Physical Visualization of the World's Happiness

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Abstract

Our team wanted to investigate the 2016 World Happiness Report, a dataset released annually by the United Nations which measures global happiness based on specific attribute scores, to determine is the data could be better understood in a physical format. The report compares data from 157 countries around the world, so we decided to build a physical visualization of a world map and a surrounding dynamic bar chart. With interactive elements within the map the user can manipulate, explore, and ultimately play with the data to analyze insightful relationships between global regions and attributes of happiness. These attributes include: economy, family, health, freedom, trust in government, and generosity.

Keywords: Physicalization, world happiness, interactive bar chart.

1 Introduction

Our primary motivation was to create a physicalization which would allow the user to explore the relationships between some of the key features in the happiness report. Incorporating a map into the physicalization intended to allow the user to compare similarities and differences between world regions and countries within each designated region. We defined our regions from those given within the report itself, these ten regions include: Western Europe, North America, Australia and New Zealand, Middle East and Northern Africa, Latin America and Caribbean, Southeastern Asia, Central and Eastern Europe, Eastern Asia, Sub-Saharan Africa, and Southern Asia. With the dataset being relatively large with all 157 countries, we wanted the user to be able to see all the data at once and be able to answer questions about the data a. Some questions we see users being interested in answering could be asking whether there is a strong relationship between geographic region and a country's overall happiness? Why do some of the most affluent countries rank the lowest when it comes to generosity? Are certain regions of the world clustered in their ranking? The surrounding bar chart is static in height and is organized by ranking in happiness with Denmark being first and Burundi last. Our visualization allows the user to toggle the happiness attributes by controlling LED lights to compare the chosen categorical value to the statically measured bar chart. This way, the user can begin to physically inspect the large amount of data in the World Happiness Report first-hand, and draw further conclusions about the interconnectedness of these relationships for themselves.

2 Related Work

Several decisions had to be made regarding the veracity of the visualization we wanted to present to the user. For instance, we did not want to alter the scale factor of the bar charts presented behind the map; either intentionally, or accidentally when we were re-scaling the values to physically create the bars. According to an article by Yvonne Jansen et al., ". . . 3D bar charts . . require low "visualization literacy" and are conceptually easy to understand. 3D bar charts are among the most commonly used 3D visualizations and are supported in most visualization and spreadsheet software" [1]. Therefore, we decided that a static set of 3D bars to represent the overall happiness ranking would be the easiest way to convey an accurate portrayal of each country's value without skewing the user's interpretation of it. In combination with the bar chart and interactive world map, we decided using an orange to blue color scale would be the best way to manipulate individual country's bars allowing the user to control and analyze the other sub-features of the data.

Another article argues how the use of physical visualizations allows for the user to better utilize our perceptual exploration skills:

"Humans have evolved a highly complex sensorimotor system that allows them to efficiently extract information from the physical world" [2].

What's more, we thought that creating a physical representation of this data would allow us to actively engage people's interest by allowing them to directly manipulate the visualization and see physical changes, which cannot be done through a computer screen. There is research that supports the idea that a physical visualization encourages people to spend more time "playing" with the data, and further inspecting it. According to the same article:

"There is anecdotal evidence that physicalizations may aid individuals in engaging with and communicating information to others more effectively than with digital representations. This popularity suggests that data physicalizations pique interest, and this interest could in turn be leveraged to have people spend more time and effort exploring and understanding important and complex data." [2].

Another article by Trevor Hogan, et al. highlights how the current monopoly of computer visualizations limits the use of human's many sensory channels. They argue that "the main sensory channel we use to perceive these representations today still remains largely exclusive to sight" leaving the rest of the sensory systems uninvolved [3]. Again, this article shows that data physicalization allows humans to interact with data visualizations in a way that they haven't before.

A study conducted by Robert Ball and Chris North investigated whether the benefit of large scale interactions come from "(1) the wider field of view that exploits peripheral vision to provide context, and (2) the opportunity for physical navigation (e.g. head turning, walking, etc.) to visually access information" [4]. The study split peripheral vision and physical navigation into independent variables and used large high-resolution displays to determine which factor increased the interactions effect. The study found that physical navigation was "more critical to improving performance" compared to peripheral vision [4]. Therefore, understanding the results from this study indicates that utilizing physical navigation within our physicalization may improve the effectiveness.

The design process of a physical visualization has not been extensively researched since the field only came recently into the spotlight. A paper by Simon Stusak and Ayfer Aslan explores the design process for this new visualization category. They break down the process into three basic steps: sketching, prototyping, and final construction. To avoid excessive time and cost and "to identify problems regarding the design and get a good impression about size and interaction possibilities", they begin the designs with sketching out possible ideas [5]. Our own design process started very similarly to this with initial sketching and idea forming with pen and paper. The second step of the article involved creating small prototypes with paper and cardboard, but due to time constraints, this is not a process we followed. The final construction of our physicalization was constructed from mapped out measurements on paper. This paper introduces an easy design process for physicalization which could potentially become a standard to follow.

Our physicalization interaction consists of direct manipulation by the user which is defined as "directly manipulating material objects that represent the objects of interest" [6]. Our physicalization utilizes this direct interaction through buttons which allows the user to enable or disable a given region on the map. They also allow for the user to toggle which feature (other than happiness) they would like to visualize within the bars. Our button implementation is a direct example of employing haptic direct manipulation through a visualization as a means of giving the user control over what aspects of the data are being visualized and allowing them to explore further our dataset.

When we were thinking about the best way to filter our physicalization by different attributes, we needed to ensure that users were able to mentally group together the appropriate countries by color. Therefore, it was important to consider Gestalt psychology. The experimenters asked subjects to rate the degree to which a central target shape grouped with either right or left flanking shapes. Across the displays, the proximal and featural relationships between the target and flankers were varied, and these included differing distances, shapes, and colors. Results indicated that both color and proximity were largely more effective [7].

A study from Gori and Spillmann sought to compare thresholds for the detection of non-uniformity in spacing, size and luminance with thresholds for grouping. For the third part of the experiment which solely considered luminance, the experimenters presented a series of 12 equi-spaced dots on a white background to participants, and systematically varied the luminance of dot triplets between trials. Results demonstrated that the threshold for perceiving stimuli as dissimilar in luminance was much smaller than the threshold for grouping. In order to perceive stimuli as grouped, stimulus differences had to be 6.6 times larger than for simple difference detection [8]. Ultimately we chose to utilize color, specifically an orange-blue color scale, as a way to visually represent the other categories of data.

Another task our team set out to accomplish was finding a reasonable way to evaluate the visualization we created. We thought that using an insight based evaluation would be an appropriate way to do so. Due to the fact that insight based evaluation can often be ambiguous and subjective. Referring to the article, *Toward Measuring Visualization Insight,* the authors refer to several characteristics of insight based evaluations, noting that defining insight can be difficult and at times vague [9]. They describe insight as being complex, deep, qualitative, unexpected, and relevant. Furthermore, the authors identify the drawbacks of traditional experimentation on measuring insight. More specifically, insight experiments can fail to capture true discovery in a dataset, and instead yield to uninspiring search/benchmark tasks. One solution to this is to use a qualitative think-aloud design, which is much more open ended. This allows for a much more high level analysis of the data visualization.

Our visualization on happiness would certainly lend well to search/benchmark tasks, as the selection of certain attributes can highlight interesting outliers in the data. However, it also lends well to insight, as users can examine the complex high level trends associated with data distributions across multiple attributes and regions, in addition to the rich country by country stories that are qualitatively uncovered. Therefore, both types of insight based tasks would be effective to evaluate the visualization.

3 Project Description

Our physicalization consists of three main parts: an interactive world map, surrounding LED light bar chart, and buttons to dynamically interact with the bar chart. With the data from the UN on world happiness, we wanted to allow the user to be able to view the static bar chart that surrounds the world map, and then compare that data to the other key features (generosity, health, freedom, etc..) by manipulating the buttons that toggle country regions and the selected data feature.

There are several justifications worth mentioning that we decided to implement in our physical visualization. The first is that we decided to scale the happiness values so that the maximum value did not exceed one foot. This was in an effort to mitigate the dimensions of the final build as well as cost.

The second justification relates to our decisions regarding representing data features through color and luminance. We did not want to overwhelm the user by using too many color variations. We also wanted to preserve the values of the features by using color in a way that tied max values to the color orange and lower values to color blue. We did this "honestly" by encoding the light color with the exact data values that they represent from the dataset.

4 Findings and Discussion

The creation of our physical data visualization yielded several insights into the dataset and relationships between different attributes for both world regions and countries. This amounted to the discovery of outliers, as well as large scale trends.

To begin, there was a major differential in happiness between the global west and global east, with the west being far more happy on average. Despite this major distinction, there were some regions with highly variable happiness, such as the Middle East and North Africa. For instance, Saudi Arabia was #34 for happiness, but Syria was #156. Northern Europe was generally the happiest overall region, boasting 6 countries in the top ten. By far, the least happy region was Sub-Saharan Africa. The happiest country was Denmark, the least happy country was Burundi.

There were also some interesting outliers discovered using our visualization. For instance, Somalia is about average for happiness, but is very low for life expectancy. Conversely, Syria is relatively high for life expectancy, but the second lowest country in terms of happiness. Additionally, Iceland is third in happiness, but is relatively low in government trust, whereas Rwanda is very low in happiness, but very high in government trust.

These outliers are not simply quirks that are easy to discover with a simple visual search. Rather, they paint descriptive pictures about the reasons each country stands where it does. Iceland is a very nice place to live, but in 2016 the Prime Minister resigned over corruption charges, leading many Icelanders to have reduced trust in the government. After the Rwandan Genocide, a new government was established to promote unity, peace, and tolerance, despite the impoverished African nation continuing to struggle with health and finances.

We noted many of these trends after constructing and testing the visualization. Moreover, when the visualization was set up in public, we noted that many users came to the same conclusions about several of these large scale trends and outliers that we did. From this passive qualitative observation, we ascertained that the insight the visualization produced was robust.

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