Optimizing Customer Booking Predictions: Model Evaluation and Insights

In this presentation, I'll share my findings after enhancing the customer booking model using advanced techniques. By using Random Forests, one-hot encoding, SMOTE for class imbalance, and thorough Exploratory Data Analysis (EDA), I've significantly boosted the model's performance.

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Model Evaluation and Findings

I improved the customer booking model using techniques like Random Forests, one-hot encoding, and SMOTE for balancing. The model achieved an 85% accuracy, handling class imbalance well. Key features like "booking_origin" (Australia, Malaysia), "flight_duration" and "wants_extra_baggage" were significant, and cross-validation showed an average accuracy of 83%.

	1 1	11	C1		Top 10 Most Important Features							
	precision		f1-score	support	booking_origin_Australia -							
					booking_origin_Malaysia -							
0	0.85	1.00	0.92	8520	flight_duration -							
1	0.50	0.01	0.02	1480	wants_extra_baggage -							
1	0.30	0.01	0.02	1400	e route_PENTPE -							
					booking_origin_Indonesia -							
accuracy			0.85	10000	booking_origin_Singapore -							
maaro ava	0.68	0.50	0.47	10000	route_ICNPEN -							
macro avg					route_JHBKTM -							
weighted avg	0.80	0.85	0.79	10000	route_KTMPEN -							
					0.00	0.05	0.10	0.15	0.20	0.25	0.30	0.35