Human Cognition and Next Generation Computing

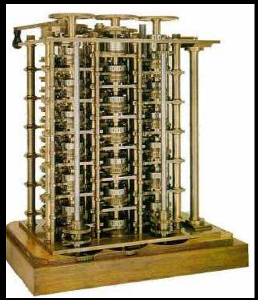
Dr. Bernice E. Rogowitz
IBM T.J. Watson Research Center
January 28, 2009

rogowtz@us.ibm.com

Charles Babbage (1791- 1871)
The Father of Computing

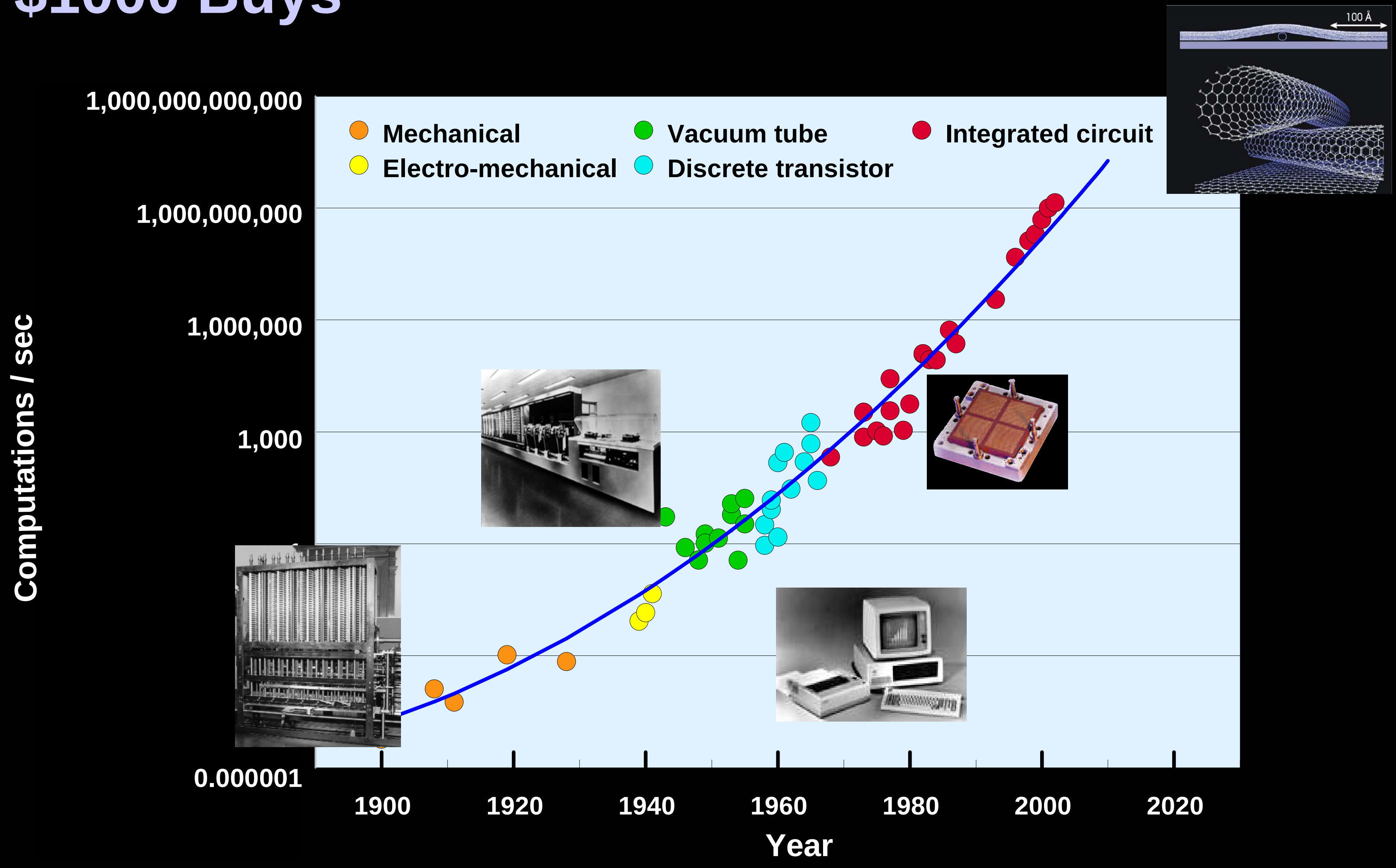
"Computers" were people hired to perform complex calculations

Babbage's machines were conceived as tools to aid human computers



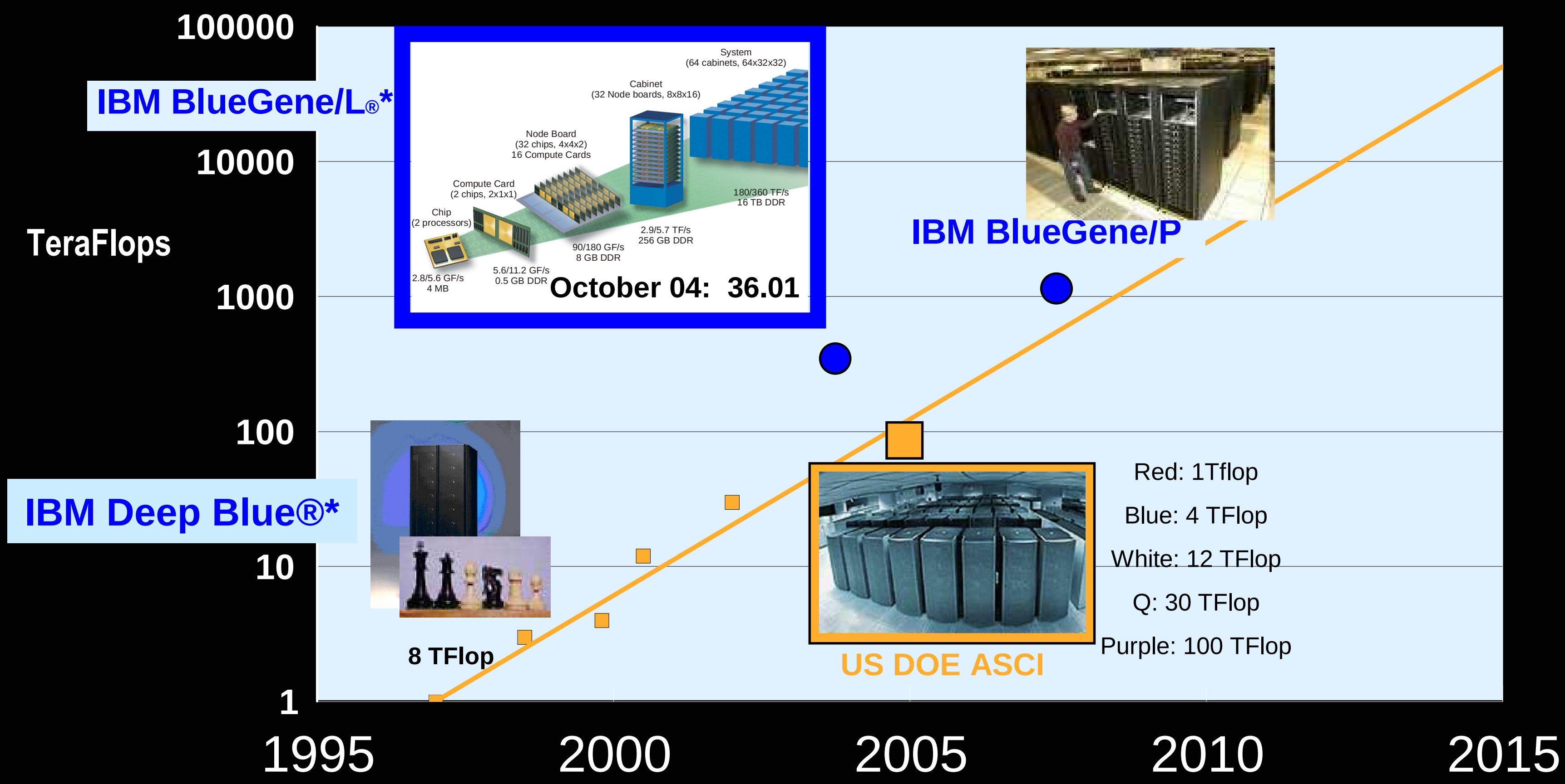
The Analytical Engine

$1000 Buys



after Kurzweil, 1999 & Moravec, 1998

Supercomputing Roadmap

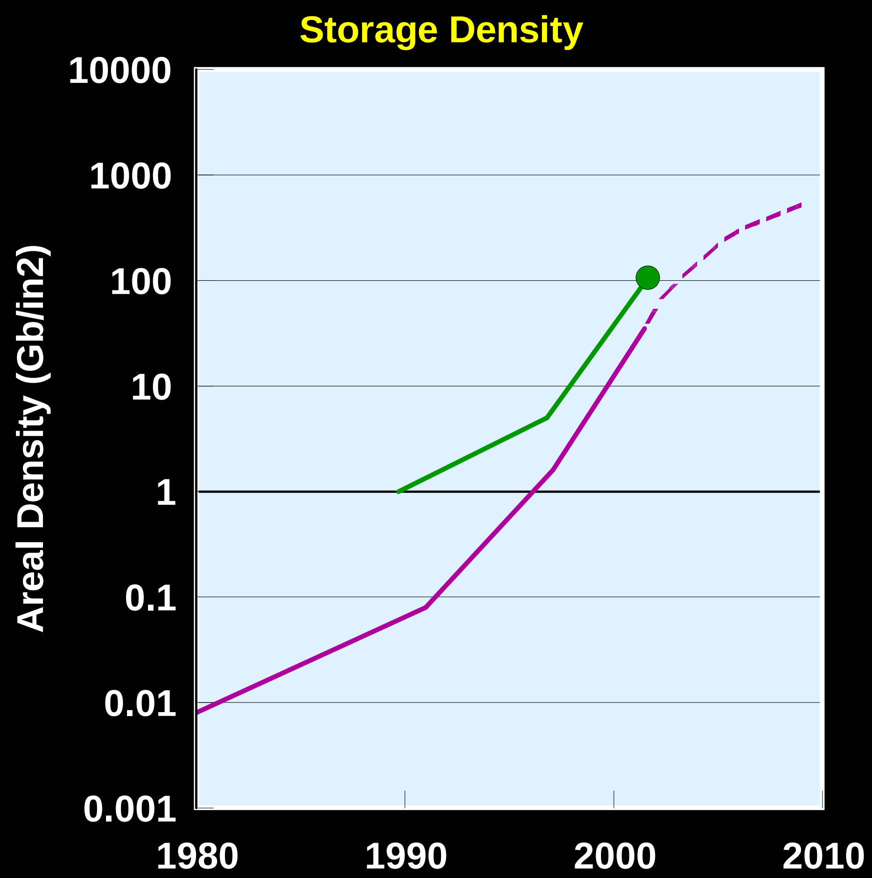


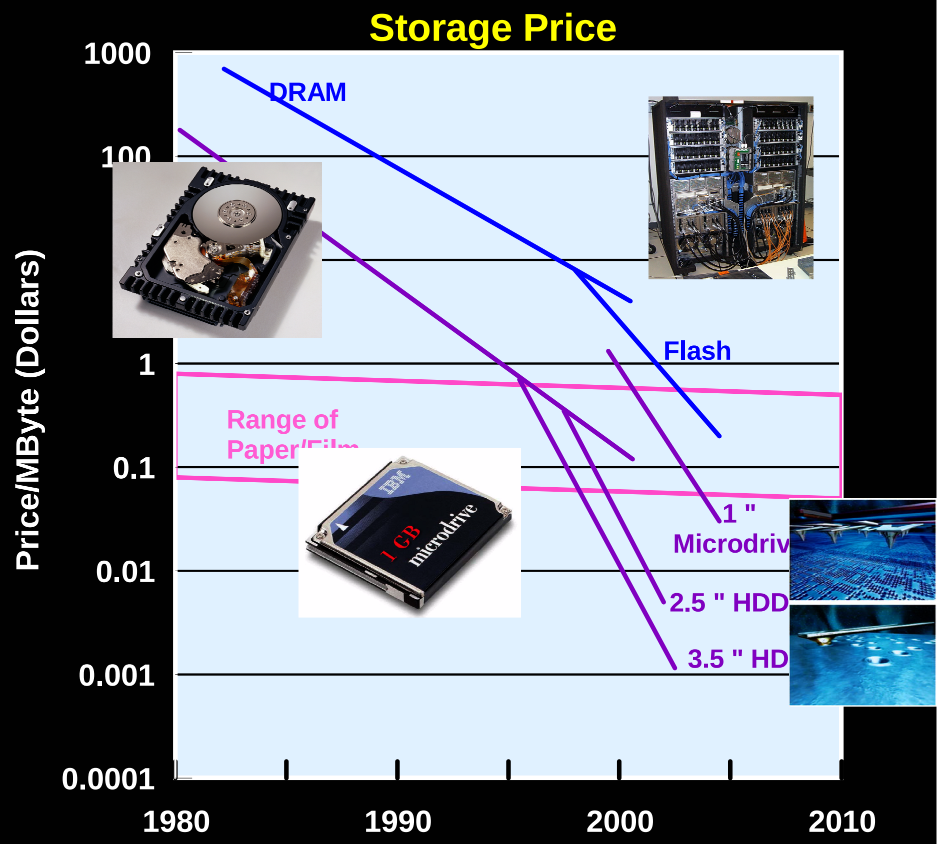
Source: ASCI Roadmap www.llnl.gov/asci, IBM

Brain ops/sec: Kurzweil 1999, The Ace of Spiritual Machines

Moravec 1998, www.transhumanist.com/volume1/moravec.htm

Storage Trends

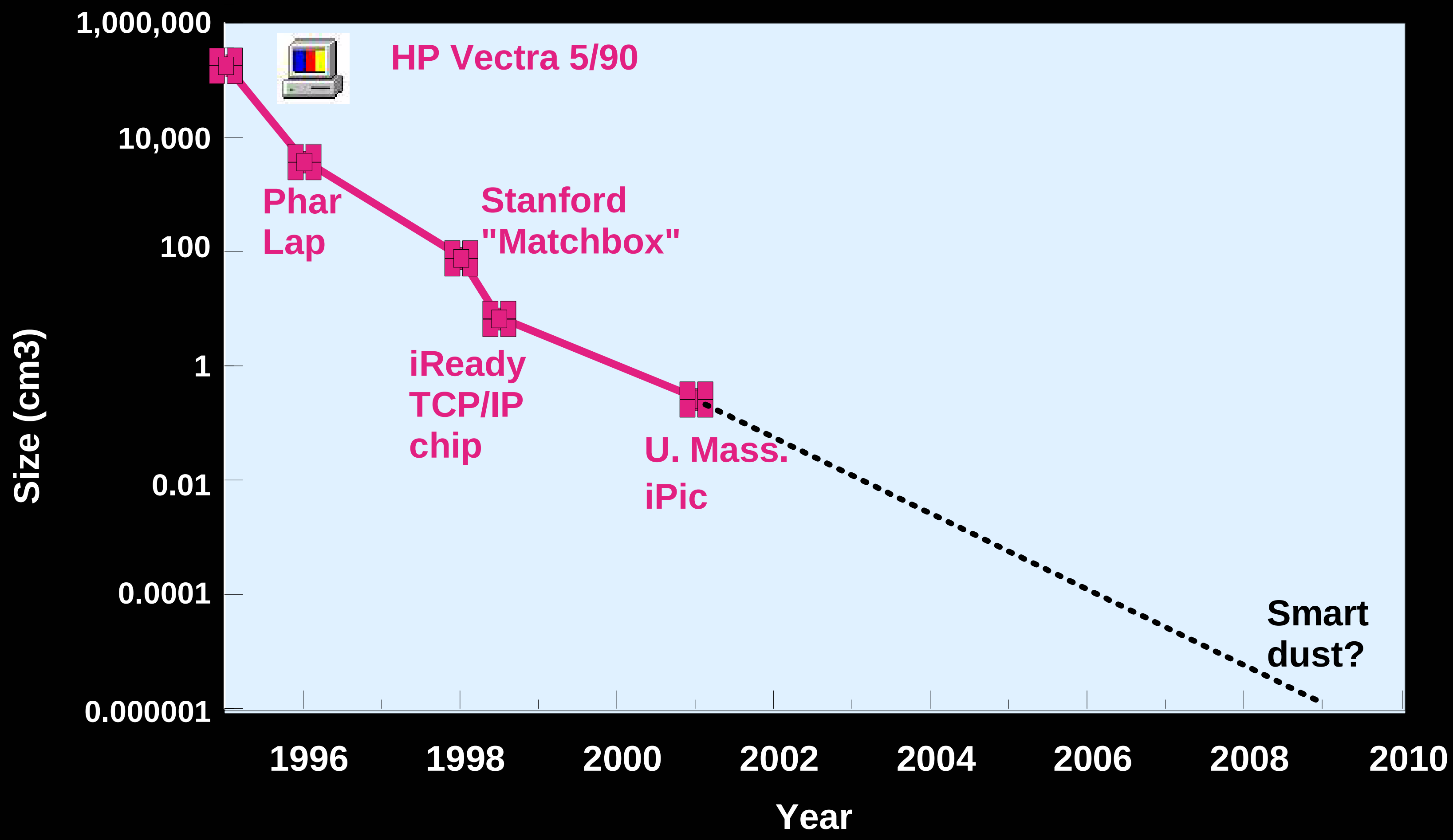




Rent Blockbuster™
Not a video... the entire store

Store all customer data
Transactions, letters, phone calls
over the span of a lifetime

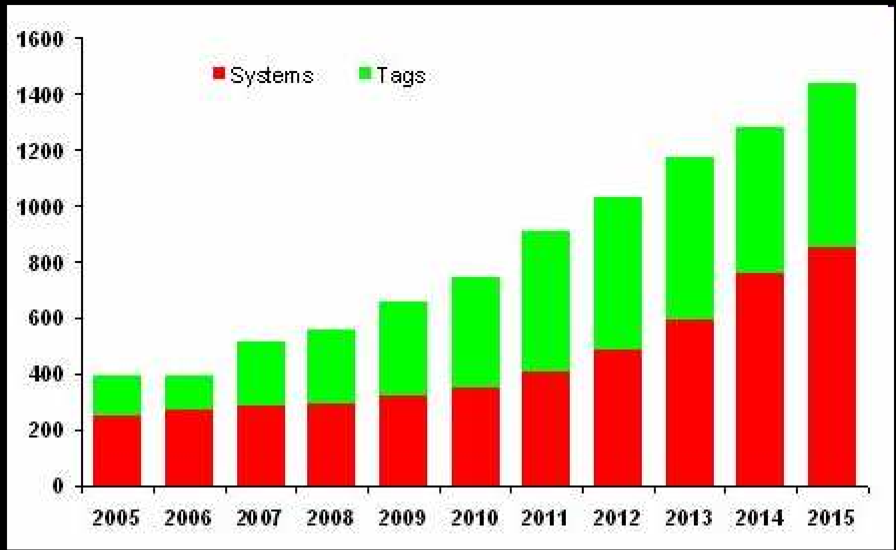
Miniaturization: e.g, the physical Size of a Web Server



Web servers with demonstrations on the internet

Wireless Sensors and RFID Tags

Wireless sensors and RFIDs growing rapidly, fueled by industry initiatives and government mandates

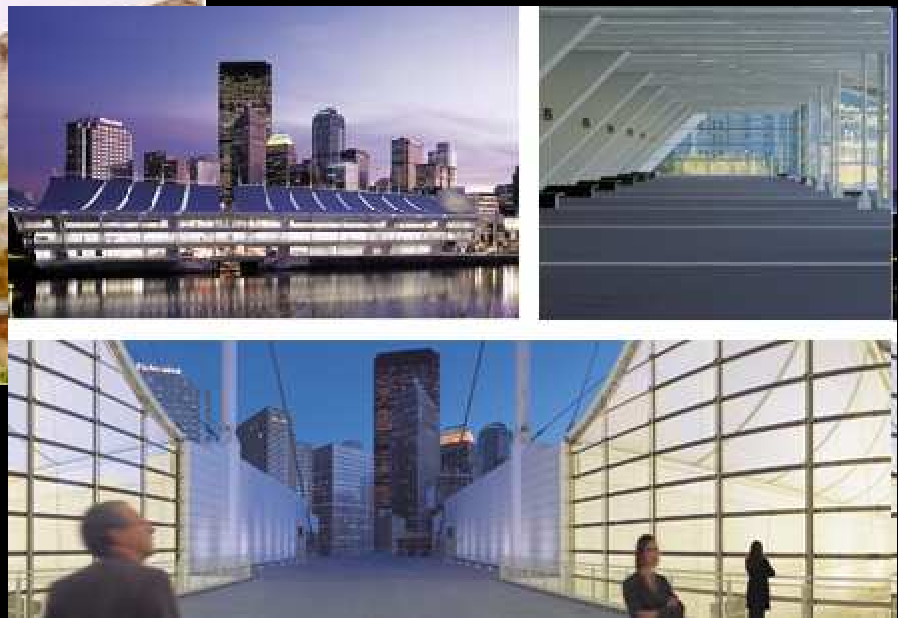


Source: RFID from Venture Development Corp, Wireless sensor data from Frost & Sullivan

Pervasive infrastructures are evolving to sense, and communicate, and construct

- Visual sensors
- Audio
- Chemical
- Biological
- Etc.

Military

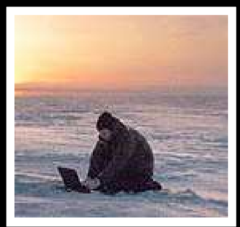


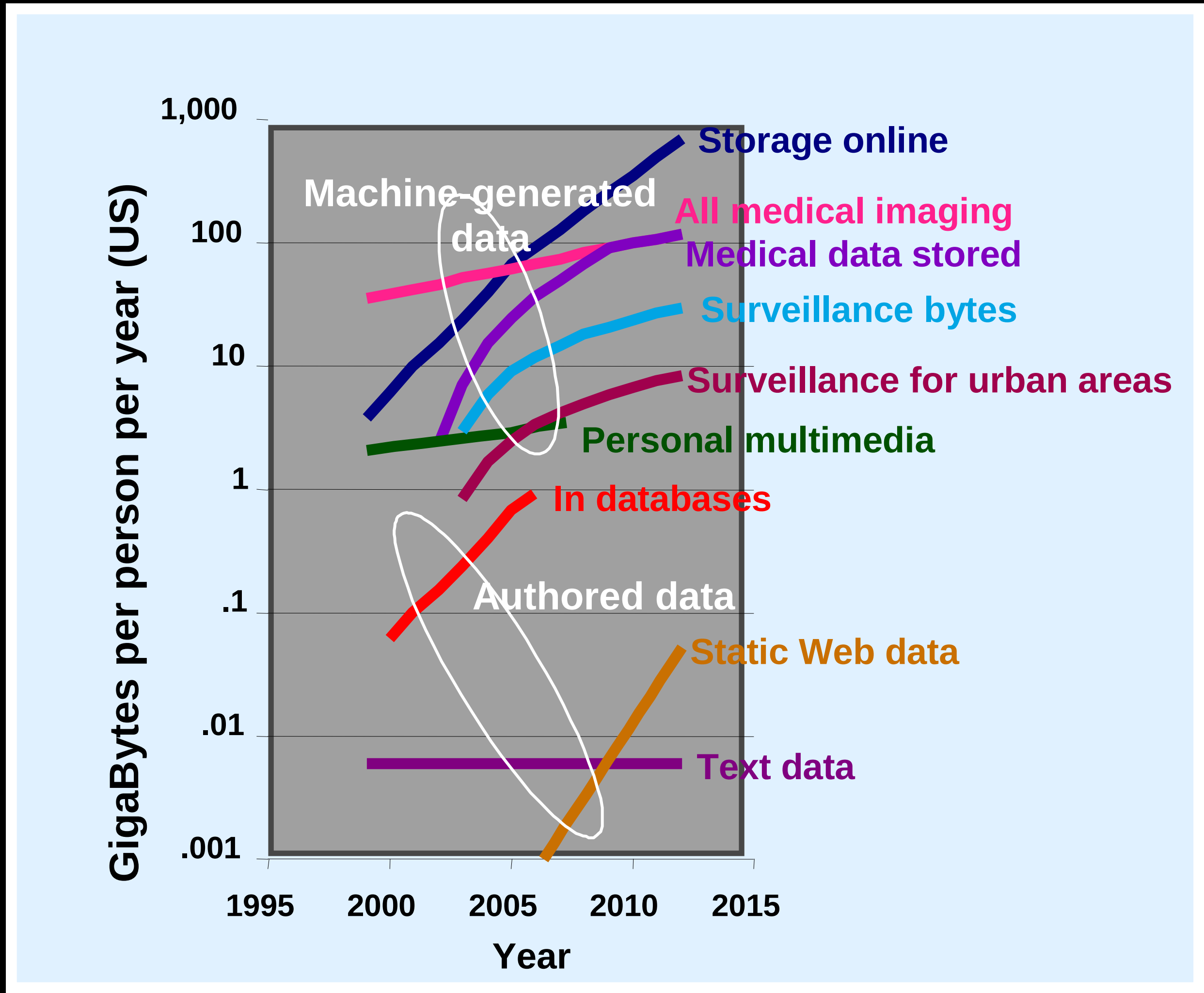
Green

Explosion of Multi-Type Data

Machine generated, time-based data are increasing exponentially

Authored Data

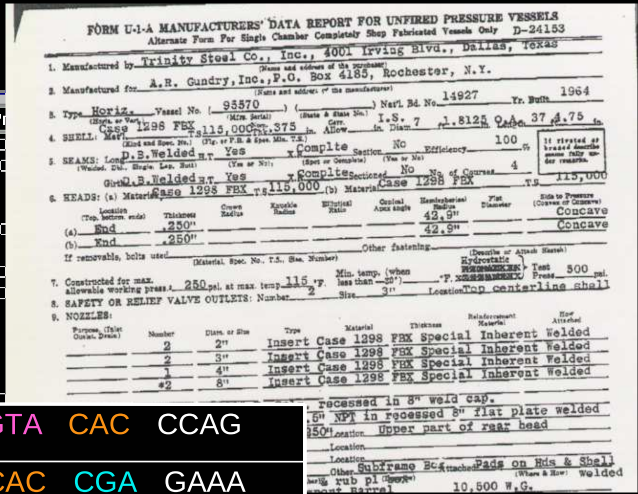




Many different types of data….

- time series
- numerical
- categorical
- field
- image
- sequence
- 3-D geometry
- text
- GIS
- graph

X	Y	Z
MXP.USD.Spot	MXP.USD.Vol.	MXP.USD.Pr
0.119	0.137	1.146E+0
0.118	0.116	-4.871E+0
0.118	0.131	51803.996
0.118	0.133	58951.086
0.119	0.116	-4.610E+0
0.118	0.133	97975.055
0.120	0.128	1.672E+0
0.120	0.134	2.777E+0
0.119	0.126	55082.316
0.118	0.129	46789.574
0.119	0.130	92753.898
0.118	0.117	1977.802
0.120	0.130	1.631E+0
0.119	0.124	[illegible]
0.119	0.129	[illegible]
0.118	0.135	[illegible]
0.118	0.123	[illegible]
0.118	0.122	[illegible]
0.118	0.122	[illegible]
0.119	0.119	[illegible]
0.119	0.124	[illegible]
0.118	0.127	[illegible]
0.118	0.116	[illegible]
0.119	0.121	[illegible]
0.119	0.118	[illegible]
0.118	0.126	[illegible]
0.118	0.120	[illegible]
0.120	0.117	[illegible]

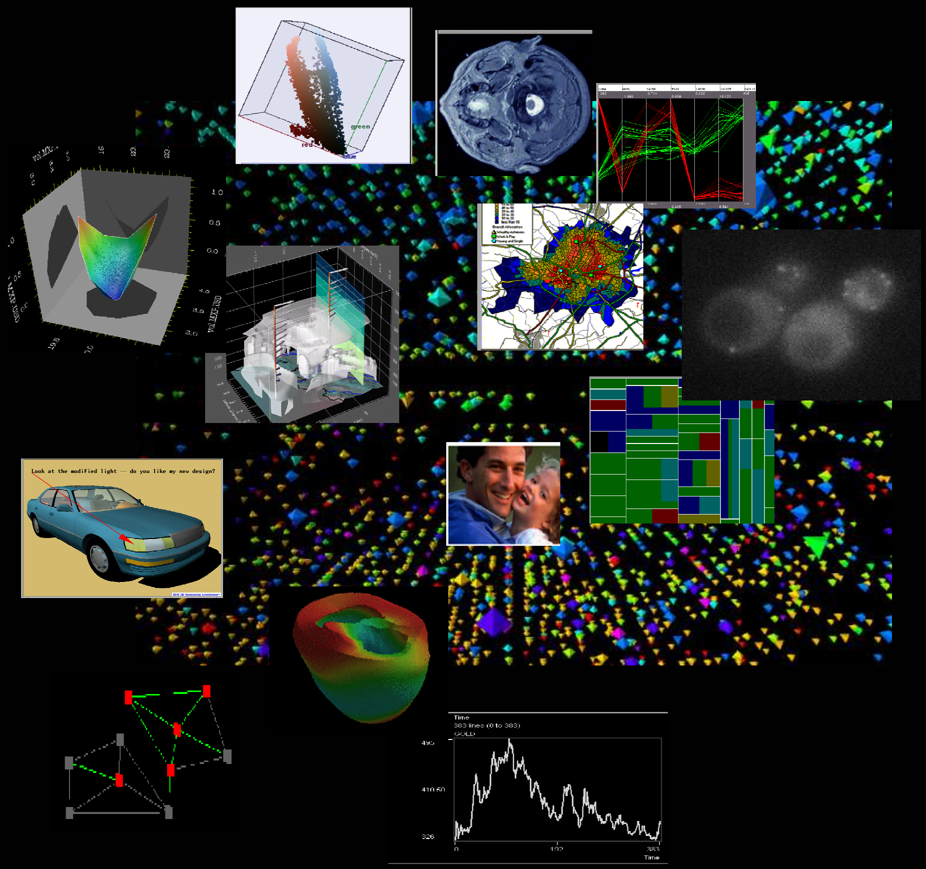

FORM U-1-A MANUFACTURERS' DATA REPORT FOR UNFIRED PRESSURE VESSELS
Alternate Form For Single Chamber Completely Shop Fabricated Vessels Only D-24153
1. Manufactured by Trinity Steel Co., Inc., 4001 Irving Blvd., Dallas, Texas
2. Manufactured for A.R. Gundry, Inc., P.O. Box 4185, Rochester, N.Y.
3. Type Horiz. Vessel No. 95570 Nat'l. Bd. No. 14927 Yr. Built 1964
4. SHELL: Mat'l. Case 1298 FBX T.S. 115,000
5. SEAMS: Long D.B.Welded H.T. Yes X.R. Complte Sectioned No Efficiency 100 %
Girth D.B.Welded H.T. Yes X.R. Complte Sectioned No No. of Courses 4
6. HEADS: (a) Material Case 1298 FBX T.S. 115,000 (b) Material Case 1298 FBX T.S. 115,000
(a) End .250" 42.9" Concave
(b) End .250" 42.9" Concave
If removable, bolts used Other fastening
7. Constructed for max. allowable working press. 250 psi. at max. temp. 115 °F. Hydrostatic Test Press. 500 psi.
8. SAFETY OR RELIEF VALVE OUTLETS: Number 2 Size 3" Location Top centerline shell
9. NOZZLES:
2 2" Insert Case 1298 FBX Special Inherent Welded
2 3" Insert Case 1298 FBX Special Inherent Welded
1 4" Insert Case 1298 FBX Special Inherent Welded
#2 8" Insert Case 1298 FBX Special Inherent Welded

AT GTA CAC CCAG
AA CAC CGA GAAA
CAC CCATGA CGA
AA CACCAC CAAC
CGA ATGAGACCC
CAC AACAACACC
AAACCCATGATG
ATGAA CAC CCAA
C CGA GTA CCCAA
CCA CGA GTA CAA

The New Challenge

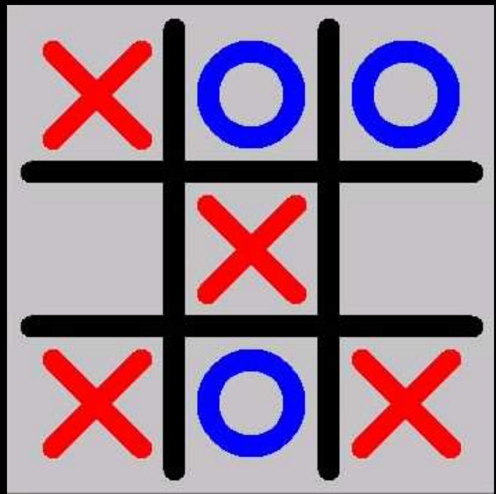
A sea of data drives increased demand for more intuitive tools for searching, retrieving, synthesizing, and understanding data

- For most applications, the key challenge is no longer the bandwidth, storage or processing speed
- The next challenge is in helping people gain insight from the information contained in these data



Matching the Representation to Human Capabilities

- **Humans are not good at computation**



For example, most people cannot complete a game of tic-tac-toe in their heads

Human Capabilities

- **Humans are excellent, however, at**
  - **Problem solving**
  - **Decision-making under uncertainty, interactively**
  - **Developing hypotheses**
  - **Seeing patterns**
  - **Synthesizing information**
- **Data need to be presented to the user in a way that serves and supports these abilities**

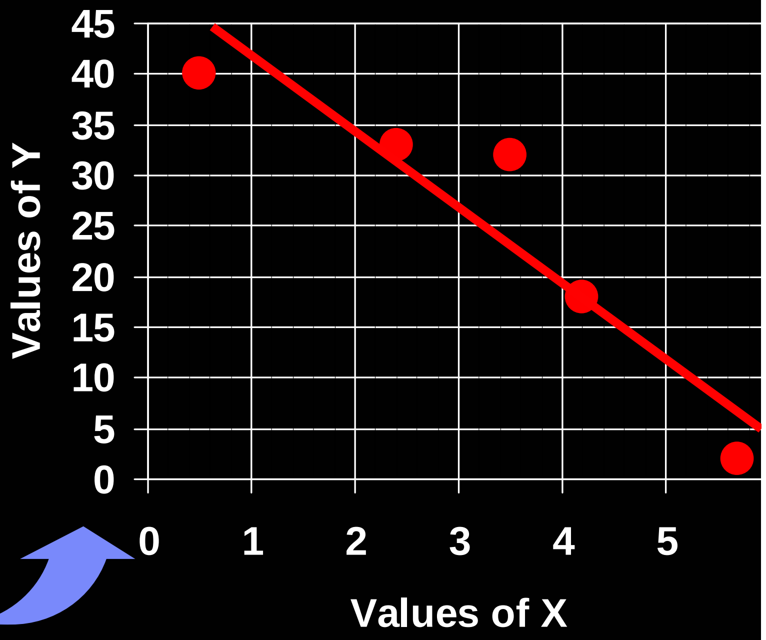
Key technologies for finding patterns, relationships, and meaning in data

- Visualization
- Interactive analysis
- Semantics

The Problem of Finding Meaning in Data is not New
Rene Descartes (1596 – 1650)

Values of X	Values of Y
0.5	40
2.4	33
5.7	2
4.2	18
3.4	32

Insight:
Represent Magnitude as a Distance

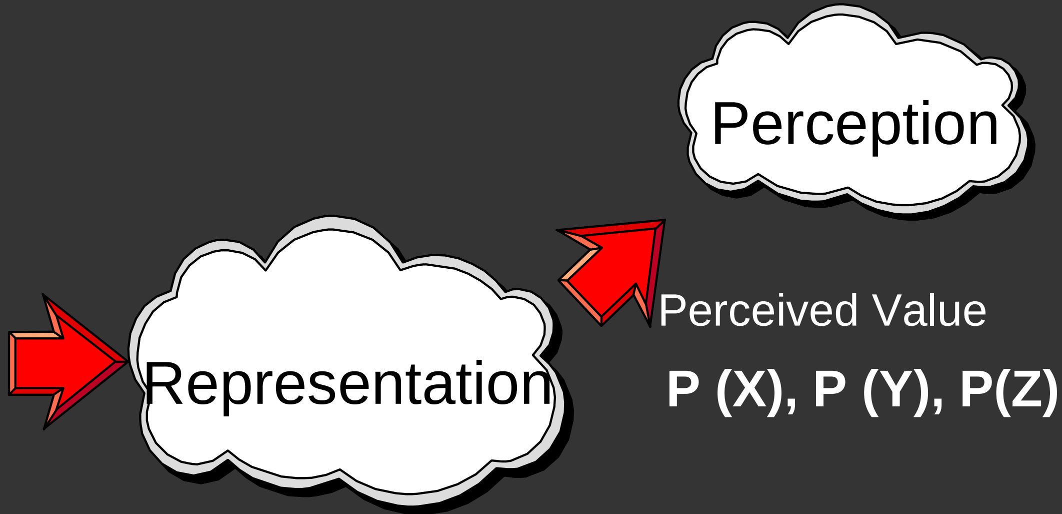


Visualization: Mapping Data onto Visual Dimensions

X Y Z

MXP.USD.Spot	MXP.USD.Vol.	MXP.USD.PnL.
0.119	0.137	1.146E+05
0.118	0.116	-4.871E+04
0.118	0.131	51803.996
0.118	0.133	58951.086
0.119	0.116	-4.610E+04
0.118	0.133	97975.055
0.120	0.128	1.672E+05
0.120	0.134	2.777E+05
0.119	0.126	55082.316
0.118	0.129	46789.574
0.119	0.130	92753.898
0.118	0.117	1977.802
0.120	0.130	1.631E+05
0.119	0.124	3258.141
0.119	0.129	31866.156
0.118	0.135	83336.172
0.118	0.123	13691.148
0.118	0.122	-8446.886
0.118	0.122	46316.340
0.119	0.119	-2.495E+04
0.119	0.124	577.027
0.118	0.127	13503.381
0.118	0.116	-5.126E+04
0.119	0.121	-4996.932
0.119	0.118	-1.944E+04
0.118	0.126	17659.311
0.118	0.120	10601.102
0.120	0.117	54997.785

Monte Carlo Risk Analysis Data



Many visual dimensions

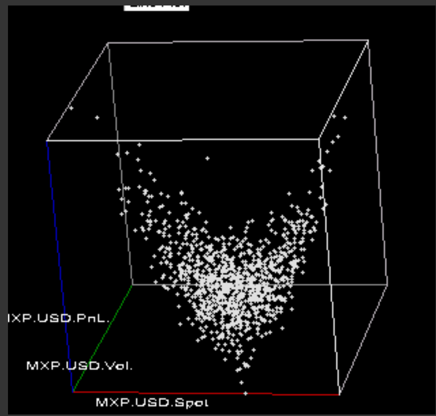
- -Lines, glyphs,
- -Color, grayscale
- -Depth, texture
- -Motion, 3D

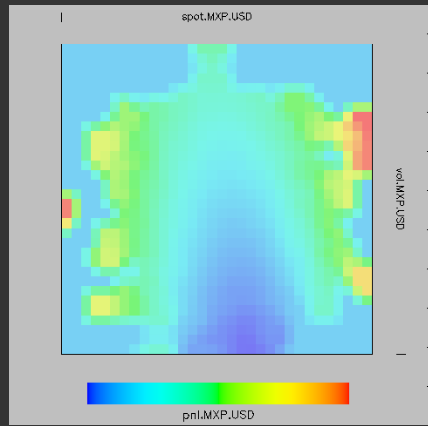
Four Visualizations of the Same Data

X	Y	Z
MXP.USD.Spot	MXP.USD.Vol.	MXP.USD.PnL.
0.119	0.137	1.146E+05
0.118	0.116	-4.871E+04
0.118	0.131	51803.996
0.118	0.133	58951.086
0.119	0.116	-4.610E+04
0.118	0.133	97975.055
0.120	0.128	1.672E+05
0.120	0.134	2.777E+05
0.119	0.126	55082.316
0.118	0.129	46789.574
0.119	0.130	92753.898
0.118	0.117	1977.802
0.120	0.130	1.631E+05
0.119	0.124	3258.141
0.119	0.129	31866.156
0.118	0.135	83336.172
0.118	0.123	13691.148
0.118	0.122	-8446.886
0.118	0.122	46316.340
0.119	0.119	-2.495E+04
0.119	0.124	577.027
0.118	0.127	13503.381
0.118	0.116	-5.126E+04
0.119	0.121	-4996.932
0.119	0.118	-1.944E+04
0.118	0.126	17659.311
0.118	0.120	10601.102
0.120	0.117	54997.785

Monte Carlo Risk Analysis Data

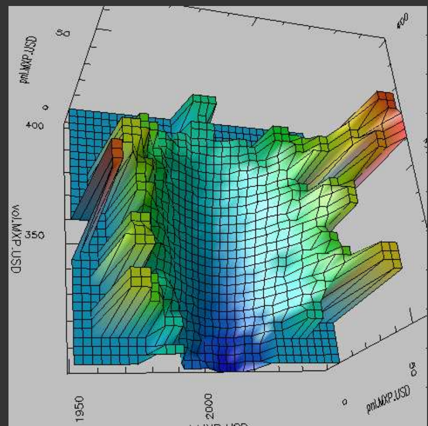
X -> x
Y-> y
Z -> z

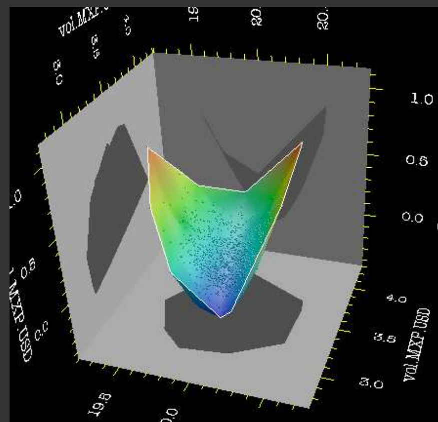




X -> x
Y-> y
Z -> hue

X -> x
Y-> y
interpolated
Z -> hue
and height



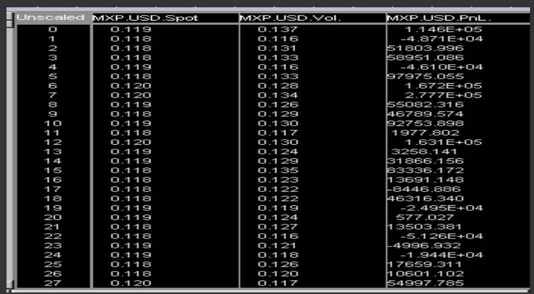


X -> x
Y -> y
Z -> interpol
hue and heig

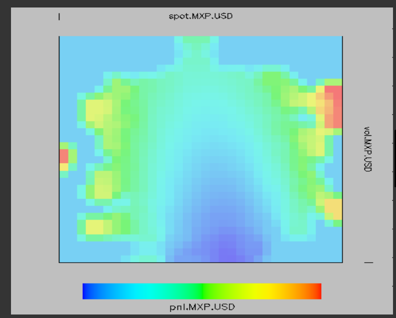
The “right” representation depends on the data, the task and the domain.

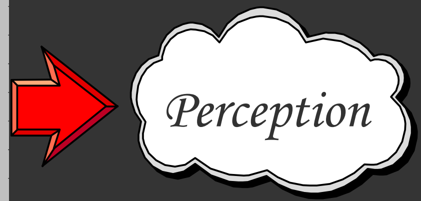
The Representation Problem- faithfully representing the patterns and relationships in the data

X Y Z



Unscaled	MXP.USD.Spot	MXP.USD.Vol.	MXP.USD.PnL.
0	0.119	0.137	1.146E+05
1	0.118	0.116	-4.871E+04
2	0.118	0.131	51803.996
3	0.118	0.133	58951.086
4	0.119	0.116	-4.610E+04
5	0.118	0.133	97975.055
6	0.120	0.128	1.672E+05
7	0.120	0.134	2.777E+05
8	0.119	0.126	55082.316
9	0.118	0.129	46789.574
10	0.119	0.130	92753.898
11	0.118	0.117	1977.802
12	0.120	0.130	1.631E+05
13	0.119	0.124	3258.141
14	0.119	0.129	31866.156
15	0.118	0.135	83336.172
16	0.118	0.123	13691.148
17	0.118	0.122	-8446.886
18	0.118	0.122	46316.340
19	0.119	0.119	-2.495E+04
20	0.119	0.124	577.027
21	0.118	0.127	13503.381
22	0.118	0.116	-5.126E+04
23	0.119	0.121	-4996.932
24	0.119	0.118	-1.944E+04
25	0.118	0.126	17659.311
26	0.118	0.120	10601.102
27	0.120	0.117	54997.785

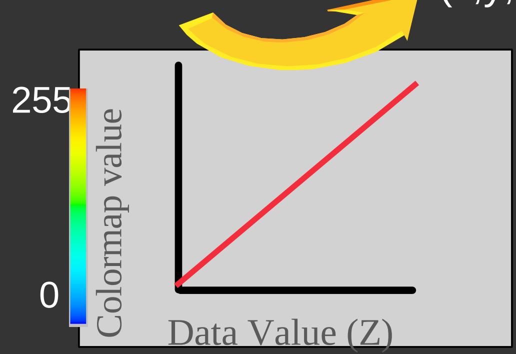


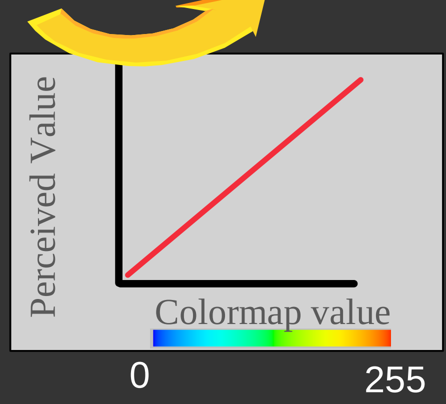


Representation Value (x,y,z)

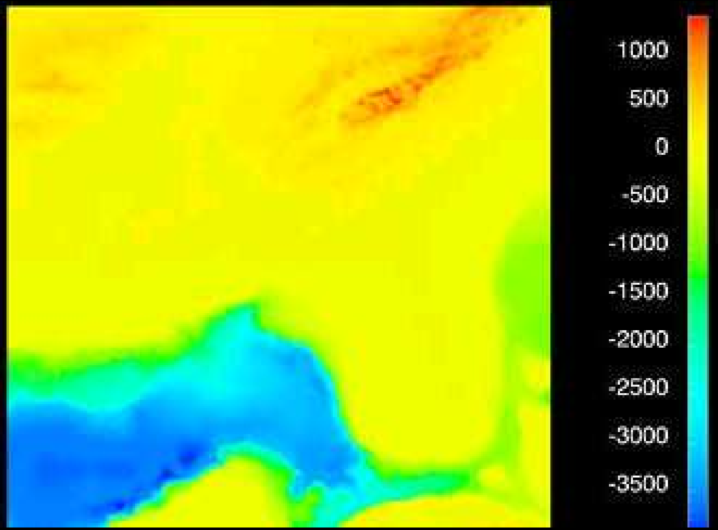
Perceived Value

P (X), P (Y), P(Z)

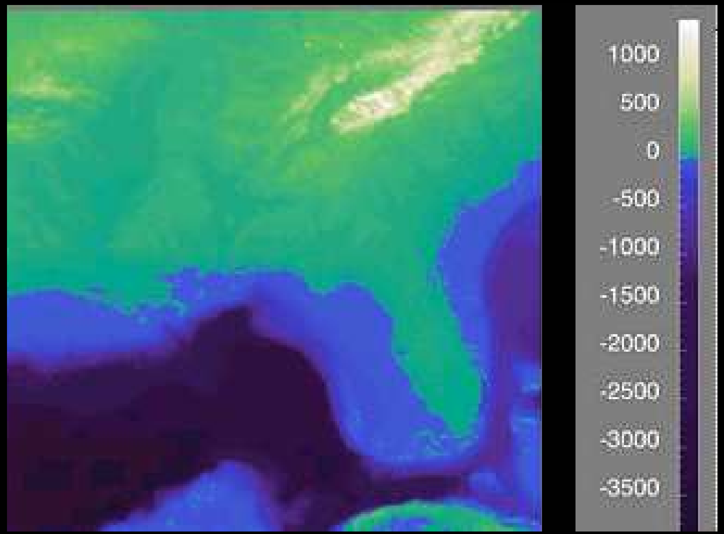




Example



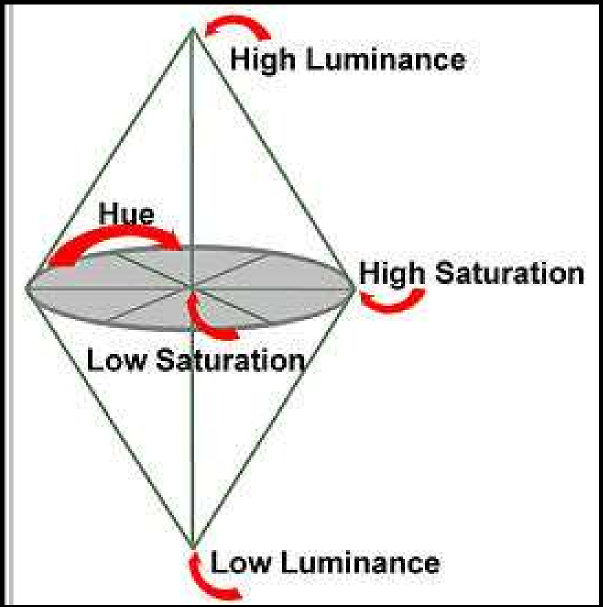
Rainbow Colormap



"Perceptual"Colormap

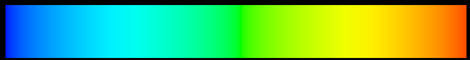
In the standard “Rainbow” color map, equal steps in the magnitude of the data do not look equal in the representation.

Color Perception Experiments test the degree to which different trajectories in 3-D color space convey magnitude information



HLS "Doublecone" colorspace

Hue trajectory



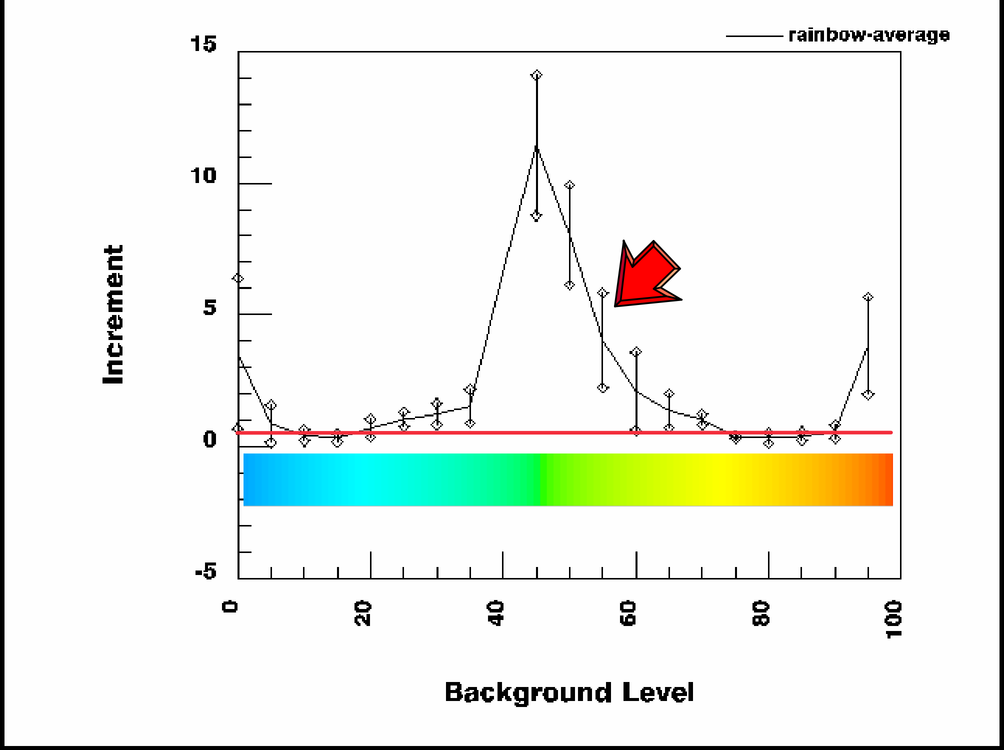
Luminance trajectory

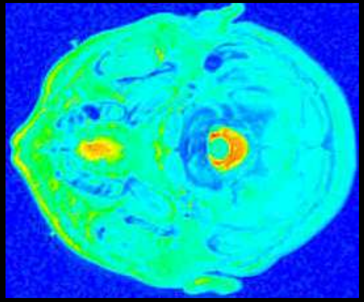
Saturation trajectory

Rainbow Color Map Result

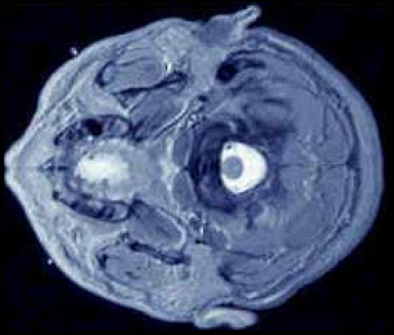
Hue-based colormaps did not provide good magnitude scales

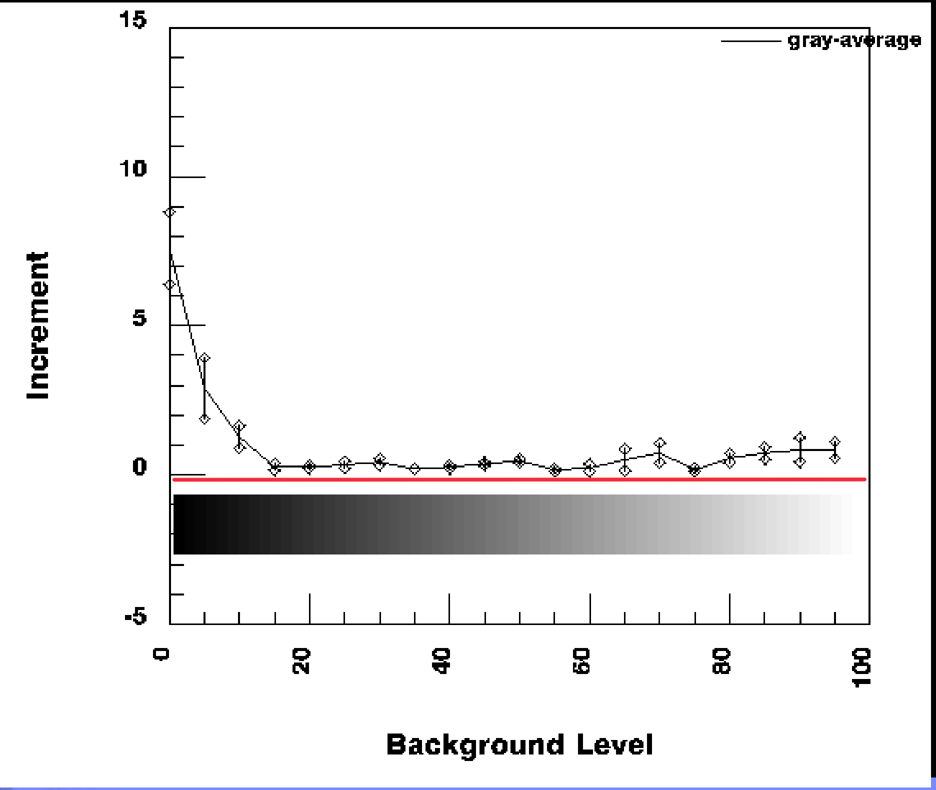
Over most of the range, equal steps in data value did not produce equal steps in perceived magnitude





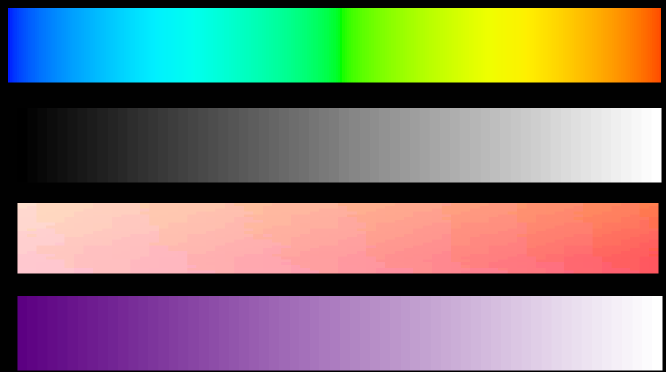
Recommendation: Monotonic Luminance Component for Representing Magnitude





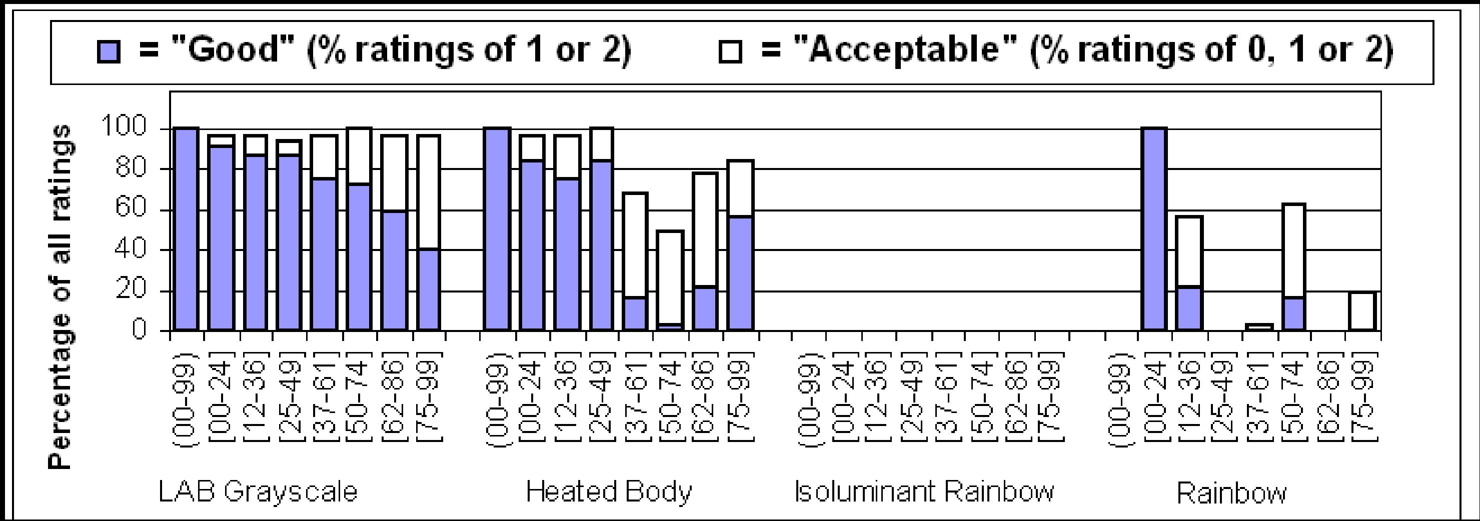
The Which Blair Project: a calibration-free method for identifying colormaps with a monotonic luminance component

Map color maps onto a photographic image of a human face.



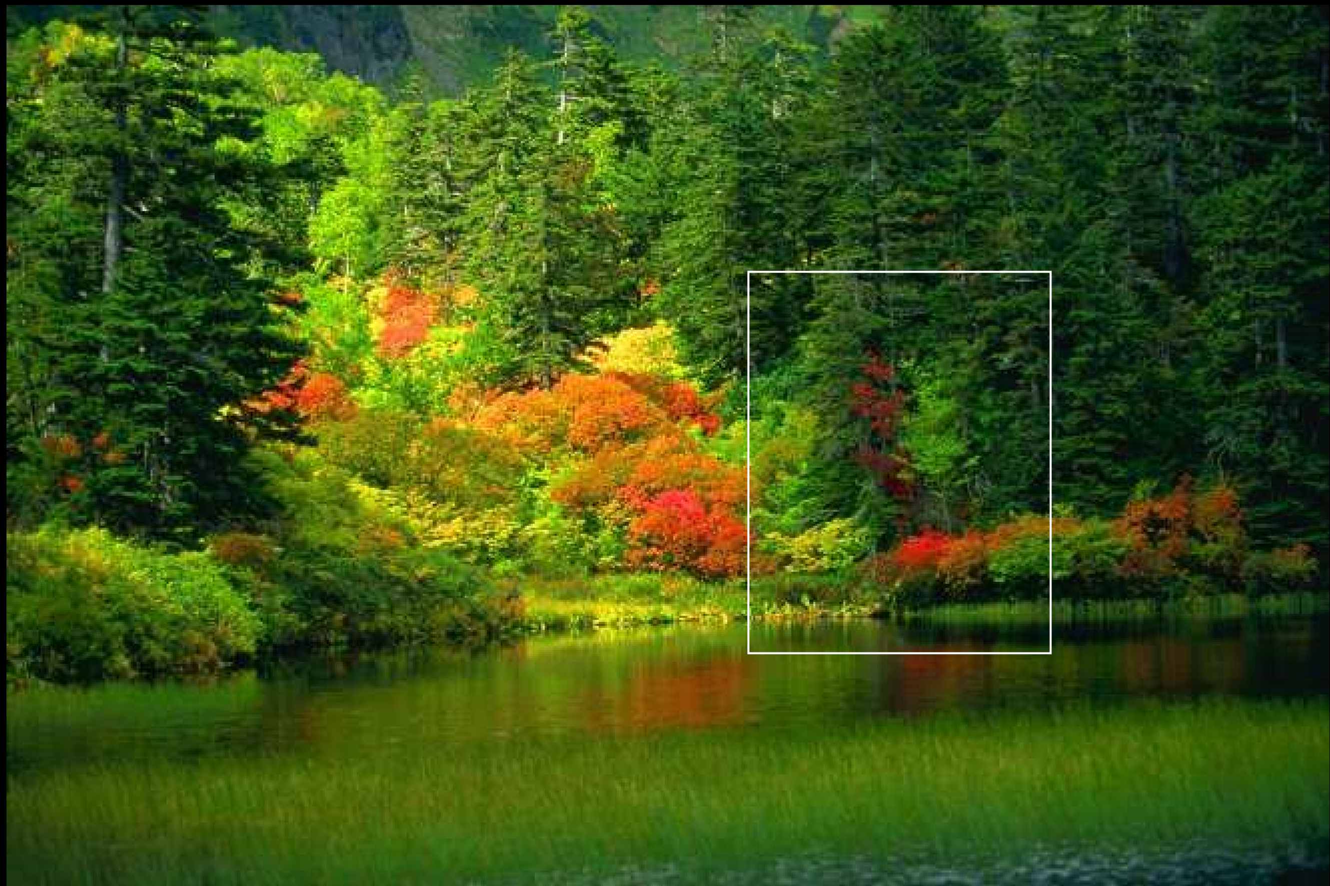
Rogowitz and Kalvin, IEEE Visualization, 2001

Perceptual Data

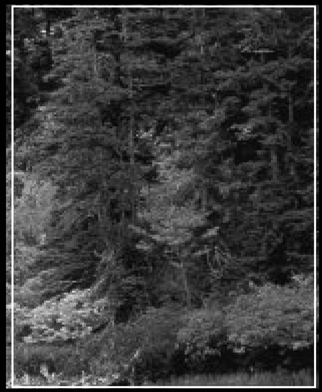


Using Color to draw attention and mark semantic regions

Using Color to highlight semantics

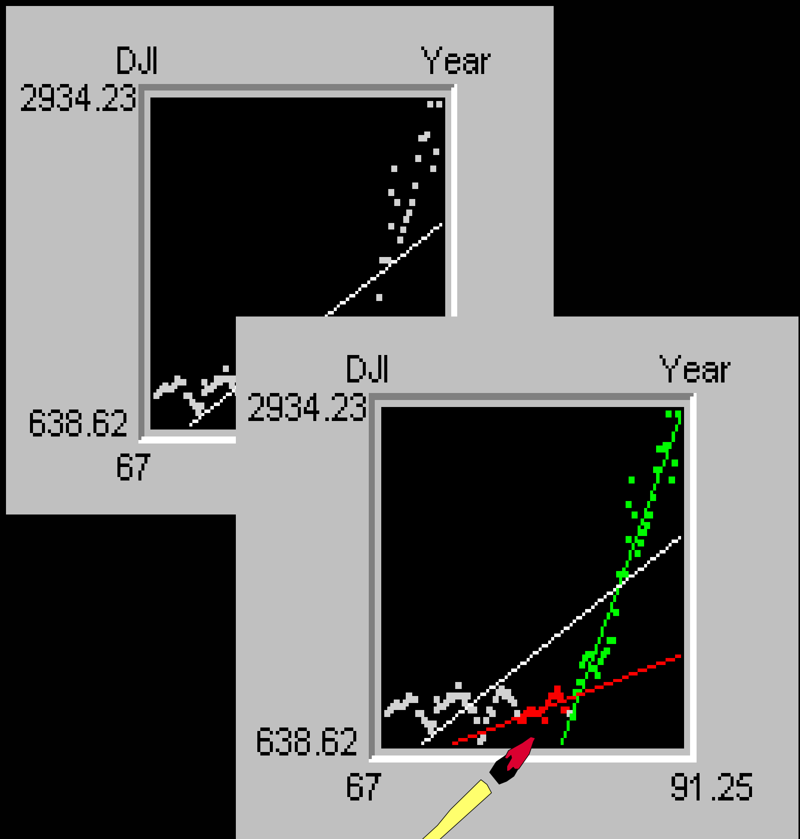


… a closer look

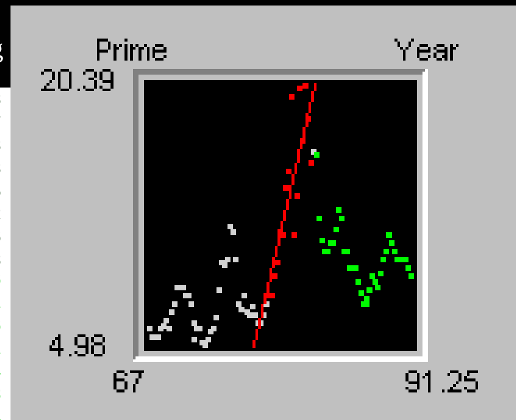


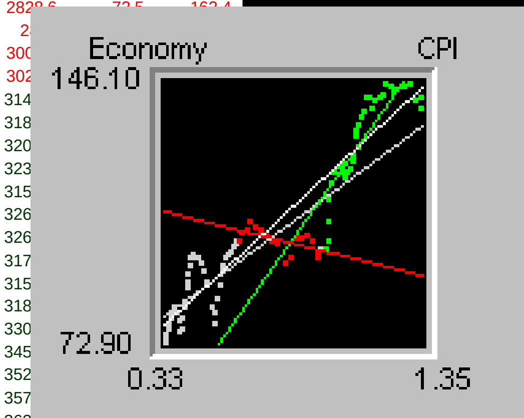
Interactive Visual Exploration

Using Color "Brushing" to help reveal linkages



Year	pop	dji	auto	housing		
67	197.892	0.329	24.165	2241.8		
67.5	198.911	0.334	24.662	2287.7		
68	199.92	0.341	25.818	2327.3		
68.5	200.898	0.349	27.661	2385.3		
69	201.881	0.357	28.784	2416.5		
69.5	202.877	0.368	29.037	2433.2		
70	204.008	0.379	30.449	2408.6		
70.5	205.295	0.389	31.573	2435.8		
71	206.668	0.399	32.893	2478.6		
71.5	207.881	0.406	34.431	2491.1		
72	209.061	0.412	35.762	2545.6		
72.5	210.075	0.418	38.033	2622.1		
73	211.12	0.427	41.542	2734		
73.5	212.092	0.442	42.542	2738.3		
74	213.074	0.468	43.211	2747.4		
74.5	214.042	0.493	46.062	2719.3	73.6	130.2
75	215.065	0.523	46.505	2642.7	66.3	124.8
75.5	216.195	0.54	49.618	2714.9	65.7	140
76	217.249	0.558	52.886	2804.4	69.9	156.4
76.5	218.233	0.57	54.991	2828.6		
77	219.344	0.587	56.999	2		
77.5	220.458	0.608	60.342	300		
78	221.629	0.627	61.24	302		
78.5	222.805	0.655	67.136	314		
79	224.053	0.685	71.174	318		
79.5	225.295	0.73	73.667	320		
80	226.656	0.78	79.407	323		
80.5	227.94	0.826	79.311	315		
81	229.054	0.872	84.943	326		
81.5	230.168	0.915	86.806	326		
82	231.29	0.944	85.994	317		
82.5	232.378	0.975	88.977	315		
83	233.462	0.979	91.607	318		
83.5	234.49	0.998	98.885	330		
84	235.525	1.021	105.133	345		
84.5	236.548	1.041	106.781	352		
85	237.608	1.057	110.393	357		
85.5	238.68	1.077	114.419	3635.8	94.1	387.2
86	239.794	1.099	118.477	3721.1	96.1	381.8
86.5	240.862	1.095	119.593	3712.4	94.8	426.4
87	241.943	1.115	119.247	3781.2	96.5	403.3
87.5	243.03	1.139	129.921	3858.9	100.8	441.3

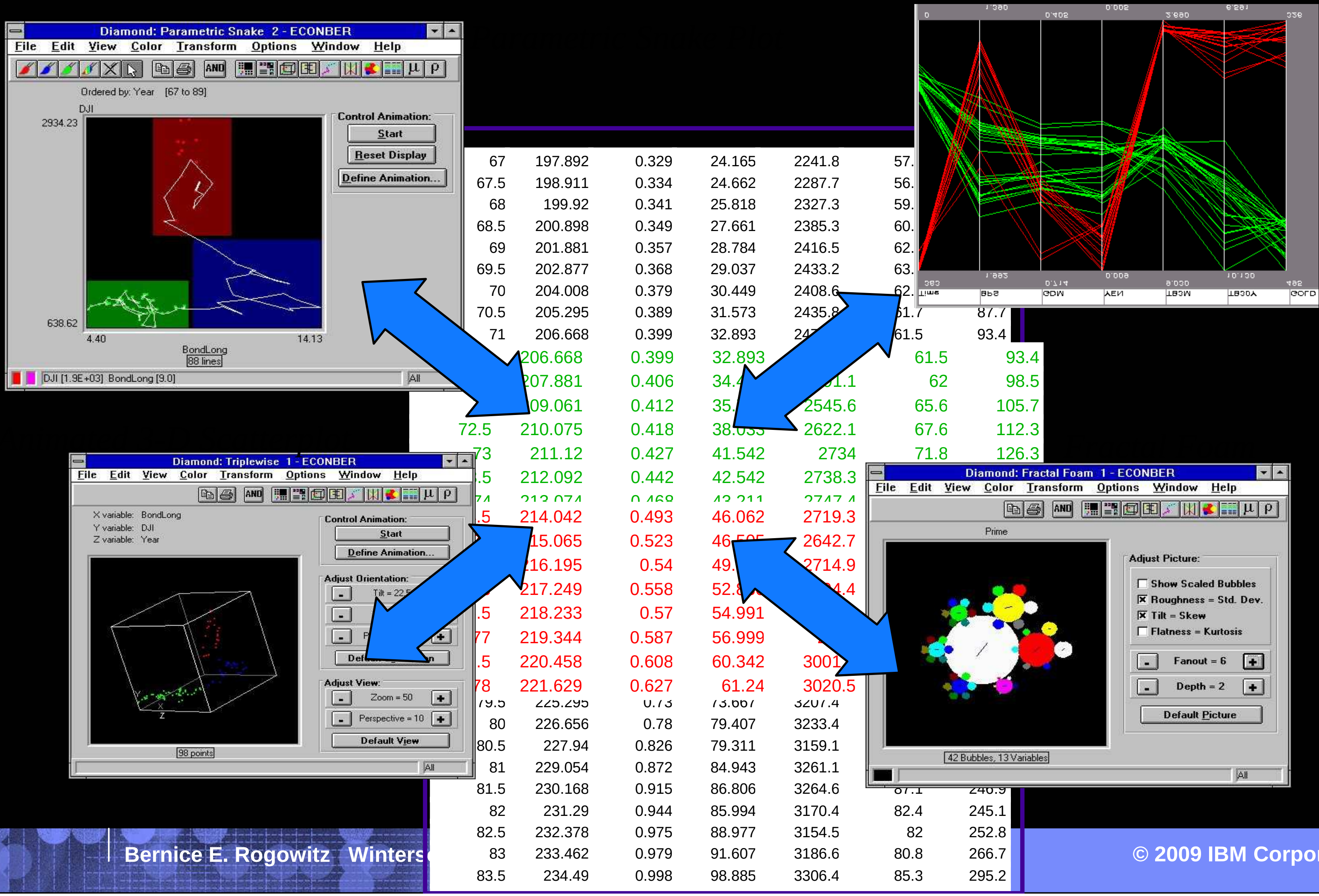




helps users explore features in high-dimensional data

Diamond

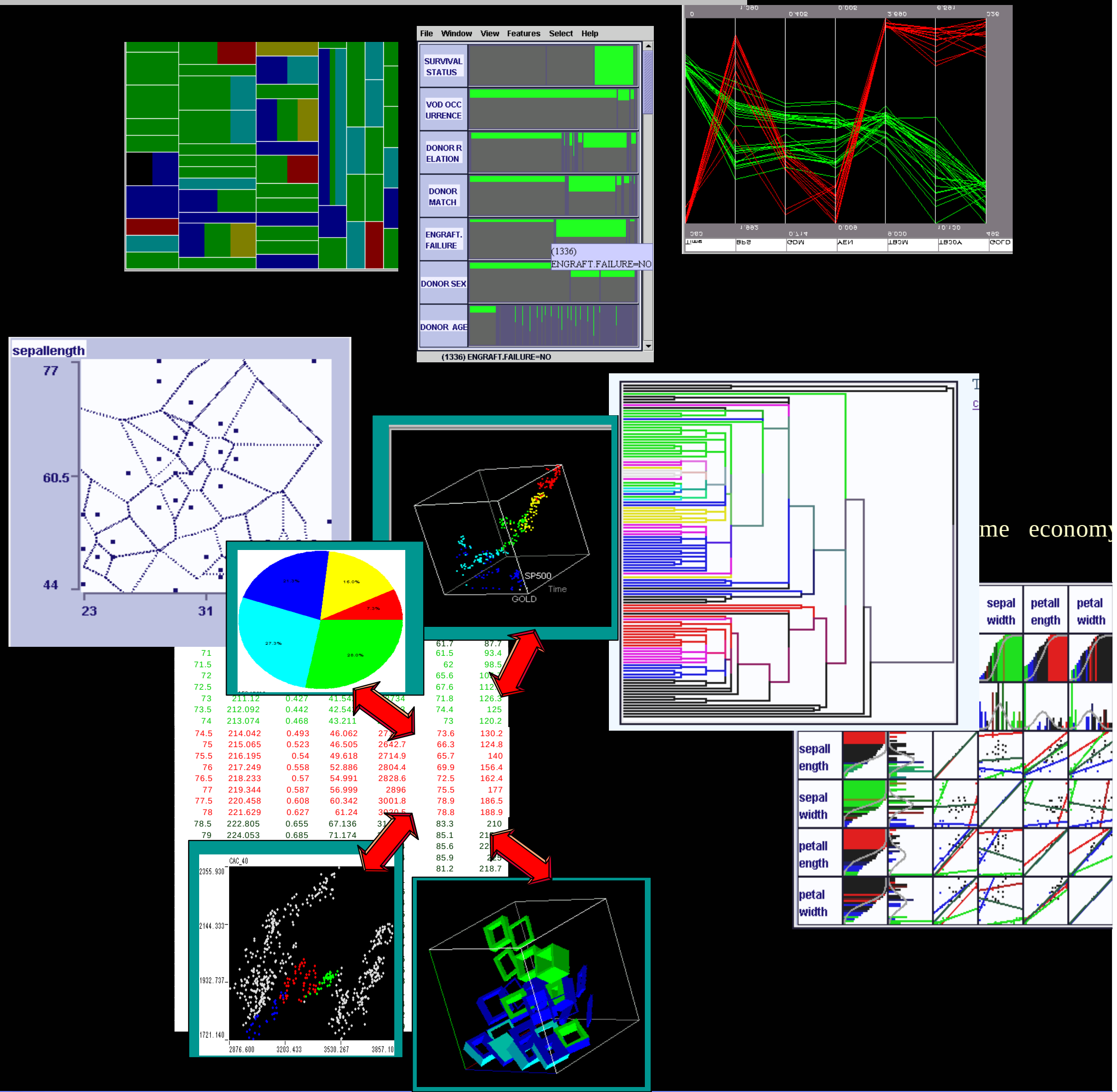
Dynamic linking ("brushing" between different data representations)



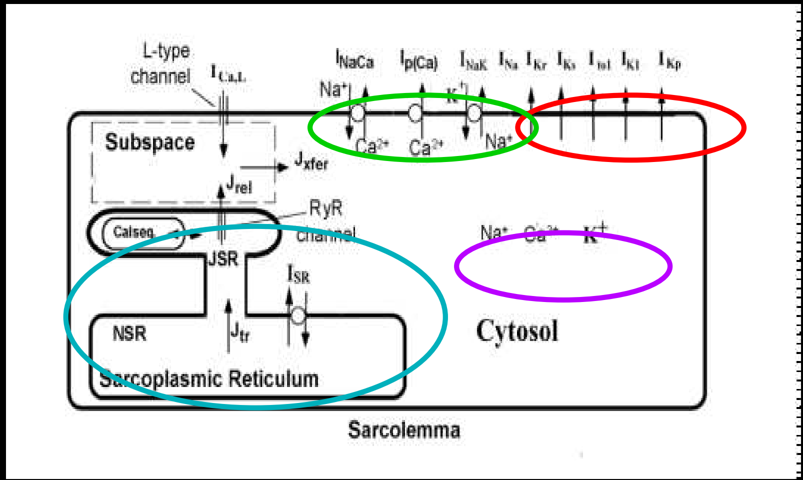
ViVA (Visualization and Visual Analysis) Workbench)

http://www.alphaworks.ibm.com/tech/viva

- JAVA/ Client server visualization and analysis engine and analysts' workbench
- Interactive analysis supports over a million rows of data
- 20 interactive visualizations
- Over 250 math functions and data handling operations



Model of a Single Heart Cell



Model Parameters:

- voltage-gated membrane currents
- voltage and/or concentration dependent membrane transporters
- mechanisms for sequestration and release of calcium within the cell
- time-varying intracellular concentrations of sodium, calcium, and potassium.

Heartbeat 101:

1. Calcium stimulates muscle contraction
2. Potassium currents restore the membrane potential to its resting value

Example: Finite Element Heart Excitation Model

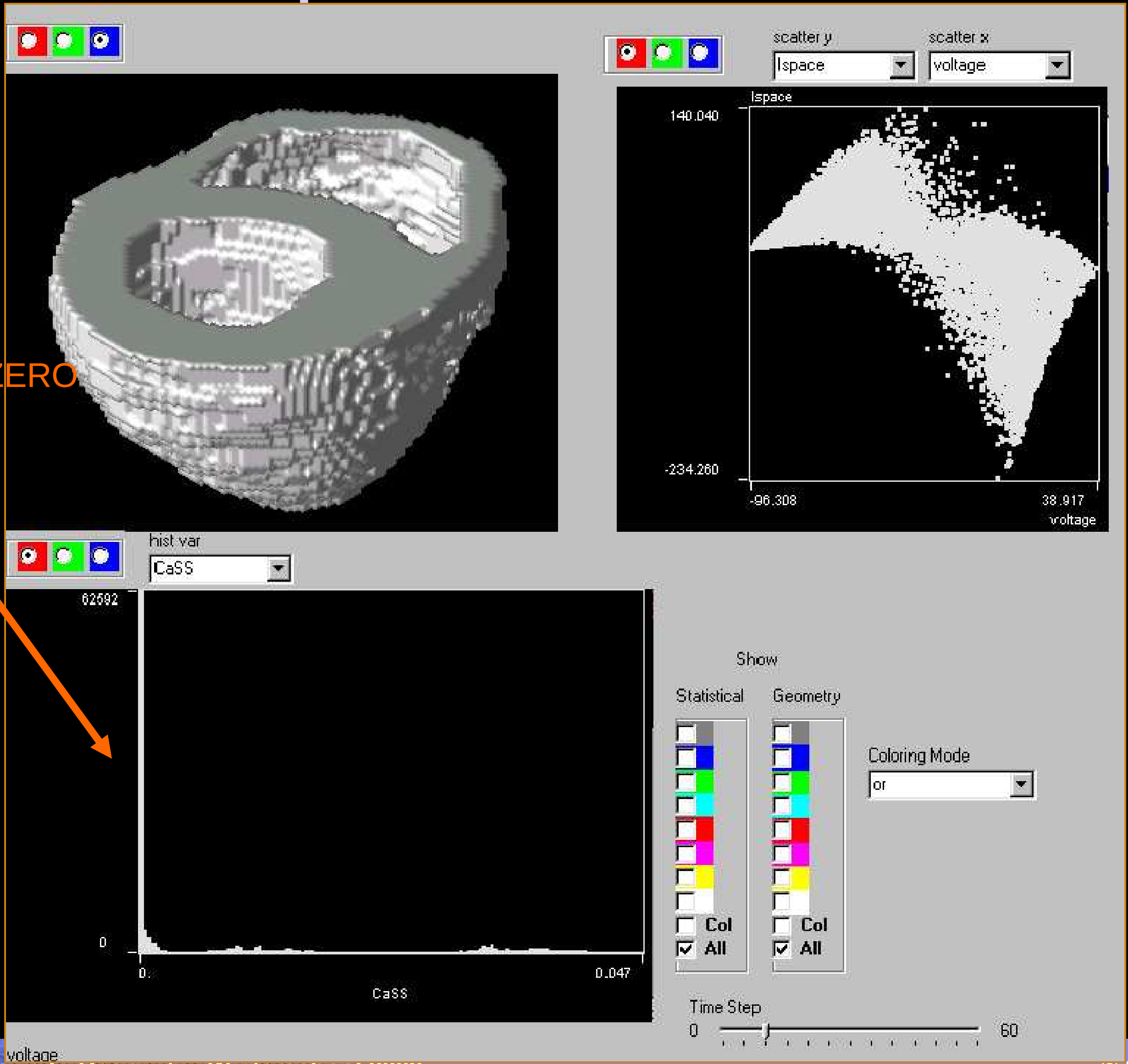
- 3D computational model for investigating heart disease.
- 150,000 nodes.
- Multiple simulation parameters at each node, 60 time steps.

V	Cai	CaNSR	CaSS	IKr	Iks	Im
67.5	198.911	0.334	24.662	2287.7	56.5	71.3
68	199.92	0.341	25.818	2327.3	59.4	77.3
68.5	200.898	0.349	27.661	2385.3	60.7	83.6
69	201.881	0.357	28.784	2416.5	62.6	85.8
69.5	202.877	0.368	29.037	2433.2	63.9	86.4
70	204.008	0.379	30.449	2408.6	62.1	85.4
70.5	205.295	0.389	31.573	2435.8	61.7	87.7
71	206.668	0.399	32.893	2478.6	61.5	93.4
71.5	207.881	0.406	34.431	2491.1	62	98.5
72	209.061	0.412	35.762	2545.6	65.6	105.7
72.5	210.075	0.418	38.033	2622.1	67.6	112.3
73	211.12	0.427	41.542	2734	71.8	126.3
73.5	212.092	0.442	42.542	2738.3	74.4	125
74	213.074	0.468	43.211	2747.4	73	120.2

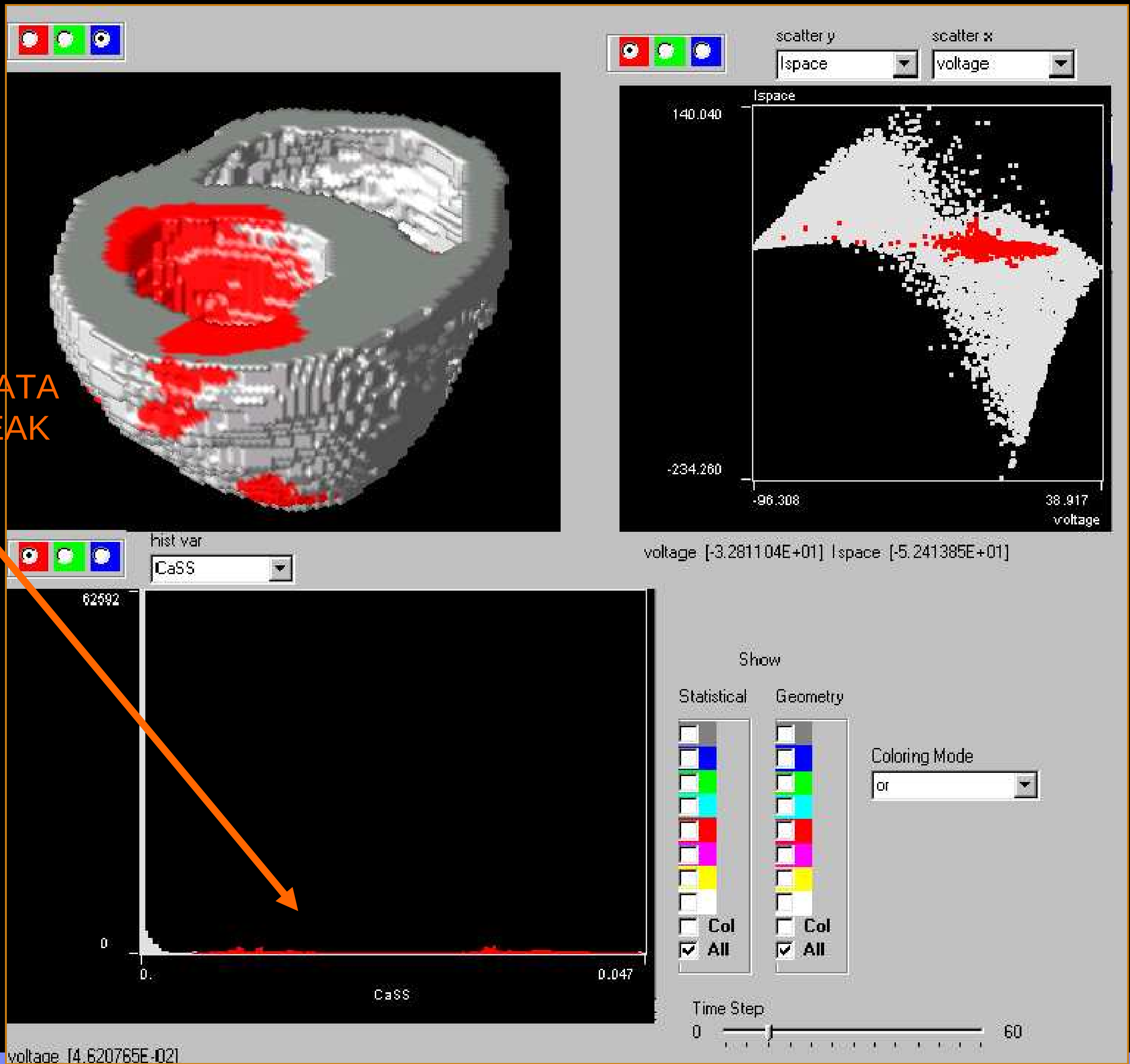
Gresh, Rogowitz, Winslow, et al, 2000
Winslow, et al, 2000
Collaboration with Johns Hopkins University

Interactive Data Exploration, linking numerical parameters and 3-D geometric representation

LARGE PEAK AT ZERO

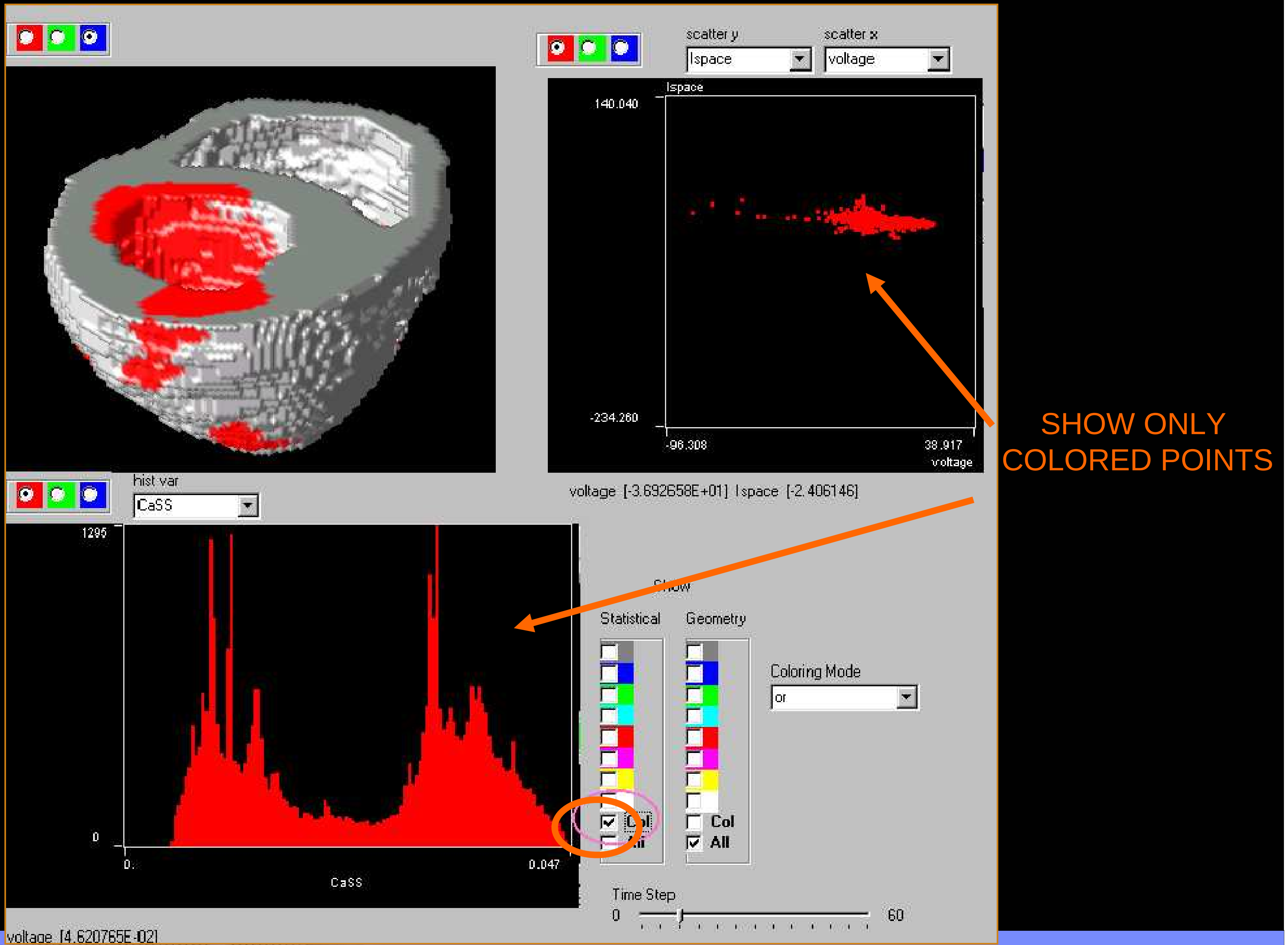


Interactive Data Exploration, linking numerical parameters and 3-D geometric representation



COLOR ONLY DATA ABOVE THE PEAK

Interactive Data Exploration, linking numerical parameters and 3-D geometric representation



Interactive Data Exploration, linking numerical parameters and 3-D geometric representation

COLOR PEAKS DIFFERENTLY

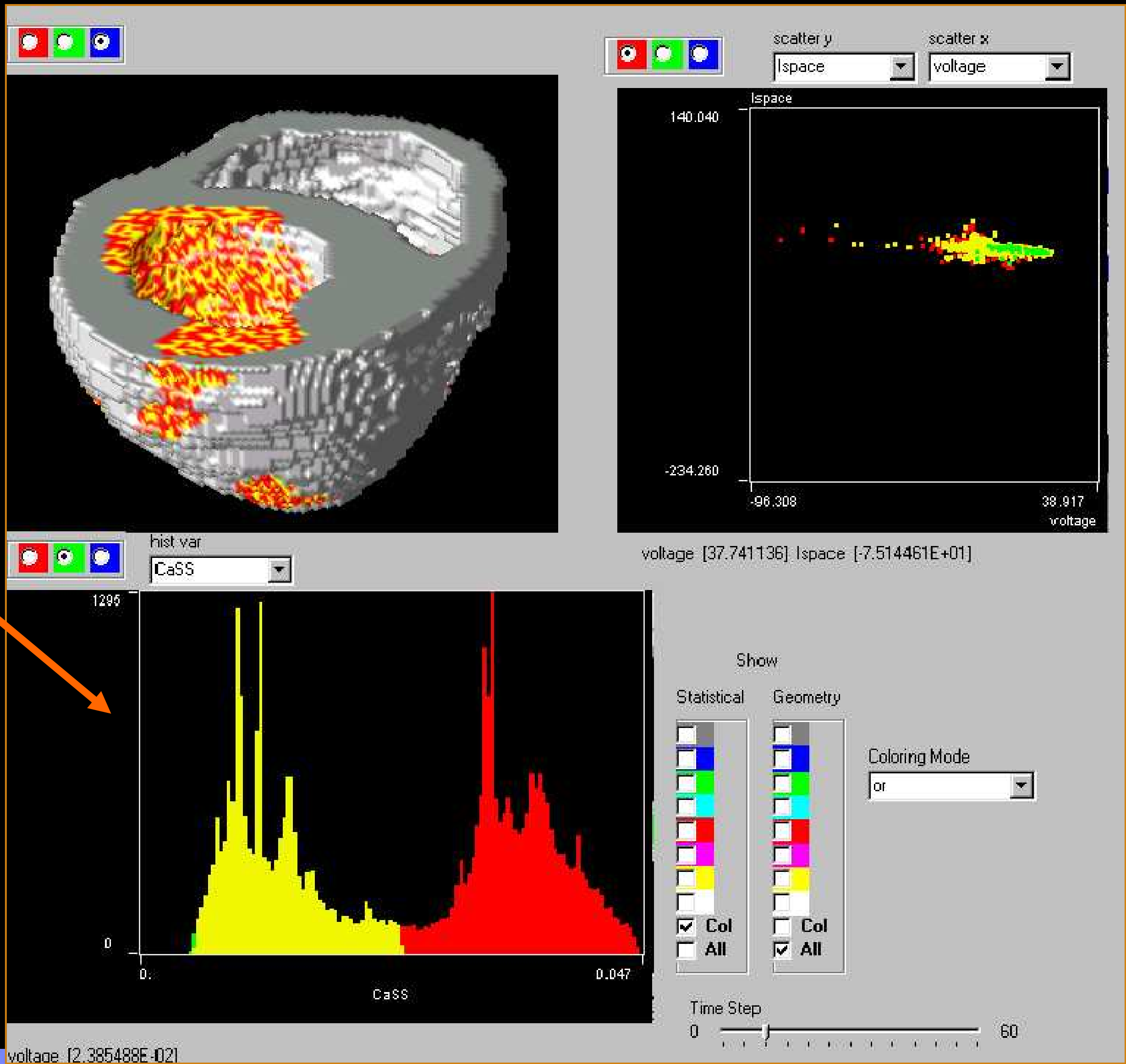


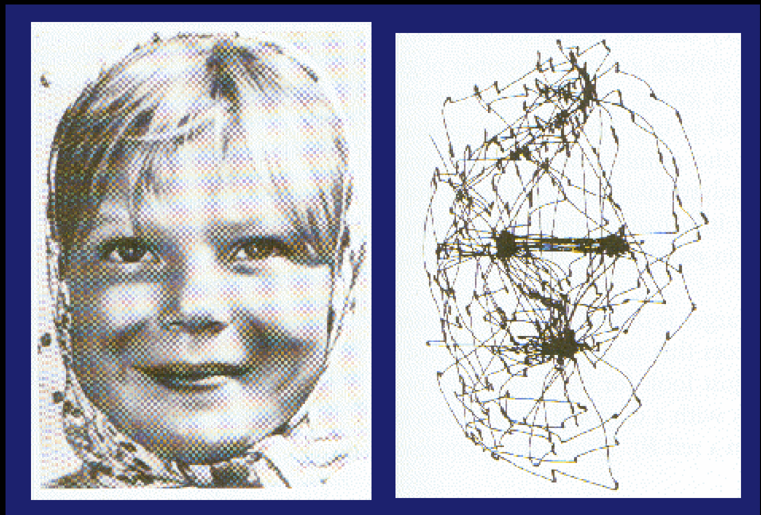
Image Semantics

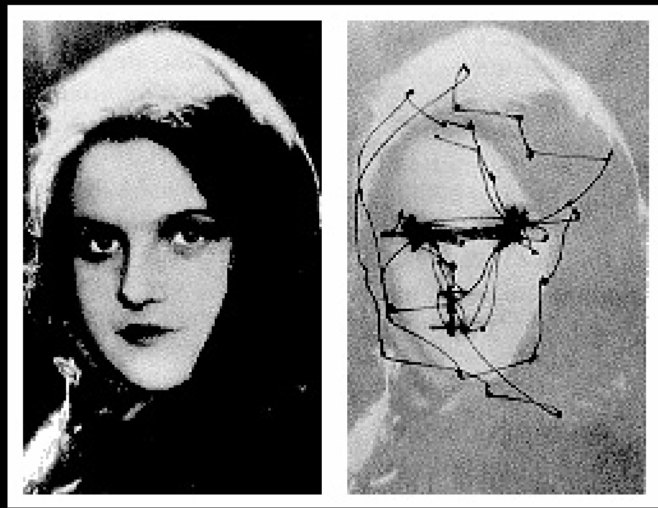
How do we capture the semantic meaning of an image?

- Standard method
  - •Extract large numbers of measurable features
  - •Create a vector of features for each image
  - •Use learning methods to identify those features that correlate with a semantic meaning (e.g., restaurant; grandma playing piano)
- Perceptual method
  - •First, identify how humans judge images
  - •Use human judgments to define the salient features
  - •Perceptually-relevant metadata

Yarbus

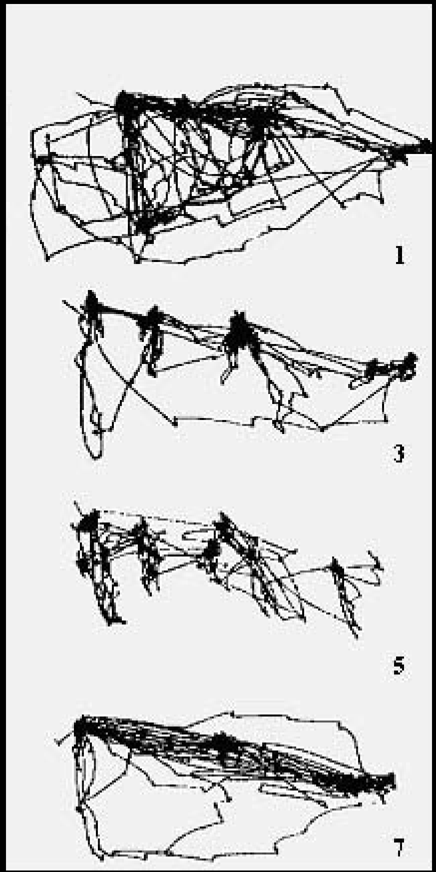
Eye-movements reveal what we look at; what we pay attention to…





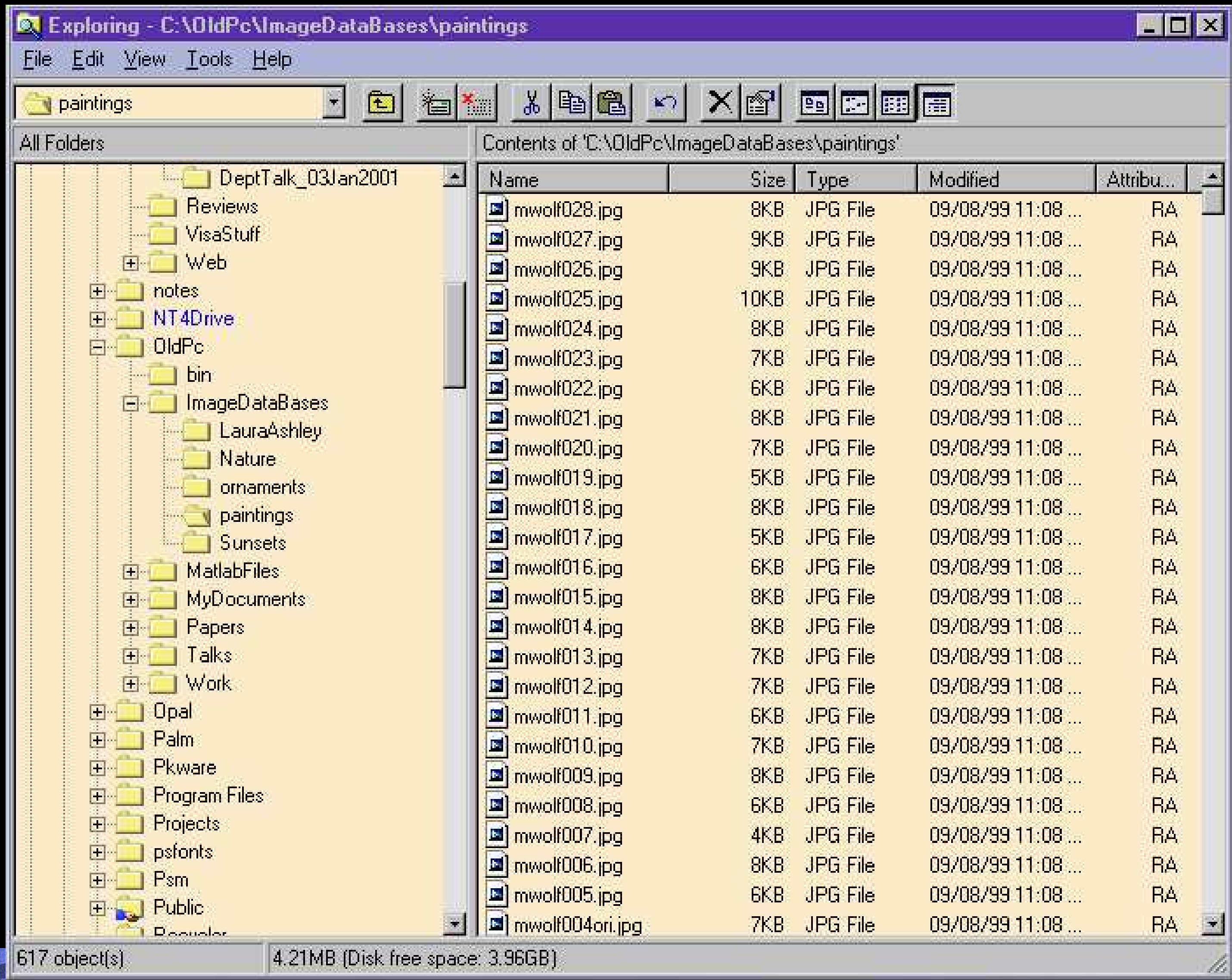
Perception is not based on a complete description of reality. We sample the information we need.

Eye-movements depend on the task



… there is no universal set of metadata

Image Navigation… this is my image directory

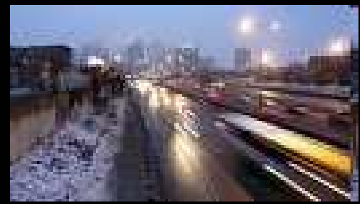


Standard Image Viewer

Goal: to categorize images semantically

Image Retrieval

Query

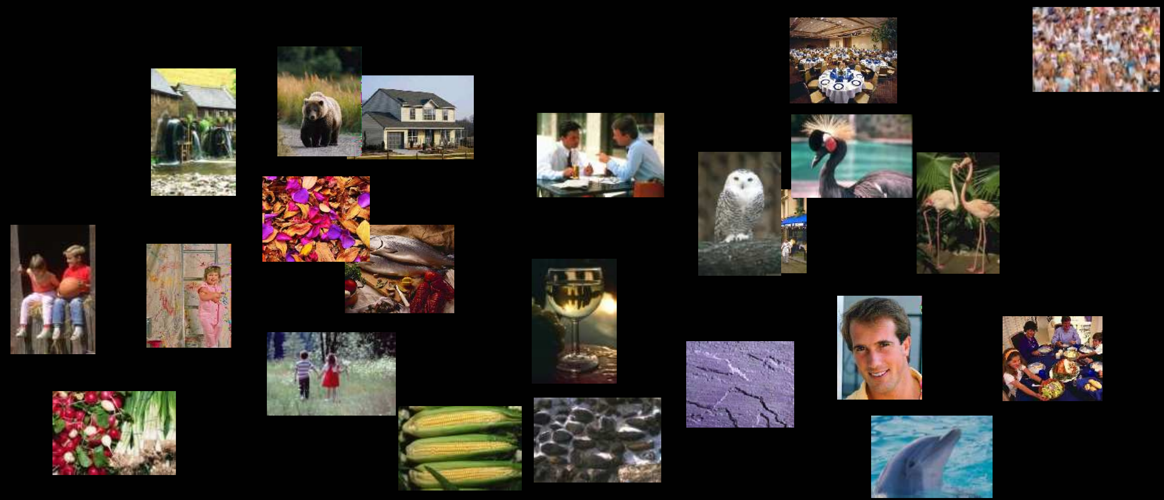


Typical features include:

- color,
- texture features,
- shape descriptors,
- edge distribution and
- their combinations.

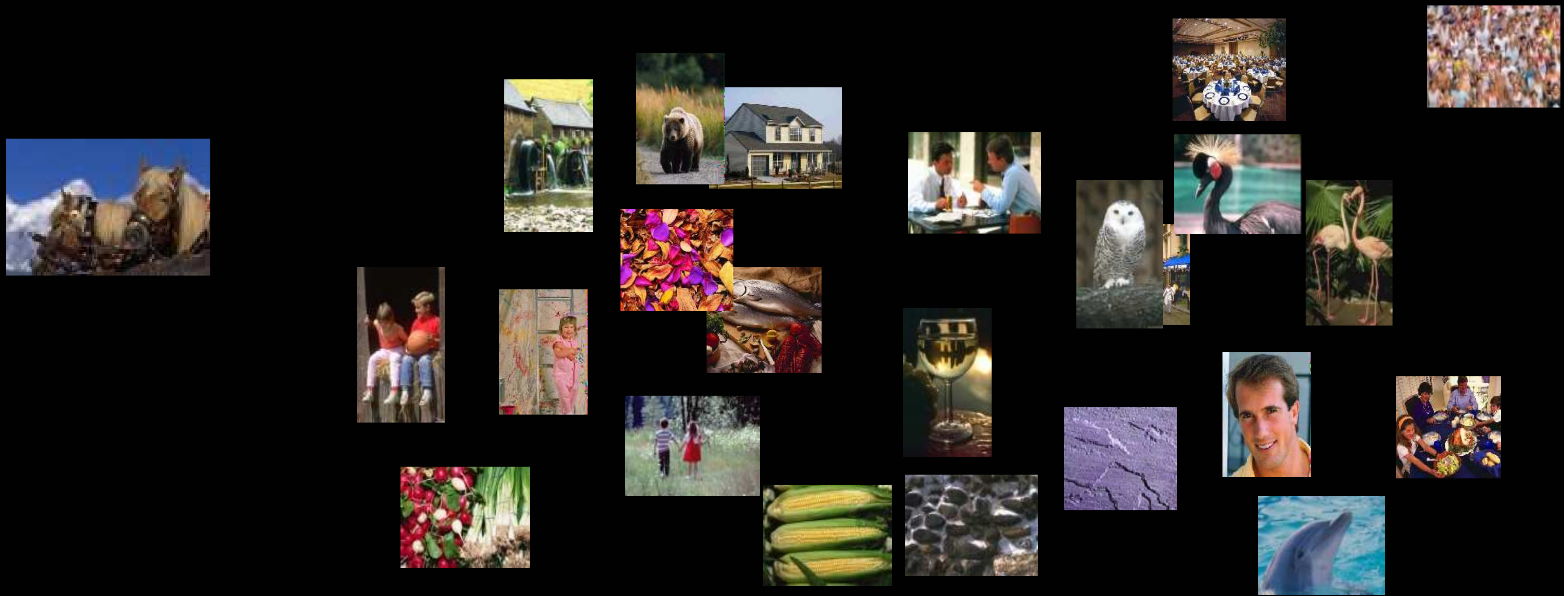
Our Approach

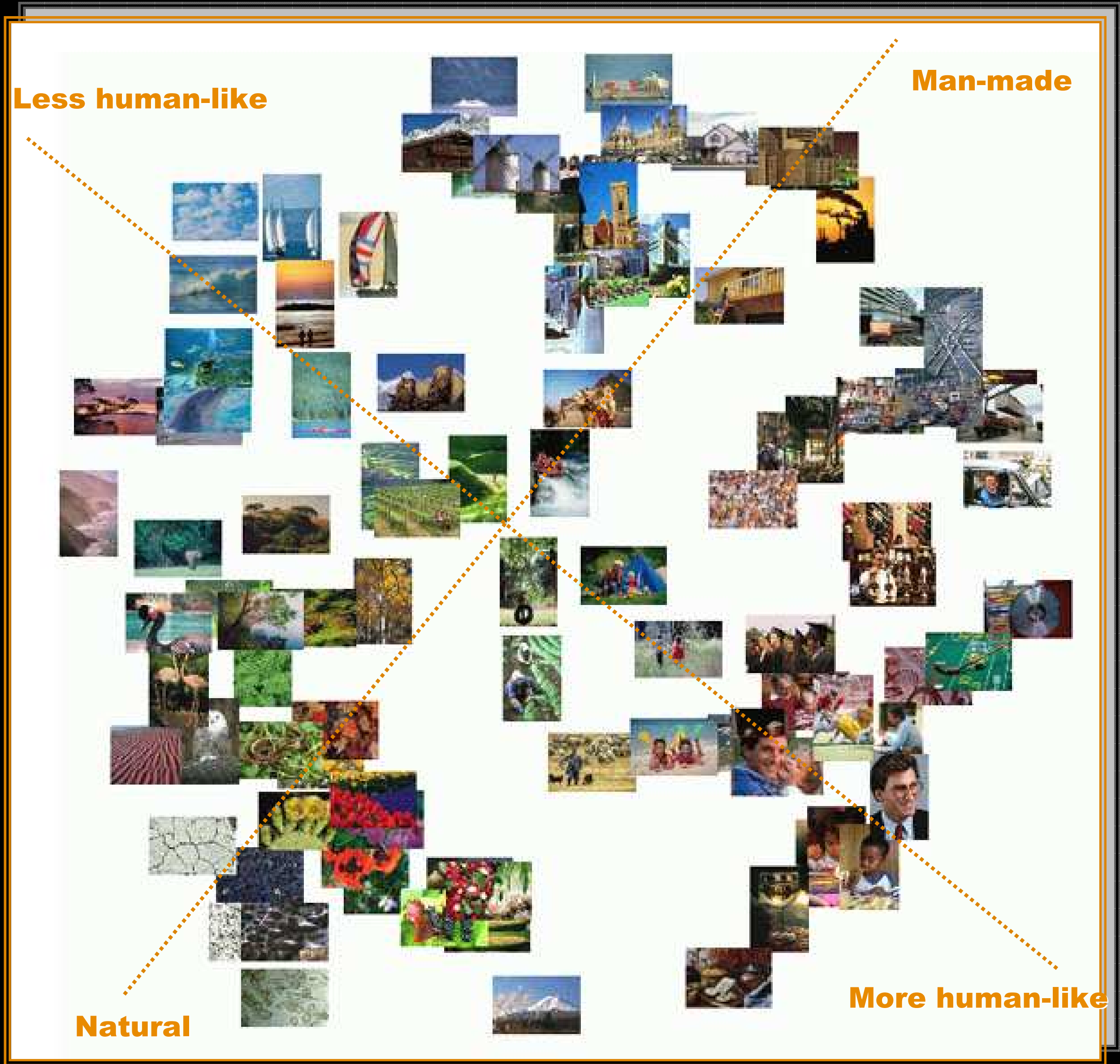
- Conduct Perceptual Experiments to understand how human observers perceive images
- Use perceptual dimensions to construct a library of perceptual features (metadata)
- Develop algorithms that use these PERCEPTUAL features for image search, retrieval, and navigation
- Build a search tool



Step 1: image similarity experiments

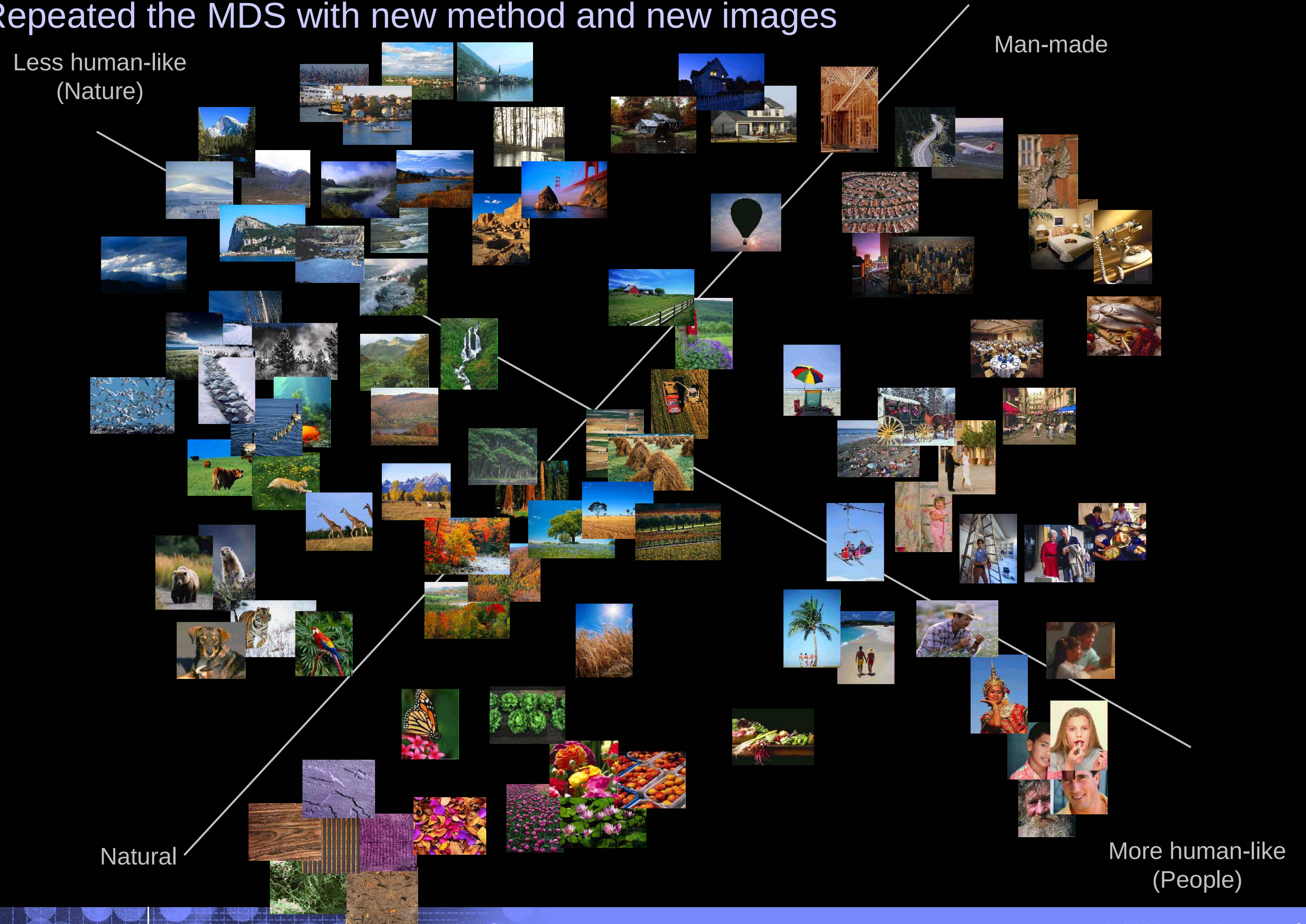
Each image compared with all other images to create a 100 x 100 similarity matrix



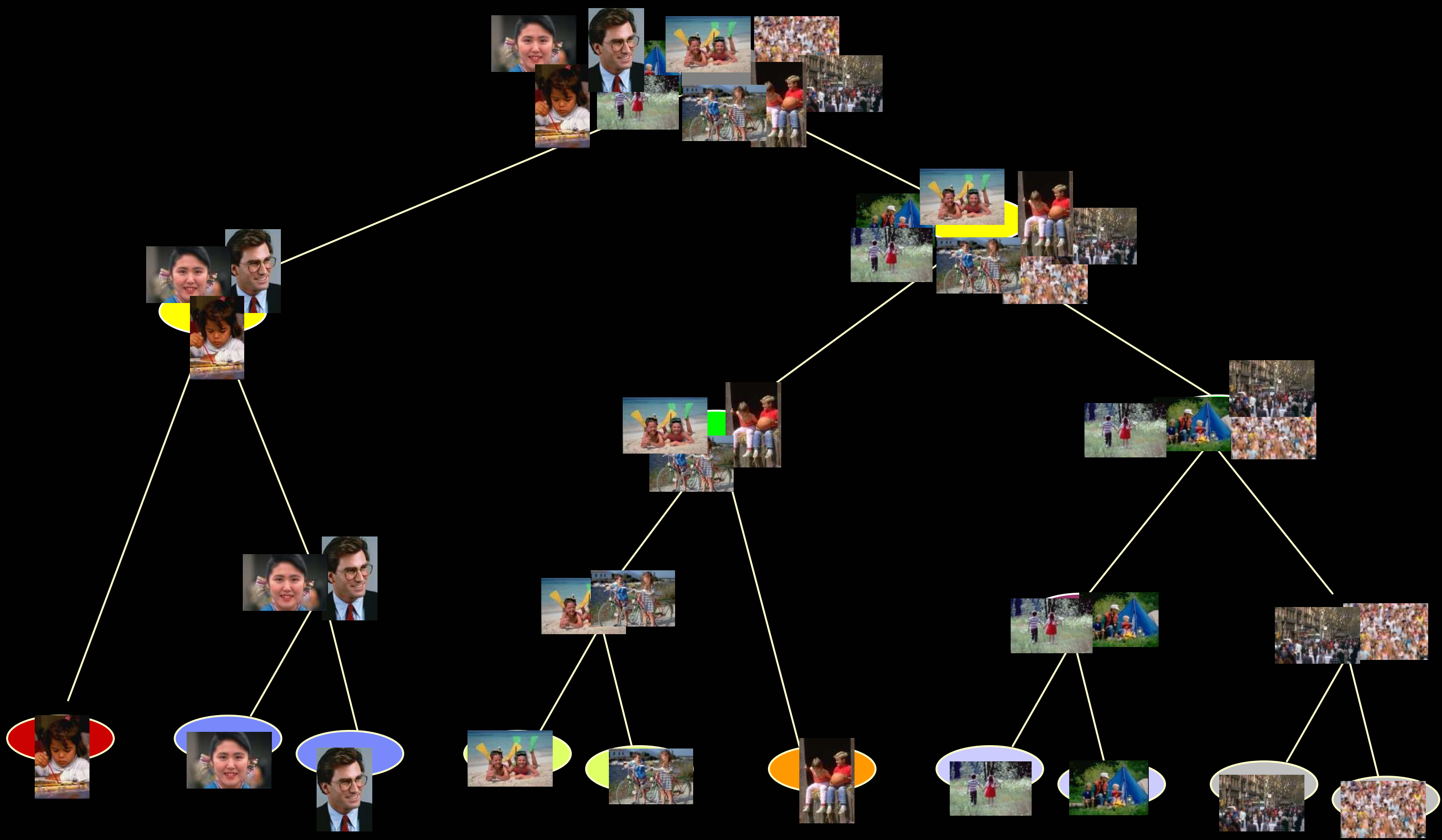


Rogowitz and Frese, 2000

Repeated the MDS with new method and new images



Hierarchical Cluster Analysis to Identify Perceptual Clusters



Mojsilovic and Rogowitz, 2001

20 categories

Experiment to Reveal Category Semantics

C18

Category name:

Description and main characteristics of the category:

Resulting Category Names

PORTRAITS

PEOPLE – “INDOORS”

CROWDED SCENES WITH PEOPLE

PEOPLE – “OUTDOORS”

OUTDOOR SCENES WITH PEOPLE

OUTDOOR ARCHITECTURE

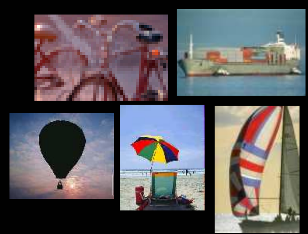
OBJECTS - INDOORS

TECHNOSCENES

INDOOR SCENES WITH OBJECTS

CITYSCAPES

OBJECTS - OUTDOORS



WATERSCAPES WITH HUMAN INFLUENCE

LANDSCAPES WITH HUMAN INFLUENCE

WATERSCAPES

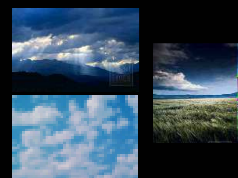
LANDSCAPES WITH MOUNTAINS

WINTER/SNOW

GREEN LANDSCAPES

LANDSCAPES WITH FIELDS AND FOLIAGE

SKY/CLOUDS



PLANTS, FRUITS & VEGETABLES

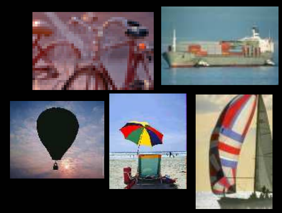
TEXTURES, PATTERNS AND CLOSE-UPS

ANIMALS

Semantics and Pictorial Features

- **We used the written descriptions gathered to generate a list of verbal descriptors for each category**
- **We have then translated these features into calculable image-processing descriptors.**

C18



Category name: *Objects outdoors*

Description and main characteristics of the category:

central objects
strong colors
bright images
regular shapes
sky

"image consisting primarily of a human face, with little or no background scene"

⇕

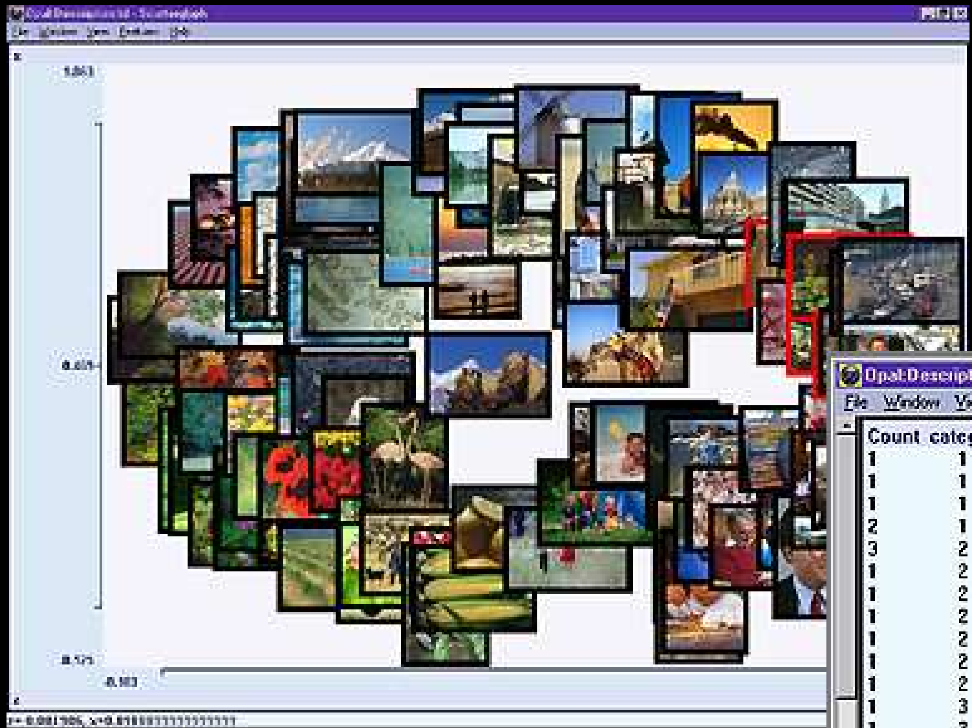
"dominant, large skin colored region "

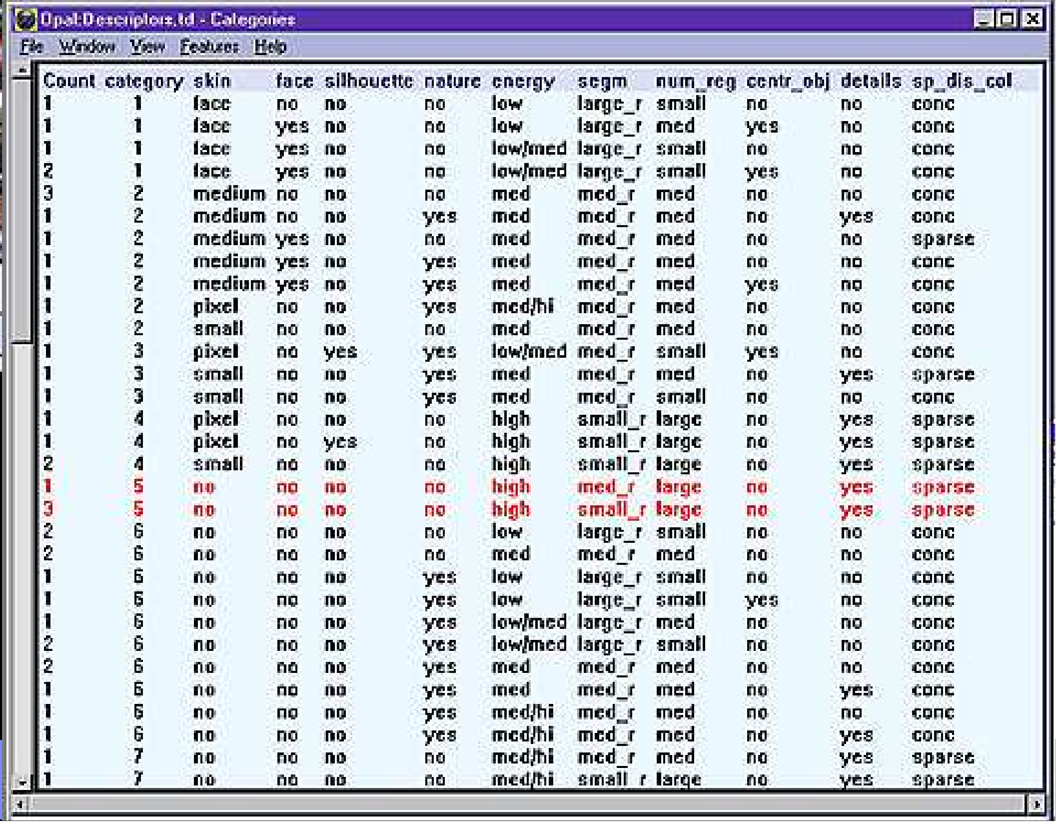
"busy scene"

⇕

"high spatial frequencies, large number of small regions"

ViVA Visualization.. Identifying a combination of features that define a category

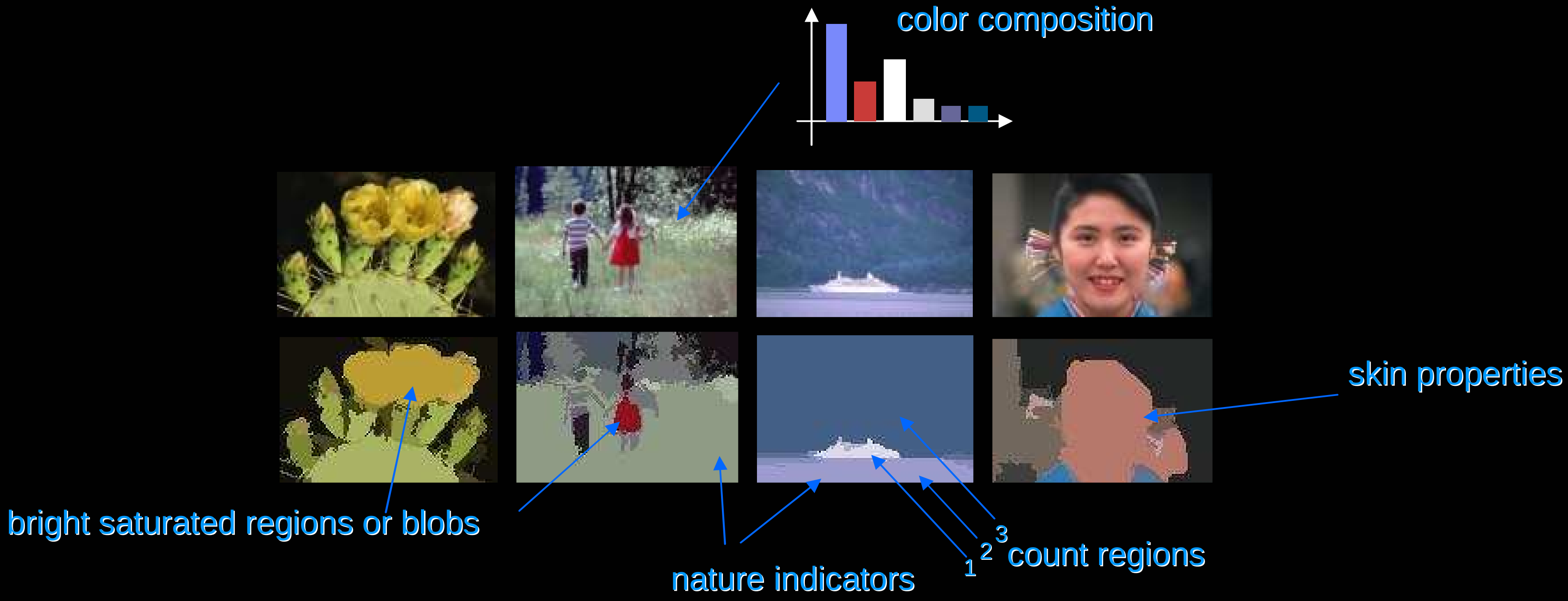




Count	category	skin	face	silhouette	nature	energy	segm	num_reg	centr_obj	details	sp_dis_col
1	1	face	no	no	no	low	large_r	small	no	no	conc
1	1	face	yes	no	no	low	large_r	med	yes	no	conc
1	1	face	yes	no	no	low/med	large_r	small	no	no	conc
2	1	face	yes	no	no	low/med	large_r	small	yes	no	conc
3	2	medium	no	no	no	med	med_r	med	no	no	conc
1	2	medium	no	no	yes	med	med_r	med	no	yes	conc
1	2	medium	yes	no	no	med	med_r	med	no	no	sparse
1	2	medium	yes	no	yes	med	med_r	med	no	no	conc
1	2	medium	yes	no	yes	med	med_r	med	yes	no	conc
1	2	pixel	no	no	yes	med/hi	med_r	med	no	no	conc
1	2	small	no	no	no	med	med_r	med	no	no	conc
1	3	pixel	no	yes	yes	low/med	med_r	small	yes	no	conc
1	3	small	no	no	yes	med	med_r	med	no	yes	sparse
1	3	small	no	no	yes	med	med_r	small	no	no	conc
1	4	pixel	no	no	no	high	small_r	large	no	yes	sparse
1	4	pixel	no	yes	no	high	small_r	large	no	yes	sparse
2	4	small	no	no	no	high	small_r	large	no	yes	sparse
1	5	no	no	no	no	high	med_r	large	no	yes	sparse
3	5	no	no	no	no	high	small_r	large	no	yes	sparse
2	6	no	no	no	no	low	large_r	small	no	no	conc
2	6	no	no	no	no	med	med_r	med	no	no	conc
1	6	no	no	no	yes	low	large_r	small	no	no	conc
1	6	no	no	no	yes	low	large_r	small	yes	no	conc
1	6	no	no	no	yes	low/med	large_r	med	no	no	conc
2	6	no	no	no	yes	low/med	large_r	small	no	no	conc
2	6	no	no	no	yes	med	med_r	med	no	no	conc
1	6	no	no	no	yes	med	med_r	med	no	yes	conc
1	6	no	no	no	yes	med/hi	med_r	med	no	no	conc
1	6	no	no	no	yes	med/hi	med_r	med	no	yes	conc
1	7	no	no	no	no	med/hi	med_r	med	no	yes	sparse
1	7	no	no	no	no	med/hi	small_r	large	no	yes	sparse

Skin = no skin,
Nature = no,
Central object = no,
Energy = high,
Number of regions = large,
Number of edges = large,
Details = yes,
Region size = {small,medium}.

Next Step: Implement the Features



- Testing the model on the new images
- “Stretching” the model

Perceptual Similarity Metric

FEATURE VECTOR FOR CATEGORY *Ci*

$$f(c_i) = [Rc_{i1}, \ldots, Rc_{iN_i}, Fc_{i1}, \ldots, Fc_{iM_i}]$$

Ni REQUIRED FEATURES $R_1, \ldots, R_{N_i}$

Mi FREQUENTLY OCCURING FEATURES $F_1, \ldots, F_{M_i}$

FEATURE VECTOR FOR IMAGE *X* WHEN COMPARED TO CATEGORY *Ci*

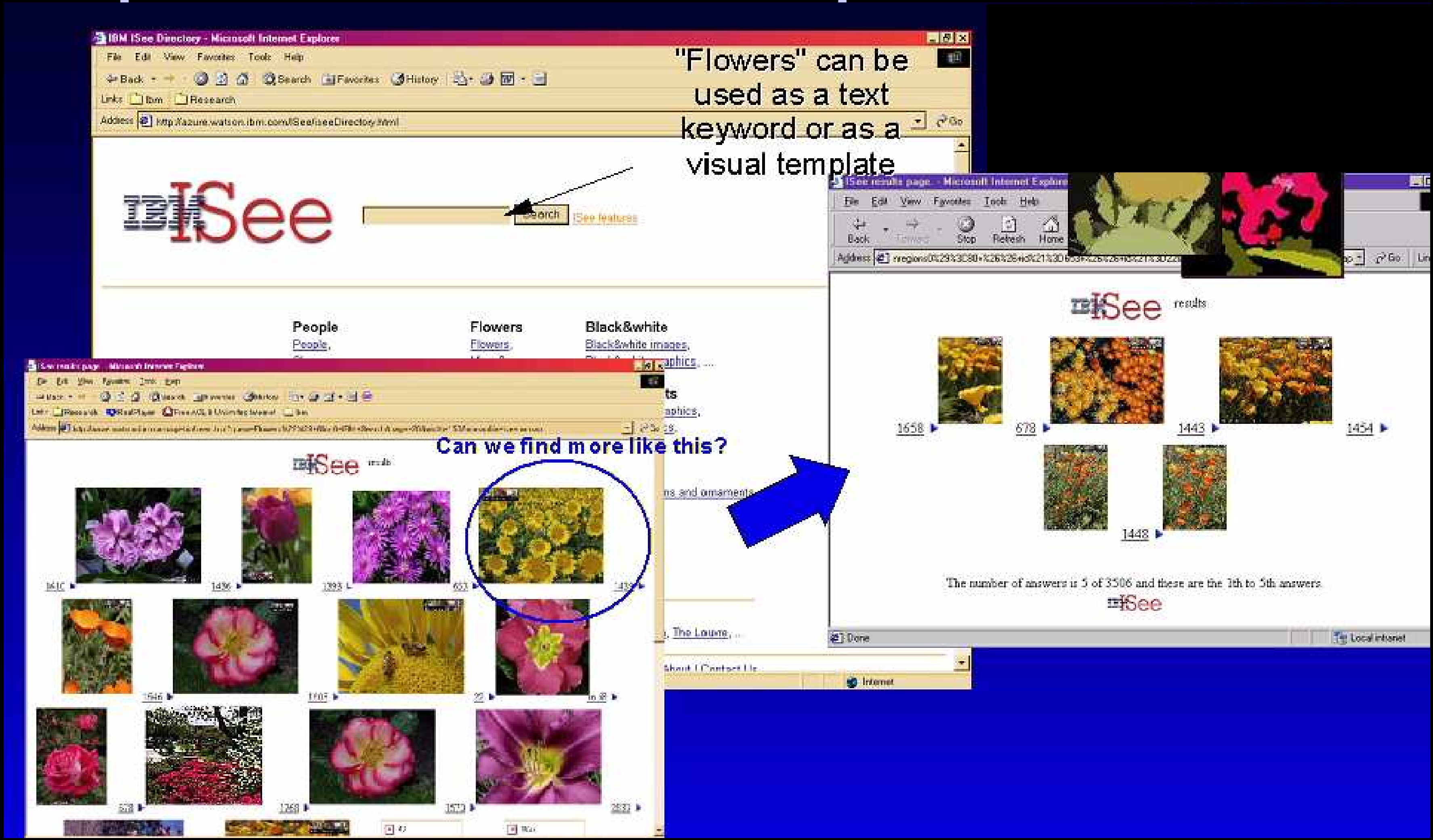
$$f(x) = [Rx_1, \ldots, Rx_{N_i}, Fx_{1i}, \ldots, Fx_{M_i}]$$

SIMILARITY BETWEEN *X* AND *Ci* IS MEASURED AS:

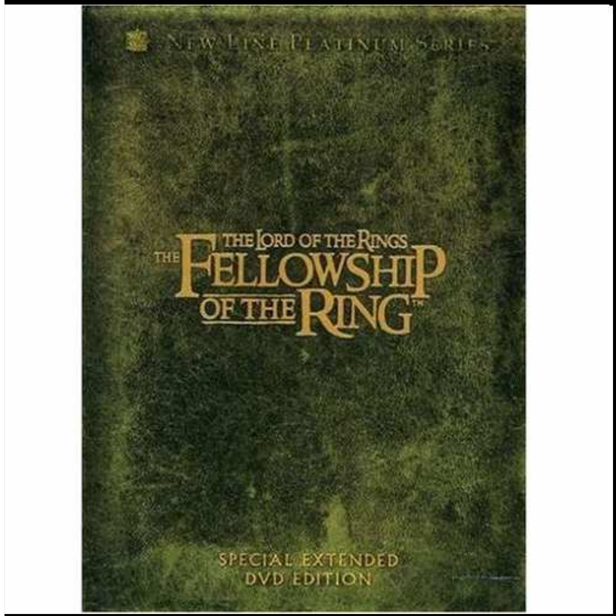
$$sim(x, c_i) = \prod_{j=1}^{N_i} \tau(Rx_j, Rc_{ij}) \cdot \frac{1}{M_i} \sum_{j=1}^{M_i} \tau(Fx_j, Fc_{ij})$$

$$\tau(a, B) = \begin{cases} 0, & (\forall i)\ a \neq b_i \\ 1, & (\exists i)\ a = b_i \end{cases}, \quad B = \{b_i\}$$

Implementation: ISee Perceptual Browser



Another approach to Semantics: Using the Community of users to find information hidden deep in media



Tags Customers Associate with This Product (What's this?)

Click on a tag to find related items, discussions, and people.

Check the boxes next to the tags you consider relevant or enter your own tags in the field below.

- fantasy (46)
- lord of the rings (42)
- tolkien (30)
- fantasy movies (24)
- adventure (17)
- dvd (15)
- orlando bloom (13)
- movie (10)
- box set (4)
- peter jackson (3)
- viggo mortensen (3)

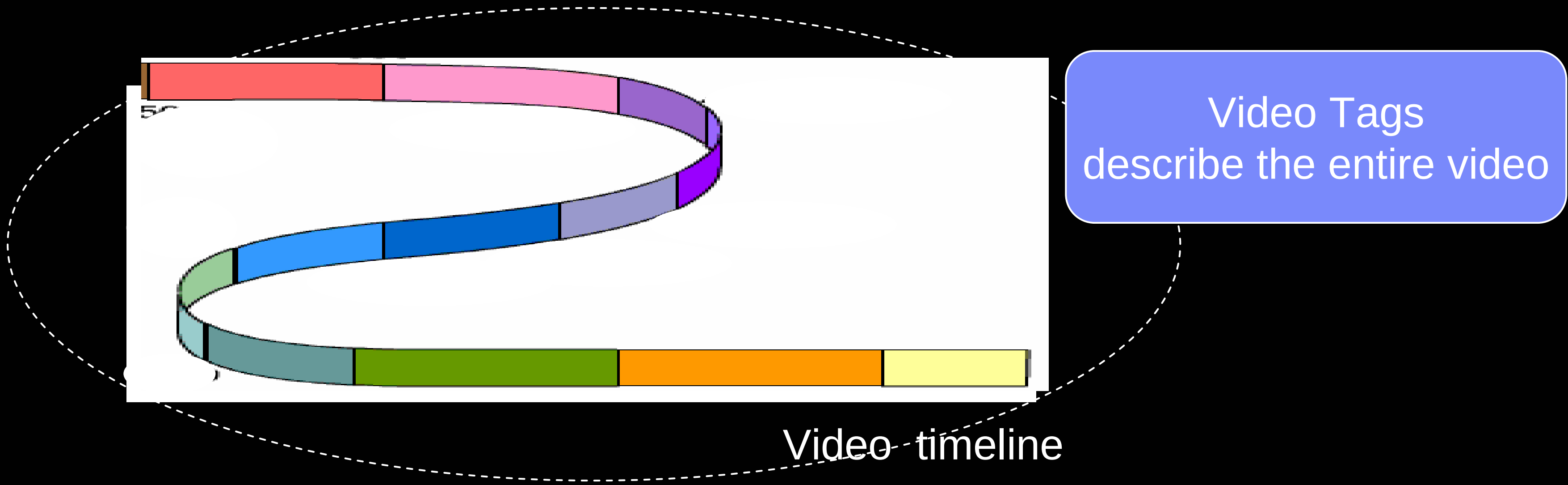
› **See all 60 tags...**

Your tags: Add
(Press the 'T' key twice to quickly access the "Tag this product" window.)

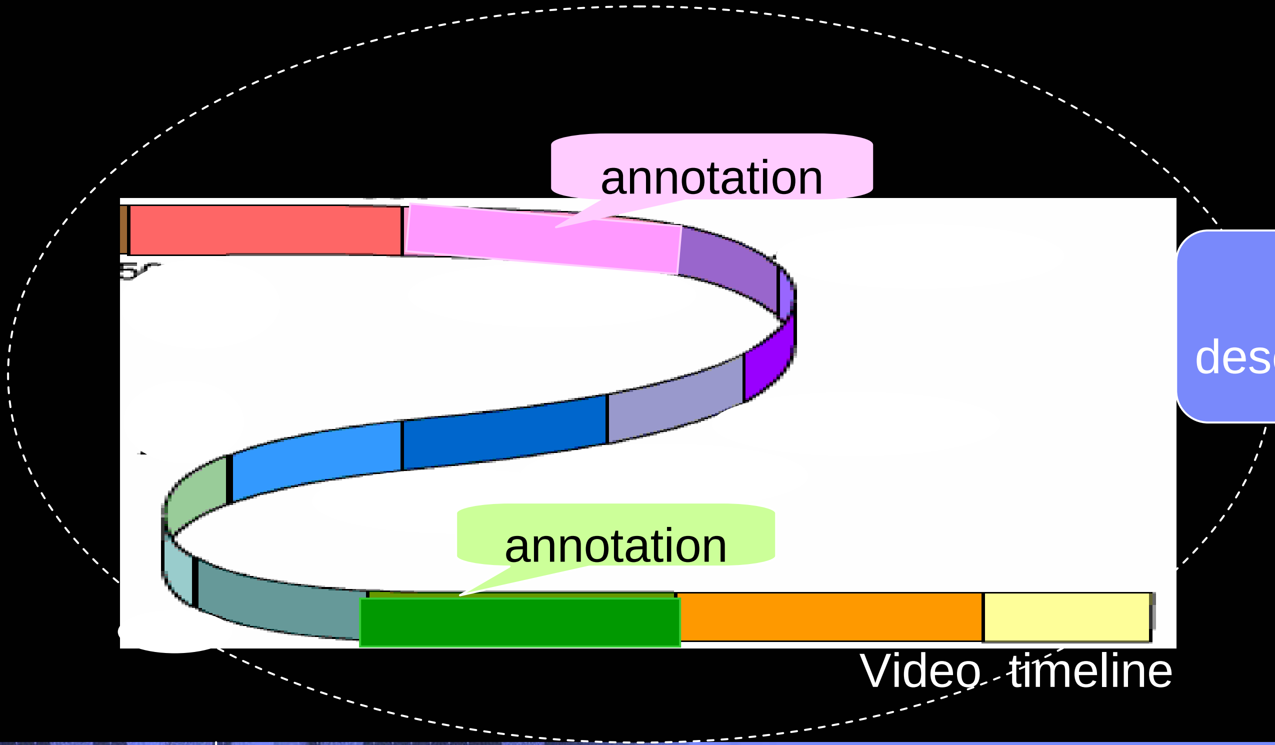
You can tell from the tags that Orlando Bloom is in this video, but you don't know where…

A Limitation of Social Tagging

- **Since tags are associated with the entire entity (e.g., video, web page, document), finding specific information within that content can be a difficult, time-intensive process.**
  - **This is especially true for content such as video, where the information sought may be a small segment within a very long presentation (e.g., your child getting his diploma in a 3-hour graduation ceremony)**

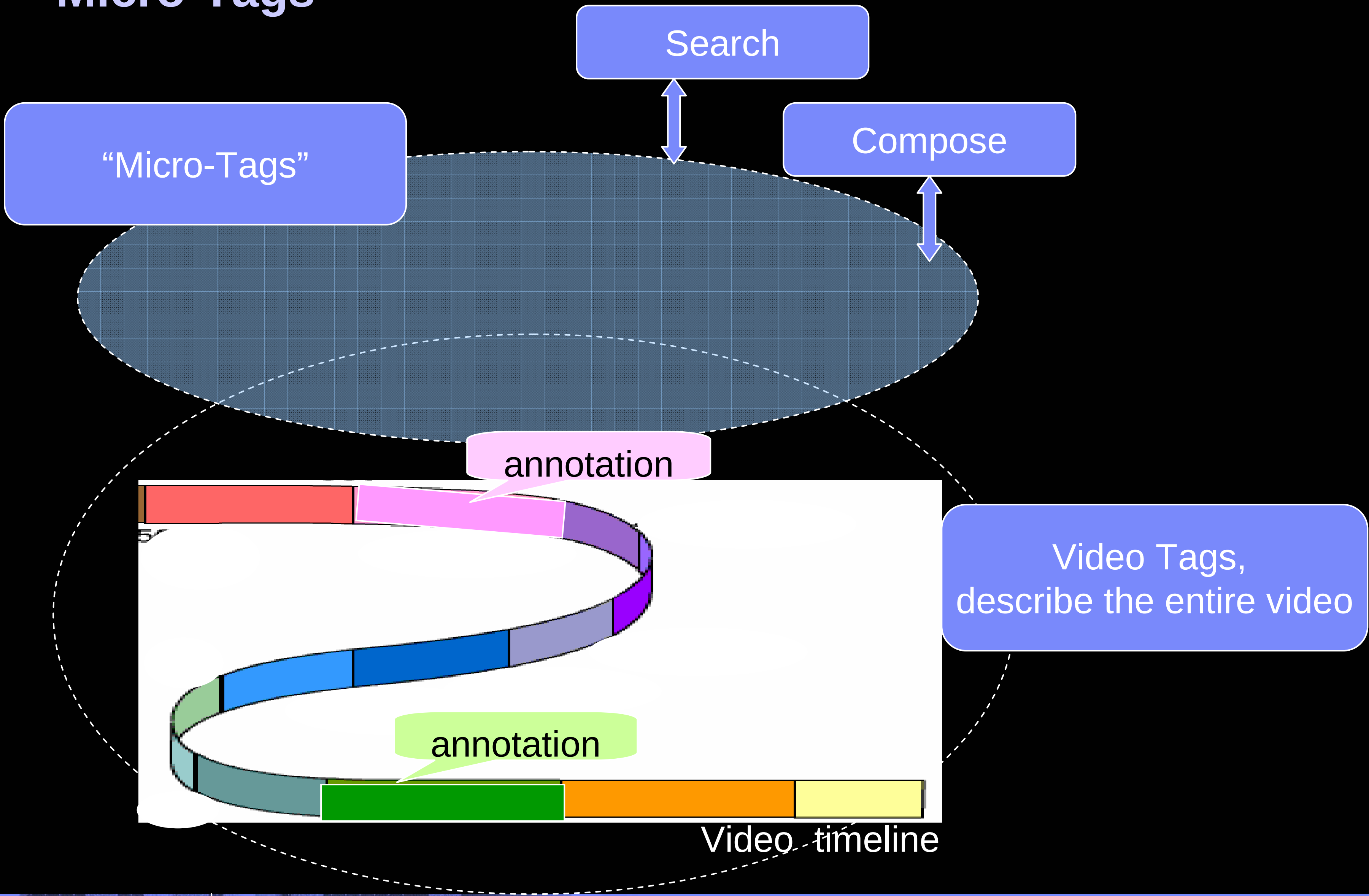


Micro-Tags



Video Tags
describe the entire video

Micro-Tags


Search
Compose
"Micro-Tags"
annotation
Video Tags,
describe the entire video
annotation
Video timeline

InSight: Users Generate Micro-tags on the video timeline (could be complemented with computer-generated annotations)

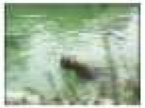
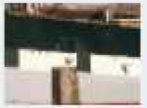
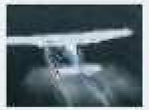
Each microtag has a

- Temporal interval
- Spatial location
- ATextual Tag

- The segment is played in situ, within the context of the video
- Micro-tags are easily searched, since each microtag is referenced by a URL

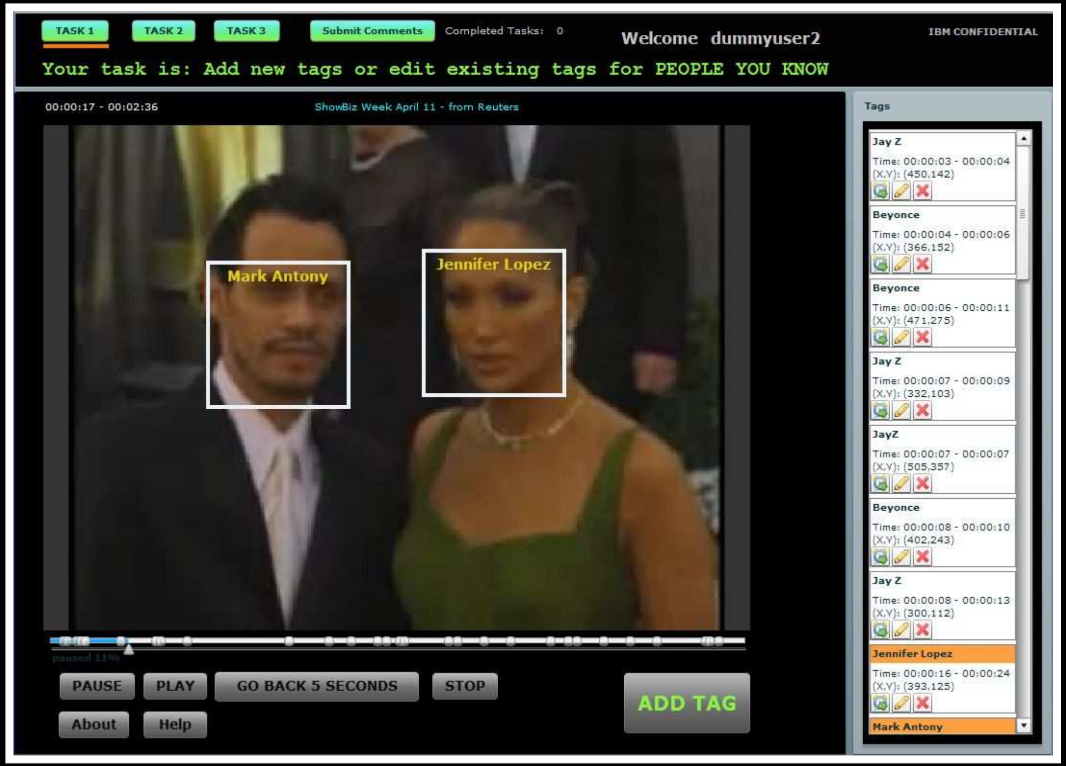
Tags for Search: the Result of a Query Across a set of Videos

Search: "sea"

Title	Added	Tags	
Bronx Zoo	Dec 22nd 2008		Seal 18:46.19 (7.71s)
New York City	Dec 22nd 2008		Seaport cruises 8.05 (27.46s)
			seagull 7:55.68 (6.76s)
IBM Corporate Service Corps - Tanzania	Dec 22nd 2008		seaside 10:23.99 (45.24s)
A State of Movement and Creativity	Dec 22nd 2008		Seaplane 3:42.79 (12.47s)

But, what if the tags are incorrect ?

Tag Editing Experiment

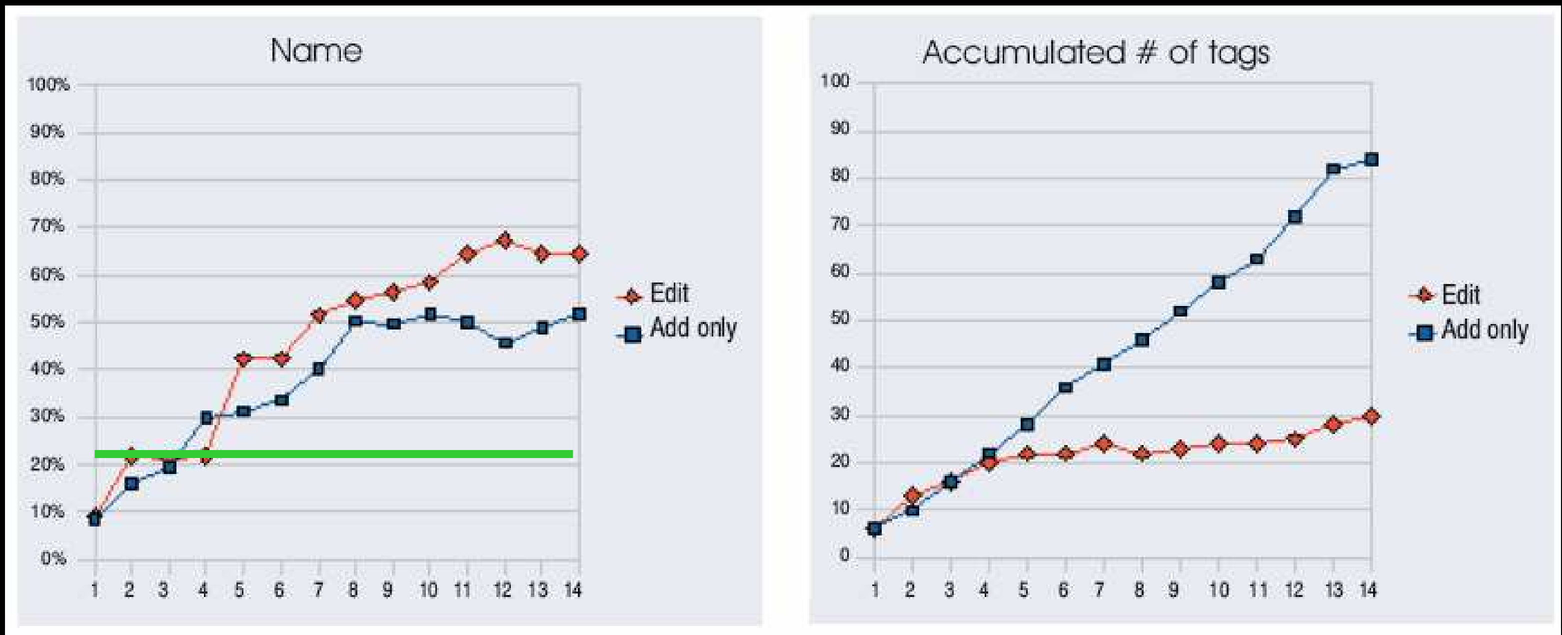


- Three Reuters ShowBiz videos, ~3min each
  - Tasks:
    - Identify Celebrities by name
    - Mark spatial region where they appear
    - Mark temporal interval

- Measuring value of the community
  - 3 conditions where tags are added
    - Individual performance (ADD)
    - See others' tags (ADD-SEE)
    - Edit or delete others' tags (ADD-EDIT)
  - N=42 in counterbalanced groups

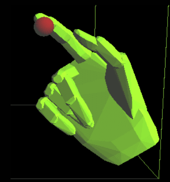
Tag Editing Improves Tag Quality and Efficiency–

- **When the community edits tags**
  - **Cumulative tag quality improves faster and provides higher asymptotic performance**
  - **The number of tags decreases**
- **Community editing improves the semantic value of the tags, making them better search terms**

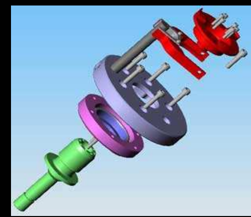


Haptics – Feeling and Shaping Virtual Environments

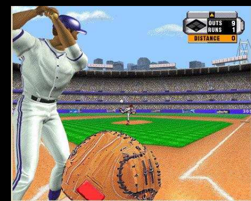
•50 Million years of evolution have given us superior visually-guided fine motor control …but our computer Systems have lagged behind, especially for the blind.



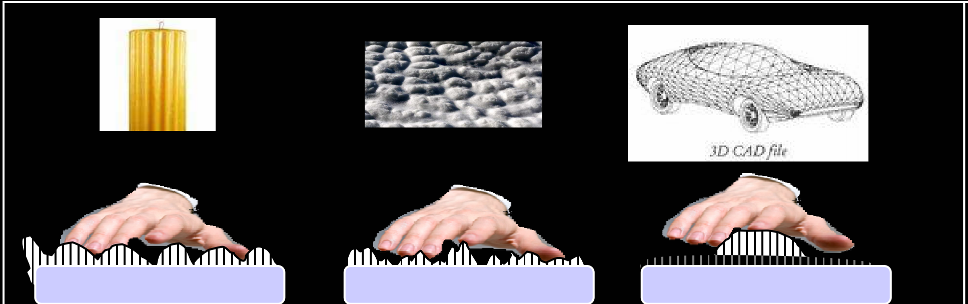
•Opportunity areas: Remote training, Virtual shopping, CAD/CAM, on-line games, 3-D internet, visual accessibility, collaboration



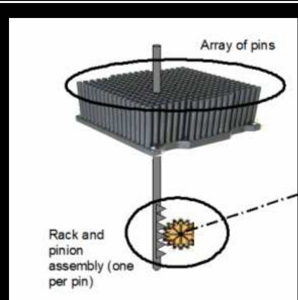
•GOAL: Provide computer-generated system that allows users to feel and edit objects, surfaces and textures in computer environments



•3-D Virtual Hand- a touch-enabled virtual device



Array of pins that reflect object and hand parameters



Haptic device on a 6-degree of freedom robot arm

Today we discussed

- Visual data representation
  - Using perceptual principles to guide the design of color maps
  - The representation depends on the cognitive task
- Visual data analysis
  - Using color to mark semantic regions
- Image libraries
  - Using human judgments of similarity to drive definition of image semantics
- Social tagging
  - Using human judgments to semantically mark regions of interest in a large corpus
- Haptic interfaces
  - Giving humans the ability to sense and express through touch

Closing Remarks

- Greater speed, bandwidth, and storage are driving a quantum leap in computational power – bigger models, more data, faster interactivity
- These will enabling new business processes and applications (e.g., bioinformatics, “green” technologies)
- Some key Research opportunities
  - Finding meaning in large, complex, multi-type data
  - Semantic search
  - Integration of human and machine intelligence (using computer algorithms and the community to provide “scaffolding”
  - Deploying compute-intensive interfaces (e.g., graphics, Virtual Reality, materials rendering, haptics)

Closing Remarks

- Greater speed, bandwidth, and storage are driving a quantum leap in computational power – bigger models, more data, faster interactivity
- These will enabling new business processes and applications (e.g. "green" technologies)
- Some key Research opportunities
  - Finding meaning in large, complex, multi-type data
  - Semantic search
  - Integration of human and machine intelligence (using computer algorithms and the community to provide "scaffolding"
  - Deploying compute-intensive interfaces (e.g., graphics, Virtual Reality, materials rendering, haptics)

Your training in human perception and cognition (and linguistics, economics, design, etc)

prepare YOU to lead the next generation of advanced technologies

hartelijk dank !