Clustering Large datasets into Price indices - CLIP

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Index Numbers Methodology



Overview

- Web Scraping
- Overcoming the Product Churn Issue
- Finding the groups
 - New Data and Forming the Index
 - 5 Results
 - **Future Work**



Web Scraping

Motivation for web scraping

- Consumer Prices Index including Owner Occupied Housing Costs (CPIH) is the most comprehensive measure of inflation in the UK
- Johnson Review published in January 2015, recommended increasing the use of alternative data sources in consumer prices



Web scraping in ONS

Prices for 33 CPIH items from 3 online retailers

TESCO Sainsbury's Waitrose

- Daily collection (around 8,000 price quotes, compared to 6,800 a month for traditional collection)
- Collects price, product name and discount type
- Ongoing since June 2014

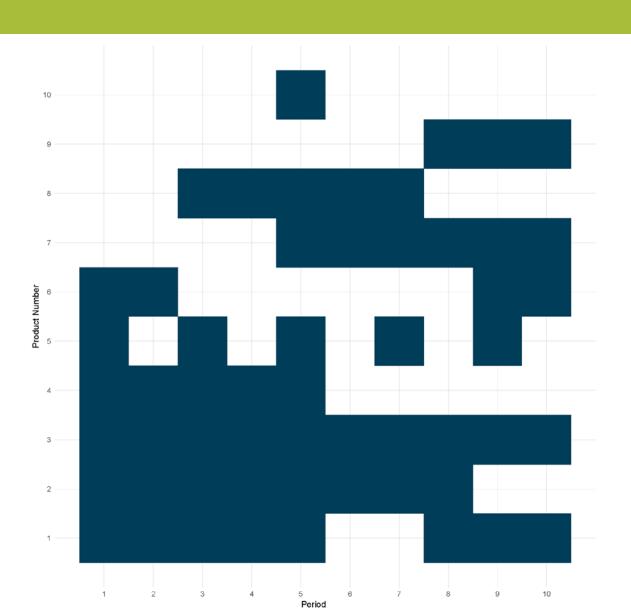
Limitations

- Market coverage
 Large retailers only, permission, regional variation?
- High product churn
 Traditional methods struggle
- Only prices not expenditure
 What do people actually buy?
- Technological difficulties
 Scraper breaks, time and cost

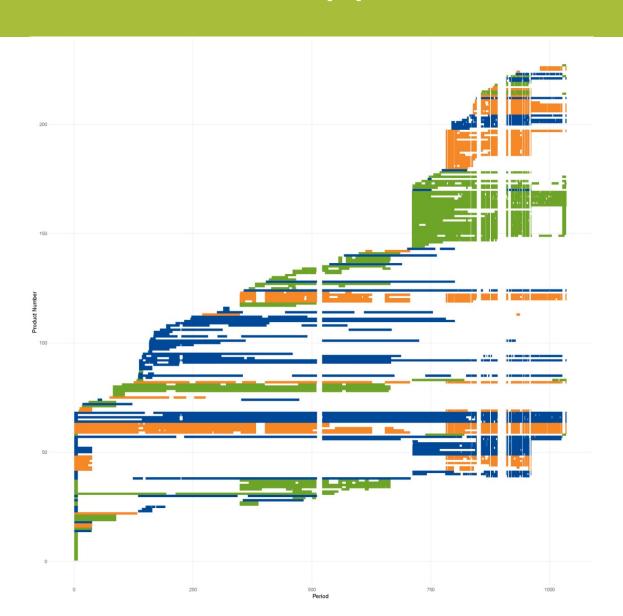
Product Churn

- Product Churn is the process of products leaving and/or entering the sample.
- This can either be:
 - Product goes out of stock, temporally leaves the sample,
 - Product is restocked, and reenters the sample,
 - Product is discontinued and permanently leaves the sample,
 - Product is new to the market
 - Products being rebranded

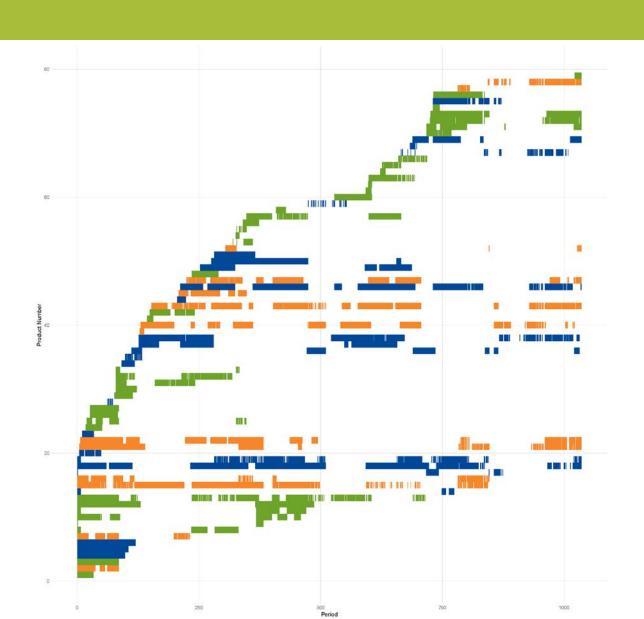
Product Churn – Example



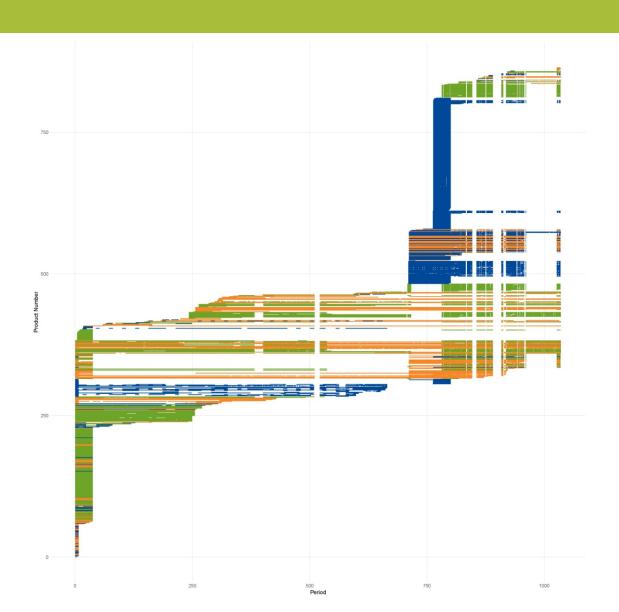
Product Churn - Apples



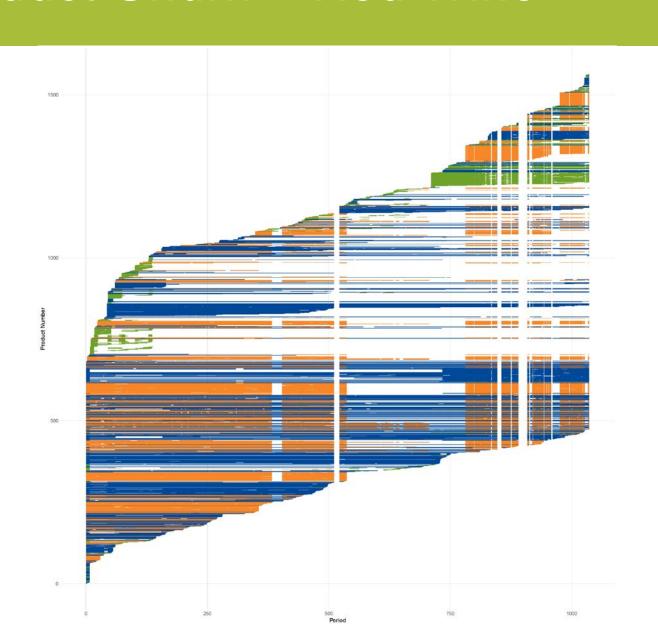
Product Churn - Strawberries



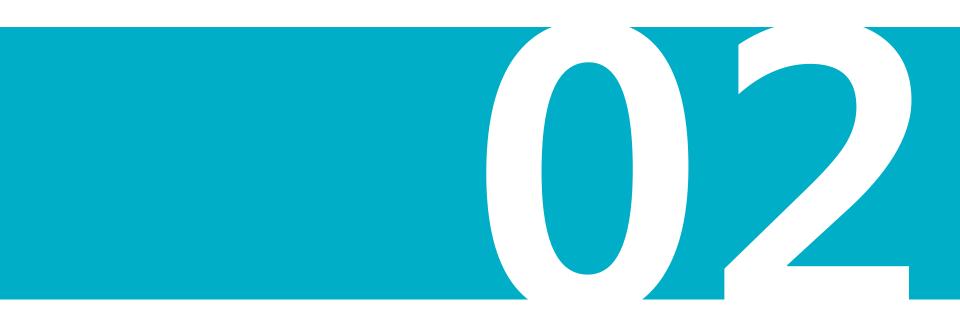
Product Churn - Tea



Product Churn – Red Wine



Overcoming the Product Churn Issue



Problems due to Product Churn

- With long datasets there is minimal chance of product being observed in every period, especially and high frequencies
- Causes problems with tradition methods

Possible Solutions

- Impute the missing prices in the appropriate period
 - ITRYGEKS
- Adjust for the change in quality due to the change in products on the market
 - FEWS
- Track groups of products over time
 - CLIP

Why track groups not products?

- Consumers have preferences.
- Preferences might be product specific, i.e.
 - Product A < Product B
- Preferences might be characteristic specific instead
 - Characteristic 1 < Characteristic 2

Why track groups not products?

- Therefore there might be a group of products who's have the consumer's preferred characteristics.
- The consumer would be indifferent to those products with their preferred characteristics
- This group is what is tracked over time

Finding the groups

How to find these groups?

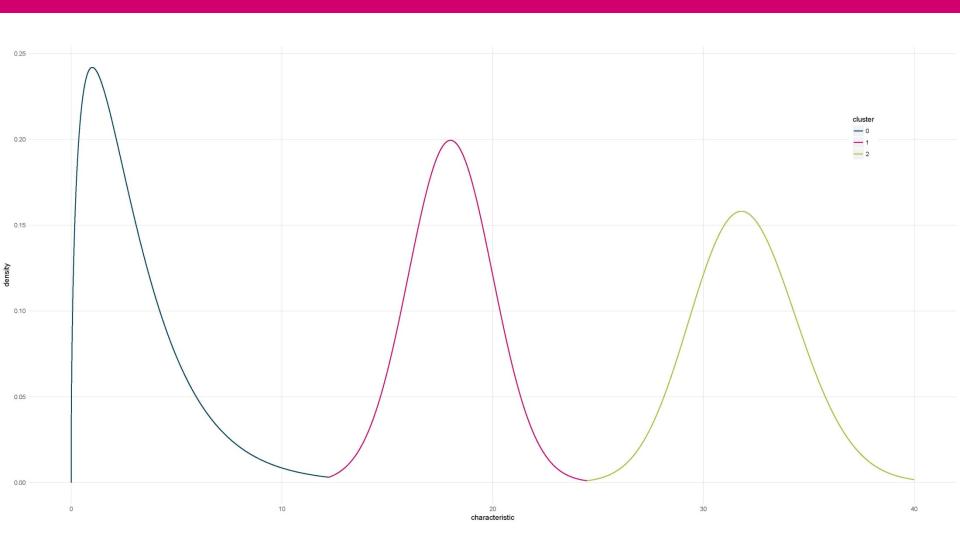
 Usually the preferences would be determined by finding utility functions and maximising under a budget constraint.

 Utility functions can't be calculated with web scraped data – lacking quantity information

Groups by clustering

- Groups are instead found by clustering the products
- Clusters are found using the Mean Shift algorithm
- Mean Shift was used as no a priori choices about cluster shapes and number of clusters

Forming Clusters



Characteristics used to form clusters

- Product Name
- Store
- Offer
- Price

Clustering - Tea







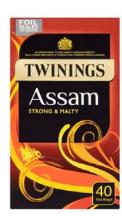












Clustering - Tea



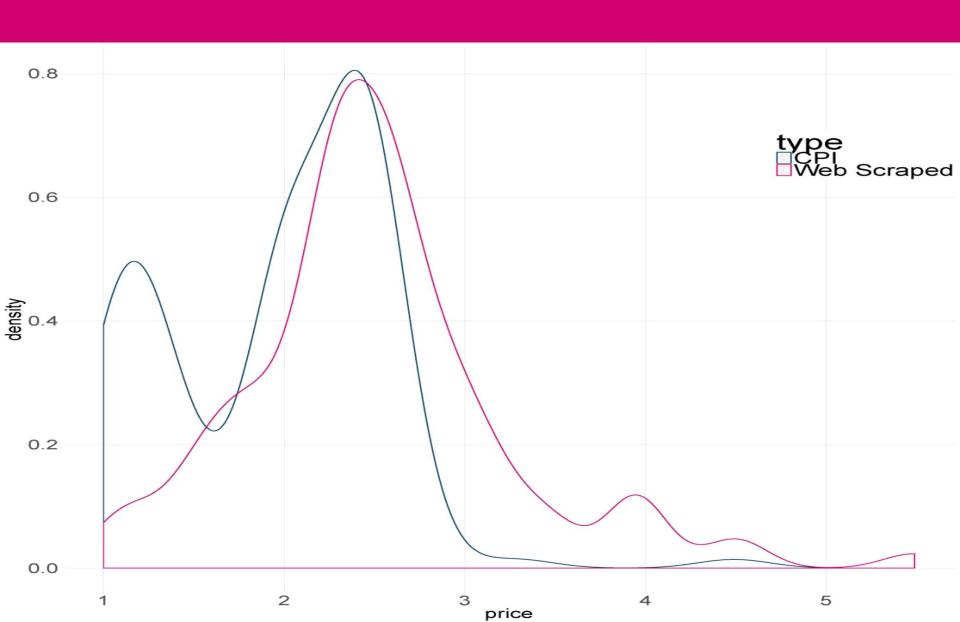








Price Distributions



Clustering - Tea













New Data and Forming the Index



What to do with new data?

- Solution 1: Recluster the data
 - Problem completely new clusters will be found

- Solution 2: Assign Data to Clusters
 - This is done using a decision tree

Assigning Data

- The decision tree finds the underlying rules that make up the cluster.
- Price is removed as a characteristic when finding the rules.
- In subsequent months when new data is collect the products are the classified using this tree
- The product mix in each cluster will vary but the cluster itself is the same

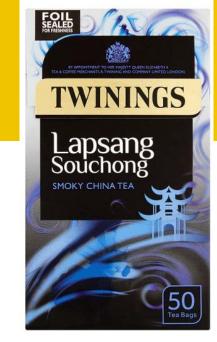
Decision Tree

Characteristics:
Product
Number = 37

Store = Tesco

Offer = NA

False



gini = 0.0 samples = 57 class = 0

True

prod_no <= 41.5 gini = 0.4918 samples = 39 class = 1

True

gini = 0.0 samples = 22 class = 1

False

gini = 0.0 samples = 17 class = 2

Forming the Index

- The price for a specific cluster is calculated as the geometric mean of the products in that cluster.
- The price for that cluster is then compared to the price for that cluster in the base month.

Price Relatives Per Cluster



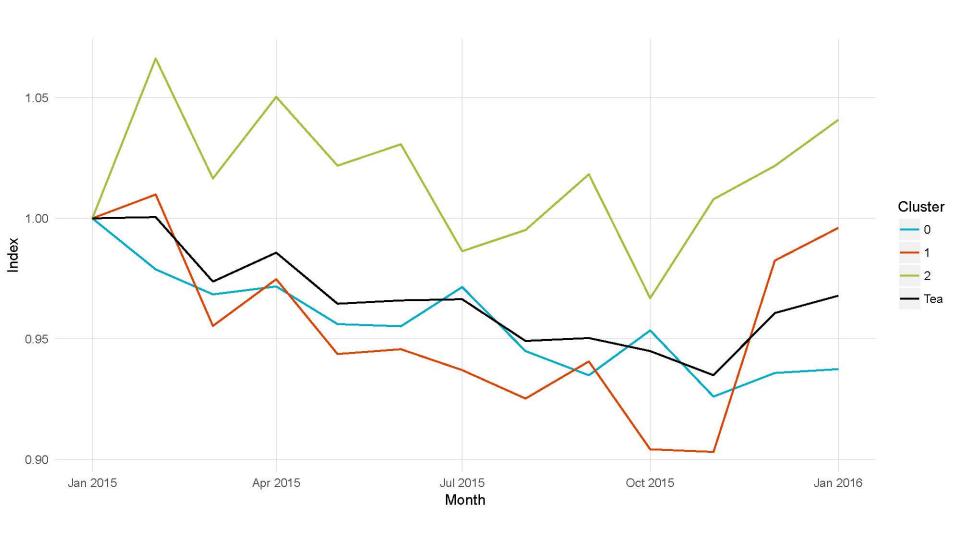
Aggregating over cluster

- The Price relatives are then aggregated over clusters to form the item index.
- These are weighted together with the following weights:

$$w_i = \frac{|C_i^0|}{\sum_k |C_k^0|}$$

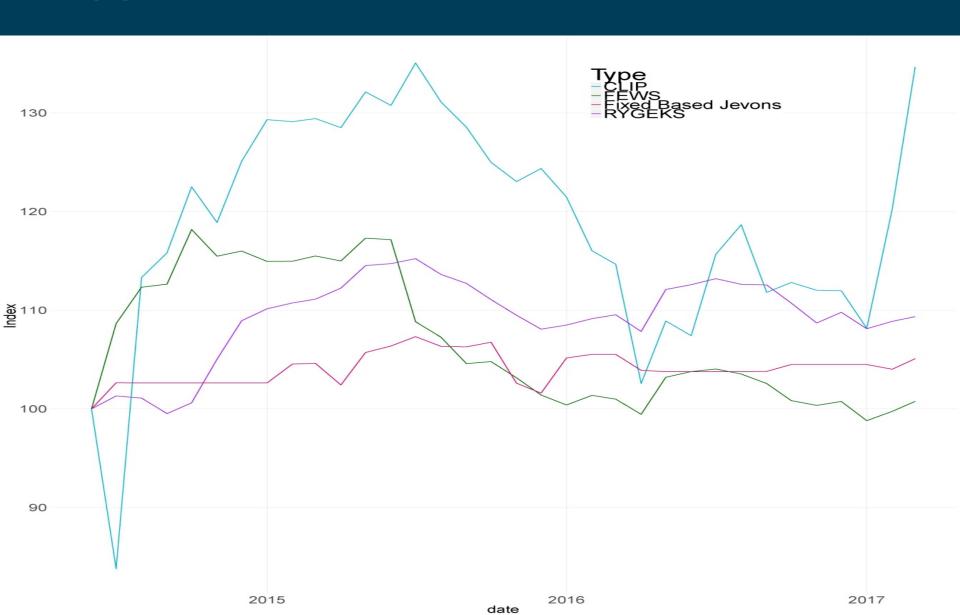
• So for this Tea Data $w_0=0.61$, $w_1=0.22$ and $w_2=0.17$

Tea CLIP

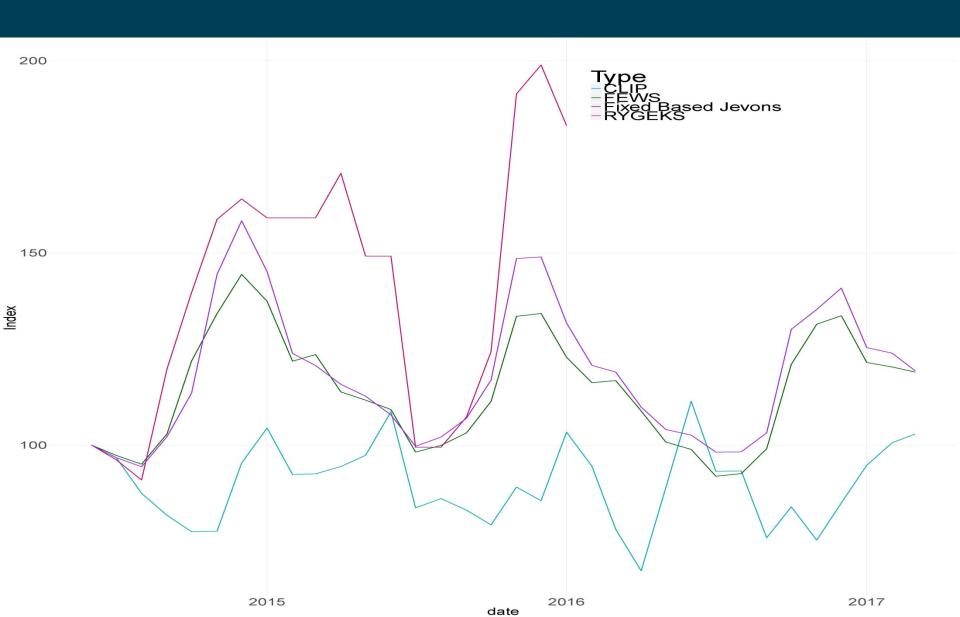


Results

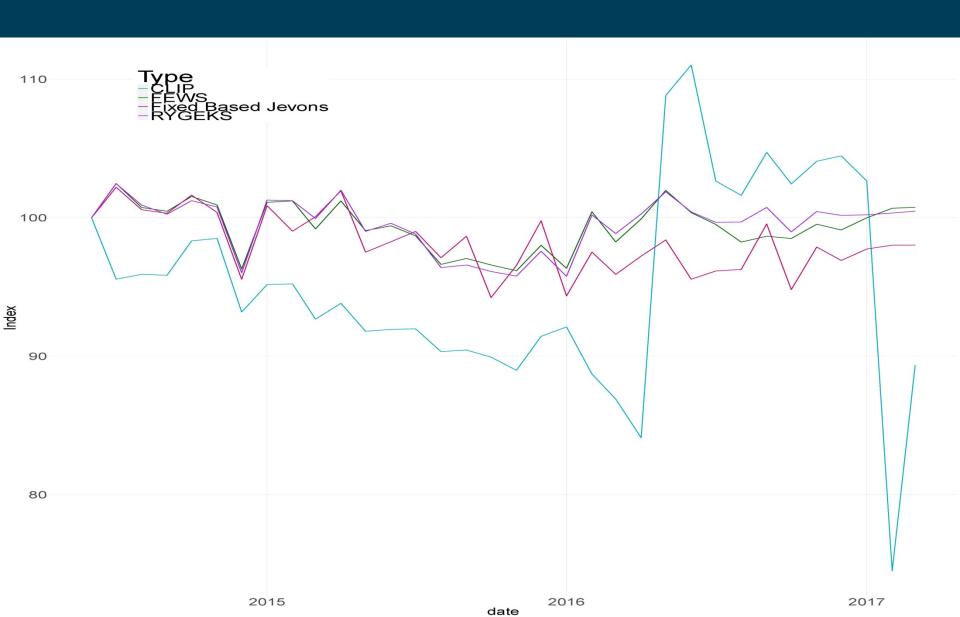
Apples



Strawberries



Tea



Red Wine



Future Work



Assessing against approach to Index Numbers

- Assessed against the Test/Axiomatic approach only fails the identity, time reversal and Price Bounce tests (Note: FEWS does as well)
- To do:
 - Economic Approach
 - Statistical Approach

Test Assumptions about Substitution

- Do consumers substitute within clusters?
- Do consumers substitute between clusters?

Clothing and other forms

- CLIP might be more suited to Clothing Items
 - ONS is to release research into this
- Testing a geometrically aggregated CLIP as well as other variants of the index

Men's Jeans



Women's coats



More Information

- More information on the CLIP along with more results can be found on the Office For National Statistics website.
 - https://www.ons.gov.uk/economy/inflationandpricein dices/articles/researchindicesusingwebscrapedprice data/clusteringlargedatasetsintopriceindicesclip

Questions?

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