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# **PREDICTION ON WALMART SALES DEMAND**

# Business Objective

- Efficiently allocate resources and accurately estimate costs and revenue based on the prediction of short-term and long-term sales performance
- Produce the 28 days ahead point forecasts for 30490 items in 42,840 time series that represent the hierarchical unit sales of Walmart, starting at the item level and aggregating to that of departments, product categories and stores in three geographical areas in US

# Approaches



## Machine Learning

- **LightGBM**

## Statistics

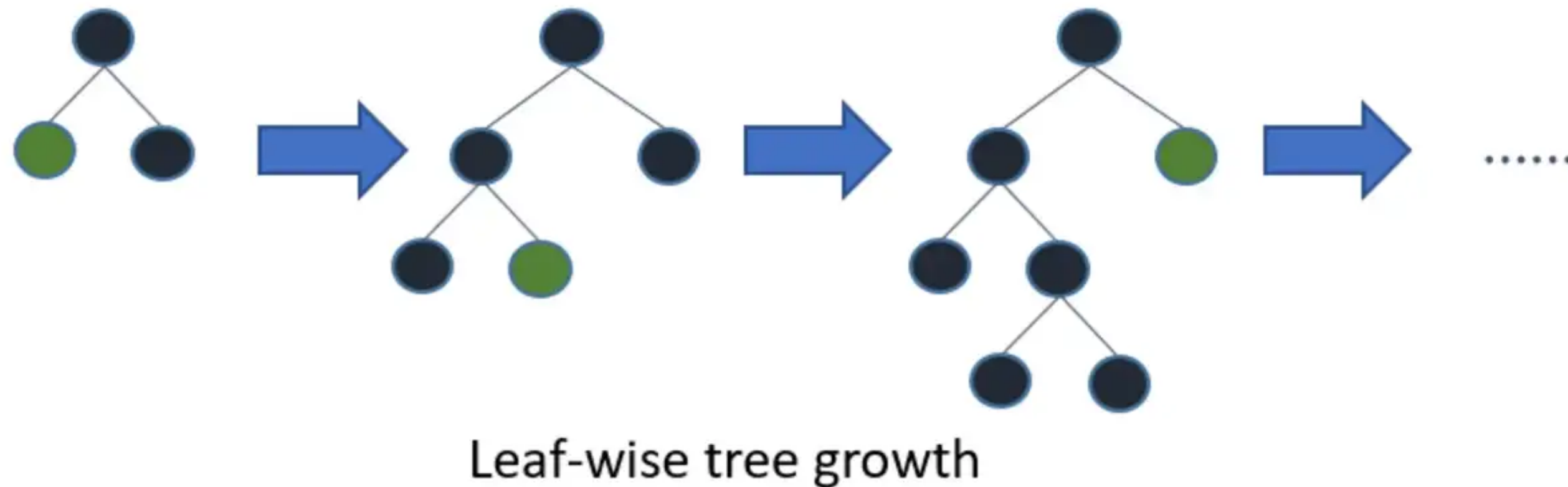
- **SARIMAX**
- **Prophet**

## Deep Learning

- **Seq2seq**
- **Transformer**

# LightGBM

- Type of ensemble modeling
- Uses tree-based learning algorithm
- Prefixed as 'light' because of its high speed



# SARIMAX

- S: Seasonality
- AR: Autoregression
- I: Integrated
- MA: Moving Average
- X: Exogenous Variable

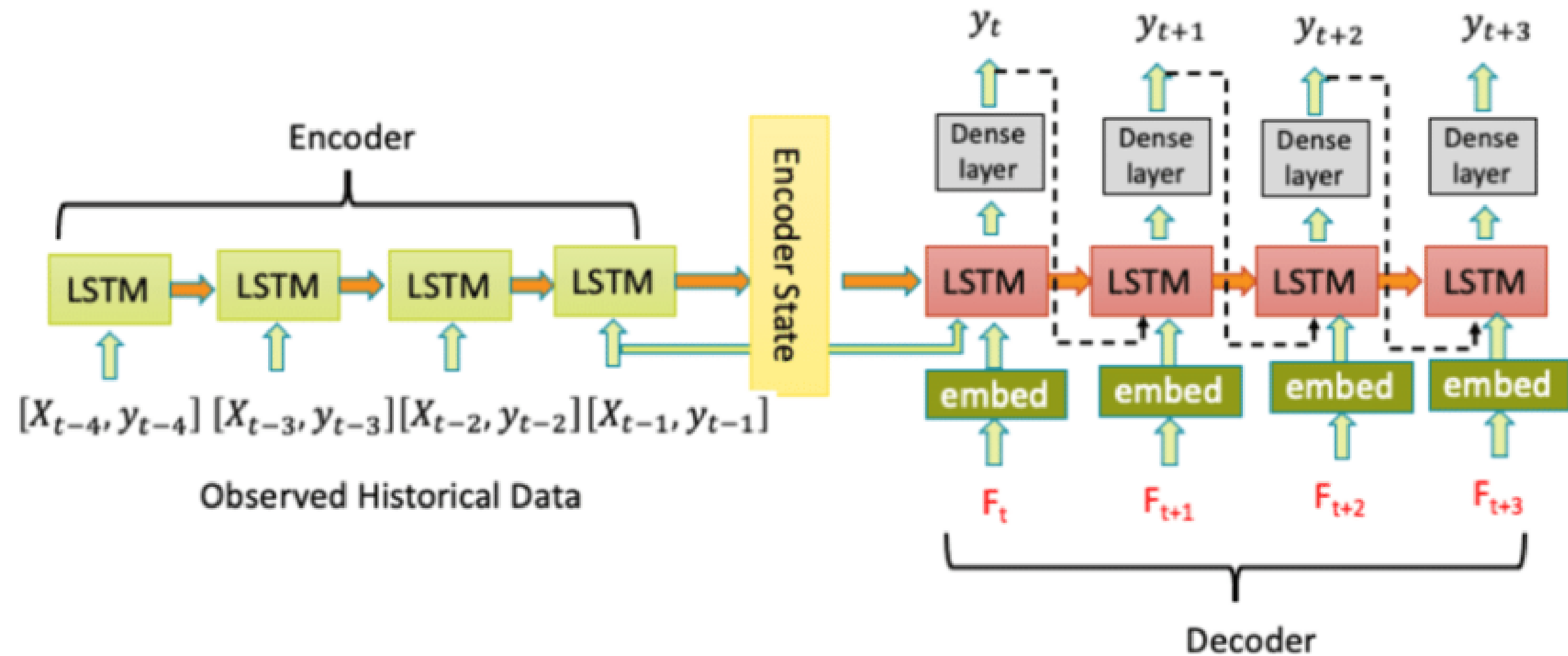
# Prophet

- Trend component
- Seasonal component
- Holiday component

$$y_t = g(t) + s(t) + h(t)$$

# Seq2seq

- Encoder
- Decoder



# Temporal Fusion Transformer

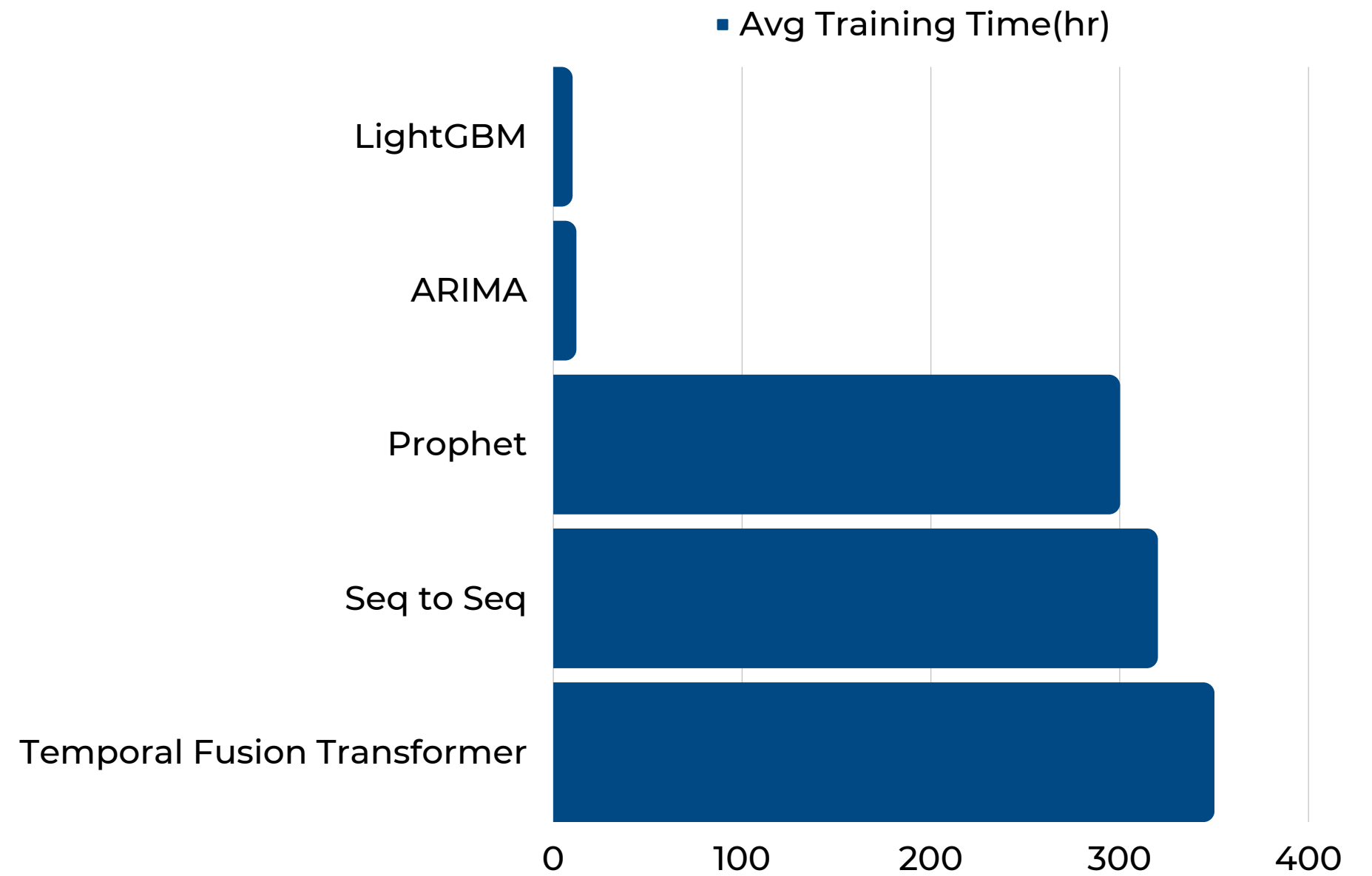
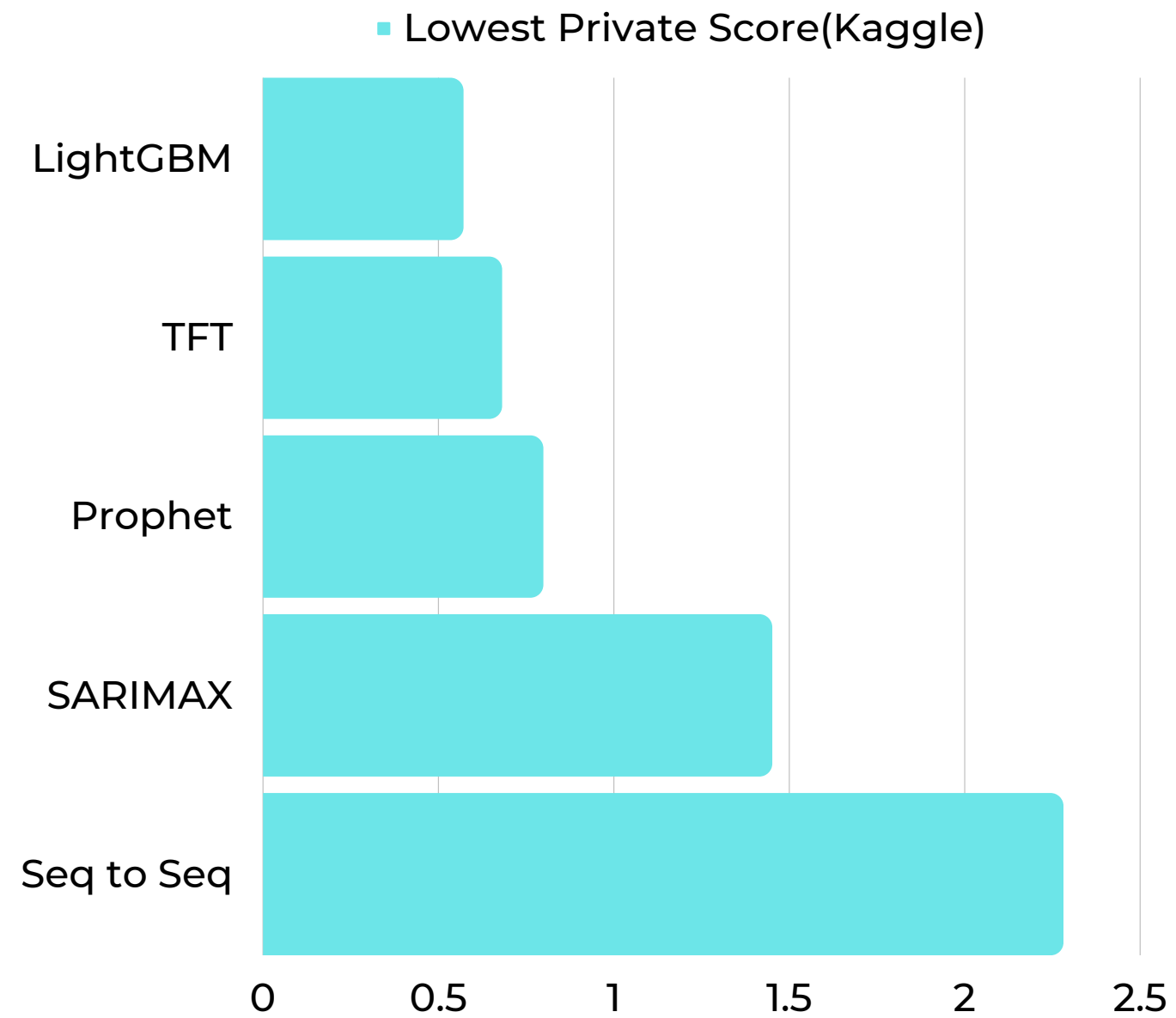
- Gating mechanisms
- Variable selection networks
- Static covariate encoder
- Interpretability



# Model Comparison

Approaches	Model	Pros	Cons
Machine Learning	LightGBM	<ul style="list-style-type: none"><li>• Faster training speed and higher efficiency</li><li>• Lower memory usage</li><li>• Better accuracy than any other boosting algorithm</li><li>• Compatibility with Large Datasets</li></ul>	<ul style="list-style-type: none"><li>• Overfitting</li><li>• Sensitive to noise data</li></ul>
Statistics	SARIMAX	<ul style="list-style-type: none"><li>• Brings seasonality as a parameter</li><li>• Supports exogenous variables</li></ul>	<ul style="list-style-type: none"><li>• Required stationary data</li><li>• Linear relationship only</li></ul>
	Prophet	<ul style="list-style-type: none"><li>• Accommodates seasonality with multiple periods</li><li>• Resilient to missing values</li><li>• Fitting the model is fast</li><li>• Enable hyperparameter tuning</li></ul>	<ul style="list-style-type: none"><li>• Dependence on past realizations is completely ignored</li><li>• Variance is presumed to be constant</li></ul>
	Seq2seq	<ul style="list-style-type: none"><li>• Much less human engineering effort</li></ul>	<ul style="list-style-type: none"><li>• less interpretable, hard to debug</li><li>• incapability of long sentences memory</li></ul>
	Transformer	<ul style="list-style-type: none"><li>• Attention allow decoder to focus on certain parts of the source</li><li>• Able to capture long-range dependencies and interactions</li></ul>	<ul style="list-style-type: none"><li>• High memory usage</li><li>• Inability to process input sequentially</li></ul>
Deep Learning			

# Performance Comparison



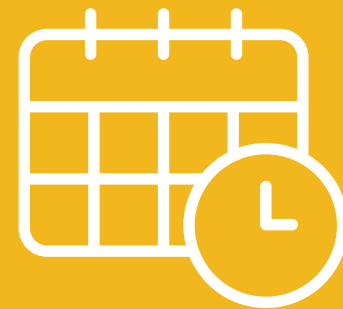
# Features

## CATEGORICAL



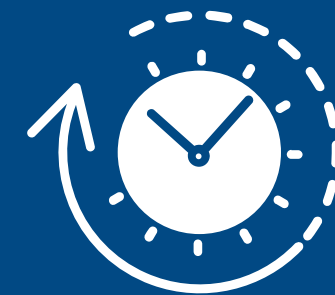
Store Id  
Dept Id  
Item Id

## TEMPORAL



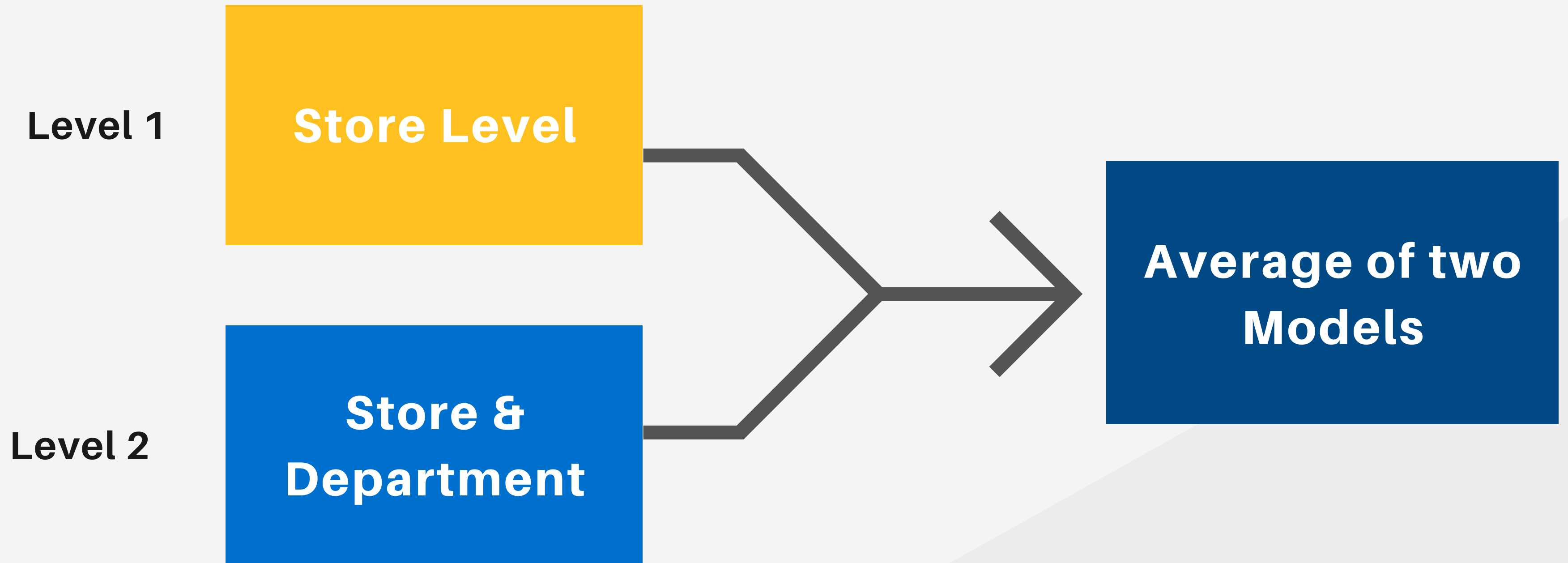
Weekday  
week\_month  
month, day  
Events  
SNAP  
Sell Price

## LAG



Past item sales  
- Item level  
- Dept level  
- Store level  
Past Sell Price  
4wks, 5wks, 6wks

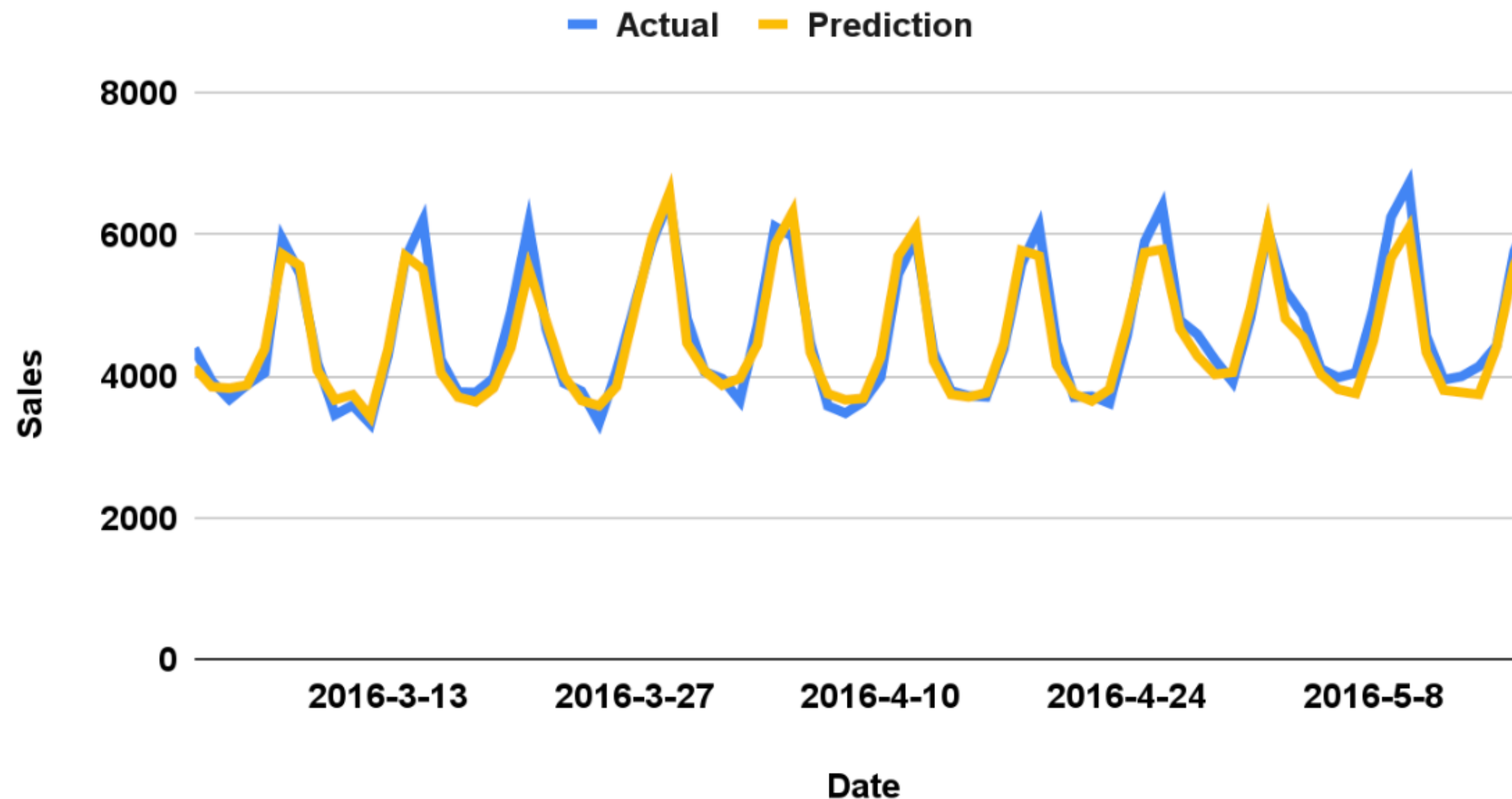
# Modeling Process



# Model Outcome

**Test Metrics: Mean Absolute Percentage Error = 4.97%**

On average our predictions have less than **5%** error from the actual sales



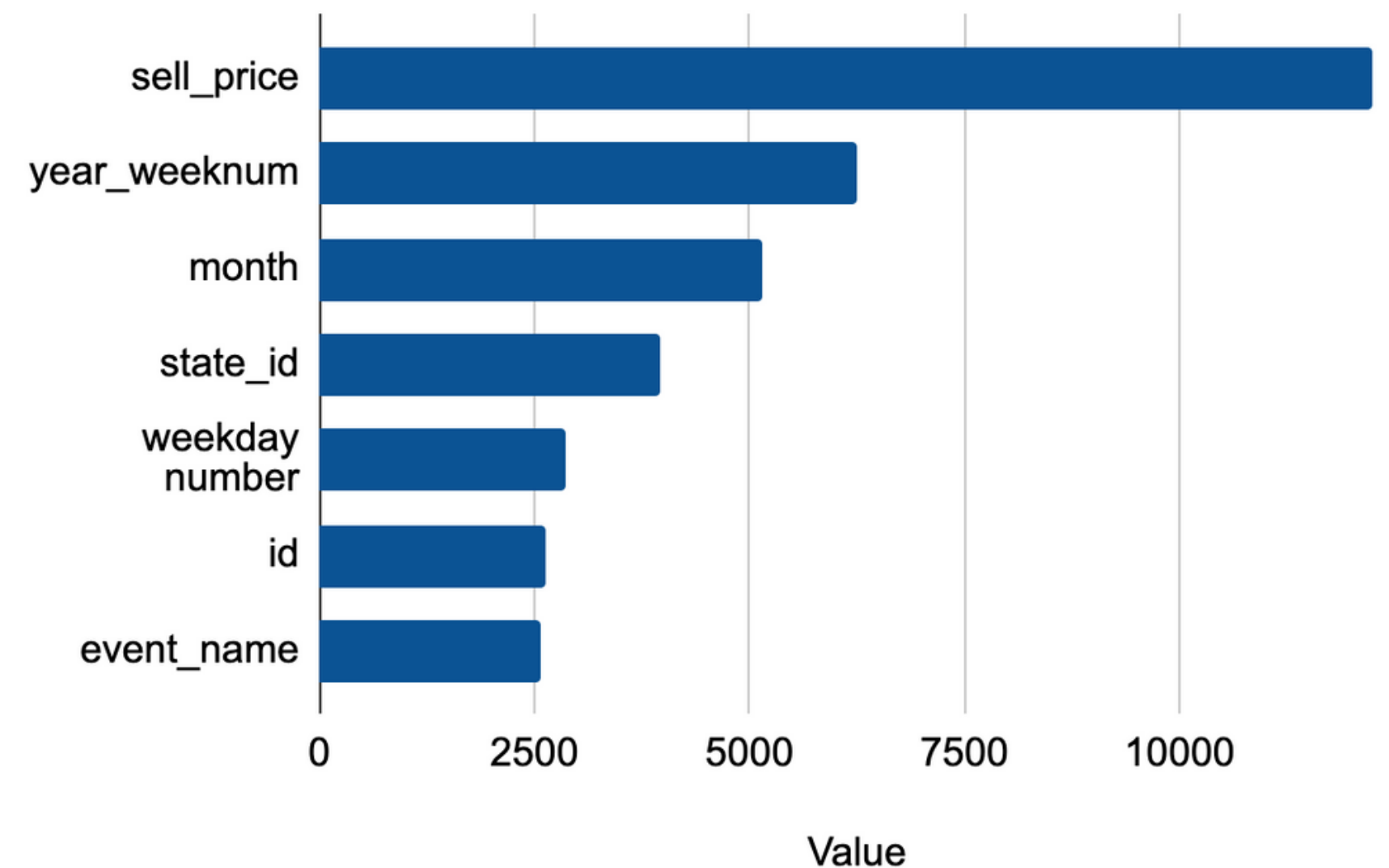
# Findings/Conclusions

Sell price is the #1 factor that impacts sales

There exist distinct patterns that follow along the calendar which are easily predictable using the historical data

The demand for the same item can vary by state as states can have different customer bases

Model Feature Importance Score





**THANK  
YOU**

