Mitigating Hotel Revenue Management System Risk Using Anomaly Detection in Short Booking Windows

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ABSTRACT

Investigating anomaly detection for improved pricing decisions for economy hotels within 48 hours. In order to satisfy demand at a price and achieve the greatest revenue, PCA, clustering, and rule-based models are used to detect anomalies in the 48-hour window using historical data and an alert system was built on top of it. These alerts were categorized to high, medium, or low alerts and sent to revenue managers, helping them adjust prices and resources accordingly and mitigate risk.

INTRODUCTION

Economy hotel chains experience high demand variability within 48 hours of each booking date. These demands do not have high visibility, affect the price, and make these hotels less competitive. The addition of anomaly detection help monitor demand in real-time and optimize revenue. Finding the right model to detect the anomaly and alerting the hotel operators to optimize their prices can increase the potential for hotels to maximize their revenue.

Issues Today	Solution
Low visibility in changing demand.	Monitor the demand in real-time.
Affects the price mark-up; reduced revenue optimization.	Build an alert mechanism in real-time anomalies in demand.
Noncompetitive pricing increases the likelihood of booking a competitor's property.	Utilization by Property managers in decisions of price for the property.

Our study is divided into 4 main steps:

Anomaly Detection → Alert → Price Optimization → Revenue Maximization

RESEARCH OBJECTIVES

- What methodology provides a robust demand forecasting model to form the best baseline?
- How can we best detect demand anomalies?
- What is the optimal margin to utilize in order to neither over detect nor under detect anomalies?

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METHODOLOGY

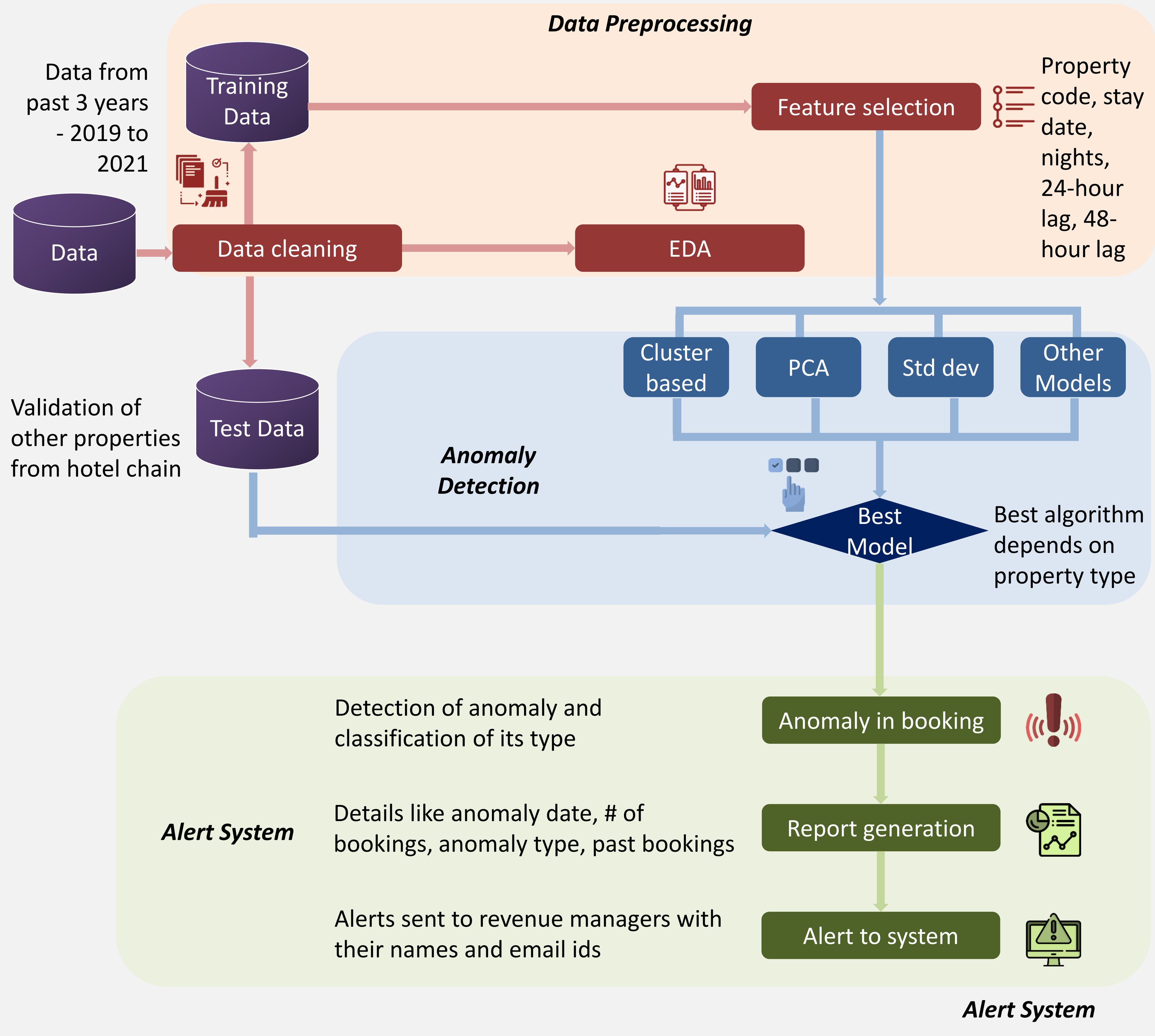


Fig 1. Methodology

MODEL REVIEW

Approaching the development of our model, a variety of algorithms was utilized to test the accuracy with the data provided, selecting the models that provided the best performance to continue. As the data was unlabeled, we focused primarily on unsupervised models. Overall, 12 models were tested on a set of three hotels. The top three model types, PCA, Clustering and Standard Deviation, were further implemented on the set of 11 hotels.

Model	Principal Component Analysis	Standard Deviation	Clustering-based
Pros	Preventative measure for sporadic anomalies	Basic, easily interpreted model	Easily visualized and interpretable
Cons	Anomalies on the low end were easily missed	Skewed data causes issues with anomaly prediction, overpredicting on the heavy tail	Clusters may include true anomalous points

ANOMALY DETECTION & ALERT SYSTEM

Among the many models used for anomaly detection for booking in the last 48-hour window, there were many underperforming models like isolation forest, clustering models, etc. The best performing models were PCA, Clustering-based detection, and standard deviation. From figure 3, the combined model was able to detect both low and high demand anomalies whereas PCA only (Figure 4) was able to identify only the high demand anomalies. Local anomalies were also discovered in the combined model.

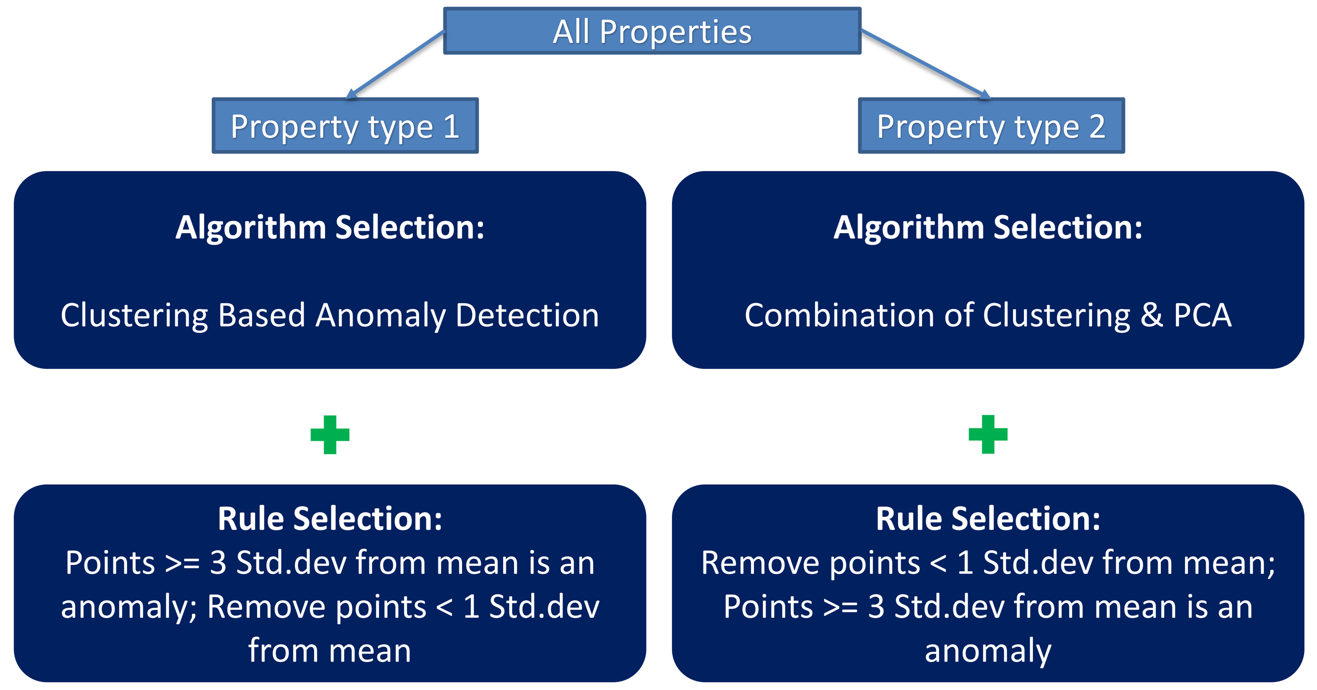


Fig 2. Model Summary for different property types

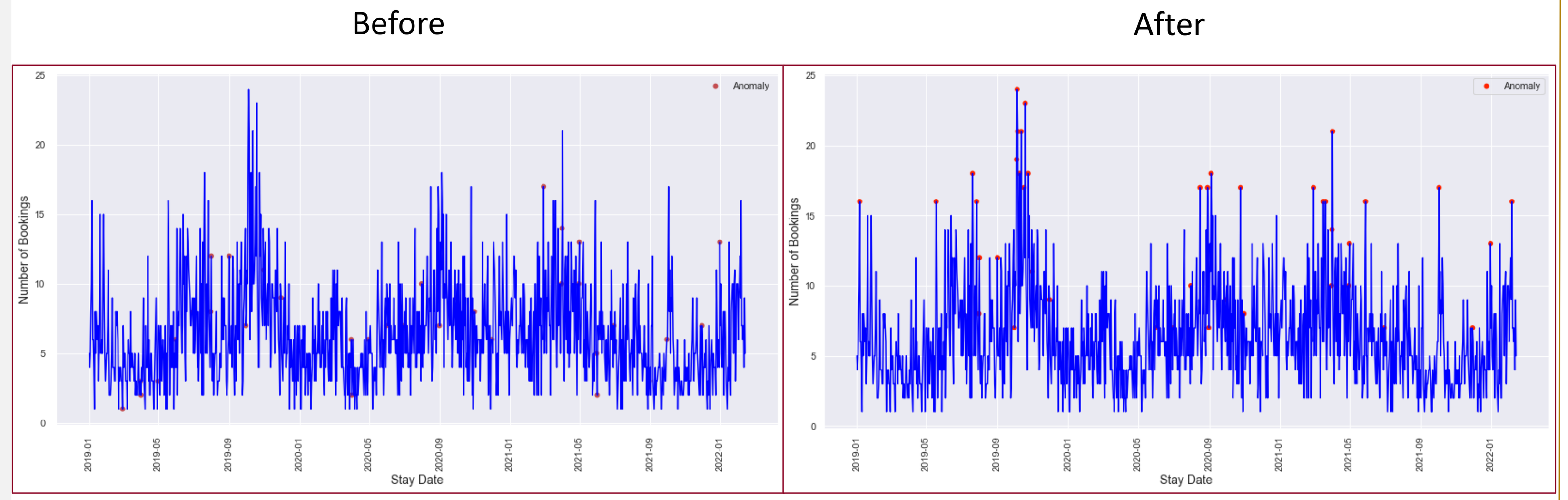
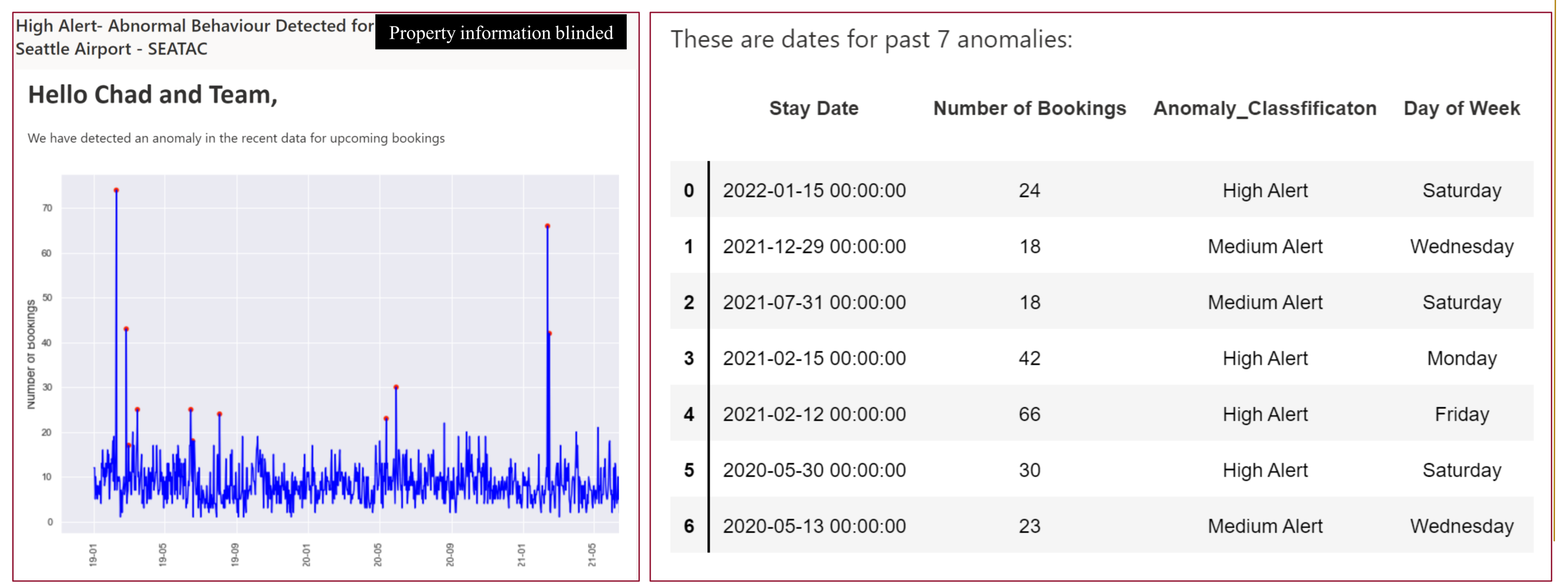


Fig 3. Model Results before and after implementation of Algorithm + Rule Selection



	Stay Date	Number of Bookings	Anomaly_Classificaton	Day of Week
0	2022-01-15 00:00:00	24	High Alert	Saturday
1	2021-12-29 00:00:00	18	Medium Alert	Wednesday
2	2021-07-31 00:00:00	18	Medium Alert	Saturday
3	2021-02-15 00:00:00	42	High Alert	Monday
4	2021-02-12 00:00:00	66	High Alert	Friday
5	2020-05-30 00:00:00	30	High Alert	Saturday
6	2020-05-13 00:00:00	23	Medium Alert	Wednesday

Fig 4. Snapshot of Email Alert after an anomaly is detected

EXPECTED IMPACT

From our combined model, an accuracy was determined through visual inspection with insight from personnel familiar with the data. The combined model produced a true positive rate around 83% and a false positive rate around 1%.

Assuming optimal pricing can be determined from the demand alert, different rates of revenue increases were predicted for each level of anomaly. From these predictions, we figured the average increase in revenue per year to be from 2.6% to 3.5%. Each day the alert helps aid the manager optimally price the bookings, a predicted an increase in revenue of 34% to 46%.

~83%	~1%
True Positive Rate = True Positives (TP) / Actual Positives	False Positive Rate = False Positives (FP) / Actual Negatives

Fig 5. Accuracy of predicted anomaly detection

Fig 6. Total increase in revenue ($) based on predicted anomaly detection

CONCLUSIONS

The profit gain and cost optimization benefits from the implementation of this product have been shown to be great. The implementation should be carried out within a submarket of suburban hotels, which can then be adapted to fit a company-wide use. From this company-wide adoption, future progressions and adaptions to this product could include a broader anomaly detection scope, allowing for earlier pricing alterations based on demand, and an automatic pricing suggestion to the revenue manager based on additional key variables: room type, demand, etc.

ACKNOWLEDGEMENTS

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