

# Using R to automate the classification of e-commerce products

Aidan Boland

4 November 2017

## Who are Clavis Insight?

# CLAVIS INSIGHT

- ▶ Global leader in action-ready insights for product manufacturers.
- ▶ We monitor online retailers to provide insights for manufacturers on their online performance.

Video link

# Brands



## Grocery, Personal, Home, & Pet



## Health & Wellness



## Beauty, Luxury, Fragrance



## Toys & Games



## Hardlines



## Data & Standards



## Alcoholic Beverages



## Consumer Elec & Home Appliances



## B2B



## Sporting & Apparel



# Retailers

450 retailers across x countries



# Volume of Data Handled

- ▶ Clavis processes a large amount of data monthly.
  - ▶  $\approx 530,000,000$  rows.
  - ▶ From 450 stores.
- ▶  $\approx 40,000$  new products added to the database monthly.
- ▶ One particular bottleneck is classifying new products, adding tags to help with further analysis.

# Classification of Products

- ▶ eCommerce sites are fast moving and no two are exactly alike.
  - ▶ Different stores have different category names and structures.
- ▶ There is a need to provide a standardized category view across multiple sites.
  - ▶ Each manufacturer has a different view of categories.
  - ▶ Need to be flexible when assigning a product to a category.

# Classification of Products



- ▶ Amazon
  - ▶ Grocery & Gourmet Food > Candy & Chocolate > Bars
- ▶ Walmart
  - ▶ Food > Candy & Gum > Chocolate



# Classification of Products

	Portfolio Availability	Price and Promotions	Ratings	Reviews	Share of Search	Menu	Total Content	Core Content	Extended Content
	?	?	?	?	?	?	?	?	?
All	44 %	90 %	61 %	47 %	36 %	22 %	54 %	61 %	92 %
Breath Fresheners	55 %	100 %	72 %	60 %	16 %	0 %	31 %	49 %	88 %
Candy - Chocolate	39 %	93 %	62 %	45 %	33 %	23 %	66 %	73 %	93 %
Candy - Non-Chocolate	59 %	83 %	59 %	41 %	17 %	20 %	32 %	41 %	88 %
Grocery	48 %	88 %	69 %	50 %	20 %	41 %	68 %	75 %	94 %

# Classification of Products

- ▶ When a new product is found on a retailer, the information is collected.
- ▶ Each new product is then classified into its correct category.
- ▶ As a manual task this is very time consuming, error prone and requires a lot of manual intervention by users.
  - ▶  $\approx$  5 hours per customer end to end.
  - ▶ Source of complaints from customers.
- ▶ The difficulty of this process was a major indication for the need to automate.

# Automating Classification

# Roadmap for Automating Classification

- ▶ Research
  - ▶ Find suitable algorithm.
- ▶ Beta testing
  - ▶ Test the algorithm within the current process.
- ▶ Integrating code
  - ▶ Build the code into the current company platform.

# Research Phase

- ▶ Task
  - ▶ Classify new products into their correct categories and subcategories (up to 8 levels).
    - ▶ Efficient.
    - ▶ Accurate.
- ▶ Solution
  - ▶ Supervised classification.

# Supervised Classification.

- ▶ Learn from the current products in order to classify new products.
- ▶ Many methods were considered (maxent, random forests, k-nn).
- ▶ Final algorithm was personalized to this particular task.
  - ▶ Classify's all levels of hierarchy simultaneously.
  - ▶ Relatively efficient (<30 seconds for 1000 products)
  - ▶ Ability to handle all languages.
- ▶ Researching and creating the algorithm is only one step.

# Beta Testing

## Shiny Application

### CLAVIS INSIGHT Dynamic Product Classification

If you are finding the tool slow, see instructions on how to run the tool on you local machine [here](#).

The cpc input file should have the following two columns; 'trusted\_rpc' and 'trusted\_product\_description', and at least one of the following columns; 'manufacturer', 'brand', 'category', 'dimension1', 'dimension2', 'dimension3', 'dimension4', 'dimension5', 'dimension6', 'dimension7', 'dimension8'

The harvest (candidate) file should have the following two columns; 'rpc' and 'Product\_Description'. If 'Harvest\_URL' and/or 'Product Image' are provided they will be displayed.

The probabilities are colour coded; **red** (too unsure to classify) , **orange** (low chance of being correct) , **yellow** (high chance of being correct) and **green** (likely to be correct) .

Report errors to [Aidan Boland](#).

Data

Hierarchical Structure

Manual Classification

Advanced

Load in cpc/training file

Browse...

Portfolio Availability-2016-11-15.csv

Upload complete

Load in harvest/candidate file

Browse...

No file selected

Perform Cross-validation

Data Overview Product Classification

#### Cross-validation

Lower percentages are better.

manufacturer	brand	category	dimension1	dimension2	dimension3	dimension4	dimension5	dimension6	dimension7	dimension8
0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

#### Manufacturer

Phillips 680

#### Brand

Phillips Norelco 286  
Phillips Sonicare 394

#### Categories

# Beta Testing

- ▶ Shiny application
  - ▶ Hosted on an internal server.
- ▶ Allows the ability to manually load in training data and new data.
- ▶ Final downloaded is in the correct format to load into the production database.
- ▶ Still manual touch.



## Full Integration

# Integration into Platform

- ▶ The backend is coded in Java.
- ▶ Algorithm is coded in R.
- ▶ Needed to integrate the R code into the backend code.
- ▶ Must follow the companies standard practices.
  - ▶ Version control (bitbucket).
  - ▶ Change testing (unit tests).

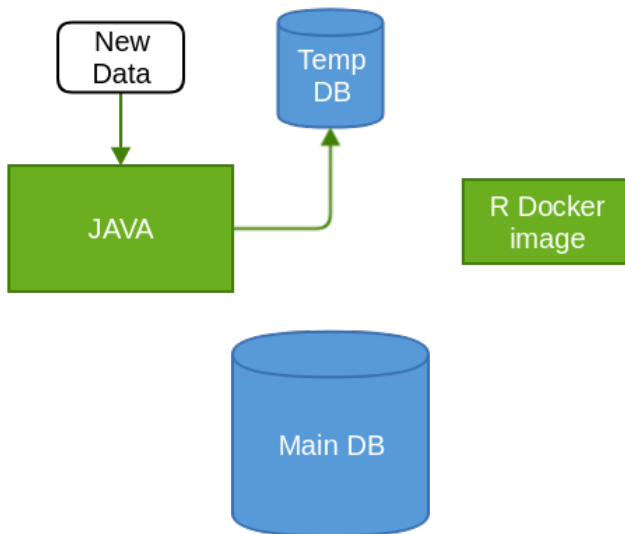
# Solution

- ▶ R library (including unit tests).
- ▶ Stored in a repository on Bitcuckett.
  - ▶ This allows version control and updates which are in line with company practices.
- ▶ The **plumber** library is used to allow the code to be called using an API.
  - ▶ Arguments in the API point the R code to the database containing the new data.
  - ▶ R code classify's the new data and updates the database with the new categories.

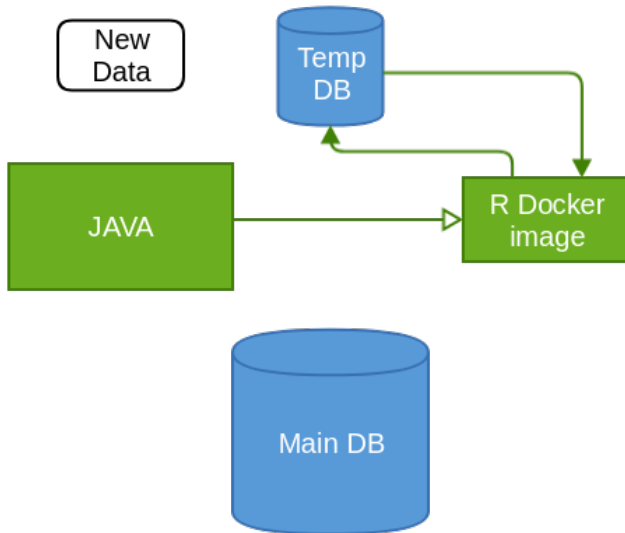
# Solution

- ▶ A Docker image containing the R library and any requirements is stored.
  - ▶ The Docker image is automatically rebuilt when code is updated or a new production branch is created.
  - ▶ R library is recompiled and unit tests are run when the Docker image is rebuilt.
- ▶ Java code can spin up a new server and run the Docker image which will contain the code and will allow calls to be made to the API.
  - ▶ Multiple Docker images can run at any one time.

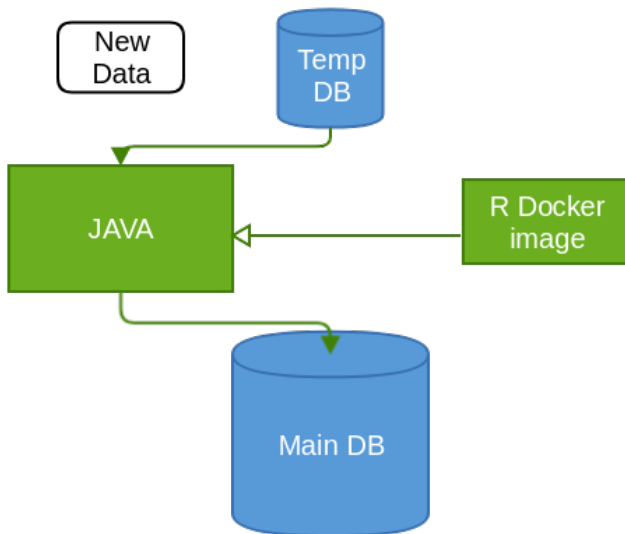
# Final Flow of Data



# Final Flow of Data



# Final Flow of Data



# Improvement in Time to Add New Products

- ▶ Before automated classification
  - ▶  $\approx$  5 hours per customer end to end.
  - ▶ 76 customers processed monthly.
  - ▶ Major source of complaint from customers.
- ▶ After automated classification
  - ▶  $\approx$  2 hours per customer end to end.
  - ▶ 159 customers processed monthly.
  - ▶ No 'red' complaints since March.