Navigation

Saurabh Gupta

Tasks

- Locomotion
  - Wheeled ground vehicle
  - Drone
  - Quadruped
  - Off-road terrain

Tasks

- Locomotion
  - Platforms:
    - Wheeled ground vehicle, Drone, Quadrupeds, Off-road terrain
  - Move safely, and gracefully. Avoid collisions.
    - Follow high-level commands
    - Visual Servoing, follow an object
- Goal-directed behavior
  - Goals known / unknown
  - Environment seen / novel

Axes of variation

Supervision Signal

Expert Trajectories ← → Reward Signals ← → Ecological Supervision ← → No supervision (SIFT + Geometry)

Environment Modeling

No Modeling (Reactive Policies) ← → Implicit Modeling (via LSTMs) ← → Explicit modeling of space (metric / topological maps)

Task

Locomotion (move safely) ← → Path following ← → Long range goals (points / semantics / visual) ← → Navigation for actions

Generalization

Extensive training on test environments ← → Drop in novel environment

Axes of variation

Abstraction

State space discretization (eg. grid world) ⟷ Discrete Actions ⟷ Continuous actions

Environment Properties

Random Mazes (limited semantics) ⟷ Real world environments

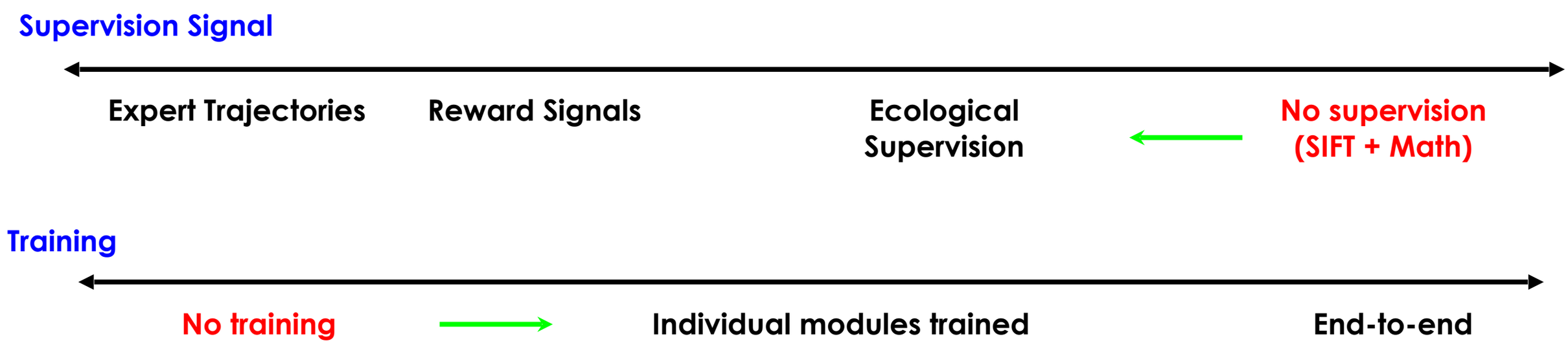
Experimental setup

Simulation ⟷ Simulation (based of real world environments) ⟷ Real world

Training

No training ⟷ Individual modules trained ⟷ End-to-end

CNNs for SLAM



Classical SLAM

- **Localization:**
  - **Semantic Visual Localization** J. Schonberger, M. Pollefeys, A. Geiger, T. Sattler arXiv 17 pdf
  - **Self-Supervised Place Recognition in Mobile Robots** S. Pillai, J. Leonard. IROS17 pdf
  - **Active neural localization** D. Chaplot arXiv17 pdf
- **Visual Odometry**
  - **Towards Visual Ego-motion Learning in Robots.** S. Pillai and J. Leonard IROS17 pdf
  - **Unsupervised Learning of Depth and Ego-motion from Video** Zhou et al. CVPR17 pdf
- **Reconstruction**
  - **Learned Stereo Machines.** Kar et al. NIPS17 pdf
  - **Differentiable ray consistency.** Tulsiani et al. CVPR17 pdf

Learned Locomotion

Environment Modeling

No Modeling (Reactive Policies) ⟷ Implicit Modeling (via LSTMs) ⟷ Explicit modeling of space (metric / topological maps)

Task

Locomotion (move safely) ⟷ Path following ⟷ Long range goals (points / semantics / visual) ⟷ Navigation for actions

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Abstraction

State space discretization (eg. grid world) ⟷ Discrete Actions ⟷ Continuous actions

- **Learning Agile and Dynamic Motor Skills for Legged Robots** J. Hwango et al. Science Robotics 18 pdf, video
- **Agile Autonomous Driving** Y. Pan et al. R:SS18 pdf, video
- **Drone Racing** E. Kaufmann et al. ICRA19 pdf, video
- **Self-supervised Deep Reinforcement Learning with Generalized Computation Graphs for Robot Navigation** G. Kahn, A. Villaflor, B. Ding, P. Abbeel, S. Levine. ICRA18 pdf, video
- **Learning to Fly by Crashing** D. Gandhi, L. Pinto, A. Gupta. IROS17 pdf, video

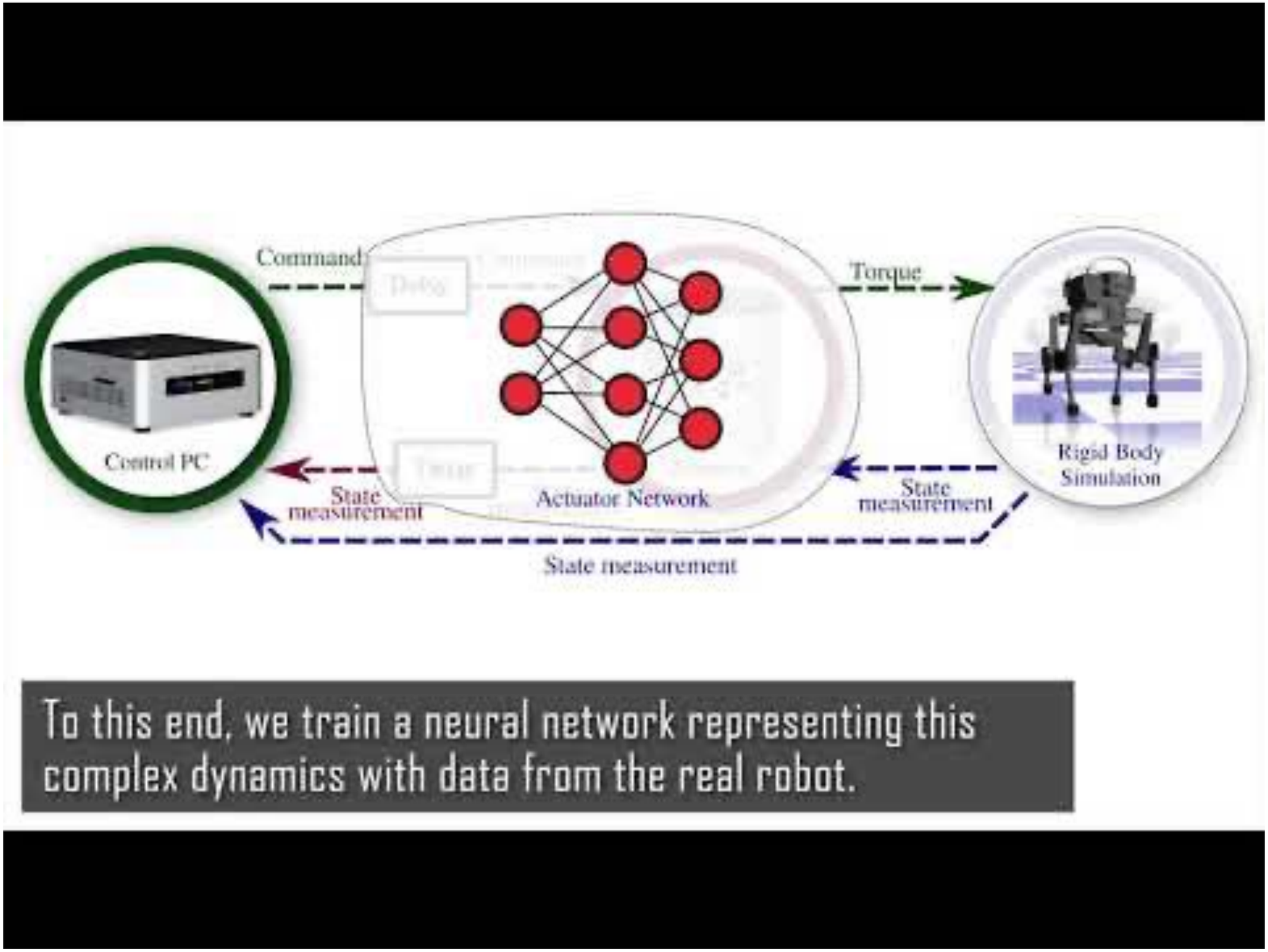
Rewards Signals, Simulation

Imitation Learning

Modularized Learning

Ecological Supervision

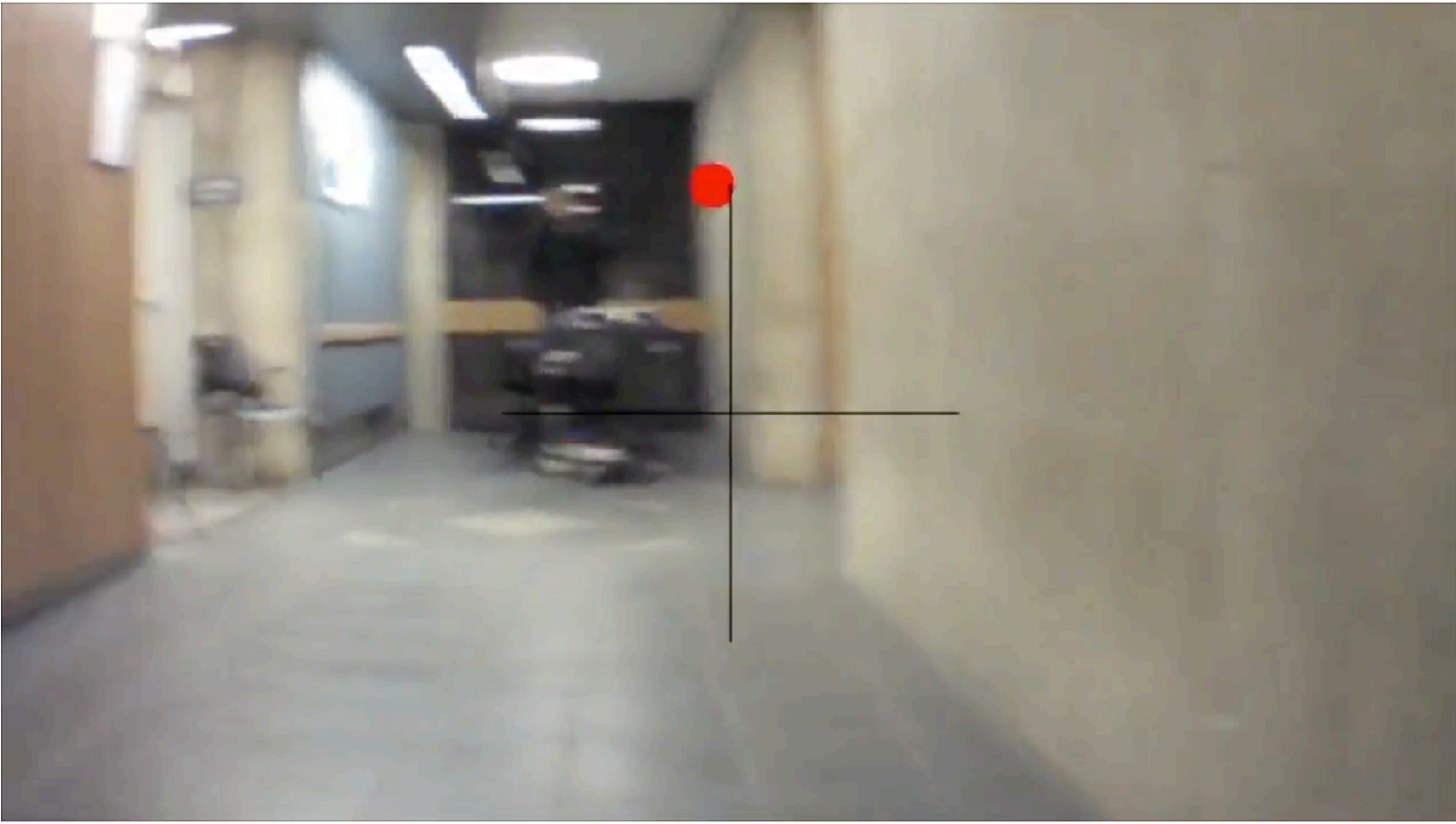
- **Learning Agile and Dynamic Motor Skills for Legged Robots** J. Hwango et al. Science Robotics 18 pdf, video



- **Agile Autonomous Driving** Y. Pan et al. R:SS18 pdf, video

- **Beauty and the Beast: Optimal Methods Meet Learning for Drone Racing** E. Kaufmann et al. ICRA19 pdf, video

Learning to Fly by Crashing D. Gandhi, L. Pinto, A. Gupta. IROS17. pdf, video



Self-supervised Deep Reinforcement Learning with Generalized Computation Graphs for Robot Navigation G. Kahn S.Levine. ICRA18. pdf, video

Self-supervised Deep Reinforcement Learning with Generalized Computation Graphs for Robot Navigation

Gregory Kahn, Adam Villaflor, Bosen Ding, Pieter Abbeel, Sergey Levine

BAIR
BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

Goal directed navigation

- Goal-directed behavior
  - Goals known / unknown
  - Environment seen / novel
- Central question is that of how to represent space?
  - Reason about what you have seen and where / what you have not seen
  - Spatial reasoning
  - Robustness to actuation noise
- For unknown environments, we may additionally need:
  - Semantic reasoning
  - Easy to build

Representations for Space

- Metric maps
  - Occupancy maps
  - Occupancy maps flavored with semantic information
- Topological maps
  - Collection of images, and connectivity information

Learned Task driven End-to-end navigation

Supervision Signal

Expert Trajectories | **Reward Signals** | **Ecological Supervision** | **No supervision (SIFT +Math)**

Task

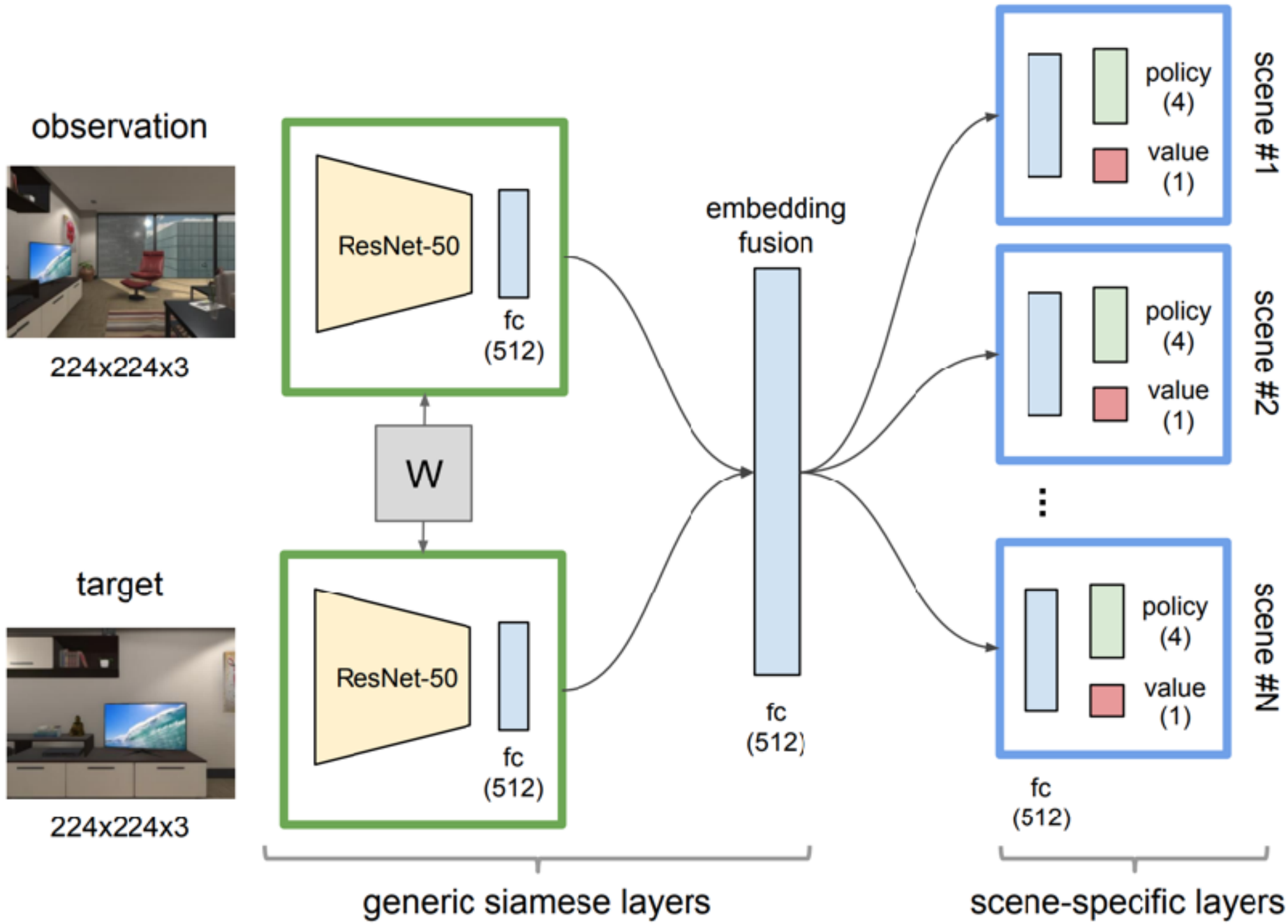
Locomotion (move safely) | **Path following** | **Long range goals (points / semantics / visual)** | **Navigation for actions**

- **Target driven visual navigation in indoor scenes using deep reinforcement learning.** Zhu, … Farhadi ICRA17 pdf, video
- **Learning to navigate in complex environments** P. Mirowski, … R. Hadsell ICLR17 pdf, video
- **Cognitive Mapping and Planning** CVPR17 pdf, video
- **Neural Topological SLAM** CVPR 20 pdf, video

Environment Modeling	Generalization
No Modeling (Reactive Policies)	Extensive training on test environments
Implicit Modeling (via LSTMs)	
Explicit modeling of space (metric / topological maps)	Drop in novel environment

Target driven visual navigation in indoor scenes using deep reinforcement learning.

Y. Zhu, …, A. Gupta, …, A. Farhadi. ICRA17. pdf, video



Simulation Environments

Abstraction

State space discretization (eg. grid world) ⟷ **Discrete Actions** ⟷ **Continuous actions**

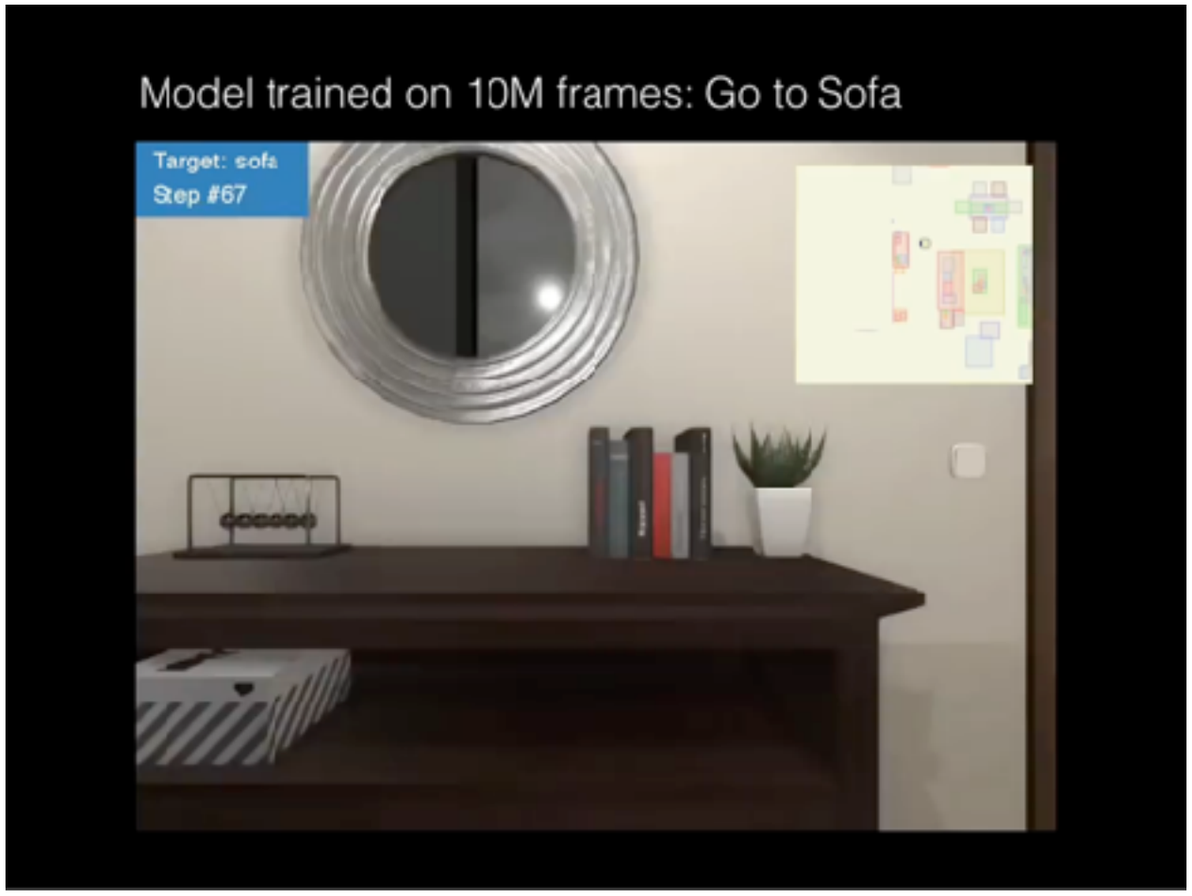
Environment Properties

Random Mazes (limited semantics) ⟷ **Real world environments**

Experimental setup

Simulation ⟷ **Simulation (based of real world environments)** ⟷ **Real world**

Simulators based off games / CG (eg: AI2Thor, VizDoom, CARLA)



Simulators based off real world scans (eg: CMPSim, Habitat, Gibson)

Visual Servoing

Environment Modeling

No Modeling (Reactive Policies) — **Implicit Modeling (via LSTMs)** — **Explicit modeling of space (metric / topological maps)**

Task

Locomotion (move safely) — **Path following** — **Long range goals (points / semantics / visual)** — **Navigation for actions**

Supervision Signal

- **Expert Trajectories**
- **Reward Signals**
- **Ecological Supervision**
- **No supervision (SIFT + Geometry)**

- **Visual Memory for Robust Path Following**
  Kumar, Gupta, ... Malik
- **End-to-end Driving via Conditional Imitation Learning** F. Codevilla, … V. Koltun ICRA18? pdf, video
- **Learning Visual Servoing with Deep Features and Fitted Q-Iteration**, Alex X. Lee, Sergey Levine, Pieter Abbeel. ICLR17. pdf
- **Zero-Shot Visual Imitation** D. Pathak, …, T. Darrell pdf, video ICLR18? pdf, video
- **Classical Visual Servoing**

Learning Visual Servoing with Deep Features and Fitted Q-Iteration

Alex X. Lee, Sergey Levine, Pieter Abbeel. ICLR17. pdf

End-to-end Driving via Conditional Imitation Learning

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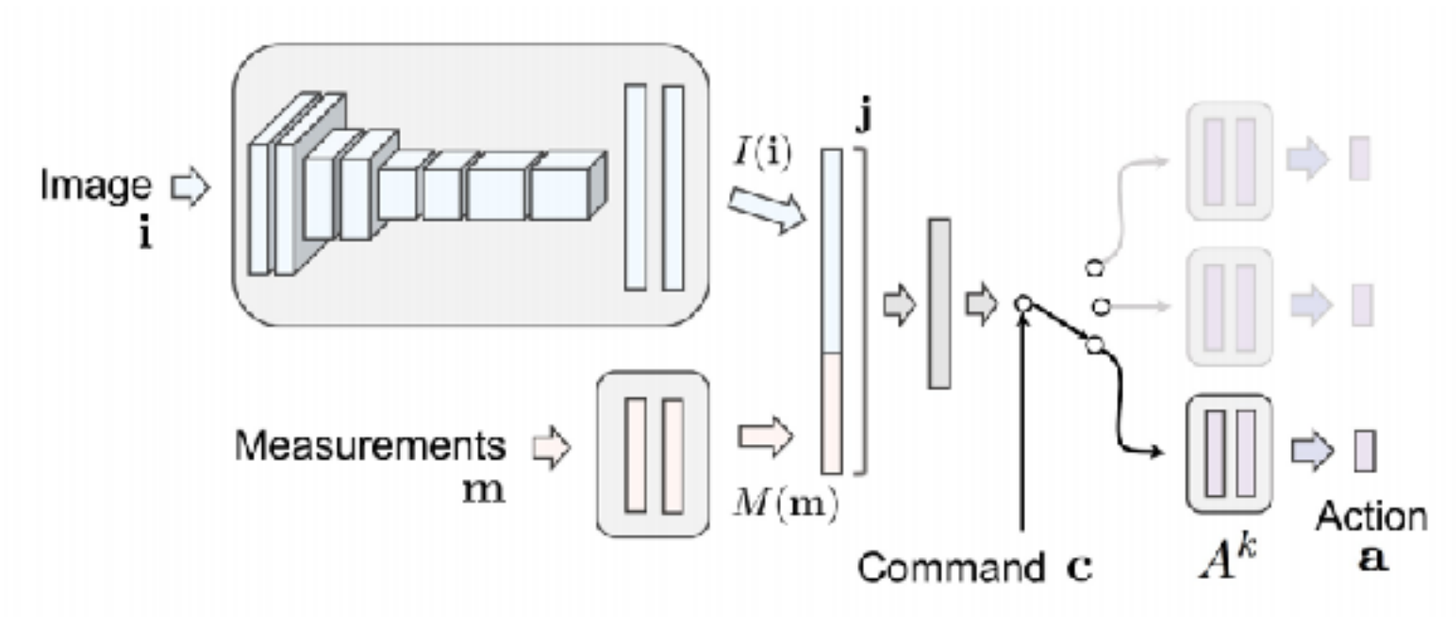


Other Unexplored Axes?

Environment Scale

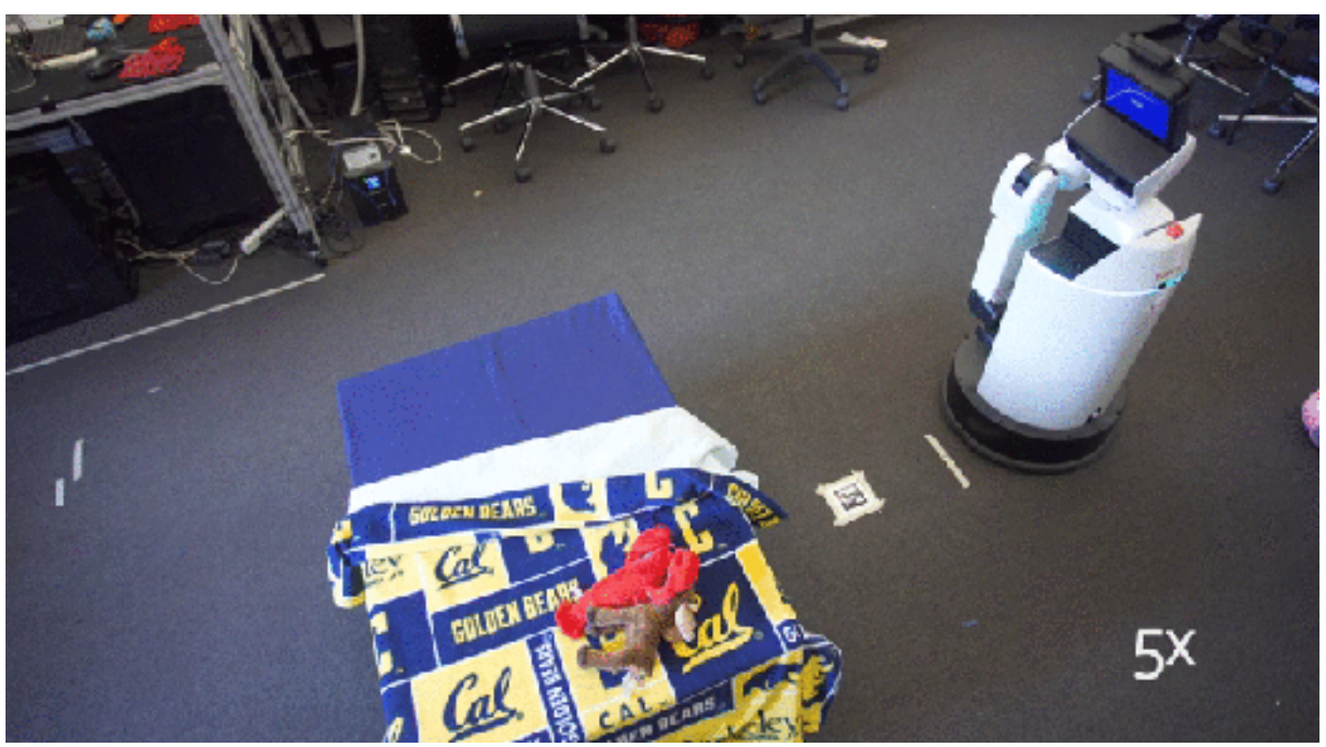
Small mazes — Houses / Offices — City Scale Environments?

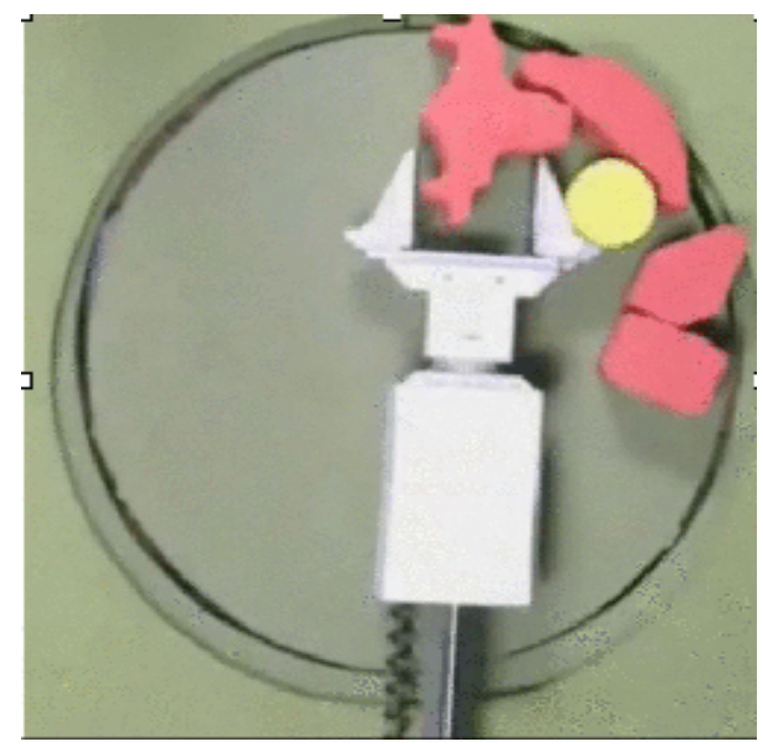
Task

Locomotion (move safely) — Path following — Long range goals (points / semantics / visual) — Navigation for actions?

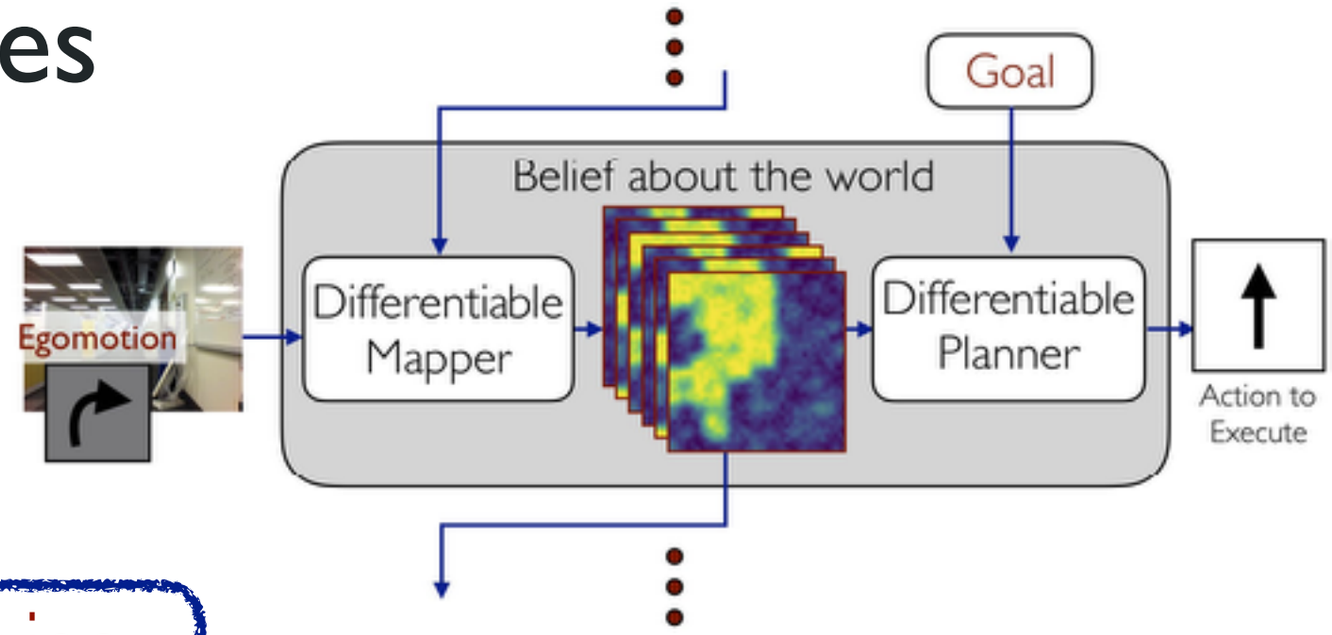
Dynamic Environments

World is static — World has objects that need to be moved around? — Reason about other agents?





Representation for Spaces

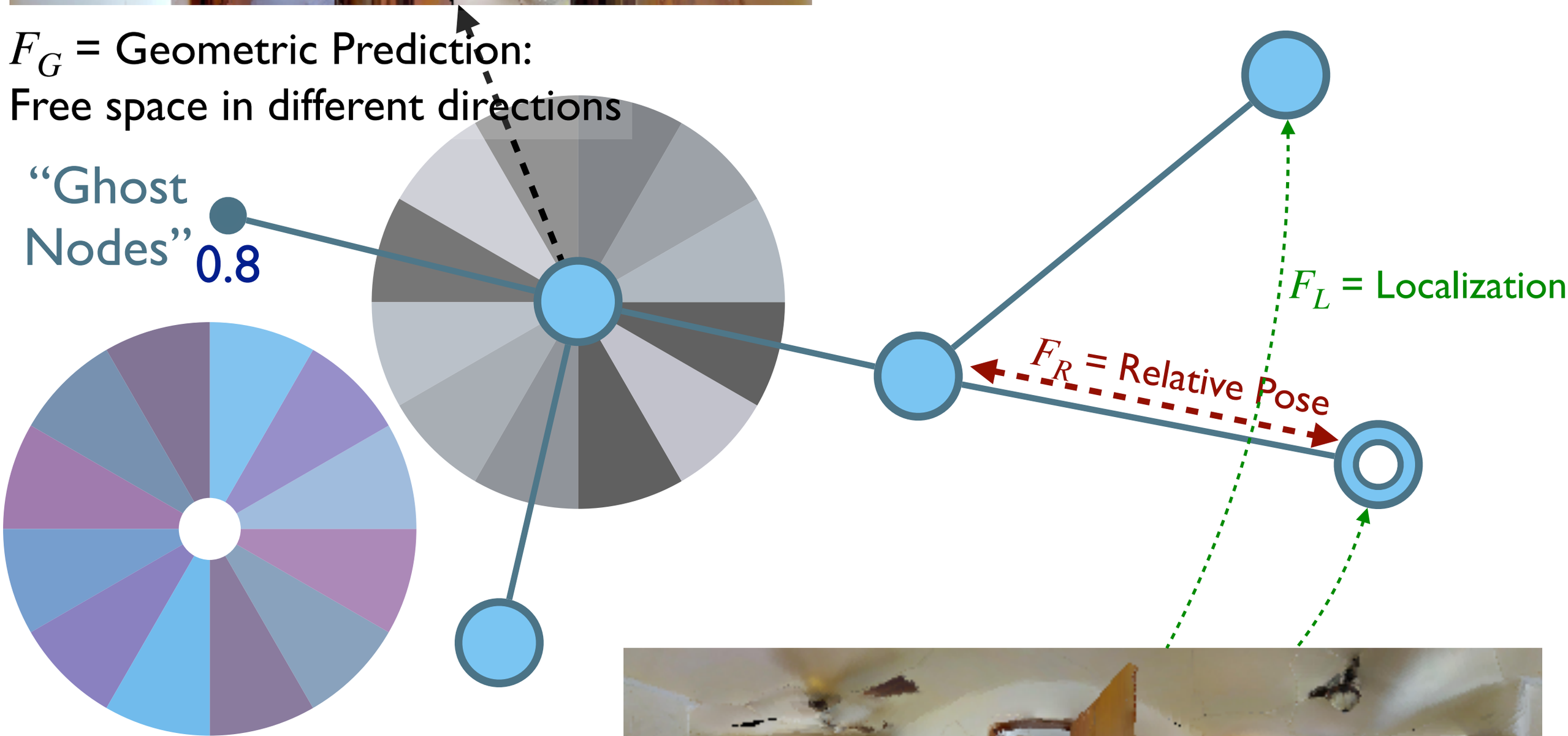


- Semantic reasoning
- Spatial reasoning
- Robustness to actuation noise
- Easy to acquire

- Topological representations (robustness to noise)
- Ease of training
  - Modular approaches
  - Training via supervised learning

Semantic Topological Representations

F_G = Geometric Prediction:
Free space in different directions



F_S = Semantic Prediction:
Closeness to target

D. S. Chaplot et al. Neural topological slam for visual navigation. In CVPR, 2020.

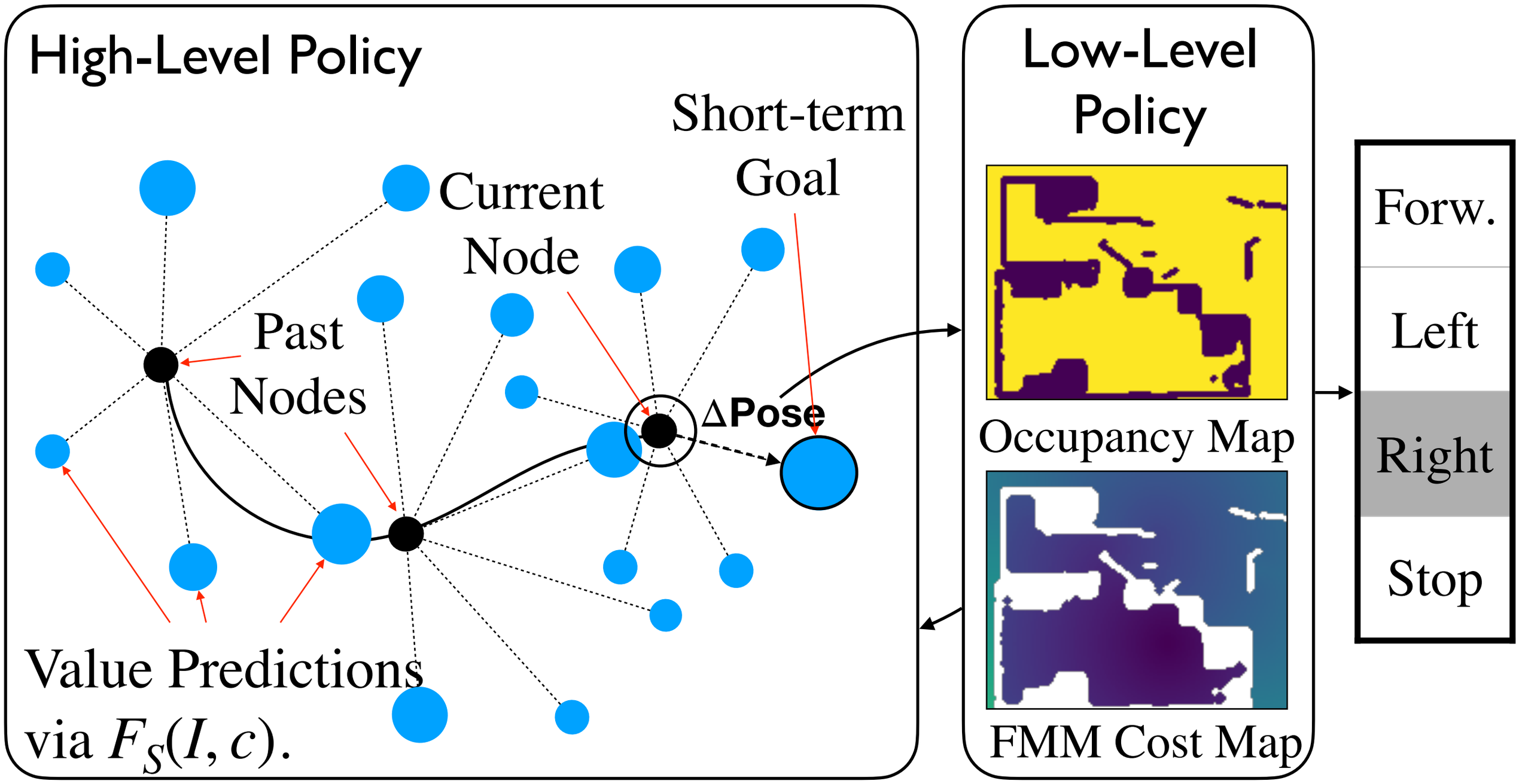
4 Functions

- $F_S(I_1, I_2)$ = Semantic Prediction: Closeness to target
- $F_G(I_1)$ = Geometric Prediction: Free directions
- $F_R(I_1, I_2)$ = Relative Pose
- $F_L(I_1, I_2)$ = Localization

D. S. Chaplot et al. Neural topological slam for visual navigation. In CVPR, 2020.

Goal-driven Navigation

Hierarchical Policy



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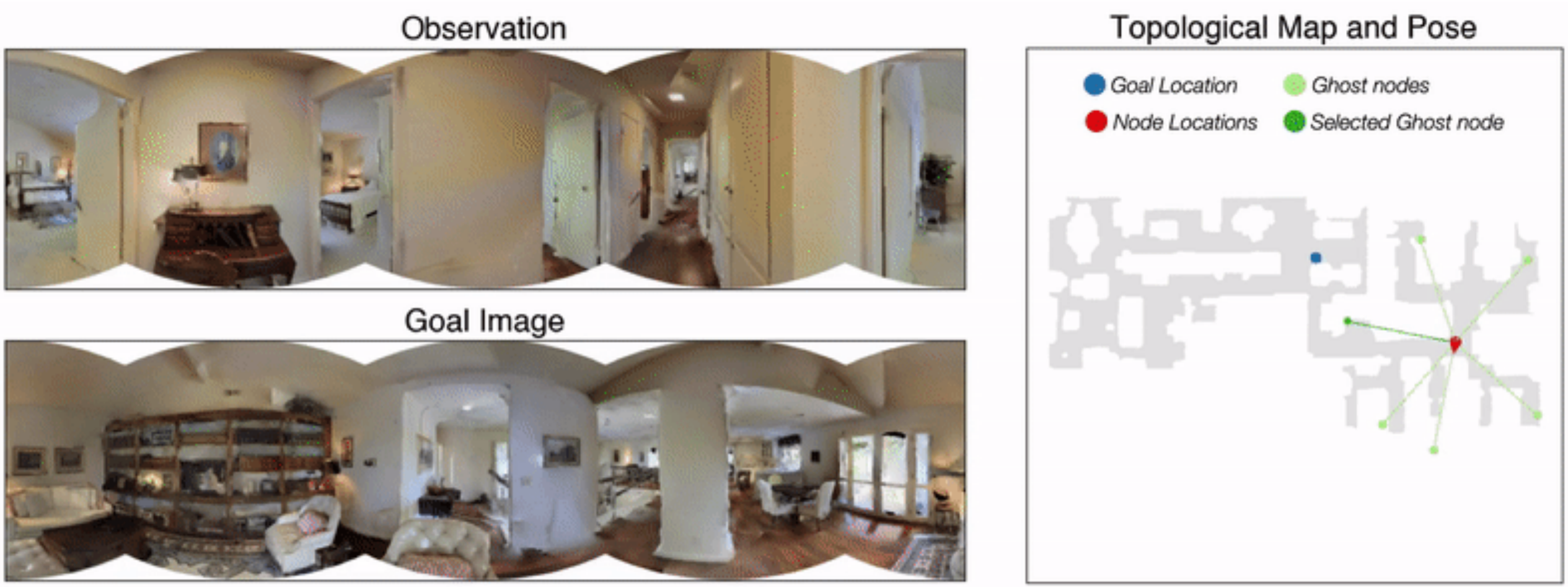
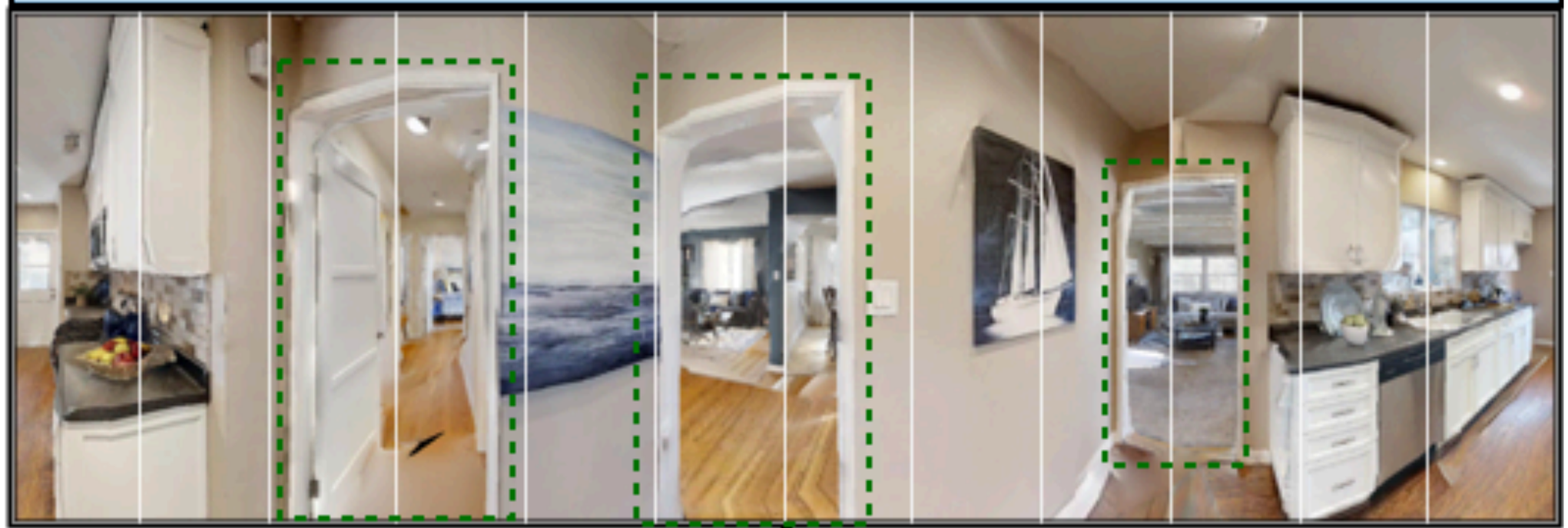
Execution (Image Goal)



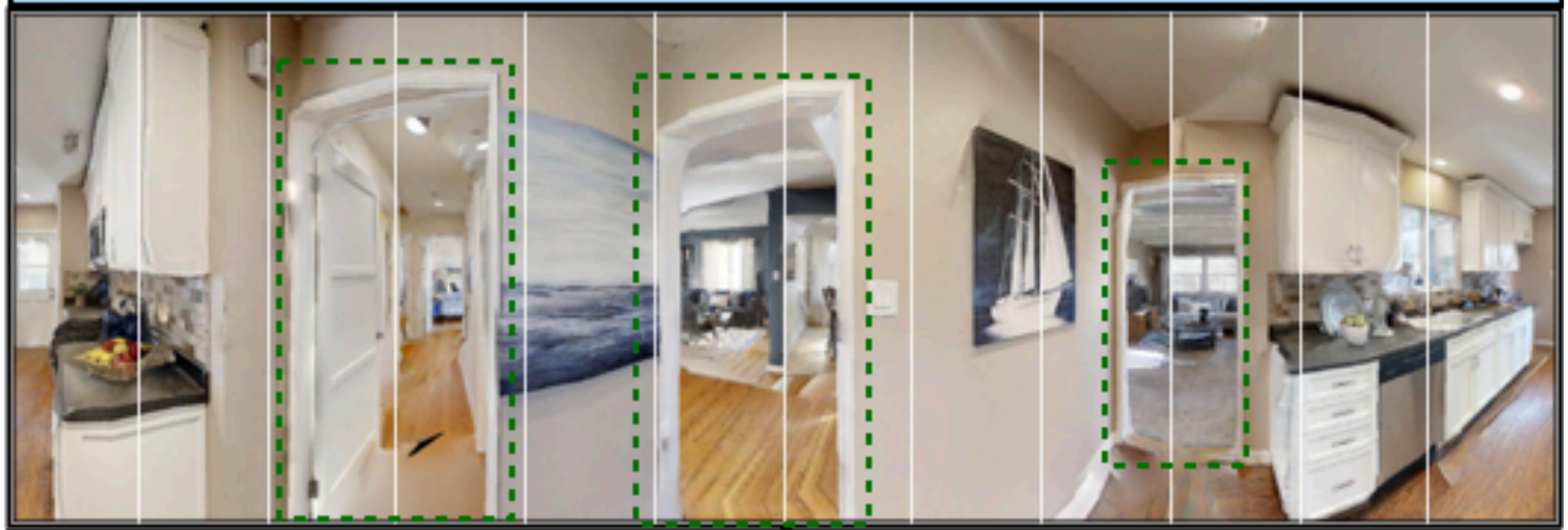
D. S. Chaplot et al. Neural topological slam for visual navigation. In CVPR, 2020.

Source Image (I_S)



0	0	0.05	0.05	0	0.91	0.87	0	0.21	0.16	0	0

Source Image (I_S)



0	0	0.68	0.69	0	0.21	0.23	0	0.16	0.16	0	0

Results

Map based methods are better than vanilla learning methods even in presence of noise.

		RGB	RGBD	RGBD (No Noise)	RGBD (No Stop)
End-to-end Learning	LSTM + Imitation	0.10	0.14	0.15	0.18
	LSTM + RL	0.10	0.13	0.14	0.17
Metric Maps	Occupancy Maps + FBE + RL		0.26	0.31	0.24
	ANS	0.23	0.29	0.35	0.39
Topo Maps	**NTS (Our)**	**0.38**	**0.43**	**0.45**	**0.60**

Robust to Actuation Noise

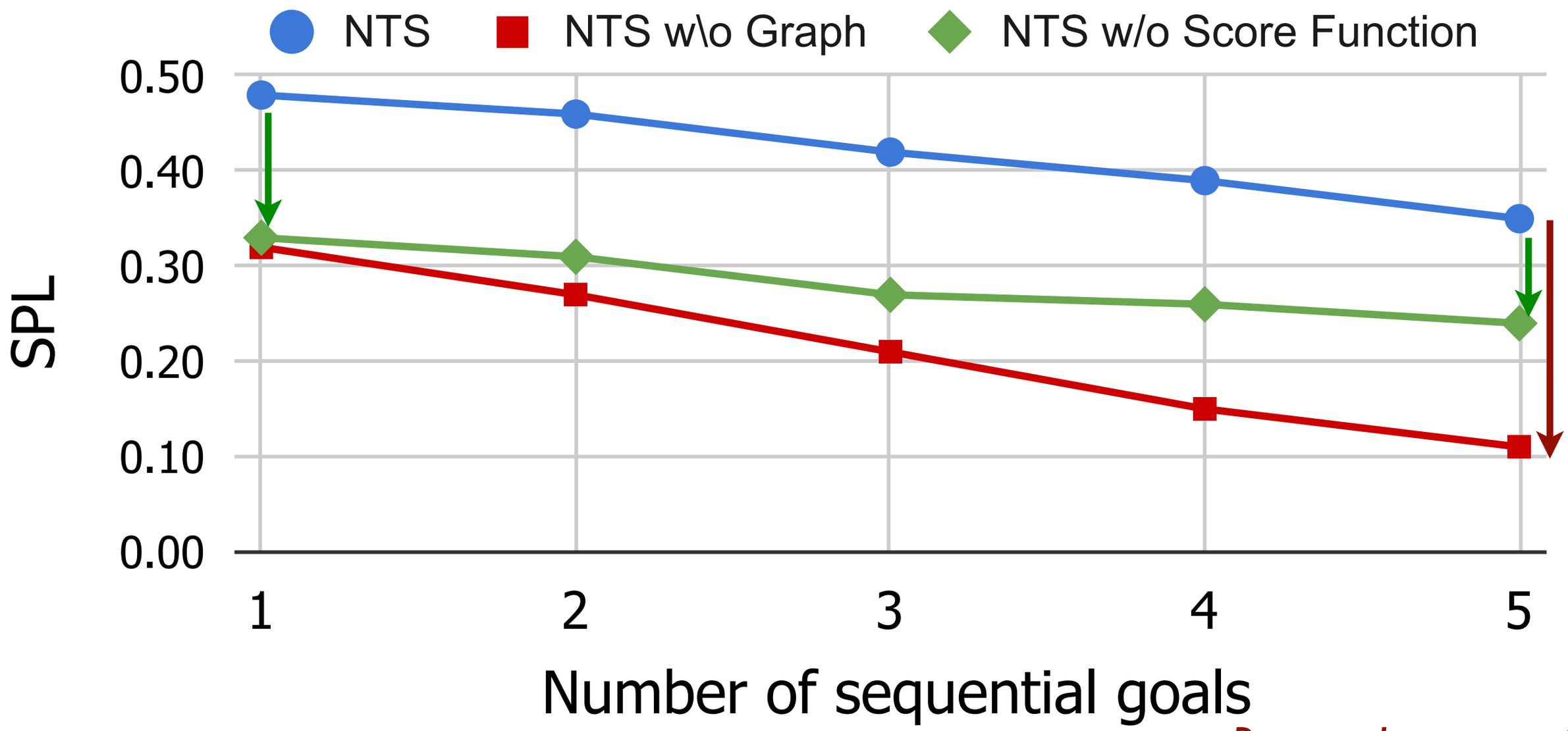
NTS is better than occupancy map models, captures and uses semantic priors.

D. S. Chaplot et al. Neural topological slam for visual navigation. In CVPR, 2020.

Results

Semantic score function improves efficiency when no prior experience with environment is available.

As experience in environment increases, utility of semantic function decreases



But, at the same time, importance of the topological representation increases

D. S. Chaplot et al. Neural topological slam for visual navigation. In CVPR, 2020.

Thanks!