Identifying and responding to extraordinary demand events in quantity-based revenue management

Nicola Rennie[1], Catherine Cleophas[1,2], Adam Sykulski[1], Florian Dost[1,3]

[1] Lancaster University, [2] Christian-Albrechts-Universität zu Kiel, [3] University of Manchester

1. Revenue Management

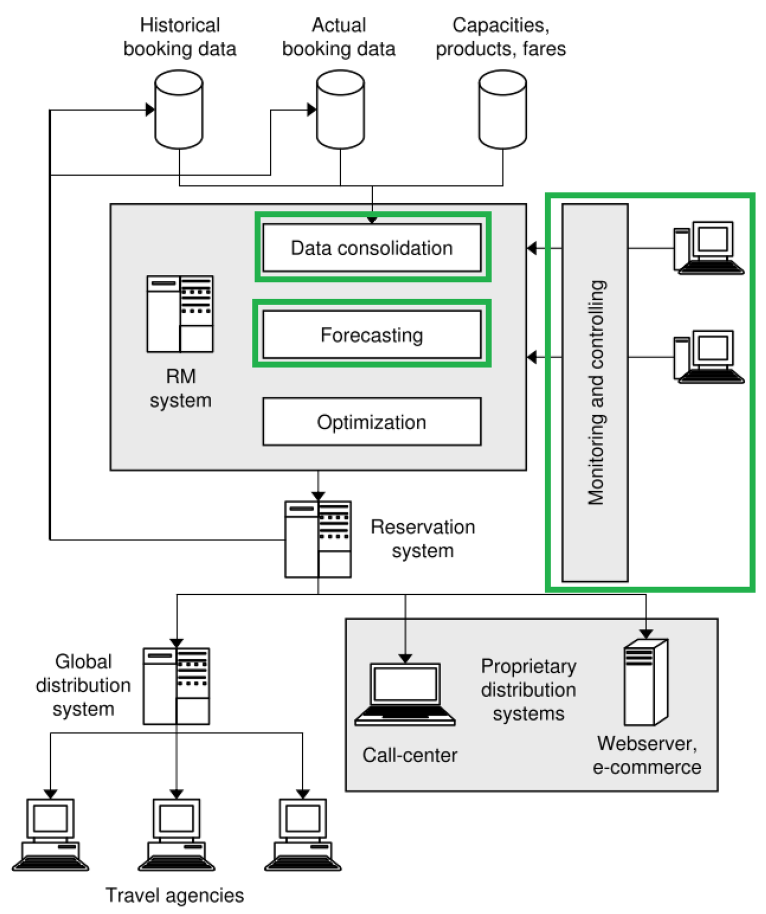
Revenue management (RM) relates to making **demand management decisions**, with the objective being to increase revenue. RM combines forecasting with optimisation techniques.

In **quantity-based RM**, airlines use inventory control to maximise revenue, and allocate seats to different price levels (**fare classes**), based on forecasts of passenger demand.

2. RM Systems and Analysts

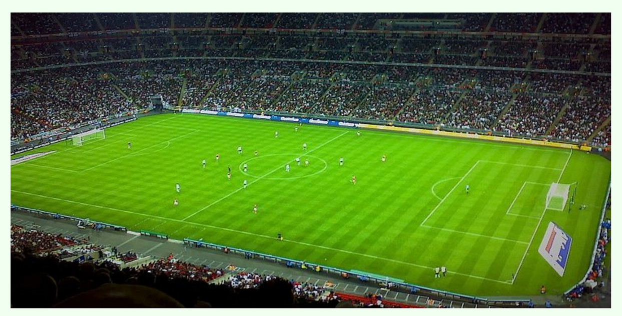
Most revenue management systems currently allow for interventions by analysts, who can make adjustments to either the forecasts or the inventory controls to improve the revenue potential of a flight.

However, humans are fallible and make mistakes. We sometimes see relationships in data that don't exist, and often fail to identify hidden patterns.



3. Extraordinary Demand Events

Extraordinary demand events cause inaccurate demand forecasts. This results in non-optimal inventory controls, and hence a loss of revenue. These demand shocks may be caused by events, which are unknown to the RM system forecast, such as carnivals or sports tournaments.



Extraordinary demand events cause two negative effects:

- Forecasts made in future by the RM system will be contaminated.
- Non-optimal inventory controls no longer reflect the demand.

4. Effect of Extraordinary Demand on Revenue

Figure 1 shows the benefits of correcting inaccurate demand forecasts.

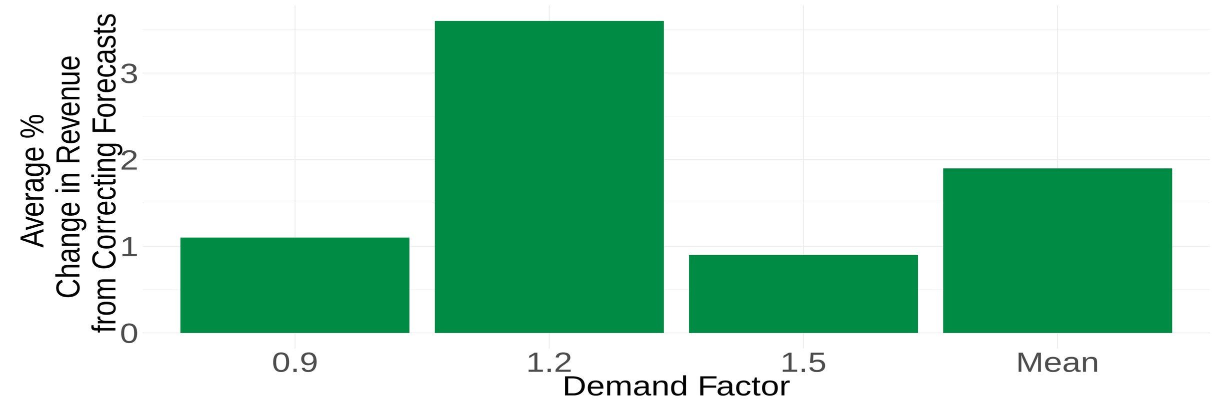


Figure 1: % Change in Revenue from Correcting Demand Forecasts

The change in revenue depends on the demand factor (ratio of demand to capacity) and the type of demand change, but is overall positive.

5. Outlier Detection

Outlier: *"an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism."* - Hawkins, 1980

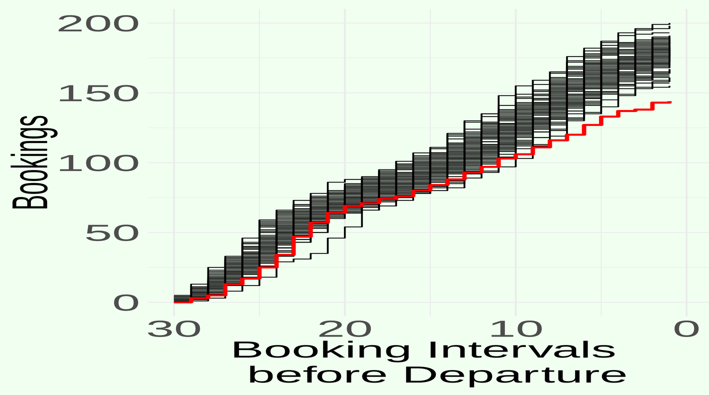


Figure 2: 25% Decrease in Demand

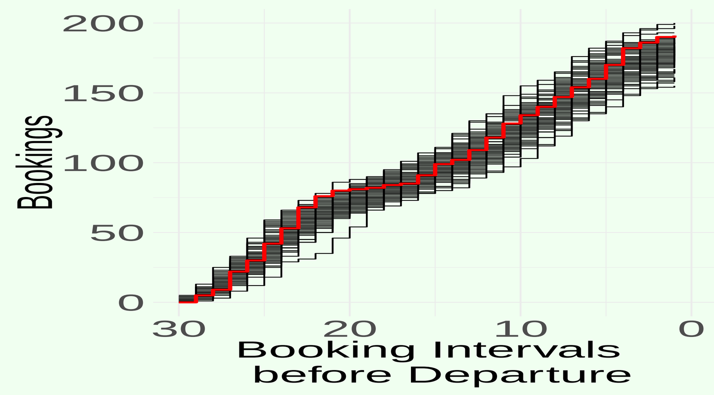


Figure 3: 25% Increase in Demand

- Outliers are caused by changes in passenger demand.
- Not all outliers are easy to spot by eye, hence the need for sophisticated outlier detection techniques.

6. Functional Depth

Functional depth is a measure of the centrality, or 'outlyingness' of an observation with respect to a given dataset. In the case of one-dimensional random variables, the **halfspace depth** of a point y_n with respect to a sample $y_1, \ldots, y_N$ drawn from distribution F is:

$$HD(y_n) = min\,\{F_N(y_n), 1 - F_N(y_n)\}$$

where F_N is the empirical cumulative distribution of the sample $y_1, \ldots, y_N$. This definition has been extended into the multivariate functional data setting. Booking curves with functional halfspace depth below some threshold are classified as outliers.

7. Results

$$BCR = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right).$$

Figure 4: Balanced Classification Rate (BCR)

- Functional depth consistently outperforms alternative outlier detection techniques.
- Large magnitude changes in demand are easiest to detect.
- Decreases in demand, rather than increases, are also easier to detect due to censoring from capacity restrictions.

8. Conclusions and Further Work

Conclusions:

- Detecting outliers and correcting forecasts has a significantly positive impact on revenue.
- Outlier detection is a viable method for automating the identification of critical flights which require analyst adjustment.

Further Work:

- Recommending actions to take after critical flight identification.
- Investigate the impact of extraordinary demand in the price-based revenue management setting.

9. References

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- D. Hawkins. *Identification of Outliers*. Chapman and Hall, 1980.
- S. López-Pintado and J. Romo. *On the Concept of Depth for Functional Data*. Journal of the American Statistical Association, 104(486):718-734, 2009.

n.rennie@lancaster.ac.uk http://lancaster.ac.uk/~rennien/