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

In [2]:
```
df = pd.read_csv("2019 Winter Data Science Intern Challenge Data Set - Sheet1.csv
df.head()
```

Out[2]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
0	1	53	746	224	2	cash	2017-03-13 12:36:56
1	2	92	925	90	1	cash	2017-03-03 17:38:52
2	3	44	861	144	1	cash	2017-03-14 4:23:56
3	4	18	935	156	1	credit_card	2017-03-26 12:43:37
4	5	18	883	156	1	credit_card	2017-03-01 4:35:11

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   order_id        5000 non-null   int64 
 1   shop_id         5000 non-null   int64 
 2   user_id         5000 non-null   int64 
 3   order_amount    5000 non-null   int64 
 4   total_items     5000 non-null   int64 
 5   payment_method  5000 non-null   object
 6   created_at      5000 non-null   object
dtypes: int64(5), object(2)
memory usage: 273.6+ KB
```

In [4]:
```
df['created_at']= pd.to_datetime(df['created_at'])
df
```

Out[4]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
0	1	53	746	224	2	cash	2017-03-13 12:36:56
1	2	92	925	90	1	cash	2017-03-03 17:38:52
2	3	44	861	144	1	cash	2017-03-14 04:23:56
3	4	18	935	156	1	credit_card	2017-03-26 12:43:37
4	5	18	883	156	1	credit_card	2017-03-01 04:35:11
...	...	...	...	...	...	...	...
4995	4996	73	993	330	2	debit	2017-03-30 13:47:17
4996	4997	48	789	234	2	cash	2017-03-16 20:36:16
4997	4998	56	867	351	3	cash	2017-03-19 05:42:42
4998	4999	60	825	354	2	credit_card	2017-03-16 14:51:18
4999	5000	44	734	288	2	debit	2017-03-18 15:48:18

5000 rows × 7 columns

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

Out[5]:
```
order_id                   int64
shop_id                    int64
user_id                    int64
order_amount               int64
total_items                int64
payment_method            object
created_at        datetime64[ns]
dtype: object
```

In [6]:
```
df = df.sort_values(['created_at'],ascending=True)
df
```

Out[6]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
1862	1863	39	738	536	4	cash	2017-03-01 00:08:09
1741	1742	39	910	268	2	cash	2017-03-01 00:10:19
3228	3229	97	912	324	2	cash	2017-03-01 00:14:12
1267	1268	80	798	290	2	credit_card	2017-03-01 00:19:31
2689	2690	49	799	258	2	credit_card	2017-03-01 00:22:25
...	...	...	...	...	...	...	...
2630	2631	53	940	112	1	credit_card	2017-03-30 23:12:13
1685	1686	34	818	244	2	cash	2017-03-30 23:16:10
1474	1475	21	815	142	1	cash	2017-03-30 23:26:54
317	318	52	848	292	2	cash	2017-03-30 23:41:34
2457	2458	95	700	168	1	credit_card	2017-03-30 23:55:35

5000 rows × 7 columns

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

Out[7]:

	order_id	shop_id	user_id	order_amount	total_items
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.00000
mean	2500.500000	50.078800	849.092400	3145.128000	8.78720
std	1443.520003	29.006118	87.798982	41282.539349	116.32032
min	1.000000	1.000000	607.000000	90.000000	1.00000
25%	1250.750000	24.000000	775.000000	163.000000	1.00000
50%	2500.500000	50.000000	849.000000	284.000000	2.00000
75%	3750.250000	75.000000	925.000000	390.000000	3.00000
max	5000.000000	100.000000	999.000000	704000.000000	2000.00000

In [8]:
```
AOV = sum(df.order_amount)/len(df.total_items)
print("The Average Order Value is:", AOV)
```

```
The Average Order Value is: 3145.128
```

In [ ]:

1a) A Better Way To Evaluate the data

Calculating the AOV per shop

In [9]:

```
#grouping the revenue generated by each shops together with sum aggregate
revenue_per_shop = df.groupby(['shop_id'])['order_amount'].agg('sum')
revenue_per_shop.name ='Revenue'
#grouping the items sold by each shops together with sum aggregate
items_per_shop = df.groupby(['shop_id'])['total_items'].agg('sum')
items_per_shop.name = 'Items'
#grouping the orders taken by each shops together with count aggregate

orders_per_shop = df.groupby(['shop_id'])['total_items'].agg('count')
orders_per_shop.name = 'Orders'

#Adding them to a new dataFrame
df_per_shop = pd.concat([revenue_per_shop, orders_per_shop, items_per_shop], axis

#Calculating Average Order value(AOV) and Average Item Value (AIV) per shop
aov_per_shop = df_per_shop['Revenue']/df_per_shop['Orders']
aov_per_shop.name = 'AOV'
aiv_per_shop = df_per_shop['Revenue']/df_per_shop['Items']
aiv_per_shop.name = 'AIV'
df_per_shop = pd.concat([revenue_per_shop, orders_per_shop , aov_per_shop, aiv_pe
df_per_shop
```

Out[9]:

shop_id	Revenue	Orders	AOV	AIV	Items
1	13588	44	308.818182	158.0	86
2	9588	55	174.327273	94.0	102
3	14652	48	305.250000	148.0	99
4	13184	51	258.509804	128.0	103
5	13064	45	290.311111	142.0	92
...	...	...	...	...	...
96	16830	51	330.000000	153.0	110
97	15552	48	324.000000	162.0	96
98	14231	58	245.362069	133.0	107
99	18330	54	339.444444	195.0	94

In [ ]:

In [10]:
```
#Replacing Shop_id as the table index
df_per_shop.reset_index(inplace=True)
df_per_shop
```

Out[10]:

	shop_id	Revenue	Orders	AOV	AIV	Items
0	1	13588	44	308.818182	158.0	86
1	2	9588	55	174.327273	94.0	102
2	3	14652	48	305.250000	148.0	99
3	4	13184	51	258.509804	128.0	103
4	5	13064	45	290.311111	142.0	92
...	...	...	...	...	...	...
95	96	16830	51	330.000000	153.0	110
96	97	15552	48	324.000000	162.0	96
97	98	14231	58	245.362069	133.0	107
98	99	18330	54	339.444444	195.0	94
99	100	8547	40	213.675000	111.0	77

In [11]:
```
#Using various metrics to calculate the AOV and AIV
print("Mean AOV:",df_per_shop['AOV'].mean())
print("Median AOV:",df_per_shop['AOV'].median())
print("Mode AOV:",df_per_shop['AOV'].mode()[0])

print("Mean AIV:",df_per_shop['AIV'].mean())
print("Median AIV:",df_per_shop['AIV'].median())
print("Mode AIV:",df_per_shop['AIV'].mode()[0])
```

```
Mean AOV: 3136.834087887025
Median AOV: 308.8897584973166
Mode AOV: 162.85714285714286
Mean AIV: 407.99
Median AIV: 153.0
Mode AIV: 153.0
```

In [12]:
```
AOV = sum(df_per_shop.Revenue)/sum(df_per_shop.Orders)
print("The Average Order Value is:", AOV)


AIV = sum(df_per_shop.Revenue)/sum(df_per_shop.Items)
print("The Average Order Value is:", AIV)
```

```
The Average Order Value is: 3145.128
The Average Order Value is: 357.92152221412965
```

In [13]:
```
#Checking out the metric overview of the DataFrame to figure out the issue with t
df_per_shop.describe()
```

Out[13]:

	shop_id	Revenue	Orders	AOV	AIV	Items
count	100.000000	1.000000e+02	100.000000	100.000000	100.000000	100.000000
mean	50.500000	1.572564e+05	50.000000	3136.834088	407.990000	439.360000
std	29.011492	1.216218e+06	7.287737	23935.881130	2557.462906	3396.366111
min	1.000000	6.840000e+03	35.000000	162.857143	90.000000	67.000000
25%	25.750000	1.293050e+04	44.750000	263.675962	132.750000	88.000000
50%	50.500000	1.488750e+04	50.000000	308.889758	153.000000	100.000000
75%	75.250000	1.760000e+04	55.000000	336.628352	168.250000	111.250000
max	100.000000	1.199018e+07	68.000000	235101.490196	25725.000000	34063.000000

The average AOV is now $407.99, which is also higher than projected for a single shoe purchase price range. This indicates that some of the orders are incorrect. The fact that the mean number appears to be greater indicates that the data may contain outliers that skew the results. The minimum AOV is 90, which appears to be a reasonable price.

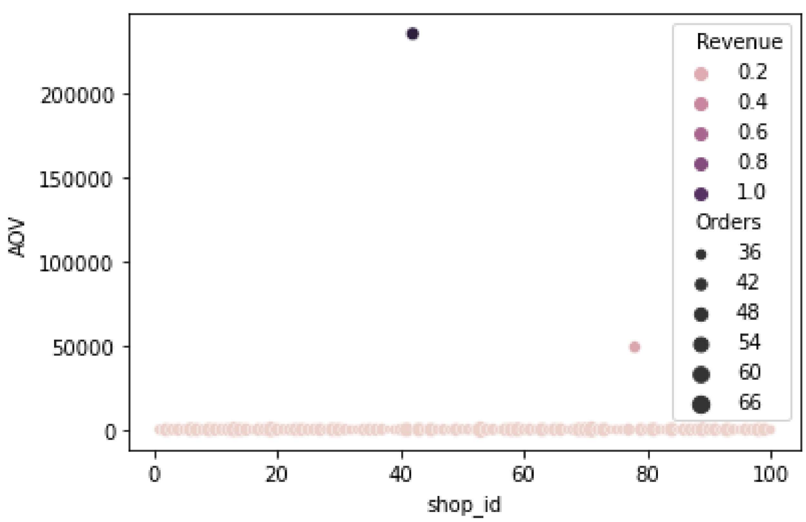
With a maximum AOV of 25725, it looks that someone is selling sneakers for a ridiculous amount.

The sneaker price ($168) appears to be affordable till 75 percent of the distribution.

Let's take a closer look at the data distribution.

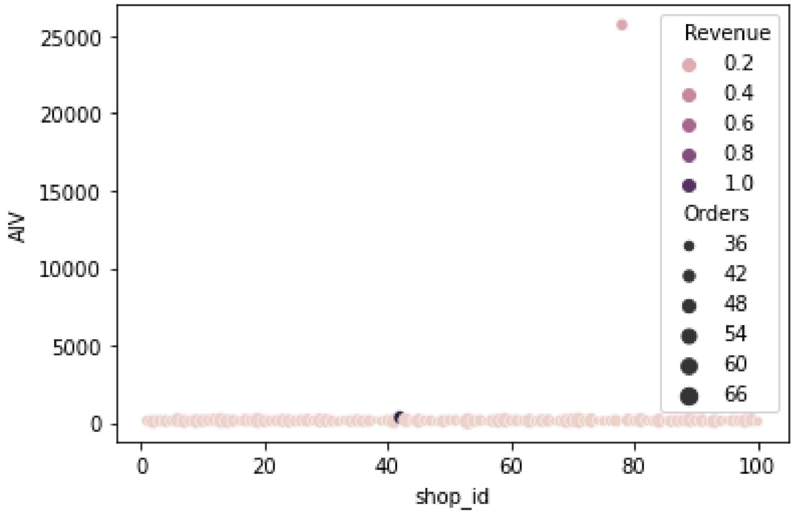
In [14]:
```
#Visualizing the AOV to find outliers (Suspicious Activities)
sns.scatterplot( x = 'shop_id', y = 'AOV', data = df_per_shop, hue = 'Revenue', s
```

Out[14]: <AxesSubplot:xlabel='shop_id', ylabel='AOV'>



In [15]:
```
#Visualizing the AIV to find outliers(Suspicious Activities)
sns.scatterplot( x = 'shop_id', y = 'AIV', data = df_per_shop, hue = 'Revenue', s
```

Out[15]: <AxesSubplot:xlabel='shop_id', ylabel='AIV'>



In [16]:
```
df_per_shop.index
```

Out[16]: RangeIndex(start=0, stop=100, step=1)

In [17]:
```
#Finding the Outliers
Outlier = []
for i, j in zip(df_per_shop.shop_id, df_per_shop.AOV):
    if j > 20000 and i != 'NaN':
        Outlier.append([i, j])
print(Outlier)
```

[[42, 235101.49019607843], [78, 49213.04347826087]]

In [18]:
```
#Identifying and bringing out the outlier
a = df_per_shop.loc[df_per_shop.shop_id.isin([42,78])]
a
```

Out[18]:

	shop_id	Revenue	Orders	AOV	AIV	Items
41	42	11990176	51	235101.490196	352.0	34063
77	78	2263800	46	49213.043478	25725.0	88

In [19]:
```
#Checking Out The Outlier
df.loc[df.shop_id == 42]
```

Out[19]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
4421	4422	42	736	704	2	credit_card	2017-03-01 12:19:49
2018	2019	42	739	352	1	debit	2017-03-01 12:42:26
2491	2492	42	868	704	2	debit	2017-03-01 18:33:33
4646	4647	42	607	704000	2000	credit_card	2017-03-02 04:00:00
520	521	42	607	704000	2000	credit_card	2017-03-02 04:00:00
2987	2988	42	819	1056	3	cash	2017-03-03 09:09:25
4231	4232	42	962	352	1	cash	2017-03-04 00:01:19
60	61	42	607	704000	2000	credit_card	2017-03-04 04:00:00
409	410	42	904	704	2	credit_card	2017-03-04 14:32:58
2766	2767	42	970	704	2	credit_card	2017-03-05 10:45:42
2297	2298	42	607	704000	2000	credit_card	2017-03-07 04:00:00
15	16	42	607	704000	2000	credit_card	2017-03-07 04:00:00
1911	1912	42	739	704	2	cash	2017-03-07 05:42:52
835	836	42	819	704	2	cash	2017-03-09 14:15:15
3998	3999	42	886	352	1	debit	2017-03-09 20:10:41
1364	1365	42	797	1760	5	cash	2017-03-10 06:28:21
1436	1437	42	607	704000	2000	credit_card	2017-03-11 04:00:00
4625	4626	42	809	352	1	credit_card	2017-03-11 08:21:26
308	309	42	770	352	1	credit_card	2017-03-11 18:14:39
3903	3904	42	975	352	1	debit	2017-03-12 01:28:31
3697	3698	42	839	352	1	debit	2017-03-12 02:45:09

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
2153	2154	42	607	704000	2000	credit_card	2017-03-12 04:00:00
979	980	42	744	352	1	debit	2017-03-12 13:09:04
1471	1472	42	907	1408	4	debit	2017-03-12 23:00:22
1367	1368	42	926	1408	4	cash	2017-03-13 02:38:34
938	939	42	808	1056	3	credit_card	2017-03-13 23:43:45
4767	4768	42	720	704	2	credit_card	2017-03-14 10:26:08
1362	1363	42	607	704000	2000	credit_card	2017-03-15 04:00:00
4326	4327	42	788	704	2	debit	2017-03-16 23:37:57
1602	1603	42	607	704000	2000	credit_card	2017-03-17 04:00:00
1929	1930	42	770	352	1	credit_card	2017-03-17 08:11:13
1562	1563	42	607	704000	2000	credit_card	2017-03-19 04:00:00
2053	2054	42	951	352	1	debit	2017-03-19 11:49:12
4868	4869	42	607	704000	2000	credit_card	2017-03-22 04:00:00
1520	1521	42	756	704	2	debit	2017-03-22 13:10:31
2609	2610	42	868	704	2	debit	2017-03-23 18:10:14
4745	4746	42	872	352	1	debit	2017-03-24 00:57:24
1104	1105	42	607	704000	2000	credit_card	2017-03-24 04:00:00
3332	3333	42	607	704000	2000	credit_card	2017-03-24 04:00:00
1512	1513	42	946	352	1	debit	2017-03-24 13:35:04
40	41	42	793	352	1	credit_card	2017-03-24 14:15:41
3513	3514	42	726	1056	3	debit	2017-03-24 17:51:05
4294	4295	42	859	704	2	cash	2017-03-24 20:50:40
3651	3652	42	830	352	1	credit_card	2017-03-24 22:26:58

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
4882	4883	42	607	704000	2000	credit_card	2017-03-25 04:00:00
834	835	42	792	352	1	cash	2017-03-25 21:31:25
2003	2004	42	934	704	2	cash	2017-03-26 09:21:26
2273	2274	42	747	704	2	debit	2017-03-27 20:48:19
2969	2970	42	607	704000	2000	credit_card	2017-03-28 04:00:00
4056	4057	42	607	704000	2000	credit_card	2017-03-28 04:00:00
2835	2836	42	607	704000	2000	credit_card	2017-03-28 04:00:00

Order details from Shop_id 42 shows some anomalies with $704000 order amount and with total items 2000, and average item value of just $352.0. This could be that the shop is a high end one but the variation of its price in relation to the other shops will skew our results and give inaccurate results.

In [20]:
```
df.loc[df.shop_id == 78]
```

Out[20]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
4311	4312	78	960	51450	2	debit	2017-03-01 03:02:10
4412	4413	78	756	51450	2	debit	2017-03-02 04:13:39
4040	4041	78	852	25725	1	cash	2017-03-02 14:31:12
2821	2822	78	814	51450	2	cash	2017-03-02 17:13:25
2492	2493	78	834	102900	4	debit	2017-03-04 04:37:34
4715	4716	78	818	77175	3	debit	2017-03-05 05:10:44
511	512	78	967	51450	2	cash	2017-03-09 07:23:14
4420	4421	78	969	77175	3	debit	2017-03-09 15:21:35
3780	3781	78	889	25725	1	cash	2017-03-11 21:14:50
160	161	78	990	25725	1	credit_card	2017-03-12 05:56:57
3167	3168	78	927	51450	2	cash	2017-03-12 12:23:08
2922	2923	78	740	25725	1	debit	2017-03-12 20:10:58
3705	3706	78	828	51450	2	credit_card	2017-03-14 20:43:15
2270	2271	78	855	25725	1	credit_card	2017-03-14 23:58:22
1056	1057	78	800	25725	1	debit	2017-03-15 10:16:45
4918	4919	78	823	25725	1	cash	2017-03-15 13:26:46
2906	2907	78	817	77175	3	debit	2017-03-16 03:45:46
3403	3404	78	928	77175	3	debit	2017-03-16 09:45:05
3724	3725	78	766	77175	3	credit_card	2017-03-16 14:13:26
1193	1194	78	944	25725	1	debit	2017-03-16 16:38:26
493	494	78	983	51450	2	cash	2017-03-16 21:39:35
2818	2819	78	869	51450	2	debit	2017-03-17 06:25:51

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
1384	1385	78	867	25725	1	cash	2017-03-17 16:38:06
1452	1453	78	812	25725	1	credit_card	2017-03-17 18:09:54
2548	2549	78	861	25725	1	cash	2017-03-17 19:36:00
1204	1205	78	970	25725	1	credit_card	2017-03-17 22:32:21
4192	4193	78	787	77175	3	credit_card	2017-03-18 09:25:32
617	618	78	760	51450	2	cash	2017-03-18 11:18:42
3151	3152	78	745	25725	1	credit_card	2017-03-18 13:13:07
2512	2513	78	935	51450	2	debit	2017-03-18 18:57:13
3440	3441	78	982	25725	1	debit	2017-03-19 19:02:54
4079	4080	78	946	51450	2	cash	2017-03-20 21:14:00
3101	3102	78	855	51450	2	credit_card	2017-03-21 05:10:34
2690	2691	78	962	77175	3	debit	2017-03-22 07:33:25
4505	4506	78	866	25725	1	debit	2017-03-22 22:06:01
2564	2565	78	915	77175	3	debit	2017-03-25 01:19:35
4584	4585	78	997	25725	1	cash	2017-03-25 21:48:44
3085	3086	78	910	25725	1	cash	2017-03-26 01:59:27
2495	2496	78	707	51450	2	cash	2017-03-26 04:38:52
2773	2774	78	890	25725	1	cash	2017-03-26 10:36:43
490	491	78	936	51450	2	debit	2017-03-26 17:08:19
1259	1260	78	775	77175	3	credit_card	2017-03-27 09:27:20
2452	2453	78	709	51450	2	cash	2017-03-27 11:04:04
691	692	78	878	154350	6	debit	2017-03-27 22:51:43
1529	1530	78	810	51450	2	cash	2017-03-29 07:12:01

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
1419	1420	78	912	25725	1	cash	2017-03-30 12:23:43

Order details from Shop_id 78 shows some anomalies with average item value of $25725.0, which seems impossible for a sneaker. This is an anomaly that points to a suspicious activity and will skew our results and give inaccurate results.

In [21]:
```
#Droppping the outliers from the dataset
df_per_shop.drop(a.index, inplace=True)
```

In [22]:
```
df_per_shop.loc[df_per_shop.shop_id.isin([42,78])]
```

Out[22]:

shop_id	Revenue	Orders	AOV	AIV	Items

In [23]:
```
#Rechecking the overview of the metric of the dataset after dropping the outliers
df_per_shop.describe()
```

Out[23]:

	shop_id	Revenue	Orders	AOV	AIV	Items
count	98.000000	98.000000	98.000000	98.000000	98.00000	98.000000
mean	50.306122	15016.979592	50.030612	299.682399	150.22449	99.846939
std	29.162329	3469.426421	7.350509	50.896733	23.91675	16.365259
min	1.000000	6840.000000	35.000000	162.857143	90.00000	67.000000
25%	25.250000	12803.500000	44.250000	262.661218	132.25000	88.000000
50%	50.500000	14763.000000	50.000000	308.827696	153.00000	100.000000
75%	74.750000	17478.000000	55.000000	334.631226	165.75000	111.000000
max	100.000000	23128.000000	68.000000	403.545455	201.00000	136.000000

In [ ]:

In [ ]:

In [24]:
```
#Using various metrics to calculate the AOV and AIV
print("Mean AOV:",df_per_shop['AOV'].mean())
print("Median AOV:",df_per_shop['AOV'].median())
print("Mode AOV:",df_per_shop['AOV'].mode()[0])

print("Mean AIV:",df_per_shop['AIV'].mean())
print("Median AIV:",df_per_shop['AIV'].median())
print("Mode AIV:",df_per_shop['AIV'].mode()[0])
```

```
Mean AOV: 299.68239912615485
Median AOV: 308.8276955602537
Mode AOV: 162.85714285714286
Mean AIV: 150.22448979591837
Median AIV: 153.0
Mode AIV: 153.0
```

In [ ]:

In [ ]:

In [ ]:

1b) What metric would you report for this dataset?

For AIV per shop, metrics like median or mode are preferable than mean since they are less impacted by exceptionally large values in the distribution. The median and mode in this dataset were the same. Because we're looking at 100 stores, the most common sneaker price (mode) should offer us a more realistic picture. I would report the mode value per shop rather than the AIV.

For the AOV, I would report the mean. AOV is the average order value, one order can have more that one item sold.

1c) What is its value?

Its value is $152 for AIV and 300 for AOV

Question 2:

2a) How many orders were shipped by Speedy Express in total?

```
QUERY:

SELECT COUNT(ShipperID)
FROM [Orders]
WHERE (SELECT ShipperID
```

```
        FROM [Shippers]
        WHERE ShipperName = "Speedy Express") = ShipperID;


NUMERICAL ANSWER: 54
```

2b) What is the last name of the employee with the most orders?

```
QUERY:

SELECT LastName
FROM Orders
JOIN Employees ON Orders.EmployeeID = Employees.EmployeeID
GROUP BY Employees.EmployeeID
ORDER BY COUNT(Orders.OrderID) DESC
LIMIT 1;


NUMERICAL ANSWER: Peacock
```

2C) What product was ordered the most by customers in Germany?

```
QUERY:

SELECT ProductName, SUM(Quantity) AS QuantitySum
FROM Orders, OrderDetails, Customers, Products
WHERE Country = "Germany" AND OrderDetails.orderID = Orders.OrderID AND
OrderDetails.ProductID = Products.ProductID AND Customers.CustomerID =
Orders.CustomerID
GROUP BY Products.ProductID
ORDER BY QuantitySum DESC
LIMIT 1;



NUMERICAL ANSWER: Boston Crab Meat
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

```
```