Retail demand forecasting: what we know and how it is practised

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Why is retail demand forecasting important & interesting?

- Chaos in retail
  - High street, out-of-town, on-line

- Logistics and environment
  - Packaging
  - Availability

- Service vs inventory: the trade-off
  - Poor forecasts, poor availability, excess stock: Costs

- Technical issues: 50K products x 400 stores, daily: 200K on-line offerings, human factors
Outline

1. Challenges and decisions facing a retail chain
   ▪ Forecast requirements
2. Aggregate forecasting
   ▪ Strategic Store location
3. Product SKU level demand forecasting
   ▪ Problem features
4. Many explanatory variables
   ▪ Price optimization
   ▪ Product SKU level forecasting
5. New Products
6. Channels and Social Media Retail forecasting practice
7. Practical Challenges in Retail forecasting
Challenges in Retail Forecasting

• Strategic decisions
  – Rapidly changing competitive environment
    • channels
  – Store locations
  – On-line / in-town presence
  – CRM issues, e.g. financing, loyalty cards

• Tactical
  – Categories and assortment
    • Brand forecasts
  – Promotional plan
  – On-shelf availability and service level
  – Distribution centre planning (space, fleet, staffing, service): volume forecasts by size and store

• Operational
  – ‘Big data’
    • SKU x store models for promotional planning and price optimization
  – Short life cycles/ new products/ intermittent demand
  – Rapid replenishment
Aggregate forecasting

Total Retail sales in a market (at country or regional level)

• No models linking Retail sales to more aggregate economic variables (e.g. GDP)
  – Comparison with time series alternatives ×
  – No single method performing best

• Disaggregation by channel, by product category
  – Important as total sales masks changes in channel share

• By chain
  – Including info on the store mix, e.g. age mix of stores ✓
  – Financial variables ✓

⇒ Improved accuracy
Forecasting Store Sales

- **Rapid change in UK market**
  - Shift away from out-of-town to convenience
  - Shift to on-line
  - Shift to low price

- **New store location models**
  - Variables: distance, location and image, services, competition: historical geographical set-up
  - Current Stores provide a biased sample
  - Decisions based on models + judgment
  - BUT changing purchasing behaviour and the shift to on-line?

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**Appraisal used for store closures**

**The problem**
- Current data on sales poor predictor
- Interaction with on-line

**The result**
- Reliance on judgment
Decisions:

- **Category (tactical)**
  - Brand, sku mix
  - Space allocation
- **Brand**
  - Promotional strategy (frequency)
  - Feature & display
- **SKU (operational)**
  - Revenue Optimisation
- **SKU x Store**
  - Segmented stores (e.g. in-town vs out-of-town)
- **Distribution Centre: Store x volume**
  - Logistics plan: DC volume

**Aggregation approach?**

**No research on DC dependence on demand?**
Product level features I

- Forecasts needed within different hierarchies
  - Time
    - Daily at store level for replenishment
    - Weekly at DC level for logistics (picks)
  - Product
  - Supply chain
    - Collaboration?
    - Consistency needed down each hierarchy

- Data characteristics
  - Stock-outs: demand vs sales
    - Limited data, new technologies (RFID), statistical models
  - Intermittence (lots of it)

Amazon: Out of stock ignored
Out-of-stock treated as missing values

The forecasting accuracy punch line: hierarchies, stock-outs, intermittence all matter
Intermittence – a neglected problem?

- Regular retailers (70% of SKUs intermittent per week)
- On-line (all?)
- Standard time series methods fail
- Croston the 1971 standard
- Recent activity creating new methods
- Measuring accuracy difficult
  - MAPE, MAE fail and distort
  - Zero forecast!
  - Stock measures?
  - Inventory policies based on normal distribution
  - Model cumulative demand over the order period
Product level features II

• Seasonality
  – Multiple seasonalities
  – Weekly and daily seasonals interact

• Weather impacts
  – Beer, ice-cream, barbecue
  – But forecasts: horizon, region?
    World cup effects on beer
    – win or lose

• Events

Improved model forecast accuracy
- but in a model?
Product level features III

- Promotions
  - Promotional type
  - Category
  - Lagged effects
    - Black Friday stealing sales from Xmas

- On-line reviews and social media

Promotional effects: price, feature and display across categories
Research issues and solutions in SKU level forecasting

• Aggregation and consistency
  – Top down vs bottom-up vs middle out
  – Aim for consistency
    • But no consistent best performer

• Disaggregation and explanatory variable effects
  – Disaggregate models needed for heterogeneous effects
    • Store level
    • Category SKUs
  – Many variables
    • But which ones matter?

• Price-promotional optimization
Evaluation

Key issue: relate to decision problem and lead time

• Mean Absolute error

\[ MAE = \frac{1}{m} \sum_{i=1}^{m} |Y_{t+i} - F_{t+i}| / m = \frac{1}{m} \sum_{i=1}^{m} |e_{t+i}| / m. \]

• MAPE most often used

\[ MAPE = \frac{100}{m} \sum_{i=1}^{m} \frac{|Y_{t+i} - F_{t+i}|}{Y_{t+i}} = \frac{100}{m} \sum_{i=1}^{m} \frac{|e_{t+i}|}{Y_{t+i}}. \]

• Define Relative Mean Absolute Error (compared to benchmark method \( B \)):

\[ \text{Rel } MAE_i = \frac{MAE_{A_i}}{MAE_{B_i}}. \]

• Summarize over series (for fixed lead time):

\[ MAPE = \text{Mean}(MAPE_i) \]

\[ \text{Rel } MAE = \text{Geometric Mean}(\text{Rel } MAE_i) \]

• Error < 1 method better than benchmark
• Error > 1 method worse than benchmark
Evaluation

Key issue: relate to decision problem and lead time

- Mean Absolute Error
- MAPE most often used
- Define Relative Mean Absolute Error (compared to benchmark method B):
- Summarize over series (for fixed lead time):

  \[
  MAPE = \text{Mean}(MAPE_i)
  \]

  \[
  \text{Rel MAE} = \text{Geometric Mean}(\text{Rel MAE}_i)
  \]

  - Error < 1 method better than benchmark
  - Error > 1 method worse than benchmark

The issue:

- Company KPIs poorly define
- No link to decision problem
- Software poorly configured

Consequences:

- Service/inventory tradeoff
- Inappropriate choice of forecasting method
Conclusions from SKU modelling of regular products

• Base models using last promotional uplift wholly inadequate

• **Pooling** data and models across SKUs and Stores improves estimation and forecast accuracy

• Increasingly **complex** models deliver value
  – Using focal SKU
  – Using core competitive SKUs
  – Using all SKUs in category

• **Non-linearities?**
  – Software companies emphasizing its importance

**Practical issues:**
• **Best ‘simple’ methods?**
• **Are non-linear effects valuable?**
• **Use of software**
  • **Judgment?**
New Products I

*Defined as products with less than 2 seasons data history*

- **Decision context**
  - Initial stocking
  - Short Life cycle (fashion goods: electronics)
    - Buying ahead: re-order?
  - The assortment decision: adding a new SKU to a category
  - Distributional consequences of new SKU

- **How prevalent?**
  - In UK non-food hardware, homeware and garden
    - 50% in data base have less than 2 years history

- **Retailers as manufacturers**
  - Same techniques: market testing, choice models, diffusion

- **Fashion forecasting as new product forecasting**
  - Literature on non-linear methods unconvincing
  - New methods based on clustering new products based on features
    - colour, price, segment, + click data
    - Forecasting models for clusters

*High variability?*
New Products II

New product forecasting methods for retail

- Continuity of data with past SKUs
- Judgment
- Structured judgment
  - Analogous products
  - Interactions with manufacturers ( & their forecasts)
- Attribute models of similar products (Vaidyanathan, 2011)
- Bayesian methods based on analogous products
  - Clustering (see Goodwin et al.)
  - Clustering+regression within clusters

- Major application possibilities in fashion forecasting but...;
  M&S’s views

No/ little modelling and evaluation

Practical impact: high
Channels
On-line, catalogue vs Bricks & Mortar

- Rapid growth (in some categories) in on-line
- Competition, cannibalization and complementarity between channels (strategic/tactical)
  - Generic
  - Niche
  - Search
- On-line shopping (Operational)
  - Web-site design and effects on sales
  - Individual Customer Models
    - Recommender systems (If you like that you’ll like this)
    - Returns (and profitability)
Channels: internet sources (social media) and big-data: What we know

• Customer behavioural data
  – Useful for short-term sales generation
  – Potential
    • At SKU level
    • Promotional ‘customer centric’ targeting (Kolassa)

• Social media data
  – Some value for short-term forecasting of ‘instant’ impulse products, e.g. games, music
  – Weak signals (Kolassa, 2017)
    • Do they help?
SAP F&R forecasts: causal model
By SKU and Store: 40K in 400 stores, 25K ‘regular’
All skus held at two distribution centres
Focal Horizon: 26 weeks, 1-6 days for DC
10 promotional types: promotions across chain
Focal horizon for orders: 13 weeks

Sales & Marketing
Rolling two year promotional plan store level, FMCG, DIY, ...
Analysts interventions based on:
Weather, advertising
New products

Orders to vendors monthly
Stock control
Order to stores

Promotional info
Events

Retail Forecasting in practice

Tactical & Operational

Distribution Centre:
Translates into picks
Updated daily: depends on current stock levels
Forecast horizon? 1-10 days
Staff Scheduling

Forecasts: SKU x store x day
Daily forecasts automatically prorated?
Issues in practice

- Commercial software includes ‘demand sensing’ causal capabilities and non-linear methods.
- Few companies have routinized the use of these more advanced procedures; promotional modelling remains simplistic.
- New product forecasting remains heavily judgmental and informal.
- Intermittent demand is a key problem where current ‘best practice’ research has not been adopted.
- KPIs and accuracy measurement is typically not given sufficient attention.
- Lead time issues linked to the supply chain are rarely considered.
- The area of demand planning in retailing is manpower intensive where staff may have overly limited technical expertise.
  - Some companies have a ‘data science’ team to support the core forecasting activity.
- Judgmental intervention superimposed on model based forecasts remains a significant element in retail forecasting.

More tentatively, the diffusion of best practice modelling remains slow.
What do we (not) know?

• Advanced causal methods onSKU x store data offer (substantially) improved accuracy

• Advanced new product methods promising
  – Clustering on attributes

• Machine learning methods have potential
  – But not yet well validated on a range of applications

• Social media and search data
  – Probably not valuable for aggregate retail forecasting
  – Delivers for individual customer behaviour (A ‘Kolassa’ priority – the customer of one)

• Big data from customers, IoT and in-store unproven
  – Within day valuable

• On-line and bricks-and-mortar interaction?
Issues of practice
- what gets forgotten?

• Messy inadequate data
  – Incomplete short histories; new product introductions; intermittent demand; out-of-stock
  ⇒ Routine algorithms fail to manage exceptions
  – Event history
  ⇒ Better methods lack data on which they rely

• KPIs
  – The need to link to decisions
  – Forecast error history

• Value added of judgmental interventions
  – How much should organizations rely on their software?
  – How can interventions be made more effective?
Questions and Comments?


