EDA_&_ML_Models-(LinearRehression, LogisticRegression, Kmeans, RandomForest)

January 12, 2026

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA

from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error,␣
↪classification_report, confusion_matrix, accuracy_score, roc_auc_score,␣
↪roc_curve
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler

from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
```

[2]:
```python
df = pd.read_csv("ncr_ride_bookings.csv")
df.head()
```

[2]:
```
         Date      Time    Booking ID   Booking Status   Customer ID  \
0  2024-03-23  12:29:38  "CNR5884300"  No Driver Found  "CID1982111"
1  2024-11-29  18:01:39  "CNR1326809"       Incomplete  "CID4604802"
2  2024-08-23  08:56:10  "CNR8494506"        Completed  "CID9202816"
3  2024-10-21  17:17:25  "CNR8906825"        Completed  "CID2610914"
4  2024-09-16  22:08:00  "CNR1950162"        Completed  "CID9933542"

   Vehicle Type      Pickup Location      Drop Location  Avg VTAT  Avg CTAT  \
0         eBike          Palam Vihar            Jhilmil       NaN       NaN
1      Go Sedan        Shastri Nagar  Gurgaon Sector 56       4.9      14.0
2          Auto              Khandsa      Malviya Nagar      13.4      25.8
3  Premier Sedan  Central Secretariat           Inderlok      13.1      28.5
```

```
4           Bike     Ghitorni Village        Khan Market       5.3      19.6

   …  Reason for cancelling by Customer Cancelled Rides by Driver  \
0  …                               NaN                        NaN
1  …                               NaN                        NaN
2  …                               NaN                        NaN
3  …                               NaN                        NaN
4  …                               NaN                        NaN

   Driver Cancellation Reason Incomplete Rides  Incomplete Rides Reason  \
0                         NaN              NaN                      NaN
1                         NaN              1.0        Vehicle Breakdown
2                         NaN              NaN                      NaN
3                         NaN              NaN                      NaN
4                         NaN              NaN                      NaN

  Booking Value  Ride Distance  Driver Ratings  Customer Rating  \
0           NaN            NaN             NaN              NaN
1         237.0           5.73             NaN              NaN
2         627.0          13.58             4.9              4.9
3         416.0          34.02             4.6              5.0
4         737.0          48.21             4.1              4.3

   Payment Method
0             NaN
1             UPI
2      Debit Card
3             UPI
4             UPI

[5 rows x 21 columns]
```

[3]:
```
df.shape
```

[3]: (150000, 21)

[4]:
```
df.dtypes
```

[4]:
```
Date                                  object
Time                                  object
Booking ID                            object
Booking Status                        object
Customer ID                           object
Vehicle Type                          object
Pickup Location                       object
Drop Location                         object
Avg VTAT                             float64
```

```
Avg CTAT                              float64
Cancelled Rides by Customer           float64
Reason for cancelling by Customer      object
Cancelled Rides by Driver             float64
Driver Cancellation Reason             object
Incomplete Rides                      float64
Incomplete Rides Reason                object
Booking Value                         float64
Ride Distance                         float64
Driver Ratings                        float64
Customer Rating                       float64
Payment Method                         object
dtype: object
```

[5]:
```
df.isnull().sum()
```

[5]:
```
Date                                       0
Time                                       0
Booking ID                                 0
Booking Status                             0
Customer ID                                0
Vehicle Type                               0
Pickup Location                            0
Drop Location                              0
Avg VTAT                               10500
Avg CTAT                               48000
Cancelled Rides by Customer           139500
Reason for cancelling by Customer     139500
Cancelled Rides by Driver             123000
Driver Cancellation Reason            123000
Incomplete Rides                      141000
Incomplete Rides Reason               141000
Booking Value                          48000
Ride Distance                          48000
Driver Ratings                         57000
Customer Rating                        57000
Payment Method                         48000
dtype: int64
```

[6]:
```
df = df[['Booking Status', 'Vehicle Type', 'Pickup Location', 'Drop Location',␣
↪'Avg VTAT', 'Avg CTAT', 'Booking Value', 'Ride Distance', 'Driver Ratings',␣
↪'Customer Rating', 'Payment Method']]
```

[7]:
```
df.fillna(df.median(numeric_only=True), inplace=True)
```

[8]:
```
df.isnull().sum()
```

[8]:

```
Booking Status         0
Vehicle Type           0
Pickup Location        0
Drop Location          0
Avg VTAT               0
Avg CTAT               0
Booking Value          0
Ride Distance          0
Driver Ratings         0
Customer Rating        0
Payment Method     48000
dtype: int64
```

[9]:

```
df.duplicated().sum()
```

[9]:

```
np.int64(320)
```

[10]:

```
df.describe()
```

[10]:

```
            Avg VTAT       Avg CTAT  Booking Value  Ride Distance  \
count  150000.000000  150000.000000  150000.000000  150000.000000
mean        8.445407      29.037753     478.121220      24.343568
std         3.639311       7.343053     329.339976      11.554362
min         2.000000      10.000000      50.000000       1.000000
25%         5.600000      25.000000     319.750000      17.360000
50%         8.300000      28.800000     414.000000      23.720000
75%        11.000000      32.900000     521.000000      30.650000
max        20.000000      45.000000    4277.000000      50.000000

       Driver Ratings  Customer Rating
count   150000.000000    150000.000000
mean         4.257215         4.440842
std          0.345619         0.347835
min          3.000000         3.000000
25%          4.200000         4.300000
50%          4.300000         4.500000
75%          4.300000         4.600000
max          5.000000         5.000000
```

[11]:

```
num_cols = df.select_dtypes(include=[np.number]).columns.tolist()
cat_cols = df.select_dtypes(include=["object", "category", "bool"]).columns.
 ↪tolist()
```

[12]:

```
num_cols
```

[12]:

```
['Avg VTAT',
 'Avg CTAT',
```

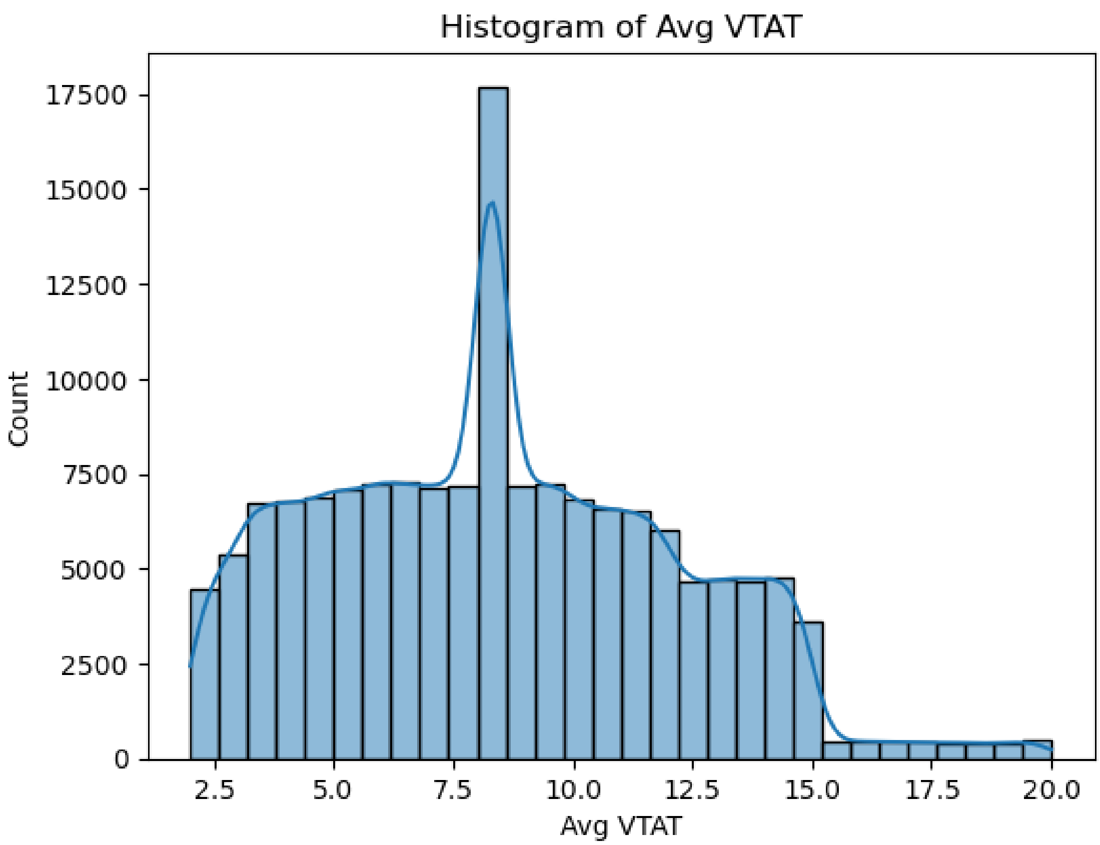
```
 'Booking Value',
 'Ride Distance',
 'Driver Ratings',
 'Customer Rating']
```

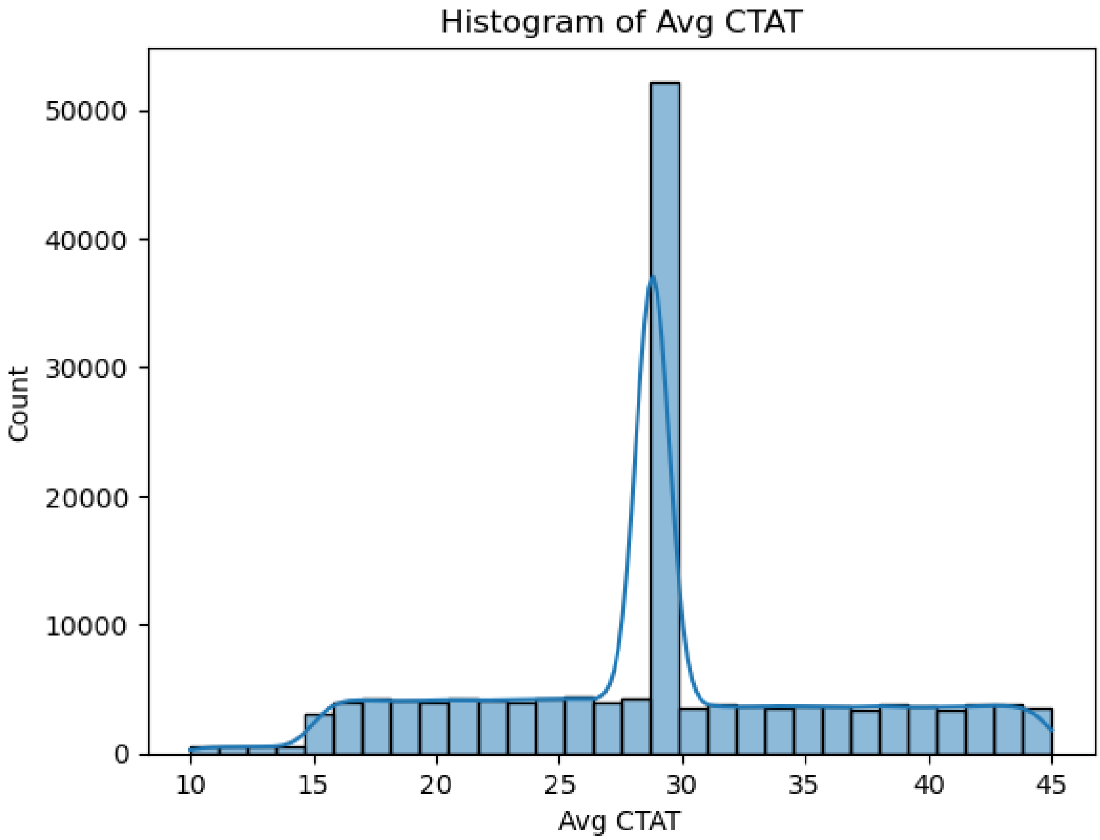
[13]:
```
cat_cols
```

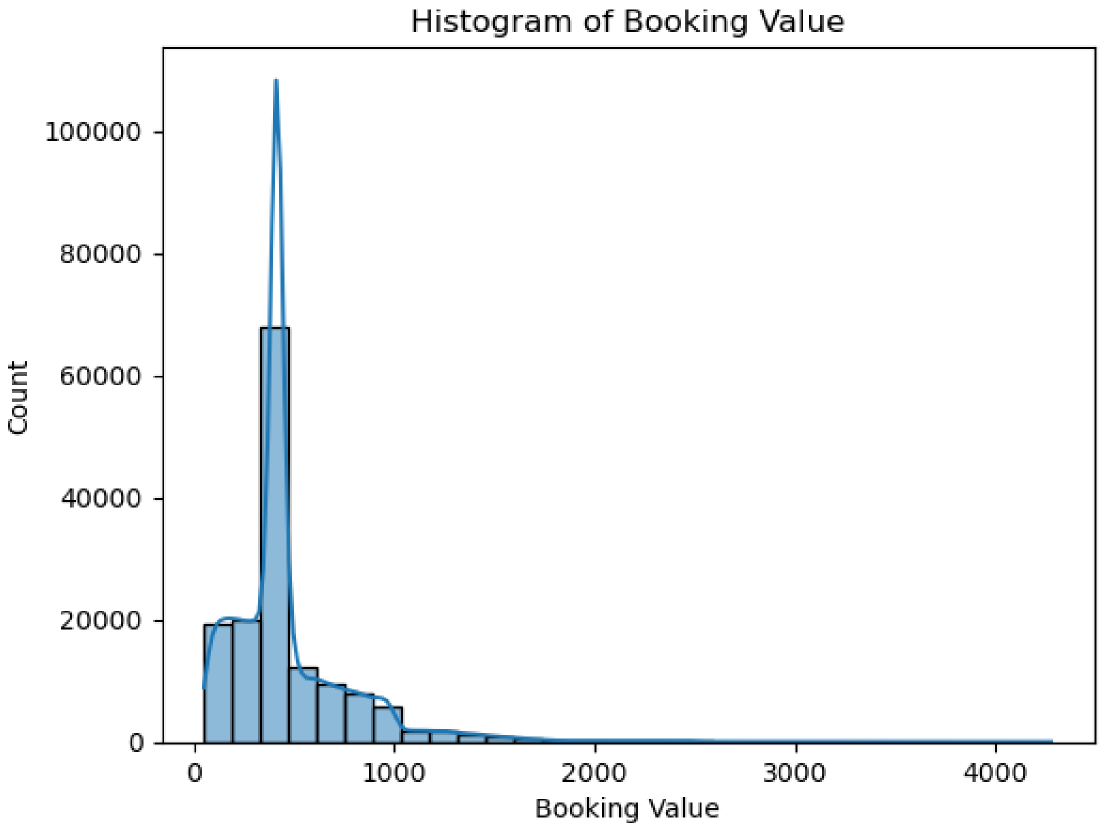
[13]:
```
['Booking Status',
 'Vehicle Type',
 'Pickup Location',
 'Drop Location',
 'Payment Method']
```

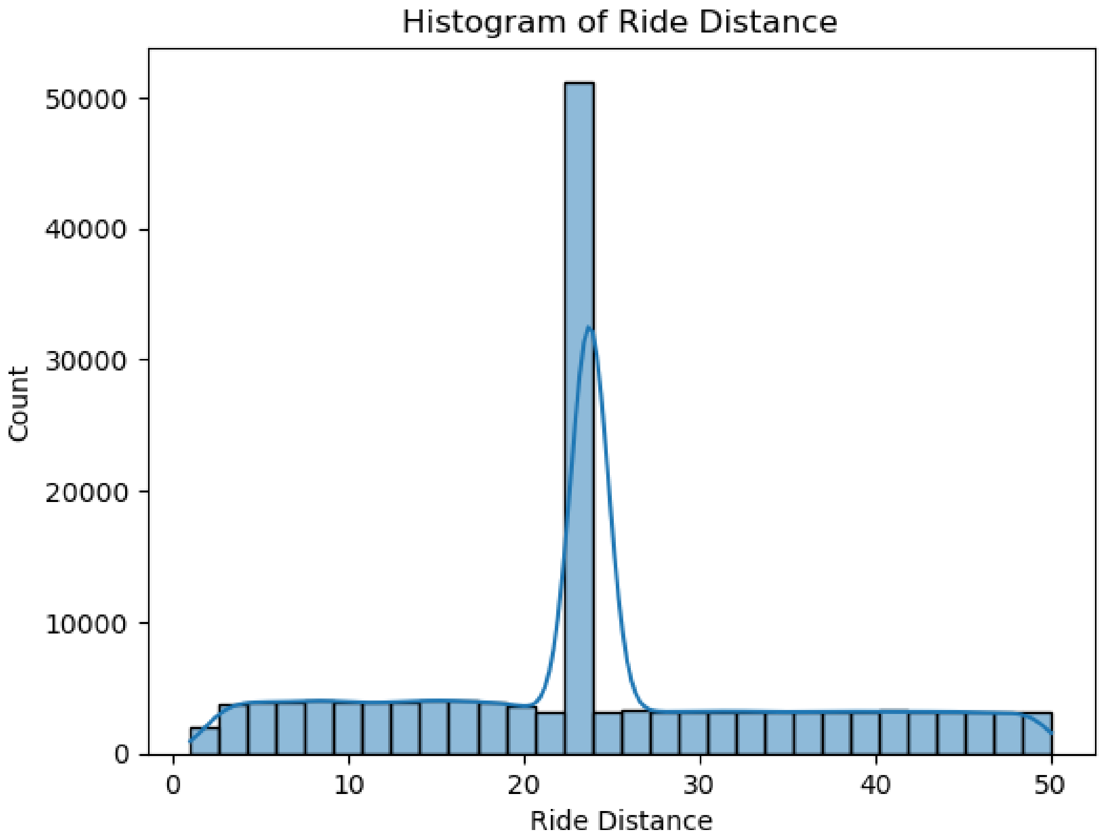
Univariate Analysis ———-

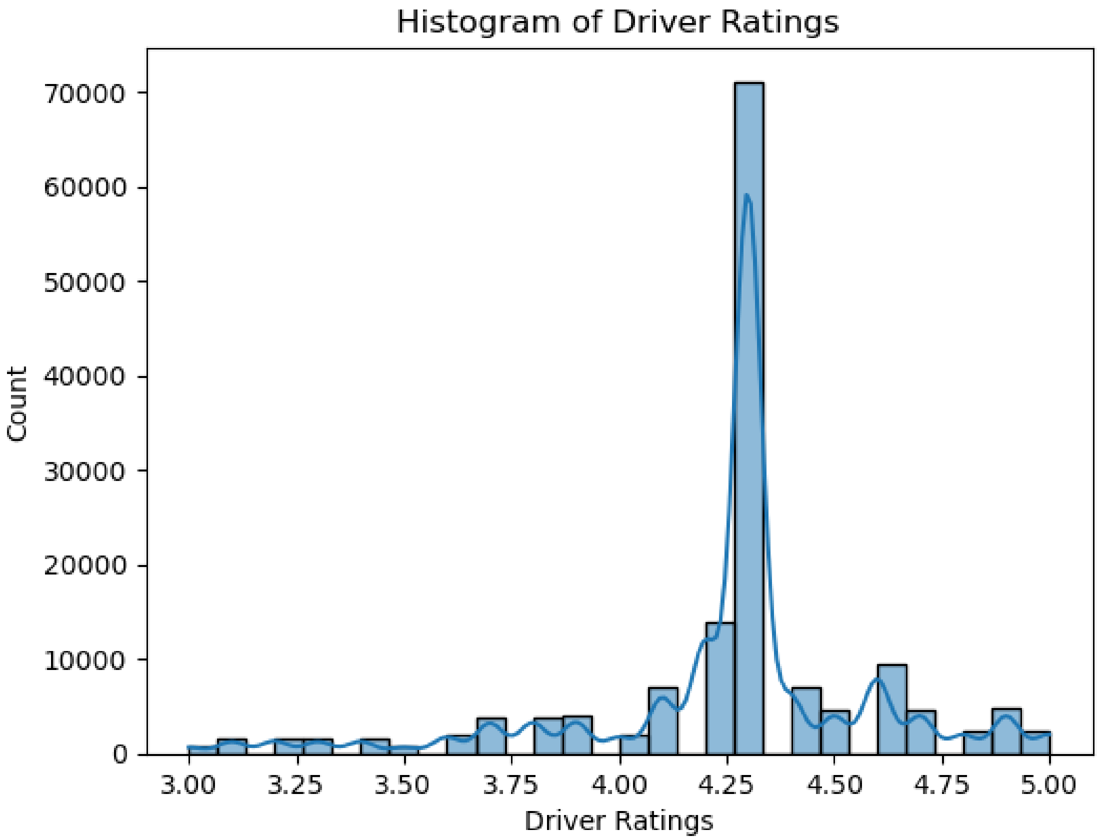
[14]:
```
for col in num_cols[:5]:
    plt.figure()
    sns.histplot(df[col].dropna(), bins=30, kde=True)
    plt.title(f"Histogram of {col}")
    plt.show()
```



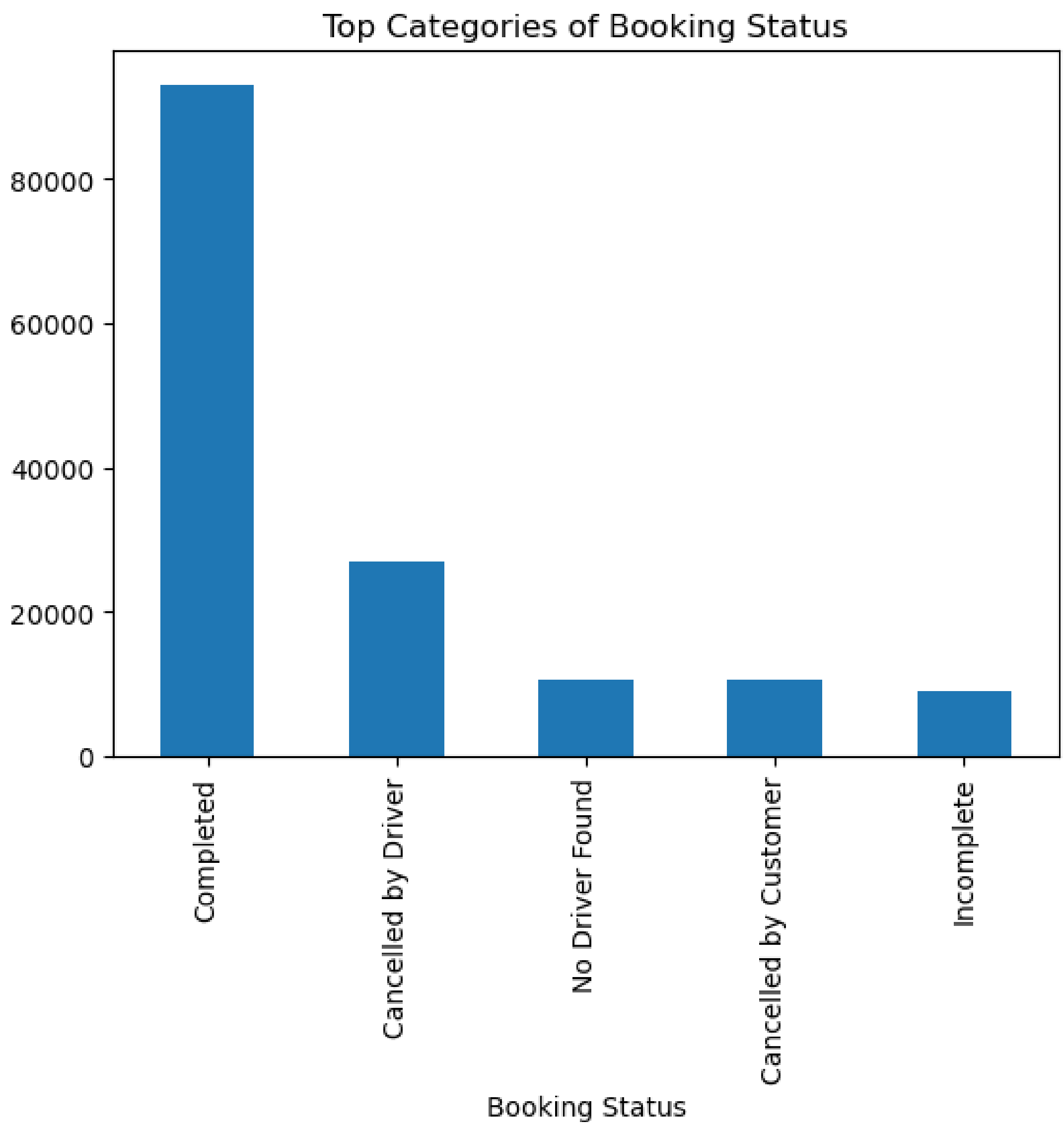

Histogram of Avg CTAT
Count
Avg CTAT
50000
40000
30000
20000
10000
0
10
15
20
25
30
35
40
45

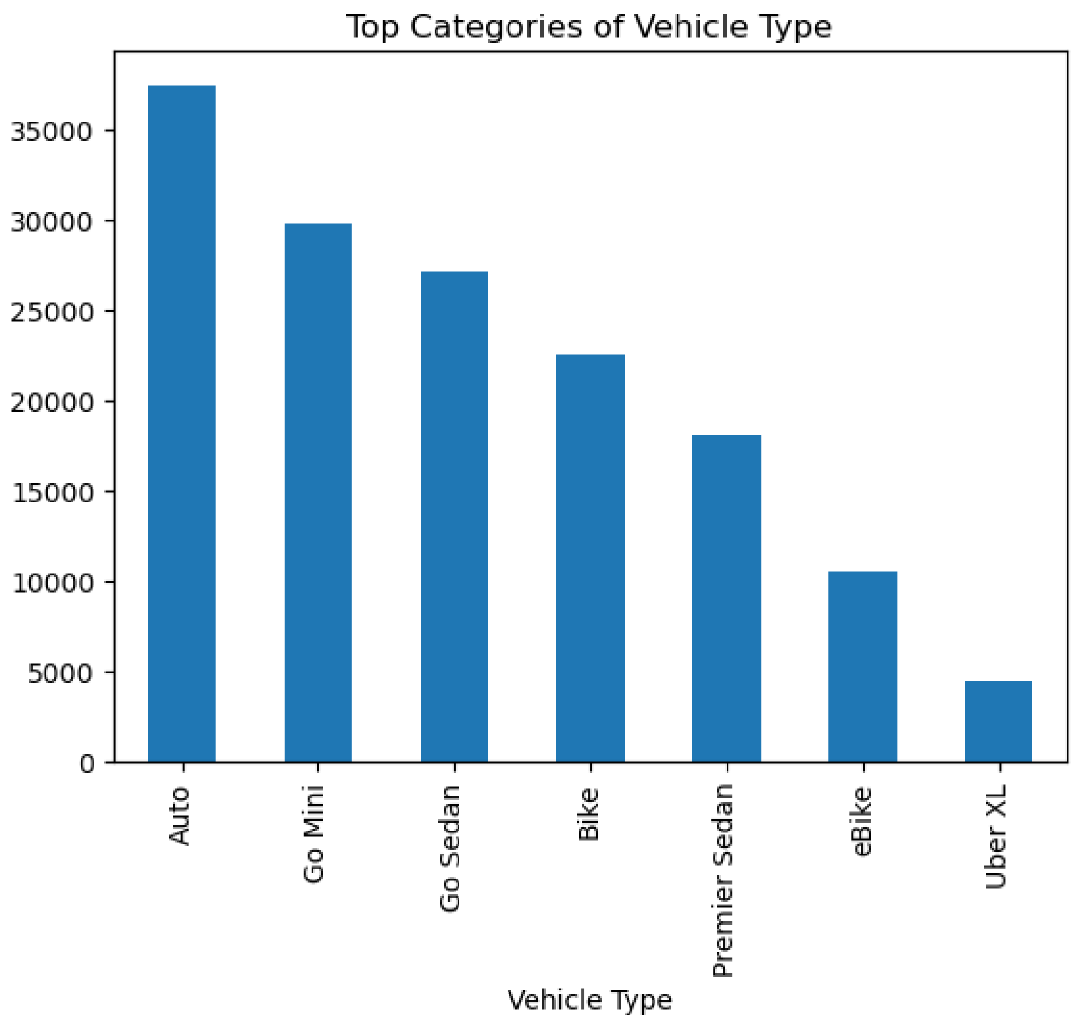

Histogram of Booking Value
Count
100000
80000
60000
40000
20000
0
0
1000
2000
3000
4000
Booking Value

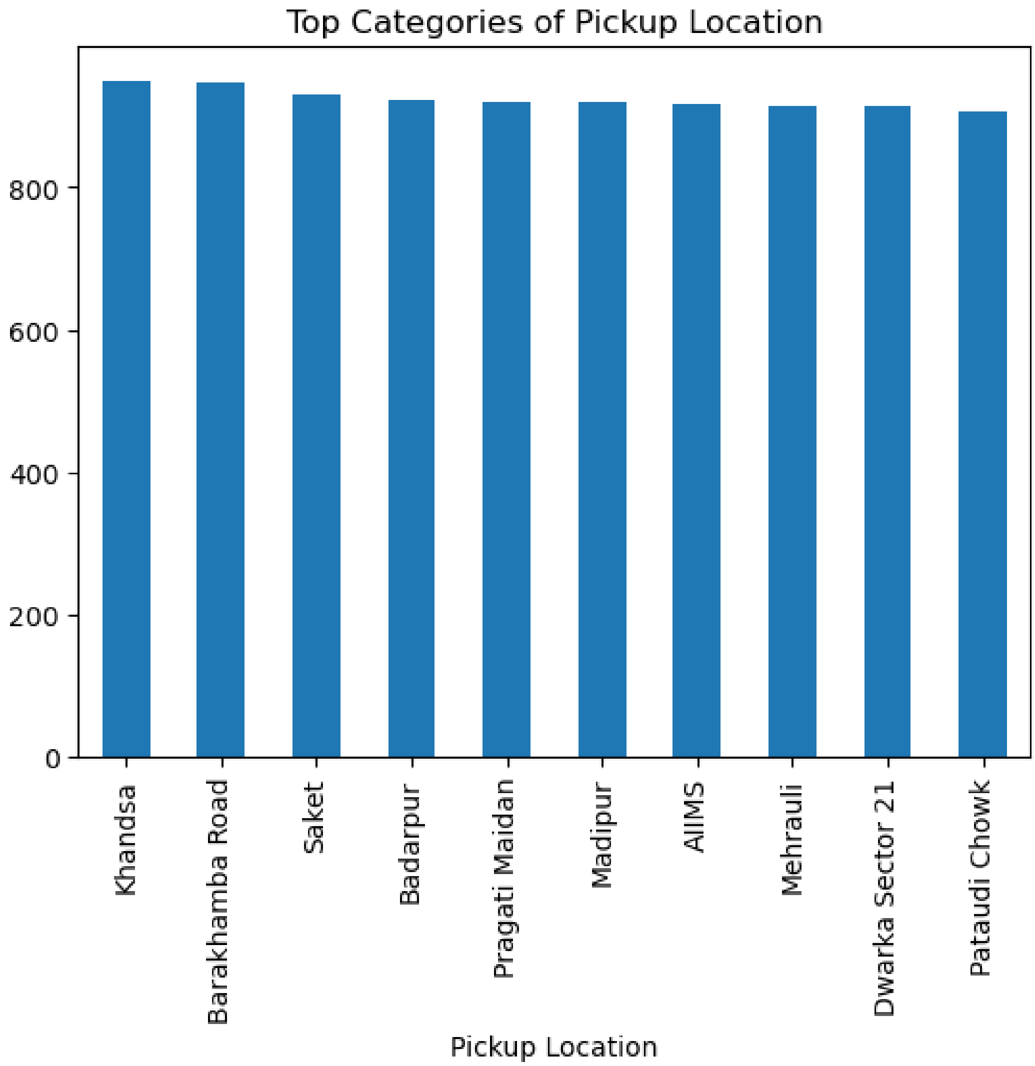

Histogram of Ride Distance
Count
50000
40000
30000
20000
10000
0
0
10
20
30
40
50
Ride Distance

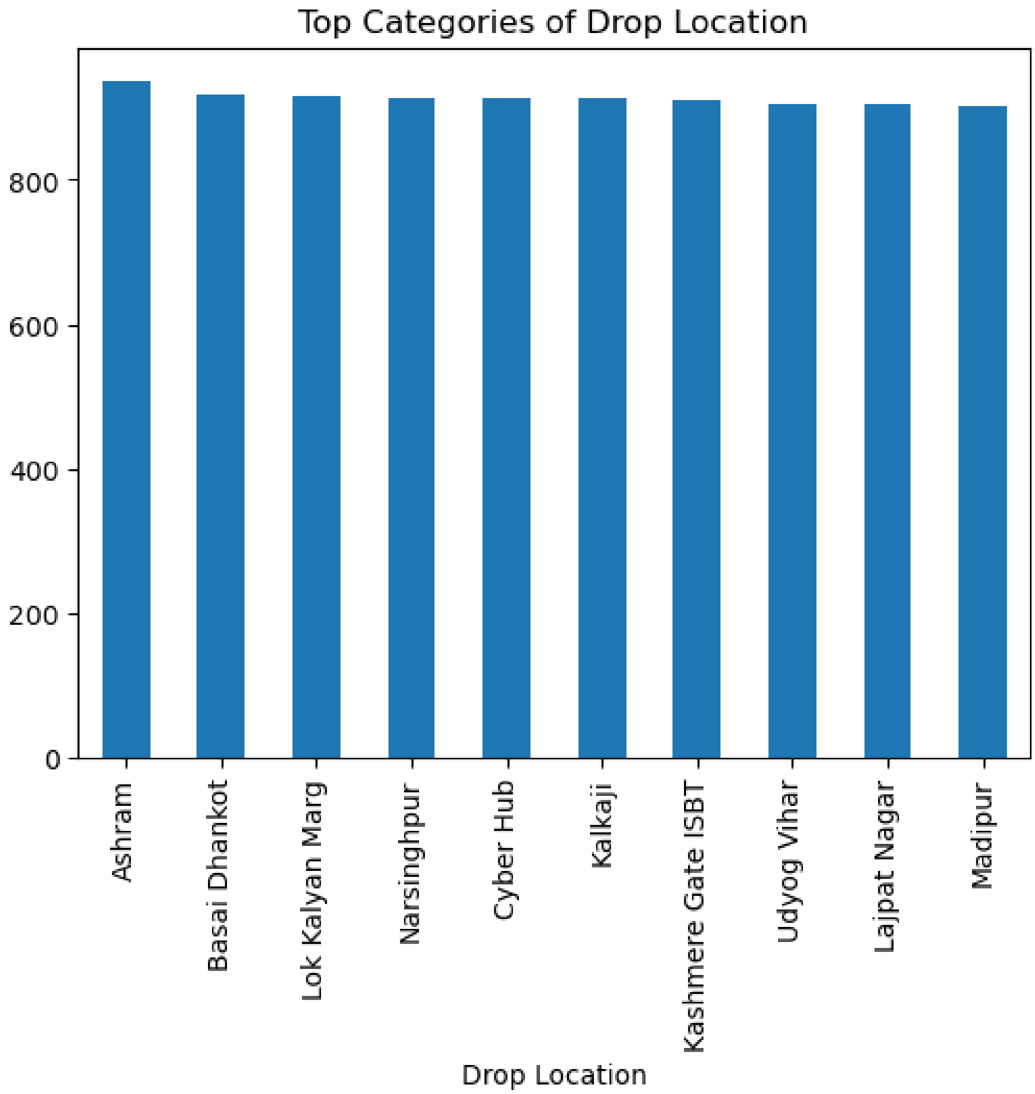


[15]:
```python
for col in cat_cols[:5]:
    plt.figure()
    df[col].value_counts().head(10).plot(kind="bar")
    plt.title(f"Top Categories of {col}")
    plt.show()
```

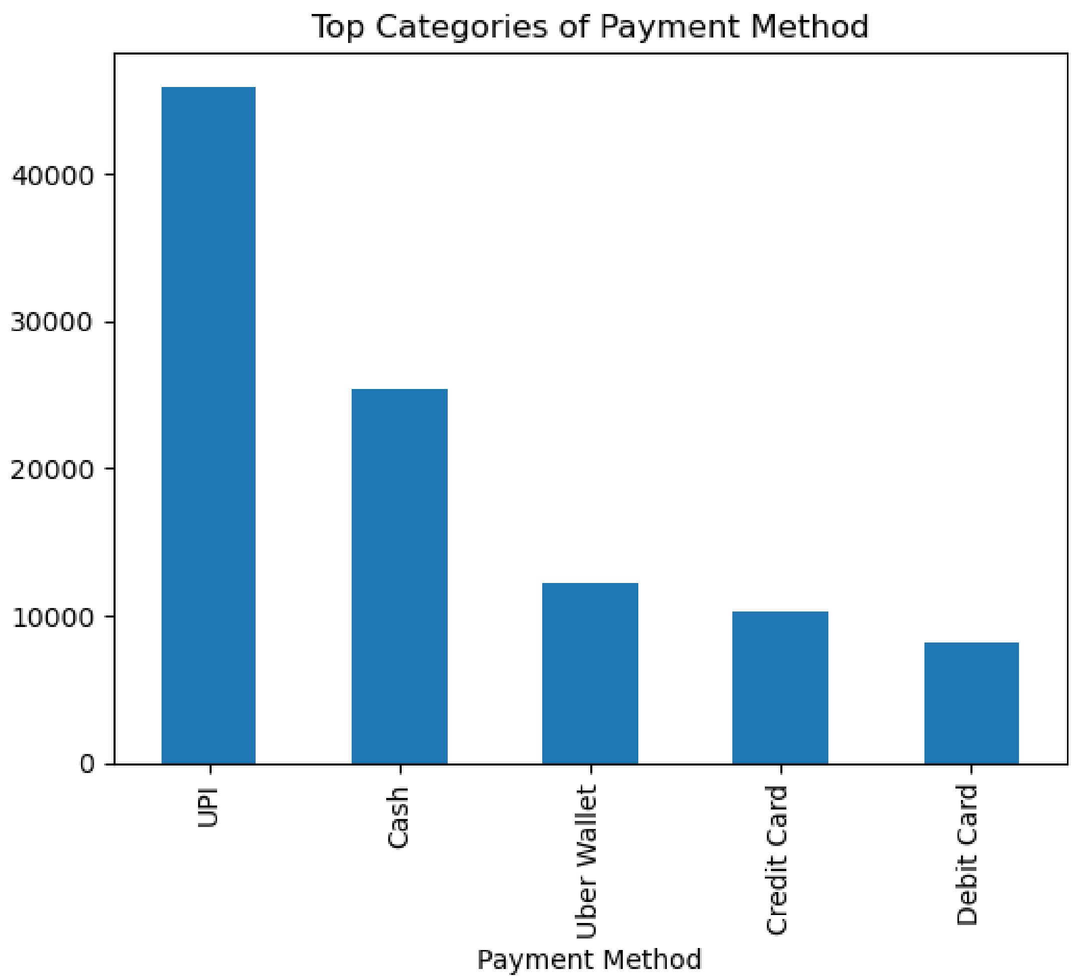

Top Categories of Booking Status
80000
60000
40000
20000
0
Completed
Cancelled by Driver
No Driver Found
Cancelled by Customer
Incomplete
Booking Status


Top Categories of Vehicle Type
35000
30000
25000
20000
15000
10000
5000
0
Auto
Go Mini
Go Sedan
Bike
Premier Sedan
eBike
Uber XL
Vehicle Type


Top Categories of Pickup Location
800
600
400
200
0
Khandsa
Barakhamba Road
Saket
Badarpur
Pragati Maidan
Madipur
AIIMS
Mehrauli
Dwarka Sector 21
Pataudi Chowk
Pickup Location

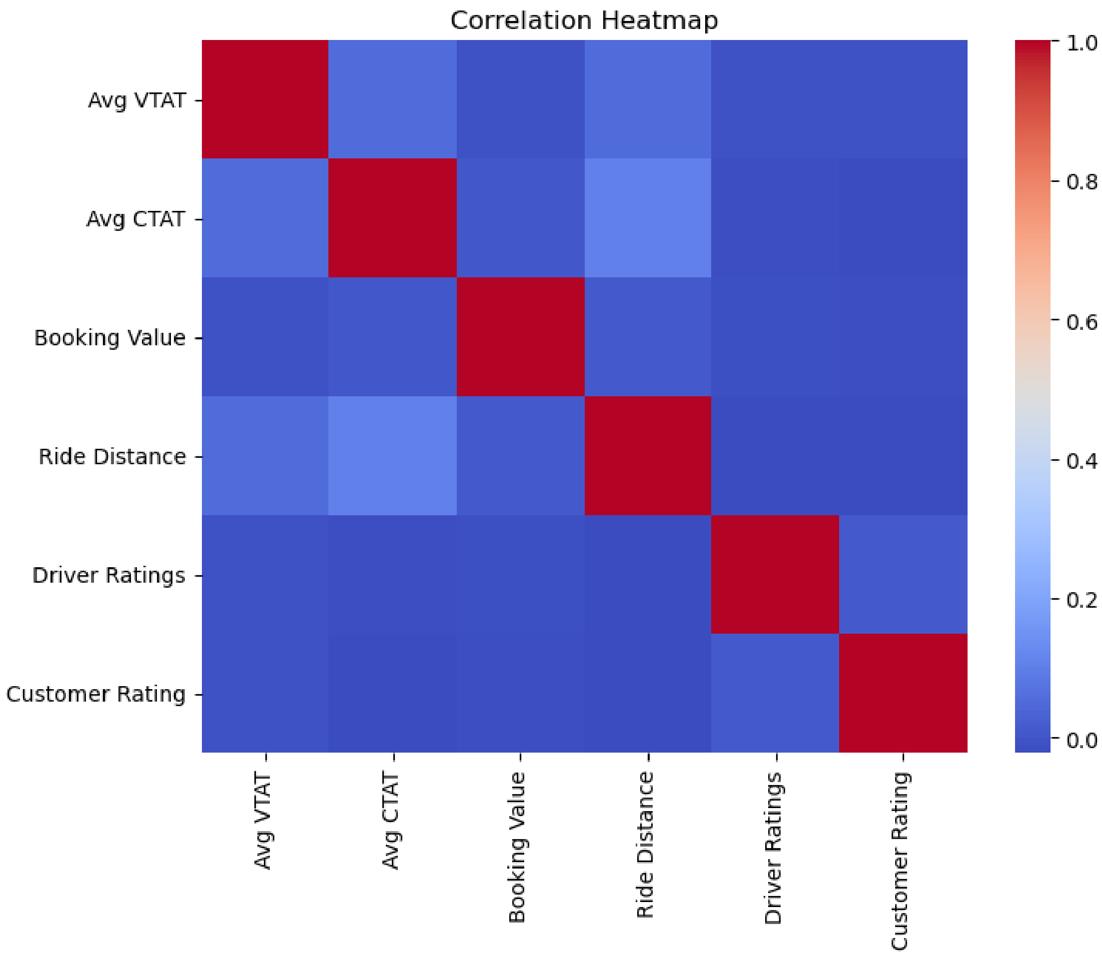


Top Categories of Drop Location
0
200
400
600
800
Ashram
Basai Dhankot
Lok Kalyan Marg
Narsinghpur
Cyber Hub
Kalkaji
Kashmere Gate ISBT
Udyog Vihar
Lajpat Nagar
Madipur
Drop Location



Correlation ———-

[16]:
```
if len(num_cols) > 1:
    plt.figure(figsize=(8,6))
    sns.heatmap(df[num_cols].corr(), cmap="coolwarm", annot=False)
    plt.title("Correlation Heatmap")
    plt.show()
```



1 Linear Regression ———-

[17]:
```
# pick numeric target for regression
linear_target = num_cols[0] if num_cols else None
```

[18]:
```
print("Linear Regression Target:", linear_target)
```

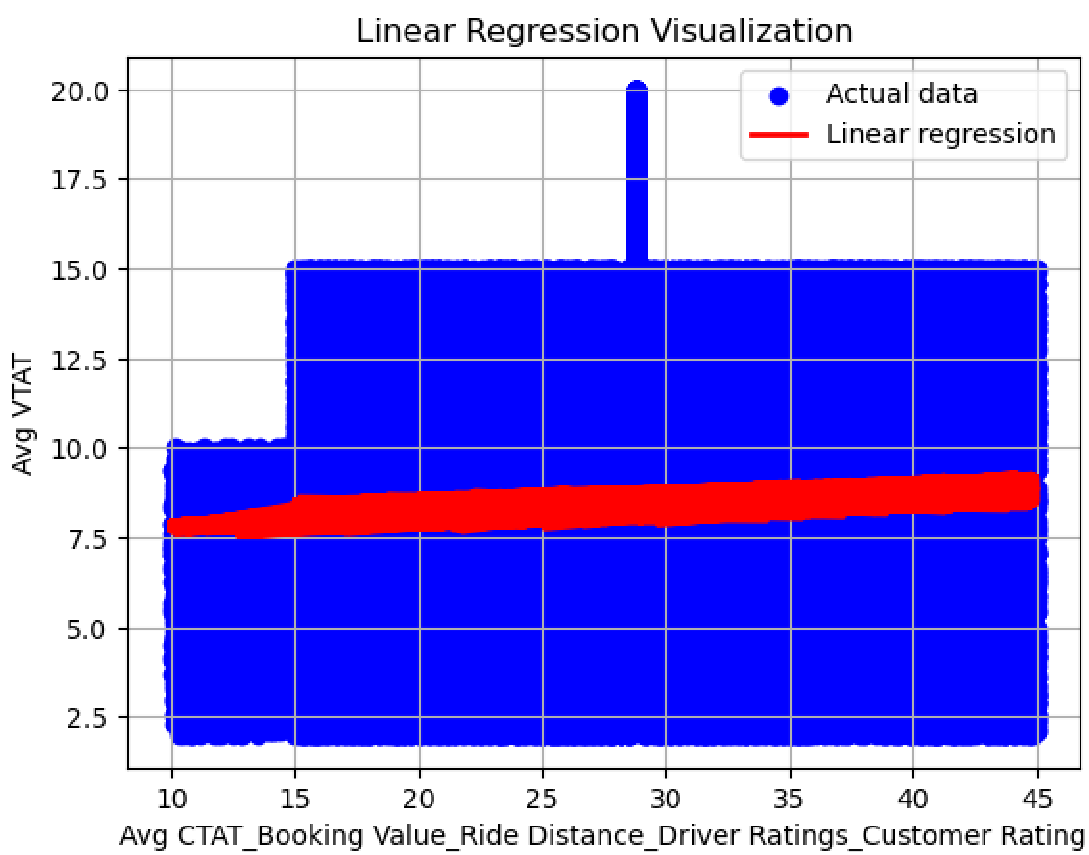
```
Linear Regression Target: Avg VTAT
```

[19]:
```
X = df[num_cols[1:]]
Y = df[linear_target]

model = LinearRegression()
model.fit(X, Y)

df['predicted_class'] = model.predict(X)
```

```python
print(df)

coefficient = model.coef_[0]
intercept = model.intercept_
print("coefficient:", coefficient)
print("intercept:", intercept)

if X.shape[1] == 1:
    plt.scatter(X, Y, color='blue', label='Actual data')
    plt.plot(X, Y, color='red', linewidth=2, label=f'Linear regression: y =␣
↪{coefficient:.2f}x + {intercept:.2f}')
else:
    feature_to_plot = X.columns[0]
    plt.scatter(X[feature_to_plot], Y, color='blue', label='Actual data')
    plt.plot(X[feature_to_plot], model.predict(X), color='red', linewidth=2,␣
↪label='Linear regression')

plt.xlabel('Avg CTAT_Booking Value_Ride Distance_Driver Ratings_Customer␣
↪Rating')
plt.ylabel(linear_target)
plt.title('Linear Regression Visualization')
plt.legend()
plt.grid(True)
plt.show()
```

```
          Booking Status   Vehicle Type         Pickup Location  \
0        No Driver Found          eBike             Palam Vihar
1             Incomplete       Go Sedan           Shastri Nagar
2              Completed           Auto                 Khandsa
3              Completed  Premier Sedan     Central Secretariat
4              Completed           Bike         Ghitorni Village
…                    …             …                     …
149995         Completed        Go Mini                 MG Road
149996         Completed        Go Mini        Golf Course Road
149997         Completed       Go Sedan  Satguru Ram Singh Marg
149998         Completed           Auto               Ghaziabad
149999         Completed  Premier Sedan         Ashok Park Main

             Drop Location  Avg VTAT  Avg CTAT  Booking Value  Ride Distance  \
0                  Jhilmil       8.3      28.8          414.0          23.72
1        Gurgaon Sector 56       4.9      14.0          237.0           5.73
2            Malviya Nagar      13.4      25.8          627.0          13.58
3                 Inderlok      13.1      28.5          416.0          34.02
4              Khan Market       5.3      19.6          737.0          48.21
…                      …       …       …             …            …
149995            Ghitorni      10.2      44.4          475.0          40.08
149996          Akshardham       5.1      30.8         1093.0          21.31
```

```
149997             Jor Bagh       2.7       23.4          852.0           15.93
149998          Saidulajab        6.9       39.6          333.0           45.54
149999  Gurgaon Sector 29         3.5       33.7          806.0           21.19

        Driver Ratings  Customer Rating Payment Method  predicted_class
0                  4.3              4.5            NaN         8.431010
1                  4.3              4.5            UPI         7.847132
2                  4.9              4.9     Debit Card         8.149164
3                  4.6              5.0            UPI         8.533886
4                  4.1              4.3            UPI         8.569115
…                  …                …              …           …
149995             3.7              4.1    Uber Wallet         9.068923
149996             4.8              5.0            UPI         8.339190
149997             3.9              4.4           Cash         8.186736
149998             4.1              3.7            UPI         9.046387
149999             4.6              4.9    Credit Card         8.441368

[150000 rows x 12 columns]
coefficient: 0.022833522302575897
intercept: 7.8980921619235165
```

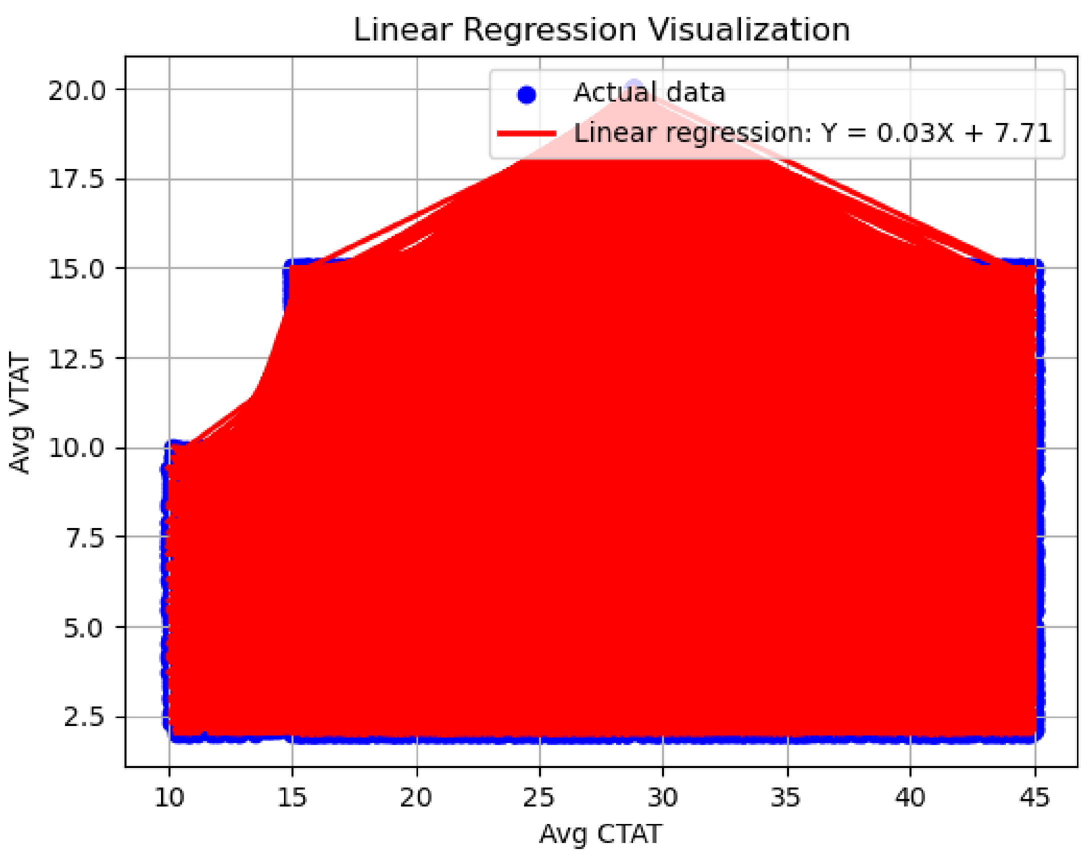


[20]:

```python
X = df['Avg CTAT'].values.reshape(-1, 1)
Y = df['Avg VTAT']

model = LinearRegression()
model.fit(X, Y)

#df['predicted_prob'] = model.predict_proba(X)[:,1]
df['predicted_class'] = model.predict(X)
print(df)

print("Intercept(B0):", model.intercept_)
print("Coefficient(B1):", model.coef_)

# Store the coefficient and intercept in variables before using them
coefficient = model.coef_[0]  # Extract the coefficient value from the array
intercept = model.intercept_

plt.scatter(X, Y, color='blue', label='Actual data')
plt.plot(X, Y, color='red', linewidth=2, label=f'Linear regression: Y =␣
↪{coefficient:.2f}X + {intercept:.2f}')

plt.xlabel('Avg CTAT')
plt.ylabel('Avg VTAT')
plt.title('Linear Regression Visualization')
plt.legend()
plt.grid(True)
plt.show()
```

```
          Booking Status   Vehicle Type         Pickup Location  \
0        No Driver Found           eBike             Palam Vihar
1             Incomplete        Go Sedan          Shastri Nagar
2              Completed            Auto                Khandsa
3              Completed   Premier Sedan     Central Secretariat
4              Completed            Bike        Ghitorni Village
…                    …             …                     …
149995         Completed         Go Mini                MG Road
149996         Completed         Go Mini       Golf Course Road
149997         Completed        Go Sedan  Satguru Ram Singh Marg
149998         Completed            Auto              Ghaziabad
149999         Completed   Premier Sedan         Ashok Park Main

             Drop Location  Avg VTAT  Avg CTAT  Booking Value  Ride Distance  \
0                  Jhilmil       8.3      28.8          414.0          23.72
1        Gurgaon Sector 56       4.9      14.0          237.0           5.73
2            Malviya Nagar      13.4      25.8          627.0          13.58
3                 Inderlok      13.1      28.5          416.0          34.02
4              Khan Market       5.3      19.6          737.0          48.21
```

```
…                      …         …         …             …              …
149995          Ghitorni      10.2      44.4         475.0          40.08
149996        Akshardham       5.1      30.8        1093.0          21.31
149997          Jor Bagh       2.7      23.4         852.0          15.93
149998       Saidulajab        6.9      39.6         333.0          45.54
149999  Gurgaon Sector 29      3.5      33.7         806.0          21.19

        Driver Ratings  Customer Rating Payment Method  predicted_class
0                  4.3              4.5            NaN         8.439408
1                  4.3              4.5            UPI         8.065948
2                  4.9              4.9     Debit Card         8.363707
3                  4.6              5.0            UPI         8.431838
4                  4.1              4.3            UPI         8.207257
…                    …                …              …                …
149995             3.7              4.1    Uber Wallet         8.833055
149996             4.8              5.0            UPI         8.489876
149997             3.9              4.4           Cash         8.303145
149998             4.1              3.7            UPI         8.711933
149999             4.6              4.9    Credit Card         8.563053

[150000 rows x 12 columns]
Intercept(B0): 7.71267486029648
Coefficient(B1): [0.02523379]
```



[21]:

```
# Drop missing values for target
target = "Booking Value"
df_lr = df.dropna(subset=[target])

# Apply log transformation to target
df_lr["log_booking_value"] = np.log1p(df_lr[target])  # log(1+x) to handle 0s

# Features (drop target, status, and transformed column)
X = df_lr.drop(columns=["Booking Status", target, "log_booking_value"])
y = df_lr["log_booking_value"]
```

[22]:

```
# Preprocessing
numeric_transformer = Pipeline([
    ("imputer", SimpleImputer(strategy="median")),
    ("scaler", StandardScaler())
])

categorical_transformer = Pipeline([
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("encoder", OneHotEncoder(handle_unknown="ignore"))
])

preprocessor = ColumnTransformer([
    ("num", numeric_transformer, [c for c in num_cols if c in X.columns]),
    ("cat", categorical_transformer, [c for c in cat_cols if c in X.columns])
])
```

[23]:

```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

[24]:

```
# Linear Regression pipeline
lin_reg_log_model = Pipeline([
    ("preprocessor", preprocessor),
    ("regressor", LinearRegression())
])
```

[25]:

```
# Fit model
lin_reg_log_model.fit(X_train, y_train)
```

[25]:

```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='median')),
```

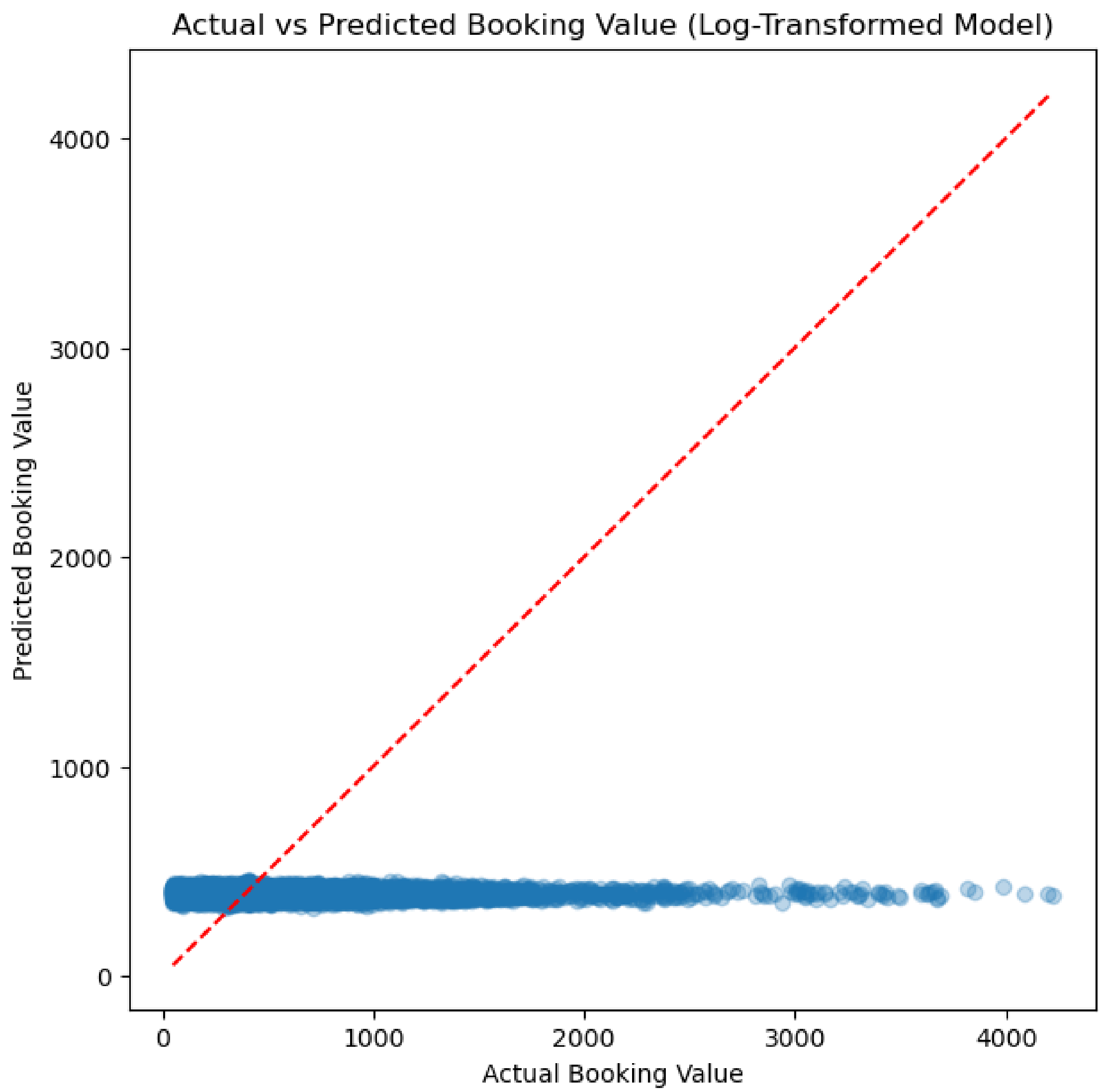
```
                                                              ('scaler',
StandardScaler())]),
                                                 ['Avg VTAT', 'Avg CTAT',
                                                  'Ride Distance',
                                                  'Driver Ratings',
                                                  'Customer Rating']),
                                                ('cat',
                                                 Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
                                                                 ('encoder',
OneHotEncoder(handle_unknown='ignore'))]),
                                                 ['Vehicle Type',
                                                  'Pickup Location',
                                                  'Drop Location',
                                                  'Payment Method'])])),
                ('regressor', LinearRegression())])
```

[26]:
```python
# Predictions in log scale
y_pred_log = lin_reg_log_model.predict(X_test)

# Convert back to original scale
y_pred = np.expm1(y_pred_log)  # reverse log1p
y_test_original = np.expm1(y_test)
```

[27]:
```python
# Evaluation
mse = mean_squared_error(y_test_original, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test_original, y_pred)

print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R² Score:", r2)
```

```
Mean Squared Error: 115599.10060619467
Root Mean Squared Error: 339.9986773594784
R² Score: -0.06743689382995588
```

[28]:
```python
# 1. Actual vs Predicted
plt.figure(figsize=(7,7))
plt.scatter(y_test_original, y_pred, alpha=0.3)
plt.plot([y_test_original.min(), y_test_original.max()],
         [y_test_original.min(), y_test_original.max()], 'r--')
plt.xlabel("Actual Booking Value")
plt.ylabel("Predicted Booking Value")
plt.title("Actual vs Predicted Booking Value (Log-Transformed Model)")
plt.show()
```



2 1. Actual vs Predicted (Log-Transformed Model)

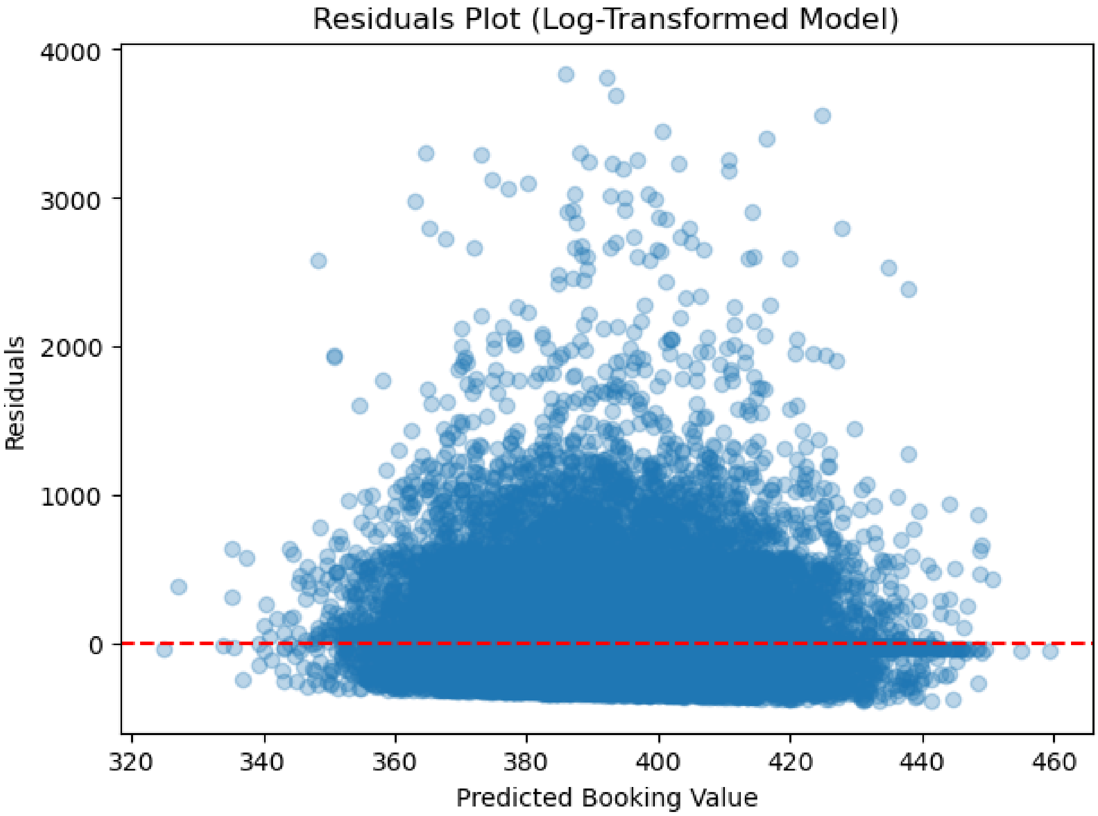
The predictions are heavily clustered in a narrow band (~300–500 range), while actual booking values span from very small amounts up to 4000+.

The red diagonal (perfect fit line) is far from most blue points → the model is underestimating high booking values and compressing predictions.

This suggests linear regression (even with log transformation) struggles to capture non-linear patterns in booking value.

[29]:
```
# 2. Residuals Plot
residuals = y_test_original - y_pred
plt.figure(figsize=(7,5))
```

```
plt.scatter(y_pred, residuals, alpha=0.3)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel("Predicted Booking Value")
plt.ylabel("Residuals")
plt.title("Residuals Plot (Log-Transformed Model)")
plt.show()
```



3 2. Residuals Plot

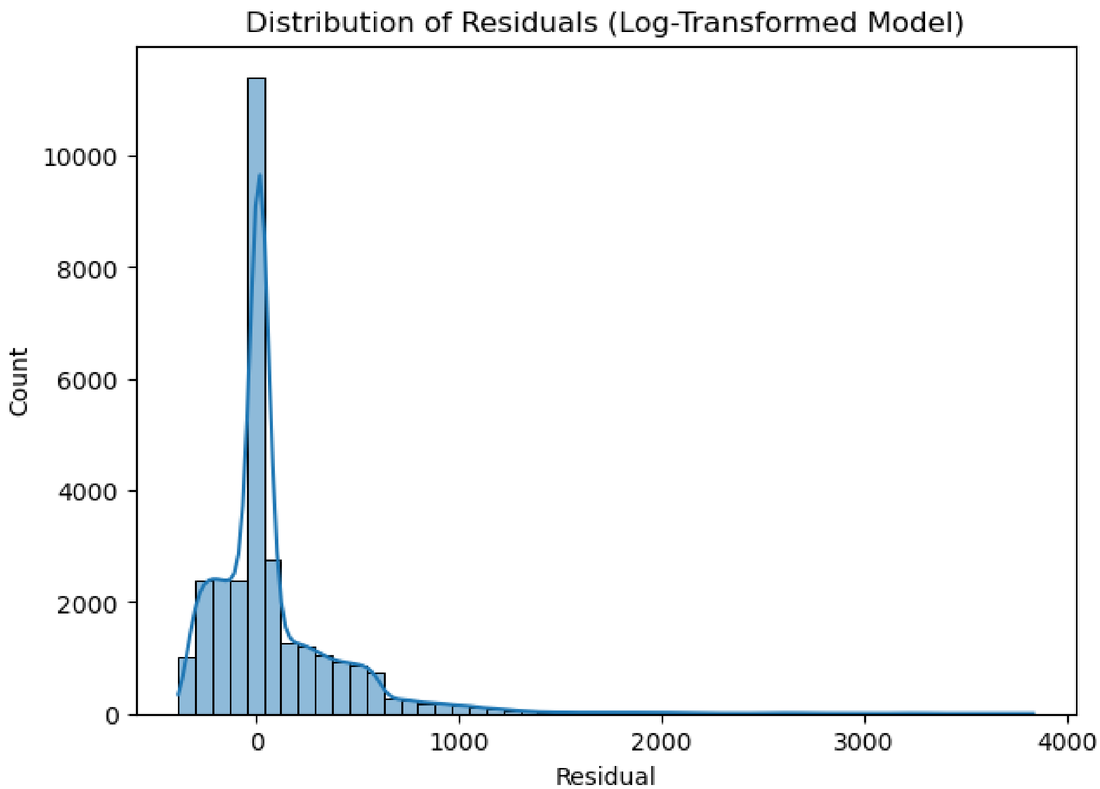
Residuals (errors) show a funnel-like shape: as predicted booking values increase, the spread of errors widens.

Many residuals are large positive values, meaning the model systematically under-predicts high fares.

Ideally, residuals should be randomly scattered around zero. Instead, we see structure → another sign linear regression is not flexible enough.

[30]:
```
# 3. Residuals Distribution
plt.figure(figsize=(7,5))
sns.histplot(residuals, bins=50, kde=True)
```

```
plt.xlabel("Residual")
plt.title("Distribution of Residuals (Log-Transformed Model)")
plt.show()
```



4 3. Residuals Distribution

The residuals distribution is heavily right-skewed.

Peak around 0 (good), but a long positive tail indicates the model frequently misses high fares by a large margin.

This reinforces that linear regression is capturing the "average trend" but not the outliers and high-value bookings.

5 Key Takeaways

Log transformation helped stabilize variance a bit, but the model is still far from accurate.

The problem seems non-linear → Linear Regression isn't flexible enough.

High-value bookings are systematically underestimated.

Next step: try a non-linear regression model (e.g., Random Forest, Gradient Boosting, or XGBoost) which can capture complex interactions between features.

6 Logistic Regression ———-

[31]:
```
# Define target
df["target"] = df["Booking Status"].apply(lambda x: 1 if x == "Completed" else␣
↪0)

X = df.drop(columns=["Booking Status", "target"])
y = df["target"]
```

[32]:
```
# Preprocessing pipelines
numeric_transformer = Pipeline([
    ("imputer", SimpleImputer(strategy="median")),
    ("scaler", StandardScaler())
])

categorical_transformer = Pipeline([
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("encoder", OneHotEncoder(handle_unknown="ignore"))
])

preprocessor = ColumnTransformer([
    ("num", numeric_transformer, [c for c in num_cols if c in X.columns]),
    ("cat", categorical_transformer, [c for c in cat_cols if c in X.columns])
])
```

[33]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

log_reg_model = Pipeline([
    ("preprocessor", preprocessor),
    ("classifier", LogisticRegression(max_iter=1000))
])

log_reg_model.fit(X_train, y_train)
```

[33]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='median')),
                                                                  ('scaler',
StandardScaler())]),
                                                  ['Avg VTAT', 'Avg CTAT',
```

```
                                                 'Booking Value',
                                                 'Ride Distance',
                                                 'Driver Ratings',
                                                 'Customer Rating']),
                                               ('cat',
                                                Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
                                                                ('encoder',
OneHotEncoder(handle_unknown='ignore'))]),
                                                ['Vehicle Type',
                                                 'Pickup Location',
                                                 'Drop Location',
                                                 'Payment Method'])])),
                ('classifier', LogisticRegression(max_iter=1000))])
```

[34]:

```python
# Predictions
y_pred = log_reg_model.predict(X_test)
y_prob = log_reg_model.predict_proba(X_test)[:, 1]
```

[35]:

```python
# Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

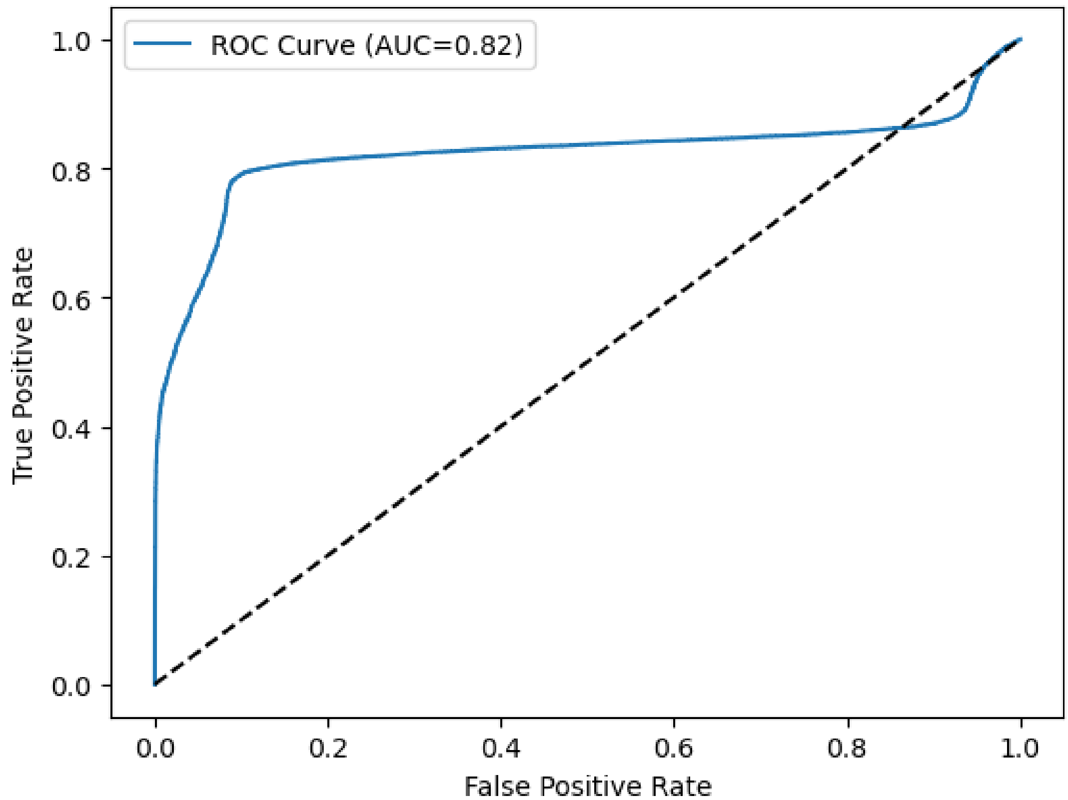
```
Accuracy: 0.8303666666666667

Confusion Matrix:
 [[10307  1051]
 [ 4038 14604]]

Classification Report:
               precision    recall  f1-score   support

           0       0.72      0.91      0.80     11358
           1       0.93      0.78      0.85     18642

    accuracy                           0.83     30000
   macro avg       0.83      0.85      0.83     30000
weighted avg       0.85      0.83      0.83     30000
```

[36]:

```python
# ROC-AUC curve (for binary classification)
if len(np.unique(y)) == 2:
    auc = roc_auc_score(y_test, y_prob)
    print("ROC-AUC:", auc)
    fpr, tpr, _ = roc_curve(y_test, y_prob)
    plt.plot(fpr, tpr, label=f"ROC Curve (AUC={auc:.2f})")
```

```
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend()
    plt.show()
```

```
ROC-AUC: 0.8220642347949073
```



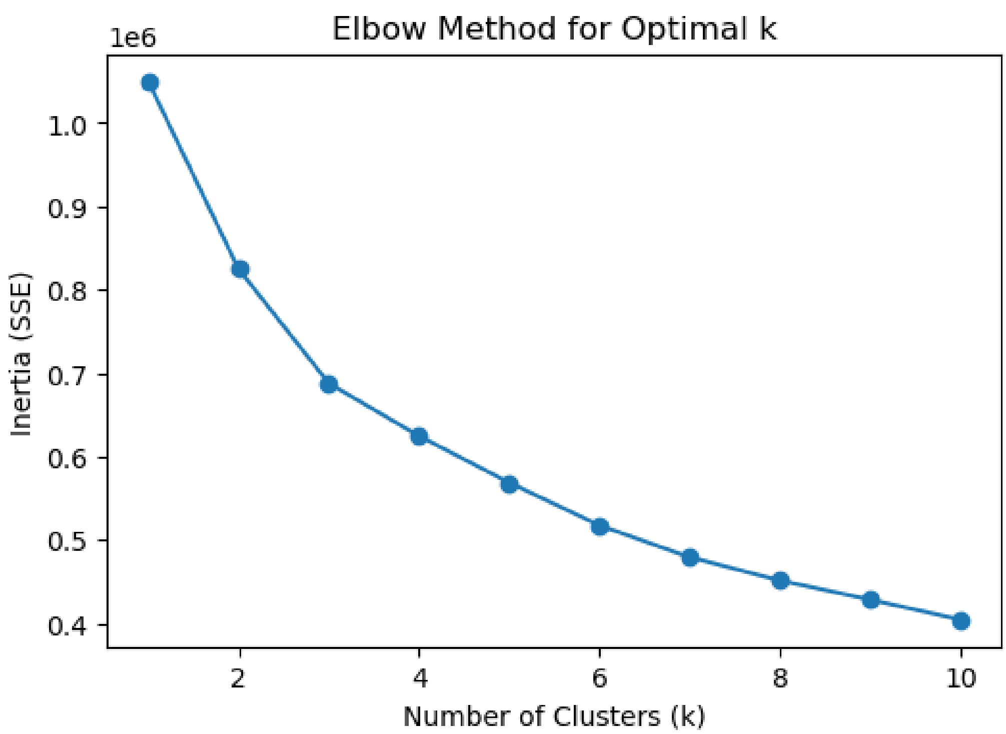
7 KMeans Clustering ———-

[37]:
```
# Select features for clustering (exclude IDs, targets, non-numeric)
features = df.drop(columns=["Booking ID", "Booking Value"], errors="ignore")  #␣
  ↪drop ID & target
X = features.select_dtypes(include=['int64','float64'])
```

[38]:
```
# Standardize data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

[39]:
```
# Elbow method to find optimal k
inertia = []
K = range(1, 11)
for k in K:
    km = KMeans(n_clusters=k, random_state=42, n_init=10)
    km.fit(X_scaled)
    inertia.append(km.inertia_)
```

[40]:
```
plt.figure(figsize=(6,4))
plt.plot(K, inertia, marker="o")
plt.xlabel("Number of Clusters (k)")
plt.ylabel("Inertia (SSE)")
plt.title("Elbow Method for Optimal k")
plt.show()
```



[41]:
```
# Fit KMeans with chosen k (say k=3 or 4 after elbow plot)
kmeans = KMeans(n_clusters=4, random_state=42, n_init=10)
df["Cluster"] = kmeans.fit_predict(X_scaled)
```

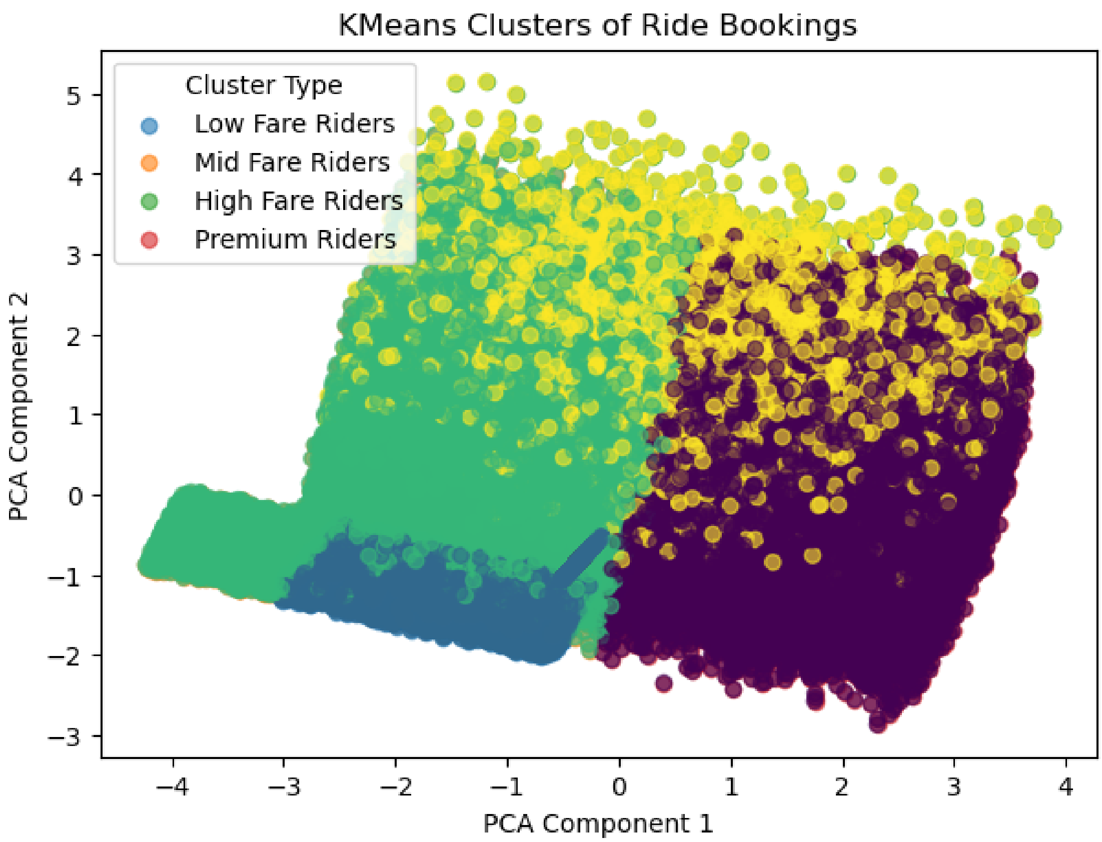
[42]:
```
# Reduce dimensions for visualization
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
```

[43]:

```python
# Example: interpret clusters by their average Booking Value
cluster_summary = df.groupby("Cluster")["Booking Value"].mean().sort_values()
print(cluster_summary)

# Map cluster numbers → meaningful names
cluster_labels = {
    cluster_summary.index[0]: "Low Fare Riders",
    cluster_summary.index[1]: "Mid Fare Riders",
    cluster_summary.index[2]: "High Fare Riders",
    cluster_summary.index[3]: "Premium Riders"
}

df["Cluster Name"] = df["Cluster"].map(cluster_labels)

plt.figure(figsize=(7,5))
for cluster, name in cluster_labels.items():
    plt.scatter(
        X_pca[df["Cluster"]==cluster,0],
        X_pca[df["Cluster"]==cluster,1],
        label=name, alpha=0.6
    )
plt.scatter(X_pca[:,0], X_pca[:,1], c=df["Cluster"], cmap="viridis", alpha=0.6)
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.title("KMeans Clusters of Ride Bookings")
plt.legend(title="Cluster Type")
plt.show()
```

```
Cluster
1    424.300054
2    507.515531
3    508.015164
0    509.015239
Name: Booking Value, dtype: float64
```

```
C:\Users\user\anaconda3\Lib\site-packages\IPython\core\pylabtools.py:170:
UserWarning: Creating legend with loc="best" can be slow with large amounts of
data.
  fig.canvas.print_figure(bytes_io, **kw)
```



8 Insights from the Graph

1. Clear Segmentation of Riders

The clusters are well-separated, meaning the KMeans algorithm has successfully grouped riders based on their booking characteristics (likely influenced by fare, ride distance, or duration).

Each cluster shows a distinct behavioral pattern, useful for targeted strategies.

2. Low Fare Riders (Blue Cluster, far left)

This group is clearly isolated, suggesting they have consistently low booking values.

Likely represent budget-conscious commuters (e.g., daily short-distance riders).

3. Mid Fare Riders (Yellow Cluster, center)

Positioned between low and high fare groups.

This group has moderate booking values, possibly occasional riders or medium-distance commuters.

4. High Fare Riders (Green Cluster, right side)

Spread across the upper-right side, showing higher variability in ride behavior.

Indicates frequent travelers with higher-than-average spending.

5. Premium Riders (Red/Purple Cluster, overlapping with High Fare)

Found on the far-right edge, they represent the highest booking values.

Likely include luxury service users, long-distance travelers, or corporate accounts.

Though close to high fare riders, they form their own elite cluster.

6. Business Implications

Low Fare Riders → Can be offered loyalty rewards or discounts to encourage frequent use.

Mid Fare Riders → Upselling opportunities (e.g., premium rides, bundled packages).

High Fare Riders → Personalized offers for long-distance trips.

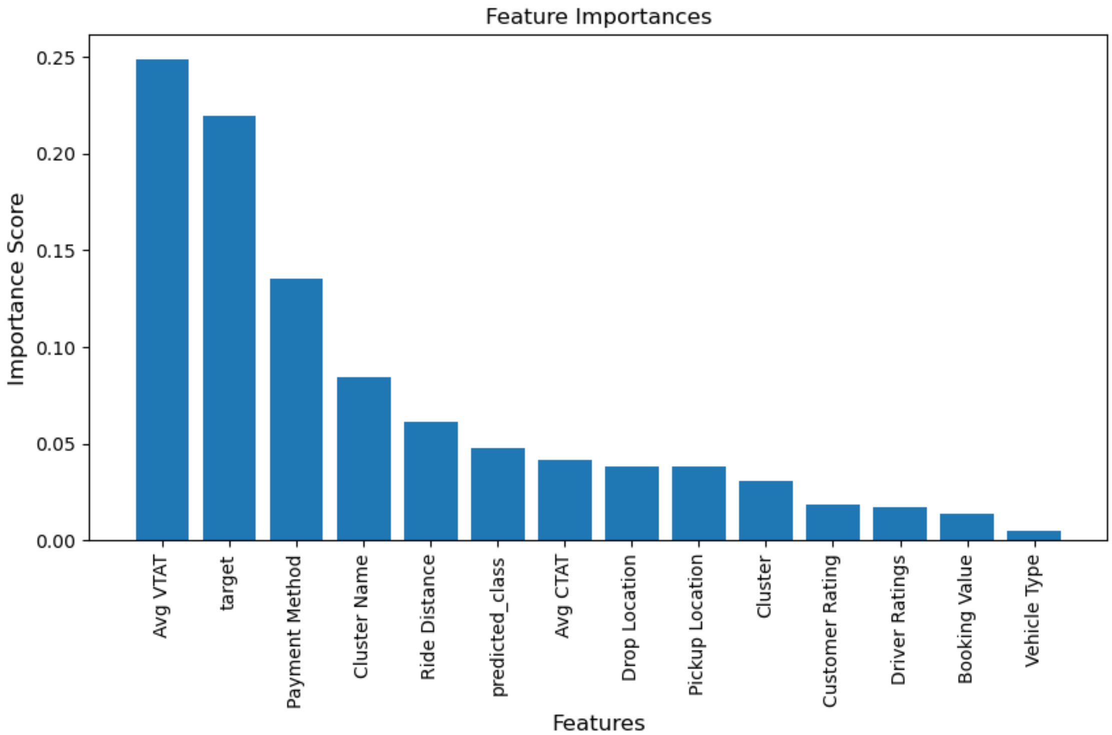
Premium Riders → Exclusive benefits (priority booking, premium customer support).

9 Random Forest Classifier ———

[44]:
```
# Make a copy
df_encoded = df.copy()

# Encode categorical variables
for col in df_encoded.select_dtypes(include=['object']).columns:
    df_encoded[col] = LabelEncoder().fit_transform(df_encoded[col].astype(str))

# Define Features & Target
X = df_encoded.drop(columns=["Booking Status"])   # features
y = df_encoded["Booking Status"]                  # target

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42)

# Model
rf_clf = RandomForestClassifier(n_estimators=100, random_state=42)
rf_clf.fit(X_train, y_train)

# Predictions
y_pred = rf_clf.predict(X_test)

# Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))

# Feature Importance
importances = rf_clf.feature_importances_
```

```
indices = np.argsort(importances)[::-1]
plt.figure(figsize=(10,5))
plt.title("Feature Importances")
plt.bar(range(X.shape[1]), importances[indices])
plt.xticks(range(X.shape[1]), X.columns[indices], rotation=90)
plt.xlabel("Features", fontsize=12)
plt.ylabel("Importance Score", fontsize=12)
plt.show()
```

```
Accuracy: 0.9621666666666666

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.55      0.68      2077
           1       0.85      0.97      0.90      5431
           2       1.00      1.00      1.00     18642
           3       1.00      1.00      1.00      1752
           4       0.95      1.00      0.97      2098

    accuracy                           0.96     30000
   macro avg       0.94      0.90      0.91     30000
weighted avg       0.96      0.96      0.96     30000


Confusion Matrix:
 [[ 1135   923     0     0    19]
 [  104  5243     0     0    84]
 [    0     0 18642     0     0]
 [    0     0     0  1752     0]
 [    1     4     0     0  2093]]
```



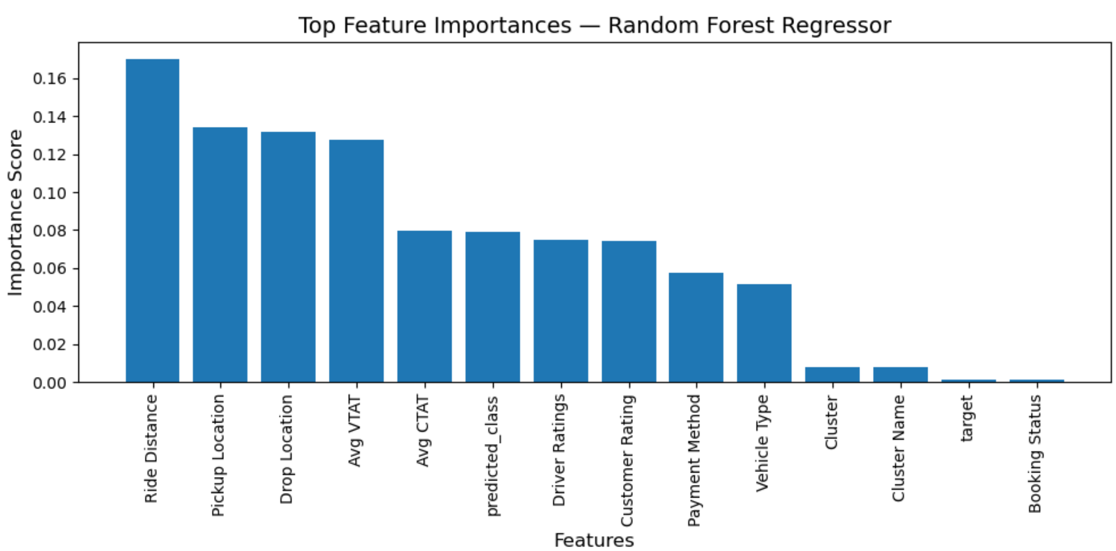
10 Random Forest Regressor ———

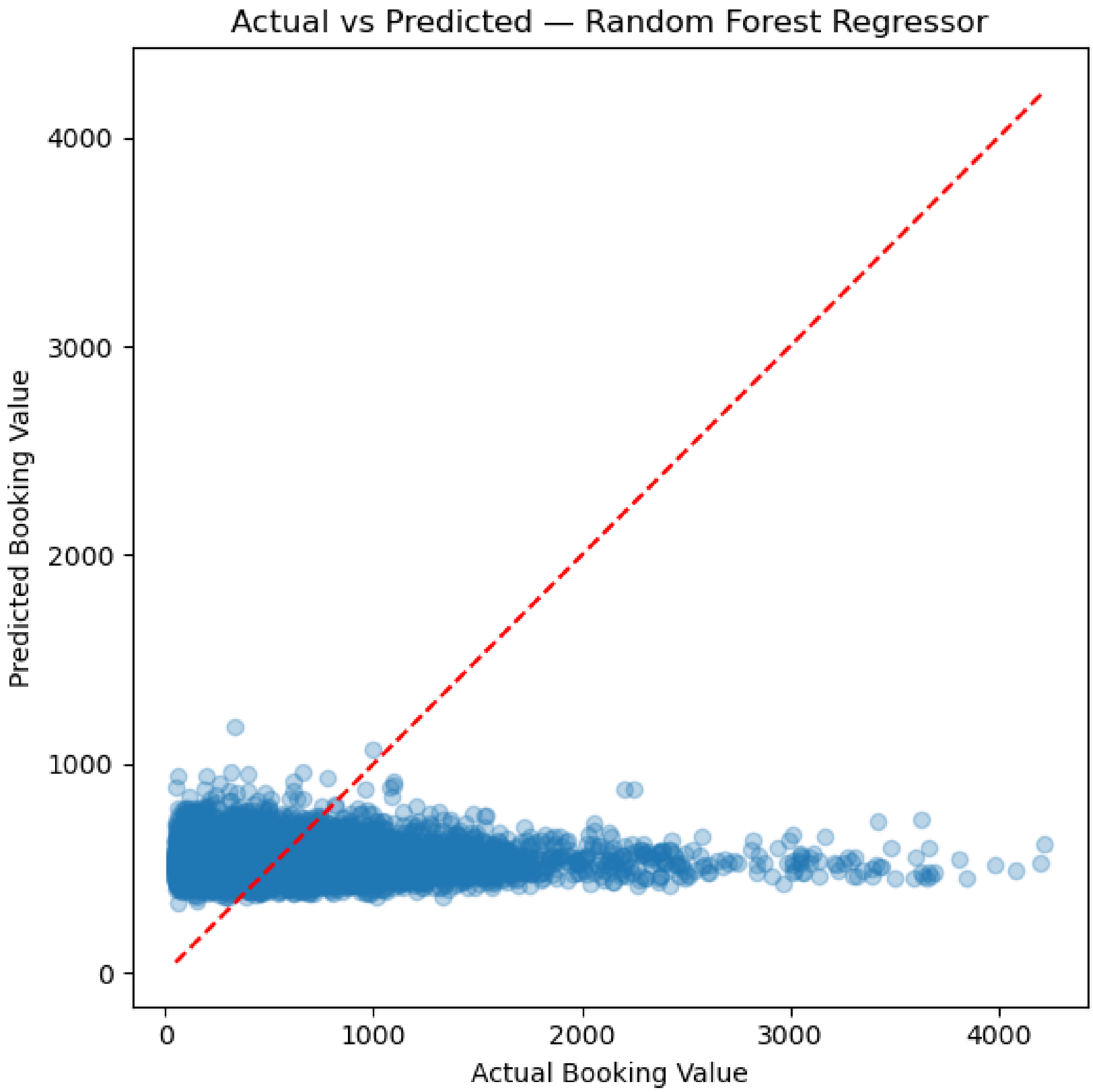
[46]:
```
# --- 1) Prep data ---
df_rf = df.copy()

# Drop rows with missing target
df_rf = df_rf.dropna(subset=["Booking Value"])

# Optional: drop pure ID columns that don't help prediction
for col in ["Booking ID", "Customer ID"]:
    if col in df_rf.columns:
        df_rf.drop(columns=[col], inplace=True)

# Impute missing values BEFORE encoding
for col in df_rf.columns:
    if df_rf[col].dtype == "object":
        df_rf[col] = df_rf[col].fillna("Unknown")
    else:
        df_rf[col] = df_rf[col].fillna(df_rf[col].median())

# Label-encode ALL object columns (trees handle integer-coded categories well)
df_enc = df_rf.copy()
```

```python
for col in df_enc.select_dtypes(include=["object"]).columns:
    df_enc[col] = LabelEncoder().fit_transform(df_enc[col].astype(str))

# --- 2) Features & target ---
X = df_enc.drop(columns=["Booking Value"])
y = df_enc["Booking Value"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# --- 3) Model ---
rf_reg = RandomForestRegressor(
    n_estimators=200,
    max_depth=None,
    random_state=42,
    n_jobs=-1
)
rf_reg.fit(X_train, y_train)

# --- 4) Predict & evaluate (compat with older sklearn) ---
y_pred = rf_reg.predict(X_test)

mse = mean_squared_error(y_test, y_pred)     # no 'squared' arg in older␣
 ↪versions
rmse = np.sqrt(mse)                          # compute RMSE manually
mae  = mean_absolute_error(y_test, y_pred)
r2   = r2_score(y_test, y_pred)

print("R² Score:", round(r2, 4))
print("MSE:", round(mse, 2))
print("RMSE:", round(rmse, 2))
print("MAE:", round(mae, 2))

# --- 5) Feature importance plot (with axis labels) ---
importances = rf_reg.feature_importances_
indices = np.argsort(importances)[::-1]

top_n = min(20, X.shape[1])  # show top 20 for readability
top_idx = indices[:top_n]

plt.figure(figsize=(10,5))
plt.title("Top Feature Importances - Random Forest Regressor", fontsize=14)
plt.bar(range(top_n), importances[top_idx])
plt.xticks(range(top_n), X.columns[top_idx], rotation=90)
plt.xlabel("Features", fontsize=12)
plt.ylabel("Importance Score", fontsize=12)
```

```
plt.tight_layout()
plt.show()

# --- 6) Predicted vs Actual scatter (helpful sanity check) ---
plt.figure(figsize=(6,6))
plt.scatter(y_test, y_pred, alpha=0.3)
m = min(y_test.min(), y_pred.min())
M = max(y_test.max(), y_pred.max())
plt.plot([m, M], [m, M], 'r--')
plt.xlabel("Actual Booking Value")
plt.ylabel("Predicted Booking Value")
plt.title("Actual vs Predicted - Random Forest Regressor")
plt.tight_layout()
plt.show()
```

```
R² Score: -0.0116
MSE: 109546.85
RMSE: 330.98
MAE: 200.8
```




Actual vs Predicted — Random Forest Regressor
Predicted Booking Value
Actual Booking Value
0
1000
2000
3000
4000
0
1000
2000
3000
4000

```
[ ]:
```