University of California, Los Angeles

Models and Methods for Sensor-Based Environment Exploration

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Overview

How to endow a robot with a "sense" of the surrounding environment?

Localization
: To interact with the environment, I need to know where I am, relative to where I have been and what I have seen.

Mapping
: Once I we know where I am, I need to know the affordances of the things around me.

Exploration
: Once I know the objects around me, I can expand my region of understanding.

Representation
: As that region grows, I must compress my understanding to fit my mind.

Outline of the Talk

1. Overview
1.1 Observability of Visual-Inertial Navigation
1.2 Scene Segmentation by Aggregation of Global Ordering Constraints
1.3 Desiging Agents with Task-Specific Minimal Representation

2. Featured Chapter: Information-Driven Autonomous Exploration

IMU Dynamics

$$
\begin{cases}
\dot{T} = V \qquad T(0) = 0 \\
\dot{R} = R\widehat{\omega} \qquad R(0) = R_0 \\
\dot{V} = \alpha \\
\dot{\omega} = w \\
\dot{\alpha} = \xi \\
\dot{\omega}_b = n_{\omega_b} \\
\dot{\alpha}_b = n_{\alpha_b} \\
\dot{\gamma} = 0 \\
\omega_{\text{imu}}(t) = \omega(t) + \omega_b(t) + n_\omega(t) \\
\alpha_{\text{imu}}(t) = R^T(t)(\alpha(t) - \gamma) + \alpha_b(t) + n_\alpha(t)
\end{cases}
\tag{1}
$$

Vision Constraints

$$y(t) \doteq \begin{bmatrix} y^1 \\ y^2 \\ \vdots \\ y^N \end{bmatrix}(t) = \begin{bmatrix} \pi(R^T(X^1 - T)) \\ \pi(R^T(X^2 - T)) \\ \vdots \\ \pi(R^T(X^N - T)) \end{bmatrix} + \begin{bmatrix} n^1(t) \\ n^2(t) \\ \vdots \\ n^N(t) \end{bmatrix}$$

Vision constraints correct for IMU biases as long as these biases are constant + noise [1].

[1] Stergios I Roumeliotis, Andrew E Johnson, and James F Montgomery. Augmenting inertial navigation with image-based motion estimation. In 'Robotics and Automation, 2002. Volume 4, pages 4326–4333.

Bounds on Indistinguishable Set

Claim (Indistinguishable Trajectories from IMU Data)

Let $g(t) = (R(t), T(t)) \in \mathrm{SE}(3)$ be such that

$$\begin{cases} \dot{R} = R(\widehat{\omega}_{\mathrm{imu}} - \widehat{\omega}_b) \\ \dot{T} = V \\ \dot{V} = R(\alpha_{\mathrm{imu}} - \alpha_b) + \gamma \end{cases} \tag{2}$$

for some known constant γ and functions $\alpha_{\mathrm{imu}}(t)$, $\omega_{\mathrm{imu}}(t)$ and for some unknown functions $\alpha_b(t), \omega_b(t)$ that are constrained to have $\|\dot{\alpha}_b(t)\| \leq \epsilon$, $\|\dot{\omega}_b(t)\| \leq \epsilon$, and $\|\ddot{\omega}_b(t)\| \leq \epsilon$ at all t, for some $\epsilon < 1$.

Bounds on Indistinguishable Set

Claim (continued)

Suppose $\tilde{g}(t) \doteq \sigma(g_1 g(t) g_1)$ for some constant $g_i = (R_i, T_i)$, $\sigma > 0$, $\|T_1\| \leq M_1$ and $|\sigma| \leq M_\sigma$. Then,

$$\|I - R_1\| \leq \frac{2\epsilon}{m(\dot{\omega}_{\text{imu}} : \mathbb{R}^+)}, \quad |\sigma - 1| \leq \frac{k_{c_1}\epsilon + M_\sigma \|I - R_1\|}{M(\dot{\alpha}_{\text{imu}} : \mathcal{I}_{c_1})}$$

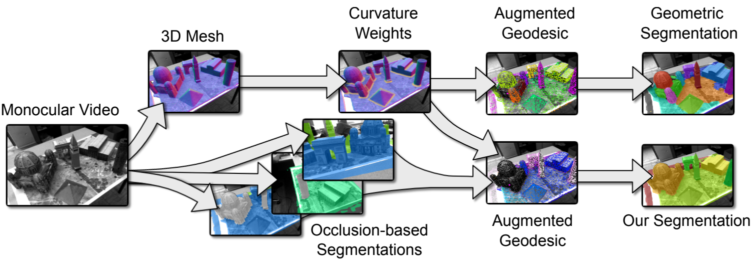
$$\|T_1\| \leq \frac{\epsilon(k_{c_2} + (2M_\sigma + 1)M_1)}{(1 - |\sigma - 1|)\, m(\ddot{\omega}_{\text{imu}} : \mathcal{I}_{c_2})}$$

$$\|(1 - R_2^T)\gamma\| \leq \frac{\epsilon(k_{c_3} + M_\sigma M_1) + (|\sigma - 1| + \epsilon) M(\omega_{\text{imu}} - \omega_b : \mathcal{I}_{c_3}) \|\gamma\|}{m(\omega_{\text{imu}} - \omega_b : \mathcal{I}_{c_3})\, (1 - |\sigma - 1|)}$$

Contributions

- First bounds on indistinguishable set with IMU bias drift.

Pipeline



Monocular Video
3D Mesh
Curvature Weights
Augmented Geodesic
Geometric Segmentation
Occlusion-based Segmentations
Augmented Geodesic
Our Segmentation

VIDEO

Comparisons

		City of Sights Frame	Scene	*Pipes1* Frame	Scene	*Pipes2* Frame	Scene	*Tree* Frame	Scene
CGAL [2]	F-Score	.803 ± .041	.787	Fails		**.915 ± .032**	**.869**	.643 ± .049	.604
	Precision	.822 ± .043	.798			.959 ± .036	.903	.633 ± .058	.608
	Recall	.785 ± .041	.776			.875 ± .041	.838	.657 ± .053	.599
WCSeg [3]	F	.775 ± .028	.732	**.730 ± .030**	**.725**	.738 ± .045	.730	.806 ± .027	.747
	P	.938 ± .033	.912	.843 ± .040	.841	.820 ± .050	.904	.885 ± .031	.889
	R	.661 ± .033	.612	.645 ± .036	.637	.676 ± .068	.612	.742 ± .038	.644
Ours (Geom. only)	F	**.923 ± .018**	**.788**	.705 ± .036	.648	.818 ± .045	.701	.720 ± .036	.729
	P	.986 ± .018	.866	.761 ± .043	.690	.820 ± .056	.751	.763 ± .036	.783
	R	.867 ± .020	.722	.658 ± .040	.612	.818 ± .047	.657	.683 ± .041	.681
Ours (Geom. + Vis.)	F	.870 ± .043	.767	.662 ± .027	.605	.804 ± .063	.648	**.828 ± .034**	**.836**
	P	.853 ± .028	.763	.689 ± .040	.611	.810 ± .064	.679	.803 ± .028	.790
	R	.888 ± .062	.770	.637 ± .030	.599	.800 ± .072	.620	.856 ± .032	.888

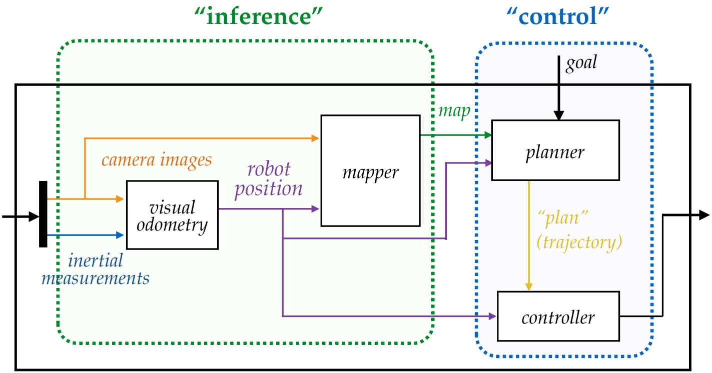
[2] L. Shapira, A. Shamir, and D. Cohen-Or. Consistent mesh partitioning and skeletonisation using the shape diameter function. Vis. Comput., 24(4):249–259, Mar. 2008

[3] O. van Kaick, N. Fish, Y. Kleiman, S. Asafi. Shape segmentation by approximate convexity analysis. ACM Trans. on Graphics, 2014.

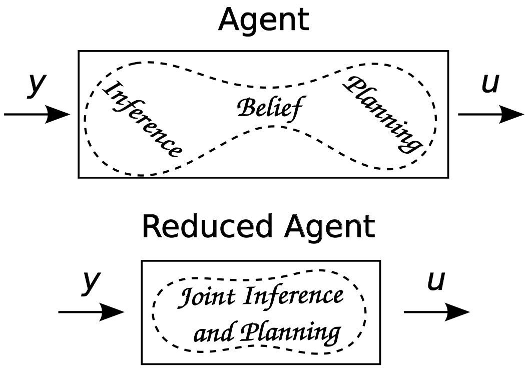
Contribution

- First bounds on indistinguishable set with IMU bias drift.
- Developed system for video segmentation leveraging image-plane segmentations.

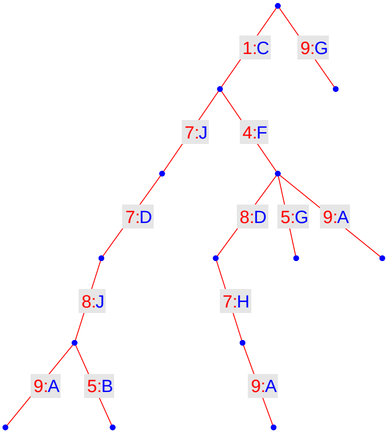
Inference and Planning



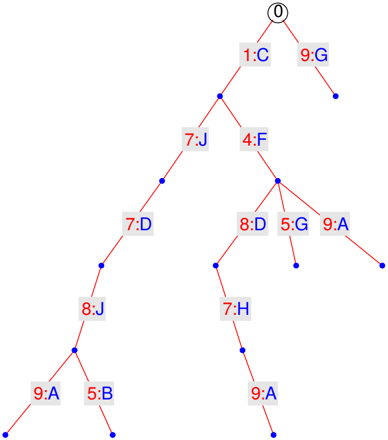
Bottleneck


Agent
y
Inference
Belief
Planning
u
Reduced Agent
y
Joint Inference
and Planning
u

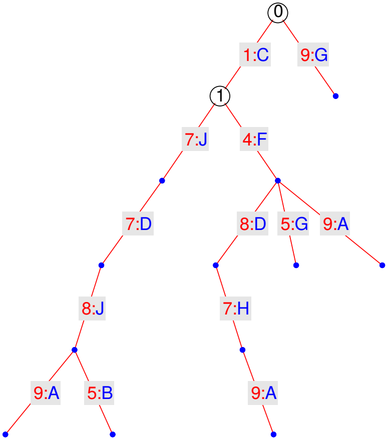
Discrete Decision Policy



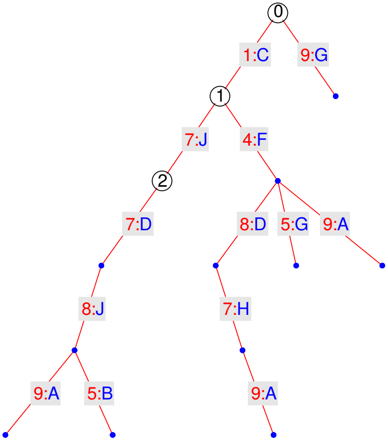
Bit-by-bit Disambiguation



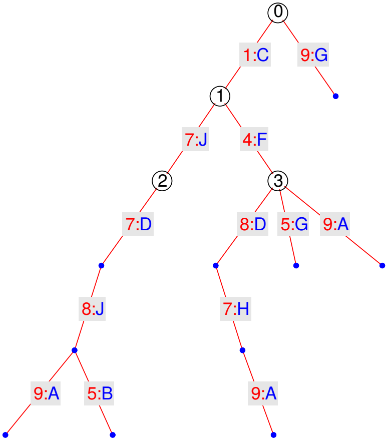
Bit-by-bit Disambiguation

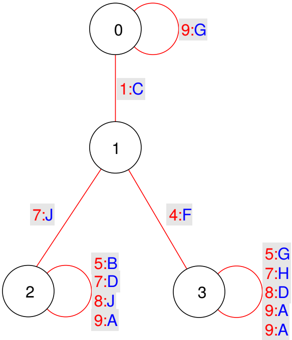


Bit-by-bit Disambiguation

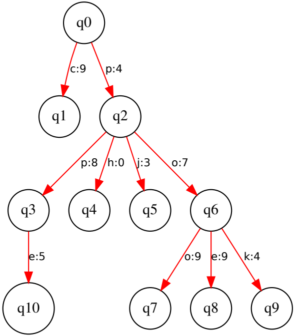


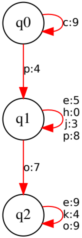
Bit-by-bit Disambiguation



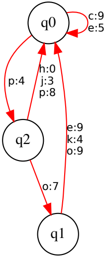


Comparison with Greedy Methods

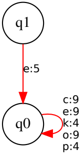




Bit-by-Bit

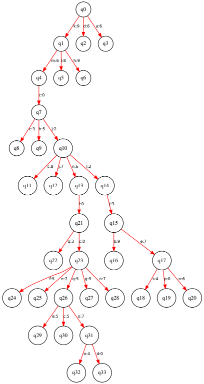


Greedy

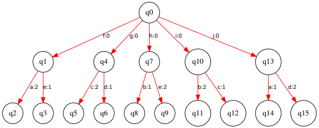


Exact

Types of Trees

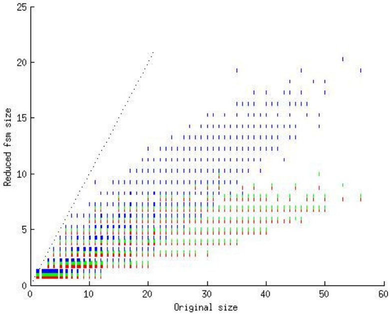


Poisson Tree

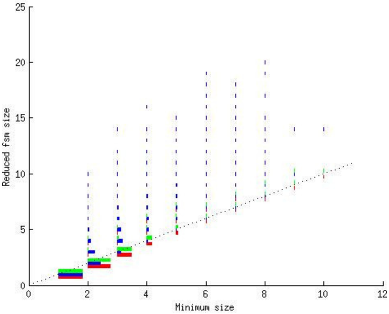


Pathological Tree

Poisson Tree Comparisons

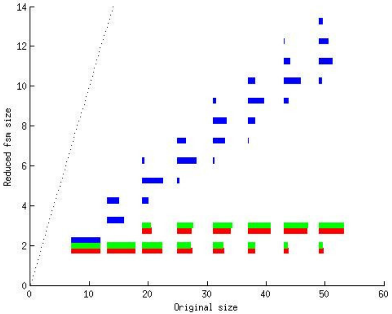


Original vs. Reduced

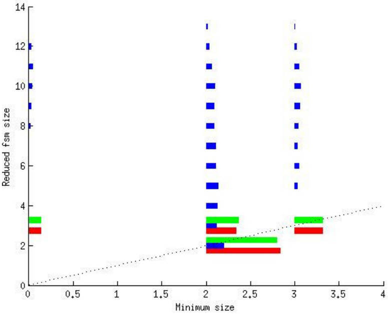


Minimum vs. Reduced

Pathological Tree Comparisons

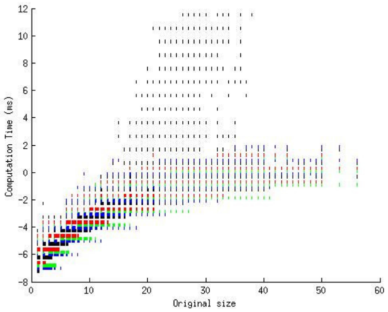


Original vs. Reduced

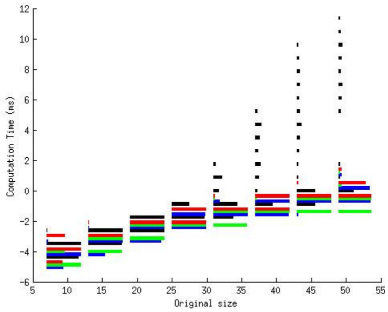


Minimum vs. Reduced

Algorithm Timing



Poisson Trees

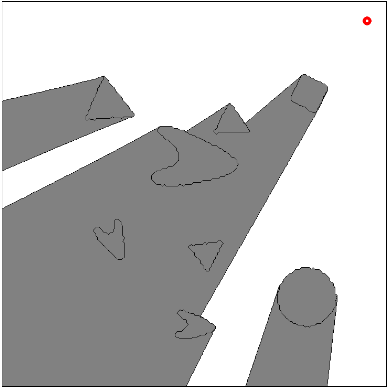


Pathological Trees

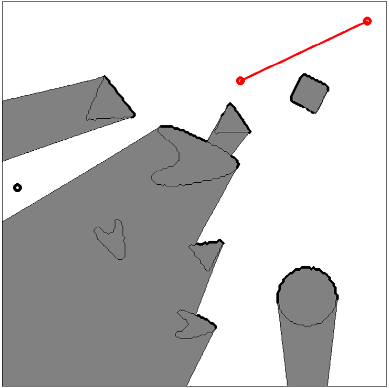
Contributions

- First bounds on indistinguishable set with IMU bias drift.
- Developed system for video segmentation leveraging image-plane segmentations.
- Developed an algorithm for in-place state reduction. Related POMDP to large body of ancient (pre-1980) research in digital circuit optimization.

Autonomous Exploration

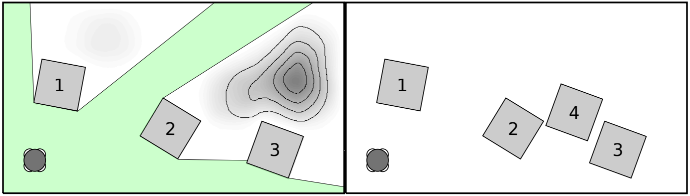


Autonomous Exploration



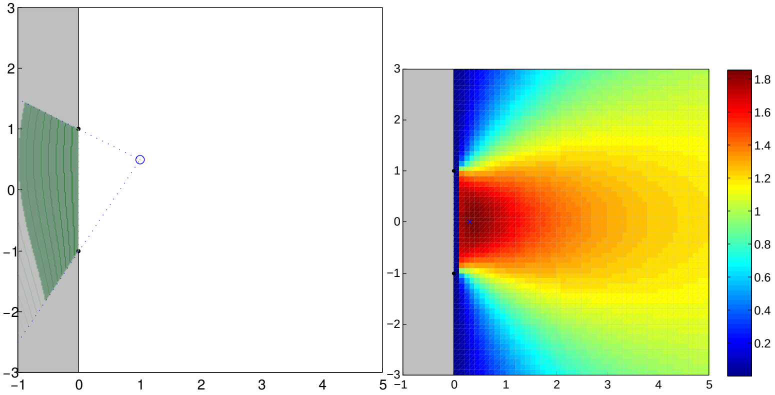
- "Frontier chasing"
- Heuristics

Exploring a Random Room

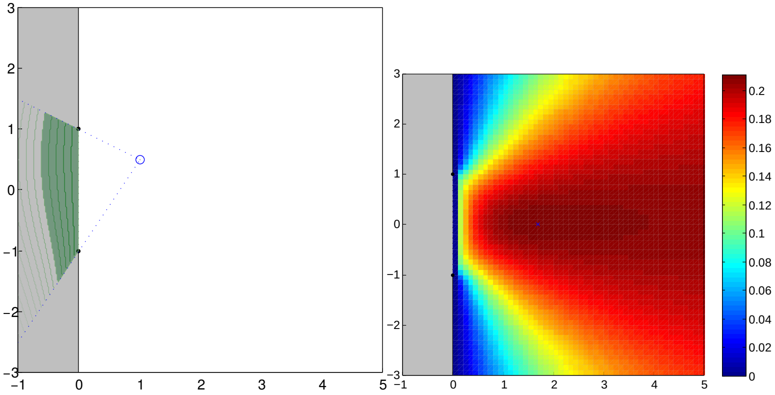


When features are coarse, the information content of an unmapped region is not always proportional to its size.

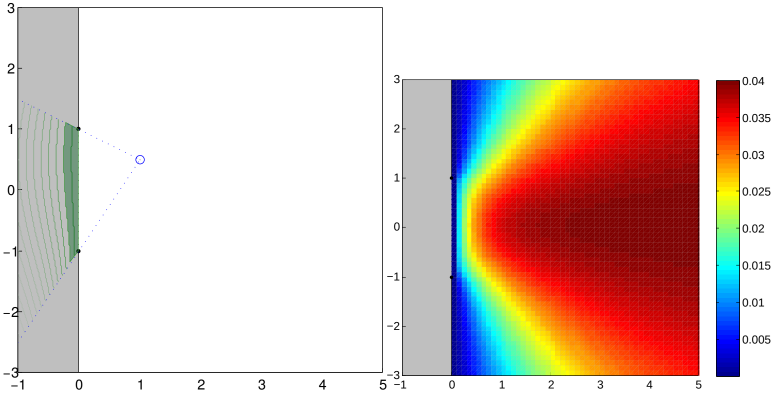
Obstacle Density Determines Viewpoint



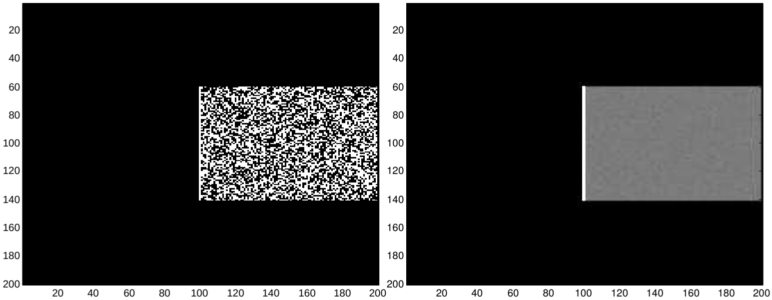
Obstacle Density Determines Viewpoint



Obstacle Density Determines Viewpoint

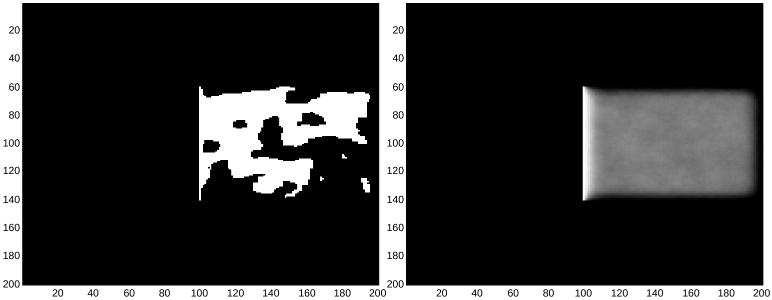


Ising-Type Obstacles



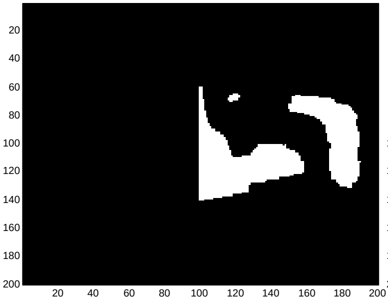
0 Iterations

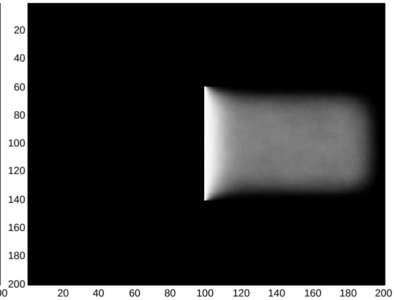
Ising-Type Obstacles



25 Iterations

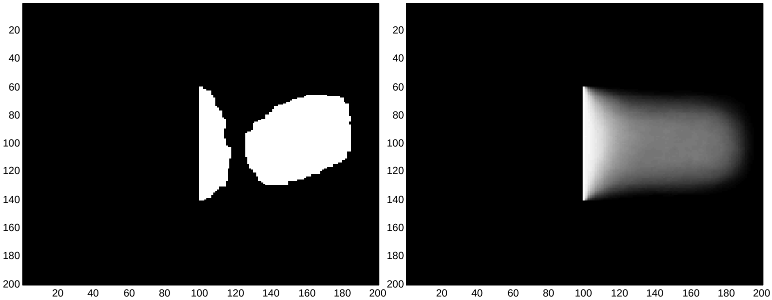
Ising-Type Obstacles





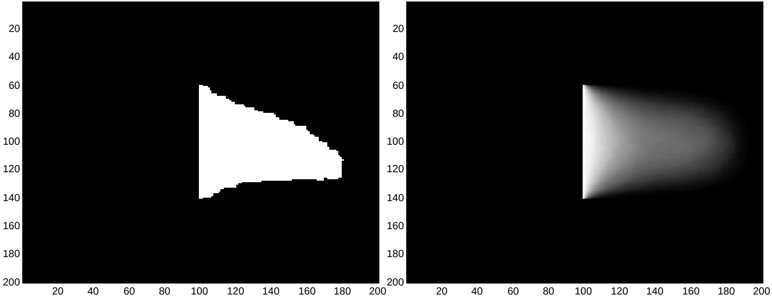
100 Iterations

Ising-Type Obstacles



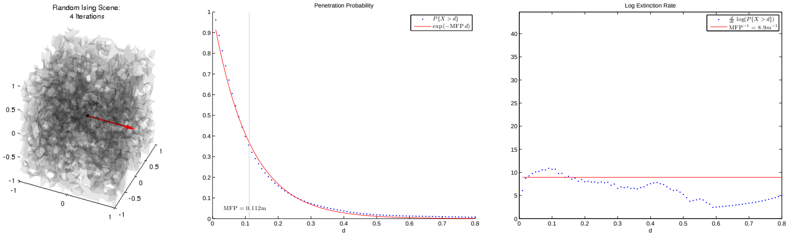
225 Iterations

Ising-Type Obstacles



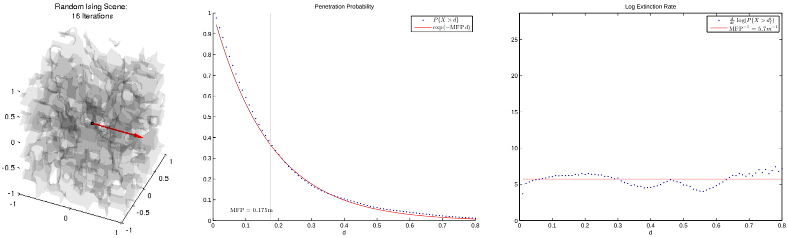
400 Iterations

Ising-Type Penetration Profiles



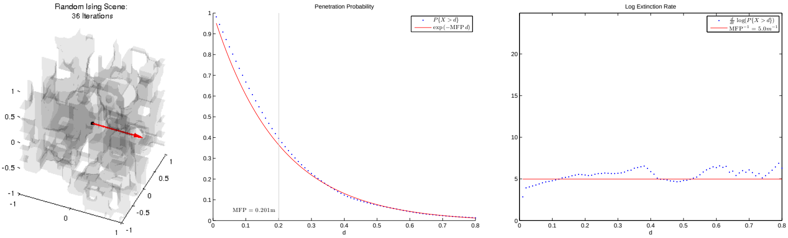
4 Iterations

Ising-Type Penetration Profiles



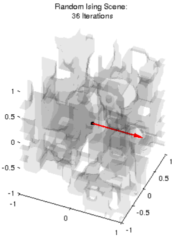
16 Iterations

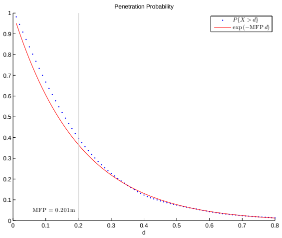
Ising-Type Penetration Profiles

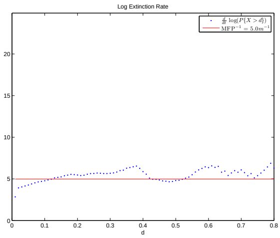


36 Iterations

Ising-Type Penetration Profiles

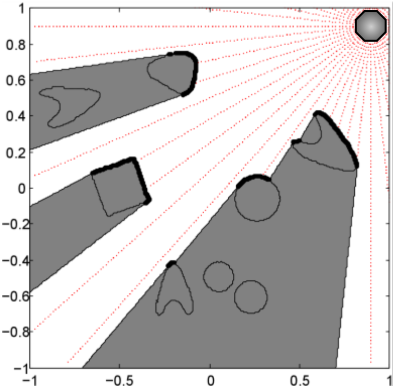






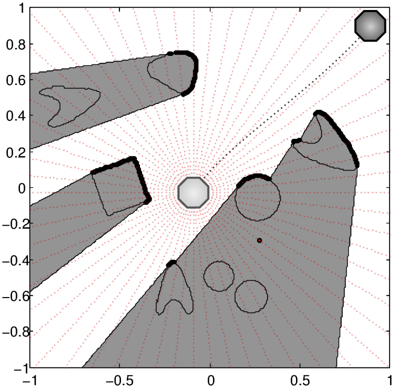
36 Iterations

Information-Seeking Control



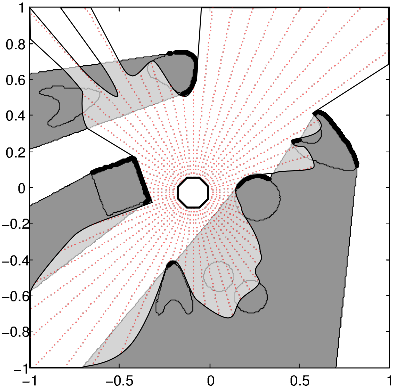
The information value of a new viewpoint is equal to the uncertainty of the measurement to be taken there.

Information-Seeking Control



The information value of a new viewpoint is equal to the uncertainty of the measurement to be taken there.

Information-Seeking Control



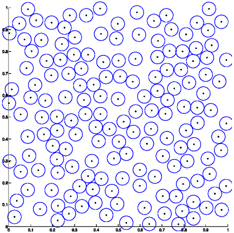
The information value of a new viewpoint is equal to the uncertainty of the measurement to be taken there.

View Value

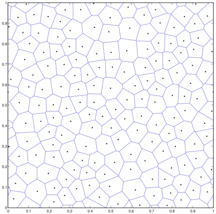
$$E_t(x) \approx \sum_{ij} \underbrace{w_i H(\mathbb{P}_t[x + g_{ij} \in \mathcal{A}])}_{\text{Marginal value of revealing point at } x + g_{ij}} \cdot \underbrace{\prod_{i'<i} \mathbb{P}_t[x + g_{i'j} \in \mathcal{A}]^{s/\,\mathrm{MFP}(x+g_{i'j})}}_{\text{Probability of revealing point at } x + g_{ij}}$$

where $H(p) = -p \log p - (1-p) \log(1-p)$.

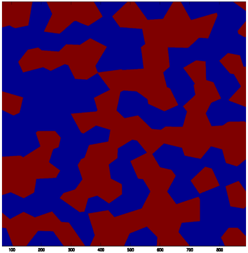
Poisson-Voronoi Proxy



Poisson-Disk Sampling

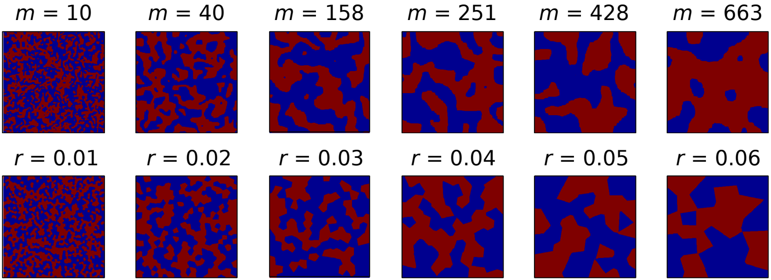


Voronoi Tesselation

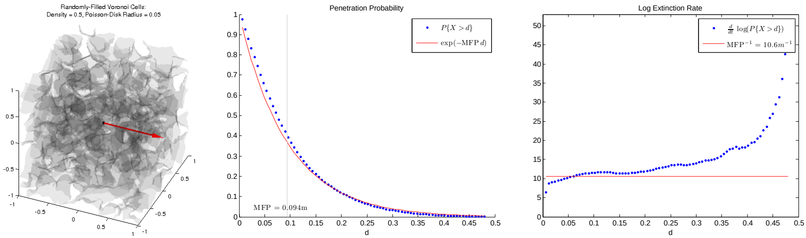


Voronoi Checkerboard

Poisson-Voronoi Proxy

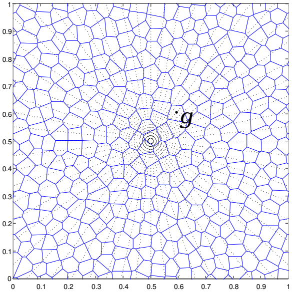


Poisson-Voronoi Proxy

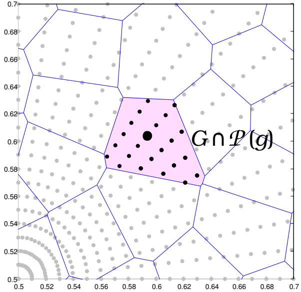


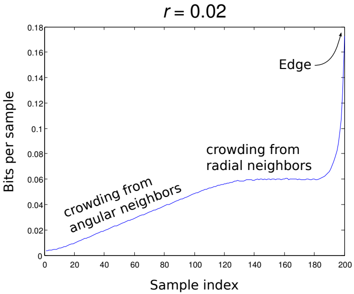
Mean free path scales directly with Poisson-disc radius, so this needs to be computed only once

Computing Graph Weights w_i

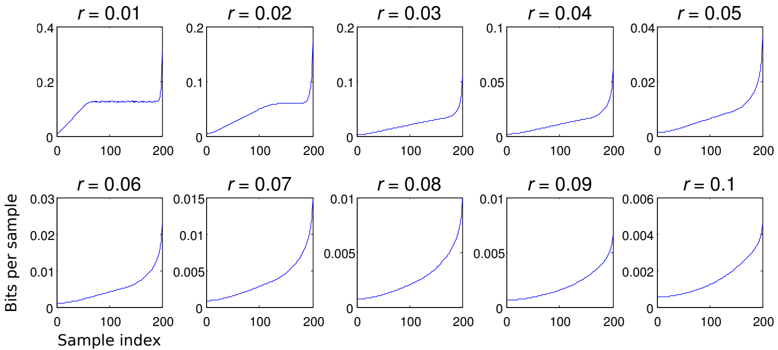


Computing Graph Weights w_i

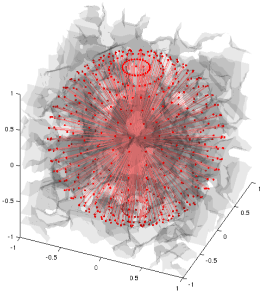


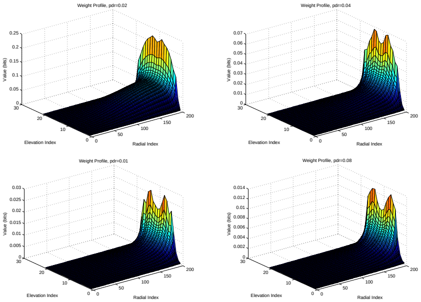


Computing Graph Weights w_i



3D Graph Weights





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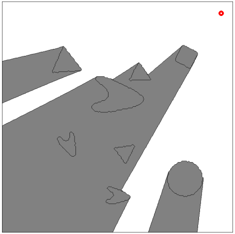
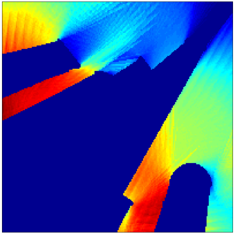


Visibility

Marginals



View Value

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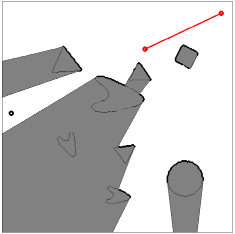

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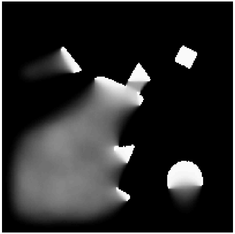

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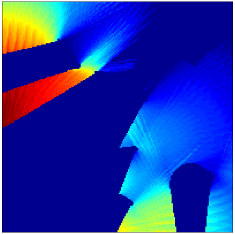

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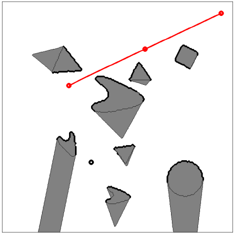

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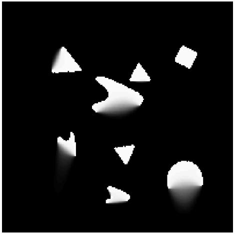

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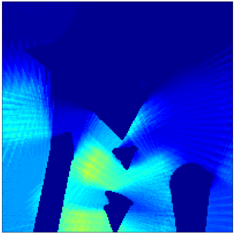

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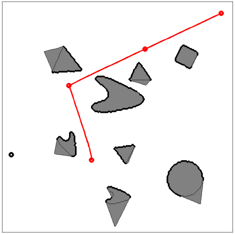

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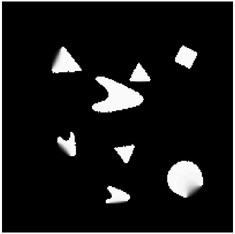

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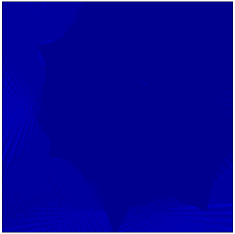

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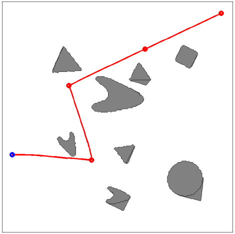

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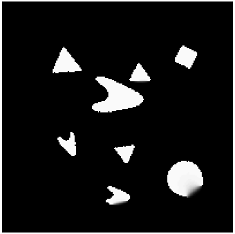

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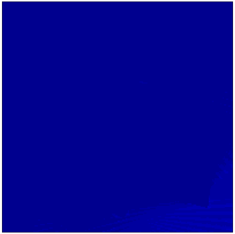

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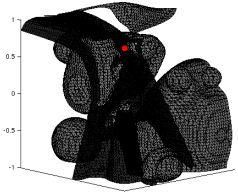

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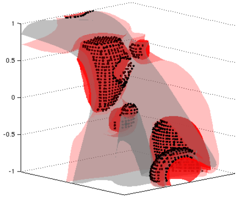

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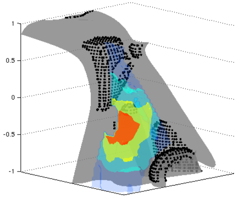

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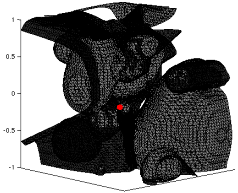

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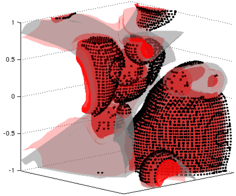

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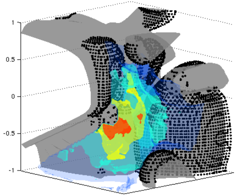

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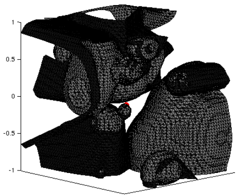

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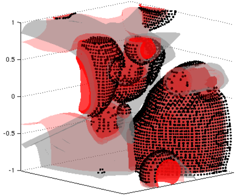

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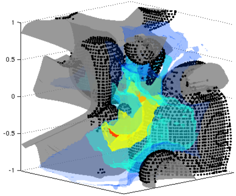

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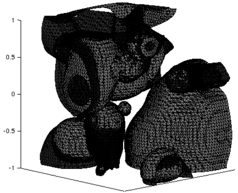

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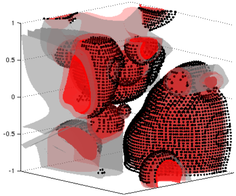

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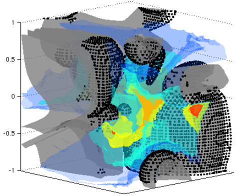

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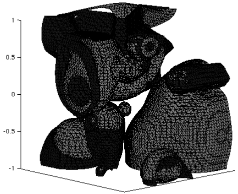

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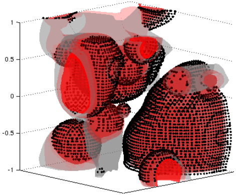

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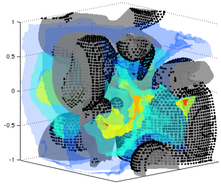

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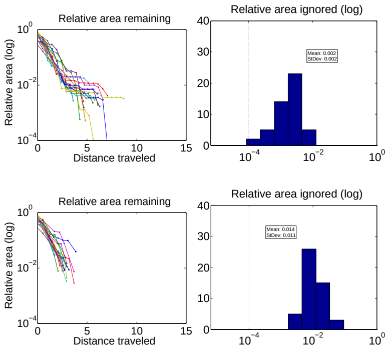
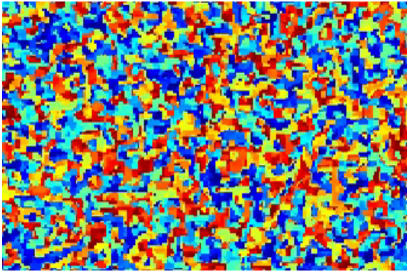
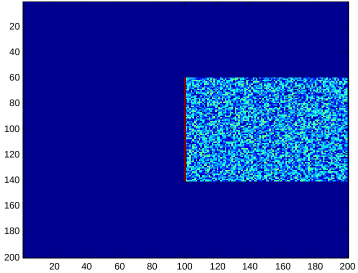
Comparisons



Speedup: Parallel Bits





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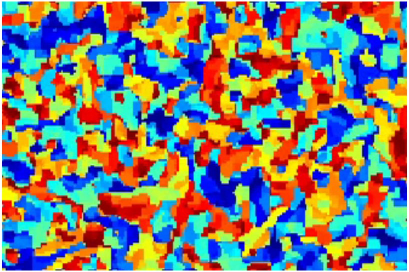

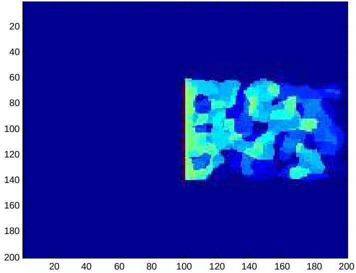

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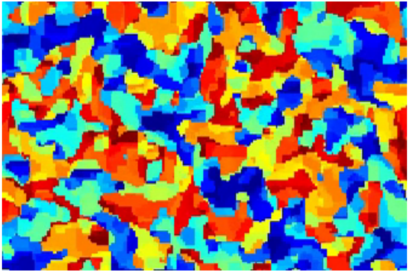

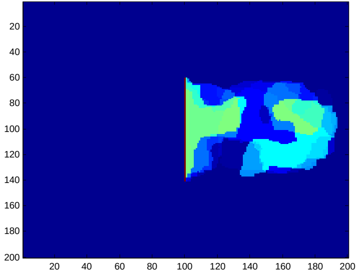

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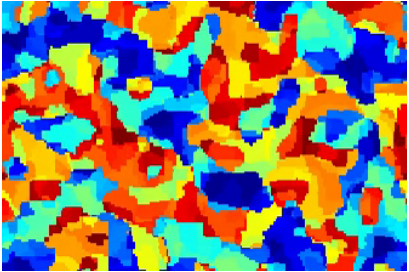
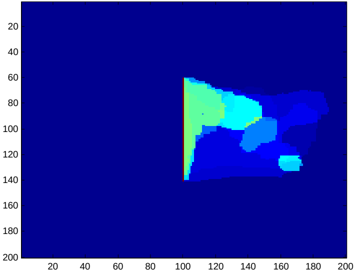
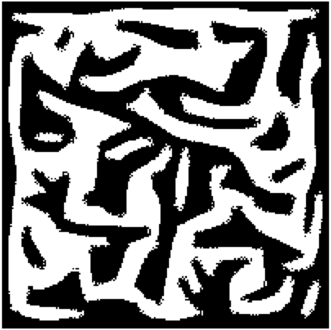
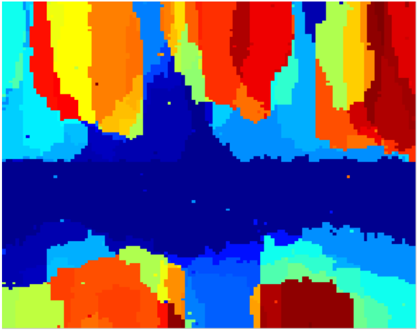


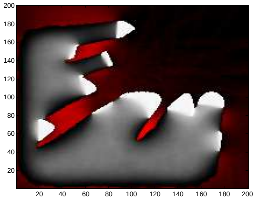


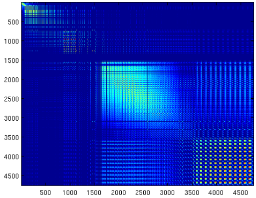
Anisotropic Prior

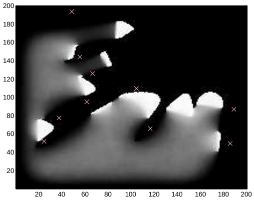




Extending the Horizon







Contribution

- First bounds on indistinguishable set with IMU bias drift.
- Developed system for video segmentation leveraging image-plane segmentations.
- Developed an algorithm for in-place state reduction. Related POMDP to large body of ancient (pre-1980) research in digital circuit optimization.
- Developed an algorithm for efficient exploration of unknown scenes with nontrivial topology

Questions

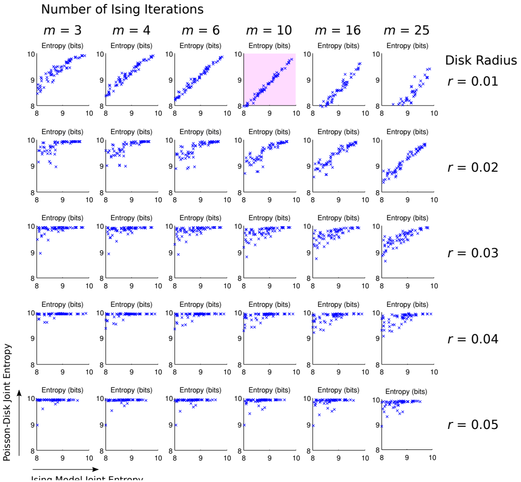
Thanks

- Konstantine Tsotsos
- Andrea Censi
- Vasiliy Karasev
- Virginia Estellers
- Brian Taylor

Special thanks to Jackie Lam :)

EMPTY

Poisson-Voronoi Proxy



Poisson-Voronoi Proxy