Assignment 3.1

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0.1 Assignment 3.1

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0.1.1 1. How can a predictive model based on these data be used by Yourcabs.com?

Yourcabs.com can utilize a predictive model to forecast instances of driver cancellations prior. to their actual occurrence. This model leverageshistorical booking data, including factors such as the time of day, location, vehicle type, and travel package, to accurately predict the probability of a driver canceling a trip. With these predictions, **Yourcabs.com** can take **proactive measures**, such as: - **Reassigning drivers** to at-risk bookings. - **Notifying customers** ahead of time if a cancellation is likely. - **Providing incentives** for drivers to complete high-risk trips.

These actions will help reduce service disruptions, improve customer satisfaction, and optimize the company's operational efficiency.

0.1.2 2. How can a profiling model (identifying predictors that distinguish canceled/uncanceled trips) be used by Yourcabs.com?

A profiling model helps **Yourcabs.com** understand the factors that contribute to driver cancellations by identifying **key predictors**. For instance, the model may show that cancellations are more frequent at certain times of the day, in specific locations, or with certain types of bookings. By gaining insight into these predictors, **Yourcabs.com** can: - **Prioritize resources** for high-risk trips, such as dispatching backup drivers or providing targeted support for bookings that are likely to be canceled. - **Adjust operational strategies** based on time, location, or other key factors to prevent cancellations. - **Implement policy changes**, such as driver incentives or customer communication, tailored to reduce cancellations where the risk is highest.

Profiling helps the company optimize its efforts, focus on the most critical areas, and improve overall service reliability.

[1]:
```python
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
```

```python
from sklearn.neural_network import MLPClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (
    confusion_matrix,
    classification_report,
    roc_auc_score,
    roc_curve,
    accuracy_score,
)
import warnings

warnings.simplefilter(action="ignore", category=FutureWarning)

# Load the dataset
df = pd.read_csv(
    "/Users/gabrielmancillas/Desktop/ADS 505-01/Mod 03/Assignments/
 ↪Taxi-cancellation-case (1).csv"
)
df.head()
```

[1]:

```
   row#  user_id  vehicle_model_id  package_id  travel_type_id  from_area_id  \
0     1    17712                12         NaN               2        1021.0
1     2    17037                12         NaN               2         455.0
2     3      761                12         NaN               2         814.0
3     4      868                12         NaN               2         297.0
4     5    21716                28         NaN               2        1237.0

   to_area_id  from_city_id  to_city_id     from_date      to_date  \
0      1323.0           NaN         NaN  1/1/13 22:33          NaN
1      1330.0           NaN         NaN  1/1/13 12:43          NaN
2       393.0           NaN         NaN   1/2/13 0:28  1/3/13 0:00
3       212.0           NaN         NaN  1/1/13 13:12          NaN
4       330.0           NaN         NaN  1/1/13 16:33          NaN

   online_booking  mobile_site_booking booking_created   from_lat  from_long  \
0               0                    0      1/1/13 8:01  13.028530   77.54625
1               0                    0      1/1/13 9:59  12.999874   77.67812
2               1                    0     1/1/13 12:14  12.908993   77.68890
3               0                    0     1/1/13 12:42  12.997890   77.61488
4               0                    0     1/1/13 15:07  12.926450   77.61206

      to_lat    to_long  Car_Cancellation
0  12.869805  77.653211                 0
1  12.953434  77.706510                 0
2  13.199560  77.706880                 0
3  12.994740  77.607970                 0
```

```
4  12.858833  77.589127                 0
```

[3]:
```
# show me the missing data
print(df.isnull().sum())
```

```
row#                        0
user_id                     0
vehicle_model_id            0
package_id               8248
travel_type_id              0
from_area_id               15
to_area_id               2091
from_city_id             6294
to_city_id               9661
from_date                   0
to_date                  4178
online_booking              0
mobile_site_booking         0
booking_created             0
from_lat                   15
from_long                  15
to_lat                   2091
to_long                  2091
Car_Cancellation            0
dtype: int64
```

[4]:
```
# Handle missing data for package_id (categorical-like) - use mode
df["package_id"].fillna(df["package_id"].mode()[0], inplace=True)

# Handle missing data for from_area_id and to_area_id - use median
df["from_area_id"].fillna(df["from_area_id"].median(), inplace=True)
df["to_area_id"].fillna(df["to_area_id"].median(), inplace=True)

# Handle missing data for from_city_id and to_city_id - use mode
df["from_city_id"].fillna(df["from_city_id"].mode()[0], inplace=True)
df["to_city_id"].fillna(df["to_city_id"].mode()[0], inplace=True)

# Handle missing data for geographical coordinates - use median
df["from_lat"].fillna(df["from_lat"].median(), inplace=True)
df["from_long"].fillna(df["from_long"].median(), inplace=True)
df["to_lat"].fillna(df["to_lat"].median(), inplace=True)
df["to_long"].fillna(df["to_long"].median(), inplace=True)

# Handle missing data for date columns (from_date, to_date)
# If the date is critical, you can drop rows, or impute with the most common␣
 ↪date (mode)
df["from_date"].fillna(df["from_date"].mode()[0], inplace=True)
```

```
df["to_date"].fillna(df["to_date"].mode()[0], inplace=True)

# Verify no missing data remains
print(df.isnull().sum())
```

```
row#                   0
user_id                0
vehicle_model_id       0
package_id             0
travel_type_id         0
from_area_id           0
to_area_id             0
from_city_id           0
to_city_id             0
from_date              0
to_date                0
online_booking         0
mobile_site_booking    0
booking_created        0
from_lat               0
from_long              0
to_lat                 0
to_long                0
Car_Cancellation       0
dtype: int64
```

[5]:

```
# Check column names
print(df.columns)
```

```
Index(['row#', 'user_id', 'vehicle_model_id', 'package_id', 'travel_type_id',
       'from_area_id', 'to_area_id', 'from_city_id', 'to_city_id', 'from_date',
       'to_date', 'online_booking', 'mobile_site_booking', 'booking_created',
       'from_lat', 'from_long', 'to_lat', 'to_long', 'Car_Cancellation'],
      dtype='object')
```

[6]:

```
df.columns = df.columns.str.strip()  # Removes leading/trailing spaces
print(df.columns)  # Verify corrected column names
```

```
Index(['row#', 'user_id', 'vehicle_model_id', 'package_id', 'travel_type_id',
       'from_area_id', 'to_area_id', 'from_city_id', 'to_city_id', 'from_date',
       'to_date', 'online_booking', 'mobile_site_booking', 'booking_created',
       'from_lat', 'from_long', 'to_lat', 'to_long', 'Car_Cancellation'],
      dtype='object')
```

[7]:

```
# Convert date columns to datetime format, specifying the correct format
df["from_date"] = pd.to_datetime(df["from_date"], format="%m/%d/%y %H:%M")
df["to_date"] = pd.to_datetime(df["to_date"], format="%m/%d/%y %H:%M")

# Extract features from corrected date columns
```

```
df["from_day"] = df["from_date"].dt.day
df["from_month"] = df["from_date"].dt.month
df["from_year"] = df["from_date"].dt.year
df["from_hour"] = df["from_date"].dt.hour

df["to_day"] = df["to_date"].dt.day
df["to_month"] = df["to_date"].dt.month
df["to_year"] = df["to_date"].dt.year
df["to_hour"] = df["to_date"].dt.hour

# Drop original date columns if not needed
df.drop(["from_date", "to_date"], axis=1, inplace=True)

df.head()
```

[7]:

```
   row#  user_id  vehicle_model_id  package_id  travel_type_id  from_area_id  \
0     1    17712                12         1.0               2        1021.0
1     2    17037                12         1.0               2         455.0
2     3      761                12         1.0               2         814.0
3     4      868                12         1.0               2         297.0
4     5    21716                28         1.0               2        1237.0

   to_area_id  from_city_id  to_city_id  online_booking  …    to_long  \
0      1323.0          15.0        32.0               0  …  77.653211
1      1330.0          15.0        32.0               0  …  77.706510
2       393.0          15.0        32.0               1  …  77.706880
3       212.0          15.0        32.0               0  …  77.607970
4       330.0          15.0        32.0               0  …  77.589127

  Car_Cancellation  from_day  from_month  from_year  from_hour  to_day  \
0                0         1           1       2013         22      12
1                0         1           1       2013         12      12
2                0         2           1       2013          0       3
3                0         1           1       2013         13      12
4                0         1           1       2013         16      12

   to_month  to_year  to_hour
0         5     2013        0
1         5     2013        0
2         1     2013        0
3         5     2013        0
4         5     2013        0

[5 rows x 25 columns]
```

[10]:

```
# Check the data types of the columns
print(df.dtypes)
```

```
row#                    int64
user_id                 int64
vehicle_model_id        int64
package_id            float64
travel_type_id          int64
from_area_id          float64
to_area_id            float64
from_city_id          float64
to_city_id            float64
online_booking          int64
mobile_site_booking     int64
booking_created        object
from_lat              float64
from_long             float64
to_lat                float64
to_long               float64
Car_Cancellation        int64
from_day                int32
from_month              int32
from_year               int32
from_hour               int32
to_day                  int32
to_month                int32
to_year                 int32
to_hour                 int32
dtype: object
```

[11]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.neural_network import MLPClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

# Assuming df is your DataFrame
# Drop the non-numeric 'booking_created' column
df_numeric = df.drop(columns=["booking_created"])

# Define target (y) and features (X)
X = df_numeric.drop("Car_Cancellation", axis=1)
y = df_numeric["Car_Cancellation"]
```

[12]:
```python
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42
)
```

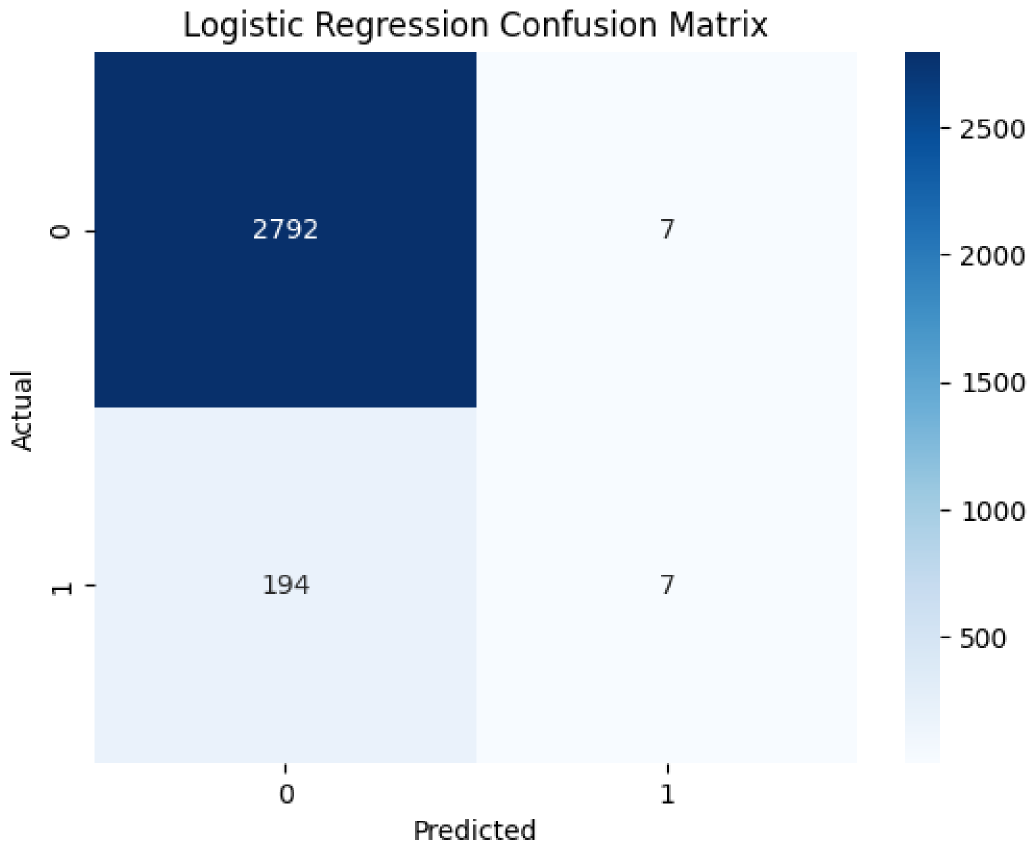
```python
# Standardize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Logistic Regression
log_model = LogisticRegression(max_iter=1000)
log_model.fit(X_train_scaled, y_train)
y_pred_log = log_model.predict(X_test_scaled)
```

[13]:
```python
# Neural Network
nn_model = MLPClassifier(hidden_layer_sizes=(50, 30), max_iter=500,␣
↪random_state=42)
nn_model.fit(X_train_scaled, y_train)
y_pred_nn = nn_model.predict(X_test_scaled)

# Decision Tree
tree_model = DecisionTreeClassifier(random_state=42)
tree_model.fit(X_train_scaled, y_train)
y_pred_tree = tree_model.predict(X_test_scaled)

# Random Forest
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train_scaled, y_train)
y_pred_rf = rf_model.predict(X_test_scaled)
```

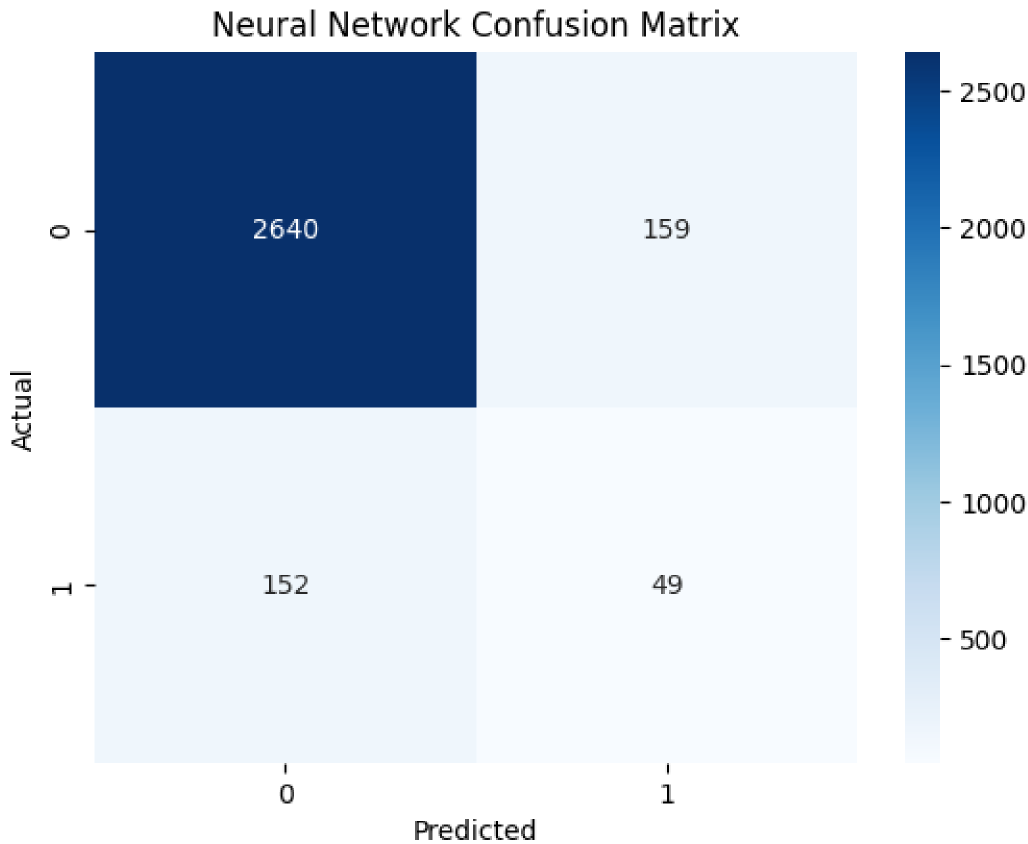
[14]:
```python
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
import matplotlib.pyplot as plt


# Function to plot confusion matrix
def plot_confusion_matrix(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
    plt.title(title)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()


# Logistic Regression
print("Logistic Regression:")
print(confusion_matrix(y_test, y_pred_log))
print(classification_report(y_test, y_pred_log))
```

```
plot_confusion_matrix(y_test, y_pred_log, "Logistic Regression Confusion␣
↪Matrix")

# Neural Network
print("Neural Network:")
print(confusion_matrix(y_test, y_pred_nn))
print(classification_report(y_test, y_pred_nn))
plot_confusion_matrix(y_test, y_pred_nn, "Neural Network Confusion Matrix")

# Decision Tree
print("Decision Tree:")
print(confusion_matrix(y_test, y_pred_tree))
print(classification_report(y_test, y_pred_tree))
plot_confusion_matrix(y_test, y_pred_tree, "Decision Tree Confusion Matrix")

# Random Forest
print("Random Forest:")
print(confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
plot_confusion_matrix(y_test, y_pred_rf, "Random Forest Confusion Matrix")
```

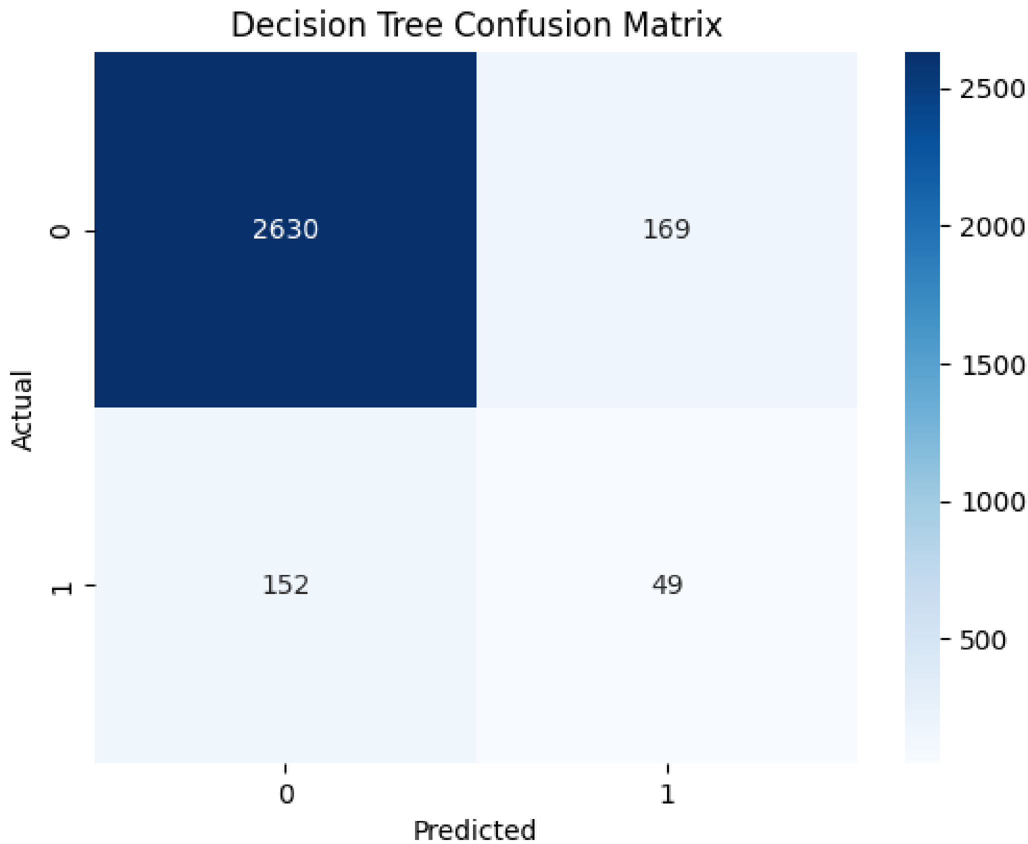
```
Logistic Regression:
[[2792    7]
 [ 194    7]]
              precision    recall  f1-score   support

           0       0.94      1.00      0.97      2799
           1       0.50      0.03      0.07       201

    accuracy                           0.93      3000
   macro avg       0.72      0.52      0.52      3000
weighted avg       0.91      0.93      0.90      3000
```



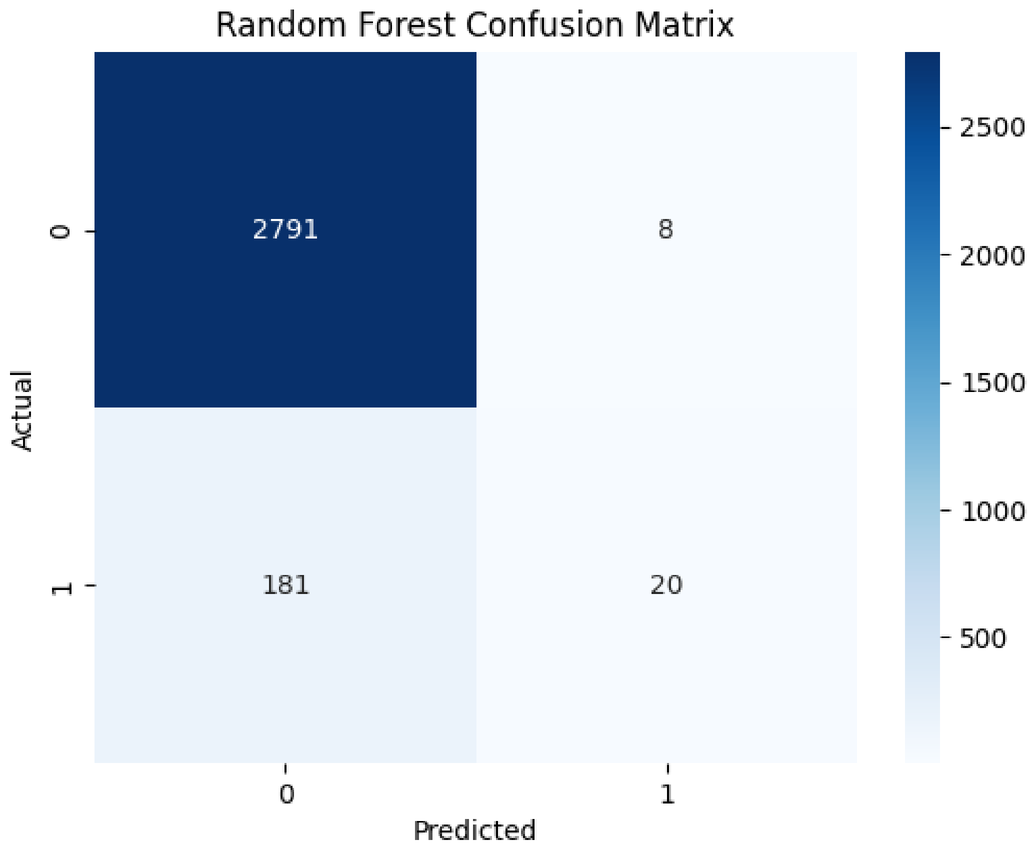

```
Neural Network:
[[2640  159]
 [ 152   49]]
              precision    recall  f1-score   support

           0       0.95      0.94      0.94      2799
           1       0.24      0.24      0.24       201

    accuracy                           0.90      3000
   macro avg       0.59      0.59      0.59      3000
weighted avg       0.90      0.90      0.90      3000
```




```
Decision Tree:
[[2630  169]
 [ 152   49]]
              precision    recall  f1-score   support

           0       0.95      0.94      0.94      2799
           1       0.22      0.24      0.23       201

    accuracy                           0.89      3000
   macro avg       0.59      0.59      0.59      3000
weighted avg       0.90      0.89      0.90      3000
```



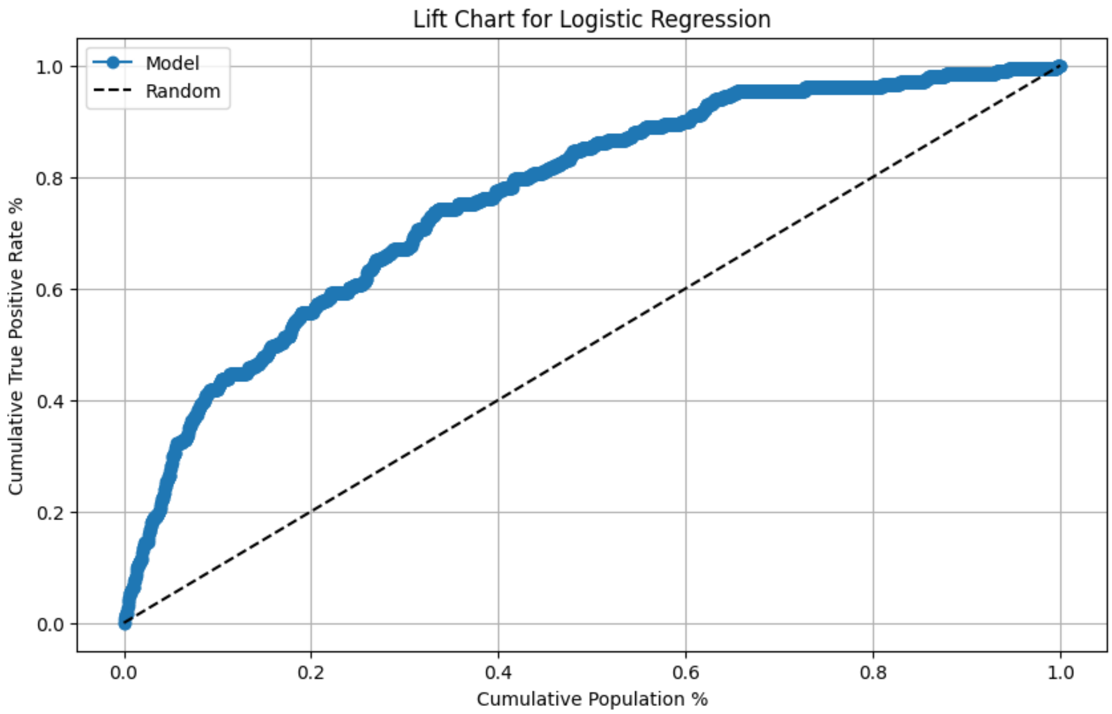

```
Random Forest:
[[2791    8]
 [ 181   20]]
              precision    recall  f1-score   support

           0       0.94      1.00      0.97      2799
           1       0.71      0.10      0.17       201

    accuracy                           0.94      3000
   macro avg       0.83      0.55      0.57      3000
weighted avg       0.92      0.94      0.91      3000
```

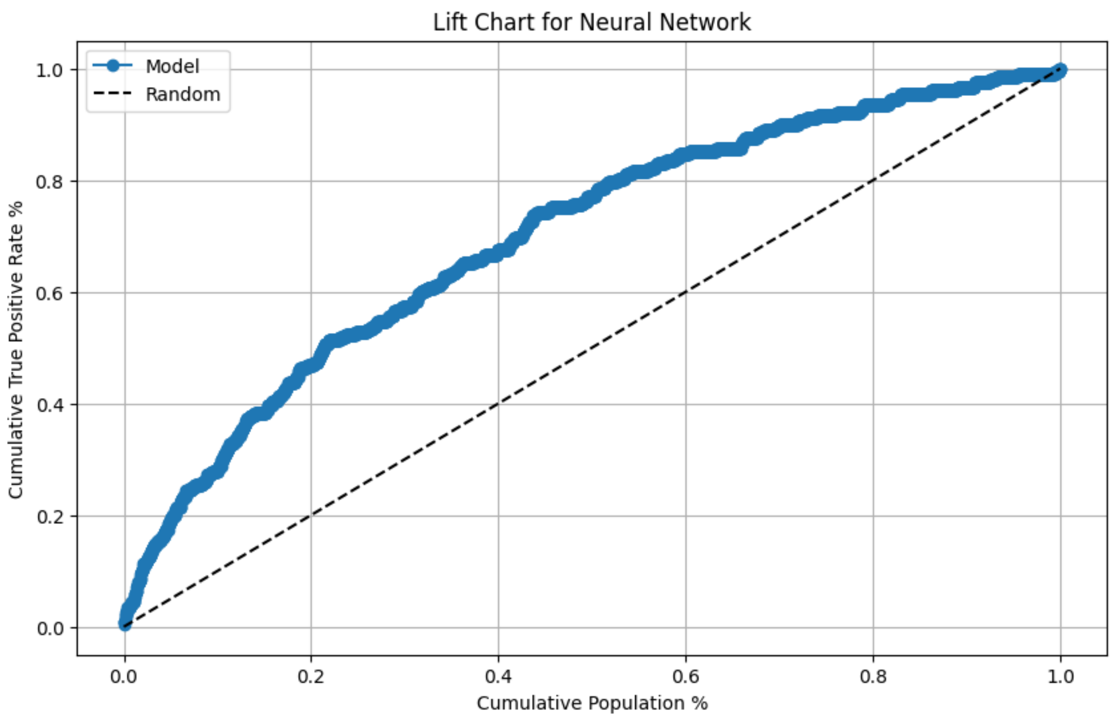


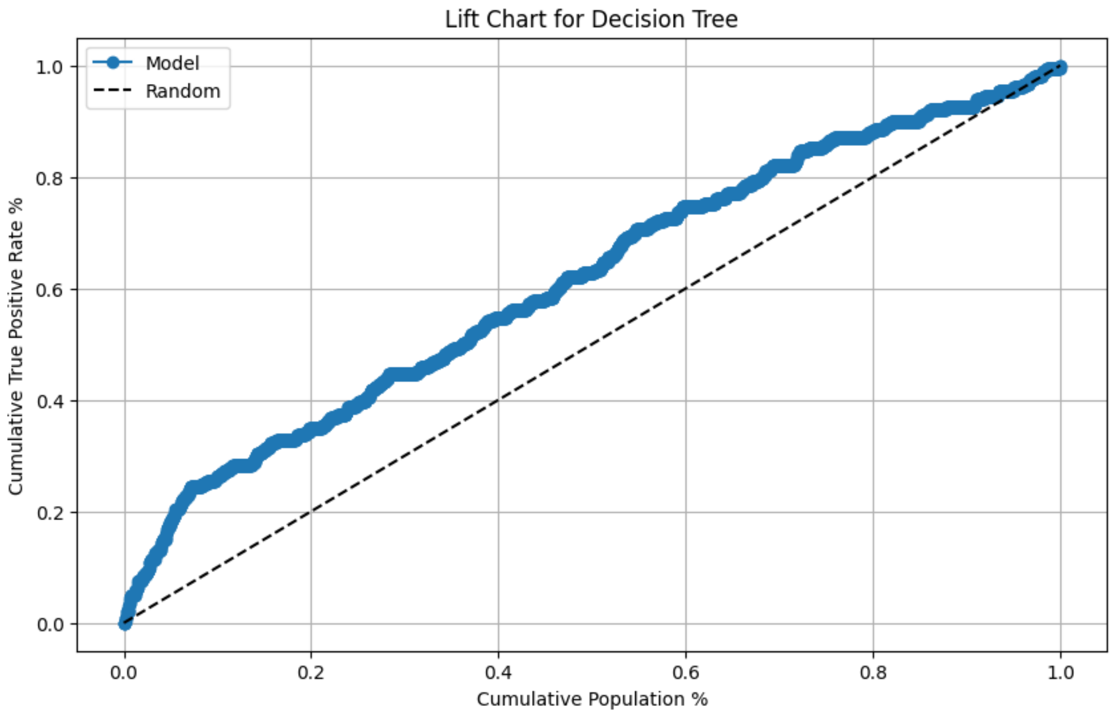
[15]:

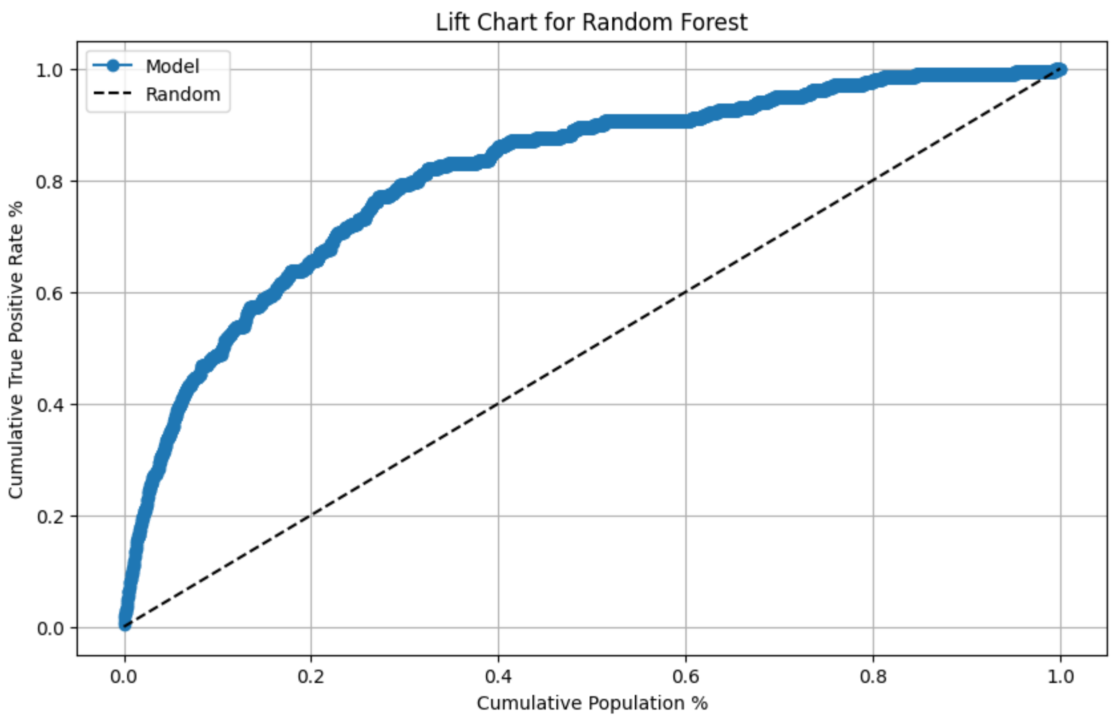
```
import numpy as np
import matplotlib.pyplot as plt


# Function to calculate lift
def calculate_lift(y_true, y_prob):
    data = pd.DataFrame({"true": y_true, "prob": y_prob})
    data = data.sort_values(by="prob", ascending=False)
    data["cumulative_true"] = np.cumsum(data["true"])
    data["cumulative_true_rate"] = data["cumulative_true"] / data["true"].sum()
    data["cumulative_population"] = np.arange(1, len(data) + 1) / len(data)
    return data


# Function to plot lift chart
def plot_lift_chart(data, title):
    plt.figure(figsize=(10, 6))
    plt.plot(
        data["cumulative_population"],
```

```python
        data["cumulative_true_rate"],
        marker="o",
        label="Model",
    )
    plt.plot([0, 1], [0, 1], "k--", label="Random")
    plt.title(title)
    plt.xlabel("Cumulative Population %")
    plt.ylabel("Cumulative True Positive Rate %")
    plt.legend()
    plt.grid(True)
    plt.show()


# Logistic Regression
y_prob_log = log_model.predict_proba(X_test_scaled)[:, 1]
lift_data_log = calculate_lift(y_test, y_prob_log)
plot_lift_chart(lift_data_log, "Lift Chart for Logistic Regression")

# Neural Network
y_prob_nn = nn_model.predict_proba(X_test_scaled)[:, 1]
lift_data_nn = calculate_lift(y_test, y_prob_nn)
plot_lift_chart(lift_data_nn, "Lift Chart for Neural Network")

# Decision Tree
y_prob_tree = tree_model.predict_proba(X_test_scaled)[:, 1]
lift_data_tree = calculate_lift(y_test, y_prob_tree)
plot_lift_chart(lift_data_tree, "Lift Chart for Decision Tree")

# Random Forest
y_prob_rf = rf_model.predict_proba(X_test_scaled)[:, 1]
lift_data_rf = calculate_lift(y_test, y_prob_rf)
plot_lift_chart(lift_data_rf, "Lift Chart for Random Forest")
```


Lift Chart for Logistic Regression
Model
Random
Cumulative True Positive Rate %
Cumulative Population %
0.0
0.2
0.4
0.6
0.8
1.0


Lift Chart for Neural Network
Model
Random
Cumulative True Positive Rate %
Cumulative Population %
0.0
0.2
0.4
0.6
0.8
1.0


Lift Chart for Decision Tree
Model
Random
Cumulative True Positive Rate %
Cumulative Population %
0.0
0.2
0.4
0.6
0.8
1.0


Lift Chart for Random Forest
Model
Random
Cumulative True Positive Rate %
Cumulative Population %
0.0
0.2
0.4
0.6
0.8
1.0

0.1.3 Business Objective and Recommendations

Business Objective: The main aim of this analysis was to anticipate **car cancellations** in order to help **Yourcabs.com** boost its operational efficiency and elevate customer satisfaction. By foreseeing which bookings are likely to be canceled, **Yourcabs.com** can take proactive measures such as reallocating resources, adjusting driver schedules, or even offering incentives to decrease cancellations. This would result in fewer service disruptions, cost savings, and an overall enhanced experience for the customers.

Data Mining Models Used: To achieve this objective, we applied four different models: 1. **Logistic Regression**: Provides a strong, interpretable baseline. Its simplicity allows for clear insight into which features impact cancellations the most. 2. **Neural Networks**: Captures complex patterns that simpler models might miss, potentially improving accuracy but at the cost of interpretability. 3. **Decision Trees**: Offers easily interpretable decision rules and handles non-linear relationships between variables. 4. **Random Forest**: Combines multiple decision trees for improved robustness and accuracy, significantly reducing the risk of overfitting.

Each model brings distinct strengths and weaknesses to the table, but Random Forest emerged as the strongest performer in this context.

Model Results: The models were evaluated based on their accuracy and ability to rank the likelihood of cancellations. Specifically: - **Random Forest**: The best performer with the highest accuracy and lift score. It had a solid ability to distinguish between cancellations and non-cancellations, making it highly practical for deployment. - **Logistic Regression**: Provided a useful baseline, though it struggled with more complex relationships in the data. - **Neural Network**: Showed promise but was prone to overfitting without substantial performance improvements. - **Decision Tree**: Worked reasonably well but did not outperform Random Forest.

The lift charts for each model confirmed the superiority of the Random Forest model in terms of predictive power. This model consistently identified high-risk cancellations, meaning it can reliably guide operational decisions.

Recommendations: We recommend **implementing the Random Forest model** within **Yourcabs.com**'s booking system to flag bookings at high risk of cancellation. This can trigger early interventions such as sending alerts to the operations team or incentivizing drivers to complete potentially problematic trips. Additionally, this system can enhance the customer experience by ensuring fewer last-minute cancellations.

Next Steps:

1. **Deploy the Random Forest model** within the live booking system to flag risky bookings automatically.
2. **Continuous monitoring** of model performance is recommended. Periodic retraining of the model will ensure that it stays relevant as booking patterns and market conditions evolve.
3. **Further optimization** could include testing additional algorithms, tuning model hyperparameters, and even integrating external data sources (e.g., weather, traffic) to refine predictions.

By utilizing this predictive capability, **Yourcabs.com** will be able to optimize its resources, reduce customer dissatisfaction, and maintain its competitive edge in a highly dynamic market.

```
[ ]:
```