CSE 564
Visualization & Visual Analytics

Visual Design and Aesthetics

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<td>Final Project preliminary report due</td>
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<td>Final project presentations</td>
<td>Final Project slides and final report due</td>
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Formal theory linking perception to visualization
Established by Jacques Bertin (1967)

- he called it ‘Image Theory’
- original book in French (*Sémiologie Graphique*)
  translated into English by W. Berg (1983)
- not formally linked to vision research
  more based on intuition
- but has been shown later by M. Green to be quite accurate
Two planar variables
- spatial dimensions
- map (arm, grip) to (x,y)

Six retinal variables
- size
- color
- shape
- orientation
- texture
- brightness

Retinal variables allow for one more variable to be encoded
- more than three variables will hamper efficient visual search
- recall low decoding speed of conjunctions
Visual variables differ in what data properties they can convey.

<table>
<thead>
<tr>
<th></th>
<th>Associative</th>
<th>Selective</th>
<th>Ordered</th>
<th>Quantitative</th>
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<tbody>
<tr>
<td>Planar</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
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<tr>
<td>Size</td>
<td></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
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<tr>
<td>Brightness</td>
<td></td>
<td>yes</td>
<td></td>
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<tr>
<td>Texture</td>
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<tr>
<td>Color</td>
<td>yes</td>
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<tr>
<td>Orientation</td>
<td>yes</td>
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<td>yes</td>
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<tr>
<td>Shape</td>
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Both are nominal qualities

**Associative**
- lowest organizational level
- enables visual grouping of all elements of a variable

**Selective**
- next lowest level
- enables viewer to isolate encoded data and ignore others
Background with same-colored object at the same brightness

- can you see the shape?
- can you count the number of gaps?
Background with different-colored object at similar brightness

- can you see the shape?
- can you count the number of gaps?
Background with different-colored object at lower brightness

- can you see the shape?
- can you count the number of gaps?
Background with different-colored object at higher brightness

- can you see the shape?
- can you count the number of gaps?
What Did we Learn from that Experiment?

Color is for ...

Brightness (intensity, luminance) is for ...
Luminance and Hue

- Luminance mapped to height
- Just hue
- Hue and luminance encode high frequency information by L

From Bergman/Rogowitz/Treinish Vis’95
ROLE OF SATURATION

ART & MONEY
#datavisualisation

This Animated Bubble Chart shows the 270 most expensive artworks sold in auction since 2008 until end 2011.

- drawing
- silkscreen
- painting
- sculpture

SORTING
- year by year
- top 10 artworks
- men / women
- dead / alive
- **by nationality**
- best-selling artists
- auction houses
- size of artworks
- date of creation (all centuries)
Which is the most important structure in each (as intended by the author)
Which one do people like better?

- perceived importance level of red object is the same
COLOR CODING AND COLORMAPS

- Color coding
  - large areas: low saturation
  - small areas: high saturation
  - maintain luminance contrast
  - break iso-luminances with borders

- Pseudo-coloring: assign colors to grey levels by indexing the grey levels into a color map
As we saw, colors can add detail information to a visualization

- instead of 256 levels get \(256^3 = 16,777,216\)

Oftentimes you have a visualization with just one variable

- this would give you a grey level image
- how to turn this into a color image for better detail

Solution 1:

- map to hue → the rainbow colormap

- can you see all adjacent colors at the same contrast?
Avoid rainbow Colormaps
Better: Linear Hue
Nominal scales
- distinct hues, but similar emphasis

Sequential scales
- vary in lightness and saturation
- vary slightly in hue

Diverging scale
- complementary sequential scales
- neutral at “zero”
Opponent colors do not mix

- can only see one of the opponents
- there is no blueish yellow
- there is no reddish green
Most common is deficiency in distinguishing red and green
Forms of Color Blindness

- Normal
- Green missing
- Red missing
- Blue missing (rare)
Ishihara Test

normal

protanopia
LINE CHARTS
8% (0.5%) of US males (females) are color deficient
  - so be careful when designing visualizations

What to do?
  - use different intensities for red-green (e.g. light green, dark red)
  - space red and green colored colors dots far apart or make large
  - add symbols to line charts
  - avoid using gradient colors to indicate data value
Use Luminance for detail, shape, and form
Use color for coding – few colors
Use strong colors for small areas
Use subtle colors to code large areas

Visualization artistry:
- Use of luminance to indicate direction