Step 1: Dataset Loading

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
import pandas as pd
df = pd.read_csv("sales_data_sample.csv", encoding="latin1")
```

In [3]:
```
df.head()
```

Out[3]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDEF
0	10107	30	95.70	2	2871.00	2/24
1	10121	34	81.35	5	2765.90	5/7
2	10134	41	94.74	2	3884.34	7/1
3	10145	45	83.26	6	3746.70	8/25
4	10159	49	100.00	14	5205.27	10/10

5 rows × 25 columns

In [4]:
```
df.tail()
```

Out[4]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	OR
2818	10350	20	100.00	15	2244.40	
2819	10373	29	100.00	1	3978.51	
2820	10386	43	100.00	4	5417.57	
2821	10397	34	62.24	1	2116.16	
2822	10414	47	65.52	9	3079.44	

5 rows × 25 columns

In [5]:
```
df.shape
```

Out[5]:
```
(2823, 25)
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['ORDERNUMBER', 'QUANTITYORDERED', 'PRICEEACH', 'ORDERLINENUMBER',
       'SALES', 'ORDERDATE', 'STATUS', 'QTR_ID', 'MONTH_ID', 'YEAR_ID',
       'PRODUCTLINE', 'MSRP', 'PRODUCTCODE', 'CUSTOMERNAME', 'PHONE',
       'ADDRESSLINE1', 'ADDRESSLINE2', 'CITY', 'STATE', 'POSTALCODE',
       'COUNTRY', 'TERRITORY', 'CONTACTLASTNAME', 'CONTACTFIRSTNAME',
       'DEALSIZE'],
      dtype='object')
```

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2823 entries, 0 to 2822
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   ORDERNUMBER       2823 non-null   int64  
 1   QUANTITYORDERED   2823 non-null   int64  
 2   PRICEEACH         2823 non-null   float64
 3   ORDERLINENUMBER   2823 non-null   int64  
 4   SALES             2823 non-null   float64
 5   ORDERDATE         2823 non-null   object 
 6   STATUS            2823 non-null   object 
 7   QTR_ID            2823 non-null   int64  
 8   MONTH_ID          2823 non-null   int64  
 9   YEAR_ID           2823 non-null   int64  
 10  PRODUCTLINE       2823 non-null   object 
 11  MSRP              2823 non-null   int64  
 12  PRODUCTCODE       2823 non-null   object 
 13  CUSTOMERNAME      2823 non-null   object 
 14  PHONE             2823 non-null   object 
 15  ADDRESSLINE1      2823 non-null   object 
 16  ADDRESSLINE2      302 non-null    object 
 17  CITY              2823 non-null   object 
 18  STATE             1337 non-null   object 
 19  POSTALCODE        2747 non-null   object 
 20  COUNTRY           2823 non-null   object 
 21  TERRITORY         1749 non-null   object 
 22  CONTACTLASTNAME   2823 non-null   object 
 23  CONTACTFIRSTNAME  2823 non-null   object 
 24  DEALSIZE          2823 non-null   object 
dtypes: float64(2), int64(7), object(16)
memory usage: 551.5+ KB
```

Step 2: Data Cleaning and Preprocessing

In [8]:

```
df.isnull().sum()
```

Out[8]:
```
ORDERNUMBER            0
QUANTITYORDERED        0
PRICEEACH              0
ORDERLINENUMBER        0
SALES                  0
ORDERDATE              0
STATUS                 0
QTR_ID                 0
MONTH_ID               0
YEAR_ID                0
PRODUCTLINE            0
MSRP                   0
PRODUCTCODE            0
CUSTOMERNAME           0
PHONE                  0
ADDRESSLINE1           0
ADDRESSLINE2        2521
CITY                   0
STATE               1486
POSTALCODE            76
COUNTRY                0
TERRITORY           1074
CONTACTLASTNAME        0
CONTACTFIRSTNAME       0
DEALSIZE               0
dtype: int64
```

In [9]:
```
df['ADDRESSLINE2'] = df['ADDRESSLINE2'].fillna("Unknown")
df['POSTALCODE'] = df['POSTALCODE'].fillna("Unknown")
df['TERRITORY'] = df['TERRITORY'].fillna("Unknown")
```

In [10]:
```
df.duplicated().sum()
```

Out[10]:
```
np.int64(0)
```

In [11]:
```
df['ORDERDATE'] = pd.to_datetime(df['ORDERDATE'])
```

In [12]:
```
df['COUNTRY'] = df['COUNTRY'].str.title()
df['STATUS'] = df['STATUS'].str.title()
df['DEALSIZE'] = df['DEALSIZE'].str.title()
```

In [13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2823 entries, 0 to 2822
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype         
---  ------            --------------  -----         
 0   ORDERNUMBER       2823 non-null   int64         
 1   QUANTITYORDERED   2823 non-null   int64         
 2   PRICEEACH         2823 non-null   float64       
 3   ORDERLINENUMBER   2823 non-null   int64         
 4   SALES             2823 non-null   float64       
 5   ORDERDATE         2823 non-null   datetime64[ns]
 6   STATUS            2823 non-null   object        
 7   QTR_ID            2823 non-null   int64         
 8   MONTH_ID          2823 non-null   int64         
 9   YEAR_ID           2823 non-null   int64         
 10  PRODUCTLINE       2823 non-null   object        
 11  MSRP              2823 non-null   int64         
 12  PRODUCTCODE       2823 non-null   object        
 13  CUSTOMERNAME      2823 non-null   object        
 14  PHONE             2823 non-null   object        
 15  ADDRESSLINE1      2823 non-null   object        
 16  ADDRESSLINE2      2823 non-null   object        
 17  CITY              2823 non-null   object        
 18  STATE             1337 non-null   object        
 19  POSTALCODE        2823 non-null   object        
 20  COUNTRY           2823 non-null   object        
 21  TERRITORY         2823 non-null   object        
 22  CONTACTLASTNAME   2823 non-null   object        
 23  CONTACTFIRSTNAME  2823 non-null   object        
 24  DEALSIZE          2823 non-null   object        
dtypes: datetime64[ns](1), float64(2), int64(7), object(15)
memory usage: 551.5+ KB
```

Step 3: Exploratory Data Analysis (EDA)

In [14]:
```
df.describe()
```

Out[14]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SAL
count	2823.000000	2823.000000	2823.000000	2823.000000	2823.0000
mean	10258.725115	35.092809	83.658544	6.466171	3553.8890
min	10100.000000	6.000000	26.880000	1.000000	482.1300
25%	10180.000000	27.000000	68.860000	3.000000	2203.4300
50%	10262.000000	35.000000	95.700000	6.000000	3184.8000
75%	10333.500000	43.000000	100.000000	9.000000	4508.0000
max	10425.000000	97.000000	100.000000	18.000000	14082.8000
std	92.085478	9.741443	20.174277	4.225841	1841.8651

In [15]:

```
df['STATUS'].value_counts()
```

Out[15]:

```
STATUS
Shipped       2617
Cancelled       60
Resolved        47
On Hold         44
In Process      41
Disputed        14
Name: count, dtype: int64
```

In [16]:

```
df.groupby('COUNTRY')['SALES'].sum().sort_values(ascending=False)
```

Out[16]:
```
COUNTRY
Usa            3627982.83
Spain          1215686.92
France         1110916.52
Australia       630623.10
Uk              478880.46
Italy           374674.31
Finland         329581.91
Norway          307463.70
Singapore       288488.41
Denmark         245637.15
Canada          224078.56
Germany         220472.09
Sweden          210014.21
Austria         202062.53
Japan           188167.81
Switzerland     117713.56
Belgium         108412.62
Philippines      94015.73
Ireland          57756.43
Name: SALES, dtype: float64
```

In [17]:
```
df.groupby('PRODUCTLINE')['SALES'].sum().sort_values(ascending=False)
```

Out[17]:
```
PRODUCTLINE
Classic Cars        3919615.66
Vintage Cars        1903150.84
Motorcycles         1166388.34
Trucks and Buses    1127789.84
Planes               975003.57
Ships                714437.13
Trains               226243.47
Name: SALES, dtype: float64
```

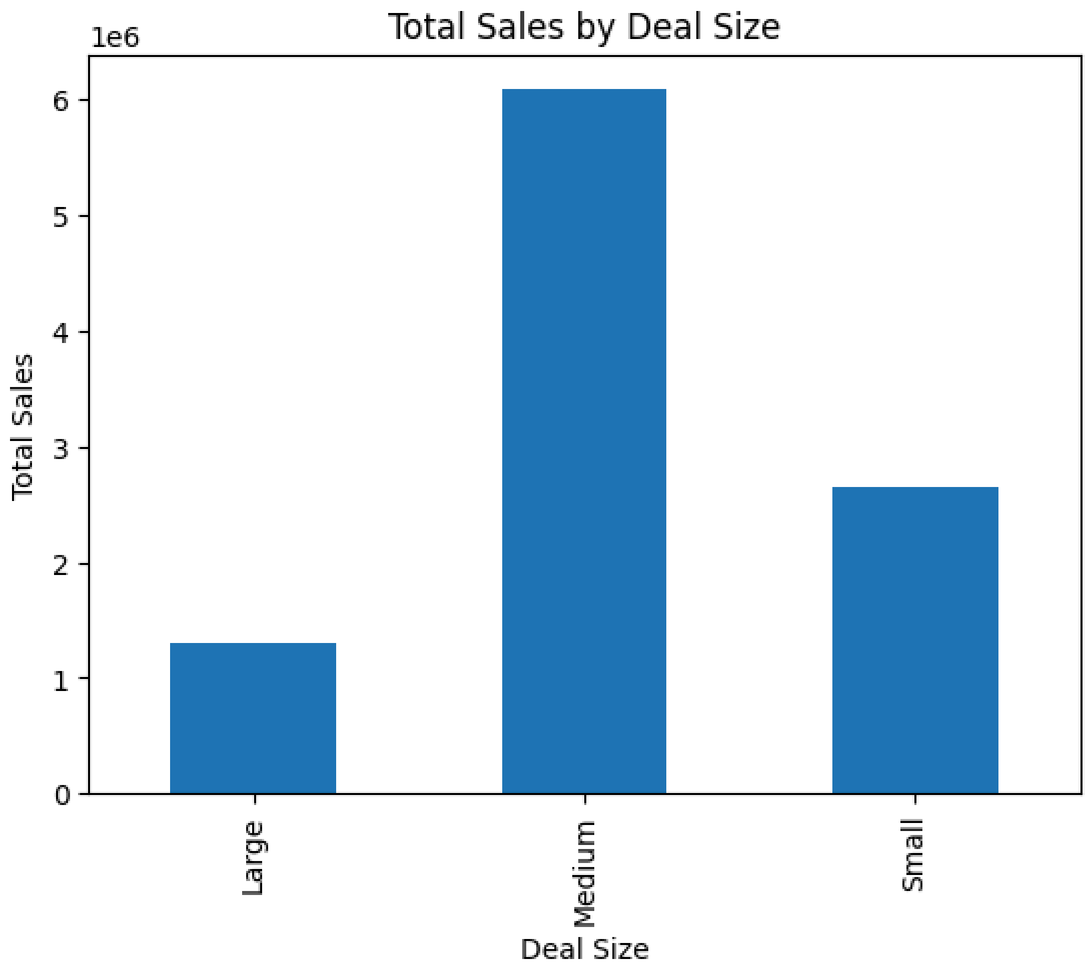
In [18]:
```
df[['SALES','QUANTITYORDERED','PRICEEACH']].corr()
```

Out[18]:

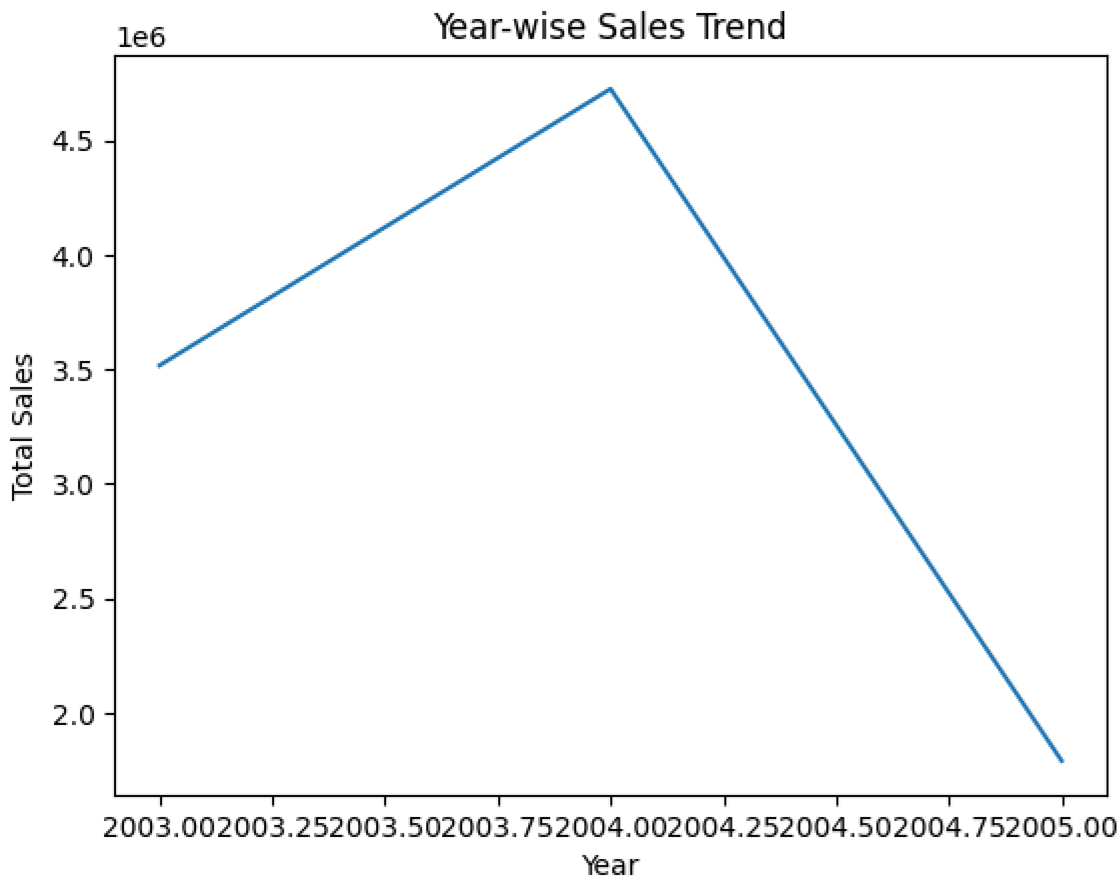
	SALES	QUANTITYORDERED	PRICEEACH
SALES	1.000000	0.551426	0.657841
QUANTITYORDERED	0.551426	1.000000	0.005564
PRICEEACH	0.657841	0.005564	1.000000

Step 4: Data Visualization

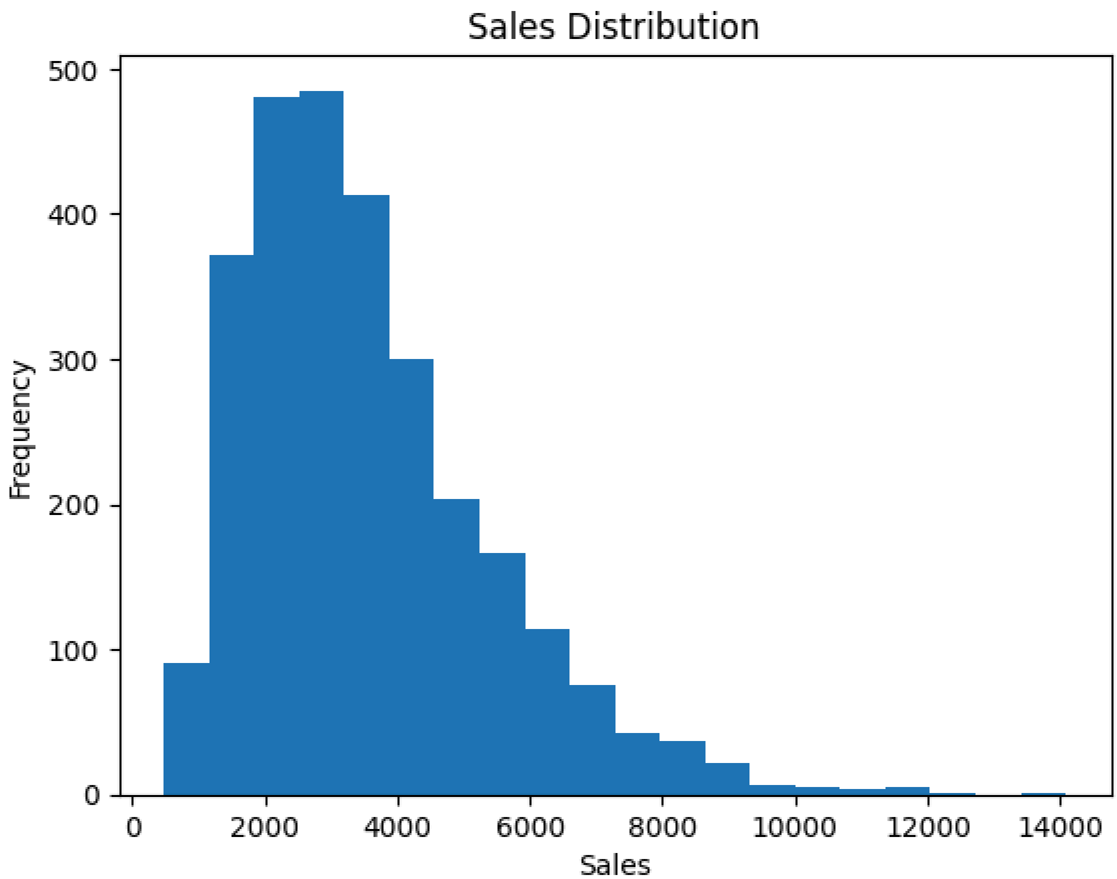
In [19]:
```
df.groupby('DEALSIZE')['SALES'].sum().plot(kind='bar')
plt.title("Total Sales by Deal Size")
plt.xlabel("Deal Size")
plt.ylabel("Total Sales")
plt.show()
```



In [20]:
```
df.groupby('YEAR_ID')['SALES'].sum().plot(kind='line')
plt.title("Year-wise Sales Trend")
plt.xlabel("Year")
plt.ylabel("Total Sales")
plt.show()
```

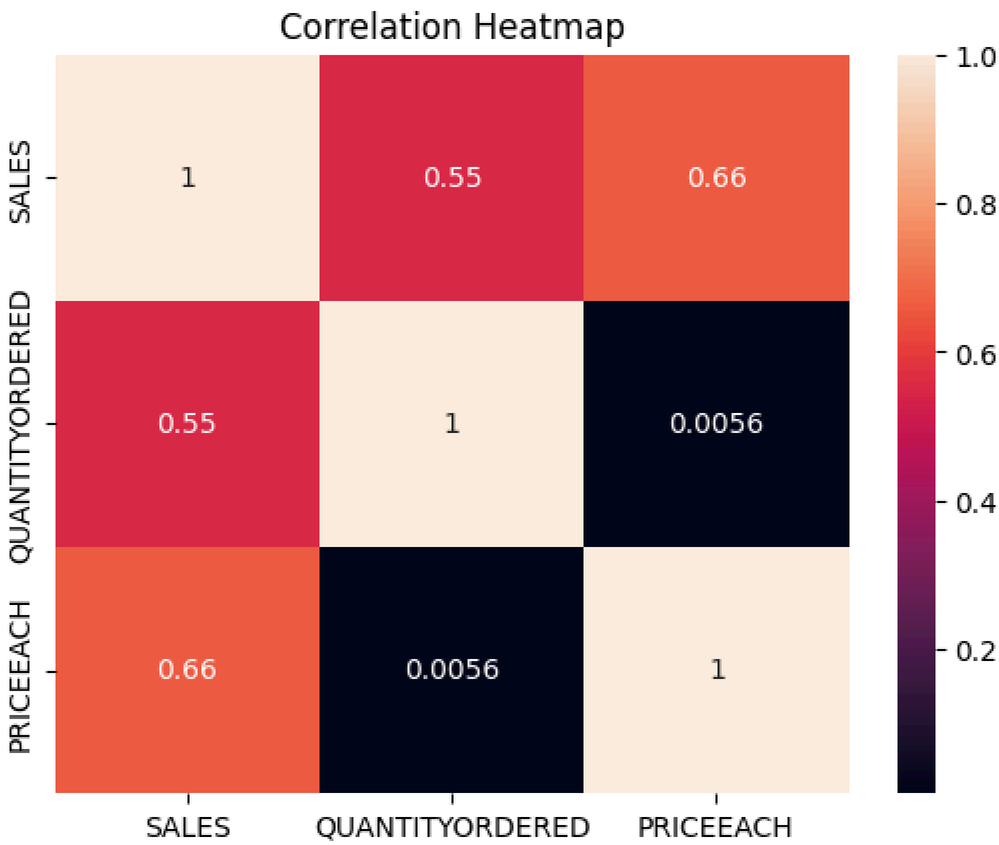


In [21]:
```
plt.hist(df['SALES'], bins=20)
plt.title("Sales Distribution")
plt.xlabel("Sales")
plt.ylabel("Frequency")
plt.show()
```

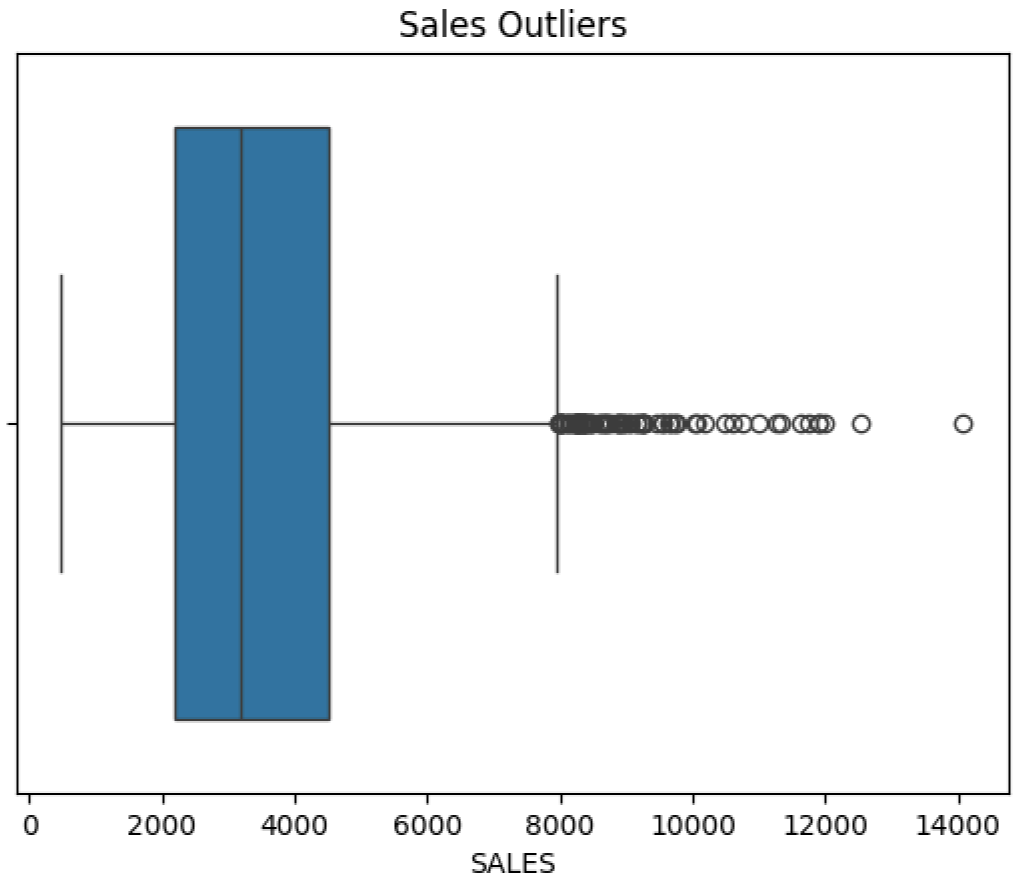


In [22]:

```
sns.heatmap(
    df[['SALES','QUANTITYORDERED','PRICEEACH']].corr(),
    annot=True
)
plt.title("Correlation Heatmap")
plt.show()
```



In [23]:
```
sns.boxplot(x=df['SALES'])
plt.title("Sales Outliers")
plt.show()
```



Step 5: Insights and Interpretation

Sales by Deal Size Large deals generate the highest total sales, followed by medium and small deals, indicating that targeting larger orders significantly boosts revenue.

Year-wise Sales Trend Sales have been increasing year over year, showing a positive growth trend and suggesting that business strategies are effectively driving revenue.

Product Line Performance Quantity ordered shows almost no correlation with price per item, meaning customers do not significantly change order volume based on product price.

Sales Distribution & Outliers Sales values are right-skewed with some extreme high values, indicating that a few large transactions dominate revenue, which could affect forecasting and inventory planning.