Heterogeneous Adversarial Play in Interactive Environments

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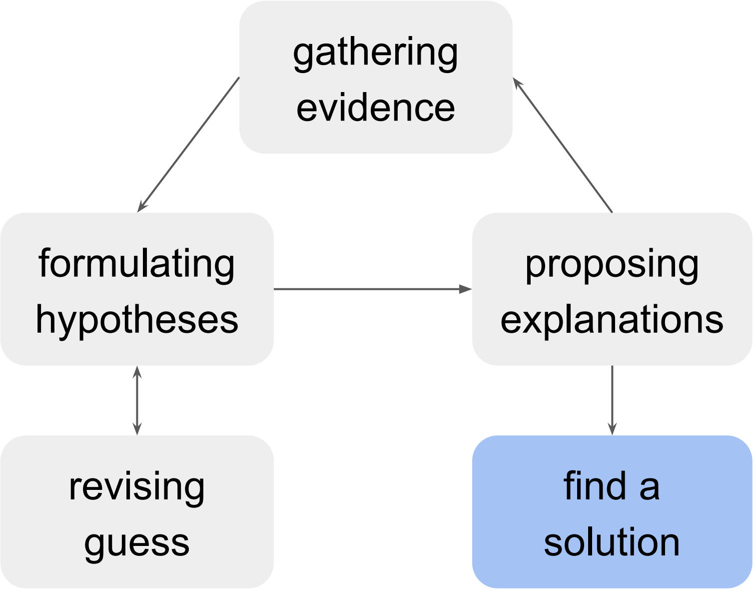
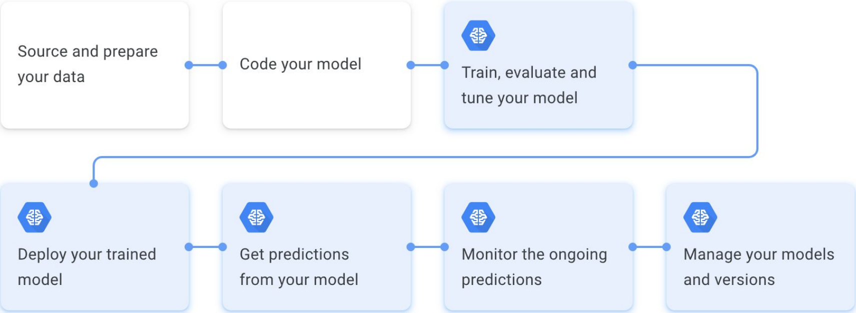
Previous Work

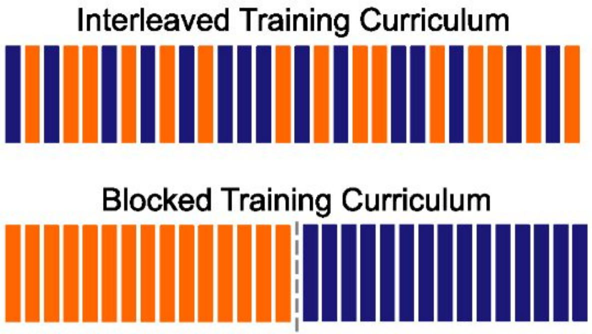
Learning by Actively Interacting with the World

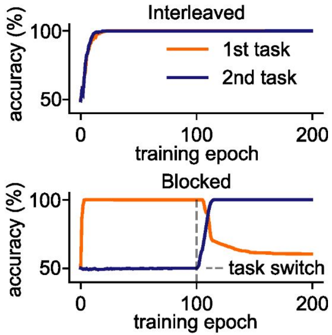
Lori Blahey / epl.ca



We cannot just iterate !







Humans, but not machines, seem to **benefit** from training regimes that blocked one task at a time, especially when they had a prior bias to **represent stimuli** in a way that encouraged **task separation**.

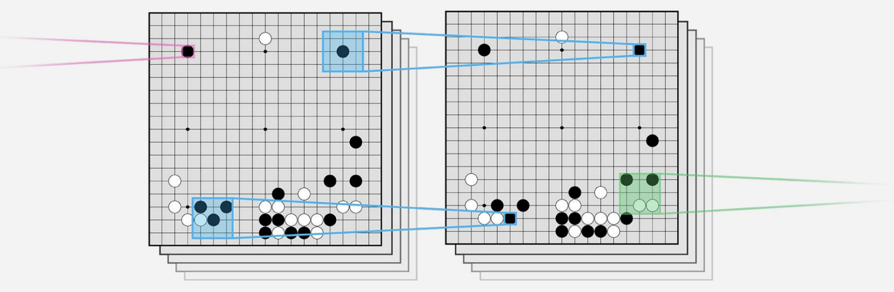
Self-Play
From AlphaGo

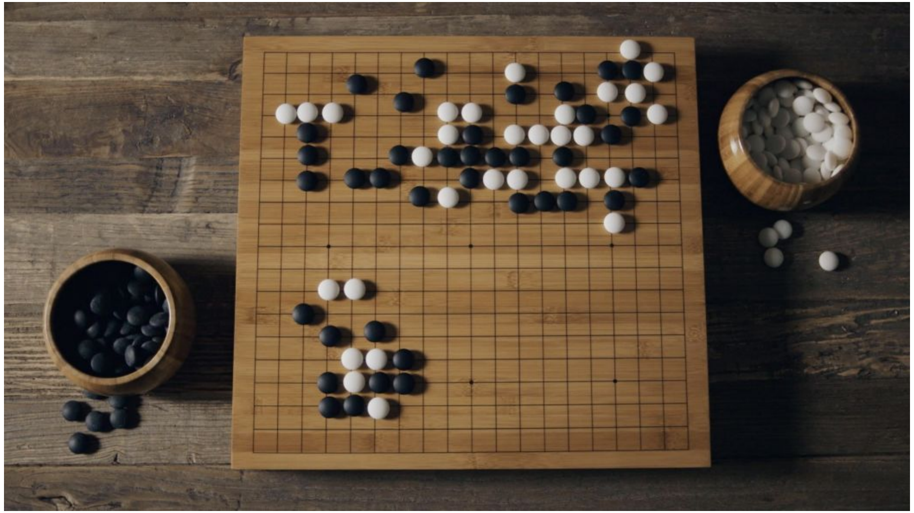
Why is Go hard for computers to play?

Game tree complexity = b^d

Brute force search intractable

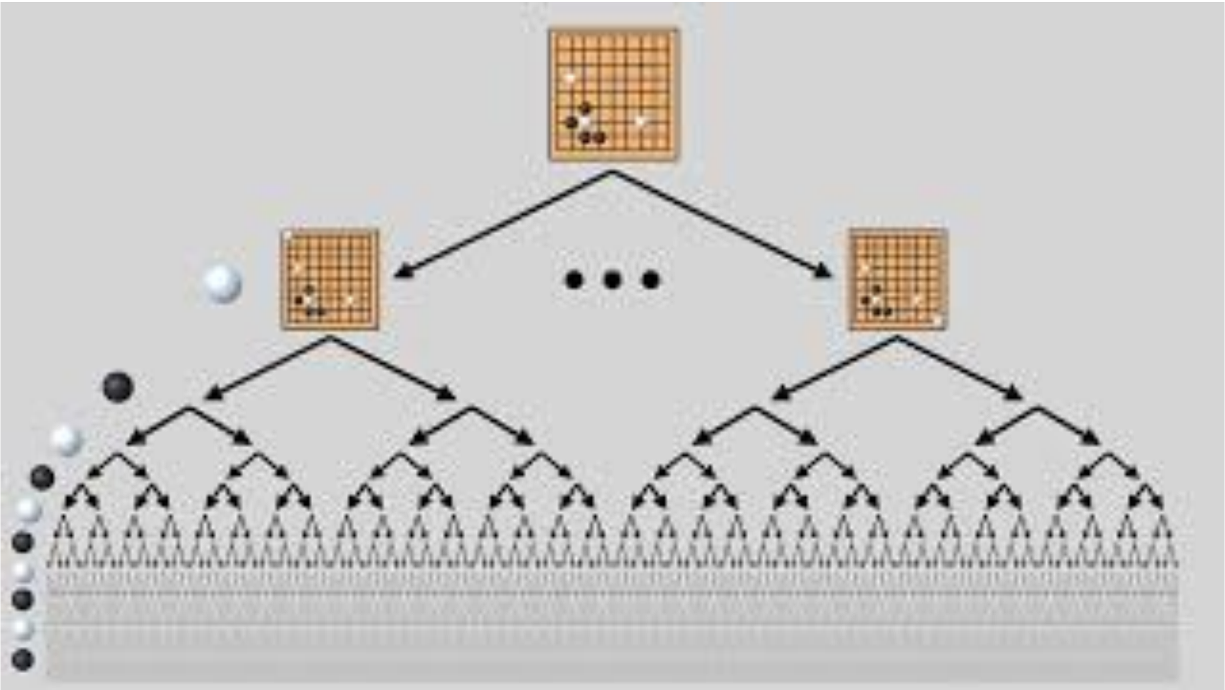
- Search space is huge
- "Impossible" for computers to evaluate who is winning





Source: AlphaGo-tutorial-slides (2016 ICML)

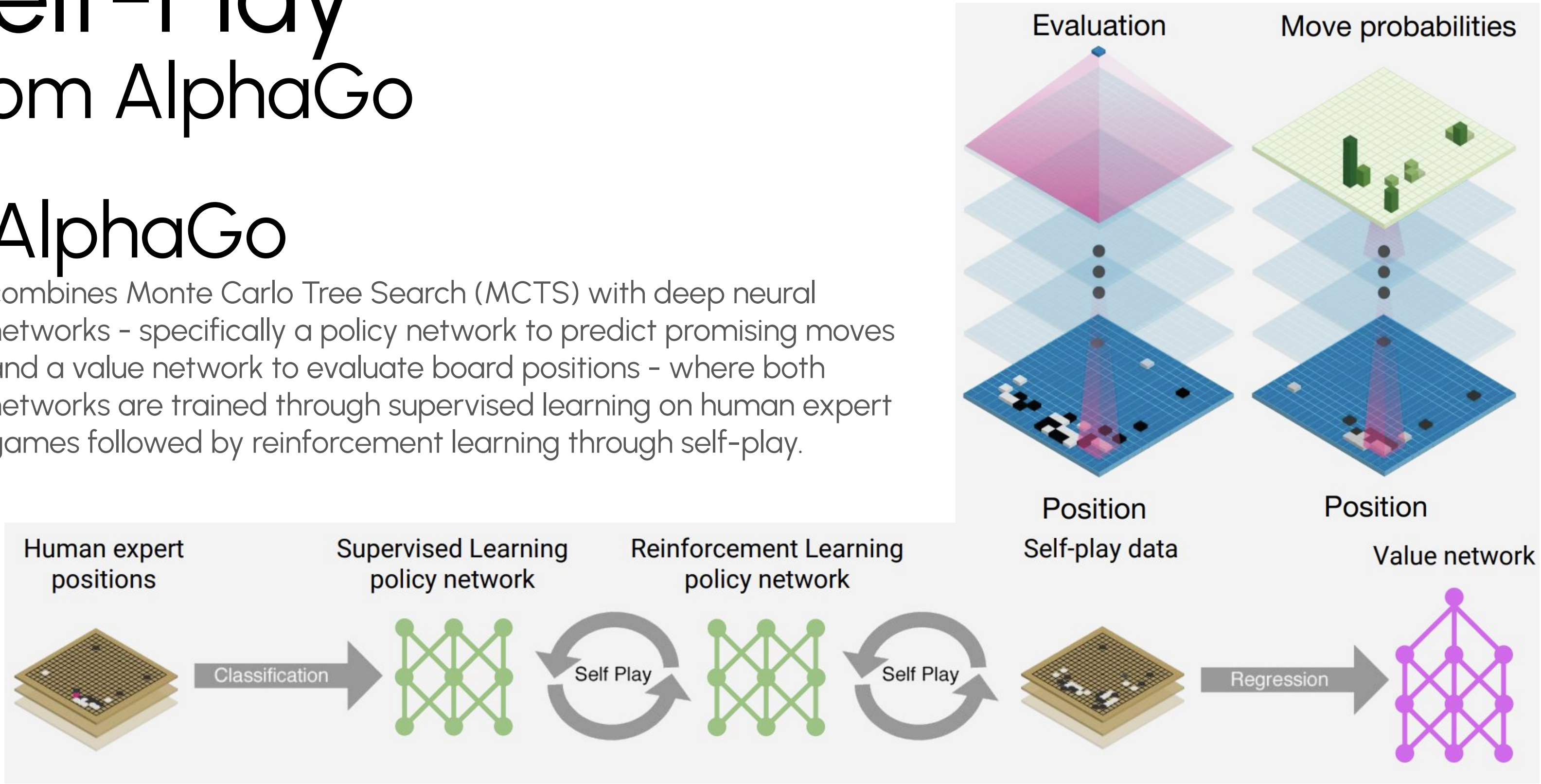
Self-Play
From AlphaGo



Self-Play
From AlphaGo

AlphaGo

combines Monte Carlo Tree Search (MCTS) with deep neural networks - specifically a policy network to predict promising moves and a value network to evaluate board positions - where both networks are trained through supervised learning on human expert games followed by reinforcement learning through self-play.



Source: AlphaGo-tutorial-slides (2016 ICML)

Self-Play
From AlphaGo

Supervised learning

Policy network: 12 layer convoluti

Training data: 30M positions from

Training algorithm: maximise likel

$$\Delta\sigma \propto \frac{\partial \log}{}$$

Training time: 4 weeks on 50 GPU

Results: 57% accuracy on held out test data (state-of-the art was 44%)

Google DeepMind

Reinforcement learni

Policy network: 12 layer convolution

Training data: games of self-play be

Training algorithm: maximise wins z

$$\Delta\sigma \propto \frac{\partial \log p_{}}{\partial}$$

Training time: 1 week on 50 GPUs u

Results: 80% vs supervised learning.

Google DeepMind

Reinforcement learning of value networks

Value network: 12 layer convolutional neural network

Training data: 30 million games of self-play

Training algorithm: minimise MSE by stochastic gradient descent

$$\Delta\theta \propto \frac{\partial v_\theta(s)}{\partial\theta}(z - v_\theta(s))$$

Training time: 1 week on 50 GPUs using Google Cloud

Results: First strong position evaluation function - previously thought impossible

Google DeepMind

Source: AlphaGo-tutorial-slides (2016 ICML)

Self-Play
Key Challenges

Challenge 1: Position Evaluation

- How do we know if the current state is good or bad?
- In Go: Who's winning in the middle of the game?
- No clear reward signal until the very end
- Traditional evaluation functions break down

Challenge 2: Curriculum Design

- What tasks should we practice next?
- How do we generate experiences that actually help learning?
- Too easy → no improvement
- Too hard → agent gets stuck or learns poorly
- Need the "Goldilocks zone" of difficulty

The Core Problem:

Self-play needs to solve both evaluation and curriculum generation simultaneously while the agent is still learning

Interactive Self-Play

Why Self-Play in Human/Machine Learning

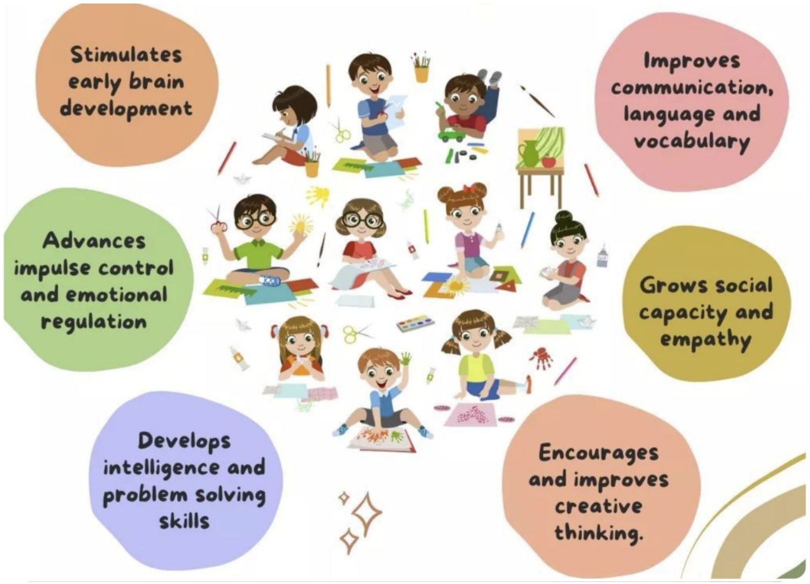
For human: foundation for learning

- Self-Play enables children to engage in **active hypothesis testing**, crucial for theory formation and causal learning
- Interactive play, especially with expert-designed curricula, scaffolds cognitive development
- Physical and social play enable **embodied learning**

For machines:

- Interactive agents that "play" can **autonomously generate learning examples**, refine its strategies, discover new behaviors, such providing rich, self-supervised learning signals that drive more effective learning.

Examples: Reinforcement Learning, Auto-Curriculum Learning



Source: Think Right

Interactive Self-Play

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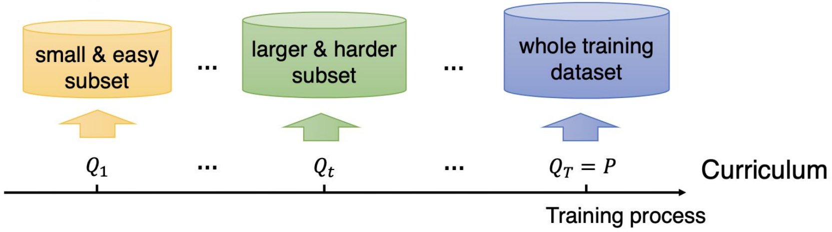
Examples: Reinforcement Learning, Auto-Curriculum Learning

Source: Think Right

Why Curriculum

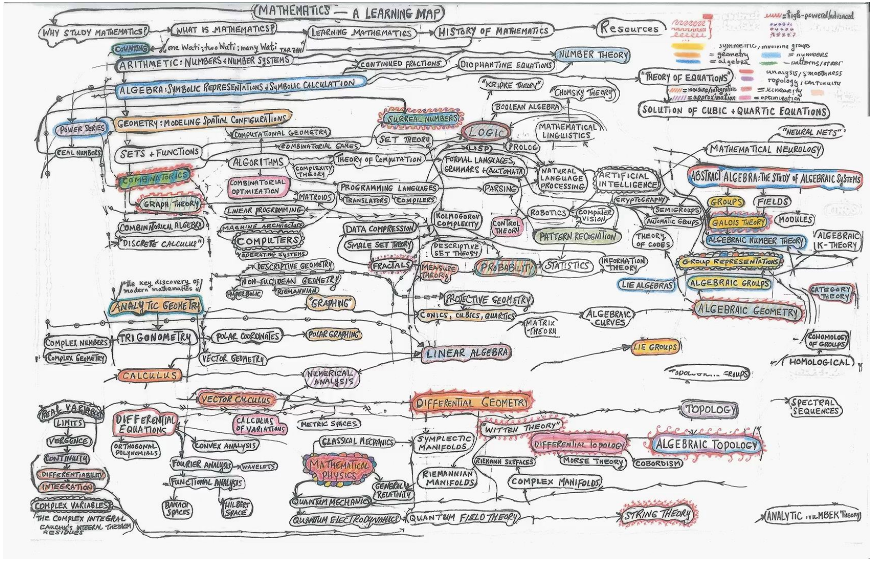
Learn Better when Experiences Build Progressively

- Humans and machines **learn faster** when experiences build progressively.
- Curricula help learners form **more abstract and transferable representations**, and gradual scaffolding **avoids cognitive overload** and keeps learners **motivated**
- Curriculum reduces the risk of **getting stuck in poor solutions (local minima)** by guiding learning through progressively harder tasks.



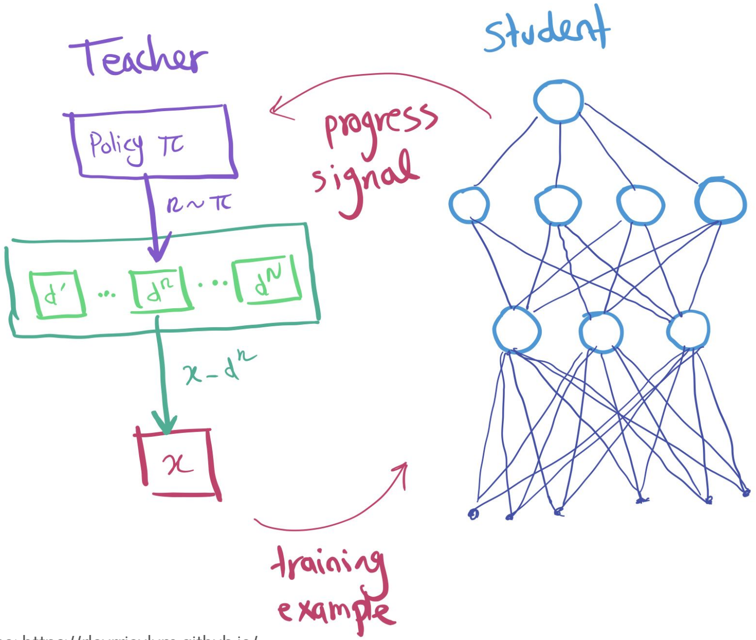
An example: Data Curriculum

Source: kitzorz



An example: You can never learn Math from Calculus

Auto-Curriculum
Curriculum Learning in Interactive Environments



Source: https://rlcurriculum.github.io/

An intuitive idea:
An expert defines a fixed curriculum for training

- Agents are not ideal students—they may learn at different paces, encounter unique challenges, and their capabilities can evolve unpredictably

Another intuitive idea:
Consider a teacher-student setup in which the teacher dynamically manages the learning process

- On what basis should the teacher evaluate and update the learning process?

Auto-Curriculum

Curriculum Learning in Interactive Environments

	Actions do not affect the state of the world	Actions change state of the world dynamically
Learns a model of outcomes	Multi-armed bandits	Reinforcement Learning
Given model of stochastic outcomes	Decision theory	Markov Decision Process

$$P(\text{pick task } k) = (1-\gamma)\frac{w_k(t)}{\sum_{i=1}^{K} w_i(t)} + \frac{\gamma}{K}$$

$$w_k(t+1) = \begin{cases} w_k(t)e^{\gamma\hat{r}(t)/K} & \text{selected task} \\ w_k(t) & \text{other tasks} \end{cases}$$

$$\hat{r}(t) = \frac{r(t)}{P(\text{pick task } k)}$$

Source: https://rlcurriculum.github.io/

A simple soluiton: Multi-armed bandit

An expert defines a fixed curriculum for training

- The idea is to have one "arm" per task, and try to find which tasks has the highest reward. In our case, reward really means "student progress".

Auto-Curriculum
Curriculum Learning in Interactive Environments

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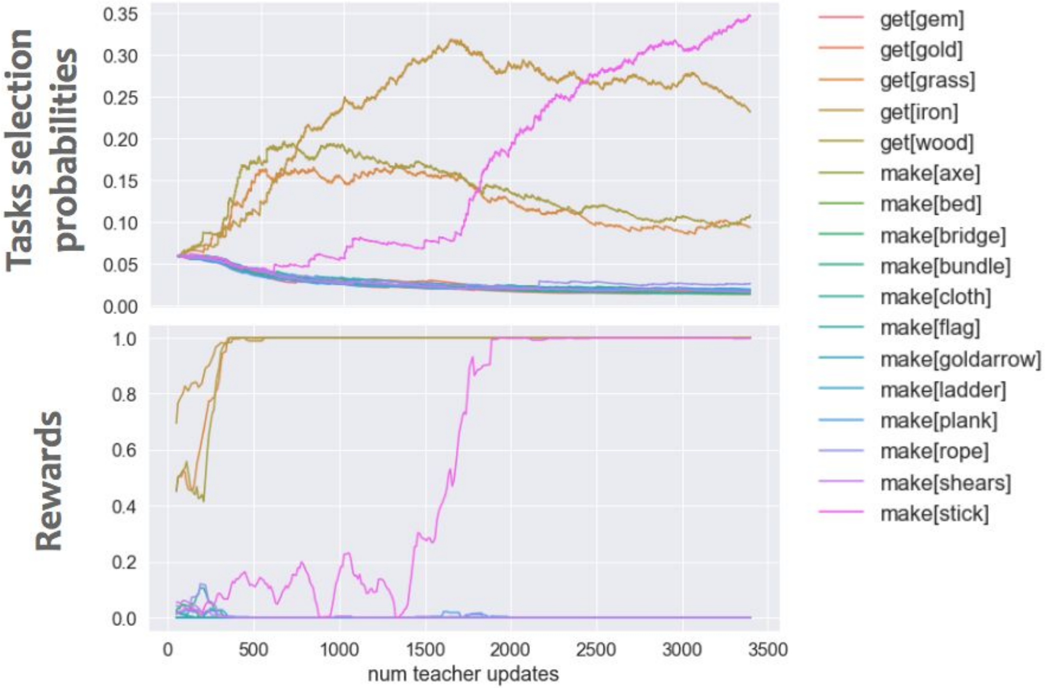
Progress Signal	Definition
Prediction gain (PG)	$\nu_{PG} := L(x,\theta) - L(x,\theta')$
Gradient prediction gain (GPG)	$\nu_{GPG} := \lVert\nabla L(x,\theta)\rVert_2^2$
Self prediction gain (SPG)	$\nu_{SPG} := L(x',\theta) - L(x',\theta') \quad x' \sim D_k$
Target prediction gain (TPG)	$\nu_{TPG} := L(x',\theta) - L(x',\theta') \quad x' \sim D_N$
Mean prediction gain (MPG)	$\nu_{MPG} := L(x',\theta) - L(x',\theta') \quad x' \sim D_k, k \sim U_N$
Gradient variational complexity gain (GVCG)	$\nu_{GVCG} := [\nabla_{\phi,\psi} KL(P_\phi \Vert Q_\psi)]^\top \nabla_\phi \mathbb{E}_{\theta\sim P_\phi} L(x,\theta)$
L2 gain (L2G)	$L_{L2}(x,\theta) = L(x,\theta) + \frac{\alpha}{2}\lVert\theta\rVert_2^2$

Auto-Curriculum
Curriculum Learning in Interactive Environments

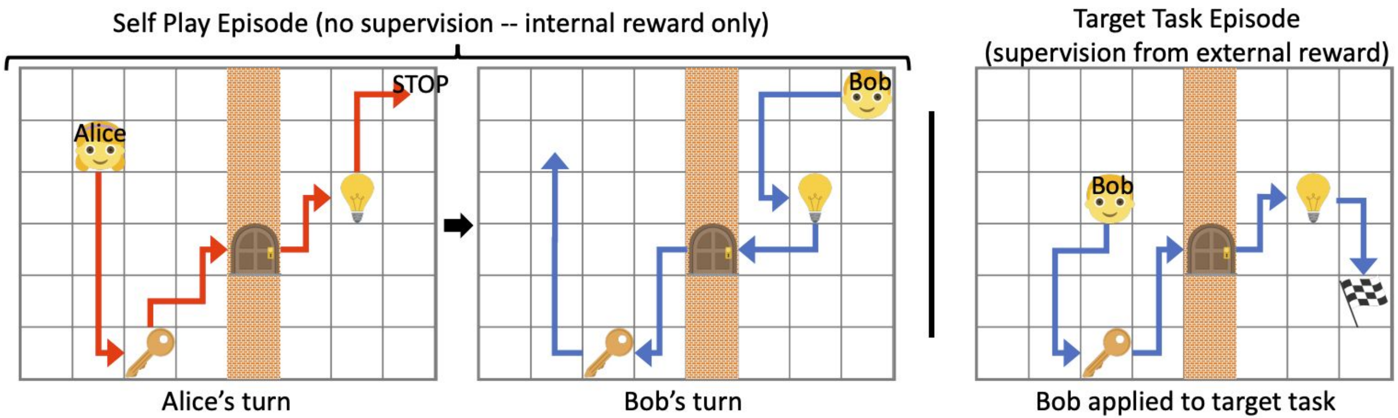


Source: https://rlcurriculum.github.io/

Auto-Curriculum
The Asymmetric Self-Play Idea

Another idea:
Two versions of the same agent:

- Alice will "propose" the task by doing a sequence of actions
- Bob must undo or repeat them, respectively.



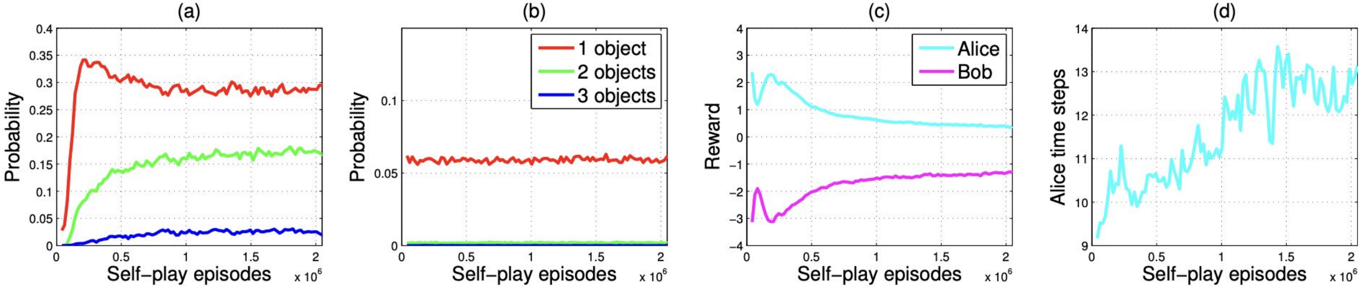
Source: Intrinsic Motivation and Automatic Curricula via Asymmetric Self-Play, ICLR.

Auto-Curriculum

Automatically Generating Curriculum

Algorithm 1 Pseudo code for training an agent on a self-play episode

function SELFPLAYEPISODE(REVERSE/REPEAT, $t_{\text{MAX}}, \theta_A, \theta_B$)
  $t_A \leftarrow 0$
  $s_0 \leftarrow$ env.observe()
  $s^* \leftarrow s_0$
  while True **do**
    # Alice's turn
    $t_A \leftarrow t_A + 1$
    $s \leftarrow$ env.observe()
    $a \leftarrow \pi_A(s, s_0) = f(s, s_0, \theta_A)$
    if $a =$ STOP **or** $t_A \geq t_{\text{Max}}$ **then**
      $s^* \leftarrow s$
      env.reset()
      break
    env.act(a)
  $t_B \leftarrow 0$
  while True **do**
    # Bob's turn
    $s \leftarrow$ env.observe()
    if $s = s^*$ **or** $t_A + t_B \geq t_{\text{Max}}$ **then**
      break
    $t_B \leftarrow t_B + 1$
    $a \leftarrow \pi_B(s, s^*) = f(s, s^*, \theta_B)$
    env.act(a)
  $R_A \leftarrow \gamma \max(0, t_B - t_A)$
  $R_B \leftarrow -\gamma t_B$
  policy.update(R_A, θ_A)
  policy.update(R_B, θ_B)
  return



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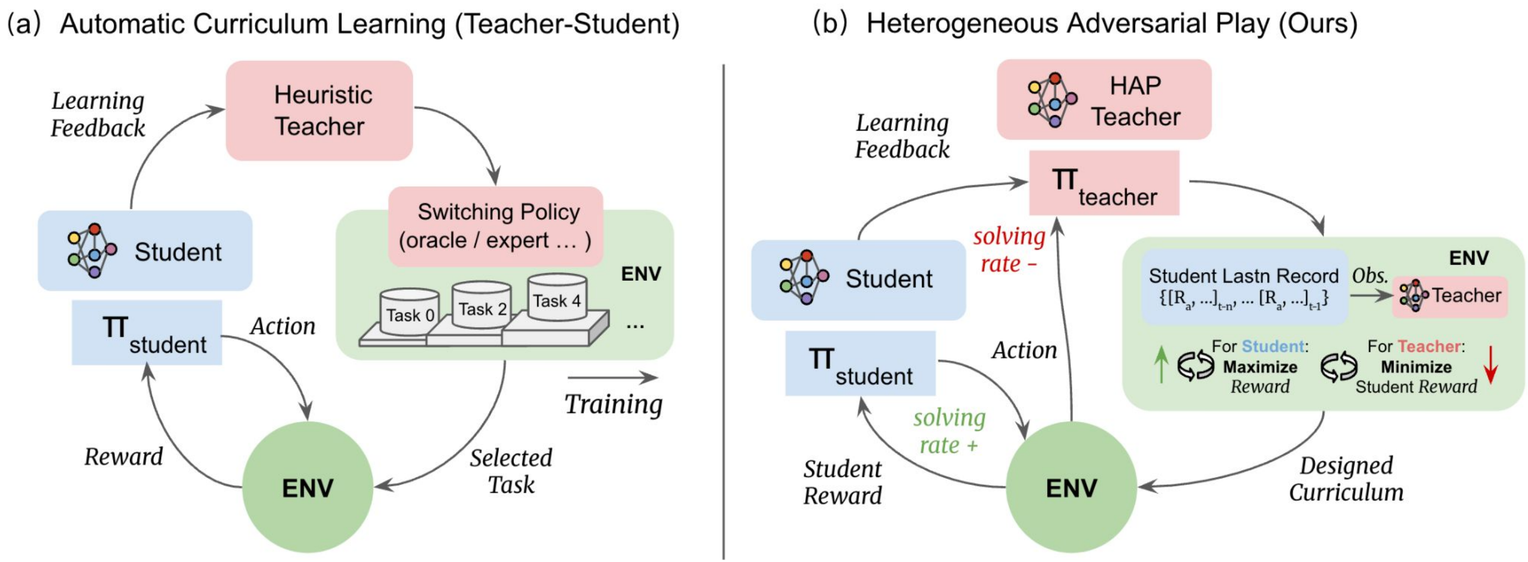
Heterogeneous Adversarial Play
Teacher-Student Interplay as Adversarial Game



At the simplest level: the task generator is rewarded if the problem solver **cannot** solve the problem, and the problem solver is so if the proposed challenge is **addressed**.

Heterogeneous Adversarial Play

Teacher-Student Interplay as Adversarial Game

Consider the task space $\mathcal{C} = \{C_1, C_2, \ldots, C_N\}$, where each C_i is a unique task.

The student:

- Student agent learns a solve policy $\pi(a|s, C; \theta)$ in environment $\mathcal{E}$:

$$\max_{\theta} \; J_{\text{student}}(\theta) = \mathbb{E}_{C \sim p_\phi(C)} \left[\mathbb{E}_{\tau \sim \pi(\cdot|C;\theta)} \left[R(\tau; C) \right] \right]$$

The teacher:

- The teacher agent evaluates the student's current learning state and strategically selects appropriate tasks.

$$\max_{\phi} \; J_{\text{teacher}}(\phi) = \mathbb{E}_{C \sim p_\phi(C)} \left[\mathbb{E}_{\tau \sim \pi(\cdot|C;\theta)} \left[-R(\tau; C) \right] \right]$$

Heterogeneous Adversarial Play

Adversarial Formulation

Algorithm 1: Heterogeneous Adversarial Play (HAP) Training Loop

Data: Initial θ, ϕ; learning rates α, β

while *not converged* **do**

  ; /* 1. Teacher's Adversarial Task Selection: */

  Generate task distribution: $p_\phi(C) \propto \exp(\phi)$;

  ; /* Minimization strategy: Sample task $C \sim p_\phi(C)$ to challenge current π */

  ; /* 2. Student's Policy Maximization: */

  Execute $\pi(a|s, C; \theta)$, collect trajectory τ;

  Compute reward signal: $R(\tau; C) = \sum_{t=0}^{H} \gamma^t r_t$;

  Update θ to *maximize* returns:;

    $\theta \leftarrow \theta + \alpha \nabla_\theta \mathbb{E}_\tau [R(\tau; C)]$;

  ; /* 3. Teacher's Adversarial Update: */

  Update ϕ to *minimize* student success:;

    $\phi \leftarrow \phi - \beta \nabla_\phi \mathbb{E}_C \left[R(\tau; C)\right]$;

  where $\nabla_\phi J_{\text{teacher}} = -\mathbb{E}_C \left[\nabla_\phi \log p_\phi(C) \cdot R(\tau; C)\right]$;

end

Zero-sum game between the teacher and student can also be modeled as a **minimax game** for ease of implementation:

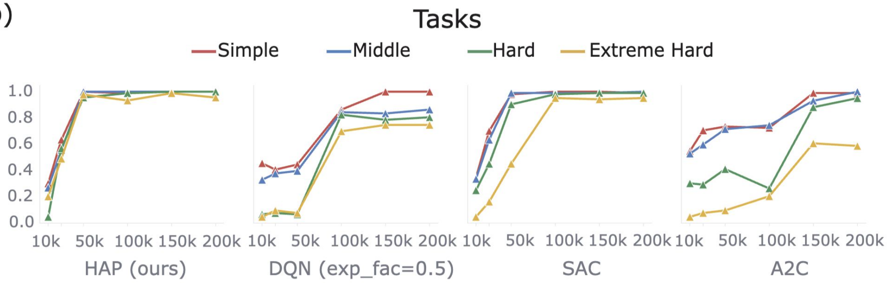
$$\min_\phi \max_\theta \; J(\theta, \phi)$$

Heterogeneous Adversarial Play
A Preliminary Study

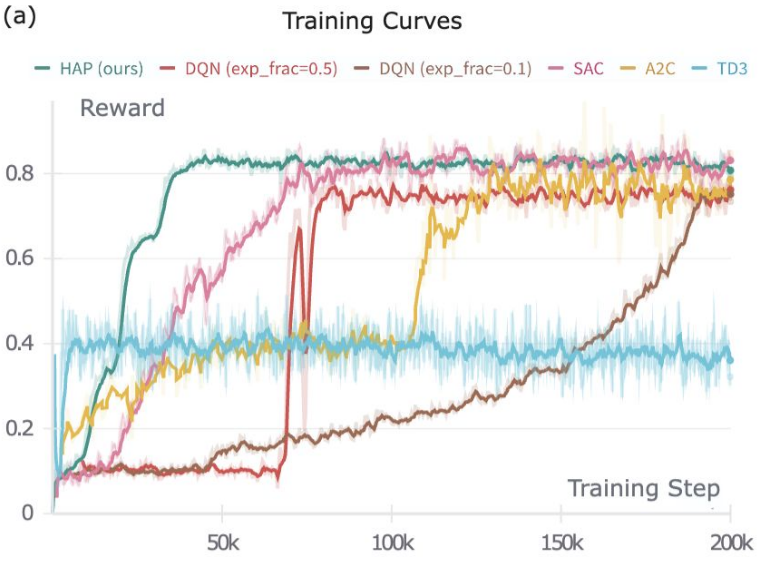
We discover the advantages of HAP through an intuitive navigation experiment.

- Simple: 2 grids
- Middle: 4 grids
- Hard: 8 grids
- Extreme Hard: 16 grids

(b)



(a)

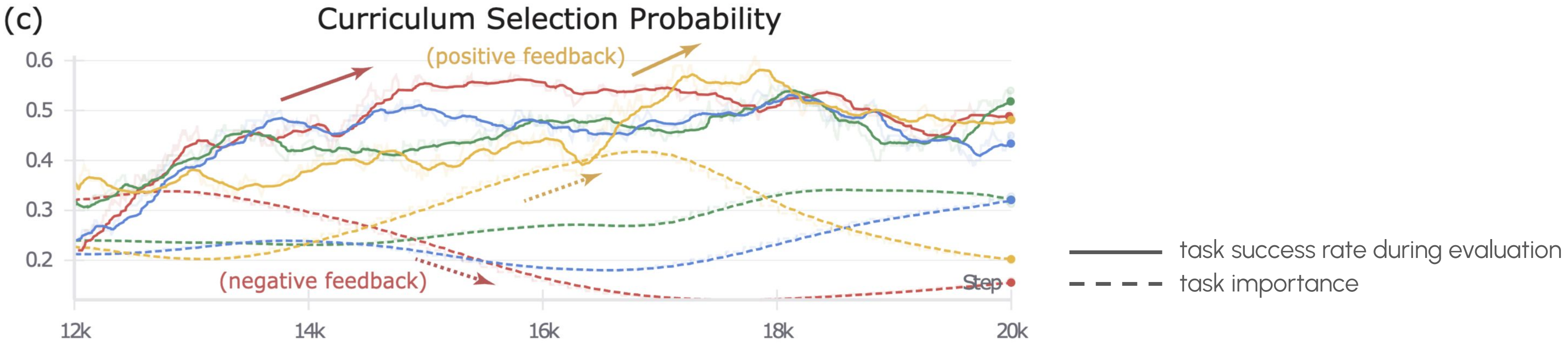


Heterogeneous Adversarial Play

A Preliminary Study

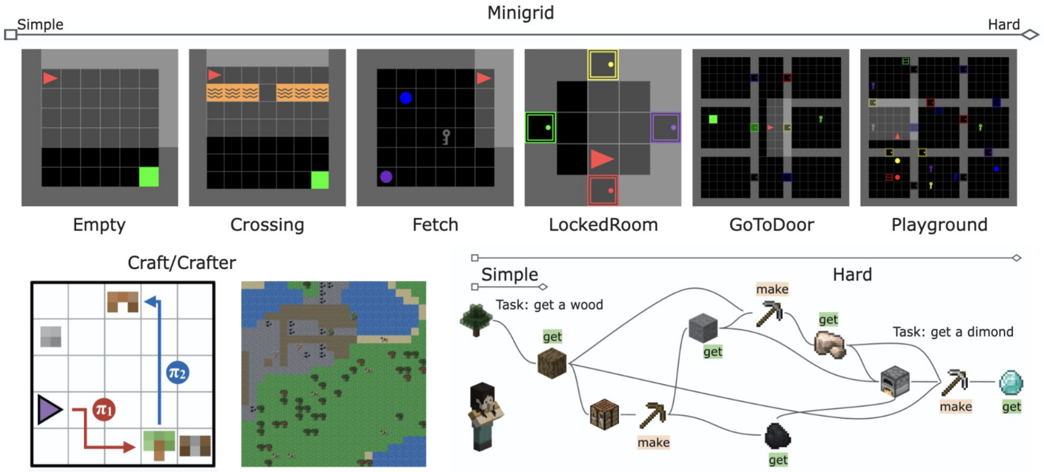
HAP benefits from two key design elements:

- (i) a positive feedback loop, where the teacher increases the sampling probability of a task the learner fails often, thereby accelerating the learner's acquisition in a specific skill
- (ii) a negative feedback mechanism, which lowers the sampling probability for tasks the learner has already mastered.



Heterogeneous Adversarial Play
Testing in Complex Multi-task Scenes

- Top: Minigrid environment with six selected tasks.
- Bottom Left: CRAFT and Crafter environments
- Bottom Right: A portion of the task dependency graph. Starting from the root node, any path defines a multi-step task that an agent must complete when interacting with the environment.



Heterogeneous Adversarial Play

Testing in Complex Multi-task Scenes

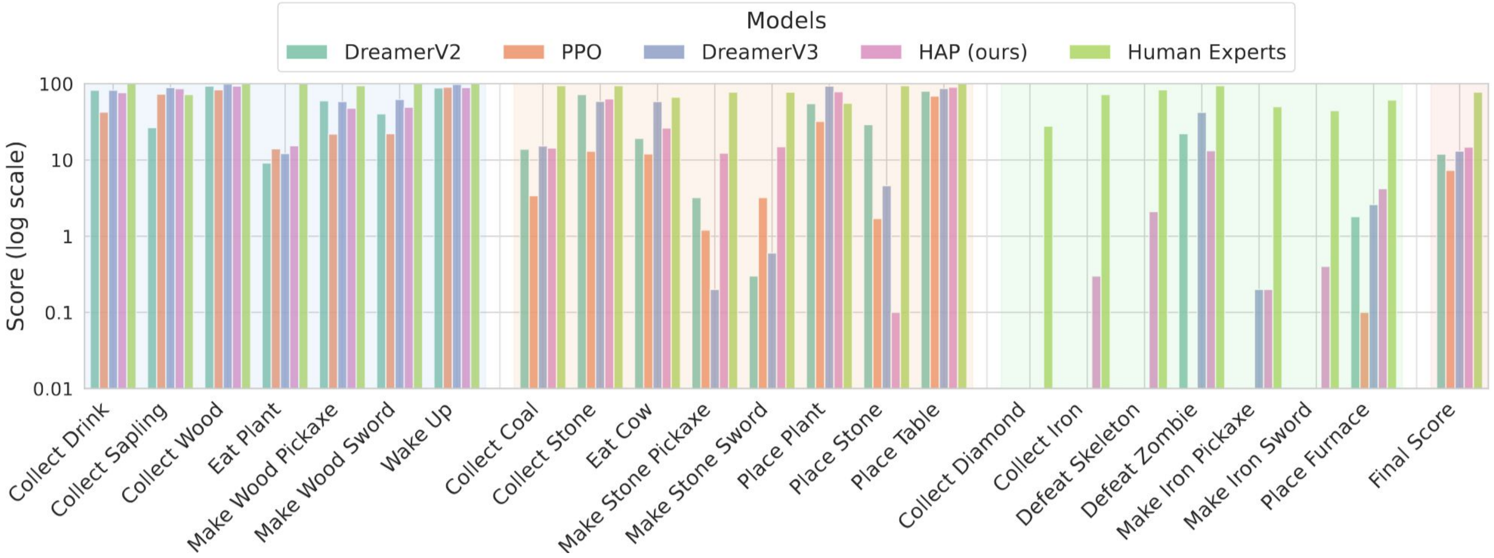
From Results: An active curriculum not only promotes **faster convergence** but also **bolsters stability** across tasks.

Env	DQN	A2C	PPO	SAC	TD3	DreamerV3	TSCL	EXP3	HAP	Human
	Algorithms									
Minigrid										
Easy	**0.98**	0.94	0.88	0.97	0.95	0.96	0.96	0.97	0.92	1.00
Middle	0.24	0.25	0.22	0.27	0.26	0.34	0.21	0.24	**0.46**	0.78
Hard	0.00	0.00	0.00	0.13	0.08	0.18	0.16	0.18	**0.20**	0.46
General	0.407	0.397	0.367	0.457	0.43	0.493	0.443	0.463	**0.527**	0.747
CRAFT										
Easy	0.78	0.84	0.87	0.87	0.86	0.89	**0.94**	0.91	0.88	0.94
Middle	0.26	0.45	0.48	0.42	0.42	0.55	0.24	0.56	**0.63**	0.86
Hard	0.02	0.14	0.12	0.15	0.14	0.27	0.03	0.24	**0.31**	0.66
General	0.278	0.415	0.426	0.413	0.407	0.516	0.307	0.513	0.562	0.802
Crafter										
Easy	0.61	0.79	**0.94**	0.91	0.84	0.91	0.82	0.87	0.91	0.99
Middle	0.28	0.37	0.67	0.47	0.39	0.66	0.45	0.58	**0.68**	0.82
Hard	0.00	0.00	0.47	0.22	0.29	0.52	0.00	0.02	**0.58**	0.74
General	0.297	0.387	0.693	0.533	0.507	0.697	0.423	0.49	**0.723**	0.85

Heterogeneous Adversarial Play

Qualitative Analysis on Crafter Scores

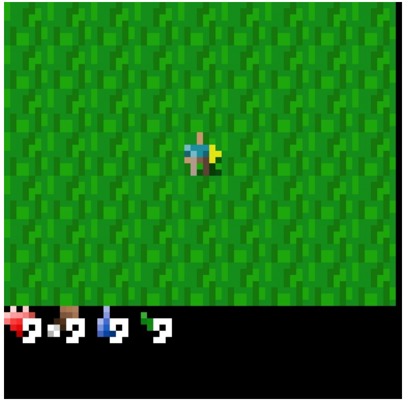
From Results: An active curriculum not only promotes **faster convergence** but also **bolsters stability** across tasks.



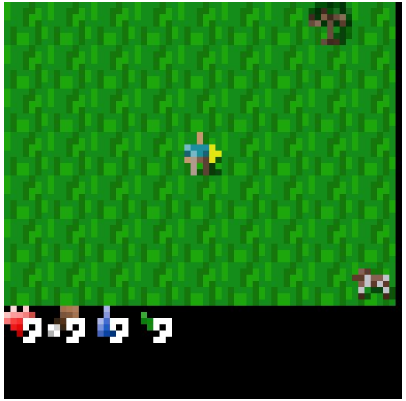
Heterogeneous Adversarial Play

Demos

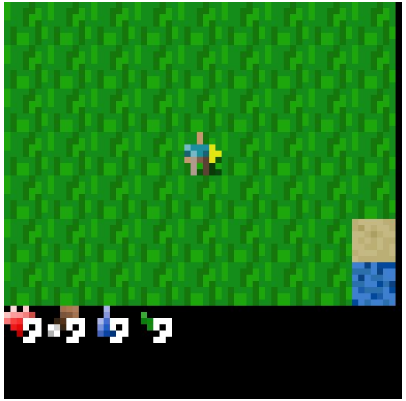
From Results: An active curriculum not only promotes **faster convergence** but also **bolsters stability** across tasks.



Reward (achievement) : 13



Reward: 15



Reward: 5

Reward: 3

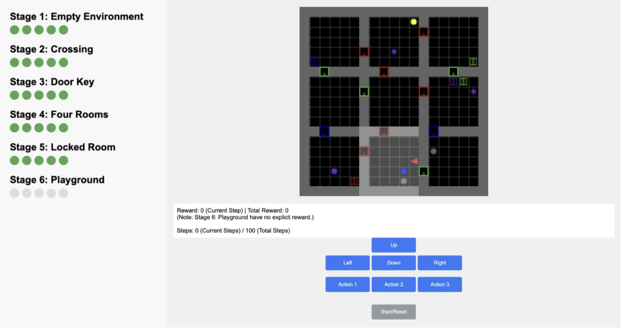
Good cases

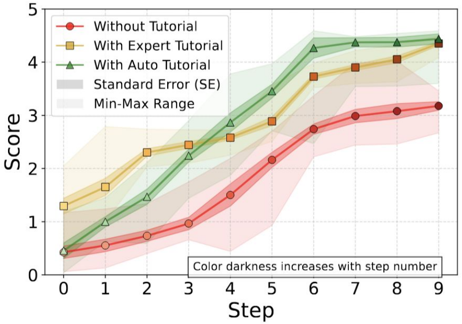
Bad cases

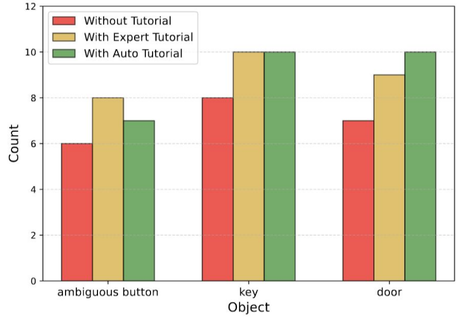
Heterogeneous Adversarial Play
Validation on Human Study

We conduct a human study to compare the curriculum proposed by the teacher model of HAP against expert-designed pedagogical strategies from human subjects. We find that:

- The presence of well-designed curriculum significantly accelerated early-stage mastery for both humans and models.
- While humans showed greater improvement within a single step when provided with expert step-by-step tutorials, the HAP framework offered more flexible, adaptive curricula tailored to individual behaviors.

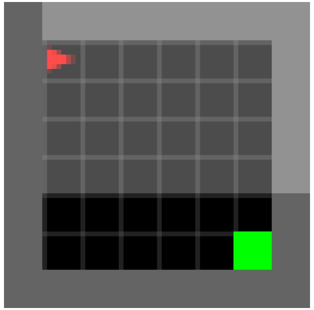


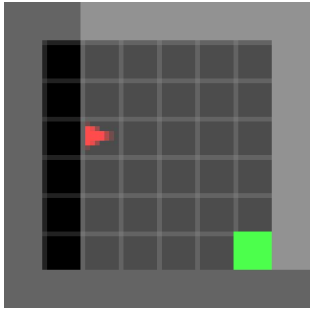




Heterogeneous Adversarial Play

Demos

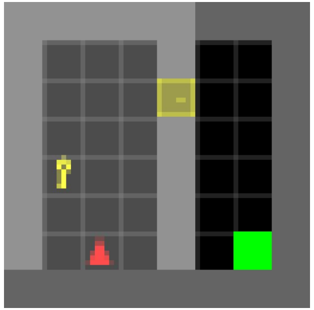




Bad cases

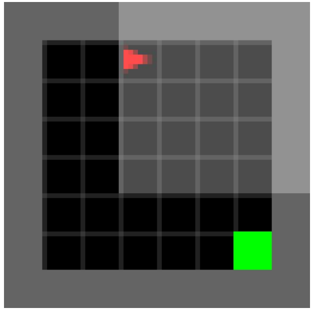
(Open the Door /

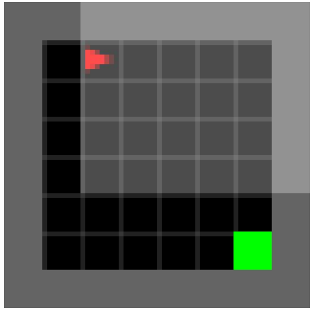
Use key)

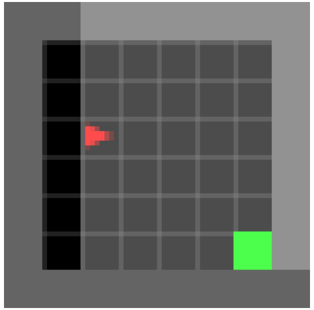


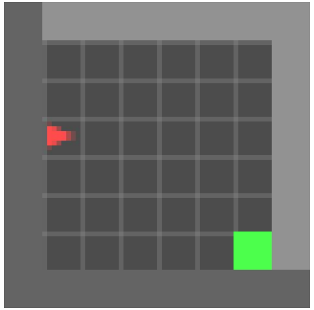
Curriculum

Generated by HAP





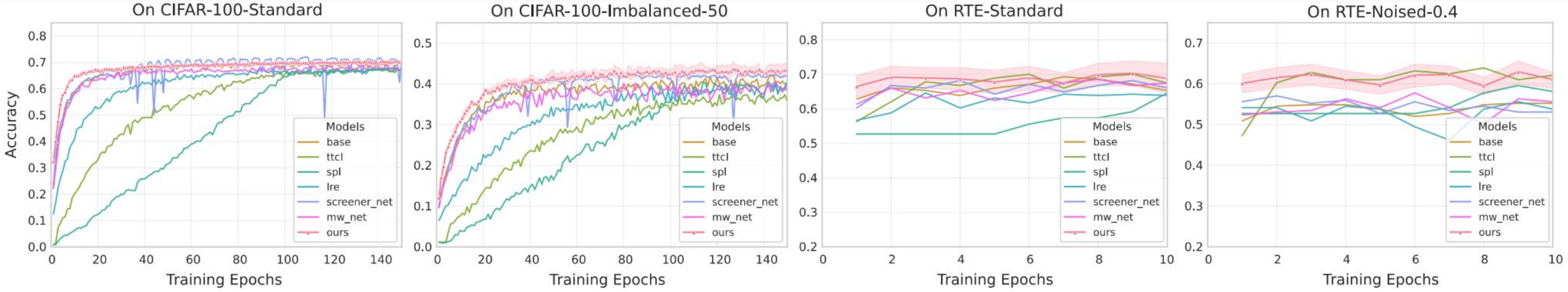




Good cases

Heterogeneous Adversarial Play
Further Study on Self-Supervised Learning

From Results: An active curriculum not only promotes **faster convergence** but also **bolsters stability** across tasks, **especially in harder settings**.



Heterogeneous Adversarial Play
Summary

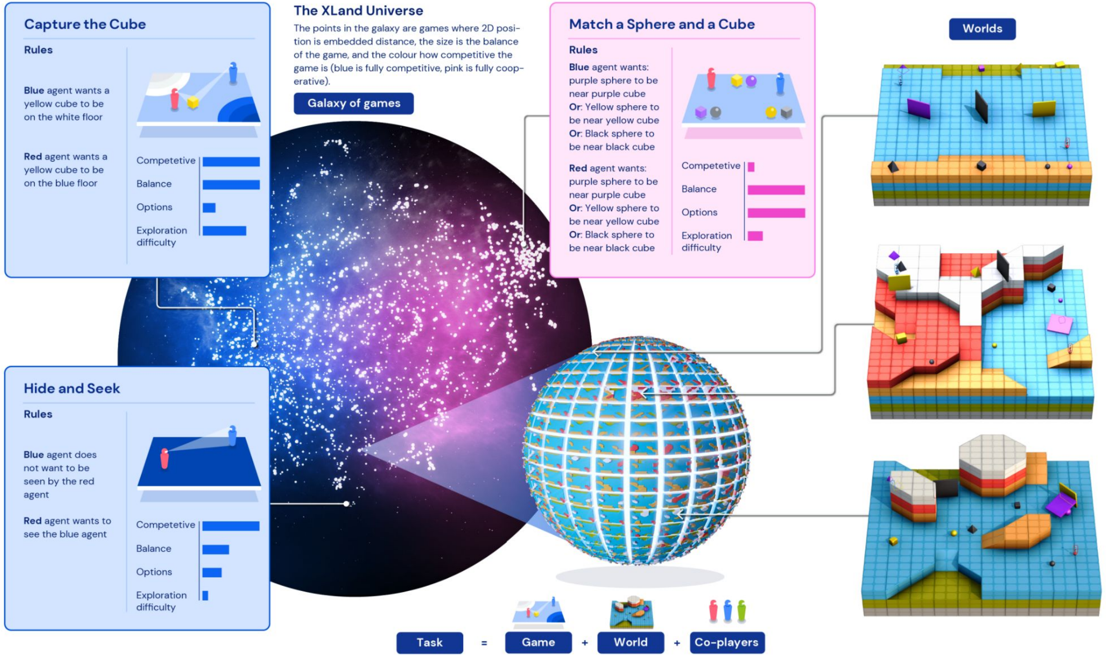
- We propose Heterogeneous Adversarial Play, a zero-sum game framework where distinct teacher and student networks co-adapt dynamically, enabling automated curriculum design without predefined task hierarchies or symmetric architectures.
- Our method achieves superior performance in complex, multi-task environments and supervised learning benchmarks, demonstrating faster convergence and robustness to noisy/imbalanced data compared to state-of-the-art baselines.
- HAP's emergent curricula mirror human pedagogical strategies—such as revisiting foundational skills during plateaus and scaling difficulty contextually—while offering personalized adaptation that surpasses fixed, expert-designed teaching approaches.

Heterogeneous Adversarial Play
Future Extension

- Open-ended Play
- Synthetic Data Generation via Self-play

Open-ended Play

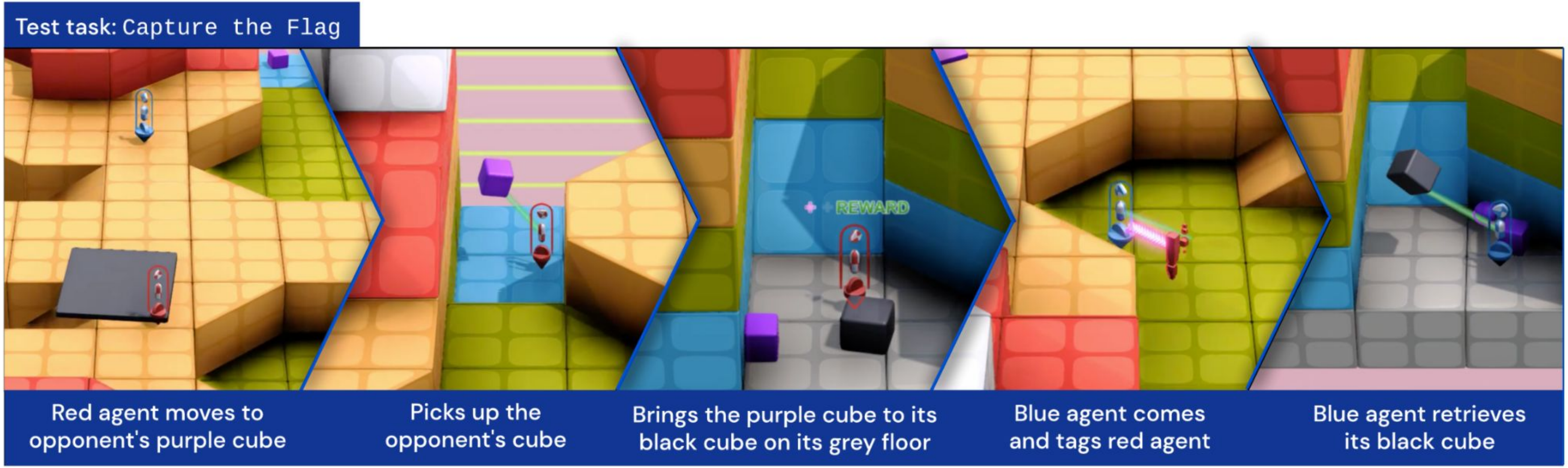
Generally capable agents emerge from open-ended play



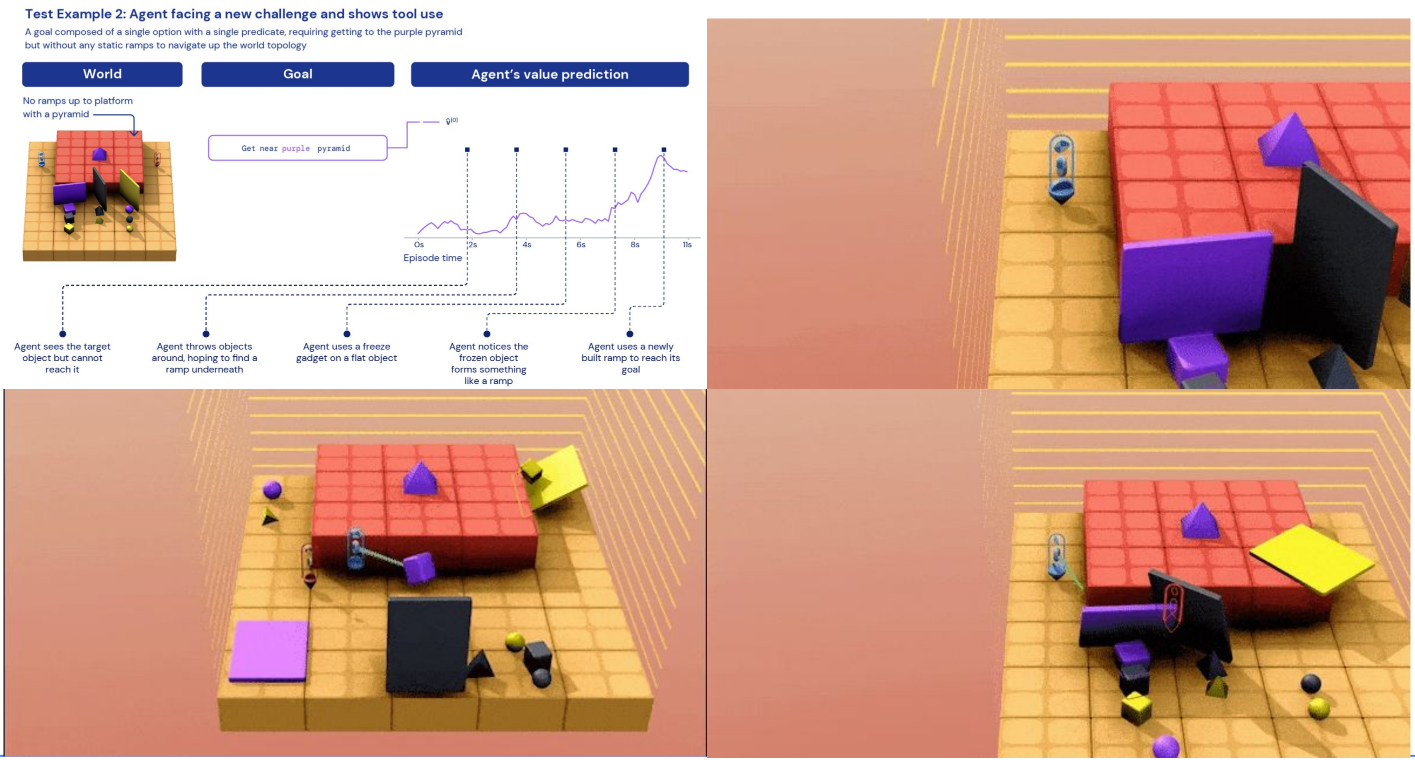
Open-ended neural agents, trained in a universe of ever-changing, automatically generated tasks and games, manifest highly generalizable problem-solving and social skills—pointing the way toward generally capable artificial intelligence systems.

Open-ended Play

Generally capable agents emerge from open-ended play



Open-ended Play



Open-ended Play

Emergent tool use from multi-agent interaction

Thank You for Watching !