```
### Bank Marketing Effectiveness ###
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import pandas as pd
!pip install tensorflow
```

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Requirement already satisfied: tensorflow in /usr/local/lib/python3.11/dist-packages (2.18.0)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.4.0)
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```

```
# upload data and mount drive
# Kyle uploading file
from google.colab import drive
drive.mount('/content/drive/')

path = '/content/drive/My Drive/Colab Notebooks/data/bank-additional-full.csv'

bank = pd.read_csv(path, sep=';')
print(bank.head())
print(bank.info())


# Link to site for feature descriptions! https://archive.ics.uci.edu/dataset/222/bank+marketing
# Downloading from site includes 2 zip files.  The one I am thinking we use is the full set under the file name: bank-additional-
```

```
Mounted at /content/drive/
   age        job  marital    education  default housing loan    contact  \
0   56  housemaid  married     basic.4y       no      no   no  telephone
1   57   services  married  high.school  unknown      no   no  telephone
2   37   services  married  high.school       no     yes   no  telephone
3   40     admin.  married     basic.6y       no      no   no  telephone
4   56   services  married  high.school       no      no  yes  telephone

  month day_of_week  ...  campaign  pdays  previous     poutcome emp.var.rate  \
0   may         mon  ...         1    999         0  nonexistent          1.1
1   may         mon  ...         1    999         0  nonexistent          1.1
2   may         mon  ...         1    999         0  nonexistent          1.1
3   may         mon  ...         1    999         0  nonexistent          1.1
4   may         mon  ...         1    999         0  nonexistent          1.1

   cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
0          93.994          -36.4      4.857       5191.0  no
1          93.994          -36.4      4.857       5191.0  no
```

```
2         93.994          -36.4      4.857       5191.0  no
3         93.994          -36.4      4.857       5191.0  no
4         93.994          -36.4      4.857       5191.0  no

[5 rows x 21 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             41188 non-null  object 
 2   marital         41188 non-null  object 
 3   education       41188 non-null  object 
 4   default         41188 non-null  object 
 5   housing         41188 non-null  object 
 6   loan            41188 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
None
```

```
# Upload data
# Richard uploading file

#file_path = r"C:\Users\Richard Kianos\Downloads\bank-additional-full.csv"
#bank = pd.read_csv(file_path, sep=';')

# Preview Dataset
#print(bank.head())
#bank.info()
```

Intro to set

This set is from the UCI archive uploaded in 2014 descibing the data collected over a 30-month period from a portugese bank in their attempts to get clients to subscribe to a bank term deposit. The target variable y holds the values of either 'yes' or 'no' on whether they subscribed or not. This is what we will be predicting.

```
# Drop 'duration' column according to reccomendation by dataset post
bank.drop('duration', axis=1, inplace=True)
```

```
# Check shape of set
print('Number of instances: ', bank.shape[0])
print('Number of attributes: ', bank.shape[1] - 1) # -1 for target variable

# Check and print number of null values
print('\nNumber of null values:\n', bank.isnull().sum())
```

```
Number of instances:  41188
Number of attributes:  19

Number of null values:
 age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
campaign          0
```

```
pdays            0
previous         0
poutcome         0
emp.var.rate     0
cons.price.idx   0
cons.conf.idx    0
euribor3m        0
nr.employed      0
y                0
dtype: int64
```

To Do:

- Introduce set and create 1 or 2 plots for exploratory analysis. #I know we have our target variable already but do you think it would be useful to add some features like interaction_count (total number of interactions with the bank) to add some depth to the set since it's pretty clean already LOL.
- Non-supervised learning. Maybe k-means clustering for customer groups based on age, demographics, or behavior. I feel like we could maybe try and use maybe like PCA or Lasso regularization to implement some kind of Dimensionality Reduction but lmk what you think!
- At least 2 supervised ML techniques with one being ANN. We could maybe try to run a couple of other ML's in comparison so see how the ANN performs.

```
# Exploratory analysis

# Generate descriptive statistics for numerical columns
numerical_summary = bank.describe()

# Generate descriptive statistics for categorical columns
categorical_summary = bank.describe(include=['object'])

# Display numerical summary
print("Numerical Summary:")
display(numerical_summary)

# Display categorical summary
print("Categorical Summary:")
display(categorical_summary)
```

Numerical Summary:

	age	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000
mean	40.02406	2.567593	962.475454	0.172963	0.081886	93.575664	-40.502600	3.621291	5167.035911
std	10.42125	2.770014	186.910907	0.494901	1.570960	0.578840	4.628198	1.734447	72.251528
min	17.00000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.634000	4963.600000
25%	32.00000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.344000	5099.100000
50%	38.00000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	4.857000	5191.000000
75%	47.00000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.961000	5228.100000
max	98.00000	56.000000	999.000000	7.000000	1.400000	94.767000	-26.900000	5.045000	5228.100000

Categorical Summary:

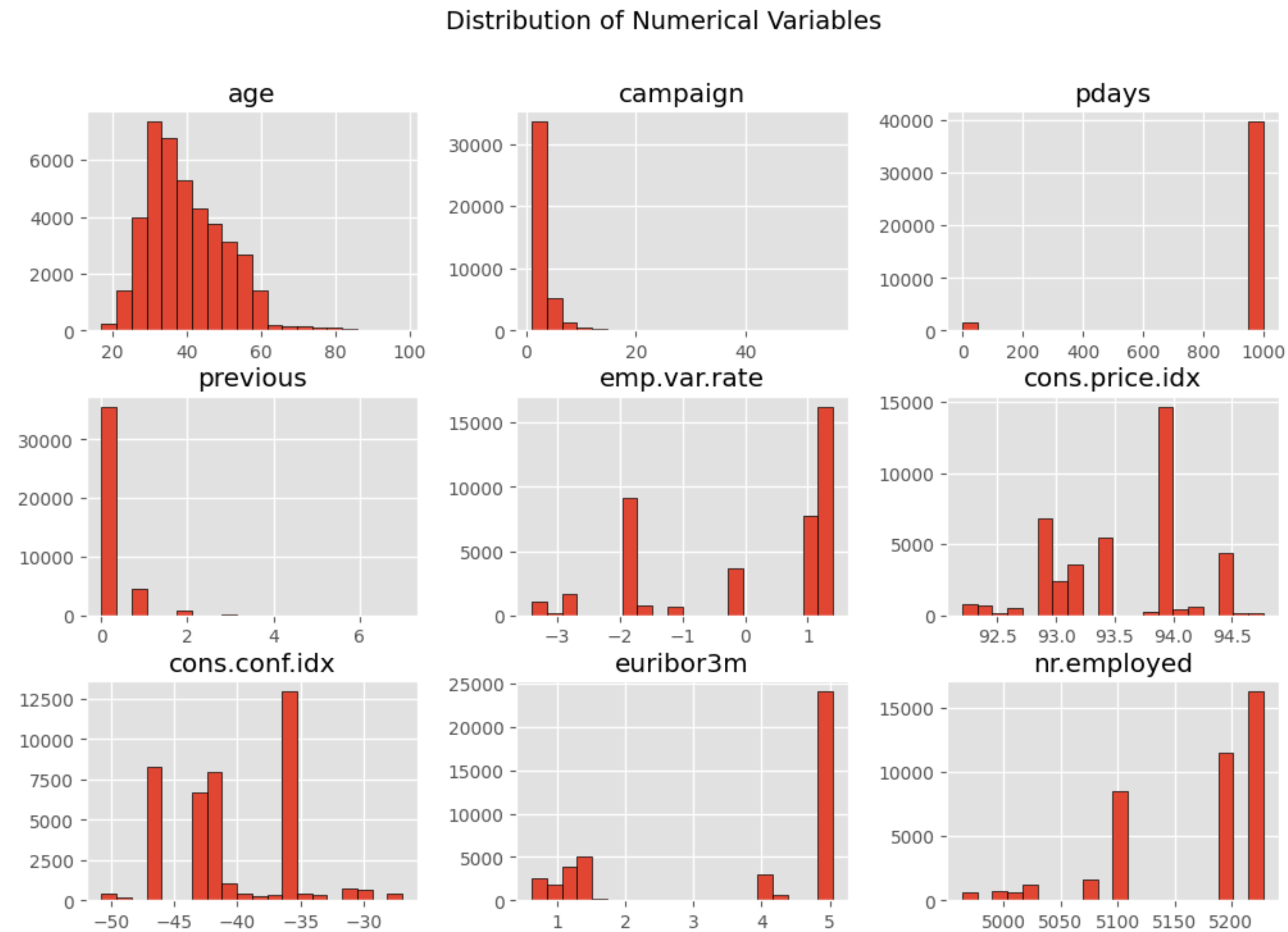
	job	marital	education	default	housing	loan	contact	month	day_of_week	poutcome	y
count	41188	41188	41188	41188	41188	41188	41188	41188	41188	41188	41188
unique	12	4	8	3	3	3	2	10	5	3	2
top	admin.	married	university.degree	no	yes	no	cellular	may	thu	nonexistent	no
freq	10422	24928	12168	32588	21576	33950	26144	13769	8623	35563	36548

```
import matplotlib.pyplot as plt
import seaborn as sns

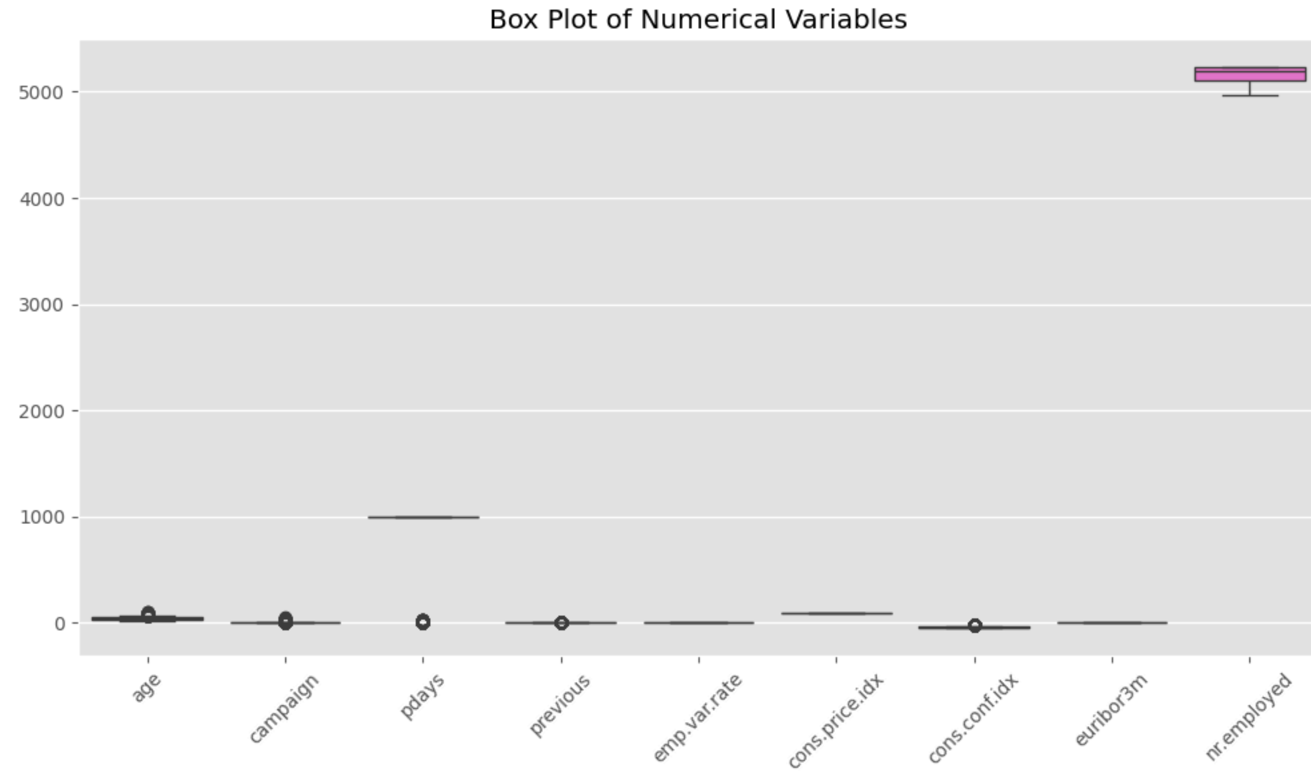
# Set plot style
plt.style.use("ggplot")

# Figure 1: Histogram for numerical variables
bank.hist(figsize=(12, 8), bins=20, edgecolor='black')
```

```
plt.suptitle("Distribution of Numerical Variables", fontsize=14)
plt.show()
```




```
# Figure 2: Boxplot for numerical variables to detect outliers
plt.figure(figsize=(12, 6))
sns.boxplot(data=bank.select_dtypes(include=['int64', 'float64']))
plt.xticks(rotation=45)
plt.title("Box Plot of Numerical Variables")
plt.show()
```

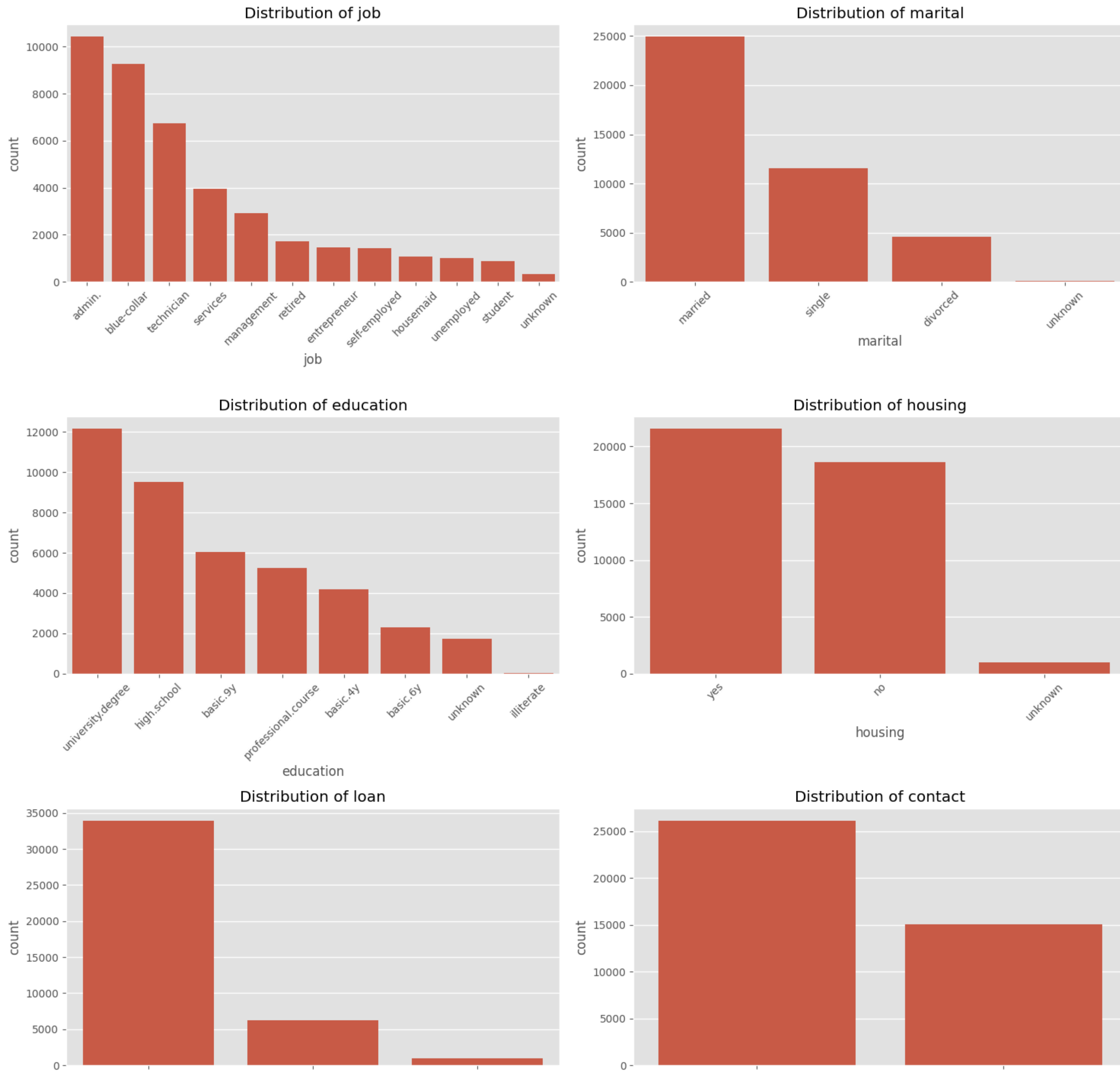



```
# Figure 3: Bar chart for categorical variables
categorical_cols = ['job', 'marital', 'education', 'housing', 'loan', 'contact', 'month', 'day_of_week']
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(15, 20))

for col, ax in zip(categorical_cols, axes.flatten()):
    sns.countplot(x=bank[col], ax=ax, order=bank[col].value_counts().index)
    ax.set_title(f"Distribution of {col}")

    # Fix the warning by ensuring fixed tick locations
    ax.set_xticks(range(len(bank[col].value_counts().index)))
    ax.set_xticklabels(bank[col].value_counts().index, rotation=45)

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

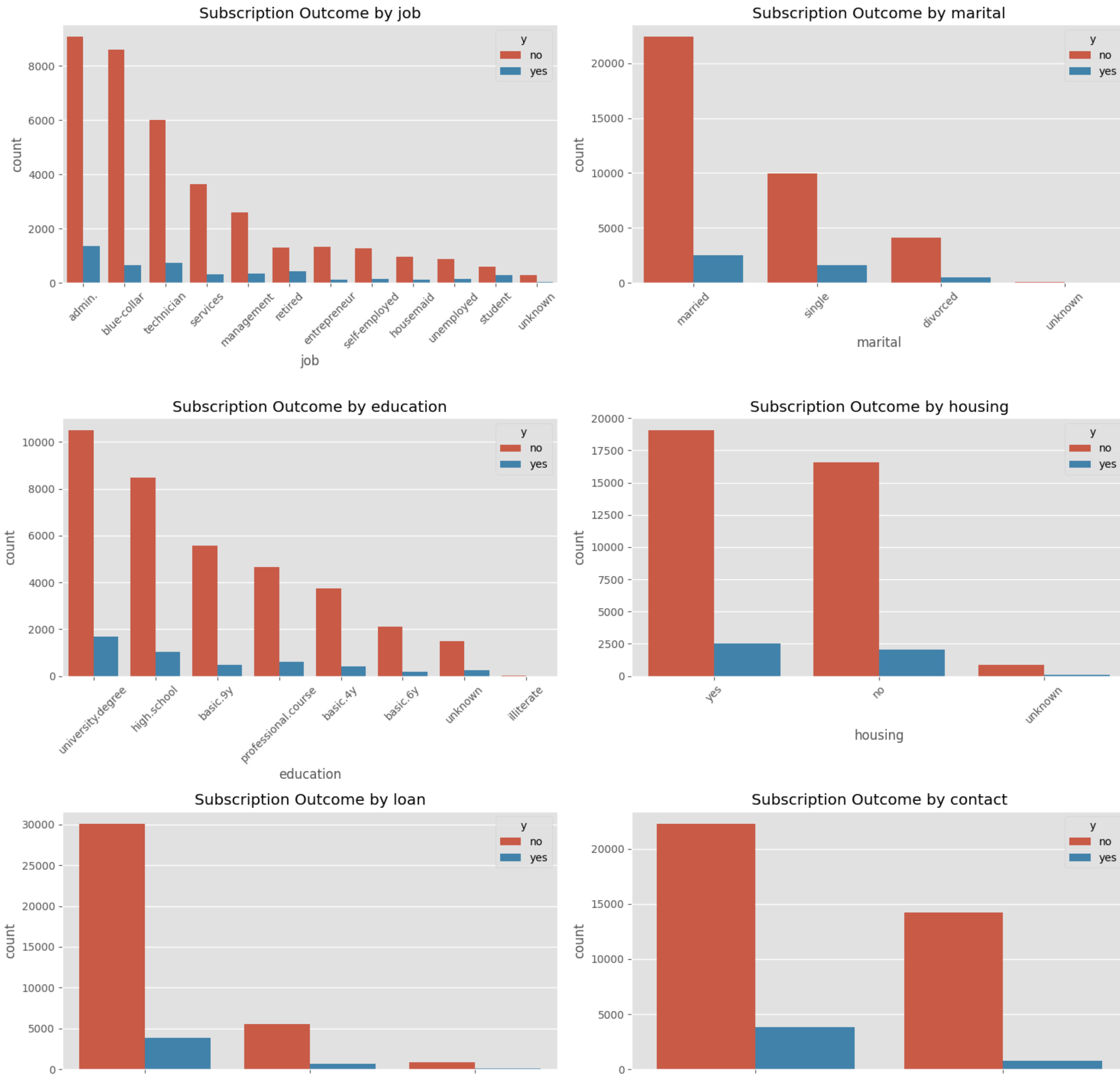



```
# Figure 4: Subscription rate comparison for categorical variables
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(15, 20))

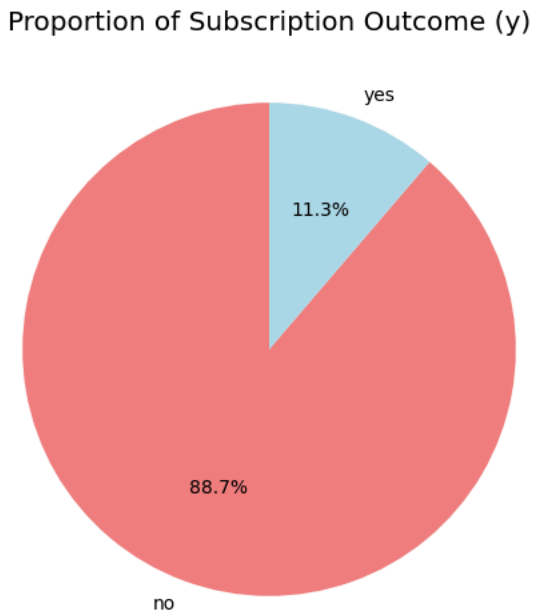
for col, ax in zip(categorical_cols, axes.flatten()):
    sns.countplot(x=bank[col], hue=bank['y'], ax=ax, order=bank[col].value_counts().index)
    ax.set_title(f"Subscription Outcome by {col}")

    # Fix: Ensure fixed tick positions before setting labels
    ax.set_xticks(range(len(bank[col].value_counts().index)))
    ax.set_xticklabels(bank[col].value_counts().index, rotation=45)

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




```
# Figure 5: Pie chart for subscription outcome
plt.figure(figsize=(6, 6))
bank['y'].value_counts().plot(kind='pie', autopct='%1.1f%%', colors=['lightcoral', 'lightblue'], startangle=90)
plt.title("Proportion of Subscription Outcome (y)")
plt.ylabel("")
plt.show()
```




```
# Figure 6: Line chart for success rates by month with labels
plt.figure(figsize=(10, 5))

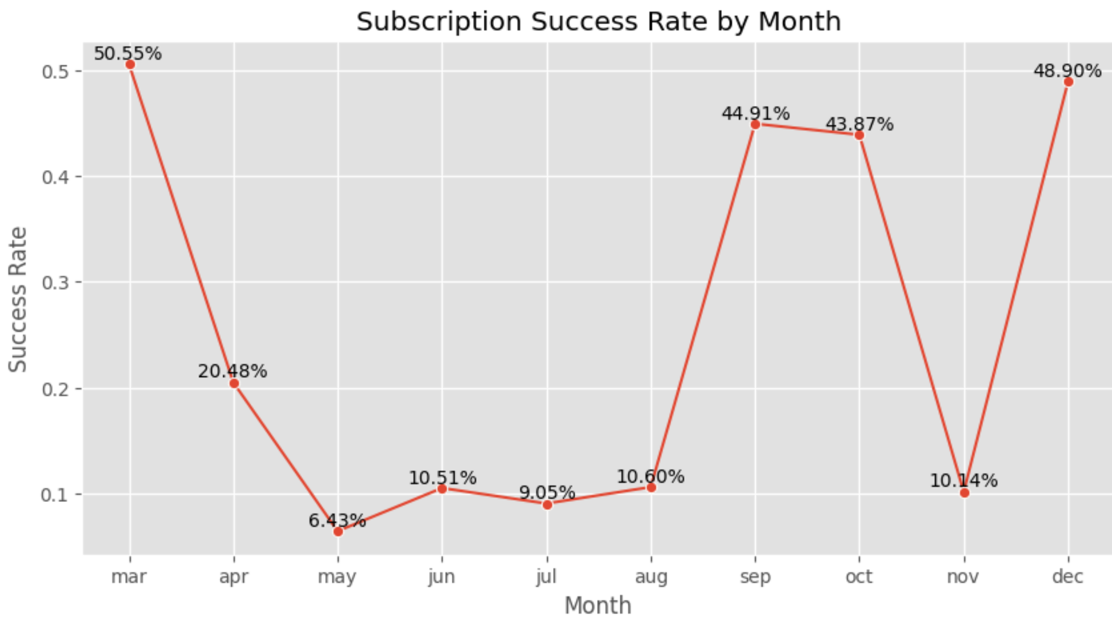
# Compute success rates by month
success_rates = bank.groupby("month")["y"].apply(lambda x: (x == "yes").mean()).reset_index()

# Ensure months are in correct order (if not already)
month_order = ['jan', 'feb', 'mar', 'apr', 'may', 'jun', 'jul', 'aug', 'sep', 'oct', 'nov', 'dec']
success_rates['month'] = pd.Categorical(success_rates['month'], categories=month_order, ordered=True)
success_rates = success_rates.sort_values('month')

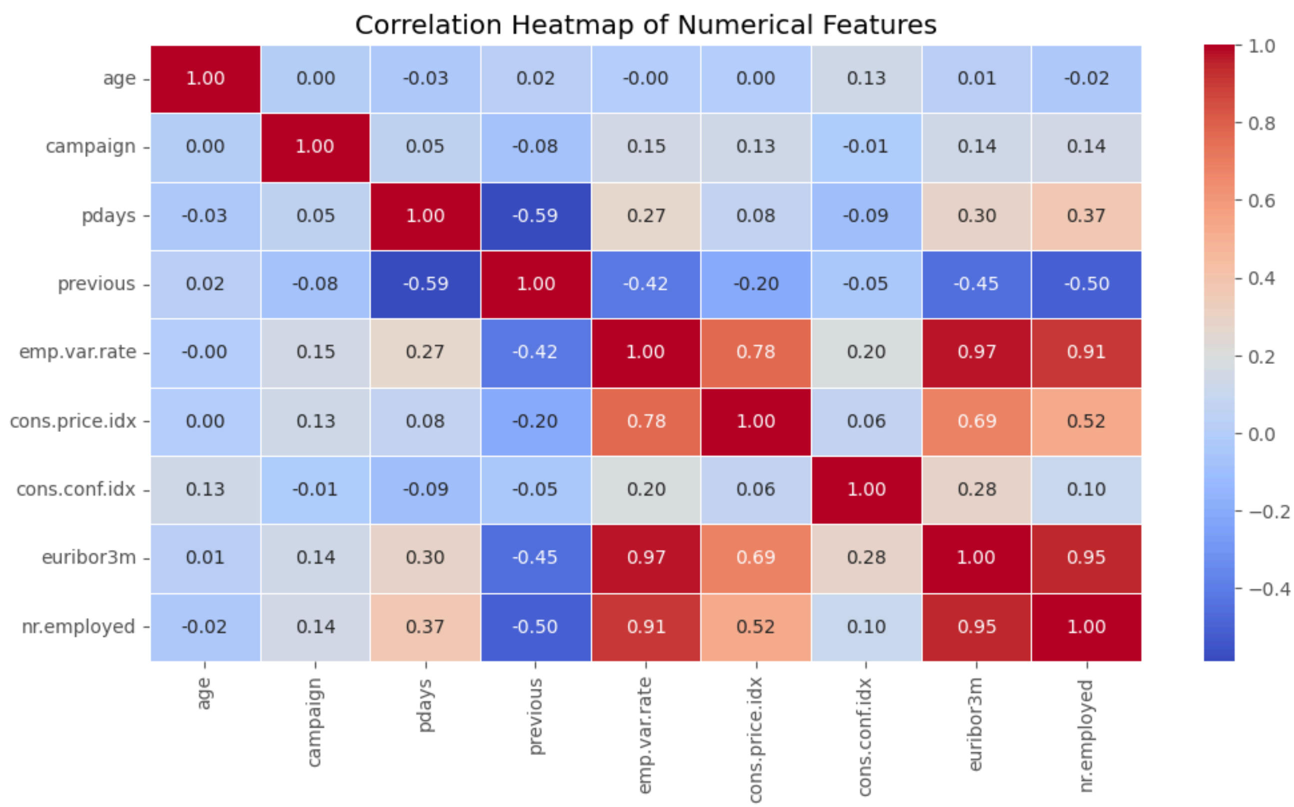
# Plot line chart
sns.lineplot(x=success_rates['month'], y=success_rates['y'], marker='o', linestyle='-')

# Add labels above each point
for i, txt in enumerate(success_rates['y']):
    plt.text(success_rates['month'].iloc[i], txt + 0.005, f"{txt:.2%}", ha='center', fontsize=10)

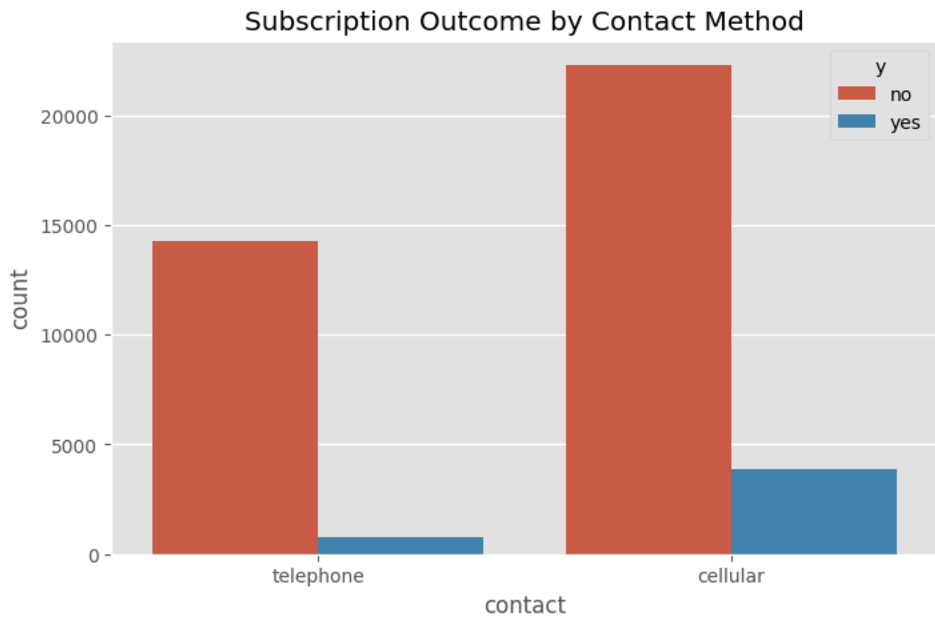
plt.title("Subscription Success Rate by Month")
plt.xlabel("Month")
plt.ylabel("Success Rate")
plt.show()
```




```
# Figure 7: Heatmap for correlations
plt.figure(figsize=(12, 6))
sns.heatmap(bank.select_dtypes(include=['int64', 'float64']).corr(), annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap of Numerical Features")
plt.show()
```




```
# Figure 8: Count plot for contact method success rate
plt.figure(figsize=(8, 5))
sns.countplot(x=bank['contact'], hue=bank['y'])
plt.title("Subscription Outcome by Contact Method")
plt.show()
```



Preprocessing with One-hot encoding

```
# Identify categorical columns (dype = "object")
categorical_attributes = bank.select_dtypes(include=["object"]).columns.tolist()
#print("Categorical Features:", categorical_attributes)

# Encode target variable with LabelEncoder
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
bank['y'] = le.fit_transform(bank['y'])

# Check to make sure y is all numerical now
#print("\nChecking to see if y is numerical",bank["y"].value_counts())

# Identify binary (0/1) features
binary_features = [col for col in bank.columns if bank[col].nunique() == 2]  # Columns with only 2 unique values (0 & 1)

# Identify true numerical features (non-binary)
non_binary_features = [col for col in bank.select_dtypes(include=["int64", "float64"]).columns if col not in binary_features]

# Remove y if it got pulled into non_binary_features
if "y" in non_binary_features:
  non_binary_features.remove("y")

#print("Binary features (excluded from scaling):", binary_features)
#print("Numerical features to be scaled:", non_binary_features)

# Initialize StandardScaler
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

# Apply StandardScaler to non-binary features
bank[non_binary_features] = scaler.fit_transform(bank[non_binary_features])


# Import OneHotEncoder, convert categorical features, update dataset
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(sparse_output=False, drop='first')
encoded_features = ohe.fit_transform(bank[categorical_attributes])
encoded_feature_names = ohe.get_feature_names_out(categorical_attributes)
encoded_bank = pd.DataFrame(encoded_features, columns=encoded_feature_names)
bank = pd.concat([bank.drop(categorical_attributes, axis=1), encoded_bank], axis=1)

# Check if full set is numerical now
#print("is dataset numerical?",bank.head())


# Check the transformed dataset
```

```
#print(bank.head())
bank.rename(columns={"y_1":"y"}, inplace = True) # y kept getting renamed into y_1
#print(bank['y'].value_counts())



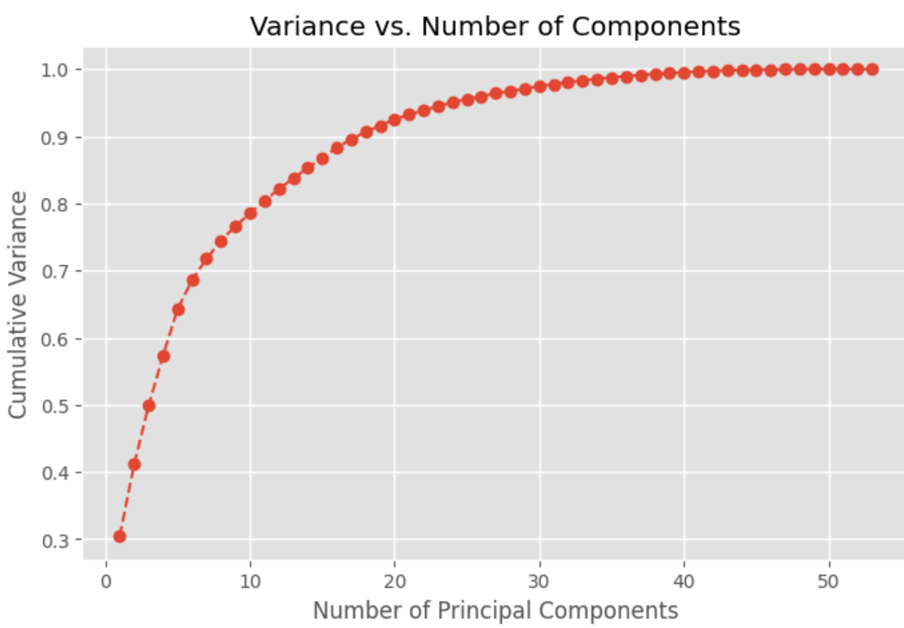
# Apply PCA to reduce dimensionality
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import numpy as np


# Test the PCA on all features then try just the numerical ones to see what happens

# Apply PCA on all features
pca = PCA(n_components=None)  # Keep all components initially
X_pca = pca.fit_transform(bank)

# Explained variance ratio
explained_variance = np.cumsum(pca.explained_variance_ratio_)

# Plot explained variance
plt.figure(figsize=(8,5))
plt.plot(range(1, len(explained_variance) + 1), explained_variance, marker='o', linestyle='--')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Variance')
plt.title('Variance vs. Number of Components')
plt.grid(True)
plt.show()
```




```
# Choose optimal number of components (18 components describes about 90%ish of variance)
optimal_components = 18

# Apply PCA again with the chosen number of components
pca = PCA(n_components=optimal_components)
X_pca_final = pca.fit_transform(bank)

# Convert PCA results into a DataFrame
bank_pca = pd.DataFrame(X_pca_final, columns=[f"PC{i+1}" for i in range(optimal_components)])

# Display the transformed dataset
bank_pca.head()
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC
0	1.324657	-0.952342	1.486270	-0.050549	-0.675770	0.788213	0.113977	0.022708	-0.139761	-0.261350	-0.390760	0.496273	-0.040838	-0.580
1	1.365205	-0.962601	1.511332	0.016299	-0.773613	0.880190	0.184620	0.172084	-0.777908	0.341711	-0.622264	0.788327	-0.418895	-0.370
2	1.302272	-0.391052	0.192457	-0.885925	0.037873	0.841655	0.234715	0.462441	-0.310320	0.925289	0.207672	0.948280	-0.433490	-0.369
3	1.323209	-0.516715	0.450334	-0.736856	-0.086811	0.861223	0.207967	0.443486	0.127630	-0.177633	-0.397894	0.396388	-0.067973	-0.594
4	1.321590	-0.911130	1.402140	-0.068858	-0.676760	0.836942	0.152153	0.056258	-0.638824	0.487637	-0.606635	0.908108	-0.381357	-0.372

```
# Get top contributing features for the first few principal components
pca_components = pd.DataFrame(pca.components_, columns=bank.columns)

# Show the top 10 absolute values for PC1 and PC2
print("Top features contributing to PC1:\n", pca_components.iloc[0].abs().nlargest(10))
print("\nTop features contributing to PC2:\n", pca_components.iloc[1].abs().nlargest(10))
```

```
Top features contributing to PC1:
 euribor3m              0.479421
emp.var.rate           0.477189
nr.employed            0.459174
cons.price.idx         0.361701
previous               0.304852
pdays                  0.225961
contact_telephone      0.108081
poutcome_nonexistent   0.106971
cons.conf.idx          0.099484
campaign               0.097686
Name: 0, dtype: float64

Top features contributing to PC2:
 pdays                  0.603128
previous               0.460701
cons.conf.idx          0.423357
age                    0.277422
cons.price.idx         0.270664
emp.var.rate           0.158317
euribor3m              0.145378
poutcome_nonexistent   0.115387
poutcome_success       0.101094
contact_telephone      0.080417
Name: 1, dtype: float64
```

Observations

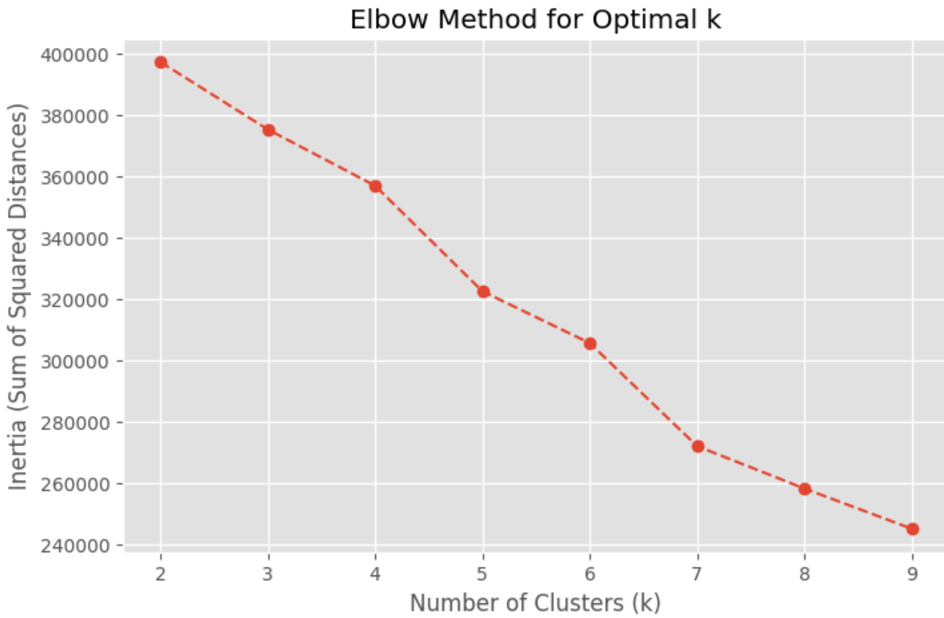
- My concern is that the onehotencoded variables could be dispropotionately be being dropped while we run the PCA
- There are some OHE variables present in the features contributing to the Principal Components from the PCA so there's the chance that meaningful ones are being retained?
- Going to run the k-means clustering on this PCA and see how it performs

```
from sklearn.cluster import KMeans

# Test different k values
inertia = []
K_range = range(2, 10)

for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=0)
    kmeans.fit(X_pca)
    inertia.append(kmeans.inertia_)  # Store sum of squared distances to cluster centers

# Plot Elbow Method to visually see where "best" k could be
plt.figure(figsize=(8, 5))
plt.plot(K_range, inertia, marker='o', linestyle='--')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia (Sum of Squared Distances)')
plt.title('Elbow Method for Optimal k')
plt.grid(True)
plt.show()
```

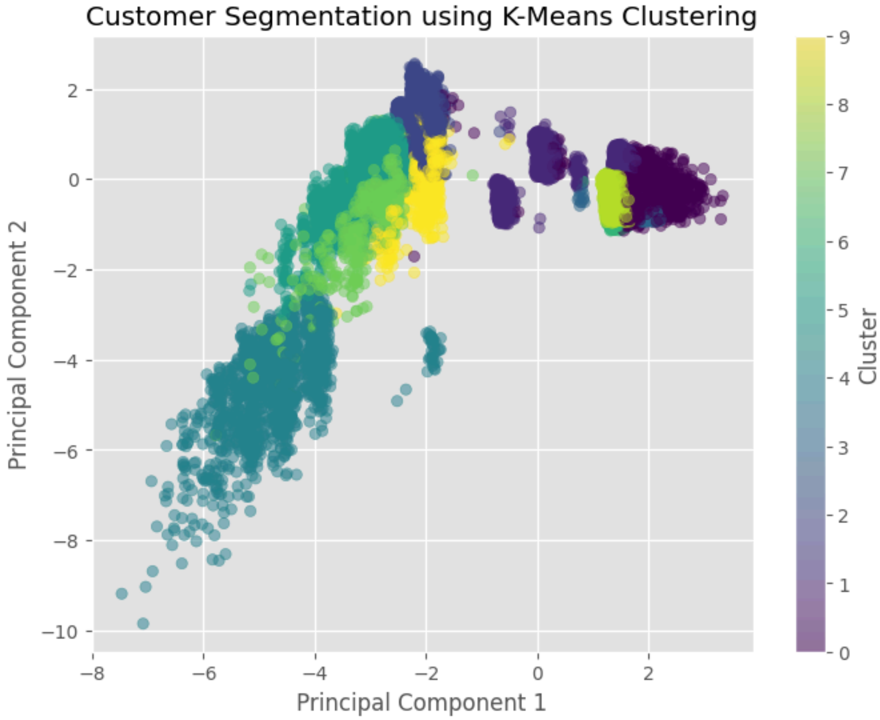



```
k = 10
kmeans = KMeans(n_clusters=k, random_state=0)
bank["Cluster"] = kmeans.fit_predict(X_pca)

print(bank["Cluster"].value_counts())
```

```
Cluster
1    7900
6    7519
3    6078
2    5467
8    4973
7    2832
5    1875
9    1838
4    1515
0    1191
Name: count, dtype: int64
```

```
plt.figure(figsize=(8, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=bank["Cluster"], cmap='viridis', alpha=0.5)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('Customer Segmentation using K-Means Clustering')
plt.colorbar(label='Cluster')
plt.show()
```



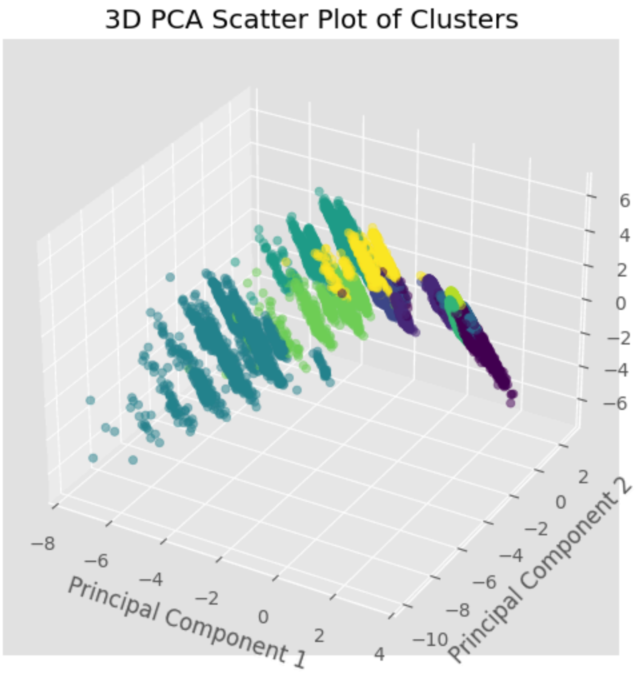

```
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt

# Create 3D scatter plot using PC1, PC2, and PC3
fig = plt.figure(figsize=(8, 6))
ax = fig.add_subplot(111, projection='3d')

# Scatter plot of clusters
ax.scatter(X_pca[:, 0], X_pca[:, 1], X_pca[:, 2], c=bank["Cluster"], cmap='viridis', alpha=0.5)

# Labels
ax.set_xlabel("Principal Component 1")
ax.set_ylabel("Principal Component 2")
ax.set_zlabel("Principal Component 3")
ax.set_title("3D PCA Scatter Plot of Clusters")

plt.show()
```



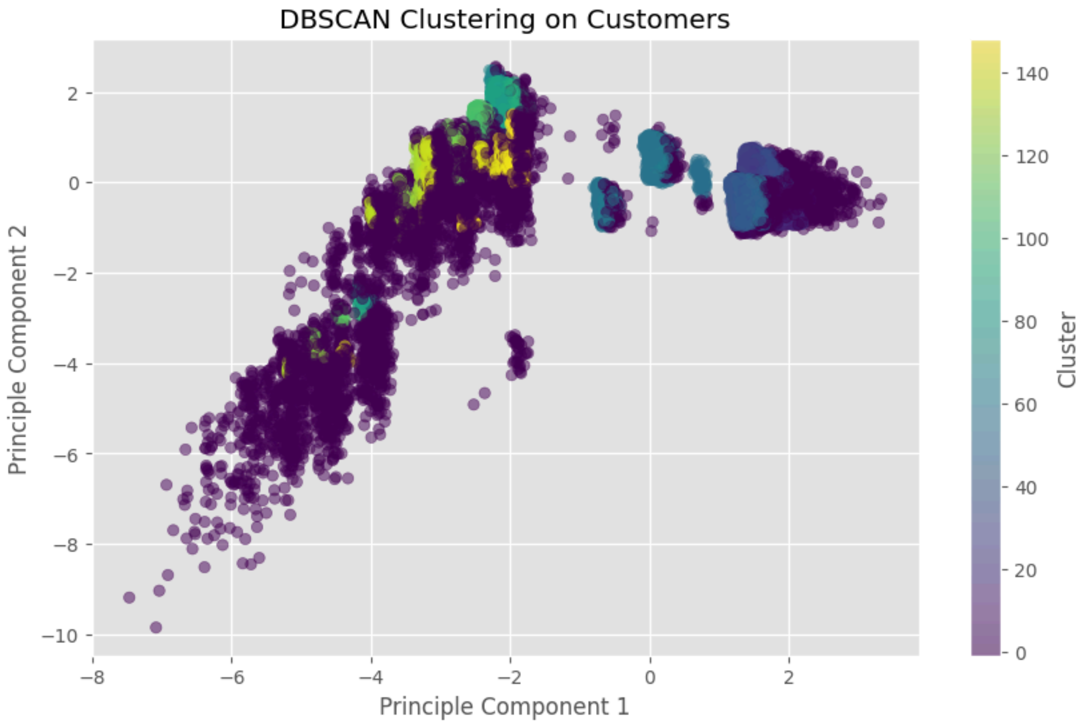
Density-Based-Clustering (DBSCAN)

```
from sklearn.cluster import DBSCAN
import matplotlib.pyplot as plt

# Standardize numerical features before clustering
scaler = StandardScaler()
X_scaled = scaler.fit_transform(bank[non_binary_features])

# Apply DBSCAN Clustering
dbscan = DBSCAN(eps=0.3, min_samples=10)
bank['DBSCAN_Cluster'] = dbscan.fit_predict(X_scaled)

# Scatter Plot of Clusters
plt.figure(figsize=(10, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=bank["DBSCAN_Cluster"], cmap='viridis', alpha=0.5)
plt.title("DBSCAN Clustering on Customers")
plt.xlabel("Principle Component 1")
plt.ylabel("Principle Component 2")
plt.colorbar(label="Cluster")
plt.show()
```



Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split


# Prepare dataset (handle missing values and encode categorical variables)
X = bank[non_binary_features].fillna(bank[non_binary_features].median())
y = bank['y']

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train Random Forest Model
rf_model = RandomForestClassifier(n_estimators=100, max_depth=6, random_state=42, class_weight={0: 1, 1: 3})

rf_model.fit(X_train, y_train)

# Predictions
y_pred = rf_model.predict(X_test)

# Model Evaluation
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Random Forest Accuracy: 0.8696285506190823
              precision    recall  f1-score   support

         0.0       0.94      0.92      0.93      7303
         1.0       0.44      0.50      0.47       935

    accuracy                           0.87      8238
   macro avg       0.69      0.71      0.70      8238
weighted avg       0.88      0.87      0.87      8238
```

XGBoost

```
# Import XGBoost
from xgboost import XGBClassifier
```

```
from sklearn.metrics import accuracy_score, classification_report

# Train XGBoost model with class weight adjustment (scale_pos_weight handles class imbalance)
xgb_model = XGBClassifier(n_estimators=100, max_depth=6, learning_rate=0.1, scale_pos_weight=3, random_state=42)

# Fit the model to training data
xgb_model.fit(X_train, y_train)

# Make predictions
y_pred_xgb = xgb_model.predict(X_test)

# Evaluate model performance
accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
classification_report_xgb = classification_report(y_test, y_pred_xgb)

# Display results
print("XGBoost Accuracy:", accuracy_xgb)
print("XGBoost Classification Report:\n", classification_report_xgb)
```

```
XGBoost Accuracy: 0.8716921582908473
XGBoost Classification Report:
               precision    recall  f1-score   support

         0.0       0.93      0.92      0.93      7303
         1.0       0.44      0.50      0.47       935

    accuracy                           0.87      8238
   macro avg       0.69      0.71      0.70      8238
weighted avg       0.88      0.87      0.88      8238
```

Cluster Comaprisons

```
bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 55 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   age                           41188 non-null  float64
 1   campaign                      41188 non-null  float64
 2   pdays                         41188 non-null  float64
 3   previous                      41188 non-null  float64
 4   emp.var.rate                  41188 non-null  float64
 5   cons.price.idx                41188 non-null  float64
 6   cons.conf.idx                 41188 non-null  float64
 7   euribor3m                     41188 non-null  float64
 8   nr.employed                   41188 non-null  float64
 9   job_blue-collar               41188 non-null  float64
 10  job_entrepreneur              41188 non-null  float64
 11  job_housemaid                 41188 non-null  float64
 12  job_management                41188 non-null  float64
 13  job_retired                   41188 non-null  float64
 14  job_self-employed             41188 non-null  float64
 15  job_services                  41188 non-null  float64
 16  job_student                   41188 non-null  float64
 17  job_technician                41188 non-null  float64
 18  job_unemployed                41188 non-null  float64
 19  job_unknown                   41188 non-null  float64
 20  marital_married               41188 non-null  float64
 21  marital_single                41188 non-null  float64
 22  marital_unknown               41188 non-null  float64
 23  education_basic.6y            41188 non-null  float64
 24  education_basic.9y            41188 non-null  float64
 25  education_high.school         41188 non-null  float64
 26  education_illiterate          41188 non-null  float64
 27  education_professional.course 41188 non-null  float64
 28  education_university.degree   41188 non-null  float64
 29  education_unknown             41188 non-null  float64
 30  default_unknown               41188 non-null  float64
 31  default_yes                   41188 non-null  float64
 32  housing_unknown               41188 non-null  float64
 33  housing_yes                   41188 non-null  float64
 34  loan_unknown                  41188 non-null  float64
 35  loan_yes                      41188 non-null  float64
 36  contact_telephone             41188 non-null  float64
 37  month_aug                     41188 non-null  float64
```

```
 38  month_dec                       41188 non-null  float64
 39  month_jul                       41188 non-null  float64
 40  month_jun                       41188 non-null  float64
 41  month_mar                       41188 non-null  float64
 42  month_may                       41188 non-null  float64
 43  month_nov                       41188 non-null  float64
 44  month_oct                       41188 non-null  float64
 45  month_sep                       41188 non-null  float64
 46  day_of_week_mon                 41188 non-null  float64
 47  day_of_week_thu                 41188 non-null  float64
 48  day_of_week_tue                 41188 non-null  float64
 49  day_of_week_wed                 41188 non-null  float64
 50  poutcome_nonexistent            41188 non-null  float64
 51  poutcome_success                41188 non-null  float64
 52  y                               41188 non-null  float64
```

```
# Re-run K-Means
#k = 10
#kmeans = KMeans(n_clusters=k, random_state=0)
#bank["Cluster"] = kmeans.fit_predict(X_pca)
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=10, random_state=0, n_init=10)
bank['Cluster'] = kmeans.fit_predict(X_pca)

# Re-run DBSCAN
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=10)
bank['Cluster_DBSCAN'] = dbscan.fit_predict(X_scaled)



print(bank[['Cluster', 'Cluster_DBSCAN']].head())
```

```
   Cluster  Cluster_DBSCAN
0        4               0
1        4               0
2        4               0
3        4               0
4        4               0
```

```
print(bank.columns.tolist())  # Check all column names
```

```
['age', 'campaign', 'pdays', 'previous', 'emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed', 'job
```

```
from sklearn.decomposition import PCA

# Apply PCA to reduce dimensions
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Add principal components to the DataFrame
bank['PC1'] = X_pca[:, 0]
bank['PC2'] = X_pca[:, 1]

# Verify the new columns
print(bank[['PC1', 'PC2']].head())
```

```
        PC1       PC2
0  1.269177 -0.884510
1  1.269026 -0.909010
2  1.272062 -0.419006
3  1.271607 -0.492506
4  1.269177 -0.884510
```

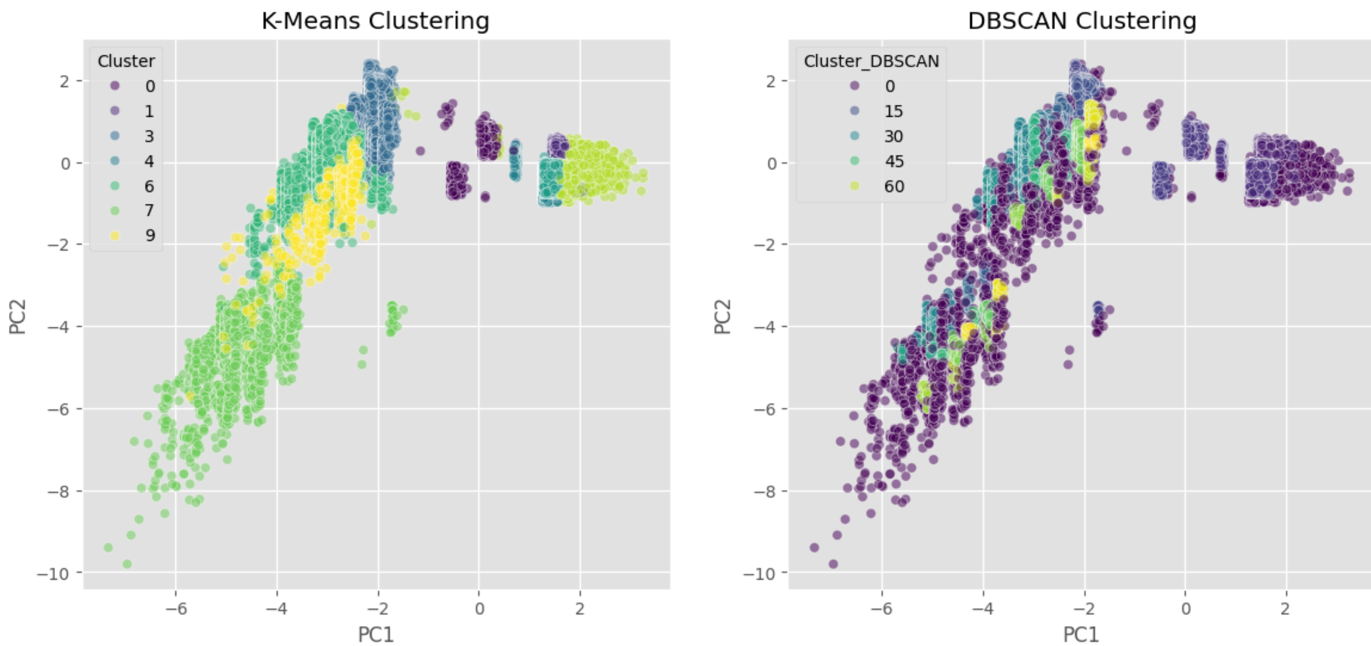
```
import matplotlib.pyplot as plt
import seaborn as sns

# Ensure 'Cluster' and 'Cluster_DBSCAN' exist
if 'Cluster' in bank.columns and 'Cluster_DBSCAN' in bank.columns:
    fig, axes = plt.subplots(1, 2, figsize=(14, 6))

    # K-Means Clustering Scatter Plot
    sns.scatterplot(data=bank, x='PC1', y='PC2', hue='Cluster', palette='viridis', alpha=0.5, ax=axes[0])
    axes[0].set_title("K-Means Clustering")
```

```
    # DBSCAN Clustering Scatter Plot
    sns.scatterplot(data=bank, x='PC1', y='PC2', hue='Cluster_DBSCAN', palette='viridis', alpha=0.5, ax=axes[1])
    axes[1].set_title("DBSCAN Clustering")

    plt.show()
else:
    print("Error: 'Cluster' or 'Cluster_DBSCAN' column is missing from the dataset.")
```



Start coding or generate with AI.

Neural Network

```
from tensorflow.keras.layers import Input
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Define input layer explicitly
autoencoder = Sequential([
    Input(shape=(X_scaled.shape[1],)),  # Proper way to define input shape
    Dense(32, activation='relu'),
    Dense(16, activation='relu'),
    Dense(32, activation='relu'),
    Dense(X_scaled.shape[1], activation='linear')
])



#Training and Extracting Features
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Input
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans, DBSCAN
import matplotlib.pyplot as plt
import seaborn as sns

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)  # Assuming 'X' contains numerical features

# Define Autoencoder
input_layer = Input(shape=(X_scaled.shape[1],))
```

```
encoded = Dense(32, activation='relu')(input_layer)
encoded = Dense(16, activation='relu', name="encoded_layer")(encoded)  # Bottleneck layer
decoded = Dense(32, activation='relu')(encoded)
decoded = Dense(X_scaled.shape[1], activation='linear')(decoded)

autoencoder = Model(inputs=input_layer, outputs=decoded)
autoencoder.compile(optimizer='adam', loss='mse')
autoencoder.fit(X_scaled, X_scaled, epochs=10, batch_size=32, verbose=1)

# Extract Encoded Features
encoder = Model(inputs=autoencoder.input, outputs=autoencoder.get_layer("encoded_layer").output)
X_encoded = encoder.predict(X_scaled)  # Encoded dataset

# Convert to DataFrame
encoded_df = pd.DataFrame(X_encoded, columns=[f'Enc_{i}' for i in range(X_encoded.shape[1])])
```

```
Epoch 1/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.2449
Epoch 2/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0034
Epoch 3/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - loss: 0.0018
Epoch 4/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 0.0012
Epoch 5/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 6s 3ms/step - loss: 7.6503e-04
Epoch 6/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 5.6155e-04
Epoch 7/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 4.7647e-04
Epoch 8/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 6s 3ms/step - loss: 3.2681e-04
Epoch 9/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3.0468e-04
Epoch 10/10
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 6s 3ms/step - loss: 2.1592e-04
1288/1288 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step
```

```
# Clusters
# Apply K-Means Clustering
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
encoded_df['KMeans_Cluster'] = kmeans.fit_predict(X_encoded)

# Apply DBSCAN Clustering
dbscan = DBSCAN(eps=0.5, min_samples=10)
encoded_df['DBSCAN_Cluster'] = dbscan.fit_predict(X_encoded)

# Check cluster distribution
print("K-Means Cluster Counts:\n", encoded_df['KMeans_Cluster'].value_counts())
print("DBSCAN Cluster Counts:\n", encoded_df['DBSCAN_Cluster'].value_counts())
```

```
K-Means Cluster Counts:
 KMeans_Cluster
1    27624
0    11412
2     2152
Name: count, dtype: int64
DBSCAN Cluster Counts:
 DBSCAN_Cluster
0     7715
3     6629
11    5694
4     5160
1     4309
      ...
46      10
33      10
10      10
66      10
```