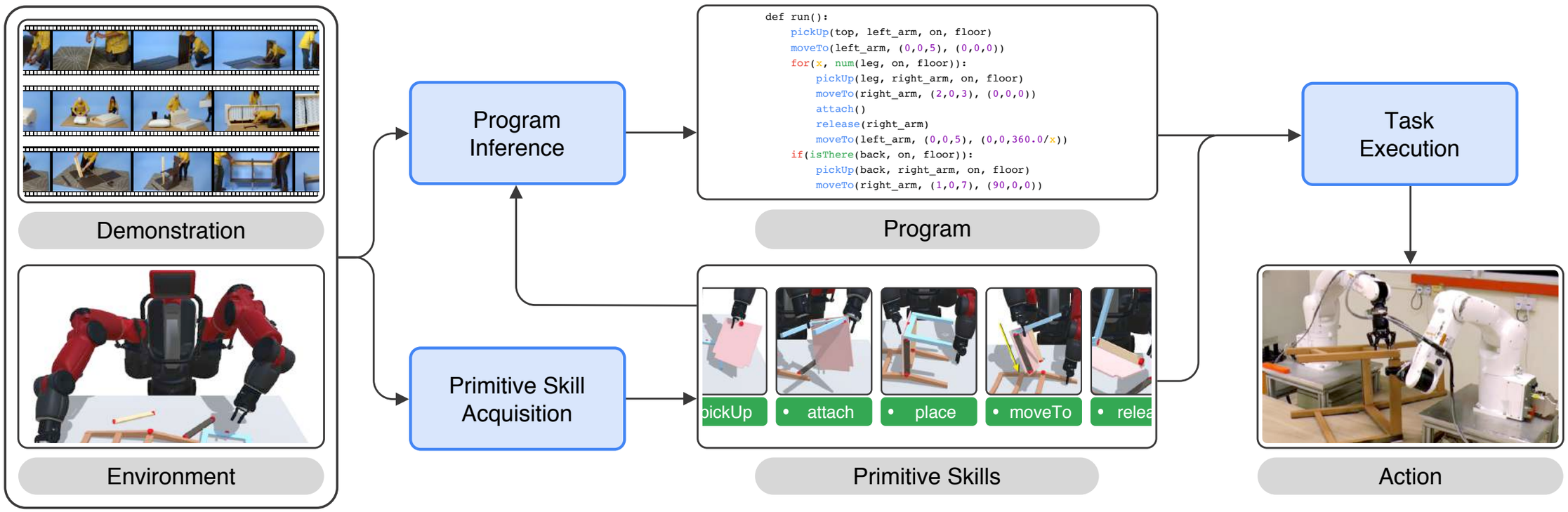
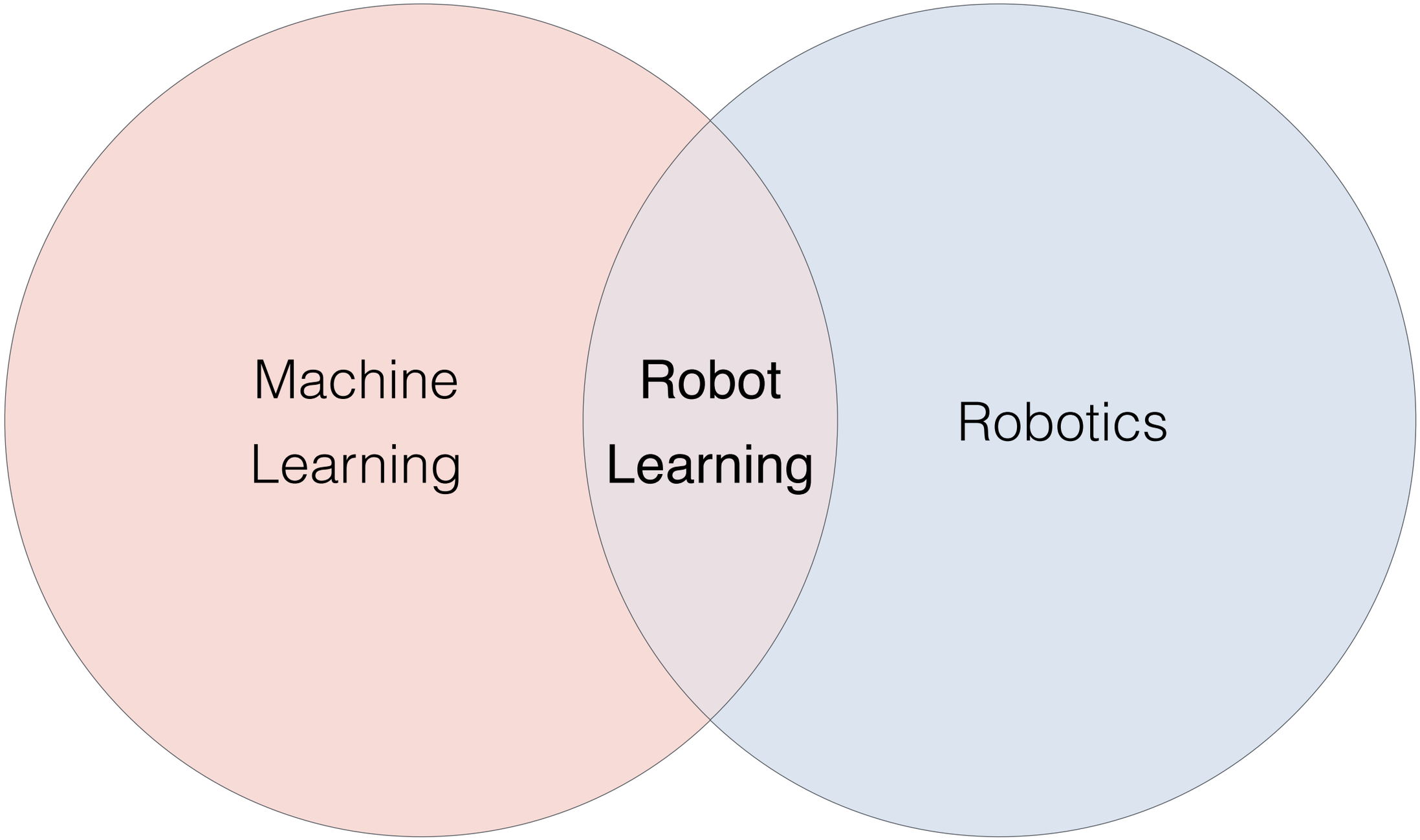
Program-Guided Framework for Interpreting and Acquiring Complex Skills with Learning Robots

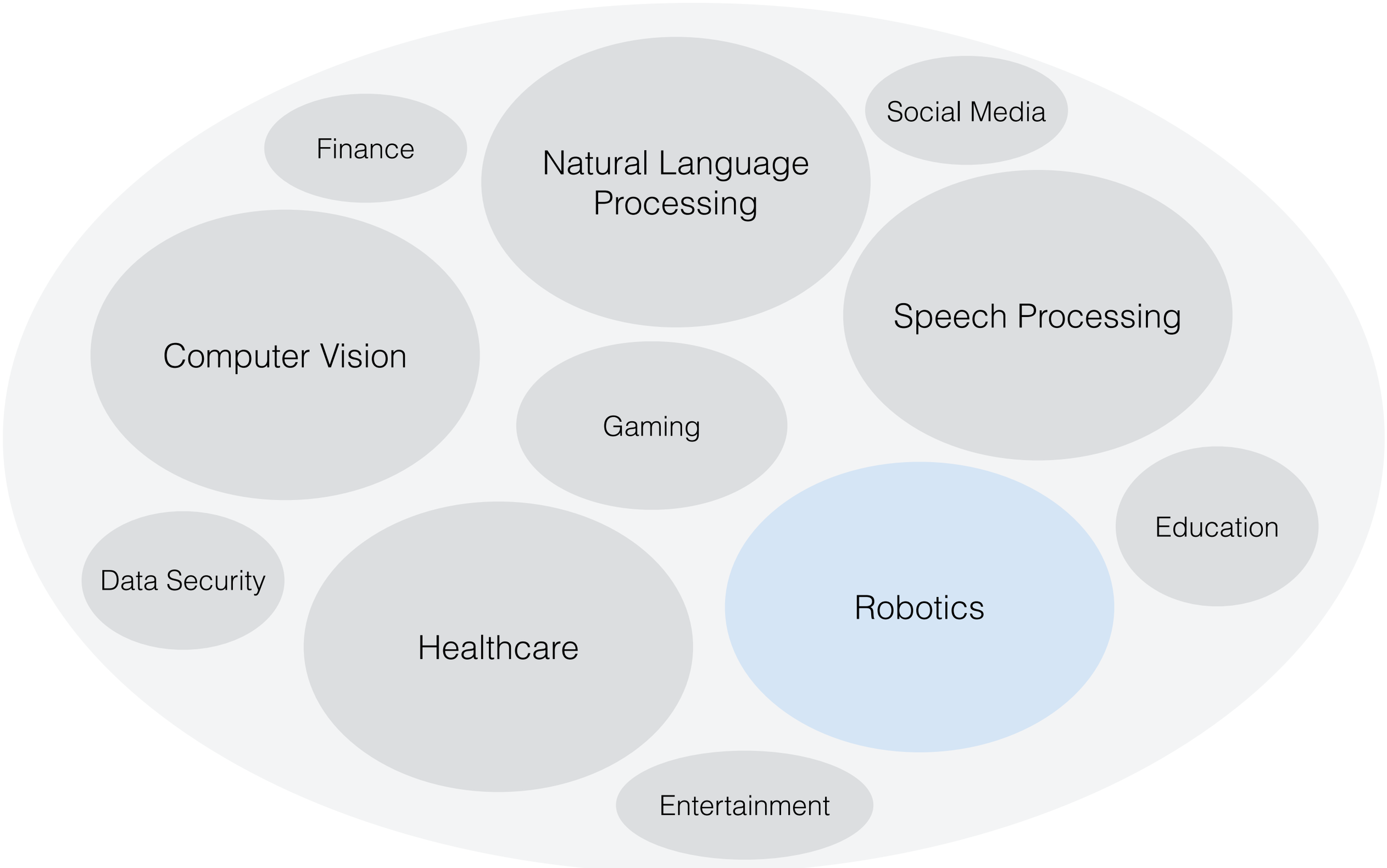


Shao-Hua Sun

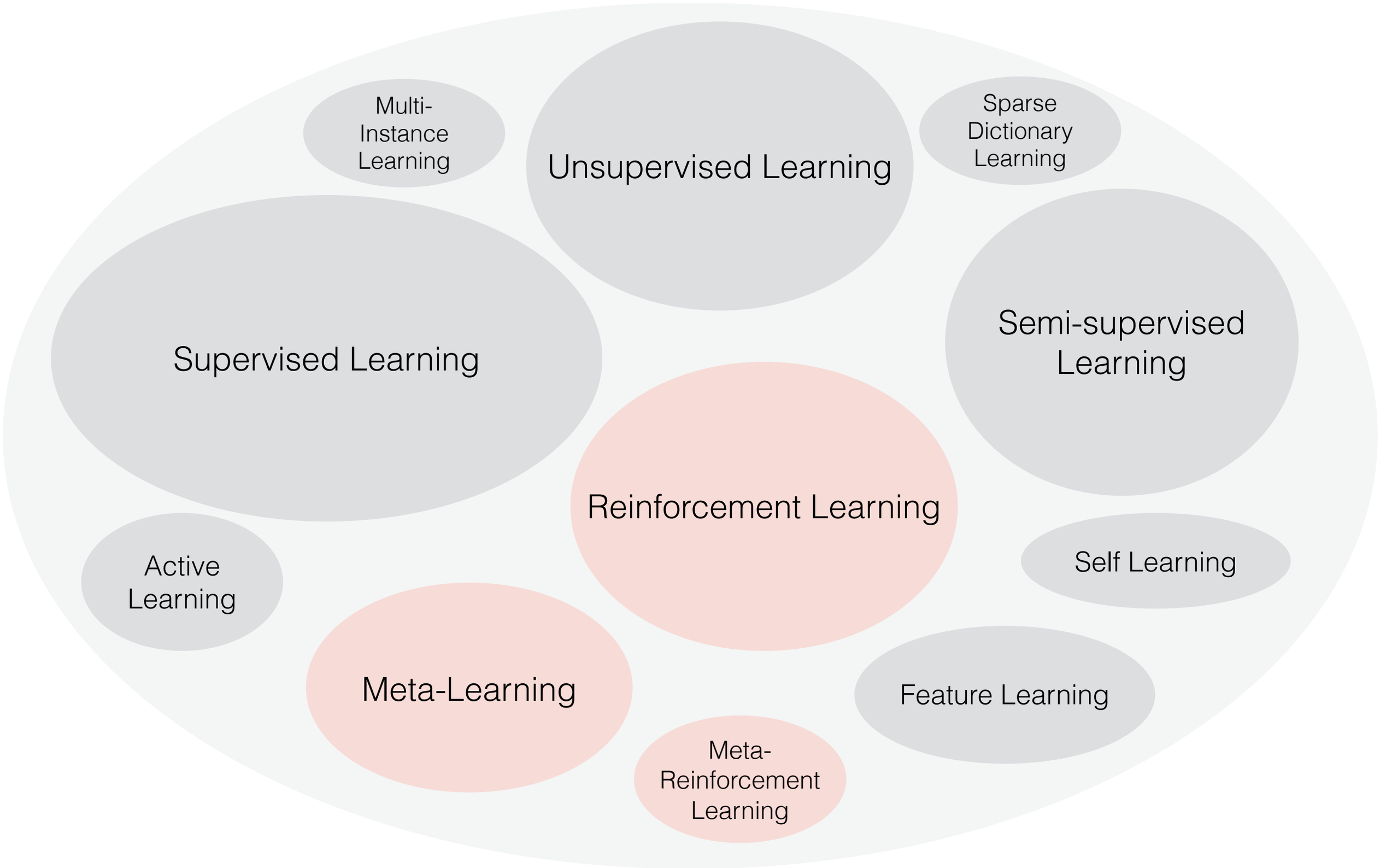
Ph.D. candidate in Computer Science
at the University of Southern California (USC)


Machine
Learning
Robot
Learning
Robotics

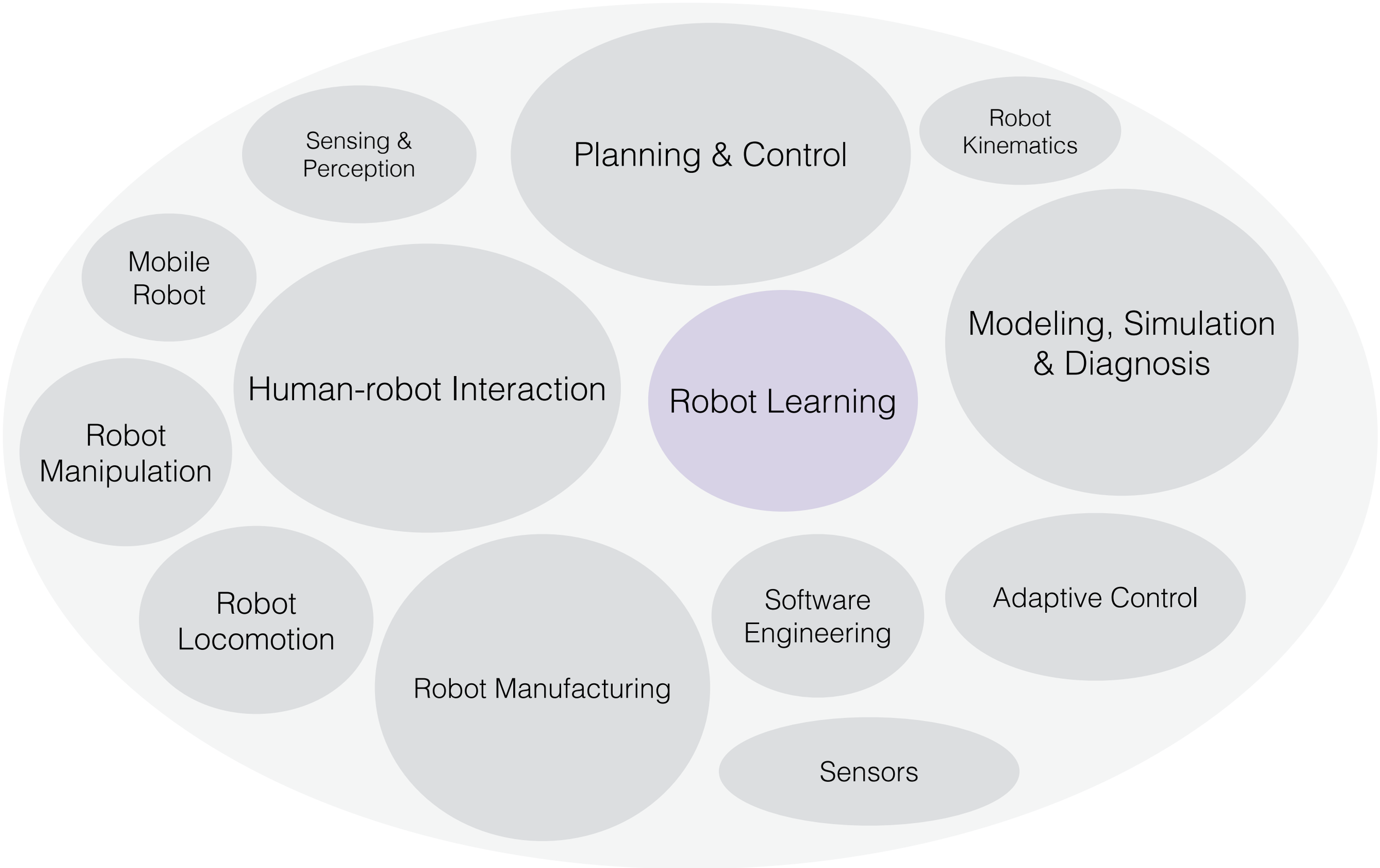
Applications of AI



Learning Problems



Robotics


Sensing & Perception
Planning & Control
Robot Kinematics
Mobile Robot
Modeling, Simulation & Diagnosis
Human-robot Interaction
Robot Learning
Robot Manipulation
Robot Locomotion
Robot Manufacturing
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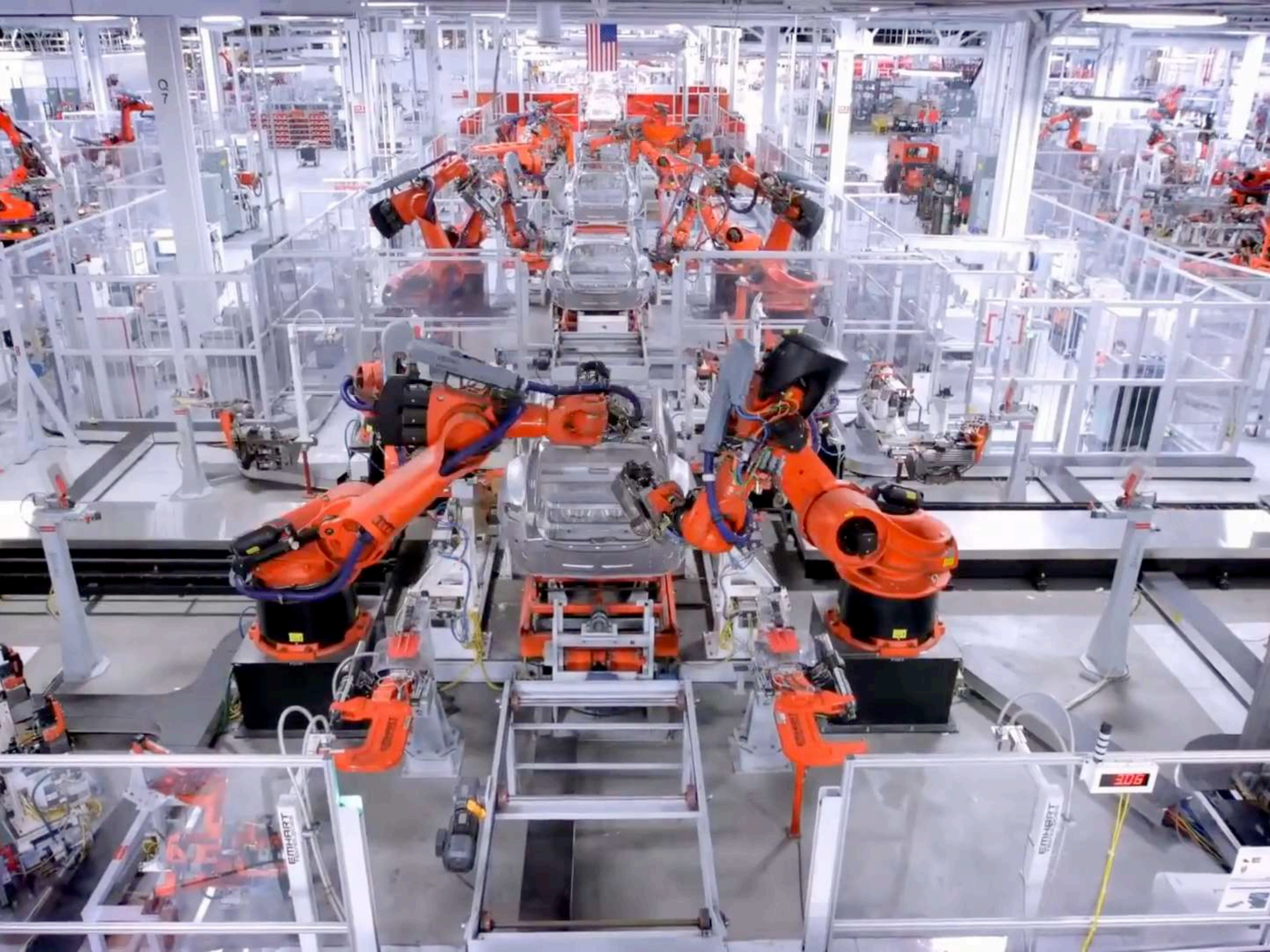
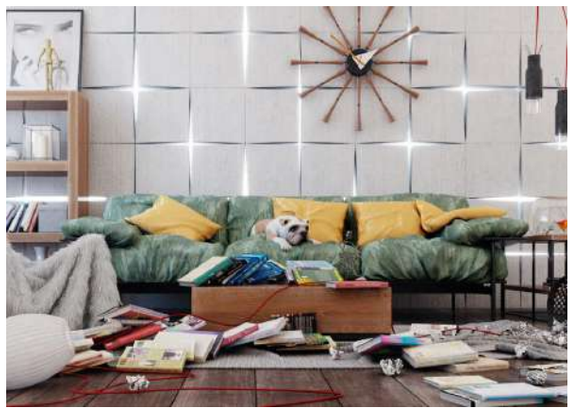

306

Robot Learning

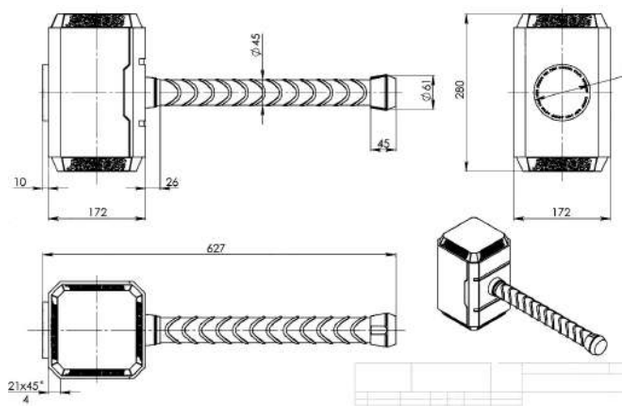
Environment

Structured



Unstructured

Object



Known

Unseen

Task

Pre-defined / Pre-programmed

Diverse and Novel

Supervised Learning

Image Classification

Model	image size	# parameters	Mult-Adds	Top 1 Acc. (%)	Top 5 Acc. (%)
Inception V2 [29]	224×224	11.2 M	1.94 B	74.8	92.2
NASNet-A (5 @ 1538)	**299×299**	**10.9 M**	**2.35 B**	**78.6**	**94.2**
Inception V3 [60]	299×299	23.8 M	5.72 B	78.8	94.4
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NASNet-A (7 @ 1920)	**299×299**	**22.6 M**	**4.93 B**	**80.8**	**95.3**
ResNeXt-101 (64 x 4d) [68]	320×320	83.6 M	31.5 B	80.9	95.6
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Zoph *et al.* Learning Transferable Architectures for Scalable Image Recognition

Instance Segmentation

Figure 5. More results of **Mask R-CNN** on COCO test images, using ResNet-101-FPN and running at 5 fps, with 35.7 mask AP (Table 1).

He *et al.* Mask R-CNN

Visual Question Answering

Method	VQA v2 test-dev				VQA v2 test-std			
	All	Yes/no	Numb.	Other	All	Yes/no	Numb.	Other
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Deeper LSTM Q norm. I [7] as reported in [1]	–	–	–	–	54.22	73.46	35.18	43.83
MCB [7] as reported in [1]	–	–	–	–	62.27	78.82	38.28	53.36
UPMC-LIPS [1]	–	–	–	–	65.71	82.07	41.06	57.12
Athena	–	–	–	–	67.59	82.51	44.19	59.87
LV-NUS	–	–	–	–	66.77	81.80	46.29	58.30
HDU-USYD-UNCC	–	–	–	–	68.09	84.50	45.39	59.01
Proposed model								
ResNet features T=7, single network	62.07	79.20	39.46	52.62	62.27	79.32	38.77	52.59
Image features from bottom-up attention, adaptive K, single network	65.32	81.82	44.21	56.05	65.67	82.20	43.90	56.26
ResNet features T=7, ensemble	66.34	83.36	43.17	57.10	66.73	83.71	43.77	57.20
Image features from bottom-up attention, adaptive K, ensemble	**69.87**	**86.08**	**48.99**	**60.80**	**70.34**	**86.60**	**48.64**	**61.15**

Table 3. Comparison of our best model with competing methods. Excerpt from the official *VQA v2 Leaderboard* [1].

Teney *et al.* Tips and Tricks for Visual Question Answering: Learnings from the 2017 Challenge

Machine Translation

Source	'The reason Boeing are doing this is to cram more seats in to make their plane more competitive with our products,' said Kevin Keniston, head of passenger comfort at Europe's Airbus.
PBMT	'La raison pour laquelle Boeing sont en train de faire, c'est de concentrer davantage de sièges pour prendre leur avion plus compétitive avec nos produits', a déclaré Kevin M. Keniston, chef du confort des passagers de l'Airbus de l'Europe.
GNMT	'La raison pour laquelle Boeing fait cela est de créer plus de sièges pour rendre son avion plus compétitif avec nos produits', a déclaré Kevin Keniston, chef du confort des passagers chez Airbus.
Human	'Boeing fait ça pour pouvoir caser plus de sièges et rendre ses avions plus compétitifs par rapports à nos produits', a déclaré Kevin Keniston, directeur de Confort Passager chez l'avionneur européen Airbus.
Source	When asked about this, an official of the American administration replied: "The United States is not conducting electronic surveillance aimed at offices of the World Bank and IMF in Washington."
PBMT	Interrogé à ce sujet, un responsable de l'administration américaine a répondu : "Les Etats-Unis n'est pas effectuer une surveillance électronique destiné aux bureaux de la Banque mondiale et du FMI à Washington".
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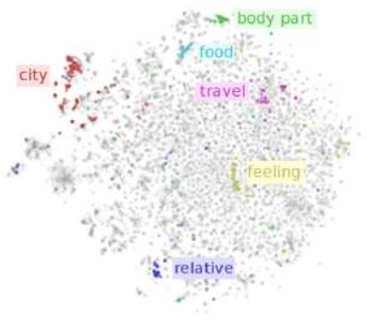
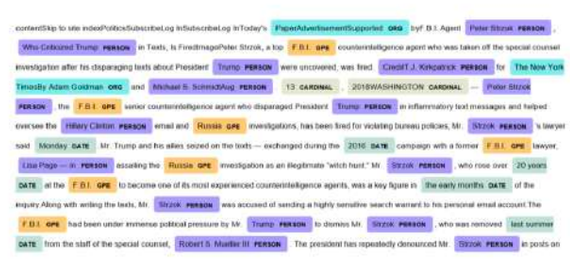
Wu *et al.* Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

Word Embeddings



On word embeddings - Part 1 by Ruder

Named Entity Recognition



Named Entity Recognition and Classification with Scikit-Learn by Susan Li
Esteves *et al.* Named Entity Recognition in Twitter using Images and Text

Question Answering

- Input Question:

```
Where do water droplets collide with ice
crystals to form precipitation?
```

- Input Paragraph:

```
... Precipitation forms as smaller droplets
coalesce via collision with other rain drops
or ice crystals within a cloud. ...
```

- Output Answer:

```
within a cloud
```

System	Dev EM	Dev F1	Test EM	Test F1
Leaderboard (Oct 8th, 2018)				
Human	-	-	82.3	91.2
#1 Ensemble - nlnet	-	-	86.0	91.7
#2 Ensemble - QANet	-	-	84.5	90.5
#1 Single - nlnet	-	-	83.5	90.1
#2 Single - QANet	-	-	82.5	89.3
Published				
BiDAF+ELMo (Single)	-	85.8	-	-
R.M. Reader (Single)	78.9	86.3	79.5	86.6
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5
Ours				
$\text{BERT}_{\text{BASE}}$ (Single)	80.8	88.5	-	-
$\text{BERT}_{\text{LARGE}}$ (Single)	84.1	90.9	-	-
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$\text{BERT}_{\text{LARGE}}$ (Sgl.+TriviaQA)	**84.2**	**91.1**	**85.1**	**91.8**
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Table 2: SQuAD results. The BERT ensemble is 7x systems which use different pre-training checkpoints and fine-tuning seeds.

Devlin *et al.* BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Speech Recognition

Word Error Rate

Senone set	Model/combination step	WER devset ngram-LM	WER test ngram-LM	WER devset LSTM-LMs	WER test LSTM-LMs
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9k	BLSTM+ResNet+LACE+CNN-BLSTM	9.6	7.2	7.7	5.4
9k-puhpurn	BLSTM+ResNet+LACE	9.7	7.4	7.8	5.4
9k-puhpurn	BLSTM+ResNet+LACE+CNN-BLSTM	9.7	7.3	7.8	5.5
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-	Confusion network combination			7.4	5.2
-	+ LSTM rescoring			7.3	5.2
-	+ ngram rescoring			7.2	5.2
-	+ backchannel penalty			7.2	5.1

Xiong *et al.* The Microsoft 2017 Conversational Speech Recognition System

Speech Synthesis (text-to-speech)

Van Den Oord *et al.* WaveNet: A Generative Model for Raw Audio

Supervised Learning

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Zoph *et al.* Learning Transferable Architectures for Scalable Image Recognit

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He *et al.* Mask R-CNN

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Teney *et al.* Tips and Tricks for Visual Question Answering: Learnings from the 2017 Challenge

Machine Translation

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	... c'est de concentrer davantage de ... nos produits", a déclaré Kevin M. ... de l'Europe.
	... plus de sièges pour rendre son ... vin Keniston, chef du confort des
	...rendre ses avions plus compétitifs ...n, directeur de Confort Passager
	...ministration replied: "The United ...t offices of the World Bank and
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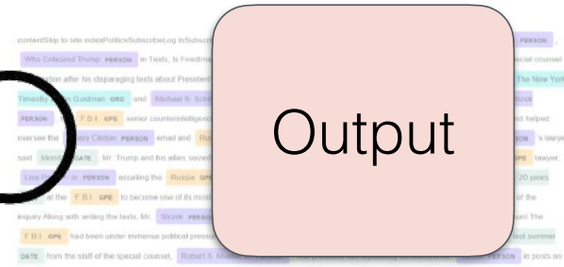
Word Embeddings

On word embeddings - Part 1 by Ruder

Named Entity Recognition

Output



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- Output Answer:
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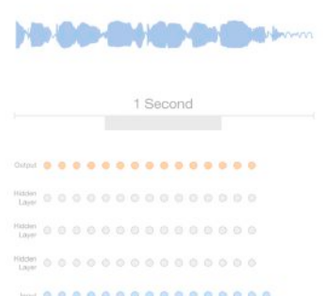

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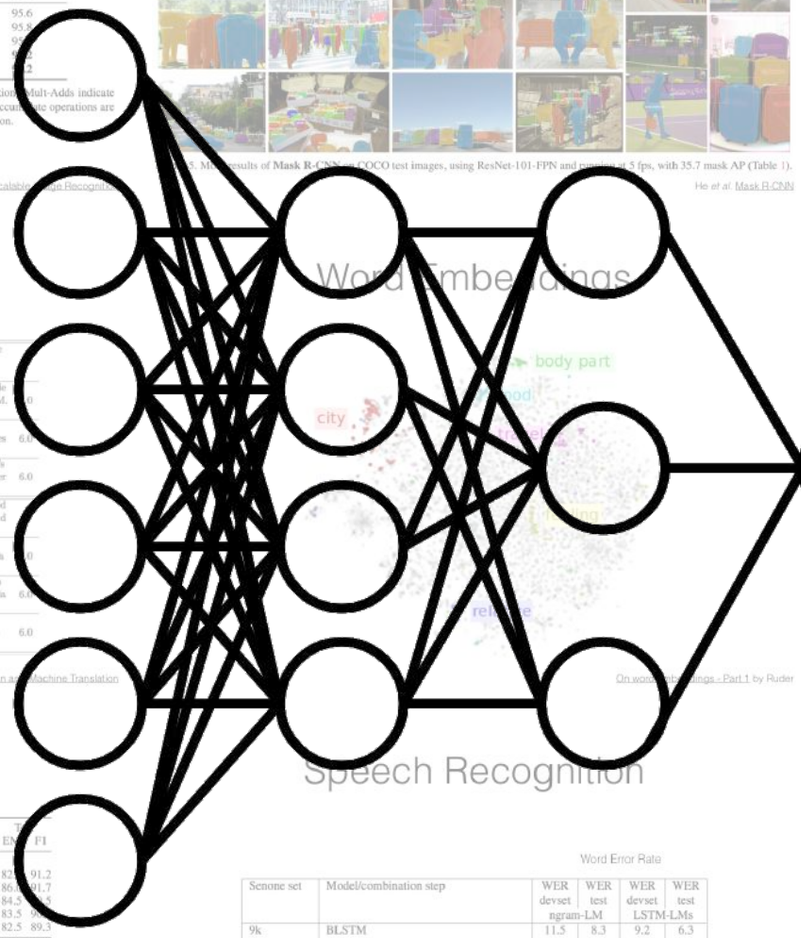

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Zoph *et al.* Learning Transferable Architectures for Scalable [illegible] Recognit[illegible]

Instance Segmentation

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ResNet features 7×7, single network	62.07	79.20	36.66	52.62	62.27	79.32	36.77	52.59
Image features from bottom-up attention, adaptive K, single network	65.32	81.82	44.21	56.05	65.67	82.20	43.90	56.26
ResNet features 7×7, ensemble	66.34	83.36	43.15	57.10	66.93	83.71	43.77	57.20
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Teney *et al.* Tips and Tricks for Visual Question Answering: Learnings from the 2017 Challenge

Word Embeddings

On word embeddings - Part 1 by Ruder

Named Entity Recognition

Named Entity Recognition and Classification with Scikit-Learn by Susan Li
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Question Answering

- Input Question:
  Where do water droplets collide with ice crystals to form precipitation?
- Input Paragraph:
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System	Dev EM	Dev F1	Test EM	Test F1
Leaderboard (Oct 8th, 2018)				
Human	-	-	82.3	91.2
#1 Ensemble - nlnet	-	-	86.0	91.7
#2 Ensemble - QANet	-	-	84.5	90.1
#1 Single - nlnet	-	-	83.5	90.1
#2 Single - QANet	-	-	82.5	89.3
Published				
BiDAF+ELMo (Single)	-	85.8	-	-
R.M. Reader (Single)	78.9	86.3	79.5	86.6
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5
Ours				
$BERT_{BASE}$ (Single)	80.8	88.5	-	-
$BERT_{LARGE}$ (Single)	84.1	90.9	-	-
$BERT_{LARGE}$ (Ensemble)	85.8	91.8	-	-
$BERT_{LARGE}$ (Sgl.+TriviaQA)	**84.2**	**91.1**	**85.1**	**91.8**
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Table 2: SQuAD results. The BERT ensemble is 7x systems which use different pre-training checkpoints and fine-tuning seeds.

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Speech Recognition

Word Error Rate

Senone set	Model/combination step	WER devset ngram-LM	WER test ngram-LM	WER devset LSTM-LMs	WER test LSTM-LMs
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27k	BLSTM	11.4	8.0	9.3	6.3
27k-puhpurn	BLSTM	11.3	8.0	9.2	6.3
9k	BLSTM+ResNet+LACE+CNN-BLSTM	9.6	7.2	7.7	5.4
9k-puhpurn	BLSTM+ResNet+LACE	9.7	7.4	7.8	5.4
9k-puhpurn	BLSTM+ResNet+LACE+CNN-BLSTM	9.7	7.3	7.8	5.5
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-	Confusion network combination			7.4	5.2
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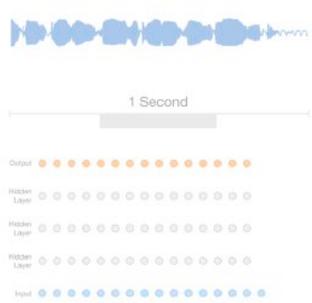
Xiong *et al.* The Microsoft 2017 Conversational Speech Recognition System

Speech Synthesis (text-to-speech)



Van Den Oord *et al.* WaveNet: A Generative Model for Raw Audio

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Inception ResNet V2 [58]	299×299	55.8 M	13.2 B	80.1	95.1
NASNet-A (7 @ 1920)	**299×299**	**22.6 M**	**4.93 B**	**80.8**	**95.3**
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Zoph *et al.* Learning Transferable Architectures for Scalable Image Recognition

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Fig. 5. More results of **Mask R-CNN** on COCO test images, using ResNet-101-FPN and running at 5 fps, with 35.7 mask AP (Table 1).

He *et al.* Mask R-CNN

Visual Question Answering

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LSTM Language-only (blind model) [1]	-	-	-	-	44.26	67.01	31.55	27.37
Deeper LSTM Q norm. I [7] (as reported in [1])	-	-	-	-	54.22	73.46	35.18	41.83
MCB [7] (as reported in [1])	-	-	-	-	62.27	78.82	38.28	53.36
UPMC-LIP6 [1]	-	-	-	-	65.71	82.07	41.06	57.12
Athena	-	-	-	-	67.59	82.51	44.19	59.87
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Teney *et al.* Tips and Tricks for Visual Question Answering: Learnings from the 2017 Challenge

English sentence

France is never cold in September

French sentence

la france est jamais froid en septembre

Machine Translation

GNMT	Etats-Unis n'effectuent pas de surveillance électronique à l'intention des bureaux de la Banque mondiale et du FMI à Washington".
	Interrogé sur le sujet, un responsable de l'administration américaine a répondu: "les Etats-Unis ne mènent pas de surveillance électronique visant les sièges de la Banque mondiale et du FMI à Washington".
Human	6.0

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Speech Recognition

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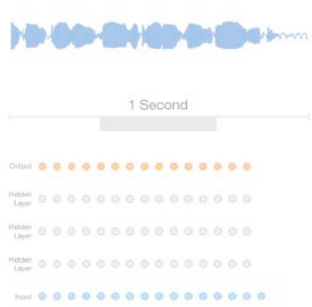
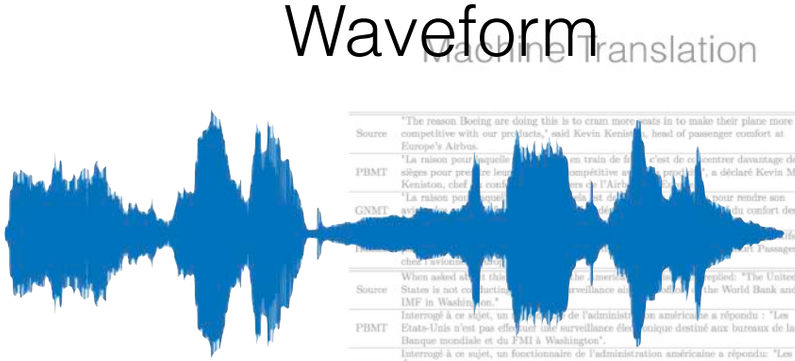
Xiong *et al.* The Microsoft 2017 Conversational Speech Recognition System

Speech Synthesis (text-to-speech)

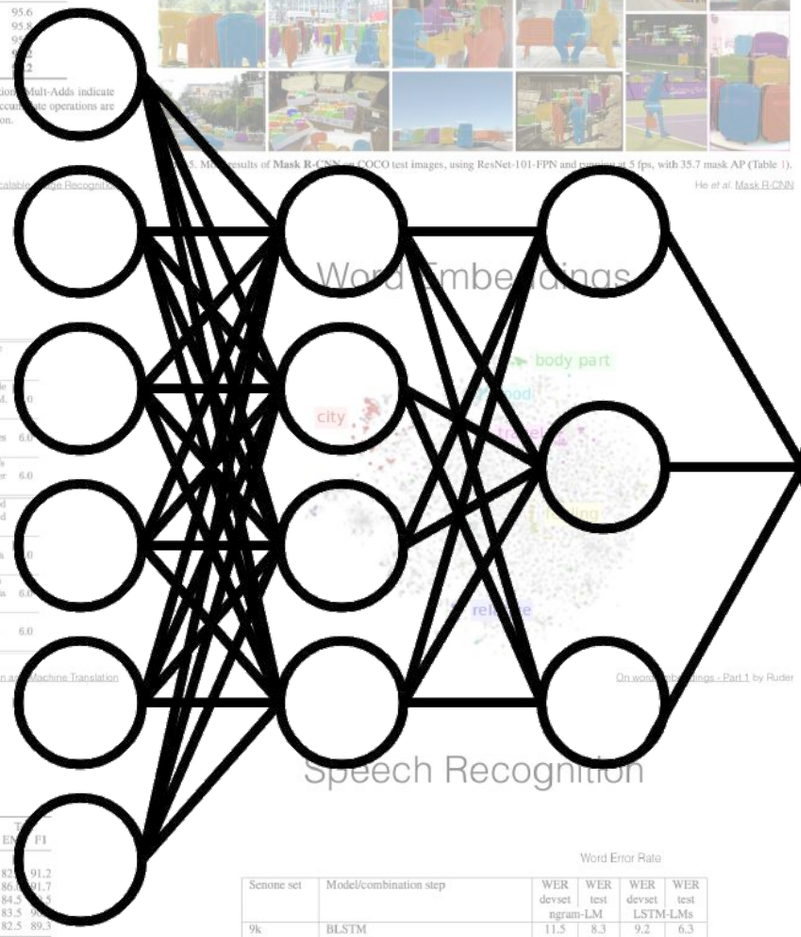


Van Den Oord *et al.* WaveNet: A Generative Model for Raw Audio

Automatic Speech Recognition



Waveform



Text

This is a supervised learning method

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Zoph *et al.* Learning Transferable Architectures for Scalable Image Recognition

Instance Segmentation

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Deeper LSTM Q norm. I [7] (as reported in [·])	-	-	-	-	54.22	73.46	35.18	41.83
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UPMC-LIP6 [·]	-	-	-	-	65.71	82.07	41.06	57.12
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Teney *et al.* Tips and Tricks for Visual Question Answering: Learnings from the 2017 Challenge

Machine Translation

Source	"The reason Boeing are doing this is to cram more seats in to make their plane more competitive with our products," said Kevin Keniston, head of passenger comfort at Europe's Airbus.
PBMT	"La raison pour laquelle [illegible] est de se concentrer davantage de sièges pour pouvoir [illegible] compétitive [illegible], a déclaré Kevin M. Keniston, chef [illegible]
GNMT	"La raison pour [illegible] pour rendre son [illegible] du confort des
Source	When asked about this [illegible] replied: "The United States is not [illegible] the World Bank and IMF in Washington."
PBMT	Interrogé à ce sujet, un [illegible] a répondu : "Les États-Unis n'est pas [illegible] de la Banque mondiale et du FMI à Washington".
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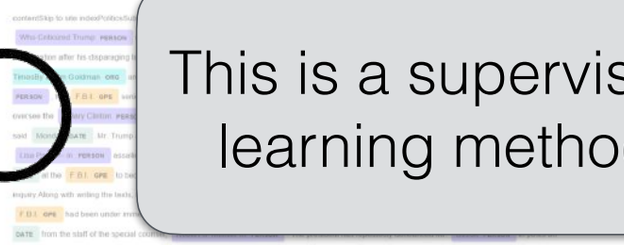
Named Entity Recognition



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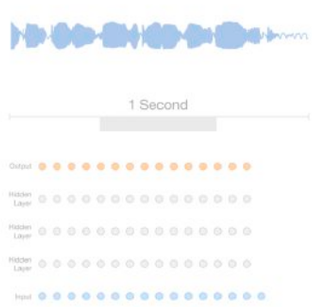

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Machine Translation

Input

	...eats in to make their plane more ... head of passenger comfort at
	... c'est de concentrer davantage de ... nos produits", a déclaré Kevin M. ... de l'Europe.
	... plus de sièges pour rendre son ... vin Keniston, chef du confort des
	...rendre ses avions plus compétitifs ...n, directeur de Confort Passager
	...ministration replied: "The United ...t offices of the World Bank and
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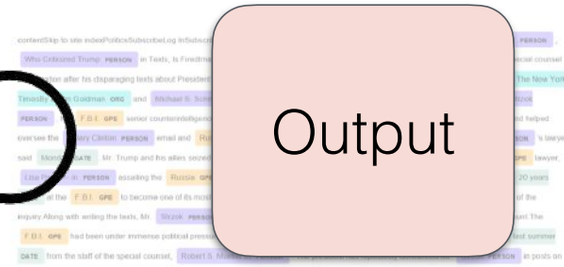
Wu *et al.* Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

Word Embeddings

On word embeddings - Part 1 by Ruder

Named Entity Recognition

Output



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System	Dev EM	Dev F1	Test EM	Test F1
Leaderboard (Oct 8th, 2018)				
Human	-	-	82.3	91.2
#1 Ensemble - nlnet	-	-	86.0	91.7
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Published				
BiDAF+ELMo (Single)	-	85.8	-	-
R.M. Reader (Single)	78.9	86.3	79.5	86.6
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5
Ours				
$BERT_{BASE}$ (Single)	80.8	88.5	-	-
$BERT_{LARGE}$ (Single)	84.1	90.9	-	-
$BERT_{LARGE}$ (Ensemble)	85.8	91.8	-	-
$BERT_{LARGE}$ (Sgl.+TriviaQA)	**84.2**	**91.1**	**85.1**	**91.8**
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Speech Recognition

Word Error Rate

Senone set	Model/combination step	WER devset ngram-LM	WER test ngram-LM	WER devset LSTM-LMs	WER test LSTM-LMs
9k	BLSTM	11.5	8.3	9.2	6.3
27k	BLSTM	11.4	8.0	9.3	6.3
27k-puhpum	BLSTM	11.3	8.0	9.2	6.3
9k	BLSTM+ResNet+LACE+CNN-BLSTM	9.6	7.2	7.7	5.4
9k-puhpum	BLSTM+ResNet+LACE	9.7	7.4	7.8	5.4
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-	Confusion network combination			7.4	5.2
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Xiong *et al.* The Microsoft 2017 Conversational Speech Recognition System

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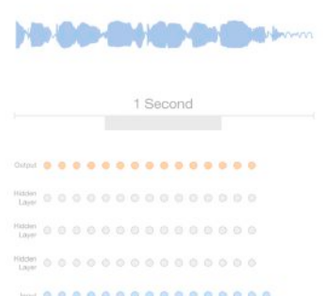
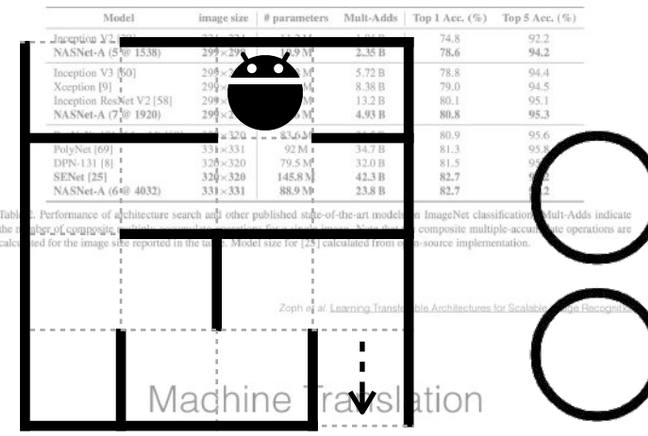


Van Den Oord *et al.* WaveNet: A Generative Model for Raw Audio

Supervised Learning

Image Classification



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Inception ResNet V2 [58]	299×299	55.8 M	13.2 B	80.1	95.1
NASNet-A (7@ 1920)	299×299	22.6 M	**4.93 B**	**80.8**	**95.3**
Inception V4	299×299	42.7 M	12.3 B	80.9	95.6
PolyNet [69]	331×331	92 M	34.7 B	81.3	95.8
DPN-131 [8]	320×320	79.5 M	32.0 B	81.5	95.8
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Table 2. Performance of architecture search and other published state-of-the-art models on ImageNet classification. Mult-Adds indicate the number of composite multiply-accumulate operations for a single image. Note that composite multiply-accumulate operations are calculated for the image size reported in the table. Model size for [25] calculated from open-source implementation.

Zoph et al. Learning Transferable Architectures for Scalable Image Recognition

Instance Segmentation

Fig. 5. More results of **Mask R-CNN** on COCO test images, using ResNet-101-FPN and running at 5 fps, with 35.7 mask AP (Table 1).

He et al. Mask R-CNN

Visual Question Answering

Method	VQA v2 test-dev				VQA v2 test-std			
	All	Yes/no	Numb.	Other	All	Yes/no	Numb.	Other
Prior (most common answer in training set) [ ]	–	–	–	–	25.98	61.20	0.36	1.17
LSTM Language-only (blind model) [ ]	–	–	–	–	44.26	67.01	31.55	27.37
Deeper LSTM Q norm. I [7] (as reported in [ ])	–	–	–	–	54.22	73.46	35.18	41.83
MCB [ ] (as reported in [ ])	–	–	–	–	62.27	78.82	38.28	53.36
UPMC-LIP6 [ ]	–	–	–	–	65.71	82.07	41.06	57.12
Athena	–	–	–	–	67.59	82.51	44.19	59.87
LV-NUS	–	–	–	–	66.77	81.80	46.29	58.30
RDU-USYD-UNCC	–	–	–	–	68.09	84.91	45.39	59.01
Proposed model								
ResNet features 7×7, single network	62.07	79.20	36.46	52.62	62.27	79.32	36.77	52.59
Image features from bottom-up attention, adaptive K, single network	65.32	81.82	44.21	56.05	65.67	82.20	43.90	56.26
ResNet features 7×7, ensemble	66.34	83.38	43.17	57.10	66.93	83.71	43.77	57.20
Image features from bottom-up attention, adaptive K, ensemble	**69.87**	**86.08**	**48.99**	**61.80**	**70.34**	**86.60**	**48.64**	**61.15**

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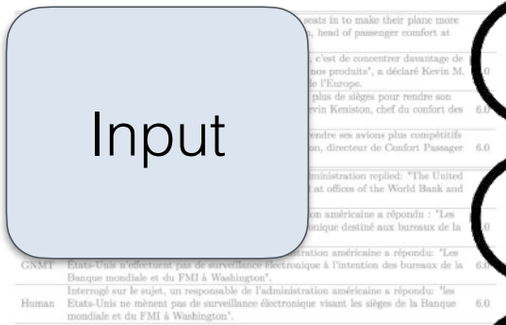
Teney et al. Tips and Tricks for Visual Question Answering: Learnings from the 2017 Challenge

Machine Translation

Input



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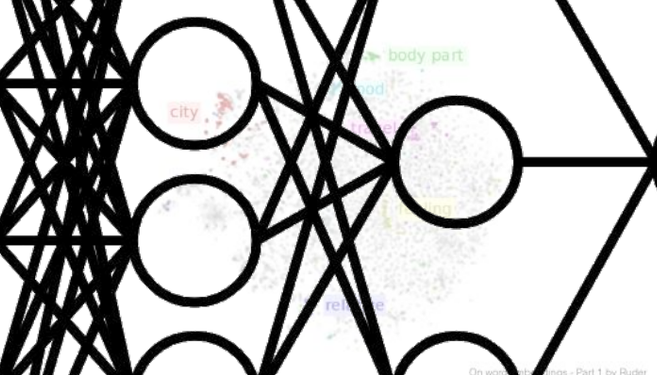
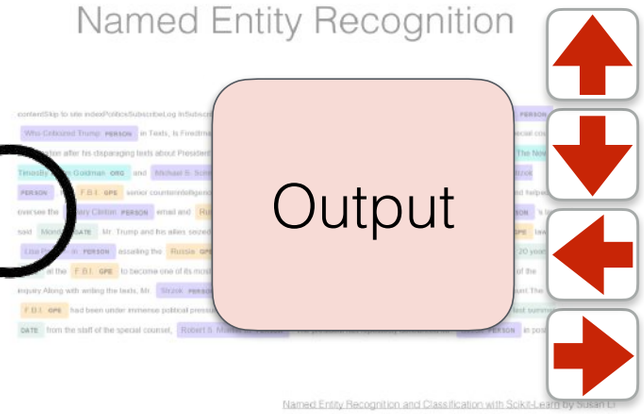


On word embeddings - Part 1 by Ruder

Named Entity Recognition



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Named Entity Recognition and Classification with Scikit-Learn by Susan Li

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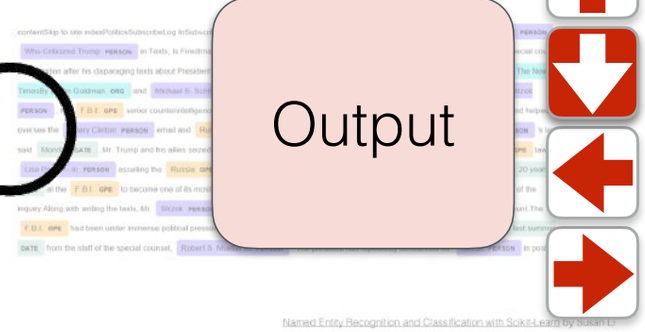

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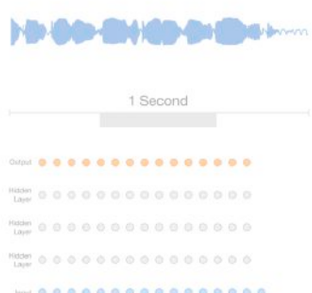

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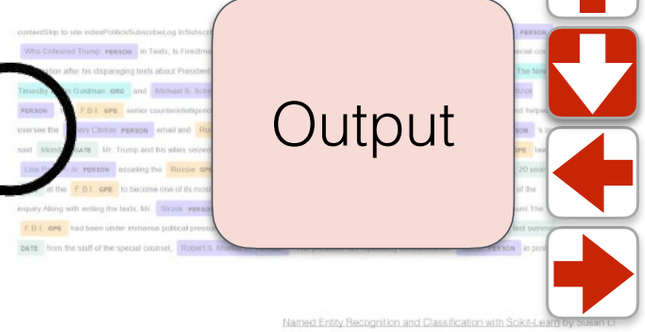

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$BERT_{BASE}$ (Single)	80.8	88.5	-	-
$BERT_{LARGE}$ (Single)	84.1	90.9	-	-
$BERT_{LARGE}$ (Ensemble)	85.8	91.8	-	-
$BERT_{LARGE}$ (Sgl.+TriviaQA)	**84.2**	**91.1**	**85.1**	**91.8**
$BERT_{LARGE}$ (Ens.+TriviaQA)	**86.2**	**92.2**	**87.4**	**93.2**

Table 2: SQuAD results. The BERT ensemble is 7x systems which use different pre-training checkpoints and fine-tuning seeds.

Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

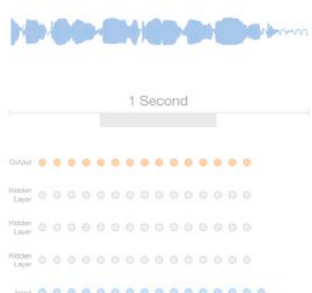
Speech Recognition

Word Error Rate

Senone set	Model/combination step	WER devset ngram-LM	WER test ngram-LM	WER devset LSTM-LMs	WER test LSTM-LMs
9k	BLSTM	11.5	8.3	9.2	6.3
27k	BLSTM	11.4	8.0	9.3	6.3
27k-puhpum	BLSTM	11.3	8.0	9.2	6.3
9k	BLSTM+ResNet+LACE+CNN-BLSTM	9.6	7.2	7.7	5.4
9k-puhpum	BLSTM+ResNet+LACE	9.7	7.4	7.8	5.4
9k-puhpum	BLSTM+ResNet+LACE+CNN-BLSTM	9.7	7.3	7.8	5.5
27k	BLSTM+ResNet+LACE	10.0	7.5	8.0	5.8
-	Confusion network combination			7.4	5.2
-	+ LSTM rescoring			7.3	5.2
-	+ ngram rescoring			7.2	5.2
-	+ backchannel penalty			7.2	5.1

Xiong et al. The Microsoft 2017 Conversational Speech Recognition System

Speech Synthesis (text-to-speech)



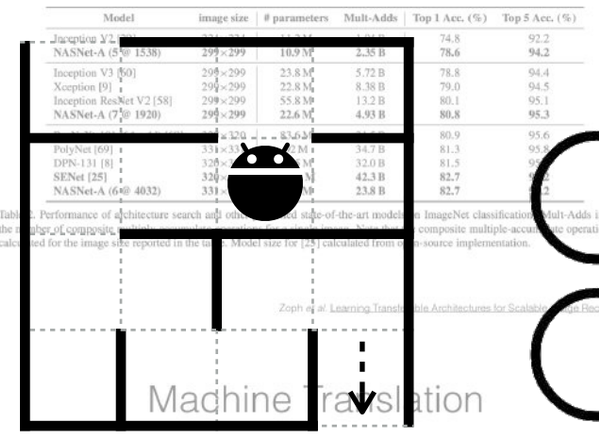
Van Den Oord et al. WaveNet: A Generative Model for Raw Audio

Input

Output

Supervised Learning

Image Classification



Model	image size	# parameters	Mult-Adds	Top 1 Acc. (%)	Top 5 Acc. (%)
Inception V3 [50]	299×299	23.8 M	5.72 B	78.8	94.4
Xception [9]	299×299	22.8 M	8.38 B	79.0	94.5
Inception ResNet V2 [58]	299×299	55.8 M	13.2 B	80.1	95.1
NASNet-A (7@ 1920)	299×299	**22.6 M**	**4.93 B**	**80.8**	**95.3**
PolyNet [69]	331×331	92 M	34.7 B	81.3	95.8
DPN-131 [8]	320×320	80 M	32.0 B	81.5	95.8
SENet [25]	320×320	115.3 M	**42.3 B**	**82.7**	96.2
NASNet-A (6@ 4032)	331×331	88.9 M	**23.8 B**	**82.7**	96.2

Zoph et al. Learning Transferable Architectures for Scalable Image Recognition

Instance Segmentation

He et al. Mask R-CNN

Visual Question Answering

Method	VQA v2 test-dev All	Yes/no	Numb.	Other	VQA v2 test-std All	Yes/no	Numb.	Other
Prior (most common answer in training set) [ ]	–	–	–	–	25.98	61.20	0.36	1.17
LSTM Language-only (blind model) [ ]	–	–	–	–	44.26	67.01	31.55	27.37
Deeper LSTM Q norm. I [7] (as reported in [ ])	–	–	–	–	54.22	73.46	35.18	41.83
MCB [ ] (as reported in [ ])	–	–	–	–	62.27	78.82	38.28	53.36
UPMC-LIP6 [ ]	–	–	–	–	65.71	82.07	41.06	57.12
Athena	–	–	–	–	67.59	82.51	44.19	59.87
LV-NUS	–	–	–	–	66.77	81.80	46.29	58.30
HDU-USYD-UNCC	–	–	–	–	68.09	84.91	45.39	59.01
Proposed model								
ResNet features 7×7, single network	62.07	79.20	36.46	52.62	62.27	79.32	36.77	52.59
Image features from bottom-up attention, adaptive K, single network	65.32	81.82	44.21	56.05	65.67	82.20	43.90	56.26
ResNet features 7×7, ensemble	66.34	83.36	43.15	57.10	66.93	83.71	43.77	57.20
Image features from bottom-up attention, adaptive K, ensemble	**69.87**	**86.08**	**48.99**	**61.80**	**70.34**	**86.60**	**48.64**	**61.15**

Table 3. Comparison of our best model with competing methods. Excerpt from the official *VQA v2 Leaderboard* [ ].

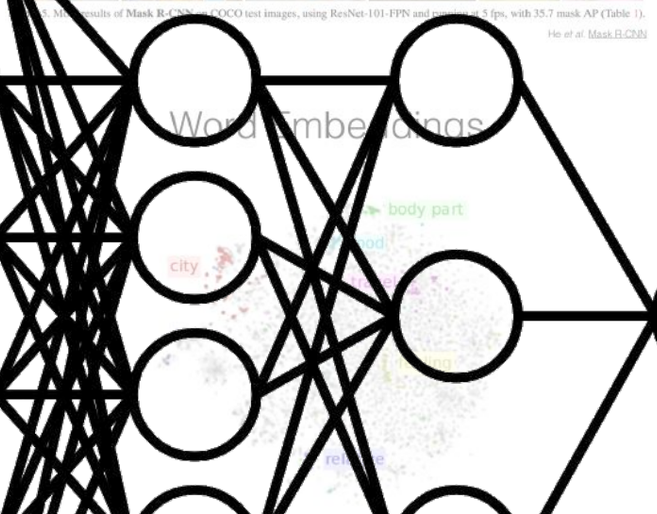
Teney et al. Tips and Tricks for Visual Question Answering: Learnings from the 2017 Challenge

Machine Translation

	newstest2014 EN-DE	newstest2014 EN-FR	newstest2015 EN-DE	newstest2015 EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		
GNMT + RL [38]	24.6	39.92		
ConvS2S [9]	25.16	40.46		
MoE [32]	26.03	40.56		
Deep-Att + PosUnk Ensemble [39]		40.4		
GNMT + RL Ensemble [38]	26.30	41.16		
ConvS2S Ensemble [9]	26.36	**41.29**		
Transformer (base model)	27.3	38.1		
Transformer (big)	**28.4**	**41.8**		

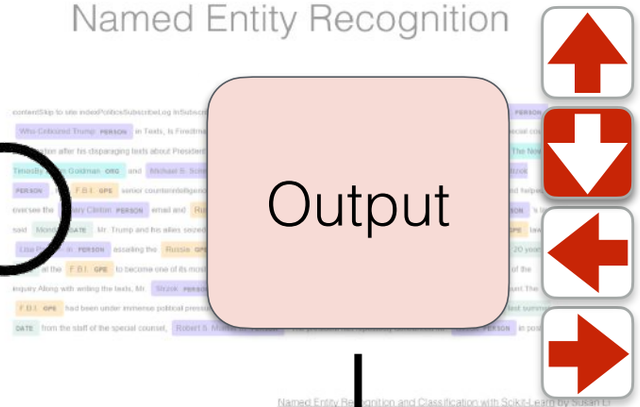
Wu et al. Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

Word Embeddings



On word embeddings - Part 1 by Ruder

Named Entity Recognition



Named Entity Recognition and Classification with Scikit-Learn by Susan Li

Esteves et al. Named Entity Recognition in Twitter using Images and Text

Input

Output

Question Answering

- Input Question:
  Where do water droplets collide with ice crystals to form precipitation
- Input Paragraph:
  ... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. ...
- Output Answer:
  within a cloud

System	Dev EM	Dev F1	Test EM	Test F1
Leaderboard (Oct 8th, 2018)				
Human	-	-	82.3	91.2
#1 Ensemble - nlnet	-	-	86.0	91.7
#2 Ensemble - QANet	-	-	84.5	90.1
#1 Single - nlnet	-	-	83.5	90.1
#2 Single - QANet	-	-	82.5	89.3
Published				
BiDAF+ELMo (Single)	-	85.8	-	-
R.M. Reader (Single)	78.9	86.3	79.5	86.6
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5
Ours				
$BERT_{BASE}$ (Single)	80.8	88.5	-	-
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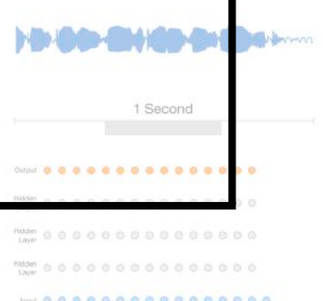
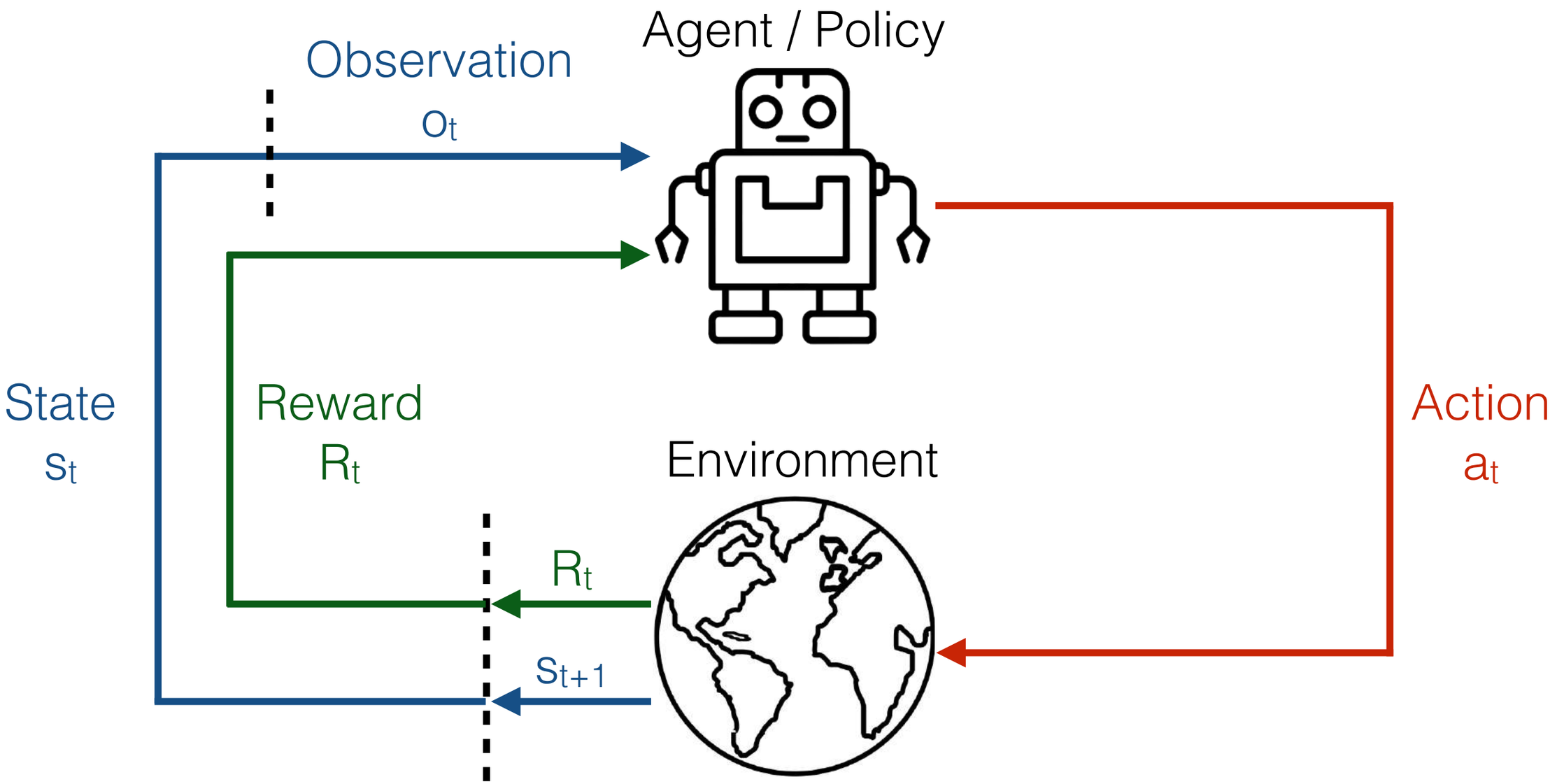


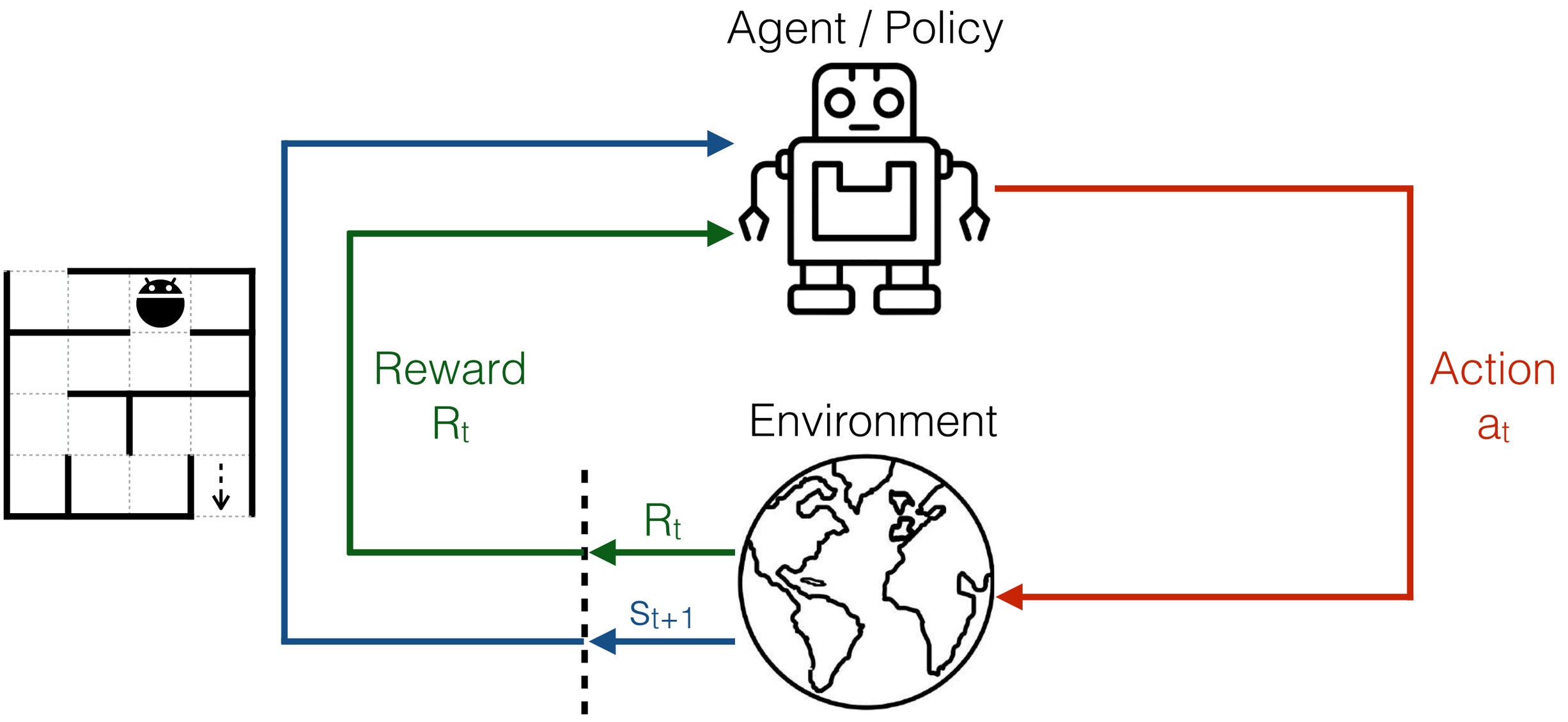
Van Den Oord et al. WaveNet: A Generative Model for Raw Audio

Robot Learning via Reinforcement Learning



Goal: maximize $\sum_{t=0}^{t=H} \gamma^t R_t(s_t, a_t)$

Robot Learning via Reinforcement Learning



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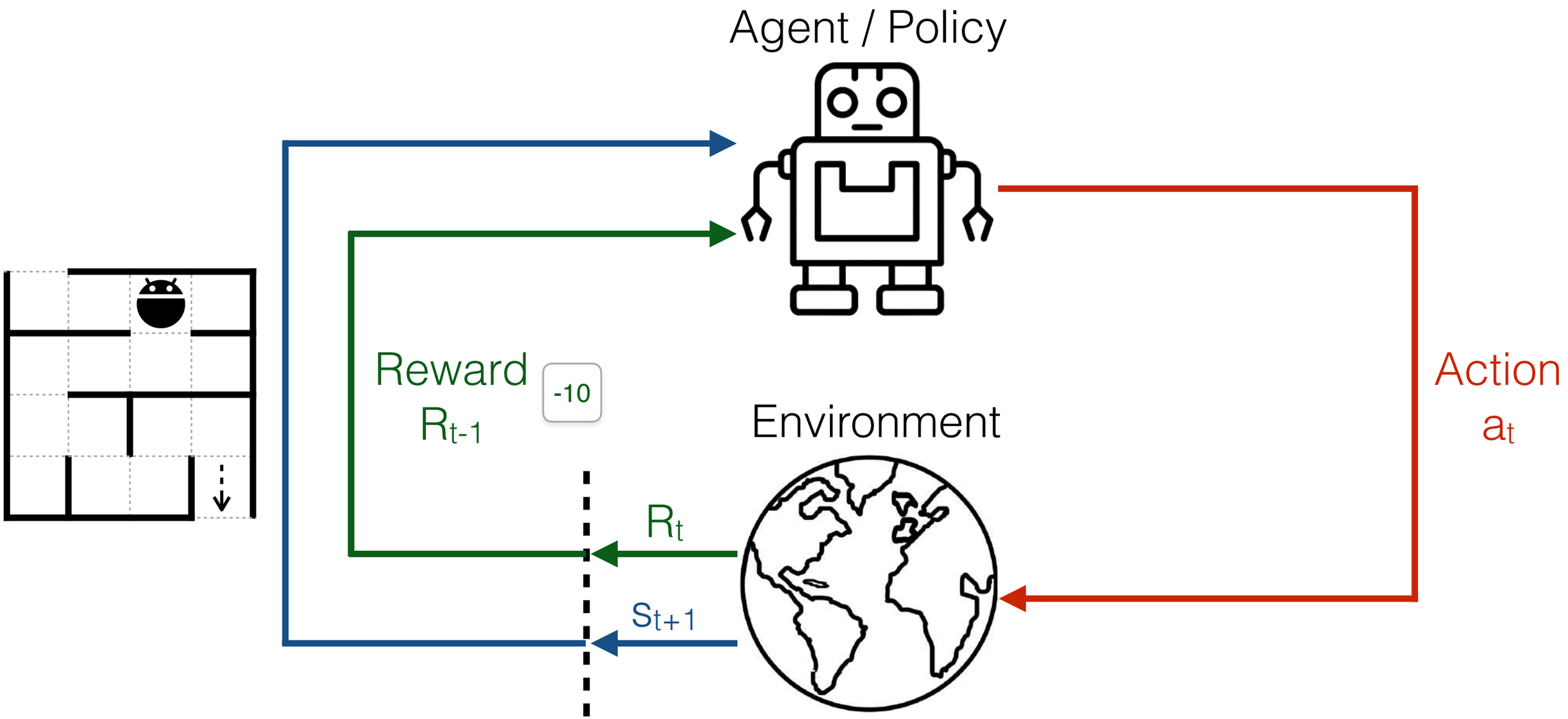
Robot Learning via Reinforcement Learning



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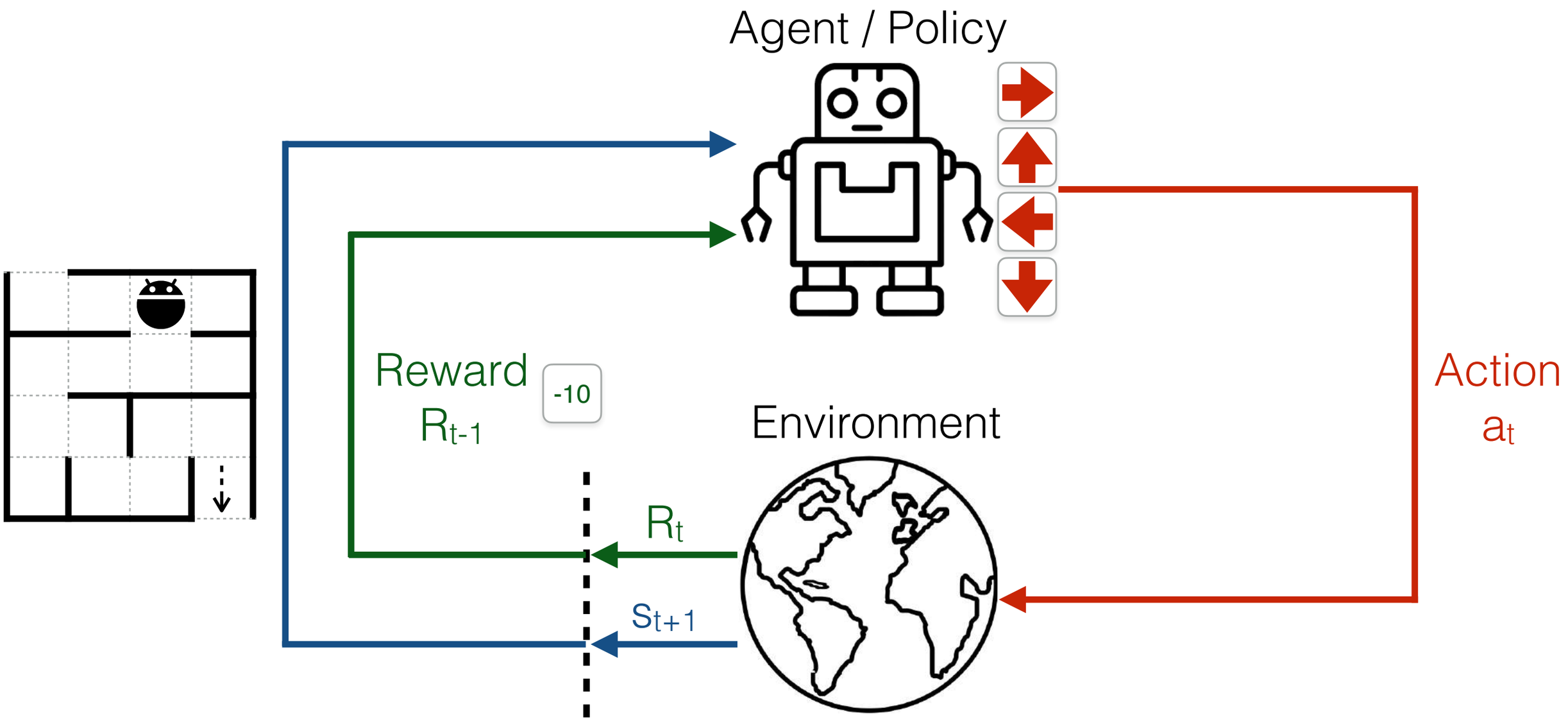
Robot Learning via Reinforcement Learning



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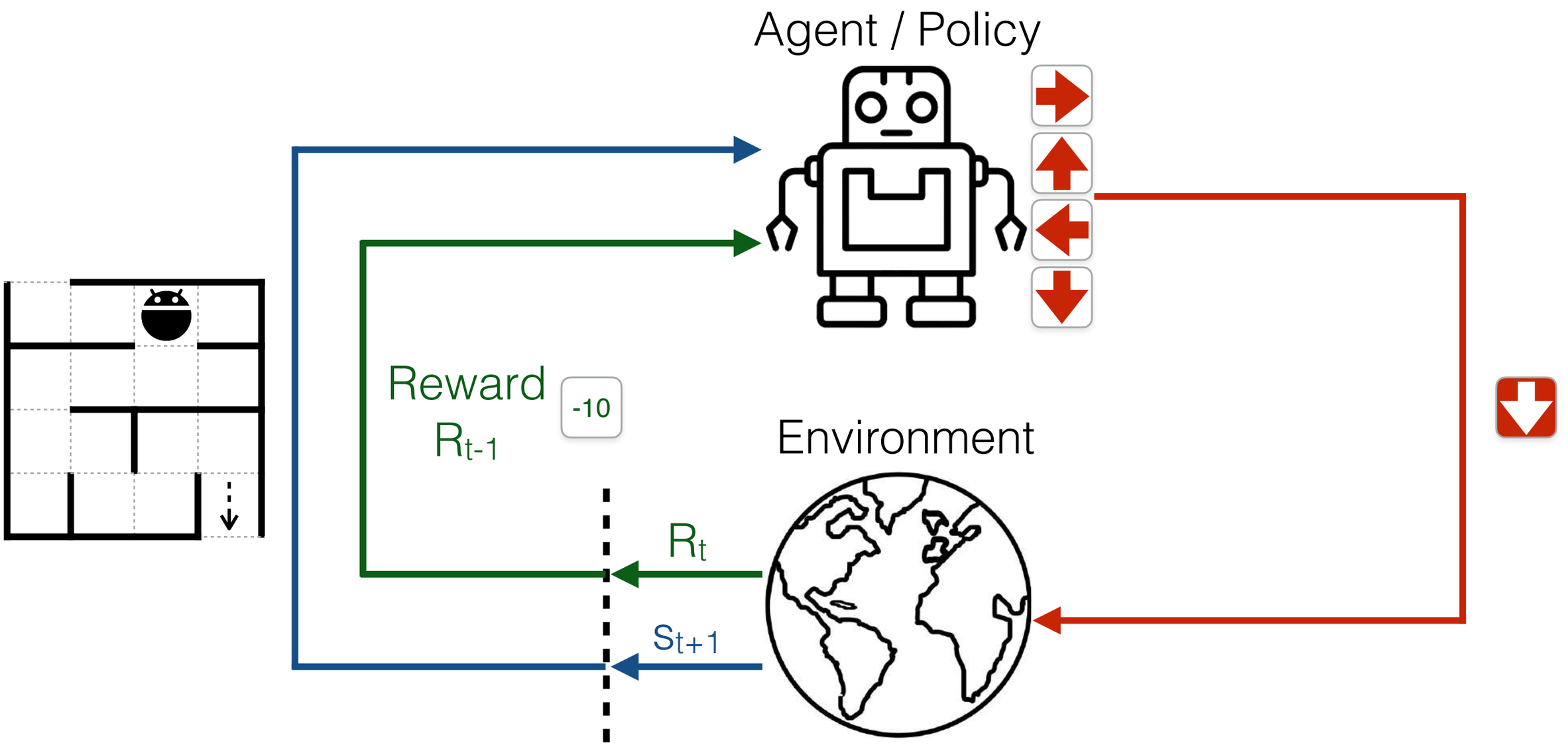

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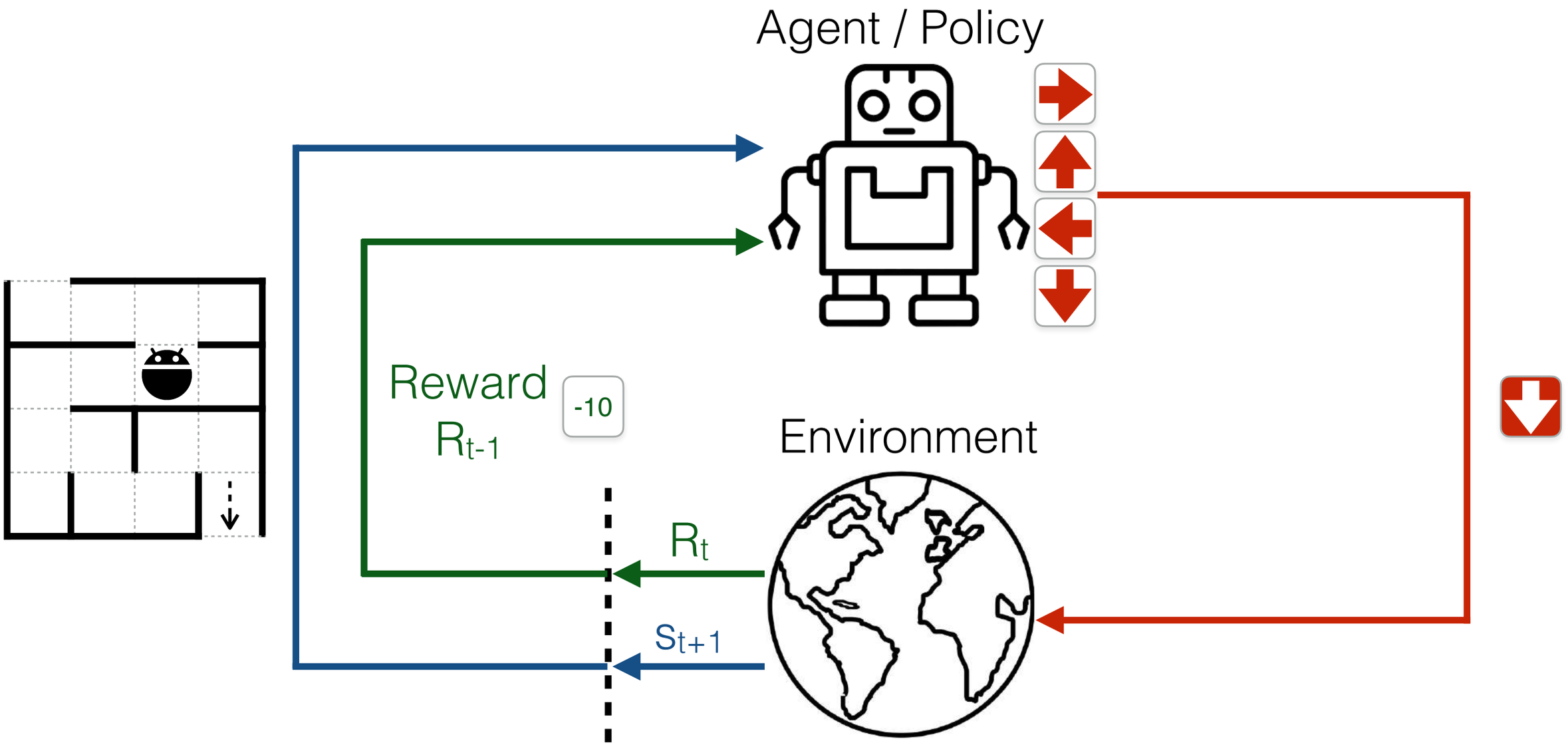

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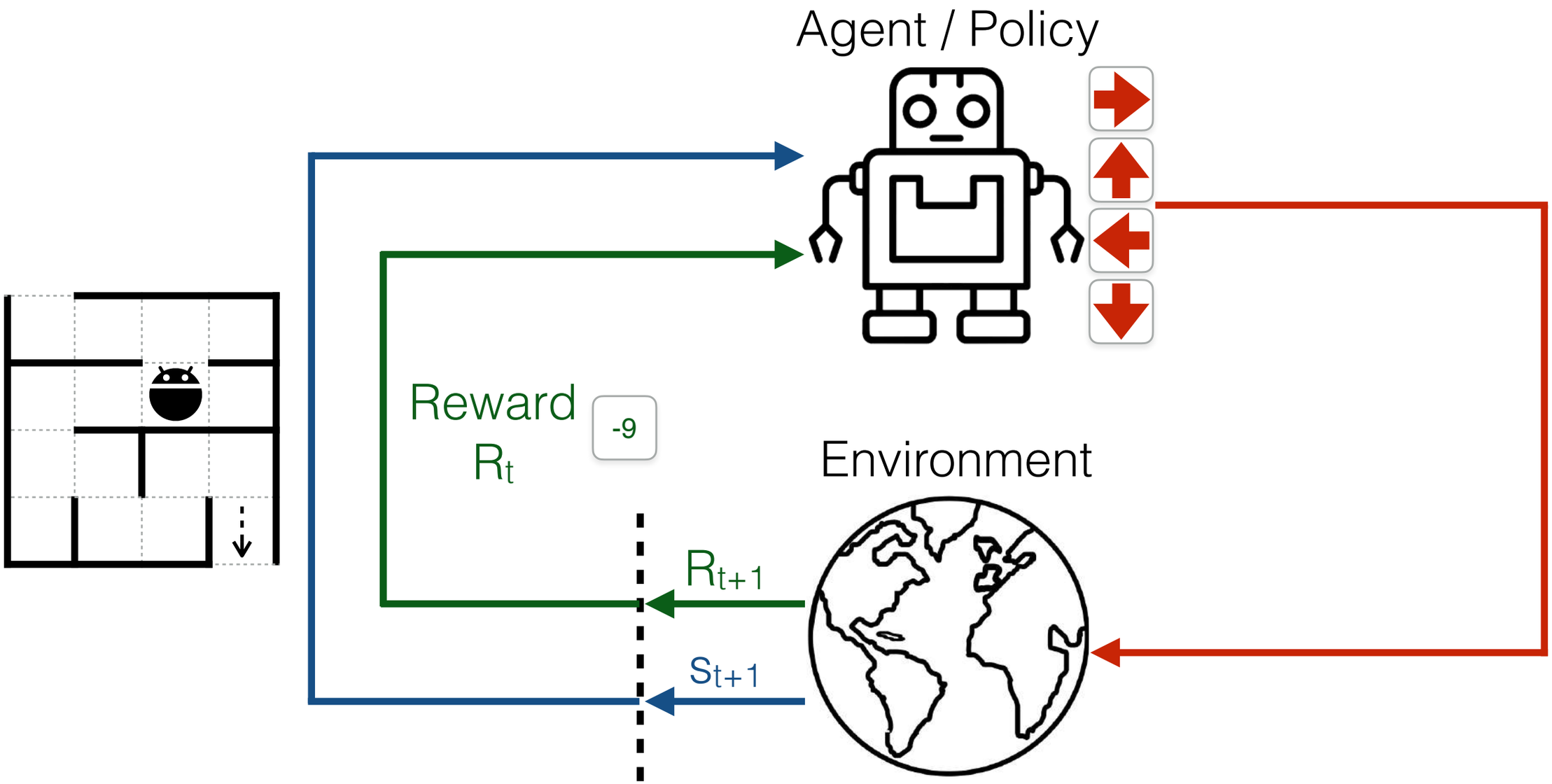
Robot Learning via Reinforcement Learning



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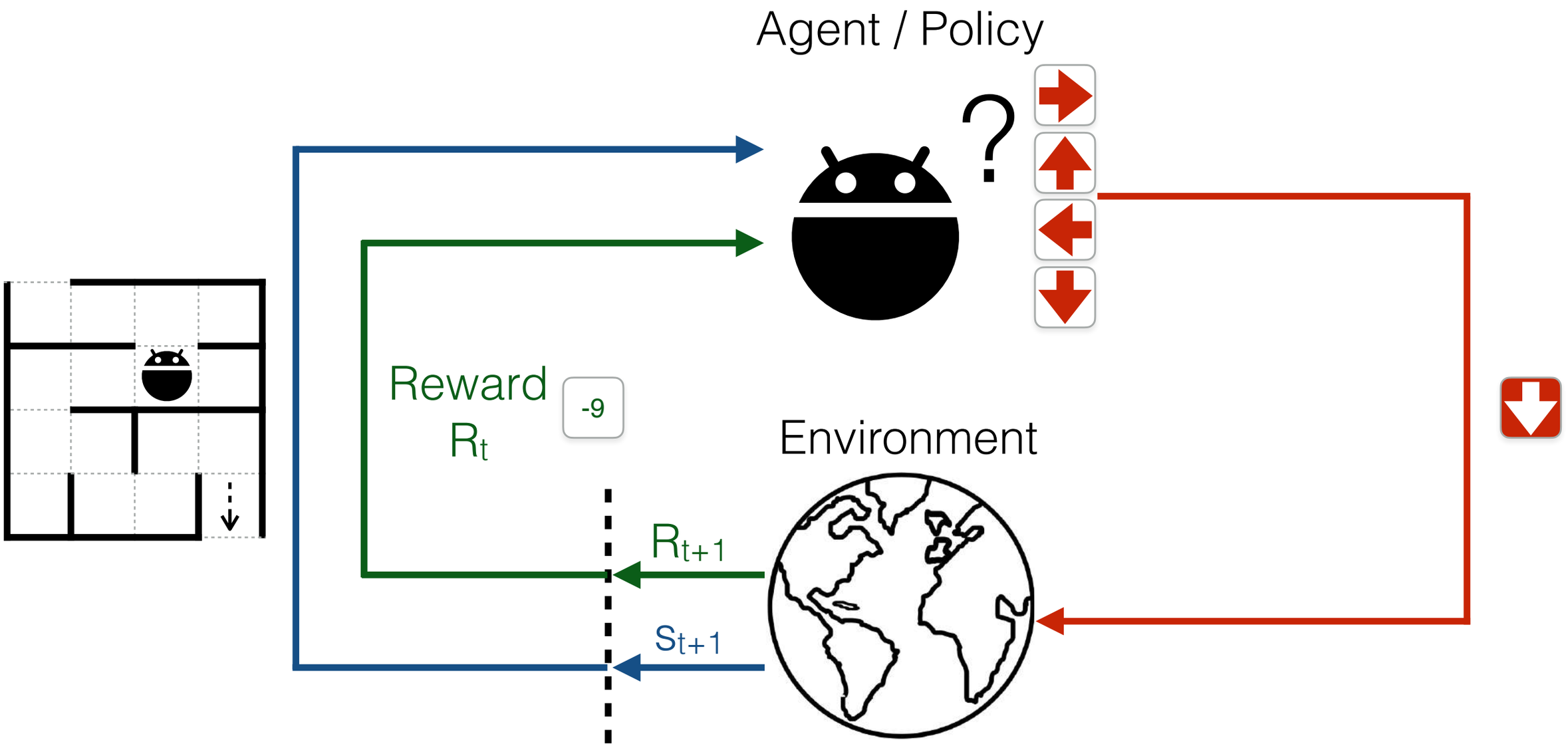
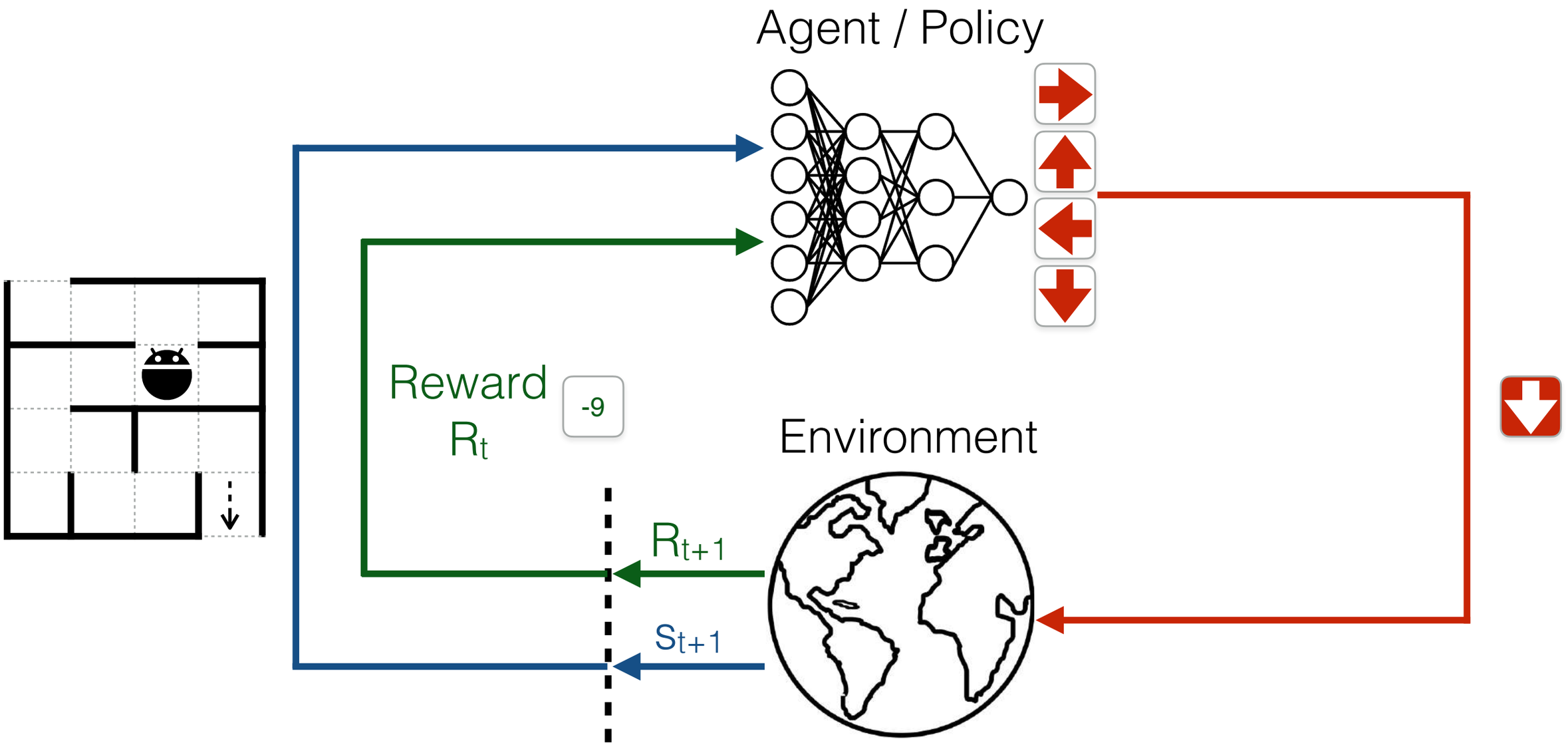
Robot Learning via Reinforcement Learning



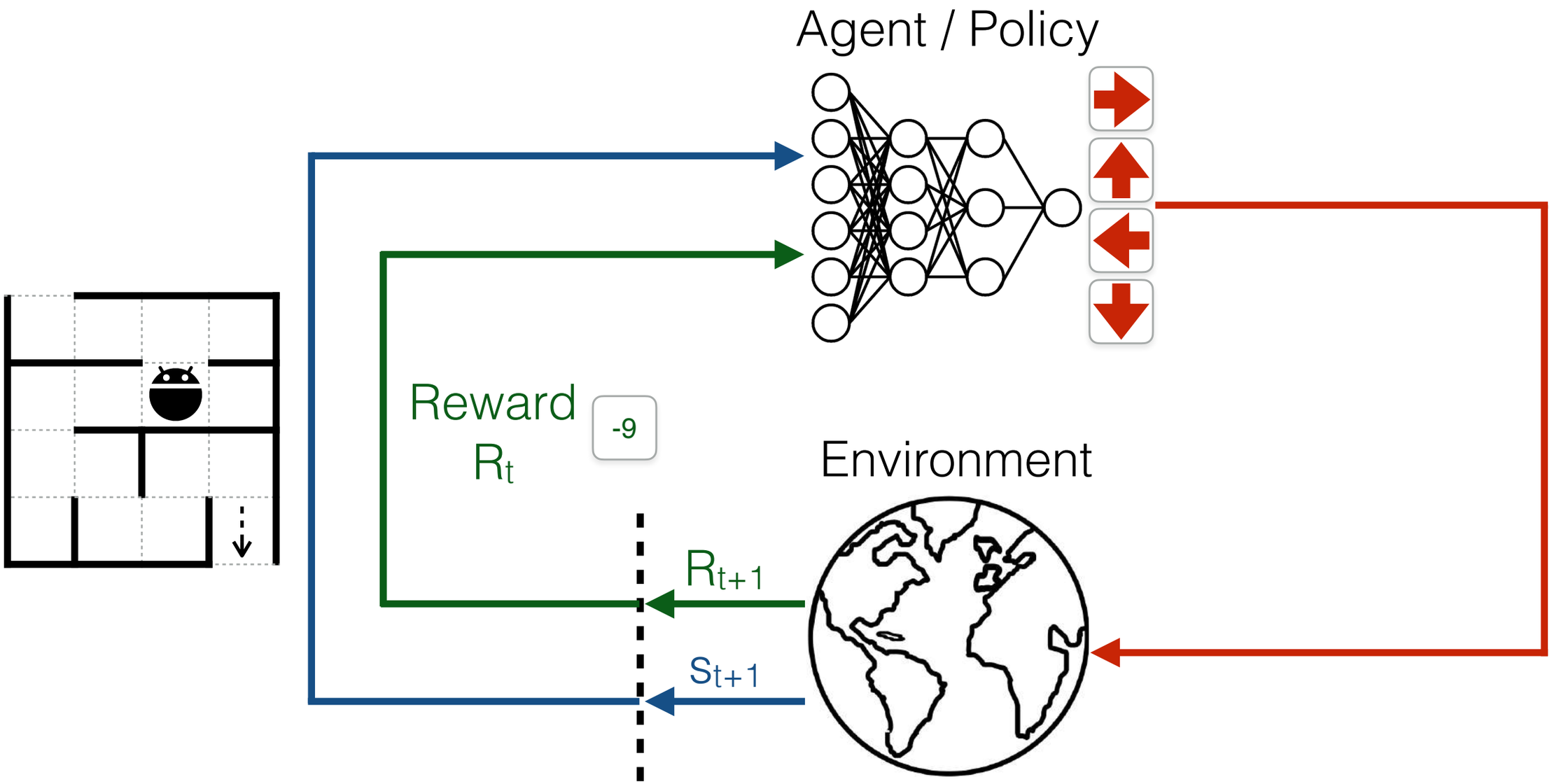
Goal: maximize $\sum_{t=0}^{t=H} \gamma^t R_t(s_t, a_t)$

Robot Learning via Deep Reinforcement Learning



Goal: maximize $\sum_{t=0}^{t=H} \gamma^t R_t(s_t, a_t)$

Robot Learning via Deep Reinforcement Learning



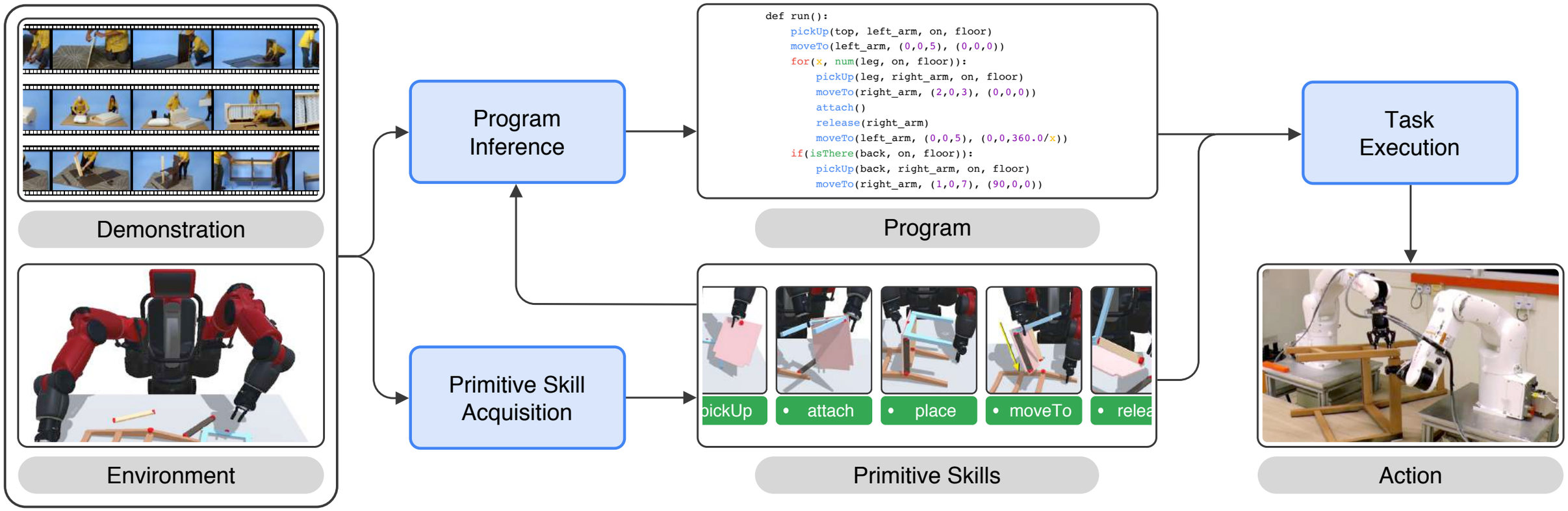
Uninterpretable

Not generalizable

Limited to short-horizon tasks

No skill-reuse

Program-Guided Framework for Interpreting and Acquiring Complex Skills with Learning Robots



Interpretable

Programmatic / Generalizable

Hierarchical

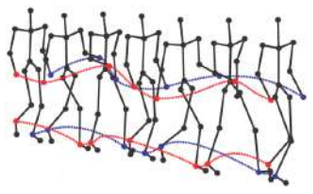
Modular

Program-Guided Framework for Interpreting and Acquiring Complex Skills with Learning Robots

Skill Specification → Program → High-level Plan → Low-level Execution

Video demonstration

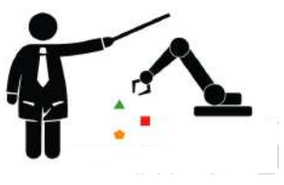
Trajectory demonstration



Language instruction

Stir-fry the onions until tender, and repeat this for garlic and carrots, if you have soy sauce, add some. Pour 2/3 cups the whisked eggs into the stir-fried and scramble.

Reward



Actions (sub-skills)

`Jump` `Crawl` `Walk`

Perceptions

`isCurb()` `isCeiling()`

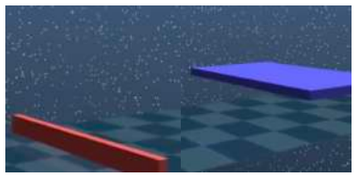
Control Flows

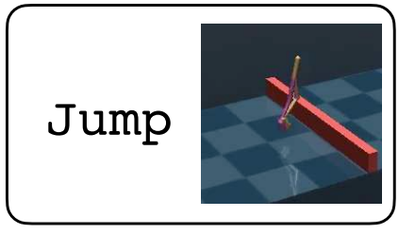
`while` `if` `else` `elseIf`

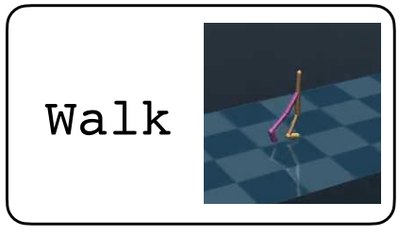
Program

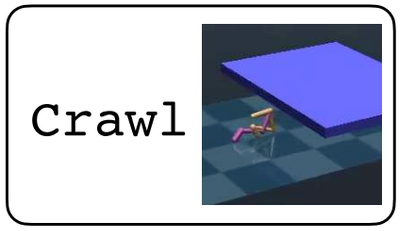
```
DEF run()
    while True:
        if isCurb():
            jump
        elseIf isCeiling():
            crawl()
        else:
            walk()
```

Observation

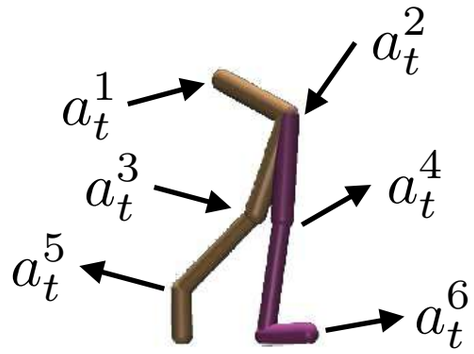








Low-level execution

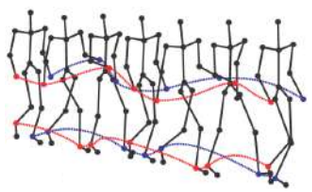


Program Inference

Skill Specification → Program → High-level Plan → Low-level Execution

Video demonstration

Trajectory demonstration



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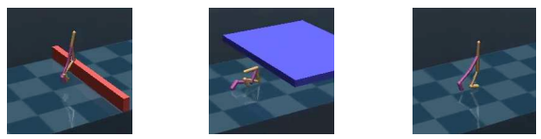

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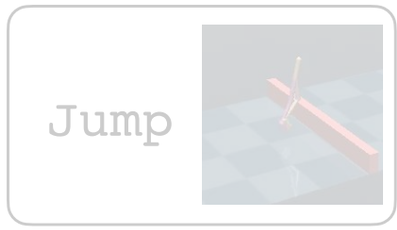

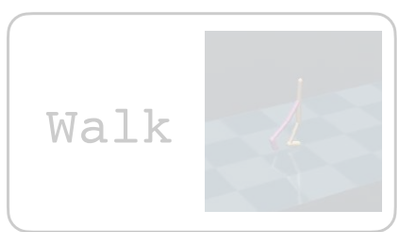

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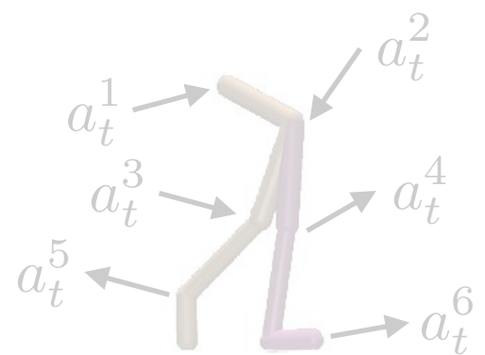
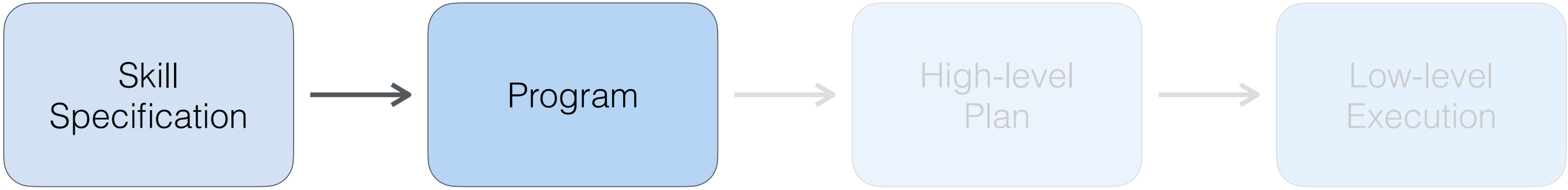


Neural Program Synthesis from Diverse Demonstration Videos

ICML 2018



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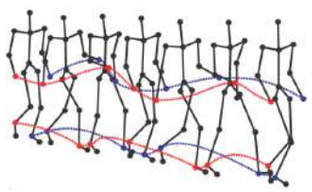

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            walk()
```



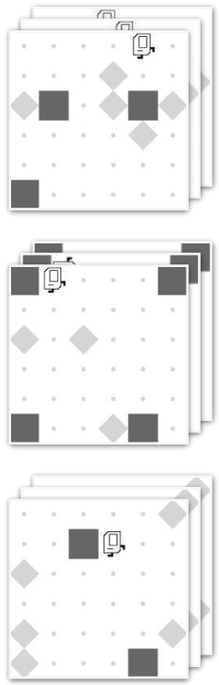
Hyeonwoo Noh


Sriram Somasundaram

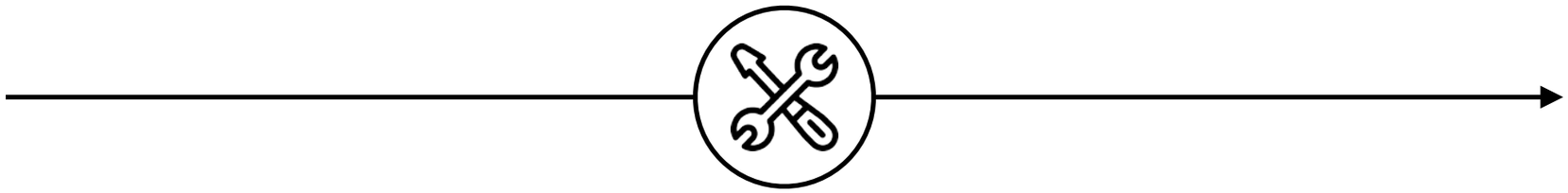

Joseph J. Lim

Imitation Learning

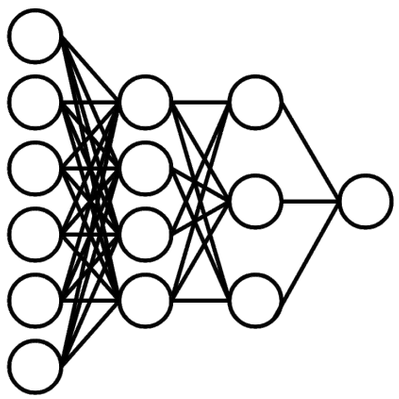
Demonstrations



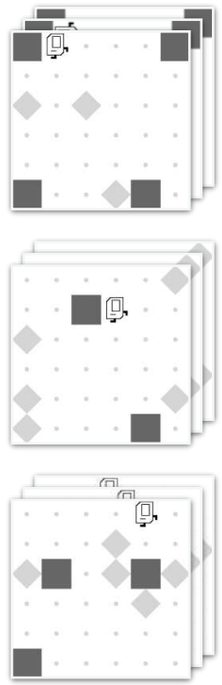
Imitate



Neural Network
Policy

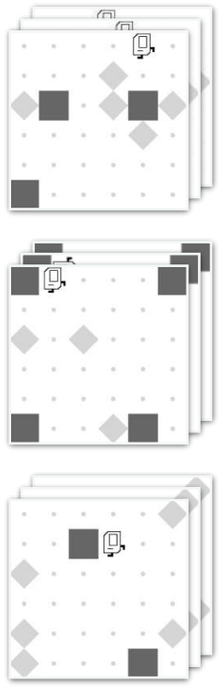


Execution



Imitation Learning by Synthesizing Programs

Demonstrations

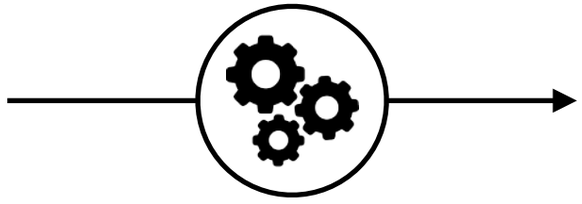


Synthesize

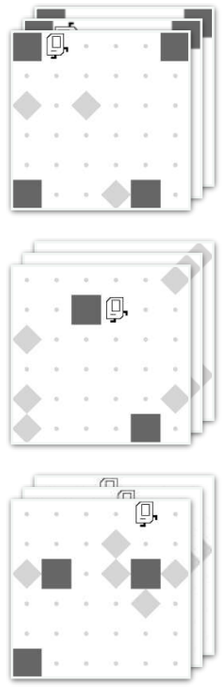
Program Policy

```
DEF run()
    if isFontClear():
        move
    else:
        turnLeft
    move
    turnLeft
    repeat(2):
        turnRight
        putMarker
```

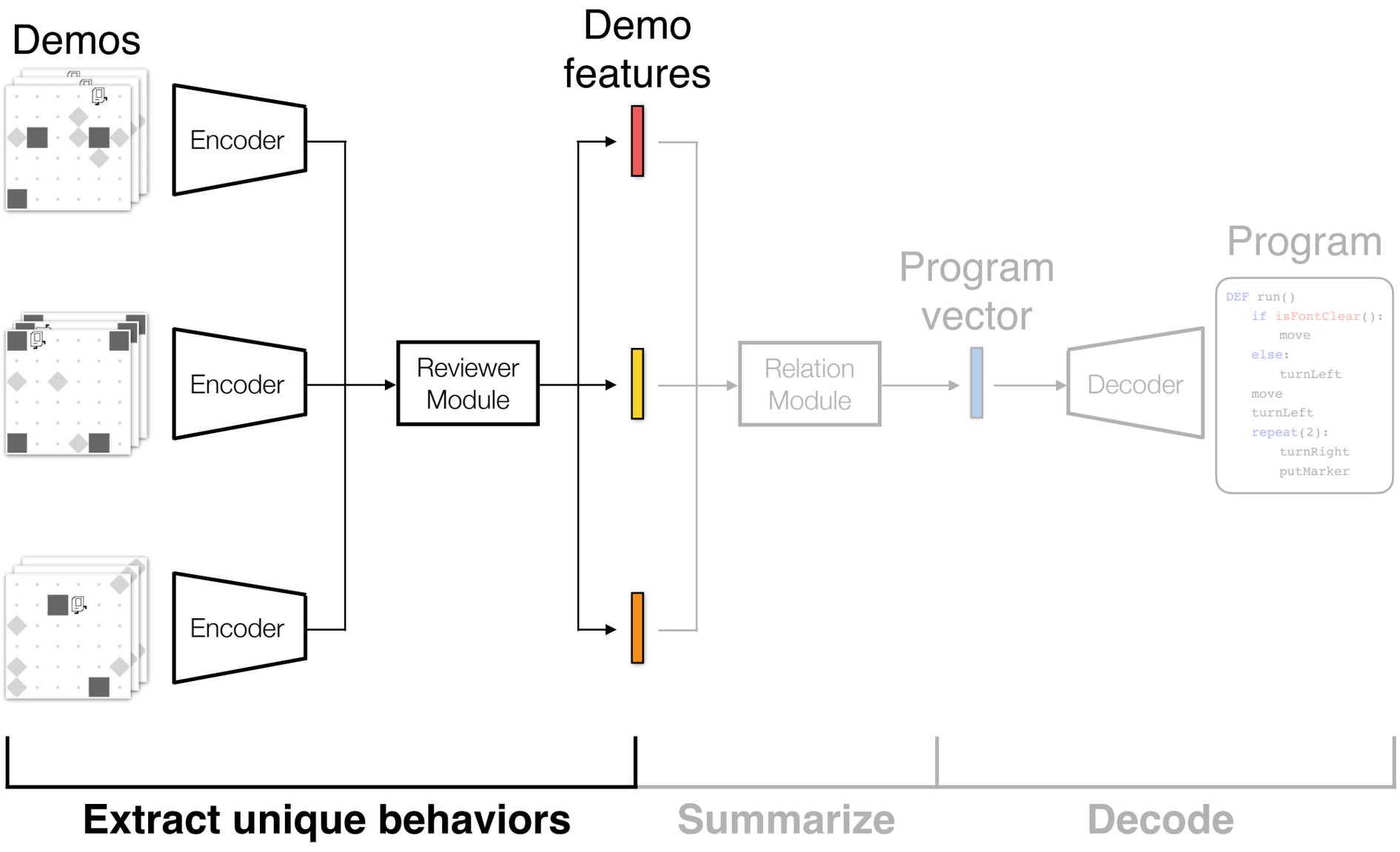
Execute



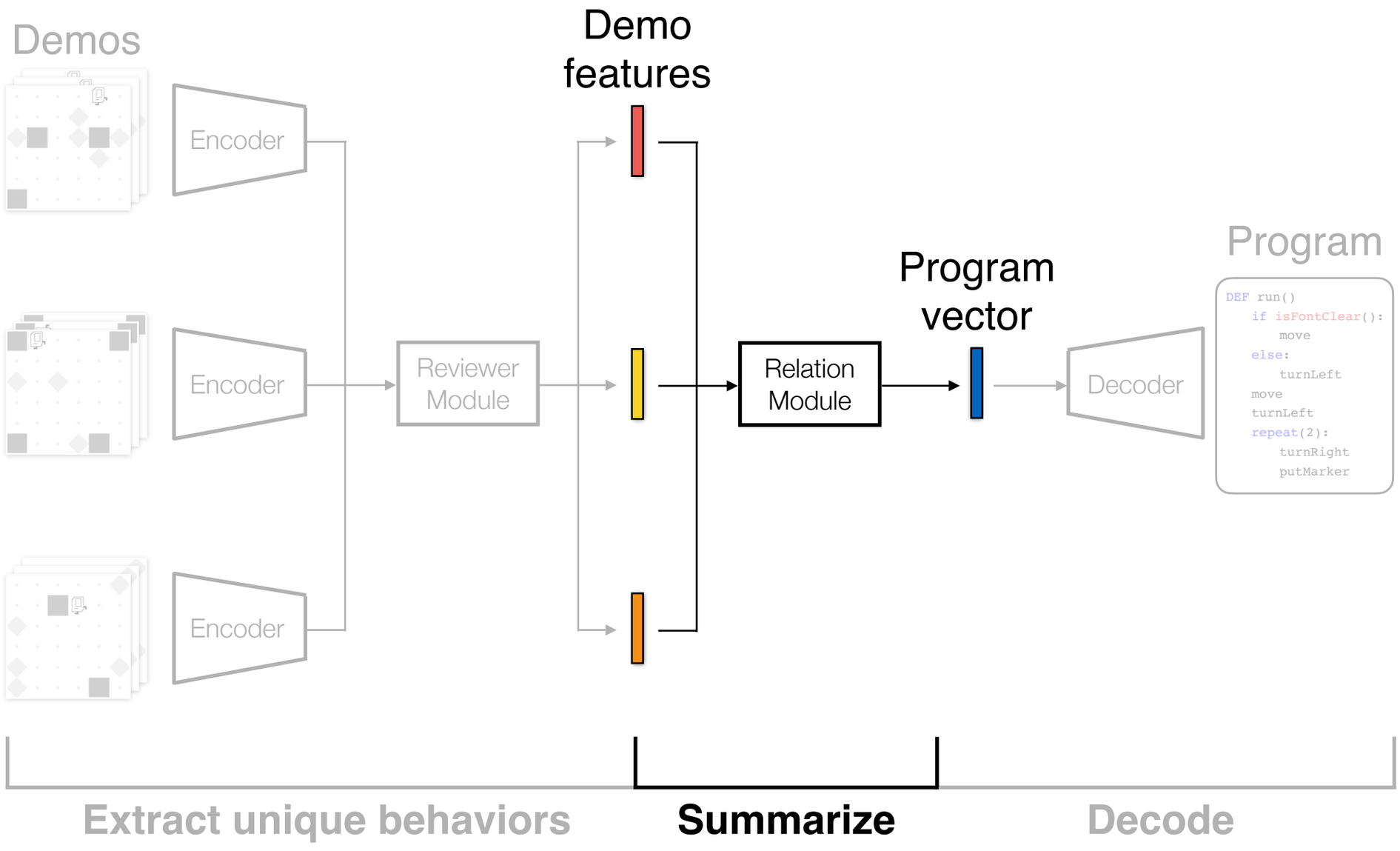
Execution



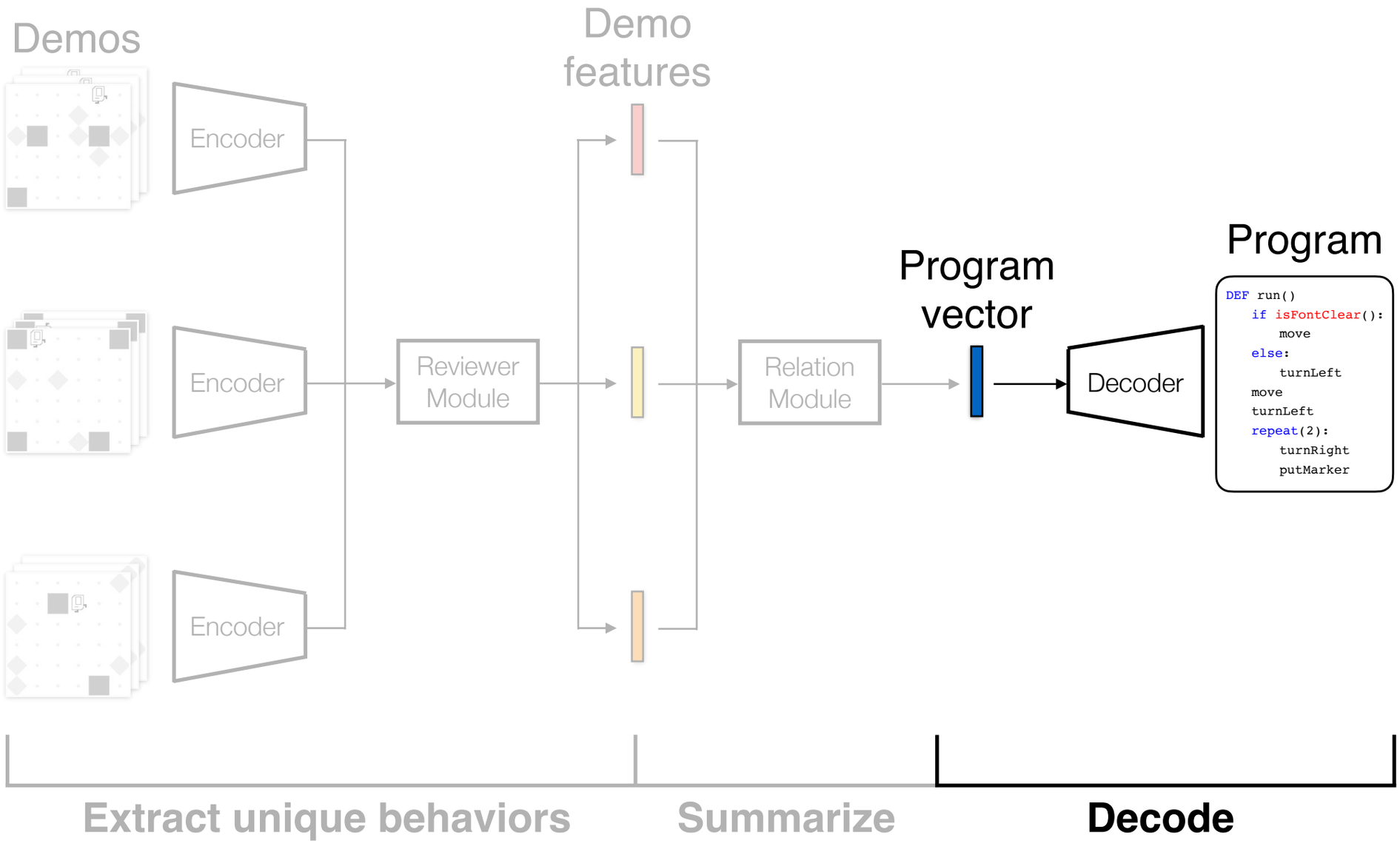
Model Overview



Model Overview



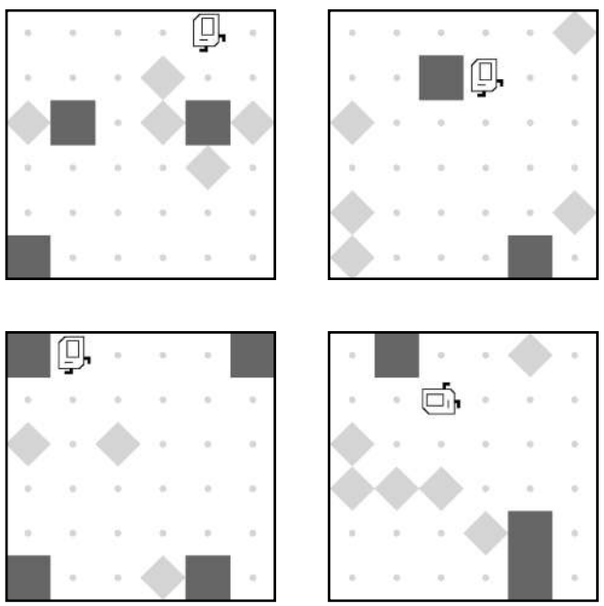
Model Overview



Environments

Karel

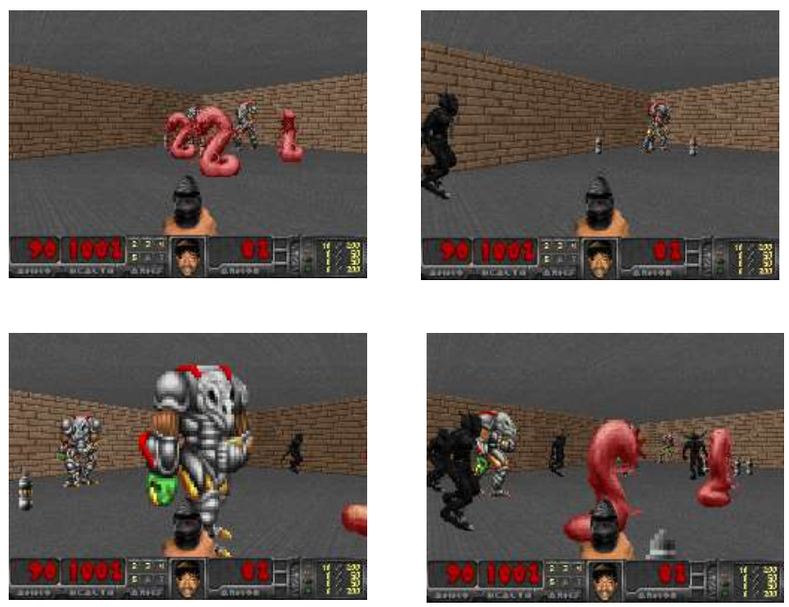
```
DEF run()
   if isFontClear():
      move
   else:
      turnLeft
   move
   turnLeft
   repeat(2):
      turnRight
      putMarker
```



Richard E Pattis. “Karel the robot: a gentle introduction to the art of programming.” John Wiley & Sons, Inc., 1981

ViZDoom

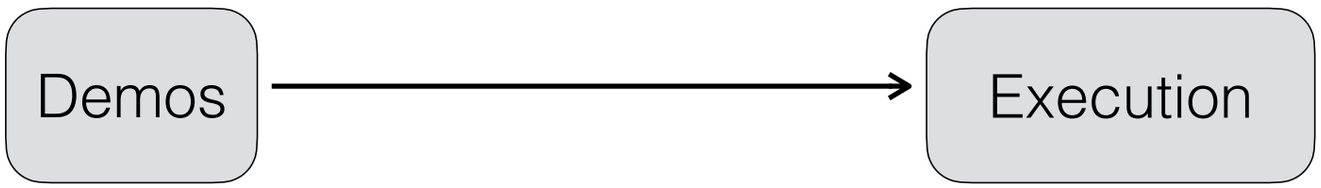
```
DEF run()
   while isFontClear(HellKnight):
      attack
      moveForward
   if isThere(Demon):
      moveRight
   else:
      moveLeft
      moveBackward
```



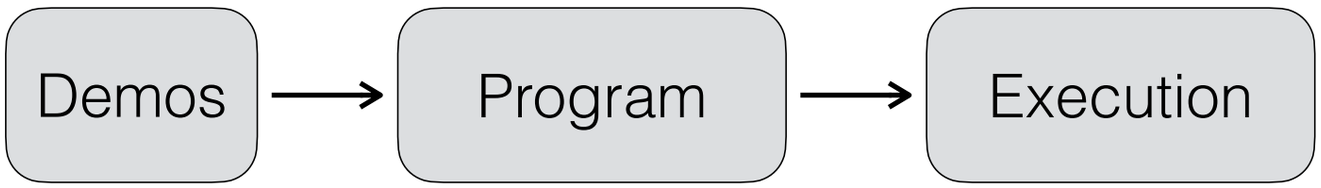
Kempka et al., “Vizdoom: A doom-based ai research platform for visual reinforcement learning.” In CIG, 2016

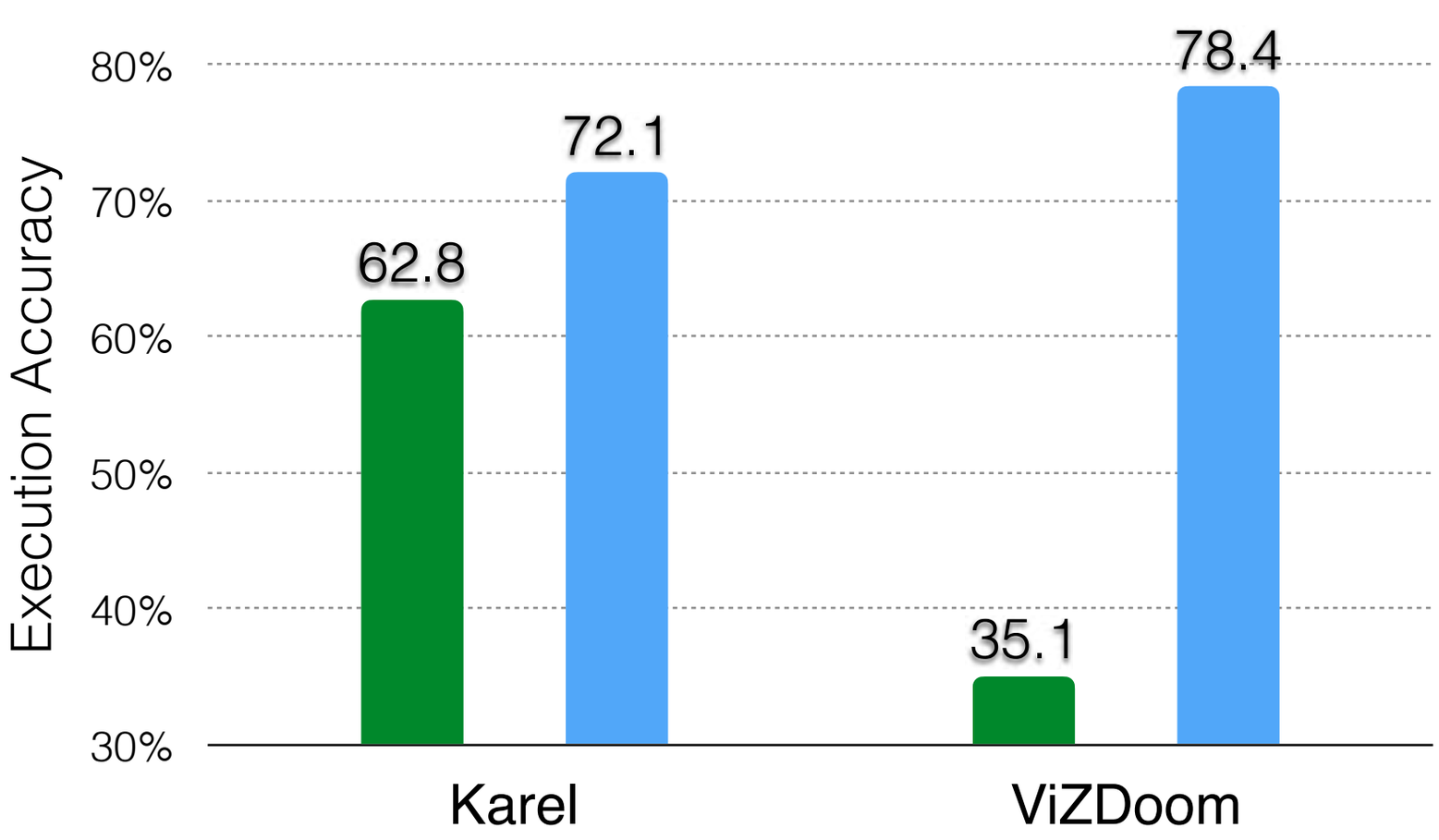
Quantitative Results

Neural Network Policy



Program Policy






```
DEF run()
    if isFontClear():
        move
    else:
        turnLeft
    move
    turnLeft
    repeat(2):
        turnRight
        putMarker
```

9/10 demos

Major branch

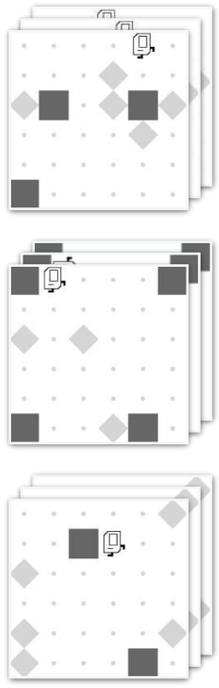
Minor branch

1/10 demos

Takeaway

- Synthesize **programs** to **imitate demonstrations**

Demonstrations

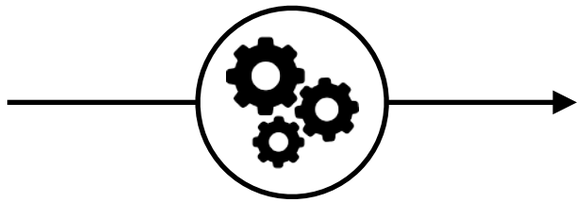


Synthesize

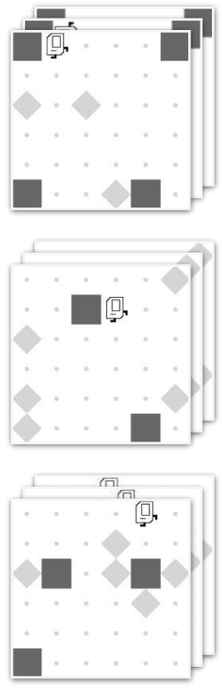
Program Policy

```
DEF run()
    if isFontClear():
        move
    else:
        turnLeft
    move
    turnLeft
    repeat(2):
        turnRight
        putMarker
```

Execute

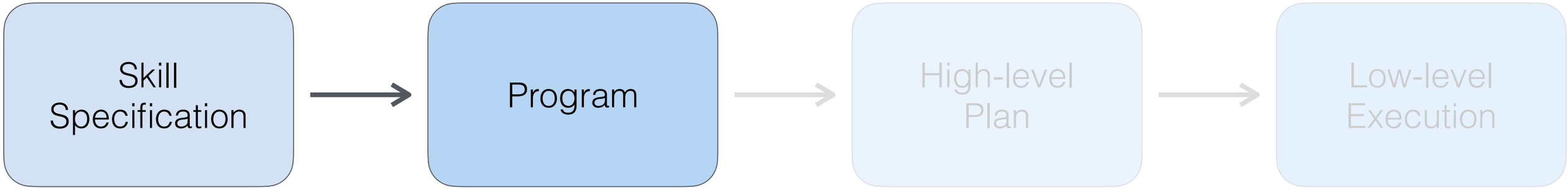


Execution



Learning to Synthesize Programs as Interpretable and Generalizable Policies

NeurIPS 2021



Reward

Program

```
DEF run()
    while True:
        if isCurb():
            jump
        elseIf isCeiling():
            crawl()
        else:
            walk()
```

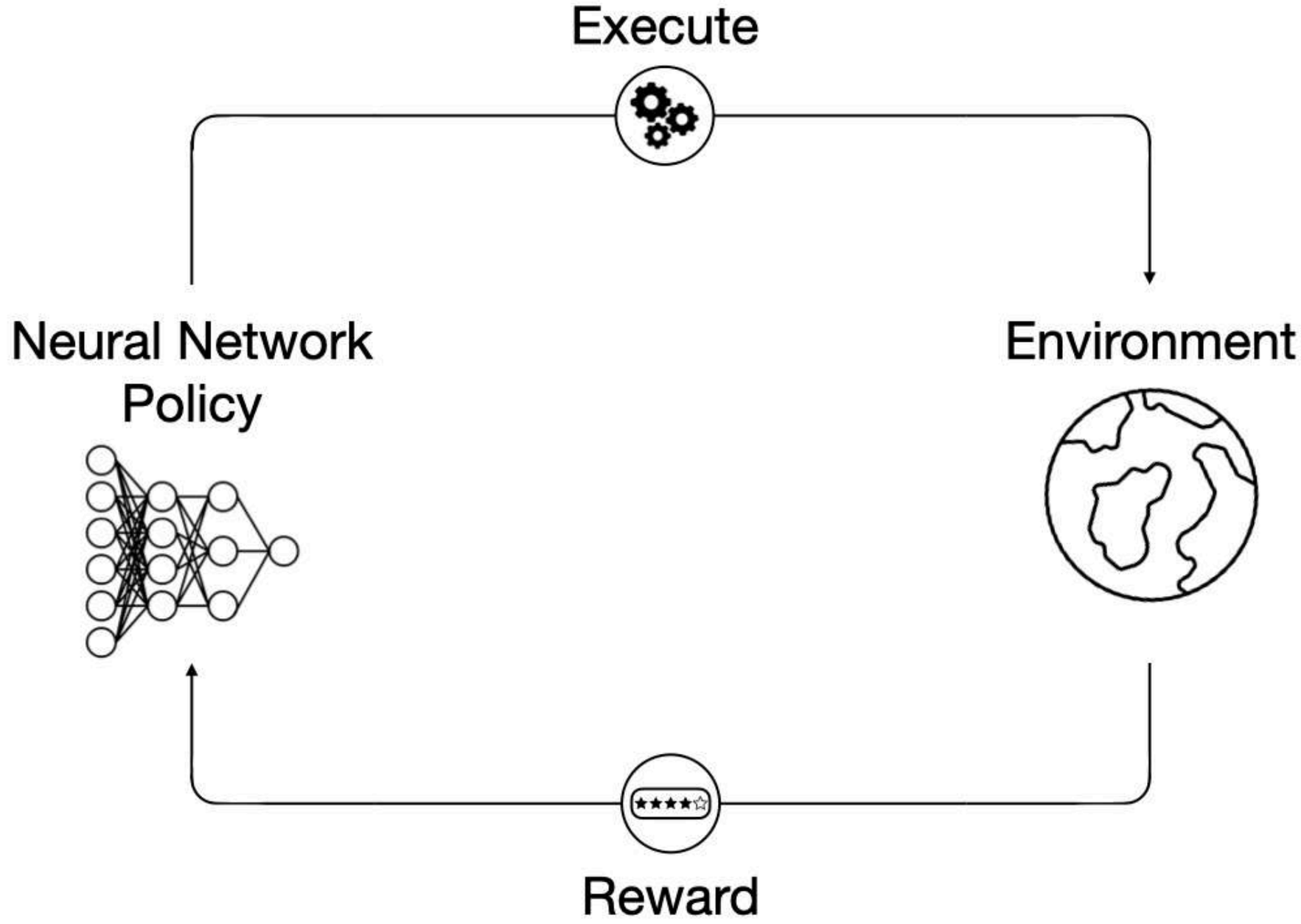


Dweep Trivedi

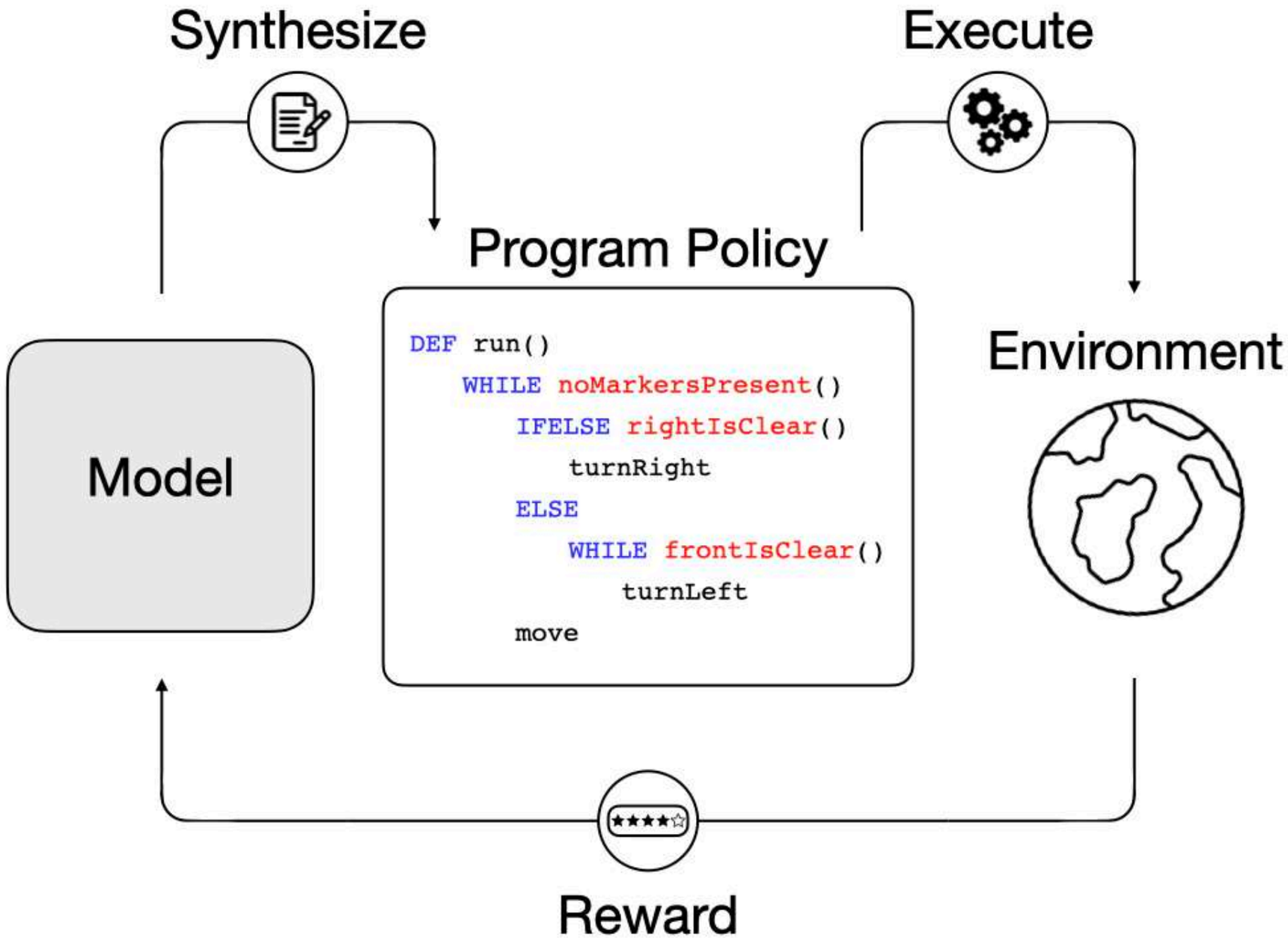

Jesse Zhang


Joseph J. Lim

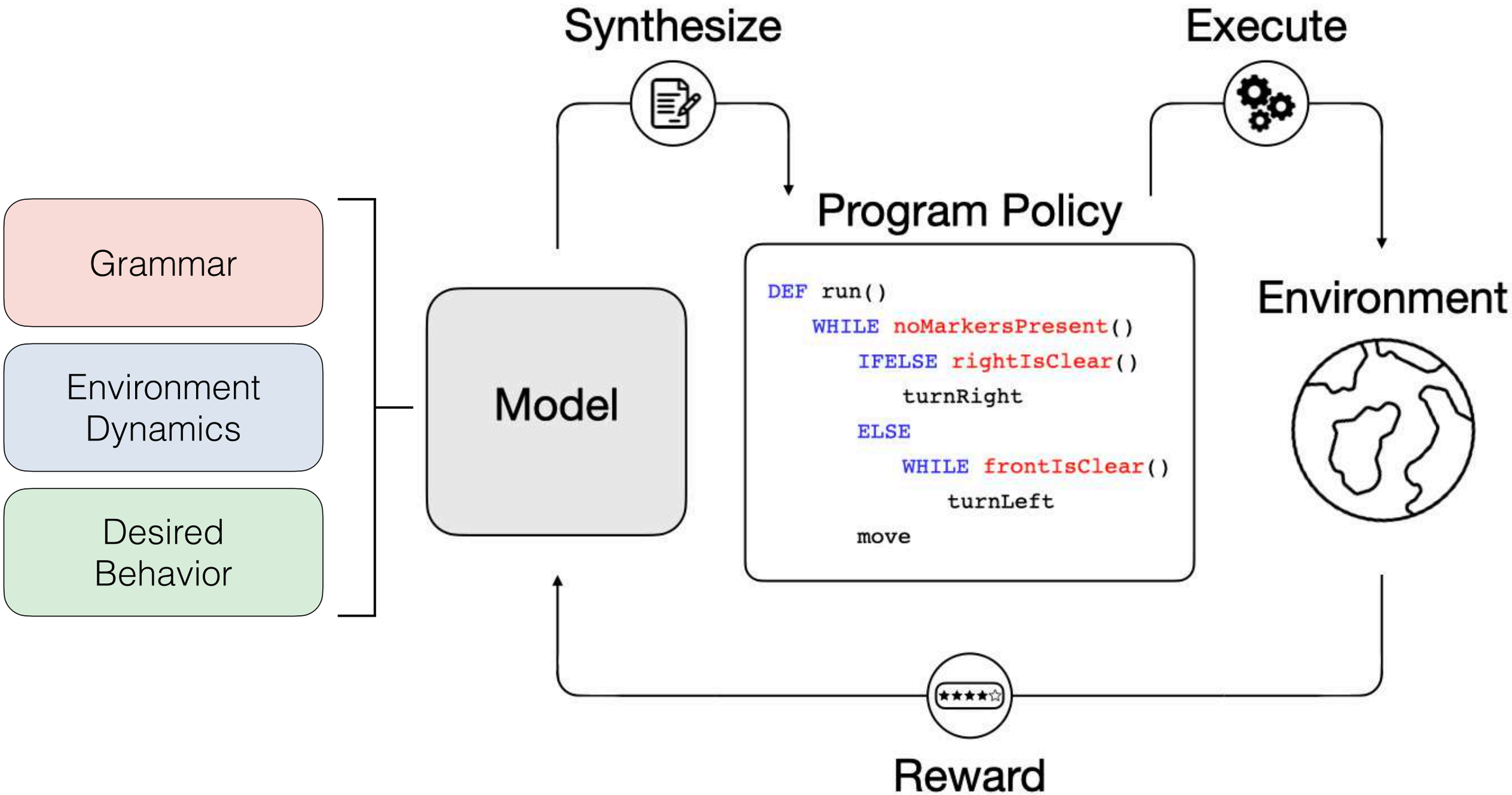
Reinforcement Learning



Reinforcement Learning by Synthesizing Programs



Reinforcement Learning by Synthesizing Programs



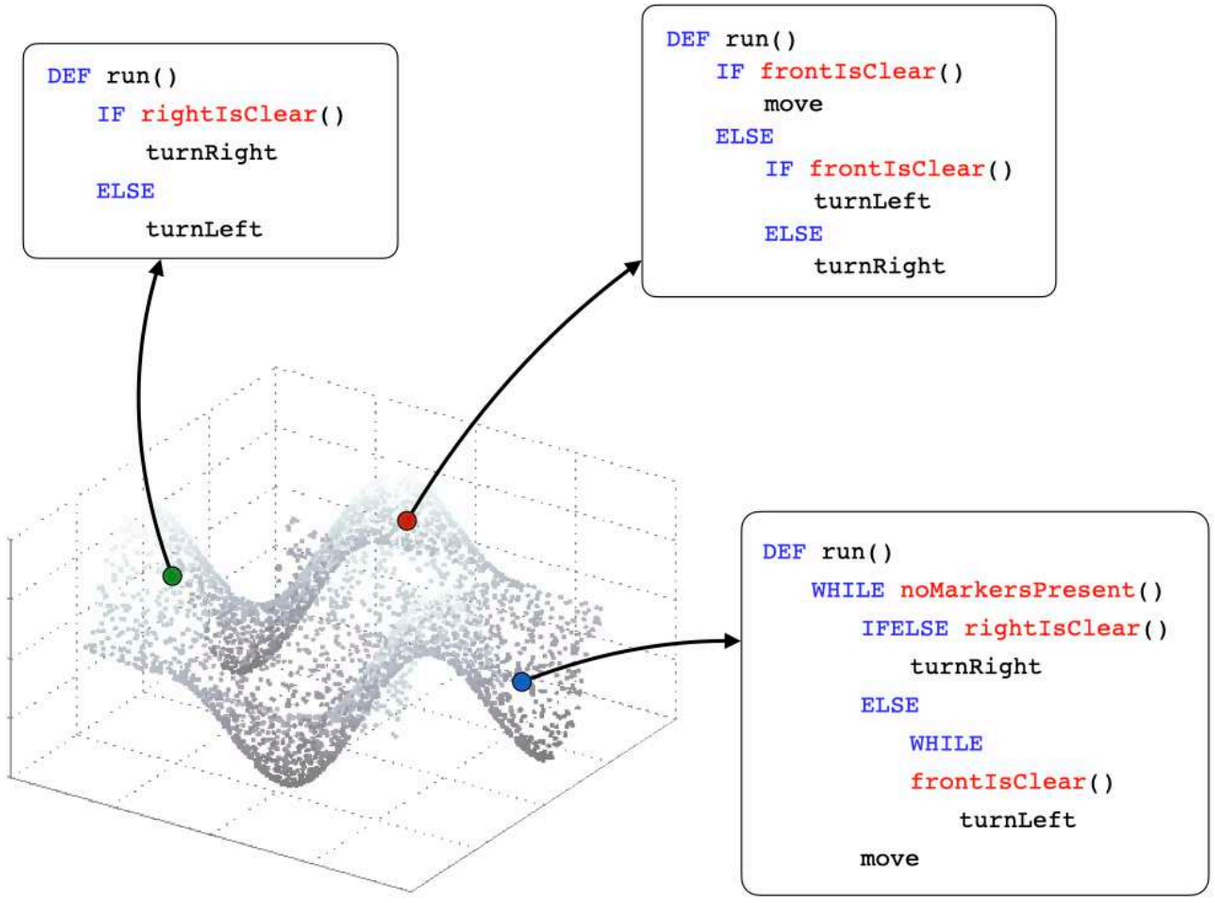
Method Overview

Stage 1

Learn a program embedding space from randomly generated programs

Grammar

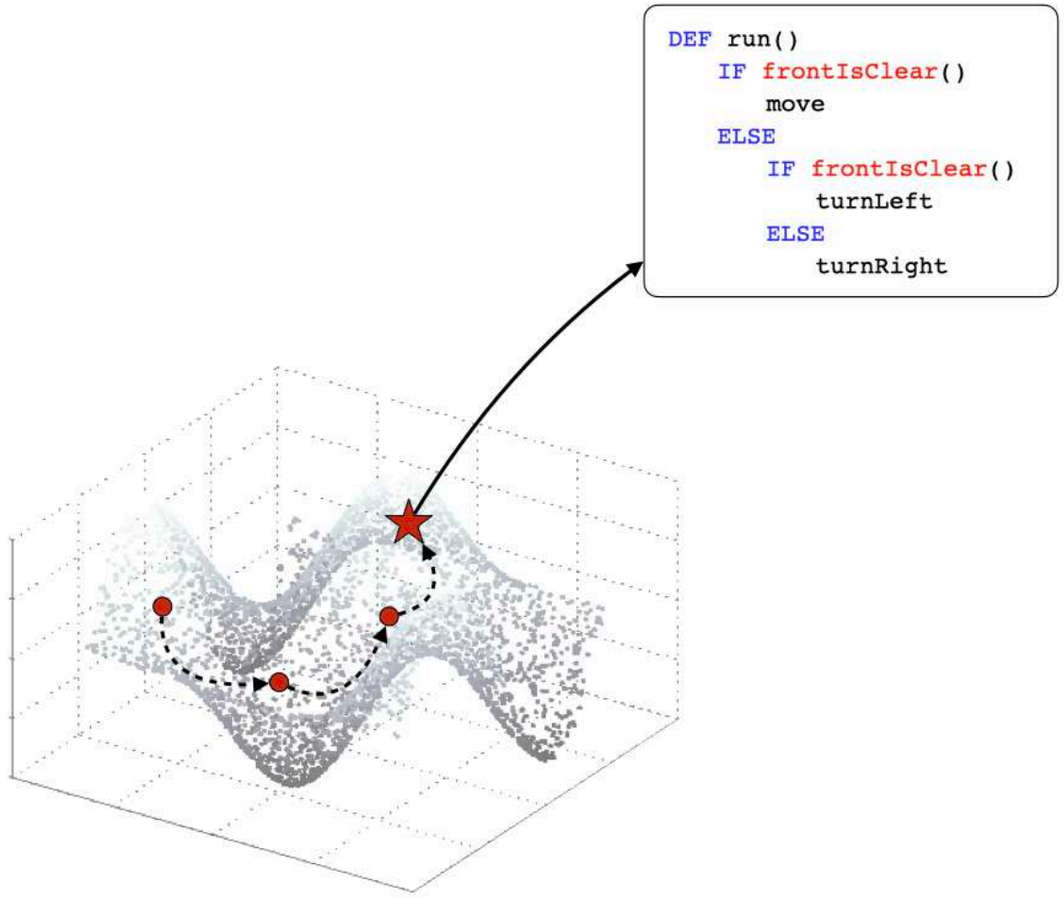
Environment Dynamics



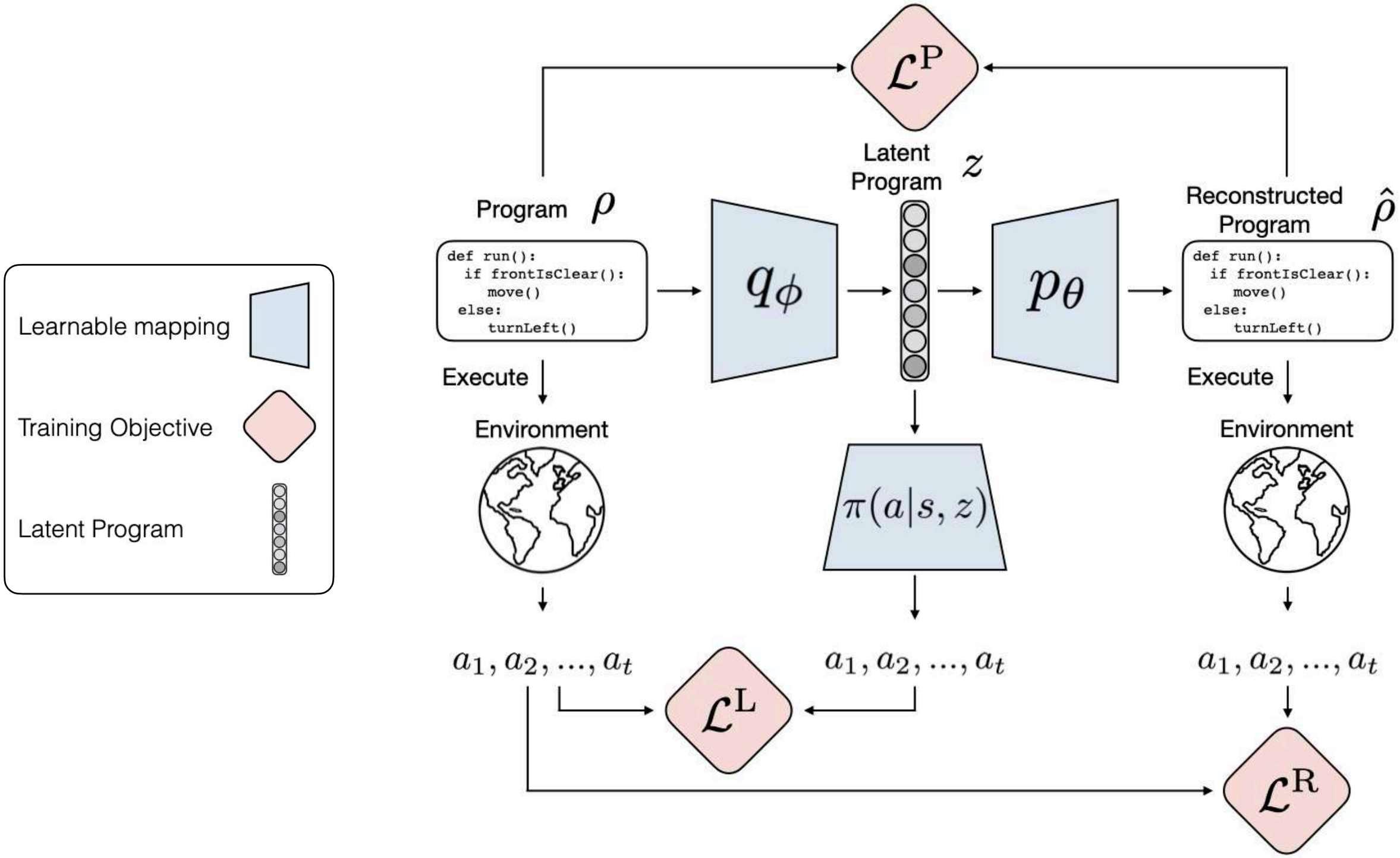
Stage 2

Search for a task-solving program

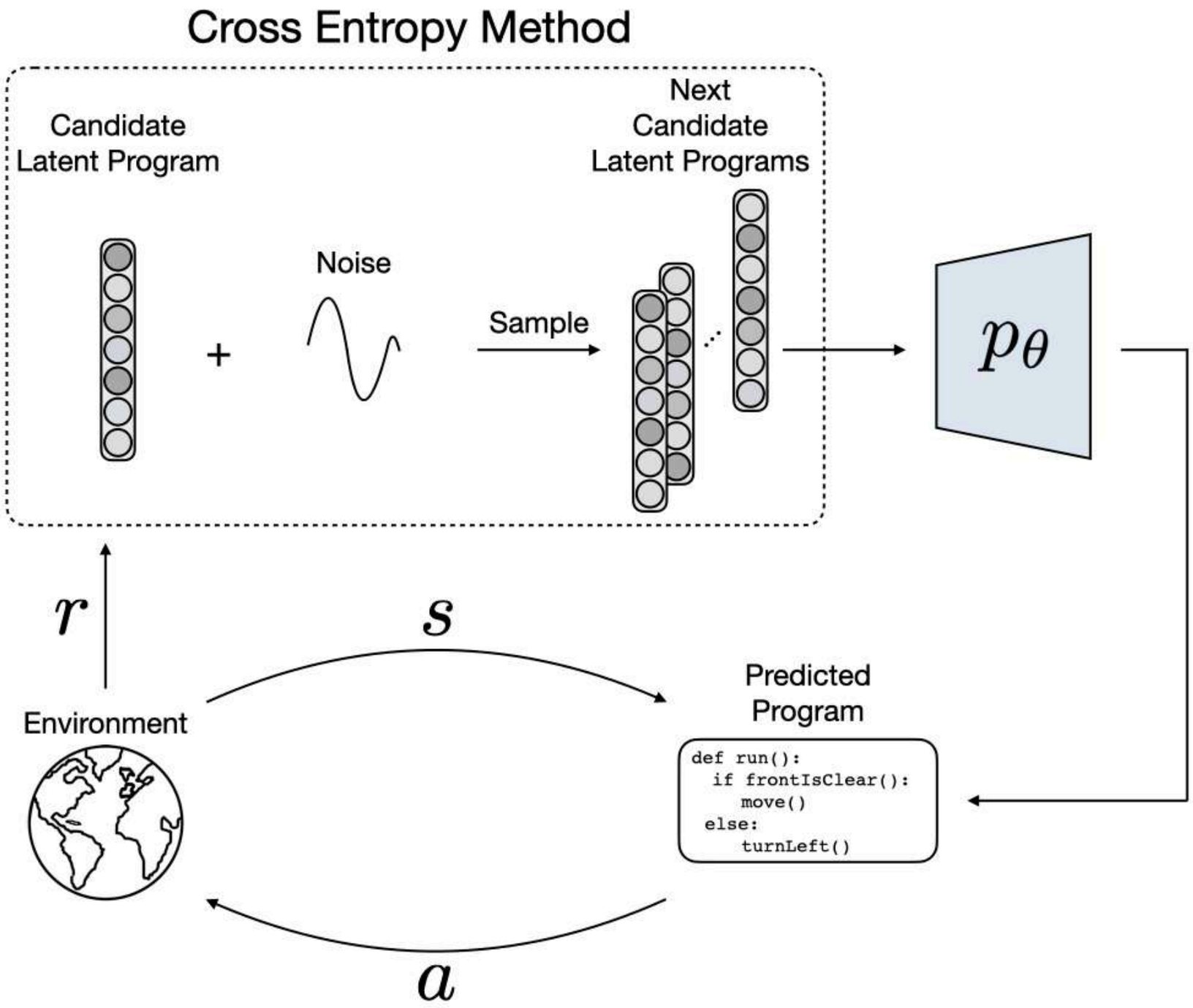
Desired Behavior



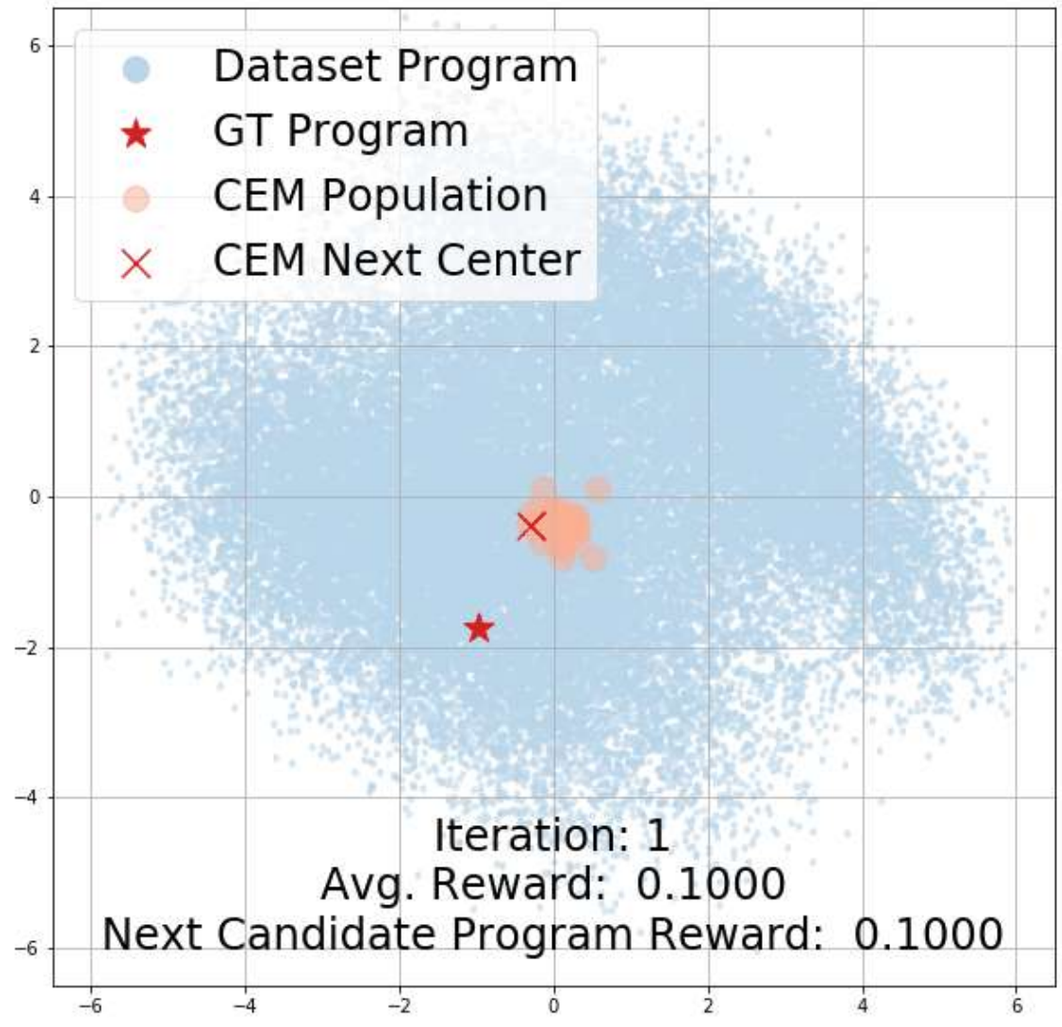
Stage 1: Learning a Program Embedding Space



Stage 2: Latent Program Search with Cross Entropy Method

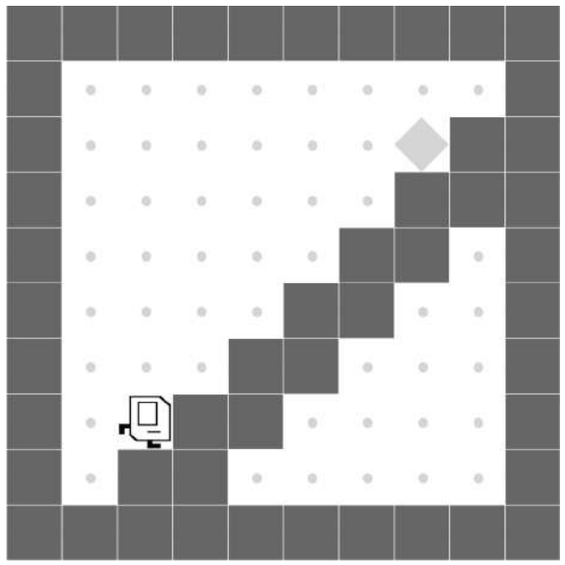


Cross Entropy Method Trajectory Visualization

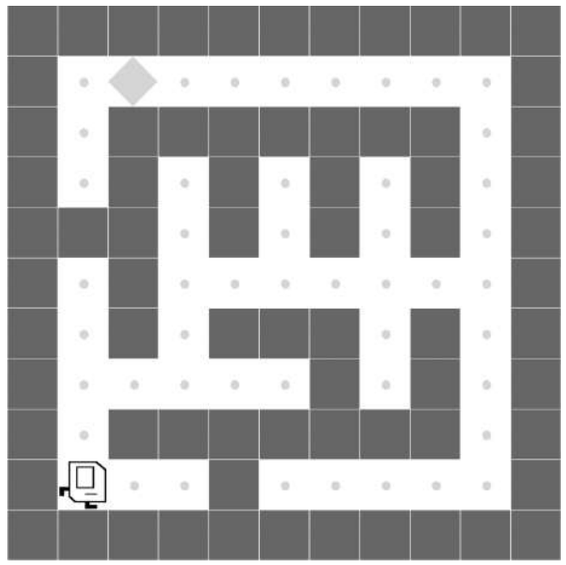


Karel Tasks

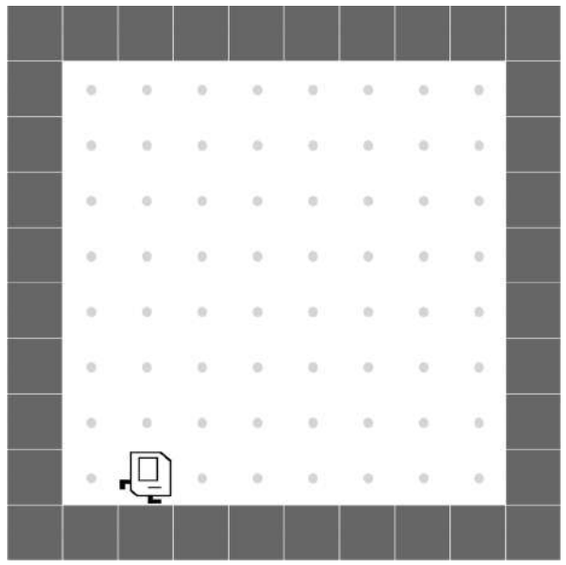
StairClimber



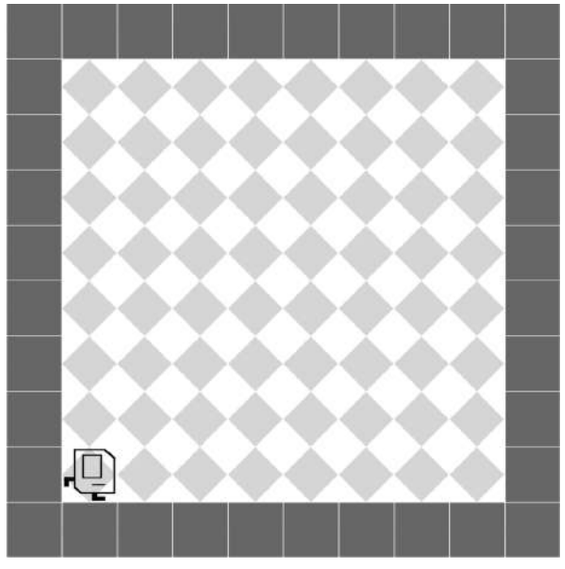
Maze



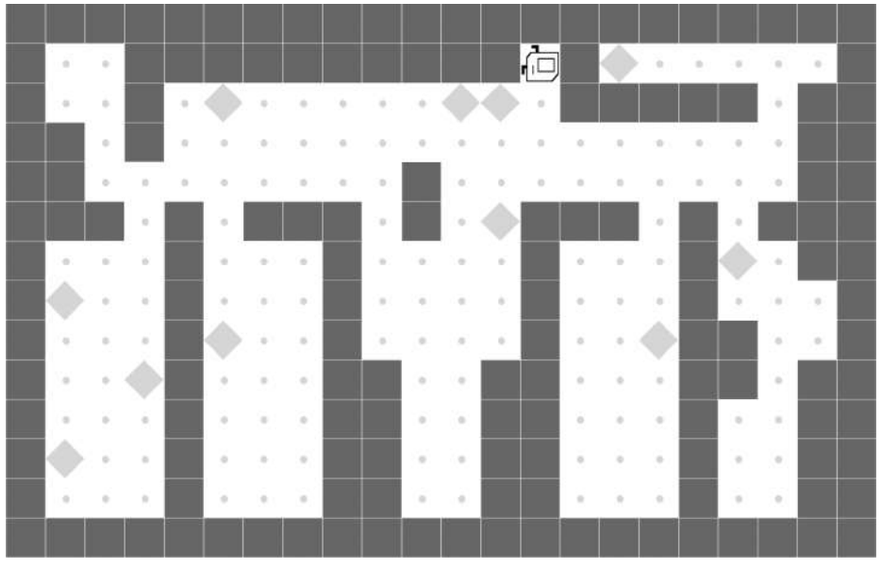
FourCorners



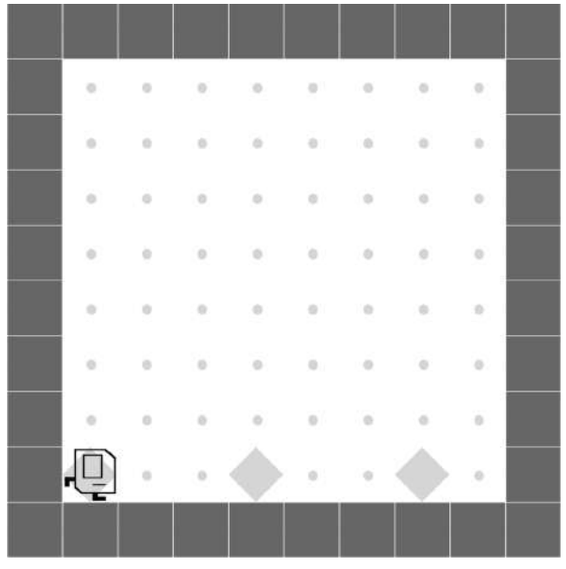
Harvester



CleanHouse

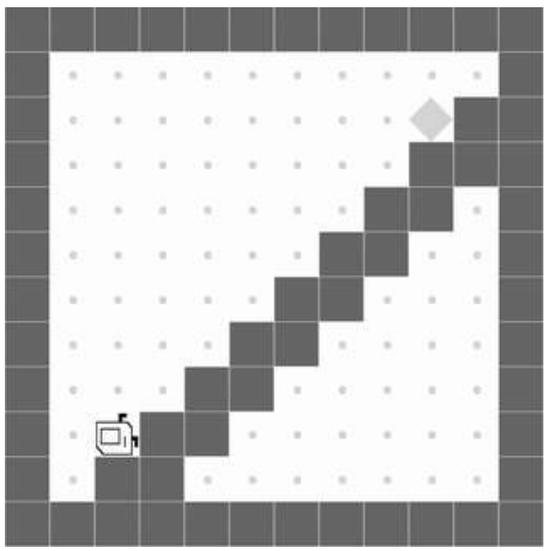


TopOff

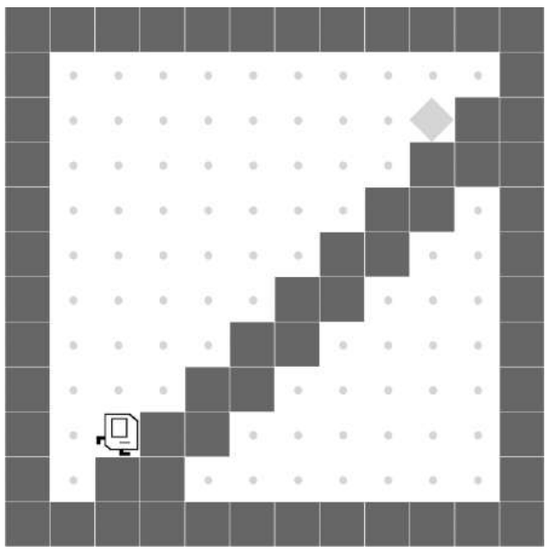


Qualitative Results

StairClimber

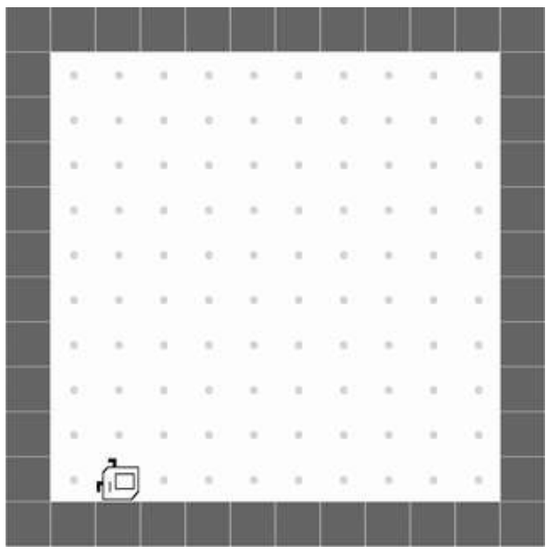


DRL

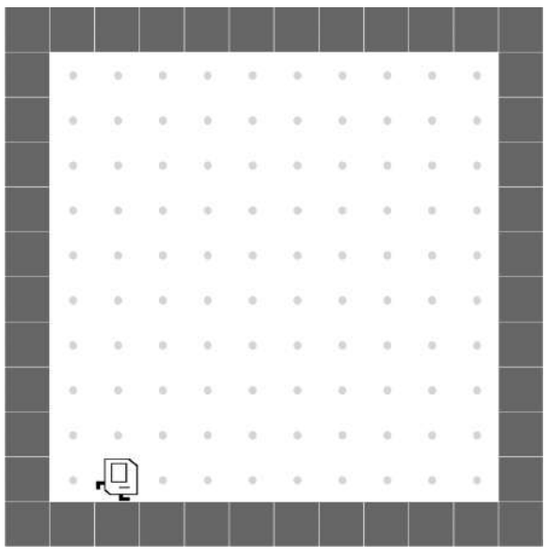


LEAPS

FourCorners

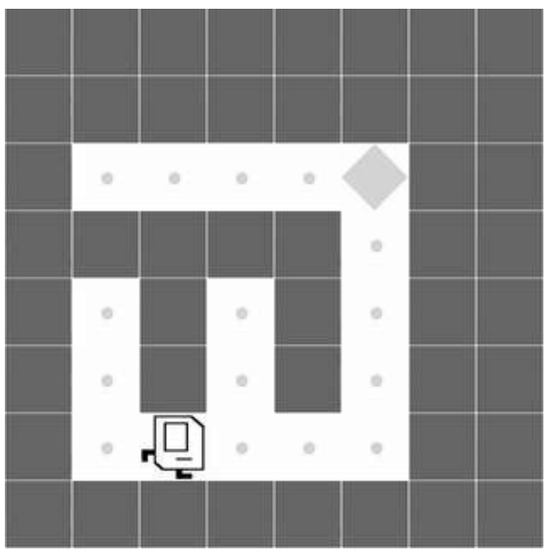


DRL

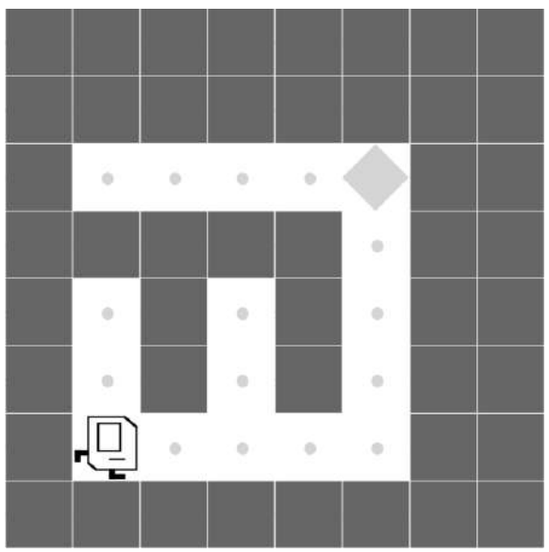


LEAPS

Maze

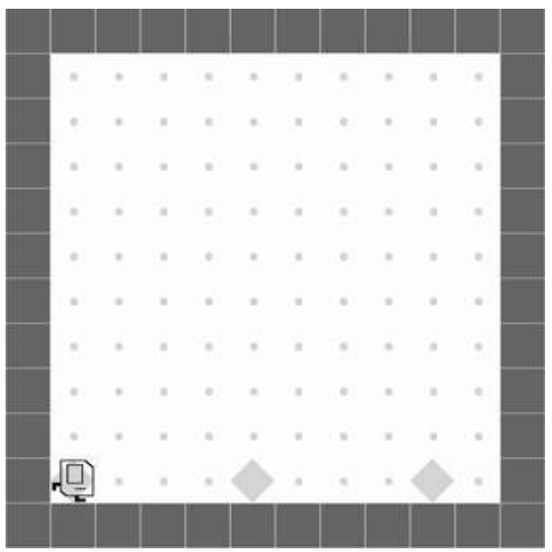


DRL

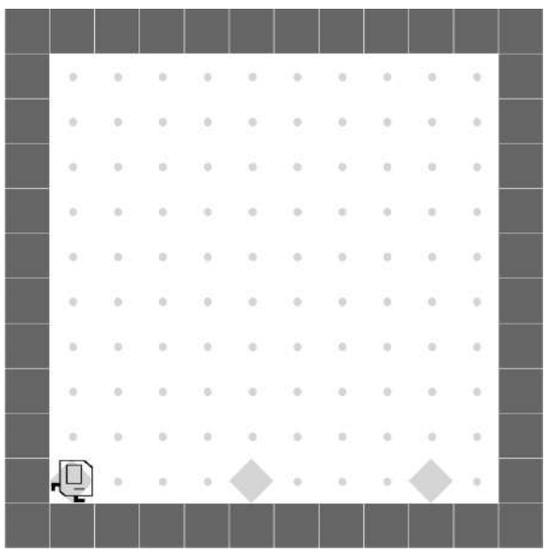


LEAPS

TopOff

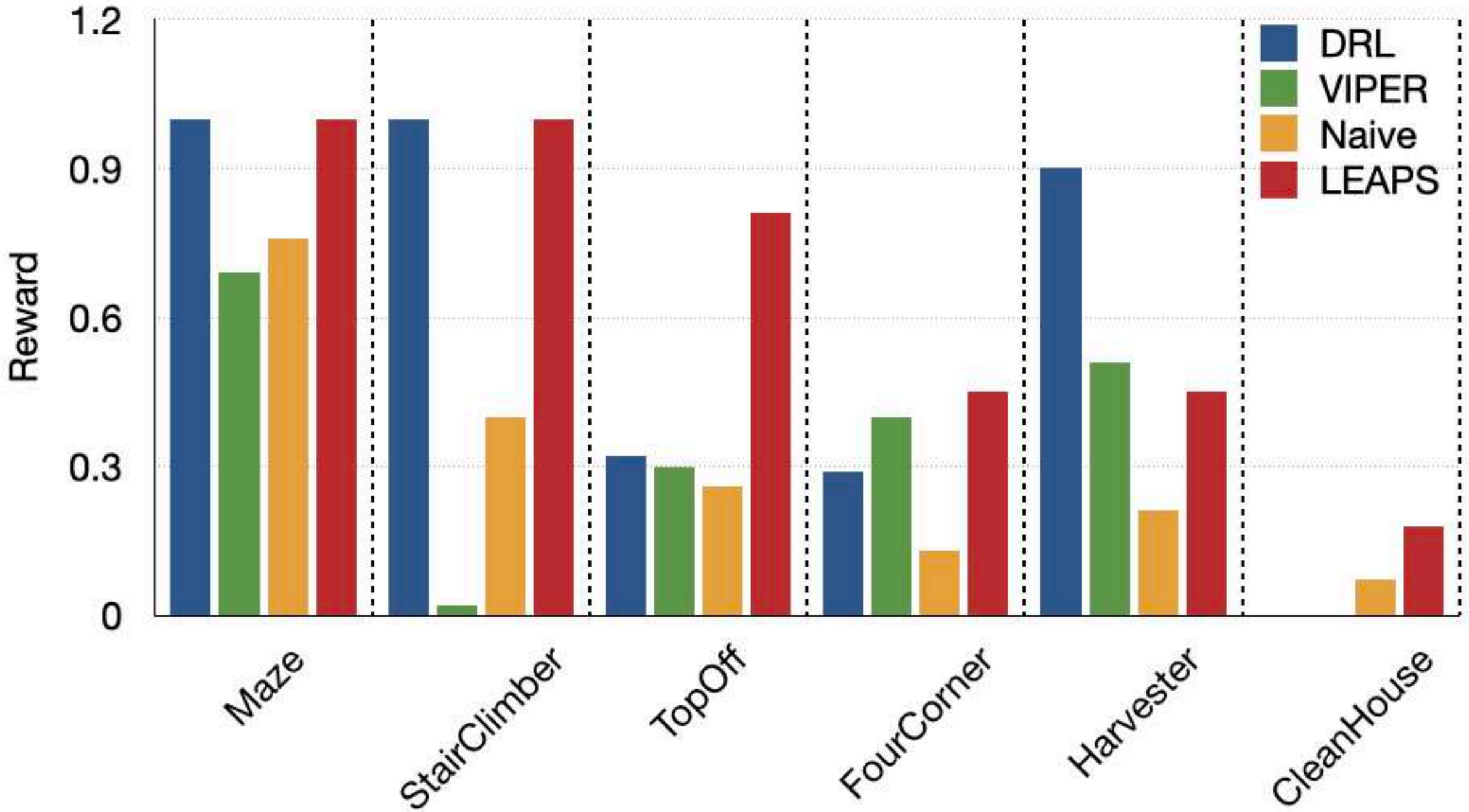


DRL



LEAPS

Quantitative Results

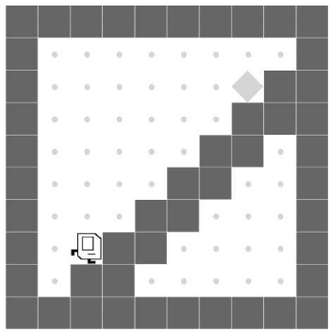


Zero-shot Generalization

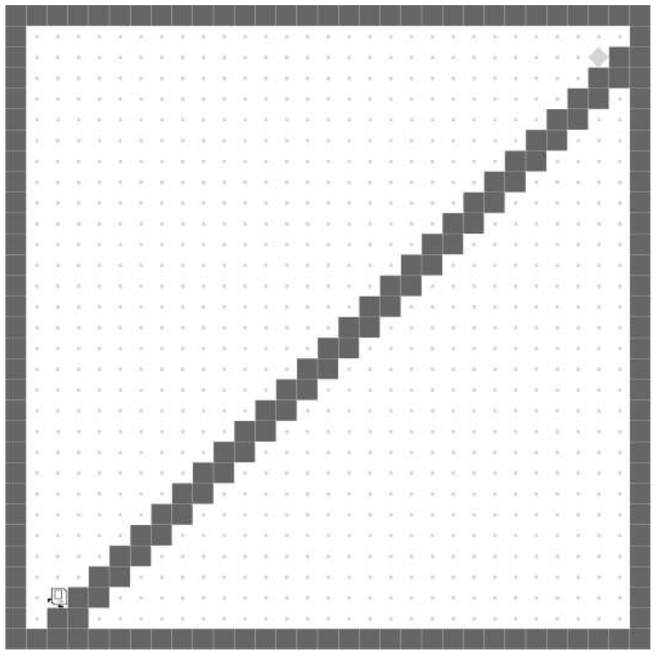
Learning on 8x8 grids

Evaluation on 100x100 grids

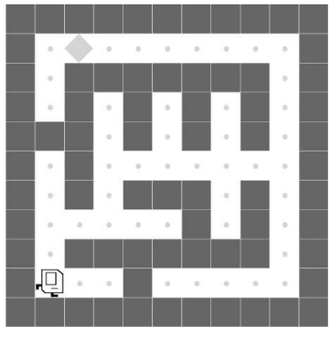
StairClimber



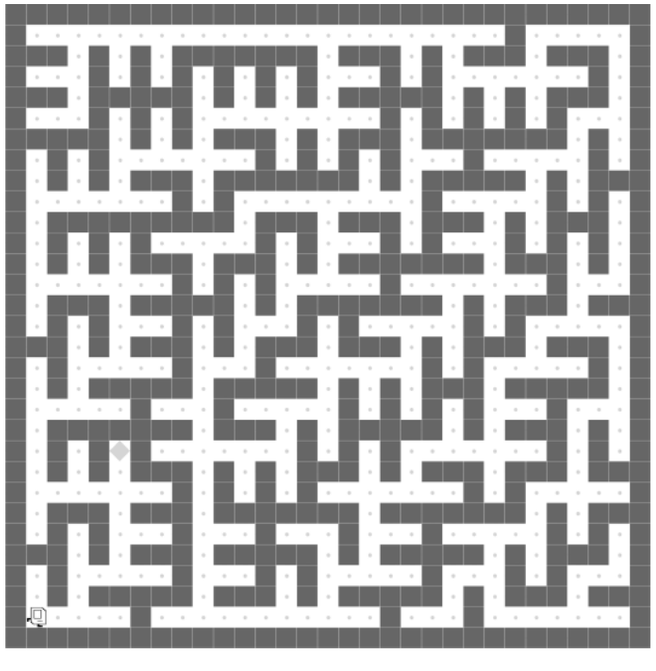
```
DEF run()
   WHILE noMarkersPresent()
      turnRight
      move
   WHILE rightIsClear()
      turnLeft
```



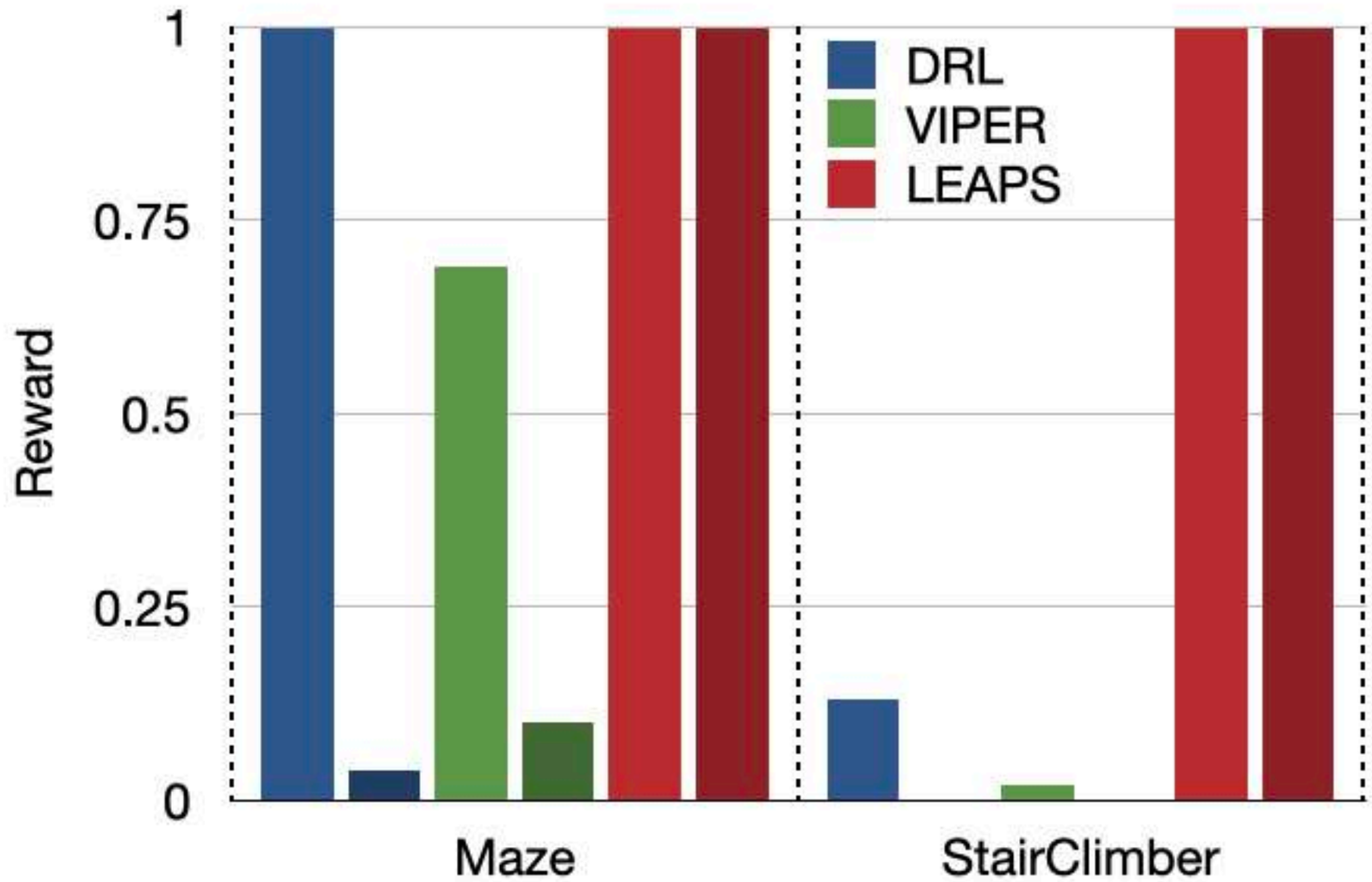
Maze



```
DEF run()
   IF frontIsClear()
      turnLeft
   WHILE noMarkersPresent()
      turnRight
      move
```

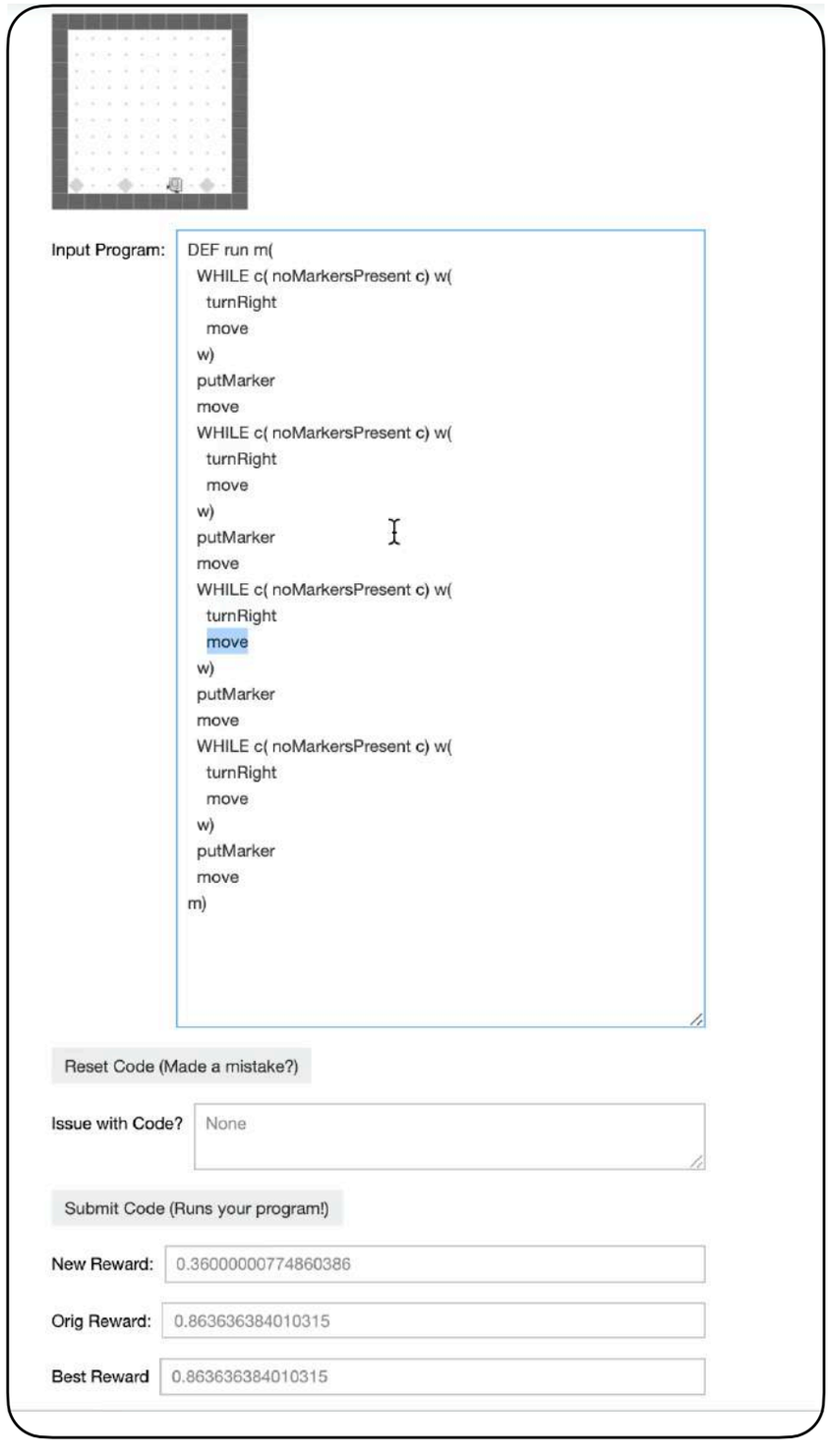


Zero-shot Generalization

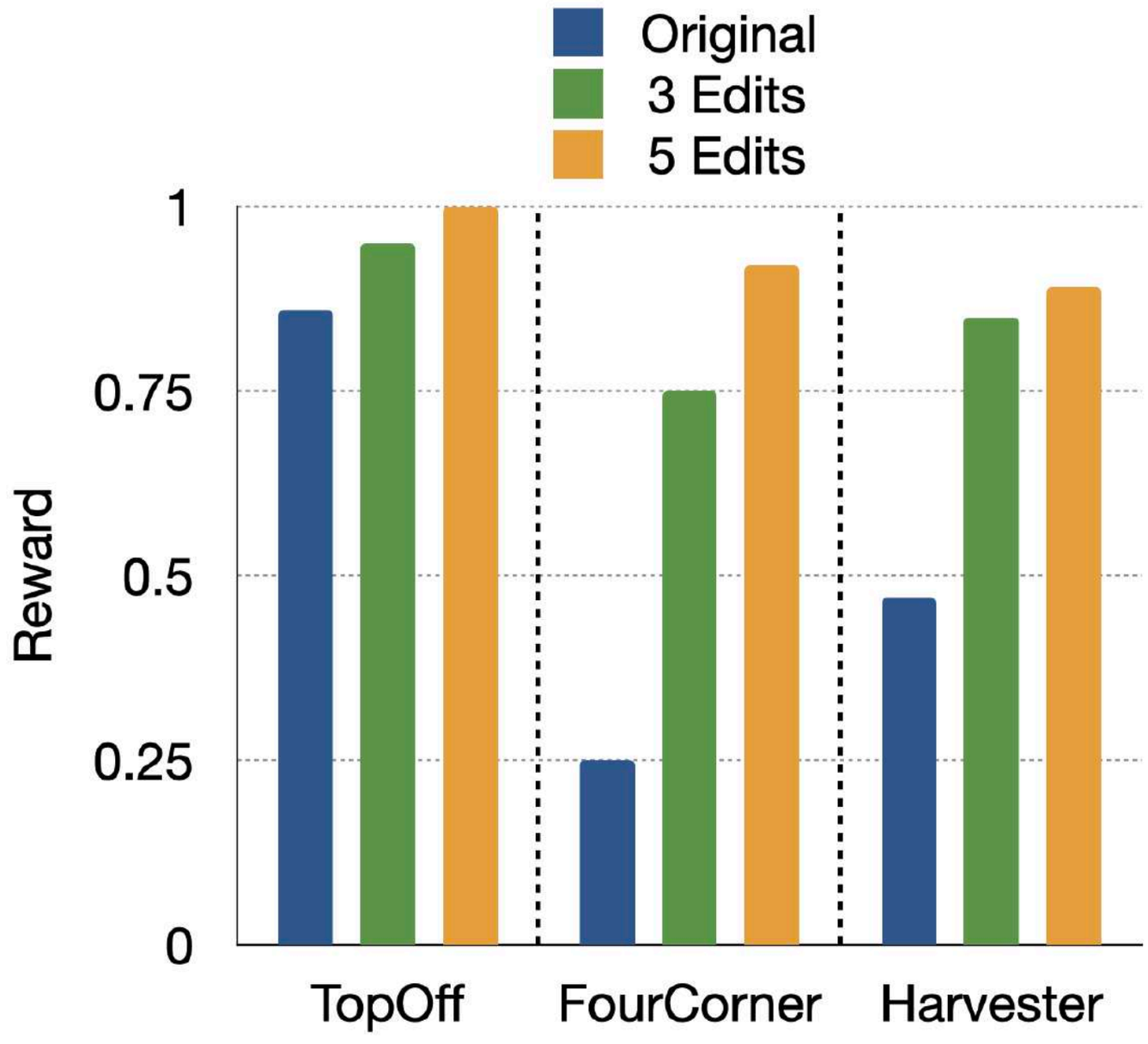


Interpretability

Human Debugging Interface

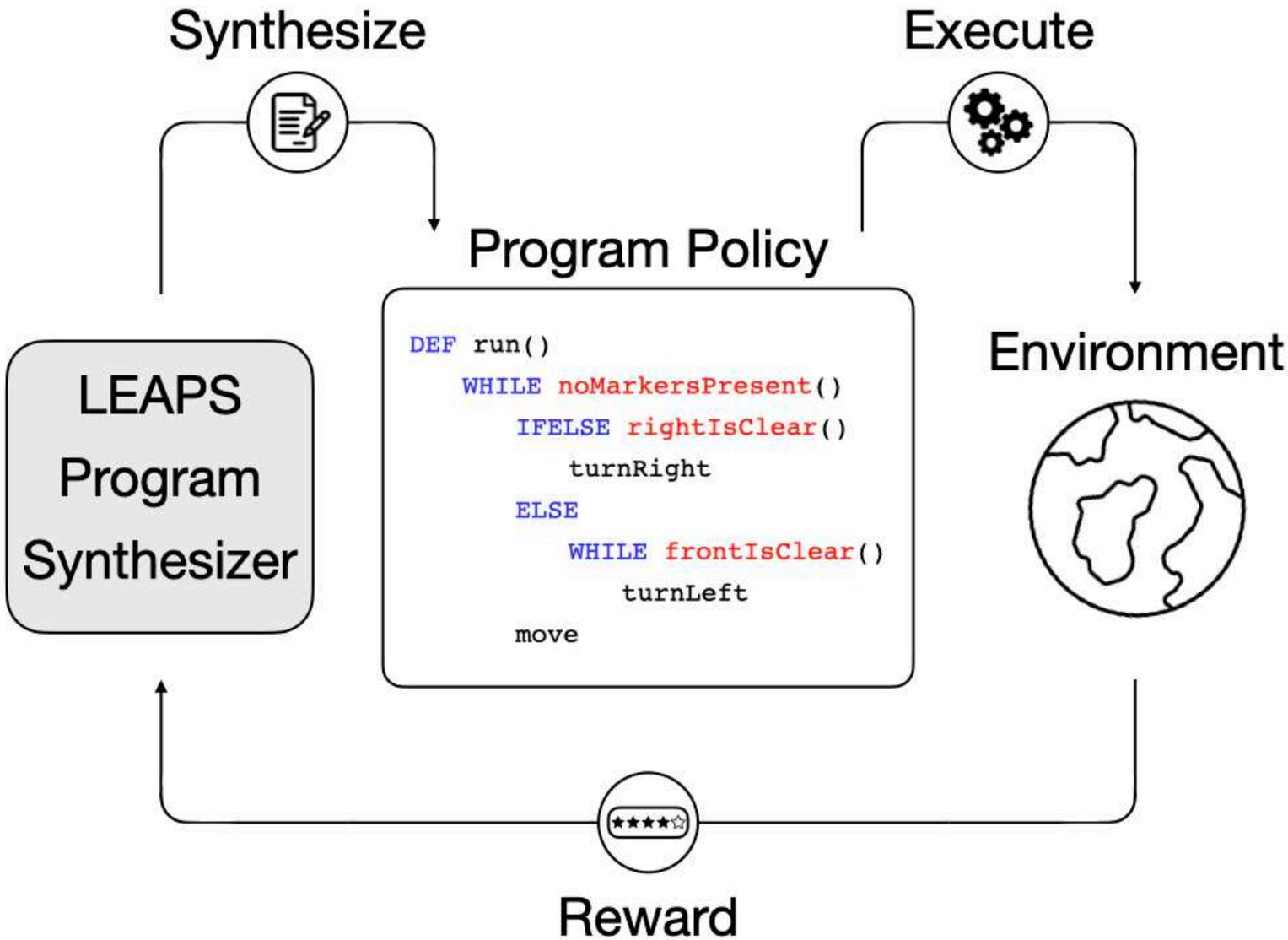


Improved Performance



Takeaway

- Synthesize **generalizable** and **interpretable programs** from rewards

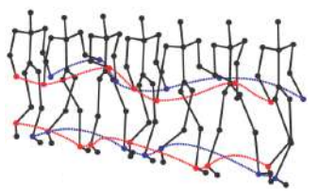


Program Inference

Skill Specification → Program → High-level Plan → Low-level Execution

Video demonstration

Trajectory demonstration

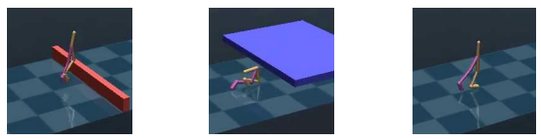


Language instruction

> Stir-fry the onions until tender, and repeat this for garlic and carrots, if you have soy sauce, add some. Pour 2/3 cups the whisked eggs into the stir-fried and scramble.

Reward

Actions (sub-skills)



`Jump` `Crawl` `Walk`

Perceptions

`isCurb()` `isCeiling()`

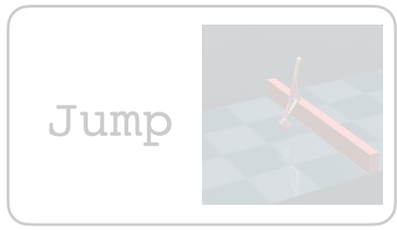
Control Flows

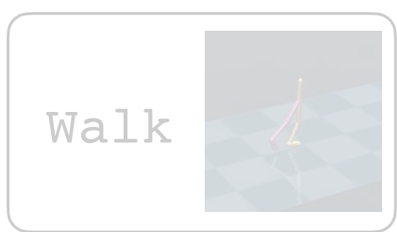
`while` `if` `else` `elseIf`

Program

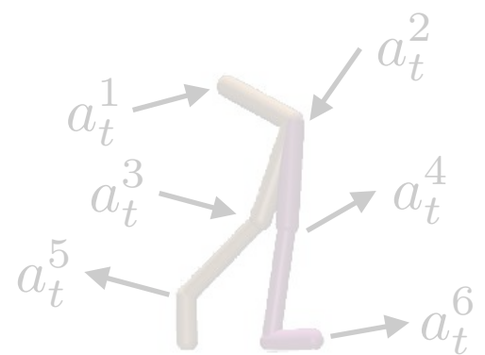
```
DEF run()
    while True:
        if isCurb():
            jump
        elseIf isCeiling():
            crawl()
        else:
            walk()
```

Observation



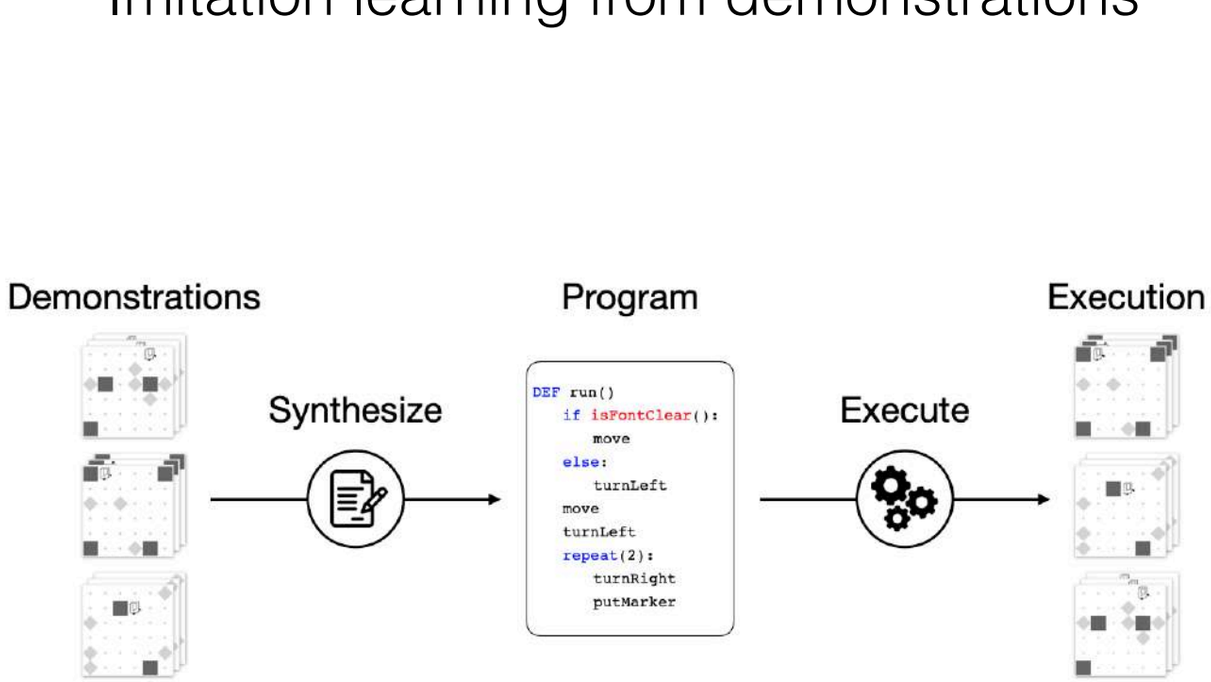


Low-level execution

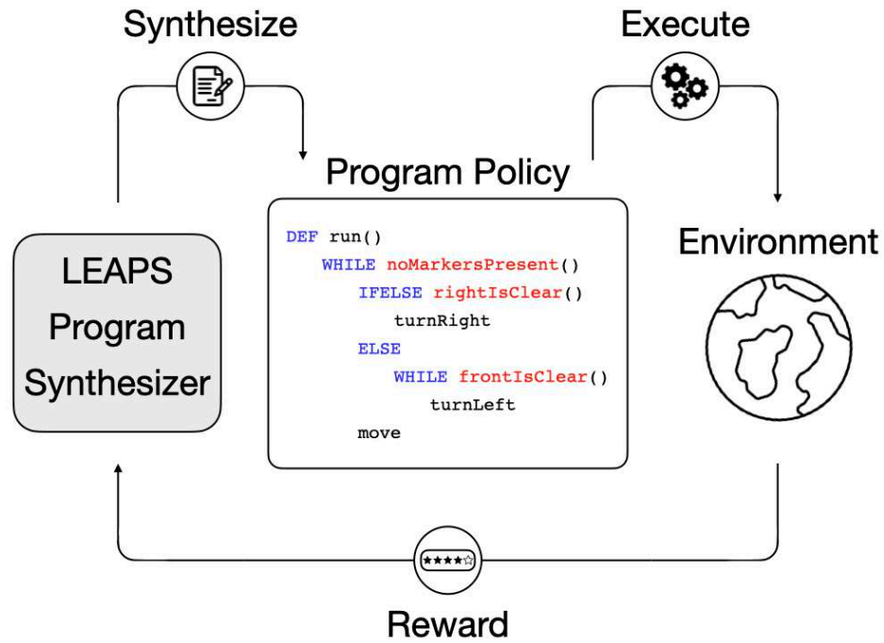


Program Inference

Imitation learning from demonstrations

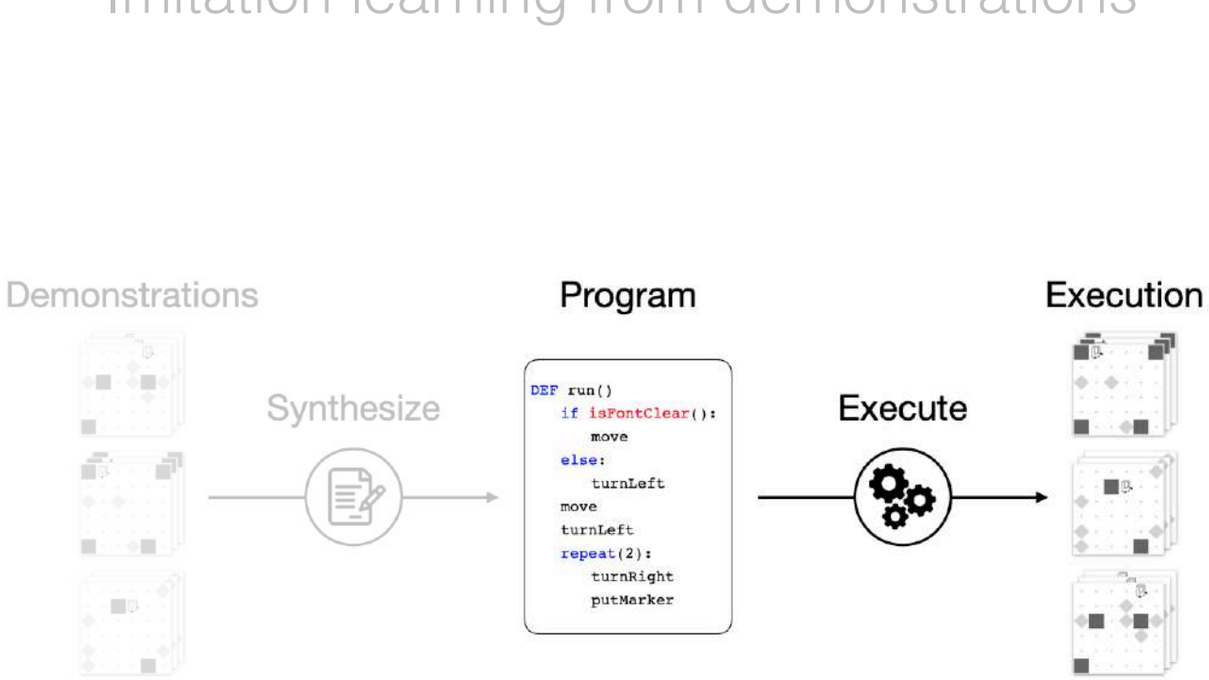


Reinforcement learning from rewards

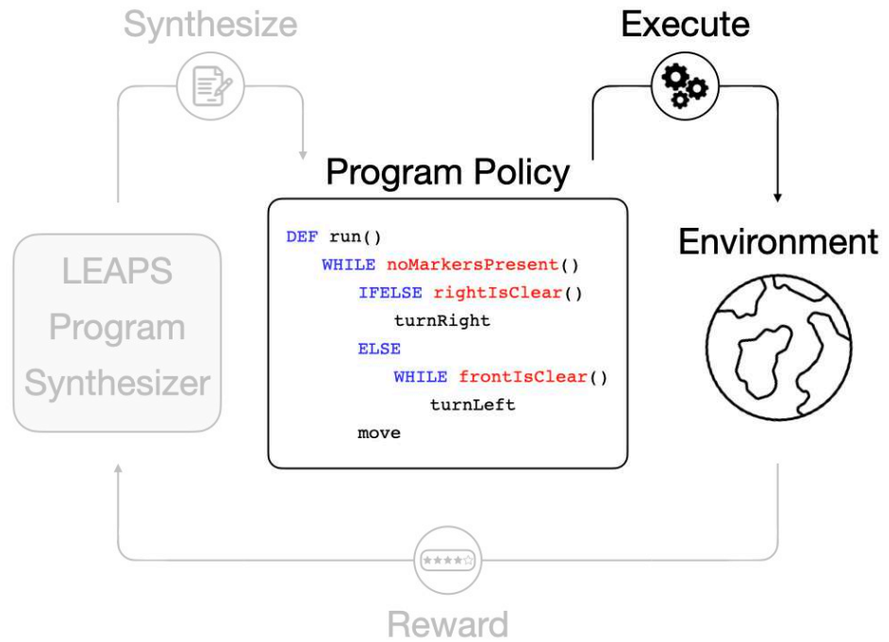


Program Inference

Imitation learning from demonstrations



Reinforcement learning from rewards



Task Execution

Skill Specification

Video demonstration

Trajectory demonstration

Language instruction

Stir-fry the onions until tender, and repeat this for garlic and carrots, if you have soy sauce, add some. Pour 2/3 cups the whisked eggs into the stir-fried and scramble.

Reward

Program

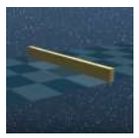
Actions (sub-skills)

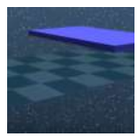

Jump


Crawl


Walk

Perceptions


isCurb()

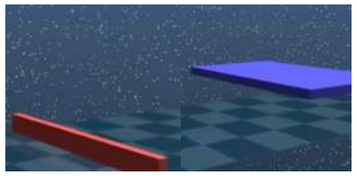

isCeiling()

Control Flows

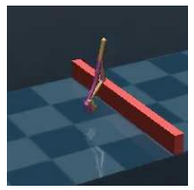
while | if | else | elseIf

```
DEF run()
    while True:
        if isCurb():
            jump
        elseIf isCeiling():
            crawl()
        else:
            walk()
```

Observation



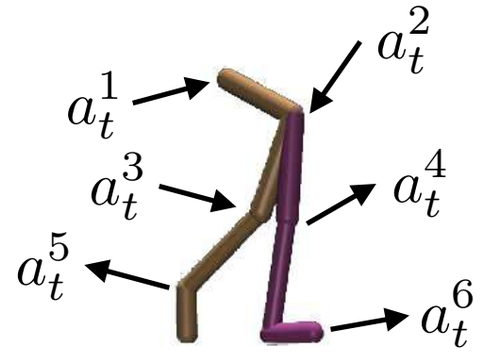
Jump



Walk

Crawl

Low-level execution



Program Guided Agent

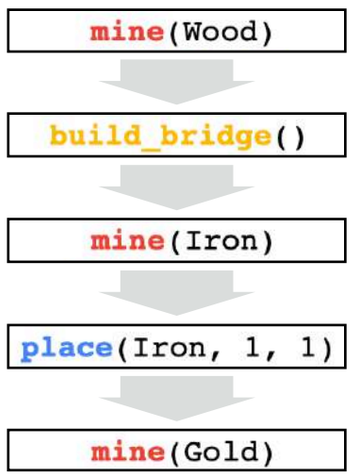
ICLR 2020 (Spotlight)

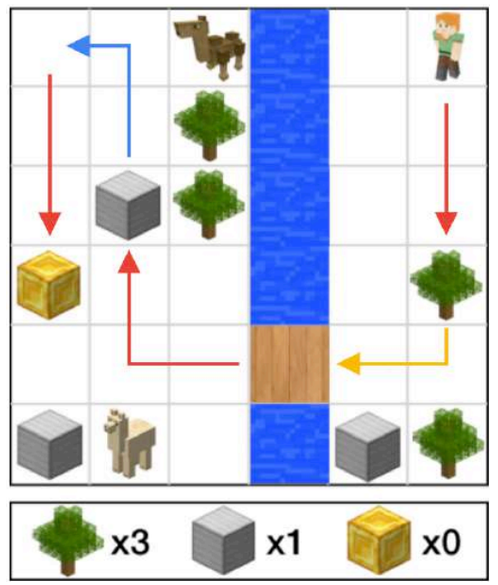
Skill Specification → Program → High-level Plan → Low-level Execution

Te-Lin Wu

Joseph J. Lim

```
def run():
  if is_there[River]:
    mine(Wood)
    build_bridge()
    if agent[Iron]<3:
      mine(Iron)
    place(Iron, 1, 1)
  else:
    goto(4, 2)
  while env[Gold]>0:
    mine(Gold)
```



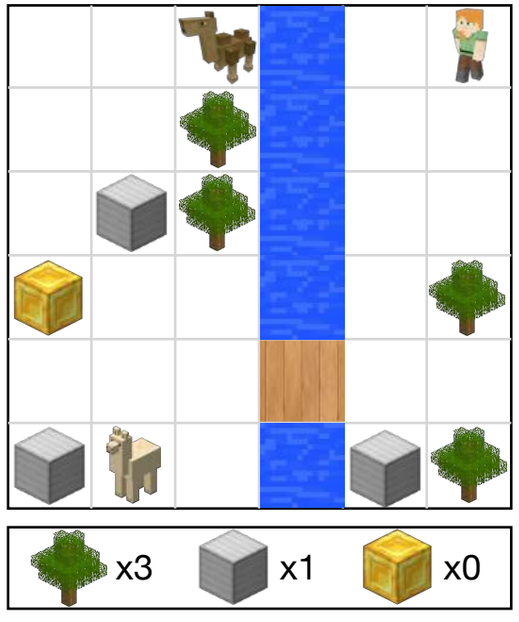


Problem Formulation

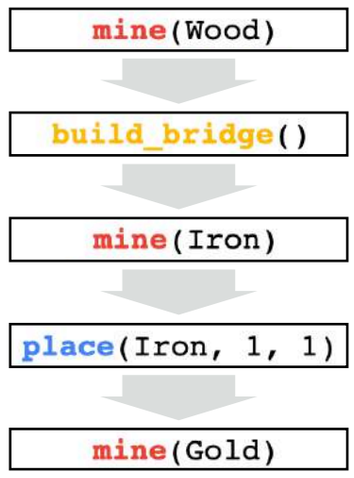
Program (task)

```
def run():
  if is_there[River]:
    mine(Wood)
    build_bridge()
    if agent[Iron]<3:
      mine(Iron)
    place(Iron, 1, 1)
  else:
    goto(4, 2)
  while env[Gold]>0:
    mine(Gold)
```

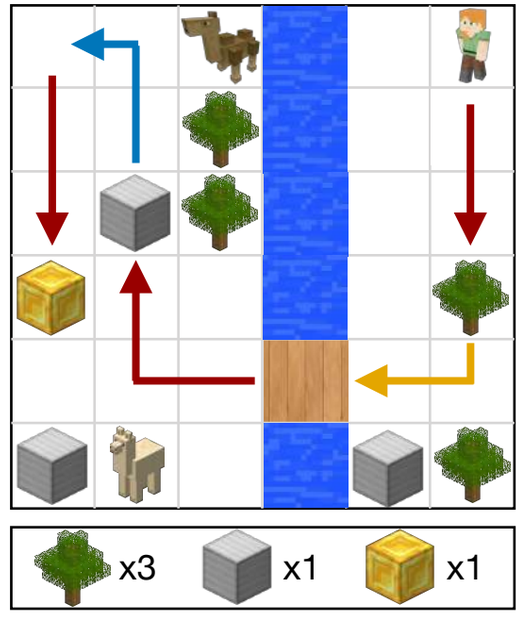
Observation



Plan (subtasks)



Execution



Instructions

Programs

```
def run()
   if is_there[River]:
      mine(Wood)
      build_bridge()
      if agent[Iron] < 3:
         mine(Iron)
      place(Iron, 2, 3)
   else:
      goto(4, 2)
   while env[Gold] > 0:
      mine(Gold)
```

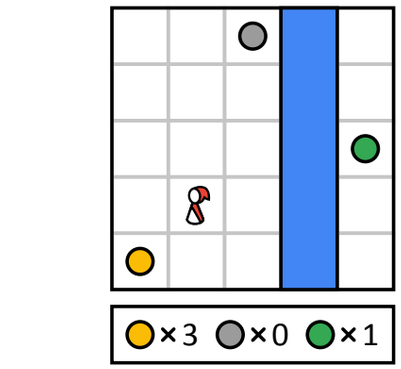
```
def run()
   while agent[Wood] <= 11:
      place(Wood, 2, 4)
      place(Iron, 1, 1)
      place(Iron, 8, 5)
      mine(Gold)
      mine(Gold)
   mine(Gold)
   repeat(4):
      sell(Gold)
      sell(Iron)
```

Natural Language Descriptions

If a river is in the environment, mine a wood and then use it to build a bridge. And then if agent has less than there iron, place an iron at (2,3). Otherwise if no river, goto location (4,2). Finally, whenever there's still gold in the environment, mine a gold.

While agent has no more than 11 wood, place wood at (2,4) and iron at (1,1), then place iron at (8,5) and mine gold twice, then mine gold. After the preceding procedure, sell gold and sell iron 4 times.

End-to-end Learning Baseline



State

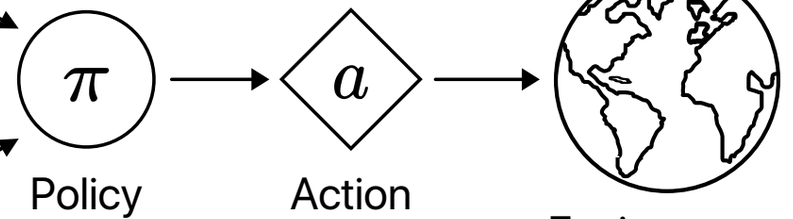
```
def run():
  while env[Gold] > 0:
    mine(Gold)
  if is_there[River]:
    build_bridge()
    place(Wood, 2, 3)
```

Program

```
If an agent has more
than 1 iron, place an
iron on (2,3), and then
if there are less than 3
gold in the environment,
mine gold; otherwise,
goto (4,2). While gold
in the environment is
larger than 2, keep
mining gold.
```

Language description

OR

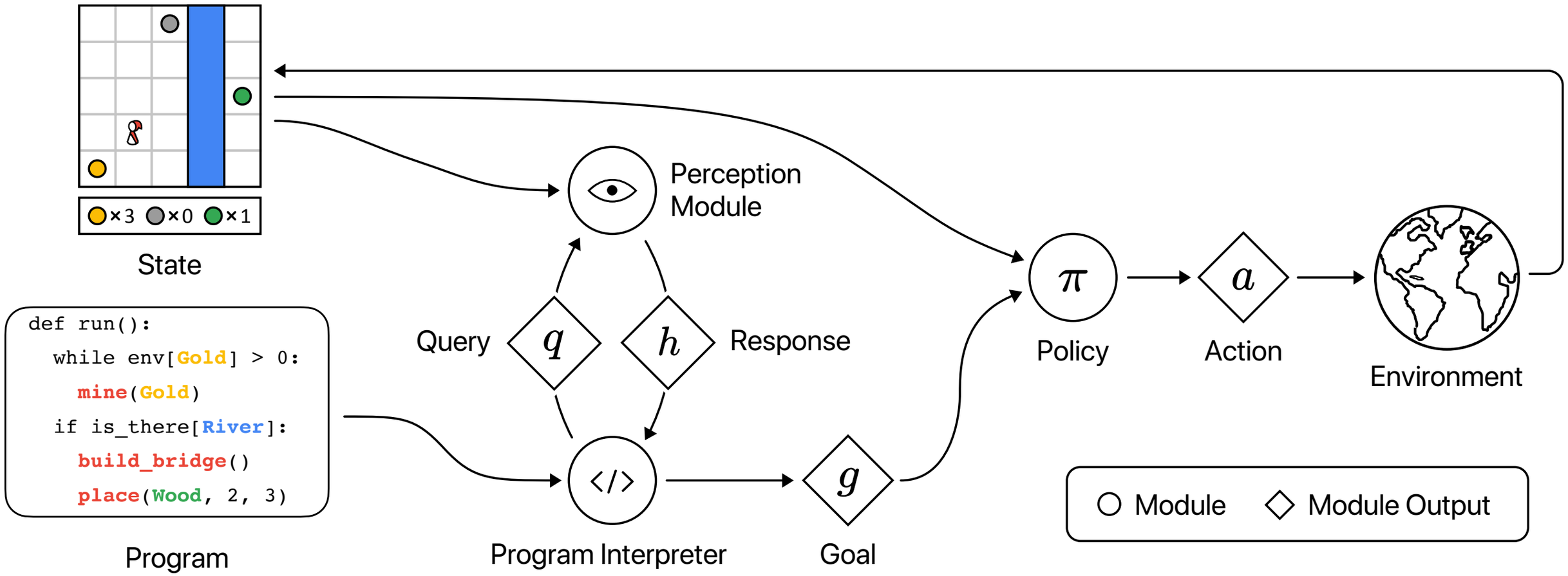


Policy

Action

Environment

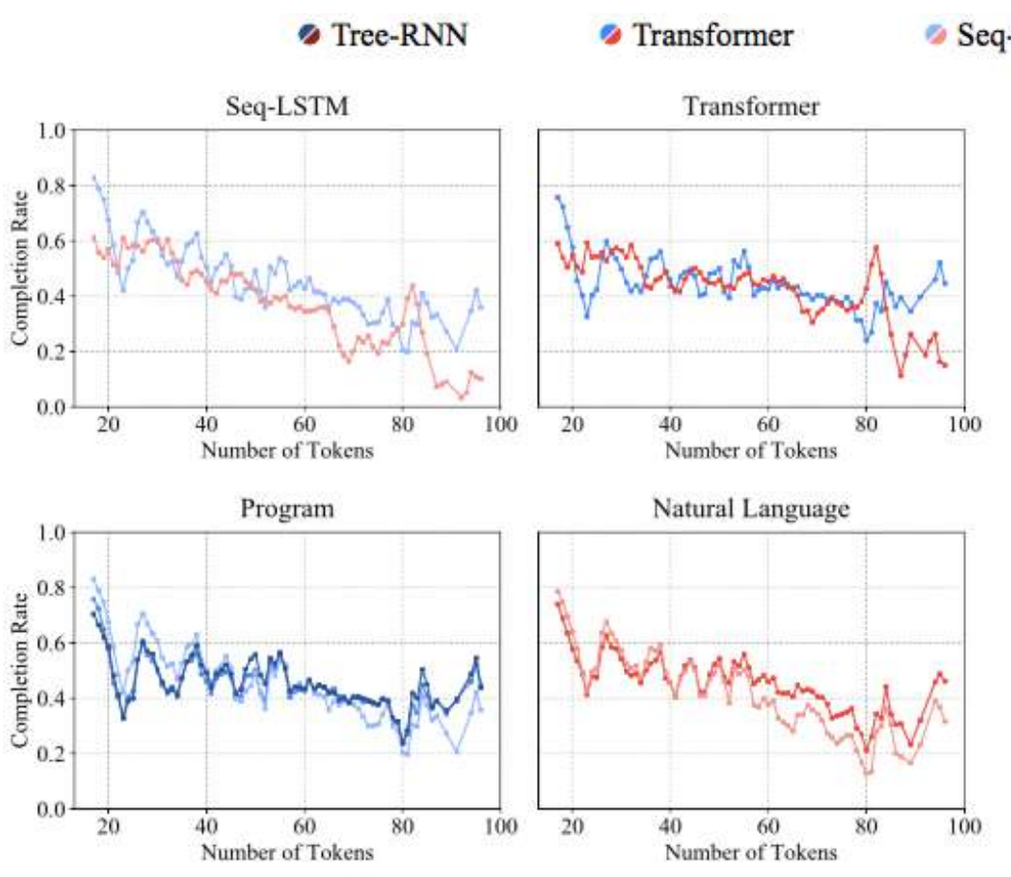
Program Guided Agent



Quantitative Results

Generalization

Instruction		Natural language descriptions		Programs				
Method		Seq-LSTM	Transformer	Seq-LSTM	Tree-RNN	Transformer	Ours (concat)	Ours
Dataset	test	54.9±1.8%	52.5±2.6%	56.7±1.9%	50.1±1.2%	49.4±1.6%	88.6±0.8%	94.0±0.5%
	test-complex	32.4±4.9%	38.2±2.6%	38.8±1.2%	42.2±2.4%	40.9±1.5%	85.2±0.8%	91.8±0.2%
Generalization gap		40.9%	27.2%	31.6%	15.8%	17.2%	3.8%	2.3%



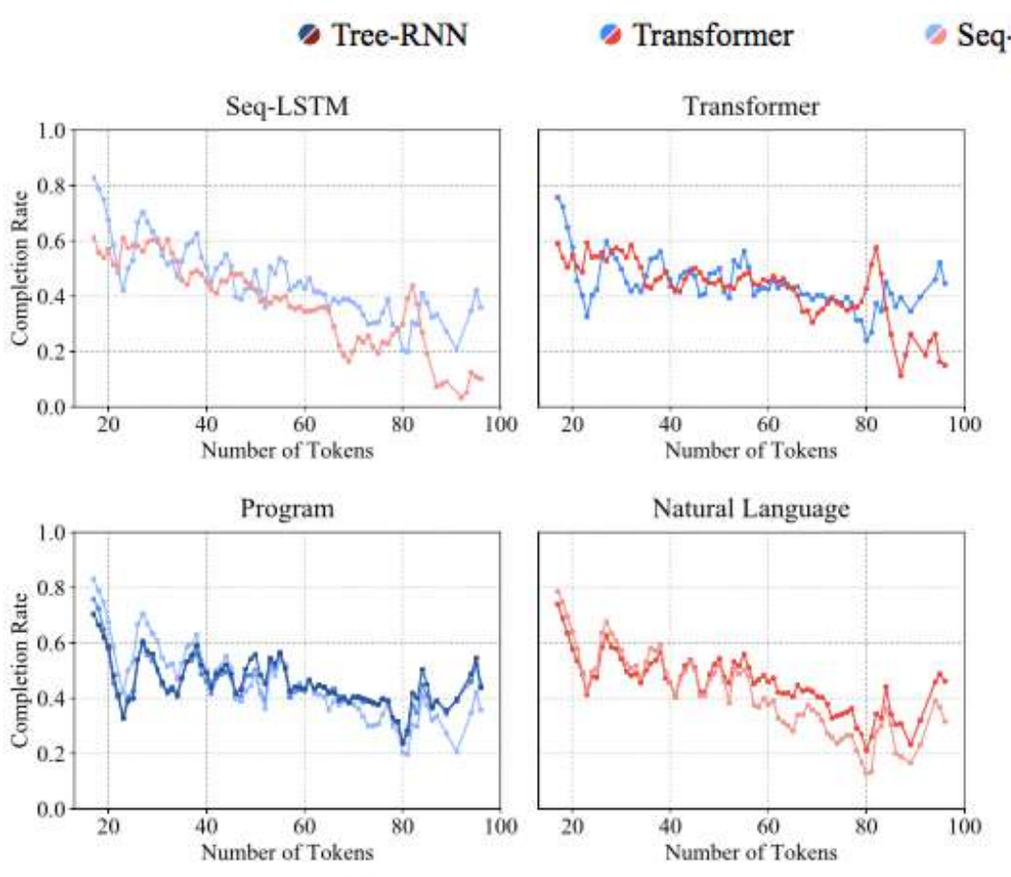
(a) Instruction Length

(b) Instruction Complexity

Quantitative Results

Natural Languages < Programs

Instruction Method		Natural language descriptions		Programs				
		Seq-LSTM	Transformer	Seq-LSTM	Tree-RNN	Transformer	Ours (concat)	Ours
Dataset	test	54.9±1.8%	52.5±2.6%	56.7±1.9%	50.1±1.2%	49.4±1.6%	88.6±0.8%	94.0±0.5%
	test-complex	32.4±4.9%	38.2±2.6%	38.8±1.2%	42.2±2.4%	40.9±1.5%	85.2±0.8%	91.8±0.2%
Generalization gap		40.9%	27.2%	31.6%	15.8%	17.2%	3.8%	2.3%



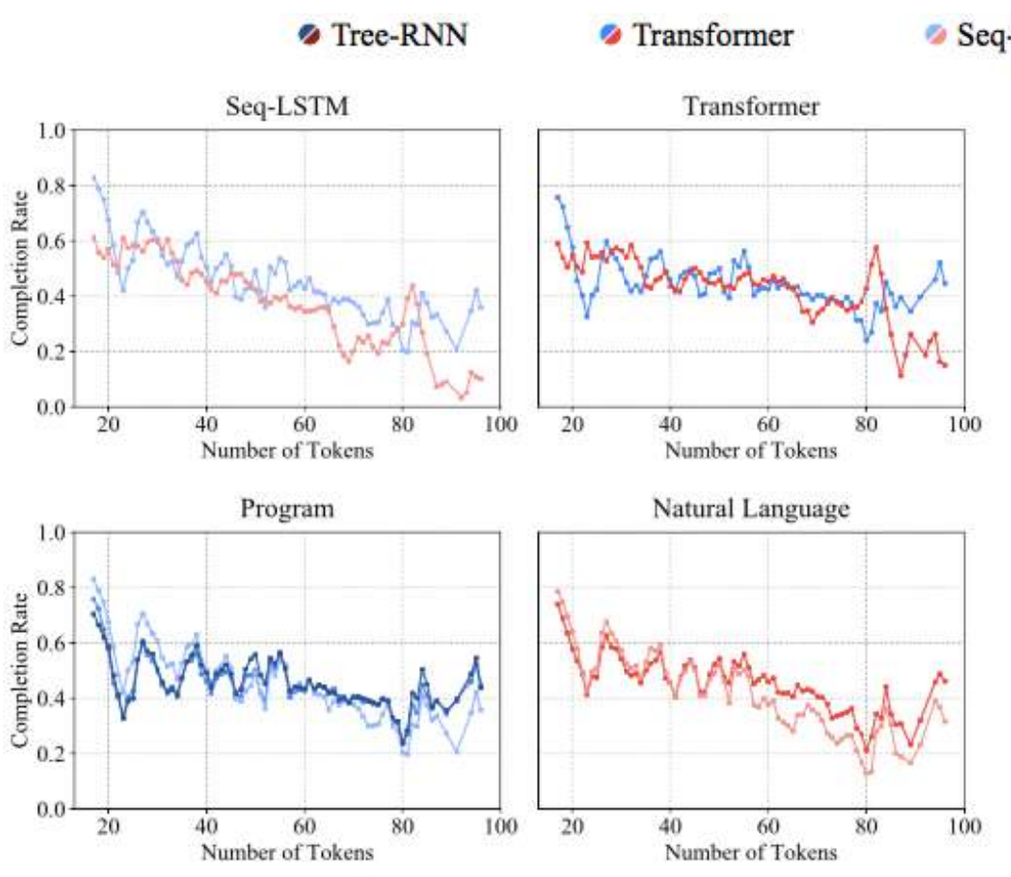
(a) Instruction Length

(b) Instruction Complexity

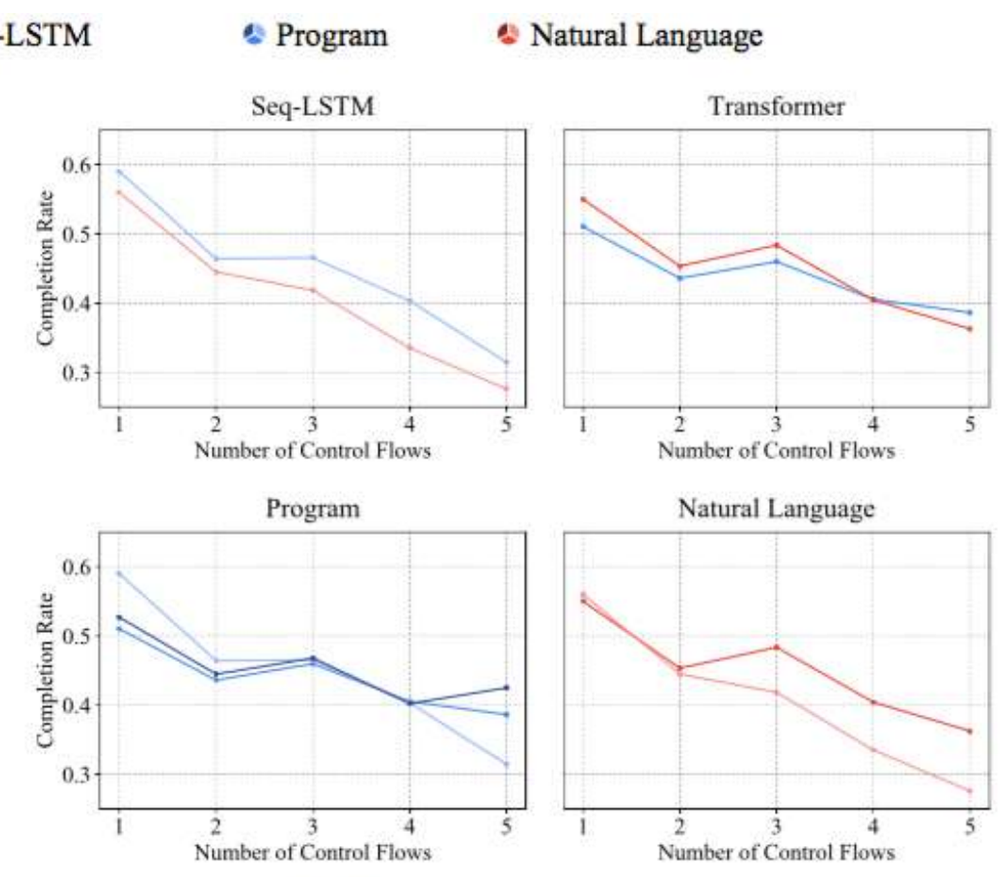
Quantitative Results

End-to-end < Ours (modular)

Instruction Method		Natural language descriptions		Programs				
		Seq-LSTM	Transformer	Seq-LSTM	Tree-RNN	Transformer	Ours (concat)	Ours
Dataset	test	54.9±1.8%	52.5±2.6%	56.7±1.9%	50.1±1.2%	49.4±1.6%	88.6±0.8%	94.0±0.5%
	test-complex	32.4±4.9%	38.2±2.6%	38.8±1.2%	42.2±2.4%	40.9±1.5%	85.2±0.8%	91.8±0.2%
Generalization gap		40.9%	27.2%	31.6%	15.8%	17.2%	3.8%	2.3%



(a) Instruction Length



(b) Instruction Complexity

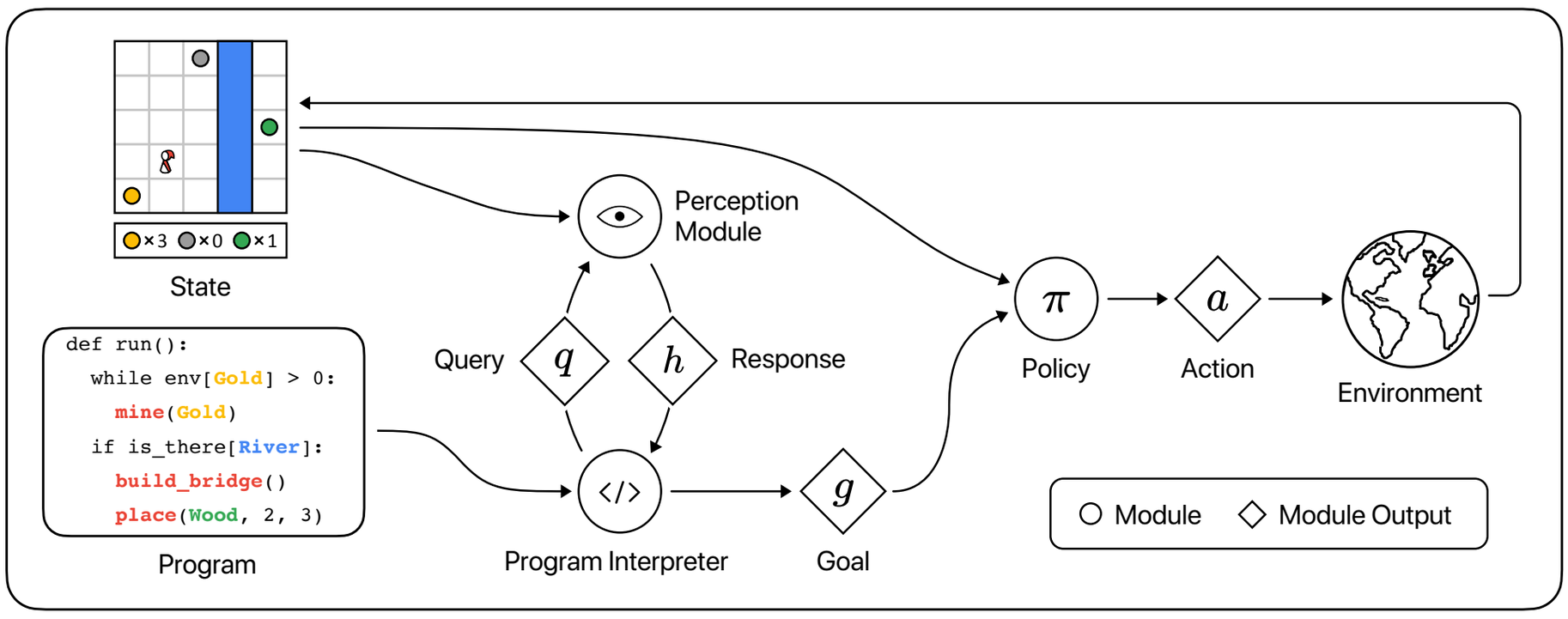
Takeaway

- Specific tasks using **programs**

Program

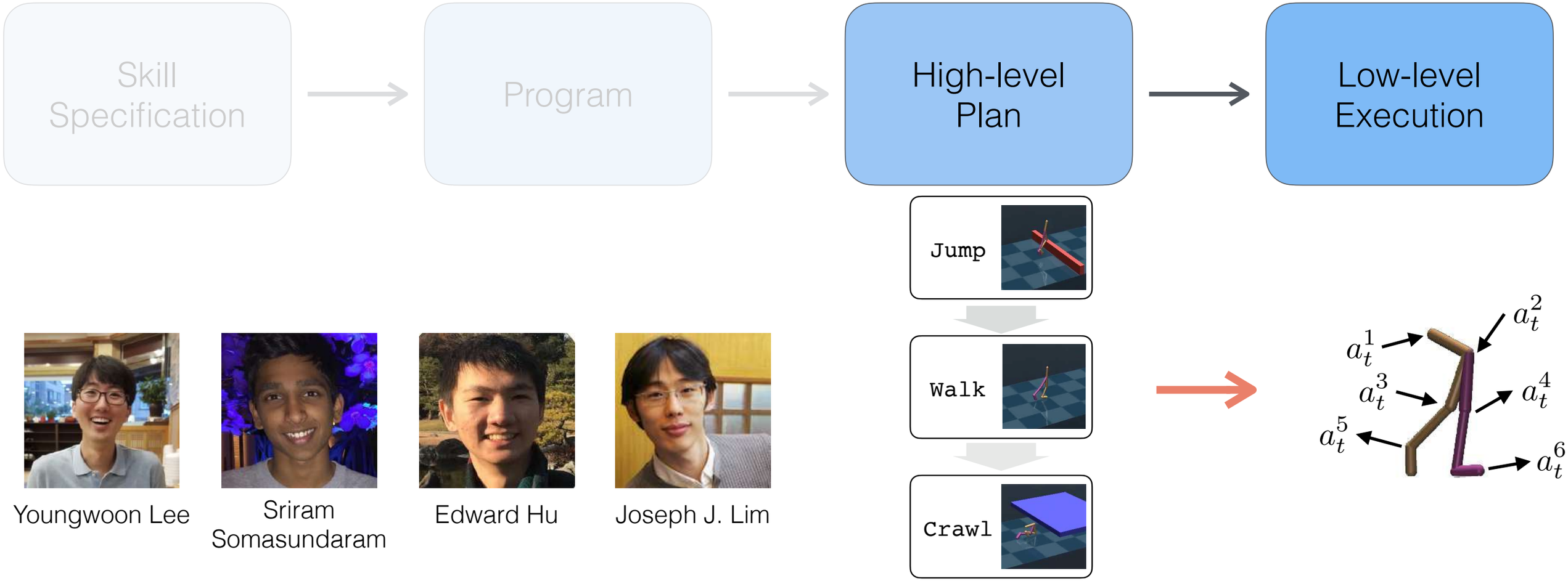
```
def run():
  if is_there[River]:
    mine(Wood)
    build_bridge()
    if agent[Iron]<3:
      mine(Iron)
    place(Iron, 1, 1)
  else:
    goto(4, 2)
  while env[Gold]>0:
    mine(Gold)
```

- Leverage the structure of programs with **a modular framework**



Composing Complex Skills by Learning Transition Policies

ICLR 2019



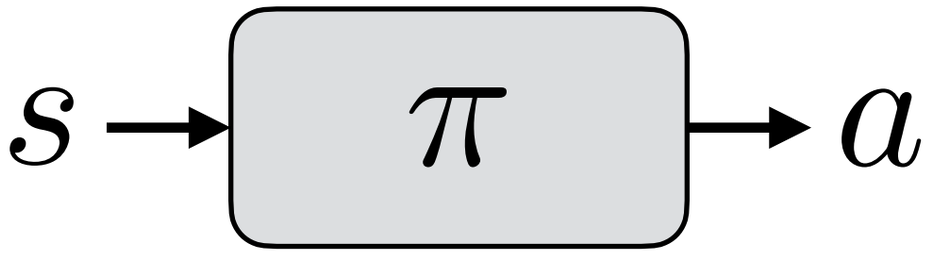
Youngwoon Lee

Sriram Somasundaram

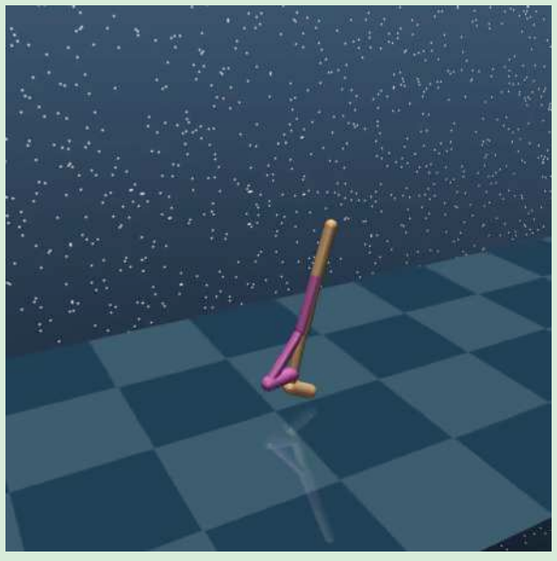
Edward Hu

Joseph J. Lim

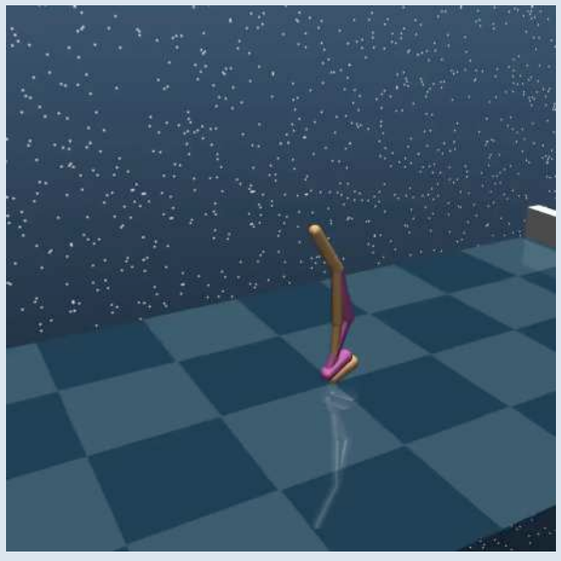
Learned Skills



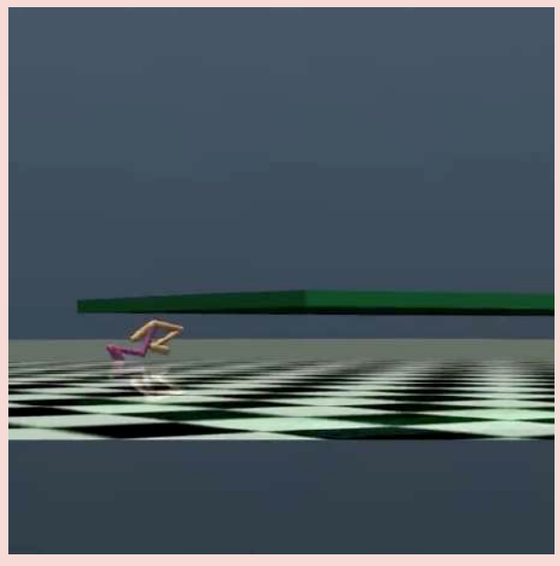
Walk



Jump



Crawl



Compose Complex Skills

High-level plan

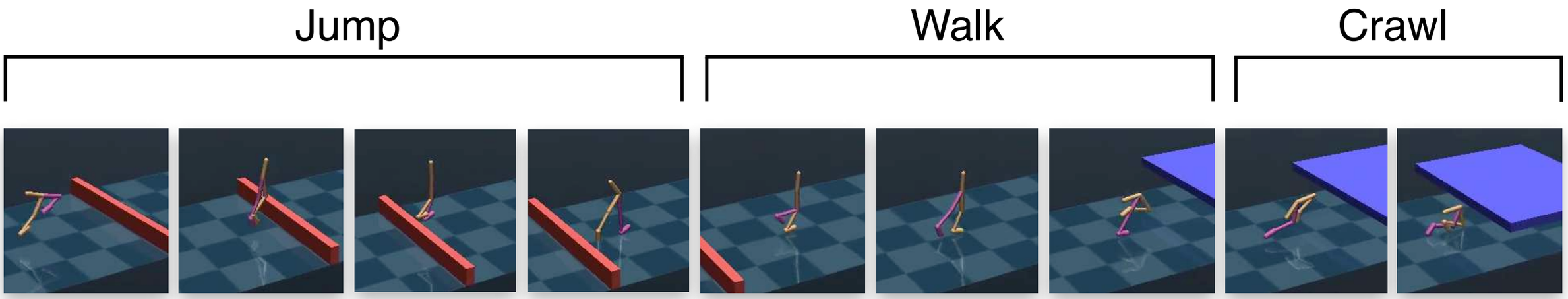
Jump

Walk

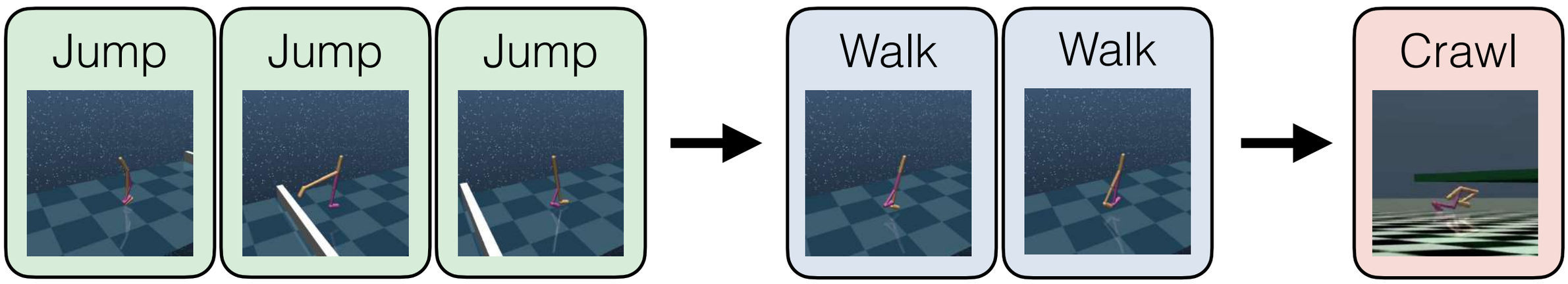
Crawl

Compose Complex Skills

High-level plan

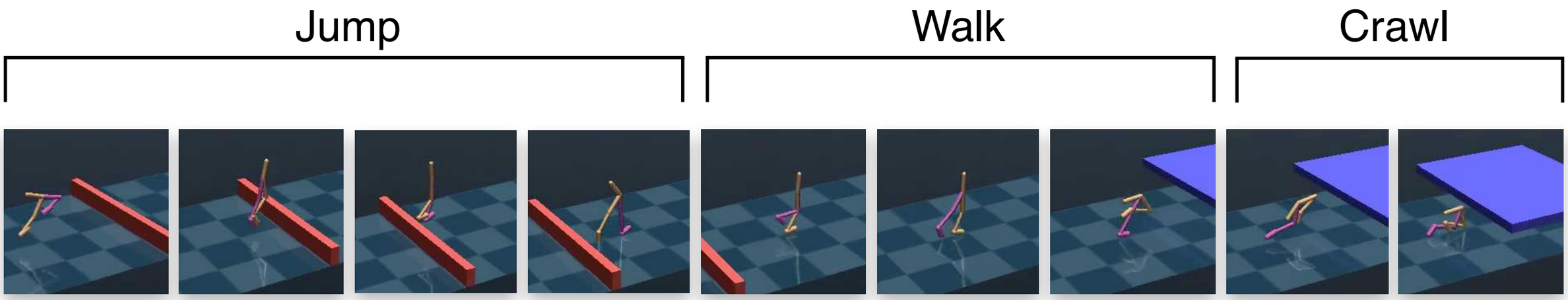


Sequentially execute corresponding policies

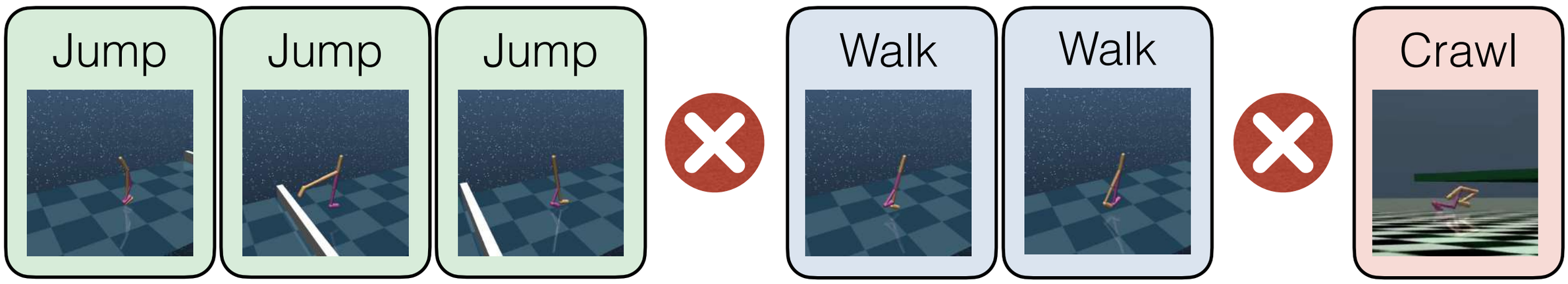


Compose Complex Skills

High-level plan



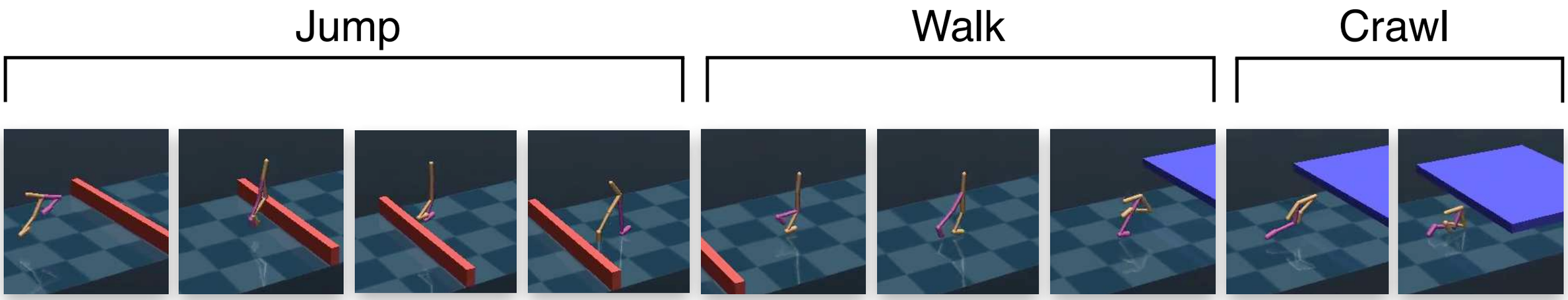
Sequentially execute corresponding policies



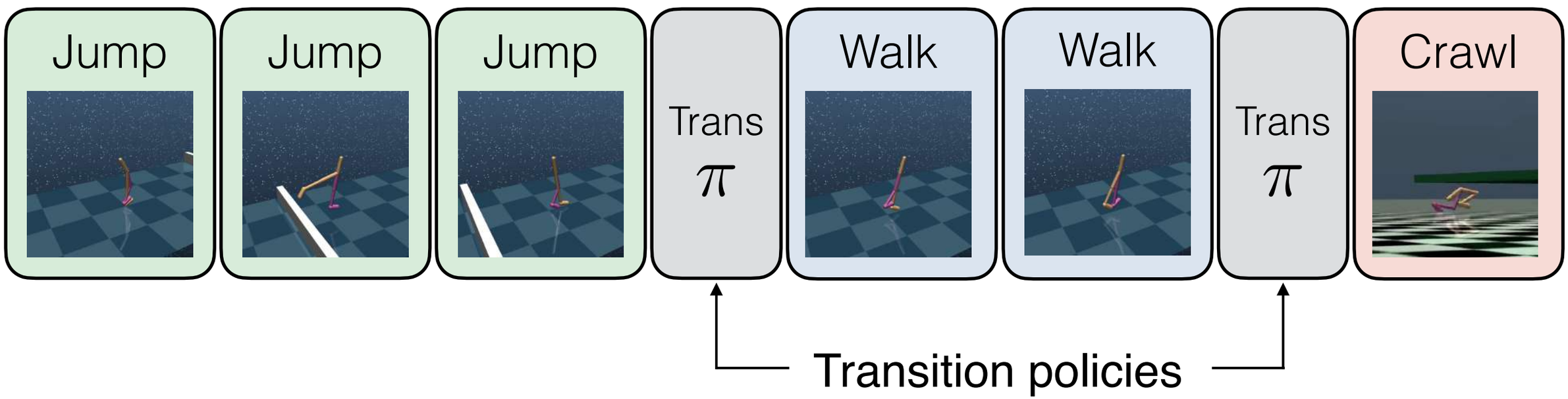
An **end state** of a previous policy might not be a good **initial state** of the following policy

Compose Complex Skills

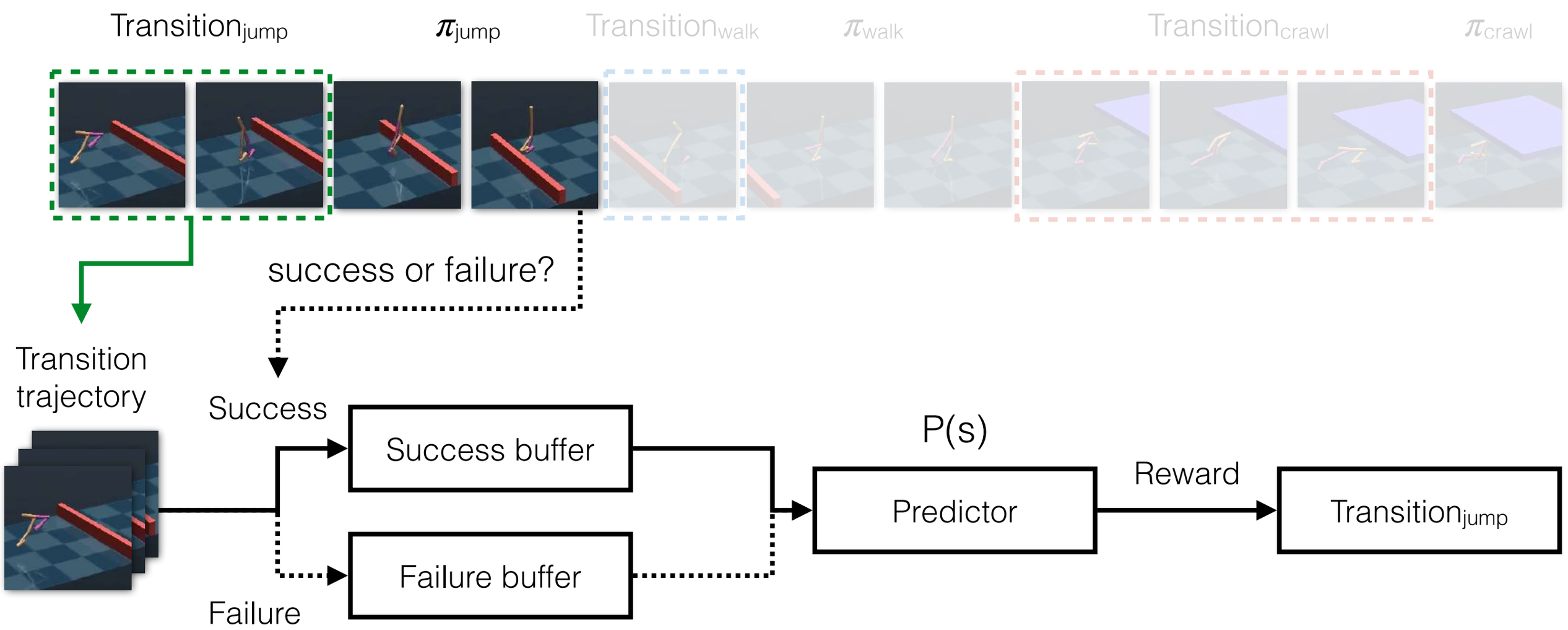
High-level plan



Sequentially execute corresponding policies

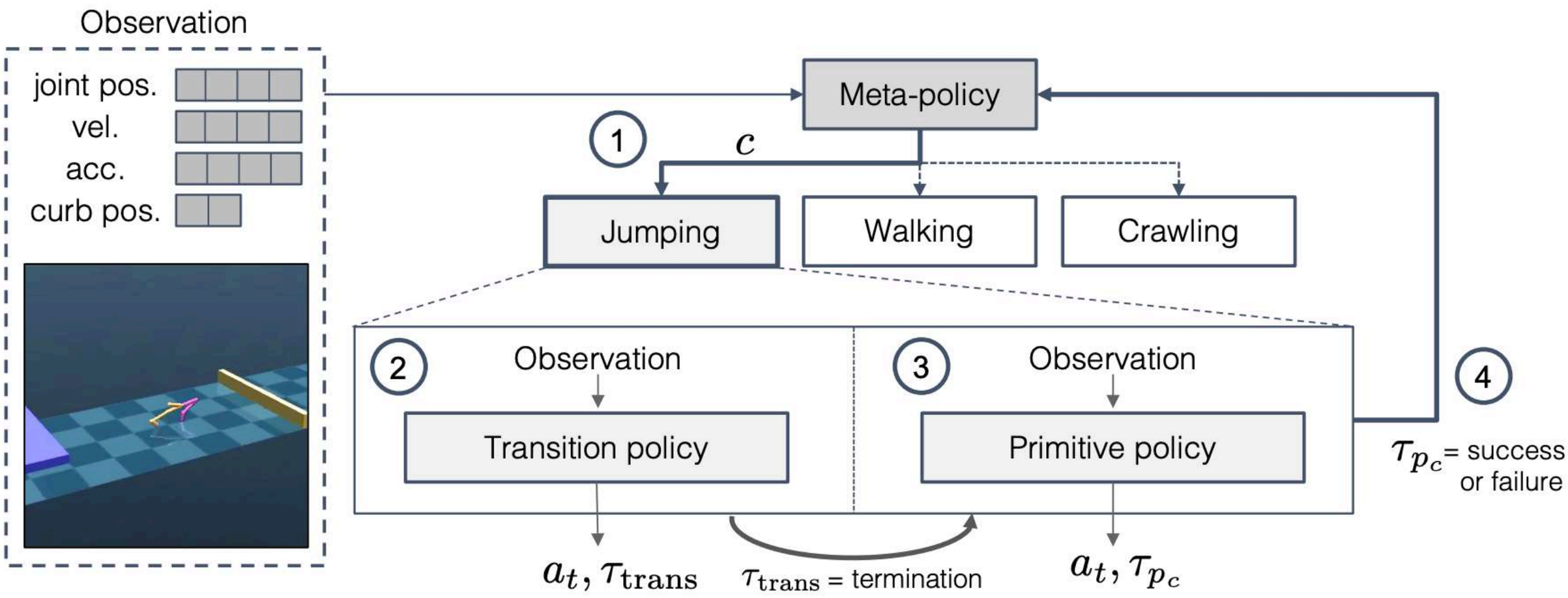


Learning Transition Policies



- **Predictor** learns to judge if a state is good for executing the next policy
- **Transition policy** learns from the predicted rewards

Modular Framework



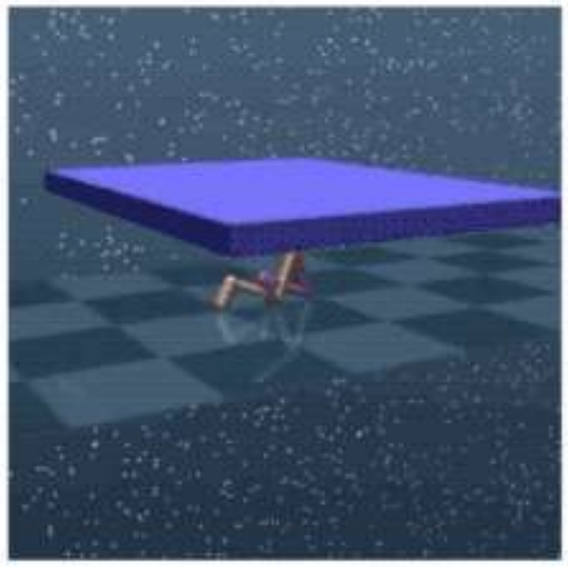
Qualitative Results

Locomotion

Crawl

Transition

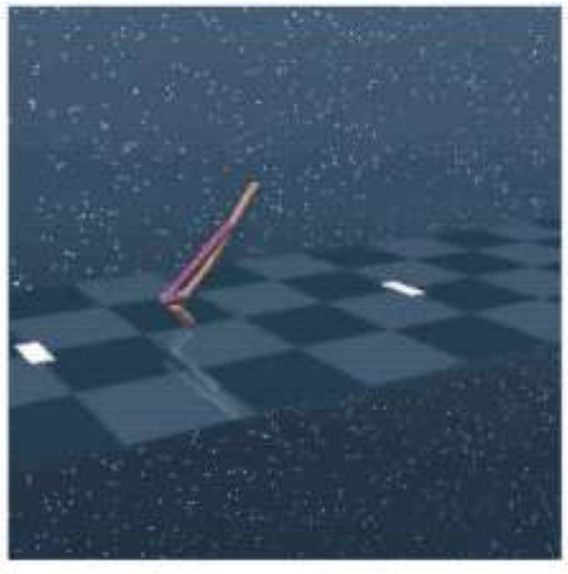
Walk



Walk Forward

Transition

Walk Backward

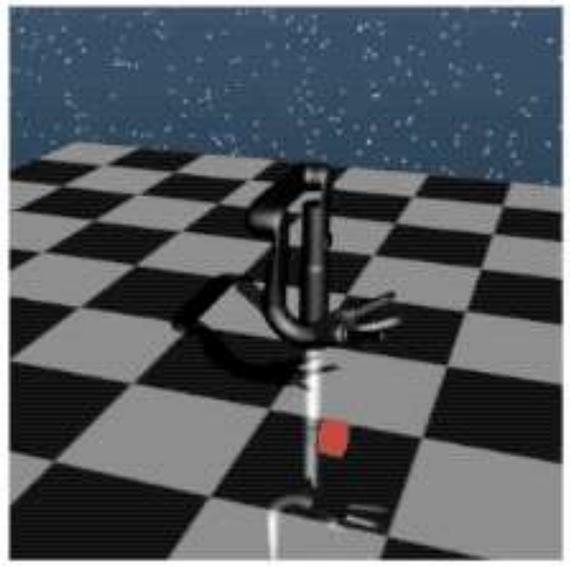


Manipulation

Pick

Transition

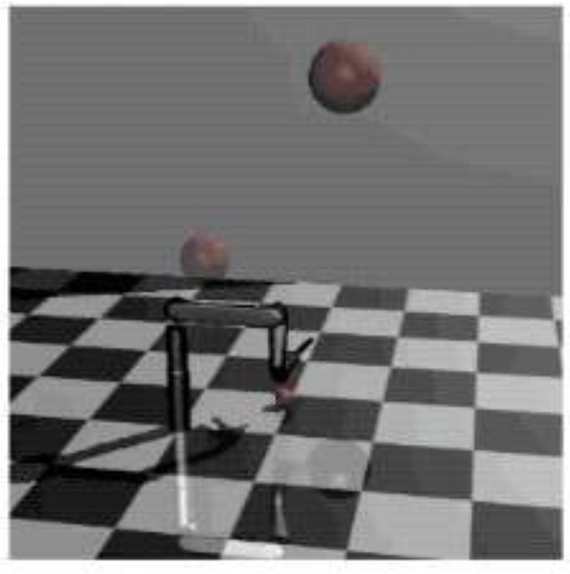
Pick



Toss

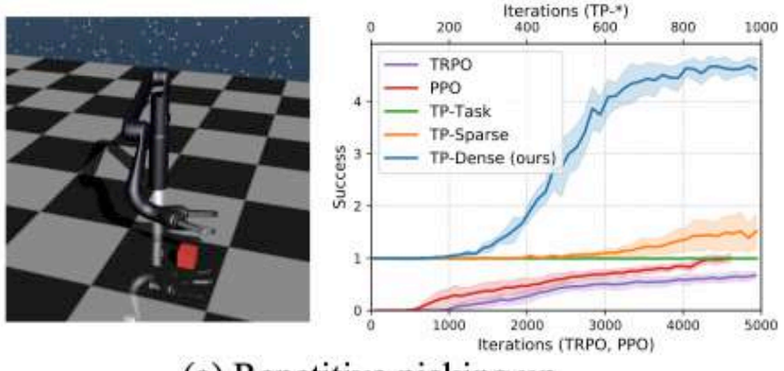
Transition

Hit

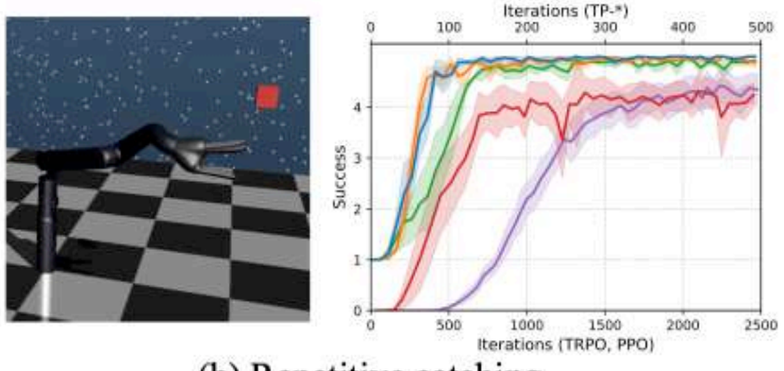


Quantitative Results - Sample Efficiency

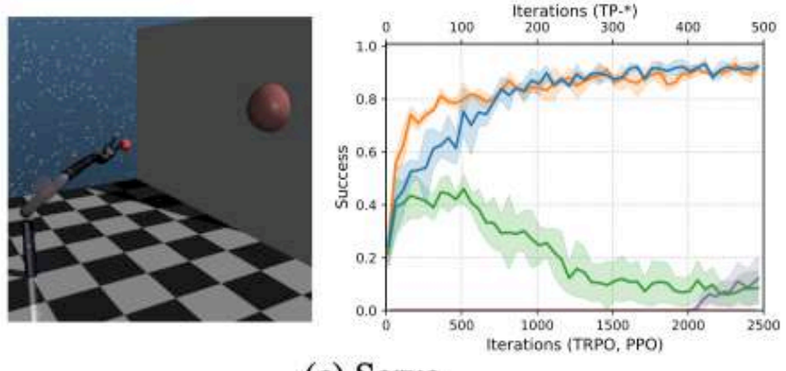
Manipulation



(a) Repetitive picking up

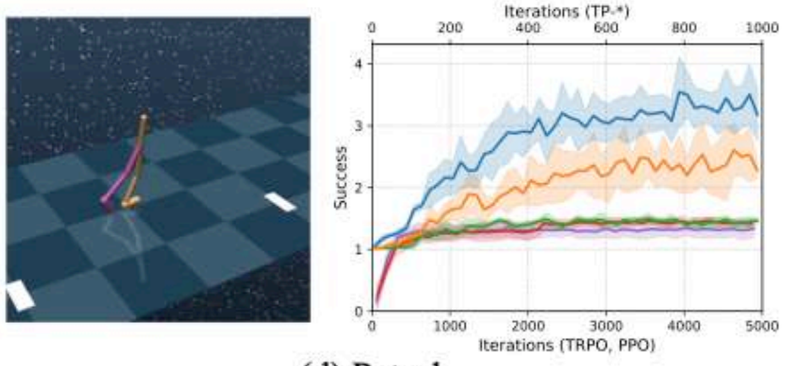


(b) Repetitive catching

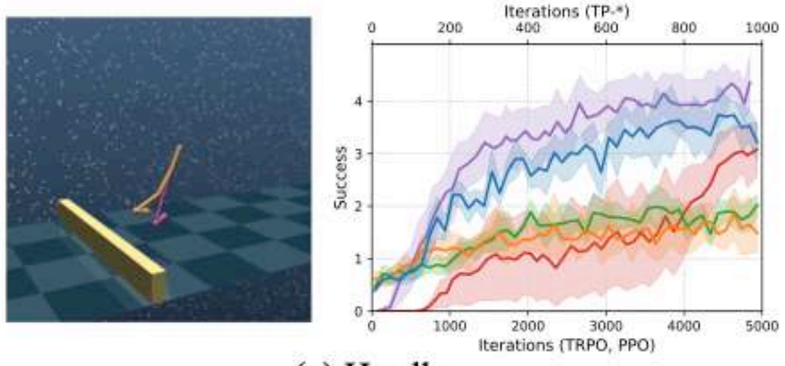


(c) Serve

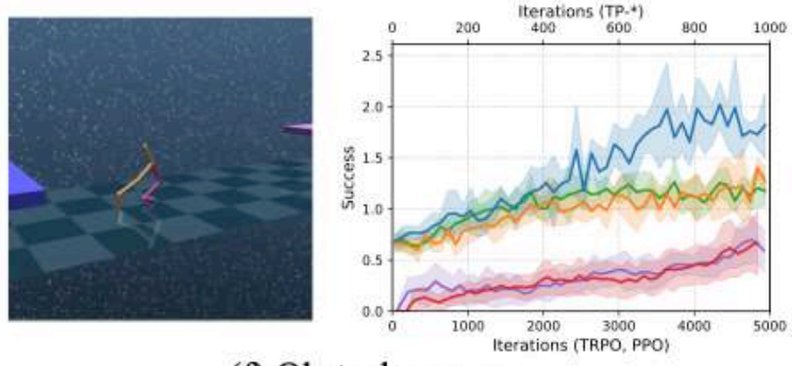
Locomotion



(d) Patrol

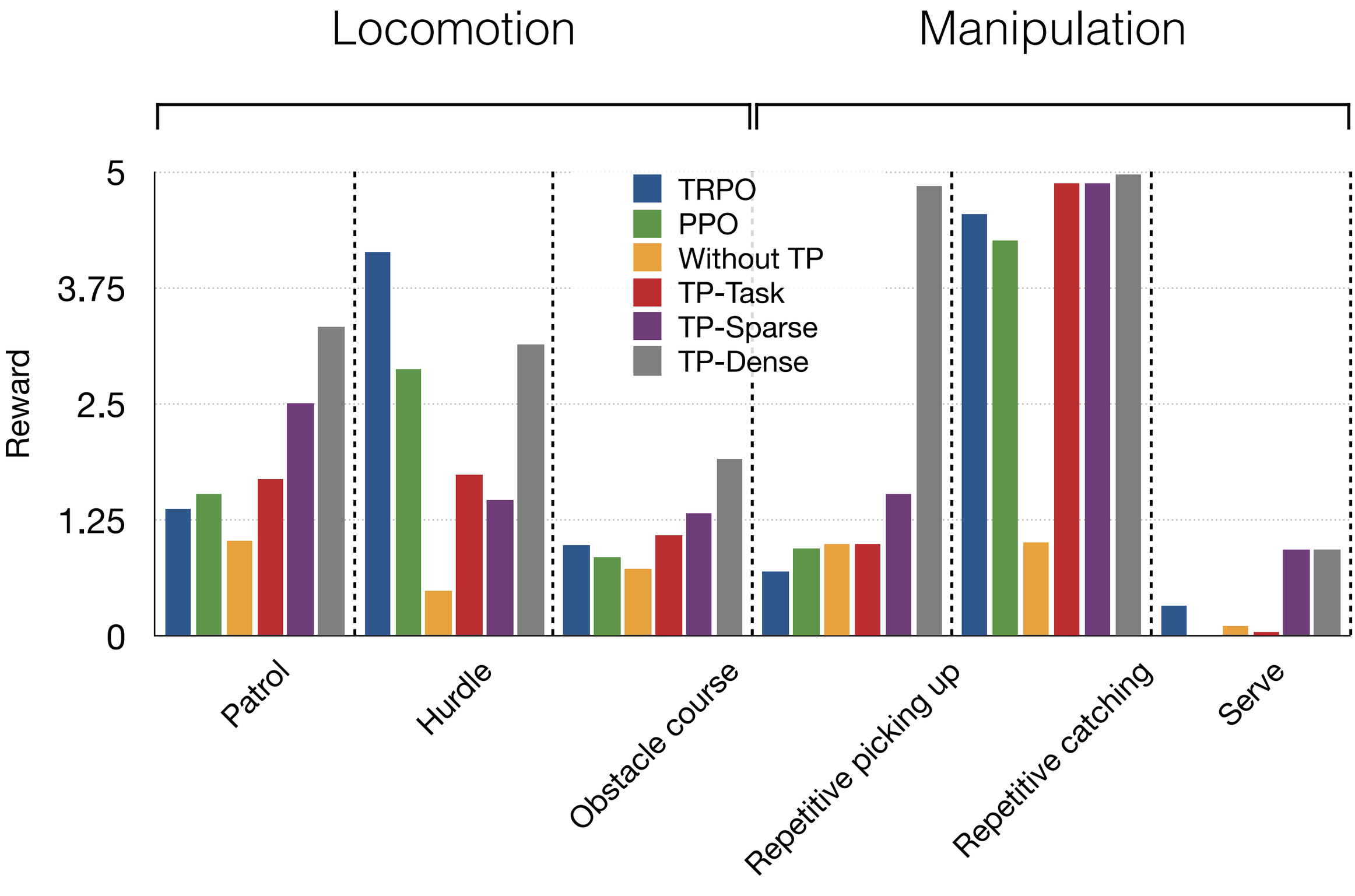


(e) Hurdle



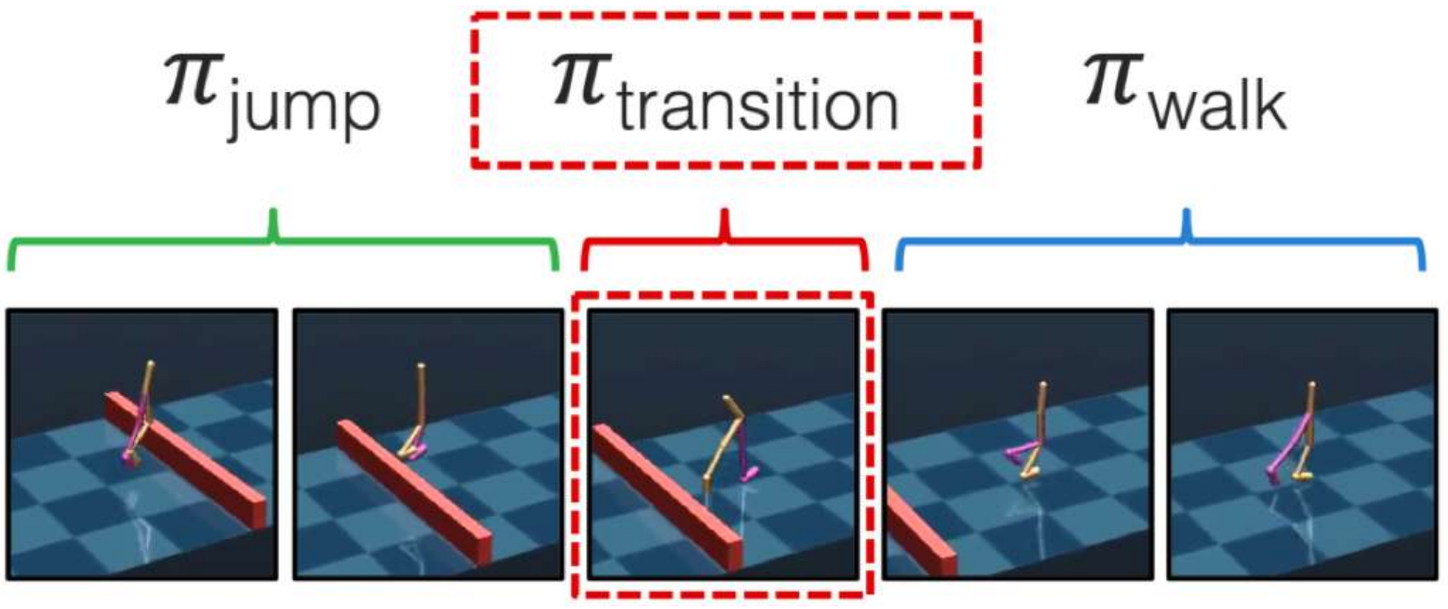
(f) Obstacle course

Quantitative Results - Reward



Takeaway

- Learning **transition policies** to smoothly compose learned skills

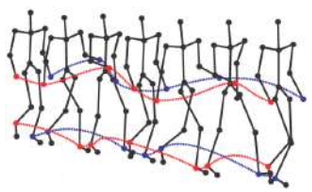


Program Inference

Skill Specification → Program → High-level Plan → Low-level Execution

Video demonstration

Trajectory demonstration

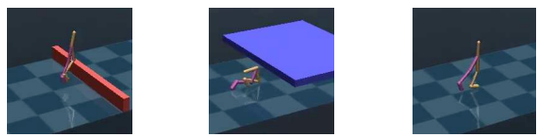


Language instruction

> Stir-fry the onions until tender, and repeat this for garlic and carrots, if you have soy sauce, add some. Pour 2/3 cups the whisked eggs into the stir-fried and scramble.

Reward

Actions (sub-skills)



`Jump` `Crawl` `Walk`

Perceptions

`isCurb()` `isCeiling()`

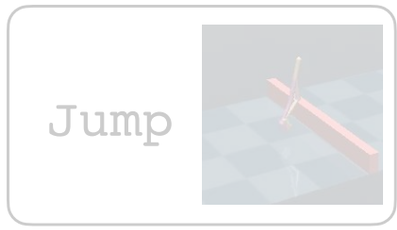
Control Flows

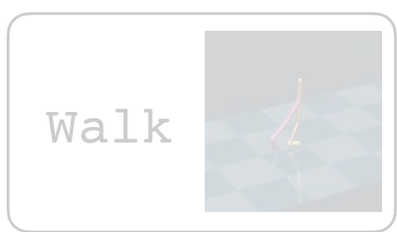
`while` `if` `else` `elseIf`

Program

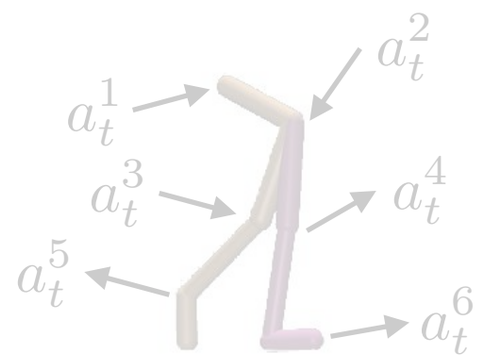
```
DEF run()
    while True:
        if isCurb():
            jump
        elseIf isCeiling():
            crawl()
        else:
            walk()
```

Observation





Low-level execution



Task Execution

Skill Specification

Video demonstration

Trajectory demonstration

Language instruction

Stir-fry the onions until tender, and repeat this for garlic and carrots, if you have soy sauce, add some. Pour 2/3 cups the whisked eggs into the stir-fried and scramble.

Reward

Program

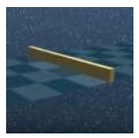
Actions (sub-skills)

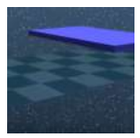

Jump


Crawl


Walk

Perceptions


isCurb()

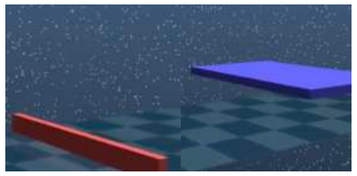

isCeiling()

Control Flows

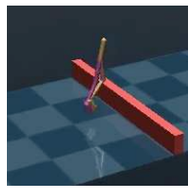
while | if | else | elseIf

```
DEF run()
    while True:
        if isCurb():
            jump
        elseIf isCeiling():
            crawl()
        else:
            walk()
```

Observation



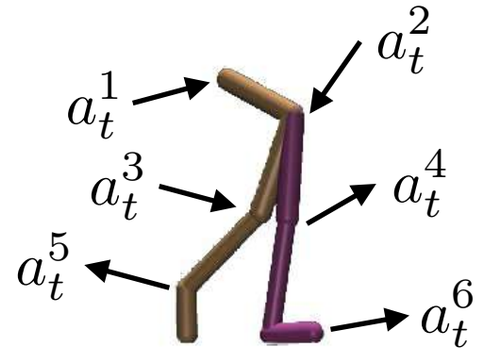
Jump



Walk

Crawl

Low-level execution



Primitive Skill Acquisition

Skill Specification → Program → High-level Plan → Low-level Execution

Video demonstration

Trajectory demonstration

Language instruction

Stir-fry the onions until tender, and repeat this for garlic and carrots, if you have soy sauce, add some. Pour 2/3 cups the whisked eggs into the stir-fried and scramble.

Reward

Actions (sub-skills)

Jump

Crawl

Walk

Perceptions

isCurb()

isCeiling()

Control Flows

while | if | else | elseIf

Program

```
DEF run()
    while True:
        if isCurb():
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        elseIf isCeiling():
            crawl()
        else:
            walk()
```

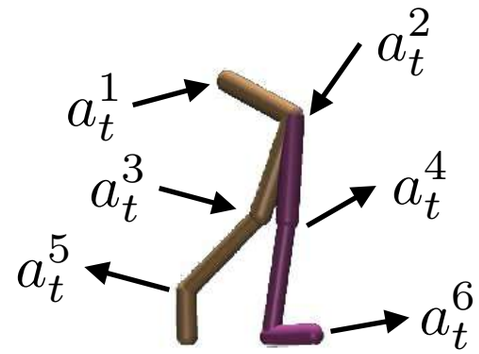
Observation

Jump

Walk

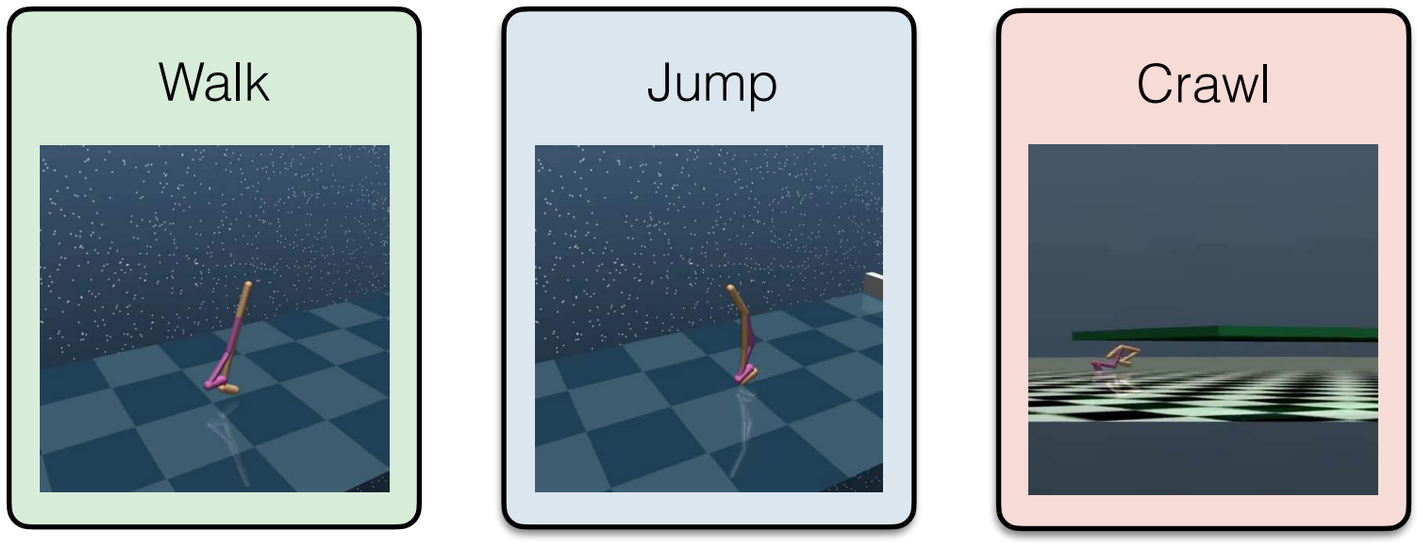
Crawl

Low-level execution



Primitive Skill Acquisition

- Goal: acquire a diverse set of primitive skills efficiently



Primitive Skill Acquisition

- Goal: acquire a diverse set of primitive skills efficiently

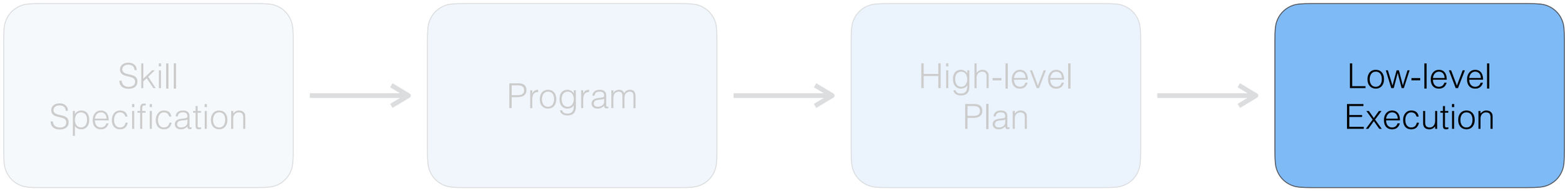
- Key directions

Meta-learning
Meta-RL

Learning from
experts

Multimodal Model-Agnostic Meta-Learning via Task-Aware Modulation

NeurIPS 2019 (Spotlight)

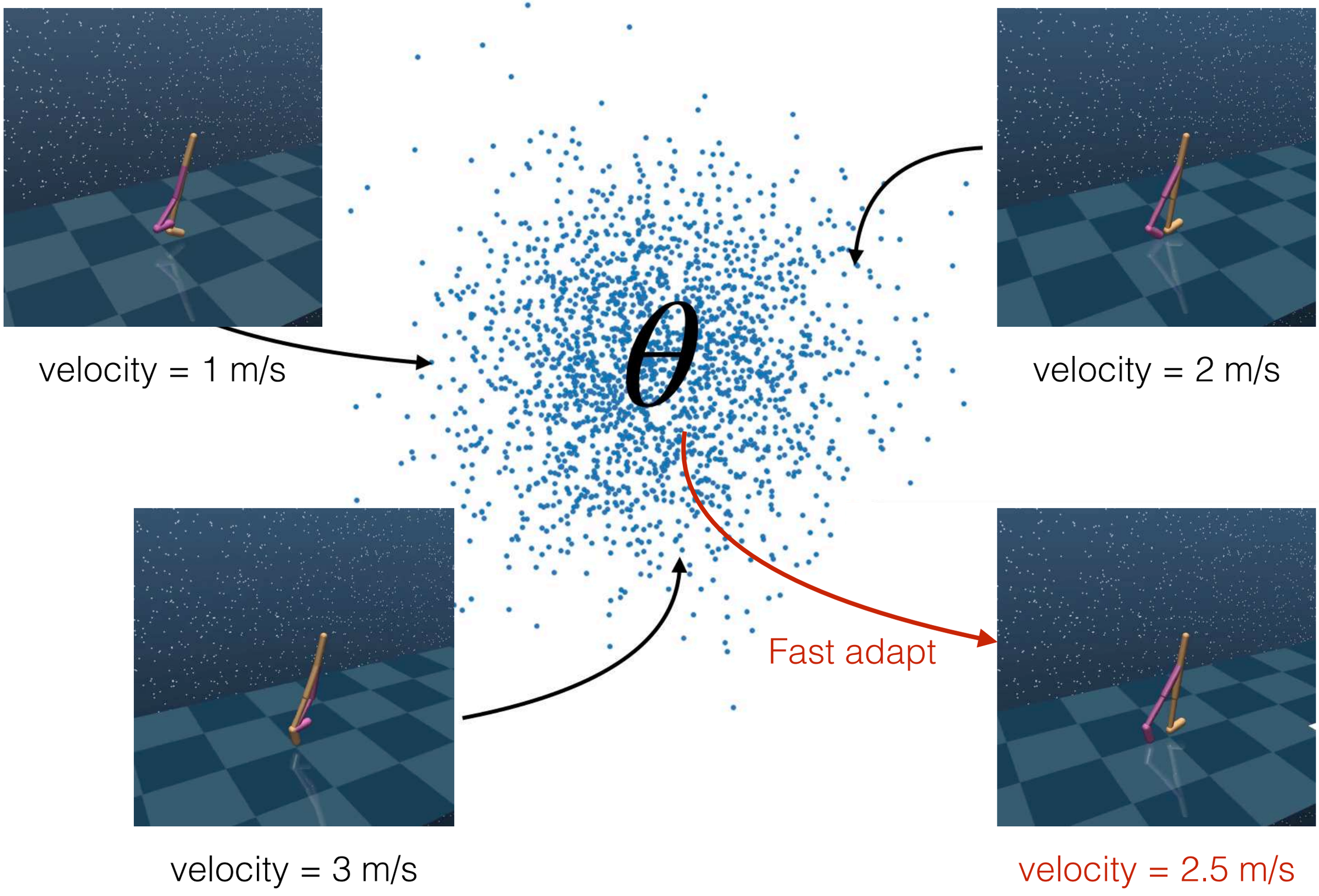



Risto Vuorio


Hexiang Hu

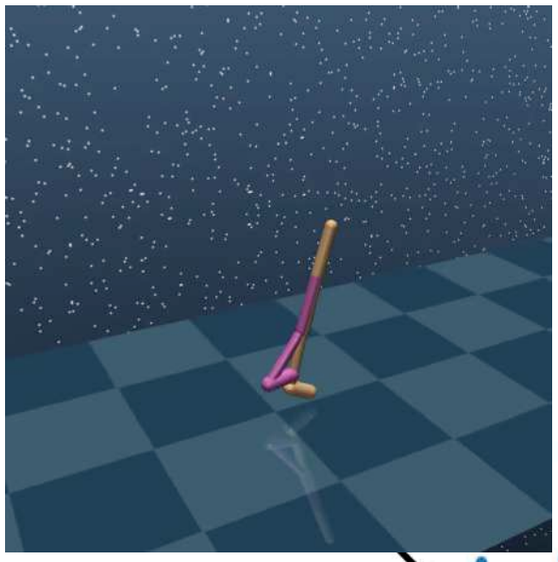

Joseph J. Lim

Model-Agnostic Meta-Learning (MAML)

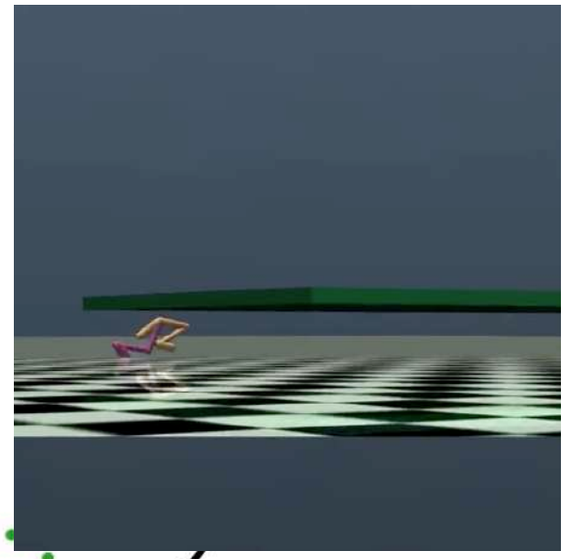


Multimodal Task Distribution

Walk



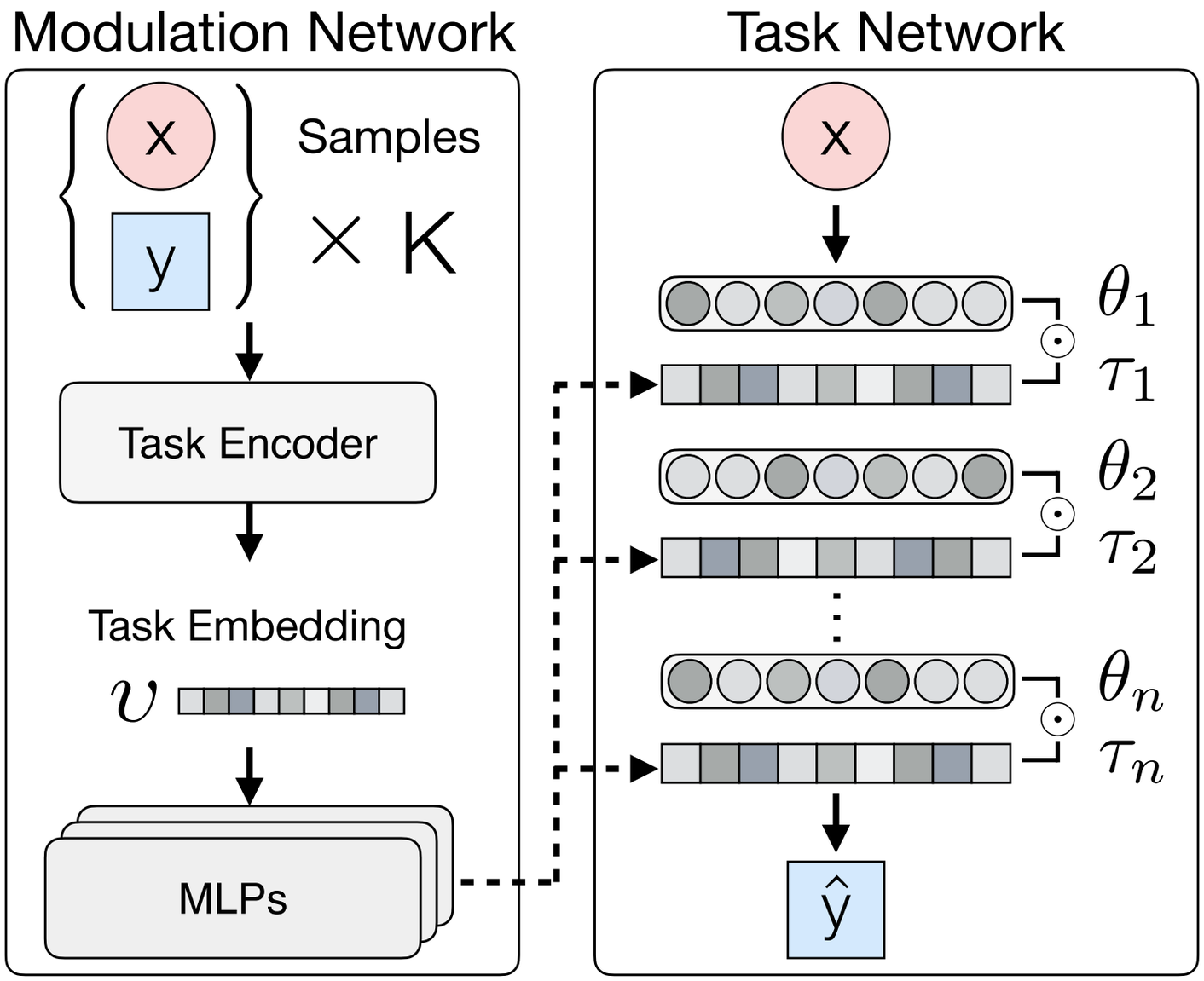
Crawl



θ

Jump

Multimodal Model-Agnostic Meta-Learning (MMAML)



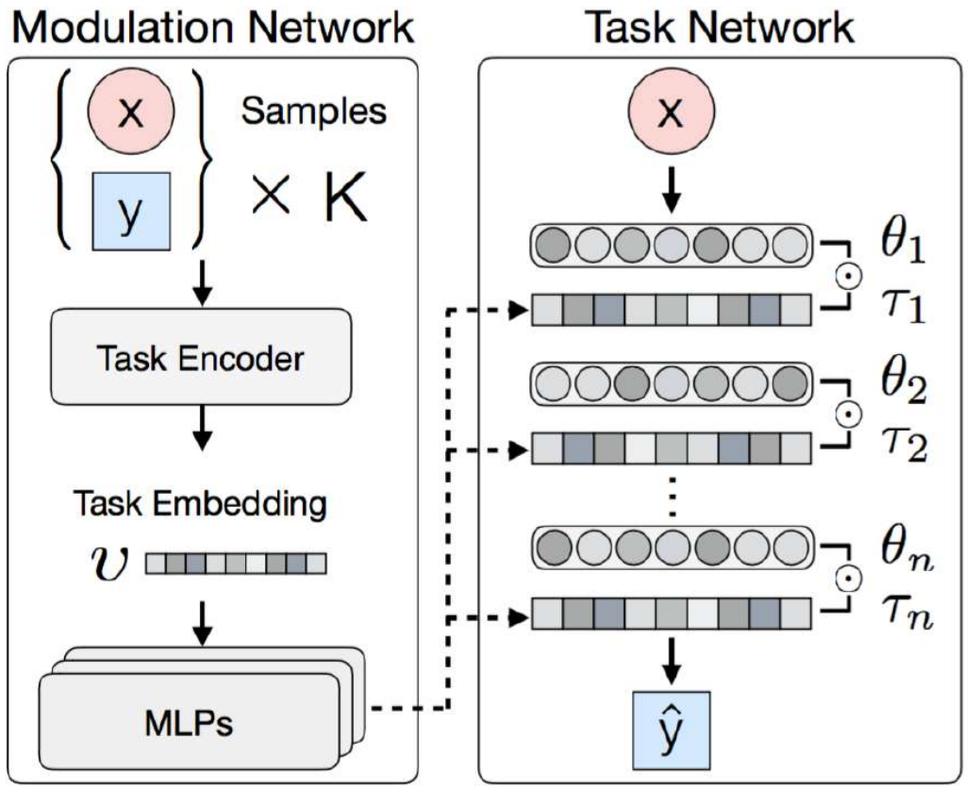
Training Algorithm

Outer loop

- Task Encoder: produce the task embedding ω_g
- MLPs: modulate the task network blocks ω_h

Inner loop

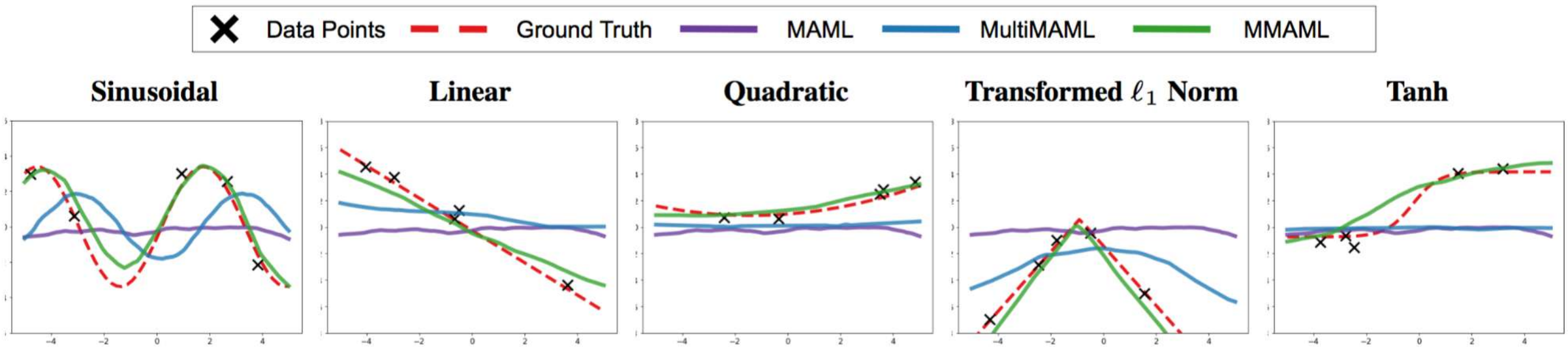
- Task network: fast adapt through gradient updates θ



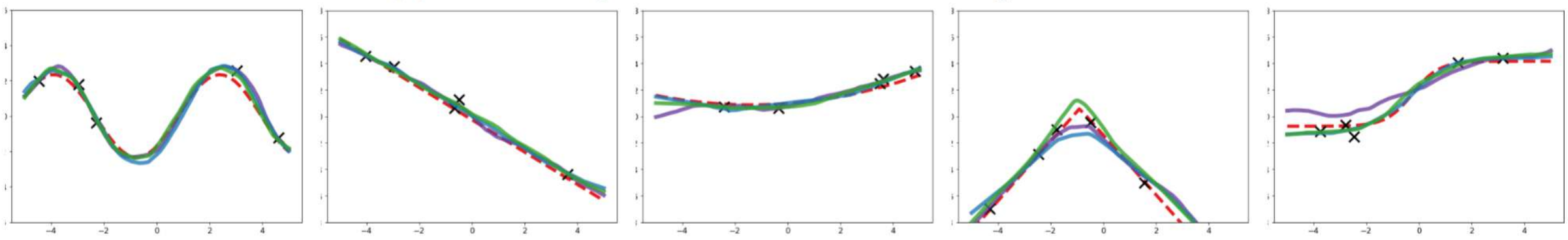
Algorithm 1 MMAML META-TRAINING PROCEDURE.

Input: Task distribution $P(\mathcal{T})$, Hyper-parameters α and β
Randomly initialize θ and ω.
while not DONE **do**
  Sample batches of tasks $\mathcal{T}_j \sim P(\mathcal{T})$
  for all j **do**
    Infer $\upsilon = h(\{x, y\}_K; \omega_h)$ with K samples from $\mathcal{D}^{\text{train}}_{\mathcal{T}_j}$.
    Generate parameters $\tau = \{g_i(\upsilon; \omega_g) \mid i = 1, \cdots, N\}$ to modulate each block of the task network f.
    Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_j}(f(x; \theta, \tau); \mathcal{D}^{\text{train}}_{\mathcal{T}_j})$ w.r.t the K samples
    Compute adapted parameter with gradient descent: $\theta'_{\mathcal{T}_j} = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_j}\left(f(x; \theta, \tau); \mathcal{D}^{\text{train}}_{\mathcal{T}_j}\right)$
  end for
  Update θ with $\beta \nabla_\theta \sum_{T_j \sim P(\mathcal{T})} \mathcal{L}_{\mathcal{T}_j}\left(f(x; \theta', \tau); \mathcal{D}^{\text{val}}_{\mathcal{T}_j}\right)$
  Update ω_g with $\beta \nabla_{\omega_g} \sum_{T_j \sim P(\mathcal{T})} \mathcal{L}_{\mathcal{T}_j}\left(f(x; \theta', \tau); \mathcal{D}^{\text{val}}_{\mathcal{T}_j}\right)$
  Update ω_h with $\beta \nabla_{\omega_h} \sum_{T_j \sim P(\mathcal{T})} \mathcal{L}_{\mathcal{T}_j}\left(f(x; \theta', \tau); \mathcal{D}^{\text{val}}_{\mathcal{T}_j}\right)$
end while

Regression



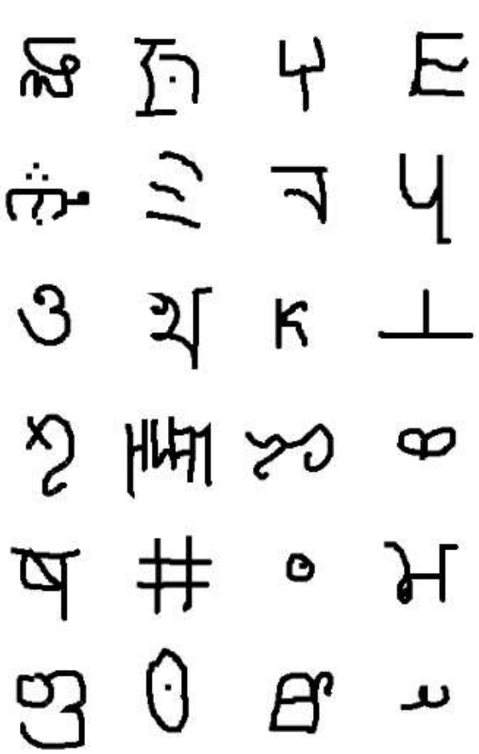
(a) MMAML **post modulation** vs. other prior models

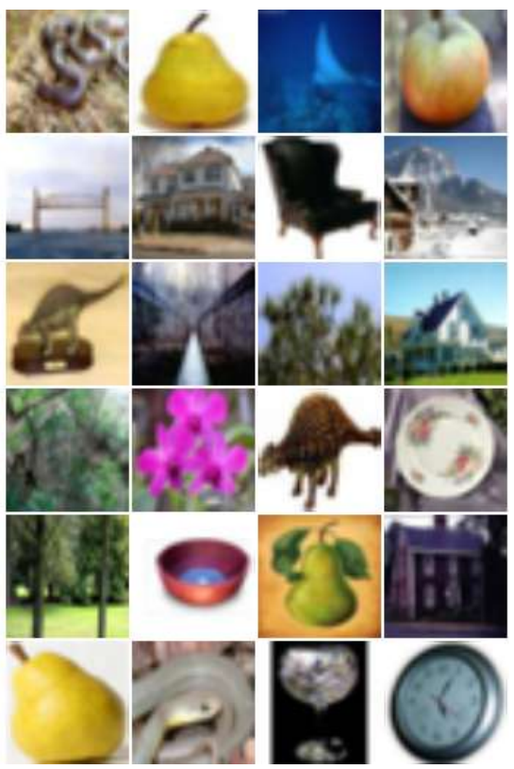


(b) MMAML **post adaptation** vs. other posterior models

Method	2 Modes		3 Modes		5 Modes	
	Post Modulation	Post Adaptation	Post Modulation	Post Adaptation	Post Modulation	Post Adaptation
MAML [1]	-	1.085	-	1.231	-	1.668
Multi-MAML	-	0.433	-	0.713	-	1.082
LSTM Learner	0.362	-	0.548	-	0.898	-
Ours: MMAML (Softmax)	1.548	0.361	2.213	**0.444**	2.421	0.939
Ours: MMAML (FiLM)	2.421	**0.336**	1.923	**0.444**	2.166	**0.868**

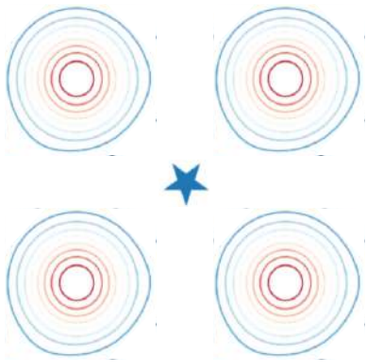
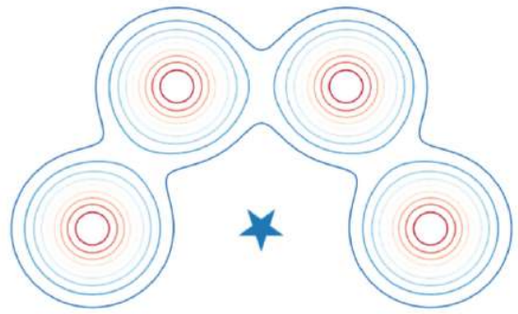
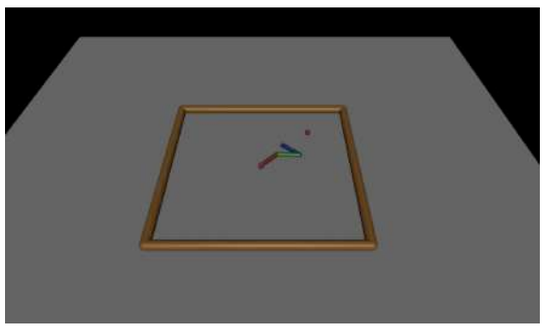
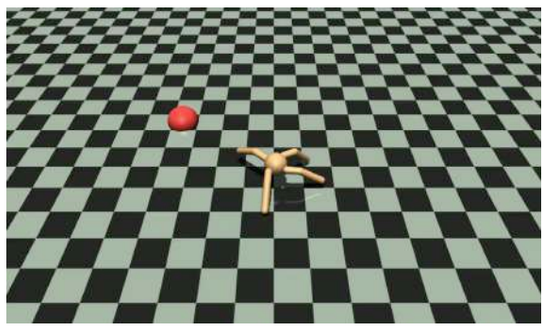
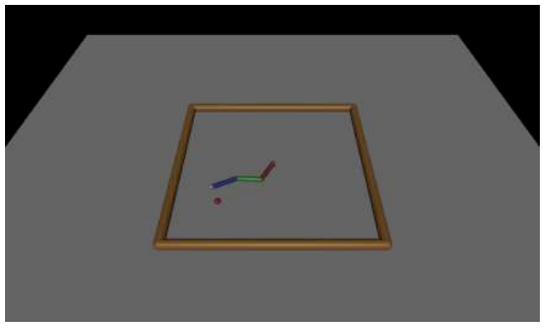
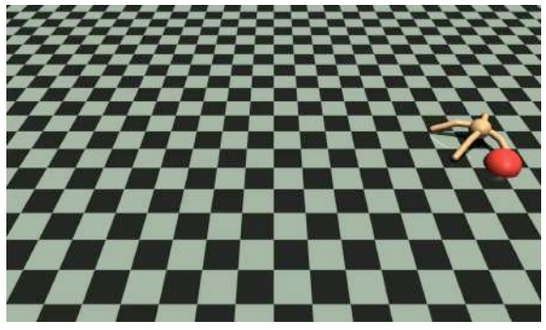
Image Classification



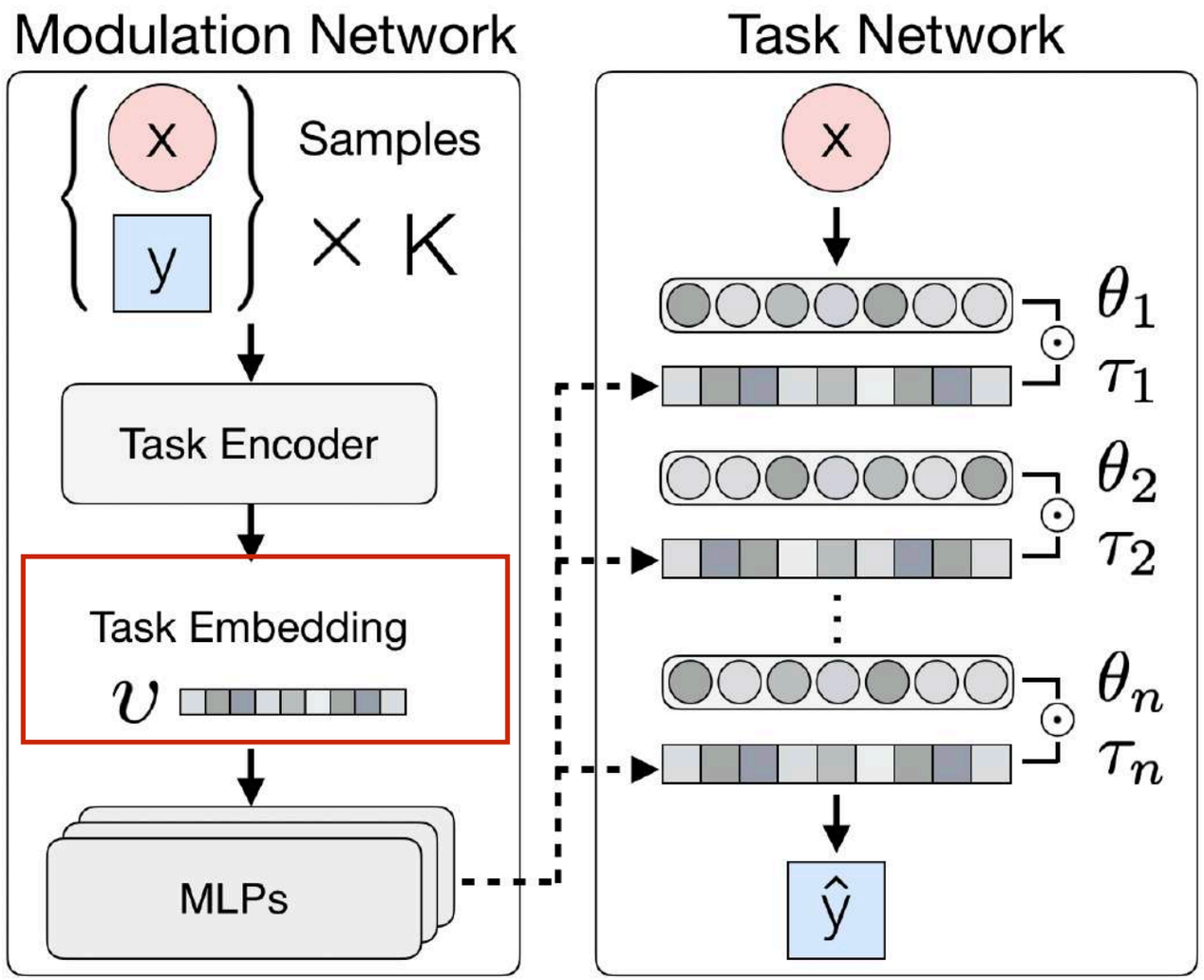


Method & Setup	**2 Modes**			**3 Modes**			**5 Modes**			
Way	5-way		20-way	5-way		20-way	5-way		20-way	
Shot	1-shot	5-shot	1-shot	1-shot	5-shot	1-shot	1-shot	5-shot	1-shot	3-shot
MAML [1]	66.80%	77.79%	44.69%	54.55%	67.97%	28.22%	66.00%	70.87%	44.69%	56.57%
Multi-MAML	66.85%	73.07%	**53.15%**	55.90%	62.20%	**39.77%**	71.94%	76.94%	58.66%	61.11%
MMAML (ours)	**69.93%**	**78.73%**	47.80%	**57.47%**	**70.15%**	36.27%	**72.02%**	**78.13%**	**60.13%**	**63.52%**

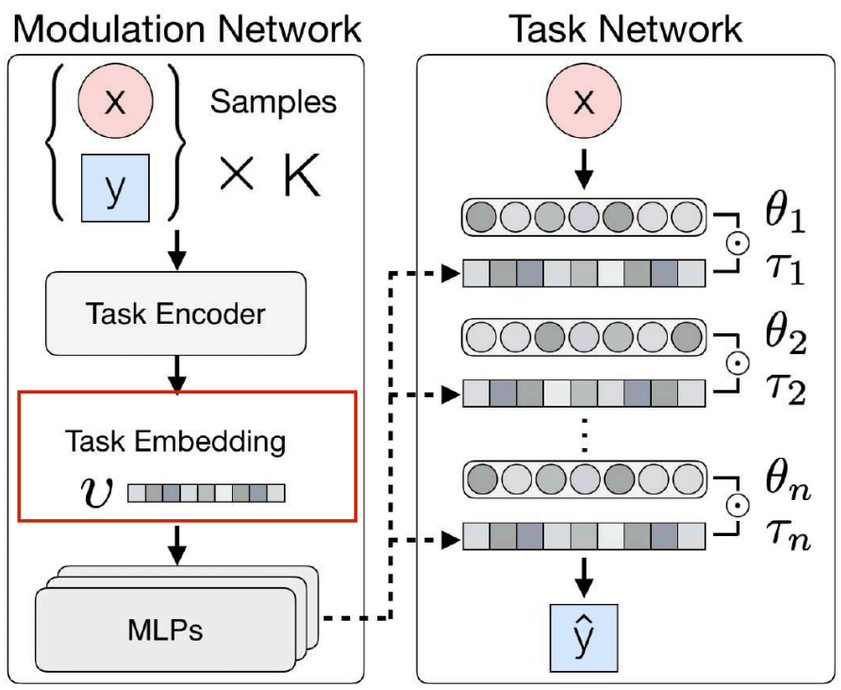
Reinforcement Learning

	Reacher	Ant
Goal modes		
ProMP		
Ours		

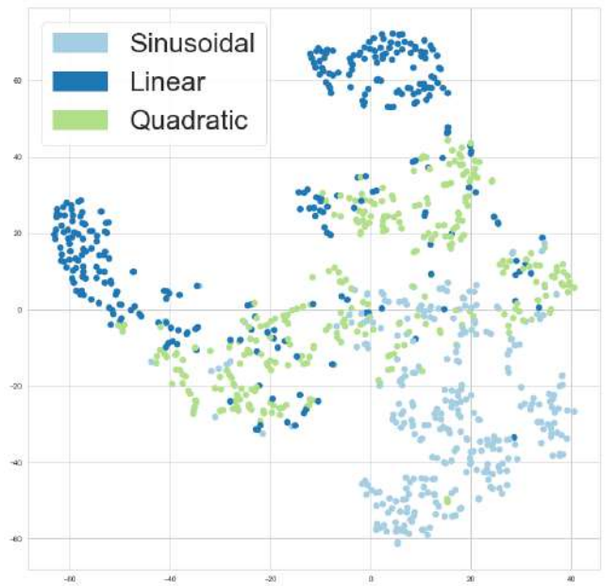
Learned Task Embedding (tSNE plot)



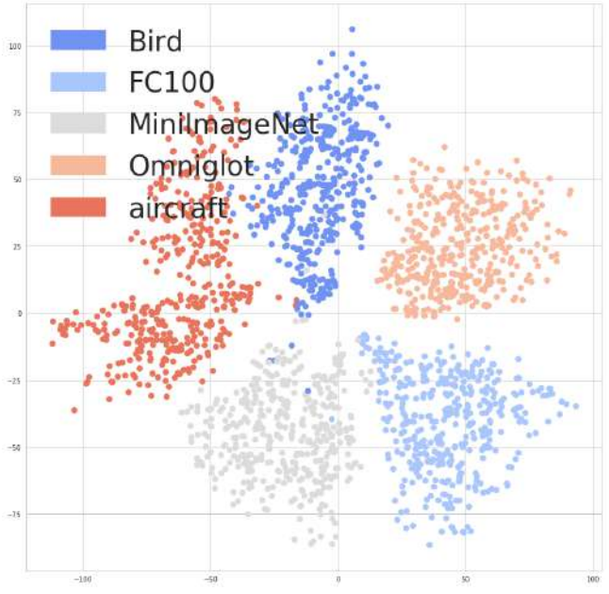
Learned Task Embedding (tSNE plot)



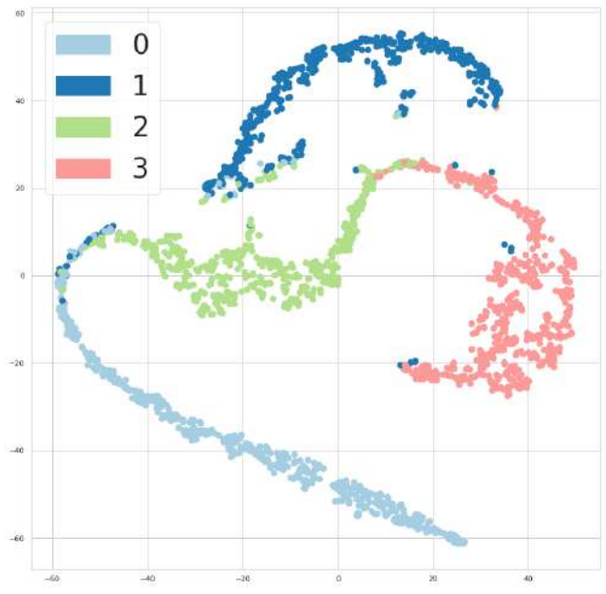
3-mode Regression



5-mode Classification

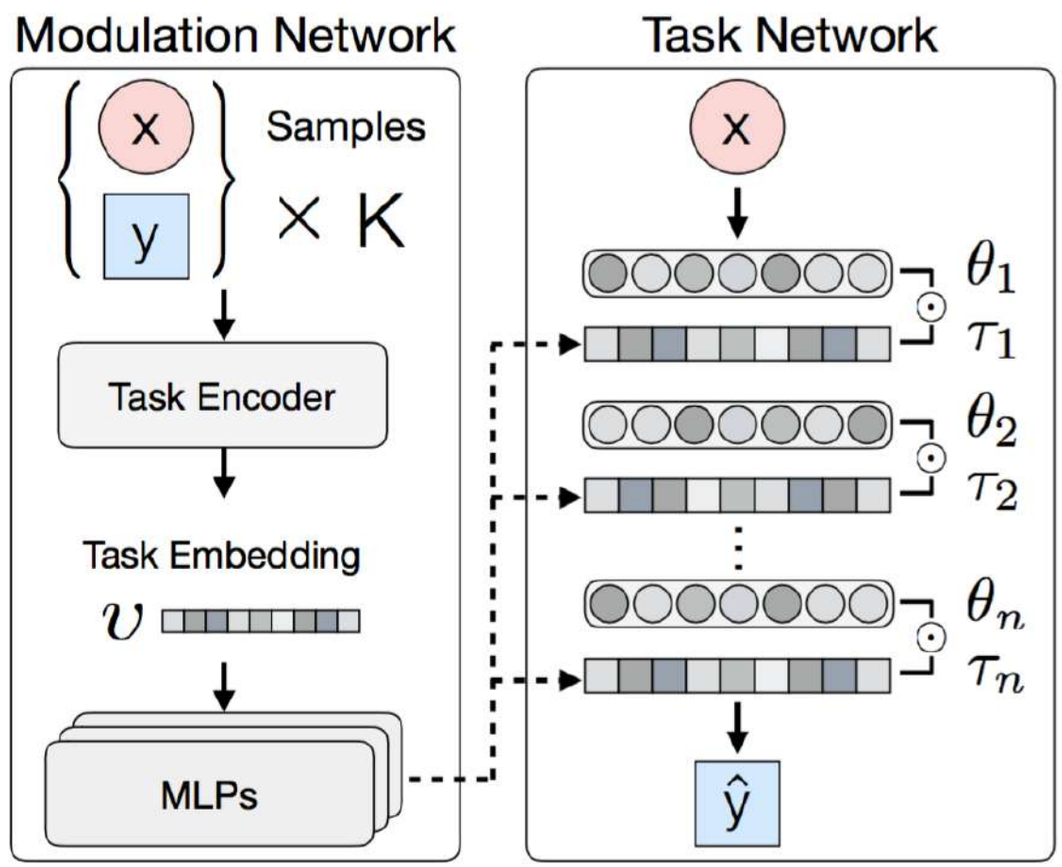


4-mode Reacher



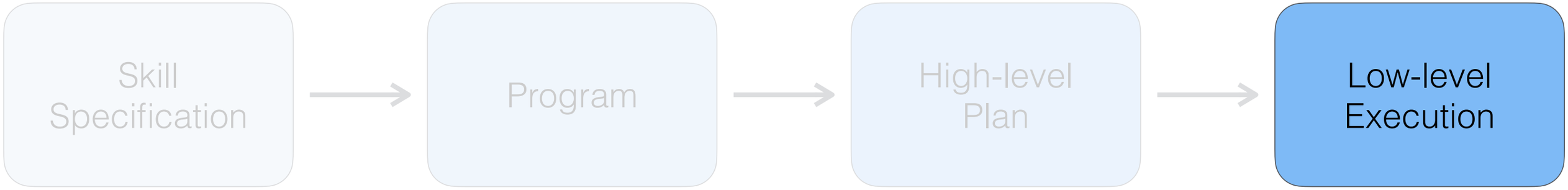
Takeaway

- MAML struggles at learning from **multimodal task distributions**
- We propose **multimodal MAML** to alleviate the issue



Skill-based Meta-Reinforcement Learning

ICLR 2022



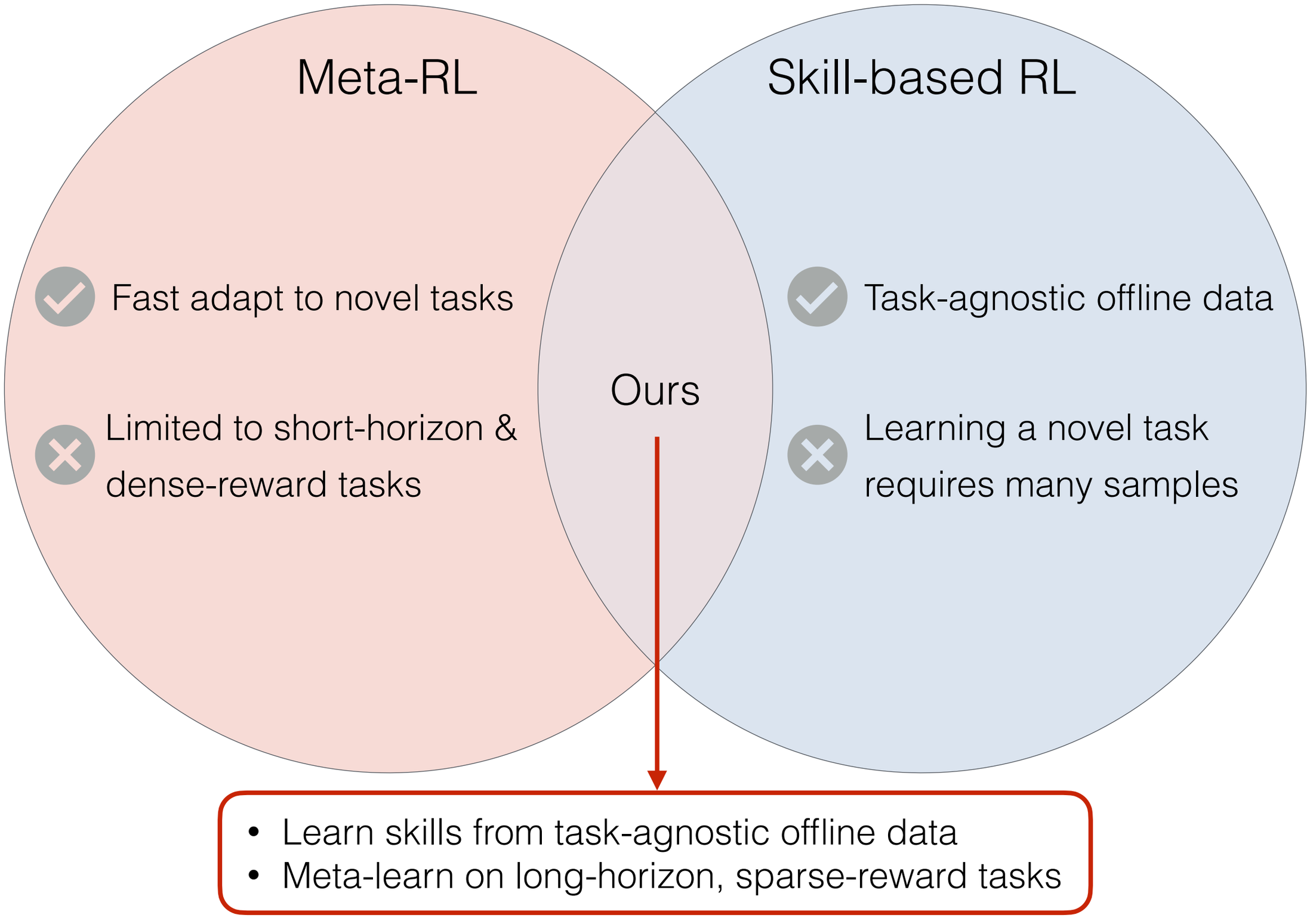

Taewook Nam


Karl Pertsch

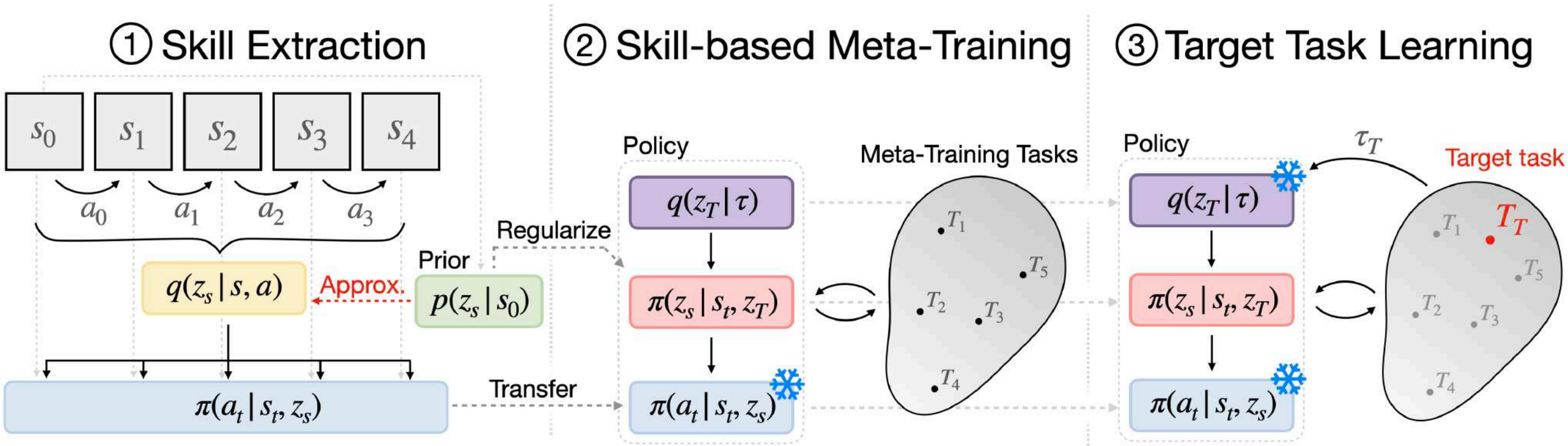

Sung Ju Hwang


Joseph J. Lim

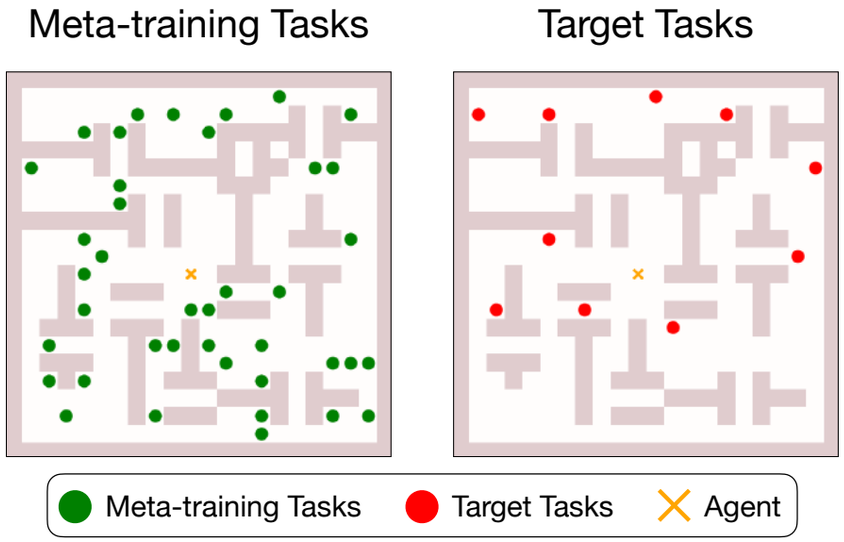
Meta-RL with Skills



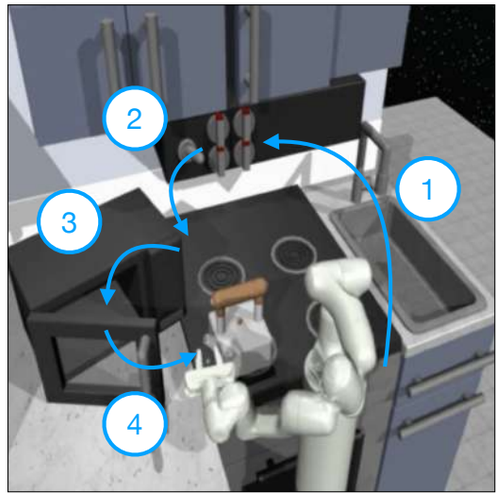
SiMPL: **S**ki**l**l-based **M**eta **P**olicy **L**earning

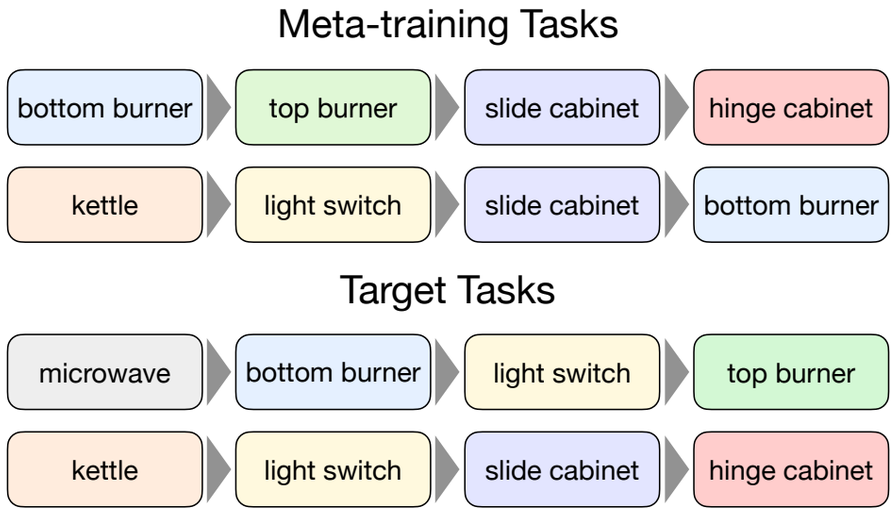


Environments



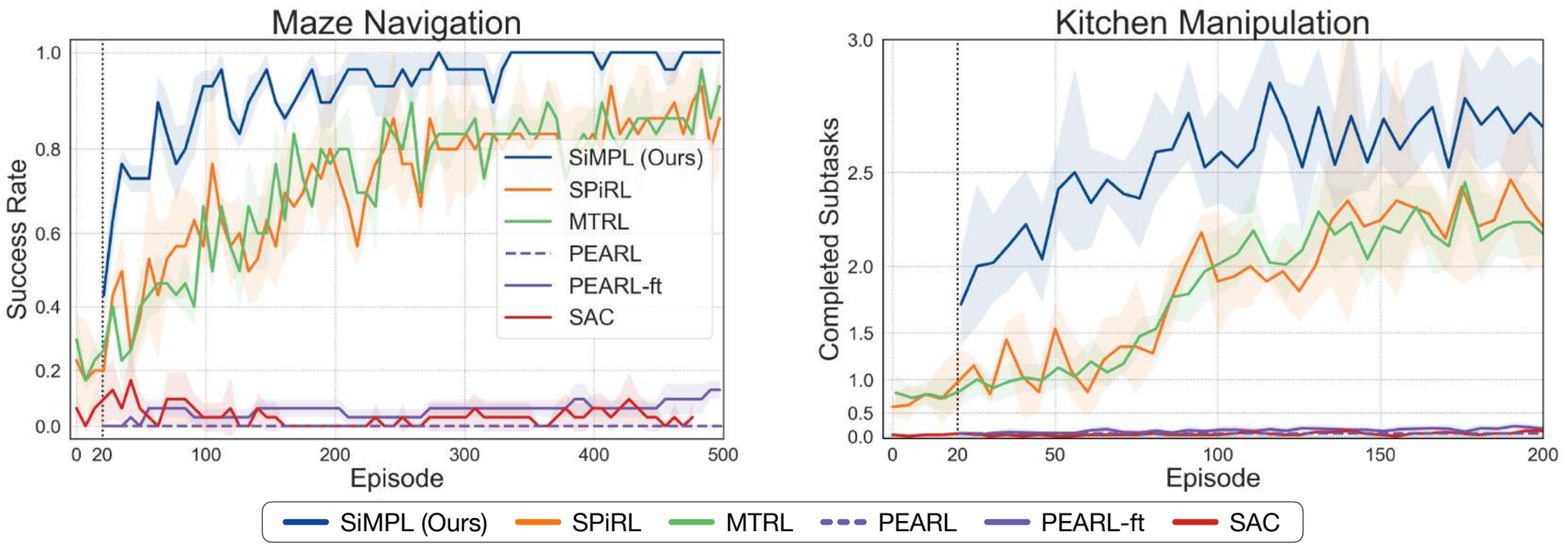
(a) Maze Navigation

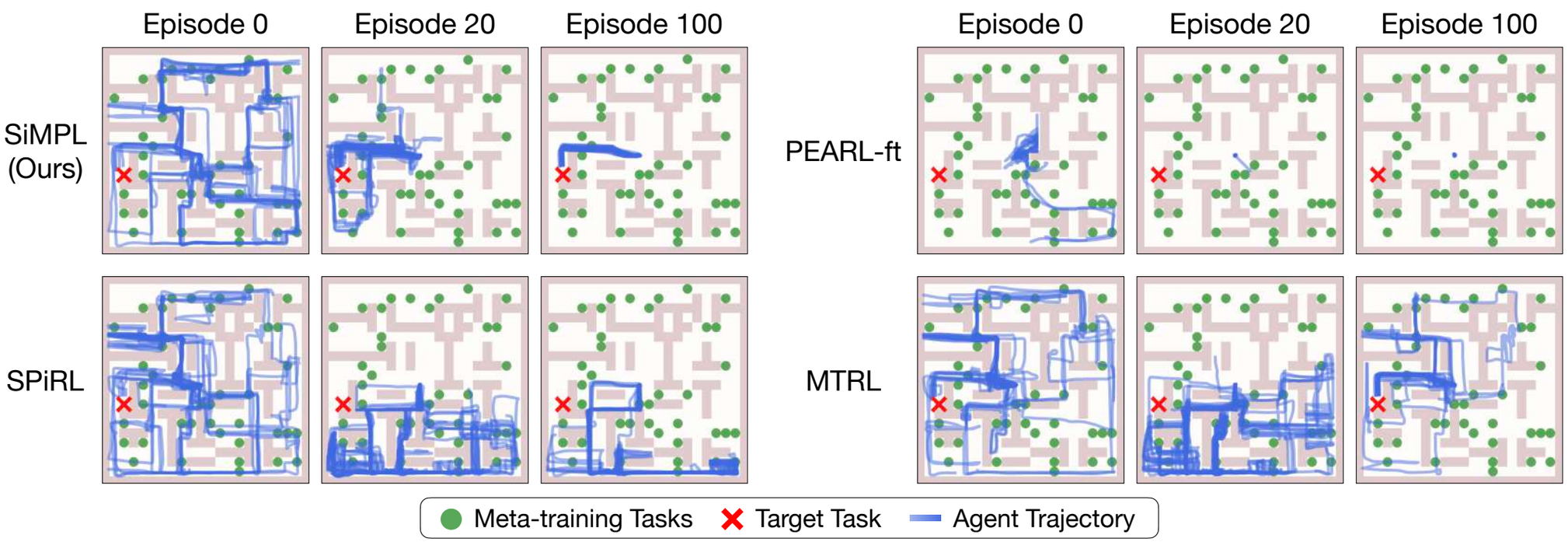




(b) Kitchen Manipulation

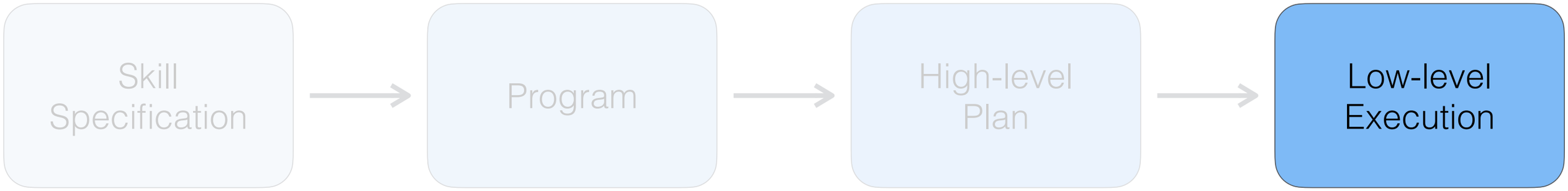
Results


Maze Navigation
Success Rate
1.0
0.8
0.6
0.4
0.2
0.0
0
20
100
200
300
400
500
Episode
SiMPL (Ours)
SPiRL
MTRL
PEARL
PEARL-ft
SAC
Kitchen Manipulation
Completed Subtasks
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
20
50
100
150
200
Episode
SiMPL (Ours)
SPiRL
MTRL
PEARL
PEARL-ft
SAC


Episode 0
Episode 20
Episode 100
SiMPL (Ours)
SPiRL
PEARL-ft
MTRL
Meta-training Tasks
Target Task
Agent Trajectory

Generalizable Imitation Learning from Observation via Inferring Goal Proximity

NeurIPS 2021

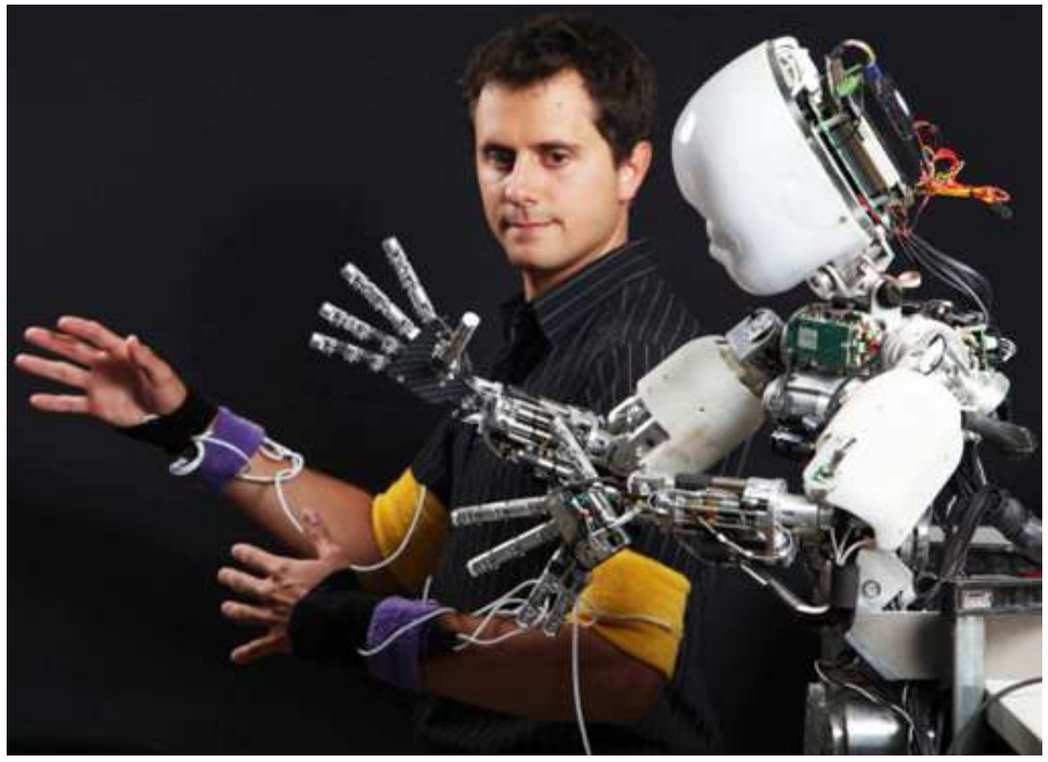



Youngwoon Lee


Andrew Szot


Joseph J. Lim

Learning from **Demonstration**

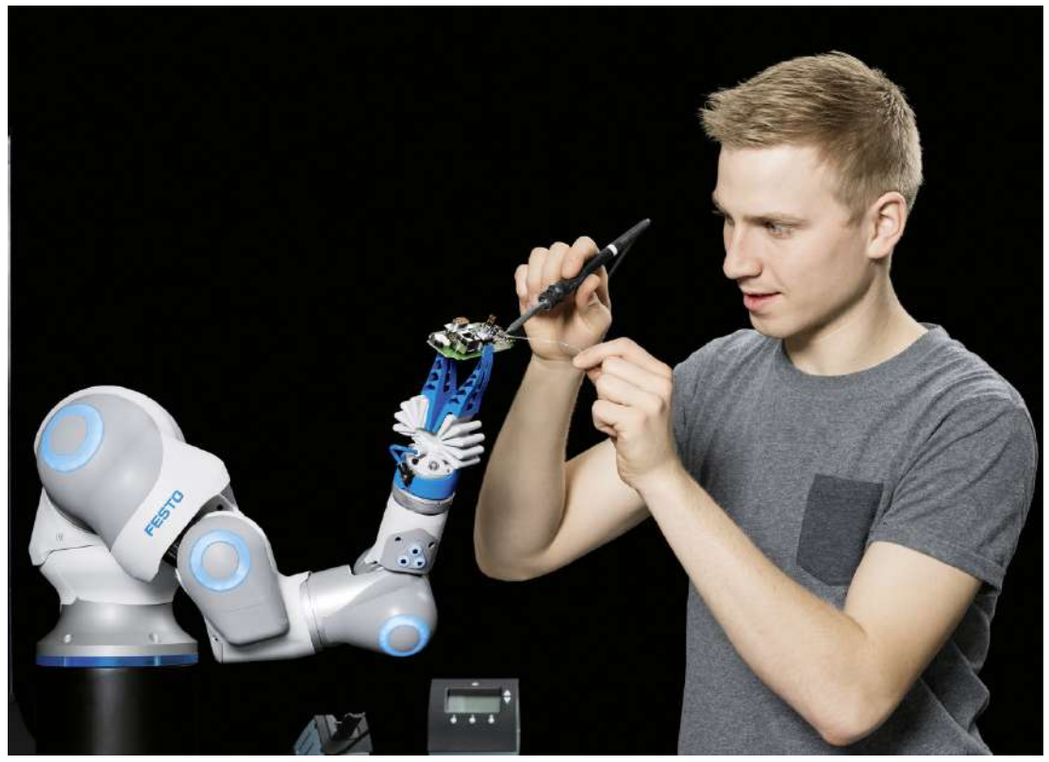


with expert's actions

Demo: $\{s_1, a_1, s_2, a_2, s_3, a_3, \ldots\}$

vs.

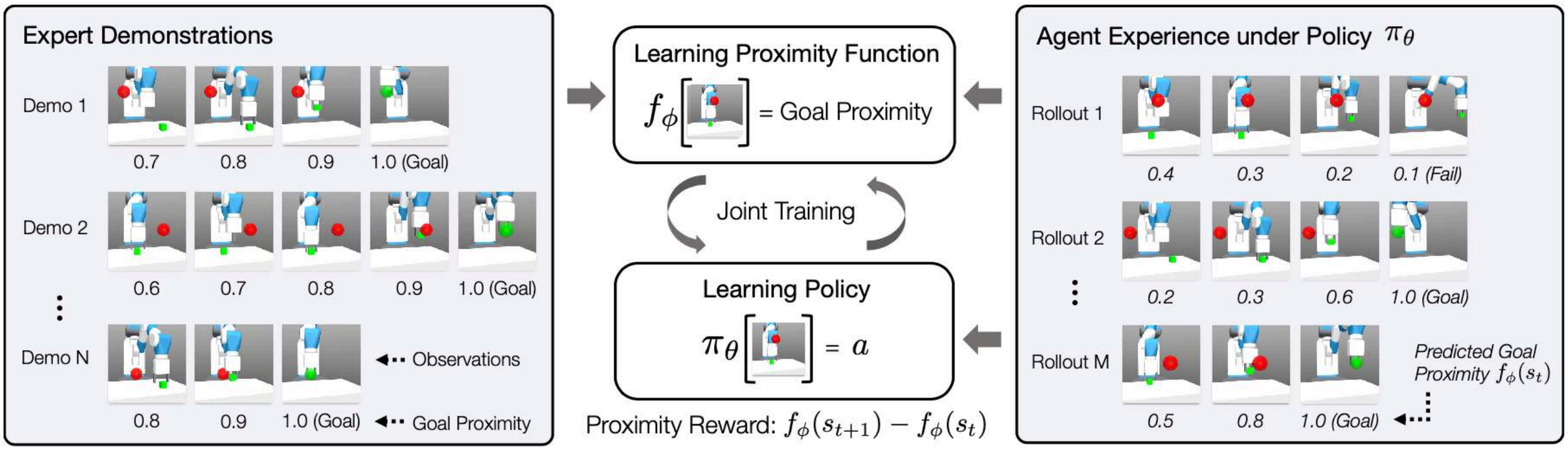
Learning from **Observation**



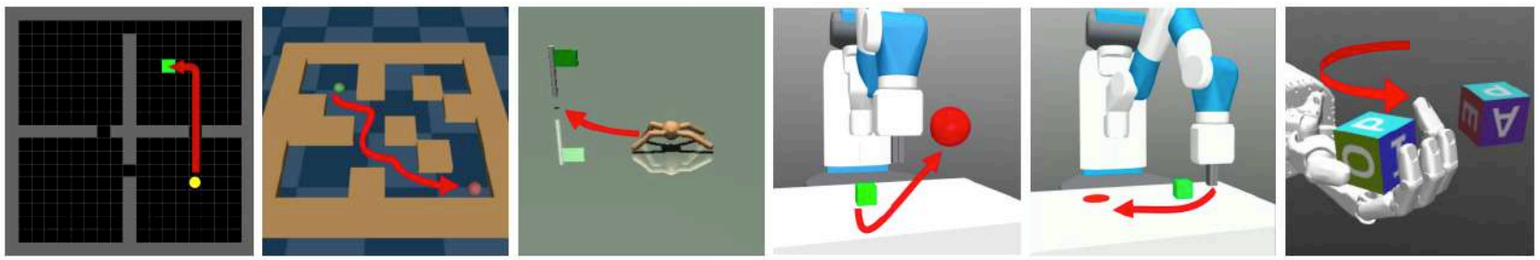
without expert's actions

Demo: $\{s_1, s_2, s_3, \ldots\}$

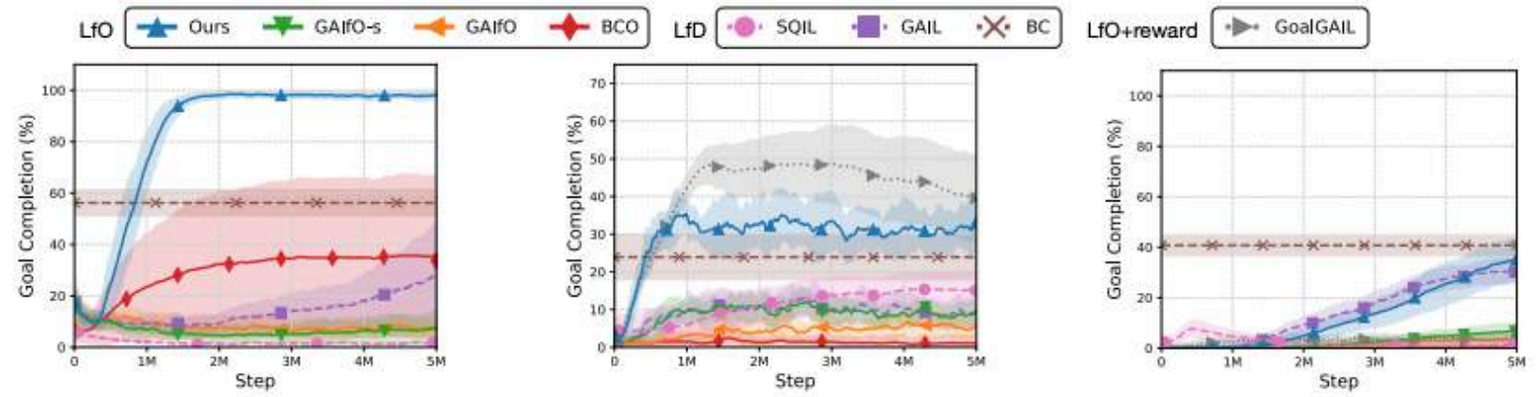
Learning from Observation via Inferring Goal Proximity



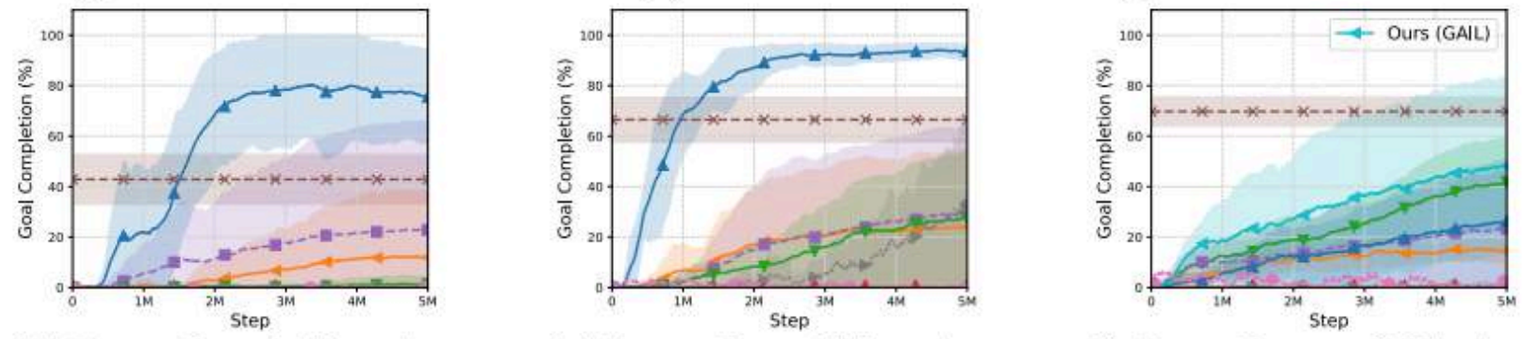
Experiments



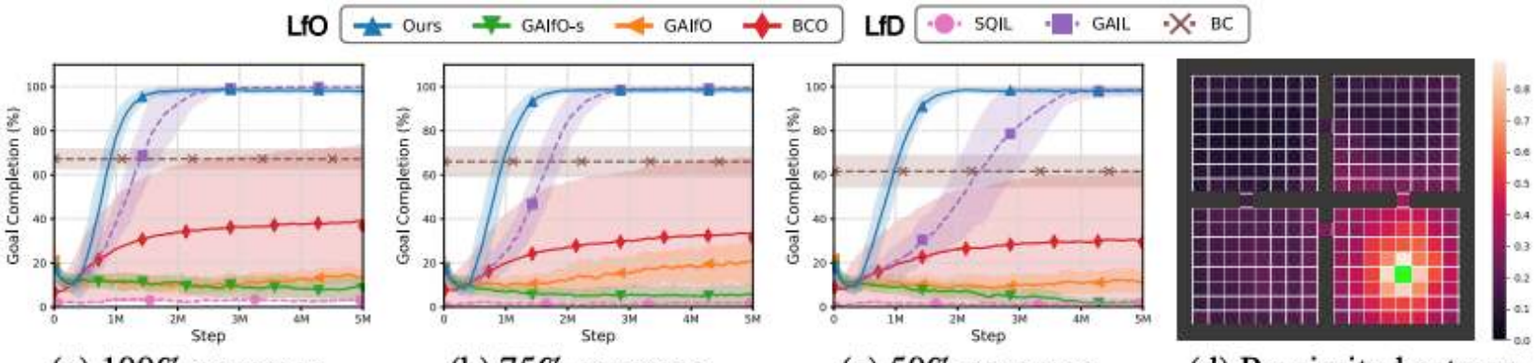
(a) NAVIGATION (b) MAZE2D (c) ANT REACH (d) FETCH PICK (e) FETCH PUSH (f) HANDROTATE



(a) NAVIGATION 25% (b) MAZE2D 50% (c) ANT REACH 0.05 noise

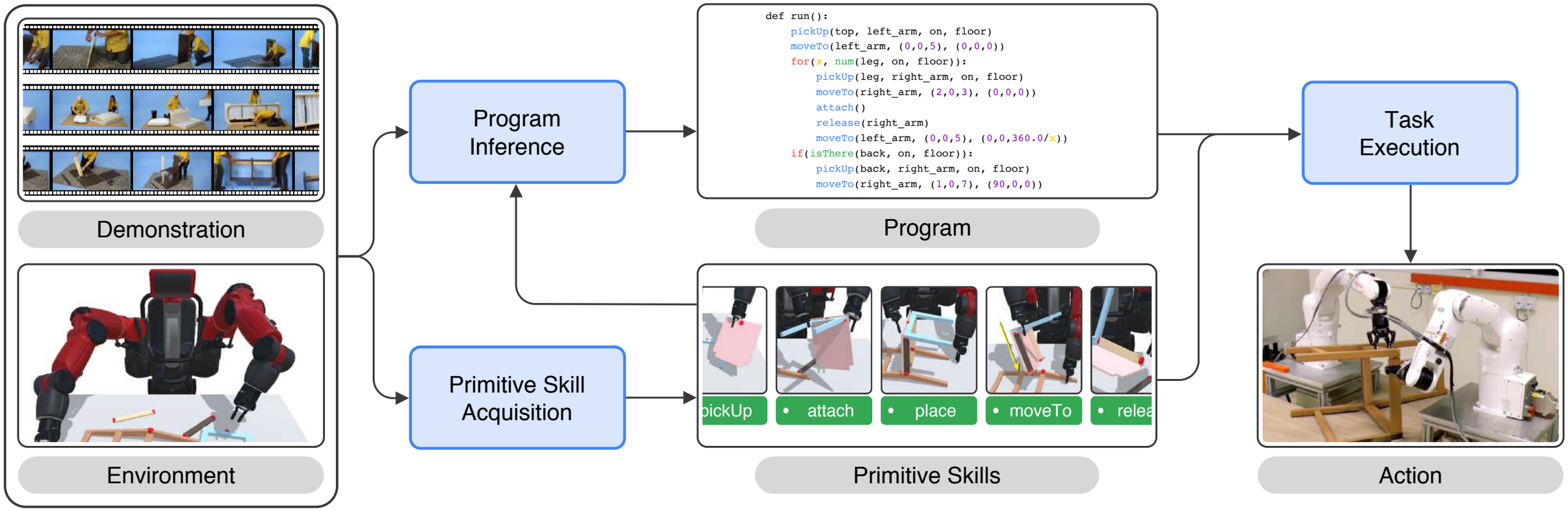


(d) FETCH PICK 1.75x noise (e) FETCH PUSH 1.75x noise (f) HAND ROTATE 0.35 noise



(a) 100% coverage (b) 75% coverage (c) 50% coverage (d) Proximity heatmap

Program-Guided Framework for Interpreting and Acquiring Complex Skills with Learning Robots



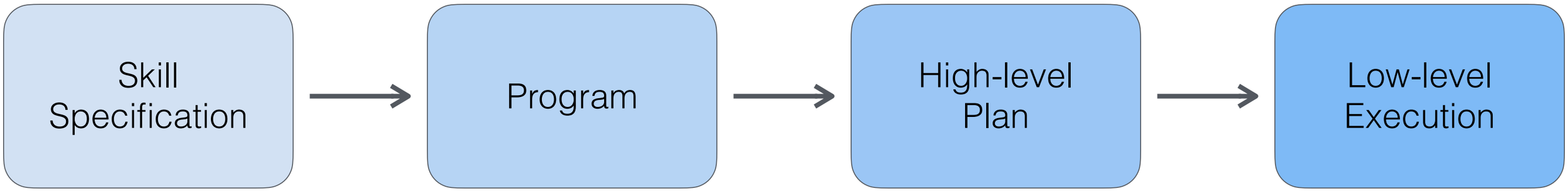
Interpretable

Programmatic / Generalizable

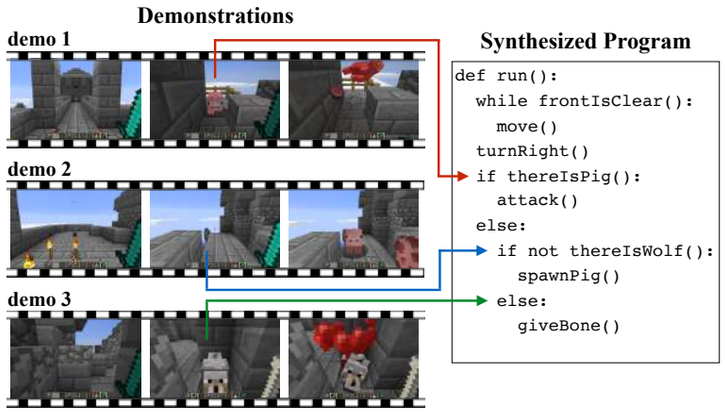
Hierarchical

Modular

Program-Guided Framework for Interpreting and Acquiring Complex Skills with Learning Robots



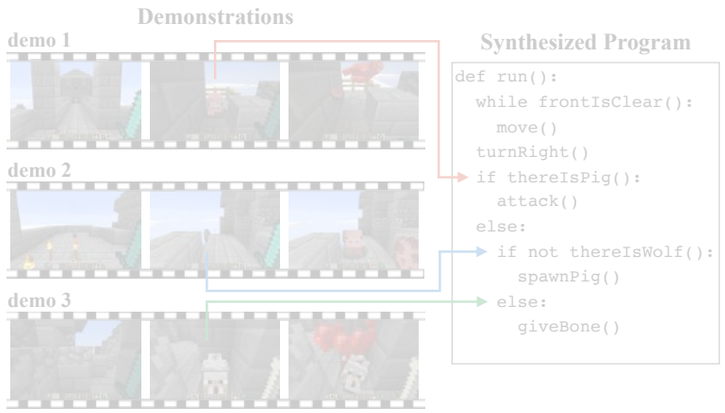
Neural Program Synthesis from Diverse Demonstration Videos



ICML 2018

Skill Specification → Program → High-level Plan → Low-level Execution

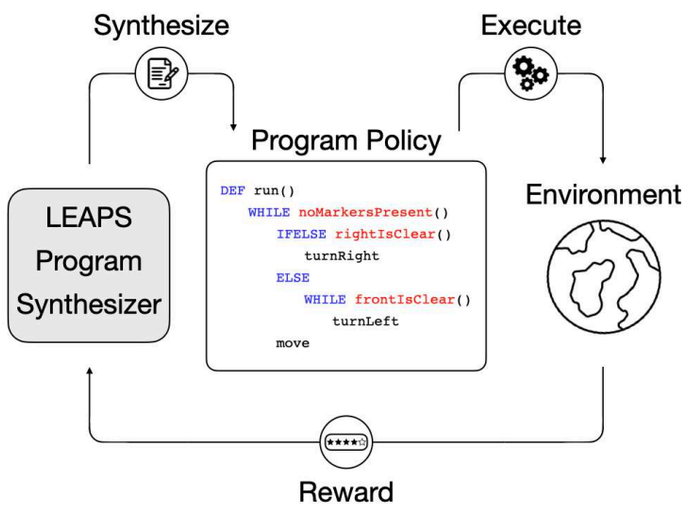
Neural Program Synthesis
from Diverse Demonstration Videos



ICML 2018

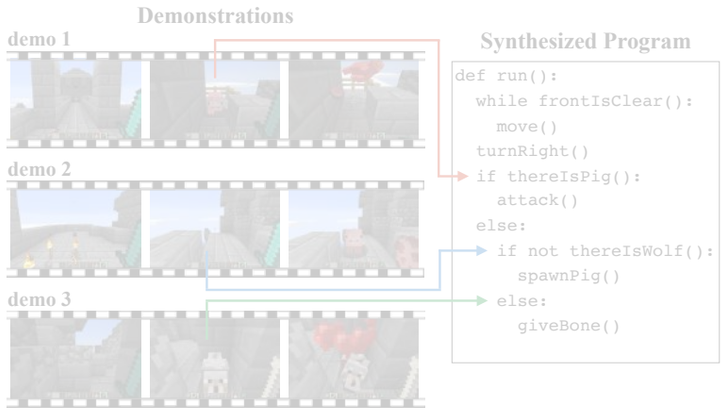
Skill Specification → Program → High-level Plan → Low-level Execution

Learning to Synthesize Programs as
Interpretable and Generalizable Policies



NeurIPS 2021

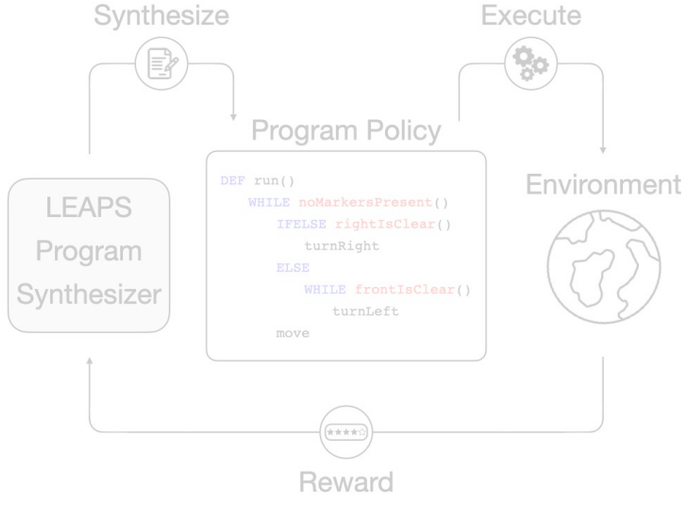
Neural Program Synthesis from Diverse Demonstration Videos



ICML 2018

Skill Specification → Program → High-level Plan → Low-level Execution

Learning to Synthesize Programs as Interpretable and Generalizable Policies



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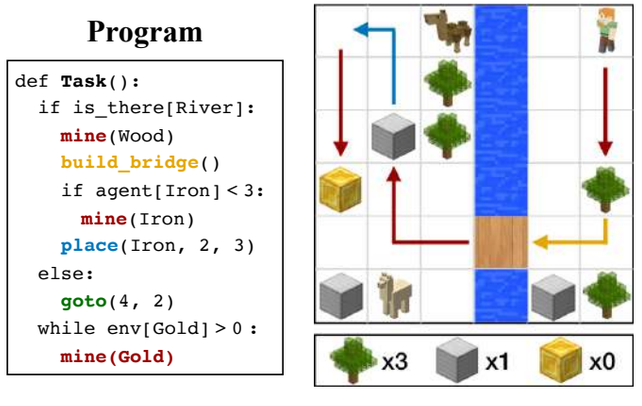
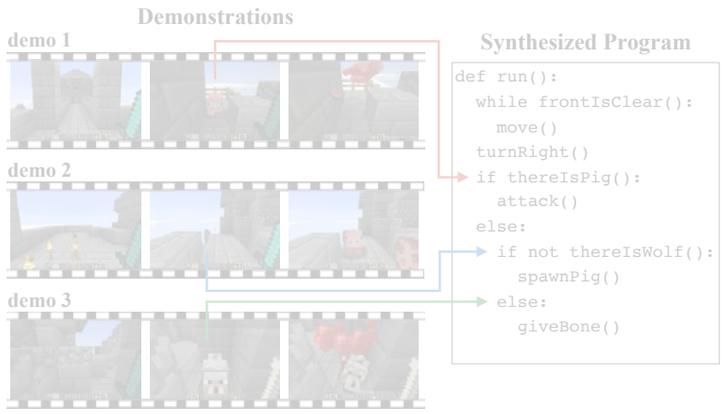
Program Guided Agent



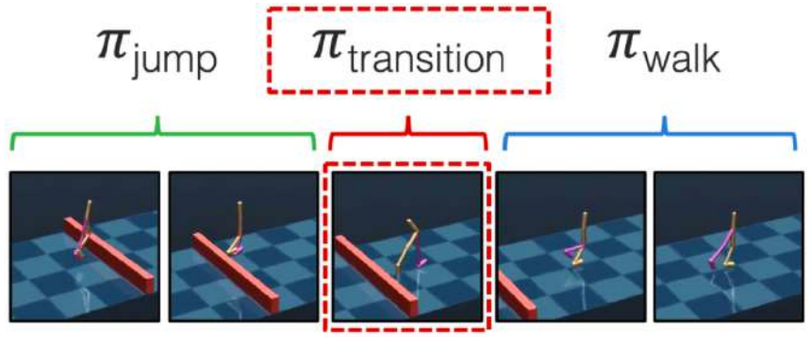
ICLR 2020 (Spotlight)

Neural Program Synthesis
from Diverse Demonstration Videos



ICML 2018

Composing Complex Skills
by Learning Transition Policies



ICLR 2019

Skill Specification → Program → High-level Plan → Low-level Execution

Learning to Synthesize Programs as
Interpretable and Generalizable Policies

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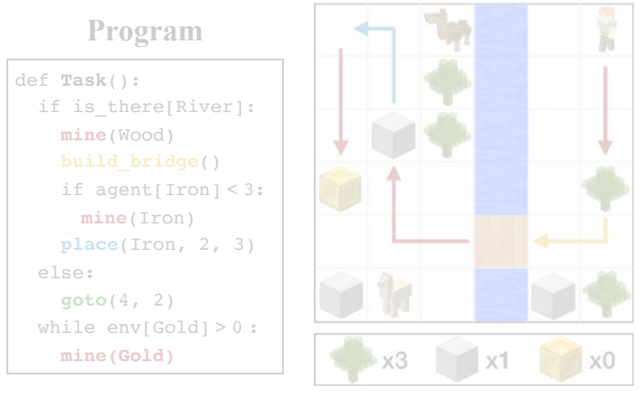
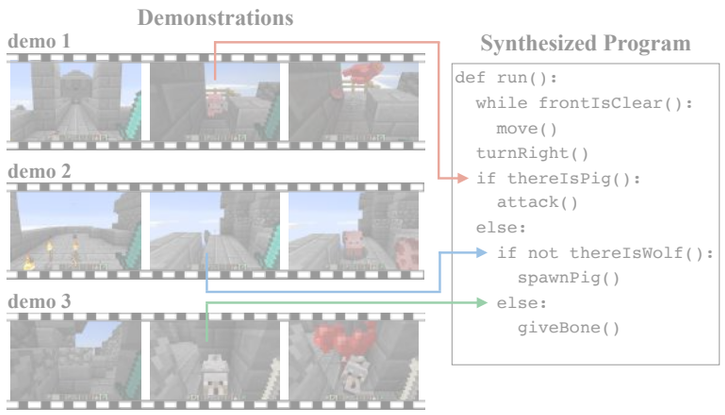
Program Guided Agent

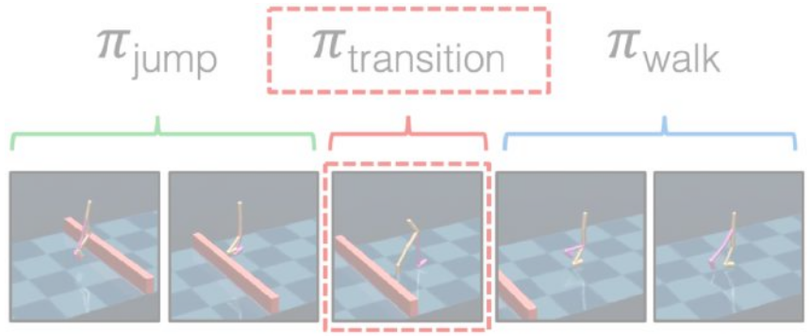


ICLR 2020 (Spotlight)

Neural Program Synthesis from Diverse Demonstration Videos



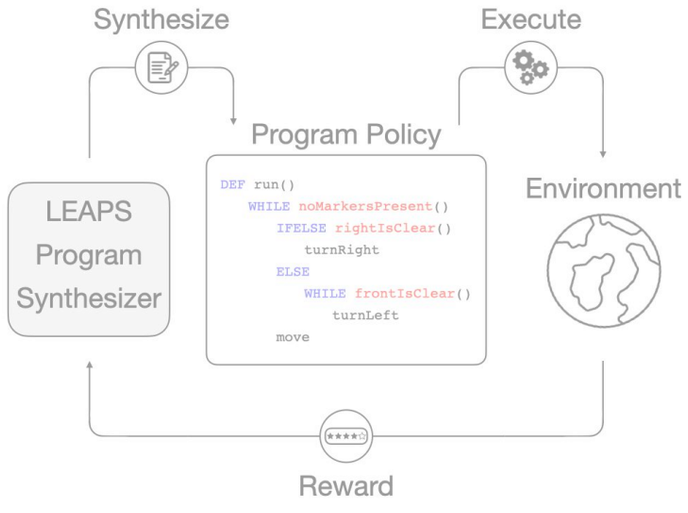
ICML 2018



ICLR 2019

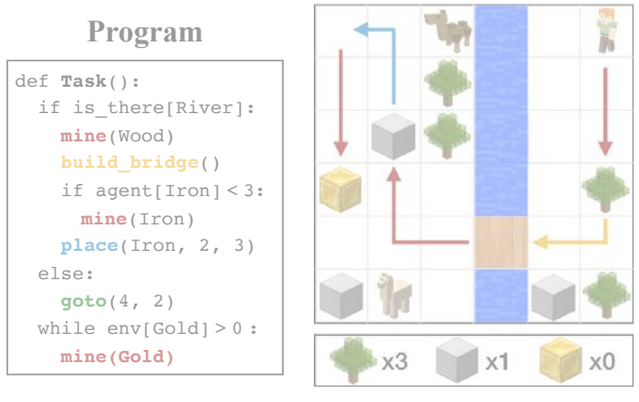
Skill Specification → Program → High-level Plan → Low-level Execution

Learning to Synthesize Programs as Interpretable and Generalizable Policies



NeurIPS 2021

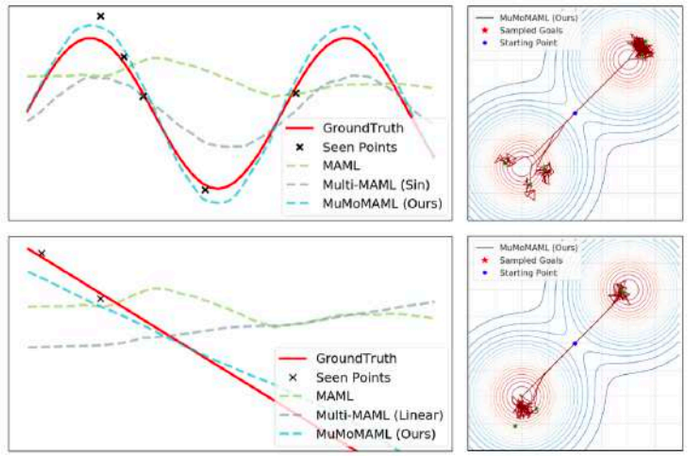
Program Guided Agent



ICLR 2020 (Spotlight)

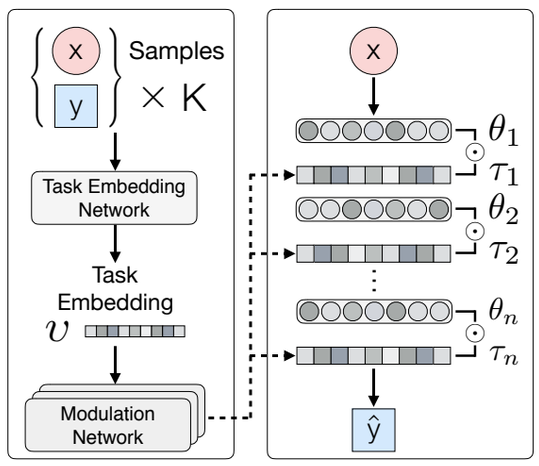
Low-level Execution

Toward Multimodal Model-Agnostic Meta-Learning



Meta-learning workshop @ NeurIPS 2018

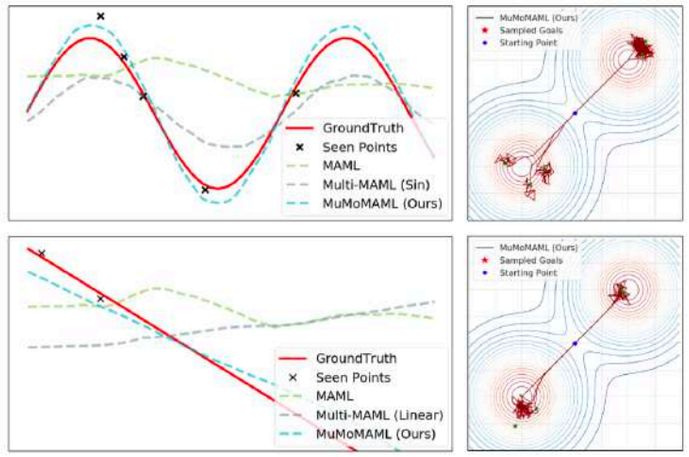
Multimodal Model-Agnostic Meta-Learning via Task-Aware Modulation



NeurIPS 2019 (Spotlight)

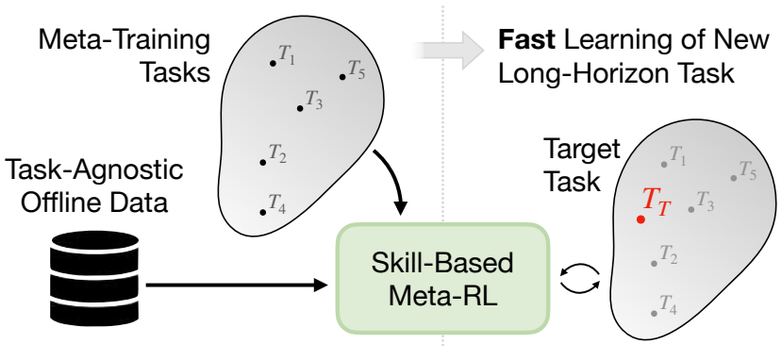
Low-level Execution

Toward Multimodal Model-Agnostic Meta-Learning



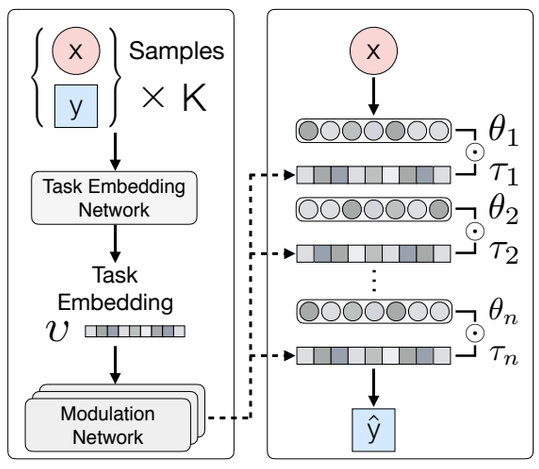
Meta-learning workshop @ NeurIPS 2018

Skill-based Meta-Reinforcement Learning



ICLR 2022

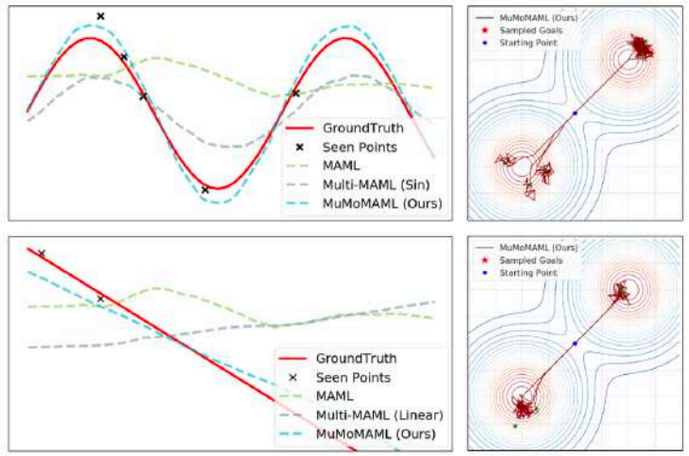
Multimodal Model-Agnostic Meta-Learning via Task-Aware Modulation



NeurIPS 2019 (Spotlight)

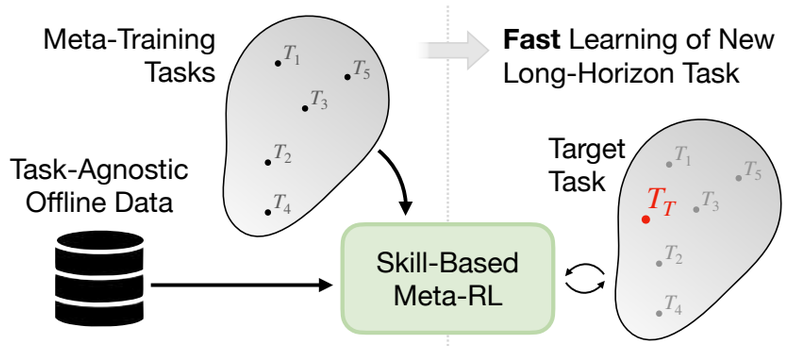
Low-level Execution

Toward Multimodal Model-Agnostic Meta-Learning



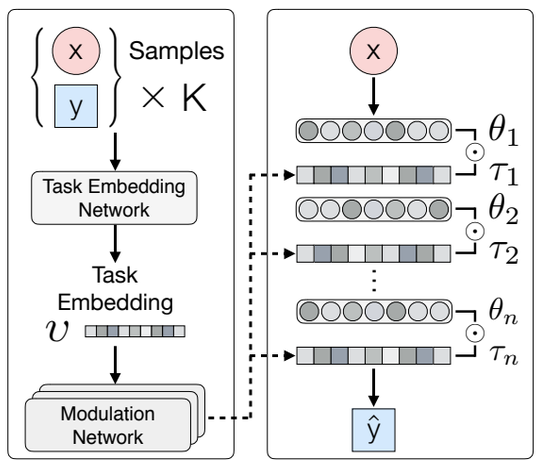
Meta-learning workshop @ NeurIPS 2018

Skill-based Meta-Reinforcement Learning



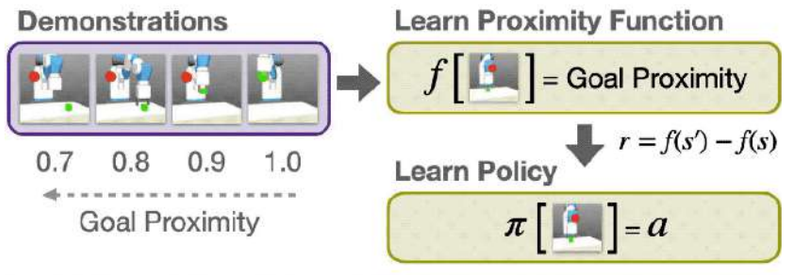
ICLR 2022

Multimodal Model-Agnostic Meta-Learning via Task-Aware Modulation



NeurIPS 2019 (Spotlight)

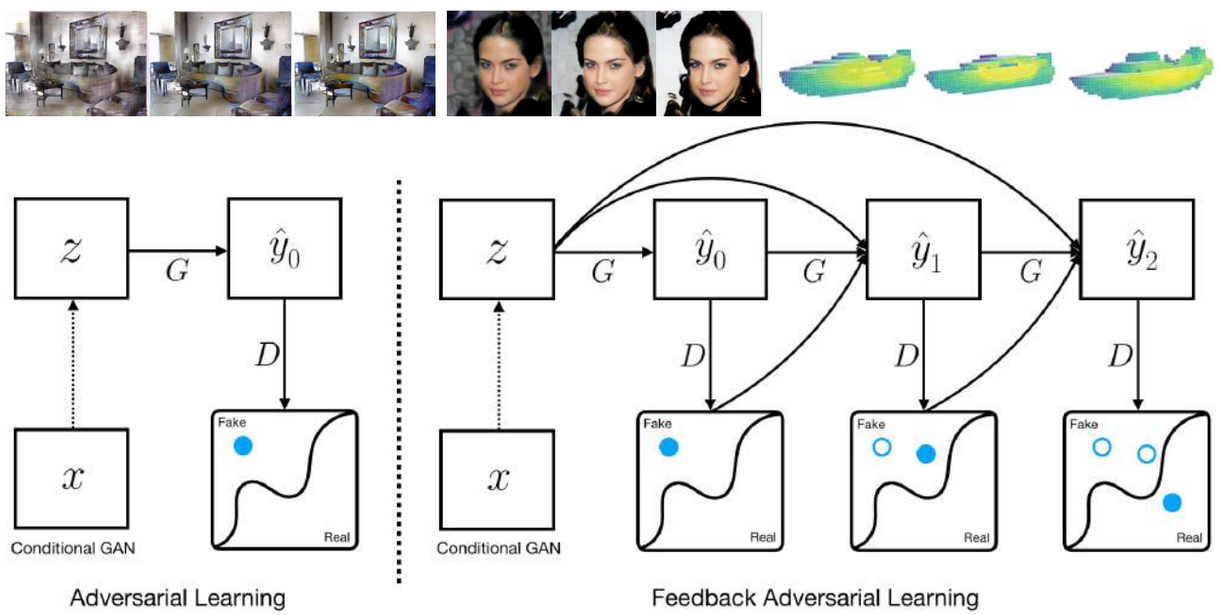
Generalizable Imitation Learning from Observation via Inferring Goal Proximity



NeurIPS 2021

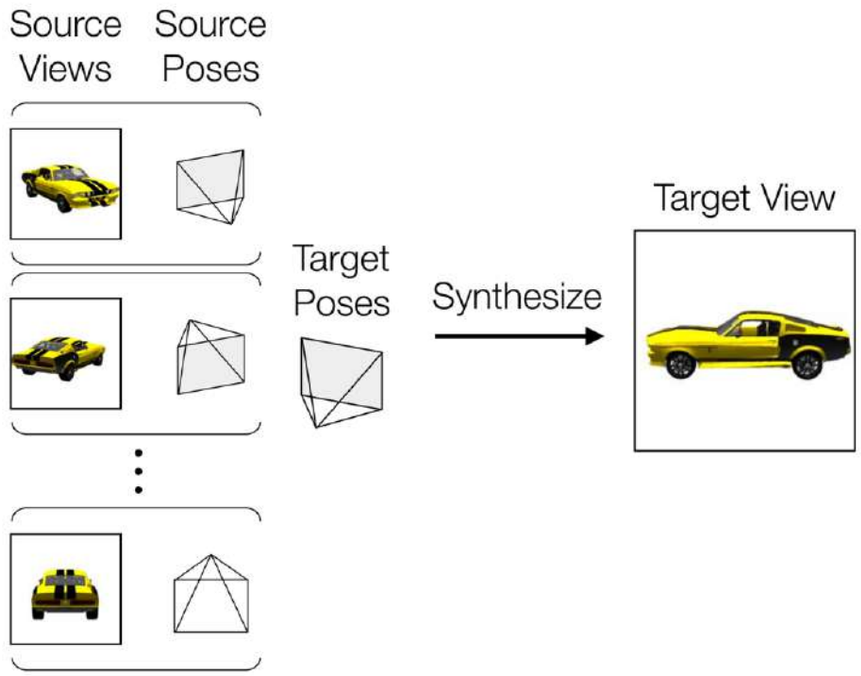
Computer Vision / Image Synthesis / GAN

Feedback Adversarial Learning:
Spatial Feedback for Improving Generative Adversarial Networks

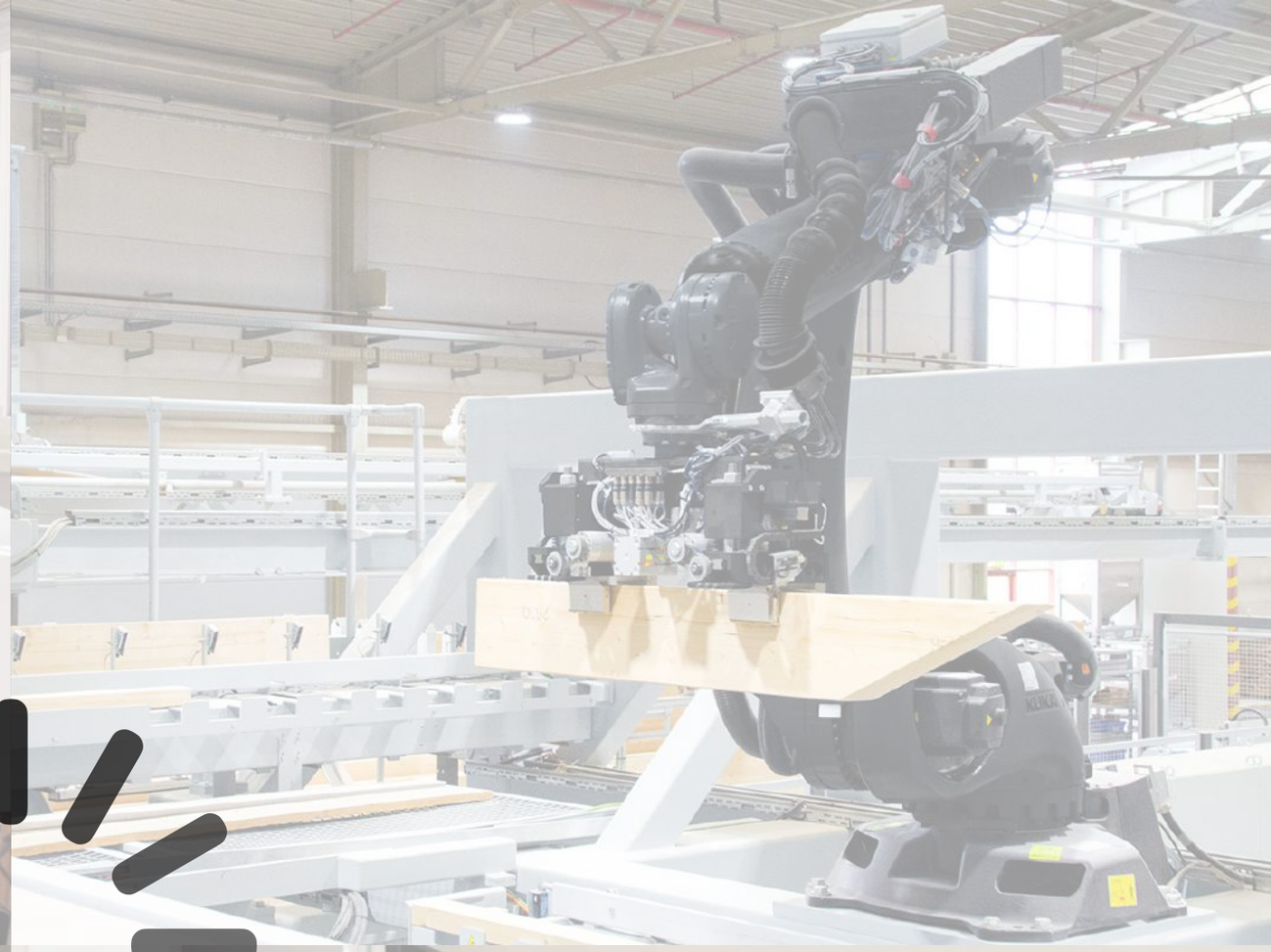


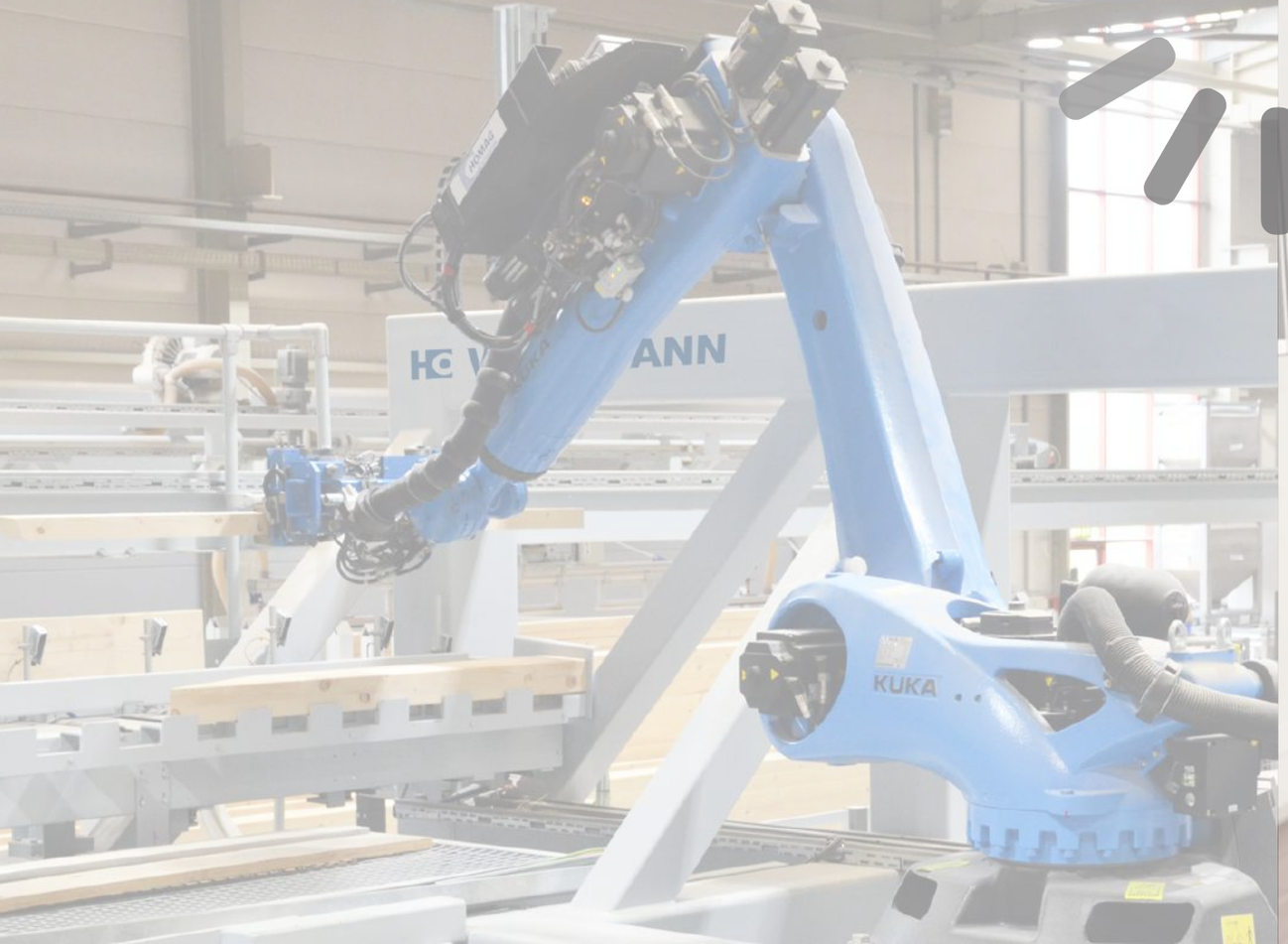
CVPR 2019

Multi-view to Novel view:
Synthesizing Views with Self-Learned Confidence



ECCV 2018

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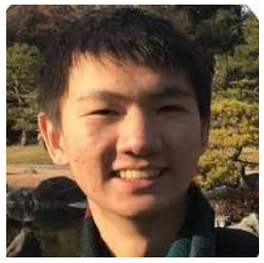

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Te-Lin Wu

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Andrew Szot

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Thank You

Questions?