Proactive Mapping

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École des Ponts
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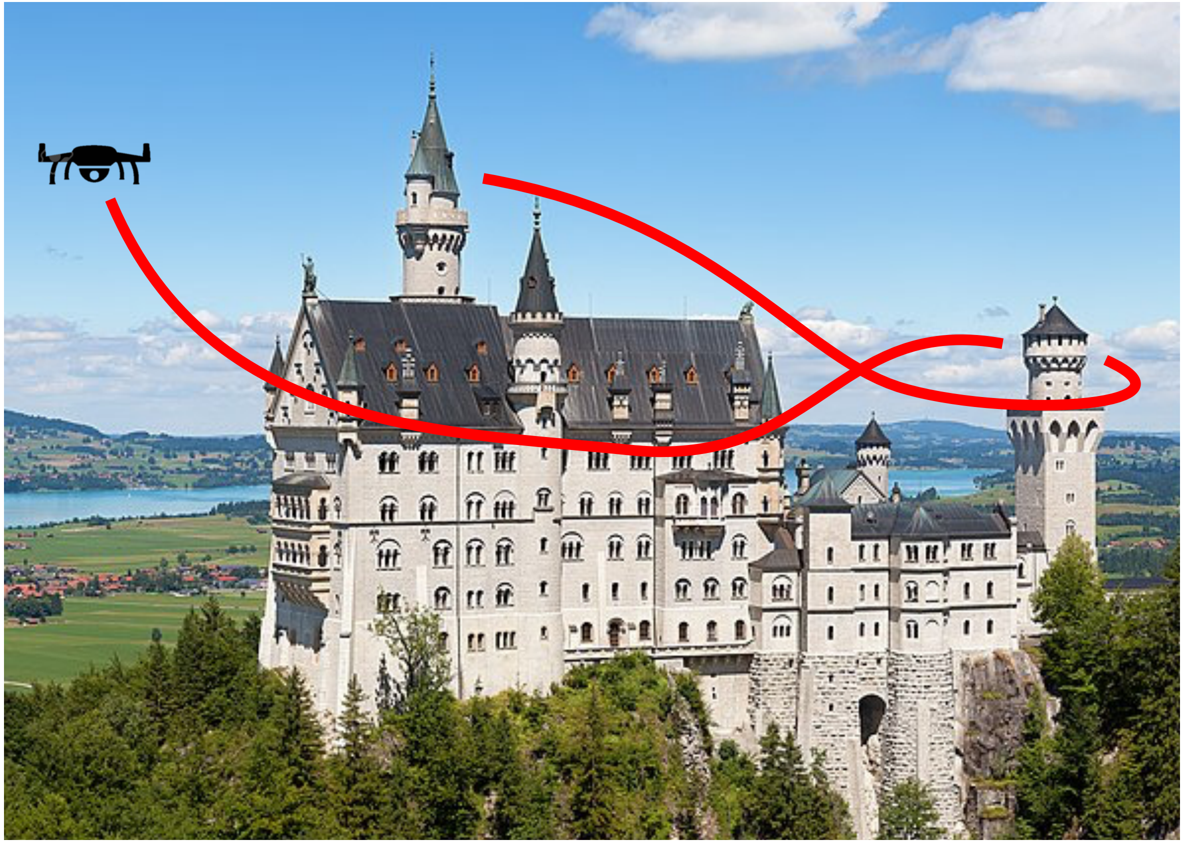
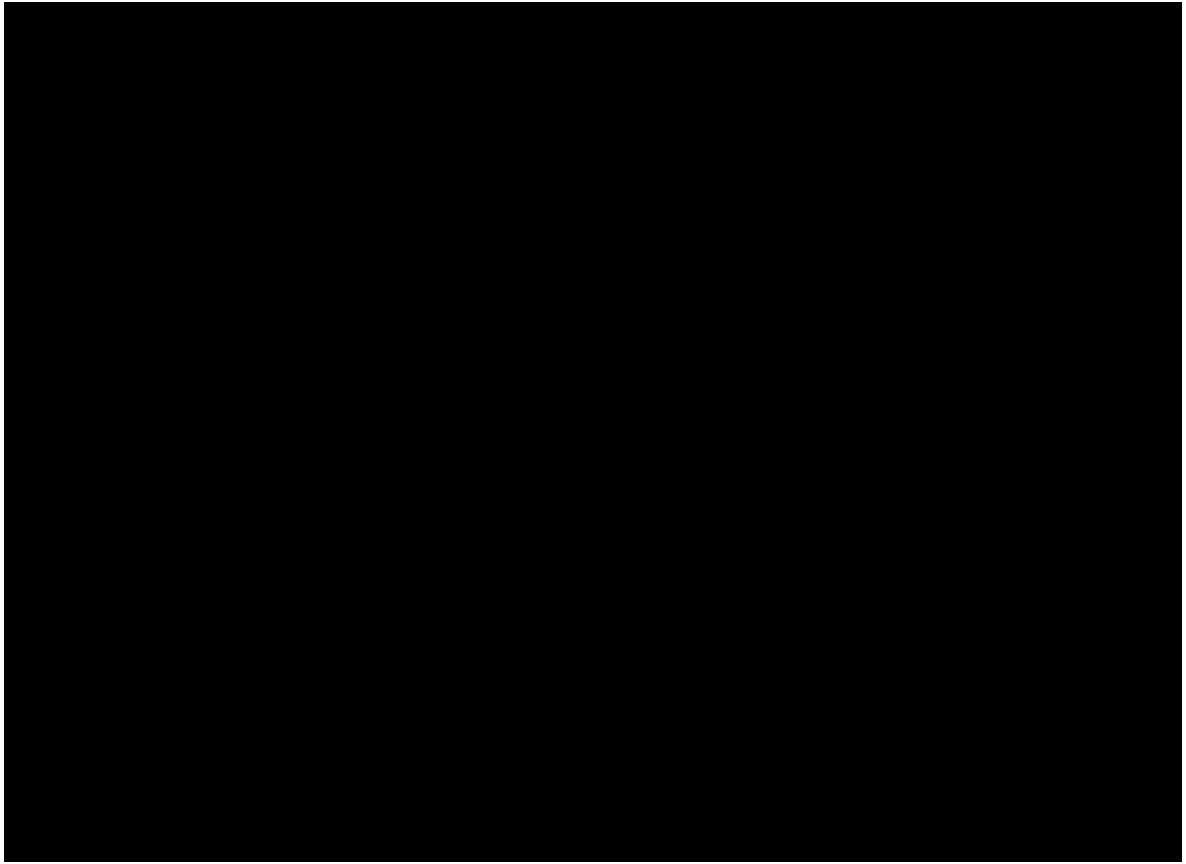
mapping

mapping



mapping

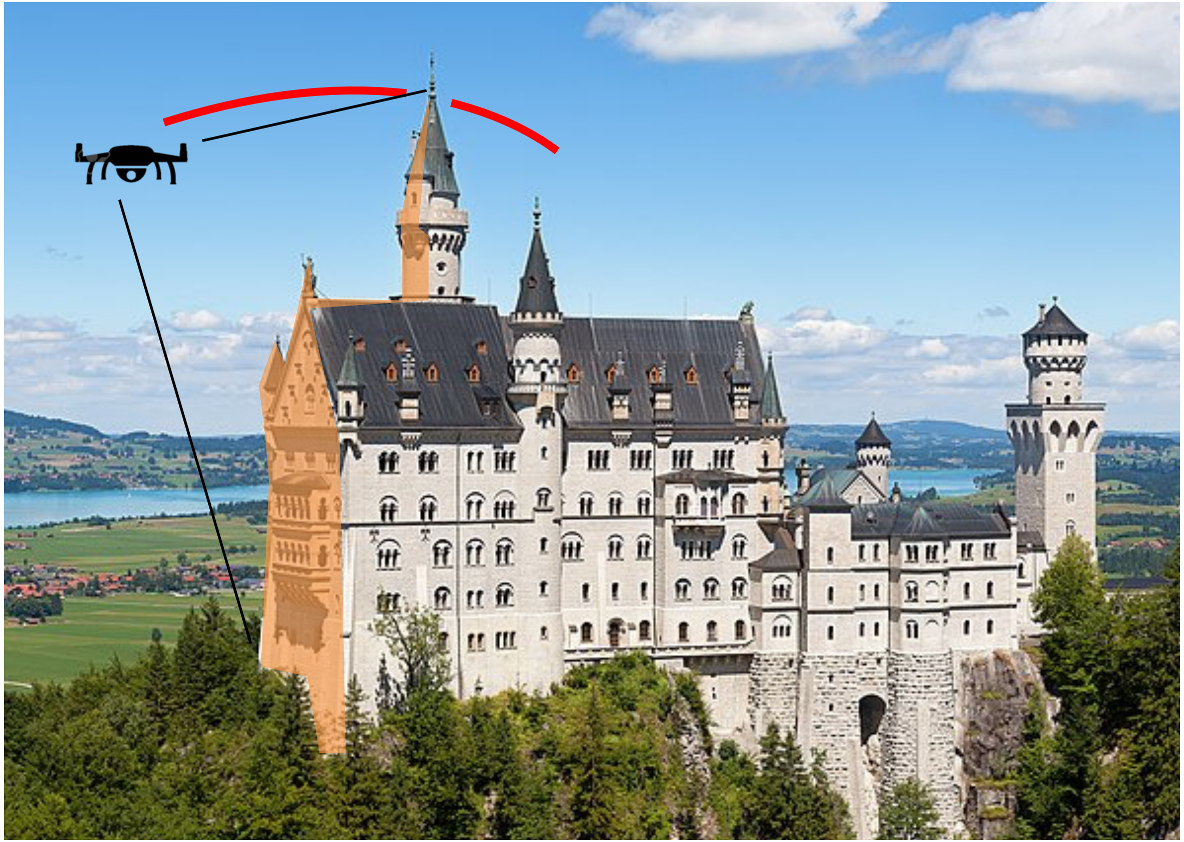
automatic mapping



next best view problem

our approach

1. **Build a function** gain(pose) that predicts, for any given camera pose, how much new surface we will see from this camera pose, given what we saw so far.



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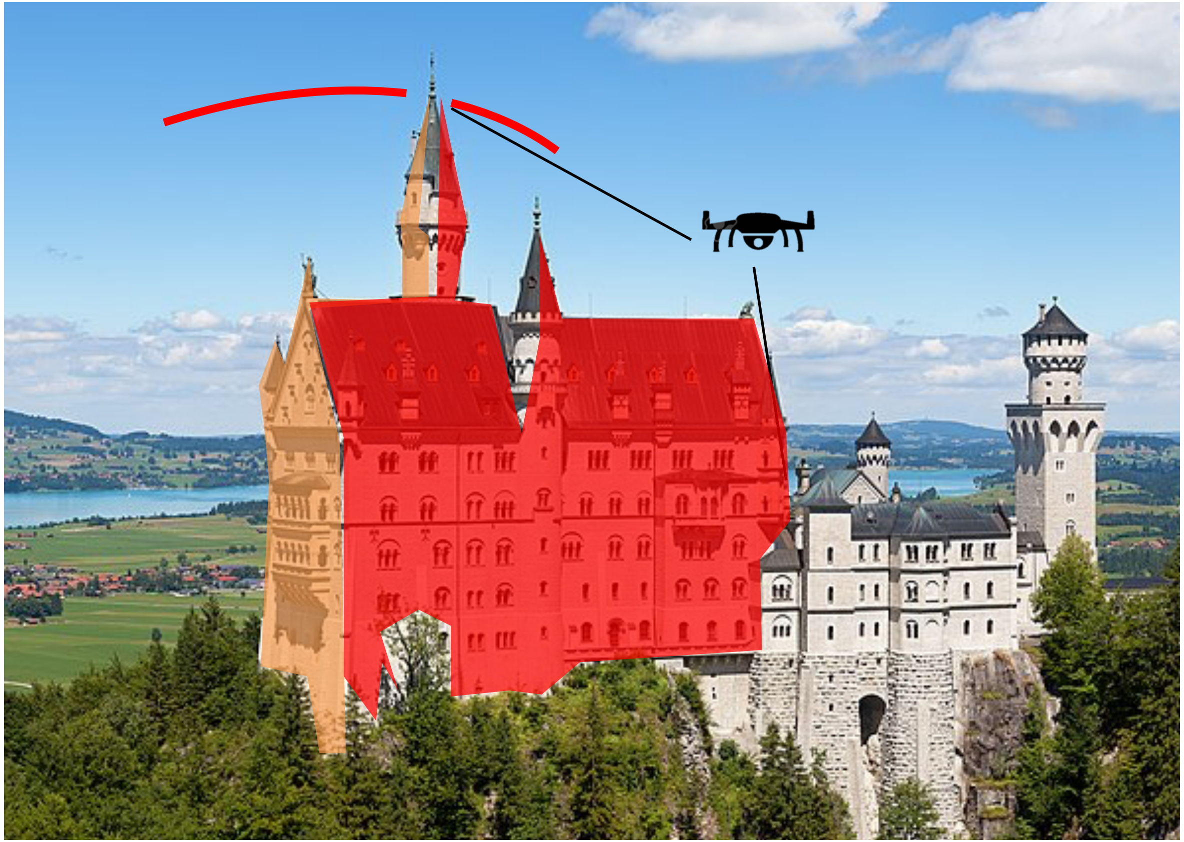
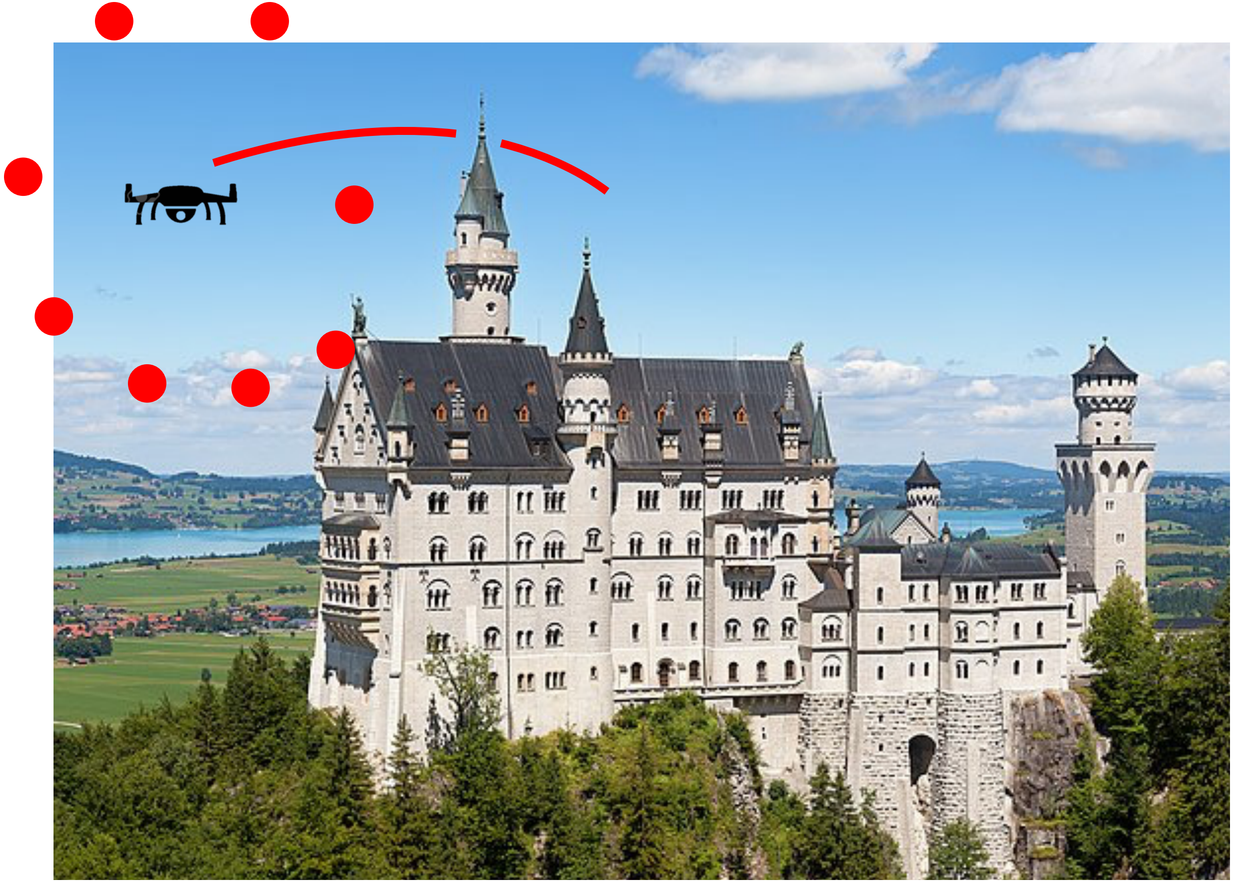


our approach

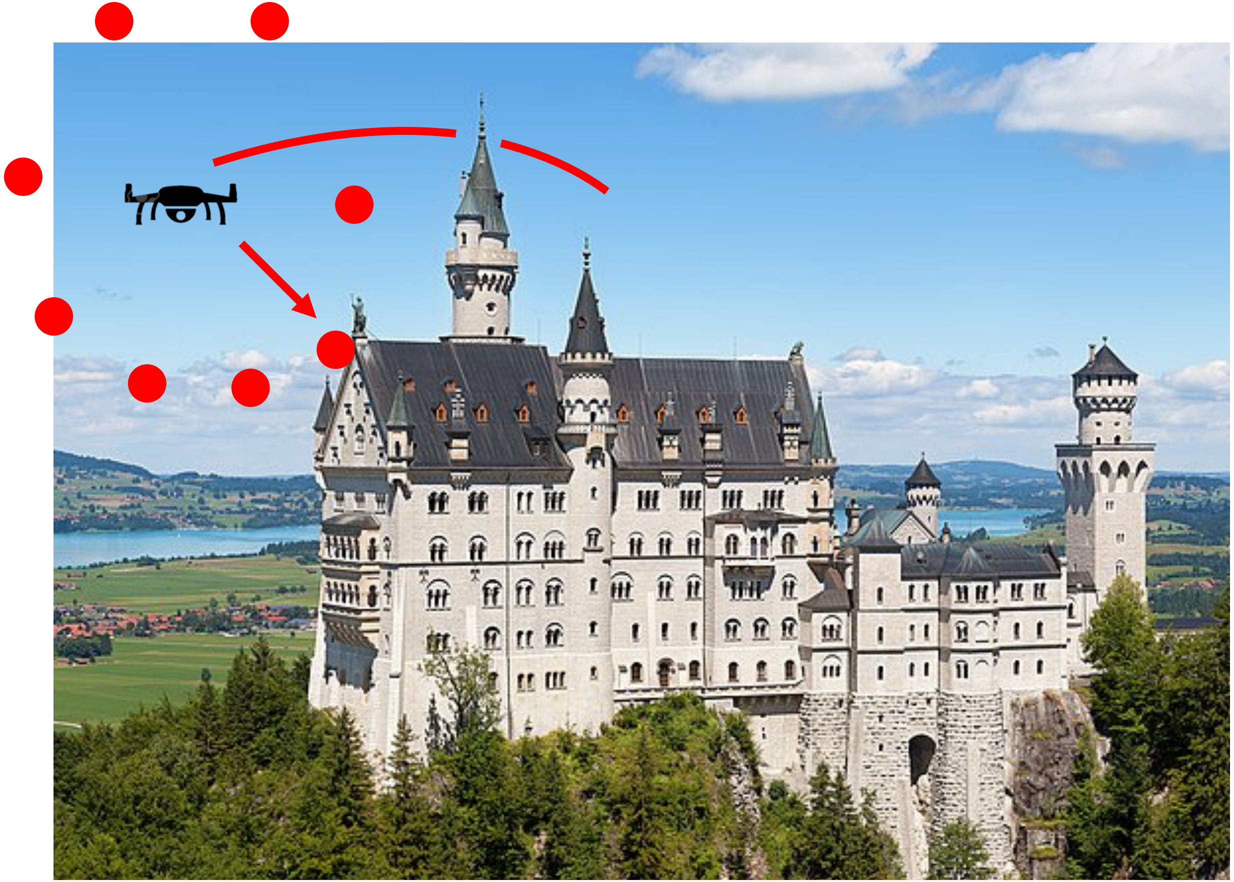
2. **Sample poses** around the current pose, evaluate gain for each of them



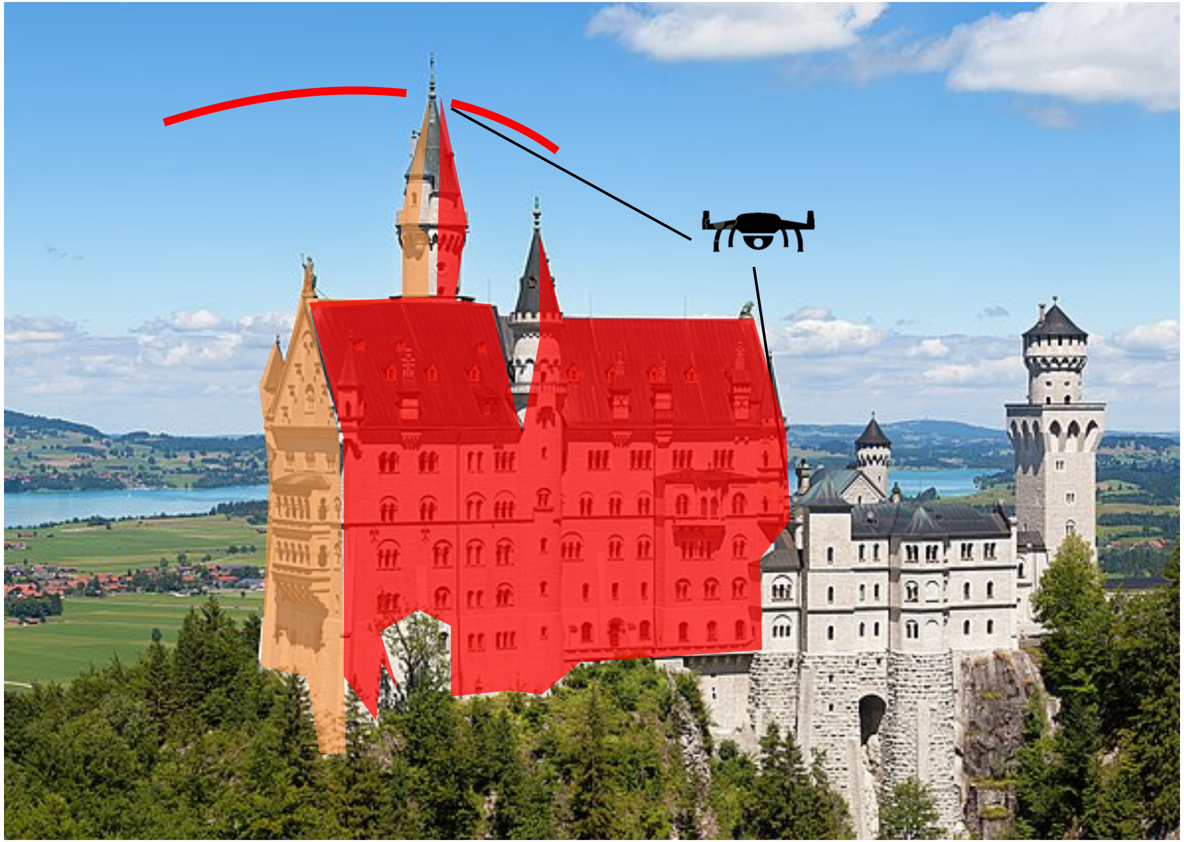
our approach

2. Sample poses around the current pose, evaluate gain for each of them,

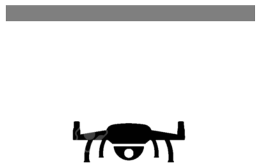
and **move to the pose with the highest gain**



computing gain(pose)



what can we predict from a bunch of views?



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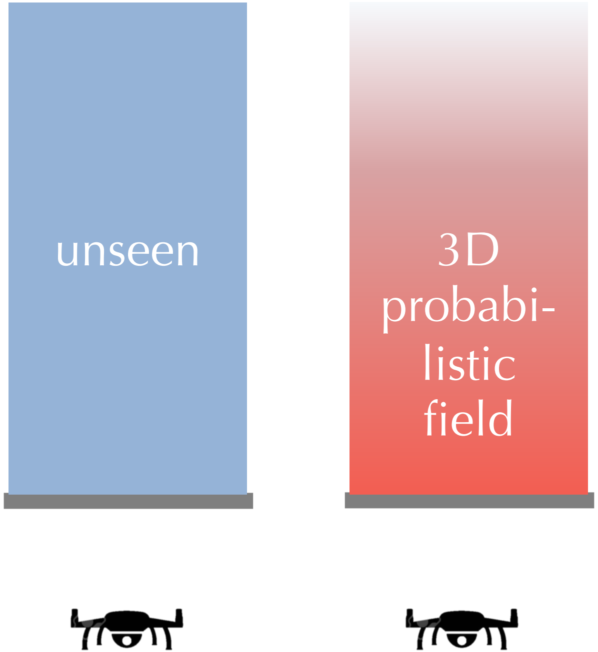

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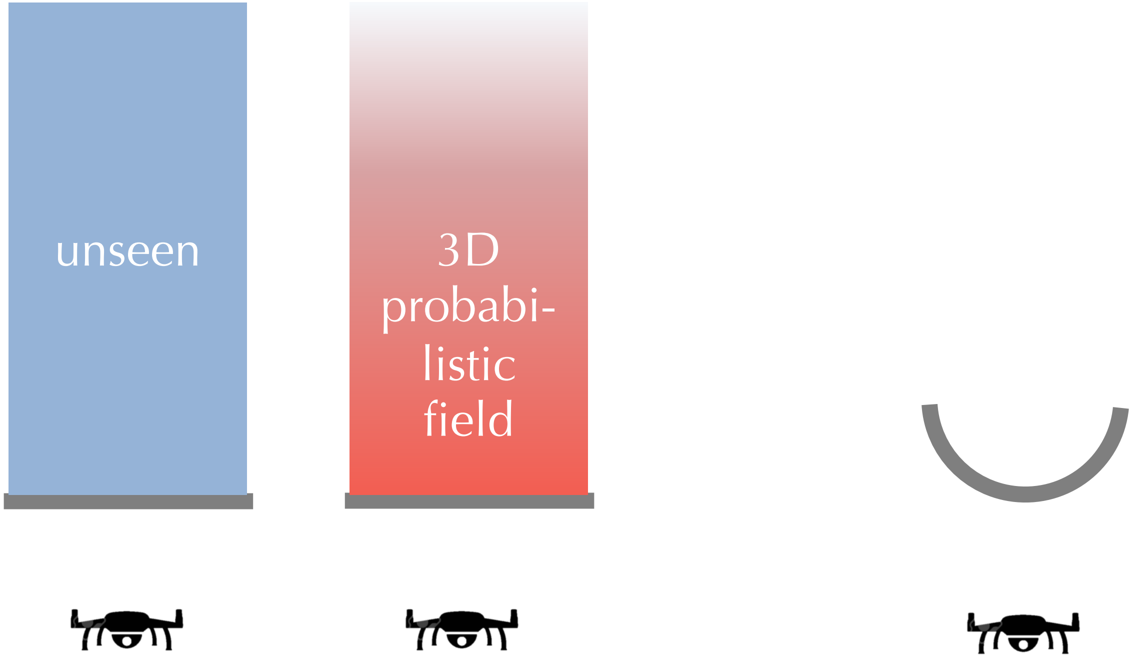

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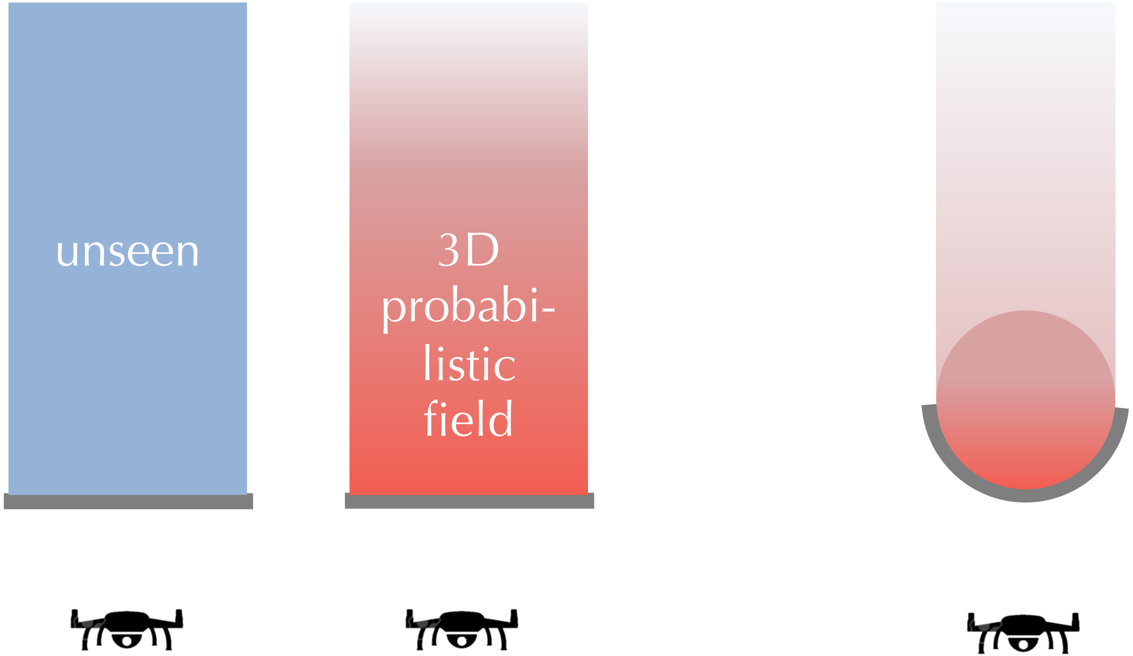

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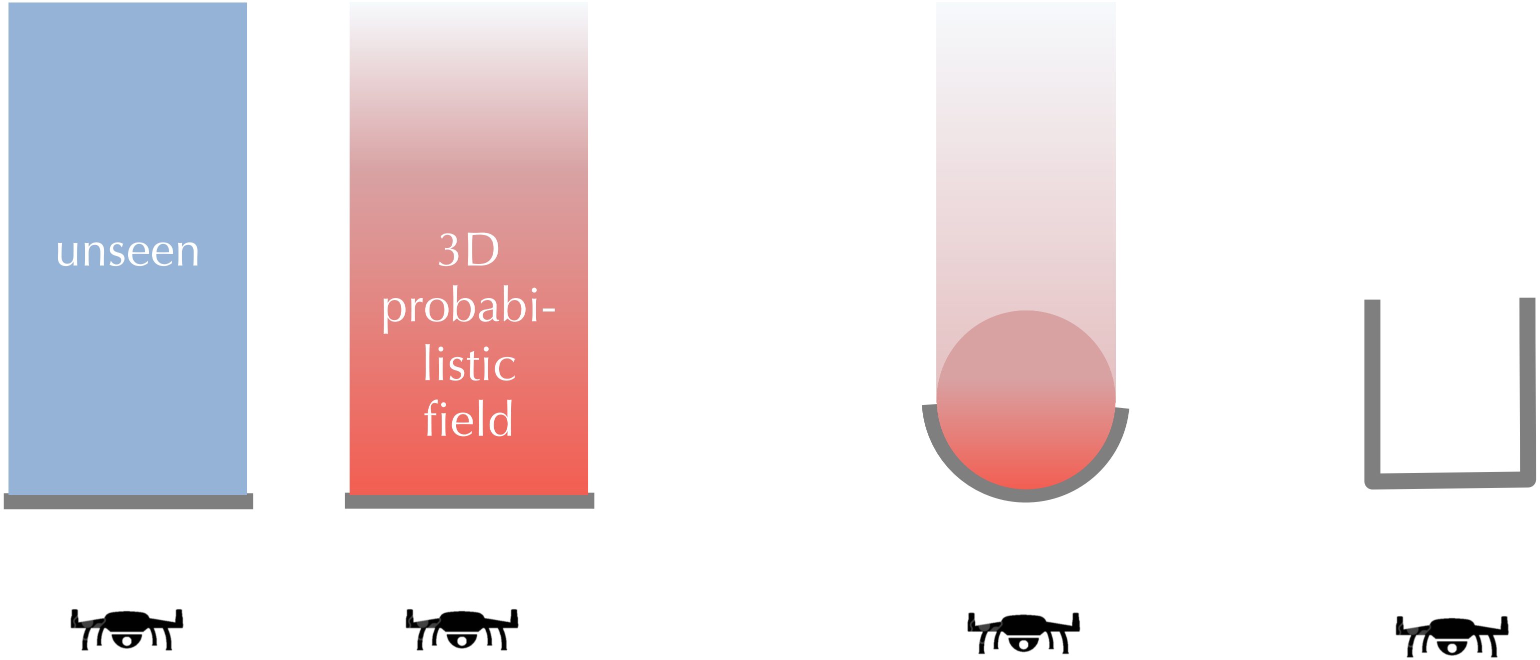

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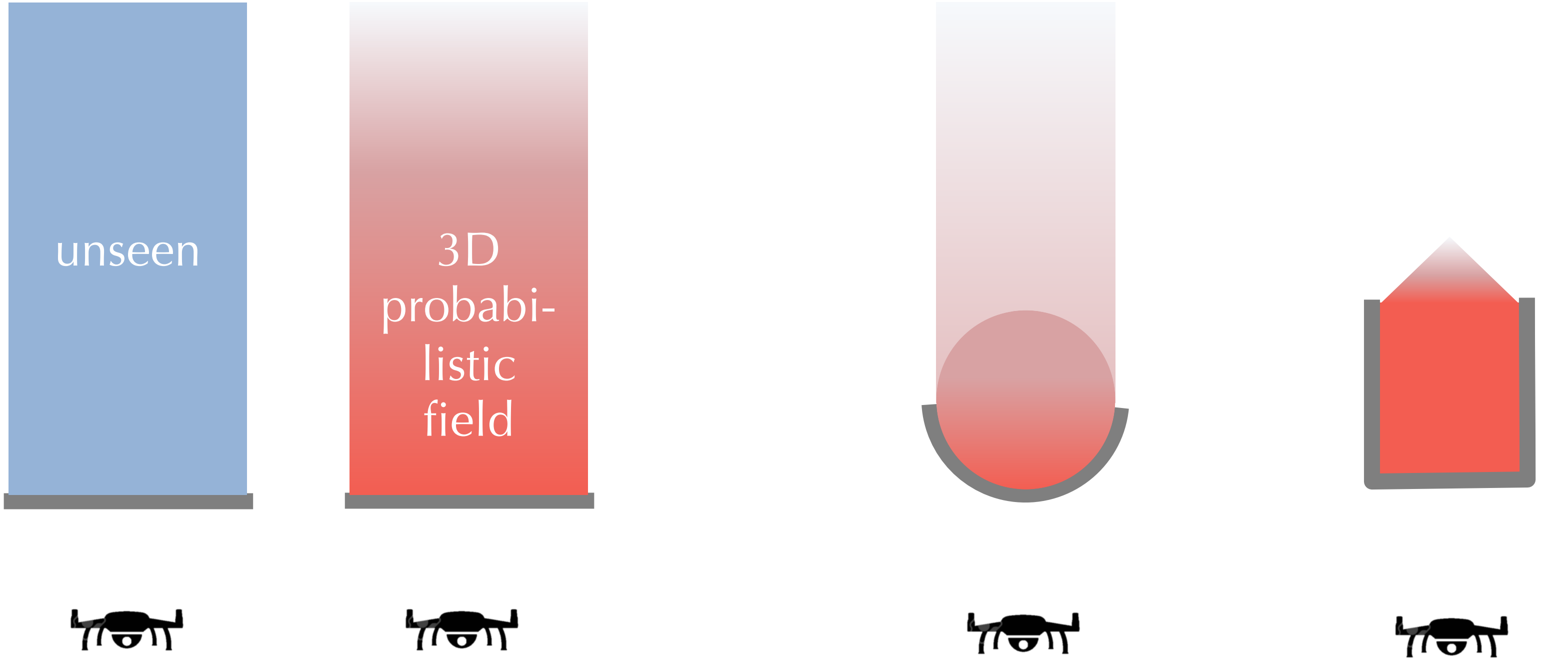


A 3D probabilistic field on the reconstruction

represented with a deep architecture

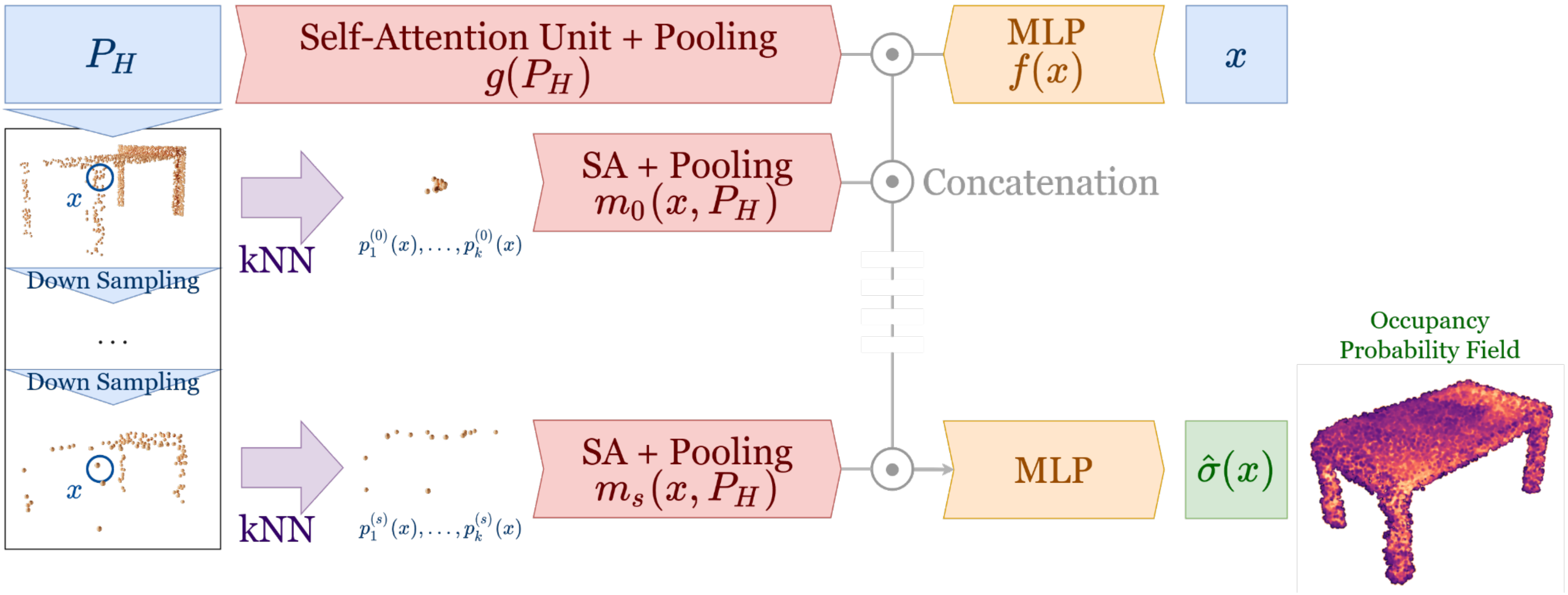
→ scalable, can learn some prior

3D probabilistic field

Predicting the 3D probabilistic field σ

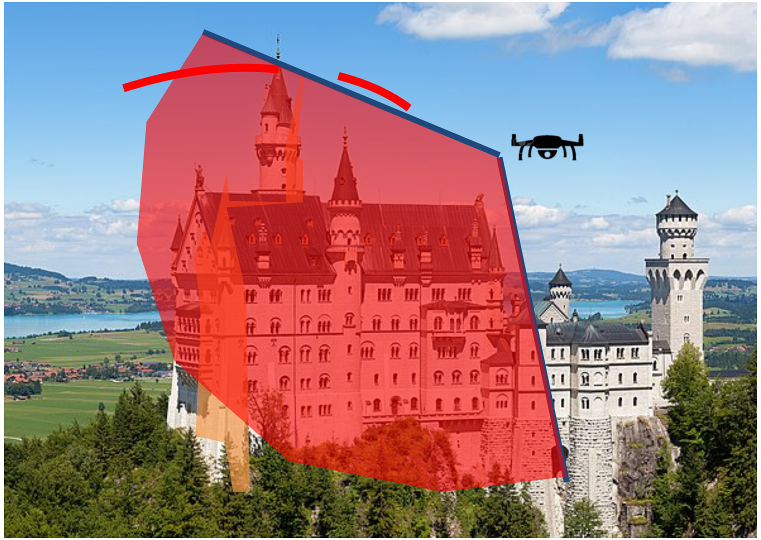
$\sigma_t(p) = F(p,$ camera history at time t, merged depth maps at $t)$

architecture of F(.)



predicting gain(pose)

Integrating over the 3D probabilistic field can give the surface coverage gain!



[**SCONE: Surface Coverage Optimization in Unknown Environments by Volumetric Integration.** Antoine Guédon, Pascal Monasse, and Vincent Lepetit. Spotlight at NeurIPS 2022]

predicting gain(pose)

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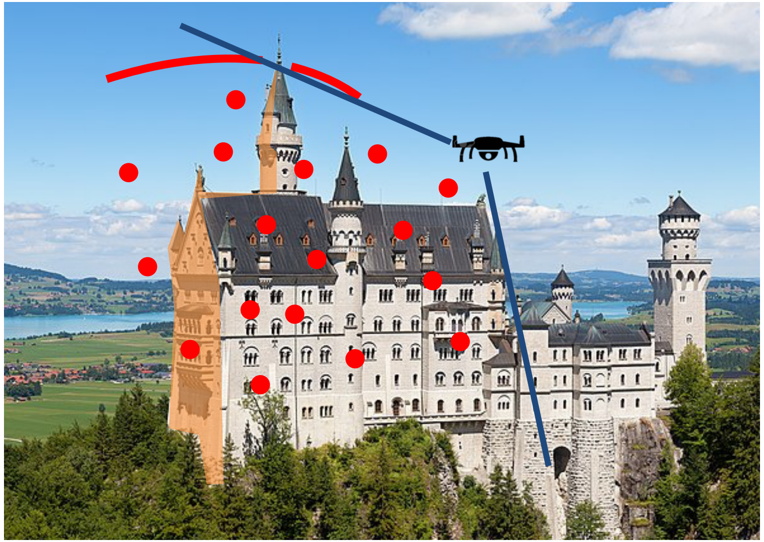
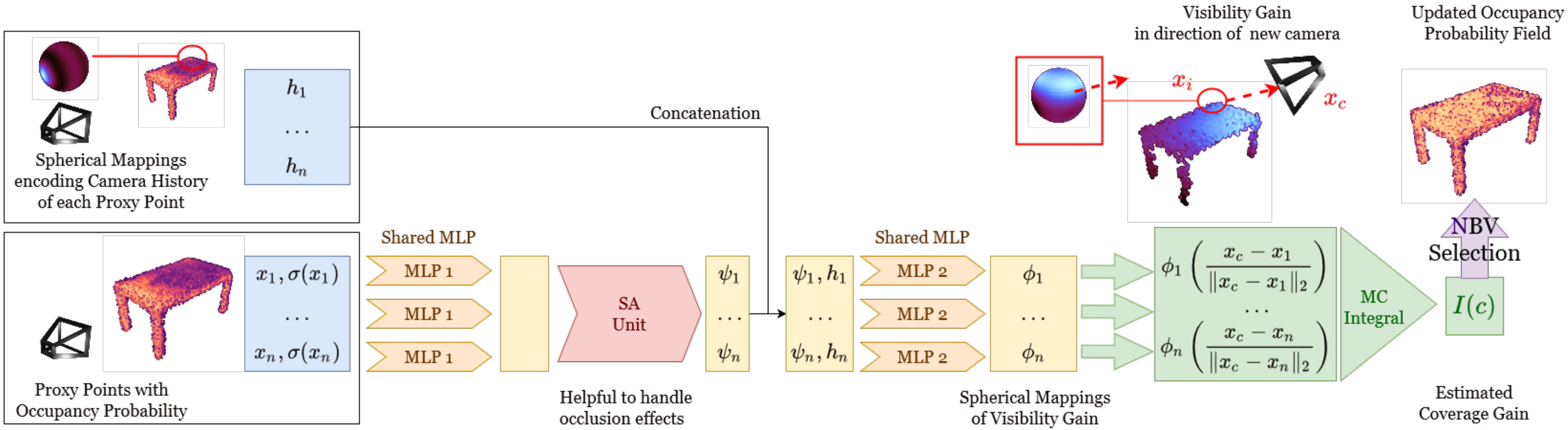


gain(pose) = sum_i gain_points($\{ p_i \}$)$_i$

with gain_points($\{ p_i \}$) = $G(\{ p_i, \sigma_t(p_i) \}$, camera history at t)

and points $\{ p_i \}$ in the field of view of pose:

architecture of *G*(.)



self-supervision of $F(.)$ and $G(.)$

- $\sigma_t(p) = F(p,$ camera history at time t, merged depth maps at $t)$
- gain_points$(\{ p_i \}) = G(\{ p_i, \sigma_t(p_i) \}$, camera history at $t)$

1. store I = (camera history, observations)

self-supervision of $F(.)$ and $G(.)$

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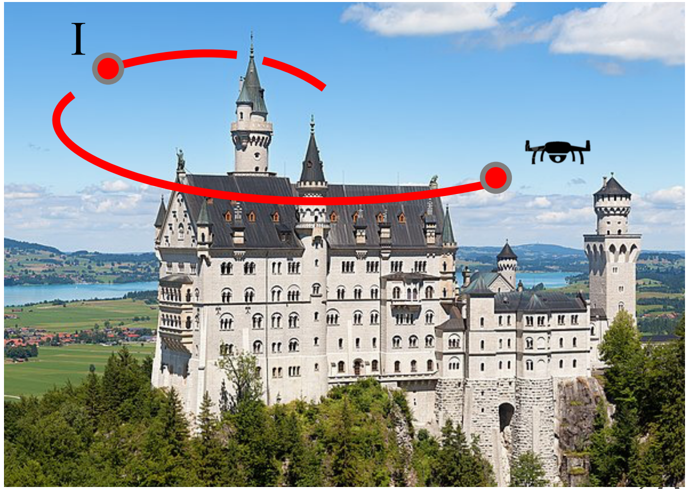
1. store I = (camera history, observations)
2. fly for a while



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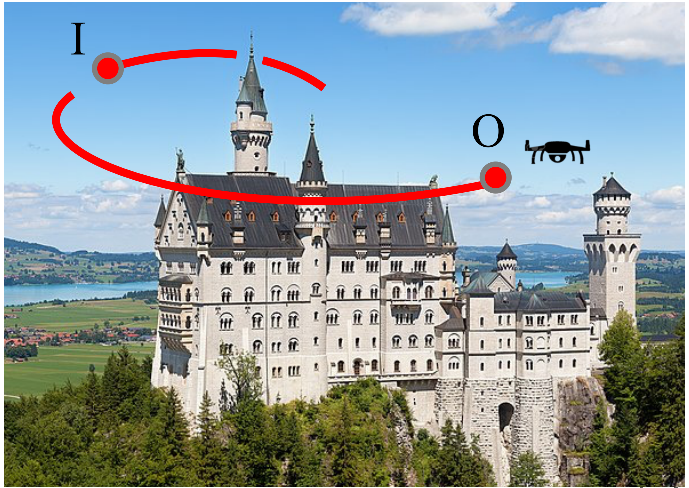
1. store I = (camera history, observations)
2. fly for a while
3. estimate and store
   O = (volume, surface)



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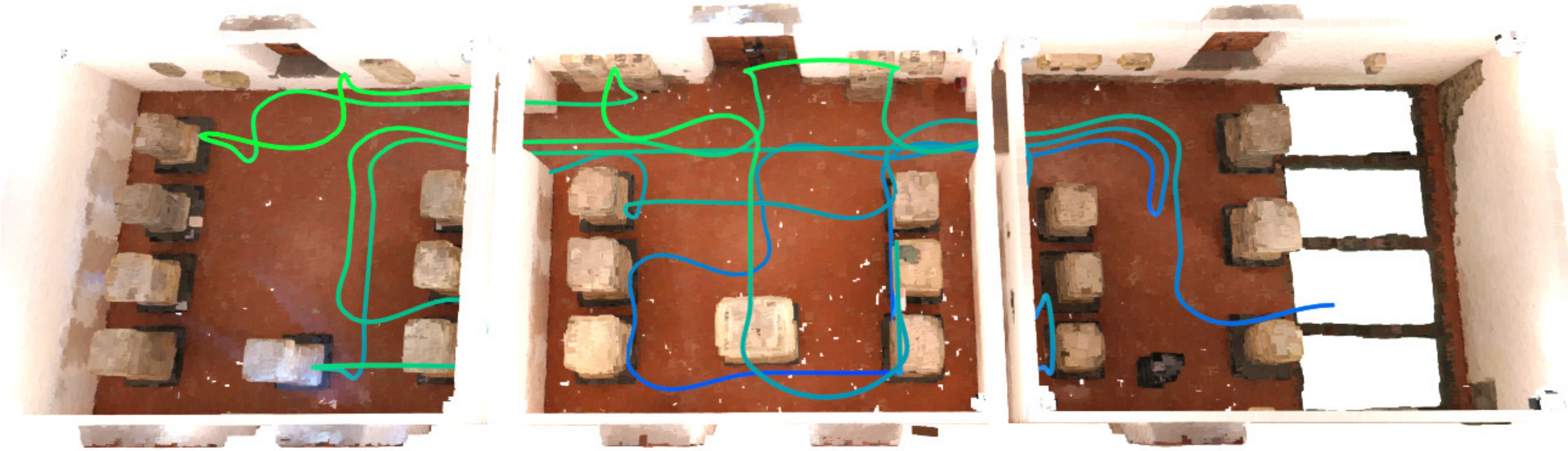
1. store I = (camera history, observations)
2. fly for a while
3. estimate and store
   O = (volume, surface)
4. train F and G using many (I, O) pairs

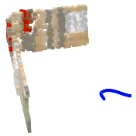
[SCONE: Surface Coverage Optimization in Unknown Environments by Volumetric Integration. Antoine Guédon, Pascal Monasse, and Vincent Lepetit. Spotlight at NeurIPS 2022]

MACARONS: Mapping And Coverage Anticipation with RGB ONline Self-supervision. Antoine Guédon, Tom Monnier, Pascal Monasse, and Vincent Lepetit. CVPR 2023.

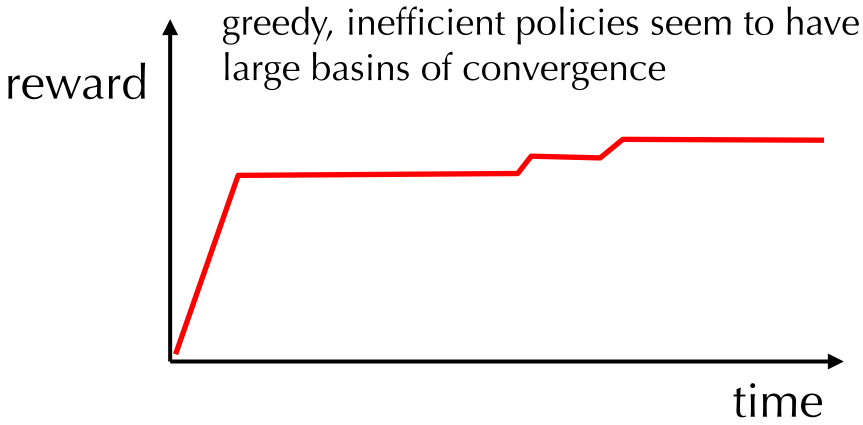
greedy exploration does not work well indoor

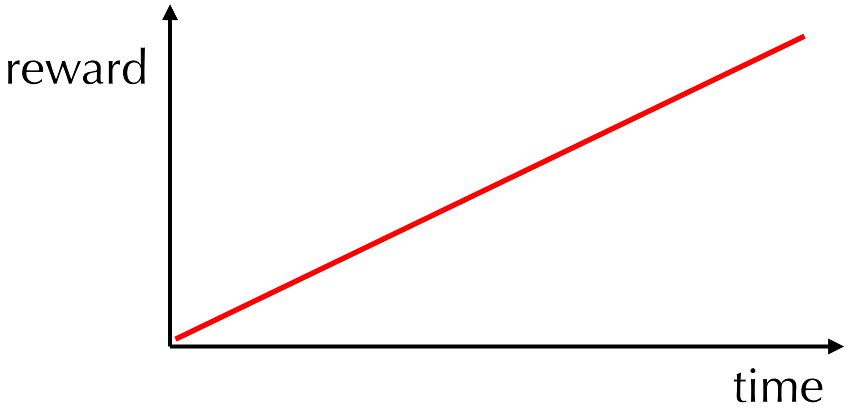


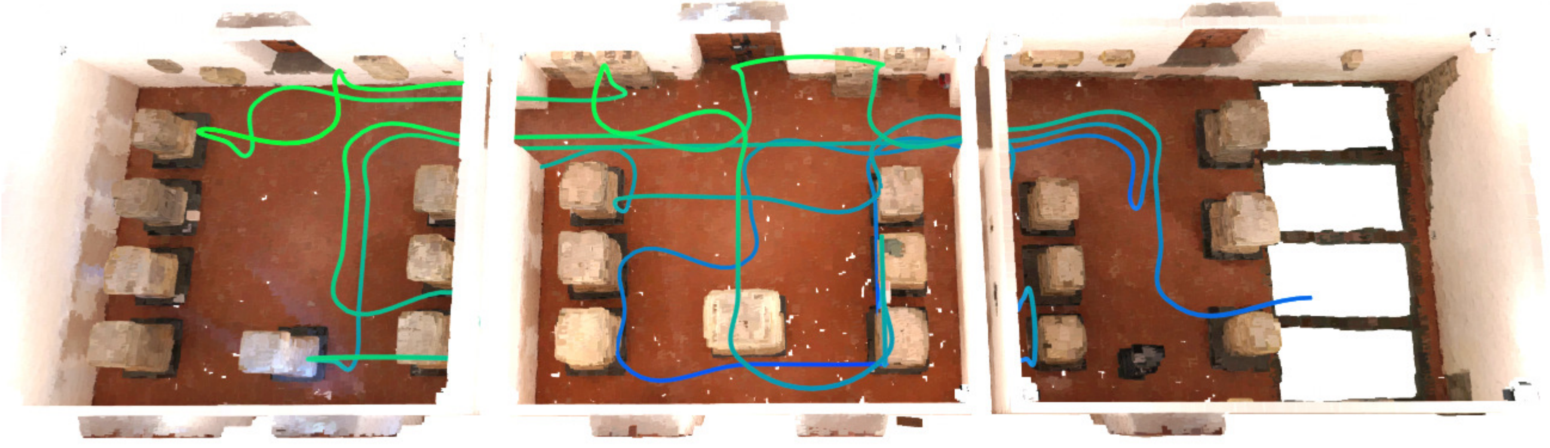
trying reinforcement learning

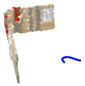


why RL does not work well here

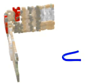






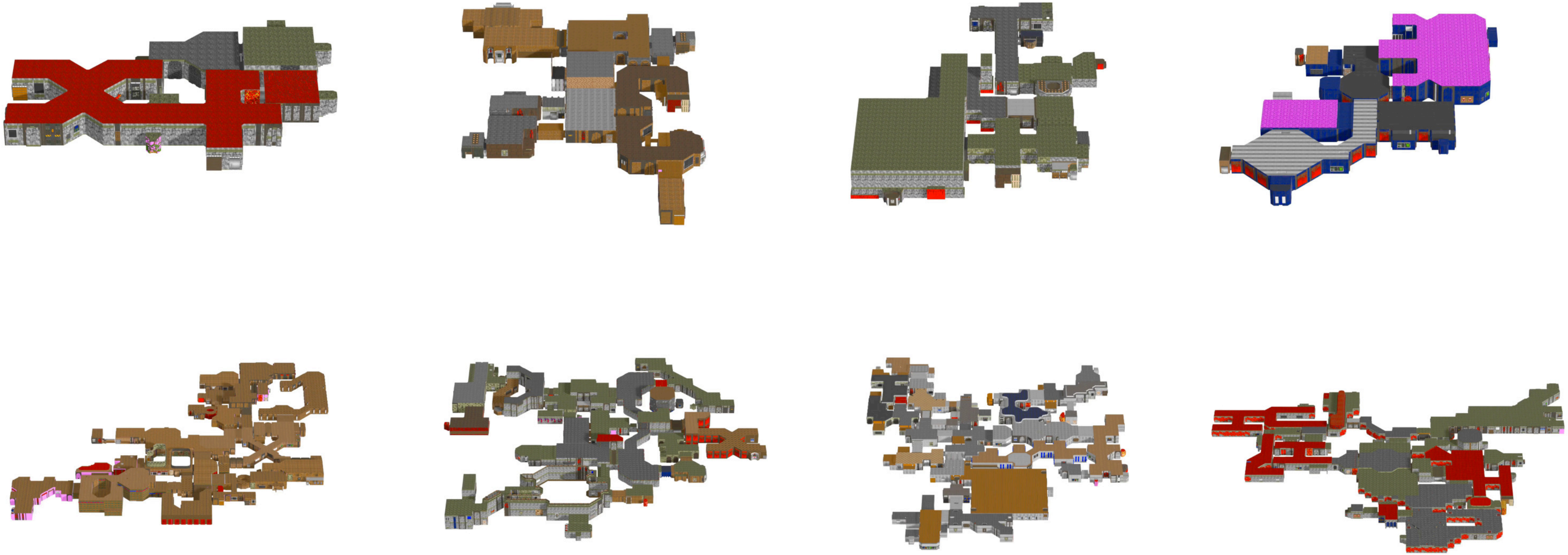


PPO (RL)



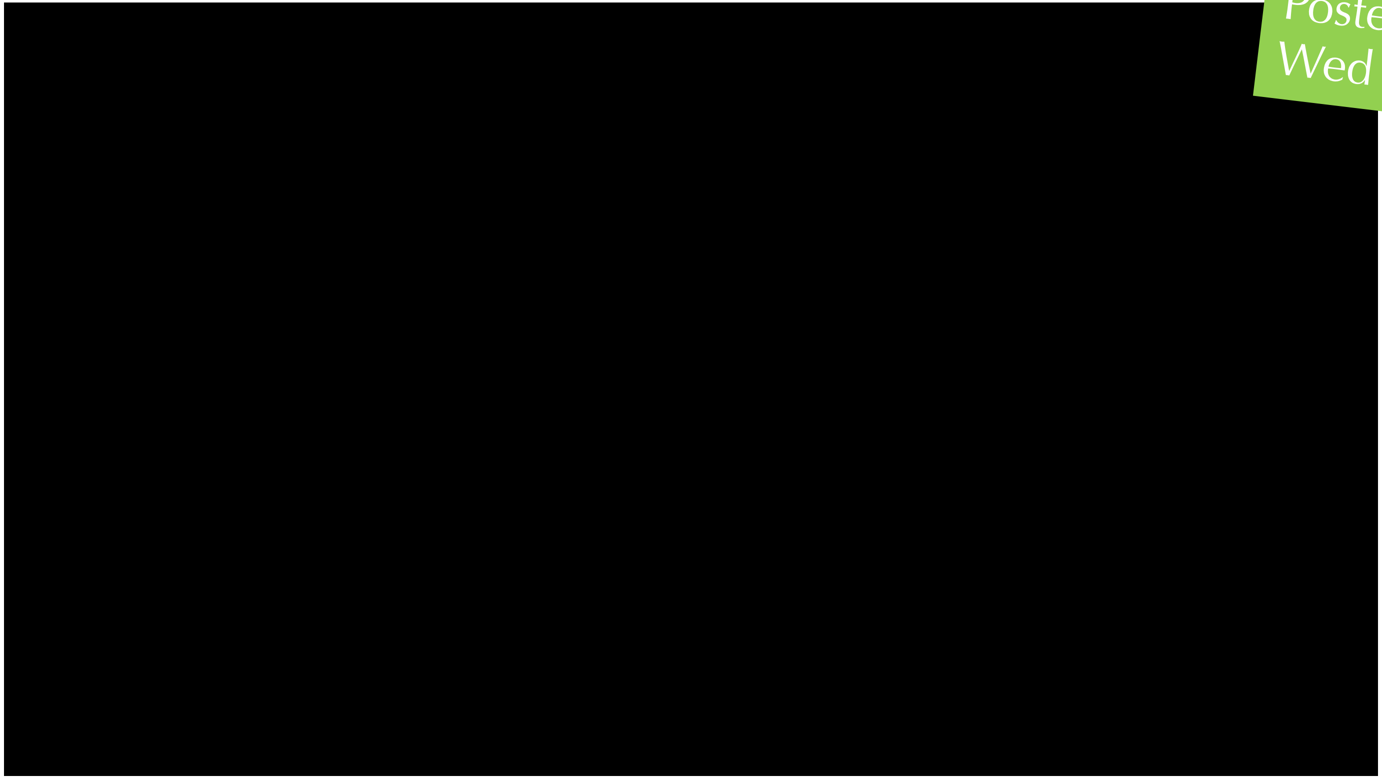
ours - new

new dataset (in preparation)



shameless ad for a cvpr'24 poster

Poster Session 2
Wed PM #50



[SuGaR: Surface-Aligned Gaussian Splatting for Efficient 3D Mesh Reconstruction and High-Quality Mesh Rendering. Antoine Guédon and Vincent Lepetit. CVPR 2024.]

Frosting

SuGaR

Frosting

Antoine Guédon

Shiyao Li

Thanks for listening!