universität freiburg

# Information Gain Exploration

## Utilizing Full Posterior Maps for Enhanced Exploration

Master – Computer Science

Robot Learning Lab
Robin Steiger
Lisbon, March 2024

# Introduction

- Active Exploration
- Gain-based Exploration
- Full Map Posteriors

# Exploration

Robot actively performs actions to gather information during SLAM

Strategies:

- Random Exploration
- Frontier Exploration
- Information-Gain Exploration

# Information Gain-based Exploration Using Rao-Blackwellized Particle Filters

*Stachniss, Grisetti, Burgard*

- Leverage Particle filters for maximizing information gain
- Pose and Map uncertainty
- Theory:
- Entropy:
  - Map: ∀ measurement, ∀ positions, ∀ particles
  - Trade off: Cost vs. Information Gain
- Practice:
  1. Draw particle (weight)
  2. Predict laser beams
  3. Update Map & calculate Entropy
  4. Pose Entropy only
  5. Add Entropies

- Pose: ∀ trajectories

Novelty:

- FMP-Maps
- FMP-Entropy

# Information Gain-based Exploration Using Rao-Blackwellized Particle Filters

*Formulas*

*Stachniss, Grisetti, Burgard*

1. Information Gain:
   - General $I(\hat{z}, a_t) = H(p(m, x_{1:t}|d_t)) - H(p(m, x_{1:t}, \hat{x}|d_t, a_t, \hat{z}))$
   - Expected Gain $E[I(a_t)] = \int_{\hat{z}} p(\hat{z}|a_t, d_t) \cdot I(\hat{z}, a_t) d\hat{z}$
   - Single particle $\approx \int_{\hat{z}} \sum_p \omega_t \cdot p(\hat{z}|a_t, m, x_{1:t}, d_t) \cdot p(m|x_{1:t}, d_t) \cdot I(\hat{z}, a_t) d\hat{z}$
   - Approximation $DrawParticle \rightarrow Raycasting \rightarrow UpdateMap \rightarrow CompareEntropies$
2. Entropy
   - General $H(p(x_{1:t}, m|d_t)) \approx H(p(x_{1:t}|d_t)) + \sum \omega \cdot H(p(m|x_{1:t}, d_t))$
   - Approximation $H(p(x_t, m|d_t)) \approx H(p(x_t|d_t)) + \sum \omega \cdot H(p(m|x_t, d_t))$

     $\approx ShannonEntropie + MapEntropies \rightarrow$

     - $\sum_p \omega \cdot log(\omega) + \sum_p (\omega \cdot -\sum_c p(c) \log p(c) + (1 - p(c)) \log(1 - p(c)))$

# Information Gain-based Exploration Using Rao-Blackwellized Particle Filters

*Formulas*

*Stachniss, Grisetti, Burgard*

1. Information Gain:

$$I(\hat{z}, a_t) = H(p(m, x_{1:t}|d_t)) - H(p(m, x_{1:t}, \hat{x}|d_t, a_t, \hat{z}))$$

- Single particle $\approx \int_{\hat{z}} \sum_p \omega_t \cdot p(\hat{z}|a_t, m, x_{1:t}, d_t) \cdot p(m|x_{1:t}, d_t) \cdot I(\hat{z}, a_t) d\hat{z}$
- Approximation $DrawParticle \rightarrow Raycasting \rightarrow UpdateMap \rightarrow CompareEntropies$

2. Entropy

- General $H(p(x_{1:t}, m|d_t)) \approx H(p(x_{1:t}|d_t)) + \sum \omega \cdot H(p(m|x_{1:t}, d_t))$
- Approximation $H(p(x_t, m|d_t)) \approx H(p(x_t|d_t)) + \sum \omega \cdot H(p(m|x_t, d_t))$

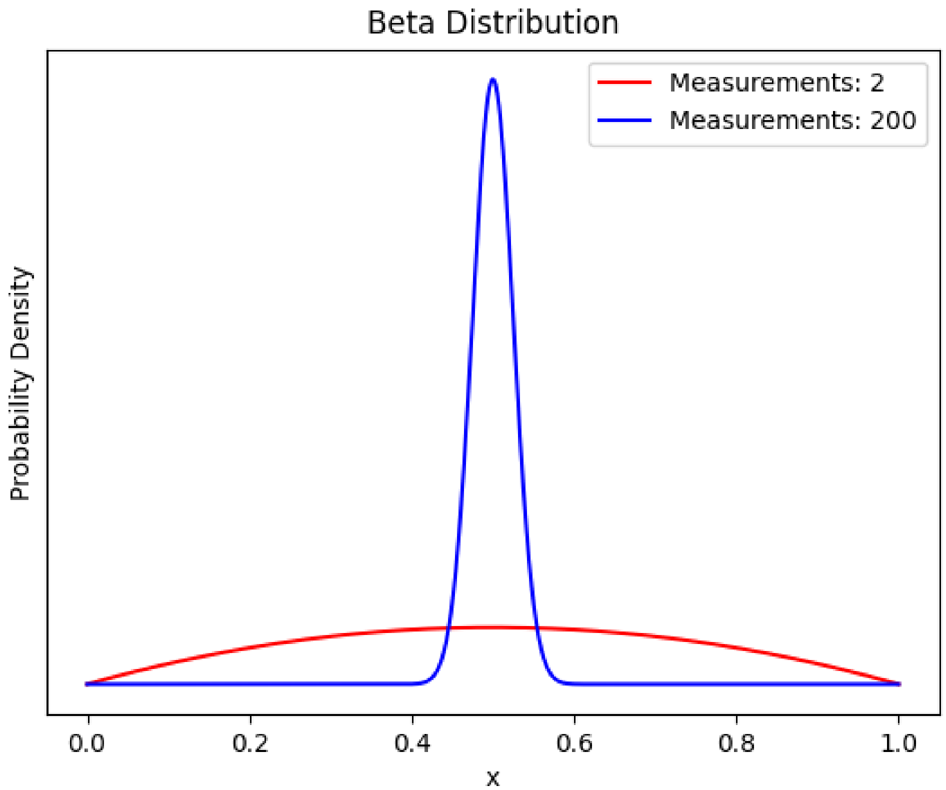
$\approx ShannonEntropie + MapEntropies \rightarrow$

\- $\sum_p \omega \cdot log(\omega) + \sum_p (\omega \cdot - \sum_c p(c) \log p(c) + (1 - p(c)) \log(1 - p(c)))$

# Closed-Form Full Map Posteriors for Robot Localization with Lidar Sensors

*Luft, Schaefer, Schubert, Burgard*

- Traditional map only OCC-probability – not uncertainty
- Structures smaller than resolution
- Reflection Model: $l_{ref} = \frac{\alpha}{\alpha+\beta}$
  $\alpha{:}Hits, \beta{:}Misses$
- Posterior: $bel(occ) = Beta(\alpha, \beta)$



# Closed-Form Full Map Posteriors for Robot Localization with Lidar Sensors

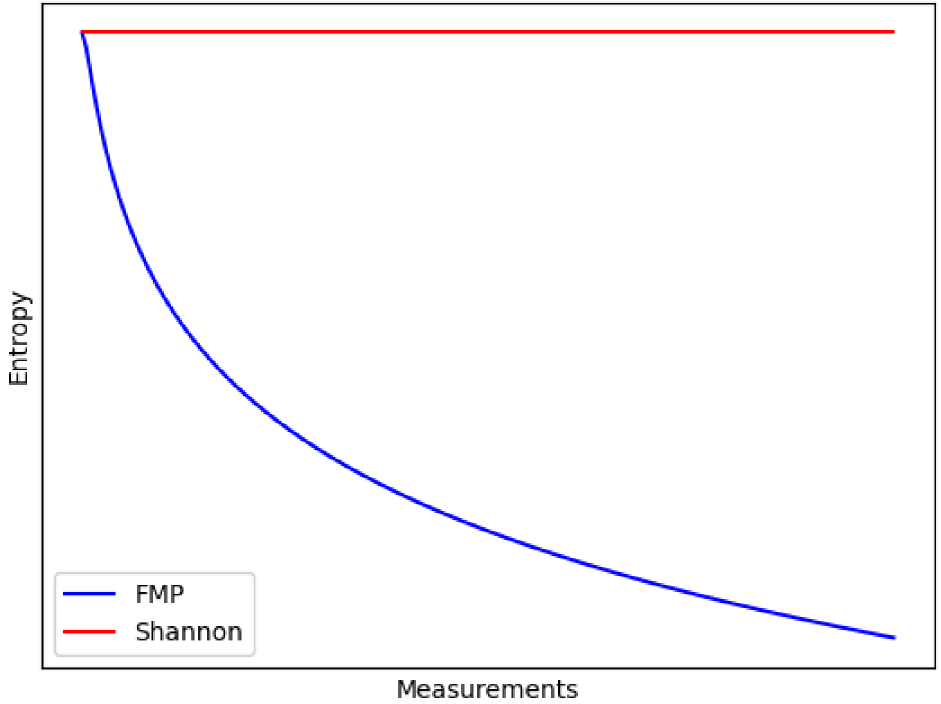
*Luft, Schaefer, Schubert, Burgard*

- Traditional map only OCC-probability – not uncertainty
- Structures smaller than resolution
- Reflection Model: $l_{ref} = \frac{\alpha}{\alpha+\beta}$

  $\alpha{:}Hits, \beta{:}Misses$

- Posterior: $bel(occ) = Beta(\alpha, \beta)$

$$H(Shannon) = occ \cdot log(occ) + (1 - occ) \cdot log(1 - occ)$$
$$H(Beta(\alpha,\beta)) = ln(Beta(\alpha,\beta)) + (\alpha + \beta - 2) \cdot \psi(\alpha + \beta)$$
$$-(\alpha - 1) \cdot \psi(\alpha) - (\beta - 1) \cdot \psi(\beta)$$



# Motivation

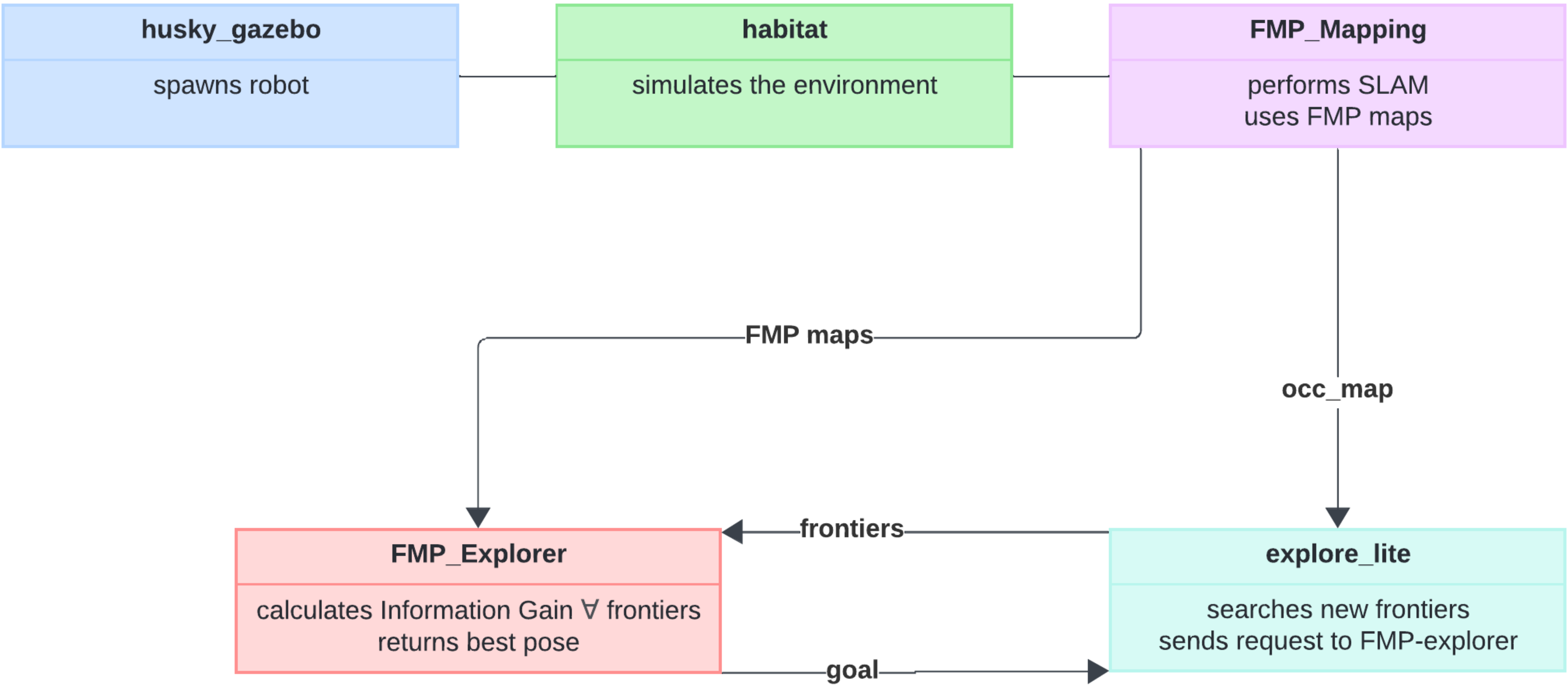
- Information gain important!
- Utilizing uncertainty of maps **and** poses
- Full Map posterior:
  - Half occupied cells
  - More accuracy
  - Fast calculation

- Information Gain
- Using FMP – Maps
- In ROS environment

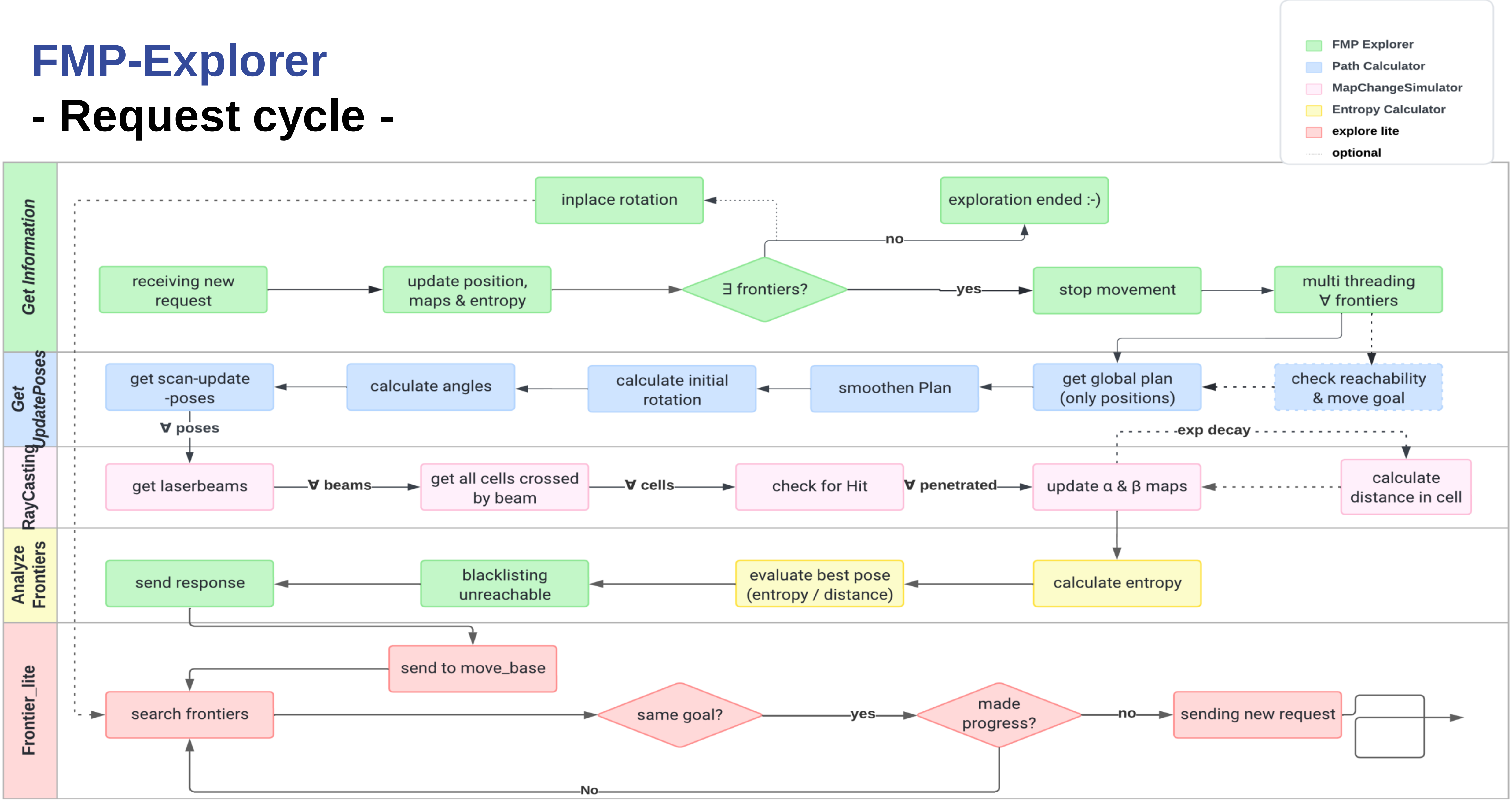
# Implementation

- Environment
- Request Cycle

# FMP-Explorer
## - Setup -



# FMP-Explorer
## - Request cycle -



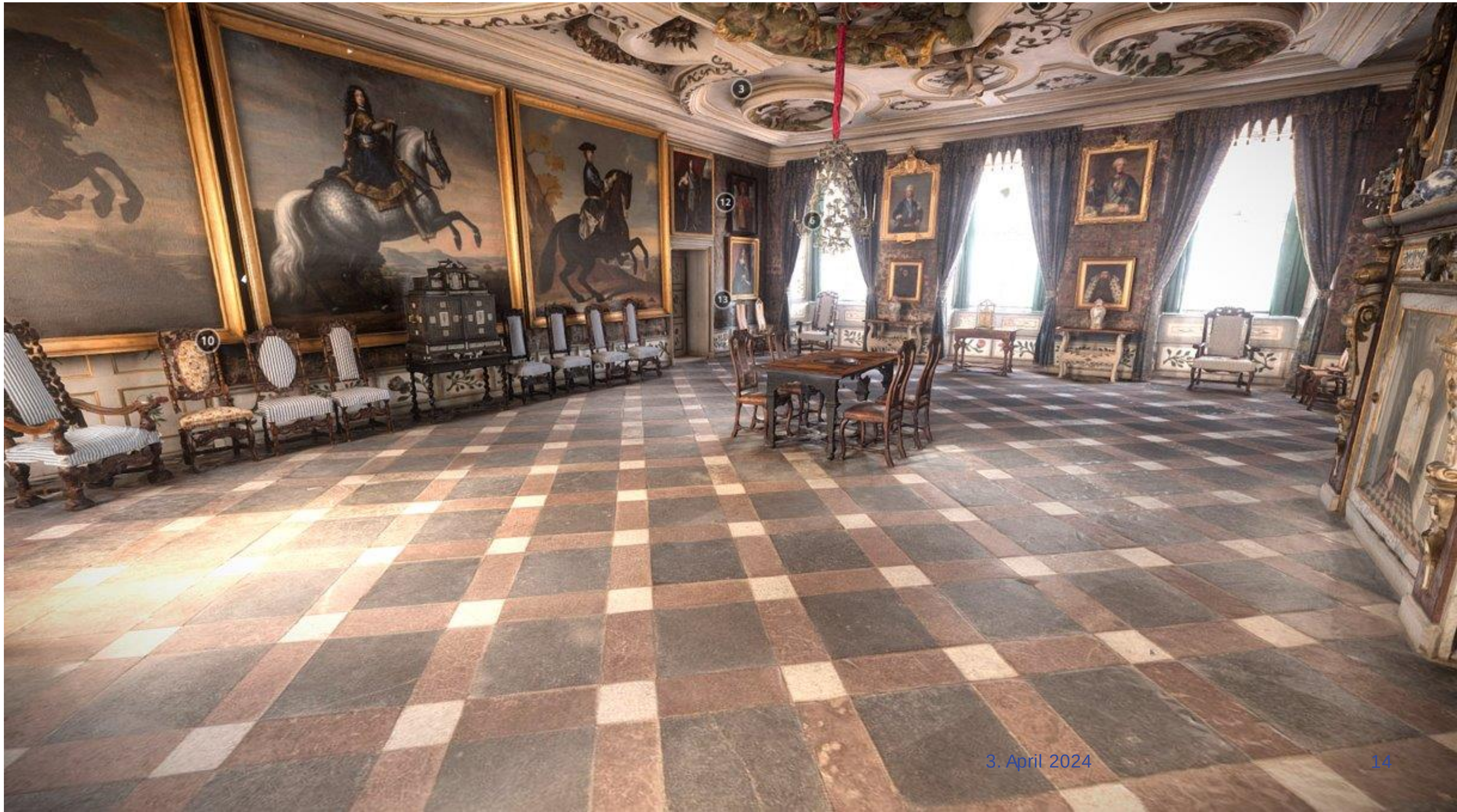
# Testing

- Scenarios
- Results

# Testing

## 1. Skloster – dining hall

- Big room
- Few small structures

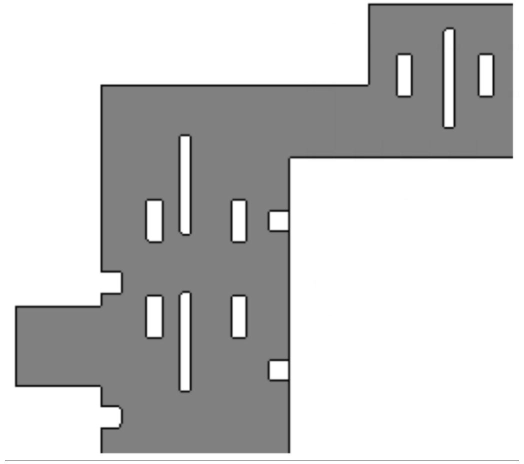


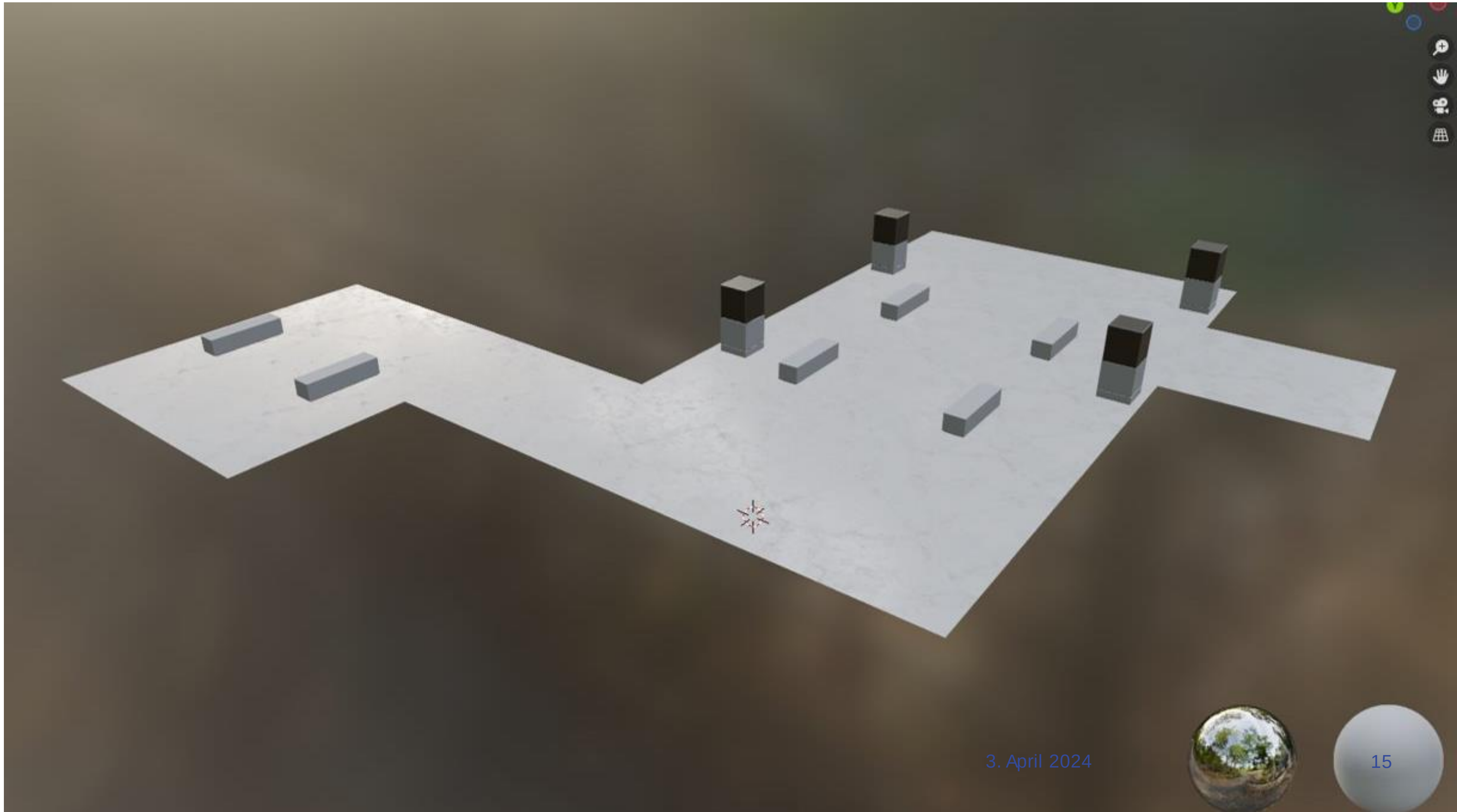
# Testing



## 2. Gallery

- Big hall
- Big structures



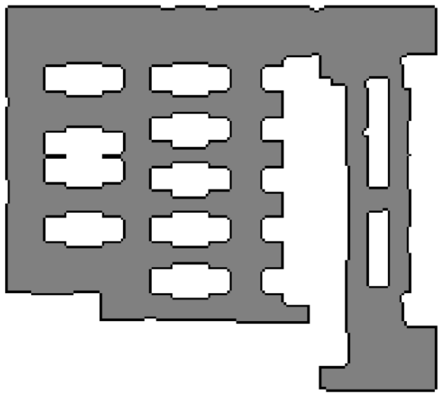


# Testing



## 3. Restaurant

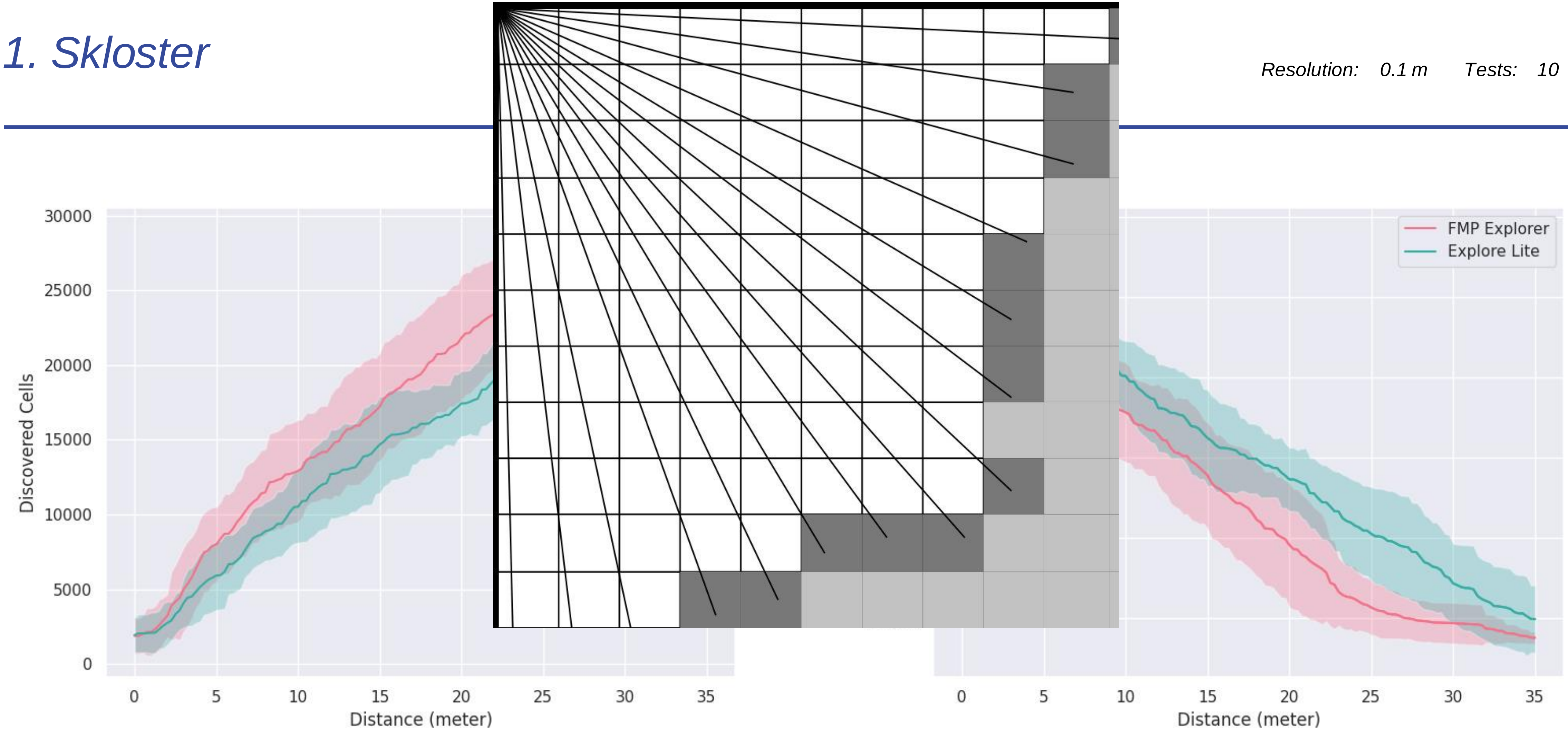
- Winding room
- Many small objects
- Narrow



# Results

## *1. Skloster*

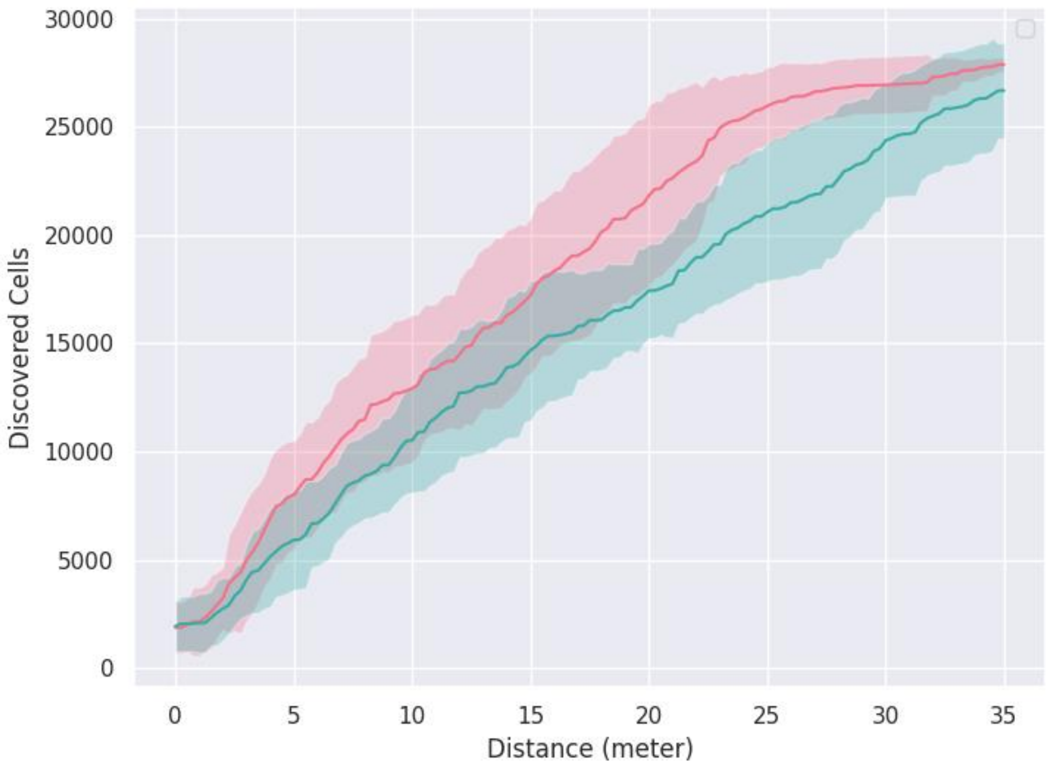
*Resolution: 0.1 m  Tests: 10*

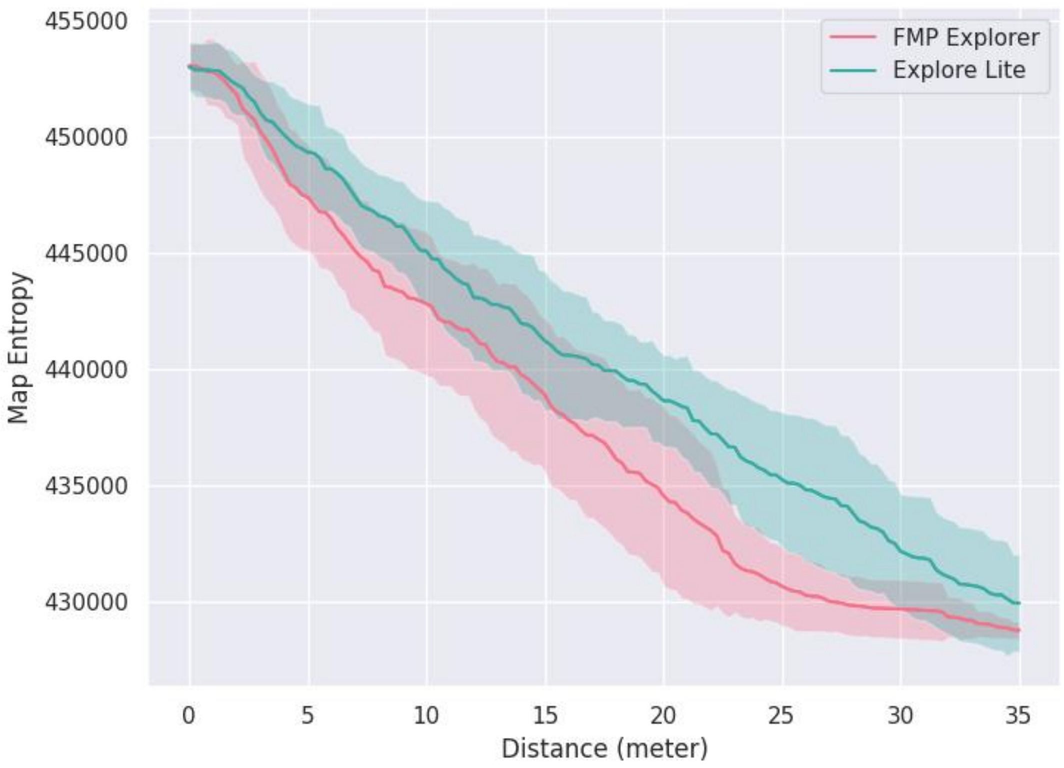


# Results

## *1. Skloster*

*Resolution:* *0.1 m* *Tests:* *10*

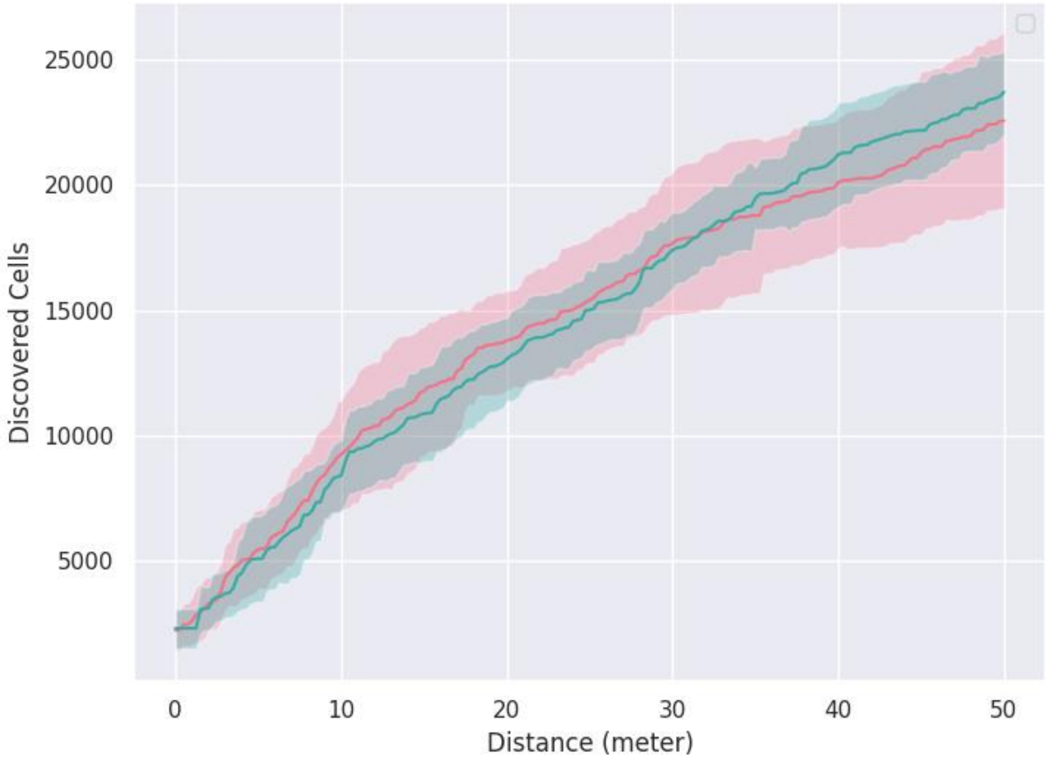


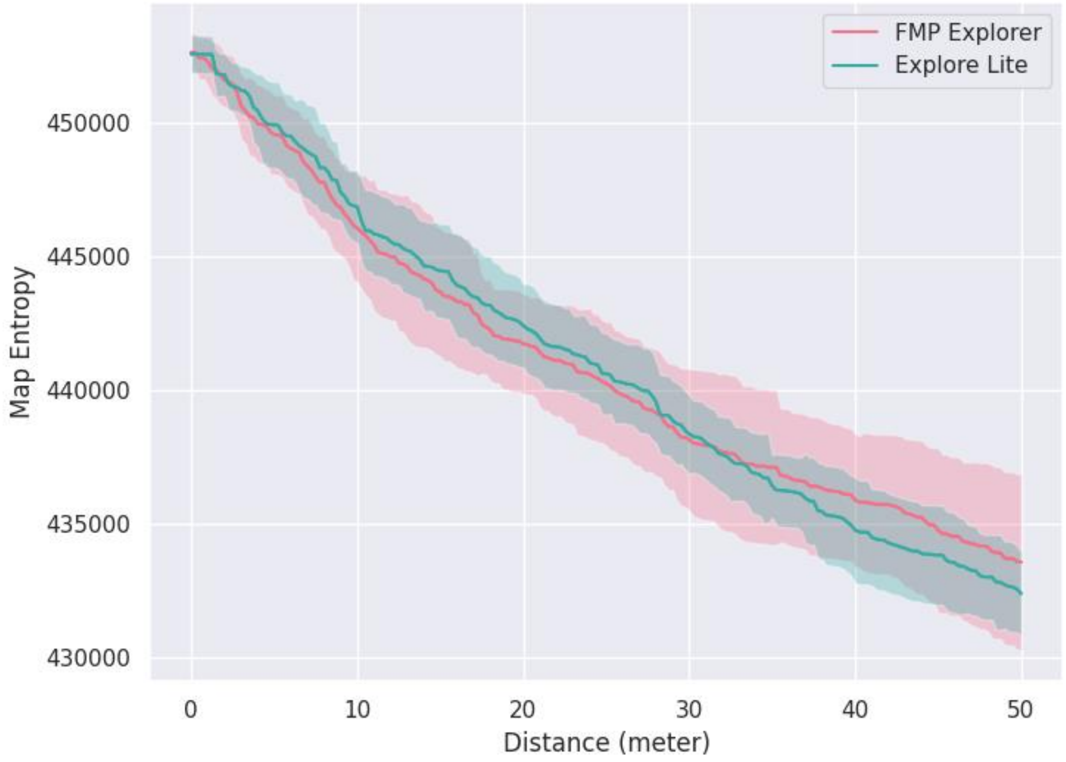



# Results

## *2. Gallery*

*Resolution: 0.1 m  Tests: 10*

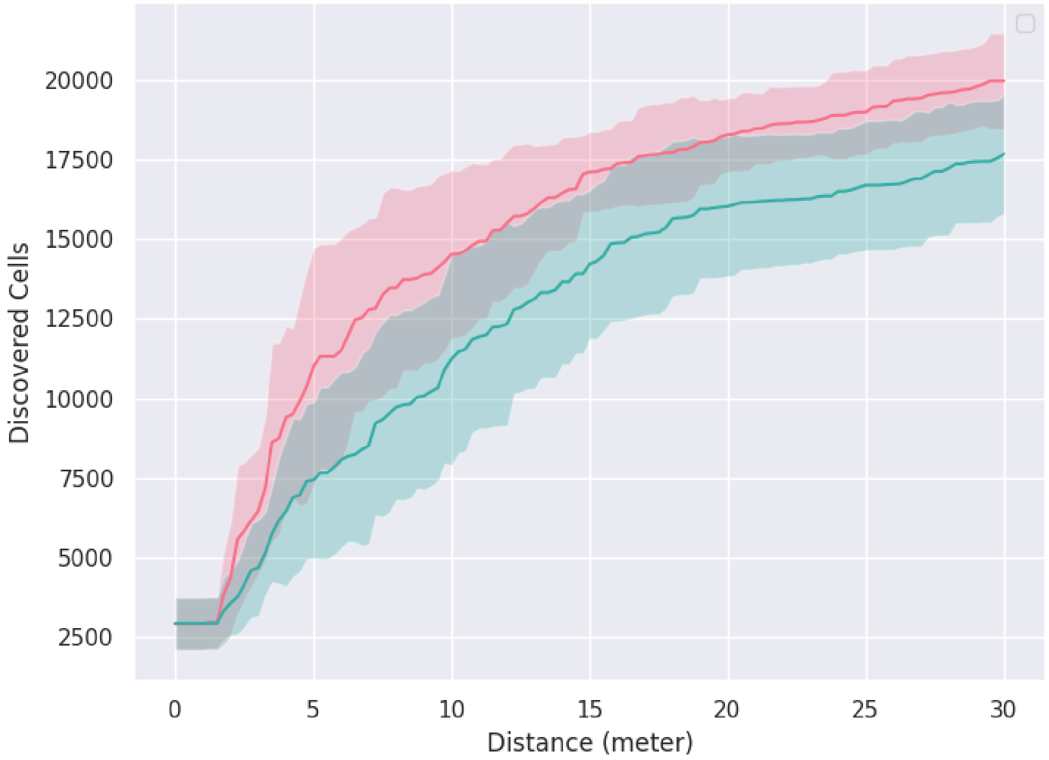


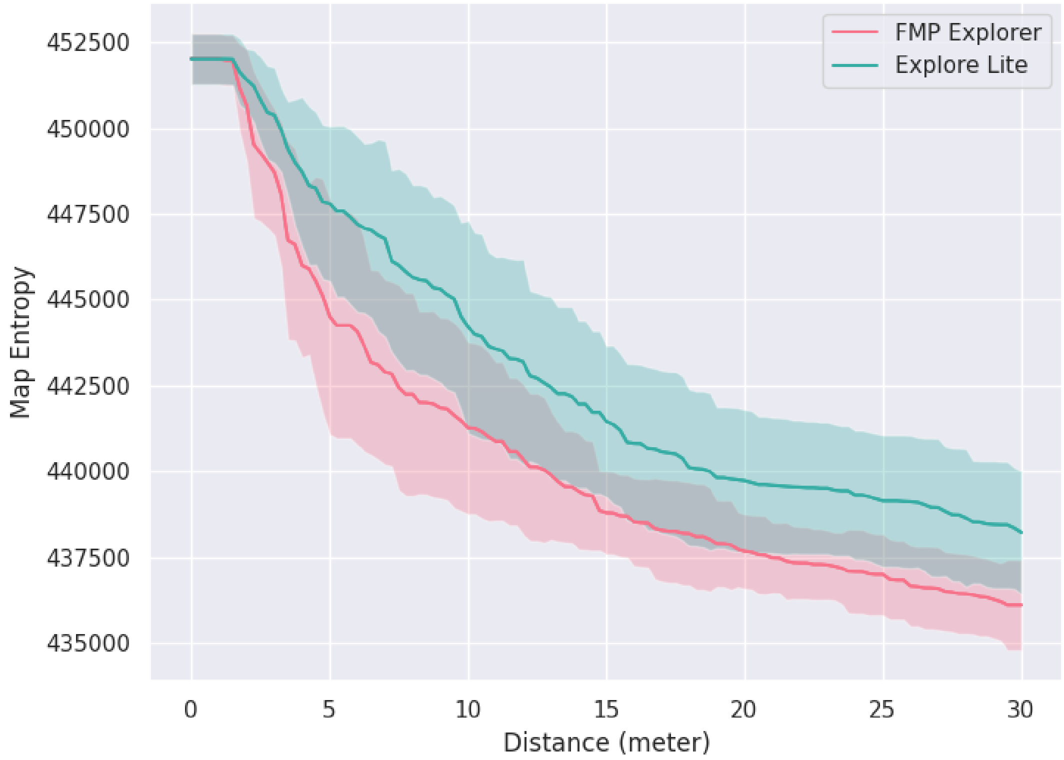



# Results

## *3. Restaurant*

*Resolution: 0.1 m Tests: 10*

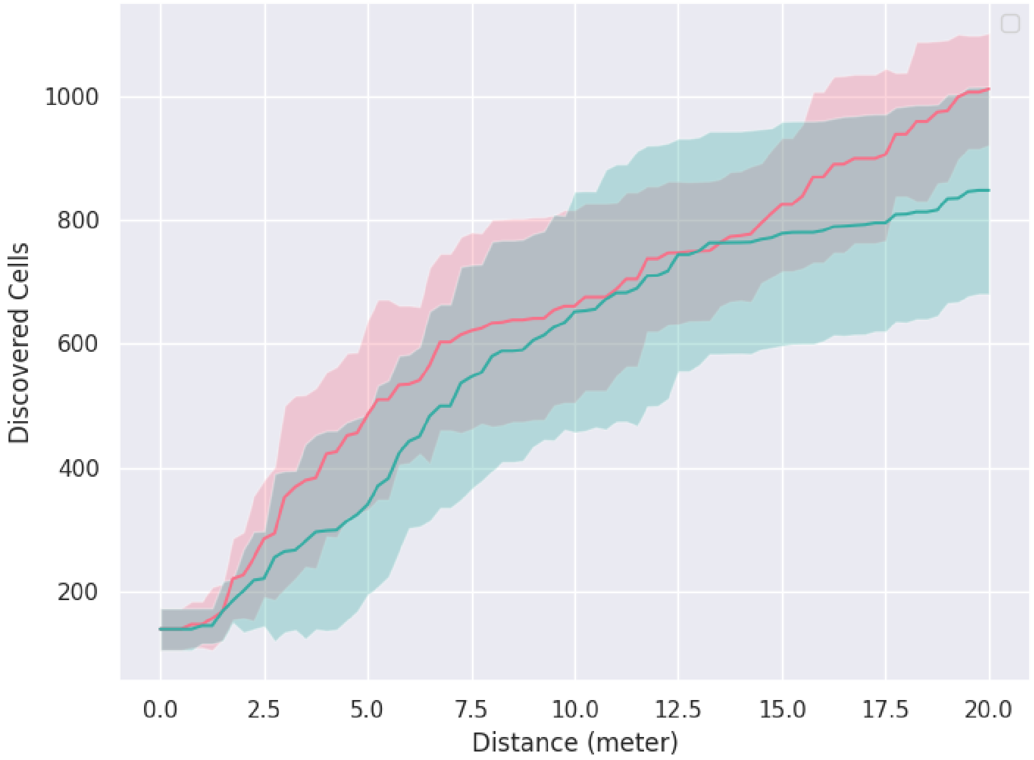


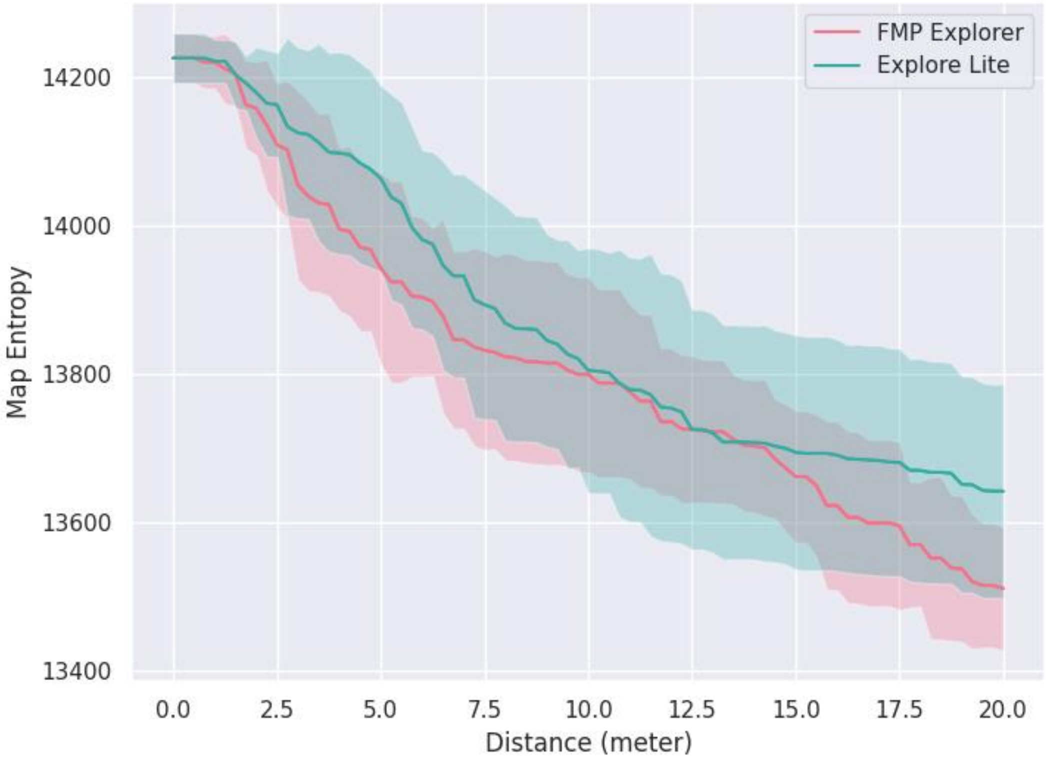



# Results

## *1. Skloster*

*Resolution:* *0.5 m* *Tests:* *6*

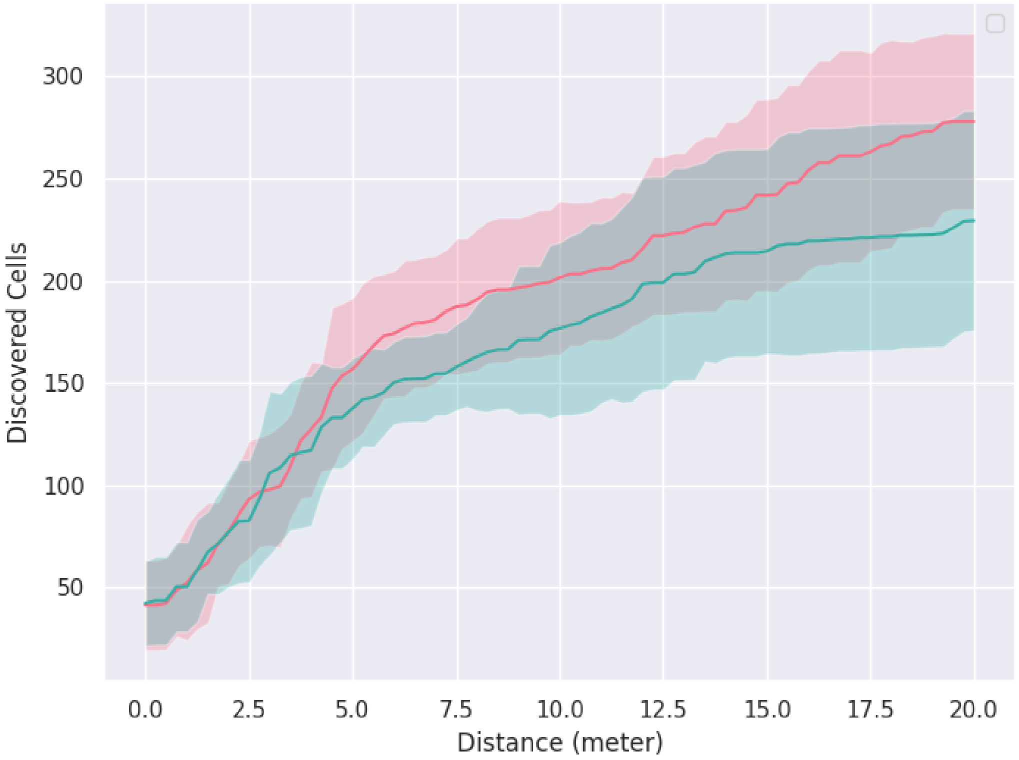


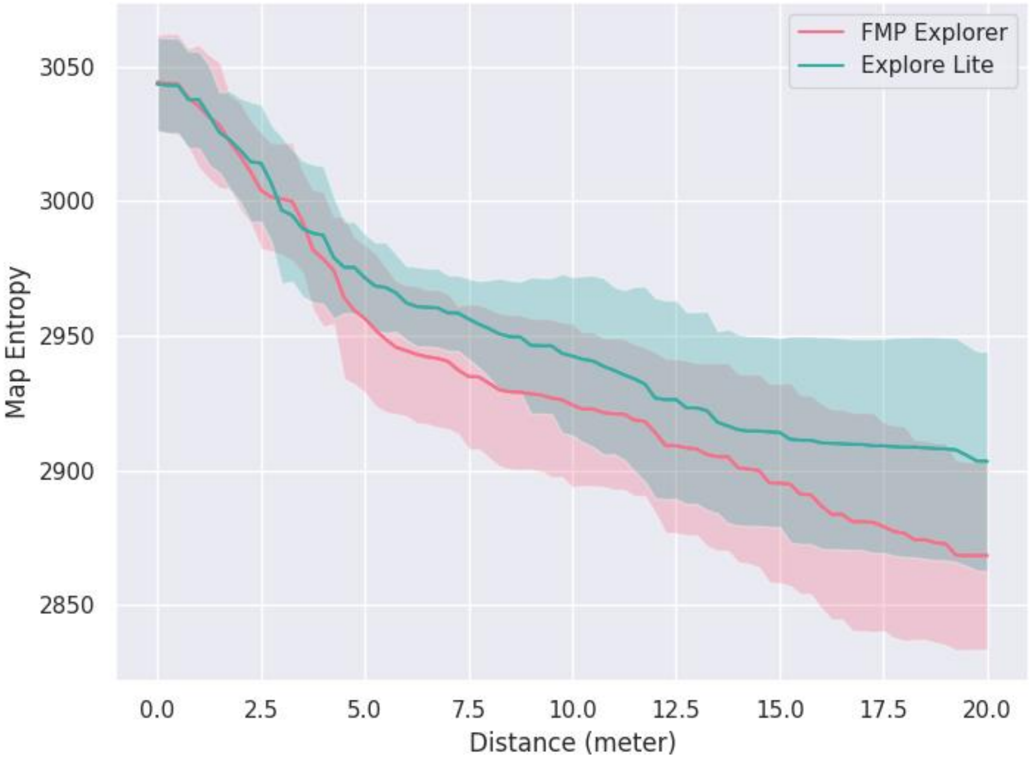



# Results

## *1. Skloster*

*Resolution: 1 m* *Tests: 9*

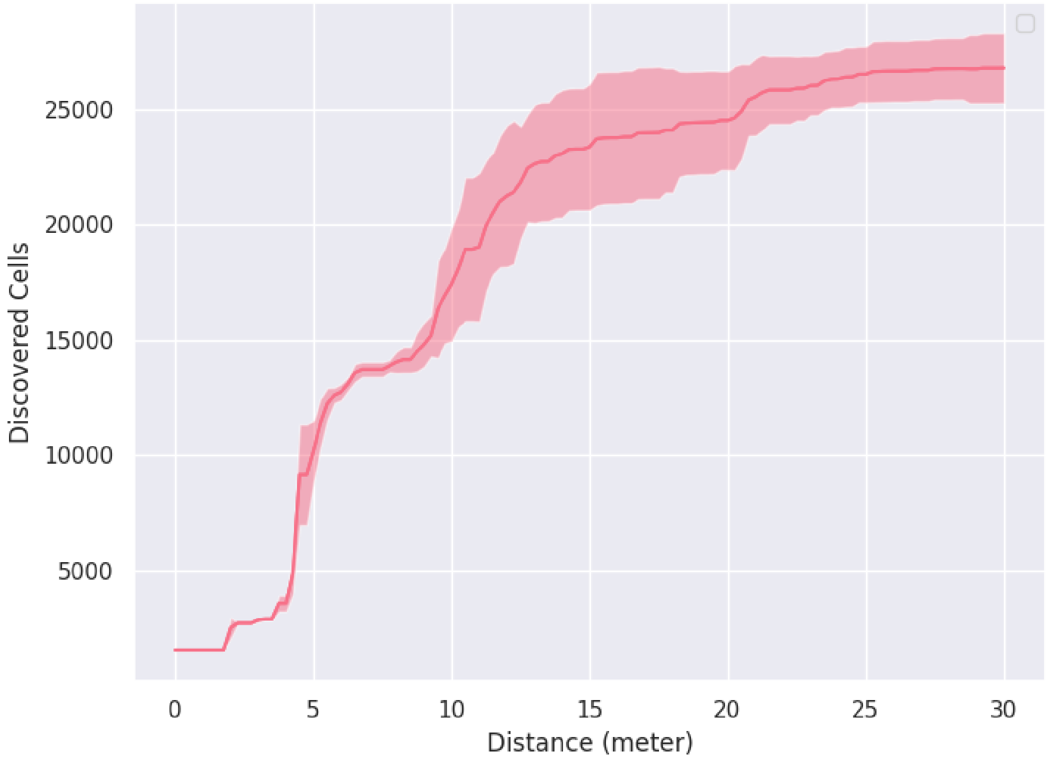


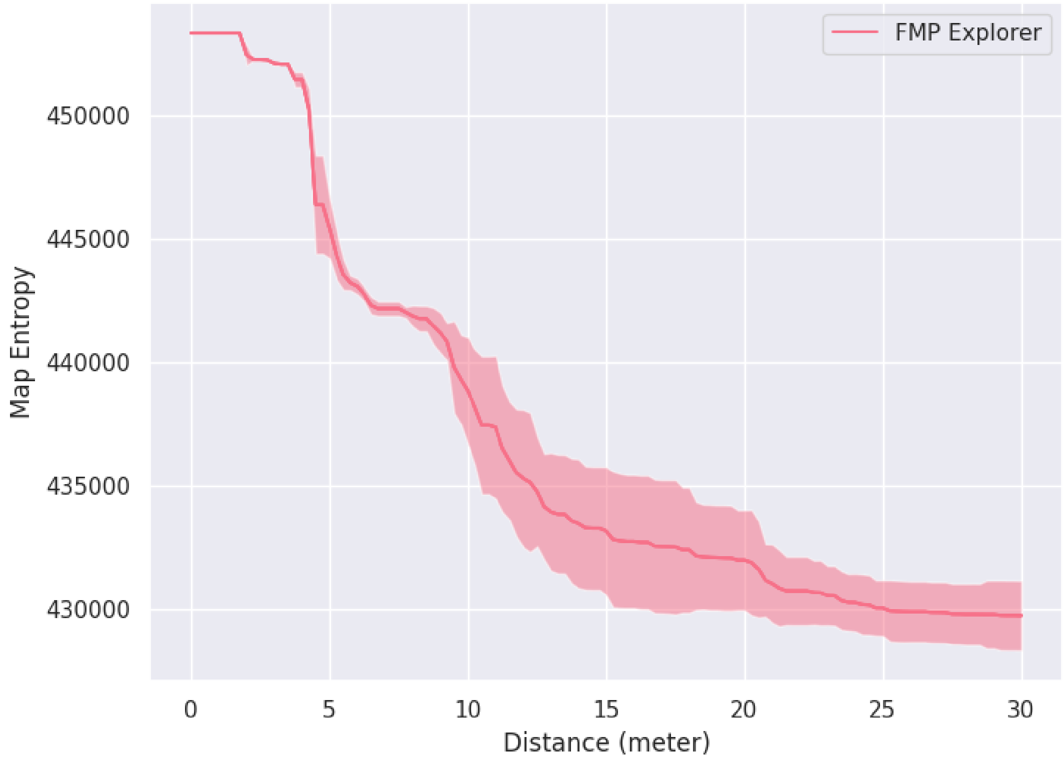



# Results

## *1. Skloster Variance*

*Resolution: 0.1 m Tests: 6*



# Conclusion

- Interpretation
- Future Work

# Conclusion

*Interpretation - Ideas*

**Challenges:**

- Computational effort
- Only a bit better
- Unrealistic to use

**Advantages:**

- Actually working
- Small structures:
  - Significantly better
- Low resolution:
  - Faster
  - Performance still good

For certain scenarios might be an interesting idea to use.

# Conclusion

## *Future Work (present work)*

- RoboCup – Restaurant Scenario
  - SLAM
  - Serving many customers
- Combining Exploration with Destination
  - Optimization
  - Low resolution
  - Finding most informative path

# Thanks for attending :-)

Robin Dominic Steiger

Robot Learning Lab Freiburg

Telefone  +49 157 3484 5522

steigerobin@hotmail.de

# FMP-Explorer
## - Classes -