Learning good views through intelligent galleries

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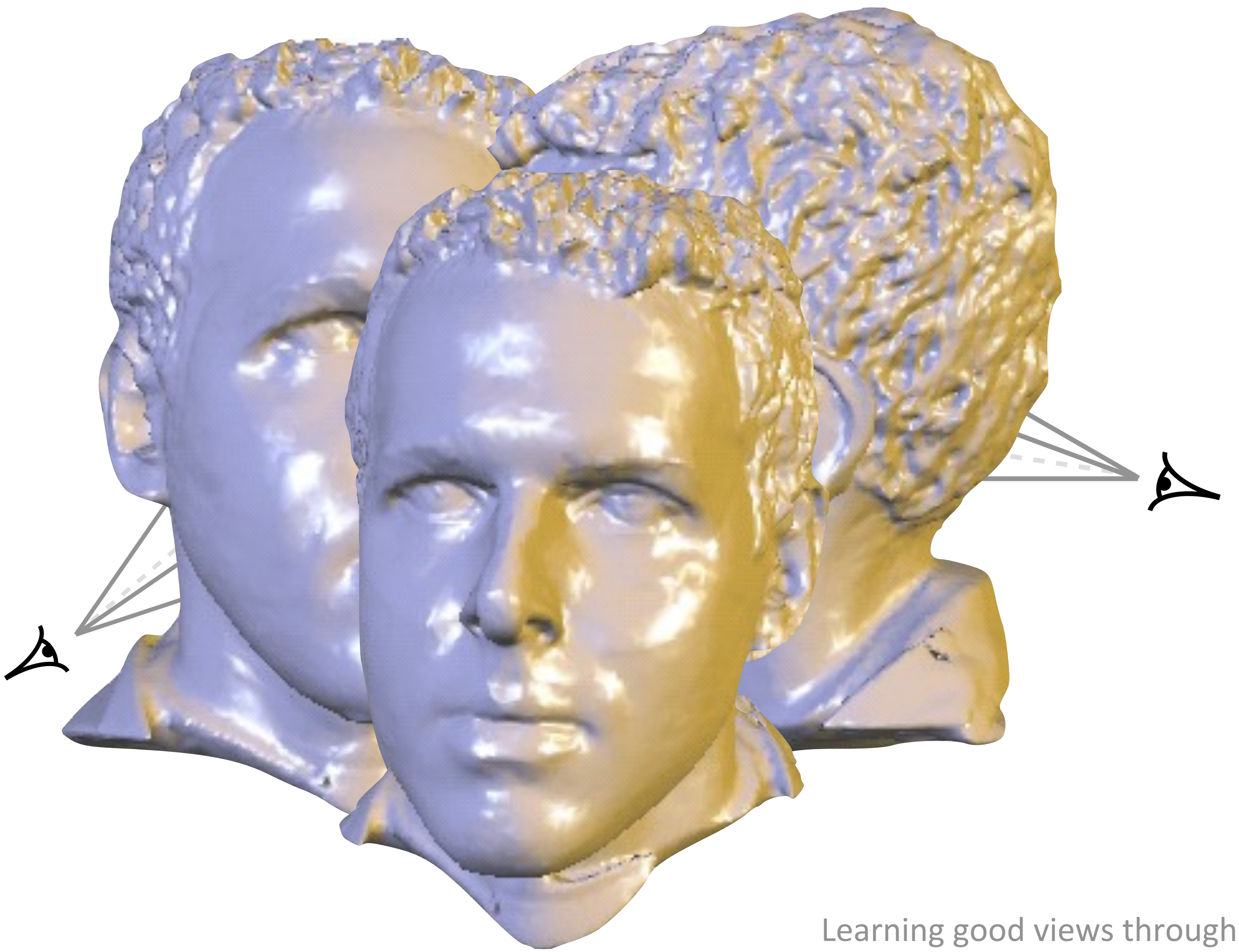
Camera Placement Problem: Non-linear



Vieira et al., 2009

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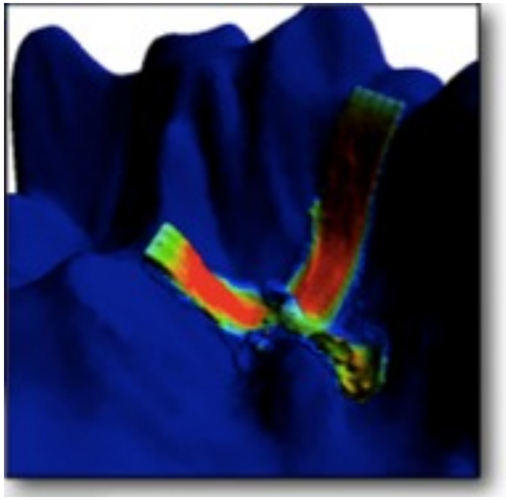
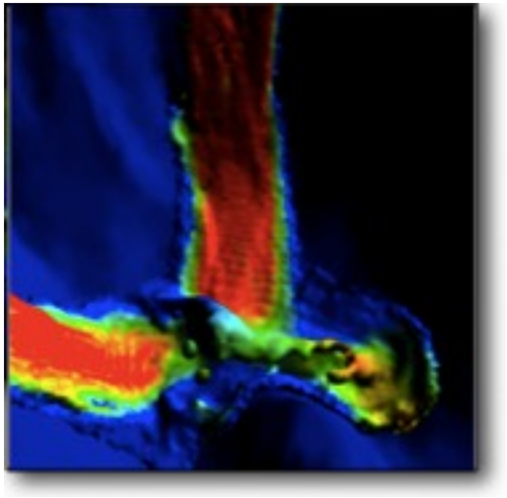
Camera Placement Problem: Subjectivity



Designer Best View



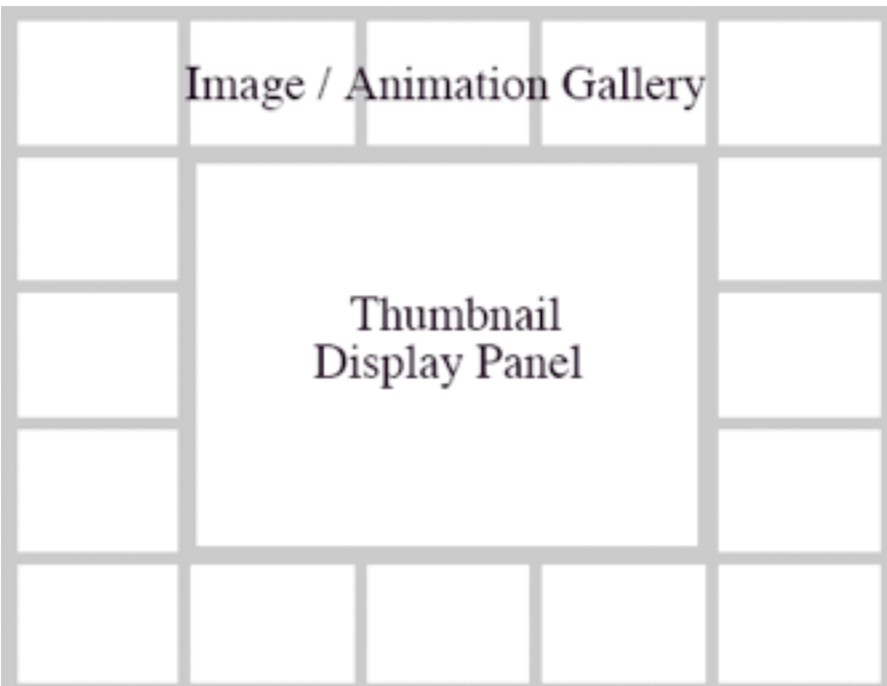
Fluid Specialist Best View

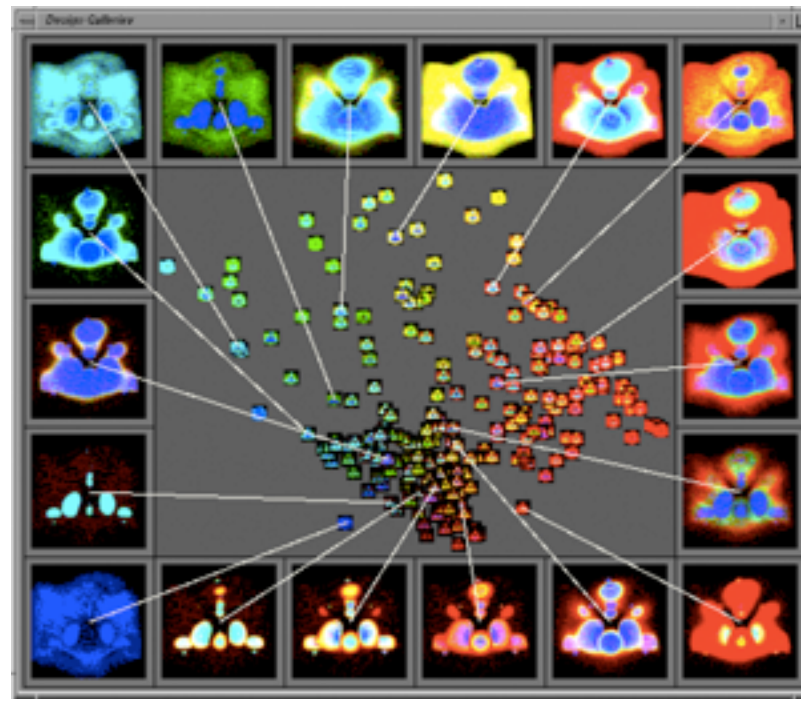
Vieira et al., 2009

Our Approach: Learning

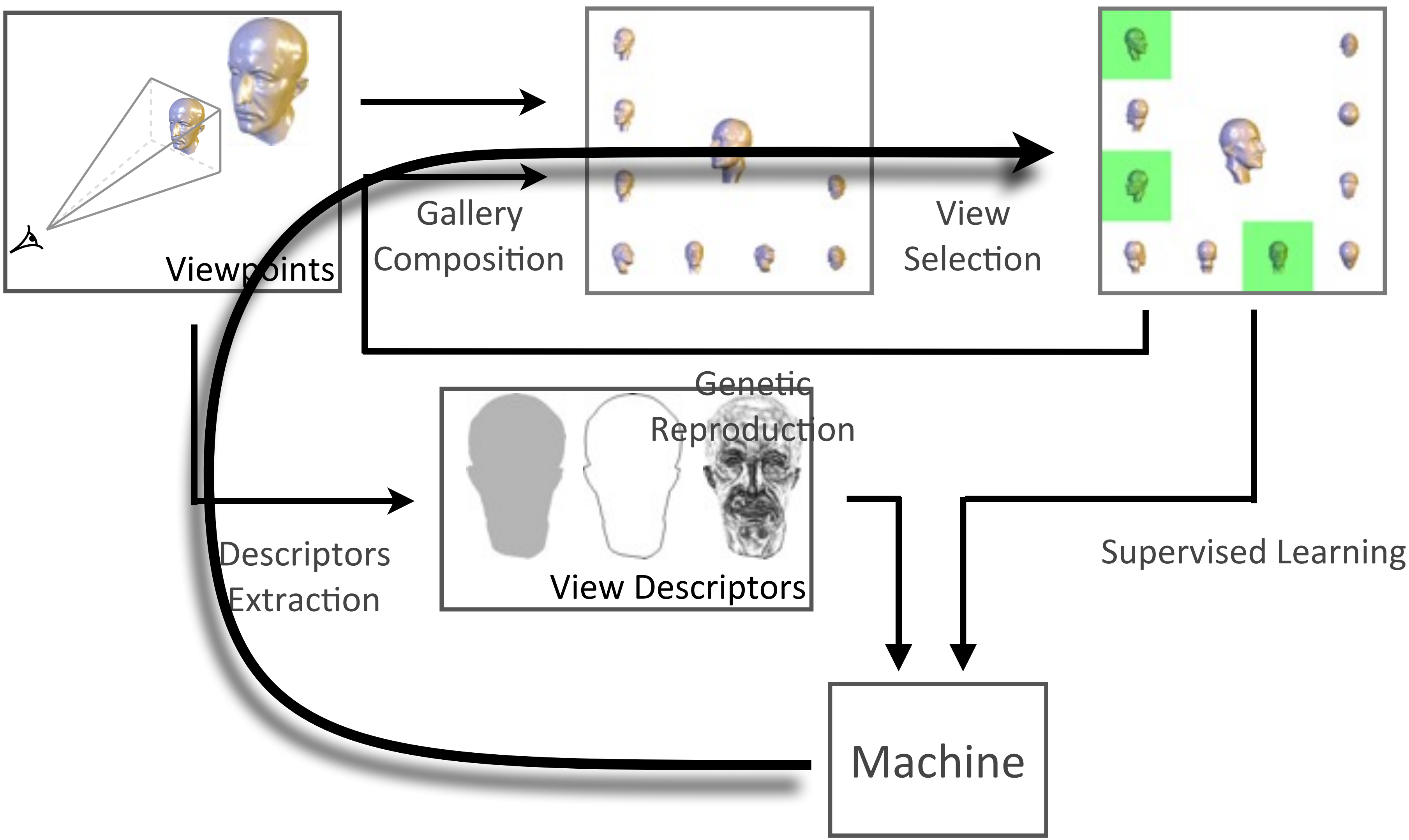
Exploring multidimensional view space

Design Galleries *(Marks et al., 1997)*





Learning + Design Galleries = Intelligent Galleries



Vieira et al., 2009

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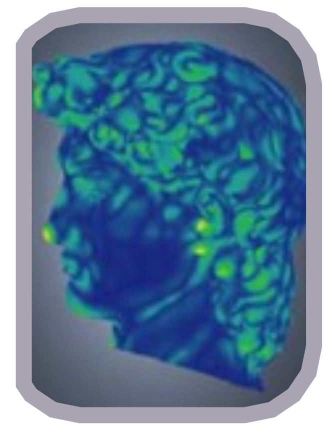
Summary

1. Related Work
2. Supervised Learning
3. Intelligent Galleries
4. Results

Related Work

Main trend: Optimize a single criteria

Viewpoint Entropy
Vázquez et al (2001)



Mesh Saliency
Lee et al (2005)

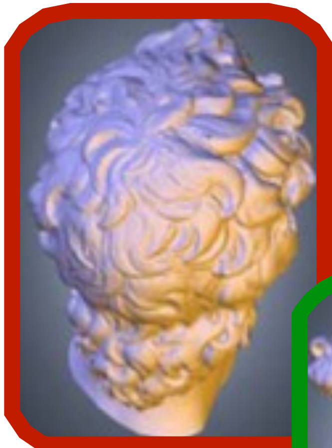
Visibility Ratio

Curvature Entropy

Silhouette length

Polonsky et al (2005)

Future Work in Previous Work



Curvature

Saliency

Curvature

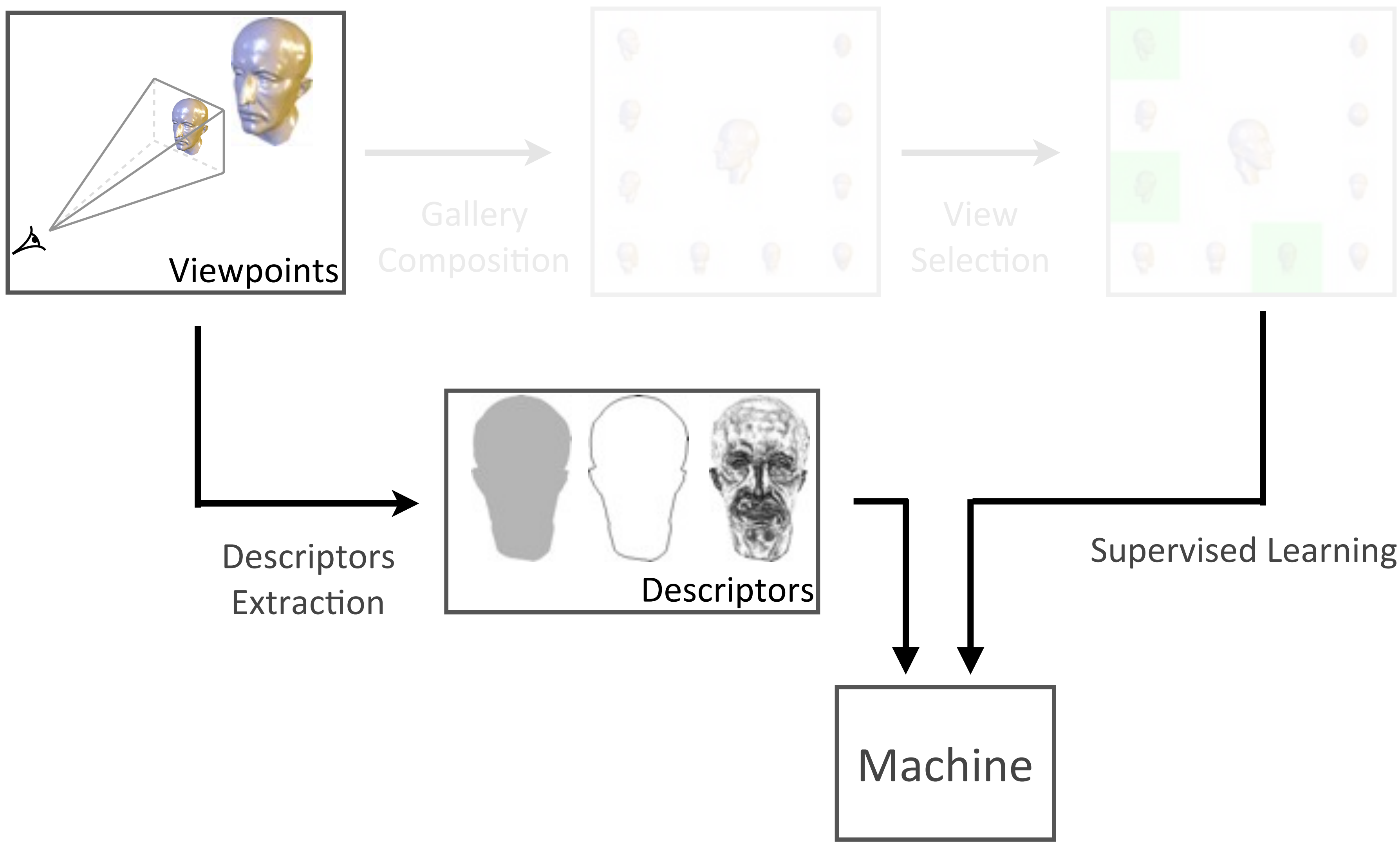
Saliency

"No one descriptor does a perfect job…."

"…since each descriptor does a reasonably good job on a majority of inputs, we are confident that it is possible to combine them to amplify the advantage that each has."

Polonsky et al. (2005)

Learning + Design Galleries = Intelligent Galleries

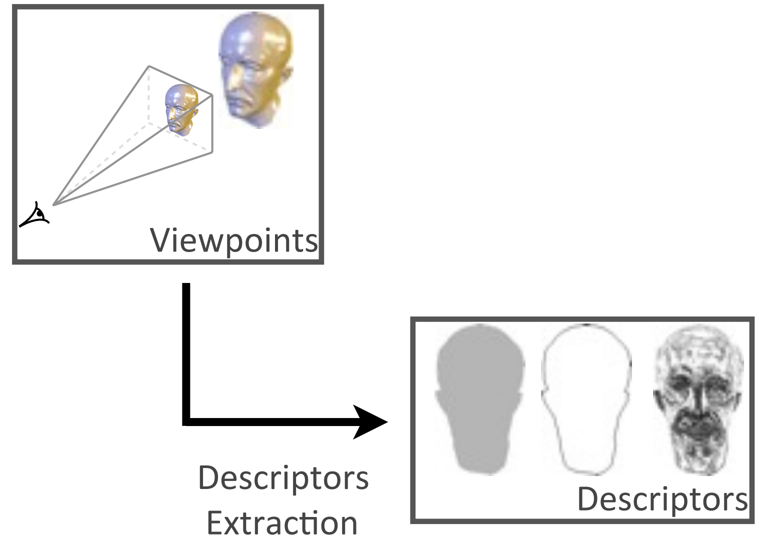


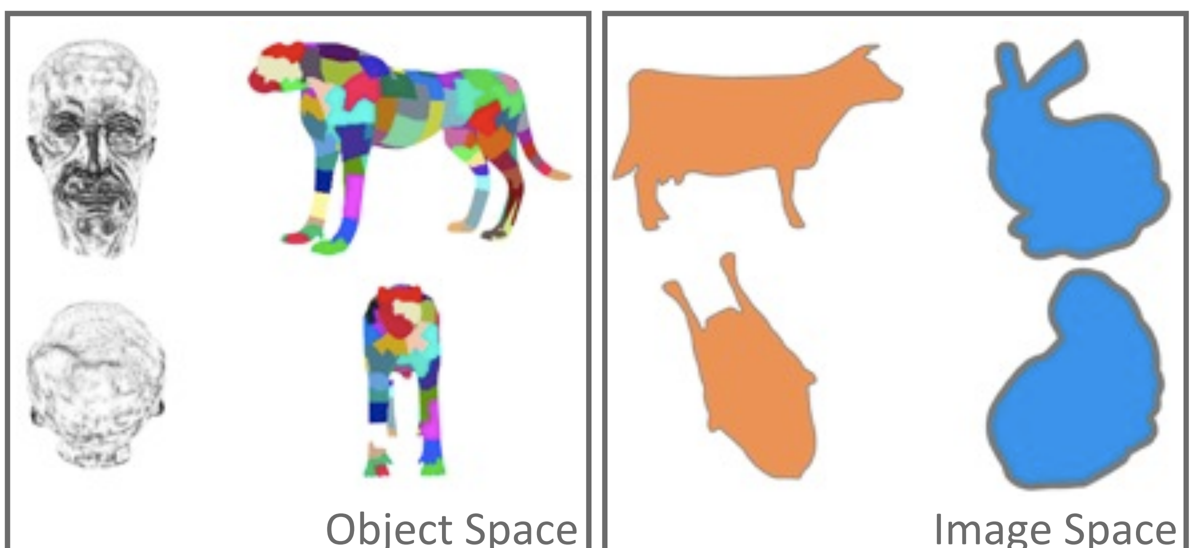
Vieira et al., 2009

View Descriptors

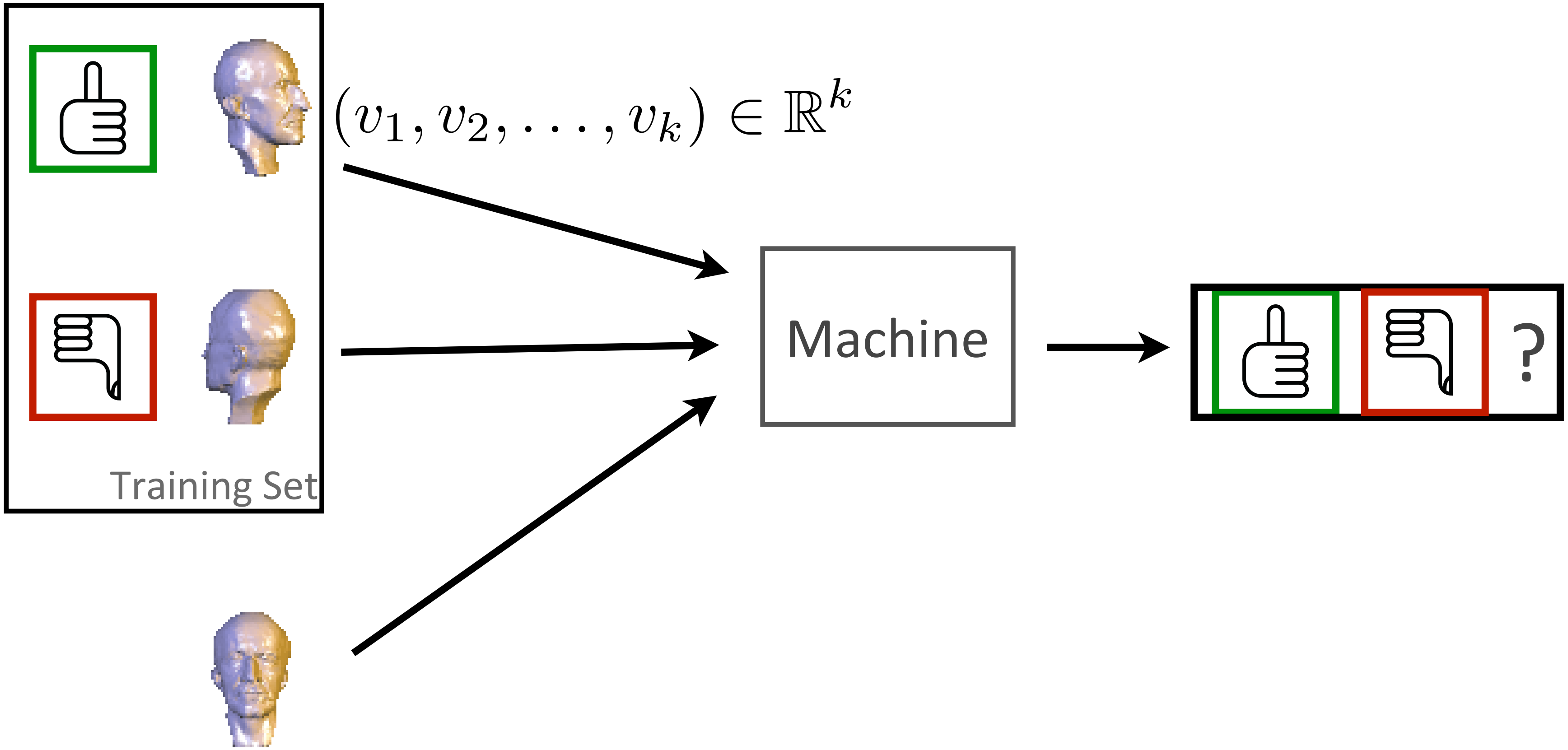
- Mean Curvature
- Visible 3D Surface
- Foreground Alignment
- Silhouette Complexity

...





Supervised Learning Machine



Support Vector Machines (SVM)

Binary classifier

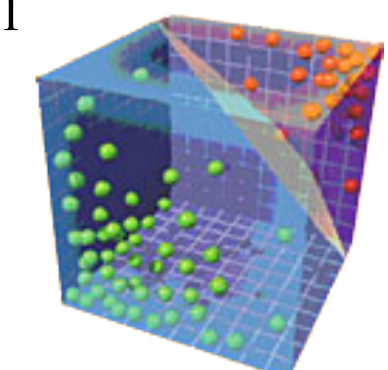
$$\hat{g} : \mathbb{R}^k \rightarrow \{-1, 1\}$$

$$v \rightarrow sign\left(\hat{f}(v)\right) = \{-1, 1\}$$

$$\hat{f}(v) = \sum_j \alpha_j \; s_j \langle \varphi(v_j), \varphi(v) \rangle + b$$

$$\underset{w,\gamma}{\text{MAX}} \quad \gamma - C \sum_{i=1}^{l} \varepsilon_i$$

$$\text{subject to } \; y_i \langle w, \Phi(x_i) \rangle \underset{i=1,\ldots,l}{\geq} \gamma - \varepsilon_i \;, \; \varepsilon_i \geq 0 \;, \quad \|w\|^2 = 1$$



- Non-linear classification
- Efficiently computed for small training sets
- Optimal in the sense of VC statistical learning theory

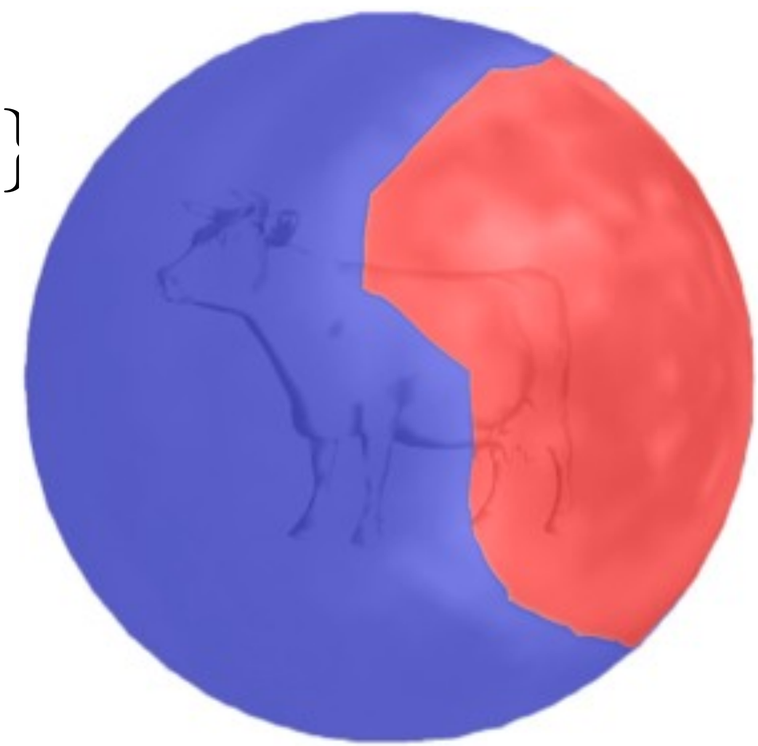
Ordering views with SVM

SVM binary classifier

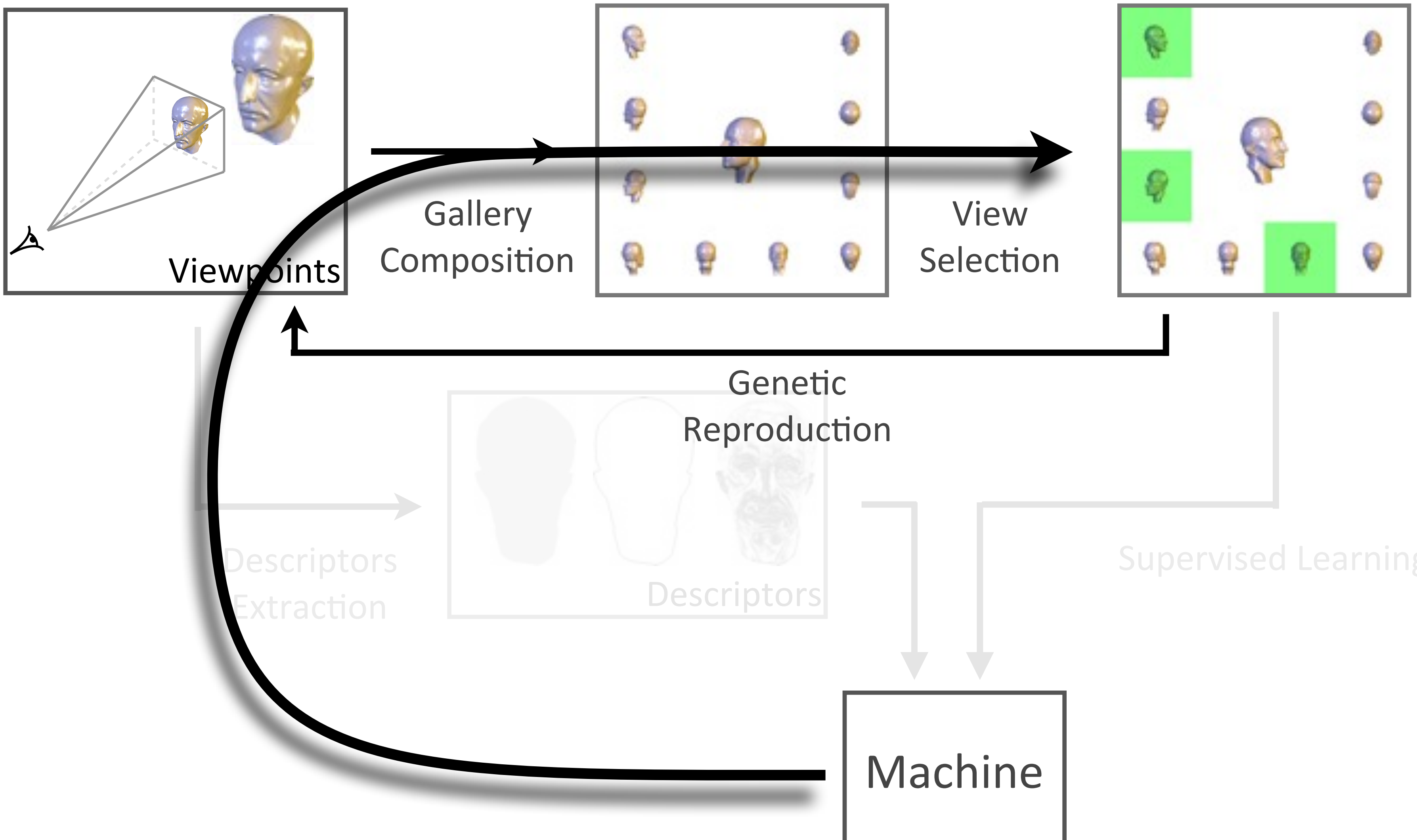
$$v \to sign\left(\hat{f}(v)\right) \in \{-1, 1\}$$

SVM adaptation

$$v \to \hat{f}(v) \in \mathbb{R}$$



Learning + Design Galleries = Intelligent Galleries



Vieira et al., 2009

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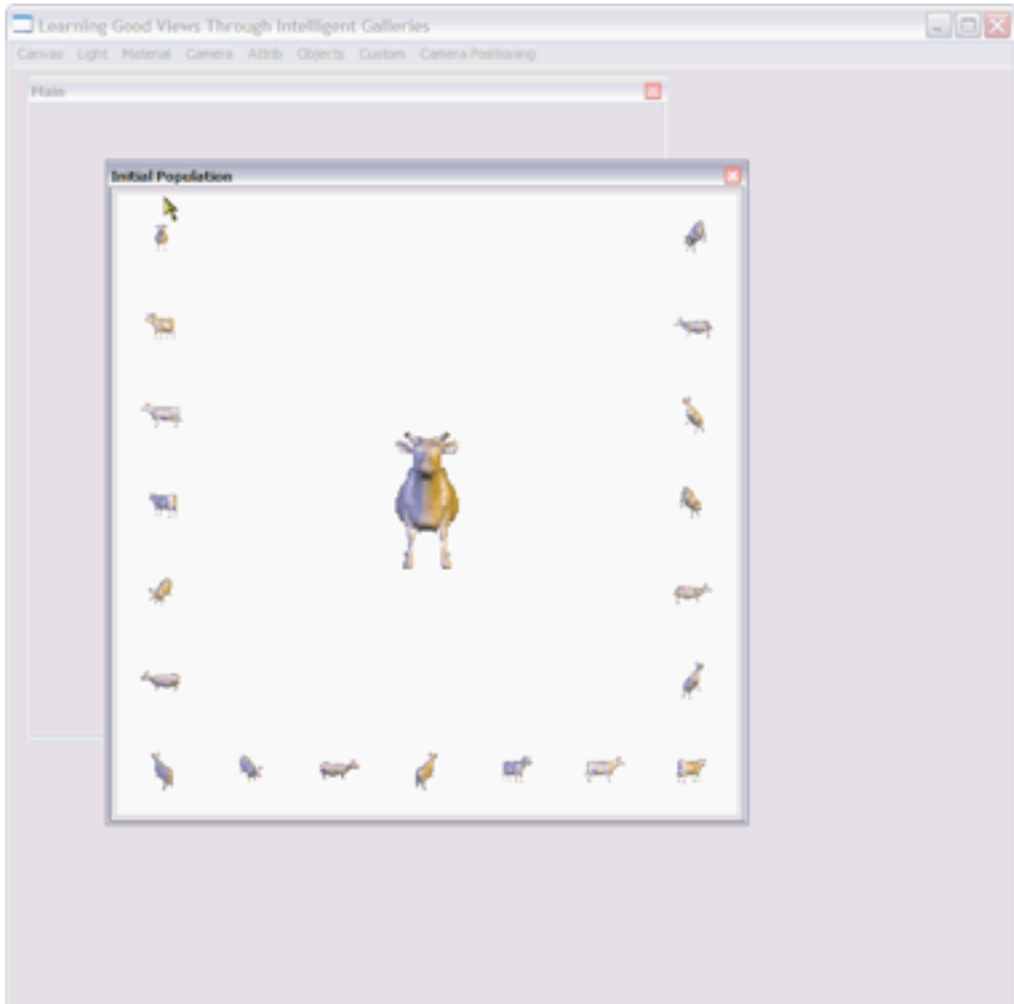
Intelligent Galleries

Learning through design galleries



Automatic View Selection

Automatic Ordering

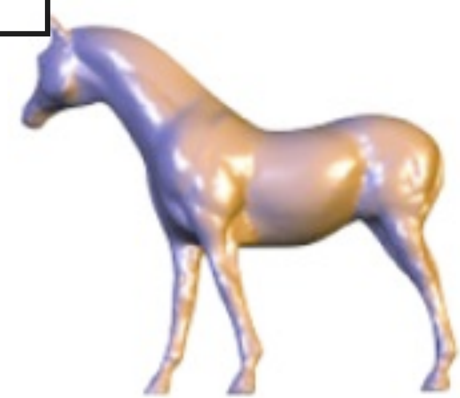
Training

Results

Automatic Selection for Similar Models

# of galleries: 4

Trained view



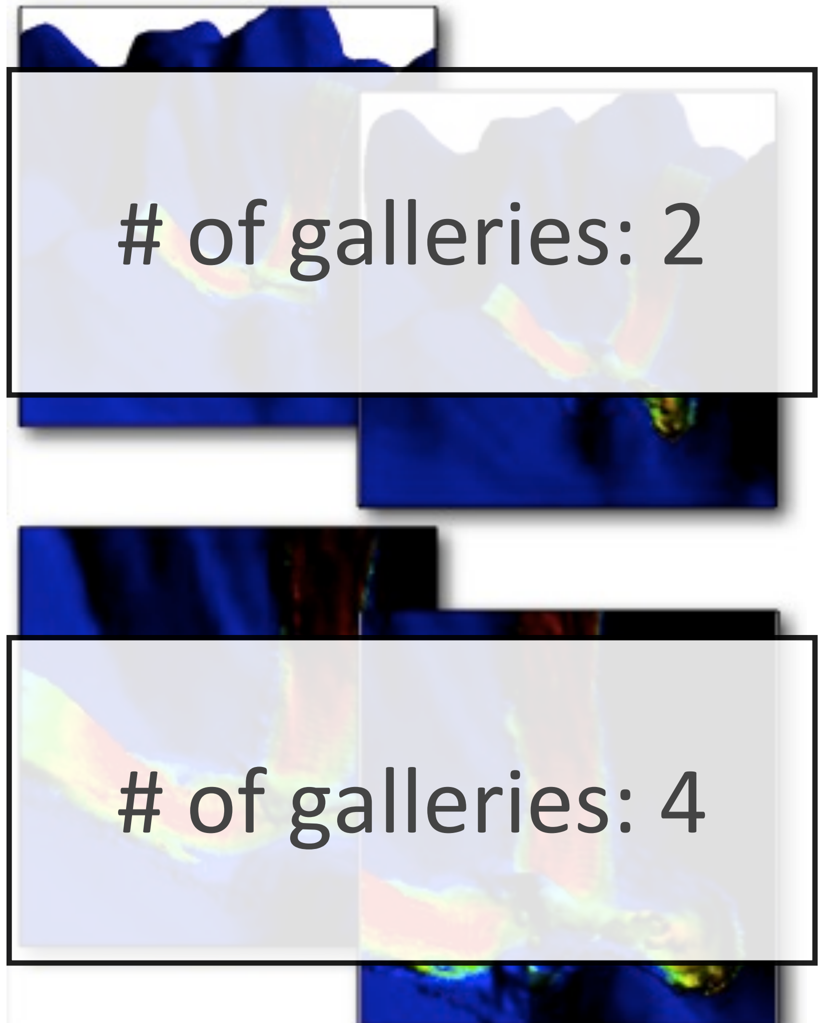
Subjectivity

Designer Selection

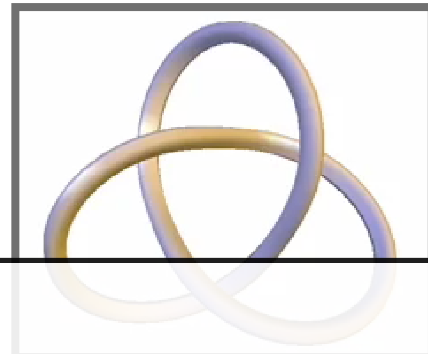
Machine Selection from Designer Experience

Fluid Specialist Selection

Machine Selection from Fluid Specialist Experience

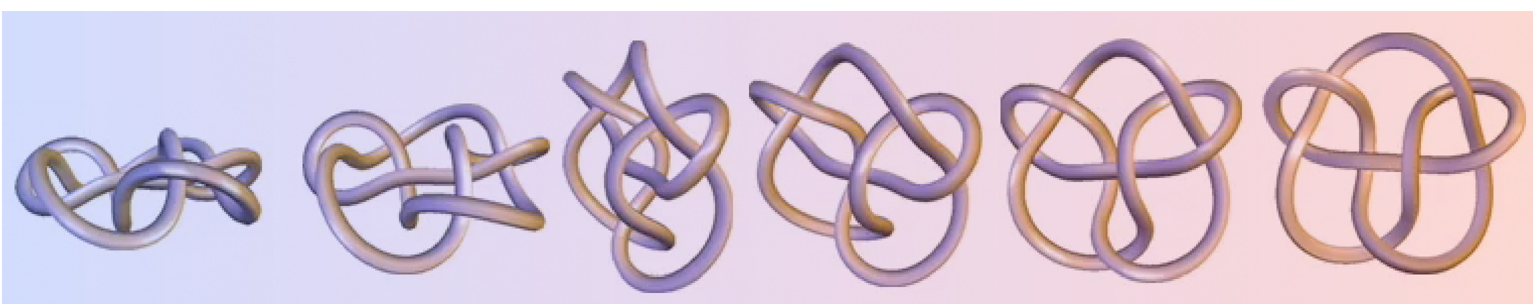


Challenging Scenes: 3D Knots



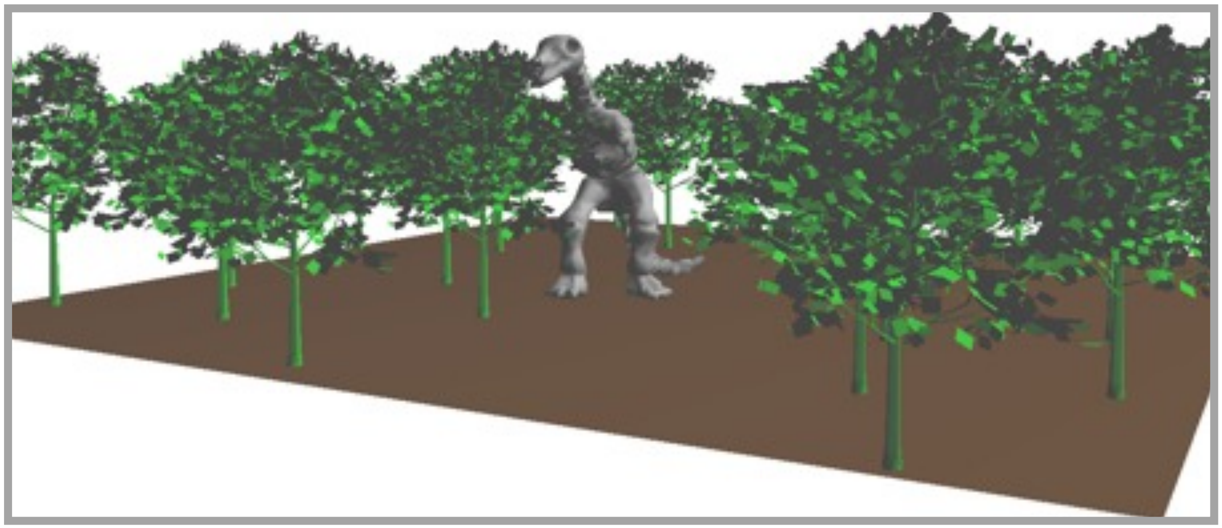
# of galleries: 2

Automatic
View Classification

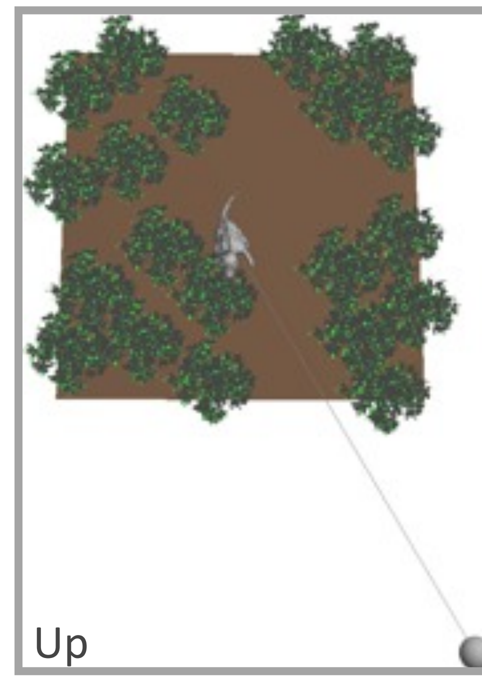


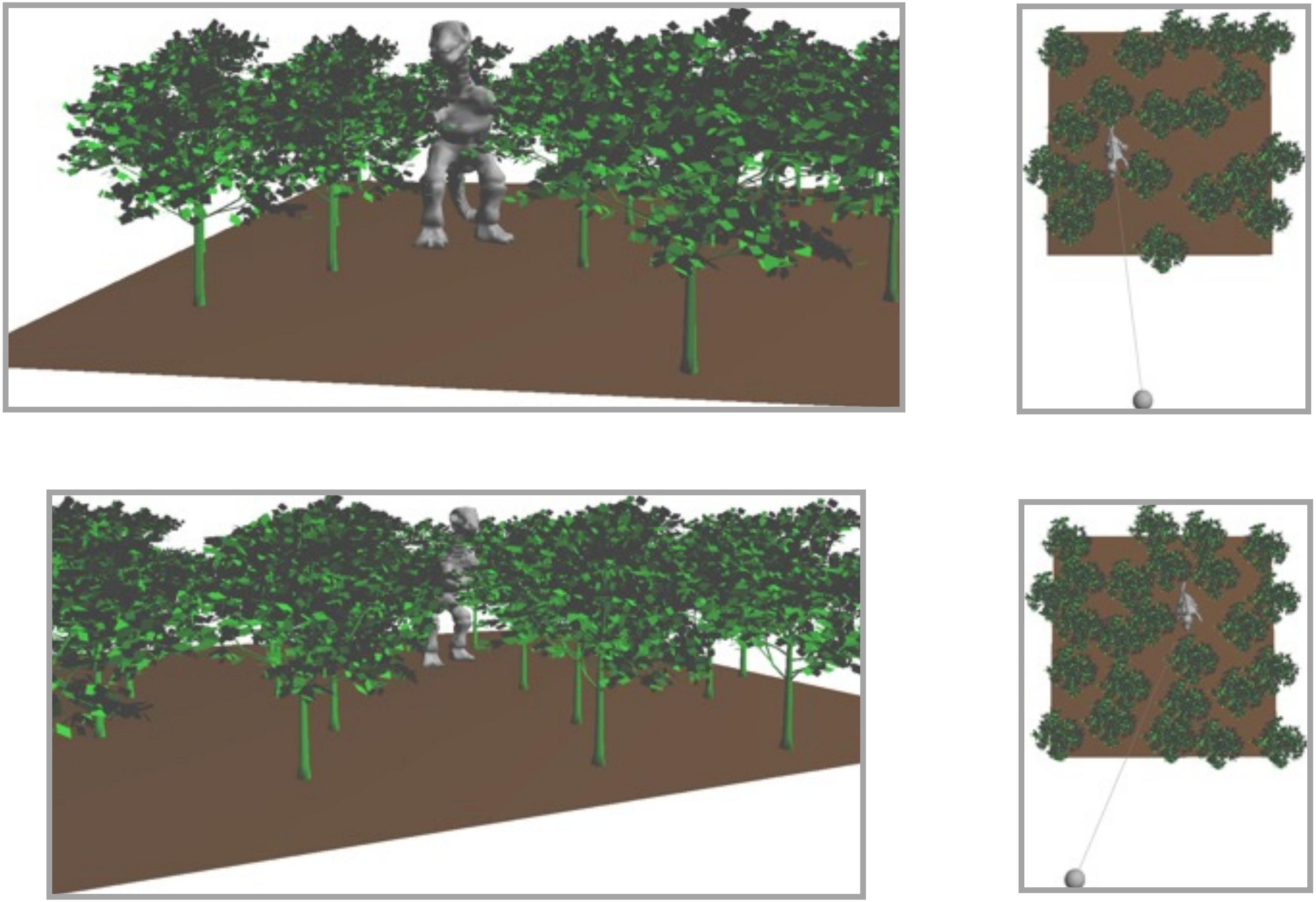
Increasing View Quality

High Depth / Occlusion Scenes



Trained Best View





Automatically Selected Best Views

Vieira et al., 2009

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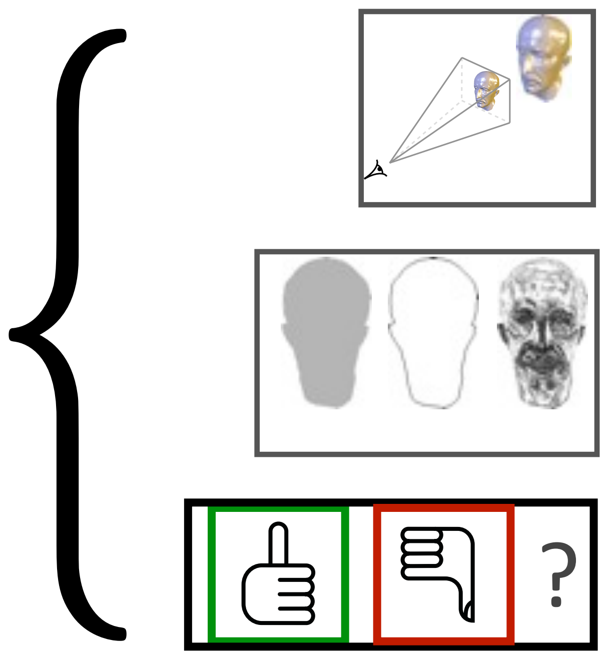
Timings

- Models Size: 10k~100k triangles
- Average Preprocessing time: 2~4 seconds

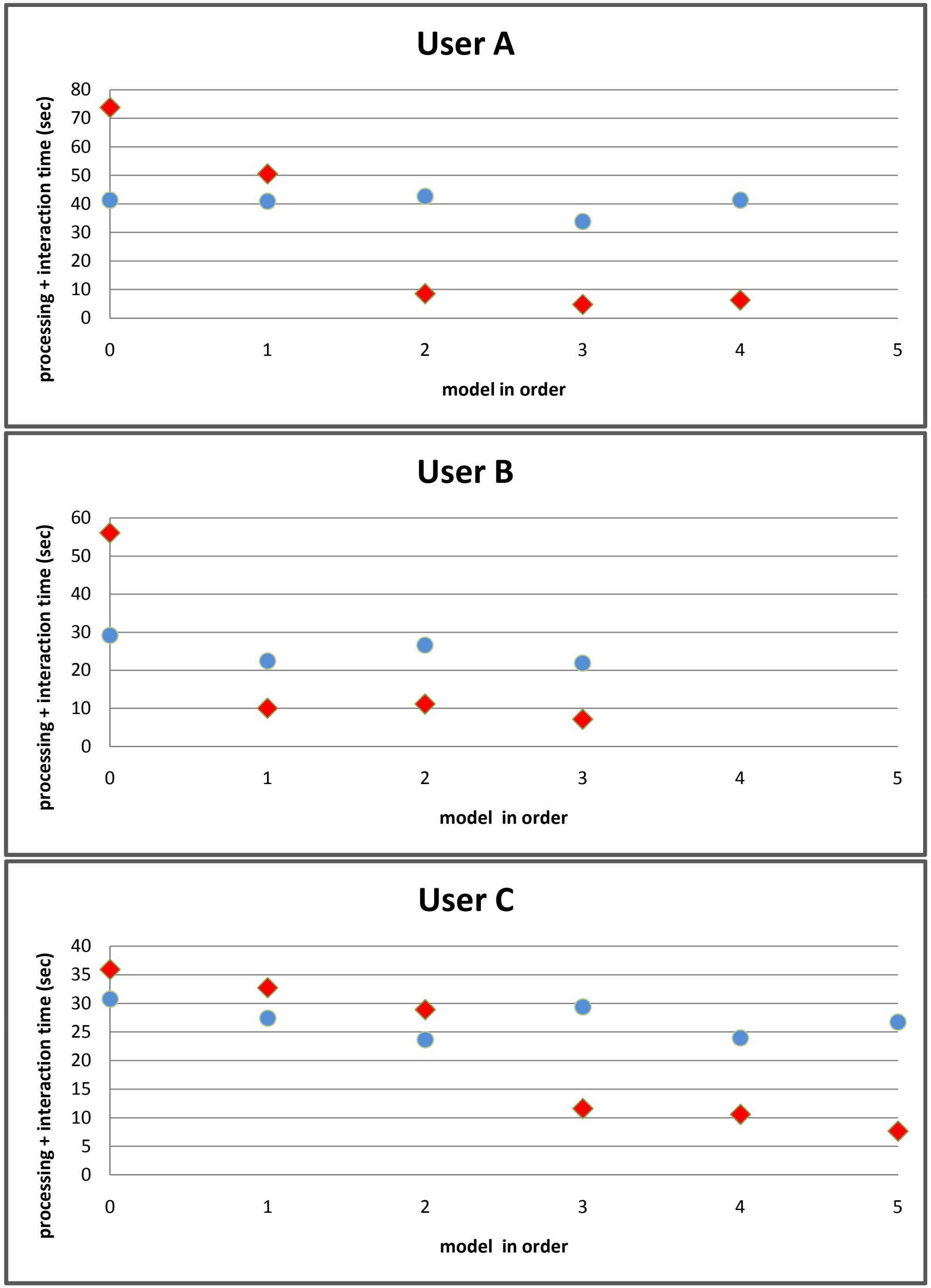
- Average Processing time per view:

  ~0.15 seconds



1. Rendering
2. View Descriptors Extraction
3. SVM Classification

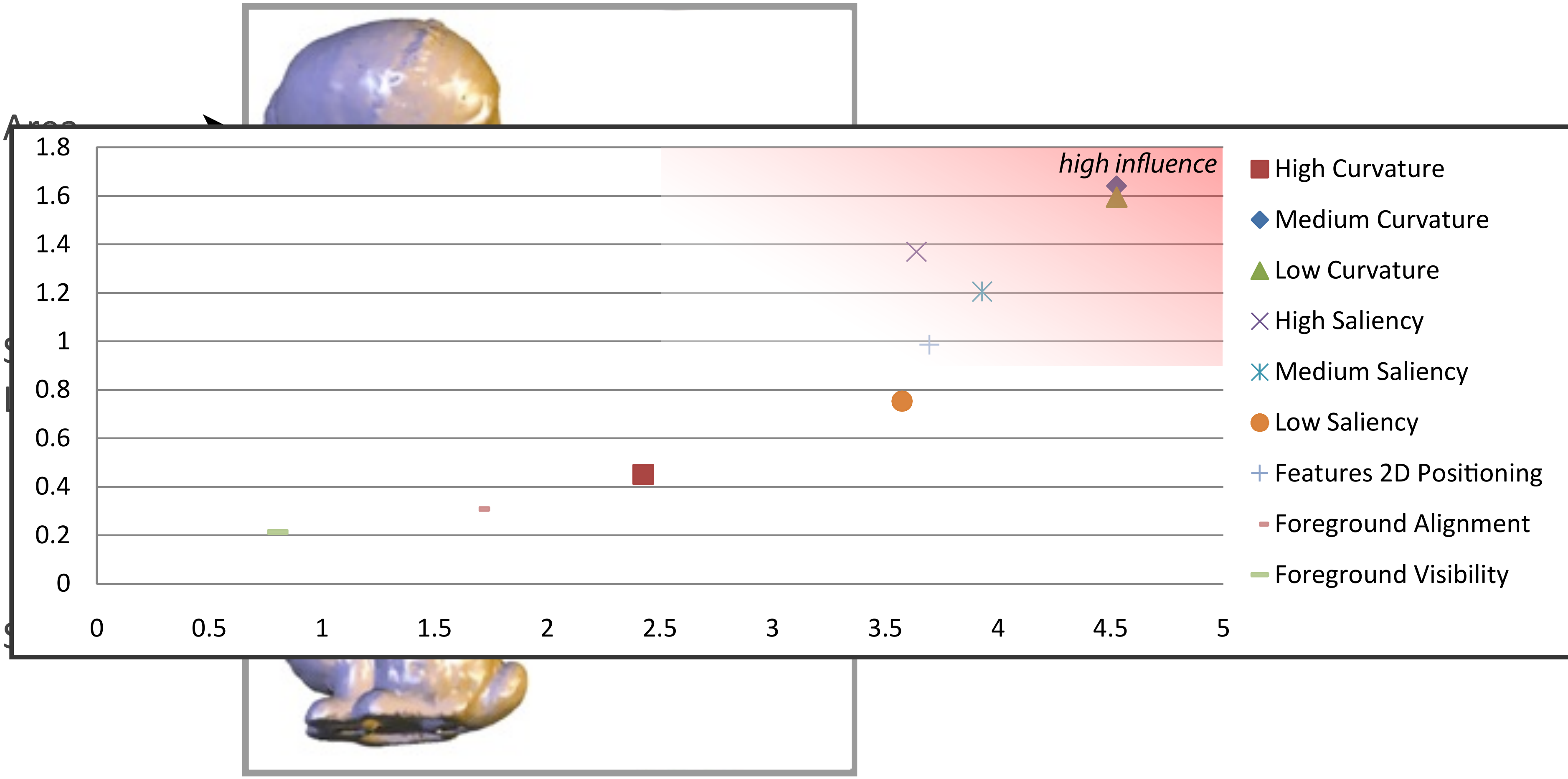
Learning Curve



intelligent gallery

blender

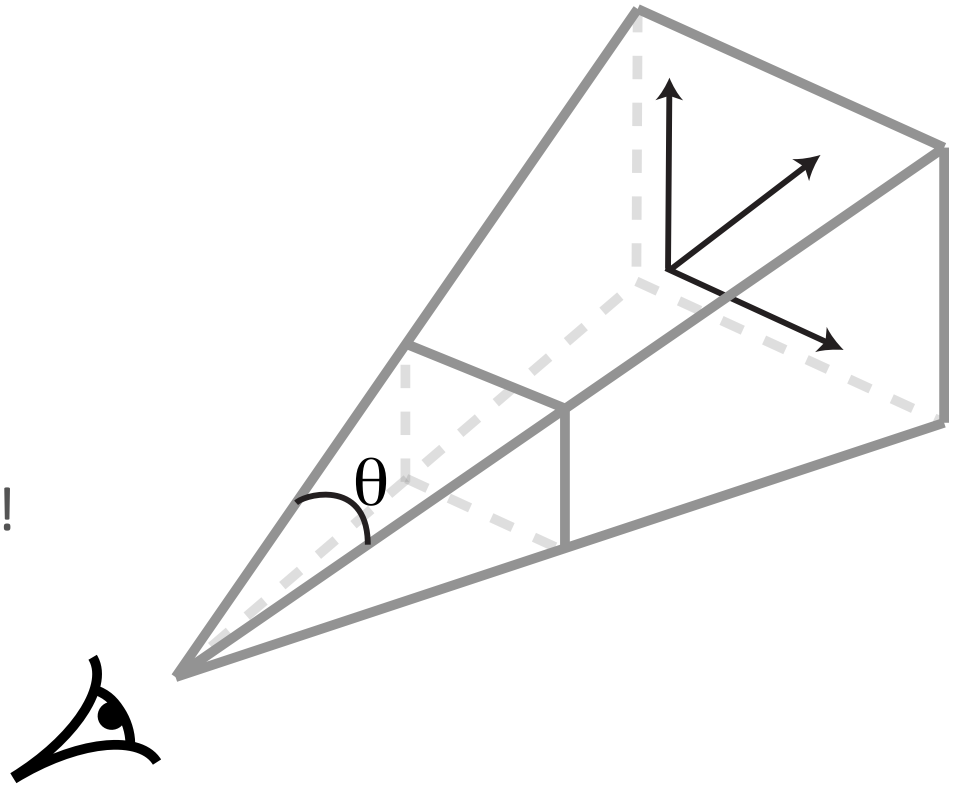
Comparison


high influence
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
High Curvature
Medium Curvature
Low Curvature
High Saliency
Medium Saliency
Low Saliency
Features 2D Positioning
Foreground Alignment
Foreground Visibility

Limitations: Number of Parameters

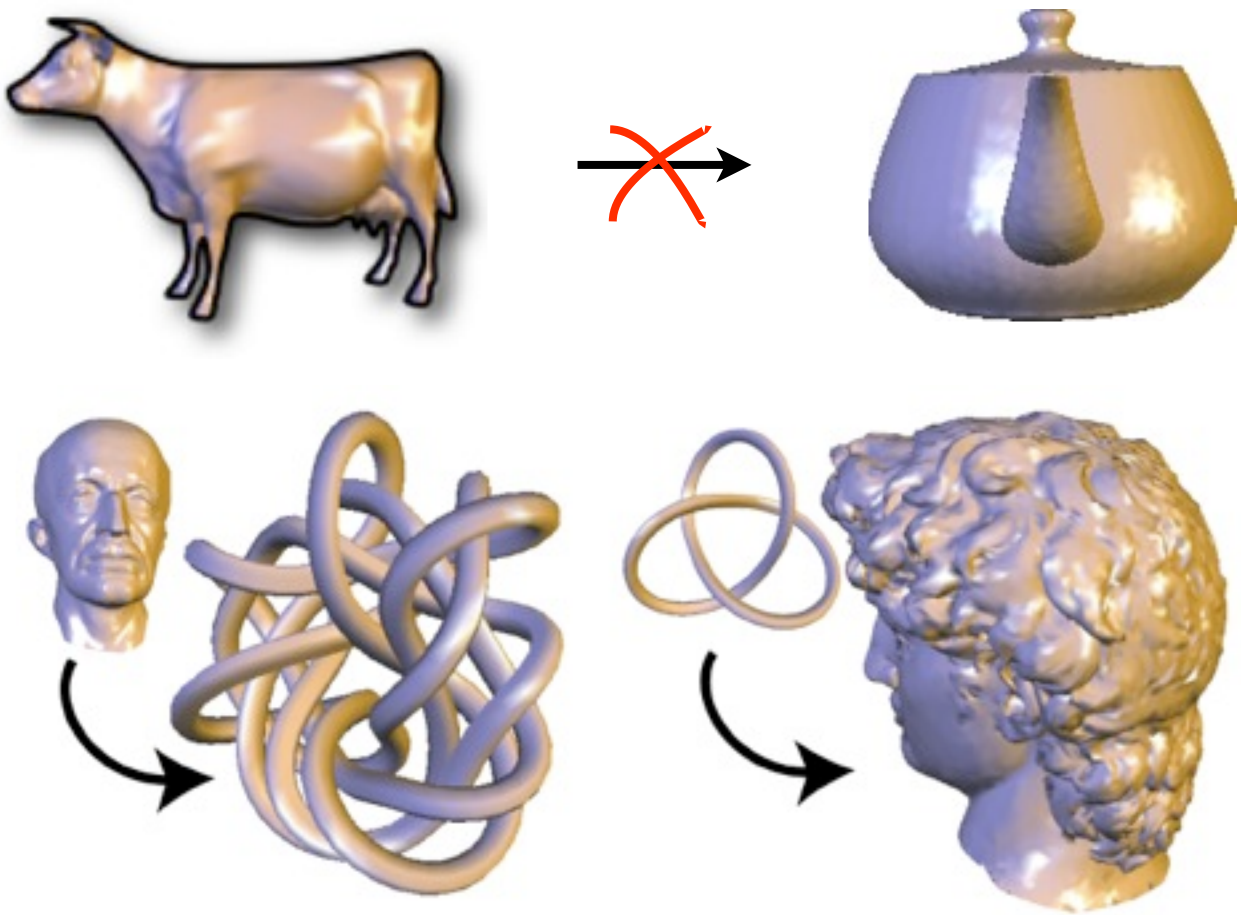
1. Position
2. Direction
3. Up Vector
4. Field of View
5. Near/Far Clipping Plane

$\Rightarrow$ k=9 $\Rightarrow$ 512 initial views!

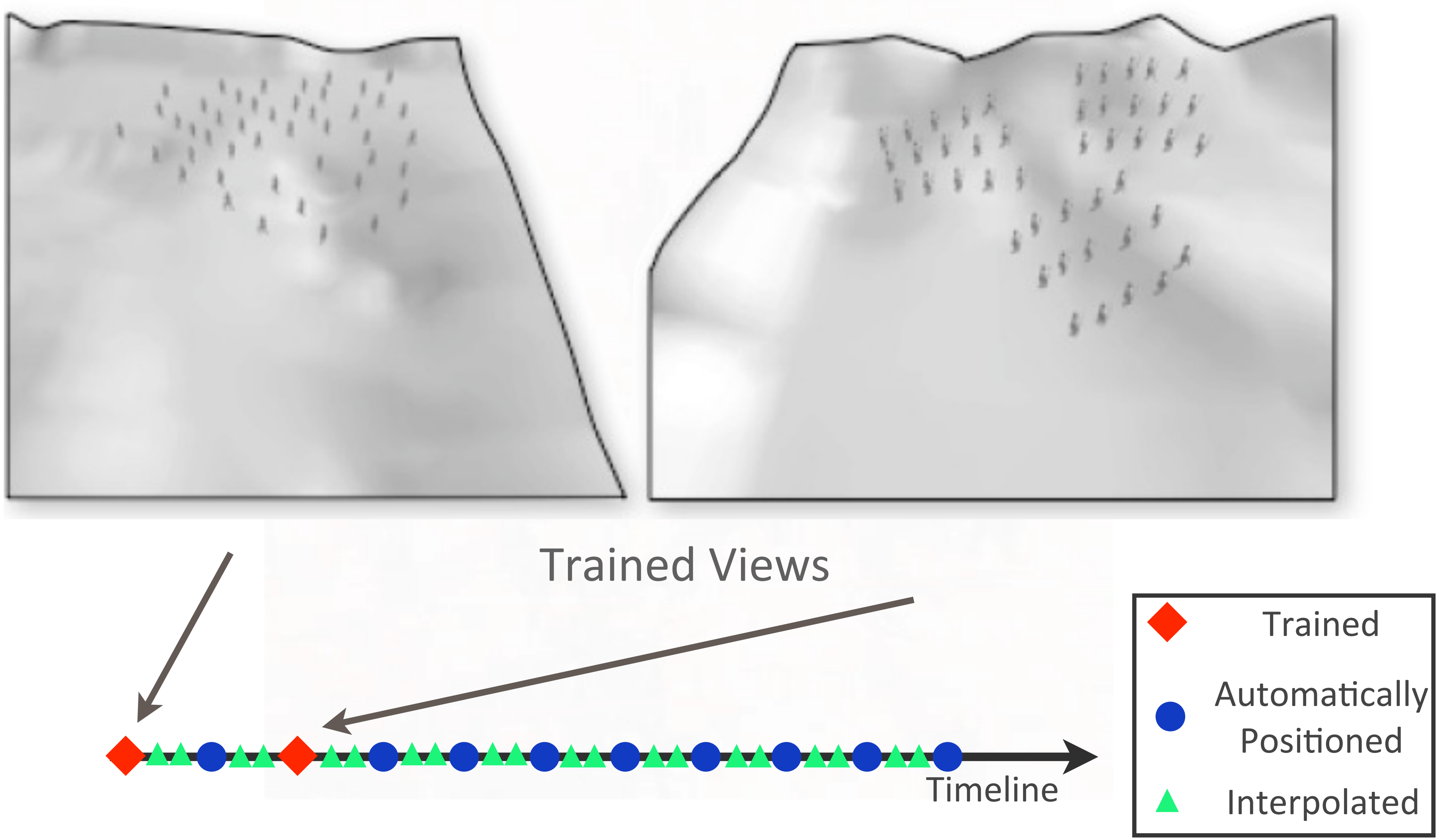


At least 2^k views in the initial gallery!

Similar Objectives Restriction

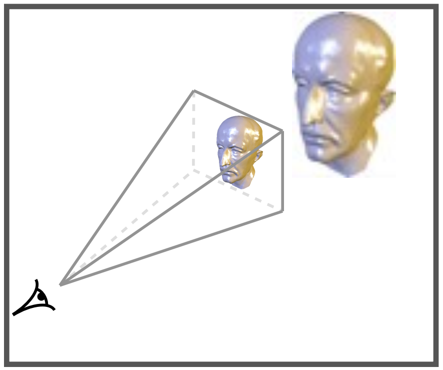


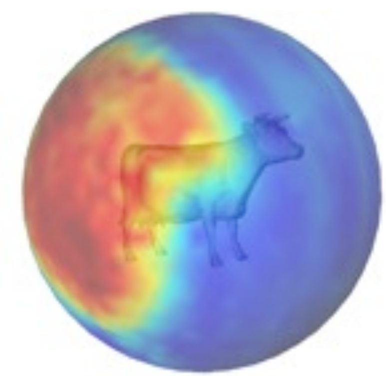
Application to 3D Video



Vieira et al., 2009

Future Work





- Greater set of descriptors
- Intelligent Galleries for other applications
- Enforce explicit design rules

Thank you for your attention!

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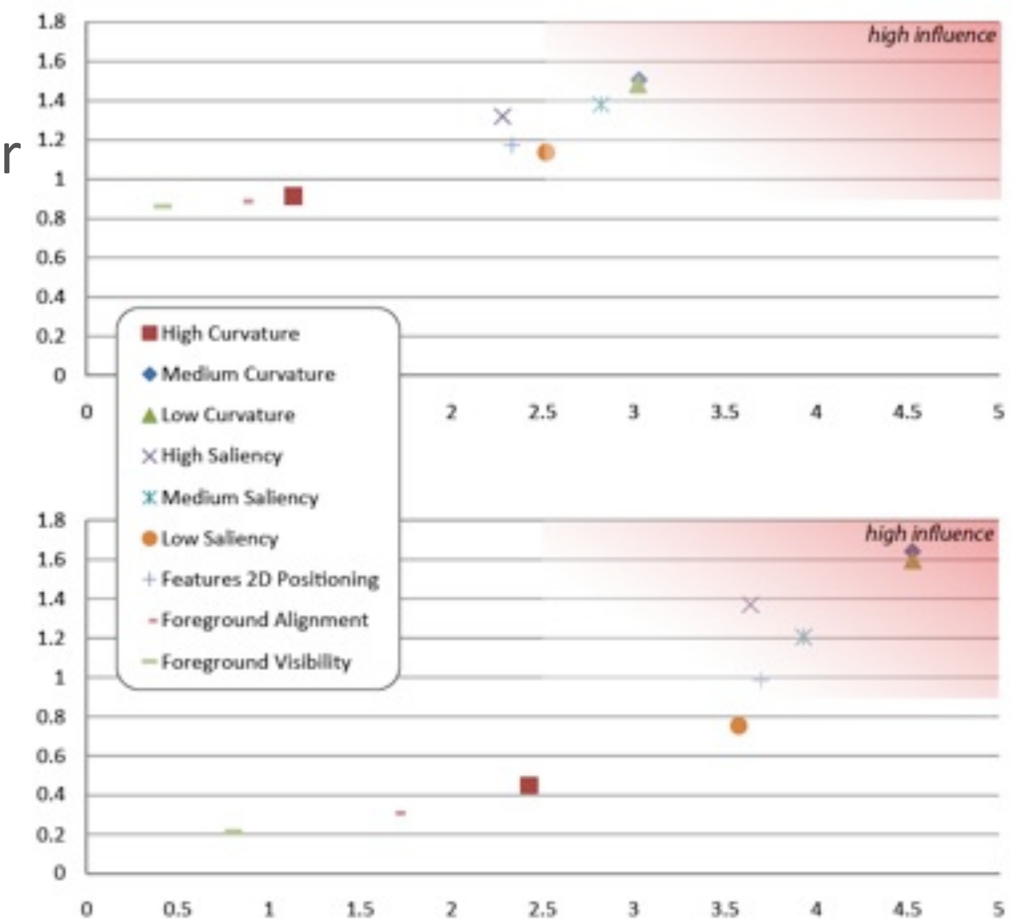
SVM Analysis

- Descriptor Influence:

  Correlation between descriptor values and SVM classification on the training set

- Sigma Optimization:

  Maximization of descriptors influence



SVM Minimization

$$S = \left\{ (x_i, y_i) \ ; \ i = 1, \ldots, l \right\}$$

$$\text{MIN} \ \ L(w, S) = \left\| y - Xw \right\|^2$$

$$\frac{\partial L(w, S)}{\partial w} = -2X^T y + 2X^T X w = 0$$

$$(X^T X) w = X^T y \ \Longrightarrow \ w = (X^T X)^{-1} X^T y$$

Kernels

$$\Phi : \mathbb{R}^2 \rightarrow \mathbb{R}^5$$

(x,z) ® (x,z,x^2,z^2,xz)

$$K(x,z) = \left\langle \Phi(x), \Phi(z) \right\rangle$$

$$K(x,z) = K_1(x,z) + K_2(x,z)$$

$$K(x,z) = cK_1(x,z)$$

$$K(x,z) = K_1(x,z)K_2(x,z)$$

$$K(x,z) = K_1(x,z)^d$$

Kernels

Linear Kernel: $$K(x,z) = \langle x, z \rangle$$

Polynomial Kernel: $$K(x,z) = \sum_{i=1}^{l} a_i \langle x, z \rangle^i$$

Gaussian Kernel: $$K(x,z) = e^{\left(-\frac{\|x-z\|^2}{2\sigma^2}\right)}$$

Anova Kernel: $$K(x,z) = \langle \Phi_d(x), \Phi_d(z) \rangle$$

$$\Phi_d : x \rightarrow (\Phi_A(x))_{|A|=d}$$

$$\Phi_A(x) = \prod_{i \in A} x_i = x_i A$$

Kernels

Linear Kernel: $K(x,z) = \langle x, z \rangle$

Polynomial Kernel: $K(x,z) = \sum_{i=1}^{l} a_i \langle x, z \rangle^i$

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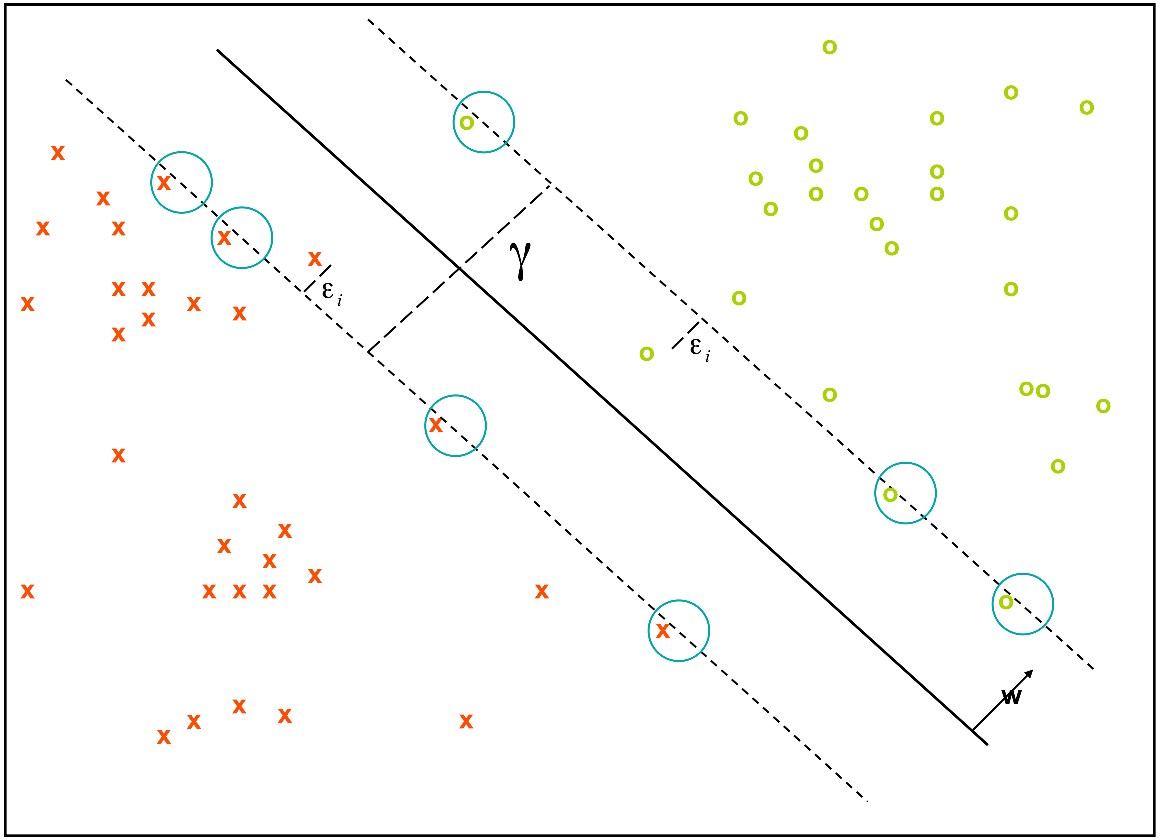
$$\Phi_d : x \rightarrow (\Phi_A(x))_{|A|=d}$$

$$\Phi_A(x) = \prod_{i \in A} x_i = x_i A$$

SVM

- Convex Optimization (Stability)
- Quadratic Problem (Precision)



SVM Solution

$$\underset{w,\gamma}{\mathrm{MAX}} \quad \gamma - C\sum_{i=1}^{l} \varepsilon_i$$

$$\text{subject to } \; y_i \left\langle w, \Phi(x_i) \right\rangle_{i=1,\ldots,l} \geq \gamma - \varepsilon_i \;,\; \varepsilon_i \geq 0 \;, \quad \|w\|^2 = 1$$

$$\alpha_i \left[y_i \left\langle w^*, \Phi(x_i) \right\rangle - (\gamma - \varepsilon_i) \right] = 0 \quad \rightarrow \quad \alpha_i \neq 0 \; \forall i \in SV$$