

03

Human Perception and Information Processing

Notice

- **Author**

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Bibliography

- **Many examples are extracted and adapted from**
 - ◆ **Interactive Data Visualization: Foundations, Techniques, and Applications,**
Matthew O. Ward, Georges Grinstein, Daniel Keim, 2015
 - ◆ **Visualization Analysis & Design,**
Tamara Munzner, 2015

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- **What Is Perception?**
- **Physiology**
- **Perceptual Processing**
- **Perception in Visualization**
- **Metrics**
- **Cognition**

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Introduction to Data Visualization

What Is Visualization?
Relationship between Visualization and Other Fields.
The Visualization Process.
Data Foundations.
Human Perception and Information Processing.
Semiology of Graphical Symbols.
The Visual Variables.

Visualization Techniques

Visualization Techniques for Spatial Data
Visualization Techniques for Geospatial Data
Visualization Techniques for Time-Oriented Data
Visualization Techniques for Multivariate Data
Visualization Techniques for Trees, Graphs, and Networks
Text and Document Visualization

Interaction Concepts and Techniques

Interaction Operators, Operands and Spaces (screen, object, data, attributes)
Visualization Structure Space (Components of the Data Visualization)
Animating Transformations
Interaction Control
Designing Effective Visualizations
Comparing and Evaluating Visualization Techniques

Visualization Systems

Systems Based on Data Type
Systems Based on Analysis Type
Text Analysis and Visualization
Modern Integrated Visualization Systems
Toolkits

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Practical information

Build your team

Teams registration				
Please insert your student id in a grey area for the next available group				
G-ID	ID - 1	Name - 1	ID - 2	Name - 2
G01	42614	Pedro Rafael Marques Ferreira	43043	Sofia Cristina Fraga Pereira
G02	41654	Rodolfo Simões Ferreira	41698	Sérgio Bairos Pimentel
G03				
G04	45872	Abel Vaz Correia Silva	45483	Rodrigo Martins Cardoso
G05	45526	Miguel Henrique Rodrigues de Almeida	45625	Maria Portugal Queiroga Nogueira
G06	42486	António Caeiro	41774	Tomás Pessanha
G07				
G08	53502	Rafael Filipe Lopes Peixinho	52112	Paulo Fernando Lourenço Santos
G09				
G10				
G11				
G12				
G13				
G14				
G15				
G16				
G17				
G18				
G19				
G20				

Next Week

- **Lecture and Lab session on Wednesday, March 28th**
 - ◆ **Some rooms**
 - ◆ **Some hours**
- **You are expected to have Tableau 10.5 installed in your laptop.**
- **The team registration should be concluded up to March 30**

What Is Perception?

What is perception?

What is perception?

- Most define perception as the process of:
 - ◆ **recognizing** (being aware of);
 - ◆ **organizing** (gathering and storing);
 - ◆ and **interpreting** (binding to knowledge) **sensory information**.

What is perception?

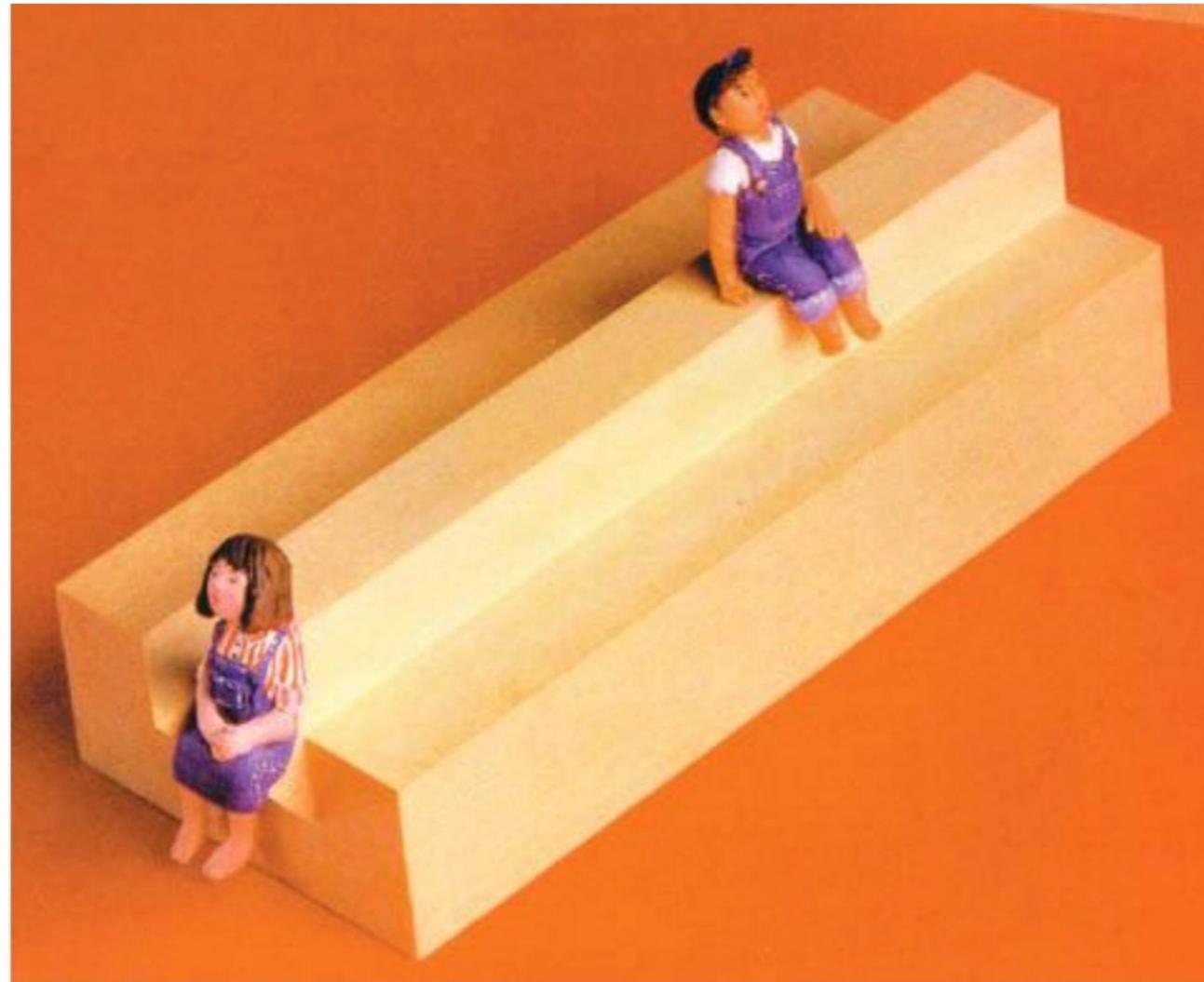
- Most define perception as the process of:
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 - ◆ **organizing** (gathering and storing);
 - ◆ and **interpreting** (binding to knowledge) **sensory information**.

- Perception is the process by which we **interpret the world around us, forming a mental representation of the environment**.

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 - ◆ **recognizing** (being aware of);
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 - ◆ and **interpreting** (binding to knowledge) **sensory information**.
- Perception is the process by which we **interpret the world around us, forming a mental representation of the environment**.
- **The brain makes assumptions about the world to overcome the inherent ambiguity in all sensory data, and in response to the task at hand.**

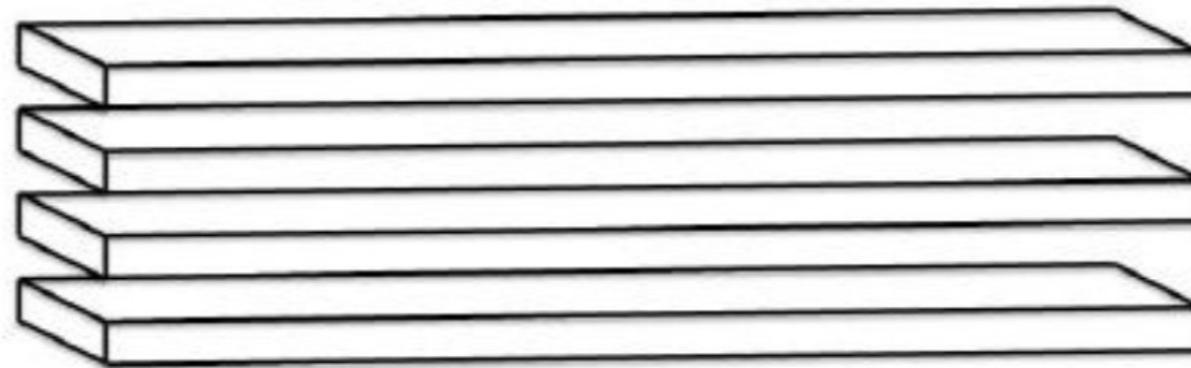
The brain makes assumptions !



Two seated figures, making sense at a higher, more abstract level, but still disturbing. On closer inspection, these seats are not realizable. (Image courtesy N. Yoshigahara.)

Figure 3.1 (Matthew Ward, et. all)

The brain makes assumptions !



Four \neq three. As in Figure 3.1, this object would have a problem being built (there are four boards on the left and three on the right).

Figure 3.2 (Matthew Ward, et. all)

The brain makes assumptions !

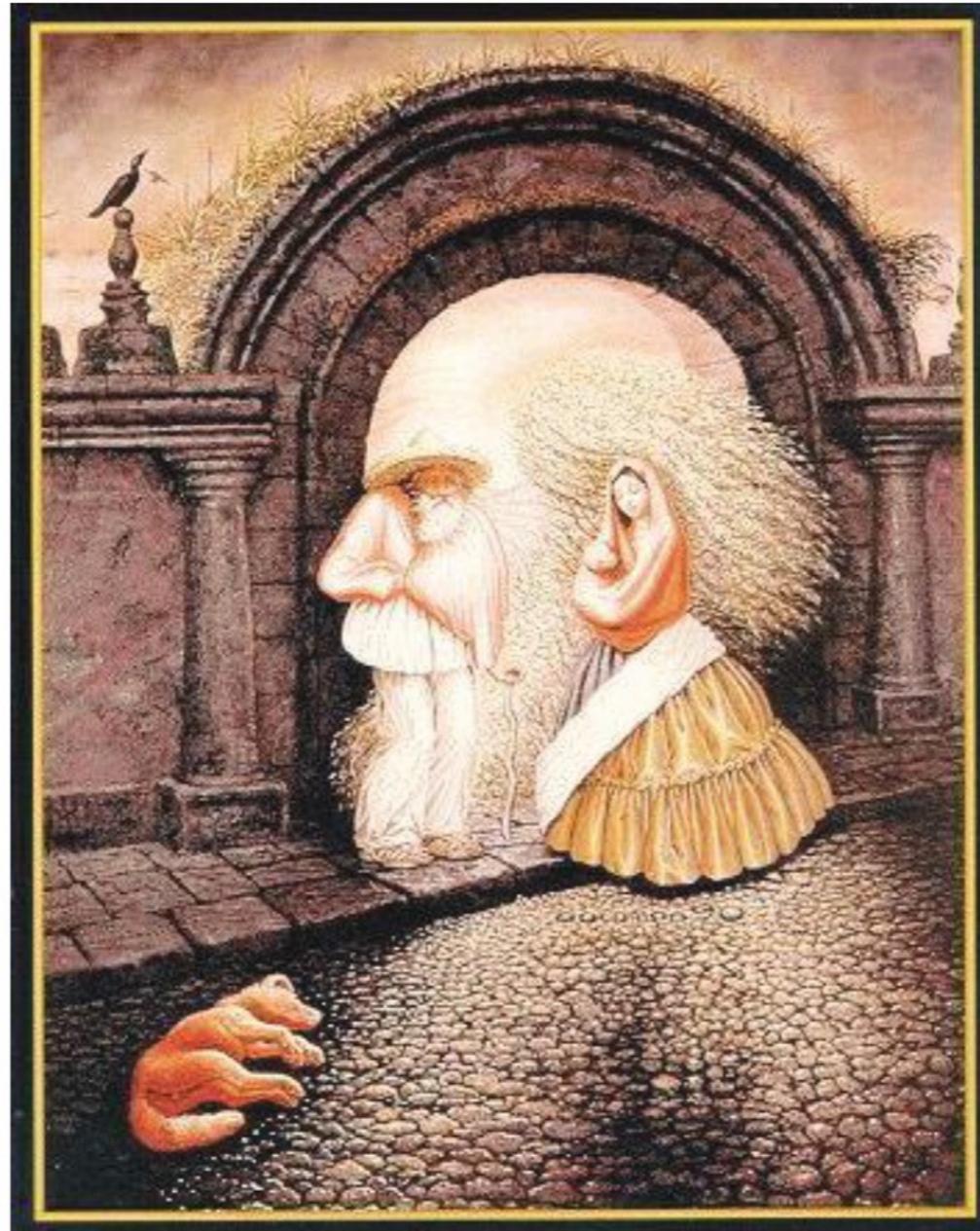


Figure 3.3 (Matthew Ward, et. all)

A more complex illusion: there are two people drawn as part of the face.

The brain makes assumptions !

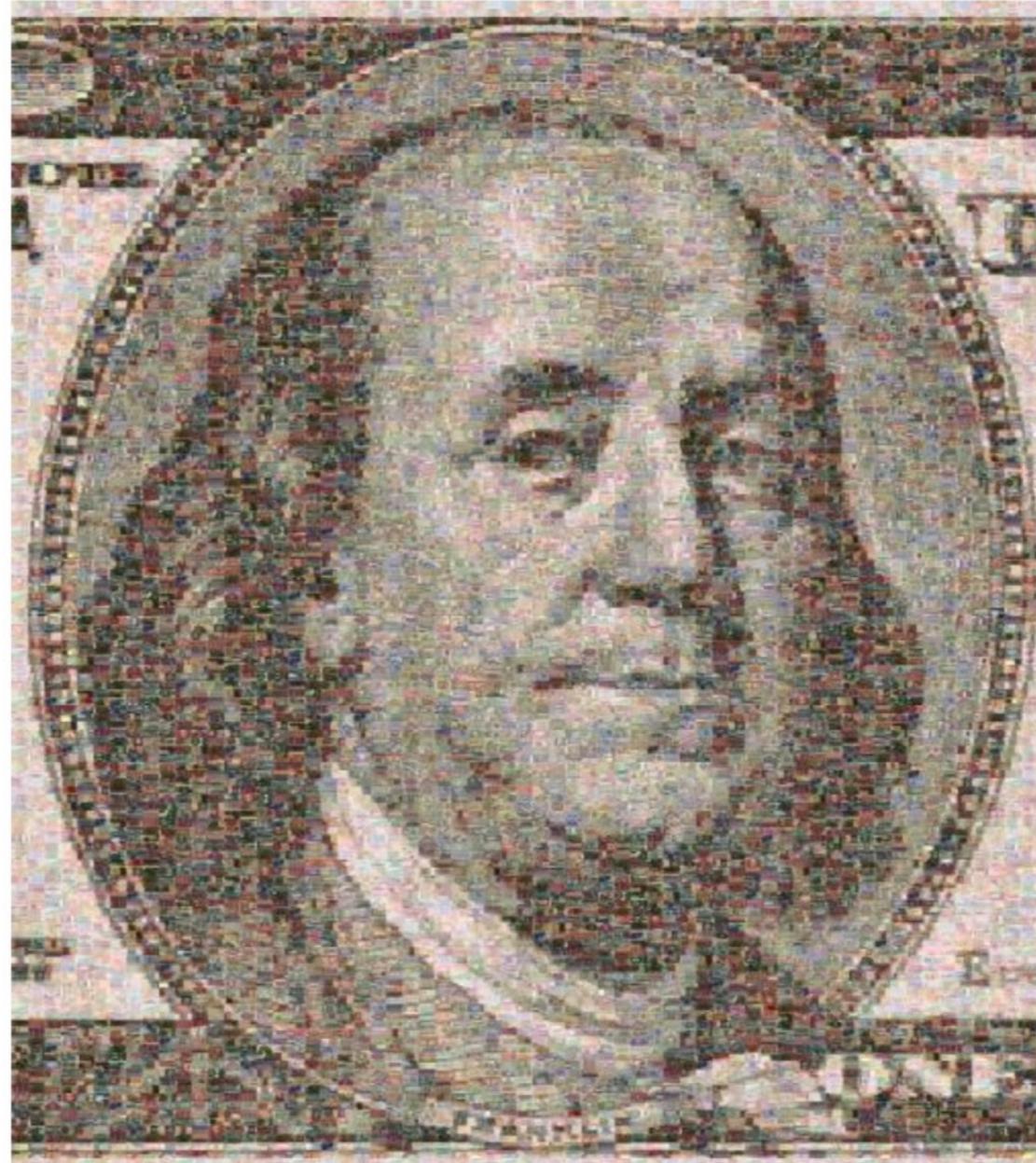


Figure 3.4
(Matthew Ward, et. all)

Photomosaic of Benjamin Franklin using images of international paper money or bank notes. (Photomosaic[®] by Robert Silvers, <http://www.photomosaic.com>.)

The brain makes assumptions !

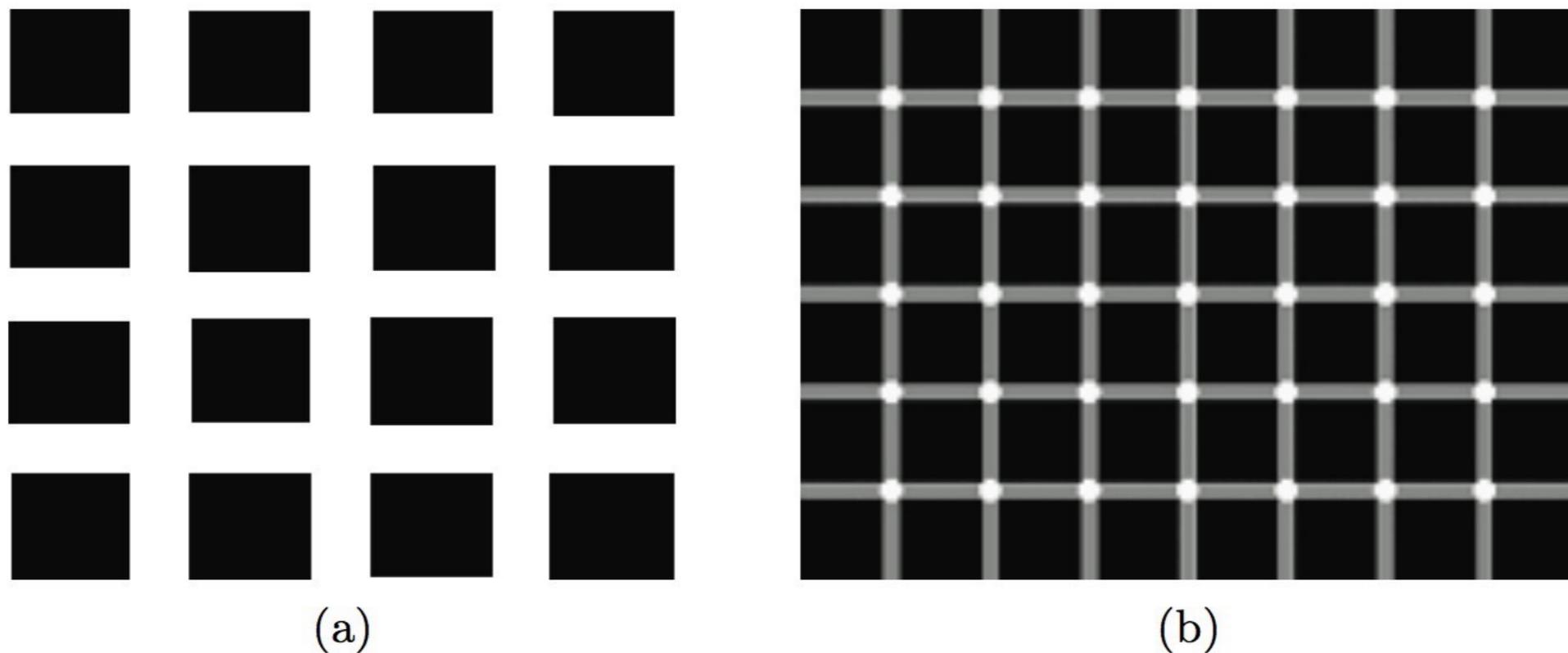


Figure 3.5
(Matthew Ward, et. all)

Close-up view of the eye in Figure 3.4. (Photomosaic[®] by Robert Silvers, <http://www.photomosaic.com>.)

The brain makes assumptions !

- Our vision system is, foremost, **not static**, and secondly, often not under our full control.

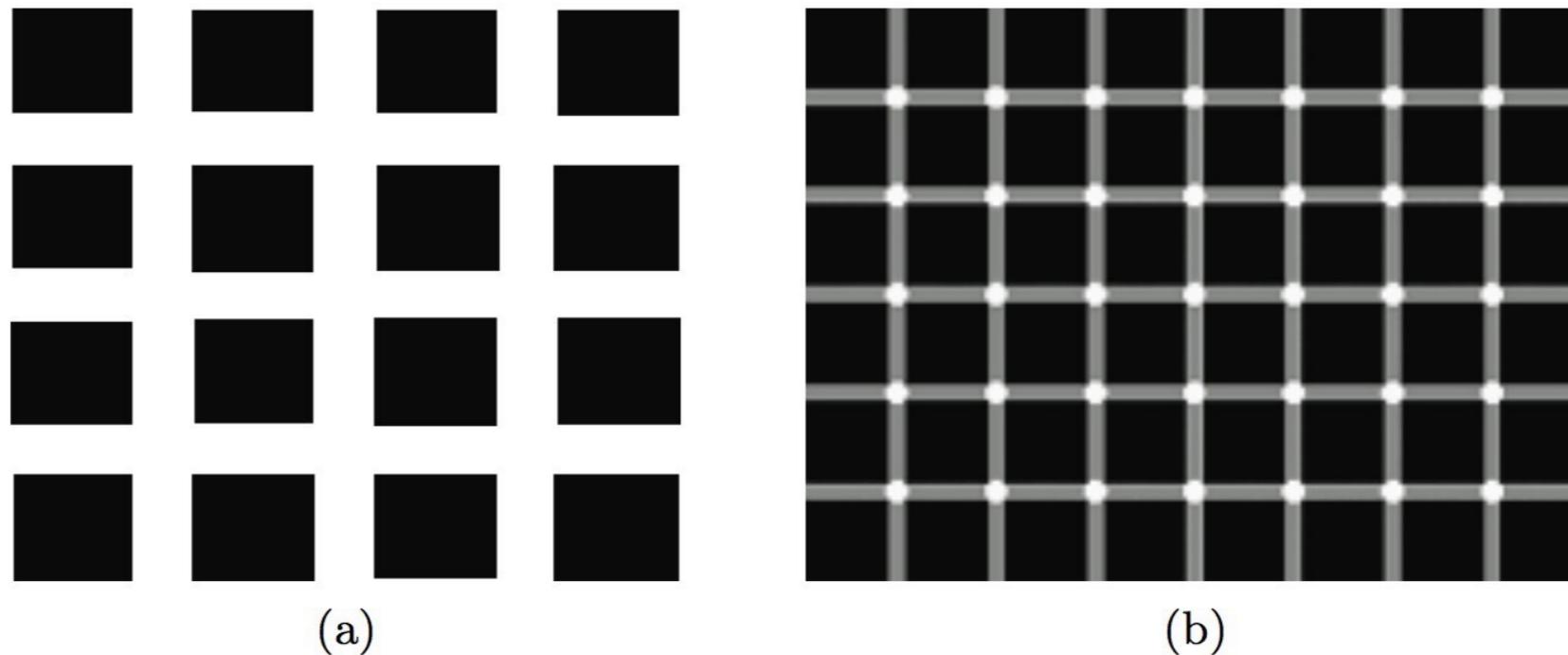


The Hermann grid illusion: (a) illusory black squares appear over the complete image as you gaze at it; (b) similar to (a) but even more dynamic and engaging.

Figure 3.6 (Matthew Ward, et. all)

The brain makes assumptions !

- When we **visualize data**, we need to **make sure that no such interferences are present** that would impede the understanding of what we are trying to convey in the visualizations.



The Hermann grid illusion: (a) illusory black squares appear over the complete image as you gaze at it; (b) similar to (a) but even more dynamic and engaging.

The study of perception

- The study of perception is to identify the whole process of perception, **from sensation to knowledge**. What is causing the lines not to appear perfectly straight?

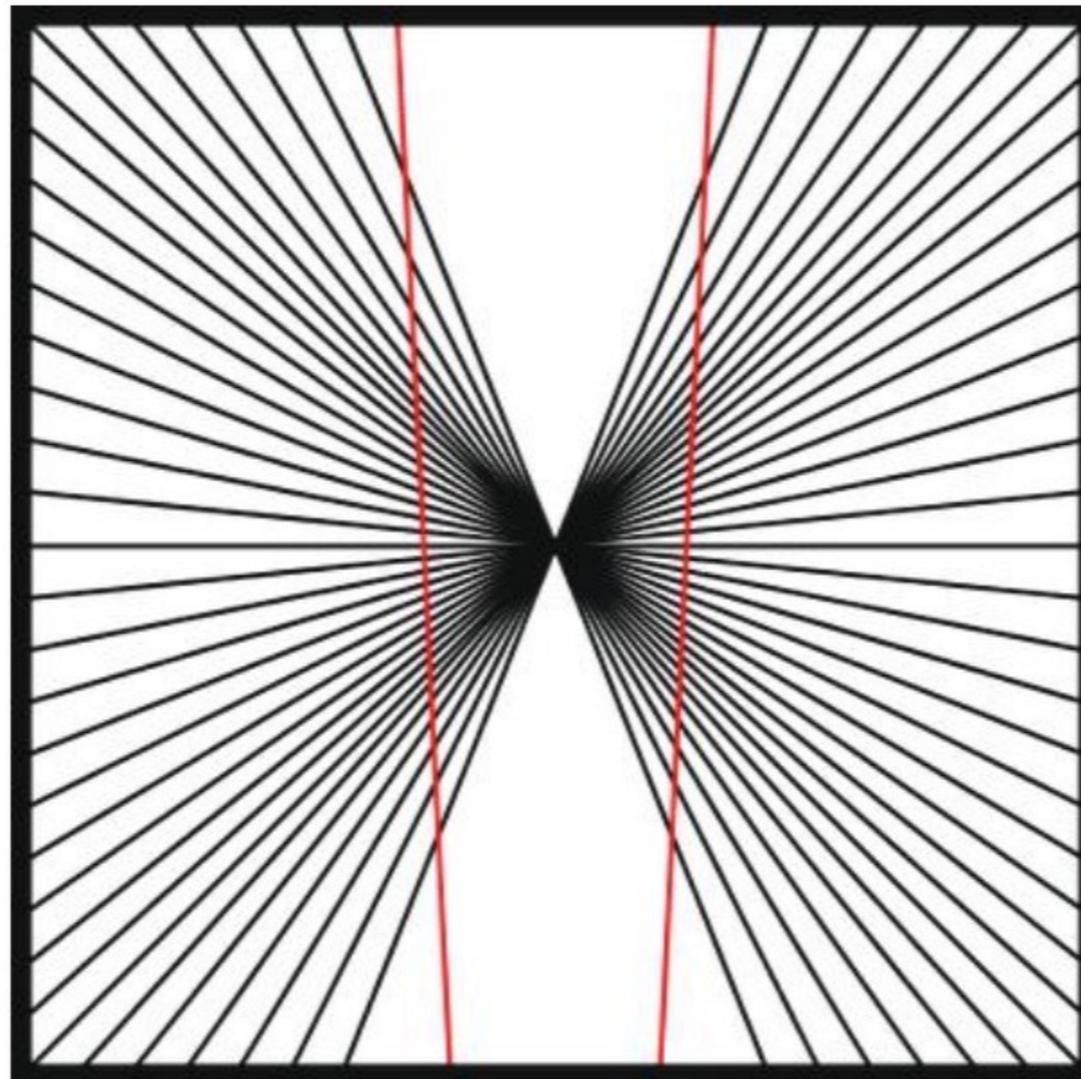


Figure 3.7
(Matthew Ward, et. all)

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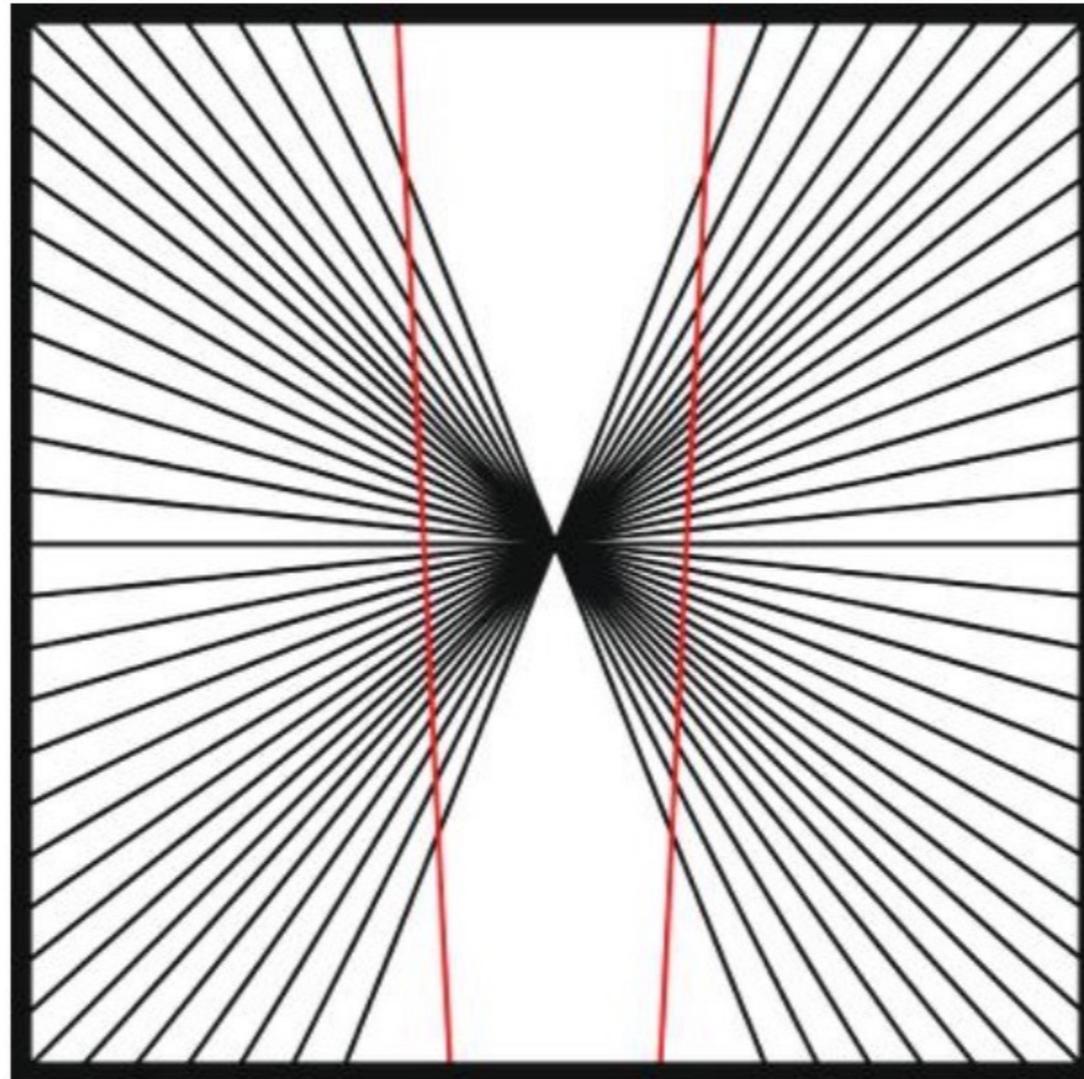


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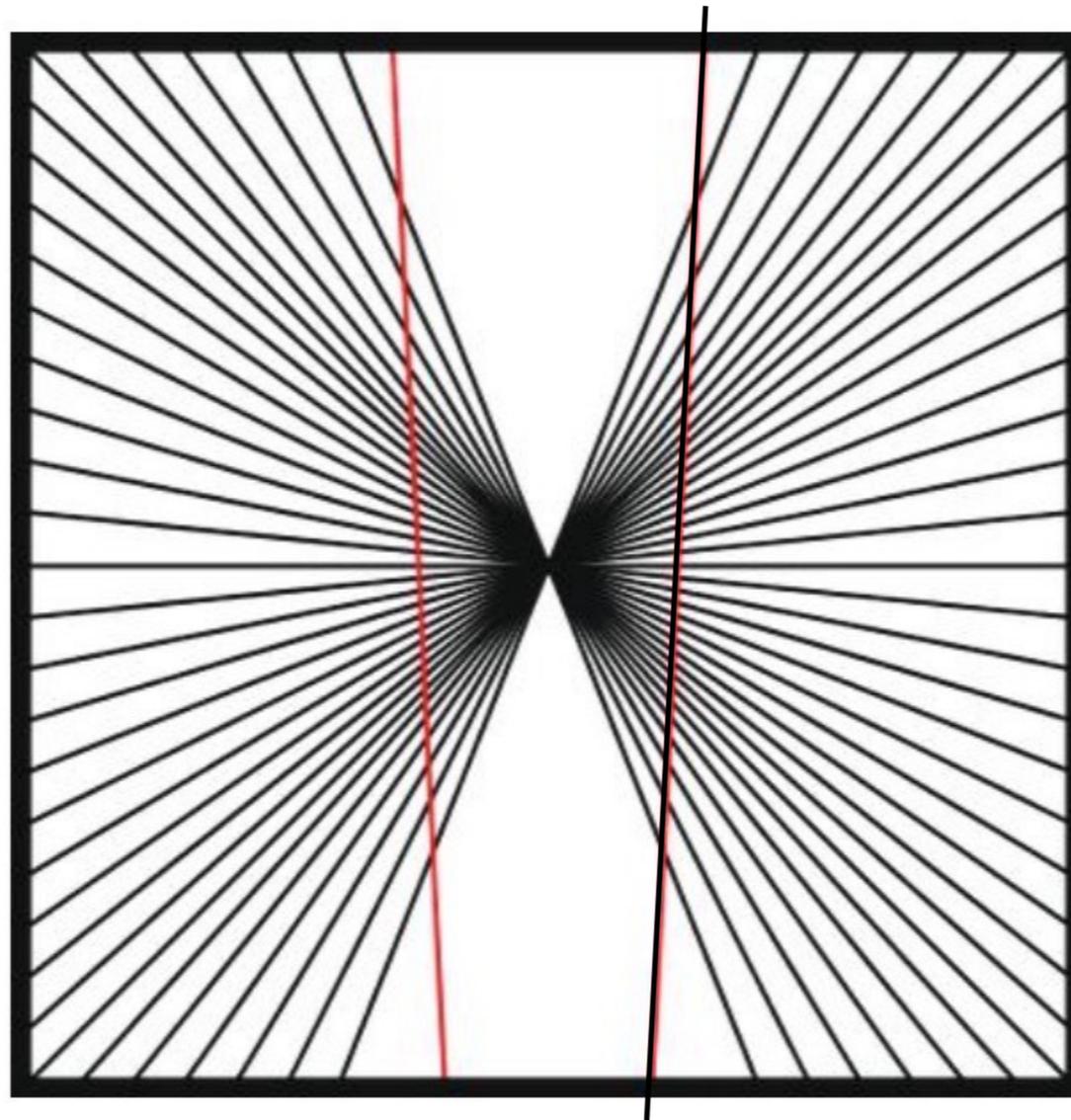


Figure 3.7
(Matthew Ward, et. all)

The study of perception

- The study of perception is to identify the whole process of perception, **from sensation to knowledge**. What is causing the triangle to stand out?

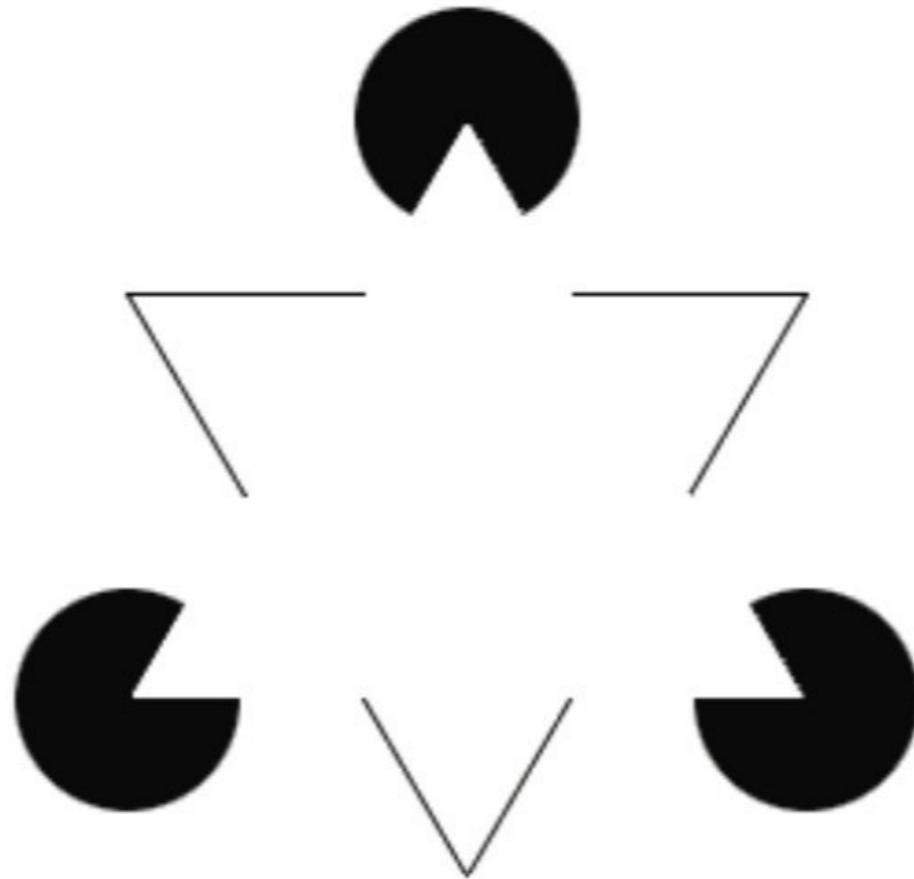


Figure 3.7
(Matthew Ward, et. all)

The study of perception

- Two main approaches to the study of perception: One deals with **measures**, and the other with **models**. **Both are linked**.
- ◆ Measurements can help in the **development of a model**, and in turn, a **model** should help **predict future outcomes**, which can then be measured to validate the model.
- ◆ We can measure **low-level sensory perception** (which line is longer) or **higher level perception** (can you recognize the bird in this scene?).

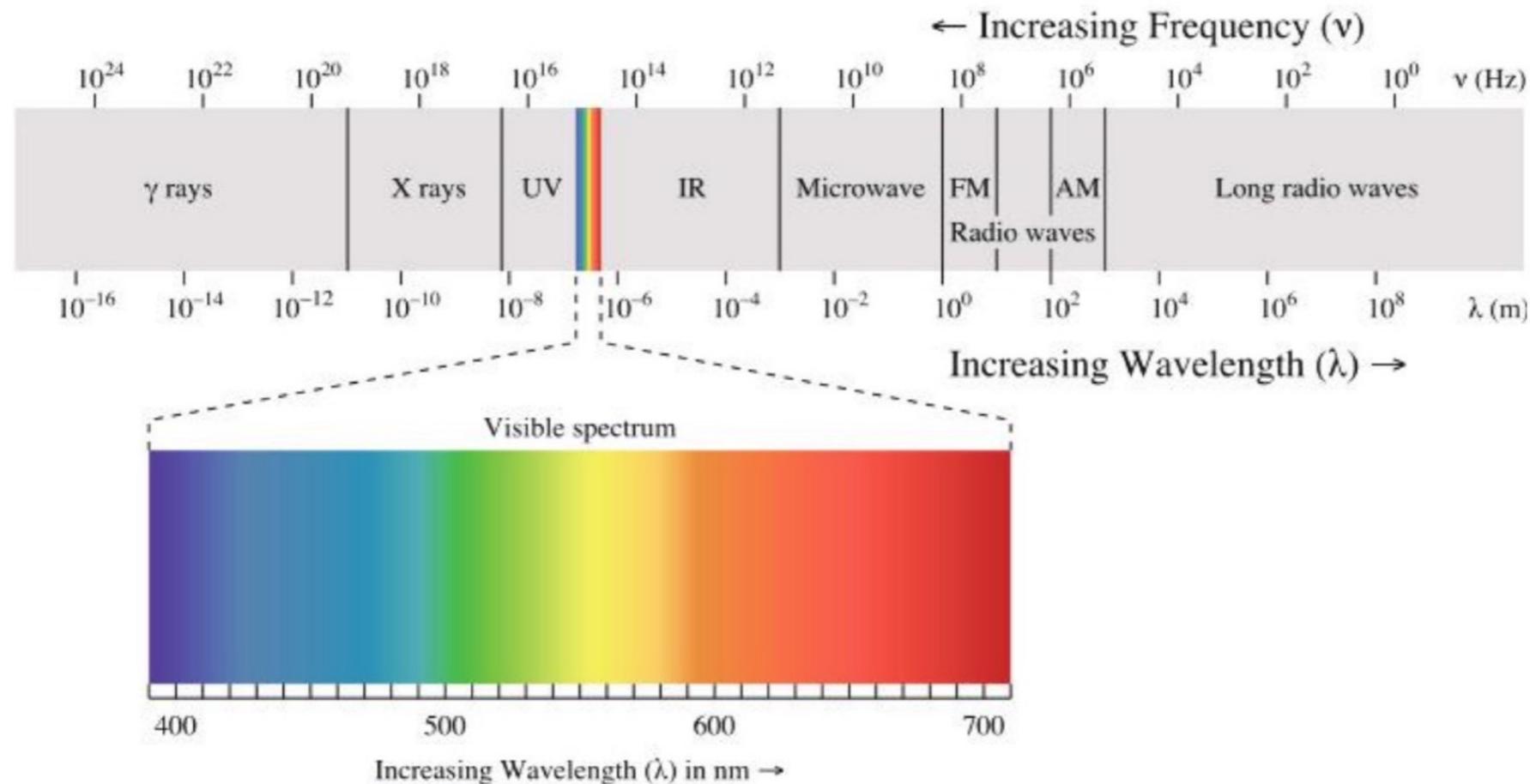
Physiology

Physiology

- **Visible Spectrum**
- **Anatomy of the Visual System**
- **Visual Processing**
- **Eye Movement**

Visible Spectrum

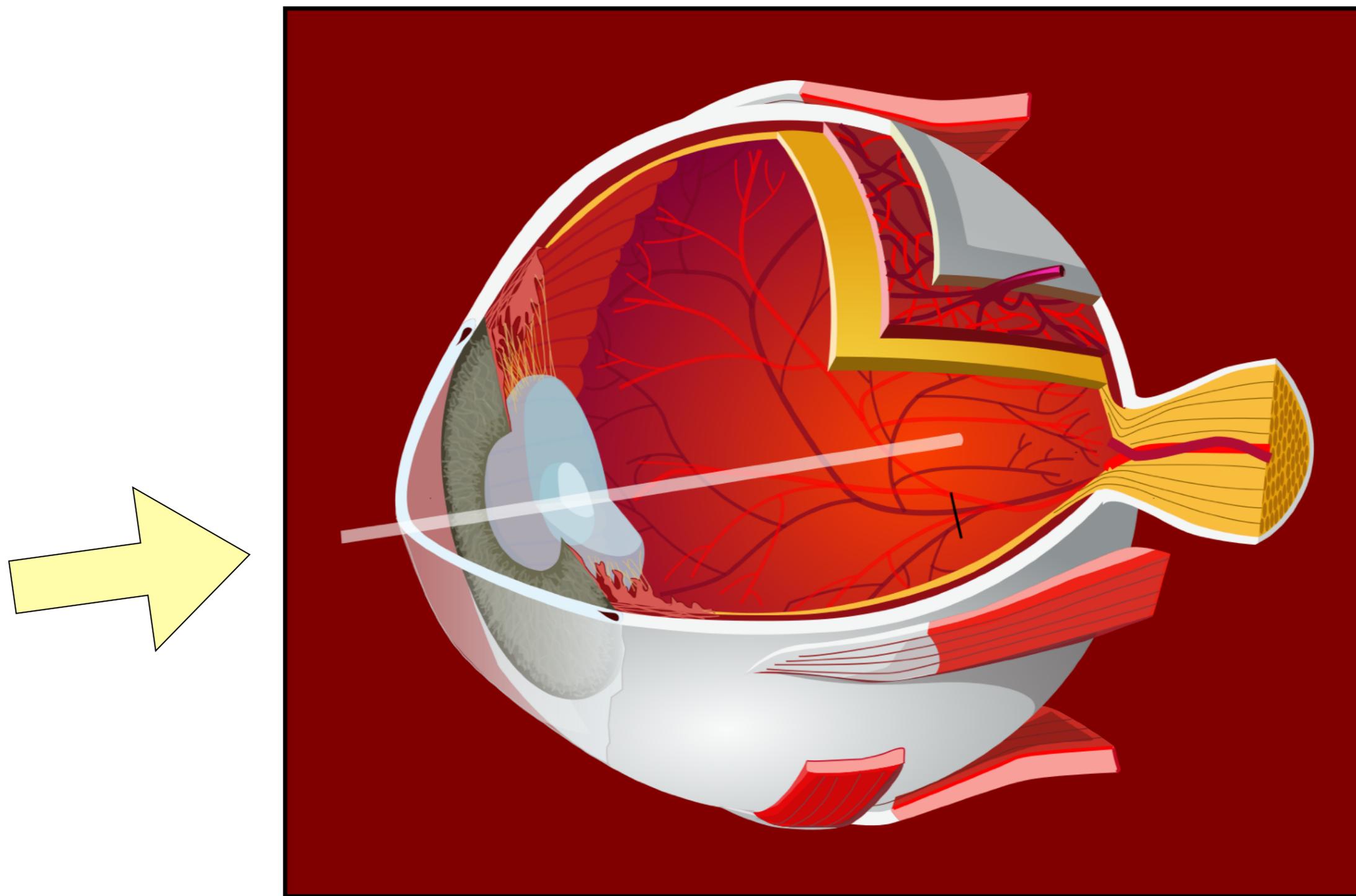
- The range is very much dependent on the individual.
- **Color blindness** and **total blindness** in humans are the result of an individual not responding to certain wavelengths.



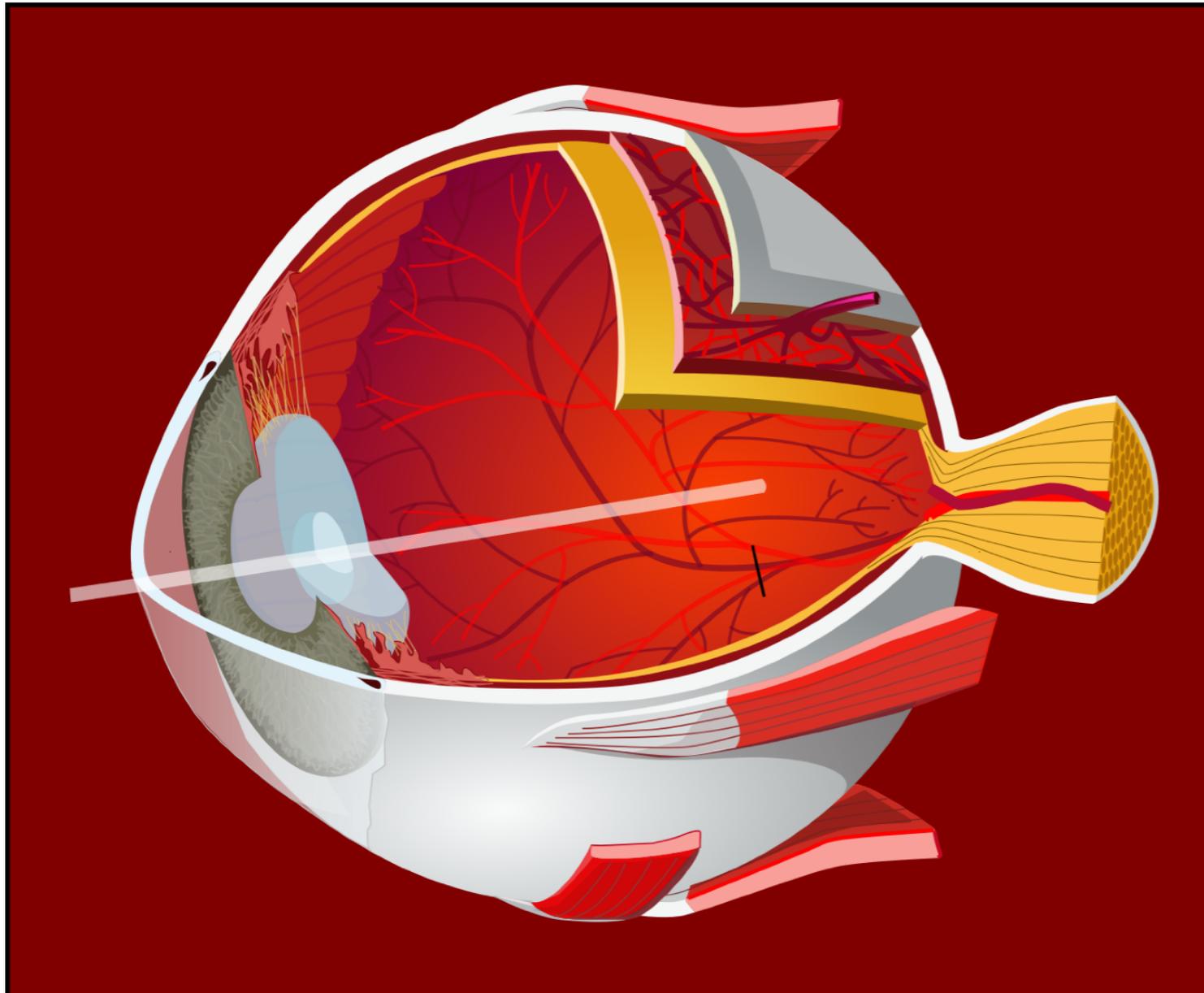
The electromagnetic spectrum with an expanded visible light spectrum [269]. (Image courtesy Wikimedia Commons.)

Figure 3.8 - (Matthew Ward, et. all)

Anatomy of the Visual System



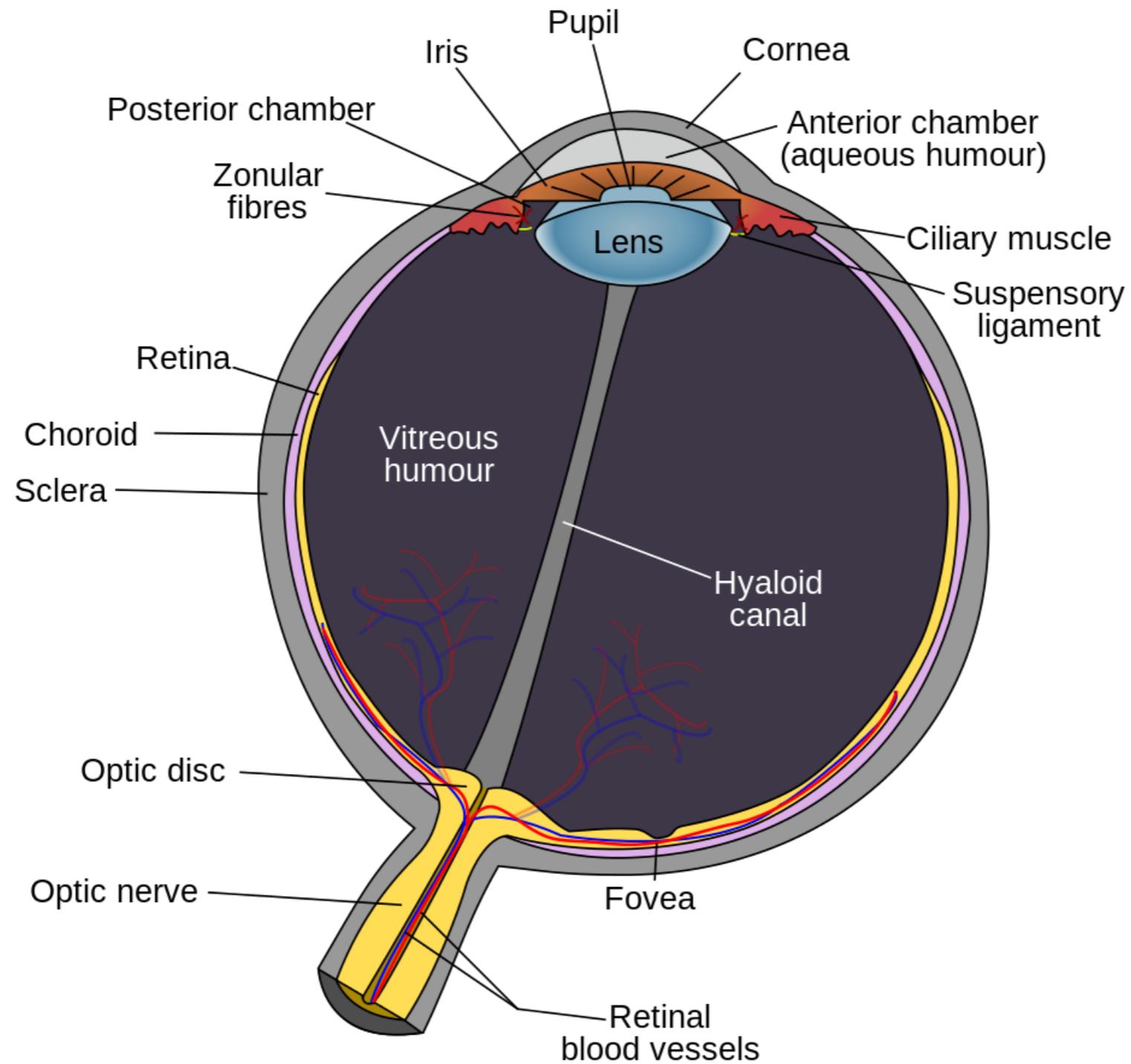
Anatomy of the Visual System



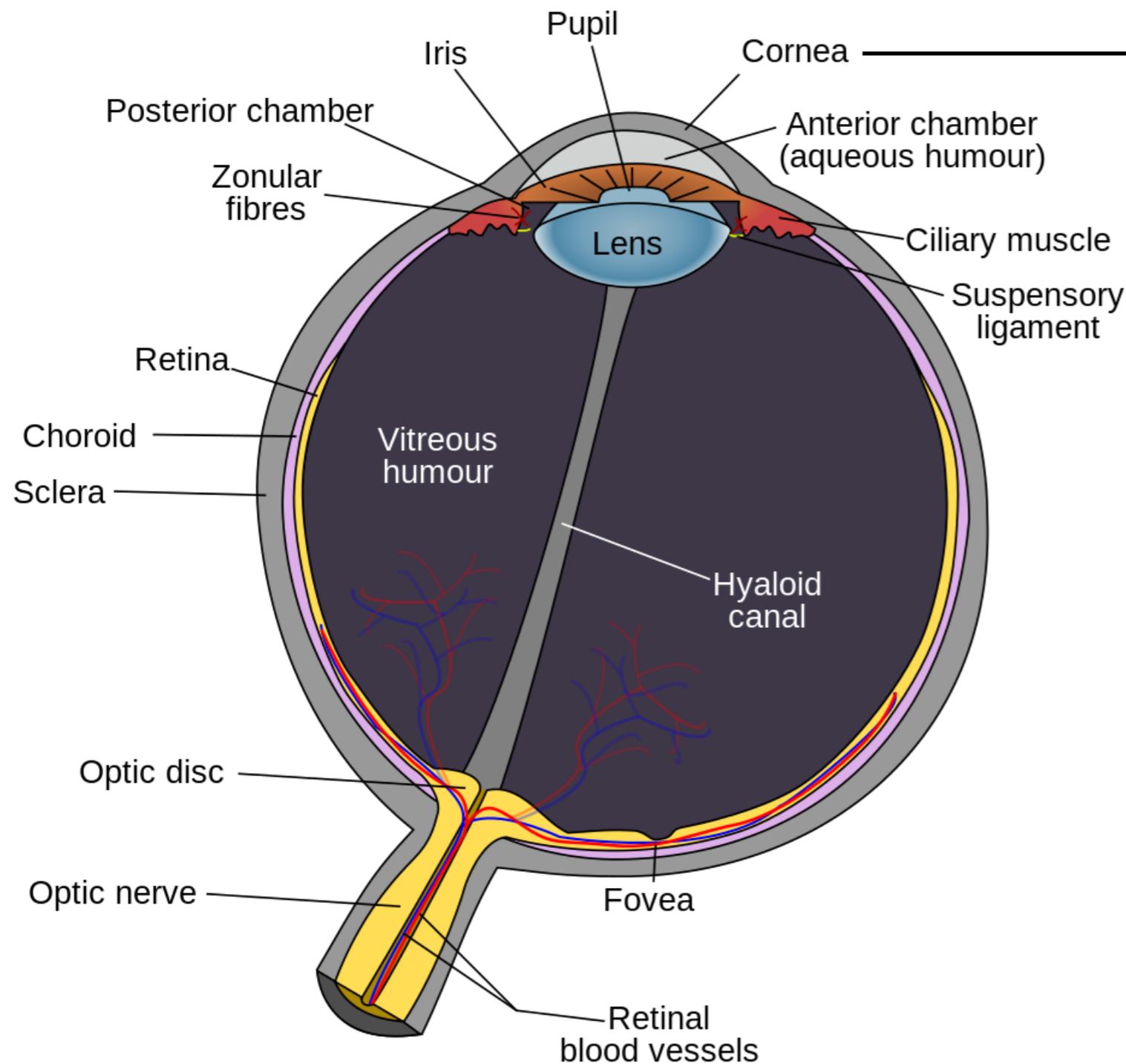
Connected to the head and brain by **six motion control muscles** and **one optic nerve**.

Six muscles are generally considered as motion controllers, providing the **ability to look at objects** in the scene. Tend to maintain the **eye-level with the horizon** when the head is not perfectly vertical and in **stabilization of images**.

Anatomy of the Visual System



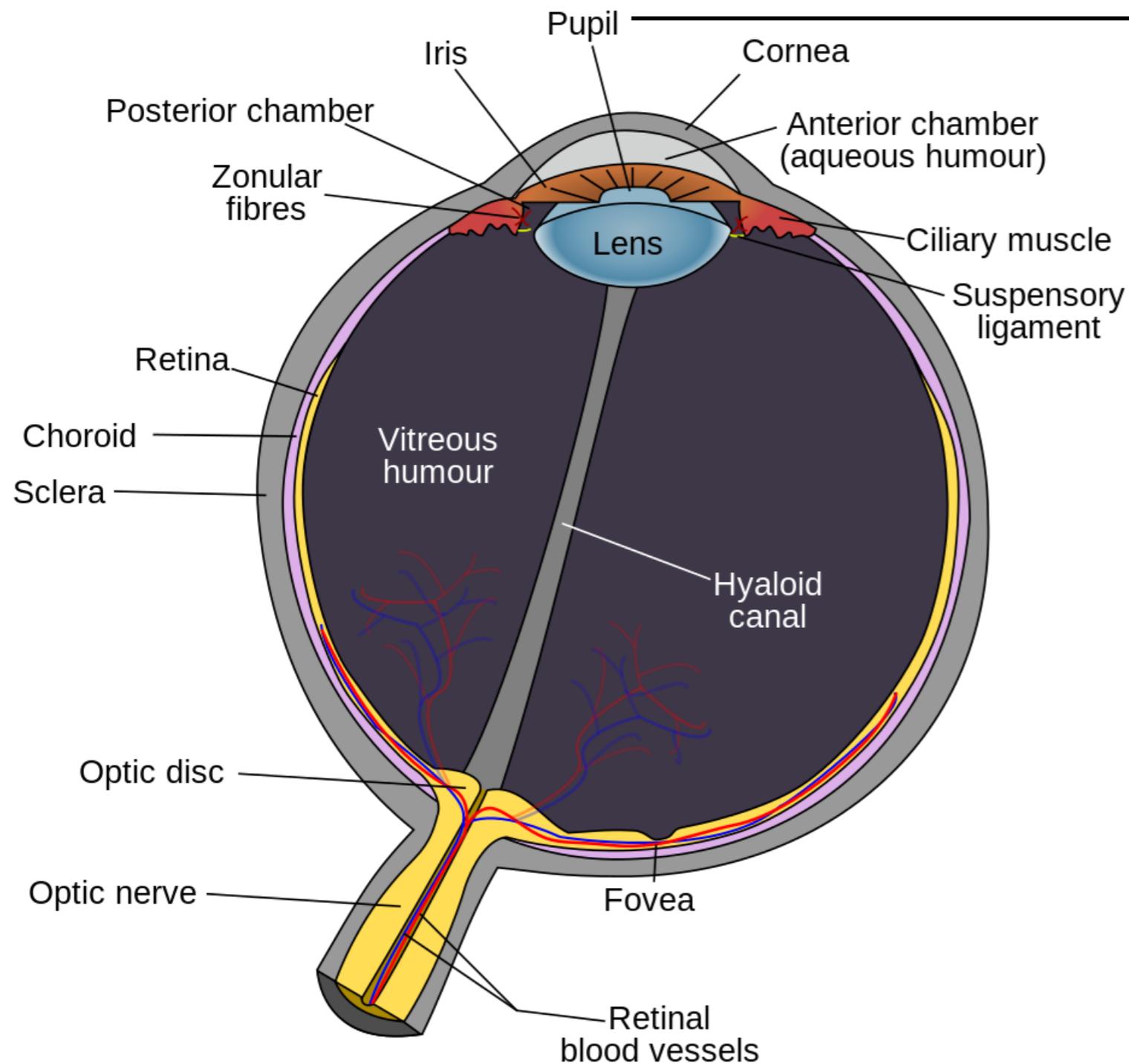
Anatomy of the Visual System



the **exterior cover** of the front of the eye:

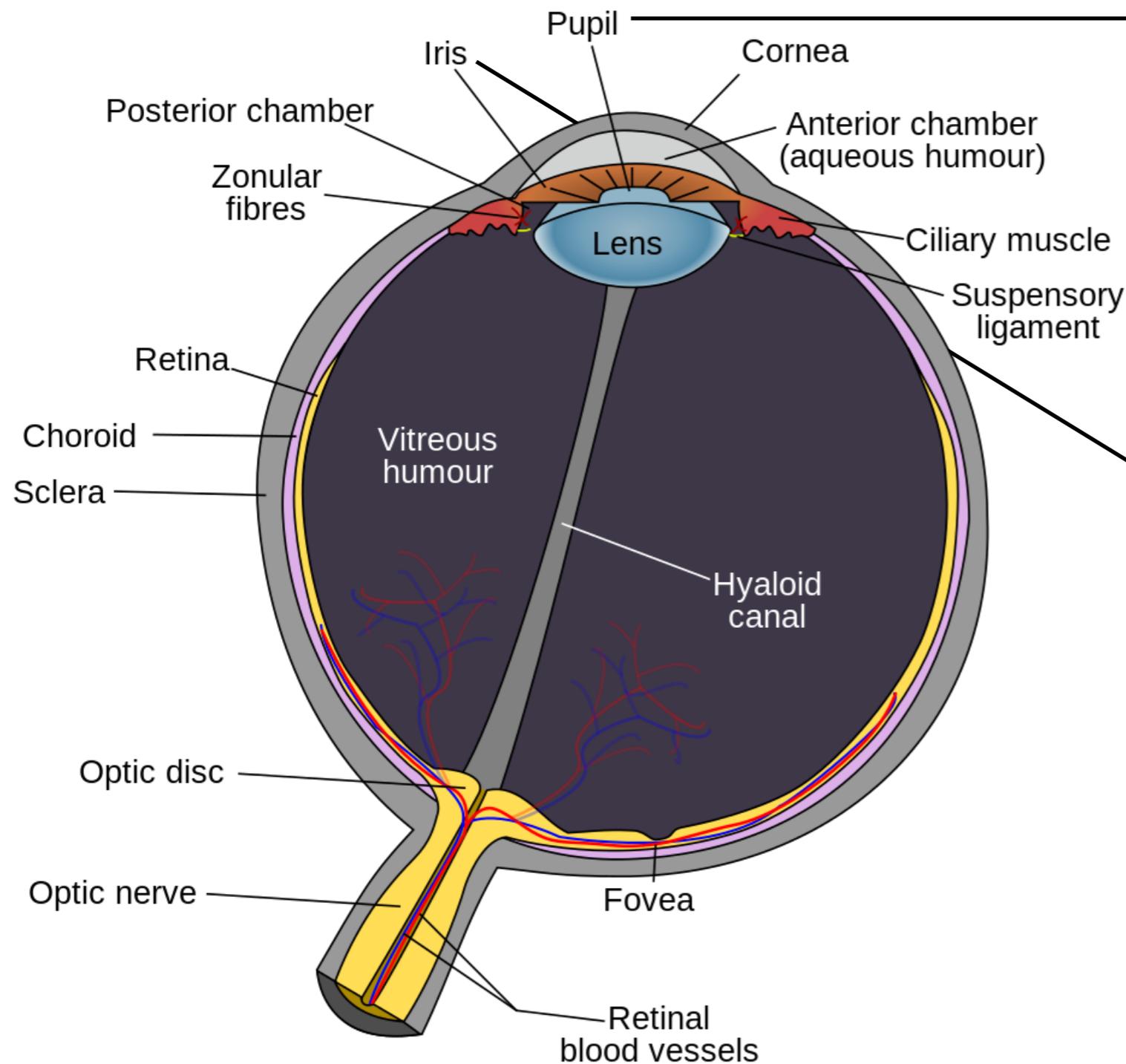
- acting as a **protective mechanism** against physical damage to the internal structure
- it also serves as **one lens focusing the light from the surrounding scene** onto the main lens

Anatomy of the Visual System



a **circular hole in the iris**, similar in function to an aperture stop on a photographic camera

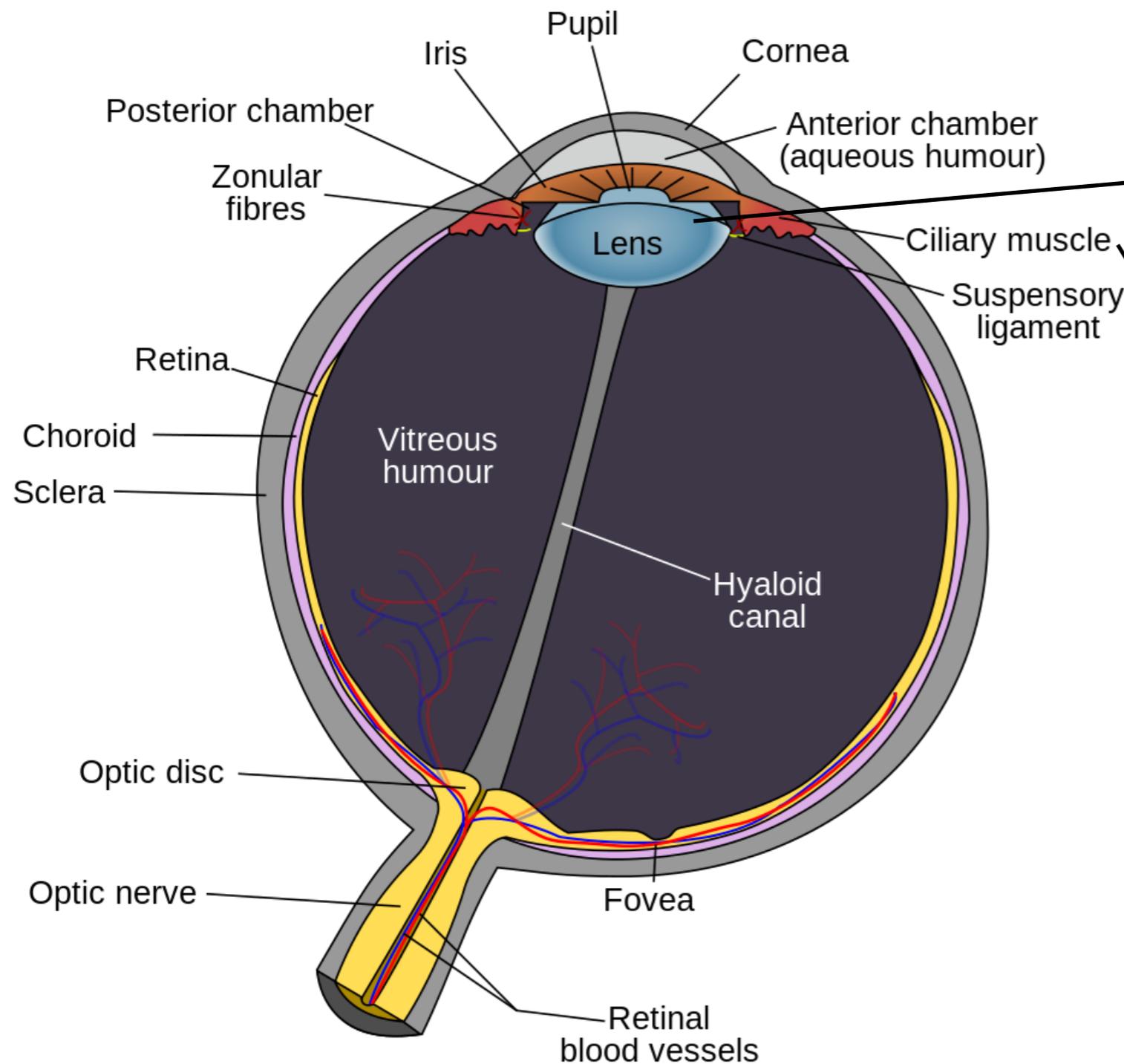
Anatomy of the Visual System



a **circular hole in the iris**, similar in function to an aperture stop on a photographic camera

The **iris** is a colored annulus containing **radial muscles for changing the size of the pupil opening**

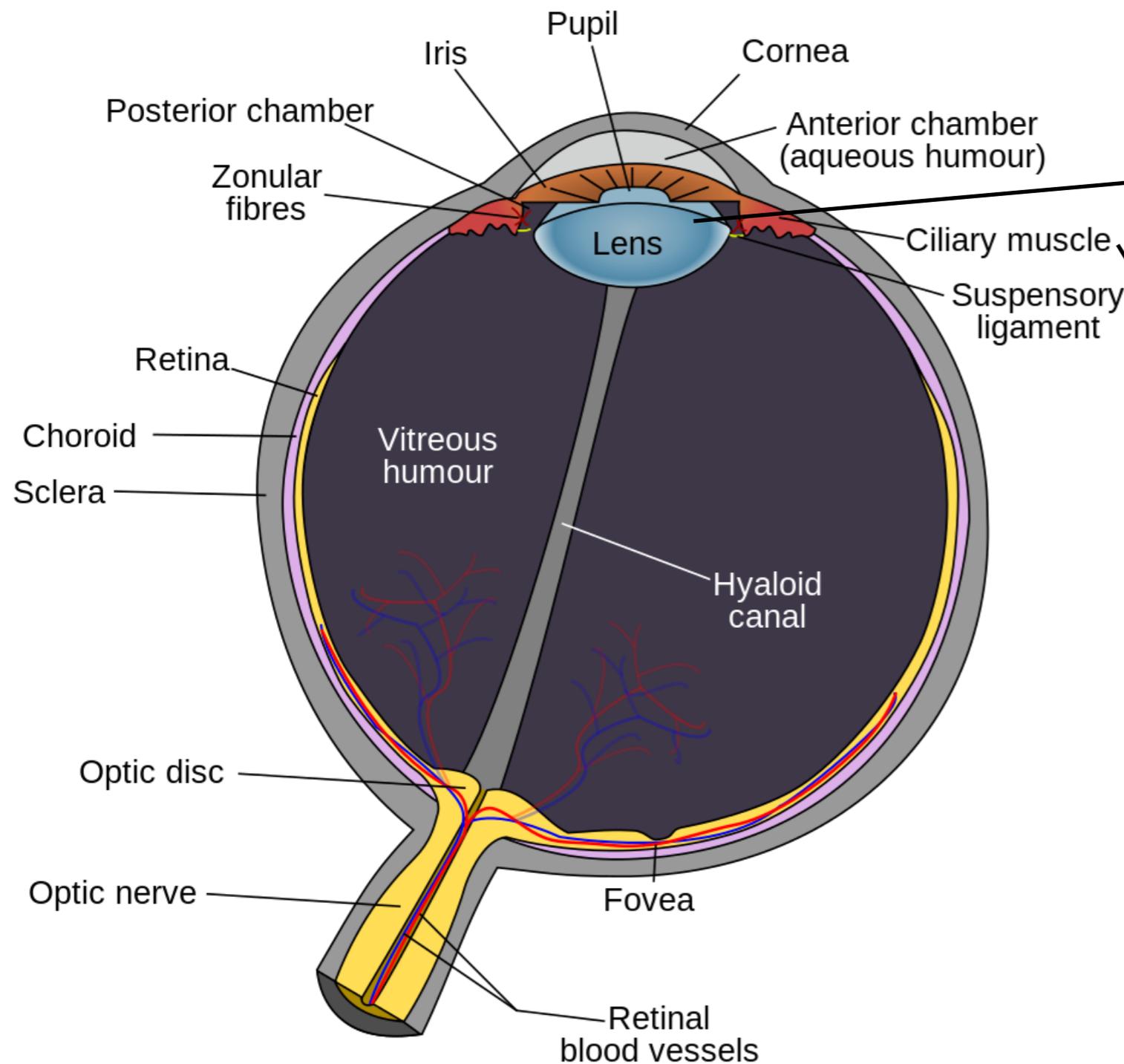
Anatomy of the Visual System



The third major component is the **lens**, whose **crystalline** structure is similar to onion skin.

Surrounded by the **ciliary body, a set of muscles**, the lens can be stretched and compressed, changing the thickness and curvature of the lens and consequently **adjusting the focal length of the optical system**.

Anatomy of the Visual System

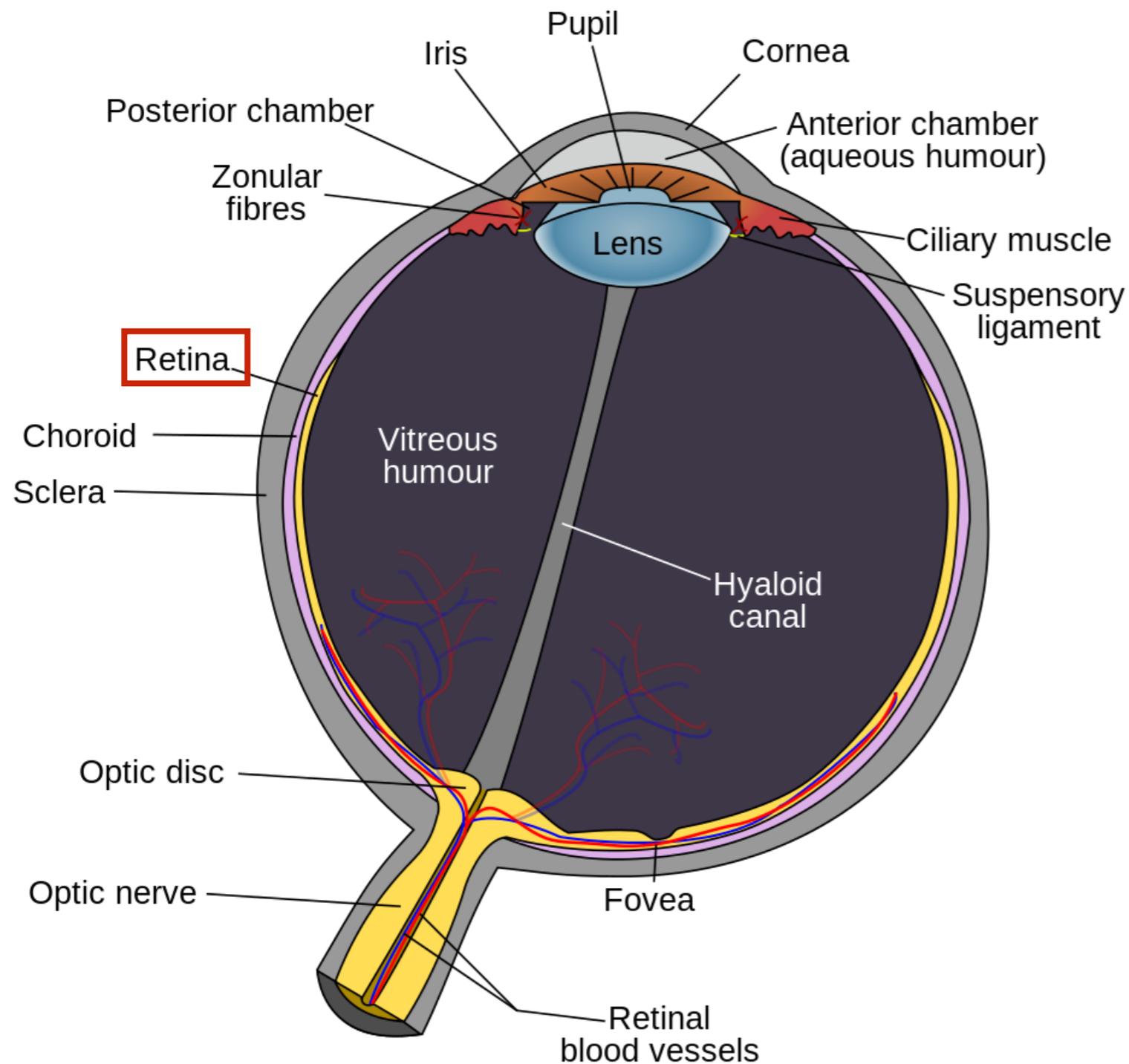


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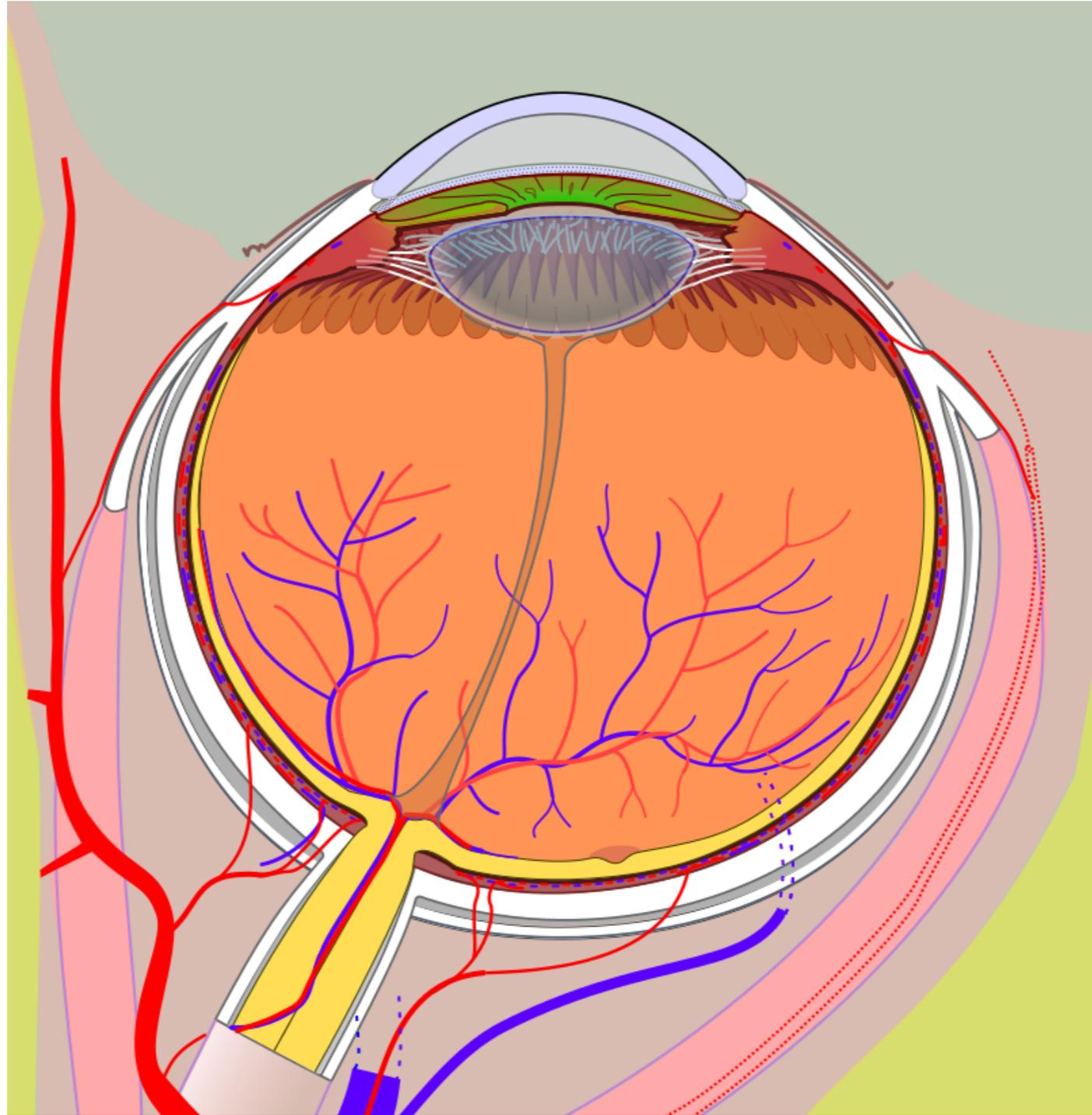
The **elasticity of the lens** determines the range of shape changes possible, which is **lost as one ages**, leaving the lens in a slightly stretched state

Anatomy of the Visual System



Once the light has passed through this lens system, the final light rays are projected onto the **photoreceptive layer**, called the **retina**.

Anatomy of the Visual System: Retina



Anatomy of the Visual System: Retina

- Two types of photosensitive cells: **rods** and **cones**
- **Rods** are primarily responsible for **intensity** perception. They are associated with **scotopic vision, night vision**, operating in clusters for increased sensitivity in very low light conditions.

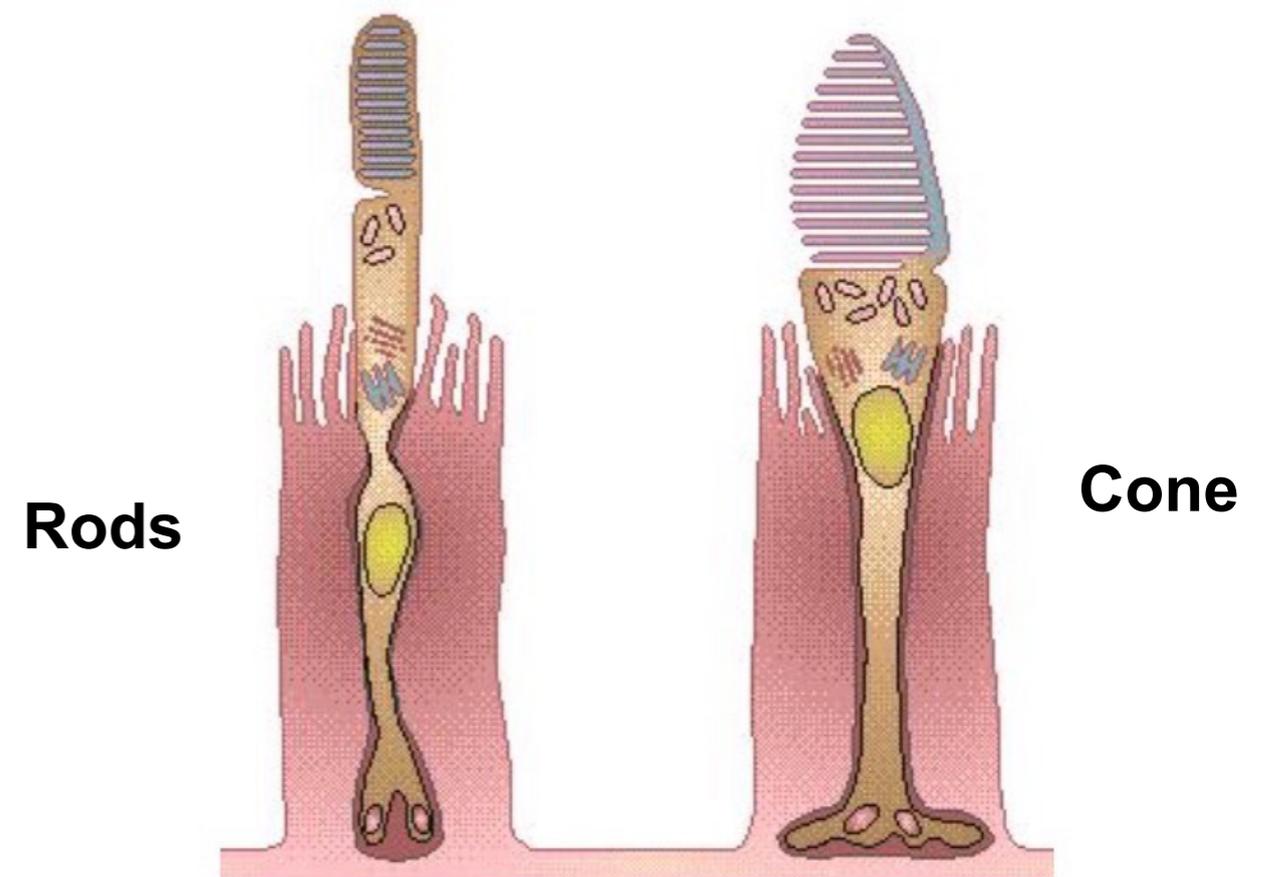
Rods



Human rod (left) and cone (right).

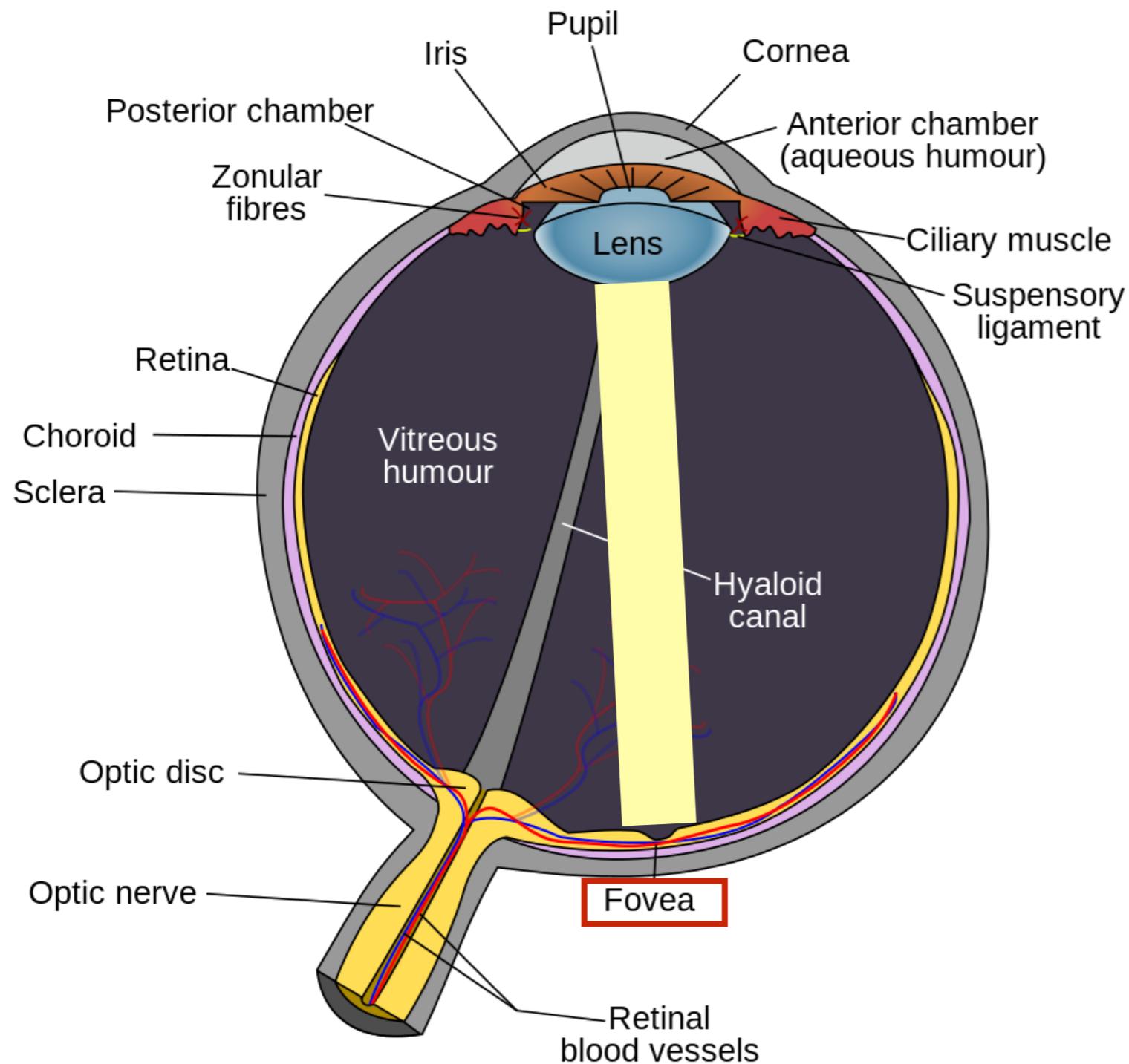
Anatomy of the Visual System: Retina

- Two types of photosensitive cells: **rods** and **cones**
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 - **Cones** for **color** perception
- **Rods** are typically ten times **more sensitive** to light than cones

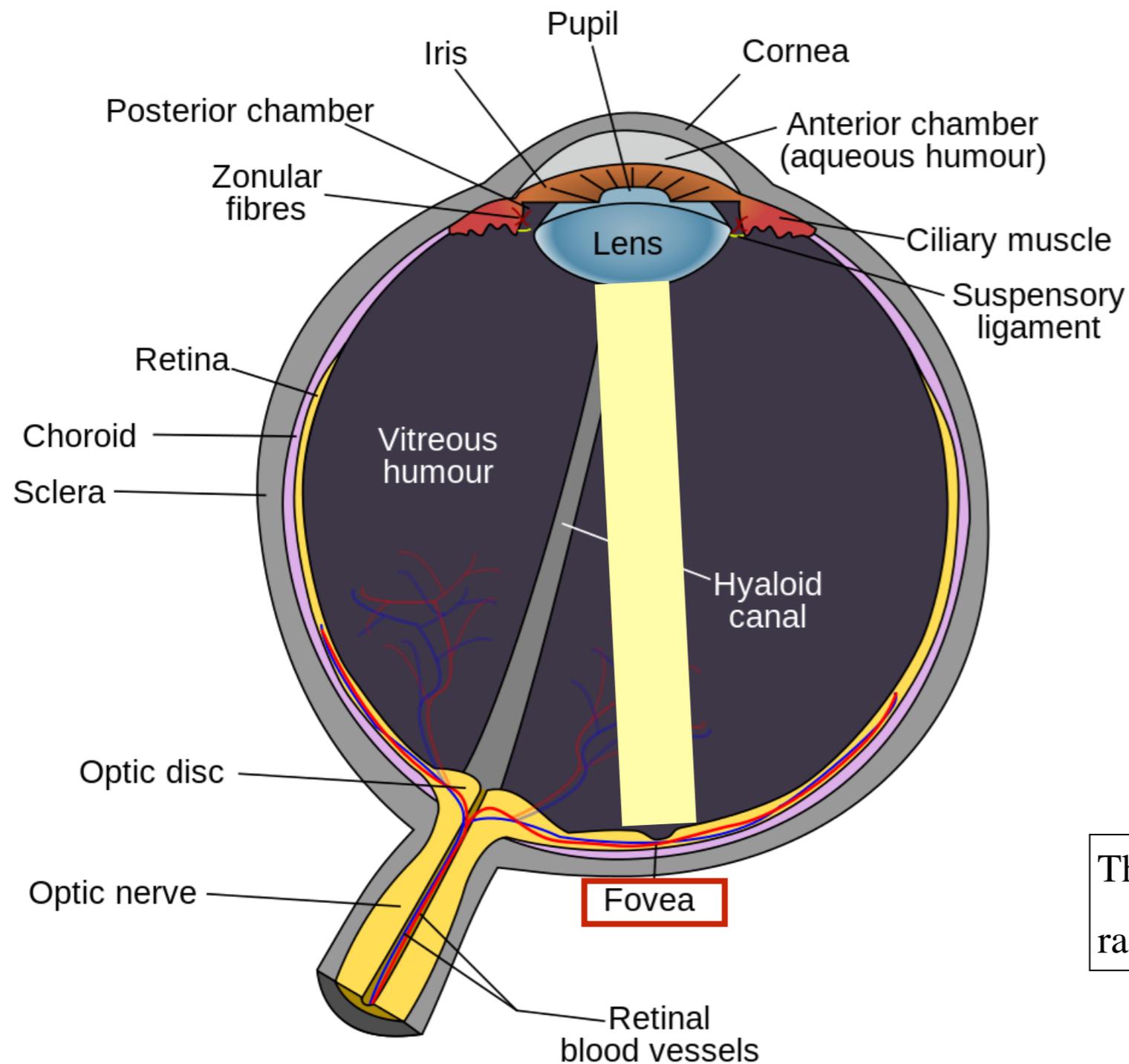


Human rod (left) and cone (right). (Image © Colour4Free.)

Anatomy of the Visual System: Retina

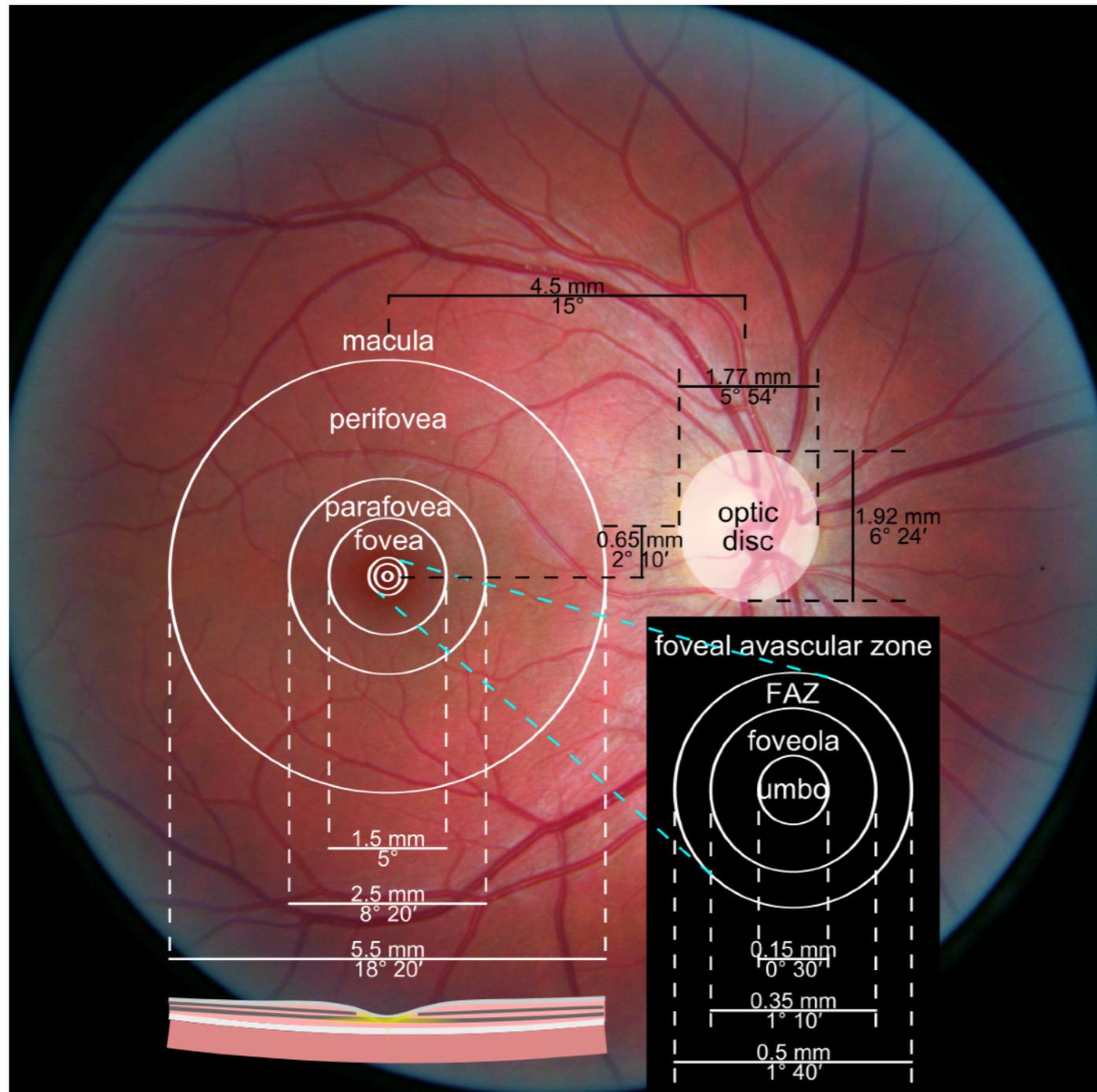


Anatomy of the Visual System: Retina



The structure of the retina is roughly radially symmetric around the **fovea**.

Anatomy of the Visual System: Retina



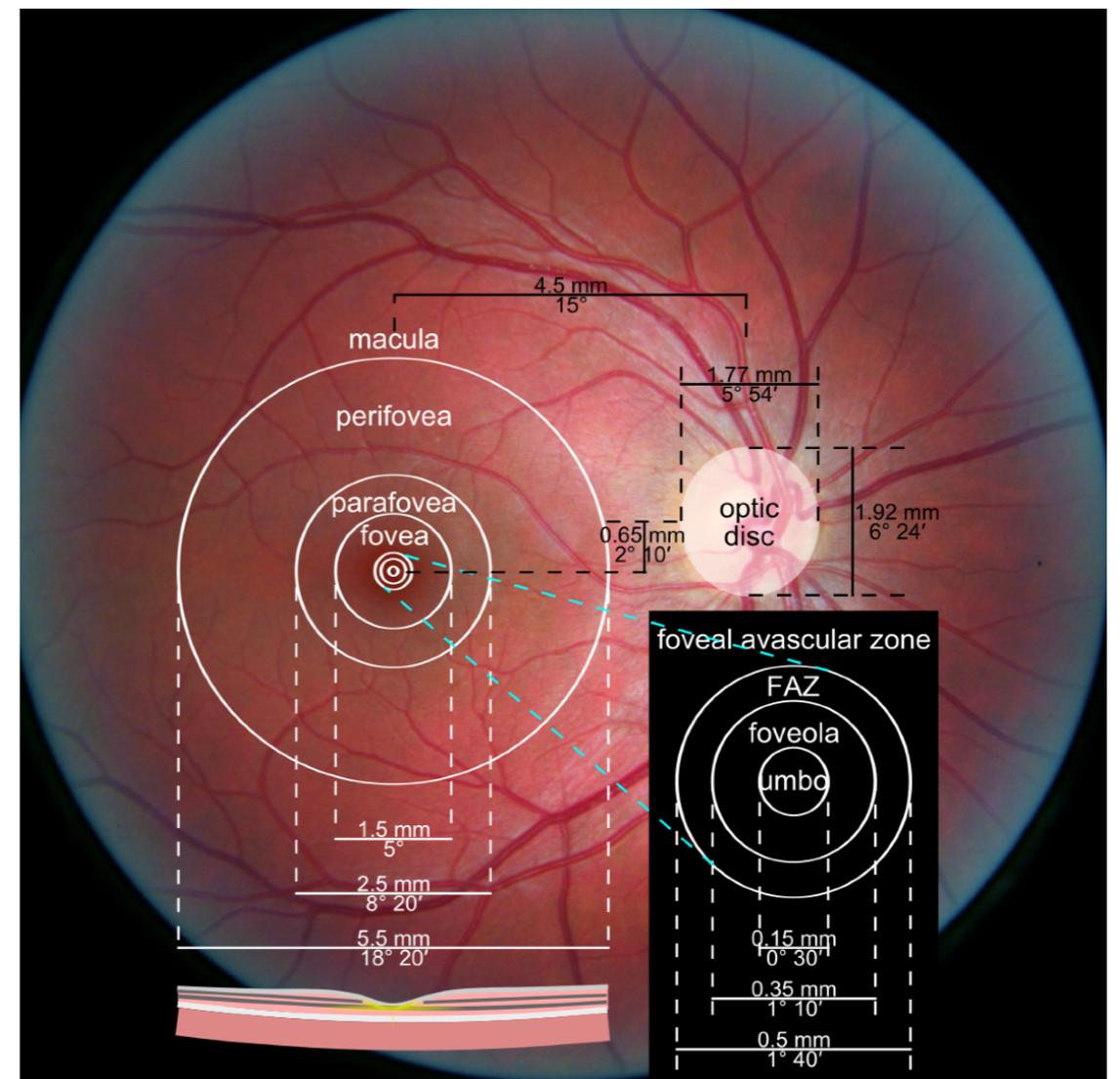
The structure of the retina is roughly radially symmetric around the **fovea**.

The fovea **contains only cones**, and linearly, there are about **147,000 cones per millimeter**.

The fovea is the **region of sharpest vision**.

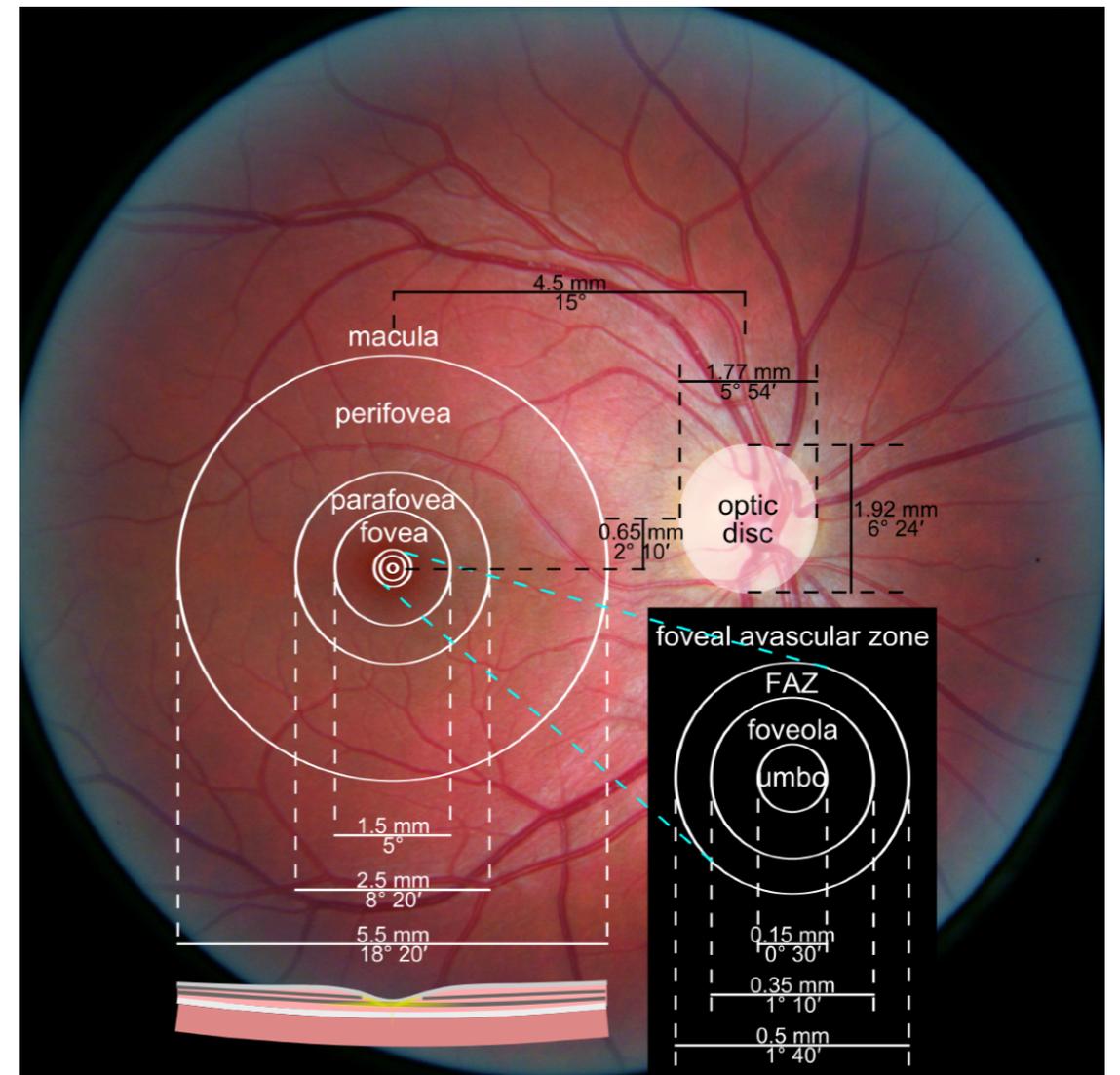
Anatomy of the Visual System: Retina

- There is an overall distribution of all cells across the retina, with the **highest concentration occurring at the center of our visual field in the fovea** and reducing in coverage toward the edges.



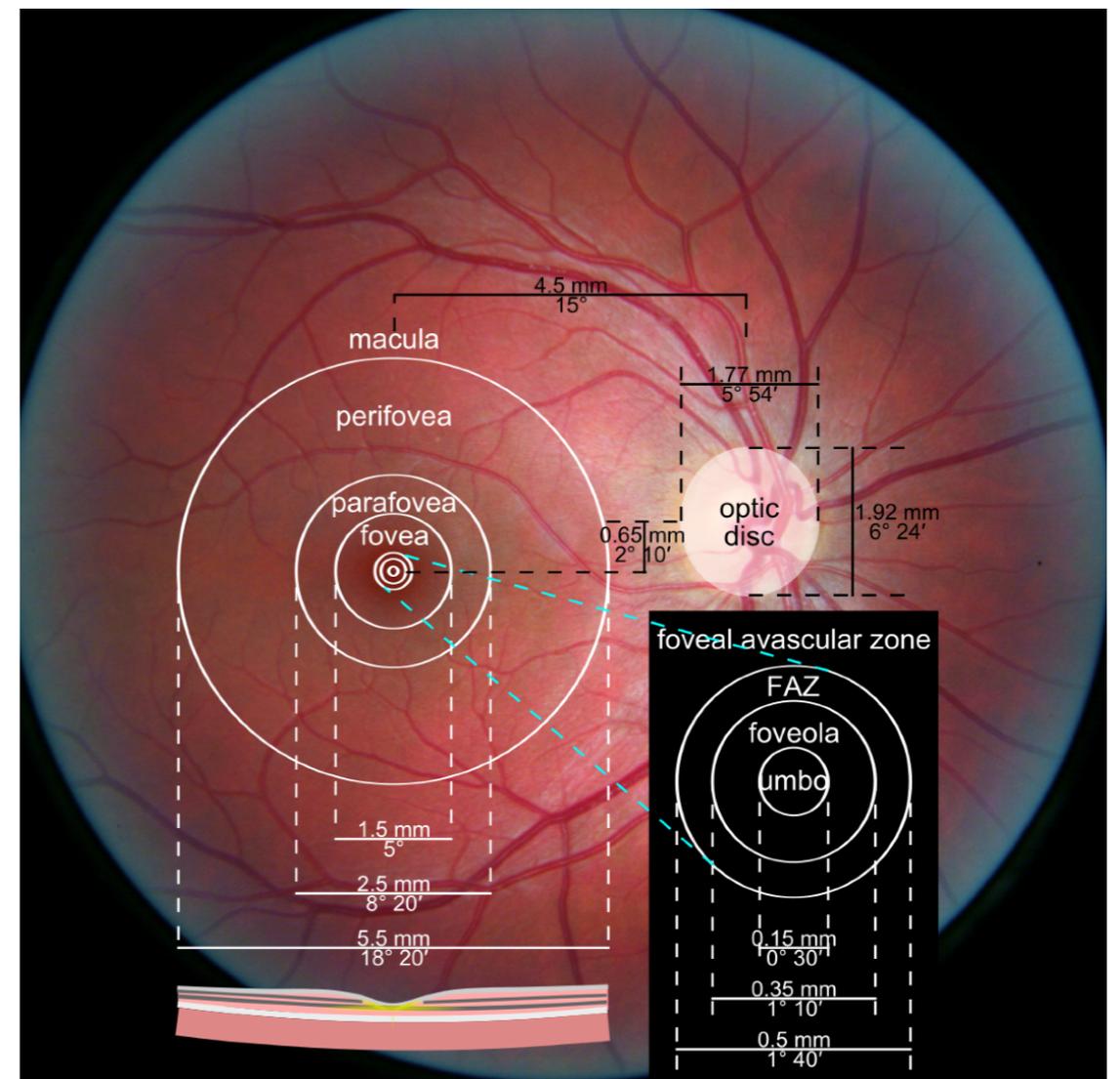
Anatomy of the Visual System: Retina

- There is an overall distribution of all cells across the retina, with the **highest concentration occurring at the center of our visual field in the fovea** and reducing in coverage toward the edges.
- The **fovea** consists of **only cone receptors**, and no rods, for highly detailed and exact vision.



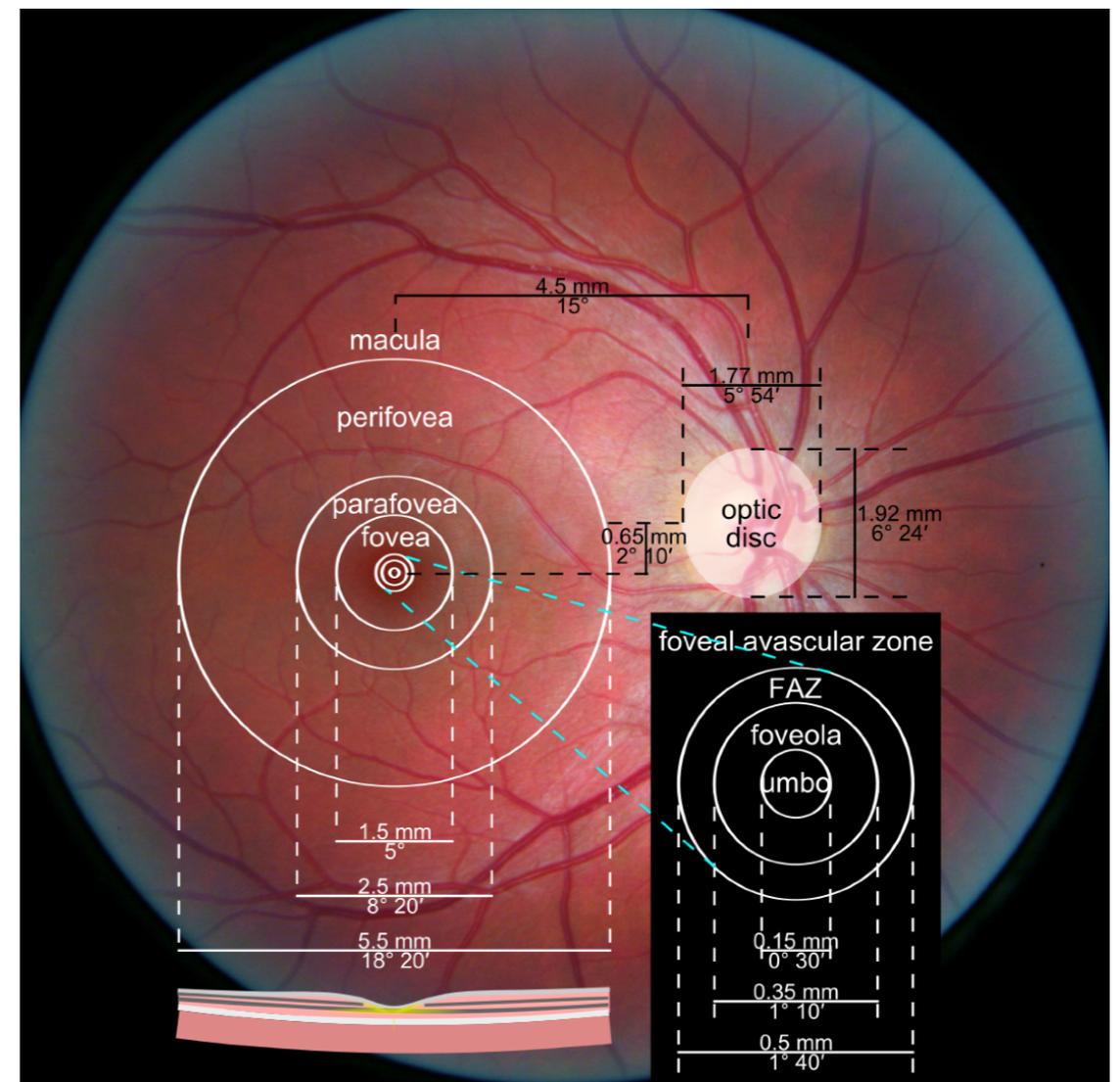
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- The **parafovea** with an outer ring of 2.5-mm diameter, with significantly more rods than cones.



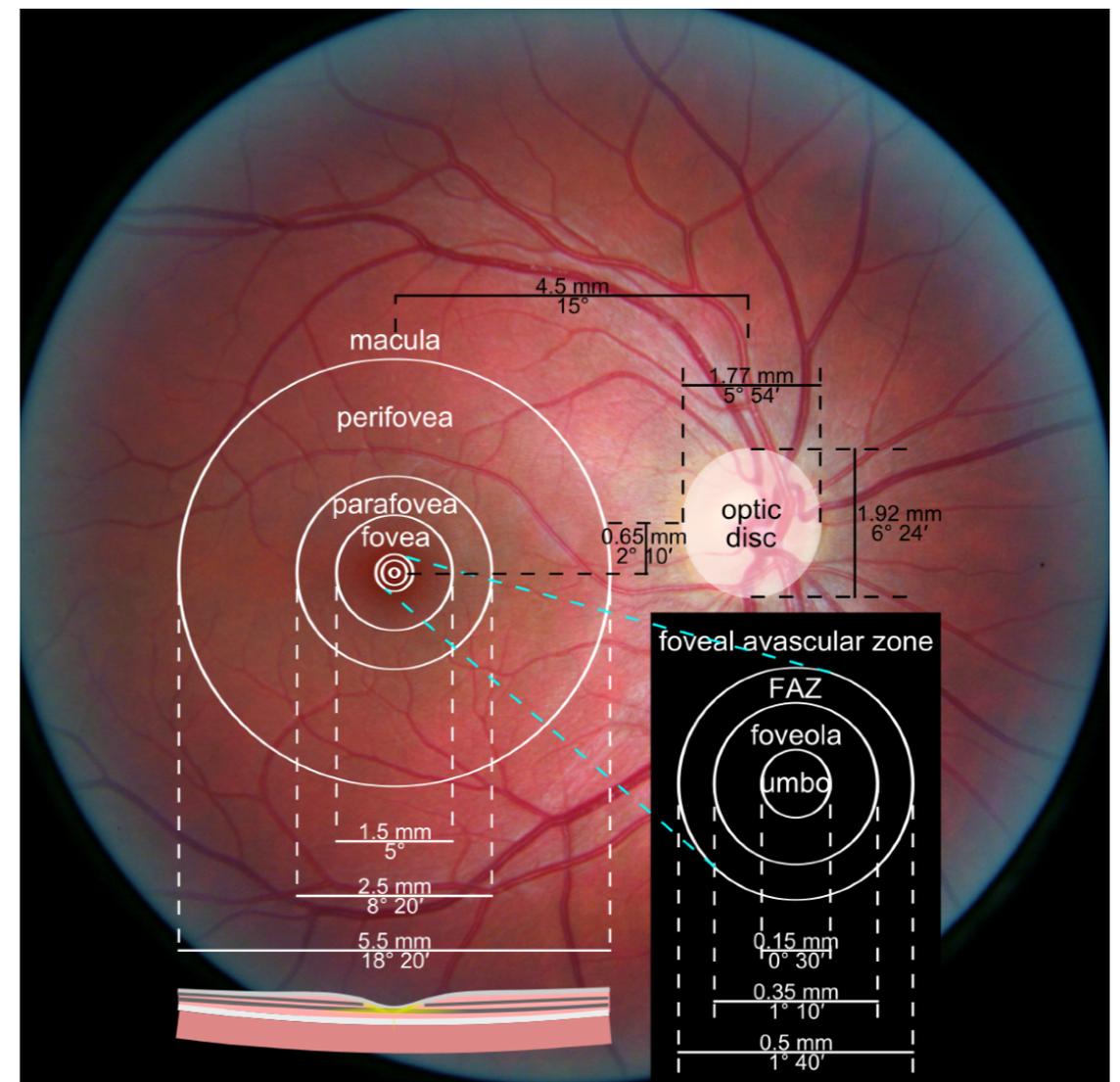
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- The **perifovea** with an outer ring of 5.5- mm diameter



Anatomy of the Visual System: Retina

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- The **fovea** consists of **only cone receptors**, and no rods, for highly detailed and exact vision.
- The **parafovea** with an outer ring of 2.5-mm diameter, with significantly more rods than cones.
- The **perifovea** with an outer ring of 5.5- mm diameter
- The **peripheral retina**, covering approximately 97.25% of the total retinal surface and consisting largely of rods.

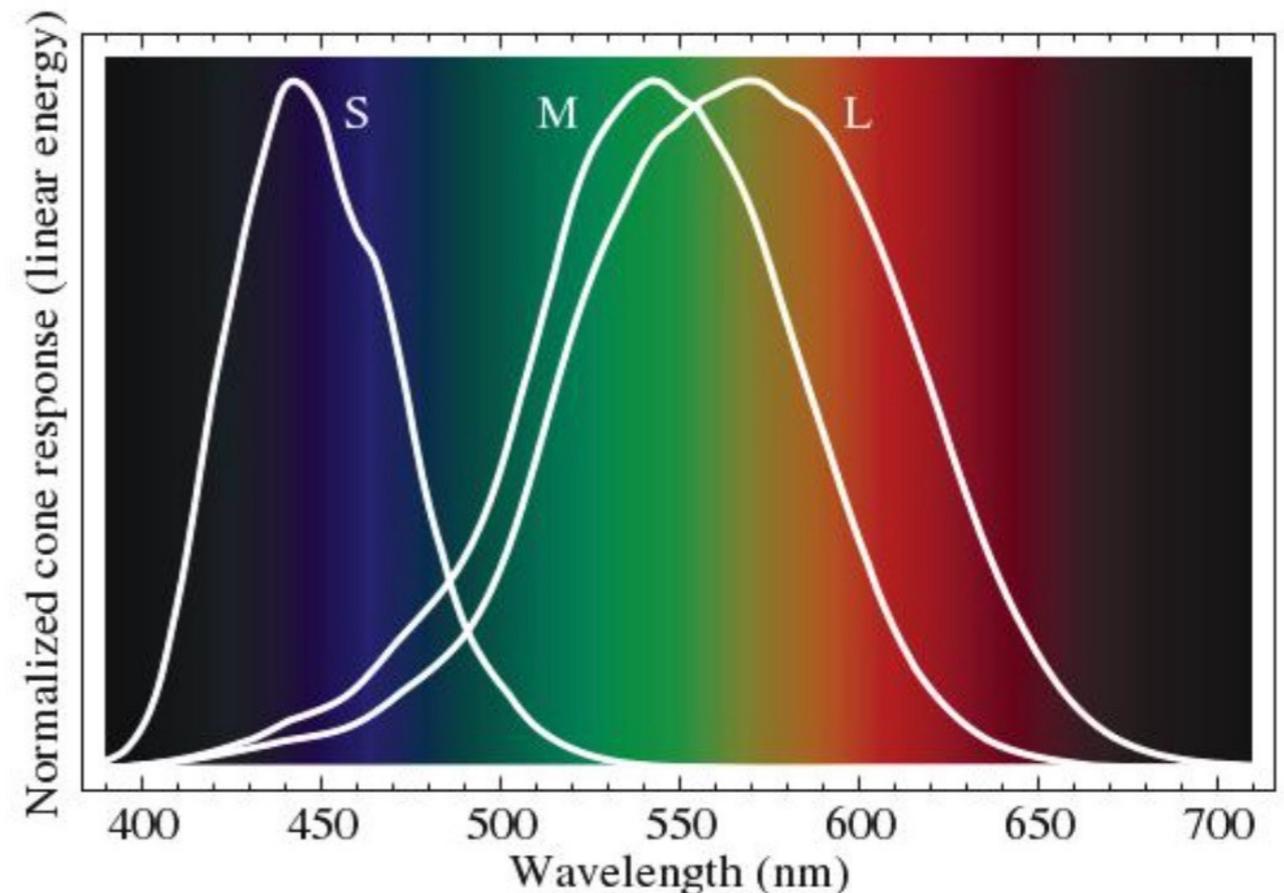


Anatomy of the Visual System: Retina - Rods

- **Rods** are the most sensitive type of photoreceptor cells available in the retina.
- As these cells are thought to be achromatic, **we tend to see objects at night in shades of gray.**
- Rods do operate, within the visible spectrum between approximately 400 and 700 nm.
- It has been noted that **during daylight** levels of illumination, **rods** become hyper-polarized, or completely saturated, and thus **do not contribute to vision.**

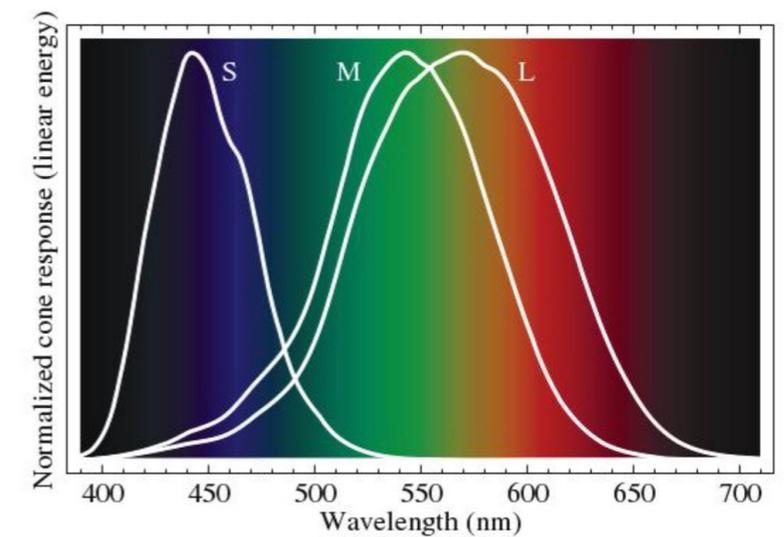
Anatomy of the Visual System: Retina - Cones

- **Cones** provide photopic vision, i.e., are responsible for **day vision**.
- There are three types of cones in the human eye: **S** (short), **M** (medium), and **L** (long) wavelengths.
- The three types have been associated with color combinations using **R** (red), **G** (green), and **B** (blue).



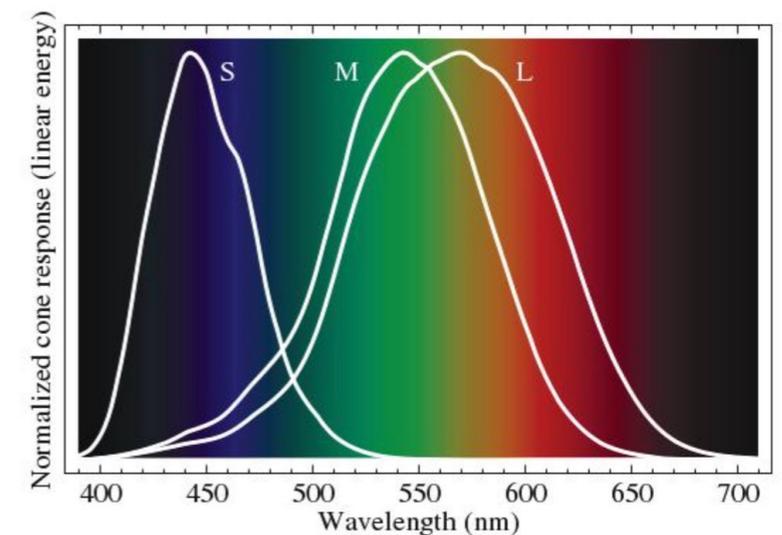
Anatomy of the Visual System: Retina - Cones

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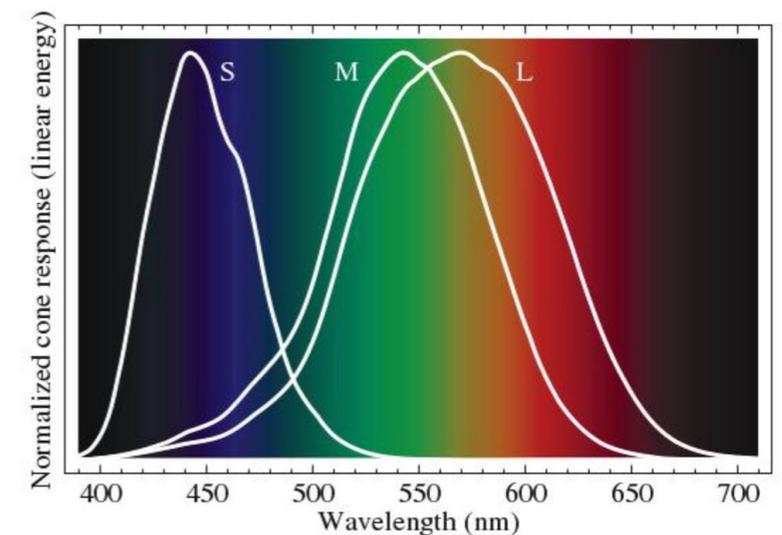
Anatomy of the Visual System: Retina - Cones

- Three types of **cones**: S (short), M (medium), and L (long) wavelengths.
- ◆ There are considerably **fewer S cones**, compared to the number of M and L cones



Anatomy of the Visual System: Retina - Cones

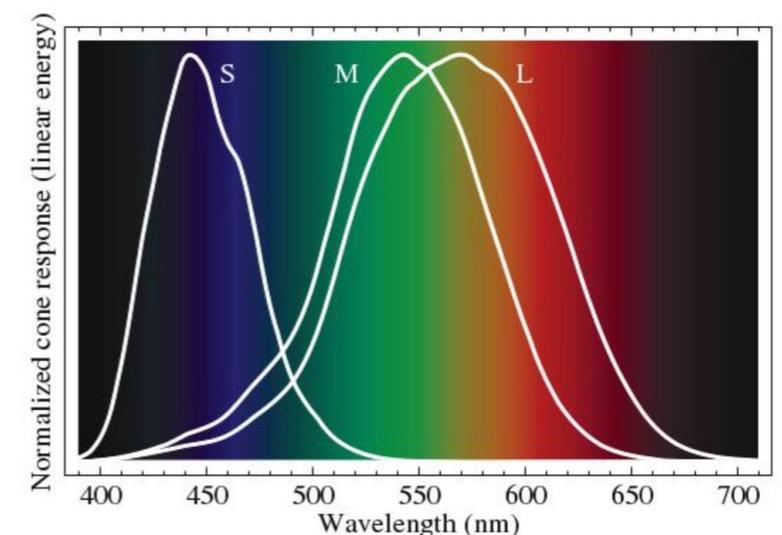
- Three types of **cones**: S (short), M (medium), and L (long) wavelengths.
 - ◆ There are considerably **fewer S cones**, compared to the number of M and L cones
 - ◆ Humans can visually perceive all the colors within the standard visible spectrum



Anatomy of the Visual System: Retina - Cones

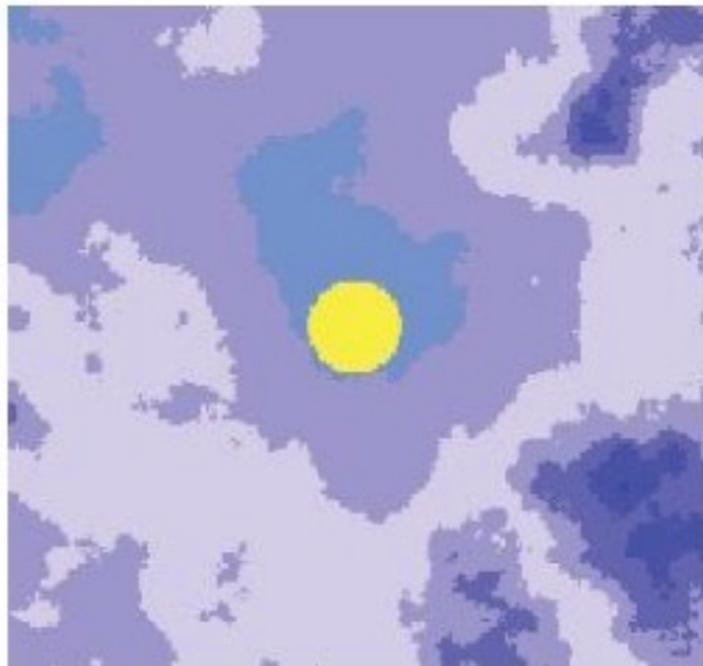
- Three types of **cones**: S (short), M (medium), and L (long) wavelengths.
 - ◆ There are considerably **fewer S cones**, compared to the number of M and L cones
 - ◆ Humans can visually perceive all the colors within the standard visible spectrum
- **Cones** are not sensitive over a large fixed wavelength range but rather over a **small moving-window-based range**.

Cones tend to adapt to the average wavelength where there is sensitivity above and below their peaks, and a shift in their response curve occurs when the average background wavelength changes.



Anatomy of the Visual System: blind spot

- Where the optic nerve meets the retina, a blind spot occurs, due to the lack of photoreceptive cells



1 2 3 4 5 6

Blind spot discovery by identifying disappearance of target.

Figure 3.12 - (Matthew Ward, et. all)

Visual system

- Because the human eye contains a **limited number of rods and cones** (about **120 million rods** and **6 million cones**), it **can only manage a certain amount of visual information over a given time frame.**

Figure 3.8 - (Matthew Ward, et. all)

Visual system

- Because the human eye contains a **limited number of rods and cones** (about **120 million rods** and **6 million cones**), it **can only manage a certain amount of visual information over a given time frame**.
- The **optic nerve** only contains about **one million fibers**; thus the eye must perform a significant amount of visual processing before transmitting information to the brain.

Figure 3.8 - (Matthew Ward, et. all)

Visual system

- Because the human eye contains a **limited number of rods and cones** (about **120 million rods** and **6 million cones**), it **can only manage a certain amount of visual information over a given time frame**.
- The **optic nerve** only contains about **one million fibers**; thus the eye must perform a significant amount of visual processing before transmitting information to the brain.
- Additionally, the information transferred from these two types of cells is not equivalent. The **eye contains separate systems** for encoding **spatial properties** (e.g., size, location, and orientation), and **object properties** (e.g., color, shape, and texture).

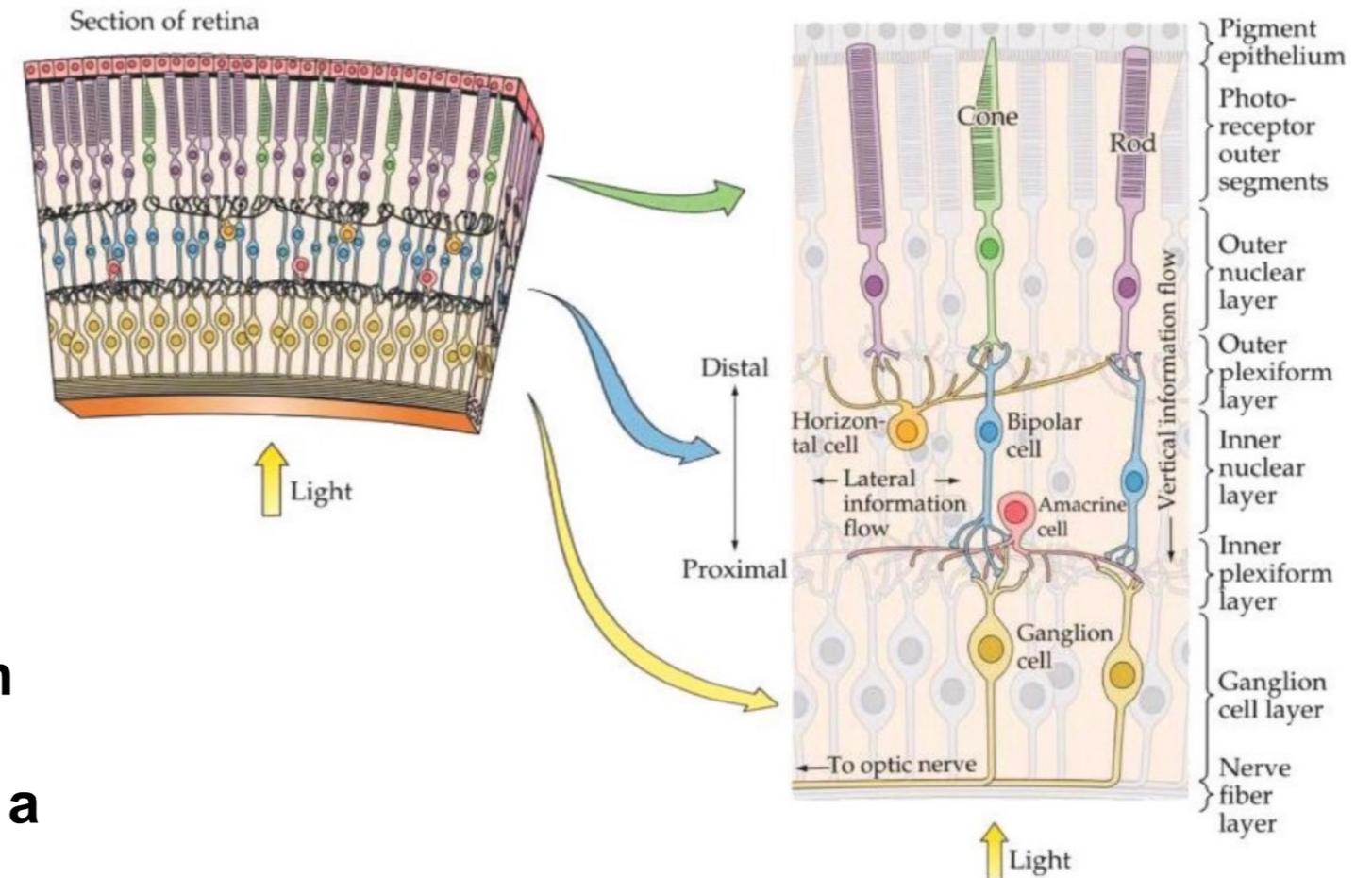
Figure 3.8 - (Matthew Ward, et. all)

Visual Processing

- The **Retina** is complex layer of many neurons and photoreceptive cells

- The retina is already performing some kinds of image compression, and possibly segmentation.

- This reduction of retinal stimulation is required, as there are only about a million optic nerve fibers relaying image information to the brain.



A representation of a retinal cross-section. (Image © The Brain from Top to Bottom.)

Visual Processing

- **Each Brain hemisphere receives visual information from both eyes, possibly to help with the perception of depth.**
- **As there is so much visual processing performed at both the eyes and within the brain, these linked organs form an integral visual system.**

Eye Movement

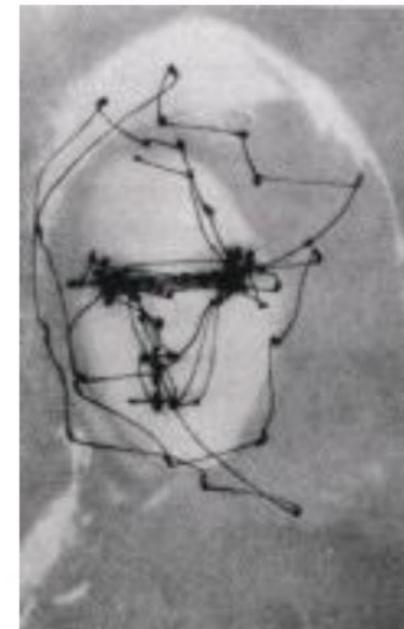
- There are a variety of eye movements performed for scene interpretation:
- **Smooth pursuit movements:** the eyes move smoothly instead of in jumps.
 - ◆ The angles from the normal to the face are equal (left and right as well as up and down).
 - ◆ For example, to make a pursuit movement, look at your forefinger at arms' length and then move your arm left and right while fixating on your fingertip.
- **Vergence eye movements:** moving a finger closer to the face and staring at it will force the eyes inward, resulting in vergence movement. Defocusing to merge depths in illusions is another example.

Eye Movement

- **Saccadic eye movements:** these result from **multiple targets of interest** (not necessarily conscious). The eye moves as much as **1000 degrees per second**, bringing the gaze on those targets within **25 msec**.
 - ◆ It holds its position once on target.
 - ◆ Selected targets are determined in the frontal part of the cerebral cortex.
 - ◆ The selection is discriminatory, dependent on a variety of parameters, and somewhat random.



(a)



(b)

Figure 3.15 - (Matthew Ward, et. all)

(a) The face used to study eye tracking. (b) The results of the tracking of the gaze.

Eye Movement

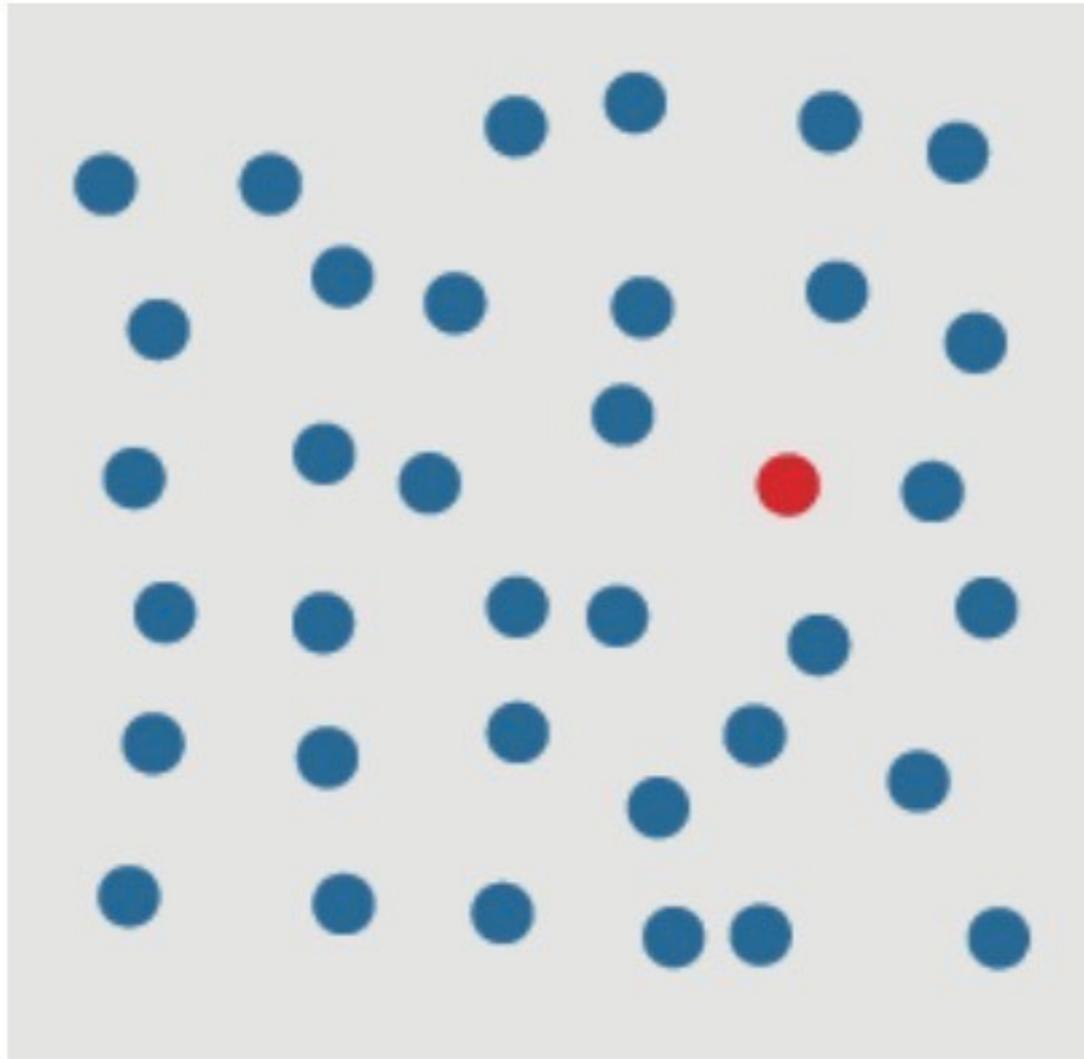
- **Saccadic masking** or suppression occurs during two states between saccadic views.
 - ◆ The gap produced is ignored (some say blocked).
 - ◆ A continuous flow of information is interpreted, one that makes sense.
 - ◆ The higher-level visual system filters out the blurred images acquired by the low-level one, and only the two saccadic stop views are seen.

Perceptual Processing

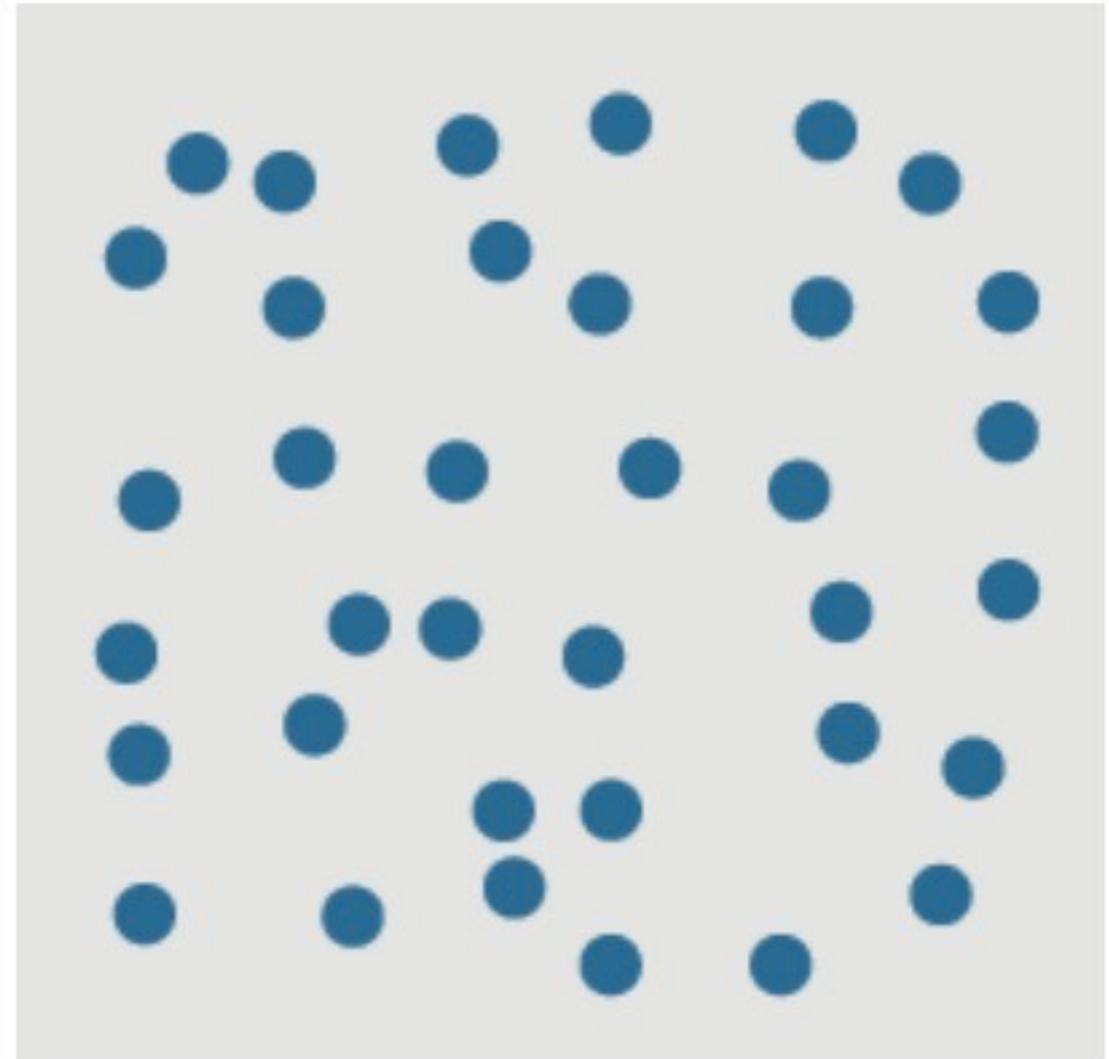
Perceptual Processing

- **Preattentive Processing**
- **Theories of Preattentive Processing**
- **Feature Hierarchy**
- **Change Blindness**

“Preattentive” properties



(a) Target is present in a sea of blue circle distractors.

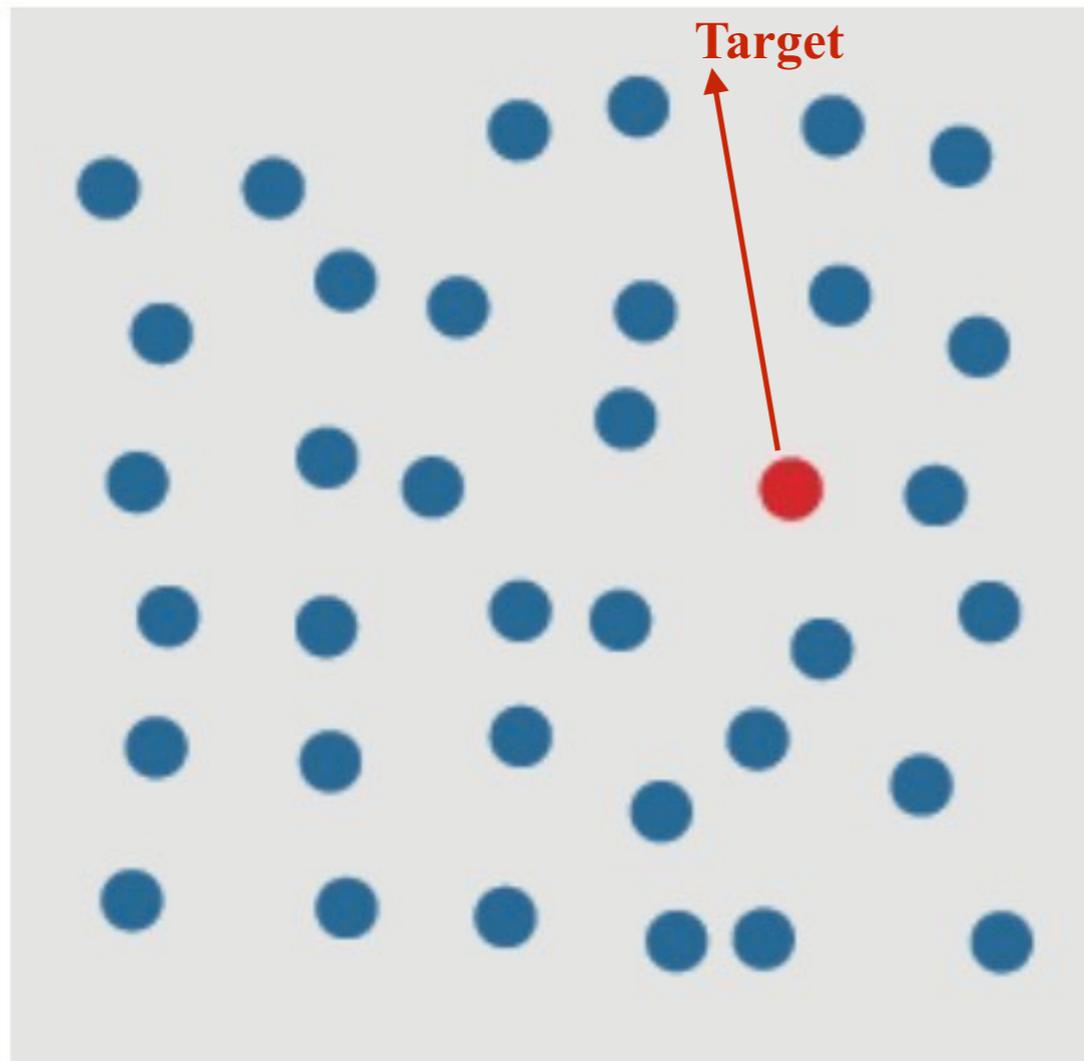


(b) Target is absent.

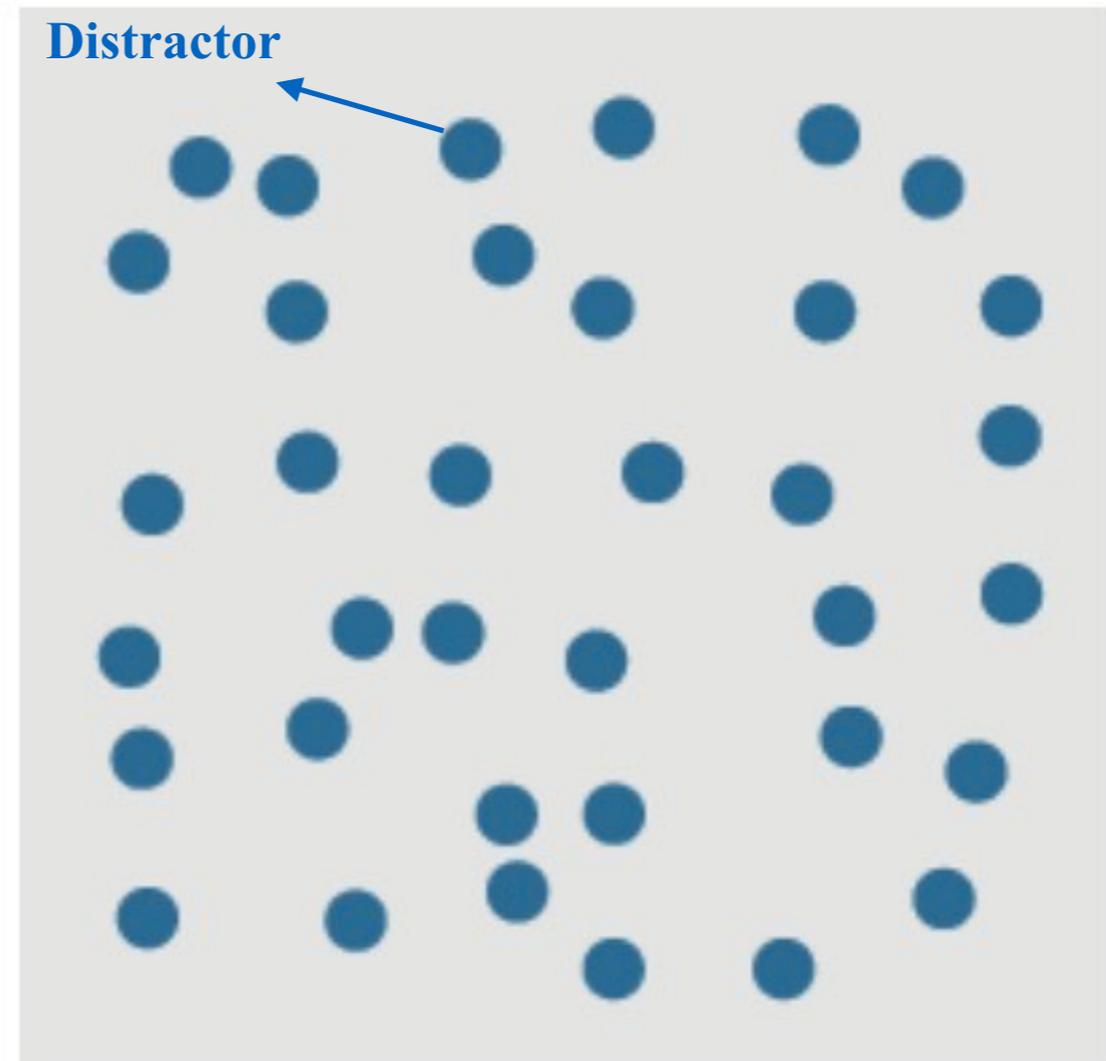
An example of searching for a target red circle based on a difference in hue.

Figure 3.18 - (Matthew Ward, et. all)

“Preattentive” properties



(a) Target is present in a sea of blue circle distractors.

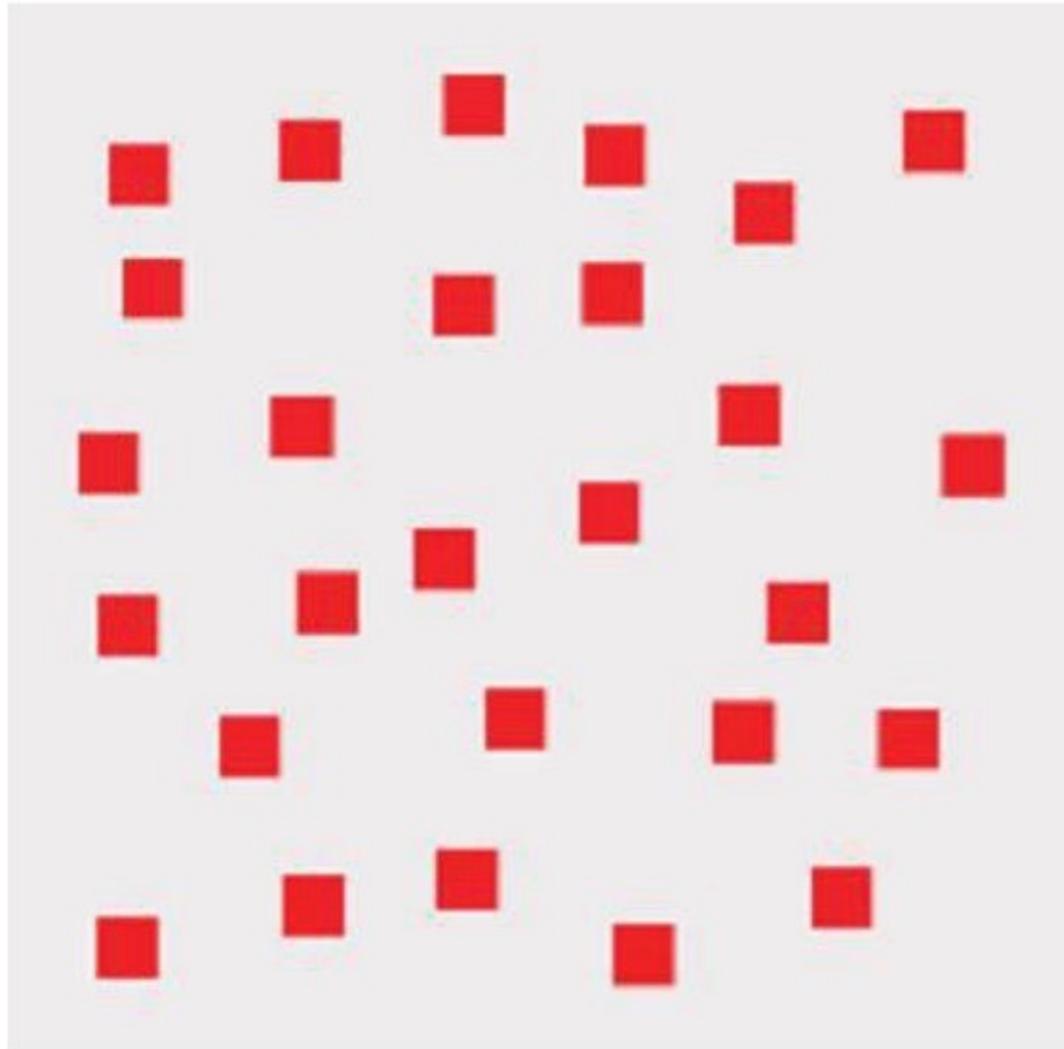


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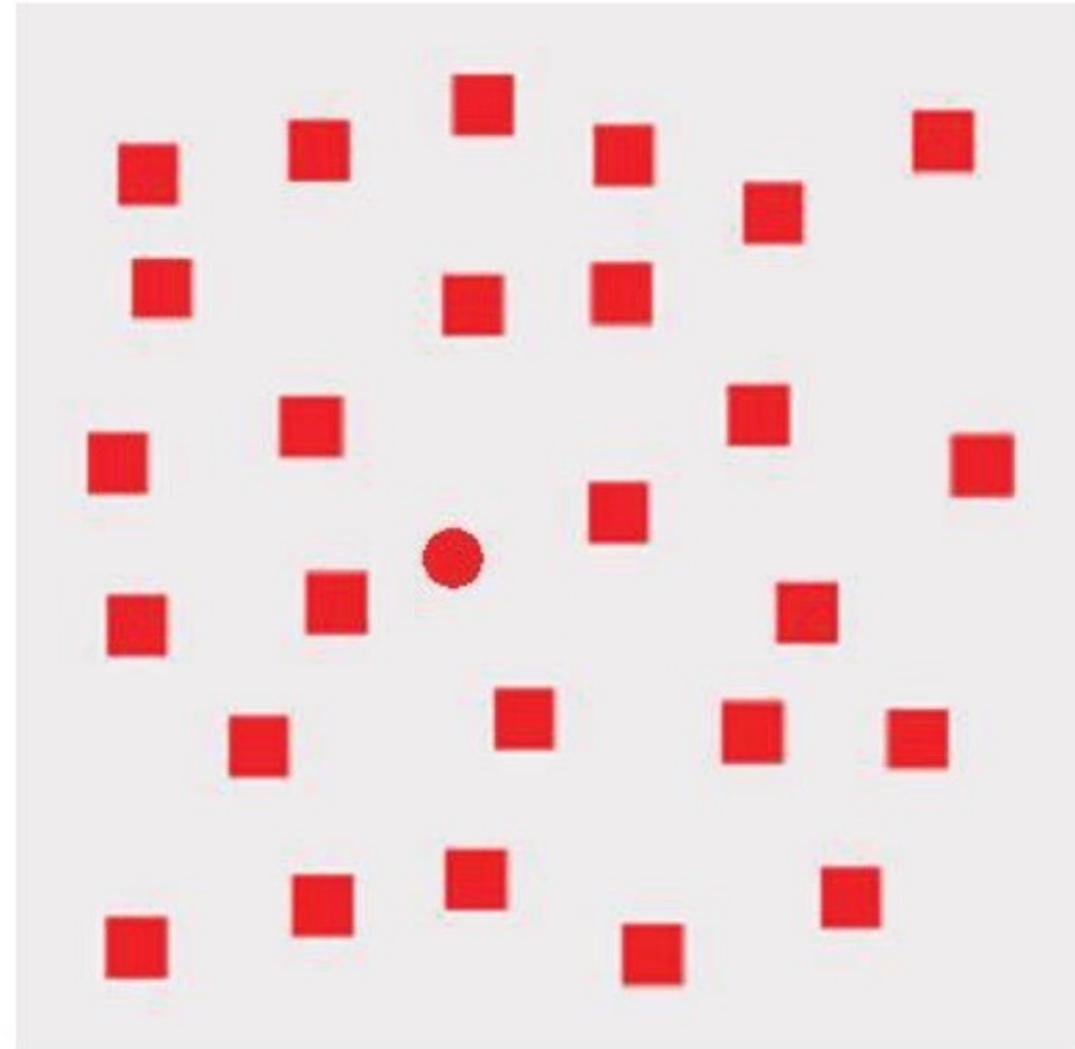
An example of searching for a target red circle based on a difference in hue.

Figure 3.18 - (Matthew Ward, et. all)

“Preattentive” properties



(a) Target is absent in a sea of red square distractors.

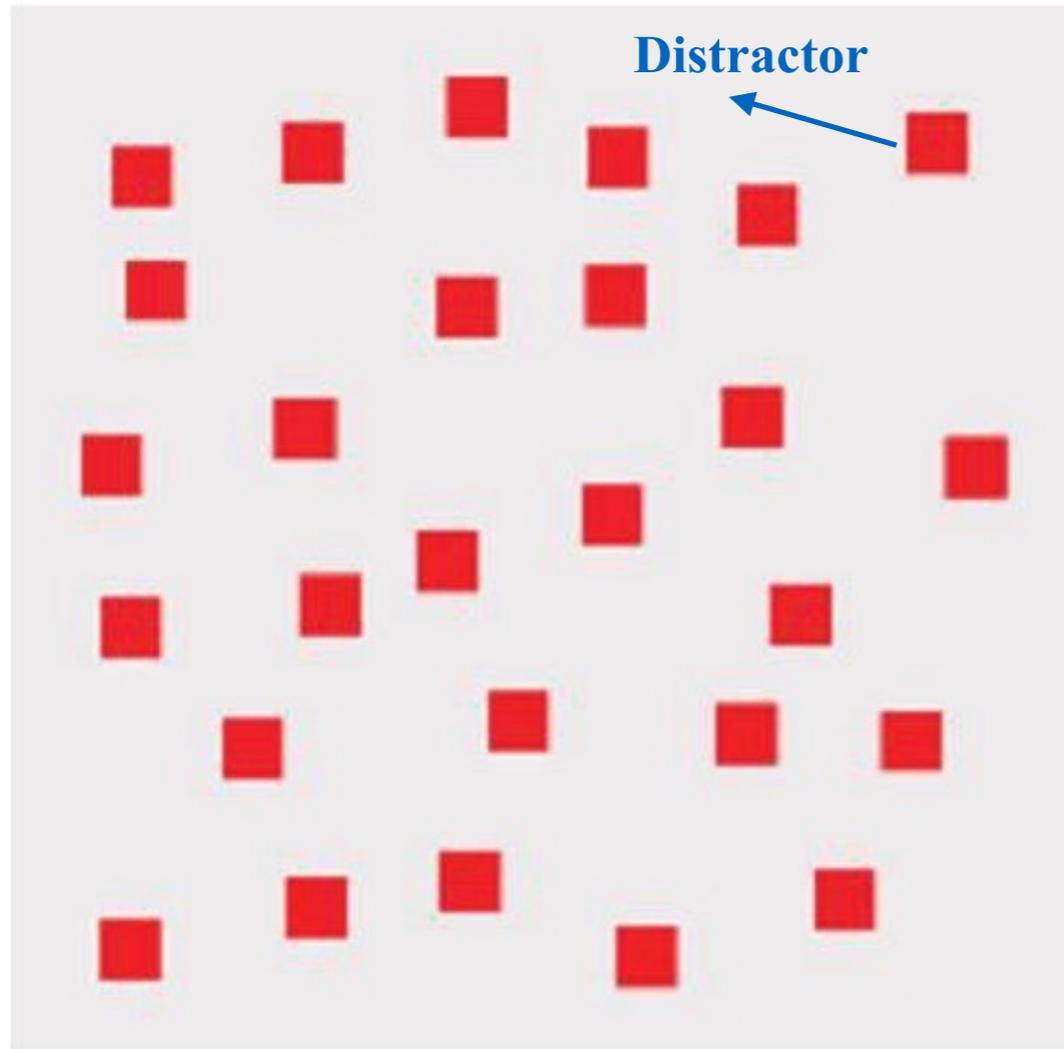


(b) Target is present.

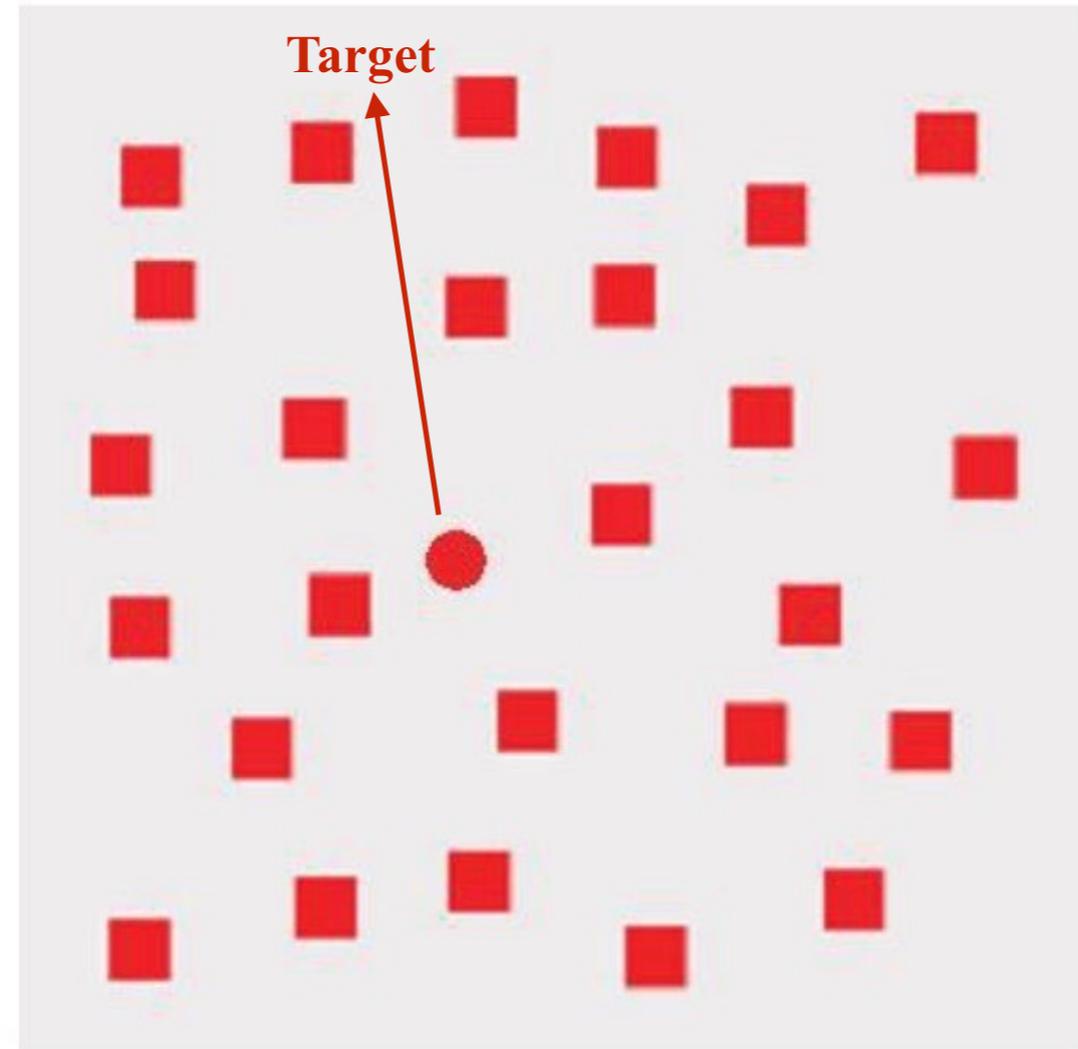
An example of searching for a target red circle based on a difference in curvature.

Figure 3.19 - (Matthew Ward, et. all)

“Preattentive” properties



(a) Target is absent in a sea of red square distractors.



(b) Target is present.

An example of searching for a target red circle based on a difference in curvature.

Figure 3.19 - (Matthew Ward, et. all)

Perceptual Processing: “preattentive” properties

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- ◆ Typically, tasks that can be performed on large multi-element displays in **less than 200 to 250 milliseconds** are considered preattentive.

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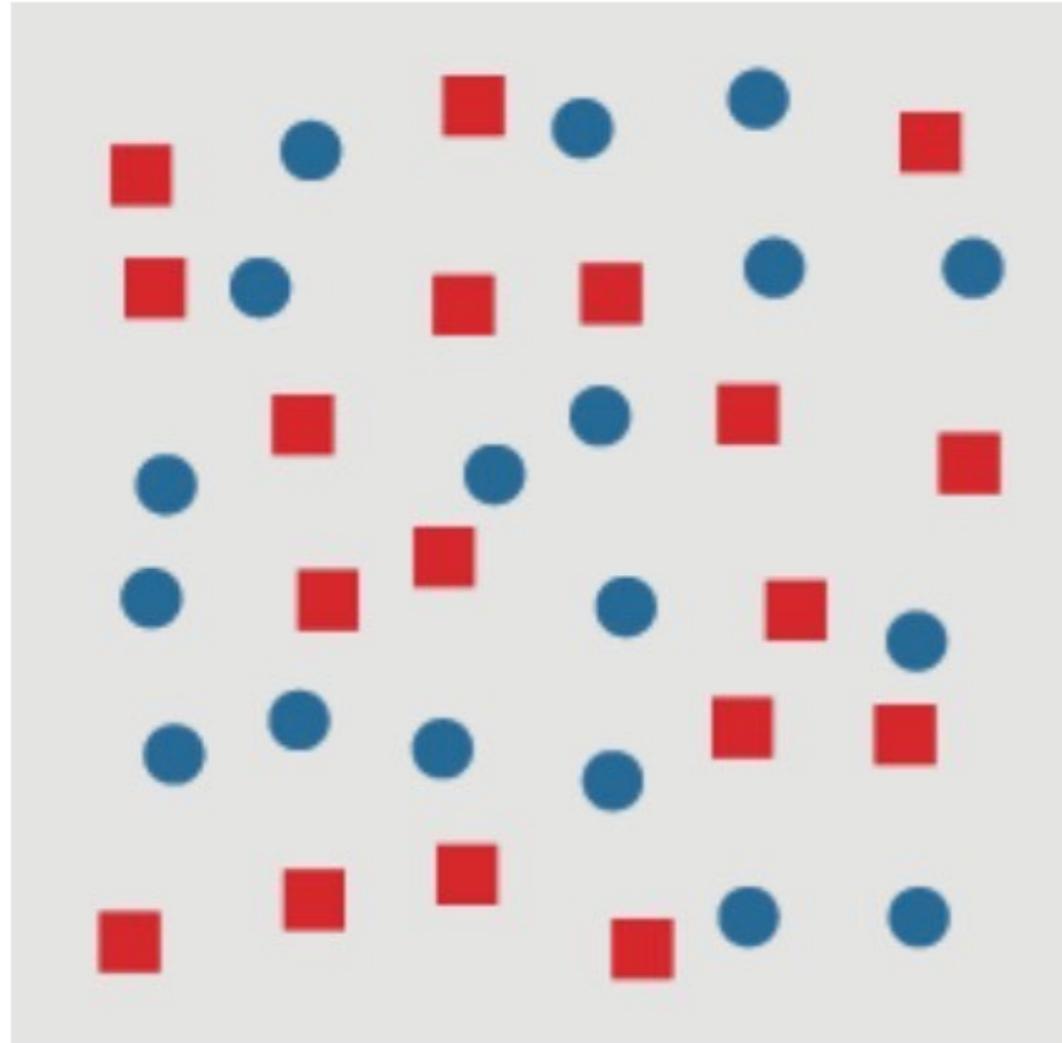
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- ◆ We now know that **attention plays a critical role** in what we see, even at this early stage of vision.
- ◆ Typically, tasks that can be performed on large multi-element displays in **less than 200 to 250 milliseconds** are considered preattentive.
- ◆ This suggests that **certain information** in the display is **processed in parallel** by the **low-level visual system**.

“Preattentive” properties

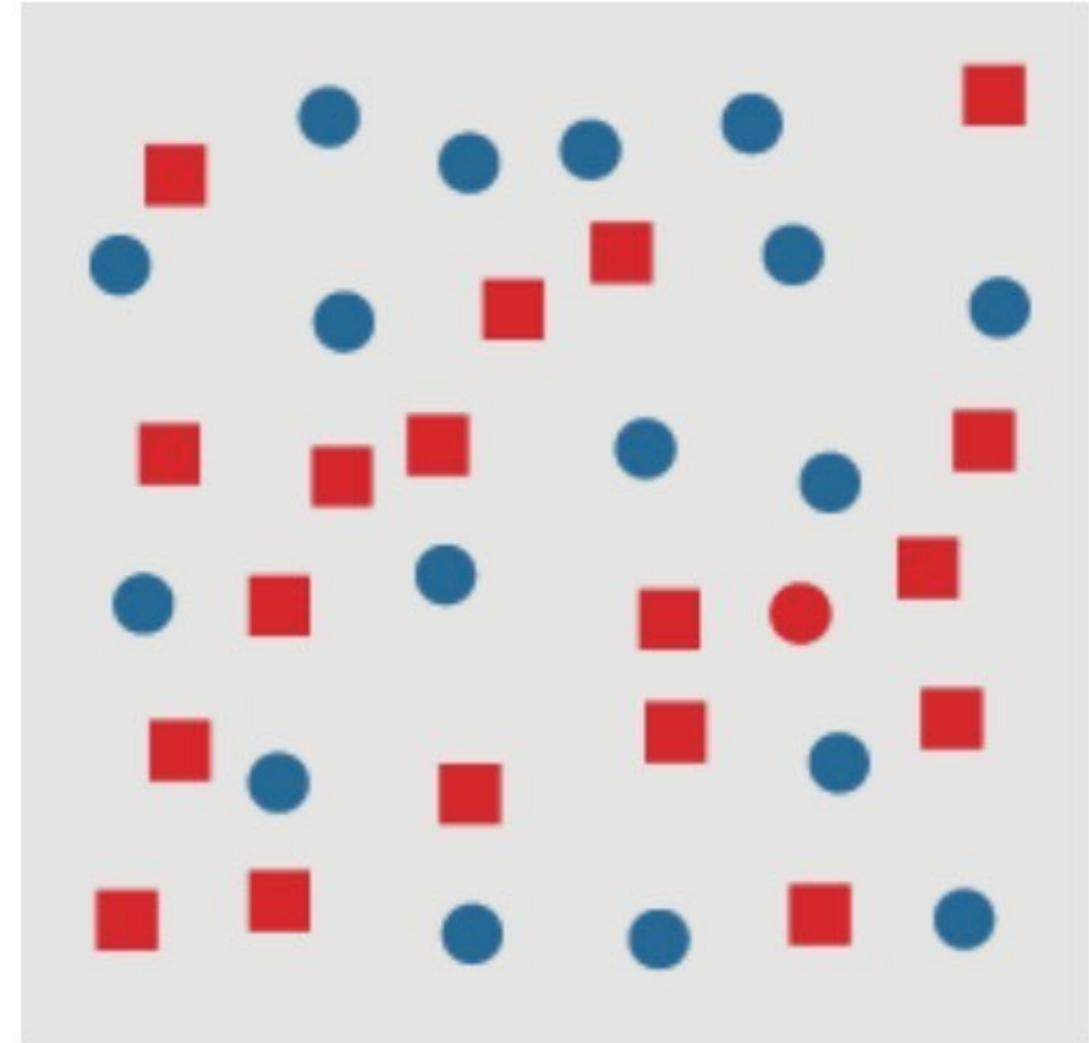
An example of a conjunction search for a target red circle.

Figure 3.20 - (Matthew Ward, et. all)

“Preattentive” properties



(a) Target is absent in a sea of red square and blue circle distractors.

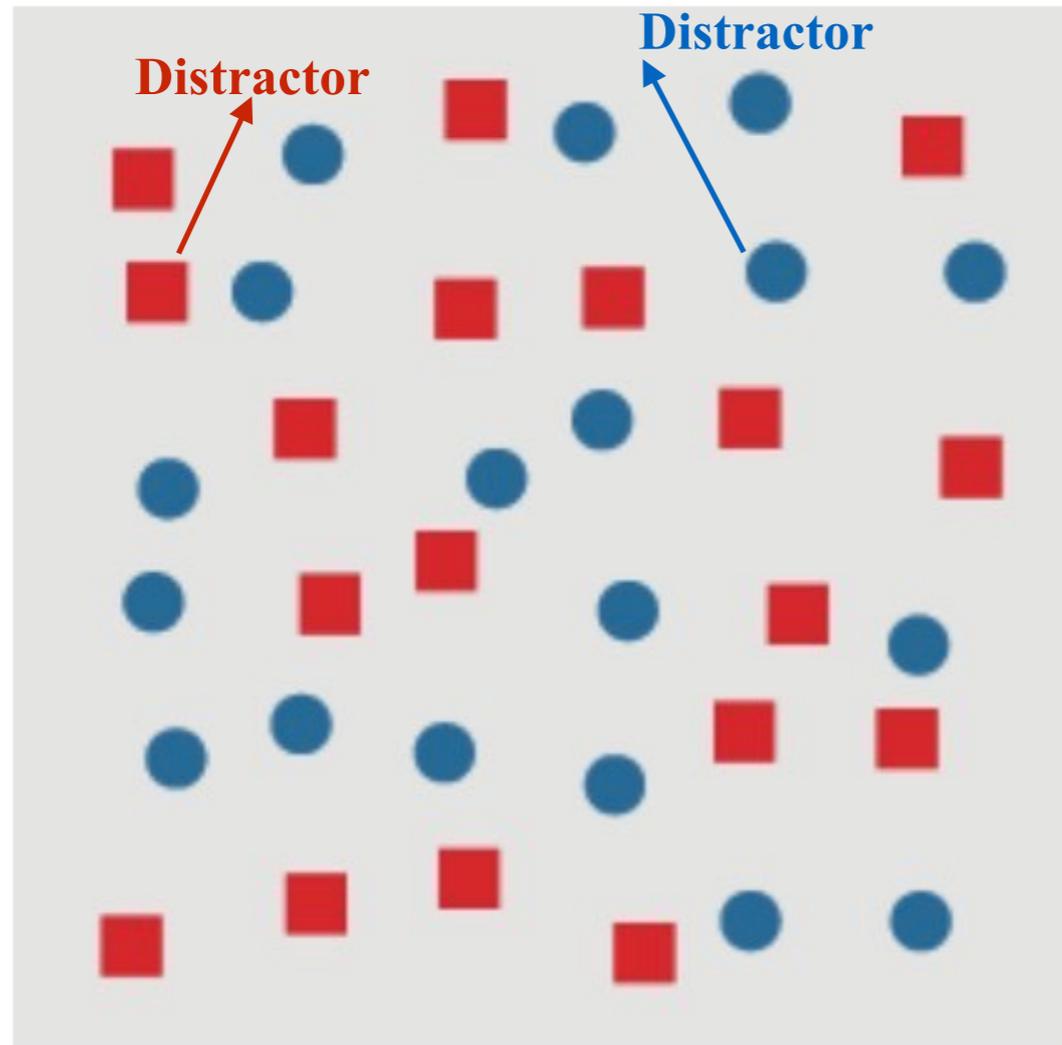


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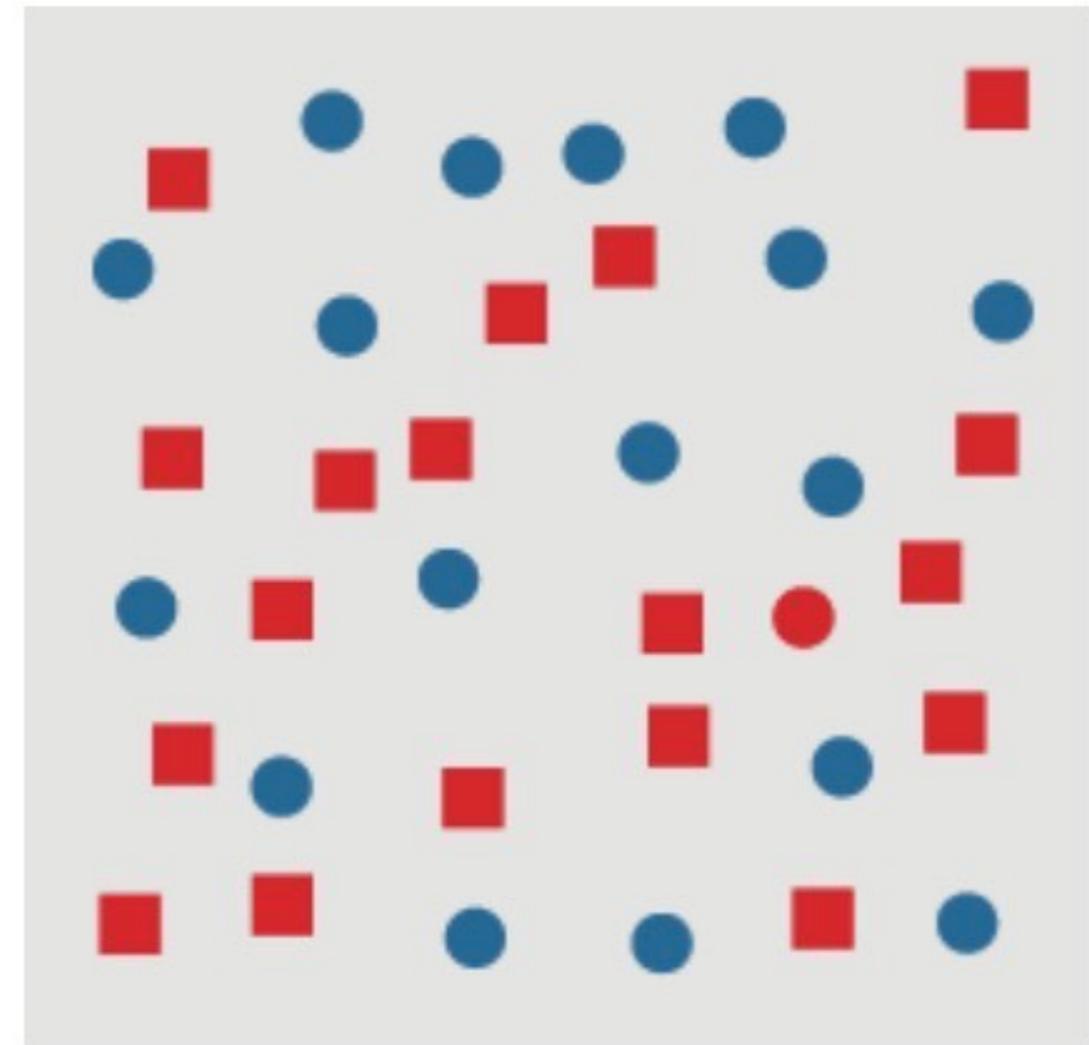
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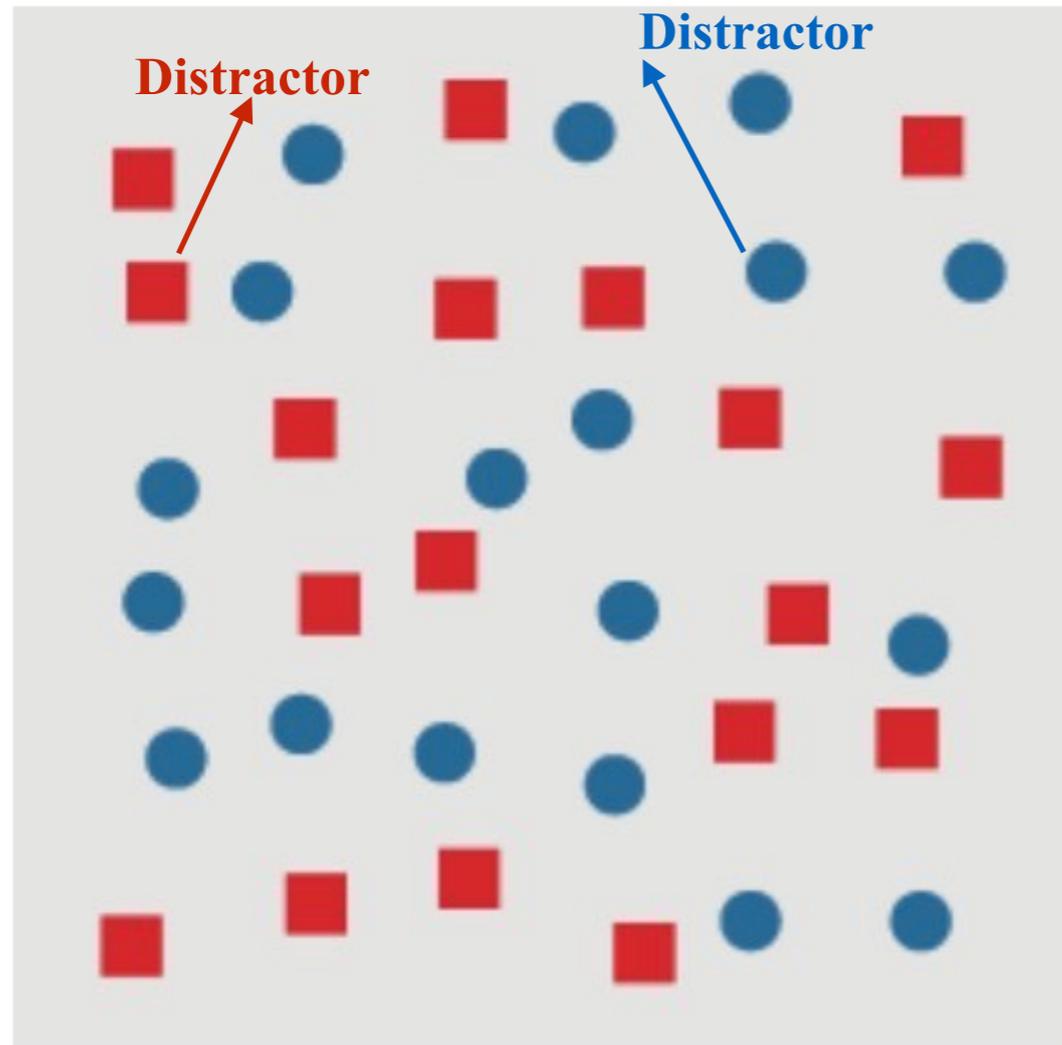


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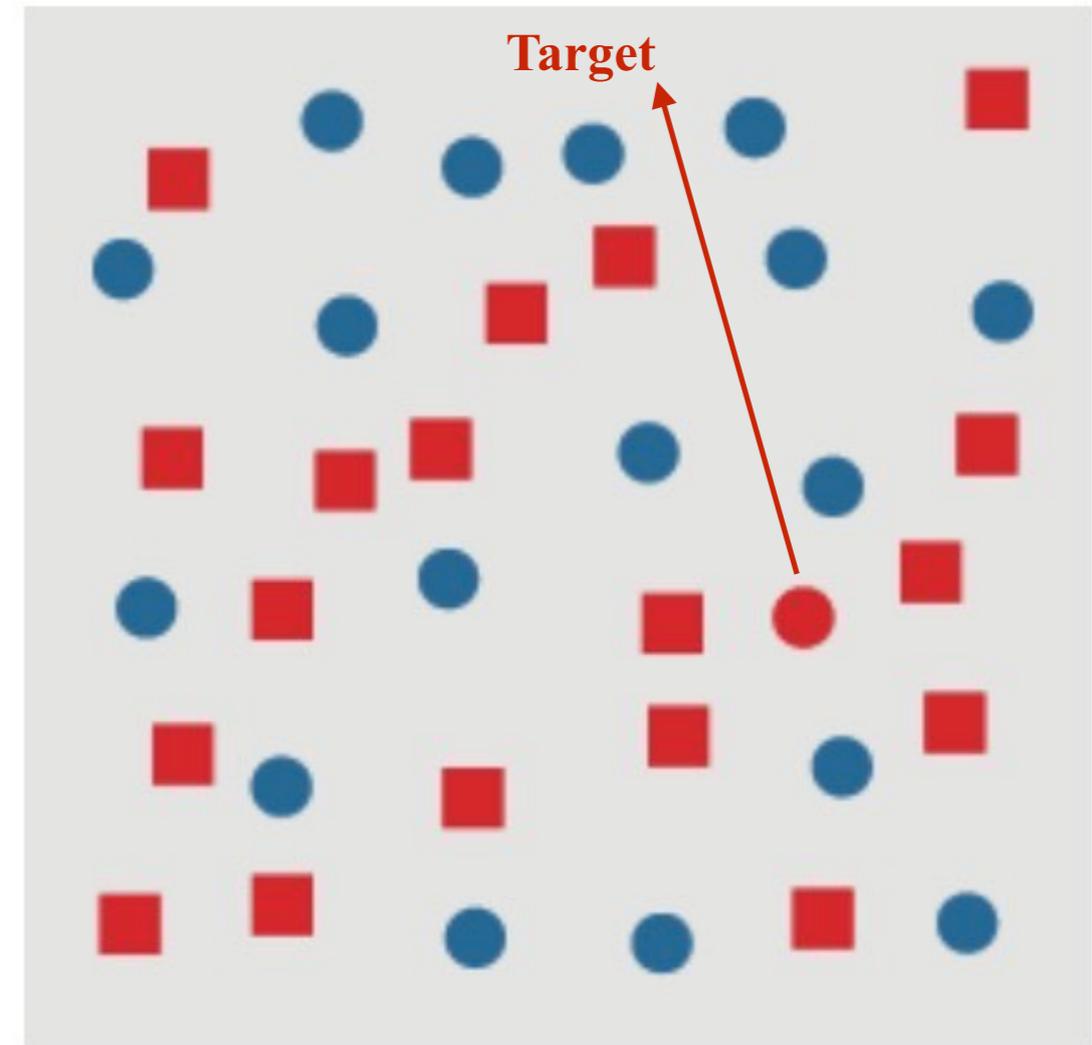
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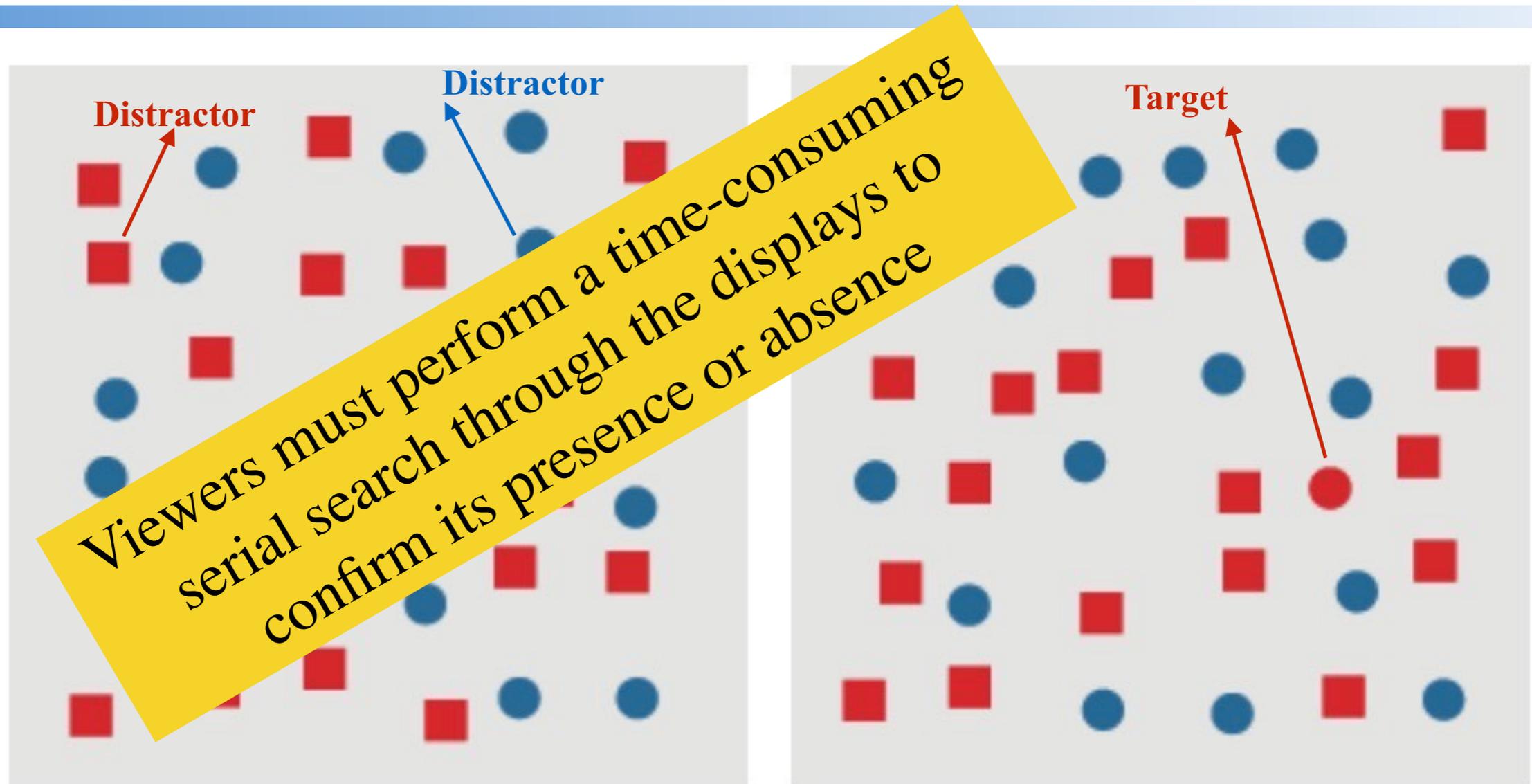


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 - A **red circle target** is made up of two features: **red** and **circular**.
 - One of these features is present in each of the **distractor** objects (**red squares** and **blue circles**).
 - The visual system has no unique visual property to search for when trying to locate the target. If a viewer searches for red items, the visual system always returns true. Similarly, a search for circular items always sees blue circles.

“Preattentive” properties

- **Visual features that have been identified as preattentive:**
 - **length, width, size, curvature, number, terminators, intersection, closure, hue, intensity, flicker, direction of motion, binocular luster, stereoscopic depth, 3D depth cues, and lighting direction.**

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- **The key perceptual attributes associated with the above include **luminance** and **brightness**, **color**, **texture**, and **shape****
 - ◆ **Luminance** is the measured amount of light coming from some place.
 - ◆ **Brightness** is the perceived amount of light coming from a source (is a nonlinear function of the amount of light emitted by the source) [Paper ≠ Screen].
 - ◆ **Texture** is the characteristic appearance of an area or surface.

“Preattentive” visual tasks

- **Target detection.**
 - Users rapidly and accurately **detect the presence or absence** of a “**target**” element with a unique visual feature **within a field of distractor elements.**

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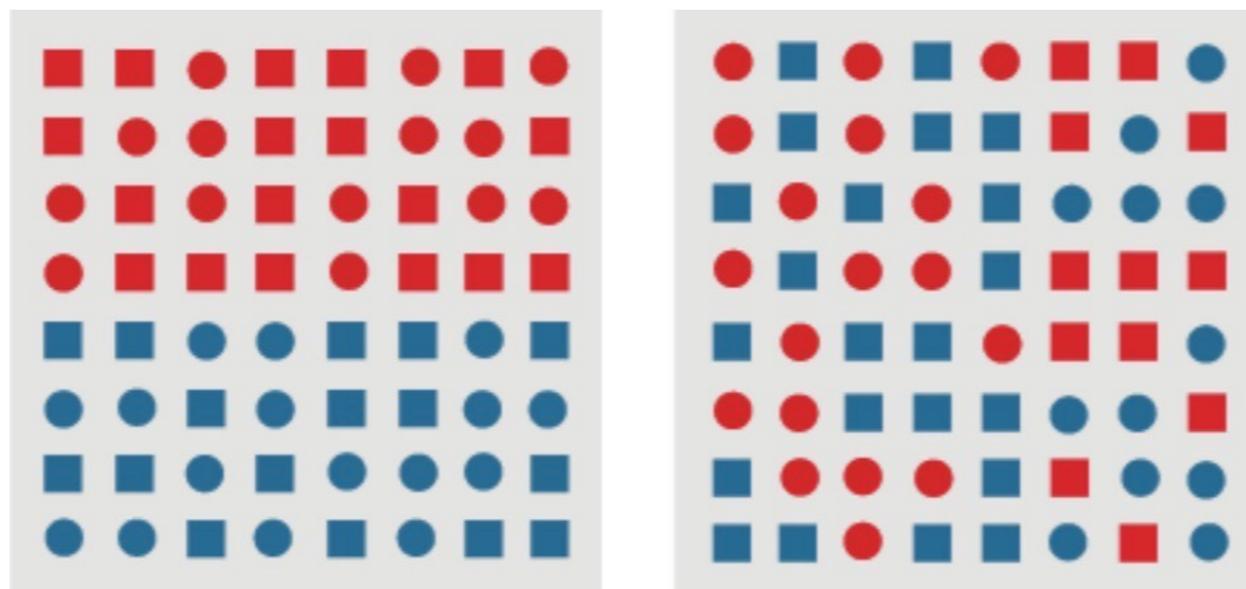
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- **Counting and estimation**

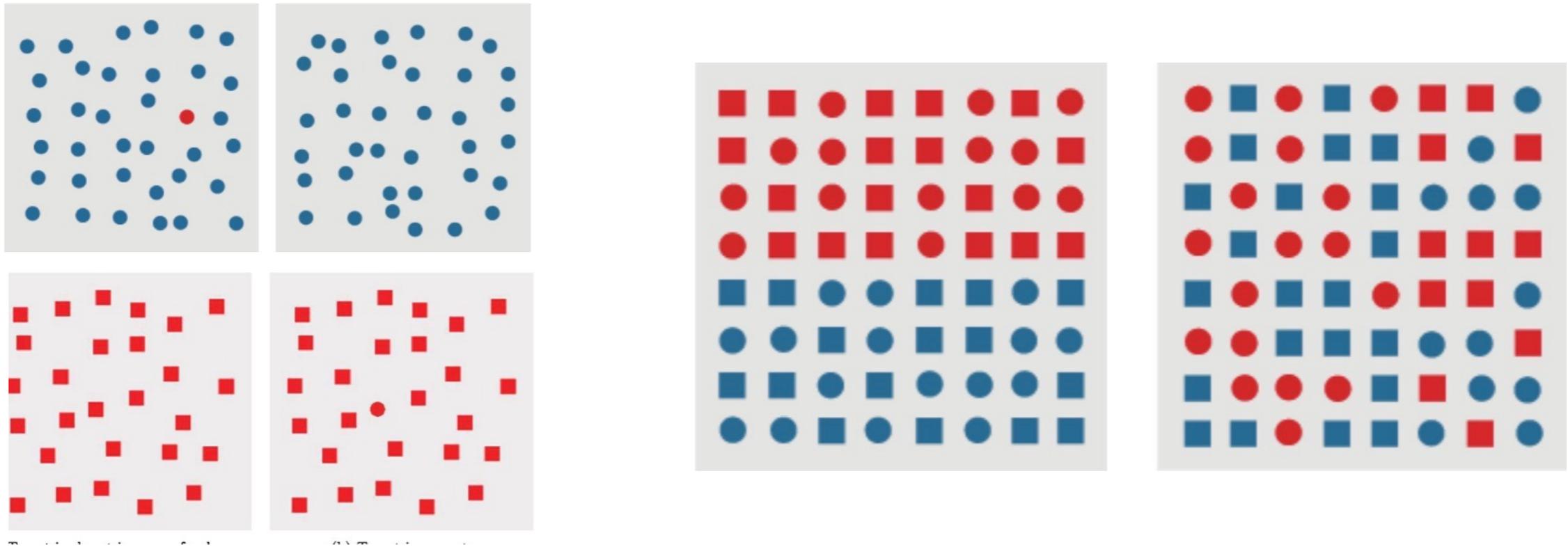
- ◆ Users count or estimate the number of elements with a unique visual feature.

Theories of Preattentive Processing

- **Feature Integration Theory (Anne Treisman)**
 - **Texton Theory**
 - **Similarity Theory**
 - **Guided Search Theory**
-
- **Postattentive Vision**

Feature Integration Theory (Anne Treisman)

- She starts by studying two important problems:
 - she tried to determine **which visual properties** are detected **preattentively**;
 - she formulated a hypothesis about how the **human visual system performs preattentive processing**
- Treisman ran experiments using **target** and **boundary** detection



Feature Integration Theory (Anne Treisman)

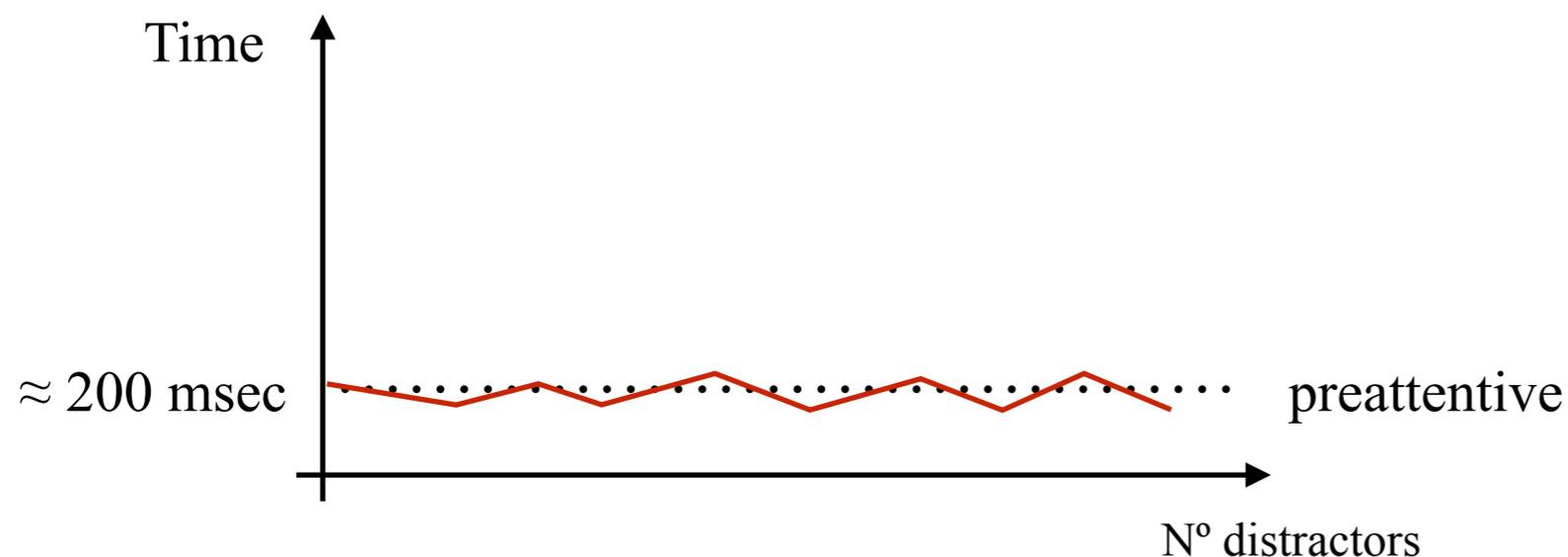
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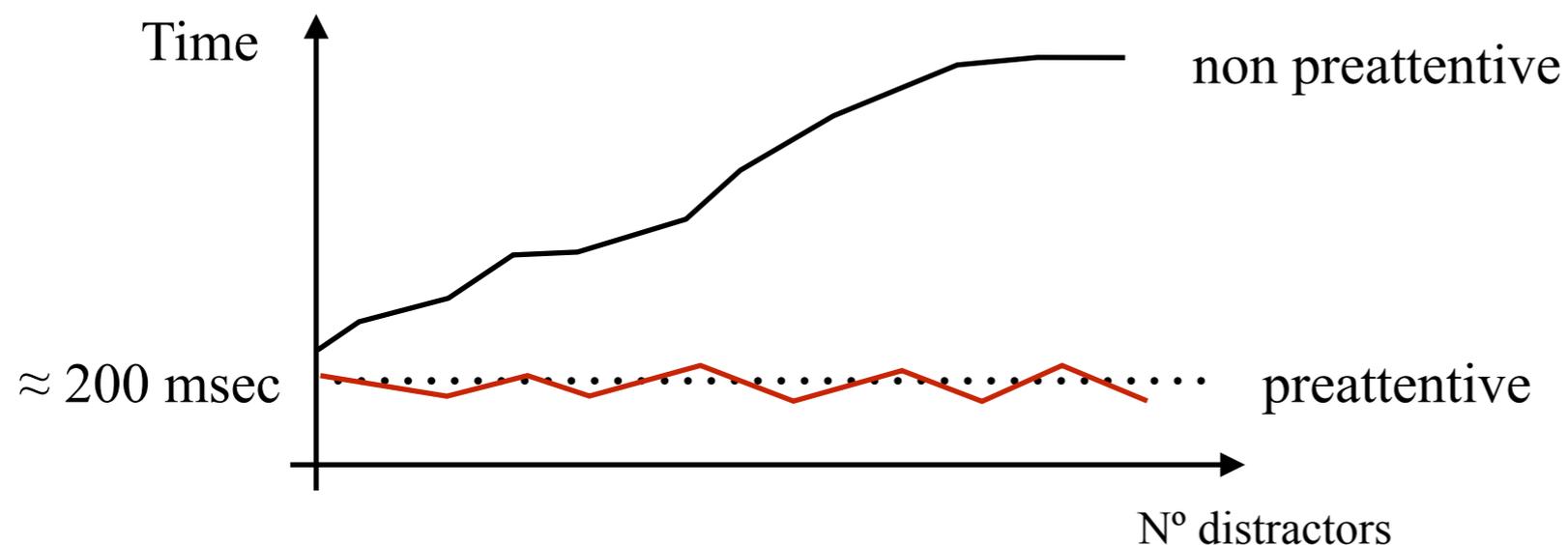
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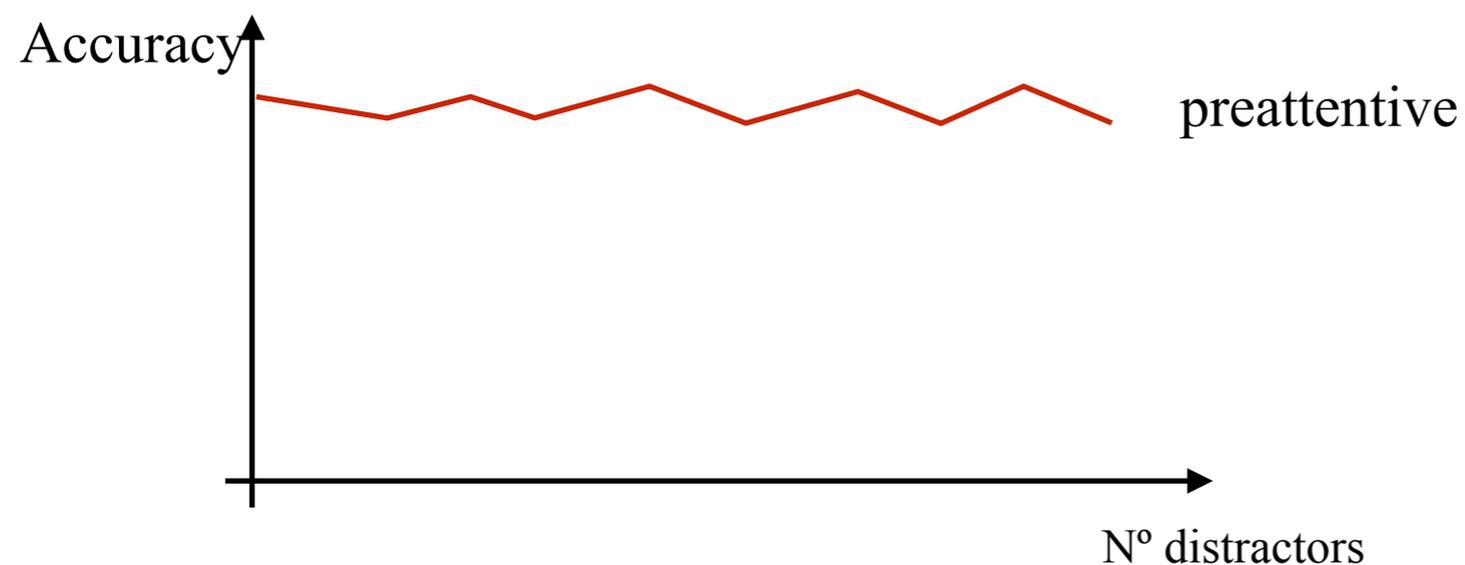
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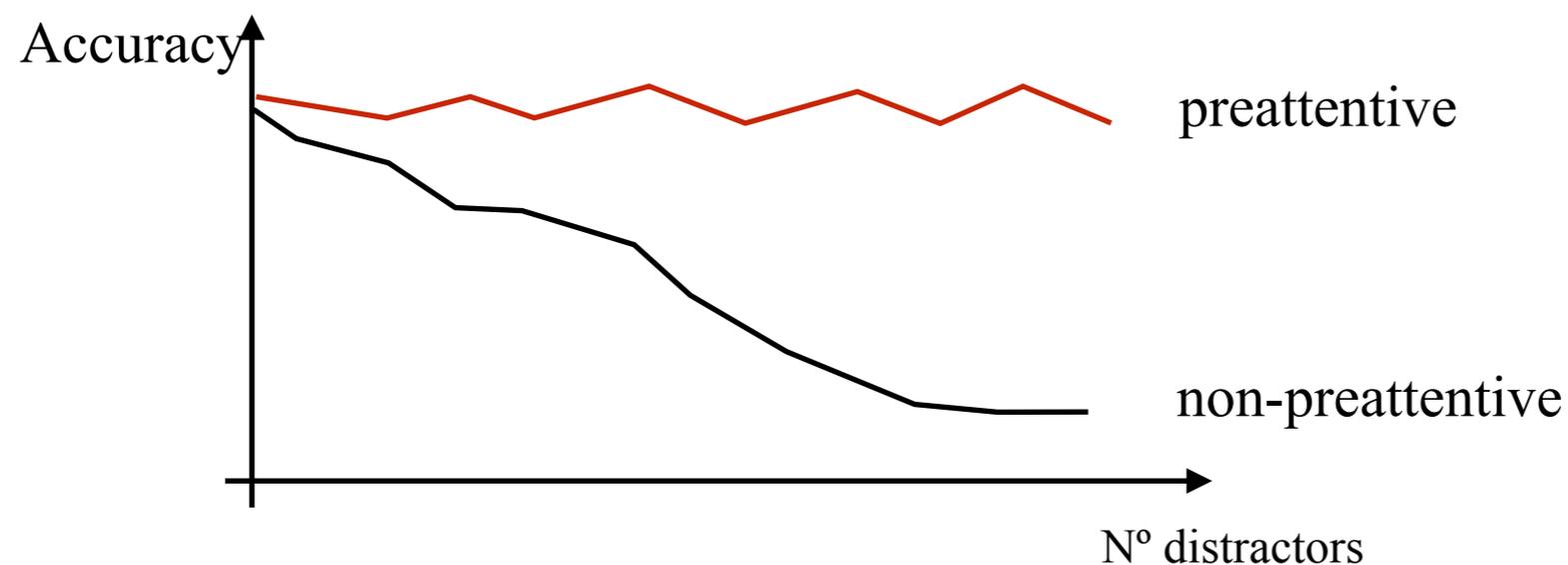


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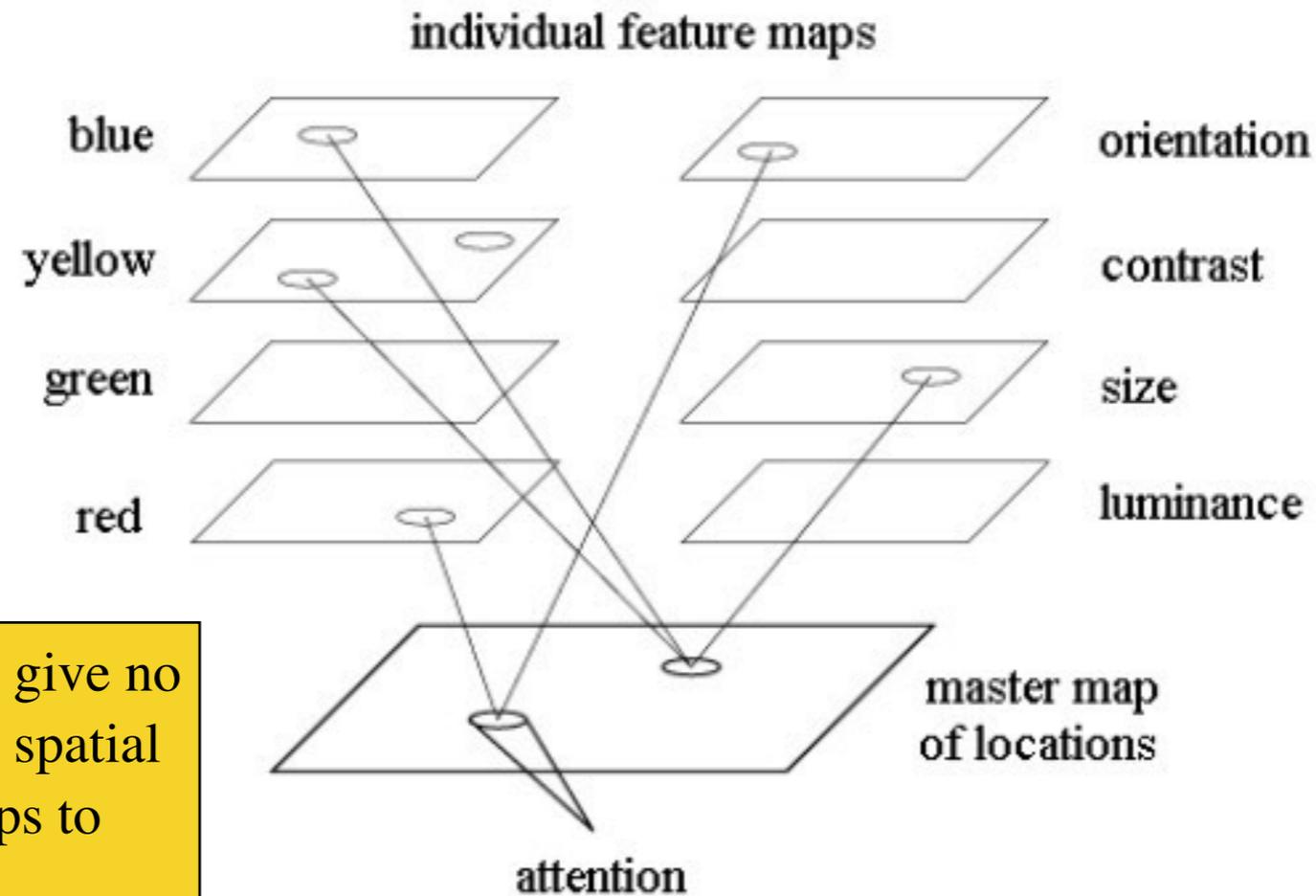
Feature Integration Theory (Anne Treisman)

- List of visual features that are detected preattentively
 - Some of these features are asymmetric:
 - A **sloped line** in a sea of **vertical lines** can be detected preattentively
 - A **vertical line** in a sea of **sloped lines** **cannot** be detected preattentively
 - **Different types of background distractors** may have an impact on the target feature

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 - **Different types of background distractors** may have an impact on the target feature
- To explain the preattentive features and processing they propose a “Feature Integration Theory”
 - ◆ A model of low-level human vision made up of a set of feature maps. Each **feature map** registers activity in response to a specific visual feature
 - ◆ and a **master map of locations**.

Feature Integration Theory (Anne Treisman)



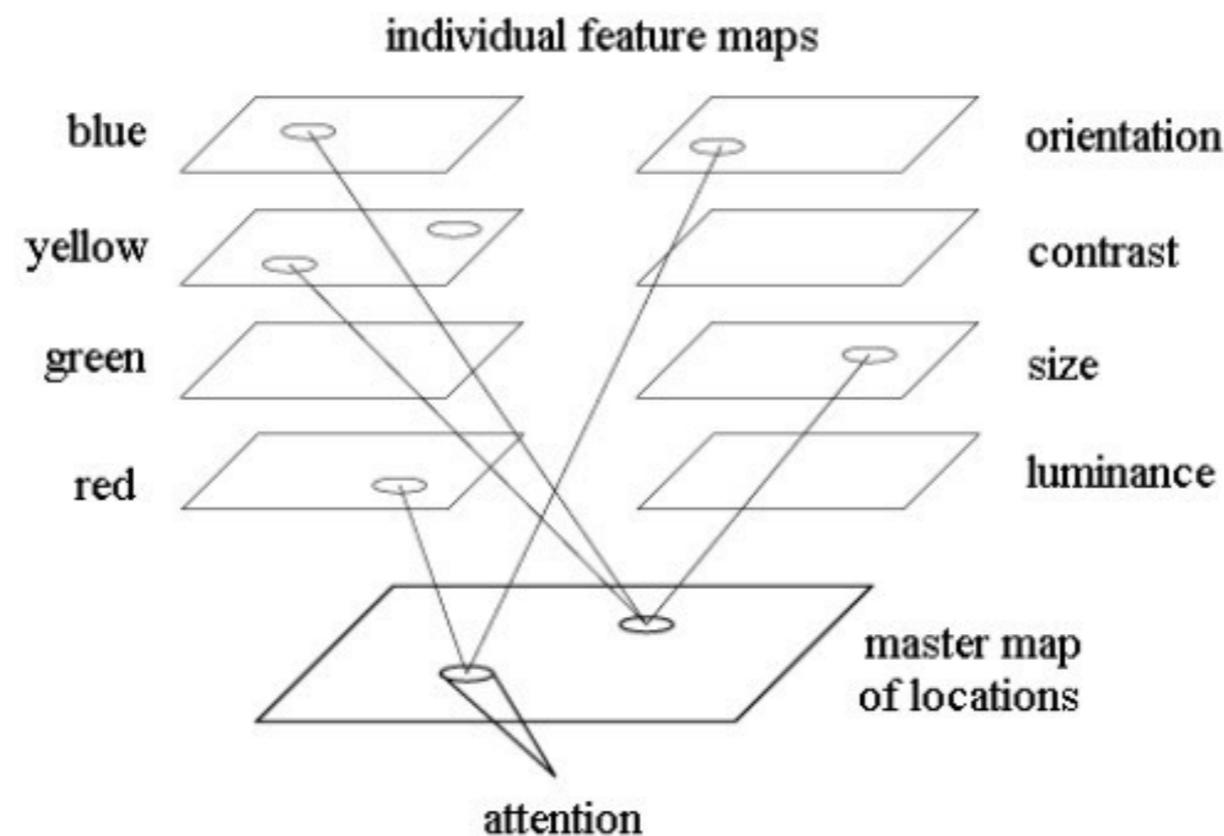
the individual feature maps give no information about location, spatial arrangement, or relationships to activity in other maps.

Treisman's feature integration model for early vision; individual maps can be accessed to detect feature activity; focused attention acts through a serial scan of the master map of locations.

Figure 3.22 - (Matthew Ward, et. all)

Feature Integration Theory (Anne Treisman)

- If the **target has a unique feature**, one can simply access the given **feature map** to see if any activity is occurring
- Feature maps are encoded in parallel, so feature detection is almost instantaneous.
- A conjunction target cannot be detected by accessing an individual feature map.



Feature Integration Theory (Anne Treisman)

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- Relaxing the **strict dichotomy of features** being detected as being either in **parallel** or in **serial**
 - For example, a **long vertical line** can be detected immediately among a group of **short vertical lines**.
 - **As the length of the target shrinks, the search time increases**, because the target is harder to distinguish from its distractors.
 - At some point, the target line becomes shorter than the distractors. If the length of the target continues to decrease, search time decreases, because the degree of similarity between the target and the distractors is now decreasing.

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 - Treisman hypothesizes that a significant target-nontarget feature difference would allow individual feature maps to ignore non target information
 - Example: **green horizontal bar** within a set of **red horizontal bars** and **green vertical bars**. Wolfe showed that search times are independent of display size!

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 - Example: **green horizontal bar** within a set of **red horizontal bars** and **green vertical bars**. Wolfe showed that search times are independent of display size!
 - If color constituted a significant feature difference, the red color map could inhibit information about red horizontal bars. Thus, the search reduces to finding a green horizontal bar in a sea of green vertical bars.

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- He suggested that the early visual system detects a group of features called **textons**, that can be classified into three general categories:
 - elongated blobs (e.g., line segments, rectangles, ellipses) with specific properties such as hue, orientation, and width;
 - terminators (ends of line segments);
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 - terminators (ends of line segments);
 - crossings of line segments.
- Julesz believed that only a **difference in textons** or in **their density** can be detected **preattentively**.

Texton Theory (Bela Julesz)

- Even when each appear **very different in isolation**, it may be difficult, if not impossible, to differentiate any pattern when in a texture or grid.

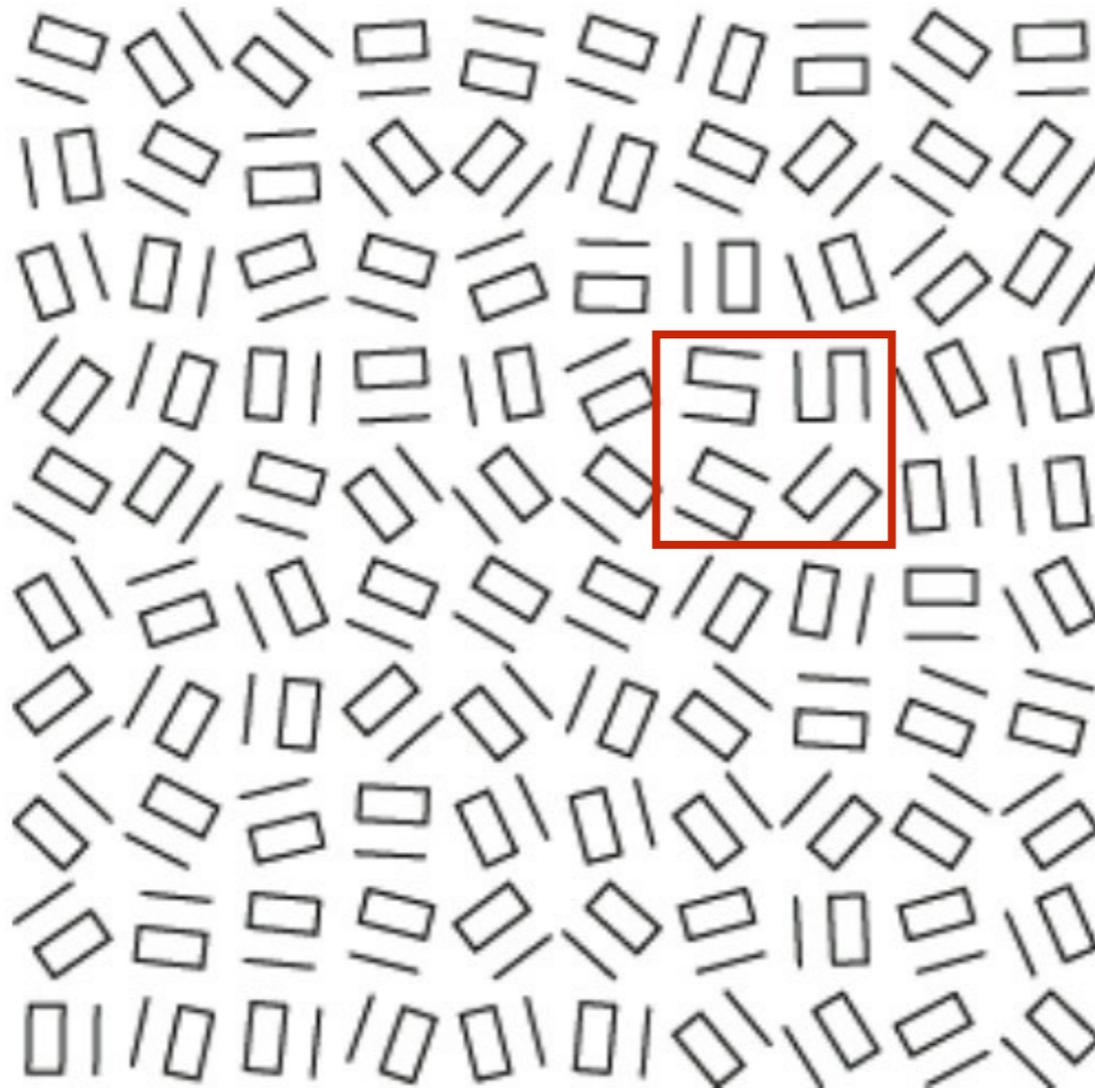


Two simple textons, easily differentiable.

Figure 3.23 - (Matthew Ward, et. all)

Texton Theory (Bela Julesz)

- Julesz used **texture segregation**



Although the two objects look very different in isolation, they are actually the same texton. Both are made up of the same set of line segments, and each has two terminators.

A target group of b-textons is difficult to detect in a background of a-textons when a random rotation is applied.

Figure 3.24 - (Matthew Ward, et. all)

Similarity Theory (Quinlan and Humphreys)

- They investigated **conjunction searches**:
 - Search time may depend on the **number of items of information required to identify the target**
 - Search time may depend on **how easily a target can be distinguished from its distractors**, regardless of the presence of unique preattentive features

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 - Search time may depend on **how easily a target can be distinguished from its distractors**, regardless of the presence of unique preattentive features
- Model:
 - ◆ Assumes that search ability **varies continuously**, depending on both the **type of task** and the **display** conditions
 - ◆ Search time is based on two criteria:
 - T-N similarity is the amount of **similarity** between the **targets** and **nontargets**
 - N-N similarity is the amount of **similarity within the nontargets** themselves

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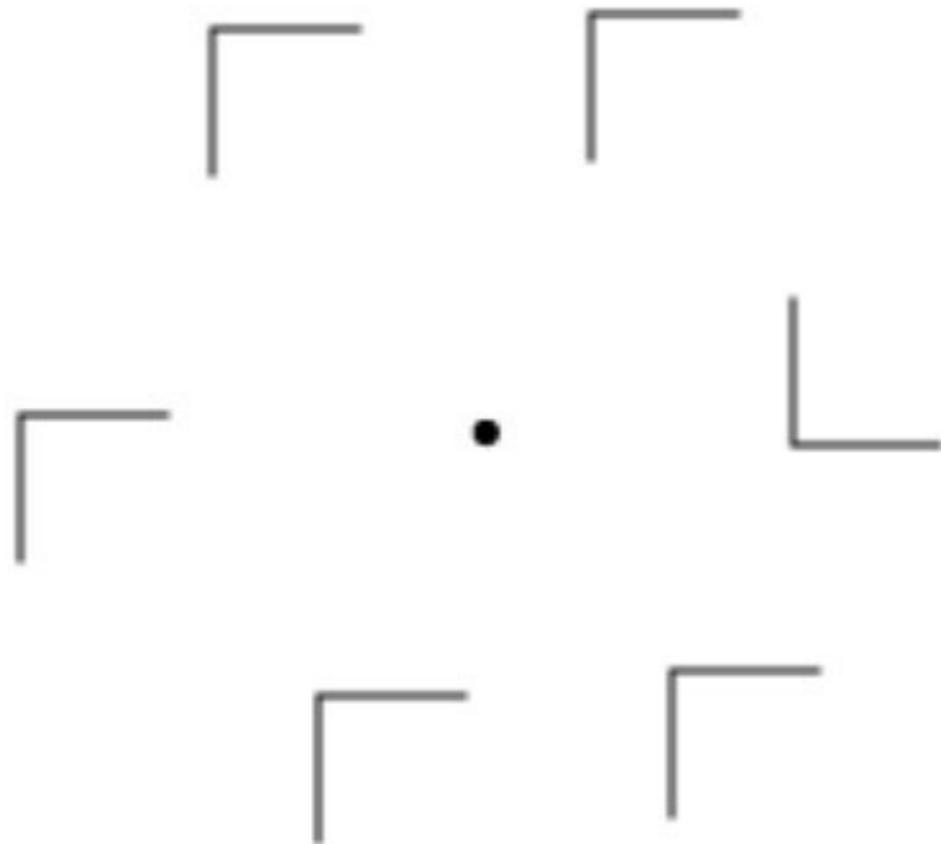
(a) High N-N (nontarget-nontarget) similarity allows easy detection of target L.

(b) Low N-N similarity increases the difficulty of detecting the target L.

Example of N-N similarity affecting search efficiency for a target shaped like the letter L.

Figure 3.25 - (Matthew Ward, et. all)

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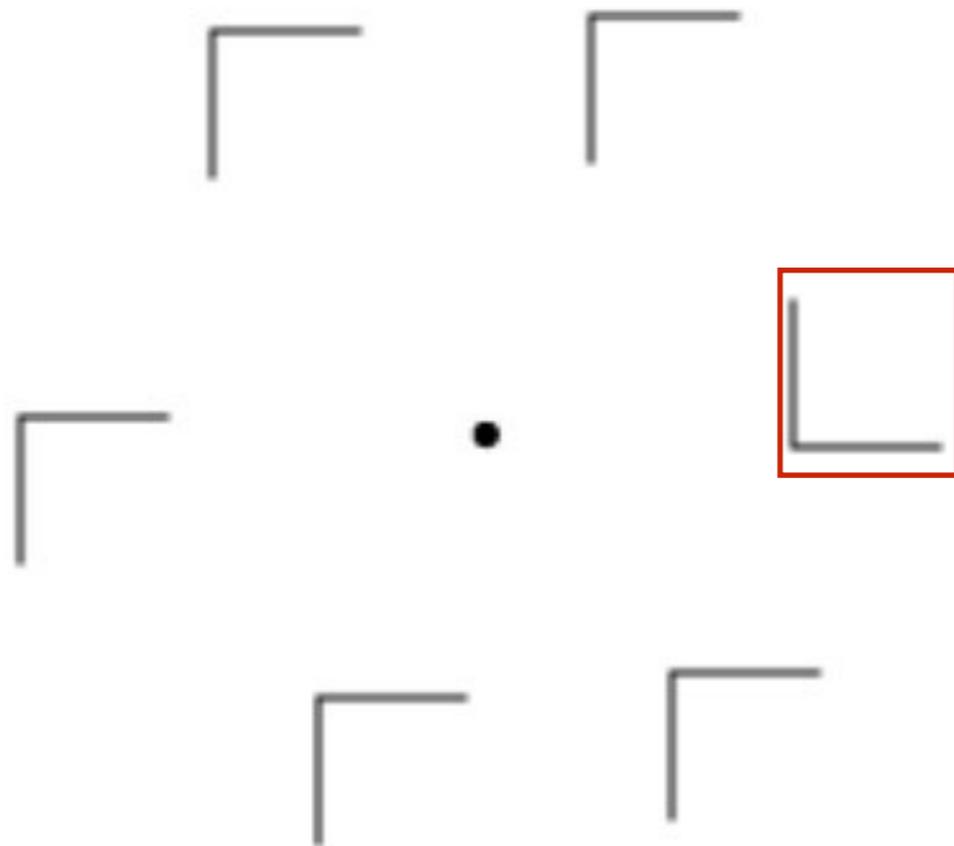


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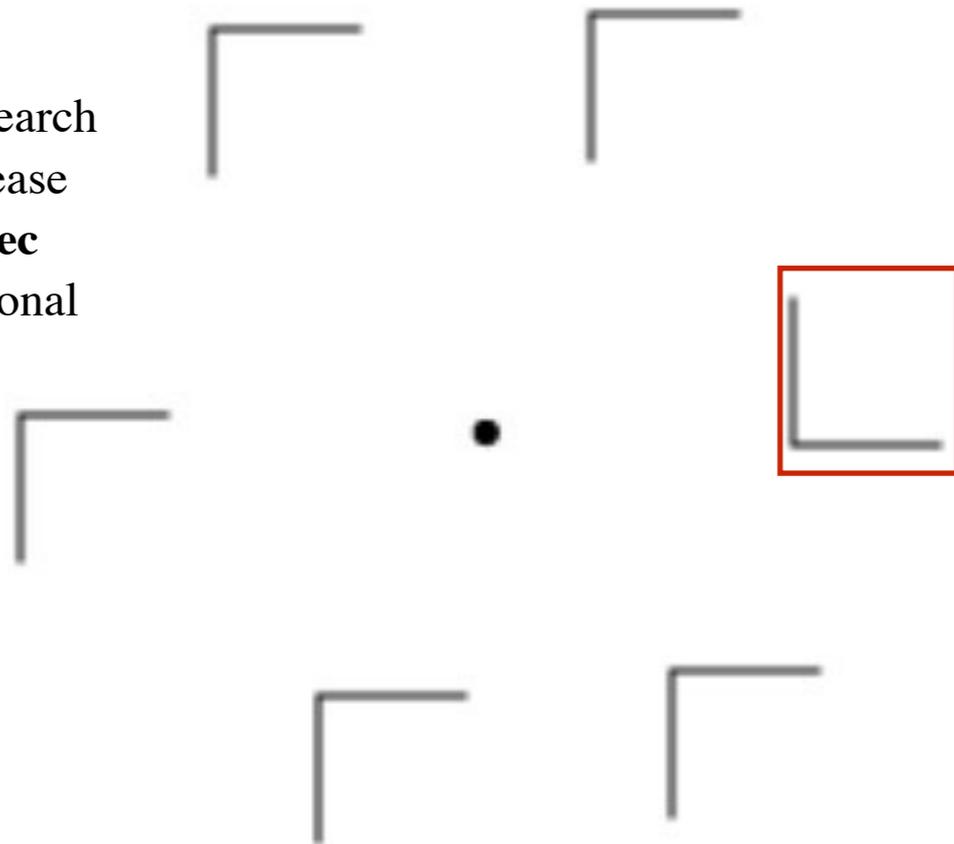
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average search
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per additional
distractor

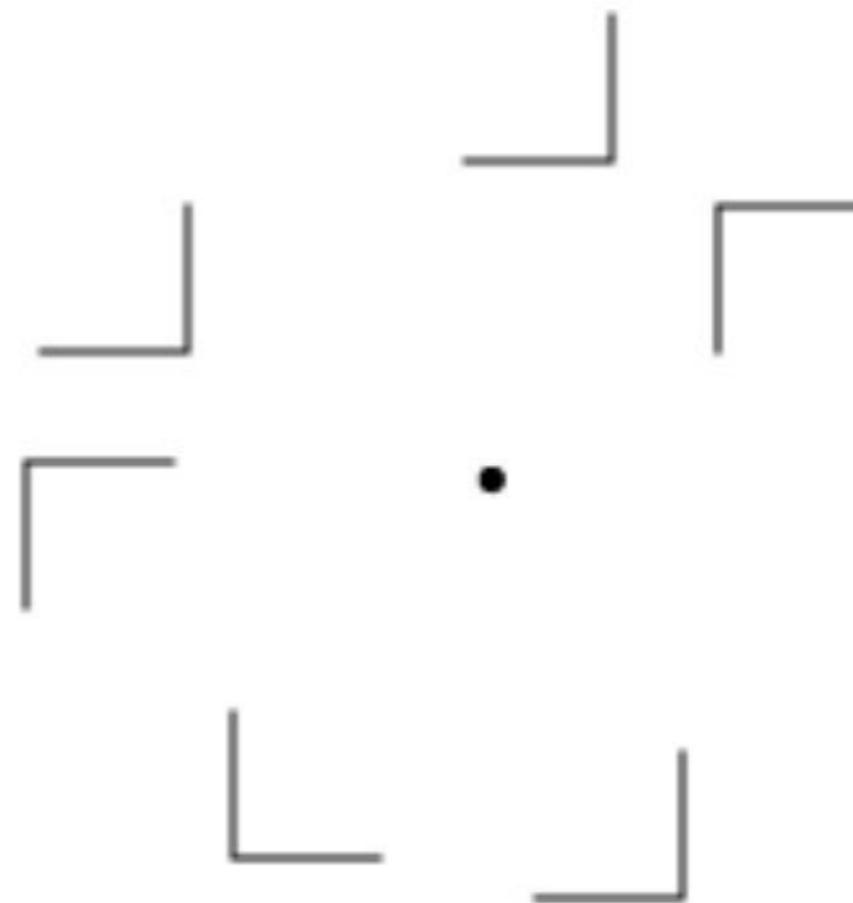


(a) High N-N (nontarget-nontarget) similarity allows easy detection of target L.

Example of N-N similarity affecting search efficiency for a target shaped like the letter L.

Figure 3.25 - (Matthew Ward, et. all)

Similarity Theory (Quinlan and Humphreys)

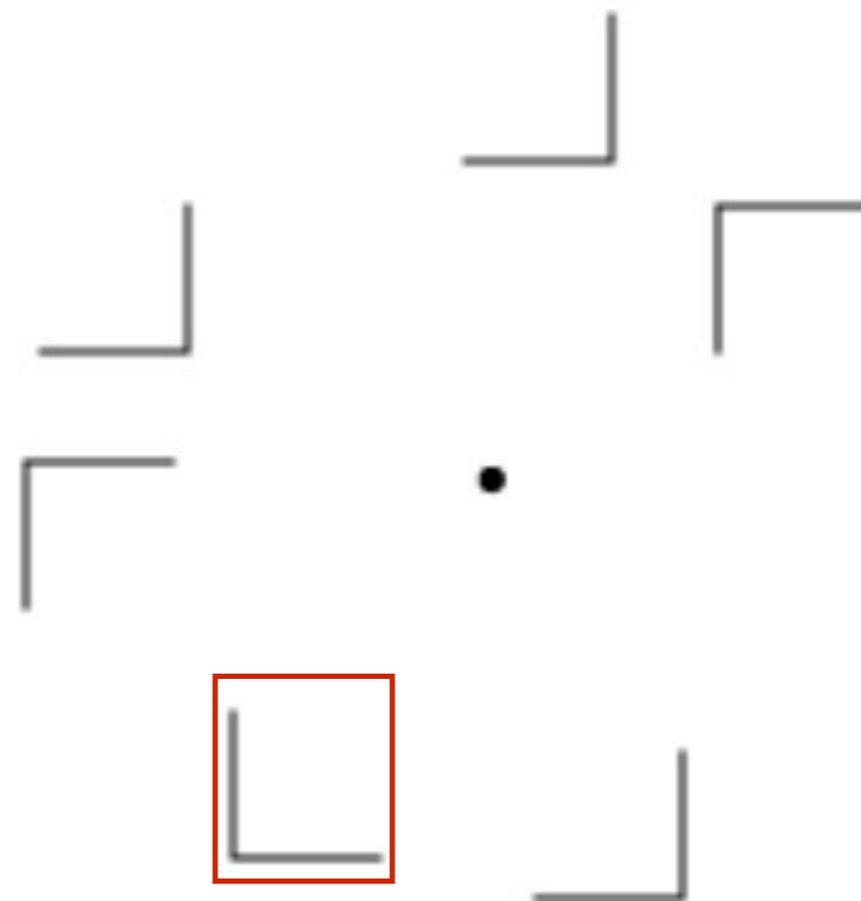


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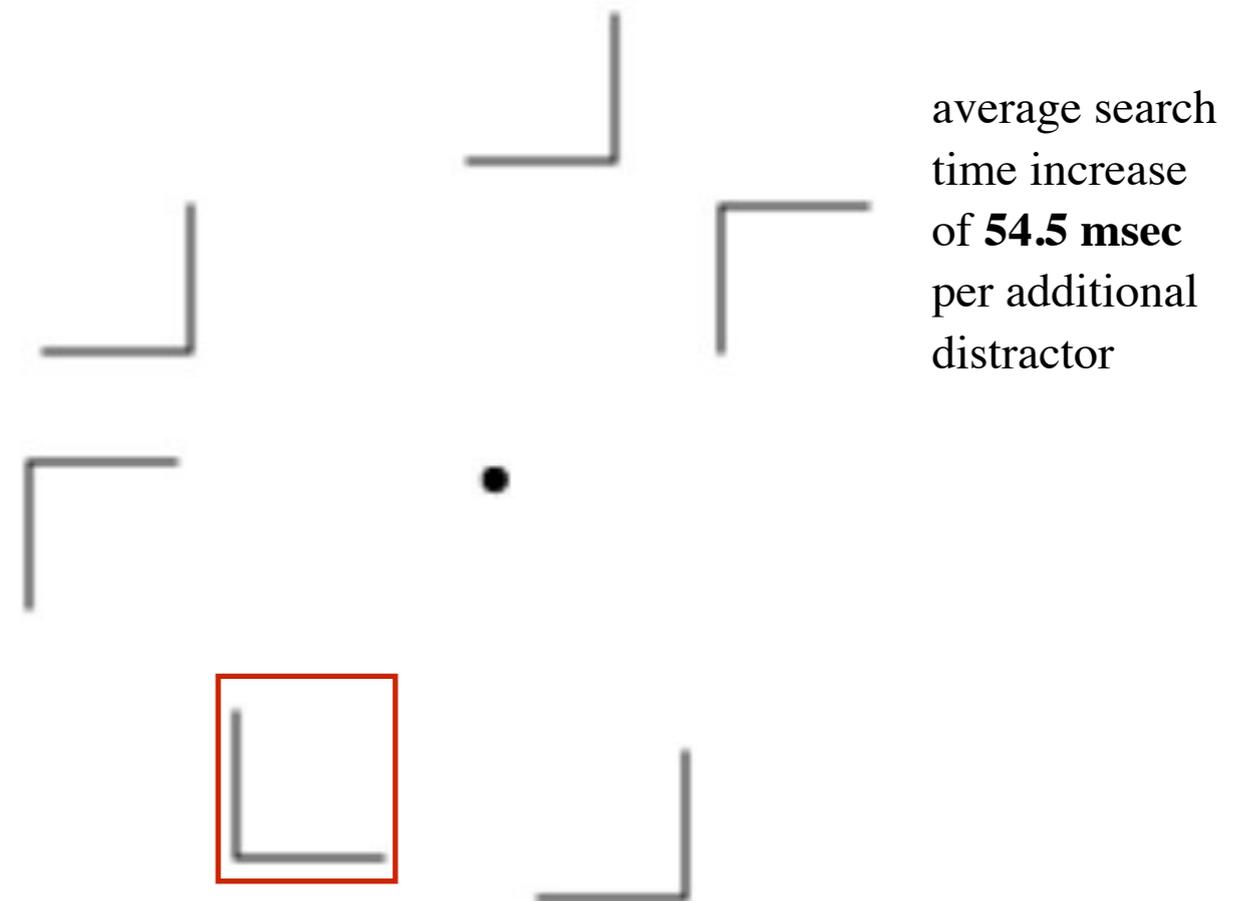


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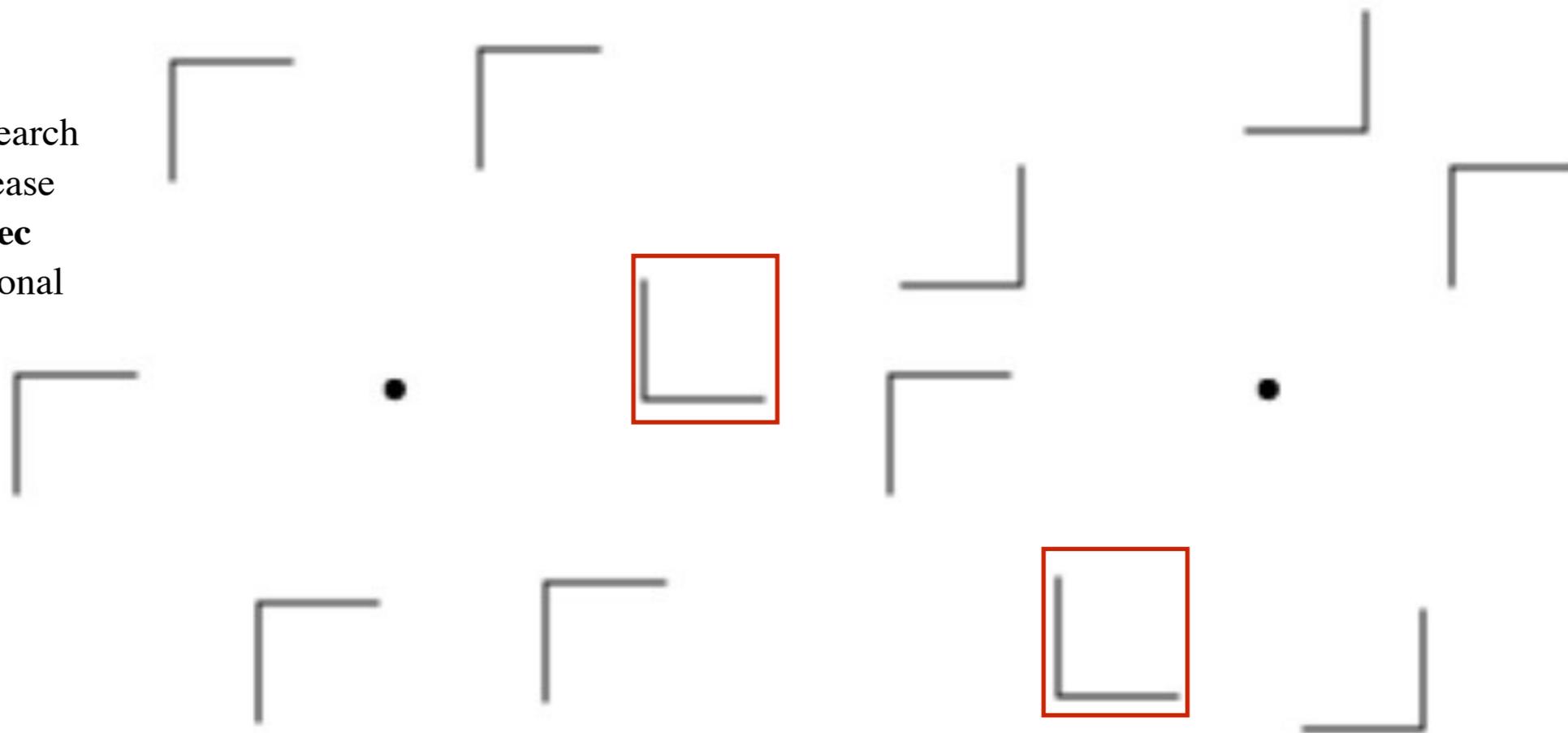
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time increase
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average search
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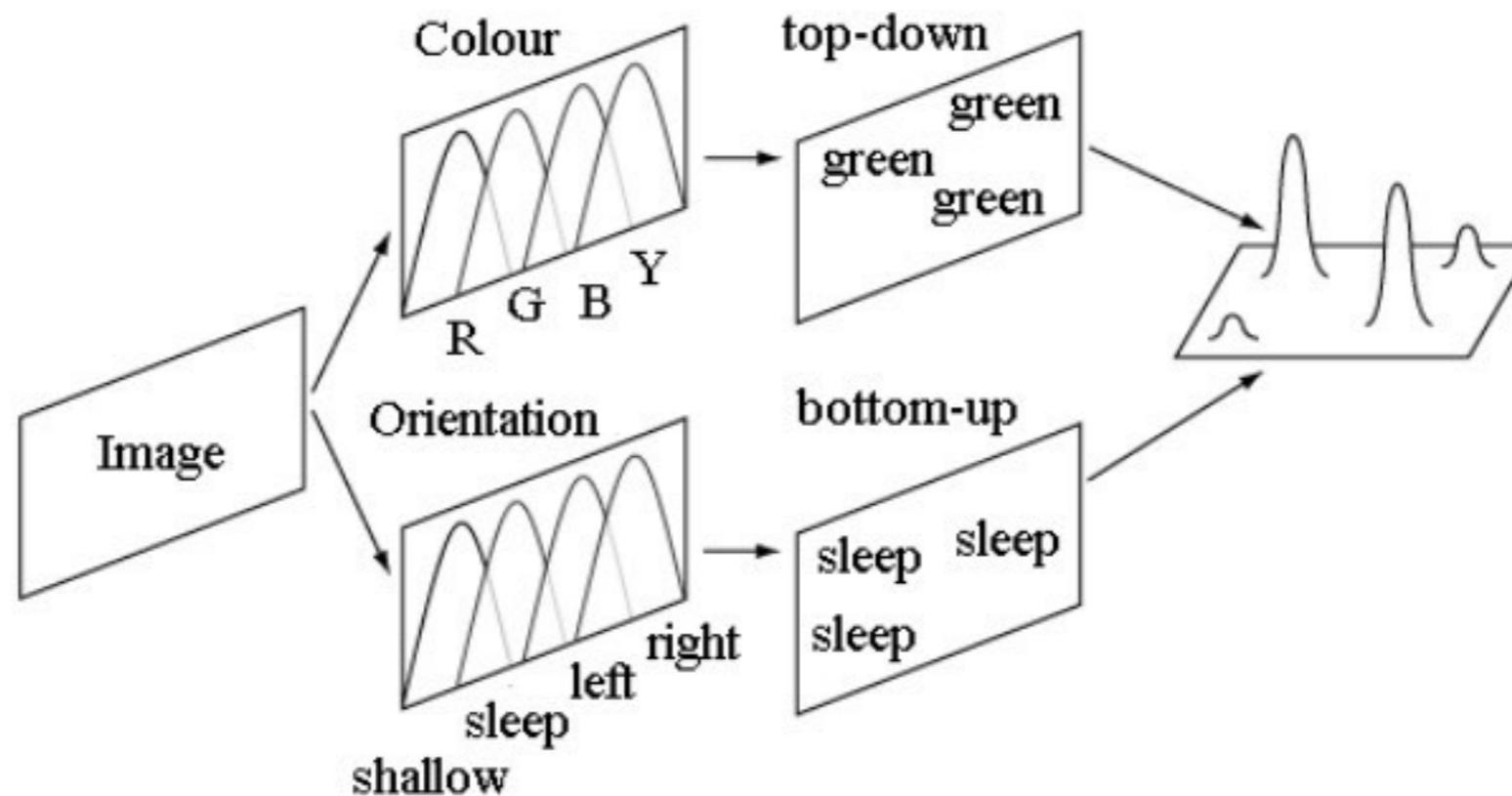
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Guided Search Theory (Jeremy Wolfe)

- He hypothesized that an **activation map** based on both **bottom-up** and **top-down** information is constructed during visual search.
- Attention is drawn to peaks in the activation map that represent areas in the image with the largest combination of bottom-up and top-down influence.
- Early vision divides an image into **individual feature maps**, i.e., one map for each feature type (e.g., one map for color, one map for orientation, and so on).
- Within each map, a **feature is filtered into multiple categories**. For example, in the color map there might be independent representations for red, green, blue, and yellow

Guided Search Theory (Jeremy Wolfe)



Framework for guided search, the user wants to find a green steep target; image is filtered into categories for each feature map. Bottom-up and top-down activation “mark” regions of the image; an activation map is built by combining bottom-up and top-down information, attention is drawn to the highest “hills” in the map [174].

Figure 3.26 - (Matthew Ward, et. all)

Guided Search Theory (Jeremy Wolfe)

- **Bottom-up activation** follows feature categorization. It measures how different an element is from its neighbors.
- Differences for each relevant feature map are computed and combined (e.g., how different are the elements in terms of color, how different are they in terms of orientation?)

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- **A subject's attention is drawn from hill to hill in order of decreasing activation.**

Guided Search Theory (Jeremy Wolfe)

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 - **High T-N similarity causes a reduction in the target elements’ bottom-up activation.**
 - **Provides a possible explanation for situations where conjunction search can be performed preattentively**

Postattentive Vision

- **Preattentive** processing asks in part:
 - What visual properties draw our eyes, and therefore our focus of attention, to a particular object in a scene?
- An equally interesting question is:
 - What happens to the visual representation of an object when we stop attending to it and look at something else?

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- The intuitive belief that a **rich visual representation accumulates** as we look at more and more of a scene ...
 - ◆ **Appears not to be true.**

Postattentive Vision

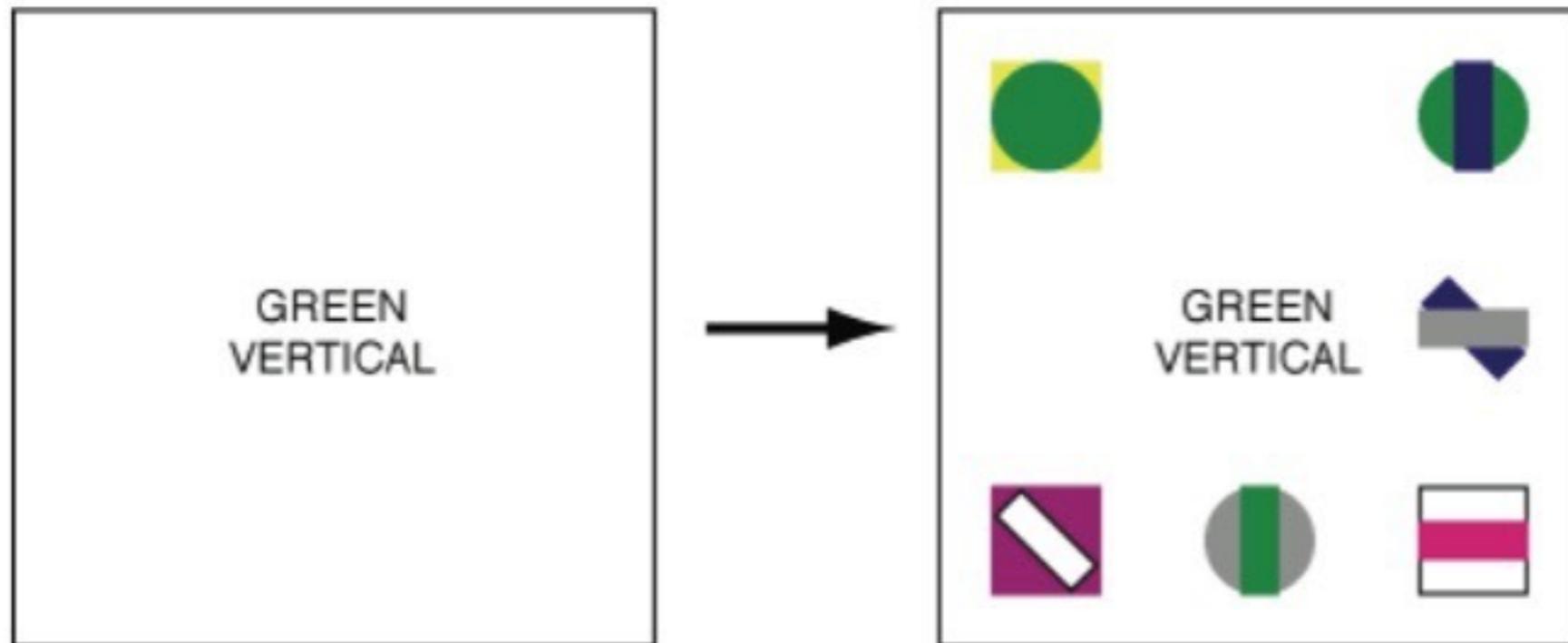
- Wolfe designed **targets** with two critical properties:
 - The targets were formed from a **conjunction of features** (e.g., they could not be detected preattentively).
 - The targets were **arbitrary combinations of colors and shapes** (e.g., they were not objects that could be semantically recognized and remembered on the basis of familiarity).

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- Wolfe initially tested two search types (response-time search)
 - ◆ **Traditional search**: Text on a blank screen was shown to identify the target. This was followed by a display containing 4, 5, 6, 7, or 8 potential target objects in a 3 × 3 array (formed by combinations of seven colors and five shapes).
 - ◆ **Postattentive search**

Postattentive Vision

■ Traditional search



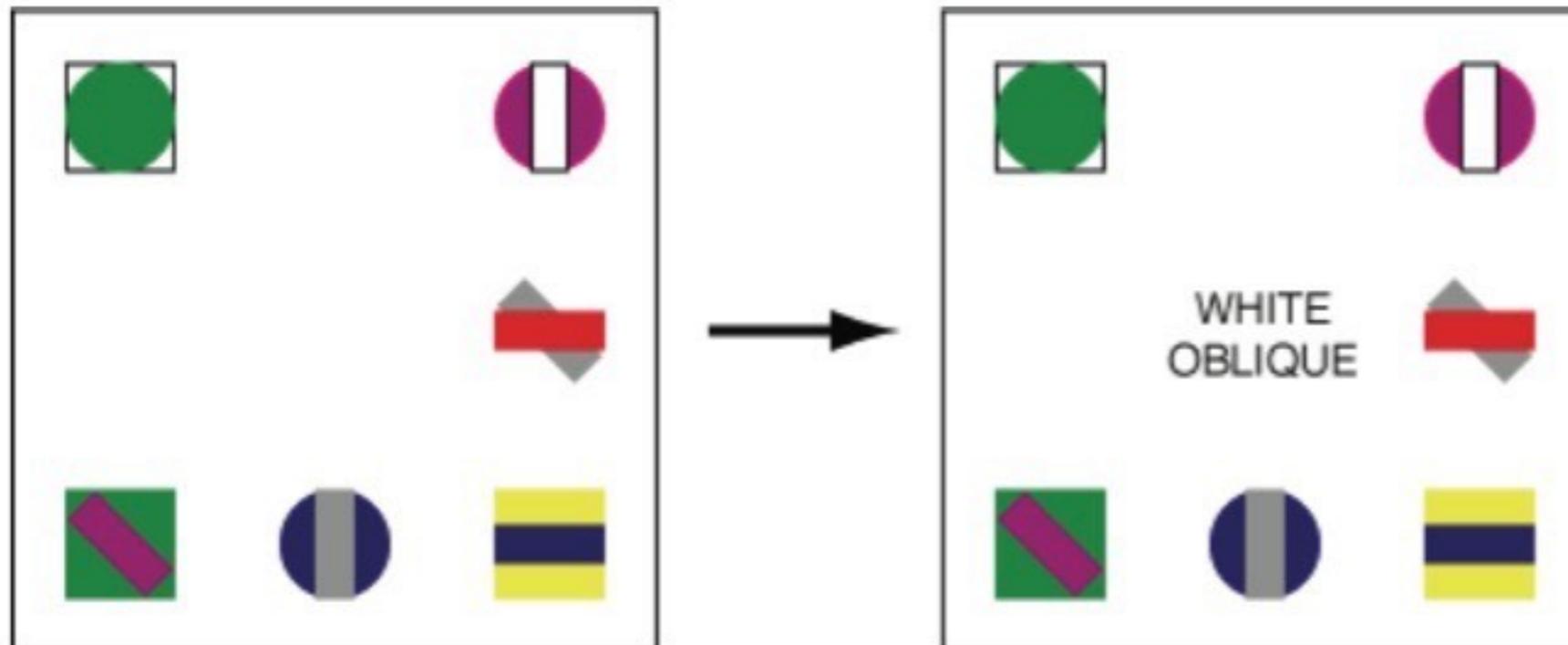
Search for color-and-shape conjunction targets:

- **no preview of the scene is shown** (although text identifying the target is shown prior to the search)
- in this case, the green vertical target is present

Figure 3.27 - (Matthew Ward, et. all)

Postattentive Vision

■ Postattentive search



Search for color-and-shape conjunction targets:

- a **preview of the scene is shown**, followed by text identifying the target;
- in this case, a white oblique target is not present

Figure 3.27 - (Matthew Ward, et. all)

Postattentive Vision

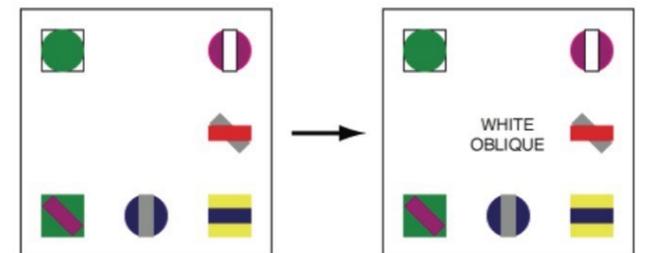
- **Postattentive search**
 - **The display to be searched was shown to the user for a specific duration (up to 300 msec)**
 - **Text identifying the target was then inserted into the scene**
 - **Results showed that the postattentive search was as slow (or slower) than the traditional search, with approximately 25–40 msec per object required for the target present trials.**

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- **Previewing the scene provides no advantage to the viewer for finding a conjunction target**



Feature Hierarchy

- Based on our understanding of **low-level human vision**, one promising strategy for multidimensional visualization is to **assign different visual features to different data attributes** (e.g., building a data-feature mapping that maps data to a visual representation).

Feature Hierarchy

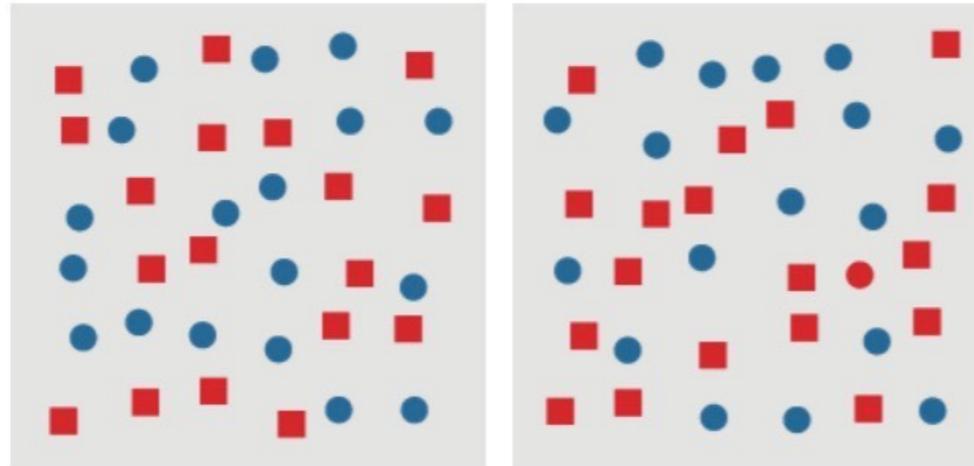
- Based on our understanding of **low-level human vision**, one promising strategy for multidimensional visualization is to **assign different visual features to different data attributes** (e.g., building a data-feature mapping that maps data to a visual representation).
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- One key **requirement of this method** is a data-feature mapping that **does not produce visual interference**

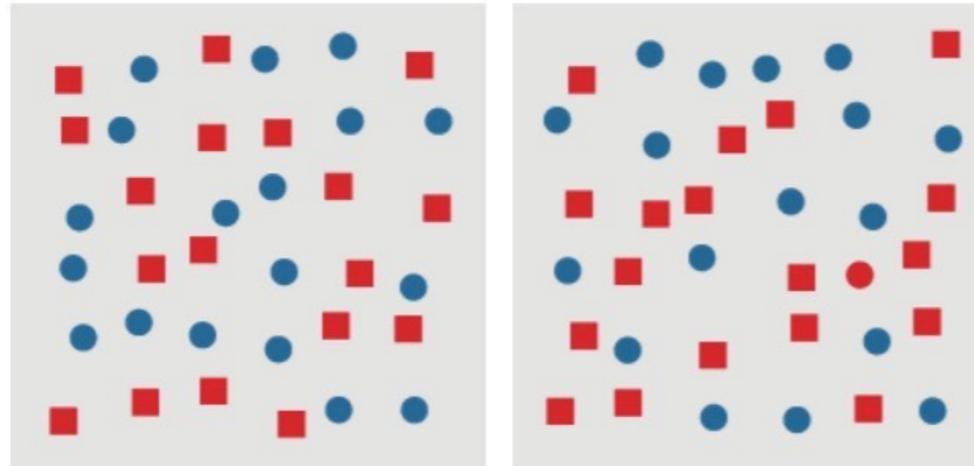
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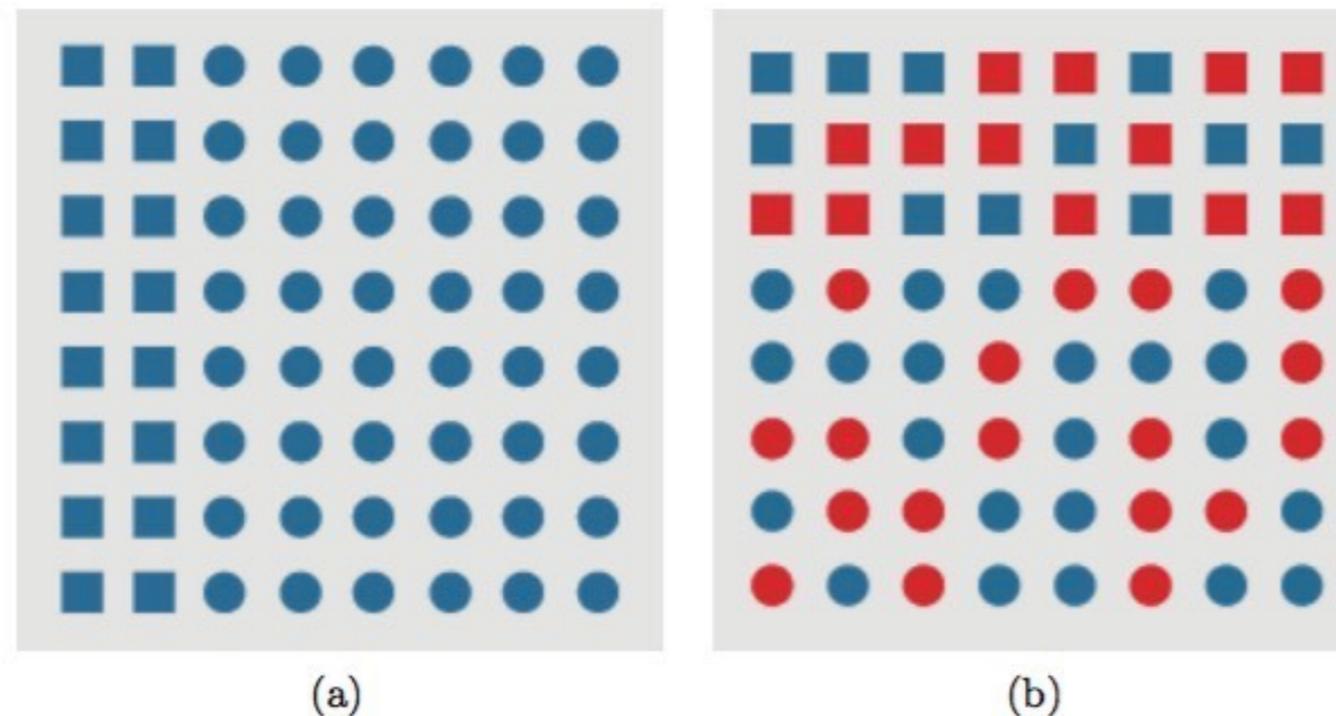
- One simple example of **visual interference** is the conjunction



- An important type of interference results from a feature hierarchy that appears to exist in the visual system. **For certain tasks**, the **visual system seems to favor one type of visual feature over another**.
- For example, during **boundary detection**, researchers have shown that the visual system **favors color over shape**

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Another example of hue-on-form feature hierarchy: (a) a vertical form boundary is preattentively identified when hue is held constant; (b) a horizontal form boundary cannot be preattentively identified when hue varies randomly in the background.

Change Blindness

- **The goal of human vision is not to create a replica or image of the seen world in our heads.**

Change Blindness

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- A much better metaphor for vision is that of a **dynamic and ongoing construction project**, where the products being built are **short-lived models of the external world** that are **specifically designed for the current visually guided tasks** of the viewer.

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-
- What we “see” when confronted with a new scene **depends** as much on our **goals** and **expectations** as it does on the array of light that enters our eyes.

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- **New research in psychophysics has shown that an interruption in what is being seen (i.e., a blink, an eye saccade, or a blank screen) renders us “blind” to significant changes that occur in the scene during the interruption**

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Figure 3.30 - (Matthew Ward, et. all)

Change Blindness

- New research in psychophysics has shown that an **interruption in what is being seen** (i.e., a blink, an eye saccade, or a blank screen) **renders us “blind” to significant changes** that occur in the scene during the interruption
- A list of possible explanations for why change blindness occurs in our VS:
 - **Overwriting**: information that was not abstracted from the first image is lost.
 - **First Impression**: hypothesis that only the initial view of a scene is abstracted.
 - **Nothing Is Stored**: after a scene has been viewed and information has been abstracted, no details are represented internally.
 - **Everything Is Stored, Nothing Is Compared**: only compared is requested
 - **Feature Combination**: details from an initial view might be combined with new features from a second view.

Further Reading and Summary



Q&A

Further Reading

- **Pag 81 - 117 from Interactive Data Visualization: Foundations, Techniques, and Applications, Matthew O. Ward, Georges Grinstein, Daniel Keim, 2015**

What you should know

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 - Process the sensorial information of the world around us, forming a mental representation of the environment

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- **The role of measurements and theories in the study of perception.**
- **The visible spectrum, its composition the relation with color and many forms of blindness.**
- **The eye main components and their role in the human vision system**
 - The motion control muscles; cornea, pupil, iris and the crystalline;
 - Retina: Rods and cones; the differences, the roles, the placement, the relative quantities.

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- **The concept of Preattentive Processing.**
 - Why the name Preattentive is not completely correct?
 - Examples of visual properties
 - Examples of tasks (Target detection, Boundary detection, Region tracking, ...)
 - Time to performed on large multi-element displays in less than 200 to 250 milliseconds
 - What is the meaning of conjunction target
 - key perceptual attributes: luminance, brightness, color, texture, and shape.

What you should know

- **How to Measuring preattentive task performance (response time and accuracy)**

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- **How to Measuring preattentive task performance (response time and accuracy)**
- **Some of features that are detected preattentively are asymmetric**
- **Different types of background distractors may have a impact on the target feature**
- **Some ideas from main perception theories and models**
 - Some conjunction search tasks have been shown to be preattentive
 - Texton Theory (elongated blobs, terminators, crossings). Difference in textons or in their density
 - Search time is based on two criteria: T-N similarity and N-N similarity
 - T-N similarity $\hat{=} \Rightarrow E_f \cdot v$
 - N-N similarity $v \Rightarrow E_f \cdot v$

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- **Postattentive Vision**

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Q&A

Perception in Visualization

Perceptual Processing

- A visualization of intelligent agents competing in simulated e-commerce

auctions:

- **x-axis** is mapped to **time**;
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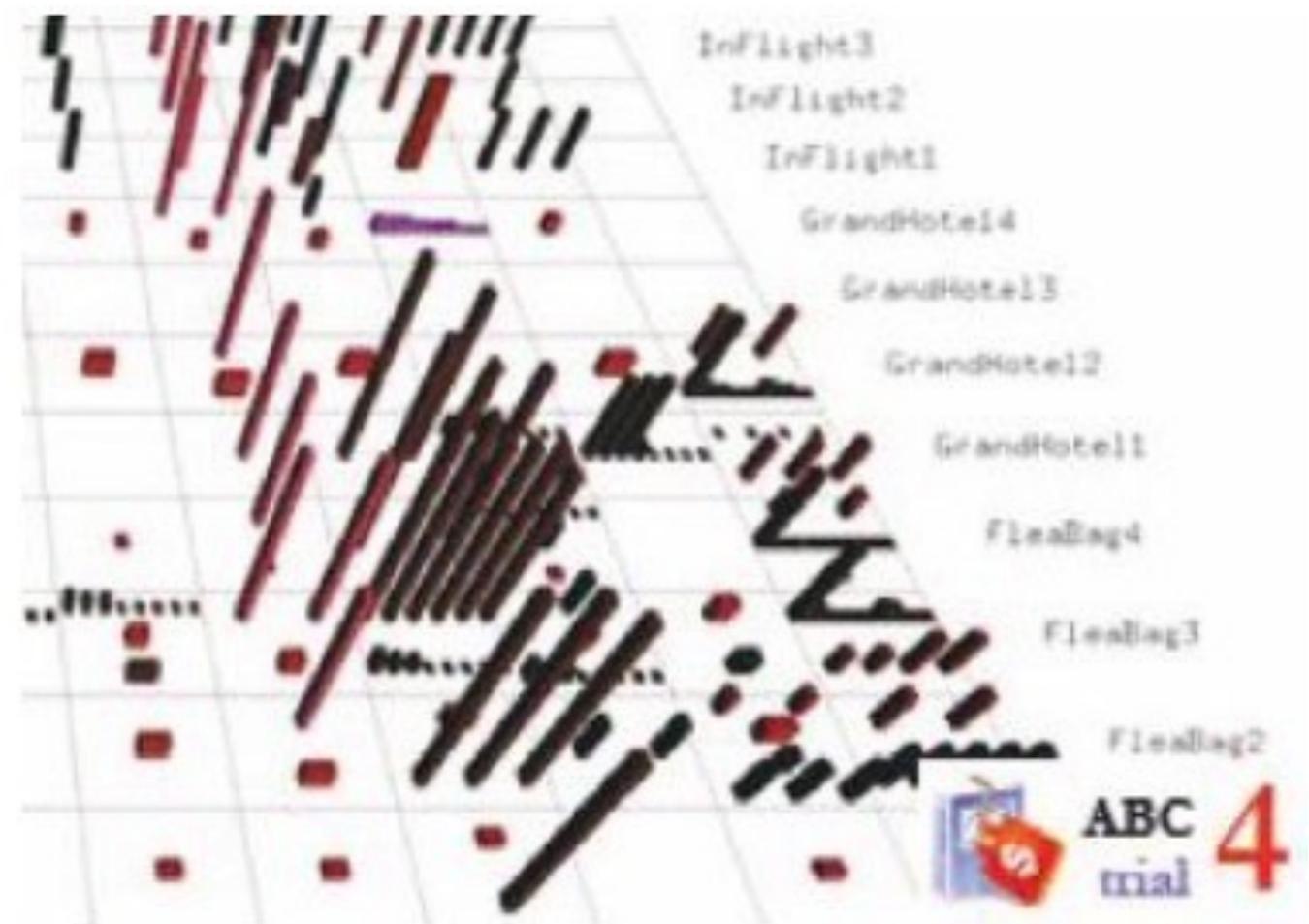


Figure 3.31 - (Matthew Ward, et. all)

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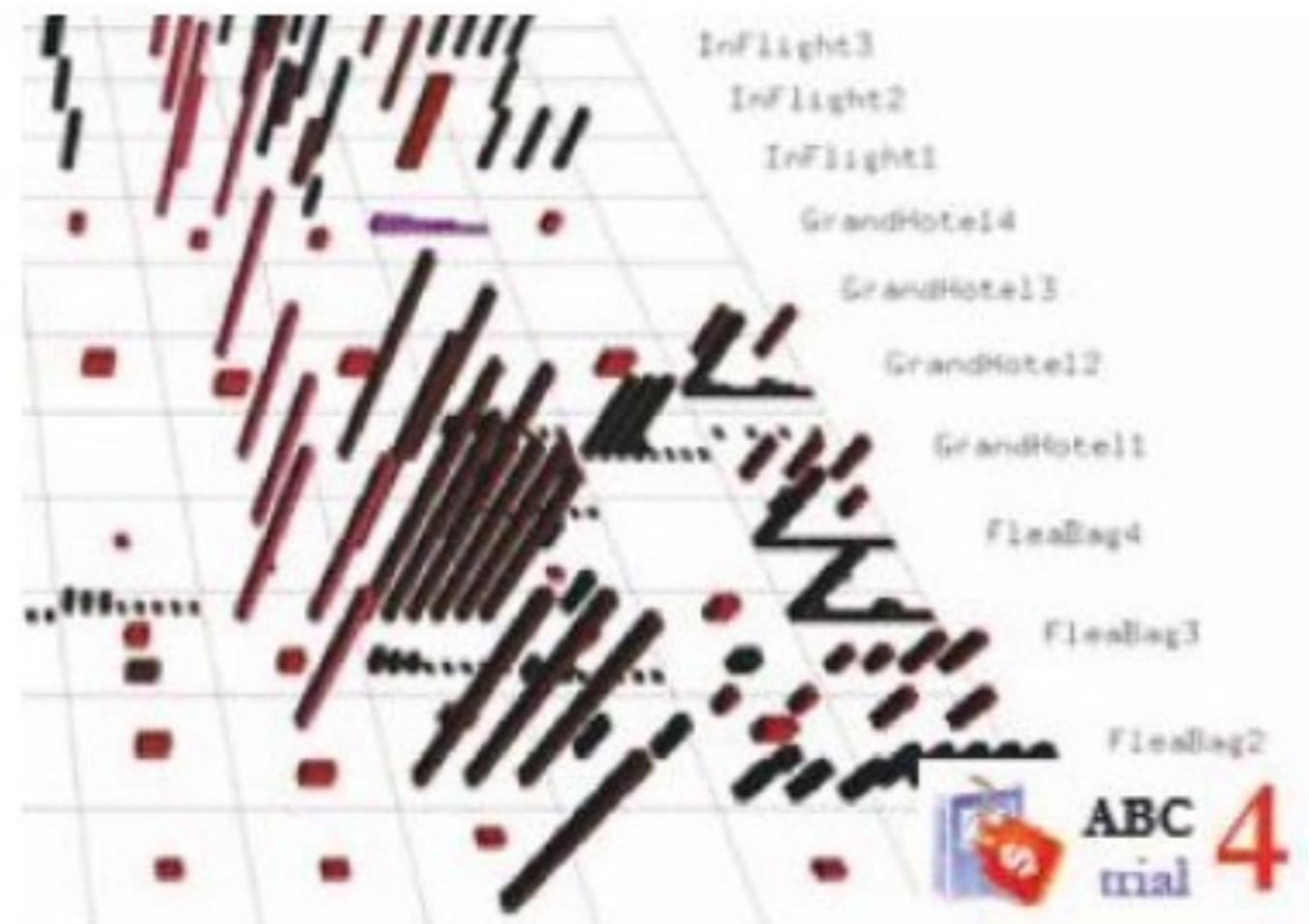


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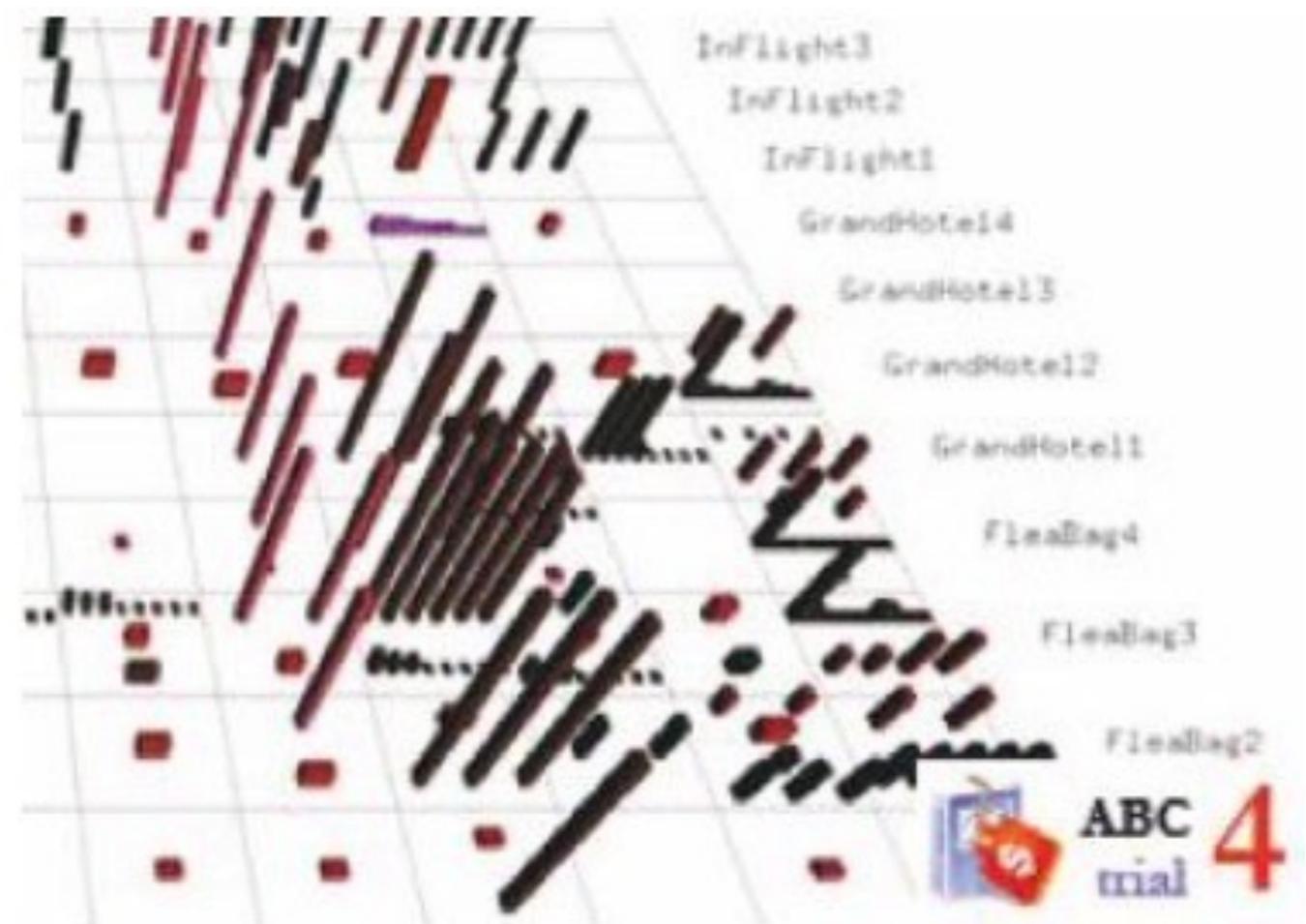


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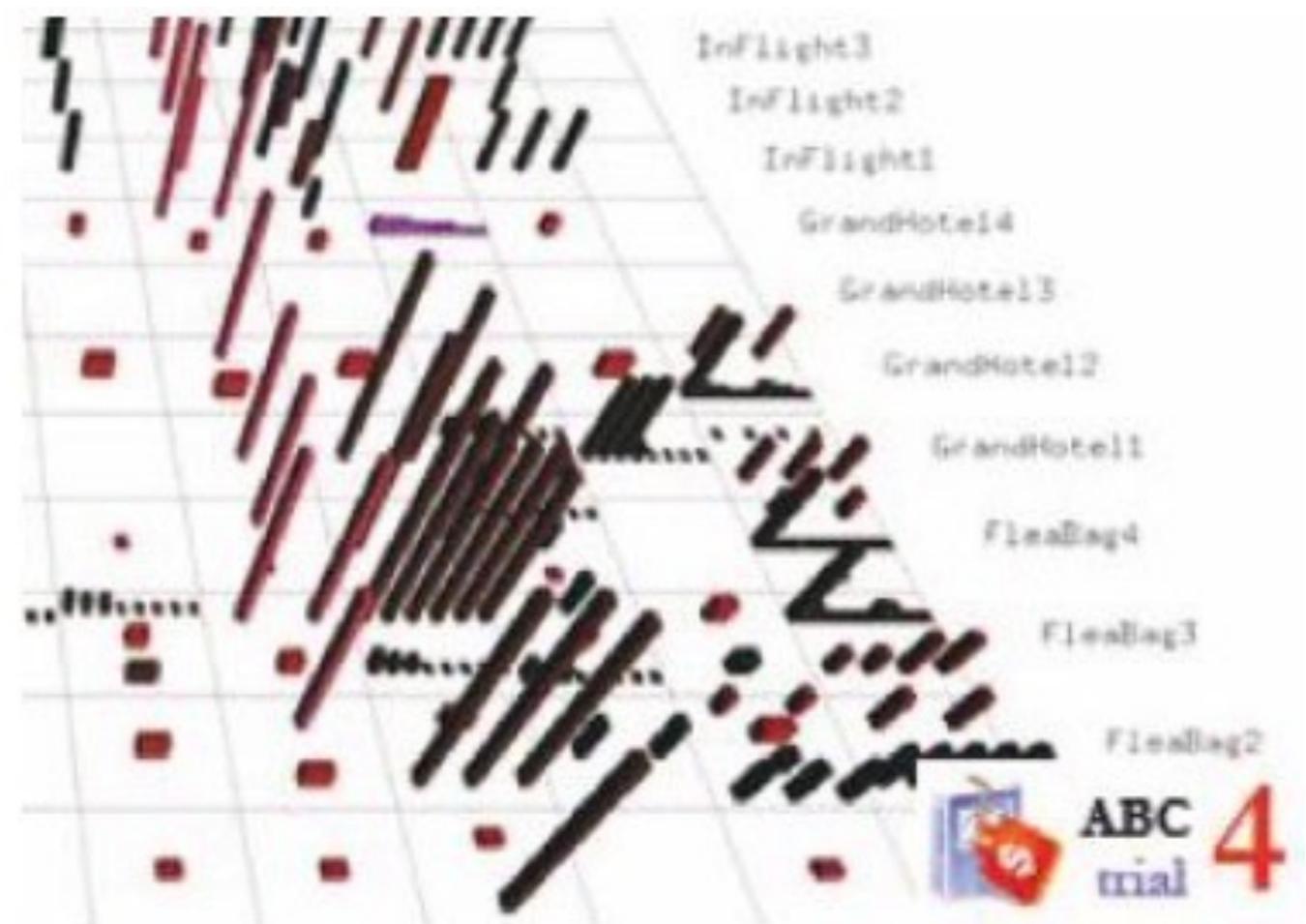


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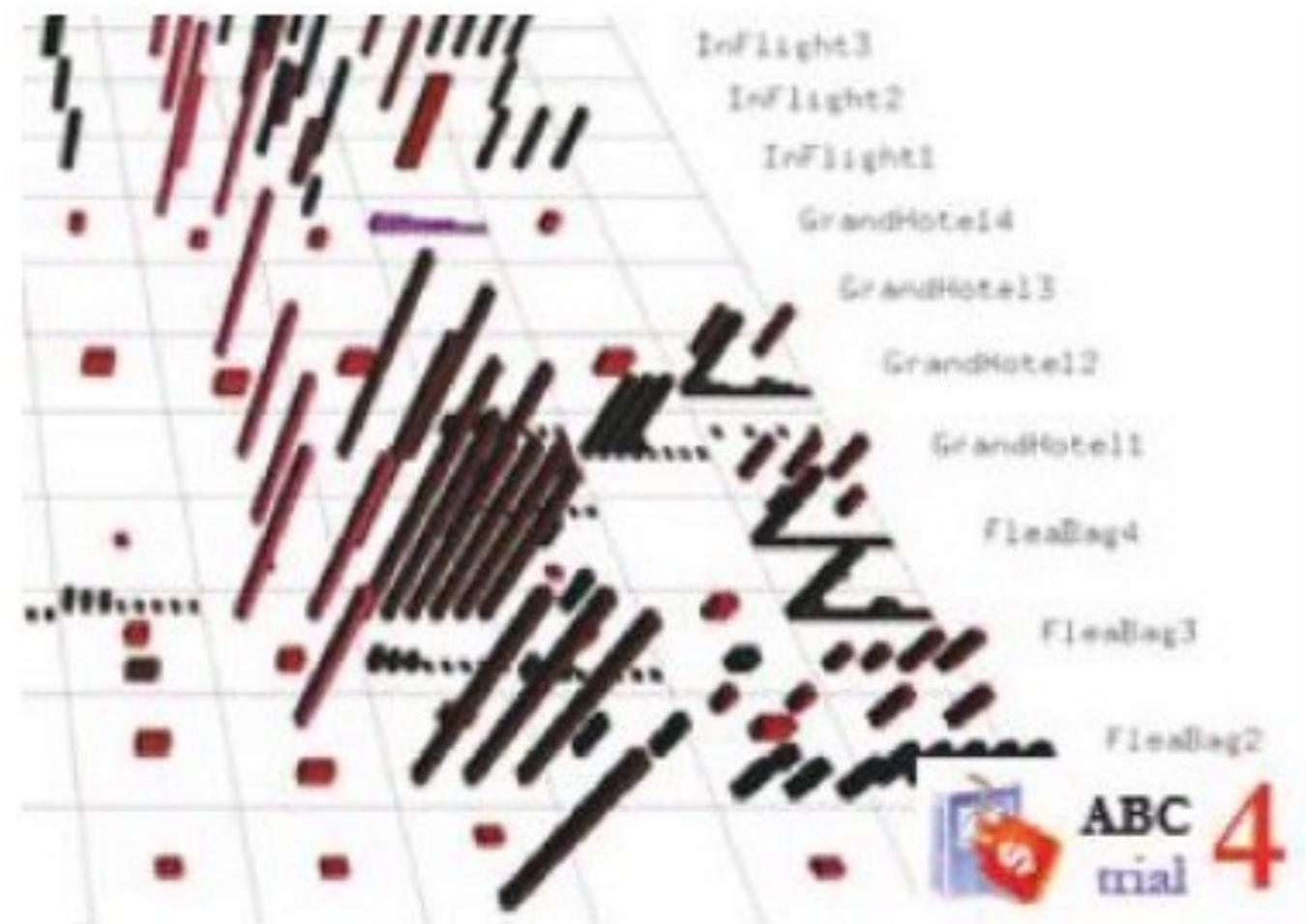
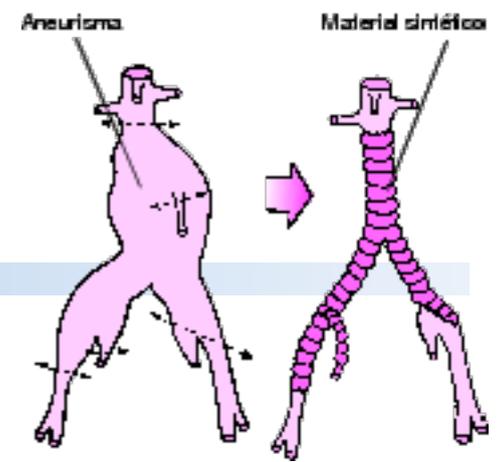


Figure 3.31 - (Matthew Ward, et. all)

Perceptual Processing



- A visualization of a CT scan of an abdominal aortic aneurism:

- **yellow** represents the **artery**;
- **purple** represents the **aneurism**;
- **red** represents **metal tines**
in a set of stents inserted into
the artery to support its wall
within the aneurism.

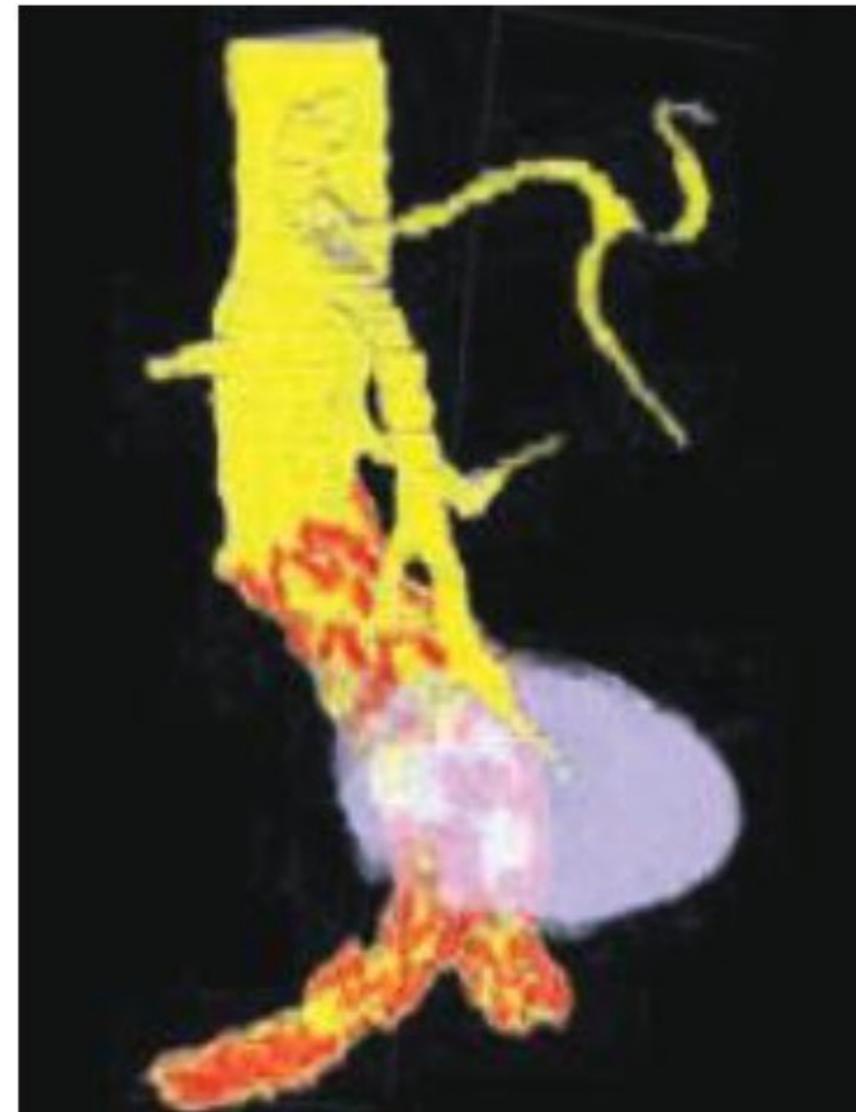


Figure 3.31 - (Matthew Ward, et. all)

Perceptual Processing

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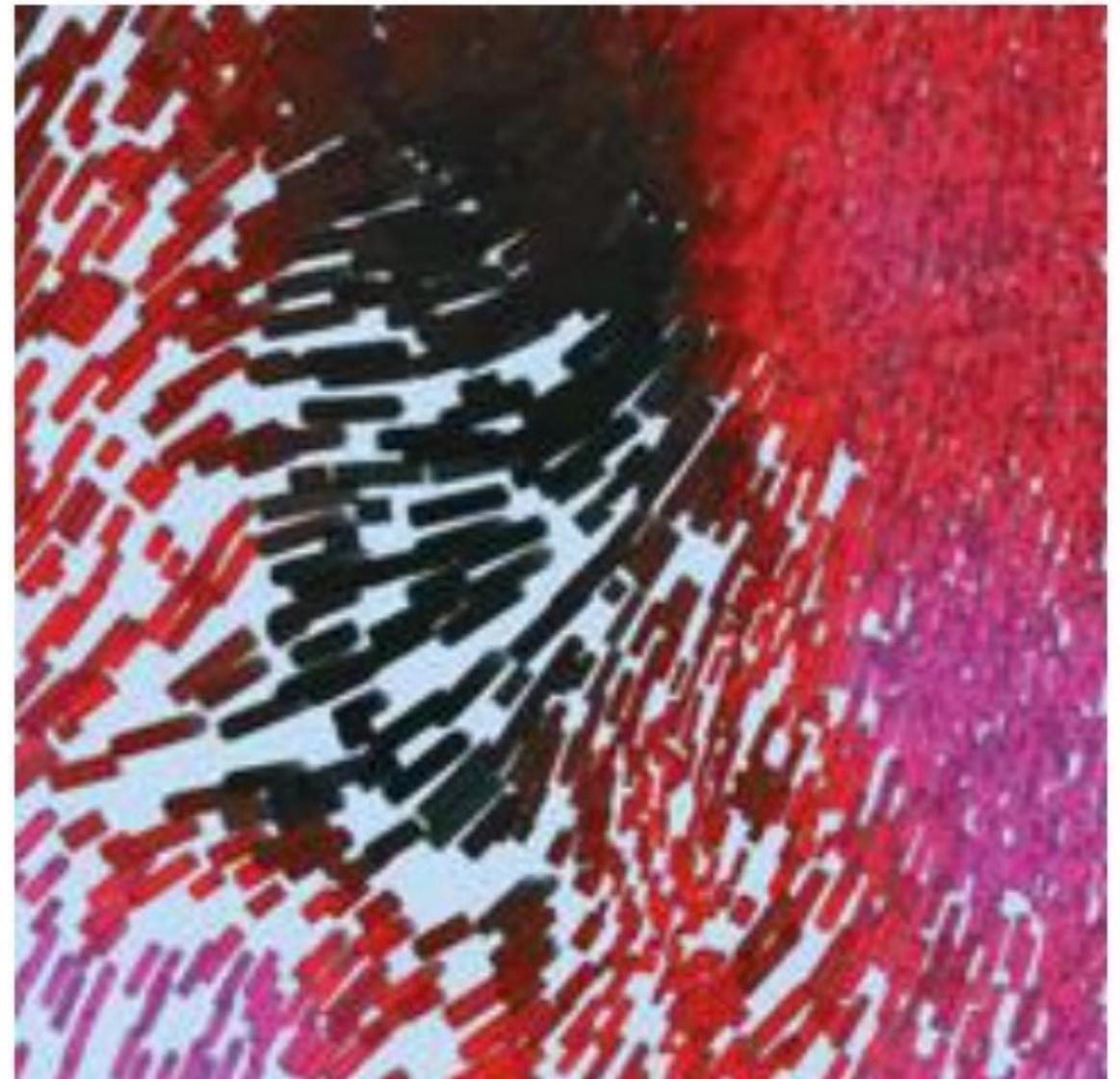


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for stronger winds),

- **pressure** is mapped to **size** (larger strokes for higher pressure).



Figure 3.31 - (Matthew Ward, et. all)

Perceptual Processing

- **Color**
- **Texture**
- **Motion**
- **Memory issues**

- **Recommended reading:**

- **Subtleties of Color**

- <http://earthobservatory.nasa.gov/blogs/elegantfigures/2013/08/05/subtleties-of-color-part-1-of-6/>

- **Color Models**

- http://dba.med.sc.edu/price/irf/Adobe_tg/models/main.html

- **Check:**

- <http://colorbrewer2.org>

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 - ◆ A significant number of people (mostly men), are **color blind**.

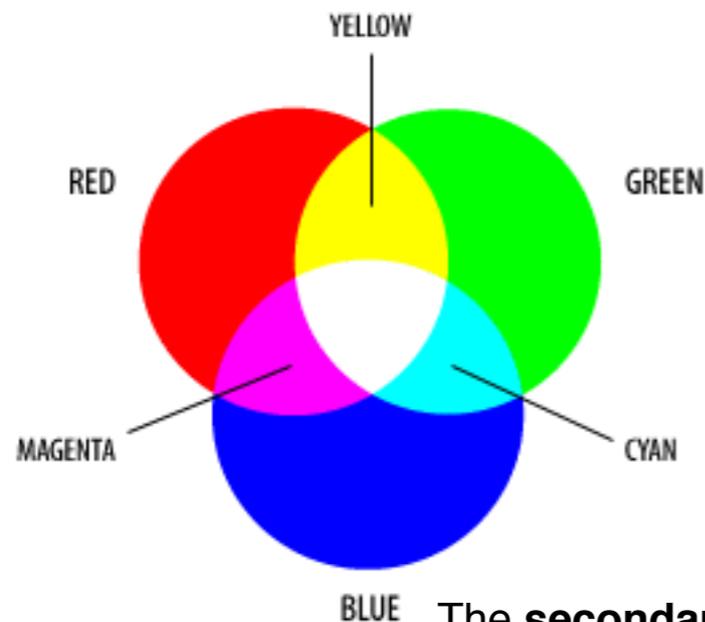
- The **principles behind the effective use of color to represent data** were developed over the course of more than a century of work by **cartographers**, and refined by **researchers** in perception. Issues that complicate color choices:
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 - ◆ **Light colors on a dark field** are perceived **differently than dark colors on a bright field**, which can complicate some visualization tasks, such as target detection.

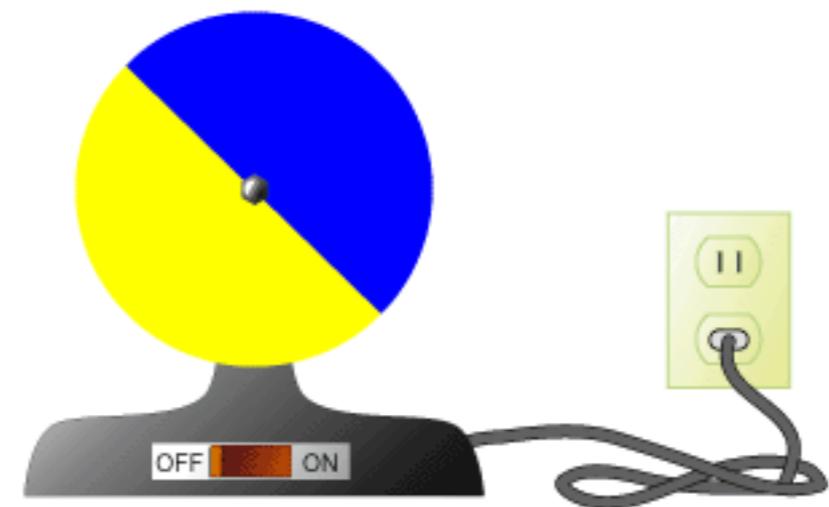
Color: The RGB (CMY) Color Model

■ RGB: Additive Colors

- ◆ Is produced by any combination of solid spectral colors that are optically mixed by being placed closely together, or by being presented in very rapid succession. Under these circumstances, two or more colors may be perceived as one color.



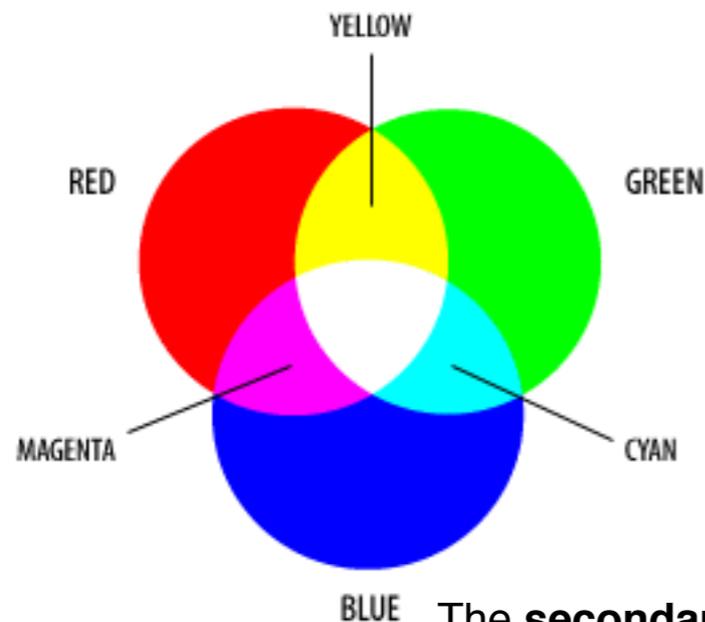
BLUE The **secondary colors of RGB, cyan, magenta, and yellow**, are formed by the mixture of two of the primaries and the exclusion of the third



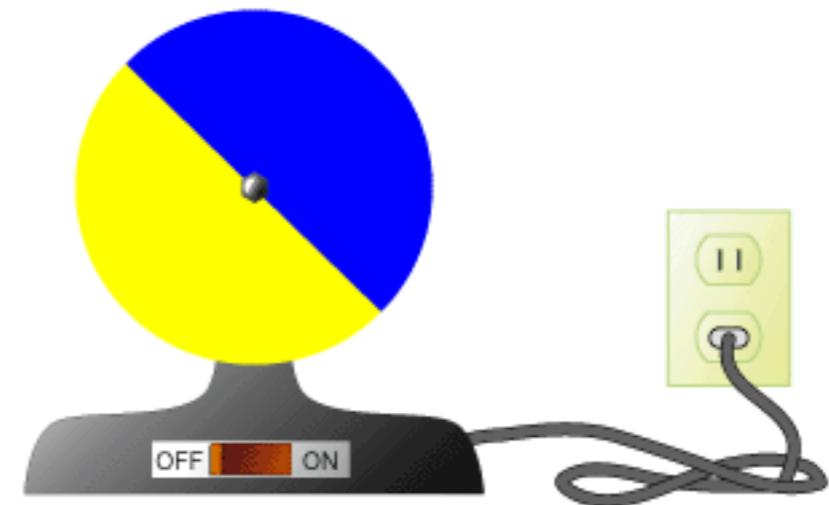
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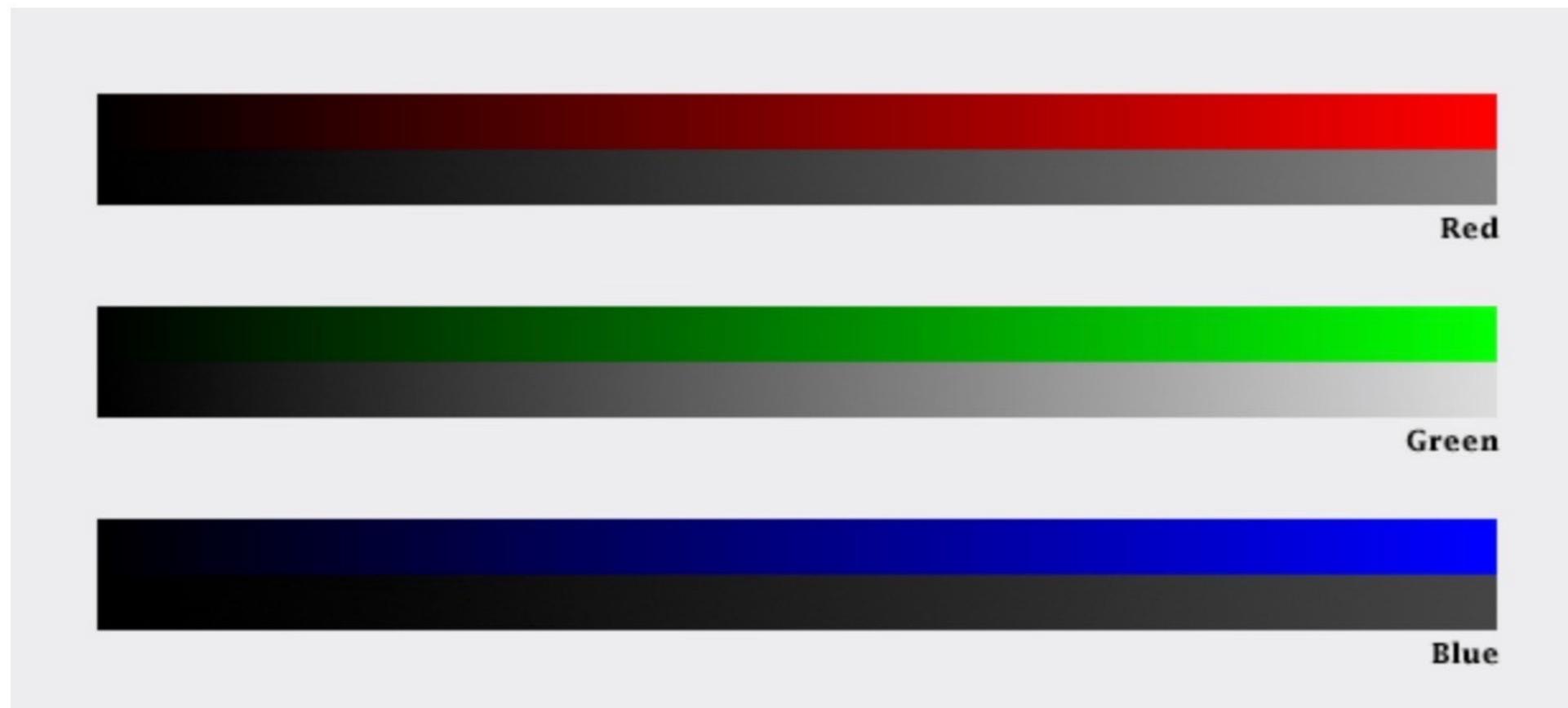


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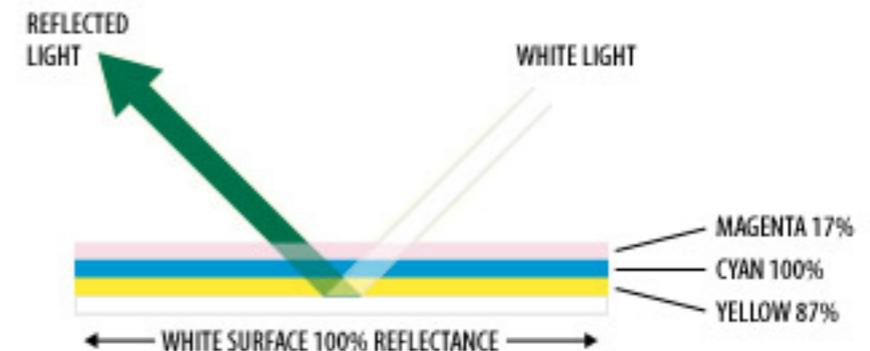
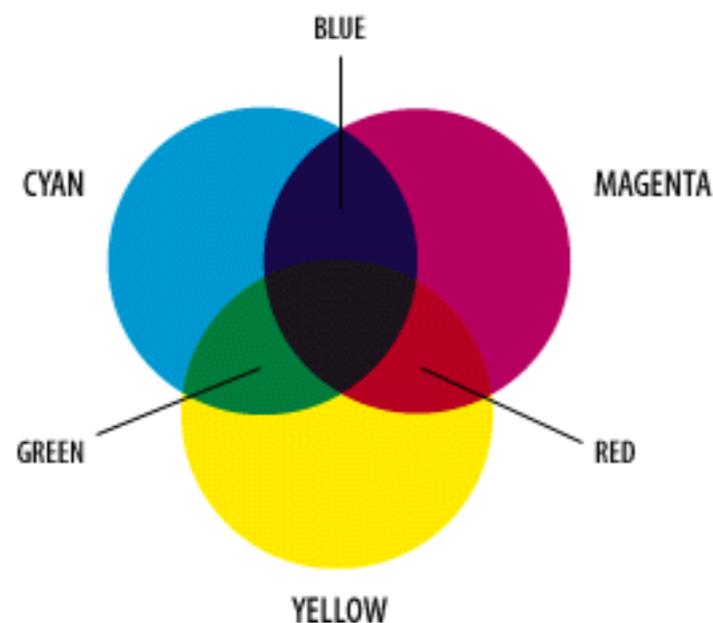
- Computers calculate color using the RGB model. Unfortunately, **we see green as brighter than red**, which **itself is brighter than blue**, so colors specified in terms a computer understands (RGB intensities from 0-255) don't always translate well to how we see.



Color: The RGB (CMY) Color Model

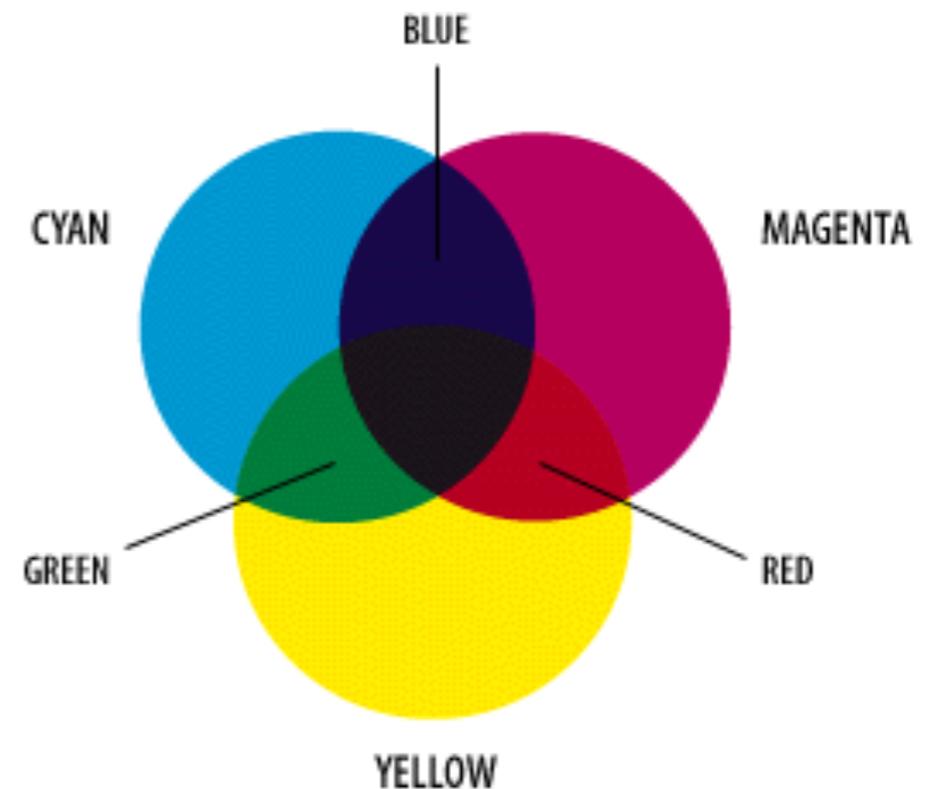
■ CMY(K): Subtractive Colors

- ◆ Subtractive colors are seen when pigments in an object absorb certain wavelengths of white light while reflecting the rest.
- ◆ They correspond roughly to the primary colors in art production



Color: The RGB and the CMY Color Models

- Colors from CMY(K) are different from RGB colors
 - ◆ Just as the **primary colors of CMY** are the **secondary colors of RGB**,
 - ◆ The **primary colors of RGB** are the **secondary colors of CMY**.
 - ◆ The colors created by the subtractive model of CMY don't look exactly like the colors created in the additive model of RGB.
 - ◆ Particularly, CMY cannot reproduce the brightness of RGB colors.

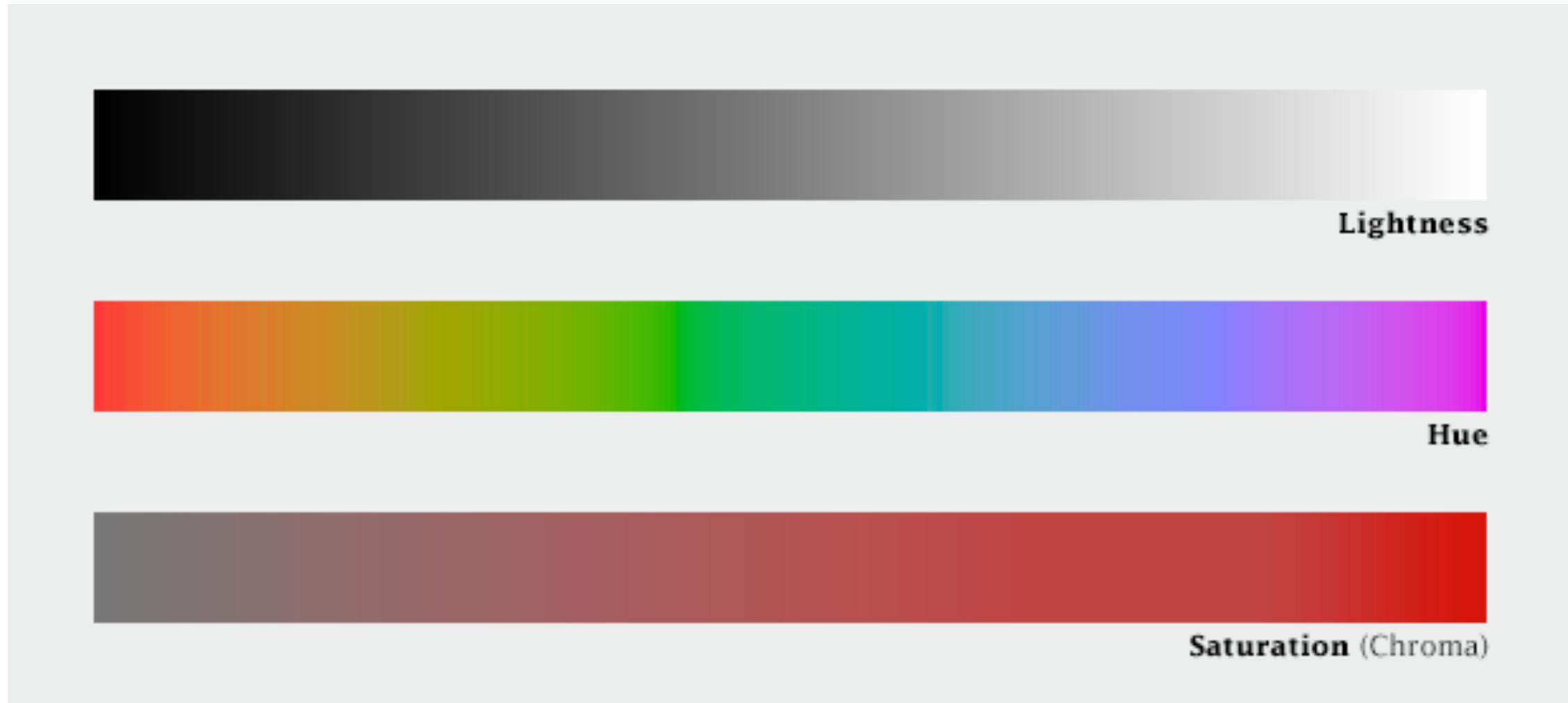


Color: Munsell's model

- Although our **eyes see color through retinal cells that detect red, green, and blue light, we don't think in RGB.**
- Rather, **we think about color in terms of**
 - ◆ **lightness** (black to white);
 - ◆ **hue** (red, orange, yellow, green, blue, indigo, violet);
 - ◆ **saturation** (dull to brilliant).
- These three variables (originally defined by **Albert H. Munsell**) are the foundation of any color system based on human perception.

Color: Munsell's model

- Lightness, hue, and saturation (sometimes called chroma)



Color: Munsell's model - Hue

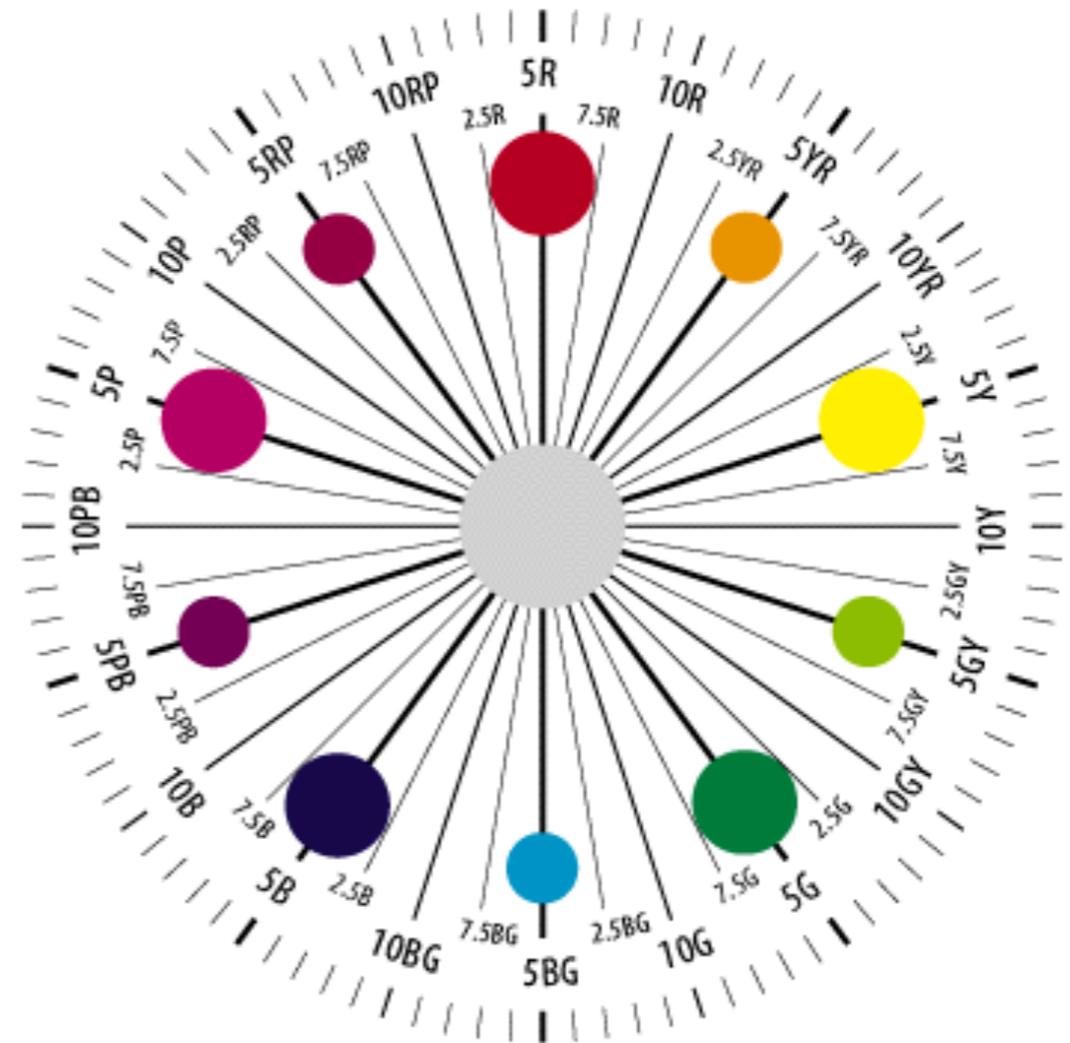
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Color: Munsell's model - Hue

- **Hue** as "the quality by which we distinguish one color from another."
- He selected five principle colors: red, yellow, green, blue, and purple; and five intermediate colors: yellow-red, green-yellow, blue-green, purple-blue, and red-purple;

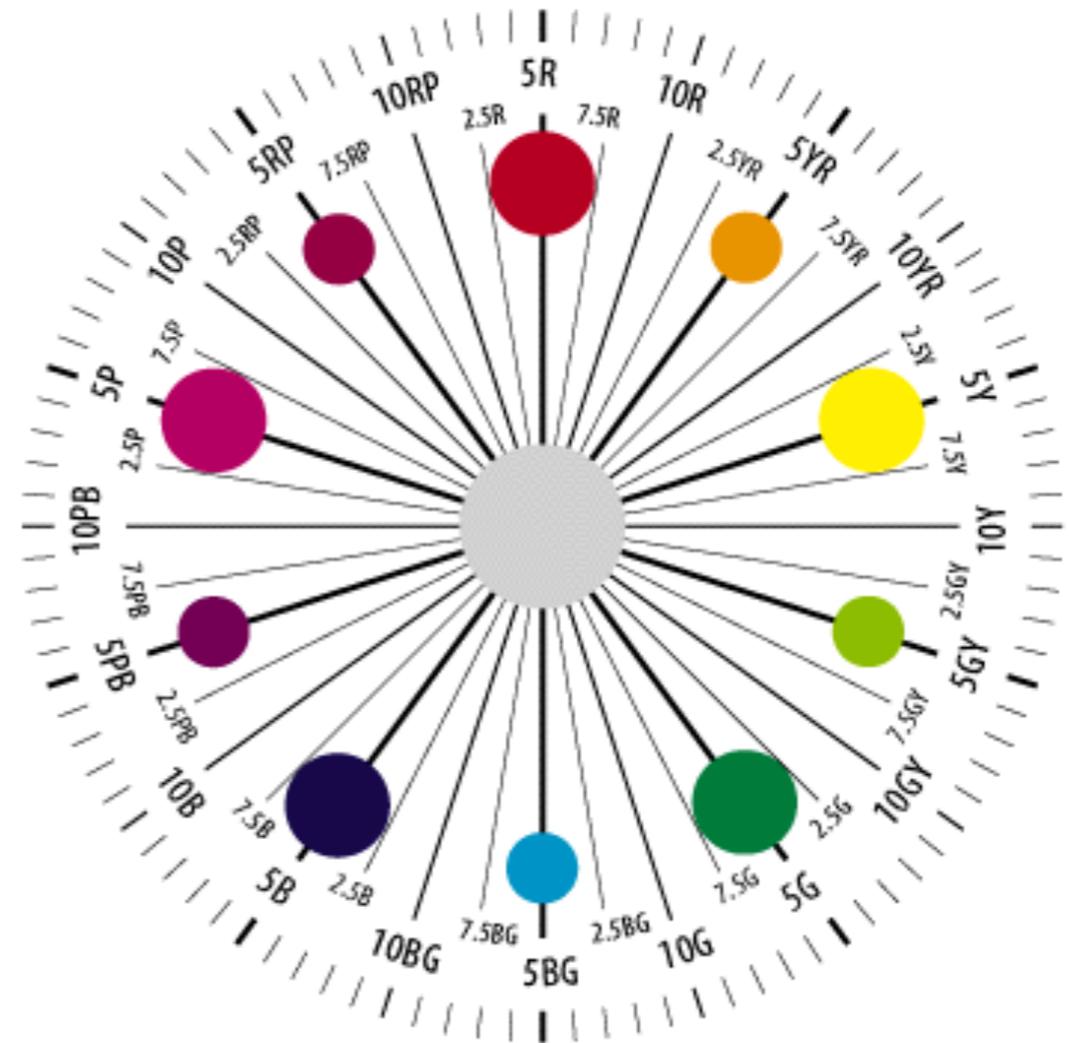
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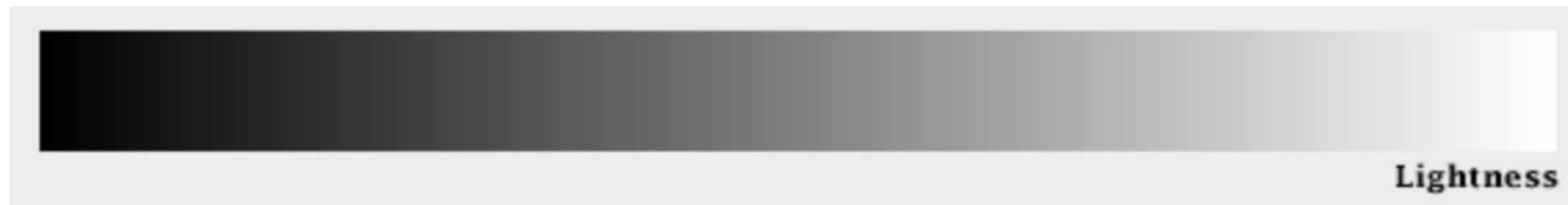
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- They are arranged in a wheel measured off in **100 compass points**;
- Each primary and intermediate color was allotted **ten degrees**



Color: Munsell's model - lightness

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- Munsell's **scale of lightness** (or value) is **visual, or perceptual**. That is, it's based on how we see differences in relative light, not on a strict set of mathematical values from a light source or illuminant

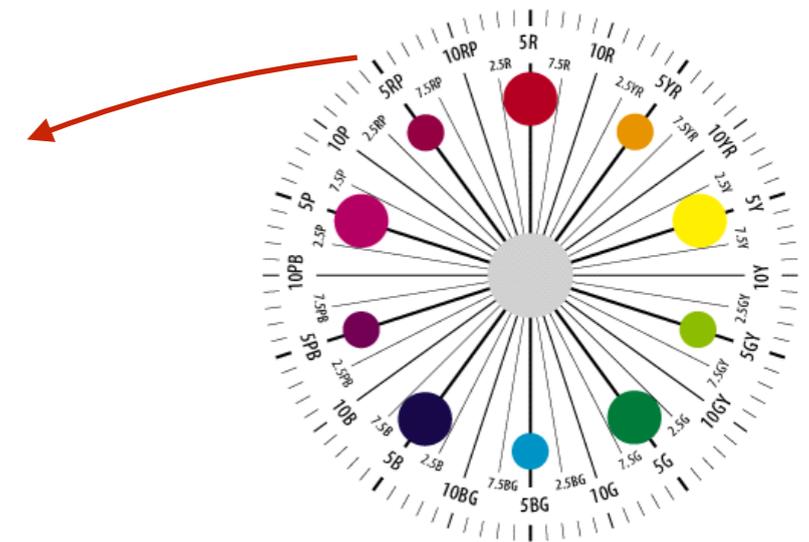
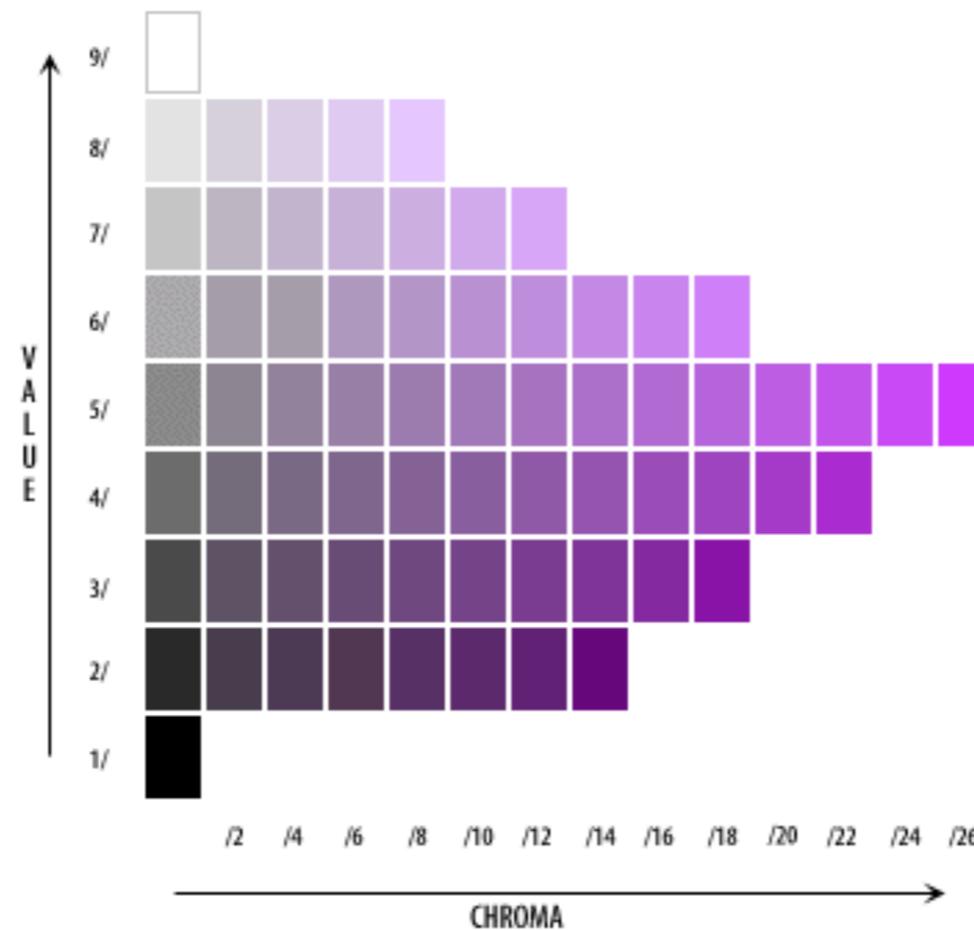
Color: Munsell's model - Saturation (or Chroma)

- **Chroma** is the quality that **distinguishes the difference from a pure hue to a gray shade.**
- Thus 7.5YR 7/12 indicates a **yellow-red hue** tending toward yellow with a Value (lightness) of 7 and a chroma of 12:



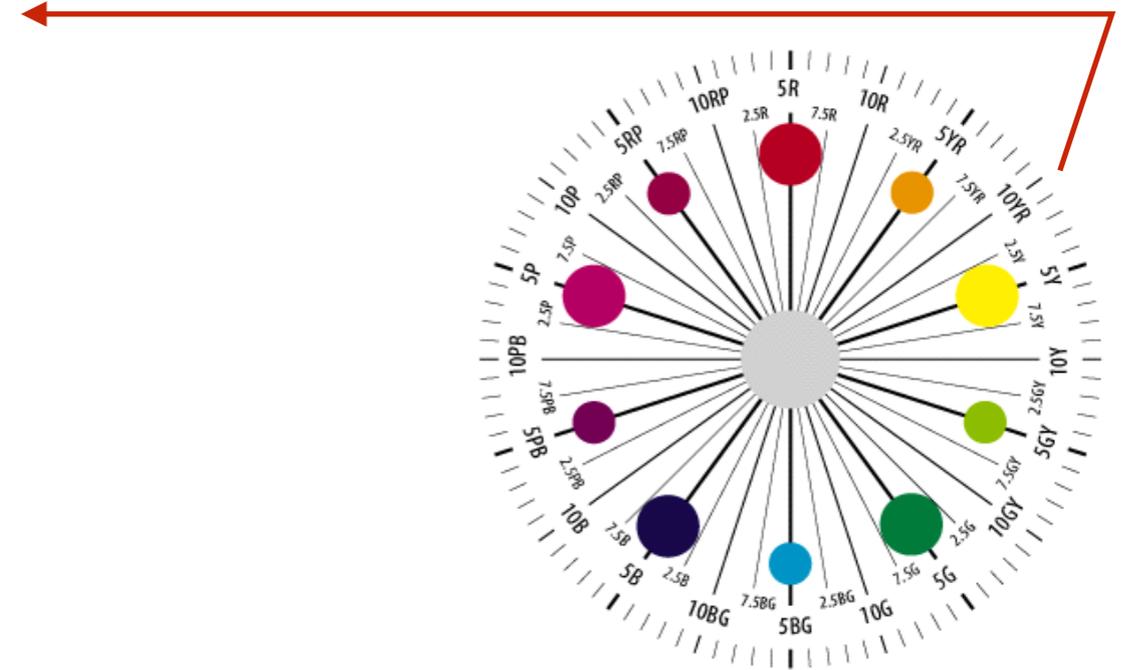
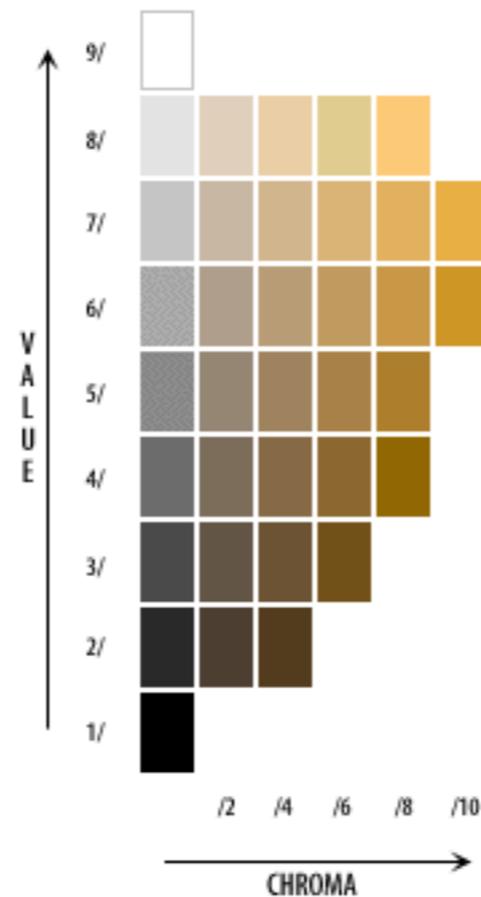
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- **Chroma is not uniform** for every hue at every value (lightness).
- Munsell saw that full chroma for individual hues might be achieved at very different places in the color sphere. For example, the fullest chroma for hue 5RP (red-purple) is achieved at 5/26:



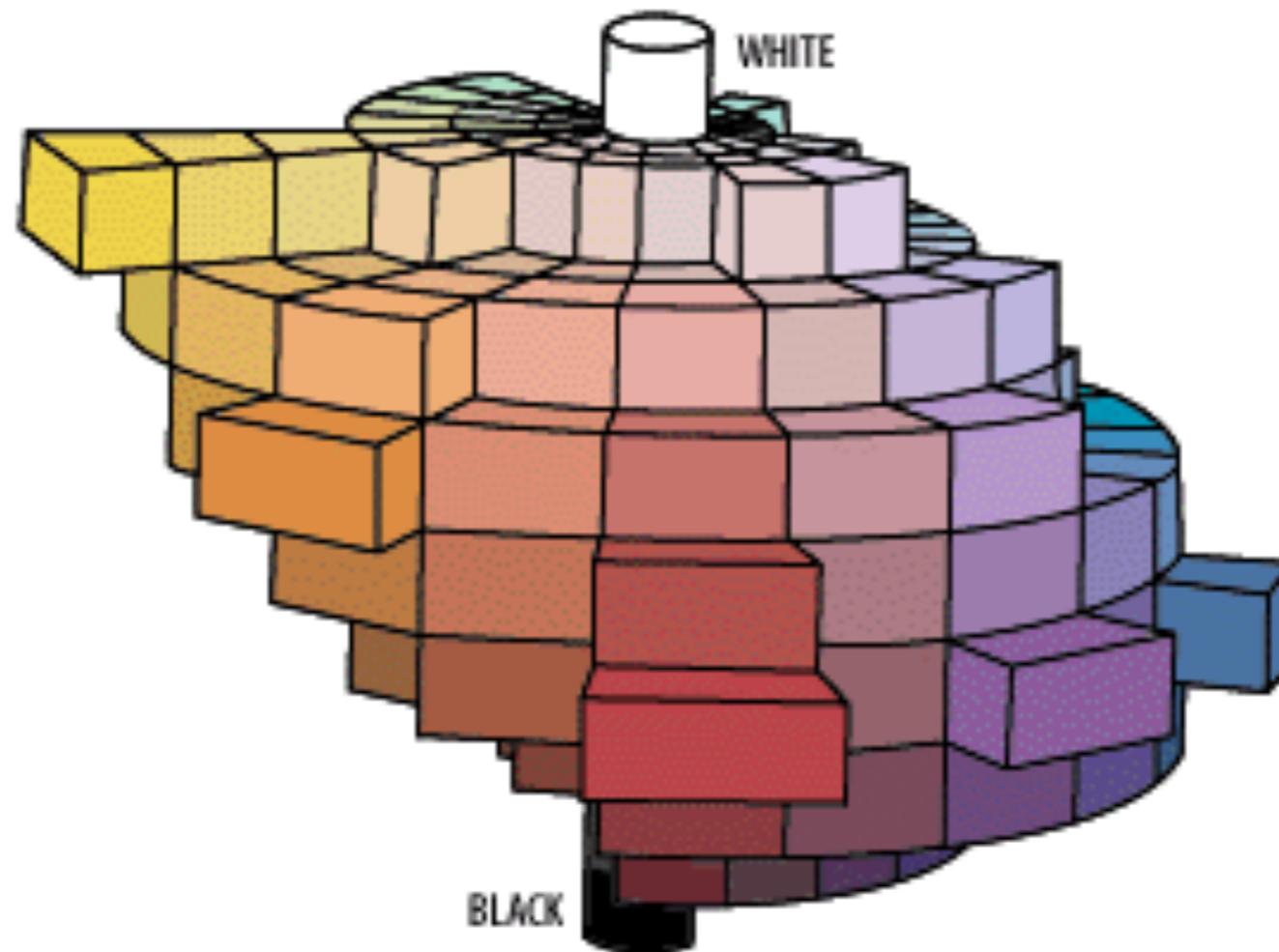
Color: Munsell's model - Saturation (or Chroma)

- **Chroma is not uniform** for every hue at every value (lightness).
- Another color such as 10YR (yellowish yellow-red) has a much shorter chroma axis and reaches fullest chroma at 7/10 and 6/10:



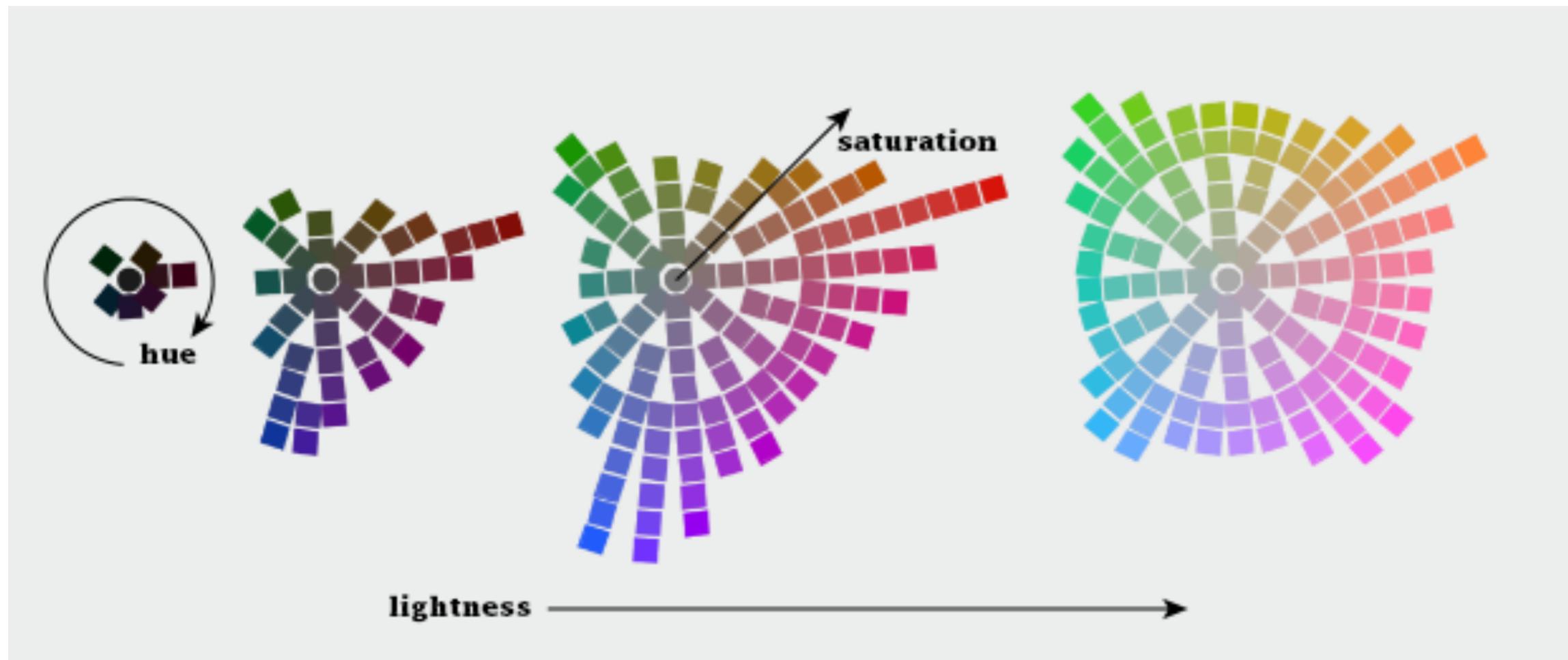
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- A three-dimensional solid representation of Munsell's system would look like the following:



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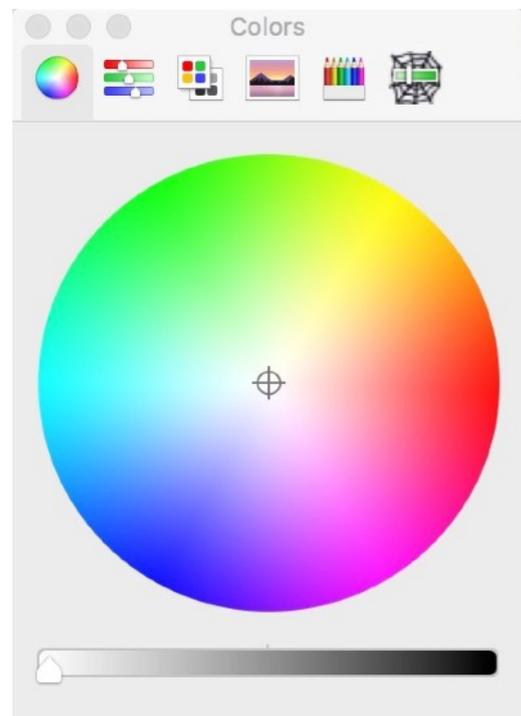
- Projections of three-dimensional solid representation of Munsell's system would look like the following:



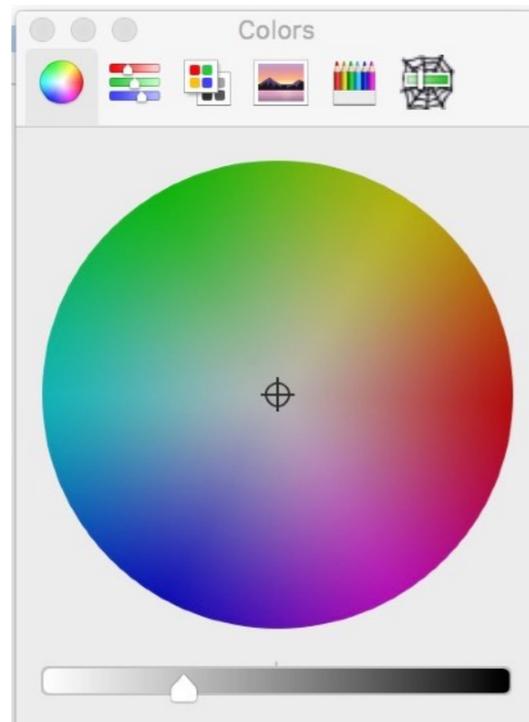
Color: Other color models

- **Color perception was mapped by the International Commission on Illumination (CIE - Commission Internationale de l'Éclairage in French):**
 - ◆ **CIE L*a*b, for example, is used internally by Adobe Photoshop to interpolate color gradients and convert images from RGB (screen) to CMYK (print).**
 - ◆ **CIE L*C*h [lightness, chroma (saturation), hue]**

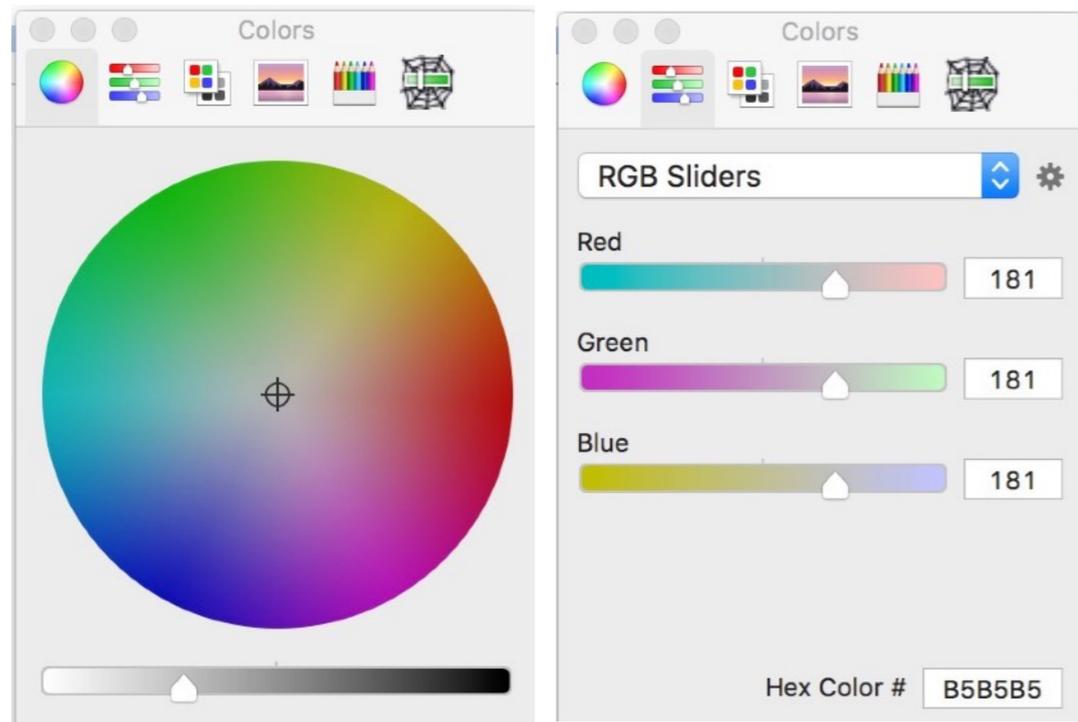
Color: pickup colors



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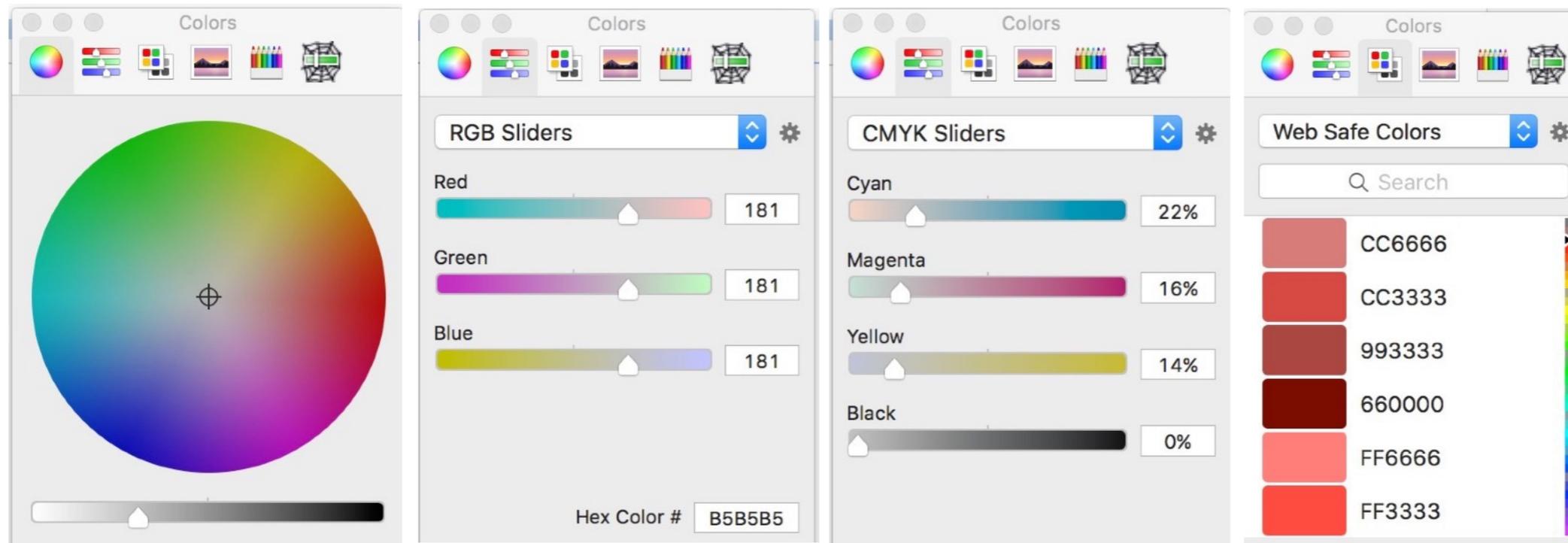
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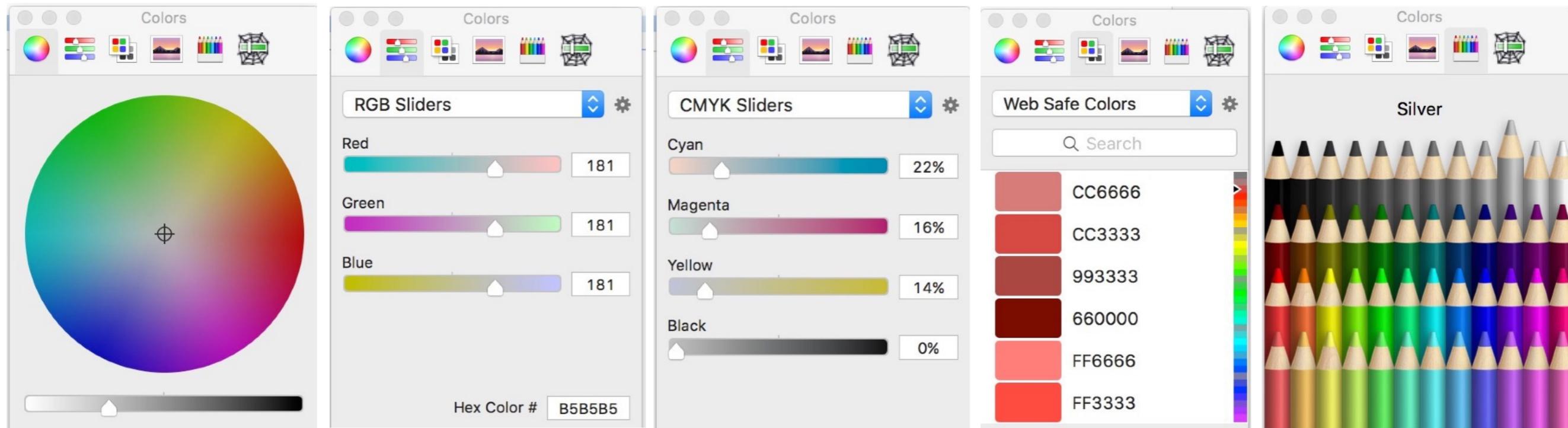
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- To control the **difference viewers perceive between different colors**, as opposed to the distance between their positions in RGB space.

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 - ◆ **Distinguishability.** Within a discrete collection of colors, **every color is equally distinguishable from all the others** (i.e., no specific color is “easier” or “harder” to identify).

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 - ◆ **Perceptual balance.** A **unit step anywhere** along the color scale **produces a perceptually uniform difference in color.**
 - ◆ **Distinguishability.** Within a discrete collection of colors, **every color is equally distinguishable from all the others** (i.e., no specific color is “easier” or “harder” to identify).
 - ◆ **Flexibility.** Colors can be selected from any part of color space (e.g., the selection technique is not restricted to only greens, or only reds and blues).

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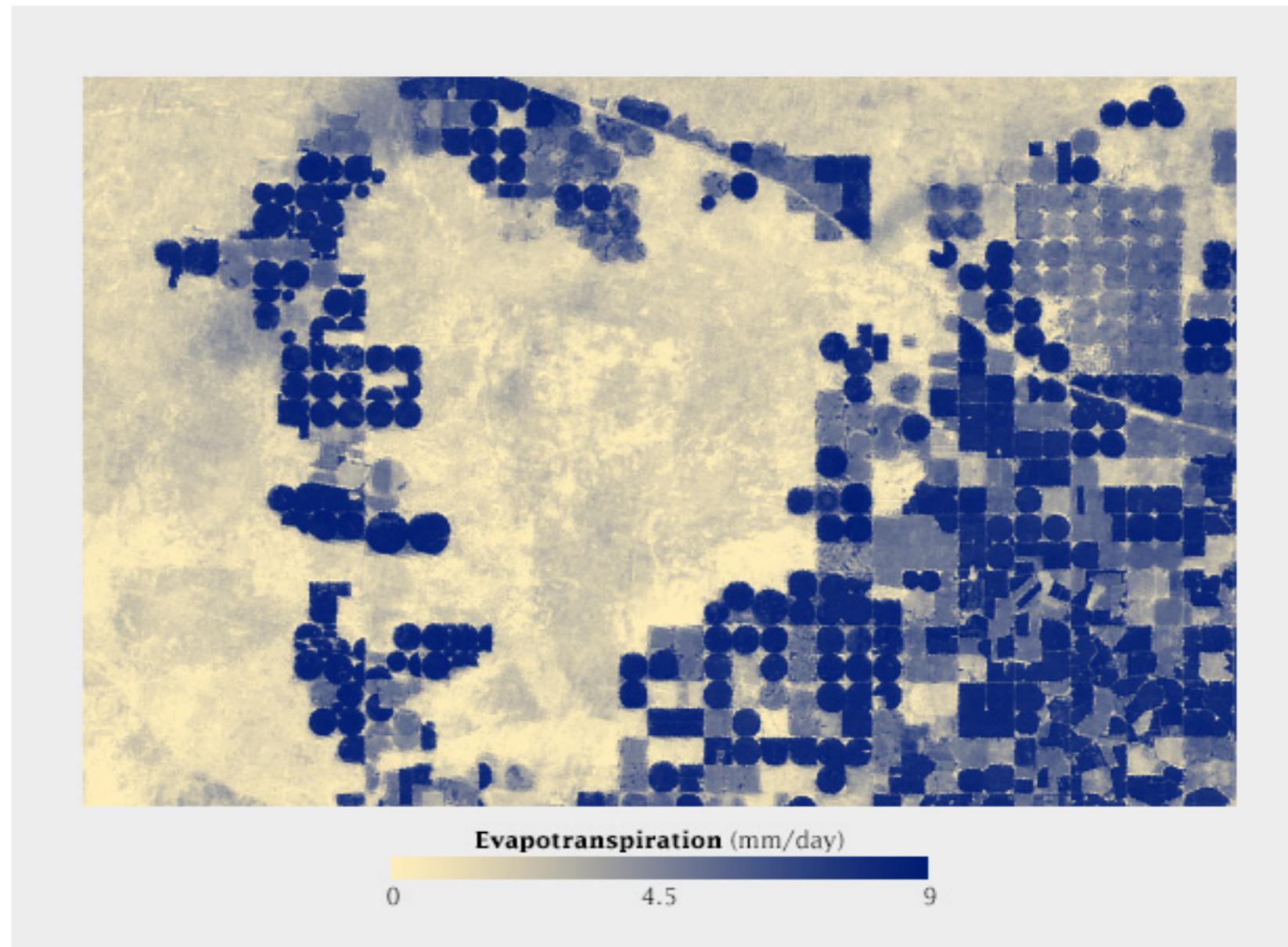
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- Ware constructed a color scale that spirals up around the luminance axis to maintain a uniform simultaneous contrast error along its length. His solution matched or outperformed traditional color scales for metric and form identification tasks.
- Healey and Enns showed that color distance, linear separation, and color category must all be controlled to select discrete collections of equally distinguishable colors.

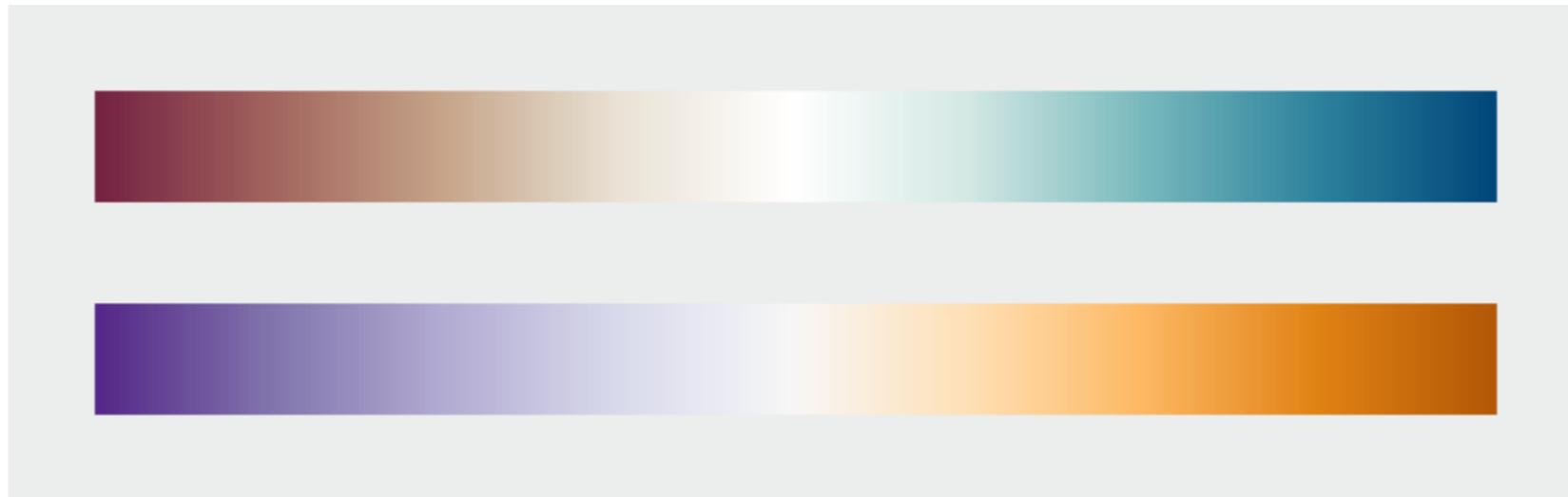
Color: Sequential Data



Sequential data lies along a smooth continuum, and is suited to a palette with a linear change in lightness, augmented by simultaneous shifts in hue and saturation.

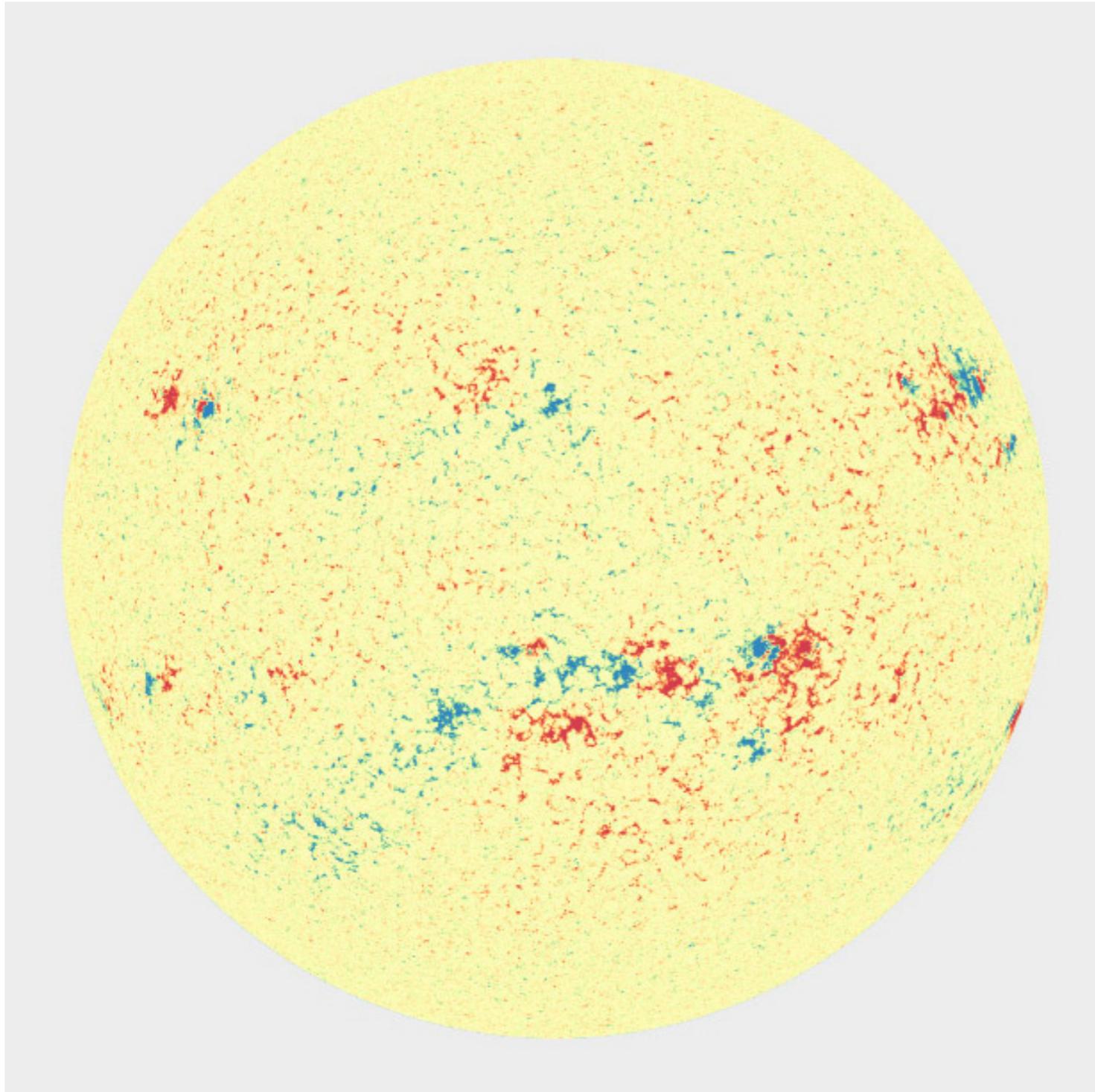
Color: Divergent Data

- Data that **varies from a central value** (or other breakpoint) is known as **divergent** or bipolar data.
 - ◆ (Ex: profits and losses; differences from the norm (daily temperature compared to the monthly average); change over time.)



Divergent palettes, each composed of two sequential palettes merged with a neutral color. (Derived from the NASA Ames Color Tool (top) and Color Brewer.)

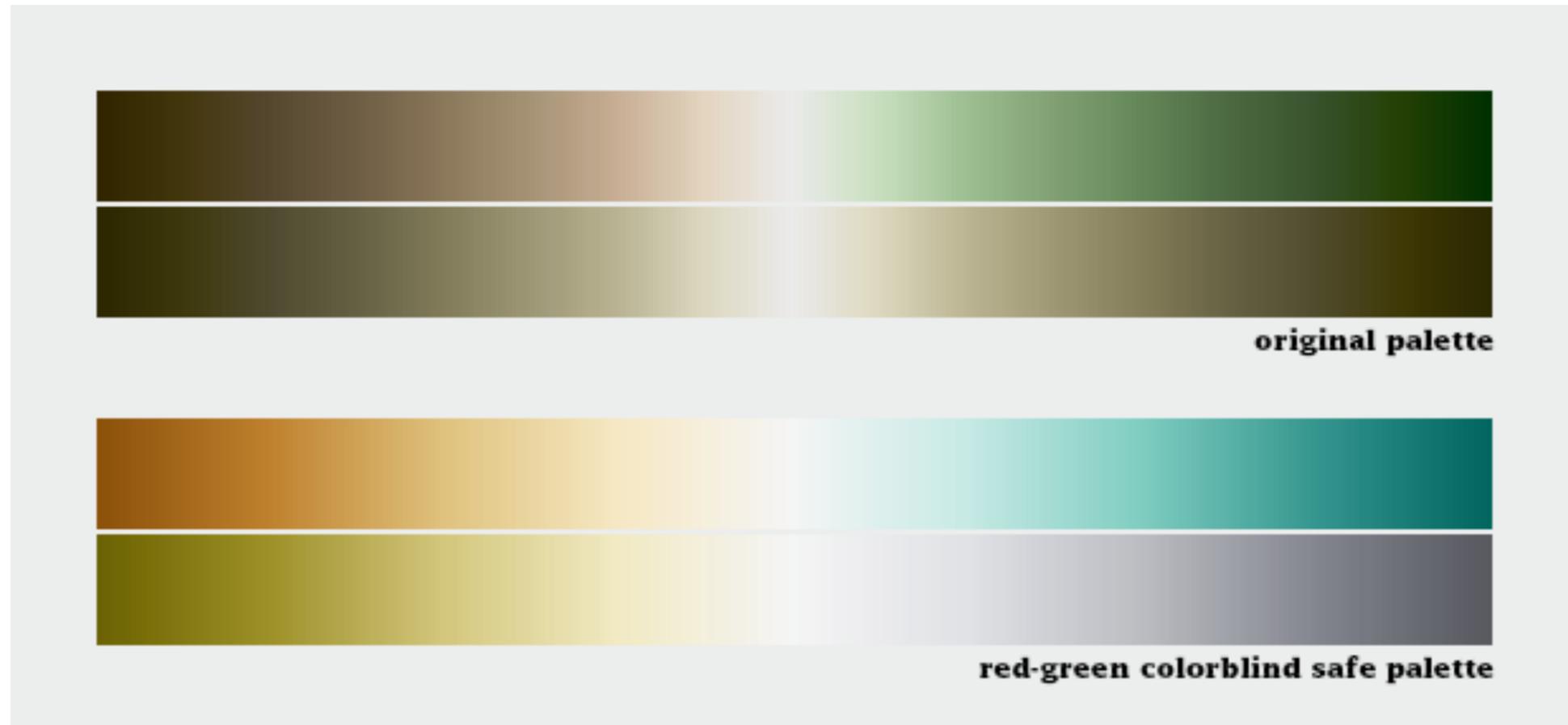
Color: Divergent Data



A magnetogram is a map of magnetic fields, in this case on the surface of the Sun.

A **divergent palette** suits this data because the north polarity (red) and south polarity (blue) are both measurements of the same quantity (magnetism), just with opposite signs

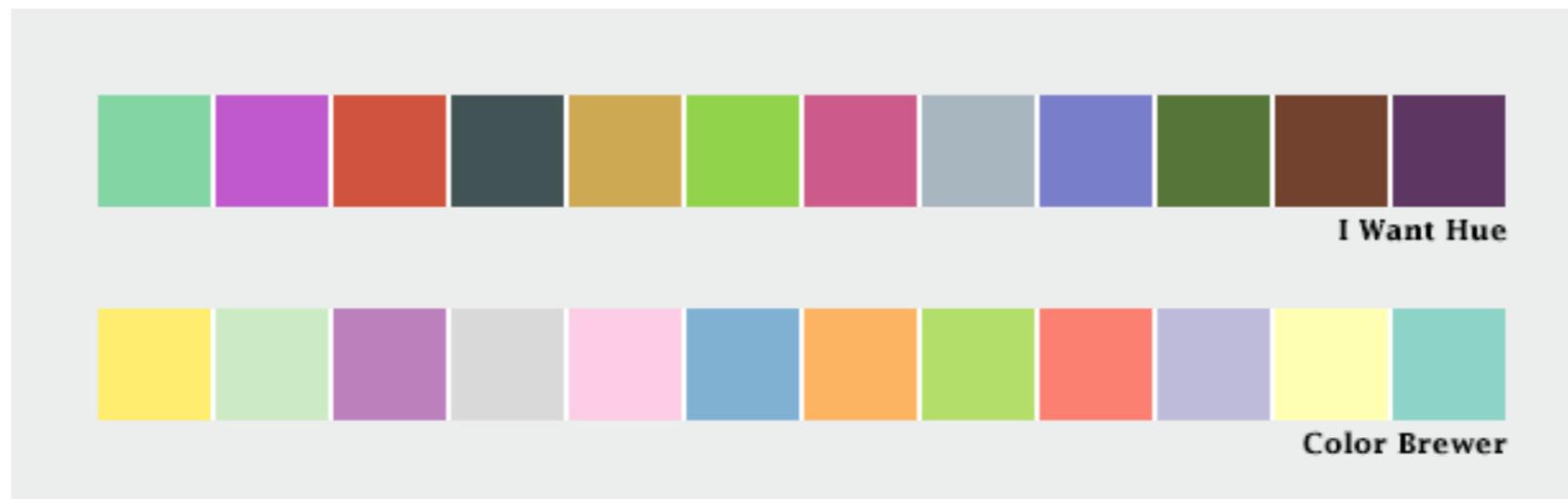
Color: Divergent Data - color blind



About 5 percent of people (almost all of them men) are color blind!

Color: Qualitative data

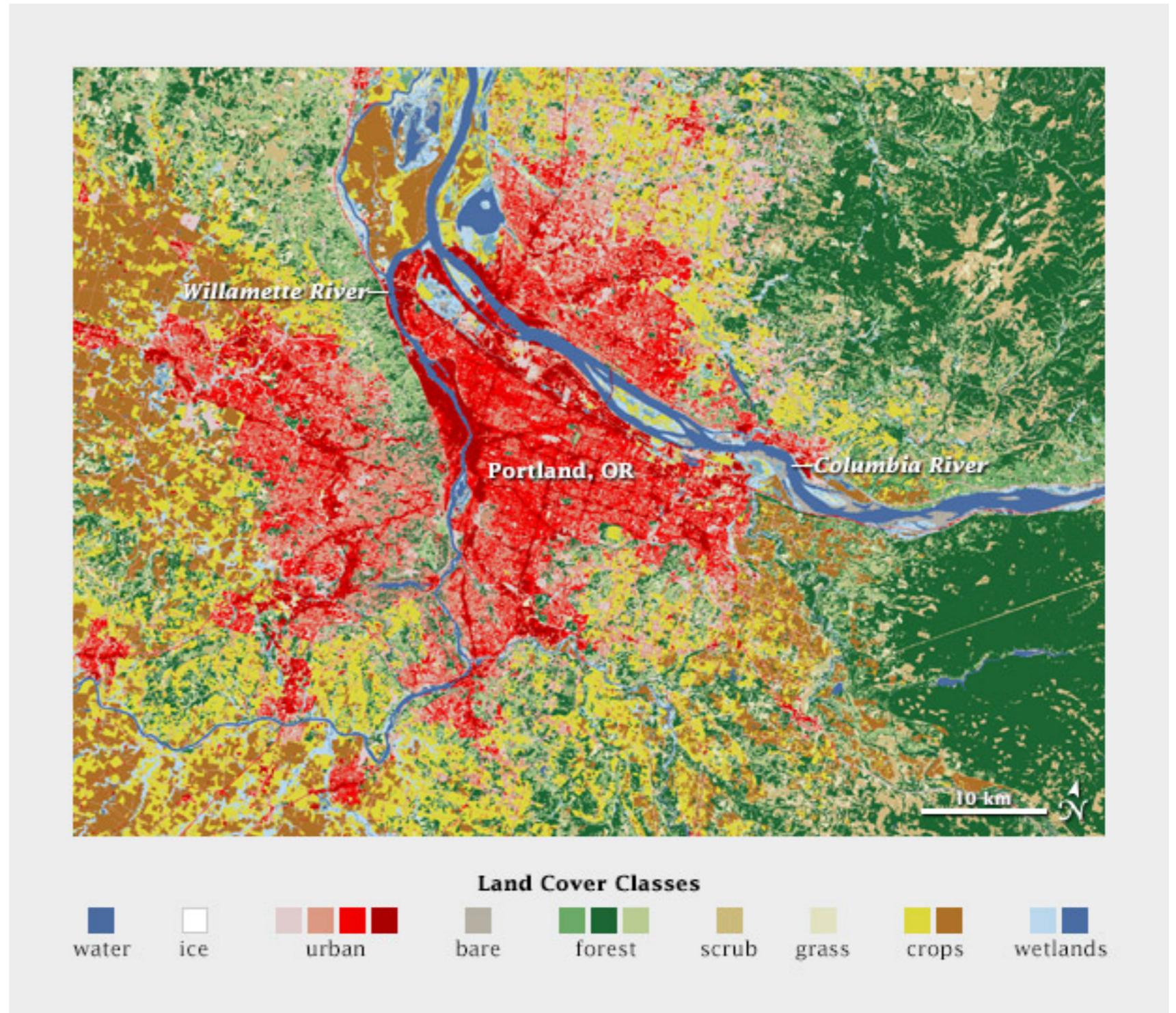
- **Qualitative data** (known as categorical or thematic data) is distinct from sequential and divergent data: **instead of representing proportional relationships, color is used to separate areas into distinct categories**



Color: Qualitative data - Grouped color Scheme

■ Qualitative data

A **grouped color scheme** allows the USGS to simultaneously show **16 different land cover classes** in a single **map** of the area surrounding Portland, Oregon.



Color: connecting Color to Meaning

- This may sound obvious, but it's an underused principle. Whenever possible, make **intuitive palettes**.

Color: connecting Color to Meaning

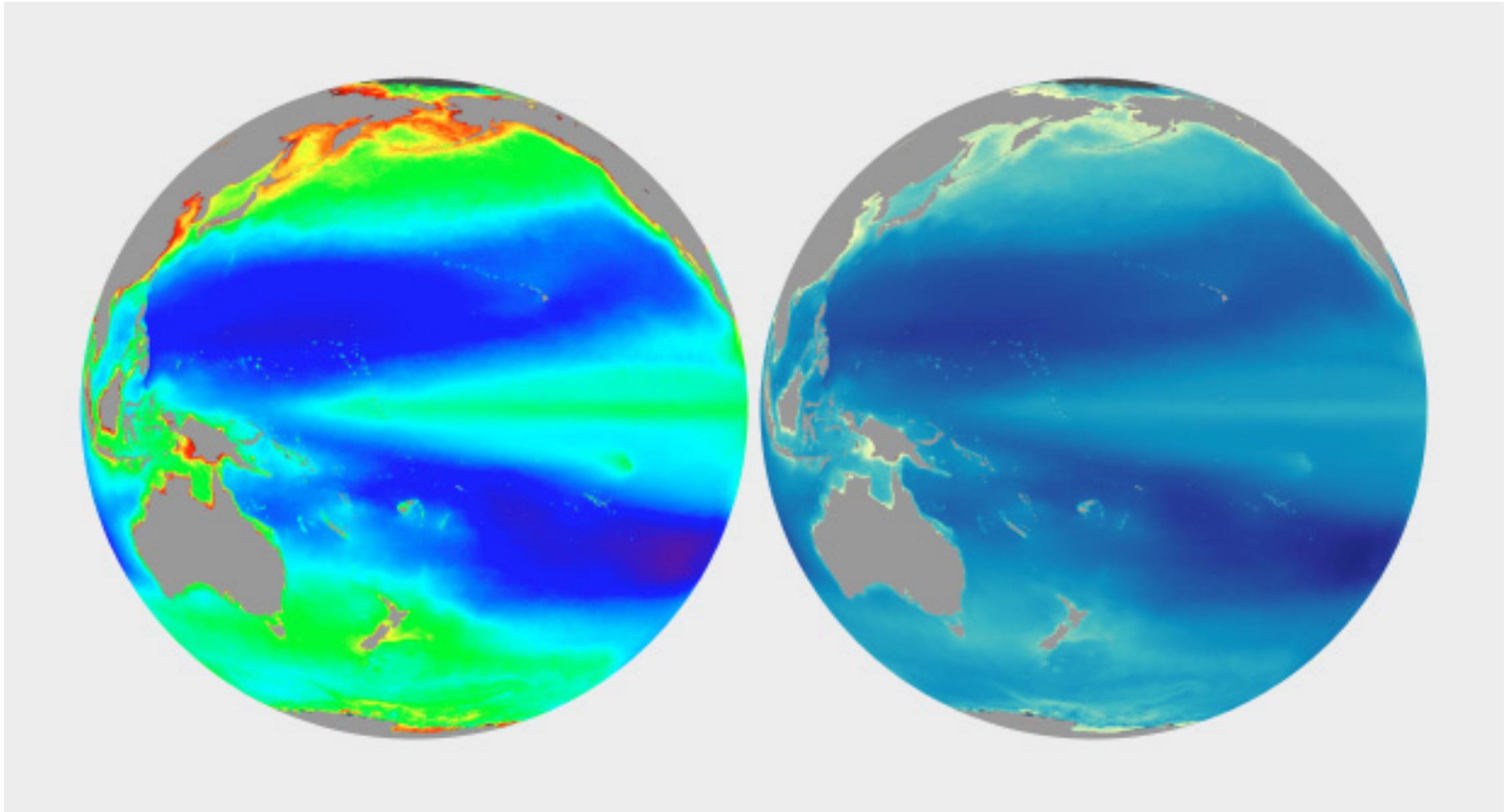
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- This may sound obvious, but it's an underused principle. Whenever possible, make **intuitive palettes**.
- **Some conventional color schemes**, especially those used in scientific visualization, **are difficult for non-experts to understand**.
- Visualizations should be as easy as possible to interpret, so try to find a color scheme that matches the audience's preconceptions and cultural associations:
 - ◆ Vegetation is green, barren ground is gray or beige.
 - ◆ Water is blue. Clouds are white.
 - ◆ Red, orange, and yellow are hot (or at least warm); blue is chilly.

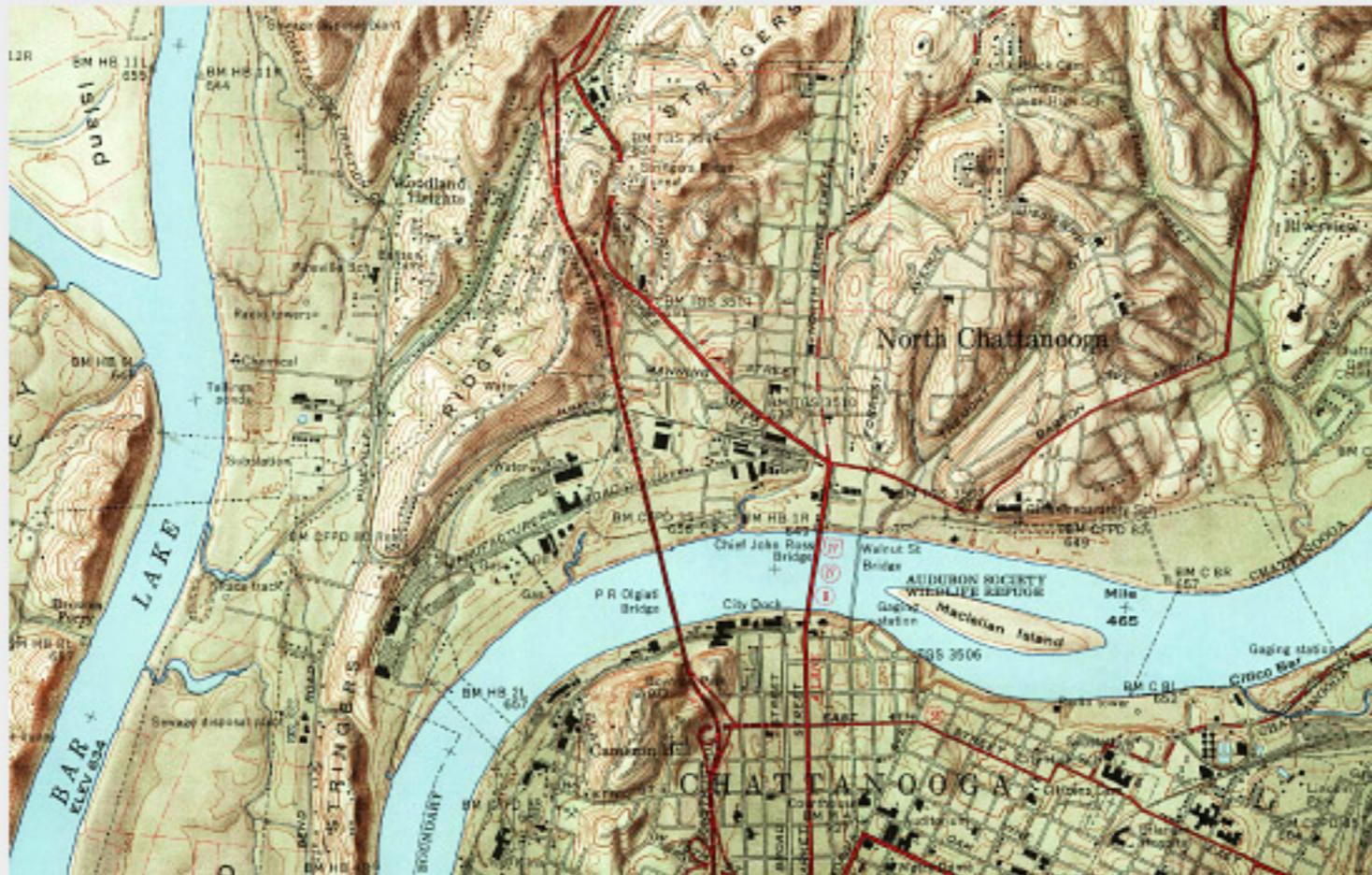
Color: connecting Color to Meaning

- The unnatural colors of the rainbow palette (left) are often difficult for novice viewers to interpret

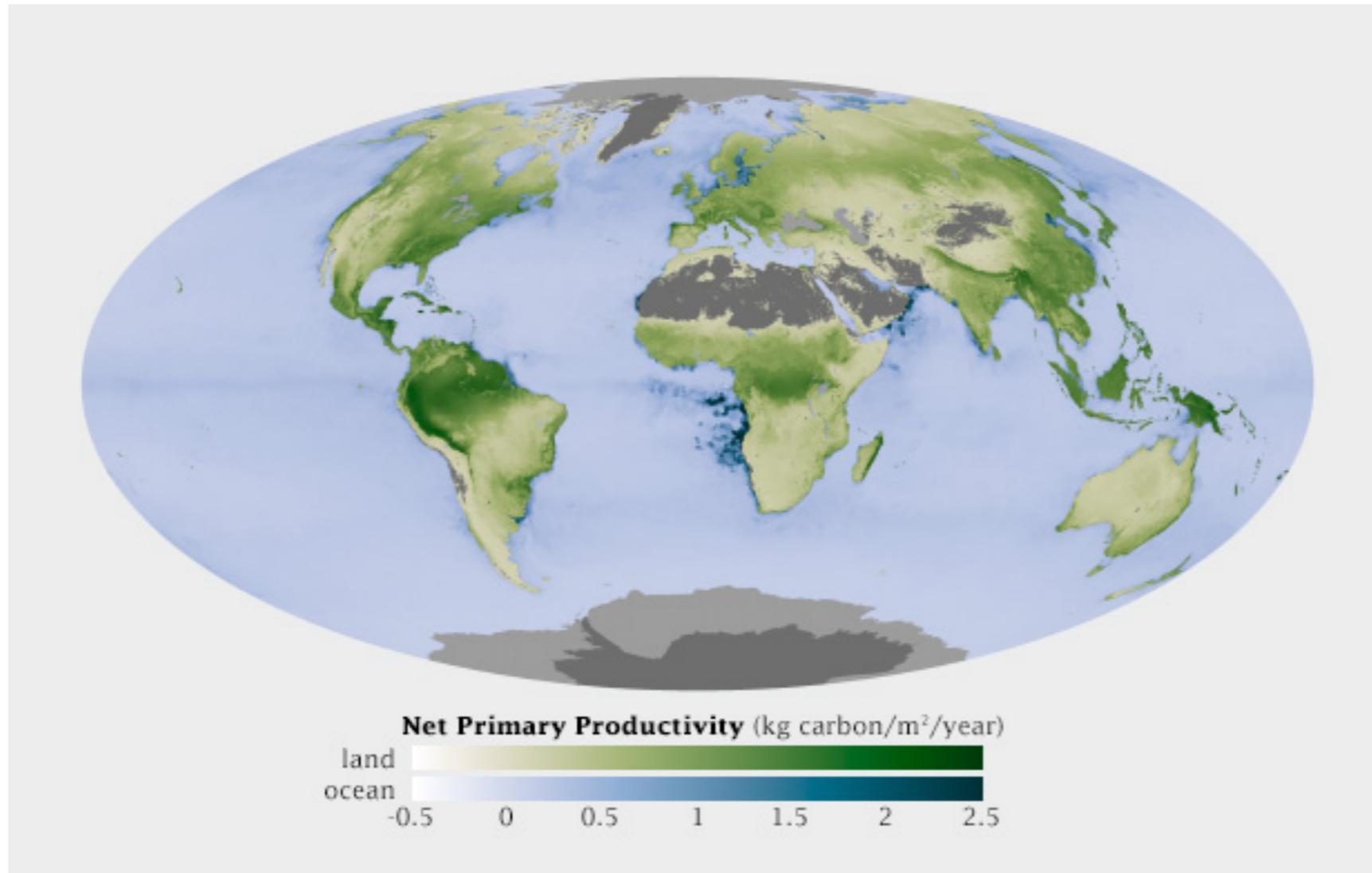


Color: Layering

- The combination of two or more datasets often tell a story better than a single dataset, and the best visualizations tell stories. The **color schemes for multiple datasets displayed together need to be designed together**, and complement one another

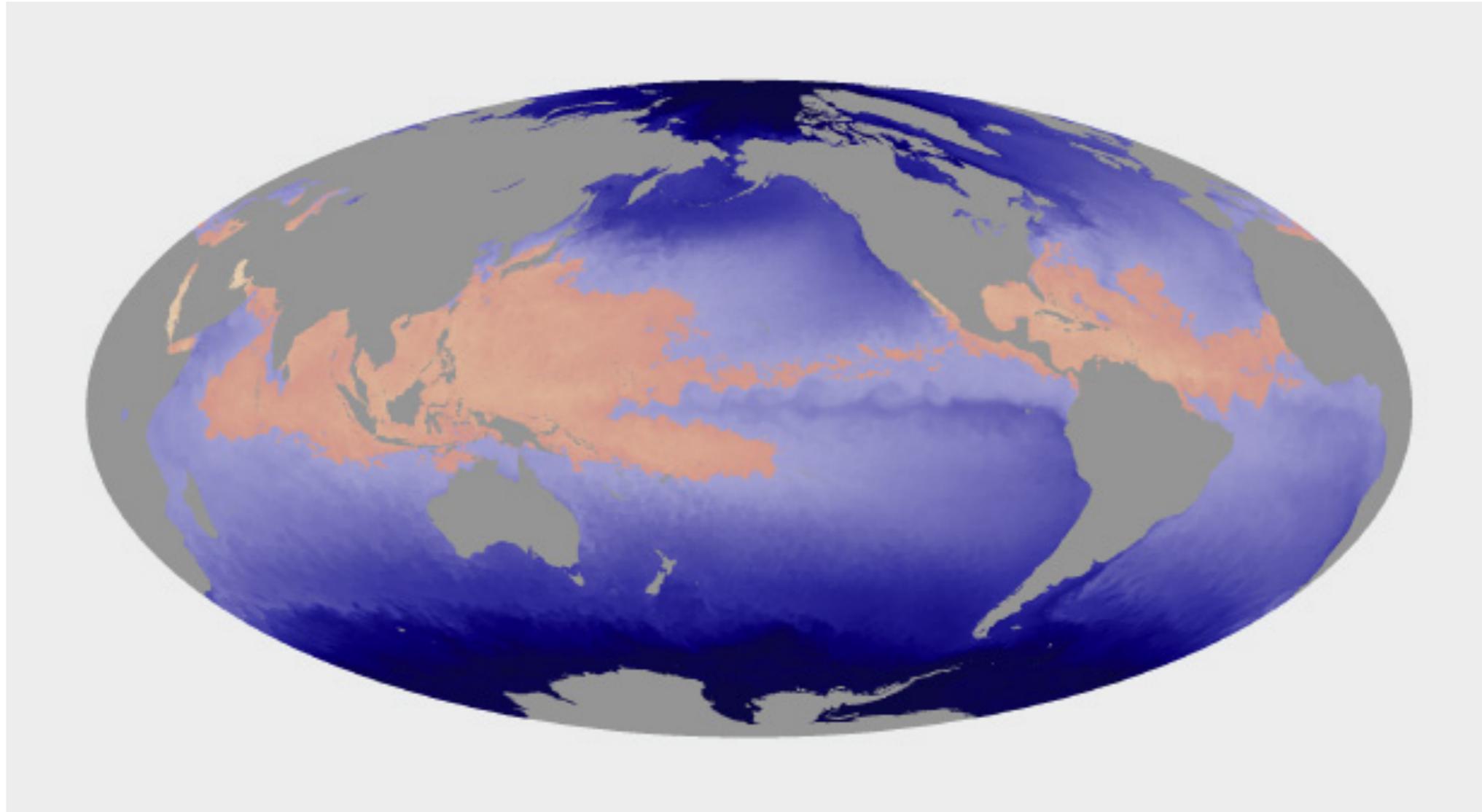


Color: Complementary Datasets



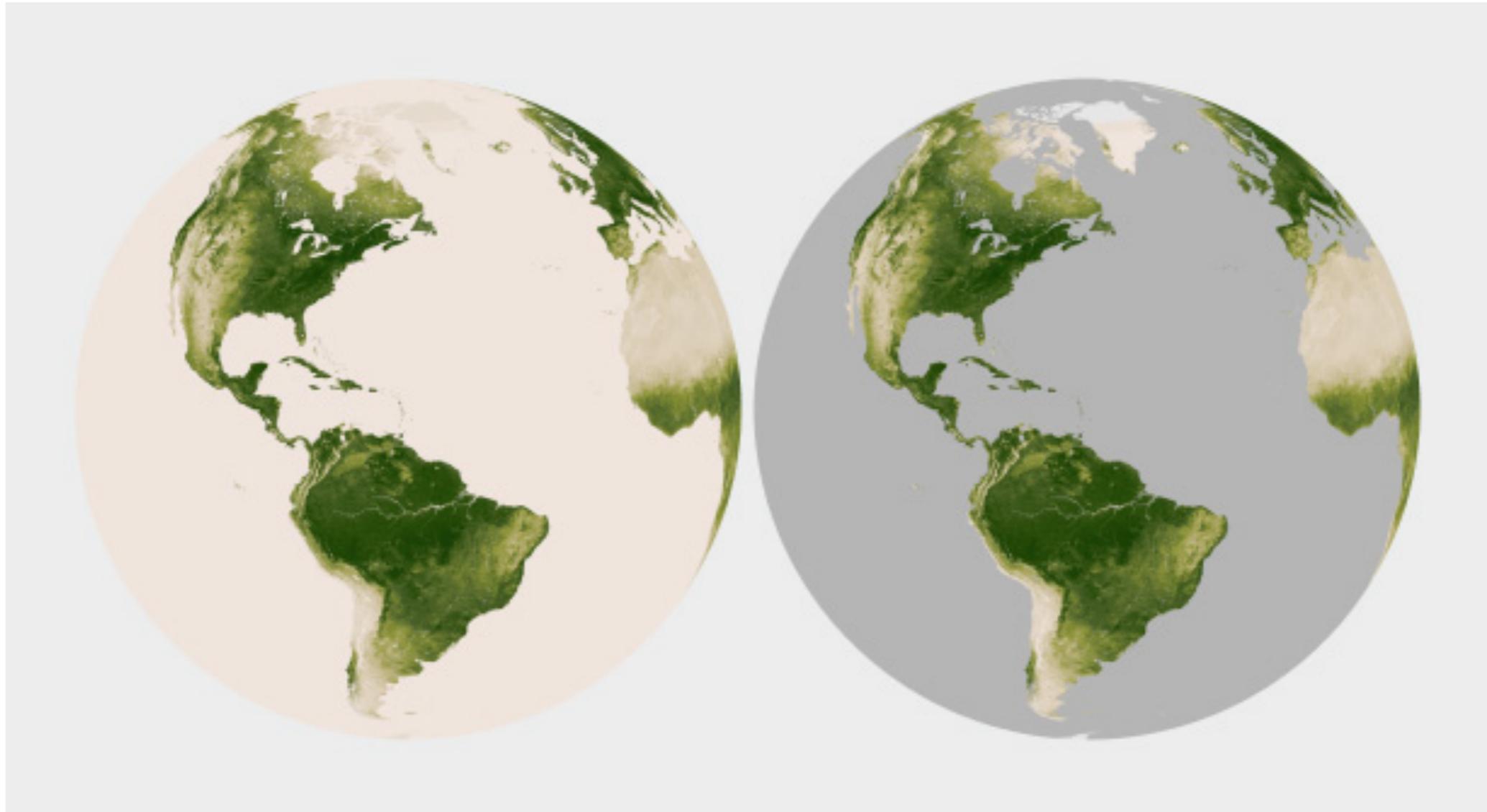
This map shows **net primary productivity** [a measure of the how much plants breathe (technically the amount of carbon plants take from the atmosphere and use to grow each year)] **on land and in the ocean**. **The two datasets are qualitatively different** (phytoplankton growing in the ocean, terrestrial plants on land), but quantitatively the same. **The green land NPP is easily distinguishable from the blue oceans, but the relative lightness matches for a given rate of carbon uptake.**

Color: Non-diverging Breakpoints



Hurricanes and other tropical cyclones are **able to form and strengthen** in waters over 82° Fahrenheit. This ocean temperature map **uses rose and yellow to distinguish the warm waters that can sustain tropical cyclones from cool water, colored blue.** (Map based on [Microwave OI SST Data](#) from [Remote Sensing Systems](#).)

Color: Use Color to Separate Data from Non-Data



Missing or invalid data should be clearly separated from valid data. Simply replacing the light beige used to represent water in this map of land vegetation (left) with gray causes the land surfaces to stand out. ([Vegetation maps](#) adapted from the NOAA [Environmental Visualization Laboratory](#).)

Texture

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- **Individual values of an attribute control its corresponding texture dimension.** The result is a texture pattern that changes its visual appearance based on data in the underlying data set.
 - ◆ Grinstein et al. visualized multidimensional data with “stick-figure” icons whose limbs encode attribute values stored in a data element; when the stickmen are arrayed across a display, they form texture patterns whose spatial groupings and boundaries identify attribute correspondence

Texture: “stick-figure” icons

- Two most important variables are mapped to the two display dimensions
- Other variables are mapped to angles and/or length of limbs of the stick figures.

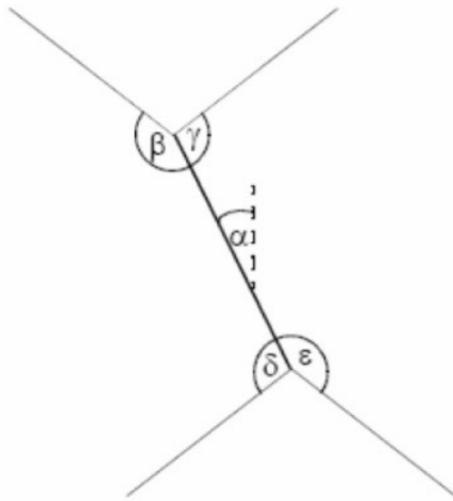
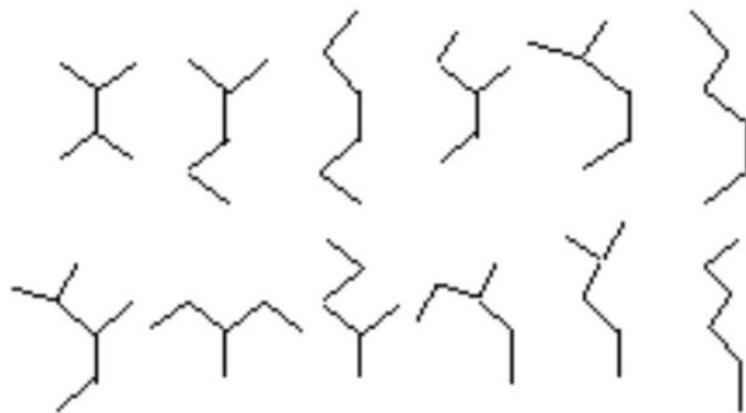
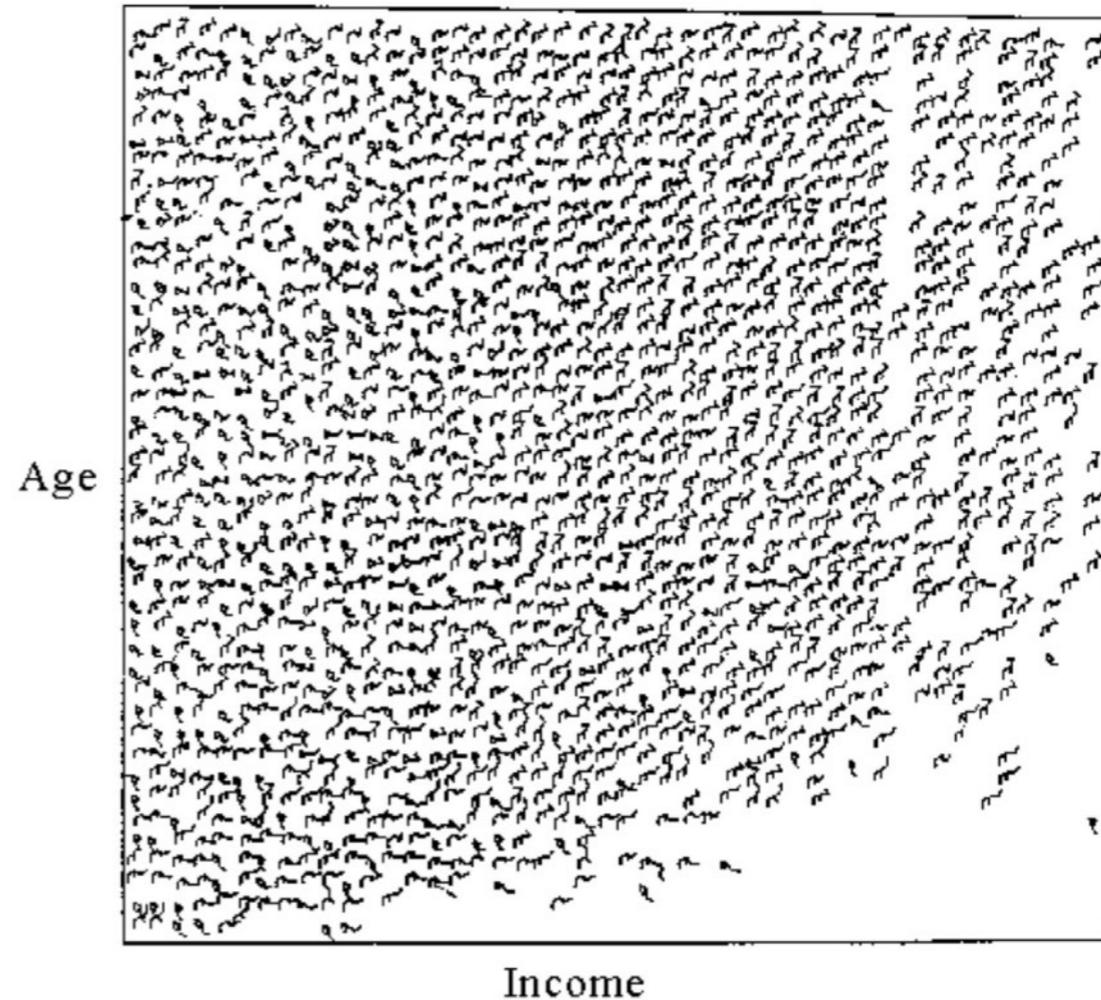


Illustration of a stick figure (5 angles and 5 limbs)



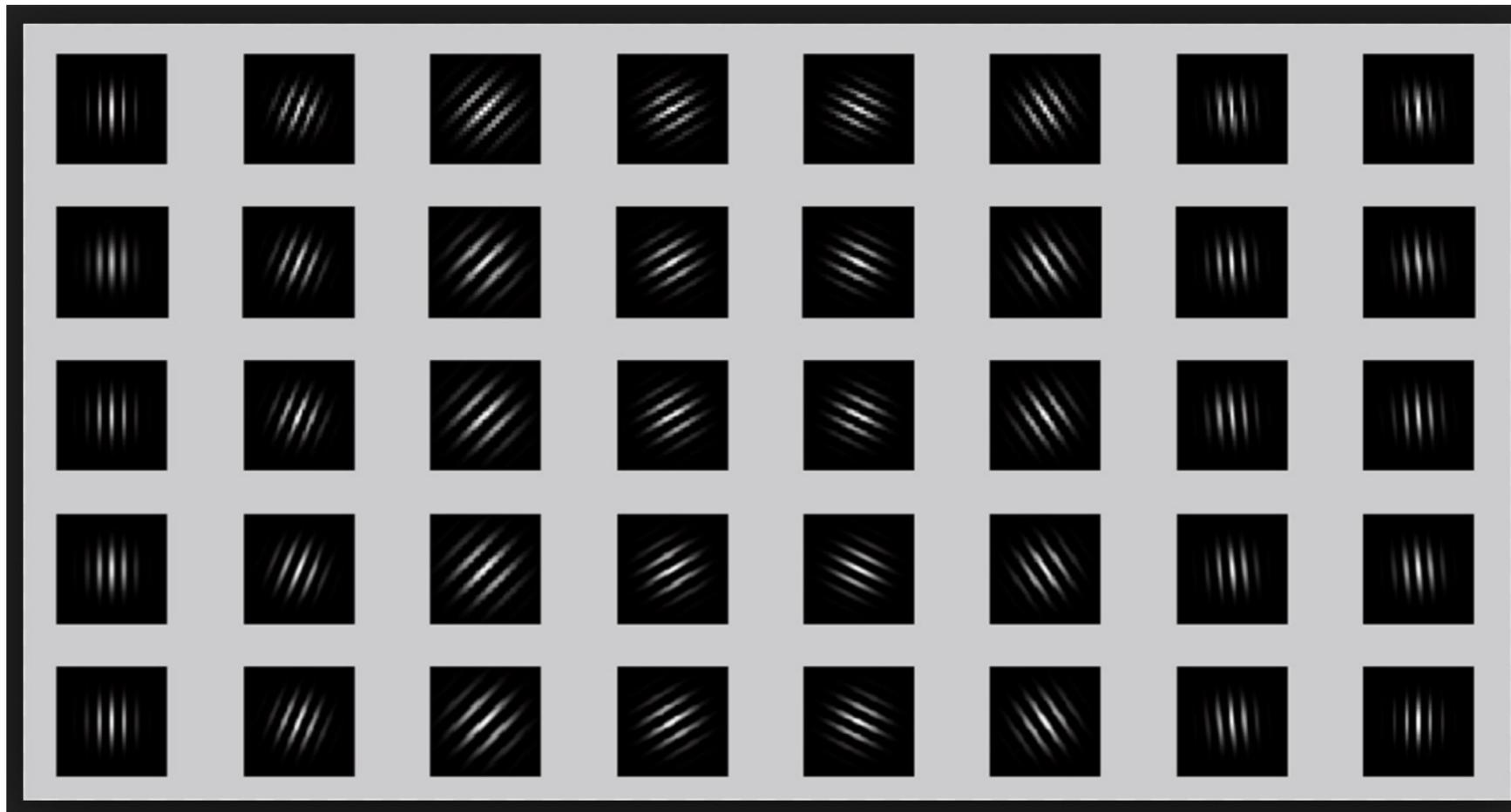
A family of 12 stick figures that have 10 features



Occupation, education levels, marital status, and gender are mapped to stick figure features

Texture: Gabor filters

- Ware and Knight designed **Gabor filters** that modified their orientation, size, and contrast, based on the values of three independent data attributes



In [image processing](#), a **Gabor filter**, named after [Dennis Gabor](#), is a [linear filter](#) used for edge detection

Texture: more ...

- Healey and Enns constructed perceptual texture elements (or **pexels**) that varied in **size**, **density**, and **regularity**; results showed that size and density are perceptually salient, but **variations in regularity are much more difficult to identify**.
- **2D orientation** can also be used to encode information: a difference of 15 degrees is sufficient to rapidly distinguish elements from one another. Certain 3D orientation properties can also be detected by the low-level visual system

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- Object velocity, **direction of motion** and **pattern of motion**
 - ◆ See Matthew O. Ward bag - 122 - 124

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- **Short-term memory** analyzes information from both sensory and long-term storage. It has limited information capacity. It occurs at a high level of processing, but the time span is limited typically to less than 30 seconds.
- **Long-term memory** is complex and theoretically limitless, much like a data warehouse. This storage is multi-coded, redundantly stored, and organized in a complex network structure. Information retrieval is a key problem and access is unreliable and slow.

Metrics

- **Resource Model of Human Information Processing**
- **Absolute Judgment of 1D Stimuli**
- **Absolute Judgment of Multidimensional Stimuli**
- **Relative Judgment**
- **Expanding Capabilities**
- **The Relationship to Immediate Memory**
- **The Role of Recoding**
- **The Role of Focus and Expectation**

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- These and related issues are important in the study of data and information visualization.

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- **How should color be used** to present information?

Metrics: **Absolute** Judgment of 1D Stimuli

- **Subject experimentation:**
 - ◆ For **each primitive stimulus**, whether it be visual, auditory, taste, touch, or smell, we measure the number of distinct levels of this stimulus that the average participant can identify with a high degree of accuracy.

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- ◆ Miller called this level the “**channel capacity**” for information transfer by the human.

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- **Position on a line** (Hake/Gardner): Varied the position of a pointer located between two markers. Most subjects were able to correctly label between 10 and 15 levels, though this increased with longer exposure [3.25 bits].

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- **Color** (Eriksen): In experiments that varied single color parameters, it was found that users could **correctly classify 10 levels of hue** and **5 levels of brightness**, or 3.1 and 2.3 bits, respectively.
- **Line geometry** (Pollack): In this experiment, **line length, orientation, and curvature** were tested. The results were: **2.6–3 bits for line length** (depending on duration), **2.8–3.3 bits for orientation**, and **2.2 bits for curvature** with constant arc length (while only 1.6 bits for constant chord length).

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- **Dot in a square** (Klemmer/Frick): Given that a dot in a square is actually **two position measurements** (vertically and horizontally) we should get a capacity that is twice that of gauging the position of a marker on a line (**6.5 bits**), but it was measured at **4.6 bits**.

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- **Size, brightness, and hue** (Eriksen): In an experiment combining **geometry** and color, the size, hue, and brightness of shapes were varied. The sum of the individual capacities is **7.6 bits**, but a capacity of only **4.1 bits** was observed.

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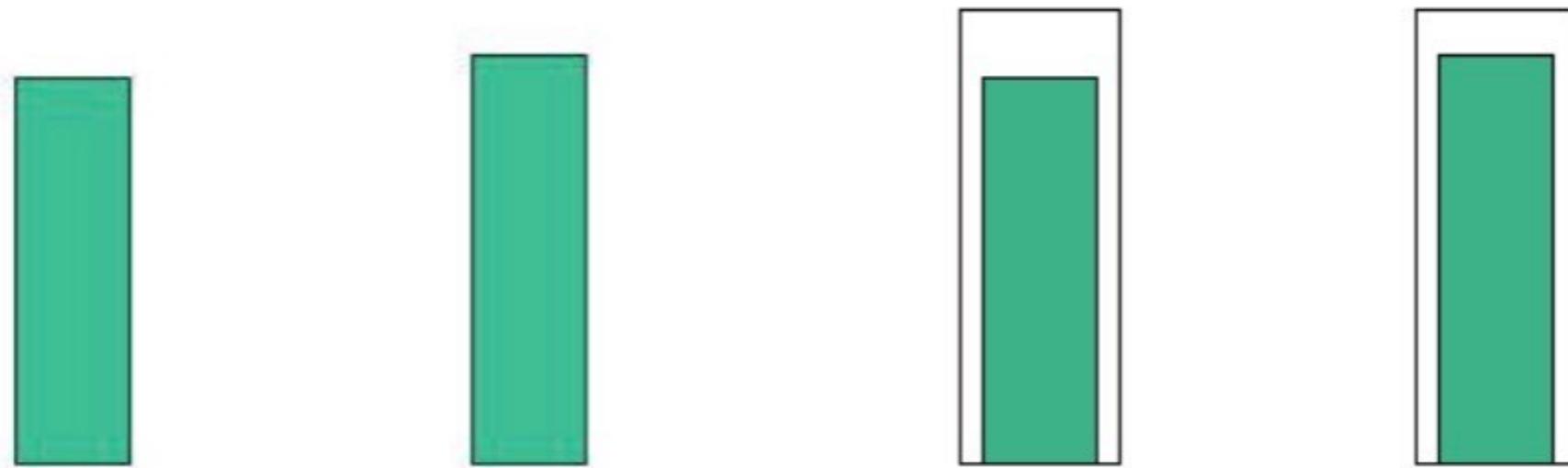
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- Combining different stimuli does **enable us to increase the amount of information being communicated, but not at the levels we might hope.**
- The added stimuli resulted in the **reduction of the discernibility of the individual attributes.**
- With that said, however, **having a little information about a large number of parameters seems to be the way we do things.**

Metrics: **Relative** Judgment

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- William Cleveland emphasis, rather than on **absolute measurement** (classification), was on **relative judgment**: detection of differences, rather than extracting a numeric value.



The boxes on the left are not the same size, but it is difficult to estimate the magnitude of the difference. The same boxes are shown on the right. The encapsulating frame makes it easier to gauge the relative difference between them.

Figure 3.33 - (Matthew Ward, et. all)

Metrics: **Relative** Judgment

- William Cleveland experiments **showed errors in perception** ordered as follows (**increasing error**):
 1. position along a common scale;
 2. position along identical, nonaligned scales;
 3. length;
 4. angle/slope (though error depends greatly on orientation and type);
 5. area;
 6. volume;
 7. color hue, saturation, density (although this was only informal testing).

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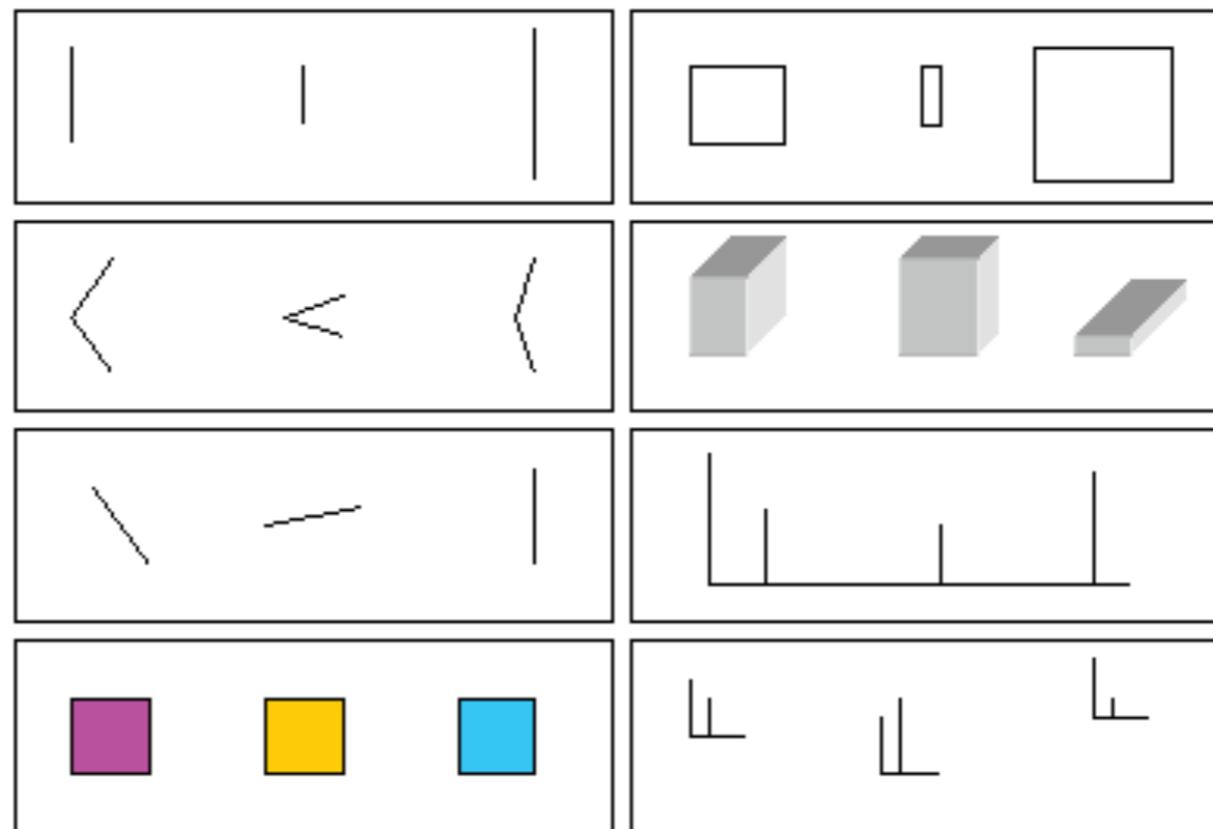
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Examples of graphical attributes used in perceptual experiments. Left column (from top): length, angle, orientation, hue. Right column: area, volume, position along a common scale, position along identical, nonaligned scales.

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Metrics: Weber's and Stevens's Laws

- **Weber's Law:**

- ◆ The likelihood of **detecting a change** is **proportional to the relative change**, not the absolute change, of a graphical attribute.

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◆ Stevens' Law

- ◆ The **perceived scale** in **absolute measurements** is the **actual scale raised to a power**.
 - For linear features, this power is between 0.9 and 1.1;
 - for area features, it is between 0.6 and 0.9,
 - for volume features it is between 0.5 and 0.8.

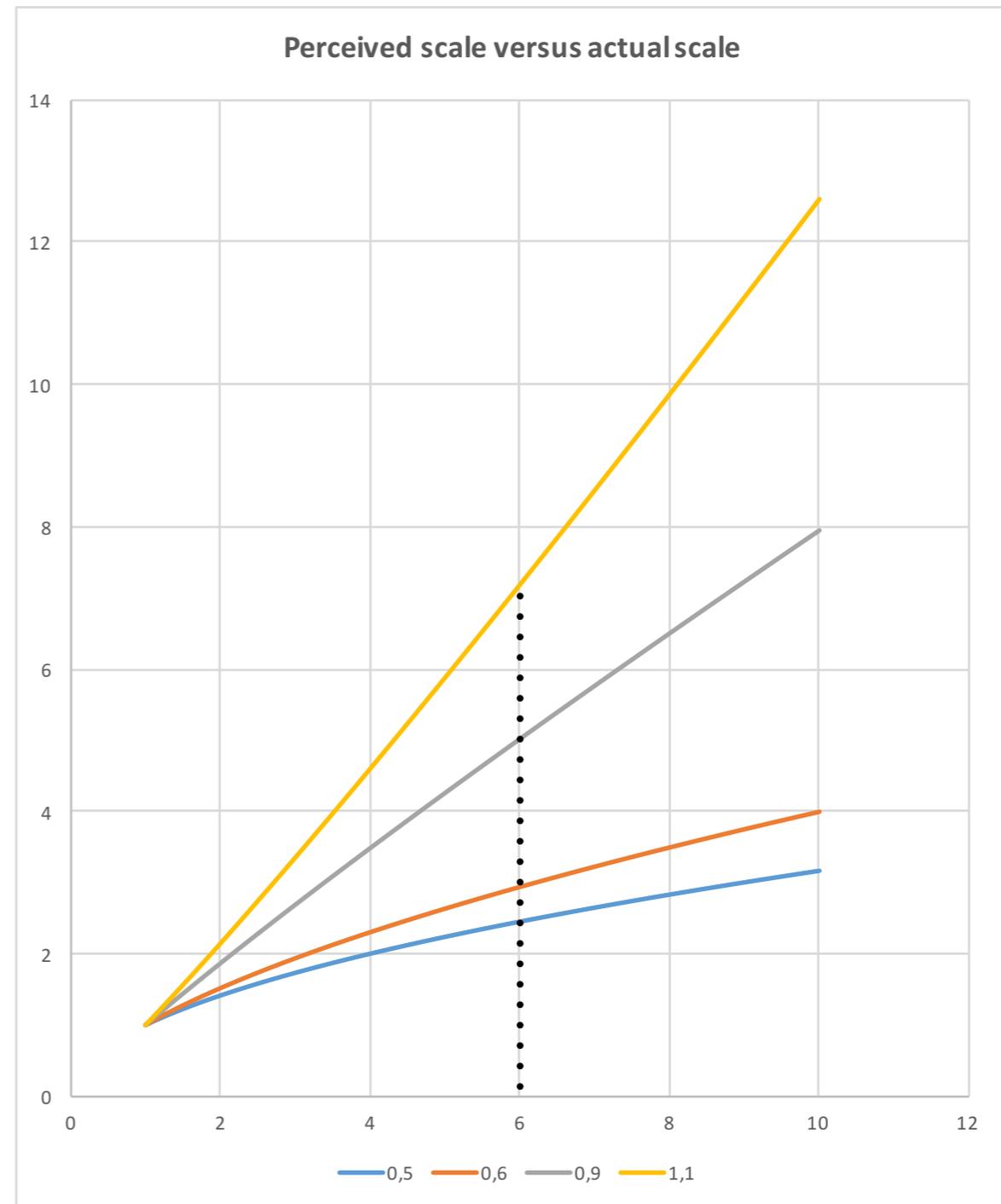
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■ Stevens' Law

- ◆ Linear features: [0.9 , 1.1]
- ◆ Area features: [0.6 and 0.9]
- ◆ Volume features [0.5 and 0.8]

■ Real value of 6

- ◆ Linear: perceived as 5 to 7
- ◆ Area: perceived as 2.9 to 5
- ◆ Volume: perceived as 2.5 to 4,2



Metrics: Weber's and Stevens's Laws

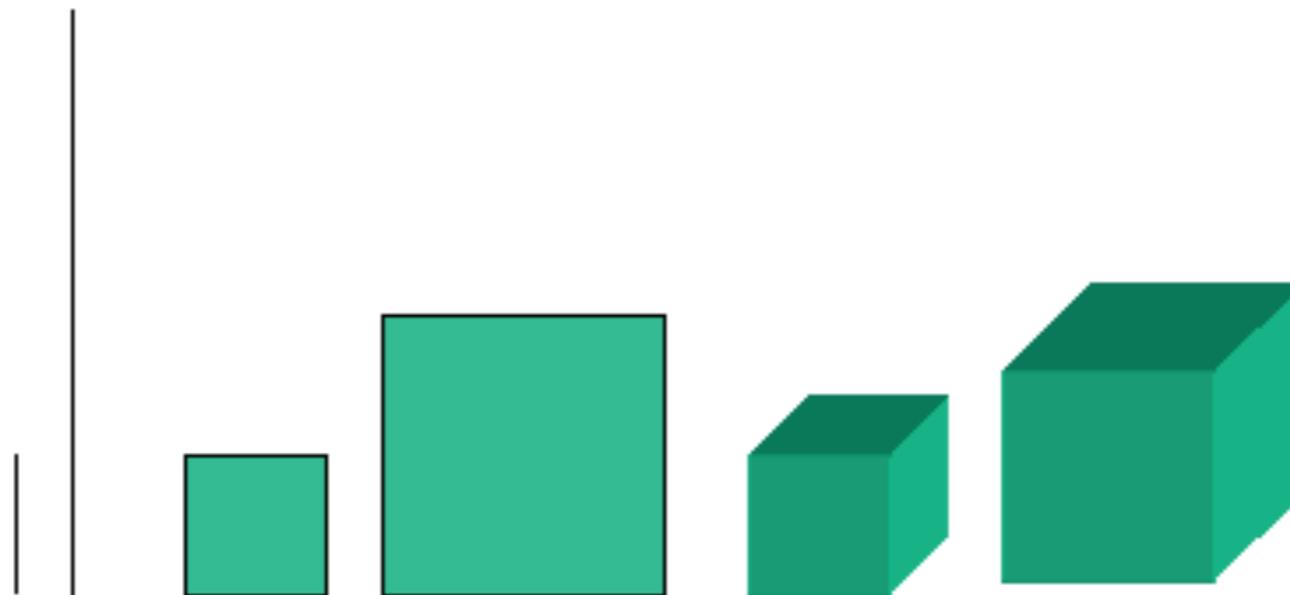


Illustration of Stevens' Law. The size ratio for each pair is 1:4. This magnitude is readily apparent in the lines, but it is easily underestimated in the squares and cubes.

Figure 3.35 - (Matthew Ward, et. all)

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 - ◆ **increasing the dimensionality with caution and in a limited way**
 - ◆ reconfigure the problem to be a **sequence of different absolute judgments**, rather than simultaneous stimuli.

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■ The Relationship to Immediate Memory

- ◆ **short- term memory is used for very short-term recall, often immediately after a stimulus has been received. Studies have shown the span of short- term memory to be approximately 7 items (or less)**

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■ The Role of Focus and Expectation

Further Reading and Summary



Q&A

Further Reading

- Pag 118 - 163 from **Interactive Data Visualization: Foundations, Techniques, and Applications**, Matthew O. Ward, Georges Grinstein, Daniel Keim, 2015

- **Subtleties of Color**
 - ◆ <http://earthobservatory.nasa.gov/blogs/elegantfigures/2013/08/05/subtleties-of-color-part-1-of-6/>

- **Color Models**
 - ◆ http://dba.med.sc.edu/price/irf/Adobe_tg/models/main.html

- **Check:**
 - ◆ <http://colorbrewer2.org>

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- **How to use texture to convey information.**

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- What are the **Weber’s** and **Stevens’s** Laws
- Strategies to **expand our communication capabilities**

Recommended activities

- **Start to seek for the elements to choose your subject**
 - **Data**
 - <https://www.kaggle.com/datasets>
 - Look for data-providers. For instance look at this:
 - <https://sqlbelle.com/2015/01/16/data-sets-for-bianalyticsvisualization-projects/>
 - <https://www.springboard.com/blog/free-public-data-sets-data-science-project/>
 - <http://infosthetics.com>
 - http://www.ipcc-data.org/observ/clim/cru_ts2_1.html
 - **Questions that worth (at least to you) to be addressed**
 - **Type of visualizations that can be useful**
 - **Papers that address the same or similar, or just related to the problems that you consider**



Q&A