## UK Online Store Retail Transactions

### Dataset Variable Information:

- 1. InvoiceNo: Invoice number. Nominal, a 6-digit integral number uniquely assigned to each transaction. If this code starts with letter 'c', it indicates a cancellation.
- 2. StockCode: Product (item) code. Nominal, a 5-digit integral number uniquely assigned to each distinct product.
- 3. Description: Product (item) name. Nominal.
- 4. Quantity: The quantities of each product (item) per transaction. Numeric.
- 5. InvoiceDate: Invoice Date and time. Numeric, the day and time when each transaction was generated.
- 6. UnitPrice: Unit price. Numeric, Product price per unit in sterling.
- 7. CustomerID: Customer number. Nominal, a 5-digit integral number uniquely assigned to each customer.
- 8. Country: Country name. Nominal, the name of the country where each customer resides.

## > Establishing Python Library Packages

#### Show code

### > Dataset Overview

$\Rightarrow$		InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Coui
	0	536365	85123A	WHITE HANGING HEART T- LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	Uı King
	1	536365	71053	WHITE METAL	6	2010-12-01	3.39	17850.0	U <sub>I</sub> Vina

### > Dataset Summary Overview

#### Show code

```
Cclass 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
# Column Non-Null Count Dtype
--- --- 0 InvoiceNo 541909 non-null object
1 StockCode 541909 non-null object
2 Description 540455 non-null object
3 Quantity 541909 non-null int64
4 InvoiceDate 541909 non-null datetime64[ns]
5 UnitPrice 541909 non-null float64
6 CustomerID 406829 non-null float64
7 Country 541909 non-null object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

### > // Observations

#### Show code

### Observation

- · Dataset has 8 columns
- Max Row numbers: 541,909
- "Description" and "CustomerID" have lesser row count; possibly null values
- Description = 540,455 total rows
- CustomerID = 406,829 total rows
- "CustomerID" datatype is float64; convert into str object

>

### Show code

## CLEANING | Null Values

### > Count nulls

### Show code



	0
InvoiceNo	0
StockCode	0
Description	1454
Quantity	0
InvoiceDate	0
UnitPrice	0
CustomerID	135080
Country	0

dtype: int64

# > .describe(): 'Description' overview

### Show code

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7		InvoiceNo	StockCode	Description	Country
	count	541909	541909	540455	541909
	unique	25900	4070	4223	38
	top	573585	85123A	WHITE HANGING HEART T-LIGHT HOLDER	United Kingdom
	freq	1114	2313	2369	495478

## > // Observations

### Show code

### Observation

where using 'StockCode' as identifier:

- 4070 unique rows on 'StockCode'
- 1454 null values on 'StockCode'

- 'StockCode' = 541,909 total row
- 'Description' = 540,455 total rows
- // most likely, 1,454 'StockCode' rows have no corresponding 'Description', (541,909 540,455)

> .

Show code

> [Description] Nulls

Show code

> ~~ Investigate: 'Description' Null Values

Show code

// Objective: investigate the nature of null values on column 'Description' by identifying significant null rows

// Method:

- · Generate a dataframe with 3 columns:
- 1. 'StockCode' = lists out unique rows
- 2. 'Count' = shows the number of occurrences of each unique 'StockCode'
- 3. 'Description' = provides the corresponding description for each 'StockCode'
- Create specific dataframes then concatenate ON unique 'StockCode'

> Create Dataframe: unique 'StockCode' & corresponding counts

StockCode	
10002	71
10080	23
10120	30
10123C	3
10123G	0
gift_0001_20	10
gift_0001_30	7
gift_0001_40	3
gift_0001_50	4
m	1
****	

4070 rows × 1 columns

dtype: int64

> Create Dataframe: excluding 'Description' nulls on 'raw'

### Show code

<<class 'pandas.core.frame.DataFrame'>
 Index: 540455 entries, 0 to 541908
 Data columns (total 8 columns):

Data	columns (total	al 8 columns):	
#	Column	Non-Null Count	Dtype
0	InvoiceNo	540455 non-null	object
1	StockCode	540455 non-null	object
2	Description	540455 non-null	object
3	Quantity	540455 non-null	int64
4	InvoiceDate	540455 non-null	datetime64[ns]
5	UnitPrice	540455 non-null	float64
6	CustomerID	406829 non-null	float64
7	Country	540455 non-null	object
dtype	es: datetime6	4[ns](1), float64	(2), int64(1), object(4)
memoi	ry usage: 37.	1+ MB	

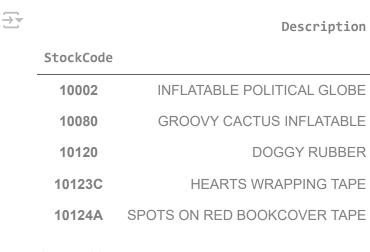
# > // Observations

### Show code

### Observation

- 540,455 max rows as per excluding NAs (original 541,909 max rows)
- 'StockCode' = 540,455 total rows (previously 541,909)
- 1,454 rows are 'Description' nulls as per calculation and section: counting nulls
- > Create Dataframe: unique 'StockCode' & corresponding 'Description'

### Show code



dtype: object

> Concatenate Dataframe: unique StockCode + Counts + 'Description'

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	StockCode	Count	Description
3536	85123A	2313	WHITE HANGING HEART T-LIGHT HOLDER
1348	22423	2203	REGENCY CAKESTAND 3 TIER
3515	85099B	2159	JUMBO BAG RED RETROSPOT
2733	47566	1727	PARTY BUNTING
180	20725	1639	LUNCH BAG RED RETROSPOT
885	21854	0	NaN
886	21858	0	NaN
2786	62095B	0	NaN
937	21923	0	NaN
2593	35951	0	NaN

4070 rows × 3 columns

### > // Observations

### Show code

### Observation

- 4070 unique 'StockCode' values (consistent with section:.describe(): 'Description' overview)
- highest count at 2,313 = 'StockCode' 85123A, WHITE HANGING HEART T-LIGHT HOLDER
- Merge DataFrames: 'unique\_stocks' and 'raw'

### Show code



<<class 'pandas.core.frame.DataFrame'> Index: 541909 entries, 160128 to 40383 Data columns (total 10 columns).

Data	COTUMNIS (COCAT	To COTUMNIS).	
#	Column	Non-Null Count	Dtype
0	InvoiceNo	541909 non-null	object
1	StockCode	541909 non-null	object
2	Description_x	540455 non-null	object
3	Quantity	541909 non-null	int64
4	InvoiceDate	541909 non-null	<pre>datetime64[ns]</pre>
5	UnitPrice	541909 non-null	float64
6	CustomerID	406829 non-null	float64

7 Country 541909 non-null object
8 Count 541909 non-null int64
9 Description\_y 541797 non-null object
dtypes: datetime64[ns](1), float64(2), int64(2), object(5)
memory usage: 45.5+ MB

### > // Observations

#### Show code

### Observation

- Description\_x = 540,455 total rows (from 'raw)
- Description\_y = 541, 797 total rows (from 'unique\_stocks')
- CustomerID = 406, 829 total rows
- CustomerID datatype = float64 (must be converted into 'object')
- 541, 909 max total rows

## > Refine generated dataframe

### Show code

$\overline{\Rightarrow}$		InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Descrip <sup>-</sup>
	0	536365	85123A	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	WI HANG HEAF LI HOL
	1	536365	71053	6	2010-12-01	3.39	17850.0	United	WI ME

## > Count remaining nulls

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	0
InvoiceNo	0
StockCode	0
Quantity	0
InvoiceDate	0
UnitPrice	0
CustomerID	135080
Country	0
Description	112

dtype: int64

### > // Observations

### Show code

### Observation

- There are still 112 nulls on 'Description'
- 135,080 nulls on 'CustomerID'

## > ~~Investigate: 'Description' Remaining Null Values

### Show code

// Objective: examine nature of nulls on [Description]; specifically, those that could pose as irrelevant rows for the sales transaction analysis

// Method: identify nature of 'Description' nulls accounting corresponding values on the following: (1) 'UnitPrice' (2) 'Quantity' (3) 'CustomerID'

Create DataFrame: examine nulls

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Index: 112 entries, 1259 to 14 Data columns (total 5 columns):

#	Column	Non-Null Count	Dtype
0	index	112 non-null	int64
1	UnitPrice	112 non-null	float64
2	Description	0 non-null	object
3	Quantity	112 non-null	int64
4	CustomerID	0 non-null	float64
1.4	67 164/0		. / . \

dtypes: float64(2), int64(2), object(1)

memory usage: 5.2+ KB

null\_zero\_unitprice.describe()

<b>→</b>	index		UnitPrice	Quantity	CustomerID
	count	112.000000	112.0	112.000000	0.0
	mean	129823.839286	0.0	-8.196429	NaN
	std	83493.428445	0.0	16.003288	NaN
	min	1970.000000	0.0	-102.000000	NaN
	25%	75228.500000	0.0	-11.000000	NaN
	50%	143303.500000	0.0	-4.000000	NaN
	75%	171576.500000	0.0	-1.000000	NaN
	max	497301.000000	0.0	57.000000	NaN

raw[raw['Description'].isna()].describe()

$\overline{\Rightarrow}$		Quantity	InvoiceDate	UnitPrice	CustomerID
	count	112.000000	112	112.0	0.0
	mean	-8.196429	2011-03-19 12:59:55.178571520	0.0	NaN
	min	-102.000000	2010-12-01 14:32:00	0.0	NaN
	25%	-11.000000	2011-01-28 14:48:15	0.0	NaN
	50%	-4.000000	2011-04-01 16:40:30	0.0	NaN
	75%	-1.000000	2011-04-28 15:06:15	0.0	NaN
	max	57.000000	2011-11-24 10:36:00	0.0	NaN
	std	16.003288	NaN	0.0	NaN

### Show code

### Observation

• 112 rows are zero in 'UnitPrice' and null in both 'Description' and 'CustomerID'

Since these 112 rows have insufficient information, they are considered irrelevant for the transaction analysis and should be removed.

> Review null row count on working dataset

### Show code

Reviewing null count on working dataset

	0
InvoiceNo	0
StockCode	0
Quantity	0
InvoiceDate	0
UnitPrice	0
CustomerID	135080
Country	0
Description	112

dtype: int64

Remove: null rows on 'Description'

$\rightarrow \downarrow$	Updated
	opaacea

d dataset: reviewing null count

	0
InvoiceNo	0
StockCode	0
Quantity	0
InvoiceDate	0
UnitPrice	0
CustomerID	134968
Country	0
Description	0

dtype: int64

### > // Observations

### Show code

### Observations

- 'Description' has now zero nulls
- 'CustomerID' has 134,968 nulls

Show code

# > [CustomerID] Nulls

### Show code

The remaining nulls on CustomerID are consired relevant rows hence be kept.

// Objective: refine column 'CustomerID'

// Method:

- 1. rename those nulls with 'NA'
- 2. convert datatype float64 into int64 (to remove decimals), then str 'object'
- > Replace: null values with 'NA'

### Show code

→ Updated dataset: reviewing null count

	0	
InvoiceNo	0	
StockCode	0	
Quantity	0	
InvoiceDate	0	
UnitPrice	0	
CustomerID	0	
Country	0	
Description	0	

dtype: int64

# > .describe(): dataset overview 'object'

### Show code

$\Rightarrow$		InvoiceNo	StockCode	CustomerID	Country	Description
	count	541797	541797	541797	541797	541797
	unique	25788	3958	4373	38	3823
	top	573585	85123A	NA	United Kingdom	WHITE HANGING HEART T-LIGHT HOLDER
	freq	1114	2313	134968	495366	2380

## > NULL-CLEAN Working Dataset

### Show code

<class 'pandas.core.frame.DataFrame'>
 Index: 541797 entries, 0 to 541908
 Data columns (total 8 columns):

>

### Show code

# CLEANING | Duplicate Rows

> Count Duplicate Rows

Show code

**→** 5270

> Remove: duplicate rows

Show code

> .shape: updated dataset

Show code

**→** (536527, 8)

> // Observations

### Observation

- Updated dataset = 536,527 max total rows (previously 541,797)
- Removed 5,270 duplicate rows

> .

Show code

# INVESTIGATE COLUMNS OF DATASET

# COLUMNS | Examine Nature of numeric values

# > .describe() numberic values

### Show code



	Quantity	InvoiceDate	UnitPrice
count	536527.000000	536527	536527.000000
mean	9.623219	2011-07-04 09:28:59.156911360	4.633627
min	-80995.000000	2010-12-01 08:26:00	-11062.060000
25%	1.000000	2011-03-28 11:34:00	1.250000
50%	3.000000	2011-07-19 14:29:00	2.080000
75%	10.000000	2011-10-18 17:05:00	4.130000
max	80995.000000	2011-12-09 12:50:00	38970.000000
std	219.152804	NaN	97.243424

> // Observation

### Show code

### Observation

- 'Quantity' = -80,995.00 extreme min value
- 'UnitPrice' = -11062.06 extreme min value
- 'InvoiceDate' = December 2010 to 2011 transaction range of dataset

>

#### Show code

> [UnitPrice] Extreme Values

### Show code

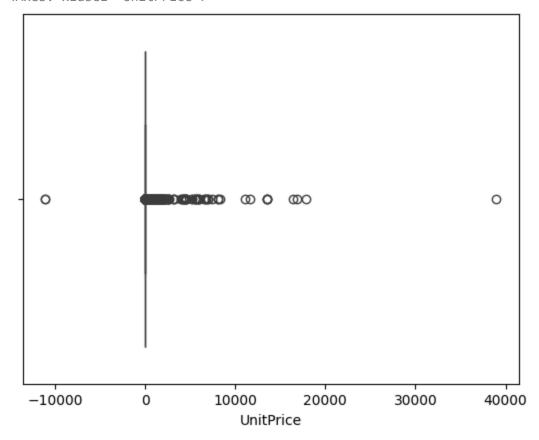
~~Investigate: 'UnitPrice' extreme values

#### Show code

```
Overview of Current Working Dataset
   <class 'pandas.core.frame.DataFrame'>
   Index: 536527 entries, 0 to 541908
   Data columns (total 8 columns):
    # Column Non-Null Count Dtype
                  -----
    --- ----
      InvoiceNo 536527 non-null object
    1 StockCode 536527 non-null object
    2 Quantity 536527 non-null int64
    3 InvoiceDate 536527 non-null datetime64[ns]
    4 UnitPrice 536527 non-null float64
    5 CustomerID 536527 non-null object
    6 Country 536527 non-null object
    7 Description 536527 non-null object
   dtypes: datetime64[ns](1), float64(1), int64(1), object(5)
   memory usage: 36.8+ MB
```

> Check Outlier: boxplot 'UnitPrice'

<Axes: xlabel='UnitPrice'>



> Check Outlier: isolate values >10,000 'UnitPrice'

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	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
15016	C537630	AMAZONFEE	-1	2010-12-07 15:04:00	13541.33	NA	United Kingdom
15017	537632	AMAZONFEE	1	2010-12-07 15:08:00	13541.33	NA	United Kingdom
16232	C537644	AMAZONFEE	-1	2010-12-07 15:34:00	13474.79	NA	United Kingdom
16356	C537651	AMAZONFEE	-1	2010-12-07 15:49:00	13541.33	NA	United Kingdom
43702	C540117	AMAZONFEE	-1	2011-01-05 09:55:00	16888.02	NA	United Kingdom
43703	C540118	AMAZONFEE	-1	2011-01-05 09:57:00	16453.71	NA	United Kingdom
4							<b>•</b>

### Show code

### Observation

• 'UnitPrice' values > 10000 have alphameric 'StockCode' values {instead of alphanumeric}

Hence, investigate nature of extreme values accounting columns (1) UnitPrice,

(2) StockCode, (3) Quantity, (4) Description

## > Examine 'StockCode' Alphamerics

### Show code

// Objective: find patterns on 'StockCode' related to the extreme values found on 'UnitPrice'

### // Method:

- 1. create a dataframe isolating only alphameric values on 'StockCode'
- 2. create a dataframe of unique alphameric 'StockCode'& corresponding counts
- 3. create dataframe printing out the following:

- (1) unique alphameric 'StockCode'
- (2) each corresponding 'Description'
- (3) each corresponding count of 'StockCode' occurences
- (4) each corresponding most reoccurring value on 'Quantity' and 'UnitPrice'
- > Create Dataframe: .info() alphameric 'StockCode'

### Show code

> Create Dataframe: unique alphameric 'StockCode' & corresponding counts

### Show code

> Create Dataframe: unique alphameric 'StockCode' + Description + Count + Quantity + UnitPrice



	StockCode	Description	Count	Max_Quantity	Max_UnitPrice
0	AMAZONFEE	AMAZON FEE	34	-1	13541.330
1	В	Adjust bad debt	3	1	-11062.060
2	BANK CHARGES	Bank Charges	37	-1	15.000
3	CRUK	CRUK Commission	16	-1	1.600
4	D	Discount	77	-1	11.840
5	DCGSSBOY	BOYS PARTY BAG	11	1	3.290
6	DCGSSGIRL	GIRLS PARTY BAG	13	2	3.290
7	DOT	DOTCOM POSTAGE	710	1	3.290
8	M	Manual	566	-1	1.250
9	PADS	PADS TO MATCH ALL CUSHIONS	4	1	0.001
10	POST	POSTAGE	1256	1	18.000
11	S	SAMPLES	62	-1	33.050

### Show code

### Observation:

- 2,790 alphameric 'StockCode' rows
- 13 unique alphameric 'StockCode' values
- Most identified alphameric 'StockCode' are not relevant to the sales transaction analysis; all shall be removed except:
- 1. DCGSSBOY = BOYS PARTY BAG
- 2. DCGSSGIRL = GIRLS PARTY BAG
- 3. D = Discount
- List: alphameric StockCode values to exclude

```
→ ['POST',
     'DOT',
     'BANK CHARGES',
     'S',
     'AMAZONFEE',
     'm',
     'PADS',
     'Β',
     'CRUK']
```

Remove: alphameric StockCode values on Working Dataframe

### Show code

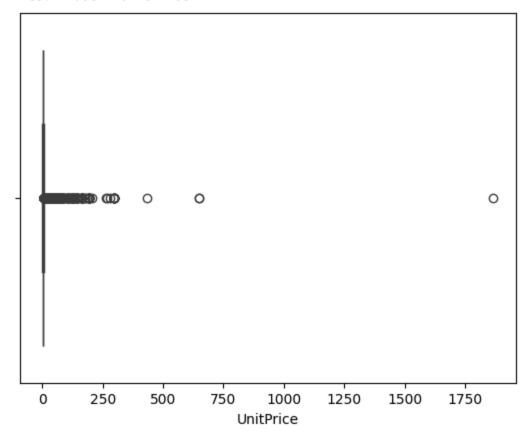


Previewing details of the updated Working DataFrame

	Quantity	InvoiceDate	UnitPrice
count	533838.000000	533838	533838.000000
mean	9.651321	2011-07-04 10:50:14.597461760	3.301370
min	-80995.000000	2010-12-01 08:26:00	0.000000
25%	1.000000	2011-03-28 11:34:00	1.250000
50%	3.000000	2011-07-19 15:23:00	2.080000
75%	10.000000	2011-10-18 17:10:00	4.130000
max	80995.000000	2011-12-09 12:50:00	1867.860000
std	219.652203	NaN	5.336549

> Updated: boxplot 'UnitPrice'





### Show code

### Observations

- 533,838 total rows of the updated working dataframe
- 2,689 rows with alphameric StockCodes were removed after being identified as postage and bad debt records. While some of these rows were also recognized as outliers, all were deemed not relevant to the transaction analysis of retail products.
- Their removal improved the distribution of 'UnitPrice' by reducing extreme values.

## Updated 'UnitPrice' status:

- 1. minimum value = 0 (previously -11,062.06)
- 2. maximum value = 1867.86 (previously 38,970)
- > Examine 'StockCode' AlphaNumerics

### Show code

# > Count: alphanumerics on StockCode

### Show code

### count

StockCode	
2	433968
8	62423
4	11368
1	7574
7	7142
3	5691
9	4633
5	633
С	144
D	116
6	112
g	34

dtype: int64

> Check: details of 'C' StockCode

- 0		-
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	InvoiceNo	StockCode	CustomerID	Country	Description
count	144	144	144	144	144
unique	144	1	30	4	1
top	536540	C2	14911	EIRE	CARRIAGE
freq	1	144	85	108	144

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	De
1423	536540	C2	1	2010-12-01 14:05:00	50.0	14911	EIRE	(
12119	537368	C2	1	2010-12-06 12:40:00	50.0	14911	EIRE	(
12452	537378	C2	1	2010-12-06 13:06:00	50.0	14911	EIRE	(
19975	537963	C2	1	2010-12-09 11:30:00	50.0	13369	United Kingdom	(
20016	538002	C2	1	2010-12-09 11:48:00	50.0	14932	Channel Islands	(
515000	579768	C2	1	2011-11-30 15:08:00	50.0	14911	EIRE	(
516484	579910	C2	1	2011-12-01 08·52·00	50.0	14911	EIRE	( 

# > Check: details of 'D' StockCode

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### count

### Description

Discount	77
GIRLS PARTY BAG	13
BOYS PARTY BAG	11
BOXED GLASS ASHTRAY	5
ebay	3
SUNJAR LED NIGHT NIGHT LIGHT	2
CAMOUFLAGE DOG COLLAR	2
OOH LA LA DOGS COLLAR	2
HAYNES CAMPER SHOULDER BAG	1

dtype: int64

> Check: details of 'g' StockCode

InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	De
539492	gift_0001_40	1	2010-12-20 10:14:00	34.04	NA	United Kingdom	Dotc Gif
562933	gift_0001_30	1	2011-08-10 16:51:00	25.00	NA	United Kingdom	Dotc Gif
558066	gift_0001_50	1	2011-06-24 15:45:00	41.67	NA	United Kingdom	Dotc Gif
558068	gift_0001_20	1	2011-06-24 15:51:00	16.67	NA	United Kingdom	Dotc Gif
558614	gift_0001_10	1	2011-06-30 15:56:00	8.33	NA	United Kingdom	Dotc Gif
	gift_0001_50	1	2011-06-30 15:56:00	41.67	NA	United Kingdom	Dotc Gif
561513	gift_0001_40	1	2011-07-27 15:12:00	33.33	NA	United Kingdom	Dotc Gif
562420	gift_0001_20	1	2011-08-04 16:38:00	16.67	NA	United Kingdom	Dotc Gif
564760	gift_0001_10	1	2011-08-30 10:47:00	8.33	NA	United Kingdom	Dotc Gif
539958	gift_0001_50	1	2010-12-23 13:26:00	42.55	NA	United Kingdom	Dotc Gif
564760	gift_0001_30	1	2011-08-30 10:47:00	25.00	NA	United Kingdom	Dotc
564761	gift_0001_30	30	2011-08-30 10:48:00	0.00	NA	United Kingdom	Dotc
564762	gift_0001_10	30	2011-08-30 10:48:00	0.00	NA	United Kingdom	Dotc Gif
564974	gift_0001_10	2	2011-08-31 15:32:00	8.33	NA	United Kingdom	Dotc Gif

565231	gift_0001_30	1	2011-09-02 09:26:00	25.00	NA	United Kingdom	Dotc Gif
573585	gift_0001_20	1	2011-10-31 14:41:00	16.67	NA	United Kingdom	Dotc Gif
557500	gift_0001_20	1	2011-06-20	16.67	NA	United	Dotc ▼

### Show code

### Observations

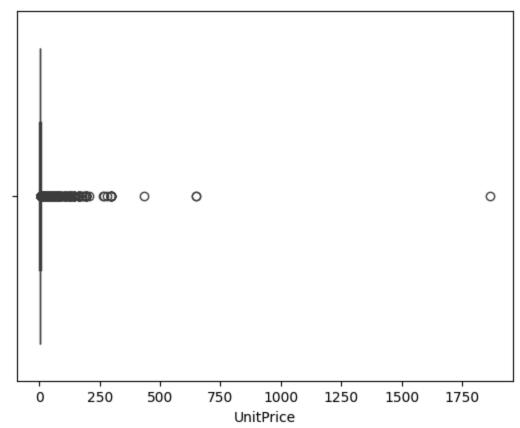
- 144 rows starting with 'C' = CARRIAGE; remove since these are not sales transactions
- 39 rows starting with 'D' = has several descriptions; but remove 'ebay' records since these are not sales transactions
- 34 rows starting with 'g' = gift vouchers; since no further details were found, these will be assumed as purchased vouchers since the values on 'Quantity' are non-negatives
- > Remove: alphanumeric 'StockCode' on Working DataFrame

> Check Outlier: boxplot 'Unitprice'

### Show code

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<Axes: xlabel='UnitPrice'>



### > // Observations

### Show code

### Observations

- 533,691 total rows of the updated working dataframe
- 147 rows with alphaNumeric StockCodes were removed after being identified as postages (CARRIAGE and ebay), as deemed not relevant to the transaction analysis of retail products.
- > Updated Working Dataframe

	Quantity	InvoiceDate	UnitPrice
count	533691.000000	533691	533691.000000
mean	9.653483	2011-07-04 10:47:59.492515584	3.288980
min	-80995.000000	2010-12-01 08:26:00	0.000000
25%	1.000000	2011-03-28 11:34:00	1.250000
50%	3.000000	2011-07-19 15:23:00	2.080000
75%	10.000000	2011-10-18 17:10:00	4.130000
max	80995.000000	2011-12-09 12:50:00	1867.860000
std	219.682317	NaN	5.280487

### Show code

### Observation

- 'UnitPrice' = 0 (minimum value)
  - Examine

# > [UnitPrice] Zero Values

0		_
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-16		_

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	De
622	536414	22139	56	2010-12-01 11:52:00	0.0	NA	United Kingdom	RE C
1971	536546	22145	1	2010-12-01 14:33:00	0.0	NA	United Kingdom	C
1972	536547	37509	1	2010-12-01 14:33:00	0.0	NA	United Kingdom	MI
2025	536553	37461	3	2010-12-01 14:35:00	0.0	NA	United Kingdom	
2406	536589	21777	-10	2010-12-01 16:50:00	0.0	NA	United Kingdom	RE W

### Show code

### Observation

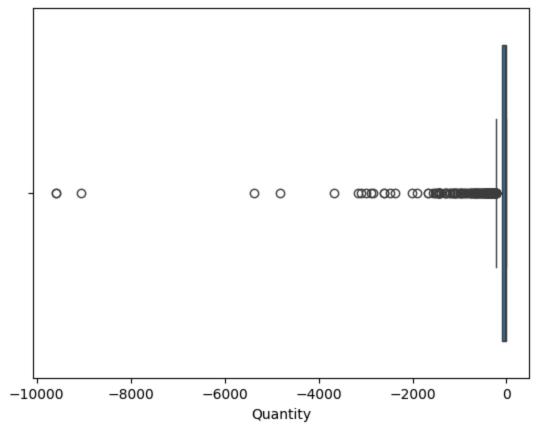
- 2,380 rows have zero values on 'UnitPrice'
- There are positive (+) and negative (-) values on 'Quantity'
  - Examine those that have negative values
- Create DataFrame: zero unitprice & negative quantity

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	7	~

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	D€
225529	556690	23005	-9600	2011-06-14 10:37:00	0.0	NA	United Kingdom	
225530	556691	23005	-9600	2011-06-14 10:37:00	0.0	NA	United Kingdom	
225528	556687	23003	-9058	2011-06-14 10:36:00	0.0	NA	United Kingdom	
115818	546152	72140F	-5368	2011-03-09 17:25:00	0.0	NA	United Kingdom	
4								•

> Create boxplot: zero unitprice & negative quantity





## > Check Outlier: isolate values

### Show code

Rows having extreme values ( <= -4000) on 'Quantity'

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	De
225529	556690	23005	-9600	2011-06-14 10:37:00	0.0	NA	United Kingdom	



## > // Observations

- 5 rows are extreme values, with zero in 'UnitPrice' and negative values in 'Quantity'. While these are considered outliers and ideally should be removed, they represent distinct transactions (except for the "throw away" record) and will therefore be retained.
- A "throw away" product description has been found

Examine more of those "throw away" rows on the main dataframe; all of these will be removed as they are not relevant to the transaction analysis of products being sold by the retailer

### raw.info()

```
→▼ <class 'pandas.core.frame.DataFrame'>
   Index: 533691 entries, 0 to 541908
   Data columns (total 8 columns):
      Column
                   Non-Null Count
                                   Dtype
                   -----
    0
      InvoiceNo 533691 non-null object
    1 StockCode 533691 non-null object
    2 Quantity 533691 non-null int64
       InvoiceDate 533691 non-null datetime64[ns]
    4 UnitPrice 533691 non-null float64
    5 CustomerID 533691 non-null object
    6 Country 533691 non-null object
    7 Description 533691 non-null object
   dtypes: datetime64[ns](1), float64(1), int64(1), object(5)
   memory usage: 36.6+ MB
```

> Count Rows: 'throw away' product description in main dataframe

### Show code



> Remove Row: 'throw away' product description

-0	$\overline{}$
	~

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	
540422	C581484	23843	-80995	2011-12-09 09:27:00	2.08	16446	United Kingdom	
61624	C541433	23166	-74215	2011-01-18 10:17:00	1.04	12346	United Kingdom	
225529	556690	23005	-9600	2011-06-14 10:37:00	0.00	NA	United Kingdom	1
225530	556691	23005	-9600	2011-06-14 10:37:00	0.00	NA	United Kingdom	1
4287	C536757	84347	-9360	2010-12-02 14:23:00	0.03	15838	United Kingdom	٤
4								•

# > Updated Working Dataframe on 'UnitPrice'

### Show code

Overviewing numeric datatypes

	Quantity	InvoiceDate	UnitPrice
count	533690.000000	533690	533690.000000
mean	9.663559	2011-07-04 10:48:18.389215232	3.288986
min	-80995.000000	2010-12-01 08:26:00	0.000000
25%	1.000000	2011-03-28 11:34:00	1.250000
50%	3.000000	2011-07-19 15:23:00	2.080000
75%	10.000000	2011-10-18 17:10:00	4.130000
max	80995.000000	2011-12-09 12:50:00	1867.860000
std	219.559157	NaN	5.280490

> Create DataFrame: zero unitprice & positive quantity

Total rows with zero unitprice & positive quantity = 1144

Previewing the first 20 rows, sorted by 'Quantity' in descending order

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	
502122	578841	84826	12540	2011-11-25 15:57:00	0.0	13256	United Kingdom	Α
74614	542504	37413	5568	2011-01-28 12:03:00	0.0	NA	United Kingdom	

# UK Online Store Retail Transactions

# > Create DataFrame: zero unitprice & positive quantity

### Show code

Total rows with zero unitprice & positive quantity = 1144

Previewing the first 20 rows, sorted by 'Quantity' in descending order

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	
502122	578841	84826	12540	2011-11-25 15:57:00	0.0	13256	United Kingdom	A
74614	542504	37413	5568	2011-01-28 12:03:00	0.0	NA	United Kingdom	
220843	556231	85123A	4000	2011-06-09 15:04:00	0.0	NA	United Kingdom	W
263885	560040	23343	3100	2011-07-14 14:28:00	0.0	NA	United Kingdom	
115807	546139	84988	3000	2011-03-09 16:35:00	0.0	NA	United Kingdom	
74615	542505	79063D	2560	2011-01-28 12:04:00	0.0	NA	United Kingdom	
203751	554550	47566B	1300	2011-05-25 09:57:00	0.0	NA	United Kingdom	Т
160541	550460	47556B	1300	2011-04-18 13:18:00	0.0	NA	United Kingdom	
82795	543258	84611B	1287	2011-02-04 16:06:00	0.0	NA	United Kingdom	
422750	573114	20713	1000	2011-10-27 15:36:00	0.0	NA	United Kingdom	
80665	543051	79062D	960	2011-02-03 10:15:00	0.0	NA	United Kingdom	AS
380687	569830	23343	800	2011-10-06 12:38:00	0.0	NA	United Kingdom	
38261	539494	21479	752	2010-12-20	0.0	NA	United	\\ ▶

### Show code

• A "thrown away" product description has been found

All of these will be removed from the main dataset as they are not relevant to the transaction analysis of products being sold by the retailer

> Count Rows: 'thrown away' product description in main dataframe

### Show code

<b>→</b>		InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Des
	82794	543257	84611B	-1430	2011-02-04 16:06:00	0.0	NA	United Kingdom	th
	82795	543258	84611B	1287	2011-02-04 16:06:00	0.0	NA	United Kingdom	th
	4				0044 00 04			1.1 141	•

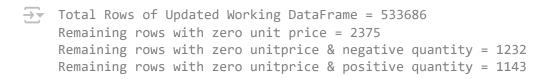
> Remove Rows: 'thrown away' product description

-6	_	_
	→	$\nabla$
-	_	_

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	
540422	C581484	23843	-80995	2011-12-09 09:27:00	2.08	16446	United Kingdom	
61624	C541433	23166	-74215	2011-01-18 10:17:00	1.04	12346	United Kingdom	
225530	556691	23005	-9600	2011-06-14 10:37:00	0.00	NA	United Kingdom	1
225529	556690	23005	-9600	2011-06-14 10:37:00	0.00	NA	United Kingdom	1
4287	C536757	84347	-9360	2010-12-02 14:23:00	0.03	15838	United Kingdom	S
4								•

## > Count Rows: remaining rows

### Show code



## > // Observations

### Show code

### Observations

- 1 row with the 'throw away' product description have been removed
- 4 rows with the 'thrown away' product description have been removed
- 533, 686 total rows on updated working dataframe
- 2,375 rows remaining with zero values in 'UnitPrice'. Although these rows have zero values, they will not be removed, as many represent valid transactions, including placement orders and canceled transactions

> [Quantity] Extreme Values

Show code

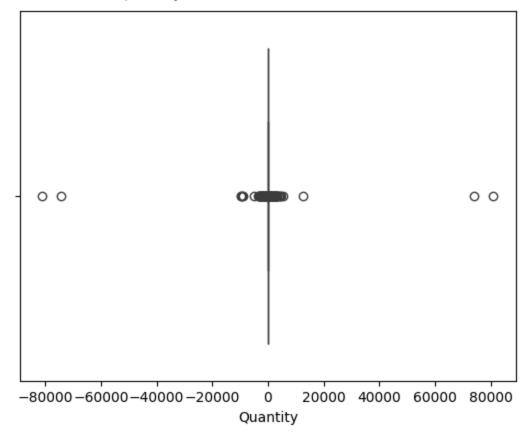
> ~~Investigate: 'Quantity' extreme values

Show code

> Check Outlier: boxplot 'Quantity'

Show code

<Axes: xlabel='Quantity'>



> Check Outlier: isolate values



	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	De
6161	<b>9</b> 541431	23166	74215	2011-01-18 10:01:00	1.04	12346	United Kingdom	
4								•

#### Show code

### Observations:

- 'Quantity' Negative values could possibly have a corresponding transaction having a (+) value on 'Quantity' ~{Matching Transactions: order placement and cancelled}
  - Hence, further examine the nature of dataset particularly on column 'Quantity'
- [Quantity] Matching Transactions: placement and cancelled

### Show code

// Objective: identify order transactions of those cancelled transactions (having matching details on particular columns while positive (+) on 'Quantity' values) prior the cancellation; accounting the following columns:

- Exact Values = (1) StockCode (2) Quantity [absolute value] (3) CustomerID (4) Description (5) Country (6) UnitPrice
- Variation of values = (7) InvoiceNo (8) InvoiceDate
- Identify: matching placement-and-cancelled transactions



	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	]
61619	541431	23166	74215	2011-01-18 10:01:00	1.04	12346	United Kingdom	CE
61624	C541433	23166	-74215	2011-01-18 10:17:00	1.04	12346	United Kingdom	CE
84148	543370	22839	2	2011-02-07 14:51:00	14.95	12359	Cyprus	3
154936	C549955	22839	-2	2011-04-13 13:38:00	14.95	12359	Cyprus	3
423970	573173	22941	2	2011-10-28 10:10:00	8.50	12362	Belgium	(
4								•

### Show code

- 4, 202 rows are matching transactions of placement orders (+ postive in 'Quantity' value) that were eventually cancelled (- negative in 'Quantity' value)
  - Investigate this generated dataframe of matching transactions
- > ~~Investigate: matching placement-and-cancelled transactions

Show code

> Their InvoiceNo

-	_	_
-	-0	$\nabla$
4	_	_

count

2066

InvoiceNo	
5	2140

dtype: int64

С

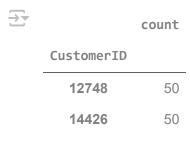
> Their Total Number of Distinct Customers

### Show code



> Listing some of their distinct customers

### Show code



dtype: int64

> Overview: transaction behavior of CustomerID 12748

		-
-	_	-
		~

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	
124794	546991	84929	6	2011-03-18 13:08:00	0.55	12748	United Kingdom	FR
124921	C546997	84929	-6	2011-03-18 13:32:00	0.55	12748	United Kingdom	FR
471159	576623	23057	144	2011-11-15 17:12:00	1.00	12748	United Kingdom	(
473390	C576831	23057	-144	2011-11-16 14:56:00	1.00	12748	United Kingdom	(
4								•

#### Show code

### Observations

The Matching Placement-and-Cancelled Transaction isolated dataframe has varying transaction trends

- 1. Some order placement transactions were recorded first prior cancellation\*\*
- 2. While, some cancelled\*\* transactions were recorded first prior order placement.

\*\*assuming all cancelled tranctions have negative values on 'Quantity'; and all 'InvoiceNo' starting with'C'

~~ These observations are not unsuaul in e-commerce, particularly finding cancelled InvoiceNo transactions appear before the order placements in terms of recorded date and time. There are several factors affecting this such as System Processing Delays, Data Sync Issues, etc.

Although the identified rows are classified as Matching Placement-and-Cancelled Transactions, these will not be removed despite their summation results in a net zero. Removing the identified 4,202 rows could skew and affect the analysis of the total transactions (accounting order placements and canceled transactions)

# COLUMNS | Examine Nature of object values

## > .describe() object values

### Show code

$\Rightarrow$		InvoiceNo	StockCode	CustomerID	Country	Description
	count	533686	533686	533686	533686	533686
	unique	25244	3940	4364	38	3810
	top	573585	85123A	NA	United Kingdom	WHITE HANGING HEART T-LIGHT HOLDER
	freq	1113	2301	133922	488663	2368

### > // Observations

### Show code

### Observations

- 25,244 rows are unique on 'InvoiceNo'; indicating some transactions have same invoice numbers (normal for e-commerce transactions)
- 3,940 rows are unique on 'StockCode' but 3,810 unique rows on 'Description'; indicating varying StockCode values could have same 'Description'
- 4,364 rows are unique on 'CustomerID'; indicating there are repeat customers

## > Updated Working Dataset

$\rightarrow$	<class 'pandas.core.frame.dataframe'=""></class>							
	Inde	lex: 533686 entries, 0 to 541908						
	Data	Data columns (total 8 columns):						
	#	Column	Non-Null Count	Dtype				
	0	InvoiceNo	533686 non-null	object				
	1	StockCode	533686 non-null	object				
	2	Quantity	533686 non-null	int64				
	3	InvoiceDate	533686 non-null	<pre>datetime64[ns]</pre>				
	4	UnitPrice	533686 non-null	float64				
	5	CustomerID	533686 non-null	object				
	6	Country	533686 non-null	object				

7 Description 533686 non-null object

dtypes: datetime64[ns](1), float64(1), int64(1), object(5)

memory usage: 36.6+ MB

# SUMMARY

- 533, 686 total rows on Working Dataset (previously 541,909)
- 8, 223 rows were removed (1.52% of the raw dataset)

112 rows were zero in 'UnitPrice' and null in both 'Description' and 'CustomerID'; they have insufficient information

5.270 were duplicate rows

## **UK Online Store Retail Transactions**

### SUMMARY

- 533, 686 total rows on Working Dataset (previously 541,909)
- 8, 223 rows were removed (1.52% of the raw dataset)
  - 112 rows were zero in 'UnitPrice' and null in both 'Description' and 'CustomerID'; they have insufficient information
  - 5,270 were duplicate rows
    - 2,689 rows with alphameric StockCodes; identified as postage and bad debt records; deemed not relevant to the transaction analysis of retail products.
  - 147 rows with alphanumeric StockCodes; identified as carriages and ebay; deemed not relevant to the transaction analysis of retail products.
  - 1 row with the 'throw away' product description have been removed
  - 4 rows with the 'thrown away' product description have been removed
- 4, 202 rows are matching transactions of placement orders (+ postive in 'Quantity' value) that were eventually cancelled (- negative in 'Quantity' value)
- > Export Working DataFrame as CSV Files for Exploratory Data Analysis

