# Studying Biases in Visualization Research: Framework and Methods

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**Abstract** In this chapter, we propose and discuss a lightweight framework to help organize research questions that arise around biases in visualization and visual analysis. We contrast our framework against the cognitive bias codex by Buster Benson. The framework is inspired by Norman's Human Action Cycle [1] and classifies biases into three levels: perceptual biases, action biases, and social biases. For each of the levels of cognitive processing, we discuss examples of biases from the cognitive science literature, and speculate how they might also be important to the area of visualization. In addition, we put forward a methodological discussion on how biases might be studied on all three levels, and which pitfalls and threats to validity exist. We hope that the framework will help spark new ideas and guide researchers that study the important topic of biases in visualization.

## 1 Introduction

"Look, the earth is flat. I can see it with my own eyes." At sea-level, the curvature of the earth is too small to be perceivable to the human eye. The illusion of a flat earth is no hallucination. It is a limitation of the perceptual system. Yet, the realization that our planet is (relatively) spherical dates back to the early Greek philosophers around 600 BC. And the realization did not occur due to paying more attention to the visual

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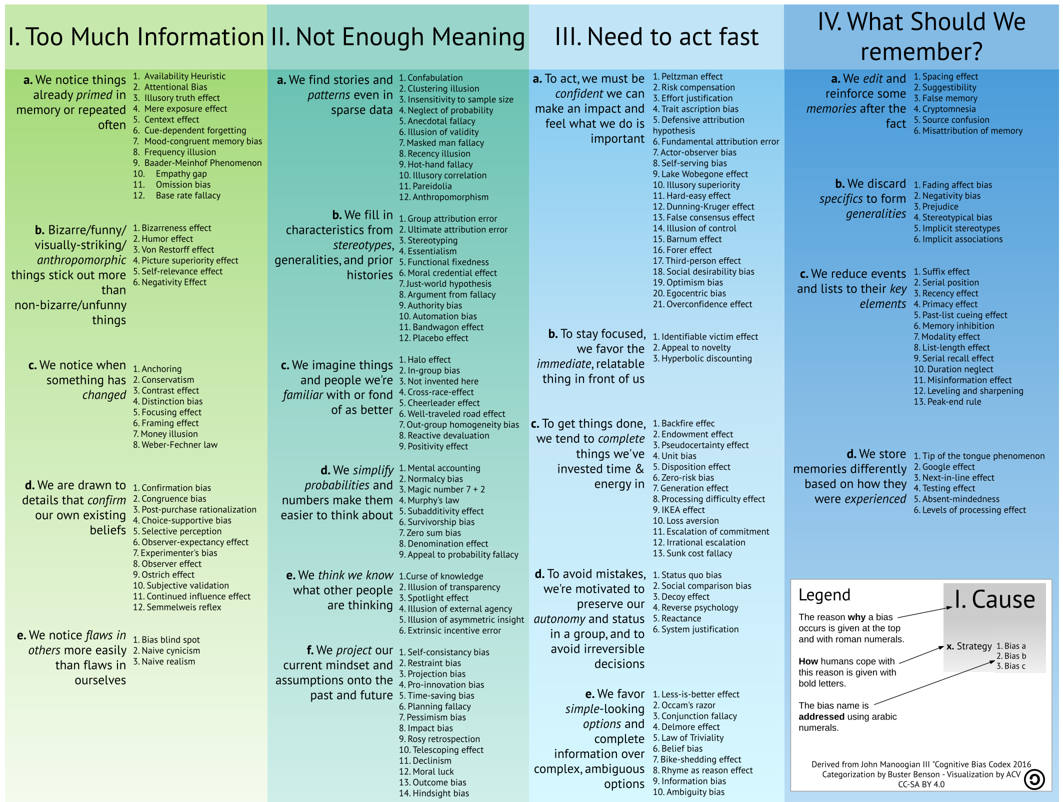


**Fig. 1** The Cognitive Bias Codex by Buster Benson maps biases according to cause and coping strategy. This image contains hyperlinks to wikipedia for easy look-ups. Simply click on the name of any bias to open a browser and look-up the bias.

impression, it came due to considering mathematical observations about the rotation of the night-sky and bodies of water—through science.

The scientific method was devised to investigate natural phenomena that are hidden from human sight. Either because they were too small, too large, too fast, too slow or too rare for human perception. The human body and thus its perceptual system were crafted by evolution to enable survival of a primate in the savanna. Capabilities like objective measurement or accurate judgment of the external world are neither necessary nor helpful for survival. Being able to make decisions quickly with limited information and limited resources could make the difference between death by saber-tooth or last-minute escape. Therefore, the human mind is equipped with heuristics that help decision making with the aim of survival.

Todays world is drastically different! Yet, human perceptual and decision making processes remain largely unchanged. People nowadays have to deal with different types of information, different amounts of information, and make much more delicate decisions. Decisions, such as quickly detecting a critical pattern in an x-ray image, can make the difference between life and death. Decisions, such as stock-investments derived from numbers displayed on a computer screen, can influence the global economy. To gain trust in such decisions, visual inspection and communication of the underlying data and models is often an essential component. Ideally, the data and models are mapped to visual presentations that are easy to process and easy to convert into mental representations. The visual presentations should be as accurate as possible. Or as as Edward Tufte put it: Keep the lie factor between 0.95 and 1.05 [2]. So in theory, accurately presenting information with respect to the visual system should yield accurate decisions.

Still, our saber-tooth-fearing minds interfere. Not only is the visual system imperfect, our cognitive system has its pitfalls as well. Even when a system provides information perfectly honest, human biases might distort the information and lead to imperfect or outright bad decisions. For example, a business person might invest further into a project that had already cost more than expected, as the relative prospective investment to finalize the project appears smaller than the retrospective cost of not completing the project. The **sunk cost fallacy** is the reason why many publicly funded projects cost more than previously anticipated. Nobody likes to tear down the already overpriced 80%-complete 100 million dollar airport. We might just invest another 10 million dollars to complete it—and then another. Could an accurate visualization have helped the business person? Should it have overemphasized the additional costs?

The body of research on such biases is extremely large. Since Tversky and Kahnemann received a Nobel price for their work on biases in 2002, research regarding biases has sprouted into all kinds of fields. From distortions in perception to distortions of complex social phenomena, the spectrum of biases is very wide. A systematic (reduced) overview of the most prominent biases can be seen in Figure 1. In this figure, biases are classified in three levels of hierarchy. The first level separates the assumed high-level reasoning behind the existence of the biases. All of them are rooted in the limited perceptual and memory-related capabilities. There is either too much information available, too little meaning in our model, too little time to integrate the information, or too much information to memorize.

The second level of ordering describes strategies to cope with this reasoning. Each strategy leads to several different distortions or biases. For example, the **availability heuristic** (see Figure 1 at I.a.1.), describes the phenomenon that we assume things to be more frequent or important depending on how easy, or how available our mental recollection of them is [3]. It's much easier remembering the 911 attack on the World Trade Center, than a toddler drowning in a home swimming pool. This leads to a misconception. People overestimate the risk of becoming a victim of a terrorist attack and underestimate the risk of drowning in a swimming pool. Another example: The **Dunning Kruger effect** (see Figure 1 at III.a.12.) describes the phenomenon that people with little experience in a subject overestimate their knowledge in that subject, while people with lots of experience underestimate their knowledge: "The more I learn, the more I realize how much I don't know". The anti-vaxxer thinks he has understood the required field of medicine to evaluate the efficacy of vaccinations, while the medical researcher carefully considers different explanations and possible errors in their experimental setup. However, in such a scenario many other biases are at play.

These examples could easily benefit from visualizations depicting the real data. But, what if even with high quality visualizations biases persist. There is little research on biases in the field of visualization [4–6], with the exception of the DECISIVe workshops at VIS. Most of the aspects that have been addressed, relate to perceptual or cognitive limitations (e.g., magic number $7 \pm 2$) that are familiar to researchers in human-computer interaction. Other areas have been largely ignored though.

In this book chapter, we draft and discuss a simple conceptual framework that can be used to guide research on biases in visualization. The framework proposes a 3-tier model of perception, action and choice, where each tier corresponds to different methods to study bias effects.

We hope that the framework will help us shed further light into the following aspects: What are interesting research questions on biases in VIS, and how can we methodologically address them? What has already happened in the cognitive sciences and what can we learn from the results and pitfalls in this large body of research.

This chapter is based on a workshop paper [7] presented the DECISIVe Workshop at the IEEE VIS conference 2017. The book chapter incorporates the discussions from the workshop and extends the suggestions regarding the use of certain methods for different levels of biases in our framework.

## 2 A framework to study biases

The field of research on cognitive biases is large, thus organizing biases has been attempted in multiple ways. Buster Benson (see Fig. 1) ordered biases according to causes and strategies. Ellis and Dix [6] propose categorizing biases that occur during interpretation of visualization and those that occur later during reasoning. However some biases may occur on lower levels of perception (e.g., spider-like shapes [8] or word superiority [9]) and on higher levels of reasoning shaped by culture (e.g., the belief of a just world [10]).

Our framework is inspired by Don Norman's venerable Human Action Cycle [1]. His cycle describes seven steps that humans follow also when interacting with computers. The seven steps are further classified into three stages: (1) the goal formation stage, when the user forms a goal for her/his interaction (2) the execution stage, in which a user translates the goal into actions and executes them, and (c) the evaluation stage, in which feedback from the UI is received, interpreted, and compared to the user's expectations.

This model can be considered a "medium-level" model. The whole task of "perceiving" (see Figure 2) is a lower-level loop on its own. On the other hand, the whole action loop in itself can be considered a sub-step in a higher-level loop model of bounded rational-choice. Naturally, these levels are not hard biological limits [11], as the cross-talk between individual steps across layers do also occur. Specifically, from a neuro-cognitive perspective, perception is less a "step-wise" open-loop procedure, but rather the convergence to a stable neural attractor state in a continuous closed-loop [11]. Perception is an active process. However, methods exist to interrupt the loop. By breaking the loop, individual steps can be studied to find step-based effects.

The idea of our framework is to provide a frame of reference when investigating a bias. In this frame of reference, different biases can occur on, or between different levels. And different methods and methodologies might be necessary to investigate biases on different levels.

Our framework differs from the categorization presented in Fig. 1 as it refers to different levels of cognitive processing, as where Buster Bensons categorization follows a "cause-strategy" logic. Our framework works orthogonally to the categorization as it provides a multi-scale model of cognitive processing. While the categorization of Benson is helpful in organizing biases, it provides little insight in how to analyze, measure and counter-act a bias methodologically. Our framework aims to help in studying cognitive biases in visualization research by suggesting methods for the different levels of cognitive processing where biases may occur.

For example, the clustering illusion is caused by an systematic tendency of the pattern recognition step in the motor-sensory-motor loop (see Fig. 2. This step is prone to overemphasizing possible patterns. Further, cross-talk is at play. When a person is looking for a certain pattern (i.e. bounded rational-choice step: Intent), his attention is directed towards such patterns (crosstalk). This attention pre-activates the sensory systems and in turn leads to biased evaluation and pattern recognition. Identifying and understanding such a bias in visualization, would require identifying methods to isolate the steps. Other biases can be mapped similarly.

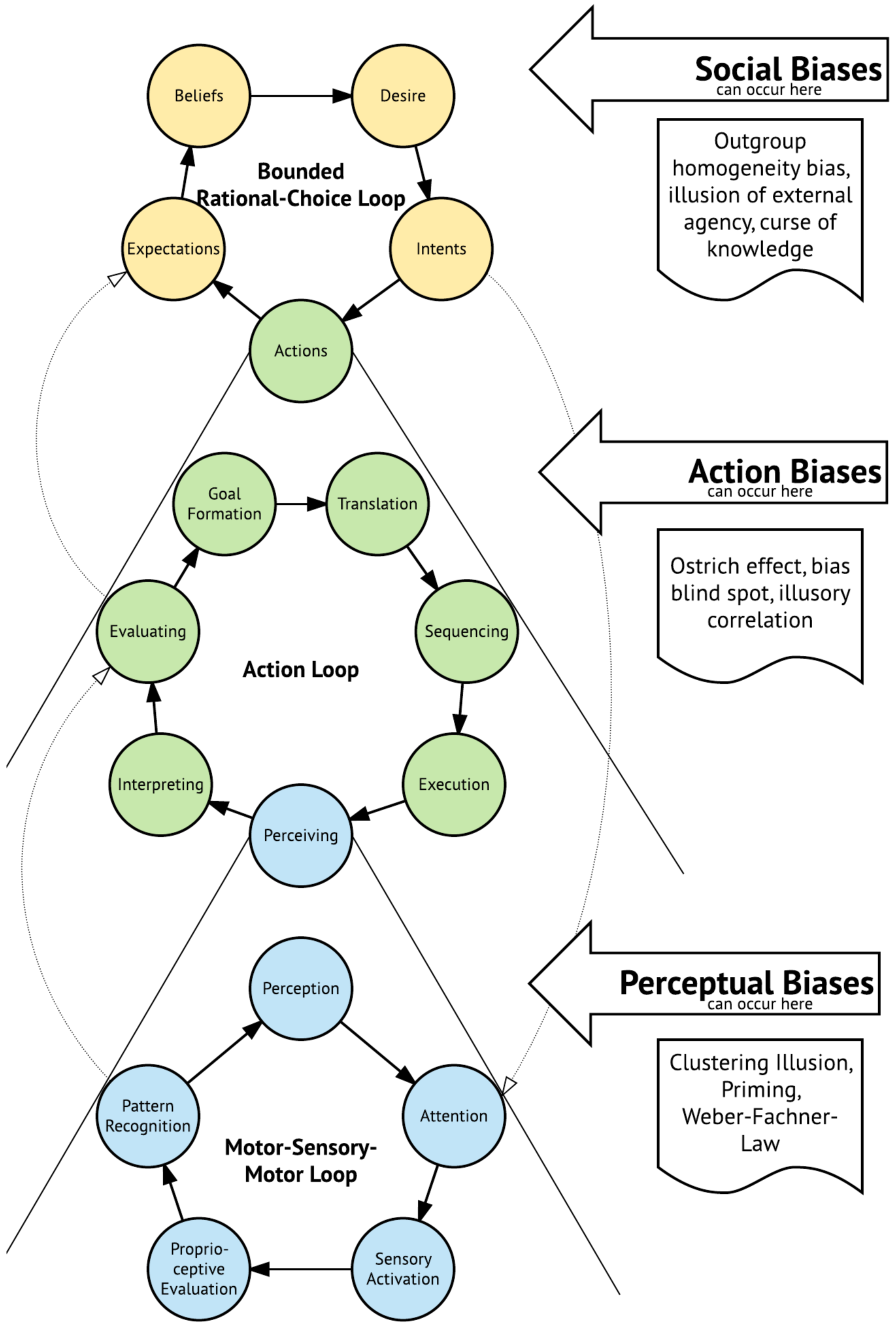


**Fig. 2** Layered closed-loop perception, action, and choice model. Since no hard boundaries exist between layers, cross-talk is part of the closed loop model (see exemplary dashed arrows).

## 2.1 Perceptual Biases

Perceptual biases refer to biases that occur on a perceptual level. In our framework, this layer is based on the motor-sensory-motor loop by Ahissar and Assa [11]. Examples of such biases are the clustering illusion, Weber-Fechner Law, or priming biases. The perception itself is biased here. One cannot “unsee” the distortion caused by the bias.

The **clustering illusion** [12, 13] is a bias, that explains why people see patterns in small sets of of random data. People underestimate the consequence of variance and how even little sets of random data might have clustered data. A typical example is, that if you throw a dice three times and it turns out three sixes, people will assume that the dice is unfair. And they might feel quite confident about it. However, the sequence “1-2-3” is equally probable as the sequence “6-6-6”, since the throws are statistically independent. This bias is important for visualization research, as users of a visualization could over-interpret low-density scatter-plots and draw causal conclusions were non exist. Creating proper null plots, that is, visualization showing simulated data from the null hypothesis, could be a remedy for this bias [14, 15].

The **Weber-Fechner Law** is a famous finding of early psychophysics indicating that differences between stimuli are detected on a logarithmic scale. It takes more additional millimeters of radius to discern two larger circles than two smaller circles [16]. This type of bias is probably one of the most researched biases in visualization research [17, 18].

**Priming** relates to findings from theories of associative memory. It refers to the idea that concepts are more quickly activated after a similar concept has been activated. The “prime” warms up the neural circuitry associated with the target, which allows faster recognition of the target. The term “so_p” is more easily completed to “soup” if you have heard terms like *butter, bread, spoon*. It’s more easily recognized as “soap”, when terms like *shower, water, bath* were heard before [19, 20]. This could have effects on recognizing patterns or separability in visual perception, if such patterns or results have been pre-activated [21].

## 2.2 Action Biases

Action biases refer to biases made in decision making. That is, when the perception is adequately mapped to a mental representation. Yet, the interpretation or evaluation of the percept is distorted. These biases can be reduced by training. However, even skilled people underestimate how much they are prone to biased decision making—as stated by the Bias Blind Spot [22]. These biases occur on the second loop in our research framework—the human action loop [1]

Typical examples of action biases are the ostrich effect, illusory correlation, anchoring effects and the aforementioned availability heuristic. **The ostrich effect** [23] describes an individual’s tendency to overlook information that is psychologically uncomfortable, like the proverbial ostrich that buries his head in the sand. If you want to know why you tend to forget your full schedule, when accepting reviewer invitations: Blame the ostrich effect. It is important to study this bias in visualization research, as users might overlook information (such as a busy schedule) and make decisions not in their best interest. Visualizations aware of risks and consequences could try to compensate for such effects [24].

**Illusory correlation** refers to the tendency of humans to seek correlation in events that occur contingently in time [25]. Humans seek meaning in things that occur at the same time. This leads them to overestimate correlation of low frequency events with other less familiar high frequency events. Giving your son the name “Osama” seems inappropriate to a person inexperienced in Arabic naming frequencies, as their association with this name might be most strongly with Osama bin Laden. However, the name Timothy does not evoke such associations as it also occurs frequently in other contexts (other than the Oklahoma City Bombing by Timothy McVeigh). Illusory correlations also seem to be the reason for racial stereotyping. Such effects could be countered in a visualization by emphasizing proportions of populations. Good examples are absolute risk visualizations as euler glyphs [26].

## *2.3 Social Biases*

Social biases refer to biases that affect judgment on a social level. These effects occur on the highest level, the bounded rational-choice loop, because of cumulative effects on lower levels or because of imperfect memory. Social biases occur because of systematic biases during socialization (e.g., limited linguistic capacity implies limited cognitive capacity [27]). Famous biases in this category are the curse of knowledge, the outgroup homogeneity bias, or the illusion of external agency. Social biases should be affected by culture, while action biases should not.

The **outgroup homogeneity bias** refers to the phenomenon that people tend to see people outside their own peer group to be more homogeneous than their own in-group [28]. This is on the one hand caused by the availability heuristic—I have more memories of individual differences among my friends than among others. It is, on the other hand, also caused by imperfect memory, and stereotypical memories. That’s why one might believe that foreigners are all “terrorists and free-loaders” and might not be able to perceive the diversity of motivation in foreigners. It might be interesting to investigate, for example, whether labeled data in a scatterplot visualization leads to improved separability if one of the labels refers to a typical out-group and another to an in-group of the user.

The **curse of knowledge** refers to the phenomenon that once a person has acquired knowledge they may no longer be able to take the perspective of someone not having that knowledge [29]. This is why teaching or writing are hard. You yourself always understand what you intended to write. Everyone else might have a harder time grasping your ideas. This is also relevant for visualization research. When designing a visualization iteratively, it merges the collective knowledge of end user and developer [30]. In the end, both believe the visualization is perfectly intuitive.

They might however overlook features that are based on their extensive knowledge from the development phase. New users might have a harder time understanding what your intricate visualization design might mean.

The **illusion of external agency** [31] refers to the illusion that the quality of an experience that is explained to have been optimized for the recipient is rated as better than an experience without such explanation. The external agents reality, however random it might actually be, causes a differently constructed internal reality. This is important in visualization as something that might be mistaken for a recommendation, e.g. the first item on a list, is perceived to be a better solution than any other. Even if no such recommendation was ever planned. Visualization should be careful in depicting information first, if there is no intention behind this choice.

## 3 Methodological considerations when studying biases

It is important to understand how biases affect judgments, specifically as visualization usually aims at providing objective information. However, studying such biases is not as easy as it might seem. Some biases might counteract each other, and experiments have to be meticulously planned to isolate the desired effect from other effects.

By identifying on which level of cognitive processing the bias occurs, it becomes simpler to pick a method to identify and measure the strength of the bias in a given scenario.

### *3.1 Perceptual biases*

Perceptual biases can be measured quite effectively using methods from psychophysics such as *staircase procedures* [32]. These procedures are designed to measure detection thresholds or just-noticeable differences between stimuli, by adaptively approaching indiscernible small differences [33].

If we take the **clustering illusion** (see section 2.1) as an example, the bias reflects the amount of non-existing patterns detected by a user. If we assume, that such patterns are more readily detected (despite their absence) in smaller sample sizes, we contrast two scatterplots side-by-side (as seen in Fig. 3 where either plot does, or does not contain patterns. We now ask participants, which plot shows patterns, and which does not. By adjusting the sample sizes on both plots, and randomizing which of the two actually contains a pattern, we can determine the effect of sample size on detecting patterns. However, since participants could also guess correctly, we need to determine the threshold of detection using for example the aforementioned stair-case procedure [34]. For this purpose we decrease the sample size from a starting value, by *n* samples (e.g., 1,000 in a first step, *n*=50, 950 in a second step) until we the users start detecting patterns. We then start increasing the sample size by *n* until the users stop detecting the patterns. At this point we start decreasing the sample sizes again (and repeat the whole process). The mean of the inflection points determines the sample size where the bias starts working. By presenting more than two plots, we can increase certainty by reducing the guessing probability.

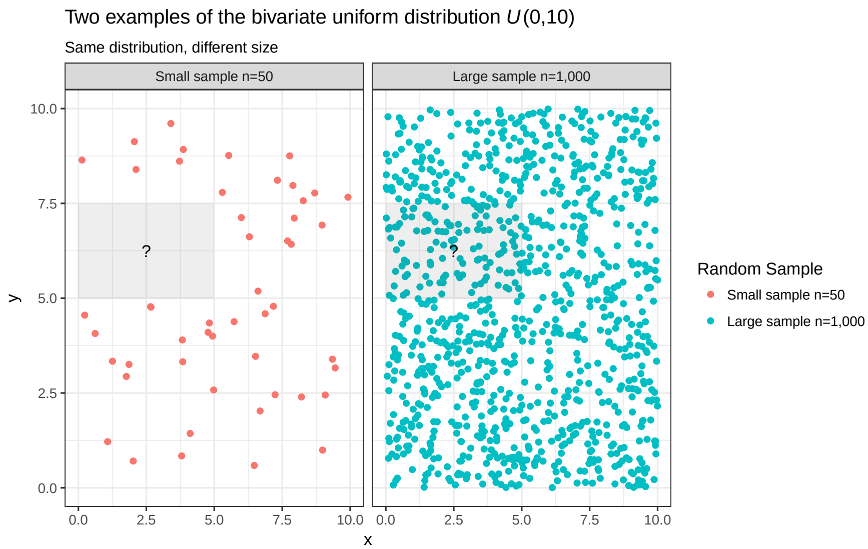


**Fig. 3** Clustering illusion in two scatterplots. Is there a pattern in the region with the question mark?

If we want to investigate the effect of priming in visualizations other methods can be used. One approach aims at cutting the closed loop in the motor-sensory-motor loop [11]. This can be achieved by *subliminal activation* of primes ($< 100ms$) and backward masking (showing another stimulus), before the priming stimulus even reaches higher levels of cognitive processing.

A suitable example for subliminal activation to detect the effect of priming could be constructed as follows. Assuming that the previous exposure to a scatterplot with two classes primes the separability of classes in a second visualization [21]. The higher the separability in the first plot, the easier it is to detect the separability in the second. To prevent that the separability of the first plot causes an increase on the second plot by higher levels of cognition, one must prevent the first plot to reach such levels (see Figure 4). By merely exposing the first plot for times less than 100ms and immediately showing a masking stimulus for a longer period of time (e.g., a masking cross), the first plot is not evaluated on a higher cognitive level. Only the pre-activation of lower-level neurons helps with increasing separability in the second plot.

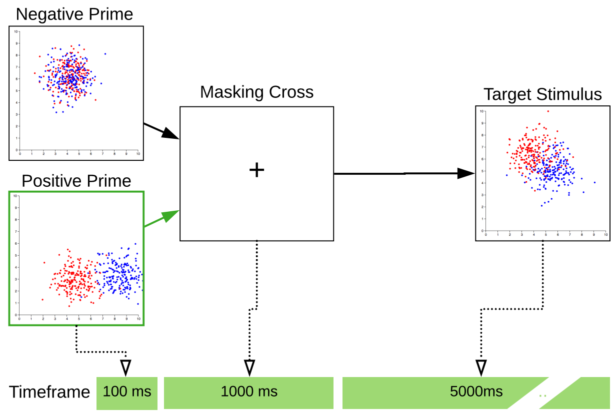


**Fig. 4** Experimental procedure for subliminal activation. By masking the subliminal prime (either negative of positive) with a non-subliminal mask, higher levels of cognition are prevented from influencing the decision on the target stimulus.

## *3.2 Action biases*

Methods to measure **action biases** are already far more diverse and tailored to the bias. For example, studies measuring anchoring effects explicitly try to minimize the effect, by instructing participants to disregard the anchor. The anchoring effect refers to the bias that any stimulus presented before an estimation task serves as an anchor for this estimation. For example: If we tell you the number 14 and then ask you how many species of penguins exist, your reply is going to be closer to 14 than if we had told you the number 412 before. In this case your reply would be closer to 412, even if we told you this number should have no influence on the next question and instructed you to ignore it. But, how do you map such a procedure to visualization research?

An anchoring effect can indirectly be caused by letting participants derive or read numeric outcomes from a serious of unrelated tasks. The numeric outcome should affect later evaluation due to the aforementioned *anchoring effect*. As an example, one could ask participants to first read a correlation coefficient—either large ($r = .95$) or small ($n = .05$)—and then let participants estimate correlation coefficients from bivariate scatterplots. Depending on the numeric value number in two different preconditions the correlation coefficient of the target stimulus should be shifted upwards for large anchors and downwards for smaller anchors (see Figure 5). In this case, the estimated and reported correlation coefficient would be larger (e.g., $r = .5$ instead of the actual $r = .4$), if the larger correlation were shown to the participants.

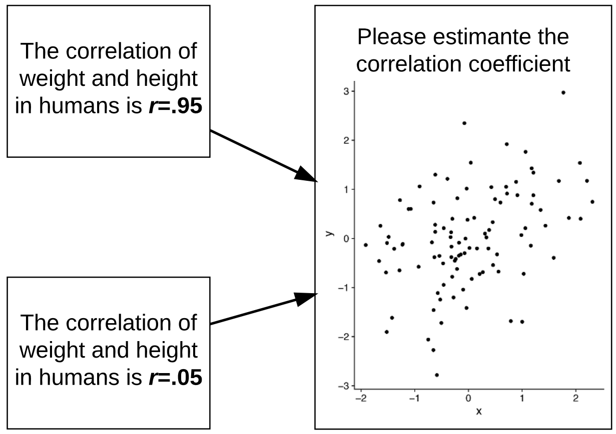


**Fig. 5** Participants first see either the upper text or the lower text, then the target is presented. The results from the left column (either A $r = .95$ or B $r = .5$) should affect the estimation of the target question on the right (where $r = .4$ is correct).

### *3.3 Social biases*

If you address **social biases**, the methodology is even more dependent on the individual bias. If a bias is based on other biases, one must make an effort to estimate the biases' individual contributions to the overall effect and reduce additional systematic measurement errors.

For instance, if you wanted to measure the **outgroup homogeneity bias** in a visualization, one could imagine visualizing very similar or even the same data but present it in different contexts. Similar data (i.e., same statistical properties) could be used to depict data of the participants ingroup and in another case of the participants outgroup. Then the participant is asked to rate the similarity of samples from the data (see Figure 6). The challenge is to ensure that no lower-level biases cause a measurable bias (e.g., anchoring, priming, pattern illusion). To reduce such effects, one could run the exact same study in an abstract fashion, that is, without the labels and tasks giving away the context for the respective groups.

As an example, one could imagine comparing politicians with respect to their similarity in a given party. Voters are—if the bias is present—more likely to rate the similarity of party members, if they would traditionally vote for the opposing party (see Figure 6).

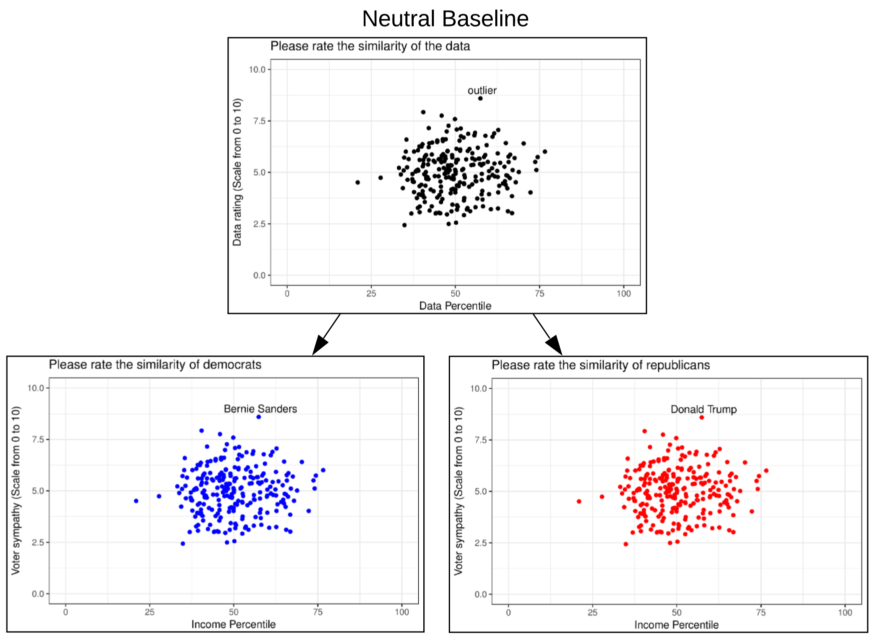


**Fig. 6** Depending on the political orientation of the participant, different ratings of similarity are expected for the lower two visualizations, although the distributions are exactly the same. The colors are shown for comprehensibility. In a real experiment, no difference in color should be used.

## *3.4 Application of the Framework to Derive a Model*

In order to utilize the framework when conceptualizing new research for a given bias, one should identify where in the framework the bias is "active". Where does the "irrational behavior" occur. Then one must aim at finding ways to minimize error from other processes in the framework.

If a bias works on the perceptual level, one must figure out a way to reduce the influence of the bounded rational-choice loop and the action loop. Mostly this is achieved, by applying methods from psychophysics research.

On the other hand, if a social bias is at work one must make sure that no lower levels of perception influence decision making. For this reason, the data in our example task were exactly the same preventing slight differences in the pattern recognition step at a lower level. However, the choice of color could also affect the judgment.

### *3.5 Threats to Validity*

In an open letter from Daniel Kahneman [35] published in *Nature*, the Nobel laureate asks researchers in the field of social priming to be cautious to publish results quickly without extensive consideration and replication. Inexperienced researchers might overlook systematic errors in experimental setups that cause distorted data indicating bias effects where none are present. The replication crisis [36] has shown that many social-psychological experiments were not reproducible. Therefore, measures to enhance reproducibility must be undertaken. It is crucial to identify methods, their benefits, and pitfalls, to understand how reliable findings actually are.

To ensure that biases are measured to the highest of standards, the VIS community should also follow guidelines as presented in the open letter by Kahneman [35]. However, it makes sense to start with small setups and first gather hypotheses. The guidelines should increase reproducibility and encompass rules such as reporting confidence intervals for long term meta-analytical research [37], open-data, preregistration of trials, and publishing of negative findings. In summary, he suggests:

- Effects should be reported using *confidence intervals* to enable long term meta-analytical cumulative research [37].
- Studies should provide all data as *open data* to allow other researchers to verify findings or even look for other explanations. If possible, release all analysis code.
- If possible, trials should be *pre-registered*, e.g., in the Open-Science-Framework.
- Sample sizes should be large enough, to ensure sufficient *statistical power* to match the expected effect size.
- Use technology to ensure all data is recorded.
- Publish *negative findings*.
- Several groups should try to validate the results of other groups. Kahneman proposed *daisy chaining*, where the results of each lab are replicated by the following lab.
- Replication should be conducted on the five most robust effects, if five groups participate in the daisy chain.
- Have guest researchers from within the daisy chain to ensure confident replication.
- Replication studies should have *larger samples* than original studies.

## 4 Conclusion

We presented a lightweight framework that helps to classify bias research in visualization. Our framework provides a frame of reference for selecting research methods, when trying to identify a bias in visualization research. We believe that visual biases are a fascinating area with ample opportunities for future work. Focusing on perceptual and action biases first seems a viable road to start this process, specifically as higher-level biases are highly vulnerable to methodological flaws, apparent in the huge discussions about Kahneman's famous work on "thinking fast and slow" [35]. However, carefully studying low-level perceptual and action biases will make up for a good underpinning, not only for better understanding high-level phenomena eventually, but also as a way to better understand decision making with visualization in general. Good practice such as reproducibility through publishing all data, codes and experimental setup, using confidence intervals to allow for meta-analysis, and reporting negative findings will be essential in this process.

As soon as such effects will be better understood in visualization, we also can start to counteract them. However, this will raise important philosophical questions: In how far is it valid to correct for these biases? Challenging current views [2], should a visualization "lie" to counteract biases and improve decision making? While for perceptual biases the answer might be quite clear, what about higher-level biases? Should the visualization decide what is in the best interest of the user? For example, may a visualization override the users preference to not know unpleasant information and counteract the ostrich effect? Much future research will be needed to answer these questions and to integrate the existence of biases into visualization research.

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