Ahmet Selimhan SAHIN FLO Project

Istanbul Bilgi University

118203061

Warehouse Optimization

Within this kernel we will analyse sales data of an UK online retailer. As storage area may be expensive and fast delivery on time is important to prevail over the competition we like to help the retailer by predicting daily amounts of sold products.

In [1]:
```
hide-output
pip install catboost;
```

```
Requirement already satisfied: catboost in d:\programs\anaconda\lib\site-packages (1.0.6)
Requirement already satisfied: scipy in d:\programs\anaconda\lib\site-packages (from catboos
t) (1.7.3)
Requirement already satisfied: matplotlib in d:\programs\anaconda\lib\site-packages (from cat
boost) (3.5.1)
Requirement already satisfied: graphviz in d:\programs\anaconda\lib\site-packages (from catbo
ost) (0.20.1)
Requirement already satisfied: numpy>=1.16.0 in d:\programs\anaconda\lib\site-packages (from
catboost) (1.21.5)
Requirement already satisfied: pandas>=0.24.0 in d:\programs\anaconda\lib\site-packages (from
catboost) (1.4.2)
Requirement already satisfied: plotly in d:\programs\anaconda\lib\site-packages (from catboos
t) (5.6.0)
Requirement already satisfied: six in d:\programs\anaconda\lib\site-packages (from catboost)
(1.16.0)
Requirement already satisfied: pytz>=2020.1 in d:\programs\anaconda\lib\site-packages (from p
andas>=0.24.0->catboost) (2021.3)
Requirement already satisfied: python-dateutil>=2.8.1 in d:\programs\anaconda\lib\site-packag
es (from pandas>=0.24.0->catboost) (2.8.2)
Requirement already satisfied: pyparsing>=2.2.1 in d:\programs\anaconda\lib\site-packages (fr
om matplotlib->catboost) (3.0.4)
Requirement already satisfied: packaging>=20.0 in d:\programs\anaconda\lib\site-packages (fro
m matplotlib->catboost) (21.3)
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atplotlib->catboost) (0.11.0)
Requirement already satisfied: pillow>=6.2.0 in d:\programs\anaconda\lib\site-packages (from
matplotlib->catboost) (9.0.1)
Requirement already satisfied: fonttools>=4.22.0 in d:\programs\anaconda\lib\site-packages (f
rom matplotlib->catboost) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in d:\programs\anaconda\lib\site-packages (f
rom matplotlib->catboost) (1.3.2)
Requirement already satisfied: tenacity>=6.2.0 in d:\programs\anaconda\lib\site-packages (fro
m plotly->catboost) (8.0.1)
Note: you may need to restart the kernel to use updated packages.
```

In [113…
```
pip install shap
```

```
Requirement already satisfied: shap in d:\programs\anaconda\lib\site-packages (0.41.0)
Requirement already satisfied: numba in d:\programs\anaconda\lib\site-packages (from shap)
(0.55.1)
Requirement already satisfied: pandas in d:\programs\anaconda\lib\site-packages (from shap)
(1.4.2)
Requirement already satisfied: packaging>20.9 in d:\programs\anaconda\lib\site-packages (from
shap) (21.3)
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(1.7.3)
Requirement already satisfied: scikit-learn in d:\programs\anaconda\lib\site-packages (from s
hap) (1.0.2)
Requirement already satisfied: slicer==0.0.7 in d:\programs\anaconda\lib\site-packages (from
shap) (0.0.7)
Requirement already satisfied: tqdm>4.25.0 in d:\programs\anaconda\lib\site-packages (from sh
ap) (4.64.0)
Requirement already satisfied: numpy in d:\programs\anaconda\lib\site-packages (from shap)
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Requirement already satisfied: cloudpickle in d:\programs\anaconda\lib\site-packages (from sh
ap) (2.0.0)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in d:\programs\anaconda\lib\site-pack
ages (from packaging>20.9->shap) (3.0.4)
Requirement already satisfied: colorama in d:\programs\anaconda\lib\site-packages (from tqdm>
4.25.0->shap) (0.4.4)
Requirement already satisfied: setuptools in d:\programs\anaconda\lib\site-packages (from num
ba->shap) (61.2.0)
Requirement already satisfied: llvmlite<0.39,>=0.38.0rc1 in d:\programs\anaconda\lib\site-pac
kages (from numba->shap) (0.38.0)
Requirement already satisfied: pytz>=2020.1 in d:\programs\anaconda\lib\site-packages (from p
andas->shap) (2021.3)
Requirement already satisfied: python-dateutil>=2.8.1 in d:\programs\anaconda\lib\site-packag
es (from pandas->shap) (2.8.2)
Requirement already satisfied: six>=1.5 in d:\programs\anaconda\lib\site-packages (from pytho
n-dateutil>=2.8.1->pandas->shap) (1.16.0)
Requirement already satisfied: joblib>=0.11 in d:\programs\anaconda\lib\site-packages (from s
cikit-learn->shap) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in d:\programs\anaconda\lib\site-packages
(from scikit-learn->shap) (2.2.0)
Note: you may need to restart the kernel to use updated packages.
```

In [3]:

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

import seaborn as sns
sns.set()

from catboost import CatBoostRegressor, Pool, cv
from catboost import MetricVisualizer

from sklearn.model_selection import TimeSeriesSplit
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

from scipy.stats import boxcox
from os import listdir

import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.filterwarnings("ignore", category=UserWarning)
warnings.filterwarnings("ignore", category=RuntimeWarning)
warnings.filterwarnings("ignore", category=FutureWarning)

import shap
shap.initjs()
```

In [4]:
```
import pandas as pd
import numpy as np
data = pd.read_csv('C:/Users/Selimhan/Desktop/FLO project/data.csv',encoding= 'unicode_escape
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	17850.0	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

We can see that the datafile has information given for each single transaction. Take a look at the InvoiceNo and the CustomerID of the first entries. Here we can see that one customer with ID 17850 of the United Kingdom made a single order that has the InvoideNo 536365. The customer ordered several products with different stockcodes, descriptions, unit prices and quantities. In addition we can see that the InvoiceDate was the same for these products.

In [5]:
```
data.shape
```

Out[5]:
```
(541909, 8)
```

The data has 541909 entries and 8 variables.

Get an initial feeling for the data by exploration

Missing values

How many % of missing values do we have for each feature?

In [6]:
```
missing_percentage = data.isnull().sum() / data.shape[0] * 100
missing_percentage
```

Out[6]:
```
InvoiceNo       0.000000
StockCode       0.000000
Description     0.268311
Quantity        0.000000
InvoiceDate     0.000000
UnitPrice       0.000000
CustomerID     24.926694
Country         0.000000
dtype: float64
```

Almost 25 % of the customers are unknown! That's very strange. In addition we have 0.2 % of missing descriptions. This looks dirty. Let's gain a further impression by considering some examples.

In [7]:
```
data[data.Description.isnull()].head()
```

Out[7]:

	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

How often do we miss the customer as well?

In [8]:
```
data[data.Description.isnull()].CustomerID.isnull().value_counts()
```

Out[8]:
```
True    1454
Name: CustomerID, dtype: int64
```

And the unit price?

In [9]:
```
data[data.Description.isnull()].UnitPrice.value_counts()
```

Out[9]:
```
0.0    1454
Name: UnitPrice, dtype: int64
```

In cases of missing descriptions we always miss the customer and the unit price as well. Why does the retailer records such kind of entries without a further description? It seems that there is no sophisticated procedure how to deal with and record such kind of transactions. This is already a hint that we could expect strange entries in our data and that it can be difficult to detect them!

Missing Customer IDs

In [10]:
```
data[data.CustomerID.isnull()].head()
```

Out[10]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
622	536414	22139	NaN	56	12/1/2010 11:52	0.00	NaN	United Kingdom
1443	536544	21773	DECORATIVE ROSE BATHROOM BOTTLE	1	12/1/2010 14:32	2.51	NaN	United Kingdom
1444	536544	21774	DECORATIVE CATS BATHROOM BOTTLE	2	12/1/2010 14:32	2.51	NaN	United Kingdom
1445	536544	21786	POLKADOT RAIN HAT	4	12/1/2010 14:32	0.85	NaN	United Kingdom
1446	536544	21787	RAIN PONCHO RETROSPOT	2	12/1/2010 14:32	1.66	NaN	United Kingdom

In [11]:
```
data.loc[data.CustomerID.isnull(), ["UnitPrice", "Quantity"]].describe()
```

Out[11]:

	UnitPrice	Quantity
count	135080.000000	135080.000000
mean	8.076577	1.995573
std	151.900816	66.696153
min	-11062.060000	-9600.000000
25%	1.630000	1.000000
50%	3.290000	1.000000
75%	5.450000	3.000000
max	17836.460000	5568.000000

That's bad as well. The price and the quantities of entries without a customer ID can show extreme outliers. As we might want to create features later on that are based on historical prices and sold quantities, this is very disruptive. Our first advice for the retailer is to setup strategies for transactions that are somehow faulty or special. And the question remains: Why is it possible for a transaction to be without a customer ID. Perhaps you can purchase as a quest but then it would of a good and clean style to plugin a special ID that indicates that this one is a guest. Ok, next one: Do we have hidden nan-values in Descriptions? To find it out, let's create a new feature that hold descriptions in lowercase:

Hidden missing descriptions

Can we find "nan"-Strings?

In [12]:
```
data.loc[data.Description.isnull()==False, "lowercase_descriptions"] = data.loc[
    data.Description.isnull()==False,"Description"
].apply(lambda l: l.lower())

data.lowercase_descriptions.dropna().apply(
    lambda l: np.where("nan" in l, True, False)
).value_counts()
```

Out[12]:
```
False    539724
True        731
Name: lowercase_descriptions, dtype: int64
```

Can we find empty ""-strings?

In [13]:
```
data.lowercase_descriptions.dropna().apply(
    lambda l: np.where("" == l, True, False)
).value_counts()
```

Out[13]:
```
False    540455
Name: lowercase_descriptions, dtype: int64
```

We found additional, hidden nan-values that show a string "nan" instead of a nan-value. Let's transform them to NaN:

In [14]:
```
data.loc[data.lowercase_descriptions.isnull()==False, "lowercase_descriptions"] = data.loc[
    data.lowercase_descriptions.isnull()==False, "lowercase_descriptions"
].apply(lambda l: np.where("nan" in l, None, l))
```

As we don't know why customers or descriptions are missing and we have seen strange outliers in quantities and prices as well as zero-prices, let's play safe and drop all of these occurences.

In [15]:
```
data = data.loc[(data.CustomerID.isnull()==False) & (data.lowercase_descriptions.isnull()==Fa
```

Just to be sure: Is there a missing value left?

In [16]:
```
data.isnull().sum().sum()
```

Out[16]:
```
0
```

The Time period

How long is the period in days?

In [17]:
```
data["InvoiceDate"] = pd.to_datetime(data.InvoiceDate, cache=True)

data.InvoiceDate.max() - data.InvoiceDate.min()
```

Out[17]:
```
Timedelta('373 days 04:24:00')
```

Datafile starts with timepoint 2010-12-01 08:26:00

Datafile ends with timepoint 2011-12-09 12:50:00

The invoice number

How many different invoice numbers do we have?

In [18]:
```
data.InvoiceNo.nunique()
```

Out[18]:
```
22186
```

In the data description we can find that a cancelled transactions starts with a "C" in front of it. Let's create a feature to easily filter out these cases:

In [19]:
```
data["IsCancelled"]=np.where(data.InvoiceNo.apply(lambda l: l[0]=="C"), True, False)
data.IsCancelled.value_counts() / data.shape[0] * 100
```

Out[19]:
```
False    97.81007
True      2.18993
Name: IsCancelled, dtype: float64
```

2,2 % of all entries are cancellations

In [20]:
```
data.loc[data.IsCancelled==True].describe()
```

Out[20]:

	Quantity	UnitPrice	CustomerID
count	8896.000000	8896.000000	8896.000000
mean	-30.882981	18.862815	14991.575202
std	1170.746458	444.590459	1707.208018
min	-80995.000000	0.010000	12346.000000
25%	-6.000000	1.450000	13506.000000
50%	-2.000000	2.950000	14895.000000
75%	-1.000000	4.950000	16393.000000
max	-1.000000	38970.000000	18282.000000

All cancellations have negative quantites but positive, non-zero unit prices. Given this data we are not easily able to understand why a customer made a return and it's very difficult to predict such cases as there could be several, hidden reasons why a cancellation was done. Let's drop them

In [21]:
```
data = data.loc[data.IsCancelled==False].copy()
data = data.drop("IsCancelled", axis=1)
```

Stockcodes

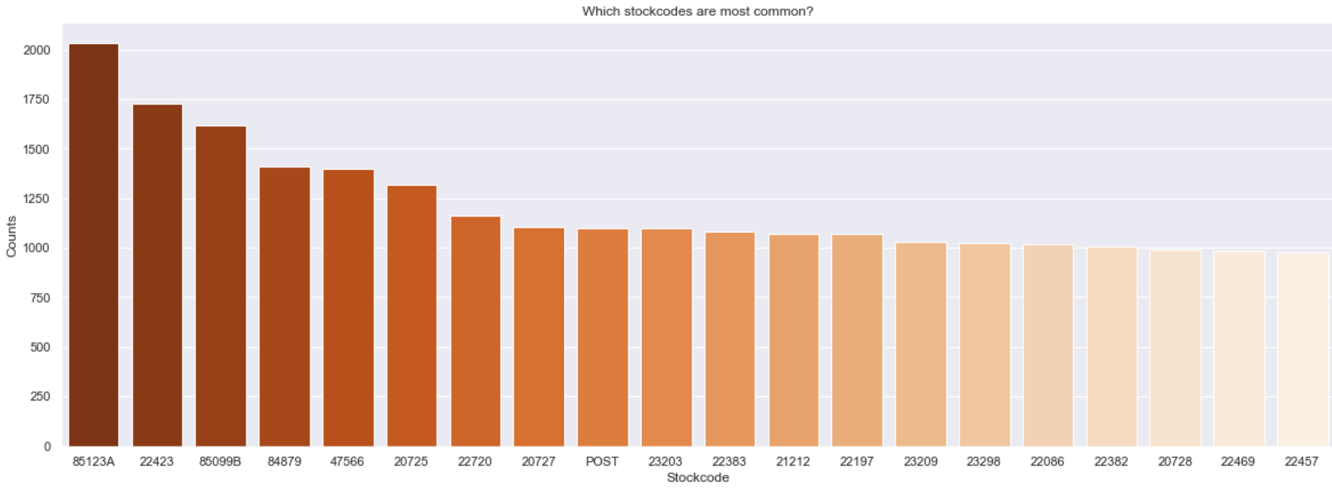
How many unique stockcodes do we have?

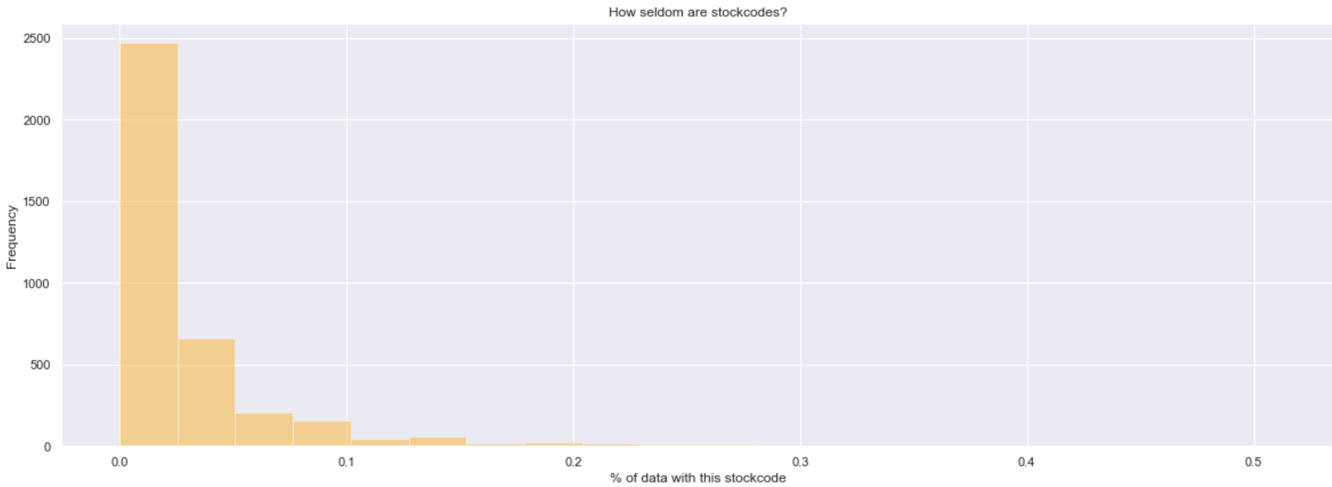
In [22]:
```
data.StockCode.nunique()
```

Out[22]:
```
3663
```

Which codes are most common?

In [23]:
```
stockcode_counts = data.StockCode.value_counts().sort_values(ascending=False)
fig, ax = plt.subplots(2,1,figsize=(20,15))
sns.barplot(stockcode_counts.iloc[0:20].index,
            stockcode_counts.iloc[0:20].values,
            ax = ax[0], palette="Oranges_r")
ax[0].set_ylabel("Counts")
ax[0].set_xlabel("Stockcode")
ax[0].set_title("Which stockcodes are most common?");
sns.distplot(np.round(stockcode_counts/data.shape[0]*100,2),
             kde=False,
             bins=20,
             ax=ax[1], color="Orange")
ax[1].set_title("How seldom are stockcodes?")
ax[1].set_xlabel("% of data with this stockcode")
ax[1].set_ylabel("Frequency");
```





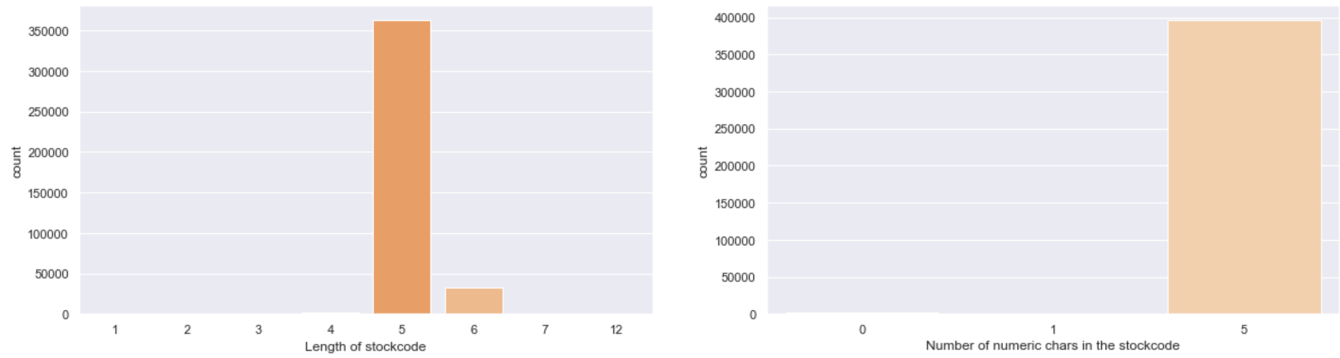
- Do you the the POST in the most common stockcode counts?! That's a strange one! Hence we could expect strange occurences not only in the descriptions and customerIDs but also in the stockcode. OHOHOH! It's code is shorter than the others as well as not numeric.
- Most stockcodes are very seldom. This indicates that the retailer sells many different products and that there is no strong secialization of a specific stockcode. Nevertheless we have to be careful as this must not mean that the retailer is not specialized given a specific product type. The stockcode could be a very detailed indicator that does not yield information of the type, for example water bottles may have very different variants in color, name and shapes but they are all water bottles.

Let's count the number of numeric chars in and the length of the stockcode:

In [24]:
```
def count_numeric_chars(l):
    return sum(1 for c in l if c.isdigit())

data["StockCodeLength"] = data.StockCode.apply(lambda l: len(l))
data["nNumericStockCode"] = data.StockCode.apply(lambda l: count_numeric_chars(l))
```

In [25]:
```
fig, ax = plt.subplots(1,2,figsize=(20,5))
sns.countplot(data["StockCodeLength"], palette="Oranges_r", ax=ax[0])
sns.countplot(data["nNumericStockCode"], palette="Oranges_r", ax=ax[1])
ax[0].set_xlabel("Length of stockcode")
ax[1].set_xlabel("Number of numeric chars in the stockcode");
```



Even though the majority of samples has a stockcode that consists of 5 numeric chars, we can see that there are other occurences as well. The length can vary between 1 and 12 and there are stockcodes with no numeric chars at all!

In [26]:
```
data.loc[data.nNumericStockCode < 5].lowercase_descriptions.value_counts()
```

Out[26]:
```
postage                    1099
manual                      290
carriage                    133
dotcom postage               16
bank charges                 12
pads to match all cushions    4
Name: lowercase_descriptions, dtype: int64
```

Oops,again something that we don't want to predict. Again this indicates that the retailer does not speparate well between special kind of transactions and valid customer-retailer transactions. Let's drop all of these occurences:

In [27]:
```
data = data.loc[(data.nNumericStockCode == 5) & (data.StockCodeLength==5)].copy()
data.StockCode.nunique()
```

Out[27]:
```
2783
```

In [28]:
```
data = data.drop(["nNumericStockCode", "StockCodeLength"], axis=1)
```

Descriptions

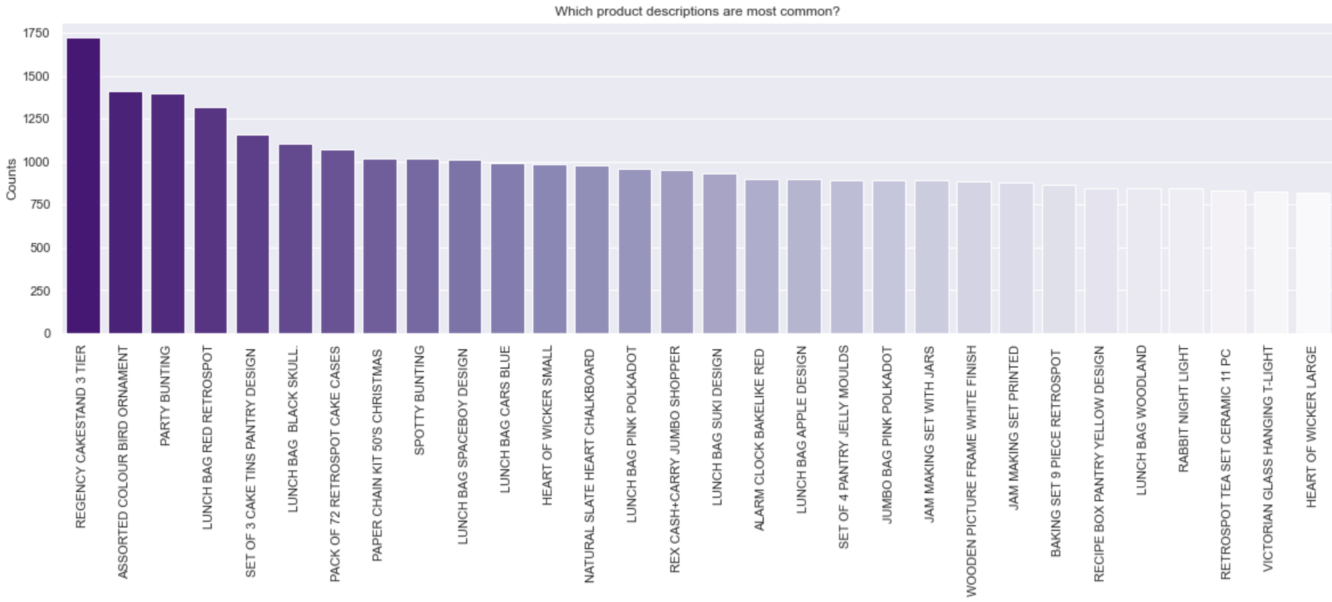
How many unique descriptions do we have?

In [29]:
```
data.Description.nunique()
```

Out[29]:
```
2983
```

And which are most common?

In [30]:
```
description_counts = data.Description.value_counts().sort_values(ascending=False).iloc[0:30]
plt.figure(figsize=(20,5))
sns.barplot(description_counts.index, description_counts.values, palette="Purples_r")
plt.ylabel("Counts")
plt.title("Which product descriptions are most common?");
plt.xticks(rotation=90);
```

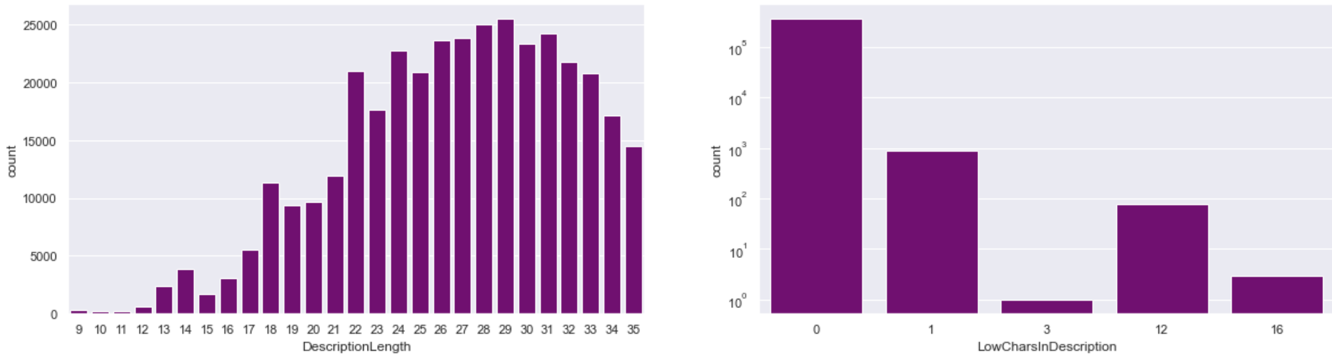


Ok, we can see that some descriptions correspond to a similar product type. Do you see the multiple occurences of lunch bags? We often have color information about the product as well. Furthermore the most common descriptions seem to confirm that the retailer sells various different kinds of products. All descriptions seem to consist of uppercase chars. Ok, now let's do some addtional analysis on the descriptions by counting the length and the number of lowercase chars.

In [31]:
```
def count_lower_chars(l):
    return sum(1 for c in l if c.islower())
```

In [32]:
```
data["DescriptionLength"] = data.Description.apply(lambda l: len(l))
data["LowCharsInDescription"] = data.Description.apply(lambda l: count_lower_chars(l))
```

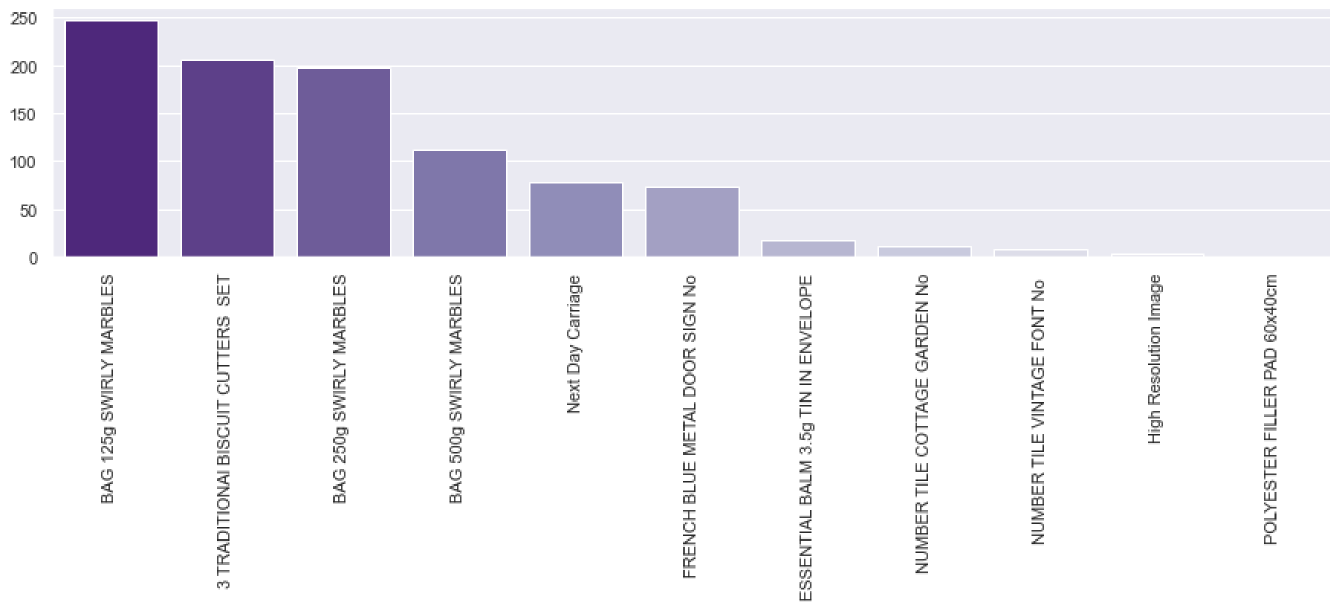
In [33]:
```
fig, ax = plt.subplots(1,2,figsize=(20,5))
sns.countplot(data.DescriptionLength, ax=ax[0], color="Purple")
sns.countplot(data.LowCharsInDescription, ax=ax[1], color="Purple")
ax[1].set_yscale("log")
```



Oh, great! Almost all descriptions do not have a lowercase chars, but we have found exceptional cases!

In [34]:
```
lowchar_counts = data.loc[data.LowCharsInDescription > 0].Description.value_counts()

plt.figure(figsize=(15,3))
sns.barplot(lowchar_counts.index, lowchar_counts.values, palette="Purples_r")
plt.xticks(rotation=90);
```



Next day carriage and high resolution image are strange! Let's compute the fraction of lower with respect to uppercase letters:

In [35]:
```
def count_upper_chars(l):
    return sum(1 for c in l if c.isupper())

data["UpCharsInDescription"] = data.Description.apply(lambda l: count_upper_chars(l))
```

In [36]:
```
data.UpCharsInDescription.describe()
```

Out[36]:
```
count    362522.000000
mean         22.572291
std           4.354845
min           3.000000
25%          20.000000
50%          23.000000
75%          26.000000
max          32.000000
Name: UpCharsInDescription, dtype: float64
```

In [37]:
```
data.loc[data.UpCharsInDescription <=5].Description.value_counts()
```

Out[37]:
```
Next Day Carriage        79
High Resolution Image     3
Name: Description, dtype: int64
```

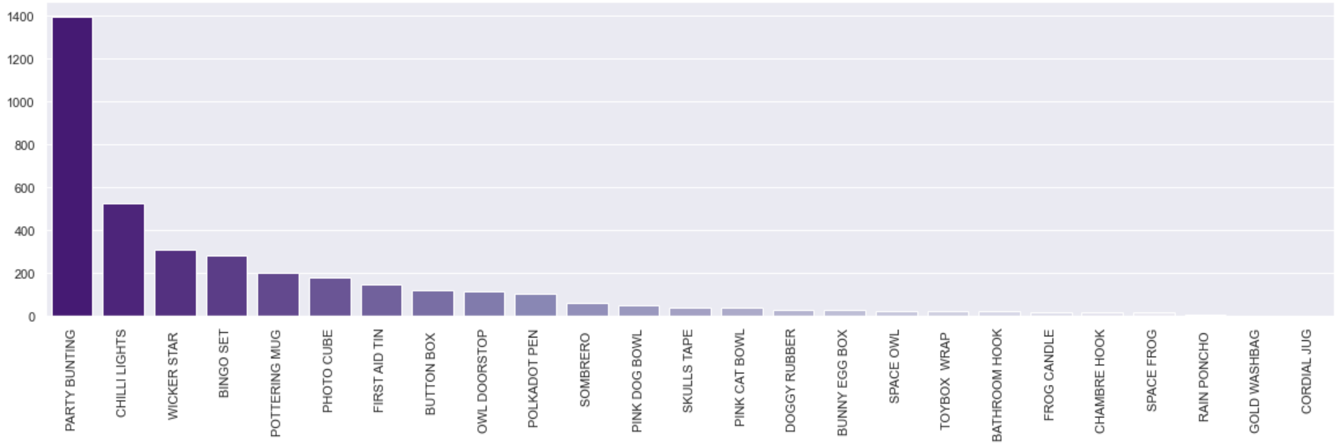
It's strange that they differ from the others. Let's drop them:

In [38]:
```
data = data.loc[data.UpCharsInDescription > 5].copy()
```

And what about the descriptions with a length below 14?

In [39]:
```
dlength_counts = data.loc[data.DescriptionLength < 14].Description.value_counts()

plt.figure(figsize=(20,5))
sns.barplot(dlength_counts.index, dlength_counts.values, palette="Purples_r")
plt.xticks(rotation=90);
```



Ok, descriptions with small length look valid and we should not drop them. Ok, now let's see how many unique stock codes do we have and how many unique descriptions?

In [40]:
```
data.StockCode.nunique()
```

Out[40]:
```
2781
```

In [41]:
```
data.Description.nunique()
```

Out[41]:
```
2981
```

We still have more descriptions than stockcodes and we should continue to find out why they differ.

In [42]:
```
data.groupby("StockCode").Description.nunique().sort_values(ascending=False).iloc[0:10]
```

Out[42]:
```
StockCode
23236    4
23196    4
23413    3
23244    3
23126    3
23203    3
23209    3
23366    3
23131    3
23535    3
Name: Description, dtype: int64
```

Wow, we still have stockcodes with multiple descriptions. Let's look at an example:

In [43]:
```
data.loc[data.StockCode == "23244"].Description.value_counts()
```

Out[43]:
```
ROUND STORAGE TIN VINTAGE LEAF    96
STORAGE TIN VINTAGE LEAF           7
CANNISTER VINTAGE LEAF DESIGN      2
Name: Description, dtype: int64
```

Ok, browsing through the cases we can see that stockcodes are sometimes named a bit differently due to missing or changed words or typing errors. None the less they look ok and we can continue.

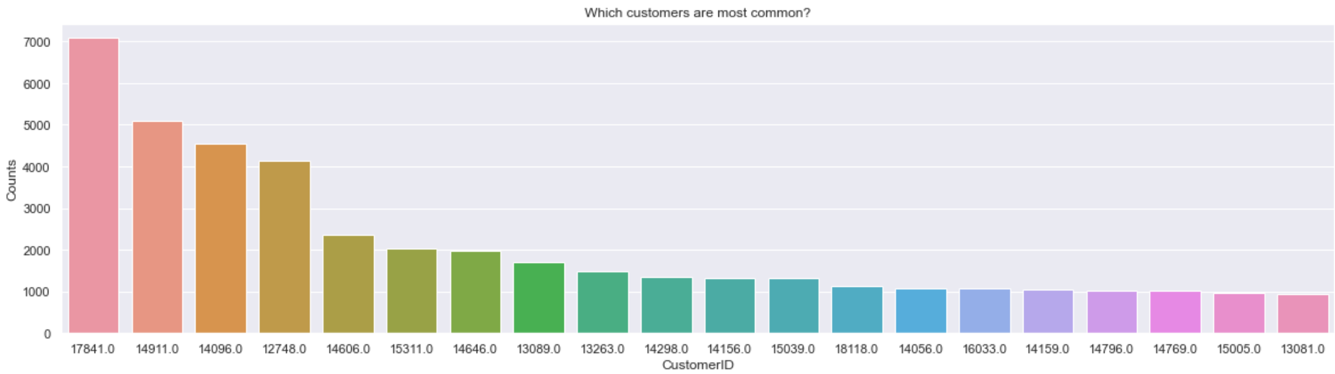
Customers

In [44]:
```
data.CustomerID.nunique()
```

Out[44]:
```
4315
```

In [45]:
```
customer_counts = data.CustomerID.value_counts().sort_values(ascending=False).iloc[0:20]
```

```
plt.figure(figsize=(20,5))
sns.barplot(customer_counts.index, customer_counts.values, order=customer_counts.index)
plt.ylabel("Counts")
plt.xlabel("CustomerID")
plt.title("Which customers are most common?");
#plt.xticks(rotation=90);
```



Countries

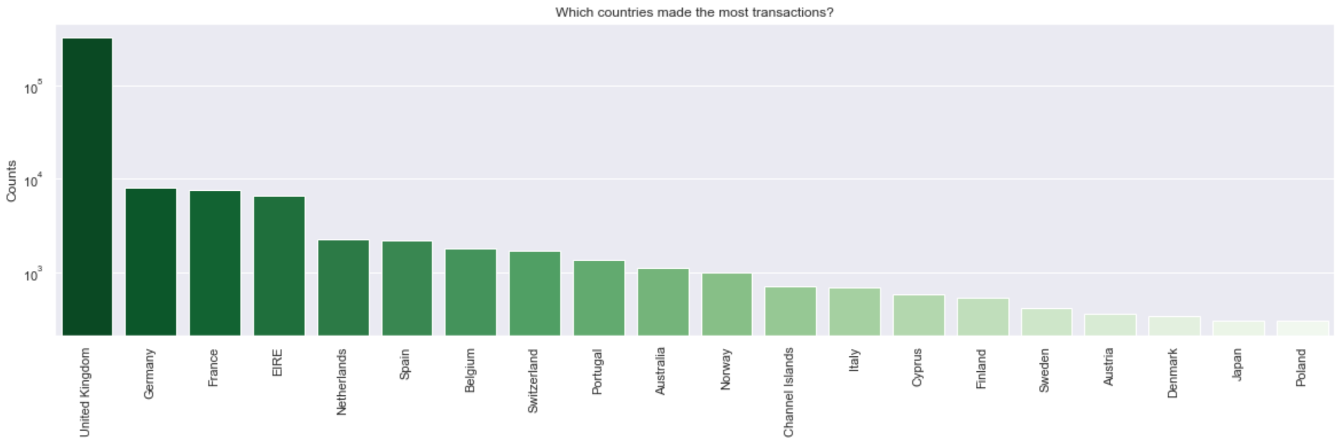
How many unique countries are delivered by the retailer?

In [46]:
```
data.Country.nunique()
```

Out[46]:
```
37
```

And which ones are most common?

In [47]:
```
country_counts = data.Country.value_counts().sort_values(ascending=False).iloc[0:20]
plt.figure(figsize=(20,5))
sns.barplot(country_counts.index, country_counts.values, palette="Greens_r")
plt.ylabel("Counts")
plt.title("Which countries made the most transactions?");
plt.xticks(rotation=90);
plt.yscale("log")
```



We can see that the retailer sells almost all products in the UK, followed by many european countries. How many percentage of entries are inside UK?

In [48]:
```
data.loc[data.Country=="United Kingdom"].shape[0] / data.shape[0] * 100
```

Out[48]:
```
89.10192031784572
```

Let's create a feature to indicate inside or outside of the UK:

In [49]:
```
data["UK"] = np.where(data.Country == "United Kingdom", 1, 0)
```

Unit Price

In [50]:
```
data.UnitPrice.describe()
```

Out[50]:
```
count    362440.000000
mean          2.885355
std           4.361812
min           0.000000
25%           1.250000
50%           1.790000
75%           3.750000
max         649.500000
Name: UnitPrice, dtype: float64
```

Again, we have strange occurences: zero unit prices!

In [51]:
```
data.loc[data.UnitPrice == 0].sort_values(by="Quantity", ascending=False).head()
```

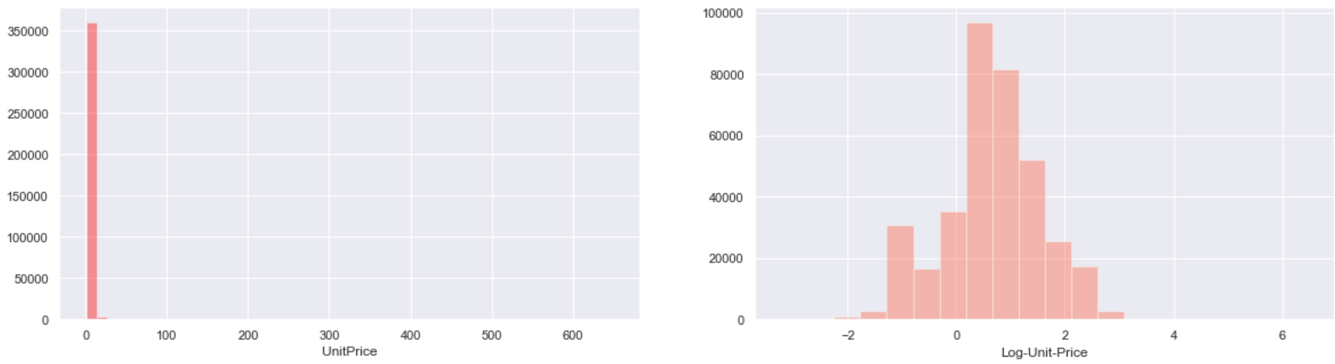
Out[51]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	lower
502122	578841	84826	ASSTD DESIGN 3D PAPER STICKERS	12540	2011-11-25 15:57:00	0.0	13256.0	United Kingdom	asst
298054	562973	23157	SET OF 6 NATIVITY MAGNETS	240	2011-08-11 11:42:00	0.0	14911.0	EIRE	set of
436428	574138	23234	BISCUIT TIN VINTAGE CHRISTMAS	216	2011-11-03 11:26:00	0.0	12415.0	Australia	
314746	564651	23268	SET OF 2 CERAMIC CHRISTMAS REINDEER	192	2011-08-26 14:19:00	0.0	14646.0	Netherlands	
314748	564651	21786	POLKADOT RAIN HAT	144	2011-08-26 14:19:00	0.0	14646.0	Netherlands	

That's not good again. It's not obvious if they are gifts to customers or not :-(Let's drop them:

In [52]:
```
data = data.loc[data.UnitPrice > 0].copy()
```

In [53]:
```
fig, ax = plt.subplots(1,2,figsize=(20,5))
sns.distplot(data.UnitPrice, ax=ax[0], kde=False, color="red")
sns.distplot(np.log(data.UnitPrice), ax=ax[1], bins=20, color="tomato", kde=False)
ax[1].set_xlabel("Log-Unit-Price");
```



In [54]:
```
np.exp(-2)
```

Out[54]: 0.1353352832366127

In [55]:
```
np.exp(3)
```

Out[55]: 20.085536923187668

In [56]:
```
np.quantile(data.UnitPrice, 0.95)
```

Out[56]: 8.5

Let's focus transactions with prices that fall into this range as we don't want to make predictions for very seldom products with high prices. Starting easy is always good!

In [57]:
```
data = data.loc[(data.UnitPrice > 0.1) & (data.UnitPrice < 20)].copy()
```

Quantities

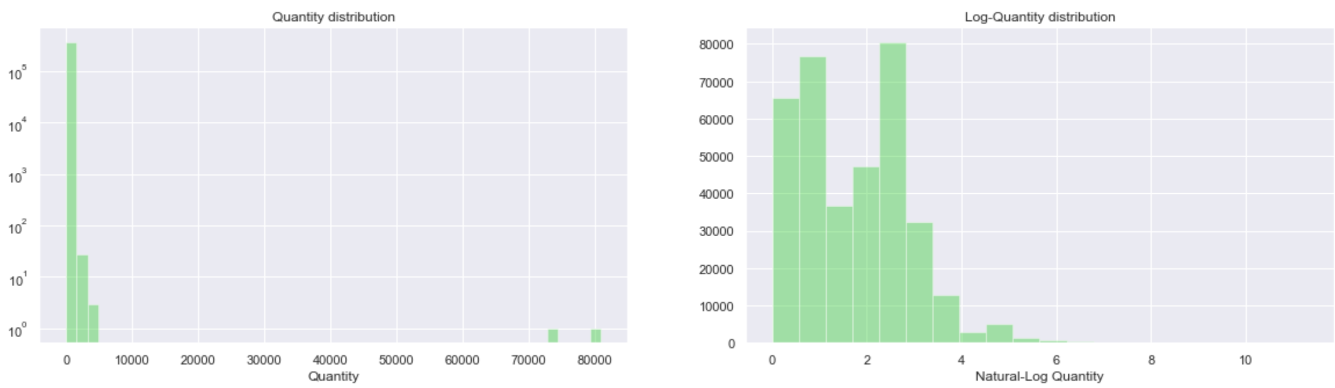
Ok, the most important one - the target. Let's take a look at its distribution:

In [58]:
```
data.Quantity.describe()
```

Out[58]:
```
count    361608.000000
mean         13.024112
std         187.566510
min           1.000000
25%           2.000000
50%           6.000000
75%          12.000000
max       80995.000000
Name: Quantity, dtype: float64
```

Ok, most products are sold in quantities from 1 to 12. But, we have extreme, unrealistic outliers again:

In [59]:
```
fig, ax = plt.subplots(1,2,figsize=(20,5))
sns.distplot(data.Quantity, ax=ax[0], kde=False, color="limegreen");
sns.distplot(np.log(data.Quantity), ax=ax[1], bins=20, kde=False, color="limegreen");
ax[0].set_title("Quantity distribution")
ax[0].set_yscale("log")
ax[1].set_title("Log-Quantity distribution")
ax[1].set_xlabel("Natural-Log Quantity");
```



As you can see by the log-transformed distribution it would make sense to make a cut at:

In [60]:
```
np.exp(4)
```

Out[60]: 54.598150033144236

In [61]:
```
np.quantile(data.Quantity, 0.95)
```

Out[61]:
```
36.0
```

In this case we would still cover more than 95 % of the data!

In [62]:
```
data = data.loc[data.Quantity < 55].copy()
```

Focus on daily product sales

As we like to predict the daily amount of product sales, we need to compute a daily aggregation of this data. For this purpose we need to extract temporal features out of the InvoiceDate. In addition we can compute the revenue gained by a transaction using the unit price and the quantity:

In [63]:
```
data["Revenue"] = data.Quantity * data.UnitPrice

data["Year"] = data.InvoiceDate.dt.year
data["Quarter"] = data.InvoiceDate.dt.quarter
data["Month"] = data.InvoiceDate.dt.month
data["Week"] = data.InvoiceDate.dt.week
data["Weekday"] = data.InvoiceDate.dt.weekday
data["Day"] = data.InvoiceDate.dt.day
data["Dayofyear"] = data.InvoiceDate.dt.dayofyear
data["Date"] = pd.to_datetime(data[['Year', 'Month', 'Day']])
```

As the key task of this kernel is to predict the amount of products sold per day, we can sum up the daily quantities per product stockcode :

In [64]:
```
grouped_features = ["Date", "Year", "Quarter","Month", "Week", "Weekday", "Dayofyear", "Day",
                    "StockCode"]
```

This way we loose information abount customers, countries and price information but we will recover it later on during this kernel. Besides the quantities let's aggregate the revenues as well:

In [65]:
```
daily_data = pd.DataFrame(data.groupby(grouped_features).Quantity.sum(),
                          columns=["Quantity"])
daily_data["Revenue"] = data.groupby(grouped_features).Revenue.sum()
daily_data = daily_data.reset_index()
daily_data.head(5)
```

Out[65]:

	Date	Year	Quarter	Month	Week	Weekday	Dayofyear	Day	StockCode	Quantity	Revenue
0	2010-12-01	2010	4	12	48	2	335	1	10002	60	51.00
1	2010-12-01	2010	4	12	48	2	335	1	10125	2	1.70
2	2010-12-01	2010	4	12	48	2	335	1	10133	5	4.25
3	2010-12-01	2010	4	12	48	2	335	1	16014	10	4.20
4	2010-12-01	2010	4	12	48	2	335	1	16016	10	8.50

How are the quantities and revenues distributed?

In [66]:
```
daily_data.loc[:, ["Quantity", "Revenue"]].describe()
```

Out[66]:

	Quantity	Revenue
count	195853.000000	195853.000000
mean	14.964244	28.181114
std	18.809496	43.938183
min	1.000000	0.120000
25%	3.000000	6.950000
50%	9.000000	15.300000
75%	20.000000	30.600000
max	411.000000	1266.300000

As we can see by the min and max values the target variable shows extreme outliers. If we would like to use it as targets, we should exclude them as they will mislead our validation. As I like to use early stopping this will directly influence training of predictive models as well.

In [67]:
```
low_quantity = daily_data.Quantity.quantile(0.01)
high_quantity = daily_data.Quantity.quantile(0.99)
print((low_quantity, high_quantity))
```

```
(1.0, 88.48000000001048)
```

In [68]:
```
low_revenue = daily_data.Revenue.quantile(0.01)
high_revenue = daily_data.Revenue.quantile(0.99)
print((low_revenue, high_revenue))
```

```
(0.78, 204.0)
```

Let's only use target ranges data that are occupied by 90 % of the data entries. This is a first and easy strategy to exclude heavy outliers but we should always be aware of the fact that we have lost some information given by the remaining % we have excluded. It could be nice and useful in general to understand and analyse what has caused these outliers.

In [69]:
```
samples = daily_data.shape[0]
```

In [70]:
```
daily_data = daily_data.loc[
    (daily_data.Quantity >= low_quantity) & (daily_data.Quantity <= high_quantity)]
daily_data = daily_data.loc[
    (daily_data.Revenue >= low_revenue) & (daily_data.Revenue <= high_revenue)]
```

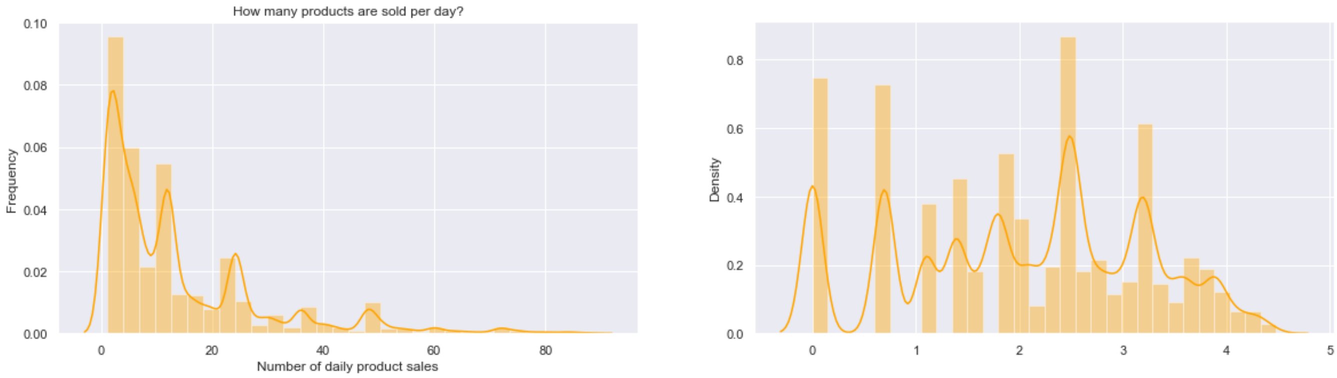
How much entries have we lost?

In [71]:
```
samples - daily_data.shape[0]
```

Out[71]:
```
5258
```

Let's take a look at the remaining distributions of daily quantities:

In [72]:
```
fig, ax = plt.subplots(1,2,figsize=(20,5))
sns.distplot(daily_data.Quantity.values, kde=True, ax=ax[0], color="Orange", bins=30);
sns.distplot(np.log(daily_data.Quantity.values), kde=True, ax=ax[1], color="Orange", bins=30)
ax[0].set_xlabel("Number of daily product sales");
ax[0].set_ylabel("Frequency");
ax[0].set_title("How many products are sold per day?");
```



We can see that the distributions are right skewed. Lower values are more common. In addition the daily sales quantities seem to be multimodal. A daily sale of 1 is common as well as a quantity of 12 and 24. This pattern is very interesting and leads to the conclusion that quantities are often divisible by 2 or 3. In a nutshell we can say that specific products are often bought as single quantites or in a small bunch.

How to predict daily product sales?

In this kernel I like to use catboost as predictive model. The prediction of daily quantities and revenues are both regression tasks and consequently I will use the catboost regressor. The loss and metric I like to use is the root mean square error (RMSE):

$$E = \sqrt{1/N \ \sum_{n=1}^{N} (t_n - y_n)^2}$$

It computes the error between the target value tn and the predicted value yn per sample, takes the square to make sure that both, positive and negative deviations, contribute to the sum the same way. Then the mean is taken by dividing with the total amount N of samples (entries) in the data. And finally to obtain an impression of the error for single predictions, the root is taken. What should we keep in mind when working with this loss and metric function? :-) It's heavily influenced by outliers! If we have some predictions that are far away from the targets, they will guide the mean towards higher values as well. Hence it could be that we will make nice predictions for a majority of samples but the RMSE is still high due to high errors for a minority of samples.

Validation strategy

As the data covers only one year and we have a high increase of sold products during pre-christmas period, we need to select validation data carefully. I will start with validation data that covers at least 8 full weeks (+ remaining days). After generating new features by exploring the data, I will use a sliding window time series validation that should help us to understand if the model is able to solve the prediction task during both times: pre-christmas season and non-christmas season.

Catboost family and hyperparameter class

To easily generate new models and compare results between them I wrote some classes:

Hyperparameter Class

This class holds all important hyperparameters we have to set before training like the loss function, the evaluation metric, the max depth of trees, the number of max number of trees (iterations) and the l2_leaf_reg for regularization to avoid overfitting.

In [73]:
```
class CatHyperparameter:
```

```
    def __init__(self,
                 loss="RMSE",
                 metric="RMSE",
                 iterations=1000,
                 max_depth=4,
                 l2_leaf_reg=3,
                 #learning_rate=0.5,
                 seed=0):
        self.loss = loss,
        self.metric = metric,
        self.max_depth = max_depth,
        self.l2_leaf_reg = l2_leaf_reg,
        #self.learning_rate = learning_rate,
        self.iterations=iterations
        self.seed = seed
```

Catmodel class

This model obtains a train & validation pool as data or pandas dataframes for features X and targets y together with a week. It's the first week of our validation data and all other weeks above are used as well. It trains the model and can show learning process as well as feature importances and some figures for result analysis. It's the fastest choice you can make for playing around.

In [74]:
```
class Catmodel:

    def __init__(self, name, params):
        self.name = name
        self.params = params

    def set_data_pool(self, train_pool, val_pool):
        self.train_pool = train_pool
        self.val_pool = val_pool

    def set_data(self, X, y, week):
        cat_features_idx = np.where(X.dtypes != np.float)[0]
        x_train, self.x_val = X.loc[X.Week < week], X.loc[X.Week >= week]
        y_train, self.y_val = y.loc[X.Week < week], y.loc[X.Week >= week]
        self.train_pool = Pool(x_train, y_train, cat_features=cat_features_idx)
        self.val_pool = Pool(self.x_val, self.y_val, cat_features=cat_features_idx)

    def prepare_model(self):
        self.model = CatBoostRegressor(
                loss_function = self.params.loss[0],
                random_seed = self.params.seed,
                logging_level = 'Silent',
                iterations = self.params.iterations,
                max_depth = self.params.max_depth[0],
                #learning_rate = self.params.learning_rate[0],
                l2_leaf_reg = self.params.l2_leaf_reg[0],
                od_type='Iter',
                od_wait=40,
                train_dir=self.name,
                has_time=True
            )

    def learn(self, plot=False):
        self.prepare_model()
        self.model.fit(self.train_pool, eval_set=self.val_pool, plot=plot);
        print("{}, early-stopped model tree count {}".format(
            self.name, self.model.tree_count_
        ))

    def score(self):
```

```python
        return self.model.score(self.val_pool)

    def show_importances(self, kind="bar"):
        explainer = shap.TreeExplainer(self.model)
        shap_values = explainer.shap_values(self.val_pool)
        if kind=="bar":
            return shap.summary_plot(shap_values, self.x_val, plot_type="bar")
        return shap.summary_plot(shap_values, self.x_val)

    def get_val_results(self):
        self.results = pd.DataFrame(self.y_val)
        self.results["prediction"] = self.predict(self.x_val)
        self.results["error"] = np.abs(
            self.results[self.results.columns.values[0]].values - self.results.prediction)
        self.results["Month"] = self.x_val.Month
        self.results["SquaredError"] = self.results.error.apply(lambda l: np.power(l, 2))

    def show_val_results(self):
        self.get_val_results()
        fig, ax = plt.subplots(1,2,figsize=(20,5))
        sns.distplot(self.results.error, ax=ax[0])
        ax[0].set_xlabel("Single absolute error")
        ax[0].set_ylabel("Density")
        self.median_absolute_error = np.median(self.results.error)
        print("Median absolute error: {}".format(self.median_absolute_error))
        ax[0].axvline(self.median_absolute_error, c="black")
        ax[1].scatter(self.results.prediction.values,
                      self.results[self.results.columns[0]].values,
                      c=self.results.error, cmap="RdYlBu_r", s=1)
        ax[1].set_xlabel("Prediction")
        ax[1].set_ylabel("Target")
        return ax

    def get_monthly_RMSE(self):
        return self.results.groupby("Month").SquaredError.mean().apply(lambda l: np.sqrt(l))

    def predict(self, x):
        return self.model.predict(x)

    def get_dependence_plot(self, feature1, feature2=None):
        explainer = shap.TreeExplainer(self.model)
        shap_values = explainer.shap_values(self.val_pool)
        if feature2 is None:
            return shap.dependence_plot(
                feature1,
                shap_values,
                self.x_val,
            )
        else:
            return shap.dependence_plot(
                feature1,
                shap_values,
                self.x_val,
                interaction_index=feature2
            )
```

Hyperparameter-Search class

This is a class for hyperparameter search that uses Bayesian Optimization and Gaussian Process Regression to find optimal hyperparameters. I decided to use this method as the computation of the score for one catfamily model may be expensive. In this case bayesian optimization could be a plus. As this optimization methods takes some time as well you should try random search as well as this may be faster.

In [75]:
```
pip install GPyOpt
```

```
Requirement already satisfied: GPyOpt in d:\programs\anaconda\lib\site-packages (1.2.6)
Requirement already satisfied: numpy>=1.7 in d:\programs\anaconda\lib\site-packages (from GPy
Opt) (1.21.5)
Requirement already satisfied: scipy>=0.16 in d:\programs\anaconda\lib\site-packages (from GP
yOpt) (1.7.3)
Requirement already satisfied: GPy>=1.8 in d:\programs\anaconda\lib\site-packages (from GPyOp
t) (1.10.0)
Requirement already satisfied: six in d:\programs\anaconda\lib\site-packages (from GPy>=1.8->
GPyOpt) (1.16.0)
Requirement already satisfied: cython>=0.29 in d:\programs\anaconda\lib\site-packages (from G
Py>=1.8->GPyOpt) (0.29.28)
Requirement already satisfied: paramz>=0.9.0 in d:\programs\anaconda\lib\site-packages (from
GPy>=1.8->GPyOpt) (0.9.5)
Requirement already satisfied: decorator>=4.0.10 in d:\programs\anaconda\lib\site-packages (f
rom paramz>=0.9.0->GPy>=1.8->GPyOpt) (5.1.1)
Note: you may need to restart the kernel to use updated packages.
```

In [76]:
```
import GPyOpt

class Hypertuner:

    def __init__(self, model, max_iter=10, max_time=10,max_depth=6, max_l2_leaf_reg=20):
        self.bounds = [{'name': 'depth','type': 'discrete','domain': (1,max_depth)},
                       {'name': 'l2_leaf_reg','type': 'discrete','domain': (1,max_l2_leaf_reg
        self.model = model
        self.max_iter=max_iter
        self.max_time=max_time
        self.best_depth = None
        self.best_l2_leaf_reg = None

    def objective(self, params):
        params = params[0]
        params = CatHyperparameter(
            max_depth=params[0],
            l2_leaf_reg=params[1]
        )
        self.model.params = params
        self.model.learn()
        return self.model.score()

    def learn(self):
        np.random.seed(777)
        optimizer = GPyOpt.methods.BayesianOptimization(
            f=self.objective, domain=self.bounds,
            acquisition_type ='EI',
            acquisition_par = 0.2,
            exact_eval=True)
        optimizer.run_optimization(self.max_iter, self.max_time)
        optimizer.plot_convergence()
        best = optimizer.X[np.argmin(optimizer.Y)]
        self.best_depth = best[0]
        self.best_l2_leaf_reg = best[1]
        print("Optimal depth is {} and optimal l2-leaf-reg is {}".format(self.best_depth, sel
        print('Optimal RMSE:', np.min(optimizer.Y))

    def retrain_catmodel(self):
        params = CatHyperparameter(
            max_depth=self.best_depth,
            l2_leaf_reg=self.best_l2_leaf_reg
        )
        self.model.params = params
        self.model.learn(plot=True)
        return self.model
```

Time series validation Catfamily

This model holds the information about how to split the data into validation chunks and it organizes the training with sliding window validation. Furthermore it can return a score as the mean over all RMSE scores of its models.

In [77]:
```python
class CatFamily:

    def __init__(self, params, X, y, n_splits=2):
        self.family = {}
        self.cat_features_idx = np.where(X.dtypes != np.float)[0]
        self.X = X.values
        self.y = y.values
        self.n_splits = n_splits
        self.params = params

    def set_validation_strategy(self):
        self.cv = TimeSeriesSplit(max_train_size = None,
                                  n_splits = self.n_splits)
        self.gen = self.cv.split(self.X)

    def get_split(self):
        train_idx, val_idx = next(self.gen)
        x_train, x_val = self.X[train_idx], self.X[val_idx]
        y_train, y_val = self.y[train_idx], self.y[val_idx]
        train_pool = Pool(x_train, y_train, cat_features=self.cat_features_idx)
        val_pool = Pool(x_val, y_val, cat_features=self.cat_features_idx)
        return train_pool, val_pool

    def learn(self):
        self.set_validation_strategy()
        self.model_names = []
        self.model_scores = []
        for split in range(self.n_splits):
            name = 'Model_cv_' + str(split) + '/'
            train_pool, val_pool = self.get_split()
            self.model_names.append(name)
            self.family[name], score = self.fit_catmodel(name, train_pool, val_pool)
            self.model_scores.append(score)

    def fit_catmodel(self, name, train_pool, val_pool):
        cat = Catmodel(name, train_pool, val_pool, self.params)
        cat.prepare_model()
        cat.learn()
        score = cat.score()
        return cat, score

    def score(self):
        return np.mean(self.model_scores)

    def show_learning(self):
        widget = MetricVisualizer(self.model_names)
        widget.start()

    def show_importances(self):
        name = self.model_names[-1]
        cat = self.family[name]
        explainer = shap.TreeExplainer(cat.model)
        shap_values = explainer.shap_values(cat.val_pool)
        return shap.summary_plot(shap_values, X, plot_type="bar")
```

Baseline model & result analysis

Let's see how good this model performs without feature engineering and hyperparameter search:

In [78]:
```
daily_data.head()
```

Out[78]:

	Date	Year	Quarter	Month	Week	Weekday	Dayofyear	Day	StockCode	Quantity	Revenue
0	2010-12-01	2010	4	12	48	2	335	1	10002	60	51.00
1	2010-12-01	2010	4	12	48	2	335	1	10125	2	1.70
2	2010-12-01	2010	4	12	48	2	335	1	10133	5	4.25
3	2010-12-01	2010	4	12	48	2	335	1	16014	10	4.20
4	2010-12-01	2010	4	12	48	2	335	1	16016	10	8.50

In [79]:
```
week = daily_data.Week.max() - 2
print("Validation after week {}".format(week))
print("Validation starts at timepoint {}".format(
    daily_data[daily_data.Week==week].Date.min()
))
```

```
Validation after week 49
Validation starts at timepoint 2010-12-06 00:00:00
```

In [80]:
```
X = daily_data.drop(["Quantity", "Revenue", "Date"], axis=1)
daily_data.Quantity = np.log(daily_data.Quantity)
y = daily_data.Quantity
params = CatHyperparameter()

model = Catmodel("baseline", params)
model.set_data(X,y, week)
model.learn(plot=True)
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))
baseline, early-stopped model tree count 65
```

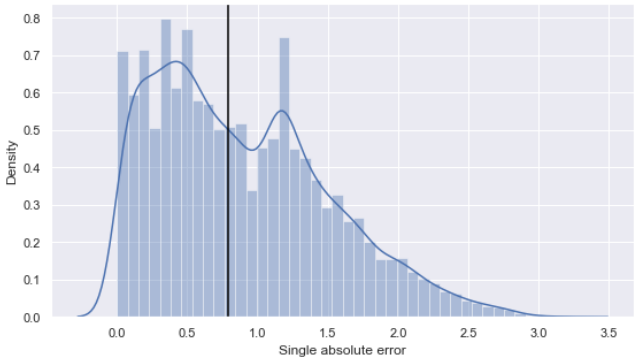
If you have forked this kernel and are in interactive model you can see that the model loss has converged. How big is the evaluated root mean square error on validation data?

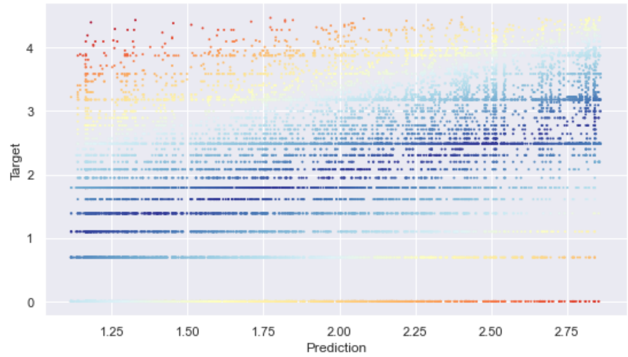
In [81]:
```
model.score()
```

Out[81]:
```
0.20887036435793205
```

In [82]:
```
model.show_val_results();
```

```
Median absolute error: 0.7892396677686456
```

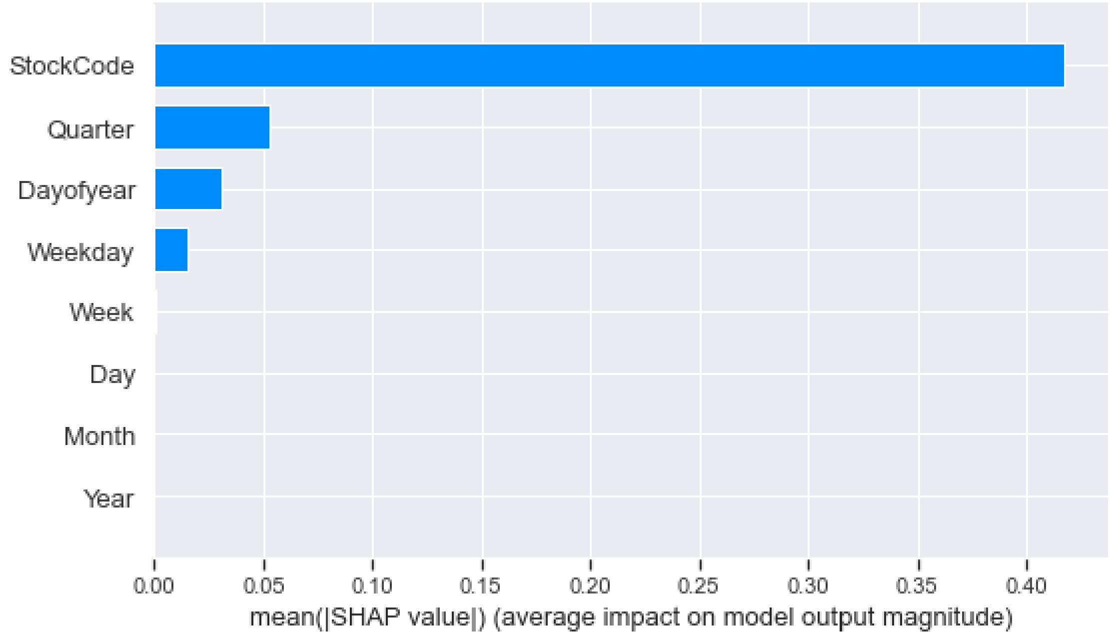




- We can see that the distribution of absolute errors of single predictions is right skewed.
- The median single error (black) is half of the RMSE score and significantly lower.
- By plotting the target versus prediction we can see that we made higher errors for validation entries that have high true quantity values above 30. The strong blue line shows the identity where

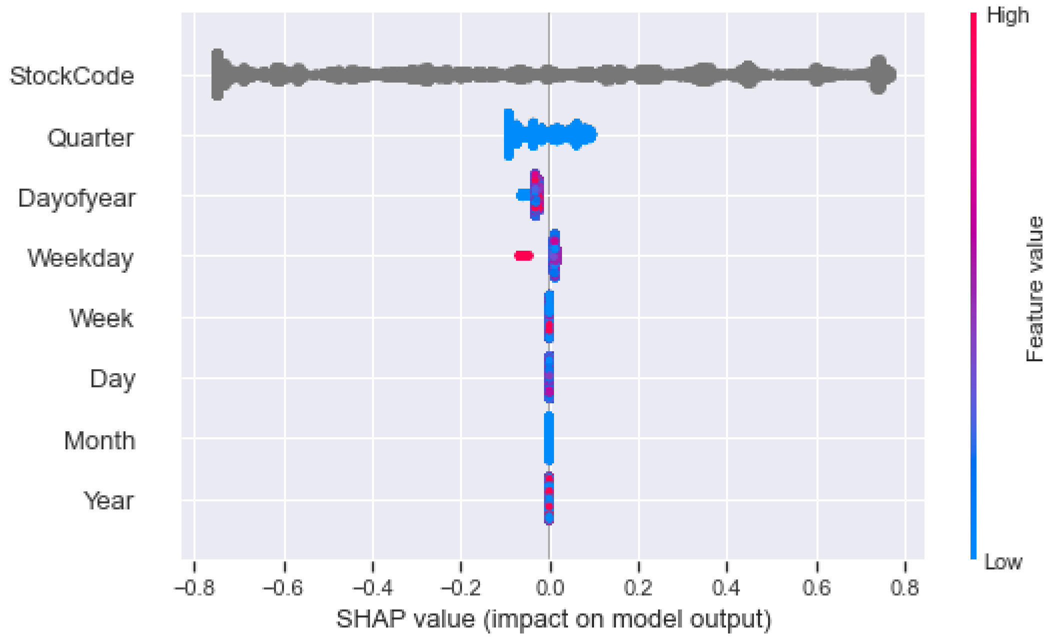
predictions are close to target values. To improve we need to make better predictions for products with true high quantities during validation time.

In [83]:
```
model.show_importances()
```



- We can see that the stock code as well as the description of the products are very important. They do not have a color as they are not numerical and do not have low or high values.
- The weekday is an important feature as well. We have already seen this by exploring the data. Low values from monday up to thursday are those days where the retailer sales most products. In contrast high values (friday to sunday) only yield a few sales.

In [84]:
```
model.show_importances(kind=None)
```



- Take a look at the weekday to understand this plot: Low values (0 to 3) correspond to Monday, Tuesday, Wednesday and Thursday. These are days with high amount of product sales (high quantity target values). They are colored in blue and push towards higher sharp values and consequently to higher predicted quantity values. Higher weekday values suite to friday, saturday and sunday. They are colored in red and push towards negative sharp values and to lower predicted values. This confirms to the observations we made during exploration of weekday and the sum of daily quantities.

- The StockCode and the Description are important features but they are also very complex. We have seen that we have close to 4000 different stock codes and even more descriptions. To improve we should try to engineer features that are able to descripe the products in a more general way.

In [85]:
```
np.mean(np.abs(np.exp(model.results.prediction) - np.exp(model.results.Quantity)))
```
Out[85]:
```
9.707322246045605
```

In [86]:
```
np.median(np.abs(np.exp(model.results.prediction) - np.exp(model.results.Quantity)))
```
Out[86]:
```
4.77030760517831
```

Feature engineering

Creating product types

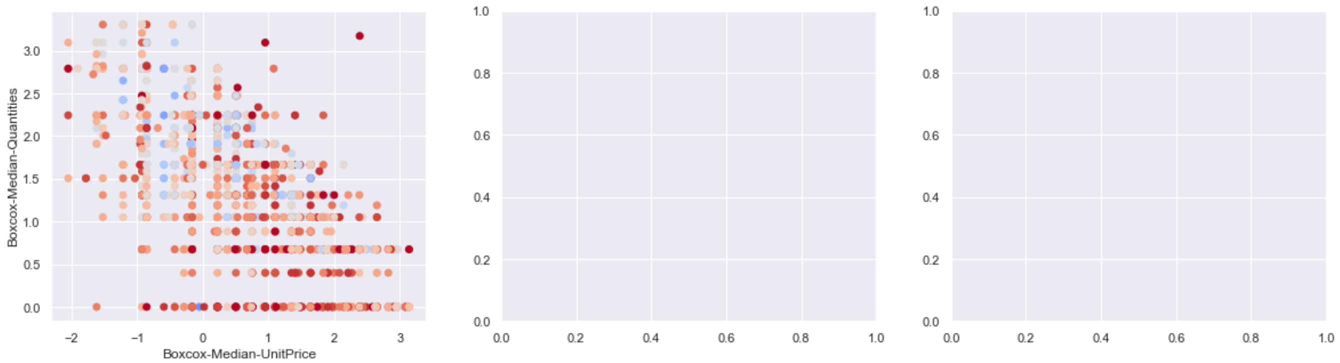
In [87]:
```
products = pd.DataFrame(index=data.loc[data.Week < week].StockCode.unique(), columns = ["Medi

products["MedianPrice"] = data.loc[data.Week < week].groupby("StockCode").UnitPrice.median()
products["MedianQuantities"] = data.loc[data.Week < week].groupby("StockCode").Quantity.media
products["Customers"] = data.loc[data.Week < week].groupby("StockCode").CustomerID.nunique()
products["DescriptionLength"] = data.loc[data.Week < week].groupby("StockCode").DescriptionLe
#products["StockCode"] = products.index.values
org_cols = np.copy(products.columns.values)
products.head()
```
Out[87]:

	MedianPrice	MedianQuantities	Customers	DescriptionLength
71053	3.75	4.0	137	19.0
22752	8.50	2.0	163	28.0
21730	4.95	3.0	64	33.0
22633	2.10	4.0	263	22.0
22632	2.10	4.0	227	25.0

In [88]:
```
for col in org_cols:
    if col != "StockCode":
        products[col] = boxcox(products[col])[0]
```

In [89]:
```
fig, ax = plt.subplots(1,3,figsize=(20,5))
ax[0].scatter(products.MedianPrice.values, products.MedianQuantities.values,
           c=products.Customers.values, cmap="coolwarm_r")
ax[0].set_xlabel("Boxcox-Median-UnitPrice")
ax[0].set_ylabel("Boxcox-Median-Quantities")
```
Out[89]:
```
Text(0, 0.5, 'Boxcox-Median-Quantities')
```



In [90]:
```
X = products.values
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

In [91]:
```
km = KMeans(n_clusters=30)
products["cluster"] = km.fit_predict(X)

daily_data["ProductType"] = daily_data.StockCode.map(products.cluster)
daily_data.ProductType = daily_data.ProductType.astype("object")
daily_data.head()
```

Out[91]:

	Date	Year	Quarter	Month	Week	Weekday	Dayofyear	Day	StockCode	Quantity	Revenue	ProductTy
0	2010-12-01	2010	4	12	48	2	335	1	10002	4.094345	51.00	
1	2010-12-01	2010	4	12	48	2	335	1	10125	0.693147	1.70	
2	2010-12-01	2010	4	12	48	2	335	1	10133	1.609438	4.25	
3	2010-12-01	2010	4	12	48	2	335	1	16014	2.302585	4.20	
4	2010-12-01	2010	4	12	48	2	335	1	16016	2.302585	8.50	

Baseline for product types

In [92]:
```
daily_data["KnownStockCodeUnitPriceMedian"] = daily_data.StockCode.map(
    data.groupby("StockCode").UnitPrice.median())

known_price_iqr = data.groupby("StockCode").UnitPrice.quantile(0.75)
known_price_iqr -= data.groupby("StockCode").UnitPrice.quantile(0.25)
daily_data["KnownStockCodeUnitPriceIQR"] = daily_data.StockCode.map(known_price_iqr)
```

In [93]:
```
to_group = ["StockCode", "Year", "Month", "Week", "Weekday"]

daily_data = daily_data.set_index(to_group)
daily_data["KnownStockCodePrice_WW_median"] = daily_data.index.map(
    data.groupby(to_group).UnitPrice.median())
daily_data["KnownStockCodePrice_WW_mean"] = daily_data.index.map(
    data.groupby(to_group).UnitPrice.mean().apply(lambda l: np.round(l, 2)))
daily_data["KnownStockCodePrice_WW_std"] = daily_data.index.map(
    data.groupby(to_group).UnitPrice.std().apply(lambda l: np.round(l, 2)))

daily_data = daily_data.reset_index()
```

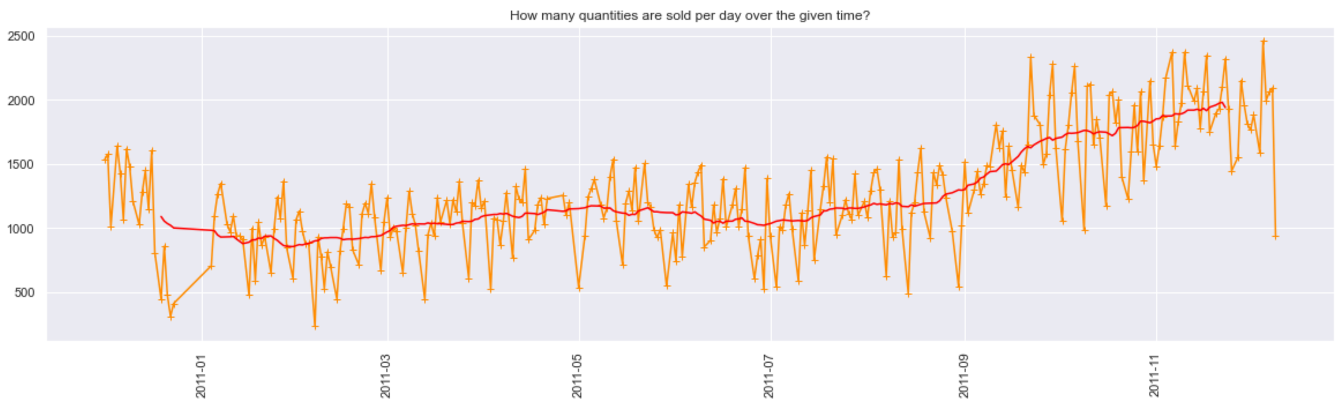
In [94]:
```
daily_data.head()
```

Out[94]:

	StockCode	Year	Month	Week	Weekday	Date	Quarter	Dayofyear	Day	Quantity	Revenue	ProductTy
0	10002	2010	12	48	2	2010-12-01	4	335	1	4.094345	51.00	
1	10125	2010	12	48	2	2010-12-01	4	335	1	0.693147	1.70	
2	10133	2010	12	48	2	2010-12-01	4	335	1	1.609438	4.25	
3	16014	2010	12	48	2	2010-12-01	4	335	1	2.302585	4.20	
4	16016	2010	12	48	2	2010-12-01	4	335	1	2.302585	8.50	

In [95]:

```
plt.figure(figsize=(20,5))
plt.plot(daily_data.groupby("Date").Quantity.sum(), marker='+', c="darkorange")
plt.plot(daily_data.groupby("Date").Quantity.sum().rolling(window=30, center=True).mean(),
        c="red")
plt.xticks(rotation=90);
plt.title("How many quantities are sold per day over the given time?");
```



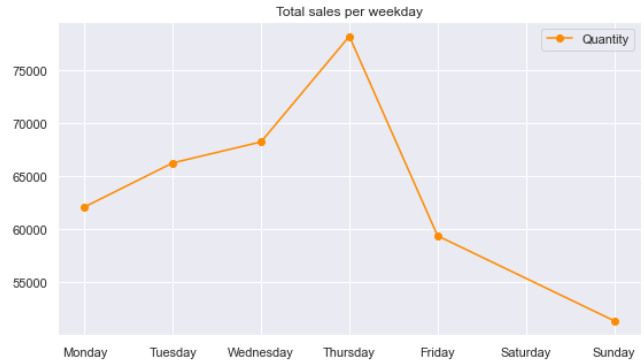
In [96]:

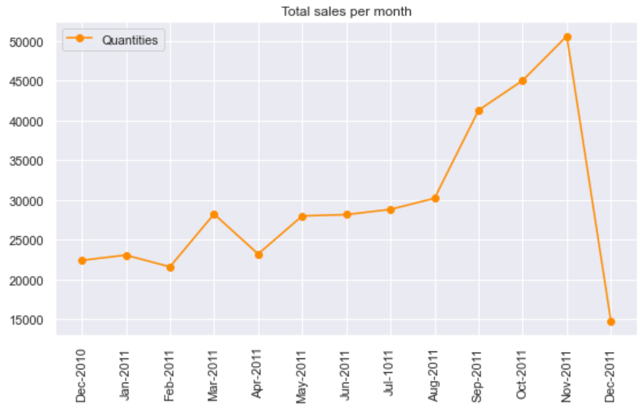
```
fig, ax = plt.subplots(1,2,figsize=(20,5))

weekdays = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday"]
yearmonth = ["Dec-2010", "Jan-2011", "Feb-2011", "Mar-2011", "Apr-2011", "May-2011",
             "Jun-2011", "Jul-1011", "Aug-2011", "Sep-2011", "Oct-2011", "Nov-2011",
             "Dec-2011"]

daily_data.groupby("Weekday").Quantity.sum().plot(
    ax=ax[0], marker='o', label="Quantity", c="darkorange");
ax[0].legend();
ax[0].set_xticks(np.arange(0,7))
ax[0].set_xticklabels(weekdays);
ax[0].set_xlabel("")
ax[0].set_title("Total sales per weekday");

ax[1].plot(daily_data.groupby(["Year", "Month"]).Quantity.sum().values,
    marker='o', label="Quantities", c="darkorange");
ax[1].set_xticklabels(yearmonth, rotation=90)
ax[1].set_xticks(np.arange(0, len(yearmonth)))
ax[1].legend();
ax[1].set_title("Total sales per month");
```





Both visualisations yield further interesting insights:

- Thursday seems to be the day on which most products are sold.
- In contrast friday, and sunday have very low transactions
- On saturday there are no transactions at all
- The pre-Christmas season starts in september and shows a peak in november
- Indeed february and april are month with very low sales.

Let's create some new features for our daily aggregation that may be helpful to make better predictions:

In [97]:
```
daily_data["PreChristmas"] = (daily_data.Dayofyear <= 358) & (daily_data.Dayofyear >= 243)
```

In [98]:
```
for col in ["Weekday", "Month", "Quarter"]:
    daily_data = daily_data.set_index(col)
    daily_data[col+"Quantity_mean"] = daily_data.loc[daily_data.Week < week].groupby(col).Qua
    daily_data[col+"Quantity_median"] = daily_data.loc[daily_data.Week < week].groupby(col).Q
    daily_data[col+"Quantity_mean_median_diff"] = daily_data[col+"Quantity_mean"] - daily_dat
    daily_data[col+"Quantity_IQR"] = daily_data.loc[
        daily_data.Week < week].groupby(col).Quantity.quantile(0.75) - daily_data.loc[
        daily_data.Week < week].groupby(col).Quantity.quantile(0.25)
    daily_data = daily_data.reset_index()
daily_data.head()
```

Out[98]:

	Quarter	Month	Weekday	StockCode	Year	Week	Date	Dayofyear	Day	Quantity	...	WeekdayQuanti
0	4	12	2	10002	2010	48	2010-12-01	335	1	4.094345	...	
1	4	12	2	10125	2010	48	2010-12-01	335	1	0.693147	...	
2	4	12	2	10133	2010	48	2010-12-01	335	1	1.609438	...	
3	4	12	2	16014	2010	48	2010-12-01	335	1	2.302585	...	
4	4	12	2	16016	2010	48	2010-12-01	335	1	2.302585	...	

5 rows × 30 columns

In [99]:
```
to_group = ["StockCode", "PreChristmas"]
daily_data = daily_data.set_index(to_group)
daily_data["PreChristmasMeanQuantity"] = daily_data.loc[
    daily_data.Week < week].groupby(to_group).Quantity.mean().apply(lambda l: np.round(l, 1))
daily_data["PreChristmasMedianQuantity"] = daily_data.loc[
    daily_data.Week < week].groupby(to_group).Quantity.median().apply(lambda l: np.round(l, 1
```

```
daily_data["PreChristmasStdQuantity"] = daily_data.loc[
    daily_data.Week < week].groupby(to_group).Quantity.std().apply(lambda l: np.round(l, 1))
daily_data = daily_data.reset_index()
```

In [100…

```
for delta in range(1,4):
    to_group = ["Week","Weekday","ProductType"]
    daily_data = daily_data.set_index(to_group)

    daily_data["QuantityProducttypeWeekWeekdayLag_" + str(delta) + "_median"] = daily_data.gr
        to_group).Quantity.median().apply(lambda l: np.round(l,1)).shift(delta)

    daily_data = daily_data.reset_index()
    daily_data.loc[daily_data.Week >= (week+delta),
                   "QuantityProductTypeWeekWeekdayLag_" + str(delta) + "_median"] = np.nan
```

In [101…

```
data["ProductType"] = data.StockCode.map(products.cluster)
```

In [102…

```
daily_data["TransactionsPerProductType"] = daily_data.ProductType.map(data.loc[data.Week < we
```

About countries and customers

In [103…

```
delta = 1
to_group = ["Week", "Weekday", "ProductType"]
daily_data = daily_data.set_index(to_group)
daily_data["DummyWeekWeekdayAttraction"] = data.groupby(to_group).CustomerID.nunique()
daily_data["DummyWeekWeekdayMeanUnitPrice"] = data.groupby(to_group).UnitPrice.mean().apply(l

daily_data["WeekWeekdayAttraction_Lag1"] = daily_data["DummyWeekWeekdayAttraction"].shift(1)
daily_data["WeekWeekdayMeanUnitPrice_Lag1"] = daily_data["DummyWeekWeekdayMeanUnitPrice"].shi

daily_data = daily_data.reset_index()
daily_data.loc[daily_data.Week >= (week + delta), "WeekWeekdayAttraction_Lag1"] = np.nan
daily_data.loc[daily_data.Week >= (week + delta), "WeekWeekdayMeanUnitPrice_Lag1"] = np.nan
daily_data = daily_data.drop(["DummyWeekWeekdayAttraction", "DummyWeekWeekdayMeanUnitPrice"],
```

In [104…

```
daily_data["TransactionsPerStockCode"] = daily_data.StockCode.map(
    data.loc[data.Week < week].groupby("StockCode").InvoiceNo.nunique())
```

In [105…

```
daily_data.head()
```

Out[105]:

	Week	Weekday	ProductType	StockCode	PreChristmas	Quarter	Month	Year	Date	Dayofyear	...	Qu
0	48	2	19.0	10002	True	4	12	2010	2010-12-01	335	...	
1	48	2	11.0	10125	True	4	12	2010	2010-12-01	335	...	
2	48	2	14.0	10133	True	4	12	2010	2010-12-01	335	...	
3	48	2	14.0	16014	True	4	12	2010	2010-12-01	335	...	
4	48	2	19.0	16016	True	4	12	2010	2010-12-01	335	...	

5 rows × 43 columns

In [106…

```
daily_data["CustomersPerWeekday"] = daily_data.Month.map(
```

```
    data.loc[data.Week < week].groupby("Weekday").CustomerID.nunique())
```

In [107…

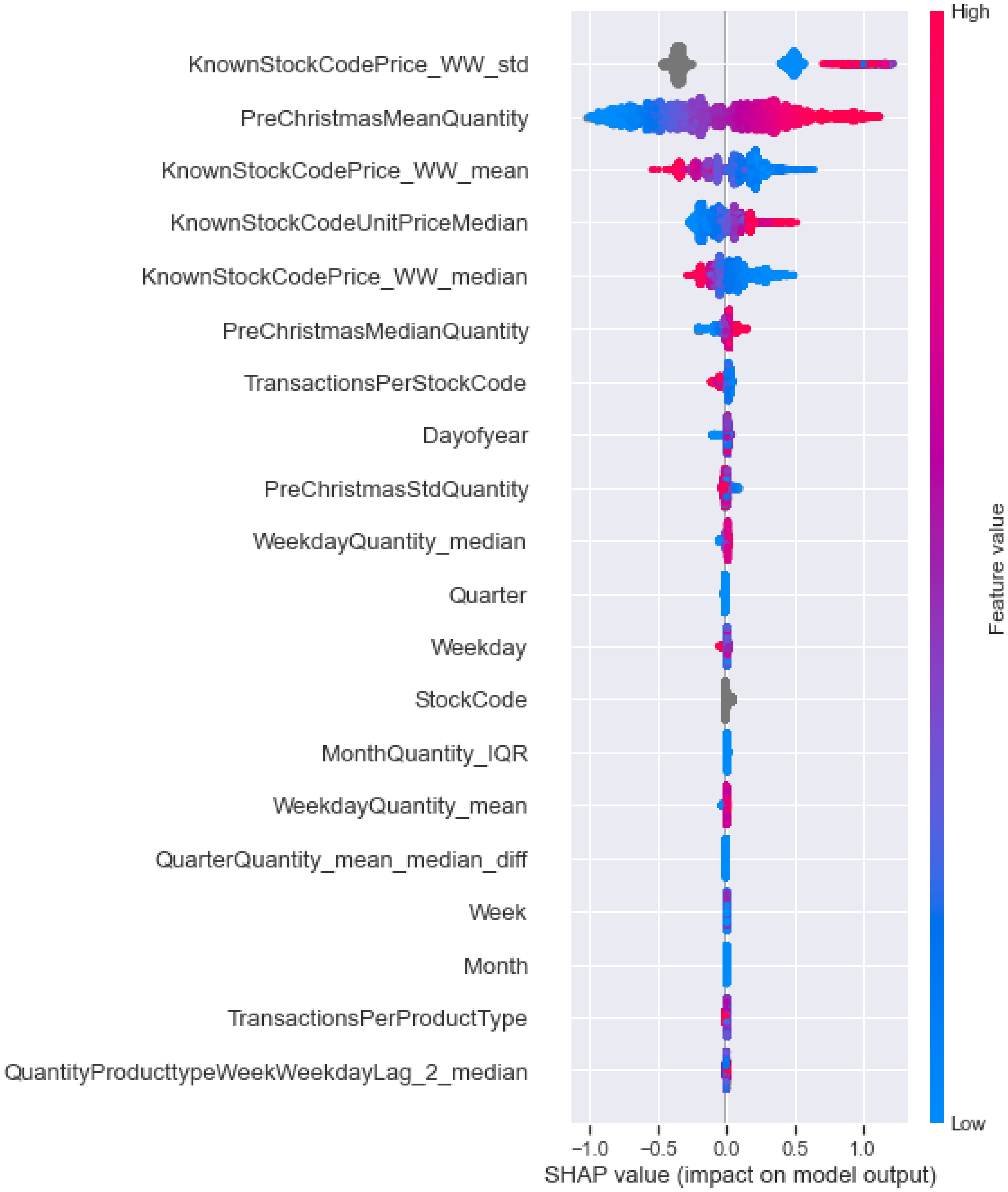
```
X = daily_data.drop(["Quantity", "Revenue", "Date", "Year"], axis=1)
y = daily_data.Quantity
params = CatHyperparameter()

model = Catmodel("new_features_1", params)
model.set_data(X,y, week)
model.learn(plot=True)
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))
new_features_1, early-stopped model tree count 274
```

In [108…

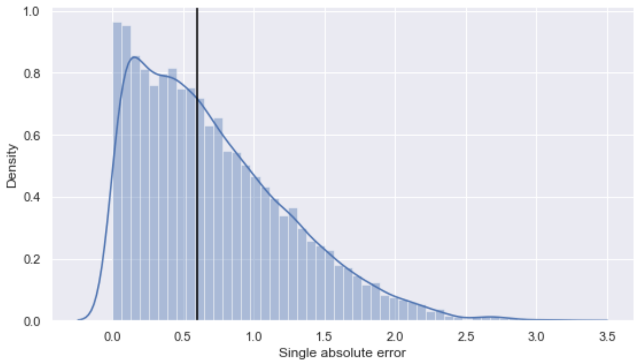
```
model.show_importances(kind=None)
```

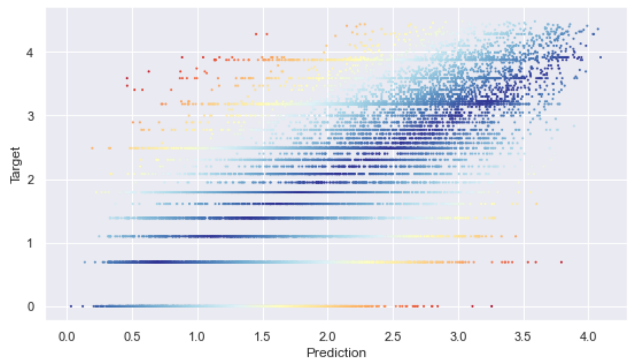


In [109…

```
model.show_val_results();
```

```
Median absolute error: 0.6040601289997191
```





In [110…
```
np.mean(np.abs(np.exp(model.results.prediction) - np.exp(model.results.Quantity)))
```
Out[110]:
```
7.7942483790358486
```
In [111…
```
np.median(np.abs(np.exp(model.results.prediction) - np.exp(model.results.Quantity)))
```
Out[111]:
```
4.004933795604551
```
In [ ]:

In [ ]: