Demand Reference Models and Forecasting Implications

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Presentation outline

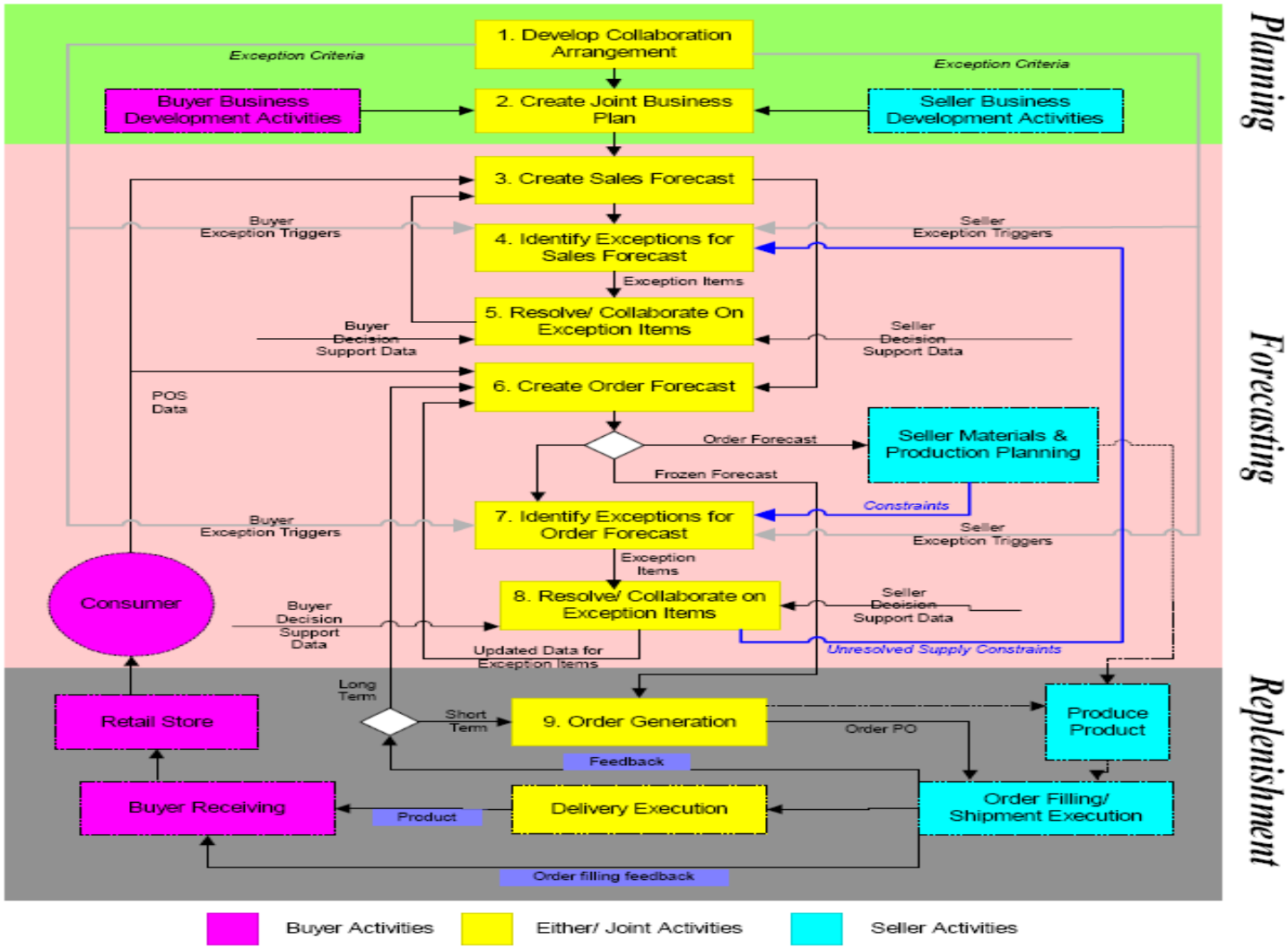
- Introduction – CPFR & Promotional Forecasting
- Case Company Overview
- Demand Reference Models
- Forecasting Promotions through Regression
- Conclusion

Introduction

- Supply chain management tools
  - Vendor Managed Inventory (1980); Efficient Consumer Response (1992) (Automatic Replenishment); Continuous Replenishment; Quick Response (Hammond, 1990); Accurate Response (Fisher et al. 1994); Collaborative Planning Forecasting and Replenishment (CPFR) (mid-nineties) by VICS-Association (Voluntary Inter-industry Commerce Standards)– "higher level of collaboration between trading partners"

- CPFR is a web based supply chain framework to collaboratively plan, collectively forecast the demand and replenish accordingly. Key objective is to provide trading partners with a roadmap for collaboration, via which they can integrate their demand and supply planning and execution processes.

CPFR framework (VICS)



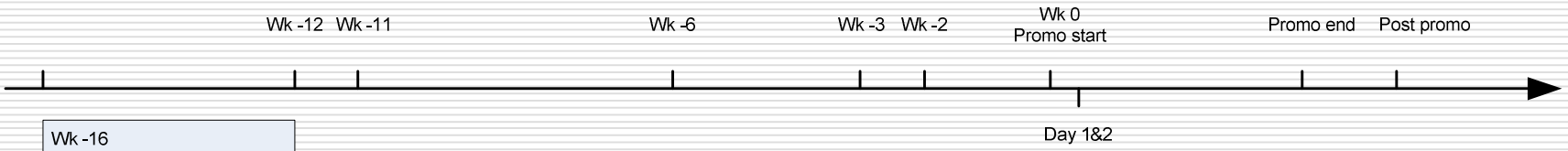
CPFR

- VICS roadmap is a framework – it is not very specific on what data to exchange and how to use these data in forecasting models, what models to apply, how to handle exceptions etc.
- Literature on CPFR: VICS framework (Fliedner, 2003) and modifications; benefits of CPFR (Robins, 1998); experiences and difficulties (Barratt & Oliviera, 2001) ; case studies (Smaros, 2007). – Many papers are not specific in the details of the forecasting approaches and/or fail to provide hard evidence of achieved benefits.
- Theoretical (modelling) papers: Aviv (2002 & 2007): quantitative model showing the benefits of CF depends on explanatory power of supply chain partners and supply side agility.
- Forecasting promotions: very little in the OR/Ops Man literature; few papers in the Marketing literature: Cooper et al., (1999) and Divakar et al., (2005) $\rightarrow$ causal models

Case Company Overview

- Largest soft drink producer and distributor in the world.
- In the UK, the company manufactures and distributes about 240 million cases of soft drinks a year
- UK Product portfolio: large (>= 1 Ltr) PET bottles (43%), 330ml cans and multi-packs (24%); small bottles (and other) (33%)
- Office in Nottingham (Customer Logistics), which looks after the 400 largest customers (including the main grocery retailers, wholesale customers, national retail outlets and the main brewers). They take customer orders and manage their customers' demands through CPFR (for largest customers only – Tesco, Sainsbury's, Morrisons, Asda, Somerfield).
- Nottingham team: Customer Demand Analysts (CDAs) / Inventory Managers (VMI)
- Sales are strongly driven by promotions.

Planning cycle



Wk -16
16-week rolling horizon forecast by commercial team

Wk -12
- Rolling forecast incorporated in production plans
- Material requirements calculated

Wk -11 to 1
- Materials ordered in line with supplier lead times
- Material an production plans continually updated in line with forecast amendments

Wk -6
- CDA Collaborative plans overlaid into company forecasts

Wk -3 to 0
- Planners scrutinise next 3 wks to ensure adequate stock cover

Wk -2 to 0
- Shipments to customer depot

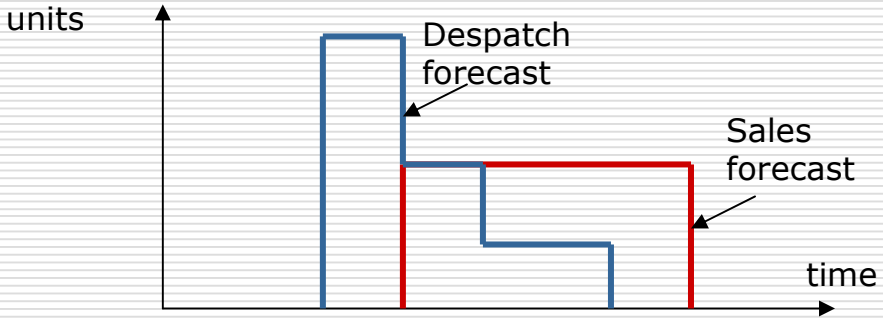
Day 1-2
- Initial sales monitored to predict performance vs forecast

Day 2 to end
- Production and replenishment aligned with true demand by VMI

Post promo
- Evaluation of promo and feedback

Current Promotional Forecasting Approach

- The retailer and manufacturer agree at the beginning of the year on a provisional promotional calendar , listing all the major deals and timings. This can be updated throughout the year.
- Wk-6: confirmation of the deal (detailed mechanism is set); CDA makes sales and despatch forecast.



- CDAs look at historical performance of previous like deals; may calculate averages and look at trend and seasonal effects; and based on own experience, come up with a figure. This is a time-consuming, manual, not very-well documented, not standardized approach; no 'real' forecasting model is applied. The figures are communicated with the retailer and the retailer usually agrees. (The retailers don't make any forecasts – they play a crucial role in providing relevant information). In general, the forecasts are quite good (MAPE: 24 – 36%).
- Case company wants to automate forecasting approach.

Demand Reference Model

- Aviv (2007): DRM is a model that specifies the dependency of the demand process on information that the parties can individually or collectively observe in the market. RDM can be highly quantitative or not; but should play a key role in assessing the value of Collaborative Forecasting.
- We constructed a conceptual RDM (a matrix), which lists factors and information signals (rows) that may influence demand (without specifying the exact dependencies) together with a number of information attributes or characteristics (columns).
- Relevant information attributes include:
  - Observer (who?) / source of information
  - Availability (when? long, intermediate, short term $\rightarrow$ planning cycle)
  - Reliability and accuracy of information
  - Action-ability (responsiveness to information, where in the supply chain?)
  - Importance in forecasting, planning & replenishment
  - Cost of obtaining information
  - Is this factor used in the current forecasting approach?

DRM Demand Factors

- **Promotional information:**
  - Promotional slots (timing, duration); Type of promotion (bogof, 2-for, 3-for, half price, …); Structure of promotion (ad feature, type of display, GE information, # of stores running the promotion, …); Effectiveness of promotion (% redemption rate); Changes to promotional plans
- **Pricing information:**
  - Base retail price; percentage discount
- **Seasonality / special dates:**
  - Winter / Spring / Summer / Autumn; Temperature / weather; Easter / Christmas; Back to school / bank holidays / Olympics …
- **Trend / life cycle information:**
  - Growth / decline / stable; New versus mature products
- **Cannibalisation & competitor information:**
  - 'Conflicting' deals running in same or different stores at the same time; Competitor deals running on the same time
- **Other complicating factors:**
  - Poor execution of promotion in store; New type of promotion with no history; Unplanned in-store promotions; Regional differences

Information attributes → ↓Demand factors & information signals	Source	Availability	Reliability/ Accuracy	Action-ability	Importance
Promotional information					
• Promotional slots (timing)	CCE + Retailer (calendar)	Intermediate (Week-6)	Correct (80%)	Actionable	Extremely important
• Type of promotion	CCE + Retailer (calendar)	Intermediate (Week-6)	Correct (70%)	Actionable	Extremely important
• Structure of promotion	CCE + Retailer (calendar)	Short term (Week -2)	Correct (50-70%)	Actionable	Very important
• Changes to planned promotion	Retailer	Short term (Week-1)	Known when communicated	Sometimes	Very important
• Effectiveness of promotion	Retailer (EPOS)	During event	Correct (90%)	Sometimes	Very important
- during promotion	CCE + Retailer (Sales history)	After event	Correct	Always	Very important
- after promotion	Retailer (Sales history)	After event (not all retailers)	Correct	Limited	Somewhat important
- % redemption rate			Correct		
Pricing information					
Retail sales price (as a surrogate for type of promotion)	Retailer	Always	Correct	Actionable	Extremely important
Seasonality/Special dates					
• Winter, Spring, Summer, Autumn	Public Calendar	Always	Correct	Actionable	Important
• Weather/Temperature	Short term - news; Long term - historical data	Always	Correct (70-90%)	Sometimes	Somewhat important
• Easter / Christmas	Public calendar	Always	Correct	Actionable	Extremely important
• Back to School/ Bank holidays	Public calendar	Always	Correct	Actionable	Important
Trend and product life cycle information					
• Growth/decline	CCE (demand history)	Always	Correct	Actionable	Very Important
• New/mature products	CCE (demand history)	Always	Correct	Actionable	Very Important
Cannibalisation & Competitor information					
• CCE products in promotion in the same or different store	CCE	Most of the time	Correct	Sometimes	Somewhat important
• CCE and competitor products in promotion at the same time (in same or different store)	Retailer	Not always	Correct	Not actionable	Somewhat important
Complicating factors					
• Poor execution of promotion in store	Retailer + CCE	During event	Correct (50%)	Limited	Very important
• New type of promotion with no history	Retailer + CCE	Intermediate	Correct (40-50%)	Limited	Important
• Unplanned in-store promotion	Retailer	After event	Correct (50%)	Not actionable	Important
• Regional difference (Habits/preferences)	Retailer/other party	Sometimes for regional deals	Requires further analysis –data is not available		

Demand Reference Model

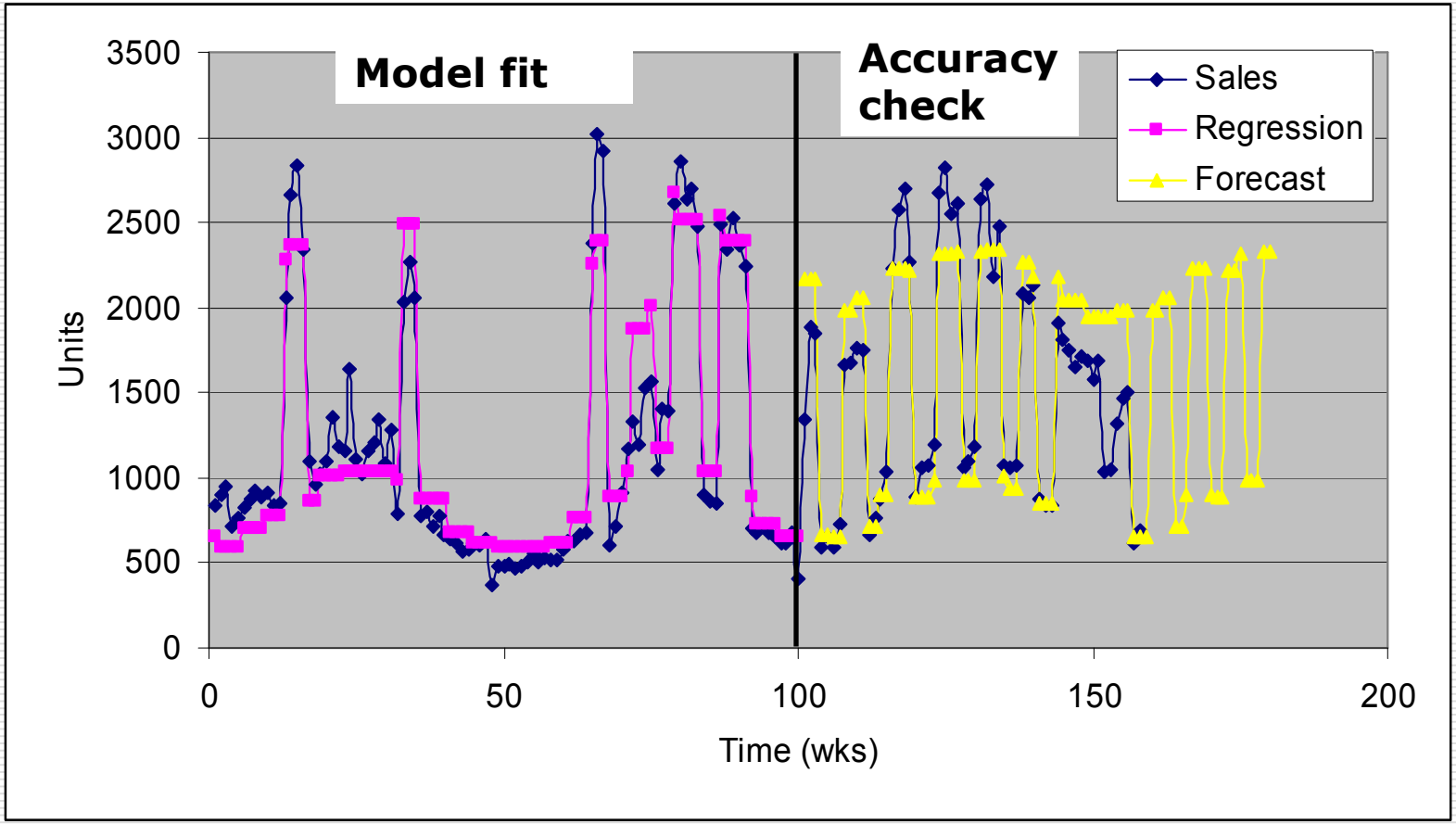
- DRM combines demand factors and information attributes. The aim is to reveal:
  - What information should be exchanged?
  - Who should exchange the information?
  - What information is important and useful or actionable?
  - Where are the complexities? What can be improved in the current CPFR arrangement / CF approach ?

  → DRM should be able to assess the overall benefit of CPFR. We think that if you construct a DRM for different industry sectors, you probably find different information needs and different types of collaboration.

Forecasting Promotions through Regression

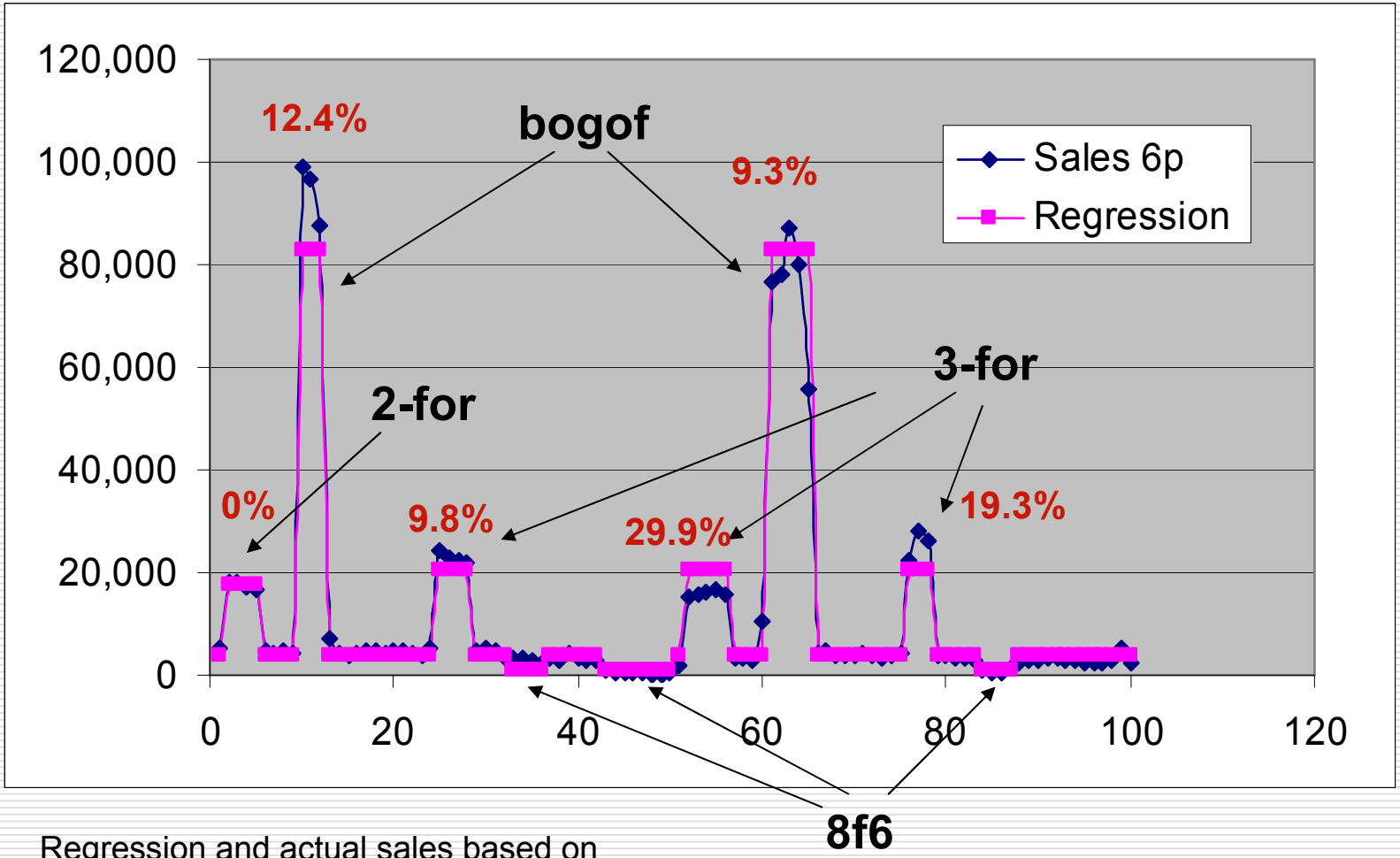
- DRM model identifies a number of factors that may explain demand. We apply the multiple linear regression technique (causal model) to construct forecasting models and to test and evaluate the importance of different factors.
- Data: weekly UK sales data (in cases) for each SKU for two retailers, together with the promotional calendars 2005-2007
- We use the 2005-2006 data to fit the model; then we apply the model on the 2007 data and measure performance through the accuracy (MAPE) of the 2007 promotional forecasts (out of sample accuracy check).
- We also compare the regression based forecast with a very simple technique:
  - Forecast for next deal = actual av. weekly sales of the most recent deal under 'similar' conditions
- Dependent variable: weekly sales volume (in cases)
- Independent (explanatory) variables: different factors identified in DRM (type of promotion, price, display, temperature, Christmas, bank holiday ,…)

Out-of-sample accuracy check



Model with only two explanatory variables (average temperature, percentage discount) – R^2 = .91; Adj R^2 = .91) – Impulse-buy product (500ml bottles Y)

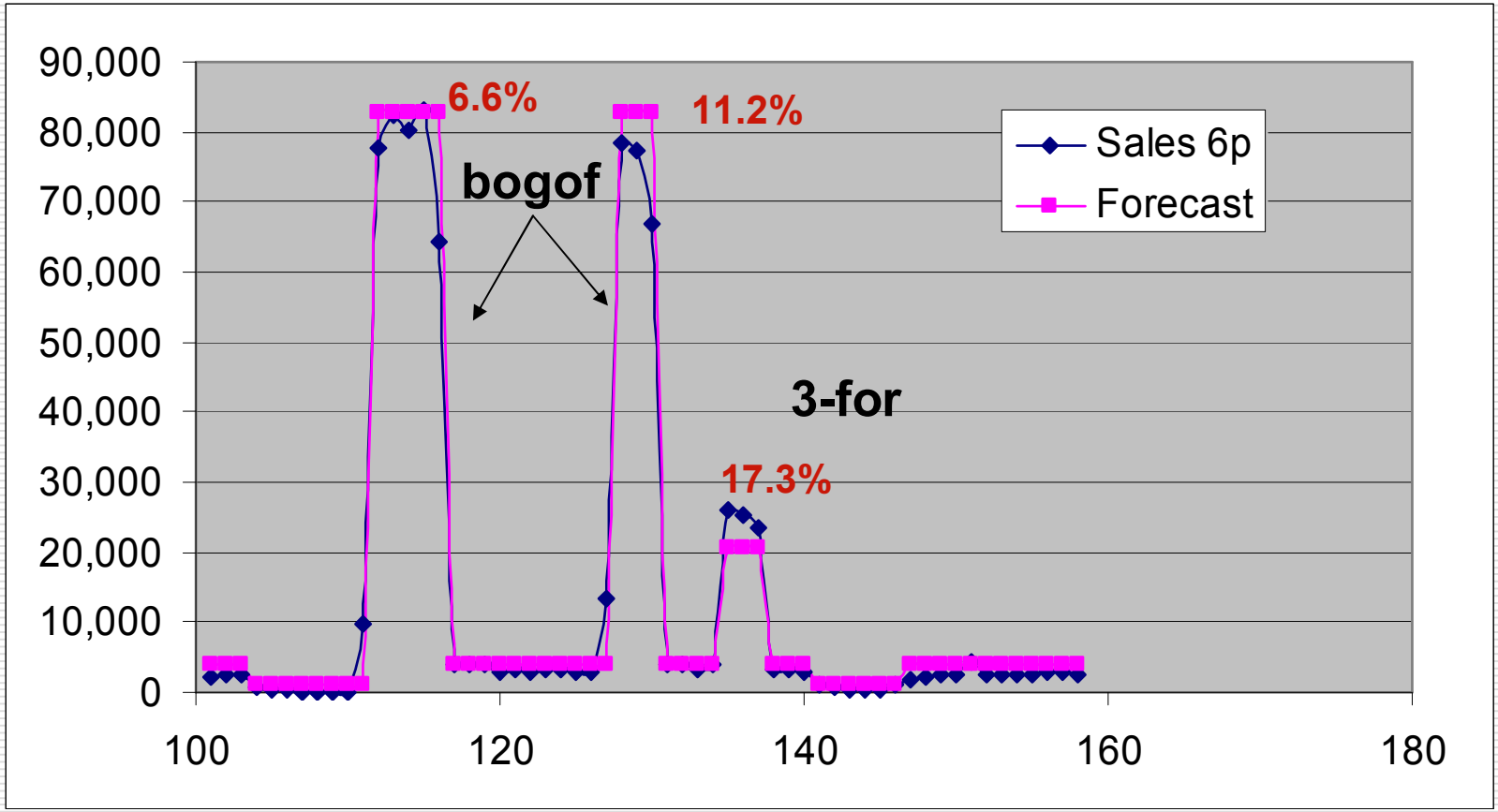
Regression example: 6pk cans product X



Regression and actual sales based on 2005&2006 data; (adj) R^2 = 0.97

APE = absolute percentage error

Forecast example: 6pk cans product X



The regression model was good; very similar behaviour in promotions in 2007 compared to what happened in 2005 and 2006 → good forecast.

Selecting Forecasting / Regression Models

- Many models possible (with meaningful) combinations of explanatory variables.
- Continuous variables (e.g. temp., % discount) vs Categorical (0/1 or yes/no variables)
- Interaction effects $\rightarrow$ explosion of no of categorical variables
- Our selection is based on a number of criteria:
  - We prefer simple models with few explanatory variables (preferably continuous), which are easy to obtain
  - The model should be able to predict all different types of promotions that occurred in the past
  - Signs of coefficients: should be meaningful (intuitively)
    - As price decreases, sales will increase; hence coefficient for price should be –ve
    - As temperature increases, sales will increase; hence coefficient for temp should be +ve
    - As promotions will normally increase sales, the sign of promotional factors should be +ve
  - High R^2

Regression analysis: results

- Groups of products (2L, 500ml, 6-pack cans, etc), within each group same deals / promos are offered → similar models (same explanatory variables) for products within each group
- Relatively few (3/4) explanatory factors in each model
  - Percentage discount (PD)
  - Bogof (yes/no) (+ display GE)
  - Christmas (yes/no) (2L)
  - Temperature (500 ml)
  - For few products PD does not work well → replace by categorical vars to model each type of promo
- Retailer 1: average $R^2 = 0.83$
- Retailer 2: average $R^2 = 0.59$

Forecast accuracy

Retailer 1	Mature products					
# products	# bogof	#2-for	# 3-for	other	total	
32	(141) 64	(48) 112	(23) 5	(2) 13	194	
MAPE	18.56%	21.09%	14.08%	12.09%	19.47%	
Retailer 1	New products					
# products	# bogof	#2-for	# 3-for	other	total	
21	(83) 50	(40) 36	(1) 2	(4) 24	112	
MAPE	25.94%	22.04%	56.81%	33.28%	26.81%	**22.16%**

Retailer 2	Mature products					
# products	# bogof	#2-for	# 3-for	other	total	
42	(105) 60	(203) 96	(23) 15	(2) 14	185	
MAPE	20.29%	17.05%	36.57%	55.33%	22.58%	
Retailer 2	New products					
# products	# bogof	#2-for	# 3-for	other	total	
8	(10) 21	(3) 18	(0) 0	(3) 8	47	
MAPE	18.80%	31.23%	(--)	21.67%	24.05%	**22.88%**

Regression Forecast vs Naïve Forecast

Retailer 1	bogof		2-for		3-for		Other		All	
MAPE	RF	NF	RF	NF	RF	NF	RF	NF	RF	NF
2 L	14.44	18.14	18.53	25.40	11.95	19.83	9.40	32.91	14.67	24.35
6 pk	15.16	22.49	34.27	11.90	15.51	99.27	(-)	(-)	21.16	23.98
500 ml	35.94	46.63	13.75	18.90	(-)	(-)	(-)	(-)	16.06	21.79
All	17.02	23.60	18.95	18.88	14.08	67.49	9.40	32.91	**17.39**	**23.34**

Retailer 2	bogof		2-for		3-for		Other		All	
MAPE	RF	NF	RF	NF	RF	NF	RF	NF	RF	NF
2 L	23.70	24.24	15.18	36.12	0.77	28.81	54.22	112.38	23.46	40.29
6 pk	19.10	28.59	16.27	26.10	55.25	97.95	56.81	118.03	22.38	37.82
500 ml	(-)	(-)	16.40	26.52	(-)	(-)	(-)	(-)	16.40	26.52
All	21.49	26.33	15.89	29.78	33.46	70.29	55.33	114.80	**22.52**	**38.28**

Current forecast performance: retailer 1: 23.9%
retailer 2: 24.4%

Conclusion & further work

- DRM can help to identify meaningful factors for forecasting models; it may reveal areas for improvement (collaborative arrangement; information exchange; data accuracy;…)
- The regression models work well (for most products): the average MAPE is (slightly) better than the current forecast performance and results are obtained almost instantly (currently it may take CDAs 30min – 2hours to forecast a single promotion).
- The case company is very pleased with these results: some of the models are currently being tested and used within the company. The company also realises the need for (more) accurate input data.
- Further Research: fine-tune current DRM models; compare DRM in different sectors; look at supply / replenishment side ($\rightarrow$ Supply Reference Model)