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

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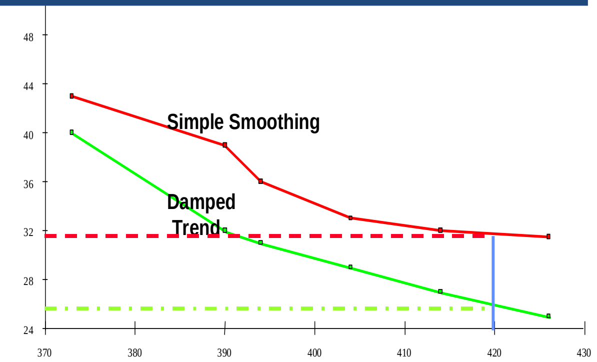
Why is retail demand forecasting important & interesting?

- 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

Service - inventory tradeoff curves



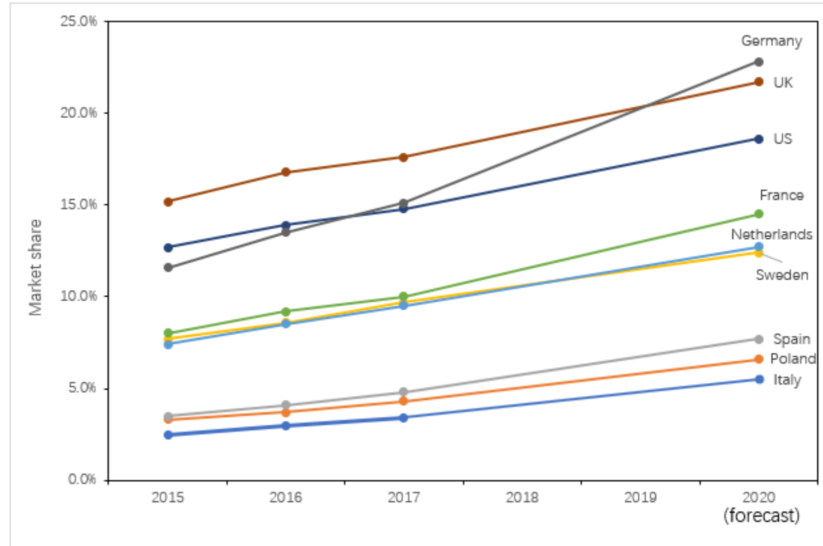
Outline

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 Conclusions
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

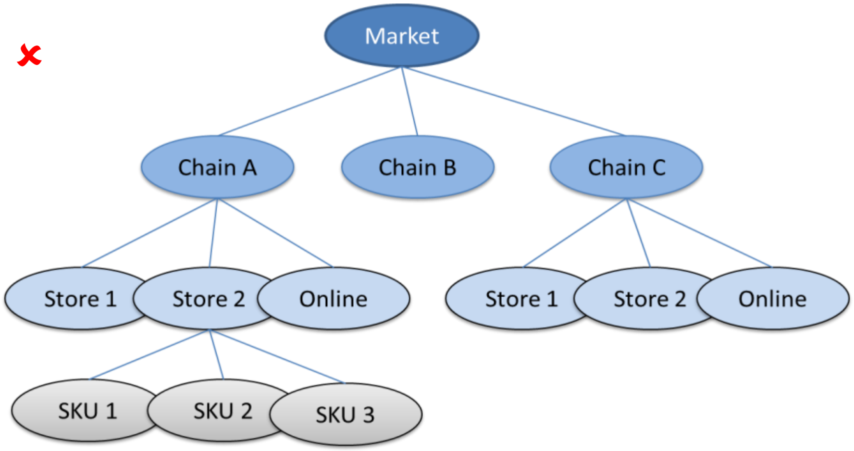
Online shares of Retail Trade



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

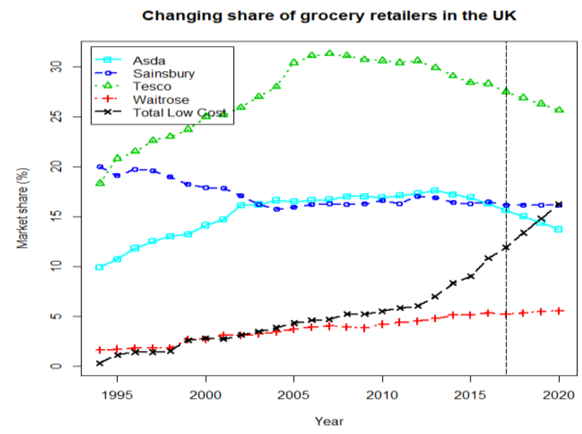


- Disaggregation by channel, by product category
  - Important as total sales masks changes in channel share

- 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?



Appraisal used for store closures

The problem

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

The result

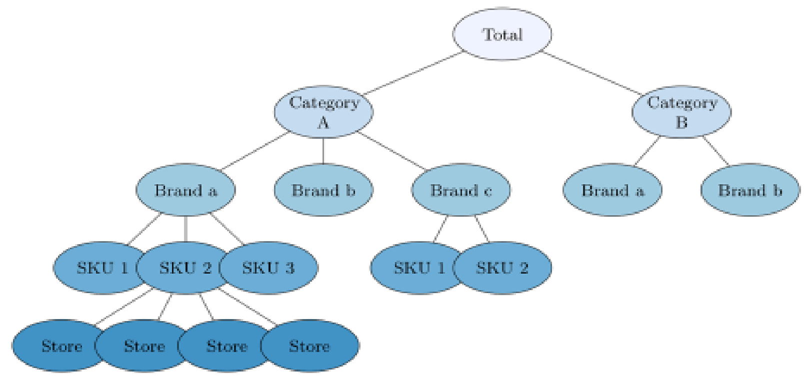
- *Reliance on judgment*

Tactical & Operational

Product level demand forecasting

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

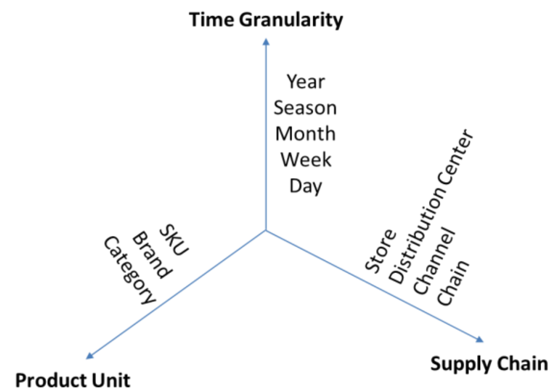


Aggregation approach?

No research on DC dependence on demand?

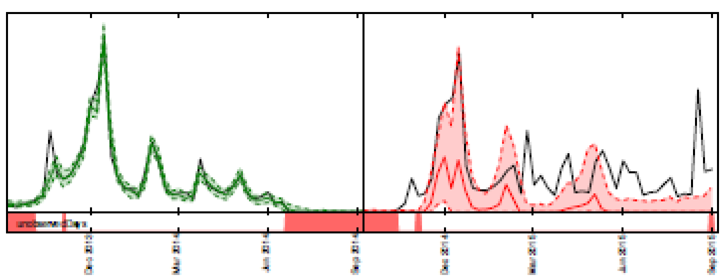
Product level features I

- 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

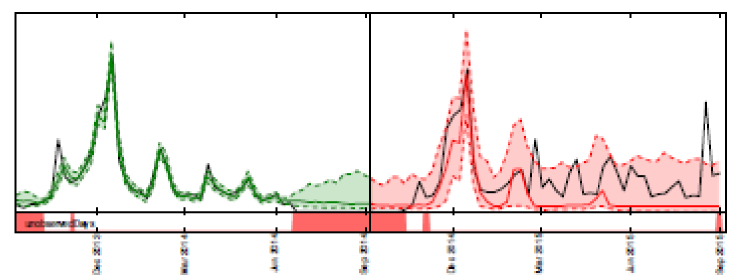


Multidimensional hierarchies

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



Amazon:Out of stock ignored



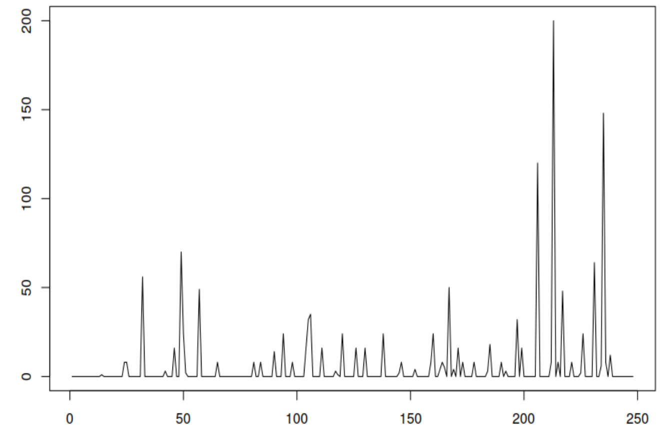
Out-of-stock treated as missing values

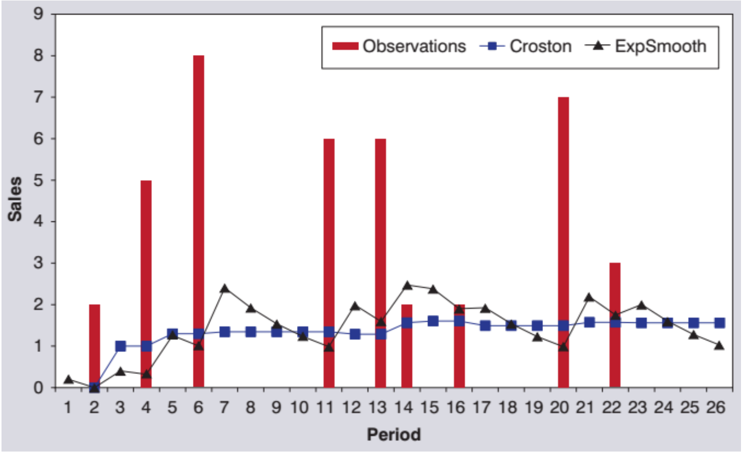
  - Intermittence (lots of it)

The forecasting accuracy punch line:
hierarchies, stock-outs, intermittence all matter

Intermittence – a neglected problem?

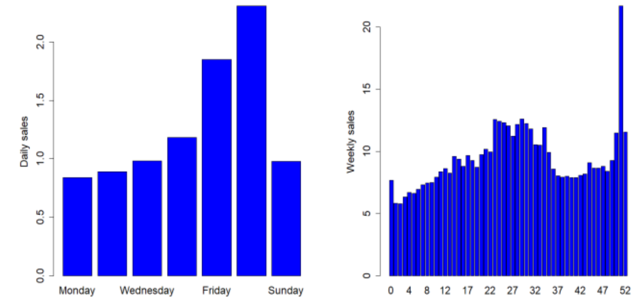
- Regular retailers (70% of SKUs intermittent per week)
- On-line (all?)
- Standard time series methods fail
- Croston the 1971 standard
- Recent activity creating new methods
- Measuring accuracy difficult
  - MAPE, MAE fail and distort
  - Zero forecast!
  - Stock measures?
  - Inventory policies based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





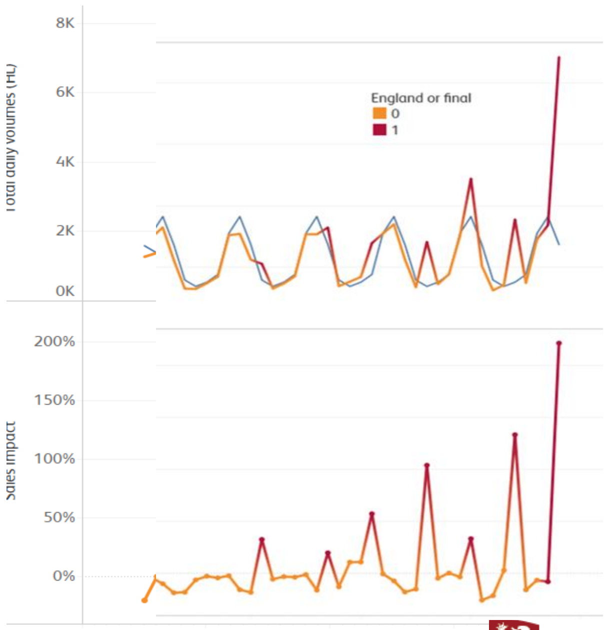
Product level features II

- Seasonality
  - Multiple seasonalities
  - Weekly and daily seasonals interact



Daily and weekly beer sales

- Weather impacts
  - Beer, ice-cream, barbecue
  - But forecasts: horizon, region?



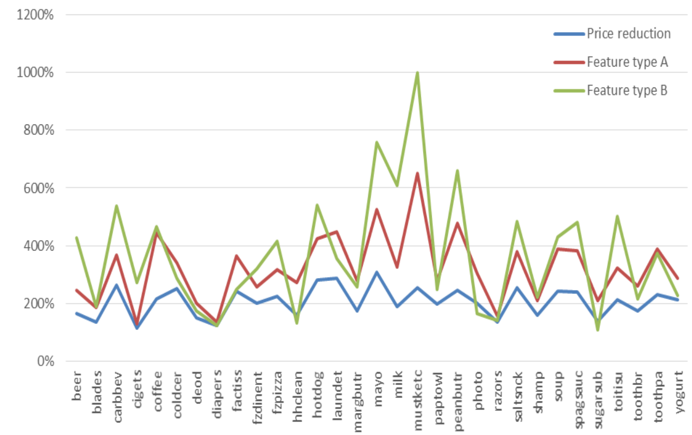
World cup effects on beer – win or lose

- 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

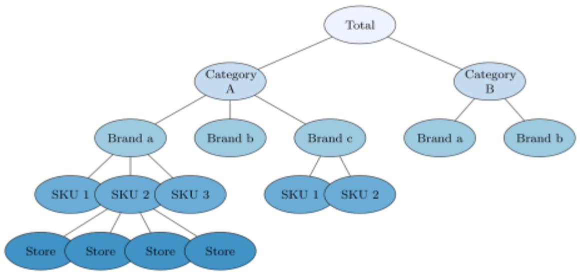


Promotional effects: price, feature and display across categories

- On-line reviews and social media

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

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

- 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*):

$$\mathrm{RelMAE}_i = {MAE_{Ai}}\big/{MAE_{Bi}}$$

- Summarize over series (for fixed lead time):

$$MAPE = \underset{i}{Mean}(MAPE_i)$$

$$\mathrm{RelMAE} = Geometric\ \underset{i}{Mean}(\mathrm{RelMAE}_i)$$

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

Evaluation

Key issue: relate to decision problem and lead time

- Mean A
- MAPE r
- Define ... od *B*):
- Summarize over series (for fixed lead time):

The issue:

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

Consequences:

- Service/inventory tradeoff
- Inappropiate choice of forecasting method

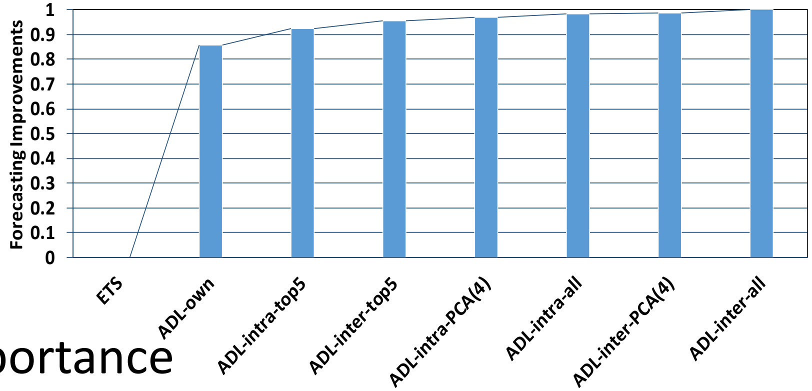
$$MAPE = \underset{i}{Mean}(MAPE_i)$$

$$\mathrm{Rel}MAE = Geometric\ \underset{i}{Mean}(\mathrm{Rel}MAE_i)$$

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

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

High variability?

- 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

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

No/ little modelling and evaluation

Practical impact: high

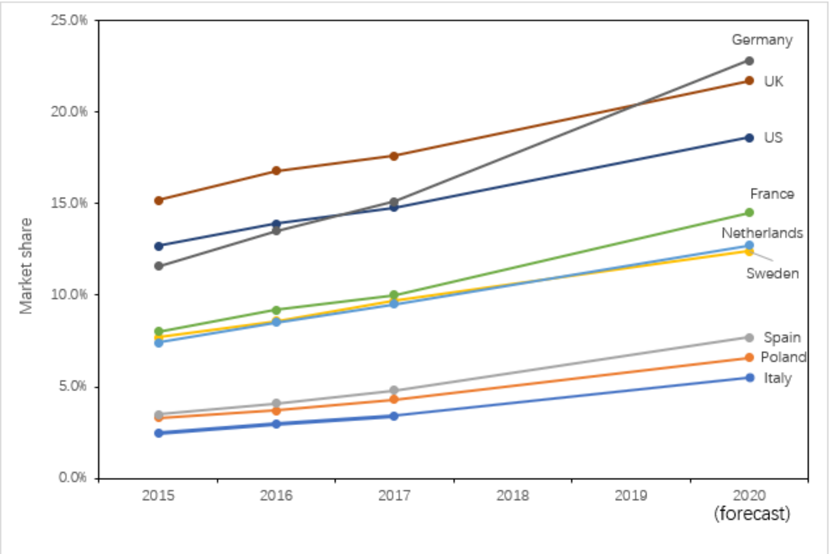
- Major application possibilities in fashion forecasting but…;

  M&S's views

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)

Online shares of Retail Trade



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?

Tactical & Operational

Variety of practices: bricks-and-mortar and on-line

Retail Forecasting in practice

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

Promotional info
Events

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

Orders to vendors monthly
Stock control
Order to stores

Forecasts: **SKU x store x day**
Daily forecasts automatically prorated?

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

Issues in practice

Interviews + presentations from 10 international companies: Household, groceries, fashion, convenience stores

- 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 on sku 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?

- By practitioners
- By researchers
- By software designers

- 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?

Fildes, R., Ma, S., & Kolassa, S. (2018). Retail forecasting: Research and practice. *Working Paper 2018:4*. Lancaster University.

Kolassa, S. (2017). Commentary: Big data or big hype? *Foresight: The International Journal of Applied Forecasting*, 22-23.

Schaer, O., Kourentzes, N., & Fildes, R. (2019). Demand forecasting with user-generated online information. *International Journal of Forecasting*, 197-212.

Ma, S., & Fildes, R. (2017). A retail store SKU promotions optimization model for category multi-period profit maximization. *European Journal of Operational Research, 260*, 680-692