Visualizing Personal Nutrition Intake and Emotions

Category: Research

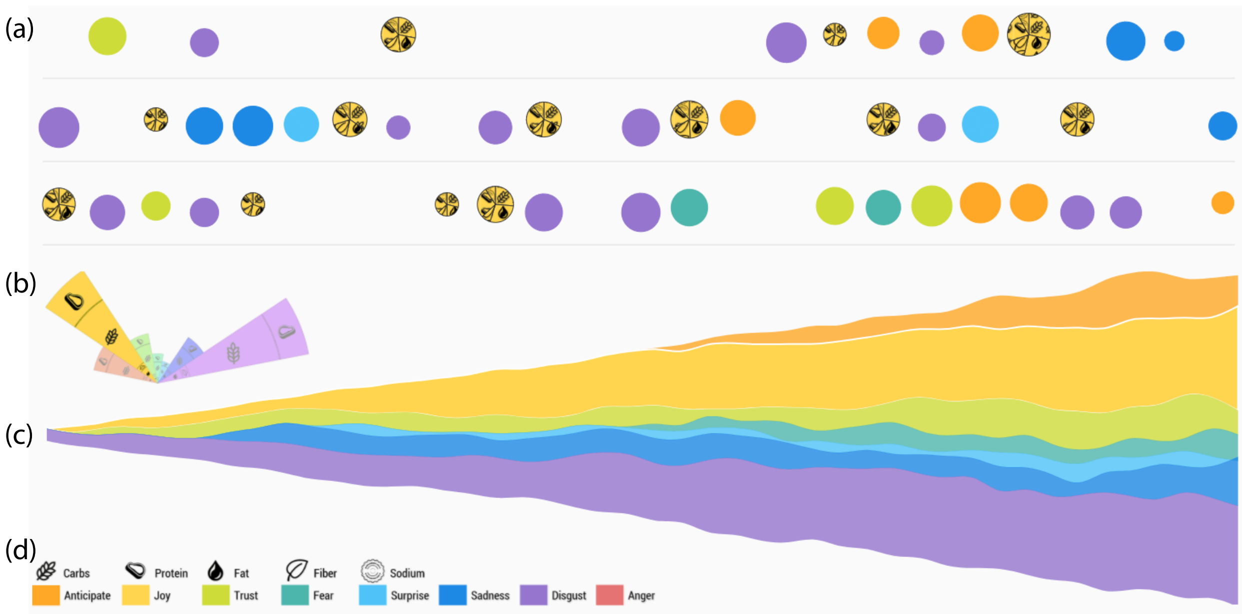


Figure 1. The visualization interface illustrates one participant's food-mood logging data over 3.5 weeks, where all joyful meals are highlighted. (a) The *Timeline Layout of Molecules* shows the sequential trend of emotional food records. Molecules highlighted with textures provide an overview of nutritional distribution among joyful meals; (b) The accumulative *Streamgraph* reveals the evolution of calories intake per emotional category; (c) The *Stacked Rose Diagram* demonstrates the overall distributional pattern of emotional nutrition intake; (d) The legend.

Abstract—Food is vital to human life. Recent studies indicate that there is influence between food and emotional wellbeing, but existing tools seldom provide insights on it. To fill this gap, we propose to build digital profiles on users food log data with emotion records. Information visualization is used to enable users to visually explore their food journeys while to reveal the correlation between personal nutrition intake and emotions. We designed a two-level visual representation featuring self-designed glyphs and novel storytelling layouts for nutrition-emotion visualization. The entire solution is implemented as a web-based interactive interface enriched with dynamics. Evaluations verify that our designs boast pleasant aesthetics and achieve more effective storytelling due to improved visual intuition.

Index Terms—Food, Emotion, Sentiment Analysis, Animation, Visual Design, Visualization

1 Introduction

Food plays a vital role in our lives. It provides the nutrients and energy to support our daily activities and keep us alive [26]. While sometimes we also eat for emotional or habitual reasons [11]. Food consumption contributes to memorable moments and improves emotional health, as eating behaviours may reduce anxiety and discomfort [9]. We spend almost one to two hours per day [16,21] to select, prepare, and consume our meals, while there are quite amount of population spent more time on an average day engaged in eating and drinking activities [16].

However, existing applications do not provide equal insights to the amount of attention that we pay to our nutrition intake and its potential emotional effect. Then how can we record and review our food consumption and the emotions that accompanied them? How can we make these memories as delicious as the food we ate? To bridge this gap, we propose a solution that leverages information visualization to build digital profiles on personal food logging data. We aim to enable users to explore, interact with and understand their food journeys. We also want to encourage the users to dig out the interesting correlation between their nutrition intake and relevant emotional effect.

Based on the collected logging data time series, we designed a set of representations to achieve storytelling visualization of both food and emotion information. We integrated and represented these data through implementing a web-based interface, which features rich interactions, interesting animations and wide accessibility across browsers. The major contributions of this work are summarized as:

1. Designed and implemented a two-level visualization consisting of the Molecule representation and the RoseViz implemented with a set of self-designed glyphs, which illustrates the nutritional information in a textural representation.
2. Designed and implemented the Timeline Layout of Molecules and the accumulative Streamgraph, and applied natural animations to facilitate resonance with dynamic storytelling.
3. Leveraged information visualization on food logging data with emotion records to reveal the correlation between nutrition intake and emotions.

The rest of this report is organized as follows. Related work is reviewed in Section 2, followed by a description of the tasks, dataset and data processing workflow in Section 3. Section 4 elaborates the design concerns of the novel visual representations and layouts proposed by this work. Section 5 explains how our solution is implemented and the methodologies being used. User evaluation is debriefed and discussed in Section 6. Finally, we conclude the work in Section 7.

2 Related Work

2.1 Nutrition-Emotion Relationships

Food and emotions are linked in different ways. On one hand, there is an influence of emotion on food preference. On the other hand, nutrition intake affects the individuals mood and feelings. The former relationship has been investigated quite extensively, whereas the latter has only gained more attention recently as a possible indicator towards food choices [18]. It has been proven that caloric content of diets affects cognitive capacity and particular nutrients influence cognition by acting on molecular systems or cellular processes. Meanwhile, other actions of lifestyle modalities also impose cognitive influence on the brain health as an integrated effect [15]. Moreover, emerging research indicates that variability exists across individuals [19], which as a result raises the significance of individual-scoped study on the relationship between the nutrition intake and personal emotional effect.

2.2 Sentiment Analysis

Sentiment analysis is to determine the sentiment of an individual with respect to some topics [12]. It has not been well studied yet but gaining popularity in recent research. Some state-of-the-art works classify sentiments into two categories as positive and negative, or define a third category as neutral. For example, the Recursive Neural Tensor Network (RNTN) model developed by Socher et al. [28], which leverages deep learning over a Treebank to predict sentiment distributions into five dimensions (from very negative to very positive via neutral). Cambria et al. [7] promoted a knowledge-based framework called SenticNet for opinion mining. It utilizes the sentiment dimensions modeled on The Hourglass of Emotions [8], a derivative of Plutchiks Wheel of Emotions [22].

Mohammad [20] created a classifier to detect emotions using tweets with emotion word hashtags as labeled data. It inspired the usage of user-provided indications of emotional content, e.g. emoticons, Emoji, and hashtags. Dystemo [27] is a distant supervision method automatically producing emotion classifiers from tweets labeled using existing or easy-to-produce emotion lexicons. It utilizes Balanced Weighted Voting (BWV) classifier to overcome imbalance in emotion distribution and on heuristics for detecting neutral tweets. It adopts the Geneva Emotion Wheel, version 2.0 (GEW) [24] as the sentiment model that covers 20 discrete emotion categories frequently stated in self-assessments. The latter two approaches are especially relevant to our context of sentiment analysis on the unstructured data such as logs, microblogs and social media posts.

2.3 Food Log Analysis

While “Dietary Control” is gaining increasing attention in the field of healthcare, a lot of food-logging tools have sprouted up catering to both commercial and research purpose. They serve mostly as a meal diary and hardly ever include emotional information related to the time point of food intake. In usage, most tools require users to manually log food contents and nutrition information and do not generate analytical feedback. FoodLog [1, 2] is one of the few systems that enable automatic food logging and nutrition analysis leveraging image processing. It is a multimedia food-recording tool that achieves easy logging by food-image detection and food-balance estimation to categorize each meal into one pre-defined category based on the component recognition. There is still a gap in rewarding the logging efforts with interesting analytical reviews. Although FoodLog offers a timeline visualization of logged data to enable basic review on both component statistic and original food images, a more informative visualization going beyond timeline diary is needed to enable users to explore, interact, and understand their food journey. EmotionWatch [17] introduced a novel approach to visualize log time series by constructing visual summaries of public emotions, which can be inspiring in our context of food-emotion log visualization.

3 Data and Task Description

Food is one of the things that contribute most to the memorable moments in our lives. It not only plays a vital role to our physical health, but also the mentally wellbeing. Added to the fact that nutrition intake proves to be relevant to human emotion. We believe it worth to build personal profiles on what we eat and how we feel and to dig out the interesting inherent pattern of personal food-emotion relationships. Thus we propose to construct a digital diary of our food consumption and the emotions that accompanied them. On one hand, we aim to leverage information visualization to present our food journey as delicious as the food itself. On the other hand, we would like to gain analytical capability to reflect how food and emotions are correlated for a specific individual.

We approach this problem in the following process. First, we recruit users to log food details and their emotional feelings at the dining moment. We collect the logged data, process it and transform the relevant information into metrics needed. Then we come up with designs of storytelling visual representations. We iterate the designs according to users feedback in order to better convey the relevant information, such as how fun the food journey looks like, how nutation and emotions are influencing each other, etc. Ultimately we implement an interactive web-based visualization interface for users to explore, interact, and understand their food-emotion journey.

3.1 Dataset Description

We collect the data from 19 individuals who have been manually logging their detailed food-emotion information over 3.5 weeks. The food-emotion log dataset contains 563 entries in total. Each entry consists of up to 4 dimensions, including the loggers device token, submission date and time, original log text (ideally) containing both emotion and food descriptions, and a photo of the meal. Null value is allowed for each dimension.

3.2 Data Processing

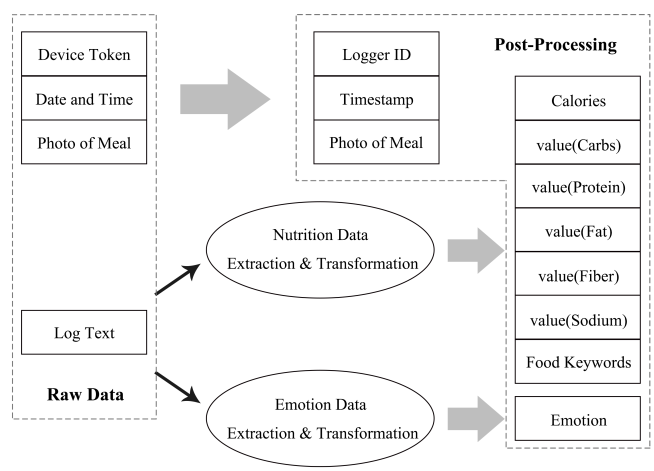


Figure 2. An overview of data processing workflow.

As demonstrated by Figure 2, the data processing workflow achieves data transformation and information extraction, and eventually adds 8 new columns to the original dataset. Among all the steps, two tasks are especially crucial.

- T1: Extract the food keywords from original log texts and transform them into nutrition data columns.
- T2: Extract emotion tags and translate into a categorical sentiment annotation.

3.2.1 Nutrition Data Extraction and Transformation

We firstly processed each log entry and extract the food keywords out of text manually. Terms regarding to proportion, for example ’one bowl of rice' or '100g beef', are noted down as complementary information to calculate the nutrition. Inspired by [1, 2], we then took the steps of interpreting photos of meals into information following the same logic. The photos were utilized to either (1) validate the food keywords according to image contents, or (2) complement the information of food details including the quantitative estimation of each component. Afterwards, we fed all the food information into MyFitnessPal, an open-source tool for calculating nutritions, to transform the food componential and proportional details into nutritional values. The numbers are calculated by MyFitnessPal by linking its well recognized nutrition dataset with the proportional values of each distinct component taken in the meal. [13] As a result, the following columns are generated and added to the original dataset: Calories, Value of [Carbs, Protein, Fat, Fiber, Sodium] and Food Keywords.

3.2.2 Emotion Data Extraction and Annotation

Mining sentiments from natural language is a very difficult because it involves intense understandings of most of the explicit and implicit information conveyed by language structures. Inspired by the logic used by [20,27], we extracted the emotion lexicons and ideograms i.e., Emoji as a set of emotion tags and utilize them for emotional categorization. To be specific, on one hand we untilized the extracted emotion lexicons such as 'happy' or 'very sad' as the emotional keywords and map them manualy to the most relevant category defined by the Plutchik's Wheel of Emotions. Therefore, a HAPPY log got annotated as Joy*1 while a VERY SAD log won Sadness*2. On the other hand we made a full use of the Emoji stickers shown in the logs for categorization. As a priori preparation, we carried out the work to classify all the common Emojis into one unit in the Plutchik's Wheel of Emotions or Neutral if it is really far from sentiment. Hence, if e.g. a greif face appeared in the log, we map it into Sadness and add a Sadness*1 to the annotation of this log. After finishing the annotating work of a log, we counted the annotations and define the majority of mappings as its categorization. As a result, a new column containing emotion annotation is added.

Plutchik's Wheel Of Emotions. To tackle with the task of emotion categorization and annotation, we adopt the model of Plutchiks Wheel Of Emotions [23] due to its simplicity by suggesting only 8 primary emotions: joy and sadness; anger and fear; trust and disgust; and surprise and anticipation. As the model defines, each emotion is culturally independent while each pair is defined as opposite. It makes the problem manageable and visualization potentially simpler. In addition, the model shows connectivity between the ideas of an emotion circle with a color wheel, which eases our work in mapping and validating the color-coding for each emotion annotation. Another advantage of this model is its potential extensibility, due to the derivation possibility of forming eight human feelings by mixing two adjacent basic emotions, and the decomposition possibility by expressing each primary emotion at three different degrees of intensities. For example, serenity is a lesser degree of joy and ecstasy is a more intense one.

4 Visual Representations

The goals of our visualization are defined as to describe:

- G1: The key features of each meal taken, i.e., emotional status and nutrition information;
- G2: The evolving pattern of personal nutrition intake and emotional status.

To accomplish the first goal, we propose a two-level visualization combining the Molecule representation (as in Figure 4) and the RoseViz (as in Figure 5) with an embedded tag cloud (as in Figure 5(b)) to illustrate crucial information in both emotional and nutritional dimensions. A set of novel glyphs (as in Figure 6 (b)) is designed to enhance the visual intuition. Interactions are added to enable users to explore the details of each meal. Regarding to the second goal, we introduce a Timeline Layout of Molecules (Figure 9 (b)) to present trend storytelling, and an accumulative Streamgraph (Figure 8) to dynamically reveal the evolving patterns of personal food intake and emotions. Explorative interactions are implemented to assist analysis

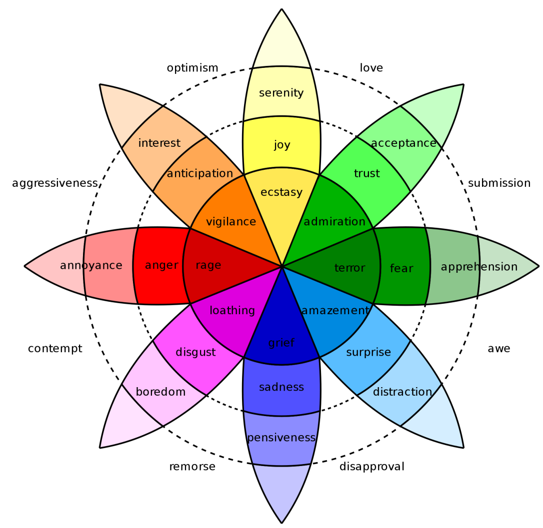


Figure 3. Plutchik's wheel of emotions.

on an aggregation level. For example, by hovering on an emotional segment in the Streamgraph, one can trigger the highlighted textures on all relevant Molecules to observe the nutritional distribution of the meals. It also triggers the Stacked Rose Diagram (Figure 1 (c)) to appear, which demonstrates an overview of emotion-nutrition distributions. Being consistent among all visual representations, emotion is measured categorically and represented by the same color-coding scheme (Figure 1 (d)). Nutrition information is measured quantitatively and represented by numerical attributes such as length and size.

4.1 Color Coding of Emotions

Studies in the field of color psychology have proven that color influences perceptions, though in an unobvious way. It adds to the complexity of picking a color for each emotion. Thus, it makes the color-coding of visualizations more challenging. To reduce the complexity of this task and the risk of misleading in color hints, I adopt the color scheme in consistent with Plutchik's Wheel. The model has long been used and widely accepted in terms of emotional perception.

As shown in Figure 1 (d), there are eight colors defined. Each color maps to a specific emotion category, e.g. orange for anticipate, yellow for joy, green for trust, blue-green for fear, light blue for surprise, dark blue for sadness, purple for disgust and pink for anger. The colors have been shifted for a certain offset from the original colors in Plutchik's Wheel for aesthetic purpose.

As described in Algorithm 1, color-coding is implemented in the following way. The color parameters are computed using the HSL model first, and then converted to a color hex code using the RGB model values. RGB is a more compatible across browses aligning with the display mechanism. It is especially helpful in the Timeline Layout of Molecules (Figure 4 (b)) because it enables random subtle color difference within each emotion category in terms of saturation and luminance. It therefore makes the consecutive Molecules that belong to the same emotion category more distinguishable from each other while not cause ambiguity with another category. It also makes the overall visualization vive.

4.2 Visual Encoding of Per-Meal Representation

A two-level visualization is proposed for per-meal representation. The first level is the Molecule representation, where each color stands for a certain emotion category and size, or radius, represents the calories of the meal. The second level is a rose-like representation called RoseViz, which is triggered when users hover on the related Molecule. RoseViz demonstrates both the calories value and the nutritional distribution. It

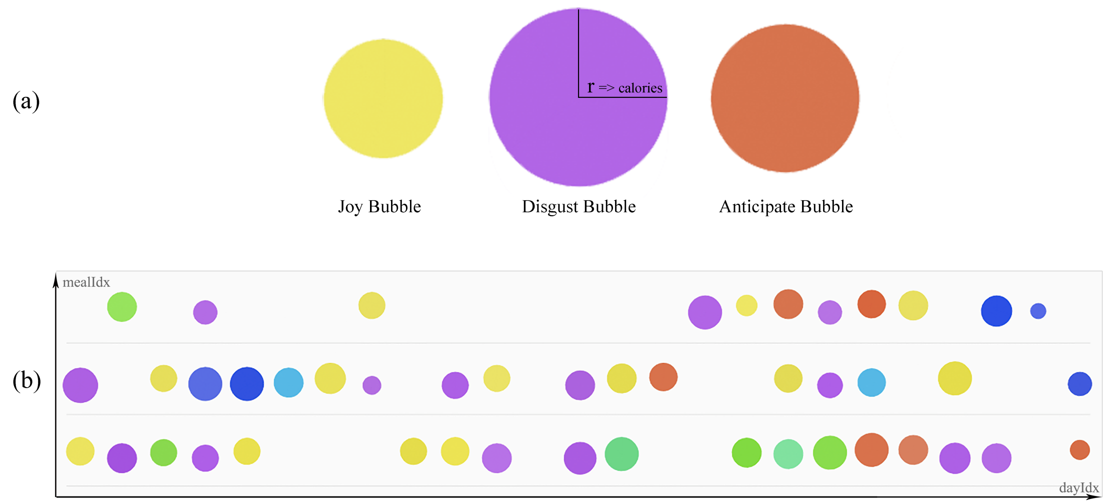


Figure 4. The Molecule representation. (a) Description of visual attributes. (b) Timeline Layout of Molecules.

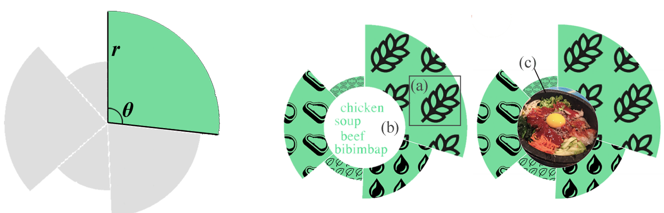


Figure 5. RoseViz A derivation of Rose Diagram proposed by this work. (a) Texture representing a nutritional component. (b) Tag cloud of food keywords. (c) Photo of the dishes.

is color-coded in the similar way as the upper-level Molecule where each color is to hint its associate emotional status. However, it utilizes a set of self-designed glyphs as textures to intuitively distinguish the nutritional components. It also demonstrates the detailed information of each meal, including a tag cloud embedded in the middle showing the keywords of the food content and a photo of the meal. The photo can be called appearing by a click on the tag cloud area.

4.2.1 Molecule Representation

Food is made up of molecules. Inspiration of the Molecule representation comes from the term molecular gastronomy. Molecular gastronomy is a sub-discipline of food science that seeks to investigate the transformation of food ingredients and the social, artistic and technical components linked to culinary activities [10]. Following the similar concepts, we use the artistic approach of visualization with the design of Molecule to represent the technical facts (e.g., nutritional value) and social aspect (e.g., emotional effect) of food.

Two major visual attributes of the Molecule representation are coded to convey the crucial information. First, color is coded by emotion annotation. Second, the radius of a Molecule (as shown in Figure 4 (a)), also reflected by its size, is coded by the value of calories intake via the meal. The reason why we reflect calories per meal is that it hints the weight of each meal in the loggers food-emotion profile and the overall evolving pattern.

As illustrated in Figure 4 (b), the Molecules are positioned in a layout where x-axis represents the day index increasing from left to right and y-axis represents the meal index from top to bottom along the order of time of the day. To be specific, meal index is defined as Breakfast-1, Lunch-2 or Dinner-3. It is a dual-timestamp layout so as to better reveal the potential underlying trends of data time series. We name it as the Timeline Layout of Molecules.

Users can explore in the layout and interact with the Molecules by hovering on them. A hover event triggers the appearance of RoseViz, the second-level visualization, that illustrates the detailed food information, e.g., nutritional distribution and food keywords.

4.2.2 RoseViz - A Derivation of Rose Diagram

Rose diagram is famous for being invented by Florence Nightingale, a statistician and medical reformer, to communicate the deaths of soldiers during the Crimean war. The original Nightingale Rose Diagram [5] is drawn on a polar coordinate system. All the categories of data are divided into equal segments on the radial chart by equal distribution of the angle. The proportion of the value that each segment within a category represents is coded by the area size of the associative ring. Thus, the radius of each segment extending from the polar center indicates the proportional value but not linearly.

We propose a simplified derivation of Nightingale Rose Diagram (as in Figure 5), named as RoseViz. It is designed to demonstrate the information per meal including the values and distribution of nutritional components. The RoseViz representation is color-coded holistically using the same color annotating the emotion of this meal. The nutritional distribution is reflected quantitatively by way of area size, jointly indicated by the angle and radius of each petal. To be specific, the angle is coded as a certain portion of PI, being linear to the relative proportion of the demonstrated nutritional component. Similarly, the radius is coded as magnification of the predefined unit length, linear to the product of both the absolute calories value and the relative proportion. Formulas are shown as follows:

$$\theta = \pi \times \frac{NutritionValue_{target}}{NutritionValue_{total}} \tag{1}$$

$$r = R_{ref} \times \frac{Calories_{target}}{Calories_{ref}} \times \frac{NutritionValue_{target}}{NutritionValue_{total}} \tag{2}$$

In addition, RoseViz also enables detailed exploration on the dining details. There is a tag cloud embedded in the middle (as in Figure 5 (b)) showing the keywords of food taken. A photo (as in Figure 5 (c)) of the dishes, if uploaded by the logger, can be called appearing by a click on the tag cloud area.

4.2.3 Glyphs for Nutrition Representation

Nutrition analysis is conducted at the detailed level of nutritional components. An approach is needed to distinguishing the five major components visually without interfering the already used visual attributes. We chose to use the filling textures because it imposes direct visual impact. According to the principle of simplicity, visual description

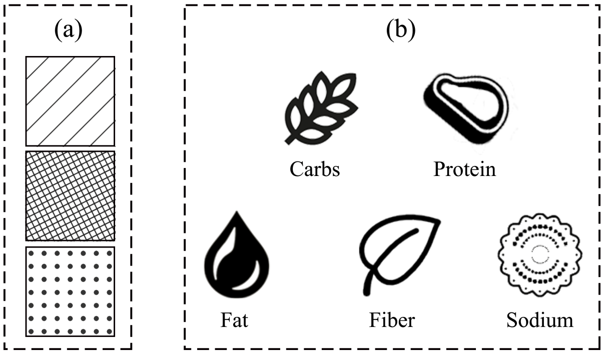


Figure 6. (a) Existing commonly used textures; (b) Self-designed nutrition glyphs.

should not cause unnecessary perceptual complexity or huge additional learning efforts. Since the existing common textures, e.g., circles, lines, bricks, etc. (as in Figure 6 (a)) may cause obscure connections and more learning efforts, we decide to discard using them for component representation. Instead, we designed a set of simple glyphs (Figure 6 (b)) based on their widely accepted semantics that are closely linked to the nutritional components. The goal is to bring intuitive indication on relevant nutrition element based on common knowledge and thus reduce the learning efforts for the users.

4.3 Visual Encoding of Accumulative Representation

4.3.1 Streamgraph Representation

Streamgraph is a type of stacked area graph. It gets famous since 2008 when Byron [6] introduced it to visualize the box office revenues for 7500 movies over 21 year. A Streamgraph layout emphasizes legibility of individual layers, arranging them distinctly around a central axis. It results in a flowing and organic shape that brings a natural indication of river and waves. To exploit the intuitive visual hints, we decide to use Streamgraph to represent the wave of emotions. Twin goals aim to be achieved: to show the data time series while to convey the evolving sum that indicates the overall pattern. The Streamgraph makes it possible to satisfy both goals at once because the heights of the individual layers are quantitatively comparable, meanwhile the height of the overall graph as an addition of all layers is changing in a distinguishable way overtime.

Figure 7 illustrates the Streamgraph design. The graph consists of a set of layers, corresponding to the time series of nutritional values, specifically value of calories intake distributed into different emotion categories. The thickness of each layer reflects the accumulative value of calories intake by the meals annotated with specific emotion category. The overall stack reflects the evolving sum of calories intake, via the overall height evolving along the loggers timeline.

To be specific, there are four ingredients to be paid important attention in order to generalize the Streamgraph visualization. The first one is the geometry, which is critical because it determines the overall slopes and curvature of the individual layers. The relevant shape parameter is set silhouette in our context. It sets the baseline of the whole graph to be in the middle and adjust the algorithms for slope and curvature computations accordingly. The second is the ordering of the layers. We adopt the ordering of emotion categories based on the Plutchik's Wheel, starting from Anticipate towards Anger in a clockwise way. It is on the one hand conforming to the aesthetic criteria considering the associative color distribution. On the other hand it forms a partition between relatively positive emotions and negative ones. The third ingredient is labeling. As with any visualization, labels are important. The organic forms of a Streamgraph result to more complex mechanism in terms of labeling visual display. Due to simple nature of our dataset and to avoid additional complexity, we decide not to always present the labels, and instead we use external legends and interactions as an alternative solution. Last but not least, color choice is critical. Good choices enable viewers to distinguish different layers while enhance the illustration of multiple data dimensions without adding complexity. The same color-coding scheme with per-meal visualizations is used here for consistency.

Streamgraph can intuitively reveal the patterns underlying the personal logs. For example, the pattern of dominance in emotional food intake is hinted by the relative area size of each layer in the stream. Additional interactions are added to enable further explorations. For example, by hovering on a layer one can ignite all the relevant meals belonging to the selected emotion category with a proportional overview of each meal and the nutritional distributions displayed on the Molecules. In the meantime, this interaction triggers the appearance of the Stacked Rose Diagram that reveals the overall distributive pattern of emotion-nutrition values. The hovered emotion category also is highlighted in the Stacked Rose Diagram.

4.3.2 Stacked Rose Diagram

In consistent with RoseViz designed for per meal representation, the Stacked Rose Diagram (as in Figure 1 (c)) is designed to represent the overall aggregation of the emotion-nutrition distributions based on the entire dataset. Namely it visualizes all the data entries covering the entire time range. The Stacked Rose Diagram is a derivative implementation of Nightingale's Rose Chart where each petal gets distributed the same angle to represent a categorical partition of emotions.

The Stacked Rose Diagram is constructed as follows. The petals are color-coded according to their emotion categories. The radius of each petal is linearly coded by the total calories intake from the meals with the specific emotion annotation. Within the petals, the distribution among nutritional values of different components is represented linearly as a certain proportion of the radius. It consequently conveys a visual intuition through the size of area.

Glyphs are used to label the represented nutritional components. Different petal will be highlighted when the associate emotion category gets hovered in the Streamgraph. Meanwhile the others turn fading.

4.4 Animation Design Rationale

Animation has been used in visual representation to assist storytelling, especially for describing the time series variations []. Different from those transition methods implemented for facilitating visualization on large scale data, we use animation to amplify the users' feelings on watching the final representation.

We try to leverage animation to make the trend visualization persuasive and memorable. The animation design rational are described in the following two aspects:

- A1: Reveal the emotion as a reaction to external events
- A2: Bridge the linguistic expressions of emotion and the visual forms through the design

5 IMPLEMENTATION

We pick two participants' logs as sample to process and implement as pilot visualization. The sample datasets contains 39 and 46 valid entries respectively.

5.1 Data Preprocessing and Analysis

5.1.1 Methodology

The result of processed data is stored as a CSV (comma-separated values) file with which it is easy to program. A CSV file stores tabular records in plain text where each line represents a data record and each record consists of identical list of fields separated by commas. It is best used to represent sets or sequences of records corresponding to a single relation, and features good compatibility across all mainstream computer platforms.

In order to make the visual exploring experience accessible to normal users, we implement the designs using D3.js [4], a JavaScript library for manipulating documents based on data. D3.js leverages HTML, SVG and CSS. It is based on web standards and thus featuring full modern-browser capabilities and good compatibility. In addition, it supports powerful visualization components including efficient visual

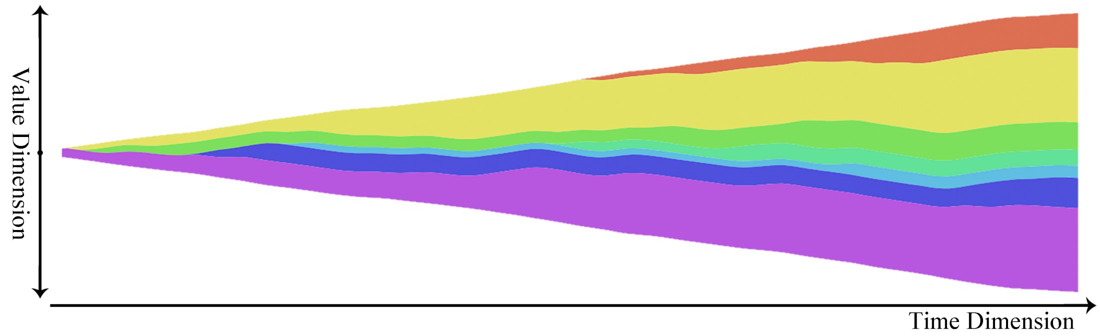


Figure 7. The Streamgraph illustrates the accumulative emotion-nutrition information

binding and interactive representations, and a data-driven approach to DOM (Document Object Model) manipulation. Hence, it is an ideal environment for web implementation in our context.

5.2 Interactions and Animations

5.2.1 Handling Visual Clutter

Due to the limitation of space, visual clutter may happen in the Timeline Layout of Molecules when the second-layer RoseViz is displaying. It hinders the visual exploration process because the neighboring Molecules get blocked.

Inspired by the Fisheye Distortion [3] methodology, we proposed a dynamic repositioning approach (as in Algorithm 1) to handling this problem.

Algorithm 1 Repositioning Molecules when RoseViz is triggered

if hover event triggered by a Molecule **then**
  $x_{hovered} \leftarrow$ x-coordinate value of the hovered Molecule
  for each Molecule other than the hovered one **do**
    $day_{index} \leftarrow$ the day index of this Molecule
    $x \leftarrow$ x-coordinate value of this Molecule
  if $x < x_{hovered}$ **then**
    $x_{update} \leftarrow \text{move}(x, day_{index})$
if hover event released **then**
  for each Molecule other than the hovered one **do**
    $x_{update} \leftarrow$ original x-coordinate value of this Molecule
return x_{update}

By using this approach, whenever RoseViz gets triggered, the x-coordinate values of all other Molecules get recalculated using the day indexes based on their distance and relative position (left or right) to the hovered Molecule. As shown in Figure 8 (b), consequently all other Molecules except the hovered one are repelled. Therefore, the visual clutter between the RoseViz and Molecules is avoided.

5.2.2 Animations

Animation is an interesting element of information visualization. Well-crafted animated visualizations can further boast their effectiveness in terms of perception, persuasion, storytelling, etc. Therefore, carefully designing meaningful and effective animations is an important task. Two sets of animations have been added to this work. On one hand, catering to the inherent needs of time series data, timeline animations are implemented similarly to a play effect. On the other hand, since some visual elements, e.g. the river-like Streamgraph, have direct links to the entities in the real life, we designed and implemented some natural animations to add dynamics and make the visualization more vivid.

Timeline Animation Timeline animation is to play the visualization by gradually drawing a subset of data according to their timestamps. To be specific, we sequentially draw the Molecules based on their day indexes and meal indexes. Meanwhile we fade in the Streamgraph linearly from left to right based on the day indexes. The timeline animation will play every time when users launch or refresh the web-based interface. It contributes to conveying the time-series changes in the way of unfolding narrative and telling the stories overtime to show the evolving process.

Natural Animation Using Perlin Noise Natural animations are effective in making the visualization more vivid and influential, especially when there are natural visual elements such as the river-like Streamgraph. It adds dynamics to the entire representation and builds a direct link between the visualizations and the elements in our real life. As a result it evokes users emotions.

Inspiration of designing the animations comes from Shiffmans book, i.e., *The Nature of Code* [25], where he introduced various models of applying basic mathematics and physics concepts from the nature to programming. Examples include but are not restricted to forces, flow field, fractals, oscillations, etc. Regarding to the Streamgraph, we designed the animations by simulating natural oscillations and flow field considering the inherent attributes of river that it flows and waves continuously. As for the Molecules, since the layout make them perceived analogical to stars in the sky, we designed animation to imitate stars winkling by way of oscillating their radius.

The animations are implemented via the approaches based on Perlin Noise [25]. Perlin Noise is a type of gradient noise that enables to better represent the complexity of natural phenomena in visual effects. I utilized a multi-pass noise algorithm developed by Gentle [14]. To be specific, the function of *simplex2* is used as an interface to generate 2D perlin noise and simplex noise. In addition, when implementing the animations of Streamgraph, I build the parameters to include also time-dimension offset in order to simulate the flow field effect of real rivers.

6 Evaluation

To evaluate the visual designs proposed in this work, we carried out two experiments. The first experiment aims to evaluate whether the RoseViz representation enhances the intuition perceived by the users in practical usage. The second one is to evaluate the effectiveness of self-designed nutrition glyphs regarding ease of learning and usability. We also collect daily dietary data from 19 participants to evaluate the visualization based on real cases.

6.1 Evaluation on RoseViz

The goal of the first evaluation is to compare the visual intuition provided by our design of RoseViz versus a traditional visualization approach as Ring Graph, which is commonly used for representing distributions. 10 participants (six female) aged between 18 and 60 took part in the first experiments. During the experiment, each participant was given three pair of visualizations. Each pair of visualizations depicts the same underlying data of a meal but using different visual representations. One is visualized with RoseViz and another one with Ring Graph (as shown in Figure 9).

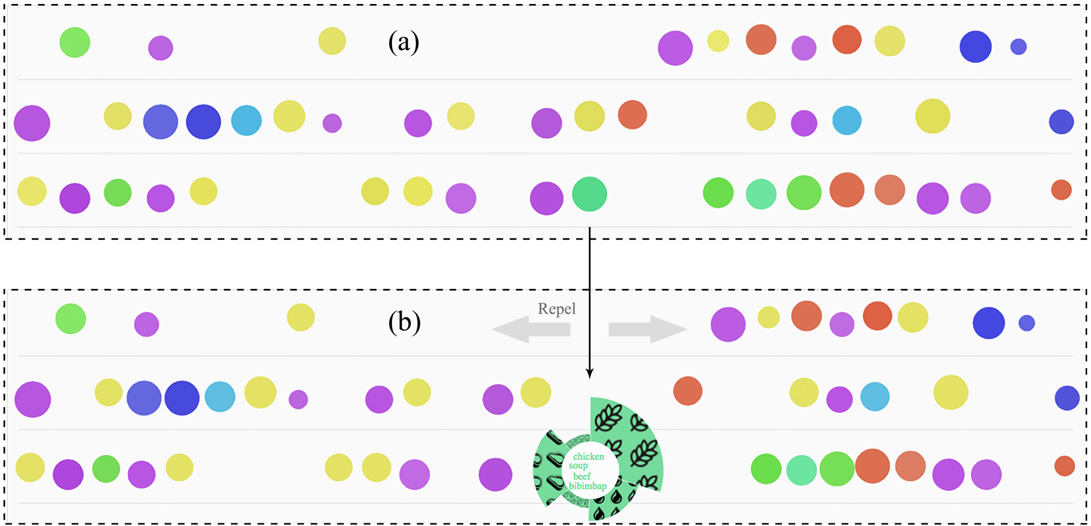
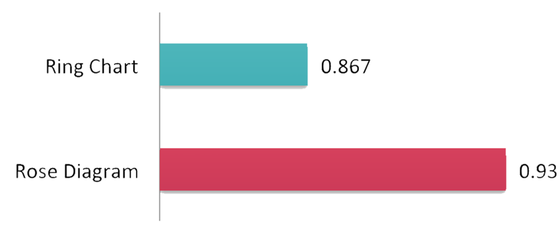


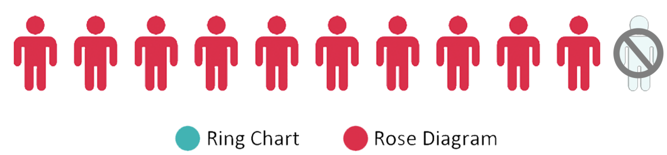
Figure 8. (a) The Timeline Layout of Molecules in original positioning; (b) Repositioning Molecules when RoseViz is triggered.

(a) **(b)**

Figure 9. An example pair to be compared: (a) Rose Diagram representation; (b) Ring Graph representation.



(a) Results Of Accuracy



(b) Results Of Preference

Figure 10. User evaluation results on RoseViz and Ring Chart.

Participants were asked to order the value nutritional components for each meal after one minute. They were then requested to give a preference on which design made it easier for them to finish the task.

The results of the first experiment are shown in Figure 10. Overall, RoseViz outperforms in terms of accuracy during the tasks of ordering the nutritional values. (Accuracy is calculated as: if the participant failed to order a meal with 100% correctness, then he/she got 0% accuracy for this task.) All participants expressed that they preferred the RoseViz representation because it is clearer in showing the value by area size. In addition, they perceive it simper and more aesthetic.

6.2 Evaluation on Nutrition Glyphs

The goal of the second evaluation is to compare the level of learning efforts required for users to build perceptive connection between visual items and specific nutritional components by using our self-designed nutrition glyphs versus using the traditional textures, e.g., lines, bricks, etc. Six participants (four female) aged between 24 and 28 were recruited.

During the experiment, participants first received an introduction on the rules of mappings between a set of common textures (as in Figure 6 (a)) and the nutritional components. They were allowed to read the rules for 10 seconds and try to memorize it. We then ask them to do a test on mapping the texture to the nutritional component based on the rules. After one minute for a rest, we gave the participants another introduction on of the mapping rules between our self-designed glyphs (as in Figure 6 (b)) and the nutritional components. Similarly, after 10 seconds they did another test on the mappings.

As a result, all the six participants achieved 100% correctness on the mapping task with our self-designed glyphs. While the correctness of the mapping task using common textures reached only 70% on average. The results of second experiment validate that our glyphs are easier to memorize and thus lower down the necessary learning efforts required for the users. According to users' feedback, the glyphs can build direct hints on represented nutritional components with better visual intuition.

6.3 Evaluation on Real Cases

We conduct a user study to evaluate the visualization design through collecting participants' reports on their daily food log. There are total 19 participants (seven female) recruited from local universities. We find three distinct patterns from the results as in Figure 11, Figure 12, and Figure 13.

7 Conclusion and Future Work

Nutrition intake and sentiment analysis have long been at the interest of researchers. As recent studies indicate that the correlation between nutrition and emotion exists, it becomes inspiring while challenging to study the topics that combine both. Our work intends to approach this topic leveraging information visualization. We propose to build personal profiles for our users based on their food and mood logging data. We design a set of visual representations for nutrition-emotion

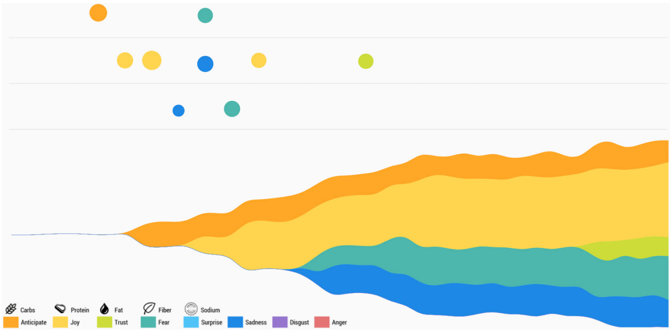


Figure 11. The visualization result of participant #1.

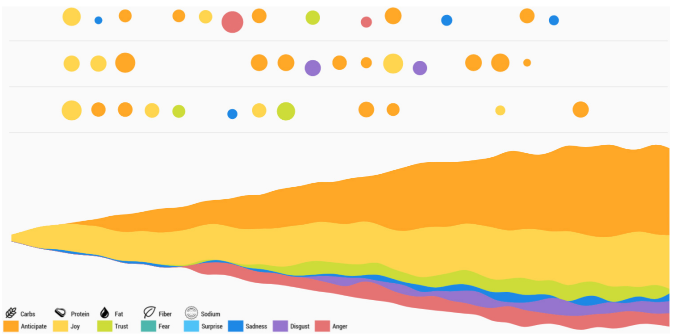


Figure 12. The visualization result of participant #19.

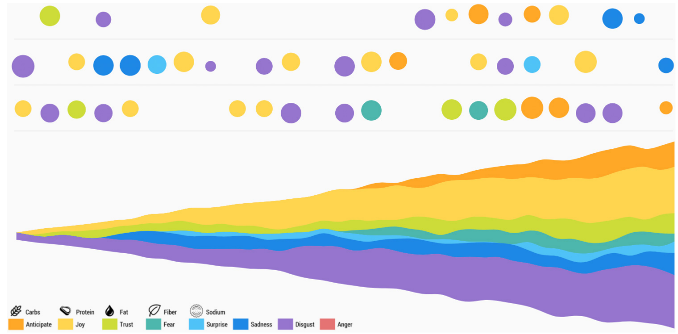


Figure 13. The visualization result of participant #20.

visualization and novel layouts to enable timeline storytelling and to reveal the evolving patterns. The integrate solution is implemented as a web-based interactive interface enriched with explorative interactions and dynamic animations. We conduct the evaluations on our solution with two user studies, which verified the aesthetics of our designs and their effectiveness brought by better-perceived intuition.

As for future work, efforts have been planned majorly in the following two directions. On one hand, we want to apply machine-learning approaches to the data processing steps, for example to achieve automatic food word extraction, nutritional information transformation, and emotion category recognition. On the other hand, since emerging research reveals that the influence of diet on human brain is not a standalone effect but integrated with actions of other lifestyle modalities, there is huge potential to work on combining more dimensions such as exercise or sleep data collected from sensors.

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