Three Stages to Intelligent Agent's Tool-use: Use, Understand and Innovate

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Abstract

The ability to use tools was once thought to be unique for humans and a significant indicator of intelligence. Recently, increasing studies show that similar but much simpler tool-use capability exists in animals like chimpanzees and crows. This motivates us to create an intelligent agent which is at least able to handle easy tool-use scenarios like animals. In this article, we analyse the difficulties and possible solutions to creating such agents. We propose that there are three stages for agents to use tools, from simply using the tools, to understanding tools' affordance and functionality, and to ultimately capable of inventing new tools and using existing tools in an innovative way.

1 Introduction

Recently, more and more animals' behaviors to use tools are observed, which surprises researchers and shakes the belief that tool-use ability only exists in humans. For example, chimpanzee is able to use stones with a sharp end for cracking walnuts. And a special species of crows in New Zealand is able to turn a straight stick into a hook to catch worms more efficiently.

Although these tool-use cases are simple, we may want to explore whether we can design an intelligent agent which is able to use tools appropriately in the same scenarios as animals do. Vaesen [4] proposes that there are nine crucial cognitive capacities involving in tool-use, enhanced hand-eye coordination, body schema plasticity, causal reasoning, function representation, executive control, social learning, teaching, social intelligence, and language. In the scene of creating an agent capable to use tools, we can first ignore the social and language aspects which are relevant to more complex tool-use capabilities in humans. The remaining challenges can be classified into two aspects: (1). how to perceive the tools and surrounding environment and control the agent itself; (2). how to understand the functionality and affordance of objects and simulate the effects of different tools.

In the following sections, we first focus on the first challenge and discuss how to make agents able to use tools, even though agents may not understand what they are doing and why they should do so. Then we propose possible ways to solve the two challenges altogether, thus making agents understand the tools' functionality and even create new tools.

2 Learn to use tools

In this section, we mainly focus on the results, which means that we only care about agents' behaviors and may ignore their awareness of tools' functionality.

Learning by demonstration [2] is possibly the most naive and straightforward way for agents to learn to use tools. It is achieved by providing agents with many example state to action mappings. Statistical models or other modelling methods are employed to learn from example mappings and generalize to unseen states. In this way, agents will learn to use correct tools which best fit the pre-trained models, like maximizing the likelihood in statistical modelling scenario.

Another way resorts to the idea of reinforcement learning. The agent will be trained in a simulated or real world with no example mappings or prior knowledge. It learn the functionality and affordance of different objects implicitly through trials and errors [1].

3 Understand tool's functionality and affordance

The methods in the last section model the tool's functionality implicitly through statistical modelling or reinforcement learning. In this section, we propose a way to model the knowledge of tool-use explicitly by a specific model.

Johnson-Frey [3] discovers that in human brains, different areas are responsible for representing (1). knowledge about tools and their usages; (2). acquired skills to use tools physically. Inspired by this, we can separate the component for understanding the surrounding environment from the component for conducting physical operations. For example, we can utilize an autoencoder architecture for encoding the functionality and affordance of objects and use another neural network for turning the encoding into physical operations. In this way, we will split the thinking stage and operating stage in using tools and model tools' fucntionality explicitly.

4 Create new tools or new tool-use ways

In this section, we will talk about how to make the agent able to behave more intelligently and make innovations based on acquired tool-use knowledge.

The main challenge in creating new tools lie in two aspects. The first challenge is how to enable the agent to model the physical world and simulate the results of applying one object to current tasks.

The second challenge is how to search in the sparse and vast object-operation space to find an appropriate way to modify one object into a proper tool and use it correctly.

The first challenge is about physical simulation and with development in corresponding area we can simulate the outcome of an operation almost correctly. To solve the second challenge, one possible idea is to reduce the vast space to a smaller latent space. We can train an variational autoencoder network based on training data and the encoder network will be able to reduce the original sparse space to an appropriate latent space. We then can sample from the latent space and use the decoder to turn the sampling back into an object-operation pair. In this way, we do not need to search in the original sparse and reduntant space and can do simulation more efficiently.

References

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