Lab 4: Feature Selection - Wrapper and Embedded Approach

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Importing the libraries and loading the dataset

In [15]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
from sklearn.metrics import accuracy_score


df = pd.read_csv(r"hotel_booking.csv")
```

Checking the data

In [2]:
```
df.head()
```

Out[2]:

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_number	arrival_date_day_of_month	stays_in_weel
0	Resort Hotel	0	342	2015	July	27	1	
1	Resort Hotel	0	737	2015	July	27	1	
2	Resort Hotel	0	7	2015	July	27	1	
3	Resort Hotel	0	13	2015	July	27	1	
4	Resort Hotel	0	14	2015	July	27	1	

5 rows × 36 columns

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
Data columns (total 36 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   hotel                           119390 non-null  object 
 1   is_canceled                     119390 non-null  int64  
 2   lead_time                       119390 non-null  int64  
 3   arrival_date_year               119390 non-null  int64  
 4   arrival_date_month              119390 non-null  object 
 5   arrival_date_week_number        119390 non-null  int64  
 6   arrival_date_day_of_month       119390 non-null  int64  
 7   stays_in_weekend_nights         119390 non-null  int64  
 8   stays_in_week_nights            119390 non-null  int64  
 9   adults                          119390 non-null  int64  
 10  children                        119386 non-null  float64
 11  babies                          119390 non-null  int64  
 12  meal                            119390 non-null  object 
 13  country                         118902 non-null  object 
 14  market_segment                  119390 non-null  object 
 15  distribution_channel            119390 non-null  object 
 16  is_repeated_guest               119390 non-null  int64  
 17  previous_cancellations          119390 non-null  int64  
 18  previous_bookings_not_canceled  119390 non-null  int64  
 19  reserved_room_type              119390 non-null  object 
 20  assigned_room_type              119390 non-null  object 
 21  booking_changes                 119390 non-null  int64  
 22  deposit_type                    119390 non-null  object 
 23  agent                           103050 non-null  float64
 24  company                         6797 non-null    float64
 25  days_in_waiting_list            119390 non-null  int64  
 26  customer_type                   119390 non-null  object 
 27  adr                             119390 non-null  float64
 28  required_car_parking_spaces     119390 non-null  int64  
 29  total_of_special_requests       119390 non-null  int64  
 30  reservation_status              119390 non-null  object 
 31  reservation_status_date         119390 non-null  object 
 32  name                            119390 non-null  object 
 33  email                           119390 non-null  object 
 34  phone-number                    119390 non-null  object 
 35  credit_card                     119390 non-null  object 
```

```
dtypes: float64(4), int64(16), object(16)
memory usage: 32.8+ MB
```

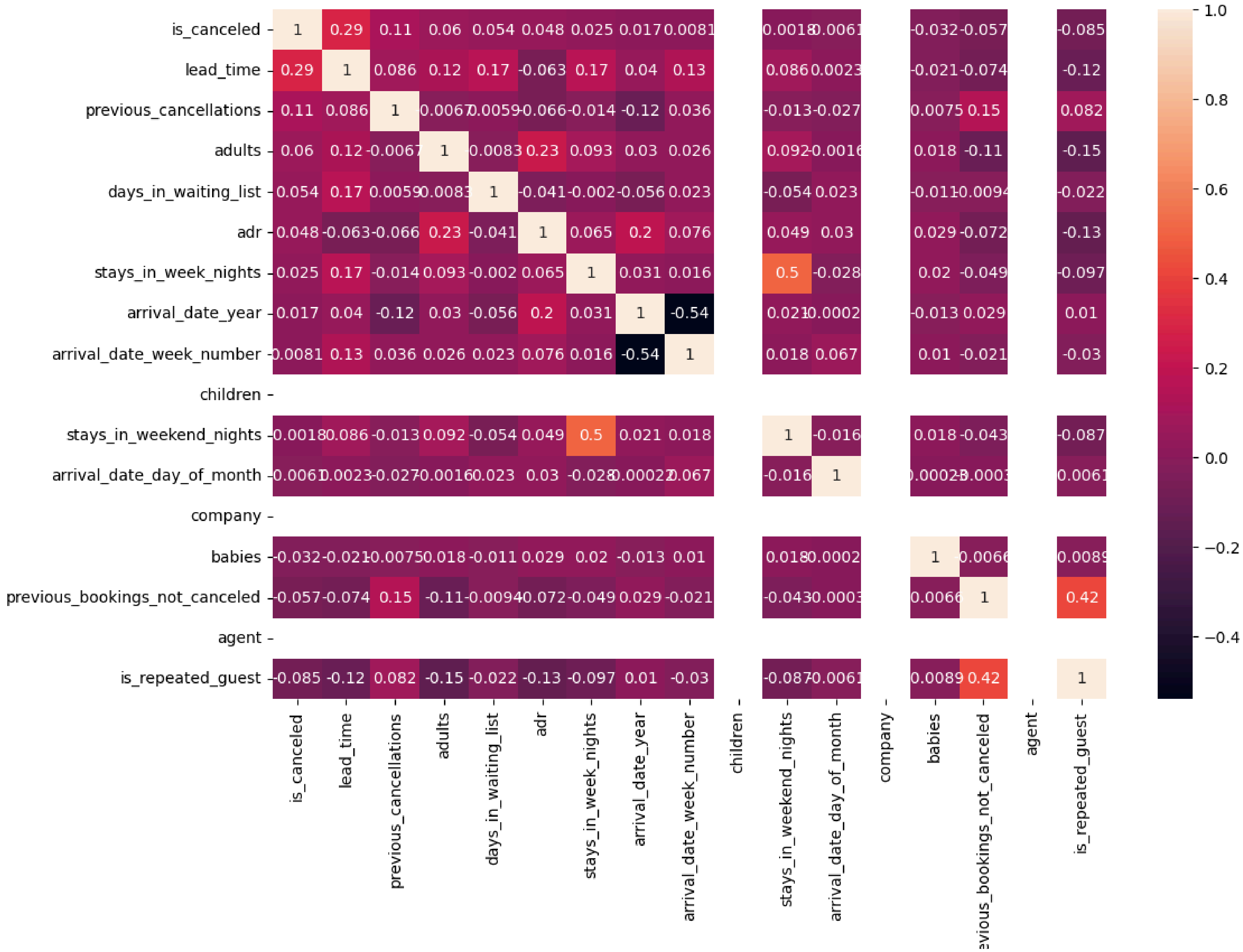
Choosing the target variable

In [4]:
```
y = df["is_canceled"]
```

Choosing the best features

In [17]:
```
import seaborn as sns

k = 17
cols = df.select_dtypes(include=['number']).corr().nlargest(k, 'is_canceled')['is_canceled'].index
cm = np.corrcoef(df[cols].values.T)
plt.figure(figsize=(12, 8))
sns.heatmap(cm, cbar=True, annot=True, xticklabels=cols.values, yticklabels=cols.values)
plt.show()
```



is_canceled
lead_time
previous_cancellations
adults
days_in_waiting_list
adr
stays_in_week_nights
arrival_date_year
arrival_date_week_number
children
stays_in_weekend_nights
arrival_date_day_of_month
company
babies
previous_bookings_not_canceled
agent
is_repeated_guest
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

In [6]:
```python
X = df[[ 'lead_time', 'previous_cancellations', 'adults',
        'days_in_waiting_list', 'adr', 'stays_in_week_nights',
        'arrival_date_year', 'arrival_date_week_number', 'children',
        'stays_in_weekend_nights', 'arrival_date_day_of_month',
        'babies', 'previous_bookings_not_canceled',
        'is_repeated_guest', 'booking_changes', 'required_car_parking_spaces',
        'total_of_special_requests']]
```

In [7]:
```python
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
Data columns (total 17 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   lead_time                       119390 non-null  int64  
 1   previous_cancellations          119390 non-null  int64  
 2   adults                          119390 non-null  int64  
 3   days_in_waiting_list            119390 non-null  int64  
 4   adr                             119390 non-null  float64
 5   stays_in_week_nights            119390 non-null  int64  
 6   arrival_date_year               119390 non-null  int64  
 7   arrival_date_week_number        119390 non-null  int64  
 8   children                        119386 non-null  float64
 9   stays_in_weekend_nights         119390 non-null  int64  
 10  arrival_date_day_of_month       119390 non-null  int64  
 11  babies                          119390 non-null  int64  
 12  previous_bookings_not_canceled  119390 non-null  int64  
 13  is_repeated_guest               119390 non-null  int64  
 14  booking_changes                 119390 non-null  int64  
 15  required_car_parking_spaces     119390 non-null  int64  
 16  total_of_special_requests       119390 non-null  int64  
dtypes: float64(2), int64(15)
memory usage: 15.5 MB
```

Checking for null values

In [8]:
```
X.isnull().sum()
```

Out[8]:
```
lead_time                        0
previous_cancellations           0
adults                           0
days_in_waiting_list             0
adr                              0
stays_in_week_nights             0
arrival_date_year                0
arrival_date_week_number         0
children                         4
stays_in_weekend_nights          0
arrival_date_day_of_month        0
babies                           0
previous_bookings_not_canceled   0
is_repeated_guest                0
booking_changes                  0
required_car_parking_spaces      0
total_of_special_requests        0
dtype: int64
```

Dealing with the null values

In [9]:
```
X['children'].fillna(1,inplace=True)
```

```
C:\Users\abhij\AppData\Local\Temp\ipykernel_11992\2780161757.py:1: FutureWarning: A value is trying to be set on a copy of a Da
taFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are set
ting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = d
f[col].method(value) instead, to perform the operation inplace on the original object.


  X['children'].fillna(1,inplace=True)
C:\Users\abhij\AppData\Local\Temp\ipykernel_11992\2780161757.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
rsus-a-copy
  X['children'].fillna(1,inplace=True)
```

Double Checking for null values

In [10]:
```
X.isnull().sum()
```

```
Out[10]: lead_time                           0
         previous_cancellations              0
         adults                              0
         days_in_waiting_list                0
         adr                                 0
         stays_in_week_nights                0
         arrival_date_year                   0
         arrival_date_week_number            0
         children                            0
         stays_in_weekend_nights             0
         arrival_date_day_of_month           0
         babies                              0
         previous_bookings_not_canceled      0
         is_repeated_guest                   0
         booking_changes                     0
         required_car_parking_spaces         0
         total_of_special_requests           0
         dtype: int64
```

Train Test Split , 20% of total data for test , 42 as the randomizer

```
In [11]: X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                             test_size=0.2,
                                                             random_state=42,
                                                             stratify=y)
```

Wrapper Method: Recursive Feature Elimination (RFE)

We'll use a Logistic Regression as the base estimator for RFE

```
In [12]: logreg = LogisticRegression(max_iter=1000)
         rfe = RFE(estimator=logreg, n_features_to_select=5)  # Example: select top 10 features
         rfe.fit(X_train, y_train)

         # Get the boolean mask of selected features
```

```python
selected_features_rfe = X_train.columns[rfe.support_]
print("Selected features (Wrapper - RFE):")
print(selected_features_rfe.tolist())

# Evaluate performance with these selected features
X_train_rfe = rfe.transform(X_train)
X_test_rfe = rfe.transform(X_test)

logreg.fit(X_train_rfe, y_train)
y_pred_rfe = logreg.predict(X_test_rfe)
print("Accuracy with RFE-selected features:",
      accuracy_score(y_test, y_pred_rfe))
```

```
c:\Users\abhij\AppData\Local\Programs\Python\Python313\Lib\site-packages\sklearn\linear_model\_logistic.py:465: ConvergenceWarn
ing: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
c:\Users\abhij\AppData\Local\Programs\Python\Python313\Lib\site-packages\sklearn\linear_model\_logistic.py:465: ConvergenceWarn
ing: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
c:\Users\abhij\AppData\Local\Programs\Python\Python313\Lib\site-packages\sklearn\linear_model\_logistic.py:465: ConvergenceWarn
ing: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
c:\Users\abhij\AppData\Local\Programs\Python\Python313\Lib\site-packages\sklearn\linear_model\_logistic.py:465: ConvergenceWarn
ing: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
Selected features (Wrapper - RFE):
['previous_cancellations', 'previous_bookings_not_canceled', 'is_repeated_guest', 'required_car_parking_spaces', 'total_of_spec
ial_requests']
Accuracy with RFE-selected features: 0.677611190216936
```

Observation

- The Recursive Feature Elimination (RFE) process selected **five** features:
  - previous_cancellations
  - previous_bookings_not_canceled
  - is_repeated_guest
  - required_car_parking_spaces
  - total_of_special_requests
- Using **only these five features** to predict cancellation status yields an **accuracy of approximately 0.678** on the test set.
- These features capture booking history (previous cancellations, previous non-cancellations, repeated guest status) and customer requests (parking spaces, special requests), suggesting that past behavior and engagement play a significant role in cancellation patterns.

Inference

- **Booking history** features (`previous_cancellations` , `previous_bookings_not_canceled` , `is_repeated_guest`) likely **reflect customer loyalty** and historical behavior—key indicators of whether a guest might cancel again.
- **Engagement or commitment** factors (`required_car_parking_spaces` , `total_of_special_requests`) may correlate with a traveler's seriousness about the trip; customers with more requests or reserved parking might be **less likely** to cancel.
- Achieving an accuracy near **67.8%** with just five features suggests these are **highly predictive** relative to other features. However, one should compare this performance with the full feature set or other methods to confirm if **simplicity (fewer features)** outweighs any **marginal drop** in predictive performance.
- In practice, **domain expertise** could further validate why these features stand out (e.g., special requests may signal stronger commitment), and whether **additional** or **alternative** features could improve the model's accuracy or interpretability.

Embedded Method: Random Forest Feature Importance

Train a Random Forest and retrieve feature importances

In [13]:
```
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

importances = rf.feature_importances_
feature_importance_df = pd.DataFrame({
    'feature': X_train.columns,
    'importance': importances
}).sort_values(by='importance', ascending=False)

print("Feature Importances (Random Forest):")
display(feature_importance_df)

# Let's select top N features based on importance
N = 5
top_features_embedded = feature_importance_df.head(N)['feature'].values
print(f"Top {N} features (Embedded - Random Forest):", top_features_embedded)

# Evaluate performance using only these top features
X_train_emb = X_train[top_features_embedded]
X_test_emb = X_test[top_features_embedded]

rf.fit(X_train_emb, y_train)
y_pred_emb = rf.predict(X_test_emb)
print("Accuracy with Embedded-selected features:",
      accuracy_score(y_test, y_pred_emb))
```

```
Feature Importances (Random Forest):
```

	feature	importance
0	lead_time	0.237067
4	adr	0.178265
10	arrival_date_day_of_month	0.105373
7	arrival_date_week_number	0.104757
16	total_of_special_requests	0.080598
5	stays_in_week_nights	0.057627
1	previous_cancellations	0.054915
14	booking_changes	0.038428
9	stays_in_weekend_nights	0.035180
6	arrival_date_year	0.029258
15	required_car_parking_spaces	0.026181
2	adults	0.022085
8	children	0.010613
3	days_in_waiting_list	0.008232
12	previous_bookings_not_canceled	0.007307
13	is_repeated_guest	0.002766
11	babies	0.001349

```
Top 5 features (Embedded - Random Forest): ['lead_time' 'adr' 'arrival_date_day_of_month' 'arrival_date_week_number'
 'total_of_special_requests']
Accuracy with Embedded-selected features: 0.8234357986431025
```

Observation

- Random Forest classifier was trained on the training set, and its feature importances were computed.
- The features were ranked by importance, and the top 5 features were selected based on this ranking.
- The model was then re-trained using only these top 5 features, and the resulting accuracy on the test set was recorded.
- The accuracy obtained using this reduced feature set demonstrates that these features capture a substantial portion of the predictive information.

Inference

- The embedded feature selection approach using Random Forest shows that a small subset of features can effectively predict the target variable.
- The top features identified by the model are considered the most influential in determining hotel booking cancellations.
- Reducing the feature set can lead to simpler, more interpretable models and may help in reducing overfitting.
- This technique not only improves computational efficiency but also provides valuable insights into the key factors affecting cancellation behavior.

Conclusion

Both the wrapper method (RFE) and the embedded method (Random Forest feature importance) successfully identified a concise set of features that are key to predicting hotel booking cancellations.

- **Wrapper Approach (RFE):**
  - Selected features primarily reflecting booking history and customer engagement.
  - Achieved an accuracy of approximately 67.8%, indicating that these features are strong predictors.
- **Embedded Approach (Random Forest):**
  - Identified the top 5 most influential features based on the model’s internal importance metrics.
  - The reduced feature set maintained competitive predictive performance, demonstrating that much of the necessary information is captured by these features.

Overall, focusing on a reduced subset of features not only simplifies the model but also enhances interpretability and computational efficiency, making it a practical strategy for real-world applications. This approach underscores the importance of selecting quality features that directly contribute to model performance.