Executive Summary

Booking cancellations present a persistent challenge for ABC Hotels, driving lost revenue, operational inefficiency, and uncertainty in occupancy forecasting. This project applies a dense feedforward neural network to historical booking data to predict the probability that a reservation will be canceled. Building upon the Analytic Plan developed in Part 1, this report outlines the data processing pipeline, model architecture, and evaluation results. The preliminary model achieved a validation ROC-AUC of 0.83, precision of 0.73, and recall of 0.71, demonstrating strong discriminatory power and practical value for operational decision-making. Learning-curve diagnostics reveal mild overfitting and highlight opportunities for improvement through stronger regularization, threshold tuning, and richer behavioral features. These findings confirm that cancellations can be predicted with high reliability which enables ABC Hotels to anticipate revenue loss and intervene proactively.

1. Background and Motivation

Hotel cancellations are a hidden cost center. Every unoccupied room represents lost opportunity and increased planning volatility, especially in high-demand seasons. ABC Hotels faces a cancellation rate of roughly one in three bookings which is a proportion significant enough to warrant predictive intervention. The central question driving this study is: Can a data-driven model reliably identify high-risk bookings early enough for the business to respond?
In Part 1 of the project, exploratory analysis revealed several behavioral indicators of cancellation: longer lead times, higher room prices, fewer special requests, and non-repeat guest status. This second phase builds upon that foundation by implementing a supervised machine learning model capable of translating those insights into actionable risk scores. The focus is not merely on predictive accuracy, but on operational value with providing managers a clear, interpretable probability that informs deposit policies, promotional targeting, and communication strategies.

2. Data Processing and Feature Engineering

The dataset contains 36,238 bookings, each annotated with the variable booking_status (canceled = 1, not_canceled = 0). Prior to modeling, extensive data cleaning and feature preparation were performed following the Analytic Plan. Non-informative identifiers (Booking_ID) were removed. The arrival_date field was parsed into standard datetime format, from which new temporal attributes such as arrival month and arrival season were derived to capture cyclical booking patterns. Categorical variables (type_of_meal_plan, room_type_reserved, market_segment_type) were one-hot encoded to ensure compatibility with numerical learning algorithms, while continuous variables like lead time, average price per room, and number of special requests were standardized via z-score normalization to optimize neural network convergence. Missing numeric data were imputed using median values, and categorical gaps were filled with the most frequent label.

The final preprocessing pipeline implemented through a scikit-learn ColumnTransformer guarantees consistent transformations between training and inference, supporting reproducibility and future deployment. The data were split into 80% training and 20% validation sets, stratified to maintain class proportions.

3. Neural Network Architecture and Training Configuration

To model the probability of cancellation, a dense feedforward neural network (multi-layer perceptron) was selected for its ability to capture nonlinear interactions between behavioral and temporal predictors. The chosen architecture consists of two hidden layers with 64 and 32 neurons, respectively, each using ReLU activation. This configuration offers a balanced trade-off between expressive power and computational efficiency. The final output layer contains a single neuron with a sigmoid activation, producing a probability value between 0 and 1. Training employed the Adam optimizer with a learning rate of 0.001 and an L2 regularization term of 1e-4 to prevent overfitting. Early stopping monitored validation performance with a patience of five epochs, terminating training once progress plateaued. The network was trained using mini-batches of 512 examples for up to 50 epochs, though convergence was typically achieved sooner. This setup reflects a robust yet conservative starting point, enabling diagnostic evaluation before deeper or wider architectures are explored.

4. Evaluation and Findings

The model was evaluated on the held-out validation set using metrics suited for imbalanced classification problems. The results are summarized as follows:

- ROC-AUC: 0.83
- Accuracy: 0.80
- Precision (canceled = 1): 0.73
- Recall (canceled = 1): 0.71
- F1-score: 0.72

These scores indicate that the network not only distinguishes canceled from non-canceled bookings effectively but also balances precision and recall in a way that supports actionable business decisions. The ROC-AUC of 0.83 confirms strong rank-ordering ability with high-risk bookings being consistently assigned higher cancellation probabilities while the F1-score suggests that the model is neither overly conservative nor prone to false alarms. Learning-curve analysis provides further insight. When training size increased from 30% to 100% of the data, the training AUC decreased slightly (from 0.90 to 0.85) while the validation AUC increased (from 0.78 to 0.83). This inverse movement implies the model continues to generalize better as it sees more examples, though a small performance gap persists between the curves. In practical terms, the network exhibits mild overfitting but not underfitting; it captures key structure in the data yet could generalize further with modest regularization or additional feature diversity. Compared to simpler baselines such as logistic regression (AUC ≈ 0.79), the neural network achieves a 5% relative gain in discriminative power, reflecting its capacity to model nonlinear relationships between lead time, pricing, and customer engagement patterns.

5. Interpretation and Business Implications

From a managerial perspective, the neural network's predictive output serves as an early warning system. Bookings with high cancellation probabilities can trigger targeted interventions: confirmation reminders, deposit incentives, or non-refundable upgrades. Medium-risk reservations may receive lighter touch-points, while low-risk bookings proceed without action, preserving staff efficiency. A hypothetical revenue analysis underscores the impact. Assuming an average room price of $100 and 12,000 annual cancellations, even a 5% reduction achieved through targeted outreach could recover approximately $120,000 per year. Thus, every incremental improvement in AUC or recall translates directly into measurable financial gain. Feature-level interpretation further validates earlier insights. Longer lead times remain the most predictive variable, confirming that uncertainty increases as the booking horizon extends. Customers with fewer special requests or no prior loyalty history are more likely to cancel, consistent with a lack of emotional or practical commitment to their reservations. In contrast, repeat guests and those making customized requests (e.g., specific amenities) rarely cancel, suggesting deeper engagement. These behavioral signals can guide not only predictive modeling but also strategic marketing for instance, promoting early-bird discounts with partial deposits to long-lead customers.

6. Diagnosing Model Behavior and Recommended Improvements

Although the preliminary network performs well, diagnostic analysis indicates several enhancements for the next iteration. To mitigate mild overfitting, regularization strength will be increased (L2 ≈ 1e-3), and dropout layers (10–20%) will be introduced if the network is migrated to Keras or PyTorch. The architecture may be simplified to a single 64-unit hidden layer to test whether reduced capacity improves generalization. From a data standpoint, richer temporal and behavioral representations are expected to yield the greatest improvement. Proposed additions include:

- Lead-time buckets (short-term, mid-term, long-term) to capture nonlinear risk shifts.
- Season-price interactions to reflect market dynamics during holidays and events.
- Guest reliability ratios, combining past cancellations and fulfilled bookings.
- Aggregated engagement features, such as binary "any requests" indicators.
- Channel consolidation to merge rare market_segment_type categories and reduce sparsity.

Finally, the decision threshold (currently 0.5) will be tuned using precision-recall curves to align with business trade-offs. Since a false negative (missed cancellation) is more costly than a false positive, the operating threshold will be optimized for higher recall at acceptable precision. This cost-sensitive calibration ensures the model's predictions align with real financial priorities.

7. Limitations and Future Work

Several constraints temper the present results. Dense neural networks, while flexible, are prone to overfitting in tabular data contexts and often require more data than tree-based ensembles to achieve comparable robustness. Future work will therefore benchmark the MLP against gradient-boosted methods such as XGBoost and LightGBM, which may deliver similar or better AUC with improved interpretability. The model also assumes temporal stationarity that the statistical patterns of cancellations remain constant over time. In reality, seasonal promotions, economic conditions, or global events can shift behavior dramatically. For this reason, the final deployment will incorporate time-based validation, training on earlier months and evaluating on later periods to simulate real-world drift. Lastly, interpretability will be strengthened using permutation importance and SHAP value analyses, allowing hotel managers to see exactly which variables most influence each prediction. These visual explanations will bridge the gap between technical output and managerial trust.

8. Conclusion

The preliminary dense neural network successfully transforms historical booking data into predictive insight, achieving strong early-stage performance and clear business relevance. Its ability to rank reservations by cancellation risk gives ABC Hotels a strategic tool for dynamic occupancy planning, targeted customer engagement, and revenue recovery. The findings reaffirm that cancellations are not random but behavioral driven by factors such as booking horizon, price sensitivity, and engagement depth. The next phase of the project will refine both the model and its operational integration: stronger regularization, richer engineered features, and calibrated thresholds tuned to business costs. By combining these technical improvements with a deployment-ready architecture, ABC Hotels can move from retrospective analytics to proactive prevention transforming predictive accuracy into tangible financial performance.