adidas

February 4, 2024

1 Presenting myself and the goals of the project

Welcome. My name is Victor and I'm here to create some insights about how the Adidas sales were from the year of 2020 to 2021.

I'll explore:

1. How the regions of the United States of America differ on operating profit and volume of sales?
2. Should a retailer be cut off and its investment reallocated on another retailer?
3. Which class of product is the best seller on each region?
4. Which city is the gold mine for Adidas?
5. Which is the more efficient approach for sales?

2 Starting the fun!!

Importing the most common libraries needed through the analysis.

[275]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

I will select only the variables that are of interest to answer the risen questions.

The variables that are being selected refers to:

`Retailer`: Retailer that made the sales

`Invoice Date`: Date that were recorded the sales information considering retailer

`Region`: Region of the USA where it's the city of the retailer

`City`: City at where the retailer is located

`Product`: Category of the products

`Units Sold`: Number of units solds of a category of product in a day by retailer

`Total Sales`: Number of sales of a category of product made in a day by retailer

`Operating Profit`: The profit obtained by each record in the data frame

`Operating Margin`: How much profit a retailer makes per dollar of sales

`Sales Method`: In which channel the products were sold (online, outlet or in-store)

Importing the data and observing how it is structured regards on columns names, index type, missing values, duplicated values.

[276]:
```
adidas_df = pd.read_excel('/content/Adidas US Sales Datasets.xlsx',
                          usecols=['Retailer',
                                   'Invoice Date',
                                   'Region',
                                   'City',
                                   'Product',
                                   'Units Sold',
                                   'Total Sales',
                                   'Operating Profit',
                                   'Operating Margin',
                                   'Sales Method',])
adidas_df.head()
```

[276]:
```
      Retailer Invoice Date     Region      City                    Product  \
0  Foot Locker   2020-01-01  Northeast  New York      Men's Street Footwear
1  Foot Locker   2020-01-02  Northeast  New York    Men's Athletic Footwear
2  Foot Locker   2020-01-03  Northeast  New York    Women's Street Footwear
3  Foot Locker   2020-01-04  Northeast  New York  Women's Athletic Footwear
4  Foot Locker   2020-01-05  Northeast  New York              Men's Apparel

   Units Sold  Total Sales  Operating Profit  Operating Margin Sales Method
0        1200     600000.0          300000.0              0.50     In-store
1        1000     500000.0          150000.0              0.30     In-store
2        1000     400000.0          140000.0              0.35     In-store
3         850     382500.0          133875.0              0.35     In-store
4         900     540000.0          162000.0              0.30     In-store
```

Converting the name of each columns to lowercase and snakecase that it is the pattern followed in python.

[277]:
```
adidas_df.columns = (adidas_df
                     .columns
                     .str.lower()
                     .str.replace(' ', '_'))
adidas_df.columns
```

[277]:
```
Index(['retailer', 'invoice_date', 'region', 'city', 'product', 'units_sold',
       'total_sales', 'operating_profit', 'operating_margin', 'sales_method'],
      dtype='object')
```

Checking for missing values and at the same time assessing the data types of each variable.

[278]:
```
adidas_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9648 entries, 0 to 9647
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   retailer          9648 non-null   object
 1   invoice_date      9648 non-null   datetime64[ns]
 2   region            9648 non-null   object
 3   city              9648 non-null   object
 4   product           9648 non-null   object
 5   units_sold        9648 non-null   int64
 6   total_sales       9648 non-null   float64
 7   operating_profit  9648 non-null   float64
 8   operating_margin  9648 non-null   float64
 9   sales_method      9648 non-null   object
dtypes: datetime64[ns](1), float64(3), int64(1), object(5)
memory usage: 753.9+ KB
```

As we may see above, the number of entries for each variable is equal to the number of rows represented by the RangeIndex, therefore, there are no missing values in this data set.

When checked for duplicated values is returned to us that are none duplicated rows.

[279]:
```
adidas_df.isna().sum()
```

[279]:
```
retailer            0
invoice_date        0
region              0
city                0
product             0
units_sold          0
total_sales         0
operating_profit    0
operating_margin    0
sales_method        0
dtype: int64
```

[280]:
```
adidas_df.duplicated().sum()
```

[280]:
```
0
```

The columns `retailer`, `region`, `city`, `product` and `sales_method`are object-types. In order to optimize the data manipulation and as well create categorical variables, as they statistically already are, I'll convert them from objects to category type. As they all are nominal type, that is not ordered/ordinal, it's not necessary to define order between the values of each variable

[281]:
```
object_variables = ['retailer','region','city','product','sales_method']
adidas_df[object_variables] = adidas_df[object_variables].astype('category')
adidas_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9648 entries, 0 to 9647
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   retailer          9648 non-null   category
 1   invoice_date      9648 non-null   datetime64[ns]
 2   region            9648 non-null   category
 3   city              9648 non-null   category
 4   product           9648 non-null   category
 5   units_sold        9648 non-null   int64
 6   total_sales       9648 non-null   float64
 7   operating_profit  9648 non-null   float64
 8   operating_margin  9648 non-null   float64
 9   sales_method      9648 non-null   category
dtypes: category(5), datetime64[ns](1), float64(3), int64(1)
memory usage: 427.3 KB
```

3 Going for the insights!!

3.1 How the regions of the United States of America differ on operating profit and volume of sales?

First things first, let's study the regions of the USA for the Adidas brand between the years of start of 2020 and end of 2021 and its impact on sales.

We can see that the West and Northeast regions are the most common throughout the data frame, composing around 25% of the observations each.

[282]:
```
(adidas_df['region']
 .value_counts(normalize=True)
 .round(3))
```

[282]:
```
West         0.254
Northeast    0.246
Midwest      0.194
South        0.179
Southeast    0.127
Name: region, dtype: float64
```

We may check then the region that solds the most units of all products.

[283]:
```
region_units = (adidas_df
                .groupby('region',as_index=False)
```

```
                 .agg({'units_sold':np.sum})
                 .sort_values('units_sold', ascending=False)
                 .reset_index(drop=True))

region_units
```

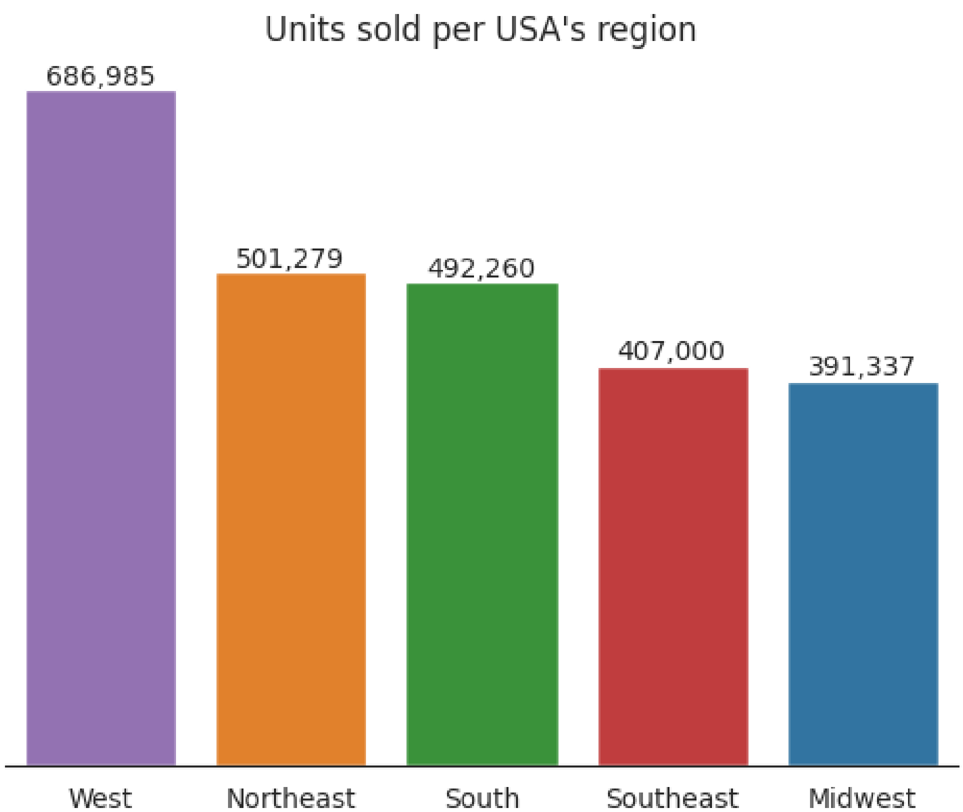
[283]:

```
      region  units_sold
0       West      686985
1  Northeast      501279
2      South      492260
3  Southeast      407000
4    Midwest      391337
```

As expected West and Northeast figures on the top regions.

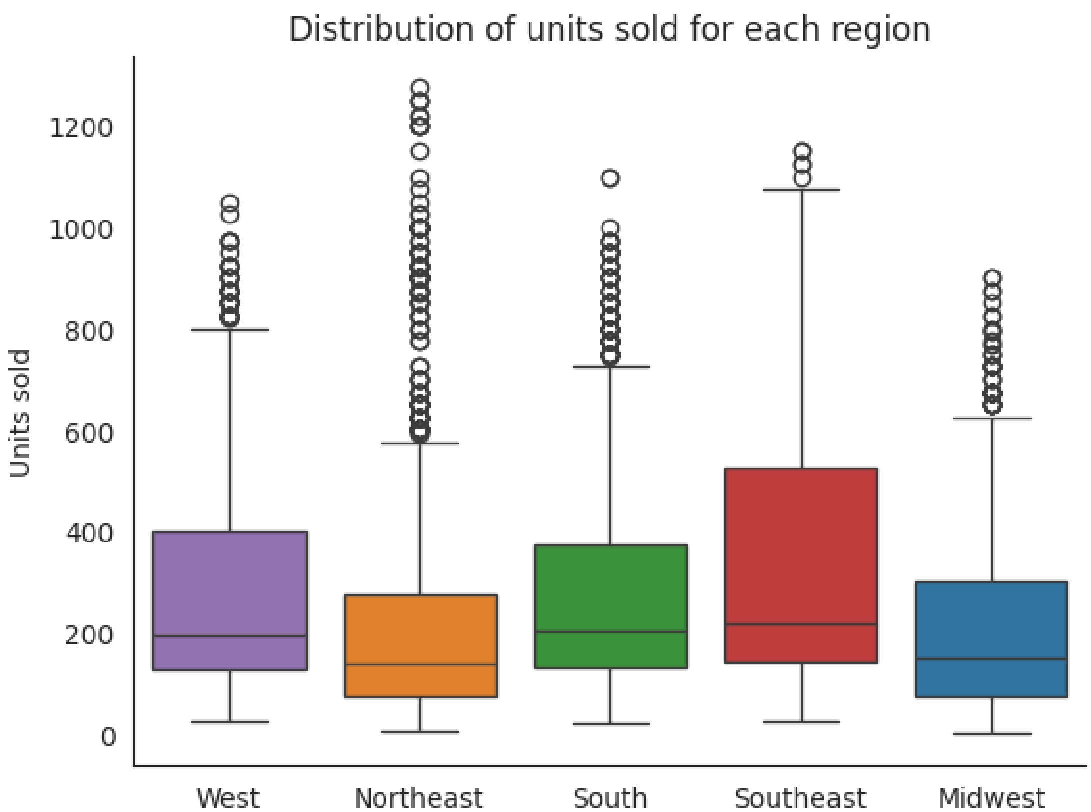
[284]:

```
ax = sns.barplot(data=region_units,
                 x='region',
                 y='units_sold',
                 hue='region',
                 order=['West',
                        'Northeast',
                        'South',
                        'Southeast',
                        'Midwest'])

for i in range(len(region_units.index)):
    ax.bar_label(ax.containers[i], fontsize=10, fmt='{:,.0f}')

sns.color_palette('pastel')
sns.despine(left=True)
ax.set_yticks([])
ax.set_ylabel(None)
ax.set_xlabel(None)
ax.set_title('Units sold per USA\'s region')
plt.show()
```



Further, we can assess which region is the most regular in its sales.

[285]:
```
ax = sns.boxplot(adidas_df,
                 x='region',
                 y='units_sold',
                 hue='region',
                 order=['West',
                        'Northeast',
                        'South',
                        'Southeast',
                        'Midwest'])

sns.despine()
ax.set_title('Distribution of units sold for each region')
ax.set_ylabel('Units sold')
ax.set_xlabel(None)
plt.show()
```



[286]:
```
region_stats = adidas_df.groupby('region')[['units_sold']].describe().T
region_stats
```

[286]:
```
region                 Midwest    Northeast        South    Southeast  \
units_sold count   1872.000000  2376.000000  1728.000000  1224.000000
           mean     209.047543   210.976010   284.872685   332.516340
           std      173.974630   203.637531   216.864248   261.424311
           min        0.000000     7.000000    19.000000    26.000000
           25%       75.000000    75.000000   131.000000   143.750000
           50%      150.000000   140.000000   203.000000   217.000000
           75%      300.000000   275.000000   375.000000   525.000000
           max      900.000000  1275.000000  1100.000000  1150.000000

region                    West
units_sold count   2448.000000
           mean     280.631127
           std      206.045948
           min       26.000000
           25%      128.000000
           50%      196.000000
           75%      400.000000
```

```
max    1050.000000
```

[287]:
```python
adidas_df.groupby('region')['units_sold'].std().sort_values(ascending=False)
```

[287]:
```
region
Southeast    261.424311
South        216.864248
West         206.045948
Northeast    203.637531
Midwest      173.974630
Name: units_sold, dtype: float64
```

[288]:
```python
from scipy.stats import iqr
def spread_measure(var):
    return iqr(var)

adidas_df.groupby('region')['units_sold'].apply(spread_measure).
 ↪sort_values(ascending=False)
```

[288]:
```
region
Southeast    381.25
West         272.00
South        244.00
Midwest      225.00
Northeast    200.00
Name: units_sold, dtype: float64
```

The USA's region **that sells the most units** of products is the **West region** and the **worst seller**, **Midwest**.

Assessing despite regularity of sales, **Midwest stands out as the most regular** having the **lowest standard deviation and IQR**. The region that presented the **most irregularity** was the **Southeast** with the **greatest standard deviation and IQR.** Although, be regular is not always good, once a region may be a bad seller always, for example.

Yet, volume of sales doesn't shows that the West region is the more profitable e.g. once it can sells most low-profit products that generates lower profits. Always good to reinforce: **"correlation determines no causation"**

Assessing now the profit generated by region.

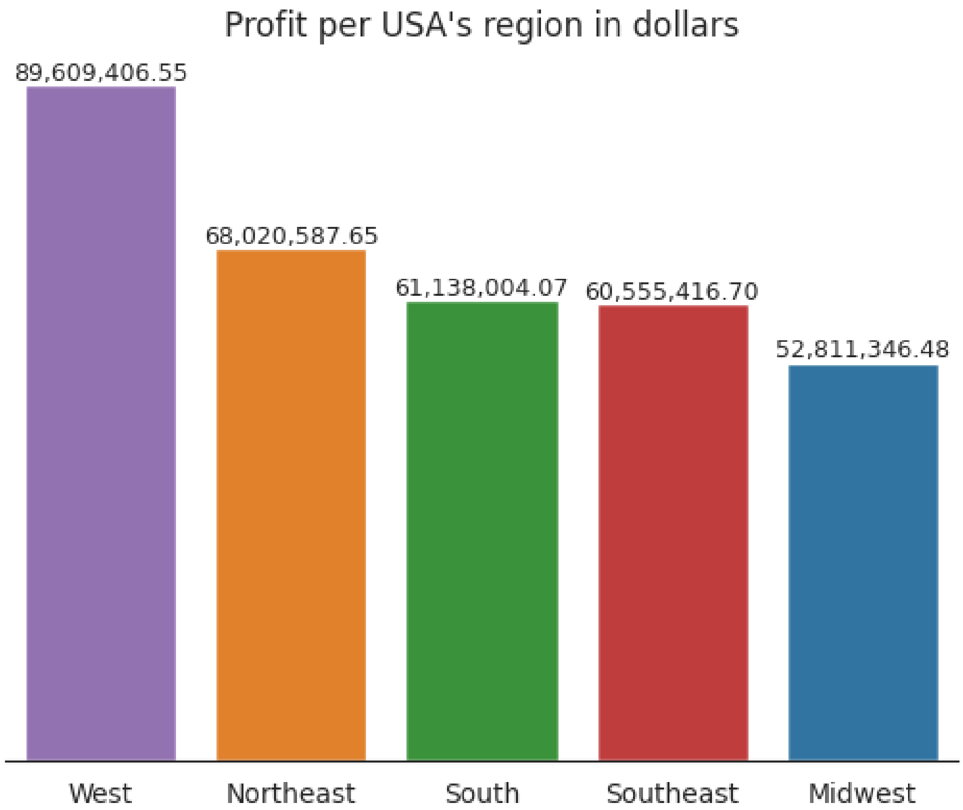
[289]:
```python
region_profit = (adidas_df
                 .groupby('region', as_index=False)
                 .agg({'operating_profit':np.sum})
                 .sort_values('operating_profit', ascending=False)
                 .reset_index(drop=True))
region_profit
```

[289]:

	region	operating_profit
0	West	89609406.55
1	Northeast	68020587.65
2	South	61138004.07
3	Southeast	60555416.70
4	Midwest	52811346.48

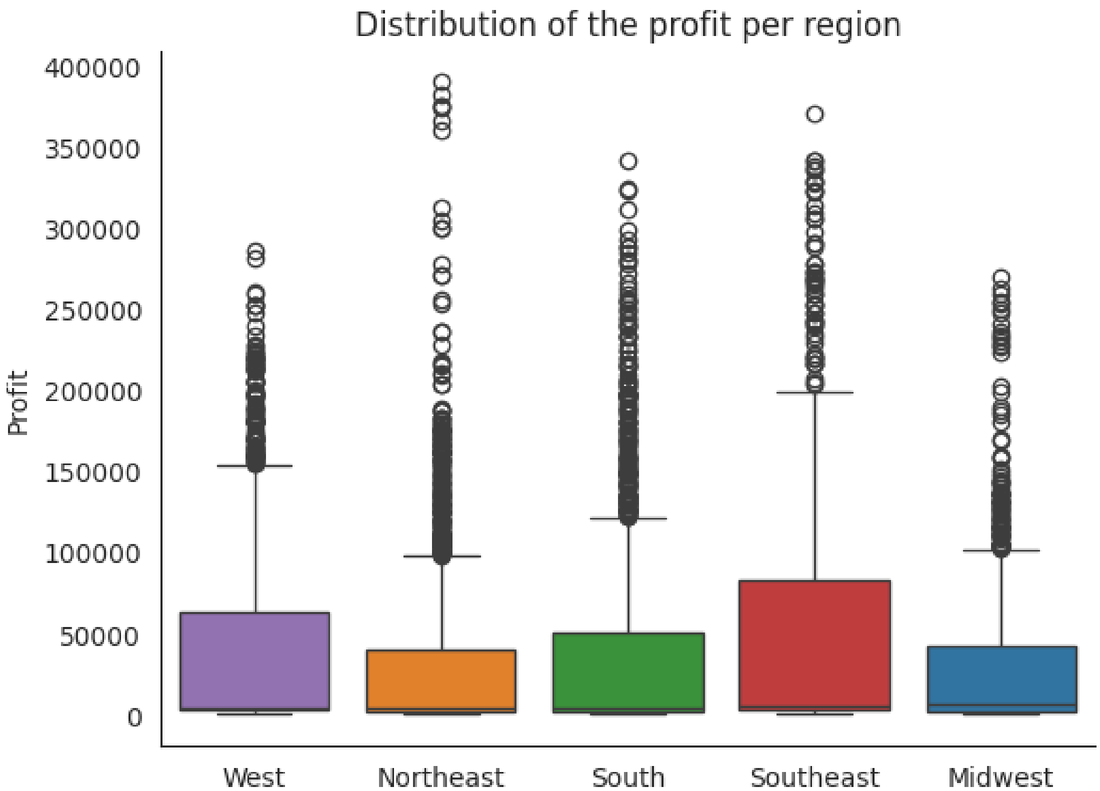
[290]:

```
ax = sns.barplot(data=region_profit,
                 x='region',
                 y='operating_profit',
                 hue='region',
                 order=['West',
                        'Northeast',
                        'South',
                        'Southeast',
                        'Midwest'])

for i in range(len(region_profit)):
    ax.bar_label(ax.containers[i], fontsize=9, fmt='{:,.2f}')

sns.despine(left=True)
ax.set_ylabel(None)
ax.set_xlabel(None)
ax.set_yticks([])
ax.set_title('Profit per USA\'s region in dollars')
plt.show()
```



Compairing the yield among the dates given by the data set, one can infer about which region delivers the profit in the most regular way.

[291]:
```
ax = sns.boxplot(adidas_df,
                 x='region',
                 y='operating_profit',
                 hue='region',
                 order=['West',
                        'Northeast',
                        'South',
                        'Southeast',
                        'Midwest'])

sns.despine()
ax.set_ylabel('Profit')
ax.set_xlabel(None)
ax.set_title('Distribution of the profit per region')
plt.show()
```



[292]:
```
op_profit_df = adidas_df.groupby('region')[['operating_profit']].describe().T
op_profit_df
```

[292]:
```
region                          Midwest      Northeast          South  \
operating_profit count      1872.000000    2376.000000    1728.000000
                 mean      28211.189359   28628.193455   35380.789392
                 std       40253.139912   48551.335194   59520.152739
                 min           0.000000      75.200000     217.580000
                 25%        1498.420000    1401.047500    2020.865000
                 50%        6012.520000    3680.000000    4031.000000
                 75%       42000.000000   39859.375000   50156.250000
                 max      270000.000000  390000.000000  341250.000000

region                        Southeast           West
operating_profit count      1224.000000    2448.000000
                 mean      49473.379657   36605.149734
                 std       71817.845047   52845.142286
                 min         339.300000     308.700000
                 25%        2795.545000    2342.495000
                 50%        5753.520000    4254.960000
                 75%       82937.500000   63000.000000
```

```
            max    371250.000000  286000.000000
```

[293]:
```
adidas_df.groupby('region')['operating_profit'].std().
 ↪sort_values(ascending=False)
```

[293]:
```
region
Southeast    71817.845047
South        59520.152739
West         52845.142286
Northeast    48551.335194
Midwest      40253.139912
Name: operating_profit, dtype: float64
```

[294]:
```
from scipy.stats import iqr
def spread_measure(var):
    return iqr(var)

adidas_df.groupby('region')['operating_profit'].apply(spread_measure).
 ↪sort_values(ascending=False)
```

[294]:
```
region
Southeast    80141.9550
West         60657.5050
South        48135.3850
Midwest      40501.5800
Northeast    38458.3275
Name: operating_profit, dtype: float64
```

Evaluating if the outliers are caused by some special date as christmas, thanksgiving day, black friday or even 4th of july.

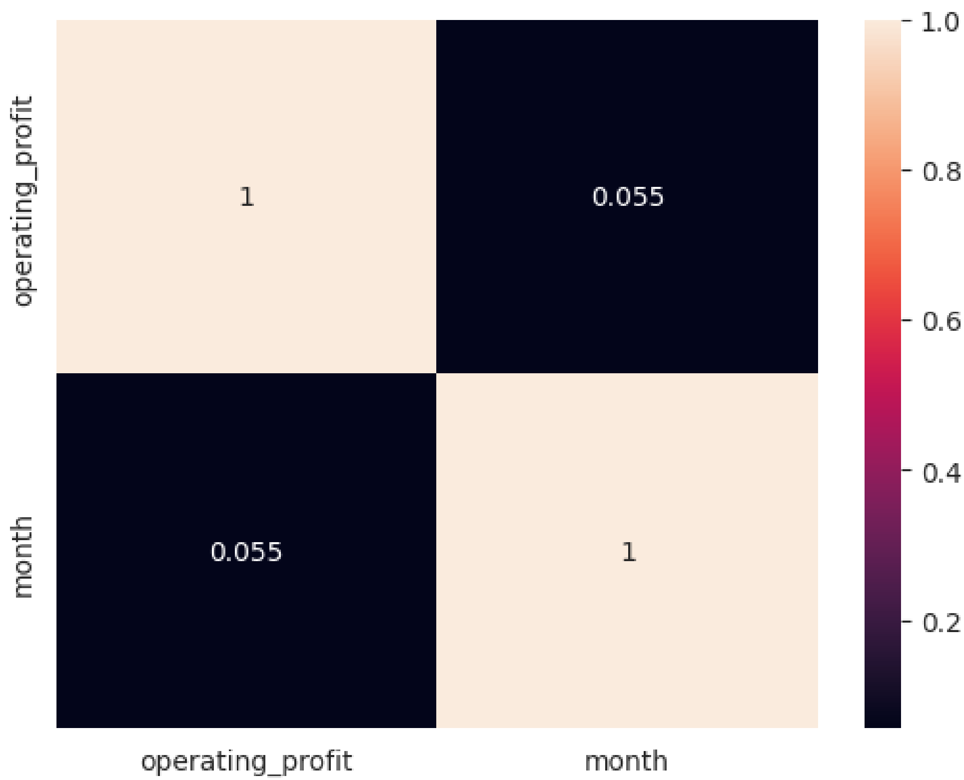
[295]:
```
from scipy.stats import iqr
holidays = ['2020-07-04',
            '2021-07-04',
            '2020-12-25',
            '2021-12-25',
            '2020-11-26',
            '2021-11-25',
            '2020-11-27',
            '2021-12-25']

inferior_whis = adidas_df['operating_profit'].quantile(0.25) - 1.5 *␣
 ↪iqr(adidas_df['operating_profit'])
superior_whis = adidas_df['operating_profit'].quantile(0.75) + 1.5 *␣
 ↪iqr(adidas_df['operating_profit'])
```

```
outliers = adidas_df[(adidas_df['operating_profit'] < inferior_whis) |
    (adidas_df['operating_profit'] > superior_whis)]
outliers[outliers['invoice_date'].isin([holidays])]
```

[295]:
```
Empty DataFrame
Columns: [retailer, invoice_date, region, city, product, units_sold,
total_sales, operating_profit, operating_margin, sales_method]
Index: []
```

Seeing if there is a correlation between the month in which the sale had been made, the operating margin and the operating profit

[296]:
```
adidas_df['month'] = adidas_df['invoice_date'].dt.month

corr = adidas_df[['operating_profit','month']].corr()
sns.heatmap(corr, annot=True)
plt.show()
```



Once the correlation between `operating_profit` and `month` are close to zero we can infer that there is almost zero correlation between them. Thus, this special dates, on the given data, doesn't cause an abnormal consumption of adidas produts.

3.1.1 Conclusion

- The region that presented the most regularity was Midwest having both, standard deviation and IQR, the smaller between all evaluated. In contrast, Southeast leads again as the most irregular.
- As shown above, the profit obtained between the start of 2020 and end of 2021 by Adidas had the West as its most profitable region, and the Midwest as its worst.
- Despite the Southeast solds, in units, lower quantities than the South, we may observe that the profit is almost the same, having less discrepancy if compared on regards the difference of quantities of product solds between the two regions. Thus, allowing to create a hypothesis that the Southeast sells more high-profit products than the South region, whose main products are low-profit.
- Special dates didn't impact on the Adidas' profit from 2020 to 2021

Checking if there is evidence of linear correlation between `operating_profit` and `units_sold`:

[297]:
```
sns.regplot(data=adidas_df,
            x='units_sold',
            y='operating_profit',
            color='#840c95',
            ci=100,
            line_kws=dict(color='#ff4200'))

sns.despine()
plt.title('Profit according to units sold')
plt.xlabel(' Units Sold')
plt.ylabel('Profit (dollars)')
plt.show()
```

Once there is apparently a linear correlation with low margin of error, that due to the use of confidence interval (ci) at the maximum, between the `units_sold` and `operating_profit` we can measure using the Pearson coefficient. It results on a high positive correlation value (0.89).

[298]:
```
adidas_df[['units_sold','operating_profit']].corr()
```

[298]:

	units_sold	operating_profit
units_sold	1.000000	0.892379
operating_profit	0.892379	1.000000

[299]:
```
sns.heatmap(adidas_df[['units_sold','operating_profit']].corr(),
            annot=True)

plt.title('Correlation between units sold and profit rate')
plt.show()
```

For this particular case, we may infer that there is a positive correlation between the `operating_profit` and `units_sold` variables but we can't say that one causes the other.

3.2 Should a retailer be cut off and its investment reallocated on another retailer?

For start let's subset the `adidas_df` and group it by `retailers` brands.

[300]:
```
retailer_invest = (adidas_df
                   .groupby('retailer', as_index=False)
                   .agg({'operating_margin':np.mean})
                   .sort_values('operating_margin', ascending=False)
                   .reset_index(drop=True))
retailer_invest
```

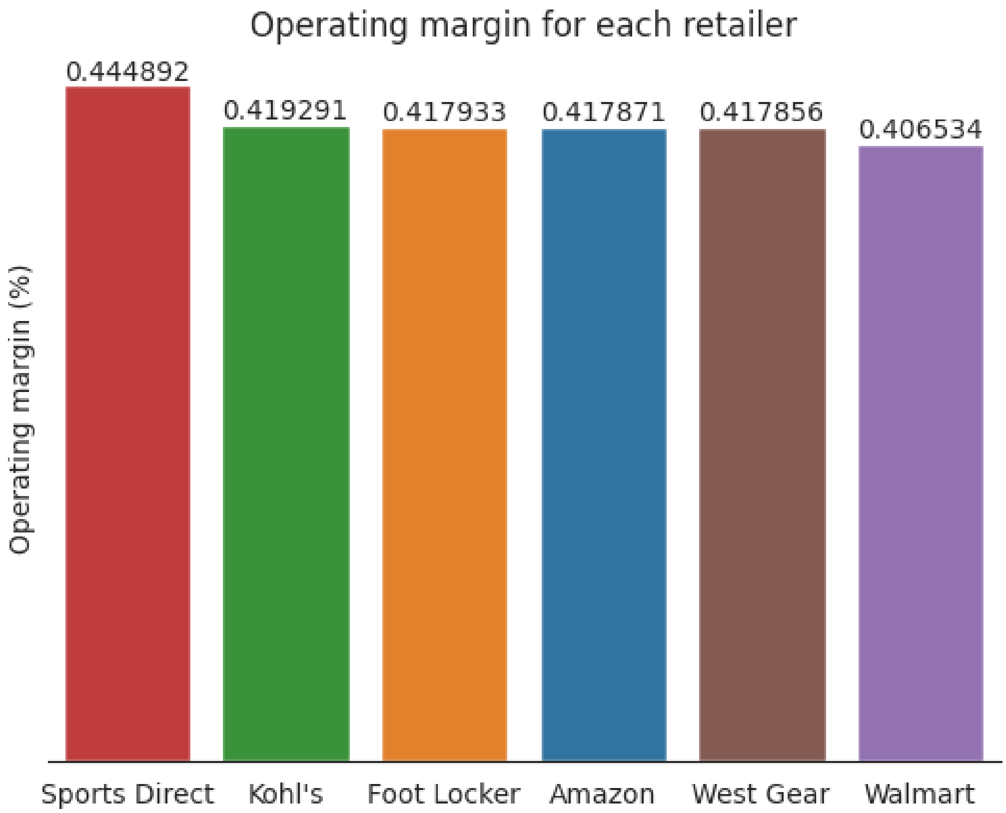
[300]:

	retailer	operating_margin
0	Sports Direct	0.444892
1	Kohl's	0.419291
2	Foot Locker	0.417933
3	Amazon	0.417871
4	West Gear	0.417856

```
5        Walmart          0.406534
```

Next, we plot a bar plot with the intent to make clearer the comparison between all of the retailers considering the `operating_margin`.

```
[301]: ax = sns.barplot(data=retailer_invest,
                 x='retailer',
                 y='operating_margin',
                 hue='retailer',
                 order=['Sports Direct',
                        'Kohl\'s',
                        'Foot Locker',
                        'Amazon',
                        'West Gear',
                        'Walmart'])

for i in range(len(retailer_invest)):
    ax.bar_label(ax.containers[i], fontsize=10)

sns.despine(left=True)
ax.set_yticks([])
ax.set_ylabel('Operating margin (%)')
ax.set_xlabel(None)
ax.set_title('Operating margin for each retailer')
plt.show()
```

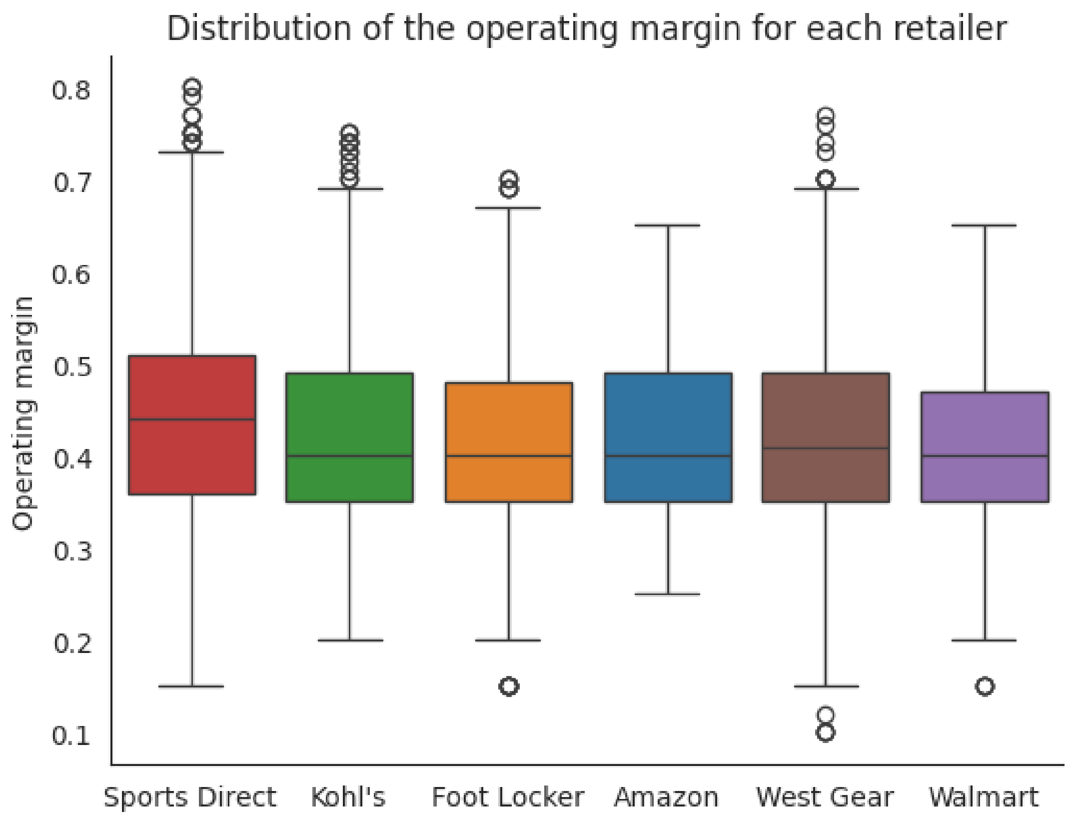


Sports Direct is clear the best-seller retailer. Yet, the others all remain with little differences, in order to select if a retail should be cut off, a descriptive statistics is a reliable tool to start analyzing it.

Assessing for the distribution of the sales for each retailer with the intent to see which brand is the most regular once it turns the investment safer.

[302]:
```
ax = sns.boxplot(adidas_df,
                 x='retailer',
                 y='operating_margin',
                 hue='retailer',
                 order=['Sports Direct',
                        'Kohl\'s',
                        'Foot Locker',
                        'Amazon',
                        'West Gear',
                        'Walmart'])


sns.despine()
ax.set_xlabel(None)
ax.set_ylabel('Operating margin')
ax.set_title('Distribution of the operating margin for each retailer')
```

```
plt.show()
```



Looking for the descriptive statistics of each retailer operating profit we get:

[303]:
```
descriptive_stats = (adidas_df
                     .groupby('retailer')[['operating_profit']]
                     .describe())

descriptive_stats
```

[303]:

	operating_profit					\
	count	mean	std	min	25%	
retailer						
Amazon	949.0	30367.232150	44192.495075	166.40	1661.9200	
Foot Locker	2637.0	30611.348051	51194.484899	0.00	1504.8000	
Kohl's	1030.0	35739.080175	48292.449414	249.60	2445.9750	
Sports Direct	2032.0	36581.178622	58018.483181	227.04	2058.9600	
Walmart	626.0	41185.387556	65699.002068	403.20	2620.7400	
West Gear	2374.0	36085.877498	56359.734717	93.38	2011.0825	

```
                     50%      75%       max
retailer
Amazon         3931.200  47250.0  290625.0
Foot Locker    4314.940  40500.0  382500.0
Kohl's         4166.240  67875.0  236250.0
Sports Direct  4145.040  57750.0  341250.0
Walmart        4822.580  64000.0  390000.0
West Gear      4607.945  54000.0  341250.0
```

[304]:
```
adidas_df.groupby('retailer')['operating_profit'].std().
 ↪sort_values(ascending=False)
```

[304]:
```
retailer
Walmart          65699.002068
Sports Direct    58018.483181
West Gear        56359.734717
Foot Locker      51194.484899
Kohl's           48292.449414
Amazon           44192.495075
Name: operating_profit, dtype: float64
```

[305]:
```
from scipy.stats import iqr
def spread_measure(var):
    return iqr(var)

adidas_df.groupby('retailer')['operating_profit'].apply(spread_measure).
 ↪sort_values(ascending=False)
```

[305]:
```
retailer
Kohl's           65429.0250
Walmart          61379.2600
Sports Direct    55691.0400
West Gear        51988.9175
Amazon           45588.0800
Foot Locker      38995.2000
Name: operating_profit, dtype: float64
```

The Walmart has the biggest standard deviation and the second biggest IQR being the more unstable retailer on regards the operating profit.

One can think of what may cause these outliers observed in the operating margin boxplot. Evaluating on regards the holidays and special dates (christmas, black friday, thanksgiving day, 4th of july) date we get:

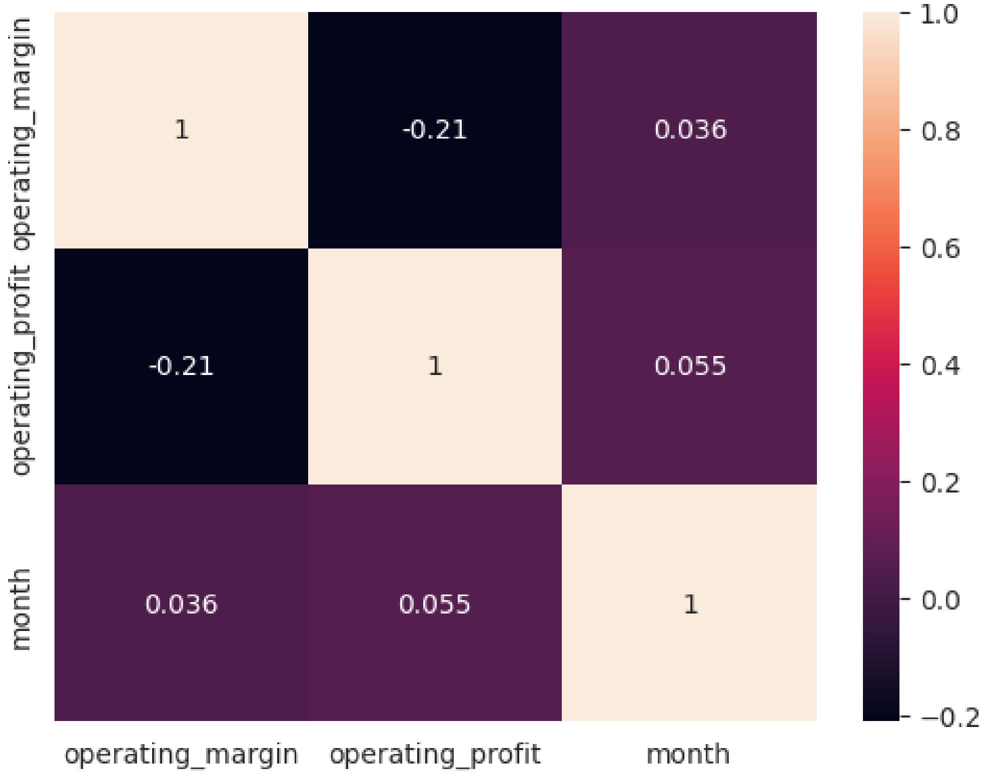
[306]:
```
from scipy.stats import iqr
holidays = ['2020-07-04',
            '2021-07-04',
            '2020-12-25',
```

```
            '2021-12-25',
            '2020-11-26',
            '2021-11-25',
            '2020-11-27',
            '2021-12-25']

inferior_whis = adidas_df['operating_margin'].quantile(0.25) - 1.5 *␣
 ↪iqr(adidas_df['operating_margin'])
superior_whis = adidas_df['operating_margin'].quantile(0.75) + 1.5 *␣
 ↪iqr(adidas_df['operating_margin'])

outliers = adidas_df[(adidas_df['operating_margin'] < inferior_whis) |␣
 ↪(adidas_df['operating_margin'] > superior_whis)]
outliers[outliers['invoice_date'].isin([holidays])]
```

[306]:
```
Empty DataFrame
Columns: [retailer, invoice_date, region, city, product, units_sold,
total_sales, operating_profit, operating_margin, sales_method, month]
Index: []
```

Seeing if there is a correlation between the month in which the sale had been made, the operating margin and the operating profit

[307]:
```
corr = adidas_df[['operating_margin','operating_profit','month']].corr()
sns.heatmap(corr, annot=True)
plt.show()
```



Once none outliers are correlated to special dates and the correlation between month and the operating profit and margin are close to zero, we can infer that those were caused by an alternative event. By contrast, `operating_margin` and `operating_profit` shows a slight negative correlation.

Evaluating the behavior through the days of the month for each retailer in order to see if one impacts in order sales.

3.2.1 Conclusion

- The Walmart has the biggest standard deviation an the second biggest IQR. Considering all that, with only the given data, this may be the channel of sales whose investment could be reallocated to Sports Direct in order to increase the profit of the company.
- Special dates didn't impact on the Adidas' operating profit from 2020 to 2021.

3.3 Which class of products is the best-seller on each region?

With the intent to have a better visualization on the products, regions and units sold all together, a pivot table is made summing the values of `units_sold` per `region` and `product` types.

[308]:
```
prod_and_reg = (adidas_df
                .pivot_table(index='product',
                             columns='region',
                             values='units_sold',
```

```
                              aggfunc=np.sum))

prod_and_reg
```

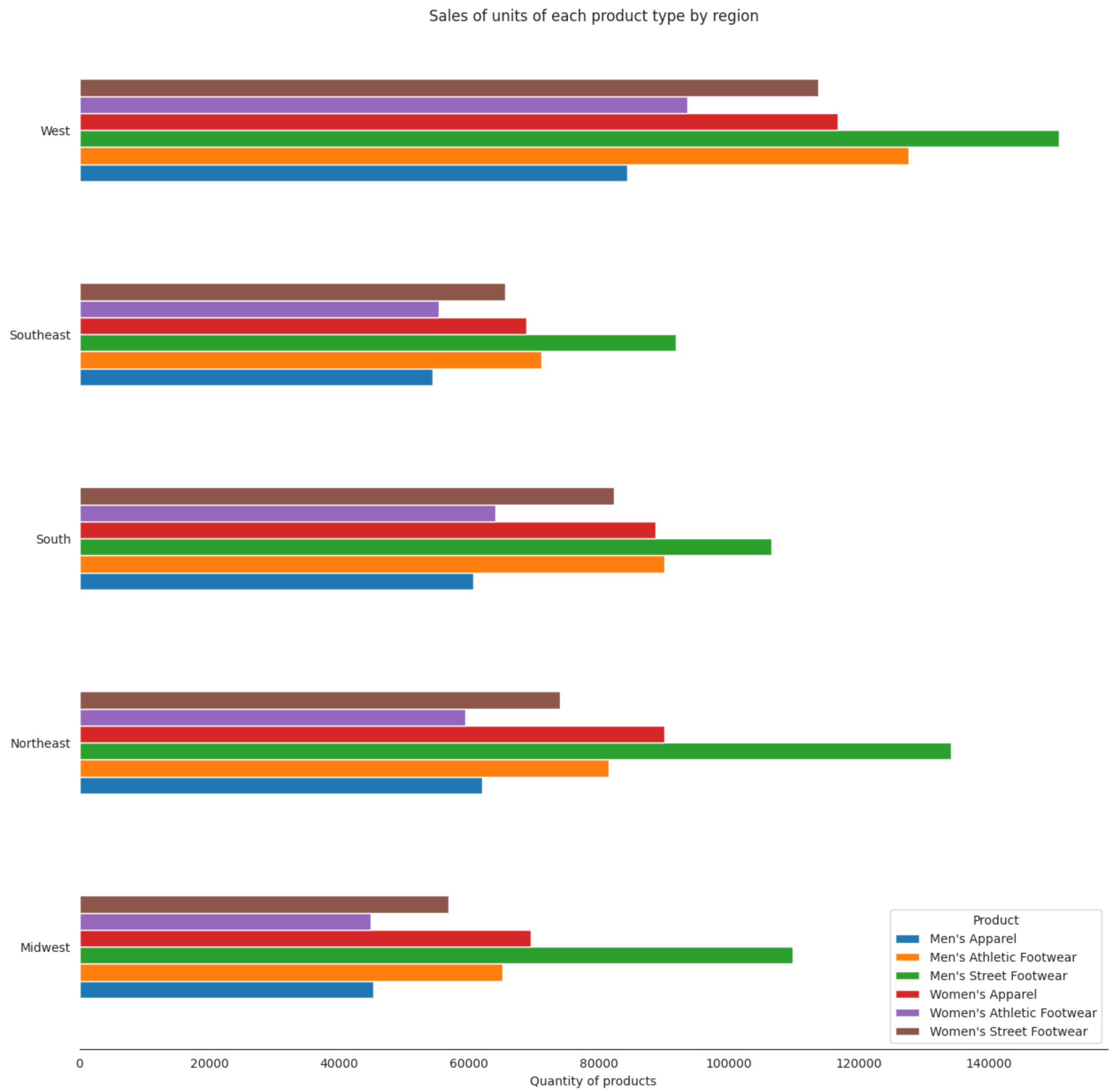
[308]:

```
region                       Midwest  Northeast   South  Southeast    West
product
Men's Apparel                  45304      62031   60641      54385   84322
Men's Athletic Footwear        65120      81474   90079      71129  127724
Men's Street Footwear         109861     134252  106545      91867  150795
Women's Apparel                69435      90048   88740      68839  116765
Women's Athletic Footwear      44808      59464   63998      55292   93674
Women's Street Footwear        56809      74010   82257      65488  113705
```

Plotting a bar plot making it more intuitive and clear.

[309]:

```
prod_and_reg.T.plot(kind='barh',legend=True, figsize=(15,15))

sns.despine(left=True)
sns.set_style('white')
plt.legend(title='Product',fontsize=10,loc='best')
plt.xlabel('Quantity of products')
plt.ylabel(None)
plt.xticks(rotation=0)
plt.title('Sales of units of each product type by region')
plt.show()
```



Obtaining the best seller products types for each region:

[310]:
```
print('The best-sellers types of products by Adidas per region are:')
for region in prod_and_reg.columns:
    product = prod_and_reg.loc[:,region].idxmax()
    print(f'{region}: {product}')
```

```
The best-sellers types of products by Adidas per region are:
Midwest: Men's Street Footwear
Northeast: Men's Street Footwear
South: Men's Street Footwear
Southeast: Men's Street Footwear
West: Men's Street Footwear
```

3.3.1 Conclusion

One can conclude then that the products from Adidas that are the best-sellers in USA's regions, given by the data set, are from the category Men's Street Footwear

3.4 Which city is the gold mine for Adidas?

In order to determine the cities that provides more profit the following process was done

[311]:
```
city_df = (adidas_df
            .groupby('city', as_index=False)
            .agg({'units_sold':np.sum,
                  'total_sales':np.sum,
                  'operating_profit':np.sum,
                  'operating_margin':np.mean})
            .sort_values(['operating_margin'], ascending=False)
            .reset_index(drop=True))

city_df.head(3)
```

[311]:

	city	units_sold	total_sales	operating_profit	operating_margin
0	Birmingham	63327	17633424.0	9147581.39	0.553565
1	Knoxville	66077	18067440.0	8493660.06	0.506574
2	Detroit	50095	18625433.0	8135894.02	0.475764

3.4.1 Conclusion

Thus, despite having less `total_sales` and `units_sold` than the second and third, Birmingham have the best `operating_margin` being the best city for sales

3.5 Which is the more efficient approach for sales?

To choose the more efficient approach will be taken into account the variables `sales_method` ,`operating_margin` and `total_sales` once these consider the volume of sales and the profit rate and the manner that the sale was closed.

[312]:
```
(adidas_df
 .groupby('sales_method')
 .agg({'operating_margin':np.mean,
       'total_sales':np.sum})
 .sort_values('operating_margin',ascending=False))
```

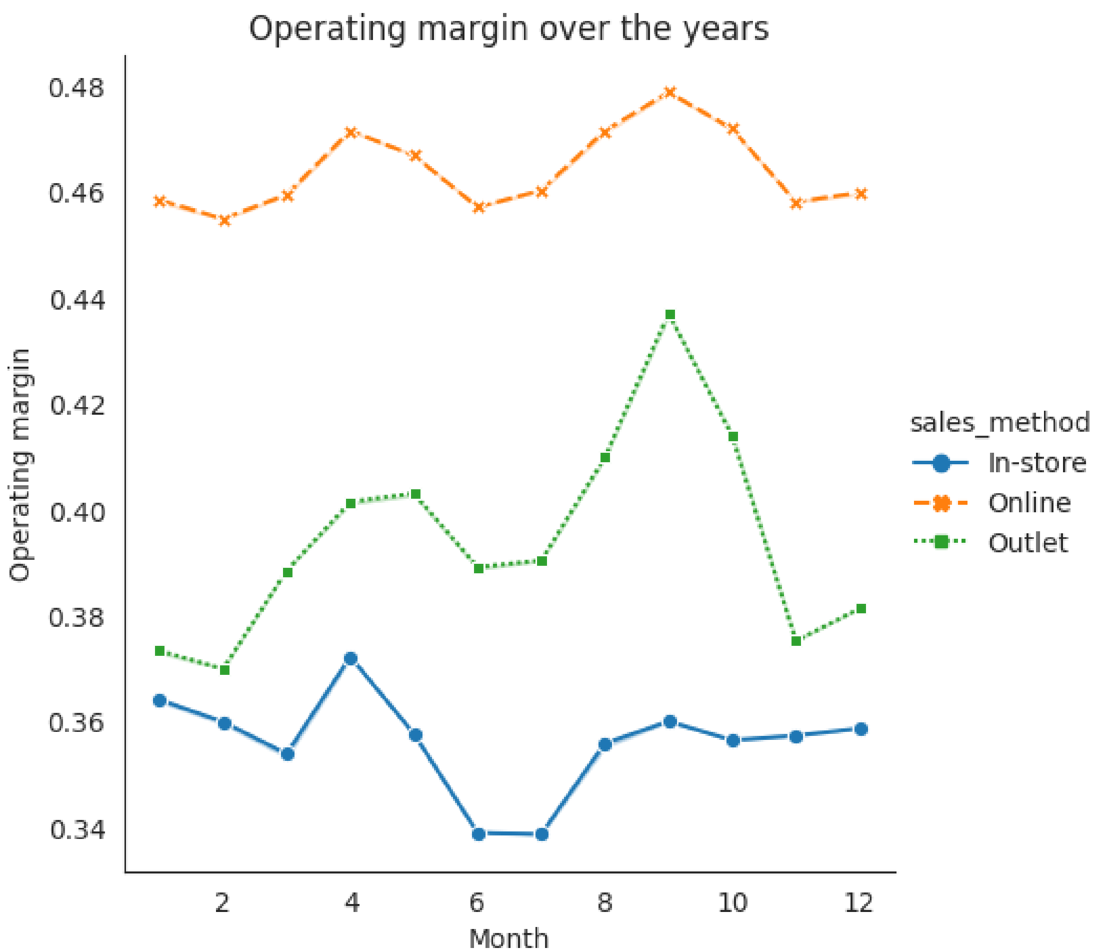
[312]:

sales_method	operating_margin	total_sales
Online	0.464152	247672882.0
Outlet	0.394876	295585493.0
In-store	0.356121	356643750.0

Let's evaluate how the operating margin was affected over the years covered on the dataset

[313]:

```
ax = sns.relplot(data=adidas_df,
                 x='month',
                 y='operating_margin',
                 hue='sales_method',
                 kind='line',
                 markers=True,
                 style='sales_method',
                 errorbar=('ci',0.95))

plt.title('Operating margin over the years')
ax.set_ylabels('Operating margin')
ax.set_xlabels('Month')
plt.show()
```



3.5.1 Conclusion

We can observe that in the range of two years the sales made online presented a decrease while on outlets and in-store, an increase. Yet, at the moment of this data collection, online remains as the most profitable channel of sales, having the highest operating margin.