Online Retail Analysis

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[Task One] Loading the Data

```
data <- read_csv("online_retail_II.csv")
summary(data)
```

```
##    Invoice            StockCode         Description           Quantity
##  Length:1067371     Length:1067371     Length:1067371     Min.   :-80995.00
##  Class :character   Class :character   Class :character   1st Qu.:     1.00
##  Mode  :character   Mode  :character   Mode  :character   Median :     3.00
##                                                           Mean   :     9.94
##                                                           3rd Qu.:    10.00
##                                                           Max.   : 80995.00
##
##   InvoiceDate                      Price            Customer ID
##  Min.   :2009-12-01 07:45:00   Min.   :-53594.36   Min.   :12346
##  1st Qu.:2010-07-09 09:46:00   1st Qu.:     1.25   1st Qu.:13975
##  Median :2010-12-07 15:28:00   Median :     2.10   Median :15255
##  Mean   :2011-01-02 21:13:55   Mean   :     4.65   Mean   :15325
##  3rd Qu.:2011-07-22 10:23:00   3rd Qu.:     4.15   3rd Qu.:16797
##  Max.   :2011-12-09 12:50:00   Max.   : 38970.00   Max.   :18287
##                                                    NA's   :243007
##    Country
##  Length:1067371
##  Class :character
##  Mode  :character
##
##
##
##
```

From the summary above, we see:

- Negative Prices
- Large Prices
- Negative Quantities
- Missing Data (NA's)

It's hard to interpret what these points of data mean, and if they need to be altered before performing analysis. From this, it's clear that we need to look at the data quality.

[Task Three] Handling Returns and Data Cleaning

In this section I will investigate the anomalous data identified in the summary above. First I'll be looking into the data for which there are negative quantities.[1]

```
data %>% filter(Quantity <= 0)
```

Table 1: Head of the Filtered Quantity Data (22,950 rows)

Invoice	Description	Quantity	Price	Customer ID
C489449	PAPER BUNTING WHITE LACE	-12	2.95	16321
C489449	CREAM FELT EASTER EGG BASKET	-6	1.65	16321
C489449	POTTING SHED SOW 'N' GROW SET	-4	4.25	16321
C489449	POTTING SHED TWINE	-6	2.10	16321
C489449	PAPER CHAIN KIT RETRO SPOT	-12	2.95	16321
C489449	SAVE THE PLANET MUG	-12	1.25	16321

It seems like there are a large amount of quantities which are negative. From the context for the CSV, these are cancelled transactions indicated by the "C" in the invoice. If not removed, these cancelled transactions will count as revenue as they have a positive price associated with them. Further investigation shows that these invoice codes have no regular counter part (ie. no double-counting is occuring), so we can just safely remove all of the cancelled invoice codes.

Along with these are some observations of returns, negative quantities with no "C". Because some objects may be purchased before the data collection period, we want to remove their corresponding returns. We could do this by searching for matches of particular quantity, customer ID, and stock code, however, because I'm limited on time, and because this is a very small portion of the data set (6,000 observations), **I am going to remove these returns instead**.

Investigating Other Anomalous Data

Next I investigate what observations are strictly below zero.

```
data %>% filter(Price < 0)
```

Table 2: Negative Price Data (5 rows)

Invoice	Description	Quantity	Price	Customer ID
A506401	Adjust bad debt	1	-53594.36	NA
A516228	Adjust bad debt	1	-44031.79	NA
A528059	Adjust bad debt	1	-38925.87	NA
A563186	Adjust bad debt	1	-11062.06	NA
A563187	Adjust bad debt	1	-11062.06	NA

Data which is less than zero is there to adjust for bad debt. It's unrelated to revenue and, due to the large numbers, may influence any statistics we generate about the data. As such I will remove these observations from the dataset.

Next it'll be worth looking into the large values for price

[1] Task Three has been integrated into my data cleaning, as this is where I originally dealt with the returned items and because it would effect the analysis in Task Two.

```r
data %>% arrange(desc(Price)) %>% head()
```

Table 3: Observations with Largest Prices

Invoice	Description	Quantity	Price	Customer ID
C556445	Manual	-1	38970.00	15098
C512770	Manual	-1	25111.09	17399
512771	Manual	1	25111.09	NA
C520667	Bank Charges	-1	18910.69	NA
C580605	AMAZON FEE	-1	17836.46	NA
C540117	AMAZON FEE	-1	16888.02	NA

Seems like there are many observations in the data which may not be related to actual purchases in the store. For the purposes of this analysis I'll leave these in, as it would take a significant amount of effort to remove them, but given more time I would ask for clarification about observations labelled:

- Manual
- AMAZON FEE
- Bank Charges
- DOTCOM Postage
- Adjust Bad Debt

As they seem like they should not be used in calculations of revenue.

Next we will check on the missing Customer ID data.

```r
data %>% filter(is.na(`Customer ID`), Quantity > 0)
```

Table 4: Head of Missing Customer ID Observations (238,801 rows)

Invoice	Description	Quantity	Price	Customer ID
489525	BLUE PULL BACK RACING CAR	1	0.55	NA
489525	SET/6 3D KIT CARDS FOR KIDS	1	0.85	NA
489548	FELTCRAFT DOLL ROSIE	1	2.95	NA
489548	FELT TOADSTOOL LARGE	12	1.25	NA
489548	FELTCRAFT DOLL MOLLY	3	2.95	NA
489548	LARGE HEART MEASURING SPOONS	1	1.65	NA

It seems as though this data is still useful, it should only be filtered out if we explicitly need to use the customer ID in our analysis.

Clean Data

From the above investigation, it's clear that some of the data needs to be removed before we can summarise and visualise the data. The code below filters out all of the troublesome observations identified previously.

```r
# Remove the cancelled invoices
cancelled_invoices <- data %>% filter(grepl("C", Invoice))
cancelled_invoices <- cancelled_invoices$Invoice %>% unique()

filtered_data <- data %>% filter(!(Invoice %in% cancelled_invoices))

# Remove all returns
```

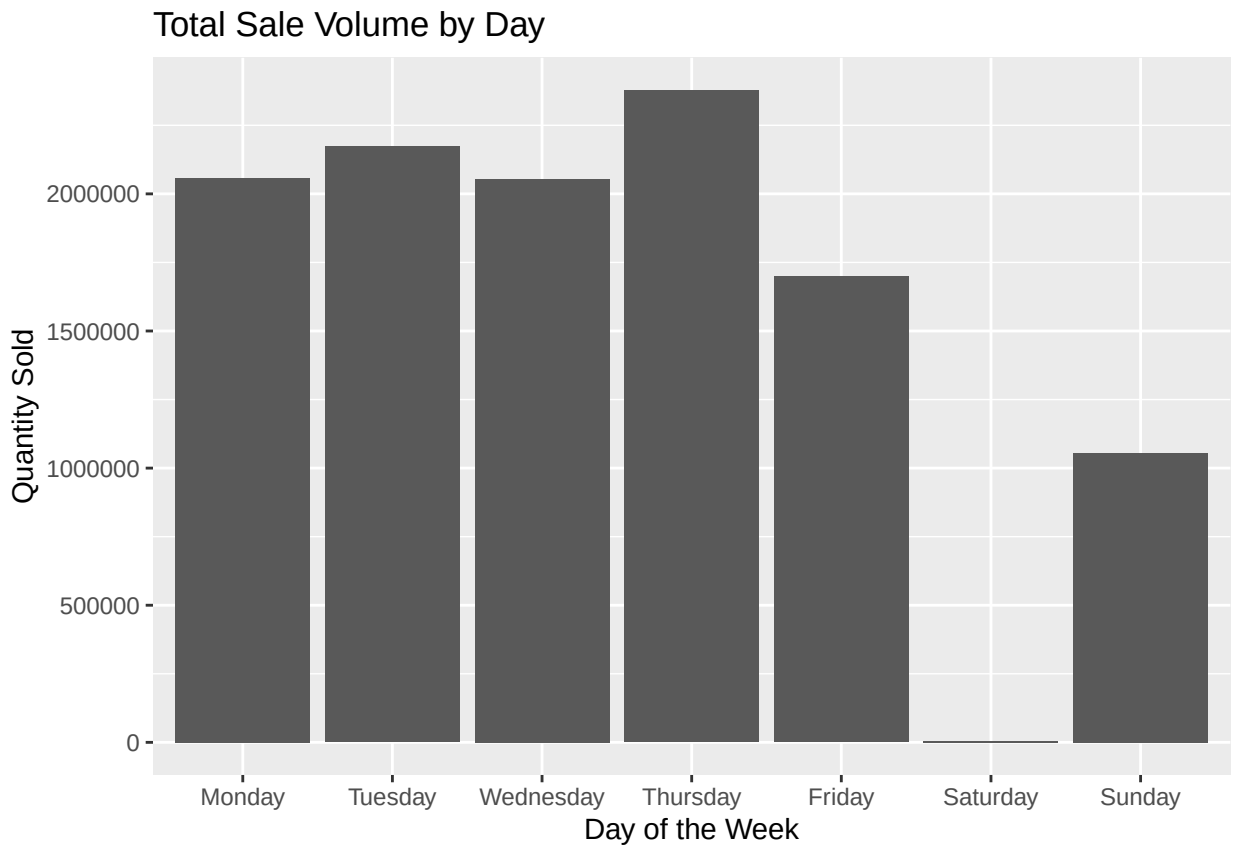
```r
filtered_data <- filtered_data %>% filter(Quantity > 0)

# Remove invoices with negative pricing
filtered_data <- filtered_data %>% filter(Price > 0)
```

[Task Two] Plotting the Data

Before modelling the data, it's a good idea to do some exploratory analysis and investigate what relationships lie in the data.

Plotting Sales Volumes

```r
filtered_data <- filtered_data %>% mutate(dow = weekdays(InvoiceDate))

filtered_data$dow <- factor(filtered_data$dow,
                            levels = c("Monday", "Tuesday", "Wednesday",
                                       "Thursday", "Friday", "Saturday", "Sunday"),
                            ordered = TRUE)

ggplot(data = filtered_data, aes(x = dow)) +
  geom_bar(aes(weight = Quantity)) +
  labs(title = "Total Sale Volume by Day",
       x = "Day of the Week",
       y = "Quantity Sold")
```



There's an abnormally small number of sales on Saturdays. Because their customers are mostly wholesalers, we also see a reduced number of customers toward the weekend which we can see in the Friday and Sunday total. Because of this, it's likely the low number of sales on Saturday is due to the store being closed, but this should be confirmed with the owner.

Plotting Revenue Share

Unfortunately, I was not able to finish this plot. Given more time, I would have used the top 10 customer IDs and products to limit the number of groupings there were in the plot. I have however summarised the data, which conveys much of the same information that the plot would have.

```
lastest_date <- filtered_data$InvoiceDate %>%
  unique() %>%
  .[order(., decreasing = TRUE)] %>%
  .[[2]]

prev_month_data <- filtered_data %>% filter(year(InvoiceDate) == year(lastest_date),
                                    month(InvoiceDate) == month(lastest_date - dmonths(1)))

prev_month_data <- prev_month_data %>% mutate(revenue = Quantity * Price)

# Grab the top 10 customers
customer_id_summ <- prev_month_data %>%
  group_by(`Customer ID`) %>%
  summarise(total_rev = sum(revenue)) %>%
  arrange(desc(total_rev)) %>% head(11)

top_10_customers <- customer_id_summ$`Customer ID`[2:11]

stock_code_summ <- prev_month_data %>%
  group_by(`StockCode`) %>%
  summarise(total_rev = sum(revenue)) %>%
  arrange(desc(total_rev)) %>% head(10)

top_10_products <- stock_code_summ$StockCode

#
# Set all labels except for the top 10 of customer ID and Stock code to "Other"
#

# Plot, given the correctly labelled data:

# ggplot(data = prev_month_data, aes(x = StockCode, fill = `Customer ID`)) +
#   geom_bar(aes(weight = Price)) +
#   labs(title = "Last Month's Revenue by Product and Customer",
#        x = "Product",
#        y = "Total Revenue (£)",
#        legend = "Prodduct")
```

Table 5: Top 10 Customers by Revenue

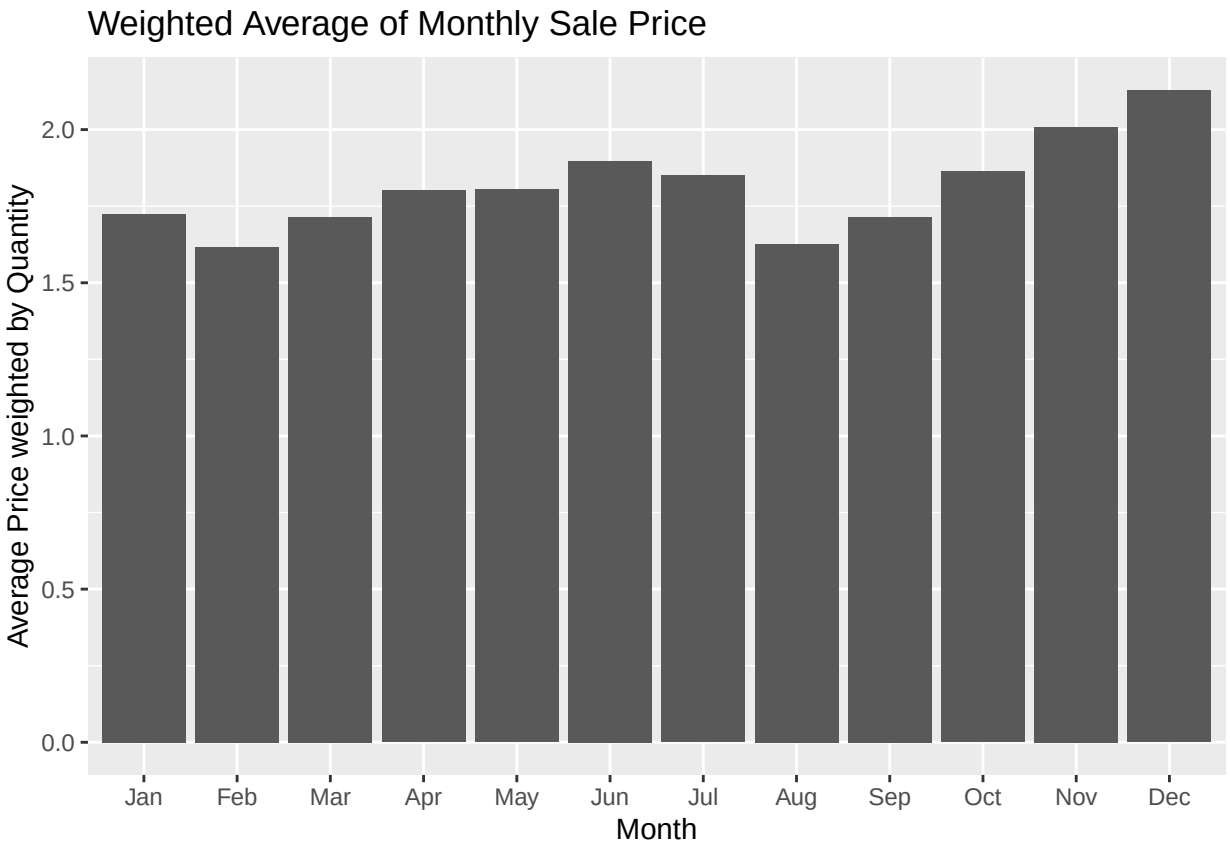
Customer	Total Revenue
17450	27869.45
14096	27827.78
14646	25375.41
14911	22720.73
14088	16851.61
18102	15331.08
17511	13522.22
17389	12361.36
12748	10639.23
13081	9467.26

Table 6: Top 10 Products Sold by Revenue

Product	Total Revenue
DOT	36905.40
23084	34556.72
22086	28985.04
22197	14195.60
85123A	14136.70
22423	13799.58
22910	12944.49
23355	11824.42
85099B	11641.37
79321	11485.77

Plotting Average Price Weighted by Quantity Sold

```
monthly_data <- filtered_data %>% mutate(month = months(InvoiceDate, abbreviate = TRUE),
                                         year = year(InvoiceDate))

monthly_summary <- monthly_data %>%
  group_by(month) %>%
  summarise(weighted_average = weighted.mean(Price, w = Quantity))

monthly_summary$month <- factor(monthly_summary$month,
                                levels = c("Jan", "Feb", "Mar",
                                           "Apr", "May", "Jun",
                                           "Jul", "Aug", "Sep",
                                           "Oct", "Nov", "Dec"),
                                ordered = TRUE)

ggplot(data = monthly_summary, aes(x = month)) +
  geom_bar(aes(weight = weighted_average)) +
  labs(title = "Weighted Average of Monthly Sale Price",
       x = "Month",
       y = "Average Price weighted by Quantity")
```



From this we can see that there's some seasonal trends in the data. It slowly climbs to a peak throughout January-June and in August-December. The peak in December is likely caused by a higher demand in gift-ware during Christmas, especially because the store sells Christmas decorations. I'm unsure what the July peak is caused by. It may be worth asking a subject matter expert, such as the owner, who might have more intuition.

[Task Four] Predicting Monthly Revenue

To forecast next month's revenue I will consider the following models. For all of the models, it will be important to convey the uncertainty in our estimate to the owner.

Linear Regression

Create a linear model using the price, quantity, and timestamps within the data. The response variable of interest would be Total Revenue, calculated through $Price \times Quantity$. Revenue could then be aggregated over each month, and both the month and year could be used as explanatory variables. This means it would be a rather simple model, and wont require hundreds of variables (like if customer ID was a explanatory variable).

Uncertainty of the prediction can be very easily conveyed through confidence intervals.

The metrics which will be of interest include:

- Price
- Quantity

- Timestamps

ARIMA Model

Because the intention is to forecast this months revenue, and because we have timeseries data, an ARIMA model would also be suitable here. An ARIMA model should be fairly reliable for forecasting only one one month ahead, however, there might be wide confidence intervals due to only having two years of data.

Similarly to above, I would aggregate the total revenue monthly and use this as the data that's fed into the ARIMA model.

While experimenting with different models in the ARIMA family, I would also investigate integrating a seasonal component through a SARIMA model. Seasonality is common in financial data (higher sales during certain periods), and is clearly present in this data, as shown in the Weighted Average plot above. To do this, however, we would need a larger backlog of data.

The metrics which will be of interest include:

- Price
- Quantity
- Timestamps

Uncertainties to explore:

For each of the above models, the below uncertainties would need to be taken into account:

- What plans the retailer has for discounts during the Christmas period, and if this is different from previous years
- Are new items being sold in the store? How might this effect sales?

And generally, it will be worth asking the retailer if they're making any changes to how they're running the business in the coming month (new website, new membership program, etc.). Past data wont give a great forecast if it isn't representative of what's happening this month.

Other Models

Given more time, I would do a literature review and investigate what models are explored in "Forecasting: Principles and Practice" by Rob J Hyndman and George Athanasopoulos. The text is openly available here and is a great resource to help interpret and utilise timeseries data.

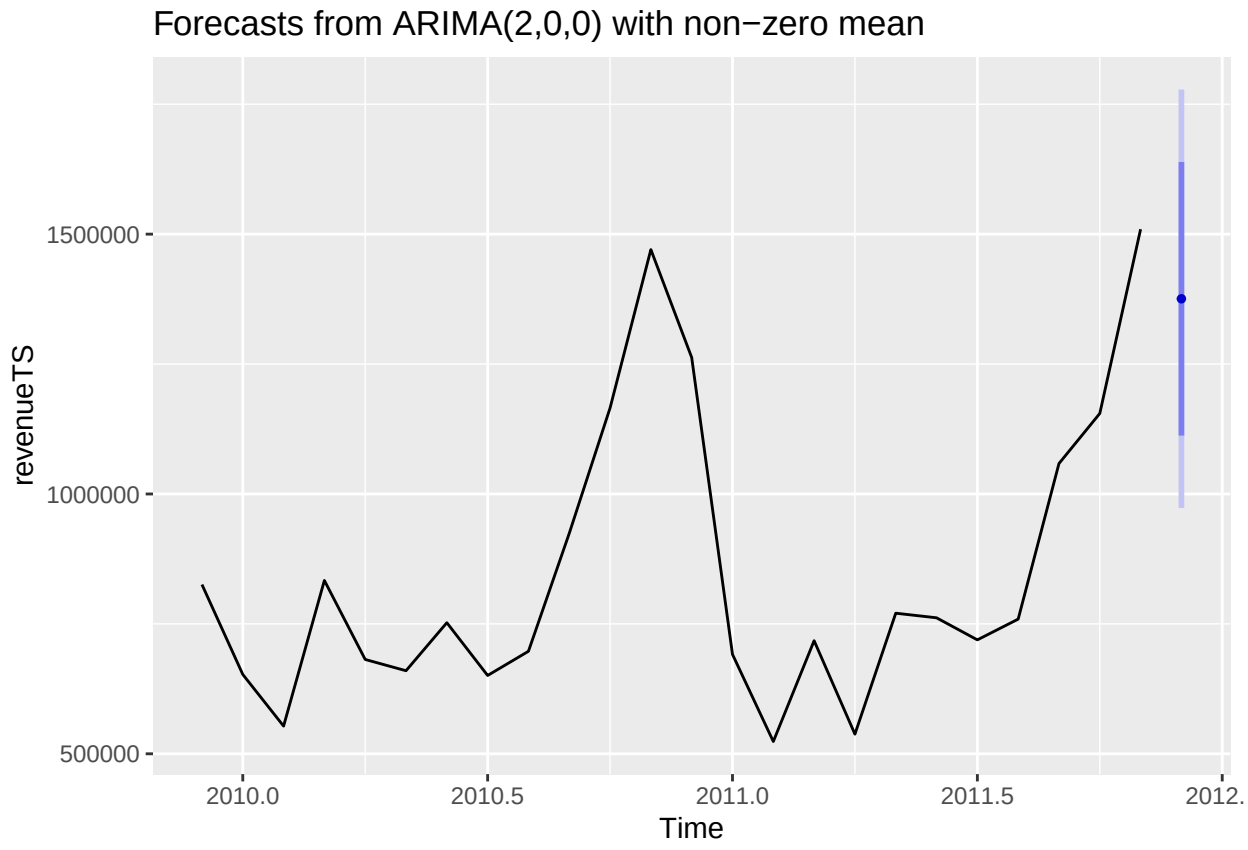
[4b] Best Approach

Of the two models above, I would reccomend the ARIMA model as the best approach. It' takes advantage of the timeseries nature of the data's more natural for this kind of data and, while more complex than the linear model approach, is not overly complex for the increase in accuracy it may provide. The methodology is well established, and there are existing libraries in R (namely forecast) which make the implementation straight forward and quick.

[4c] Implementation of Chosent Solution

For my implementation I'm using an ARIMA model. Largely, this is because it provides some quick functionality for comparing the historical data to the prediction. If given more time, I would choose to compare a few methods I've researched and compare them. Or, I would ask for advice from peers, since I have limited experience in the area.

```r
library(forecast)

revenueTS <- monthly_data %>%
  mutate(Revenue = Price*Quantity,
         date = floor_date(as.Date(InvoiceDate), "month")) %>%
  group_by(date) %>%
  summarise(total_revenue = sum(Revenue)) %>%
  arrange(date)

# Remove the current days we have from that month
revenueTS <- revenueTS %>% filter(date < "2011-12-01")

revenueTS <- revenueTS %>% select(total_revenue) %>% ts(start = c(2009, 12),
                                                        end = c(2011, 11),
                                                        deltat = 1/12)

model <- auto.arima(revenueTS, lambda = "auto")

model %>% forecast(h = 1) %>% autoplot()
```



The model above shows the prediction for the total amount of revenue earnt during December of 2011, along with confidence intervals. The darker band is an 80% confidence interval, and the lighter band is a 95% confidence interval.

I'm not confident in the forecast due to the numerous "high price" observations I did not remove when cleaning the data. However, ignoring this, I think it's a fairly good estimate. There's a significant amount of

uncertainty associated with it due to a lack of past data, but it seems inline with the trend I'd expect the data to take. Although admittedly, the spike in June is not present in this plot, but was apparent in the Weighted Average plot. It might be worth investigating this given more time.

Given more time I would do a more thorough analysis where I'm more involved in the modelling process. I would look into exploring daily/weekly summaries of the data, as the monthly data here is quite limiting and does not give a good prediction of total revenue. It may also be worth exploring the results of linear regression and seeing how they compare to the estimate here.

As to whether or not I would reccomend a new ferrari based on this forecast, that's a different matter altogether. In 2011, the conversion rate from stirling to USD was around £1 GBP = $1.6025 USD. Around then a new ferrari was about $225,325 USD; which is around £140,000! Even if he can afford it (which it seems like he can) I would not reccomend spending this much money on a Ferrari.