Retail Sales Forecasting at Walmart

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The biggest challenge as a forecasting practitioner

The boss says:

I need a forecast of …

A forecaster should respond:

Why?

Today's Focus

The boss says:

I need a better sales forecast

What the boss really means:

We have an issue staying in-stock on certain items and think that pricing may be causing a problem

Domain Overview: Item Flow

Manufacturer

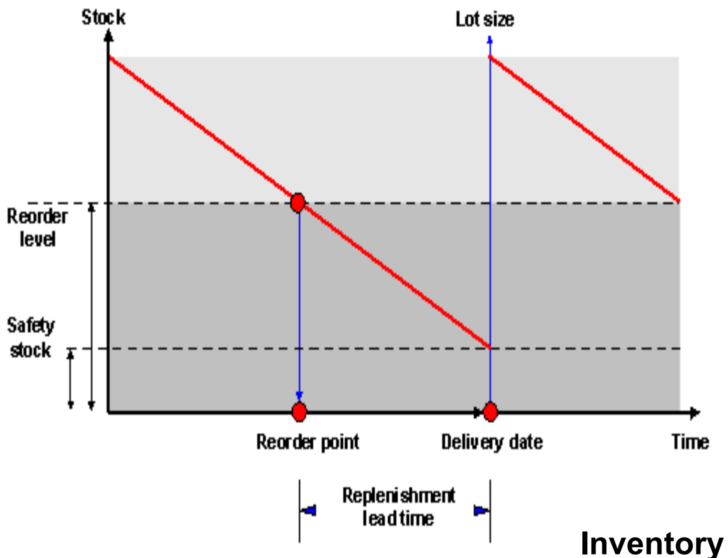
Fulfillment Center

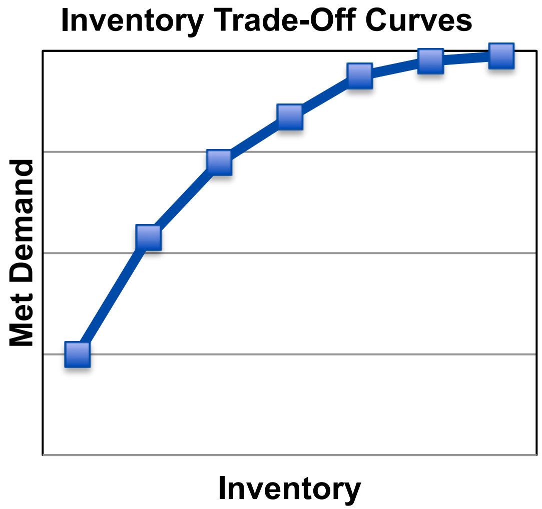
Customer

Replenishment

Pricing

Domain Overview: Replenishment





Objective

- Maintain lowest inventory level to meet the expected customer service level

Challenges

- Variable or long lead time items
- Uncertain forecasts
- Limited budgets
- Network flow constraints
- Holiday peaks
- Met demand and inventory trade off
- Leveraging store orders and inventory

Domain Overview: Pricing

Customers deserve the lowest price that we can offer at all times

Objective

- Set the item price to drive sales

Challenges

- What is a fair price?
- How much will we sell?
- How long will inventory last?
- What is impact to other items?

Domain Overview: Forecasts and Price

- Replenishment:
  - place order based on a forecast of an assumed future price
  - $O = F(f(P))$
- Pricing:
  - set the price based on a predicted forecasts of possible prices
  - $P = G(f(p))$
- Pricing happens after inventory is purchased

Tradeoffs

different problems

require

different solutions

Possible Forecast Objectives for an Item

- Forecast Demand
- Forecast a Distribution
- Forecast by Location
- Forecast by Customer
- Forecast Sales
- Forecast In-stock Rates
- Forecast Profit Margin
- Forecast Social Media Posts

Objective is to Improve the Customer Metrics

- Replenishment:
  - Forecast Demand Distribution
  - Assume in-stock in the future
  - Focus on upper percentiles of distribution

- Pricing:
  - Forecast Sales
  - Predict future in-stock rates

- Demand and Sales can differ based on in-stock rates
- Imputation of data can either improve or worsen forecasts depending on use
- A good mean forecast may generate a bad 95th percentile

Error Metrics

- Error
  - Defines the accuracy of the forecasts
  - $E = \Sigma \mid f - a \mid^2$
- Bias
  - Defines if the forecasts on average are high or low
  - $B = \Sigma (f - a)$
- Volatility
  - Defines how much the forecast changes over time
  - $V = \Sigma \mid f_t - f_{t-1} \mid^2$
- Feel free to weight and normalize these metrics according to use case
- When deciding between models, you must make tradeoffs between metrics

Tradeoffs: Error Metrics

- Replenishment:
  - High volatility can cause huge overstocks
  - Volatility trumps accuracy and bias
- Pricing:
  - Bias can be ignored depending on objectives
  - Accuracy trumps bias and volatility
- True impact must be determined through experimentation and simulation

Tradeoffs: Timescales

- Replenishment:
  - Set by the ordering lead times
  - Generally days to months
- Pricing:
  - Set by pricing strategy
  - Varies from seconds to months
- Long time scales must include seasonality, with short time scales it is optional

Tradeoffs: Computation Speed

- Replenishment:
  - Slow reaction times allow for slower forecasting
  - There is time to correct and change orders
- Pricing:
  - Fast reaction times demand faster forecasting
  - Must react quickly due to immediate customer impact

Tradeoffs

	Replenishment	Pricing
Objective	Demand Distribution	Mean Sales
Metric	Low Volatility	High Accuracy
Timescale	Long	Short
Speed	Slow	Fast

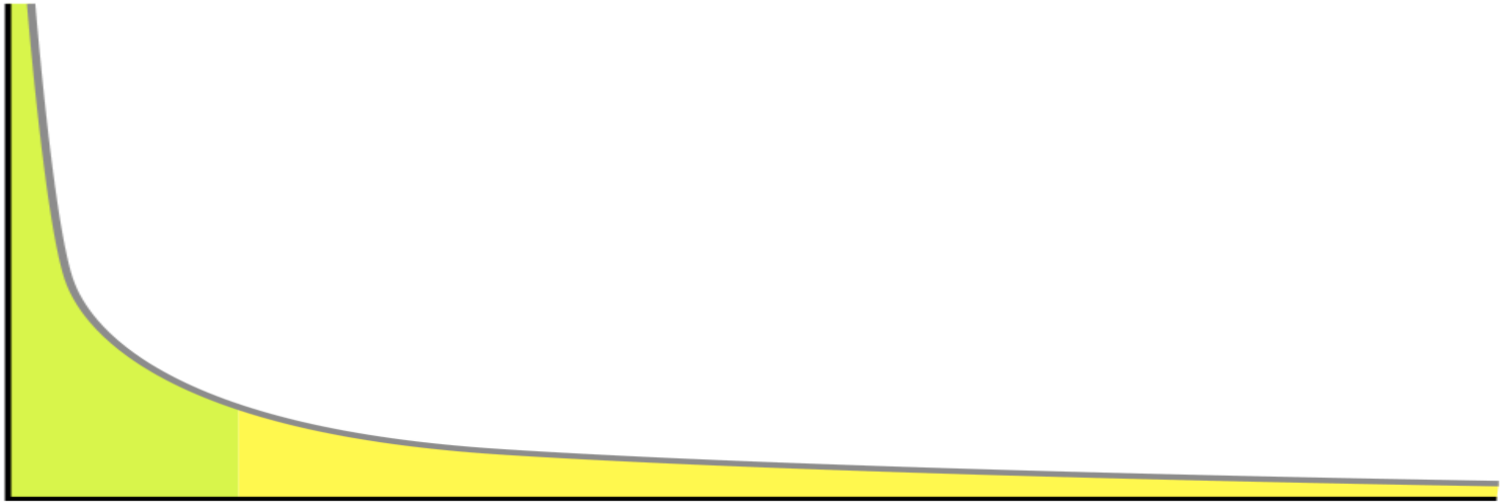
Item Size

- Walmart Stores
  - ~12k Stores
  - ~200k items per store
  - ~2b unique store/items to forecast
  - ~40b item/item correlations

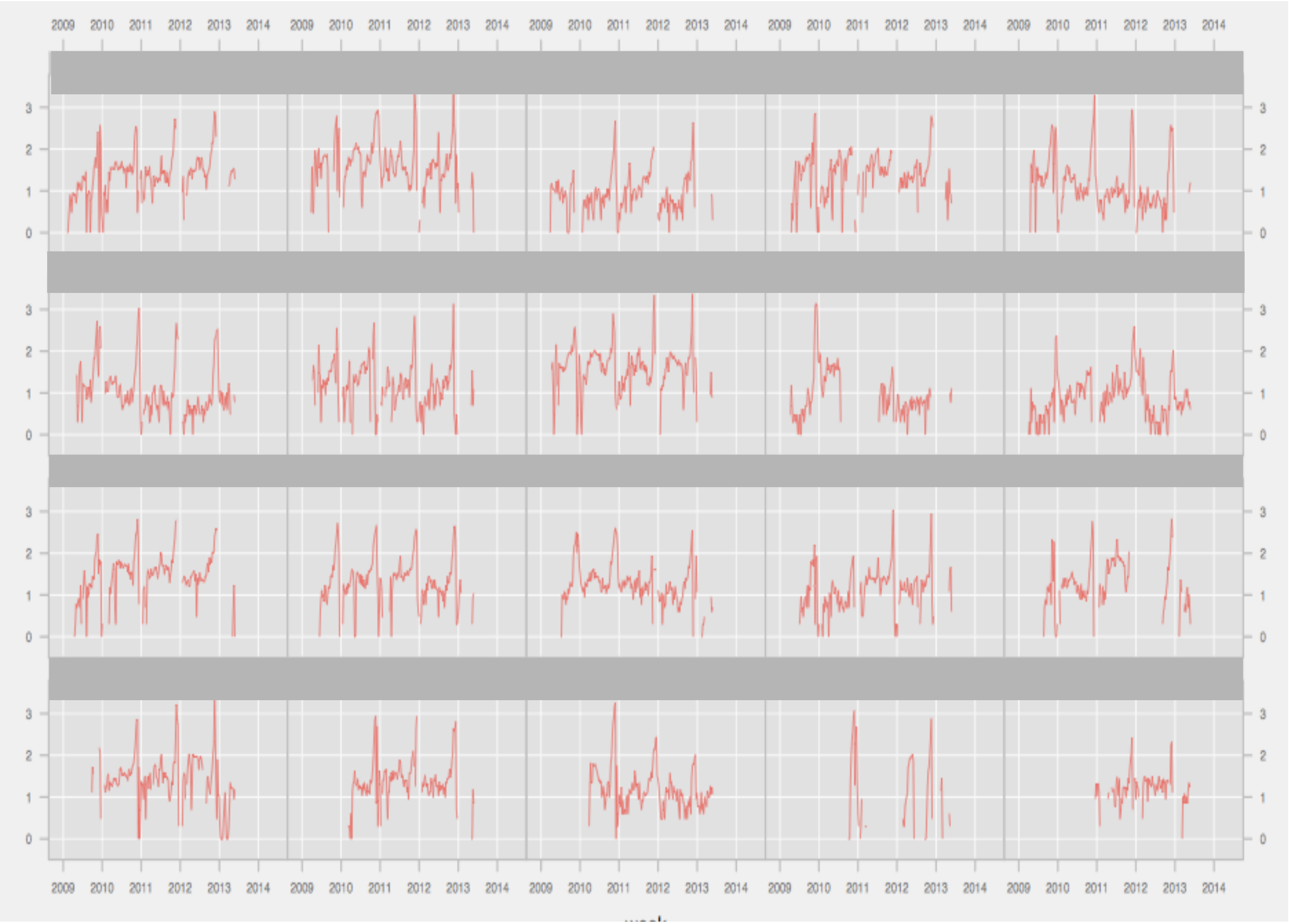
- Walmart.com
  - >50m items
  - 40k ZIP codes
  - ~2t unique ZIP/items to forecast
  - ~2000t item/item correlations

Walmart.com Item Information

- >50m items
- Each item has 100s to 1000s of attributes
- Few items sell consistently and have a long and complete time series
- Sales can be sparse and occasional stock-outs lead to missing data
- New items with no or relatively short sales history



Modeling: Sample Sales Data



New Tradeoffs

	Replenishment	Pricing
Objective	Demand Distribution	Mean Sales
Metric	Low Volatility	High Accuracy
Timescale	Long	Short
Speed	**Fast**	**Very Fast**

Walmart

Item Characterization

History

Complete

- Pick your favorite method
- Most are generally “good enough”

Partial

- Off the shelf methods fail quickly
- This is the hard part

None

- Can’t use time series methods
- Machine Learning problem

Sales

Consistent

- “Regular” distribution
- Most are generally “good enough”

Intermittent

- Many zeros with occasional sales
- Be careful how the forecast is used

None

- This is pretty simple

Partial History

- Why do we have partial history?
  - Recently introduced item
  - Items go out of stock
  - Data feeds are corrupted
- What can we do?
  - We have lots of items, some items with excellent history
  - Share information across items
- New problems:
  - How should they share information?
  - Which items should share information?
  - What information should they share?

Modeling

- Requirements
  - Fast
  - Include seasonality
  - Low volatility
  - Allow for missing data
  - Share information across items
- Our plan:
  - Cluster like items together
  - Calculate seasonal components
  - Forecast demand with multivariate DLMs
  - Estimate distribution function

Multivariate Dynamic Linear Model

$$\mathbf{Y}_t = \left[\begin{array}{ccc|ccc} 1 & & & \psi(t) & & \\ & \ddots & & & \ddots & \\ & & 1 & & & \psi(t) \end{array}\right] \begin{bmatrix} \boldsymbol{\mu}_t \\ \boldsymbol{\alpha}_t \end{bmatrix} + \boldsymbol{\epsilon}_t,$$

$$\begin{bmatrix} \boldsymbol{\mu}_t \\ \boldsymbol{\alpha}_t \end{bmatrix} = \begin{bmatrix} \boldsymbol{\mu}_{t-1} \\ \boldsymbol{\alpha}_{t-1} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_{1t} \\ \boldsymbol{\varepsilon}_{2t} \end{bmatrix},$$

$$\boldsymbol{\epsilon}_t \sim N(0, \sigma^2 \mathbf{I}_n) \;\&\; \begin{pmatrix} \boldsymbol{\varepsilon}_{1t} \\ \boldsymbol{\varepsilon}_{2t} \end{pmatrix} \sim N\left(0, \sigma^2 \begin{bmatrix} g_1 \mathbf{W}_1 & \\ & g_2 \mathbf{W}_2 \end{bmatrix}\right)$$

- Local level seasonal DLM
- Y is a vector of demand for a panel of n items
- g are variance scalars
- W are correlation matrices
  - Diagonals of W determine temporal smoothing
  - Off-diagonals of W determine cross section smoothing
- Models like DLM can be computed iteratively = fast

Modeling: Clustering

- Computing a DLM across 1b entities is probably overkill

- Possible similarity metrics:
  - Euclidean distance
    - L1 or L2 norm has issues with scale
  - Pearson correlation
    - cosine angle is susceptible to outliers
  - Spearman correlation
    - ranked vectors is our Goldilocks metric

- Cluster via your favorite K-means variant

- Leverage semantic information to improve sparsity issues

Final Thoughts: Ensembling

- Generally, ensembling gives better forecasts with fewer outliers
- Fit models with different parameters and use CV to identify best combination

$$y^*_{it} = w_1 y^1_{it} + w_2 y^2_{it} + \ldots + w_p y^p_{it} \text{ s.t. } w_i \geq 0 \ \& \ \sum_i w_i \approx 1$$

- Forecasts may be correlated so you want parameters to be non negative
- Many ways to do this – LASSO, NNLS, Bagging, etc
- Boosting/Random Forests additionally helps to incorporate other predictors

Questions