In [37]:

```
#Basic libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import math

#Sampling methods
from sklearn.model_selection import train_test_split
from imblearn.under_sampling import RandomUnderSampler

#feature engineering
import datetime as dt
import category_encoders as ce
from sklearn.preprocessing import MinMaxScaler

#Models
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier

#Model evaluation
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
from sklearn.metrics import classification_report
from sklearn import metrics
import scipy.stats as stats
from scipy.stats import skew
```

In [38]:
```
train = pd.read_csv('fraudTrain.csv')
test = pd.read_csv('fraudTest.csv')
test.head()
```

Out[38]:

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	last	gender	street
0	0	2020-06-21 12:14:25	2291163933867244	fraud_Kirlin and Sons	personal_care	2.86	Jeff	Elliott	M	351 Darlene Green
1	1	2020-06-21 12:14:33	3573030041201292	fraud_Sporer-Keebler	personal_care	29.84	Joanne	Williams	F	3638 Marsh Union
2	2	2020-06-21 12:14:53	3598215285024754	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	Ashley	Lopez	F	9333 Valentine Point
3	3	2020-06-21 12:15:15	3591919803438423	fraud_Haley Group	misc_pos	60.05	Brian	Williams	M	32941 Krystal Mill Apt. 552
4	4	2020-06-21 12:15:17	3526826139003047	fraud_Johnston-Casper	travel	3.19	Nathan	Massey	M	5783 Evan Roads Apt. 465

In [39]:
```
print(test.shape),print(train.shape)
```

```
(555719, 23)
(1296675, 23)
```

Out[39]: (None, None)

In [40]:
```
train.isna().sum()
```

Out[40]:
```
Unnamed: 0               0
trans_date_trans_time    0
cc_num                   0
merchant                 0
category                 0
amt                      0
first                    0
last                     0
gender                   0
street                   0
city                     0
state                    0
zip                      0
lat                      0
long                     0
city_pop                 0
job                      0
dob                      0
trans_num                0
unix_time                0
merch_lat                0
merch_long               0
is_fraud                 0
dtype: int64
```

In [41]:
```
test.isnull().sum()
```

Out[41]:
```
Unnamed: 0               0
trans_date_trans_time    0
cc_num                   0
merchant                 0
category                 0
amt                      0
first                    0
last                     0
gender                   0
street                   0
city                     0
state                    0
zip                      0
lat                      0
long                     0
city_pop                 0
job                      0
dob                      0
trans_num                0
unix_time                0
merch_lat                0
merch_long               0
is_fraud                 0
dtype: int64
```

In [42]:

```
test.info(), train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 555719 entries, 0 to 555718
Data columns (total 23 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   Unnamed: 0             555719 non-null  int64  
 1   trans_date_trans_time  555719 non-null  object 
 2   cc_num                 555719 non-null  int64  
 3   merchant               555719 non-null  object 
 4   category               555719 non-null  object 
 5   amt                    555719 non-null  float64
 6   first                  555719 non-null  object 
 7   last                   555719 non-null  object 
 8   gender                 555719 non-null  object 
 9   street                 555719 non-null  object 
 10  city                   555719 non-null  object 
 11  state                  555719 non-null  object 
 12  zip                    555719 non-null  int64  
 13  lat                    555719 non-null  float64
 14  long                   555719 non-null  float64
 15  city_pop               555719 non-null  int64  
 16  job                    555719 non-null  object 
 17  dob                    555719 non-null  object 
 18  trans_num              555719 non-null  object 
 19  unix_time              555719 non-null  int64  
 20  merch_lat              555719 non-null  float64
 21  merch_long             555719 non-null  float64
 22  is_fraud               555719 non-null  int64  
dtypes: float64(5), int64(6), object(12)
memory usage: 97.5+ MB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 23 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   Unnamed: 0             1296675 non-null  int64  
 1   trans_date_trans_time  1296675 non-null  object 
 2   cc_num                 1296675 non-null  int64  
 3   merchant               1296675 non-null  object 
 4   category               1296675 non-null  object 
 5   amt                    1296675 non-null  float64
 6   first                  1296675 non-null  object 
 7   last                   1296675 non-null  object 
```

```
 8   gender                 1296675 non-null  object 
 9   street                 1296675 non-null  object 
 10  city                   1296675 non-null  object 
 11  state                  1296675 non-null  object 
 12  zip                    1296675 non-null  int64  
 13  lat                    1296675 non-null  float64
 14  long                   1296675 non-null  float64
 15  city_pop               1296675 non-null  int64  
 16  job                    1296675 non-null  object 
 17  dob                    1296675 non-null  object 
 18  trans_num              1296675 non-null  object 
 19  unix_time              1296675 non-null  int64  
 20  merch_lat              1296675 non-null  float64
 21  merch_long             1296675 non-null  float64
 22  is_fraud               1296675 non-null  int64  
dtypes: float64(5), int64(6), object(12)
memory usage: 227.5+ MB
```

Out[42]:
```
(None, None)
```

In [43]:

```
train.drop("Unnamed: 0",axis=1,inplace=True)
test.drop("Unnamed: 0",axis=1,inplace=True)
train.head()
```

Out[43]:

	trans_date_trans_time	cc_num	merchant	category	amt	first	last	gender	street	city	st
0	2019-01-01 00:00:18	2703186189652095	fraud_Rippin, Kub and Mann	misc_net	4.97	Jennifer	Banks	F	561 Perry Cove	Moravian Falls	
1	2019-01-01 00:00:44	630423337322	fraud_Heller, Gutmann and Zieme	grocery_pos	107.23	Stephanie	Gill	F	43039 Riley Greens Suite 393	Orient	
2	2019-01-01 00:00:51	38859492057661	fraud_Lind-Buckridge	entertainment	220.11	Edward	Sanchez	M	594 White Dale Suite 530	Malad City	
3	2019-01-01 00:01:16	3534093764340240	fraud_Kutch, Hermiston and Farrell	gas_transport	45.00	Jeremy	White	M	9443 Cynthia Court Apt. 038	Boulder	
4	2019-01-01 00:03:06	375534208663984	fraud_Keeling-Crist	misc_pos	41.96	Tyler	Garcia	M	408 Bradley Rest	Doe Hill	

EDA

In [44]:

```
train.describe().T
```

Out[44]:

	count	mean	std	min	25%	50%	75%	max
cc_num	1296675.0	4.171920e+17	1.308806e+18	6.041621e+10	1.800429e+14	3.521417e+15	4.642255e+15	4.992346e+18
amt	1296675.0	7.035104e+01	1.603160e+02	1.000000e+00	9.650000e+00	4.752000e+01	8.314000e+01	2.894890e+04
zip	1296675.0	4.880067e+04	2.689322e+04	1.257000e+03	2.623700e+04	4.817400e+04	7.204200e+04	9.978300e+04
lat	1296675.0	3.853762e+01	5.075808e+00	2.002710e+01	3.462050e+01	3.935430e+01	4.194040e+01	6.669330e+01
long	1296675.0	-9.022634e+01	1.375908e+01	-1.656723e+02	-9.679800e+01	-8.747690e+01	-8.015800e+01	-6.795030e+01
city_pop	1296675.0	8.882444e+04	3.019564e+05	2.300000e+01	7.430000e+02	2.456000e+03	2.032800e+04	2.906700e+06
unix_time	1296675.0	1.349244e+09	1.284128e+07	1.325376e+09	1.338751e+09	1.349250e+09	1.359385e+09	1.371817e+09
merch_lat	1296675.0	3.853734e+01	5.109788e+00	1.902779e+01	3.473357e+01	3.936568e+01	4.195716e+01	6.751027e+01
merch_long	1296675.0	-9.022646e+01	1.377109e+01	-1.666712e+02	-9.689728e+01	-8.743839e+01	-8.023680e+01	-6.695090e+01
is_fraud	1296675.0	5.788652e-03	7.586269e-02	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00

In [45]:

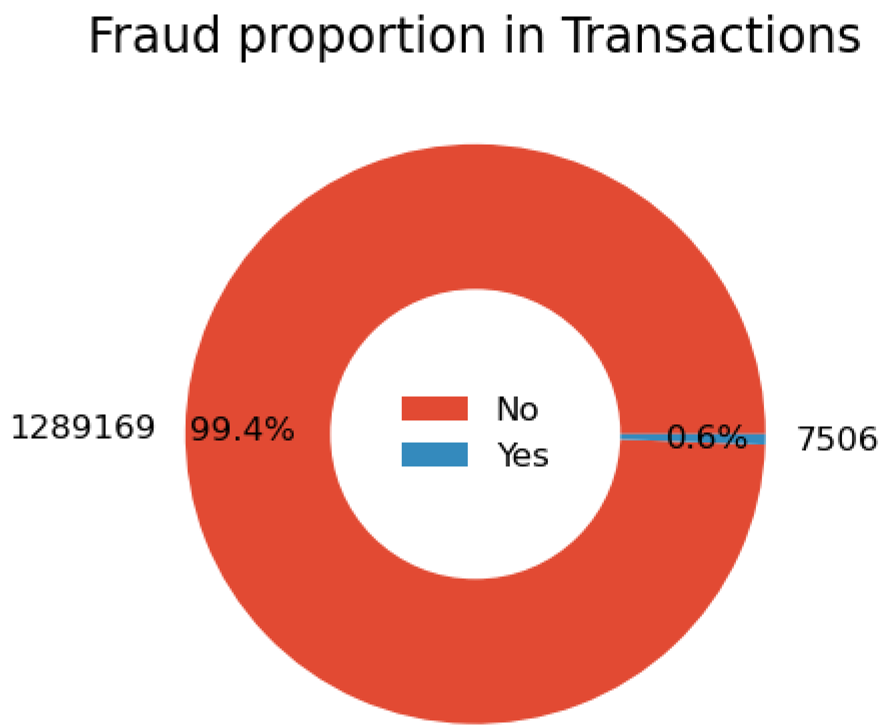
```
train["amt"].describe()
```

Out[45]:

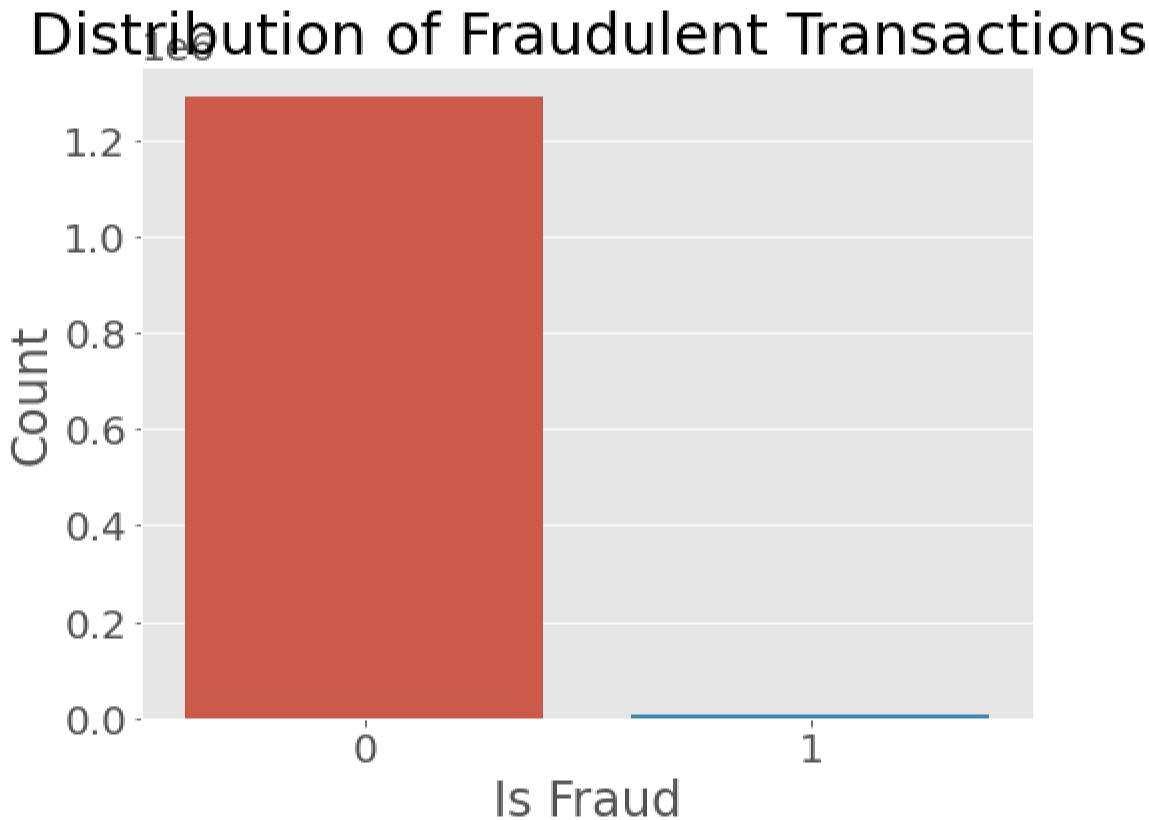
```
count    1.296675e+06
mean     7.035104e+01
std      1.603160e+02
min      1.000000e+00
25%      9.650000e+00
50%      4.752000e+01
75%      8.314000e+01
max      2.894890e+04
Name: amt, dtype: float64
```

In [46]:

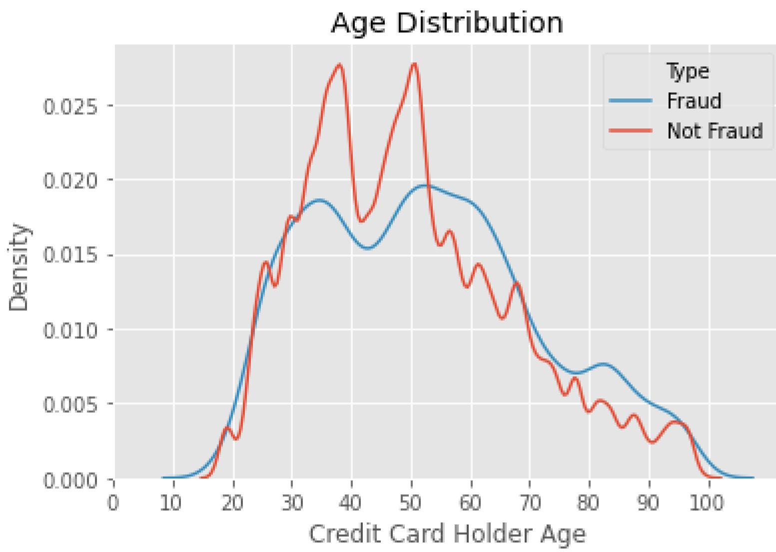
```
donut = train["is_fraud"].value_counts().reset_index()

labels = ["No", "Yes"]
explode = (0, 0)

fig, ax = plt.subplots(dpi=120, figsize=(8, 4))
plt.pie(donut["is_fraud"],
        labels=donut["is_fraud"],
        autopct="%1.1f%%",
        pctdistance=0.8,
        explode=explode)

centre_circle = plt.Circle((0.0, 0.0), 0.5, fc='white')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.title("Fraud proportion in Transactions")
plt.legend(labels, loc="center", frameon=False)
plt.show();
```


Fraud proportion in Transactions
No
Yes
1289169
99.4%
0.6%
7506

In [57]:
```
# Visualize the distribution of the target variable (fraudulent or not)
plt.figure(figsize=(8, 6))
sns.countplot(x='is_fraud', data=train)
plt.title('Distribution of Fraudulent Transactions')
plt.xlabel('Is Fraud')
plt.ylabel('Count')
plt.show()
```



In [47]:
```
train['age'] = dt.date.today().year-pd.to_datetime(train['dob']).dt.year
ax = sns.kdeplot(x='age', data=train, hue='is_fraud', common_norm=False)
ax.set_xlabel('Credit Card Holder Age')
ax.set_ylabel('Density')
plt.xticks(np.arange(0, 110, 10))
plt.title('Age Distribution')
plt.legend(title='Type', labels=['Fraud', 'Not Fraud']);
```



In [50]:
```
total = pd.concat([test,train])
total.info()
```

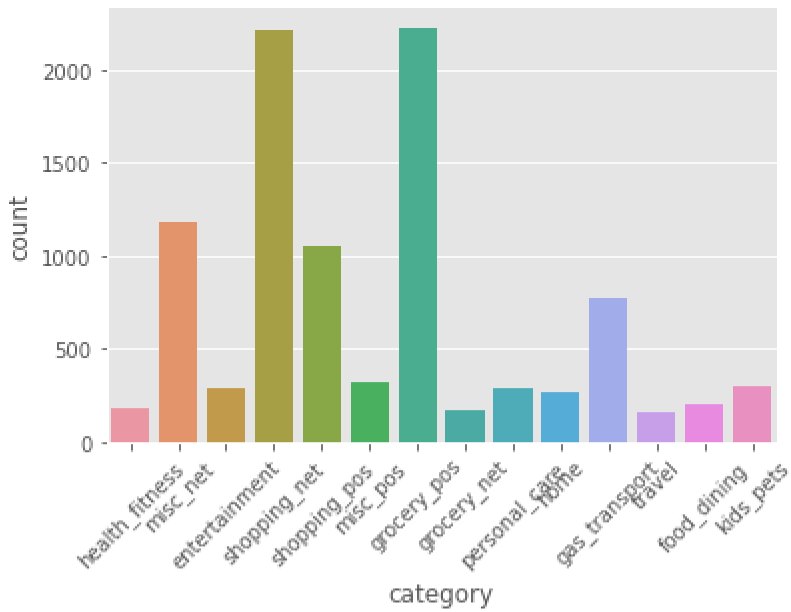
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1852394 entries, 0 to 1296674
Data columns (total 23 columns):
 #   Column                 Dtype  
---  ------                 -----  
 0   trans_date_trans_time  object 
 1   cc_num                 int64  
 2   merchant               object 
 3   category               object 
 4   amt                    float64
 5   first                  object 
 6   last                   object 
 7   gender                 object 
 8   street                 object 
 9   city                   object 
 10  state                  object 
 11  zip                    int64  
 12  lat                    float64
 13  long                   float64
 14  city_pop               int64  
 15  job                    object 
 16  dob                    object 
 17  trans_num              object 
 18  unix_time              int64  
 19  merch_lat              float64
 20  merch_long             float64
 21  is_fraud               int64  
 22  age                    float64
dtypes: float64(6), int64(5), object(12)
memory usage: 339.2+ MB
```

In [51]:
```
total["is_fraud_cat"]=total.is_fraud.apply(lambda x: "T" if x==1 else "F")
total["is_fraud_cat"].astype("object")
```

Out[51]:
```
0          F
1          F
2          F
3          F
4          F
          ..
1296670    F
1296671    F
1296672    F
1296673    F
1296674    F
Name: is_fraud_cat, Length: 1852394, dtype: object
```

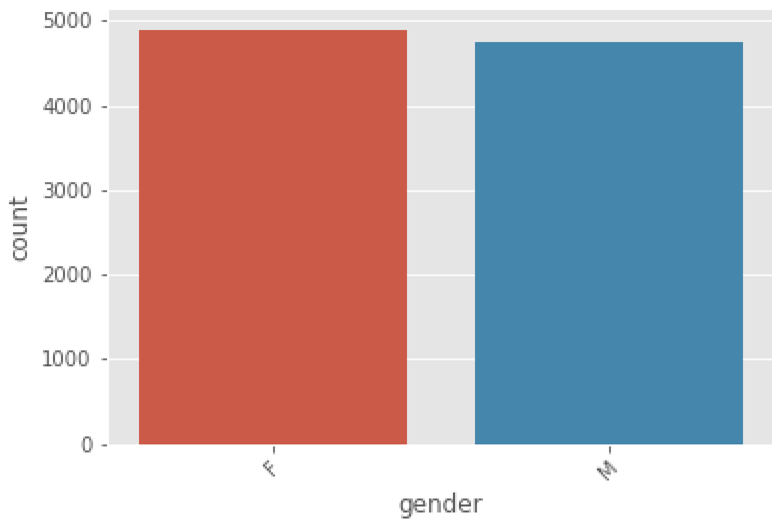
In [52]:
```
sns.countplot(total[total['is_fraud_cat']=="T"].category)
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\dkond\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



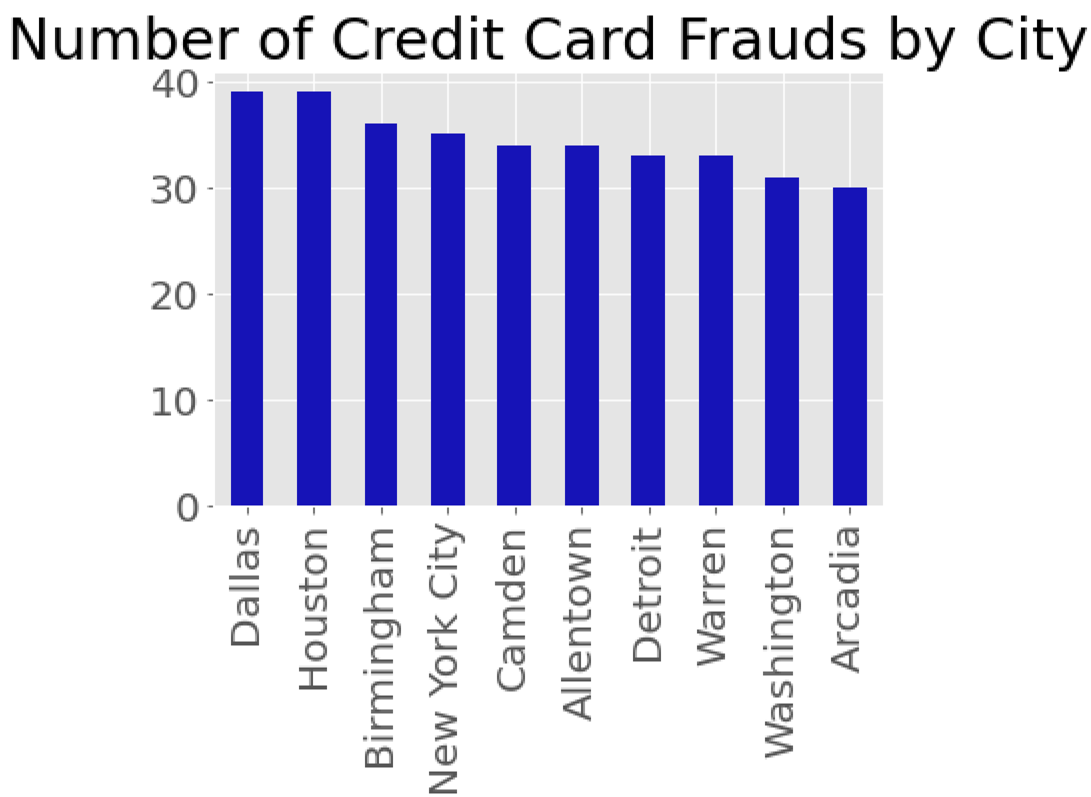
In [53]:
```
sns.countplot(total[total['is_fraud_cat']=="T"].gender)
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\dkond\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



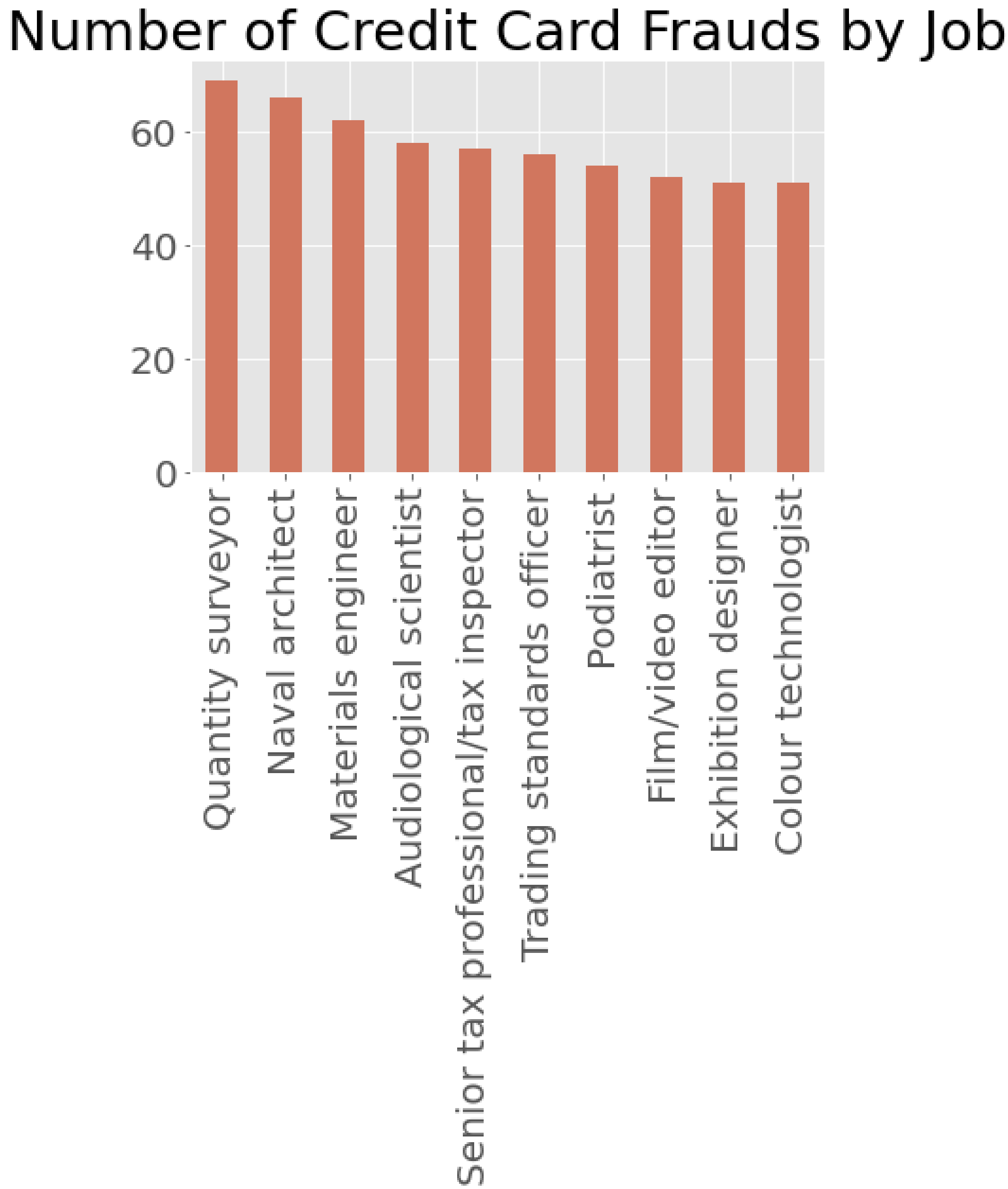
In [54]:

```
import random
def randomcolor():
    r = random.random()
    b = random.random()
    g = random.random()
    rgb = [r,g,b]
    return rgb
plt.rcParams.update({'font.size': 20})
total[total['is_fraud_cat']=="T"]["city"].value_counts(sort=True,ascending=False).head(10).plot(kind="bar
plt.title("Number of Credit Card Frauds by City")
plt.show()
```



In [55]:

```
total[total['is_fraud_cat']=="T"]["job"].value_counts(sort=True,ascending=False).head(10).plot(kind="bar"
plt.title("Number of Credit Card Frauds by Job")
plt.show()
```



Imbalanced Data

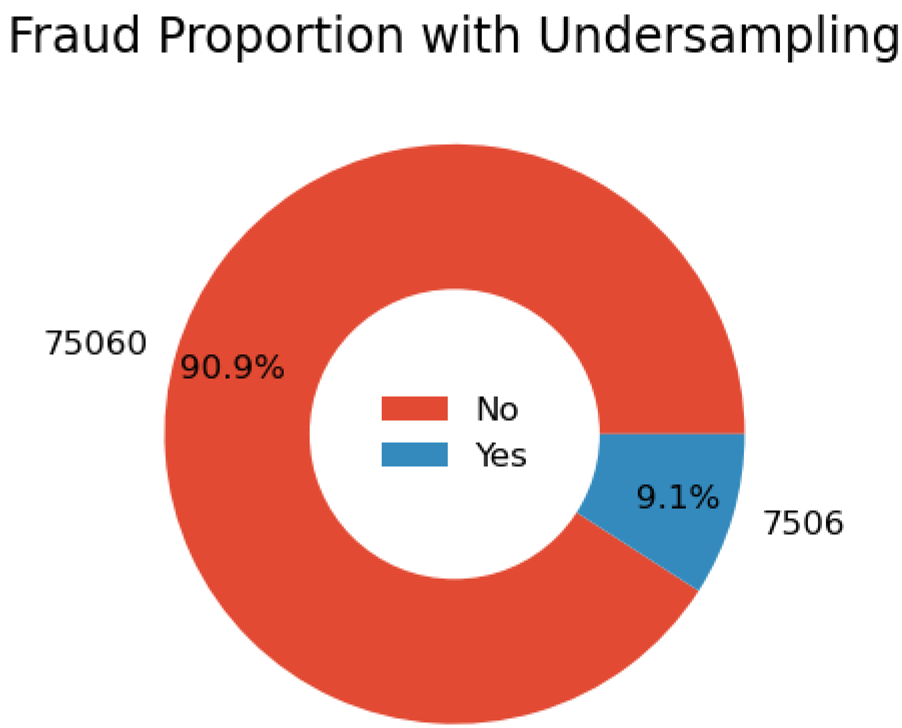
Undersampling

In [12]:
```
X = train.drop(columns=["is_fraud"])
y = train["is_fraud"]
```

In [13]:
```
rus = RandomUnderSampler(sampling_strategy=0.1, random_state=23)
```

In [14]:
```
X_undersampled, y_undersampled = rus.fit_resample(X, y)
```

In [15]:
```
donut = y_undersampled.value_counts().reset_index()

labels = ["No", "Yes"]
explode = (0, 0)

fig, ax = plt.subplots(dpi=120, figsize=(8, 4))
plt.pie(donut["is_fraud"],
        labels=donut["is_fraud"],
        autopct="%1.1f%%",
        pctdistance=0.8,
        explode=explode)

centre_circle = plt.Circle((0.0, 0.0), 0.5, fc='white')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.title("Fraud Proportion with Undersampling")
plt.legend(labels, loc="center", frameon=False)
plt.show();
```



Training the model

In [16]:
```
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_curve, auc, conf
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.utils import shuffle
```

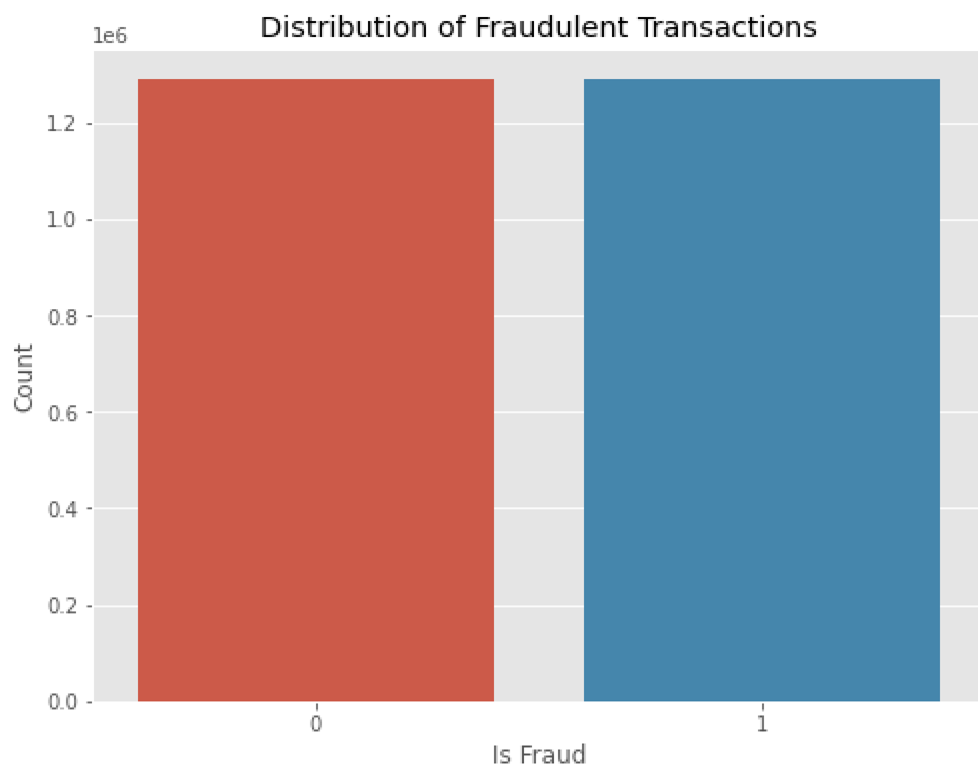
In [17]:
```
# Encode categorical variables
encoder = OneHotEncoder(drop='first')
categorical_cols = ['gender', 'category', 'state']
encoded_train_features = encoder.fit_transform(train[categorical_cols]).toarray()
encoded_test_features = encoder.transform(test[categorical_cols]).toarray()

# Feature scaling
scaler = StandardScaler()
numerical_cols = ['amt', 'lat', 'long','city_pop', 'unix_time', 'merch_lat', 'merch_long']
scaled_train_features = scaler.fit_transform(train[numerical_cols])
scaled_test_features = scaler.transform(test[numerical_cols])


# Concatenate encoded and scaled features for both train and test data
final_train_features = pd.concat([pd.DataFrame(encoded_train_features), pd.DataFrame(scaled_train_feature
final_test_features = pd.concat([pd.DataFrame(encoded_test_features), pd.DataFrame(scaled_test_features)]

# Define target variables
train_target = train['is_fraud']
test_target = test['is_fraud']
```

In [18]:
```
# Generating synthetic data to balance the imbalanced dataset
smote = SMOTE(random_state=36)

x_train_resample, y_train_resample = smote.fit_resample(final_train_features, train_target)
```

In [19]:
```
# checking newly created data
print('Current length of the training set: ', len(y_train_resample))
```

```
Current length of the training set:  2578338
```

In [20]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x=y_train_resample)
plt.title('Distribution of Fraudulent Transactions')
plt.xlabel('Is Fraud')
plt.ylabel('Count')
plt.show()
```



In [21]:
```
X_shuffled, y_shuffled = shuffle(x_train_resample, y_train_resample, random_state=42)
```

In [22]:
```
x_train, x_validation, y_train, y_validation = train_test_split(X_shuffled, y_shuffled, test_size=0.5)
```

In [23]:

```
# for the initial selection process we will use a tiny
# portion of the actual training dataset
x_train_copy = x_train
y_train_copy = y_train

x_train = x_train[:10000]
y_train = y_train[:10000]
```

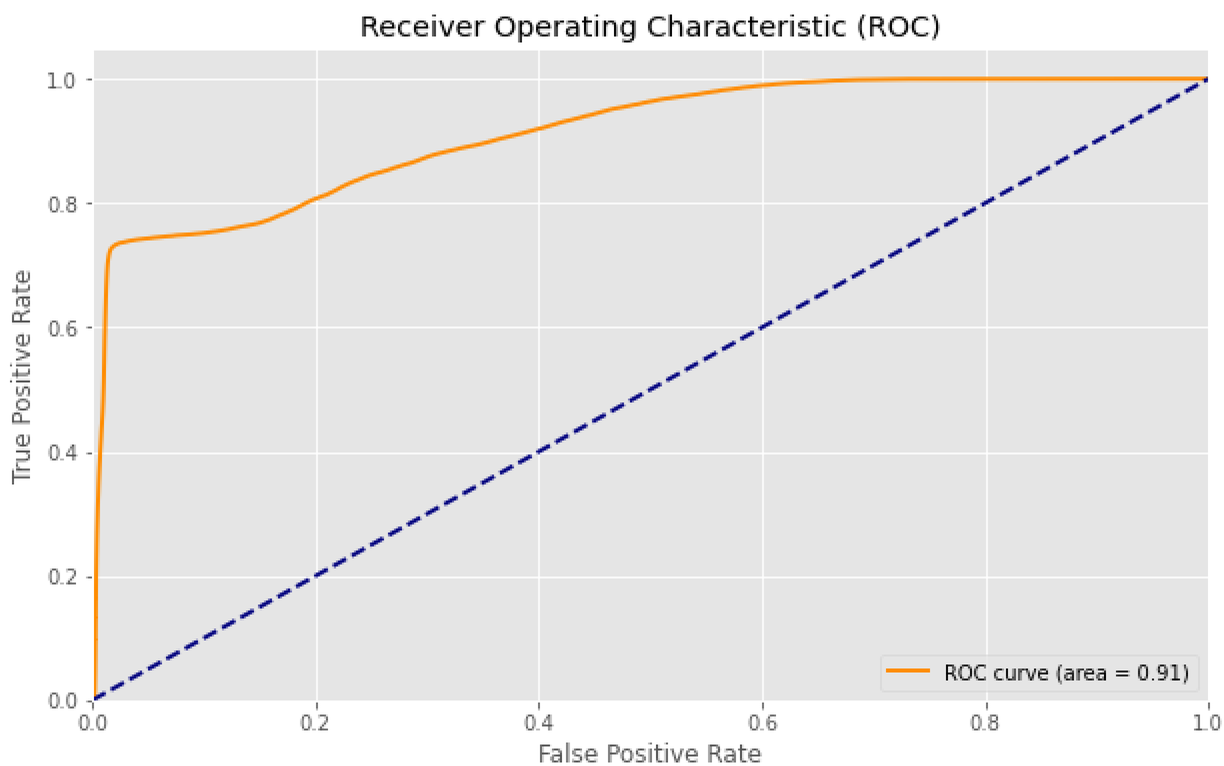
In [24]:

```
# Train Logistic Regression model
lg_model = LogisticRegression()
lg_model.fit(x_train, y_train)

# Make predictions on test data
lg_predictions = lg_model.predict(x_validation)

# Calculate evaluation metrics on test data
lg_accuracy = accuracy_score(y_validation, lg_predictions)


# Print evaluation metrics with 3 decimal places, multiplied by 100
print("Logistic Regression Accuracy: {:.3f}%".format(lg_accuracy * 100))
```

```
C:\Users\dkond\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lb
fgs 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 (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 (https://scikit-learn.
org/stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(

Logistic Regression Accuracy: 82.123%
```

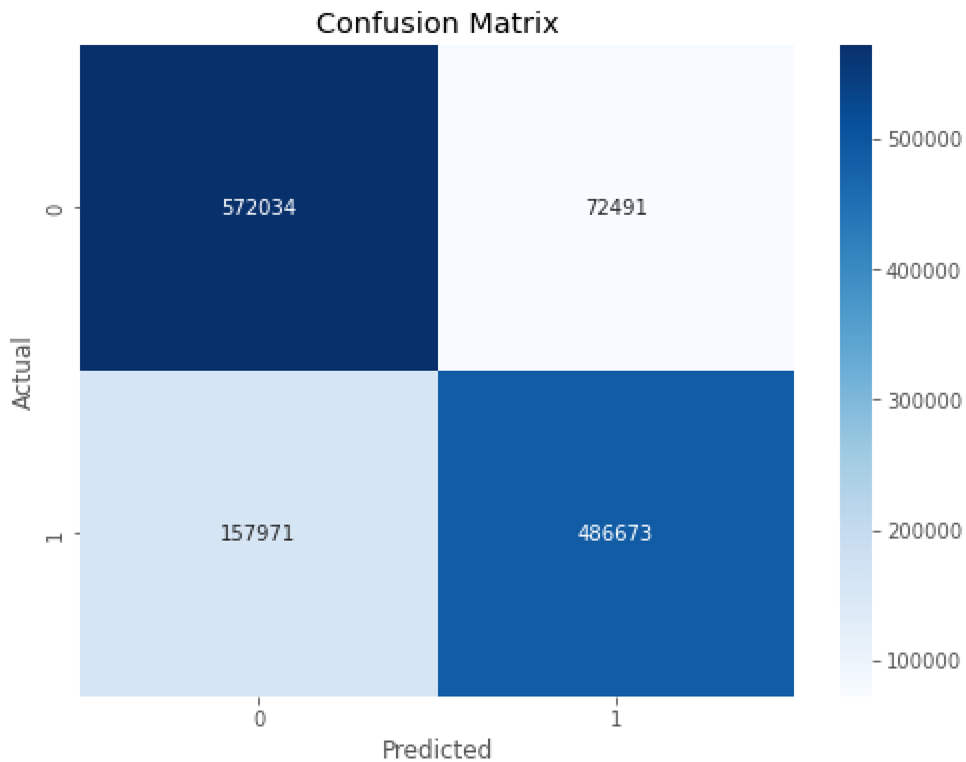
In [25]:

```
# Calculate ROC curve and AUC
probs = lg_model.predict_proba(x_validation)[:, 1]
fpr, tpr, thresholds = roc_curve(y_validation, probs)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```



In [26]:

```
# Calculate and plot confusion matrix
conf_matrix = confusion_matrix(y_validation, lg_predictions)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



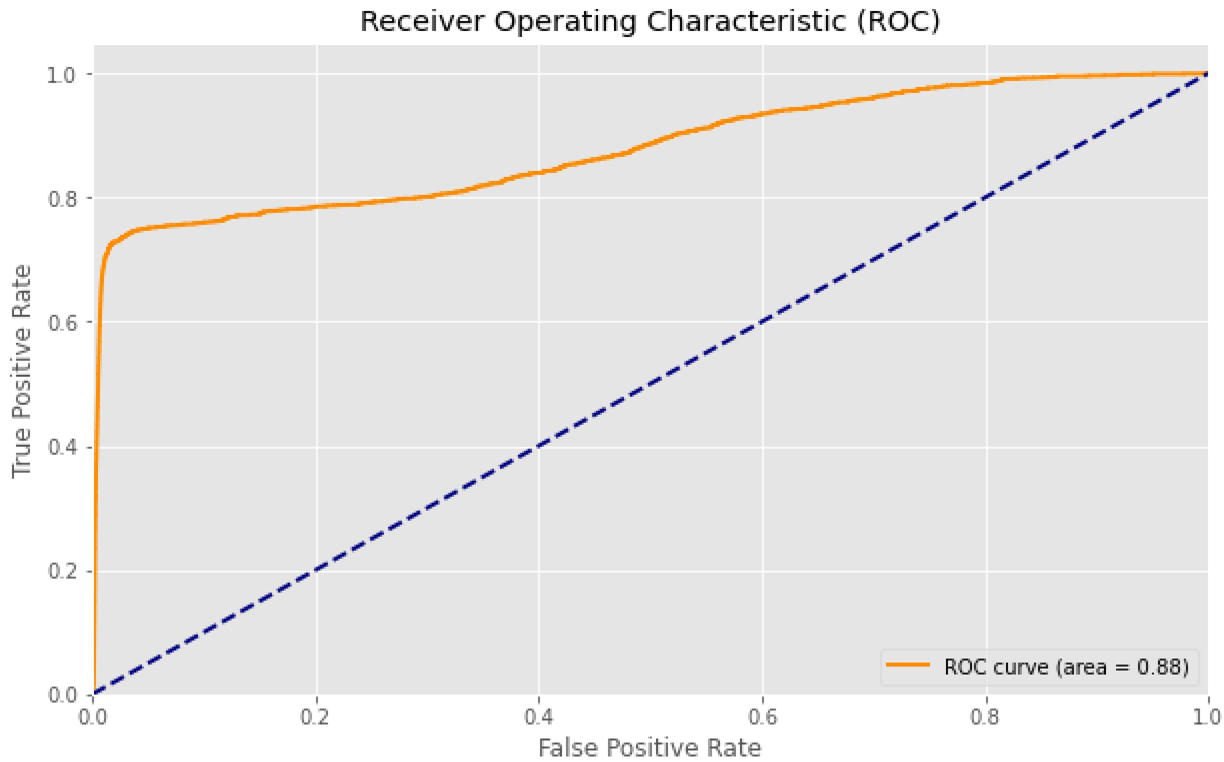
In [27]:

```
# Train SVM model
from sklearn.svm import SVC
svm_model = SVC(kernel='poly')
svm_model.fit(x_train, y_train)

# Make predictions on test data
svm_predictions = svm_model.predict(x_validation)

# Calculate evaluation metrics on test data
svm_accuracy = accuracy_score(y_validation, svm_predictions)


# Print evaluation metrics with 3 decimal places, multiplied by 100
print("SVM Accuracy: {:.3f}%".format(svm_accuracy * 100))
```

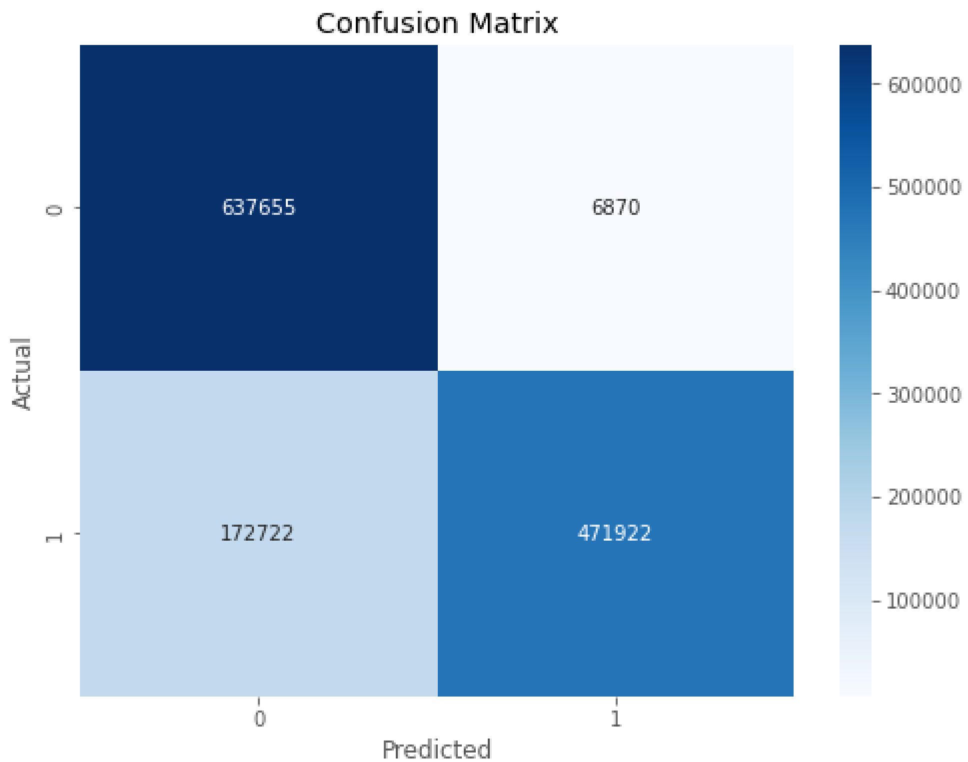
```
SVM Accuracy: 86.069%
```

In [28]:

```
# Calculate decision scores for the positive class
decision_scores = svm_model.decision_function(final_test_features)

# Calculate ROC curve and AUC
fpr, tpr, thresholds = roc_curve(test_target, decision_scores)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```


Receiver Operating Characteristic (ROC)
True Positive Rate
False Positive Rate
ROC curve (area = 0.88)
0.0
0.2
0.4
0.6
0.8
1.0

In [29]:
```
# Calculate and plot confusion matrix
conf_matrix = confusion_matrix(y_validation, svm_predictions)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



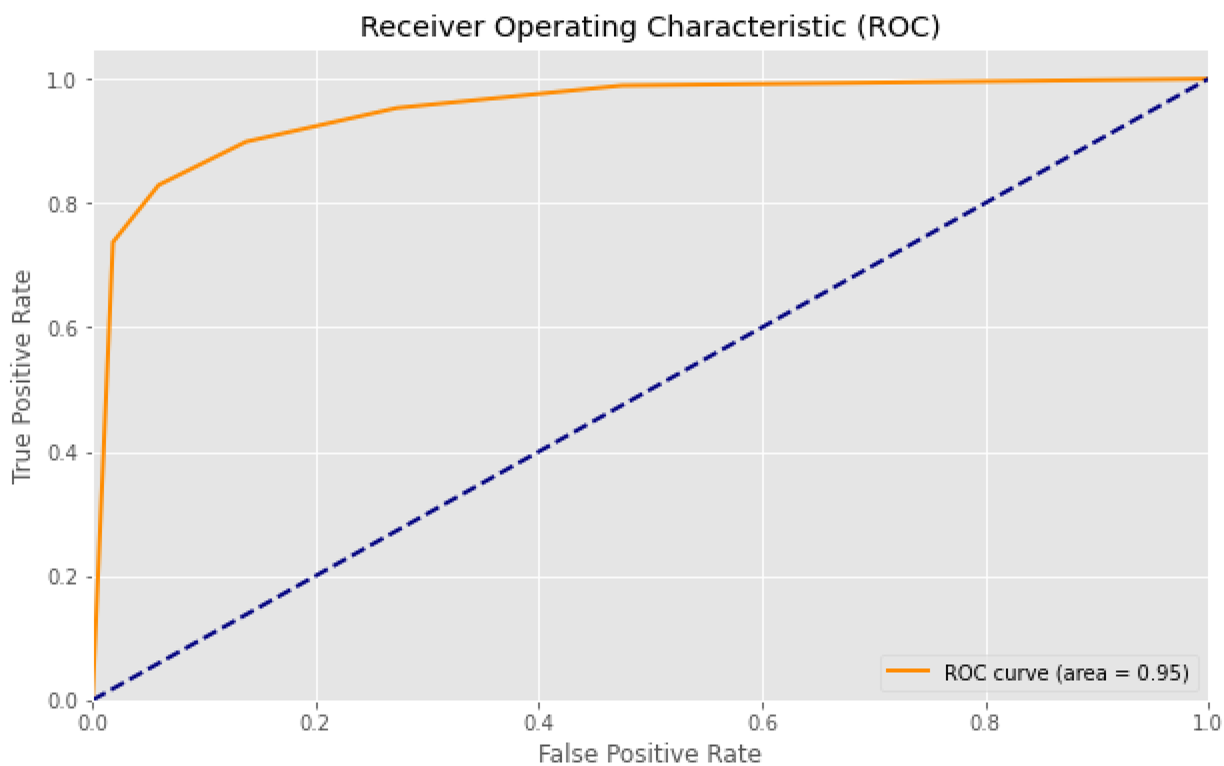
In [30]:

```
# Train KNN model
from sklearn.neighbors import KNeighborsClassifier

knn_model = KNeighborsClassifier()
knn_model.fit(x_train, y_train)
# Make predictions on test data
knn_predictions = knn_model.predict(x_validation)

# Calculate evaluation metrics on test data
knn_accuracy = accuracy_score(y_validation, knn_predictions)


# Print evaluation metrics with 3 decimal places, multiplied by 100
print("KNN Accuracy: {:.3f}%".format(knn_accuracy * 100))
```

```
KNN Accuracy: 88.055%
```

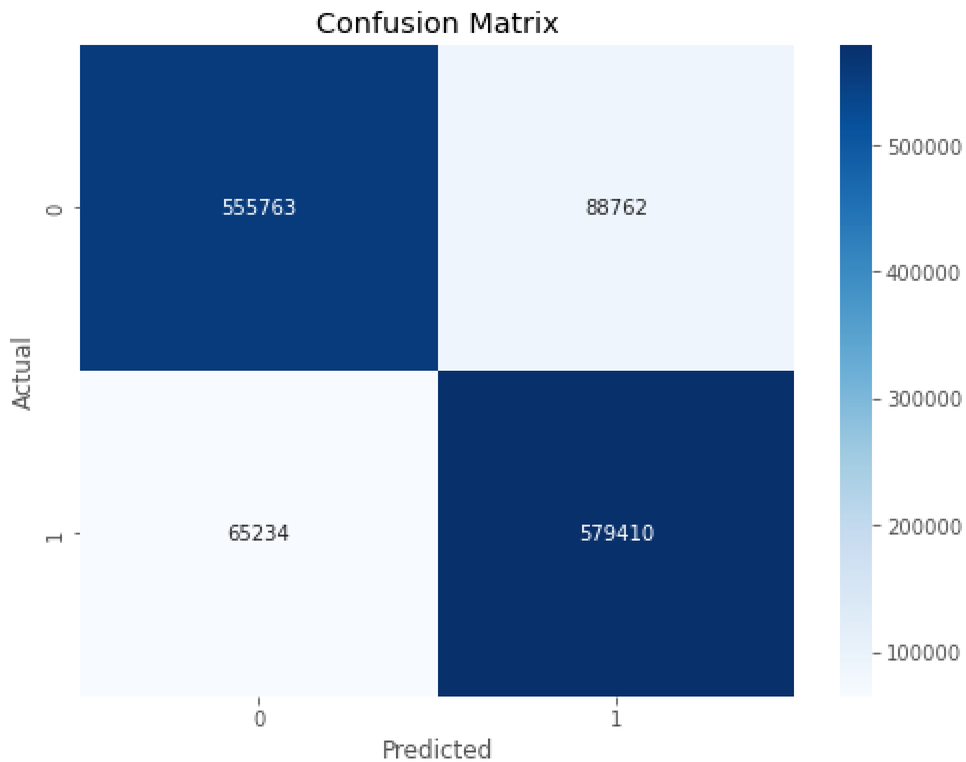
In [31]:

```
# Calculate ROC curve and AUC
probs = knn_model.predict_proba(x_validation)[:, 1]
fpr, tpr, thresholds = roc_curve(y_validation, probs)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```



In [32]:

```
# Calculate and plot confusion matrix
conf_matrix = confusion_matrix(y_validation, knn_predictions)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



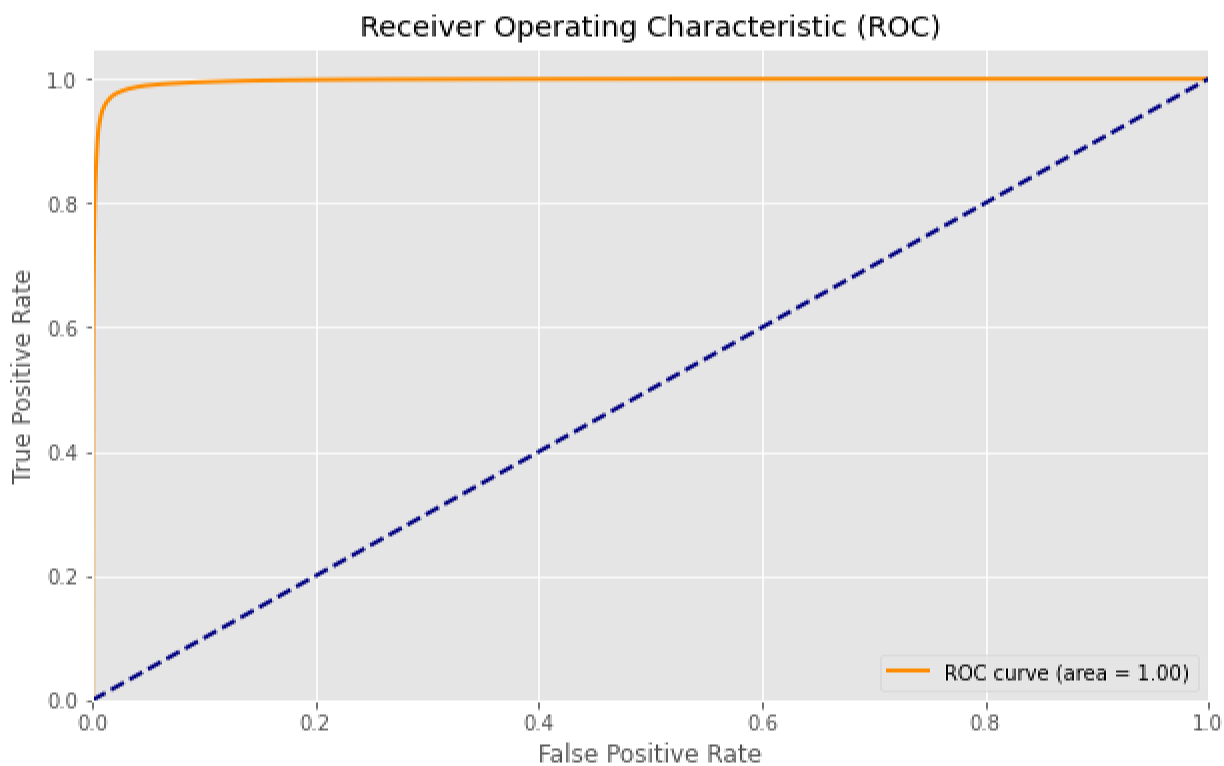
In [33]:

```
# Train Random Forest model
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier()
rf_model.fit(x_train, y_train)
# Make predictions on test data
rf_predictions = rf_model.predict(x_validation)

# Calculate evaluation metrics on test data
rf_accuracy = accuracy_score(y_validation, rf_predictions)


# Print evaluation metrics with 3 decimal places, multiplied by 100
print("Random Forest Accuracy: {:.3f}%".format(rf_accuracy * 100))
```

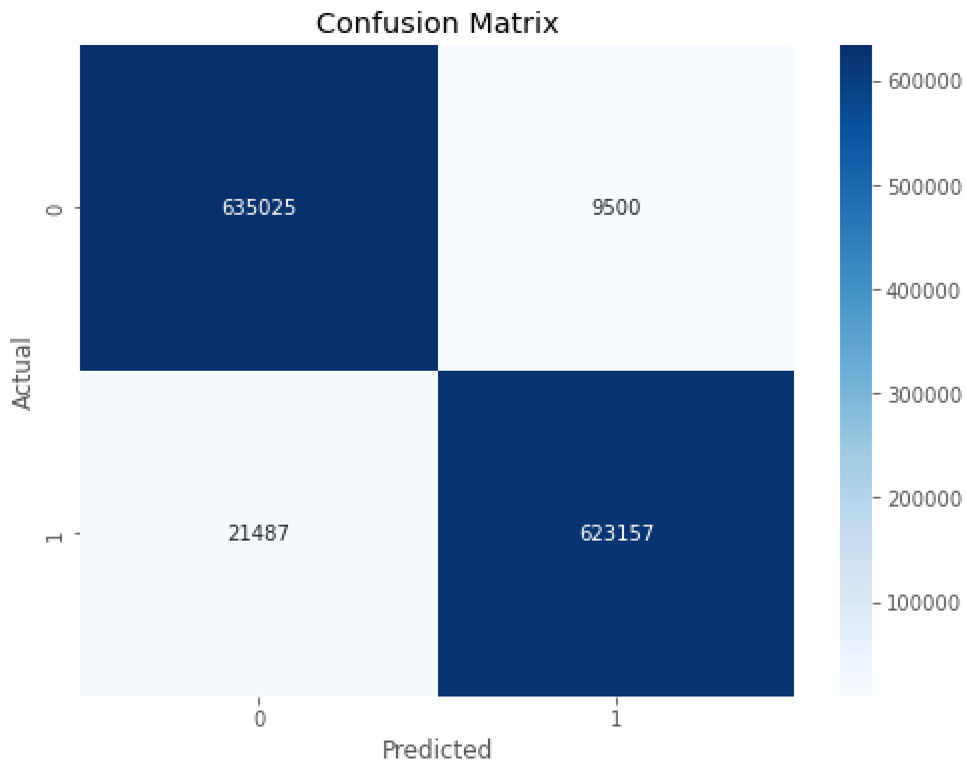
```
Random Forest Accuracy: 97.596%
```

In [34]:

```
# Calculate ROC curve and AUC
probs = rf_model.predict_proba(x_validation)[:, 1]
fpr, tpr, thresholds = roc_curve(y_validation, probs)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```



In [35]:
```
# Calculate and plot confusion matrix
conf_matrix = confusion_matrix(y_validation, rf_predictions)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



In [36]:

```
import pandas as pd
from sklearn.metrics import roc_auc_score, f1_score, precision_score, recall_score

# Define model names and instances
model_names = ['Logistic Regression', 'SVM', 'KNN', 'Random Forest']
model_instances = [lg_model, svm_model, knn_model, rf_model]

# Initialize lists to store accuracy and ROC scores
accuracy_scores = []
roc_scores = []
f1_scores = []
precision_scores = []
recall_scores = []

# Calculate accuracy and ROC scores for each model
for model in model_instances:
    predictions = model.predict(final_test_features)
    accuracy = accuracy_score(test_target, predictions)
    roc_score = roc_auc_score(test_target, predictions)
    accuracy_scores.append(accuracy)
    roc_scores.append(roc_score)
    f1_scores.append(f1_score(test_target, predictions))
    precision_scores.append(precision_score(test_target, predictions))
    recall_scores.append(recall_score(test_target, predictions))

# Create a DataFrame to compare results
results_df = pd.DataFrame({
    'Model': model_names,
    'Accuracy': accuracy_scores,
    'ROC Score': roc_scores,
    'F1 Score': f1_scores,
    'Precision Score': precision_scores,
    'Recall Score': recall_scores,
})

# Print the comparison table
print(results_df)
```

```
                 Model  Accuracy  ROC Score  F1 Score  Precision Score  \
0  Logistic Regression  0.918964   0.823722  0.064832         0.033927   
1                  SVM  0.971955   0.854268  0.168401         0.095083   
2                  KNN  0.840139   0.806912  0.036004         0.018431   
3        Random Forest  0.985331   0.917637  0.308918         0.188789   

   Recall Score  
0      0.727739  
1      0.735664  
2      0.773427  
3      0.849417  
```