Issues in Retail Forecasting

- Chaos in retail

High street, out-of-town, on-line

- Logistics and environment
- Service and availability
- Technical issues of scale; 50K products x 1000 stores, 500K + on-line

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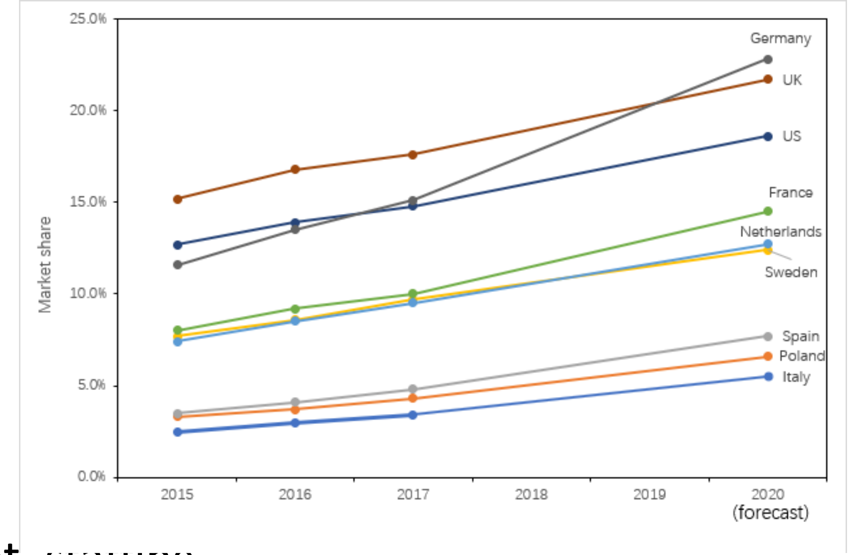
Outline

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

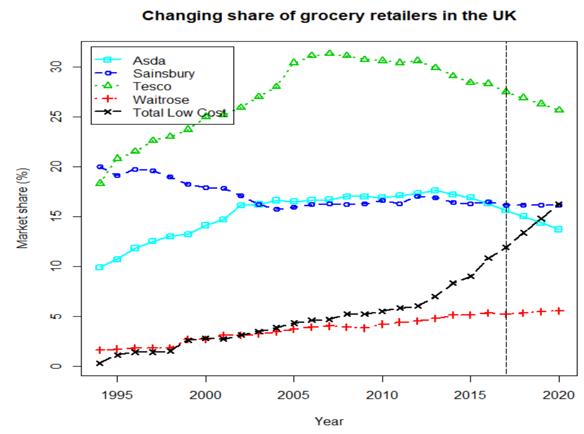
Online shares of Retail Trade



Strategic

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

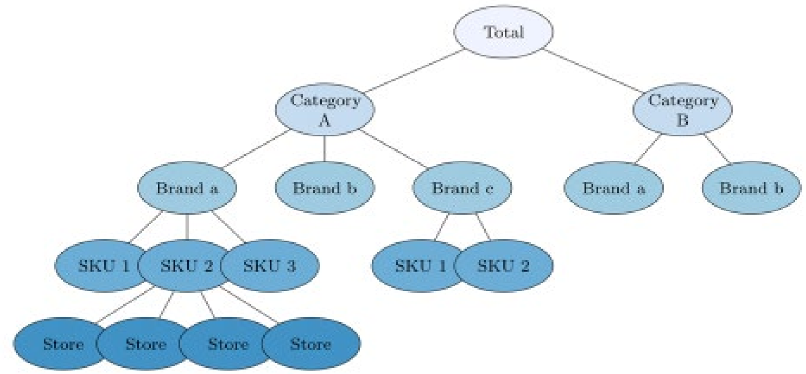
- *Current data on sales poor predictor*
- *Interaction with on-line*

The result

- *Reliance on judgment*

Tactical & Operational

Product level demand forecasting



Decisions:

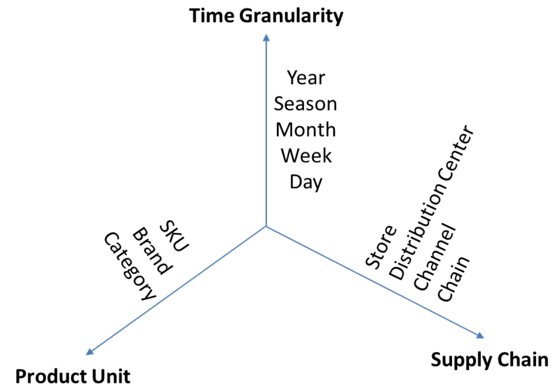
- Category (tactical)
  - Brand, sku mix
  - Space allocation
- Brand
  - Promotional strategy (frequency)
  - Feature & display
- SKU (operational)
  - Revenue Optimisation
- SKU x Store
  - Segmented stores (e.g. in-town vs out-of-town)
- Distribution Centre: Store x volume
  - Logistics plan: DC volume

Aggregation approach?

No research on DC dependence on demand?

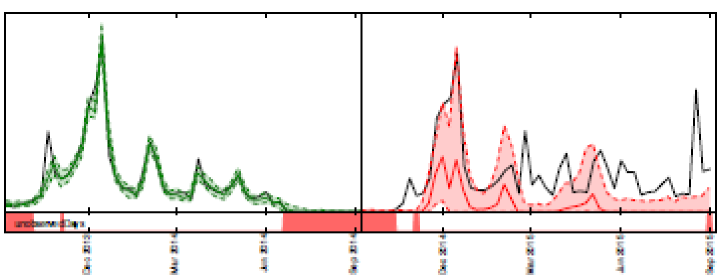
Product level features I

- 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

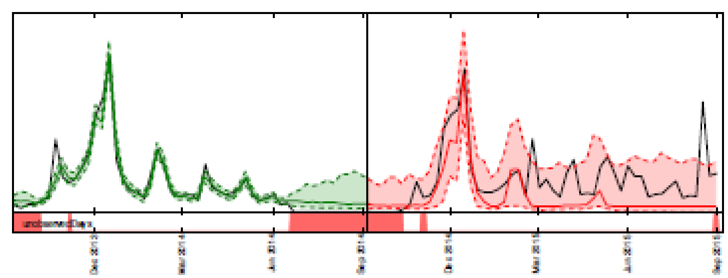


Multidimensional hierarchies

- 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

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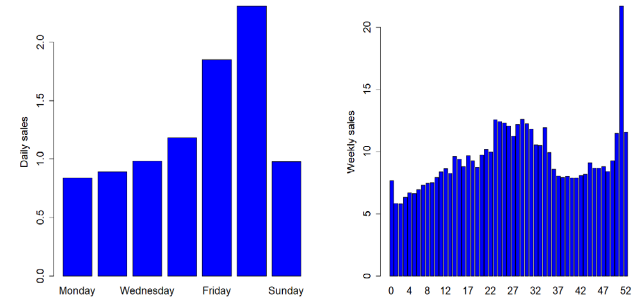
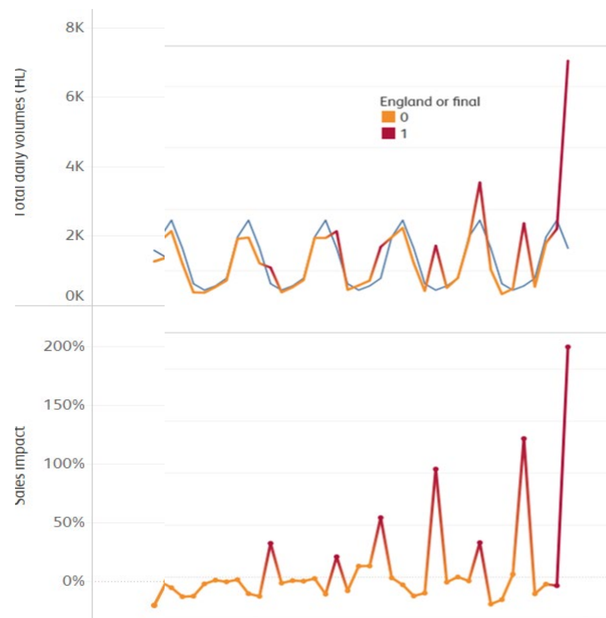
Product level features II

- Seasonality
  - Multiple seasonalities
  - Weekly and daily seasonals interact



Daily and weekly beer sales

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



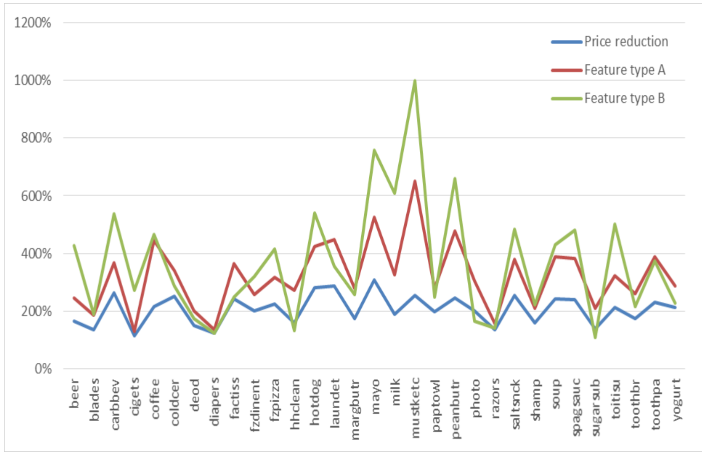
World cup effects on beer – win or lose

- 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

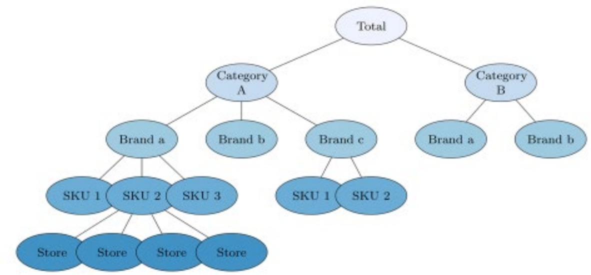


Promotional effects: price, feature and display across categories

- 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 (weather, events, seasonality, competition, social media)
    - But which ones matter?
- Price-promotional optimization

Demand models & Price optimization studies

Table 1
The studies on retailing promotion optimization

Paper	Data	Planning level	Cross-product influences	Cross-period influences	Forecast validation	Business Rules
Mulhern & Leone(1991)	Panel	Brand	Yes	No	No	No
Tellis &Zufryden (1995)	Panel	Brand	Yes	Yes	No	No
Vilcassim & Chintagunta(1995)	Panel	Brand	Yes	No	No	No
Ailawadi et al. (2007a)	Store	Category	Yes	Yes	No	No
Natter et al.(2007)	Store	SKU	Yes	No	No	No
Ferreira et al.(2015)	Store	SKU	Yes	No	No	No
Cohen et al.(2014)	Store	SKU	No	Yes	No	Yes
This study	Store	SKU	Yes	Yes	Yes	Yes

Shaohui et al., 2018, EJOR

Academic work limited

- Commercial implementations, e.g. SAP, SAS

Evaluation

Key issue: relate to decision problem and lead time

- Mean A
- MAPE r
- Define ... hod *B*):

The issue:

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

Consequences:

- Service/inventory tradeoff
- Inappropiate choice of forecasting method

- Summa... (for fixed lead time):

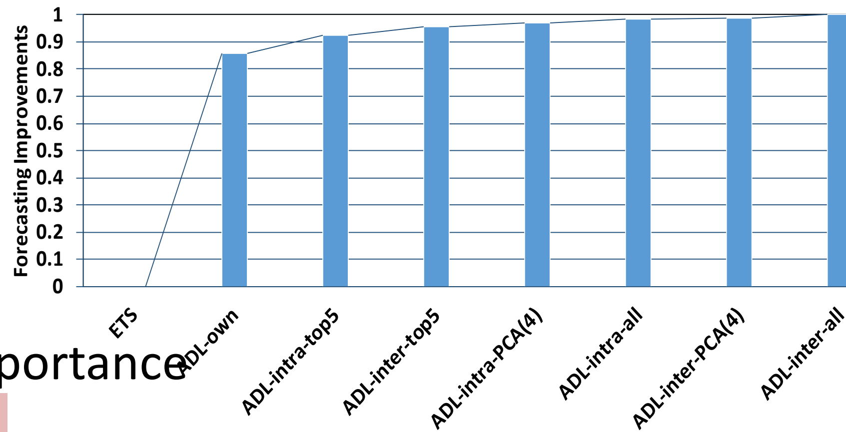
$$MAPE = \underset{i}{Mean}(MAPE_i)$$

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

- 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
New product forecasting methods for retail

Decision context

Initial stocking

Short Life cycle (fashion goods: electronics)

Buying ahead: re-order?

The assortment decision: adding a new SKU to a category

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

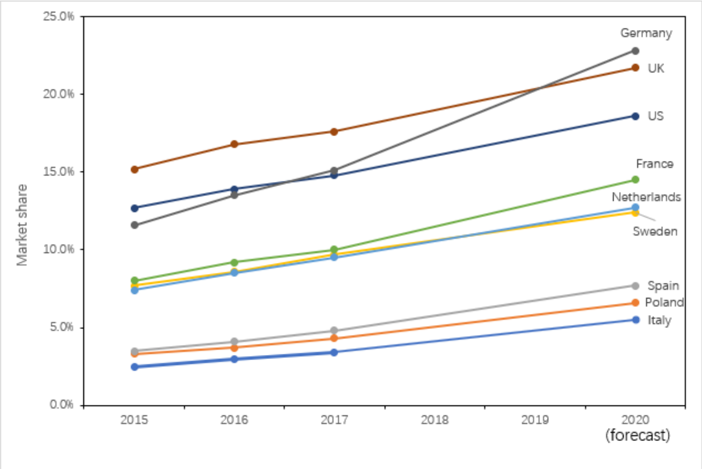
No/ little modelling and evaluation

Practical impact: high

Channels
On-line, catalogue vs Bricks & Mortar

- Rapid growth (in some categories) in on-line
- Competition, cannibalization and complementarity between channels (strategic/ tactical)
- Customer behavioural data in on-line shopping (Operational)
  - Web-site design and effects on sales
  - Individual Customer Models
    - Recommender systems (If you like that you'll like this)
  - 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?

Online shares of Retail Trade



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?

Research issues in Retail forecasting

- Robust methods for SKU level forecasting
  - Many market drivers + Uncertainty
  - Internet Sources: Big data applications
  - Integration of customer data in SKU/ Brand demand forecasting
  - Greater granularity (Aggregation across time/ skus)
- Characterizing retail data
  - Best models with promotions (Ramos/ Fildes)
  - Category/ Competitive/ brand effects.
  - Omni-retailing: complementarity between on-line and store
  - Short data series

And other issues?

  - Within-day ordering
  - New products
  - Practice and the software interface: integrating the demand planners
  - Collaboration with suppliers?
  - Benefits of machine learning?

Questions and Comments?

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