TRANSFORMING DEMAND FORECASTING: LEVERAGING TRANSFORMER MODELS AND DEMAND-SENSING IN THE FMCG INDUSTRY

BUSINESS PROBLEM

The fast-moving consumer goods (FMCG) industry is a competitive market where best in class demand forecasting drives product availability leading to superior financial performance. Companies in this space are looking for new and innovative demand forecasting methods to improve forecasting accuracy to enhance their competitive position.

Consequences of Poor Forecasting

- **UNAVAILABLE PRODUCTS** – Lack of stock leading to unmet customer demand
- **LOST SALES** – Missed revenue opportunities and decreased market share
- **INCREASED SUPPLY CHAIN COSTS** – Higher expenses due to rushed shipments and wasted resources
- **DIMINISHED CUSTOMER SATISFACTION** – Eroded trust and loyalty from repeated service failures

BUSINESS BENEFITS

INCREASED BRAND REPUTATION
Enhanced product availability boosting brand image

COST OPTIMIZATION
Efficient production planning reducing costs

INCREASED REVENUE
Preventing stock-outs to maximize sales

RESEARCH OBJECTIVES

- Can transformer models effectively improve demand forecasting accuracy?
- What are the benefits of integrating external factors with current demand forecasting methods?
- How does the combination of transformer models and demand-sensing techniques compare to traditional forecasting methods?

RESEARCH TOOL-KIT

python · amazon web services · PyTorch · Amazon SageMaker · S3 · Hugging Face

ANALYTICS PROBLEM

01. Data Integration & Preprocessing – Gather and process consumption, sentiment, product & competitor interest, and shipment data for analysis

02. iTransformer Embedding – Encode data into tokens, applying Transformer-based techniques for temporal and variate correlation

03. Attention & Nonlinear Learning – Utilize self-attention and Feed-Forward Networks to learn from large lookback windows and diverse variates

04. Demand Sensing – Combine short-term sensing with long-term trends to enhance forecasting accuracy

05. Comprehensive Forecast – Output a nuanced demand forecast, integrating diverse datasets for operational and strategic planning.

METHODOLOGY

Data Integration
- -Combine the Social Media Data and the Historical Demand Data
- -Align the datasets based on the Week_number and the Year attributes

Historical Data, Amazon Reviews → Data Integration

Allows the data to be analyzed together and fully understand the impacts

Data Cleaning
- -Prepare the data to be used for modeling purposes
- -Remove outliers, handle missing values, and normalize features

Handing missing values · Normalize · Correct Outliers

Prepares the data to be used for modeling

Model Architecture and Training
- -iTransformer model architecture is used to create the demand forecast
- -Demand sensing use case was built separately

Model Architecture · Feature Selection · Training & Validation

Creates a demand forecast that can be compared to traditional forecasting models

Benchmarking and Validation
- -Compare the iTransformer performance to the TimesNet model using MSE and MAE
- -Compare various models for demand sensing and implement the best performing one based RMSE

MSE · MAE · RMSE

Measure the performance of the models in order to deliver business insights to the client

Outcome
- -Demonstrate trade-offs of implementing an iTransformer model
- -Reflect on improvements for future work

Supply Chain Optimization · S&OP Planning · Market insights

Deliver insights to the client

Figure 1: Methodology explaining the research process and the steps that were taken to create, train, and validate the transformer model

DATA

Product level shipment and consumption data for ~3 years. Includes information at the product level including product names and weekly demand levels.

External data was extracted from Amazon and Google Trends at a brand level to measure customer sentiments and gain an understanding of brand and competitor interest.

Data is then integrated and cleaned to allow visualizations to be made and a holistic model to be created.

MODEL BUILDING

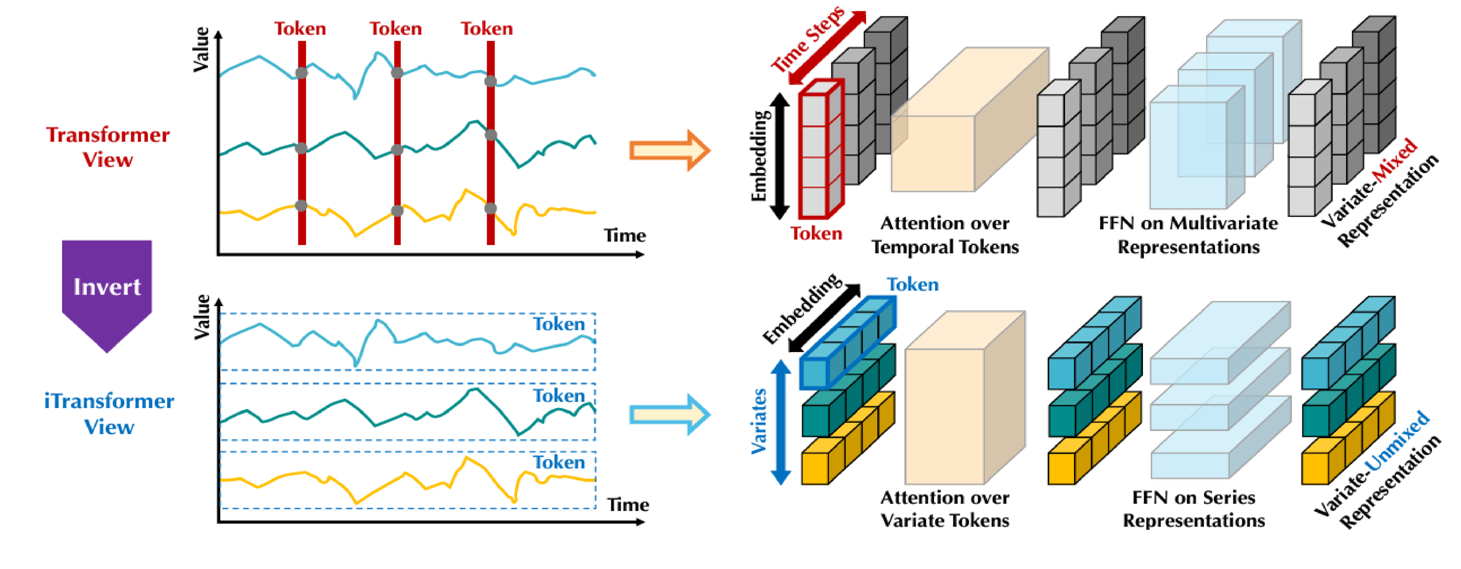
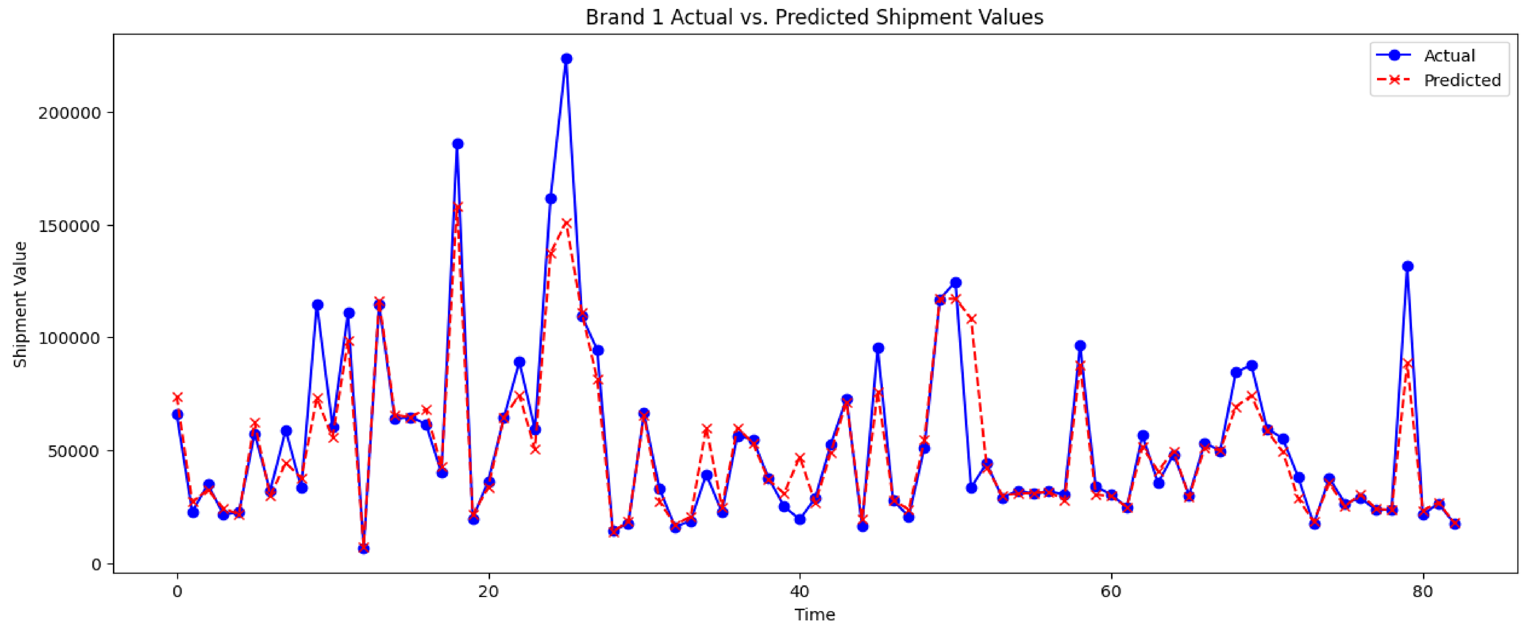
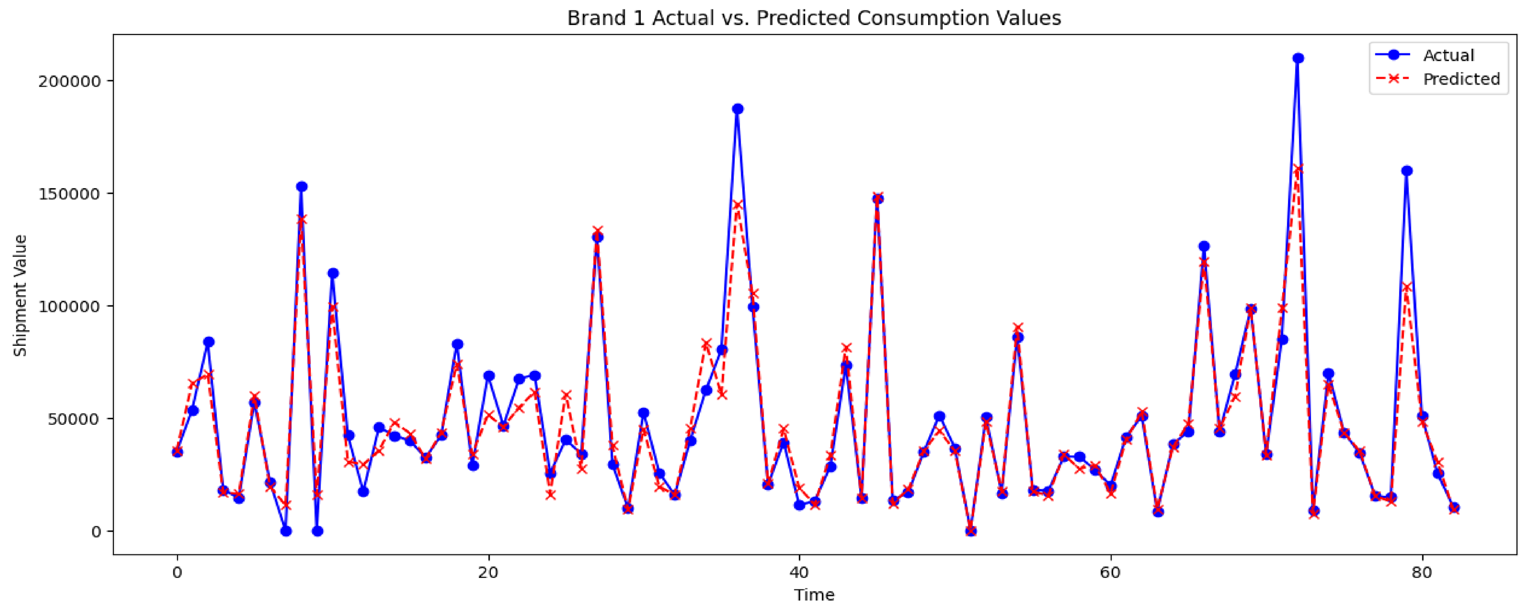


Figure 2: iTransformer architecture

DEMAND SENSING RESULTS

Model	Shipment			Consumption		
	Ensemble	Gradient Boosting	XGBoost	Ensemble	Gradient Boosting	XGBoost
MSE	15,834.61	15,322.67	16,890.92	11,768.22	12,841.09	15,788.81





TRANSFORMER RESULTS

Dataset	Prediction Length	iTransformer		TimesNet	
		MSE	MAE	MSE	MAE
ETTm1	48	0.313	0.356	0.470	0.493
	96	0.342	0.376	0.546	0.532
	192	0.382	0.396	0.636	0.570

iTRANSFORMER FORECAST

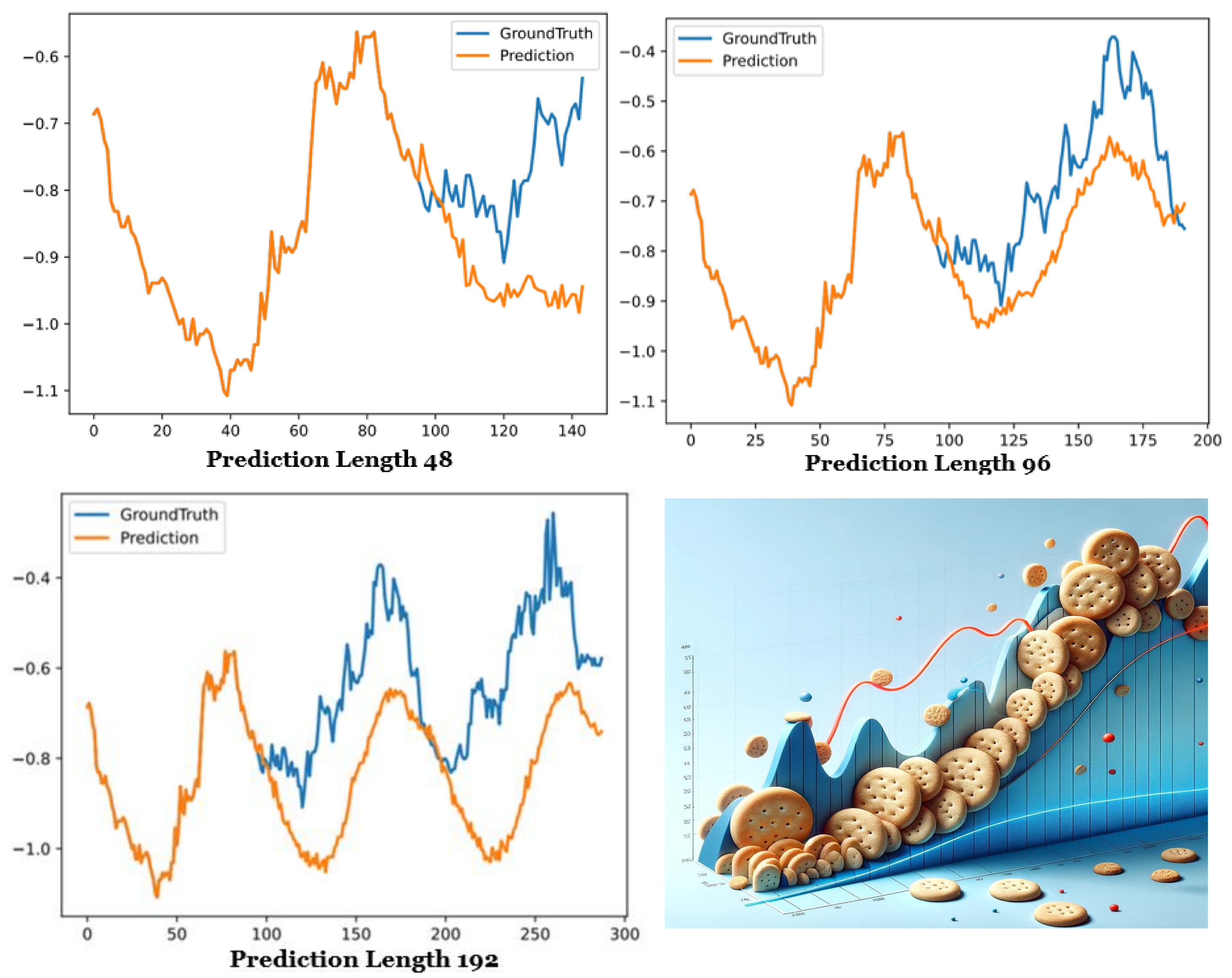


Figure 3: iTransformer forecast with Sequence & Prediction Lengths

CONCLUSION & INSIGHTS

Transformer Insights

DATA INTENSIVE
- Requires thousands of datapoints
- Data duplication improved results
- Suitable for legacy products

COSTLY
- More costly than traditional approaches
- Costs must be weighed against benefits with competetive context in mind

Demand Sensing Insights

DATA BREADTH
- Google trends competitor data was significant
- Cross channel sentiment from social media data

PRODUCT TYPE
- Performance driven by tendency to review a product
- Effective for high value products
- Effective for products that are highly susceptive to the economy

PRODUCT LIFE CYCLE DEVELOPMENT

Dataset Size & Granularity
10+ years of historical data
Regional demand data

External Data Sources
Social media data
Regional weather data

Cost Benefit Analysis
Performance versus costs
Competitive landscape

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