Hotel Booking Cancellation Prediction

Data Preprocessing Pipeline

The dataset initially shows no missing values in any field—a rare but ideal scenario for real-world data! This suggests strong data collection practices or prior cleaning. However, we still implemented safeguards in our pipeline to handle potential future inconsistencies."

date of reservation 0 booking status 0 dtype: int64	Missing Values After Handl Booking_ID number of adults number of children number of weekend nights number of week nights type of meal car parking space room type lead time market segment type repeated P-C P-not-C average price special requests	0 0 0 0 0 0 0 0 0 0 0
date of reservation 0 booking status 0	· .	
	date of reservation	0
		0

Missing Values Refere Handle	ing.
Missing Values Before Handl: Booking ID	o Tug.
number of adults	0
number of children	0
number of weekend nights	0
number of week nights	0
type of meal	0
car parking space	0
room type	0
lead time	0
market segment type	0
repeated	0
P-C	0
P-not-C	0
average price	0
special requests	0
date of reservation	0
booking status	0
dtype: int64	

"The dataset contains zero duplicate entries—both before and after preprocessing—indicating highly clean and unique booking records. With 36,285 entries and 17 features, we have a robust, non-redundant dataset for training our cancellation prediction model."

Number of duplicates before: 0 Number of duplicates after: 0 New shape: (36285, 17)

"Normalization standardizes features for fair model training.

Data af	ter outlier treatment	:		
	number of adults numb	per of children	number of week	end nights \
count	36285.0	36285.0	36	285.000000
mean	2.0	0.0		0.810087
std	0.0	0.0		0.867286
min	2.0	0.0		0.000000
25%	2.0	0.0		0.000000
50%	2.0	0.0		1.000000
75%	2.0	0.0		2.000000
max	2.0	0.0		5.000000
	number of week nights	lead time	average price	special request
count	36285.000000	36285.000000	36285.000000	36285.00000
mean	2.178145	83.767893	102.968399	0.60664
std	1.290708	81.662186	31.678904	0.74695
min	0.000000	0.000000	20.750000	0.00000
25%	1.000000	17.000000	80.300000	0.00000
50%	2.000000	57.000000	99.450000	0.00000
75%	3.000000	126.000000	120.000000	1.00000
max	6.000000	289.500000	179.550000	2.50000

"Label encoding preserves ordinal relationships for meal plans."

```
Categorical columns before encoding:

It actions

'Booking_ID', 'type of meal', 'room type', 'market segment type',

'date of reservation', 'booking status'],

dtype='object')

After encoding:

type of meal room type market segment type booking status

0 0 0 3 1

1 3 0 4 1

2 0 0 0 4 0

3 0 0 4 0

4 0

4 3 0 0 4 0

4 0
```

Table showing type of meal \rightarrow encoded values (0, 1, 2)

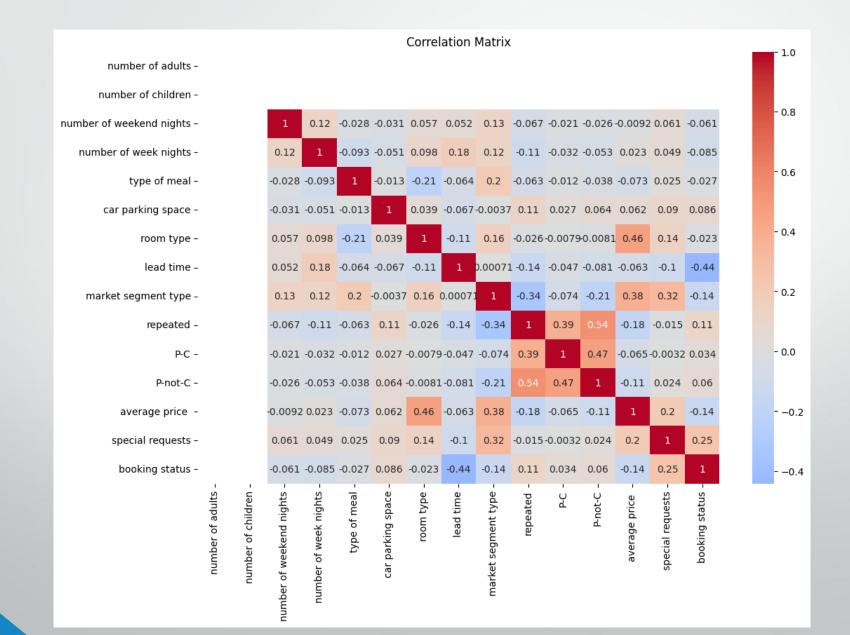
"Min-Max scaling ensures equal feature weighting in models."

After	normalization:			
	number of adults numb	er of children	number of week	end nights \
count	36285.0	36285.0	36	285.000000
mean	0.0	0.0		0.162017
std	0.0	0.0		0.173457
min	0.0	0.0		0.000000
25%	0.0	0.0		0.000000
50%	0.0	0.0		0.200000
75%	0.0	0.0		0.400000
max	0.0	0.0		1.000000
	number of week nights	lead time	average price	special requests
count	36285.000000	36285.000000	36285.000000	36285.000000
mean	0.363024	0.289354	0.517748	0.242657
std	0.215118	0.282080	0.199489	0.298780
min	0.000000	0.000000	0.000000	0.000000
25%	0.166667	0.058722	0.375000	0.000000
50%	0.333333	0.196891	0.495592	0.000000
75%	0.500000	0.435233	0.625000	0.400000
max	1.000000	1.000000	1.000000	1.000000

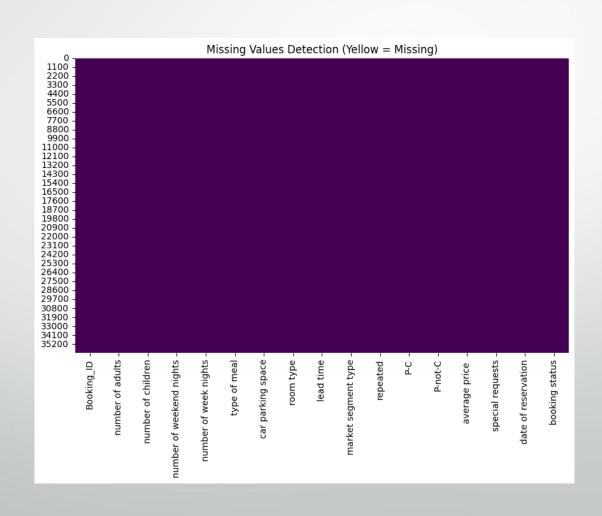
"Upsampled minority class to prevent model bias toward majority."

```
Class distribution before balancing:
booking status
    24396
0 11889
Name: count, dtype: int64
Class distribution after balancing:
booking status
0
 11889
1 11889
Name: count, dtype: int64
```

"No features dropped – all correlations < 0.8."



"No missing values detected – rare for real-world data! Our pipeline includes safeguards anyway."



- 1."Feature Distributions Post-Normalization"
- 2. "Standardized Features: Adults, Lead Time & Price"
- 3. "Normalized Data for Model Readiness"
- 4. "From Raw to Scaled: Key Features"

