

Information Theory in Volume Visualization

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Today's Menu

- Entropy
- Joint and Conditional Entropy
- Information Channel
- Mutual Information
- Entropy Rate
- Informational Divergence

Entropy

- Random variable X taking values in an alphabet X

$$X : \{x_1, x_2, \dots, x_n\}, p(x) = \Pr\{X = x\}, p(X) = \{p(x), x \in X\}$$

- **Shannon entropy** $H(X)$: uncertainty, information, homogeneity, uniformity

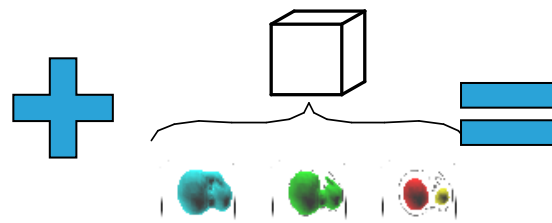
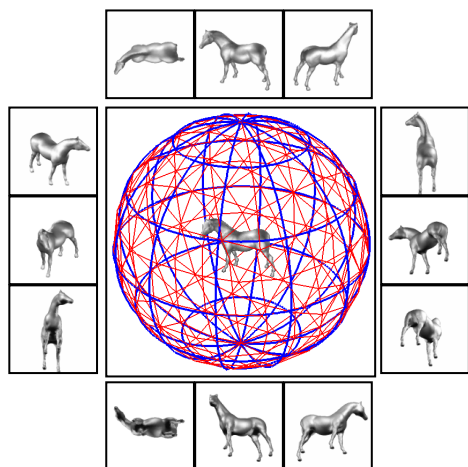
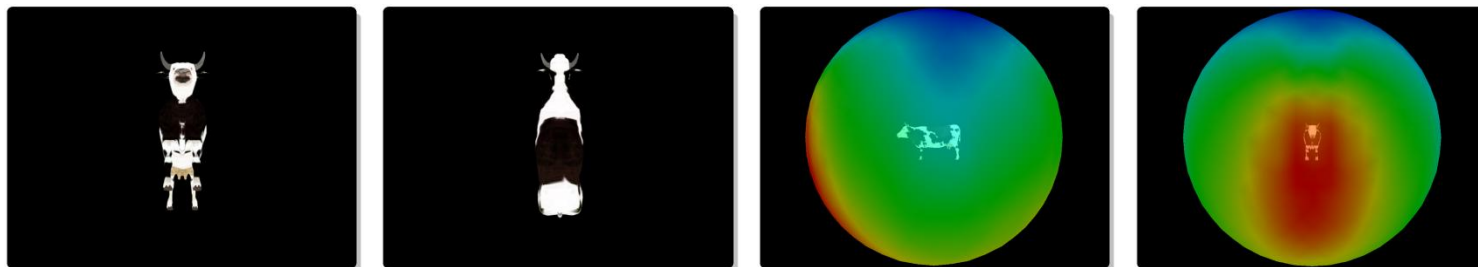
$$H(X) = - \sum_{x \in X} p(x) \log p(x) \equiv - \sum_{i=1}^n p(x_i) \log p(x_i)$$

- **Viewpoint entropy** $H(v)$ based on triangle area ratio

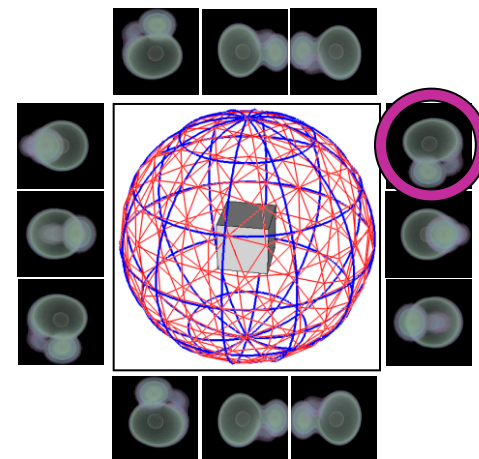
$$H(v) = - \sum_{i=0}^{N_f} \frac{a_i}{a_t} \log \frac{a_i}{a_t},$$

View Selection for Set of Iso-Surfaces

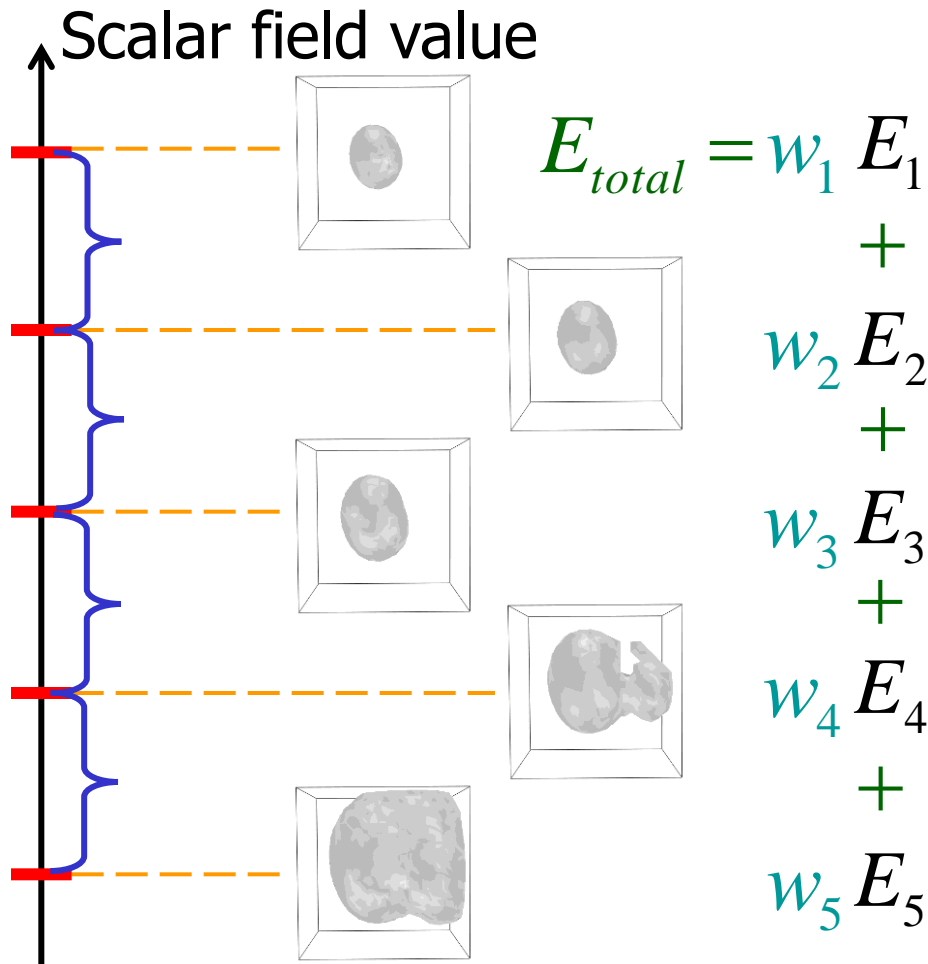
- Decompose volume into feature sub-volumes
- Surface-based method for local optimal viewpoints
- Find global compromise between local optimal viewpoints



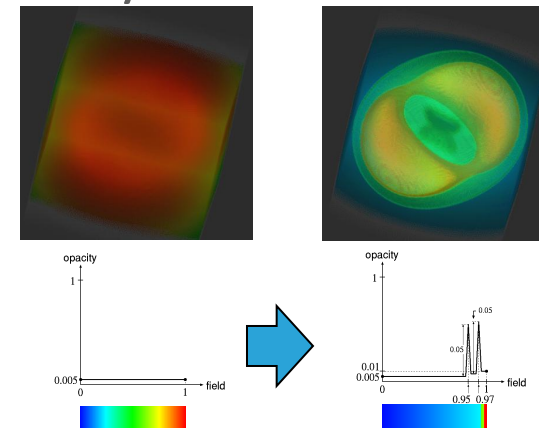
Feature sub-volumes



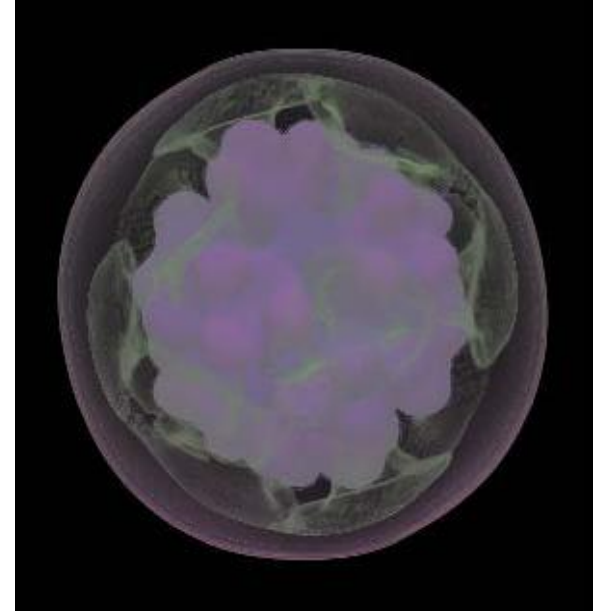
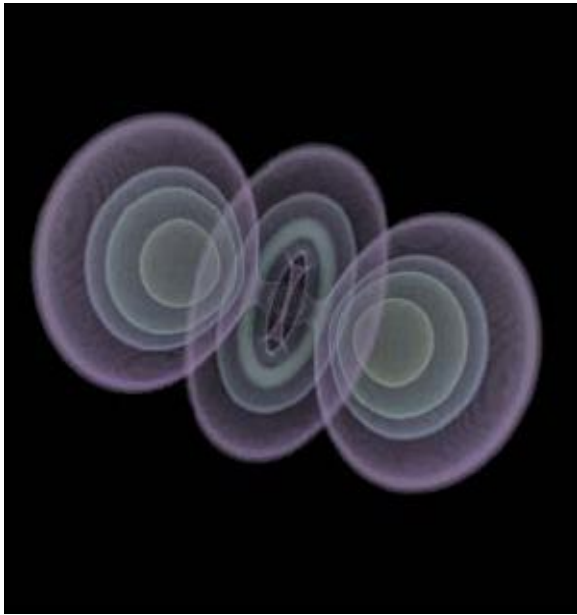
View Selection for Set of Iso-Surfaces



- Calculate the weighted sum of the viewpoint entropies of the extracted iso-surfaces
- Assign higher weights to feature iso-surfaces with opacity transfer functions



View Selection for Set of Iso-Surfaces



Derived Entropy Measures

- Discrete random variable Y in an alphabet \mathcal{Y}

$$\mathcal{Y} : \{y_1, y_2, \dots, y_n\}, p(y) = \Pr\{Y = y\}$$

- **Joint entropy** $H(X, Y)$

$$H(X, Y) = - \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(x, y) \log p(x, y)$$

- **Conditional entropy** $H(Y|X)$

$$H(Y | X) = \sum_{x \in \mathcal{X}} p(x) H(Y | x) = - \sum_{x \in \mathcal{X}} p(x) \sum_{y \in \mathcal{Y}} p(y | x) \log p(y | x)$$

$$= - \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(x, y) \log p(y | x)$$

$$p(x, y) = p(x)p(y | x) = p(y)p(x | y)$$

View Selection for Volume Data

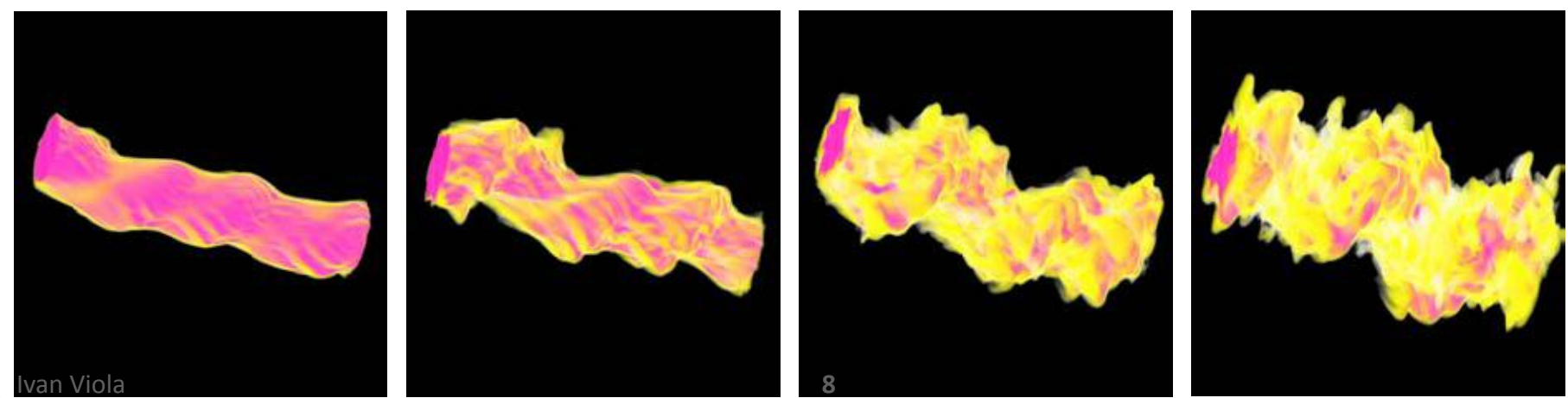
- 3D or 4D scalar fields (over time)
- Probability function q_j

$$q_j \equiv q_j(V) = \frac{1}{\sigma} \cdot \frac{v_j(V)}{W_j} \quad \text{where, } \sigma = \sum_{j=0}^{J-1} \frac{v_j(V)}{W_j}$$

- Importance W_j : voxel opacity and information content
- View selection for time-series uses Conditional entropy

$$H(X) = H(X_1) + H(X_2 | X_1) + \dots + H(X_n | X_{n-1}); H(X_2 | X_1) = - \sum_{x_1 \in X_1} \sum_{x_2 \in X_2} p(x_1, x_2) \log p(x_2 | x_1)$$

[Bordoloi and Shen 2005]

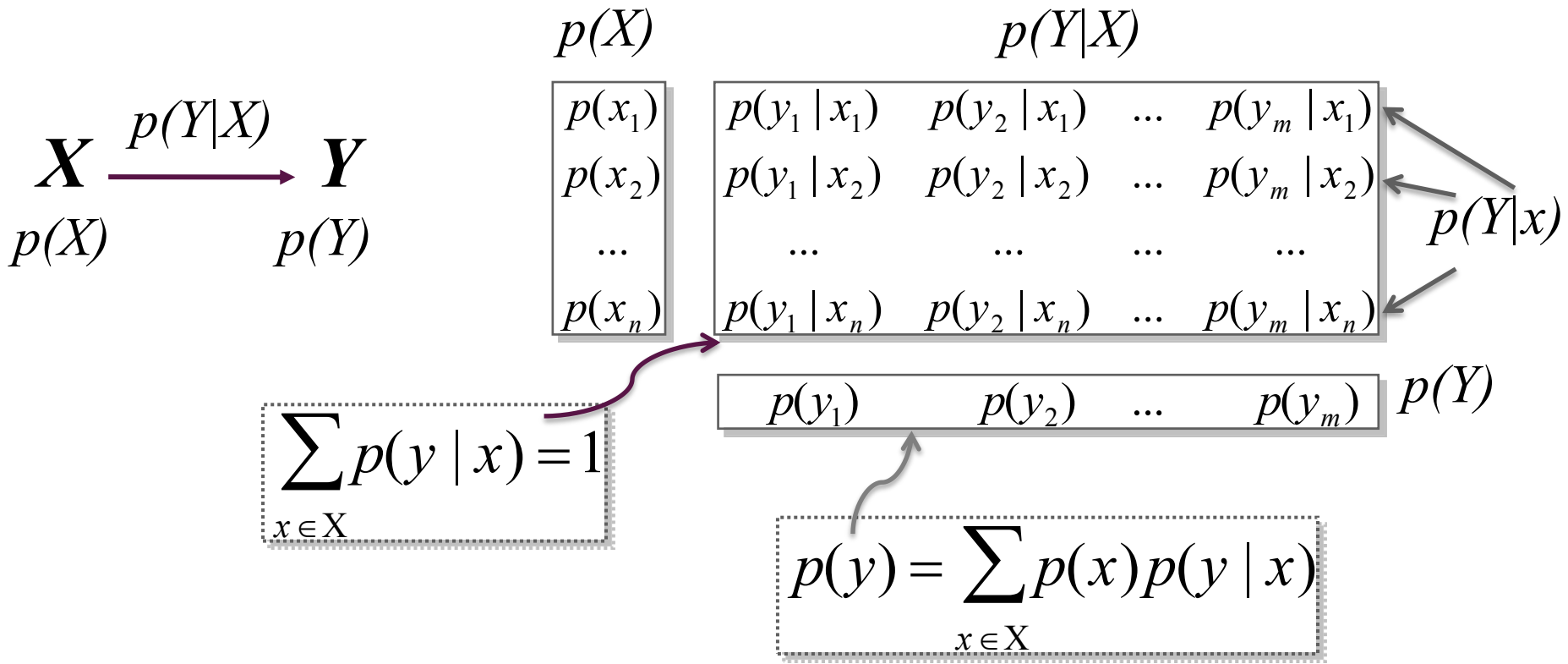


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Information Channel

■ Communication or information channel $X \rightarrow Y$



Mutual Information

- Mutual information $I(X, Y)$: shared information, correlation, dependence, information transfer

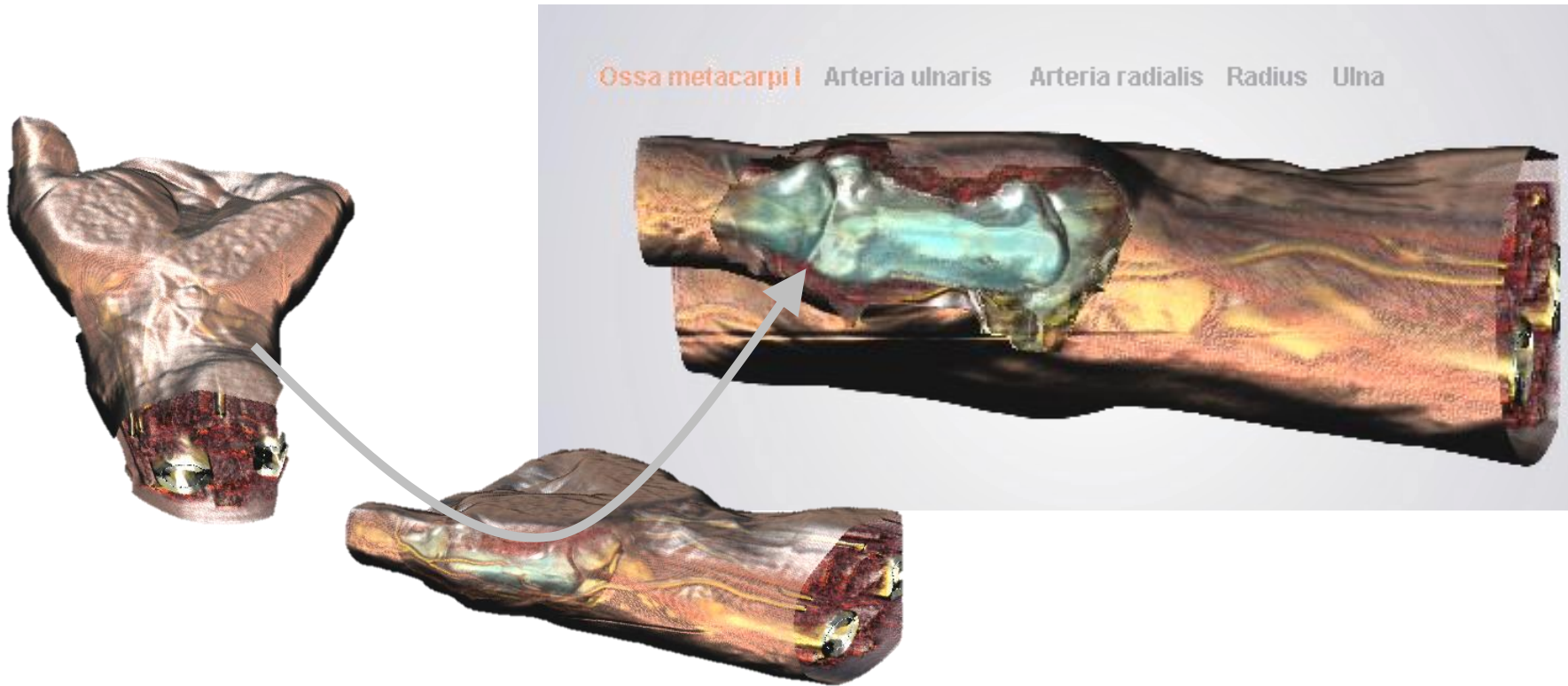
$$I(X, Y) = H(Y) - H(Y | X) = \sum_{x \in X} \sum_{y \in Y} p(x, y) \log \frac{p(x, y)}{p(x)p(y)}$$
$$= \sum_{x \in X} p(x) \sum_{y \in Y} p(y | x) \log \frac{p(y | x)}{p(y)}$$

- Viewpoint Mutual Information $I(v, O)$: dependence of viewpoint v on set of objects O

$$I(V, O) = \sum_{x \in X} \sum_{y \in Y} p(v, o) \log \frac{p(v, o)}{p(v)p(o)} = \sum_{v \in V} p(v) \sum_{o \in O} p(o | v) \log \frac{p(o | v)}{p(o)} = \sum_{v \in V} p(v) I(v, O)$$

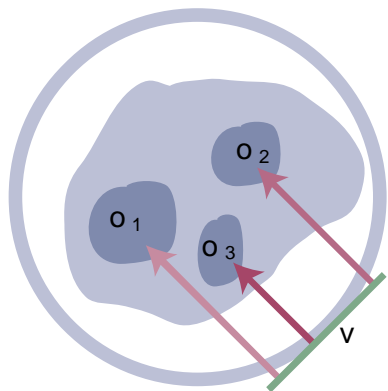
View Selection for Volumetric Objects

- Characteristic view
- Emphasis of focus object
- Guided navigation between characteristic views



Viewpoint Estimation

object-space distance weight



visibility estimation

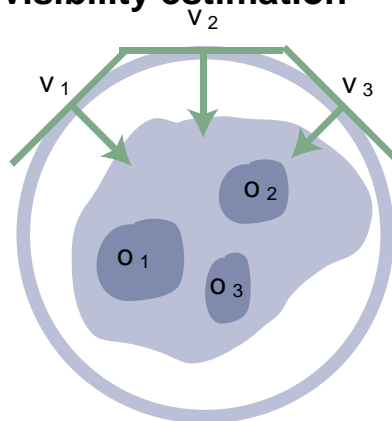
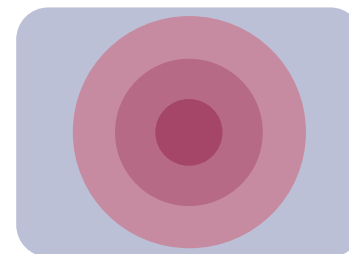
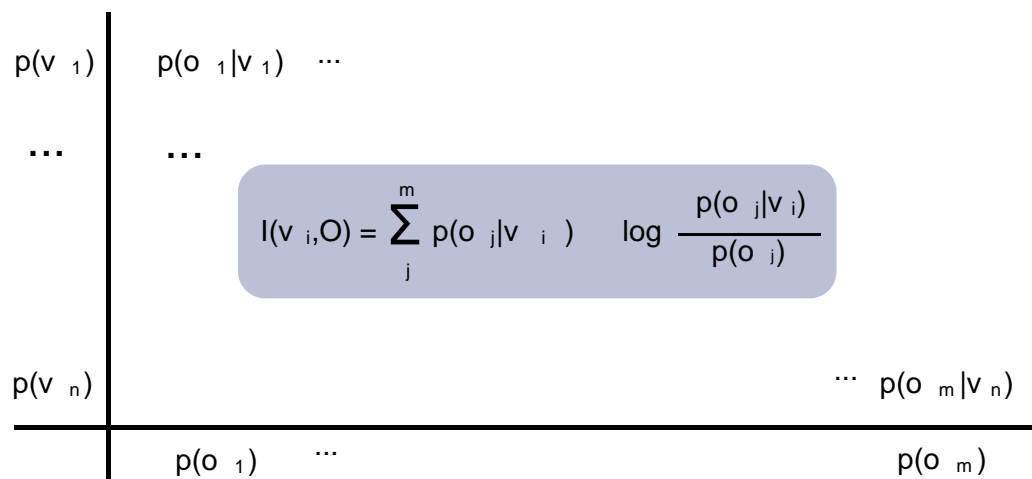


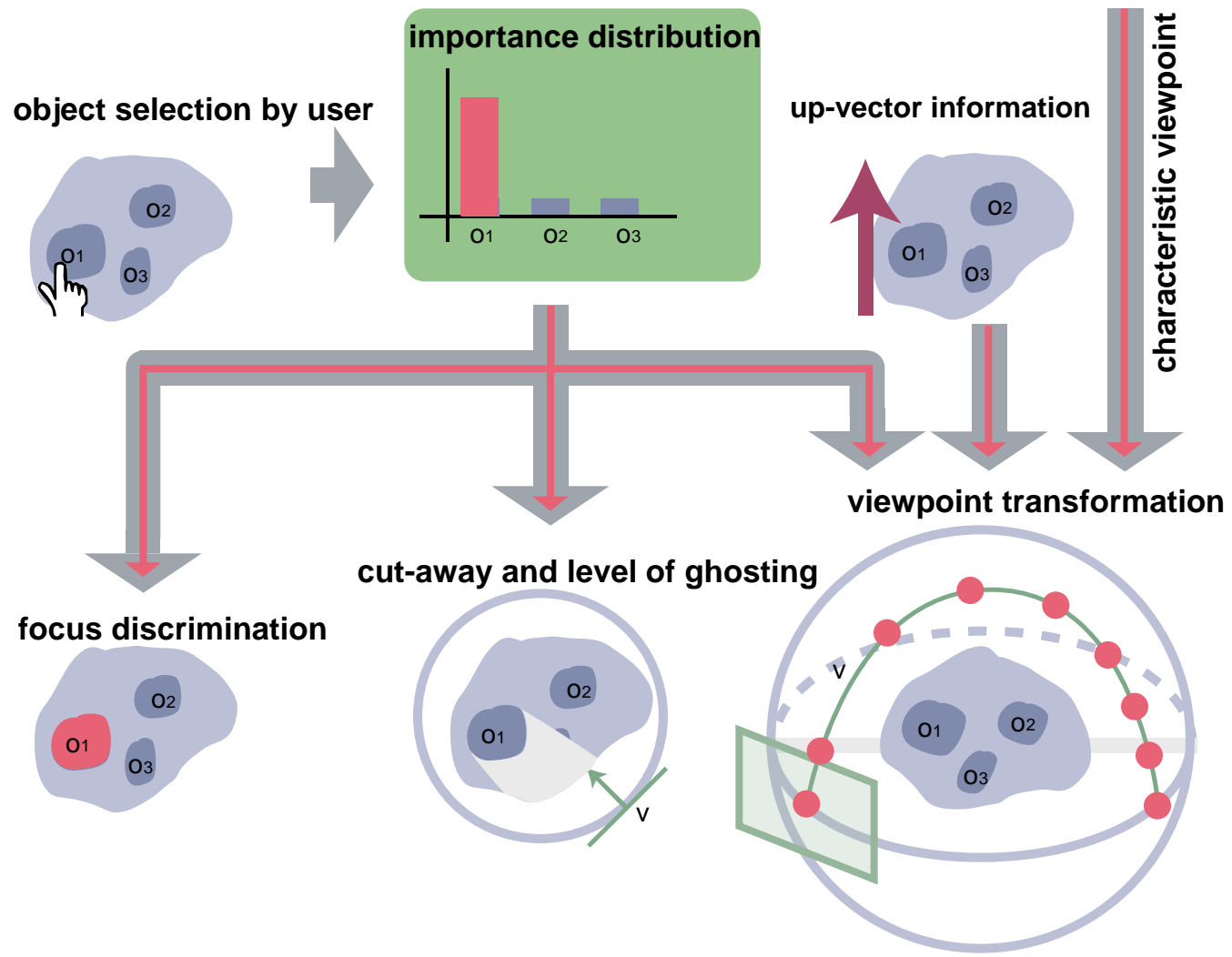
image-space weight



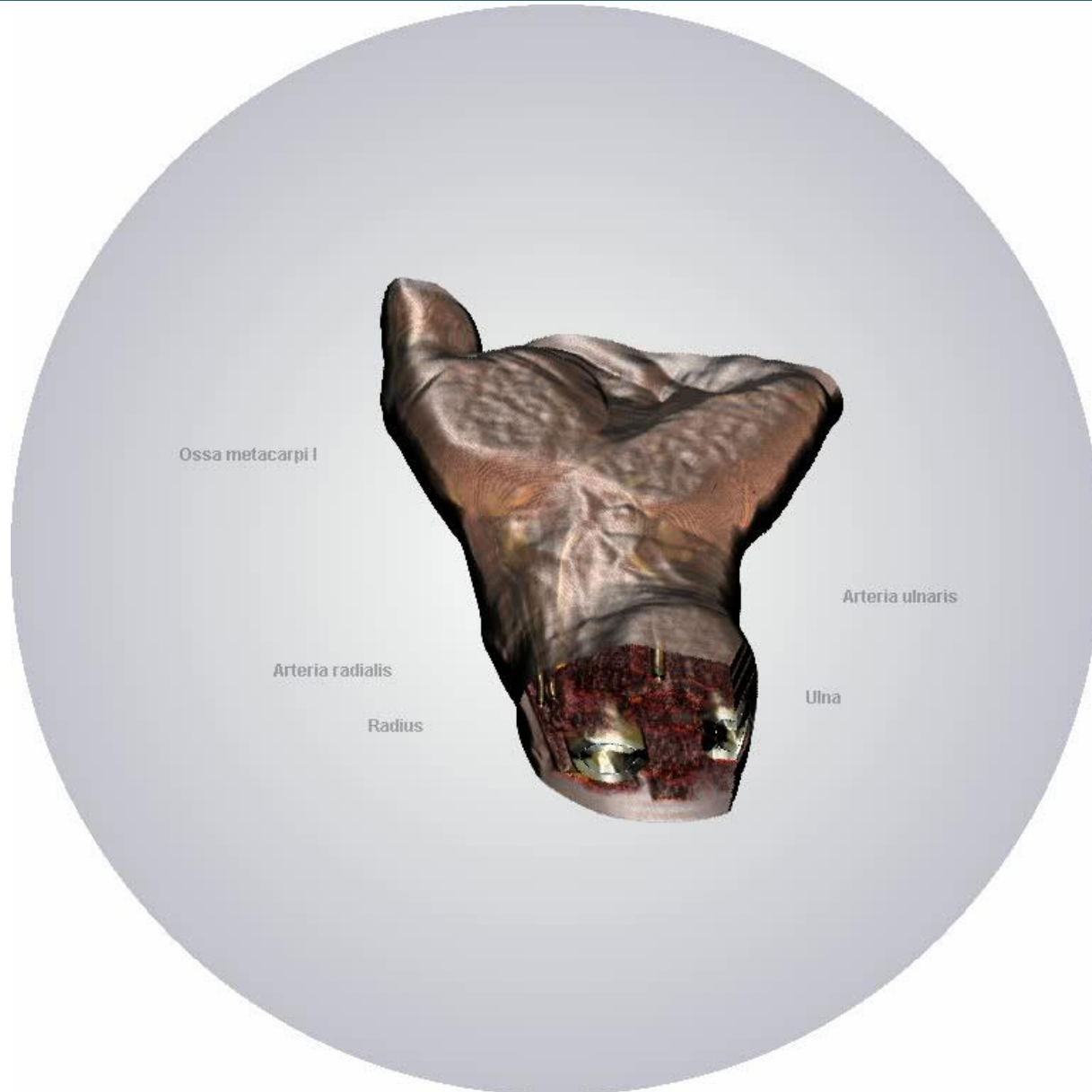
information-theoretic framework for optimal viewpoint estimation



Focus of Attention

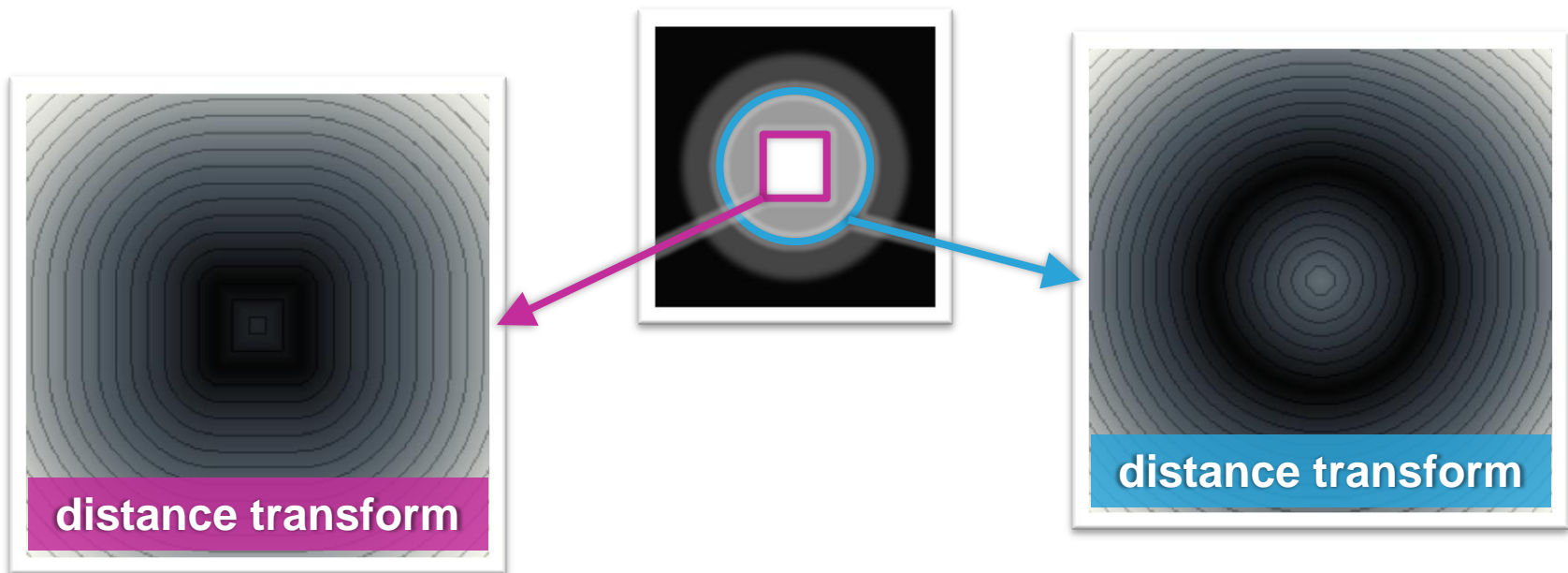


View Selection for Volumetric Objects



Iso-Surface Similarity Maps

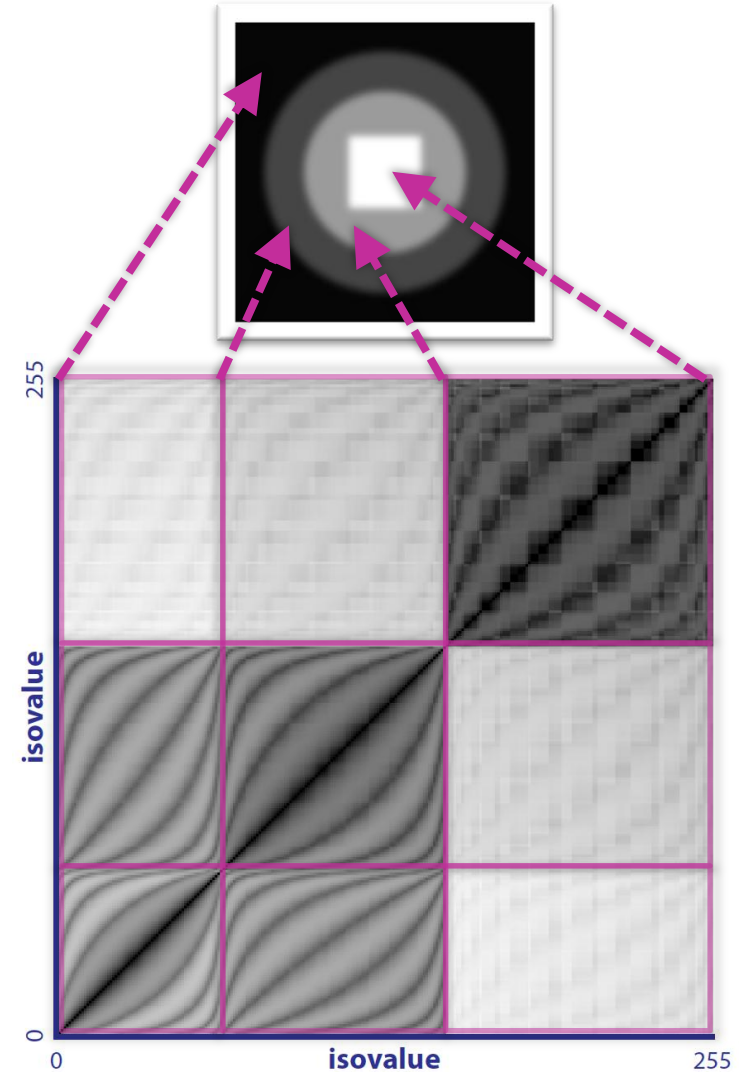
- Compare iso-surfaces through evaluating mutual information of their distance volume
 - X and Y are **independent**: $I(X, Y) = 0$
 - X and Y are **identical**: $I(X, Y) = H(X) = H(Y)$



Iso-Surface Similarity Maps

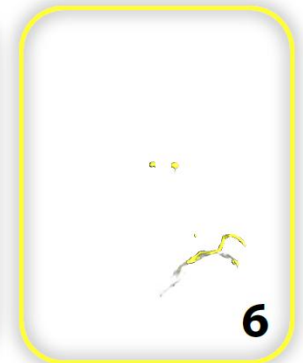
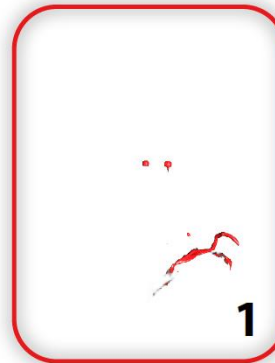
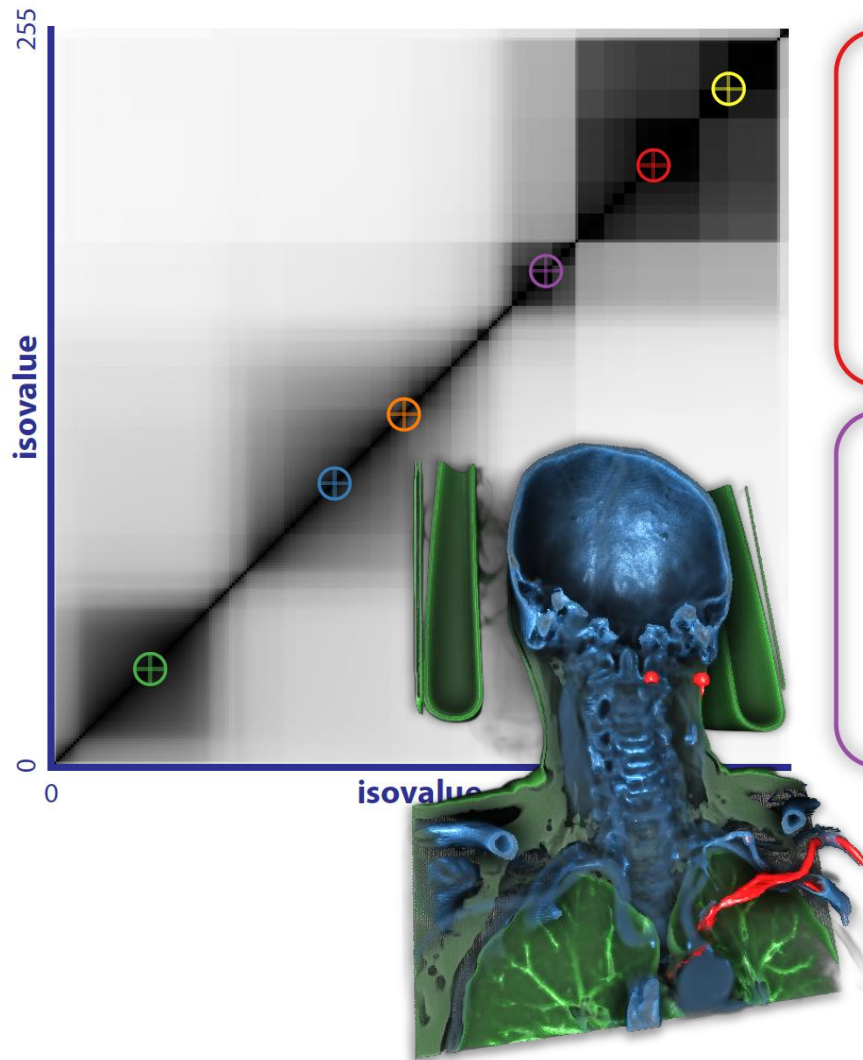
■ Normalized measure

$$\hat{I}(X, Y) = \frac{2I(X, Y)}{H(X) + H(Y)}$$



Iso-Surface Similarity Maps

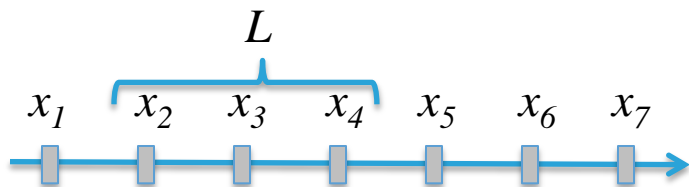
■ Selection of characteristic iso-surfaces



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Entropy Rate



- Shannon entropy

$$H(X) = - \sum_{x \in X} p(x) \log p(x)$$

- Joint entropy of L vector

$$H(X^L) = - \sum_{x^L \in X^L} p(x^L) \log p(x^L)$$

- Entropy rate

represents the average information content per symbol in a stochastic process

$$h = \lim_{L \rightarrow \infty} \frac{H(X^L)}{L} = \lim_{L \rightarrow \infty} (H(X^L) - H(X^{L-1}))$$

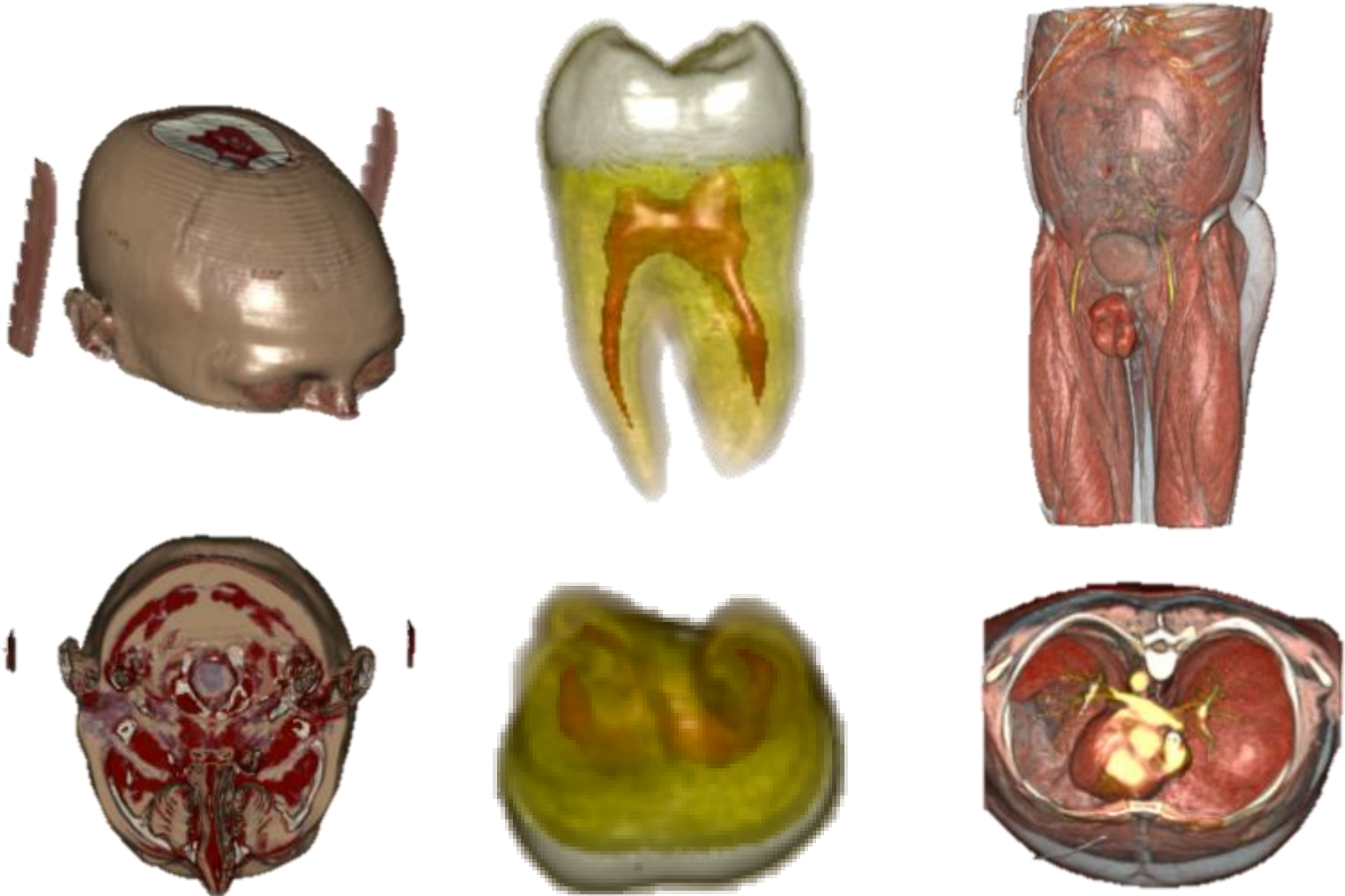
Similarity-Based Exploded Views

- A two step process is proposed to automatically obtain the partitioning planes:
 - Explosion axis: selection of the most structured view
 - Partitioning of the data: slices are grouped according to the maximization of a similarity criterion



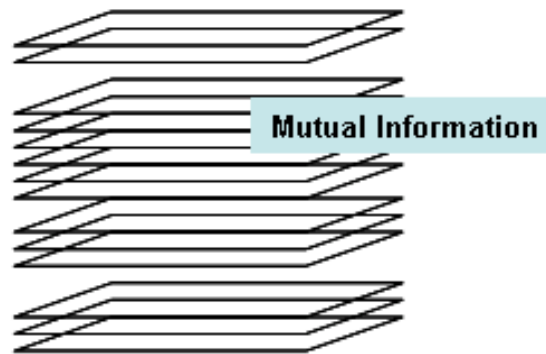
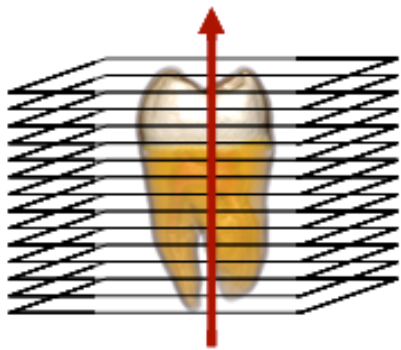
Similarity-Based Exploded Views

- **Structured View** measured through Entropy Rate
captures the randomness or unpredictability of a system

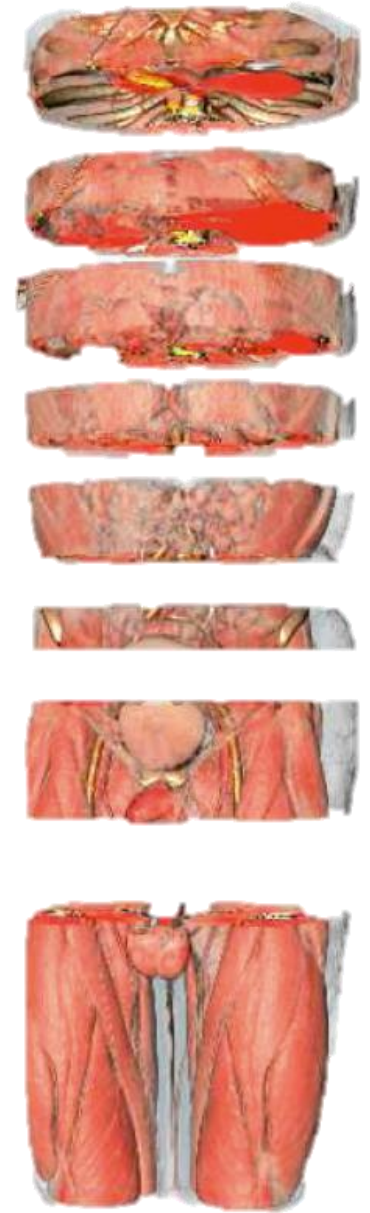
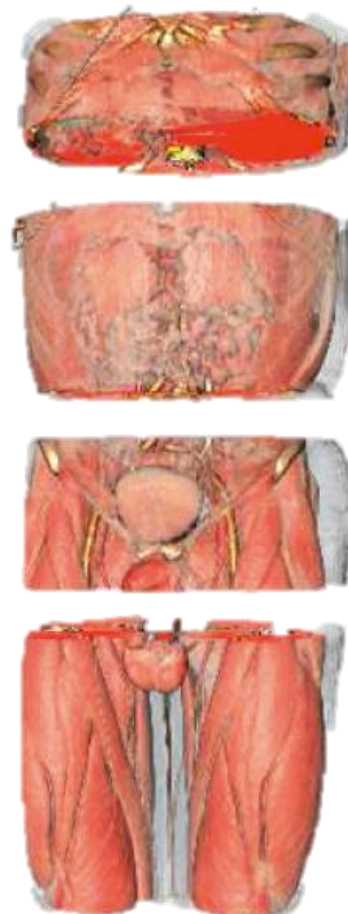
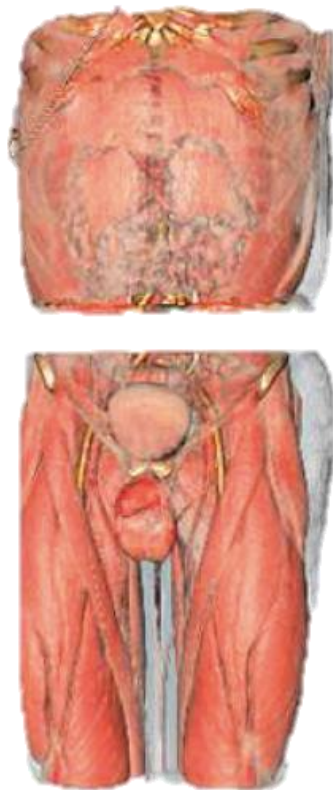
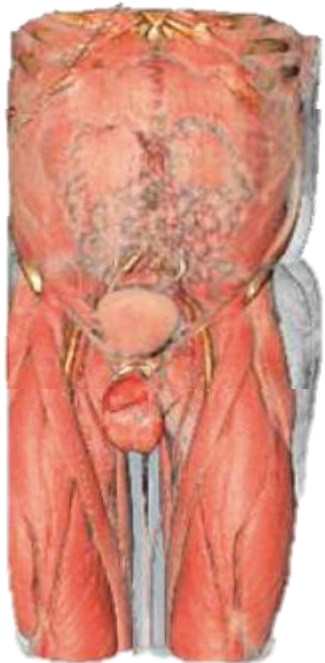


Similarity-Based Exploded Views

- **Bottom-up Grouping:** group the most similar slices or slabs through normalized mutual information
degree of similarity or shared information between two slices or slabs



Similarity-Based Exploded Views



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Informational Divergence

- **Informational divergence** (relative entropy or Kullback-Leibler distance)

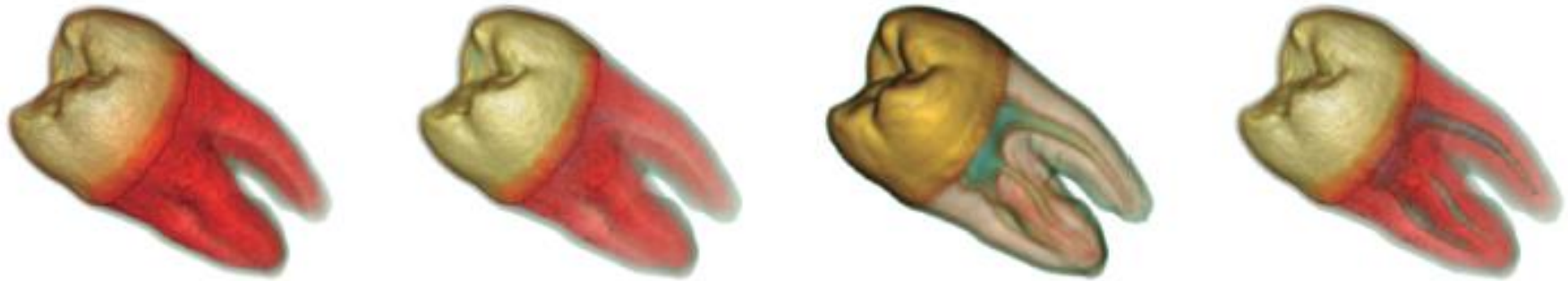
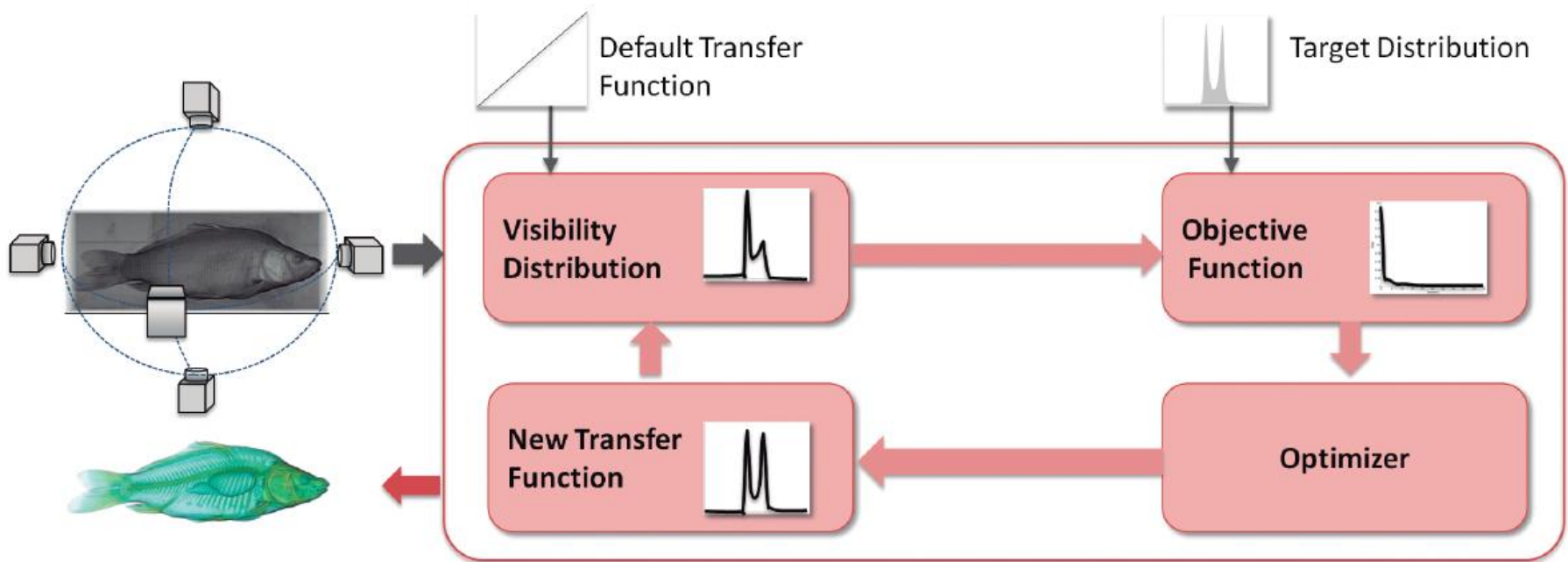
$D_{KL}(p, q)$: how much p is different from q (on a common alphabet X)

$$D_{KL}(p, q) = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)}$$

- Convention: $0 \log 0/q = 0$ and $p \log p/0 = \infty$
- $D_{KL}(p, q) \geq 0$
- Not a true metric or *distance*
- Mutual information is a special case

$$I(X, Y) = D_{KL}(p(X, Y), p(X)p(Y))$$

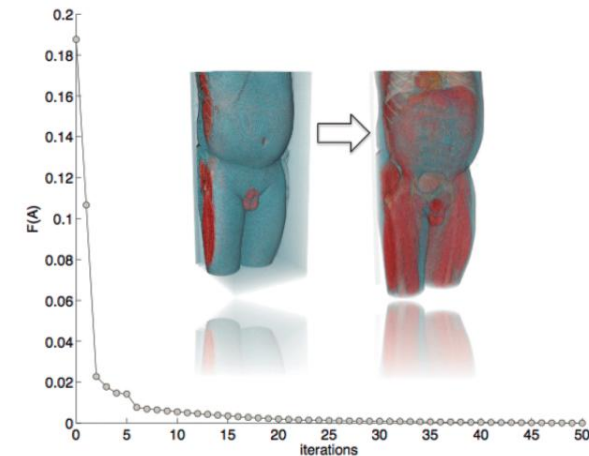
Transfer Functions for Scalar Fields



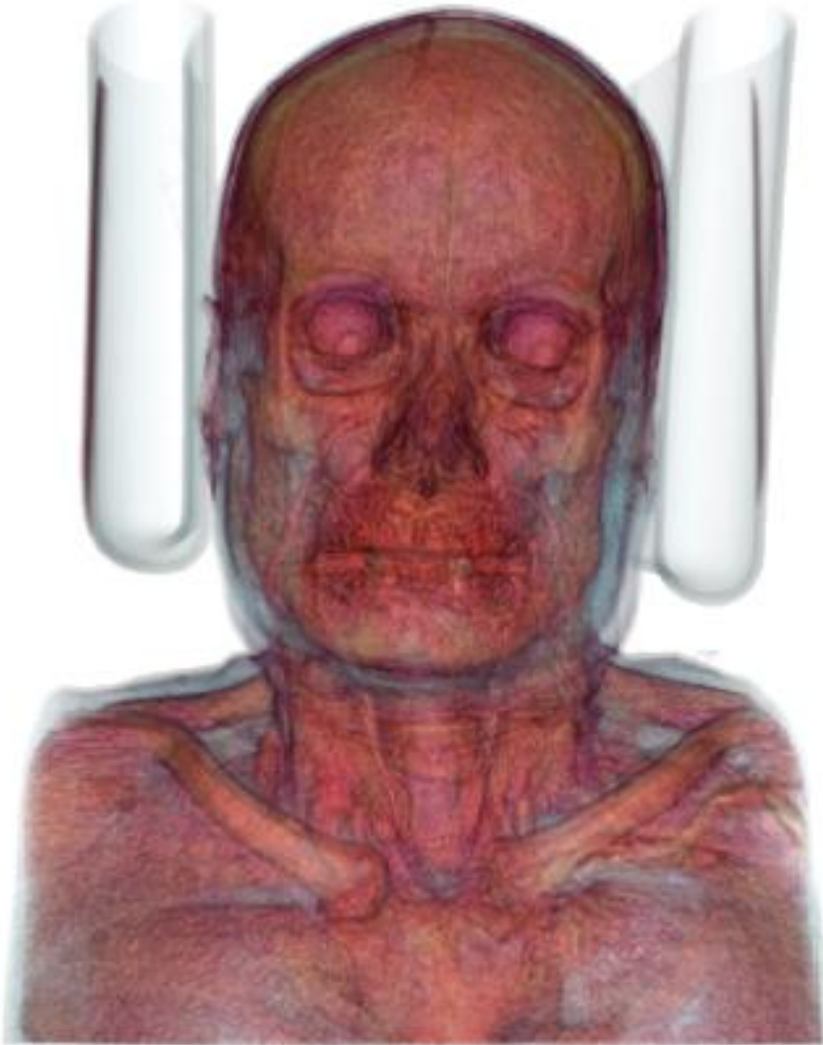
Transfer Functions for Scalar Fields

- Target Function: Intuitive specification of visual prominence for density values
- Minimize informational divergence ($F(A)$) between the average projected visibility distribution from viewpoints and a target distribution
- Optimizer: Steepest Gradient Descent

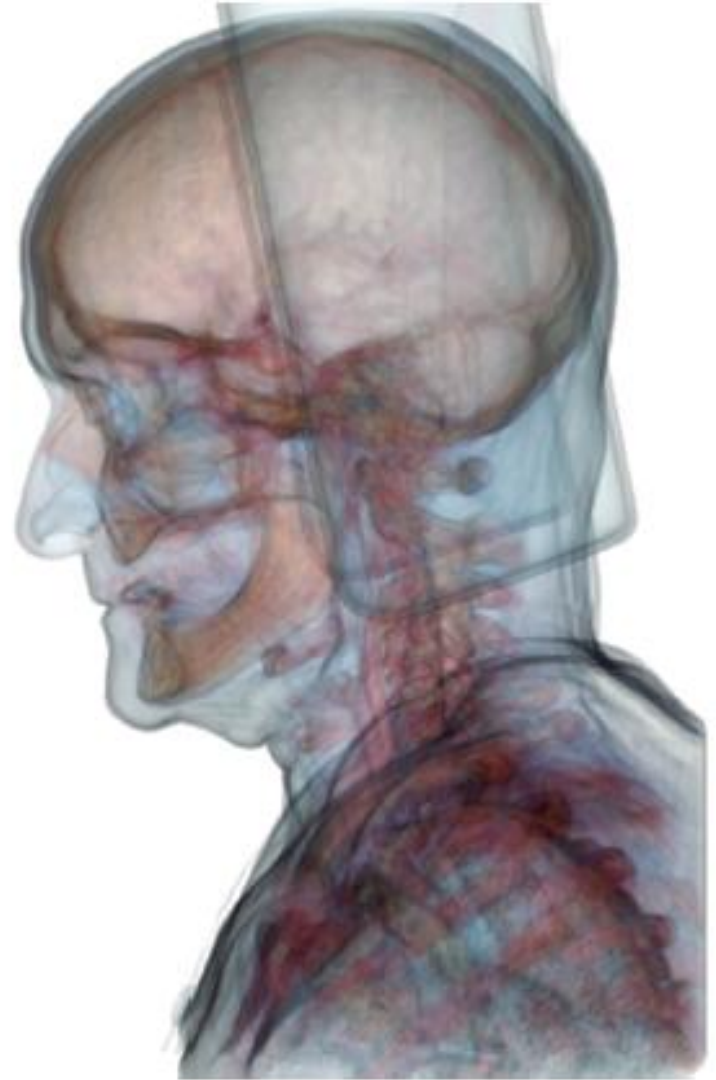
$$A^t = A^{t-1} - s^{t-1} \nabla F(A)$$
$$\nabla F(A) = \left(\frac{\partial F(A)}{\partial \alpha_0}; \frac{\partial F(A)}{\partial \alpha_1}; \dots; \frac{\partial F(A)}{\partial \alpha_{n-1}} \right)$$



Transfer Functions for Scalar Fields



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References

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Thank you!

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