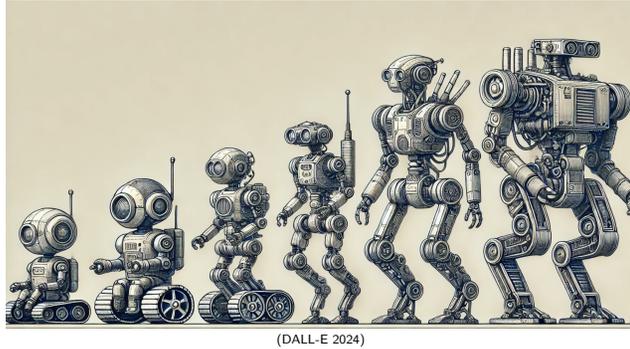## 6. Body-Brain Coevolution

- ▶ So far, weights and structure of neural networks are evolved for a task.
- ▶ Optimize the policy for a given physical structure.
- ▶ Evolutionary algorithms can optimize both body and brain.
- ▶ Physical body could be a substrate for open-ended evolution.


(DALL-E 2024)

Joint Evolution of Policy and Structure

- ▶ The agent's environment, including body structure, is parameterized.
- ▶ Both the agent's policy (weights) and the body structure (parameters) evolved.
- ▶ Coevolution allows discovering optimal body design for the task.
- ▶ The policy is optimized for the body, making it believable.


(Wang et al. 2020)
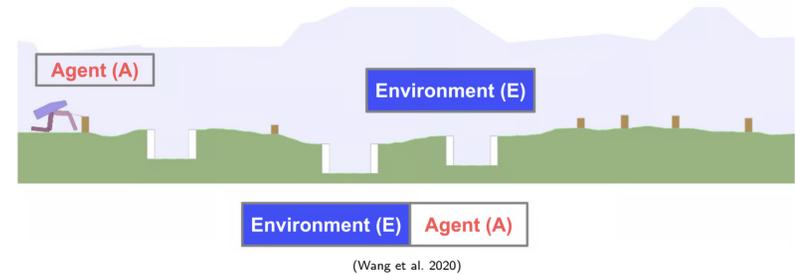
Rewarding Difficult Design Choices

- ▶ Agents are rewarded for trying more difficult designs.
- ▶ Example: Carrying the same payload using smaller legs might be rewarded more.
- ▶ Example: Balanced walk with longer legs may be rewarded more.
- ▶ Such designs can serve as stepping stones for better agents.


(Ha 2019)
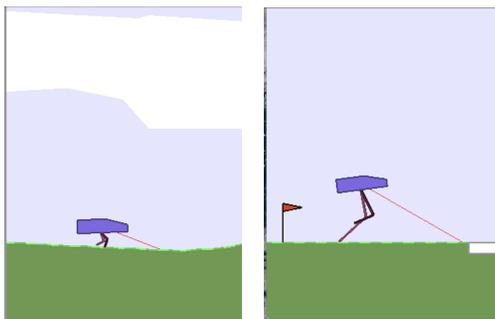
Optimizing Body for a Task

- ▶ The agent evolves a body structure better suited for specific tasks.
  - ▶ A longer and heavier rear leg helps maintain balance and get over obstacles and gaps.
- ▶ The policy coevolves with the body, resulting in natural behavior for the body.

Embedded Demo:

(https://designrl.github.io)
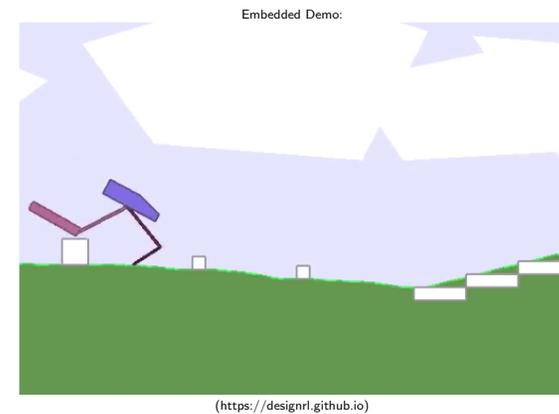
Optimizing Under a Constraint

- ▶ What if evolved to optimize material use?
  - ▶ Smallest legs that still allow running fast.

Embedded Demo:


(https://designrl.github.io)
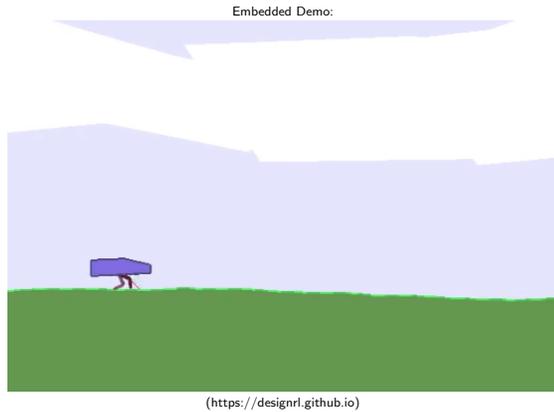
Combining Constraints

- ▶ Lightest legs while getting over obstacles.
- ▶ Still longer rear leg, but as short as feasible.

Embedded Demo:


(https://designrl.github.io)
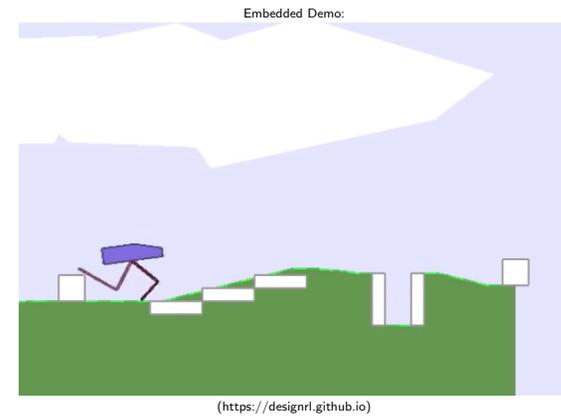
Removing Design Constraints

- ▶ What happens if design constraints are removed?
- ▶ Extreme designs may evolve that utilize loopholes.
- ▶ Example: A very tall agent falls over and lands near the exit.
- ▶ Design constraints and performance goals need to be balanced.

Embedded Demo:

(https://designrl.github.io)

Embedded Demo:

(https://designrl.github.io)
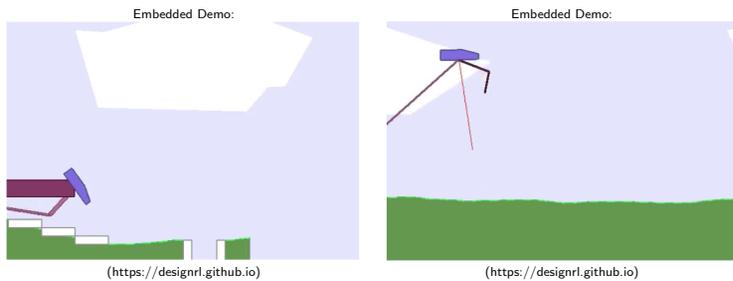
7. Co-Evolving Agents and Static Environments

- ▶ In addition to the body, the environment can also change
- ▶ E.g. the track for the bipedal walker.
- ▶ Co-evolution of problems and solutions.
- ▶ Open-ended evolution may result.


(Wang et al. 2020)
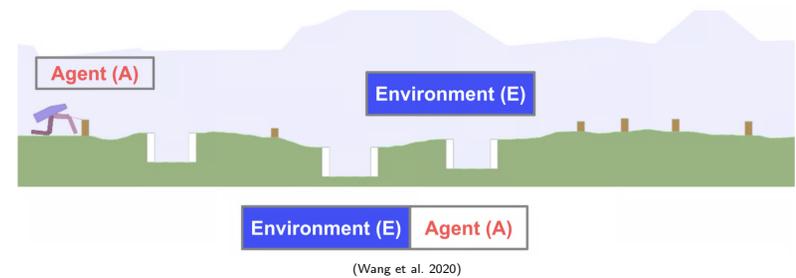
POET Algorithm Overview

- ▶ POET (Paired Open-Ended Trailblazer) is designed for co-evolving agents and environments.
- ▶ It generates new environments and agents, optimizing their performance over time.
- ▶ Three key tasks in each iteration:
  - ▶ Environment generation.
  - ▶ Agent optimization.
 - ▶ Agent transfer between environments.

(Wang et al. 2020)
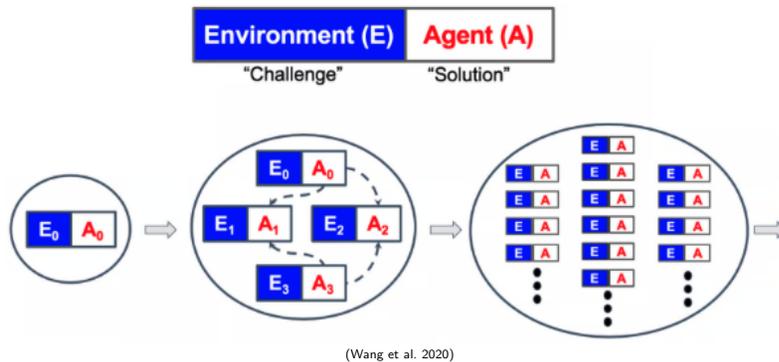
Environment Generation in POET

- ▶ Environments are generated by mutating parameters of existing ones.
- ▶ Parameters include stump height, gap width, stair height, number of stairs, and surface roughness.
- ▶ Only environments that provide suitable challenges and novelty are added.


(Wang et al. 2020)
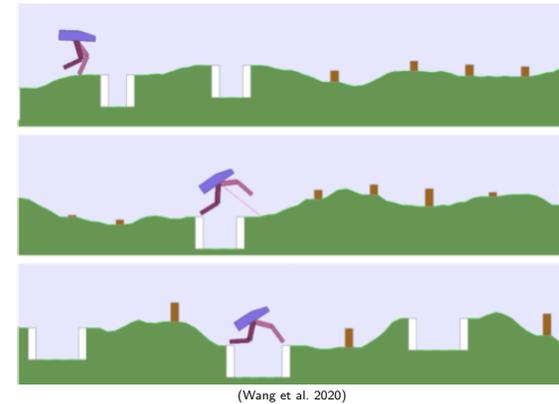
Environment Generation in Enhanced POET

- ▶ Use a CPPN to generate y for each x.
- ▶ More varied and natural environments.
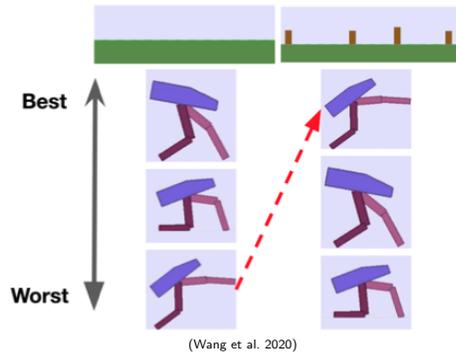

(Wang et al. 2020)
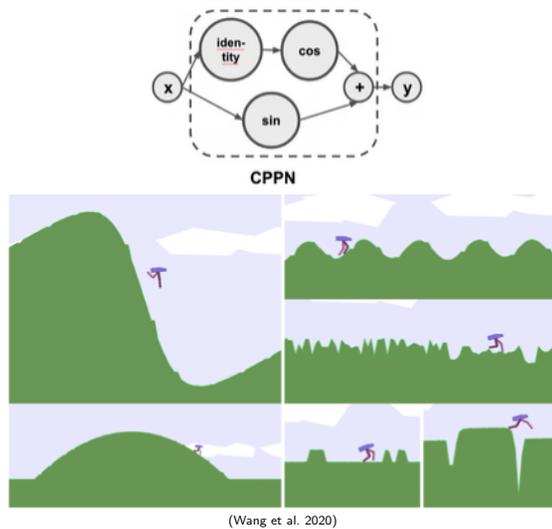
Agent Optimization in POET

- ▶ Agents optimized through neuroevolution (ES).
- ▶ The goal is to maximize the agent's performance in traversing the environment.
- ▶ Agent optimization is independent, which facilitates parallel processing.

(Wang et al. 2020)
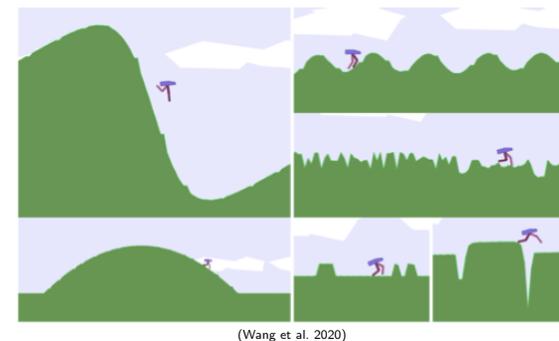
Agent Transfer in POET

- ▶ Agents are transferred between environments to foster adaptation.
- ▶ Successful strategies from one environment may help in another.
- ▶ Transfer helps agents escape local optima.
- ▶ Diversity important: Different agents may perform well in different environments.
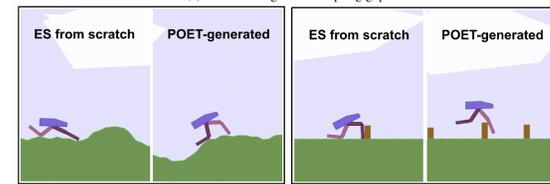

(Wang et al. 2020)

POET vs. ES

- ▶ POET generates novel solutions that ES alone cannot achieve.
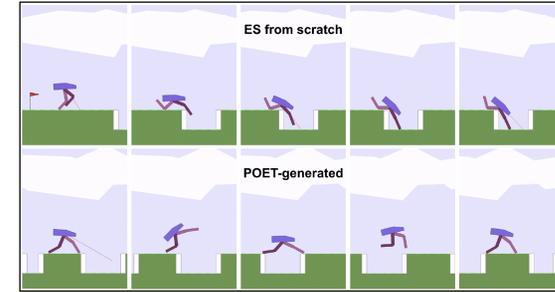
(a) Generated agents attempting gaps

(b) Generated agents on rough surfaces   (c) Generated agents attempting stumps

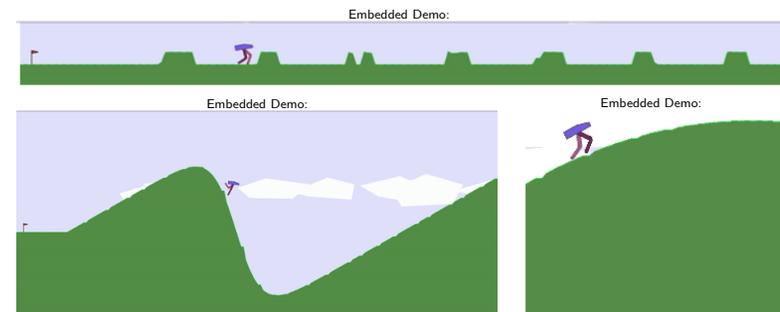(Wang et al. 2019)

POET vs. Curricular Learning

- ▶ Curricular learning set up with gradually more challenging environments.
- ▶ POET finds solutions to much more complex environments.
  - ▶ Transfers from other environments form stepping stones.
  - ▶ POET utilizes stepping stones; curricular cannot.

(Wang et al. 2019)

POET Results

- ▶ Agents successfully navigate complex terrain.

(https://www.uber.com/blog/enhanced-poet-machine-learning/)

POET Results

- ▶ Agents successfully navigate complex terrain.

Embedded Demo:

Embedded Demo:

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(https://www.uber.com/blog/enhanced-poet-machine-learning/)
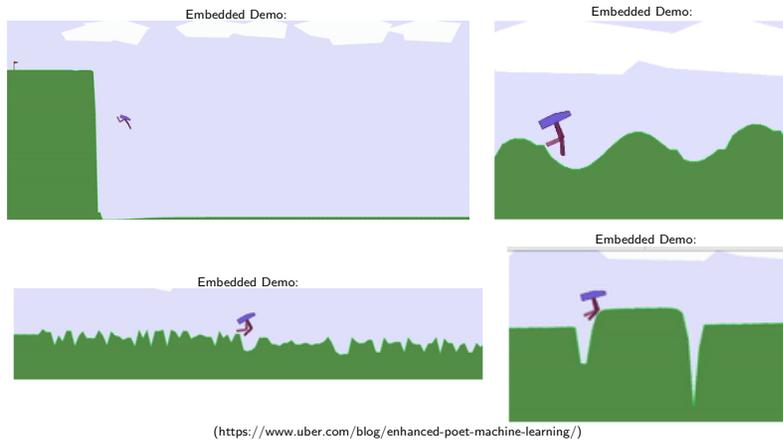
POET Performance

- ▶ Quantitatively, POET can solve harder problems.
- ▶ Enhanced POET can keep discovery going longer.

(Wang et al. 2019)

(Wang et al. 2020)
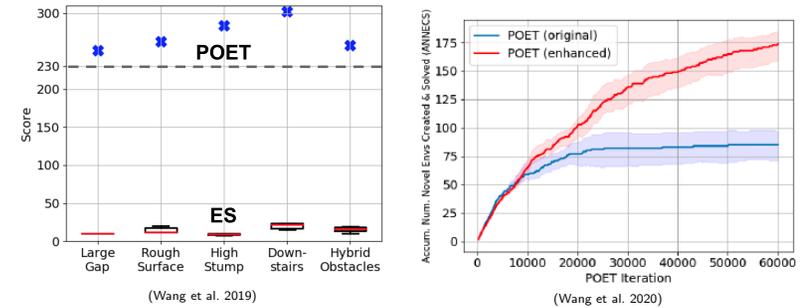
8. Coevolution of Agents and Dynamic Environments

- ▶ A quadruped chaser robot is coevolved with an escapee.
- ▶ As the chaser evolves to catch, the escapee evolves to evade.
- ▶ This continuous feedback loop enhances the capabilities of both agents.
- ▶ A competitive coevolution process.

(Tang et al. 2020)
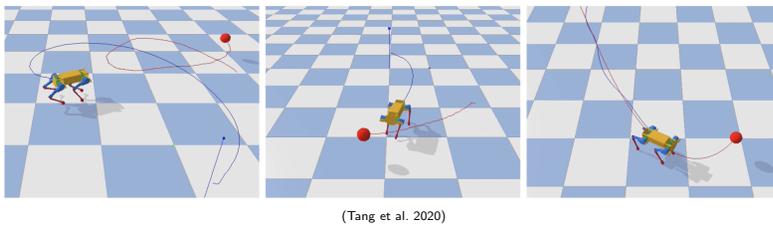
Encouraging Behavioral Diversity

- ▶ Diverse strategies are encouraged through different d_{min} (i.e. catch) thresholds for escapee robots.
- ▶ Smaller thresholds encourage quick dodges, while larger ones promote broader evasive movements.
- ▶ This diversity allows for the development of robust chaser strategies.
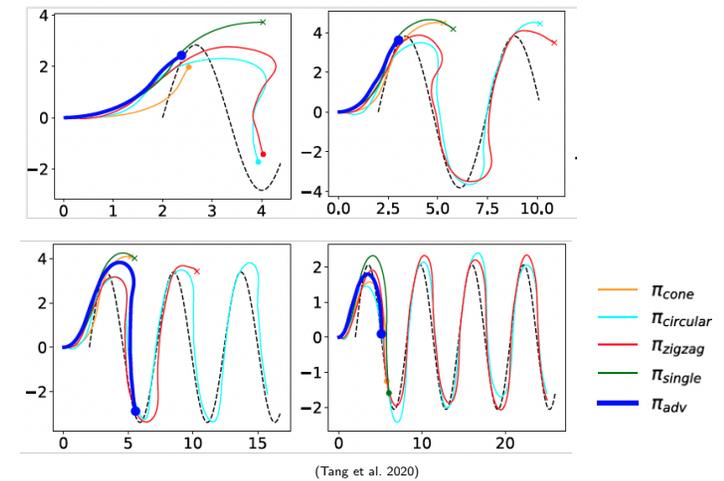
(Tang et al. 2020)
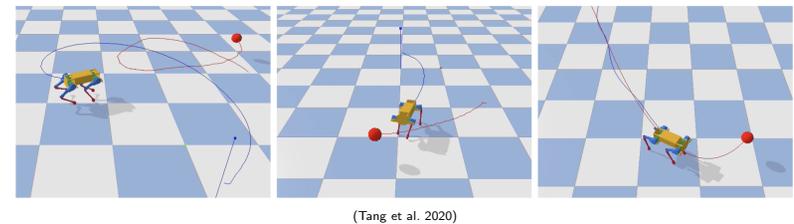
Baseline Comparisons

- ▶ Three baseline methods emulate escapee movement:
  - ▶ Cone: chasing forward
  - ▶ Circular: chasing random moves
  - ▶ Zigzag: chasing a zigzagging escapee
- ▶ Evolve against each one and compare to coevolution.

(Tang et al. 2020)
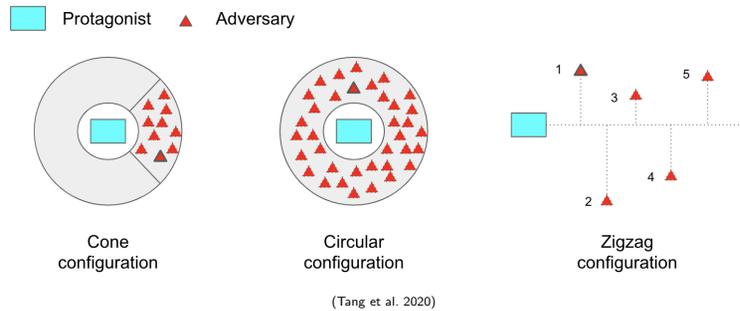
Coevolution Performance vs. Baseline

- ▶ Escapee moves with constant speed in a sine pattern (with varying amplitude and frequency).
- ▶ Coevolved agents catch it early (indicated by a dot).
- ▶ Baseline policies struggle to catch, and often the robot falls (x)

π_{cone}
$\pi_{circular}$
π_{zigzag}
π_{single}
π_{adv}

(Tang et al. 2020)

Demo link: `https://youtu.be/XNWYjOJZGJA`

Is Neuroevolution Open-ended?

- ▶ Ingredients for open-ended neuroevolution already exist.
  - ▶ Large populations, weak selection, and neutral mutations can be scaled up with computational power.
  - ▶ Extinction events, evolvable representations can promote evolvability.
  - ▶ Expressive encodings could enable continuous exploration of more complex solutions.
  - ▶ Coevolution of agents and environments (body, task, adversaries) presents new challenges for evolution to continue.

(Lehman & Miikkulainen 2015)

(Meyerson et al. 2020)

(Ha 2019)
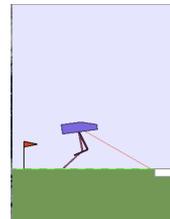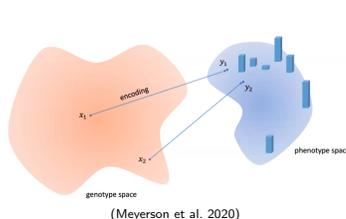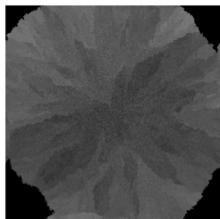
Complexity Can Be Created, but Is It Open-Ended?

- ▶ The process runs out of steam eventually.
  - ▶ E.g. not seeing major transitions.
- ▶ What is still missing?
  - ▶ E.g. do agents need to modify the environment with permanent artifacts?
- ▶ Why do even we care whether complexity is open-ended?

(Based on Gillings et al. 2016)
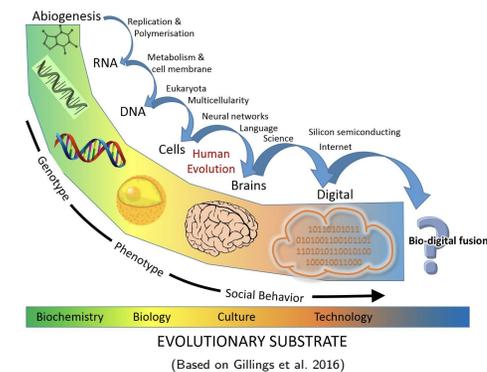
Ultimate Goal: General Intelligence

- ▶ Better understanding of biological evolution and the origins of intelligence.
- ▶ The ability to adapt indefinitely is a key feature of artificial general intelligence.
- ▶ We need open-ended neuroevolution to develop artificial systems at the same level.

EVOLUTIONARY SUBSTRATE

(Based on Gillings et al. 2016)