Name: Gurjit Singh Sid:N01634963 Assignment2 Machine Learning

This step imports necessary Python libraries for data manipulation (pandas, numpy), visualization (matplotlib, seaborn), machine learning (sklearn for model training, evaluation, and feature selection), handling imbalanced data (SMOTE), and suppressing warnings.

```
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
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix, roc_auc_score
from sklearn.feature_selection import RFE
from imblearn.over_sampling import SMOTE
import warnings
warnings.filterwarnings('ignore')
```

Load dataset

```
data = pd.read_csv('bank.csv', header=0)
data = data.dropna()  # Drop missing values
```

Display basic info

```
print(f"Dataset Shape: {data.shape}")
print(f"Columns: {list(data.columns)}")
```

```
Dataset Shape: (41188, 21)
Columns: ['age', 'job', 'marital', 'education', 'default', 'housing',
'loan', 'contact', 'month', 'day_of_week', 'duration', 'campaign',
'pdays', 'previous', 'poutcome', 'emp_var_rate', 'cons_price_idx',
'cons_conf_idx', 'euribor3m', 'nr_employed', 'y']
```

Group basic education levels into one category

```
data['education'] = np.where(data['education'].isin(['basic.4y',
'basic.6y', 'basic.9y']), 'Basic', data['education'])
```

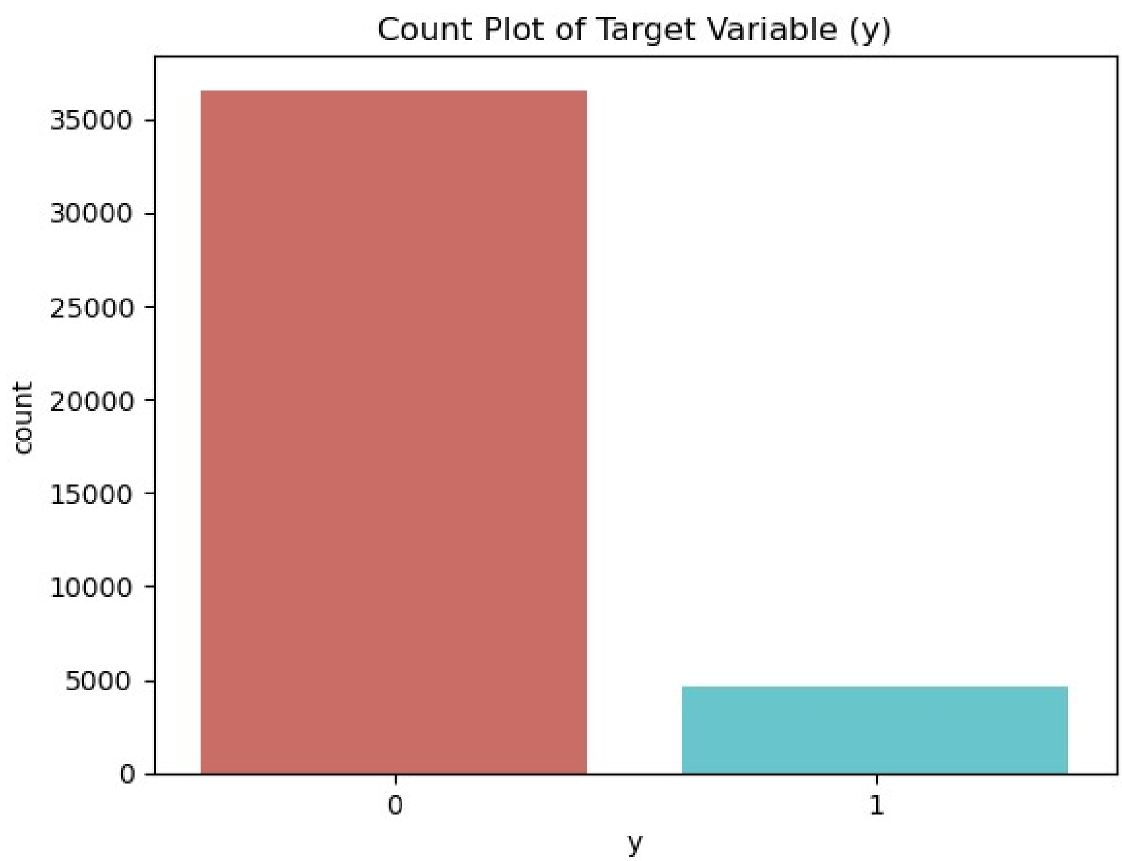
Display unique values after modification

```
print("Unique education levels:", data['education'].unique())
```

```
Unique education levels: ['Basic' 'unknown' 'university.degree'
'high.school' 'professional.course'
 'illiterate']
```

Data visualization

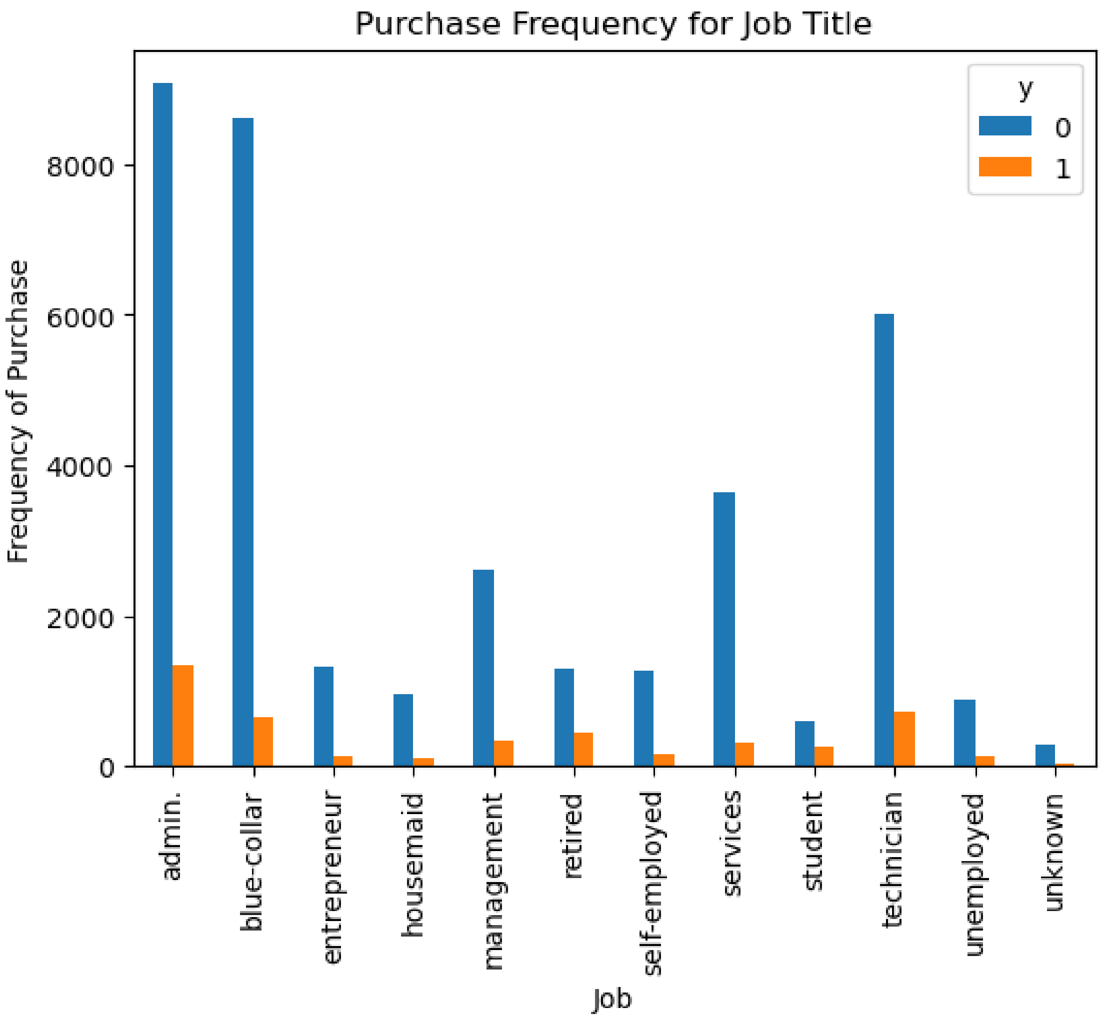
```
sns.countplot(x='y', data=data, palette='hls')
plt.title("Count Plot of Target Variable (y)")
plt.show()
plt.savefig('count_plot')
```



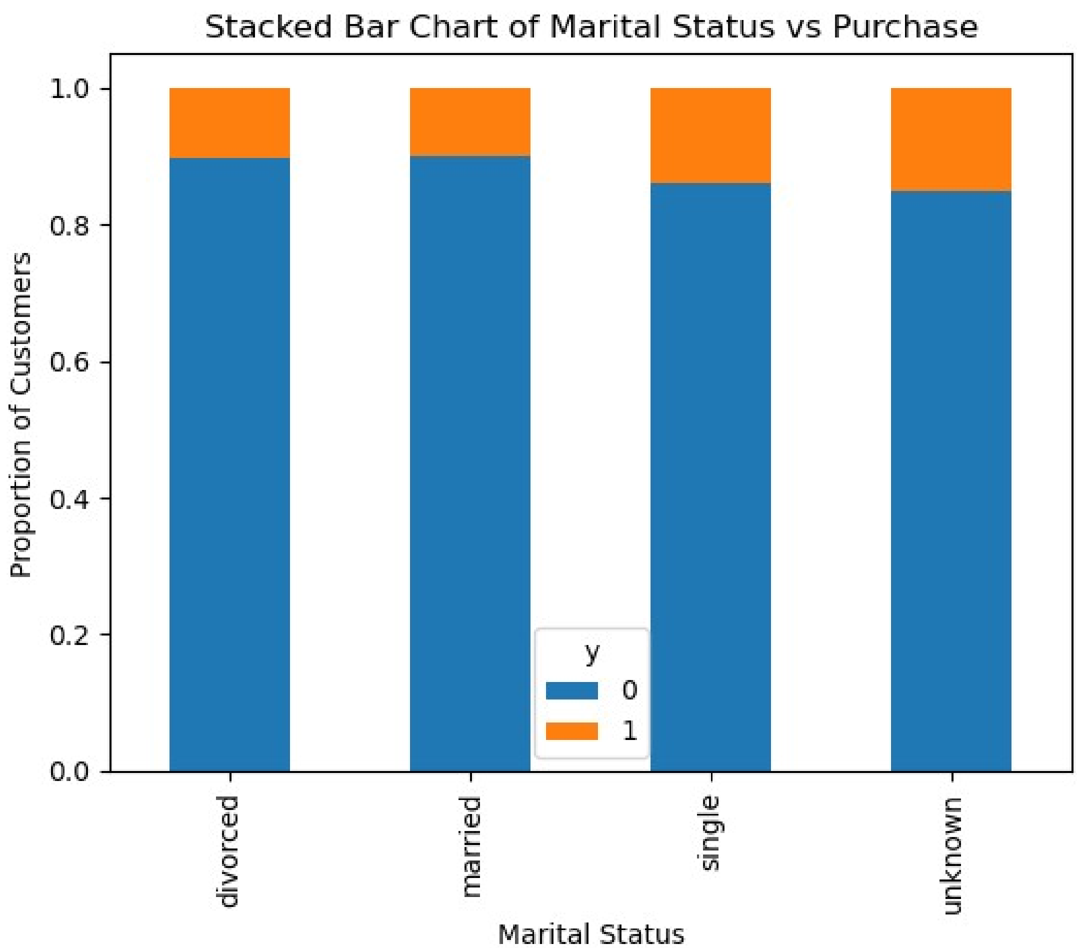

```
<Figure size 640x480 with 0 Axes>
```

```
%matplotlib inline
pd.crosstab(data.job,data.y).plot(kind='bar')
```

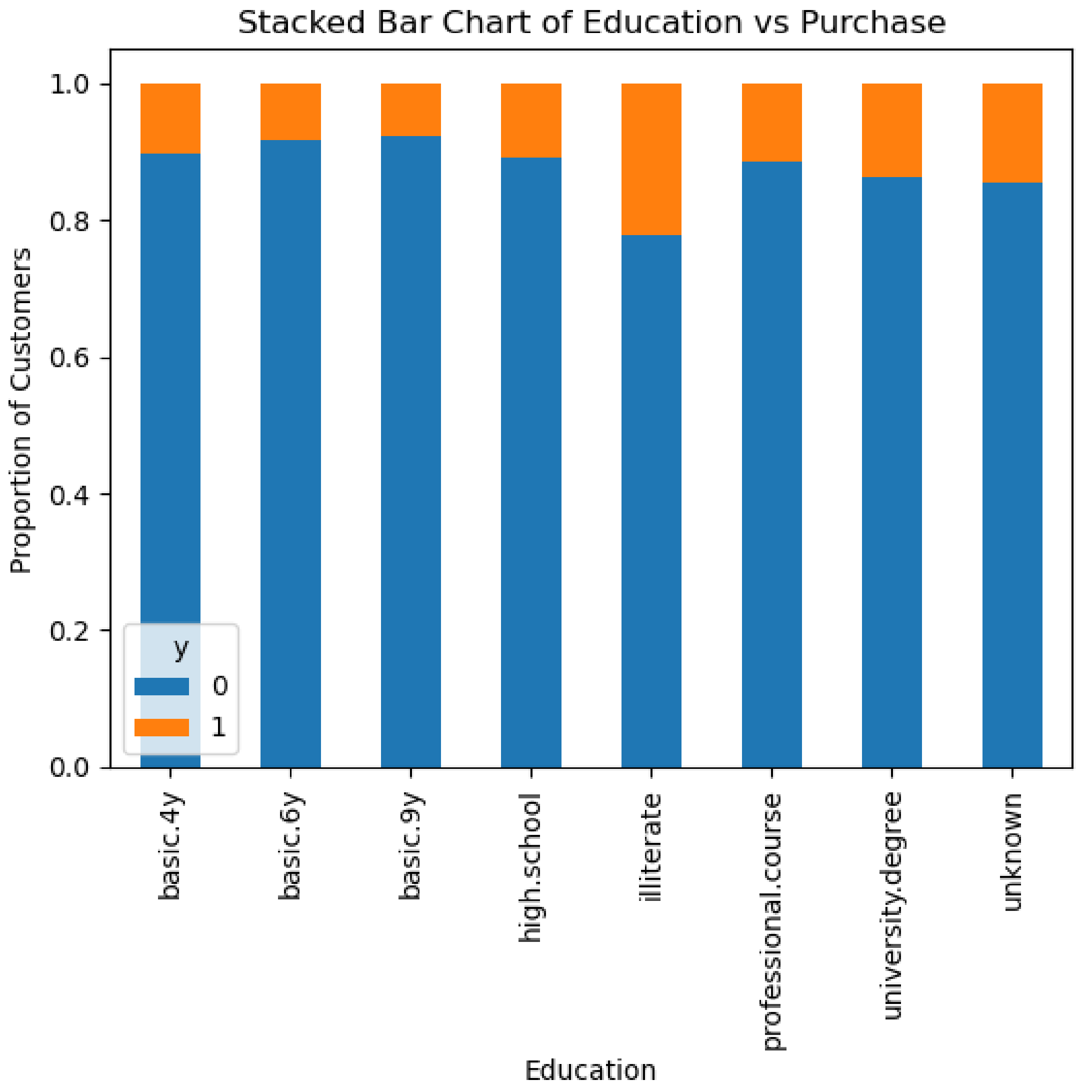
```
plt.title('Purchase Frequency for Job Title')
plt.xlabel('Job')
plt.ylabel('Frequency of Purchase')
plt.savefig('purchase_fre_job')
```



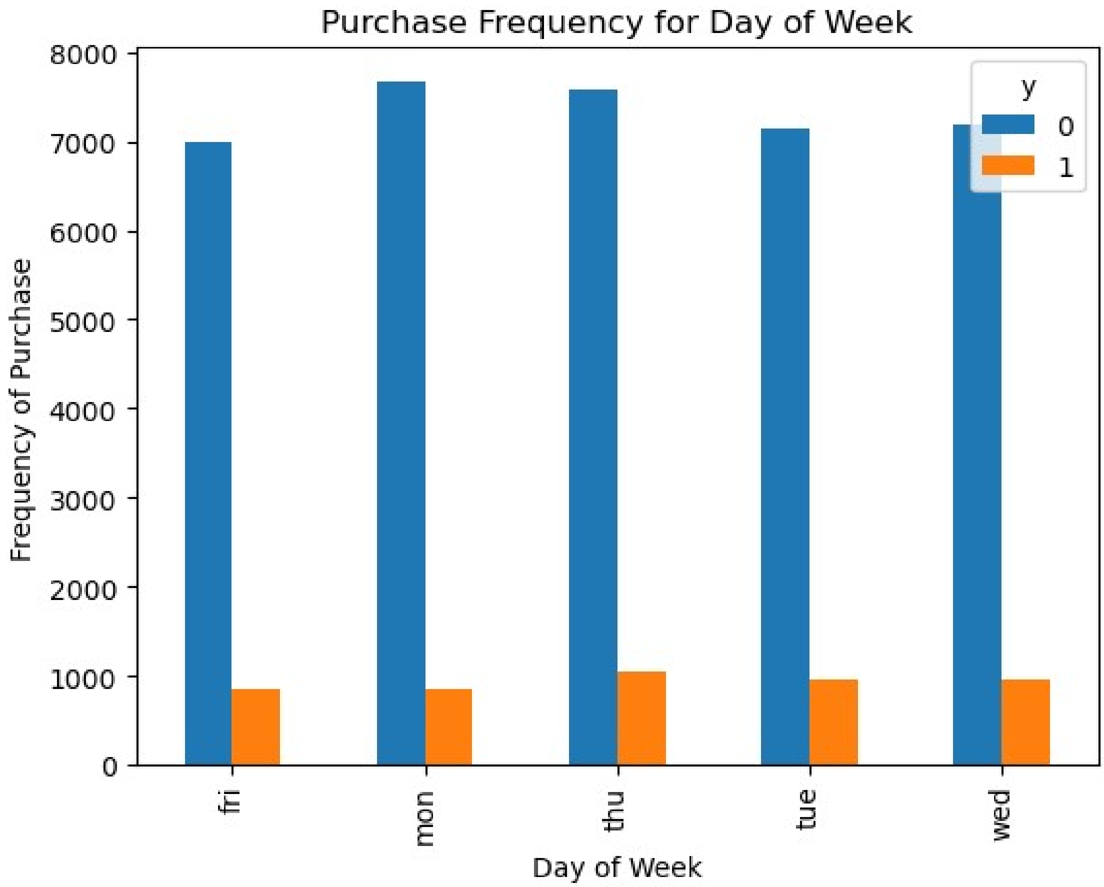

```
table=pd.crosstab(data.marital,data.y)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar',
stacked=True)
plt.title('Stacked Bar Chart of Marital Status vs Purchase')
plt.xlabel('Marital Status')
plt.ylabel('Proportion of Customers')
plt.savefig('mariral_vs_pur_stack')
```



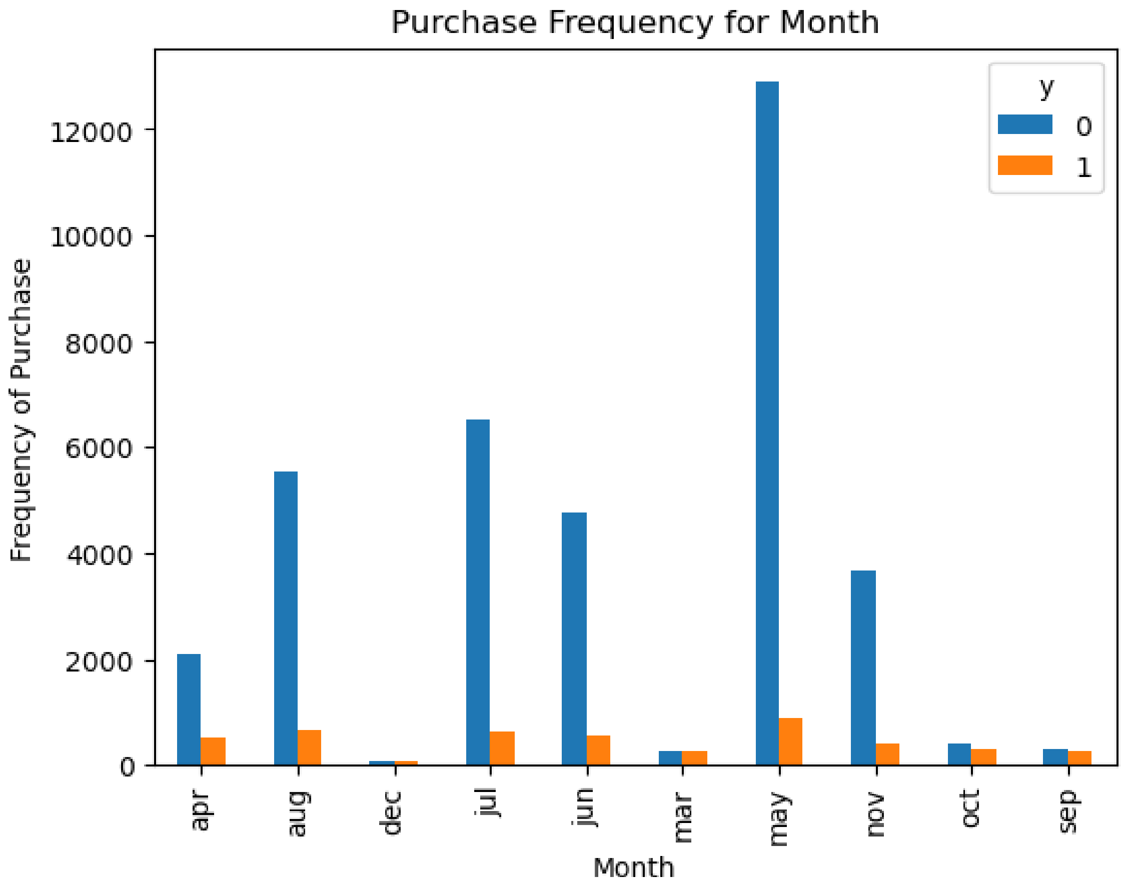

```
table=pd.crosstab(data.education,data.y)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar',
stacked=True)
plt.title('Stacked Bar Chart of Education vs Purchase')
plt.xlabel('Education')
plt.ylabel('Proportion of Customers')
plt.savefig('edu_vs_pur_stack')
```



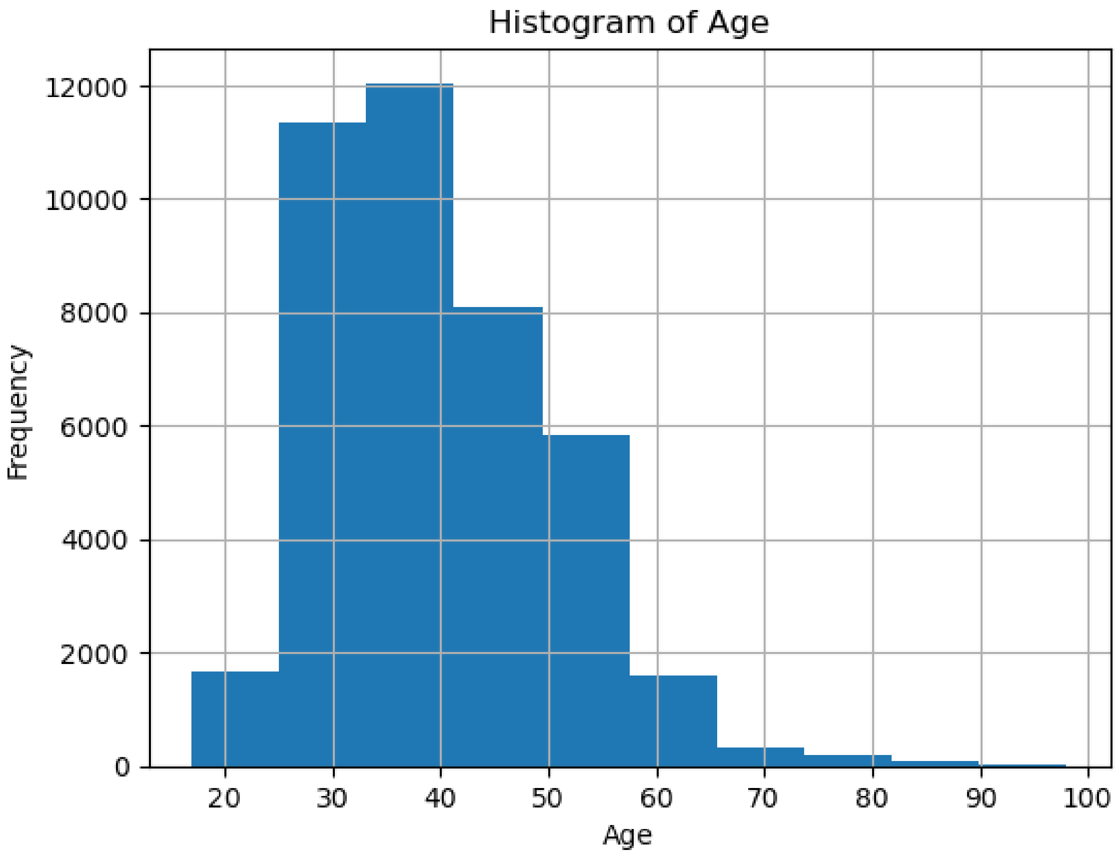

```
pd.crosstab(data.day_of_week,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Day of Week')
plt.xlabel('Day of Week')
plt.ylabel('Frequency of Purchase')
plt.savefig('pur_dayofweek_bar')
```



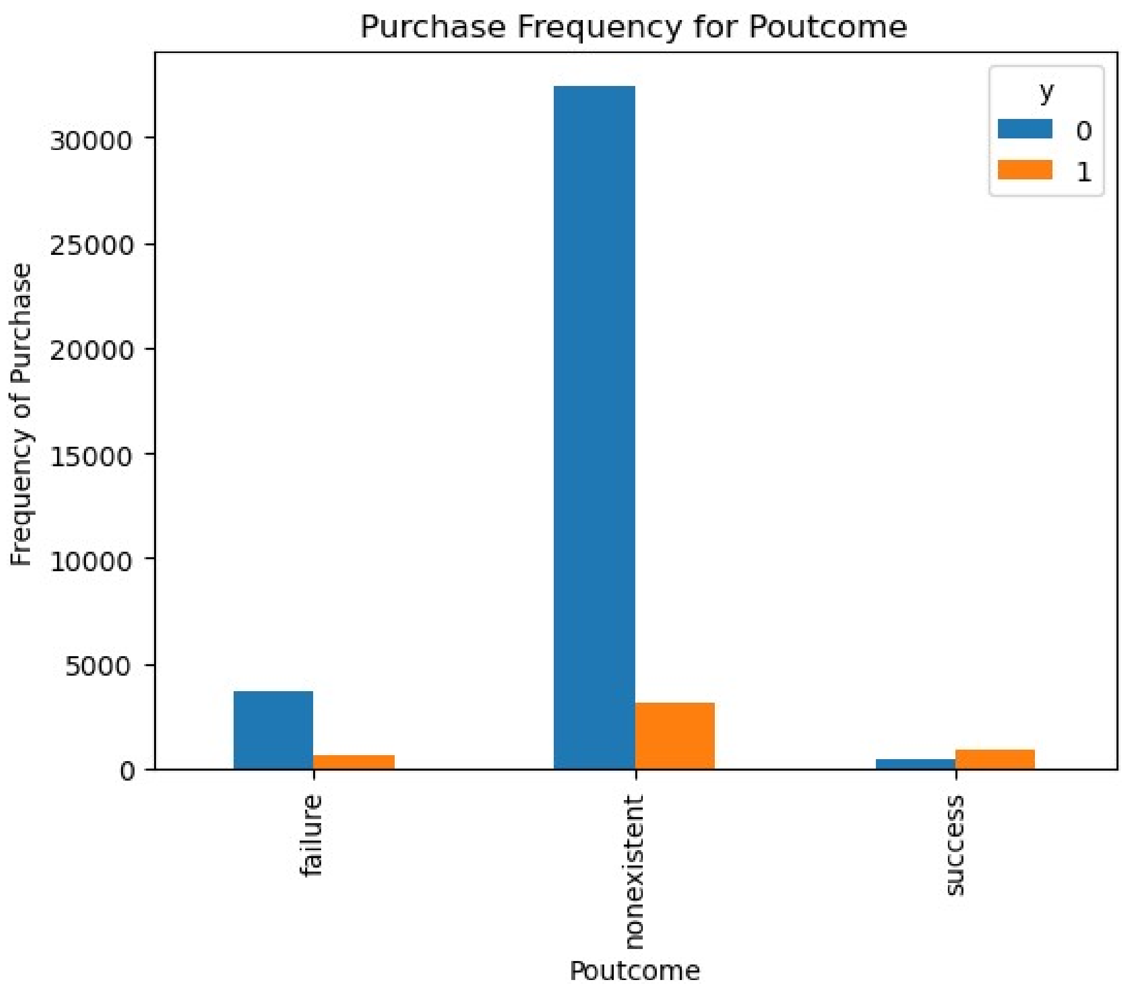

```
pd.crosstab(data.month,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Month')
plt.xlabel('Month')
plt.ylabel('Frequency of Purchase')
plt.savefig('pur_fre_month_bar')
```




```
data.age.hist()
plt.title('Histogram of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.savefig('hist_age')
```




```
pd.crosstab(data.poutcome,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Poutcome')
plt.xlabel('Poutcome')
plt.ylabel('Frequency of Purchase')
plt.savefig('pur_fre_pout_bar')
```



Create categorical dummy variables

```
cat_vars = ['job', 'marital', 'education', 'default', 'housing',
'loan', 'contact', 'month', 'day_of_week', 'poutcome']
for var in cat_vars:
    cat_list = pd.get_dummies(data[var], prefix=var, drop_first=True)
    data = pd.concat([data, cat_list], axis=1)
    data.drop(var, axis=1, inplace=True)
```

Define feature set and target variable

```
y = data['y']
X = data.drop(columns=['y'])
```

Split dataset into training (70%) and testing (30%)

```
X_train, X_test, y_train, y_test = train_test_split(X, y, 
test_size=0.3, random_state=42, stratify=y)
```

Apply SMOTE to balance the dataset

```
smote = SMOTE(random_state=42)
X_train, y_train = smote.fit_resample(X_train, y_train)
```

Standardize numeric features for better performance

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Initialize and fit Logistic Regression model

```
logreg = LogisticRegression(max_iter=100)
logreg.fit(X_train, y_train)
```

```
LogisticRegression()
```

Make predictions

```
y_pred = logreg.predict(X_test)
```

Evaluate model performance

```
print("Confusion Matrix (Before Dropping Column):\n", 
confusion_matrix(y_test, y_pred))
```

```
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print(f"Accuracy: {accuracy_score(y_test, y_pred):.2f}")
print(f"ROC-AUC Score: {roc_auc_score(y_test, y_pred):.2f}")
```

```
Confusion Matrix (Before Dropping Column):
 [[10314   651]
 [  612   780]]

Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.94      0.94     10965
           1       0.55      0.56      0.55      1392

    accuracy                           0.90     12357
   macro avg       0.74      0.75      0.75     12357
weighted avg       0.90      0.90      0.90     12357

Accuracy: 0.90
ROC-AUC Score: 0.75
```

Perform Feature Selection using RFE (Recursive Feature Elimination)

Keep top 20 features

```
rfe = RFE(logreg, n_features_to_select=20)
rfe.fit(X, y)
```

```
RFE(estimator=LogisticRegression(), n_features_to_select=20)
```

Identify and drop the least informative column

```
least_informative_column = X.columns[np.argmax(rfe.ranking_)]
print(f"Removed Column: {least_informative_column}")
X.drop(columns=[least_informative_column], inplace=True)
```

```
Removed Column: default_yes
```

Re-split the dataset after dropping the column

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42, stratify=y)
```

Apply SMOTE again to balance the dataset

```
X_train, y_train = smote.fit_resample(X_train, y_train)
```

Standardize data again after column removal

```
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Train Logistic Regression again

```
logreg.fit(X_train, y_train)
```

```
LogisticRegression()
```

Predict again

Evaluate model after dropping column

```
y_pred = logreg.predict(X_test)


print("Confusion Matrix (After Dropping Column):\n",
confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
print(f"Accuracy result after dropping default_yes column:
{accuracy_score(y_test, y_pred):.2f}") # after dropping column
print(f"ROC-AUC Score: {roc_auc_score(y_test, y_pred):.2f}") # before
dropping column
```

```
Confusion Matrix (After Dropping Column):
 [[10314   651]
 [  612   780]]

Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.94      0.94     10965
           1       0.55      0.56      0.55      1392

    accuracy                           0.90     12357
   macro avg       0.74      0.75      0.75     12357
weighted avg       0.90      0.90      0.90     12357

Accuracy: 0.90
ROC-AUC Score: 0.75
```

It is clearly seen that before dropping unwanted column accuracy was 75.

After dropping unwanted column accuracy for model is 90