Identifying and responding to outlier demand in revenue management

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1. Revenue Management

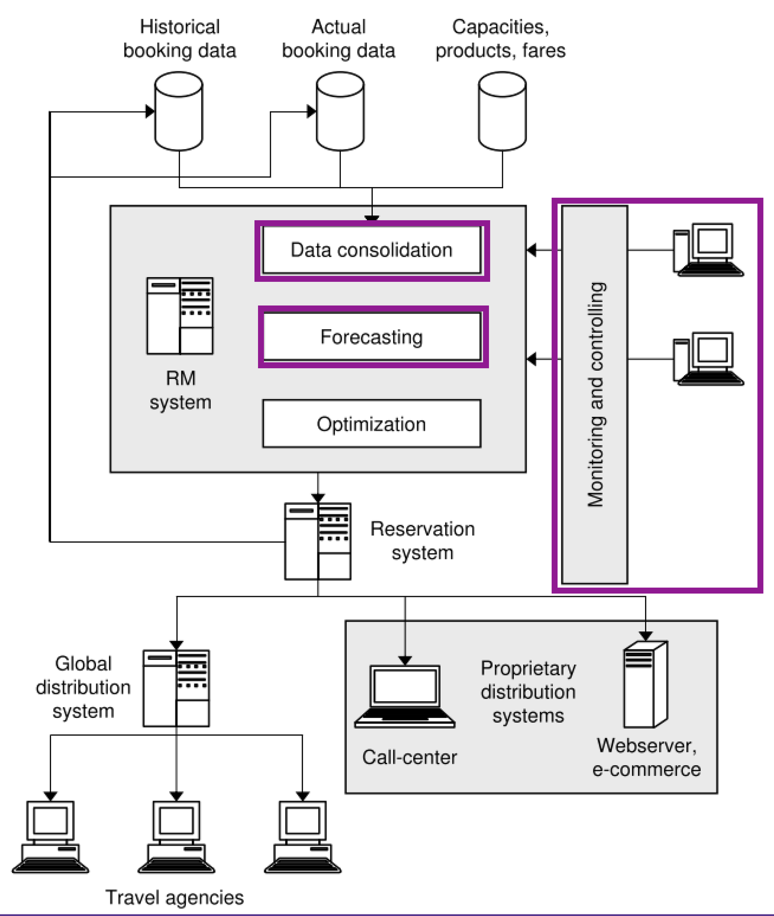
Revenue management (RM) relates to making **demand management decisions**, with the objective being to increase revenue. RM combines forecasting with optimisation techniques.

In **quantity-based RM**, companies use inventory controls to maximise revenue, and allocate resources to different price levels (**fare classes**), based on forecasts of customer 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 of outlying booking curves.

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. Outlier Demand

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

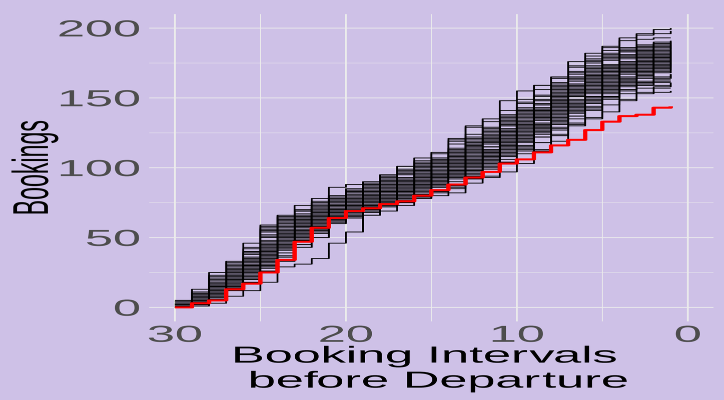


Figure 1:25% decrease in demand

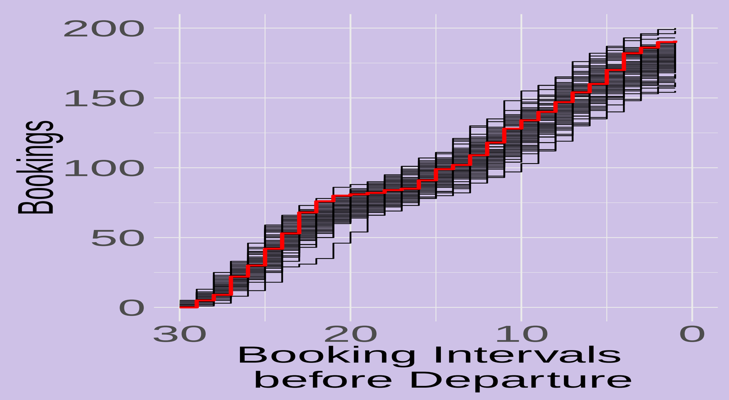


Figure 2:25% increase in demand

- Outlier demand can result in non-optimal inventory controls, and the contamination of future forecasts.
- Not all outliers are easy to spot by eye, hence the need for sophisticated outlier detection techniques.

4. 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:

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

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.

5. Extrapolation

- It is most beneficial to detect outlier demand early.
- Extrapolate beyond the observed bookings to amplify the differences between booking curves.
- Use univariate forecasting techniques e.g. ARIMA, SES, IGARCH for extrapolation.

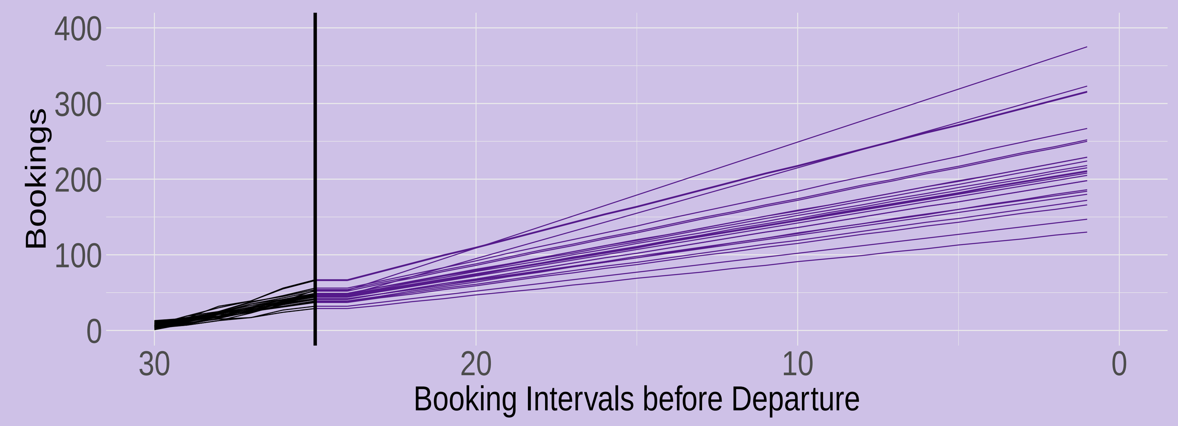


Figure 3:ARIMA extrapolation.

6. Results

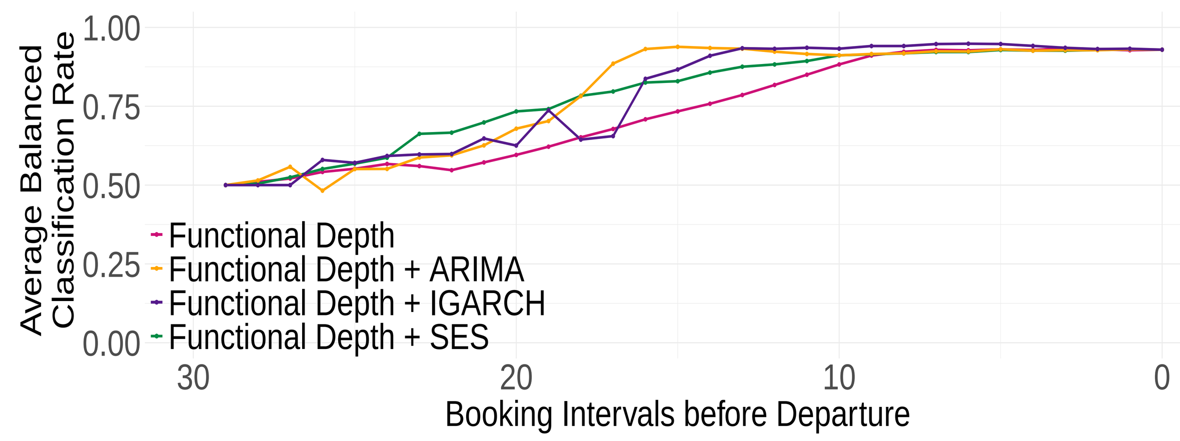


Figure 4:Balanced Classification Rate (BCR) $= \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right)$.

- Incorporating extrapolation improves the performance of functional depth for outlier detection, and outlier demand is detected earlier in the booking horizon.

7. Impact of Outlier Detection on Revenue

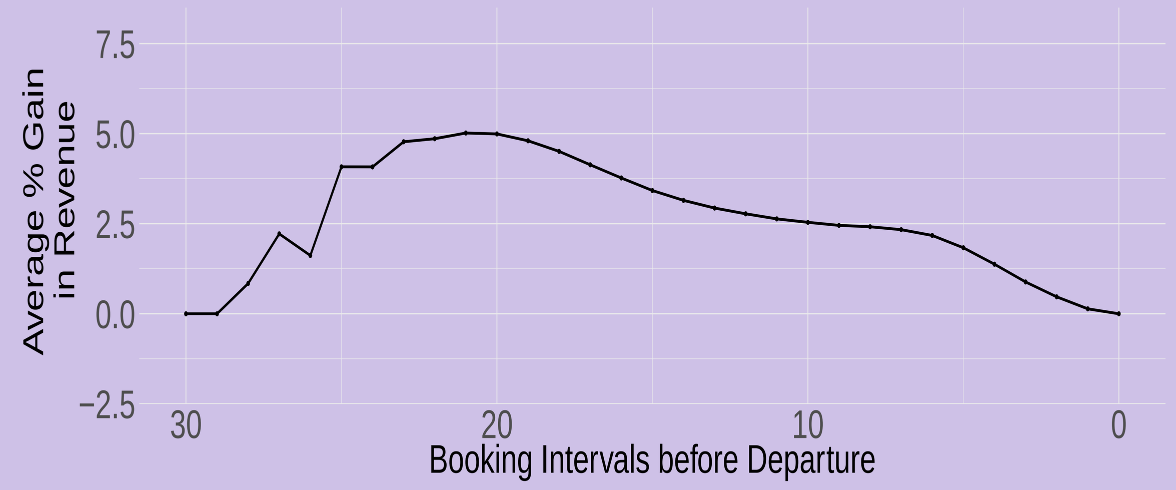


Figure 5:Gain in revenue from functional depth + ARIMA extrapolation alerts.

- Ideally, alerts should be early enough in the horizon such that any actions taken still have time to make an impact.
- However, outliers are often easier to detect later in the booking horizon.

8. Conclusions and Further Work

Conclusions:

- Outlier detection is a viable method for automating the identification of critical booking curves which require analyst adjustment.
- Incorporating extrapolation allows earlier detection of outlier demand for better impacts on revenue.

Further Work:

- Recommending actions to take after critical booking curve identification.
- Investigate the impact of extraordinary demand in the price-based revenue management setting.
- Comparing the use of outlier detection alerts with current methods in practice, on data from a real revenue management system.

9. References

- K. T. Talluri and G. J. Van Ryzin. *The Theory and Practice of Revenue Management*. Kluwer Academic Publishers, 2004.
- 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.

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