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Color Perception: Objects, Constancy, and Categories

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Abstract

Color has been scientifically investigated by linking color appearance to col-
orimetric measurements of the light that enters the eye. However, the main
purpose of color perception is not to determine the properties of incident
light, but to aid the visual perception of objects and materials in our envi-
ronment. We review the state of the art on object colors, color constancy,
and color categories to gain insight into the functional aspects of color per-
ception. The common ground between these areas of research is that color
appearance is tightly linked to the identification of objects and materials and
the communication across observers. In conclusion, we argue that research
should focus on how color processing is adapted to the surface properties
of objects in the natural environment in order to bridge the gap between
the known early stages of color perception and the subjective appearance of
color.

1. INTRODUCTION: WHAT IS COLOR?

The study of color vision in humans has been a successful enterprise for more than 100 years. In particular, the establishment of colorimetry by the International Commission on Illumination [Commission Internationale de l'Eclairage (CIE)] in 1931 has brought forward tremendous advances in the study of color in business, science, and industry (Judd 1952). During the past few decades, the processing of color information at the first stages of the visual system—in the cone photoreceptors and retinal ganglion cells—has been detailed at unprecedented levels of accuracy.

At the first stage of color processing, light is absorbed and translated into the excitations of three different classes of cones (Stockman & Sharpe 2000). At the second stage, the activity of the three classes of cones is compared in the retinal ganglion cells, resulting in the cone–opponent channels (for a review, see, for example, Dacey 2000, Gegenfurtner & Kiper 2003). There is wide consensus on the existence of a third stage of higher-level mechanisms that process specific combinations of the cone–opponent color signals and ultimately determine color discrimination and color appearance, even though their precise number and nature are still debated (Hansen & Gegenfurtner 2013, Shepard et al. 2017). Overall, color discrimination and color appearance may be approximated under controlled conditions through increasingly sophisticated color appearance models such as CIECAM02, CIELAB, and CIELUV (e.g., Fairchild 2013, Hunt & Pointer 2011).

This large body of knowledge allows us to precisely characterize the distribution of light in our environment at each individual point in space and time. For example, a hyperspectral image allows the spectral properties of light that reaches the eye to be specified (**Figure 1a**). For a standard human observer, we can calculate for each pixel the cone excitations at the first stage, the cone–opponent color signal at the second stage, and the approximate appearance of these points of light under laboratory conditions that control adaptation and context across the visual field. As a result, we can obtain a distribution of color coordinates in a color space that represents the colors of all the pixels within an object, such as the banana shown in **Figure 1**.

Unfortunately, we cannot yet predict the color appearance of the banana from this distribution of color coordinates. One difficulty with the prediction of color appearance is that existing color
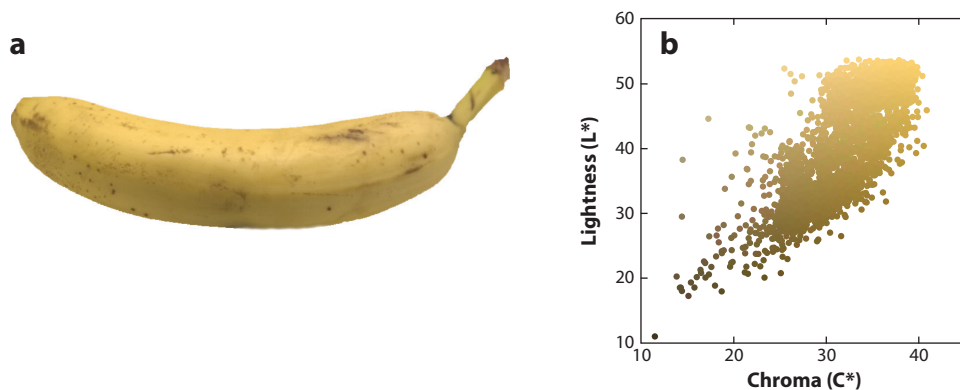

Figure 1
Object colors. (*a*) Image of a banana based on a hyperspectral image taken from Ennis et al. (2018). (*b*) Chromatic distribution of the image in panel *a*. L* is lightness and C* is chroma in CIELAB color space; the variation of hue is not shown here. Although bananas are verbally described as uniformly yellow, the light reflected off the banana's surface corresponds to a complex color distribution rather than a single point in color space.

appearance models do not capture all aspects of color appearance even under controlled laboratory conditions, such as recently shown for lightness (Koenderink et al. 2018) and saturation (Schiller et al. 2017). A more fundamental problem is that color vision is not based on static isolated points of light in space and time. The light reflected from a surface into the human eye changes over space and time. This is due not only to the dynamics of lighting and shadowing in the environment, but also to the dynamic selection and sampling of light through head and eye movements. As a result, there are many individual points of light in our field of view across eye fixations and the corresponding color coordinates may cover large regions of color space over space and time. However, the stimulation through single light points does not predict color appearance (Hofer et al. 2005, Tuten et al. 2017). Already at the retinal level, stimulation of the cones is integrated across space, resulting in a combination of chromatic and spatial information (for a review, see Brainard 2015). In addition, color appearance does not depend solely on the output at the retinal level. Even the eyes of trichromatic observers vary in filtering properties at short wavelengths, their cone sensitivities, and the relative frequencies of the different cone types (for a review, see Neitz & Neitz 2011). These individual differences at the retinal level do not predict individual differences in color appearance (Brainard et al. 2000, Hardy et al. 2005, Jordan et al. 2010, Kraft & Werner 1999, Webster et al. 2000, Werner et al. 2004). Instead, color appearance is recalibrated and normalized at a higher level of processing, which becomes apparent when wearing colored filters for an extended period of time (Neitz et al. 2002) or after cataract surgery (Delahunt et al. 2004).

In sum, the same way we would not try to explain spatial vision on the basis of individual pixels, we should not try to explain color vision on the basis of isolated color coordinates. Yet colorimetric measurements used for the scientific control of color perception in the laboratory are based on measurements of static, isolated points of light. It remains unclear how to combine these measurements over space and time to determine our perception of color in the way it works in the real world outside the laboratory. Here, we propose a different perspective on color (but see also Beck 1972).

In our everyday life, colors are not just decoration; they do serve a purpose. We use colors to identify objects and materials in our environment and to describe objects when communicating with other people. For example, we can distinguish a ripe banana from an unripe banana—even when we see them in different environments and under different illuminations—and we can tell another person about the difference in appearance of the bananas by means of the color words *yellow* and *green*. However, the link between the perception of color and the physical properties of objects and materials in our environment is not as simple and direct as our everyday experience might suggest. A single color coordinate can be assigned to an object only under severe assumptions about the object's shape and material as well as the illumination conditions. This works well only when using homogenous patches of light emitted from a light source or reflected from flat, matte surfaces under highly idealized lighting conditions. In the best case, we can successfully generate such stimuli under well-controlled laboratory conditions. These conditions differ tremendously from the complex and dynamic conditions of real life. A purely colorimetric approach thus cannot capture the primary role of color as a feature of objects and materials.

To understand the nature of color perception in the real world, we focus on the functional aspect of color rather than consider color as an isolated phenomenon. We propose that the major functions of color vision are to quickly isolate objects in scenes, to better remember these objects and scenes, and to communicate about these objects with other observers. We review three fields of research that provide insight into the functional aspect of color perception: object color vision, color constancy, and color categorization.

2. COLOR FOR OBJECTS

As illustrated by **Figure 1**, natural objects cannot be characterized by a single color coordinate but involve a polychromatic color distribution (e.g., Hansen et al. 2006, Milojevic et al. 2018, Vurro et al. 2013). The variation of chromaticity of an object is visible to some extent—for example, the brown stains and the slightly greenish stem of the banana. Yet when interpreting the perceptual information, we represent the banana as having one particular intrinsic color, a saturated yellow, and attribute the brownish stains to external factors such as pressure, which turns the skin of the banana brown. This requires observers to estimate the color that is representative of the object and disentangle the object color from other sources of chromatic variation on the object surface, such as lighting and shading, external factors (e.g., stains on the banana), and nonrepresentative object parts (e.g., the stem of the banana).

It is unclear what computations observers use to arrive at the representative color of an object. It is known that for the estimation of the lightness of objects, observers fixate at the brightest parts of the objects (apart from highlights) and use that image region as their estimate. The brightest parts of an object are often directly illuminated and least affected by shading and hence are most informative about the surface lightness of the object (Giesel & Gegenfurtner 2010, Toscani et al. 2013). There are barely any experiments that similarly investigate the perception of hue and saturation in naturalistic stimuli (but see, for example, Milojevic et al. 2018, Schiller & Gegenfurtner 2016). We discuss the role of color perception for object recognition in natural scenes and, conversely, the effect of object recognition on color perception, as demonstrated by the memory color effect. We argue that color perception and object recognition interact in order to be most informative about the identity of objects and materials in natural scenes.

2.1. Color in Object Recognition

Color helps human observers recognize objects (for review, see Bramao et al. 2011, Tanaka et al. 2001). It does so at a sensory level of fast visual encoding (Gegenfurtner & Rieger 2000, Møller & Hurlbert 1996) and during the retrieval of image information from memory (Gegenfurtner & Rieger 2000, Wichmann et al. 2002).

At the sensory level, several observations suggest that color helps with object segregation and scene segmentation. The distribution of chromatic contrast in natural scenes differs from the distribution of luminance contrast. Chromatic and luminance contrasts are statistically independent in natural scenes (Hansen & Gegenfurtner 2009). The distribution of chromatic contrast in natural scenes is more patchy; it corresponds to lower spatial frequency than luminance contrast (Yoonessi et al. 2008). In particular, low spatial frequencies for chromatic (compared with luminance) contrast are maximal for natural scenes when objects are at typical grasping distance (Parraga et al. 2002). When areas belong to the same object, they tend to have similar color and lightness; however, boundaries between objects are associated with color changes independent of lightness differences (Fine et al. 2003). These observations suggest that chromaticity conveys information about natural scenes that is different from information conveyed by luminance. In particular, it has been proposed that chromaticity is indicative for objects, whereas luminance also varies depending on shadow and shading, which are independent of objects (Kingdom et al. 2004). Take, for example, one of the photographs in **Figure 2**: Chromaticity in the photographed scene strongly changes across the different objects; luminance changes between objects (e.g., between the lemon and the Nivea can) and, owing to shade and shading, also within objects (e.g., across the green apple in the left photograph).

Several studies indicate that human observers use the particular information conveyed by color in tasks that require object detection and scene segmentation. The importance of chromatic
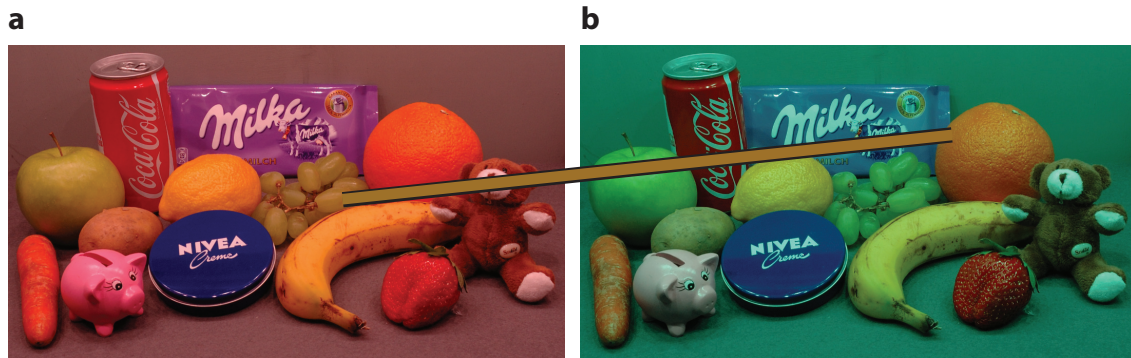
Figure 2

Color constancy. Two photographs of a scene taken under a (*a*) reddish and (*b*) greenish illumination with white balance fixed at standard illuminant D65. The bar illustrates that the colorimetric color of the grape in the left photograph under red illumination is the same as the colorimetric color of the orange in the right photograph under green illumination. Because of color constancy, we identify the surface color of the grapes in the left photograph with the surface color of the grapes in the right photograph, not with the color of the orange in the right photograph. Nevertheless, the color of the grapes does not look the same in both photographs, implying that some level of interference is involved in identifying the colors across the two photographs.

contrasts for object detection is illustrated by the observation that trichromatic observers are better at identifying fruits than dichromatic observers are (Bompas et al. 2013), though this effect is stronger at large viewing distances than at grasping distance, as suggested on the basis of scene statistics (Parraga et al. 2002). The coincidence of luminance and chromatic contrasts supports the discrimination between contours of objects and effects of shadowing (Kingdom et al. 2004). In addition, contour detection in natural scenes by human observers is based on the combination of luminance and chromatic contrasts, indicating the importance of color in segregating objects from one another and from the background (Hansen & Gegenfurtner 2017).

The important role of color in object segregation and scene segmentation is well demonstrated in camouflage (Pinna & Reeves 2015). Camouflage reverses the role of color to conceal an object through chromatic contrasts that are not aligned with object contours, either by hiding contours in the chromatic texture of the background or by adding chromatic contrasts that suggest an illusory contour (Troscianko et al. 2009). Decoupling color and shape can also be used to conceal shape from trichromatic observers that is obvious to dichromatic observers who are insensitive to the chromatic contrasts (Morgan et al. 1992). This is nicely illustrated by the hidden digit plates of the Ishihara color vision test (Ishihara 2004), in which a number is visible to dichromatic but not to normal trichromatic observers because of chromatic noise that is visible only to trichromatic observers.

In addition to object segregation and scene segmentation, the second major role of color in object recognition is related to memory retrieval and involves the identification of objects in a scene (Wichmann et al. 2002). Color is one of the features that help identify an object. For example, a yellow color may help an observer identify a banana in a scene or distinguish a lemon from a lime. For this, it is key that colors are indicative of or diagnostic for certain objects. The typical color of an object that we memorized because of our experience with the object is called a memory color. Objects with a memory color are called color diagnostic; objects that do not have a memory color are color neutral. For example, to most observers a banana is clearly associated with a yellow memory color and hence is highly color diagnostic. The mere existence of reddish bananas does not affect the color-diagnosticity of bananas when observers do not know about that kind of banana. Cars are an example of color-neutral objects because they come in many colors and are not associated with one particular color. Color enhances object recognition for

color-diagnostic objects but less so for color-neutral objects (for a review, see Bramao et al. 2011, Tanaka et al. 2001). Memory colors automatically interfere with object recognition in an object–Stroop paradigm (e.g., Naor-Raz et al. 2003) and influence where observers look (Huettig & Altmann 2011).

In sum, these interference effects demonstrate a strong contribution of color to shape segregation and object recognition. The role of color in object and material changes, such as ripening, rotting, aging, and bleaching, has not been fully explored (Yoonessi & Zaidi 2010). In this context, color helps to not only identify an object but also diagnose the condition and state of an object, and these states may be of fundamental functional importance. For example, a green tomato or berry would not yet be ripe and hence edible. State signaling is also widely used in the animal kingdom as warnings and courtship signals (for a review, see Cuthill et al. 2017).

2.2. Memory Color Effects

In addition to their role in object recognition, memory colors influence how observers perceive the colors of the objects. According to the memory color effect, the mere recognition of an object results in observers perceiving their memory color, even when the object is shown in gray scale. For example, when we see a colorimetrically gray banana, it still appears slightly yellowish because of its memory color (Hansen et al. 2006, Olkkonen et al. 2008).

The memory color effect could be shown with an achromatic adjustment method (Hansen et al. 2006, Olkkonen et al. 2008). In this method, observers adjust an object so that it looks gray to them. The object is presented on a gray background, and when the object is colorimetrically gray, it differs from the background only by lightness variation. However, to subjectively perceive color-diagnostic objects as gray, observers adjust their colors slightly toward the opposite hue direction to compensate for the subjective appearance of the objects' memory color. With this method, memory color effects could be shown with natural objects, such as fruits and vegetables (Hansen et al. 2006, Olkkonen et al. 2008), and with human-made objects, such as logos or comic characters (Kimura et al. 2013, Witzel et al. 2011). Memory color effects could also be revealed by just showing a gray banana and a slightly bluish banana side by side: The colorimetrically gray banana appears yellowish, and the bluish banana appears subjectively gray (Witzel 2016a). The advantage of these methods is that they measure a bias in perception rather than memory or judgment biases; hence, they show that memory colors affect color appearance (Witzel et al. 2016a).

The memory color effect has been reproduced with other methods. In hue scaling, observers tend to overestimate the amount of the hue that corresponds to the typical object color (Hansen & Gegenfurtner 2006), and observers overcompensate afterimages of color-diagnostic images (Lupyan 2015). Memory colors also affect where observers draw a boundary between color categories (Mitterer & de Ruiter 2008, Mitterer et al. 2009). However, it is not clear whether these are effects on perception or on judgment and categorization.

These behavioral observations are supported by neuroimaging evidence. Two independent studies (Bannert & Bartels 2013, Vandenbroucke et al. 2016) using decoding found that color-diagnostic objects (in gray or in an ambiguous color) lead to neural activity in V4 that is specific to the perception of the respective typical colors. One of these studies (Bannert & Bartels 2013) even found color-specific activity in the primary visual cortex (V1), due most likely to feedback connections. These observations suggest that seeing color-diagnostic objects to some extent involves neural activation that leads to the perception of color.

Memory color effects appear to be strongest for blue and yellow memory colors (Witzel et al. 2011). This is the same hue direction that gray adjustments (even of color-neutral objects and shapes) are most variable along, indicating observers' uncertainty about color appearance (Bosten

et al. 2015, Chauhan et al. 2014, Witzel et al. 2011). This uncertainty has been explained by the variation of color due to daylight variation. The blue-yellow hue direction corresponds to the color variation of natural daylight. Hence, the color signal resulting from light reflected off surfaces under daylight varies along the yellow-blue direction, producing uncertainty about the color signal corresponding to surfaces under daylight. Memory color effects might be the result of reducing this uncertainty through prior knowledge and expectations.

In general, a Bayesian model may capture the effect of prior knowledge on this uncertainty. Such a model takes the memory color knowledge as the prior for the uncertainty of the perceived color (i.e., the sensory signal) and predicts the memory color effect as the posterior (Witzel et al. 2016a). A simple implementation of a Bayesian model has been shown to capture some aspects of the memory color effects (Witzel et al. 2018).

3. COLOR CONSTANCY

Color can serve as a stable attribute for an object in memory only if the color assigned to the object is stable over space and time, independent of changes in illumination conditions. This stability is called color constancy. It is illustrated in the two photographs shown in **Figure 2**. The grapes look green and the orange (the fruit) looks orange in both photographs. Yet the chromaticity of the grapes under the reddish illuminant and the orange under the greenish illuminant is the same in both photographs (illustrated by the bar in **Figure 2**). Both the reflectance properties of surfaces and the illuminant spectra determine the color signal from the cones, but our perception seems to be influenced mainly by the reflectance properties. The research question behind color constancy is whether and how the visual system can disentangle the two sources of information to identify surface colors.

3.1. Conditions for Color Constancy

Measurements of color constancy in the laboratory have led to highly variable results, ranging from barely any constancy to almost perfect constancy (Foster 2011). No or zero constancy would indicate that a color match under two different illuminations was based on cone excitations only, without any correction for the illumination. Full or 100% color constancy would be reached if the match was based on the same physical object with the same reflectance function under the different illuminations. These two extreme predictions allow the quantification of a color constancy index that specifies how close the matched color is to both extremes (for a detailed review, see Foster 2011). **Figure 3** illustrates the large variability of empirical measurements over 30 years of research. How can this variability be, given that we are able to reliably assign color labels to objects in our everyday life?

Color constancy cannot work under arbitrary conditions. Surfaces and illuminants need to have certain spectral properties. Most of us have looked at an item of clothing in a badly lit store and were surprised when its color was quite different under daylight. This example illustrates the possibility that surfaces lead to the same cone excitations under one illuminant (metamerism) but to distinctly different cone excitations under another illuminant (metamer mismatching) (Cohen & Kappauf 1982, Logvinenko et al. 2014, Wyszecki & Stiles 1982). These metameric surfaces appear identical in the first case and different in the second. In such cases, color constancy is impossible because the identification of one surface excludes the identification of the others across illuminants (Logvinenko et al. 2015). However, it seems that metamerism does not arise frequently in the real world (Akbarinia & Gegenfurtner 2018, Foster et al. 2006, Zhang et al. 2016). This suggests that the situation from the clothing example is exceptional, which explains why that situation is
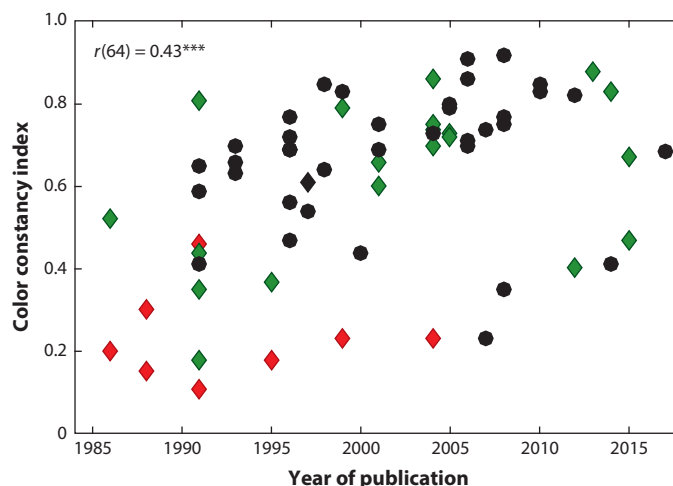
Figure 3 appears here as a scatter plot.

Figure 3

Variation of color constancy performance. The graphic illustrates the magnitude of color constancy indices (along the *y*-axis) measured by various methods over the last 30 years (time in years along the *x*-axis). Data are taken from table 1 of Foster (2011) and additional, more recent empirical articles (Allred & Olkkonen 2013, Granzier & Gegenfurtner 2012, Granzier et al. 2014, Kanematsu & Brainard 2014, Olkkonen et al. 2010, Radonjić et al. 2015a, Radonjić et al. 2015b, Weiss et al. 2017, Xiao et al. 2012). Diamonds indicate results from asymmetric matching. Green diamonds correspond to paper-match instructions, red diamonds to appearance-match instructions, and black diamonds to tasks with unspecified instructions. Black circles correspond to other methods, such as successive constancy, achromatic matching, and category constancy. The correlation between all measures and the year of publication is reported in the upper-left corner, reflecting a general tendency of color constancy indices to increase with more sophisticated methods, including full-field adaptation and naturalistic conditions (***$p < 0.001$). Asymmetric matches with appearance-match instructions (*red diamonds*) tend to yield particularly low color constancy indices.

surprising to us in everyday life. Insofar as the visual system is adapted to the conditions of its environment (e.g., Koenderink 2010), it can potentially achieve high levels of color constancy for almost all real object and materials under natural illuminants. Nevertheless, measures of color constancy may vary across studies depending on which reflectance and illuminant spectra are used in the experiments (e.g., Lucassen & Walraven 1996, Witzel et al. 2016b).

To achieve color constancy, the visual system uses numerous cues to color constancy that are available to varying degrees in different experiments (for a detailed review of cues, see Foster 2011, Smithson 2005). It has been shown quite convincingly that the degree of color constancy can be modulated between close to zero and nearly perfect by the presence of different cues (Hansen et al. 2007, Kraft & Brainard 1999). Adaptation and simultaneous local contrast are the major mechanisms that allow for constant color appearance across illuminations (Smithson & Zaidi 2004). In addition, color constancy may also involve inferring the identity of colors across illuminations by comparison to other colors that work like references or anchors. This inferential constancy is illustrated, for example, by the role of three-dimensional interreflections and shading (Bloj et al. 1999), depth segmentation (Werner 2006), specularities (Granzier et al. 2014, Lee & Smithson 2016, Witzel et al. 2017a, Yang & Maloney 2001), and memory colors (Emmerson & Ross 1987, Granzier & Gegenfurtner 2012, but see Kanematsu & Brainard 2014), as well as by the phenomenon of #theDress (see below).

Chromatic adaptation seems to have a strong effect on constancy. Although a good deal of adaptation occurs within a fraction of a second, complete adaptation takes several minutes

(Rinner & Gegenfurtner 2000). Methods such as successive surface comparisons, achromatic matching, and categorization across illuminants are well suited to allow for high levels of adaptation (**Figure 3**). Measurements of color constancy may still vary with these methods depending on the role of color memory in successive constancy (Ling & Hurlbert 2008), variation of categorization across observers and colors (e.g., Olkkonen et al. 2009, 2010), the presence of achromatic cues in achromatic matching, and more generally the presence of other colors that may serve as anchors (e.g., Linnell & Foster 2002).

Methods that involve simultaneous displays (**Figure 2**) undermine the contribution of adaptation to color constancy because the observer cannot fully adapt to both scenes at the same time. In such methods, colors cannot appear the same in both displays, and inferential constancy plays a particularly important role. For example, the grapes in both photographs of **Figure 2** appear to be different in color, but we can attribute this difference to the difference in illumination and establish a correspondence between the colors of the grapes in the two photographs. In this case, measurements of color constancy strongly depend on the instructions (Arend & Reeves 1986, Radonjić & Brainard 2016; for a review, see Foster 2011). Instructions that ask for appearance matches measure constant appearance and minimize contributions of inferential constancy. These instructions lead to particularly low measures of color constancy in simultaneous asymmetric matching tasks (**Figure 3**). In contrast, instructions that ask for surface matches allow for the combination of constant appearance and inferential constancy to identify a correspondence between surface colors across illuminations. In this case, asymmetric matching produces higher measures of color constancy that are comparable to those from other methods.

There are studies in which observers reach almost perfect color constancy of 90% and above. All these studies guaranteed in some way for adaptation (Brainard 1998; Hansen et al. 2007; Ling & Hurlbert 2008; Murray et al. 2006; Olkkonen et al. 2009, 2010) or used naturalistic scenes with many cues that allow for inferential constancy (Allred & Olkkonen 2013, Brainard 1998). Interestingly, there is a (significant) trend toward higher constancy indices across years of publication for the sample of constancy studies considered in **Figure 3** [$r(64) = 0.43$, $p < 0.001$]. This trend may be explained by the increased use of naturalistic environments and naturalistic tasks.

In sum, the variability of measurements of color constancy is understandable if we consider that color constancy depends on the spectral properties of surfaces and illuminants used as stimuli, as well as on the presence of cues that allow for adaptation, simultaneous contrast, and anchoring. Presumably, most situations in everyday life involve full-field adaptation, local contrast, and scenes with many color cues. In these natural situations, color constancy should be at least as high as shown under optimal experimental conditions because all color constancy mechanisms come into full play.

3.2. Constancy Across Colors

A particular opportunity to investigate the mechanisms of color constancy is the variation of color constancy across different hues. We may distinguish between the variation of color constancy across different surface colors and across different illumination colors.

First, even for a homogenous set of surface reflectances, the change of the color signal across illuminations strongly depends on the surface colors (Philipona & O'Regan 2006, Vazquez-Corral et al. 2012, Witzel et al. 2015). Furthermore, measures of color constancy also strongly change depending on the surface color (Olkkonen et al. 2009, 2010; Witzel et al. 2016b).

Second, color constancy potentially differs depending on illumination color. It has long been hypothesized that color constancy should be better for naturally occurring illumination changes.

However, empirical evidence has been scant, and several thorough explorations did not find any major differences between illumination changes along the daylight axis compared with other color directions (Delahunt & Brainard 2004, Rüttiger et al. 1999). More positive results were presented by Hurlbert and colleagues (Pearce et al. 2014, Radonjić et al. 2016). These authors proposed illumination discrimination as a useful new measure of color constancy under different illuminant colors. In illumination discrimination, an observer has to detect the difference between two illuminations of a scene shown in sequence. Under such conditions, observers have a blue bias: They are less sensitive to changes toward the blue direction of daylight (Pearce et al. 2014, Radonjić et al. 2016). Along similar lines, we recently investigated potential differences in constancy along numerous different color directions and also found a blue bias. Achromatic adjustments are generally shifted toward blue and color constancy tends to be higher the closer the illumination color is to daylight blue, where color constancy is best (Weiss et al. 2017). It remains to be seen whether the biases in both tasks—achromatic matching and illumination discrimination—are based on the same mechanisms and how well they agree. The situation is complicated because color discrimination itself, without any illumination changes, exhibits some subtle biases (Giesel et al. 2009, Krauskopf & Gegenfurtner 1992).

In sum, the blue bias suggests that color constancy might be adapted to daylight illuminations and shadowing (see also Winkler et al. 2015). This further supports the general idea that color constancy is an adaptation to natural viewing condition.

3.3. #theDress

In 2015, a photo of a dress (#theDress) created a buzz in social media around the world. The striking feature of that photo was that a large proportion of observers saw the colors of the body of #theDress blue and the lace black, whereas others saw them as white and gold. The perceived colors for different observers for both body and lace were distributed in a continuous range of hues close to the daylight locus (Gegenfurtner et al. 2015, Lafer-Sousa et al. 2015). The color signals of the pixels for both the body and the lace were also distributed along the daylight locus (Gegenfurtner et al. 2015). This alignment of pixel color signals in the image makes it possible to attribute the color variation either to the fabric or to the lighting conditions (Witzel et al. 2017b). Some observers implicitly assumed the dress to be in the shadow, implying a bluish dark lighting, and hence they saw #theDress as white and gold, which is comparatively light and yellowish. In contrast, other observers believed the lighting to be white and bright and saw #theDress as blue and black or in some cases blue and brown (Aston & Hurlbert 2017; Chetverikov & Ivanchei 2016; Toscani et al. 2017; Uchikawa et al. 2017; Wallisch 2017; Witzel et al. 2017a,b). The variation of the pixel colors along the daylight locus contributed to the magnitude of the individual differences: Rotating the colors away from the daylight axis (e.g., so that the pixels are greenish and purplish) strongly reduces the individual differences (Gegenfurtner et al. 2015).

An interesting aspect of #theDress is that the perception is stable over time for most observers (Lafer-Sousa et al. 2015). However, the color perception of the dress in that photo can be biased by cutting out the dress and pasting it on a background with different local contrasts or a background that suggests a certain interpretation of the lighting conditions (Drissi Daoudi et al. 2017, Lafer-Sousa et al. 2015, Witzel et al. 2017b). Biasing the perception of the dress colors influences how observers subsequently see the #theDress with the original background (Drissi Daoudi et al. 2017, Lafer-Sousa & Conway 2017, Witzel et al. 2017b). This influence on perceived color occurs even for observers who otherwise have a stable percept of the dress. That the perceived colors of #theDress can be primed, but not consciously changed, highlights the important role of unconscious inferences and implicit assumptions in color appearance.

Overall, the dress provides an example in which the inferential mechanisms of color constancy provide ambiguous information. The fact that this phenomenon is surprising to so many people all over the world illustrates how rare such failures of color constancy are in everyday life.

4. COLOR CATEGORIZATION

We are able to perceive and discriminate a wide range of different colors along the dimensions of hue, lightness, and saturation (e.g., Linhares et al. 2008, Masaoka et al. 2013). However, when communicating about colors, we do not refer to metric evaluations of hue, lightness, and saturation. Instead, we use color terms that group many different colors into a small number of color categories (**Figure 4**). For example, the color term *green* refers to a large range of different colors that are all called green. *Black*, *white*, *gray*, *pink*, *red*, *orange*, *yellow*, *green*, *blue*, *purple*, and *brown* are English basic color terms. Basic color terms are the most common color terms that are understood by most speakers of a language (for the original idea and criteria of basic color terms, see Berlin & Kay
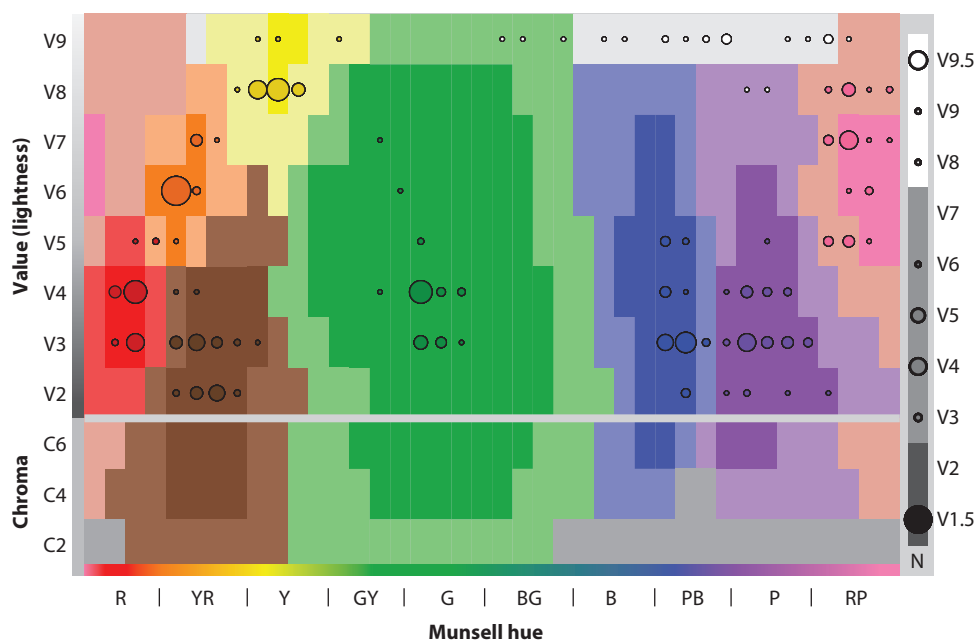

Figure 4

Color categorization. The upper eight rows illustrate the distribution of (German) color categories across hue (*x*-axis: R, red; YR, yellow-red; Y, yellow; GY, green-yellow; G, green; BG, blue-green; B, blue; PB, purple-blue; P, purple; RP, red-purple) and lightness (*y*-axis: V2–V9, value 2–9) of Munsell color chips. The lowest three rows show the distribution of categories across three comparatively low levels of chroma (*y*-axis: C2–C6, chroma 2–6) at medium lightness (V5). The bar on the right corresponds to categories for achromatic chips (neutral N) at ten lightness levels (from value 1.5 to 9.5). Color chips that were categorized with over 90% consistency across observers and repeated measurements (under different illuminations) are displayed as areas in saturated colors. Pale colors, mainly at the boundaries between categories, indicate consistency below 90%. Circles indicate that observers chose the respective chip as the prototype of the corresponding color category; the size of the circles represents the frequency of choices. The figure is adapted from figure 8 in Olkkonen et al. (2010), with permission from the Association for Research in Vision and Ophthalmology, and two additional data sets (under neutral illumination).

1969). Examples of nonbasic color terms are *chartreuse* and *mauve*, whose meaning is not shared consistently across all speakers of English. There is a continuum of different levels of basicness between the least and the most basic color terms (e.g., Lindsey & Brown 2014; for a review, see Witzel 2018).

The color categories of the basic color terms vary in size, implying that some color terms refer more precisely to particular colors than other terms do. This is illustrated by **Figure 4**. For example, the color terms *red* and *yellow* refer to a limited range of colors, whereas *green* can mean many different shades of green. Even if we consider that the Munsell color system does only approximately control perceived color differences, the differences between those categories across all three dimensions of color appearance are so large that they cannot be explained by imprecisions of the Munsell system. Hence, *red* and *yellow* convey much more precise information about a particular color than *green* does, which may refer to a wide range of possible colors that are all called *green*. In addition, color categorization is highly consistent for colors at the center of the categories (**Figure 4**) but varies around the boundaries between categories (pale areas). This implies that color terms are more reliable in describing colors in the center than at the boundaries of the categories. As a consequence, color categories are not equally informative about all colors; instead, they inform speakers more precisely and more reliably about some colors to the detriment of other perceivable colors. Where these color categories come from and how they are related to continuous color perception are some of the biggest open problems in color science (Witzel 2018). Here, we focus on the relationship between color perception and color categorization. First, we review studies suggesting that language and categorization shape color perception. Then, we discuss studies providing evidence for the inverse—namely, that linguistic categories are the result of the categorical nature of color perception.

4.1. Category Effects on Color Perception

Color vision has long been the prime example for categorical perception (Bornstein & Korda 1984, Bornstein et al. 1976). According to the idea of categorical perception, pairs of otherwise equidistant colors are perceived as more different when they belong to two different categories (e.g., red and brown, cf. **Figure 5b**) than when they belong to the same category (both either brown or red). Such effects on the perception of color difference that are specific to categories are called category effects.

Perception has been measured mainly through response times for discriminating different colors in speeded suprathreshold discrimination (Bornstein & Korda 1984) and through measures of subjective color appearance (Kay & Kempton 1984). One of the major challenges is, of course, to operationalize the notion of equidistance. Over many years, it has proven difficult to determine distances in color space for color differences beyond just noticeable differences (MacAdam 1942, Wuerger et al. 1995). How then can we disentangle category effects and discrimination? One way is to test for interaction effects, in which category effects occur in one condition but not in a condition in which the influence of language is knocked out. In other words, the pairs of color stimuli would always be the same. Four major kinds of interaction effects have been reported.

First, cross-cultural studies have shown that category effects are specific to the language of observers (e.g., Kay & Kempton 1984; Roberson et al. 2000, 2008; Thierry et al. 2009; Winawer et al. 2007). For example, Russian has a boundary between dark blue (*siniy*) and light blue (*goluboy*) that English does not have (Moss et al. 1990). Russian-speaking, but not English-speaking, observers respond faster to color differences across the siniy–goluboy boundary than to color differences within siniy or within goluboy (Winawer et al. 2007). Similar cross-cultural effects have been found for speeded discrimination tasks in Korean (Roberson & Pak 2009; Roberson et al. 2008, 2009)
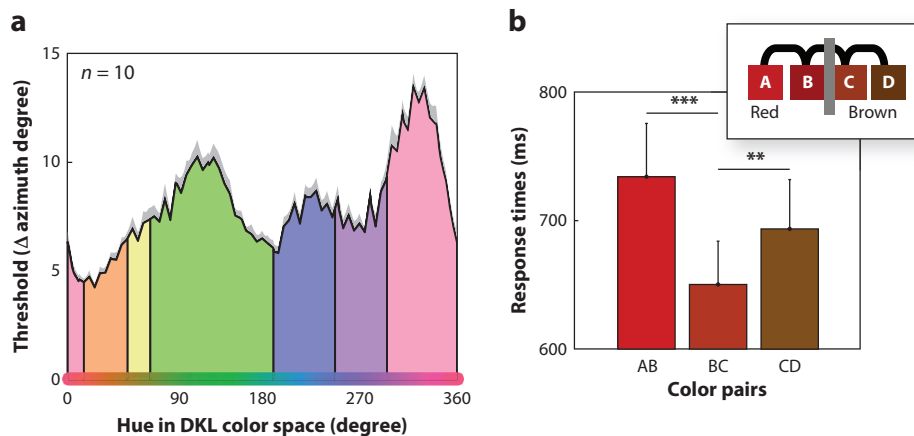
a

b

Figure 5

Category effects on color perception. (*a*) Categorical sensitivity. The diagram shows how the sensitivity to color differences changes across hue. The *x*-axis corresponds to hue in DKL color space, and the *y*-axis to discrimination thresholds. Adapted from Witzel & Gegenfurtner (2013). Note that the green-blue boundary is unlike the others in that it coincides with a local minimum of discrimination thresholds. (*b*) Categorical facilitation. The bars along the *x*-axis of the main graphic correspond to color pairs that are composed of the colors illustrated by the inset. The *y*-axis of the main graphic represents response times in speeded discrimination. Note that discriminating the color pair BC, in which B and C belong to different categories (i.e., red and brown), is fastest even though the distances between colors control for sensitivity to color differences. Adapted from Witzel & Gegenfurtner (2016). Abbreviation: DKL, Derrington-Krausfopf-Lennie. **$p < 0.01$; ***$p < 0.001$.

and for color appearance tasks in Greek (Athanasopoulos et al. 2010) and in languages of non-industrialized communities (Roberson et al. 2000, 2005). The language-specific effects show that category effects on perception are malleable in that they depend on the language one has learned.

Second, it has been found that category training resulted in different category effects before and after learning new categories (Clifford et al. 2012, Kwok et al. 2011, Özgen 2004, Özgen & Davies 2002, Zhou et al. 2010). For example, observers who were trained to categorize green colors into two novel green categories (green1 and green2) would show category effects on response times at the acquired novel category border.

Third, there is evidence that verbal interference undermines category effects (Gilbert et al. 2006, Pilling et al. 2003, Roberson & Davidoff 2000, Winawer et al. 2007, Witthoft et al. 2003). A verbal interference task is meant to occupy resources specifically required for verbal labeling to interrupt effects of language on perception. Tests for category effects under verbal interference were compared with conditions of no interference and with conditions of nonverbal interference. Findings showed that category effects on color discrimination occurred without interference and with nonverbal interference but disappeared under verbal interference.

The lateralized category effect is a fourth kind of interaction effect. Several studies found that category effects occur only or more strongly in the right visual field but not at all or less strongly in the left visual field (Drivonikou et al. 2007, Gilbert et al. 2006, Roberson et al. 2008, Zhou et al. 2010). Visual information from the right visual field is processed in the left hemisphere and language is also processed in the left hemisphere for almost all people who are right-handed (for a review, see Ocklenburg et al. 2014). The observation that the category effect is lateralized to the left hemisphere suggested that language processing is involved in those category effects. Although several studies found evidence in support of the lateralized category effect, many other

studies could not reproduce the effect, even in extensive series of experiments and with carefully calibrated color stimuli (Brown et al. 2011; Suegami et al. 2014; Webster & Kay 2012; Witzel & Gegenfurtner 2011, 2015, 2016). It has been suggested that the lateralization of the category effect occurs only at early stages and disappears at later stages of visual processing, possibly due to transfer through the corpus callosum (Roberson et al. 2008, Constable & Becker 2017). However, it is not yet clear what exactly determines whether lateralization effects occur.

Taken together, several kinds of interaction effects support the idea that linguistic color categorization influences speeded color discrimination and color appearance. Besides those interaction effects, another approach consists of comparing a measure of continuous color perception that is absent of any category effects (perceptual reference) with a category-probing measure that is hypothesized to yield category effects. This approach allows testing for category effects along the hierarchy of color processing (Witzel 2018).

First, the known cone–opponent dimensions of the second-stage mechanisms can be used as a perceptual reference, and the sensitivity to color differences can serve as the category-probing measure. We refer to the sensitivity to color differences as the basic ability to detect small differences between colors. Sensitivity can be measured through discrimination thresholds under optimal conditions. In case categorical perception acts even at this basic level, sensitivity should be higher—and thresholds lower—at the category boundaries than within the categories. However, this is not the case (cf. **Figure 5a**): There is no category effect at this low sensory level of color processing (Bachy et al. 2012; Cropper et al. 2013; Danilova & Mollon 2014; Roberson et al. 2009; Witzel & Gegenfurtner 2013, 2018). The sensitivity to color differences is related to the second-stage mechanisms rather than color categories (Brown et al. 2011; Lindsey et al. 2010; Witzel & Gegenfurtner 2013, 2018), hence confirming earlier evidence for the role of second-stage mechanisms in color discrimination (Krauskopf & Gegenfurtner 1992).

Second, we can use those empirical discrimination thresholds as the perceptual reference and test for category effects on other performance measures (response times and error rates) in a speeded, suprathreshold discrimination task. In this case, category effects on response times and error rates have been observed around an isoluminant hue circle (Witzel & Gegenfurtner 2015) and at the red–brown boundary (Witzel & Gegenfurtner 2016) (see **Figure 5b**). We call these effects categorical facilitation in the sense that they facilitate speeded discrimination of suprathreshold stimuli beyond what is predicted by sensitivity. Interestingly, the categorical facilitation effects occurred only in naïve, unexperienced observers with high response times, but they disappeared for trained observers who became experts in the task and responded fast and automatically (Witzel & Gegenfurtner 2015).

It has been proposed that category effects on color discrimination are a result of perceptual learning (Özgen 2004, Özgen & Davies 2002). When observers communicate about colors, they are led to discriminate colors at the category boundaries because they need to judge whether those colors at the boundaries belong to one or the other category. In this way, communication leads specifically to practice in discrimination that may produce lower discrimination thresholds (i.e., higher sensitivity to color differences) at the boundary due to perceptual learning. Perceptual learning could explain language-specific category effects and category effects for novel categories. However, effects of verbal interference suggest that category effects may be modulated in the same observers without learning experience across interference conditions. This contradicts effects of perceptual learning (Winawer et al. 2007). In addition, the absence of category effects on discrimination thresholds and sensitivity further undermines the idea that category effects are the result of perceptual learning (Roberson et al. 2009; Witzel & Gegenfurtner 2013, 2016, 2018).

Others have suggested that linguistic categorization occurs automatically when seeing colors and the categorical information is combined with perceptual information about color differences

to reinforce perceptual discrimination when the differences between colors coincide with the differences between categories (Bornstein & Korda 1984). This interpretation is supported by the effects of verbal interference (Pilling et al. 2003, Roberson & Davidoff 2000, Winawer et al. 2007) and would be in line with the lateralized category effect (Gilbert et al. 2006). Yet this explanation cannot account for the observation that category effects disappear in observers who are highly trained in color discrimination (Witzel & Gegenfurtner 2015).

The detrimental effect of training on categorical facilitation has been explained by the idea that observers are used to paying attention to categorical distinctions in everyday life color communication and hence by default automatically direct their attention to color differences that distinguish categories. Once observers are trained to focus on fine-grained color discrimination, rather than categorical distinctions, category effects disappear. Those categorical facilitation effects can also be explained by a Bayesian approach that integrates knowledge about linguistic categories and sensory signals (Bae et al. 2015, Cibelli et al. 2016, Holmes et al. 2017): With training, the precision of the sensory signal increases and hence the influence of the category cue decreases, leading to the disappearance of category effects.

4.2. Perceptual Determinants of Color Categories

It is well established that the number of basic color categories and the extensions of the color categories across color space strongly vary depending on the language community (e.g., 11 categories in English and German, cf. **Figure 4** and Berlin & Kay 1969; 5 in Himba and Berinmo, cf. Roberson et al. 2005; 15 in Korean, cf. Roberson et al. 2008; 12 in Russian, cf. Winawer et al. 2007). Nevertheless, there is evidence for statistical regularities across languages (Gibson et al. 2017; Kay & Regier 2003; Lindsey & Brown 2006, 2009; Lindsey et al. 2015). In particular, the prototypes of the categories seem to be relatively stable across languages (Berlin & Kay 1969, Regier et al. 2005, Rosch Heider 1972). Moreover, infants show categorical responses to color, even though they have not yet acquired language and do not know color terms (Bornstein et al. 1976; Franklin & Davies 2004; Franklin et al. 2005, 2008; Ozturk et al. 2013; Skelton et al. 2017; Yang et al. 2016). These categorical responses suggest that color categories develop in infants before language acquisition (infant color categories). Both infant color categories and cross-cultural commonalities in categorization indicate that categorization is shaped by determinants that are independent from languages. Several approaches have been suggested to explain color categorization by characteristics of color perception (perceptual determinants).

One approach proposed that the category prototypes of red, yellow, green, blue, black, and white have particular perceptual properties that make them more salient than other colors and qualify them as focal colors (Regier et al. 2005, Rosch Heider 1972). Several perceptual properties have been identified that could explain the perceptual salience of those category prototypes.

First, the hues of cross-cultural prototypes (typical hues) approximately correspond to unique hues. Unique hues are the elementary colors of which every other color is mixed (for a review, see Kuehni 2014; Valberg 2001). However, it is not clear how typical hues and unique hues are linked to known mechanisms of color perception. In particular, neither typical and unique hues nor category boundaries systematically correspond to the cone–opponent dimensions of the second-stage mechanisms (De Valois & De Valois 1993; Emery et al. 2017; Malkoc et al. 2005; Witzel & Gegenfurtner 2013, 2018; Wuerger et al. 2005). A recent study suggested that categorical responses by infants are related to the cone–opponent second-stage mechanisms (Skelton et al. 2017). This observation contrasts with the finding that color categories in adults do not systematically relate to second-stage mechanisms. It is not yet clear how exactly categorical responses by infants relate to the categories for basic color terms by adults.

It has also been suggested that color categories are inherent to the geometry of perceptual color space. Most of the studies investigating color categorization used a set of standard color chips—namely, the maximally saturated chromatic and the achromatic Munsell chips (Munsell Color Services 2007). The maximal saturation varies across hue and lightness in this set of Munsell chips. The prototypes of chromatic color categories are located close to local maxima in saturation, or bumps, of that set of Munsell chips (Jameson & D'Andrade 1997, Regier et al. 2007). As a result, colors in that stimulus set are more different within than across categories (Regier et al. 2007). By definition, the prototypes of achromatic categories (black, gray, white) correspond to minimum saturation. As a result, prototype choices across languages correlate with the saturation of the particular set of Munsell chips (Lindsey et al. 2016, Witzel 2016b, Witzel et al. 2015).

Furthermore, the maximally saturated Munsell chips corresponding to red, yellow, green, and blue prototypes have a high sensory singularity; that is, they reflect light in a more reliable and predictable way (Philipona & O'Regan 2006, Vazquez-Corral et al. 2012). This finding fits the observation that color categorization across illumination changes is most constant in the center of the categories close to the category prototypes (Olkkonen et al. 2009, 2010). These observations suggest that the stability of categories across illumination changes (category constancy) is linked to the stability across individuals and languages. However, the relationship between sensory singularities and category prototypes strongly depends on the bumps of saturation in the set of maximally saturated Munsell chips (Witzel et al. 2015). Moreover, in contrast to the results for category constancy (Olkkonen et al. 2009, 2010), there is no relationship between color categorization and perceptual color constancy when controlling for saturation and measuring perceptual constancy through asymmetric matching (Witzel et al. 2016b) or achromatic adjustments (Weiss et al. 2017). Hence, higher category constancy for colors within than at the boundaries of color categories (Olkkonen et al. 2009, 2010) is either an effect of saturation or the result of categorization being generally less consistent at category boundaries.

Taken together, many of the observations in support of the notion of focal colors depend on the saturation in the classical set of maximally saturated Munsell chips (Witzel 2016b, Witzel et al. 2015). However, high saturation at the category prototypes is not a feature of human color perception but a peculiarity of that particular stimulus set (Witzel & Franklin 2014). Whether and how perceptual properties determine color categories are still unclear. The observations of cross-cultural regularities and categorical responses by infants alone do not prove that color categories are determined by color perception. Infants might acquire categorical information through shared attention and other kinds of interaction with their social agents (e.g., their parents) that do not depend on language. Cross-cultural commonalities and infant color categories could also have an ecological origin. For example, they could be related to statistical regularities of color distributions in the visual environment (Yendrikhovskij 2001, Steels & Belpaeme 2005), and infants might internalize these regularities early in development. In this way, the visual environment would shape color categorization through early experience rather than color categories being a consequence of hard-wired mechanisms of color processing.

Recent approaches have introduced the idea that color categories need to be informative in communication. They explain color categorization across cultures through the information of color categories about colored surfaces and objects (Baddeley & Attewell 2009, Gibson et al. 2017, Kirby et al. 2007, Regier et al. 2015, Steels & Belpaeme 2005). As an alternative to the focal color account, it has been suggested that category prototypes are a consequence rather than the cause of linguistic categorization: Once category boundaries are linguistically determined, their prototypes develop to be maximally representative for each category—that is, to be closest to members of their own, and furthest from members of other categories (Abbott et al. 2016). According to our functional perspective on color, color categories inform observers about functionally relevant

objects. This approach relates the informative value of color terms in communication to the identification of objects and materials through color.

5. CONCLUSION AND OUTLOOK

We reviewed the state of the art on object colors, color constancy, and color categories to gain insight into the functional aspects of color perception. All three areas of research reveal phenomena in which color appearance is tightly linked to identification of objects and materials and to communication across observers. Memory color effects imply that the color appearance of colorimetrically defined lights changes depending on the object, on which the color is shown, and depending on the observer's familiarity with the object. The phenomenon of #theDress provides a striking example in which the same image with the same chromatic distribution is seen differently depending on the interpretation of the relationship between the dress and the lighting in the scene. Category effects further suggest that color perception is influenced by the observer's language.

Although all these effects illustrate the malleability of the relationship between color sensation and colorimetric properties of light, these are neither random nor arbitrary. Instead, such effects operate in a direction that stabilizes the perception of objects and materials as they naturally occur in our environment, or that supports color communication. First, memory color effects stabilize the association between the subjective color sensation and the corresponding color-diagnostic objects in the environment. This implies that the experience with the (color-diagnostic) objects partly adapts color appearance to object identity through familiarization. Second, scene interpretation as well as the other mechanisms of color constancy allows for almost perfect identification of objects and materials across illumination changes under natural conditions. This shows that color vision in humans is tuned to identifying objects and materials across illuminations in the natural environment. Third, category effects reinforce the perception of differences at the category boundary that are important for communicating colors across observers. Hence, these effects have the potential to stabilize the function of color in order to identify and communicate object properties across changing environments. They highlight that color perception involves processes of coordination and adaptation that reinforce the link between subjective color appearance and the physical properties of objects and materials in the world.

We argue for a new perspective on color that considers color primarily as a property of objects and materials. From this perspective, color research should focus on how color processing is adapted to the surface properties of objects in the natural environment in order to bridge the open gap between the known early stages of color perception and the subjective appearance of color (e.g., Koenderink 2010). In particular, object color perception, color constancy, and color categorization strongly select chromatic information conveyed by the proximal stimulus. Object color perception reduces the complex polychromatic distribution of objects and materials to one object color that is taken to be representative of the object (e.g., Milojevic et al. 2018). It is an open question how the visual system extracts the representative color from the polychromatic distribution of the proximal stimulus. Mechanisms of color constancy select color information that is in line with natural viewing conditions. Whether the adaptation of the visual system to the spectral properties in the environment is the result of the evolution of fixed hard-wired mechanisms or develops at least to some degree through learning remains unanswered (Witzel et al. 2016b). Color categorization is most precise and reliable for some perceivable colors to the detriment of other colors, and it is unknown why color categorization does not convey information about all perceivable colors. Linking color appearance and color categorization to objects and materials in the natural environment may solve the fundamental mysteries of color perception by providing an ecological origin of color appearance and categorization.

SUMMARY POINTS

1. Color helps us see things quicker and remember them better.

2. Memory about object colors interacts with uncertainty about color appearance.

3. Color constancy depends on spectral properties, the presence of cues, and the colors of surfaces and illuminations and is adapted to natural viewing conditions.

4. The phenomenon of #theDress illustrates how inferential mechanisms of color constancy shape color appearance to achieve object recognition.

5. Linguistic color categories prioritize the communication of some colors to the detriment of other colors.

6. Linguistic color categories modulate color perception at a high level of processing.

7. These phenomena highlight that color serves the purpose of informing observers about relevant objects in the world, and call for a functional perspective on color perception.

FUTURE ISSUES

1. What are the precise spectral characteristics of illuminants and reflectances that maximize constant color appearance?

2. What are the anchors and priors used in inferential constancy?

3. To what extent do we learn color constancy by experiencing how object colors change across natural illumination changes?

4. Why is color naming not equally informative about all perceivable colors?

5. What information about object colors do color categories select and convey in communication?

6. Is there a common theoretical framework for top-down effects on color perception that explains categorical facilitation, memory effects, and #theDress?

7. How can we scientifically define and control colors as object and material properties (rather than light properties)?

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Contents

Errata

An online log of corrections to *Annual Review of Vision Science* articles may be found at
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