**Data Wrangling and Analysis Process - Amazon versus In-Store Prices**

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An open source data set produced by Alberto Cavallo, co-founder of MIT’s Billion Price Project was used for this project. The original data set was used to determine if prices in store was significantly different than prices on-line. Cavallo and team gathered prices from multiple products, in multiple countries on-line and in-store. Multiple teams gathered prices manually and through a price scrapping app developed by Cavallo.

For this project, a subset of the full data set was used. The data set contained 5 categories of products with prices on multiple items in-store and online.

**Data Set:**

My project will wrangle and analyze a small subset of Cavallo’s multi-country data. I will focus on the US price comparisons only comparing the in store prices with the Amazon price.

Raw Data file was downloaded from: <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FXXOUHF>

Goal1– To determine if there is a cost benefit of purchasing various product categories at Amazon or in the physical store

Goal2 – To determine if sale items have better pricing on-line or in the store

Goal3 – Determine if there is bigger price gap between online and retail correlates to difference between the time the item was compared online and in store

**Data Wrangling Approach:**

* Import data original\_amazon\_compare.csv into R
* Used dplyr library to wrangle data set
* Used ggplot2 library to visualize data

The data contains many columns (variables) that are not needed for my analysis so I will first clean the data table and only select the columns I need...

price – price in store

id – item number

price\_amazon – price on amazon

sale\_online – the item was on sale online

PRICETYPE – if the item was on sale in store

datediff – difference between time purchase online – in store

category – groupings of product type (electronics, office supply, etc.)

The data contained prices across multiple price points. To offset weighing deltas from higher priced items, percent difference was used to compare difference.

p\_difference was calculated based on the delta of price from in-store versus on-line

p\_difference = (amazon – in-store)/ in-store

**Data Errors –**

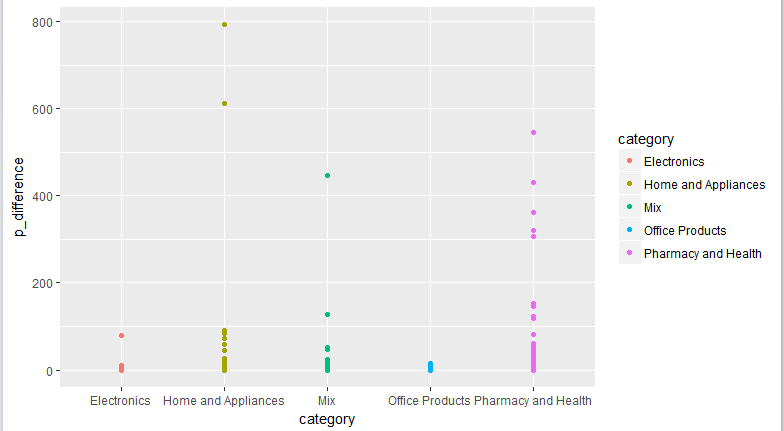
The next step in analyzing data was to visualize the various categories to develop an approach to analysis. Upon inspection, it was evident that there were several large errors embedded in the data. Data errors include –

* Product ID transferring into In-Store Prices
* Errors in decimal placement - ex – 6.99 (in-store) but typed as 69.9 (amazon)
* Errors in data entry – ex – Door has online price 2,130 and in-store price of 3.97
* There were subtle errors where some items did appear to be erroneous but differences and product type were unclear since amazon may charge higher prices for small items to compensate for shipping and handling

The data set contained over 3900 rows so manual inspection of each item was not feasible.

**Handling Outliers –**

Using a scattered plot, I could identify the p\_difference that was the threshold for extreme outliers.



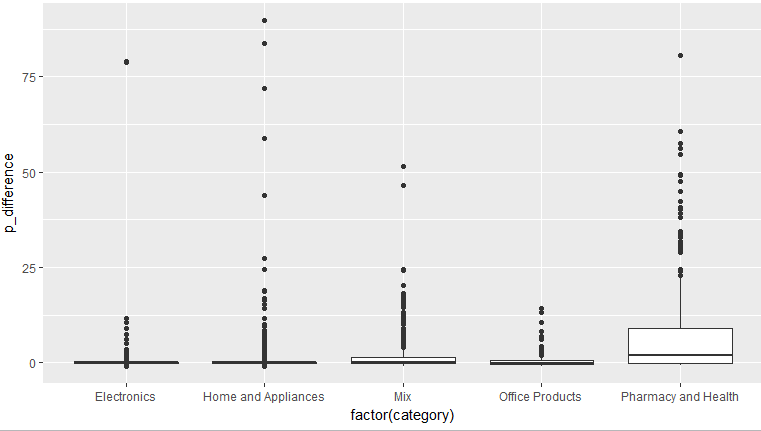
**Figure 1 – Scatter plot of p\_difference by category**

From the plot I found that after a p\_difference of >100, the price gap was too extreme to be a reasonable difference.

I used that difference to remove the obvious difference. To remove values, I created a vector containing the values that exceeded my threshold, then removed that vector from the data set.

I then attempted to used statistical tests to identify outliers, using the Outlier packaged, I applied the Grubbs test to identified the extreme outliers from each end of the distribution. This worked but needed multiple iterations as it only identified the one point. The other issue was that this test was designed for normal distribution data sets. This data was non-normal in its distribution.

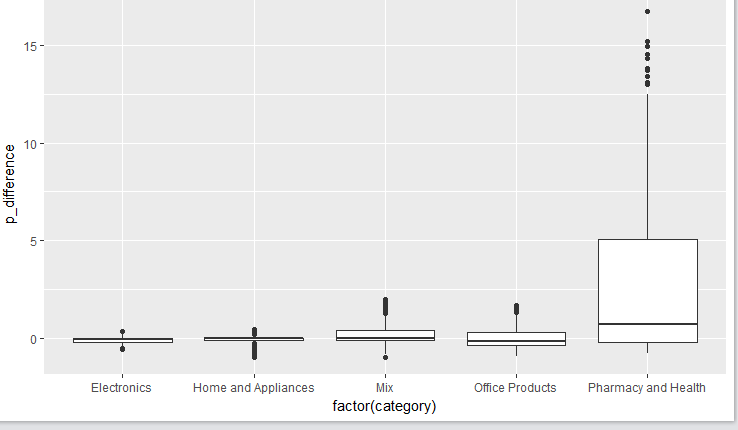
Since the data was non-normal, I applied the median 1.5 IQR method to determine thresholds for upper and lower point removal. Calculated each category’s upper and lower IQR, then examined the data at those thresholds to determine if the removal of points beyond the upper and lower thresholds were reasonable to remove.



**Figure 2 -Box Plot prior to removal of outliers**

Once I determined the reasonable thresholds, I removed the data points exceeding those thresholds on the upper and lower ends.

The new data set continues to show excessive spread but the difference seems more reasonable and more a function of actual price differences versus differences due to entry errors.

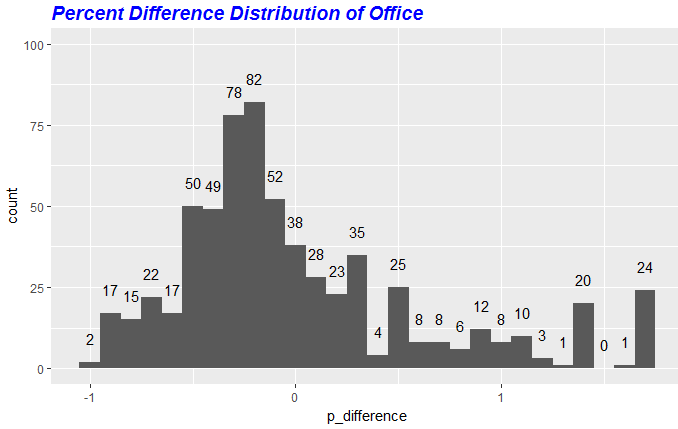


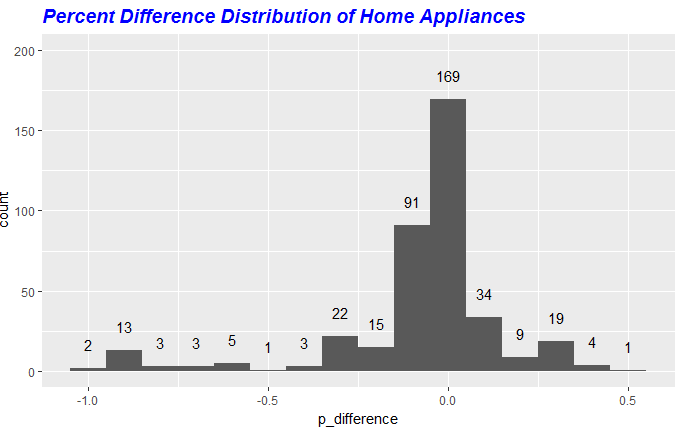
**Figure 3 – Box Plot after outlier removal**

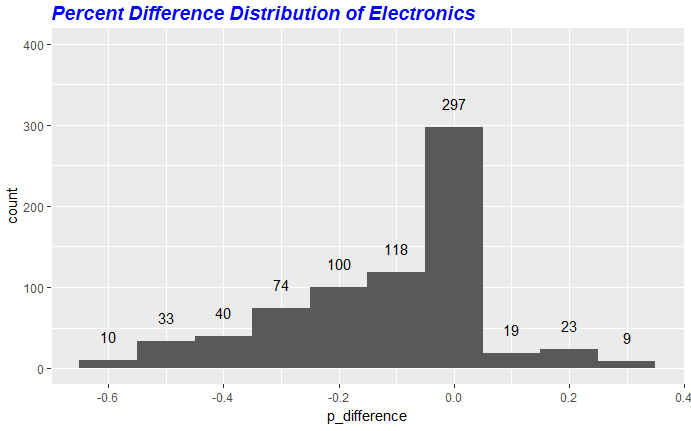
**Testing Hypothesis –**

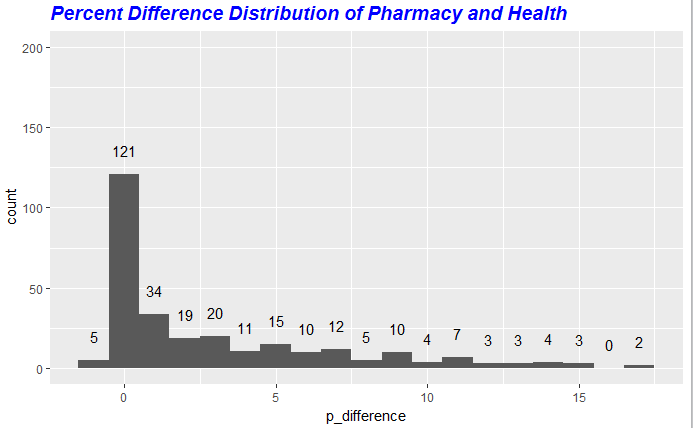
Since the data is non-normal, even after the removal of outliers, I cannot test my hypothesis or predict all price differences with my current sample set.

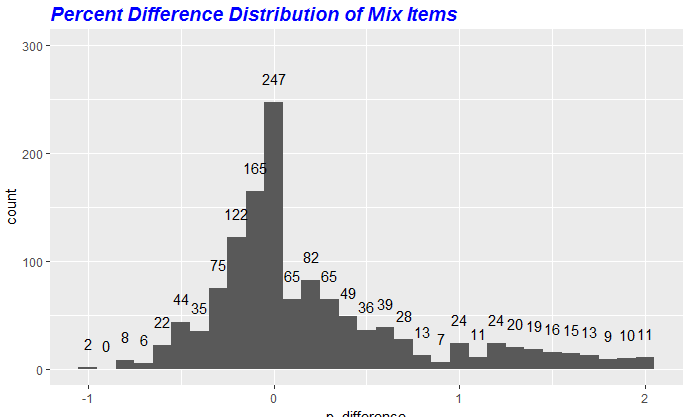
My first hypothesis is to determine if one product has a better price distribution or skew towards Amazon versus in Store. I can test this visually with a simple distribution plot











To determine the percentage of time it was better or neutral to purchase in store, I created new column assigning 0 if the price was better on-line and 1 if the price was better in store or same price.

The averages of the product categories showed –

mean(pharm\_health$bias)

[1] 0.625

> mean(electronics\_set$bias)

[1] 0.2365145

> mean(home\_app$bias)

[1] 0.5101523

> mean(mix$bias)

[1] 0.5304212

> mean(office$bias)

[1] 0.369906

> mean(pharm\_health$bias)

[1] 0.625

From the averages, you can see a price advantage if you purchase office and electronic products online.

**Determining if Sale Items Correlates to Better Price On-line:**