Forecasting Retail Demand
(including earthquakes and pandemics)

Stephan Kolassa, SAP
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PUBLIC

Lancaster University Management School

THE BEST RUN SAP

Why does a retailer need forecasts?
(Not an SAP customer)

my local

fresh, friendly, convenient, out of business

Why does a retailer need forecasts?
(Not an SAP customer)

fresh, friendly, convenient, *out of business*

Went into the Reading Store - I would say they had 2% of stock out
fridges and rows of shelves were empty.

wholemeal bread 2 for £1 now cheapest brown loaf 69p. all the
decent beer and wine deals gone. All the half price deals gone. used

Very disappointed in new My Local store in Leigh-on-sea Essex.
9.30 on Wednesday morning.
Fresh fruit and Veg shelves nearly empty.
No potatoes but some found out the back.

made a huge mistake initially in that stocks were VERY low - even of
essentials like milk - with too many empty spaces on the shelves. By
this week it has improved a little but still low on stock. You have a

and I must say why have you empty shelves - you never have any
four pint green milk - I mean Never - I don't know if the staff don't
order enough - but I see the milk being delivered I go over at break
time and there is only red or blue four pints available - you ask the
staff they say its all gone - and they won't look in the back fridges for
you - My Local what a waste of time.

,practically empty shelves

Having spoken to your manager o at least four occasions complaining
that no Daily Mirrors were available yet again
For goodness sakes how difficult is it to order Britons most popular
newspaper my dog would make a better job or being manager.
This so called shop is situated in Purbrook in Waterlooville and long
may I lay empty as that's what it deserves

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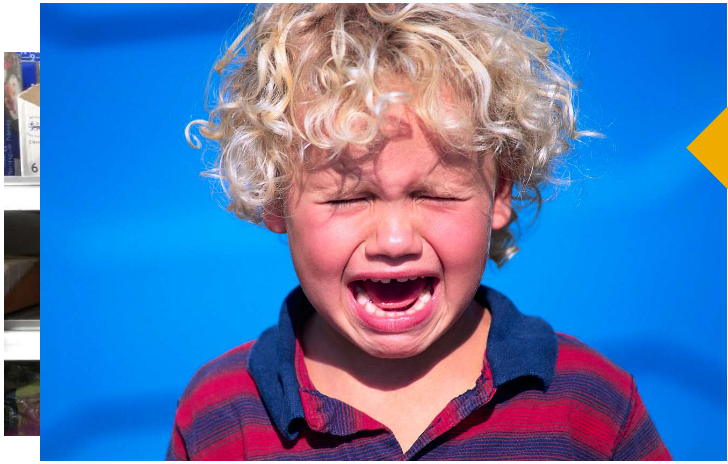

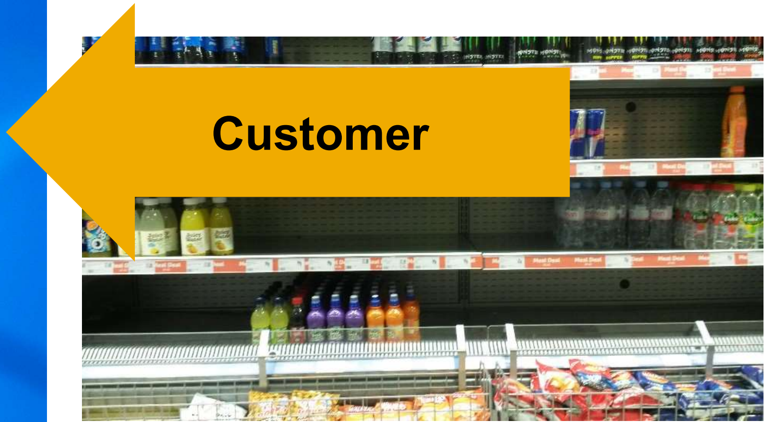

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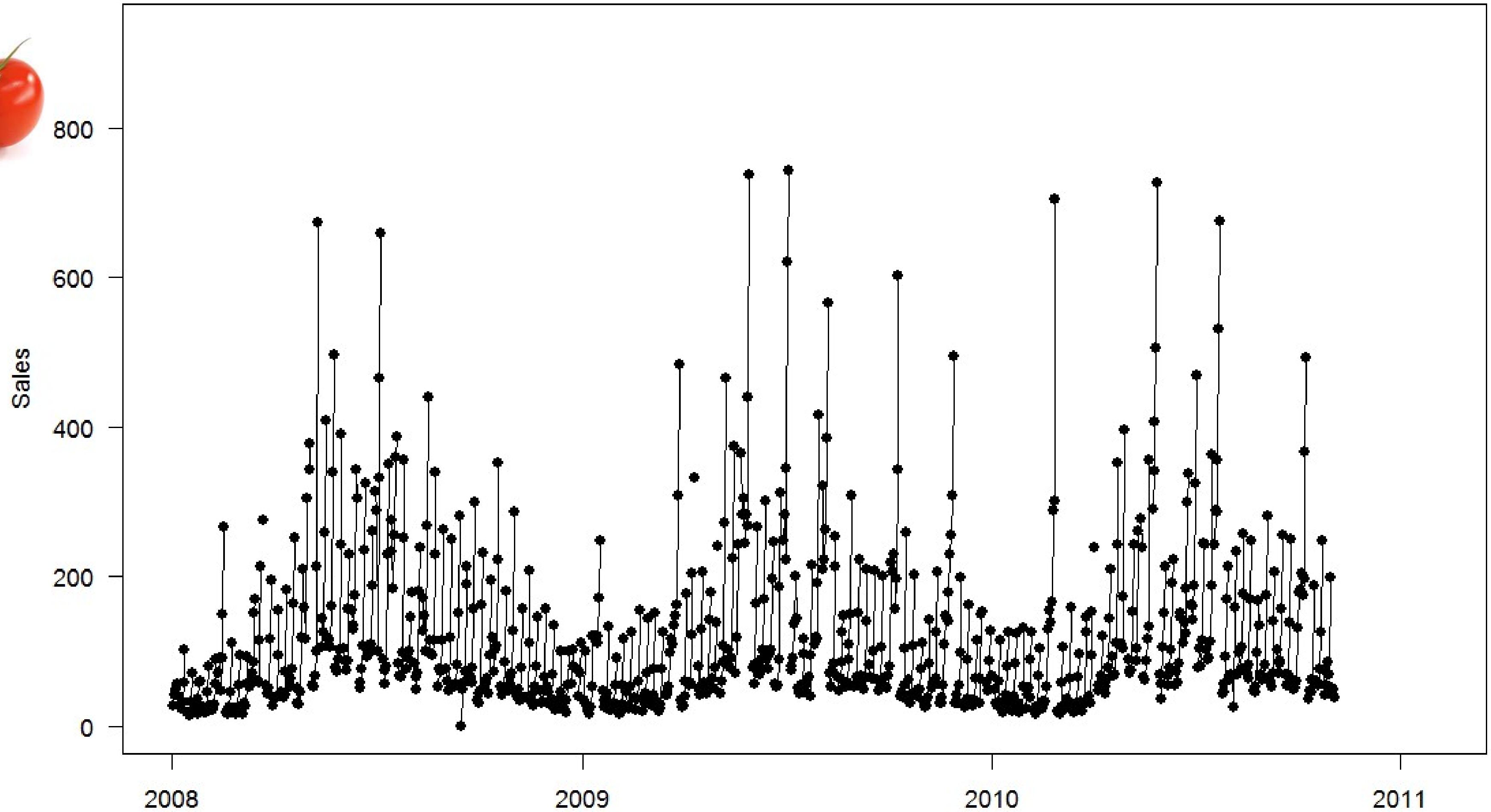
Why does a retailer need forecasts?

- Strategic planning
  - Where to open new stores
  - Whether or not to add new product lines
  - Other strategic decisions (e.g., Every Day Low Price vs. promotion strategy etc.)

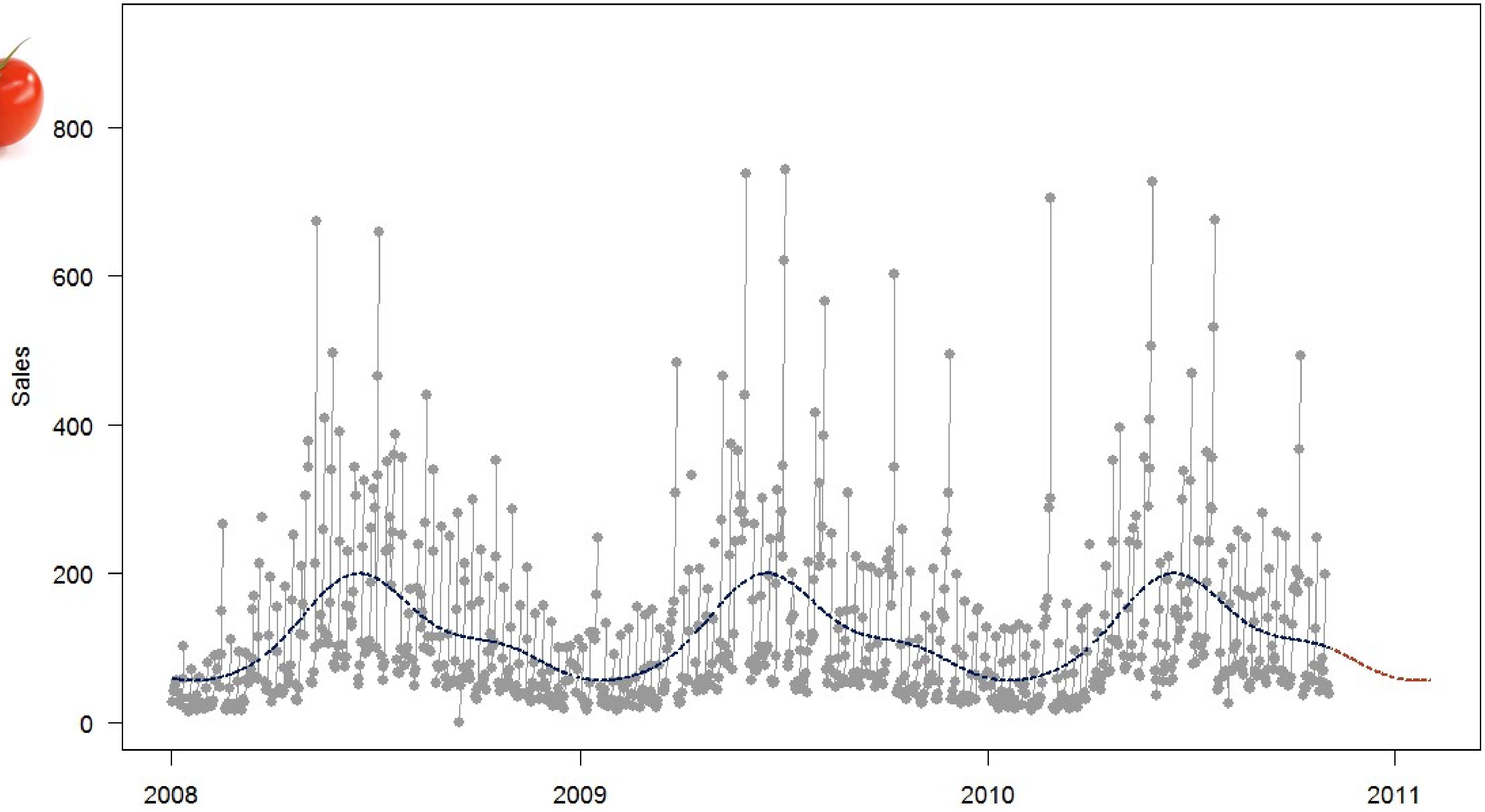
- Tactical planning
  - Assortment planning
  - Allocation planning
  - Price optimization
  - Promotion planning
  - Supplier negotiations
  - Logistics

- Operational planning
  - Store replenishment

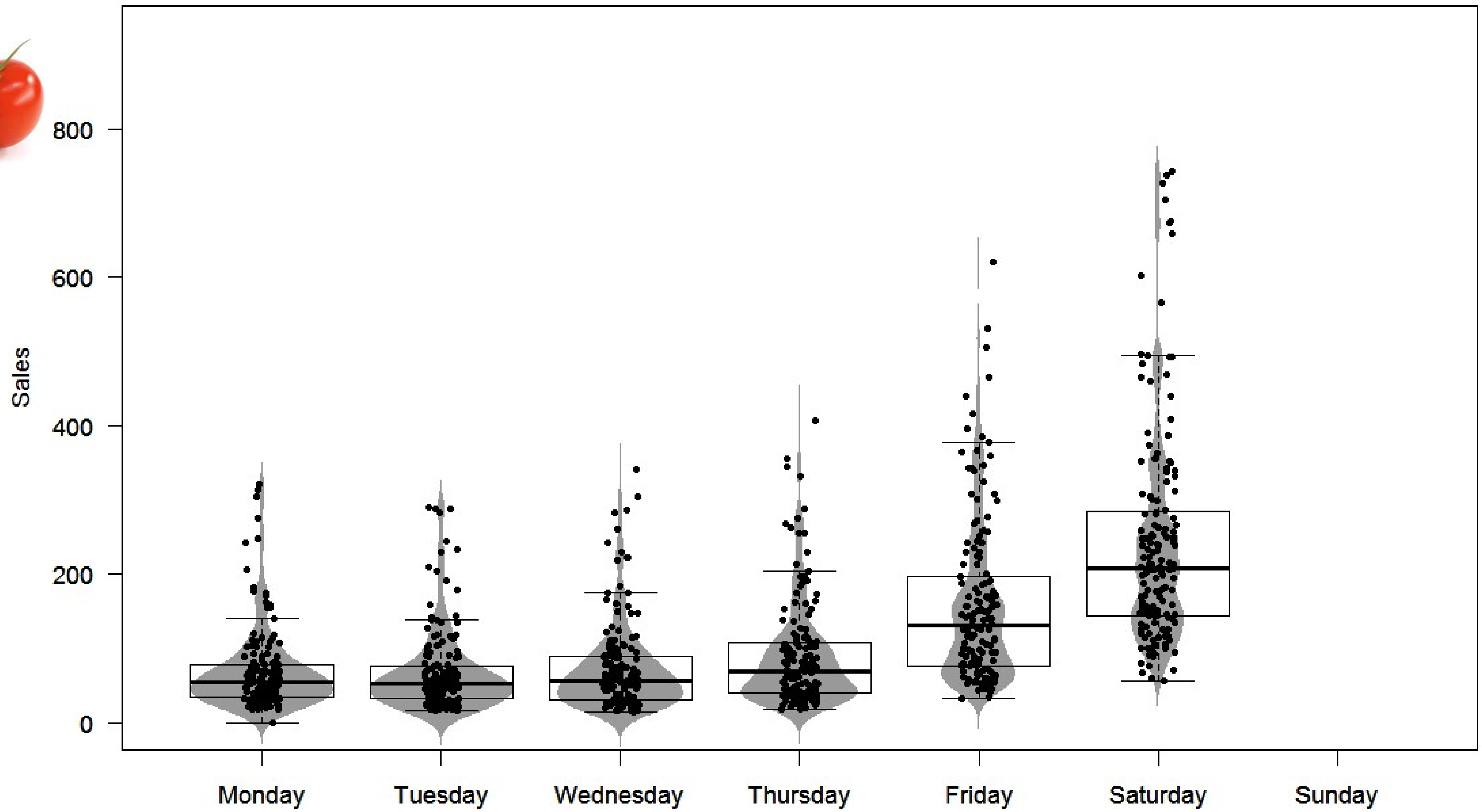
A sales time series on SKU × store × day granularity



Fit and forecast
Model with seasonality

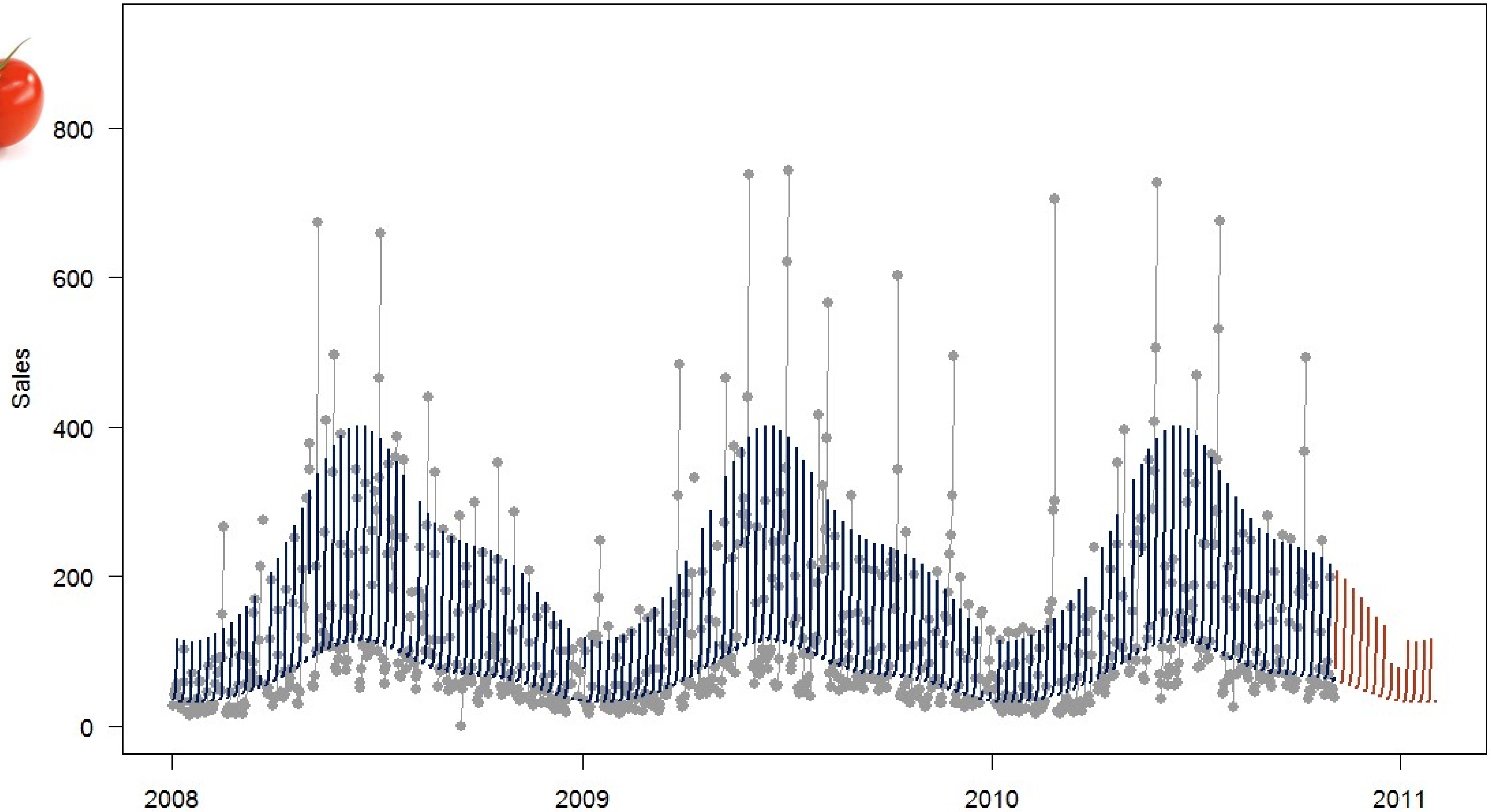


Sales per day of week

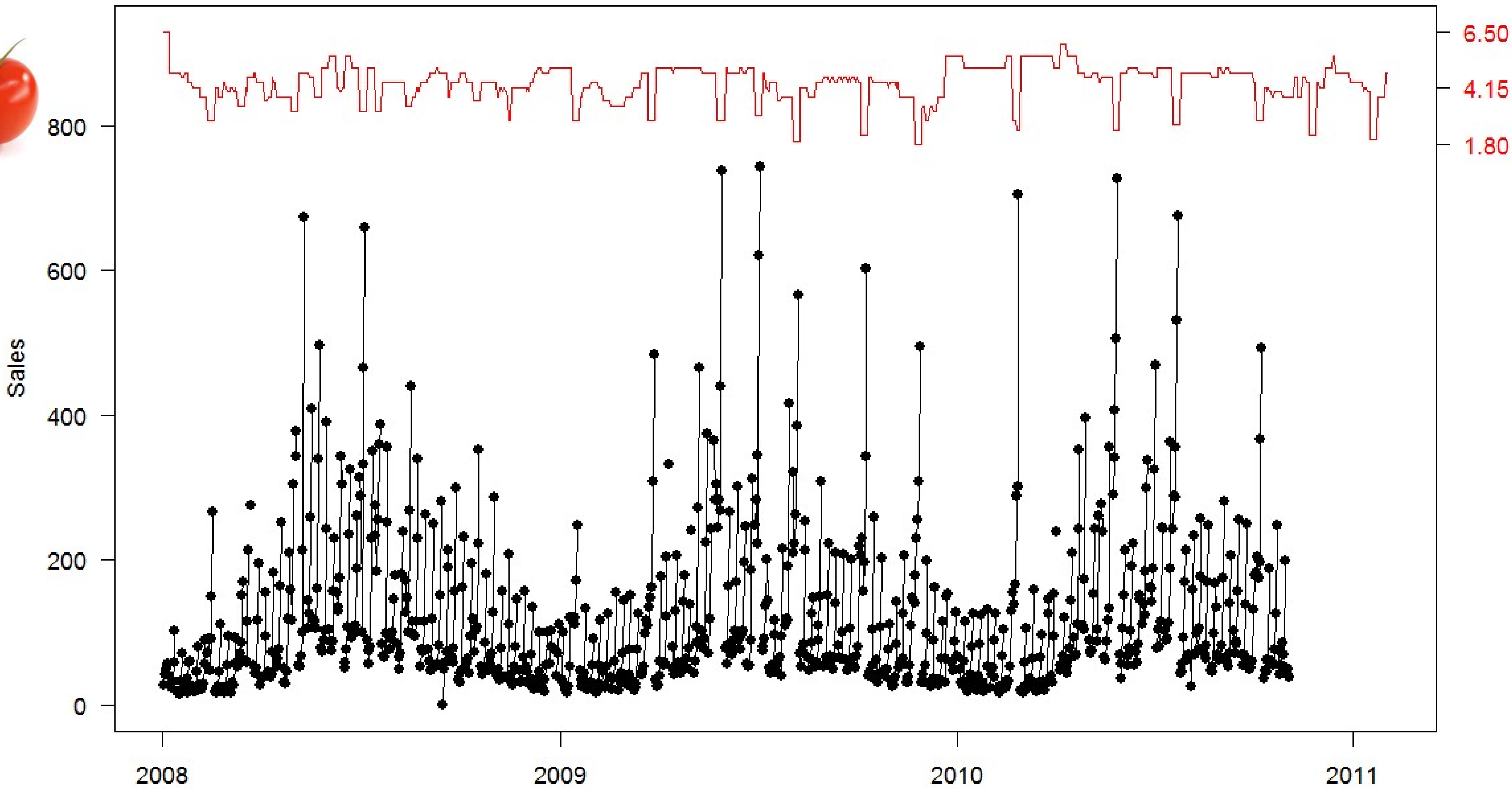


Fit and forecast

Model with seasonality and day of week

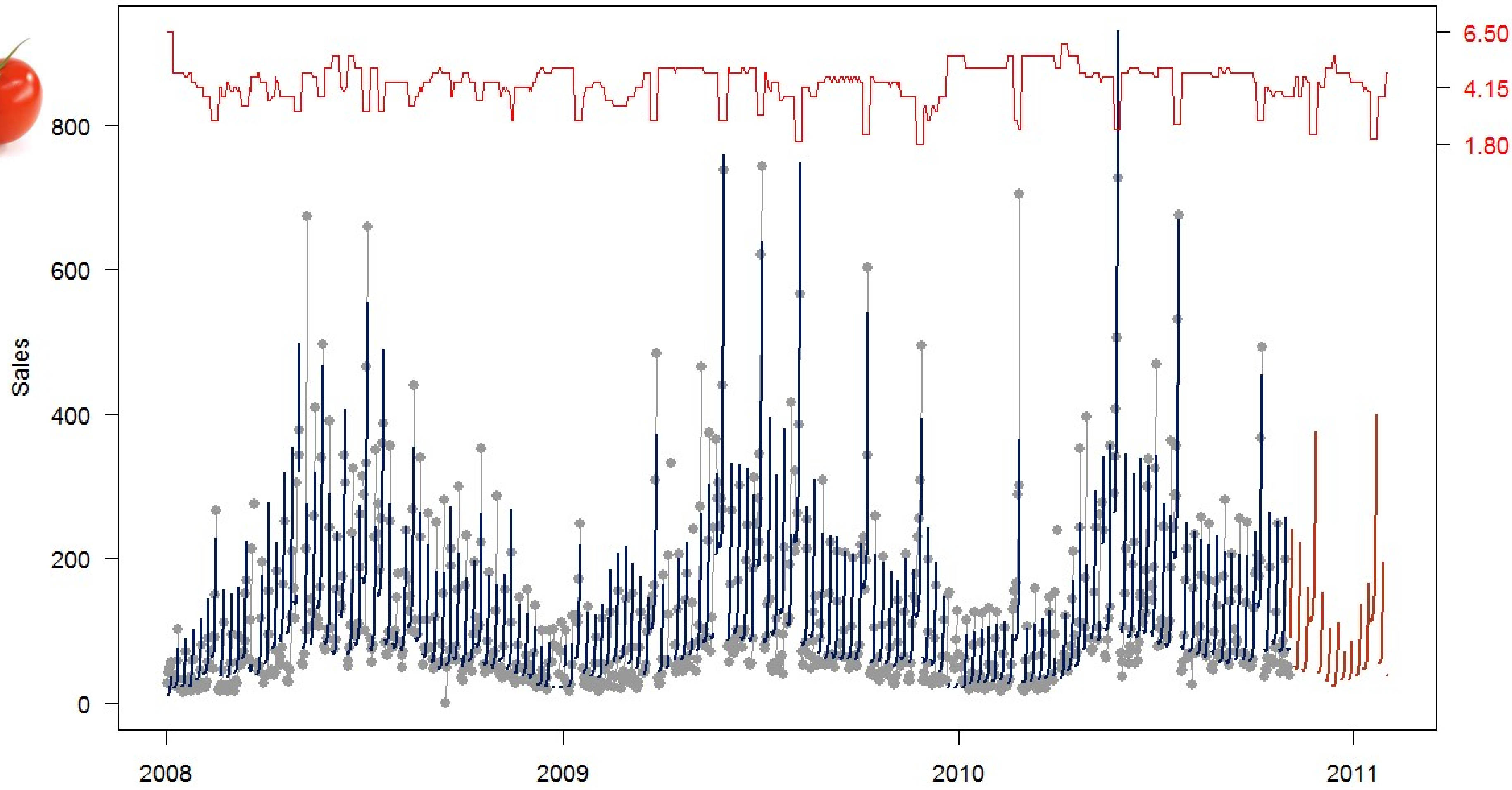


Sales with prices



Fit & forecast

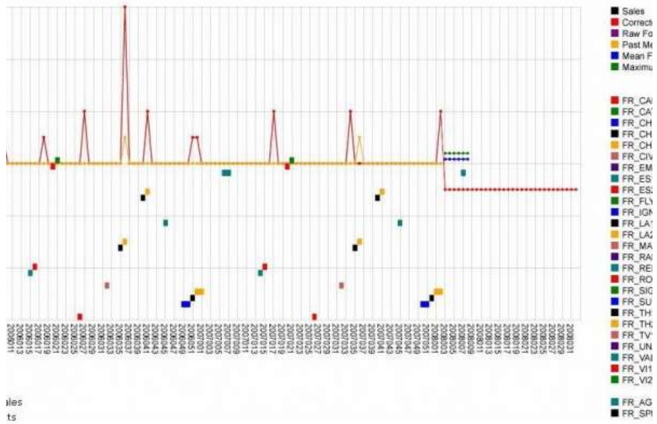
Model with seasonality, day of week and price

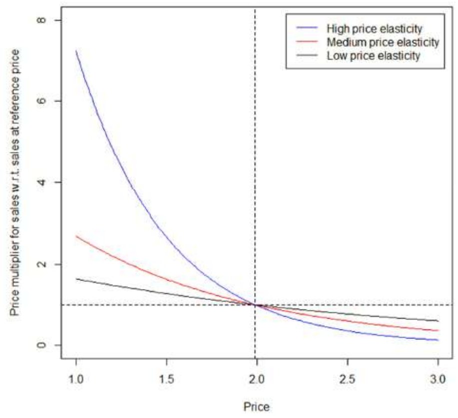


Causal factors

Not a typo

- Promotions
  - TPR
  - BOGO
  - BnX@x%GmY@y%
  - Conditions (coupons)
  - Rewards (other coupons, or gift cards, or airline miles, …)
  - Lots of tactics
  - Suppression effects on regular sales
- Calendar events
  - Christmas
  - Chinese New Year
  - Day of month effects
  - Holidays
- Other stuff
  - Weather
  - Cannibalization/complementarity
  - …





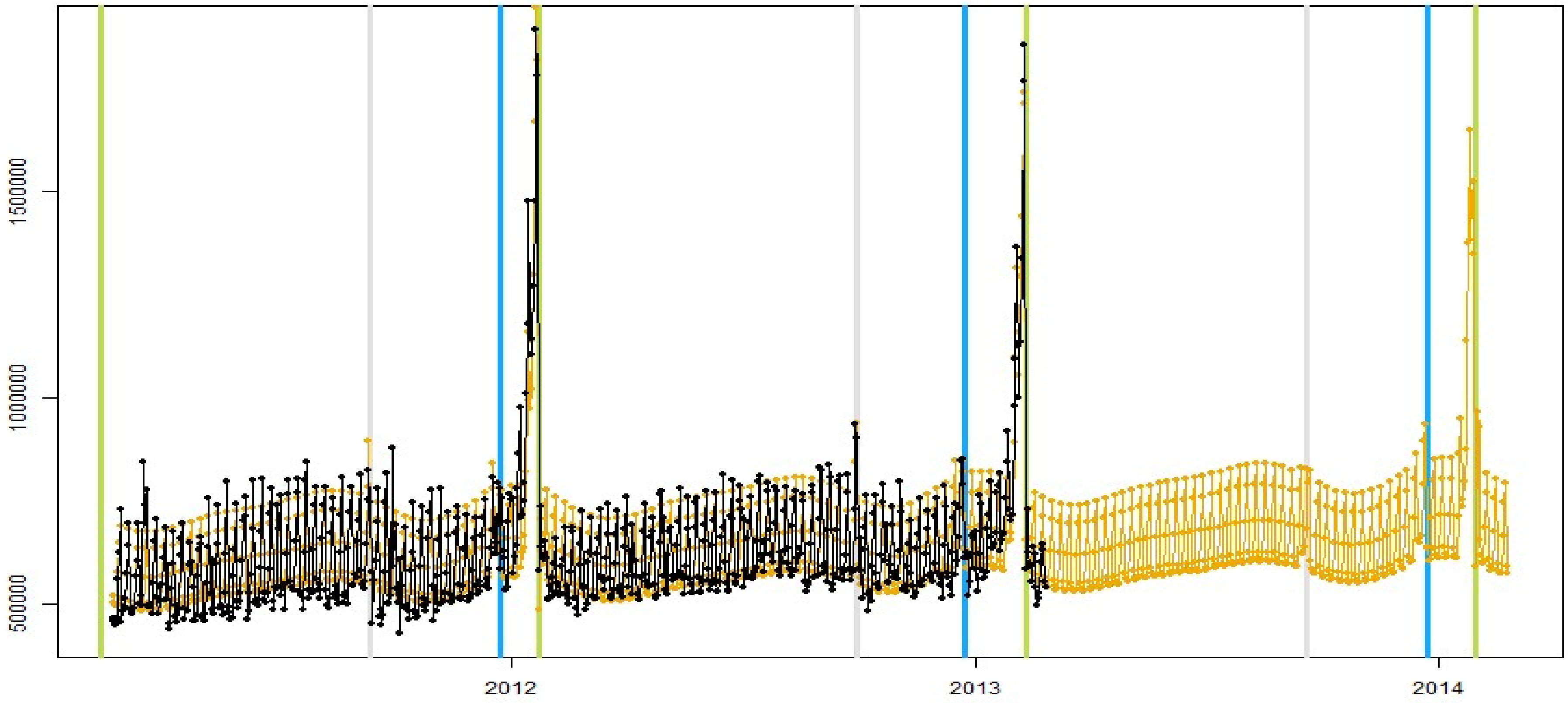

```
NEW_PRICE"(((((!(NW_SAVER|NW_MULTIBUY)&!(PS_MULTIBUY|PS_TPR))*(PRICE[t]/1)))+((((!(NW_SAVER|NW_MULTIBUY)&(PS_MULTIBUY|PS_TPR))|((NW_SAVER|NW_MULTIBUY)&!(PS_MULTIBUY|PS_TPR)))*(PRICE[t]/2))))+((((NW_SAVER|NW_MULTIBUY)&(PS_MULTIBUY|PS_TPR))*(PRICE[t]/3))))"
```

Offer type: Discount
Offer type: Optional Multi-buy
Offer type: Enforced Multi-buy
Offer type: Optional Buy X Get X Offer Type
Offer type: Enforced Buy X Get X Offer Type
Offer type: Optional Buy X Get Y Offer Type
Offer type: Enforced Buy X Get Y Offer Type
Offer type: Invalid, Incomplete, or Inconsistent Offer
Offer type: Unsupported Offer Type
Intercept
Price: discounts and price reductions
Trend
Holidays

Day of week
Tactic
Tactic type
Suppression
Retail Coupon
Manufacturer Coupon
Loyalty
Price discount
Monetary value
Rebate
Gift Card
Loyalty Points

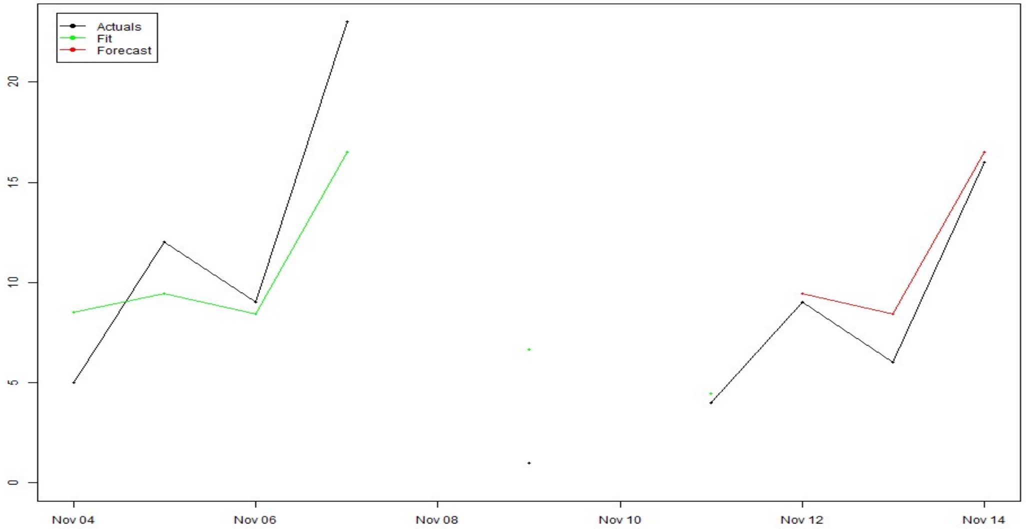
Example of calendar events

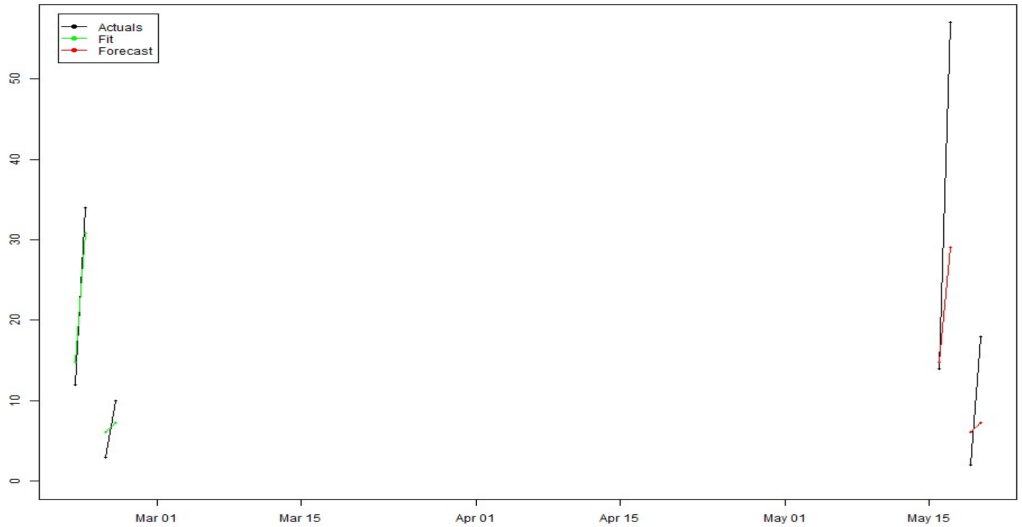
One store’s total daily sales, fit and forecast



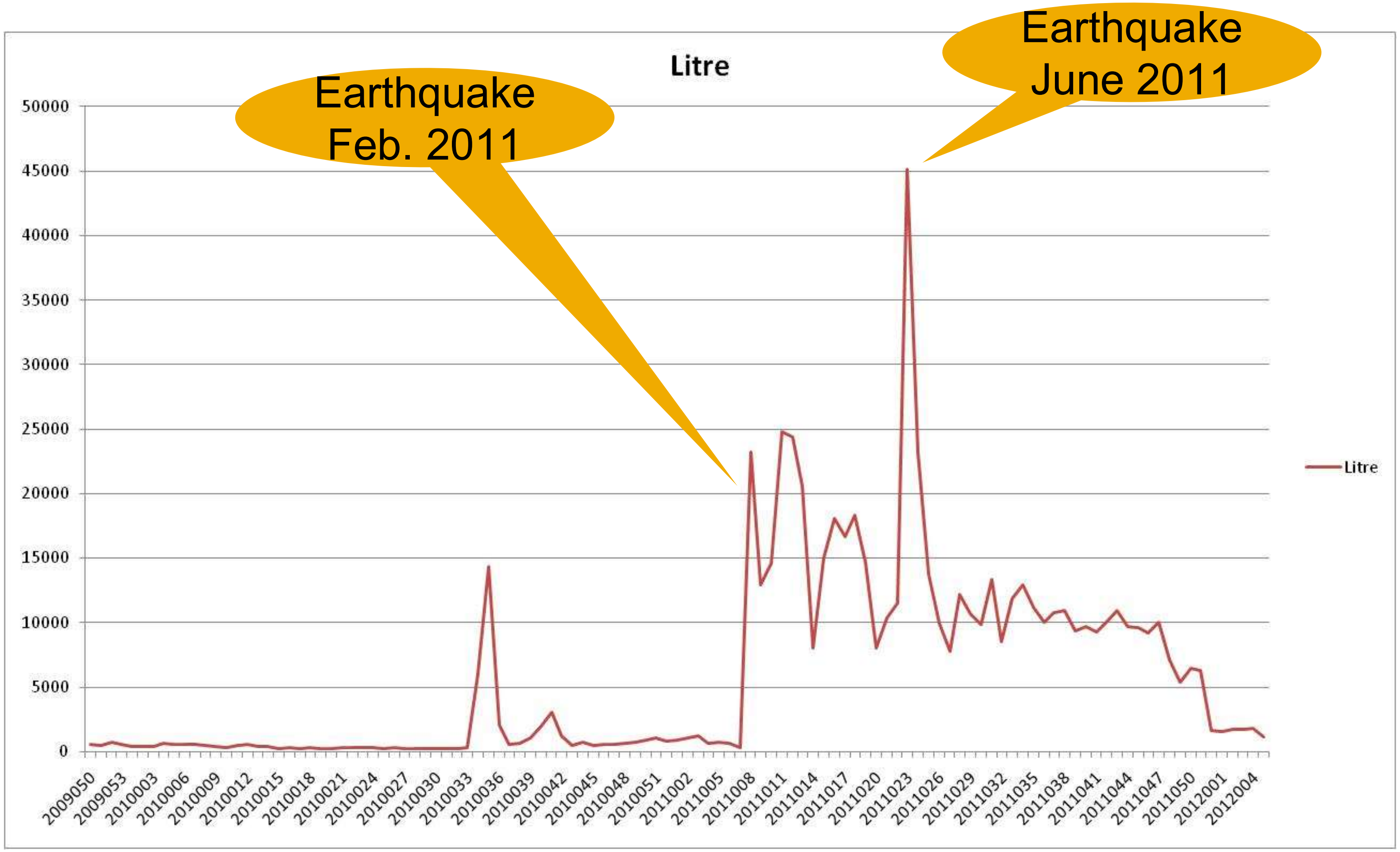
Short time series

– On average, retailers will change 30% of the assortment every year
– → only 49% of the assortment (or less) will have two years of history



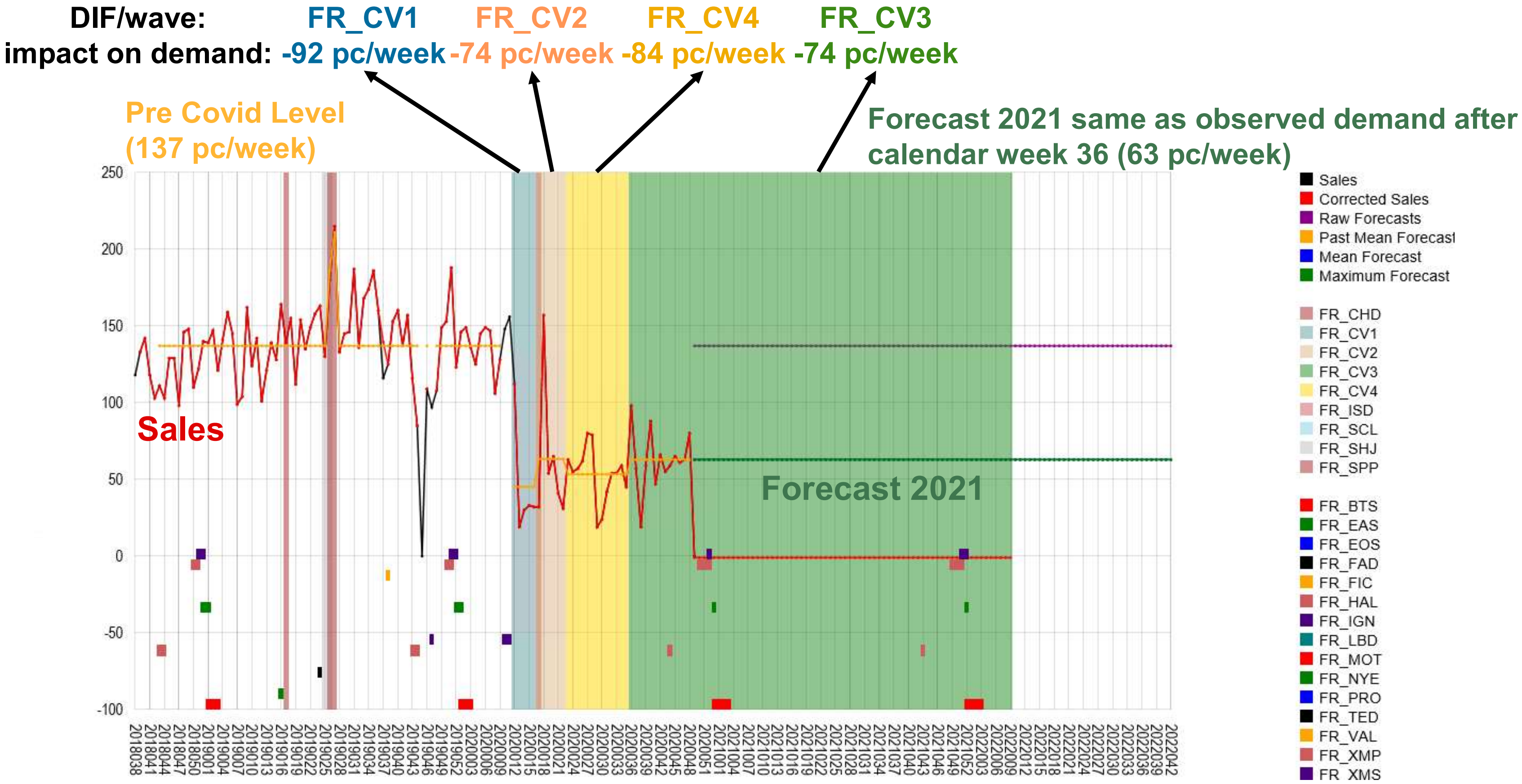


Earthquakes!
Bottled water, aggregated



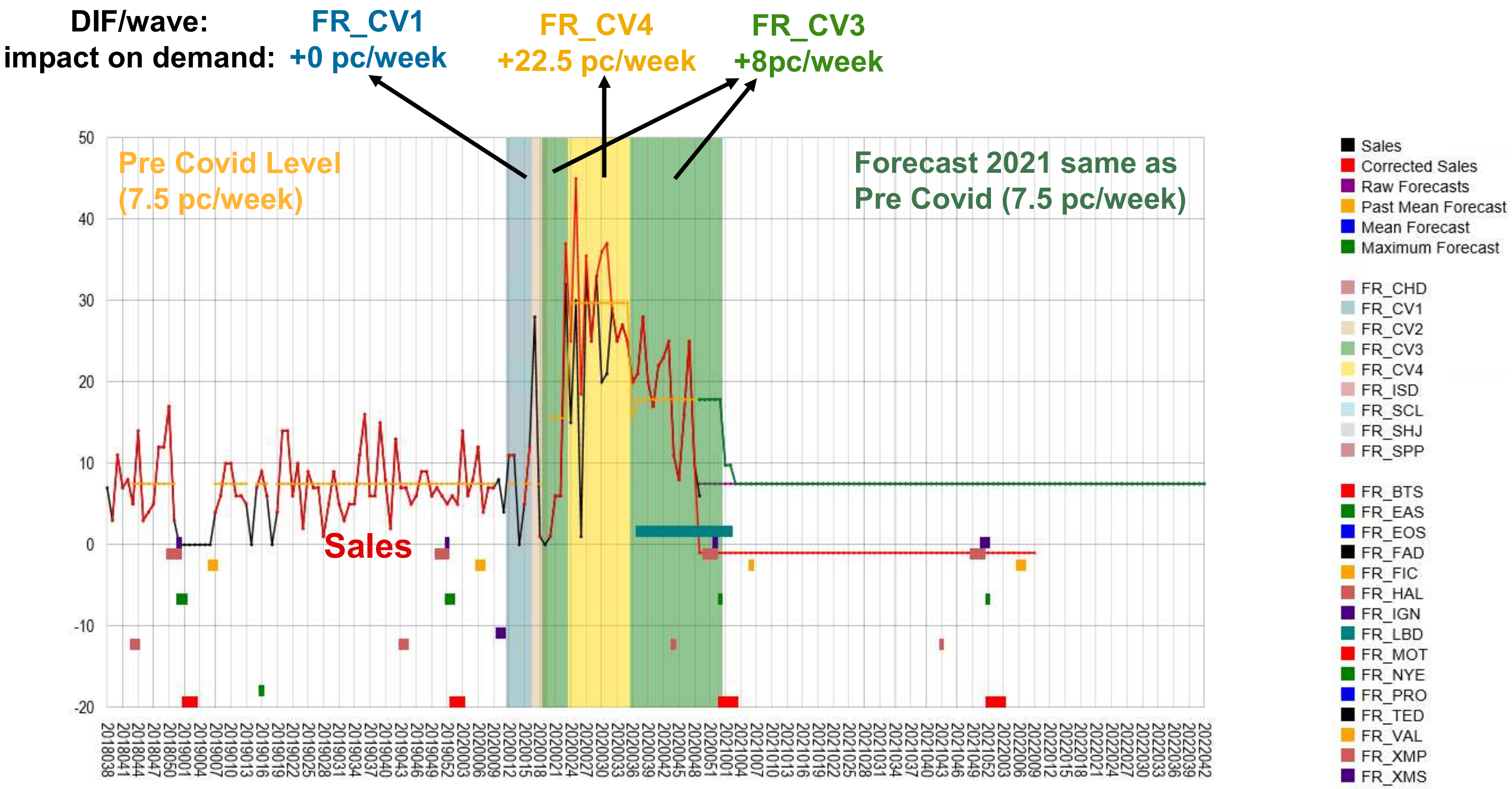
Pandemics!

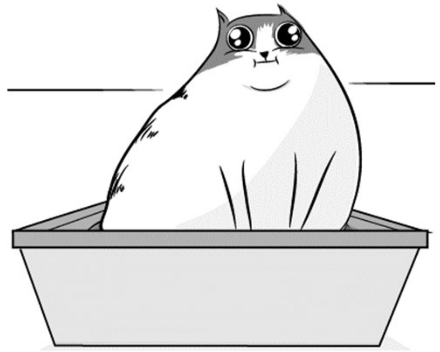
Washing powder/detergent: a new normal?



Pandemics!

Litter boxes: a return to pre-COVID?



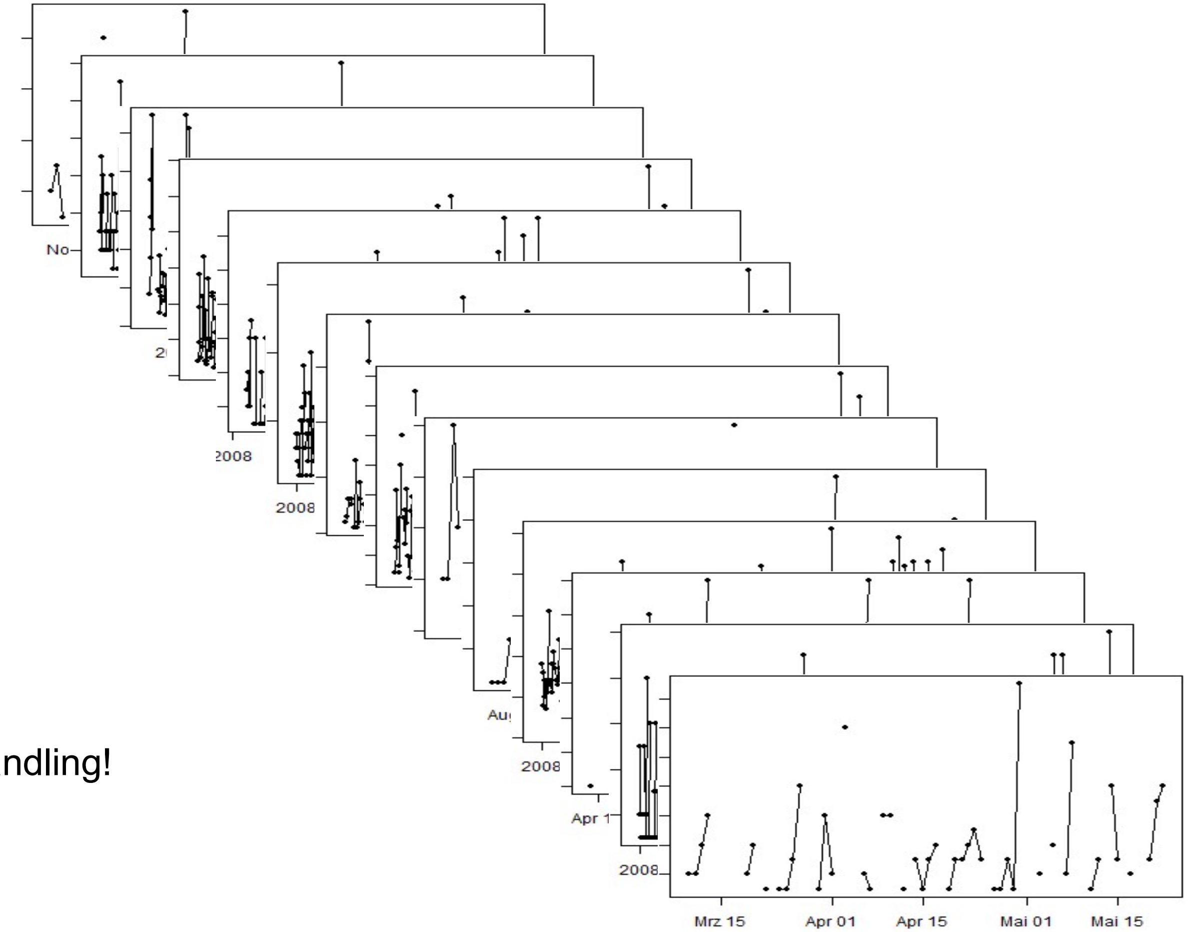


Mass data

– The dimensions of the problem:
  - 1,000-20,000 active SKUs (or more!)
  - 1,000 stores (or more!)
  - Multiple years' worth of history
  - Multiple promotion types
  - (Basket data)
  - Other influencing data

– Forecasts need to be *fast*
  - People don't like to wait
  - Critical time windows for replenishment

→ Big Data with a vengeance!
→ We need extreme robustness and exception handling!



Forecasting methods

$$\left(1-\sum_{i=1}^{p}\varphi_i\Delta^i\right)(1-\Delta)^d y_t = \left(1+\sum_{j=1}^{q}\vartheta_j\Delta^j\right)e_t$$

Trend	Seasonality		
	N (None)	A (Additive)	M (Multiplicative)
N (None)	$S_t=\alpha X_t+(1-\alpha)S_{t-1}$ $\hat{X}_t(m)=S_t$	$S_t=\alpha(X_t-I_{t-p})+(1-\alpha)S_{t-1}$ $I_t=\delta(X_t-S_t)+(1-\delta)I_{t-p}$ $\hat{X}_t(m)=S_t+I_{t-p+m}$	$S_t=\alpha(X_t/I_{t-p})+(1-\alpha)S_{t-1}$ $I_t=\delta(X_t/S_t)+(1-\delta)I_{t-p}$ $\hat{X}_t(m)=S_tI_{t-p+m}$
	$S_t=S_{t-1}+\alpha e_t$ $\hat{X}_t(m)=S_t$	$S_t=S_{t-1}+\alpha e_t$ $I_t=I_{t-p}+\delta(1-\alpha)e_t$ $\hat{X}_t(m)=S_t+I_{t-p+m}$	$S_t=S_{t-1}+\alpha e_t/I_{t-p}$ $I_t=I_{t-p}+\delta(1-\alpha)e_t/S_t$ $\hat{X}_t(m)=S_tI_{t-p+m}$
A (Additive)	$S_t=\alpha X_t+(1-\alpha)(S_{t-1}+T_{t-1})$ $T_t=\gamma(S_t-S_{t-1})+(1-\gamma)T_{t-1}$ $\hat{X}_t(m)=S_t+mT_t$	$S_t=\alpha(X_t-I_{t-p})+(1-\alpha)(S_{t-1}+T_{t-1})$ $T_t=\gamma(S_t-S_{t-1})+(1-\gamma)T_{t-1}$ $I_t=\delta(X_t-S_t)+(1-\delta)I_{t-p}$ $\hat{X}_t(m)=S_t+mT_t+I_{t-p+m}$	$S_t=\alpha(X_t/I_{t-p})+(1-\alpha)(S_{t-1}+T_{t-1})$ $T_t=\gamma(S_t-S_{t-1})+(1-\gamma)T_{t-1}$ $I_t=\delta(X_t/S_t)+(1-\delta)I_{t-p}$ $\hat{X}_t(m)=(S_t+mT_t)I_{t-p+m}$
	$S_t=S_{t-1}+T_{t-1}+\alpha e_t$ $T_t=T_{t-1}+\alpha\gamma e_t$ $\hat{X}_t(m)=S_t+mT_t$	$S_t=S_{t-1}+T_{t-1}+\alpha e_t$ $T_t=T_{t-1}+\alpha\gamma e_t$ $I_t=I_{t-p}+\delta(1-\alpha)e_t$ $\hat{X}_t(m)=S_t+mT_t+I_{t-p+m}$	$S_t=S_{t-1}+T_{t-1}+\alpha e_t/I_{t-p}$ $T_t=T_{t-1}+\alpha\gamma e_t/I_{t-p}$ $I_t=I_{t-p}+\delta(1-\alpha)e_t/S_t$ $\hat{X}_t(m)=(S_t+mT_t)I_{t-p+m}$
DA (Damped additive)	$S_t=\alpha X_t+(1-\alpha)(S_{t-1}+\phi T_{t-1})$ $T_t=\gamma(S_t-S_{t-1})+(1-\gamma)\phi T_{t-1}$ $\hat{X}_t(m)=S_t+\sum_{i=1}^{m}\phi^i T_t$	$S_t=\alpha(X_t-I_{t-p})+(1-\alpha)(S_{t-1}+\phi T_{t-1})$ $T_t=\gamma(S_t-S_{t-1})+(1-\gamma)\phi T_{t-1}$ $I_t=\delta(X_t-S_t)+(1-\delta)I_{t-p}$ $\hat{X}_t(m)=S_t+\sum_{i=1}^{m}\phi^i T_t+I_{t-p+m}$	$S_t=\alpha(X_t/I_{t-p})+(1-\alpha)(S_{t-1}+\phi T_{t-1})$ $T_t=\gamma(S_t-S_{t-1})+(1-\gamma)\phi T_{t-1}$ $I_t=\delta(X_t/S_t)+(1-\delta)I_{t-p}$ $\hat{X}_t(m)=\left(S_t+\sum_{i=1}^{m}\phi^i T_t\right)I_{t-p+m}$
	$S_t=S_{t-1}+\phi T_{t-1}+\alpha e_t$ $T_t=\phi T_{t-1}+\alpha\gamma e_t$ $\hat{X}_t(m)=S_t+\sum_{i=1}^{m}\phi^i T_t$	$S_t=S_{t-1}+\phi T_{t-1}+\alpha e_t$ $T_t=\phi T_{t-1}+\alpha\gamma e_t$ $I_t=I_{t-p}+\delta(1-\alpha)e_t$ $\hat{X}_t(m)=S_t+\sum_{i=1}^{m}\phi^i T_t+I_{t-p+m}$	$S_t=S_{t-1}+\phi T_{t-1}+\alpha e_t/I_{t-p}$ $T_t=\phi T_{t-1}+\alpha\gamma e_t/I_{t-p}$ $I_t=I_{t-p}+\delta(1-\alpha)e_t/S_t$ $\hat{X}_t(m)=\left(S_t+\sum_{i=1}^{m}\phi^i T_t\right)I_{t-p+m}$
M (Multiplicative)	$S_t=\alpha X_t+(1-\alpha)(S_{t-1}R_{t-1})$ $R_t=\gamma(S_t/S_{t-1})+(1-\gamma)R_{t-1}$ $\hat{X}_t(m)=S_t R_t^m$	$S_t=\alpha(X_t-I_{t-p})+(1-\alpha)S_{t-1}R_{t-1}$ $R_t=\gamma(S_t/S_{t-1})+(1-\gamma)R_{t-1}$ $I_t=\delta(X_t-S_t)+(1-\delta)I_{t-p}$ $\hat{X}_t(m)=S_tR_t^m+I_{t-p+m}$	$S_t=\alpha(X_t/I_{t-p})+(1-\alpha)S_{t-1}R_{t-1}$ $R_t=\gamma(S_t/S_{t-1})+(1-\gamma)R_{t-1}$ $I_t=\delta(X_t/S_t)+(1-\delta)I_{t-p}$ $\hat{X}_t(m)=(S_tR_t^m)I_{t-p+m}$
	$S_t=S_{t-1}R_{t-1}+\alpha e_t$ $R_t=R_{t-1}+\alpha\gamma e_t/S_{t-1}$ $\hat{X}_t(m)=S_tR_t^m$	$S_t=S_{t-1}R_{t-1}+\alpha e_t$ $R_t=R_{t-1}+\alpha\gamma e_t/S_{t-1}$ $I_t=I_{t-p}+\delta(1-\alpha)e_t$ $\hat{X}_t(m)=S_tR_t^m+I_{t-p+m}$	$S_t=S_{t-1}R_{t-1}+\alpha e_t/I_{t-p}$ $R_t=R_{t-1}+(\alpha\gamma e_t/S_{t-1})/I_{t-p}$ $I_t=I_{t-p}+\delta(1-\alpha)e_t/S_t$ $\hat{X}_t(m)=(S_tR_t^m)I_{t-p+m}$
DM (Damped multiplicative)	$S_t=\alpha X_t+(1-\alpha)(S_{t-1}R_{t-1}^{\phi})$ $R_t=\gamma(S_t/S_{t-1})+(1-\gamma)R_{t-1}^{\phi}$ $\hat{X}_t(m)=S_tR_t^{\sum_{i=1}^{m}\phi^i}$	$S_t=\alpha(X_t-I_{t-p})+(1-\alpha)S_{t-1}R_{t-1}^{\phi}$ $R_t=\gamma(S_t/S_{t-1})+(1-\gamma)R_{t-1}^{\phi}$ $I_t=\delta(X_t-S_t)+(1-\delta)I_{t-p}$ $\hat{X}_t(m)=S_tR_t^{\sum_{i=1}^{m}\phi^i}+I_{t-p+m}$	$S_t=\alpha(X_t/I_{t-p})+(1-\alpha)(S_{t-1}R_{t-1}^{\phi})$ $R_t=\gamma(S_t/S_{t-1})+(1-\gamma)R_{t-1}^{\phi}$ $I_t=\delta(X_t/S_t)+(1-\delta)I_{t-1}$ $\hat{X}_t(m)=\left(S_tR_t^{\sum_{i=1}^{m}\phi^i}\right)I_{t-p+m}$
	$S_t=S_{t-1}R_{t-1}^{\phi}+\alpha e_t$ $R_t=R_{t-1}^{\phi}+\alpha\gamma e_t/S_{t-1}$ $\hat{X}_t(m)=S_tR_t^{\sum_{i=1}^{m}\phi^i}$	$S_t=S_{t-1}R_{t-1}^{\phi}+\alpha e_t$ $R_t=R_{t-1}^{\phi}+\alpha\gamma e_t/S_{t-1}$ $I_t=I_{t-p}+\delta(1-\alpha)e_t$ $\hat{X}_t(m)=S_tR_t^{\sum_{i=1}^{m}\phi^i}+I_{t-p+m}$	$S_t=S_{t-1}R_{t-1}^{\phi}+\alpha e_t/I_{t-p}$ $R_t=R_{t-1}^{\phi}+(\alpha\gamma e_t/S_{t-1})/I_{t-p}$ $I_t=I_{t-p}+\delta(1-\alpha)e_t/S_t$ $\hat{X}_t(m)=\left(S_tR_t^{\sum_{i=1}^{m}\phi^i}\right)I_{t-p+m}$

For each type of trend, there are two sections of equations: the first gives recurrence forms and the second gives equivalent error-correction forms.

- Classical forecasting/time series methods
  - ARIMA (Autoregressive Integrated Moving Average)
  - Exponential Smoothing

$$\hat{\beta} = (X^tWX)^{-1}X^tWy$$

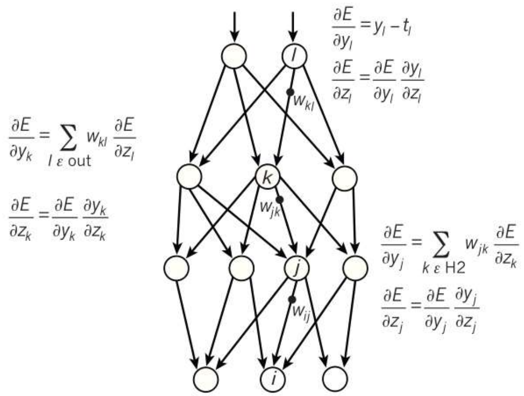
- Regression
  - Classical linear
  - Mixed (multiplicative)
  - Poisson or negative binomial

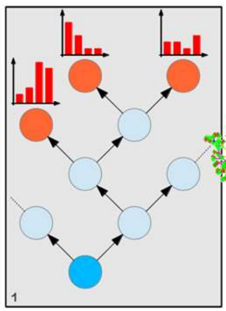
$$p(k;\lambda) = \frac{\lambda^k}{k!}e^{-\lambda}$$

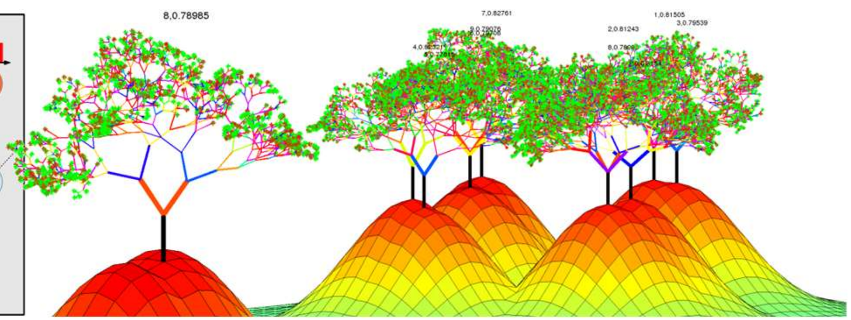
$$p(\vartheta|y) \propto p(y|\vartheta)p(\vartheta)$$

- Bayesian methods

- Machine Learning
  - Neural networks
  - Deep Learning
  - XGBoost
  - (Random Forests)







Forecasting methods

… and why they have problems in retail

- Classical forecasting/time series methods
  - ARIMA (Autoregressive Integrated Moving Average)
  - Exponential Smoothing
- Regression
  - Classical linear
  - Mixed (multiplicative)
  - Poisson or negative binomial
- Bayesian methods
- Machine Learning
  - Neural networks
  - Deep Learning
  - XGBoost
  - (Random Forests)

- ARIMAX/regression with ARIMA errors can model causals
- Model selection is non-trivial
- Missing data (→ delisting) are a major problem
- Multiple seasonalities are hard, especially if <2 years history

- In principle: add more components to level/trend/season
- In practice: a bookkeeping nightmare – and unstable
- Missing data can be handled, but again hard
- No natural way to handle metric causals

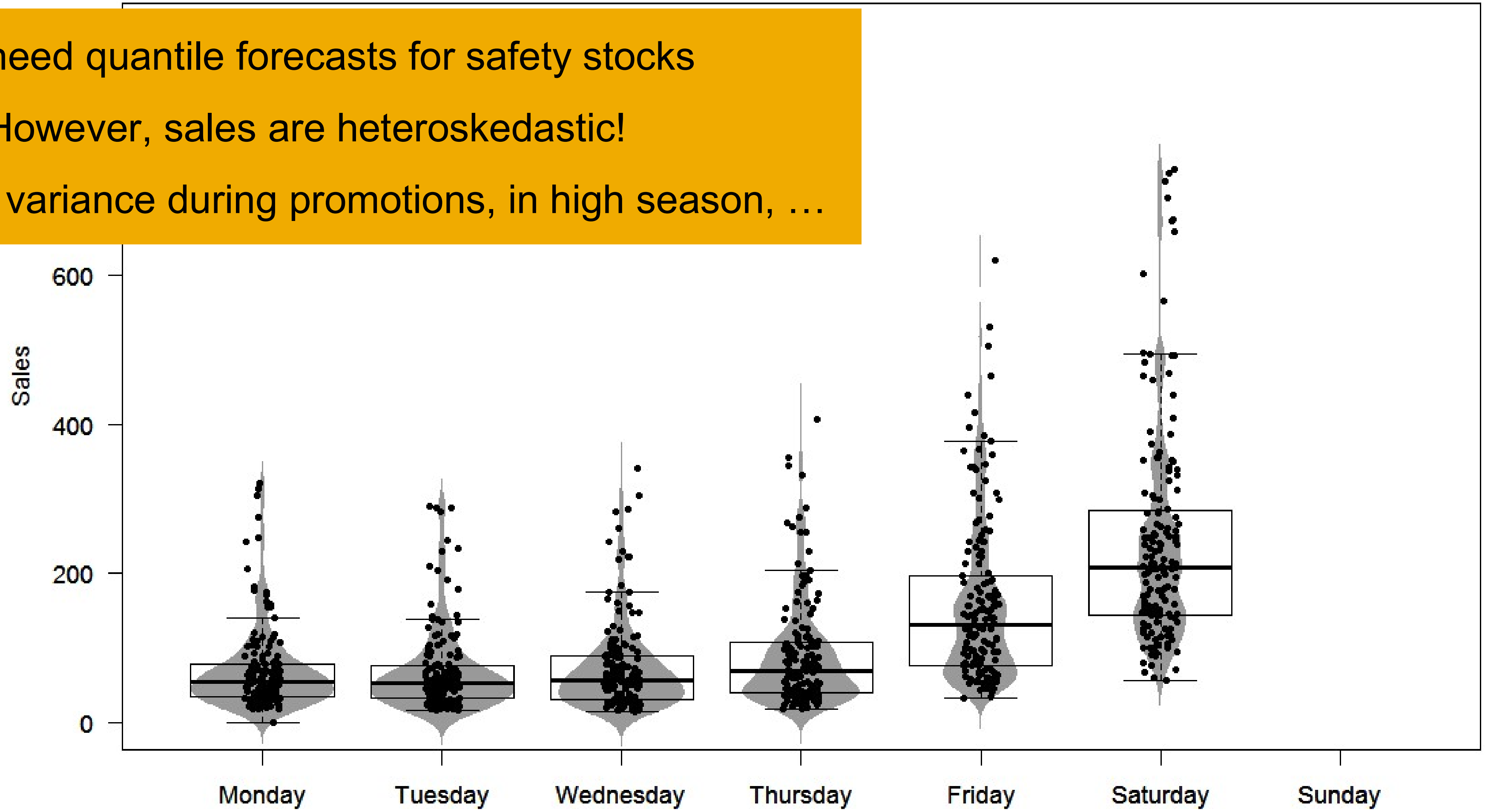
- “Black boxes”
- Users want to understand why the forecast is the way it is…
- … and may want to tweak it in specific ways

Variance and quantile forecasts for safety stocks

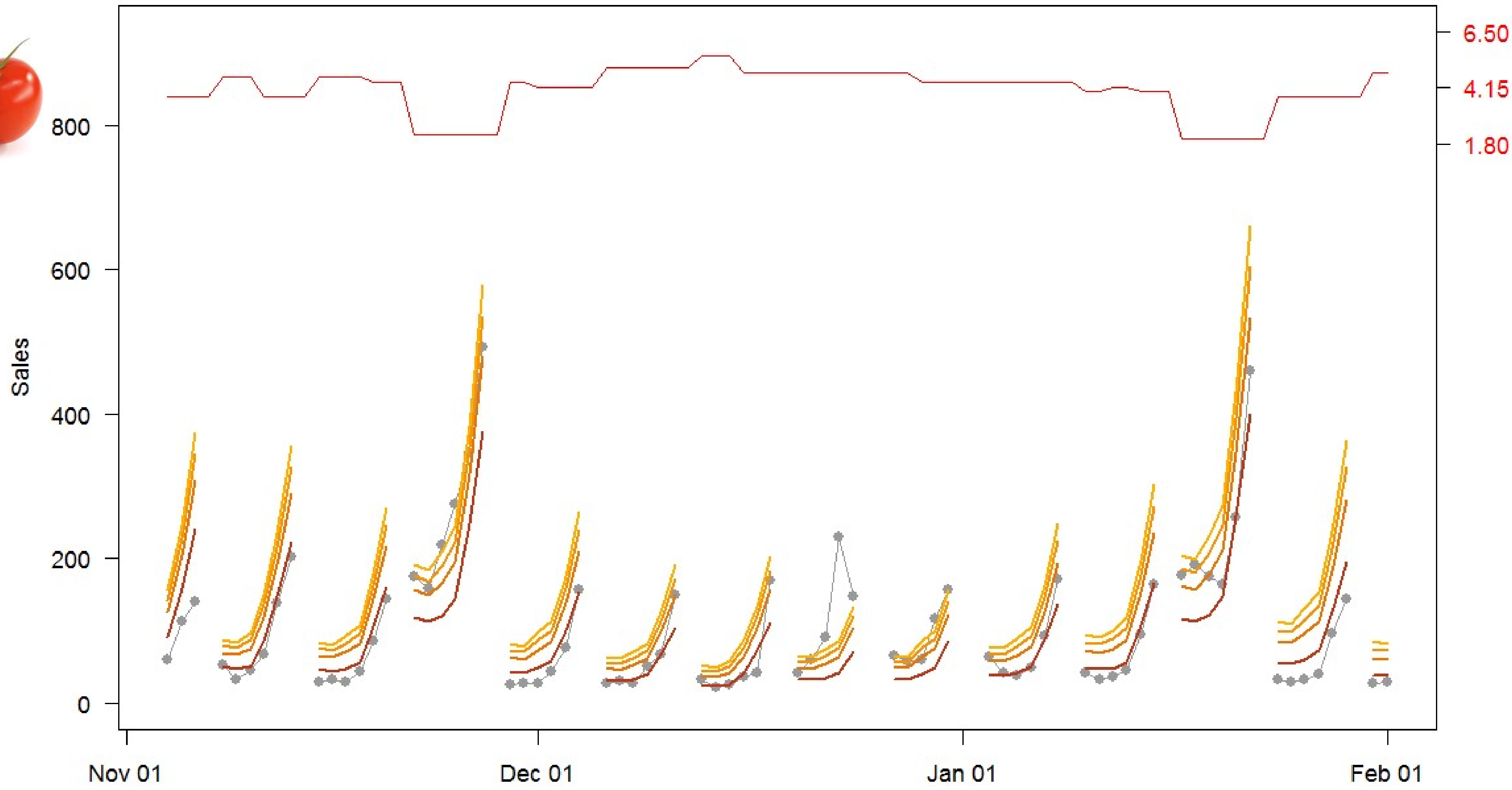
We need quantile forecasts for safety stocks

However, sales are heteroskedastic!

Also: higher variance during promotions, in high season, …



Quantile forecasts



The M5 forecasting competition

Lessons learned

Look out for the upcoming special issue of the *International Journal of Forecasting* (I'll have a commentary paper)

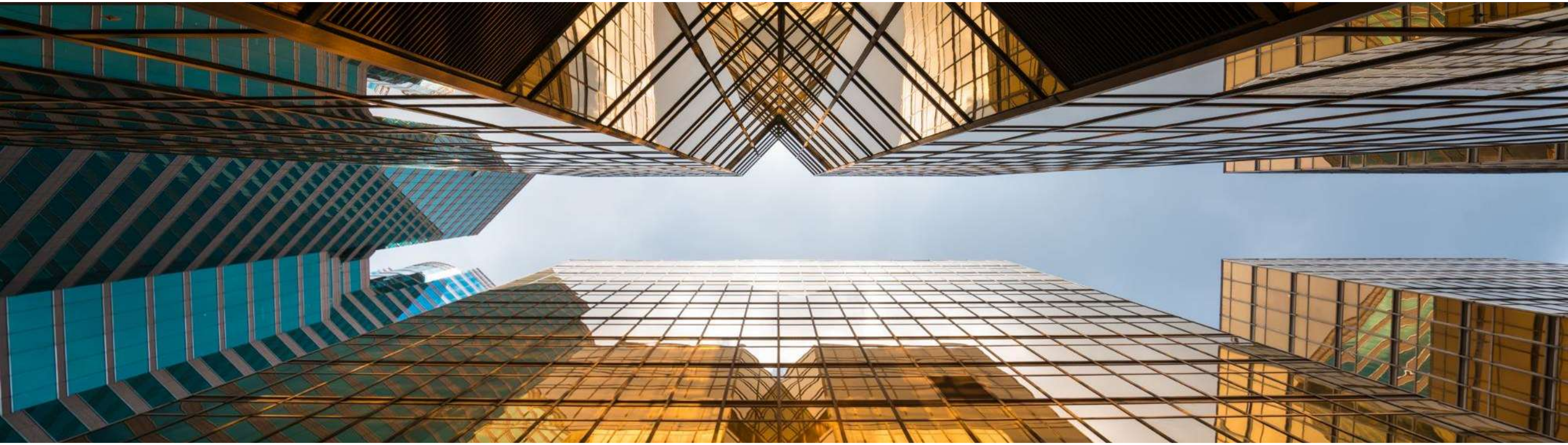
- The M5 forecasting competition used Walmart data – what can we learn from it?

- Walmart is not a typical retailer (EDLP) – will results generalize to promotions (with bad data quality)?
- Winner: South Korean student with little forecasting training…
- XGBoost is a strong contender – but note lack of interpretability!
- Only 7.5% of submissions outperformed bottom-up exponential smoothing (forecast::ets())!
  - We don't know how many submissions were abandoned…
  - … but does an almost trivial method have a 92.5% chance of outperforming Kaggle participants?
- "Uncertainty" benchmarks were not appropriate for low volume count series
  - It surprised me that better benchmarks didn't work better than ARIMA
- Will differences in forecast accuracy translate into monetary benefits?
  - Differences in quality are small
  - Subsequent decisions depend on logistical parameters
  - Literature that posits direct links between better forecasts and better stocks is not applicable to supermarket replenishment

The bottom line: how to forecast for retail?

- Don't look to standard forecasting techniques
- Regression-based techniques seem to work (pretty) well
  - Causal
  - Explainable
  - Fast
  - Reasonably robust
- Consider regularization (Lasso, Ridge Regression, Elastic Net, Bayes)
- Understand your predictive distribution
  - …and when you need an expectation vs. a quantile forecast
- Expect to spend *a lot* of time & effort cleaning & preprocessing your data
- Understand the processes that "consume" your forecast
  - Logistical rounding
  - Order or promotion optimization
- Think hard about how to assess forecast quality
  - Use simulation & stock KPIs for logistical & replenishment use
  - Beware of selection biases if using forecasts for price & promotion optimization
- Build a good rapport with the business users – ensure that they trust your statistical expertise

Questions & answers



Multiple seasonalities

- How often do you see multiple seasonalities in retail demand time series? And even when they are there, are they really useful for planning purposes?

- Quite important for *fast movers* (so we have a chance to detect the signal) that are *perishable* (so the difference in forecasts actually has an impact)
  – Fruit like strawberries
  – Meat, especially chicken (short shelf life) and BBQ meats – the store butcher may need to carve the pig into different cuts if BBQ weather is coming up
  – Bakery – more rolls than bread being bought on Saturday morning at my local baker
- Related: workforce planning, with more staff necessary on the weekend
- Other seasonalities like paycheck effects are far weaker
  – I have seen SNAP and other social safety net payments have an effect on rice and similar staples in US inner cities

Differential impact of COVID-19 by country

- Did you see differences in countries in goods demanded during the pandemic? I recall that urban legends were that Germany had a toilet paper shortage and in France condoms and wine were out of stock.

- To be honest, I haven’t done an analysis on this
- (Note that most customers still keep their data on their own servers, so I only have access to data for certain retailers that I do analyses for)
- The toilet paper shortage may have occurred in the US too, judging from the internet
- Also, the toilet paper shortage in Germany was anything but an urban legend. The pictures is from my local supermarket in Germany. That’s no toilet paper you are seeing there

COVID-19 and the new normal

- Talking about Covid-19, have you seen your sales stabilize? And how you assume its new normal now :)?

- We have seen stabilization on lower levels for some products, and returns to normalcy for others (e.g., toilet paper)
- What the new normal is is still very much up in the air, especially since different geographies stop and restart lockdowns at different times
- So I’m still very cautious about forecasting anything COVID-related

Assortment changes

- How should you consider assortment changes in the SKU forecast as a retailer? If you double the number of different tomatoes in your store, you will probably not double your tomato sales figures. Is top/down forecasting vs macro sales forecast the normal approach?

- First off, grocers typically don't have truly extreme assortment changes
  - Whether one flavor of yogurt is added or removed from the assortment does not really make all that much of a difference (the well performing flavors won't be dropped) – it kind of disappears in the noise
  - Sometimes, products get phased out and successor products get introduced. Two possibilities:
    - Graft the predecessor time series in front of the successor time series
    - Use the model fitted to the predecessor as Bayesian priors for the new series

- More important: seasonal retailers, like fashion or outdoor
  - So-called Assortment Planning is a key process every season
  - Typically forecast on aggregate levels, then disaggregate down
  - Lower granularity sales are typically quite intermittent

Shelf capacity

- How do you take care of the each store's shelf space & capacity to hold goods, i.e if I have 200 units of toilet paper, by how much do I need to reduce the number of units I can keep of toilet cleaners & tissue boxes?

- On the one hand:
  – Shelf (and backroom) space is a constraint to ordering, so only relevant after forecasting
  – We still need good store processes to ensure backroom stock is brought to the shelves in time
- On the other hand:
  – Shelf space is a key driver of on-shelf availability (OSA), a mantra in the business
  – Low shelf space → frequent out-of-stocks (OOS) → censored sales → poor forecasts (which is where the impact on forecasts come in)

Constraints on the model

- Have you faced a situation where the model has to accomplish certain criteria like business rules? For instance, forecast profiles including MLR forecasting but with specific rules for the coefficients. E.g. x1 cannot be negative, x2 and x3 cannot be together... Have you faced that with any SAP solution?

- Many coefficients need to satisfy constraints to pass the laugh test
  - Promotion & tactic uplifts need to be positive (or at least nonnegative)
  - Price sensitivity & cannibalization need to be negative (or at least nonpositive)
  - Giffen goods (https://en.wikipedia.org/wiki/Giffen_good) are not really relevant
- And yes, we enforce those constraints, since unconstrained models can violate them simply through noise
- Letting coefficients be arbitrarily large (even with the right sign) leads to really rare really bad forecasts, so we constrain coefficients within an interval
- This can be considered a kind of regularization, or of specific priors on parameters – and we all know regularization can improve forecasts

Hyperparameters

- What hyperparameters could be tuned for the time series models to have a better demand forecasting?

- In our Bayesian framework, the most important ones are the parameters of the priors – prior means are often obvious, prior variances (precision) more challenging
- Especially for longer-term forecasts, the trend dampening parameter
- We detect delisting and out of stock periods – detection parameters need to be tuned
- However, usually getting good quality data (especially about promotions) is far more important!

Supply chain quality & the impact of forecasts

- Walmart has a famously good supply chain (so does Zara) - and so are the methods used to win on Walmart data relevant for "mere mortal" retailers that can't react as quickly as they do?

- You could also turn this around: if you have a highly adaptive supply chain, then you can react immediately, so the forecasts are much *less* important for Walmart, right?
- I would say that if you have a problematic supply chain then forecasting may (may!) not be the first place you want to improve…
- … then again, better forecasts may help mitigate the weaknesses of your logistics
- There are arguments either way

Forecast combination

- Is forecasts combination from different models a winning strategy based on your retail experience?

- I am a HUGE fan of forecast combination in theory
- Unfortunately, it’s hard enough to build a single model that accounts for all the drivers explained above…
- … and models to be combined really need to be “different enough”…
- … so building multiple models yields a horrendous TCO!
- (Note that all these models would need to be maintained and updated each time a new feature is added!)
- So unfortunately, I don’t have any experience with forecast combination in retail

E-commerce

- What are your thoughts on forecasting demand in e-commerce?

- That's a whole new presentation all by itself!
- Some challenges are less important:
  – Less censoring, since central distribution centers typically have more stock
  – Better system inventory data than in stores (where more shrinkage occurs)
- Some are more important:
  – Other promotions than in brick & mortar (e.g., what is shown on the splash page)
  – We know the customer who is just surfing our site (transaction history, browsing history, cookies, …), so we may personalize promotions and prices, and recommend things
  – (So do we need to forecast who may be visiting our site, to improve forecasts for *demand*?)

Training at scale

- Could you speak a bit about methods to do training at scale? Your examples about potentially 20 million + forecasts is very true.

- The technological aspects are definitely my weakest spot (see https://datascience.stackexchange.com/q/2403/2853)...
- We are SAP, so we just throw HANA at everything and scale resources until it works
- In general:
  – Parallelize as far as possible (duh!)
  – Train/fit offline, apply/score/forecast online
  – Retrain only if information has changed (e.g., if a promotion has just started)
  – Keep last model, use as starting values for parameters in refitting
- Actually, often the bottlenecks are not the statistical model, but the sheer database operations, so the forecaster is not the person with the biggest lever

Store clustering

- Similar to the question around "grouping" SKUs, would you also recommend grouping stores (e.g., by a clustering method) before then forecasting the stores in a cluster together.

- Definitely!
- Big stores vs. small stores (may have different promotional uplifts)
- Stores in specific locations (e.g., in vacation spots like the mountains or the seaside)
- Different formats (supermarkets vs. convenience stores, even if same brand)

Automated tools

- Do you recommend using automated tools such as Amazon Forecast, DataRobot or H2O Driverless AI?

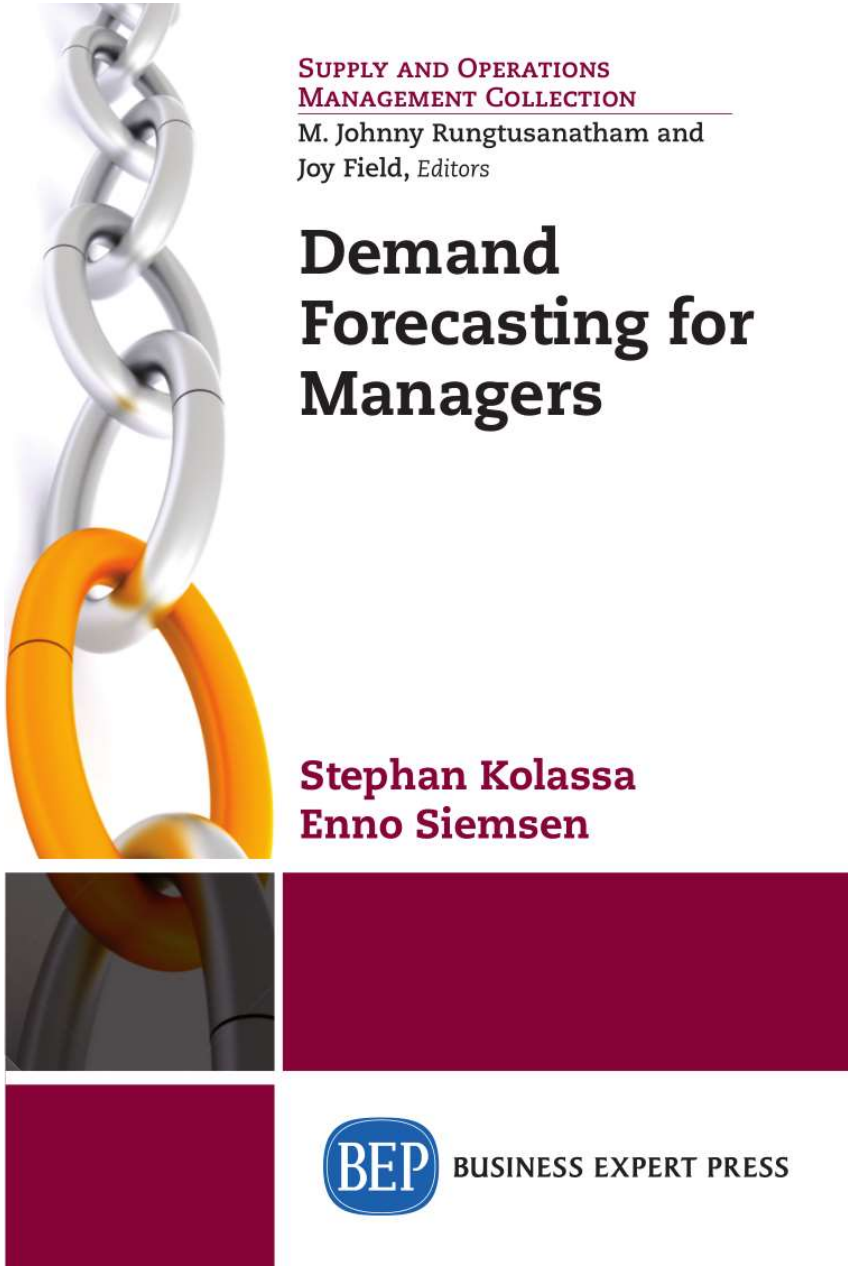
- Well, for retail I of course recommend using SAP's CARAB platform with UDF…
- These people certainly know what they are doing…
- … but as a retailer, I don't know how keen I would be on handing my data over to Amazon…
- Especially with the vast zoo of possible promotions, good parameterization and model building can really make a difference
  – Note that badly forecasted promotions can lose a lot of customer goodwill
  – So off-the-rack solutions may be limited in accuracy compared to what is possible

Thank you.

Stephan Kolassa

Data Science Expert
Stephan.Kolassa@sap.com

Honorary Researcher
Centre for Marketing Analytics and Forecasting
Lancaster University Management School
s.kolassa1@lancaster.ac.uk



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