Weekly Meeting

what I did this week

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Aug 13, 2024

Westlake University

Table of contents

1. Weekly Meeting

Westlake University 1 / 13

Weekly Meeting

Towards Self-Assembling Artificial Neural Networks through Neural Developmental Programs¹

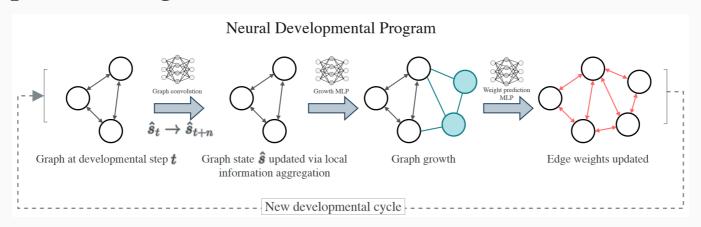


Figure 1: Neural Development Program approach for growing neural network

- Use the Neural Development Program(NDP) to control the growth of new networks
- Two training methods: **Evolutionary-based** and **Gradient-based**
- Execute experiments on MNIST, XOR, CartPole, LunarLander

Westlake University 2 / 13

¹Najarro E, Sudhakaran S, Risi S. Towards self-assembling artificial neural networks through neural developmental programs[C]

Towards Self-Assembling Artificial Neural Networks through Neural Developmental Programs

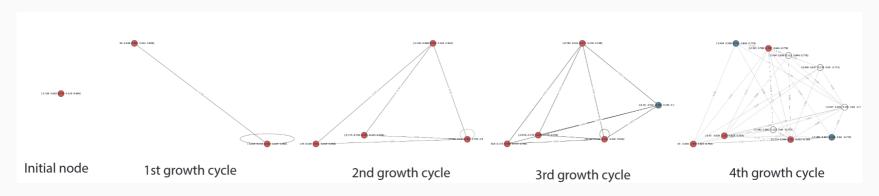


Figure 2: Developmental growth of solving the CartPole balancing task

- No indication of **robustness** or other performance advantages
- No additional information about the **topological properties** of the network

Westlake University 3 / 13

HYPERNETWORKS¹

- An approach of using a **hypernetwork** to generate the weights for another network, which is similar to the nature: the relationship between a **genotype** and a **phenotype**
- Generate weights for practical architectures by taking layer embedding vectors as inputs
- Hypernetworks are trained **end-to-end** with gradient descent together with the main network

Reflection

- The focus is not on generating networks, but on **the ability to self-explore** in a multi-task environment
- Generative networks are a means of implementation. Are there any existing methods that can achieve self-exploration capabilities to a certain extent, such as **LLM-based agents**

Westlake University 4 / 13

¹Ha D, Dai A, Le Q V. Hypernetworks[J]. arXiv preprint arXiv:1609.09106, 2016.

- Agents environments setup
 - New reasoning framework (modify the prompts)
 - Digital tasks (fine tune on the digital tasks)
 - Embodied tasks (usually with a vision module)
- Learn of reinforcement learning

Westlake University 5 / 13

AgentGym¹

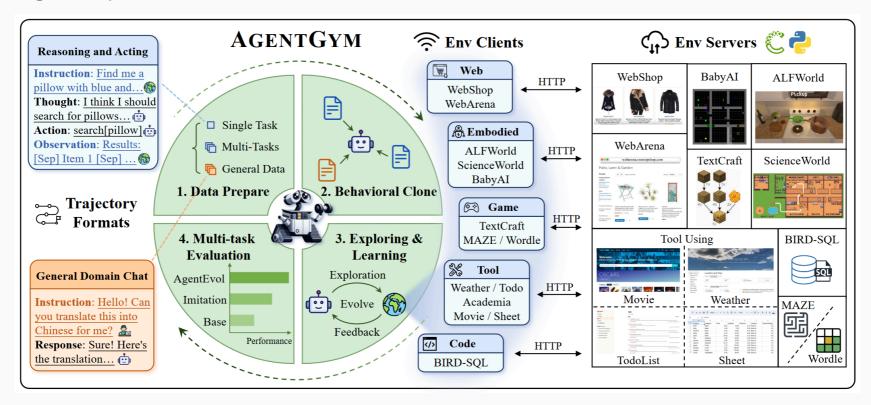


Figure 3: Overview of the AgentGym framework

Westlake University 6 / 13

¹Xi Z, Ding Y, Chen W, et al. AgentGym: Evolving Large Language Model-based Agents across Diverse Environments[J]. arXiv preprint arXiv:2406.04151, 2024.

OSWORLD¹

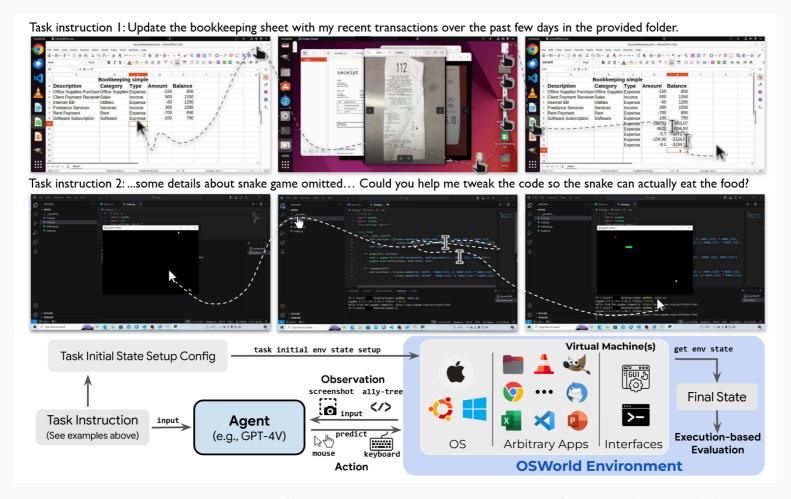


Figure 4: OSWORLD: a real computer environment for multimodal agents

Westlake University 7 / 13

¹Xie T, Zhang D, Chen J, et al. Osworld: Benchmarking multimodal agents for openended tasks in real computer environments[J]. arXiv preprint arXiv:2404.07972, 2024.

FunSearch¹

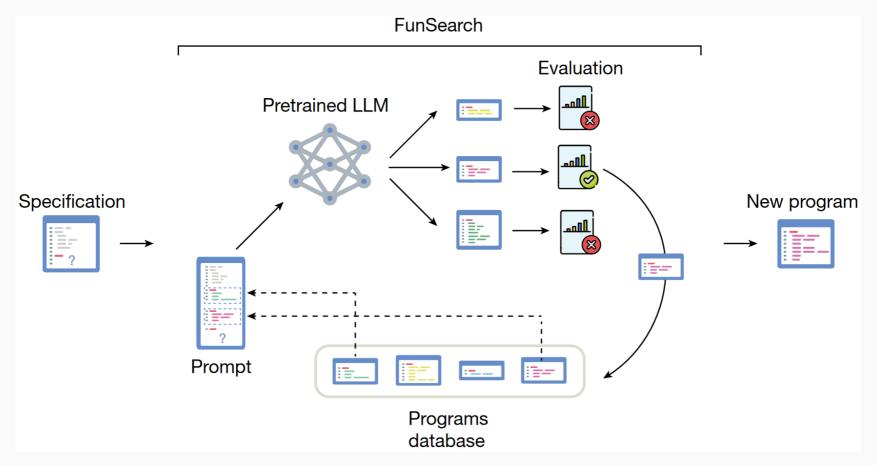


Figure 5: Overview of FunSearch

Westlake University 8 / 13

¹Romera-Paredes B, Barekatain M, Novikov A, et al. Mathematical discoveries from program search with large language models[J]. Nature, 2024, 625(7995): 468-475.

Target

- Diffusion Models as Tools for Gene Expression Genotype
- Use partial modules in a large model to adapt to different tasks —— Phenotype

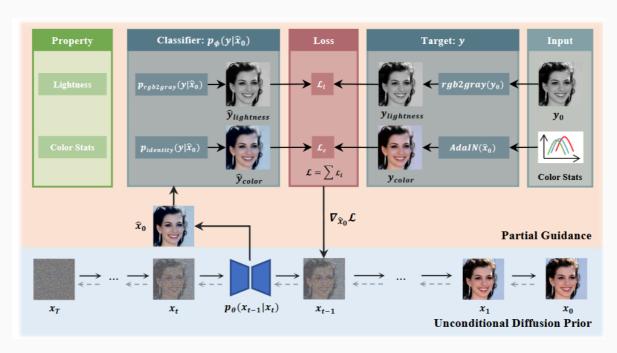


Figure 6: Overview of PGDiff Framework for Versatile Face Restoration¹

Westlake University 9 / 13

¹Yang P, Zhou S, Tao Q, et al. PGDiff: Guiding diffusion models for versatile face restoration via partial guidance[J]. Advances in Neural Information Processing Systems, 2024, 36.

Keywords

- Conditional Diffusion Models
- Pruning
- Model Selector
- Multi-task learning
- Neural Architecture Search
 - ▶ The representations of the architectures in the search space
 - ▶ Introduce diffusion models as a search algorithm

Westlake University 10 / 13

DiffusionNAG1

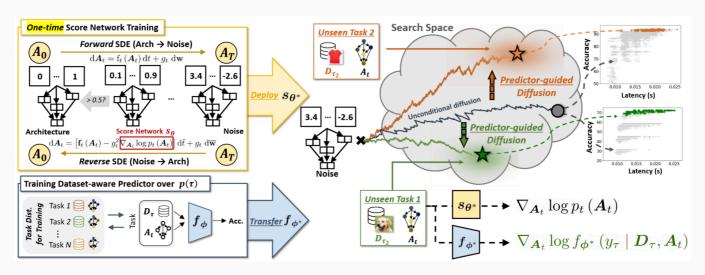


Figure 7: Overview of DiffusionNAG

- Treat the neural architecture as DAG and generate the neural architecture graph through a graph diffusion model
- Controlling the generation process using property predictors, whose gradient is used to guide the architectures towards a space with desired properties

Westlake University 11 / 13

¹An S, Lee H, Jo J, et al. DiffusionNAG: Predictor-guided Neural Architecture Generation with Diffusion Models[J]. arXiv preprint arXiv:2305.16943, 2023.

Transformer Layers as Painters¹

- Explore the role of the layers of the Transformer architecture models
- Experiments on BERT and Llama2
 - ▶ Do the layers share the representation space
 - Are all layers necessary
 - Are all middle layers doing the same thing
 - Does layer order matter
 - Can layers run in parallel

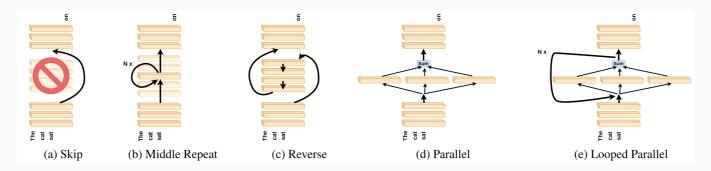


Figure 8: Different execution strategies

Westlake University 12 / 13

¹Sun Q, Pickett M, Nain A K, et al. Transformer Layers as Painters[J]. arXiv preprint arXiv:2407.09298, 2024.

LLM to extract structured data

- Encapsulate the part of LLM
- Implemente text conversion from PDF to Markdown¹

¹https://github.com/VikParuchuri/marker

Westlake University 13 / 13

Question?