Perception and Cognition

Mauricio Maurer
Justin Reiser

Volume Compositing Using Eye Tracker Data

Aidong Lu, Ross Maciejewski and David S. Ebert

Automate rendering parameter selection:

- Reduce effort for selection of parameters and
- Provide good starting point for additional investigation

Eye-tracking

- Eye movements focus near the best place to gather the desired visual information.
- Two types of basic eye movements:
  - Saccades – rapid eye movements when eye focus on one point after the other or for lubrication
  - Fixation – when eye movement stops and focus on a particular object

3D Data

- To analyze 3D data:
  - Rotate the volume: 360° in 10 seconds (not boring and not too fast)
  - Direction can be changed by user: eye movement recording is disabled
  - Semi-transparent isosurfaces: user can change isosurface values
  - Amount of importance from eye-tracking data is based on visual acuity →

Equation of visual acuity

- Visual Acuity is

Constrast sensitivity

Sensitivity Drop-off

$$H(v,e) = G(v) * M(e)$$

Velocity: deg/s Volume rotating speed in the image plane

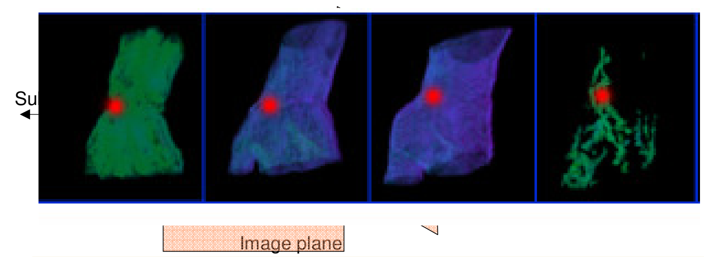
Peripheral extent: deg Measured from distance between user and screen and the pixel position to the screen center

$$G(v) = \begin{cases} 60.0, v \le 0.825 deg/s \\ 57.69 - 27.78\log_{10}(v), 0.825 < v \le 118.3 deg/s \\ 0.1, v > 118.3 deg/s \end{cases}$$

$$M(e) = \begin{cases} 1.0, e \le 5.79 deg \\ 7.49/(0.3e+1)^2, e > 5.79 deg \end{cases}$$

Data Gathering

- 2D eye movement points + corresponding volume rotation matrices
  - Saccades discarded: eye movement speed > 180 deg/s
- Each point induces a subvolume:



Data Processing

- Clustering used to combine fixation points that correspond to the same region-of-interest
- Used mean shift procedure to produce cluster centers:
  - Merged cluster with center-center distance < eye tracking accuracy
  - Small clusters removed: don't represent main focus

The result are clusters in the volume

Data Processing 2

- Data within clusters are mapped to regions in the data range;
- Use mean shift procedure to cluster data in the data range;
- The result is the initial visiting map for the importance maps
  - Segmented volumes: importance map gives the hit count to each object;
  - Unsegmented volumes: it is possible to use the data clusters to segment the volume automatically

Rendering Settings

- Values obtained in previous steps:
  - $I_v()$: importance value for each voxel
  - $ID()$: object ID for each voxel
  - $I_0()$: importance value for each object
- Viewpoint selection based on
  - Salience – G, C and an edge detection value E
  - Occlusion
  - Stability
  - Familiarity

Voxel Weight

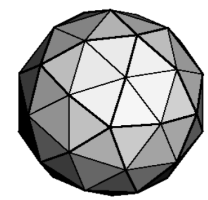
$$W(x) = w_s * \overbrace{(G+C+E)}^{Salience} * I_o(x) + w_i * I_v(x)$$

$$+ \overbrace{w_d * I_v(x) * (1 - Distance(x))}^{Familiarity}$$

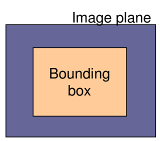
W(x) is projected into a buffer that corresponds to the view plane

$$O(v) = \overbrace{\sum_{p \in Imageplane} \prod_{x \in Volume} (1.0 + W(x))}^{Occlusion}$$

$$Good(v) = -(O(v) + \overbrace{Variance(O(v))}^{Stability})$$



Volume center and Rendering degrees



$$\frac{Area(\text{Image Plane})}{Area(\text{Bounding Box})} = 1.63$$

- Overlapping dictates the opacity of rendered objects:
  - No overlapping: object rendered at highest degree
  - Overlapping: back object rendered with highest degree as possible, front object rendered at suitable degree
- Degree $D(x)$ of all objects are initialized to 1

Volume center and Rendering degrees

Overlapping ratio of A on B

Importance of object A

$$D(x) = O_v(A,B) * f(I_0(A), I_0(B)) + (1 - O_v(A,B)) * D(A)$$

$$\text{where } f(x,y) = 0, x \le y; \frac{x-y}{y}, x > y$$

Finally, the opacity is given by:

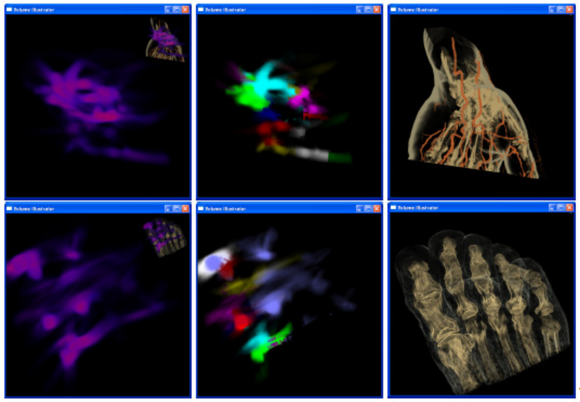
$$\text{Opacity}(x) = 0.1 + 0.7 * D(x)$$

NPR with silhouette effect

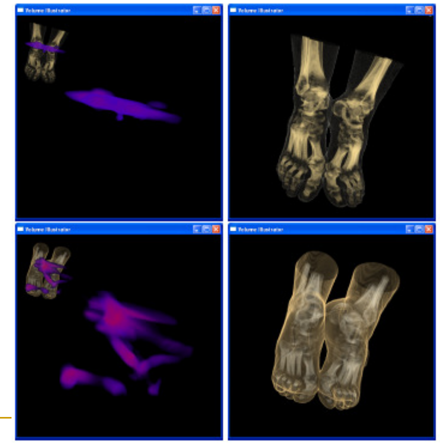
$$\text{Opacity}(x) = (\text{Gradient} \cdot \vec{\text{View}})^{\text{Sp}(x)}$$

$$\text{Sp}(x) = 10 - 9 * D(x)$$

Visiting volumes, cluster results composition results



Visiting volumes and composition results



Harnessing Preattentive Processes for Multivariate Data Visualization

Christopher Healey, Kellogg Booth, James Enns

This paper discusses guidelines for developing multivariate data visualization tools.

Our presentation begins by discussing what scientific visualization would require from such a tool.

We will then define what multivariate data visualization is and describe a part of the low-level human visual system known as preattentive processing.

Lastly, we will discuss a set of experiments and how their results can be used to come up with guidelines for developing multivariate data visualization tools.

Visualization Technique Requirements

A variety of scientific disciples such as chemistry, physics, and oceanography use visualization techniques to discover information in large datasets.

This paper describes several requirements for a successful visualization technique.

Requirements:
- Displays results in real-time
- Provides the means for user interaction
- Allows for rapid/accurate analysis of multiple aspects of the data
- Allows different users to work with subsets of the display at the same time
- Is intuitive and effortless

Features

In order to make data analysis intuitive and effortless the authors suggest designers attach features to each data element

Example Features:
• Color
• Size
• Spatial Location
• Orientation

Features
• Show the properties of individual elements and relationships between elements.
• Features are an example of multivariate data visualization

Multivariate Visualization

Displaying high-dimensional data in fewer dimensions

Multivariate Visualization Requirements

- The technique should be capable of displaying multiple independent data values simultaneously
- Users should be able to ascertain information quickly
- Information obtained by the users should be accurate

Preattentive processing

The authors use the built-in processing of the human visualization system in order to assist with visualization.

To be more specific, the authors use preattentive processing to highlight important image characteristics.

Preattentive processing involves features that can be rapidly detected by the visual system without focusing attention on a particular region of an image.

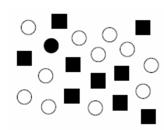
Examples of preattentive features:
Color
Size
Shape
Orientation

Conjunctions

Conjunctions are when a target object is composed of 2+ features, each of which is contained in a distractor object.

Objects that are made up of a conjunction of features do not utilize preattentive attention.

Example:



The target in this diagram has two features shape (circle) and hue (black). There are white circle distractors and black square distractors.

Therefore, we cannot use preattentive processing to find the target.

Preattentive Tasks

Target Detection is when a user needs to detect the presence/absence of a target that contains a particular preattentive feature.

Boundary Detection is when a user needs to detect a texture boundary between two groups of elements, where all the elements in each group share a common preattentive feature.

Estimation is when a user estimates the number of elements in a display that contain some preattentive feature. This can be done preattentively.

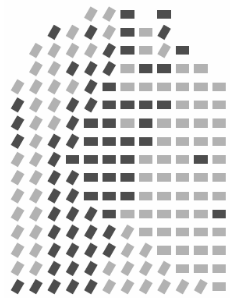
The authors conduct experiments on the use of hue and orientation in estimation.

Experiments

Users were shown a display with elements composed of two features: hue and orientation.

In different trials these features alternated meaning (landfall or lattitude).

The users were asked to estimate the number of elements that contained a particular preattentive feature (e.g. 60^0 orientation)



Another similar experiment was done, but in this experiment they varied the duration of exposure between trials

Results

- Rapid/accurate estimation is possible using either hue or orientation
- Hue does not interfere with orientation
- Orientation does not interfere with hue
- An exposure of at least 100 milliseconds should be used to ensure accuracy

Perceptual Techniques for Scientific Visualization

Christopher G. Healey

- This paper discusses how to best use features such as color and texture to visualize large multidimensional datasets
- These data sets are increasingly common and difficult to visualize using traditional techniques

Example Datasets:
- Scientific Simulation Results
- Geographic Information Systems
- Satellite Images
- Biomedical Scans

The System

- The author's system displays data in a way that makes use of how people perceive information in an image.
- Most analysis is done by the low-level visual system, allowing for rapid/accurate evaluation

Benefits:
- Trends/relationships rapidly detected
- Unexpected patterns/results quickly detected
- Natural/intuitive

Preattentive Processing

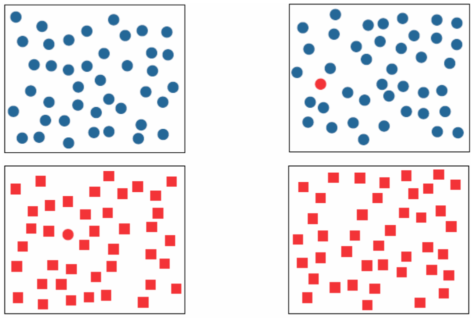
Factors determining attention can be split into bottom-up and top-down factors. The paper discusses bottom-up or preattentive factors.

Preattentive Factors:
- Detected quickly, without searching
- Detection time is independent of the number of displayed elements (good for large datasets)
- Performed in a single glance
- Dependant on the observer's goals and expectations

Examples of Preattentive Processing

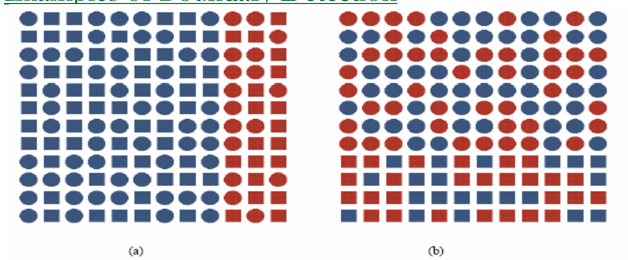
- Searching for elements with a unique feature (foraging)
- Tracking moving elements (hunting)
- Determining a texture boundary between two groups of elements (avoiding the edge of a cliff)

Examples of Target Detection



(Detect the red circles)

Examples of Boundary Detection



- A: The boundary determined by hue is easily detected, even though each set of elements has varied shape
- B: The shape boundary is harder to detect. This may be due to the fact that the two groups vary in hue and that hue is a higher priority than shape. This illustrates the fact that higher priority visual features can interfere with tasks using lower priority features

Feature Priorities

The paper mentions a few of the feature priorities determined by Callaghan.

Features in descending order of priority:
Brightness
Hue
Shape

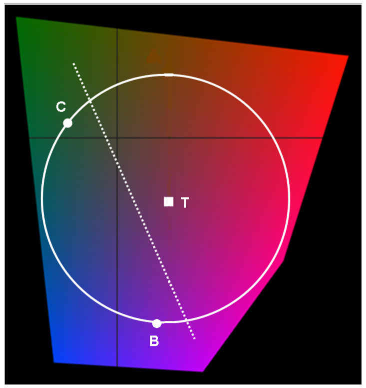
Color Selection

- Existing color selection techniques were not designed to investigate rapid/accurate detection
- The author used CIE LUV along with linear separation and color category in his color selection process

CIE LUV

- Color are specified by luminance (L*) and chromaticity (u* and v*)
  - Luminance is the physical intensity of light
  - Chromaticity is the hue and saturation, ignoring brightness
- Useful properties of LUV
  - Colors with the same L* value are isoluminant
  - Euclidean distance and color difference can be interchanged

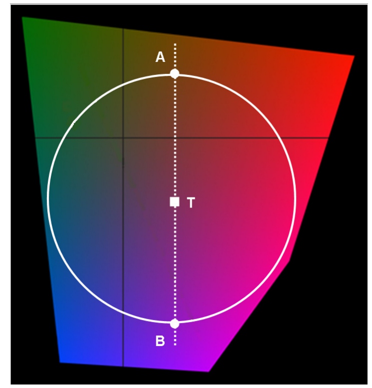
Linear Separation



When a target can be separated from distractors using a line, target detection time is independent of the number of elements (preattentive)

Original Image: Nonphotorealistic Visualization of Multidimensional Datasets, SIGGRAPH 2001, Christopher Healey

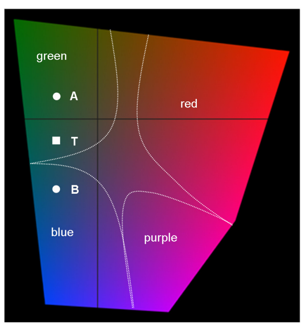
Linear Separation



When a target is collinear with distractors target detection time depends on the number of elements.

Original Image: Nonphotorealistic Visualization of Multidimensional Datasets, SIGGRAPH 2001, Christopher Healey

Color Category



The color category effect suggests that the perceived difference between a pair of colors increases when the two elements lie in different named color regions.

Image Source: Nonphotorealistic Visualization of Multidimensional Datasets, SIGGRAPH 2001, Christopher Healey

Experimental Results

The author ran a study on the effects of color distance, linear separation, and color category on target detection

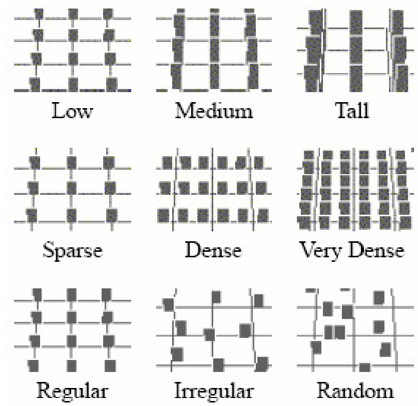
Results:

- 7 isoluminant colors can be displayed simultaneously
- Time of detection is independent of data size, suggesting that detection is being done preattentively
- Color distance, linear separation, and color category all need to be considered in order to guarantee consistent performance

Pexels

- Pexels use texture to represent multiple attributes at one location
- Pexels are thin sheets whose dimensions (density, height, regularity) represent attributes.
- The author determined that height and density are preattentive, while regularity is only useful when the user focuses in on an area of interest
- The author also determined that texture and color can be used together, but only when targets have strong salience (tall,dense).

Examples of Pexels



Dynamic View Selection for Time-Varying Volumes

Guangfeng Ji and Han-Wei Shen

Select ideal views through which the user can perceive the maximum amount of information from the time-varying dataset

- Proposes an improved view selection method for static data
- Uses the static views selection an a dynamic programming approach to select time-varying views

Static View selection

- Find a good view point through which the user can perceive the maximum amount of information. The method considers:
- Opacity distribution and projection size
- Color distribution
- Curvature information

$$u(v) = \alpha \cdot \text{opacity}(v) + \beta \cdot \text{color}(v) + \gamma \cdot \text{curvature}(v)$$

$$\alpha + \beta + \gamma = 1$$

Measurement of opacity distribution and projection size

- Large projection area with an even opacity distribution
- Use Shannon entropy function

$$\text{symbols in the set } \{a_0, a_1, \ldots, a_{n-1}\}$$

$$\text{with occurrence probability } \{p_0, p_1, \ldots, p_{n-1}\}$$

$$H(x) = -\sum_{i=0}^{n-1} p_i \cdot \log_2(p_i)$$

$$\text{image with } n \text{ pixels with opacity values } \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$$

$$p_i = \frac{\alpha_i}{\sum_{j=0}^{n-1} \alpha_j}$$

Measurement of Color Distribution

- Uses Shannon entropy function once again. Give a higher value for images with:
  - More evenly distributed and
  - Larger areas of salient colors
- Use CIE LUV color model
- Given color areas C_1, C_2, ..., C_{n-1} with areas A_1, A_2, ..., A_{n-1} and total window area T and the area of C_0 being

$$C_0 = \sum_{i=1}^{n-1} (A_i) \qquad p_i = \frac{A_i}{T}$$

Measurement of Curvature Information

- Low curvatures imply flat areas
- High curvatures often contain more information (if there is noise, a smoothing operator should be performed)
  - First calculate curvature proposed by *Kindlmann et al.*
  - Voxel color is determined by curvature: high curvatures are assigned high intensity color, low curvature receive color (0,0,0)
  - After rendered, the image intensity reflects the overall curvature of the volume

Dynamic View Selection

- Goal: allow the user to find a viewing path which shows the maximum amount of information from the time-varying dataset
  - View should move at a near-constant speed;
  - View should not change its direction abruptly;
  - Information perceived from the time-varying dataset should be maximized among all the viewing paths.

Time-Varying View Selection

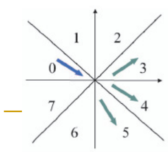
- Exponential search space

Maximum amount of info perceived from $P_{i,j}$ to some view at the final timestep

$$MaxInfo(P_{i,j,r}) = \max_{t=0..NumofRegions-1, k\in Regiont}\{u(P_{i,j}) - Cost(P_{i,j}, P_{i+1,k}) + MaxInfo(P_{i+1,k,t})\}$$

Measures the cost to move from $P_{i,j}$ to $P_{i+1,k}$ If the *jth* view point and the *kth* view are within [V_{min}, V_{max}], the cost is 0, otherwise it is +∞

Information perceived at a static view

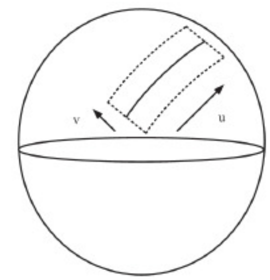


$$\{\{0,0,0,1,1,1,0,0\},\{0,0,0,0,1,1,1,0\},\{0,0,0,0,0,1,1,1\},\{1,0,0,0,0,0,1,1\},\{1,1,0,0,0,0,0,1\},\{1,1,1,0,0,0,0,0\},\{0,1,1,1,0,0,0,0\},\{0,0,1,1,1,0,0,0\}\}$$

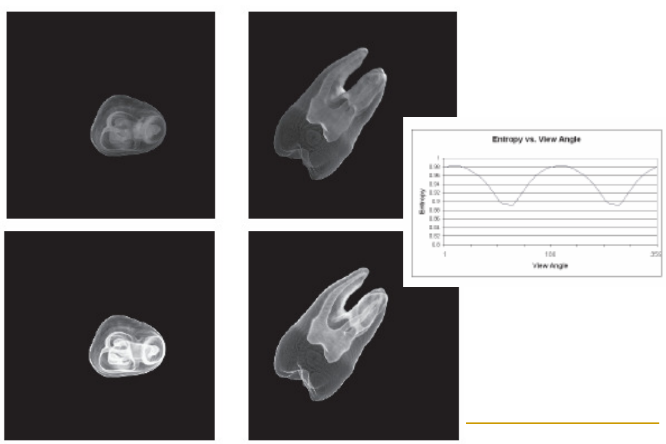
Prohibiting sharp turns

Viewing Path Between any Two Views in a Given Timestep

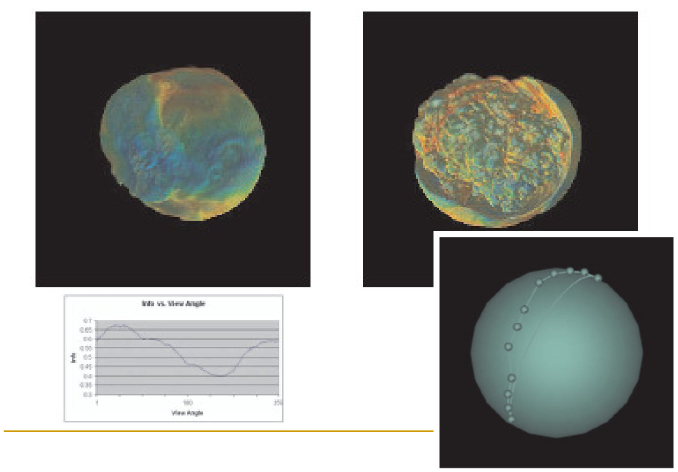
- Based on SLERP (spherical linear interpolation): shortest path connecting two points with constant angular velocity
- Possible view movements are close to the SLERP path
- Constraint to block repetitive movements:



Results 1



Results 2



On the Use of Perceptual Cues and Data Mining for Effective Visualization of Scientific Datasets

Christopher G. Healey

- Use datamining to identify areas of interest within the dataset
- Display the result of the datamining using visualization techniques based on perceptual cues

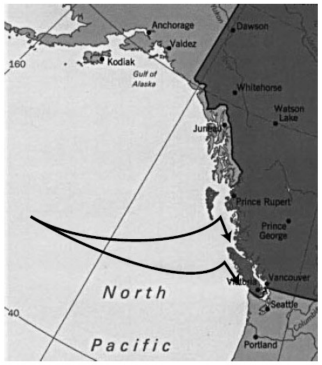
Oceanography Simulations

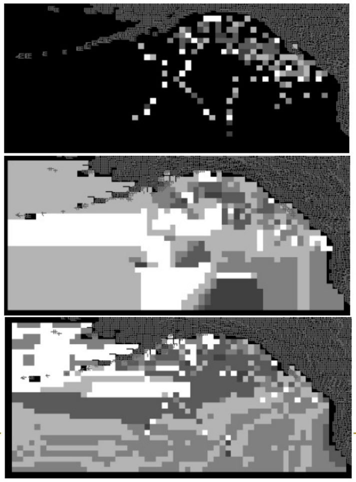
- Oceanographers want to model the growth and movement of salmon species in the northern Pacific Ocean:
  - They need a method of estimating plankton densities (sparse data between 1956 and 1964);
  - How plankton density relates to conditions like SST, current direction and current strength;
  - A method to visualize the dataset static and dynamically.

Data Mining

- Can be used to improve the efficiency of visualizing large, multidimensional dataset:
  - Reduce the amount of data to be displayed;
  - "Discover" previously unkown and potentially useful information.
- Implemented 4 different datamining techniques:
  - Two based on decision trees;
  - One based on statistical tables;
  - One based on rough sets.
- The algorithms provided extended results like: classification confidence weights, the ability to compare different classifications and the ability to identify attributes that are significant to a specific classification

Oceanography Results





Perceptual Visualization 1

- Three criteria must be considered to use n colors:
  - Color distance: the distance from each color to its neighbour is equal and above a minimum threshold (CIE LUV);
  - Linear separation: each color must be linearly separable from all the other color by a minimum threshold and
  - Color category: each color must occupy a uniquely named color region
- Up to seven isoluminant colors can be displayed simultaneously

Oceanography Visualization

- Choose to visualize SST and current strength with plankton densities
  - Plankton is displayed using color
  - SST and current strength are displayed using texture
- Five colors for plankton

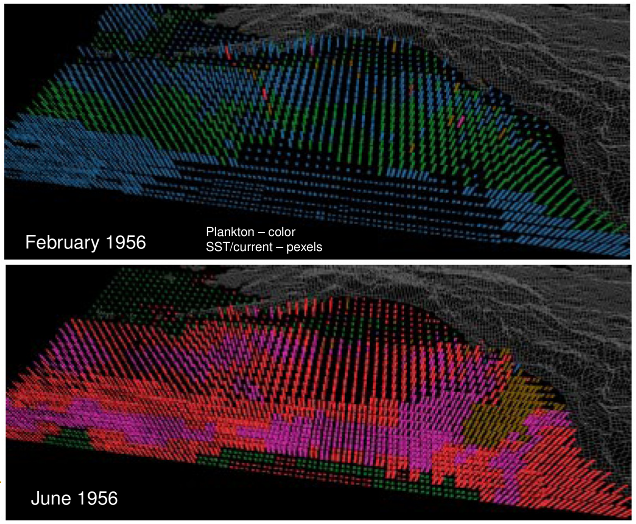
Blue	Green	Brown	Red	Purple

- Current strength mapped to height and SST to density (using Pexels)

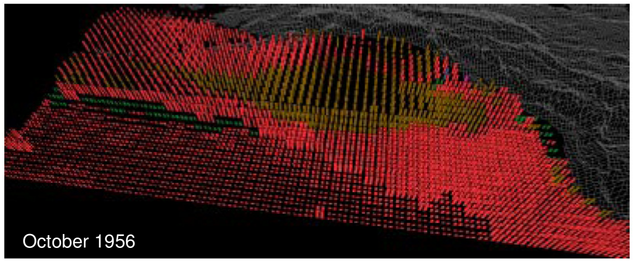
Oceanography Visualization

- Because there may be a feature preference for height over density, and current strength was deemed “more important” than SST, height was used to represent current and density to SST.

Results 1



Results 2



Plankton – color
SST/current –
pexels

Information Foraging

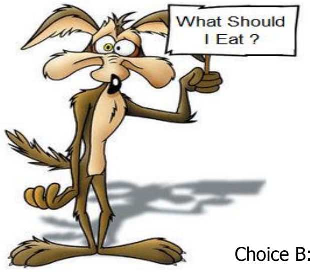
Peter Pirolli and Stuart K. Card

"A wealth of information creates a poverty of attention and a need to allocate it efficiently" – Herbert Simon

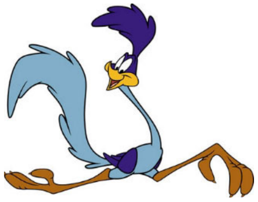
Information Foraging Theory Basics

- Derived from anthropology and behavioral ecology theories that explain how animals feed.
- Humans are informavores, they hunger for information in order to gather it and store it as a means for adapting to the world
- People search for information in a manner similar to how animals search for food
- People modify their environments and strategies to maximize the rate at which they gain information
- Information systems evolve towards states that maximize information gain

Foraging for Food

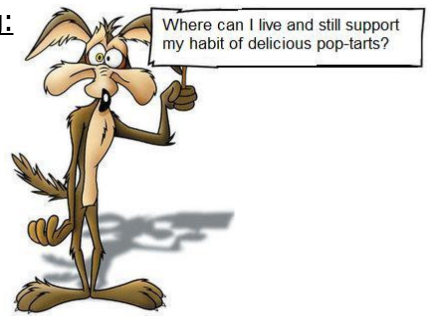


Choice A:



Choice B:

Information Foraging:



Source A: Newspaper

Source B: Website

RENT-DIRECT.COM
FAST. EASY. FUN...WITH NO BROKER'S FEE

Information Scent

- Local imperfect cues are used to search information spaces
- Predict likelihood of a path being successful
- If a source of information starts to get a weak scent the user will move to a new source
- Animal moves quickly towards a strong scent, but moves more randomly when the scent is weak.

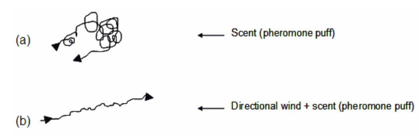


Image Source: www.websiteoptimization.com

Information Patches

- Information, like food, is often available in clusters. The sources we've been mentioning are these clusters also called patches.
- Users need to determine when it will be beneficial to stop foraging in the current patch and expend effort to find and move to another patch.
- For example, after looking at many results from a search engine you may find that the rate of information gained has decreased to the point where you need to look elsewhere for additional information.

Example Patches

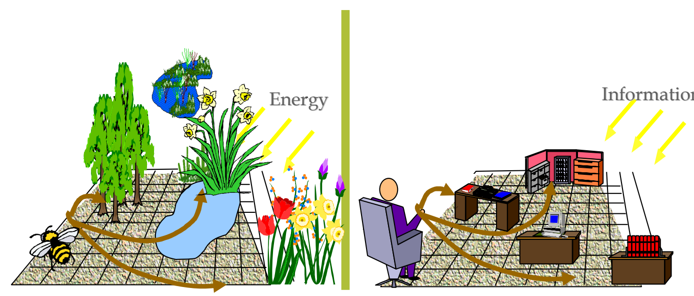


Image Source: *Large-Scale Cognition: The Psychology of Informavores*, Stuart Card

Information Diet

- The environment has multiple sources of food/information
- People choose what information to look for in the same way that predators choose their prey, by evaluating the ratio of gain to cost.
- A good source will provide a large amount of useful information and cost few resources (time,attention,energy)
- Sources with little profitability, like junkmail should be avoided because they detract from the information foragers ability to process better sources.

Satisficing

- Economics concept introduced by Herbert Simon
- We don't have infinite resources so sometimes we accept a less than perfect answer to avoid using too many resources
- For example, if my car was running low on gas and I decided to check each gas station's price before filling up, I would run out of gas before I checked them all.

Spreading Activation

- Technique for modeling human memory
- Explains how cues in the world evoke ideas in the mind and how these ideas propagate
- To start the chain a cue causes you to remember something, which in turn causes you to remember something else and so on.
- For example, a song may remind you of a dinner you had in which the song was playing in the background, which may remind you of other times you shared with the person you were eating with.

Information Foraging Theory: Applications

- User Interface Design
- Web usability analysis
- Allow for optimal design of libraries and other information warehouses (e.g. group similar subjects together so between patch time is minimized)
- Search Optimization (e.g. provide filters for searching emails)