PRODIGY_DS_03

February 6, 2025

[3]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, accuracy_score,␣
 ↪confusion_matrix, ConfusionMatrixDisplay
```

[6]:
```
bank = pd.read_csv("/content/sample_data/bank.csv")
bank.rename(columns={'y':'deposit'},inplace=True)
bank.head()
```

[6]:
```
   age         job  marital  education default  balance housing loan  contact  \
0   59      admin.  married  secondary      no     2343     yes   no  unknown
1   56      admin.  married  secondary      no       45      no   no  unknown
2   41  technician  married  secondary      no     1270     yes   no  unknown
3   55    services  married  secondary      no     2476     yes   no  unknown
4   54      admin.  married   tertiary      no      184      no   no  unknown

   day month  duration  campaign  pdays  previous poutcome deposit
0    5   may      1042         1     -1         0  unknown     yes
1    5   may      1467         1     -1         0  unknown     yes
2    5   may      1389         1     -1         0  unknown     yes
3    5   may       579         1     -1         0  unknown     yes
4    5   may       673         2     -1         0  unknown     yes
```

[ ]:
```
bank.shape
```

[ ]:
```
(11162, 17)
```

[ ]:
```
bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11162 entries, 0 to 11161
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        11162 non-null  int64
 1   job        11162 non-null  object
 2   marital    11162 non-null  object
 3   education  11162 non-null  object
 4   default    11162 non-null  object
 5   balance    11162 non-null  int64
 6   housing    11162 non-null  object
 7   loan       11162 non-null  object
 8   contact    11162 non-null  object
 9   day        11162 non-null  int64
 10  month      11162 non-null  object
 11  duration   11162 non-null  int64
 12  campaign   11162 non-null  int64
 13  pdays      11162 non-null  int64
 14  previous   11162 non-null  int64
 15  poutcome   11162 non-null  object
 16  deposit    11162 non-null  object
dtypes: int64(7), object(10)
memory usage: 1.4+ MB
```

[ ]:
```
bank.describe()
```

[ ]:
```
                age       balance           day      duration      campaign  \
count  11162.000000  11162.000000  11162.000000  11162.000000  11162.000000
mean      41.231948   1528.538524     15.658036    371.993818      2.508421
std       11.913369   3225.413326      8.420740    347.128386      2.722077
min       18.000000  -6847.000000      1.000000      2.000000      1.000000
25%       32.000000    122.000000      8.000000    138.000000      1.000000
50%       39.000000    550.000000     15.000000    255.000000      2.000000
75%       49.000000   1708.000000     22.000000    496.000000      3.000000
max       95.000000  81204.000000     31.000000   3881.000000     63.000000

              pdays      previous
count  11162.000000  11162.000000
mean      51.330407      0.832557
std      108.758282      2.292007
min       -1.000000      0.000000
25%       -1.000000      0.000000
50%       -1.000000      0.000000
75%       20.750000      1.000000
max      854.000000     58.000000
```

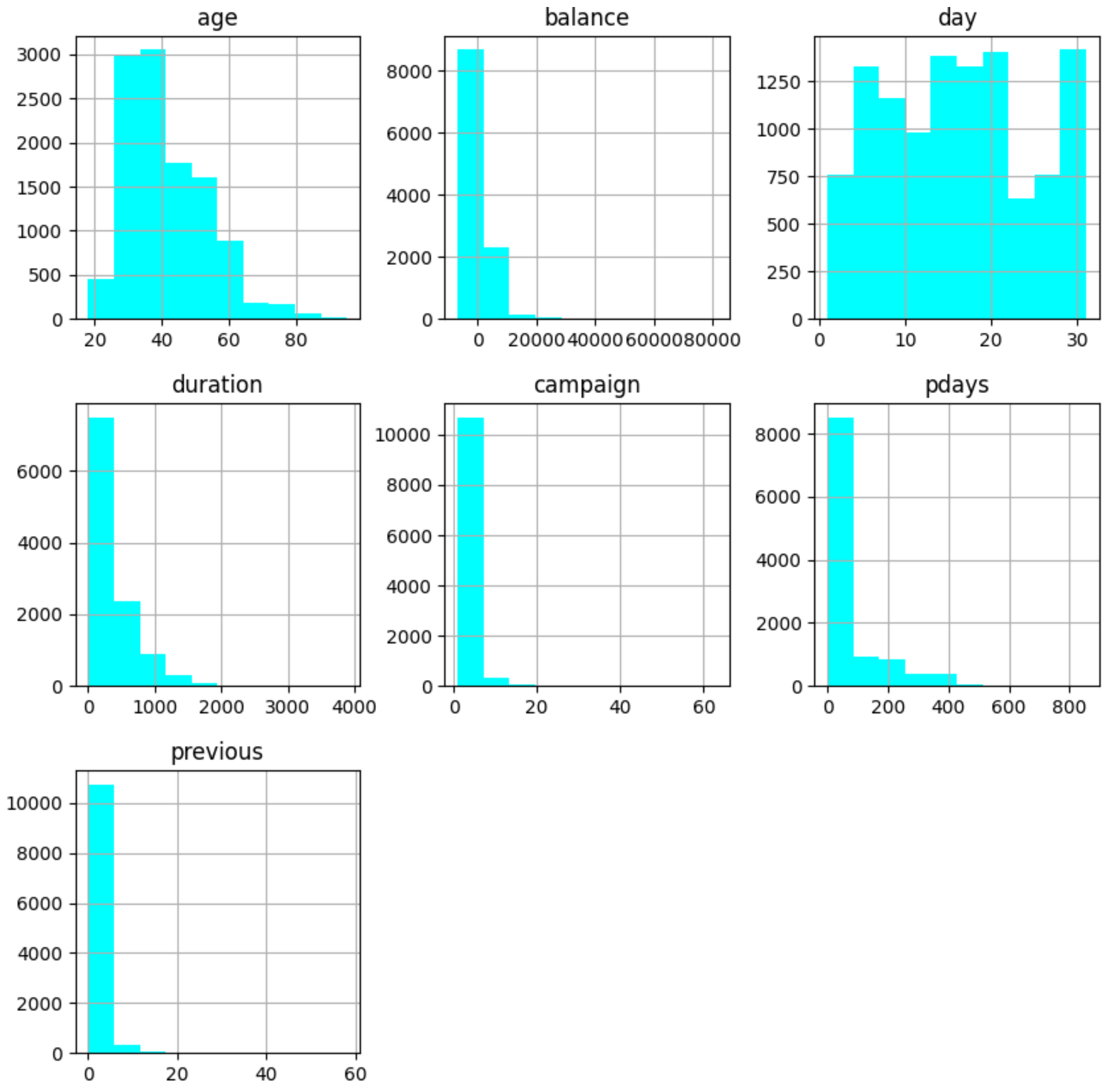
[ ]:
```
bank.isnull().sum()
```

[ ]:

```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
deposit      0
dtype: int64
```

[8]:

```
bank.hist(figsize=(10,10),color='#00FFFF')
plt.show()
```



[17]:

```
#calculate the number of riws and columns for subplots
cat_cols = bank.select_dtypes(include=['object']).columns # Define cat_cols here
num_plots = len(cat_cols)
num_rows =(num_plots+1)//2
num_cols = 2
#create a new figure
plt.figure(figsize=(20, 25)) #Adjust the figure size as needed

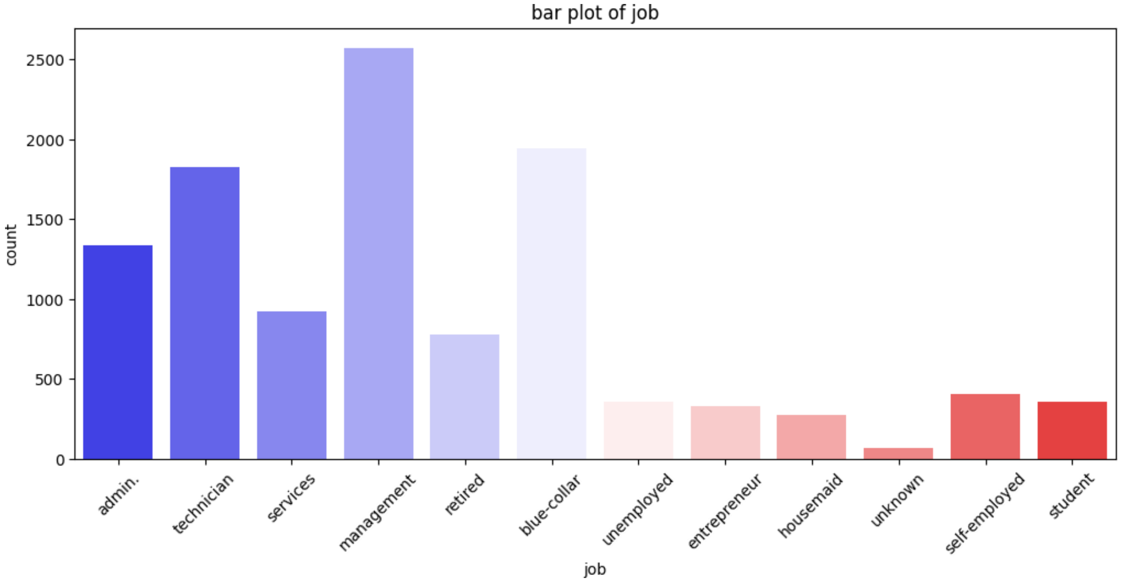
#loop through each features and create a countplot
for i,features in enumerate(cat_cols,1):
  plt.subplot(num_rows, num_cols, i) # Corrected 'sublpot' to 'subplot'
  sns.countplot(x=features,  data=bank,palette='bwr')
  plt.title(f'bar plot of {features}') # Changed 'feature' to 'features'
plt.xlabel(features) # Changed 'feature' to 'features'
plt.ylabel('count')
plt.xticks(rotation=45)

#Adjust layout to prevent overlap of subplots
plt.tight_layout()
plt.show()
```

```
<ipython-input-17-30ce9b68cb8c>:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(x=features, data=bank,palette='bwr')
```



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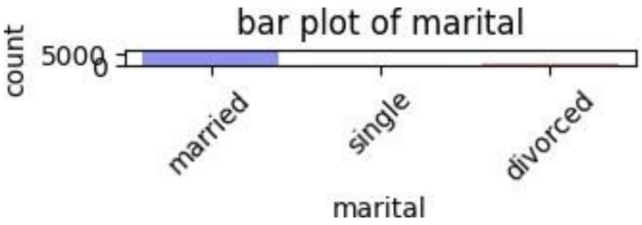

```
<ipython-input-17-30ce9b68cb8c>:12: FutureWarning:

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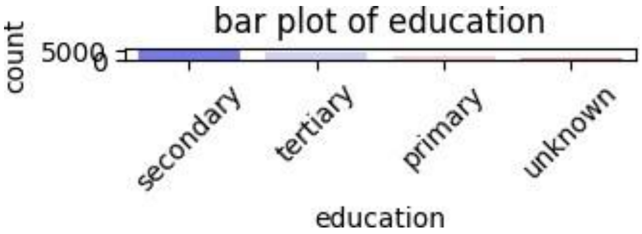
```



```
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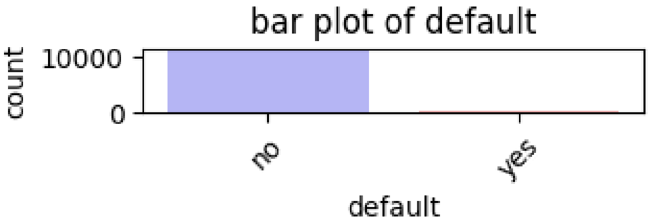

```
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```

```
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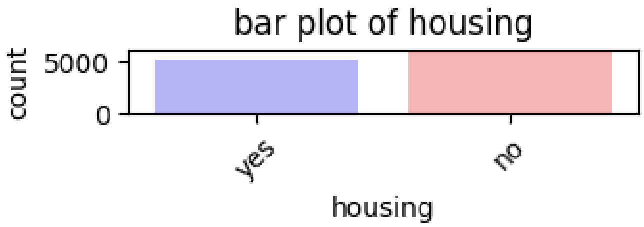
```



```
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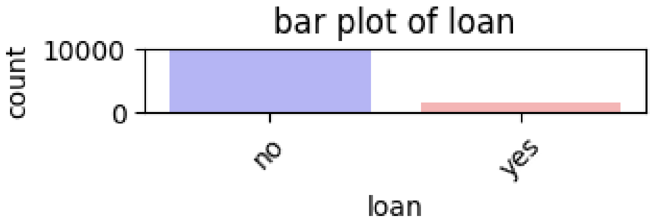
```



```
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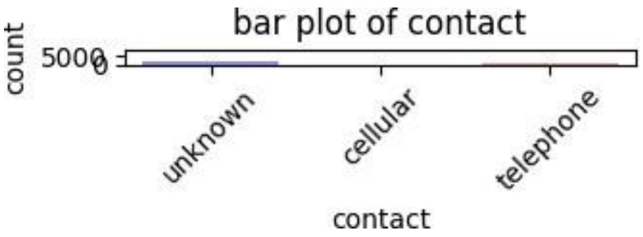
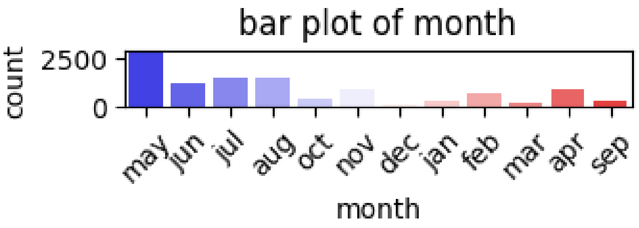
```



```
<ipython-input-17-30ce9b68cb8c>:12: FutureWarning: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

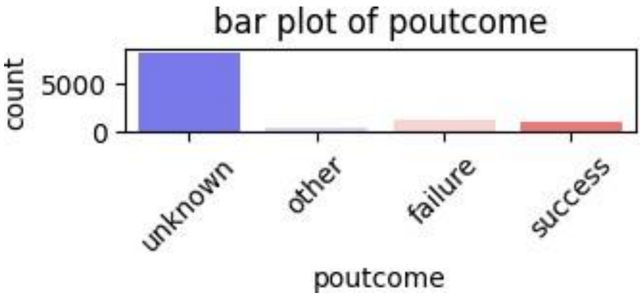
  sns.countplot(x=features, data=bank,palette='bwr')
```



```
<ipython-input-17-30ce9b68cb8c>:12: FutureWarning: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(x=features, data=bank,palette='bwr')
```



```
<ipython-input-17-30ce9b68cb8c>:12: FutureWarning:

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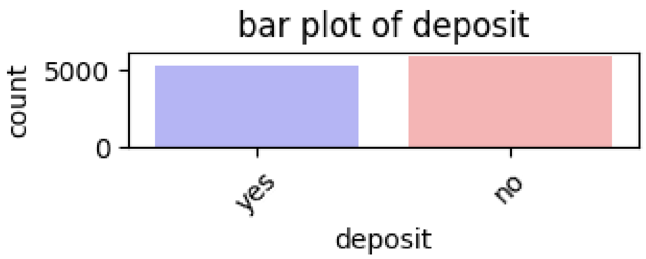
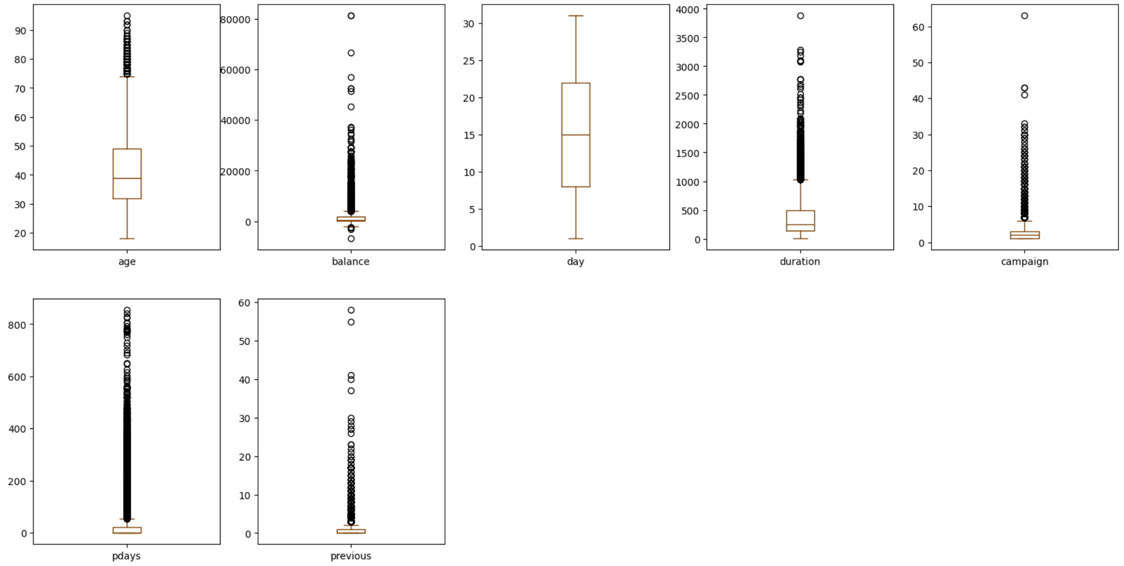
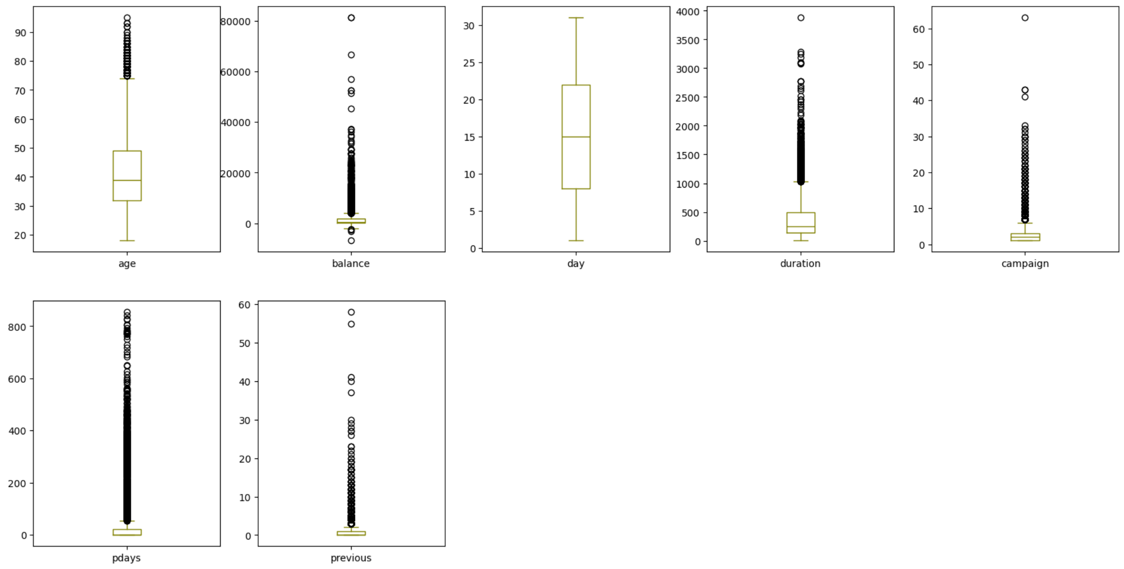
  sns.countplot(x=features, data=bank,palette='bwr')
```



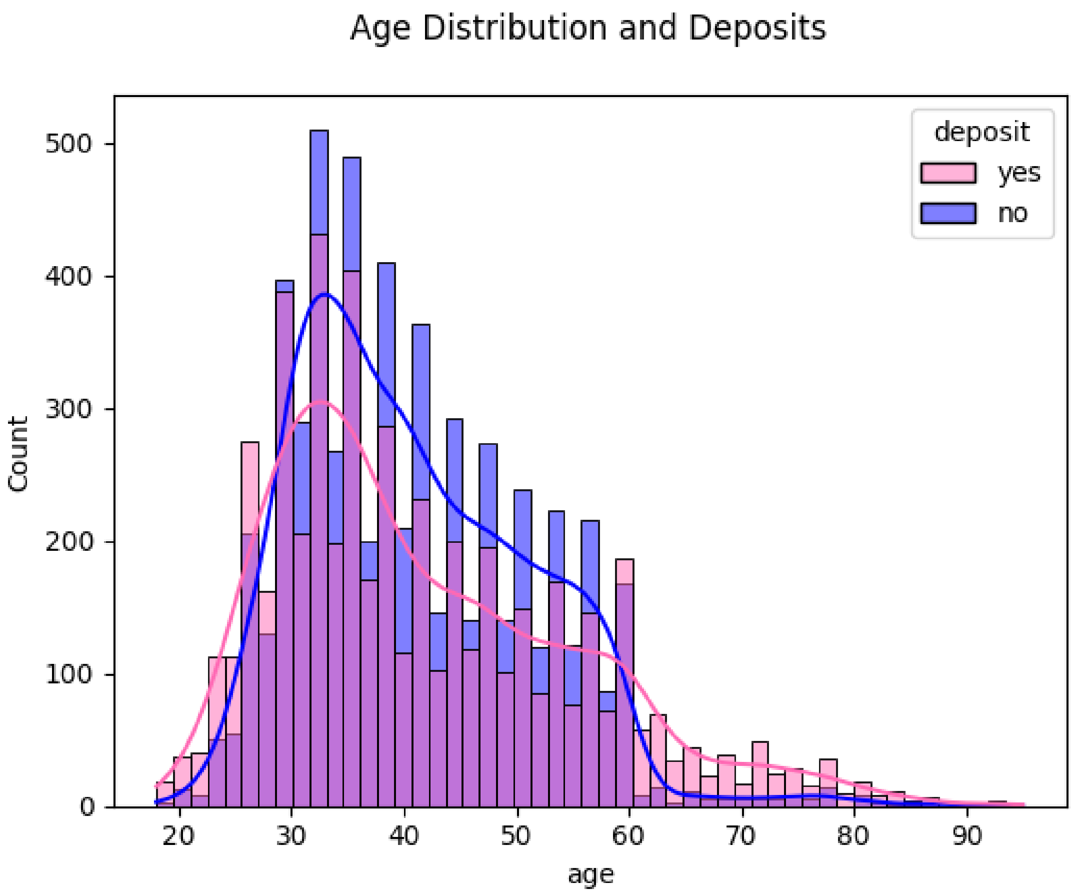
[19]:
```
bank.plot(kind='box', subplots=True, layout=(2, 5), figsize=(20, 10),␣
  ↪color='#7b3f00')
plt.show()
```



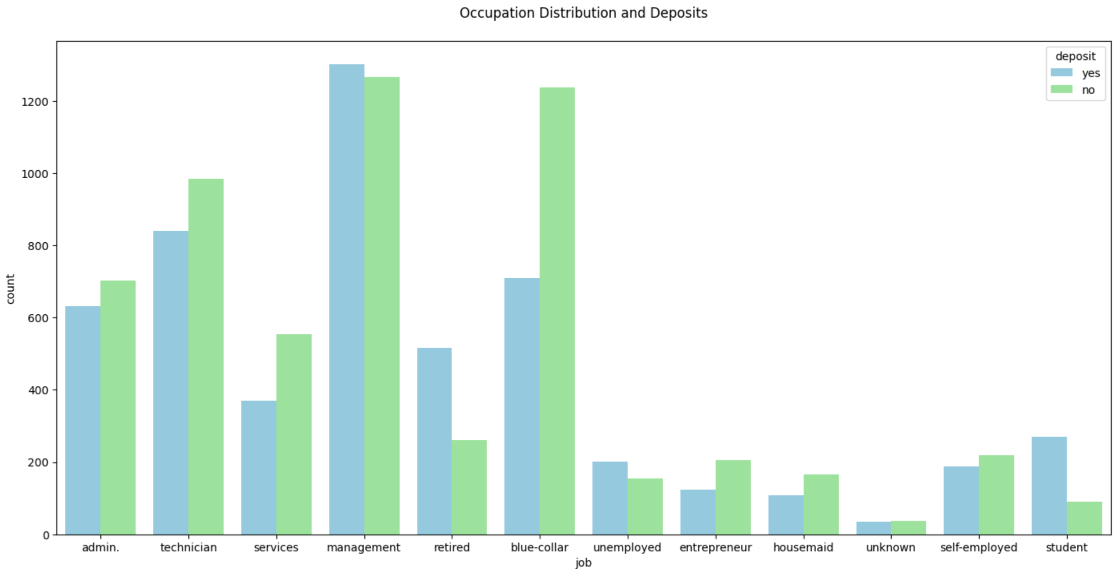
[20]:
```
bank.plot(kind='box', subplots=True, layout=(2, 5), figsize=(20, 10),␣
  ↪color='#808000')
plt.show()
```



```
[ ]: sns.histplot(x="age", data=bank, kde=True, hue="deposit", palette=["hotpink", "blue"])
     plt.title("Age Distribution and Deposits\n")
     plt.show()
```

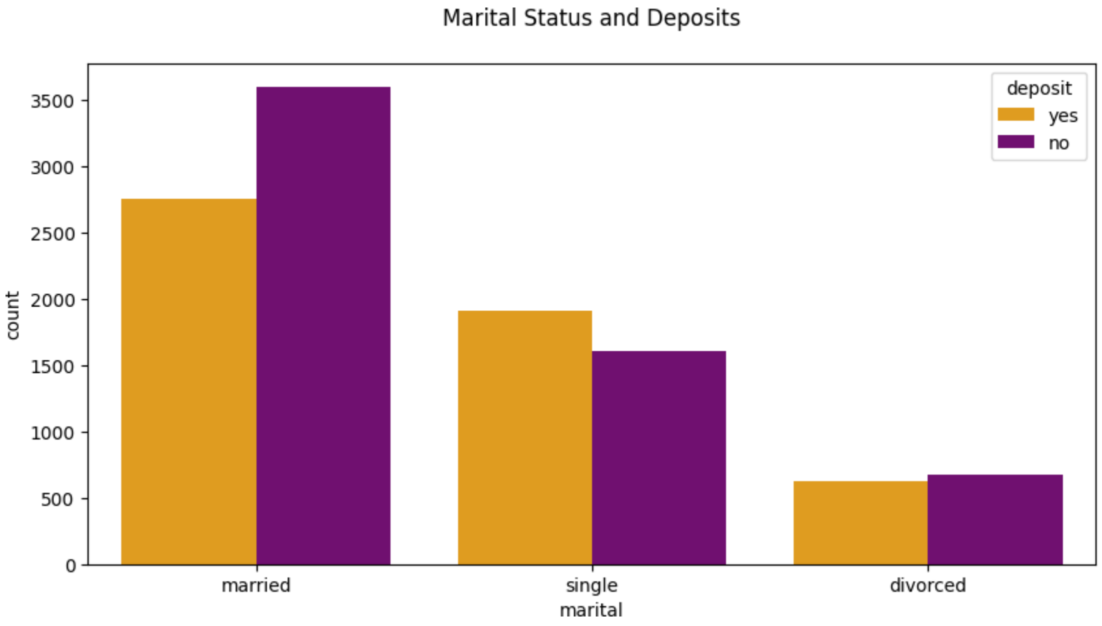


[ ]:
```
plt.figure(figsize=(17,8))
sns.countplot(x="job", data=bank, hue="deposit",␣
 ↪palette=["skyblue","lightgreen"]) # Change 'y' to 'deposit'
plt.title("Occupation Distribution and Deposits\n")
plt.show()
```



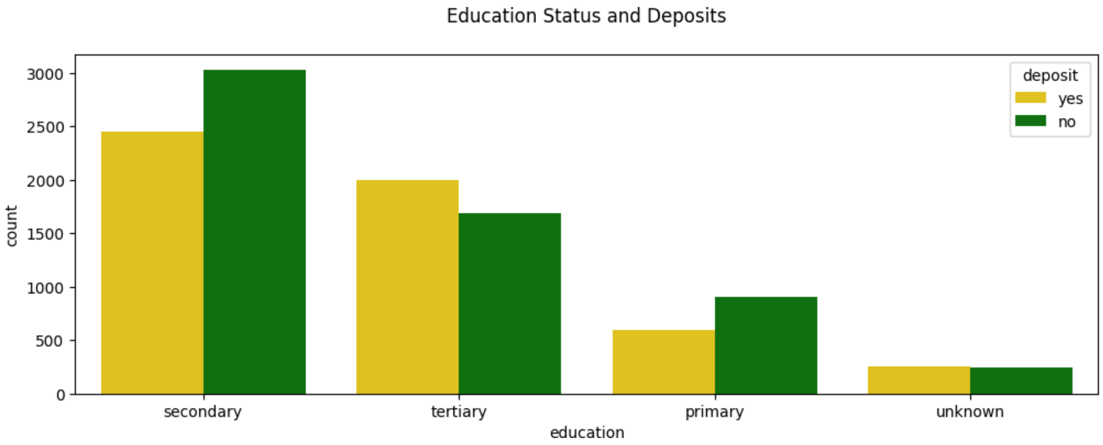
[ ]:

```
plt.figure(figsize=(10,5))
sns.countplot(x="marital", data= bank, hue ="deposit", palette =␣
 ↪["orange","purple"]) # Change 'y' to 'deposit'
plt.title("Marital Status and Deposits\n")
plt.show()
```



[ ]:

```
plt.figure(figsize=(12,4))
sns.countplot(x="education", data= bank, hue ="deposit", palette =␣
↪["gold","green"]) # Changed 'y' to 'deposit'
plt.title("Education Status and Deposits\n")
plt.show()
```



[ ]:

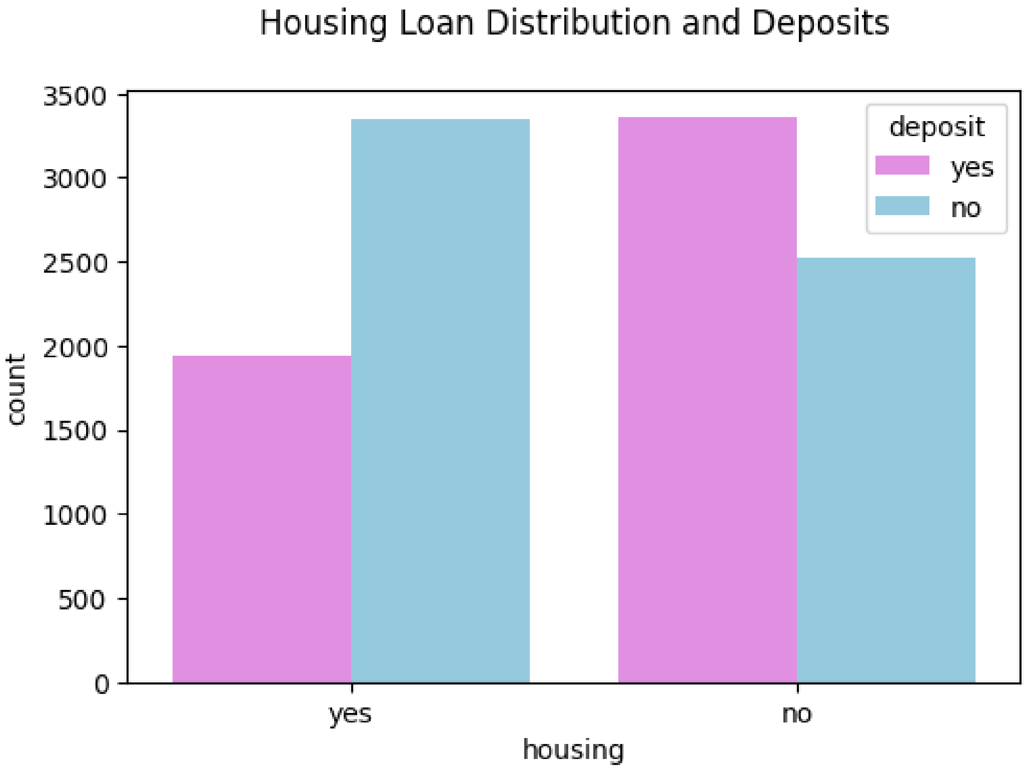
```
bank.default.value_counts()
```

[ ]:

```
default
no       10994
yes        168
Name: count, dtype: int64
```

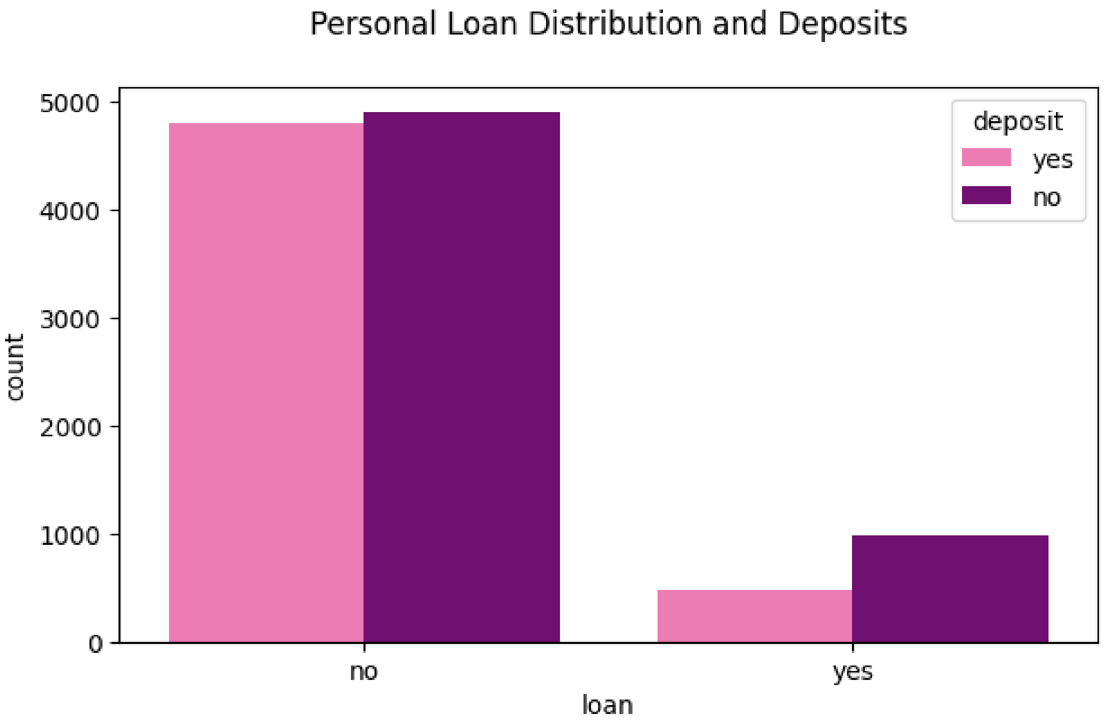
[ ]:

```
plt.figure(figsize=(6,4))
sns.countplot(x="housing", data=bank, hue="deposit",␣
↪palette=["violet","skyblue"]) # Change 'y' to 'deposit'
plt.title("Housing Loan Distribution and Deposits\n")
plt.show()
```



[ ]:

```
plt.figure(figsize=(7,4))
sns.countplot(x="loan", data= bank, hue ="deposit", palette = ["hotpink","purple"]) # Changed 'y' to 'deposit'
plt.title("Personal Loan Distribution and Deposits\n")
plt.show()
```



[ ]:

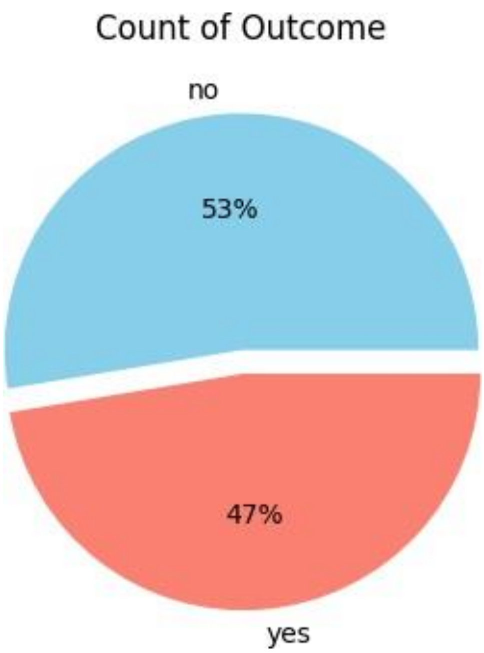
```python
# Count of Outcome
counts = bank['deposit'].value_counts() # Change 'y' to 'deposit'
keys = counts.index
data = counts.values

# Custom colors for the pie chart
colors = ['skyblue', 'salmon']

# Create the pie chart with custom colors
plt.figure(figsize=(8, 4))
explode = [0, 0.1]
plt.pie(data, labels=keys, explode=explode, autopct='%.0f%%', colors=colors)

# Add title
plt.title('Count of Outcome')

# Show the plot
plt.show()
```


Count of Outcome

```
[ ]: cols = bank.select_dtypes("object").columns
     cols
```

```
[ ]: Index(['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact',
            'month', 'poutcome', 'deposit'],
           dtype='object')
```

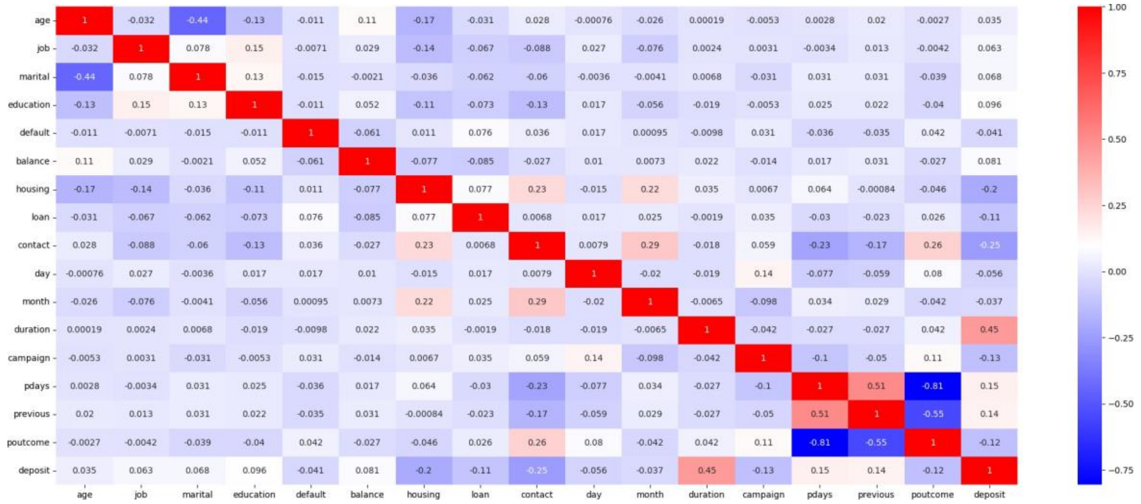
```
[ ]: le = LabelEncoder()

     bank[cols] = bank[cols].apply(le.fit_transform)
     bank.head(5)
```

```
[ ]:    age  job  marital  education  default  balance  housing  loan  contact  \
     0   59    0        1          1        0     2343        1     0        2
     1   56    0        1          1        0       45        0     0        2
     2   41    9        1          1        0     1270        1     0        2
     3   55    7        1          1        0     2476        1     0        2
     4   54    0        1          2        0      184        0     0        2

        day  month  duration  campaign  pdays  previous  poutcome  deposit
     0    5      8      1042         1     -1         0         3        1
     1    5      8      1467         1     -1         0         3        1
     2    5      8      1389         1     -1         0         3        1
     3    5      8       579         1     -1         0         3        1
     4    5      8       673         2     -1         0         3        1
```

```
[ ]: plt.figure(figsize=(25,10))
     sns.heatmap(bank.corr(), cmap='bwr', annot=True)
     plt.show()
```



```
[ ]: #Splitting input and output
     X = bank.drop("deposit", axis=1)
     y = bank.deposit

     # Initialize the StandardScaler
     scaler = StandardScaler()

     # Standardize the features
     X_scaled = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)

     # Describe the scaled features
     description = X_scaled.describe()
     print(description)
```

```
                age           job       marital     education       default  \
count  1.116200e+04  1.116200e+04  1.116200e+04  1.116200e+04  1.116200e+04
mean   2.749995e-16  4.074067e-17  6.874988e-17 -6.620359e-17  4.074067e-17
std    1.000045e+00  1.000045e+00  1.000045e+00  1.000045e+00  1.000045e+00
min   -1.950161e+00 -1.391604e+00 -1.917331e+00 -1.714823e+00 -1.236166e-01
25%   -7.749580e-01 -1.081525e+00 -3.186719e-01 -3.805006e-01 -1.236166e-01
50%   -1.873565e-01 -1.512891e-01 -3.186719e-01 -3.805006e-01 -1.236166e-01
75%    6.520742e-01  7.789471e-01  1.279987e+00  9.538215e-01 -1.236166e-01
max    4.513455e+00  2.019262e+00  1.279987e+00  2.288144e+00  8.089529e+00

            balance       housing          loan       contact           day  \
count  1.116200e+04  1.116200e+04  1.116200e+04  1.116200e+04  1.116200e+04
```

```
mean  1.018517e-17 -1.018517e-16 -5.092584e-18  1.018517e-16 -2.037033e-17
std   1.000045e+00  1.000045e+00  1.000045e+00  1.000045e+00  1.000045e+00
min  -2.596850e+00 -9.476162e-01 -3.879232e-01 -5.981494e-01 -1.740784e+00
25%  -4.360996e-01 -9.476162e-01 -3.879232e-01 -5.981494e-01 -9.094664e-01
50%  -3.033975e-01 -9.476162e-01 -3.879232e-01 -5.981494e-01 -7.814820e-02
75%   5.564233e-02  1.055280e+00 -3.879232e-01  6.233185e-01  7.531699e-01
max   2.470351e+01  1.055280e+00  2.577830e+00  1.844786e+00  1.822008e+00

              month      duration      campaign         pdays      previous  \
count  1.116200e+04  1.116200e+04  1.116200e+04  1.116200e+04  1.116200e+04
mean  -1.374998e-16  8.148134e-17  3.055550e-17  5.092584e-18 -2.037033e-17
std    1.000045e+00  1.000045e+00  1.000045e+00  1.000045e+00  1.000045e+00
min   -1.706158e+00 -1.065918e+00 -5.541683e-01 -4.811841e-01 -3.632598e-01
25%   -7.662483e-01 -6.741146e-01 -5.541683e-01 -4.811841e-01 -3.632598e-01
50%    1.736612e-01 -3.370484e-01 -1.867854e-01 -4.811841e-01 -3.632598e-01
75%    8.002676e-01  3.572503e-01  1.805976e-01 -2.811903e-01  7.305850e-02
max    1.740177e+00  1.010912e+01  2.222358e+01  7.380638e+00  2.494320e+01

           poutcome
count  1.116200e+04
mean   1.324072e-16
std    1.000045e+00
min   -2.470600e+00
25%   -4.763969e-01
50%    5.207046e-01
75%    5.207046e-01
max    5.207046e-01
```

[ ]:

```
train_X, test_X, train_y, test_y = train_test_split(X_scaled, y, test_size=0.3)

decision_tree = DecisionTreeClassifier()
decision_tree.fit(train_X,  train_y)
```

[ ]:

```
DecisionTreeClassifier()
```

[ ]:

```
print('Train Score: {}'.format(decision_tree.score(train_X, train_y)))
print('Test Score: {}'.format(decision_tree.score(test_X, test_y)))
```

```
Train Score: 1.0
Test Score: 0.7930725589728277
```

[ ]:

```
cross_val_score(decision_tree, train_X, train_y, cv=5).mean()
```

[ ]:

```
0.7783178217797448
```

[ ]:

```
ypred = decision_tree.predict(test_X)
print(classification_report(test_y,ypred))
```

```
              precision    recall  f1-score   support

           0       0.81      0.80      0.80      1774
           1       0.78      0.79      0.78      1575

    accuracy                           0.79      3349
   macro avg       0.79      0.79      0.79      3349
weighted avg       0.79      0.79      0.79      3349
```

```
[ ]: param_grid = {
         'max_depth': [3, 5, 7,10, None],
         'criterion' : ['gini', 'entropy'],
         'min_samples_leaf': [3, 5, 7, 9,10,20]
         }

     gscv = GridSearchCV(decision_tree, param_grid, cv=5, verbose=1)
     gscv.fit(train_X,    train_y)
```

```
Fitting 5 folds for each of 60 candidates, totalling 300 fits
```

```
[ ]: GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
                  param_grid={'criterion': ['gini', 'entropy'],
                              'max_depth': [3, 5, 7, 10, None],
                              'min_samples_leaf': [3, 5, 7, 9, 10, 20]},
                  verbose=1)
```

```
[ ]: clf = DecisionTreeClassifier(criterion= 'gini', max_depth= 5, min_samples_leaf␣
      ↪= 3)
     clf.fit(train_X, train_y)
```

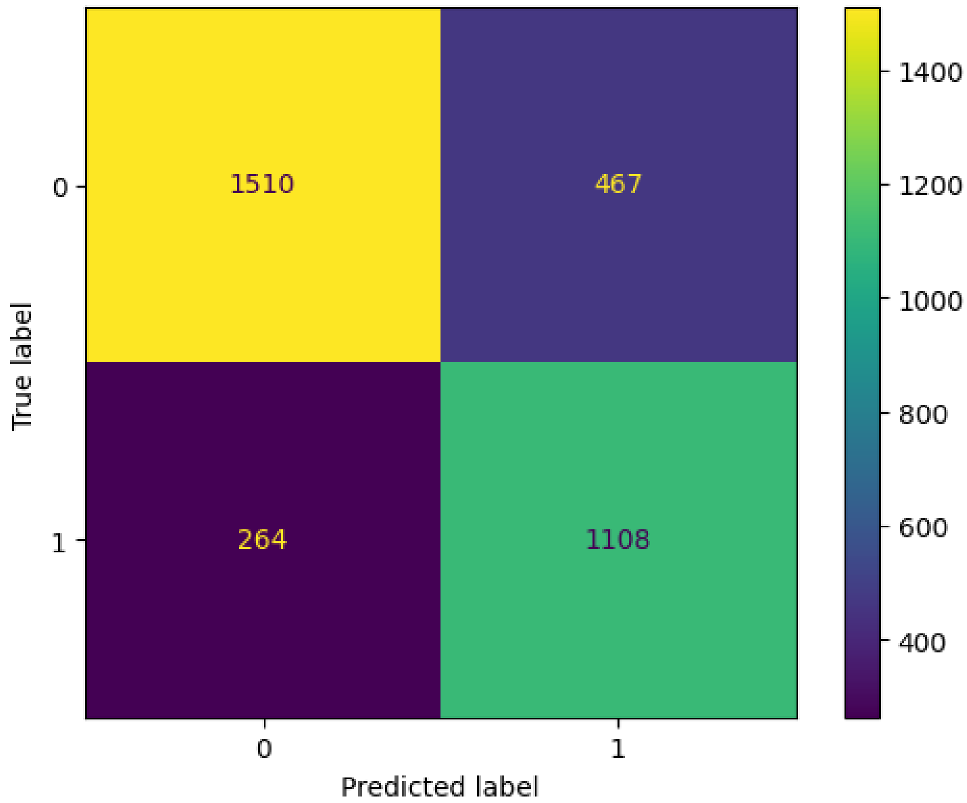
```
[ ]: DecisionTreeClassifier(max_depth=5, min_samples_leaf=3)
```

```
[ ]: print('Train Score: {}'.format(clf.score(train_X, train_y)))
     print('Test Score: {}'.format(clf.score(test_X, test_y)))
```

```
Train Score: 0.7979009343402023
Test Score: 0.7817258883248731
```

```
[ ]: pred_y = clf.predict(test_X)
```

```
[ ]: cm = confusion_matrix(pred_y, test_y)
     ConfusionMatrixDisplay(cm, display_labels=clf.classes_).plot()
     plt.show()
```



```
[ ]: print(classification_report(pred_y, test_y))
```

```
              precision    recall  f1-score   support

           0       0.85      0.76      0.81      1977
           1       0.70      0.81      0.75      1372

    accuracy                           0.78      3349
   macro avg       0.78      0.79      0.78      3349
weighted avg       0.79      0.78      0.78      3349
```

```
[ ]: accuracy = accuracy_score(test_y,pred_y)
     print("Test Accuracy of Decision Tree Classifier : {}".format(accuracy*100))
```

```
Test Accuracy of Decision Tree Classifier : 78.1725888324873
```

```
[ ]: Cross_val = cross_val_score(clf, test_X,test_y, cv=5).mean()
     print("Cross-Validation Accuracy Scores Decision Tree : ",Cross_val*100)
```

```
Cross-Validation Accuracy Scores Decision Tree :  79.72536421033844
```

[ ]:

```
from sklearn import tree

# Convert the Index object to a list
feature_names = list(X.columns)

# Plot the decision tree
fig = plt.figure(figsize=(20, 18))
t = tree.plot_tree(clf, filled=True, feature_names=feature_names)

# Show the plot
plt.show()
```