In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
data = pd.read_csv("dataset.csv", encoding="latin", dtype={'CustomerID': str})
```

In [4]:
```
data.head()
```

Out[4]:

	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	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850	United Kingdom

Just by looking at the first 5 rows of our table, we can understand the structure and datatypes present in our dataset.
We can notice that we will have to deal with time series data, integers and floats, and categorical, and text data.

Exploratory Data Analysis(EDA)
Every data science project starts with EDA as we have to understand what do we have to deal with.
I divide EDA into 2 types: visual and numerical. Let's start with numerical as the simple pandas method .describe() gives us a lot of useful information.

In [5]:
```
data.describe()
```

Out[5]:

	Quantity	UnitPrice
count	541909.000000	541909.000000
mean	9.552250	4.611114
std	218.081158	96.759853
min	-80995.000000	-11062.060000
25%	1.000000	1.250000
50%	3.000000	2.080000
75%	10.000000	4.130000
max	80995.000000	38970.000000

Just a quick look at data with the .describe() method gives us a lot of space to think.
We see negative quantities and prices, and we can see that not all records have CustomerID data.
We can also see that the majority of transactions are for quantities from 3 to 10 items, majority of items

have prices up to 5 pounds.
We have a bunch of huge outliers we will have to deal with later.

Dealing with types
.read_csv() method performs basic type check, but it doesn't do that perfectly.
That's why it is much better to deal with data types in our dataframe before any modifications to prevent additional difficulties.
Every pandas dataframe has an attribute .dtypes which will help us understand what we currently have and what data has to be casted to correct types.

In [6]:
```
data.dtypes
```

Out[6]:
```
InvoiceNo       object
StockCode       object
Description     object
Quantity         int64
InvoiceDate     object
UnitPrice      float64
CustomerID      object
Country         object
dtype: object
```

If we have DateTime data it's better to cast it to DateTime type.
We don't touch InvoiceNo for now as it seems like data in this column has not only numbers.
We saw just the first 5 rows, while pandas during import scanned all the data and found that the type here is not numerical.

In [7]:
```
data['InvoiceDate'] = pd.to_datetime(data['InvoiceDate'])
data  = data.set_index('InvoiceDate')
```

In [8]:
```
data.head()
```

Out[8]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country
InvoiceDate							
2010-12-01 08:26:00	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2.55	17850	United Kingdom
2010-12-01 08:26:00	536365	71053	WHITE METAL LANTERN	6	3.39	17850	United Kingdom
2010-12-01 08:26:00	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2.75	17850	United Kingdom
2010-12-01 08:26:00	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	3.39	17850	United Kingdom
2010-12-01 08:26:00	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	3.39	17850	United Kingdom

Dealing with null values
Next and very important step is dealing with missing values.

Normally if you encounter null values in the dataset you have to understand nature of those null values and possible impact they could have on the model.

There are few strategies that we can use to fix our issue with null values:

1. delete rows with null values

2. delete the feature with null values
3. impute data with mean or median values or use another imputing strategy (method .fillna())

In [9]:
```
data.isnull().sum()
```

Out[9]:
```
InvoiceNo            0
StockCode            0
Description       1454
Quantity             0
UnitPrice            0
CustomerID      135080
Country              0
dtype: int64
```

CustomerID has too many null values and this feature cannot predict a lot so we can just drop it.
It could be reasonable to create another feature "Amount of orders per customer".

In [10]:
```
data = data.drop(columns=['CustomerID'])
```

Let's check out what kind of nulls we have in Description:

In [11]:
```
data[data['Description'].isnull()].head()
```

Out[11]:

InvoiceDate	InvoiceNo	StockCode	Description	Quantity	UnitPrice	Country
2010-12-01 11:52:00	536414	22139	NaN	56	0.0	United Kingdom
2010-12-01 14:32:00	536545	21134	NaN	1	0.0	United Kingdom
2010-12-01 14:33:00	536546	22145	NaN	1	0.0	United Kingdom
2010-12-01 14:33:00	536547	37509	NaN	1	0.0	United Kingdom
2010-12-01 14:34:00	536549	85226A	NaN	1	0.0	United Kingdom

The data in these rows is pretty strange as UnitPrice is 0, so these orders do not generate any sales.
We can impute it with "UNKNOWN ITEM" at the moment and deal with those later during the analysis.

In [12]:
```
data['Description'] = data['Description'].fillna('UNKNOWN ITEM')
data.isnull().sum()
```

Out[12]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
UnitPrice      0
Country        0
dtype: int64
```

Checking out columns separately
It makes sense to go feature by feature and check what pitfalls we have in our data and also to understand our numbers better.

Let's continue checking the Description column. Here we can see items that were bought most often.

In [13]:
```
data['Description'].value_counts().head()
```

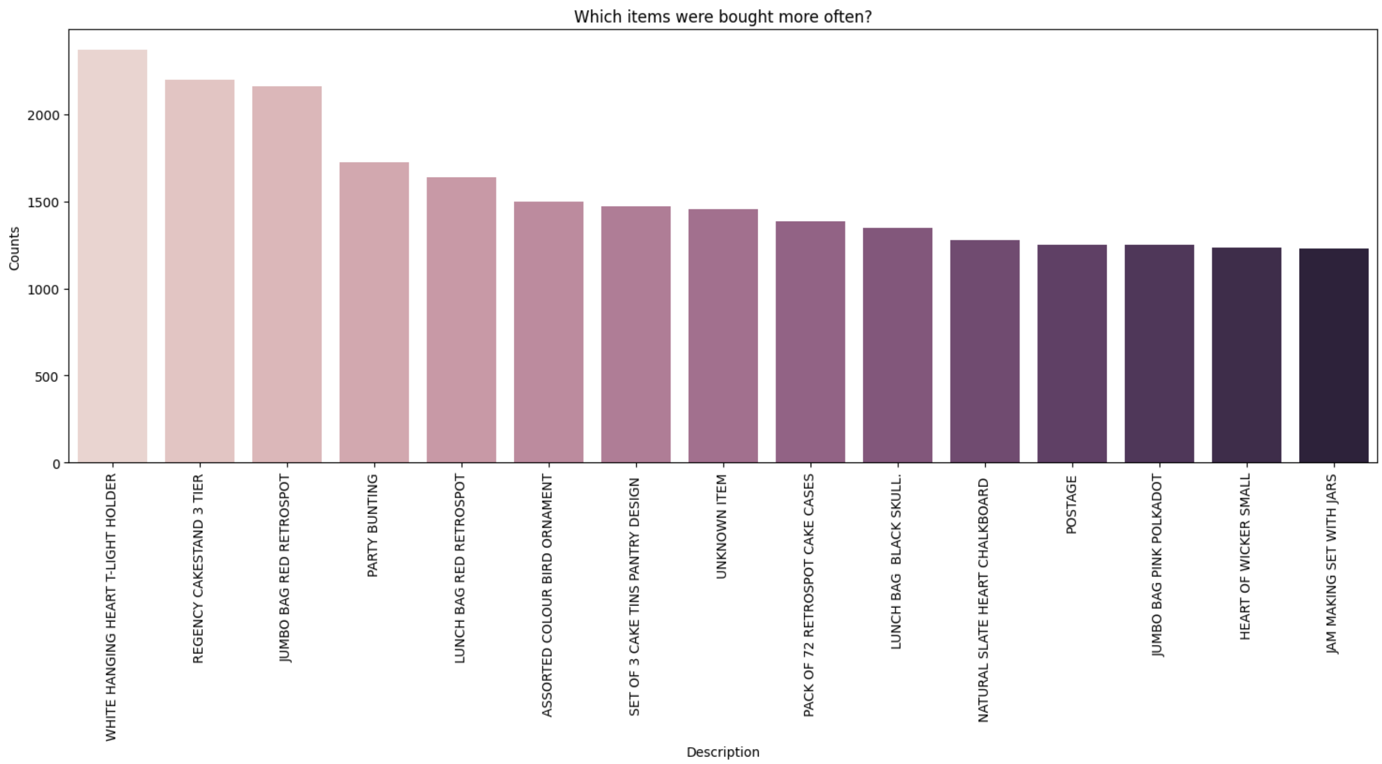
Out[13]:
```
Description
WHITE HANGING HEART T-LIGHT HOLDER    2369
REGENCY CAKESTAND 3 TIER              2200
```

```
JUMBO BAG RED RETROSPOT                2159
PARTY BUNTING                          1727
LUNCH BAG RED RETROSPOT                1638
Name: count, dtype: int64
```

Here we can see our best-selling products, items that appear in orders the most often.

To make it visually more appealing let's create a bar chart for 15 top items

In [14]:
```
item_counts = data['Description'].value_counts().sort_values(ascending=False).iloc[0:15]
plt.figure(figsize=(18,6))
sns.barplot(x=item_counts.index, y=item_counts.values, palette=sns.cubehelix_palette(15))
plt.ylabel("Counts")
plt.title("Which items were bought more often?");
plt.xticks(rotation=90);
```



In [15]:
```
data['Description'].value_counts().tail()
```

Out[15]:
```
Description
Missing                                 1
historic computer difference?....se     1
DUSTY PINK CHRISTMAS TREE 30CM          1
WRAP BLUE RUSSIAN FOLKART               1
PINK BERTIE MOBILE PHONE CHARM          1
Name: count, dtype: int64
```

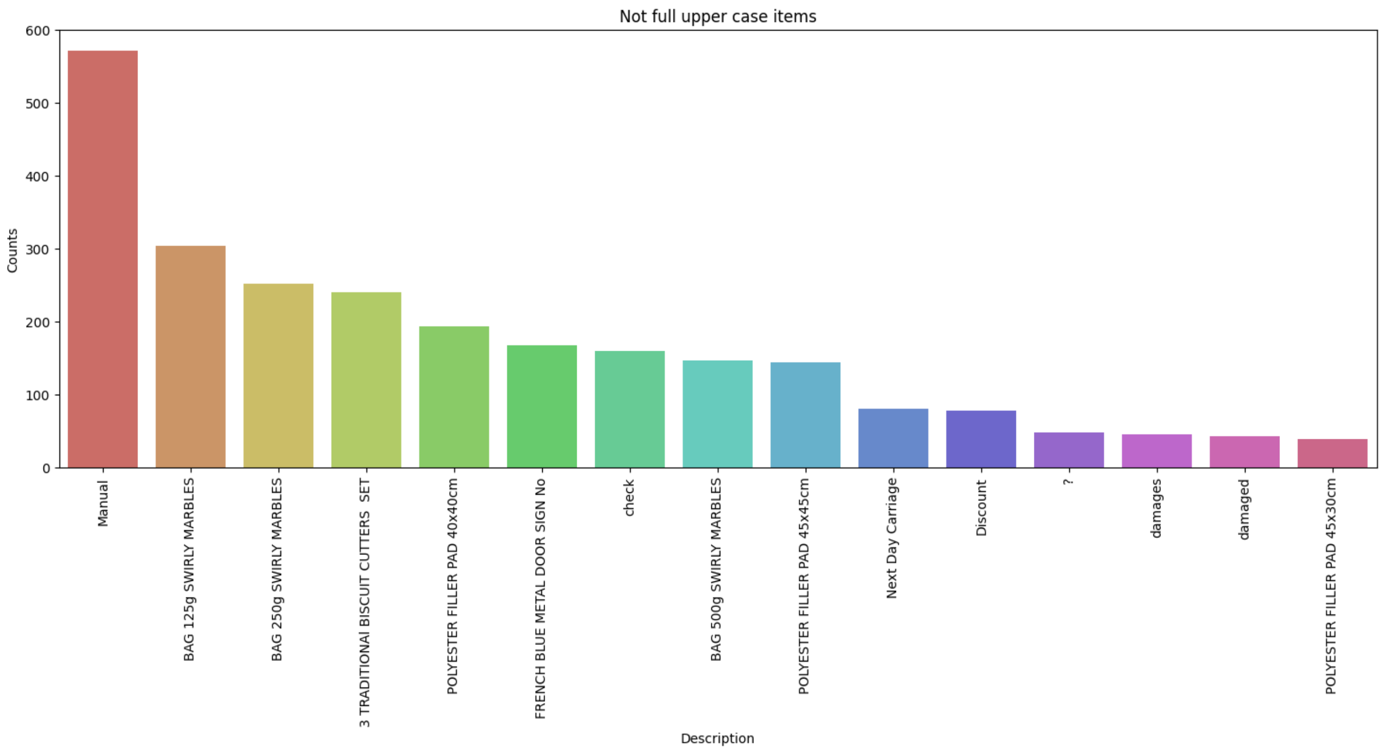
We also notice from the above code that valid items are normally uppercase and non-valid or cancelations are in lowercase.

In [16]:
```
data[~data['Description'].str.isupper()]['Description'].value_counts().head()
```

Out[16]:
```
Description
Manual                                 572
BAG 125g SWIRLY MARBLES                304
BAG 250g SWIRLY MARBLES                252
3 TRADITIONAl BISCUIT CUTTERS  SET     240
POLYESTER FILLER PAD 40x40cm           193
Name: count, dtype: int64
```

A quick check of the case of letters in the Description says that there are some units with lowercase letters in their name and also that lowercase records are for canceled items.
Here we can understand that data management in the store can be improved.

In [17]:
```
# Not full upper case items
lcase_counts = data[~data['Description'].str.isupper()]['Description'].value_counts().so
plt.figure(figsize=(18,6))
sns.barplot(x=lcase_counts.index, y=lcase_counts.values, palette=sns.color_palette("hls"
plt.ylabel("Counts")
plt.title("Not full upper case items");
plt.xticks(rotation=90);
```

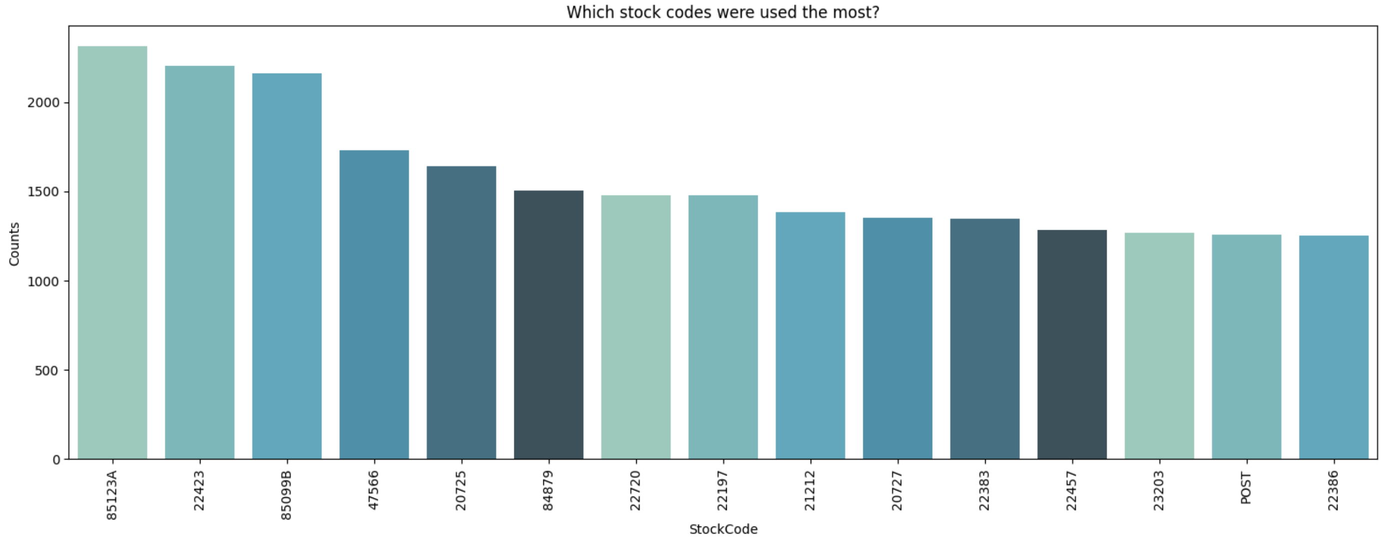


Checking out stoke codes looks like they are deeply correlated with descriptions - which makes perfect sense.

In [18]:
```
data['StockCode'].value_counts().head()
```

Out[18]:
```
StockCode
85123A    2313
22423     2203
85099B    2159
47566     1727
20725     1639
Name: count, dtype: int64
```

In [19]:
```
# Which stock codes were used the most?
stock_counts = data['StockCode'].value_counts().sort_values(ascending=False).iloc[0:15]
plt.figure(figsize=(18,6))
sns.barplot(x=stock_counts.index, y=stock_counts.values, palette=sns.color_palette("GnBu
plt.ylabel("Counts")
plt.title("Which stock codes were used the most?");
plt.xticks(rotation=90);
```

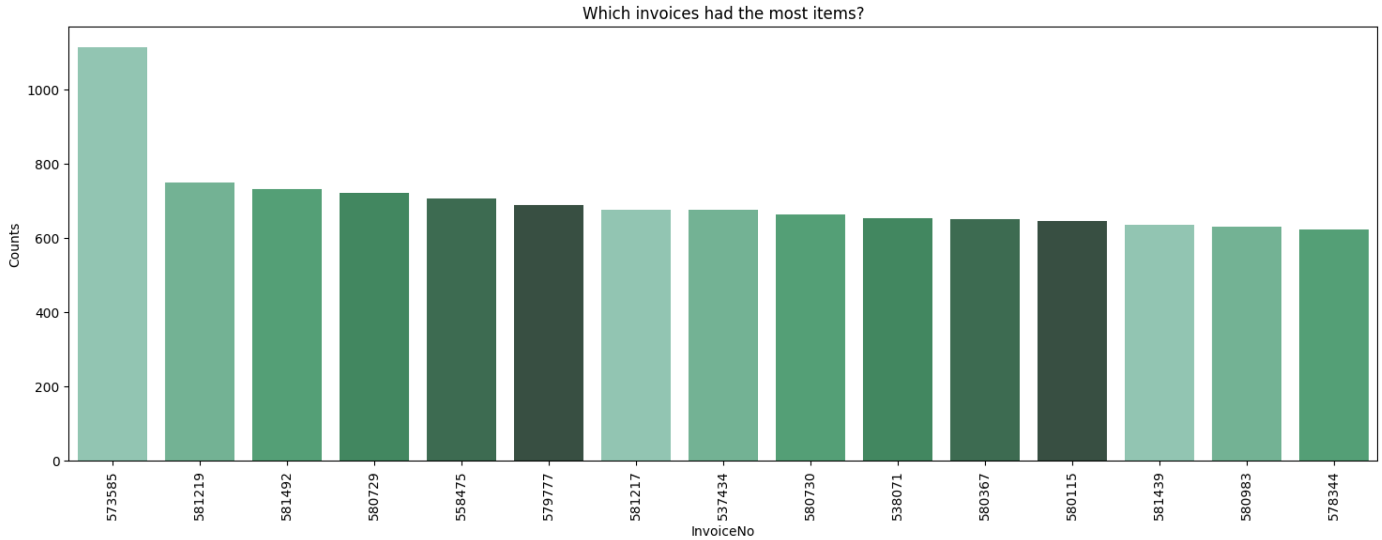


Checking out also InvoiceNo feature

In [20]:
```
data['InvoiceNo'].value_counts().tail()
```

Out[20]:
```
InvoiceNo
554023     1
554022     1
554021     1
554020     1
C558901    1
Name: count, dtype: int64
```

In [21]:
```
#  Which invoices had the most items?
inv_counts = data['InvoiceNo'].value_counts().sort_values(ascending=False).iloc[0:15]
plt.figure(figsize=(18,6))
sns.barplot(x=inv_counts.index, y=inv_counts.values, palette=sns.color_palette("BuGn_d"))
plt.ylabel("Counts")
plt.title("Which invoices had the most items?");
plt.xticks(rotation=90);
```



In [22]:
```
data[data['InvoiceNo'].str.startswith('C')].describe()
```

Out[22]:

	Quantity	UnitPrice
count	9288.000000	9288.000000
mean	-29.885228	48.393661
std	1145.786965	666.600430

min	-80995.000000	0.010000
25%	-6.000000	1.450000
50%	-2.000000	2.950000
75%	-1.000000	5.950000
max	-1.000000	38970.000000

Looks like Invoices that start with 'C' are the "Canceling"/"Returning" invoices. This resolves the mystery of negative quantities.

Although, we should've gotten deeper into the analysis of those returns, for the sake of simplicity let's just ignore those values for the moment.

We can actually start a separate project based on that data and predict the returning/canceling rates for the store.

In [23]:
```
data = data[~data['InvoiceNo'].str.startswith('C')]
```

In [24]:
```
data.describe()
```

Out[24]:

	Quantity	UnitPrice
count	532621.000000	532621.000000
mean	10.239972	3.847621
std	159.593551	41.758023
min	-9600.000000	-11062.060000
25%	1.000000	1.250000
50%	3.000000	2.080000
75%	10.000000	4.130000
max	80995.000000	13541.330000

During exploratory data analysis we can go back to the same operations and checks, just to understand how our actions affected the dataset.

EDA is the series of repetitive tasks to understand better our data.

Here, for example we get back to .describe() method to get an overall picture of our data after some manipulations.

We still see negative quantities and negative prices, let's get into those records.

In [25]:
```
# df[df['Quantity'] < 0]
data[data['Quantity'] < 0].head()
```

Out[25]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	Country
InvoiceDate						
2010-12-01 16:50:00	536589	21777	UNKNOWN ITEM	-10	0.0	United Kingdom
2010-12-02 14:42:00	536764	84952C	UNKNOWN ITEM	-38	0.0	United Kingdom
2010-12-03 15:30:00	536996	22712	UNKNOWN ITEM	-20	0.0	United Kingdom
2010-12-03 15:30:00	536997	22028	UNKNOWN ITEM	-20	0.0	United Kingdom

2010-12-03 15:30:00	536998	85067	UNKNOWN ITEM	-6	0.0	United Kingdom

Here we can see that other "Negative quantities" appear to be damaged/lost/unknown items.
Again, we will just ignore them for the sake of simplicity of analysis for this project.

In [26]:
```
data = data[data['Quantity']>0]
data.describe()
```

Out[26]:

	Quantity	UnitPrice
count	531285.000000	531285.000000
mean	10.655262	3.857296
std	156.830323	41.810047
min	1.000000	-11062.060000
25%	1.000000	1.250000
50%	3.000000	2.080000
75%	10.000000	4.130000
max	80995.000000	13541.330000

We also see negative UnitPrice, which is not normal as well.
Let's check this out:

In [27]:
```
data[data['UnitPrice'] < 0].describe()
```

Out[27]:

	Quantity	UnitPrice
count	2.0	2.00
mean	1.0	-11062.06
std	0.0	0.00
min	1.0	-11062.06
25%	1.0	-11062.06
50%	1.0	-11062.06
75%	1.0	-11062.06
max	1.0	-11062.06

In [28]:
```
data[data['UnitPrice'] == -11062.06]
```

Out[28]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	Country
InvoiceDate						
2011-08-12 14:51:00	A563186	B	Adjust bad debt	1	-11062.06	United Kingdom
2011-08-12 14:52:00	A563187	B	Adjust bad debt	1	-11062.06	United Kingdom

As there are just two rows, let's ignore them for the moment (the description gives us enough warnings, although we still need some context to understand it better)

In [29]:
```
data = data[data['UnitPrice'] > 0]
data.describe()
```

	Quantity	UnitPrice

Out[29]:

count	530104.000000	530104.000000
mean	10.542037	3.907625
std	155.524124	35.915681
min	1.000000	0.001000
25%	1.000000	1.250000
50%	3.000000	2.080000
75%	10.000000	4.130000
max	80995.000000	13541.330000

As we have finished cleaning our data and removed all suspicious records we can start creating some new features for our model.
Let's start with the most obvious one - Sales.
We have quantities, we have prices - we can calculate the revenue.

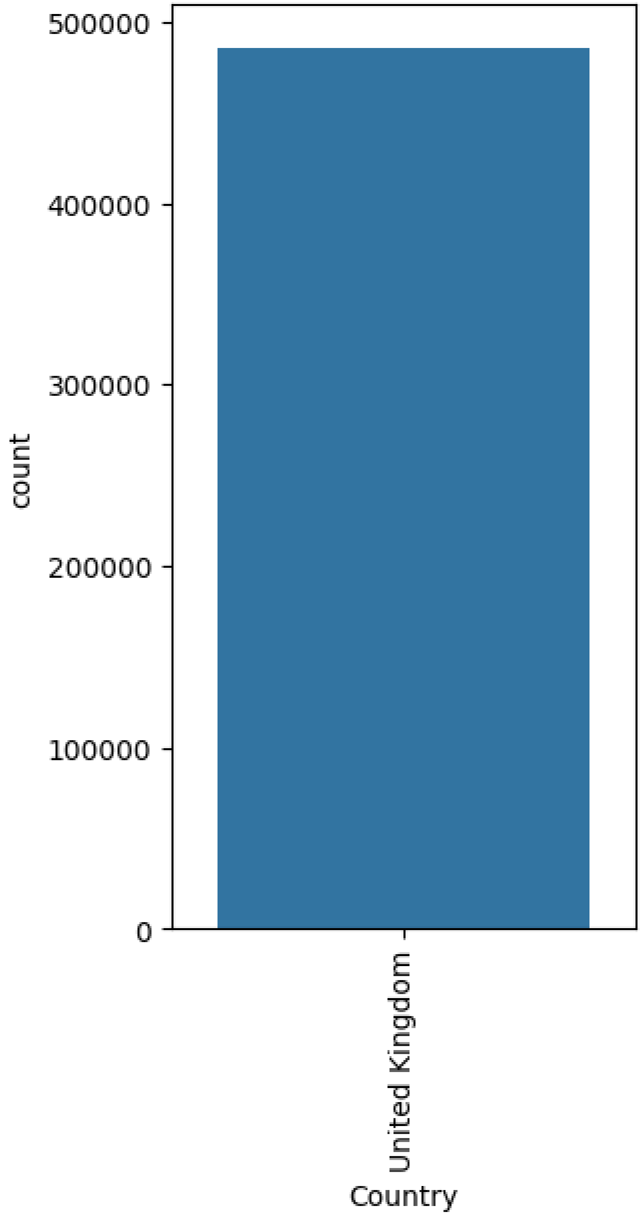
VISUAL EDA

In [30]:

```
plt.figure(figsize=(3,6))
sns.countplot(x=data[data['Country'] == 'United Kingdom']['Country'])
plt.xticks(rotation=90)
```

Out[30]:

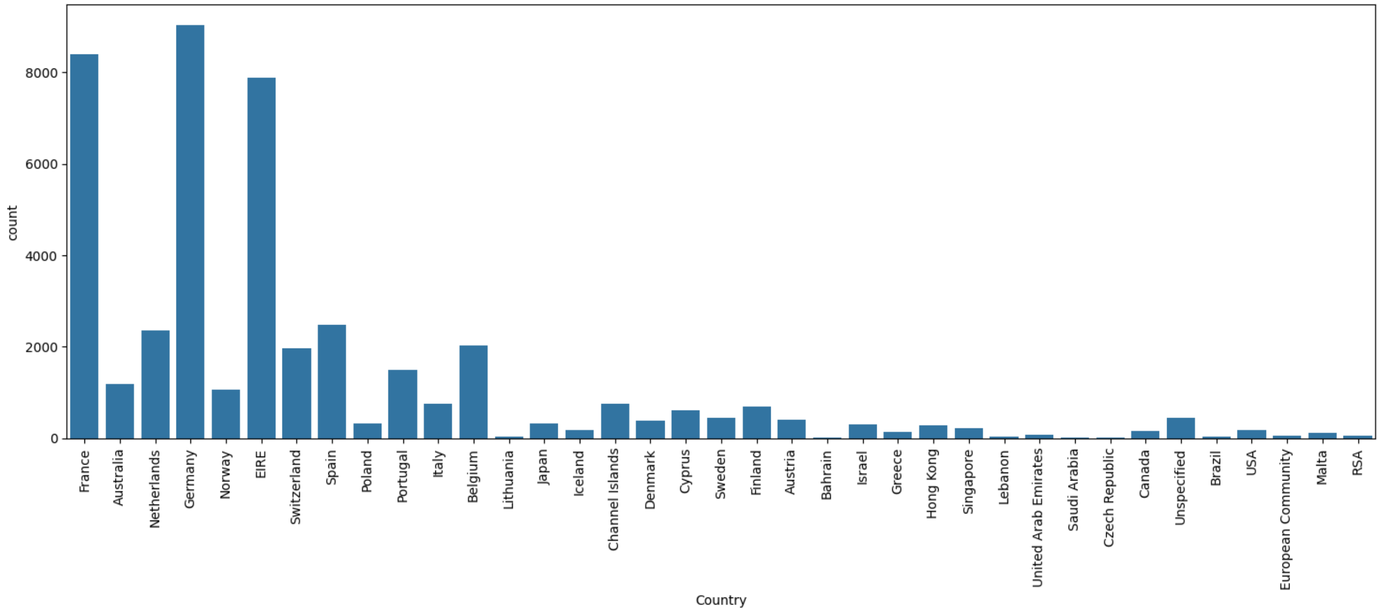
```
([0], [Text(0, 0, 'United Kingdom')])
```



In [31]:
```
plt.figure(figsize=(18,6))
sns.countplot(x=data[data['Country'] != 'United Kingdom']['Country'])
plt.xticks(rotation=90)
```

Out[31]:
```
([0,
  1,
  2,
  3,
  4,
  5,
  6,
  7,
  8,
  9,
  10,
  11,
  12,
  13,
  14,
  15,
  16,
  17,
  18,
  19,
  20,
  21,
```

```
 22,
 23,
 24,
 25,
 26,
 27,
 28,
 29,
 30,
 31,
 32,
 33,
 34,
 35,
 36],
[Text(0, 0, 'France'),
 Text(1, 0, 'Australia'),
 Text(2, 0, 'Netherlands'),
 Text(3, 0, 'Germany'),
 Text(4, 0, 'Norway'),
 Text(5, 0, 'EIRE'),
 Text(6, 0, 'Switzerland'),
 Text(7, 0, 'Spain'),
 Text(8, 0, 'Poland'),
 Text(9, 0, 'Portugal'),
 Text(10, 0, 'Italy'),
 Text(11, 0, 'Belgium'),
 Text(12, 0, 'Lithuania'),
 Text(13, 0, 'Japan'),
 Text(14, 0, 'Iceland'),
 Text(15, 0, 'Channel Islands'),
 Text(16, 0, 'Denmark'),
 Text(17, 0, 'Cyprus'),
 Text(18, 0, 'Sweden'),
 Text(19, 0, 'Finland'),
 Text(20, 0, 'Austria'),
 Text(21, 0, 'Bahrain'),
 Text(22, 0, 'Israel'),
 Text(23, 0, 'Greece'),
 Text(24, 0, 'Hong Kong'),
 Text(25, 0, 'Singapore'),
 Text(26, 0, 'Lebanon'),
 Text(27, 0, 'United Arab Emirates'),
 Text(28, 0, 'Saudi Arabia'),
 Text(29, 0, 'Czech Republic'),
 Text(30, 0, 'Canada'),
 Text(31, 0, 'Unspecified'),
 Text(32, 0, 'Brazil'),
 Text(33, 0, 'USA'),
 Text(34, 0, 'European Community'),
 Text(35, 0, 'Malta'),
 Text(36, 0, 'RSA')])
```



In [32]:

```
uk_count = data[data['Country'] == 'United Kingdom']['Country'].count()
all_count = data['Country'].count()
uk_perc = uk_count/all_count
print(str('{0:.2f}%').format(uk_perc*100))
```

91.51%

From the above plots and calculations, we can see that the vast majority of sales were made in the UK and just 8.49% went abroad.
We can say our dataset is skewed to the UK side.

Detecting outliers
There are a few different methods to detect outliers:

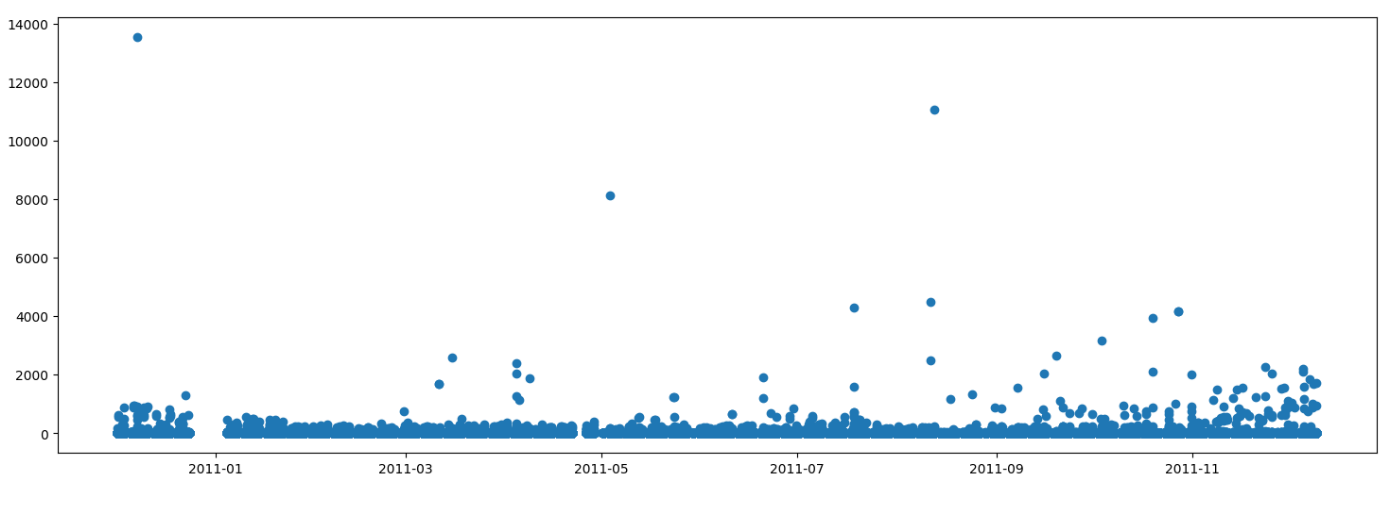
1. box plots,
2. using IQR,
3. scatter plot also works in some cases (and this is one of those).

Detecting outliers using a scatter plot is pretty intuitive. You plot your data and remove data points that visually are definitely out of range. Like in the chart below:

In [33]:

```
plt.figure(figsize=(18,6))
plt.scatter(x=data.index, y=data['UnitPrice'])
```

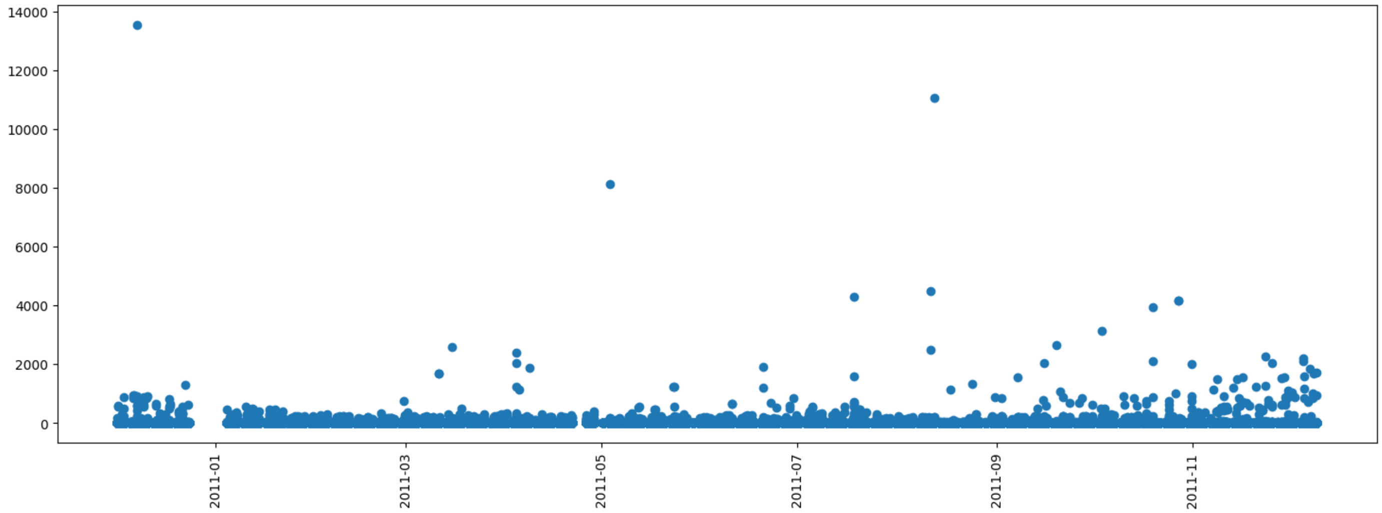
Out[33]: <matplotlib.collections.PathCollection at 0x2232602a890>



Remove obvious outliers:

In [34]:
```
publish_display_data = data[data['UnitPrice'] < 25000]
plt.figure(figsize=(18,6))
plt.scatter(x=data.index, y=data['UnitPrice'])
plt.xticks(rotation=90)
```

Out[34]:
```
(array([14975., 15034., 15095., 15156., 15218., 15279.]),
 [Text(14975.0, 0, '2011-01'),
  Text(15034.0, 0, '2011-03'),
  Text(15095.0, 0, '2011-05'),
  Text(15156.0, 0, '2011-07'),
  Text(15218.0, 0, '2011-09'),
  Text(15279.0, 0, '2011-11')])
```

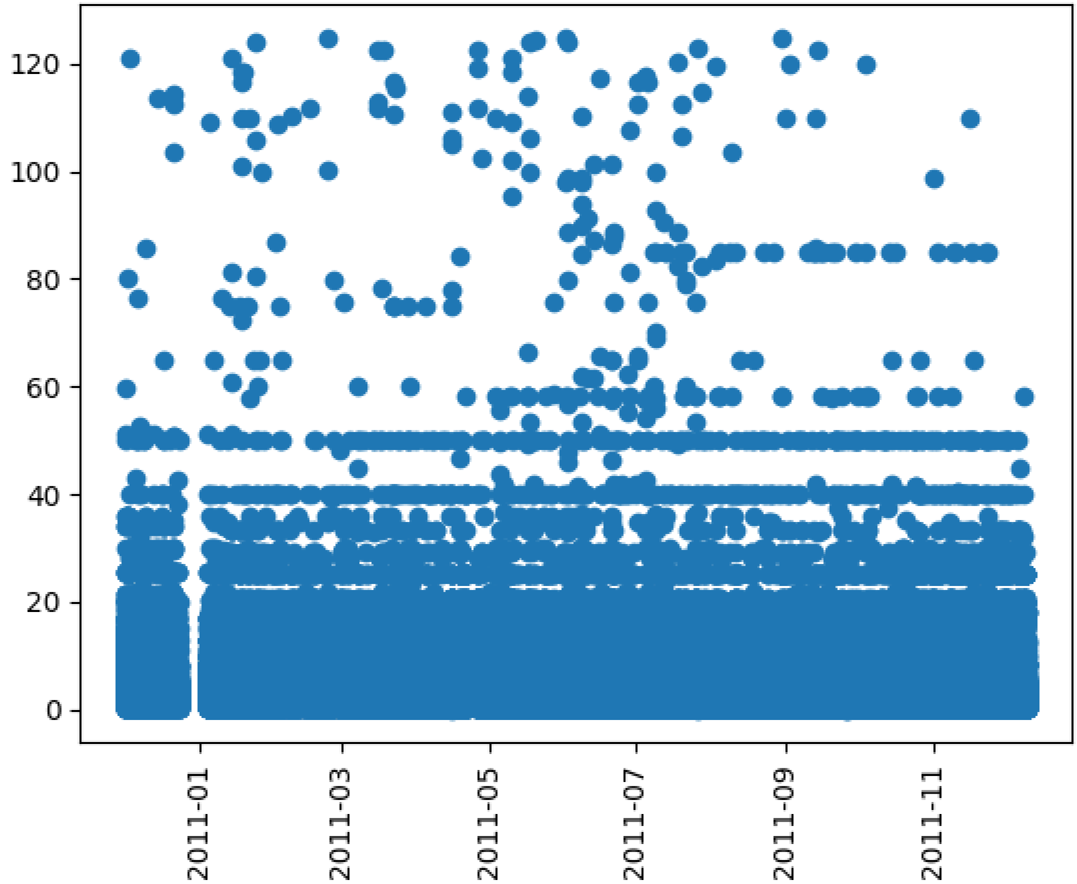


After removing obvious outliers we still see some values that are out of normal distribution.
To understand better the distribution of our data let's check out different percentiles of our numeric features:

We can see that if we remove the top 2% of our data points we will get rid of absolute outliers and will have a more balanced dataset.

In [35]:
```
data_quantile = data[data['UnitPrice'] < 125]
plt.scatter(x=data_quantile.index, y=data_quantile['UnitPrice'])
plt.xticks(rotation=90)
```

Out[35]:
```
(array([14975., 15034., 15095., 15156., 15218., 15279.]),
 [Text(14975.0, 0, '2011-01'),
  Text(15034.0, 0, '2011-03'),
  Text(15095.0, 0, '2011-05'),
  Text(15156.0, 0, '2011-07'),
  Text(15218.0, 0, '2011-09'),
  Text(15279.0, 0, '2011-11')])
```



In [36]:
```
data_quantile.describe()
```

Out[36]:

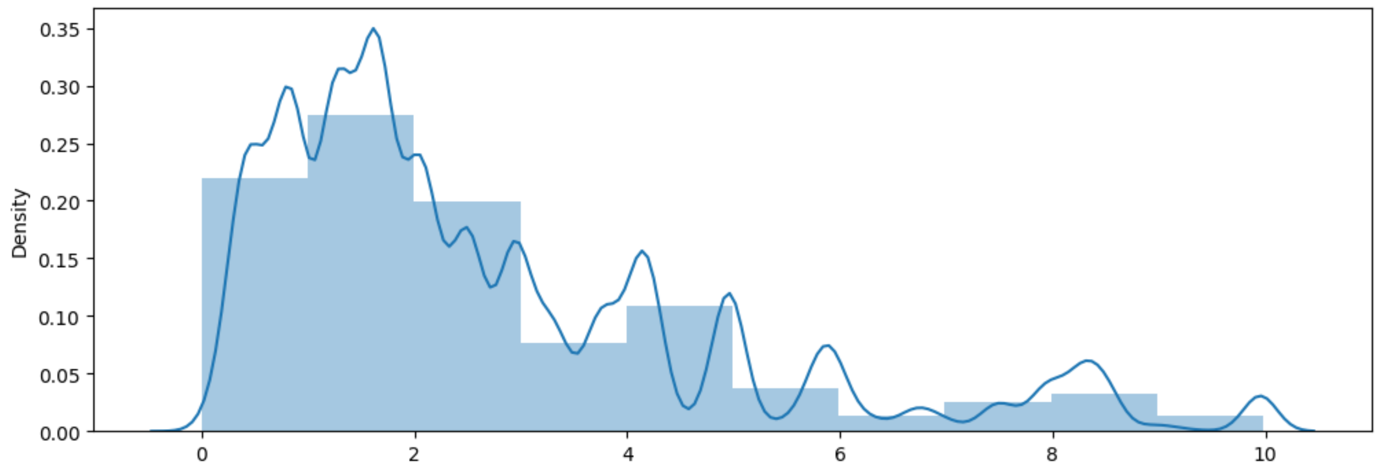
	Quantity	UnitPrice
count	529361.000000	529361.000000
mean	10.555237	3.306499
std	155.632810	4.006631
min	1.000000	0.001000
25%	1.000000	1.250000
50%	3.000000	2.080000
75%	10.000000	4.130000
max	80995.000000	124.870000

Looks like our data is almost ready for modelling.
We performed a clean up, we removed outliers that were disturbing the balance of our dataset, we removed invalid records.
Now our data looks much better! and it doesn't lose it's value.

Visually checking distribution of numeric features

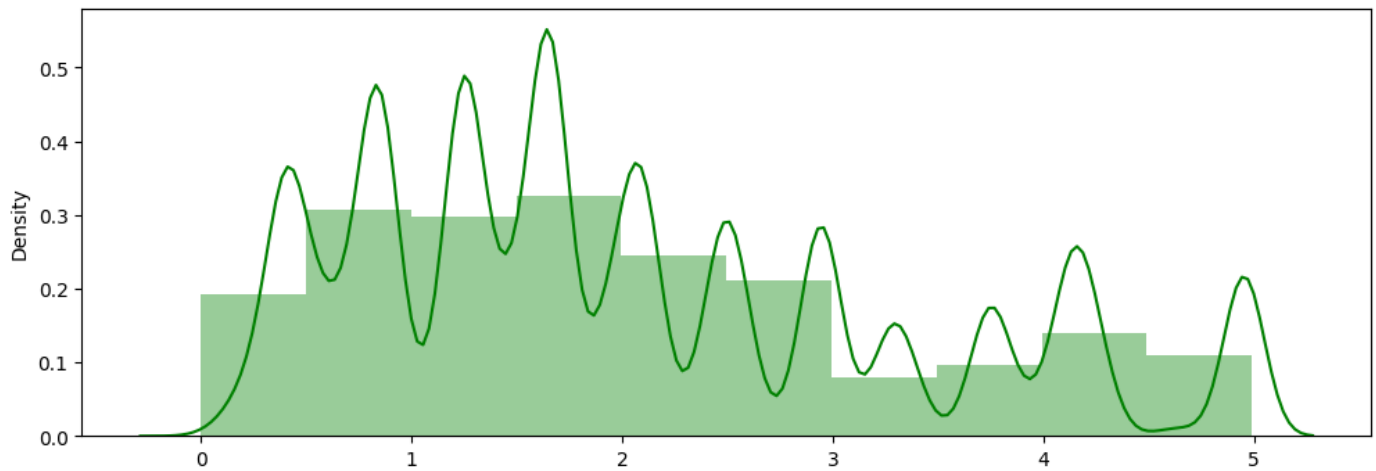
In [37]:
```
plt.figure(figsize=(12,4))
sns.distplot(data_quantile[data_quantile['UnitPrice'] < 10]['UnitPrice'].values, kde=Tru
```

Out[37]:
```
<Axes: ylabel='Density'>
```



In [38]:
```python
plt.figure(figsize=(12,4))
sns.distplot(data_quantile[data_quantile['UnitPrice'] < 5]['UnitPrice'].values, kde=True
```

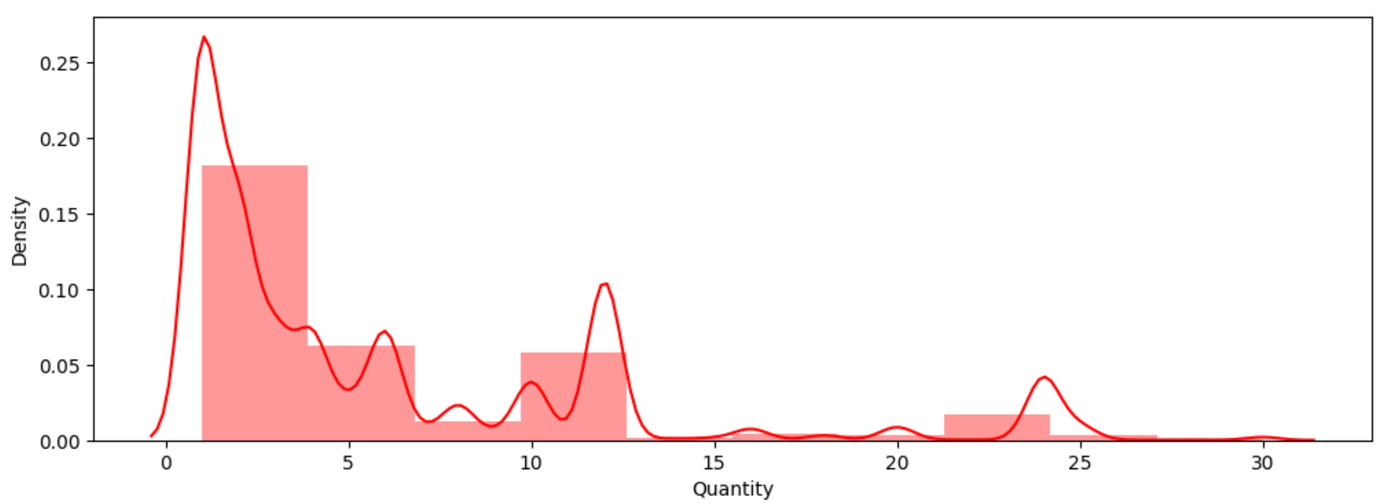
Out[38]:
```
<Axes: ylabel='Density'>
```



From these histograms, we can see that the vast majority of items sold in this store have a low price range - 0 to 3 pounds.

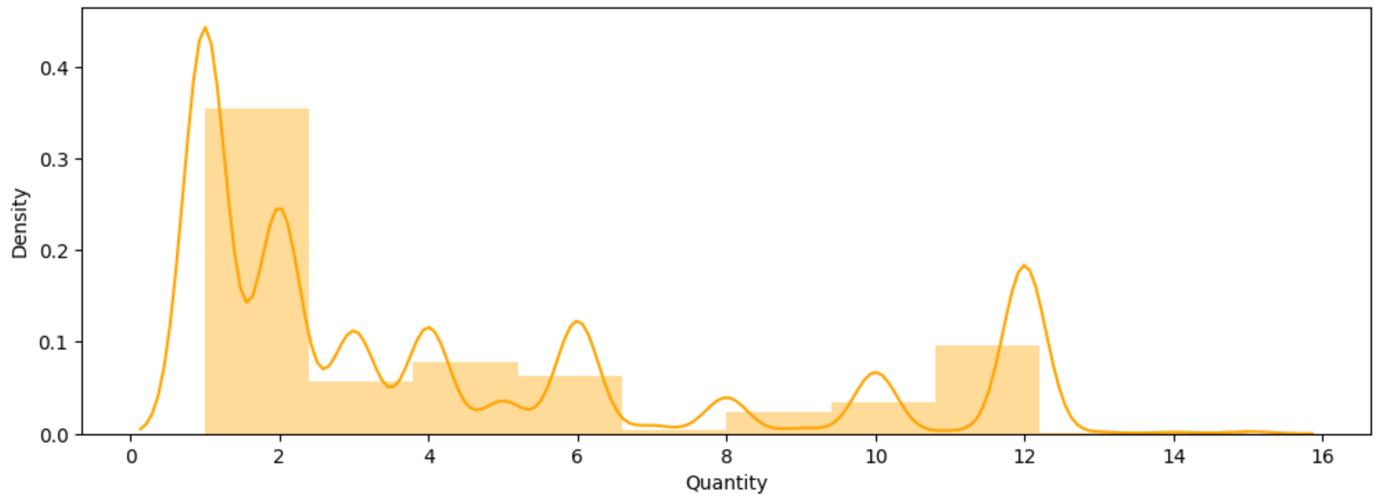
In [39]:
```python
plt.figure(figsize=(12,4))
sns.distplot(data_quantile[data_quantile['Quantity'] <= 30]['Quantity'], kde=True, bins=
```

Out[39]:
```
<Axes: xlabel='Quantity', ylabel='Density'>
```



In [40]:
```python
plt.figure(figsize=(12,4))
sns.distplot(data_quantile[data_quantile['Quantity'] <= 15]['Quantity'], kde=True, bins=
```

Out[40]: <Axes: xlabel='Quantity', ylabel='Density'>



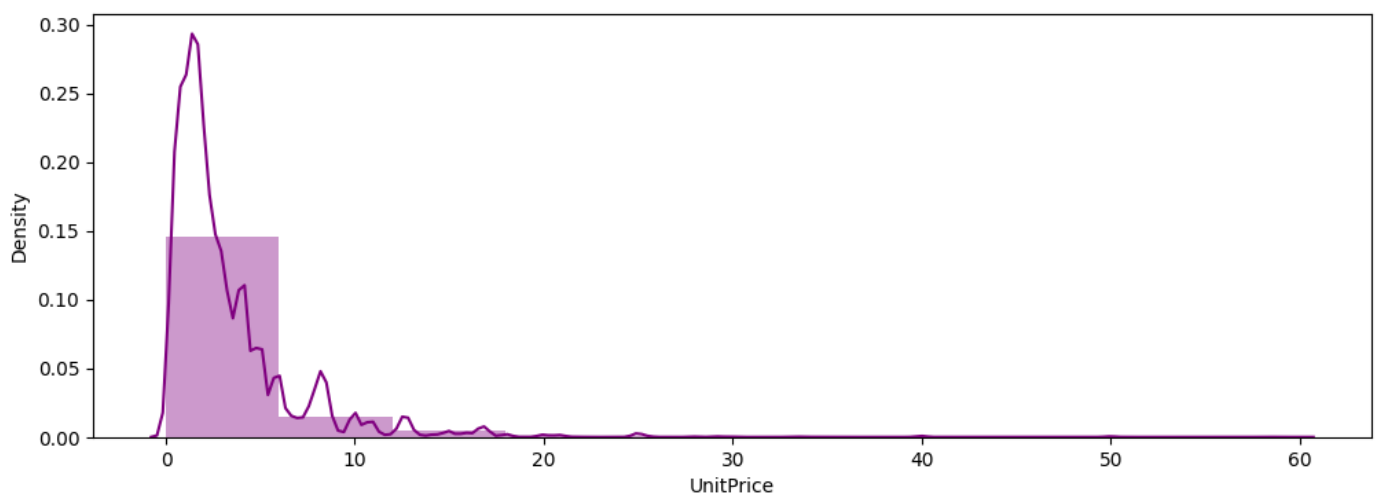
From these histograms we that people bought normally 1-5 items or 10-12

Maybe there was some kind of offers for sets?

In [41]:

```
plt.figure(figsize=(12,4))
sns.distplot(data_quantile[data_quantile['UnitPrice'] < 60]['UnitPrice'], kde=True, bins
```

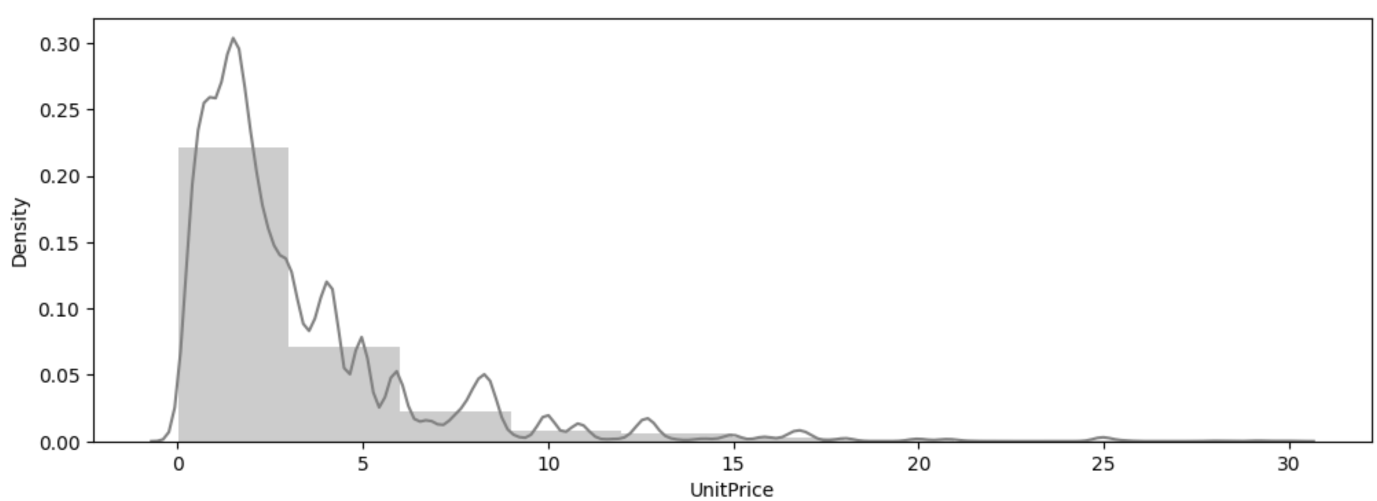
Out[41]: <Axes: xlabel='UnitPrice', ylabel='Density'>



In [42]:

```
plt.figure(figsize=(12,4))
sns.distplot(data_quantile[data_quantile['UnitPrice'] < 30]['UnitPrice'], kde=True, bins
```

Out[42]: <Axes: xlabel='UnitPrice', ylabel='Density'>



From these histograms, we can understand that majority of sales per order were in the range 1-15 pounds each.

Analysing sales over time

In [43]:
```
data_ts = data[['UnitPrice']]
data_ts.head()
```

Out[43]:

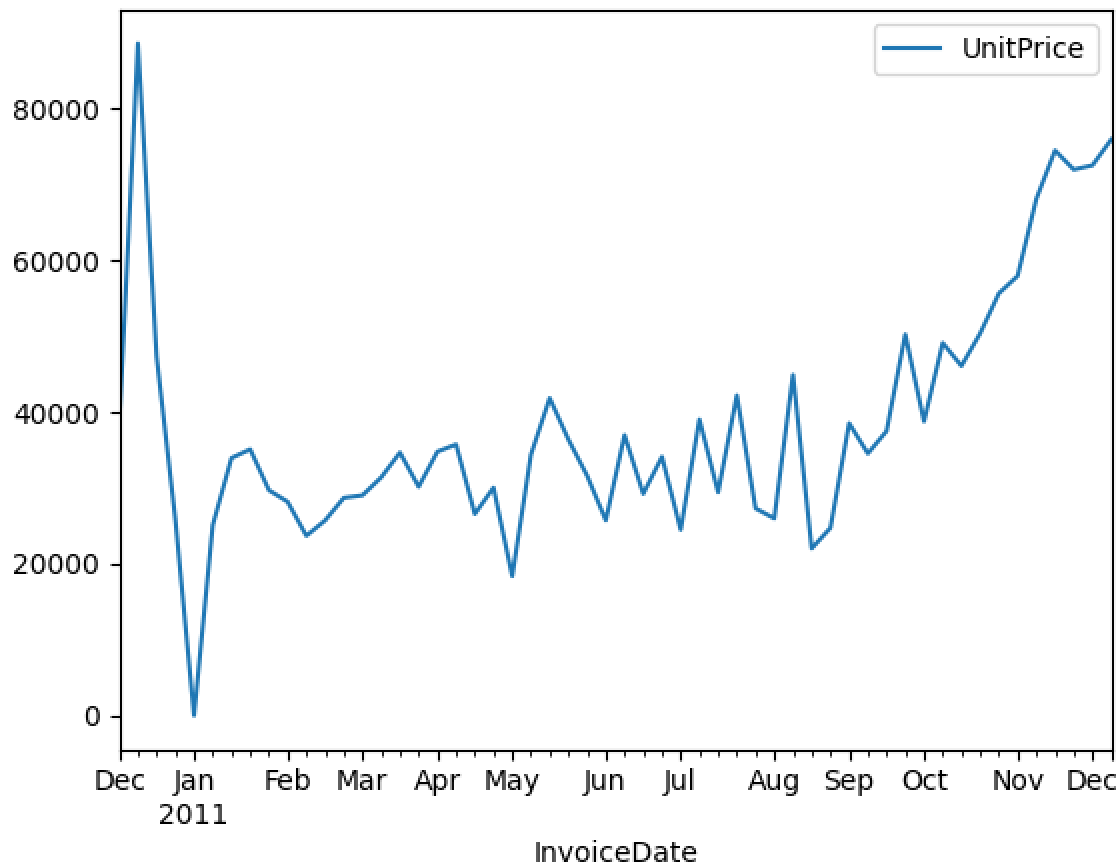
InvoiceDate	UnitPrice
2010-12-01 08:26:00	2.55
2010-12-01 08:26:00	3.39
2010-12-01 08:26:00	2.75
2010-12-01 08:26:00	3.39
2010-12-01 08:26:00	3.39

As we can see every invoice has its own timestamp (definitely based on the time the order was made). We can resample time data by, for example, weeks, and try to see if there are any patterns in our sales.

In [44]:
```
plt.figure(figsize=(18,6))
data_resample = data_ts.resample('W').sum()
data_resample.plot()
```

Out[44]:
```
<Axes: xlabel='InvoiceDate'>

<Figure size 1800x600 with 0 Axes>
```



That week with 0 sales in January looks suspicious, let's check it closer.

In [45]:
```
data_resample['12-2010':'01-2011']
```

Out[45]:

	UnitPrice
InvoiceDate	
2010-12-05	38224.49
2010-12-12	88540.65
2010-12-19	47278.94
2010-12-26	25860.39
2011-01-02	0.00
2011-01-09	25072.03
2011-01-16	33919.09
2011-01-23	35064.34
2011-01-30	29676.45

Now it makes sense - possibly, during the New Year holidays period the store was closed and didn't process orders, that's why they didn't make any sales.

Preparing data for modeling and feature creation

Now comes the most fun part of the project - building a model.
To do this we will need to create a few more additional features to make our model more sophisticated.

In [46]:

```
data_clean = data[data['UnitPrice'] < 15]
data_clean.describe()
```

Out[46]:

	Quantity	UnitPrice
count	520395.000000	520395.000000
mean	10.707578	2.978730
std	156.962876	2.669826
min	1.000000	0.001000
25%	1.000000	1.250000
50%	4.000000	2.080000
75%	12.000000	4.130000
max	80995.000000	14.960000

In [47]:

```
data_clean.index
```

Out[47]:

```
DatetimeIndex(['2010-12-01 08:26:00', '2010-12-01 08:26:00',
               '2010-12-01 08:26:00', '2010-12-01 08:26:00',
               '2010-12-01 08:26:00', '2010-12-01 08:26:00',
               '2010-12-01 08:26:00', '2010-12-01 08:28:00',
               '2010-12-01 08:28:00', '2010-12-01 08:34:00',
               ...
               '2011-12-09 12:50:00', '2011-12-09 12:50:00',
               '2011-12-09 12:50:00', '2011-12-09 12:50:00',
               '2011-12-09 12:50:00', '2011-12-09 12:50:00',
               '2011-12-09 12:50:00', '2011-12-09 12:50:00',
               '2011-12-09 12:50:00', '2011-12-09 12:50:00'],
              dtype='datetime64[ns]', name='InvoiceDate', length=520395, freq=None)
```

Quantity per invoice feature

A feature that could influence the sales output could be "Quantity per invoice". Let's find the data for this feature.

In [48]:
```
data_join = data_clean.groupby('InvoiceNo')[['Quantity']].sum()
```

In [49]:
```
data_join = data_join.reset_index()
data_join.head()
```

Out[49]:

	InvoiceNo	Quantity
0	536365	40
1	536366	12
2	536367	83
3	536368	15
4	536369	3

In [50]:
```
data_clean['InvoiceDate'] = data_clean.index
data_clean = data_clean.merge(data_join, how='left', on='InvoiceNo')
data_clean = data_clean.rename(columns={'Quantity_x' : 'Quantity', 'Quantity_y' : 'Quant
data_clean.tail(15)
```

Out[50]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	Country	InvoiceDate	QuantityInv
520380	581587	22631	CIRCUS PARADE LUNCH BOX	12	1.95	France	2011-12-09 12:50:00	105
520381	581587	22556	PLASTERS IN TIN CIRCUS PARADE	12	1.65	France	2011-12-09 12:50:00	105
520382	581587	22555	PLASTERS IN TIN STRONGMAN	12	1.65	France	2011-12-09 12:50:00	105
520383	581587	22728	ALARM CLOCK BAKELIKE PINK	4	3.75	France	2011-12-09 12:50:00	105
520384	581587	22727	ALARM CLOCK BAKELIKE RED	4	3.75	France	2011-12-09 12:50:00	105
520385	581587	22726	ALARM CLOCK BAKELIKE GREEN	4	3.75	France	2011-12-09 12:50:00	105
520386	581587	22730	ALARM CLOCK BAKELIKE IVORY	4	3.75	France	2011-12-09 12:50:00	105
520387	581587	22367	CHILDRENS APRON SPACEBOY DESIGN	8	1.95	France	2011-12-09 12:50:00	105
520388	581587	22629	SPACEBOY LUNCH BOX	12	1.95	France	2011-12-09 12:50:00	105
520389	581587	23256	CHILDRENS CUTLERY SPACEBOY	4	4.15	France	2011-12-09 12:50:00	105
520390	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	0.85	France	2011-12-09 12:50:00	105
520391	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2.10	France	2011-12-09 12:50:00	105
520392	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	4.15	France	2011-12-09 12:50:00	105
520393	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	4.15	France	2011-12-09 12:50:00	105

520394	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	4.95	France	2011-12-09 12:50:00	105

In [51]:
```
data_clean.describe()
```

Out[51]:

	Quantity	UnitPrice	InvoiceDate	QuantityInv
count	520395.000000	520395.000000	520395	520395.000000
mean	10.707578	2.978730	2011-07-05 01:44:16.782867456	533.624937
min	1.000000	0.001000	2010-12-01 08:26:00	1.000000
25%	1.000000	1.250000	2011-03-28 13:28:00	152.000000
50%	4.000000	2.080000	2011-07-20 16:12:00	300.000000
75%	12.000000	4.130000	2011-10-19 13:58:00	567.000000
max	80995.000000	14.960000	2011-12-09 12:50:00	80995.000000
std	156.962876	2.669826	NaN	903.091973

In [52]:
```
data_clean['InvoiceDate'] = pd.to_datetime(data_clean['InvoiceDate'])
```

In [53]:
```
data_clean.dtypes
```

Out[53]:
```
InvoiceNo               object
StockCode               object
Description             object
Quantity                 int64
UnitPrice              float64
Country                 object
InvoiceDate     datetime64[ns]
QuantityInv              int64
dtype: object
```

Bucketing Quantity and UnitPrice features

Based on the EDA done previously we can group these features into 6 buckets for Quantity and 5 for UnitePrice using the pandas.cut() method.

In [54]:
```
bins_q = pd.IntervalIndex.from_tuples([(0, 2), (2, 5), (5, 8), (8, 11), (11, 14), (15, 5
data_clean['QuantityRange'] = pd.cut(data_clean['Quantity'], bins=bins_q)
bins_p = pd.IntervalIndex.from_tuples([(0, 1), (1, 2), (2, 3), (3, 4), (4, 20)])
data_clean['PriceRange'] = pd.cut(data_clean['UnitPrice'], bins=bins_p)
data_clean.head()
```

Out[54]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	Country	InvoiceDate	QuantityInv	QuantityRange
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2.55	United Kingdom	2010-12-01 08:26:00	40	(5, 8]
1	536365	71053	WHITE METAL LANTERN	6	3.39	United Kingdom	2010-12-01 08:26:00	40	(5, 8]
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2.75	United Kingdom	2010-12-01 08:26:00	40	(5, 8]
3	536365	84029G	KNITTED UNION FLAG HOT	6	3.39	United Kingdom	2010-12-01 08:26:00	40	(5, 8]

			WATER BOTTLE						
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	3.39	United Kingdom	2010-12-01 08:26:00	40	(5, 8]

Extracting and bucketing dates

We have noticed that depending on the season gifts sell differently:

1. pick of sales is in the Q4
2. then it drastically drops in Q1 of the next year
3. and continues to grow till its new pick in Q4 again.

From this observation, we can create another feature that could improve our model.

In [55]:
```
data_clean['Month'] = data_clean['InvoiceDate'].dt.month
data_clean.head()
```

Out[55]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	Country	InvoiceDate	QuantityInv	QuantityRange
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2.55	United Kingdom	2010-12-01 08:26:00	40	(5, 8]
1	536365	71053	WHITE METAL LANTERN	6	3.39	United Kingdom	2010-12-01 08:26:00	40	(5, 8]
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2.75	United Kingdom	2010-12-01 08:26:00	40	(5, 8]
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	3.39	United Kingdom	2010-12-01 08:26:00	40	(5, 8]
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	3.39	United Kingdom	2010-12-01 08:26:00	40	(5, 8]

In [56]:
```
bins_d = pd.IntervalIndex.from_tuples([(0,3),(3,6),(6,9),(9,12)])
data_clean['DateRange'] = pd.cut(data_clean['Month'], bins=bins_d, labels=['q1','q2','q3
data_clean.tail()
```

Out[56]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	Country	InvoiceDate	QuantityInv	QuantityRa
520390	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	0.85	France	2011-12-09 12:50:00	105	(11
520391	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2.10	France	2011-12-09 12:50:00	105	(
520392	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	4.15	France	2011-12-09 12:50:00	105	(

520393	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	4.15	France	2011-12-09 12:50:00	105	(
520394	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	4.95	France	2011-12-09 12:50:00	105	(

Building a model

Splitting data into UK and non-UK
We have to analyze these 2 datasets separately to have more standardized data for a model because there can be some patterns that work for other countries and do not for the UK or vice versa.
Also a hypothesis to test - does the model built for the UK performs well on data for other countries?

In [57]:
```
data_uk = data_clean[data_clean['Country'] == 'United Kingdom']
data_abroad = data_clean[data_clean['Country'] != 'United Kingdom']
```

In [58]:
```
data_uk.head()
```

Out[58]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	Country	InvoiceDate	QuantityInv	QuantityRange	I
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2.55	United Kingdom	2010-12-01 08:26:00	40	(5, 8]	
1	536365	71053	WHITE METAL LANTERN	6	3.39	United Kingdom	2010-12-01 08:26:00	40	(5, 8]	
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2.75	United Kingdom	2010-12-01 08:26:00	40	(5, 8]	
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	3.39	United Kingdom	2010-12-01 08:26:00	40	(5, 8]	
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	3.39	United Kingdom	2010-12-01 08:26:00	40	(5, 8]	

Extracting features and creating dummy variables

In [59]:
```
data_uk_model = data_uk[['UnitPrice', 'QuantityInv', 'QuantityRange', 'PriceRange', 'Dat
```

In [60]:
```
data_uk_model.head()
```

Out[60]:

	UnitPrice	QuantityInv	QuantityRange	PriceRange	DateRange
0	2.55	40	(5, 8]	(2, 3]	(9, 12]
1	3.39	40	(5, 8]	(3, 4]	(9, 12]
2	2.75	40	(5, 8]	(2, 3]	(9, 12]
3	3.39	40	(5, 8]	(3, 4]	(9, 12]

4	3.39	40	(5, 8]	(3, 4]	(9, 12]

In [61]:
```
data_uk_model_copy = data_uk_model.copy()
data_uk_model_copy = pd.get_dummies(data_uk_model_copy, columns=['QuantityRange'], prefi
data_uk_model_copy = pd.get_dummies(data_uk_model_copy, columns=['PriceRange'], prefix='
data_uk_model_copy = pd.get_dummies(data_uk_model_copy, columns=['DateRange'], prefix='d
data_uk_model_copy.head()
```

Out[61]:

	UnitPrice	QuantityInv	qr_(0, 2]	qr_(2, 5]	qr_(5, 8]	qr_(8, 11]	qr_(11, 14]	qr_(15, 5000]	pr_(0, 1]	pr_(1, 2]	pr_(2, 3]	pr_(3, 4]	pr_(4, 20]	dr_
0	2.55	40	False	False	True	False	False	False	False	False	True	False	False	Fa
1	3.39	40	False	False	True	False	False	False	False	False	False	True	False	Fa
2	2.75	40	False	False	True	False	False	False	False	False	True	False	False	Fa
3	3.39	40	False	False	True	False	False	False	False	False	False	True	False	Fa
4	3.39	40	False	False	True	False	False	False	False	False	False	True	False	Fa

Scaling

As the majority of our features are in the 0-1 range it would make sense to scale the "QuantityInv" feature too. In general, scaling features is normally a good idea.

In [62]:
```
from sklearn.preprocessing import scale

data_uk_model_copy['QuantityInv'] = scale(data_uk_model_copy['QuantityInv'])
```

Train-Test Split

Now we have to split our data into train-test data to be able to train our model and validate its capabilities.

In [63]:
```
y = data_uk_model_copy['UnitPrice']
X = data_uk_model_copy.drop(columns=['UnitPrice'])
```

In [64]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state
```

Testing and validating different models

We use GridSearch and CrossValidation to test three types of regressors:

1. Linear
2. Decision Tree
3. RandomForest

In [65]:
```
from sklearn.model_selection import KFold
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.linear_model import Lasso


from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
```

Linear Regression

In [73]:
```
# Initialize the model
linear_model = LinearRegression(fit_intercept=True)

# Fit the model to your data
linear_model.fit(X_train, y_train)

# Predict using the model
y_pred_linear = linear_model.predict(X_test)
```

Decision Tree

In [74]:
```
# Initialize the model
tree_model = DecisionTreeRegressor(min_samples_split=2, min_samples_leaf=2)

# Fit the model to your data
tree_model.fit(X_train, y_train)

# Predict using the model
y_pred_tree = tree_model.predict(X_test)
```

Random Forest

In [75]:
```
# Initialize the model
forest_model = RandomForestRegressor(n_estimators=100, min_samples_split=2, min_samples_

# Fit the model to your data
forest_model.fit(X_train, y_train)

# Predict using the model
y_pred_forest = forest_model.predict(X_test)
```

Gradient Boosting Regressor

In [86]:
```
# Initialize the Gradient Boosting Regressor
gb_regressor = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1, max_depth=

# Fit the model to your training data
gb_regressor.fit(X_train, y_train)

# Make predictions on the test data
y_pred_gb = gb_regressor.predict(X_test)
```

Lasso Regressor Model

In [87]:
```
# Initialize the Lasso Regression model
lasso_regressor = Lasso(alpha=1.0, random_state=42)  # Adjust alpha as needed

# Fit the model to your training data
lasso_regressor.fit(X_train, y_train)

# Make predictions on the test data
y_pred_lasso = lasso_regressor.predict(X_test)
```

Testing and validating

In [88]:
```
# Calculate metrics for Linear Regression
print("=== Linear Regression ===")
print(f"R2 Score: {r2_score(y_test, y_pred_linear)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_linear)}")
print(f"MAE: {mean_absolute_error(y_test, y_pred_linear)}")
print()
```

```python
# Calculate metrics for Decision Tree
print("=== Decision Tree ===")
print(f"R2 Score: {r2_score(y_test, y_pred_tree)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_tree)}")
print(f"MAE: {mean_absolute_error(y_test, y_pred_tree)}")
print()

# Calculate metrics for Random Forest
print("=== Random Forest ===")
print(f"R2 Score: {r2_score(y_test, y_pred_forest)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_forest)}")
print(f"MAE: {mean_absolute_error(y_test, y_pred_forest)}")
print()

# Calculate and print metrics
print("=== Gradient Boosting Regressor ===")
print(f"R2 Score: {r2_score(y_test, y_pred_gb)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_gb)}")
print(f"MAE: {mean_absolute_error(y_test, y_pred_gb)}")
print()

# Calculate and print metrics
print("=== Lasso Regression ===")
print(f"R2 Score: {r2_score(y_test, y_pred_lasso)}")
print(f"MSE: {mean_squared_error(y_test, y_pred_lasso)}")
print(f"MAE: {mean_absolute_error(y_test, y_pred_lasso)}")
print()
```

```
=== Linear Regression ===
R2 Score: 0.7550627023964682
MSE: 1.735768891612557
MAE: 0.715300133373285

=== Decision Tree ===
R2 Score: 0.7595972901103106
MSE: 1.7036341519588327
MAE: 0.6499699179900695

=== Random Forest ===
R2 Score: 0.7636692224318875
MSE: 1.674778058902783
MAE: 0.6466656250878114

=== Gradient Boosting Regressor ===
R2 Score: 0.7635900169614377
MSE: 1.6753393551732878
MAE: 0.6743652295208982

=== Lasso Regression ===
R2 Score: -3.8394511612249715e-05
MSE: 7.08685672861932
MAE: 1.9765376622226607
```