



Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences



Visuomotor Policies

From Biology to Robots

Dr. Alex Mitrevski
Master of Autonomous Systems

- ▶ Visuomotor policy preliminaries
- ▶ Biological insights
- ▶ Visuomotor robot policies

Master's Thesis
**Visuomotor Policy Learning for Predictive
Manipulation**
Anirudh Narasimamurthy Jayasinha



Visuomotor Policy Preliminaries



What is a Visuomotor Policy?

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- ▶ This means that a visuomotor policy creates **a direct functional mapping between visual observations and the corresponding actions**
- ▶ Typically, a visuomotor policy is not based on visual information only, but **visual observations are combined with other sensory modalities**

Why Visuomotor Policies?

- ▶ Visual information is perhaps the richest source of information that a robot can consume while acting — **visuomotor policies enable the acting process to benefit from such information**



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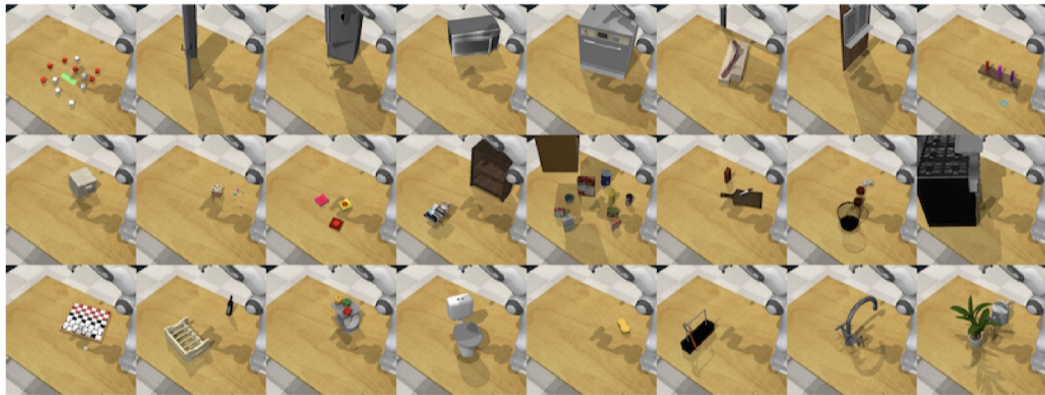
- ▶ Visual information is perhaps the richest source of information that a robot can consume while acting — **visuomotor policies enable the acting process to benefit from such information**
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- ▶ Visual information is also essential to consider in scenarios where a robot should be able to adapt its behaviour based on the observations of a cooperating human — **visuomotor policies can enable more effective human-robot collaboration**

Visual Information Can Be Beneficial for Many Robotics Scenarios



S. James et al., "RLBench: The Robot Learning Benchmark & Learning Environment," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 3019–3026, Apr. 2020.

Visuomotor Policies vs. Visual Servoing

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- ▶ Traditional visual servoing, on the other hand, **combines control theory with traditional computer vision**, such that the error estimation is done through the computation of visual features
- ▶ **The learning aspect is thus the primary distinction** between (traditional) visual servoing and the (learning-based) visuomotor policies that we discuss in this lecture

Biological Insights



Visuomotor Policies in Biological Systems

- ▶ Visuomotor policies as a concept are **directly inspired from the operation of biological systems**
 - ▶ Particularly humans exhibit an exceptional ability to use sensory information for performing a variety of coarse and fine motions



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- ▶ Considering visuomotor policies in biological systems is useful because it can inform the **design and development of visuomotor robot policies** and the **components that make such policies work in practice**

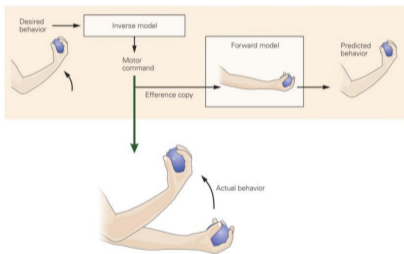
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- ▶ A study of biological visuomotor policies can also show **how contemporary approaches to visuomotor robot policies compare to their biological counterparts** and **what aspects are missing for obtaining policies that are as versatile**

Motion Simulation Using Forward Models



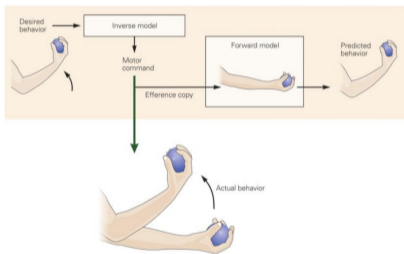
- ▶ According to studies of the central nervous system, the brain stores various **internal models** that are used during motor movements



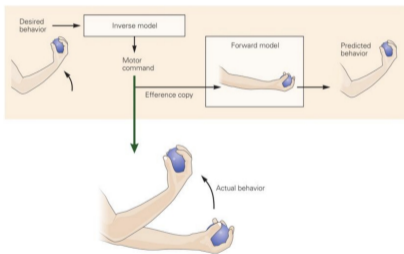
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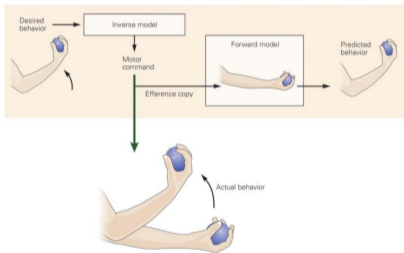


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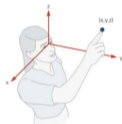
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- ▶ An **efferent signal** is a motion signal that is sent by the central nervous system; such a signal sent to the forward model is called an **efferent copy**
- ▶ Forward models, and the associated **inverse models that generate motor commands**, are learned during early childhood movements and improved continually

Movement Coordinate Systems

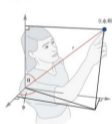


- ▶ For generating motion, the brain can use various **intrinsic or extrinsic coordinate systems**
 - ▶ According to studies of neuron firing patterns, **different coordinate systems are encoded in different parts of the brain**
 - ▶ The used coordinate system is **task-dependent**

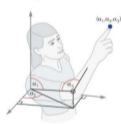
A Cartesian coordinates



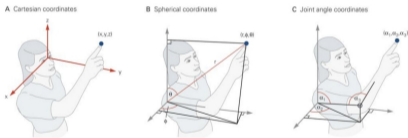
B Spherical coordinates



C Joint angle coordinates

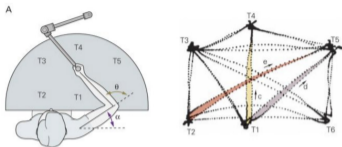


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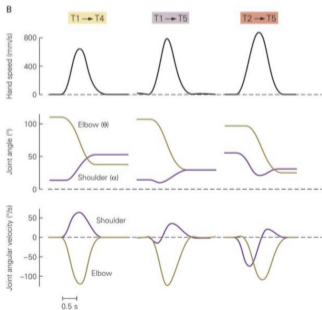


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 - ▶ The used coordinate system is **task-dependent**
- ▶ The coordinate system used for a task is typically not known directly, but can be determined:
 - ▶ **by studying neuron firing patterns during a task** or
 - ▶ **by analysing motion errors with respect to different variables and coordinate systems**

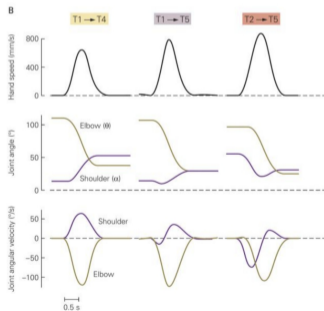
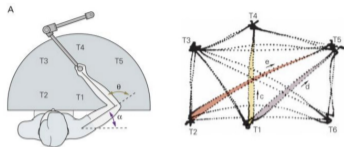
Stereotypical Motions and Motion Primitives



- ▶ Studies of reaching motions have shown that **motions usually exhibit stereotypical patterns**
 - ▶ Such studies particularly show that **straight-line motions are usually preferred to more complex arc motions**, suggesting that motion trajectories are typically planned with respect to the hand



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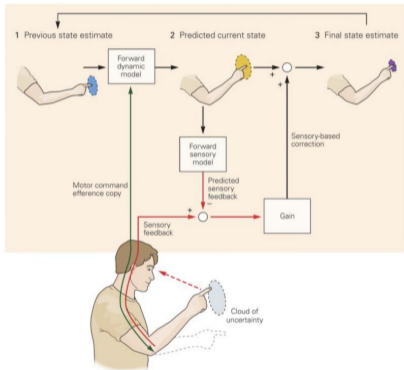


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 - ▶ Such studies particularly show that **straight-line motions are usually preferred to more complex arc motions**, suggesting that motion trajectories are typically planned with respect to the hand
- ▶ Movement studies also suggest that **complex motions are combinations of well-defined motion primitives**
 - ▶ The choice of primitives to complex motions is thought to be done **by optimising a cost associated with each primitive**
 - ▶ The applied cost function may **depend on both the task and on the properties of motion**
 - ▶ Both evolution and learning likely have an effect on the primitives and the used cost functions

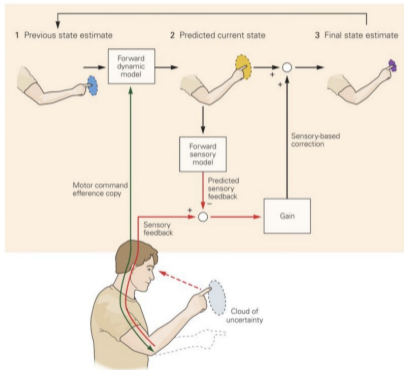
Motion Using Feedforward and Feedback Control



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 - ▶ For instance, processing and sending visual signals has been shown to introduce a $200ms$ delay

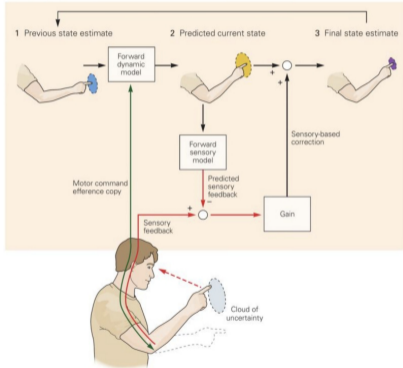


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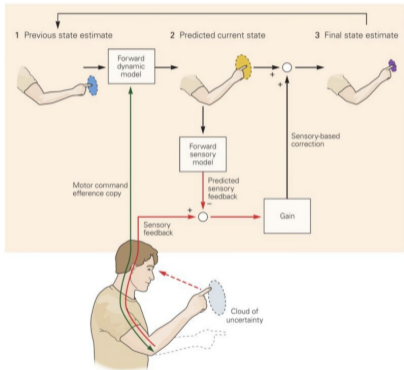
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- ▶ To account for delays in sensory feedback and inaccuracies in pure motion prediction, **an observer model** can be employed

Importance of Proprioception During Motion



A Accuracy and trajectory control

1 Arm visible



2 Arm hidden for 2 minutes

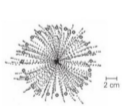


3 Arm hidden for 6 minutes

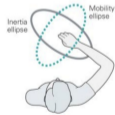
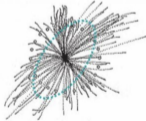


B Estimate of limb inertia

1 Normal



2 Subject with proprioceptive loss



- ▶ In studies of people who have lost the ability to make proprioceptive measurements, it has been shown that **proprioception is essential for moving accurately**

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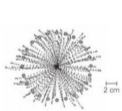


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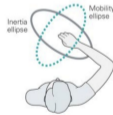
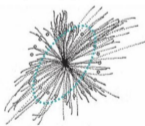


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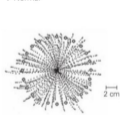


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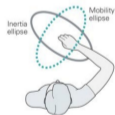
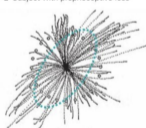


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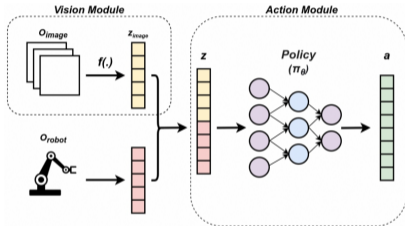
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- ▶ This overreliance on visual information means that **acting without visual information becomes impossible**

Visuomotor Robot Policies



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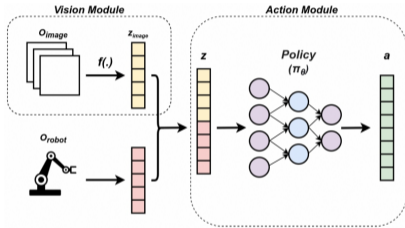
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 - ▶ **exteroceptive visual data**
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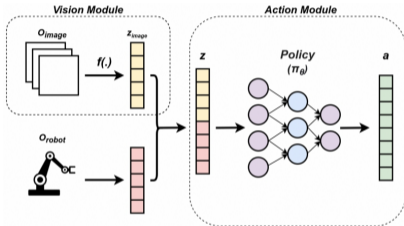
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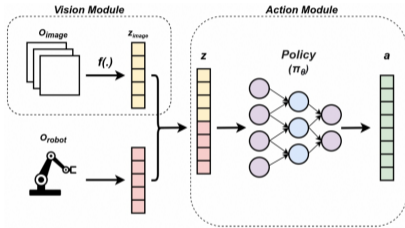
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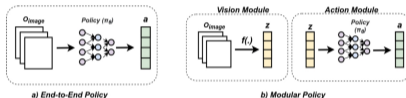


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- ▶ The visual processing module may process **a single image**, **a series of images**, or encode visual state memory through a **recurrent representation**

Feature Extraction from Visual Data

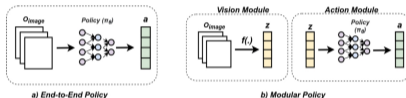
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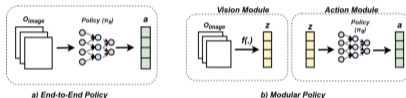
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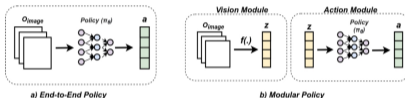
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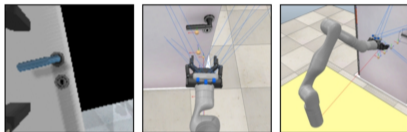
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- ▶ **End-to-end learning can also be performed with a pretrained visual component** — here, the visual component is **trained on an auxiliary task** and then **further optimised together with the policy**



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Camera Positioning for Visuomotor Control

- ▶ Visuomotor policies can be trained with cameras placed at different positions — this is typically a task-dependent aspect



Wrist View

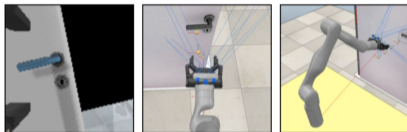
Shoulder View

Environment View

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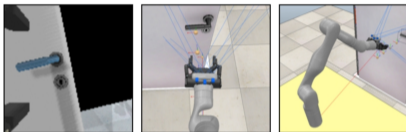
- ▶ Visuomotor policies can be trained with cameras placed at different positions — this is typically a task-dependent aspect
- ▶ Different camera positions have several implications for visuomotor policies:
 - ▶ Environment cameras **can be placed flexibly so that the robot has the best view of the relevant parts of a scene**, but **require a high level of environment engineering** — not generally applicable



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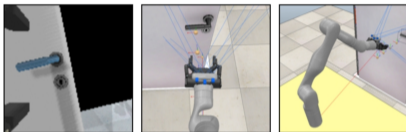
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- ▶ Wrist cameras **enable a robot to have a close-up perspective of the scene during execution**, but **typically provide a small scene view** — mostly applicable during the final segments of a task



Wrist View

Shoulder View

Environment View

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- ▶ **The source of data used for policy learning is often task-dependent**; for instance, demonstrations are typically a valuable source of expert data, but can be difficult or time-consuming to collect

Domain Randomisation

- ▶ The neural networks that are incorporated into policies are usually based on convolutional neural networks; these are **invariant to translations by design**, but not to other properties, such as brightness or background variations



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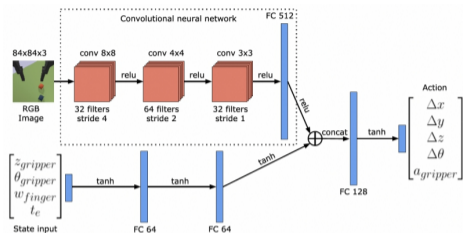
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- ▶ Randomisation during training has traditionally been the easiest to perform in simulations, but generative image models can also produce useful, photorealistic augmented data

Sensory Input Varieties



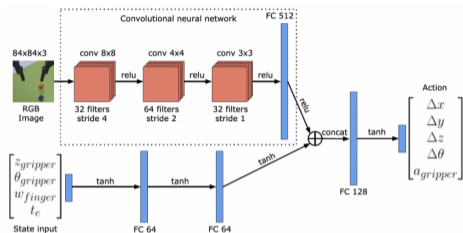
- ▶ The visual data used as an input to a visuomotor policy can take different shapes; this has an effect on the design of the network architecture used for visual data processing

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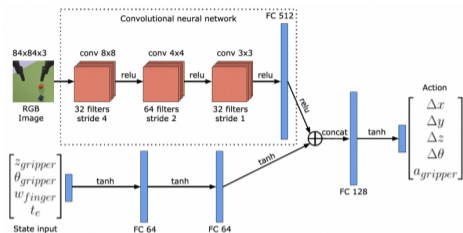
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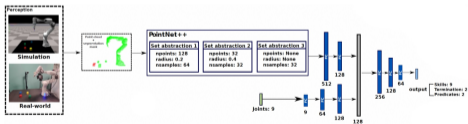
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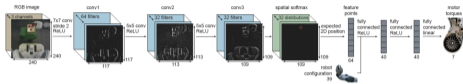
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- ▶ Alternative representations are naturally possible as well and may work better for point cloud inputs, for instance **segmentation masks**



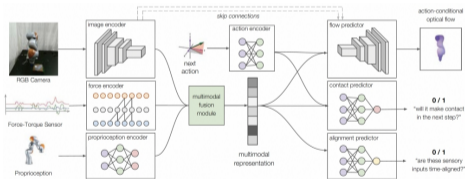
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Multimodality



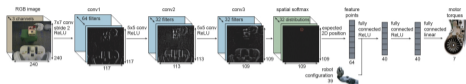
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- ▶ Multimodal policy network have **multiple modality-specific branches** that are then fused to produce a joint feature vector that represents the input to a policy



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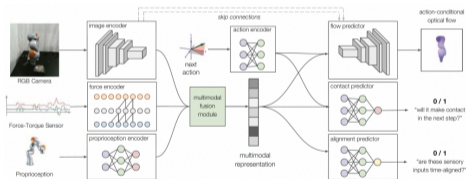
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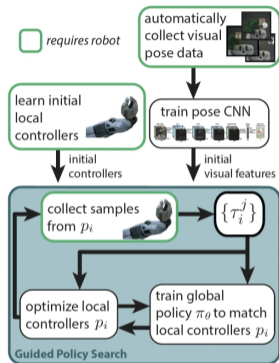
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- ▶ Fusing visual information with proprioceptive information about a robot's joints is one example of multimodality — **two modalities are processed individually and are then combined to form the policy input**



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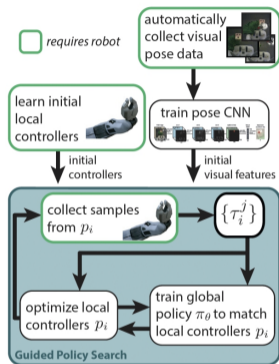
Guided Visuomotor Policy Learning



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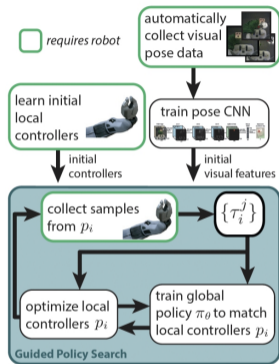
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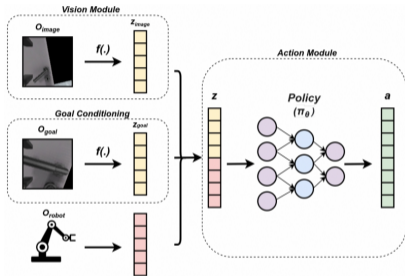


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- ▶ Forward models may also be **useful during policy execution**, which is a desirable property from a biological point of view (as we have seen before)

Goal-Conditioned Visuomotor Policies

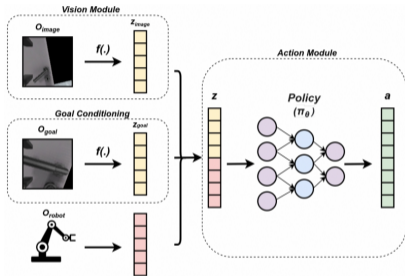
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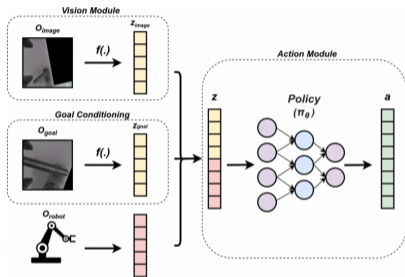
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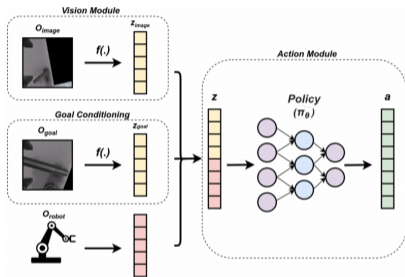
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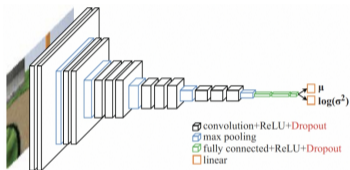


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Representing Uncertainty in Policies

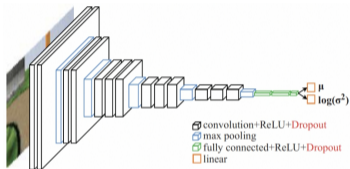
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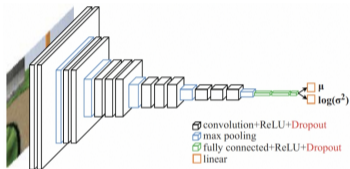
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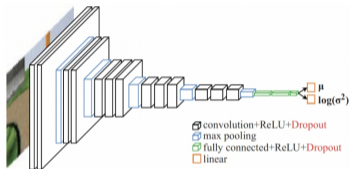
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- ▶ There are various methods of encoding uncertainty in neural networks, most of them under the umbrella of **variational Bayes methods**
- ▶ Uncertainty information about the output can **enable safety behaviours to be triggered** — that can also include asking for human help