

# Designing Visualizations for Enhancing Carbon Numeracy

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## ABSTRACT

This position statement discusses the challenges of designing visualizations to enhance the carbon numeracy of the general public. Carbon numeracy refers to an individual’s quantitative awareness of their CO<sub>2</sub> emissions, which can vary widely from grams to tons across different activities. Effective visualizations must accurately represent these ranges and facilitate quantitative comparisons. By leveraging insights from both visualization research and cognitive psychology on numerical perception and the representation of large numbers, we propose two novel design solutions to address these challenges. We aim to foster discussions on improving public carbon numeracy, ultimately aiding in mitigating climate change.

**Index Terms:** carbon numeracy, visualization

## 1 INTRODUCTION

In this position statement, we discuss how visualization designs could enhance the carbon numeracy of the general public and we propose two novel design solutions. Global warming is a pressing issue exacerbated by various factors, including individual actions. Although each person’s contribution might seem negligible in isolation, collectively, these actions significantly impact global CO<sub>2</sub> emissions [19]. On the global level, 72% of CO<sub>2</sub> emissions are related to household consumption, which includes energy use, transportation, and the consumption of goods and services [9].

According to the Paris Agreement on climate change [18], in order to limit global warming to 1.5°C, the total remaining CO<sub>2</sub> emission budget from 2018 onwards was approximately 420 billion tonnes of CO<sub>2</sub> [21]. Assuming an equal distribution of the remaining global CO<sub>2</sub> budget, this translates to about 56 tonnes of CO<sub>2</sub> per person over the next three decades. This results in an annual per capita emission target of approximately 1.9 tonnes of CO<sub>2</sub> [7], or a daily per capita emission of 5.2 kilos. The current global average per capita CO<sub>2</sub> emissions stand at around 4.8 tonnes per year, indicating that a significant reduction of more than half is necessary to meet the targets set by the Paris Agreement [13].

To achieve this reduction, it is essential to make decisions about effective changes in our lifestyle, hence to develop a high level of carbon numeracy [24, 23, 8]. Carbon numeracy involves quantitatively understanding the emissions associated with everyday choices [8]. While people have a qualitative understanding of high-emission actions, such as flying and consuming meat, they tend to underestimate the magnitudes of these actions [24, 23]. Additionally, they struggle to make quantitative comparisons between different choices, such as “years of eating food without packaging versus one year of a vegetarian diet” or “hamburgers versus a trans-Atlantic flight” [24]. Wynes et al [24] tried to shed light on

the factors that affect carbon numeracy. Notably, self-assessed personal values like “concern for climate change”, “political ideologies”, and demographic factors such as “educational background” were not significant predictors of the ability to accurately estimate carbon emissions. However, they found that carbon numeracy is mostly correlated with basic numerical skills.

Therefore, as members of the visualization community, the challenge we face lies in designing visualizations of carbon emissions that overcome problems associated with basic numerical skills. These visualizations must a) effectively represent the magnitudes of different actions, from grams to tons, and b) facilitate quantitative comparisons between them. In this position statement, we initially explore existing literature to identify challenges associated with common visualization designs, such as linear and logarithmic charts. Subsequently, we discuss findings from studies in cognitive psychology that could aid in understanding and comparing large numbers. Next, we highlight innovative designs, inspired by scientific notation, that are capable of visualizing vast orders of magnitude while enabling quantitative comparisons. Building on these insights, we propose two new design solutions. We focus on static visualization designs, as they are suitable for both printed and digital media and can offer an informative overview of the quantitative information prior to interaction.

We believe that effective visualizations can bridge the gap in understanding and empower individuals to make more informed decisions about their carbon footprints. Therefore, the objective of our position statement is to spark discussions on how the visualization community can enhance the carbon numeracy of the general public, ultimately contributing to global efforts in combating climate change.

## 2 BACKGROUND

In this section, we present related work that motivated our design. First, we explore the challenges associated with common visualization methods, such as linear and logarithmic charts. Next, we discuss insights from cognitive psychology on how people perceive large numbers. Finally, we examine novel visualization solutions inspired by scientific notation, which we believe can be applied to the visualization of individual CO<sub>2</sub> emissions to enhance carbon numeracy.

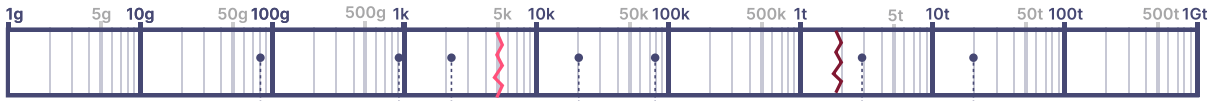
**Challenges of linear and logarithmic scales** Different daily actions have varying carbon costs. For example, sending an email may produce only a few grams of carbon emissions, while taking an overseas flight can generate several tons. If we measured all these emissions in grams, the data would cover a wide range, from 1 gram to several million grams, spanning over six orders of magnitude. Commonly used visualization methods, like bar charts with linear or logarithmic scales, are not effective at representing these vast value ranges [2, 11, 10]. Linear scales make it impossible to read and compare smaller magnitudes. While other linear visualization solutions, such as dual scale charts [12] and innovative designs like the Du Bois Wrapped Bar Chart [14] offer improvements for analyzing two disparate ranges, their effectiveness diminishes with values that span more than four orders of magnitude [2]. Logarithmic scales, which can illustrate diverse ranges, make it easier to qualitatively compare large value ranges and identify extremes. However,

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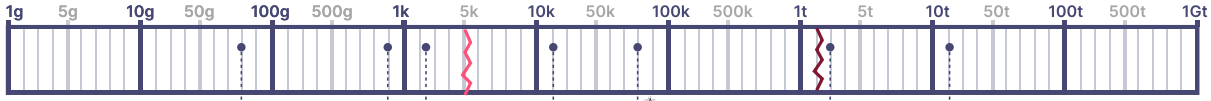
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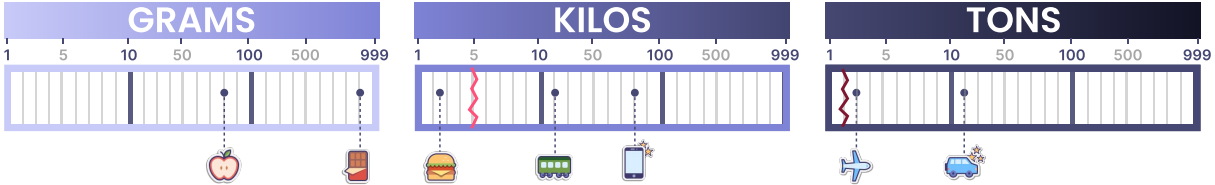
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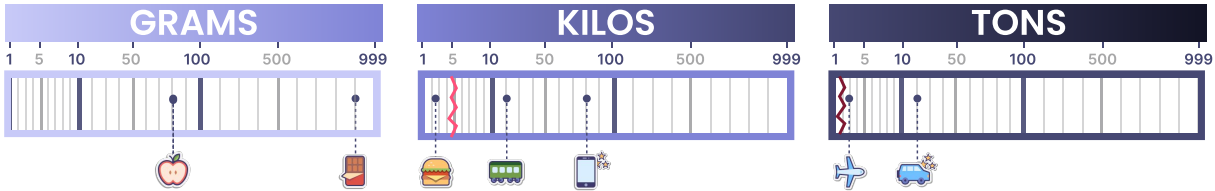
(a) Logarithmic scale



(b) Piece-wise linear scale



(c) Categorical encoding of weight units and piece-wise linear scale



(d) Categorical encoding of weight units and piece-wise linear scale with uneven pieces

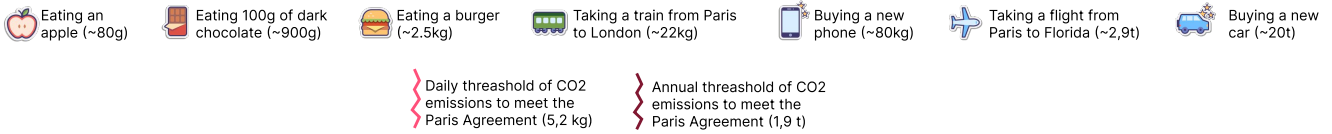


Figure 1: Visualization designs illustrating the wide range of CO2 emissions from individual actions. Icons by *Icons8*.

they present challenges for quantitative tasks, like estimating differences or ratios between values of similar or close magnitudes [10], which are crucial for enhancing carbon numeracy. Additionally, logarithmic scales can be challenging for the general public to interpret [6, 22, 17].

**The segmented linear model** Research results from cognitive psychology [16, 15] indicate that when people estimate the position of large numbers on a line, they do not follow either a purely linear or logarithmic scale. Instead, they follow a "segmented linear model", using numerical categories—such as thousand, million, and billion—to divide the number line into categories, similar to a logarithmic scale, and between these scale words, numbers are distributed linearly, resulting in a piece-wise linear scale. This behavior mirrors the way we talk about numbers, using categories for scale and numbers between 1 and 999 for detail. It also resembles how we write large numbers using scientific notation, where the value is divided into two components: the exponent, indicating the magnitude, and the mantissa, indicating the detail. Therefore, we observe that people are accustomed to separating large numbers into two parts—one related to the scale category and the other to the detail.

**Linear scaling within orders of magnitude** Visualization researchers [2, 11, 10, 4, 3], inspired by scientific notation, have

proposed novel static designs that address the limitations of linear and logarithmic scales. They separate large values into mantissa and exponent parts and visualize each component separately using different visual channels [11, 10, 4, 3], distinct marks [2], or novel scales [10, 4, 3]. For example, Hlawatsch et al. [10] introduced the Scale-Stack Bar Chart, where values are faceted per magnitude in stacked rows, starting from zero and mapping numbers linearly up to the maximum value of each scale. Inspired by this design, Braun et al. [3] proposed the Order of Magnitude Line chart, which combines both exponent and mantissa in the position Y, introducing a new visualization scale termed "linear scaling within orders of magnitude". We believe that this scale illustrates the segmented linear model well and provides an effective way to visualize values that span multiple orders of magnitude. According to the figures of Braun et al. [3], we infer that their scale is  $s(v) = e(v) + (m(v) - 1)/9$ , a piece-wise linear scale. The exponents  $e$  are equally distributed across the scale, and the mantissa values  $m$  within the range  $[1, 10[$  are linearly interpolated between two exponents. Figure 1b illustrates an example of this scale. The results of their empirical evaluation showed that visualization designs that separate large numbers into mantissa and exponent are more effective than linear and logarithmic scales for value retrieval and quantitative comparison tasks. These tasks are fundamental for carbon numeracy.

### 3 VISUALIZATION DESIGN

In this section, we present the design rationale for Figure 1c and Figure 1d. Our design choices are informed by insights from the literature on the visualization of large value ranges and cognitive psychology, described in the background section. We highlight key design decisions aimed at facilitating value estimation and quantitative comparisons between magnitudes, ultimately enhancing carbon numeracy.

**Categorical encoding of weight units: Grams, Kilos, Tons** People use numerical categories (e.g., thousands, millions) to estimate relative magnitudes of numbers [15]. For the individual carbon footprint of daily actions, the numerical categories that could describe the weight of these actions are grams, kilos, and tons. Therefore, we incorporate weight units in our design, encoding them with categorical visual variables that express order. Specifically, we use faceting by column and color intensity to represent these units. By employing redundant encoding, we aim to enhance discriminability between different magnitudes, which can lead to increased accuracy in value estimation [1]. Furthermore, as the majority of the general public has a good understanding of the relation between the units used (e.g., 10 kilos is 1,000 times more than 10 grams), we believe that the categorical encoding of weight will facilitate quantitative comparisons between values across different facets, thus reinforcing carbon numeracy. Further research is necessary to validate this hypothesis. Figure 1c and Figure 1d show the categorical encoding of the weight units.

**Enhancing detail inside magnitudes** When faceting by weight units, we reduce the number of exponents to visualize in each facet to three (units, tens, and hundreds). This makes using a linear scale feasible within this value range [11]. However, the effectiveness of linear scales strongly depends on the available display size. If the size of each facet is less than 1000 pixels, values in the range  $[1, 10[$  are not distinctive, and it becomes challenging to perform quantitative tasks accurately [20]. To address this, we recommend using a piece-wise linear scale within each facet to enhance the discriminability of mantissa for smaller scales (Figure 1c). Acknowledging that each piece of the piece-wise linear scale is not equal (e.g., the range  $[1, 10[$  is smaller than the range  $[10, 100[$ ), an alternative scale design is to encode each piece with different sizes based on the value of the exponent (Figure 1d). This idea is inspired by the spatial size that different magnitudes occupy: units (1 digit), tens (2 digits), and hundreds (3 digits). This approach could improve the perception of different magnitudes. For example, in Figure 1c the distance between the train and the new phone (difference of  $\approx 60$  kilos) is smaller than the distance between the burger and the train (difference of  $\approx 20$  kilos), while in Figure 1d the visual distances are closer to the actual differences. Further research is necessary to validate the effectiveness of these solutions.

**Assessing magnitude based on defined metrics** People's understanding of large numbers is heavily influenced by relative differences [5]. However, making quantitative comparisons between actions alone is not sufficient to assess the impact of a choice. To effectively evaluate the weight of daily action, it is essential to compare it against a defined metric or threshold, such as the daily (visualized as a wavy pink line) or annual (visualized as a wavy dark red line) threshold of individual CO<sub>2</sub> emissions to meet the criteria of the Paris Agreement. For example, based on the visualizations (Figure 1), eating a burger is equivalent to about half of the average daily emissions, taking an overseas flight is nearly equal to the entire annual carbon footprint, and buying a new car is comparable to ten years' worth of emissions. This kind of information is crucial for planning a carbon budget for the coming years and for taking compensatory actions to balance emissions. By understanding the relative impact of various activities, individuals can make

more informed decisions and adopt strategies to reduce their overall carbon footprint. Therefore, it is essential to incorporate these defined thresholds into visualization designs to enhance the carbon numeracy of the general public.

### 4 CONCLUSION

In this position statement, we have emphasized the importance of enhancing the carbon numeracy of the general public through effective visualization designs. We explored the challenges associated with representing and perceiving large value ranges, drawing insights from both the literature on visualization techniques and cognitive psychology on how people interpret large numbers. Based on these insights, we proposed and discussed two novel visualization designs (Figure 1c and Figure 1d). Controlled experiments will be necessary to evaluate the effectiveness of these visualizations for both low-level and high-level perception tasks.

Given that individual actions significantly contribute to global CO<sub>2</sub> emissions, improving carbon numeracy is crucial for meeting the targets set by the Paris Agreement. While individual carbon footprints are a primary focus, the visualizations discussed in this paper have broader applications. These visualizations can also be used to represent the carbon footprints of different countries and industries, as well as the various magnitudes of energy consumption.

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