PYTHON ASSIGNMENT

Problem Statement: Trade Reporting data Analysis

You have been given a dataset containing Regulatory trade reports for a financial institution. malikjb35/pythonTest (github.com)

Problem 1

1. Exploratory Data Analysis and provide insight from the data: Conduct analysis on the dataset to gather insights and generate relevant statistics.
2. Data Visualization: Create visualizations to present the results of the data analysis.
3. Reporting: Generate a summary report that presents the findings from the data analysis and visualizations. Include key insights.

Problem 2

- Perform required data standardisation and normalization activities.
- Find Association, correlation among columns in above dataset.
- Find categorical features from this dataset for a classification model(use reporting status column as target vector if needed)
- Implement the encoding strategy for such identified columns.
- Group similar transaction together and identify no of such similar group.

Problem 1 Solution :

1. Exploratory Data Analysis and provide insight from the data: Conduct analysis on the dataset to gather insights and generate relevant statistics

In [95]:
```
# Import the libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [96]:
```
# Load the dataset
data = pd.read_csv("D:/USER/SREE/Jupyter Notebook Workspace/Assignments/Trade R
```

```
C:\Users\SREEPARNA\anaconda3\lib\site-packages\IPython\core\interactiveshell.
py:3444: DtypeWarning: Columns (15) have mixed types.Specify dtype option on
import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

In [97]:
```
# Check Dimension of the data
print(data.shape)
```

```
(50000, 26)
```

In [98]:
```
# View the first few rows of the dataset
print(data.head())
```

```
   tradeId regulator  version assetClass                   clDateTime  \
0        1      SEBI        1         FX  2023-07-18T11:47:26.075000Z
1        2      SEBI        9         FX  2023-08-02T03:12:48.207000Z
2        3      SEBI        8         FX  2023-05-09T07:42:36.475000Z
3        4      SEBI        1         FX  2023-10-01T05:02:54.209000Z
4        5      SEBI        1         FX  2023-01-23T20:53:01.076000Z

   clStatus   cflag  eFlag                    cDateTime         method  ...
\
0      True   FULLY  False  2023-12-10T07:37:58.548000Z  NonElectronic  ...
1     False   FULLY  False  2023-10-03T22:32:10.991000Z   NotConfirmed  ...
2     False   FULLY  False  2023-03-09T20:32:31.302000Z  NonElectronic  ...
3     False   FULLY   True  2023-11-21T06:53:09.983000Z     Electronic  ...
4      True  ONEWAY  False  2023-08-05T17:06:08.895000Z     Electronic  ...

   seller                      endDate     sType  Product        price  \
0  Party1  2023-05-26T05:23:44.110000Z      Cash     Swap          NaN
1  Party2  2023-07-23T23:43:15.460000Z      Cash     Swap          NaN
2  Party2  2023-08-08T11:13:43.217000Z  Physical     Swap          NaN
3  Party2  2023-07-31T19:30:37.266000Z      Cash  forward  91773.25433
4  Party1  2023-12-04T19:38:57.326000Z      Cash     Swap          NaN

               terminationDate   party PartyId transactionType  \
0  2023-07-02T04:01:17.940000Z  PartyZ       1            EXIT
1  2023-08-15T13:25:45.442000Z  PartyX       4            EXIT
2  2023-07-07T02:03:20.354000Z  PartyX       4           TRADE
3  2023-08-02T04:55:34.632000Z  PartyK       2           TRADE
4  2023-02-08T06:49:44.186000Z  PartyX       4           TRADE

   Reporting Status
0        Failed Ack
1               ACK
2  Processing Error
3      Acknowledged
4      Acknowledged

[5 rows x 26 columns]
```

In [99]:
```
# Summary statistics
print(data.describe())
```

```
            tradeId       version          rate          price       PartyId
count  50000.000000  50000.000000  50000.000000   15014.000000  50000.000000
mean   25000.500000      4.991940   4985.640510  502292.898972      3.163600
std    14433.901067      2.593339   2892.605229  288205.734165      1.342919
min        1.000000      1.000000      0.630700     108.503208      1.000000
25%    12500.750000      3.000000   2473.364300  253646.139675      2.000000
50%    25000.500000      5.000000   4988.018500  501724.834200      3.000000
75%    37500.250000      7.000000   7484.013200  751081.198725      4.000000
max    50000.000000      9.000000   9999.865100  999940.821500      5.000000
```

In [100]:
```
# Check for missing values
print(data.isnull().sum())
```

```
tradeId                0
regulator              0
version                0
assetClass             0
clDateTime             0
clStatus               0
cflag                  0
eFlag                  0
cDateTime              0
method                 0
rate                   0
expirationDate         0
eventT                 0
mType                  0
Timestamp              0
quantity               0
seller                 0
endDate                0
sType                  0
Product                0
price              34986
terminationDate     6209
party                  0
PartyId                0
transactionType        0
Reporting Status       0
dtype: int64
```

In [101]:
```
# Impute missing values for 'price' column with the median value
median_price = data['price'].median()
data['price'].fillna(median_price, inplace=True)
```

In [102]:
```
# Impute missing values for terminationDate column with a placeholder value
data['terminationDate'].fillna(data['terminationDate'].mode()[0], inplace=True
```

In [103]:
```
# Check again for missing values
print(data.isnull().sum())
```

```
tradeId             0
regulator           0
version             0
assetClass          0
clDateTime          0
clStatus            0
cflag               0
eFlag               0
cDateTime           0
method              0
rate                0
expirationDate      0
eventT              0
mType               0
Timestamp           0
quantity            0
seller              0
endDate             0
sType               0
Product             0
price               0
terminationDate     0
party               0
PartyId             0
transactionType     0
Reporting Status    0
dtype: int64
```

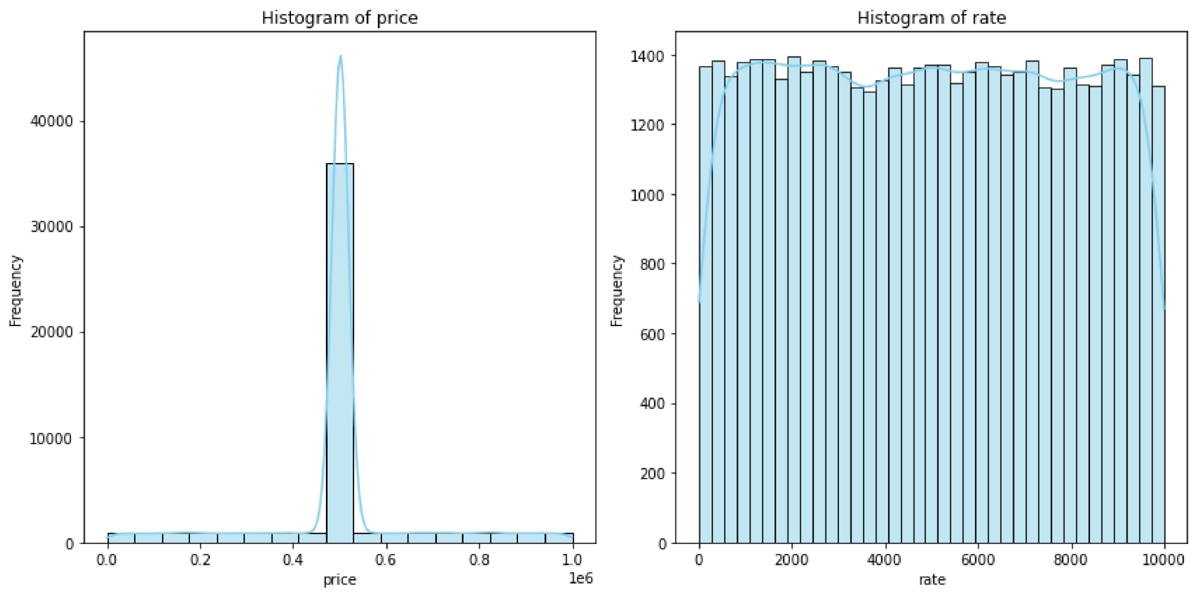
In [104]:
```
# Again summarize the statistics
print(data.describe())
```

```
            tradeId       version          rate          price       PartyId
count  50000.000000  50000.000000  50000.000000   50000.000000  50000.000000
mean   25000.500000      4.991940   4985.640510  501895.412690      3.163600
std    14433.901067      2.593339   2892.605229  157926.965540      1.342919
min        1.000000      1.000000      0.630700     108.503208      1.000000
25%    12500.750000      3.000000   2473.364300  501724.834200      2.000000
50%    25000.500000      5.000000   4988.018500  501724.834200      3.000000
75%    37500.250000      7.000000   7484.013200  501724.834200      4.000000
max    50000.000000      9.000000   9999.865100  999940.821500      5.000000
```

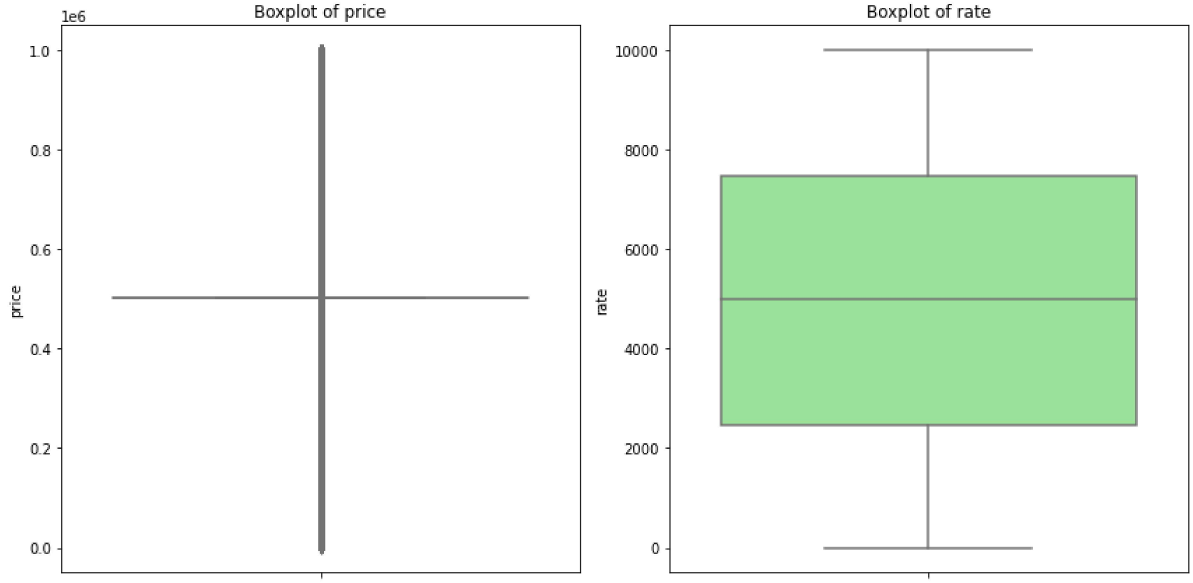
2. Data Visualization: Create visualizations to present the results of the data analysis.

In [105]:
```
# Select numerical features for analysis
numerical_features = ['price','rate']
```

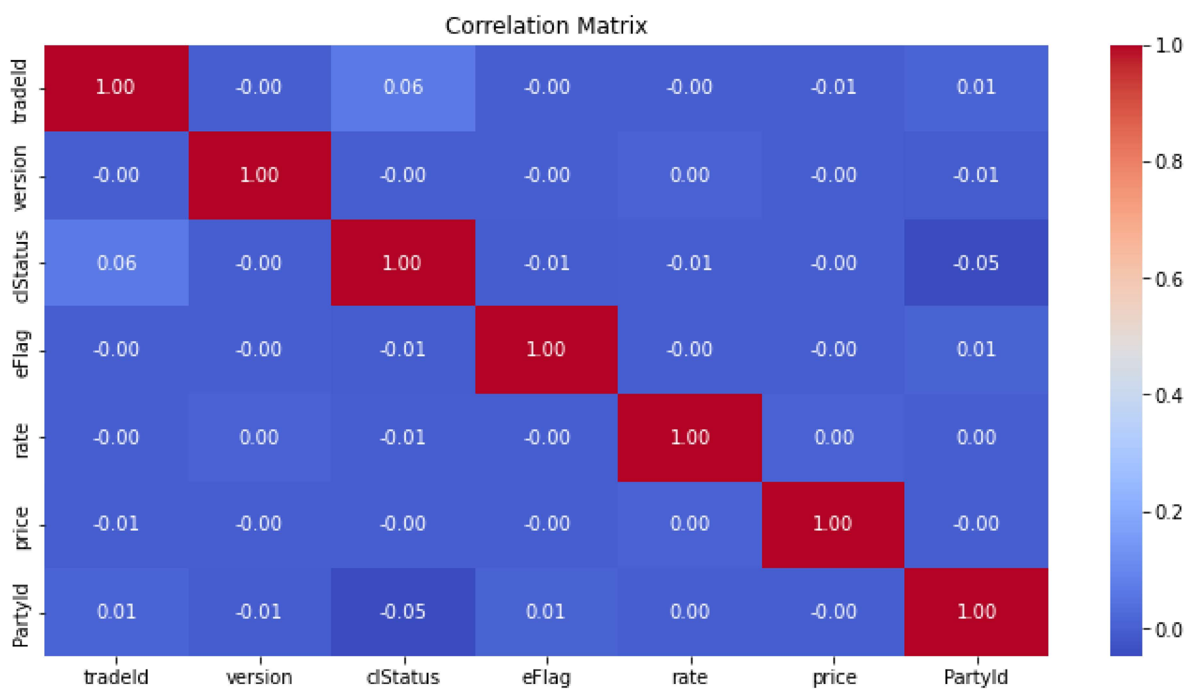
In [107]:
```python
# Visualization 1: Plot Histograms for numerical features
plt.figure(figsize=(12,6))
for i, feature in enumerate(numerical_features,1):
    plt.subplot(1,len(numerical_features),i)
    sns.histplot(data[feature], kde=True, color='skyblue')
    plt.title(f'Histogram of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



In [108]:
```python
# Visualization 2: Plot box plots for numerical features
plt.figure(figsize=(12, 6))
for i, feature in enumerate(numerical_features, 1):
    plt.subplot(1, len(numerical_features), i)
    sns.boxplot(data=data, y=feature, color='lightgreen')
    plt.title(f'Boxplot of {feature}')
    plt.ylabel(feature)
plt.tight_layout()
plt.show()
```



In [109]:
```python
# Visualization 3: Explore relationships between variables using correlation ar
plt.figure(figsize=(12, 6))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix")
plt.show()
```



	tradeId	version	dStatus	eFlag	rate	price	PartyId
tradeId	1.00	-0.00	0.06	-0.00	-0.00	-0.01	0.01
version	-0.00	1.00	-0.00	-0.00	0.00	-0.00	-0.01
dStatus	0.06	-0.00	1.00	-0.01	-0.01	-0.00	-0.05
eFlag	-0.00	-0.00	-0.01	1.00	-0.00	-0.00	0.01
rate	-0.00	0.00	-0.01	-0.00	1.00	0.00	0.00
price	-0.01	-0.00	-0.00	-0.00	0.00	1.00	-0.00
PartyId	0.01	-0.01	-0.05	0.01	0.00	-0.00	1.00

In [110]:
```
# Visualization 4: Distribution of trade statuses
plt.figure(figsize=(12, 6))
sns.countplot(x='clStatus', data=data)
plt.title('Distribution of Trade Statuses')
plt.xlabel('Trade Status')
plt.ylabel('Count')
plt.show()
```

3. Reporting: Generate a summary report that presents the findings from the data analysis and visualizations. Include key insights.

In [94]:
```python
# Summary report
summary_report = """
Summary Report:

1. Asset Class Distribution:
   - Most common asset class: {asset_class_common}
   - Least common asset class: {asset_class_least}

2. Transaction Type Distribution:
   - Most common transaction type: {transaction_type_common}
   - Least common transaction type: {transaction_type_least}

3. Price Analysis:
   - Average price: ${average_price:.2f}
   - Maximum price: ${max_price:.2f}
   - Minimum price: ${min_price:.2f}

4. Missing Values Handling:
   - Price column: Filled missing values with median
   - TerminationDate column: Filled missing values with mode

5. Count of Transactions by Asset Class:
        {asset_class_counts}

6. Distribution of Trade Statuses:
        {trade_status_counts}

"""

# Calculate statistics
average_price = data['price'].mean()
max_price = data['price'].max()
min_price = data['price'].min()
asset_class_common = data['assetClass'].mode()[0]
asset_class_least = data['assetClass'].value_counts().idxmin()
transaction_type_common = data['transactionType'].mode()[0]
transaction_type_least = data['transactionType'].value_counts().idxmin()
asset_class_counts = data['assetClass'].value_counts()
trade_status_counts=data['clStatus'].value_counts()

# Print summary report
print(summary_report.format(
    asset_class_common=asset_class_common,
    asset_class_least=asset_class_least,
    transaction_type_common=transaction_type_common,
    transaction_type_least=transaction_type_least,
    average_price=average_price,
    max_price=max_price,
    min_price=min_price,
    asset_class_counts=asset_class_counts,
    trade_status_counts=trade_status_counts
))
```

```
Summary Report:

1. Asset Class Distribution:
   - Most common asset class: FX
   - Least common asset class: FX

2. Transaction Type Distribution:
   - Most common transaction type: TRADE
   - Least common transaction type: Exit

3. Price Analysis:
   - Average price: $501895.41
   - Maximum price: $999940.82
   - Minimum price: $108.50

4. Missing Values Handling:
   - Price column: Filled missing values with median
   - TerminationDate column: Filled missing values with mode

5. Count of Transactions by Asset Class:
        FX    50000
Name: assetClass, dtype: int64

6. Distribution of Trade Statuses:
        True     26684
False    23316
Name: clStatus, dtype: int64
```

Problem 2 Solution :

- Perform required data standardisation and normalization activities.
- Find Association, correlation among columns in above dataset.
- Find categorical features from this dataset for a classification model(use reporting status column as target vector if needed)
- Implement the encoding strategy for such identified columns.
- Group similar transaction together and identify no of such similar group.

In [119]:
```python
# Import the libraries
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder
from sklearn.feature_selection import chi2
from itertools import combinations
from sklearn.preprocessing import OneHotEncoder
import numpy as np
import category_encoders as ce
```

In [113]:
```
# Data Standardization and Normalization
scaler = StandardScaler()
data_scaled = data.copy()
num_cols=data_scaled.select_dtypes(include=['float64','int64']).columns
data_scaled[num_cols]=scaler.fit_transform(data_scaled[num_cols])
```

In [134]:
```
# Check data types of each column
print(data.select_dtypes(include=['object']).dtypes)
```

```
regulator          object
assetClass         object
clDateTime         object
cflag              object
cDateTime          object
method             object
expirationDate     object
eventT             object
mType              object
Timestamp          object
quantity           object
seller             object
endDate            object
sType              object
Product            object
terminationDate    object
party              object
transactionType    object
dtype: object
```

In [137]:
```
# Association Analysis
association_matrix = np.zeros((len(data.columns), len(data.columns)))
for i, j in combinations(range(len(data.columns)), 2):
    if data.iloc[:, i].dtype == 'O' and data.iloc[:, j].dtype == 'O':
        chi2_stat, _ = chi2(data.iloc[:, i].fillna('NA').to_numpy().reshape(-1,
        association_matrix[i, j] = chi2_stat
        association_matrix[j, i] = chi2_stat

print("Association Matrix:")
print(association_matrix)
```

In [149]:
```
# Correlation Analysis
correlation_matrix = data_scaled.corr()

# Display result
print("\nCorrelation Matrix:")
print(correlation_matrix)
```

```

Correlation Matrix:
           tradeId   version  clStatus     eFlag      rate     price   PartyI
d
tradeId   1.000000 -0.002102  0.063872 -0.000457 -0.000581 -0.005098  0.01053
6
version  -0.002102  1.000000 -0.002921 -0.001846  0.003418 -0.002838 -0.00917
8
clStatus  0.063872 -0.002921  1.000000 -0.007996 -0.006058 -0.001147 -0.04748
3
eFlag    -0.000457 -0.001846 -0.007996  1.000000 -0.000535 -0.003193  0.00937
6
rate     -0.000581  0.003418 -0.006058 -0.000535  1.000000  0.003067  0.00078
1
price    -0.005098 -0.002838 -0.001147 -0.003193  0.003067  1.000000 -0.00046
7
PartyId   0.010536 -0.009178 -0.047483  0.009376  0.000781 -0.000467  1.00000
0
```

In [150]:
```
# Categorical Feature Identification
categorical_features = data.select_dtypes(include=['object']).columns.tolist()

# Display Results
print("\nCategorical Features:", categorical_features)
```

```

Categorical Features: ['regulator', 'assetClass', 'clDateTime', 'cflag', 'cDa
teTime', 'method', 'expirationDate', 'eventT', 'mType', 'Timestamp', 'quantit
y', 'seller', 'endDate', 'sType', 'Product', 'terminationDate', 'party', 'tra
nsactionType']
```

In [151]:
```
# Encoding Strategy Implementation
data_encoded = data.copy()
label_encoders = {}
for feature in categorical_features:
    le = LabelEncoder()
    data_encoded[feature] = le.fit_transform(data_encoded[feature])
    label_encoders[feature] = le

print("\nEncoded DataFrame:")
print(data_encoded)
```

```
Encoded DataFrame:
       tradeId  regulator  version  assetClass  clDateTime  clStatus  cflag  \
0            1          0        1           0       27209      True      1
1            2          0        9           0       29230     False      1
2            3          0        8           0       17571     False      1
3            4          0        1           0       37351     False      1
4            5          0        1           0        3196      True      2
...        ...        ...      ...         ...         ...       ...    ...
49995    49996          0        8           0       25309     False      2
49996    49997          0        2           0       33429     False      1
49997    49998          0        8           0       40644     False      5
49998    49999          0        2           0       37216      True      2
49999    50000          0        5           0       40767     False      3

       eFlag  cDateTime  method  ...  seller  endDate  sType  Product  \
0      False      46888       6  ...       0    19837      0        2
1      False      37735       7  ...       1    27946      0        2
2      False       9409       6  ...       1    30000      1        2
3       True      44258       1  ...       1    28937      0        3
4      False      29585       1  ...       0    46069      0        2
...      ...        ...     ...  ...     ...      ...    ...      ...
49995  False      13678       1  ...       0    48919      0        2
49996  False      46436       1  ...       0    19263      1        2
49997   True      43033       6  ...       1     2750      0        2
49998   True       8555       1  ...       0     3111      1        2
49999   True      46806       3  ...       0    39600      0        2

              price  terminationDate  party  PartyId  transactionType  \
0      501724.83420            21943      4        1                0
1      501724.83420            27234      2        4                0
2      501724.83420            22535      2        4                2
3       91773.25433            25685      0        2                2
4      501724.83420             4572      2        4                2
...             ...              ...    ...      ...              ...
49995  501724.83420            42982      2        4                0
49996  501724.83420            18105      2        4                2
49997  501724.83420            21609      4        1                0
49998  501724.83420            19112      1        3                0
49999  501724.83420                0      3        5                0

       Reporting Status
0                     3
1                     0
2                     6
3                     1
4                     1
...                 ...
49995                 5
49996                 5
49997                 5
49998                 0
49999                 2

[50000 rows x 26 columns]
```

In [152]:
```python
# Grouping Similar Transactions
similar_groups = data.groupby(['assetClass', 'transactionType']).size().reset_i

# Display results
print("\nSimilar Transaction Groups:")
print(similar_groups)
```

```
Similar Transaction Groups:
  assetClass transactionType  count
0         FX            EXIT  24366
1         FX            Exit      1
2         FX           TRADE  25633
```

In [153]:
```python
# Summary report2
summary_report2 = """
Summary Report2 :

1. Association Matrix:
   {association_matrix}

2. Correlation Matrix:
   {correlation_matrix}

3. Categorical Feature:
   {categorical_features}

4. Encoded Dataframe:
   {data_encoded}

5. Similar Transaction Groups:
   {similar_groups}


"""



# Print summary report2
print(summary_report2.format(
    association_matrix=association_matrix,
    correlation_matrix=correlation_matrix,
    categorical_features=categorical_features,
    data_encoded=data_encoded,
    similar_groups=similar_groups
))
```

```

Summary Report2 :

1. Association Matrix:
   [[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0.
  0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0.]
```

In [ ]: