Ross-Chernoff Glyphs Or: How Do We Kill Bad Ideas in Visualization?

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Abstract
As data increases in dimensionality or complexity, it becomes difficult to graphically represent data items or series in a straightforward way. Chernoff faces encode data values as features of a human face, but afford only a handful of dimensions, and can be difficult to decode. In this paper, we extend and improve Chernoff faces by merging them with the work of landscape painter Bob Ross, creating data-landscapes glyphs that directly encode data as three series with arbitrary numbers of data items per series. This is pretty obviously a bad idea, yet it is difficult to precisely articulate why, given the current state of the art in academic visualization. We propose and evaluate this technique as a way of highlighting these gaps in our ontology of bad visualization ideas, with the goal of being able to dismiss future bad ideas right out of the gate.

Author Keywords
Information Visualization; Bad Ideas; Artistic Visualization; Multidimensional Visualization; Glyph Design; Deep Learning

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

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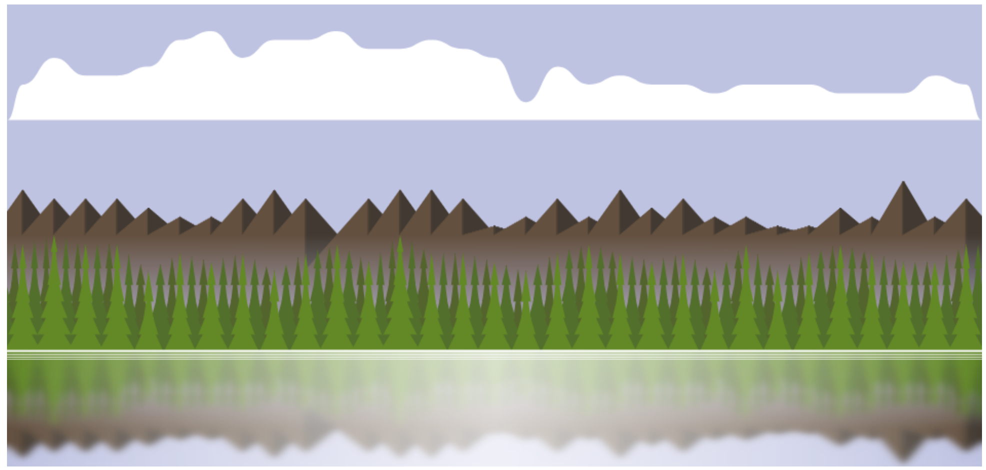

Figure 1: A meta-Ross-Chernoff visualization of Bob Ross's painting subjects, over time. Horizontal position is the season of "The Joy of Painting," the height of the treeline is the percentage of paintings depicting trees, the height of the mountains the percentage of paintings depicting mountains, and the height of the clouds is the percentage of paintings depicting clouds. From a dataset provided by FiveThirtyEight [12]

Introduction

If you have data you want to visualize, then you should select the values you care about, and then select a visual variable to encode each of those values. Some visual variables are easier to distinguish and more accurate to measure than others. If you have quantitative data with many dimensions, then you might have to select multiple visual variables. Unfortunately, as the complexity of the data increases, these visual variables are more and more difficult to disambiguate and interpret, and we are left with visual variables that are less and less suitable.

Can we generate a set of visual variables that still afford things like pop-out effects, quick summarizations, and comparisons, without these issues of interference and complexity? Enter the Chernoff face: humans are very good at recognizing faces, and in fact have specialized areas of the brain that recognize and process human faces. The same brain processes that help us identify religious figures in toast can be used to visualize high dimensional data in compact glyphs, with each facial feature encoding a different dimension.

Chernoff faces were proposed in "The use of faces to represent points in k-dimensional space graphically" [3]. From a Google Scholar search on the day of composing this sentence, the Chernoff faces paper has been cited 1,856 times (not counting the citation in this paper). Assuming a linear model of my own citations (R = 0.98), it would take over 20 years for the cumulative citations of all of my published work to have as many citations as this paper. In comparison, “Tree-maps: A space-filling approach to the visualization of hierarchical information structures,” [13] had been cited a mere 1,733 times. This is despite the fact that treemaps have seen wide use and adoption by the visualization community, with many proposed extensions. The most cited extension to Chernoff faces has been an alteration to afford asymmetrical faces (thereby doubling the potential dimensions to encode) [7]. Additionally, Chernoff faces have been criticized for being both difficult to interpret and non-orthogonal in their presentation of dimensions [15].

To put things less delicately, Chernoff faces are an example of an idea that is widely acknowledged to be bad, that is used by essentially nobody in the real world, and yet is nonetheless widely circulated in academia. Contrast this with rainbow colormaps and 3D pie charts, which have also been generally complained about, but are still seen in the wild with some frequency. It is true that many of these citations occur in historical reviews (the top 18 most cited works that cite Chernoff faces are all books or survey papers), but the work is still frequently cited even in traditional conference papers (the last occurring non-book or survey citation occurring within 6 days of my composition of this sentence, according to Google Scholar), and are actively studied. Fuchs et al. [8] report *26* different papers with empirical evaluations of face-like glyphs.

There are three overlapping explanations for the somewhat paradoxical citation popularity of Chernoff faces in the face of their apparent non-utility.

1. Chernoff faces are cited for **historical flavor and context**, rather than as a “serious” citation of a viable technique. Why visualization papers feel the need to cite things like this as frequently as do, whereas physicists don’t feel the need to continuously cite geocentric models of the solar system, nor biologists to cite works about spontaneous generation, is left unexplored.

2. Chernoff faces are cited as a **straw man**, a non-viable model to make a proposed technique for multi-dimensional data seem stronger by comparison. One hopes that reviewers are not fooled by scams like these, but you never know.

3. People believe that Chernoff faces are *almost* a good idea, but are **waiting on further iteration** before being willing to commit to their use.

Since the first two explanations are indicative of systemic and potentially fatal issues in visualization as a field of scientific inquiry, I can only conclude that, in fact, the visualization community is seeking further iteration on Chernoff faces in order to justify their no doubt incipient popularity. Therefore, in this paper I present the Ross extension to Chernoff faces, a glyph-based method of high-dimensional visualization that affords quick summarization without relying on the non-orthogonal aspects of facial recognition.

I propose this extension not in hopes of supplanting Chernoff faces (although I wouldn’t say no to a few hundred citations), but as a call to action that **we need a better vocabulary and ontology of bad ideas in visualization**. That is, we ought to be able to better identify ideas that seem *prima facie* bad for visualization, and better articulate and defend our judgments.

Related Work

Chernoff Faces

Chernoff faces were introduced in the early 70’s as a way of visualizing data with a good dozen or so dimensions. Each dimension of the data is encoded as a different facial feature. For instance, one dimension could be the angle of the eyebrows, another the curvature of the mouth. The original technical report [3] includes two case studies, a comparative clustering with dual coding, and full source code for generating your own faces. To be honest, the case studies are pretty compelling; if you choose the right features for your data, outlier detection is easy (finding the one frowning face in a sea of smiles, for instance). If you're similarly lucky with your features, clustering is probably pretty consistent (grouping together the happy faces, or the angry faces, etc.). Likewise, the reasoning for the facial encoding, that humans are well-trained (and perhaps even innately wired) to make small distinctions between faces, seems plausible. We're good at estimating gestalt facial features like emotion and gender, after all [10]. Chernoff would have to include some more citations to related work in glyph design and clustering, and perhaps throw some p-values into one of his case studies, but it's not unreasonable that, in a universe where the original paper did not exist, something very close to the Chernoff paper would be accepted into a top-tier visualization conference.

Unfortunately, there are some issues with Chernoff faces. The first are issues that have arose as a result of empirical inquiry. For instance, not all facial features are equally salient or effective [4, 18, 24]. Differences in eyebrow and mouth orientation, for instance, may be easier to detect than differences in eye or nose shape. It's also unclear if the facial design provides any benefit [25], or if people would do just as well with a glyph design that was more abstract. Face-like glyphs were the most common experimental condition in glyph evaluation papers identified by Fuchs et al. [8], yet there was no clear consensus about the utility of Chernoff faces. More traditional glyph designs (such as glyphs made up of abstract bars and lines) outperformed face-like glyphs across a variety of different tasks [2, 17, 19]. While there were some positive empirical results for Chernoff faces, I've cherry-picked my references such that I don't have to talk about them in detail. At the very least, I'm convinced that Chernoff faces are not *obviously* better than their competition, and that the benefits of the face-like design may have been oversold.

The second class of issues is that, honestly, they look silly, and fail all sorts of subjective smell tests. Data visualizations are supposed to be serious, and "clearly" present data (whatever that means [16]). If I were presented with a Chernoff face depicting serious world-changing information like disaster casualties or infant mortality or something, I'd think it was a cruel joke [6] in poor taste. Beyond the fact that they don't look very serious, Chernoff faces used on real datasets, at least in my opinion, are cumbersome, and don't give me much in the way of holistic information (see Fig. 2 if you don't believe me). They need extensive legends, and rely on so many important design parameters (which features should get which dimensions, for instance?), that it's hard to advocate their use in all but very contrived scenarios, such as when there are semantic connections between the data and the facial features (as in Fig. 3).

Bob Ross

Robert "Bob" Ross was the host of the long-running American public television show "The Joy of Painting," from 1983-1994. Each episode of the show would feature Bob Ross (or a special guest) painting a landscape painting using the wet-on-wet technique, where new paint would be quickly added to a canvas pre-treated with a coat of oil paint (usually "Magic White"). This method encourages quick, improvised paintings, as the painting must happen before the first layer dries. The paintings themselves were almost always some connection of "all-mighty" mountains, "happy little

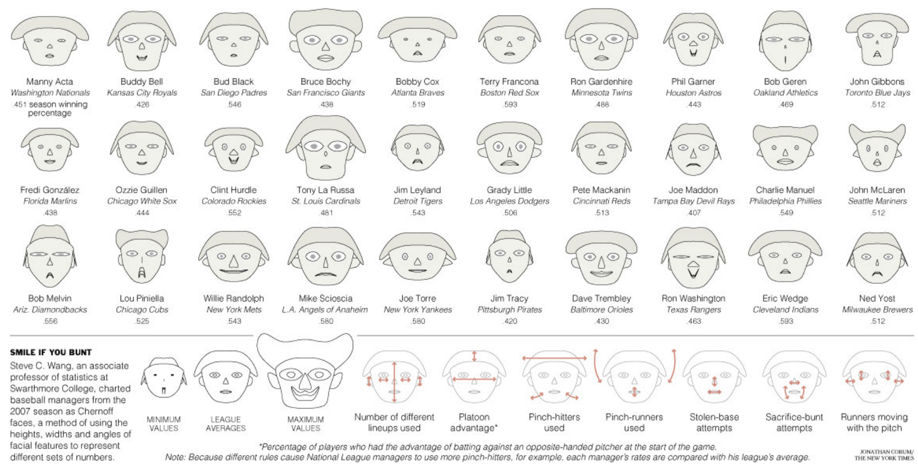

Figure 2: The most prominent example I could find of standard Chernoff faces being used by anybody, anywhere, from a New York Times article about scouting for talent in baseball [22]. We are supposed to be able to get a “holistic” picture of different team managers, but it just looks like a line up of Dick Tracy villains to me.

trees,” and “big fluffy clouds.” Fig. 1 shows the frequency of these subjects over time.

The show was popular, in no small part due to Bob’s soothing voice and positive attitude. He would make affirming statements such as: “anything we don’t like, we’ll turn it into a happy little tree or something; we don’t make mistakes, we just have happy accidents.” He would sometimes bring an animal friend such as a baby squirrel or owlet with him. A channel on the streaming platform twitch (https://www.twitch.tv/bobross) that re-aired old episodes of The Joy of Painting received over 5.6 million unique visitors in its first 24 hours [20].

Design

Since the utility of the face *qua* face in Chernoff faces is empirically murky, and people seem to like Bob Ross, it stands to reason that a Bob Ross-based modification of Chernoff faces would be at least as useful and as popular as the original. Even better, we are able to rapidly and reliably summarize and identify pictorial scenes [21] as discrete visual objects, so we can get away with calling a Bob Ross painting a “glyph.” Ergo, I propose the Ross extension to Chernoff faces, where each dimension of a data point is a different scene element in a Bob Ross-style image. Fig. 4 shows an example across three quantitative dimensions. The scene elements are composed of the three nearly ubiquitous elements of Bob Ross paintings [12]: clouds, mountains, and trees. Rustic cabins, roaring ocean waves, and other elements remain unexplored extensions.

An advantage of these scene elements is that, since they superficially resemble line or bar charts, Ross-Chernoff glyphs can be used for the original purpose of Chernoff

Figure 3: An example of a use of Chernoff-like faces that I actually like, from axios.com [9]. Different health measures for each U.S. state are encoded in semantically relevant facial features. For instance, the size of the bags under the eyes is connected to the percent of citizens who report not getting enough sleep each night.

faces (representing objects in *n*-dimensional space), but can also be used (as in Fig. 1) to represent time series data. If, for some unforeseen reason, you wish to make your own Ross-Chernoff glyphs, feel free to use the p5.js code available at https://github.com/mcorrell/ross-chernoff. Research code can sometimes be brittle and difficult to understand. To counteract this problem, I have commented the code such that it resembles the transcript of an episode of "The Joy of Painting."

The painting-like glyph is divided into slices. Each slice contains a segment of a happy little cloud, a peak of an all-mighty mountain, and at least one happy little tree from a deep, dark forest (see Fig. 4). These components are then reflected in a lake at the bottom of the glyph, for no very good reason other than the fact that Bob Ross frequently included reflective water in his paintings. If you need an ac-

Figure 4: An un-styled Ross-Chernoff glyph, encoding three dimensions. The height of a fluffy little Beziér cloud is one dimension, the height of a triangular mountain is another, and the height of a pine tree is the last. There is a lake with a reflection of the scene at the bottom, because that's what Bob Ross would have done.

tual design rationale, squint and pretend it's a redundant encoding. The actual rendering of these scene components is left to the designer, from relatively simple renderings such as in Fig. 5, to more painterly drawings such as Figs. 1 or 6. While these embellished bar-chart-like representations of data have performance issues compared to standard bar charts [26], they are at least in the same ballpark of legibility as standard visualization techniques.

Extensions

Additional dimensions can be encoded in Ross-Chernoff glyphs through the use of additonal Rossian scene elements such as rolling hills or barbed wire fences, or through the overlapping of existing scene elements (for instance, rows of mountains and foothills). For even more verisimilitude to the Bob Ross aesthetic, designers can either hand-paint their glyphs, or employ automatic styling using neural nets, as in Fig. 7. Lastly, to divide up slices, and provide more separability between dimensions, designers could

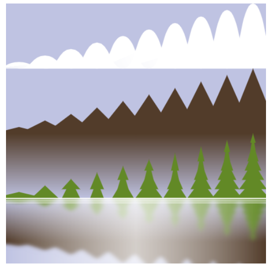

Figure 5: A sample Ross-Chernoff glyph, encoding either a single data value of 30 dimensions, or, equivalently, three time series with 10 time points.

Figure 6: A Mucha-Ross-Chernoff glyph of value per share of stock for 2017. Clouds encode Apple, mountains Amazon, and trees Google. Seasonality (Q1-Q4) is encoded by the style of the segment of the glyph.

separate the slices into seasons, an art nouveau touch that resembles the work of Alphonse Mucha (Fig. 6).

Evaluation

There are several groups of people with whom I am collaborating or otherwise enmeshed. I have access to their data, and they have invested months if not years in the success of my projects. They came to me because they couldn't solve their visualization problems on their own, and now rely on me to solve these problems. Therefore, for many

(a) A traditional linegraph of bitcoin prices.

(b) Automatically restyled as a painting.

Figure 7: Using a neural net to automatically restyle a time series, from Moritz Klack [14]. This would be a useful way of generating custom Ross-Chernoff plots, and also allows me to include "deep learning" in the author keywords.

practical purposes, I am holding them as empirical evaluation hostages. I can offer them any dumb experiment and they will be obligated to do it. Plus, since they probably have a pretty good idea of what I'm working on, participant response bias is likely to be highly pronounced [5]. In that spirit, I gave a group of experts (defined here as "people with whom I go drinking") the same data, encoded as both a Chernoff face and a Ross-Chernoff glyph (Fig. 8), and solicited free text responses. Fig. 9 shows their responses as word clouds. My participants used a slightly higher percentage of positive words (as determined by the AFINN sentiment lexicon) about the Ross-Chernoff glyph than the traditional Chernoff face ($M_1 = 2.8$%, $M_2 = 2.5$%), but this result was of course not statistically significant ($t(4) = 0.18$, $p = 0.9$). Still, I can claim that people like Ross-Chernoff glyphs "just as much" or "no worse" than the existing solution, thereby getting my foot in the door.

I could have run an quantitative comparative study on user performance, but that a) would have required a lot of work and b) since Chernoff faces have such a spotty and ambiguous evaluative record already, what's the point of comparing them directly? There are probably some things that Chernoff faces better support than Ross-Chernoff glyphs, and vice versa. These effects are probably small, and highly dependent on task, context, and design. There are so many researcher degrees of freedom [23] that I am more or less guaranteed to find at least one scenario where Ross-Chernoff faces seem to excel. Pretend I found one or two of the needles in that particular haystack, and reported them here.

Discussion

Ross-Chernoff glyph most likely, to use a term of art, suck. My intuition about this is that a) the embellishments on the individual values will introduce error in decoding the values [11, 26] and b) it is difficult for us to pick out individual features from the scene as a whole (for instance, the comparison of all trees that are third-most from the left), for some of the same reasons why we are susceptible to things like change blindness in natural images [21]. They may not suck as much as other types of glyphs in certain scenarios, but it seems like a fool's errand to enumerate each of the potentially highly idiosyncratic situations where they are better than the competition. In general, I think that Ross-Chernoff glyphs are a low value visualization [27]: they would take a lot of getting used to from stakeholders, and do not seem to have any strong and obvious benefits over, say, a collection of bars or even a star- or radar-glyph. Over the course of iterating on the designs for these glyphs, I actually got pretty good at clustering and outlier detection with these things, but that's probably true of many designs I could have potentially generated.

My question is: how do we determine that the suckitude of Ross-Chernoff glyphs is sufficiently high without, at a minimum, two or three papers worth of work? I've got some strong suspicions, but it might take one or two powerful experiments to verify them. At the very least, I'd have to grab some results from the perceptual psychology literature and hope the ecological validity doesn't degrade too much by the time I've applied them to the matter at hand. If we lived in a universe where Ross-Chernoff glyphs were already grandfathered into the academic discourse, how would we stop the profileration of Ross-Chernoff variants, and evaluations of those variants, etc. etc.? Is it possible, in principle, for any reasonably designed visualization to be sucky enough to not warrant further investigation? How do we kill a bad idea in visualization, and when is it valuable to perform this euthanasia? Are there mistakes in visualization, or just happy little accidents?

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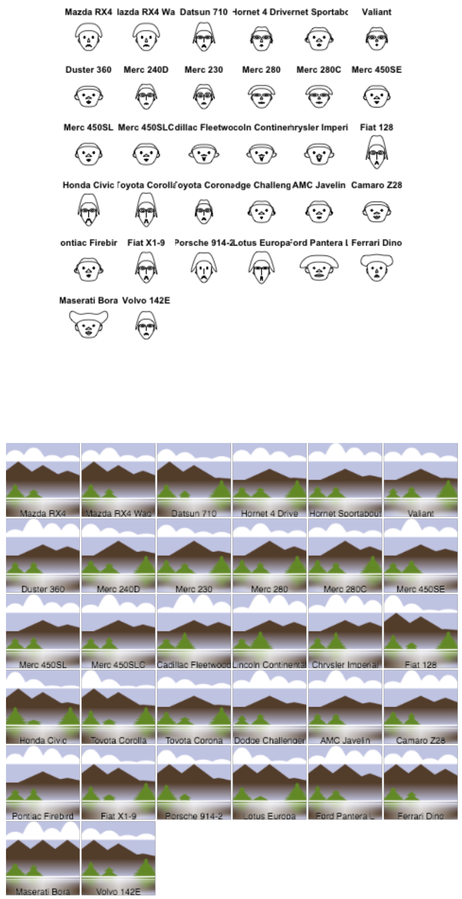

Figure 8: A comparison of Chernoff faces and Ross-Chernoff glyphs on the 1974 *Motor Trend* cars dataset [1]. Although both support outlier detection and clustering, please do not use either for data you care about.

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(a) Chernoff face descriptions.

(b) Ross-Chernoff glyph descriptions.

Figure 9: Words people used to describe Chernoff faces and Ross-Chernoff glyphs when presented with the cars dataset visualizations from Fig. 8.

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