An Overview of Retail Forecasting

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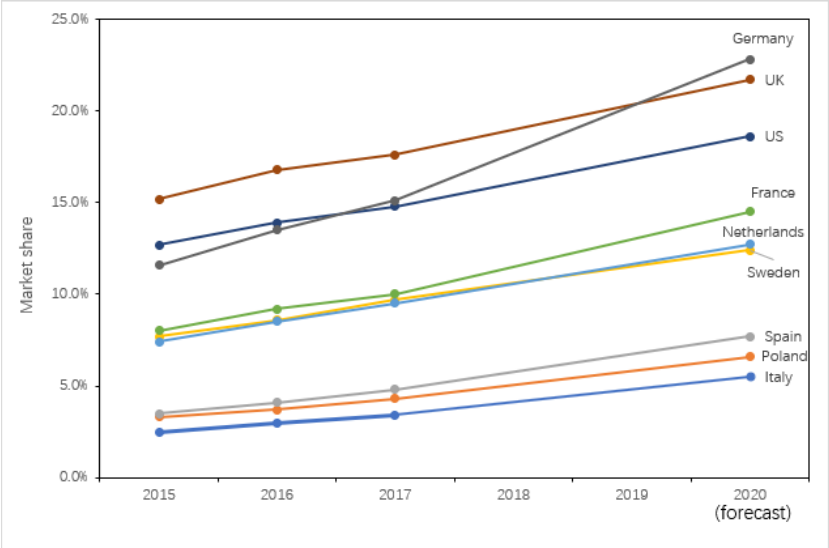
Outline

1. Challenges and decisions facing a retail chain
   - Forecast requirements
2. Aggregate forecasting
3. Product SKU level demand forecasting
   - Data Issues and Business Rules at product level
4. Many explanatory variables
   - Price optimization
   - Product SKU level forecasting Conclusions
5. New Products
6. Channels, Social Media and Big data
7. Retail forecasting practice
8. Research Issues and 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 and business rules
  - On-shelf availability and service level
  - Distribution centre planning (space, fleet, staffing, service): volume forecasts by size and store

Online shares of Retail Trade



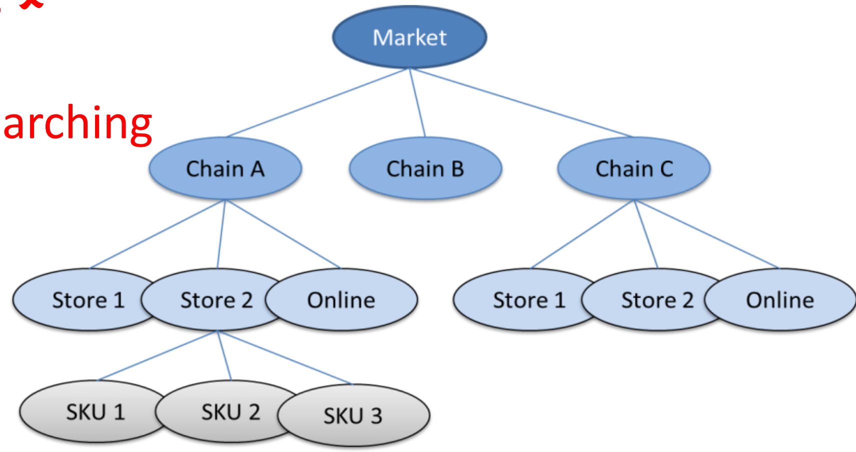
- Operational
  - ‘Big data’
    - SKU x store models for promotional planning and price optimization
  - Short life cycles/ new products/ intermittent demand
  - Rapid replenishment

Strategic

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
  - No evidence of non-linearities despite searching



- Disaggregation by channel, by product category

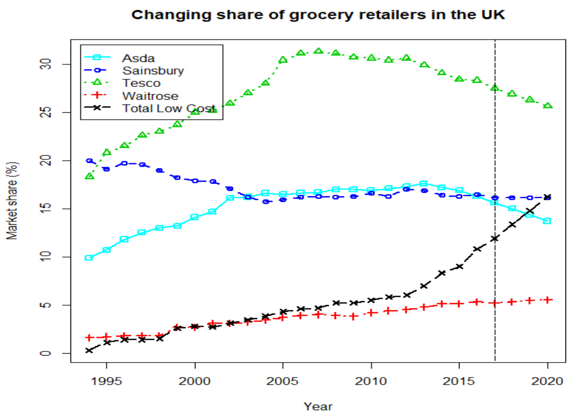
- By chain
  - Including info on the store mix, e.g. age mix of stores ✓
  - Financial variables ✓

  ⇨ **Improved accuracy**

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
  - Historically 'attraction models' based on past history but?
- Appraisal for store closures



The problem

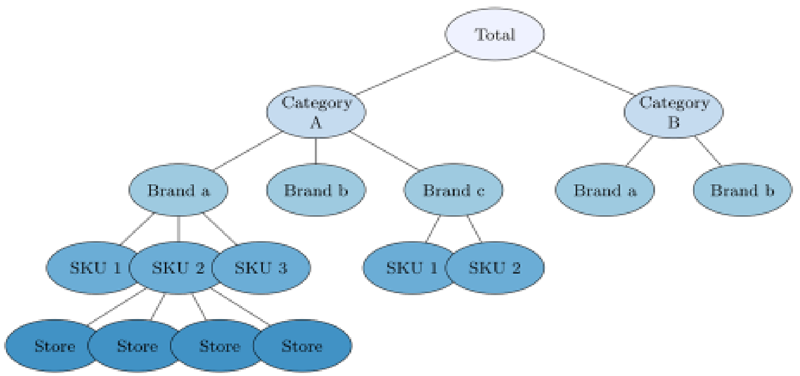
- Current data on sales poor predictor

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?

Tactical & Operational

Explanatory variables in SKU level models

$$\ln Q_{bp,t} = \beta_{bp0} + \beta_{bp,bp} \ln X_{bp,t} + \beta_{bp,b1} \ln X_{b1,t} + \beta_{bp,1p} \ln X_{1p,t} + \beta_{bp,11} \ln X_{11,t} + \varepsilon_{bp,t}.$$

- Focal price-promotion variables: X_{bp}
  - Promotion types (Temporary price, BOGOF), feature, display
- Focal brand competitors: X_{b1}
- Competitors same pack: X_{1p}
- Competitors other X_{11}

+

- Weather, events, holidays, seasonal factors

+

- Other category variables

+

- Product reviews, social media

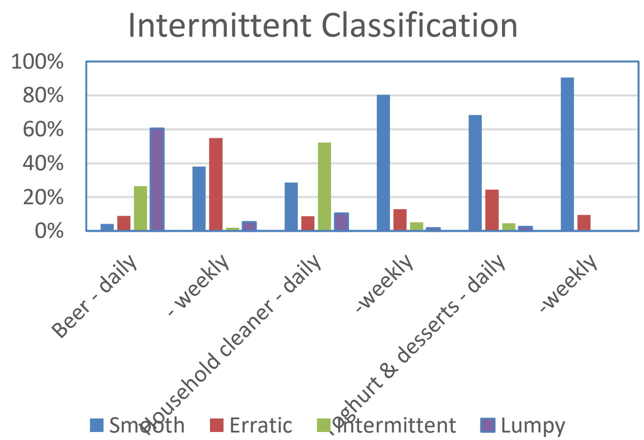
Many variables

Data issues and Business Rules

- Censored observations (out-of-stock)

Product types

- Regular (2 years min. data history)
- Intermittence



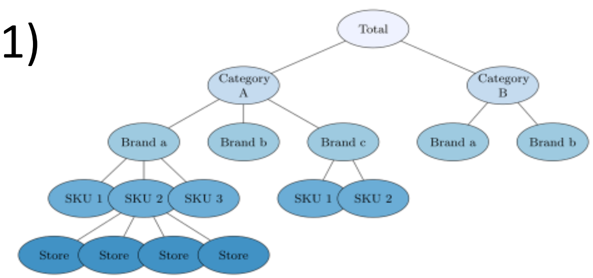
- New products
  - Dramatic variation between product categories (5% to ?)

Business Rules

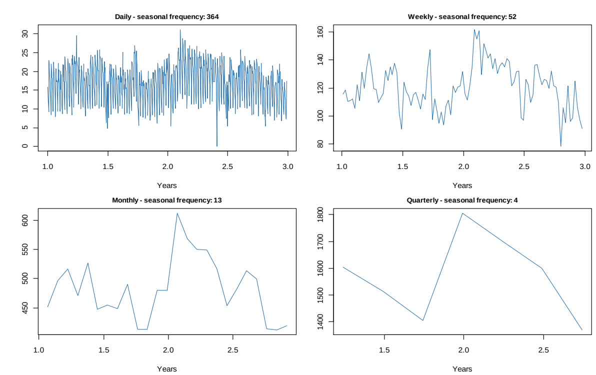
- Length, depth of promotion, no. displays
- All stores, all SKUs in brand
- Discrete pricing, smoothed price changes, corridor pricing

Research issues and solutions in SKU level forecasting in the hierarchy

- Aggregation and consistency
  - Top down vs bottom-up vs middle out
  - Consistent optimal forecasting (Hyndman et al., 2011)
    - But no consistent best performer
    - Consistency vs accuracy
    - Computational issues



- Aggregation and explanatory variable effects
  - Disaggregate models needed for heterogeneous effects
    - Store level
    - Category SKUs
  - Many variable model selection
  - Aggregation over time and intermittence



- 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

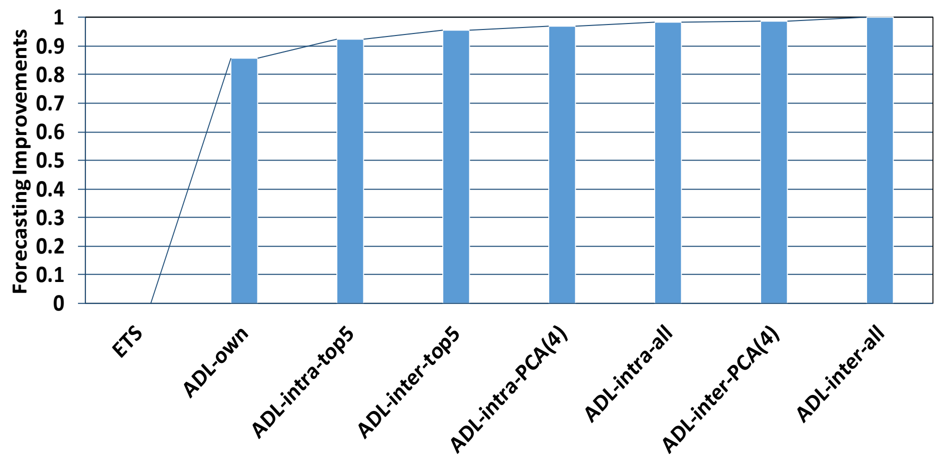
Shaohui et al., 2018, EJOR

Academic work limited

- Commercial implementations, e.g. SAP, SAS

Conclusions from SKU modelling of regular products

- Base models using last promotional uplift wholly inadequate
- Pooling across SKUs and Stores improves estimation and forecast accuracy
- Increasing complex models deliver value
  - Using focal SKU
  - using core competitive SKUs
  - Using all SKUs in category



Research issues:
- *Impact of business rules*
- *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

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.)

No/ little modelling and evaluation

Major application possibilities in fashion forecasting but…;

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)

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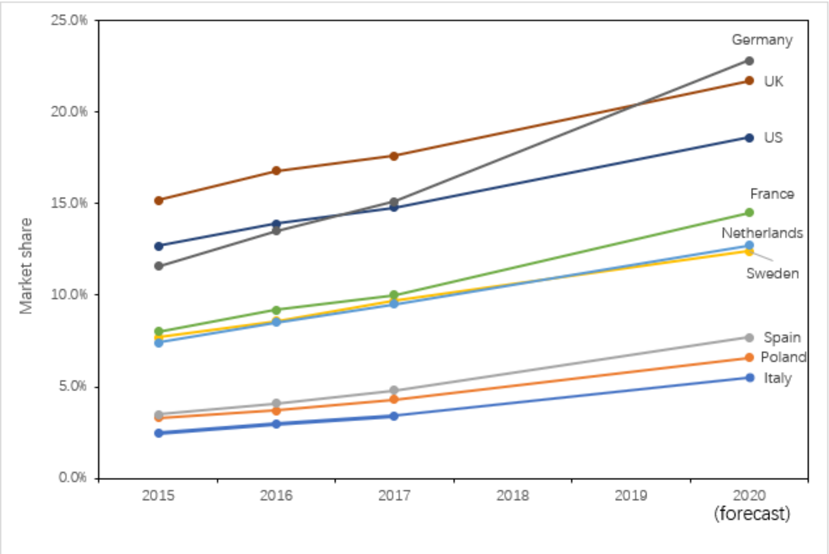

Channels: Internet sources (social media) and big-data

The Claim

- A switch to ‘Analysis and forecasting of customer behaviour’
  - Rather than aggregate SKU x location
  - Better accuracy, better insight ‘on a whole new level’

The Counter-claim (Snapp, Foresight, Spring, 2017)

- OK for important/ segmented customers
  - But done already
- At a micro-level, adding noise
  - Aggregation still required (in $s?)
- Causal models not limited by lack of ‘big data’

Channels: internet sources (social media) and big-data II

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

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, : :
4 analysts; 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

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

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 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.

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)
  - Competitive/ brand effects.
  - Omni-retailing: complementarity between on-line and store

And other issues?

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

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

- Promotional planning

- Value added of judgmental interventions

Questions and Comments?

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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