Information-Aware Powered Descent Guidance

for Entry, Descent, and Landing

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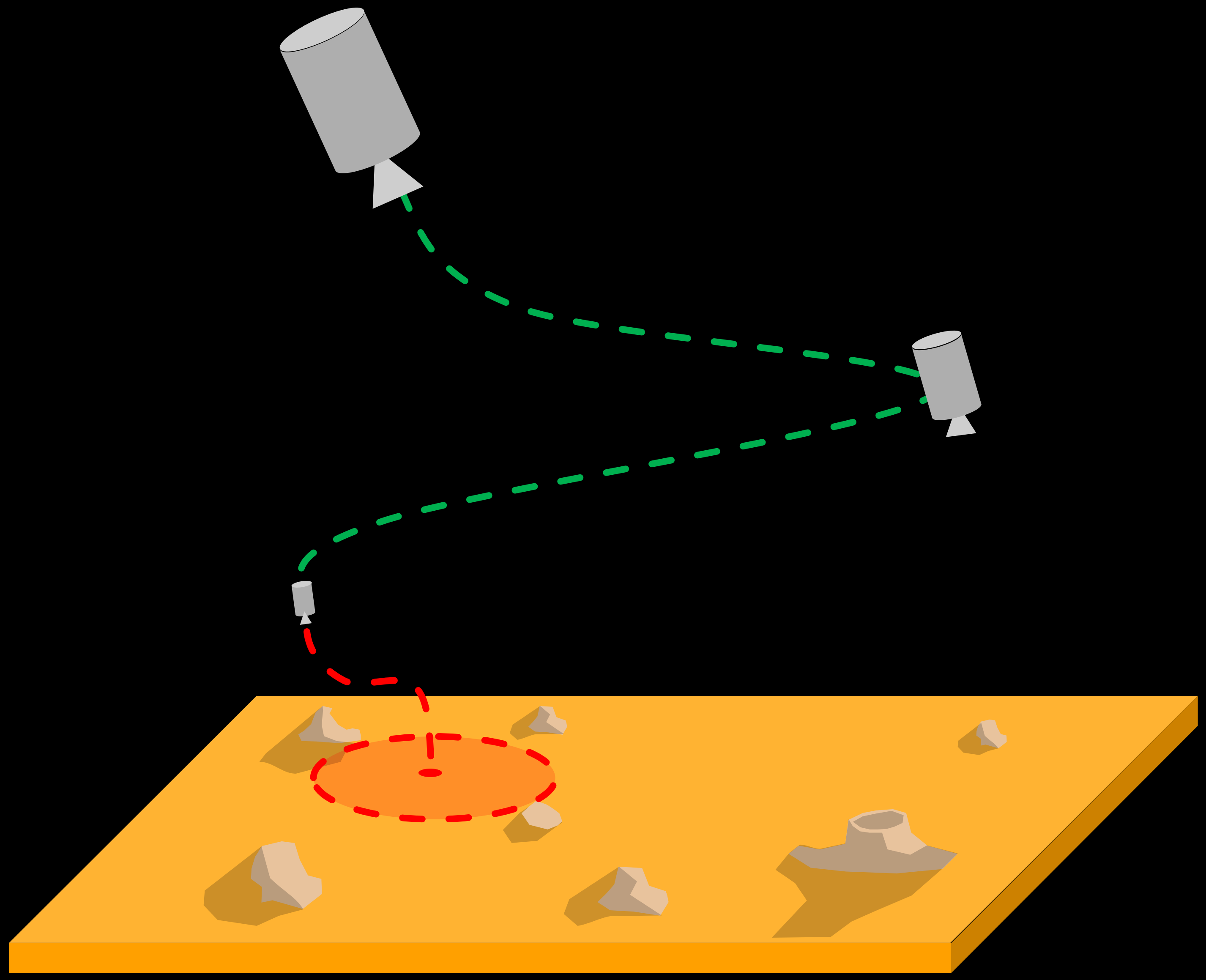
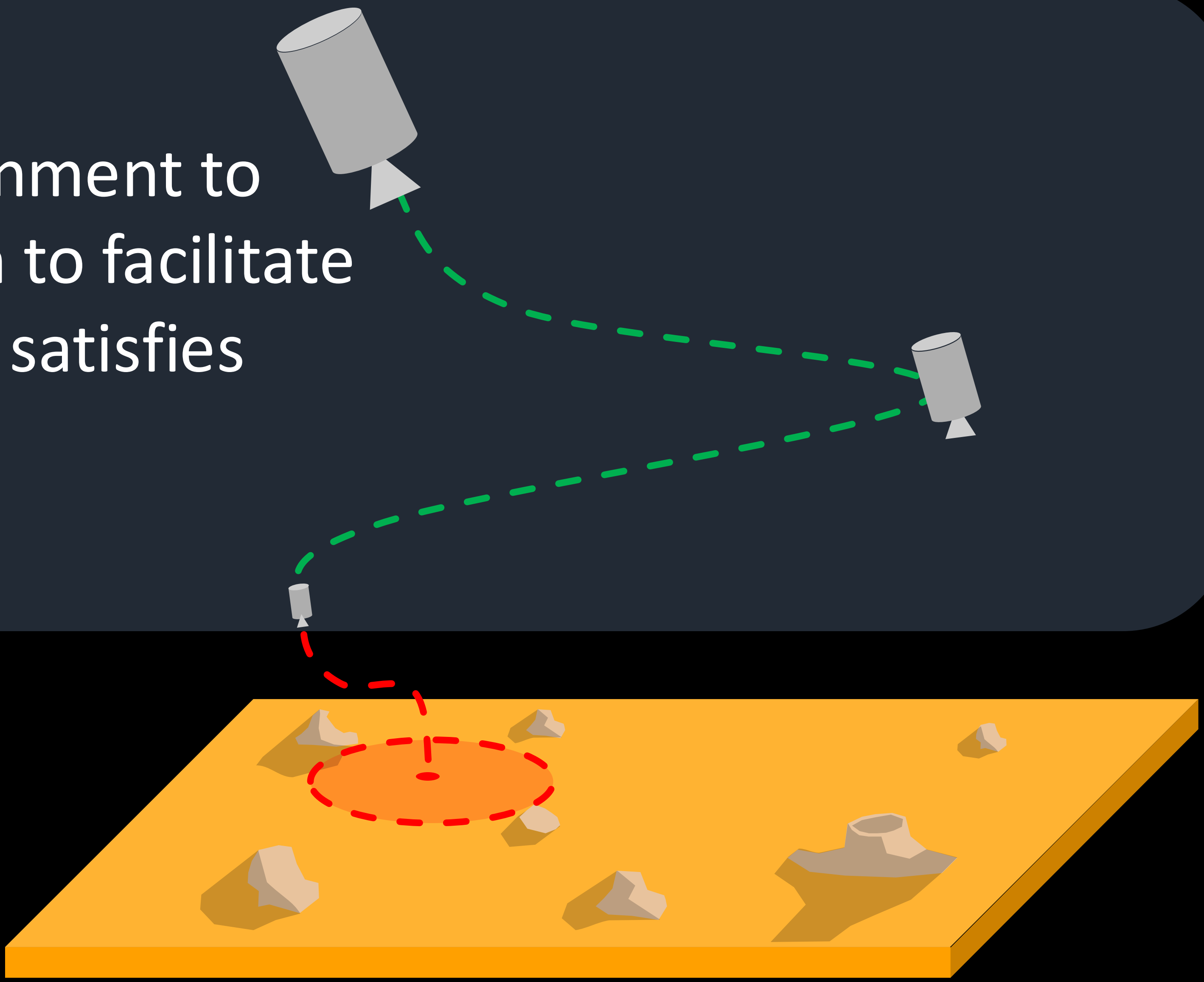
Task: Given no *a priori* information about the terrain, we seek to build an model of the terrain to inform PDG algorithms



Exploration:
Explore the environment to obtain information to facilitate a safe landing that satisfies mission objectives



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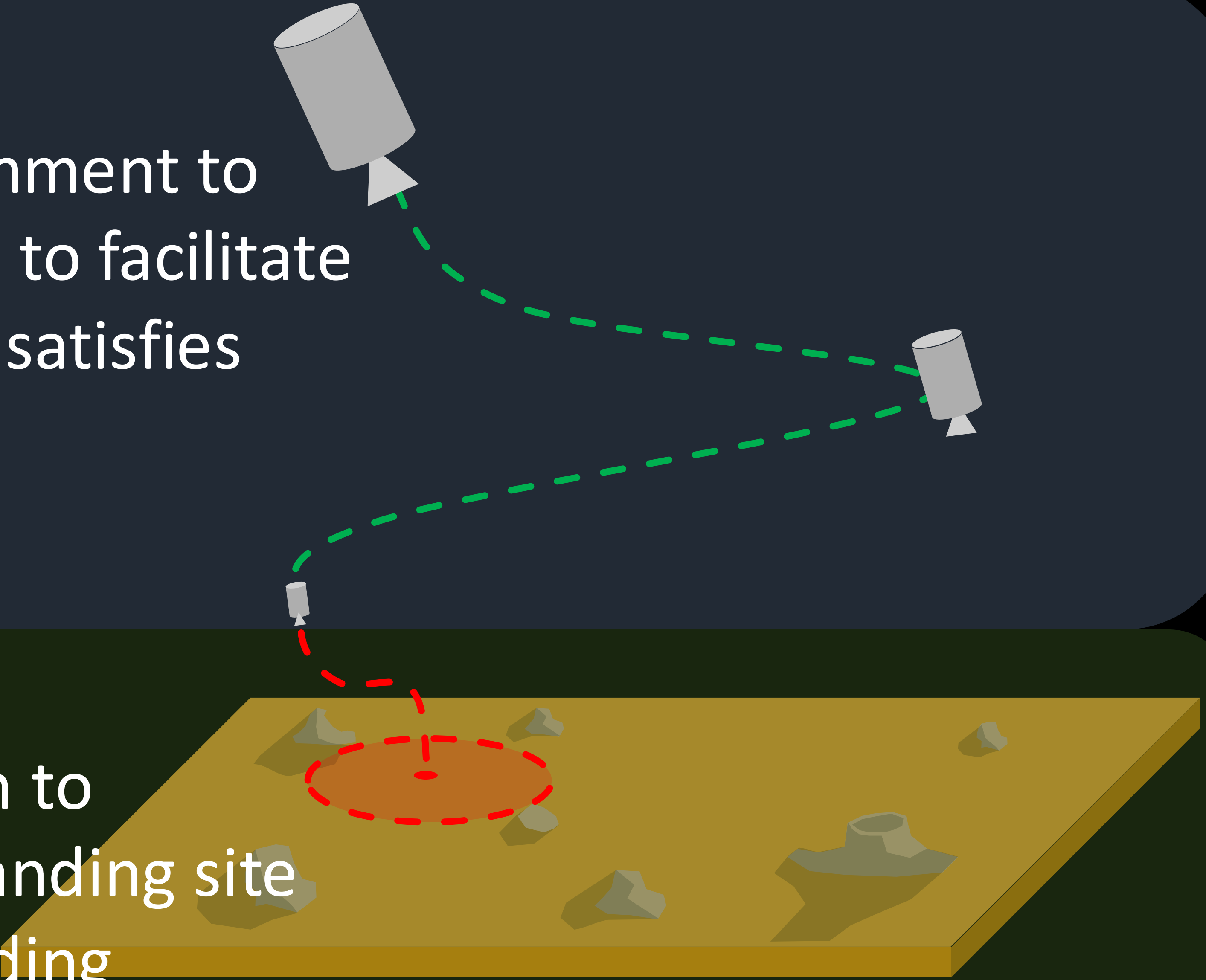

Exploitation:
Exploit information to determine a safe landing site and commit to landing

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Work on exploitation phase

Tomita et al. 2024, Buckner et al, 2024, Hayner et al, 2023

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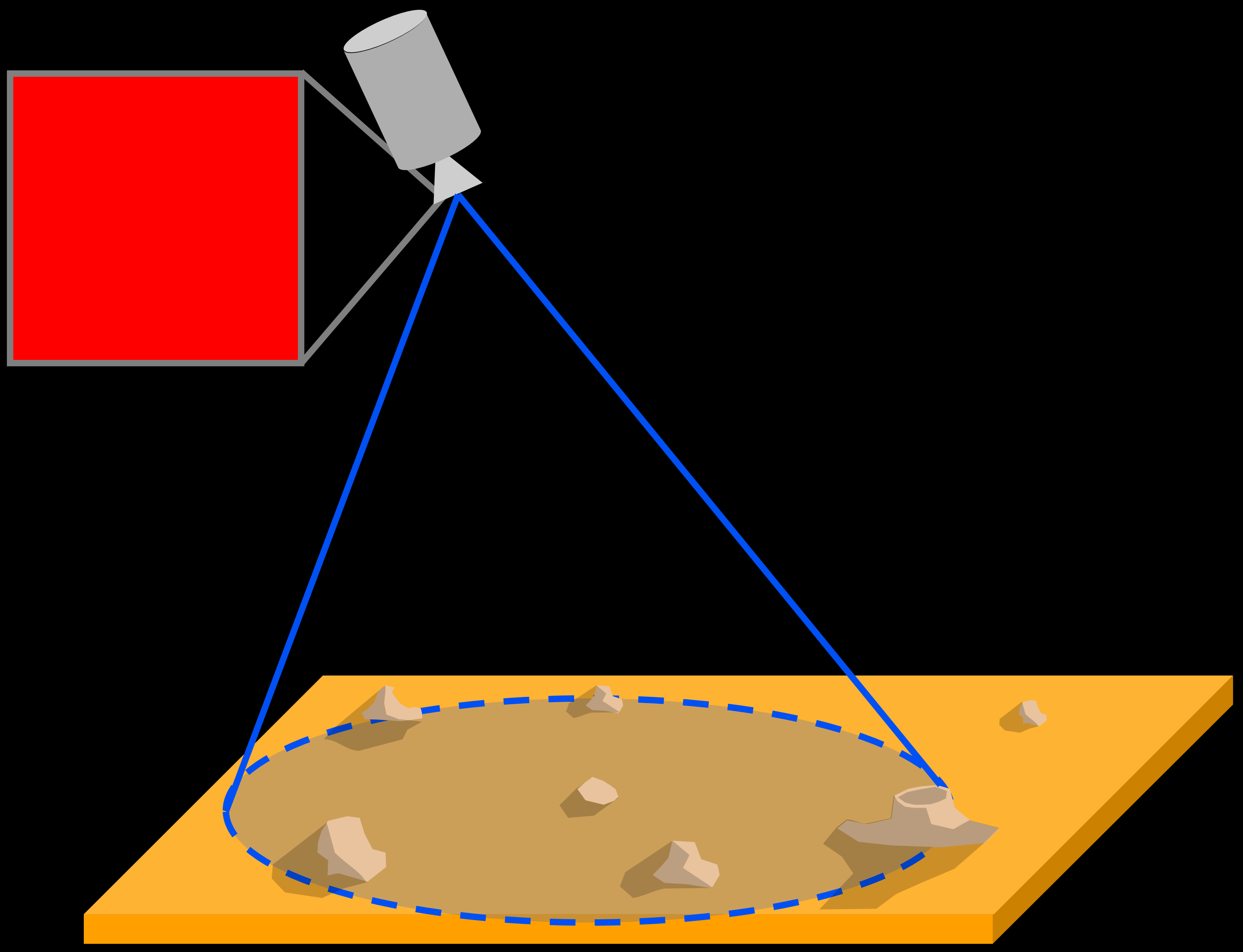

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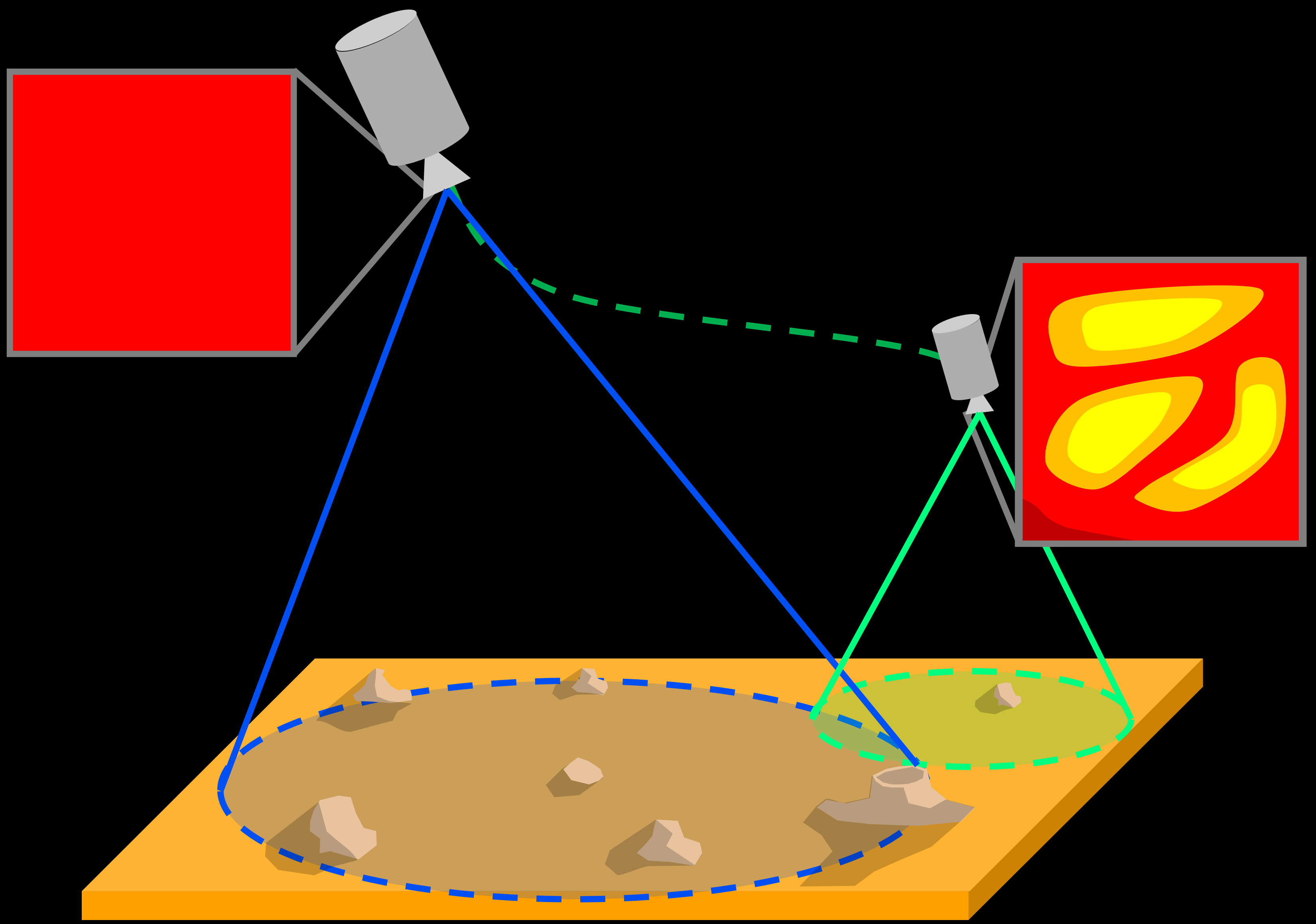

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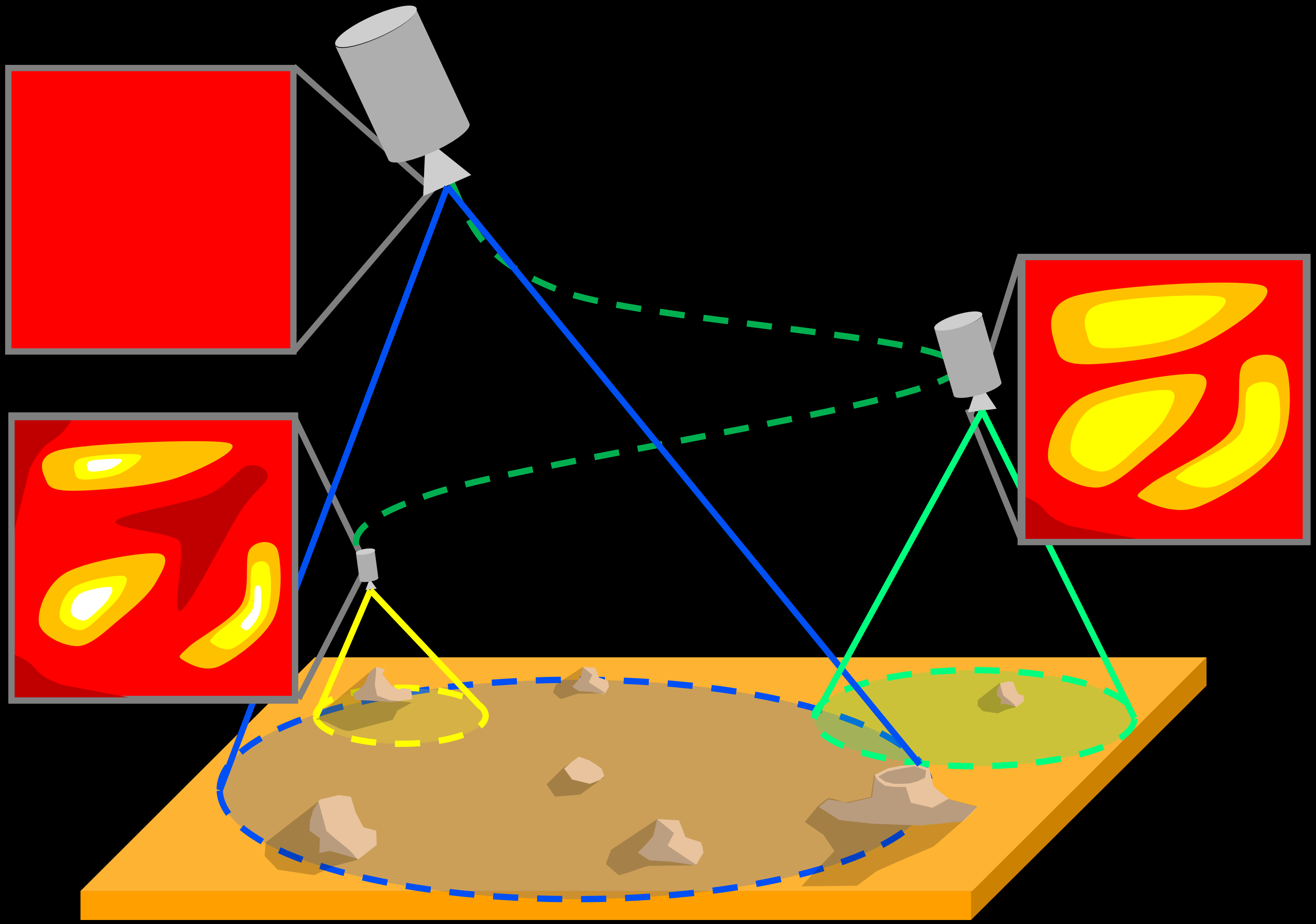
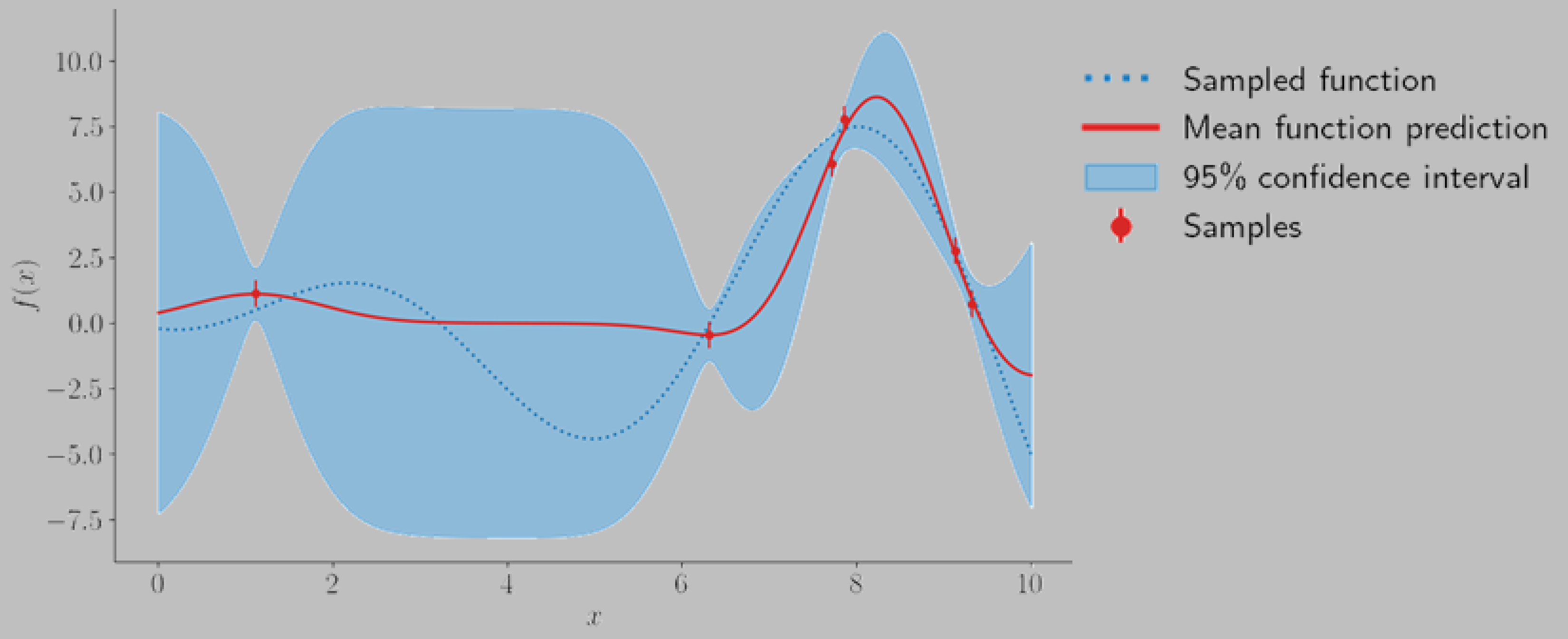


Map Representation.

The map is represented using Gaussian process regression.

Given samples of a function, **Gaussian process regression** finds a distribution of functions that the samples could have been drawn from. A Gaussian process is defined by a mean function and a covariance function.



Information map is obtained by fitting a Gaussian Process (GP) to point cloud data

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- Covariance of GP over the full map

Trajectory Optimization objective is the following

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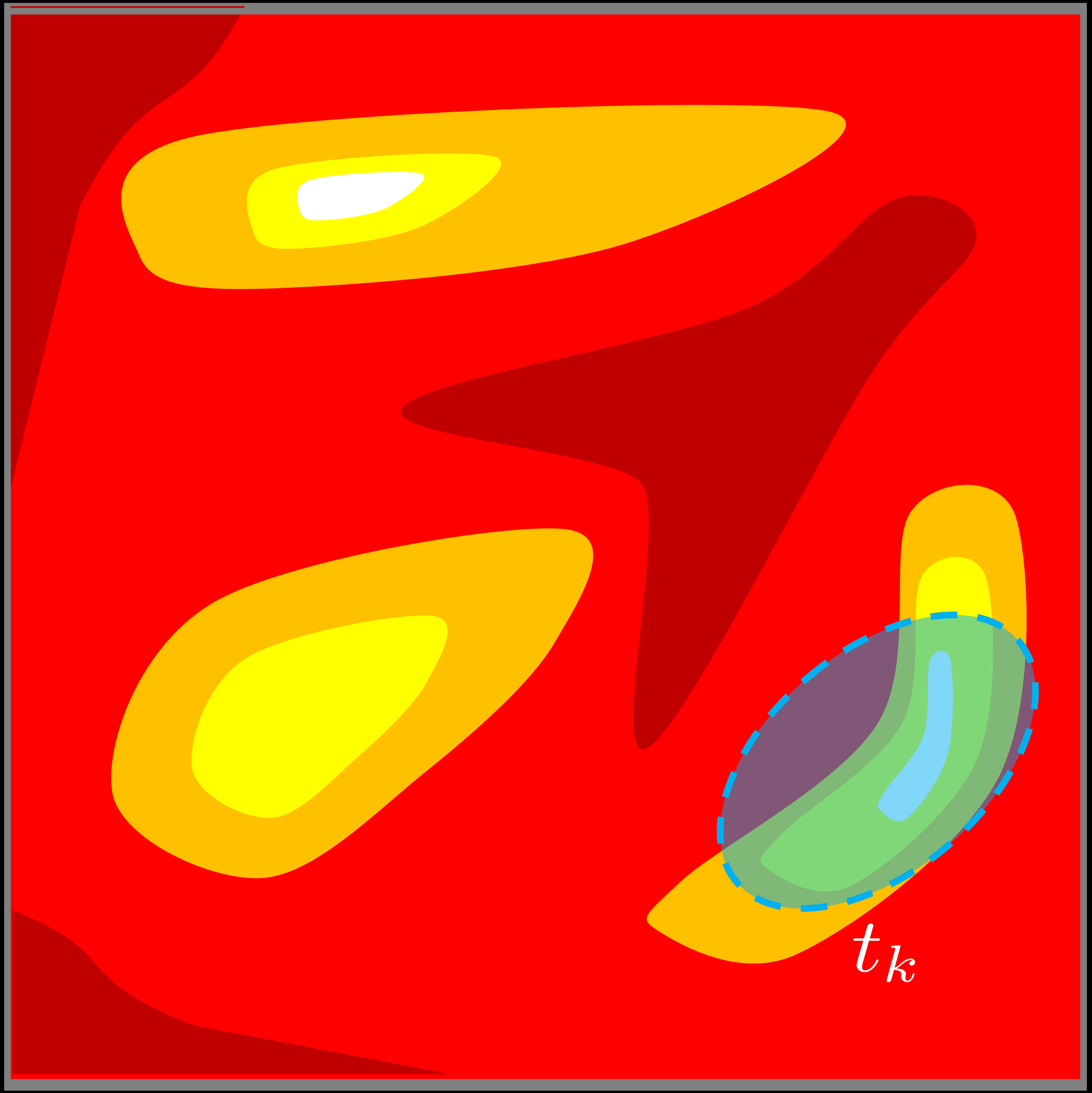

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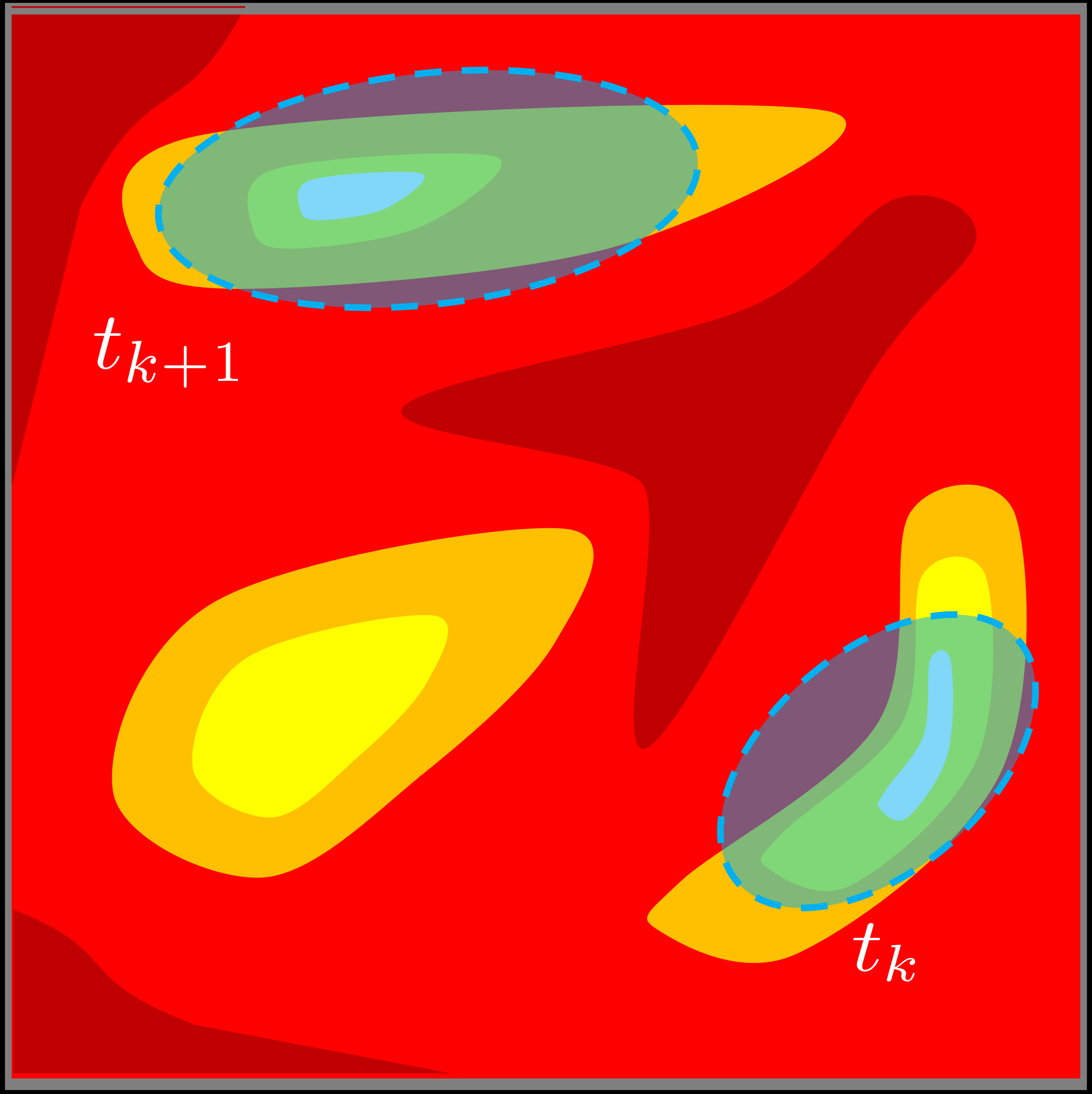

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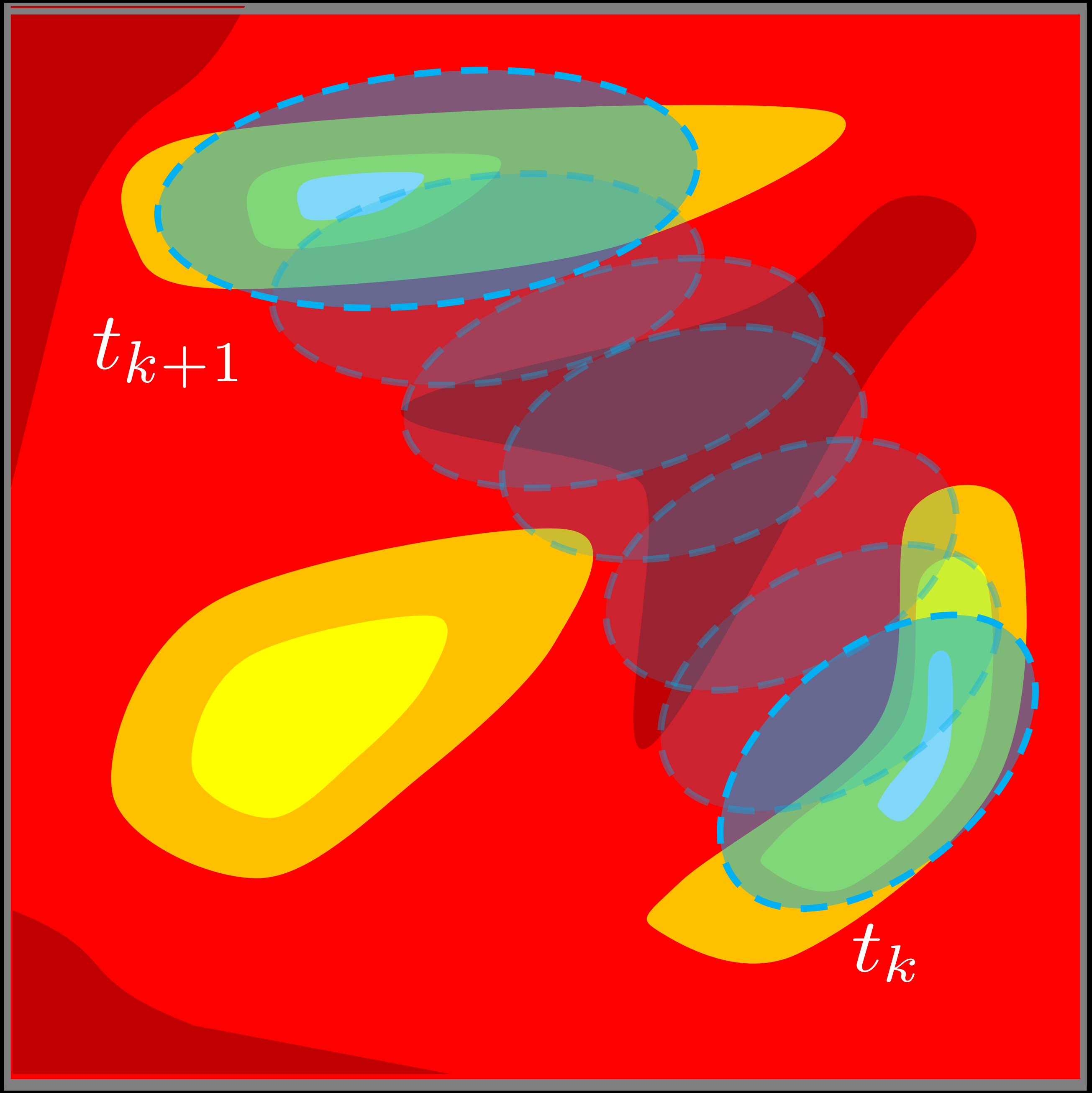

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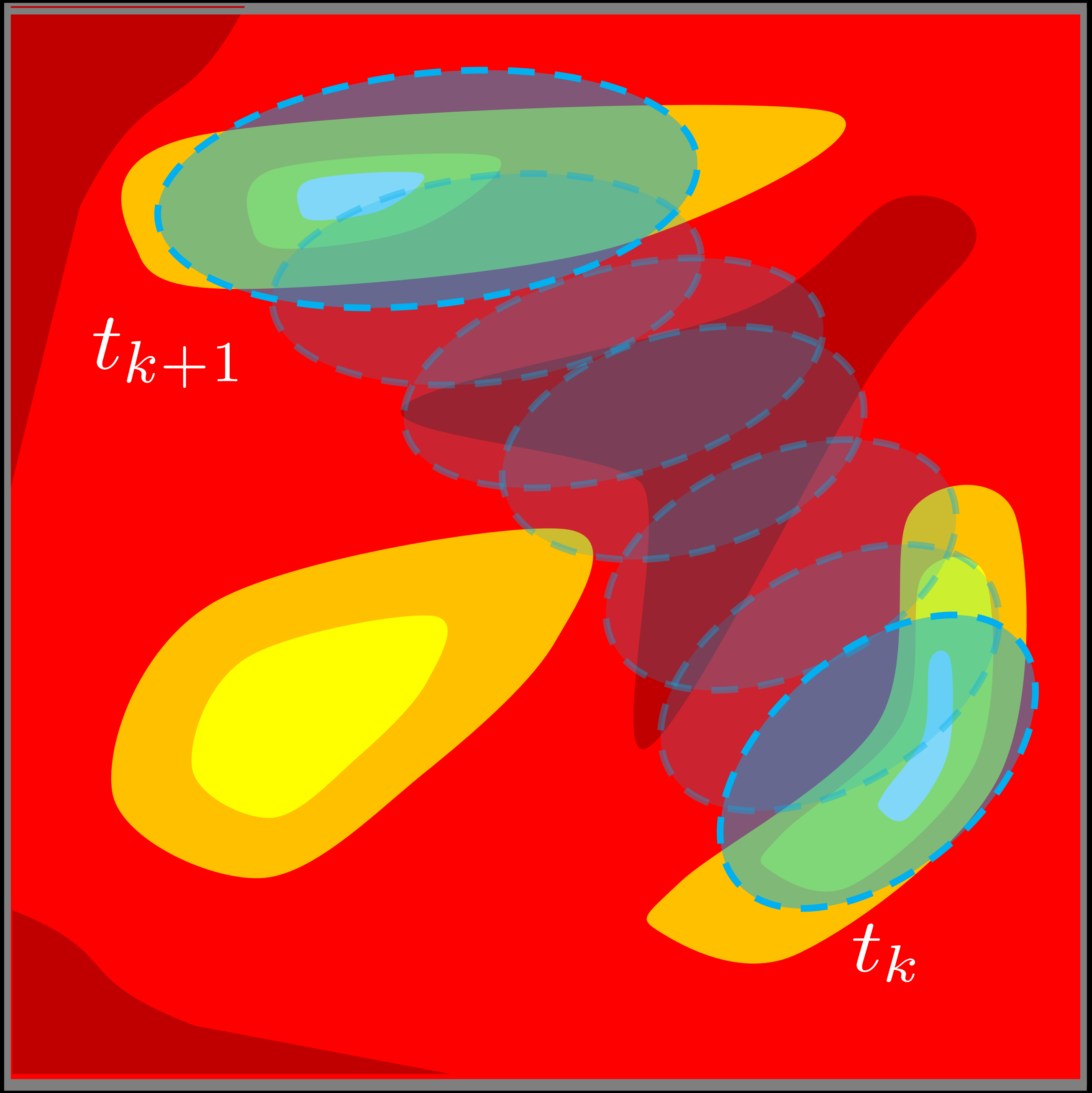
Greedy



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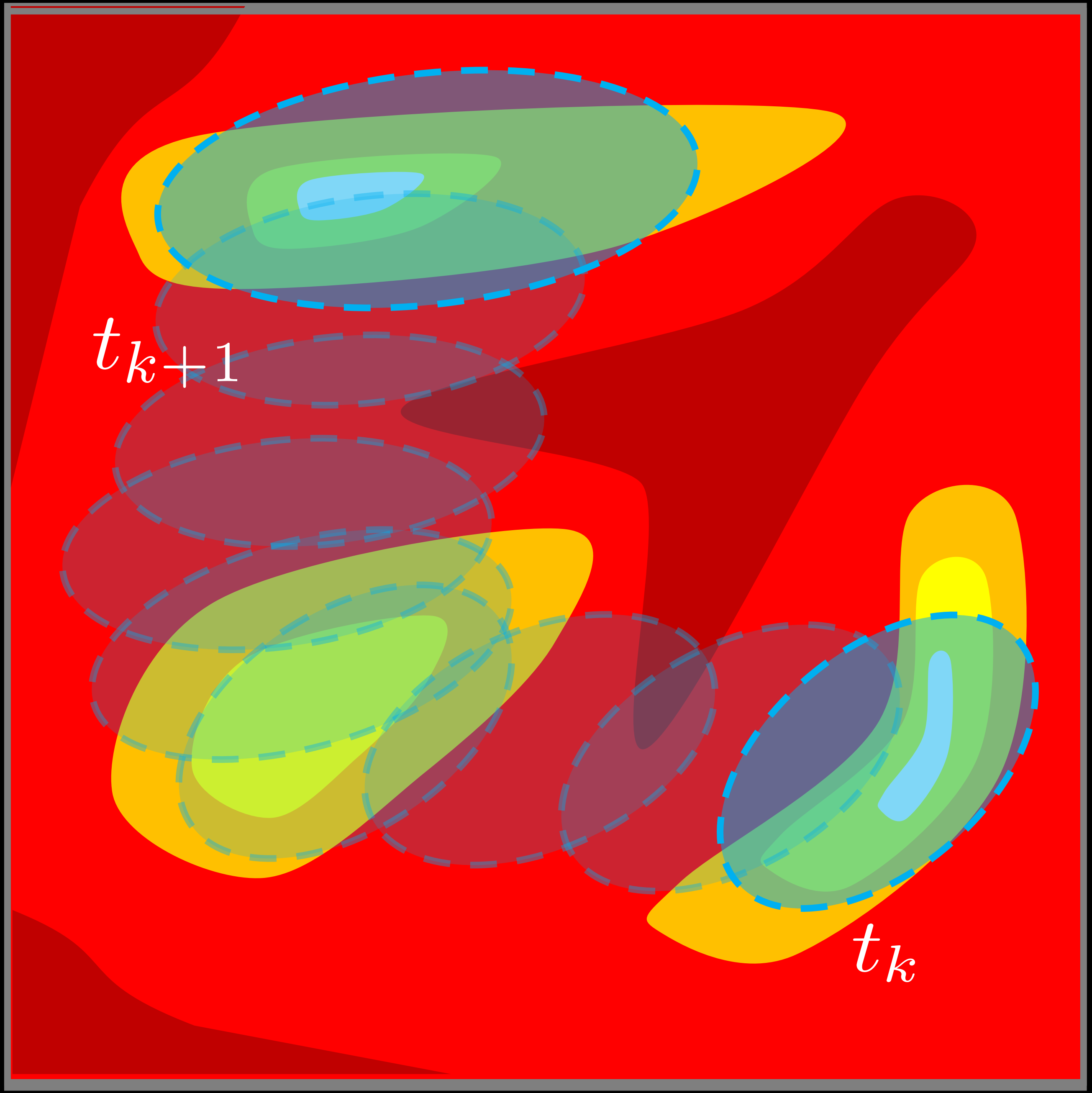
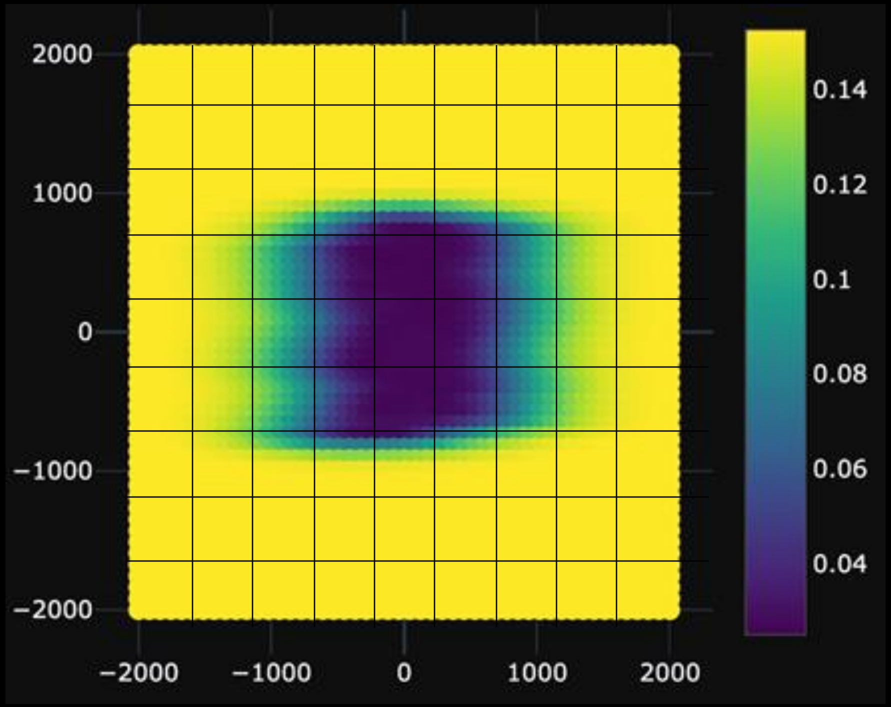
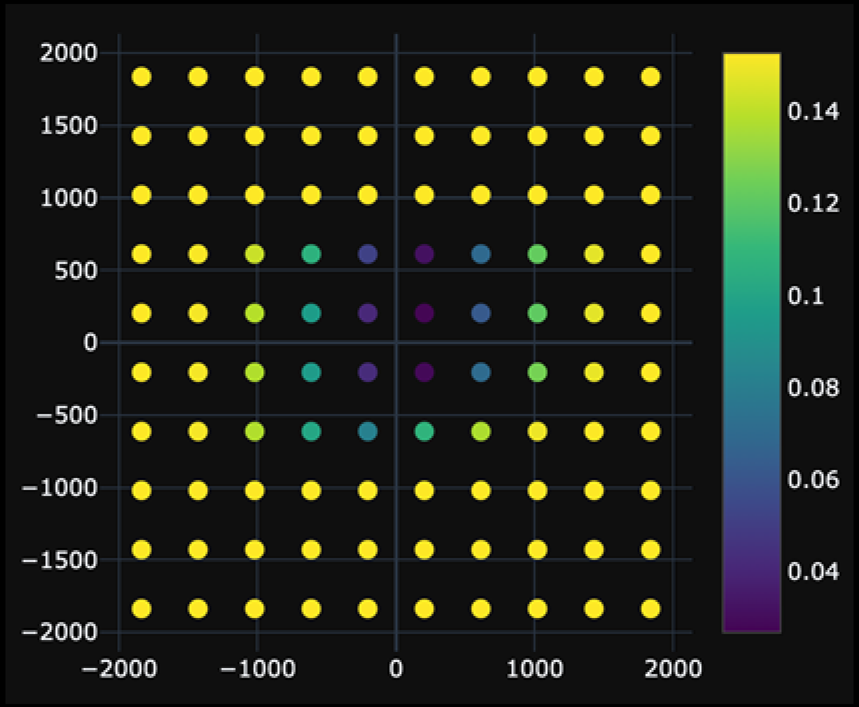


Map Discretization.

The Gaussian process is sampled over a fine grid.
The covariance of the points is binned and averaged to get a coarse grid.



Finely sampled Gaussian process.



Binned map.

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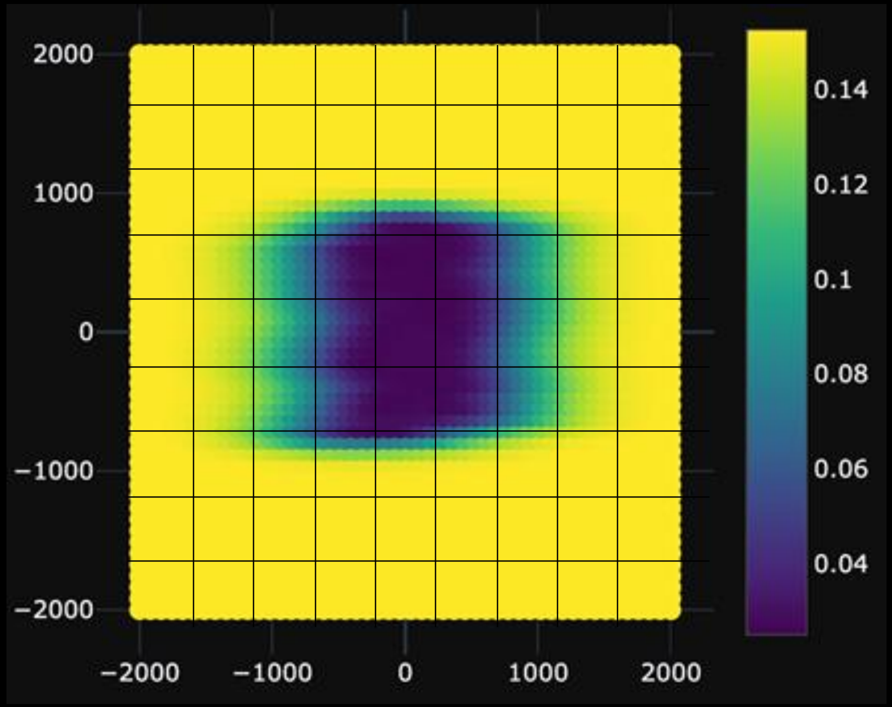

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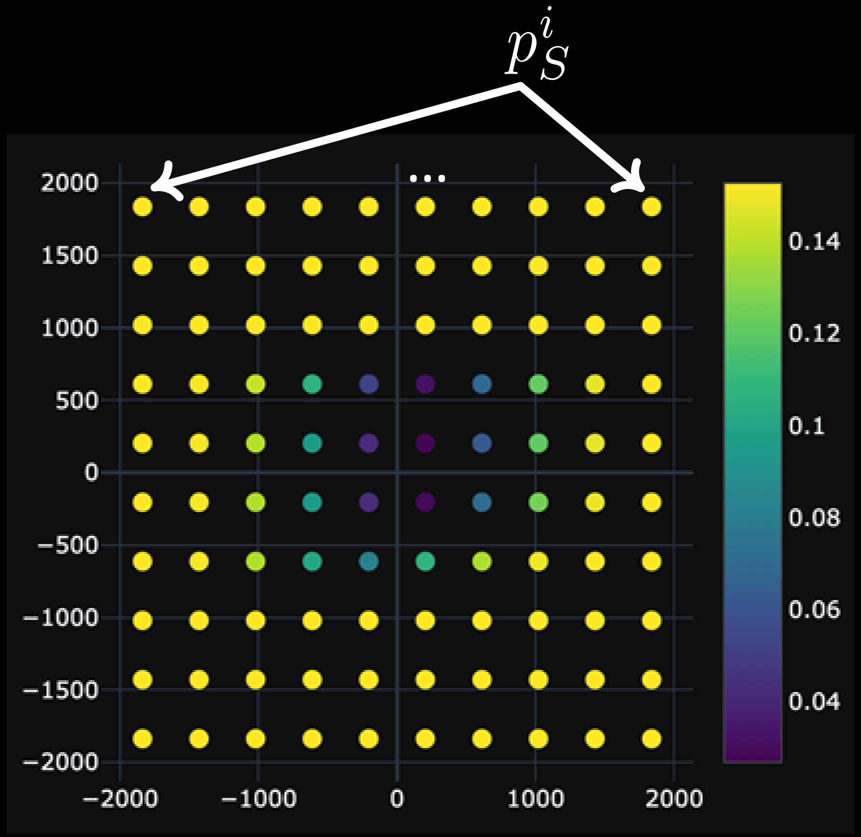

Binned map.

Map Covariance Dynamics.

To model map covariance, we make the following assumptions:

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Assumption 1:
When a given region of the environment is observed, its covariance will decrease and, when it is not observed, it will remain constant.

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Assumption 2:
The map covariance is assumed to be uniformly decreased across the sensor's frame of view (FoV).

Map Covariance Dynamics.

First, we define the norm cone $\mathcal{K}$

$$\underbrace{||A^C p_\mathcal{S}|| \leq c^\top p_\mathcal{S}}_{\text{Convex in } p_\mathcal{S}}$$

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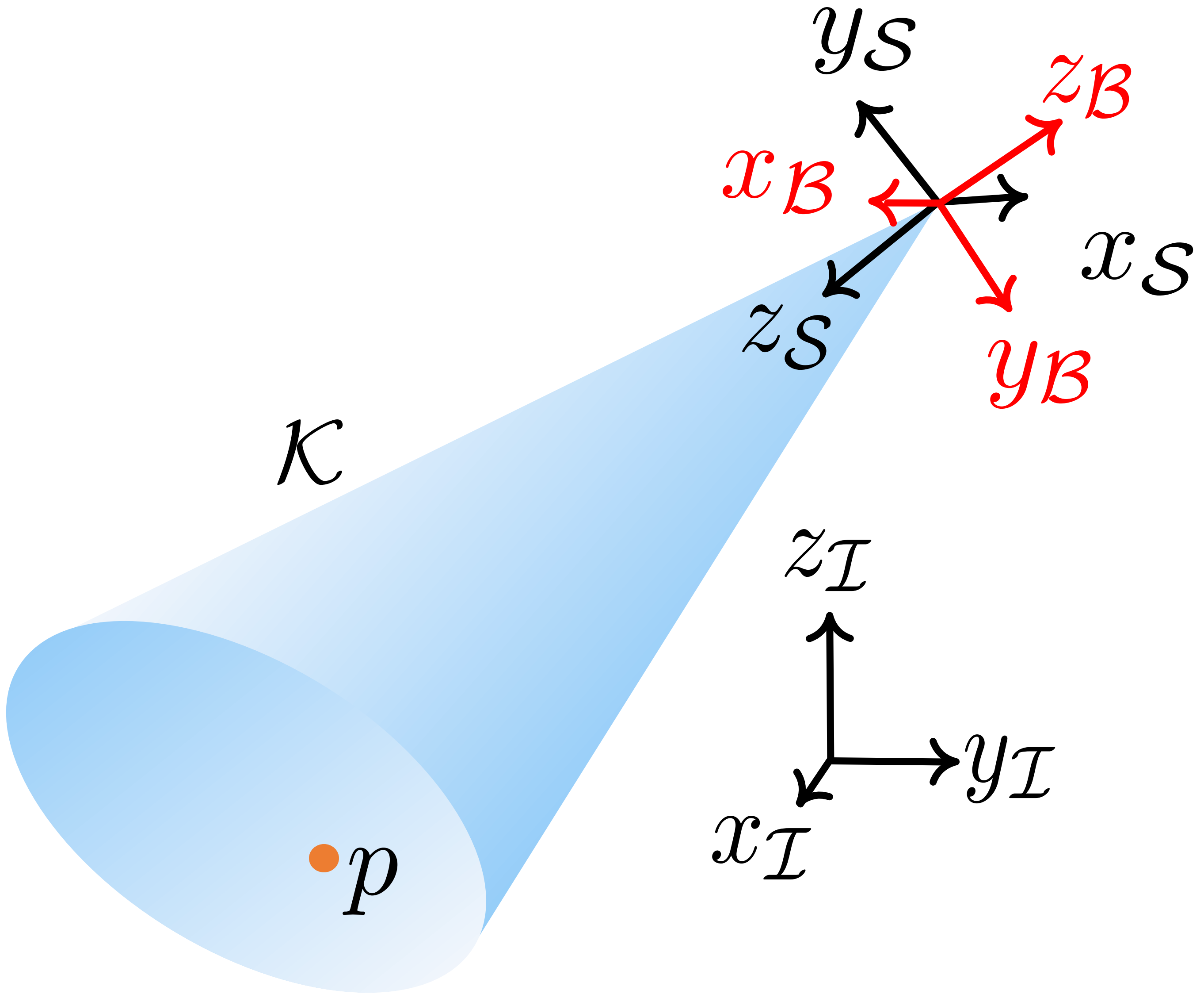

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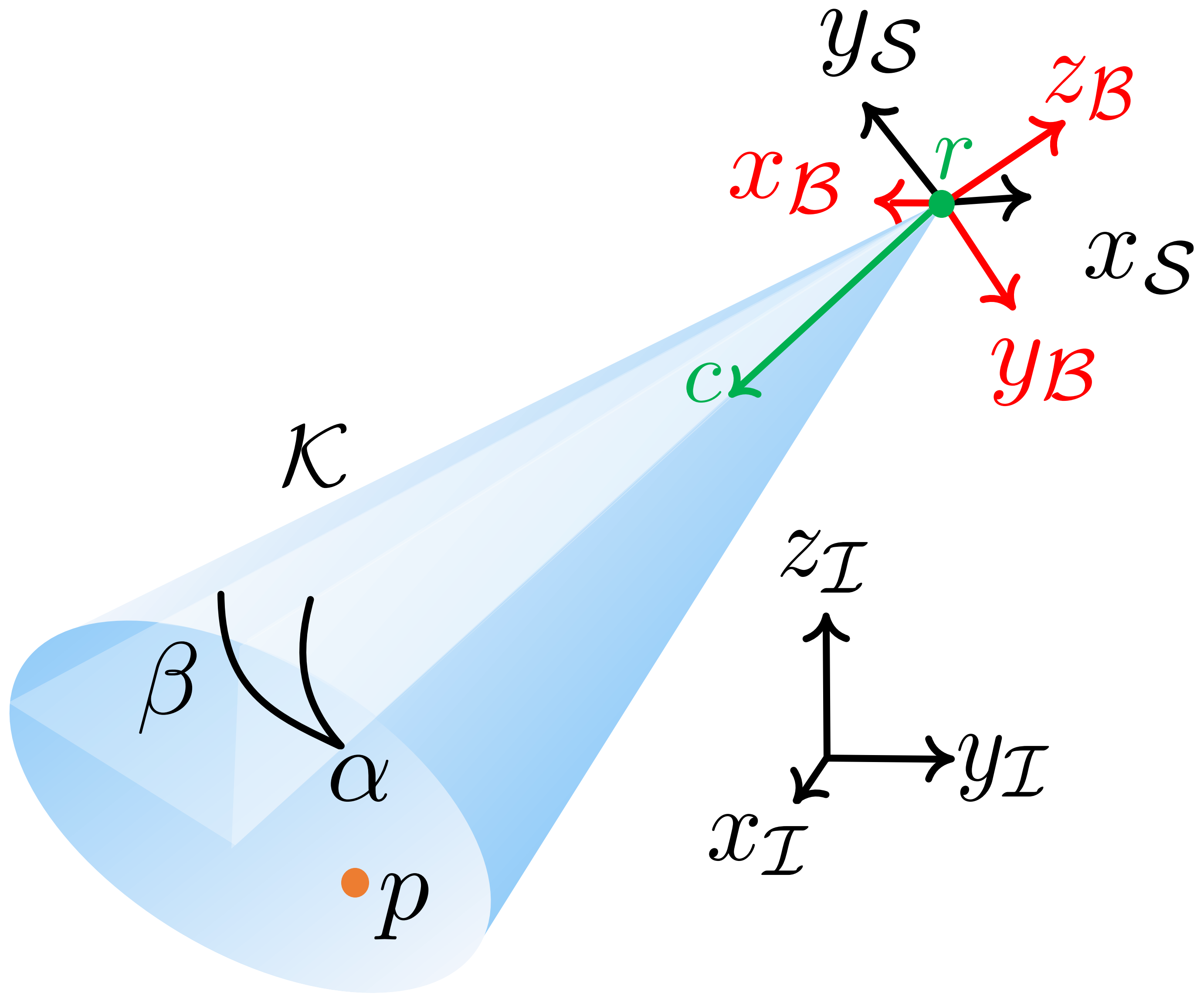
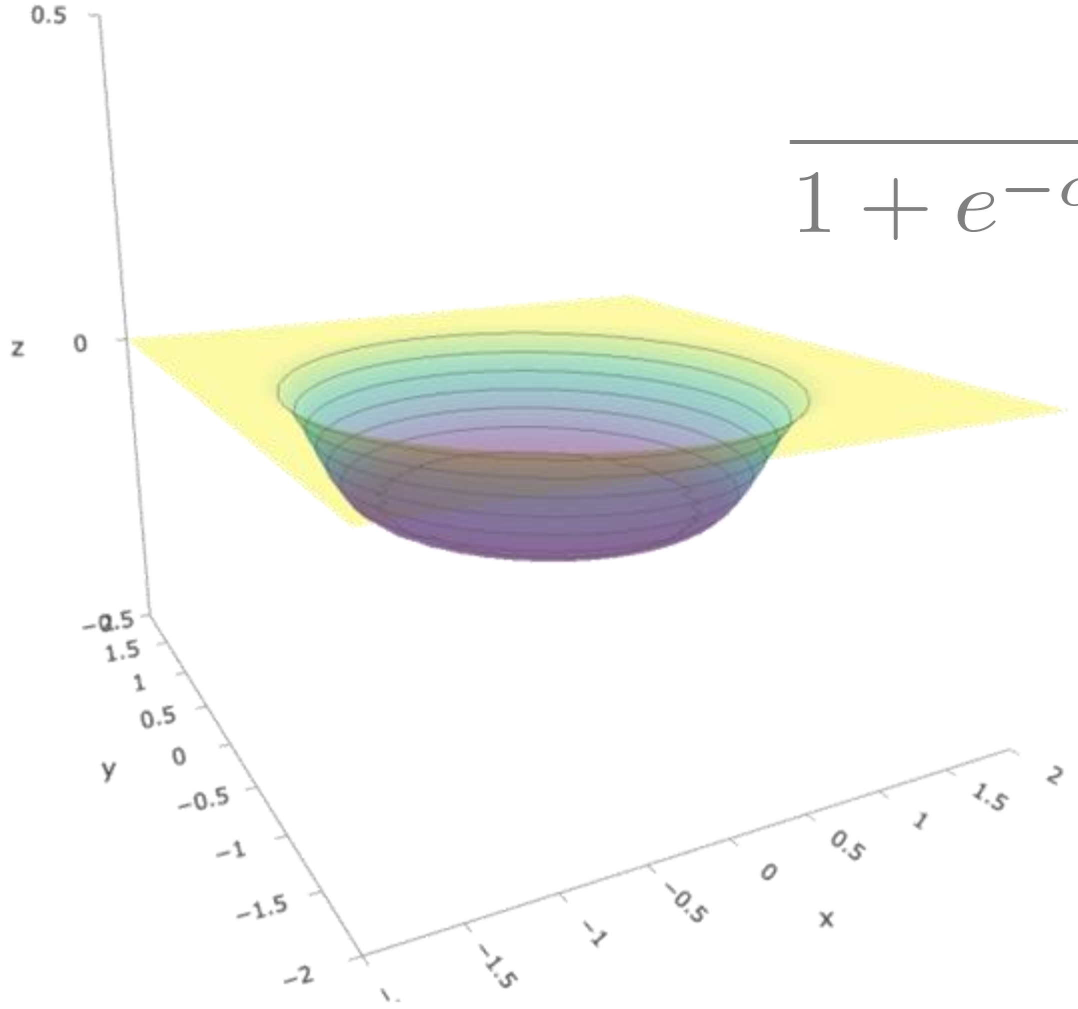
$$c \triangleq \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}^\top$$

$$A^C \triangleq \begin{bmatrix} \frac{1}{\tan(\alpha)} & 0 & 0 \\ 0 & \frac{1}{\tan(\beta)} & 0 \\ 0 & 0 & 0 \end{bmatrix}$$



Map Covariance Dynamics.

From **Assumption 1**, we choose to use a sigmoid function to decrease the covariance when points are within the LoS and leave them unchanged when they are not.



$$\frac{1-\delta}{1+e^{-\alpha \max\{0, ||A^C p_{\mathcal{S}}|| - c^\top p_{\mathcal{S}}\}^2}} - (1-\delta)$$

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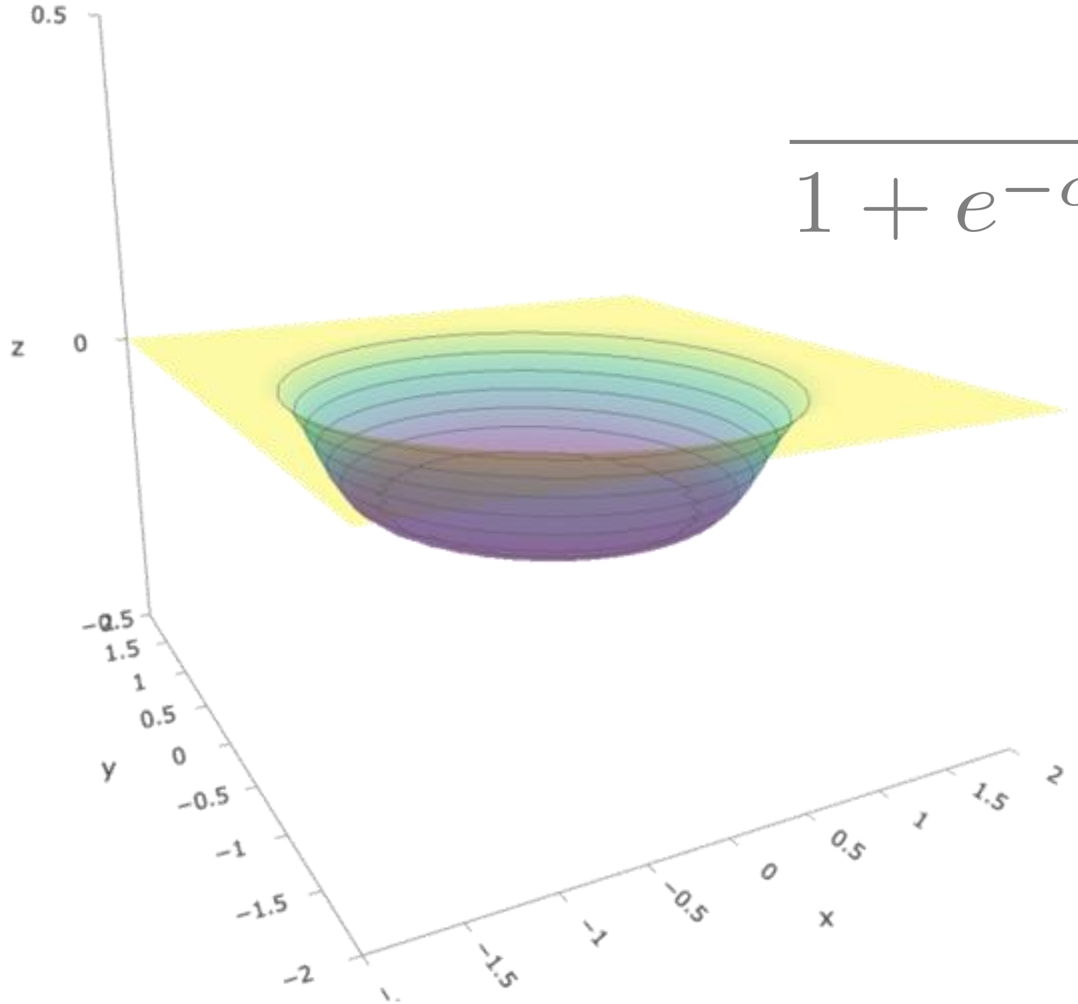

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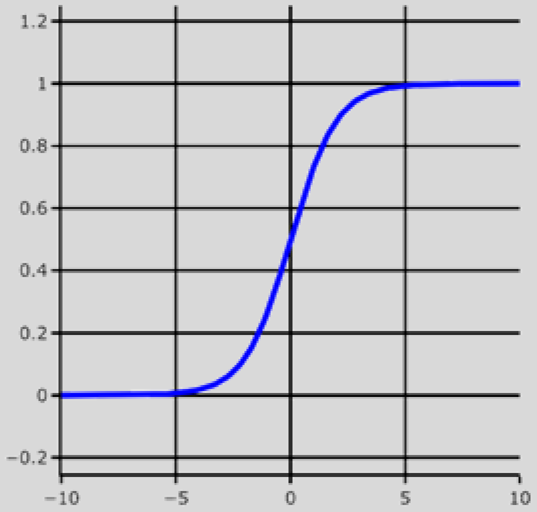

$$\frac{1}{1+e^{-\alpha x}}$$

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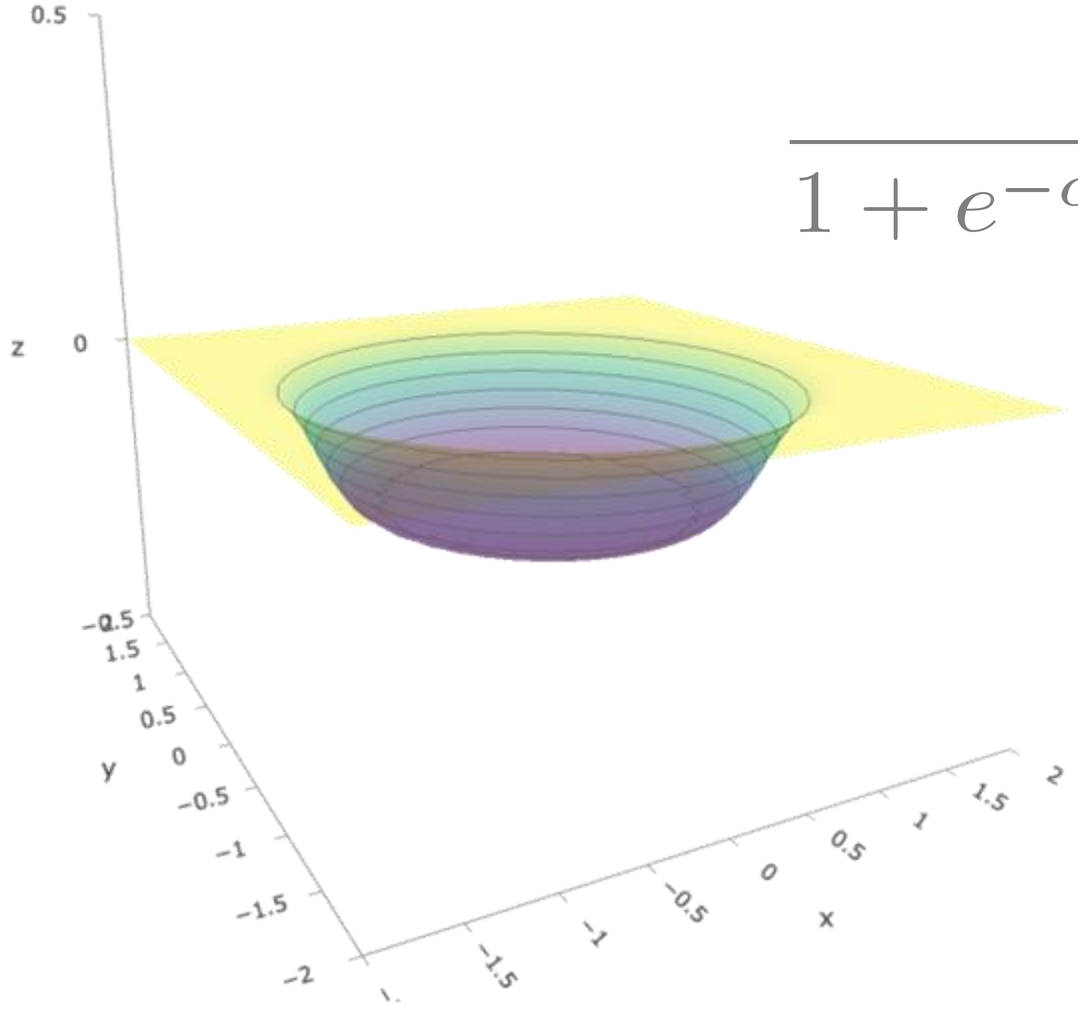

$$\frac{1-\delta}{1+e^{-\alpha \max\{0,||A^C p_S||-c^\top p_S\}^2}}-(1-\delta)$$

We use the squared max operator as in indicator function to determine if a point is within LoS or not.

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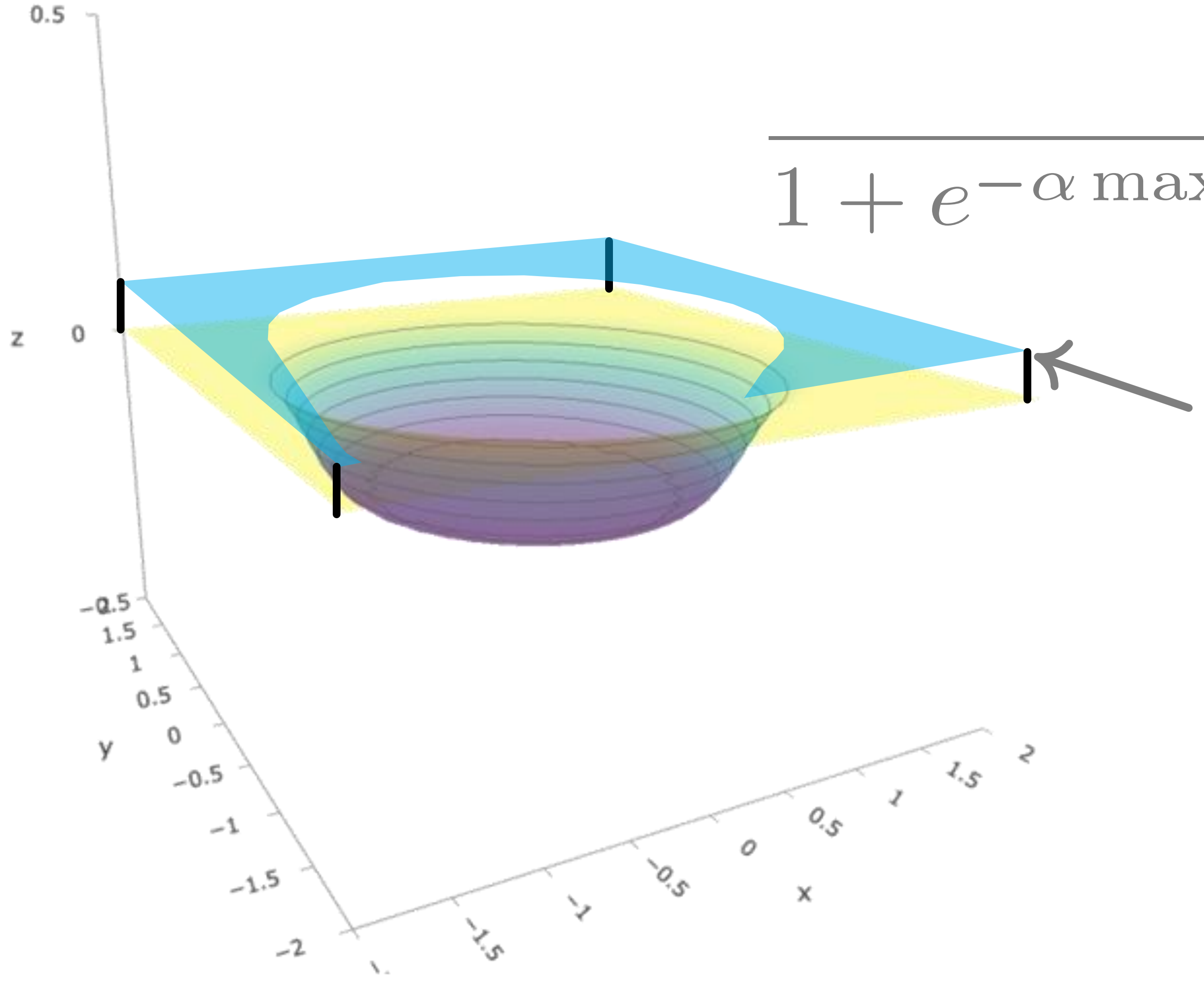

Points not in the LoS have a covariance derivative of 0, meaning they are unchanged

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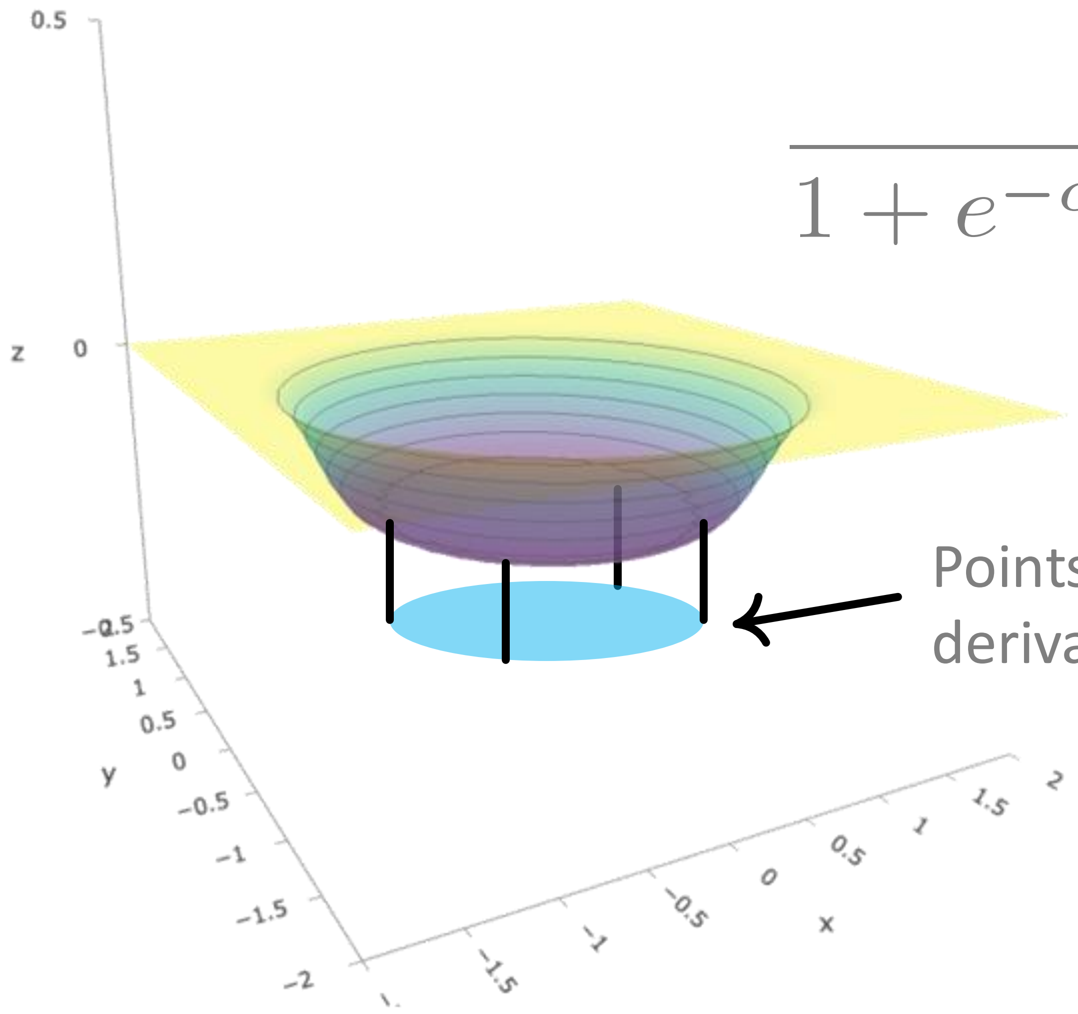

Points in the LoS have a negative covariance derivative, meaning their covariance is reduced

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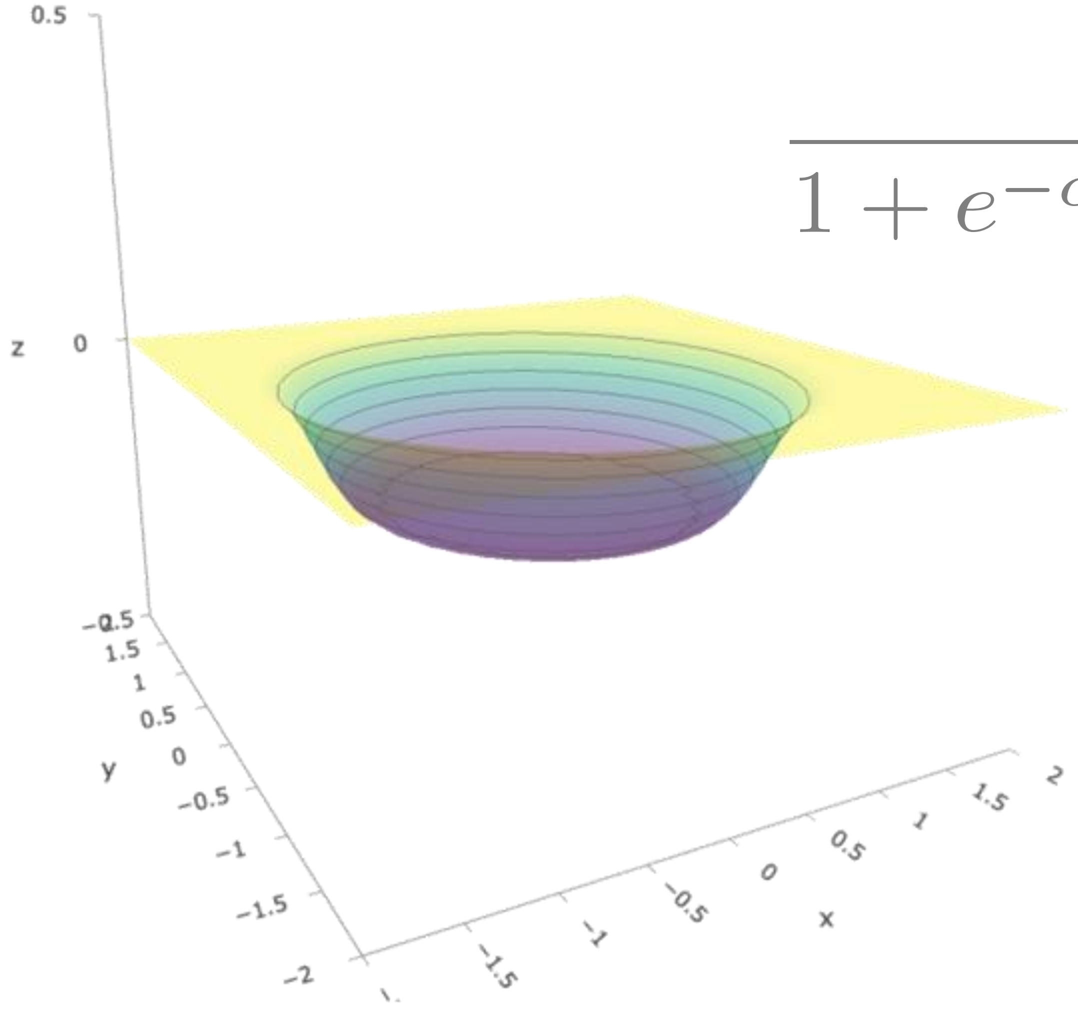

$$\frac{1-\delta}{1+e^{-\alpha \max\{0, ||A^C p_\mathcal{S}|| - c^\top p_\mathcal{S}\}^2}} - (1-\delta)$$

Tunable Parameters:

α - Determines how smoothed out the sigmoid is

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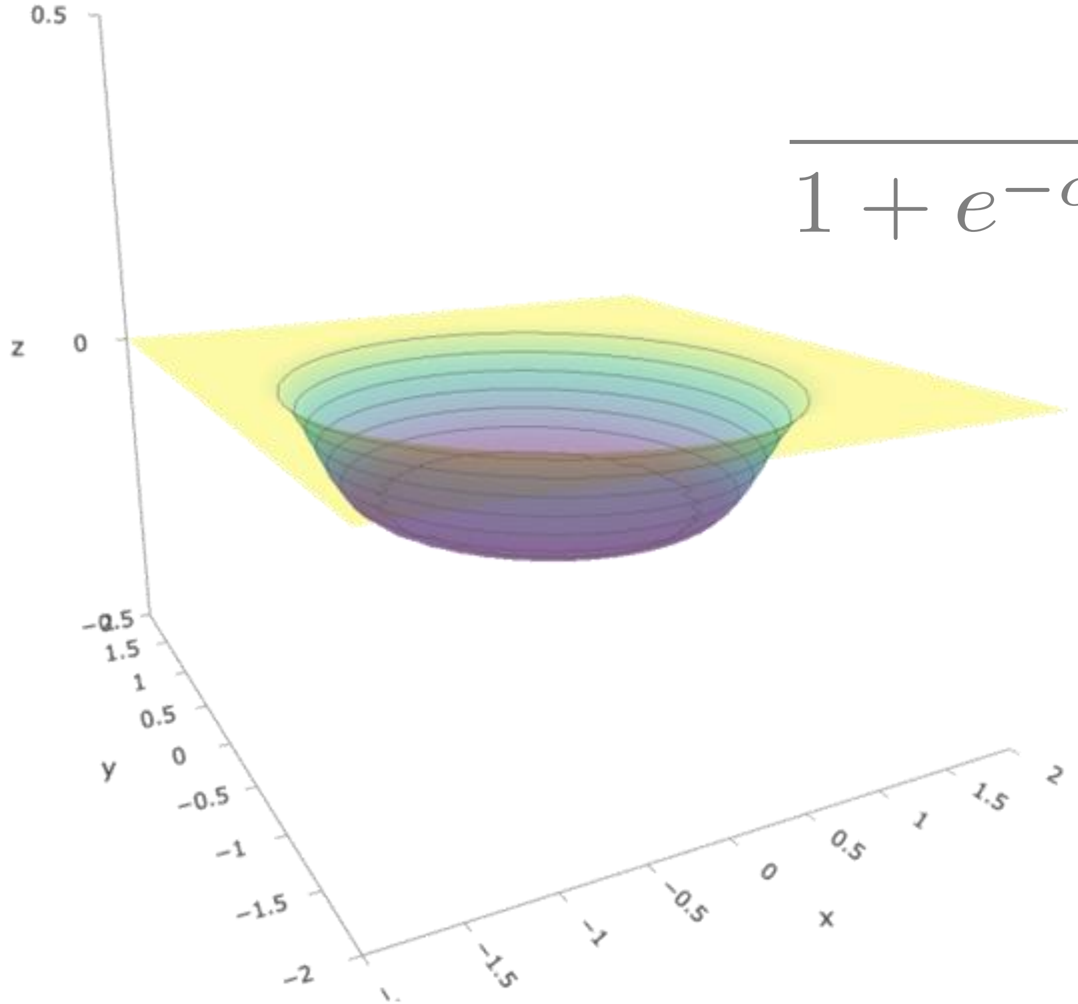

$$\frac{1-\delta}{1+e^{-\alpha \max\{0, ||A^C p_\mathcal{S}|| - c^\top p_\mathcal{S}\}^2}} - (1-\delta)$$

Tunable Parameters:

α - Determines how smoothed out the sigmoid is

δ - Determines how aggressively the covariance is reduced when observed

Map Covariance Dynamics.

Lastly, to ensure that the covariance doesn't become negative, we use the following piecewise function.

$$\dot{\sigma}(p_{\mathcal{S}}, t) = \begin{cases} \left(\frac{1-\delta}{1+e^{-\alpha \max\{0, \mathcal{K}(p_{\mathcal{S}})\}^2}} - (1-\delta) \right) & \text{if } \sigma(p_{\mathcal{S}}, t) \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

System Dynamics

We use a 6-Degree of Freedom rigid body model with mass dynamics.

Mass. $\dot{m} = -\alpha||T_{\mathcal{B}}(t)||_2,$

Position. $\dot{r}_{\mathcal{I}}(t) = v_{\mathcal{I}}(t),$

Velocity. $\dot{v}_{\mathcal{I}}(t) = \frac{1}{m}\left(C_{\mathcal{B}\to\mathcal{I}}(q_{\mathcal{B}\to\mathcal{I}}(t))T_{\mathcal{B}}(t)\right) + g_{\mathcal{I}},$

Attitude. $\dot{q}_{\mathcal{I}\to\mathcal{B}} = \frac{1}{2}\Omega(\omega_{\mathcal{B}}(t))q_{\mathcal{I}\to\mathcal{B}}(t),$

Angular Velocity. $\dot{\omega}_{\mathcal{B}}(t) = J_{\mathcal{B}}^{-1}\left(M_{\mathcal{B}}(t) - [\omega_{\mathcal{B}}(t)\times]\, J_{\mathcal{B}}\omega_{\mathcal{B}}(t)\right),$

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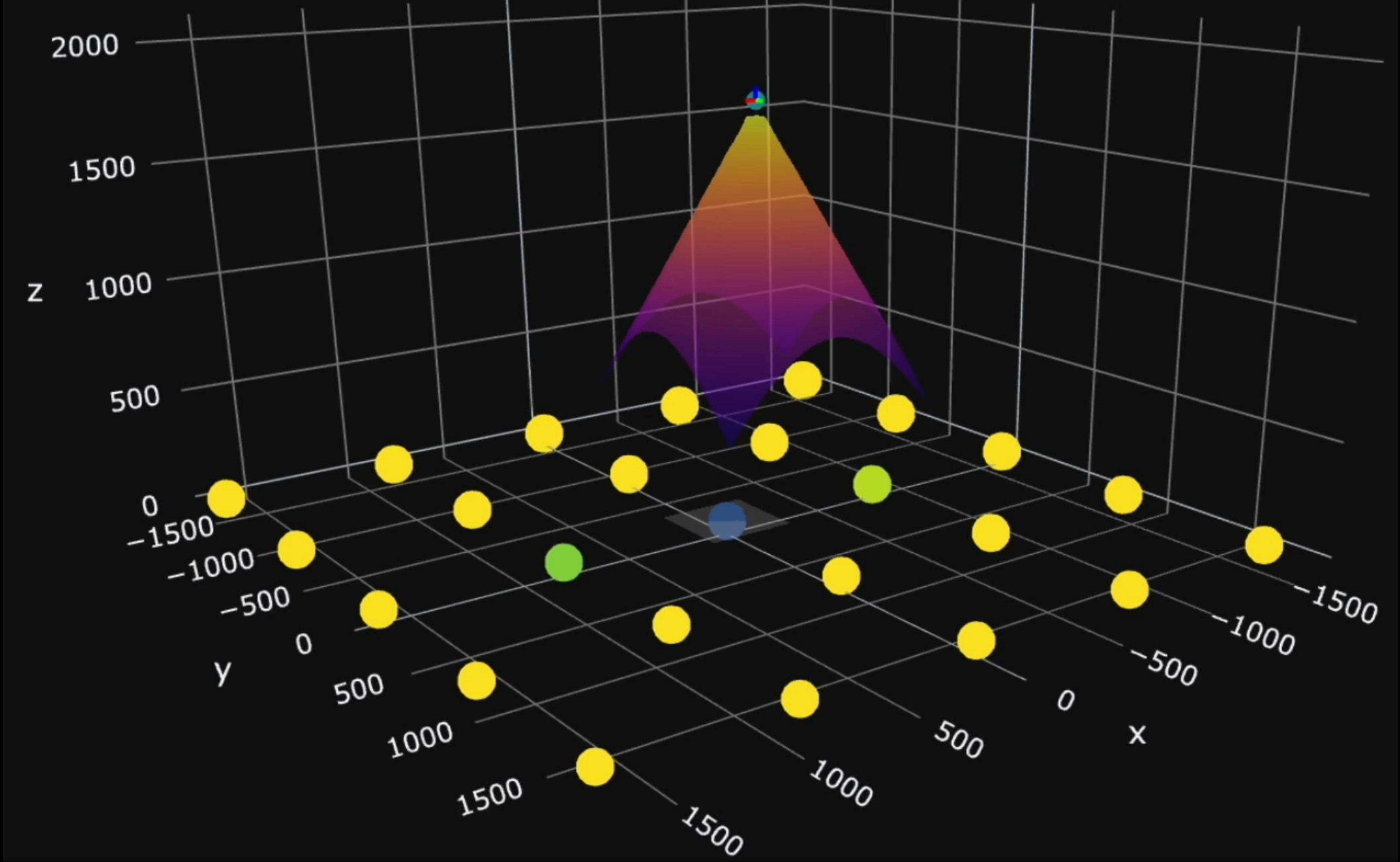
Nonlinear Trajectory Optimization Problem.

$$
\begin{aligned}
\min_{x,u} \quad & \int_{t_i}^{t_f} \sum_{i=1}^{N_{\text{grid}}} \sigma(p_{\mathcal{S},i}, t)\,dt \\
\text{s.t.} \quad & \dot{x}(t) = f(x(t), u(t)), && \forall t \in [t_i, t_f], \\
& x_{\min} \leq x(t) \leq x_{\max}, && \forall t \in [t_i, t_f], \\
& u_{\min} \leq u(t) \leq u_{\max}, && \forall t \in [t_i, t_f], \\
& x(t) \in \mathcal{X}, && \forall t \in [t_i, t_f], \\
& u(t) \in \mathcal{U}, && \forall t \in [t_i, t_f], \\
& x(t_i) \in \mathcal{X}_{t_i},
\end{aligned}
$$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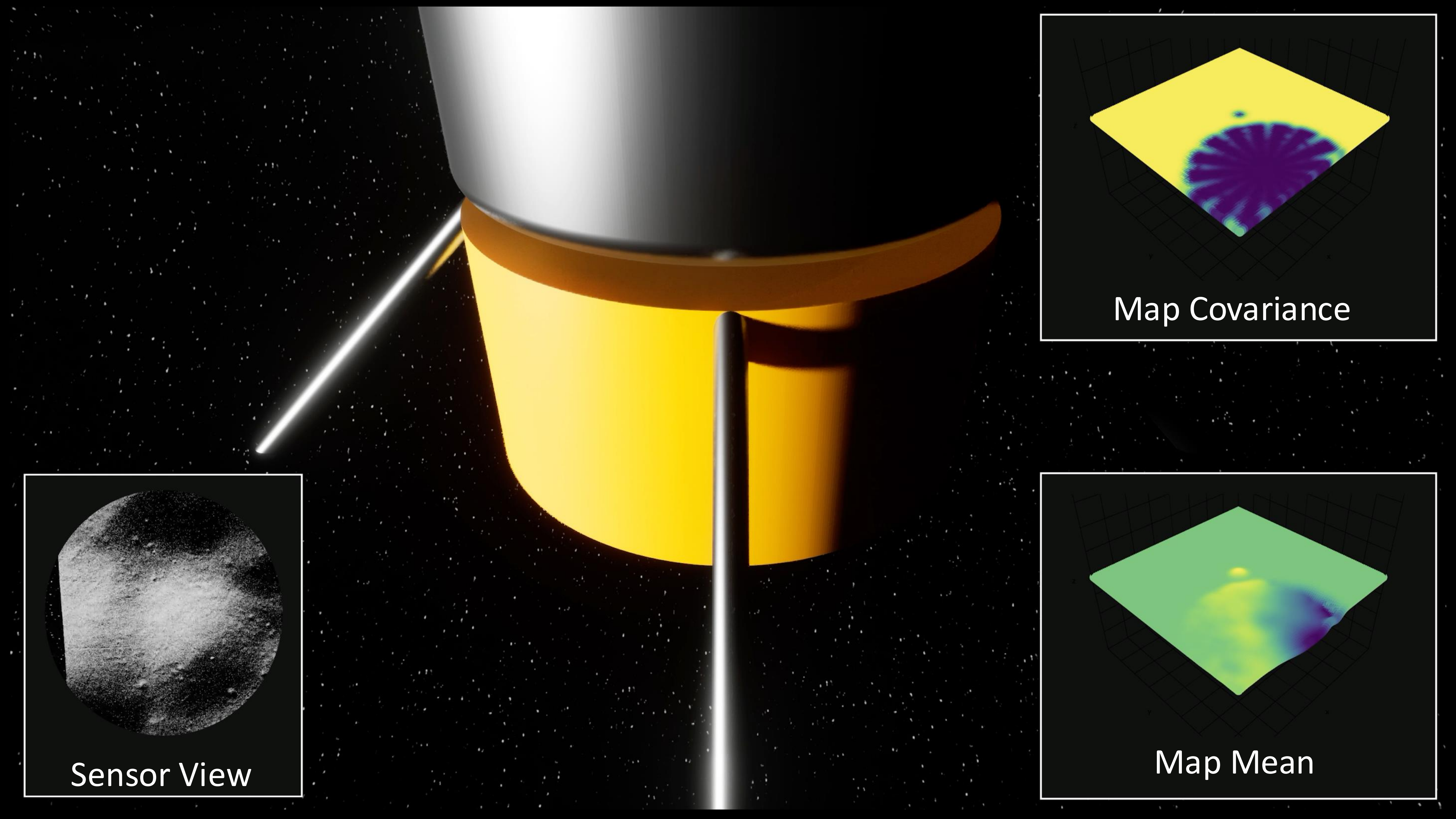
Map Covariance
Map Mean
Sensor View

Key Takeaways.

1. We propose an algorithm for maximizing information in a PDG scenario.

2. We embed this covariance as a state in our dynamics and minimize the integral.

3. We demonstrate the effectiveness of the proposed method in a high-fidelity simulated environment.

Acknowledgments

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