Project: Superstore Sales Analysis

In [1]:
```
# Import libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# visulization style setup
colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728']
sns.set_palette(colors)

plt.rcParams['figure.figsize'] = (8, 4.5)
plt.rc('axes', labelsize=10, titlesize=11)
```

In [2]:
```
# Read dataset
train_df = pd.read_csv("./data/train.csv")
```

In [3]:
```
# View
train_df.head()
```

Out[3]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Co
0	9699	CA-2017-154116	12/15/2017	12/19/2017	Standard Class	KM-16660	Khloe Miller	Consumer	
1	2230	CA-2014-128055	3/31/2014	4/5/2014	Standard Class	AA-10315	Alex Avila	Consumer	
2	2832	CA-2014-148915	11/1/2014	11/5/2014	Standard Class	ND-18370	Natalie DeCherney	Consumer	
3	9947	CA-2014-111157	3/2/2014	3/6/2014	Standard Class	NH-18610	Nicole Hansen	Corporate	
4	7985	CA-2017-152499	1/22/2017	1/25/2017	Second Class	EH-13765	Edward Hooks	Corporate	

5 rows × 21 columns

In [4]:
```
# Shape
nrows, ncols = train_df.shape
print("Number of rows:: %d" %nrows)
print("Number of columns:: %d" %ncols)
```

```
Number of rows:: 5246
Number of columns:: 21
```

In [5]:
```
# Columns
columns = train_df.columns.tolist()
print(columns)
```

```
['Row ID', 'Order ID', 'Order Date', 'Ship Date', 'Ship Mode', 'Customer ID', 'Cu
stomer Name', 'Segment', 'Country', 'City', 'State', 'Postal Code', 'Region', 'Pr
oduct ID', 'Category', 'Sub-Category', 'Product Name', 'Sales', 'Quantity', 'Disc
ount', 'Profit']
```

In [6]:
```
# Rename columns - change the case to lower and replace space with '_'
train_df.rename(columns={col: col.lower().replace(" ", "_") for col in train_df.
```

In [7]:
```
# Summary statistics for numerical columns
train_df.describe()
```

Out[7]:

	row_id	postal_code	sales	quantity	discount	profit
count	5246.000000	5246.000000	5246.000000	5246.000000	5246.000000	5246.00000
mean	5000.272589	55563.606367	218.858152	3.780976	0.158978	28.15217
std	2868.065377	31996.659575	586.869816	2.239916	0.209878	257.91150
min	2.000000	1453.000000	0.444000	1.000000	0.000000	-6599.97800
25%	2510.500000	23223.000000	17.445000	2.000000	0.000000	1.61400
50%	5011.500000	60082.500000	55.890000	3.000000	0.200000	8.47600
75%	7477.000000	90008.000000	209.835000	5.000000	0.200000	28.99125
max	9992.000000	99301.000000	17499.950000	14.000000	0.800000	8399.97600

- *We can see the extreme values in sales, quantity and profit. This suggest that there might be potential outliers present.*

In [9]:

```
# Check the records with sales equal to 17499.950000
train_df[train_df.sales == 17499.950000]
```

Out[9]:

	row_id	order_id	order_date	ship_date	ship_mode	customer_id	customer_name
2099	6827	CA-2016-118689	10/2/2016	10/9/2016	Standard Class	TC-20980	Tamara Chanc

1 rows × 21 columns

In [10]:

```
# Check the order history of the customer with highest sales
train_df[train_df.customer_id == 'TC-20980']
```

Out[10]:

	row_id	order_id	order_date	ship_date	ship_mode	customer_id	customer_name
2007	6830	CA-2016-118689	10/2/2016	10/9/2016	Standard Class	TC-20980	Tamara Chanc
2031	8338	CA-2014-153087	12/27/2014	1/3/2015	Standard Class	TC-20980	Tamara Chanc
2099	6827	CA-2016-118689	10/2/2016	10/9/2016	Standard Class	TC-20980	Tamara Chanc
3643	8339	CA-2014-153087	12/27/2014	1/3/2015	Standard Class	TC-20980	Tamara Chanc
4058	3186	CA-2014-123498	11/7/2014	11/9/2014	First Class	TC-20980	Tamara Chanc

5 rows × 21 columns

In [11]:

```
# Check the sales with same product
train_df[train_df.product_id == 'TEC-CO-10004722']
```

Out[11]:

	row_id	order_id	order_date	ship_date	ship_mode	customer_id	customer_nam
2099	6827	CA-2016-118689	10/2/2016	10/9/2016	Standard Class	TC-20980	Tamara Char
2892	4191	CA-2017-166709	11/17/2017	11/22/2017	Standard Class	HL-15040	Hunter Lop
4885	6426	CA-2016-143714	5/23/2016	5/27/2016	Standard Class	CC-12370	Christoph Cona
5132	8154	CA-2017-140151	3/23/2017	3/25/2017	First Class	RB-19360	Raymond Bu

4 rows × 21 columns

- *Its seems like the cost price of the product is high, so it might not be the outlier*

In [8]:
```
# Summary statistics for categorical columns.
train_df.describe(include='object')
```

Out[8]:

	order_id	order_date	ship_date	ship_mode	customer_id	customer_name	seg
count	5246	5246	5246	5246	5246	5246	
unique	3434	1125	1212	4	784	784	
top	CA-2017-100111	12/2/2017	9/26/2017	Standard Class	SV-20365	Seth Vernon	Con
freq	10	23	21	3087	23	23	

In [8]:
```
# Check for missing values in data
train_df.isnull().sum()
```

Out[8]:
```
row_id           0
order_id         0
order_date       0
ship_date        0
ship_mode        0
customer_id      0
customer_name    0
segment          0
country          0
city             0
state            0
postal_code      0
region           0
product_id       0
category         0
sub-category     0
product_name     0
sales            0
quantity         0
discount         0
profit           0
dtype: int64
```

In [9]:
```
# Metainformation
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5246 entries, 0 to 5245
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   row_id         5246 non-null   int64  
 1   order_id       5246 non-null   object 
 2   order_date     5246 non-null   object 
 3   ship_date      5246 non-null   object 
 4   ship_mode      5246 non-null   object 
 5   customer_id    5246 non-null   object 
 6   customer_name  5246 non-null   object 
 7   segment        5246 non-null   object 
 8   country        5246 non-null   object 
 9   city           5246 non-null   object 
 10  state          5246 non-null   object 
 11  postal_code    5246 non-null   int64  
 12  region         5246 non-null   object 
 13  product_id     5246 non-null   object 
 14  category       5246 non-null   object 
 15  sub-category   5246 non-null   object 
 16  product_name   5246 non-null   object 
 17  sales          5246 non-null   float64
 18  quantity       5246 non-null   int64  
 19  discount       5246 non-null   float64
 20  profit         5246 non-null   float64
dtypes: float64(3), int64(3), object(15)
memory usage: 860.8+ KB
```

- *There is no missing values present in data.*
- *the datatype of each columns looks right except for date columns, let's change them into datetime format.*

In [10]:
```
# Change the date column values from object to date
train_df['order_date'] = pd.to_datetime(train_df.order_date)
train_df['ship_date'] = pd.to_datetime(train_df.ship_date)
```

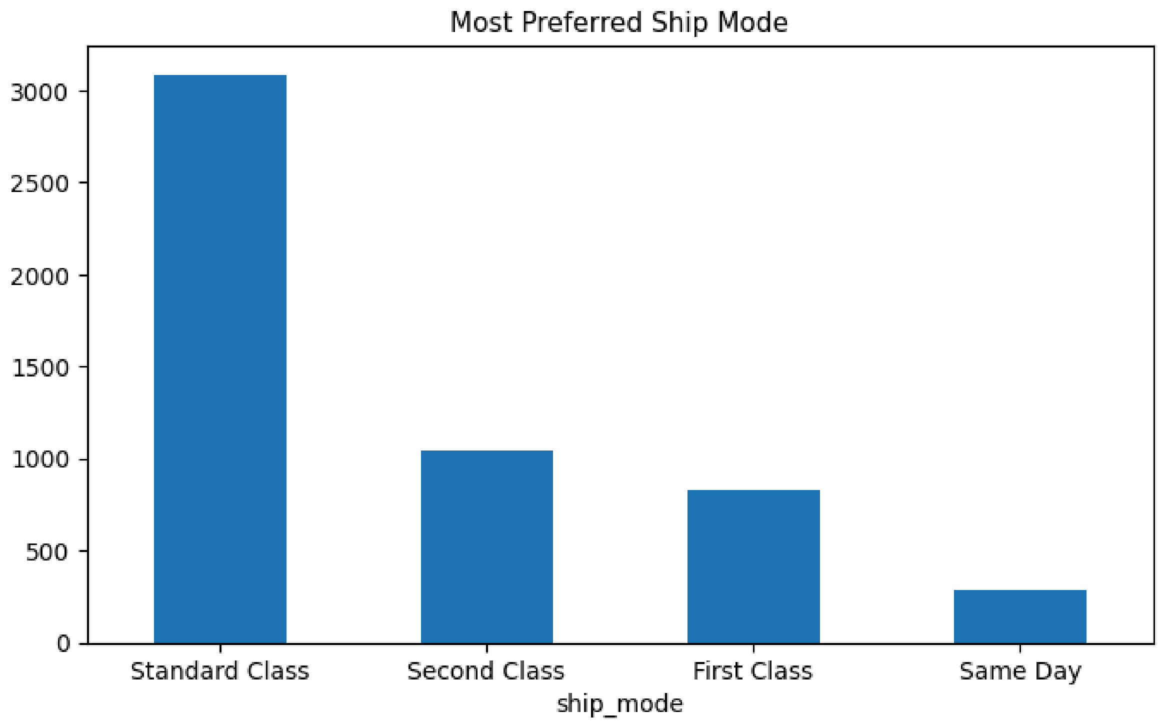
In [11]:
```
# Print unique values in categorical values
cat_features = ['ship_mode', 'segment', 'state', 'region', 'category', 'sub-cate

for col in cat_features:
    print(col)
    print(train_df[col].unique())
    print("---" * 10)
```

```
ship_mode
['Standard Class' 'Second Class' 'First Class' 'Same Day']
------------------------------
segment
['Consumer' 'Corporate' 'Home Office']
------------------------------
state
['California' 'Oregon' 'Pennsylvania' 'Illinois' 'Ohio' 'New York'
 'Washington' 'Texas' 'Alabama' 'Rhode Island' 'Connecticut' 'Utah'
 'Tennessee' 'Wisconsin' 'Massachusetts' 'Georgia' 'Nebraska' 'Oklahoma'
 'Indiana' 'Iowa' 'Delaware' 'Nevada' 'Virginia' 'Montana' 'Missouri'
 'Florida' 'Arizona' 'North Carolina' 'Kentucky' 'Colorado' 'New Jersey'
 'Michigan' 'Maryland' 'Arkansas' 'Kansas' 'Mississippi' 'New Mexico'
 'South Carolina' 'South Dakota' 'New Hampshire' 'District of Columbia'
 'North Dakota' 'Idaho' 'Louisiana' 'Vermont' 'Minnesota' 'Maine'
 'West Virginia']
------------------------------
region
['West' 'East' 'Central' 'South']
------------------------------
category
['Office Supplies' 'Technology' 'Furniture']
------------------------------
sub-category
['Paper' 'Binders' 'Storage' 'Accessories' 'Art' 'Bookcases' 'Chairs'
 'Envelopes' 'Fasteners' 'Supplies' 'Labels' 'Machines' 'Furnishings'
 'Appliances' 'Phones' 'Tables' 'Copiers']
------------------------------
```

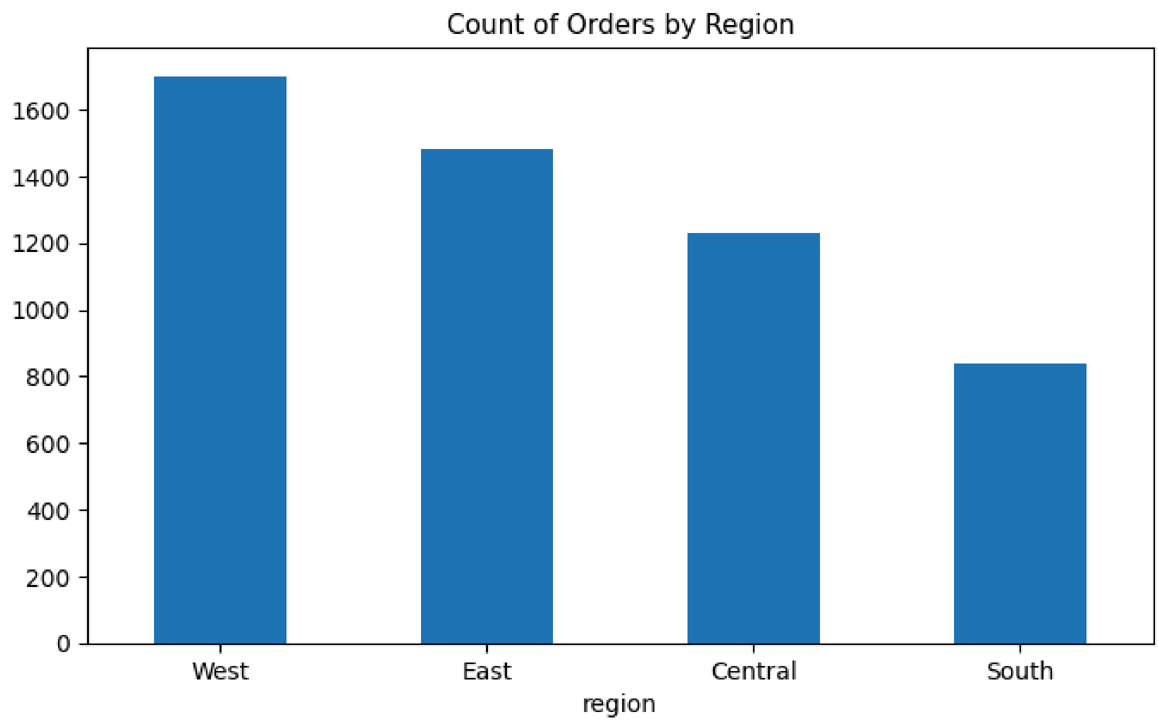
Data Visualizations

In [21]:
```
# Create a function to return a grouped data
def get_grp(col):
    return train_df.groupby(by=[col])
```

In [16]:
```
# Count of orders by ship mode.
train_df.ship_mode.value_counts().plot(kind='bar', title='Most Preferred Ship Mo
plt.xticks(rotation=0)
plt.show()
```



In [18]:
```
# Count of orders by Region
train_df.region.value_counts().plot(kind='bar', title='Count of Orders by Region
plt.xticks(rotation=0)
plt.show()
```



In [20]:
```
# Create year-month, year, month, and day column from the order_date variable.
train_df['year_month'] = train_df['order_date'].dt.strftime("%Y-%m")
train_df['year'] = train_df['order_date'].dt.year
train_df['month'] = train_df['order_date'].dt.month
train_df['day'] = train_df['order_date'].dt.day
```

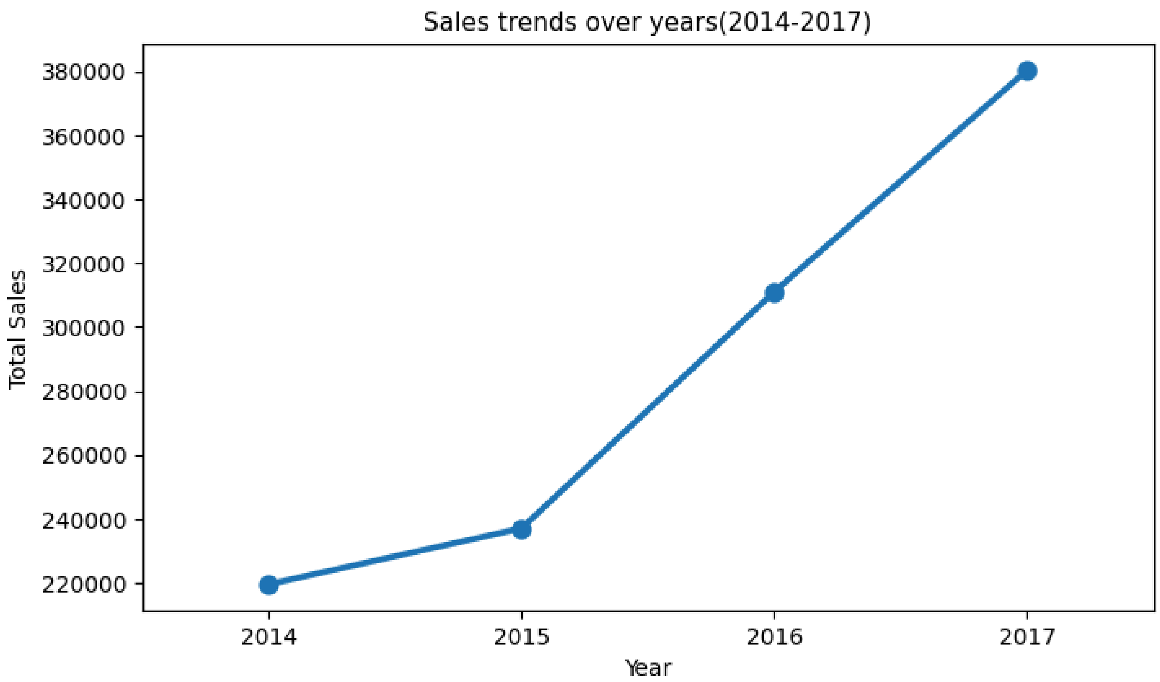
In [21]:
```
# Time take to ship the order in days
train_df['shipping_time'] = train_df['ship_date'] - train_df['order_date']
```

Sales Analysis

Let's discover the patterns and trends in sales and customer perferences.

In [ ]:
```
# Count of orders by ship mode.
train_df.ship_mode.value_counts().plot(kind='pie',
                                       colors=colors,
                                       autopct='%1.1f%%',
                                       startangle=265,
                                       counterclock=False,
                                       wedgeprops=dict(width=0.25, linewidth=3),
                                       textprops=dict(size=10, fontweight=500, c
                                       ylabel='', title='Most Preferred Ship Mod
plt.show()
```

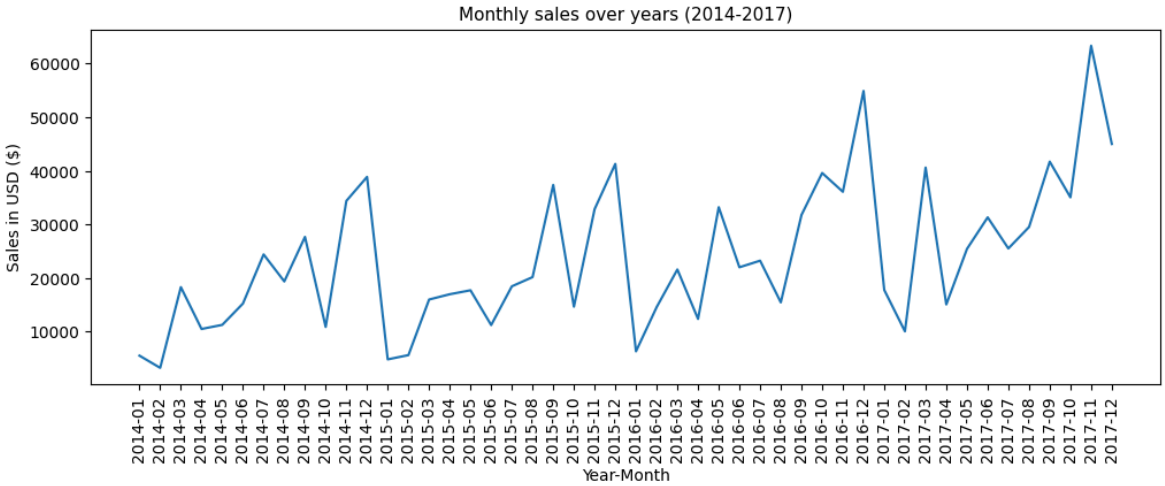
In [24]:
```
# Sales trend by year
total_sales_by_year = train_df.groupby(by=['year'])['sales'].sum()

# plot
sns.pointplot(data = total_sales_by_year)

# Add labels
plt.title("Sales trends over years(2014-2017)")
plt.xlabel("Year")
plt.ylabel("Total Sales")

plt.xticks(rotation=0)
plt.show()
```



- *This line plot shows the increasing trend in sales over the years.*
- *The highest sales can observed in year 2017.*

In [27]:
```
# Sales trend over year-months
total_sales_by_year_month = train_df.groupby(by=['year_month'])['sales'].sum().r
```

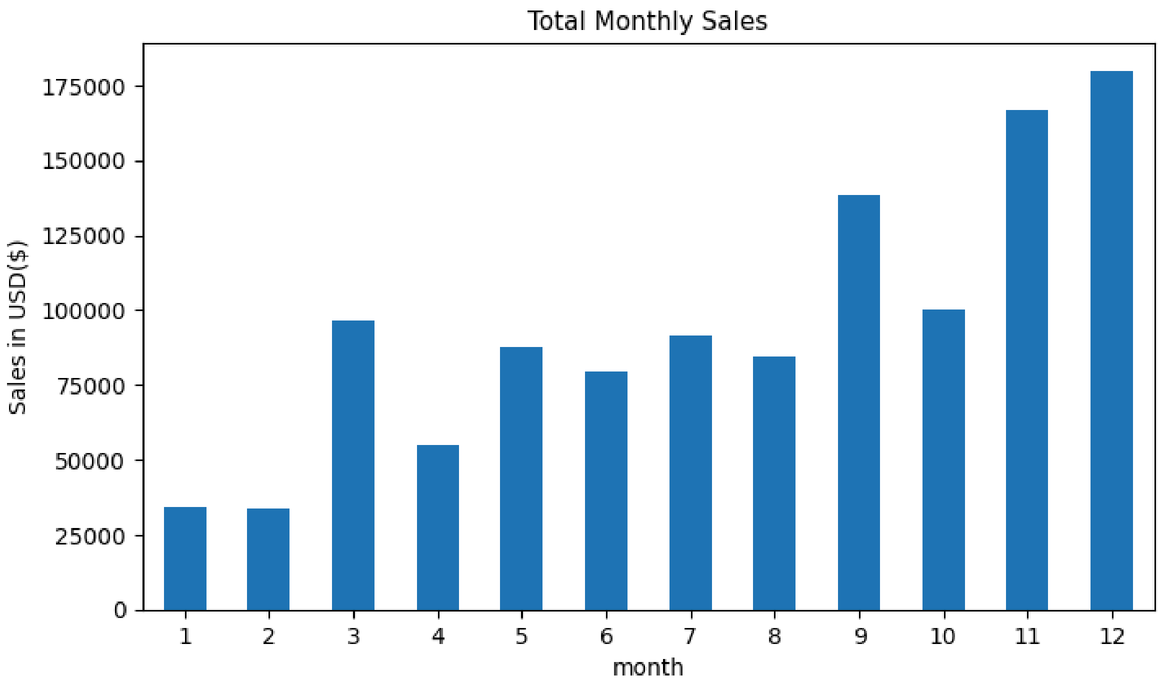
```
# plot
fig = plt.figure(figsize=(12, 4))
plt.plot(total_sales_by_year_month.year_month, total_sales_by_year_month.sales)

plt.title("Monthly sales over years (2014-2017)")
plt.xlabel("Year-Month")
plt.ylabel("Sales in USD ($)")

plt.xticks(rotation=90)
plt.show()
```



- *The line plot show monthly sales in USD over time, from January 2014 to December 2017.*
- *The graph displays the fluctuations in sales with high and low peaks.*
- *The seasonal patterns can observe in the plot with periodic increase and decrease in sales.*

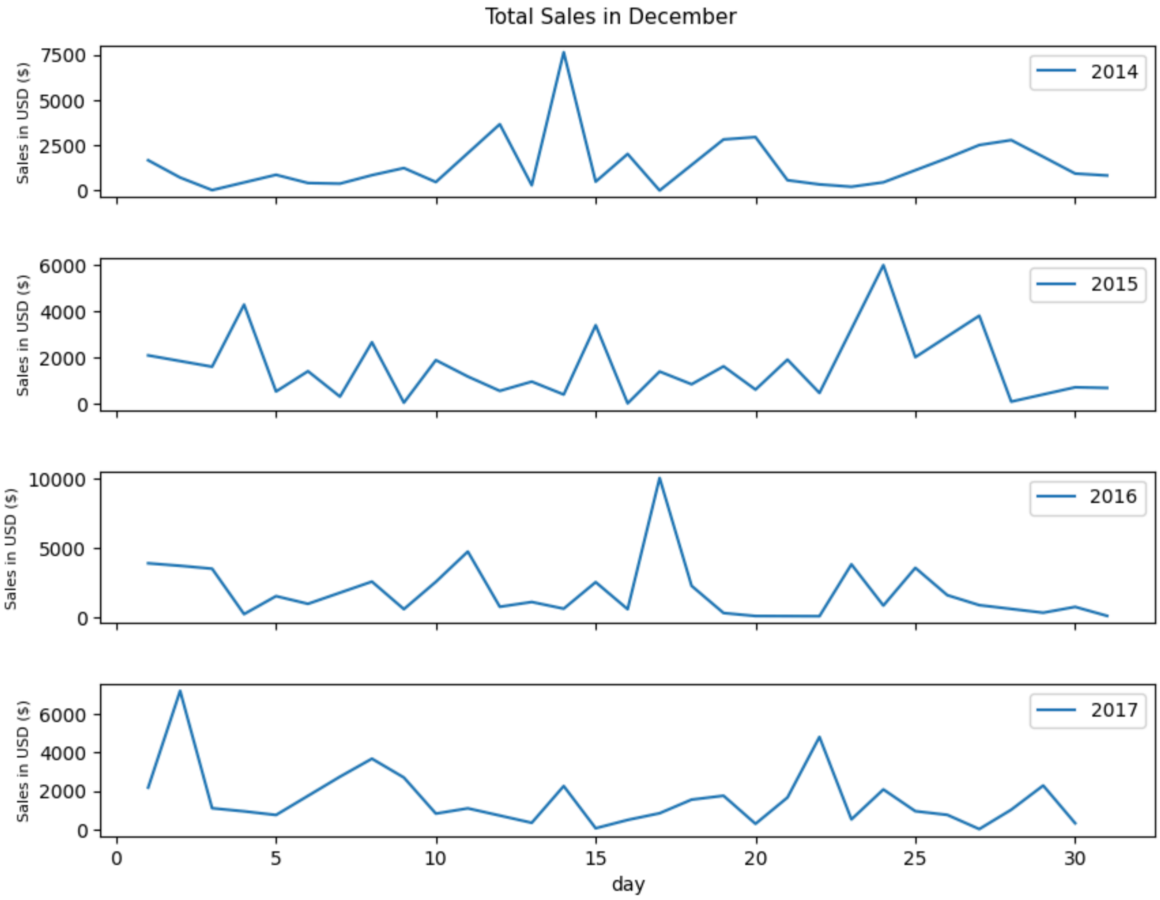
In [28]:

```
# Monthly sales
train_df.groupby(by='month')['sales'].sum().plot(kind='bar',
                                                 title='Total Monthly Sales',
                                                 ylabel='Sales in USD($)')
plt.xticks(rotation=0)
plt.show()
```



- *The bar plot shows the total monthly sales data in USD for 12-months.*
- *The highest bar at month 12 suggest the highest sales in month of december.*
- *The fluctuation in sales over months can observe.*

In [29]:
```
# Let's examine total sales in month of december for 2014, 2015, 2016, 2017
fig, ax = plt.subplots(nrows=4, ncols=1, figsize=(10, 7), sharex=True)
fig.subplots_adjust(hspace=0.4, top=0.94)

dec_2014 = train_df[(train_df.year == 2014) & (train_df.month == 12)]
dec_2015 = train_df[(train_df.year == 2015) & (train_df.month == 12)]
dec_2016 = train_df[(train_df.year == 2016) & (train_df.month == 12)]
dec_2017 = train_df[(train_df.year == 2017) & (train_df.month == 12)]

dec_2014.groupby(by='day')['sales'].sum().plot(ax=ax[0], label='2014')
ax[0].set_ylabel('Sales in USD ($)', size=8)
ax[0].legend()

dec_2015.groupby(by='day')['sales'].sum().plot(ax=ax[1], label='2015')
ax[1].set_ylabel('Sales in USD ($)', size=8)
ax[1].legend()

dec_2016.groupby(by='day')['sales'].sum().plot(ax=ax[2], label='2016')
ax[2].set_ylabel('Sales in USD ($)', size=8)
ax[2].legend()

dec_2017.groupby(by='day')['sales'].sum().plot(ax=ax[3], label='2017')
ax[3].set_ylabel('Sales in USD ($)', size=8)
ax[3].legend()

fig.suptitle("Total Sales in December", size=11)
plt.show()
```

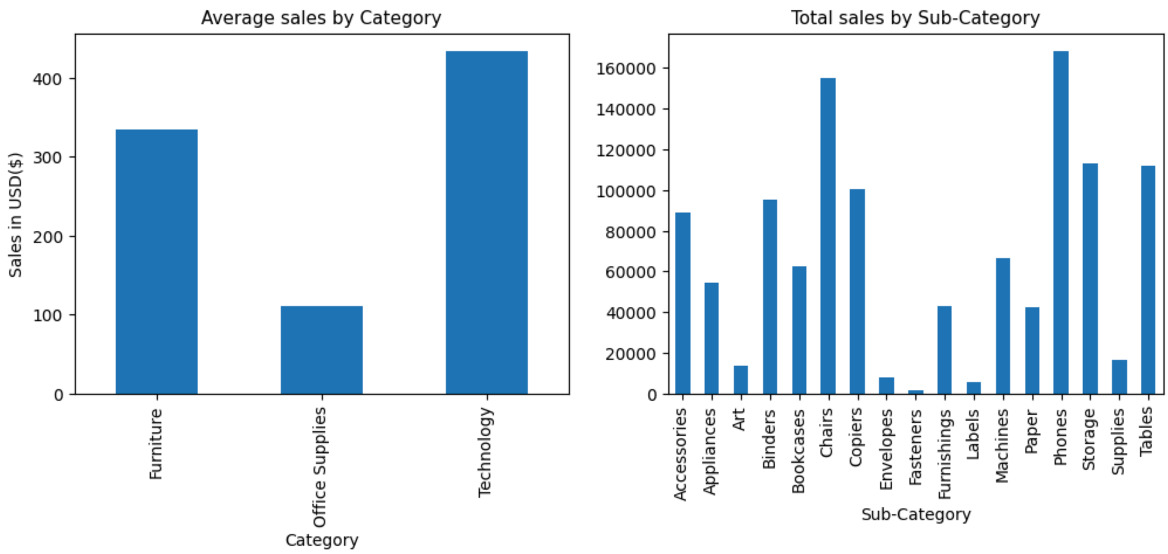


- *The above line plots for sales in december month for each year from 2014 to 2017, does not show any specific customer purchase pattern.*

Sales by Category and Sub-category

In [33]:

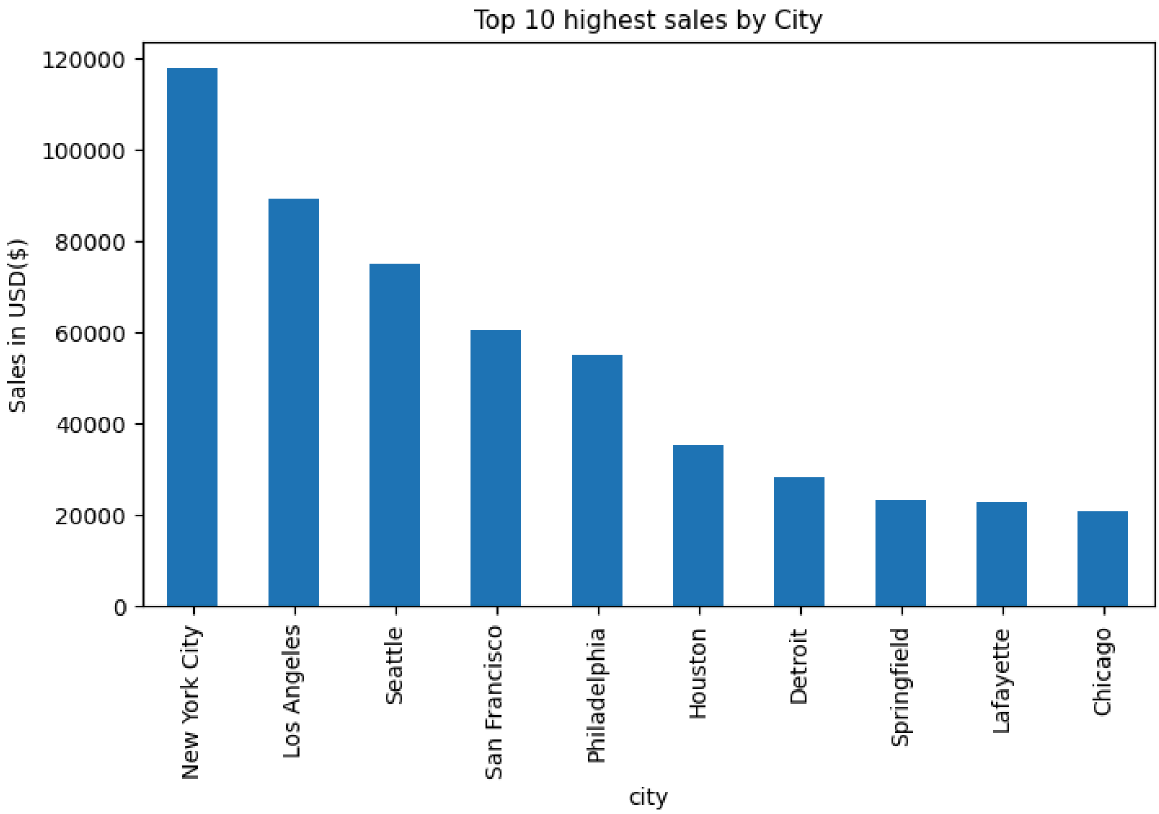
```
# Examine the sales by category and subcategory
# Data preparation
sales_cat = train_df.groupby(by=['category'])['sales'].mean()
sales_subcat = train_df.groupby(by=['sub-category'])['sales'].sum()

# Plot
fig, ax = plt.subplots(1, 2, figsize=(12, 4))
sales_cat.plot(kind='bar',
               title='Average sales by Category',
               xlabel='Category',
               ylabel='Sales in USD($)',
               ax=ax[0])

sales_subcat.plot(kind='bar',
                  title='Total sales by Sub-Category',
                  xlabel='Sub-Category', ax=ax[1])
plt.show()
```



- *The subplot shows the total sales by category and subcategory.*
- *The left bar plot compares the total sales across the different category. Highest sales are from the category technology.*
- *The right bar plots shows the total sales by sub-category with highest total sales from Phones sub-category followed by chairs from furniture*

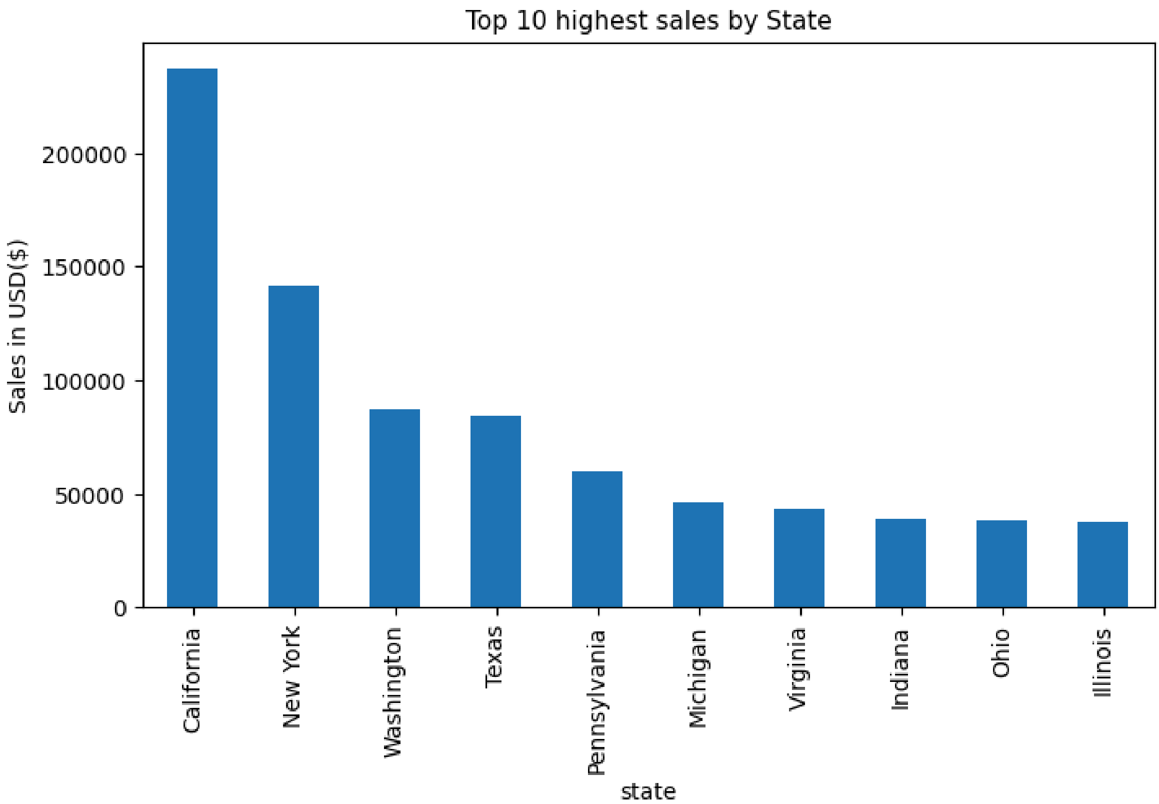
Geographical Sales Distributions

In [40]:
```
# Total sales by top 10 city
city_sales = train_df.groupby(by='city')['sales'].sum().sort_values(ascending=Fa
city_sales.head(10).plot(kind='bar',
                         title='Top 10 highest sales by City', ylabel='Sales in
plt.show()
```



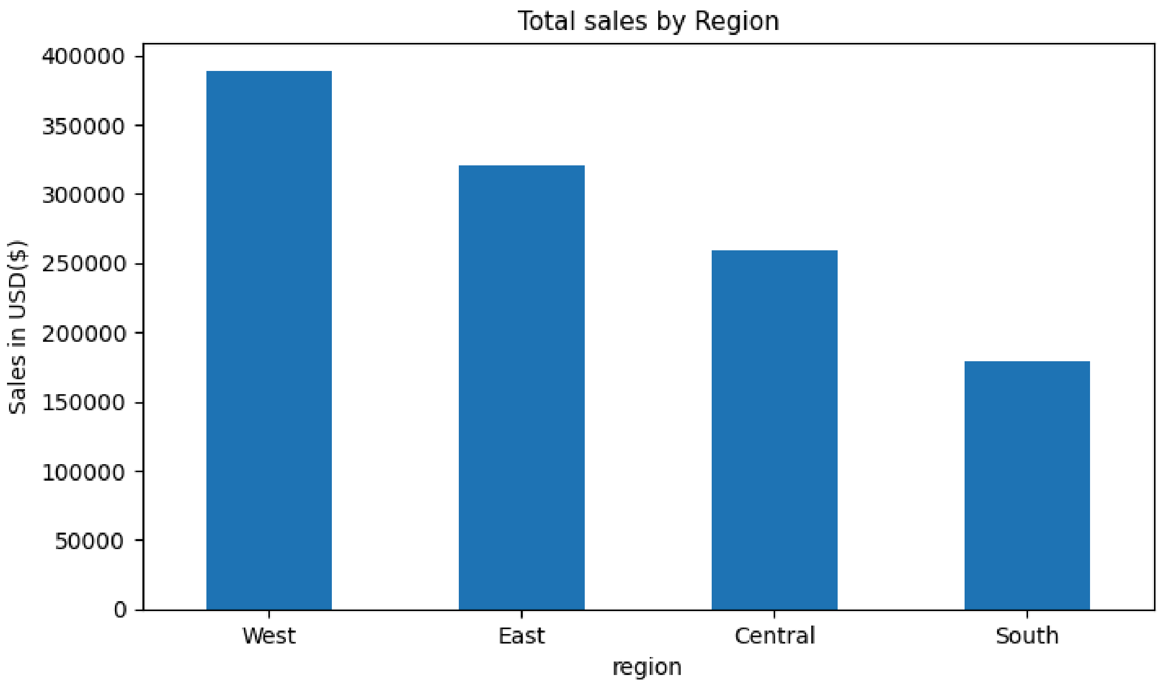
- *This bar plot compares the total sales across top 10 cities with highest sales.*
- *The highest sales are from New-York city, nearly 120,000. Los Angeles follows with sales around 80,000.*
- *The Seattle, San Francisco and philadelphia have similar sales figures, ranging between 60,000 and 70,000 indicating mid-range sales.*

In [41]:
```
# Total sales by State
state_sales = train_df.groupby(by='state')['sales'].sum().sort_values(ascending=
state_sales.head(10).plot(kind='bar',
                          title='Top 10 highest sales by State', ylabel='Sales i
plt.show()
```



- *This bar plot the total highest sales of top 10 states.*
- *California leads with highest sales among the top 10 states of US, nearly, 240,000.*

In [46]:
```
# Total sales by Region
region_sales = train_df.groupby(by='region')['sales'].sum().sort_values(ascendin
region_sales.plot(kind='bar', title='Total sales by Region', ylabel='Sales in US
plt.xticks(rotation=0)
plt.show()
```

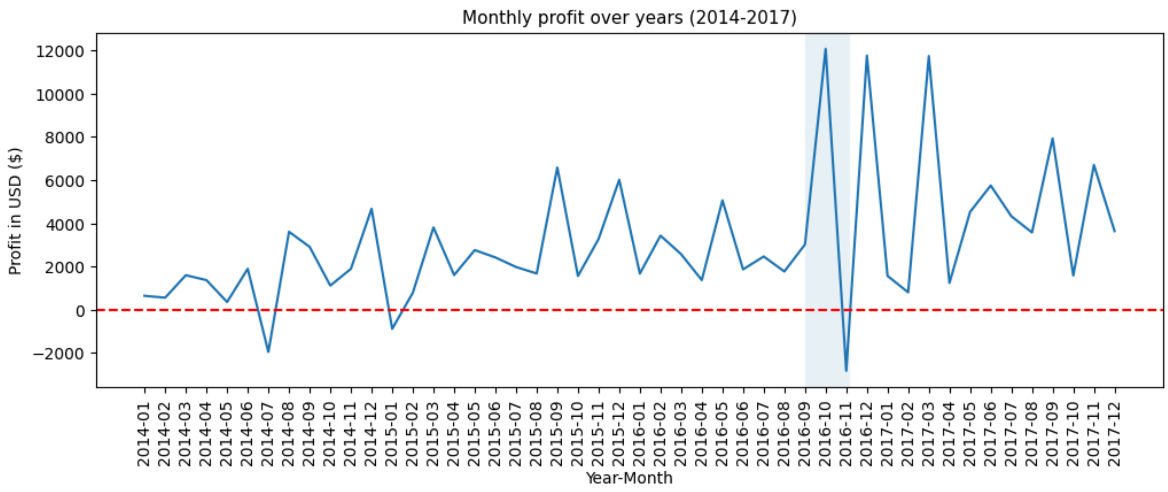


- *This bar plot compares the total sales across the different regions of US - west, east, central, and south.*
- *The total highest sales are from west region, ~$380,000.*

Profit Analysis

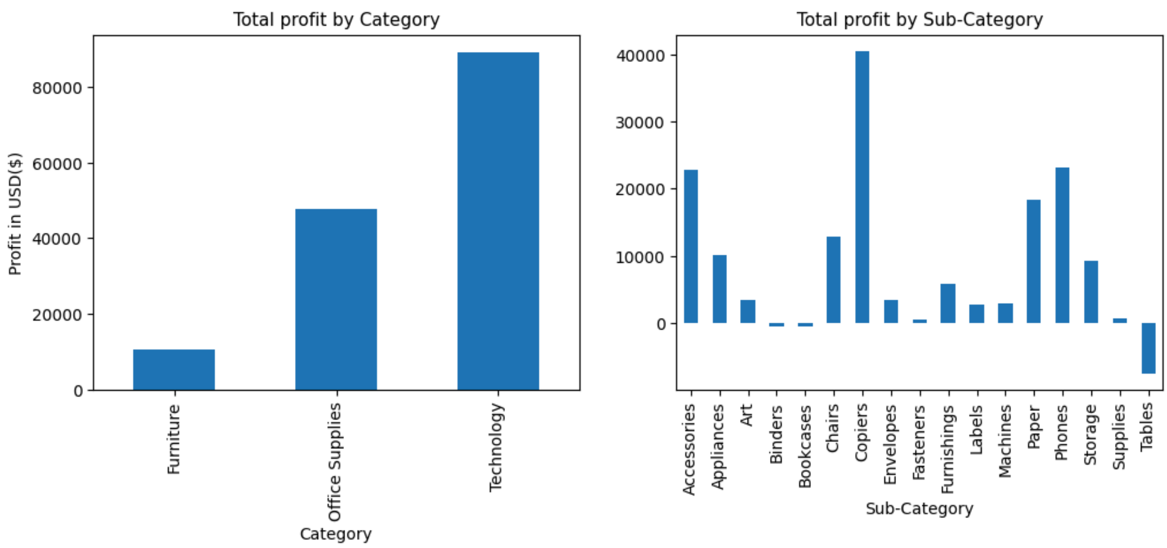
Analyze the monthly profits over the years from 2014-17

In [80]:
```
# Examine the total profits by monthly bases.
total_profit_by_year_month = train_df.groupby(by=['year_month'])['profit'].sum()

# plot
fig = plt.figure(figsize=(12, 4))
plt.plot(total_profit_by_year_month.year_month, total_profit_by_year_month.profi
plt.axhline(y=0, ls='--', color='r')
plt.axvspan(xmin=32, xmax=34.2, alpha=0.1)

plt.title("Monthly profit over years (2014-2017)")
plt.xlabel("Year-Month")
plt.ylabel("Profit in USD ($)")

plt.xticks(rotation=90)
plt.show()
```



- *The total monthly profit line plot shows the profit fluctuations over the time from January 2014, to December 2017.*
- *The line crosses the zero mark, indicates the month with both profit and loss.*
- *Significant peaks, the sharp spikes in profit exceed $10,000, suggesting the period of highest profitable month.*
- *A significant drop below zero is obeserve(you can see in shaded region), indicates a substantial loss in particular month.*

In [81]:
```
# Examine the profit by category and subcategory
profit_cat = train_df.groupby(by=['category'])['profit'].sum()
profit_subcat = train_df.groupby(by=['sub-category'])['profit'].sum()

fig, ax = plt.subplots(1, 2, figsize=(12, 4))

profit_cat.plot(kind='bar', title='Total profit by Category', xlabel='Category',
profit_subcat.plot(kind='bar', title='Total profit by Sub-Category', xlabel='Sub
plt.show()
```



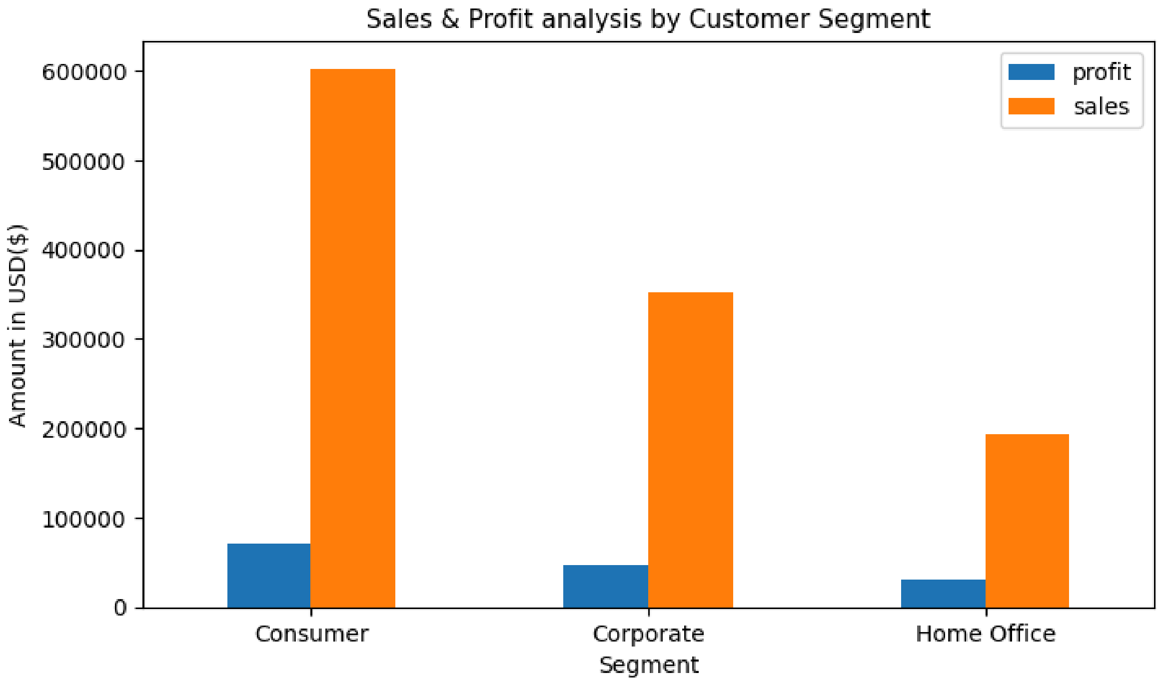
- *The above subplot compares the profits among the different category and subcategory using bar plot.*
- *The left graphs shows the highest sales lead to the highest profits, leading technology category with higest profit.*

- *While in right graphs depicts, the highest profits are from copiers and loss from the tables sub-category.*

Customer Segematation Analysis

In [123…

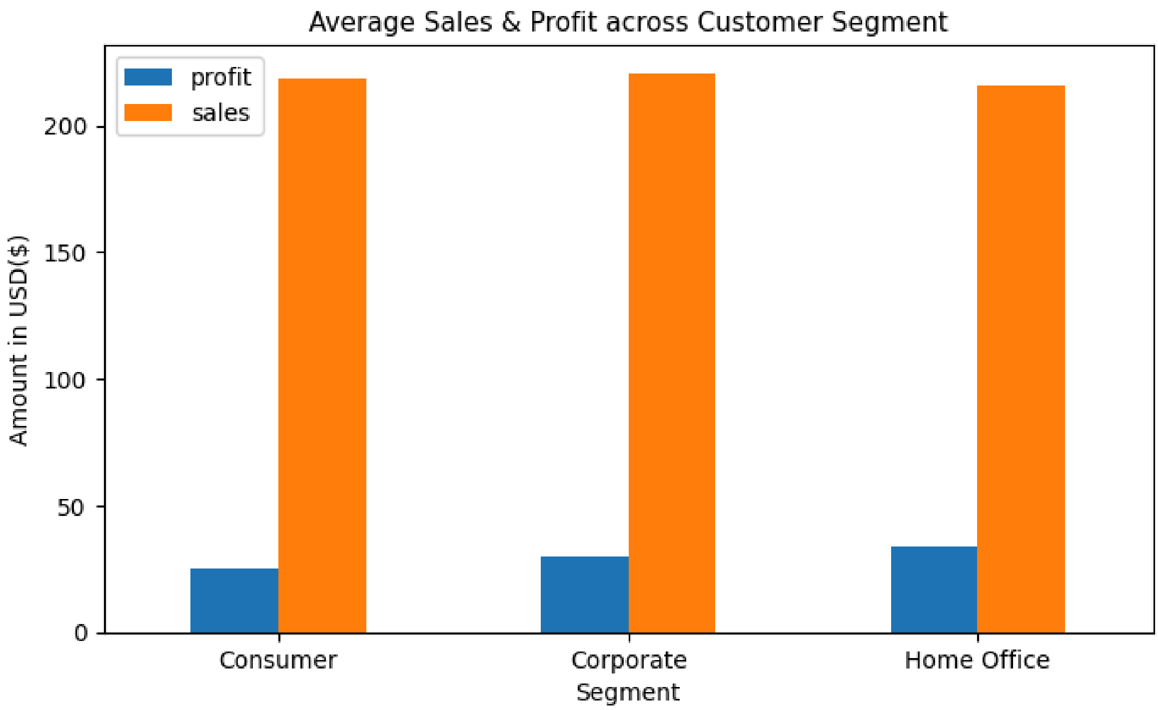
```
# Sales and Profit vs Customer segmentation
train_df.pivot_table(index='segment', values=['profit', 'sales'], aggfunc='sum')



plt.xticks(rotation=0)
plt.show()
```



- *The bar graph compares the profitablity and sales volume across three customer segements: Consumer, Corporate and Home Office.*
- *The graph indicates the high sales but low profit.*
- *Consumer Segments shows highest sales and profits, Corporate segments shows slightly lower profit.*

In [124…

```
# Average Sales and Profit vs Customer segmentation
train_df.pivot_table(index='segment', values=['profit', 'sales'], aggfunc='mean'



plt.xticks(rotation=0)
plt.show()
```



- *The above bar plot show the equal amount of total sales and profit across customer segement.*
- *It suggest that each segment, despite its unique characteristics, contributes equally to the overall profitablility on a per-customer basis.*

Let's further analyze the profit and sales by their ratio

In [35]:
```
# Sales to profit ratio
sales_profit_by_segment = train_df.groupby(by='segment').agg({'sales': 'sum', 'p
sales_profit_by_segment['sales_to_profit_ratio'] = sales_profit_by_segment['sale
sales_profit_by_segment['sales_to_profit_ratio'].reset_index()
```

Out[35]:

	segment	sales_to_profit_ratio
0	Consumer	8.609542
1	Corporate	7.398730
2	Home Office	6.425859

- *The store has higher profits are from the consumer products*

Product Analysis

In [125…
```
# Top 10 product
total_products = train_df.product_name.nunique()

# Find top 10 products by sales
product_grp = train_df.groupby(by='product_name')
product_grp_sales = product_grp['sales'].sum()
product_grp_sales.sort_values(ascending=False).head(10).reset_index()
```

Out[125…

	product_name	sales
0	Canon imageCLASS 2200 Advanced Copier	50399.8560
1	GBC Ibimaster 500 Manual ProClick Binding System	16437.1680
2	HP Designjet T520 Inkjet Large Format Printer ...	15749.9100
3	Fellowes PB500 Electric Punch Plastic Comb Bin...	11693.1080
4	Bretford Rectangular Conference Table Tops	11265.0935
5	Hewlett Packard LaserJet 3310 Copier	11159.8140
6	Cubify CubeX 3D Printer Double Head Print	9299.9690
7	Samsung Galaxy Mega 6.3	8651.7940
8	High Speed Automatic Electric Letter Opener	8187.6500
9	Ativa V4110MDD Micro-Cut Shredder	7699.8900

In [126…

```
# Find top 10 products by quantity.
product_grp_quant = product_grp['quantity'].sum()
product_grp_quant.sort_values(ascending=False).head(10).reset_index()
```

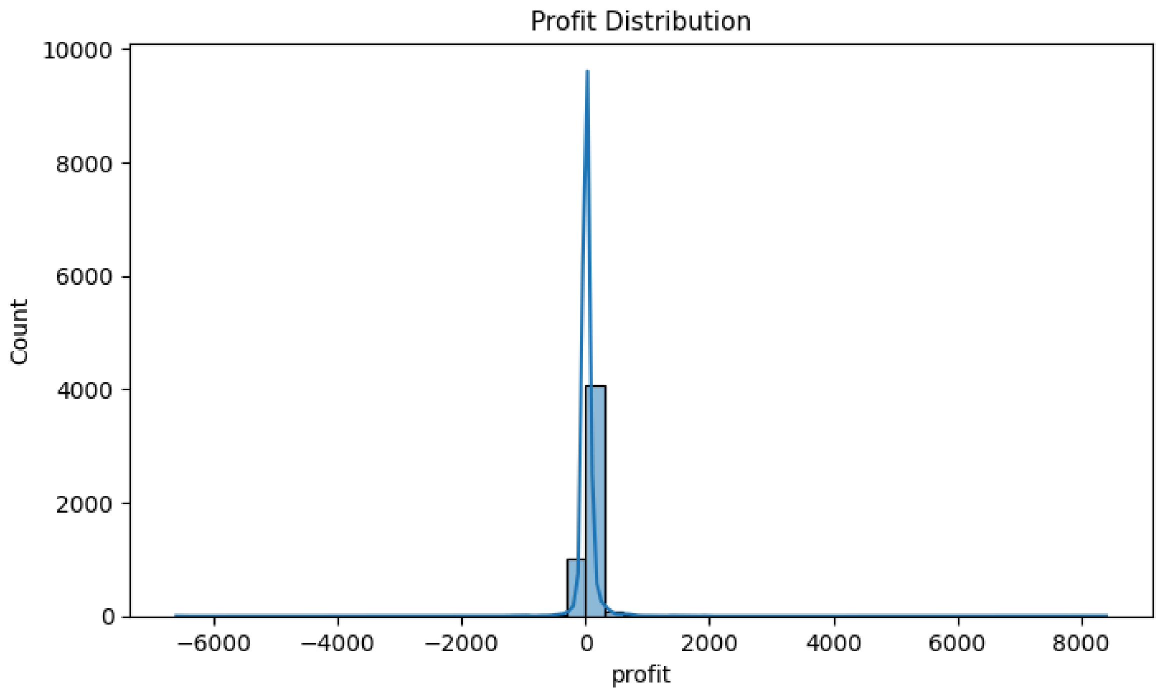
Out[126…

	product_name	quantity
0	Staples	125
1	Staple envelope	79
2	Easy-staple paper	76
3	Staples in misc. colors	56
4	KI Adjustable-Height Table	47
5	Newell 312	42
6	High-Back Leather Manager's Chair	42
7	Wilson Jones Turn Tabs Binder Tool for Ring Bi...	42
8	Bretford Rectangular Conference Table Tops	41
9	KI Conference Tables	40

- Staples is the best selling product.

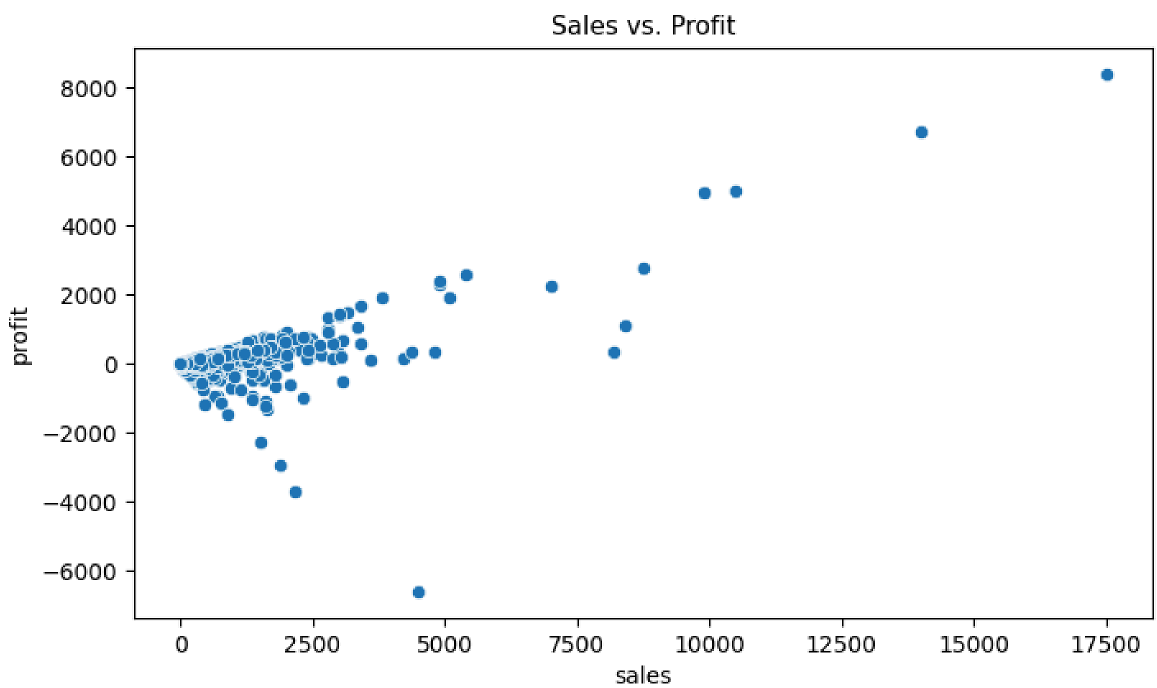
In [32]:

```
# Profit distribution
sns.histplot(train_df.profit, bins=50, kde=True)
plt.title("Profit Distribution")
plt.show()
```



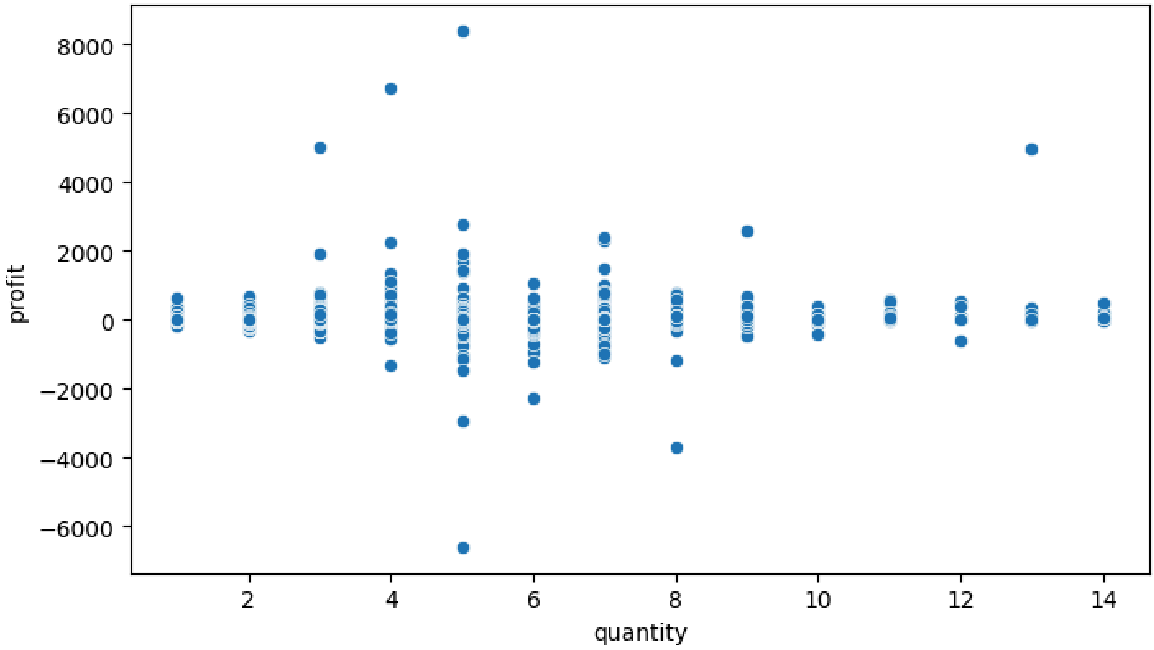
- *This histogram shows the sharp peak at zero on the profit axis, indicating a high frequency of data points, with zero profit.*
- *central peak suggest that the business is often break even refers to total revenue equals to total costs, resulting neither profit or loss*
- *Few instanaces shows the significant profit or loss, implying the low variablity in financial performances.*

In [80]:
```
# Identify the relationships between continuous variables, correlation analysis
sns.scatterplot(train_df, y='profit', x='sales')

plt.title("Sales vs. Profit")
plt.show()
```



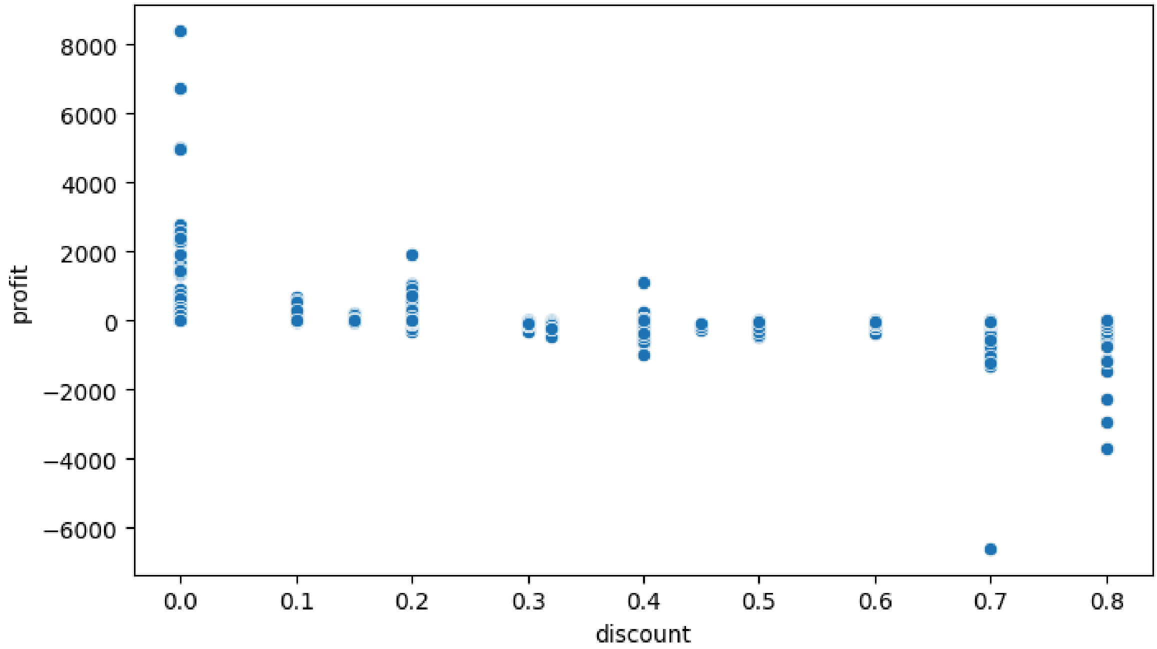
- *The above scatter plot shows the relationship between the profit and loss with most values clustered around lower sales values.*
- *As the sales increases, profit tends to increase though not strictly linearly indicating areas of both profitablity and loss.*

In [38]:
```
# correlation analysis
sns.scatterplot(train_df, x='quantity', y='profit');
```



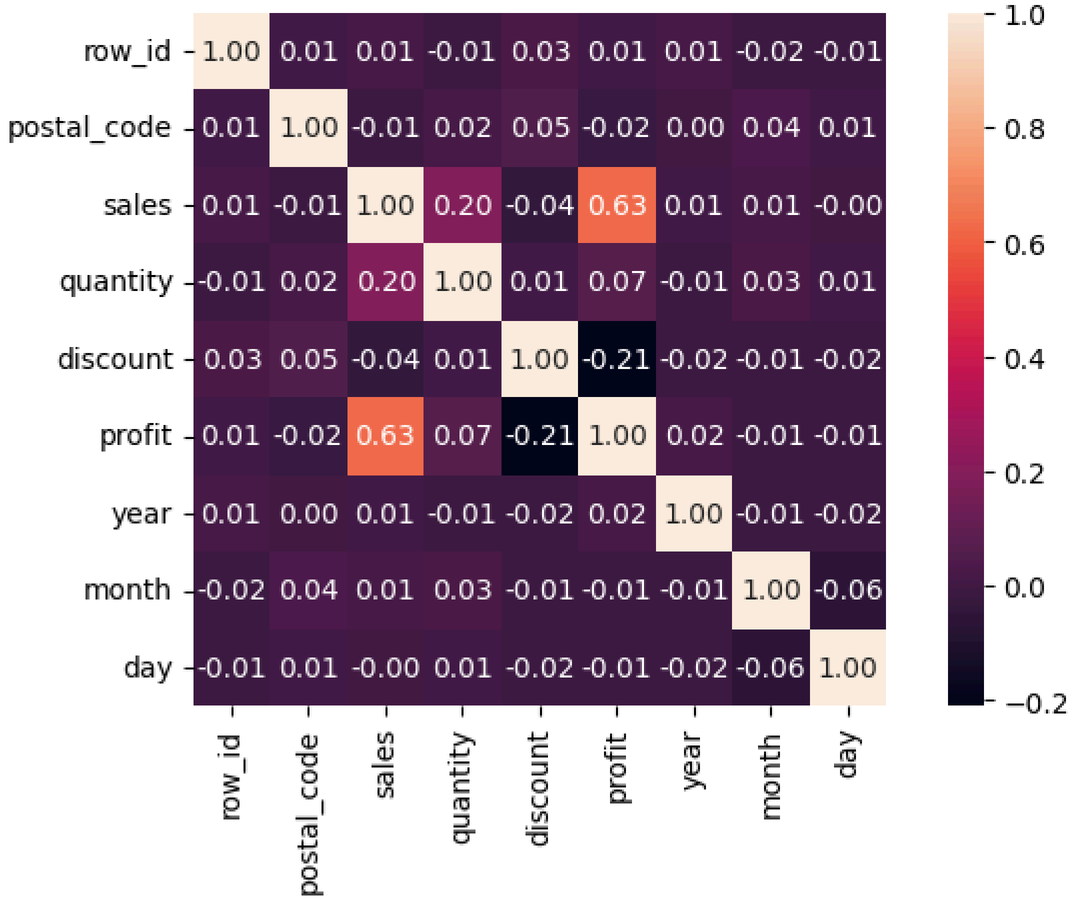
- *The above scatter plot shows the relationship between quantity and profit. Most data points are near lower qunatities, with profit varying widely.*
- *We can see that as the quantity increases beyond the 10, profit variation decreases, suggesting economies of scale.*

In [79]:
```
# correlation analysis
sns.scatterplot(train_df, x='discount', y='profit');
```



- *The above scatter plot shows the negative correlation between discount and profit, indicating that as discounts increase, profits tends to decrease.*
- *This suggest that higher discounts may lead to lower profitability, which is important consideration for pricing strategies.*

In [63]:
```
# Plot correlation heatmap for numerical variables.
sns.heatmap(train_df.corr(numeric_only=True), annot=True, fmt='.2f', square=True
```



- *The heatmap confirms our previous finding.*
- *There is strong positive correlation between profit and sales (orange square with 0.63) meaning higher sales often lead to higher profits.*
- *Positive correlation between sales and quantity*
- *While negative correlation between discounts and both with profit and sales.*

In [ ]:

```

```