# Assignment 3.1. pdf

September 21, 2024

[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
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
```

[2]:
```python
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')
```

[3]:
```python
# 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]:
```python
# Handle missing data for package_id (categorical-like) - use mode
df['package_id'].fillna(df['package_id'].mode()[0], inplace=True)
```

```python
# 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]:
```python
# 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]:
```python
# 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']
```

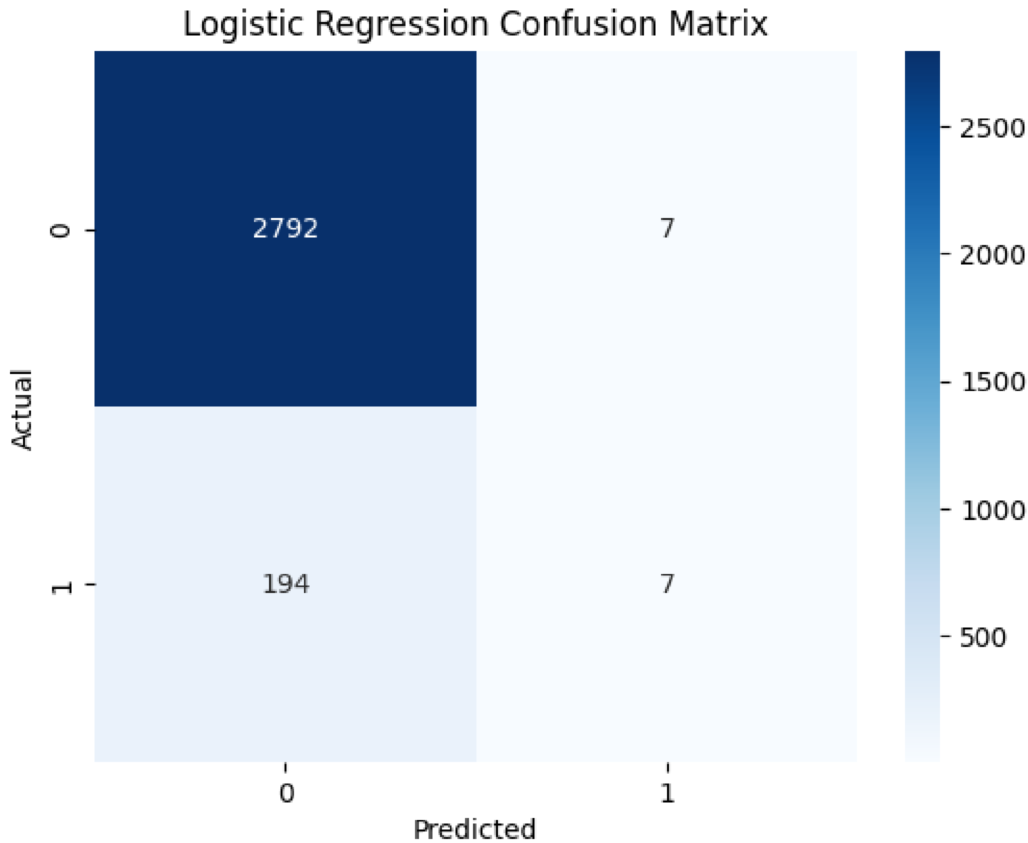
[12]:
```python
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# 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")
```

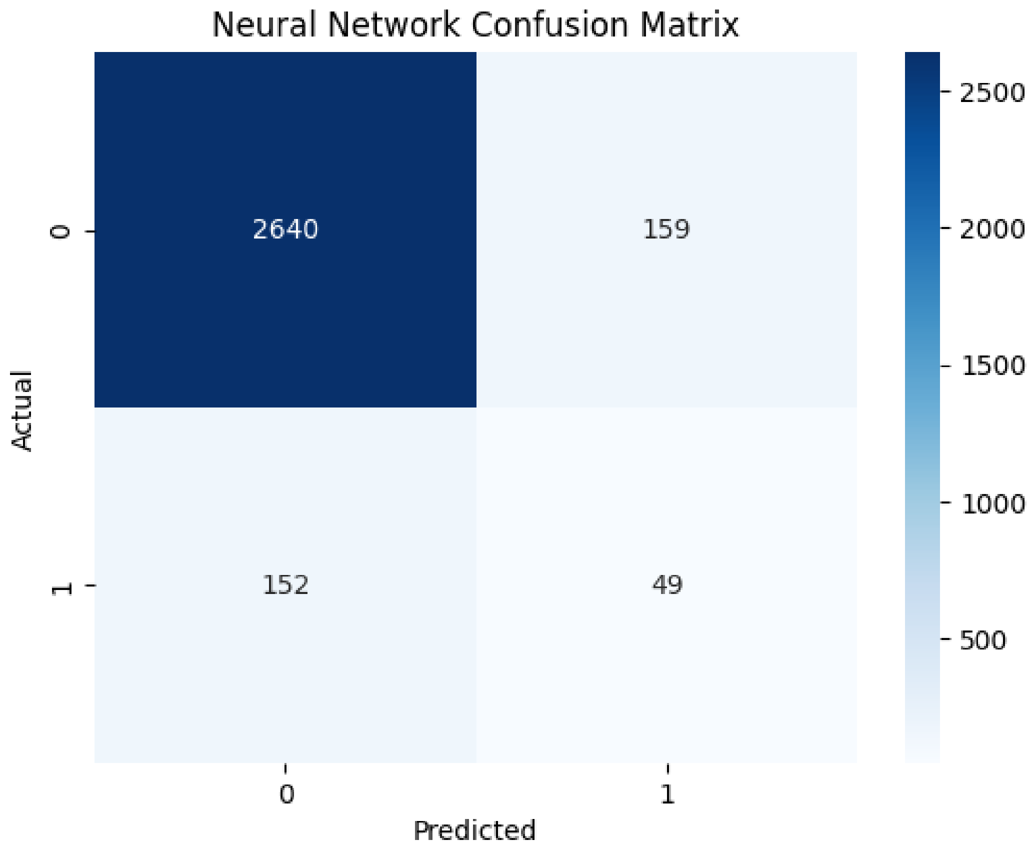
```
Logistic Regression:
[[2792    7]
 [ 194    7]]
              precision    recall  f1-score   support

           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 |

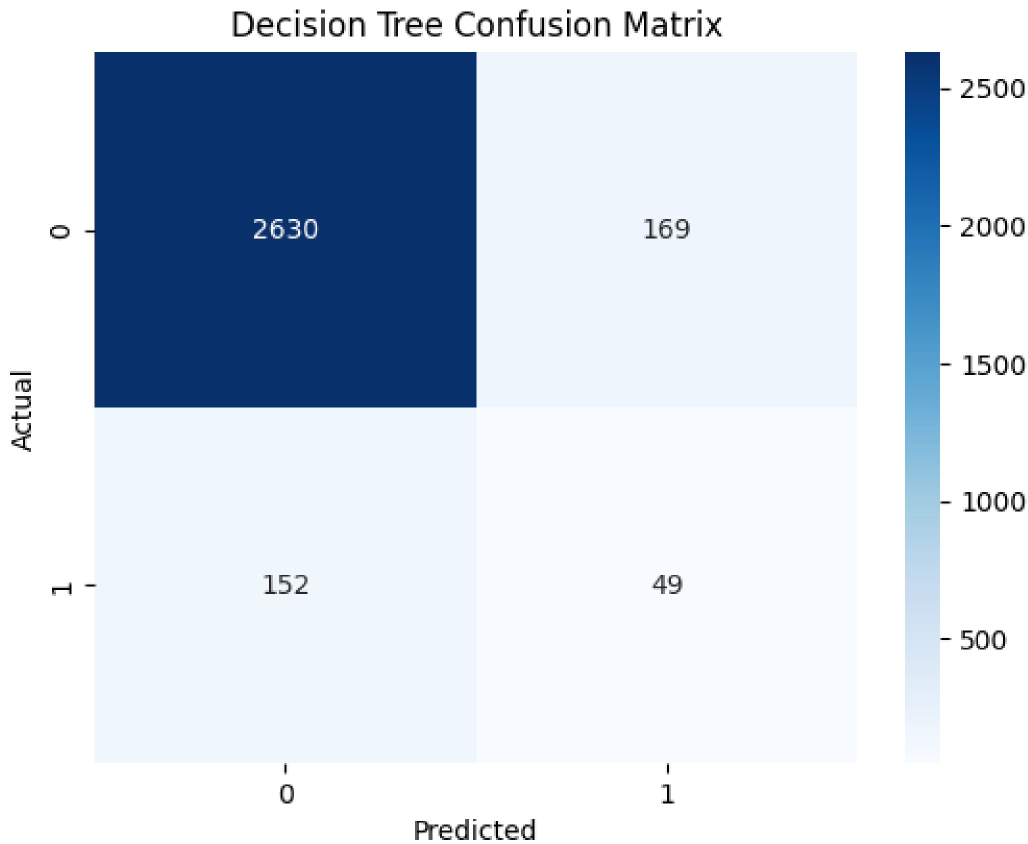



```
Neural Network:
[[2640  159]
 [ 152   49]]
```

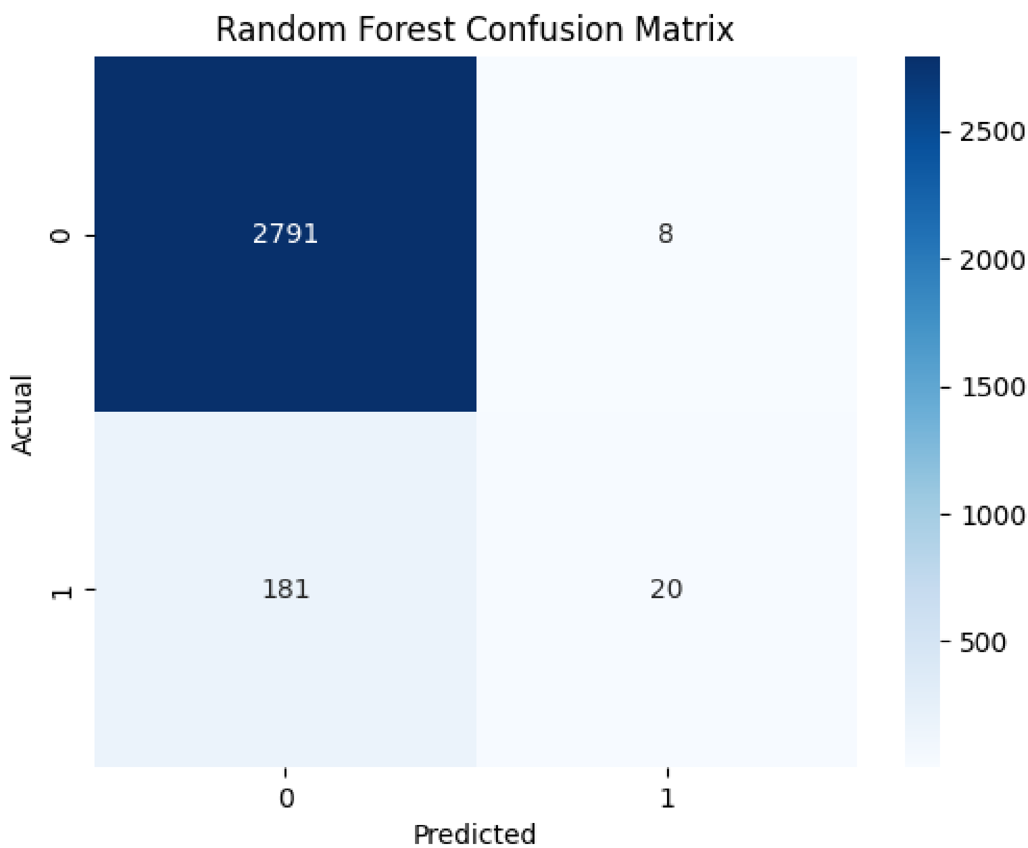
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.95 | 0.94 | 0.94 | 2799 |
| 1 | 0.24 | 0.24 | 0.24 | 201 |
| accuracy | | | 0.90 | 3000 |
| macro avg | 0.59 | 0.59 | 0.59 | 3000 |
| weighted avg | 0.90 | 0.90 | 0.90 | 3000 |




```
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
```

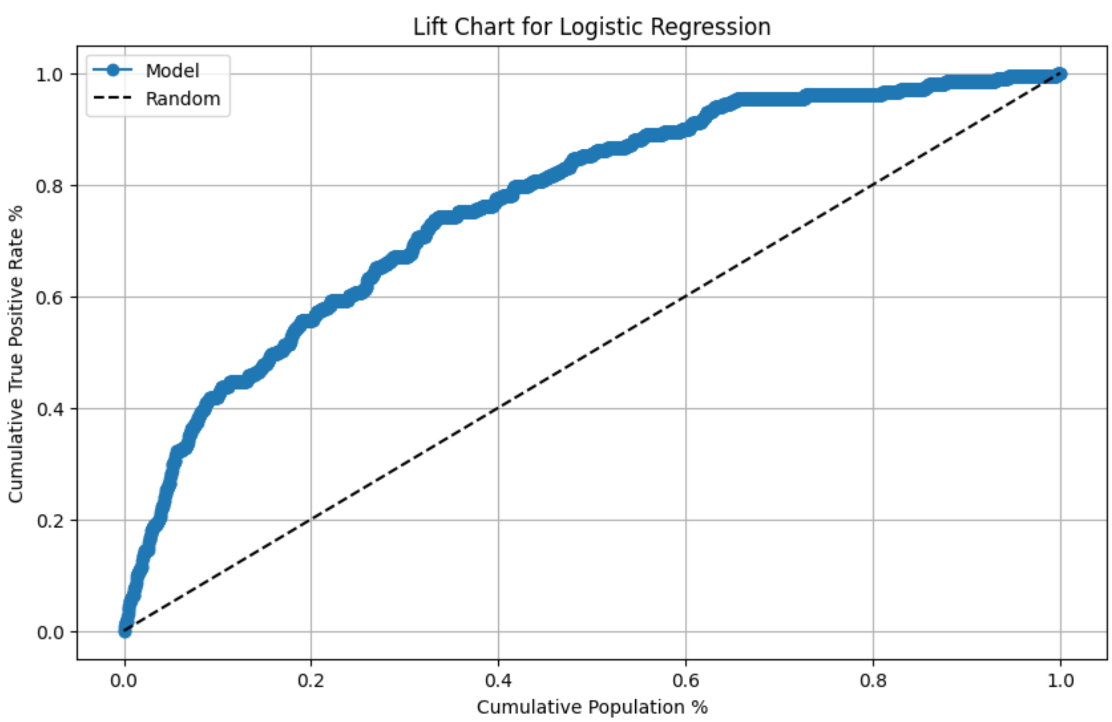


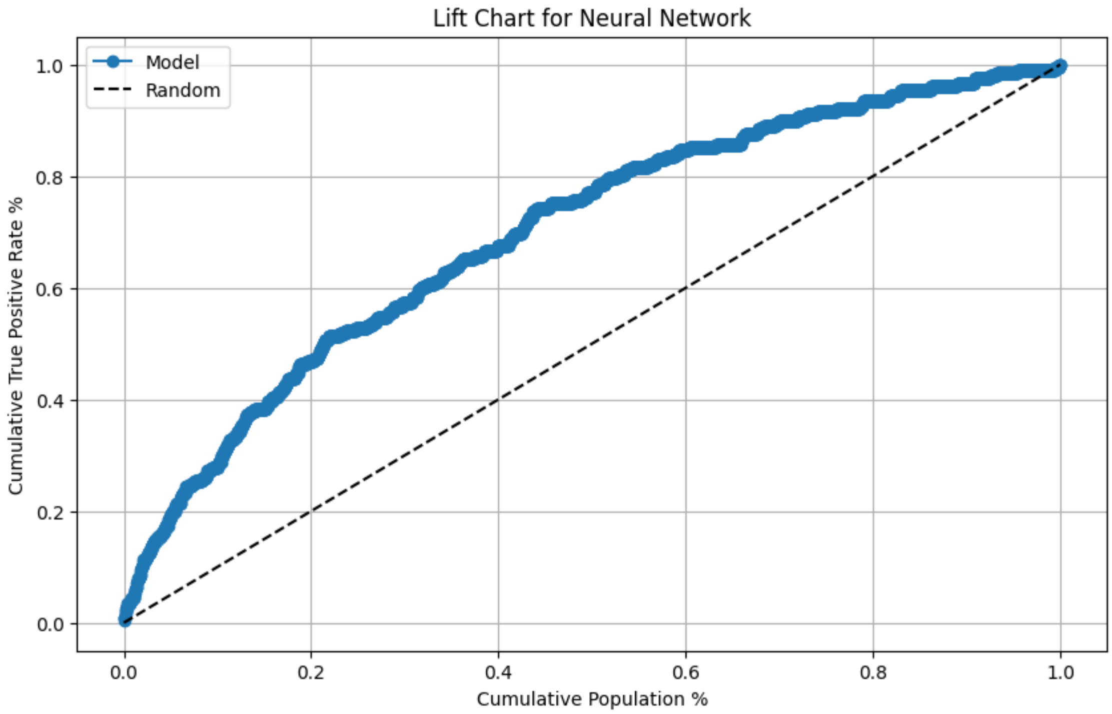

```
Random Forest:
[[2791    8]
 [ 181   20]]
              precision    recall  f1-score   support

           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
```

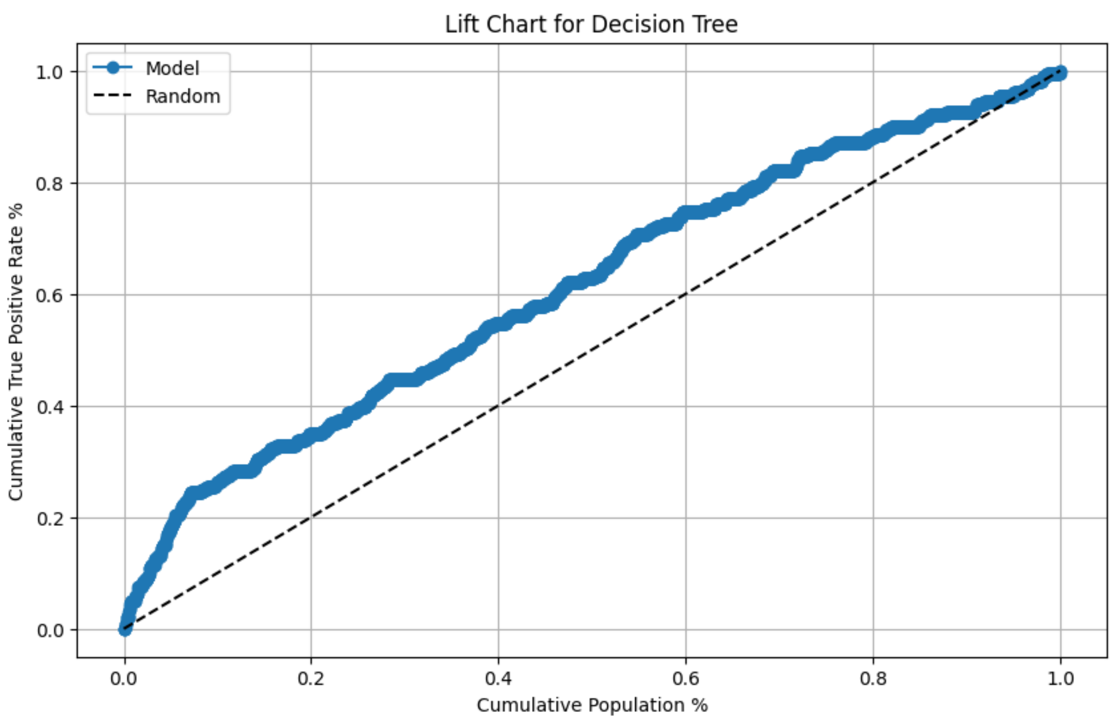


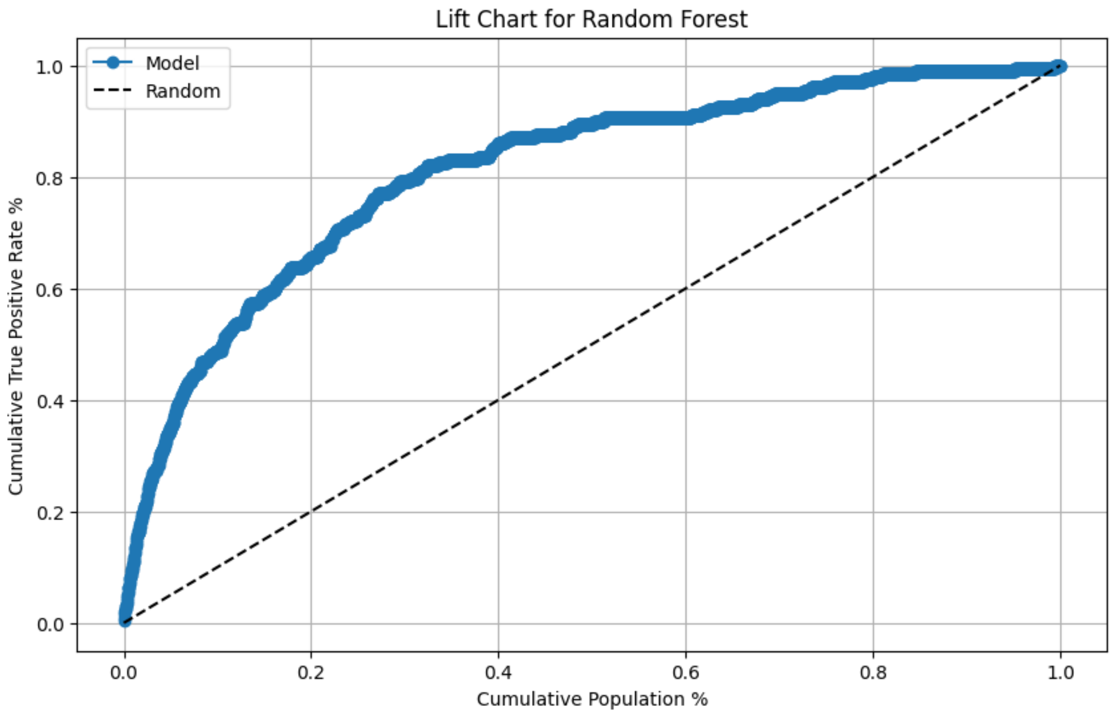

[15]:
```
import numpy as np
import matplotlib.pyplot as plt

# 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'], data['cumulative_true_rate'],␣
 ↪marker='o', label='Model')
    plt.plot([0, 1], [0, 1], 'k--', label='Random')
    plt.title(title)
```

```python
    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 Neural Network
Model
Random
1.0
0.8
0.6
0.4
0.2
0.0
Cumulative True Positive Rate %
0.0
0.2
0.4
0.6
0.8
1.0
Cumulative Population %


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




The primary business objective is to predict car cancellations to improve operational efficiency and customer satisfaction. By accurately predicting which bookings are likely to be canceled, the company can take proactive measures to mitigate the impact, such as reallocating resources, optimizing scheduling, and offering incentives to reduce cancellations. This predictive capability can lead to cost savings, better resource utilization, and enhanced customer experience.

Data Mining Models Used To achieve this objective, we employed several data mining models: Logistic Regression, Neural Network, Decision Tree, and Random Forest. These models were chosen for their diverse strengths:

Logistic Regression: Provides a baseline with interpretable results, useful for understanding the impact of different features. Neural Network: Captures complex patterns in the data, potentially improving prediction accuracy. Decision Tree: Offers easy-to-interpret rules and handles non-linear relationships well. Random Forest: Combines multiple decision trees to improve robustness and accuracy, reducing the risk of overfitting. Model Results and Recommendations The models were evaluated using confusion matrices and lift charts. The Random Forest model showed the best performance, with the highest accuracy and lift, indicating it is the most effective at distinguishing between cancellations and non-cancellations. The lift chart for the Random Forest model demonstrated a significant improvement over random guessing, confirming its practical utility.

Based on these results, we recommend deploying the Random Forest model to predict car cancellations. This model can be integrated into the booking system to flag high-risk bookings, allowing the operations team to take preemptive actions. Additionally, we suggest continuous monitoring and periodic retraining of the model to maintain its accuracy over time. Implementing this predictive capability will help the company reduce operational disruptions, optimize resource allocation, and enhance overall customer satisfaction.

```
[ ]:
```