

# Robot Assistance at Home

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# Robots That Work With People

- Robots are moving into human environments
  - Homes
  - Hospitals
  - Workplaces
- Interactions must be intuitive and safe

Time



Blade cluster  
(40 cores)

8 cores

# Now: People Accommodating Robots



Courtesy: AeroVironment



Courtesy: US Army

# Where We Need to Be



Courtesy: Kinova Robotics

# Representational Divide

A robot's view of the world is very different from our own

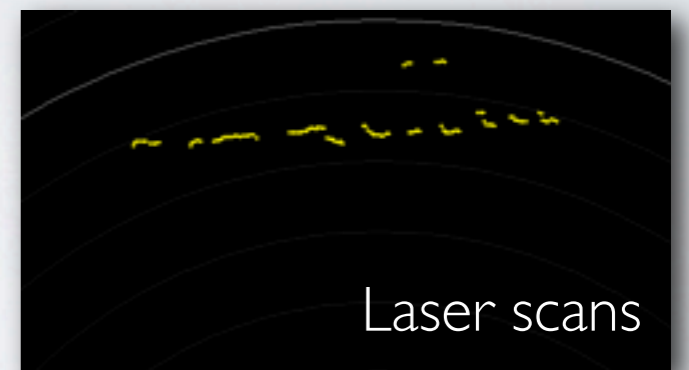
People

- Objects
- **Places**
- Actions
- People
- Events

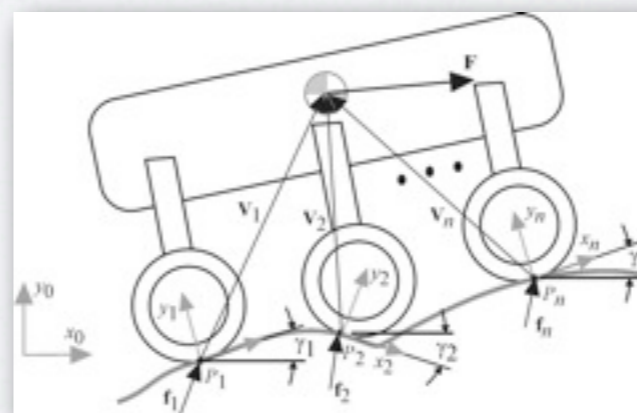
Robots

43	51	43	43	37		
44	48	63	60	60	54	
51	49	79	111	123	139	140
25	64	98	130	133	137	134
31	58	120	133	134	132	123
	78	108	135	135	125	114
		122	127	120	109	102

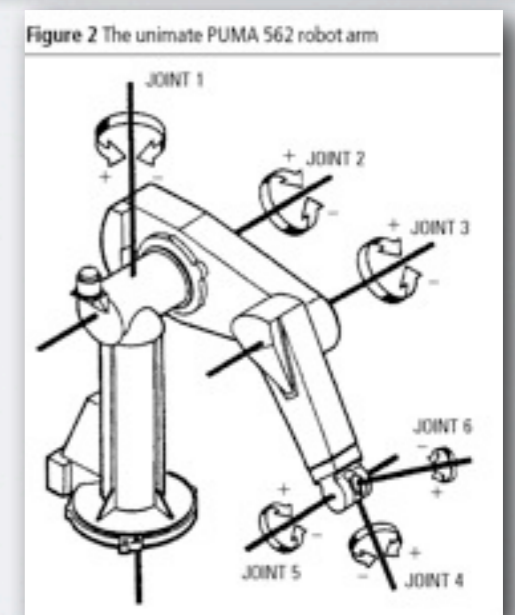
Images



Laser scans



Wheel torques



Joint angles

# Learning Semantic Maps from Natural Language

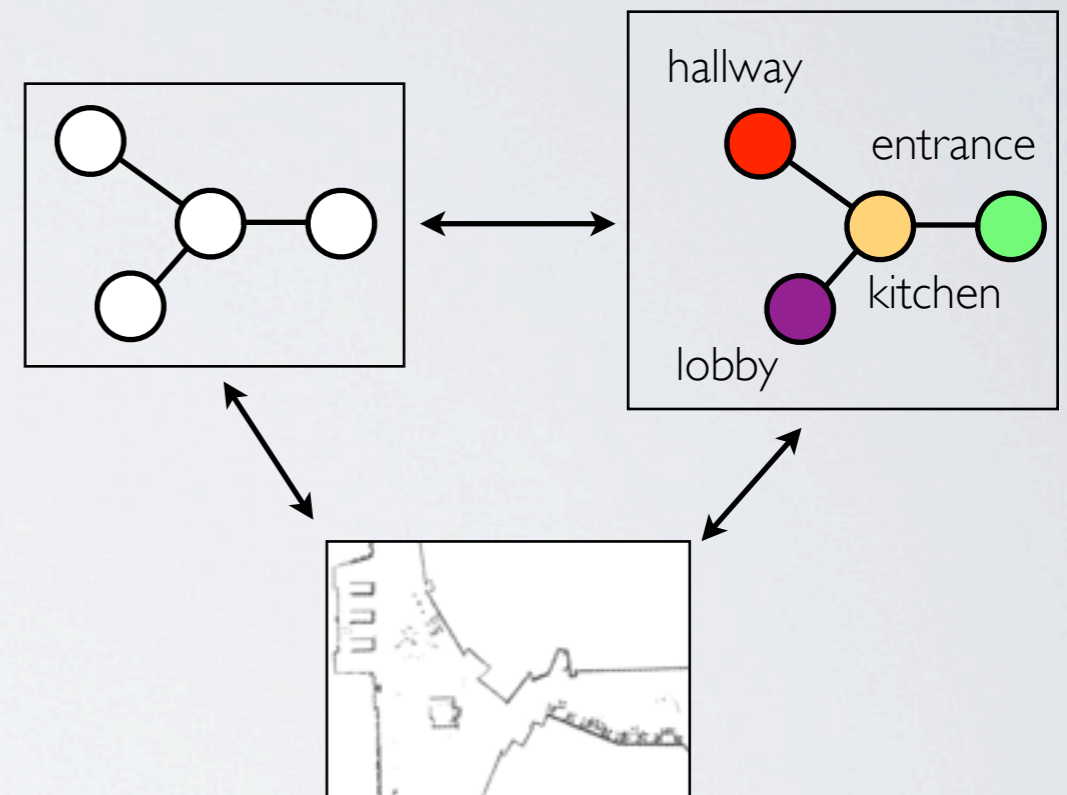
- Human-centric representations of space
  - Spatial relations
  - Semantic attributes (e.g., names, use)
  - Connectivity
- Learn knowledge representation from narrated tour
- Challenges:
  - People convey high-level concepts but robot perception is low-level
  - Spoken descriptions are ambiguous



[RSS'13 (to appear)]

# Building Semantic Maps with Natural Language

- Solution:
  - Joint metric, topologic, & semantic model supports information fusion
  - Efficient inference strategy
  - Enable layers to influence one another
  - Utilize natural language grounding framework



[RSS'13 (to appear)]

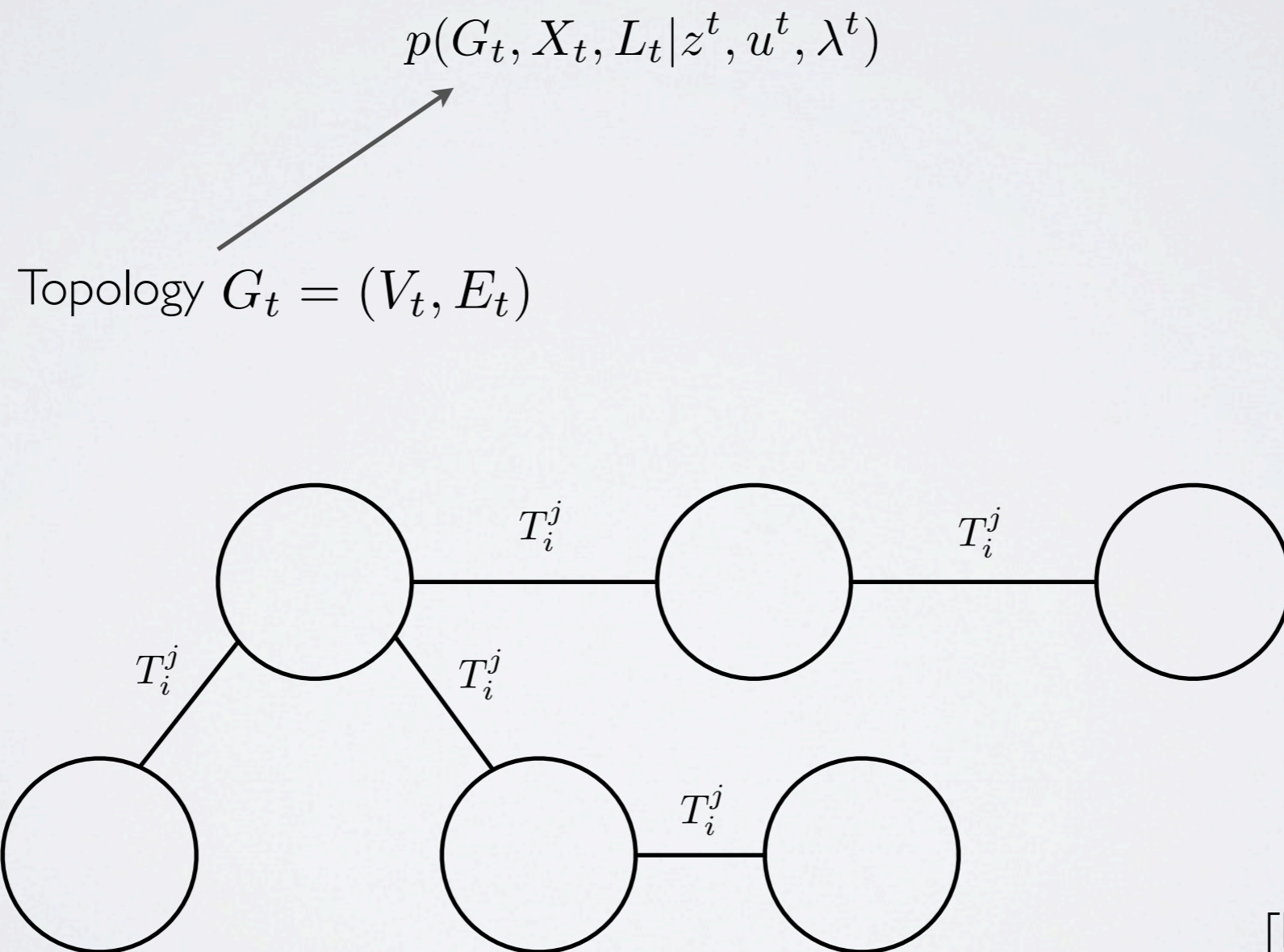
# Model: Posterior over Semantic Graphs

$$p(G_t, X_t, L_t | z^t, u^t, \lambda^t)$$

[RSS'13 (to appear)]

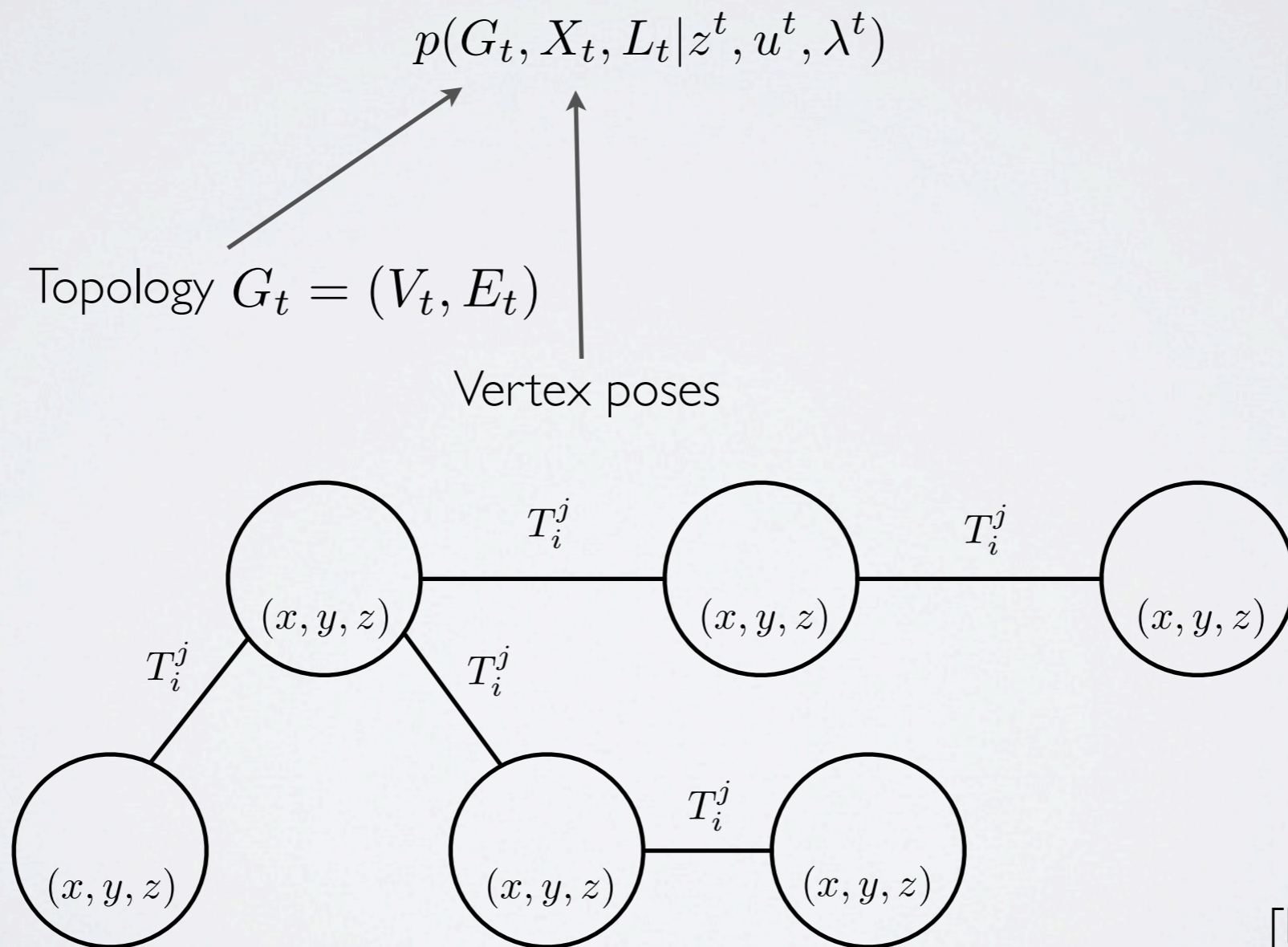


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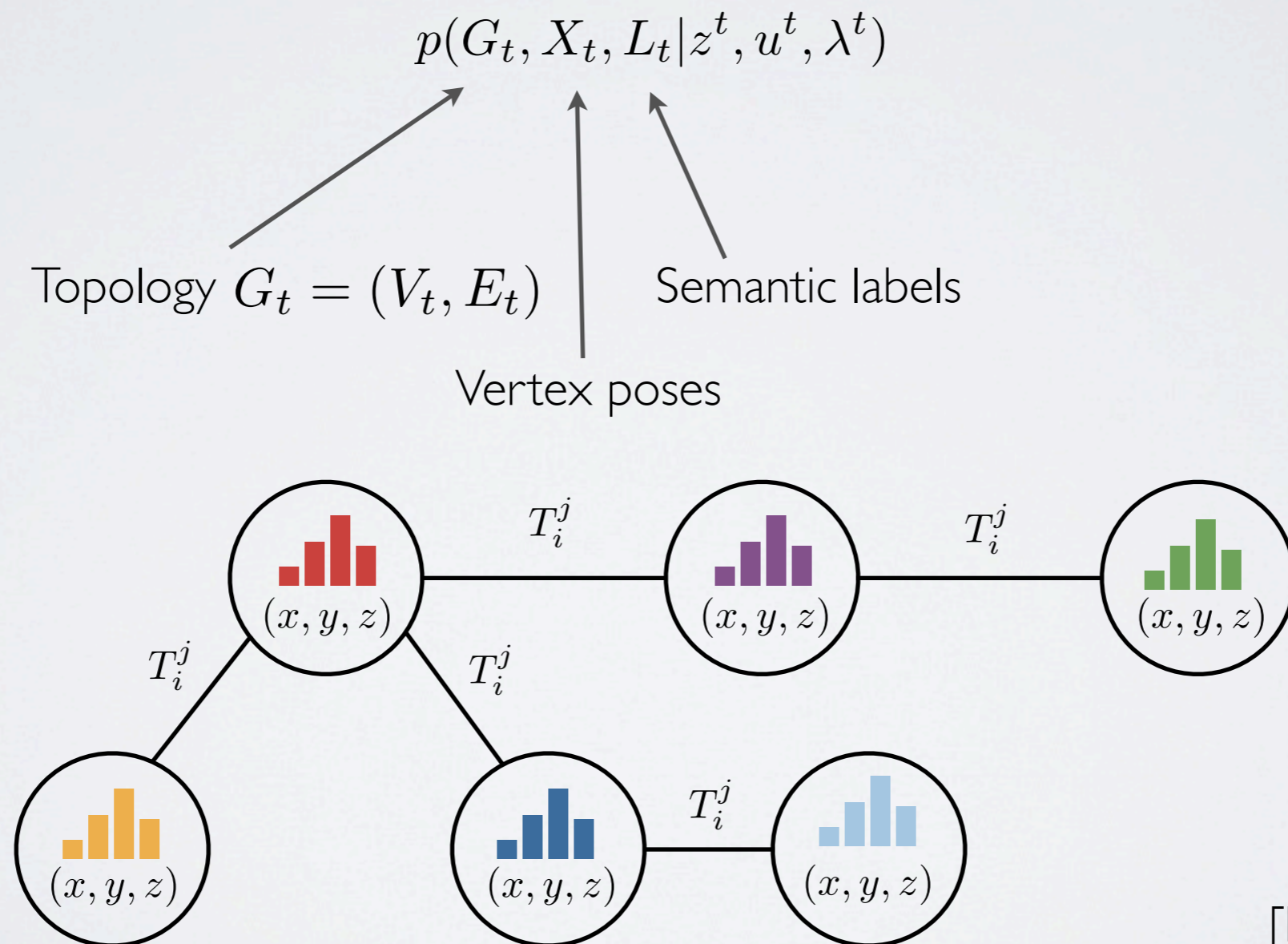
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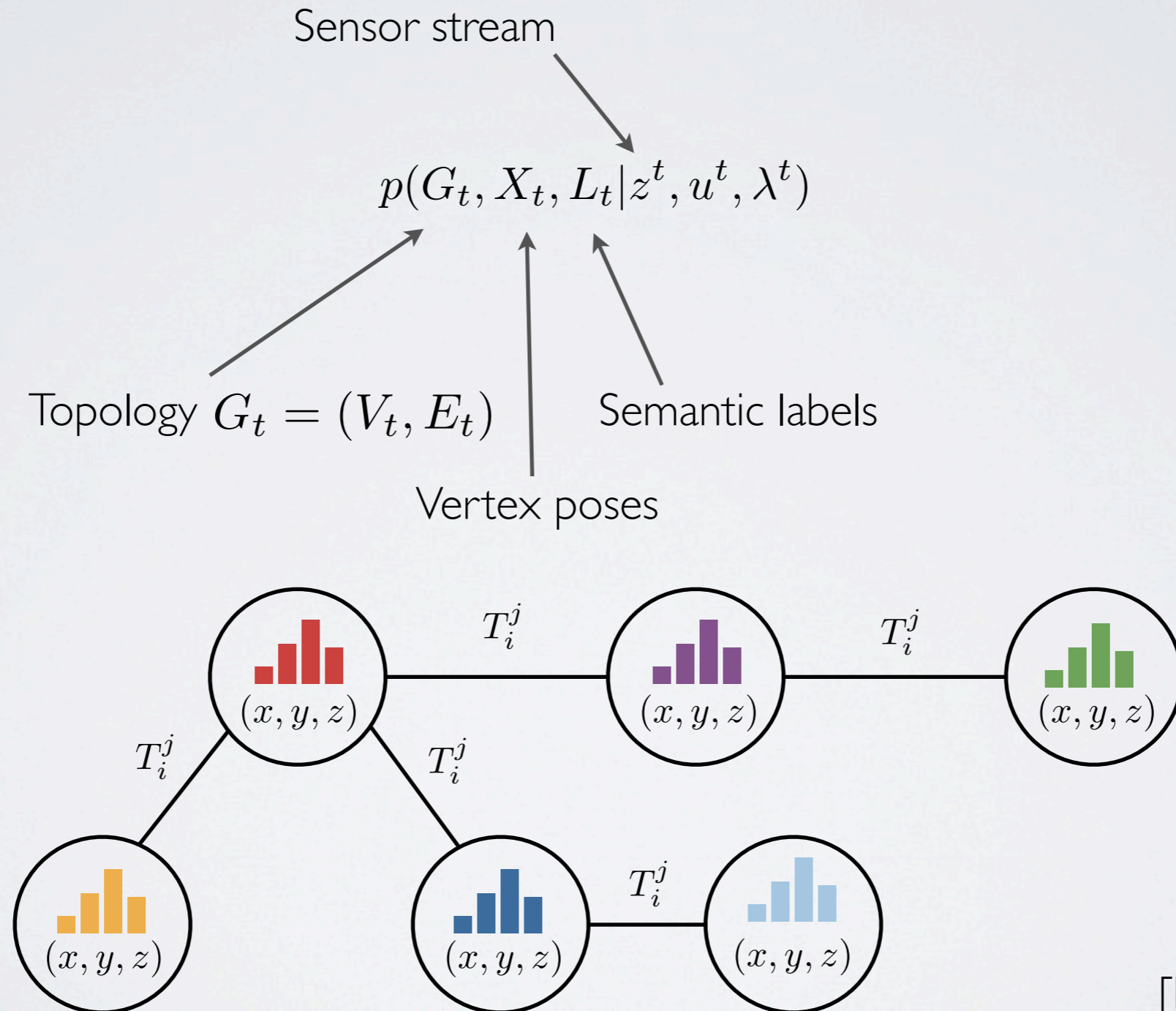
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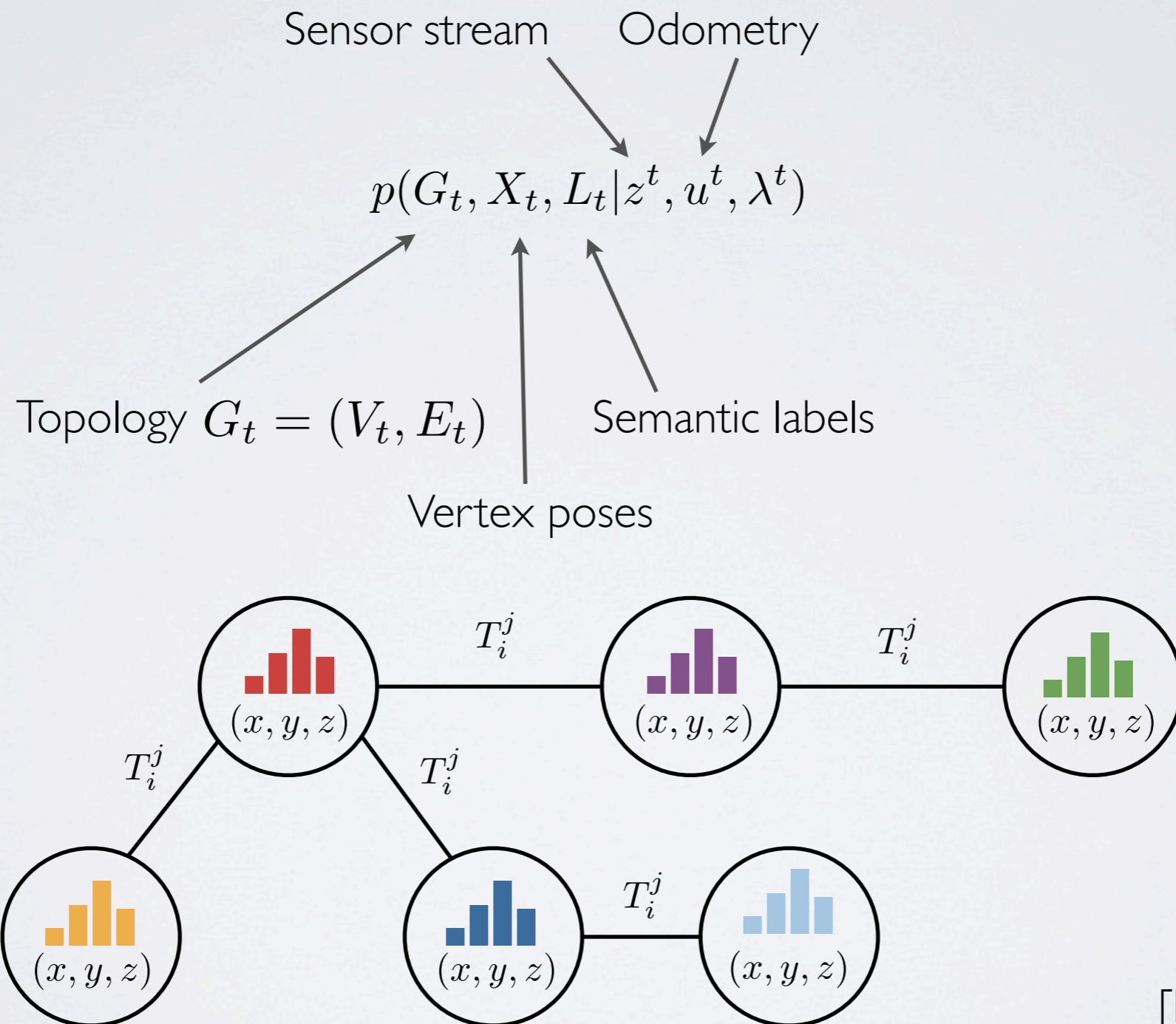
[RSS'13 (to appear)]

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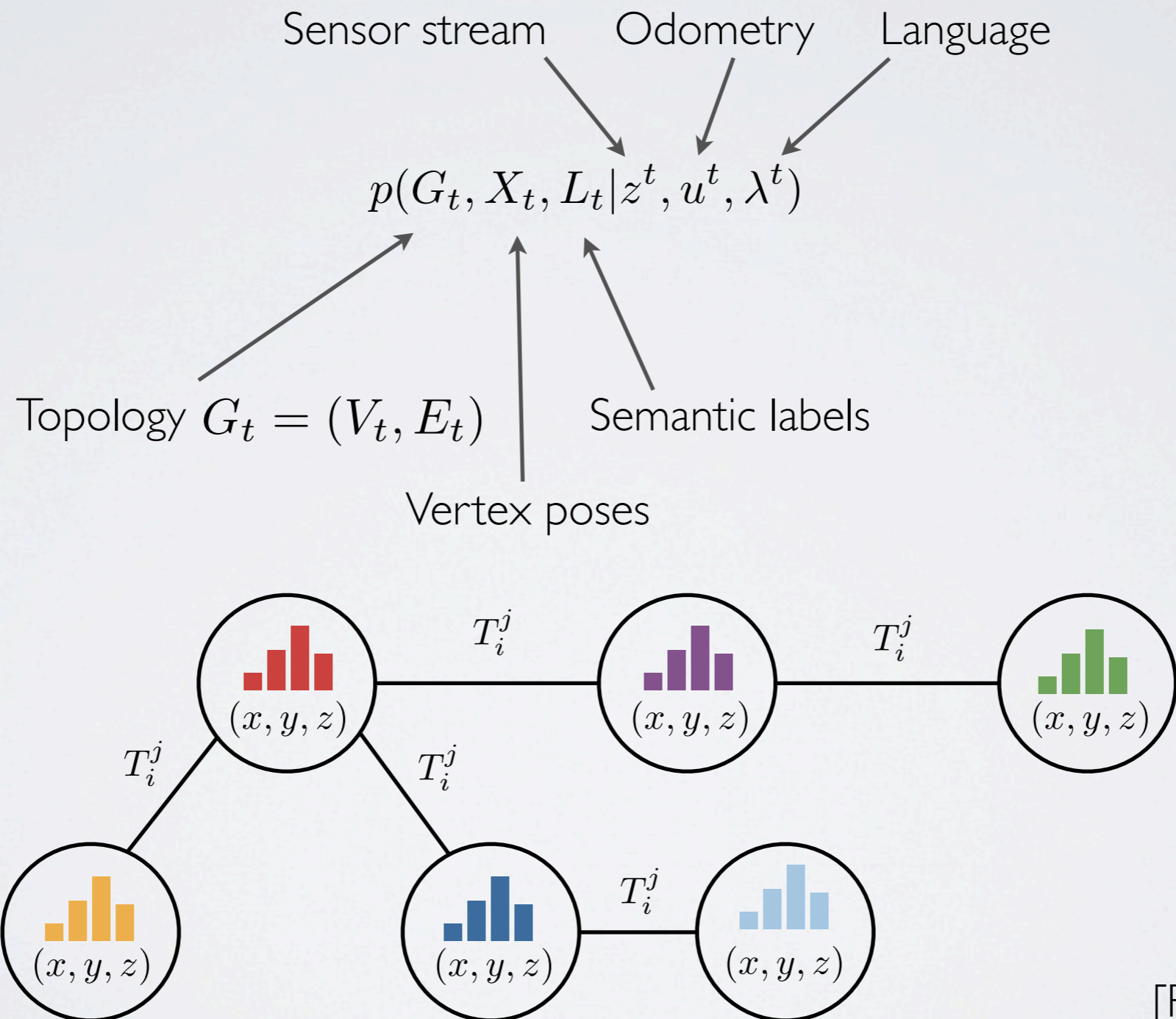
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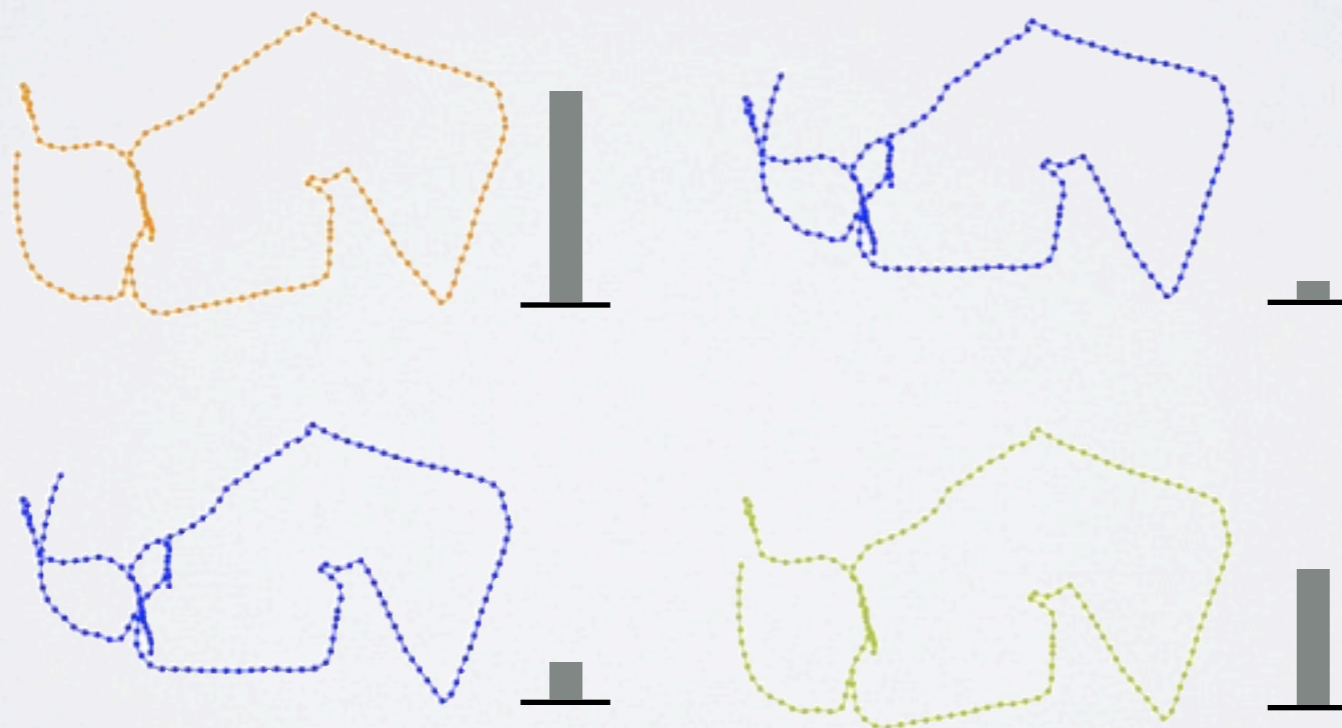
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$$p(G_t, X_t, L_t | z^t, u^t, \lambda^t) = p(L_t | X_t, G_t, z^t, u^t, \lambda^t) p(X_t | G_t, z^t, u^t, \lambda^t) p(G_t | z^t, u^t, \lambda^t)$$

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Sample-based  
representation



[RSS'13 (to appear)]



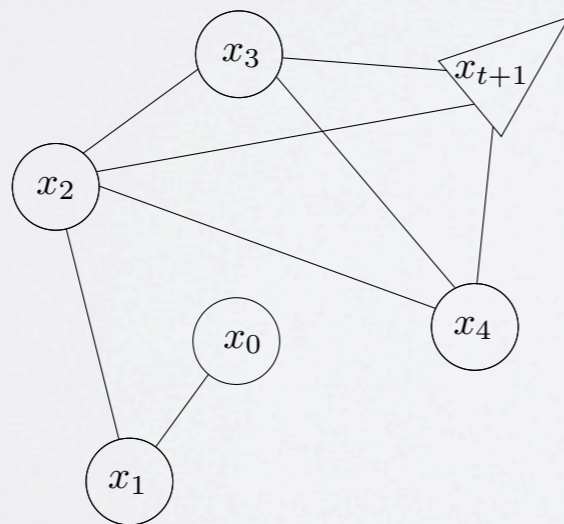
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Gaussian  
(information form)

Sample-based  
representation

$$p(X_t | G_t, z^t, u^t, \lambda^t) = \mathcal{N}^{-1}(X_t; \Sigma_t^{-1}, \eta_t)$$



	$x_0$	$x_1$	$x_2$	$x_3$	$x_4$	$x_{t+1}$
$x_0$	Black	Grey	White	White	White	White
$x_1$	Grey	Black	Grey	White	White	White
$x_2$	White	Grey	Black	Grey	Grey	Grey
$x_3$	White	White	Grey	Black	Grey	White
$x_4$	White	White	Grey	Grey	Black	Grey
$x_{t+1}$	White	White	Grey	White	Grey	Black

[RSS'13 (to appear)]

# Model: Posterior over Semantic Graphs

$$p(G_t, X_t, L_t | z^t, u^t, \lambda^t) = \underbrace{p(L_t | X_t, G_t, z^t, u^t, \lambda^t)}_{\text{Dirichlet}} p(X_t | G_t, z^t, u^t, \lambda^t) p(G_t | z^t, u^t, \lambda^t)$$

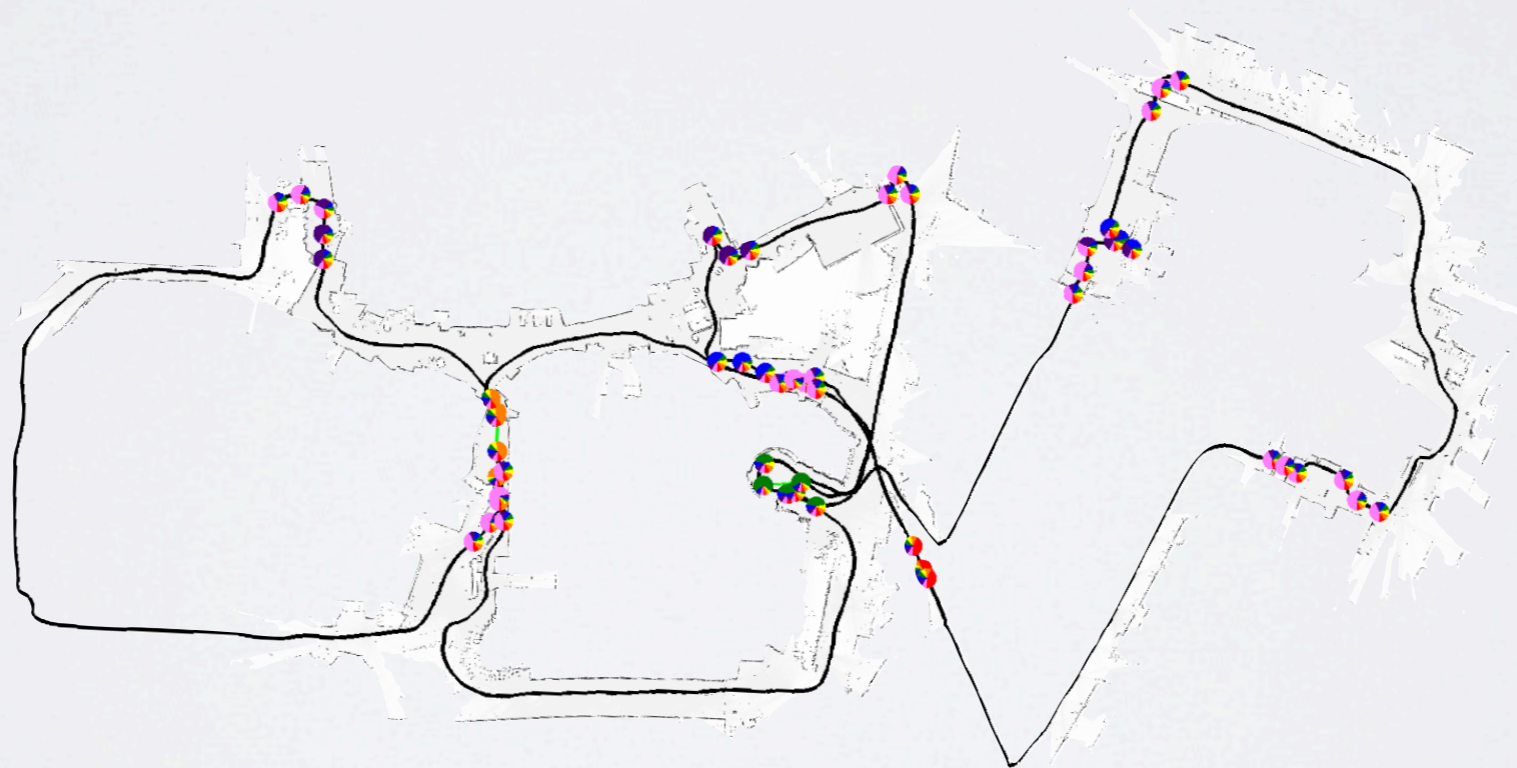
Gaussian      Sample-based  
(information form)      representation

# Model: Posterior over Semantic Graphs

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Dirichlet

Gaussian  
(information form)      Sample-based  
representation



[RSS'13 (to appear)]

# Rao-Blackwellized Particle Filter

$$\text{Input: } P_{t-1} = \left\{ G_{t-1}^{(i)}, X_{t-1}^{(i)}, L_{t-1}^{(i)} w_{t-1}^{(i)} \right\} \quad (u_t, z_t, \lambda_t)$$

for each particle  $i$

- 1 Propose modifications to topology based on metric and semantic maps
- 2 Perform Bayesian update of Gaussian
- 3 Update Dirichlet over labels based on language
- 4 Update weights based on metric observations

$$\text{Return: } P_t^{(i)} = \left\{ G_t^{(i)}, X_t^{(i)}, L_t^{(i)} w_t^{(i)} \right\}$$

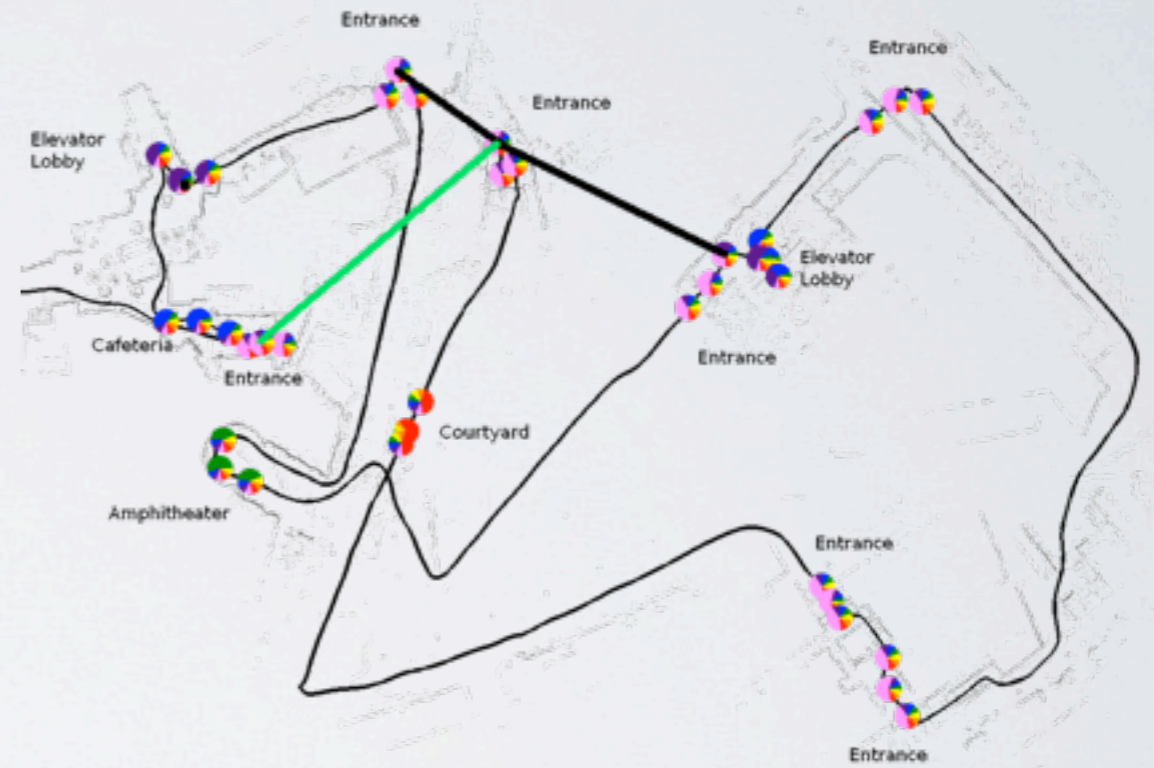
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for each particle  $i$

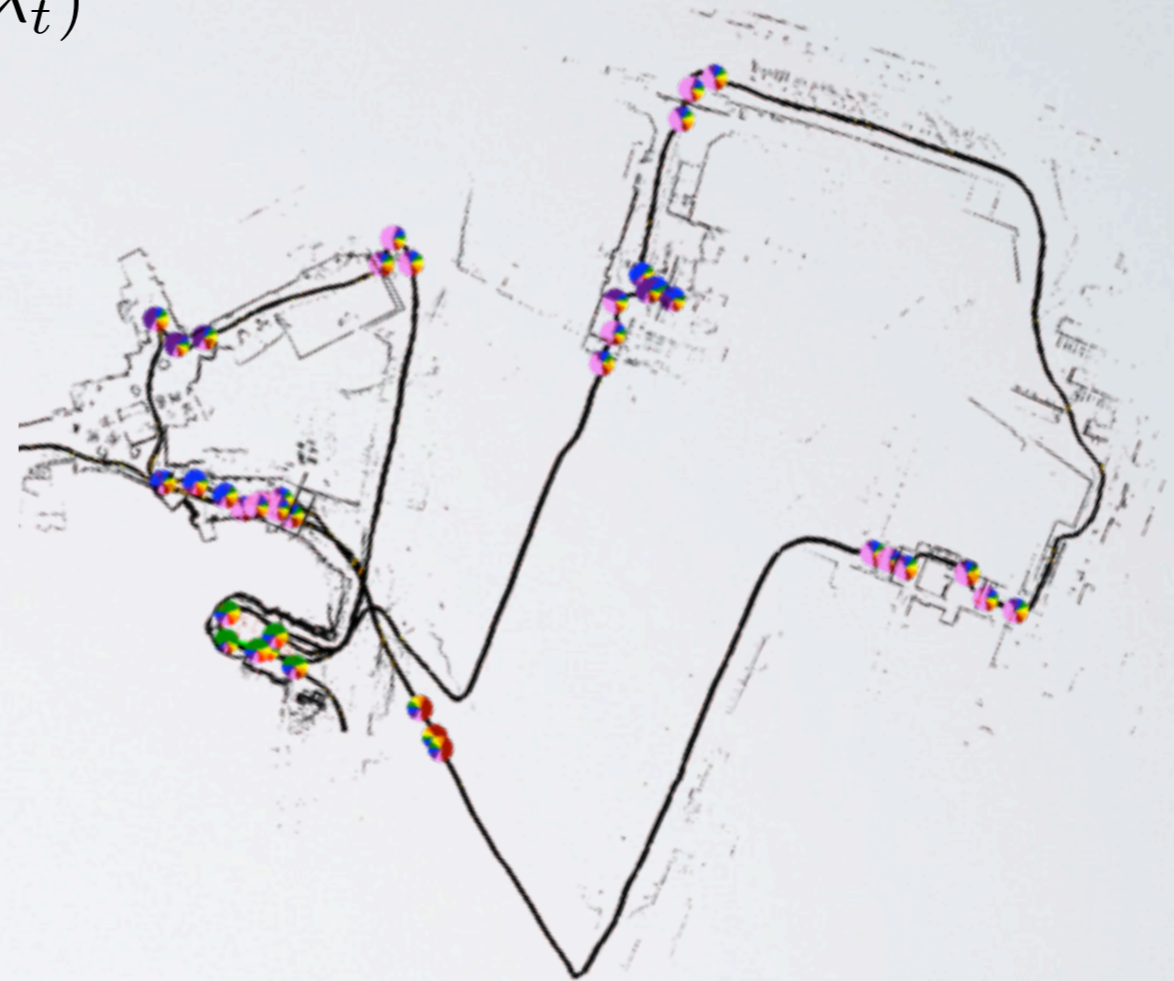
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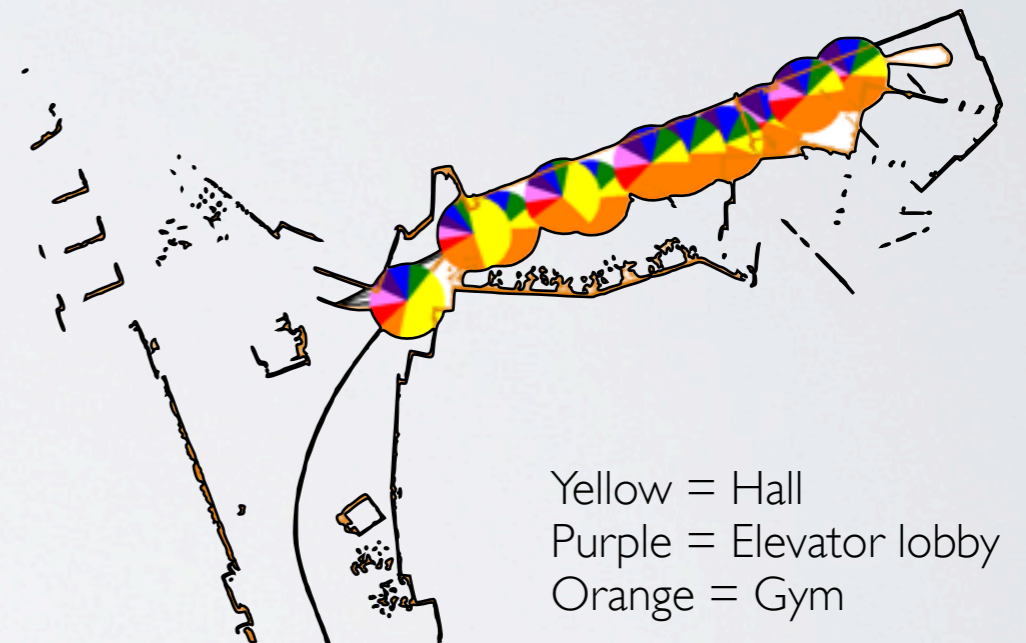
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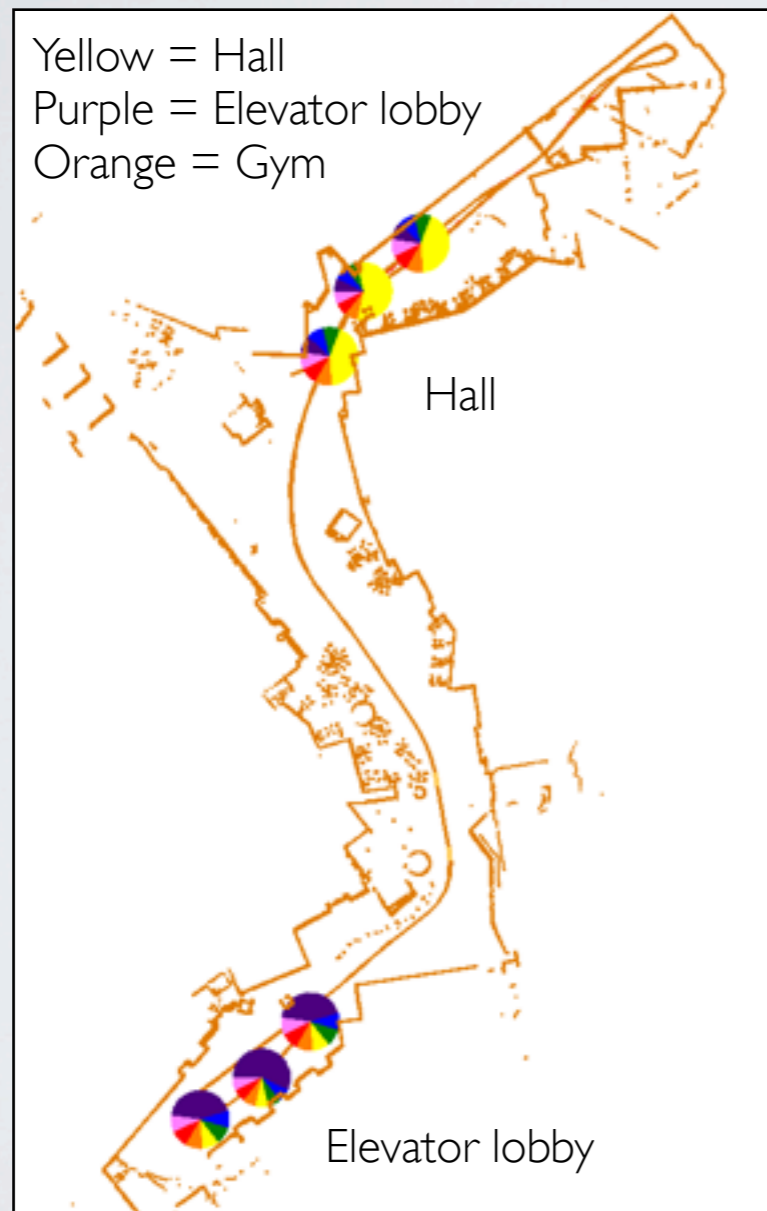
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“the gym is down the hall”



# Incorporating Natural Language Descriptions

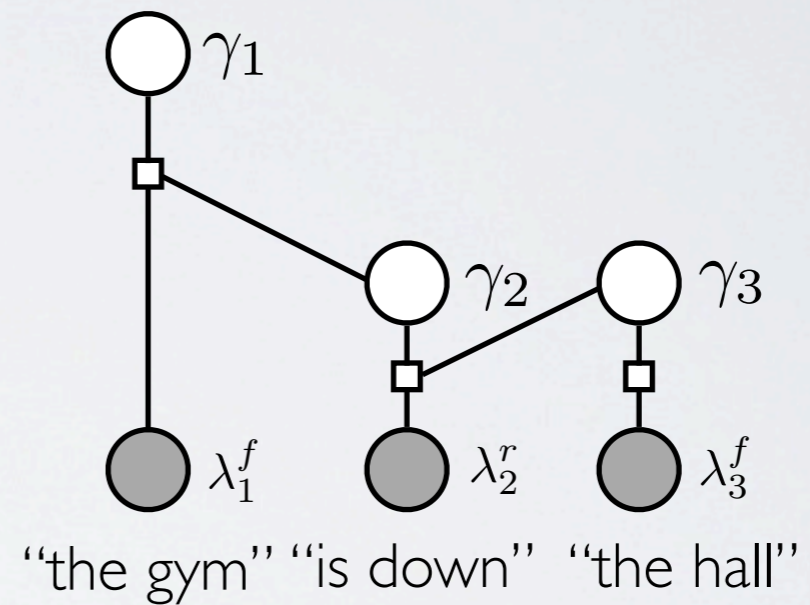
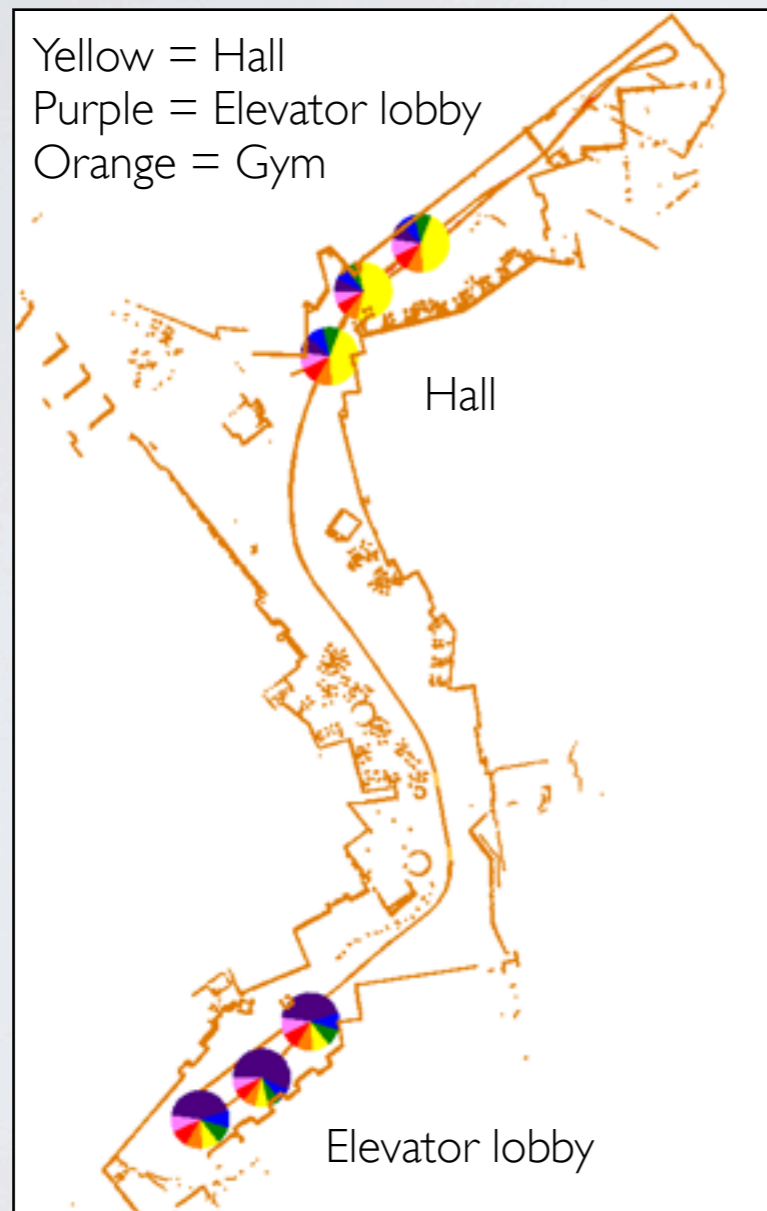
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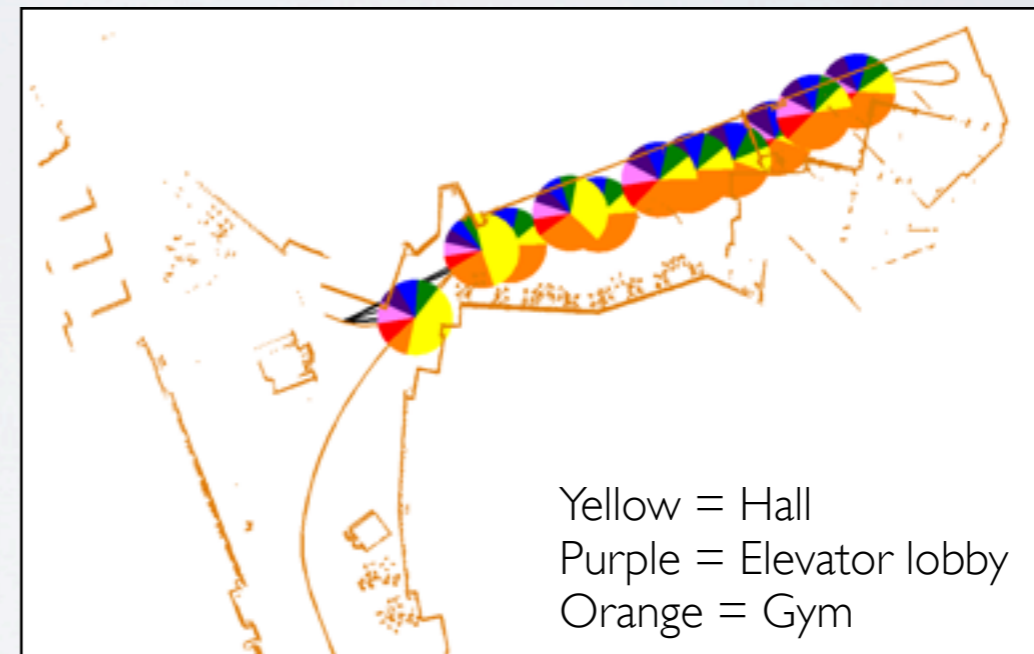
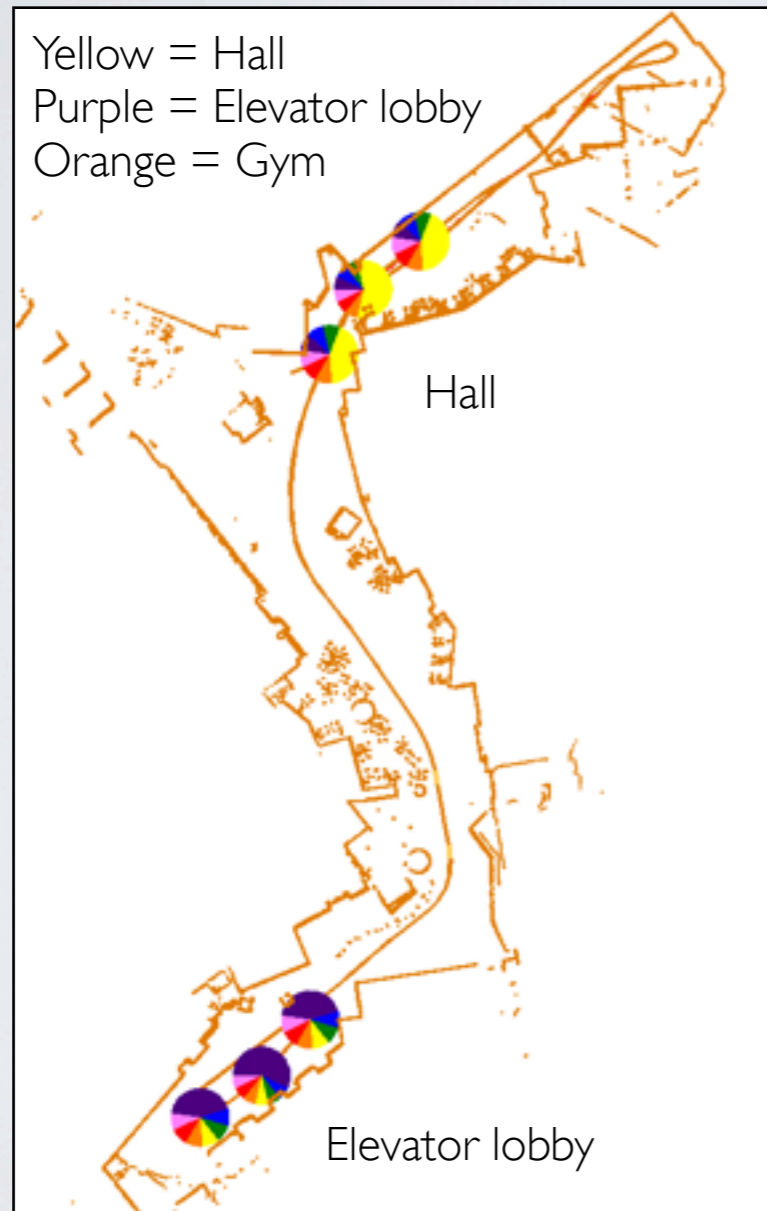
“the gym is down the hall”



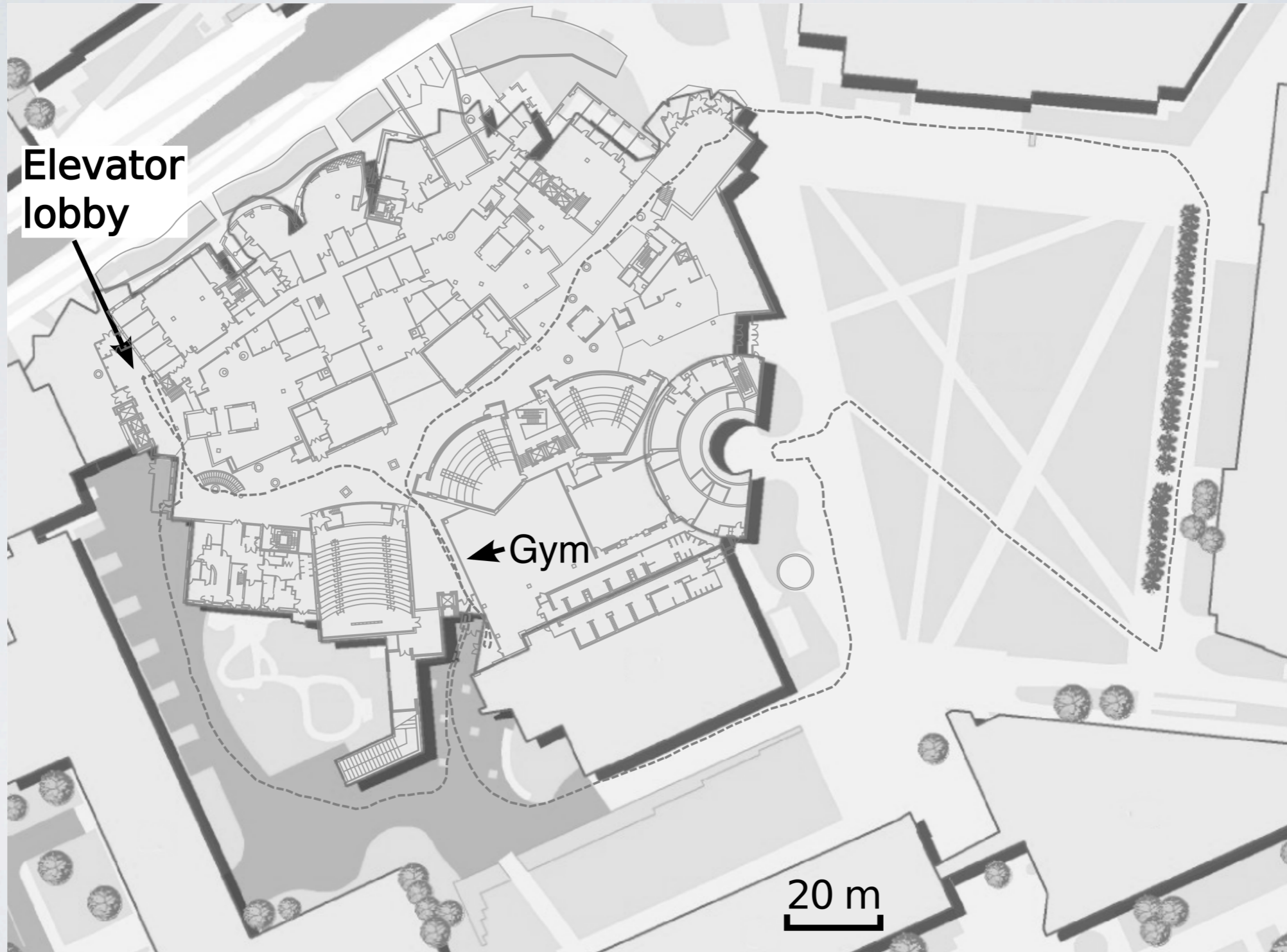
$$p(L_t^{(i)} | L_{t-1}^{(i)}, G_t^{(i)}, X_t^{(i)}, \lambda_t) = \sum_{\gamma} p(L_t^{(i)} | \gamma, L_{t-1}^{(i)}, \lambda_t) \times p(\gamma | L_{t-1}^{(i)}, G_t^{(i)}, X_t^{(i)}, \lambda_t)$$

# Incorporating Natural Language Descriptions

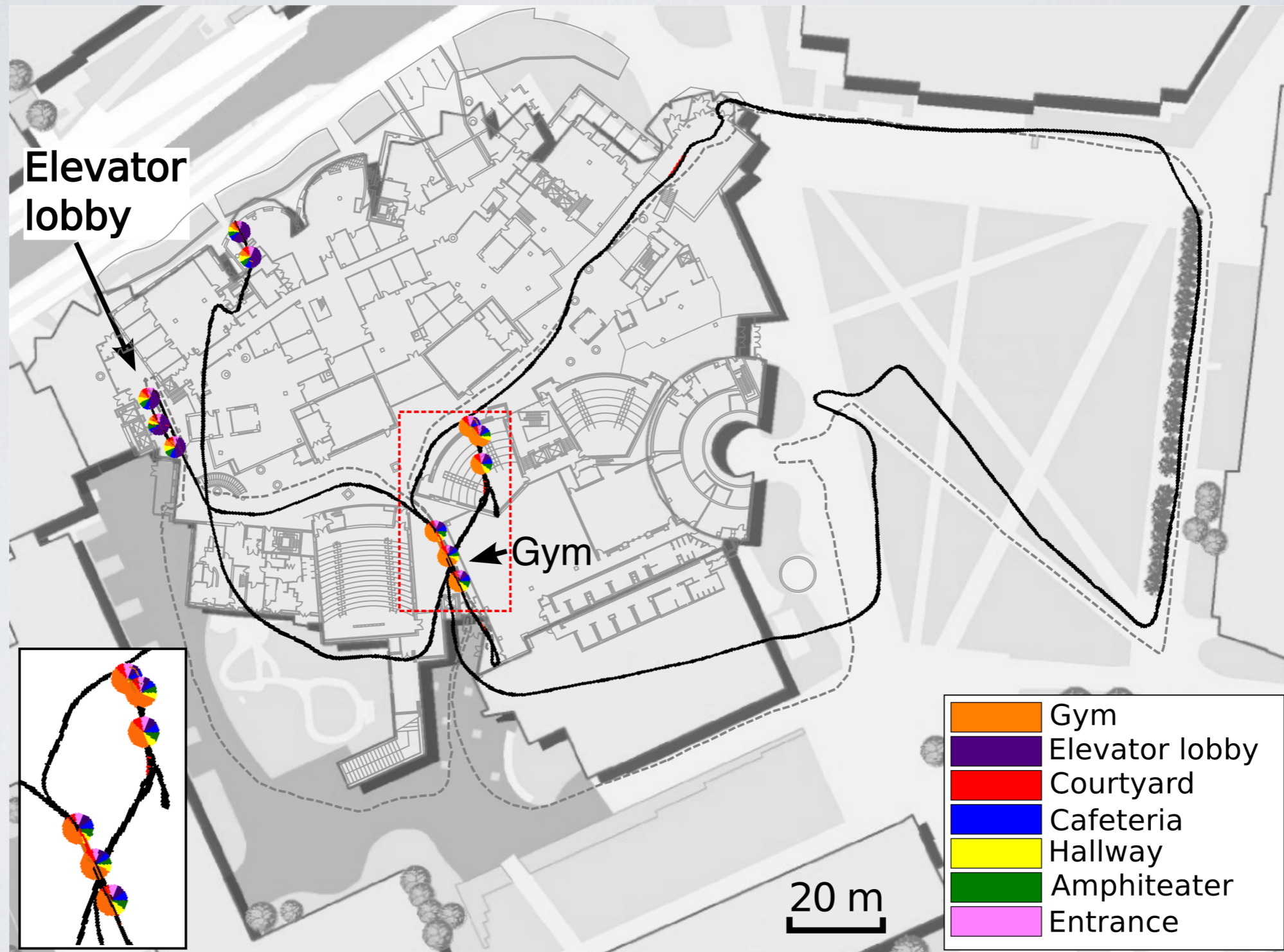
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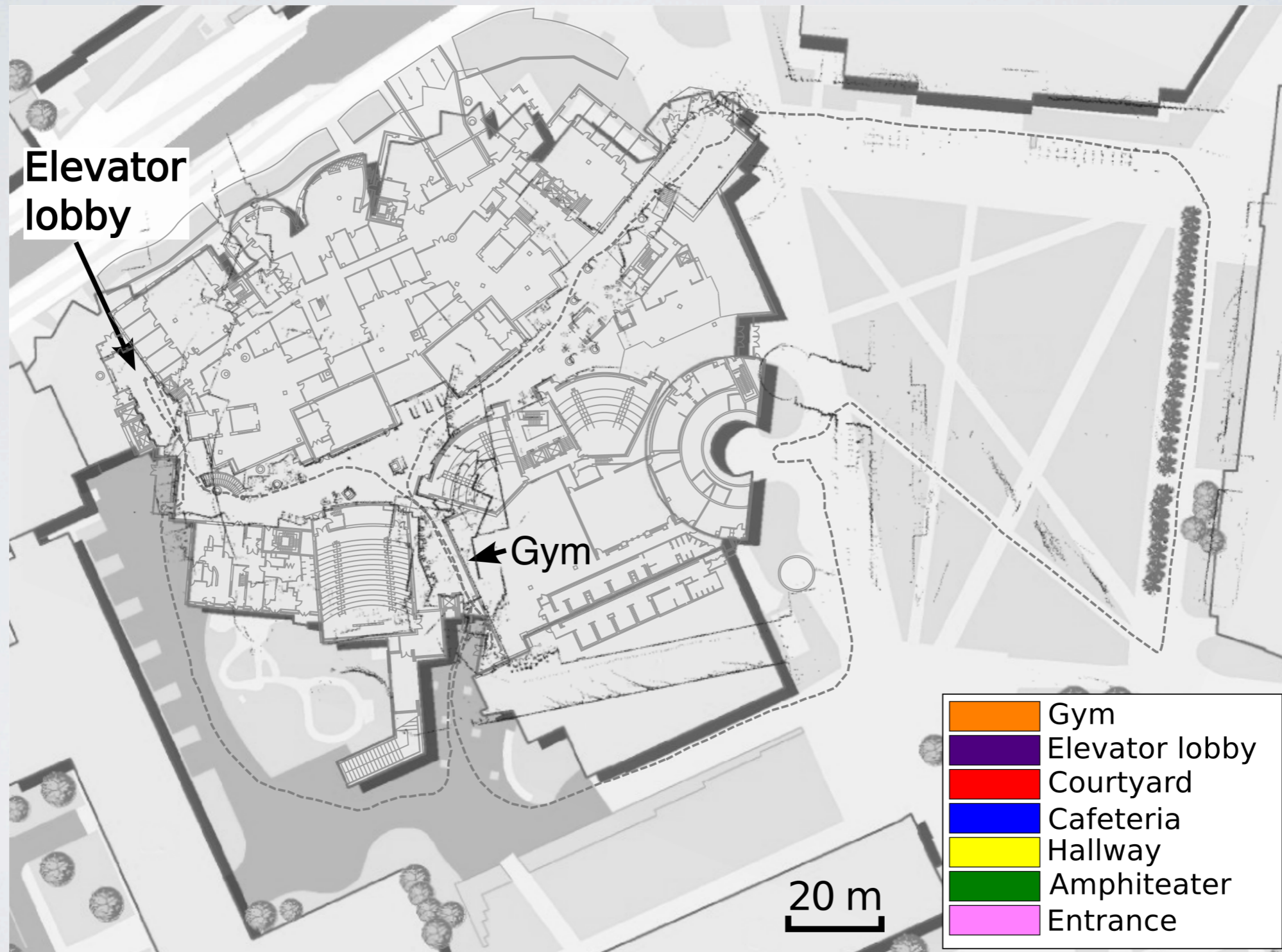
# Maps without Language Constraints



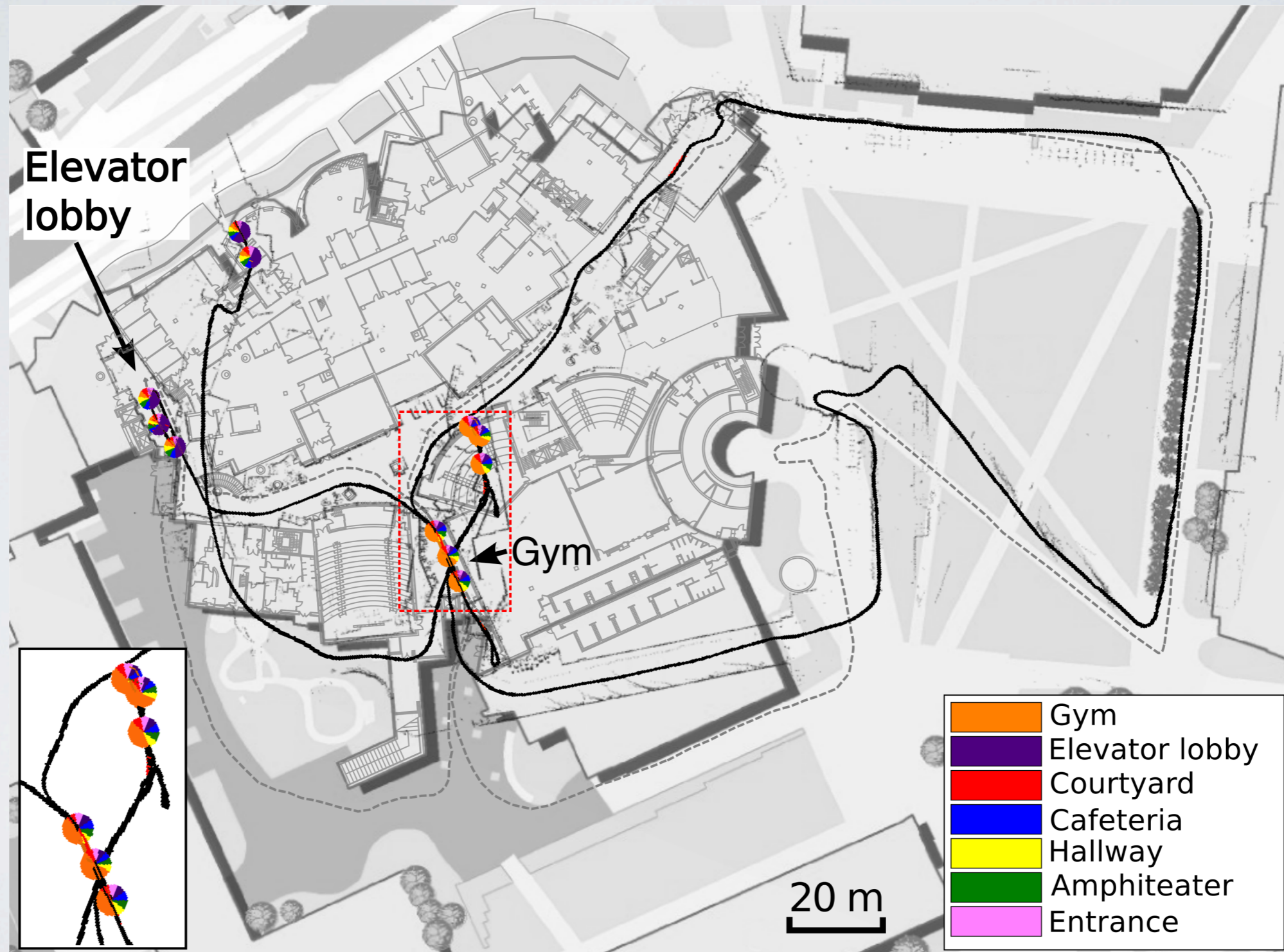
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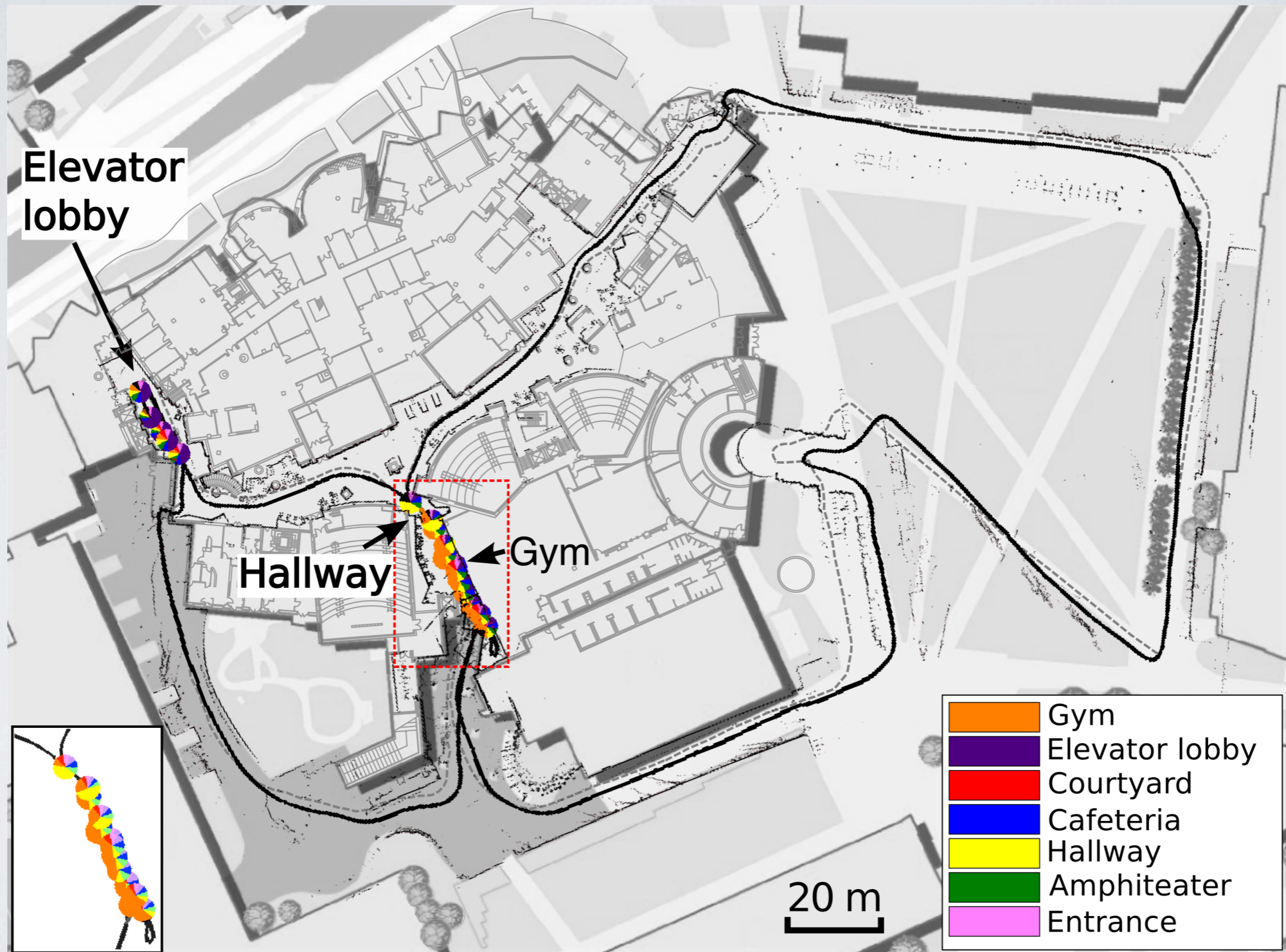
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# Maps without Language Constraints



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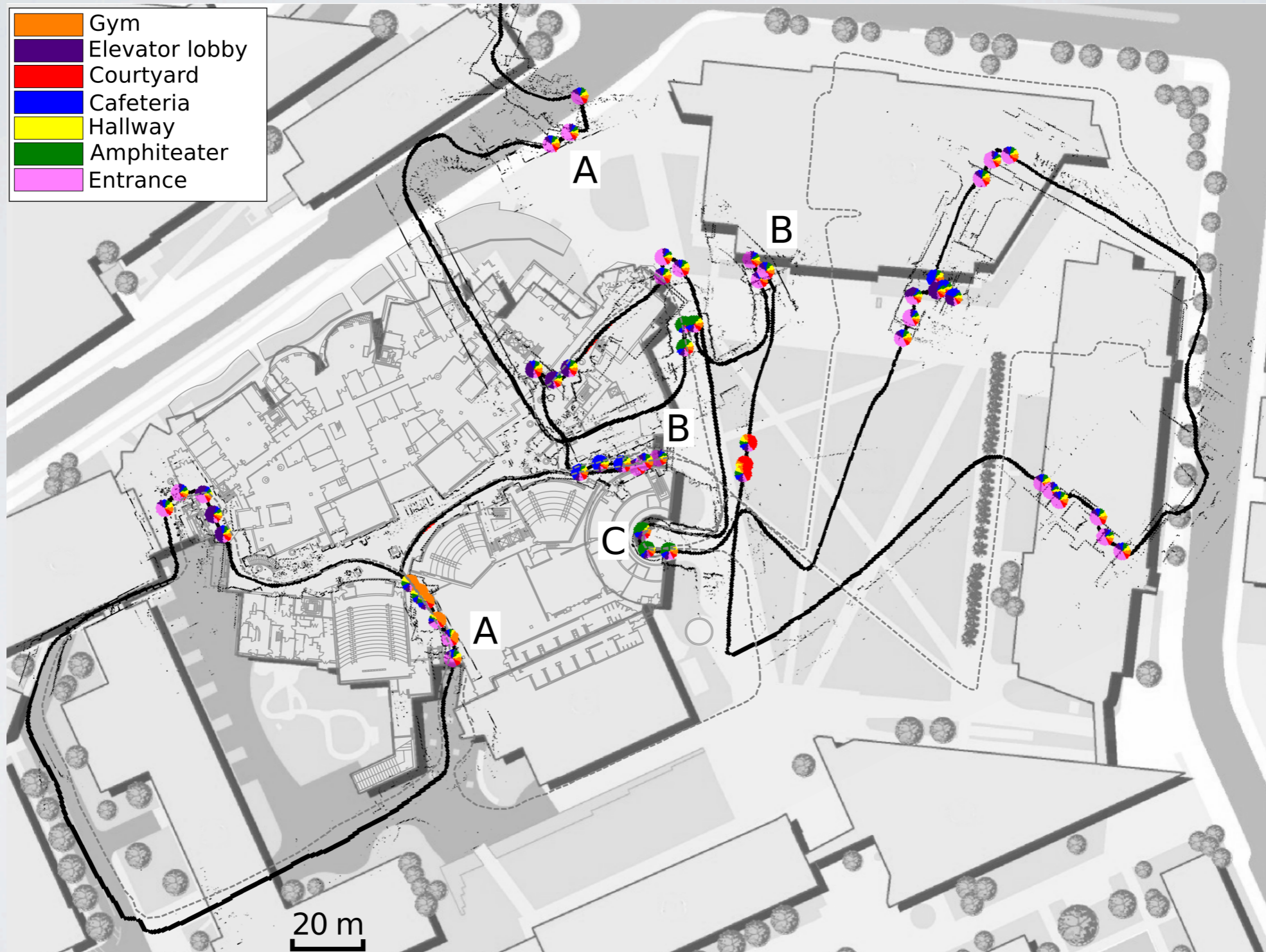


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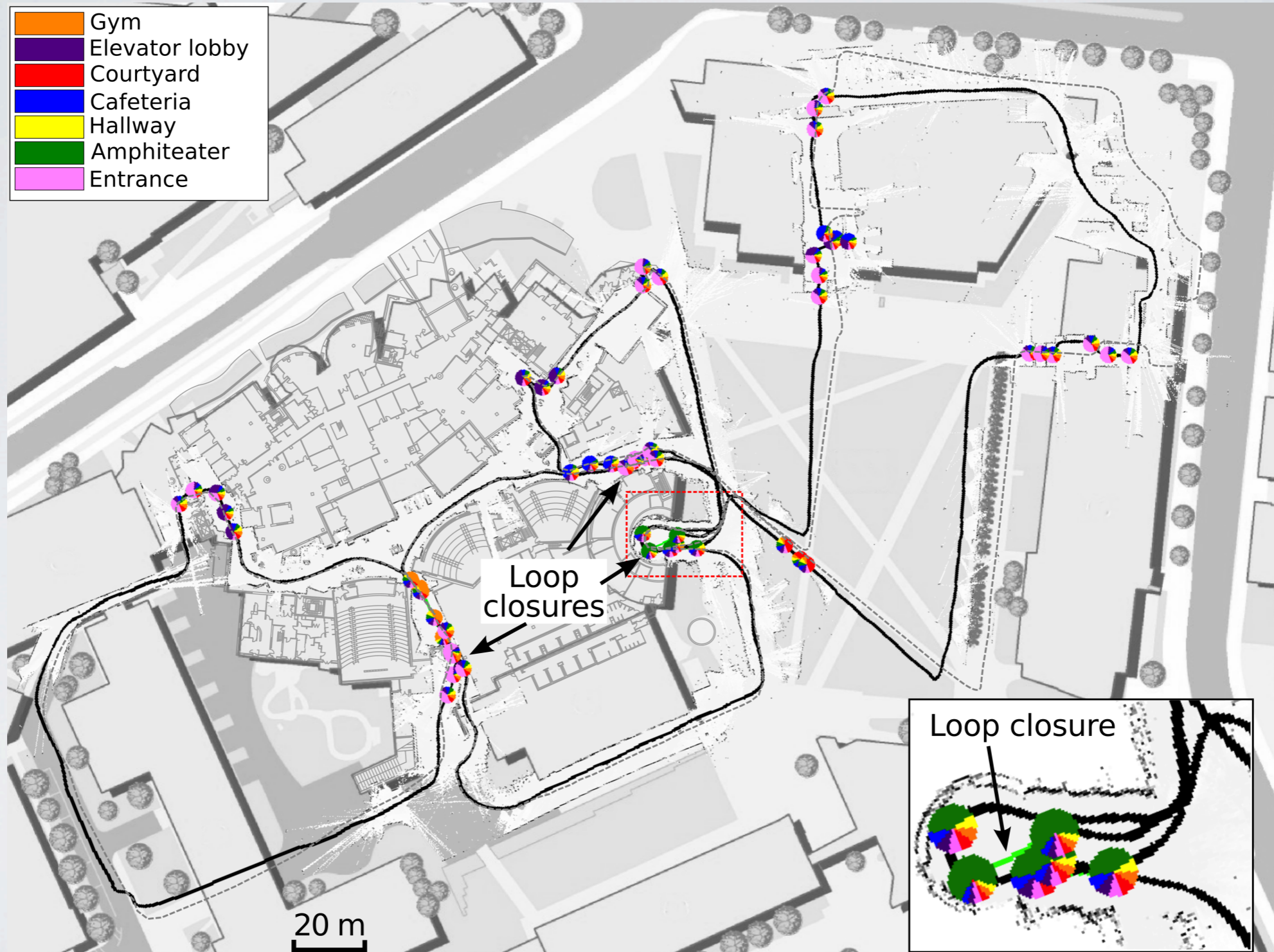




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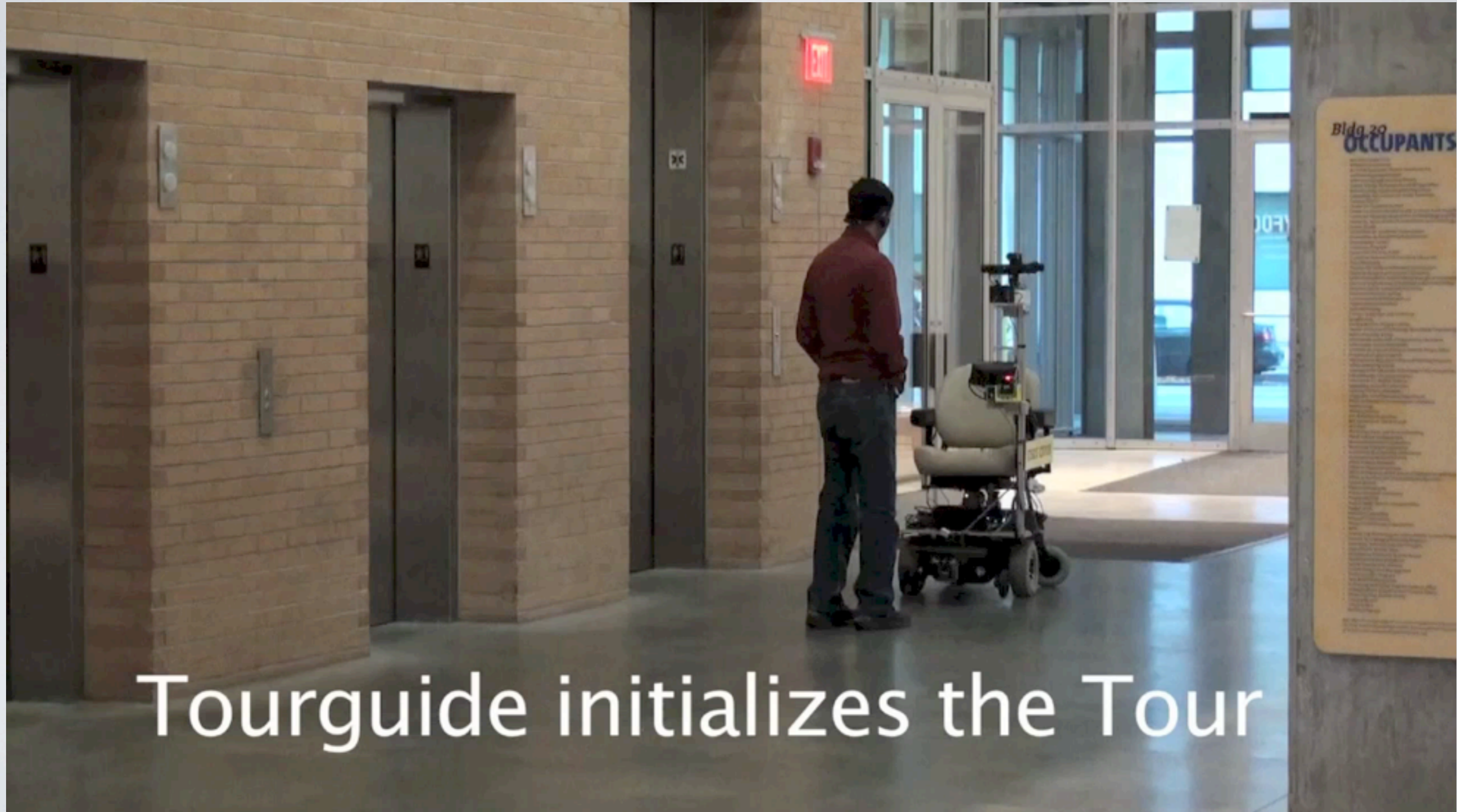


# Maps without Language Constraints



# Autonomous Narrated Tour

# Autonomous Narrated Tour



Tourguide initializes the Tour

# Questions?