BACHELOR

Integrated Label
FoodWaste, GHG Emission, and Nutritional Values

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Integrated Label: Food Waste, GHG Emission, and Nutritional Values

Bachelor End Project Report

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Abstract

Food waste presents a significant societal challenge with wide-ranging moral, ethical, and environmental consequences. Despite the widespread recognition of its negative impacts, the current labeling systems fail to comprehensively address this issue. While nutritional values and carbon emissions have their own labels, there is a need for an integrated approach. This paper proposes the development of a novel label that combines food waste, nutritional values, and emission data into a unified and informative format. The goal is to assist individuals in making healthier choices while also considering the environment, without overwhelming them with multiple labels on product packaging. By creating separate labels for each component and subsequently integrating them, consumers can gain a holistic understanding of the products they purchase. The research leverages data from ReFED, a prominent food waste organization, and the Open Food Facts data set, enabling the derivation of meaningful insights. With this data, multiple methods are created to create a final label. This leaves the door open for policymakers to decide what is the most important component or aspect of the label and choose the best fitting method. This study contributes to the broader discourse on sustainable consumption by offering a practical solution to empower consumers to make informed choices that promote environmental sustainability while considering their nutritional needs.

1 Introduction

The global food system is facing numerous challenges that require innovative solutions to promote sustainable and informed consumer choices. As the impacts of food production on human health and the environment become increasingly apparent, the need for comprehensive food labeling systems has emerged. This research paper aims to explore the development of a novel food label that incorporates essential information regarding nutritional content, carbon footprint, and food waste implications. By integrating these three vital components, this label seeks to empower consumers with the knowledge to make conscious decisions that prioritize their health and minimize environmental impacts.

1.1 Nutri-Score

Recently a new food label was introduced in the Netherlands: Nutri-Score. [15] Nutri-Score is a food labeling system that works with a color-coded system that assigns a letter grade (A to E) to food products based on their nutritional quality. Products get an A score if they have the highest nutritional value and get an E score if they have the lowest nutritional value.

The purpose of the Nutri-Score label is three-fold:

- Encouraging healthier diet choices by making nutritional values easy to understand (and featuring them prominently on the packaging);
- To provide consumers with a simpler way to compare nutritional values of similar (or same) products by comparing their Nutri-Score grades, and;
- To prompt food manufacturers to improve low-quality products through reformulation and innovation (while chasing a higher Nutri-Score grade).

It is important to clarify that a low Nutri-Score letter grade does not necessarily indicate that a particular product is inherently bad. Instead, it signifies that the product is less nutritious compared to the ideal standards, without passing judgment on its overall quality. The calculation behind Nutri-Score is designed to be simple, although the determination of the nutritional values score can be more complex. The Nutri-Score letter grade (G) is determined by the total amount of points (S). The total amount of points (S) is determined by subtracting the total positive points (P) from the total negative points (N). A lower score corresponds to a better letter grade, indicating a more favorable nutritional profile. The formula for calculating the Nutri-Score is as follows: $S = N - P$

The Nutri-Score system considers the presence of high-quality nutrients, such as protein, fiber, fruits, vegetables, nuts, legumes, and specific oils like olive, walnut, and rapeseed. These components contribute to the overall nutritional value of a product. The Nutri-Score assigns negative points to products based on the overall percentages and grams per 100 grams of these beneficial nutrients. The specific number of negative points earned can range from 0 to -5, depending on the composition.

On the other hand, low-quality nutrients, including energy density, sugars, saturated fatty acids, and salt, are considered less desirable in excessive amounts. The Nutri-Score assigns positive points to products based on the grams or kilojoules per 100 grams of these nutrients. The number of positive points can vary from 0 to 10, depending on the quantity present. [8]

It is important to note that the total amount of points earned does not necessarily result in the same Nutri-Score letter grading (A-E) for every product. There is a distinction between general food products and beverages when it comes to interpreting the Nutri-Score. [5] The table below (Table 1) illustrates the significance of the total amount of points for each sector:

Liquid/solid food	Beverages	Nutri-Score Label
Min to -1	Water	A
0 to 2	min -1	B
3 to 10	2 to 5	C
11 to 18	6 to 9	D
19 to max	10 to max	E

Table 1: Comparison of Nutri-Score points and labels for different liquid and solid foods

In addition to the general rules, it is important to note that there are special calculation rules for certain types of food, such as cheese, butter, and fat or mono products made from oil. These specific products have different calculation criteria for determining their Nutri-Score compared to the standard approach. Instead of solely considering the absolute grams of saturated fatty acids per 100 grams, the calculation takes into account the ratio of saturated fatty acids to total fats present in these products. The corresponding ratios and their associated scores can be found in Table 2.

The scoring system for beverages differs from that of general food, as it takes into account the energy content and the proportions of fruits, vegetables, legumes, nuts, rapeseed, walnut, and olive oil. The assigned points are presented in Table 3.

Points	Ratio of saturated fatty acids to total fat in %
0	<10
1	<16
2	<22
3	<28
4	<34
5	<40
6	<46
7	<52
8	<58
9	<64
10	≥ 64

Table 2: Nutri-Score points for cheese, butter, and oil-based fat or mono products

Points	Energy Density (kJ/100g or 100ml)	Sugar (g/100g or 100ml)	Share of Fruits/ Legumes/ Pulses/ Nuts/ Rapeseed/ Walnut/ Olive Oil (%)
0	≤ 0	≤ 0	≤ 40
1	≤ 30	≤ 1.5	–
2	≤ 60	≤ 3	> 40
3	≤ 90	≤ 4.5	–
4	≤ 120	≤ 6	> 60
5	≤ 150	≤ 7.5	–
6	≤ 180	≤ 9	–
7	≤ 210	≤ 10.5	–
8	≤ 240	≤ 12	–
9	≤ 270	≤ 13.5	–
10	> 270	> 13.5	> 80

Table 3: Nutri-Score points for beverages

Points	Energy (kJ)
0	≤ 335
1	> 335
2	> 670
3	> 1005
4	> 1340
5	> 1675
6	> 2010
7	> 2345
8	> 2680
9	> 3015
10	> 3350

Table 4: Negative points for energy in kJ

Points	Sugar (g)
0	≤ 4.5
1	> 4.5
2	> 9
3	> 13.5
4	> 18
5	> 22.5
6	> 27
7	> 31
8	> 36
9	> 40
10	> 45

Table 5: Negative points for sugar in grams

Points	Saturated Fat (g)
0	≤ 1
1	> 1
2	> 2
3	> 3
4	> 3
5	> 5
6	> 6
7	> 7
8	> 8
9	> 9
10	> 10

Table 6: Negative points for saturated fat in grams

Nutri-Score has been implemented in several European countries to help consumers make healthier food choices. In general, this label is perceived well and has been shown to be effective. [19] [9]

To determine the Nutri-Score of an orange, the analysis focuses on its nutritional composition per 100 grams. According to the provided nutritional information, an orange contains 186 kilojoules of energy, 8.3 grams of sugar, 0.8 grams of saturated fat, one milligram of salt, one gram of protein, and 2.1 grams of fiber [2]. The calculation begins with the negative components, where higher amounts are regarded as less favorable.

The analysis begins with the examination of the energy content (e) of the orange, referring to Table 4 for reference. As per the table, the energy content of 186 kJ in the orange does not result in any negative points ($e = 0$).

Next, the evaluation focuses on the sugar content (s), 8.3 grams per 100 grams, utilizing the scoring system outlined in Table 5. According to the table, the orange acquires one negative point due to its sugar content ($s = 1$).

Next, the evaluation centers on the saturated fat content (sf), which amounts to 0 grams, employing the scoring system presented in Table 6. According to the table, the orange does not accumulate any negative points in relation to its saturated fat content ($sf = 0$).

Next, the evaluation focuses on the sodium content (so) of the orange, which is classified as negative. The sodium content can be calculated based on the amount of salt, considering that salt is approximately 40% sodium. With an orange containing one milligram of salt, it results in $1 * 0.40 = 0.4$ milligrams of sodium. Referring to the scoring system presented in Table 7, the orange does not accrue any negative points for its sodium content ($so = 0$).

When summing up the negative points for the orange, considering energy, sugar, saturated fat, and sodium, the total is one point ($N = e + s + sf + so = 0 + 1 + 0 + 0 = 1$).

Now, the calculation of positive points ensues, with higher amounts being deemed more favorable. For the protein content (p), the orange contains one gram. Referring to Table 8, the orange does not earn any positive points for its protein content ($p = 0$).

Next, the evaluation focuses on the fiber content (fi), which amounts to 2.1 grams. Referring to Table 9 for scoring, the orange accumulates two positive points for its fiber content ($fi = 2$).

When summing up the positive points for the orange, taking into account the protein and fiber content, the total amounts to two points ($P = p + fi = 0 + 2 = 2$). Consequently, the overall score is $S = N - P = 1 - 2 = -1$. As a solid food, according to Table 1, the orange receives an A label due to its total score of -1.

Points	Sodium (mg)
0	≤ 90
1	> 90
2	> 180
3	> 270
4	> 360
5	> 450
6	> 540
7	> 630
8	> 720
9	> 810
10	> 900

Table 7: Negative points for sodium in milligram

Points	Protein (g)
0	≤ 1.6
1	> 1.6
2	> 3.2
3	> 4.8
4	> 6.4
5	> 8

Table 8: Positive points for protein in grams

Points	Fiber (g)
0	≤ 0.9
1	> 0.9
2	> 1.9
3	> 2.8
4	> 3.7
5	> 4.7

Table 9: Positive points for fiber in grams

For comparison, the Nutri-Score for orange juice gets calculated. To determine the Nutri-Score for "Appelsientje 100% puur sap mild" orange juice [7], its nutritional values per 100 milliliters need to be considered. The provided values for this orange juice are as follows: 175 kilojoules of energy, zero (0) grams of saturated fat, 8.9 grams of sugar, 0.35 grams of fiber, 0.7 grams of protein, one milligram of salt, and it is 100% orange juice.

For beverages, the negative points are determined based on specific criteria outlined in the "Energy Density (kJ/100g or 100ml)" and "Sugar (g/100g or 100ml)" columns of Table 3. With an energy content (e) of 175 kJ, orange juice accumulates six negative points ($e = 6$). Similarly, the sugar content (s) of 8.9 grams also contributes six negative points ($s = 6$). The absence of saturated fat (sf) with a quantity of zero (0) grams results in no negative points ($sf = 0$), as indicated in Table 6. Additionally, the sodium content (so) of 0.4, derived from one milligram of salt (considering the 40% sodium ratio), does not contribute any negative points ($so = 0$), as shown in Table 7. As a result, the total number of negative points amounts to 12 ($N = e + s + sf + so = 6 + 6 + 0 + 0 = 12$).

Now the positive points are calculated. In the case of orange juice, the protein content (p) of 0.7 grams does not contribute any positive points ($p = 0$), as indicated in Table 8. Similarly, the fiber content (fi) of 0.35 grams does not accumulate any positive points ($fi = 0$), as depicted in Table 9. However, since orange juice is classified as a beverage, an additional category is considered. The presence of vegetable, fruit, and nuts content (b) in the orange juice, which in this case is 100%, contributes to ten (10) positive points ($b = 10$), as outlined in Table 3. Consequently, the total positive points are calculated as $P = p + fi + b = 0 + 0 + 10 = 10$.

By subtracting the positive points (P) from the negative points (N), the score (S) is obtained by the following formula: $S = N - P$. For the given orange juice, the calculation results in $S = 12 - 10 = 2$ total points. Referring to Table 1, a score of 2 corresponds to the Nutri-Score label C for the "Appelsientje 100% puur sap mild" orange juice.

1.2 Carbon

Environmental concerns have become a significant driving force behind human development, leading to heightened public awareness of climate change and a growing interest in understanding the carbon emissions associated with various products [16]. In response to this demand, policymakers and businesses have embarked on exploring effective measures to reduce greenhouse gas (GHG) emissions.

The United Kingdom's Carbon Trust played a pioneering role in 2006 by introducing the world's first carbon label initiative, known as the Carbon Reduction Label [1]. Since then, several other countries have adopted similar labeling schemes. It is worth noting that the concept of the ecological footprint, encompassing resources such as cropland, pasture land, built-up land, forest, fish, and carbon assimilating capacity, emerged in the 1970s, predating the specific focus on carbon labels. This collective progress reflects global recognition of the need to address environmental impacts and the growing efforts to provide consumers with comprehensive information about product sustainability and carbon footprints.

Today, ecological footprint measures have evolved into widespread tools encompassing a broader range of environmental protection fields, often referred to as environmental labels. These labels offer detailed information to consumers, aiming to motivate changes in purchasing behavior that benefits the environment. In this context, the focus will be on the carbon footprint.

The discussion around "food miles" in the UK around 1976 marked a precursor to carbon labeling, with a focus on measuring the embodied carbon in traded goods resulting from transportation. The concept of a carbon footprint emerged from the broader concept of an ecological footprint, evolving into a more applicable and accurate metric. A carbon footprint is now exclusively used to measure the total amount of GHG emissions within a defined supply chain. While different researchers and agencies may apply slightly different meanings to the term, it generally represents the weight of greenhouse gas emissions throughout the life cycle of an industrial or life activity, a product or service's production process, or within a specific geographical area.

There are two main types of carbon footprints. The first is the carbon footprint of a product, which encompasses the total GHG emissions, including CO2, CH4, N2O, and other greenhouse gases, throughout its entire life cycle—from input procurement and manufacturing to transport, distribution, final consumption, and waste disposal. The second type is the carbon footprint of a company, which includes GHG emissions at the production stage. The carbon footprint of a product is the more commonly encountered type.

Carbon labels come in various forms [12], such as the Carbon Reduction Label, which provides a single numeric value for CO2 emissions, as well as "traffic light" carbon labels and others [18]. A carbon reduction label can also indicate a claim of better-than-previous performance [11]. Research suggests that both eco-labels and carbon labels are customer-driven mechanisms, with their effectiveness dependent on consumers' understanding of the labels' meaning and their underlying motivations for environmental and social responsibility, ultimately driving ethical and altruistic purchasing behaviors [12].

Carbon label measurement methodologies and standards exhibit variability across countries, regions, and even within a single jurisdiction. Nonetheless, the fundamental calculation of a carbon footprint is based on the life-cycle assessment (LCA) framework. LCA typically involves four key steps: defining the calculation goal and scope, analyzing the calculation inventory, explaining the calculation result, and assessing the comprehensive impact [10]. This approach considers the entire life cycle of a product or activity, encompassing its cradle-to-grave environmental footprint.

Within the field of LCA, there are three primary types of assessment: process LCA (bottom-up approach), input-output LCA (top-down approach), and a hybrid approach that combines both methodologies. Among these, input-output LCA, which takes a top-down perspective, is the most commonly employed method. However, process LCA serves as the foundational element for quantifying carbon footprints in several prominent standards, including ISO 14067, PAS 2050, and GHG Protocol.

- ISO 14067: This international standard, published by the International Organization for Standardization (ISO), provides guidelines for quantifying the carbon footprint of products. It outlines the principles, requirements, and procedures for conducting a life cycle assessment (LCA) to calculate the carbon emissions associated with a product throughout its entire life cycle. ISO 14067 aims to facilitate the comparison of product footprints and support informed decision-making for reducing emissions.

- PAS 2050: The Publicly Available Specification (PAS) 2050 was developed by the British Standards Institution (BSI) and provides a framework for assessing the carbon footprint of goods and services. It focuses on determining the greenhouse gas emissions associated with a product's life cycle, from raw material extraction to disposal. PAS 2050 includes guidelines for data collection, emissions calculation, and reporting, enabling companies to evaluate and communicate the environmental impact of their products.

- GHG Protocol: The Greenhouse Gas Protocol is a globally recognized standard developed by the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD). It offers comprehensive guidelines for quantifying and managing greenhouse gas emissions, including carbon footprints. The GHG Protocol consists of two key components: the Corporate Accounting and Reporting Standard, which helps companies measure and report their emissions, and the Product Life Cycle Accounting and Reporting Standard, which provides guidance for assessing the carbon footprint of products.

These standards aim to provide a consistent and transparent approach to measuring and reporting carbon footprints, allowing organizations to identify emission hotspots, set reduction targets, and track progress in mitigating climate change. They play a crucial role in promoting environmental accountability and enabling informed decision-making across industries.

In the United Kingdom, the Carbon Trust, a prominent non-governmental organization, pioneered the introduction of carbon footprint labels in 2006, as depicted in Figure 1. These labels serve as informative indicators of a product's environmental impact and are calculated in accordance with the GHG Protocol standards. The UK implementation includes two types of labels: the "CO_2 Measured Label" displaying the numeric value of GHG emissions, and the "Reducing CO_2 Label" symbolizing the manufacturer's dedication to reducing emissions throughout the manufacturing process. These labels offer consumers valuable insights into the carbon footprint of products, enabling them to make informed and environmentally-conscious purchasing decisions.

In France, two leading supermarket chains, Casino and Leclerc, have taken the initiative by introducing their own numeric carbon

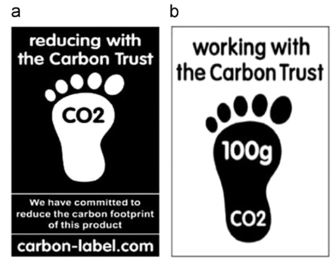

Figure 1: Carbon labels in UK. (a) Reducing CO2 label. (b) CO2 Measured label [16]

dioxide values on product labels. Both chains utilize a standardized mass unit of 100g for presenting GHG emission values. Casino's carbon label, as depicted in Figure 2(a), showcases the GHG emissions value alongside the phrase "Indice Environment" (Environment Index). The calculation methodology for Casino's label is based on the PAS 2050 standard, ensuring a consistent approach. On the other hand, Leclerc has developed its own carbon labeling standard to assess carbon footprint values. Figure 2(b) illustrates Leclerc's innovative approach, utilizing a vibrant bar chart where each color corresponds to a specific GHG emission volume.

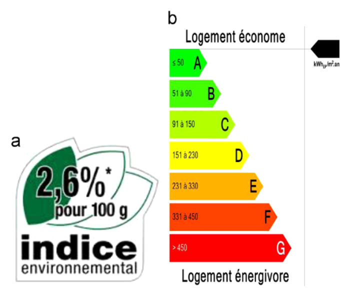

Figure 2: Carbon labels in France. (a) Indice carbone. (b) Bilan carbone. [16]

In Germany, the German Product Carbon Footprint Project, a governmental organization, launched a notable public carbon footprint labeling scheme in 2008. Figure 3 illustrates this initiative, which differs from previous examples by not including numerical carbon emission data on the label. Instead, the label serves as a clear indication that the carbon footprint of the product has been assessed. The GHG emission calculation method utilized in this scheme follows the PAS 2050-B2C (cradle to grave) approach.

Figure 3: Carbon label in Germany [16]

In the United States, the carbon labeling landscape comprises four prominent types of labels. The Carbon Fund, a local private agent, introduced the Carbon Free Certified label in 2007. This label, depicted in Figure 4(a), signifies a firm's commitment that the product's production does not contribute to global climate change harm. This is a carbon label without a concrete numeric GHG emission value. The label is shown in Figure 4(a).

Another notable carbon label in the U.S. market is the Climate Conscious Carbon Label, launched in 2007 by the Climate Conservancy. Its primary objective is to promote green consumerism and raise environmental awareness among purchasers. Figure 4(b) demonstrates this label, which does not include numeric values and relies on an unspecified carbon label accounting method.

In 2007, Timberland, a U.S. company, introduced the Timberland Green Index, a private labeling scheme based on a form of life cycle assessment (LCA) calculation. Figure 4(c) showcases this label.

Furthermore, in July 2009, retail giant Walmart unveiled its Sustainability Index initiative, which evaluates product sustainability across four key areas: energy and climate, natural resources, material efficiency, and people and community. Walmart collaborated with non-governmental organizations in America to incorporate carbon labeling into its products, requiring certification for retailers within its supply chain. Figure 4(d) illustrates Walmart's carbon label implementation, furthering its commitment to transparency and sustainability.

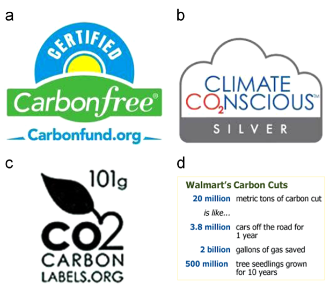

Figure 4: Carbon labels in America. (a) Carbon-free certified label. (b) Climate-conscious carbon label. (c) Timberland green index. (d) Walmart's sustainability index. [16]

The implementation of carbon labels has expanded to include various countries, encompassing both numeric and non-numeric approaches. Initially, numerical values were deemed essential for carbon labels. However, as demonstrated by the examples provided, an equal number of labels now exist with and without numerical GHG emission values.

To gauge public preferences regarding carbon labels, several surveys have been conducted. Schaefer and Blanke [18] and Upham et al. [11] found that the carbon reduction label, devoid of numerical emissions data, is more popular among consumers. This label alleviates the burden on consumers to interpret and compare numerical values in their daily lives. However, other studies, such as the one conducted by Hartikainen et al. [14], revealed that some consumers still desire more specific information from carbon labels. Additionally, Vanclay et al. [21] reported that consumers would be more inclined to use carbon emission information if it were presented in a different format.

In summary, there is ongoing debate and divergence regarding public preferences for carbon labels. However, Schaefer and Blanke [18] proposed six essential requirements for an acceptable label: completeness, transparency, reliability, clarity, availability/accessibility, and producer incentive. In general, the carbon labels examined in this context fulfill these requirements.

1.3 Food Waste

Food waste is a pressing environmental concern that necessitates immediate attention. Currently, there is no existing food label that specifically addresses the issue of food waste, despite its significant impact. The United Nations has recognized the urgency of this matter and has set a target to half the amount of global food waste by 2030, this is a goal spanning from the land, the factory, and the consumers, encompassing all aspects of the production and consumption cycle. [17]. For this research, the focus will be on the consumer's end, as it is at this stage that the majority of food waste occurs. Where households often purchase more food than they need and are unaware of the impact food waste has on the environment. [4, 13] The allure of promotions such as "Buy one get one free" often compels consumers to procure more food than necessary, inevitably leading to the disposal of surplus items. Moreover, consumers may lack the requisite knowledge to handle and store food properly, resulting in premature spoilage and subsequent disposal. Insufficient awareness of optimal storage conditions and techniques further contributes to unnecessary waste. Furthermore, misunderstandings surrounding expiration labels and other food-related indications perpetuate the discarding of edible items, exacerbating the issue of food waste [22]

To address these issues, our research aims to create a new food label to convey more information about food waste, along with nutritional and environmental impacts to the consumer.

2 Data Description

To create a label that incorporates nutritional values, carbon emission values, and food waste, it is necessary to gather relevant data. Unfortunately, there is currently no available data set that covers all three aspects. As a result, alternative data sets have been sought and subsequently merged. For the food waste component, the ReFED data set has been identified as a suitable source of data. [3] This data set can also be used for emission values. As for the nutritional values, the data set known as Open Food Facts has been discovered. [6] The data sets will be discussed further in this section.

2.1 ReFED Data Set

ReFED is a national nonprofit organization dedicated to combatting food loss and waste through data-driven solutions [3]. Their primary objective aligns with the United Nations' 2030 Sustainable Development Goals, aiming to reduce food waste by 50%. By taking informed actions, ReFED believes it is possible to solve the food waste crisis.

The ReFED data set includes information not only on food waste but also on GHG emissions. The GHG emissions in the ReFED data set are based on both upstream factors (everything it went through until this stage) and downstream factors (everything it will go through afterward, such as being thrown away or donated), resulting in a comprehensive measure of the total GHG footprint. The data set consists of 28 columns and 9035 rows, encompassing various features. The most significant features include:

- Sector: Categorized as Residential, Retail, Foodservice, Farm, or Manufacturing, indicating the sector in which food is wasted.
- Food Type: Represents the group to which the food belongs, including 'Breads & Bakery', 'Dairy & Eggs', 'Dry Goods', 'Fresh Meat & Seafood', 'Frozen', 'Prepared Foods', 'Produce', and 'Ready-to-drink Beverages'. The food types are further explained below:
  - Breads & Bakery: Includes perishable bread, bakery, and dessert items (e.g., fresh muffins, sweet breads, doughnuts, fresh-made cookies, cupcakes, cakes, cheesecakes, puddings, etc.). Also includes loaf bread, artisan bread, buns, rolls, tortillas, and flatbreads. Does not include long shelf-life cookies, crackers, brownies, or snack cakes which are considered to be Dry Goods.

- Dairy & Eggs: Includes refrigerated, non-frozen, fresh dairy products (e.g., milk, yogurt, creamers, sour cream, butter and margarine, buttermilk, etc.) as well as eggs. Also includes plant-based dairy alternatives (e.g., almond milk, soy milk) and refrigerated doughs. Note that some specialty cheeses are categorized as Prepared Foods if they are sold in the deli department for grocery retailers.
- Dry Goods: Any shelf stable items not listed under other food types.
- Fresh Meat & Seafood: Includes fresh meat, sausages, lunchmeat, seafood, and meat alternatives. Does not include frozen or canned foods. Note that some specialty meats are categorized as Prepared Foods if they are sold in the deli department for grocery retailers.
- Frozen: Any frozen food
- Prepared Foods: All food served to clients in the foodservice sector. Also includes items sold in the deli department for grocery retailers (e.g., specialty meats and cheeses, pasta salads, sushi, hummus, dips and spreads, rotisserie chicken, pre-made meals, fresh sandwiches, soups, meal kits, etc.). Note that specialty meats and cheese sold in the deli department for grocery retailers are included here, rather than in the Fresh Meat & Seafood or Dairy & Eggs food types.
- Produce: Includes fresh fruits and vegetables, packaged salads, cut fruit, value-added fruits and vegetables, fruit or veggie trays, dipped fruit, pumpkins and gourds, and herbs. Does not include floral as floral products are out of scope and not considered "food".
- Ready-to-drink Beverages: Includes fruit and vegetable juices, ready-to-drink tea and coffee drinks, shakes and smoothies, and sparkling juice. Does not include dry tea or coffee - these items are considered Dry Goods. Also does not include cows' milk or plant-based dairy alternatives - these items are categorized as Dairy & Eggs. Also does not include bottled water, soft drinks, or alcoholic beverages** - these items are out of scope and not considered "food".

- Food Category: Provides detailed information about specific food products, such as Lettuce or Kiwi. Note that this field may have limited data availability.
- Tons Waste: Measures the amount of food wasted per year in tons.
- Year: This indicates the year in which the waste quantity was recorded, ranging from 2010 to 2019.
- Tons Supply: Denotes the annual production quantity of the respective food item.
- Total MtCO2e Footprint: Quantifies the greenhouse gas emissions associated with the disposal process of food, measured in metric tons of carbon dioxide equivalent (MtCO2e). The footprint includes emissions from fugitive landfill gases, and the value can be positive or negative depending on whether the disposal process generates or absorbs greenhouse gases. This is per food type, sometimes even per product (e.g., Kiwi) per year.

The dataset exhibits fluctuations in the number of items across sectors, as illustrated in Figure 5, and variations in item quantities among different food types, as depicted in Figure 6. Figure 7 displays the distribution of items per year, demonstrating a relatively even distribution throughout the years.

Sector	Average food waste (tons)	Average GHG (MTCO2e)	Average supply (tons)
Manufacturing	446950.731376	3.709230e+06	3.930970e+07
Farm	294878.718266	3.373534e+04	2.147530e+06
Residential	70641.495176	5.075164e+05	5.117226e+05
Foodservice	36306.694316	2.031030e+05	1.986938e+05
Retail	12629.206757	8.848355e+04	4.762136e+05

Table 10: Averages per sector

Food Type	Average food waste (tons)	Average GHG (MTCO2e)	Average supply (tons)
Dairy & Eggs	138513.642603	686462.915805	3.563826e+06
Prepared Foods	114676.812725	707601.193961	1.995802e+05
Produce	80769.193555	89052.019795	9.648863e+05
Frozen	36814.789605	391628.874457	3.213594e+05
Ready-to-drink Beverages	33885.415606	166695.283313	8.362957e+05
Dry Goods	28033.886146	188221.283703	6.537704e+05
Fresh Meat & Seafood	22294.111667	397966.011956	7.691943e+05
Breads & Bakery	13350.556148	75662.707529	2.799115e+05

Table 11: Averages per food type

Year	Average food waste (tons)	Average GHG (MTCO2e)	Average supply (tons)
2010	53554.237208	261483.935887	743500.655830
2011	54853.865732	271180.721554	807420.102534
2012	55791.510338	277133.618228	827052.642502
2013	56245.544697	283965.301269	840489.247798
2014	57420.624171	290053.190207	861993.262137
2015	57349.513414	290110.611017	849978.148528
2016	59970.515990	295323.669123	862788.378777
2017	59875.429324	290875.682381	869460.581282
2018	60129.793272	300101.613000	881708.869686
2019	60254.118683	299894.854437	875788.070330

Table 12: Averages per year

In Table 10, the average values of food waste, greenhouse gas (GHG) emissions, and supply are presented for each sector. Similarly, Table 11 provides the average values per food type. Finally, Table 12 displays the average values across different years.

By leveraging the ReFED dataset, valuable insights into food waste and its associated emissions can be obtained. However, it is important to note that additional data sources may be required to comprehensively encompass nutritional values and enable the creation of a comprehensive labeling system.

2.2 Open Food Facts Data Set

To incorporate nutritional data into the label creation process, the Open Food Facts data set has been sourced. Open Food Facts is a collaborative food products database that aims to provide comprehensive information about various food items, including ingredients, allergens, nutrition facts, and other relevant details found on product labels [6]. This information is provided by people, who manually

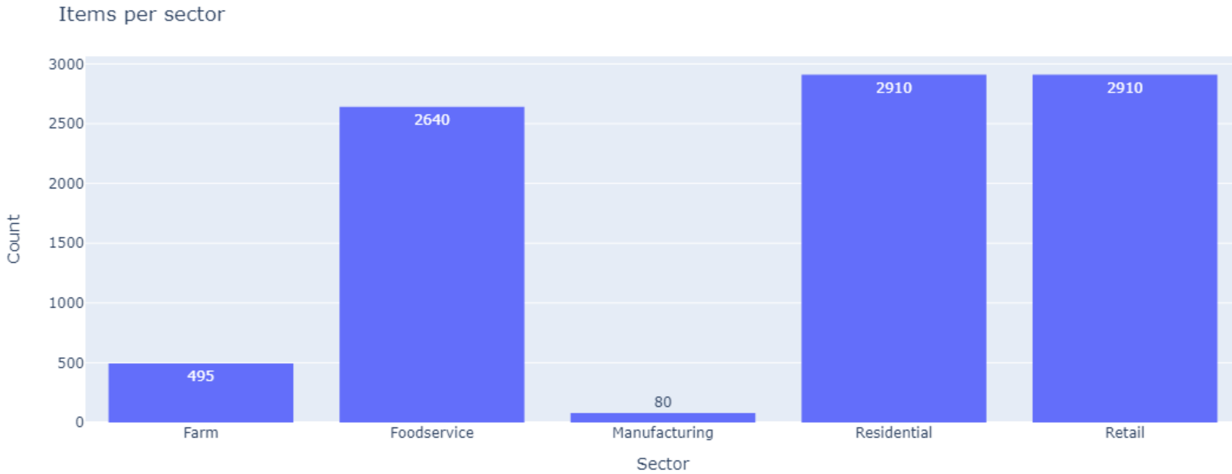

Figure 5: Distribution of items per sector for ReFED data set

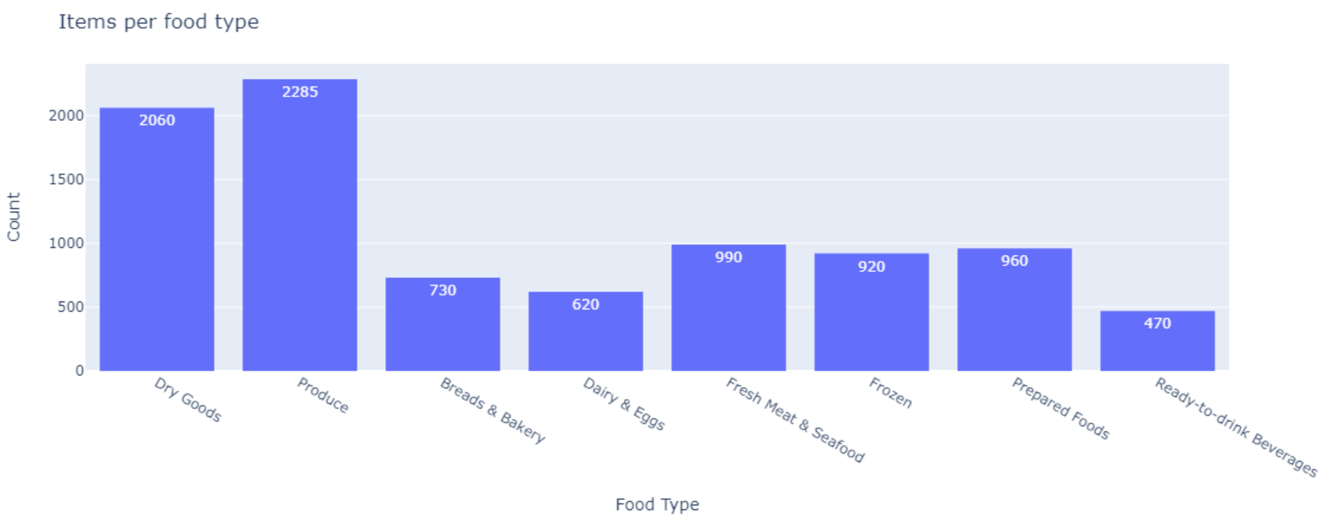

Figure 6: Distribution of items per food type for ReFED data set

enter this information into the data set.
The data set contains 2,862,921 rows and 201 columns, offering a wide range of features for each food component. Some of the notable features include:

- Product Name: This feature provides the name of a specific food product (e.g., Skyr, Fusilli).
- Main Category: This feature provides a general description of the food product category to which it belongs, aiding in identifying the broad classification of the product.
- Nutri-Score Grade: The Nutri-Score is a letter-grade scoring system ranging from A to E, designed to evaluate the overall nutritional quality of a food product. A corresponds to a good nutritional score, while E represents a less favorable score. This score is calculated per product (e.g., Nutella chocolate spread).

The ”Product Name” feature includes 1,720,719 different product names, while the ”Main Category” feature encompasses 41,688 different categories. Figure 8 provides an overview of the distribution of items per Nutri-Score grade.

By leveraging the Open Food Facts data set, valuable information regarding the nutritional composition of various food products can be accessed. The inclusion of the NutriScore Grade enables the assessment of the overall nutritional quality of each item, facilitating its incorporation into the labeling system.

The combination of the ReFED data set, which provides information on food waste and greenhouse gas emissions, with the Open Food Facts data set, which offers insights into nutritional values, allows for the creation of a more comprehensive label that encompasses multiple dimensions of food sustainability.

3 Methodology

To create a comprehensive food label incorporating food waste, GHG emissions, and nutritional value, it is crucial to consider the weighting of these three components in the label creation process.

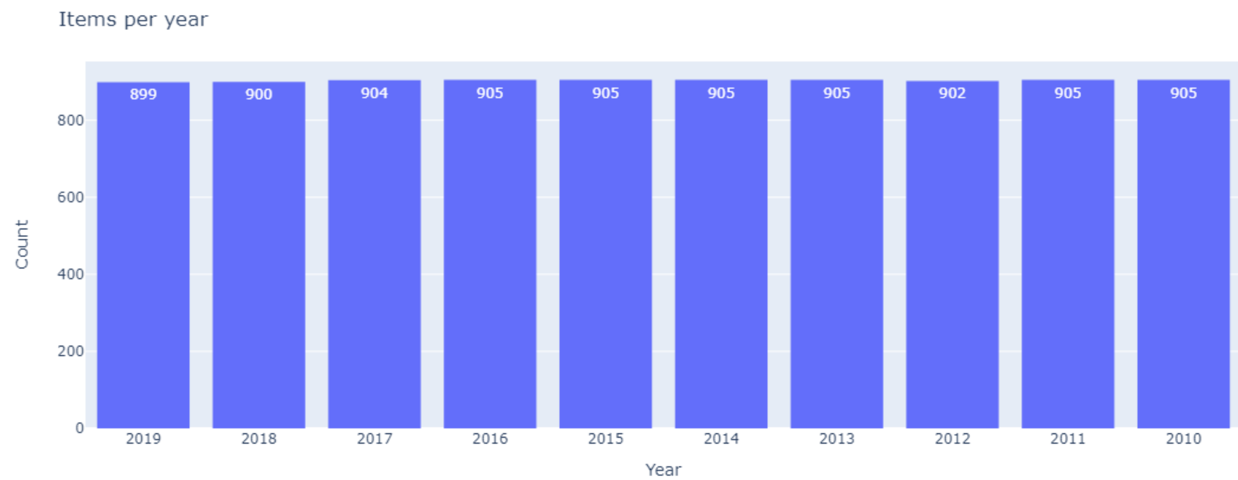

Figure 7: Distribution of items per year for ReFED data set

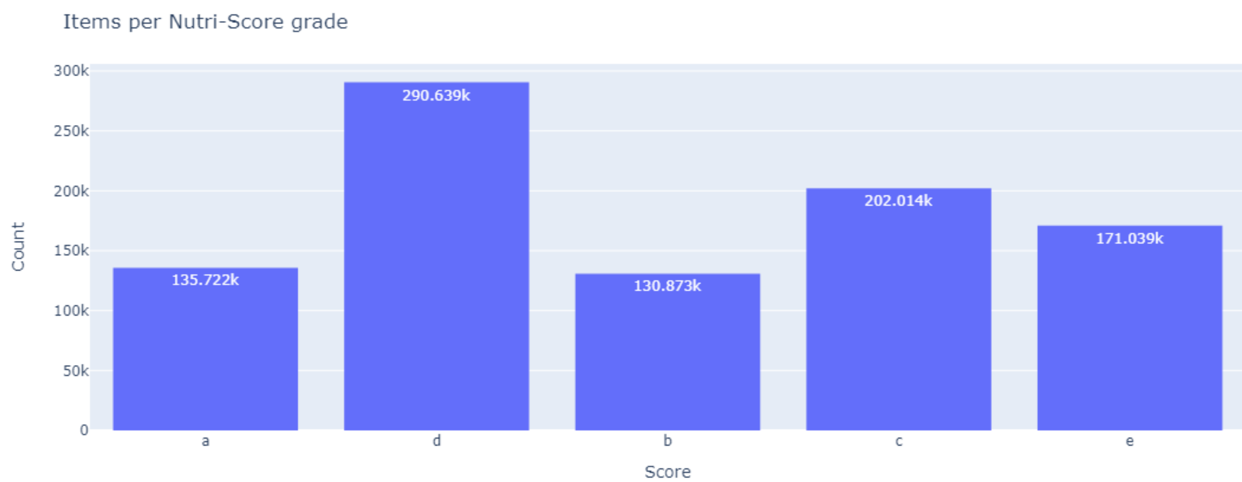

Figure 8: Distribution of items per Nutri-Score grade

Thus, a deliberate decision was made to initially develop separate labels for each component. This approach enables a thorough analysis of each aspect in isolation, ensuring a nuanced understanding before their integration.

Creating distinct labels for food waste, GHG emissions, and nutritional value enables a thorough evaluation and effective communication of their specific characteristics and impacts. This ensures that each aspect is accurately represented and prevents any overshadowing of others.

Subsequently, the separate labels can be integrated to form a comprehensive and well-balanced food label that encompasses all three components. This integration provides consumers with a holistic understanding of the overall sustainability and nutritional profile of the food products, empowering them to make informed choices based on their preferences and values.

3.1 Creating Food Waste Label

The food waste label data is generated by calculating the relative food waste (α_{rfw}) for each product (p). This value is obtained by dividing the amount of food waste (β_{fw}), which represents the quantity of food discarded during production and at the end of the supply chain of a product, by the supply (γ) of the specific product. The formula used to calculate the relative food waste for a product is as follows: $\alpha_{p,rfw} = \frac{\beta_{p,fw}}{\gamma_p}$.

To organize the food waste data set, the food types are sorted in descending order based on their relative α_{rfw} values. This sorting allows for easy comparison and identification of the food items that are most frequently wasted.

The length of the data set is denoted by 'n', representing the total number of products. The data set is then divided into segments based on intervals of $\frac{n}{x}$. With x being the number of ranks to be created. The ranks are assigned as follows:

- Rank x is determined by (this rank will include the worst scoring products):
  $1, 2, ..., \lceil \frac{n}{x} \rceil$
- Rank x-1 is determined by:

$\lceil \frac{n}{x} \rceil + 1, \left\lceil \frac{n}{x} \right\rceil + 2, ..., 2 * \left\lceil \frac{n}{x} \right\rceil$

- Rank x-2 is determined by:
  $2 * \left\lceil \frac{n}{x} \right\rceil + 1, 2 * \left\lceil \frac{n}{x} \right\rceil + 2, ..., 3 * \left\lceil \frac{n}{x} \right\rceil$
- ...
- Rank 2 is determined by:
  $(x-2) * \left\lceil \frac{n}{x} \right\rceil + 1, (x-2) * \left\lceil \frac{n}{x} \right\rceil + 2, ..., (x-1) * \left\lceil \frac{n}{x} \right\rceil$
- Rank 1 is determined by (this rank will include the best scoring products):
  $(x-1) * \left\lceil \frac{n}{x} \right\rceil + 1, (x-1) * \left\lceil \frac{n}{x} \right\rceil + 2, ..., n$

This approach ensures that the food waste data set is organized and ranked based on the relative amounts of waste for each food item.

3.2 Creating Carbon Label

The carbon label data set is created by evaluating the relative metric tons of CO_2 equivalent emissions (α_{rmtco2}) associated with each product (p). This relative value is derived by dividing the emissions (β_{mtco2}) per product by the supply (γ) of the specific product. The formula for calculating of α_{rmtco2} for a specific product is as follows: $\alpha_{p,rmtco2} = \frac{\beta_{p,mtco2}}{\gamma_p}$.

To organize the carbon label data set, the food types are sorted in descending order based on their relative emissions α_{rmtco2} values, allowing for easy comparison and identification of the most environmentally impactful food items.

The length of the data set is denoted by 'n', representing the total number of food items. The data set is then divided into segments based on intervals of $\frac{n}{x}$. With x being the number of ranks to be created. The ranks are assigned as follows:

- Rank x is determined by (this rank will include the worst scoring products):
  $1, 2, ..., \lceil \frac{n}{x} \rceil$
- Rank $x-1$ is determined by:
  $\lceil \frac{n}{x} \rceil + 1, \left\lceil \frac{n}{x} \right\rceil + 2, ..., 2 * \left\lceil \frac{n}{x} \right\rceil$
- Rank $x-2$ is determined by:
  $2 * \left\lceil \frac{n}{x} \right\rceil + 1, 2 * \left\lceil \frac{n}{x} \right\rceil + 2, ..., 3 * \left\lceil \frac{n}{x} \right\rceil$
- ...
- Rank 2 is determined by:
  $(x-2) * \left\lceil \frac{n}{x} \right\rceil + 1, (x-2) * \left\lceil \frac{n}{x} \right\rceil + 2, ..., (x-1) * \left\lceil \frac{n}{x} \right\rceil$
- Rank 1 is determined by (this rank will include the best scoring products):
  $(x-1) * \left\lceil \frac{n}{x} \right\rceil + 1, (x-1) * \left\lceil \frac{n}{x} \right\rceil + 2, ..., n$

This approach ensures that the data set for the carbon label is both organized and ranked, facilitating a clearer understanding of the relative carbon footprints associated with different food items.

3.3 Creating Nutritional Label

To generate the nutritional label, the Nutri-Score grade provided by Open Food Facts will be utilized. The Nutri-Score is a scoring system designed to assess the nutritional quality of food products, as explained in Section 1. This system assigns a corresponding score to each product based on various nutritional parameters.

To facilitate computational analysis, the letter-based Nutri-Score categories (A to E) will be converted into numerical values. The numerical equivalents assigned are as follows: $A = 1$, $B = 2$, $C = 3$, $D = 4$, and $E = 5$.

By utilizing the Nutri-Score grade from Open Food Facts and representing it numerically, a standardized nutritional label will be created for each product. This label provides consumers with easily understandable information about the overall nutritional quality of the product, calculated specifically for that particular food item. The different approaches will be compared on the overall distribution, mean, median, and distribution of the food types over the ranks.

3.4 Combining the labels

To create a combined label that incorporates all three components (food waste, GHG emissions, and nutritional value) of the dataset, various methods can be employed. This section will discuss several approaches to combining the labels and improving the scoring method according to preference.

Method 1a: Average-Based Label

One approach to combine the labels is to calculate the combined rank of a product by summing up (S) the ranks of each component: the food waste rank (f), the GHG rank (g), and the nutritional rank (n). Thus, the equation for a specific product (p) becomes $S_p = f_p + g_p + n_p$.

To ensure the combined rank represents an average value across the three components, it is divided by three, since there are three components in total. This normalization process yields the combined rank (R) of a product: $R_p = \frac{S_p}{3}$. All numerical values are rounded using the Banker's algorithm, which is a resource allocation and deadlock avoidance algorithm. In this case, it involves rounding any non-whole number values (e.g., 2.5) to the nearest even whole number (e.g., 2 or 4). This rounding approach simplifies the presentation of data, providing a clear and straightforward representation for consumers to easily understand and compare the information across different food products.

Method 1b: Average-Based Label

If the distribution of the label is not pleasing, the following can be done to arrange a 20%/20%/20%/20%/20% distribution. First, the basic calculations from method 1a are done without rounding. Based on these values (R) the data set gets sorted in descending order. Followed by distributing the correct ranks. The length of the data set is denoted by 'n', representing the total number of food items. The data set is then divided into segments based on intervals of $\frac{n}{x}$. With x being the number of ranks to be created. The ranks will then be assigned as follows:

- Rank x is determined by (this rank will include the worst scoring products):
  $1, 2, ..., \lceil \frac{n}{x} \rceil$
- Rank $x-1$ is determined by:
  $\lceil \frac{n}{x} \rceil + 1, \left\lceil \frac{n}{x} \right\rceil + 2, ..., 2 * \left\lceil \frac{n}{x} \right\rceil$
- Rank $x-2$ is determined by:
  $2 * \left\lceil \frac{n}{x} \right\rceil + 1, 2 * \left\lceil \frac{n}{x} \right\rceil + 2, ..., 3 * \left\lceil \frac{n}{x} \right\rceil$
- ...
- Rank 2 is determined by:
  $(x-2) * \left\lceil \frac{n}{x} \right\rceil + 1, (x-2) * \left\lceil \frac{n}{x} \right\rceil + 2, ..., (x-1) * \left\lceil \frac{n}{x} \right\rceil$
- Rank 1 is determined by (this rank will include the best scoring products):
  $(x-1) * \left\lceil \frac{n}{x} \right\rceil + 1, (x-1) * \left\lceil \frac{n}{x} \right\rceil + 2, ..., n$

In this case, the chosen amount of ranks is 5 ($x = 5$). The ranks are assigned as follows:

- Rank 5 is determined by (this rank will include the worst scoring products):
  $1, 2, ..., \lceil \frac{n}{5} \rceil$
- Rank 4 is determined by:
  $\lceil \frac{n}{5} \rceil + 1, \left\lceil \frac{n}{5} \right\rceil + 2, ..., 2 * \left\lceil \frac{n}{5} \right\rceil$
- Rank 3 is determined by:
  $2 * \left\lceil \frac{n}{5} \right\rceil + 1, 2 * \left\lceil \frac{n}{5} \right\rceil + 2, ..., 3 * \left\lceil \frac{n}{5} \right\rceil$
- Rank 2 is determined by:
  $3 * \left\lceil \frac{n}{5} \right\rceil + 1, 3 * \left\lceil \frac{n}{5} \right\rceil + 2, ..., 4 * \left\lceil \frac{n}{5} \right\rceil$
- Rank 1 is determined by (this rank will include the best scoring products):
  $4 * \left\lceil \frac{n}{5} \right\rceil + 1, 4 * \left\lceil \frac{n}{5} \right\rceil + 2, ..., n$

By using this approach, the ranks of food waste, GHG emissions, and nutritional value can be effectively combined into a single measure that provides an overall assessment of a product's sustainability and nutritional quality.

Method 2: Nutritional Value Counts Twice

To account for the relative importance of the labels, the formula can be modified based on the provided rankings. Considering that the nutritional value is the most important label this will lead to the following adjustments:

1. Normalize the weights based on the rank of nutritional value (n) being twice as important as the other labels. This means that the weight of nutrition should be twice the weight of GHG emissions (g) and food waste (f).
2. Adjust the denominator accordingly.

With these adjustments, the modified formula per product (p) becomes: $R_p = \frac{2n_p + g_p + f_p}{4}$.

This method gives higher weight to the nutritional rank while still considering the GHG emissions and food waste ranks, reflecting the relative importance of the nutritional value in the overall assessment.

Method 3: Weigh GHG and Food Waste More

To account for the relative importance of the labels and incorporate the perspective of minimizing waste in products with higher GHG emissions, the formula can be modified as follows per product (p): $R_p = \frac{n_p + 2(f_p + g_p)}{5}$.

This modification assigns a higher weight to the combined rank of GHG emissions and food waste, placing greater emphasis on reducing waste in products with higher emissions. By considering this perspective, the evaluation becomes more nuanced.

Method 4: Double Values Lead

Another approach is to prioritize identical values in the ranks. If two or more components have the same rank, that rank becomes the final rank, regardless of the rank of the remaining component(s). For example, if the score for Nutritional value is one and the score for GHG emissions is also one, the final rank will be one, regardless of the score for Food Waste.

For the components without double values, the ranks can be calculated using method 1 (or any other suitable method).
This method provides a straightforward way to determine the final rank while accounting for identical scores.

Method 5: Normalize Difference

In method 5, the nutritional rank (n) serves as the foundation for establishing the final rank. The differences (D) between the nutritional rank and the ranks of GHG emissions (g) and food waste (f) per product (p) are calculated using the formulas: $D_{g,p} = g_p - n_p$ and $D_{f,p} = f_p - n_p$. These differences are then normalized to a range of values using a predefined mapping.

For example, if the difference can take values from -4 to 4, the differences are mapped to normalized values using a predefined mapping table. This predefined mapping will be created by inputting all the possible difference values into the sklearn preprocessing.normalize() function. These normalized values are then added to the nutritional rank to obtain the final score (S). This is done with the following formula: $S = n + N_g + N_f$. Round the final score using Banker's algorithm to obtain a rank on an x-level system. In this particular case, the number of ranks in the final ranking system is determined by the chosen ranks for the nutritional values. For instance, if the nutritional values adopt a five (5)-level rank system, the resulting ranking system from this method will also consist of five levels.

Moreover, this method can be applied using another component as the basis, depending on which component is deemed the most significant. However, in this case, the nutritional rank is considered to be the most important component.

Method 6: K-means clustering

K-means clustering is an unsupervised machine learning algorithm that can be used to group similar data points together. In this method, the data set is divided into clusters based on the three components: food waste, GHG emissions, and nutritional value. First, the relevant data needs to be scaled using a standardization method such as the StandardScaler from the sklearn.preprocessing package. Then, the K-Means algorithm is applied to group the data into clusters. The number of clusters (K) is set to k five, corresponding to the k different scoring levels. In the case of this research, k will be five. To assign ranks to the clusters, the sum ($S = n + g + f$) of the food waste rank (f), the GHG rank (g), and the nutritional rank (n) are calculated for an individual item (i) in each cluster. The mean of these sums is determined by ($\bar{x}_c = \frac{\sum_{i=1}^{N_c} S_i}{N_c}$), where $\bar{x}_c$ represents the mean value of cluster c and N_c is the number of data points in cluster c. Based on the means, the final ranks are assigned, with the highest mean receiving a rank of k or in this research case five (5).

This method leverages machine learning techniques to create clusters and assign ranks based on the average values within each cluster.

Method 7: Extension Method 4

Method 7 builds upon method 4 by introducing additional constraints based on linear programming principles. The first constraint states that if any of the component scores (nutritional, GHG emissions, or food waste) is four or five, it can never be ranked lower than three. This constraint ensures that higher scores have a significant impact on the final rank. The second constraint is applied to the values that did not have a double value in method 4. These scores are calculated using method 1, but the above constraint is also applied. If any of the component scores are four or five, resulting in a final rank lower than three, the rank is adjusted to three.

This method adds more complexity and accuracy by incorporating linear programming constraints into the ranking process.

4 Results

This section presents the creation of a comprehensive food label that incorporates information on food waste, GHG emissions, and nutritional value. The distribution, mean, median, and food type distribution for each of the methods discussed in the previous section will be demonstrated. However, before the label can be created, the data needs to be prepared, as will be discussed in the Subsection 4.1.

This subsection will also cover the process of combining the data. Subsequently, separate label creations will be discussed, followed by the creation of combined labels. Finally, the labels will be compared between the different methods described in Section 3.

4.1 Pre-processing

Before proceeding with the data sets introduced in Section 2, it is necessary to perform some pre-processing steps to prepare the data for further analysis.

The pre-processing stage involves making adjustments and transformations to ensure that the data set can be effectively utilized. These adjustments may include tasks such as cleaning the data to remove any inconsistencies or errors, handling missing values, or other things that might affect the analysis.

By conducting these pre-processing steps, it can be ensured that the data set is in a suitable and reliable state for subsequent analysis, making it easier to derive meaningful insights and draw accurate conclusions from the data.

4.1.1 Food Waste & GHG Emissions

To prepare the ReFED data set for analysis, several adjustments were required, particularly with respect to the food waste and GHG emissions data. Initially, the data set did not display the columns accurately. Fortunately, there was a row available that provided the correct column names. This issue was resolved by selecting the appropriate row as the header and removing the three irrelevant rows.

Furthermore, all the values in the data set were initially stored as strings, which posed a challenge for calculations and analysis. To address this, the string values were converted to floating-point decimal values, enabling easier manipulation and computation.

It is worth noting that no missing values or empty cells were found in the waste, GHG emissions, and supply columns, indicating that the data set was complete in those regards. These adjustments were crucial to ensure the data set's usability and integrity, allowing for subsequent analysis and exploration of the food waste and GHG emissions data.

4.1.2 Nutrition

In order to utilize the Open Food Facts data set, a comprehensive data-cleaning process was necessary. The data set itself is considerably large, spanning approximately 8 gigabytes. Given its open nature, where individuals have the liberty to contribute product information, the data set suffers from inherent complexities and irregularities. Consequently, attempts to remove missing values (NAN) resulted in an unfortunate outcome where the data set became void of any meaningful information.

Following this attempt, a subsequent data reduction strategy was employed, aiming to streamline the data set by eliminating non-essential attributes. This involved selectively eliminating non-essential attributes, resulting in a reduction from 201 columns to a more manageable 57 columns. The selection process took into account the significance of each attribute in the calculation of the Nutri-Score, however later was realized that only three columns were actually necessary, still ensuring that essential information was retained for further analysis and evaluation.

Continuing the iterative data refinement process, an additional reduction was accomplished by applying a filtering criterion based on the presence of a valid 'nutriscore_grade'. Rows lacking a Nutri-Score grade, which serve as indicators of missing values, were removed from the data set. This filtration step significantly contributed to reducing the data set size, resulting in a diminished subset comprising 930,287 rows, representing a mere 32% of the original data set. By employing this filtration technique, the focus was directed towards retaining data instances that had complete Nutri-Score grade information. This approach facilitated the generation of more meaningful and reliable analyses from the data set.

These steps were undertaken to ensure the usefulness and practicality of the Open Food Facts data set.

4.1.3 Combining ReFED and Open Food Facts Data

To enable the effective combination of the food waste data and nutritional data, a series of steps were implemented. The first step involved establishing a common point for data set integration. The 'main_category_en' attribute played a pivotal role in this process, as it facilitated the categorization of rows from the Open Food Facts data set based on the distinct food types specified in the ReFED data set. Next, non-English rows were removed from the Open Food Facts data set, resulting in a data frame consisting of 858,531 rows. Subsequently, each row was assigned one of the predetermined food types, including 'Dry Goods', 'Produce', 'Breads & Bakery', 'Dairy & Eggs', 'Fresh Meat & Seafood', 'Frozen', 'Ready-to-drink Beverages', or 'Prepared Foods', based on their respective categories. This categorization process was primarily conducted manually by searching for specific terms. Entries that did not fall into any of these predefined groups were labeled as 'None', these can also be products that are out of the scope of ReFED data set and not considered "food", for example, bottled water, soft drinks, or alcoholic beverages. It was chosen to follow this to make the combination as best as possible. Finally, the 'None' group was removed from the data set, resulting in a final data set of 602,006 rows, which is about 21% of the original data set. Resulting in the following distribution of items per food type as can be seen in Figure 9

4.2 Creating the labels

4.2.1 Food waste

The initial step in developing the food waste label involved calculating the relative food waste, as described in Section 3.1. However, the ReFED data set presented some issues where certain relative food waste values turned out to be infinite due to extremely small values for the supply of certain products. To solve this problem, the infinite values were removed from the data set. Specifically, 350 values with very small food supply values were identified and deleted, these small values appeared in the 'Foodservice', 'Manufacturing', 'Frozen', and 'Prepared Foods' categories.

Next, the food waste needed to be ranked and integrated with the nutritional data set. To accomplish this, the ReFED data set was grouped based on food type, and the mean value ($\bar{x}_{rfw,t} = \frac{\sum \alpha_{rfw,t}}{N_t}$) of the relative tons wasted (α_{rfw}) was calculated for each food type (t), where N_t is the number of items for that food type. After analyzing the data, the following order of food types, from the highest (indicating the food type with the most average food waste) to the lowest (indicating the food type with the least average food waste), was determined: 'Ready-to-drink Beverages', 'Produce', 'Prepared Foods', 'Frozen', 'Fresh Meat & Seafood', 'Dry Goods', 'Dairy & Eggs', and 'Breads & Bakery'. Subsequently, scores were assigned to each food type, with 'Ready-to-drink Beverages' receiving the highest score of eight and 'Breads & Bakery' receiving the lowest score of one.

In order to distribute the values equally across the chosen number of ranks (in this case, five ranks), as explained in Section 3.1, certain adjustments are necessary to suit this particular scenario. Since the data sets need to be food-type-based for combining them, it is important to determine the number of items per score. To accomplish this, the len() function in Python can be utilized. By applying the len() function, the number of items can be determined as follows:

- Score 8 (Ready-to-drink Beverages) contains 470 items.
- Score 7 (Produce) contains 2285 items.

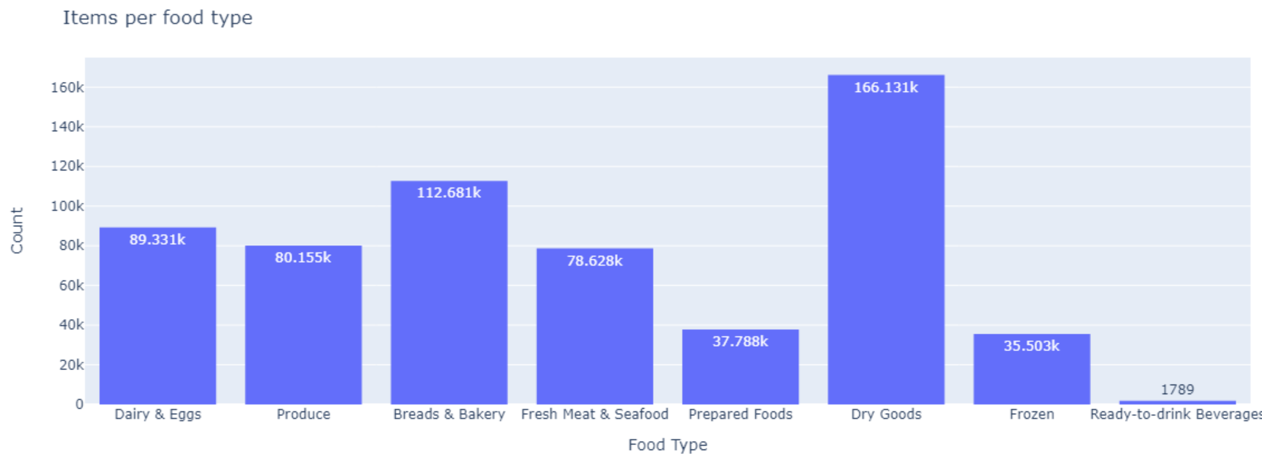

Figure 9: Distribution of items per food type for nutrional data

- Score 6 (Prepared Foods) contains 600 items.
- Score 5 (Frozen) contains 910 items.
- Score 4 (Fresh Meat & Seafood) contains 990 items.
- Score 3 (Dry Goods) contains 2060 items.
- Score 2 (Dairy & Eggs) contains 620 items.
- Score 1 (Breads & Bakery) contains 730 items.

The distribution of items can also be seen in Figure 10.

To achieve a balanced distribution across the five ranks, adjustments were made by combining scores based on the number of items, while ensuring their proximity to each other. As a result, scores one and eight, being at opposite ends, could not be combined. This was done manually. To maintain an even distribution, score three formed a rank on its own due to its significant size. Since score seven is also substantial but eight is the smallest, they were merged into a single rank. Considering the relatively smaller size of score six, it was combined with score five, which has a medium size. The smallest remaining score, score two, was then combined with score one as it is smaller than score three. This left score four to form a rank on its own. Consequently, the following grouping was established:

- Scores 8 and 7 were combined to form Rank 5, with a total amount of items of 2755.
- Scores 6 and 5 were combined to form Rank 4, with a total amount of items of 1510.
- Score 4 became Rank 3, with a total amount of items of 990.
- Score 3 became Rank 2, with a total amount of items of 2060.
- Scores 2 and 1 were combined to form Rank 1, with a total amount of items of 1350.

Following this approach, a comprehensive food waste label was created, incorporating relative waste values and ranking the food types accordingly from one to five.

4.2.2 GHG emmission

As discussed in Section 3.2, the first step involved in creating a GHG emission label is calculating the relative MTCO2e for each food type. Next, the data set was grouped based on food type, and then it was sorted in descending order based on the mean ($\bar{x}_{mtco2,t} = \frac{\sum \alpha_{mtco2,t}}{N_t}$) relative emissions ($\alpha_{mtco2}$) for each food type ($t$), with N_t the number of items for that food type. This resulted in the following order of emissions from highest (indicating the food type with the highest average GHG emissions) to lowest (indicating the food type with the lowest average GHG emissions): 'Fresh Meat & Seafood', 'Frozen', 'Ready-to-drink Beverages', 'Prepared Foods', 'Dry Goods', 'Dairy & Eggs', 'Breads & Bakery', and 'Produce'. Each food type was then assigned a score based on its emissions, with the highest-scoring food type, 'Fresh Meat & Seafood', receiving a score of eight, while the lowest-scoring food type, 'Produce', received a score of one.

To facilitate the integration of the GHG emission label with other components the ranking needed to be brought back to a five-rank system. To maintain a balanced distribution of food products across five ranks, the length of each rank, as described in Section 3.2, was used for division. Using the len() function in Python, the number of items per score was determined, resulting in the following distribution:

- Score 8 (Fresh Meat & Seafood) contains 990 items.
- Score 7 (Frozen) contains 910 items.
- Score 6 (Ready-to-drink Beverages) contains 470 items.
- Score 5 (Prepared Foods) contains 600 items.
- Score 4 (Dry Goods) contains 2060 items.
- Score 3 (Dairy & Eggs) contains 620 items.
- Score 2 (Breads & Bakery) contains 730 items.
- Score 1 (Produce) contains 2285 items.

The distribution of items can also be seen in Figure 11.

To achieve a balanced distribution across the five ranks, adjustments were made by combining scores based on the number of items while ensuring their proximity to each other. As a result, scores one and eight, being at opposite ends, could not be combined. To maintain an even distribution, score one forms a rank on its own due to its significant size. Rank four was also sizeable enough to form a rank

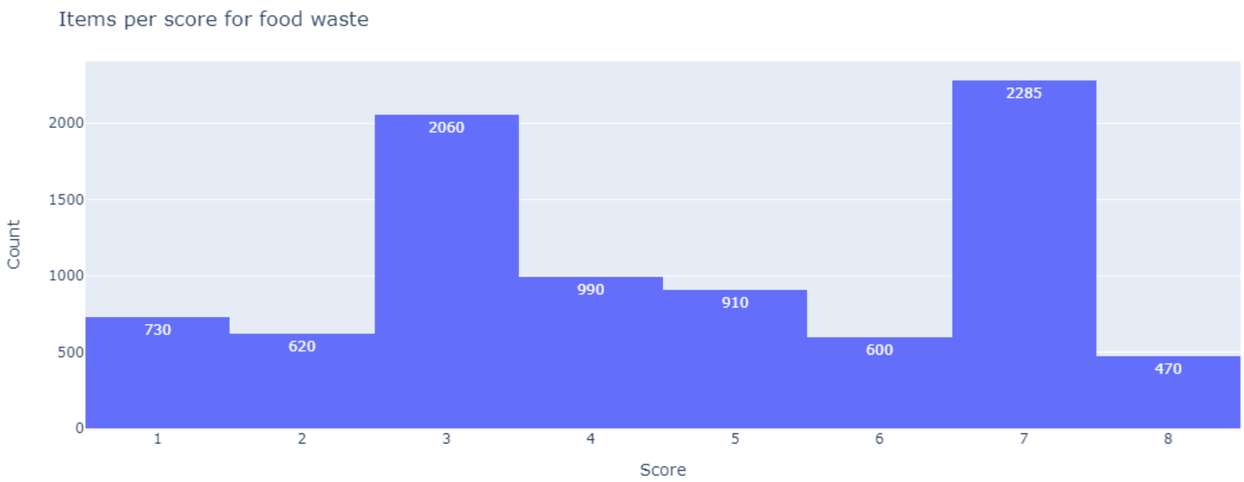

Figure 10: Distribution of items per score for food waste

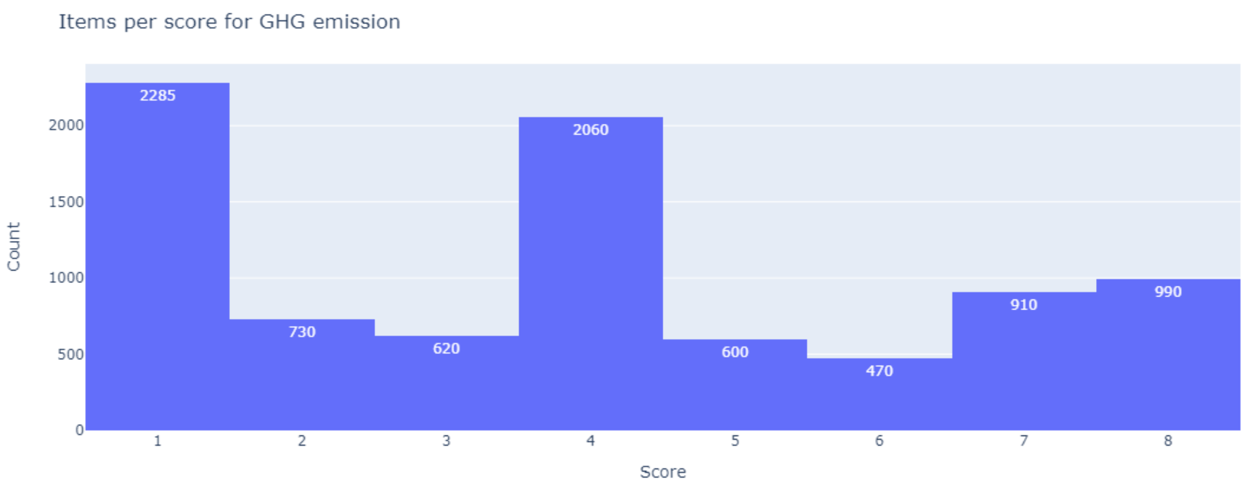

Figure 11: Distribution of items per score for GHG emission

on its own. This left three ranks to be divided. Consequently, scores two and three were combined, scores five and six were combined, and scores seven and eight were combined.

This resulted in the following grouping:

- Scores 8 and 7 were combined to form Rank 5, with a total of 1900 items.
- Scores 6 and 5 were combined to form Rank 4, with a total of 1070 items.
- Score 4 became Rank 3, with a total of 2060 items.
- Scores 3 and 2 were combined to form Rank 2, with a total of 1350 items.
- Rank 1 remained as Rank 1, with a total of 2285 items.

These adjustments ensured that each rank contained a reasonably similar number of food products, These adjustments ensured a relatively equal distribution of food products within each rank, ranging from one to five, facilitating the combination of the GHG emission label with other components.

4.2.3 Nutrition

The nutritional part of the label utilizes the Nutri-Score, which is available in the Open Facts Food data set. As explained in Section 3.3, the Nutri-Score initially employs a letter-based system (A-E). The distribution of the Nutri-Score grade is shown in Figure 8. To harmonize it with other components of the label, the letter-based Nutri-Score is converted into numerical equivalents (1-5).

By assigning numerical values to the letter-based Nutri-Score, the nutritional information becomes consistent and easily usable for the combined label.

4.2.4 Combined Label

The combined label is created by integrating the data sets and considering the ranks for food waste, GHG emission, and nutritional values. Both data sets now contain the same food types, including 'Ready-to-drink Beverages', 'Produce', 'Prepared Foods', 'Frozen', 'Fresh Meat & Seafood', 'Dry Goods', 'Dairy & Eggs', and 'Breads & Bakery', enabling a comprehensive combination.

Method 1a: Average-Based Label

The ReFED data set provides ranks for food waste and GHG emission, ranging from one to five. The Open Food Facts data set contains the nutritional rank, also ranging from one to five. To create the combined label, the ranks of all three components are summed up for each product. The resulting sum is then divided by three to obtain the final combined rank, as explained in Section 3.4.

For example, consider the product 'Potato chips'. First, the three separate ranks need to be determined, they are three for nutrition, two for food waste, and three for GHG emissions. The sum of these ranks is $S = f + g + n = 3 + 2 + 3 = 8$. Dividing the sum by three, results in $R = \frac{S}{3} = \frac{8}{3}$ by rounding this it results in a combined rank of three for 'Potato chips'.

Similarly, 'Skyr' receives a rank of one for nutrition, a rank of two for food waste, and a rank of two for GHG emission. The sum of these ranks is $S = 1 + 2 + 2 = 5$. Dividing the sum by three, we get $R = \frac{S}{3} = \frac{5}{3}$, by rounding this it results in a combined rank of one for 'Skyr.' In this case, 'Skyr' has a better overall score compared to 'Potato Chips'.

However, the distribution of products among the ranks is not ideal. Figure 12 and Table 15 illustrate the distribution of products across the ranks, with rank three being the most occurring.

The distribution per food type is shown in Figure 13. In rank five, only two food types are present: 'Frozen' and 'Ready-to-drink Beverages.' Similarly, rank one consists of 'Breads & Bakery' and 'Dairy & Eggs'.

By applying this calculation to each product, the combined label provides consumers with an overall assessment that takes into account the ranks of food waste, GHG emissions, and nutritional values.

Method 1b: Average-Based Label

To achieve a more balanced representation, method 1b can be employed to distribute the products evenly across the ranks. As can be seen in Figure 14. The distribution per food type can be seen in Figure 15. This will not be discussed further as this method will hopefully not be needed when there is a better data set. This method is also quite random as for the same average score one can have a higher score than the other.

Method 2: Nutritional Value Counts Twice

As discussed in Section 3.4, method 2 considers nutritional values twice in the ranking process. Figure 16 illustrates the distribution difference between the average-based labeling system and the nutritional value counts twice labeling system. The detailed distribution can be found in Table 15.

While more products score worse in this new method compared to the average-based labeling system, the distribution is improved. The mean rank for this method is 2.957102, closer to the ideal mean of three, compared to the mean of 2.813108 for the average-based method. The median rank remains the same at three.

However, it is important to note that distribution is not the sole aspect to consider, as other factors may hold equal importance. For instance, analyzing the distribution per food type, as shown in Figure 17, provides additional insights.

Comparing Figure 17 with Figure 13, it can be observed that the food types in rank one and rank five remain the same. However, 'Dry Goods' is now divided into three ranks instead of two. The same holds for 'Prepared Foods' and 'Fresh Meat & Seafood'.

Moreover, examining Table 16, it can be noticed that 'Skyr' and 'Potato chips' retain the same rank for both methods. However, certain products, such as 'Diced Tomatoes', exhibit different rankings. For 'Diced Tomatoes' using method 1, the score calculation is $S = f + g + n = 5 + 1 + 2 = 8$, resulting in $R = \frac{S}{3} = \frac{8}{3} \approx 3$. In contrast, it will be $R = \frac{2n+g+f}{4} = \frac{2\times2+1+5}{4} \approx 2$ for method 2 (based on the Banker's algorithm utilized in the newest version of Python).

Method 3: Weigh GHG and Food Waste More

As discussed in Section 3.4, method 3 involves weighing GHG emissions and food waste together. Figure 18 illustrates the distribution difference between the average-based labeling system and the weigh GHG and food waste together labeling system.

With this new method, there is a decrease in the presence of rank three and an increase in rank two and four compared to the average-based labeling system, resulting in a more favorable distribution. However, when considering other values, it is observed that the mean rank for the first method is 2.813108, while for the new method it is 2.785170, indicating a slightly worse performance than the first method considering the distribution. The median rank remains the same at three.

Additionally, by examining Figure 19 which displays the distribution of the weight GHG and food waste together label per food type, in comparison with Figure 13, it is found that the food types in rank one and rank five remain unchanged. However, rank three now comprises only four different food types, whereas for method 1, it consisted of seven. Similarly, rank two consists of three different food types, compared to four in method 1. Furthermore, rank four has one less food type, namely 'Produce'.

Moreover, upon reviewing Table 16, it is found that 'Skyr' and 'Potato chips' once again hold the same rank for both methods. However, certain products, such as 'Lemon cupcakes', exhibit different rankings. For 'Lemon cupcakes' using method 1, the score calculation is $S = f + g + n = 1 + 2 + 5 = 8$, resulting in $R = \frac{S}{3} = \frac{8}{3} \approx 3$. In contrast, for method 3 it will be $R = \frac{n+2(f+g)}{5} = \frac{5+2(2+1)}{5} \approx 2$.

Method 4: Double Values Lead

As discussed in Section 3.4, method 4 involves double values leading. Figure 20 illustrates the distribution difference between the average-based labeling system and the double values lead labeling system. With this new method, ranks one and five have more values compared to the average-based labeling system. Ranks two and four have fewer values, while rank three experiences a slight increase. When considering other values, it is observed that the mean rank for method 1 is 2.813108, while for method 4 it is 2.841128, indicating a slightly improved performance compared to method 1. The median rank remains the same at three.

Additionally, by examining Figure 21, which displays the distribution of the double values lead label per food type, in comparison with Figure 13, it is found that rank one includes an additional food type, namely 'Produce', compared to method 1. Rank five includes two extra food types, 'Produce' and 'Fresh Meat & Seafood'. Rank two no longer contains the food type 'Produce'. Rank three no longer includes 'Prepared Foods', and rank four now includes 'Produce'.

Moreover, upon reviewing Table 16, it is found that 'Skyr' and 'Potato chips' once again share the same rank for both methods. However, certain products, such as 'Blackberries', show different rankings. For 'Blackberries' using method 1, the score calculation is $S = f + g + n = 5 + 1 + 1 = 7$, resulting in $R = \frac{S}{3} = \frac{7}{3} \approx 2$. In contrast, for method 4, the nutritional rank is one and the GHG emission rank is also one, leading to a combined rank of one.

Method 5: Normalize Difference

As discussed in Section 3.4, method 5 involves normalizing the difference. Figure 22 illustrates the distribution difference between the average-based labeling system and the normalize difference labeling system.

In this new method, ranks one and five contain more values compared to the average-based labeling system. Ranks two and three

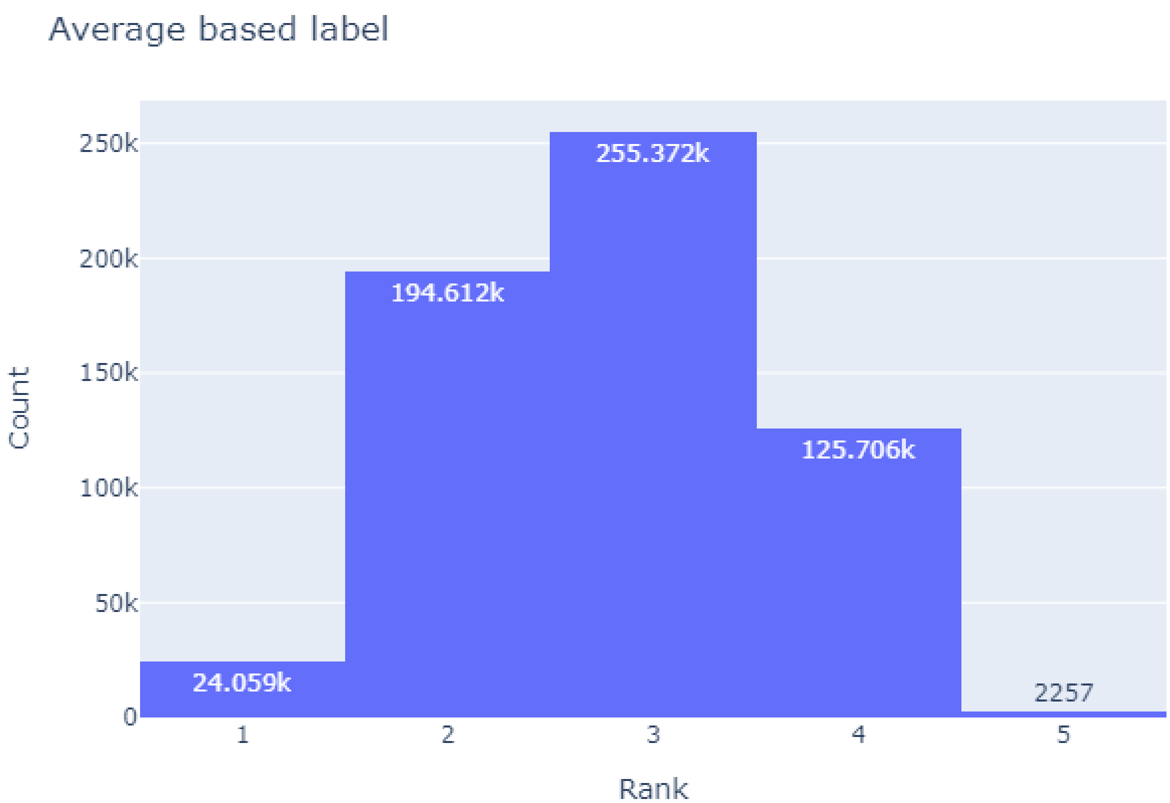

Figure 12: Distribution of average-based label (Method 1a)

have fewer values, with rank two experiencing a significant decrease. Rank four has significantly more values. When considering other values, the mean rank for the first method is 2.813108, while for the new method it is 3.070813, indicating a slight improvement over the first method. The median rank remains the same at three.

Furthermore, Figure 23 displays the distribution of the normalize difference label per food type, compared to Figure 13. Rank one includes an additional food type, namely 'Dry Goods', compared to method 1. Rank five includes two extra food types, 'Prepared Foods' and 'Fresh Meat & Seafood'. Rank three contains all the food types when using the new method. Rank two no longer includes 'Ready-to-drink Beverages', but instead has three additional food types compared to method 1: 'Frozen', 'Prepared Foods', and 'Fresh Meat & Seafood'. Additionally, rank four incorporates more food types, namely 'Dry Goods', 'Breads & Bakery', and 'Dairy & Eggs'.

Moreover, upon reviewing Table 16, 'Skyr' and 'Potato chips' share the same rank for both methods. However, certain products, such as 'Lemon cupcakes', differ. To calculate the score for 'Lemon cupcakes' using method 1, the equation $S = f + g + n = 1 + 2 + 5 = 8$ is utilized, resulting in $R = \frac{S}{3} = \frac{8}{3} \approx 3$. For method 5, the nutritional value serves as the basis, and the differences between the nutritional score (n) and the GHG emission score (g) and the difference between the nutritional score (n) and the food waste score (f) are calculated. The differences can take values such as $-4, -3, -2, -1, 0, 1, 2, 3, 4$. To normalize these differences, the sklearn preprocessing.normalize() function is employed. The resulting normalized values are listed in Table 13.

Difference	Normalized Value
-4	-0.51639778
-3	-0.38729833
-2	-0.25819889
-1	-0.12909944
0	0
1	0.12909944
2	0.25819889
3	0.38729833
4	0.51639778

Table 13: Normalized Values

To calculate the score (S) using method 5, the differences (D) are determined as follows: $D_g = g - n = 2 - 5 = -3$ and $D_f = f - n = 1 - 5 = -4$. These differences are then transformed into their respective normalized values (N) using the DataFrame created from Table 13. D_g of -3 leads to the normalized value N_g of -0.38729833 and D_f of -4 leads to the normalized value N_f of -0.51639778. The score (S) is obtained by adding the nutritional rank (n) and the normalized GHG emission score (N_g) and normalized food waste score (N_f), resulting in $S = n + N_g + N_f = 5 + -0.38729833 + -0.51639778 \approx 4$. This rank is one higher than the rank obtained with method 1.

Method 6: K-means Clustering

As discussed in Section 3.4, method 6 involves using K-means clustering. Figure 24 depicts the distribution difference between the

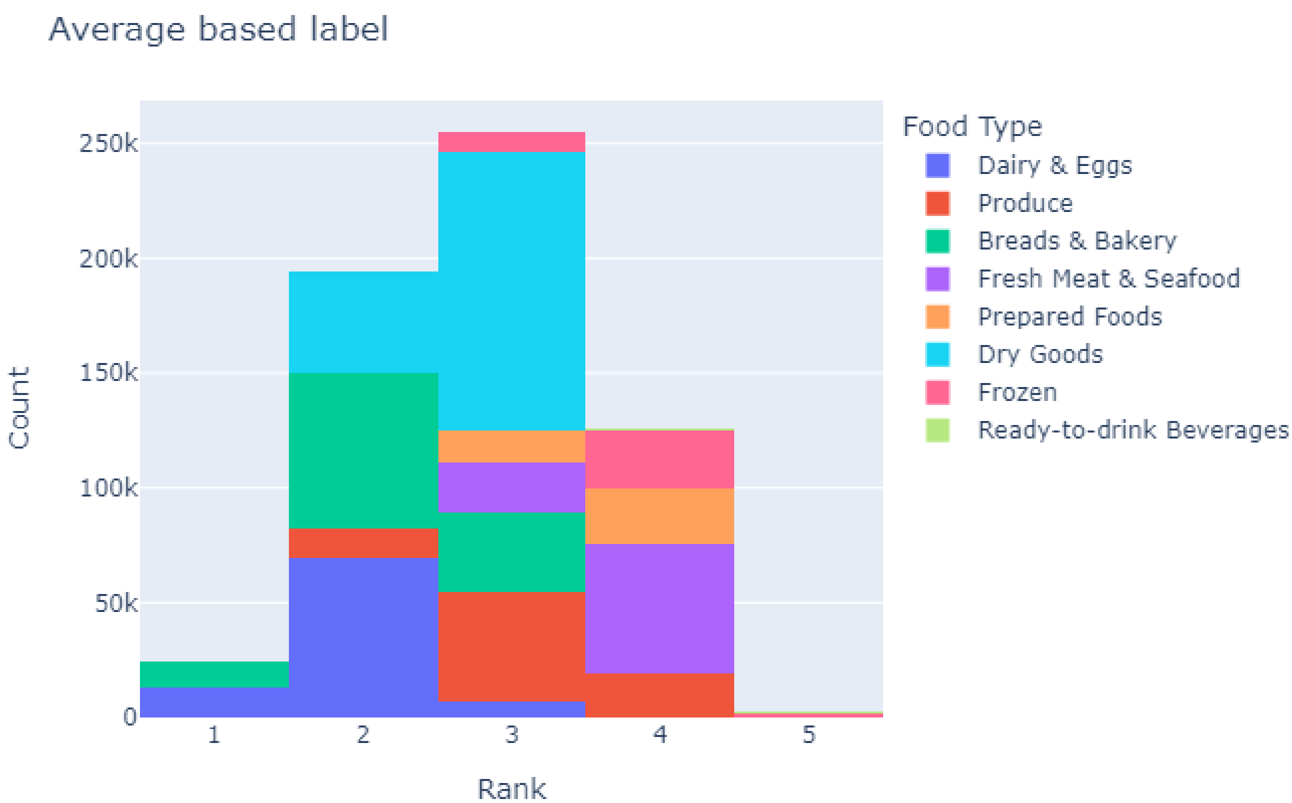

Figure 13: Distribution of average-based label per food type (Method 1a)

average-based labeling system and the K-means clustering labeling system.

In this new method, rank one and rank five have significantly more values compared to the average-based labeling system. Rank two exhibits a slight increase, while ranks three and four have considerably fewer values than method 1. The mean rank for the first method is 2.813108, whereas for the new method it is 2.544230, indicating a slight degradation in performance compared to method 1. Additionally, the median rank is three for method 1 and two for method 6, which is not an ideal outcome.

Moreover, Figure 25 shows the distribution of the K-means clustering label per food type, compared to Figure 13. Rank one and rank two include the same food types: 'Dry Goods', 'Breads & Bakery', and 'Dairy & Eggs'. However, in method 1, rank one does not have 'Dry Goods', while rank two includes an additional food type, namely 'Produce'. Rank three only contains 'Produce', whereas method 1 has seven different food types in this rank. Rank four and rank five share the same food types: 'Frozen', 'Ready-to-drink Beverages', 'Prepared Foods', and 'Fresh Meat & Seafood'. In method 1, rank four also includes 'Produce', while rank five has more food types than it has in method 1.

Furthermore, when examining Table 16, it becomes apparent that many products differ between method 1 and method 6. For example, 'Blackberries' shows a discrepancy. In method 1, the calculation for 'Blackberries' yields $S = f + g + n = 5 + 1 + 1 = 7$, resulting in $R = \frac{S}{3} = \frac{7}{3} \approx 2$. In method 6, K-means clustering is employed to divide the data set into five clusters corresponding to the five different scoring levels. To create the clusters, the KMeans function from the sklearn.cluster package is utilized, with the relevant data being scaled using the StandardScaler from the sklearn.preprocessing package. The K-means algorithm is then applied to form the clusters. However, these clusters do not possess ranks yet. To assign ranks, the food waste rank (f), GHG rank (g), and nutritional rank (n) are summed up. Hence, the equation becomes $S_i = f_i + g_i + n_i$. By utilizing the groupby() function on the clusters, the mean ($\bar{x}_c$) is calculated as $\bar{x}_c = \frac{\Sigma_{i=1}^{N_c} S_i}{N_c}$. Based on these means, the final rank is determined, with the highest mean receiving rank five. Table 14 illustrates this process (note that the clusters may vary with each run of the model).

Cluster	Mean	Rank
1	12.038232	5
2	9.820319	4
3	9.089402	3
4	8.250821	2
5	6.021136	1

Table 14: K-means Clustering

Consequently, for 'Blackberries', method 6 assigns rank three.

Method 7: Extension Method 4

As discussed in Section 3.4, method 7 involves an extension of method 4. Figure 26 illustrates the difference in distribution between the average-based labeling system and the labeling system of

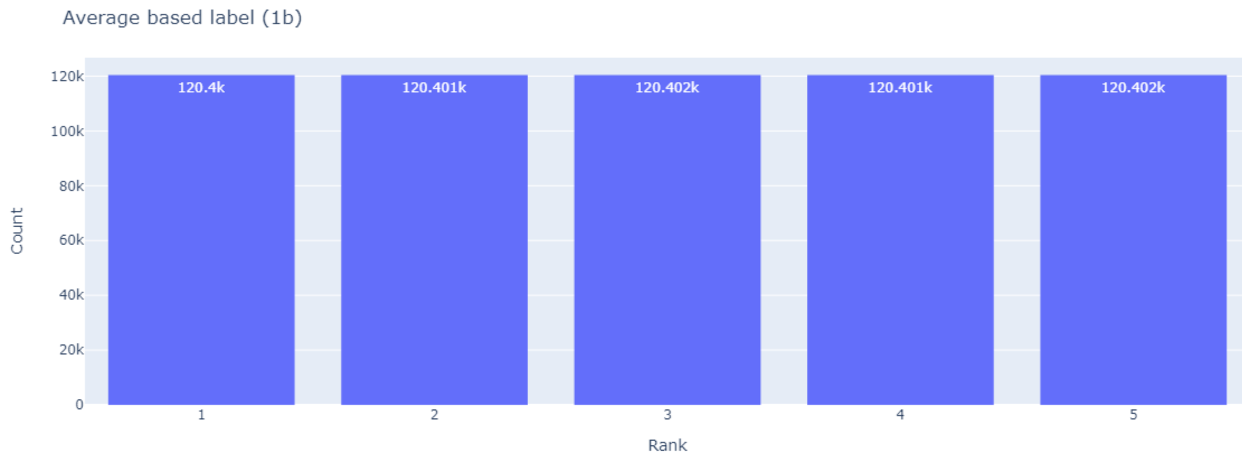

Figure 14: Distribution of average-based label (Method 1b)

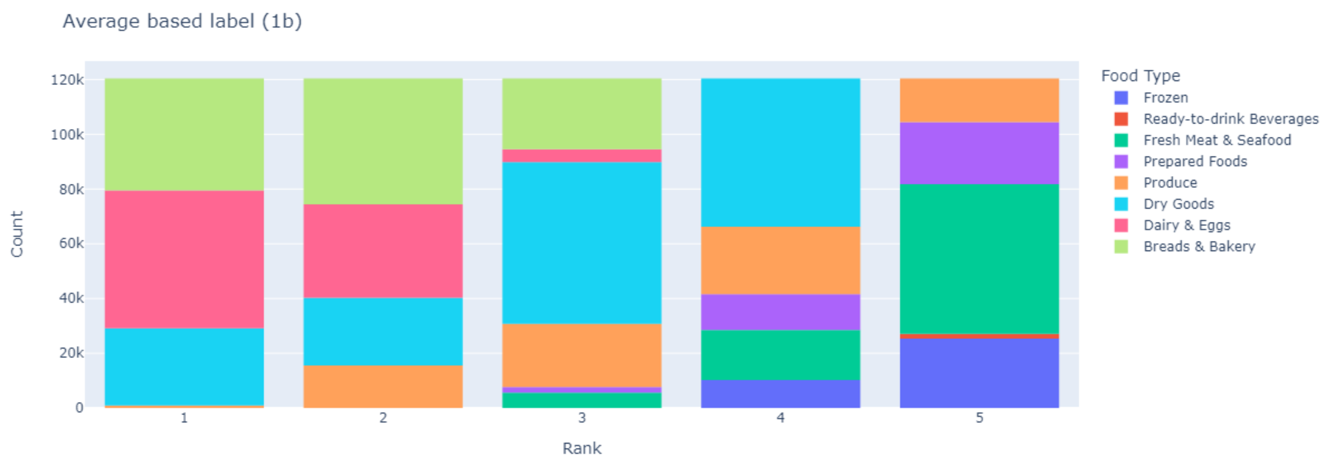

Figure 15: Distribution of average-based label per food type (Method 1b)

Extension method 4.

With this new method, the distribution becomes closer to the bell-shaped distribution, this is not the desired distribution. However, some variations from method 1 are observed. Rank five and rank three are higher than in method 1, while rank two and rank four are lower. In terms of other values, the mean rank for the first method is 2.813108, whereas for the new method it is 3.009345, which is quite close to the optimal value of three. The median rank remains the same for both methods, at three. In Figure 27 the difference in distribution between method 4 and method 7 is shown. There is only a difference in lower ranks, which is quite logical since the constraints only have an influence on these.

Additionally, Figure 28 presents the distribution of the extension method 4 label per food type, compared to Figure 13. The food types in rank one remain the same. Rank two has one fewer food type, namely 'Produce'. Rank three also has one fewer food type, namely 'Prepared Foods'. Rank four experiences a reduction of one food type as well, namely 'Produce'. On the other hand, rank five includes two additional food types, 'Frozen' and 'Fresh Meat & Seafood'.

Furthermore, when examining Table 16, 'Blackberries' shows a discrepancy. In method 1, the calculation for 'Blackberries' yields $S = f + g + n = 5 + 1 + 1 = 7$, resulting in $R = \frac{S}{3} = \frac{7}{3} \approx 2$. However, in method 7, the nutritional rank and GHG emission rank are both one, while the food waste rank is five. Since five is higher than four, the rank cannot be lower than three. Therefore, with both values being one, two is added, resulting in a rank of three for 'Blackberries'.

4.2.5 Comparing results

Table 15 displays the statistics for each labeling method. It is evident that rank three is the most common across the methods, except for methods 2 and 6, which have rank two as the most frequent. Among the methods, method 1b has the mean closest to three. Since method 1b can be disregarded, method 7 exhibits the mean closest to the optimal value. An optimal mean would be three, assuming equal occurrences of every rank (as observed in method 1b). The standard deviation (Std) indicates significant variance between ranks for method 1b, followed by method 6. In contrast, method 1a has the smallest deviation, indicating the least variability. The minimum rank for all methods is one, while the maximum is five. The median for most methods is three, except for method 6. The

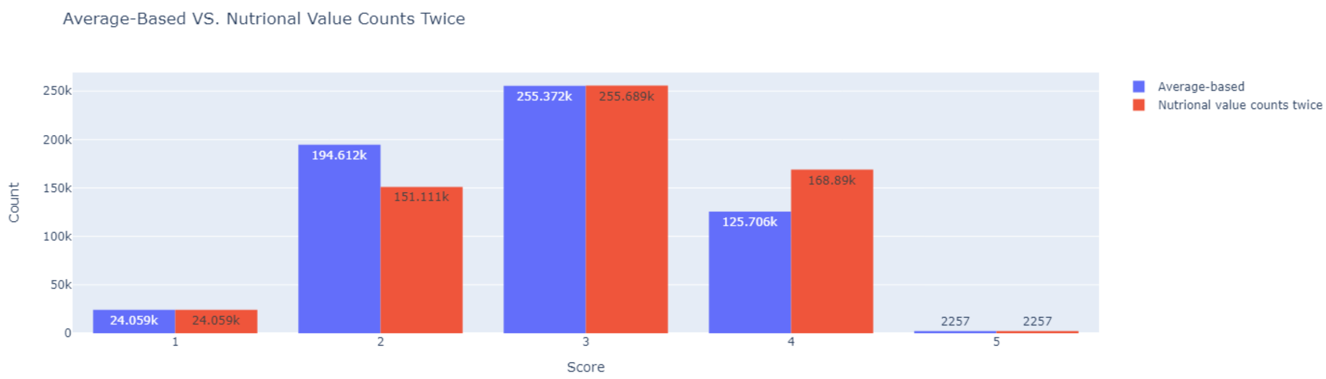

Figure 16: Distribution of average-based label vs. nutritional values counts twice label (Method 1 vs. 2)

25% quantile is mostly two, except for method 6 (one) and method 7 (three). Ideally, the quantile value would be two, indicating an equal distribution of ranks. The 75% quantile is generally three or four. The optimal value here would be four, suggesting an ideal distribution. In this case, methods 1b, 2, 5, and 6 fulfill that criterion.

Table 16 provides examples of different products, none of which have the same rank across all methods. The product 'Skyr' comes closest with only a different rank for method 6, while 'Potato chips' differs only for method 1b, and '100% orange juice' for method 6.

Table 17 displays the mean rank for each method per food type. The values in bold represent the highest mean for each food type. The overall highest mean is 4.046193, observed for method 3 in the Frozen food type.

For method 1a, 'Ready-to-drink Beverages' has the highest mean rank, while 'Dairy & Eggs' has the lowest mean rank. In method 1b, 'Frozen' obtains the highest mean rank, while 'Dairy & Eggs' achieves the lowest mean rank. Notably, 'Dairy & Eggs' attains the highest mean rank among all the methods.

In method 2, 'Ready-to-drink Beverages' secures the highest mean rank, while 'Dairy & Eggs' acquires the lowest mean rank. Similarly, method 3 exhibits 'Ready-to-drink Beverages' with the highest mean rank, which is also the overall highest mean rank for this food type. Method 3 also demonstrates the highest mean ranks for 'Fresh Meat & Seafood' and 'Frozen', while 'Dairy & Eggs' achieves the lowest mean rank in this method.

Moving on to method 4, 'Ready-to-drink Beverages' achieves the highest mean rank, whereas 'Dairy & Eggs' obtains the lowest mean rank. Method 5 shows 'Ready-to-drink Beverages' with the highest mean rank and 'Dairy & Eggs' with the lowest mean rank. Method 6 presents 'Ready-to-drink Beverages' with the highest mean rank and 'Prepared Foods' with the lowest mean rank. Notably, the means for this method are relatively close to each other compared to the other methods. Lastly, method 7 demonstrates the highest mean rank for 'Ready-to-drink Beverages' and the lowest mean rank for 'Dairy & Eggs'.

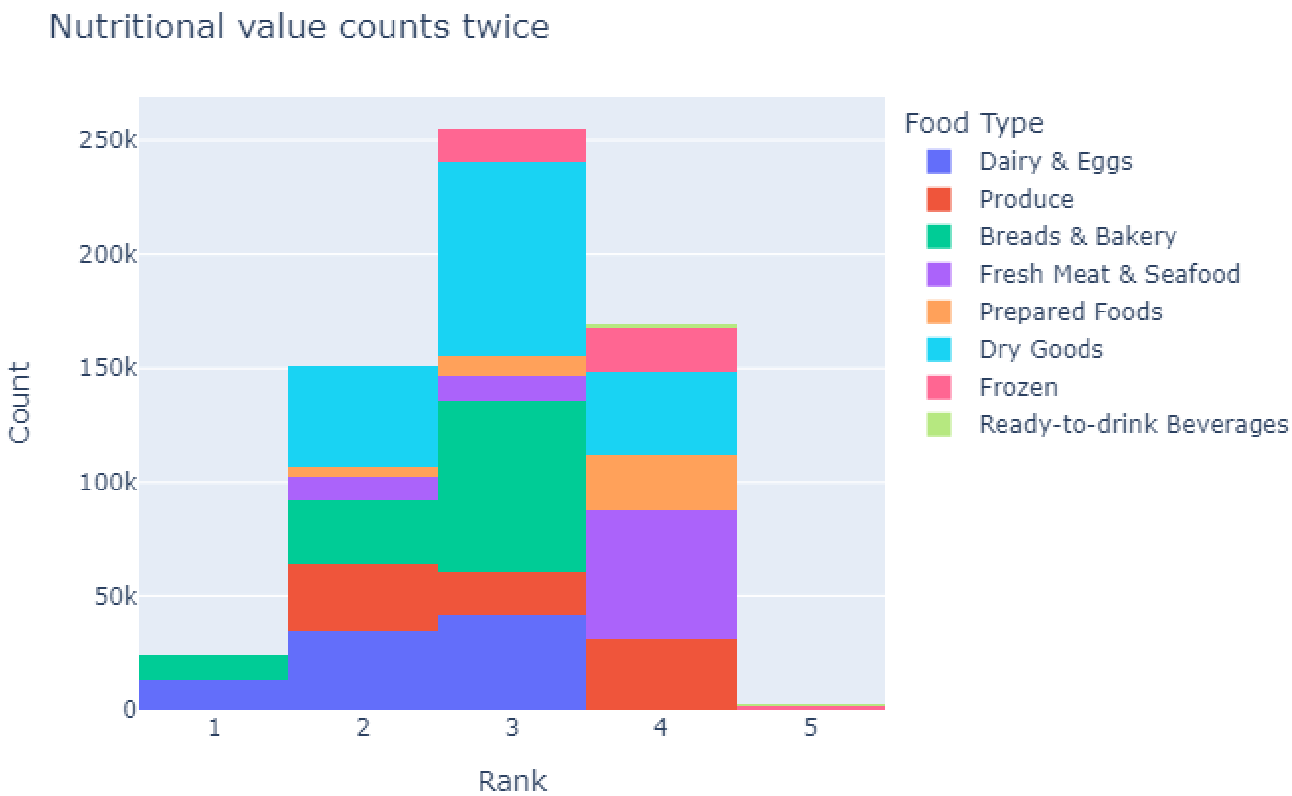

Figure 17: Distribution of nutritional value counts twice label per food type (Method 2)

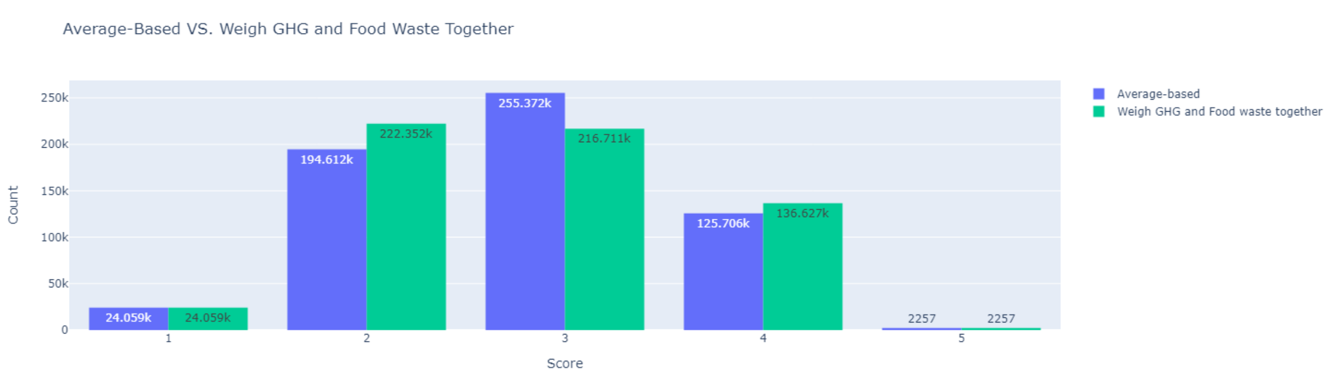

Figure 18: Distribution of average-based label vs. weigh GHG and food waste more label (Method 1 vs. 3)

Figure 19: Distribution of weigh GHG and food waste together label per food type (Method 3)

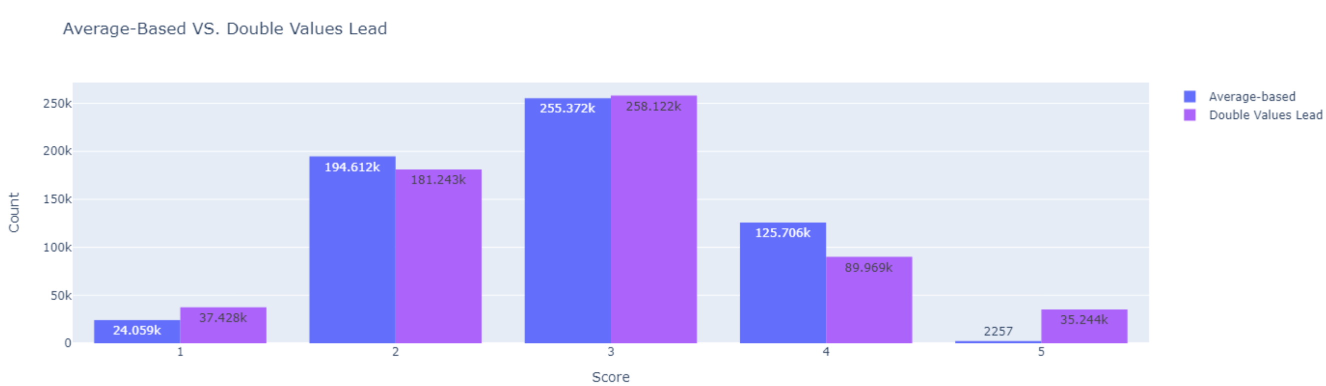

Figure 20: Distribution of average-based label vs. double values lead label (Method 1 vs. 4)

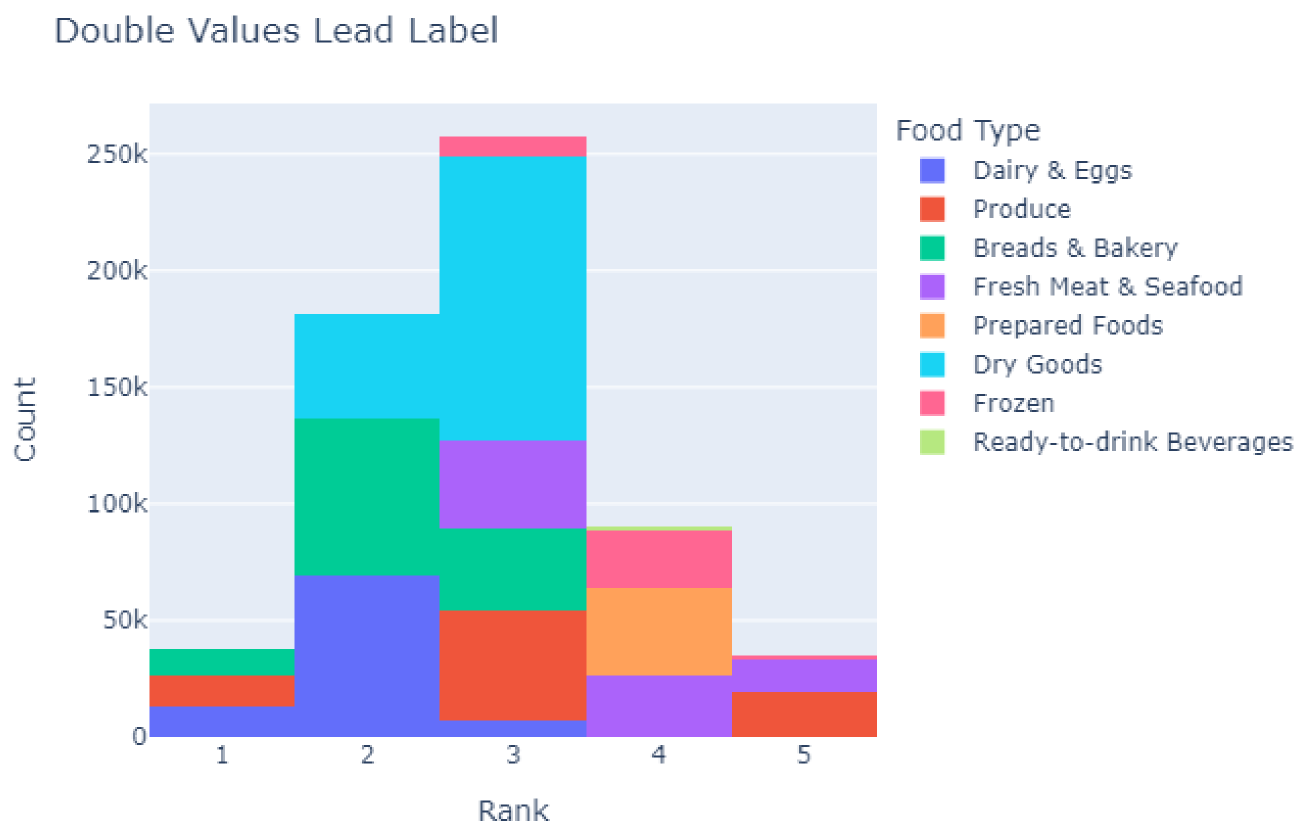

Figure 21: Distribution of double values lead label per food type (Method 4)

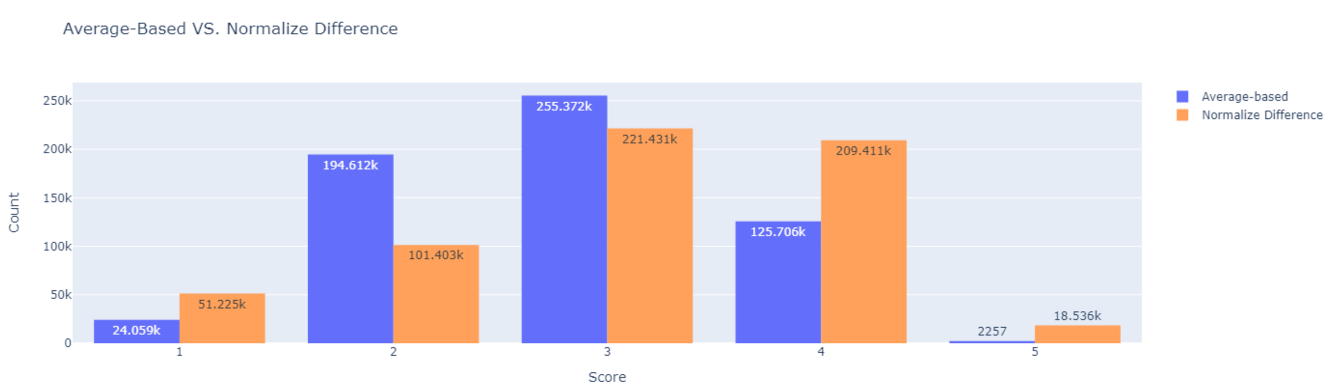

Figure 22: Distribution of average-based label vs. normalize difference label (Method 1 vs. 5)

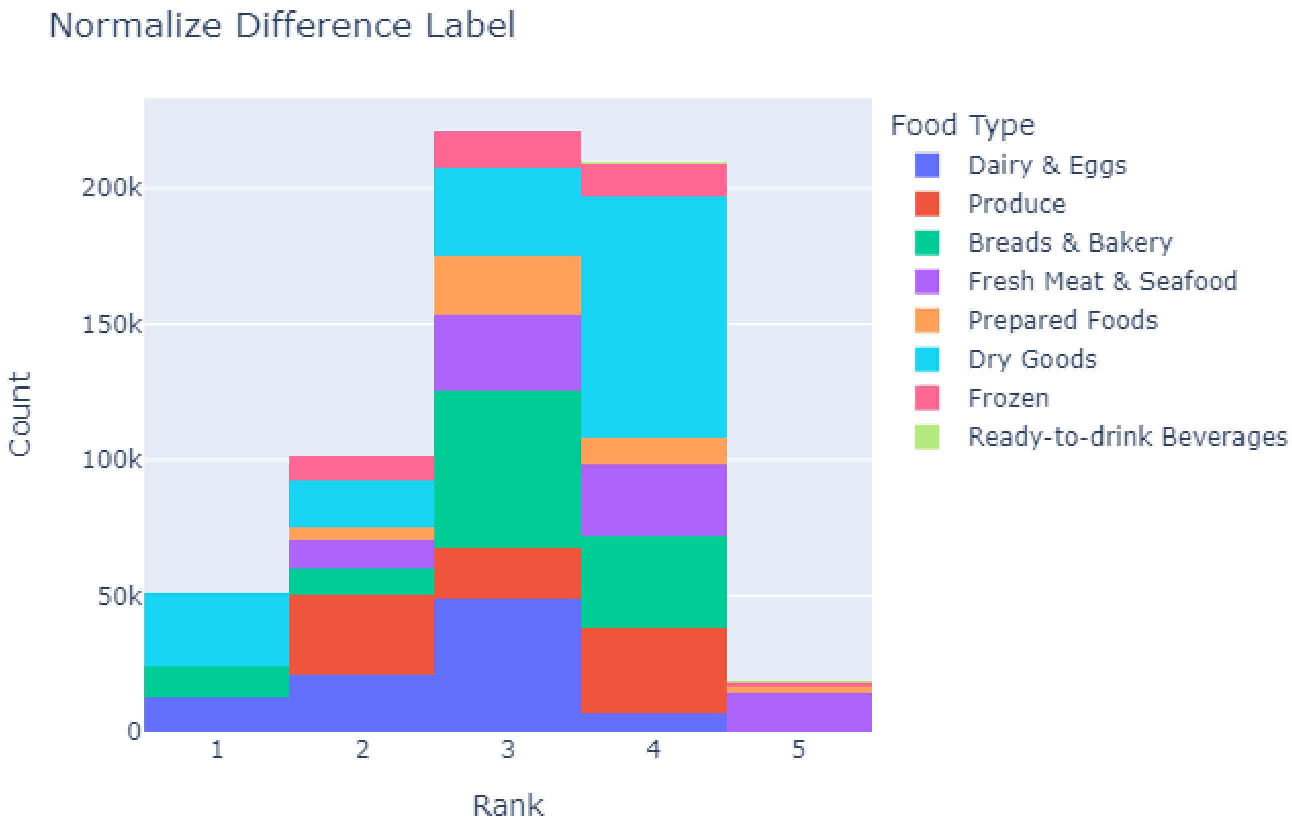

Figure 23: Distribution of normalize difference label per food type (Method 5)

Figure 24: Distribution of average-based label vs. K-means clustering label (Method 1 vs. 6)

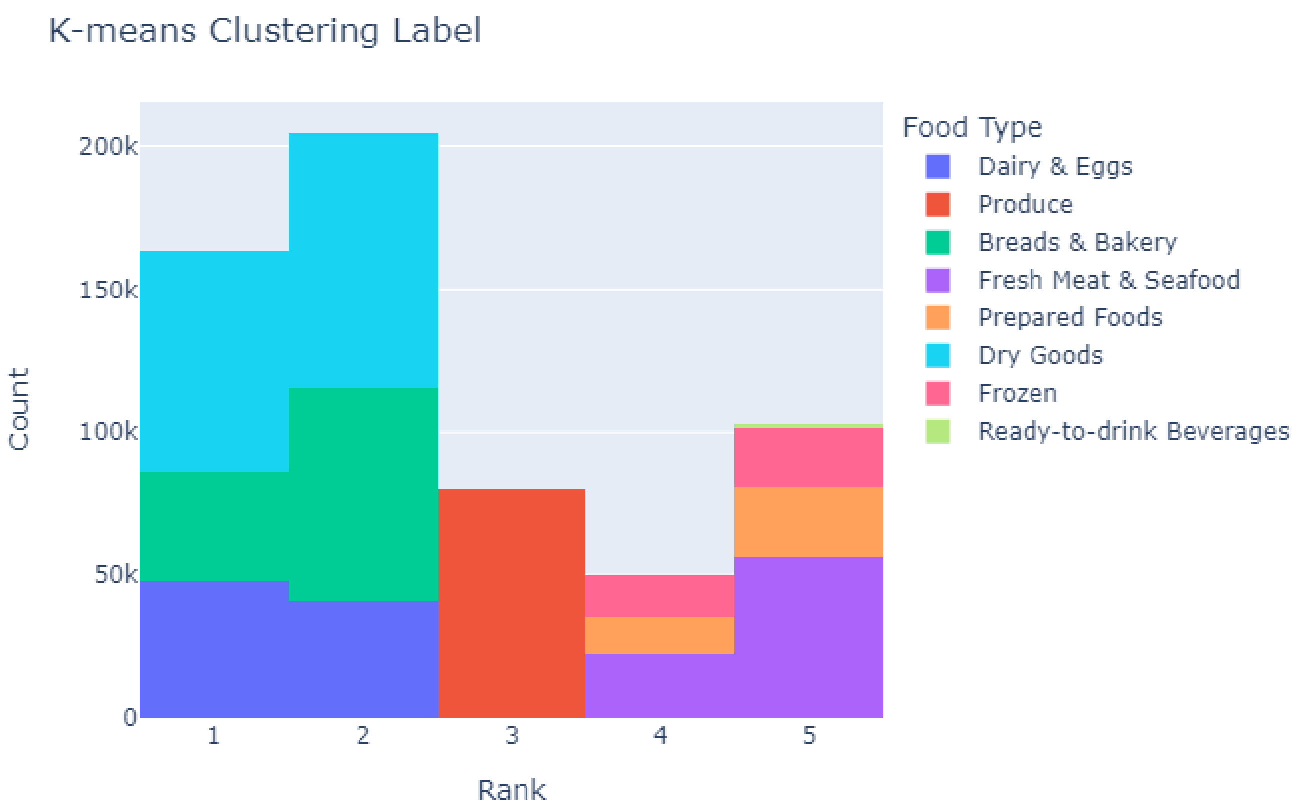

Figure 25: Distribution of K-means clustering label per food type (Method 6)

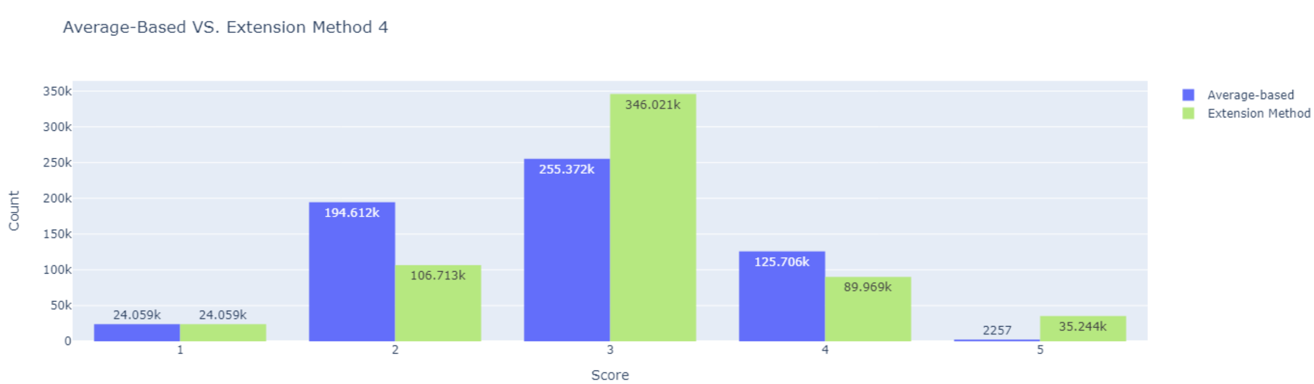

Figure 26: Distribution of average-based label vs. extension method 4 label (Method 1 vs. 7)

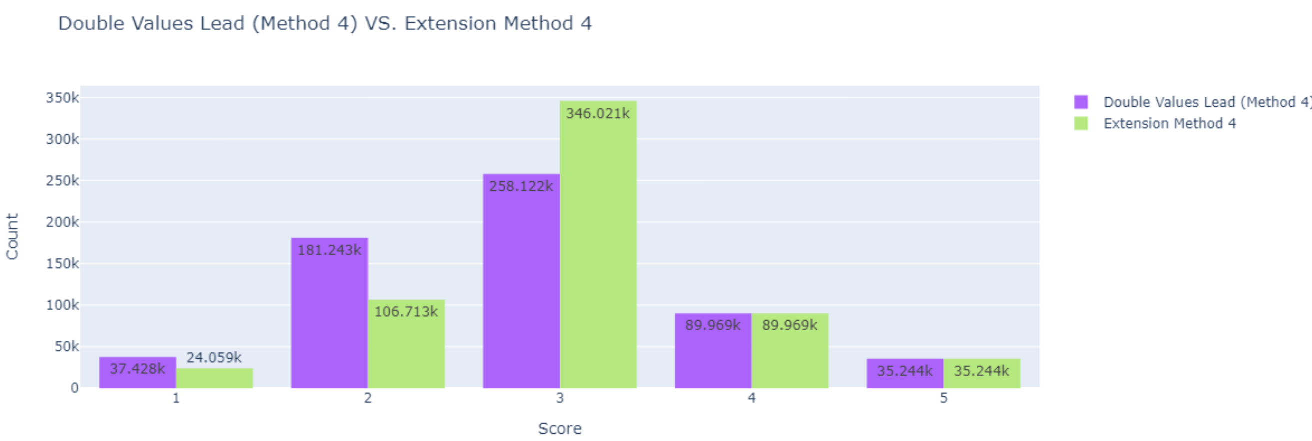

Figure 27: Distribution of double values lead label vs. extension method 4 label (Method 4 vs. 7)

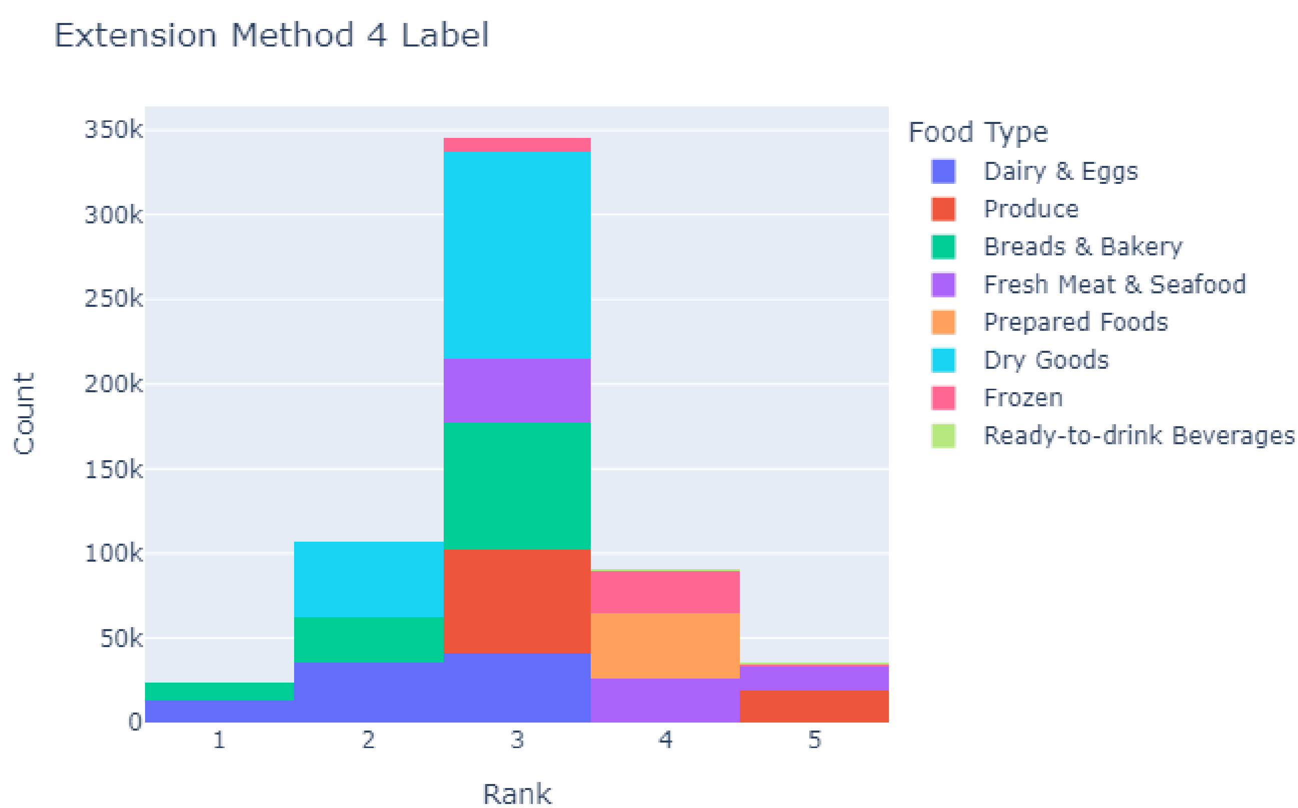

Figure 28: Distribution of extension method 4 label per food type (Method 7)

Rank (count)	Method 1a	Method 1b	Method 2	Method 3	Method 4	Method 5	Method 6	Method 7
1	24,059	120,400	24,059	24,059	37,428	51,225	163,232	24,059
2	194,612	120,401	151,111	**222,352**	181,243	101,403	**204,911**	106,713
3	**255,372**	**120402**	**255,689**	216,711	**258,122**	**221,431**	80,155	**346,021**
4	125,706	120401	168,890	136,627	89,969	209,411	50,417	89,969
5	2,257	**120,402**	2,257	2,257	35,244	18,536	103,291	35,244
Mean	2.813108	3.000007	2.957102	2.785170	2.841128	3.070813	2.544230	3.009345
Std	0.819764	1.414214	0.839389	0.851475	0.952964	0.987324	1.409718	0.848917
Min	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
25%	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000	1.000000	3.000000
50% / Median	3.000000	3.000000	3.000000	3.000000	3.000000	3.000000	2.000000	3.000000
75%	3.000000	4.000000	4.000000	3.000000	3.000000	4.000000	4.000000	3.000000
Max	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000

Table 15: Statistics for each labeling method (the values in bold are the values that occur the most for that method)

Product Name	**Food Type**	**Nutritional Rank**	**Food Waste Rank**	**GHG Rank**	**Method 1a**	**Method 1b**	**Method 2**	**Method 3**	**Method 4**	**Method 5**	**Method 6**	**Method 7**
Skyr	Dairy & Eggs	1	1	2	1	1	1	1	1	1	3	1
Potato chips	Dry Goods	3	2	3	3	2	3	3	3	3	3	3
100% orange juice	Produce	3	5	1	3	3	3	3	3	3	1	3
Lemon cupcakes	Breads & Bakery	5	1	2	3	3	3	2	3	4	2	3
Smoked sausage	Fresh Meat & Seafood	4	3	5	4	5	4	4	4	4	5	4
Diced Tomatoes	Produce	2	5	1	3	3	2	3	3	2	1	3
Blackberries	Produce	1	5	1	2	2	2	3	1	2	1	3

Table 16: Examples of products and their labels for different methods

Food Type	Nutritional Rank	Food Waste Rank	GHG Rank	Method 1a	Method 1b	Method 2	Method 3	Method 4	Method 5	Method 6	Method 7
Breads & Bakery	3.682458	1.0	2.0	2.206477	**3.150363**	2.562739	1.902566	2.206477	3.022284	2.573862	2.562739
Dairy & Eggs	3.012817	1.0	2.0	1.930416	**2.813816**	2.315344	1.853578	1.930416	2.551052	2.574442	2.315344
Dry Goods	3.327218	2.0	3.0	2.732747	2.981683	2.953380	2.732747	2.732747	**3.106585**	2.552276	2.732747
Fresh Meat & Seafood	3.278285	3.0	5.0	3.720023	2.837145	3.585237	**3.865213**	3.693048	3.558262	2.580276	3.693048
Frozen	2.742754	4.0	5.0	3.787511	3.636876	3.632932	**4.046193**	3.787511	3.156015	2.589226	3.787511
Prepared Foods	2.896951	4.0	4.0	3.644040	3.055044	3.532206	3.888166	**4.000000**	3.252911	2.518261	**4.000000**
Produce	3.089402	5.0	1.0	3.069091	2.887306	3.020311	3.000000	3.138182	3.020311	2.526908	**3.471761**
Ready-to-drink Beverages	3.904416	5.0	4.0	4.343208	2.934600	4.188373	**4.344885**	4.343208	4.060928	2.598847	4.343208

Table 17: Mean for each labeling method per food type (the values in bold are the highest mean for that food type)

5 Discussion

The development of a combined label combining food waste, GHG emissions, and nutritional values is a promising approach to promoting sustainable and nutritious food choices. This integrated label eliminates the need for separate labels for each aspect, streamlining packaging and reducing clutter. However, there are important considerations to be taken into account.

Currently, the label is static and only displays the values specific to the particular product. It does not adjust based on combinations with other products or any modifications made to the product. While this offers the convenience of immediate accessibility for consumers, it poses challenges in terms of recalculating the label when necessary.

Another consideration is that the ranking for food waste and GHG emissions are based on food types rather than individual products due to the limitations of the available data sets. Ideally, if a comprehensive data set were available, it would be possible to calculate rankings for each individual product, resulting in a more balanced distribution across different ranks (20%/20%/20%/20%/20%). However, the current approach was chosen to prioritize product-specific information available in the nutritional data set over the information available in the food waste and GHG emission data set.

It is worth noting that when using online databases like Open Food Facts, caution should be exercised, particularly when determining the Nutri-Score grade. The data used may not always align with the intended Nutri-Score, leading to mistakes. While this was considered acceptable for the current stage of label development, it is crucial to prioritize accuracy when finalizing the combined label.

Furthermore, when considering the food waste values from ReFED, it is important to acknowledge that individuals tend to underestimate the amount of waste they record. The specific information on how ReFED derived its data remains unclear, and therefore, the numbers provided in the data set were utilized. Future research should focus on investigating the methodologies employed by ReFED to ensure accurate representation. It would be valuable to examine whether ReFED utilized surveys with carefully designed questions to obtain as precise answers as demonstrated in the research conducted by van Herpen. [20]

The methods are provided as examples, and their effectiveness may depend on the specific context and requirements of the application. It is important to carefully consider the relative importance of the components and assess the appropriateness of each method for the given situation.

While analyzing the data, some values came as a surprise. It was expected that 'Dairy & Eggs' and 'Breads & Bakery' would score worse due to the anticipation of higher food waste and poorer performance in GHG emissions for 'Dairy & Eggs'. However, the most surprising finding was that 'Dairy & Eggs' consistently achieved the lowest mean rank across all methods. This contrasts with the initial expectations. Conversely, 'Frozen' stood out with a high score for food waste, which was unexpected given the perception that frozen products preserve food quality and allow for consumption at a later time. 'Produce,' consisting mainly of vegetables and fruits, was anticipated to score lower in nutritional rank. The fact that it had the highest mean score in method 7 since it will mostly score well for nutritional values and emissions, but then do quite badly for food waste. Resulting in the score not being able to go lower than three. These surprises for the nutritional values are possible due to the fact that the nutritional data may not have been properly sorted into the correct food types, which could contribute to these discrepancies.

Based on the mean values, method 7 appears to be preferred as it has the mean closest to three, followed by method 5 (excluding method 1b). However, when considering an equal distribution (e.g., 20%/20%/20%/20%/20%), method 2 seems to be the most suitable. It is important to note that these preferences are strictly based on mathematical and statistical considerations.

To make a final decision, a policy needs to be established to determine the weighting assigned to each component or whether they should be divided equally. Additionally, the extent to which each rank should be weighed must be examined. For instance, should ranks 4 and 5 carry more significance, or should only rank 5 be emphasized?

The policymaker's decision depends on the prioritization of specific components. If the nutritional value is deemed most important, methods 2 and 5 are likely to be the best fit. On the other hand, if emission and food waste are of greater importance, method 3 or method 5 with either emission or food waste as the basis could be considered. If the goal is to identify groups that closely resemble each other, method 6 may be the approach that is preferred. Alternatively, the policymaker may opt for a simple ranking where all criteria are treated equally, making method 1 the preferred choice.

It is also possible to determine a specific method for each food type or select the method based on the best score for a particular food type. For example, method 3 may be suitable for 'Breads & Bakery' and 'Dairy & Eggs'.

In summary, the combined label shows promise in facilitating sustainable and nutritious food choices. However, further refinements are necessary, such as implementing dynamic features and exploring more comprehensive data sets for ranking individual products. Attention to accuracy in nutritional data and considering the methodologies behind waste data sources will be important for future improvements. Furthermore, the creation of a policy becomes crucial to establish clear guidelines regarding the importance assigned to each component and the weightage of rank values. Defining the significance of individual components and ranks will enhance the label's clarity and enable consumers to make informed decisions.

6 Conclusion

The study involved the development of a comprehensive label that incorporates nutritional information, greenhouse gas (GHG) emissions, and food waste data. Initially, normalization and calculation were performed to generate separate labels for each component. Notably, a label for food waste was also generated, as there was no previous label in this domain. Subsequently, integration of these individual labels was carried out to create a single cohesive representation. As a result, a new food label was successfully created, encompassing information related to all three components, facilitating informed decision-making for consumers regarding both nutrition and the environment.

However, it is crucial to acknowledge that our score label is yet to undergo testing and implementation. Therefore, further research is warranted to assess its functionality and effectiveness. Preliminary observations indicate that the label with the most constraints achieves the best based on the mean. Moreover, the distribution of counts assigns greater weight to nutritional values compared to food waste and GHG emissions.

Moving forward, ongoing evaluation and refinement are necessary to ensure the label's accuracy, reliability, and practicality. By addressing these considerations, progress can be made toward a more sustainable and health-conscious future, where consumers can make well-informed choices based on comprehensive and reliable information.

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