### NEW PRODUCT PROLIFERATION

Varying lengths of series with increase in new product launches.



### INTERRELATED TIME SERIES

Highly correlated series, organized in a hierarchical structure (cannibalization and halo effects)



### IMPORTANCE EXTERNAL FACTORS

Demand is influenced by multiple business and economic factors, and calendar related events



### LARGE SCALE PROBLEM

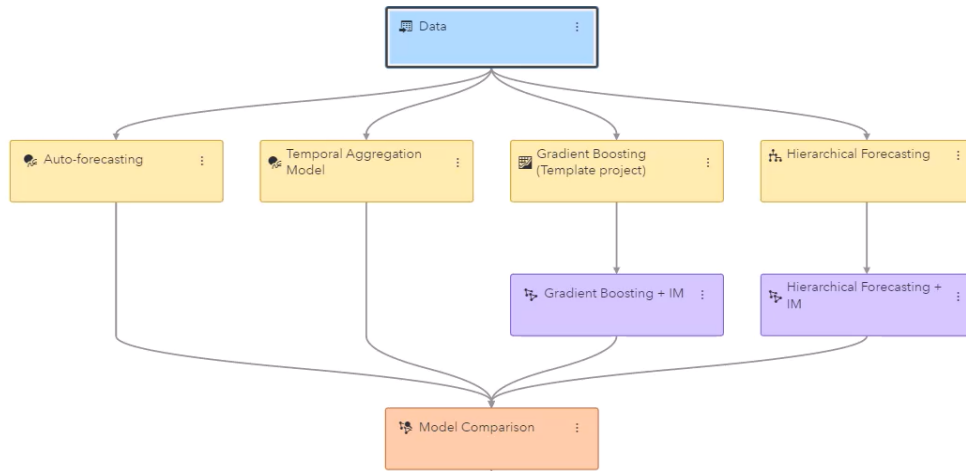
Large catalog of products w/ multiple dimensions (product, location, customer) and forecast granularities



### SPARSITY and NOISE

Intermittency, low volume and elevated noise at the detailed forecast levels

# Use Case #1: Operational Forecasting at a Large CPG Company



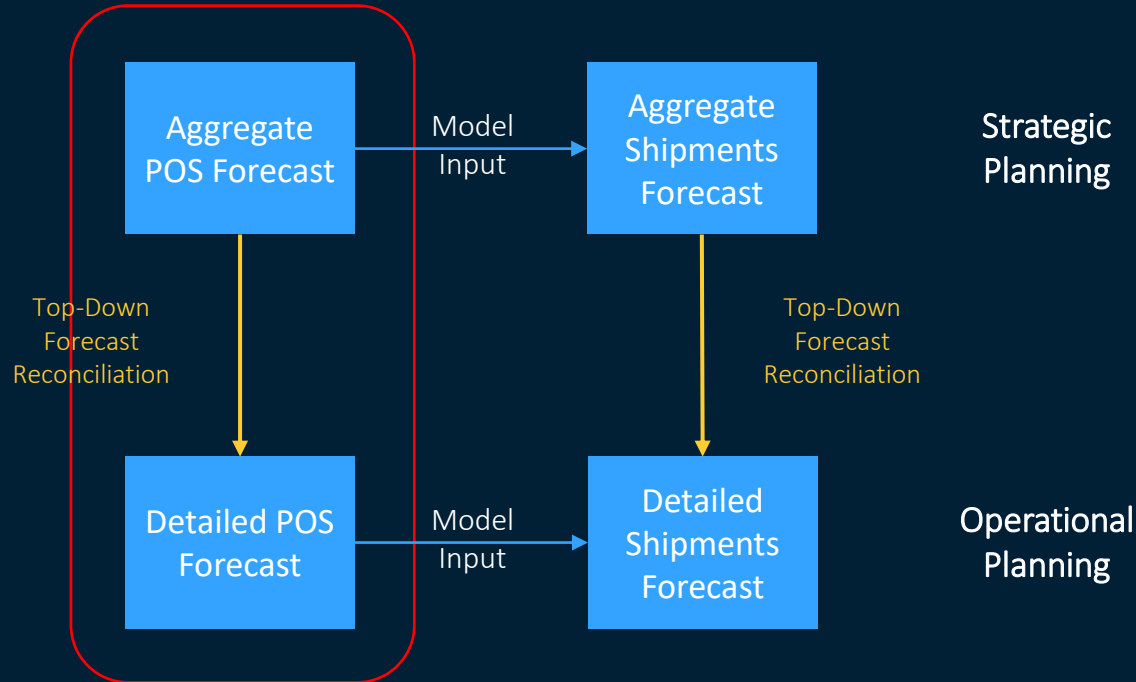
- Shipments forecast
- Product(UPC)/DC/Customer/Week level
- GBM augmented with statistical methods
- Recursive implementation
- Covariates: promotions, discontinuation and holiday events
- Temporal effects

Model Comparison

Champion	Model Name	Status	WMAE	WMAPE	WMASE	WASE	WRMSE	WAPE
★	Gradient Boosting + IM	Successful	504.2337	12.4303	0.2867	0.6895	768.9309	0.1663
	Auto-forecasting	Successful	896.9781	45.5625	11,631,096.9907	1.1033	1,179.3615	0.3295
	Hierarchical Forecasting + IM	Successful	952.6966	51.2297	0.5930	1.0913	1,235.3588	0.3453
	Temporal Aggregation Model	Successful	788.1415	56.3225	0.6937	1.1473	1,056.7853	0.3380

# Use Case #2: Consumption-Based Forecasting in CPG

## Multilevel Forecasting Process



# POS Forecast

One Size Does Not Fit All

- Hybrid (TS+ML) forecast models
- Balance accuracy + explainability
- Adjust for hierarchical differences

**Hybrid**

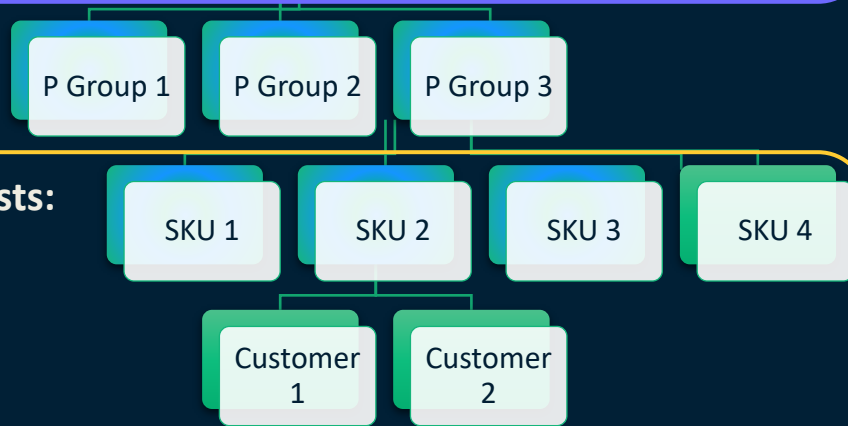


**Aggregate Forecasts:**  
**Explainability**



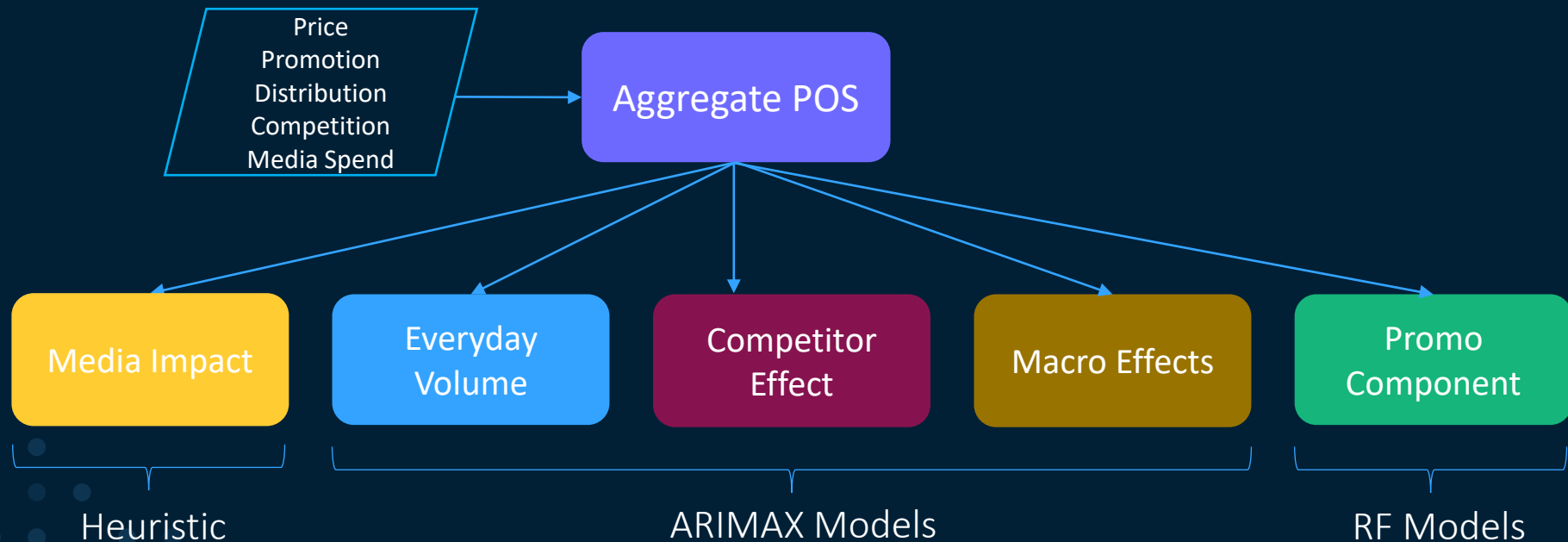
*Top-down  
reconciliation*

**Detailed Forecasts:**  
**Accuracy**



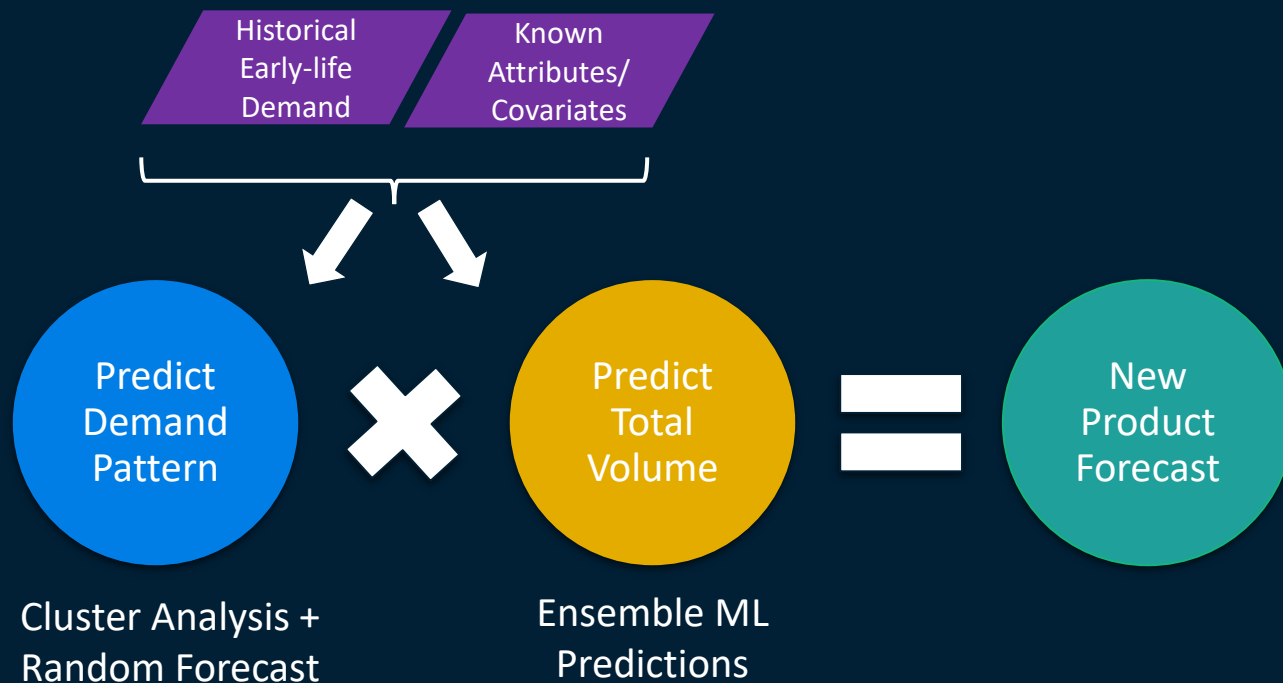
# Aggregate POS Forecast

What are the key factors that explain consumer demand?



# Use Case #3: New Product Launch in Retail

## A ML-Based Approach



# AI in Retail and CPG Demand Forecasting

## Key Findings & Practical Challenges

- Predominance of tree-based methods
- Global Models/cross-learning
- Hybrid Approaches & Ensemble
- One size does not fit all
- Interpretability vs Accuracy
- Not as many DL based implementations
- Data readiness/availability
- Companies' analytical maturity
- Implementation complexity
- Computational resources/costs
- Trust/Adoption issue

# AI in Time Series Forecasting

## Path Forward

- Technology Advancements
  - More research on interpretable DL based models
- Reduce Implementation Costs
  - Forecasting with Attention
  - Pre-trained/Foundation Model for forecasting
- Enterprise Adoption
  - Real-world applications of DL based methods across different domains
  - Forecasting practitioner strategic role in the last mile



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# Q&A

## Thank you!

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[sas.com](https://sas.com)



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