Group Q:
Laura Cuna, 20211312
Amelie Langenstein, 20210637
Tongjiuzhou Liu, 20211012
Nina Urbancic, 20211314

Business Case 3 - Recommender System

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Business Understanding

Determine Business Objectives

Determine Data Mining Goals

Data Understanding

In [149]:
```
import os
import pandas as pd
import numpy as np

import plotly.express as px
from plotly.subplots import make_subplots
import plotly.graph_objects as go
import matplotlib.pyplot as plt
import matplotlib.cm as cm
from plotnine import *
import plotnine
import seaborn as sns
import networkx as nx

from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import TransactionEncoder

from sklearn.preprocessing import StandardScaler, OneHotEncoder

from kmodes.kprototypes import KPrototypes
from sklearn.manifold import TSNE

import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=DeprecationWarning)
```

In [2]:
```
#Visualization settings
custom_params = {"axes.spines.right": False, "axes.spines.top": False}
sns.set_style("white")
```

Dataset description

Collect initial data

In [3]:
```
# Read csv files
df = pd.read_csv('retail.csv')
df_ = df.copy()
```

Describe, explore and assess data quality

In [4]:
```
#display info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  object
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB
```

In [5]:
```
pd.set_option('display.max_columns', None)
```

In [6]:

```
#display top rows
df.head(10)
```

Out[6]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
5	536365	22752	SET 7 BABUSHKA NESTING BOXES	2	12/1/2010 8:26	7.65	17850.0	United Kingdom
6	536365	21730	GLASS STAR FROSTED T-LIGHT HOLDER	6	12/1/2010 8:26	4.25	17850.0	United Kingdom
7	536366	22633	HAND WARMER UNION JACK	6	12/1/2010 8:28	1.85	17850.0	United Kingdom
8	536366	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 8:28	1.85	17850.0	United Kingdom
9	536367	84879	ASSORTED COLOUR BIRD ORNAMENT	32	12/1/2010 8:34	1.69	13047.0	United Kingdom

In [7]:

```
# Statistics summary for all variables
df.describe(include='all').transpose()
```

Out[7]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
InvoiceNo	541909	25900	573585	1114	NaN	NaN	NaN	NaN	NaN	NaN	NaN
StockCode	541909	4070	85123A	2313	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Description	540455	4223	WHITE HANGING HEART T-LIGHT HOLDER	2369	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Quantity	541909.0	NaN	NaN	NaN	9.55225	218.081158	-80995.0	1.0	3.0	10.0	80995.0
InvoiceDate	541909	23260	10/31/2011 14:41	1114	NaN	NaN	NaN	NaN	NaN	NaN	NaN
UnitPrice	541909.0	NaN	NaN	NaN	4.611114	96.759853	-11062.06	1.25	2.08	4.13	38970.0
CustomerID	406829.0	NaN	NaN	NaN	15287.69057	1713.600303	12346.0	13953.0	15152.0	16791.0	18287.0
Country	541909	38	United Kingdom	495478	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [8]:
```
df.set_index(['CustomerID','InvoiceNo']).head(50)
```

Out[8]:

CustomerID	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	Country
17850.0	**536365**	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	United Kingdom
	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	United Kingdom
	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	United Kingdom
	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	United Kingdom
	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	United Kingdom
	536365	22752	SET 7 BABUSHKA NESTING BOXES	2	12/1/2010 8:26	7.65	United Kingdom
	536365	21730	GLASS STAR FROSTED T-LIGHT HOLDER	6	12/1/2010 8:26	4.25	United Kingdom
	536366	22633	HAND WARMER UNION JACK	6	12/1/2010 8:28	1.85	United Kingdom
	536366	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 8:28	1.85	United Kingdom
13047.0	**536367**	84879	ASSORTED COLOUR BIRD ORNAMENT	32	12/1/2010 8:34	1.69	United Kingdom
	536367	22745	POPPY'S PLAYHOUSE BEDROOM	6	12/1/2010 8:34	2.10	United Kingdom
	536367	22748	POPPY'S PLAYHOUSE KITCHEN	6	12/1/2010 8:34	2.10	United Kingdom
	536367	22749	FELTCRAFT PRINCESS CHARLOTTE DOLL	8	12/1/2010 8:34	3.75	United Kingdom
	536367	22310	IVORY KNITTED MUG COSY	6	12/1/2010 8:34	1.65	United Kingdom
	536367	84969	BOX OF 6 ASSORTED COLOUR TEASPOONS	6	12/1/2010 8:34	4.25	United Kingdom
	536367	22623	BOX OF VINTAGE JIGSAW BLOCKS	3	12/1/2010 8:34	4.95	United Kingdom
	536367	22622	BOX OF VINTAGE ALPHABET BLOCKS	2	12/1/2010 8:34	9.95	United Kingdom
	536367	21754	HOME BUILDING BLOCK WORD	3	12/1/2010 8:34	5.95	United Kingdom
	536367	21755	LOVE BUILDING BLOCK WORD	3	12/1/2010 8:34	5.95	United Kingdom
	536367	21777	RECIPE BOX WITH METAL HEART	4	12/1/2010 8:34	7.95	United Kingdom
	536367	48187	DOORMAT NEW ENGLAND	4	12/1/2010 8:34	7.95	United Kingdom
	536368	22960	JAM MAKING SET WITH JARS	6	12/1/2010 8:34	4.25	United Kingdom
	536368	22913	RED COAT RACK PARIS FASHION	3	12/1/2010 8:34	4.95	United Kingdom
	536368	22912	YELLOW COAT RACK PARIS FASHION	3	12/1/2010 8:34	4.95	United Kingdom
	536368	22914	BLUE COAT RACK PARIS FASHION	3	12/1/2010 8:34	4.95	United Kingdom
	536369	21756	BATH BUILDING BLOCK WORD	3	12/1/2010 8:35	5.95	United Kingdom
12583.0	**536370**	22728	ALARM CLOCK BAKELIKE PINK	24	12/1/2010 8:45	3.75	France
	536370	22727	ALARM CLOCK BAKELIKE RED	24	12/1/2010 8:45	3.75	France
	536370	22726	ALARM CLOCK BAKELIKE GREEN	12	12/1/2010 8:45	3.75	France
	536370	21724	PANDA AND BUNNIES STICKER SHEET	12	12/1/2010 8:45	0.85	France

		StockCode	Description	Quantity	InvoiceDate	UnitPrice	Country
CustomerID	**InvoiceNo**						
	536370	21883	STARS GIFT TAPE	24	12/1/2010 8:45	0.65	France
	536370	10002	INFLATABLE POLITICAL GLOBE	48	12/1/2010 8:45	0.85	France
	536370	21791	VINTAGE HEADS AND TAILS CARD GAME	24	12/1/2010 8:45	1.25	France
	536370	21035	SET/2 RED RETROSPOT TEA TOWELS	18	12/1/2010 8:45	2.95	France
	536370	22326	ROUND SNACK BOXES SET OF4 WOODLAND	24	12/1/2010 8:45	2.95	France
	536370	22629	SPACEBOY LUNCH BOX	24	12/1/2010 8:45	1.95	France
	536370	22659	LUNCH BOX I LOVE LONDON	24	12/1/2010 8:45	1.95	France
	536370	22631	CIRCUS PARADE LUNCH BOX	24	12/1/2010 8:45	1.95	France
	536370	22661	CHARLOTTE BAG DOLLY GIRL DESIGN	20	12/1/2010 8:45	0.85	France
	536370	21731	RED TOADSTOOL LED NIGHT LIGHT	24	12/1/2010 8:45	1.65	France
	536370	22900	SET 2 TEA TOWELS I LOVE LONDON	24	12/1/2010 8:45	2.95	France
	536370	21913	VINTAGE SEASIDE JIGSAW PUZZLES	12	12/1/2010 8:45	3.75	France
	536370	22540	MINI JIGSAW CIRCUS PARADE	24	12/1/2010 8:45	0.42	France
	536370	22544	MINI JIGSAW SPACEBOY	24	12/1/2010 8:45	0.42	France
	536370	22492	MINI PAINT SET VINTAGE	36	12/1/2010 8:45	0.65	France
	536370	POST	POSTAGE	3	12/1/2010 8:45	18.00	France
13748.0	**536371**	22086	PAPER CHAIN KIT 50'S CHRISTMAS	80	12/1/2010 9:00	2.55	United Kingdom
17850.0	**536372**	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 9:01	1.85	United Kingdom
	536372	22633	HAND WARMER UNION JACK	6	12/1/2010 9:01	1.85	United Kingdom
	536373	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 9:02	2.55	United Kingdom

In [9]:
```
Description=pd.DataFrame(df['Description'].unique())
```

In [10]:
```
Description.isnull().value_counts()
```

Out[10]:
```
False    4223
True        1
dtype: int64
```

In [11]:
```
df[df['Description'].str.islower().fillna(False)]['Description'].unique()
```

Out[11]:
```
array(['amazon', 'check', 'damages', 'faulty', 'amazon sales',
       'reverse 21/5/10 adjustment', 'mouldy, thrown away.', 'found',
       'counted', 'label mix up', 'samples/damages', 'thrown away',
       'incorrectly made-thrown away.', 'showroom',
       'wrongly sold as sets', 'dotcom sold sets', 'wrongly sold sets',
       '? sold as sets?', '?sold as sets?', 'damages/display',
       'damaged stock', 'broken', 'throw away', 'wrong barcode (22467)',
       'wrongly sold (22719) barcode', 'wrong barcode', 'barcode problem',
       '?lost', "thrown away-can't sell.", "thrown away-can't sell",
       'rcvd be air temp fix for dotcom sit', 'damages?',
       're dotcom quick fix.', 'sold in set?', 'cracked', 'sold as 22467',
       'damaged', 'did  a credit  and did not tick ret', 'adjustment',
       'returned', 'wrong code?', 'wrong code', 'adjust', 'crushed',
       'damages/showroom etc', 'samples', 'mailout ', 'mailout',
       'sold as set/6 by dotcom', 'wet/rusty', 'damages/dotcom?',
       'on cargo order', 'smashed', 'reverse previous adjustment',
       'wet damaged', 'missing', 'sold as set on dotcom',
       'sold as set on dotcom and amazon', 'water damage',
       'sold as set by dotcom', 'printing smudges/thrown away',
       'to push order througha s stock was ', 'found some more on shelf',
       'mix up with c', 'mouldy, unsaleable.',
       'wrongly marked. 23343 in box', 'came coded as 20713',
       'alan hodge cant mamage this section', 'dotcom',
       'stock creditted wrongly', 'ebay',
       'incorrectly put back into stock', 'taig adjust no stock',
       'code mix up? 84930', '?display?', 'sold as 1', '?missing',
       'crushed ctn', 'test', 'temp adjustment', 'taig adjust',
       'allocate stock for dotcom orders ta',
       'add stock to allocate online orders', 'for online retail orders',
       'found box', 'website fixed',
       'historic computer difference?....se', 'incorrect stock entry.',
       'michel oops', 'wrongly coded 20713', 'wrongly coded-23343',
       'stock check', 'crushed boxes', "can't find", 'mouldy',
       'wrongly marked 23343', '20713 wrongly marked', 're-adjustment',
       'wrongly coded 23343', 'wrongly marked', 'dotcom sales',
       'had been put aside', 'damages wax', 'water damaged',
       'wrongly marked carton 22804', 'missing?', 'wet rusty',
       'amazon adjust', '???lost', 'dotcomstock',
       'sold with wrong barcode', 'dotcom adjust', 'rusty thrown away',
       'rusty throw away', 'check?', '?? missing', 'wet pallet',
       '????missing', '???missing', 'lost in space', 'wet?', 'lost??',
       'wet', 'wet boxes', '????damages????', 'mixed up', 'lost'],
      dtype=object)
```

In [12]:
```
df[df['Description'].str.isupper().fillna(False)]['Description'].unique()
```

Out[12]:
```
array(['WHITE HANGING HEART T-LIGHT HOLDER', 'WHITE METAL LANTERN',
       'CREAM CUPID HEARTS COAT HANGER', ..., 'LETTER "U" BLING KEY RING',
       'CREAM HANGING HEART T-LIGHT HOLDER',
       'PAPER CRAFT , LITTLE BIRDIE'], dtype=object)
```

In [13]:
```
df.Description.nunique()
```

Out[13]: 4223

In [14]:
```
df[df['Description'].str.isupper().fillna(False)]['Description'].nunique()
```

Out[14]: 4018

In [15]:
```
df[df['Description'].str.islower().fillna(False)]['Description'].nunique()
```

Out[15]: 127

In [16]:
```
df.StockCode.nunique()
```

Out[16]: 4070

In [17]:
```
df[df['Quantity']==0]
```

Out[17]:

InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country

In [18]:
```
pd.DataFrame(df['StockCode'].unique())
```

Out[18]:

	0
0	85123A
1	71053
2	84406B
3	84029G
4	84029E
...	...
4065	85179a
4066	23617
4067	90214U
4068	47591b
4069	23843

4070 rows × 1 columns

In [19]:
```
# Check missing values
df.isnull().sum()
```

Out[19]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

In [20]:
```
df[df['Description'].isnull()]
```

Out[20]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
622	536414	22139	NaN	56	12/1/2010 11:52	0.0	NaN	United Kingdom
1970	536545	21134	NaN	1	12/1/2010 14:32	0.0	NaN	United Kingdom
1971	536546	22145	NaN	1	12/1/2010 14:33	0.0	NaN	United Kingdom
1972	536547	37509	NaN	1	12/1/2010 14:33	0.0	NaN	United Kingdom
1987	536549	85226A	NaN	1	12/1/2010 14:34	0.0	NaN	United Kingdom
...	...	...	...	...	...	...	...	...
535322	581199	84581	NaN	-2	12/7/2011 18:26	0.0	NaN	United Kingdom
535326	581203	23406	NaN	15	12/7/2011 18:31	0.0	NaN	United Kingdom
535332	581209	21620	NaN	6	12/7/2011 18:35	0.0	NaN	United Kingdom
536981	581234	72817	NaN	27	12/8/2011 10:33	0.0	NaN	United Kingdom
538554	581408	85175	NaN	20	12/8/2011 14:06	0.0	NaN	United Kingdom

In [21]:
```
df['Country'].unique()
```

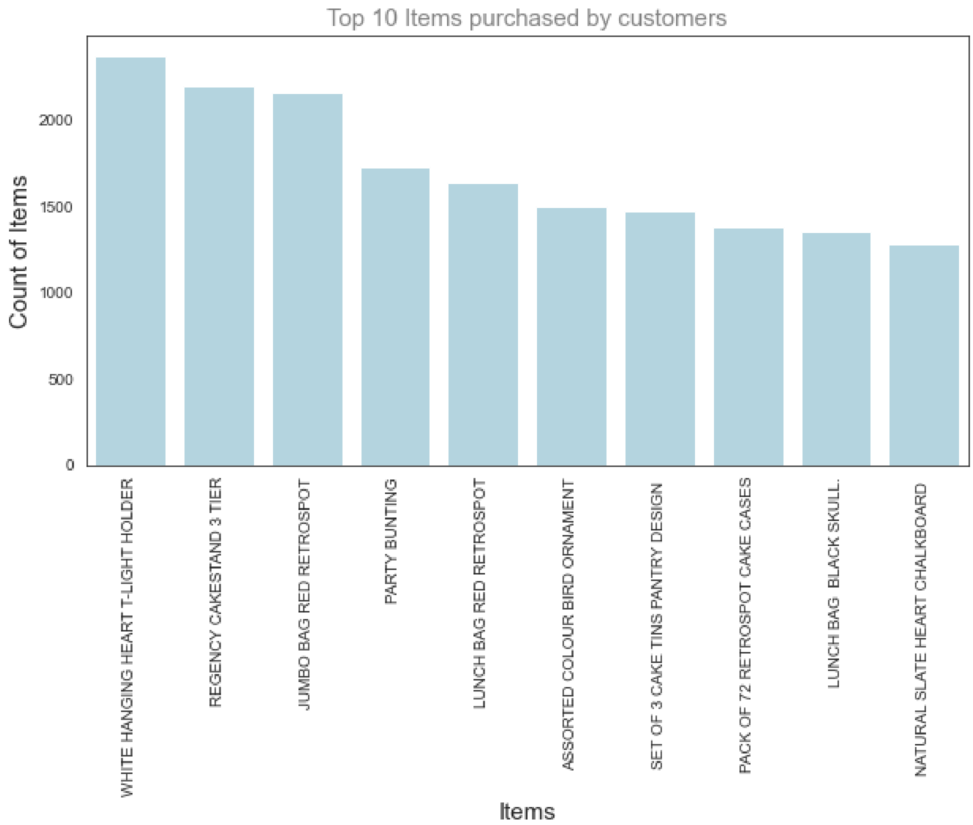
Out[21]:
```
array(['United Kingdom', 'France', 'Australia', 'Netherlands', 'Germany',
       'Norway', 'EIRE', 'Switzerland', 'Spain', 'Poland', 'Portugal',
       'Italy', 'Belgium', 'Lithuania', 'Japan', 'Iceland',
       'Channel Islands', 'Denmark', 'Cyprus', 'Sweden', 'Austria',
       'Israel', 'Finland', 'Bahrain', 'Greece', 'Hong Kong', 'Singapore',
       'Lebanon', 'United Arab Emirates', 'Saudi Arabia',
       'Czech Republic', 'Canada', 'Unspecified', 'Brazil', 'USA',
       'European Community', 'Malta', 'RSA'], dtype=object)
```

In [22]:
```
df.dtypes
```

Out[22]:
```
InvoiceNo       object
StockCode       object
Description     object
Quantity         int64
InvoiceDate     object
UnitPrice      float64
CustomerID     float64
Country         object
dtype: object
```

First Visual Exploration

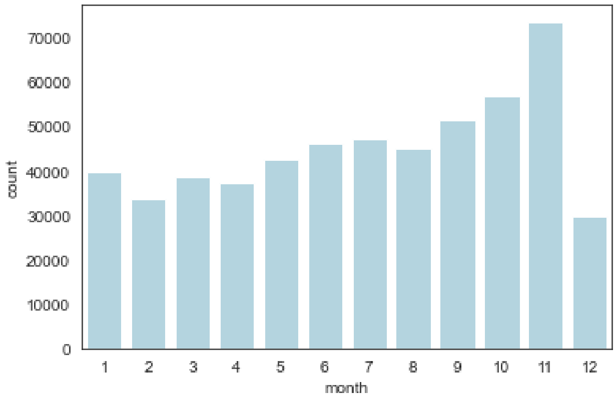
In [23]:
```
plt.figure(figsize=(10,5))
sns.barplot(x = df.Description.value_counts().head(10).index, y = df.Description.value_counts().head(10).values, c
plt.xlabel('Items', size = 15)
plt.xticks(rotation=90)
plt.ylabel('Count of Items', size = 15)
plt.title('Top 10 Items purchased by customers', color = 'grey', size = 15)
plt.show()
```



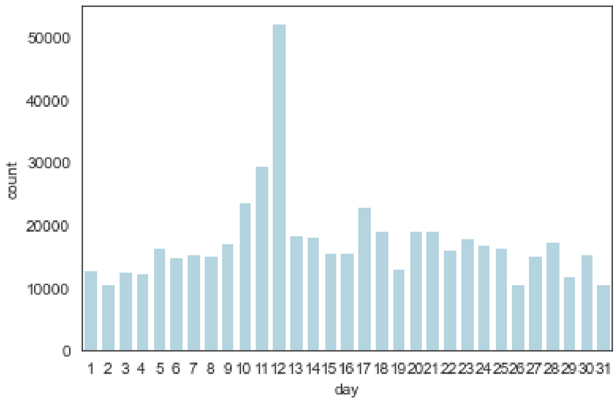
In [24]:
```
#the following EDA part should is only possible after the new features are created
#so not really part of Data Understanding, if new features are not yet created
#transform the InvoiceDate to pandas datetime
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'],dayfirst=True)
```

In [25]:
```
#create year month day and hour of orders
df['year'] = df['InvoiceDate'].dt.year

df['month'] = df['InvoiceDate'].dt.month

df['day'] = df['InvoiceDate'].dt.day

df['hour'] = df['InvoiceDate'].dt.hour

df['day_of_week']=df['InvoiceDate'].dt.weekday
```

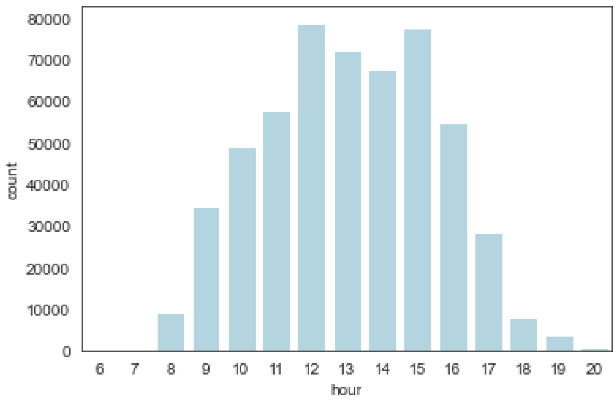
In [26]:
```
sns.countplot(df["month"].astype(int), color='lightblue')
plt.show()
```



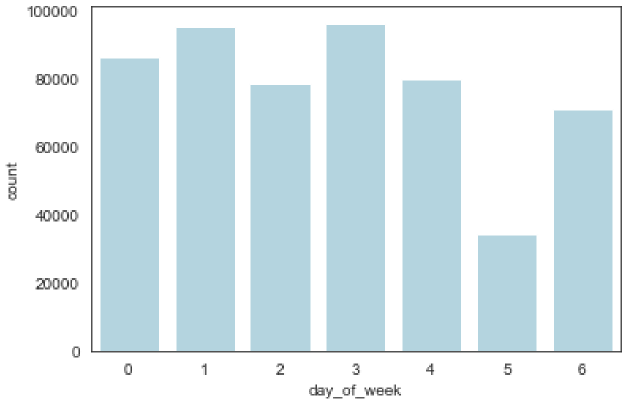
In [27]:
```
sns.countplot(df["day"].astype(int), color='lightblue')
plt.show()
```



In [28]:
```
sns.countplot(df["hour"].astype(int), color='lightblue')
plt.show()
```



In [29]:
```
sns.countplot(df["day_of_week"].astype(int), color='lightblue')
plt.show()
```



Verify data quality

In [30]:
```
#check if there are records with "quantity" less than 0
df[df['Quantity']<0]
```

Out[30]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	year	month	day	hour
141	C536379	D	Discount	-1	2010-01-12 09:41:00	27.50	14527.0	United Kingdom	2010	1	12	9
154	C536383	35004C	SET OF 3 COLOURED FLYING DUCKS	-1	2010-01-12 09:49:00	4.65	15311.0	United Kingdom	2010	1	12	9
235	C536391	22556	PLASTERS IN TIN CIRCUS PARADE	-12	2010-01-12 10:24:00	1.65	17548.0	United Kingdom	2010	1	12	10
236	C536391	21984	PACK OF 12 PINK PAISLEY TISSUES	-24	2010-01-12 10:24:00	0.29	17548.0	United Kingdom	2010	1	12	10
237	C536391	21983	PACK OF 12 BLUE PAISLEY TISSUES	-24	2010-01-12 10:24:00	0.29	17548.0	United Kingdom	2010	1	12	10
...	...	...	...	...	...	...	...	...	...	...	...	...
540449	C581490	23144	ZINC T-LIGHT HOLDER STARS SMALL	-11	2011-09-12 09:57:00	0.83	14397.0	United Kingdom	2011	9	12	9
541541	C581499	M	Manual	-1	2011-09-12 10:28:00	224.69	15498.0	United Kingdom	2011	9	12	10
541715	C581568	21258	VICTORIAN SEWING BOX LARGE	-5	2011-09-12 11:57:00	10.95	15311.0	United Kingdom	2011	9	12	11
541716	C581569	84978	HANGING HEART JAR T-LIGHT HOLDER	-1	2011-09-12 11:58:00	1.25	17315.0	United Kingdom	2011	9	12	11
541717	C581569	20979	36 PENCILS TUBE RED RETROSPOT	-5	2011-09-12 11:58:00	1.25	17315.0	United Kingdom	2011	9	12	11

10624 rows × 13 columns

In [31]:
```
#check if there are records with "UnitPrice" less than 0
df[df['UnitPrice']<0]
```

Out[31]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	year	month	day	hour
299983	A563186	B	Adjust bad debt	1	2011-12-08 14:51:00	-11062.06	NaN	United Kingdom	2011	12	8	14
299984	A563187	B	Adjust bad debt	1	2011-12-08 14:52:00	-11062.06	NaN	United Kingdom	2011	12	8	14

Data Preparation

Select data

In [32]:
```
dfp = df.copy()
```

Clean data

In [33]:
```
#Separate cancelled orders
df_canceled=dfp[dfp['InvoiceNo'].str.contains("C")]
dfp=dfp[~dfp.isin(df_canceled)].dropna(how = 'all')
dfp
```

Out[33]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	year	month	day	hou
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6.0	2010-01-12 08:26:00	2.55	17850.0	United Kingdom	2010.0	1.0	12.0	8
1	536365	71053	WHITE METAL LANTERN	6.0	2010-01-12 08:26:00	3.39	17850.0	United Kingdom	2010.0	1.0	12.0	8
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8.0	2010-01-12 08:26:00	2.75	17850.0	United Kingdom	2010.0	1.0	12.0	8
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6.0	2010-01-12 08:26:00	3.39	17850.0	United Kingdom	2010.0	1.0	12.0	8
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6.0	2010-01-12 08:26:00	3.39	17850.0	United Kingdom	2010.0	1.0	12.0	8
...	...	...	...	...	...	...	...	...	...	...	...	
541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12.0	2011-09-12 12:50:00	0.85	12680.0	France	2011.0	9.0	12.0	12
541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6.0	2011-09-12 12:50:00	2.10	12680.0	France	2011.0	9.0	12.0	12
541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4.0	2011-09-12 12:50:00	4.15	12680.0	France	2011.0	9.0	12.0	12
541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4.0	2011-09-12 12:50:00	4.15	12680.0	France	2011.0	9.0	12.0	12
541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3.0	2011-09-12 12:50:00	4.95	12680.0	France	2011.0	9.0	12.0	12

532621 rows × 13 columns

In [34]:
```
# remove the Invalid data
dfp = dfp[dfp['Quantity']>0]
dfp = dfp[dfp['UnitPrice']>0]
```

In [35]:
```
# The unique values of these 2 variables (Description & StockCode) should be equal, because each stock code represe
df_product = dfp[["Description","StockCode"]].drop_duplicates()
df_product = df_product.groupby(["Description"]).agg({"StockCode":"count"}).reset_index()
df_product = df_product[df_product["StockCode"]>1]
df_product
```

Out[35]:

	Description	StockCode
46	3 GARDENIA MORRIS BOXED CANDLES	2
61	3 WHITE CHOC MORRIS BOXED CANDLES	2
72	3D DOG PICTURE PLAYING CARDS	2
74	3D SHEET OF CAT STICKERS	2
75	3D SHEET OF DOG STICKERS	2
...	...	...
3906	WOODEN FRAME ANTIQUE WHITE	2
3935	WOVEN BERRIES CUSHION COVER	2
3936	WOVEN BUBBLE GUM CUSHION COVER	2
3937	WOVEN CANDY CUSHION COVER	2
3939	WOVEN ROSE GARDEN CUSHION COVER	2

131 rows × 2 columns

In [36]:
```
# remove the products with more than one stockcode
dfp = dfp[~dfp["Description"].isin(df_product["Description"])]
```

In [37]:
```
df_product = dfp[["Description","StockCode"]].drop_duplicates()
df_product = df_product.groupby(["StockCode"]).agg({"Description":"count"}).reset_index()
df_product = df_product[df_product["Description"] > 1]
df_product
```

Out[37]:

	StockCode	Description
36	16156L	2
94	17107D	3
111	20622	2
163	20725	2
254	20914	2
...	...	...
3203	85144	2
3237	85185B	2
3304	90014A	2
3305	90014B	2
3306	90014C	2

205 rows × 2 columns

In [38]:
```
# remove stock codes that represent multiple products:
dfp = dfp[~dfp["StockCode"].isin(df_product["StockCode"])]
```

In [39]:
```
# The post statement in the stock code shows the postage cost, let's delete it as it is not a product:
dfp = dfp[~dfp["StockCode"].str.contains("POST", na=False)]
```

In [40]:
```
#drop the lowercase in Description
dfp=dfp[dfp['Description'].str.isupper()]
dfp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 461038 entries, 2 to 541908
Data columns (total 13 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    461038 non-null  object
 1   StockCode    461038 non-null  object
 2   Description  461038 non-null  object
 3   Quantity     461038 non-null  float64
 4   InvoiceDate  461038 non-null  datetime64[ns]
 5   UnitPrice    461038 non-null  float64
 6   CustomerID   344520 non-null  float64
 7   Country      461038 non-null  object
 8   year         461038 non-null  float64
 9   month        461038 non-null  float64
 10  day          461038 non-null  float64
 11  hour         461038 non-null  float64
 12  day_of_week  461038 non-null  float64
dtypes: datetime64[ns](1), float64(8), object(4)
memory usage: 49.2+ MB
```

Construct data

In [41]:
```
#transform the InvoiceDate to pandas datetime
dfp['InvoiceDate'] = pd.to_datetime(dfp['InvoiceDate'],dayfirst=True)
dfp
```

Out[41]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	year	month	day	hou
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8.0	2010-01-12 08:26:00	2.75	17850.0	United Kingdom	2010.0	1.0	12.0	8
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6.0	2010-01-12 08:26:00	3.39	17850.0	United Kingdom	2010.0	1.0	12.0	8
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6.0	2010-01-12 08:26:00	3.39	17850.0	United Kingdom	2010.0	1.0	12.0	8
5	536365	22752	SET 7 BABUSHKA NESTING BOXES	2.0	2010-01-12 08:26:00	7.65	17850.0	United Kingdom	2010.0	1.0	12.0	8
6	536365	21730	GLASS STAR FROSTED T-LIGHT HOLDER	6.0	2010-01-12 08:26:00	4.25	17850.0	United Kingdom	2010.0	1.0	12.0	8
...	...	...	...	...	...	...	...	...	...	...	...	
541902	581587	22629	SPACEBOY LUNCH BOX	12.0	2011-09-12 12:50:00	1.95	12680.0	France	2011.0	9.0	12.0	12
541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12.0	2011-09-12 12:50:00	0.85	12680.0	France	2011.0	9.0	12.0	12
541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6.0	2011-09-12 12:50:00	2.10	12680.0	France	2011.0	9.0	12.0	12
541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4.0	2011-09-12 12:50:00	4.15	12680.0	France	2011.0	9.0	12.0	12
541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3.0	2011-09-12 12:50:00	4.95	12680.0	France	2011.0	9.0	12.0	12

461038 rows × 13 columns

In [42]:
```
#create year month day and hour of orders
dfp['year'] = dfp['InvoiceDate'].dt.year

dfp['month'] = dfp['InvoiceDate'].dt.month

dfp['day'] = dfp['InvoiceDate'].dt.day

dfp['hour'] = dfp['InvoiceDate'].dt.hour

dfp['day_of_week']=dfp['InvoiceDate'].dt.weekday
```

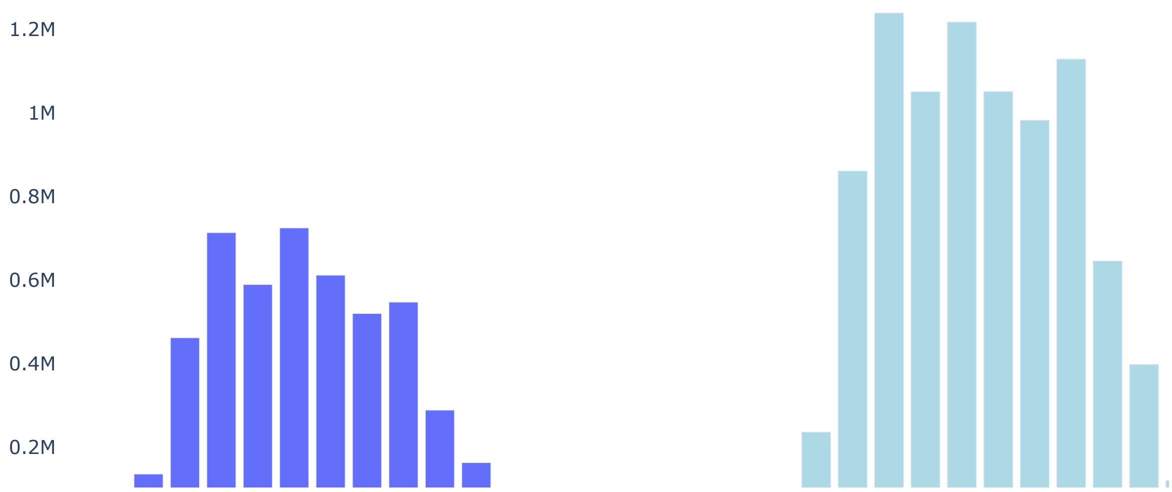
In [43]:
```
#cauculate total price
dfp['total_price'] = dfp['UnitPrice']*dfp['Quantity']
```

Explore Data (after Data Preparation because creating new features was necessary for EDA)

Q1 When do people order?

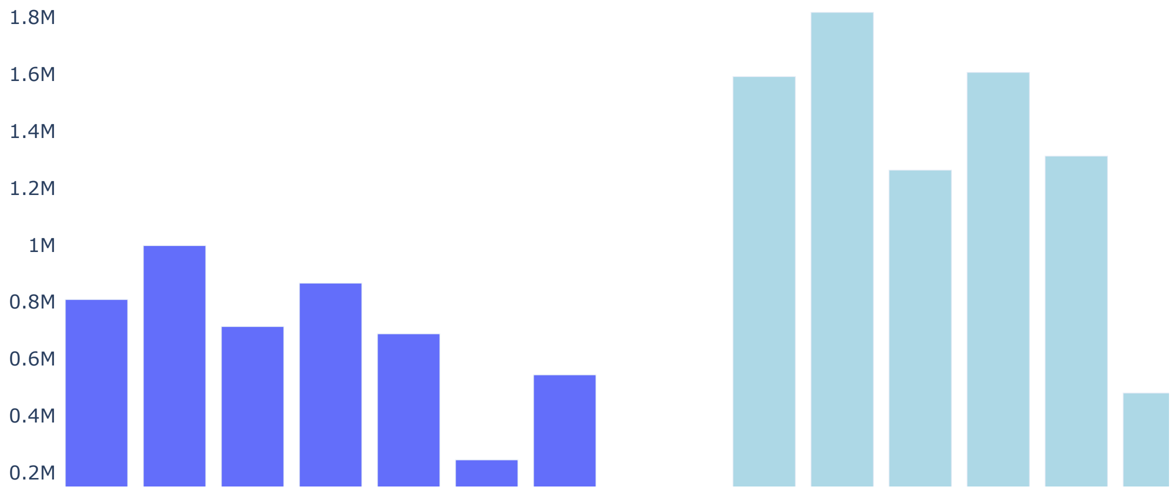
Hour of day

In [179]:
```
hour_of_day = pd.pivot_table(dfp, values=['Quantity', 'total_price'], index=['hour'],
                    aggfunc={'Quantity': sum,
                             'total_price': sum})

fig = make_subplots(rows=1, cols=2, shared_yaxes=True)

fig.add_trace(go.Bar(y=hour_of_day['Quantity'],name='Quantity'),1, 1)


fig.add_trace(go.Bar(y=hour_of_day['total_price'],name='total_price',marker=dict(color='lightblue')),1, 2)

fig.update_layout(xaxis1_title="Hour of day",)

fig.update_layout(xaxis2_title="Hour of day",)

fig.update_layout({'plot_bgcolor': 'rgba(0, 0, 0, 0)','paper_bgcolor': 'rgba(0, 0, 0, 0)',})

fig.show()
```



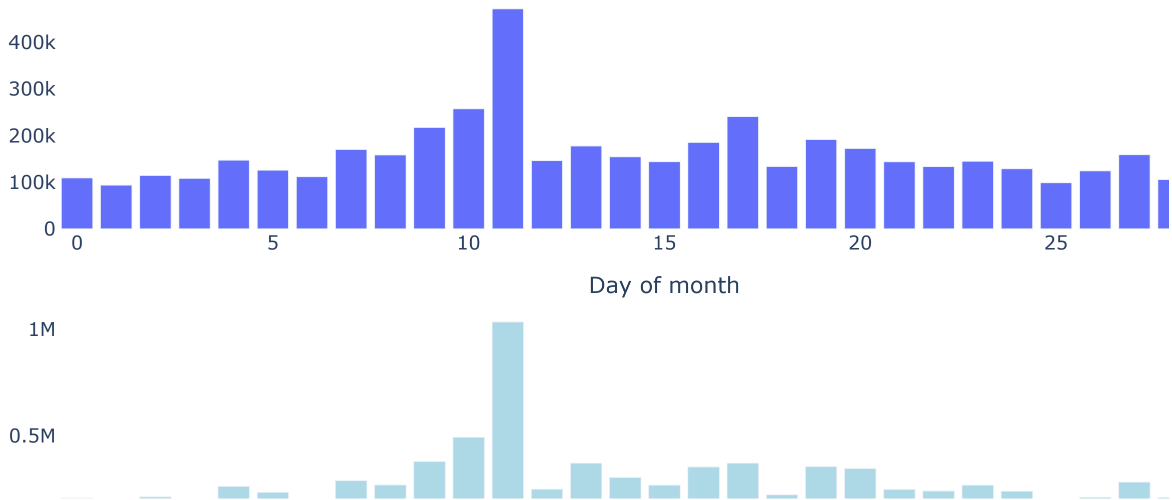
Day of Week

In [180]:
```
day_of_week = pd.pivot_table(dfp, values=['Quantity', 'total_price'], index=['day_of_week'],
                    aggfunc={'Quantity': sum,
                             'total_price': sum})

fig = make_subplots(rows=1, cols=2, shared_yaxes=True)

fig.add_trace(go.Bar(x=('Sun', 'Mon', 'Tue', 'Wed', 'Thur', 'Fri', 'Sat'),y=day_of_week['Quantity'],name='Quantity


fig.add_trace(go.Bar(x=('Sun', 'Mon', 'Tue', 'Wed', 'Thur', 'Fri', 'Sat'),y=day_of_week['total_price'],name='total

fig.update_layout(xaxis1_title='Day of Week',)

fig.update_layout(xaxis2_title='Day of Week',)

fig.update_layout({'plot_bgcolor': 'rgba(0, 0, 0, 0)','paper_bgcolor': 'rgba(0, 0, 0, 0)',})

fig.show()
```



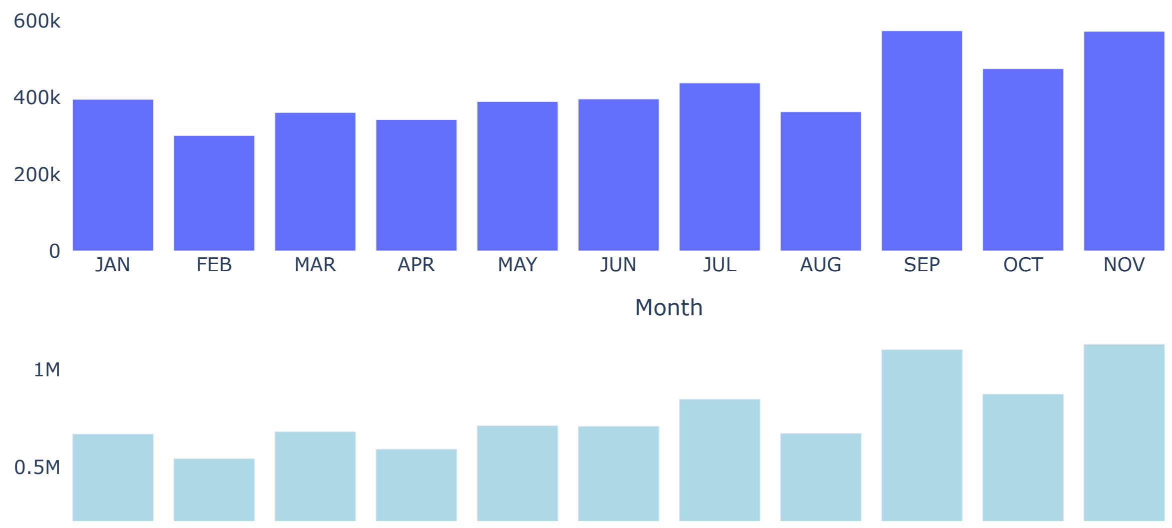
Day of month

In [182]:
```
day_of_month = pd.pivot_table(dfp, values=['Quantity', 'total_price'], index=['day'],
                    aggfunc={'Quantity': sum,
                             'total_price': sum})

fig = make_subplots(rows=2, cols=1, shared_yaxes=True)

fig.add_trace(go.Bar(y=day_of_month['Quantity'],name='Quantity'),1, 1)


fig.add_trace(go.Bar(y=day_of_month['total_price'],name='total_price',marker=dict(color='lightblue')),2,1)

fig.update_layout(xaxis1_title='Day of month',)

fig.update_layout(xaxis2_title='Day of month',)

fig.update_layout({'plot_bgcolor': 'rgba(0, 0, 0, 0)','paper_bgcolor': 'rgba(0, 0, 0, 0)',})

fig.show()
```



Month

In [183]:
```
month = pd.pivot_table(dfp, values=['Quantity', 'total_price'], index=['month'],
                       aggfunc={'Quantity': sum,
                                'total_price': sum})

fig = make_subplots(rows=2, cols=1, shared_yaxes=True)

fig.add_trace(go.Bar(x=('JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL','AUG','SEP','OCT','NOV','DEC'),y=month['Qu


fig.add_trace(go.Bar(x=('JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL','AUG','SEP','OCT','NOV','DEC'),y=month['to

fig.update_layout(xaxis1_title='Month',)

fig.update_layout(xaxis2_title='Month',)

fig.update_layout({'plot_bgcolor': 'rgba(0, 0, 0, 0)','paper_bgcolor': 'rgba(0, 0, 0, 0)',})

fig.show()
```



Q2 When do they order again?

In [48]:
```
# total orders paymemt sum for customers in each time
total_order_customer_eachtime = pd.pivot_table(dfp, values=[ 'total_price'], index=['CustomerID','InvoiceDate'],
                    aggfunc={'total_price': sum}).reset_index()
total_order_customer_eachtime=total_order_customer_eachtime[total_order_customer_eachtime['CustomerID']!='NONE']

# got the customer who has multiple records of shopping
preorder_customer = total_order_customer_eachtime[total_order_customer_eachtime.duplicated(subset=['CustomerID'],

#calculate the diffrence between dates
preorder_customer['diff']=preorder_customer.InvoiceDate.diff()

#Drop the wrong data and get the  Time difference between two orders
Time_diff=preorder_customer[~(preorder_customer.duplicated(subset=['CustomerID'],keep=False) ^ preorder_customer.

#convert 'diff' to days
Time_diff['diff_days']=Time_diff['diff'].dt.days
Time_diff
```

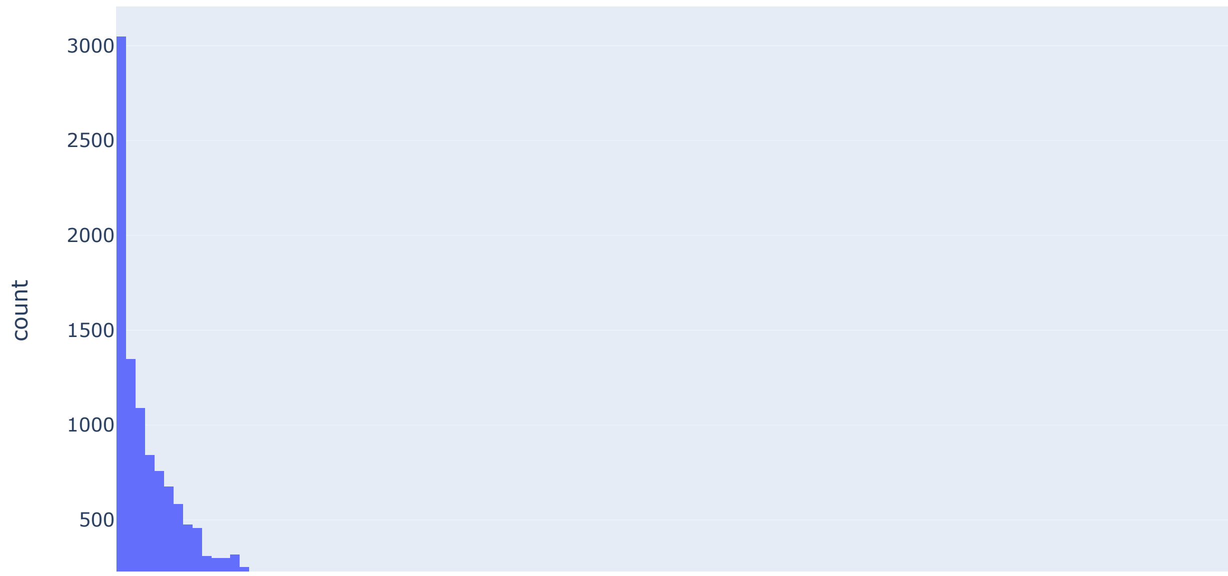
Out[48]:

	CustomerID	InvoiceDate	total_price	diff	diff_days
2	12347.0	2011-01-26 14:30:00	422.45	197 days 23:33:00	197
3	12347.0	2011-02-08 08:48:00	466.21	12 days 18:18:00	12
4	12347.0	2011-07-04 10:43:00	615.85	146 days 01:55:00	146
5	12347.0	2011-07-12 15:52:00	194.14	8 days 05:09:00	8
6	12347.0	2011-09-06 13:01:00	319.22	55 days 21:09:00	55
...	...	...	...	...	...
18057	18283.0	2011-10-27 14:38:00	91.45	15 days 23:31:00	15
18058	18283.0	2011-11-23 13:27:00	281.11	26 days 22:49:00	26
18059	18283.0	2011-11-30 12:59:00	187.52	6 days 23:32:00	6
18061	18287.0	2011-10-28 09:29:00	70.68	158 days 22:50:00	158
18062	18287.0	2011-12-10 10:23:00	800.20	43 days 00:54:00	43

13749 rows × 5 columns

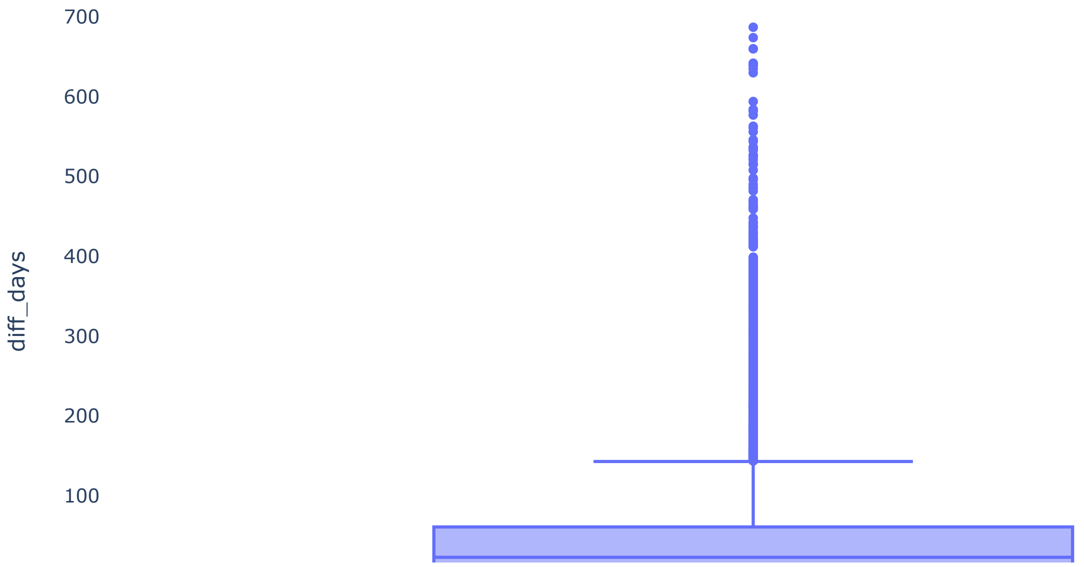
Histgram of the reorder times

In [49]:
```
fig = px.histogram(Time_diff, x="diff_days")
fig.show()
```



Box plot of the reorder times

In [184]:
```
fig = px.box(Time_diff, y="diff_days")
fig.update_layout({'plot_bgcolor': 'rgba(0, 0, 0, 0)','paper_bgcolor': 'rgba(0, 0, 0, 0)',})
fig.show()
```



Q3 What is the hottest product?

In [51]:
```
products = pd.pivot_table(dfp, values=['Quantity', 'total_price'], index=['Description'],
                          aggfunc={'Quantity': sum,
                                   'total_price': sum}).reset_index()
products
```

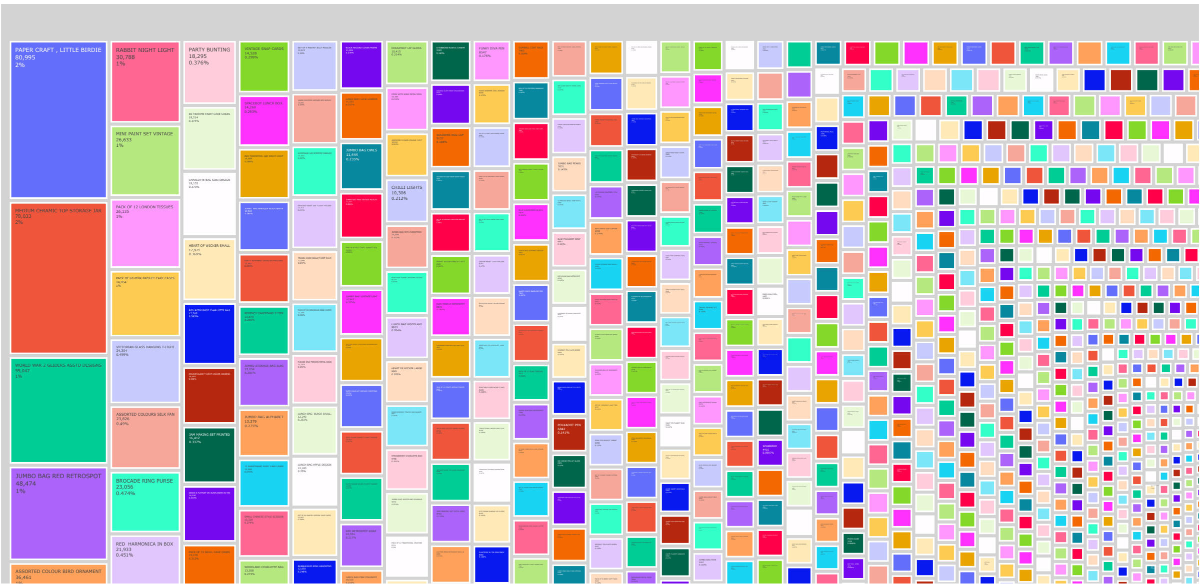
Out[51]:

	Description	Quantity	total_price
0	4 PURPLE FLOCK DINNER CANDLES	144.0	290.80
1	DOLLY GIRL BEAKER	2455.0	2891.25
2	NINE DRAWER OFFICE TIDY	59.0	909.37
3	OVAL WALL MIRROR DIAMANTE	237.0	2401.07
4	SPACEBOY BABY GIFT SET	499.0	7758.70
...	...	...	...
3431	ZINC T-LIGHT HOLDER STARS SMALL	5089.0	4197.83
3432	ZINC TOP 2 DOOR WOODEN SHELF	13.0	270.08
3433	ZINC WILLIE WINKIE CANDLE STICK	2934.0	2713.55
3434	ZINC WIRE KITCHEN ORGANISER	30.0	239.97
3435	ZINC WIRE SWEETHEART LETTER TRAY	83.0	275.62

3436 rows × 3 columns

Number of products sold Treemap

In [52]:
```
fig = px.treemap(products, path=['Description'], values='Quantity')
fig.update_traces(root_color="lightgrey",textinfo = "label+value+percent parent")
fig.update_layout(margin = dict(t=50, l=25, r=25, b=25))
fig.show()
```



Total sales of products Treemap

In [53]:
```
fig = px.treemap(products, path=['Description'], values='total_price')
fig.update_traces(root_color="lightgrey",textinfo = "label+value+percent parent")
fig.update_layout(margin = dict(t=50, l=25, r=25, b=25))
fig.show()
```

Q4 which products are most often sold together?

In [54]:
```
Q4 = dfp[dfp['InvoiceNo'].duplicated(keep=False)]
Q4['Grouped'] = Q4.groupby('InvoiceNo')['Description'].transform(lambda x:','.join(x))
```

In [55]:
```
Q4 = pd.pivot_table(Q4, values=['Quantity', 'total_price'], index=['Grouped'],
                    aggfunc={'Quantity': sum,
                             'total_price': sum}).reset_index()
```

Top sales numbers of products combination

In [56]:
```
Q4.nlargest(n=10, columns=['Quantity'])
```

Out[56]:

	Grouped	Quantity	total_price
11790	RED HARMONICA IN BOX ,PINK CREAM FELT CRAFT T...	14846.0	25317.20
15686	SWEETHEART RECIPE BOOK STAND,ABC TREASURE BOOK...	13406.0	17239.46
16614	VINTAGE PAISLEY STATIONERY SET,FLORAL FOLK STA...	13293.0	18453.21
11622	RECIPE BOX PANTRY YELLOW DESIGN,METAL SIGN HER...	12572.0	31698.16
10384	PARISIENNE KEY CABINET ,MINI PAINT SET VINTAGE...	12160.0	17198.80
11302	POPPY'S PLAYHOUSE BEDROOM ,POPPY'S PLAYHOUSE K...	11773.0	44841.31
16528	VINTAGE DOILY JUMBO BAG RED ,JUMBO BAG PAISLEY...	11105.0	44714.00
4970	FELTCRAFT 6 FLOWER FRIENDS,ROSE COTTAGE KEEPSA...	11044.0	15368.56
13607	SET 12 KIDS COLOUR CHALK STICKS,SET/20 RED RE...	10772.0	12581.08
17187	WOODEN ADVENT CALENDAR CREAM,WRAP CHRISTMAS VI...	10348.0	18820.04

Top sales amount product combination

In [57]:
```
Q4.nlargest(n=10, columns=['total_price'])
```

Out[57]:

	Grouped	Quantity	total_price
11302	POPPY'S PLAYHOUSE BEDROOM ,POPPY'S PLAYHOUSE K...	11773.0	44841.31
16528	VINTAGE DOILY JUMBO BAG RED ,JUMBO BAG PAISLEY...	11105.0	44714.00
11622	RECIPE BOX PANTRY YELLOW DESIGN,METAL SIGN HER...	12572.0	31698.16
11790	RED HARMONICA IN BOX ,PINK CREAM FELT CRAFT T...	14846.0	25317.20
8191	LANDMARK FRAME COVENT GARDEN ,LANDMARK FRAME O...	1920.0	22206.00
11369	POTTERING MUG,IF YOU CAN'T STAND THE HEAT MUG,...	6760.0	22104.80
17187	WOODEN ADVENT CALENDAR CREAM,WRAP CHRISTMAS VI...	10348.0	18820.04
16614	VINTAGE PAISLEY STATIONERY SET,FLORAL FOLK STA...	13293.0	18453.21
10037	PANTRY WASHING UP BRUSH,POPPY'S PLAYHOUSE BATH...	4896.0	18249.60
1431	BIRD HOUSE HOT WATER BOTTLE,SCOTTIE DOG HOT WA...	2746.0	17941.39

Q5 What is the largest order?

In [58]:
```
Q5 = pd.pivot_table(dfp, values=['Quantity', 'total_price','Country'], index=['InvoiceNo'],
                    aggfunc={'Quantity': sum,
                             'total_price': sum,
                             'Country':lambda x: x.mode().iat[0]}).reset_index()
```

In [59]:
```
Q5.nlargest(n=10, columns=['total_price'])
```

Out[59]:

	InvoiceNo	Country	Quantity	total_price
19441	581483	United Kingdom	80995.0	168469.60
2087	541431	United Kingdom	74215.0	77183.60
17137	576365	United Kingdom	11773.0	44841.31
16500	574941	United Kingdom	11105.0	44714.00
13224	567423	United Kingdom	12572.0	31698.16
15307	572209	United Kingdom	1920.0	22206.00
13216	567381	United Kingdom	6760.0	22104.80
11612	563614	Australia	10348.0	18820.04
8718	556917	Australia	13293.0	18453.21
4970	548203	United Kingdom	4896.0	18249.60

In [60]:
```
Q5.nlargest(n=10, columns=['Quantity'])
```

Out[60]:

	InvoiceNo	Country	Quantity	total_price
19441	581483	United Kingdom	80995.0	168469.60
2087	541431	United Kingdom	74215.0	77183.60
11375	563076	Netherlands	13406.0	17239.46
8718	556917	Australia	13293.0	18453.21
13224	567423	United Kingdom	12572.0	31698.16
15218	572035	Netherlands	12160.0	17198.80
17137	576365	United Kingdom	11773.0	44841.31
16500	574941	United Kingdom	11105.0	44714.00
4923	548011	Netherlands	11044.0	15368.56
6957	552883	Netherlands	10772.0	12581.08

Q6 What is the sales amount and total sales for the countries?

In [61]:
```
Q6 = pd.pivot_table(dfp, values=['Quantity', 'total_price'], index=['Country'],
                    aggfunc={'Quantity': sum,
                             'total_price': sum}).reset_index()
```

UK slaes

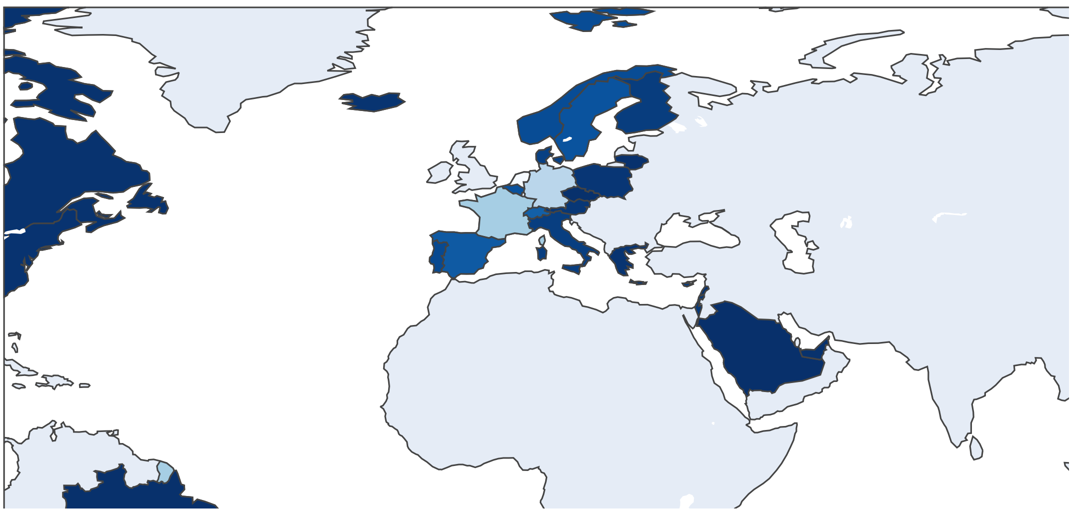
In [62]:
```
Q6[Q6['Country']=='United Kingdom']
```

Out[62]:

	Country	Quantity	total_price
36	United Kingdom	4047031.0	7704738.973

International

In [63]:
```
Q6_NUK=Q6[~(Q6['Country']=='United Kingdom')]

fig = go.Figure(data=go.Choropleth(
    locations = Q6_NUK['Country'],
    z = Q6_NUK['total_price'],
    text = Q6_NUK['Quantity'],
    locationmode='country names',
    colorscale = 'Blues',
    reversescale=True,
    colorbar_title = 'Total Sales US$',
))

fig.show()
```



Q7 Most popular products in diffrent countries

In [64]:
```
Q7 = pd.pivot_table(dfp, values=['Quantity', 'total_price'], index=['Country','Description'],
                    aggfunc={'Quantity': sum,
                             'total_price': sum}).reset_index()
Q7
```

Out[64]:

	Country	Description	Quantity	total_price
0	Australia	DOLLY GIRL BEAKER	200.0	216.0
1	Australia	10 COLOUR SPACEBOY PEN	48.0	40.8
2	Australia	12 PENCIL SMALL TUBE WOODLAND	384.0	211.2
3	Australia	12 PENCILS TALL TUBE POSY	252.0	79.8
4	Australia	12 PENCILS TALL TUBE RED RETROSPOT	12.0	10.2
...	...	...	...	...
17218	Unspecified	WRAP PAISLEY PARK	25.0	10.5
17219	Unspecified	WRAP POPPIES DESIGN	25.0	10.5
17220	Unspecified	WRAP SUKI AND FRIENDS	25.0	10.5
17221	Unspecified	WRAP WEDDING DAY	25.0	10.5
17222	Unspecified	ZINC METAL HEART DECORATION	2.0	2.5

17223 rows × 4 columns

UK

In [65]:
```
Q7[Q7['Country']=='United Kingdom'].nlargest(n=10, columns=['total_price'])
```

Out[65]:

	Country	Description	Quantity	total_price
14411	United Kingdom	DOTCOM POSTAGE	706.0	206248.77
15539	United Kingdom	PAPER CRAFT , LITTLE BIRDIE	80995.0	168469.60
15956	United Kingdom	REGENCY CAKESTAND 3 TIER	11068.0	142273.29
15555	United Kingdom	PARTY BUNTING	16973.0	93658.53
15041	United Kingdom	JUMBO BAG RED RETROSPOT	44264.0	86471.34
15241	United Kingdom	MEDIUM CERAMIC TOP STORAGE JAR	77036.0	80575.63
15533	United Kingdom	PAPER CHAIN KIT 50'S CHRISTMAS	18530.0	62742.54
13680	United Kingdom	ASSORTED COLOUR BIRD ORNAMENT	33735.0	54756.79
14145	United Kingdom	CHILLI LIGHTS	10154.0	53336.56
13825	United Kingdom	BLACK RECORD COVER FRAME	11308.0	39442.17

In [66]:
```
Q7[Q7['Country']=='United Kingdom'].nlargest(n=10, columns=['Quantity'])
```

Out[66]:

	Country	Description	Quantity	total_price
15539	United Kingdom	PAPER CRAFT , LITTLE BIRDIE	80995.0	168469.60
15241	United Kingdom	MEDIUM CERAMIC TOP STORAGE JAR	77036.0	80575.63
16854	United Kingdom	WORLD WAR 2 GLIDERS ASSTD DESIGNS	49526.0	12309.88
15041	United Kingdom	JUMBO BAG RED RETROSPOT	44264.0	86471.34
13680	United Kingdom	ASSORTED COLOUR BIRD ORNAMENT	33735.0	54756.79
15461	United Kingdom	PACK OF 12 LONDON TISSUES	25127.0	7647.80
15492	United Kingdom	PACK OF 72 RETROSPOT CAKE CASES	24986.0	15754.07
16650	United Kingdom	VICTORIAN GLASS HANGING T-LIGHT	23692.0	32321.57
13986	United Kingdom	BROCADE RING PURSE	22804.0	5958.27
13687	United Kingdom	ASSORTED COLOURS SILK FAN	21066.0	16539.92

Netherlands

In [67]:
```
Q7[Q7['Country']=='Netherlands'].nlargest(n=10, columns=['total_price'])
```

Out[67]:

	Country	Description	Quantity	total_price
9471	Netherlands	RABBIT NIGHT LIGHT	4801.0	9568.48
9537	Netherlands	ROUND SNACK BOXES SET OF4 WOODLAND	3132.0	7991.40
9638	Netherlands	SPACEBOY LUNCH BOX	4528.0	7485.60
9173	Netherlands	DOLLY GIRL LUNCH BOX	4132.0	6828.60
9535	Netherlands	ROUND SNACK BOXES SET OF 4 FRUITS	1584.0	4039.20
9506	Netherlands	RED TOADSTOOL LED NIGHT LIGHT	2388.0	3479.40
9305	Netherlands	JUMBO BAG RED RETROSPOT	2000.0	3468.00
9509	Netherlands	REGENCY CAKESTAND 3 TIER	289.0	3166.35
9045	Netherlands	5 HOOK HANGER RED MAGIC TOADSTOOL	2016.0	2923.20
9309	Netherlands	JUMBO BAG WOODLAND ANIMALS	1500.0	2629.00

In [68]:
```
Q7[Q7['Country']=='Netherlands'].nlargest(n=10, columns=['Quantity'])
```

Out[68]:

	Country	Description	Quantity	total_price
9471	Netherlands	RABBIT NIGHT LIGHT	4801.0	9568.48
9638	Netherlands	SPACEBOY LUNCH BOX	4528.0	7485.60
9173	Netherlands	DOLLY GIRL LUNCH BOX	4132.0	6828.60
9399	Netherlands	PACK OF 72 RETROSPOT CAKE CASES	4128.0	1740.00
9537	Netherlands	ROUND SNACK BOXES SET OF4 WOODLAND	3132.0	7991.40
9506	Netherlands	RED TOADSTOOL LED NIGHT LIGHT	2388.0	3479.40
9691	Netherlands	WOODLAND CHARLOTTE BAG	2310.0	1664.50
9490	Netherlands	RED RETROSPOT CHARLOTTE BAG	2100.0	1512.00
9045	Netherlands	5 HOOK HANGER RED MAGIC TOADSTOOL	2016.0	2923.20
9305	Netherlands	JUMBO BAG RED RETROSPOT	2000.0	3468.00

Germany

In [69]:
```
Q7[Q7['Country']=='Germany'].nlargest(n=10, columns=['total_price'])
```

Out[69]:

	Country	Description	Quantity	total_price
7220	Germany	REGENCY CAKESTAND 3 TIER	809.0	9061.95
7277	Germany	ROUND SNACK BOXES SET OF4 WOODLAND	1233.0	3598.95
7275	Germany	ROUND SNACK BOXES SET OF 4 FRUITS	672.0	1982.40
7464	Germany	SPACEBOY LUNCH BOX	876.0	1631.40
7115	Germany	PLASTERS IN TIN WOODLAND ANIMALS	857.0	1414.05
7168	Germany	RED KITCHEN SCALES	168.0	1339.60
6738	Germany	GUMBALL COAT RACK	562.0	1319.70
6231	Germany	6 RIBBONS RUSTIC CHARM	735.0	1313.55
7110	Germany	PLASTERS IN TIN CIRCUS PARADE	774.0	1277.10
7215	Germany	RED TOADSTOOL LED NIGHT LIGHT	728.0	1201.20

In [70]:
```
Q7[Q7['Country']=='Germany'].nlargest(n=10, columns=['Quantity'])
```

Out[70]:

	Country	Description	Quantity	total_price
7277	Germany	ROUND SNACK BOXES SET OF4 WOODLAND	1233.0	3598.95
6269	Germany	ASSORTED COLOURS SILK FAN	1164.0	853.32
7613	Germany	WOODLAND CHARLOTTE BAG	1020.0	854.00
7009	Germany	PACK OF 72 RETROSPOT CAKE CASES	1002.0	551.10
6997	Germany	PACK OF 6 BIRDY GIFT TAGS	936.0	1033.20
7464	Germany	SPACEBOY LUNCH BOX	876.0	1631.40
7115	Germany	PLASTERS IN TIN WOODLAND ANIMALS	857.0	1414.05
6798	Germany	JAM MAKING SET PRINTED	816.0	1183.20
7220	Germany	REGENCY CAKESTAND 3 TIER	809.0	9061.95
7125	Germany	POPART WOODEN PENCILS ASST	800.0	32.00

France

In [71]:
```
Q7[Q7['Country']=='France'].nlargest(n=10, columns=['total_price'])
```

Out[71]:

	Country	Description	Quantity	total_price
5687	France	RABBIT NIGHT LIGHT	4024.0	7277.20
5764	France	REGENCY CAKESTAND 3 TIER	239.0	2816.85
5758	France	RED TOADSTOOL LED NIGHT LIGHT	1315.0	2169.75
5659	France	PLASTERS IN TIN CIRCUS PARADE	1144.0	1868.40
5664	France	PLASTERS IN TIN WOODLAND ANIMALS	1144.0	1868.40
4890	France	ASSORTED COLOUR BIRD ORNAMENT	1204.0	1842.76
5817	France	ROUND SNACK BOXES SET OF4 WOODLAND	636.0	1837.80
5733	France	RED RETROSPOT MINI CASES	214.0	1662.90
5661	France	PLASTERS IN TIN SPACEBOY	1013.0	1633.05
5992	France	SPACEBOY LUNCH BOX	824.0	1568.40

In [72]:
```
Q7[Q7['Country']=='France'].nlargest(n=10, columns=['Quantity'])
```

Out[72]:

	Country	Description	Quantity	total_price
5687	France	RABBIT NIGHT LIGHT	4024.0	7277.20
5481	France	MINI PAINT SET VINTAGE	2196.0	1427.40
5758	France	RED TOADSTOOL LED NIGHT LIGHT	1315.0	2169.75
5941	France	SET/6 RED SPOTTY PAPER CUPS	1272.0	826.80
4890	France	ASSORTED COLOUR BIRD ORNAMENT	1204.0	1842.76
5567	France	PACK OF 72 RETROSPOT CAKE CASES	1176.0	612.48
5659	France	PLASTERS IN TIN CIRCUS PARADE	1144.0	1868.40
5664	France	PLASTERS IN TIN WOODLAND ANIMALS	1144.0	1868.40
5942	France	SET/6 RED SPOTTY PAPER PLATES	1116.0	883.08
5661	France	PLASTERS IN TIN SPACEBOY	1013.0	1633.05

Australia

In [73]:
```
Q7[Q7['Country']=='Australia'].nlargest(n=10, columns=['total_price'])
```

Out[73]:

	Country	Description	Quantity	total_price
322	Australia	RABBIT NIGHT LIGHT	1884.0	3375.84
427	Australia	SET OF 6 SPICE TINS PANTRY DESIGN	600.0	2082.00
351	Australia	RED TOADSTOOL LED NIGHT LIGHT	1344.0	1987.20
409	Australia	SET OF 3 CAKE TINS PANTRY DESIGN	464.0	1983.20
353	Australia	REGENCY CAKESTAND 3 TIER	180.0	1978.20
331	Australia	RED HARMONICA IN BOX	1704.0	1810.80
103	Australia	DOLLY GIRL LUNCH BOX	1024.0	1689.60
240	Australia	MINI PAINT SET VINTAGE	2952.0	1630.80
459	Australia	SPACEBOY LUNCH BOX	960.0	1584.00
347	Australia	RED RETROSPOT ROUND CAKE TINS	168.0	1503.60

In [74]:
```
Q7[Q7['Country']=='Australia'].nlargest(n=10, columns=['Quantity'])
```

Out[74]:

	Country	Description	Quantity	total_price
240	Australia	MINI PAINT SET VINTAGE	2952.0	1630.80
322	Australia	RABBIT NIGHT LIGHT	1884.0	3375.84
331	Australia	RED HARMONICA IN BOX	1704.0	1810.80
351	Australia	RED TOADSTOOL LED NIGHT LIGHT	1344.0	1987.20
175	Australia	HOMEMADE JAM SCENTED CANDLES	1080.0	1354.80
103	Australia	DOLLY GIRL LUNCH BOX	1024.0	1689.60
459	Australia	SPACEBOY LUNCH BOX	960.0	1584.00
47	Australia	BLUE HARMONICA IN BOX	720.0	763.20
238	Australia	MINI JIGSAW SPACEBOY	720.0	259.20
12	Australia	4 TRADITIONAL SPINNING TOPS	700.0	826.20

Q8 The most popluar product ordered by customer

In [75]:
```
Q8 = pd.pivot_table(dfp, values=[ 'CustomerID'], index=['Description'],
                    aggfunc={'CustomerID': 'count'}).reset_index()


Q8.sort_values('CustomerID', ascending=False).head(20)
```

Out[75]:

	Description	CustomerID
2470	REGENCY CAKESTAND 3 TIER	1723
1551	JUMBO BAG RED RETROSPOT	1618
189	ASSORTED COLOUR BIRD ORNAMENT	1408
2066	PARTY BUNTING	1396
2710	SET OF 3 CAKE TINS PANTRY DESIGN	1159
1706	LUNCH BAG BLACK SKULL.	1105
2003	PACK OF 72 RETROSPOT CAKE CASES	1068
2044	PAPER CHAIN KIT 50'S CHRISTMAS	1019
1714	LUNCH BAG SPACEBOY DESIGN	1008
1709	LUNCH BAG CARS BLUE	989
1420	HEART OF WICKER SMALL	985
1877	NATURAL SLATE HEART CHALKBOARD	980
1712	LUNCH BAG PINK POLKADOT	957
2511	REX CASH+CARRY JUMBO SHOPPER	952
121	ALARM CLOCK BAKELIKE RED	899
1708	LUNCH BAG APPLE DESIGN	895
2742	SET OF 4 PANTRY JELLY MOULDS	893
1549	JUMBO BAG PINK POLKADOT	890
3346	WOODEN PICTURE FRAME WHITE FINISH	887
1523	JAM MAKING SET WITH JARS	887

Modeling

Select modeling technique

Clustering

In [76]:
```
#Drop the newest customer
dfc=dfp.copy()
dfc=dfp[dfp.CustomerID.notnull()]
```

In [77]:
```
df_customer = pd.pivot_table(dfc, values=['InvoiceNo','Description','UnitPrice','total_price','Country','hour','d
                    aggfunc={'InvoiceNo':lambda x: len(x.unique()),
                             'Description':lambda x: len(x.unique()),
                             'UnitPrice':np.mean,
                             'total_price':sum,
                             'Country':lambda x: x.mode().iat[0],
                             'hour':np.mean,
                             'day_of_week':lambda x: x.mode().iat[0]}).reset_index()
i=[]
for j in range(len(df_customer['hour'])):
    if list(df_customer['hour'])[j]>=0 and list(df_customer['hour'])[j]<=10:
        i.append('Morning')
    elif list(df_customer['hour'])[j]>10 and list(df_customer['hour'])[j]<=13:
        i.append('Noon')
    elif list(df_customer['hour'])[j]>13 and list(df_customer['hour'])[j]<=16:
        i.append('Afternoon')
    else:
        i.append('Night')
df_customer['hour']=i

df_customer["day_of_week"].replace({0: "weekend", 1: "weekday", 2: "weekday", 3: "weekday", 4: "weekday",5: "weekda

df_customer.columns=['CustomerID', 'Country', 'Product_distinct', 'Order_times', 'Avg_product_price',
       'day_of_week', 'hour', 'total_price']

df_customer
```

Out[77]:

	CustomerID	Country	Product_distinct	Order_times	Avg_product_price	day_of_week	hour	total_price
0	12346.0	United Kingdom	1	1	1.040000	weekday	Morning	77183.60
1	12347.0	Iceland	91	7	2.700976	weekend	Noon	3727.98
2	12348.0	Finland	20	4	0.709600	weekday	Afternoon	1373.64
3	12349.0	Italy	61	1	3.990000	weekend	Morning	1196.21
4	12350.0	Norway	15	1	1.630000	weekday	Afternoon	285.90
...	...	...	...	...	...	...	...	...
4309	18280.0	United Kingdom	10	1	4.765000	weekend	Morning	180.60
4310	18281.0	United Kingdom	6	1	6.285000	weekday	Morning	64.32
4311	18282.0	United Kingdom	11	2	5.058182	weekend	Noon	164.55
4312	18283.0	United Kingdom	229	16	1.533467	weekday	Afternoon	1724.54
4313	18287.0	United Kingdom	54	3	1.471129	weekday	Morning	1447.16

4314 rows × 8 columns

Data Normalization

In [78]:
```
non_metric_features = ['Country', 'day_of_week', 'hour']
metric_features = ['Product_distinct', 'Order_times', 'Avg_product_price', 'total_price']
```

In [79]:
```
df_standard = df_customer.copy()
# Use StandardScaler to scale the data
# We don't use MinMax because we have big range values
scaler = StandardScaler().fit(df_standard[metric_features])
scaled_feat = scaler.transform(df_standard[metric_features])
scaled_feat
```

Out[79]:
```
array([[-7.06501128e-01, -4.25314213e-01, -3.85066870e-01,
         9.56350006e+00],
       [ 4.94436344e-01,  3.70524223e-01, -1.09592902e-01,
         2.52267511e-01],
       [-4.52969884e-01, -2.73949949e-02, -4.39863942e-01,
        -4.61685681e-02],
       ...,
       [-5.73063631e-01, -2.92674474e-01,  2.81351398e-01,
        -1.99432786e-01],
       [ 2.33587380e+00,  1.56428188e+00, -3.03224941e-01,
        -1.68849291e-03],
       [ 7.17605453e-04, -1.60034734e-01, -3.13563819e-01,
        -3.68491747e-02]])
```

In [80]:
```
df_standard[metric_features] = scaled_feat

# Checking mean and variance of standardized variables
df_standard[metric_features].describe().round(2)
```

Out[80]:

	Product_distinct	Order_times	Avg_product_price	total_price
count	4314.00	4314.00	4314.00	4314.00
mean	-0.00	-0.00	-0.00	0.00
std	1.00	1.00	1.00	1.00
min	-0.71	-0.43	-0.53	-0.22
25%	-0.53	-0.43	-0.21	-0.19
50%	-0.31	-0.29	-0.09	-0.15
75%	0.19	0.11	0.06	-0.04
max	20.18	26.50	48.37	30.85

In [81]:
```
df_customer = df_standard.copy()
```

Segmentation

K-prototype Cluster Algorithm

In [82]:
```
df_kprototype=df_customer.copy()
df_kprototype = df_kprototype.drop(columns='CustomerID')
df_kprototype
```

Out[82]:

	Country	Product_distinct	Order_times	Avg_product_price	day_of_week	hour	total_price
0	United Kingdom	-0.706501	-0.425314	-0.385067	weekday	Morning	9.563500
1	Iceland	0.494436	0.370524	-0.109593	weekend	Noon	0.252268
2	Finland	-0.452970	-0.027395	-0.439864	weekday	Afternoon	-0.046169
3	Italy	0.094124	-0.425314	0.104193	weekend	Morning	-0.068660
4	Norway	-0.519689	-0.425314	-0.287215	weekday	Afternoon	-0.184050
...	...	...	...	...	...	...	...
4309	United Kingdom	-0.586407	-0.425314	0.232727	weekend	Morning	-0.197398
4310	United Kingdom	-0.639782	-0.425314	0.484820	weekday	Morning	-0.212138
4311	United Kingdom	-0.573064	-0.292674	0.281351	weekend	Noon	-0.199433
4312	United Kingdom	2.335874	1.564282	-0.303225	weekday	Afternoon	-0.001688
4313	United Kingdom	0.000718	-0.160035	-0.313564	weekday	Morning	-0.036849

4314 rows × 7 columns

In [83]:
```
# Get the position of categorical columns
catColumnsPos = [df_kprototype.columns.get_loc(col) for col in list(df_kprototype.select_dtypes('object').columns)
print('Categorical columns           : {}'.format(list(df_kprototype.select_dtypes('object').columns)))
print('Categorical columns position  : {}'.format(catColumnsPos))
```

```
Categorical columns           : ['Country', 'day_of_week', 'hour']
Categorical columns position  : [0, 4, 5]
```

In [84]:
```
dfMatrix = df_kprototype.to_numpy()
dfMatrix
```

Out[84]:
```
array([['United Kingdom', -0.7065011277267473, -0.4253142130713991, ...,
        'weekday', 'Morning', 9.563500059890153],
       ['Iceland', 0.49443634371139866, 0.3705242233588832, ...,
        'weekend', 'Noon', 0.2522675112401954],
       ['Finland', -0.452969883756472, -0.027394994856257966, ...,
        'weekday', 'Afternoon', -0.04616856810388391],
       ...,
       ['United Kingdom', -0.5730636309002867, -0.2926744736663521, ...,
        'weekend', 'Noon', -0.19943278617524693],
       ['United Kingdom', 2.3358737999165555, 1.5642818780043066, ...,
        'weekday', 'Afternoon', -0.001688492905808246],
       ['United Kingdom', 0.0007176054534942018, -0.16003473426130502,
        ..., 'weekday', 'Morning', -0.036849174748048882]], dtype=object)
```

In [85]:
```
# Choosing optimal K

cost = []
for cluster in range(1, 9):
    try:
        kprototype = KPrototypes(n_jobs = -1, n_clusters = cluster, init = 'Huang', random_state = 0)
        kprototype.fit_predict(dfMatrix, categorical = catColumnsPos)
        cost.append(kprototype.cost_)
        print('Cluster initiation: {}'.format(cluster))
    except:
        break
```

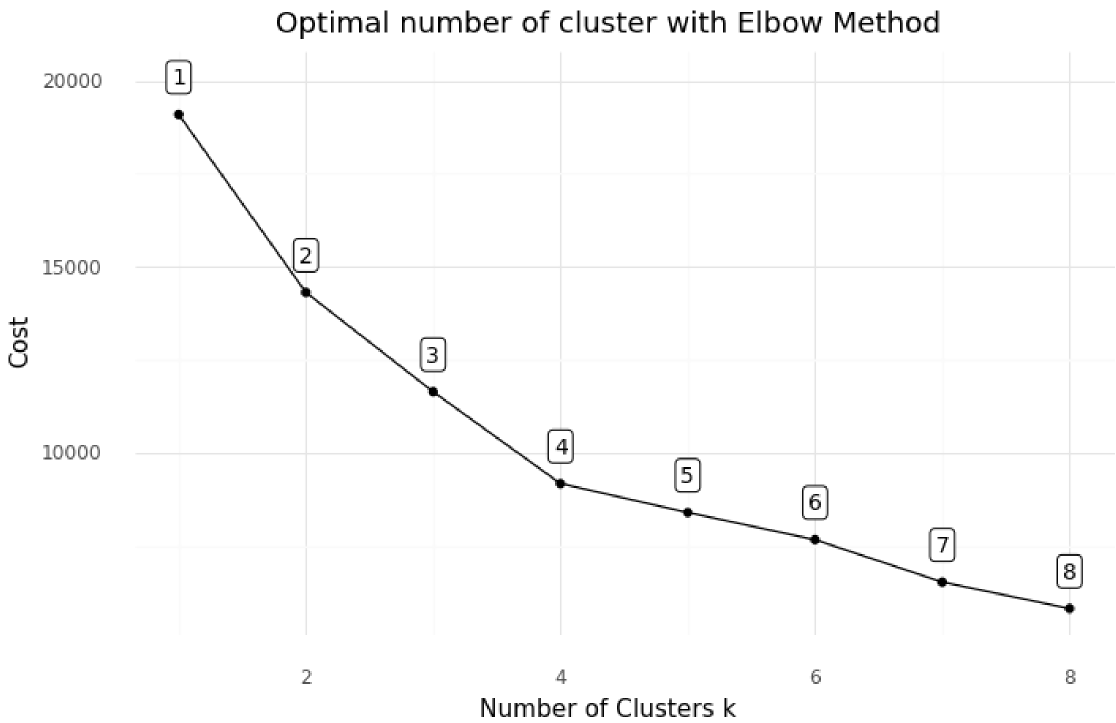
```
Cluster initiation: 1
Cluster initiation: 2
Cluster initiation: 3
Cluster initiation: 4
Cluster initiation: 5
Cluster initiation: 6
Cluster initiation: 7
Cluster initiation: 8
```

In [86]:
```
# Converting the results into a dataframe and plotting them
df_cost = pd.DataFrame({'Cluster':range(1, 9), 'Cost':cost})
df_cost
```

Out[86]:

	Cluster	Cost
0	1	19099.000000
1	2	14312.362728
2	3	11639.663022
3	4	9171.786486
4	5	8392.817217
5	6	7660.505817
6	7	6520.918419
7	8	5810.229933

In [87]:
```
# Import module for data visualization

plotnine.options.figure_size = (8, 4.8)
(
    ggplot(data = df_cost)+
    geom_line(aes(x = 'Cluster',
                  y = 'Cost'))+
    geom_point(aes(x = 'Cluster',
                   y = 'Cost'))+
    geom_label(aes(x = 'Cluster',
                   y = 'Cost',
                   label = 'Cluster'),
               size = 10,
               nudge_y = 1000) +
    labs(title = 'Optimal number of cluster with Elbow Method')+
    xlab('Number of Clusters k')+
    ylab('Cost')+
    theme_minimal()
)
```



Out[87]: <ggplot: (116825371986)>

In [88]:
```
# Fit the cluster
kprototype = KPrototypes(n_jobs = -1, n_clusters = 4, init = 'Huang', random_state = 0)
kprototype.fit_predict(dfMatrix, categorical = catColumnsPos)
```

Out[88]: array([0, 1, 1, ..., 1, 0, 1], dtype=uint16)

In [89]:
```
# Cluster centorid
kprototype.cluster_centroids_
```

Out[89]:
```
array([['1.386926284906227', '1.0213404130662456',
        '-0.080453346734412l9', '0.40838286200179363', 'United Kingdom',
        'weekday', 'Noon'],
       ['-0.27286027804548146', '-0.21842958808742355',
        '-0.025676980957130217', '-0.12526753724006912',
        'United Kingdom', 'weekday', 'Noon'],
       ['7.463013383860326', '9.194968062600534', '-0.07166157810021245',
        '11.84095425102868', 'United Kingdom', 'weekday', 'Noon'],
       ['-0.6948253467544393', '-0.3755743107945094',
        '18.245685165509762', '-0.16135092071106755', 'United Kingdom',
        'weekday', 'Noon']], dtype='<U32')
```

In [90]:
```
# Check the cost of the clusters created
kprototype.cost_
```

Out[90]:
```
9171.786485555287
```

In [91]:
```
# Add the cluster to the dataframe
df_kprototype['labels'] = kprototype.labels_
df_kprototype
```

Out[91]:

	Country	Product_distinct	Order_times	Avg_product_price	day_of_week	hour	total_price	labels
0	United Kingdom	-0.706501	-0.425314	-0.385067	weekday	Morning	9.563500	0
1	Iceland	0.494436	0.370524	-0.109593	weekend	Noon	0.252268	1
2	Finland	-0.452970	-0.027395	-0.439864	weekday	Afternoon	-0.046169	1
3	Italy	0.094124	-0.425314	0.104193	weekend	Morning	-0.068660	1
4	Norway	-0.519689	-0.425314	-0.287215	weekday	Afternoon	-0.184050	1
...	...	...	...	...	...	...	...	...
4309	United Kingdom	-0.586407	-0.425314	0.232727	weekend	Morning	-0.197398	1
4310	United Kingdom	-0.639782	-0.425314	0.484820	weekday	Morning	-0.212138	1
4311	United Kingdom	-0.573064	-0.292674	0.281351	weekend	Noon	-0.199433	1
4312	United Kingdom	2.335874	1.564282	-0.303225	weekday	Afternoon	-0.001688	0
4313	United Kingdom	0.000718	-0.160035	-0.313564	weekday	Morning	-0.036849	1

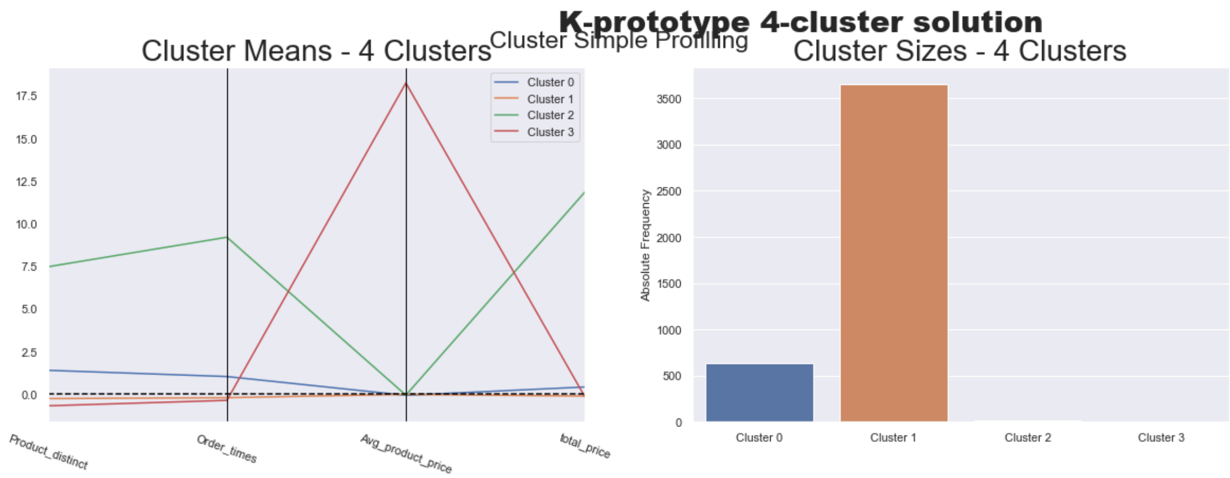
4314 rows × 8 columns

In [92]:
```
df_kprototype['labels'].value_counts()
```

Out[92]:
```
1    3657
0     632
2      17
3       8
Name: labels, dtype: int64
```

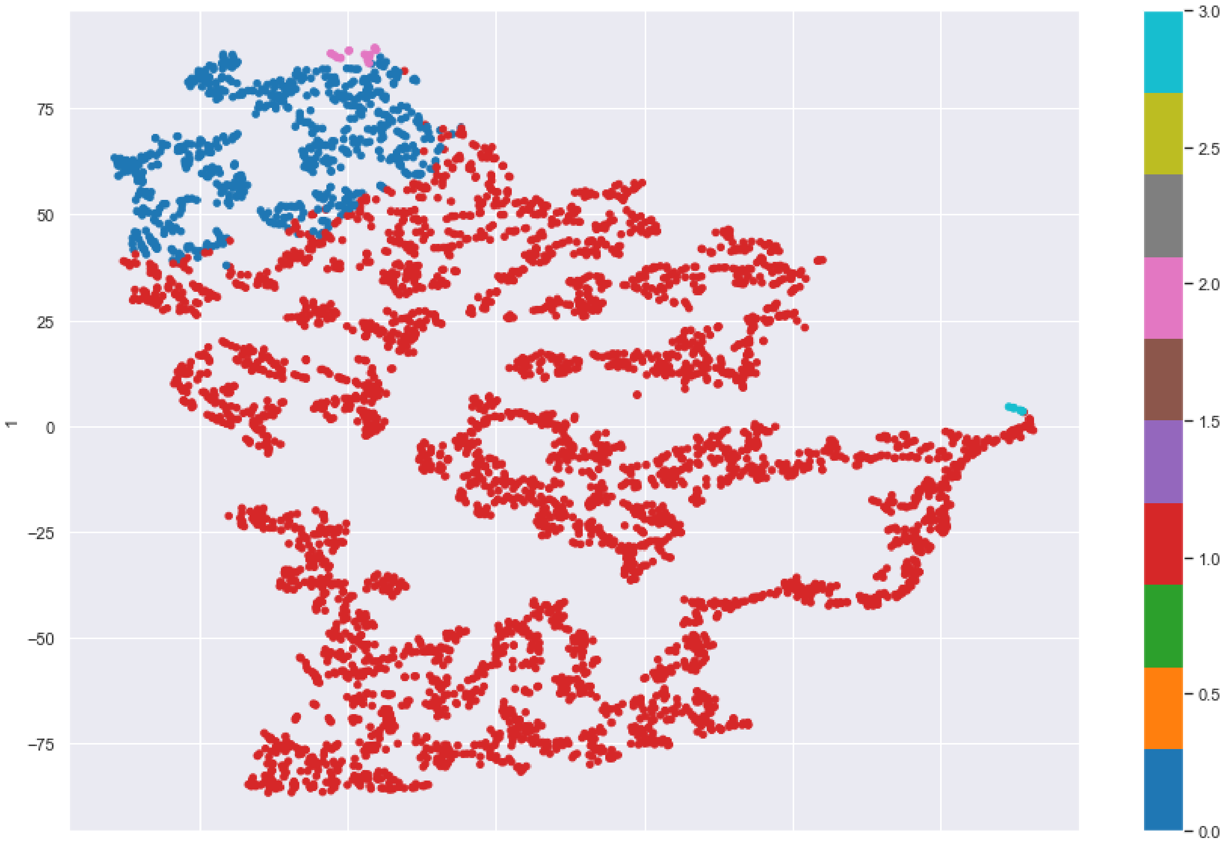
In [93]:
```
def cluster_profiles(df, label_columns, figsize, compar_titles=None):
    """
    Pass df with labels columns of one or multiple clustering labels.
    Then specify this label columns to perform the cluster profile according to them.
    """
    if compar_titles == None:
        compar_titles = [""]*len(label_columns)

    sns.set()
    fig, axes = plt.subplots(nrows=len(label_columns), ncols=2, figsize=figsize, squeeze=False)
    for ax, label, titl in zip(axes, label_columns, compar_titles):
        # Filtering df
        drop_cols = [i for i in label_columns if i!=label]
        dfax = df.drop(drop_cols, axis=1)

        # Getting the cluster centroids and counts
        centroids = dfax.groupby(by=label, as_index=False).mean()
        counts = dfax.groupby(by=label, as_index=False).count().iloc[:,[0,1]]
        counts.columns = [label, "counts"]

        # Setting Data
        pd.plotting.parallel_coordinates(centroids, label, color=sns.color_palette(), ax=ax[0])
        sns.barplot(x=label, y="counts", data=counts, ax=ax[1])

        #Setting Layout
        handles, _ = ax[0].get_legend_handles_labels()
        cluster_labels = ["Cluster {}".format(i) for i in range(len(handles))]
        ax[0].annotate(text=titl, xy=(0.95,1.1), xycoords='axes fraction', fontsize=28, fontweight = 'heavy')
        ax[0].legend(handles, cluster_labels) # Adaptable to number of clusters
        ax[0].axhline(color="black", linestyle="--")
        ax[0].set_title("Cluster Means - {} Clusters".format(len(handles)), fontsize=28)
        ax[0].set_xticklabels(ax[0].get_xticklabels(), rotation=-20)
        ax[1].set_xticklabels(cluster_labels)
        ax[1].set_xlabel("")
        ax[1].set_ylabel("Absolute Frequency")
        ax[1].set_title("Cluster Sizes - {} Clusters".format(len(handles)), fontsize=28)

    plt.subplots_adjust(hspace=0.4, top=0.90)
    plt.suptitle("Cluster Simple Profilling", fontsize=23)
    plt.show()
```

In [94]:
```
cluster_profiles(
    df = df_kprototype,
    label_columns = ['labels'],
    figsize = (20, 6),
    compar_titles = ["K-prototype 4-cluster solution"]
)
```



From the above chart we can see that cluster2 and cluster3 represent very wealthy customers and possibly retailer customers respectively

In [95]:
```
# t-SNE visualization for 5 clusters by 'k-means++ Clustering
two_dim = TSNE(random_state=42).fit_transform(df_kprototype[metric_features])
pd.DataFrame(two_dim).plot.scatter(x=0, y=1, c=df_kprototype['labels'], colormap='tab10', figsize=(15,10))
plt.show()
```



In [96]:
```
df_customer['Clusters']=df_kprototype['labels']
df_customer
```

Out[96]:

	CustomerID	Country	Product_distinct	Order_times	Avg_product_price	day_of_week	hour	total_price	Clusters
0	12346.0	United Kingdom	-0.706501	-0.425314	-0.385067	weekday	Morning	9.563500	0
1	12347.0	Iceland	0.494436	0.370524	-0.109593	weekend	Noon	0.252268	1
2	12348.0	Finland	-0.452970	-0.027395	-0.439864	weekday	Afternoon	-0.046169	1
3	12349.0	Italy	0.094124	-0.425314	0.104193	weekend	Morning	-0.068660	1
4	12350.0	Norway	-0.519689	-0.425314	-0.287215	weekday	Afternoon	-0.184050	1
...	...	...	...	...	...	...	...	...	...
4309	18280.0	United Kingdom	-0.586407	-0.425314	0.232727	weekend	Morning	-0.197398	1
4310	18281.0	United Kingdom	-0.639782	-0.425314	0.484820	weekday	Morning	-0.212138	1
4311	18282.0	United Kingdom	-0.573064	-0.292674	0.281351	weekend	Noon	-0.199433	1
4312	18283.0	United Kingdom	2.335874	1.564282	-0.303225	weekday	Afternoon	-0.001688	0
4313	18287.0	United Kingdom	0.000718	-0.160035	-0.313564	weekday	Morning	-0.036849	1

4314 rows × 9 columns

Association Rules

In [97]:
```
#merging dfp and  df_customer[['CustomerID','Clusters']] by CustomerID
df_AR = pd.merge(dfp, df_customer[['CustomerID','Clusters']], left_on='CustomerID', right_on='CustomerID', how='le
df_AR = df_AR[df_AR['Clusters'].notnull()]

# drop the wealthy customers and retailer customers to build the association rules
df_AR = df_AR[(df_AR['Clusters']==0)|(df_AR['Clusters']==1) ]
df_AR.head()
```

Out[97]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	Country	year	month	day	hour	day_of_week	total_
0	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8.0	2010-01-12 08:26:00	2.75	United Kingdom	2010	1	12	8	1	
1	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6.0	2010-01-12 08:26:00	3.39	United Kingdom	2010	1	12	8	1	
2	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6.0	2010-01-12 08:26:00	3.39	United Kingdom	2010	1	12	8	1	
3	536365	22752	SET 7 BABUSHKA NESTING BOXES	2.0	2010-01-12 08:26:00	7.65	United Kingdom	2010	1	12	8	1	
4	536365	21730	GLASS STAR FROSTED T-LIGHT HOLDER	6.0	2010-01-12 08:26:00	4.25	United Kingdom	2010	1	12	8	1	

Association Rule for cluster 0

In [98]:
```
#select cluster 0 customers
df_AR_0 = df_AR[(df_AR['Clusters']==0)]

# Create the orders of Cluster 0 to build the recommendation system
CO_orders = pd.pivot_table(df_AR_0[['InvoiceNo', 'StockCode']], values=[ 'StockCode'], index=['InvoiceNo'],
                    aggfunc={'StockCode': list}).reset_index()
CO_orders.head()
```

Out[98]:

	InvoiceNo	StockCode
0	536365	[84406B, 84029G, 84029E, 22752, 21730]
1	536366	[22633]
2	536367	[84879, 22745, 22748, 22749, 22310, 84969, 226...
3	536368	[22960, 22913, 22912, 22914]
4	536369	[21756]

In [99]:
```
# Using TransactionEncoder to encode the transaction of StockCode
TE=TransactionEncoder().fit(CO_orders['StockCode'])

CO_orders_encoded = TE.transform(CO_orders['StockCode'])

CO_orders_enc = pd.DataFrame(CO_orders_encoded, columns =TE.columns_)

CO_orders_enc.head()
```

Out[99]:

	10002	10080	10120	10124A	10124G	10125	11001	15030	15034	15036	15039	15044A	15044B	15044C	15044D	150
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F

In [100]:
```
# Calculate the support values for every possible configuration of items (thereshold of support has been chosen 0.(
CO_apriori = apriori(CO_orders_enc, min_support=0.01, verbose=1, use_colnames=True)#max_len=2,
```

```
Processing 410 combinations | Sampling itemset size 5 43
```

In [143]:
```
CO_apriori
```

Out[143]:

	support	itemsets	length
0	0.021395	(15036)	1
1	0.010100	(16156S)	1
2	0.014884	(16161P)	1
3	0.010365	(16161U)	1
4	0.010365	(16237)	1
...	...	...	...
1381	0.010233	(20727, 23206, 23208, 22384)	4
1382	0.010100	(22386, 21929, 22411, 85099B)	4
1383	0.010631	(22386, 22411, 85099B, 21931)	4
1384	0.013156	(22699, 22423, 22697, 22698)	4
1385	0.011960	(22728, 22726, 22727, 22730)	4

1386 rows × 3 columns

In [102]:
```
# counting and seeing the distribution of the number of products on the combination
CO_apriori['length'] = CO_apriori['itemsets'].apply(lambda x: len(x))
CO_apriori['length'].value_counts()
```

Out[102]:
```
1    644
2    538
3    191
4     13
Name: length, dtype: int64
```

Cluster 0 Complementary Products

In [103]:
```
# calculating the metrics for all the combinations found above
CO_rulesLift = association_rules(CO_apriori, metric="lift", min_threshold=0.0)
CO_rulesLift.sort_values(by='lift', ascending=False, inplace=True)

# Find all the possible combination of complementary products using lif higher than 2
CO_Complementary=CO_rulesLift.loc[(CO_rulesLift.lift > 2)]
CO_Complementary
```

Out[103]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
2116	(22919, 22917)	(22918)	0.011030	0.011296	0.010233	0.927711	82.129695	0.010108	13.677076
2117	(22918)	(22919, 22917)	0.011296	0.011030	0.010233	0.905882	82.129695	0.010108	10.507807
2125	(22917)	(22920, 22919)	0.011960	0.010498	0.010233	0.855556	81.494374	0.010107	6.850396
2120	(22920, 22919)	(22917)	0.010498	0.011960	0.010233	0.974684	81.494374	0.010107	39.027575
2109	(22920, 22917)	(22916)	0.011030	0.011429	0.010233	0.927711	81.174699	0.010107	13.675238
...	...	...	...	...	...	...	...	...	...
992	(23206)	(47566)	0.064983	0.087043	0.011960	0.184049	2.114457	0.006304	1.118887
818	(84879)	(22726)	0.080930	0.062458	0.010631	0.131363	2.103204	0.005576	1.079325
819	(22726)	(84879)	0.062458	0.080930	0.010631	0.170213	2.103204	0.005576	1.107597
290	(21212)	(22720)	0.068173	0.073887	0.010365	0.152047	2.057827	0.005328	1.092175
291	(22720)	(21212)	0.073887	0.068173	0.010365	0.140288	2.057827	0.005328	1.083883

2374 rows × 9 columns

In [104]:
```
# Organize the complementary products by confidence
CO_Complementary.sort_values("confidence", ascending = False, inplace = True)

# counting and Seeing the distribution of the number of products of the antecedents products
CO_Complementary['length_antecedents'] = CO_Complementary['antecedents'].apply(lambda x: len(x))
CO_Complementary.groupby('length_antecedents').median()
```

Out[104]:

length_antecedents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
1	0.050631	0.032691	0.012492	0.278215	8.267166	0.010882	1.325040
2	0.023256	0.056213	0.011827	0.548193	9.277397	0.010571	2.066845
3	0.016545	0.068173	0.011030	0.680164	9.559040	0.009873	2.913453

In [105]:
```
# counting and Seeing the distribution of the number of products of the consequents products
CO_Complementary['length_consequents'] = CO_Complementary['consequents'].apply(lambda x: len(x))
CO_Complementary.groupby('length_consequents').median()
```

Out[105]:

length_consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	length_antecedents
1	0.032691	0.050631	0.012492	0.450704	8.267166	0.010882	1.720745	1.0
2	0.056213	0.023256	0.011827	0.231969	9.277397	0.010571	1.268064	1.0
3	0.068173	0.016545	0.011030	0.163348	9.559040	0.009873	1.177301	1.0

In [106]:
```
# Create a dataframe with the length of the number of products of the antecedents and consequents products
CO_length_a=pd.DataFrame(CO_Complementary['length_antecedents'].value_counts())
CO_length_c= pd.DataFrame(CO_Complementary['length_consequents'].value_counts())
CO_ante_conseq= pd.concat((CO_length_a, CO_length_c), axis=1)
CO_ante_conseq
```

Out[106]:

	length_antecedents	length_consequents
1	1671	1671
2	651	651
3	52	52

In [107]:
```
#using only the first level combinations
CO_rulesConfidence = CO_Complementary.loc[(CO_Complementary.length_antecedents == 1)]
CO_rulesConfidence
```

Out[107]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	length_antec
876	(22916)	(22917)	0.011429	0.011960	0.010897	0.953488	79.722222	0.010760	21.242857	
884	(22918)	(22917)	0.011296	0.011960	0.010764	0.952941	79.676471	0.010629	20.995847	
888	(22920)	(22917)	0.011694	0.011960	0.011030	0.943182	78.860480	0.010890	17.389502	
890	(22918)	(22919)	0.011296	0.012226	0.010631	0.941176	76.982097	0.010493	16.792159	
883	(22916)	(22920)	0.011429	0.011694	0.010631	0.930233	79.545455	0.010498	14.165714	
...	...	...	...	...	...	...	...	...	...	
1035	(85099B)	(23343)	0.114684	0.027375	0.010233	0.089224	3.259262	0.007093	1.067907	
1933	(85099B)	(23199, 22411)	0.114684	0.014352	0.010100	0.088065	6.136003	0.008454	1.080831	
1939	(85099B)	(23201, 22411)	0.114684	0.014086	0.010100	0.088065	6.251776	0.008484	1.081123	
1183	(85099B)	(22355, 20724)	0.114684	0.022857	0.010100	0.088065	3.852839	0.007478	1.071505	
2361	(85099B)	(22386, 21929, 22411)	0.114684	0.012492	0.010100	0.088065	7.049875	0.008667	1.082871	

1671 rows × 11 columns

In [108]:
```
# Sort the database above using the lift
C0_rulesConfidence.sort_values("lift", ascending = False, inplace = True)
C0_rulesConfidence.head(20)
```

Out[108]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	length_antec
2117	(22918)	(22919, 22917)	0.011296	0.011030	0.010233	0.905882	82.129695	0.010108	10.507807	
2125	(22917)	(22920, 22919)	0.011960	0.010498	0.010233	0.855556	81.494374	0.010107	6.850396	
2112	(22916)	(22920, 22917)	0.011429	0.011030	0.010233	0.895349	81.174699	0.010107	9.450159	
2113	(22917)	(22920, 22916)	0.011960	0.010631	0.010233	0.855556	80.475694	0.010105	6.849476	
2119	(22917)	(22918, 22919)	0.011960	0.010631	0.010233	0.855556	80.475694	0.010105	6.849476	
2107	(22917)	(22916, 22919)	0.011960	0.010498	0.010100	0.844444	80.436006	0.009974	6.361082	
2111	(22920)	(22916, 22917)	0.011694	0.010897	0.010233	0.875000	80.297256	0.010105	7.912824	
879	(22916)	(22918)	0.011429	0.011296	0.010365	0.906977	80.294118	0.010236	10.628571	
878	(22918)	(22916)	0.011296	0.011429	0.010365	0.917647	80.294118	0.010236	12.004082	
2105	(22916)	(22919, 22917)	0.011429	0.011030	0.010100	0.883721	80.120482	0.009974	8.505143	
876	(22916)	(22917)	0.011429	0.011960	0.010897	0.953488	79.722222	0.010760	21.242857	
877	(22917)	(22916)	0.011960	0.011429	0.010897	0.911111	79.722222	0.010760	11.121429	
884	(22918)	(22917)	0.011296	0.011960	0.010764	0.952941	79.676471	0.010629	20.995847	
885	(22917)	(22918)	0.011960	0.011296	0.010764	0.900000	79.676471	0.010629	9.887043	
883	(22916)	(22920)	0.011429	0.011694	0.010631	0.930233	79.545455	0.010498	14.165714	
882	(22920)	(22916)	0.011694	0.011429	0.010631	0.909091	79.545455	0.010498	10.874286	
2123	(22920)	(22919, 22917)	0.011694	0.011030	0.010233	0.875000	79.329819	0.010104	7.911761	
889	(22917)	(22920)	0.011960	0.011694	0.011030	0.922222	78.860480	0.010890	12.706787	
888	(22920)	(22917)	0.011694	0.011960	0.011030	0.943182	78.860480	0.010890	17.389502	
2118	(22919)	(22918, 22917)	0.012226	0.010764	0.010233	0.836957	77.754294	0.010101	6.067313	

Cluster 0 recommendation system

In [109]:
```
def recommendation_system(stockcode, rules = C0_rulesConfidence, max_results= 5):

    # get the rules for this antecedent
    prediction = rules[rules['antecedents'] == {str(stockcode)}]

    # converting a frozen set with one element to string
    prediction = prediction['consequents'].apply(iter).apply(next)

    #set max results
    prediction =  prediction[:max_results].reset_index(drop=True)

    # link the stockcode with the unique description
    code_to_name = dfp[~dfp.duplicated(subset=['StockCode'])].copy()[['StockCode','Description']].set_index('Stock

    i=[]
    for stockid in prediction:
        i.append(code_to_name[stockid])
    return i
```

In [110]:
```
recommendation_system(22919)
```

Out[110]:
```
['HERB MARKER PARSLEY',
 'HERB MARKER PARSLEY',
 'HERB MARKER BASIL',
 'HERB MARKER THYME',
 'HERB MARKER ROSEMARY']
```

In [111]:
```
recommendation_system(22920)
```

Out[111]:
```
['HERB MARKER THYME',
 'HERB MARKER THYME',
 'HERB MARKER MINT',
 'HERB MARKER ROSEMARY',
 'HERB MARKER PARSLEY']
```

In [112]:
```
recommendation_system('85099B')
```

Out[112]:
```
['JUMBO BAG PINK POLKADOT',
 'JUMBO BAG PINK POLKADOT',
 'JUMBO BAG PINK POLKADOT',
 'JUMBO BAG PINK POLKADOT',
 'JUMBO BAG ALPHABET']
```

Cluster 0 Substitute Products

In [113]:
```
# Find all the possible combination of Substitute products using lif low than 2
C0_sub_prod=C0_rulesLift.loc[(C0_rulesLift.lift < 2)]
C0_sub_prod.median()
```

Out[113]:
```
antecedent support    0.087043
consequent support    0.087043
support               0.011827
confidence            0.136407
lift                  1.764159
leverage              0.004806
conviction            1.069809
dtype: float64
```

In [114]:
```
# counting and Seeing the distribution of the number of products on the antecedents products
C0_sub_prod['length_antecedents'] = C0_sub_prod['antecedents'].apply(lambda x: len(x))
C0_sub_prod['length_antecedents'].value_counts()
```

Out[114]:
```
1    30
Name: length_antecedents, dtype: int64
```

In [115]:
```
# Because combination of Substitute is only one, we can directly use it

C0_rulesConfidence_sub=C0_sub_prod
C0_rulesConfidence_sub.head()
```

Out[115]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	length_anteced
908	(47566)	(22993)	0.087043	0.062060	0.010764	0.123664	1.992661	0.005362	1.070298	
909	(22993)	(47566)	0.062060	0.087043	0.010764	0.173448	1.992661	0.005362	1.104536	
669	(22727)	(22423)	0.064319	0.096080	0.012226	0.190083	1.978384	0.006046	1.116065	
668	(22423)	(22727)	0.096080	0.064319	0.012226	0.127248	1.978384	0.006046	1.072104	
676	(84879)	(22423)	0.080930	0.096080	0.014751	0.182266	1.897029	0.006975	1.105396	

Cluster 0 Product Substitution system

In [116]:
```
recommendation_system(22384,C0_rulesConfidence_sub)
```

Out[116]:
```
['PARTY BUNTING']
```

In [117]:
```
recommendation_system(21212,C0_rulesConfidence_sub)
```
Out[117]: ['JUMBO BAG RED RETROSPOT']

In [118]:
```
recommendation_system(84879,C0_rulesConfidence_sub)
```
Out[118]: ['REGENCY CAKESTAND 3 TIER', 'PARTY BUNTING', 'JUMBO BAG RED RETROSPOT']

Association Rule for cluster 1

In [119]:
```
#select cluster 1 customers
df_AR_1 = df_AR[(df_AR['Clusters']==1)]

# Create the orders of Cluster 1 to build the recommendation system
C1_orders = pd.pivot_table(df_AR_1[['InvoiceNo', 'StockCode']], values=[ 'StockCode'], index=['InvoiceNo'],
                    aggfunc={'StockCode': list}).reset_index()
C1_orders.head()
```
Out[119]:

	InvoiceNo	StockCode
0	536371	[22086]
1	536374	[21258]
2	536380	[22961]
3	536382	[10002, 21912, 21832, 22411, 22379, 22381, 227...
4	536384	[82484, 84755, 22464, 21324, 22457, 22469, 224...

In [120]:
```
# Using TransactionEncoder to encode the transaction of StockCode
TE=TransactionEncoder().fit(C1_orders['StockCode'])

C1_orders_encoded = TE.transform(C1_orders['StockCode'])

C1_orders_enc = pd.DataFrame(C1_orders_encoded, columns =TE.columns_)

C1_orders_enc.head()
```
Out[120]:

	10002	10080	10120	10123C	10124A	10124G	10125	11001	15030	15034	15036	15039	15044A	15044B	15044C	150
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
3	True	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F

In [121]:
```
# Calculate the support values for every possible configuration of items (thereshold of support has been chosen 0.(
C1_apriori = apriori(C1_orders_enc, min_support=0.01, verbose=1, use_colnames=True)#max_len=2,
```
Processing 52 combinations | Sampling itemset size 4 3 2

In [122]:
```
C1_apriori.head()
```
Out[122]:

	support	itemsets
0	0.015383	(15036)
1	0.012926	(16161P)
2	0.010576	(17003)
3	0.010683	(20676)
4	0.010148	(20679)

In [123]:
```
# counting and Seeing the distribution of the number of products on the combination
C1_apriori['length'] = C1_apriori['itemsets'].apply(lambda x: len(x))
C1_apriori['length'].value_counts()
```

Out[123]:
```
1    453
2     86
3      5
4      1
Name: length, dtype: int64
```

Cluster 1 Complementary Products

In [124]:
```
# calculating the metrics for all the combinations found above
C1_rulesLift = association_rules(C1_apriori, metric="lift", min_threshold=0.0)
C1_rulesLift.sort_values(by='lift', ascending=False, inplace=True)

# Find all the possible combination of complementary products using lif higher than 2
C1_Complementary=C1_rulesLift.loc[(C1_rulesLift.lift > 2)]
C1_Complementary
```

Out[124]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
141	(22745)	(22748)	0.014208	0.015062	0.011324	0.796992	52.912387	0.011110	4.851729
140	(22748)	(22745)	0.015062	0.014208	0.011324	0.751773	52.912387	0.011110	3.971334
104	(22569)	(22570)	0.014635	0.016238	0.010042	0.686131	42.255763	0.009804	3.134313
105	(22570)	(22569)	0.016238	0.014635	0.010042	0.618421	42.255763	0.009804	2.582335
111	(22579)	(22578)	0.014315	0.023929	0.011751	0.820896	34.305370	0.011408	5.449729
...	...	...	...	...	...	...	...	...	...
91	(22423)	(23245)	0.091123	0.032475	0.012178	0.133646	4.115328	0.009219	1.116778
88	(22423)	(22720)	0.091123	0.054161	0.010789	0.118406	2.186184	0.005854	1.072873
89	(22720)	(22423)	0.054161	0.091123	0.010789	0.199211	2.186184	0.005854	1.134977
166	(84879)	(47566)	0.077022	0.069544	0.010896	0.141470	2.034259	0.005540	1.083778
167	(47566)	(84879)	0.069544	0.077022	0.010896	0.156682	2.034259	0.005540	1.094461

212 rows × 9 columns

In [125]:
```
# Organize the complementary products by confidence
C1_Complementary.sort_values("confidence", ascending = False, inplace = True)

# counting and Seeing the distribution of the number of products of the antecedents products
C1_Complementary['length_antecedents'] = C1_Complementary['antecedents'].apply(lambda x: len(x))
C1_Complementary.groupby('length_antecedents').median()
```

Out[125]:

length_antecedents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
1	0.030659	0.028095	0.012285	0.424149	12.590291	0.011316	1.684492
2	0.019976	0.029698	0.013140	0.657754	23.931722	0.011591	2.702985
3	0.014582	0.034398	0.011858	0.817145	25.853784	0.011398	5.858875

In [126]:
```
# counting and Seeing the distribution of the number of products of the consequents products
C1_Complementary['length_consequents'] = C1_Complementary['consequents'].apply(lambda x: len(x))
C1_Complementary.groupby('length_consequents').median()
```

Out[126]:

length_consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	length_antecedents
1	0.028095	0.030659	0.012285	0.442446	12.590291	0.011316	1.747514	1.0
2	0.029698	0.019976	0.013140	0.478448	23.931722	0.011591	1.887041	1.0
3	0.034398	0.014582	0.011858	0.344990	25.853784	0.011398	1.506639	1.0

In [127]:
```
# Create a dataframe with the length of the number of products of the antecedents and consequents products
C1_length_a=pd.DataFrame(C1_Complementary['length_antecedents'].value_counts())
C1_length_c= pd.DataFrame(C1_Complementary['length_consequents'].value_counts())
C1_ante_conseq= pd.concat((C1_length_a, C1_length_c), axis=1)
C1_ante_conseq
```

Out[127]:

	length_antecedents	length_consequents
1	187	187
2	21	21
3	4	4

In [128]:
```
#using only the first level combinations
C1_rulesConfidence = C1_Complementary.loc[(C1_Complementary.length_antecedents == 1)]
C1_rulesConfidence
```

Out[128]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	length_antece
111	(22579)	(22578)	0.014315	0.023929	0.011751	0.820896	34.305370	0.011408	5.449729	
121	(22698)	(22697)	0.026493	0.033437	0.021686	0.818548	24.480612	0.020800	5.326838	
141	(22745)	(22748)	0.014208	0.015062	0.011324	0.796992	52.912387	0.011110	4.851729	
68	(22617)	(22138)	0.025104	0.053840	0.019549	0.778723	14.463551	0.018198	4.275914	
125	(22698)	(22699)	0.026493	0.035359	0.019976	0.754032	21.324761	0.019040	3.921817	
...	...	...	...	...	...	...	...	...	...	
188	(22423)	(22699, 22698)	0.091123	0.019976	0.013140	0.144197	7.218330	0.011319	1.145151	
166	(84879)	(47566)	0.077022	0.069544	0.010896	0.141470	2.034259	0.005540	1.083778	
91	(22423)	(23245)	0.091123	0.032475	0.012178	0.133646	4.115328	0.009219	1.116778	
213	(22423)	(22699, 22697, 22698)	0.091123	0.017840	0.011858	0.130129	7.294235	0.010232	1.129087	
88	(22423)	(22720)	0.091123	0.054161	0.010789	0.118406	2.186184	0.005854	1.072873	

187 rows × 11 columns

In [129]:
```
# Sort the database above using the lift
C1_rulesConfidence.sort_values("lift", ascending = False, inplace = True)
C1_rulesConfidence.head(20)
```

Out[129]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	length_antece
141	(22745)	(22748)	0.014208	0.015062	0.011324	0.796992	52.912387	0.011110	4.851729	
140	(22748)	(22745)	0.015062	0.014208	0.011324	0.751773	52.912387	0.011110	3.971334	
104	(22569)	(22570)	0.014635	0.016238	0.010042	0.686131	42.255763	0.009804	3.134313	
105	(22570)	(22569)	0.016238	0.014635	0.010042	0.618421	42.255763	0.009804	2.582335	
111	(22579)	(22578)	0.014315	0.023929	0.011751	0.820896	34.305370	0.011408	5.449729	
110	(22578)	(22579)	0.023929	0.014315	0.011751	0.491071	34.305370	0.011408	1.936785	
107	(22577)	(22578)	0.024463	0.023929	0.017306	0.707424	29.563358	0.016720	3.336123	
106	(22578)	(22577)	0.023929	0.024463	0.017306	0.723214	29.563358	0.016720	3.524520	
114	(22629)	(22630)	0.023181	0.021258	0.014315	0.617512	29.047866	0.013822	2.558879	
115	(22630)	(22629)	0.021258	0.023181	0.014315	0.673367	29.047866	0.013822	2.990568	
109	(22579)	(22577)	0.014315	0.024463	0.010148	0.708955	28.980480	0.009798	3.351844	
108	(22577)	(22579)	0.024463	0.014315	0.010148	0.414847	28.980480	0.009798	1.684492	
71	(22144)	(22142)	0.022113	0.017199	0.011003	0.497585	28.930987	0.010623	1.956152	
70	(22142)	(22144)	0.017199	0.022113	0.011003	0.639752	28.930987	0.010623	2.714479	
102	(22570)	(22568)	0.016238	0.022968	0.010789	0.664474	28.930875	0.010417	2.911940	
103	(22568)	(22570)	0.022968	0.016238	0.010789	0.469767	28.930875	0.010417	1.855341	
215	(22698)	(22699, 22423, 22697)	0.026493	0.015597	0.011858	0.447581	28.697277	0.011445	1.781986	
143	(22749)	(22750)	0.022434	0.019656	0.012605	0.561905	28.586905	0.012165	2.237742	
142	(22750)	(22749)	0.019656	0.022434	0.012605	0.641304	28.586905	0.012165	2.725337	
159	(23295)	(23293)	0.017840	0.023822	0.011751	0.658683	27.649902	0.011326	2.860030	

Cluster 1 recommendation system

In [130]:
```
recommendation_system(22630,C1_rulesConfidence)
```

Out[130]: ['SPACEBOY LUNCH BOX ']

In [131]:
```
recommendation_system(22699,C1_rulesConfidence)
```

Out[131]:
```
['REGENCY CAKESTAND 3 TIER',
 'REGENCY CAKESTAND 3 TIER',
 'GREEN REGENCY TEACUP AND SAUCER',
 'REGENCY CAKESTAND 3 TIER',
 'PINK REGENCY TEACUP AND SAUCER']
```

In [132]:
```
recommendation_system(22577,C1_rulesConfidence)
```

Out[132]: ['WOODEN STAR CHRISTMAS SCANDINAVIAN', 'WOODEN TREE CHRISTMAS SCANDINAVIAN']

Cluster 1 Substitute Products

In [133]:
```
# Find all the possible combination of Substitute products using lif low than 2
C1_sub_prod=C1_rulesLift.loc[(C0_rulesLift.lift < 2)]
C1_sub_prod.median()
```

Out[133]:
```
antecedent support     0.014902
consequent support     0.033757
support                0.010683
confidence             0.727017
lift                  21.541911
leverage               0.010187
conviction             3.924288
dtype: float64
```

In [134]:
```
# counting and Seeing the distribution of the number of products on the antecedents products
C1_sub_prod['length_antecedents'] = C1_sub_prod['antecedents'].apply(lambda x: len(x))
C1_sub_prod
```

Out[134]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	length_antece
197	(22727, 22728)	(22726)	0.016665	0.029698	0.010683	0.641026	21.585040	0.010188	2.702985	
196	(22726, 22728)	(22727)	0.013140	0.037816	0.010683	0.813008	21.498783	0.010186	5.145590	

COLD START

In [135]:
```
df_CS=dfp.copy()
```

In [136]:
```
def Cold_start_function(day_of_week,hour,month,country):
    Cold_list=[]
    # recommand by The most different people bought
    # all data
    Total_pop=pd.pivot_table(df_CS, values=[ 'CustomerID'], index=['Description'],
                    aggfunc={'CustomerID':lambda x: len(x.unique()),}).reset_index().sort_values('CustomerID',asc

    # basic on the day of week
    day_pop=pd.pivot_table(df_CS[df_CS.day_of_week==day_of_week], values=[ 'CustomerID'], index=['Description'],
                    aggfunc={'CustomerID':lambda x: len(x.unique()),}).reset_index().sort_values('CustomerID',asc

    # basic on the hour
    hour_pop=pd.pivot_table(df_CS[df_CS.hour==hour], values=[ 'CustomerID'], index=['Description'],
                    aggfunc={'CustomerID':lambda x: len(x.unique()),}).reset_index().sort_values('CustomerID',asc

    # basic on the month
    month_pop=pd.pivot_table(df_CS[df_CS.month==month], values=[ 'CustomerID'], index=['Description'],
                    aggfunc={'CustomerID':lambda x: len(x.unique()),}).reset_index().sort_values('CustomerID',asc

    # basic on location
    country_pop=pd.pivot_table(df_CS[df_CS.Country==country], values=[ 'CustomerID'], index=['Description'],
                    aggfunc={'CustomerID':lambda x: len(x.unique()),}).reset_index().sort_values('CustomerID',asc

    # basic on local and the day of week
    c_day_pop=pd.pivot_table(df_CS[(df_CS.Country==country)&(df_CS.day_of_week==day_of_week)], values=[ 'Customer
                    aggfunc={'CustomerID':lambda x: len(x.unique()),}).reset_index().sort_values('CustomerID',asc

    # basic on local  on the hour
    c_hour_pop=pd.pivot_table(df_CS[(df_CS.Country==country)&(df_CS.hour==hour)], values=[ 'CustomerID'], index=[
                    aggfunc={'CustomerID':lambda x: len(x.unique()),}).reset_index().sort_values('CustomerID',asc

    # basic on local  on the month
    c_month_pop=pd.pivot_table(df_CS[(df_CS.Country==country)&(df_CS.month==month)], values=[ 'CustomerID'], inde
                    aggfunc={'CustomerID':lambda x: len(x.unique()),}).reset_index().sort_values('CustomerID',asc

    # got the popular product from diffrent suggestion
    Cold_list.append(Total_pop['Description'][:2].to_list())
    Cold_list.append(day_pop['Description'][:2].to_list())
    Cold_list.append(hour_pop['Description'][:2].to_list())
    Cold_list.append(month_pop['Description'][:2].to_list())
    Cold_list.append(country_pop['Description'][:2].to_list())
    Cold_list.append(c_day_pop['Description'][:2].to_list())
    Cold_list.append(c_hour_pop['Description'][:2].to_list())
    Cold_list.append(c_month_pop['Description'][:2].to_list())

    Cold_list = np.unique([str(item[0]) for item in Cold_list])

    return Cold_list
```

Test Cold Start

In [137]:
```
#the input is the datetime and location, we can got it when the user enter the website
# Tuesday 10:00 February 'United Kingdom'
Cold_start_function(2,10,2,'United Kingdom')
```

Out[137]:
```
array(['REGENCY CAKESTAND 3 TIER', 'SET OF 3 CAKE TINS PANTRY DESIGN '],
      dtype='<U33')
```

In [138]:
```
# Monday 9:00 April 'France'
Cold_start_function(1,9,4,'France')
```

Out[138]:
```
array(['LUNCH BAG APPLE DESIGN', 'LUNCH BAG SPACEBOY DESIGN ',
       'RABBIT NIGHT LIGHT', 'REGENCY CAKESTAND 3 TIER'], dtype='<U26')
```

In [139]:
```
#Sunday 18:00 December 'Germany'
Cold_start_function(0,18,12,'Germany')
```

Out[139]:
```
array(['6 RIBBONS RUSTIC CHARM', 'REGENCY CAKESTAND 3 TIER',
       'ROUND SNACK BOXES SET OF4 WOODLAND '], dtype='<U35')
```