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Predictive Learning of Sensorimotor Information as a Key for Cognitive Development

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***Abstract*— Inspired by cognitive and psychological studies, many computational models have been proposed for enabling robots to learn and develop like human infants. Sensorimotor contingencies have been suggested to play a key role in cognitive development in both humans and robots. However, there are a variety of contingency models designed for specific tasks and scenarios, yet no unified architecture has been presented that can produce continuous development or account for the link between different levels of cognitive abilities. We suggest that predictive learning of sensorimotor information is a core mechanism for learning contingencies and thus enables infants and robots to acquire various types of cognitive functions such as self-other detection, goal-directed action, helping behavior, etc. This paper first presents a theory for cognitive development based on predictive learning and gives three examples of robot experiments to support it. We then extend the theory to discuss a potential underlying mechanism of developmental disorders. This theory suggests that difficulties in social interaction in autism spectrum disorder might be caused by a different tolerance for prediction error from that of typically developing people.**

I. Introduction

A promising approach for designing cognitive mechanisms for robots is learning from human cognition. Researchers can especially gain insights into the principle of human intelligence by investigating the developmental mechanisms of infants. Among the various theories about infant development, contingency learning has recently attracted a great amount of attention from researchers [1], [2]. Contingency is defined as the co-occurrence of two consecutive states or the triadic relationship between the states and an action that produces the state change. Many behavioral studies have shown that infants are sensitive to contingencies and exploit them to effectively interact with the environment [3], [4].

Inspired by developmental studies, robotics researchers have proposed various types of computational models for robot development [5]–[7]. Object manipulation [8], self-other detection [9], [10], imitation [11], and joint attention [12]–[14] have been achieved in robots by employing contingency learning. However, despite successful results in the above studies, no unified model has been presented to account for the underlying mechanism for continuous development. It is supposed that infants are endowed with limited innate capabilities yet can acquire various types and levels of cognitive functions by applying their inherent abilities to multiple modalities, tasks, and situations. Previous computational models, in contrast, focused on specific tasks and scenarios; thus, the scalability of these models is difficult to assess.

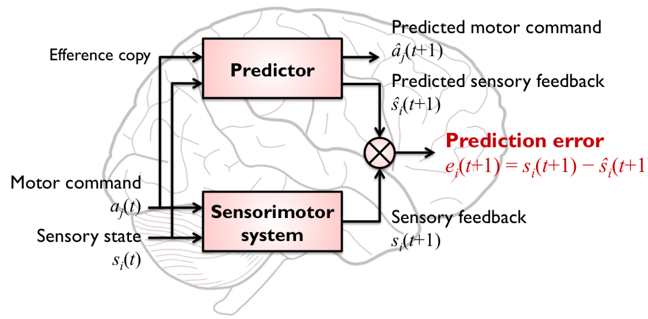

Fig. 1. A basic architecture of predictive learning of sensorimotor information. The predictor learns to predict sensorimotor signals ($\hat{s}_i(t+1)$ and $\hat{a}_j(t+1)$) at time $t+1$ based on the current signals ($s_i(t)$ and $a_j(t)$) at t. The actual sensory feedback $s_i(t+1)$ obtained from the sensorimotor system at $t+1$ is used as a reference to calculate the prediction error: $e_i(t+1) = s_i(t+1) - \hat{s}_i(t+1)$. The goal of predictive learning is to minimize $e_i(t+1)$.

We propose a theory for cognitive development based on predictive learning of sensorimotor information. Predictive learning is defined as a process to minimize a prediction error, which is calculated as the difference between an actual sensory feedback and a predicted one. For example, infants come to be able to differentiate themselves from others and to intentionally control their own bodies by updating their internal model though the minimization of a prediction error. Minimizing an error caused by the observation of others' actions leads to social behaviors such as imitation and helping actions. This paper presents a theory based on predictive learning and shows how robots can acquire different levels of cognitive functions through sensorimotor predictive learning. The theory is further extended to explain an underlying mechanism of autism spectrum disorder. We suggest that atypical tolerance for a prediction error might be a cause of their social difficulties.

II. A Theory for Cognitive Development Based on Predictive Learning

A. Basic Architecture of Predictive Learning

It has been suggested that the human brain creates an internal model of the world [15]. Through interaction with the environment, humans learn to acquire an internal model based on sensorimotor experiences to control their own body and to simulate the dynamics of the environment. Recent studies in neuroscience further revealed that the

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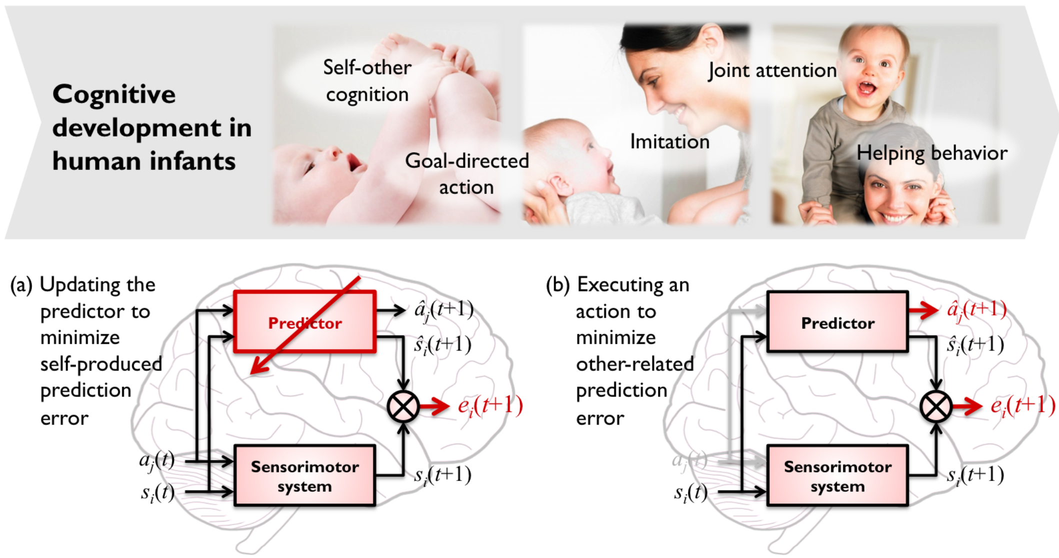


Fig. 2. Cognitive development in human infants (top) and predictive learning as an underlying mechanism for development (bottom). The first phase of predictive learning ((a) at the bottom) is an update of the predictor through minimizing the prediction error $e_i(t+1)$, which is mainly caused by the immaturity of infants' own actions. This process allows infants to acquire the abilities of self-other cognition, goal-directed action, etc. The second phase ((b) at the bottom) is the execution of the motor command $\hat{a}_j(t+1)$ produced by the predictor to minimize $e_i(t+1)$. In this phase, $e_i(t+1)$ is mainly caused by the weak predictability of others' actions; therefore, minimizing it leads to social behaviors such as imitation and helping actions.

internal model represents information in a predictive manner [16], [17]. Predictive coding of sensorimotor signals enables humans to effectively react to the environment.

Figure 1 illustrates a basic architecture for predictive learning that is modified from [18]. The architecture consists of two modules: The first one (bottom) is the sensorimotor system (i.e., the body), which produces the sensory feedback $s_i(t+1)$ of target i at time $t+1$ in response to the current sensory state $s_i(t)$ and the motor command $a_j(t)$ at t. The target i can be any entity (e.g., one's own body, other individuals, and objects in the environment) perceived by sensory systems such as vision, audio, tactile, and somatic senses. The second module (top) is the predictor (i.e., the internal model of the body), which receives $s_i(t)$ and the efferent copy of $a_j(t)$, and then predicts both the sensory state $\hat{s}_i(t+1)$ and the motor command $\hat{a}_j(t+1)$ at $t+1$. Unlike traditional theories of predictive coding [16]–[18], this architecture supposes that the predictor predicts not only sensory states but also motor signals, which are employed to properly react to the environment. The goal of predictive learning is to minimize the prediction error $e_i(t+1)$, which is calculated as the difference between $s_i(t+1)$ and $\hat{s}_i(t+1)$:

$$e_i(t+1) = s_i(t+1) - \hat{s}_i(t+1). \quad (1)$$

B. Cognitive Development through Predictive Learning

We propose a theory for cognitive development based on predictive learning. Figure 2 represents cognitive behaviors infants acquire in the first few years of life (top) and the architecture of predictive learning as the underlying mechanism for development (bottom). There are mainly two phases in predictive learning ((a) and (b) at the bottom of Fig. 2), which are associated with different cognitive functions (note that the two phases are interlinked during development):

1) Updating the predictor to minimize self-produced prediction error: The first phase is an update of the predictor through the sensorimotor experiences of infants' own actions (see Fig. 2 (a)). Infants are born with an immature predictor that does not allow them to know where to detect their own body or how to control it. For example, young infants often gaze at their hands and feet, and put them into their mouth in order to obtain multimodal perceptions of their body. Such experiences allow them to learn the internal model of their body (i.e., body image [19]) by minimizing the prediction error $e_i(t+1)$. This process also leads to the development of self-other cognition [20]. One's own body is recognized as a perfectly predictable target after acquiring the body image, whereas the bodies of other individuals are recognized as weakly predictable—but not unpredictable owing to social relationship—targets. Thus, infants become able to differentiate themselves from others, and social partners from non-social objects by comparing their predictabilities.

Goal-directed actions such as reaching and grasping an object are also acquired by updating the predictor. Neonates seem to not yet have intentions or desired goals; thus, they only produce reflexes or seemingly random motions (i.e., so called body babbling). Once they accidentally produce an interesting outcome during their movement, they target it as a goal of their actions and try to reproduce it by repeating the movement [21]. This behavior becomes more intentional and accurate through the improvement of the predictor.

2) Executing an action to minimize other-related prediction error: The second phase of predictive learning is the execution of the motor command $\hat{a}_j(t+1)$ produced by the predictor in order to minimize the prediction error $e_i(t+1)$ (see Fig. 2 (b)). The predictor is employed not only when executing infants' own actions but also when observing others' actions; however, infants do not necessarily differentiate them. If the predictor is still too immature to differentiate themselves from others, infants perceive actions presented by others as if the actions were their own. Such assimilation of one's self and others (correspondence between them in the later stage) enables infants to recognize others' actions and to predict the goal of the actions based on their internal model. Of particular interest here is that the predictor behaves like a mirror neuron or mirror neuron system [22], [23]. As the predictor learns to associatively predict sensorimotor signals, the observation of others' actions $s_i(t)$ induces not only the next sensory state $\hat{s}_i(t+1)$ but also the corresponding motor command $\hat{a}_j(t+1)$ like the activation of mirror neurons.

Executing $\hat{a}_j(t+1)$ then leads to the emergence of social behaviors such as imitation and helping actions. As mentioned before, actions generated by other individuals are not perfectly predictable and thus produce a certain level of prediction error even after updating the predictor. This prediction error $e_i(t+1)$ triggers the execution of the predicted action $\hat{a}_j(t+1)$ to minimize $e_i(t+1)$. Imitation, for example, is achieved by generating $\hat{a}_j(t+1)$ as a motor output while other individuals are still performing the actions. Helping behaviors, which seem to require higher cognitive capabilities, can be also generated by the same mechanism. If others fail in achieving actions or take a longer time to perform them, infants detect a large prediction error $e_i(t+1)$ that motivates the infants to execute $\hat{a}_j(t+1)$ in order to minimize $e_i(t+1)$. This resultant behavior looks as if infants help others though they may not have such an intention. This theory suggests that infants' social behaviors might originate from non-social motivation (i.e., minimizing the prediction error) rather than from social motivation.

III. Case Studies of Robot Development Based on Predictive Learning

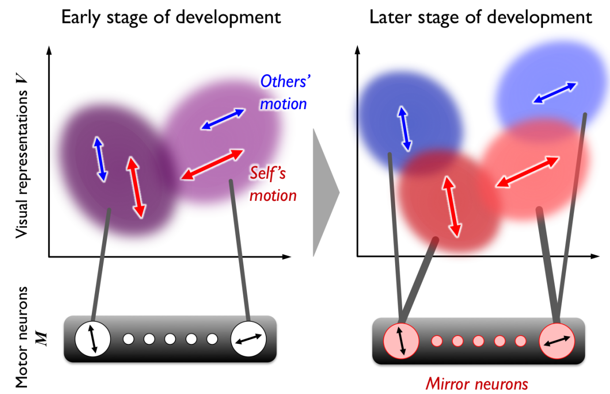
This section presents previous robotic experiments to support this theory: self-other cognition and goal-directed action are given as examples for the first phase of predictive learning (Fig. 2 (a)), while the emergence of helping behavior is given as an example for the second phase (Fig. 2 (b)).

A. Emergence of Mirror Neuron System through Development of Self-Other Cognition

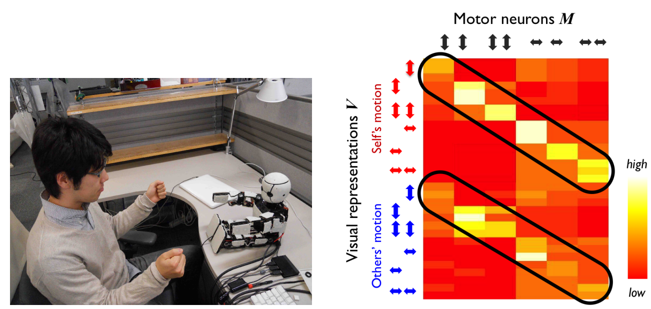
As described in Section II-B, the self and others can be differentiated by their predictabilities. One's own behavior is almost perfectly predictable whereas others' behaviors are less predictable. We hypothesized that the ability of self-other cognition develops through the process of updating the predictor and that mirror neuron systems emerge as a by-product of self-other cognition.

Figure 3 (a) depicts a computational model for the development of self-other cognition [24], [25]. A robot learns the predictor by associating motor neurons $\boldsymbol{M}$ with visual representations $\boldsymbol{V}$ through interactions with a caregiver (see the left picture in Fig. 3 (b) for the experimental setting). In the early stage of development (the left part of Fig. 3 (a)), the robot has immature perceptual ability like young infants and thus cannot differentiate motions produced by itself and others. They are categorized in the same cluster in the visual space despite their differences in spatial positions and temporal delay. However, as the robot develops, it gradually improves its perception and discriminates its own motions from those performed by others (the right part of Fig. 3 (a)). This developmental change from self-other assimilation to self-other discrimination enables the robot to acquire mirror neuron-like systems. Motor neurons $\boldsymbol{M}$ are associated with both its and others' motions owing to the non-differentiated clusters in the early stage of development. The experimental result shown in the right part of Fig. 3 (b) shows the acquired sensorimotor mapping. The strong connections between $\boldsymbol{M}$ and $\boldsymbol{V}$ for both its and others' motions represent the function of mirror neuron systems.

This model based on predictive learning sheds light on debates on the origin of mirror neuron systems. Meltzoff and Moore [26] have suggested that infants are endowed with supramodal representation in their brain, where the equivalence between the self and others are examined. Heyes [27], in contrast, proposed the associative learning theory,



(a) A computational model for the development of self-other cognition. Visual representations $\boldsymbol{V}$ are associated with motor neurons $\boldsymbol{M}$ while the acuity of visual perception gradually improves over development. This developmental change results in the association between the self's motion and others' motion via motor neurons (i.e., mirror neuron systems).



(b) Experimental setting for human-robot interaction (left) and the result of sensorimotor learning (right). The stronger associations between the self's motion and corresponding motor neurons, and between others' motion and the same motor neurons indicate capability similar to mirror neuron systems.

Fig. 3. Emergence of mirror neuron system though the development of self-other cognition based on predictive learning (adapted from [24], [25]).

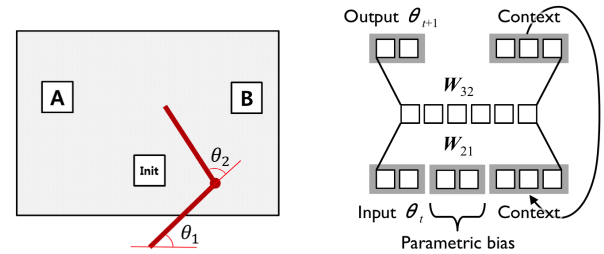
which does not suppose self-other equivalence and instead emphasizes postnatal mapping between one's own movement and others' movement. The model presented here bridges the gap between these contradicting theories; Predictive learning is a type of associative learning and utilizes self-other equivalence to facilitate the association. We suggest that this theory provides a more general architecture for mirror neuron systems.

B. Hierarchical Development of Goal-Directed Action

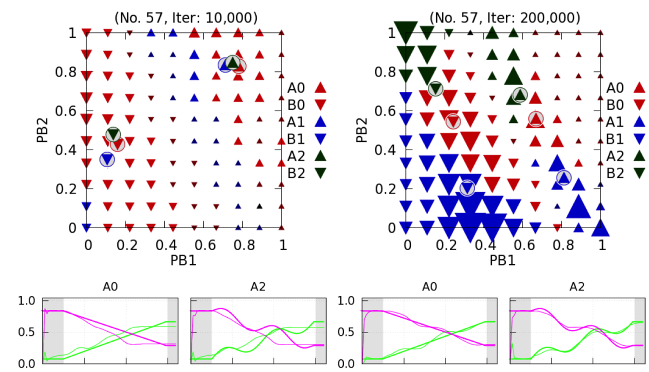
The second example is the development of goal-directed actions. Behavioral studies have shown that infants exhibit a hierarchical representation of actions [28], [29]. If the goal of an action is salient, infants tend to imitate only the goal while ignoring the means (i.e., how to achieve the goal). If the goal state is not underlined, they reproduce the process to reach the goal. These findings indicate that the goal has a higher priority than the means; thus, the goal is selectively imitated by infants.

We hypothesized that differences in the prediction error might cause the hierarchical representation of actions [30]. The goal, which is defined as the difference between the initial and final states, involves the largest change in the action, whereas the means is the process to reach the goal and therefore usually involves a smaller change. This difference between the goal and means appears in their prediction error, which affects learning speed. A larger prediction error for the goal is expected to be minimized first, whereas a smaller error concerning the means is minimized later. The process of such staged learning is considered as the hierarchical representation of actions.

To verify this hypothesis, we designed a simple reaching task for a two-link robot and trained it employing a recurrent neural network with parametric bias (RNNPB) (see Fig. 4 (a)) [30]. RNNPB [31] can memorize multiple time series of data in one network. PB values, which are static parameters, are self-organized through learning to differentiate the data patterns. Figure 4 (b) shows the close analysis of the learning process: the PB values (top) and the output of the network (bottom) after 10,000 (left) and 200,000 (right) training iterations. Here, the network was trained with six types of reaching actions: the combinations of two goals (A and B) and three means (0: straight trajectory; 1: sinusoidal curve; 2: sinusoidal curve with double frequency). The important finding is that the network exhibited a hierarchical development like infants. After 10,000 iterations of training, the RNNPB differentiated only the goals (see the left part of Fig. 4 (b)). The six circles with a triangle inside are separated only into two groups: (A0, A1, A2) and (B0, B1, B2). The output of the RNNPB also reproduced only the goal of the actions. After 200,000 iterations of training, the RNNPB finally differentiated all six actions (see the right side of Fig. 4 (b)). The output of the network now accurately imitated both the goal and means. Although such nonlinear development was not explicitly designed in this model, predictive learning produced a hierarchical representation owing to the different dynamics of the actions.



(a) Experimental setting for a reaching task (left) and a recurrent neural network used for robot learning (right). A two-link robot learns to reach for the targets (A and B) using three different means. The network allows the robot to acquire multiple actions by differentiating parametric biases.



(b) Analysis of the parametric biases (top) and the output of the network (bottom). After 10,000 iterations of training (left), the network reproduces only the goals but not the means. Two clusters in the PB space show the internal representation. The network after 200,000 iterations of training (right) finally reproduces both the goal and means.

Fig. 4. Hierarchical development of goal-directed action based on predictive learning (adapted from [30]).

C. Emergence of Helping Behavior

The third example is the emergence of helping behavior. In contrast to the above two experiments, which focused on the process of updating the predictor (i.e., the first phase of predictive learning), this experiment demonstrates how a predicted action can be utilized to generate social behaviors (i.e., the second phase of predictive learning). Behavioral studies revealed that helping behaviors are already observed in 14-month-old infants [32], [33]. For example, if an experimenter drops a clothespin on the floor while hanging a towel, infants approach the experimenter and hand over the pin to him. In another situation, if infants see an experimenter trying to put books into a closed shelf, they come to open the door so that the experimenter, whose hands are occupied with the books, can pursue his desired action. Interestingly, these pro-social behaviors are voluntarily generated. Infants help others even without receiving social signals (e.g., gesture and speech) requesting their help or offering a reward for their helping actions. Psychologists have suggested that infants' pro-social behaviors might be motivated by their understanding of others' intention (called emotion-sharing theory) and/or by their recognition of others' goal (called goal-alignment theory) [34]. The former theory assumes the ability to estimate others' internal minds, whereas the latter requires only the ability to process observable events.

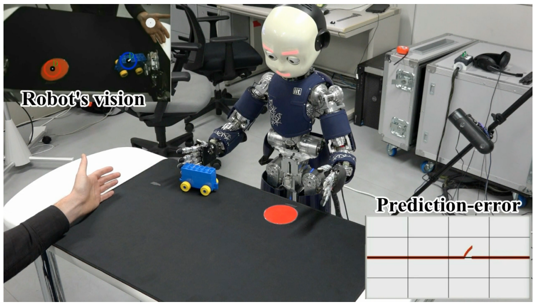


Fig. 5. Emergence of helping behavior based on predictive learning. The robot is pushing a blue car on behalf of the person because the person could not fulfill the goal. The increased prediction error shown at the bottom right corner triggers an execution of the robot's action.

We proposed a robotic model inspired by the goal-alignment theory [35]. The key idea was that a robot produces helping actions by minimizing a prediction error. The robot first acquires action repertoires through updating the predictor. The acquired predictor is then used to predict the future state of observed others' actions and to estimate a prediction error regarding the actions. If other individuals successfully perform the task, the prediction error remains small. If they fail in achieving the task, the prediction error increases, which triggers the robot's action. Figure 5 shows an experiment where the humanoid robot iCub pushes a blue car on behalf of the person stretching his left arm. As the blue car was too far for the person to push, the robot detected an increased prediction error as shown at the bottom right corner in Fig. 5, and then executed the predicted action (i.e., pushing the car). This result suggests that seemingly pro-social behaviors can emerge from non-social motivations, such as the minimization of prediction error.

IV. Autism Spectrum Disorder Caused by Atypical Tolerance for Prediction Error

The robotic experiments described in Section III demonstrated the importance of predictive learning in cognitive development. The next question is whether the theory of predictive learning can account for the underlying mechanism of developmental disorders.

Autism spectrum disorder (ASD) is characterized by difficulties in social communication (e.g., establishing joint attention and understanding others' intentions) [36]. While traditional research has focused on the social aspects of ASD, recent studies closely investigated atypical perception [37] and atypical information processing in ASD [38], [39]. The hypotheses called 'weak central coherence' [38] and 'difficulty in sensorimotor integration' [39] suggest that a weaker ability to integrate information and/or a stronger ability to process primitive features may cause social deficiencies in ASD. As sensorimotor information is processed hierarchically in the human brain, an imbalance between the higher and lower levels could result in a difficulty in acquiring higher cognition (i.e., social cognition).

Inspired by the above hypotheses, we propose a computational model of ASD. Figure 6 illustrates the conceptual

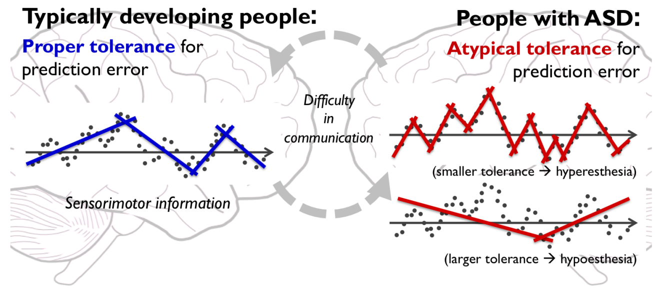


Fig. 6. A potential underlying mechanism for ASD. Typically developing people (left) apply a proper tolerance for prediction error and thus acquire appropriate internal models with adaptability (multiple lines in the left graph). People with ASD (right), on the other hand, adopt a smaller or a larger tolerance for prediction error and thus obtain strictly or loosely fitting models without adaptability or reactivity (the upper and lower graphs in the right part, respectively). Such differences in their internal models may cause difficulties in social interaction.

model based on the theory of predictive learning. Let us assume that sensorimotor signals are represented as data points in the graphs, and internal models using linear regression are applied to recognize the signals. According to [39], people with ASD seem to have an atypical tolerance for prediction error. Typically developing people adopt a proper tolerance for prediction error, as seen in the left part of Fig. 6, and thus acquire adequate internal models. The models represented by multiple lines loosely fit the data points, indicating that they can easily adapt to environmental changes. In contrast, people with ASD obtain different internal models from typically developing people (see the right part of Fig. 6). Their tolerance for prediction error is either too small or too large. A smaller tolerance generates strictly fitting models with lower adaptability (the upper graph), whereas a larger tolerance results in loosely fitting models with less reactivity (the lower graph). These two types bear analogy to hyperesthesia and hypoesthesia, respectively, which are commonly observed in ASD. We suggest that ASD shares the common underlying mechanism for cognition with typically developing people but appears as two extremes due to their atypical tolerance [40].

This model further provides an insight into the mechanism of social deficiencies. Figure 6 indicates that social difficulties are caused by the difference between the internal models of typically developing people and those of people with ASD, rather than by disabilities in ASD. In other words, people with and without ASD should be able to communicate if they share internal models and a perceptual world. To verify this, we have been developing a head-mounted display system to simulate atypical perception in ASD [41]. This system allows typically developing people to experience atypical perception and thus share, though not exactly the same, internal models with ASD. We aim to further investigate the influence of atypical tolerance for predictive error on social abilities.

V. Conclusion

This paper has proposed a theory for cognitive development based on predictive learning. Minimizing prediction error by updating the predictor and/or executing a predicted action leads to the development of cognitive functions. Robotic experiments provided supportive results for it: The abilities for self-other detection, goal-directed action, and helping behavior were successfully acquired by robots through sensorimotor predictive learning.

The theory, however, has a limitation in producing higher cognition. The computational model for helping behavior, for example, does not suppose the differentiation between the self from others. In order to enable a robot to recognize observed others' actions based on its internal model, we assumed that the robot does not discriminate the self from others despite their different perspectives. To cope with this issue, we intend to integrate all models with self-other cognition (i.e., the first model) so that the robot can ensure the correspondence between itself and others, which is a basis for social cognition.

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