

# Postgraduate Coursework for Data Visualization module INM402

## Impact on food of the UK sugar reduction programme, 2015–18

### Introduction

#### Background to topic

The voluntary sugar reduction programme challenges all sectors of the UK food industry to reduce sugar content by 20% between 2015 – 2020 (assessed as sales weighted average total sugar content in g/100g) in the categories of food that contribute most to the sugar intakes of children aged < 18 y. The reductions in sugar should also be accompanied by reductions in calories where possible [1]. The programme is one part of the government's strategy to address obesity – a huge public health concern due to its contribution to chronic disease and consequent impact on health resources.

There is a full report about programme progress between 2015 and 2018 available in the public domain [2] which includes some basic visualizations (bar charts and pie charts), and also a summary report including infographics [3]. The findings about impact to date are not clear-cut. For some food product categories, it appears that reasonable progress has been made, but for others sugar content has increased. Regrettably, even in the summary report, complexities related to data collection impede readers' interpretation of the findings. While it is essential to include details about limitations pertaining to comparisons, the inevitable drawback is muddying of message communication.

Data analysts at Public Health England (PHE) – the institution which oversees the sugar reduction programme – suggested the programme as my data visualization assignment topic. It appears there is a wealth of information included in the full report that additional visualizations could effectively harness to further explore and elucidate the patterns of progress towards the sugar reduction ambition. I took up their suggestion, as the topic offered interest and challenge.

Although data on sugary drinks are included in the existing reports, I decided only to consider the data on foods. This was first because changes in sugar content could be attributed to the Soft Drinks Industry Levy introduced in 2016 [4] rather than the sugar reduction programme per se; second because additional analysis including visualizations has already been undertaken by academic groups [5, 6], and third because the food-related data alone were sufficient foundation for a series of useful new visualizations. I felt this series would be more coherent if based on just one of the two data subsets.

#### Approach used for visualizations

I used a “declarative” approach to visualization creation (meaning the analyst specifies what the results of a computation should be rather than how the results should be computed [7]), using the Litvis software, which provides a “notebook” environment integrating live coding input, rendered output and textual narrative [8]. Litvis is open-source (available at <https://www.gicentre.net/litvis>) and uses the functional language Elm together with the Vega-Lite grammar of interactive graphics [9]. This grammar is based on Leland Wilkinson's “*Grammar of Graphics*” – a system with seven classes embedded in a data flow which specifies the order in which a raw dataset is transformed to a statistical graphic [10].

## Source of data and manipulation for the new visualizations

The excel tables included as appendices to the year 2 report on progress [2] were the source of data for my visualizations. The report – *Niblett et al (2019) Sugar reduction: Report on progress between 2015 and 2018* – is available at

<https://www.gov.uk/government/publications/sugar-reduction-progress-between-2015-and-2018>

I copied the data from Tables 1-6, 8-9 and Appendix Tables 2-6 into new excel spreadsheets, from which data relating to the following variables were selected to enable calculations and comparisons to address the research questions:

- Dependent variables: Sugar content; Calorie content; % change in sugar and calorie content; Total sales weight, and Sugar sales weight
- Independent variables: Product category (ten), source of data (four = “Out-Of-Home” (*OOH = food from restaurants, pubs and cafes*); manufacturer; retailer, and “In-Home” (*IH = food from manufacturers and retailers*)), and time point (for which baseline year was 2017 for the two product categories “Cakes” and “Morning goods”, and 2015 for the other eight).

*What are the research questions that your data visualization will help you to answer?*

### Research Questions

*Principal research question to be addressed in this project:*

What are the patterns of variation in progress made towards the 20% reduction ambition over the first 2 years of the programme?

*This question will be addressed by considering the following questions:*

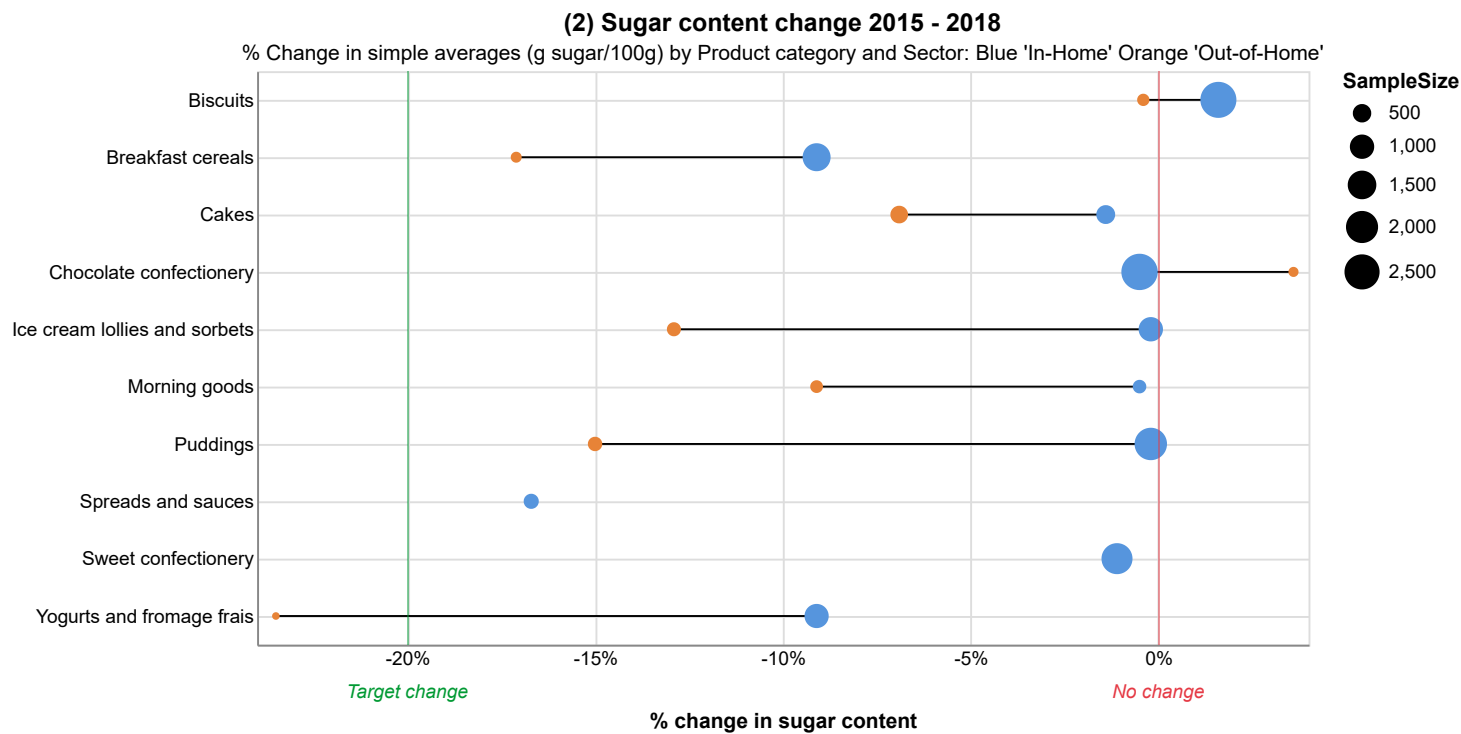
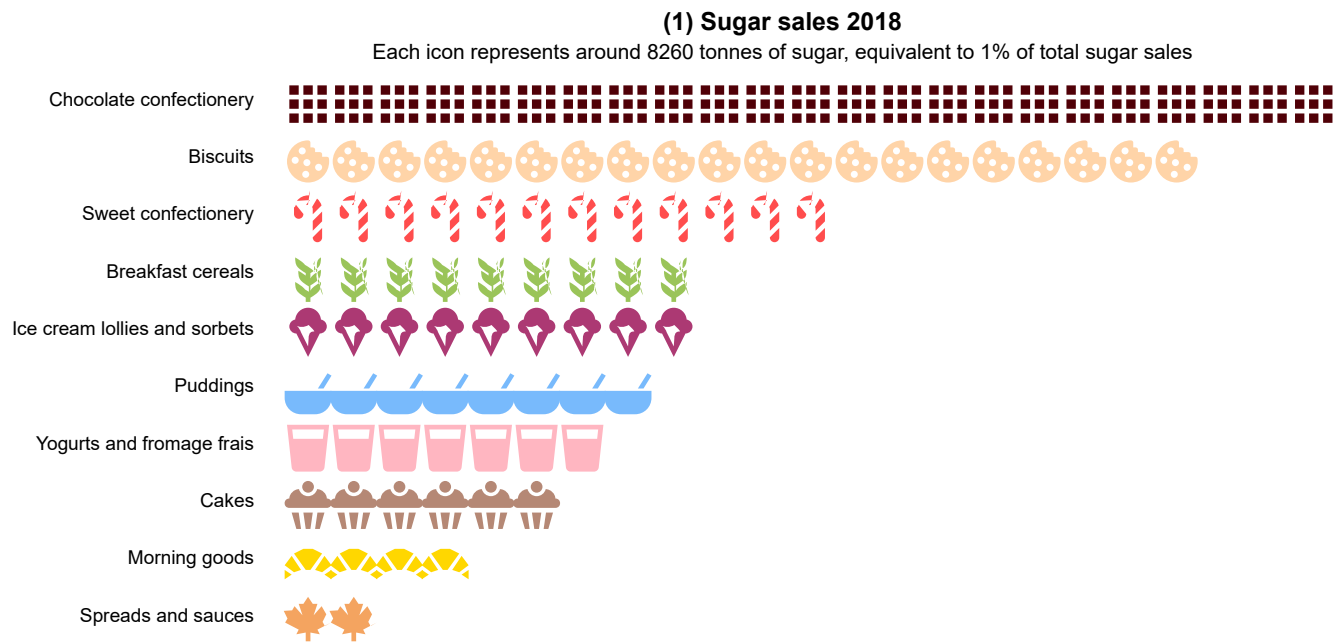
RQ1) To what extent has sugar content per 100g decreased overall, and for the relevant product categories?

RQ2) To what extent have changes in sugar content been accompanied by changes in calorie content overall, for the relevant product categories, and for individual products?

RQ3) How does progress towards the sugar reduction ambition differ between the Out-Of-Home and In-Home sectors?

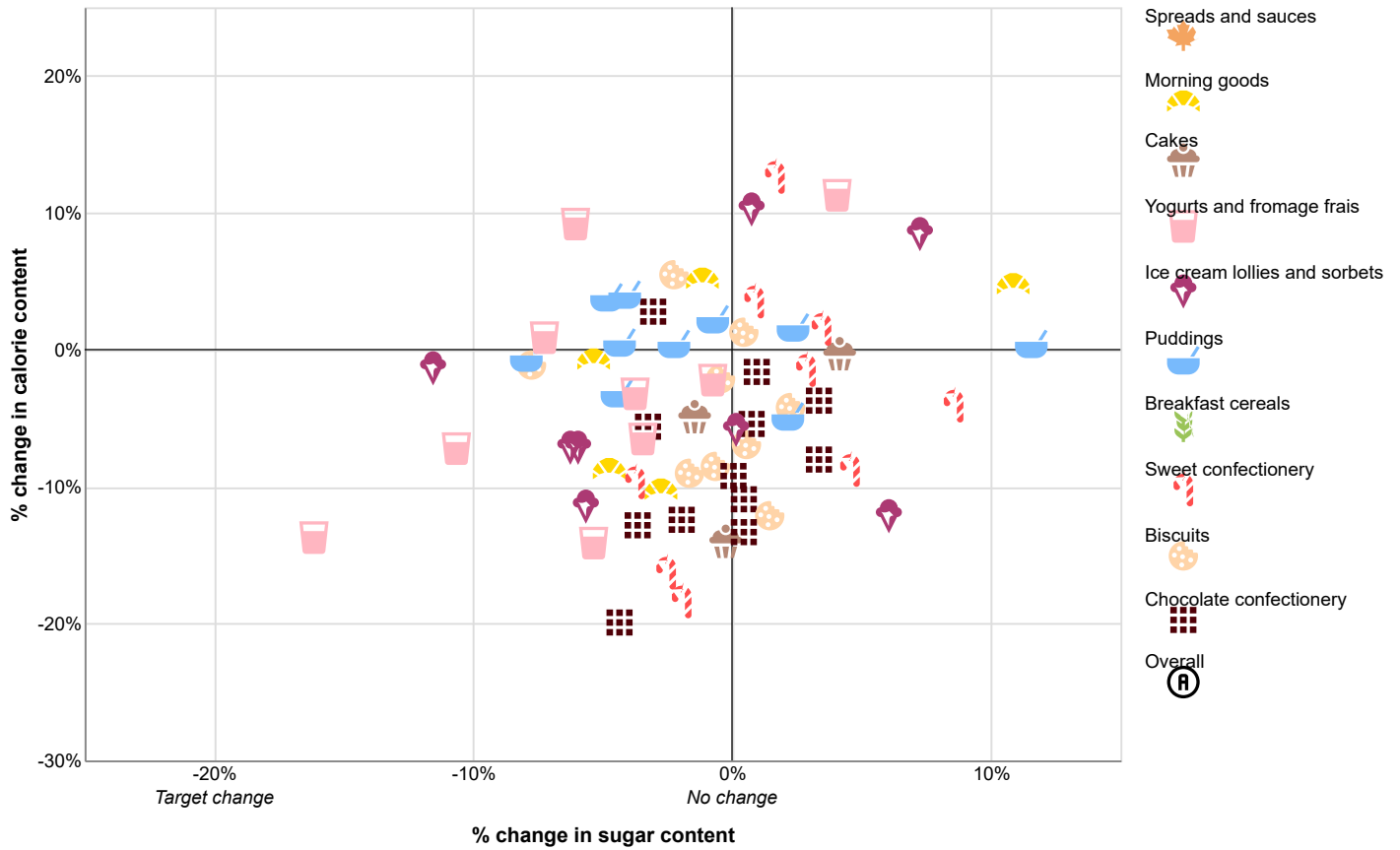
## The Visualization

Insert your visualization(s) here.

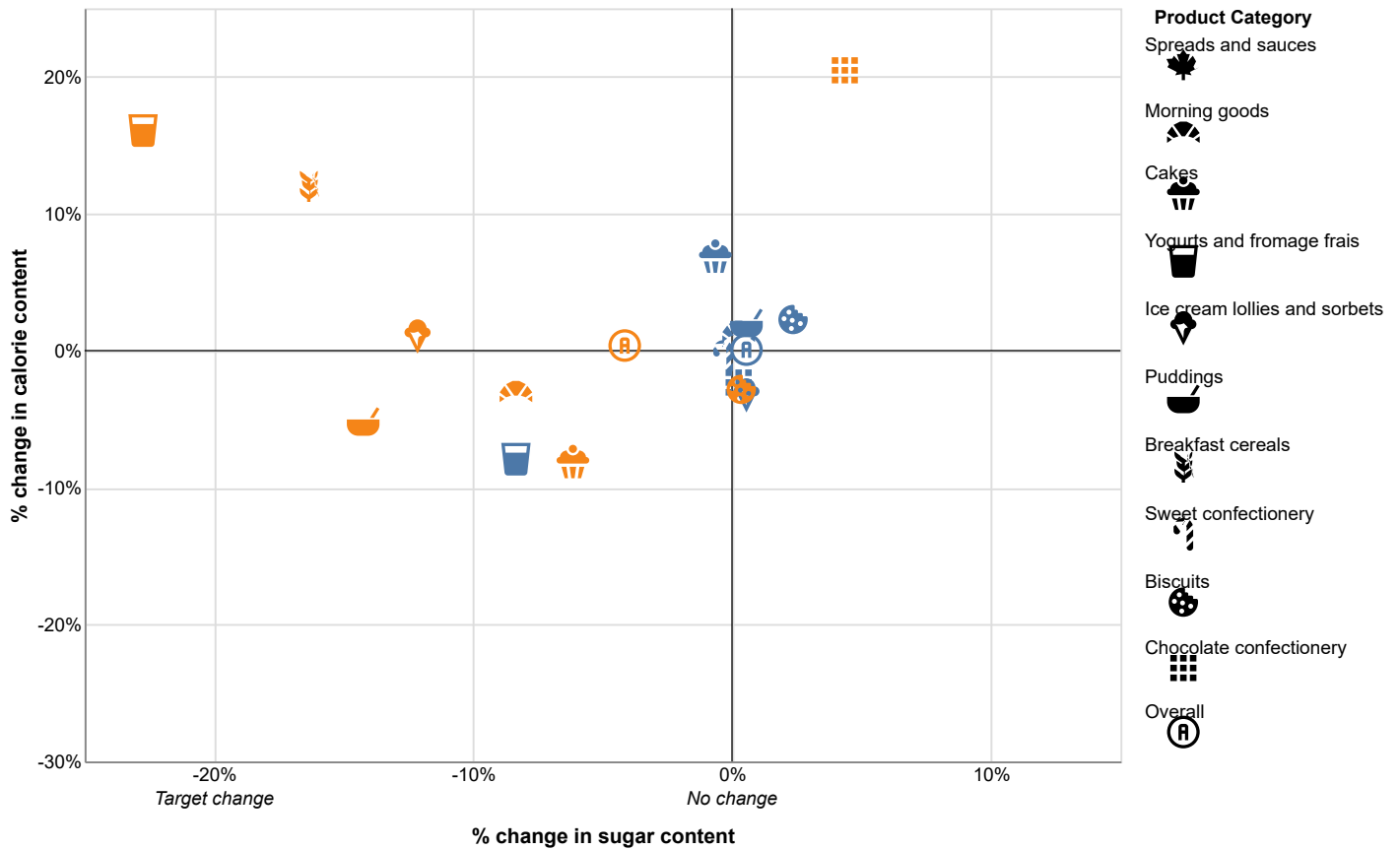


### (3) Calorie change vs. sugar content change, 2015 - 2018

(3A) Sales weighted average changes for individual food retailers' or manufacturers' branded products ('Out-of-home' sector)

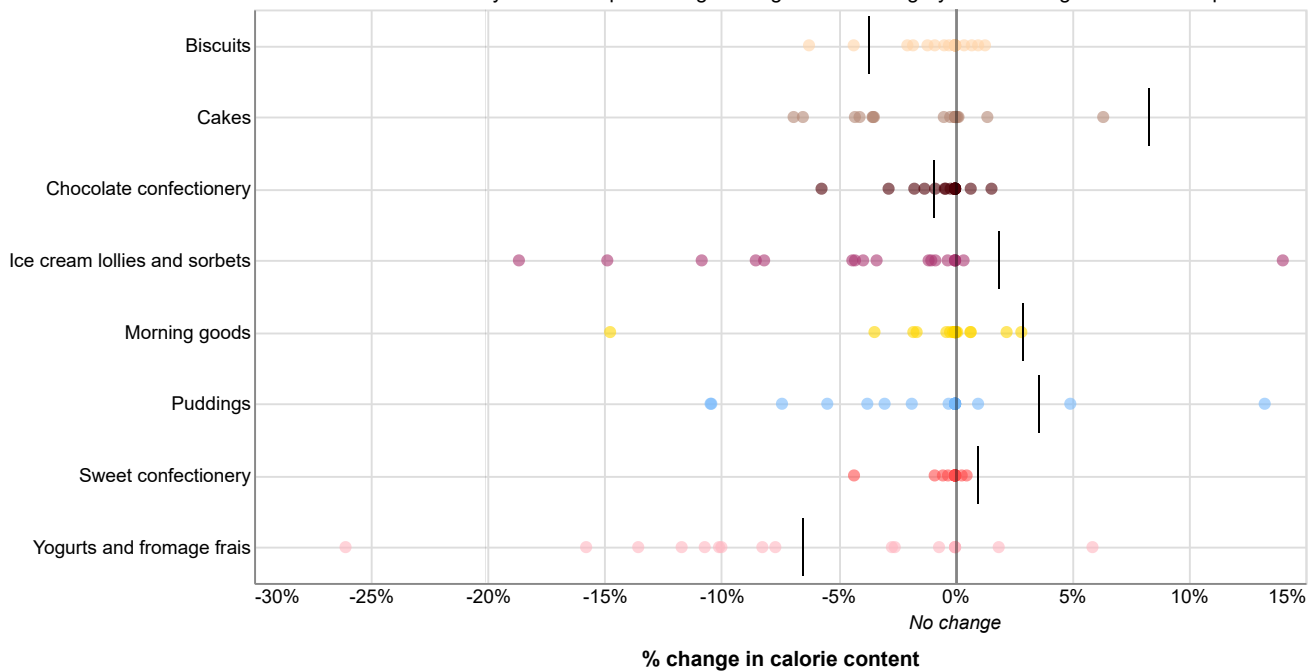


(3B) % change in simple averages by product category and sector: Blue, 'In-Home' Orange 'Out-Of-Home'



#### (4) Calorie change in 'single serve' portions - food retailers' or manufacturers' branded products

'Out-of-Home' sector only. Ticks: Simple average change across category Dots: Change for individual products



## Insights

*What has your visualization allowed you to discover about your data that help you answer your research question(s)?*

*Note: When referring to Product categories, I use abbreviated names and upper-case initials in order to distinguish them from individual foods.*

### Viz1) Pictorial Bar chart

*(Source data from excel Table #5; equivalent Figure in report #14)*

While this viz does not address the research questions directly, its value is in setting the context for Viz2 - 4. It shows which categories are most important with respect to sugar sales (and by implication to the population's sugar intake), and thereby identifying these as the categories of most significance in Viz2 - 4. While the magnitude of sales values by category was clear from the source data, Viz1 reveals the prominence of Chocolate and Biscuits, and relative insignificance of Spreads.

### Viz2) Connected Dotplot

*(Source data from excel Tables #1 and #8; no equivalent viz in report)*

With respect to RQ1, and when examined together with Viz1, Viz2 shows the categories with greatest % sugar decrease (Breakfast cereals, Yogurts and Spreads) are not those contributing most to the UK population's sugar intake. It shows that only one of the ten product categories in one of the two sectors attains the sugar reduction ambition of >20% decrease (Yogurts in the IH sector).

With respect to RQ3, Viz2 shows foods purchased for OOH consumption generally have greater average sugar decreases than those for IH consumption (apart from Chocolate), and that the OOH statistics are likely to be less reliable than IH due to smaller source samples.

Viz2 also shows that within the IH sector, sugar content change values for Morning goods, Spreads and Cakes are based on smaller samples, and so may be less reliable, than other categories' values.

### **Viz3) Scatterplot**

*(Source data from excel Tables #1 #3 #8 & #9; no equivalent viz in report)*

Viz3A addresses RQ2 by examining whether changes in sugar content have been accompanied by changes in calorie content for various manufacturers and retailers (data are not available for the OOH sector). It indicates that calorie content changes are not associated with sugar changes, since the scatterplot shows high variability and no clear correlation between the two measures (although it is still possible that the changes are associated at the level of individual products).

Viz3A shows that while several companies' product categories on average have decreased their sugar content in line with the sugar reduction ambition (left side of Viz3A), for many of these calorie content increased, contrary to the reduction ambition (top left quadrant). There are even companies for which product categories simultaneously increased sugar content and decreased calorie content (base right quadrant).

Viz3B addresses RQ3 by examining the correlation between simple average sugar and calorie changes for foods grouped by whether the foods were purchased for OOH and IH consumption. More of the IH average changes are close to the intersection of the axes (signaling only small changes), while two of the OOH food groups, Chocolate and Yogurts, show much larger changes, both of which are increases in average calorie content rather than decreases.

Viz3B also reveals that:

- By comparing the position of the blue and red A symbols, one can see that the OOH sector performs better overall for sugar decrease than IH (the trend already demonstrated by Viz2), but that the two sectors have similar extent of change in calorie content (an increase of nearly 2%);
- Some of the average category values in Viz3B are not where one would predict them to be from Viz3A, for example the Cake symbol for the IH sector is higher in Viz3B than any of the Cake symbols in Viz3A, while the Yogurt symbol is lower than you would expect the mean of the values in Viz3A to be located. These drifts alert users to the existence of methodological issues that may shape the findings. In fact, the discrepancies may relate to the use of different metrics (sales weighted averages in Viz3A; simple averages in Viz3B), and/or the existence of bias due to a subset of manufacturers and retailers data being used in Viz 3A (response rate was 75%).

### **Viz4) Dotplot**

*(Source data from excel Table #3 and #Appendix5; no equivalent viz in report)*

The viz addresses RQ2 by plotting changes in calorie content /portion for products consumed on a single occasion (single serve) products, and reveals:

- for most products there has been little change in calorie content (dots clustered around zero);
- the categories differ greatly in the extent of within-category variation – Biscuits, Sweets and Chocolate have small ranges, while those for Ice-creams, Yogurts and Puddings are large;
- there is a tendency for the distributions to be negatively skewed, indicating that averages may mislead with respect to representing the central tendency of data values;
- the overall values for the categories (the ticks) are often located some distance from where one would predict the mean or median. This indicates the sample of products for which calorie data were made available to PHE for publication do not represent the categories as a whole.

# Design Justification

*Why have you designed your visualizations this way? Consider design approaches (e.g. session 2) and your use of visual variables (channels), layout and interaction.*

I designed the visualizations for communication (rather than as tools to aid analysis) and chose the remit that they should be self-sufficient in print, but with flexibility to obtain more details if accessed online. Hence the visualizations incorporate tooltips so that users can gain more details about individual points. I assumed explanatory textual or audio narrative would accompany the visualizations, so they should be “*exhibitory*” rather than “*explanatory*” [11, p.86]. While I do not always endorse Tufte’s principle of “*Maximize the data-ink ratio, within reason*” [12, p.96], I find it useful to guide design. Thus to ease communication of “message(s)” I removed axis marker ticks; minimized grid lines; maximized titles’ conciseness, and omitted footnotes about methods (e.g. different baseline years) and annotations to draw attention to significant features.

Below, for each viz I justify my visual encoding choices using terms as outlined by Kirk [11, p.135]:

- “*Marks*” are the visual placeholders (e.g. point, line, shape) representing data items; while
- “*Attributes*” are variations in the visual appearance of marks (e.g. position, size, colour, and symbol), representing the values associated with each item.

(Marks correspond to Vega-Lite marks, and attributes correspond to Vega-Lite encoding channels).

For convenience I used colour as a single channel, rather than make use of the three separate attributes of hue, saturation and luminance [13]. By viewing the visualizations on the website <https://www.color-blindness.com/coblis-color-blindness-simulator/> I ensured that the colours of my colourmap were distinguishable by users with the most common form of colour blindness.

## **Viz1) Pictorial Bar chart**

*% of total sugar sales by Product category*

Using the options in Kirk’s Tables 6.1 and 6.2 [11], the marks + attributes combination for this viz are: Line + (Size (Length) /Symbol /Colour; or: Point + Quantity /Symbol /Colour.

- I chose bars rather than points on a line to encode the quantitative dependent variable of Sugar sales, because although the attribute Position ranks above that of Size with respect to accuracy of perceptual tasks related to quantitative variables [11, p.191], the use of Length allowed for the substitution of bars by repeated symbols.
- The nominal independent variable of Product Category was double encoded with Colour and Symbol. I wanted to immediately engage the audience at the start of the series of visualizations and remind them that the statistics relate to food. In fact, not simply food – the project is about sweet treats and tasty snacks that are part of most of our lives as sources of pleasure and guilt. So, in accord with the data humanism approach, advocated by Georgia Lupi who espouses “*..designing ways to connect numbers to what they really stand for: knowledge, behaviors, people*” [14], I chose the symbols to populate the bar chart to be recognizably intuitive, and the colours to be consistent with the nature of the product categories. I aimed to attract the audience’s attention, in line with findings of Michelle Borkin and colleagues who showed use of colour and human recognizable objects enhance the memorability of visualizations [15].
- I chose a horizontal orientation for bars in preference to vertical, because for the latter the category names would have been too long for the labels to have been written horizontally, and text at an angle is harder to read.

## **Viz2) Connected Dotplot**

*Sugar content change, by Product category and Sector*

The marks + attributes combination is Shape (circle) + Position /Size /Colour.

- I used Position to encode the quantitative dependent variable Sugar content change, first because, as mentioned above, changes in positions along a common scale are better distinguished than changes in length, as demonstrated by Cleveland and McGill [16]; and second because a bar chart would have required me to use Colour or Pattern to encode the other quantitative variable Sample size, and these attributes are ranked lower than Size with respect to accuracy of perceptual tasks related to quantitative variables [11, p.191].
- I included lines to connect the shapes within each product category for the two sectors, to facilitate users' comparison of the distances (representing the differences in values) between them.
- I used circles not squares, given the evidence humans prefer curved over sharp angled shapes [17].
- To encode the categories of the binary independent variable Sector, I used complementary colours for maximum contrast. I used orange and blue, to save red and green for the "support lines".
- Support lines were added to provide additional visual cues to facilitate interpretation of distance – as predicted by Cleveland and McGill [16] – from the key values of zero (no change) and 20% reduction (corresponding to the sugar reduction ambition). Red was allocated to "no change" since this was the undesirable value of the two.
- To encode the variable Sample size, I used the attribute Size. When using direct proportionality, the points with the smallest samples were hardly visible, so I used power scaling to rescale the points' size. Experimentation resulted in choice of 0.80 as exponent, even lower than the Flannery correction factor 0.87 shown in some experiments to correct perceptual misjudgment of areas [18].

## **Viz3) Scatterplot**

*Calorie content changes v. Sugar content changes by Product category*

This is the only visualization for which both the independent and dependent variables are quantitative. I used a scatterplot because plotting one variable against the other facilitates identification of patterns in co-variability. The marks + attributes combination is Point + Position / Symbol /Colour.

- As stated above, Position is the highest-ranking attribute for perceptual accuracy with respect to quantitative variables, so this attribute was used to situate each point in relation to each axis.
- Hue is the highest ranked channel for categorical data after spatial position, and the number of discriminable steps for colours for coding small separated regions is limited to between six and twelve [13, p.226]. So, for visual encoding of the independent variable Product category, it was beneficial to use an additional channel to increase distinguishability. Therefore, in Viz3A I used both Colour and Symbols to distinguish the eight categories of the independent variable Product categories. As described above for Viz1, the symbols were chosen to be recognizably intuitive. The colours used were as for Viz1 – chosen to evoke the foods, and enable distinguishability.
- In Viz3B, I used the attributes of Symbols to distinguish the product categories as above, and of Colour to distinguish the binary variable Sector. I used complementary colours for maximum contrast and chose orange and blue over red and green to be consistent with Viz2. Finally, the axes were emphasized to highlight the key values of zero (no change) to help users identify whether the values were positive (undesirable) or negative.

## **Viz4) Dotplot**

*Calorie content changes for "single serve products" by Product category*



The marks + attributes combination is Shape (circle) + Position /Colour.

- The quantitative dependent variable Calorie content change was encoded using position along a scale, as justified above for Viz2. Circles were chosen as the shape to plot the multiple values of individual products, and ticks for the average values, because when these shapes were reversed the plot appeared cluttered.
- For consistency, the colours used to encode the nominal independent variable Product Category were the same as used for Viz1 and Viz3A (choices justified above).
- There was some occlusion caused by plotting several marks at the same value position. So the circles were plotted with slight opacity to aid expression of value frequency.

## Validation

*Evaluate the degree to which your visualization has helped to answer your research questions. What are the strengths and limitations of your design in answering your questions? What might you do differently if you were to do this exercise again?*

### **Viz1) Pictorial Bar chart**

*% of total sugar sales by Product category*

#### *Strengths*

Viz1 has clarity and character. These were achieved through removing “chart-junk” [12, p.107], and use of symbols rather than simple bars. By rounding the values for percentage sales, the emphasis was placed on general sense-making. I had used the sales data from 2018 rather than 2015/17 because the datasets on which the statistics are based were larger for the former, particularly for Cakes and Morning goods, and so the bars are likely to better reflect the UK population’s food intake patterns. But in fact the choice of baseline or final values was not important, because the aim of the viz was to provide context, not to offer precise value judgements [11, p.190].

#### *Weaknesses*

The key limitation is that the original data do not relate to change so the viz does not directly address the RQs.

However Viz1 does contribute to the success of addressing the research questions, by indicating which are the most important product categories; familiarizing users with the symbols and colours (to enhance comprehensibility of the later visualizations which directly address the RQs), and justifying the category ordering to be used later.

I also created a more informative visualization with three elements (to illustrate how sugar content combined with total sales volume resulted in the patterns of sugar sales shown in Viz1), but narrowly chose to include Viz1. Viz11 (provided as Appendix1 at the base of this notebook) contains extra useful context, for example, revealing the relatively high volume of Yogurt sales, and high sugar content of Spreads. However I deemed the mental energy needed to process comparisons between the three elements of Viz11 detracted from my goals of providing a simple and interesting first viz to engage users.

### **Viz2) Connected Dotplot**

*Sugar content change, by Product category and Sector*

#### *Strengths*

- The guide-bars facilitate comparison against the sugar reduction ambition
- The lines connecting the OOH and IH values facilitate comparison of values between the sectors.

### *Limitations related to data*

- Average values for the two sectors are not provided (to be added later)
- Points are missing for Sweets, and Spreads and sauces for the OOH sector, so the sectors cannot be compared for these two product categories (data for these categories are not available)
- “Simple averages” rather than “Sales weighted averages” (SWA) are used, and SWA data provide a better indication of population intake (SWA data are not available for the OOH sector).
- The user is not told that baseline years vary (2017 for Cakes and Morning goods and 2015 for the other eight product categories). This is a data limitation that would affect the users’ interpretation. This situation was common in this project – whereby a choice was made to leave out valuable contextual information in favour of minimising complexity of the visualization.

### *Weaknesses relating to design*

- The key for sector colour would have ideally been provided in a legend rather than the title (lack of coding skills meant the guide bars’ colours were included with the sectors’, so the legend was cut)
- The order of the Product categories differs from that in Viz1 (the categories remained in alphabetical order because my attempts to change the ordering were unsuccessful)
- The size of the points is not directly proportional to the sample size, and so misrepresents these data. The Tufte “*Lie Factor*” (size of effect shown in graphic/size of effect in data) [12, p.57] is less than one, since the distortion is in the direction of understatement.

## **Viz3) Scatterplot**

### *Calorie content changes v. Sugar content changes by Product category*

#### *Strengths*

- In both elements of Viz3, Calorie content change is plotted against Sugar content change, thus enabling exploration of the two variables’ co-variation. This is key to addressing RQ2.
- Viz3B enables comparison of the sector overall values, revealing both sectors have not changed calorie content, while only the OOH sector shows a decrease in sugar content.

#### *Weaknesses*

- The data type differs between plots – the data points in Viz3A are “Sales weighted averages”, while in Viz3B they are “Simple averages” (SWA data are not available for the OOH sector)
- Points are missing for IH Breakfast cereals and Spreads (these categories do not have “single serve” data available, because consumers take multiple portions)
- Use of symbols gives a misleading impression of the data values (corners rather than centres of the symbols are plotted at the correct locations, and guidance on coding is needed to adjust this)
- Ideally sample size would have been integrated in the Viz, however visual encoding using the attribute Size (as in Viz2) was not viable, as comparisons would be confounded by use of symbols
- Some of the symbols plot on top of each other and so cannot be distinguished from each other. To address this, the plot would ideally incorporate interactivity enabling the user to click on the legend and select one or more categories to be made visible.

When trialing the use of circles rather than symbols, due to the disadvantages outlined above of using symbols in a scatterplot (misleading location, and their size leading to overlap), it became clear that the colourmap devised led to the colour attribute not being sufficiently associative [19] to easily distinguish the categories. However, even if I had spent more time selecting a better combination of colours, I would still have confronted the limits on the capacity of human attention for visual features. These limits influence the effectiveness of information visualizations which include a high number of nominal categories. Use of interactivity to limit the number of categories shown at a time would have allowed “*more efficient comprehension of the visualization*” [20].

## Viz4) Dotplot

*Calorie content changes for “single serve products” by Product category*

### *Strengths*

- Viz4 concisely summarizes data on Calorie changes, which of all the dependent variables considered is that of greatest real-world consequence. The purpose of reducing sugar content is reduction in obesity. So since sugar content was found to have changed without simultaneous reduction in calorie content (Viz3B), one might contend the programme has not benefited the nation's population. But by showing the large variability within product categories, Viz4 can be used to counter this argument, by indicating there is potential for improvement in those foods which have not improved to date.
- Viz4 demonstrates how product categories vary in their within-category variability (Sweets, Chocolate and Biscuits show very little variation). So together with Viz1 (which show Sweets, Biscuits and Chocolate are the categories contributing most to the population's sugar intake), Viz4 can inform prioritization by PHE of manufacturers and retailers for advocacy.

### *Weaknesses*

- Viz4 only includes data from the IH sector (data were not available for OOH)
- The order of the Product categories differs from that in Viz1 (as is the case for Viz2 the categories remained in alphabetical order in Viz4 because I was not able to reorder)
- Some colours are too pale – the small circles not easily visible on the white background.

## Conclusions

What would I do differently with hindsight? The journey of learning how to use Litvis has been difficult, since there are no textbooks or online interactive tutorials as exist for other coding tools. With hindsight I should have invested time early on to harvest techniques from examples of visualizations from lectures, github etc. An example – to discover how to specify the endpoints of axes I initially tried to infer the commands. Trial and error failed, then I found the correct approach in an example of past coursework.

The value of my visualizations was in revealing patterns of variability in progress made towards the 20% reduction ambition over the first 2 years of the programme. But limitations in the data available for inclusion in the visualizations hinder their interpretation. As for all research projects, the support that data visualization can provide to the process is constrained by the data quality and availability.

Now to close with a definition: *“Data Visualization is the visual representation and presentation of data to facilitate understanding”* [11, p.15]. I will value others' appraisals as to whether my visualizations indeed aided their comprehension of the progress of the UK sugar reduction programme.

## References

*Add references from literature that you have used to support your design justification.*

### **References for background to research questions**

- [1] **Tedstone A, Targett V, Owtram G, Pyne V, Allen R, Bathrellou K, et al.** Sugar Reduction: *Achieving the 20% – A technical report outlining progress to date, guidelines for industry, 2015 baseline levels in key foods and next steps*. London: Public Health England; 2017.
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## References for methods

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## References to support design

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[19] **Roth RE**. *Visual Variables*. In International Encyclopedia of Geography. Edited by Richardson D, Castree N, Goodchild M, Kobayashi A, Liu W, R. M: John Wiley & Sons; 2017: 1–11

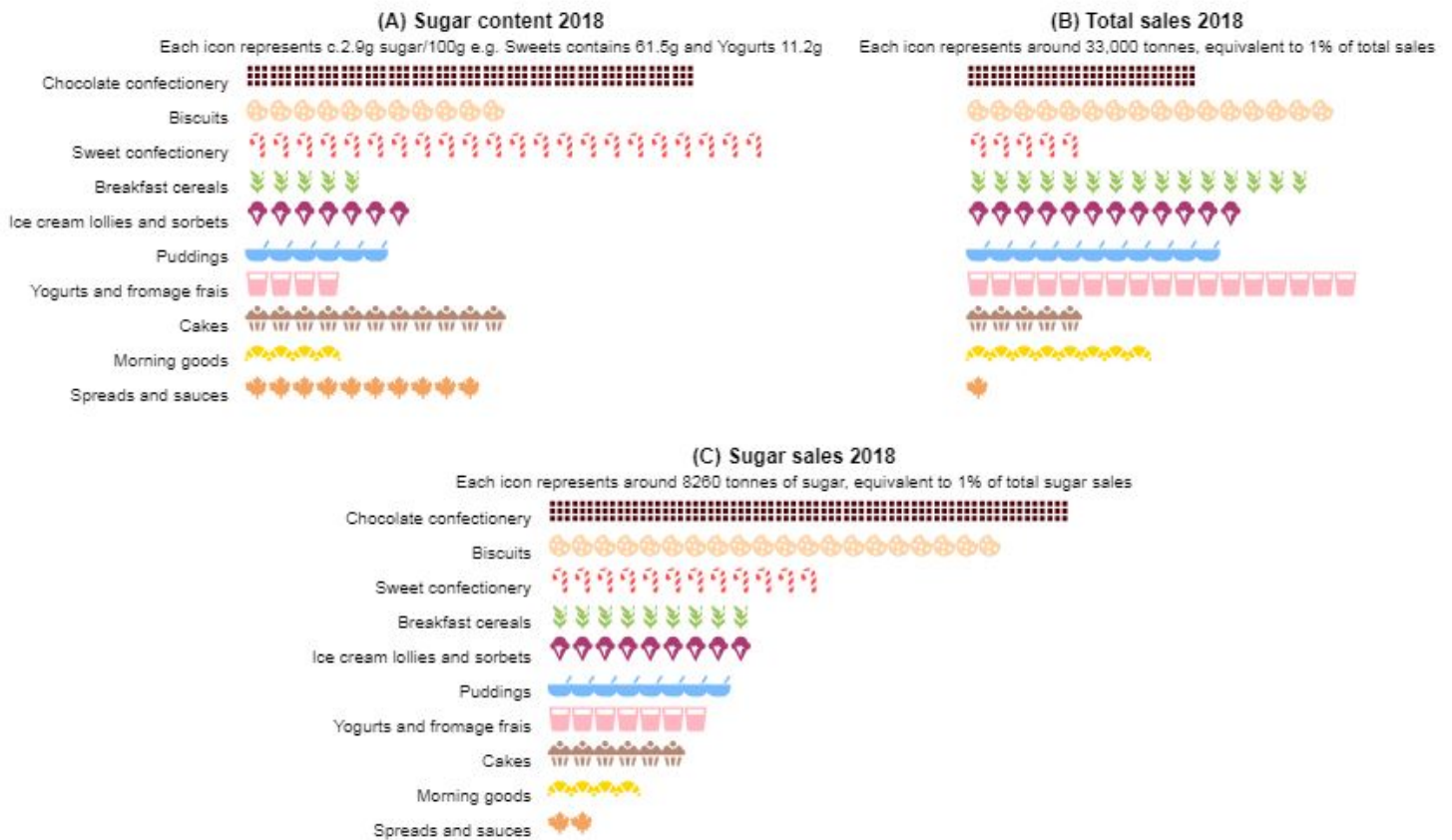
[20] **Haroz S, Whitney D**. How capacity limits of attention influence information visualization effectiveness. *IEEE Transactions on Visualization and Computer Graphics* 2012; 18:2402–2410.

## Appendix1

**Viz11: Barchart initially considered for inclusion instead of Viz1**

## Sugar sales by food product categories, 2018

Sugar content in g/100g (A) combined with Total sales weight (B) results in Total sugar sales weight (C)



## Appendix2

The SVG code specifications for the icons used in several charts is provided in the notebook. The code was obtained from the food/drink folder on <https://iconify.design/icon-sets/mdi/>