Super Store Sales Data Analysis

In [1]:
```
# Import Library

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
# Import data
df = pd.read_csv('../data/clean_super_store_data.csv' )
```

In [3]:
```
# Setting opiton for showing all columns
pd.set_option('display.max_columns', None)
```

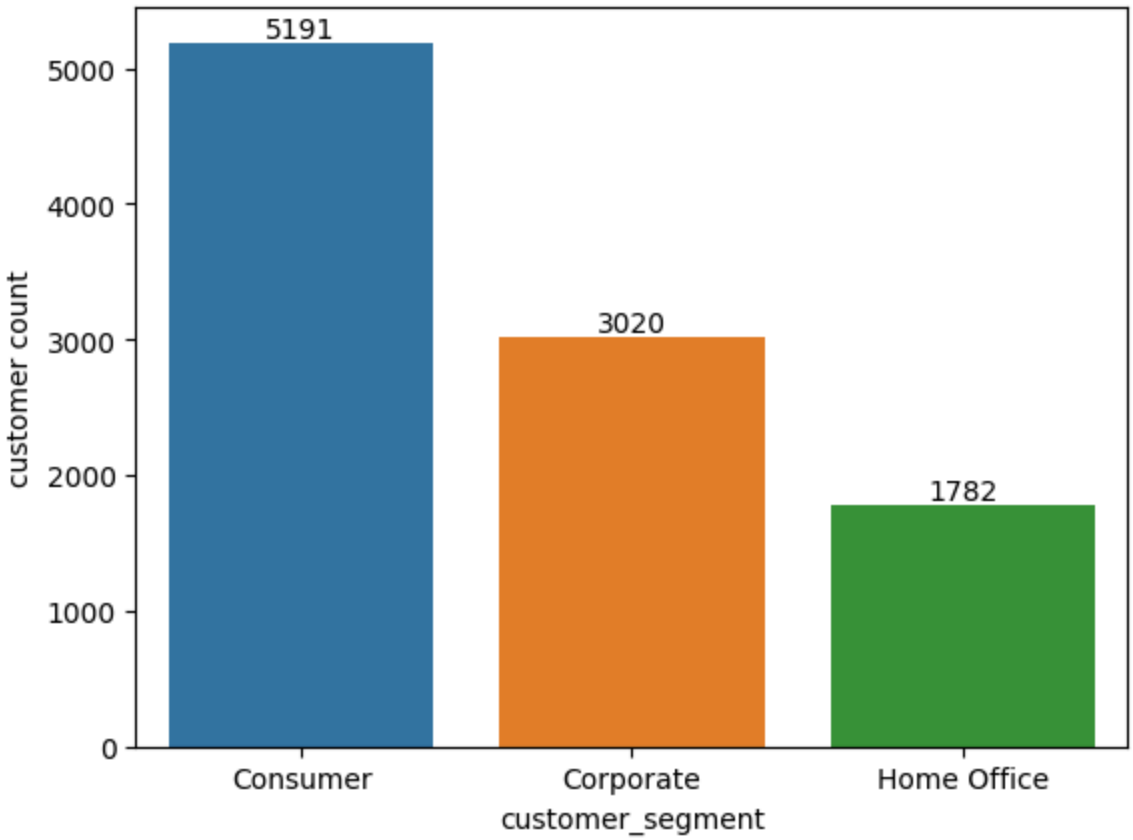
In [4]:
```
# Inforamtion about dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9993 entries, 0 to 9992
Data columns (total 22 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   customer_name          9993 non-null   object 
 1   customer_segment       9993 non-null   object 
 2   region                 9993 non-null   object 
 3   state                  9993 non-null   object 
 4   city                   9993 non-null   object 
 5   product_name           9993 non-null   object 
 6   category               9993 non-null   object 
 7   sub_category           9993 non-null   object 
 8   order_date             9993 non-null   object 
 9   order_month            9993 non-null   int64  
 10  order_year             9993 non-null   int64  
 11  ship_date              9993 non-null   object 
 12  ship_month             9993 non-null   int64  
 13  ship_year              9993 non-null   int64  
 14  delivery_time_in_days  9993 non-null   int64  
 15  ship_mode              9993 non-null   object 
 16  sales                  9993 non-null   float64
 17  quantity               9993 non-null   int64  
 18  discount               9993 non-null   float64
 19  discount_amount        9993 non-null   float64
 20  cost                   9993 non-null   float64
 21  profit                 9993 non-null   float64
dtypes: float64(5), int64(6), object(11)
memory usage: 1.7+ MB
```

Customer Segment Analysis

Customer Count In Customer Segement

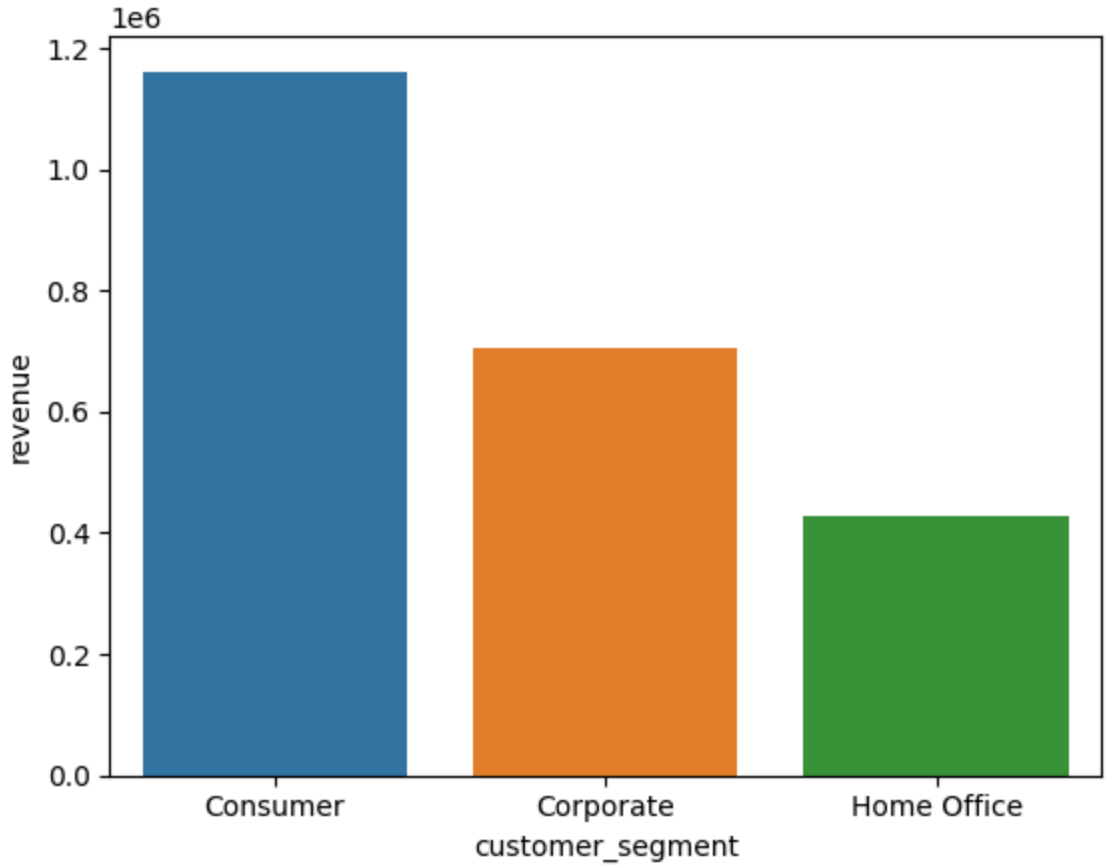
In [5]:
```
ax = sns.countplot(data = df , x = 'customer_segment' , hue = 'customer_segment' )
ax.set(ylabel= 'customer count')
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



Revenue Generated By Each Customer Segment

In [6]:
```
cust_seg_rev = df.groupby('customer_segment')['sales'].sum().reset_index(name= 'revenu
```

In [7]:
```
ax = sns.barplot(data= cust_seg_rev , x = 'customer_segment' , y = 'revenue' , hue= 'c
plt.show()
```



In [8]:
```
# Dividing the customer revenue by 1 million
cust_seg_rev['revenue'] = cust_seg_rev['revenue'] / 1000000
```

In [9]:
```
# Format the values to show as million dollar
cust_seg_rev['revenue'] = cust_seg_rev['revenue'].map('${:,.2f}M'.format)
```

In [10]:
```
cust_seg_rev
```

Out[10]:

	customer_segment	revenue
0	Consumer	$1.16M
1	Corporate	$0.71M
2	Home Office	$0.43M

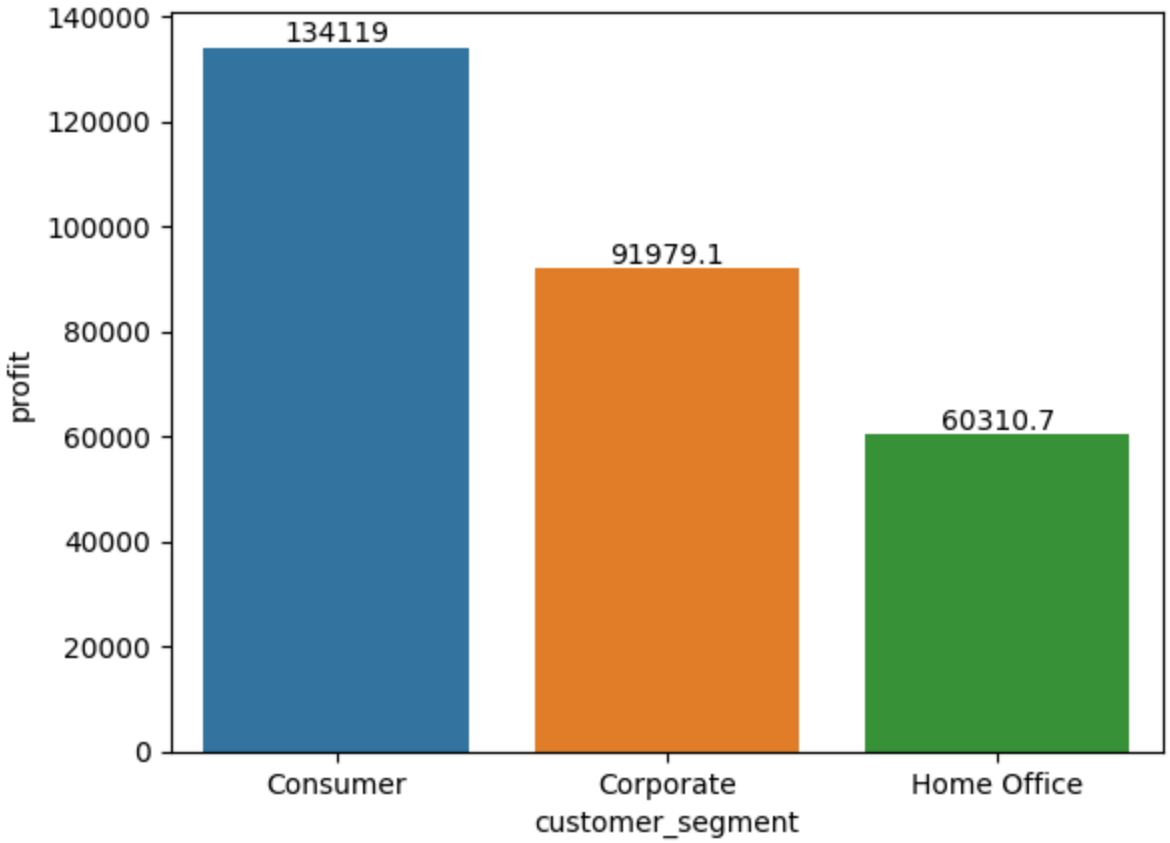
Profit Generated By Each Customer Segment

In [11]:
```
cust_seg_profit = df.groupby('customer_segment')['profit'].sum().reset_index(name= 'pr
cust_seg_profit
```

Out[11]:

	customer_segment	profit
0	Consumer	134119.2092
1	Corporate	91979.1340
2	Home Office	60310.7373

In [12]:
```
ax = sns.barplot(data =  cust_seg_profit , x = 'customer_segment' , y = 'profit' , hue
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



Revenue Generated By Each Customer Segment In Each Year

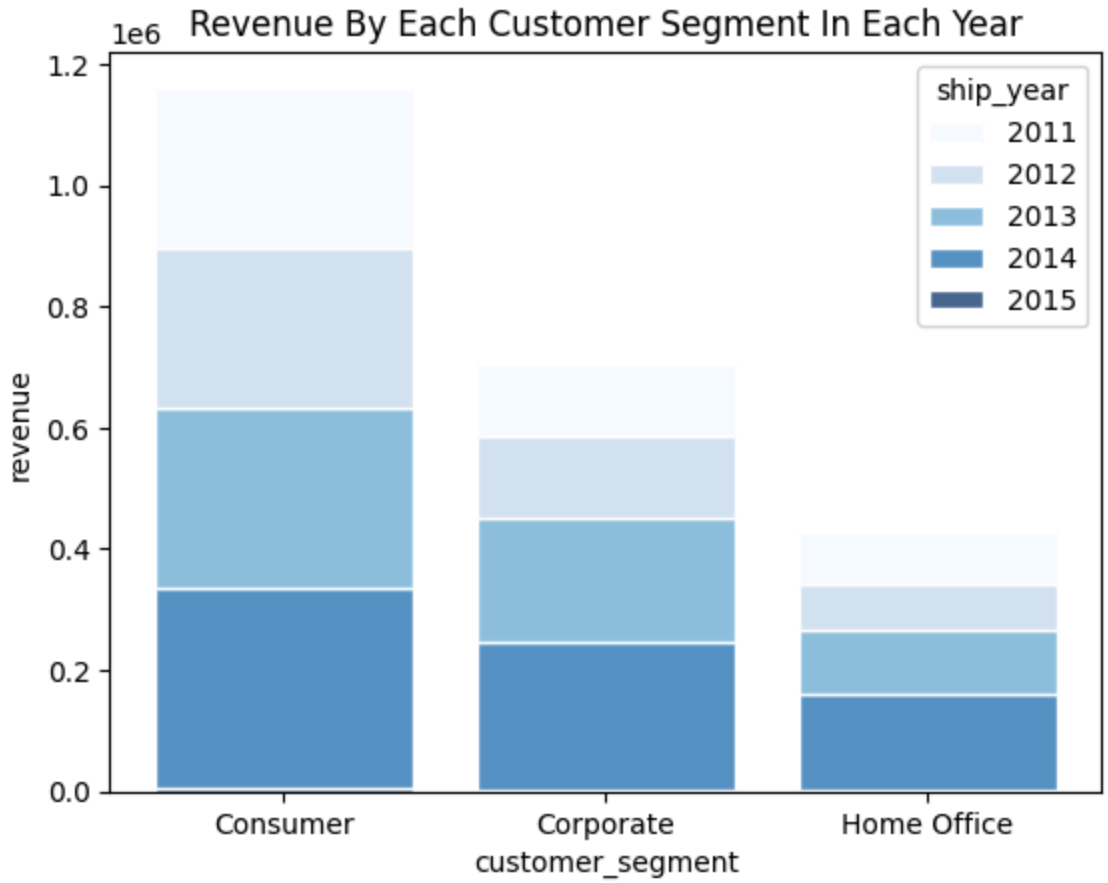
In [13]:
```
cust_seg_rev_y = df.groupby(['customer_segment' , 'ship_year'])['sales'].sum().reset_i
cust_seg_rev_y
```

Out[13]:

	customer_segment	ship_year	revenue
0	Consumer	2011	263436.4766
1	Consumer	2012	265223.0893
2	Consumer	2013	296328.4252
3	Consumer	2014	331767.1671
4	Consumer	2015	4646.1868
5	Corporate	2011	120263.0307
6	Corporate	2012	135960.6899
7	Corporate	2013	204791.9348
8	Corporate	2014	243568.1234
9	Corporate	2015	1562.5880
10	Home Office	2011	86402.3138
11	Home Office	2012	78258.7228
12	Home Office	2013	105165.0970
13	Home Office	2014	158392.2589
14	Home Office	2015	1153.3840

In [14]:

```
ax = sns.histplot(
    cust_seg_rev_y,
    x='customer_segment',
    # Use the value variable here to turn histogram counts into weighted
    # values.
    weights='revenue',
    hue='ship_year',
    multiple='stack',
    palette='Blues' ,
    # Add white borders to the bars.
    edgecolor='white',
    # Shrink the bars a bit so they don't touch.
    shrink=0.8
)
ax.set_title('Revenue By Each Customer Segment In Each Year')
# Add ylabel.
ax.set_ylabel('revenue')
plt.show()
```



From the above graphs we can see that maximum number of customers `(5191)` are from `Consumer` customer_segment .

So other analysis of customer_segment follow `Consumer` customer_segment :

- `Maximum revenue` was generated by `Consumer segment ($1.6 M)`
- `Maximum profit` was generated by `Consumer segment ($ 134,119)`
- In each year Consumer segment generated highest revenue

Customer Anaysis

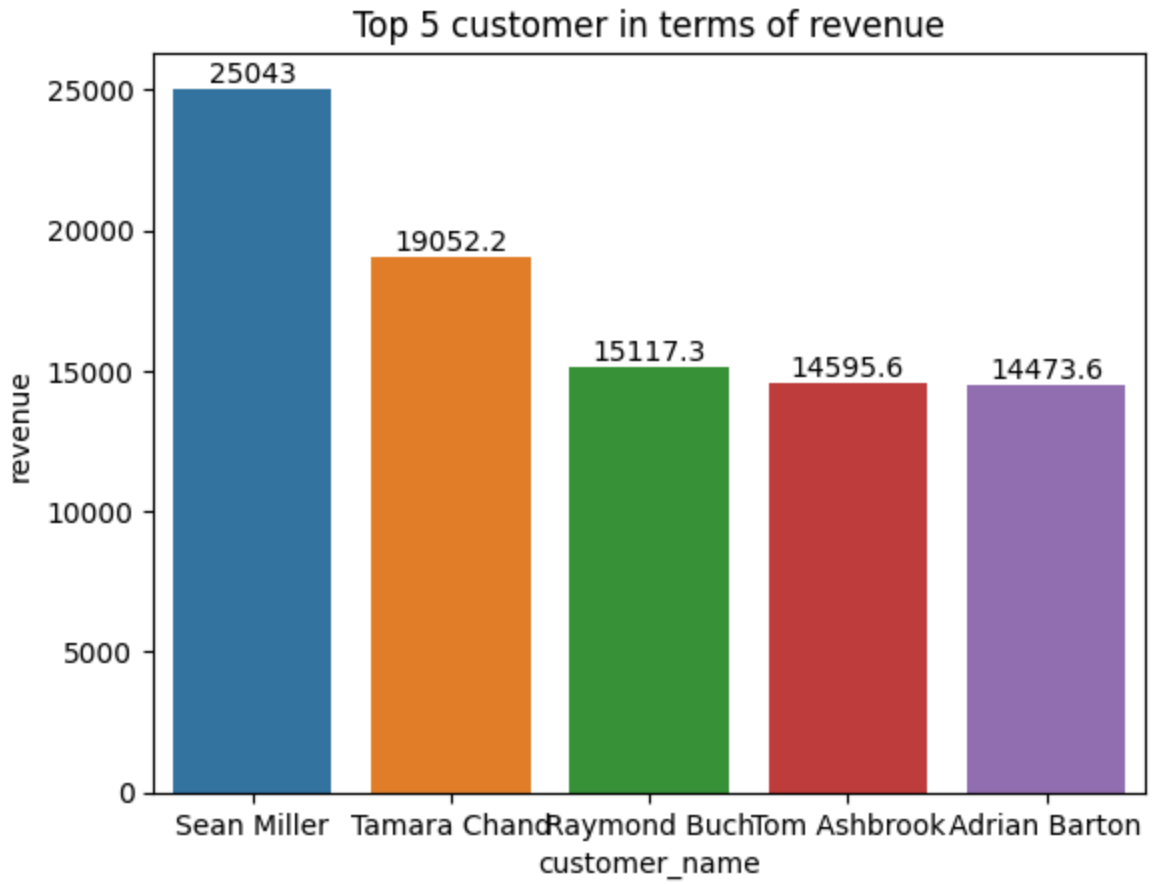
Top 5 Customers interms of Sales

In [15]:
```
top_5_customer = df.groupby(['customer_name'])['sales'].sum().reset_index(name= 'rever
top_5_customer
```

Out[15]:

	customer_name	revenue
686	Sean Miller	25043.050
730	Tamara Chand	19052.218
622	Raymond Buch	15117.339
757	Tom Ashbrook	14595.620
6	Adrian Barton	14473.571

In [16]:
```
ax = sns.barplot(data = top_5_customer , x = 'customer_name' , y= 'revenue' , hue = 'c
plt.title('Top 5 customer in terms of revenue')
# sns.set_theme({'figure.figsize' : (7 ,4)})
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



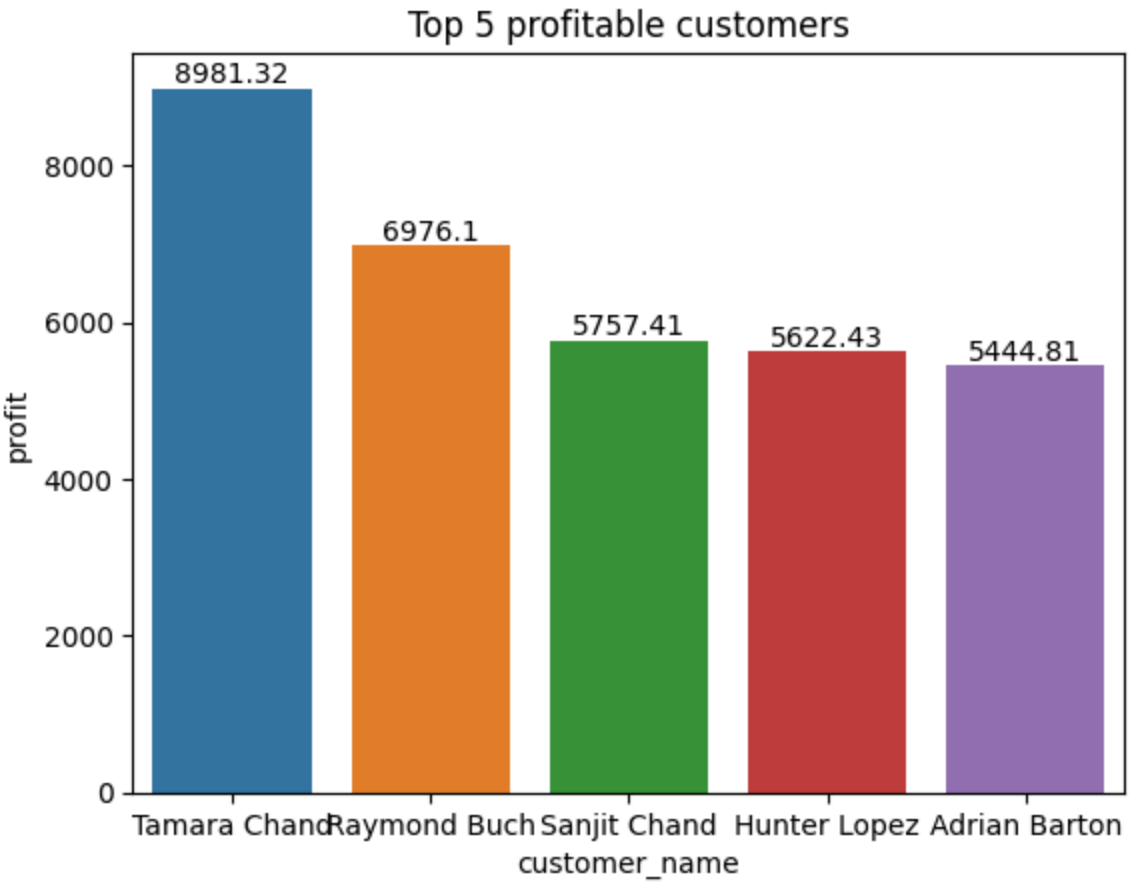
Top 5 Profitable Customers

In [17]:
```
top_5_profitable_customer = df.groupby(['customer_name'])['profit'].sum().reset_index(
top_5_profitable_customer
```

Out[17]:

	customer_name	profit
730	Tamara Chand	8981.3239
622	Raymond Buch	6976.0959
671	Sanjit Chand	5757.4119
334	Hunter Lopez	5622.4292
6	Adrian Barton	5444.8055

In [18]:
```
ax = sns.barplot(data = top_5_profitable_customer , x = 'customer_name' , y= 'profit'
plt.title('Top 5 profitable customers')
# sns.set_theme({'figure.figsize' : (7 ,4)})
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



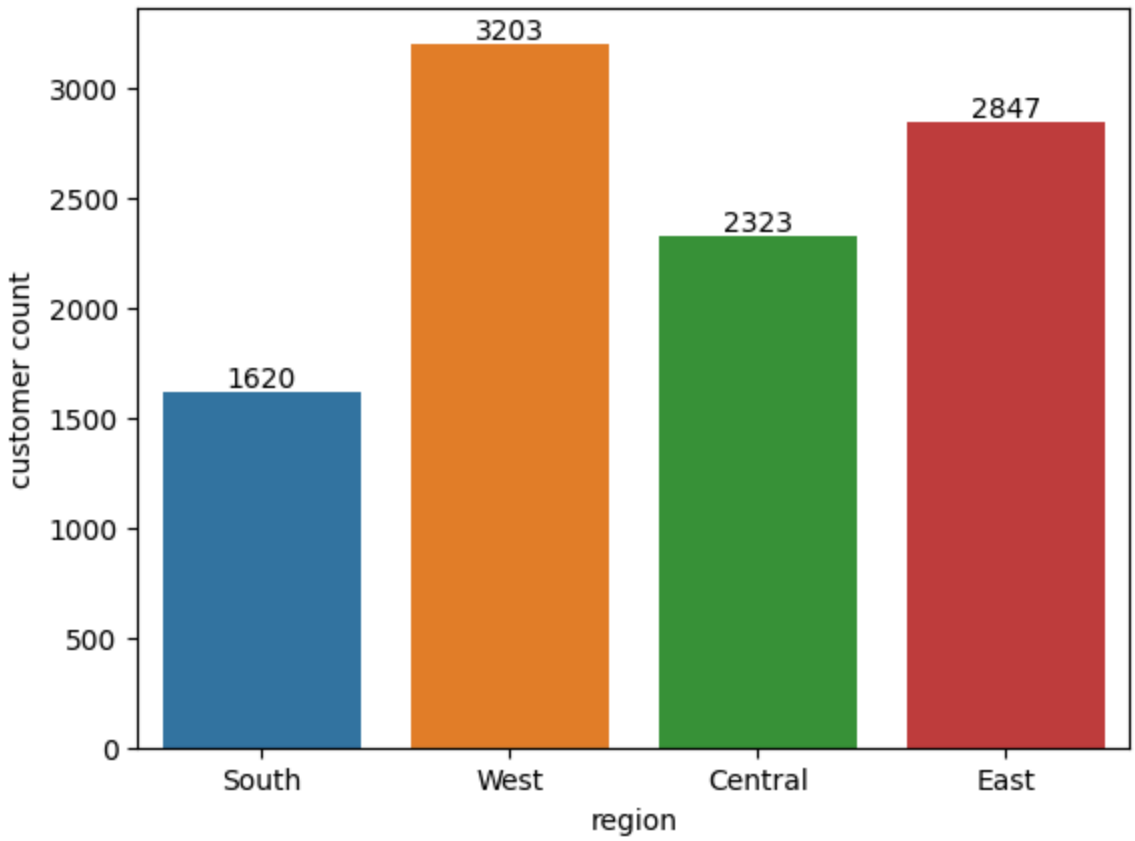
- In `revenue analysis Sean Miller ($25043)` is the `top customer` and the `2nd highest` revenue generator customer was `Tamara Chand ($19052)`.
- In `profit analysis Sean Miller` was not in the top 5 customer list but `Tamara Chand ($8981)` was the `top customer`.

  So, from both analysis `Tamara Chand` is evolved as most `valuable customer` .

Regional Analysis

Customer Count by Region

In [19]:
```
ax = sns.countplot(data = df , x = 'region' , hue = 'region' )
ax.set(ylabel= 'customer count')
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



Revenue by Region

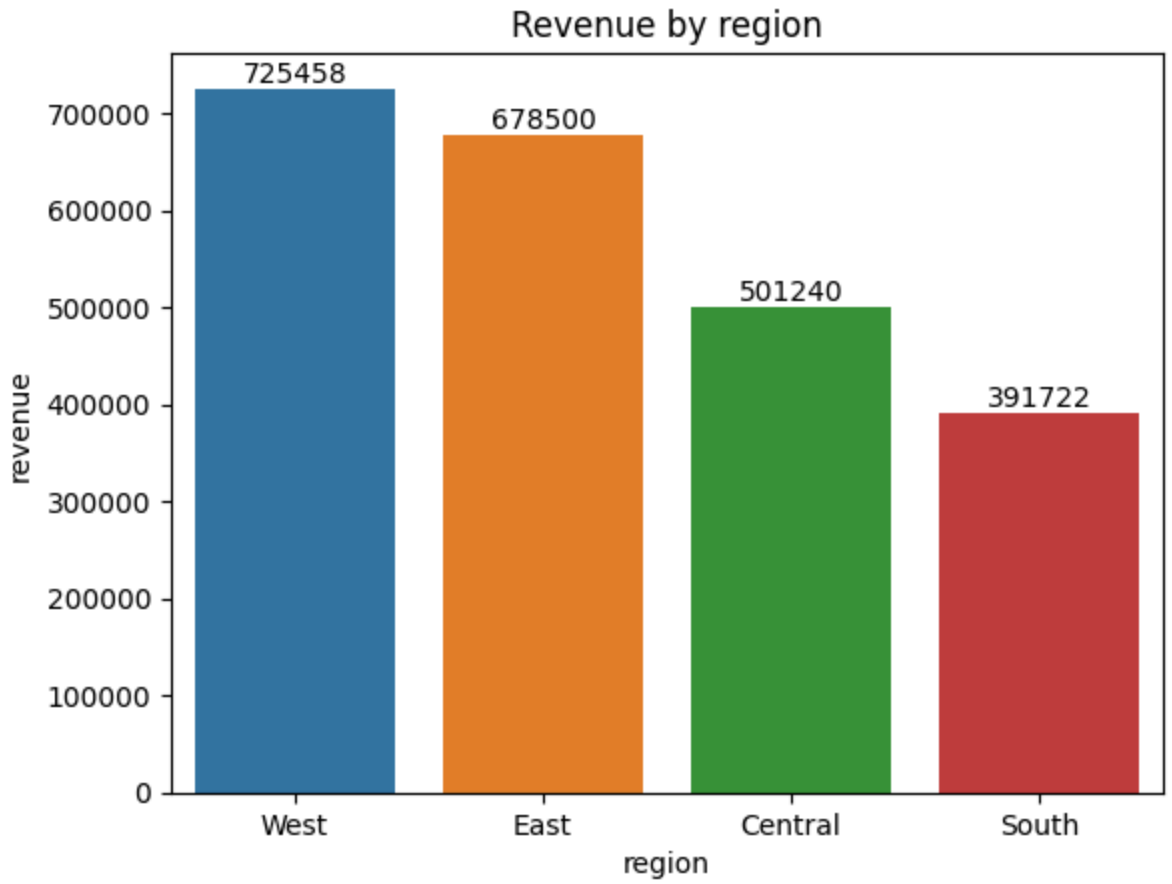
In [20]:
```
revenue_reg = df.groupby(['region'])['sales'].sum().reset_index(name= 'revenue').sort_
revenue_reg
```

Out[20]:

	region	revenue
3	West	725457.8245
1	East	678499.8680
0	Central	501239.8908
2	South	391721.9050

In [21]:
```
ax = sns.barplot(data = revenue_reg , x = 'region' , y= 'revenue' , hue = 'region' )
plt.title('Revenue by region')
# sns.set_theme({'figure.figsize' : (7 ,4)})
for bars in ax.containers:
```

```
    ax.bar_label(bars)
plt.show()
```



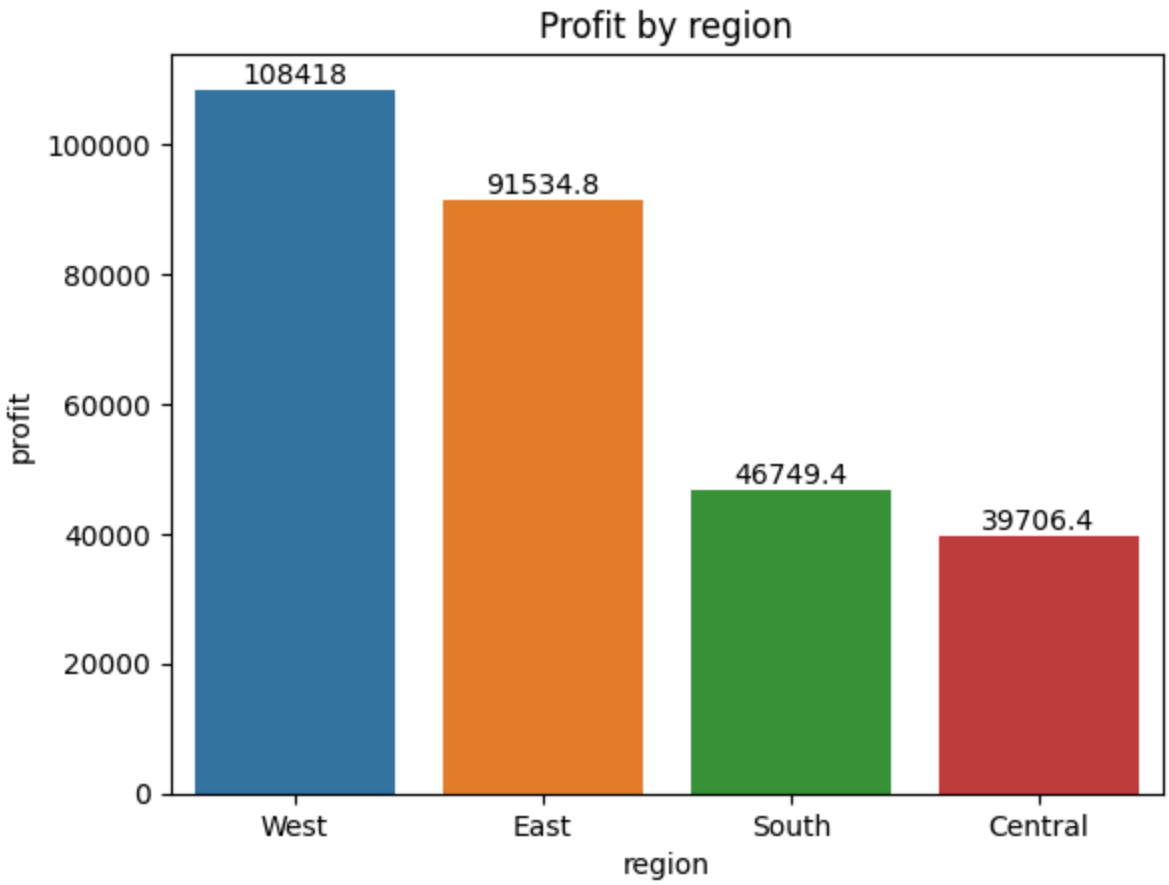
Profit by Region

In [22]:
```
profit_reg = df.groupby(['region'])['profit'].sum().reset_index(name= 'profit').sort_v
profit_reg
```

Out[22]:

	region	profit
3	West	108418.4489
1	East	91534.8388
2	South	46749.4303
0	Central	39706.3625

In [23]:
```
ax = sns.barplot(data = profit_reg , x = 'region' , y= 'profit' , hue = 'region' )
plt.title('Profit by region')
# sns.set_theme({'figure.figsize' : (7 ,4)})
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



Revenue Generated By Each region In Each Year

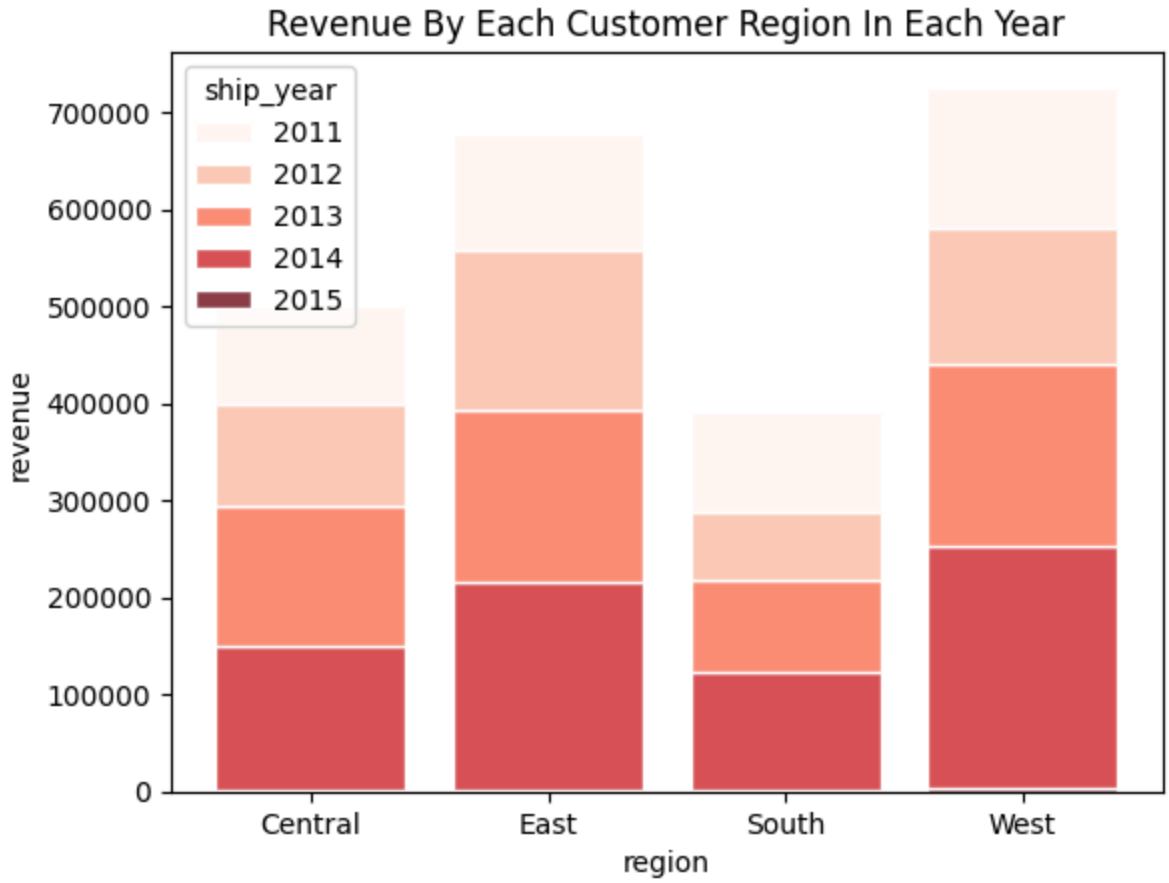
In [24]:
```
region_rev_y = df.groupby(['region' , 'ship_year'])['sales'].sum().reset_index(name= '
region_rev_y
```

Out[24]:

	region	ship_year	revenue
0	Central	2011	102899.8606
1	Central	2012	103222.5780
2	Central	2013	146225.8940
3	Central	2014	147991.2334
4	Central	2015	900.3248
5	East	2011	119710.8710
6	East	2012	164991.7110
7	East	2013	177437.3720
8	East	2014	215752.5180
9	East	2015	607.3960
10	South	2011	103284.7955
11	South	2012	71324.5485
12	South	2013	93957.1255
13	South	2014	121275.9715
14	South	2015	1879.4640
15	West	2011	144206.2940
16	West	2012	139903.6645
17	West	2013	188665.0655
18	West	2014	248707.8265
19	West	2015	3974.9740

In [25]:

```
ax = sns.histplot(
    region_rev_y,
    x='region',
    # Use the value variable here to turn histogram counts into weighted
    # values.
    weights='revenue',
    hue='ship_year',
    multiple='stack',
    palette='Reds' ,
    # Add white borders to the bars.
    edgecolor='white',
    # Shrink the bars a bit so they don't touch.
    shrink=0.8
)
ax.set_title('Revenue By Each Customer Region In Each Year')
# Add ylabel.
ax.set_ylabel('revenue')
plt.show()
```



From the above graphs we can see that `maximum customers (3203)` were from `west region` and `minimum customers (1620)` were from `south region` . So other analysis of region follows `west region` customer_segment :

- `Maximum revenue` was generated by `west region ($725458)`
- `Maximum profit` was generated by `west region ($108418)`
- In every year `west region` generated maximum revenue

Intersting matter is that `South region` had minimum customers . But in profit generation it was the `3rd highest` profit generator region among the four regions .

State Anaysis

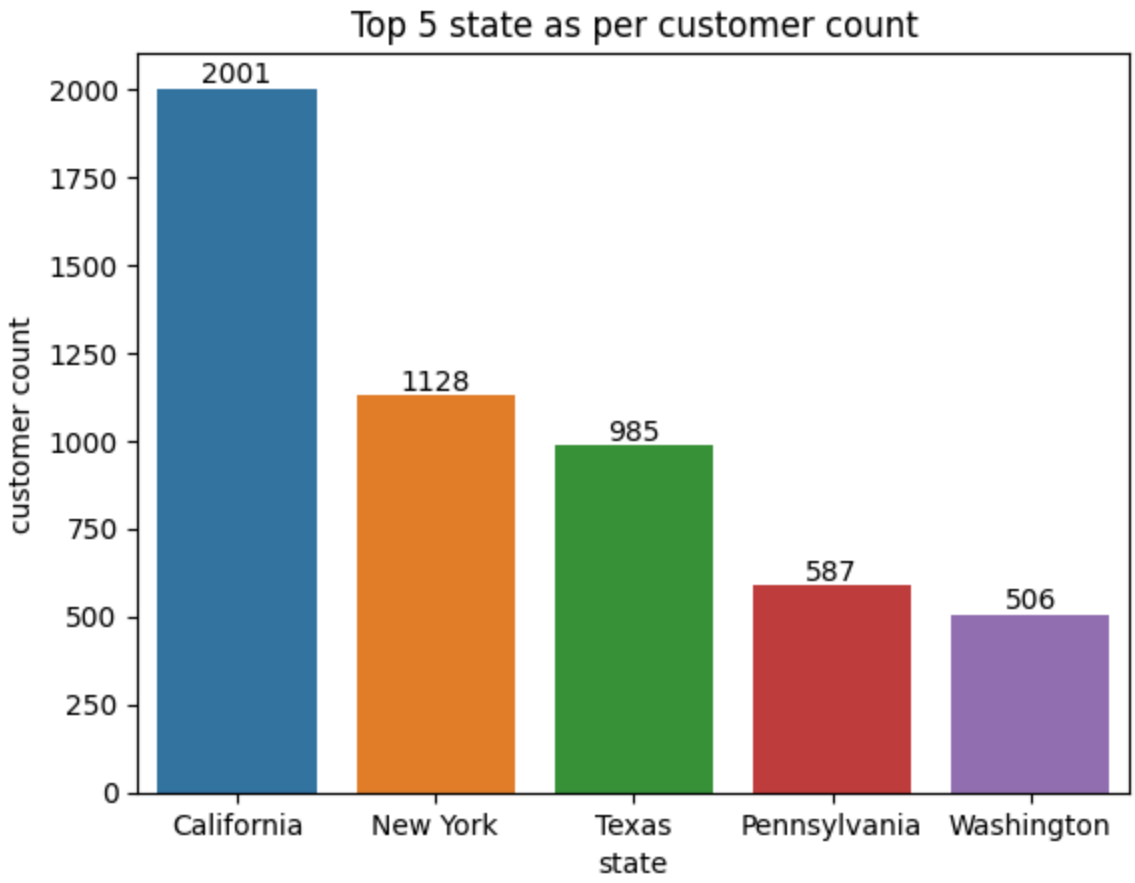
Top 5 state by customer count

In [26]:
```
top_5_state_customer = df.groupby(['state'])['state'].count().reset_index(name= 'custo
top_5_state_customer
```

Out[26]:

	state	customer count
3	California	2001
30	New York	1128
41	Texas	985
36	Pennsylvania	587
45	Washington	506

In [27]:
```
ax = sns.barplot(data = top_5_state_customer , x = 'state' , y= 'customer count' , hue
plt.title('Top 5 state as per customer count')
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



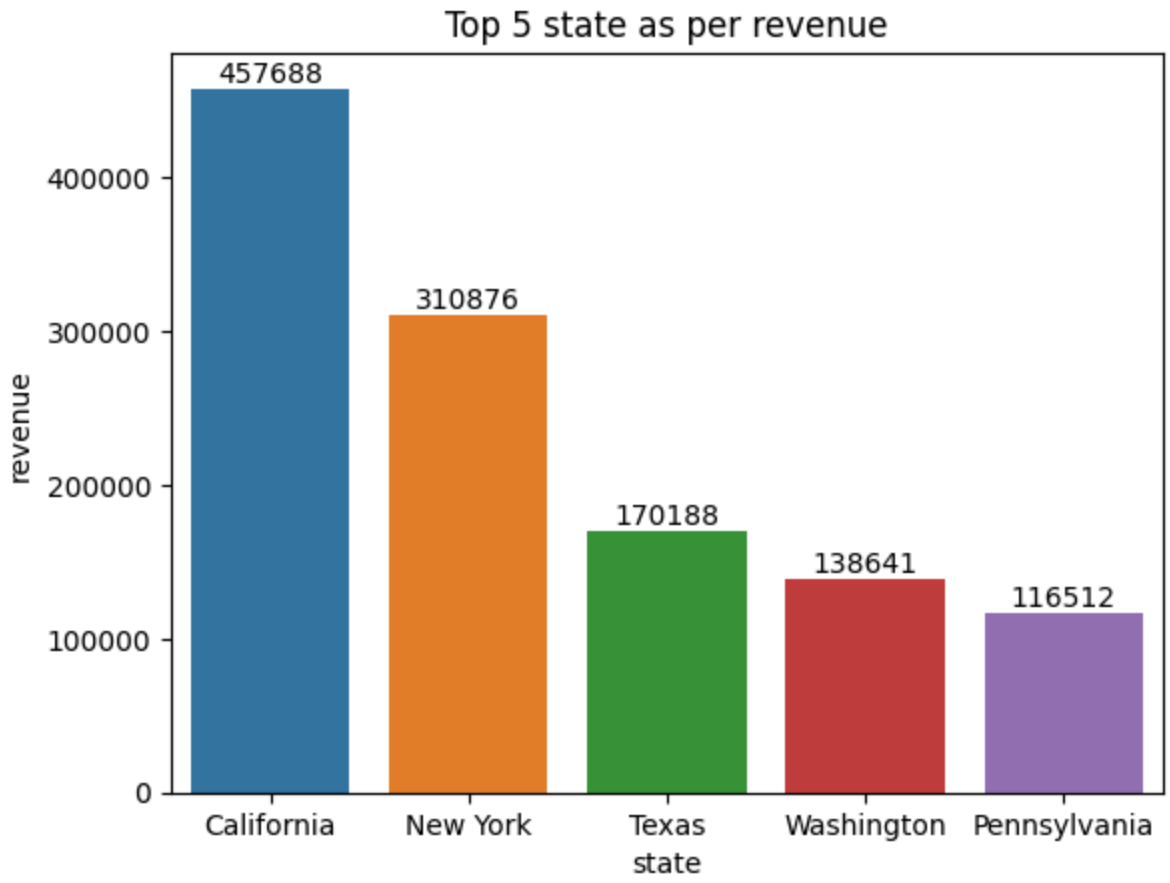
Top 5 state by revenue

In [28]:
```
top_5_state_rev = df.groupby(['state'])['sales'].sum().reset_index(name= 'revenue').so
top_5_state_rev
```

Out[28]:

	state	revenue
3	California	457687.6315
30	New York	310876.2710
41	Texas	170188.0458
45	Washington	138641.2700
36	Pennsylvania	116511.9140

In [29]:
```
ax = sns.barplot(data = top_5_state_rev , x = 'state' , y= 'revenue' , hue = 'state' )
plt.title('Top 5 state as per revenue')
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



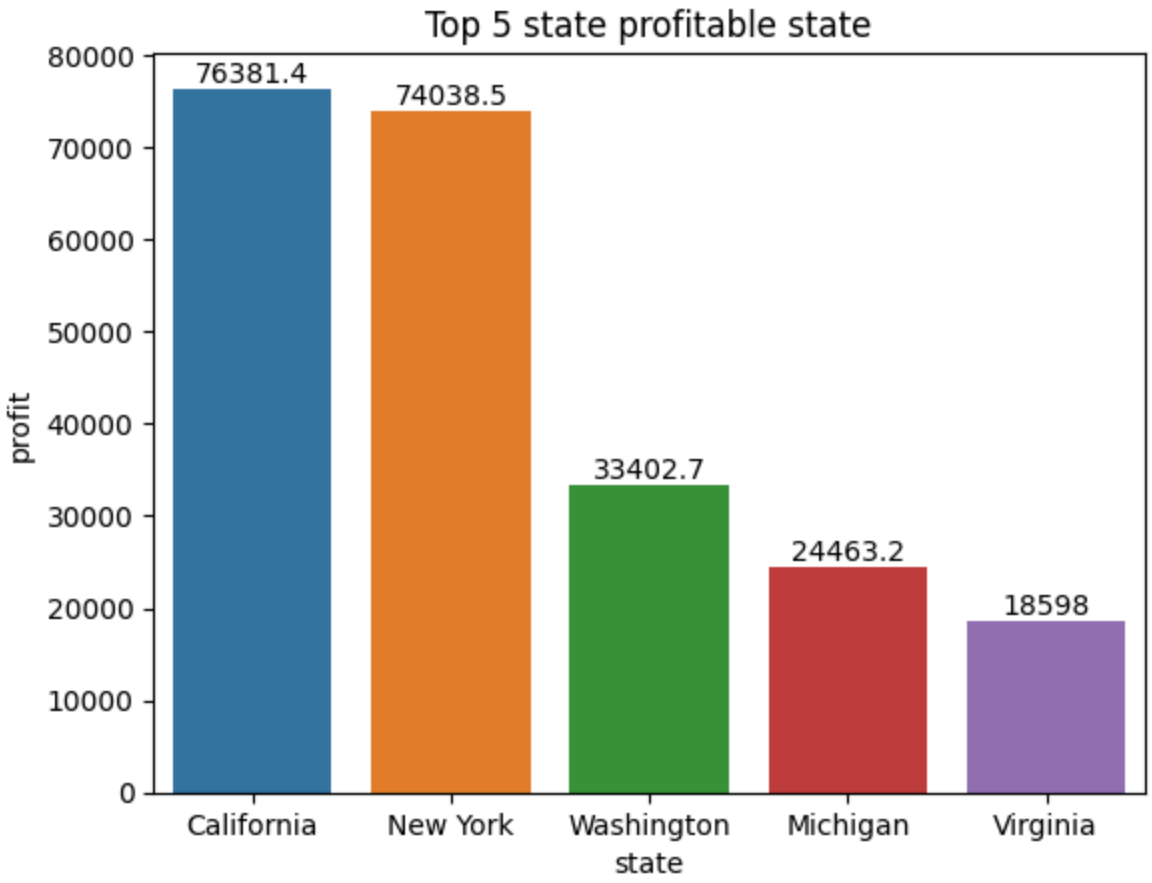
Top 5 state by profit

In [30]:
```
top_5_profitable_state =df.groupby(['state'])['profit'].sum().reset_index(name= 'profi
top_5_profitable_state
```

Out[30]:

	state	profit
3	California	76381.3871
30	New York	74038.5486
45	Washington	33402.6517
20	Michigan	24463.1876
44	Virginia	18597.9504

In [31]:
```
ax = sns.barplot(data = top_5_profitable_state , x = 'state' , y= 'profit' , hue = 'st
plt.title('Top 5 state profitable state')
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



Comparison of profit among Texas , Pennsylvania , Michigan and Virginia state

In [32]:
```
pofit_com_state = df.query("state in ('Texas' , 'Pennsylvania' , 'Michigan' , 'Virgini
pofit_com_state
```

Out[32]:

state	profit
Michigan	24463.1876
Virginia	18597.9504
Pennsylvania	-15559.9603
Texas	-25729.3563

- From the above graphs we can see that from top 5 state `maximum customers` were from `California State (2001)` and `minimum customers` were from `Washington (506)` .
- In the revenue section we can see that maximum revenue was generated also from `California State ($457687)` but minimum was generated from `Pennsylvania state ($116511)` . Although `Pennsylvania state` holds more `customer (587)` than `Washington state (506)` but was generated less revenue than `Washington state ($138641)`
- In the profit section we can see different scenario. Profit Generartion states didn't follow the all aspects of customer distribution of states .

  Top profit generation state was `California State ($76381)` which followed the customer distribuiton and revenue distribution. `Washington state` holds `minimum customer (506)` interms of top 5 states . But in `revenue genration` it holds the `4th position ($138641)` . Alongside it holds `3rd postion ($33402)` in `profit generation` .

  In pofit section `4th and 5th postion` is obtained by `Michigan ($24463) and Virginia ($18598)` . But `Michigan` and `Virginia` doesn't hold any positon in top 5 customer distribution and revenue distribution .

  From the above query we can see that `Texas` and `Penniserlvia` cities incurred `loss` of `($25729)` and `($15559)` respectively . As a result `Texas` and `Penniserlvia` are not included in the top 5 profitable state.

City Analysis

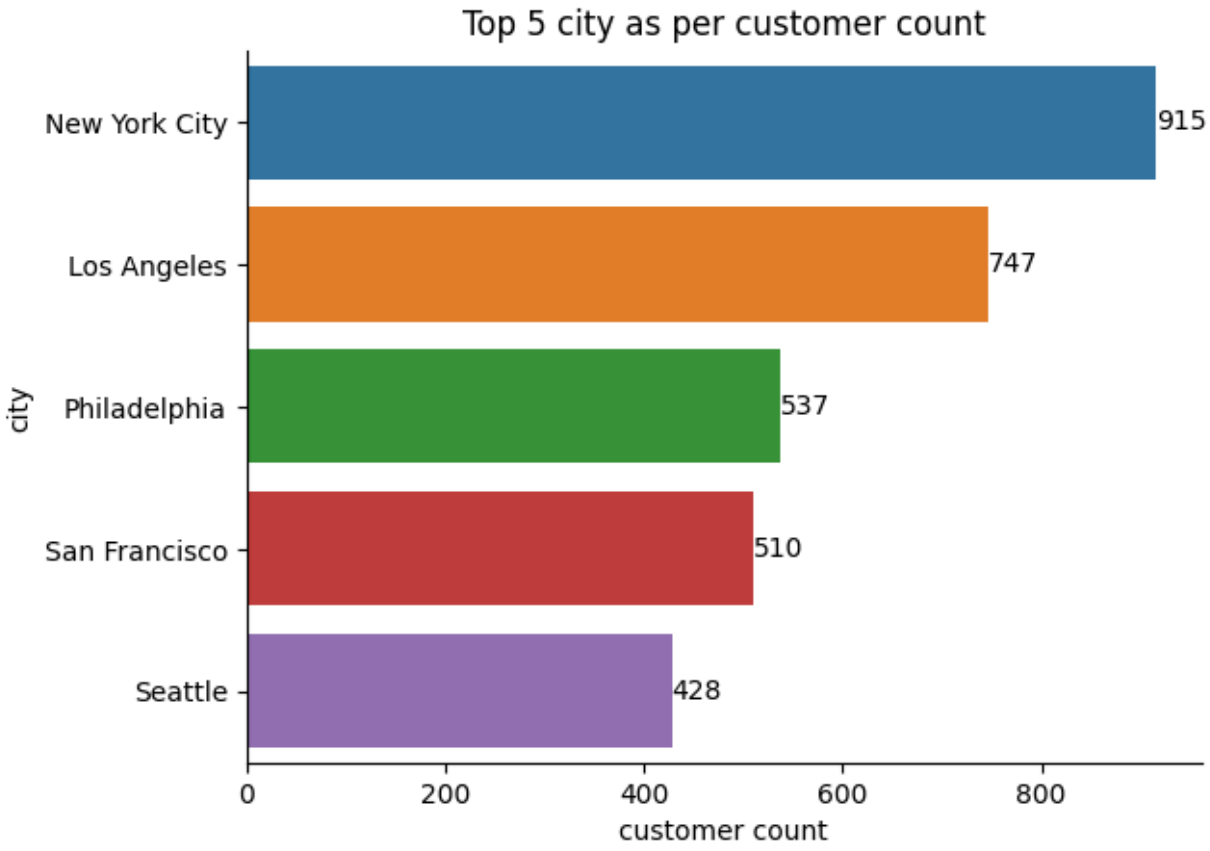
Top 5 city by customer count

In [33]:
```
top_5_city_customer = df.groupby(['city'])['city'].count().reset_index(name= 'customer
top_5_city_customer
```

Out[33]:

	city	customer count
329	New York City	915
266	Los Angeles	747
374	Philadelphia	537
438	San Francisco	510
452	Seattle	428

In [34]:
```
ax = sns.barplot(data = top_5_city_customer , x = 'customer count' , y= 'city' , hue =
plt.title('Top 5 city as per customer count')
sns.despine()
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



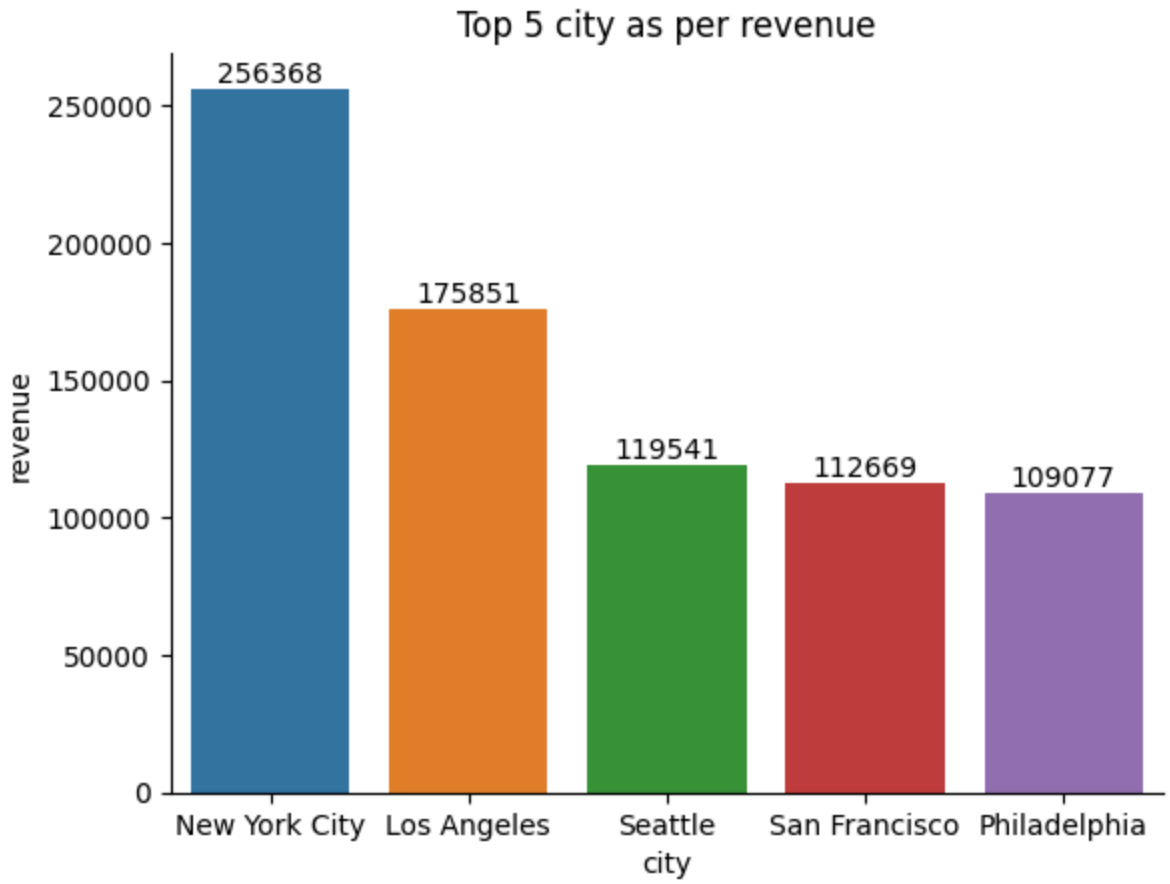
Top 5 city by revenue

In [35]:
```
top_5_city_revenue = df.groupby(['city'])['sales'].sum().reset_index(name= 'revenue').
top_5_city_revenue
```

Out[35]:

	city	revenue
329	New York City	256368.161
266	Los Angeles	175851.341
452	Seattle	119540.742
438	San Francisco	112669.092
374	Philadelphia	109077.013

In [36]:
```
ax = sns.barplot(data = top_5_city_revenue , x = 'city' , y= 'revenue' , hue = 'city'
plt.title('Top 5 city as per revenue')
sns.despine()
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



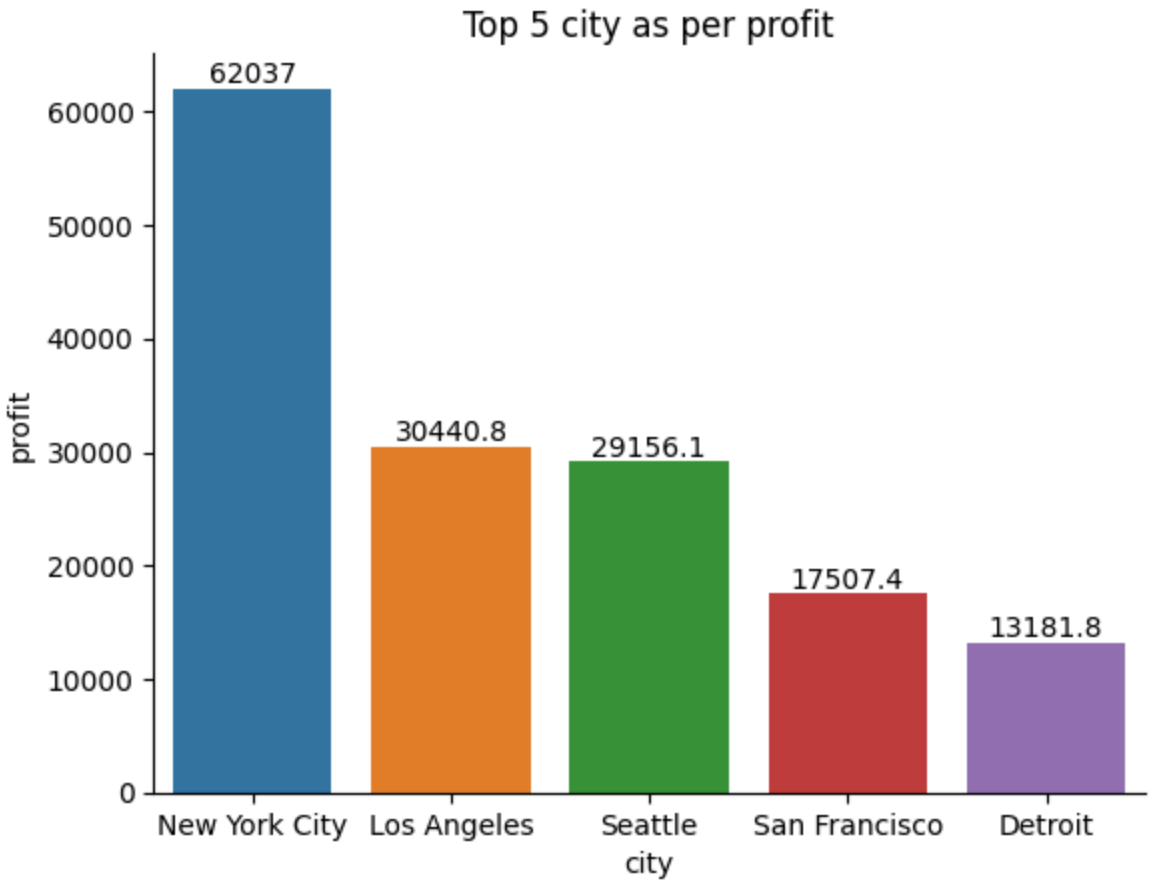
Top 5 city by profit

In [37]:
```
top_5_city_profit = df.groupby(['city'])['profit'].sum().reset_index(name= 'profit').s
top_5_city_profit
```

Out[37]:

	city	profit
329	New York City	62036.9837
266	Los Angeles	30440.7579
452	Seattle	29156.0967
438	San Francisco	17507.3854
123	Detroit	13181.7908

In [38]:
```
ax = sns.barplot(data = top_5_city_profit , x = 'city' , y= 'profit' , hue = 'city' )
plt.title('Top 5 city as per profit')
sns.despine()
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



Comparison of profit between Philadelphia city and Detroit city

In [39]:
```
pofit_com_city= df.query("city in ('Philadelphia' , 'Detroit')")[['city' , 'profit']].
pofit_com_city
```

Out[39]:

city	profit
Detroit	13181.7908
Philadelphia	-13837.7674

- From the above graphs we can see that from top 5 city `maximum customers` are from `New York City (915)` and `minimum customers` are from `Seattle (428)` city.
- In the revenue section we can see that maximum revenue is generated also from `New York City ($256368)` but minimum is generated from `Philadelphia city ($109077)` . Although `Philadelphia city` holds more `customer (537)` than `San Francisco city (510)` and `Seattle city (428)` but generate less revenue than `San Francisco city ($112669)` and `Seattle city ($119540)`
- In the profit section we can see :

  Top profit generation city is `New York City ($62036)` which follows the customer distribuiton and revenue distribution.

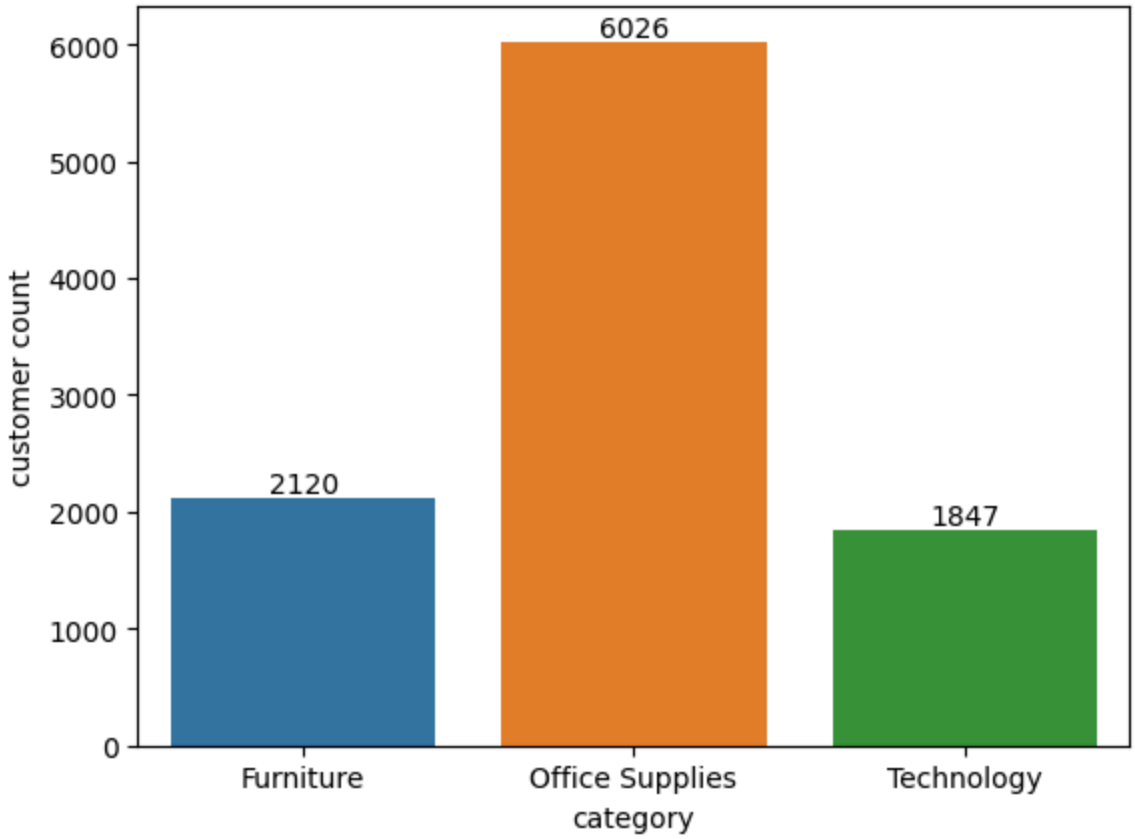
  In pofit section `5th postion` is obtained by `Detroit ($13181) city` . But `Philadelphia city doesn't exists` in profit section. Though this city exists in `3rd position in customer distribution` and `5th position in revenue distribution` .

  From the above query of profit between `Philadelphia city and Detroit city` , we can see that `Philadelphia city incurred loss of ($13837)` . But `Detroit city` is generated proft of ($13181). This is why Detroit city obtained 5th postion in profit distribution.

Product Category Analysis

Customer count by product category

In [40]:
```
ax = sns.countplot(data = df , x = 'category' , hue = 'category' )
ax.set(ylabel= 'customer count')
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



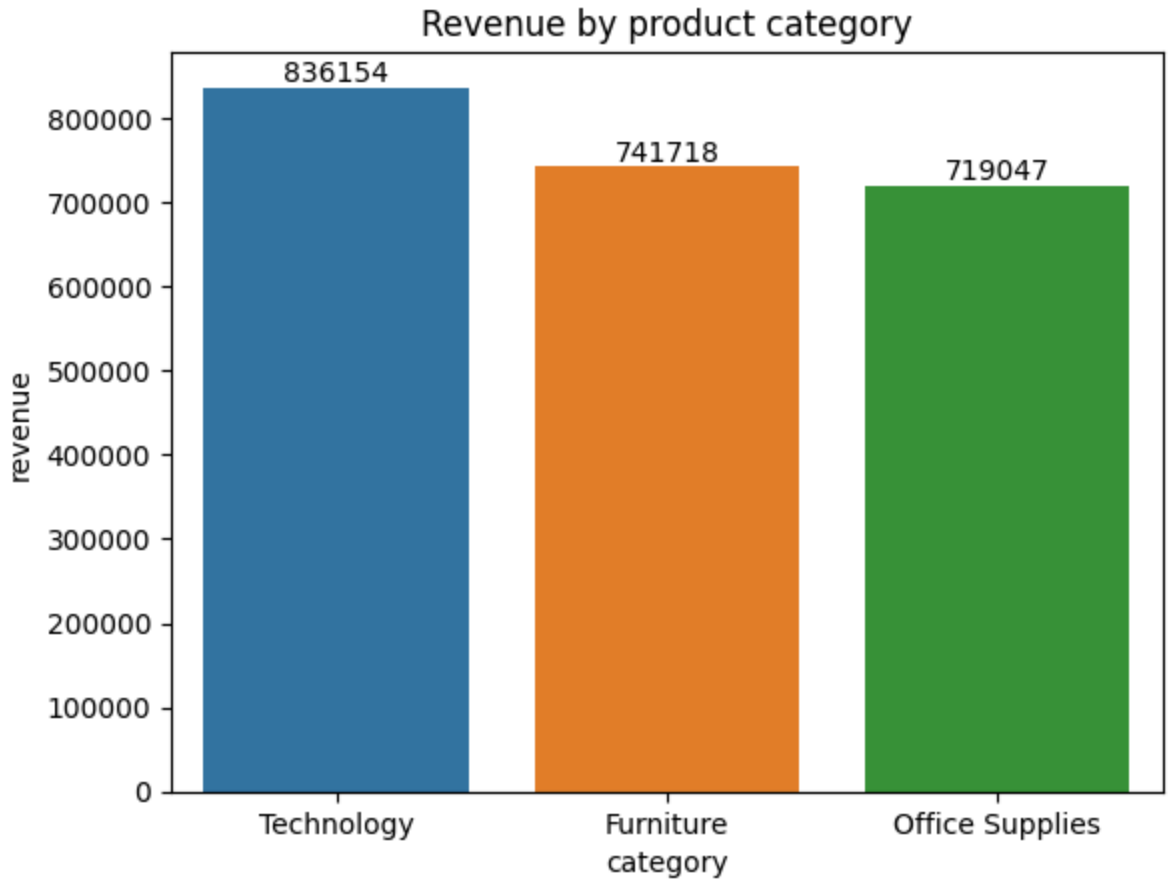
Revenue by product category

In [41]:
```
revenue_ctg = df.groupby(['category'])['sales'].sum().reset_index(name= 'revenue').sor
revenue_ctg
```

Out[41]:

	category	revenue
2	Technology	836154.0330
0	Furniture	741718.4233
1	Office Supplies	719047.0320

In [42]:
```
ax = sns.barplot(data = revenue_ctg , x = 'category' , y= 'revenue' , hue = 'category'
plt.title('Revenue by product category')
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



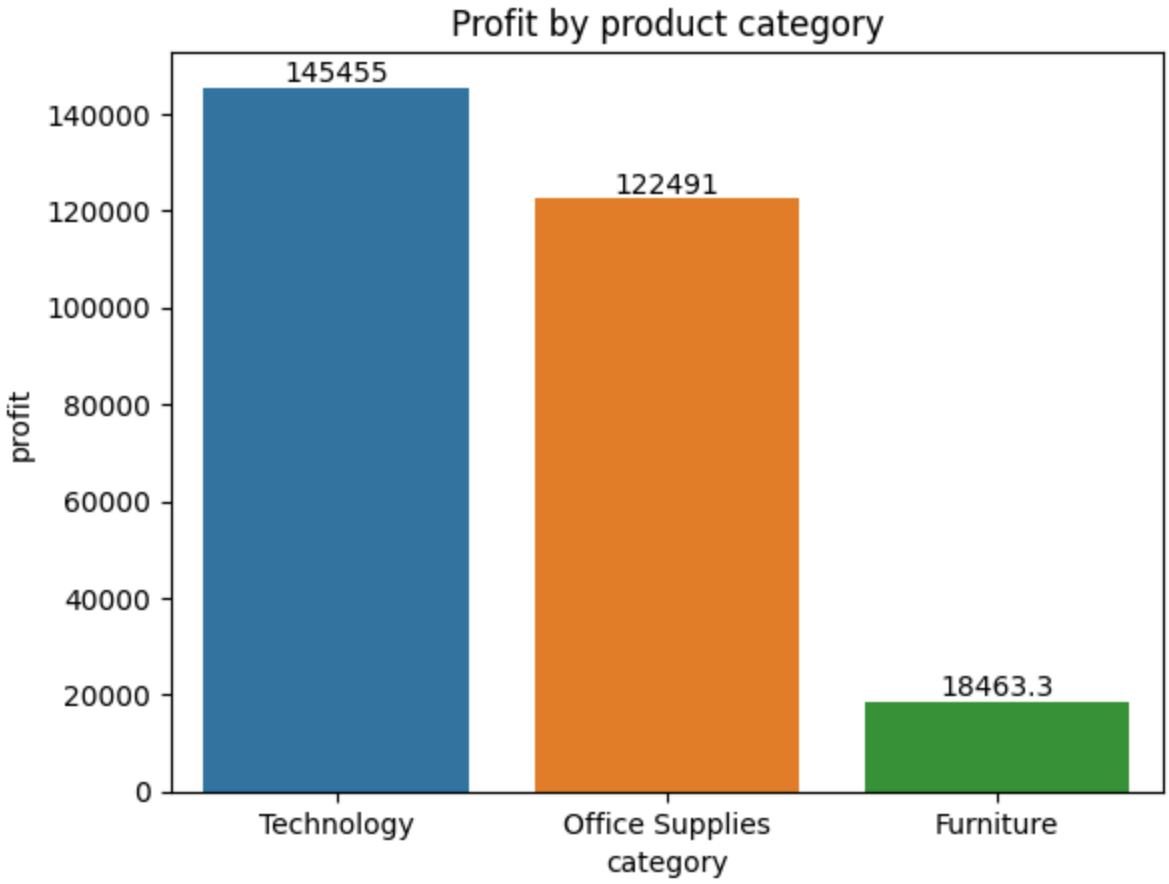
Profit by product category

In [43]:
```
profit_ctg = df.groupby(['category'])['profit'].sum().reset_index(name= 'profit').sort
profit_ctg
```

Out[43]:

	category	profit
2	Technology	145454.9481
1	Office Supplies	122490.8008
0	Furniture	18463.3316

In [44]:
```
ax = sns.barplot(data = profit_ctg , x = 'category' , y= 'profit' , hue = 'category' )
plt.title('Profit by product category')
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



- From the above graphs we can see that `maximum customers (6026)` purchased `Office Supplies` category products and `minimum customers (1847)` purchased `Technology category` products .
    - In revenue analysis we can see that `Technology category ($836154)` contributes `maximum revenue` . `Furniture ($741718)` and `Office Supplies($719047)` hold the `2nd and 3rd postiton` repsectively in revenue distribution. Technology and Furniture category hold less customer than Office Supplies category but contribute more rvenue than Office Supplies category . Because products of Technology and Furniture category are more expensive than products of Office Supplies .
- In profit analysis we can see that `Technology category ($145454)` contributes `maximum profit` . `Office Supplies($122490)` and `Furniture ($18463)` hold the `2nd and 3rd postiton` repsectively in profit distribution. Here Office Supplies category provides more profit than Furniture category becuse lower cost of Office Supplies category products .

Product Analysis

Top 10 selling products interms of quntity

In [45]:
```
top_10_product_qyt = df.groupby(['product_name' ])['quantity'].sum().reset_index().sor
```

```
top_10_product_qyt
```

Out[45]:

	product_name	quantity
1491	Staples	876
940	KI Adjustable-Height Table	74
1502	Storex Dura Pro Binders	71
258	Avery Non-Stick Binders	71
697	GBC Premium Transparent Covers with Diagonal L...	67
1448	Situations Contoured Folding Chairs, 4/Set	64
427	Chromcraft Round Conference Tables	61
589	Eldon Wave Desk Accessories	61
1633	Wilson Jones Turn Tabs Binder Tool for Ring Bi...	59
770	Global Wood Trimmed Manager's Task Chair, Khaki	59

Top 10 products interms of revenue

In [46]:
```
top_10_product_rev =df.groupby(['product_name' ])['sales'].sum().reset_index(name= 're
top_10_product_rev
```

Out[46]:

	product_name	revenue
403	Canon imageCLASS 2200 Advanced Copier	61599.824
648	Fellowes PB500 Electric Punch Plastic Comb Bin...	27453.384
443	Cisco TelePresence System EX90 Videoconferenci...	22638.480
784	HON 5400 Series Task Chairs for Big and Tall	21870.576
684	GBC DocuBind TL300 Electric Binding System	19823.479
686	GBC Ibimaster 500 Manual ProClick Binding System	19024.500
803	Hewlett Packard LaserJet 3310 Copier	18839.686
785	HP Designjet T520 Inkjet Large Format Printer ...	18374.895
681	GBC DocuBind P400 Electric Binding System	17965.068
811	High Speed Automatic Electric Letter Opener	17030.312

Top 10 profitable products

In [47]:
```
top_10_product_profit =df.groupby(['product_name' ])['profit'].sum().reset_index(name=
top_10_product_profit
```

Out[47]:

	product_name	profit
403	Canon imageCLASS 2200 Advanced Copier	25199.9280
648	Fellowes PB500 Electric Punch Plastic Comb Bin...	7753.0390
803	Hewlett Packard LaserJet 3310 Copier	6983.8836
399	Canon PC1060 Personal Laser Copier	4570.9347
785	HP Designjet T520 Inkjet Large Format Printer ...	4094.9766
164	Ativa V4110MDD Micro-Cut Shredder	3772.9461
18	3D Systems Cube Printer, 2nd Generation, Magenta	3717.9714
1274	Plantronics Savi W720 Multi-Device Wireless He...	3696.2820
893	Ibico EPK-21 Electric Binding System	3345.2823
1831	Zebra ZM400 Thermal Label Printer	3343.5360

Top 10 costlier product

In [48]:
```
top_10_product_cost = df.groupby(['product_name' ])['cost'].sum().reset_index(name= 'c
top_10_product_cost
```

Out[48]:

	product_name	cost
403	Canon imageCLASS 2200 Advanced Copier	36399.89
443	Cisco TelePresence System EX90 Videoconferenci...	24449.56
784	HON 5400 Series Task Chairs for Big and Tall	21870.58
983	Lexmark MX611dhe Monochrome Laser Printer	21419.87
474	Cubify CubeX 3D Printer Double Head Print	19979.94
681	GBC DocuBind P400 Electric Binding System	19843.24
648	Fellowes PB500 Electric Punch Plastic Comb Bin...	19700.35
686	GBC Ibimaster 500 Manual ProClick Binding System	18263.52
1041	Martin Yale Chadless Opener Electric Letter Op...	17955.39
684	GBC DocuBind TL300 Electric Binding System	17589.96

Top 10 discounted products

In [49]:
```
top_10_product_discounted = df.groupby(['product_name' ])['discount_amount'].sum().res
top_10_product_discounted
```

Out[49]:

	product_name	discount_amount
443	Cisco TelePresence System EX90 Videoconferenci...	11319.24
983	Lexmark MX611dhe Monochrome Laser Printer	6578.96
403	Canon imageCLASS 2200 Advanced Copier	5599.98
474	Cubify CubeX 3D Printer Double Head Print	5369.99
681	GBC DocuBind P400 Electric Binding System	5280.64
686	GBC Ibimaster 500 Manual ProClick Binding System	5250.74
684	GBC DocuBind TL300 Electric Binding System	4458.05
784	HON 5400 Series Task Chairs for Big and Tall	4079.69
648	Fellowes PB500 Electric Punch Plastic Comb Bin...	4067.18
475	Cubify CubeX 3D Printer Triple Head Print	3999.99

Delivery time Analysis

Average delivery time

In [50]:
```
avg_delivery_time =  df['delivery_time_in_days'].mean()
avg_delivery_time
```

Out[50]:
```
np.float64(3.958871209846893)
```

Average delivery time is 4 days

Relationship between average delivery time and revenue in each year

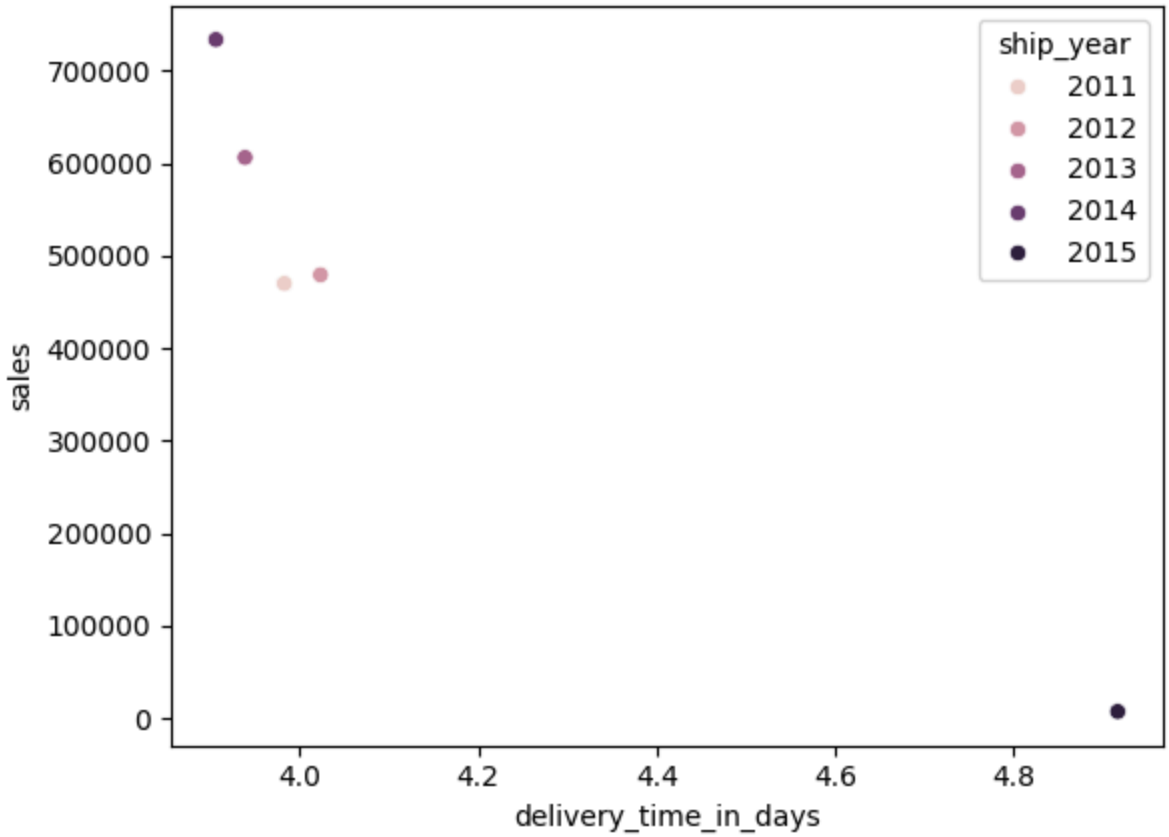
In [51]:
```
corr_sales_avg_delivery_time = df.groupby(['ship_year'])[['delivery_time_in_days' , 's
corr_sales_avg_delivery_time
```

Out[51]:

ship_year	delivery_time_in_days	sales
2011	3.982465	470101.8211
2012	4.022994	479442.5020
2013	3.938402	606285.4570
2014	3.905740	733727.5494
2015	4.916667	7362.1588

In [52]:
```
sns.scatterplot(data= corr_sales_avg_delivery_time ,  x = 'delivery_time_in_days' , y
```

Out[52]:
```
<Axes: xlabel='delivery_time_in_days', ylabel='sales'>
```



In this graph we can see that in 2012 , 2013 and 2014 as average delivery time was decreased total revenue was increased . In 2015 average delivery time was increased but the revenue value was too little compare to other years. Because year 2015 includes only January month.