

Robot Learning Seminar

WS 2021/22

Robot Learning Lab

Albert-Ludwigs-Universität Freiburg

Friday, 22nd October 2021



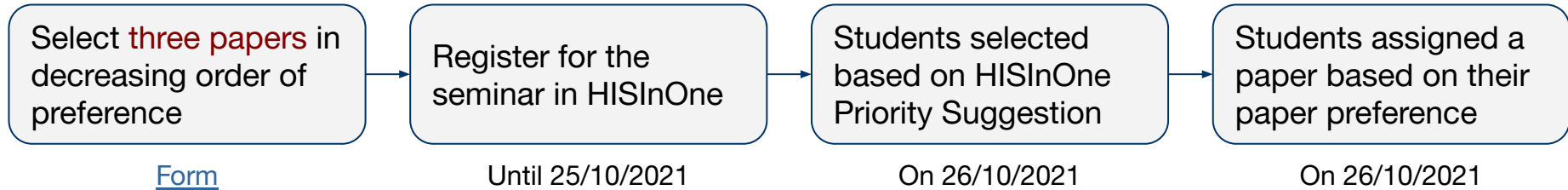
**UNI
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Evaluation

Evaluation	Due Date
Paper Abstract	14/01/2022
Seminar Presentation	11/02/2022
Paper Summary	25/02/2022

- Abstract → **At most 2 pages**
- Presentation → **At most 20 minutes**
- Summary → **At most 7 pages** excluding bibliography and figures
- Final grade → Abstract, Presentation, Summary, Seminar participation

Enrollment Procedure



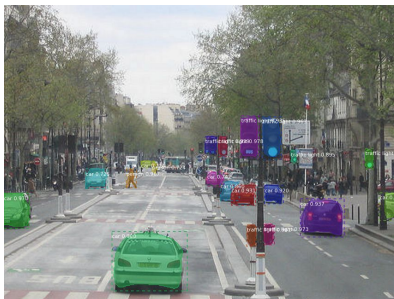
Robot Learning

- Tremendous progress on complex, high dimensional data
 - Speech Recognition
 - Computer Vision
 - Natural Language Understanding
- Autonomous systems smart enough to operate in the real world

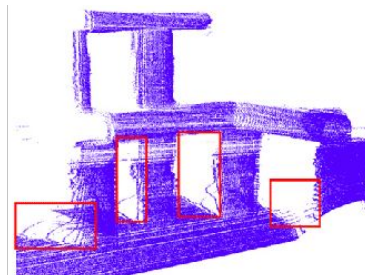
Sensors → Perception → World Model → Planning → Control → Action

Perception

- Complex environments



- Noisy observations and sensors



Mask R-CNN for object detection and instance segmentation on Keras and TensorFlow, Waleed et. al., 2017

Rohit Mohan and Abhinav Valada, "EfficientPS: Efficient Panoptic Segmentation", arXiv preprint arXiv:2004.02307, 2020. Patil, Ashok Kumar & Kumar, G Ajay & Kim, Tae-Hyoung & Chai, Young-Ho. (2018). Hybrid approach for alignment of a pre-processed three-dimensional point cloud, video, and CAD model using partial point cloud in retrofitting applications.

International Journal of Distributed Sensor Networks. 14. 155014771876645. 10.1177/1550147718766452.

Unknown, Open World

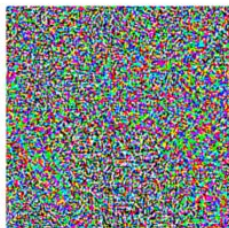
- Unknown world → Many unlabelled samples
- Uncertainty estimation
- Adversarial attacks



“panda”

57.7% confidence

+ .007 ×



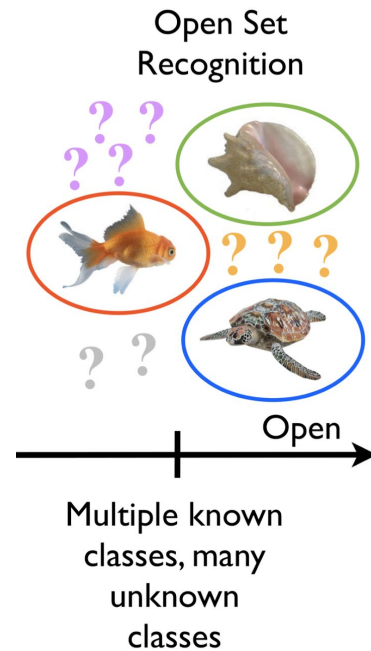
noise

=



“gibbon”

99.3% confidence



Towards Open Set Recognition, Scheirer et. al., 2012

Explaining and Harnessing Adversarial Examples, Goodfellow et. al., 2014

Autonomous Decision Making

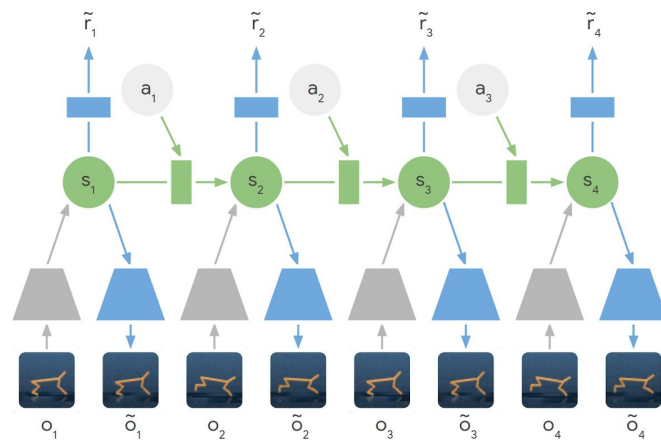
- Reinforcement learning for short- and long-term decision making



Reinforcement Learning

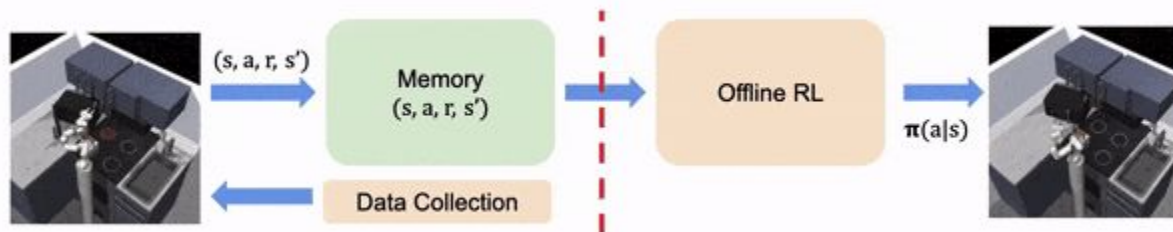
- Model free RL
 - Adapts to complex scenarios
 - Directly optimise policy
 - Data intensive

- Model-based RL
 - Learns a world model
 - Promise of better generalisation



Expensive Real World Data

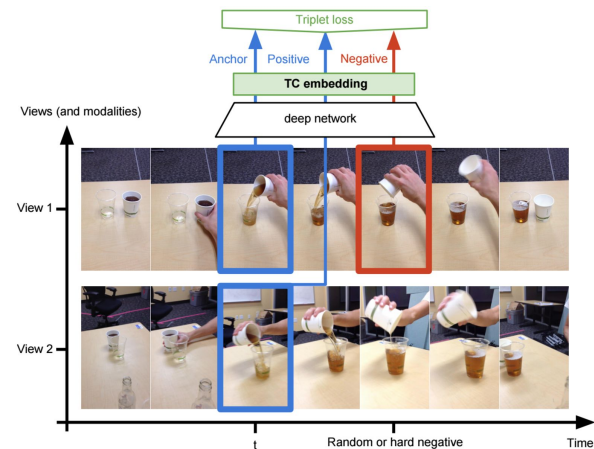
- Sim2Real
 - Domain adaptation
 - Action and dynamics noise
- Offline RL
 - Large amounts of unstructured data
 - Little annotated / expert data



Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection. Sergey Levine, Peter Pastor, Alex Krizhevsky, Deirdre Quillen
D4RL: Datasets for Deep Data-Driven Reinforcement Learning, Justin Fu, Aviral Kumar, Ofir Nachum, George Tucker, Sergey Levine

Weak- and Self-Supervision

- Provide labels for simpler tasks
 - Object presence and absence
 - Consistency over time
 - Viewpoint invariance
- Reduce oversight
 - Automatic resets
 - Reward labelling

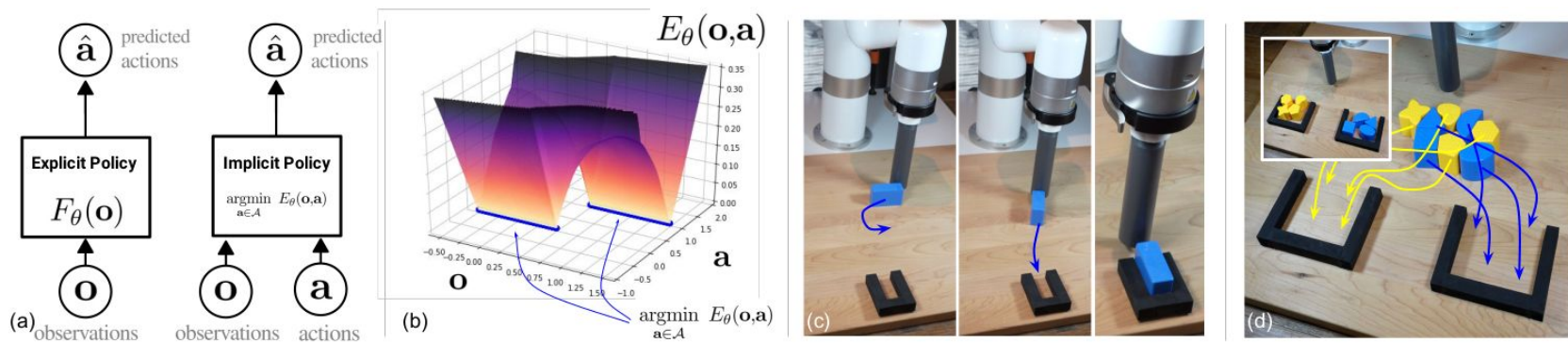


Time-Contrastive Networks: Self-Supervised Learning from Video, Sermanet et. al., 2018
TossingBot: Learning to Throw Arbitrary Objects, Zeng et. al., 2019.

Seminar Topics

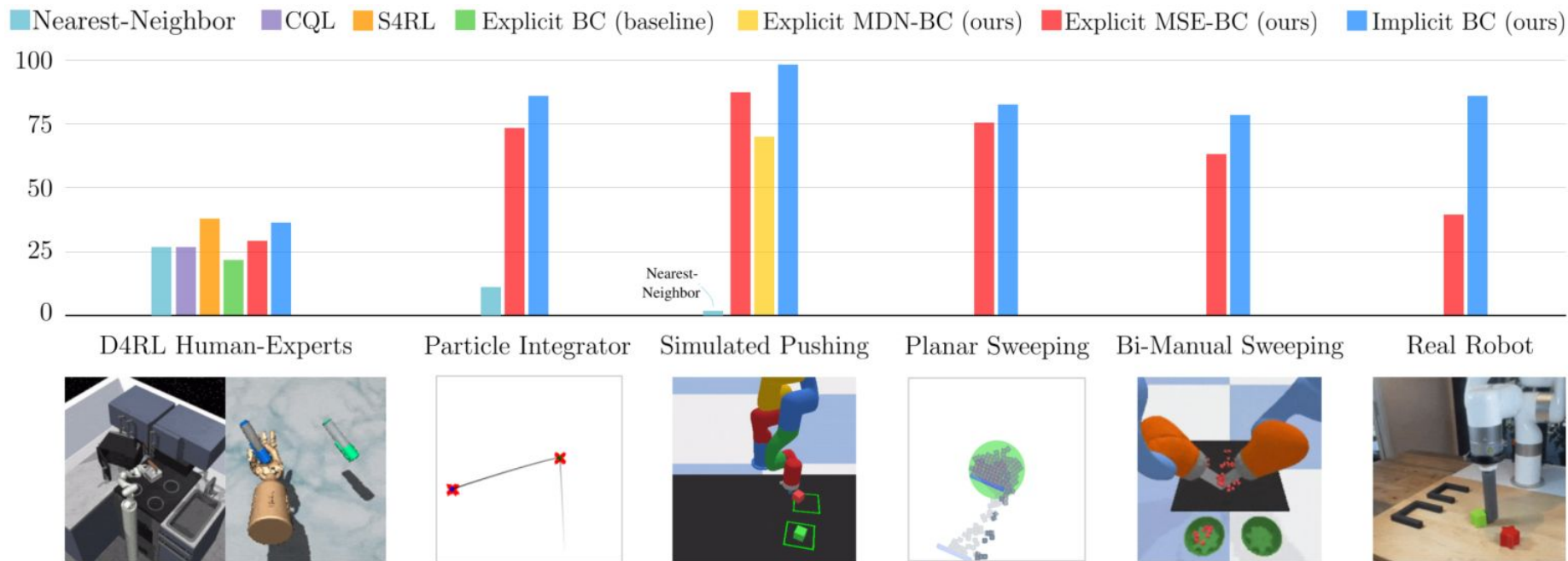
1. Implicit Behavioral Cloning

- Behavioral Cloning is one of the easiest methods to learn real-world robotic skills
- Propose policy to be modeled implicitly, not explicitly
- Demonstrate great improvement in contact-rich and discontinuous tasks through experimentation



Source: Florence et al.

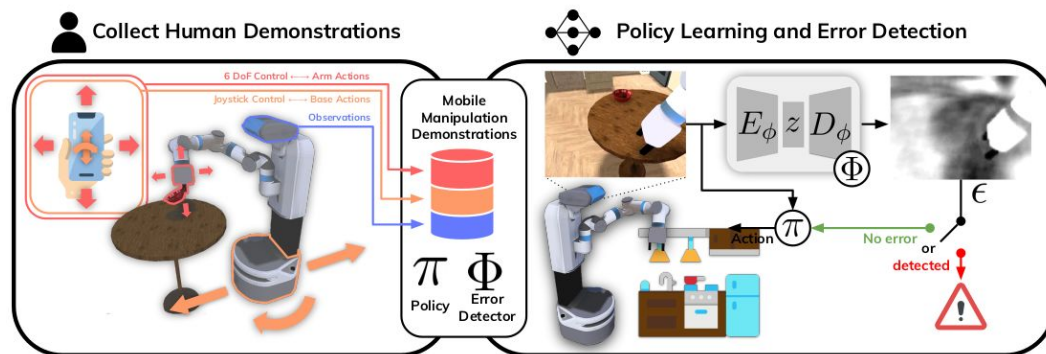
1. Implicit Behavioral Cloning



Source: Florence et al.

2. Error-Aware Imitation Learning from Teleoperation Data for Mobile Manipulation

- An approach to efficiently collect human demonstrations for mobile manipulation and learn long-horizon tasks from them
- Learned detection of out-of-distribution states
- Evaluation in a realistic simulated kitchen environment



Source: Wong et al.

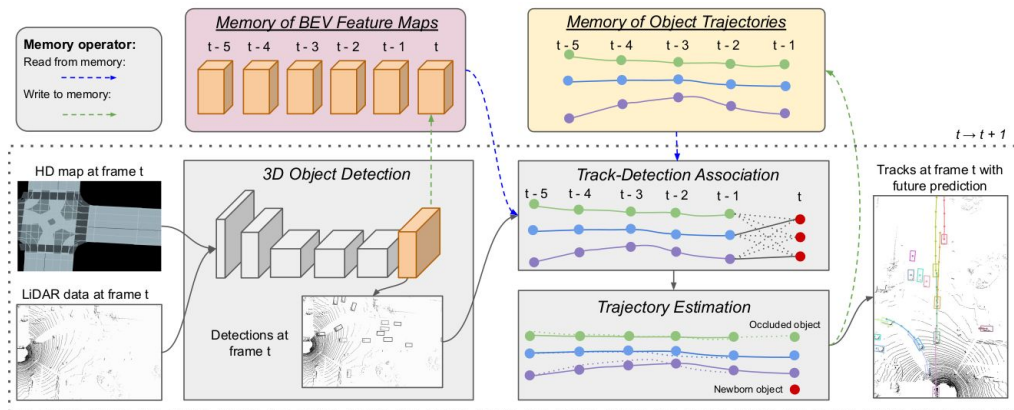
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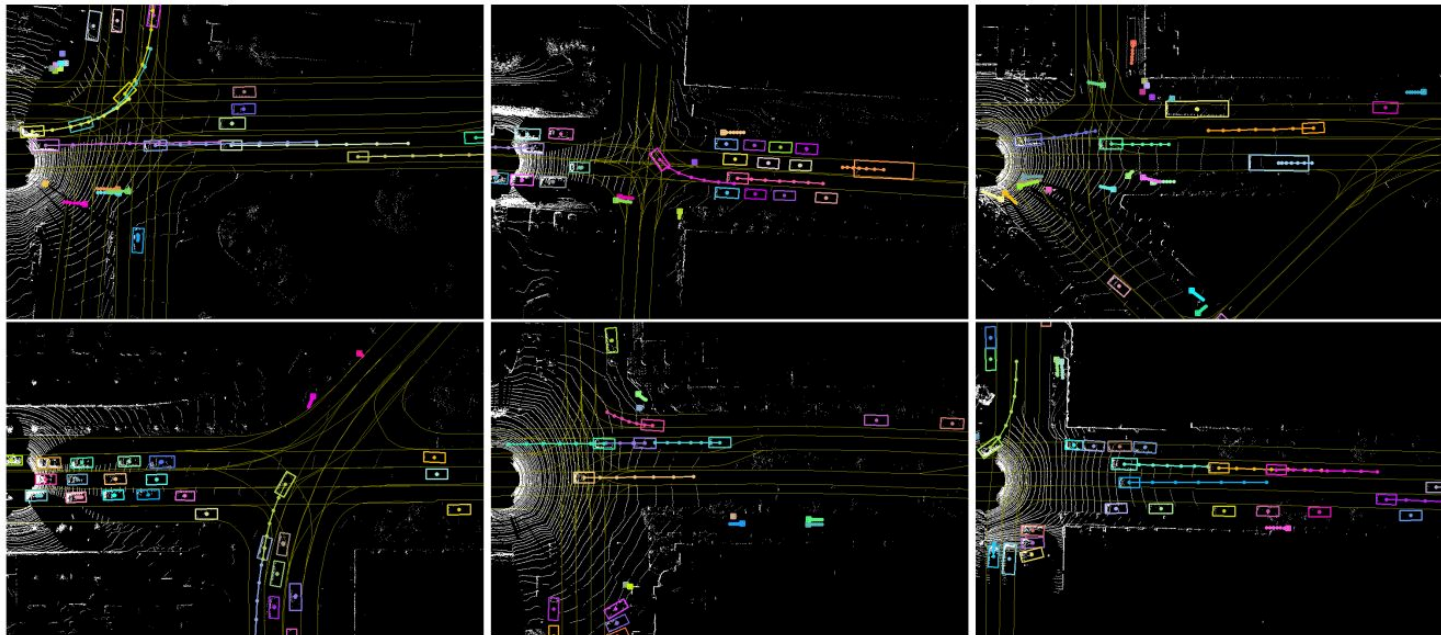
3. PnPNet: End-to-End Perception and Prediction in autonomous driving with Tracking in the Loop

- End-to-end approach for object detection, tracking, and prediction in autonomous driving
- Utilizes joint trajectory representation in tracking and prediction
- Shows greater robustness against long-term occlusions



Source: Liang et. al.

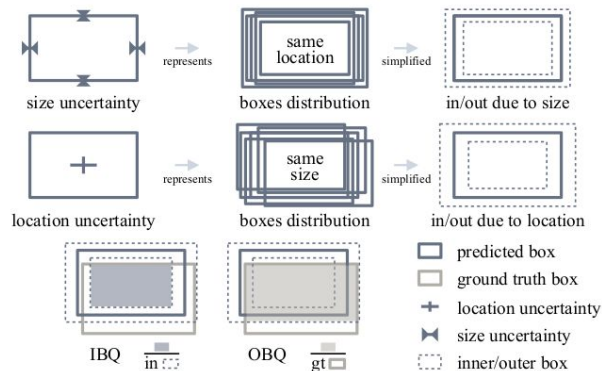
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Source: Liang et. al.

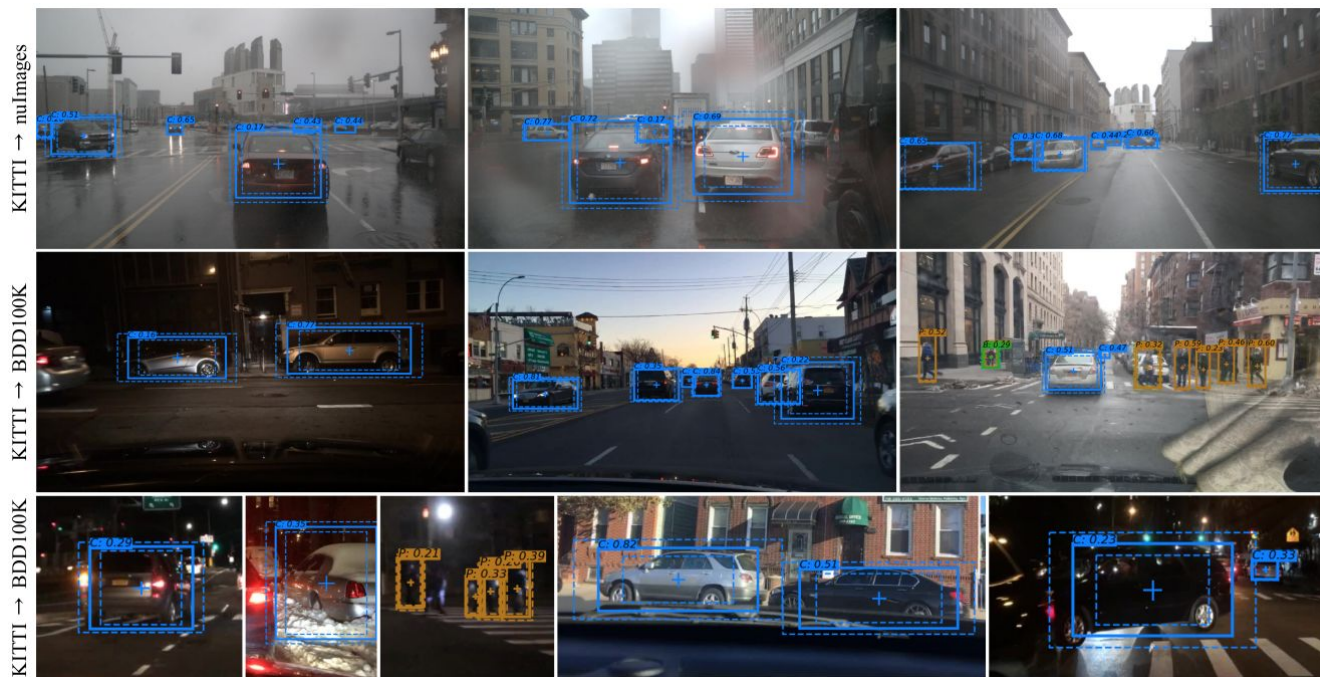
4. CertainNet: Sampling-free Uncertainty Estimation for Object Detection

- Approach for assessing uncertainty in each output of a detection network
- Mapping of images to a hyper space, which is used to determine uncertainty in objectness, location, size, and class
- Transfers better to out-of-domain data than competing approaches



Source: Liang et. al.

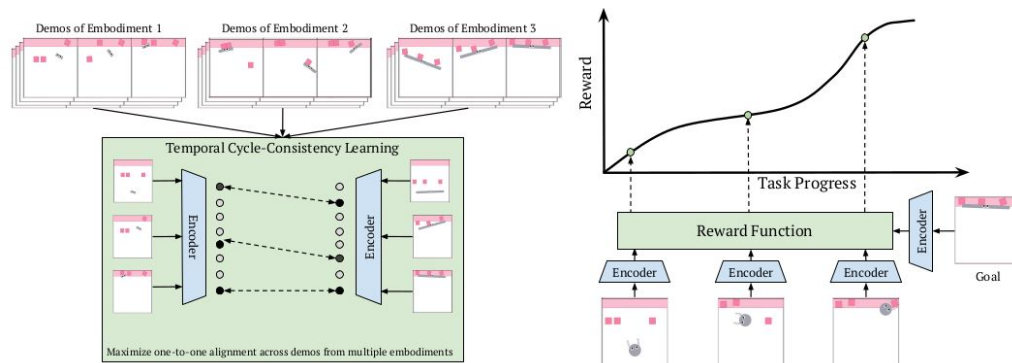
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Source: Gasperini et. al.

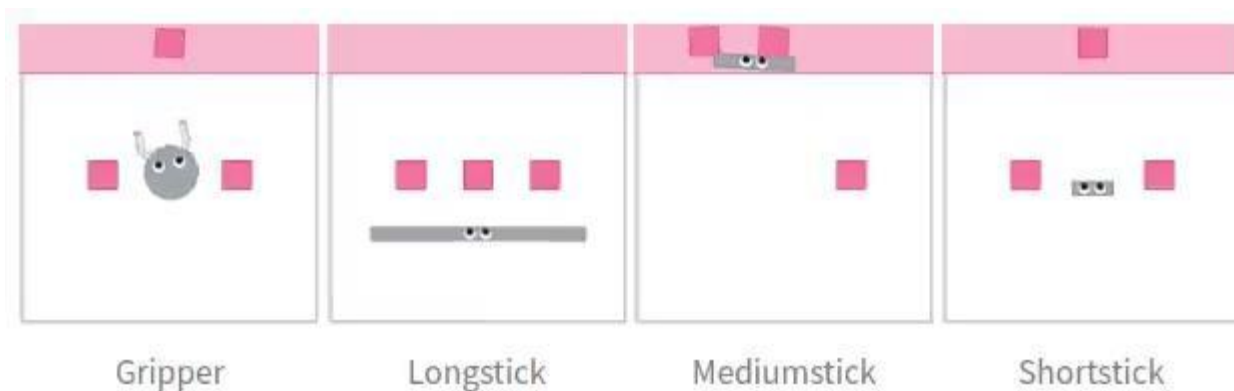
5. XIRL: Cross-embodiment Inverse Reinforcement Learning

- Addresses the problem of learning a task from demonstrations of differently embodied agents
- A task progress encoder is used to assess task completion
- Delta in completion provides dense reward for RL task under a given embodiment



Source: Zakka et al.

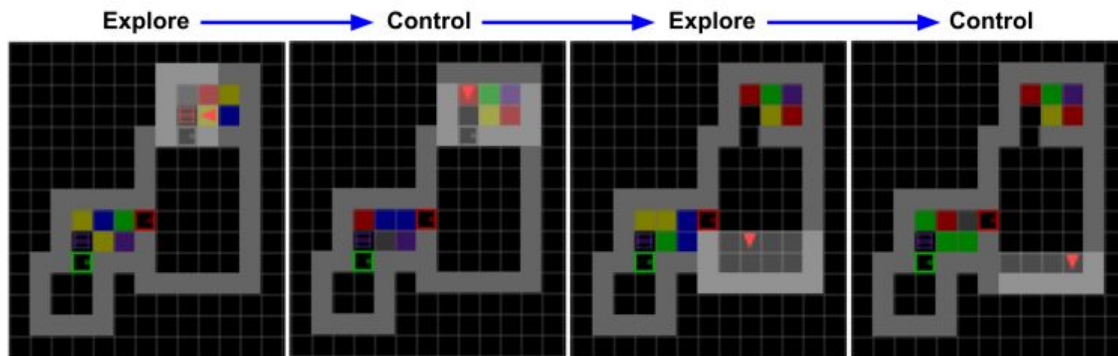
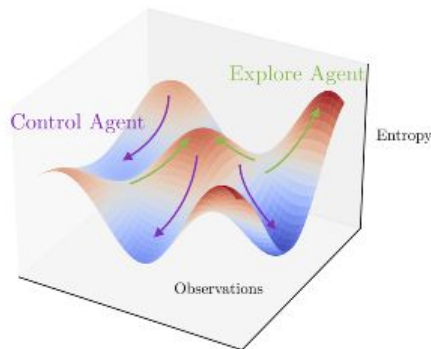
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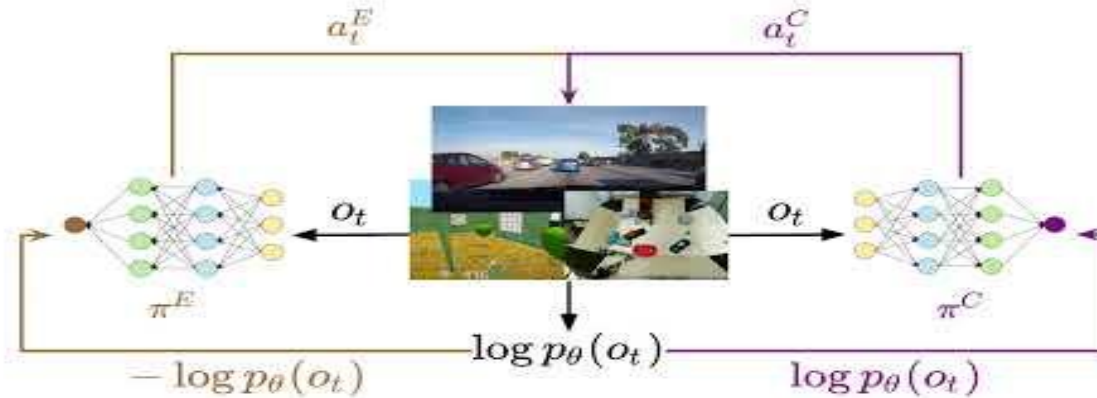
6. Explore and Control with Adversarial Surprise

- Approach to avoid reward engineering by providing intrinsic motivation for exploration based on an adversarial game
- Two policies compete, attempting to either minimize or maximize *surprise*
- The approach learns more quickly and explores more thoroughly than competing baselines



Source: Fickinger et al.

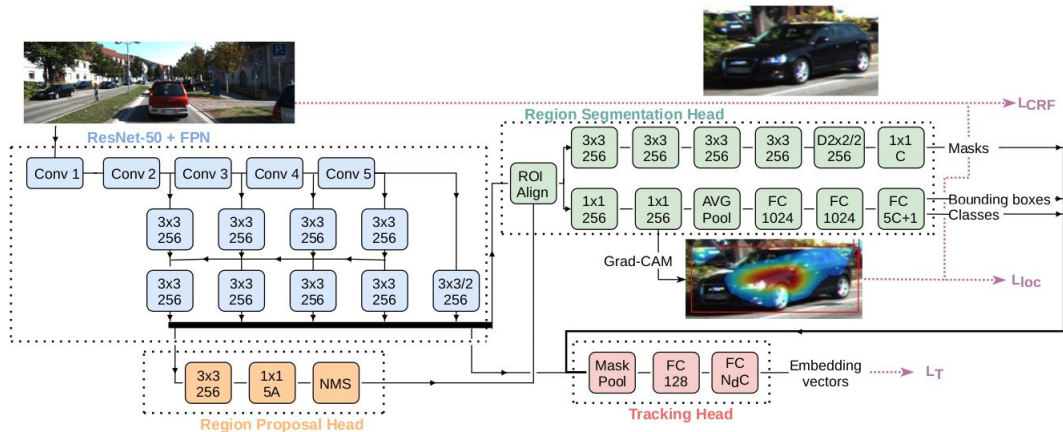
6. Explore and Control with Adversarial Surprise



The force of our approach is the information-theoretic formulation of the game, which makes it general and theoretically sound.

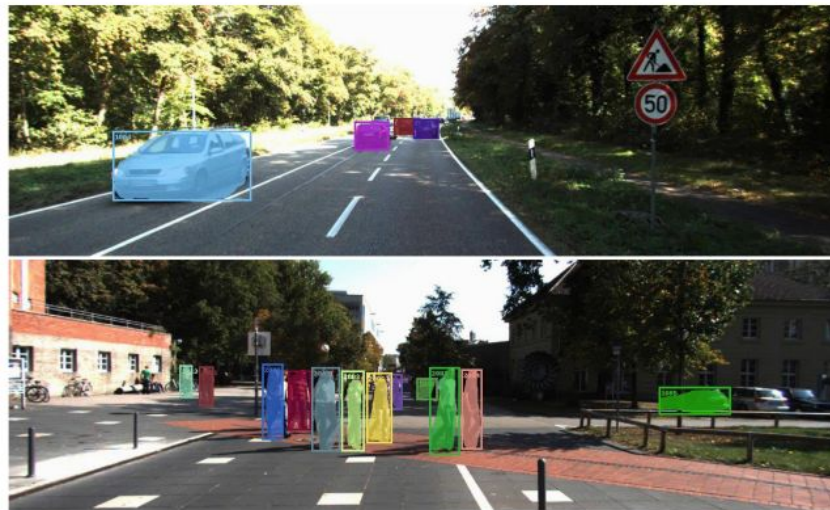
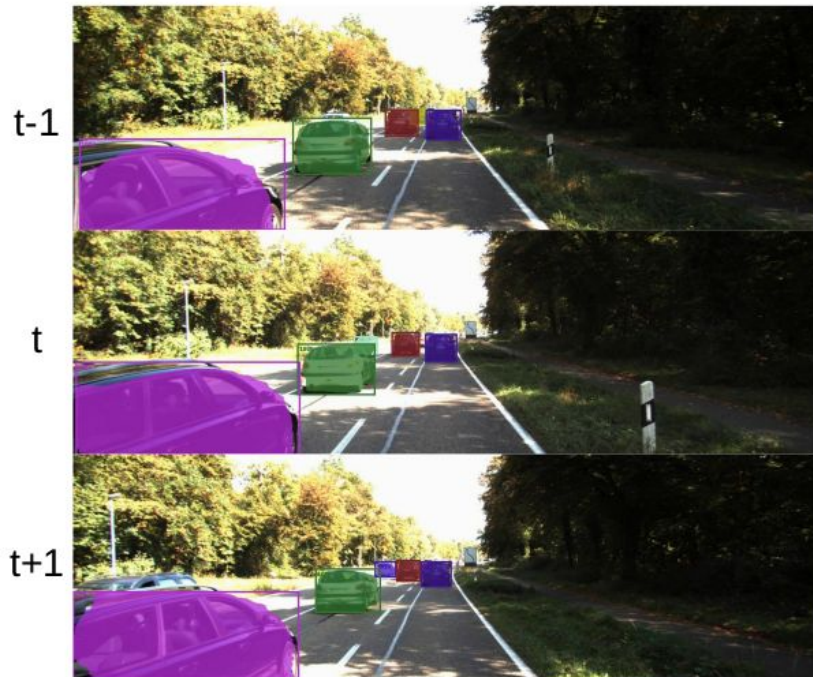
7. Weakly Supervised Multi-Object Tracking and Segmentation

- Addresses high annotation cost for instance segmentation data
- Extracts heatmaps from classification head of network to use as foreground cues
- Uses a supervised learning task to support an unsupervised one



Source: Ruiz et al.

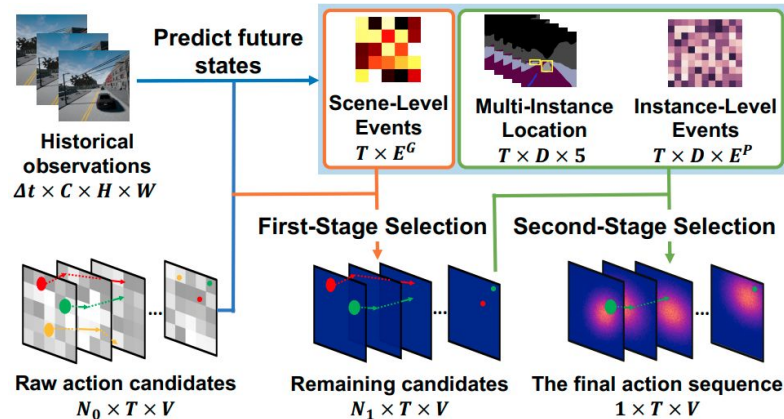
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Source: Ruiz et al.

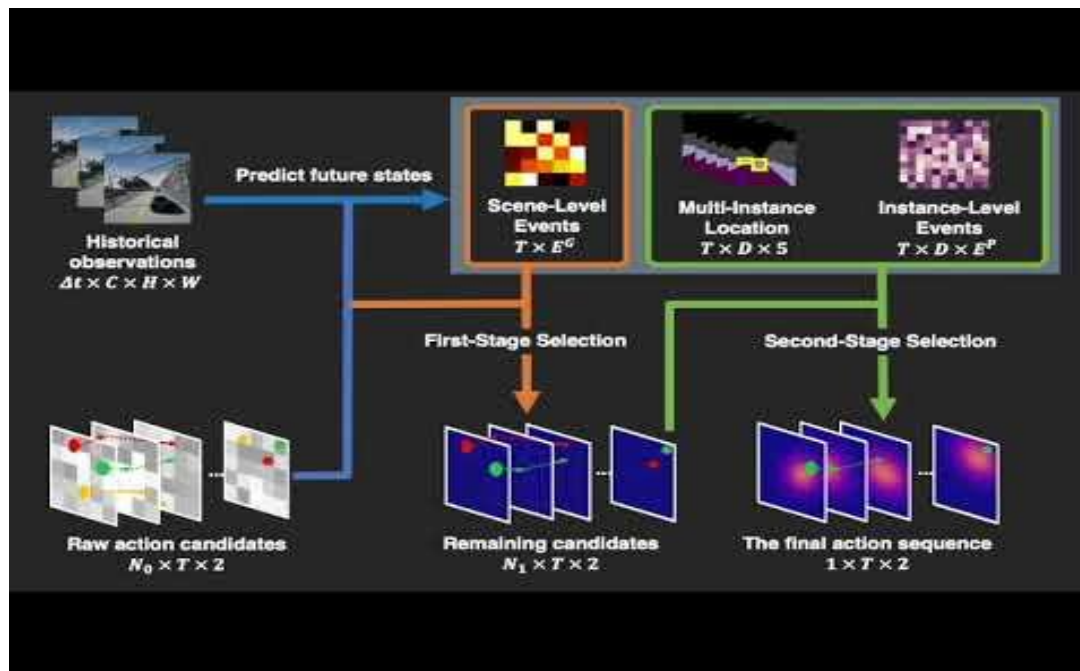
8. Instance-Aware Predictive Navigation in Multi-Agent Environments

- Approach for predicting motions in multi agent scenarios and using this prediction to select safe control actions
- Learn to predict multiple hypothetical scenes including agent interactions
- Two-Stage action selection strategy based on prediction capability



Source: Cao et al.

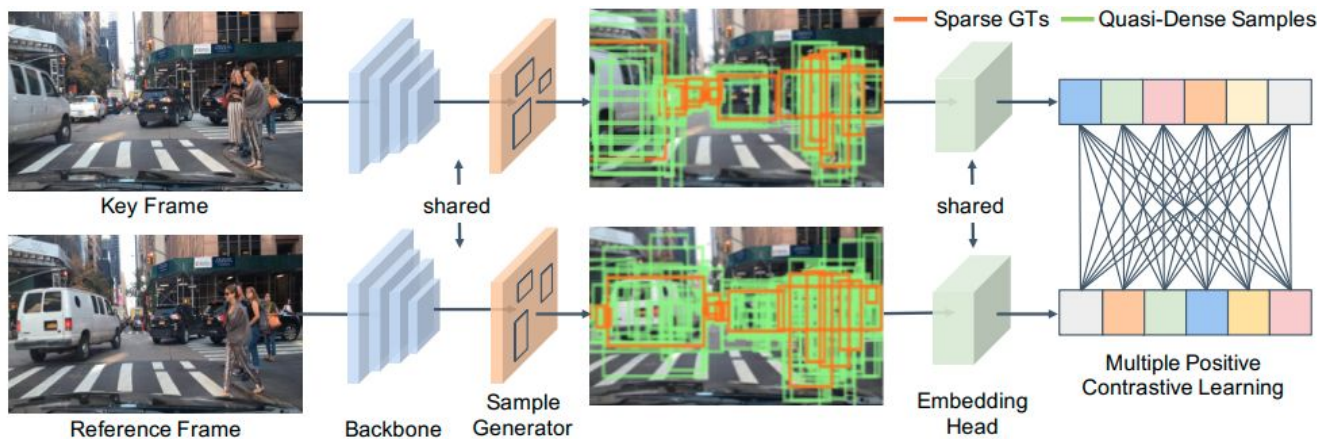
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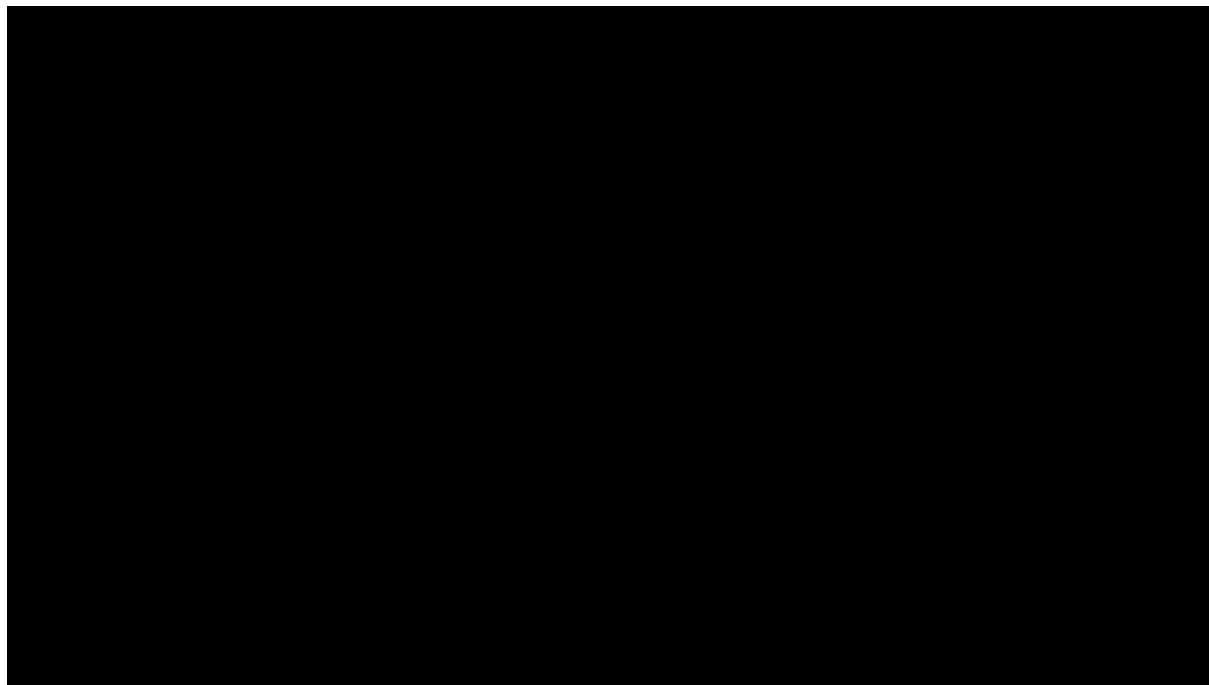
9. Quasi-Dense Similarity Learning for Multiple Object Tracking

- Approach to integrating visual similarity as strong prior in tracking objects
- Learn dense similarity metric between RoIs generated by proposal network
- Nearest neighbor search in embedding space of similarity metric is used to associate regions and match them



Source: Pang et al.

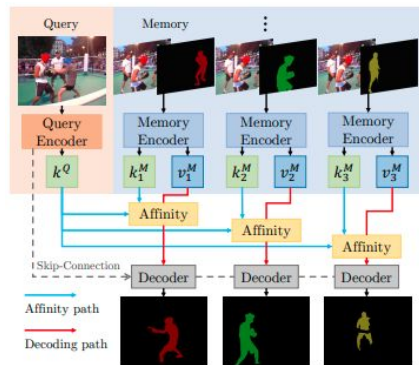
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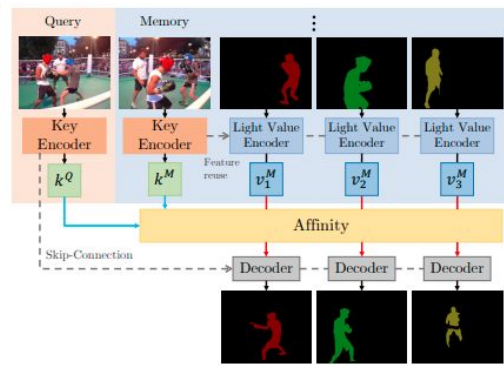
Source: Pang et al.

10. Rethinking Space-Time Networks with Improved Memory Coverage for Efficient Video Object Segmentation

- Approach for video object segmentation
- Learn general RGB correspondence as opposed to object-wise correspondence
- Use and analyze uncommon similarity function



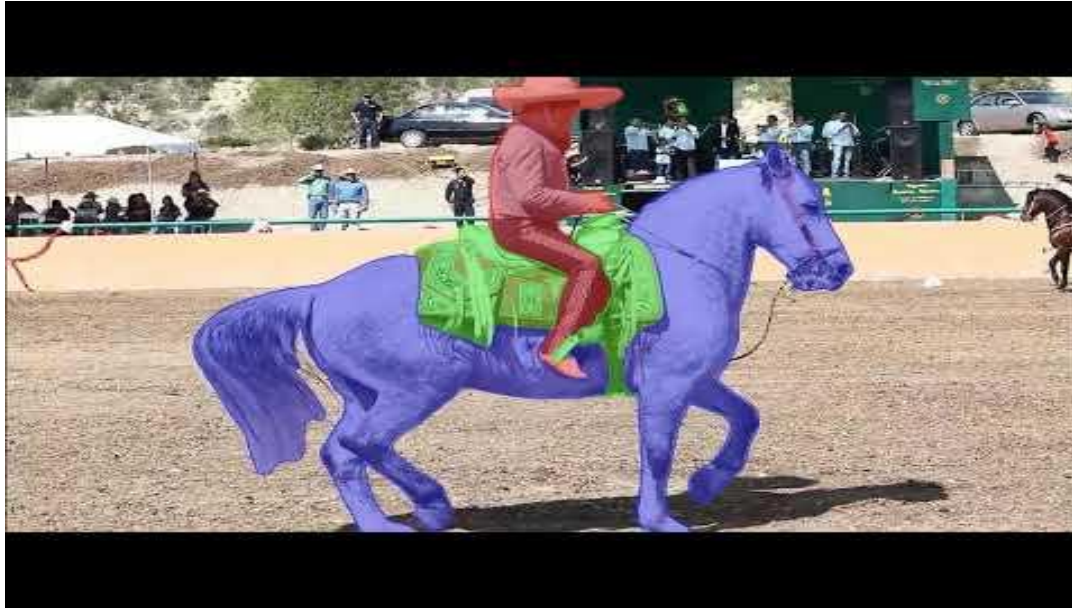
(a) STM and variants



(b) STCN (Ours)

Source: Cheng et al.

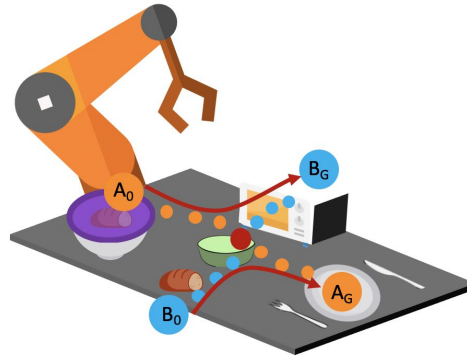
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Source: Cheng et al.

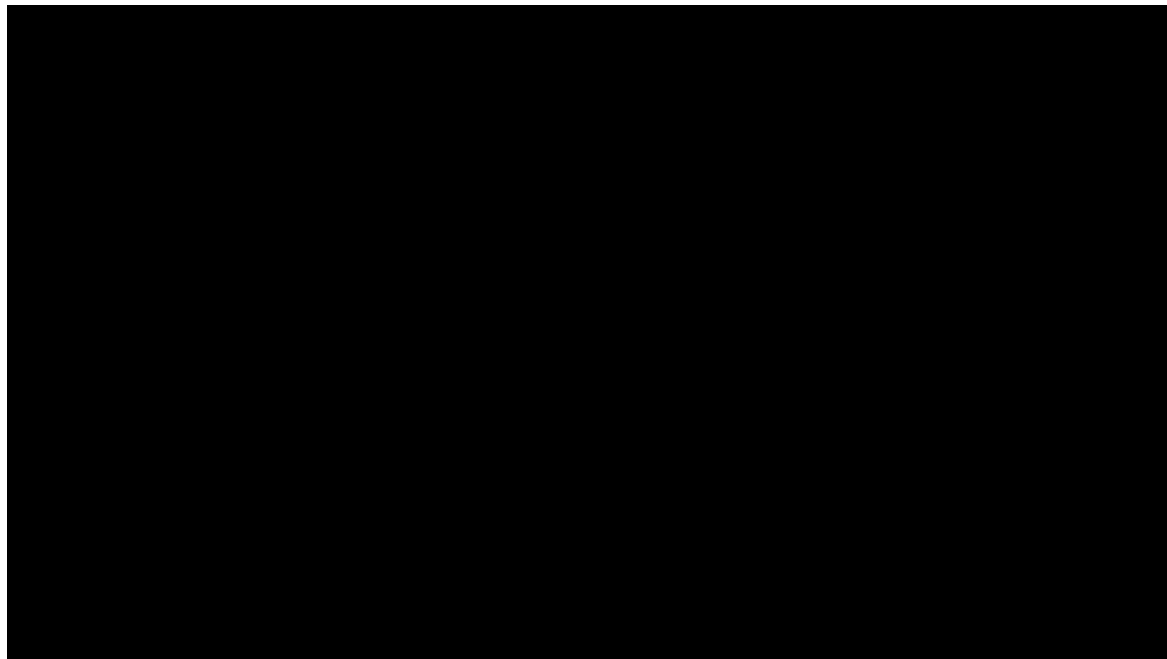
11. GTI: Learning to Generalize Across Long-Horizon Tasks from Human Demonstrations

- Approach to generating policies for novel tasks from separate demonstrations in imitation learning
- Exploit overlap of tasks in latent space to explore task space
- Learned policies are reactive and robust



Source: Mandlekar et al.

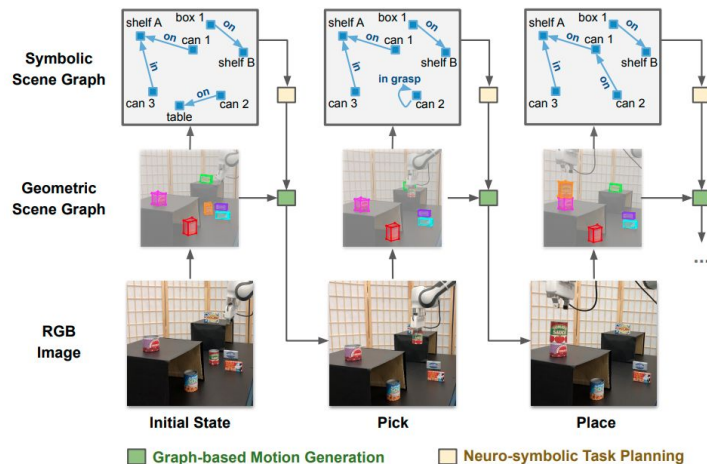
11. GTI: Learning to Generalize Across Long-Horizon Tasks from Human Demonstrations



Source: Mandlekar et al.

12. Hierarchical Planning for Long-Horizon Manipulation with Geometric and Symbolic Scene Graphs

- Visually grounded long-horizon planning of rearrangement tasks
- Use visually grounded scenegraph representation to structure task state
- Train two policies: One for high-level planning, one for immediate action selection



Source: Zhu et al.



12. Hierarchical Planning for Long-Horizon Manipulation with Geometric and Symbolic Scene Graphs

Real Robot Experiments

Task Goal

On(Soup, Shelf A) **In(Tomato, Shelf A)**

Next Subgoal: **On(Tomato, Prepush Area)**



symbolic scene graph

Source: Zhu et al.

Questions