VECA: A New Benchmark and Toolkit for General Cognitive Development

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Abstract

The developmental approach, simulating a cognitive development of a human, arises as a way to nurture a human-level commonsense and overcome the limitations of data-driven approaches. However, neither a virtual environment nor an evaluation platform exists for the overall development of core cognitive skills. We present the VECA (Virtual Environment for Cognitive Assessment), which consists of two main components: (i) a first benchmark to assess the overall cognitive development of an AI agent, and (ii) a novel toolkit to generate diverse and distinct cognitive tasks. VECA benchmark virtually implements the cognitive scale of Bayley Scales of Infant and Toddler Development-IV (Bayley-4), the gold-standard developmental assessment for human infants and toddlers. Our VECA toolkit provides a human toddler-like embodied agent with various human-like perceptual features crucial to human cognitive development, e.g., binocular vision, 3D-spatial audio, and tactile receptors. We compare several modern RL algorithms on our VECA benchmark and seek their limitations in modeling human-like cognitive development. We further analyze the validity of the VECA benchmark, as well as the effect of human-like sensory characteristics on cognitive skills.

Introduction

Building a cognitive intelligent agent with human-like commonsense is a milestone of artificial intelligence (Zhu et al. 2020). Human cognition is an interpretable and sample-efficient general intelligence, encompassing diverse abilities like information processing, intuitive psychology, and goal setting (Lake et al. 2017; Sloman 1999). These core cognitive skills naturally construct in an early stage of human development, often with limited experiences. Hence one of the emerging paths towards such mental capabilities is to mimic such cognitive development of a human, i.e., a developmental approach. (Doya and Taniguchi 2019; Silver et al. 2021) The goal of the developmental approach is to simulate a human’s neuro-cognitive developmental process and enable continual life-long learning with active interactions.

However, the developmental approach currently lacks both the assessment for cognitive development and the general environment to simulate the development. Several benchmarks only target specific cognitive skills of an AI agent, such as intuitive physics (Bakhtin et al. 2019) or intuitive psychology (Shu et al. 2021). None of them covers the overall development of distinct cognitive skills like object-relatedness, memory, and sensorimotor development. Embodied agent simulators are the closest thing to mimic human biological features, since they give realistic egocen-
critical in human’s learning; humans learn by collecting HRTF, and human-like tactile receptors. These features are development, e.g., binocular vision, spatialized audio with model human sensory characteristics influential to cognitive development, e.g., binocular vision, HRTF-based spatialized audio, and human-like tactile receptor. These features are critical in human’s learning: humans learn by collecting rich multimodal perception (e.g., vision, audio, tactile) from their surroundings (Landau, Smith, and Jones 1998; Tacca 2011) and actively interacting (Franchak, van der Zalm, and Adolph 2010; Vogt et al. 2018) with objects. Our VECA environment and benchmark are available to public for research purposes at https://github.com/snuhcs/veca/.

We assess several representative RL algorithms with our VECA benchmark, including policy gradient methods (Espeholt et al. 2018; Schulman et al. 2017; Haarnoja et al. 2018) and curiosity-driven learning (Burda et al. 2019), and find that there is still a long way to go to reach the human-level cognitive capabilities. Experimental results show that goal-driven learning (IMPALA, the policy gradient method) initially outperforms the unsupervised exploration without explicit reward (curiosity-driven learning), but it prematurely converges and marginally improves from a random policy. Furthermore, we demonstrate the validity of our VECA benchmark by measuring the solvability and complexity of its tasks. Our results show that all the tasks are solvable, and their difficulties are well-distributed. We also observe that the mastery of cognitive skill is much more difficult to acquire than the emergence of the skill. Ablation study reveals that our VECA’s human-like sensory features meaningfully affect the development of cognitive skills.

In summary, our key contributions are as follows:

- We develop the VECA benchmark, a first benchmark to assess the overall development of core cognitive skills of an AI agent. Our benchmark virtually implements the Bayley-4, a standard developmental delay assessment tool of a human.
- We introduce a novel VECA toolkit that can easily generate various tasks measuring diverse cognitive skills. Our VECA toolkit supports human toddler-like agents with rich human-like perception and interaction capabilities.
- Our work is first to provide diverse human biomimetic sensory features on multimodal sensation, e.g., binocular vision, HRTF-based spatialized audio, and human-like tactile receptor.
- Using our VECA benchmark, We study the limitation of several modern RL algorithms in simulating human-like cognitive development. Moreover, we analyze the validity of VECA benchmark and VECA toolkit’s human-like sensory characteristics.

**Background & Related Works**

In terms of human-like embodiment or cognitive development assessment, our work is related to prior works on (1)
cognitive tests for AI agents, (2) cognitive developmental robotics, and (3) embodied agent simulator.

**Cognitive Test for AI Agents** To verify the human-like cognitive capability of AI, prior works introduced cognitive tests for AI agents. For instance, TOMNet (Rabinowitz et al. 2018) applies the Sally-Anne test to an AI agent, a psychological test measuring a person’s socio-cognitive ability of false belief (Wimmer and Perner 1983). Thorough benchmarks exist for specific cognitive skills, e.g., physical reasoning and intuitive physics (Bakhtin et al. 2019), productive and systematic generalization under uncertainty (Vedantam et al. 2021), and intuitive psychology (Shu et al. 2021). In contrast, our VECA benchmark assesses diverse core cognitive functions which emerge in the early stage of human development. To narrow the gap between the human test and its virtual counterpart, we use a toddler avatar embodied with a number of human-like features, unlike puzzle-solving (Bakhtin et al. 2019) or dataset-based (Shu et al. 2021) benchmarks.

**Cognitive Developmental Robotics** Cognitive Developmental Robotics *physically embodies* an agent to a human baby-like robot to study how human’s higher cognitive functions emerge through real-world interaction (Asada et al. 2009). Humanoid robot platforms in these works faithfully mimic the human toddler’s body (Metta et al. 2010), e.g., joint flexibility, soft skin, and human-like appearance. However, robot platforms are cost-inefficient to train and test AI algorithms; it is more cost-effective, scalable, and safe using virtual environments and agents (Zhao, Queraltà, and Westerlund 2020). Furthermore, it is challenging to enable the standard and repeatable testing procedures of Bayley-4 assessment with existing robotics platforms.

**Realistic Simulators for Embodied AI.** Embodied AI researchers hypothesize that intelligence emerges from interacting with its surroundings, just like humans (Smith and Gasser 2005). To verify it and faithfully simulate the real-world entity, virtual agents embody egocentric sensory inputs as well as interaction capability with the environment. Prior environments for embodied AI agents focus on photorealistic indoor simulation (Gibson 1988), vision-language tasks (Wu et al. 2018), robot simulation with realistic robot sensors and dynamics (Koenig and Howard 2004), audio-visual multimodal learning (Chen et al. 2020), and predefined object-specific interaction (Kolve et al. 2017). By contrast, our VECA provides unique features to model cognitive development, which none of the existing environments offers. In particular, VECA incorporates a suite of human-like features such as tactile sensing, soft skin, HRTF spatialized audio, and baby-like morphology, which are all essential to implementing the Cognitive Scale of Bayley-4. For more clear understanding, we qualitatively compare our VECA with other embodied AI simulators in Table 1 in terms of features they support.

### Table 1: Comparing features of our VECA with other embodied agent simulators.

| Environments            | 3D | Extensible | Phys | EgoVis | Audio | Tactile | Interactive | Humanoid |
|-------------------------|----|------------|------|--------|-------|---------|-------------|----------|
| ALE (Bellemare et al. 2013) | X  | X          | X    | X      | X     | X       | X           | X        |
| DM Lab (Beattie et al. 2016) | O  | △          | X    | O      | X     | X       | X           | X        |
| OpenAI Universe (OpenAI 2016) | O  | O          | X    | O      | X     | X       | X           | X        |
| VizDoom (Kempka et al. 2016) | O  | X          | O    | X      | X     | X       | X           | X        |
| Arena (Song et al. 2020) | O  | O          | O    | X      | X     | X       | X           | X        |
| Malmo (Johnson et al. 2016) | O  | O          | O    | X      | X     | O       | X           | X        |
| Gibson (Xia et al. 2018) | O  | X          | O    | O      | X     | X       | O           | X        |
| MINOS (Savva et al. 2017) | O  | X          | X    | O      | X     | X       | X           | X        |
| House3D (Wu et al. 2018) | O  | △          | X    | O      | X     | X       | X           | X        |
| HoME (Brodeur et al. 2017) | O  | △          | O    | O      | X     | X       | X           | X        |
| AI2-THOR (Kolve et al. 2017) | O  | O          | O    | O      | X     | O       | X           | X        |
| Soundspaces (Chen et al. 2020) | X  | O          | O    | O      | X     | X       | X           | X        |
| VECA                    | O  | O          | O    | O      | O     | O       | O           | O        |

VECA Environment & Toolkit

Bayley-4 is a valid and reliable assessment tool for human development (N. Bayley 2019), but our focus is an AI agent, not a human. The question naturally arises: “Is the Bayley-4 test also valid for virtual AI agents?”. Bayley-4 consists of tasks that are most meaningful with a human-like embodiment; For instance, task (2a) needs binocular human eyes and a toddler’s posture. General cognitive development is closely related to biological factors (Ranjitkar et al. 2019), which virtual AI agents do not acquire or develop. To substantiate the virtualization of Bayley-4, the test subject agent should embody human toddler-like biological features in
both sensory input and action capability.

VECA toolkit introduces a human-like multisensory embodied agent and an immersive virtual environment, as shown in the overview Figure 1. VECA agent receives highly multimodal sensations simulating human characteristics and does joint-level or animation-based actions. The immersive VECA environment enables physical and animated interactions with surrounding objects.

Human-like Multisensory Embodied Agent

A VECA agent embodies three major components: rich human-like multimodal-multisensory perception, human toddler avatar, and joint-level physics. Inspired by researches in human multisensory learning (Stein 2012; Moustafa 1999), we provide four important sensory modalities: vision, audio, tactile, and proprioception. Studies show that multi-modal sensory experiences, mainly vision, audio, tactile, and proprioception, facilitates early development (Murphy 1997) and learning (Chandrasekaran 2017). We further augment them with human biological characteristics crucial for cognitive development, which is detailed in Figure 3.

Human-like Vision. In imitation of human binocular vision, the VECA agent receives binocular vision input through two eye pupils of the toddler avatar. Binocular vision plays a key role in a part of core cognitive abilities and their development, e.g., depth and space perception (van Hof, van der Kamp, and Savelsbergh 2006). Another important trait of an infant’s vision system is biological development, in which visual acuity (Dobson and Teller 1978) and color sensitivity (Adams, Maurer, and Cashin 1990) steadily grow in the first few months (Valenti 2006). We model such deficient color vision and sharpness with multiple visual filters varying, e.g., focal length, grayscale, and blur. We allow the parametrized manipulation of these features to simulate a particular developmental stage of the vision system.

Human-like Audio. We introduce HRTF (head-related transfer function) spatialization filter to facilitate blind-spot recognition and audio source localization of a VECA agent. Diffraction and reflection properties of human body structures like the head or torso greatly affect auditory processing (Bögelein et al. 2018) and early auditory development (Tollin 2009). The phase and impulse difference of audio signal between two ears makes it possible (Gardner and Martin 1995). HRTF models such physical interaction between human anatomy and the sound source with a transfer function of azimuth, elevation, and frequency. HRTF datasets collect audio data from human subject’s ears varying source locations to model the input-output transfer curve. We use the KEMAR dataset (Gardner 1994), which uses a dummy head instead of a real person. Since the KEMAR dataset only supports discrete spherical coordinates, we apply bilinear interpolation as in (Sousa and Queiroz 2010) to enable arbitrary coordinates. Post-processed audio data \( y_{i(t, d, \theta, \varphi)} \) our VECA agent perceives on its left(L) and right(R) ear is,

\[
y_{i(t, d, \theta, \varphi)} = \min \{ 1/|d^2_i|, d_{TH} \} \cdot F(\mathbf{H}(f(x(t), \theta, \varphi)))
\]

where \( x(t) \) the source audio data, \( i = \{ L, R \} \) indicating the left(L) or right(R) ear, \( d_i \) the distance of the sound source, \( \theta \) the polar angle, \( \varphi \) the azimuth, \( d_{TH} \) a minimum audible distance, \( H \) the KEMAR HRTF function, \( f \) the discrete fourier transform, and \( F \) the inverse discrete fourier transform. The function \( H \) is thus the composition of binocular interpolation and the discrete HRTF function \( H \).

Human-like Tactile. We simulate the human tactile sensation by modeling a soft and flexible skin covering a toddler avatar’s rigid-body bones. Tactile perception plays a significant role in early cognitive development; toddlers unconsciously learn cognitive skills through tactile interaction like mouthing or grabbing. (Gibson 1988; Piaget and Cook 1952). Tactile perception is critical in sensorimotor development (Dusing 2016), which consists a large portion of the Bayley-4 test. Prior work naively simulates such tactile sensation by measuring collision force on a single contact point (Juliani et al. 2018). In contrast, we mimic four essential features of a biological tactile receptor: soft skin elasticity (Wang et al. 2021), multiple contact points, sensory threshold (Lawless and Heymann 1999), and sensory habituation (Song, Banks, and Bewick 2015). First, a tactile sensor converts the elastic deformation of the local skin area above it into a sensor signal. Inspired from Hooke’s law for elastic body and prior works (El Bab et al. 2008; Ren et al. 2018), the initial sensor value is proportional to the displacement of
the skin area. Second, we place multiple tactile sensors on each triangle face of the agent’s mesh, which can simul-
taneously activate. Third, we cut off the sensory value with an
absolute threshold. Finally, we model the sensory habitua-
tion with exponential decay, following the study of (Thomp-
sen and Spencer 1966). The tactile sensory input $T_i(s, t)$ of
$i$-th sensor is thus formulated as follows:

$$T_i(s, t) = \sigma (\min \{1, s/s_{max}\} e^{-\lambda t})$$

where $\sigma(x) = \begin{cases} 0, & x < \delta \\ x, & x \geq \delta \end{cases}$ (Cutoff function)

$s$ is the displacement of skin area around $i$-th sensor, $t$ the
time (number of frames) passed from an initial stimulus,
$s_{max}$ the maximum displacement of skin area, $\lambda$ the decay
rate, and $\delta$ the absolute threshold of sensory value.

**Proprioception.** To supply the kinesthetic senses like
limb position and movement, our VECA provides the raw
vector quantity of bones and joints, e.g., bone orientation,
current angle, and angular velocity of the joints. These pro-
rioceptive senses play a critical role in human motor and
sensorimotor development. However, their biological recep-
tors are noisy and difficult to simulate; these propriocep-
tors rely heavily on the human musculoskeletal anatomy
since they are pressure sensors within muscles and joints.

**Human Toddler Avatar.** We model a humanoid agent
with a human toddler-like appearance and joint-level mo-
tion capability, as studies show that baby-like morphology
affects the human cognitive development (Dusina 2016) and
AI agent’s learning (Bambach et al. 2018). The physical
avatar has 47 bones with 82 degrees of freedom and human
joint-like angular constraints. Skin mesh overlays the bones,
and the mesh adaptively changes with the bone orientation
to model the soft skin. Accurate mesh collider and bone mod-
eling enable the agent to interact physically with the objects.

We also support an animation-based avatar and interac-
tion to trade-off task complexity with the physical plausi-
bility. For complex tasks, controlling an agent entirely with
the joint-level actions and physical interactions may be diffi-
cult. Stable primitive toddler-like actions (e.g., walk, rotate,
crawl) and object interactions (e.g., grab, open, step on) are
animated, similar to (Kolve et al. 2017).

**Implementation Detail** We use Unity3D game engine as
an environment simulator to support a 3D realistic scene
rendering and physics engine. VECA environment is a 3D
Euclidean space with Newtonian physics and a downward
gravitational force. VECA provides a series of features to
facilitate AI algorithm development: First, VECA supports
parallel execution of environment along with batched sam-
pling from a multi-task or multi-agent environment. Sec-
ond, to enable training on a remote server with abundant
resources, VECA can communicate information through the
socket network interface. Third, VECA includes an easy-to-
use python API resembling the OpenAI Gym interface that
can easily integrate with existing AI algorithms.

VECA task-generation toolkit is an extensive set of APIs
for creating cognitive tasks in a VECA environment. Using
the toolkit, we additionally generated a number of embodied
AI tasks for various cognitive skills: joint-level control, un-
derstanding the context of objects, multimodal learning, and
multi-agent RL.

**Virtualized Bayley-Scale Assessment**

**Bayley Scales Assessment** The Bayley Scales of Infant
and Toddler Development (Bayley Scales Test) (N. Bayley
2019) is a gold standard (Carey et al. 2009) of development
assessment tool for a child aged 1 to 42 months. Its main
goal is to monitor the child’s developmental progress lon-
gitudinally or to identify a human child with developmental
delay. A structured series of developmental tasks constitutes
the Bayley Scales Test. The score is given per task when the
test subject makes a correct behavioral response in the task
scenario (Albers and Grieve 2007). The test’s standardized
administration and scoring procedures should not be viol-
ated to precisely compare the child’s performance. To claim
the validity and clinical utility of the test and its metrics,
large-scale standardization research is conducted on 1,700
typically developing children.

The latest edition of Bayley Scales Test (Bayley-
4) (N. Bayley 2019) uses the five-scale framework: Cogni-
tive, Language, Motor, Social-Emotional, and Adaptive
Behavior. We use Cognitive scale in this work, since it focuses
on the development of cognitive processing aspects.

**Cognitive Scale** The Cognitive Scale of Bayley-4 consists
of 81 task items that measure diverse cognitive processing
aspects in early development, e.g., exploration and manipu-
lation, object relatedness, concept formation, memory, sen-
sorimotor development (N. Bayley 2019). We list several no-
table cognitive processes the scale examines.

- Information-processing tasks including novelty prefer-
ence, habituation, and anticipation of patterns, which cor-
relate with later cognitive functioning (Rose et al. 2012).
- Problem-solving, a higher-order information processing
that involves thinking or reasoning, memory, and synthe-
sis of information (Greiff et al. 2015).
- Play activities facilitating cognitive growth and symbol
understanding (Frost, Wortham, and Reifel 2008).
- One-to-one correspondence, counting, and cardinal-
ity (Geary et al. 2018).

Language development, one of the fundamental cognitive
abilities, is mainly measured on a separate Language Scale.
Note that the goal of the scale is not to quantify the entire
cognition or intelligence of a human subject; rather, it checks
whether core cognitive skills expected in a certain age have
actually emerged.

**Virtualizing the Bayley-4 Cognitive Scale**

For a benchmark of general cognitive development, we vir-
tually implement the cognitive scale of Bayley-4 with our
VECA toolkit. We are permitted to adapt the Bayley-4 in
a virtual environment for research purposes. Figure 4 de-
scribes how we port a Bayley-4 task to the VECA environ-
ment. A Bayley-4 task contains three main components: task
& materials setup, item instructions, and scoring. We first
model the task environment and materials in a VECA environment; for example, we arrange prop materials or prepare a caregiver’s audio clips. Next, we develop the item instructions as a scenario and produce it with materials and a caregiver avatar. Finally, we design a reward structure that returns a score depending on the agent’s behavior. Score 2 means a consistent proficiency of skill, whereas score 1 implies that skill is inconsistent but emerging. Score 0 represents the absence of skill. Note that the correctness of behavioral response is algorithmically determined, unlike the real-world Bayley-4 test in which a human tester subjectively determines its correctness. For instance, the task Looks at Object in Figure 2a defines the “looking” as the cosine similarity of head and object direction > 0.95.

**Metrics** Bayley-4 provides several standardized metrics for its sub-scales (N. Bayley 2019) that our VECA benchmark can leverage. The total raw score is simply a sum of each task score, which converts to three standardized metrics: scaled scores, age equivalent, and growth scale values. Scaled Scores uses the biological age of the participant to normalize the raw score. Age Equivalent shows the developmental age of a normative human child equivalent to the raw score. Growth Scale Values (GSV) are used to track the child’s growth over time, and it has a mean and std value of 500 and 25. A score conversion table exists that maps the total raw score to other metrics. We only use three metrics from Bayley-4, except the scaled scores, since it is difficult to decide the VECA agent’s exact biological age.

**Experiments**

We evaluate four aspects of our VECA benchmark toolkit. First, we share the benchmark results of four representative baselines and show that using standardized metrics of Bayley-4, the cognitive capability of AI can be directly compared to the human. Second, we validate our virtualized Bayley-4 tasks by analyzing the solvability and complexity of each task, following the protocol of (Bakhtin et al. 2019). Third, we show that VECA's human-like sensory characteristics meaningfully affect the development of cognitive skills by training certain tasks where these features are crucial. Finally, we demonstrate that our VECA toolkit can create diverse cognitive tasks with different difficulties by varying the difficulty setup of our toolkit-generated tasks.

To run VECA Unity3D application, we use Intel(R) Core(TM) i7-6700K with 32GB RAM on Windows 10 OS. We use Xeon Gold 5218 CPU with 256GB RAM and four NVIDIA TITAN XP 12GBs on a Ubuntu 16.04 to train the agent algorithm. We sample binocular RGB vision data in a resolution of 84x84. No blur or grayscaling is applied to the agent’s vision. We sample the audio data at the rate of 22050Hz and converted the audio data to frequency-domain by FFT with the window size of 1024. Minimum audible distance \(d_{TH} = 20\), threshold of tactile sensory value \(\delta = 0.05\), decay rate of tactile sensory value \(\lambda = 0.0\). Tactile input has a dimension of 3296.
Figure 5: Learning curve of baseline policy learners (IMPALA, CUR) on our VECA benchmark, evaluated with Bayley-4 metrics. x-axis is the number of training iterations in millions, and y-axis is Mean Episode Reward (5a), Total Raw Score (5b), Age Equivalents in months (5c), and Growth Value Scales (5d). Performances are measured per $2 \times 10^4$ steps.

**Baselines.** Three distinct types of baseline methods are used for our experiments: (i) Policy Gradient, (ii) Curiosity-driven Learning, and (iii) Random Agent. We use three modern policy gradient algorithms for our evaluation: IMPALA (Espeholt et al. 2018) as a baseline of our benchmark, and PPO (Schulman et al. 2017) and SAC (Haarnoja et al. 2018) to assess the VECA toolkit itself. These methods represent goal-driven learning with explicit rewards. We first implemented parallelized PPO and SAC that can train with our VECA environment. We also revise the IMPALA implementation of (Küttler et al. 2019) to support our VECA with diverse settings. For curiosity-driven Learning (CUR), we used the dynamics-based curiosity model of intrinsic reward (Pathak et al. 2017) revised for our benchmark. CUR learns without any supervision; the only reward signal is the intrinsic prediction error of observation input. It represents unsupervised exploration, which aligns with how humans learn in the early stage of development (Gibson 1988). Random agent samples actions from the uniform distribution in 6-dimensional action space.

**VECA Benchmark Baselines and Metrics.** We compare three baselines on our VECA benchmark. We train IMPALA and CUR(policy learners) with the entire VECA tasks, which are uniformly sampled at random per episode. Both the CUR and IMPALA agents are trained for 1M steps.

Table 3 lists our hyperparameter setup for IMPALA and CUR algorithms.

We describe three Bayley-4 metrics used in our VECA benchmark: Total Raw Scores(TRS), Age Equivalent, and Growth Scale Value(GSV). TRS is measured as a sum of each task score in our VECA benchmark, as follows.

$$TRS = \sum_{i=1}^{N} (\text{score})_{T_i}$$

where $D = \{T_i\}_{i=1,..,N}$ is the VECA benchmark task set, and $(\text{score})_{T_i}$ is the score an agent attained on task $T_i$. This score is converted to Age Equivalent and GSV score using the standardized score conversion table of Bayley-4 (N. Bayley 2019). In addition to Bayley-4 metrics, we measure the mean episode reward over the previous 100 episodes.

Figure 5 shows that the policy learners train to surpass the random agent over time, but it is still in the level of early human infant, leaving plenty of room for reaching human-level cognition. Policy learners achieve an age equivalent of 5 months and GSV value 477, which is a lower $17.88\%$ of normative human baby data. It shows that these developmental psychology-based metrics give a more intuitive understanding of the developmental status, unlike RL metrics. Note that the IMPALA achieves early improvement with faster convergence, but the CUR constantly improves towards a higher score. Such finding is in contrast with how humans learn; unsupervised exploration dominates in the early development, but it proceeds to goal-driven learning in the later stage.

**Validity Analysis.** We evaluate the validity our VECA benchmark in two folds: (i) solvability and the complexity of each task, (ii) the complexity of the overall VECA benchmark. We use a random agent to analyze the task complexity, e.g., a solution probability of random agent or the number of random trials to solve a portion of tasks. The solution prob-
ability $p_{i=1,2}^{sol}$ is calculated as,

$$p_{i}^{{sol}} = \frac{x_{i}^{success}}{(x_{i}^{success} + x_{i}^{fail})}$$

(2)

where $i = \{1, 2\}$ indicates the score 1 or 2, $x_{i}^{success}$ the number of success cases of scoring, and $x_{i}^{fail}$ the number of failure cases of scoring. Likewise, the success percentage of VECA benchmark $p_{i=1,2}^{succ}$ is, for $t \in \mathbb{N}$,

$$p_{i}^{succ}(t) = \max\left(p_{i}^{succ}(t-1), \frac{n_{i}^{1}(t)}{n_{i}^{1}(t) + n_{i}^{2}(t)}\right)$$

(3)

where $i = \{1, 2\}$ also indicates the score 1 or 2, $t$ the number of random attempts, $p_{i}^{succ}(t)$ the success percentage of VECA benchmark on $t$ attempts, $n_{i}^{1}(t)$ the number of succeeded tasks on $t$-th attempt, and $x_{i}^{fail}(t)$ the number of failed tasks on $t$-th attempt. $p_{i}^{succ}(0) = 0$ for both $i = 1, 2$.

Figure (6a) shows that all the VECA benchmark tasks are solvable with well-distributed task complexity. Tasks with a higher template index tend to be more difficult, which aligns with how the original Bayley-4 tasks are organized. A clear percentage gap of score-1 curve and score-2 curve in Figure (6b) implies that score-2 of VECA benchmark, a mastery of a certain cognitive skill, is much more difficult to achieve than the emergence of the skill. Furthermore, the random agent fails to solve 100% of tasks even after a large number of trials, suggesting that completely solving our benchmark is a highly challenging goal.

**Effect of Human-like Perception.** We now study the effect of human-like sensory features on cognitive tasks. We use the *KickSqueakyBall* task for audio perception, which should 3D-localize the transient and dynamic sound source. For tactile perception, we use the *GrabBlock* task, a sensorimotor task that should physically grab a large block with both hands and lift it. Details of these tasks are described in

![Figure 8: Learning curve of PPO agent varying the audio (8a) and tactile (8b) support. x-axis is the number of training steps in millions, and y-axis is the mean task score.](image-url)

Table 2. PPO is used for the agent training, and its hyperparameter setting is listed in Table 3.

For the *Kick Squeaky Ball* task, we augment the reward function with a helper reward calculated as $0.01 \cos \theta$, where $\theta$ is the angle between the agent’s velocity vector and the displacement vector from the agent to the ball. To encourage the agent to move its hands to the object, *Grab Block* task gives a helper reward calculated as $d_{l-1} - d_{l}$, where the sum-of-distance $d_{l} = |R_{l} - O_{l}| + |L_{l} - O_{l}|$, and $L_{l}$ the position vector of left hand, $R_{l}$ the position vector of right hand, and $O_{l}$ the position vector of object.

Noticeable performance gap of learning curves in Figure 8 shows that VECA’s human-like sensory features are crucial in the development of cognitive skills. The agent with HRTF-spatialized audio attains much higher performance faster than the agents without them. Like a human, audio spatialization due to physical body structure appears to be crucial in the sound source localization of a VECA agent. The same applies to the VECA’s tactile sensation; tactile sensation seems to play an essential role in the sensorimo-
The agent should get closer to the ball to kick it.

The agent should navigate to the desired object among multiple objects. +1 reward for navigating to the correct object, and -1 reward for wrong objects.

Multiple agents are placed in each room, and the target object is in one of those rooms. All agents receive +1 reward if each agent reaches the object.

The goal is to grab and lift an object with joint-level control. The reward is proportional to the vertical elevation of the object, when the object is close enough to each hand.

Table 2: Task descriptions of VECA toolkit-generated cognitive tasks, which are used for the experiments Effect of Human-like Perception and Usefulness of VECA Toolkit.

| Task                  | Description                                      |
|-----------------------|--------------------------------------------------|
| Kick Squeaky Ball     | A squeaky ball with a buzzing sound comes out of walls and bounces around. The agent should get closer to the ball to kick it. |
| Object Nav            | The agent should navigate to the desired object among multiple objects. +1 reward for navigating to the correct object, and -1 reward for wrong objects. |
| Multi Agent Nav       | Multiple agents are placed in each room, and the target object is in one of those rooms. All agents receive +1 reward if each agent reaches the object. |
| Grab Block            | The goal is to grab and lift an object with joint-level control. The reward is proportional to the vertical elevation of the object, when the object is close enough to each hand. |

Table 3: Hyperparameter setup for each RL algorithm.

| Method | Hyperparameters                                      |
|--------|------------------------------------------------------|
| IMPALA | Batch size 8, α 0.99, γ 0.99, ε 0.01, lr 0.00148, Entropy cost 0.0006, Momentum 0, Grad Clip 40, Reward Clipping |
| CUR    | Batch size 8, λ 0.95, γ 0.99, lr 0.001, No feature learning, Entropy coeff. 0.001, External coeff. 0, Internal coeff. 1 |
| PPO    | Batch size 8, γ 0.99, Grad Clip 5, λ 0.95, Entropy coeff. 0.03, Clip ratio 0.2 |
| SAC    | Batch size 64, lr 0.00025, γ 0.99, Entropy coeff. 0.01, Grad Clip 5 |

Usefulness of VECA Toolkit. To show that our VECA toolkit covers a diverse domain of tasks with variable difficulty, we pick several representative toolkit-generated tasks assessing distinct cognitive skills, and train VECA agents on them with PPO and SAC. Diverse tasks and their domains that we evaluate include GrabBlock for joint-level control, ObjectNav for navigation and visual recognition, KickSqueakyBall for multimodal learning, and MultiAgentNav for multi-agent RL. We vary task difficulty by changing the level design of the task environment, e.g., more complex indoor scenes. Refer to Table 2 for task descriptions, and Table 3 for the hyperparameter setup of RL algorithms. Results in Figure 7 show that these tasks are trainable, and the difficulty level is controllable.

Conclusion & Future Works

We introduced a new VECA toolkit that can generate diverse and distinct cognitive tasks for a human-like agent. Using our toolkit, we developed a novel VECA benchmark that measures the overall cognitive development of an AI agent for the first time. Our evaluation with the VECA benchmark revealed that current RL algorithms need a significant improvement to acquire general cognitive skills like a human.

In future works, we plan to extend our benchmark to the different Language and Motor Scales of Bayley-4, and test cognitive models beyond RL agents, e.g., NLP models, planning, and cognitive architectures. To evaluate the fidelity of our VECA toddler agent to the real human toddler, we also plan to motion-capture a human toddler’s movement and compare it with the motion dynamics of our VECA agent.

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