Carnegie Mellon University
The Robotics Institute

# Translating Robot Skills: Learning Unsupervised Skill Correspondences across Domains

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Vikash Kumar, Stuart Anderson, Jean Oh

# The Marvelous Human

[1] Video: https://www.youtube.com/watch?v=qjaTp5MwqbQ&

# The Marvelous Human

Ability #1:

Humans have well-developed motor skills that we can execute with little effort.

# The Marvelous Human

Ability #1:

Humans have well-developed motor skills that we can execute with little effort.

Ability #2:

Humans can reason abstractly about the sequence of skills a demonstrator uses; and find corresponding skills to execute ourselves.

How can we enable robots with these abilities?

How can robots learn correspondences between their own skills, and those of a demonstrator (whether human, or robot, with different embodiments)?

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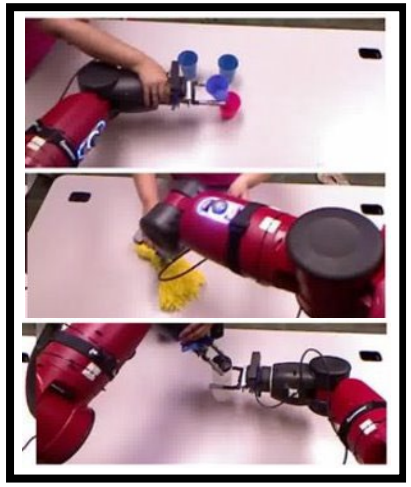
This enables robots to:

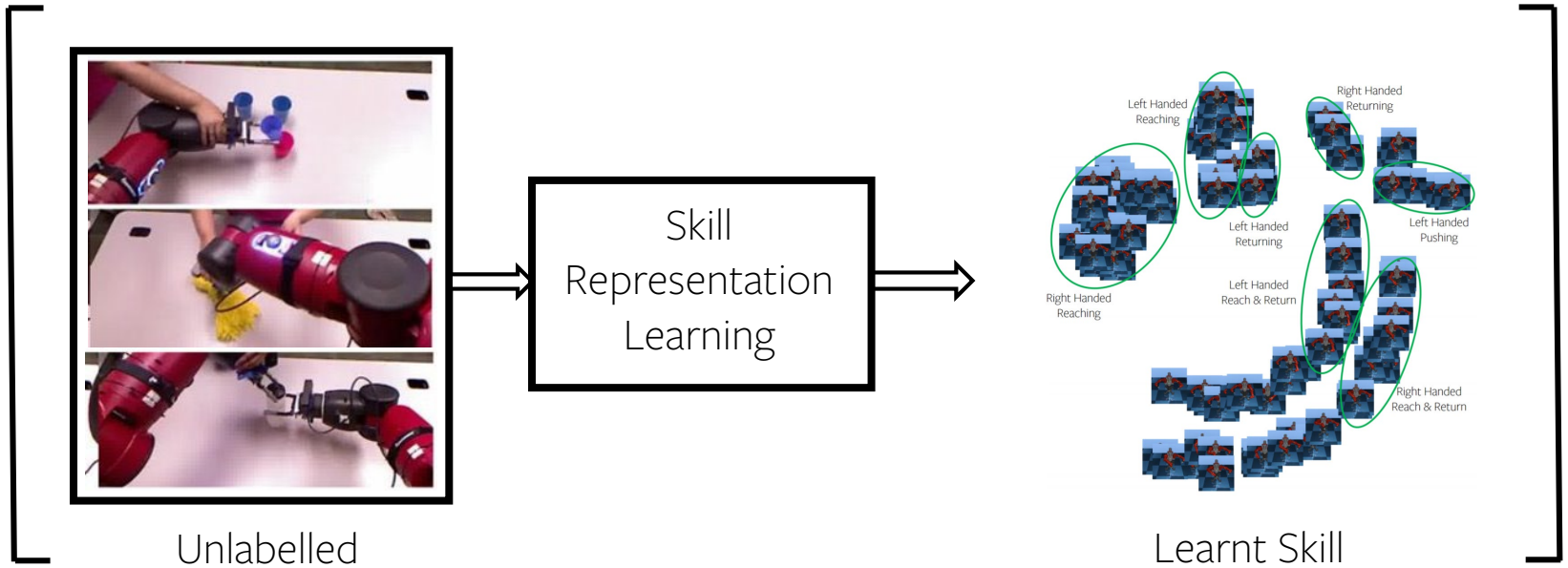
Adopt demonstrator task strategies for themselves;
Compose existing skills to broaden their repertoire of tasks.

# Problem Setting



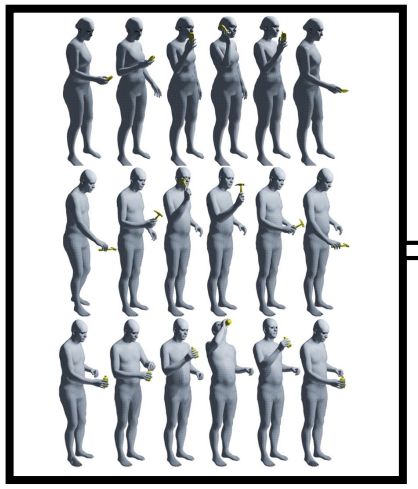
Unlabelled
Demonstration Data

# Problem Setting



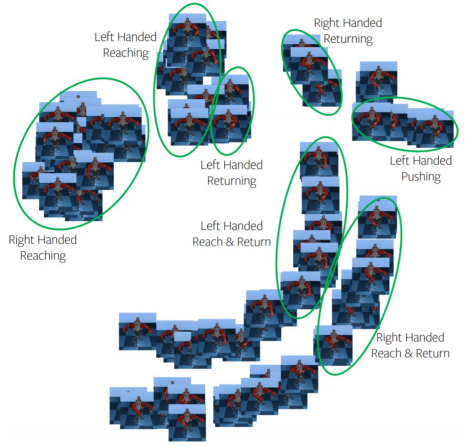

T. Shankar, A. Gupta, “Learning Robot Skills with Temporal Variational Inference”, ICML 2020

Demonstrator
(Source Domain)



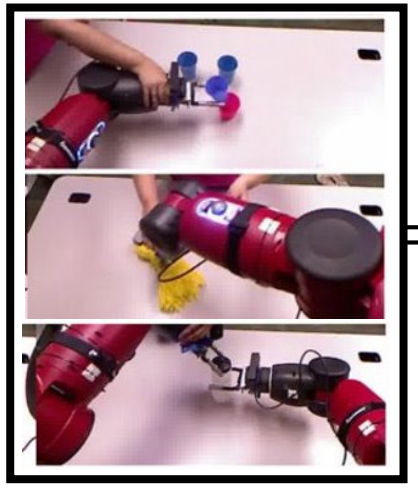
Demonstration data

Skill
Representation
Learning



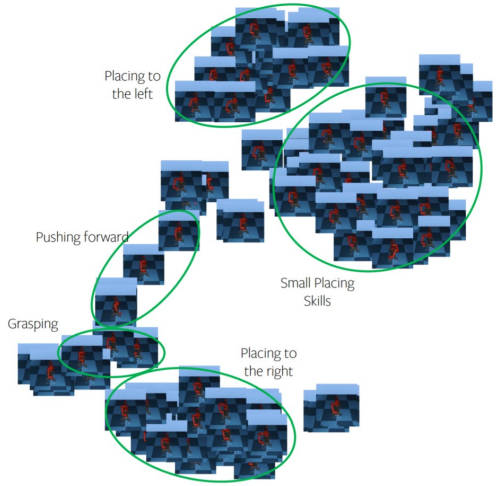

Learnt Skill Representation

Learner
(Target Domain)



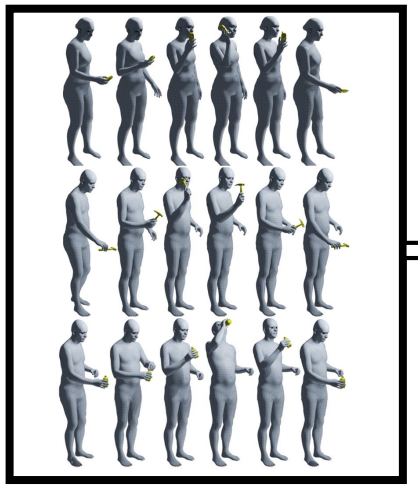
Demonstration data

Skill
Representation
Learning



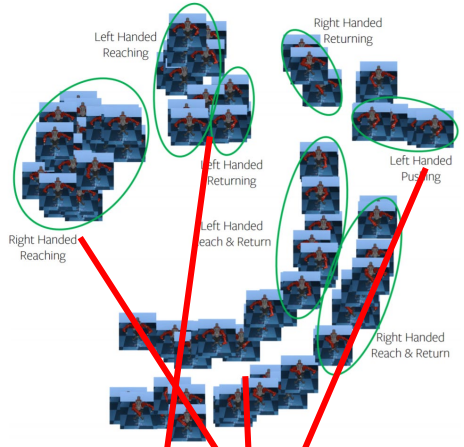

Learnt Skill Representation

Demonstrator
(Source Domain)



Demonstration data

Skill
Representation
Learning

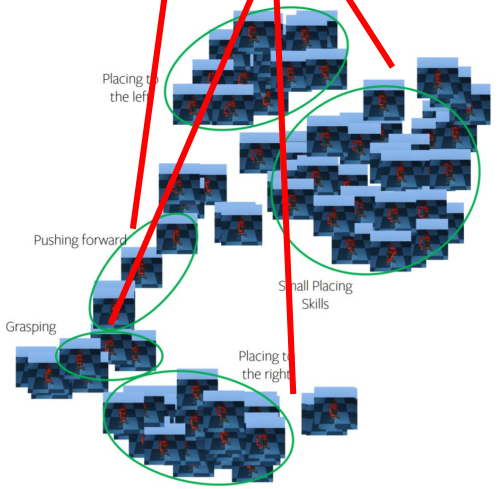



Learnt Skill Representation

Learner
(Target Domain)

Demonstration data

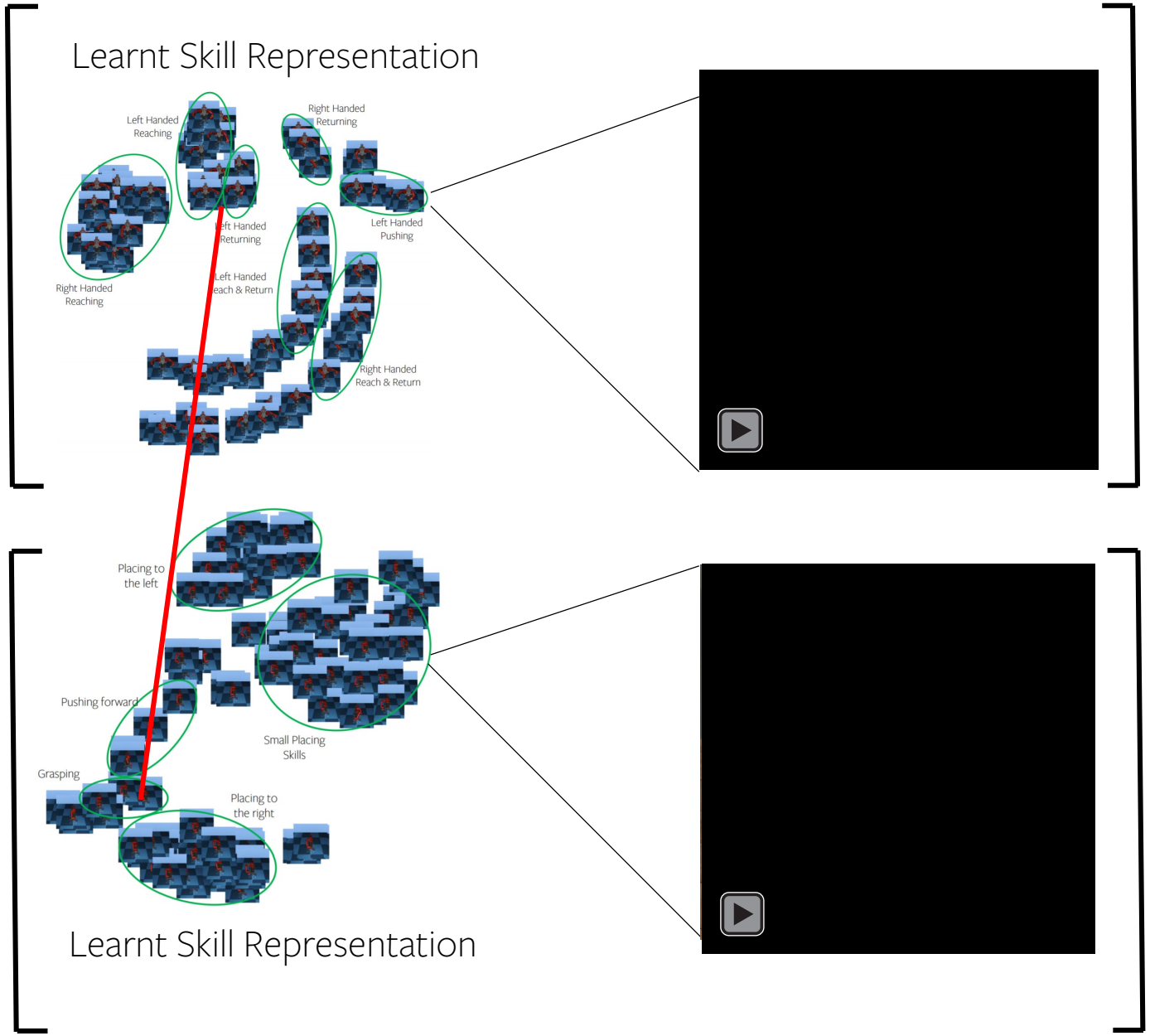
Skill
Representation
Learning



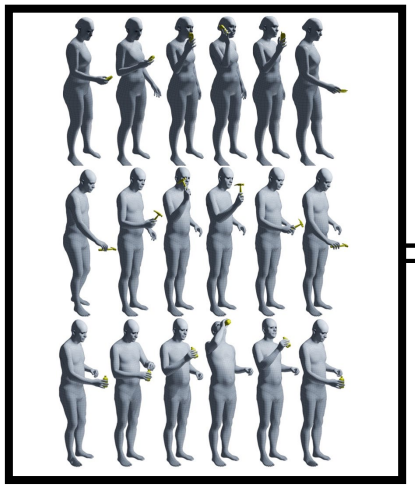

Learnt Skill Representation

Source Domain

Target Domain

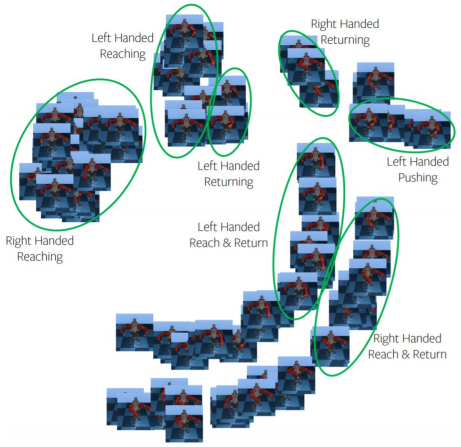


Demonstrator
(Source Domain)



Demonstration data

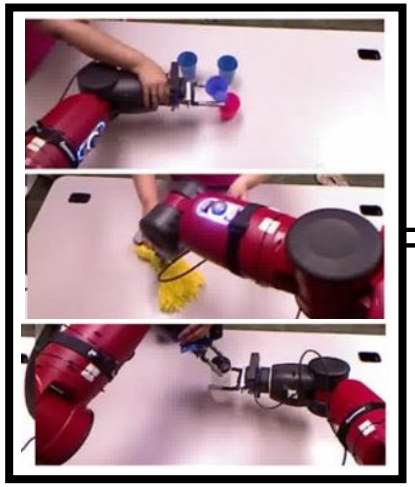
Skill
Representation
Learning




Learnt Skill Representation

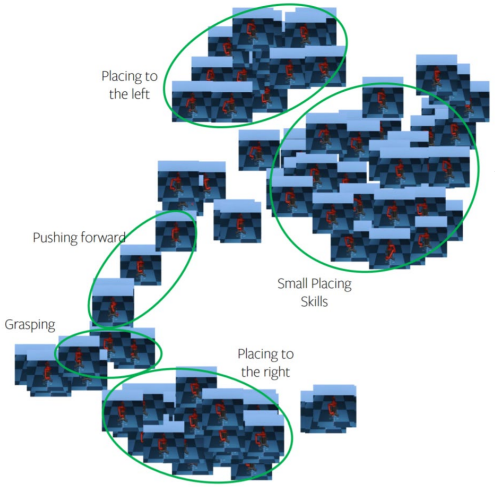
$f$

Learner
(Target Domain)



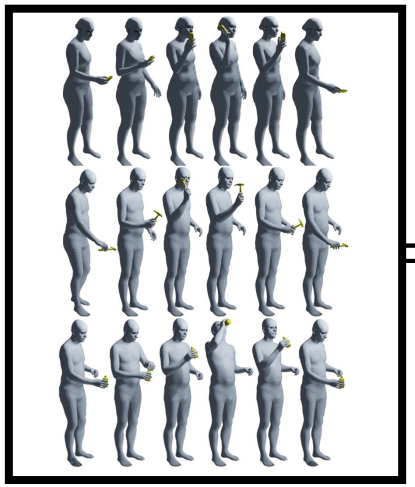
Demonstration data

Skill
Representation
Learning



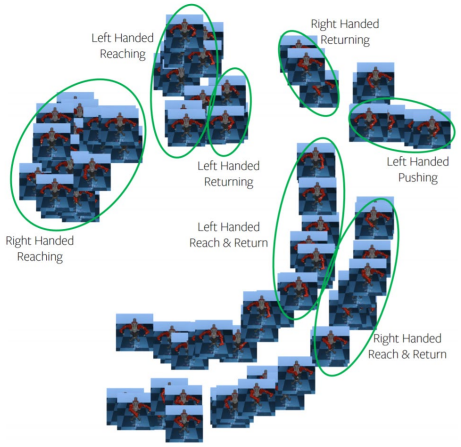

Learnt Skill Representation

Demonstrator
(Source Domain)



Demonstration data

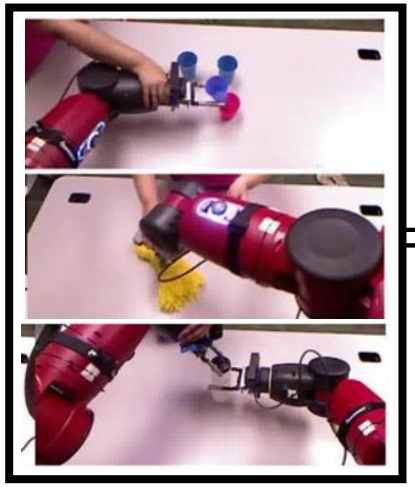
Skill
Representation
Learning




Learnt Skill Representation

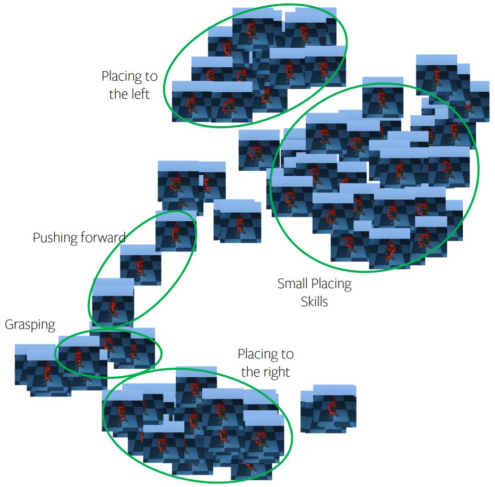
$f$

Learner
(Target Domain)



Demonstration data

Skill
Representation
Learning



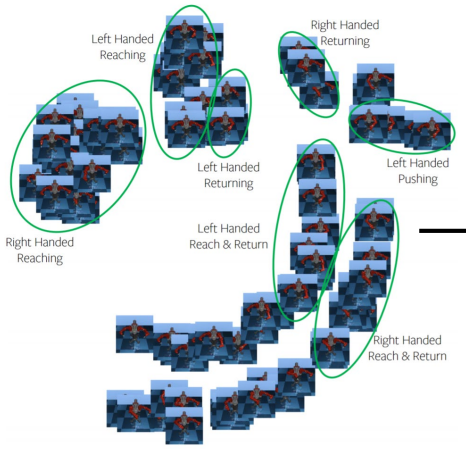

Learnt Skill Representation

Insight:

Learning skill correspondences is equivalent to unsupervised machine translation.

Source Domain

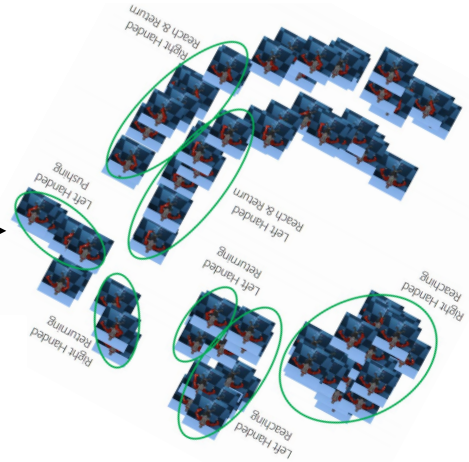
Learnt Skill Representation



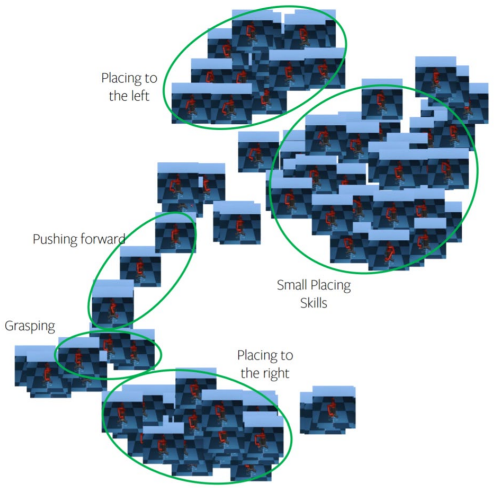

$T_{\mathrm{S}\to\mathrm{T}}$

Translation Model

Translated Skill Space



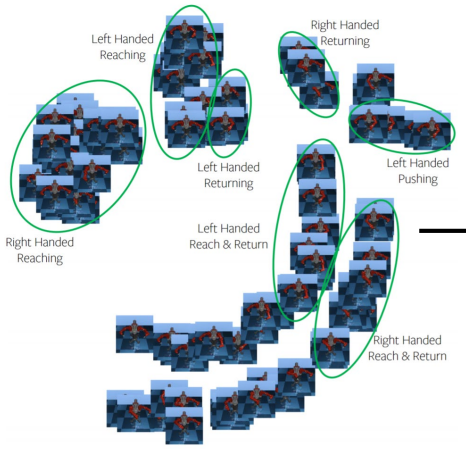
Target Domain




Learnt Skill Representation

Source Domain

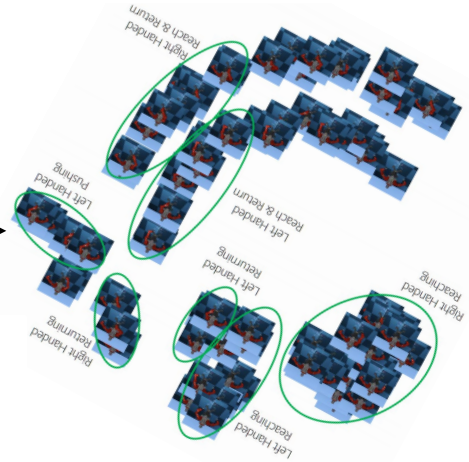
Learnt Skill Representation



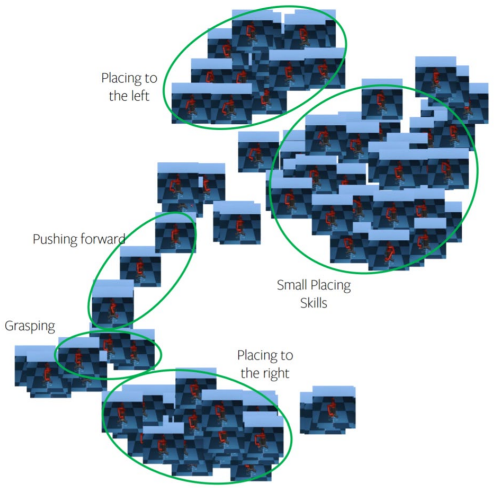

$T_{\mathrm{S}\to\mathrm{T}}$

Translation Model

Translated Skill Space



Target Domain




Learnt Skill Representation

How do we learn this translation model?

Insight:

Agents with different embodiments use similar sequences of skills to solve similar tasks.

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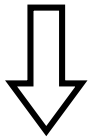
Agents with different embodiments use similar sequences of skills to solve similar tasks.

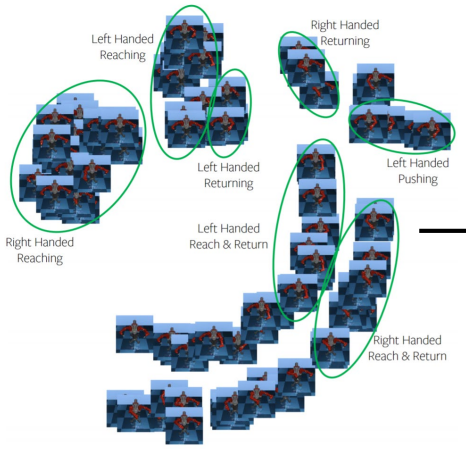


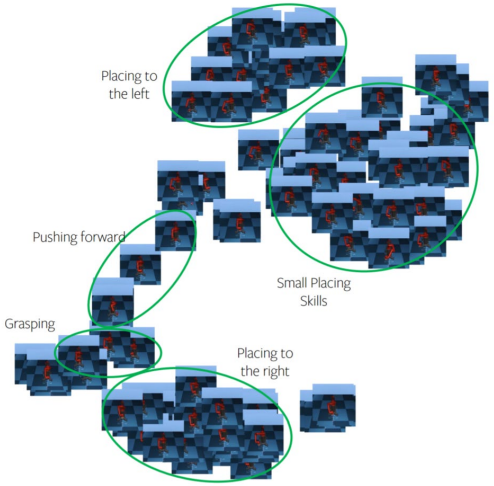
Sequences of skills should belong to similar distributions, irrespective of embodiment.

Source Domain

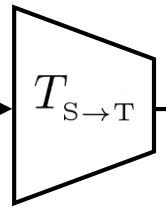
Target Domain

Learnt Skill Representation



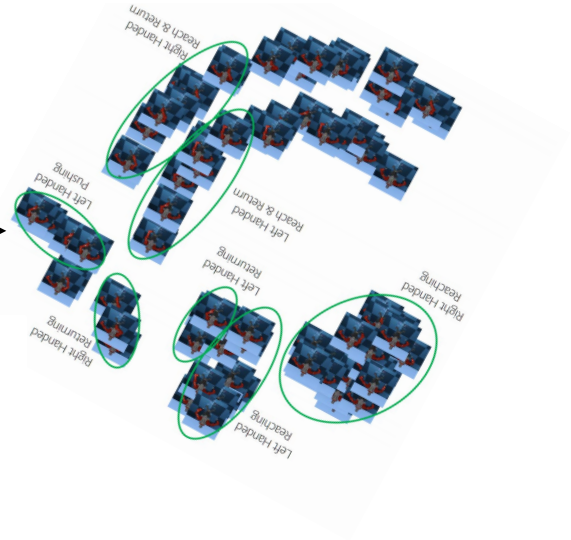



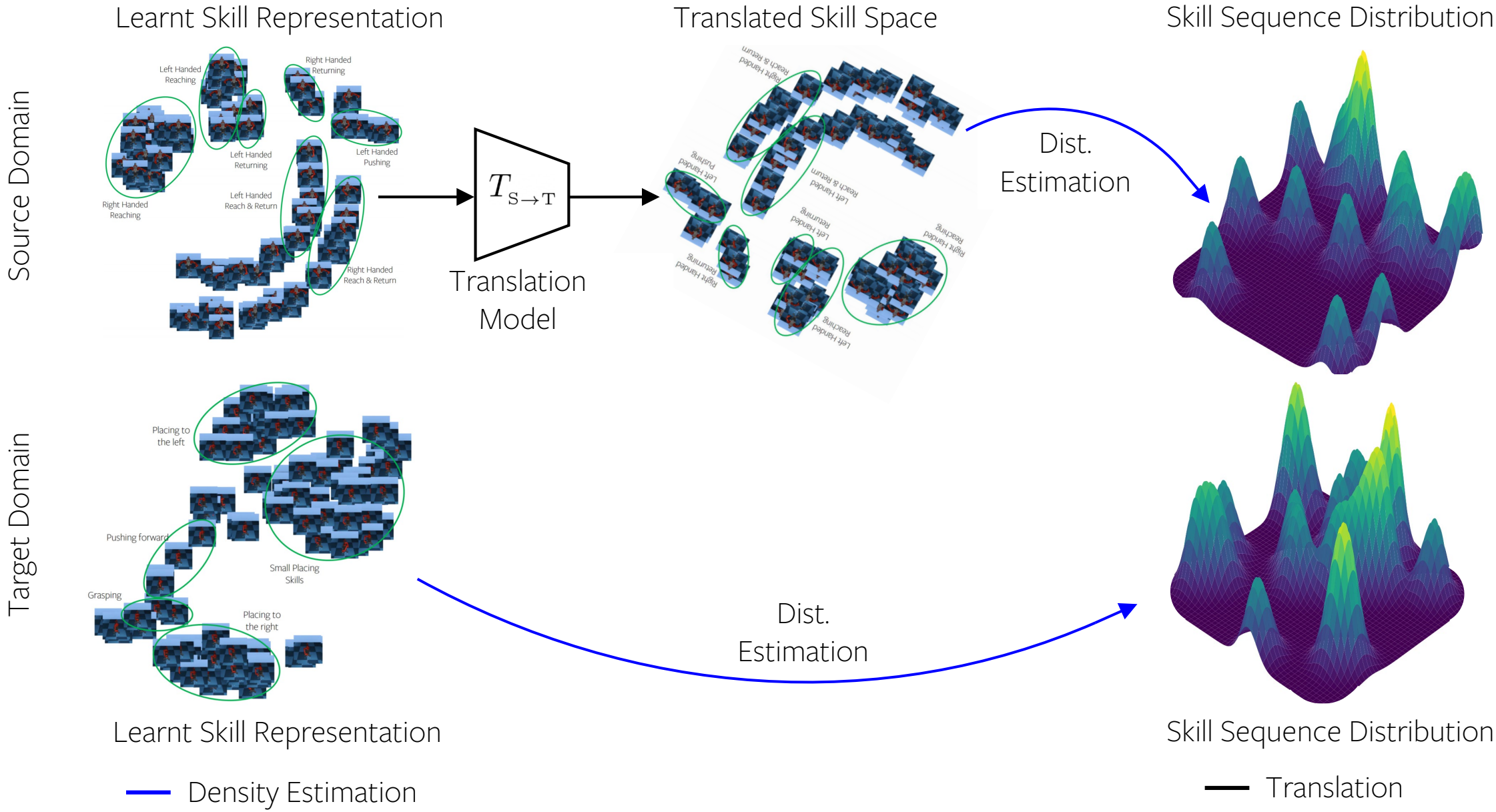

Learnt Skill Representation

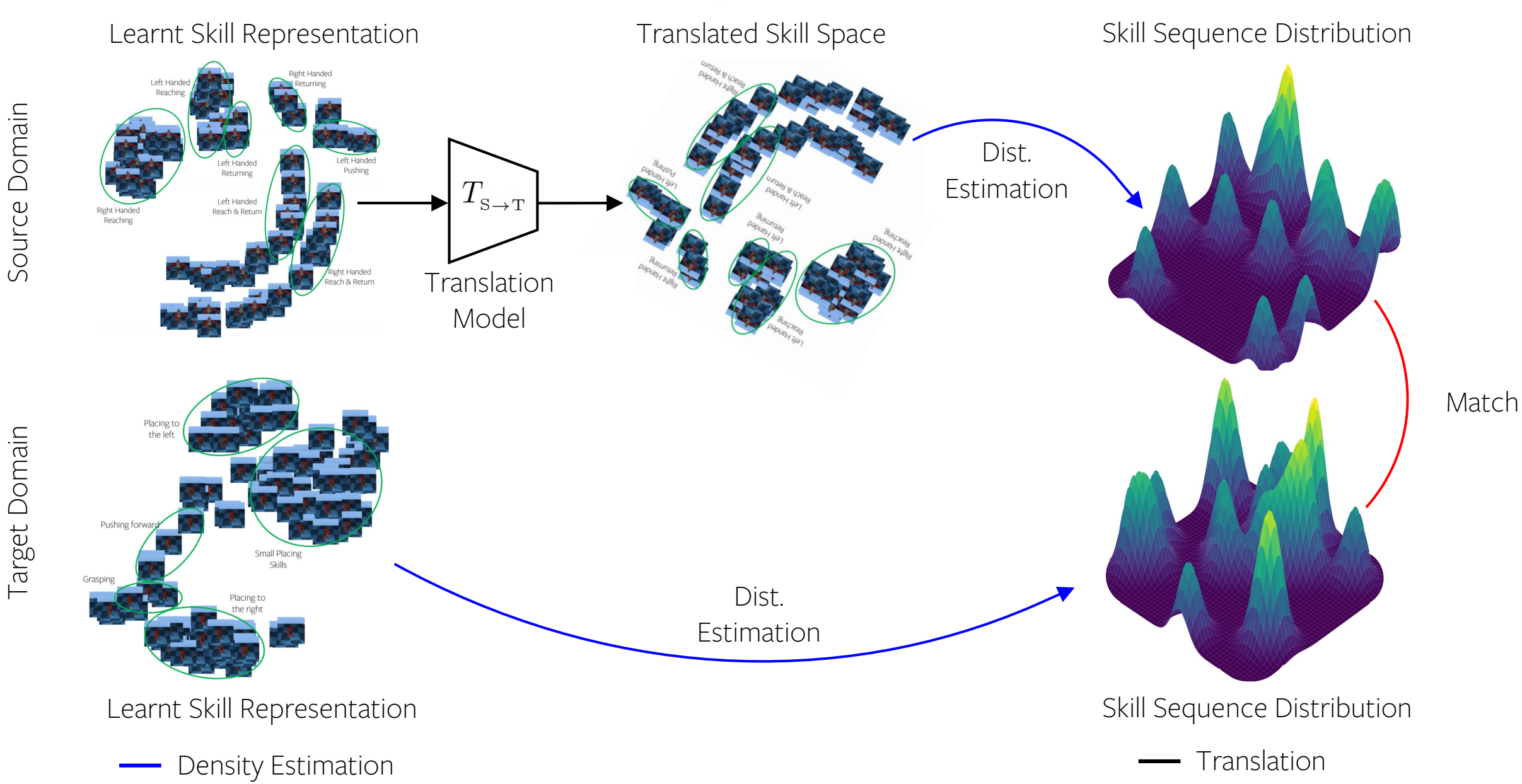



Translation Model

Translated Skill Space




Learnt Skill Representation
Translated Skill Space
Skill Sequence Distribution
Source Domain
Left Handed Reaching
Right Handed Returning
Left Handed Returning
Left Handed Pushing
Right Handed Reaching
Left Handed Reach & Return
Right Handed Reach & Return
$T_{S \to T}$
Translation Model
Dist. Estimation
Target Domain
Placing to the left
Pushing forward
Small Placing Skills
Grasping
Placing to the right
Dist. Estimation
Learnt Skill Representation
Skill Sequence Distribution
Density Estimation
Translation


Learnt Skill Representation
Translated Skill Space
Skill Sequence Distribution
Source Domain
Left Handed Reaching
Right Handed Returning
Left Handed Returning
Left Handed Pushing
Right Handed Reaching
Left Handed Reach & Return
Right Handed Reach & Return
$T_{S \to T}$
Translation Model
Dist. Estimation
Match
Target Domain
Placing to the left
Pushing forward
Small Placing Skills
Grasping
Placing to the right
Dist. Estimation
Learnt Skill Representation
Skill Sequence Distribution
Density Estimation
Translation

# Results

# Aligned skills across all agents

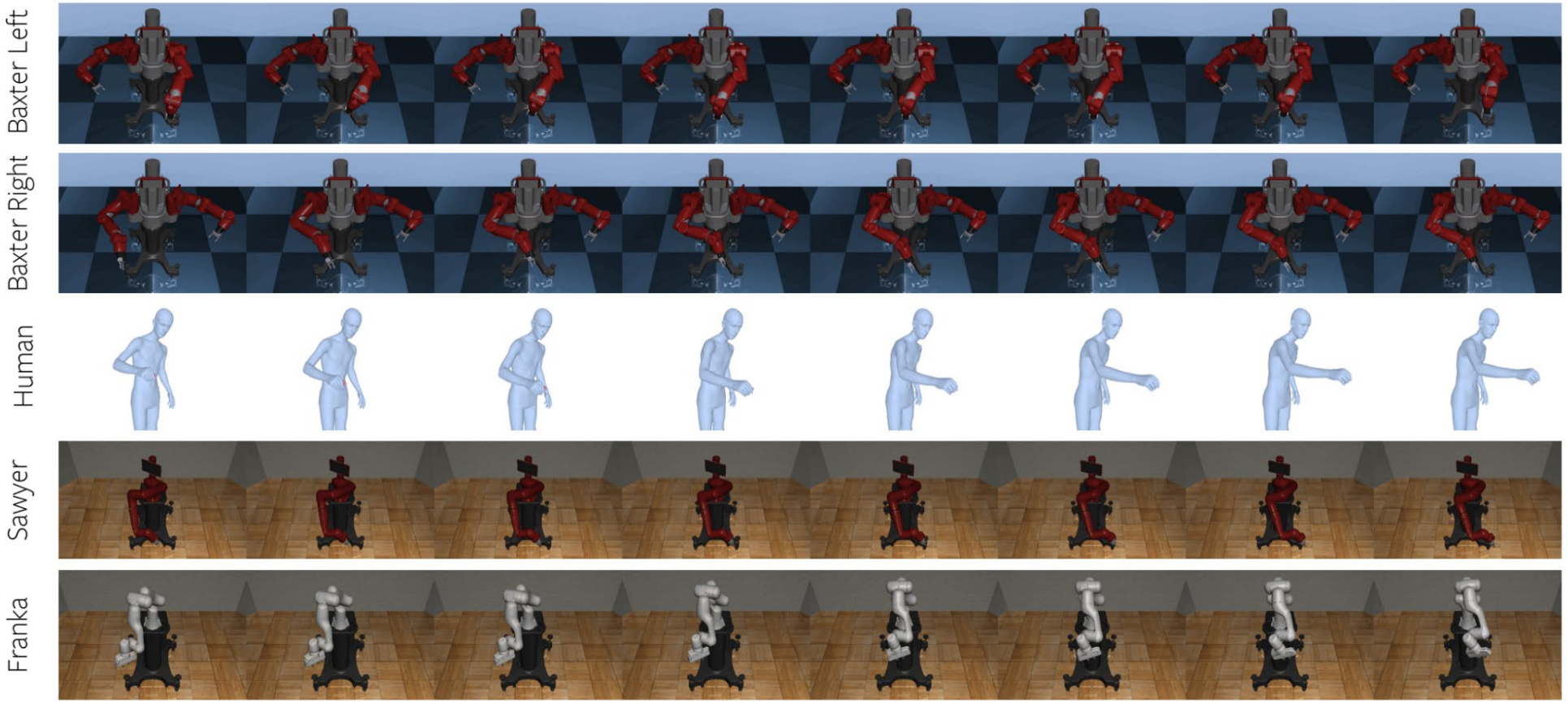
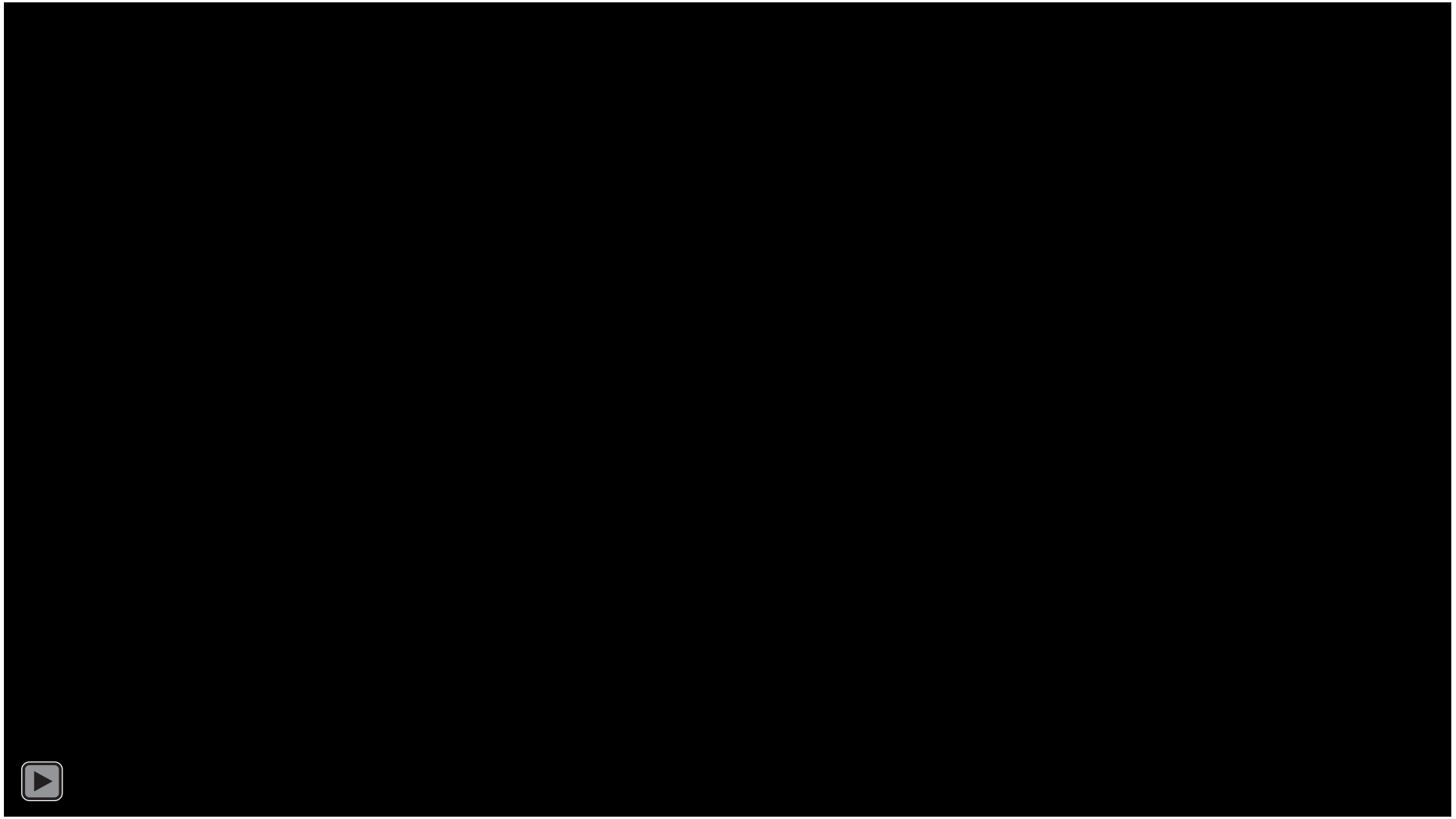



*Figure 1.* Sample skill correspondences learnt by our unsupervised approach, across the 4 different morphological robots and a human demonstrator. We visualize a "placing skill" as translated by our approach, used to place objects to the left of each of the agents. Note the semantic correspondence between these skills, despite our approach being completely unsupervised.

# Translating Individual Skills

Source Domain
Franka

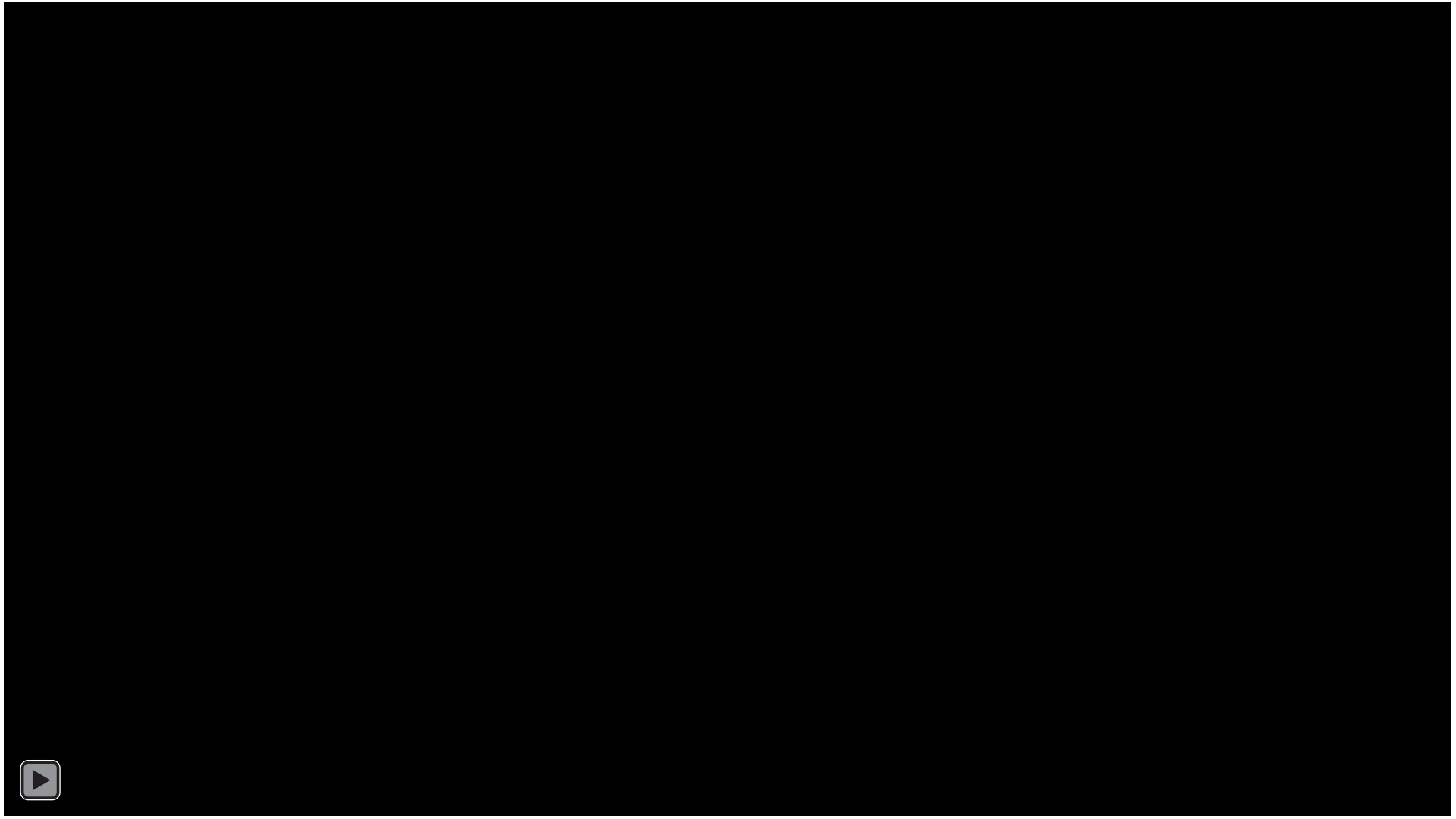
Target Domain
Sawyer



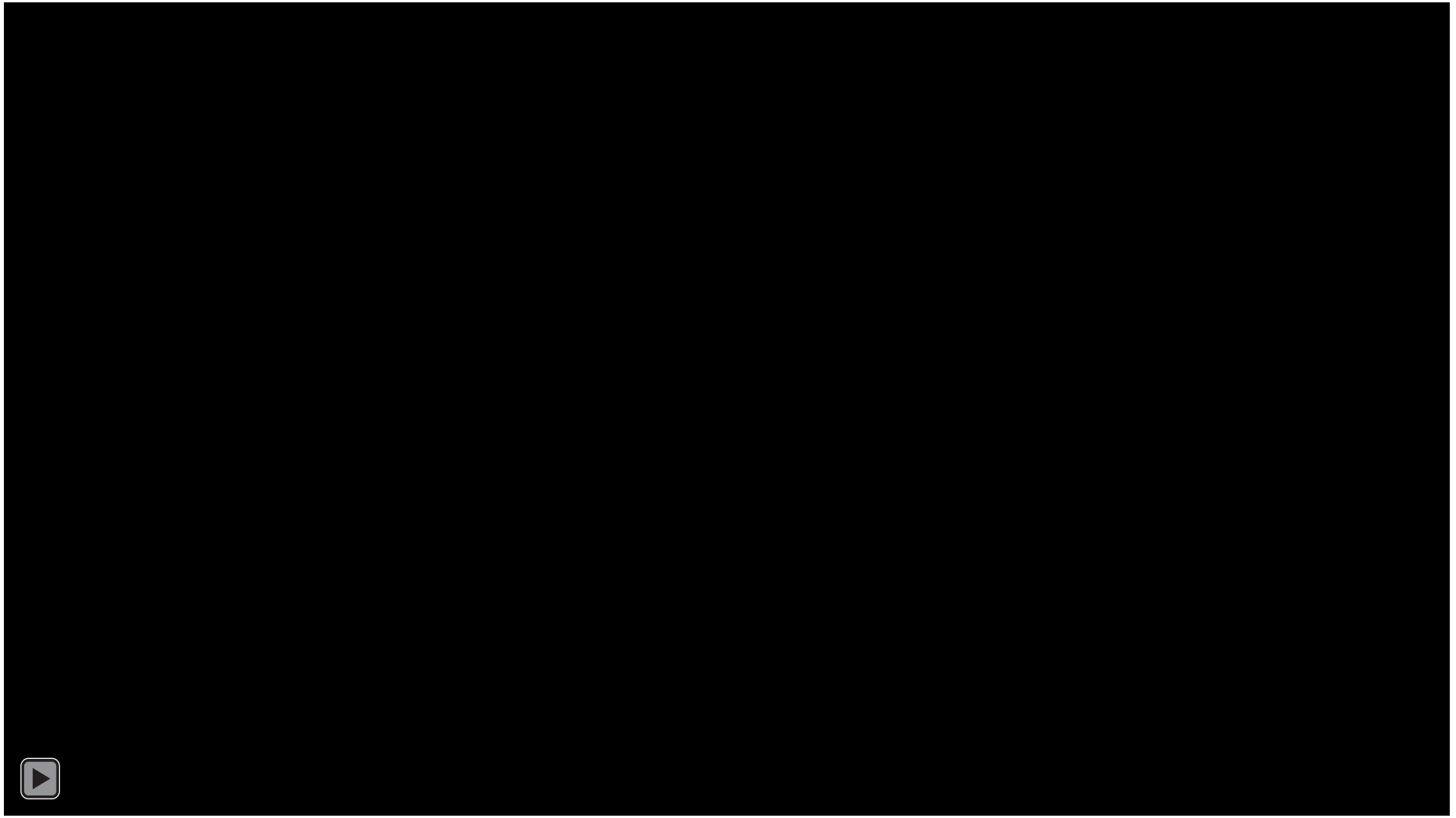
# Translating Individual Skills

Source Domain
Human

Target Domain
Baxter



# Translating Entire Trajectories

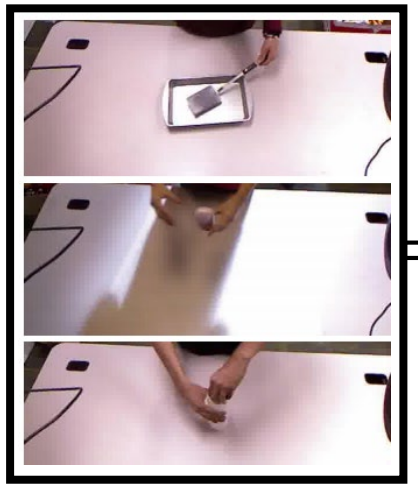


Source Domain
Human

Target Domain
Franka

# Future Directions

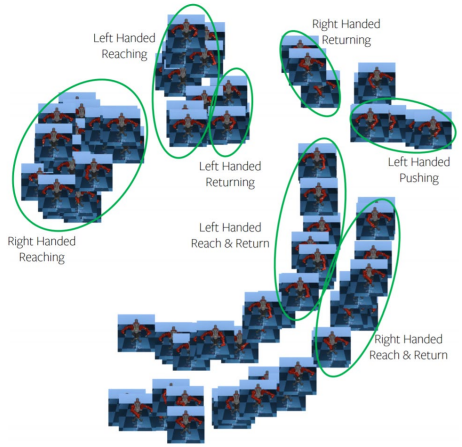
Source
Domain



Human

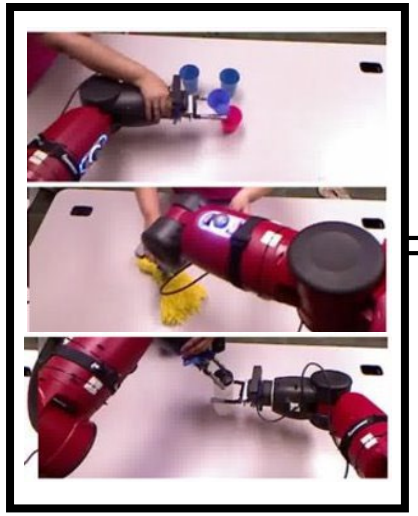
Instruction / Demonstration data!

Skill Representation Learning



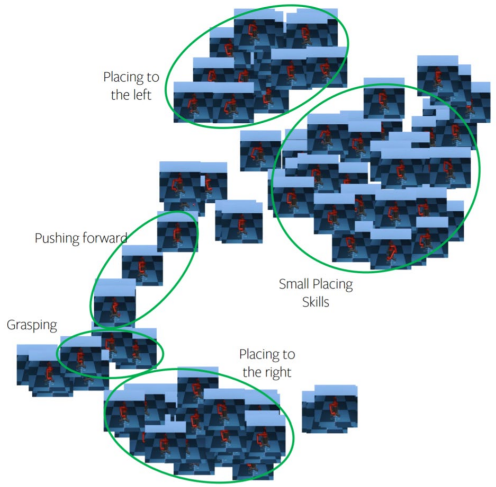

Learnt Skill Representation

Target
Domain



Demonstration data

Skill Representation Learning




Learnt Skill Representation

# Thank you!

Scan for more!

Or e-mail me:

tanmay.shankar@gmail.com