On the identification of sales forecasting model in the presence of promotions

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Journal of Operational Research Society, (2014), Forthcoming

This work was supported by the SAS/IIF research grant

Promotional Support Systems

In "Analysis of judgemental adjustments in the presence of promotions" (Trapero et al., 2013) we showed that:

- Simple statistical promotional models outperform on average human adjustments
- Not all information of human judgment is captured by simple promotional models
- There is room for improvement with more advanced promotional modelling

Furthermore:

- There is an apparent gap in the published work (and software) for promotional support systems for SKU level predictions
- Existing brand level promotional models have limitations:
    1. Require extensive model inputs → feasibility and cost considerations
    2. Complex input variable selection is required → which are the relevant promotions?
    3. Promotions are often multicollinear → difficult to estimate their impact and get reliable forecasts
    4. These models require past promotion history → promotional forecasts for new products?
    5. These models do not capture the demand dynamics adequately

These limitations explain the observed reliance on expert adjustments (Lawrence et al., 2000; Fildes and Goodwin, 2007)

Case Study

A manufacturing company specialized in household detergent products → data available:

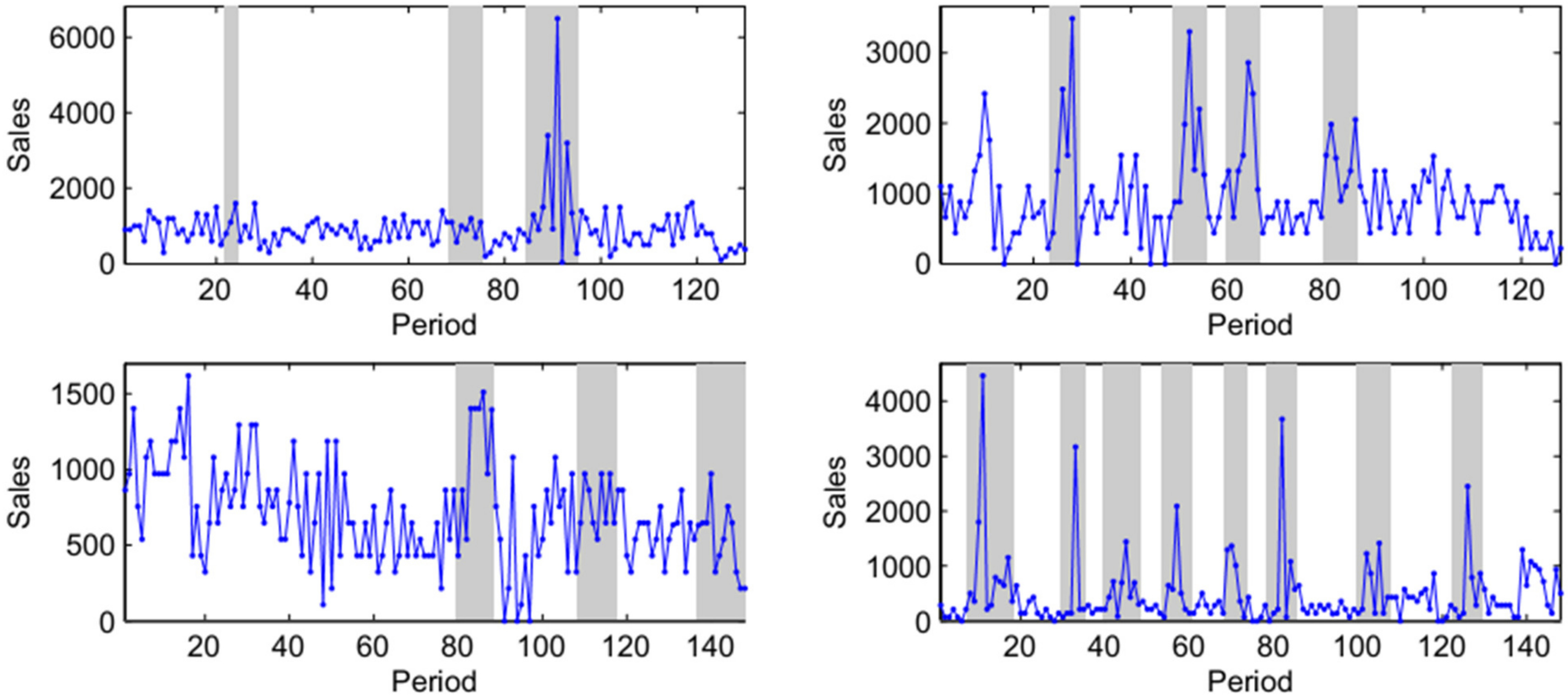
- Shipments
- One-step-ahead system forecasts (SF)
- One-step-ahead adjusted or final forecasts (FF)
- Promotional information:
  1. Price cuts
  2. Feature advertising
  3. Shelf display
  4. Product category (22 categories)
  5. Customer (2 main customers)
  6. Days promoted in each week

The data contains 60 SKUs (all contain promotions)

Data withheld for out-of-sample forecast evaluation
Some products do not contain promotions in the parameterisation (historical) sample

Case Study

Example time series



Periods highlighted in grey have some type of promotion

Models

Statistical Promotional Model

The proposed promotional model contains the following elements:

- **Principal component analysis of promotional inputs**: The 26 promotional inputs are combined a new composite inputs that are no longer multicollinear* → Only a few new inputs are needed now, simplifying the model.

- **Pooled regression**: When an SKU does not have promotions in each history, we pool together information from other SKUs (the product category information is available to the model) to identify an average promotional effect. When enough promotional history for an SKU is available we do not pool information from other products

- **Dynamics of promotions**: Carry-over effects of promotions, after they are finished, are captured

- **Dynamics of the time series**: Demand dynamics are modelled for both promotional and non-promotional periods.

*Two inputs are called multicollinear when it is impossible to distinguish what is the effect of each individual input on the forecasted demand.
For instance, assuming that we run two promotions running in parallel, resulting in a sales uplift of +300%, it is impossible to identify the individual impact of each promotion. This is very problematic is it is possible that the promotions can also run separately.

Models
Benchmarks

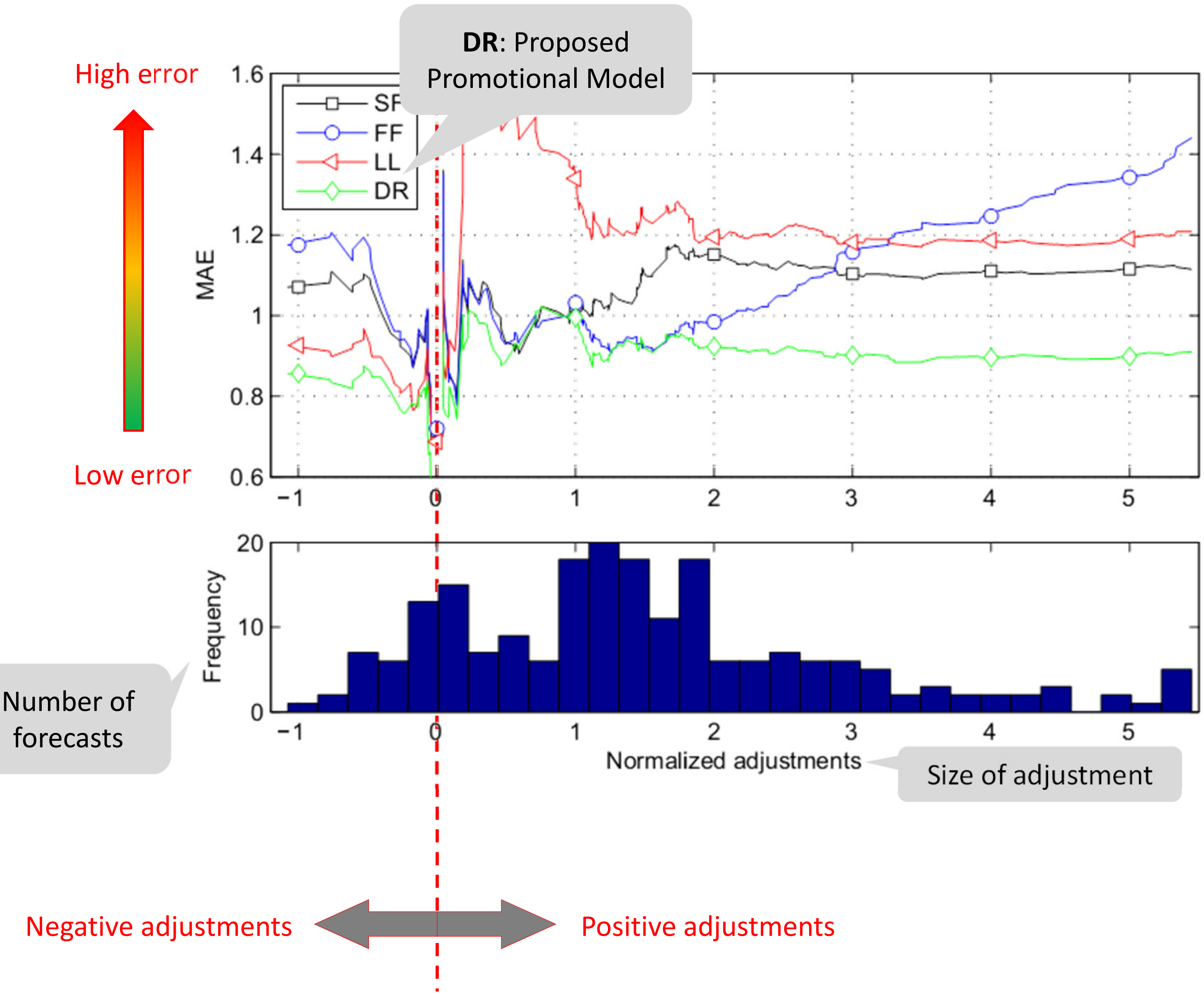
A series of benchmark models are used to assess the performance of the proposed promotional model

- System Forecast (**SF**): The baseline forecast of the case study company
- Final Forecast (**FF**): This is the SF adjusted by human experts in the company
- **Naïve**: A simple benchmark that assumes no structure in the demand data
- Exponential Smoothing (**SES**): An established benchmark that has been shown to perform well in supply chain forecasting problems. It cannot capture promotions
- Last Like promotion (**LL**): This is a SES forecast adjusted by the last observed promotion. When a promotion occurs the forecast is adjusted by the impact of the last observed promotion

Note that only FF and LL can capture promotions from our benchmarks

Case Study
Results

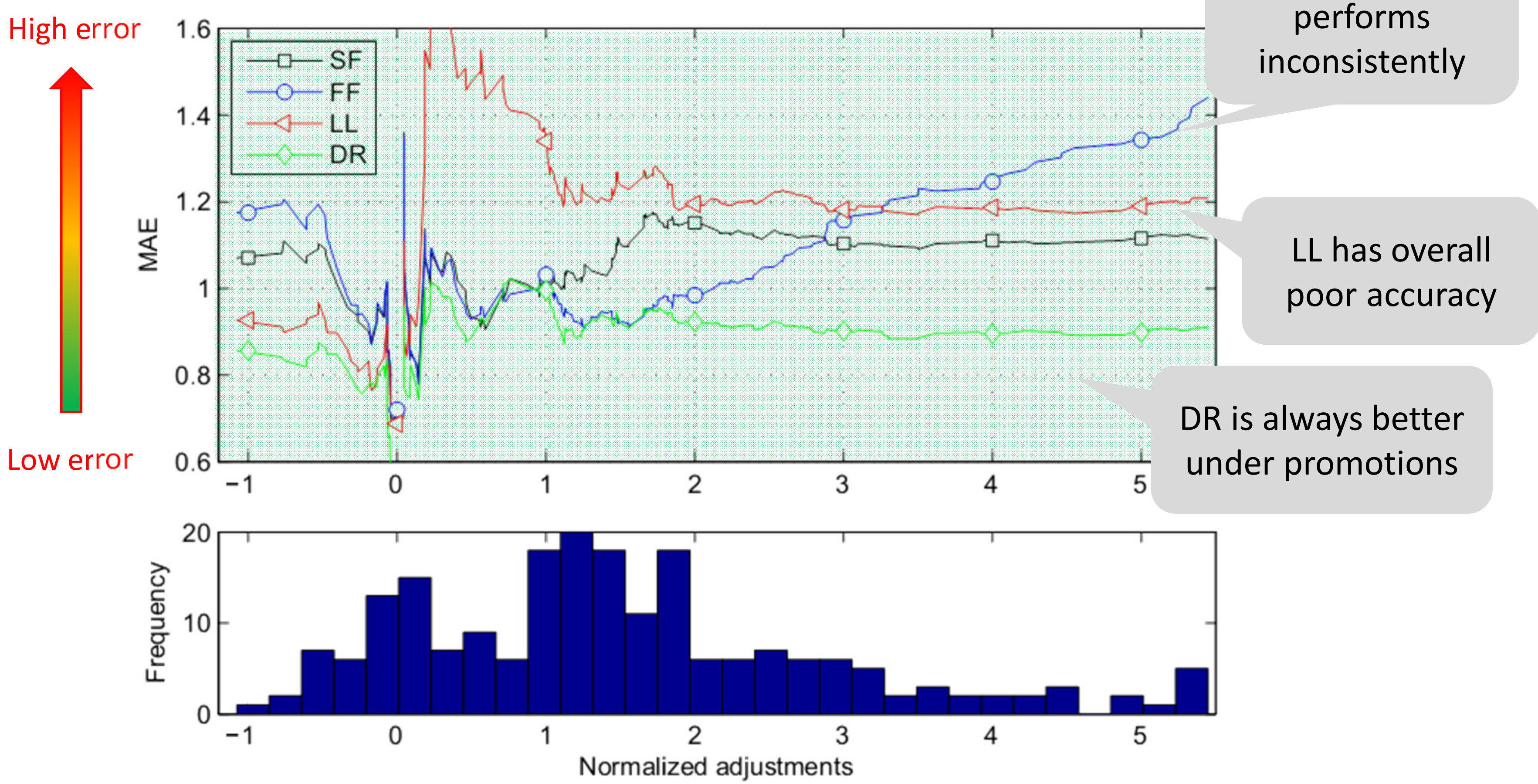
Forecast accuracy under promotions



Case Study

Results

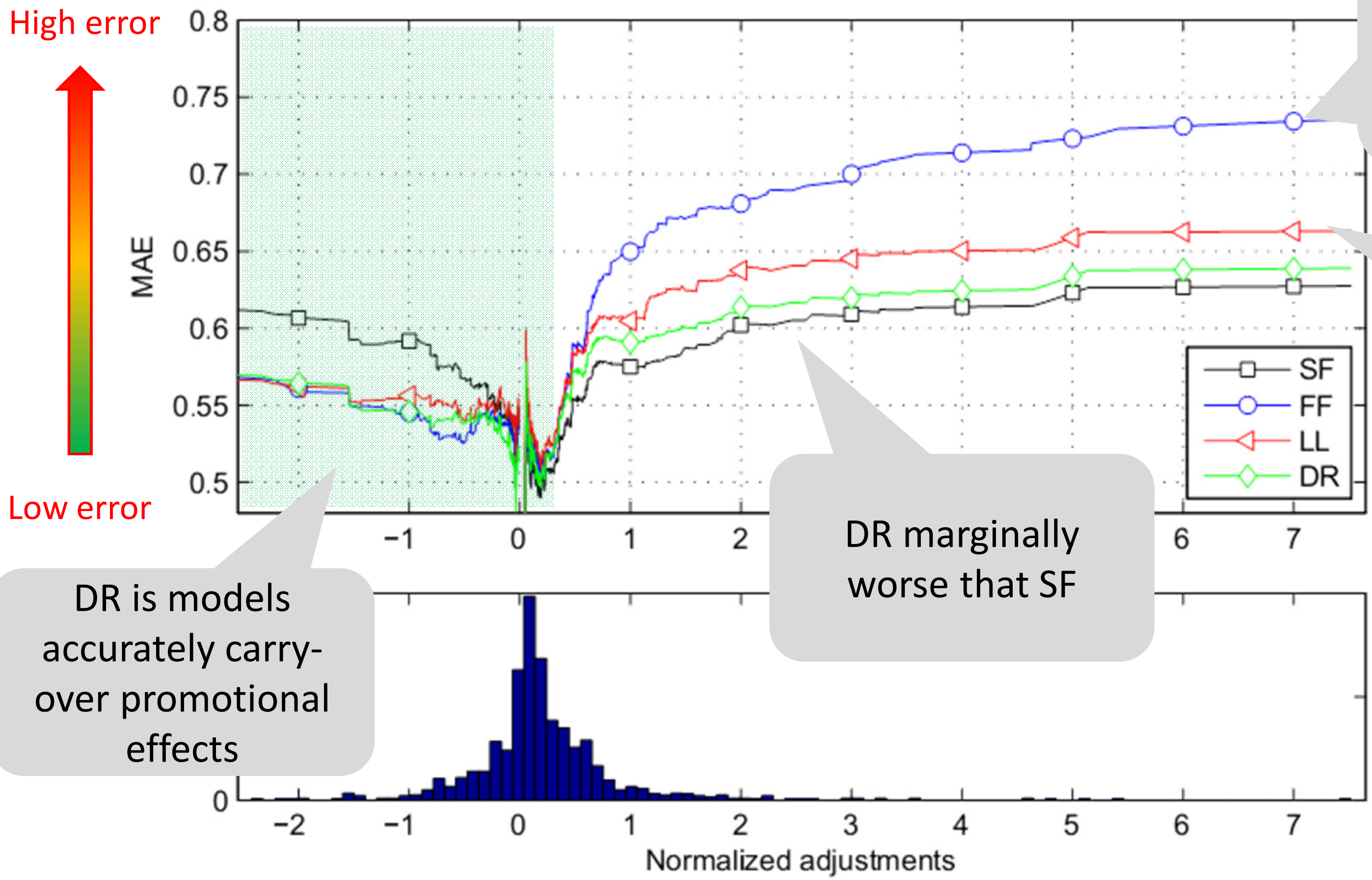
Forecast accuracy under promotions



DR is more accurate than human experts and statistical benchmarks in promotional periods

Case Study
Results

Forecast accuracy in non-promotional periods



Human judgment performs poorly → No reason for positive adjustments?

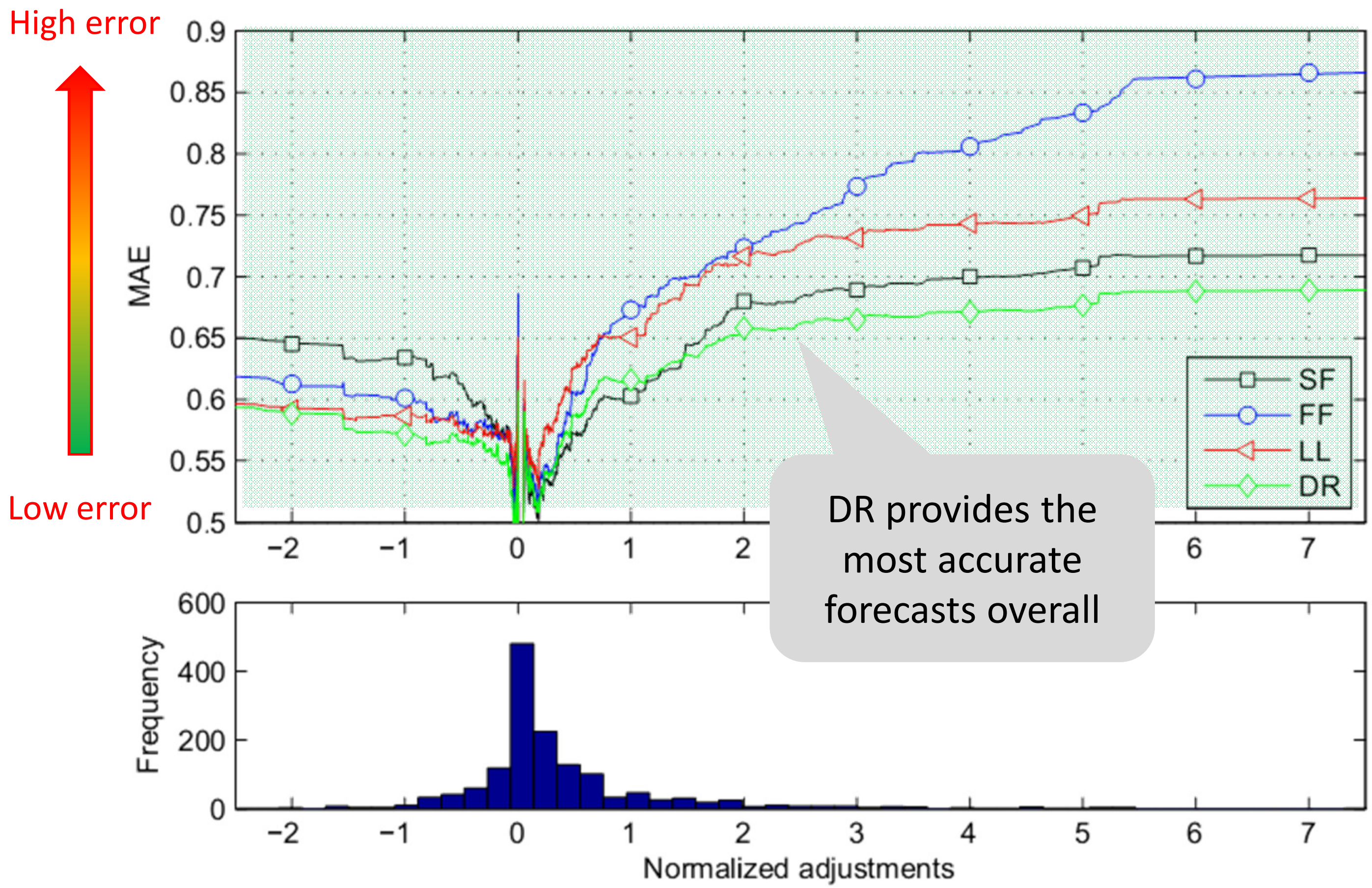
LL has overall poor accuracy

DR marginally worse that SF

DR is models accurately carry-over promotional effects

DR accurately captures carry-over promotional effects. SF is marginally better because the forecasts are based on adjusted historical demand. DR is modelled in raw data.

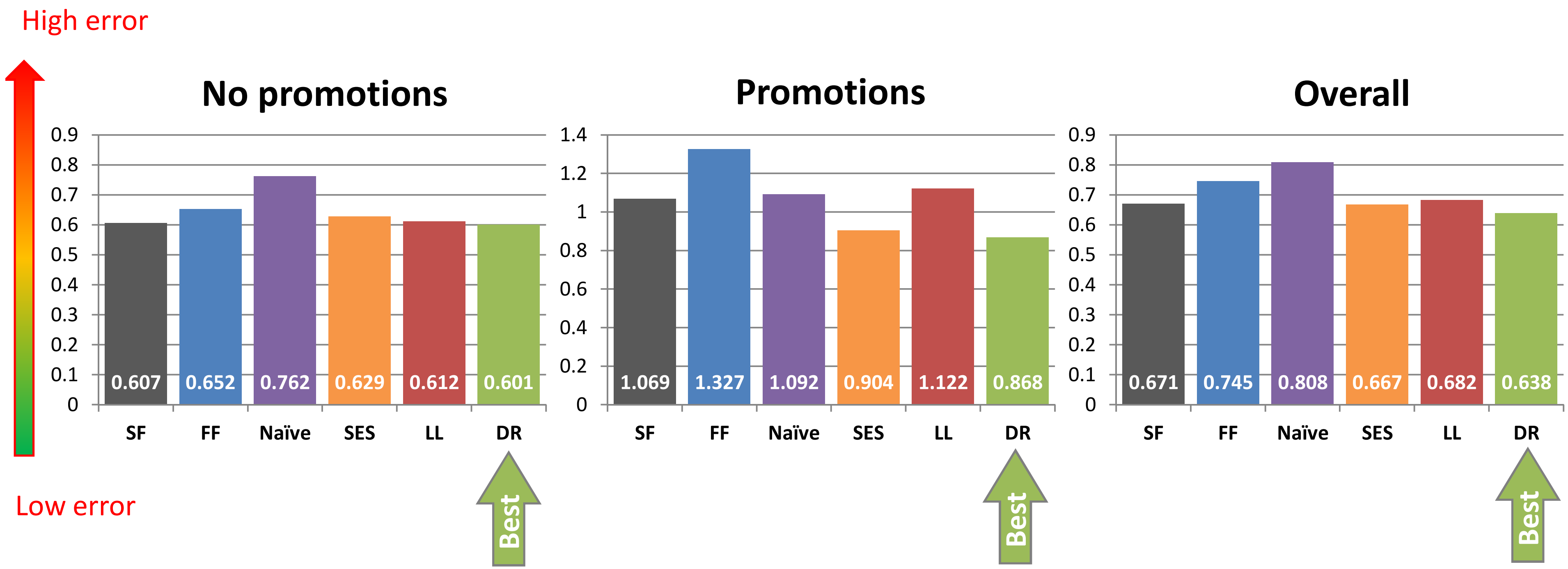
Overall forecast accuracy



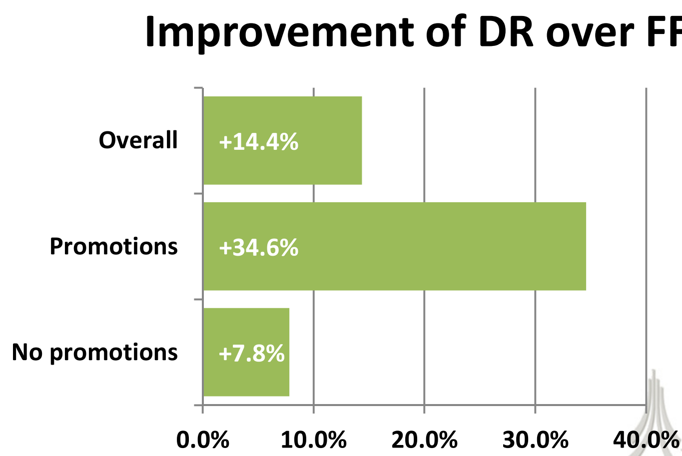
The proposed advanced statistical promotional model captures most of the human expert information, in a systematic way, producing superior forecasts.

Case Study

Results



- Proposed promotional model is consistently the most accurate
- Substantially outperforms current case study company practice (FF)
- Major improvements during promotional periods



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www.forecasting-centre.com

Conclusions

1. Proposed statistical promotional model significantly outperform human experts and statistical benchmarks

2. Company can benefit from increased automation of the forecasting process and reduced effort of experts to maintain forecasts, while accuracy is increased

3. Can produce promotional forecasts when there is no or limited promotional history for an SKU

4. Overcomes limitations of previous promotional models

5. Final model is relatively simple

Detailed analysis, findings and references in the paper:

http://kourentzes.com/forecasting/2014/04/19/on-the-identification-of-sales-forecasting-models-in-the-presence-of-promotions/