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Social Affordance Tracking over Time - A Sensorimotor Account of False-Belief Tasks

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Abstract

False-belief task have mainly been associated with the explanatory notion of the theory of mind and the theory-theory. However, it has often been pointed out that this kind of high-level reasoning is computational and time expensive. During the last decades, the idea of embodied intelligence, i.e. complex behavior caused by sensorimotor contingencies, has emerged in both the fields of neuroscience, psychology and artificial intelligence. Viewed from this perspective, the failing in a false-belief test can be the result of the impairment to recognize and track others' sensorimotor contingencies and affordances. Thus, social cognition is explained in terms of low-level signals instead of high-level reasoning. In this work, we present a generative model for optimal action selection which simultaneously can be employed to make predictions of others' actions. As we base the decision making on a hidden state representation of sensorimotor signals, this model is in line with the ideas of embodied intelligence. We demonstrate how the tracking of others' hidden states can give rise to correct false-belief inferences, while a lack thereof leads to failing. With this work, we want to emphasize the importance of sensorimotor contingencies in social cognition, which might be a key to artificial, socially intelligent systems.

Keywords: social cognition, sensorimotor signals, affordances, false-beliefs, theory of mind.

Introduction

Social cognition benefits highly from our ability to infer and predict others' percepts and future actions. Such inferences have been postulated to occur on two levels; low-level sensorimotor contingencies (SMCs) and high-level goal and mental state inferences. While the former phenomenon has been explained with help of the simulation theory (ST) and embodied cognition, the later inferences are commonly addressed with help of the theory-theory (TT) and accounts of the theory of mind (ToM) (Dindo, Donnarumma, Chersi, & Pezzulo, 2015). While the simulation theory is supported by biological concepts such as mirror neurons, the ToM is rooted in psychological approaches to social cognition.

One cornerstone of the theory of mind are "false-belief tests", which, according to the TT approach, necessitate the ability to track and infer others' mental states, beliefs and intentions. Since both young children and autistic children fail false-belief tasks to a great extent, these tests are usually presented as a measure of advanced social intelligence. A recent proposal, however, views false-belief tasks in the light of SMCs, with an emphasis on social affordances and working memory (Brincker, 2014). Instead of tracking and inferring others' mental states, which is computationally expensive, the memory of past affordances, individual and shared, could be involved in false-belief inferences. As social SMCs and affordances belong to low-level cognitive mechanisms, the tracking of these signals comes at a lower cost than mentalizing. While executive functions are of relevance for false-belief tasks, see e.g. (Devine & Hughes, 2014), we want to emphasize the importance of the understanding and incorporation of others' SMCs into action prediction.

In this work, we investigate whether low-level social SMC signals can give rise to false-belief inferences, a phenomenon commonly believed to be caused by high-level cognitive reasoning. To this end, we develop a computational model that demonstrates how the tracking of social affordances allows for false-belief inferences. In order to include the temporal evolution of social interaction and make use of the predictive nature of cognition as proposed by the ST, we make use of a Bayesian generative model which, based on hidden variables and prior knowledge, selects the optimal action towards a given goal. While the presented model is generally applicable and not confined to false-belief tasks, we demonstrate its generative power with help of the well-known Sally-Anne test.

False-Belief Tasks and the Theory of Mind

The Sally-Anne story goes as follows. Sally and Anne are playing with a marble and two boxes, box A and B. Sally puts the marble into box A and leaves the room. In her absence, Anne takes the marble from box A and puts it into box B. Upon Sally's return, the question is: Where will Sally look for the marble? In a clinical or research setting, this story is often either demonstrated with help of a pair of dolls or illustrated with a comic stripe. Participants, asked where Sally will look for the marble, can give two answers. When passing the false-belief test, they successfully infer that Sally can by no means know that Anne moved the marble. Thus, they infer that Sally carries the false-belief that the marble is still in box A, as this is the location where she put it. Failing the false-belief test on the other hand implies that this inference is not accomplished. Instead, the actual current location of the marble, box B, is pointed out to be the goal of Sally's next action.

In an early study, Baron-Cohen et al. (Baron-Cohen, Leslie, & Frith, 1985) showed that healthy children and children with Down syndrome are able to pass the Sally-Anne test in 85-86 % in all cases, while autistic children pass only in around 20 % of all trials. These and other findings have led to the belief that autistic children lack the ability to infer others' mental states and to develop, if at all, this trait later than their peers. Furthermore, even healthy children pass explicit false-belief tests only from an age of two-five, which is interpreted as a developmental account of a theory of mind (Apperly, 2012).

In the view of the TT and ToM, mind reading is the ability of humans to understand others' beliefs, desires, intentions and mental states by logically reasoning about their behavior with help of mental theories of the human mind. In the Sally-Anne story, Sally's desire to obtain the marble is hindered by her false-belief about the location of the object. The interpretation of ToM with respect to the role of mental states and beliefs differs within the research community (Apperly, 2012). This difficulty is only enhanced due to the fact that different false-belief tasks test varying aspects of ToM and subjects show diverging performances in different tests.

Hence, we claim here that TT can not fully account for the experimental evidence of false-belief tasks. Instead, the understanding of others' SMC signals as well as executive cognitive processes and low-level action constraints, such as spatial and temporal conditions and goal-directedness, have to be considered (Butterfill & Apperly, 2013).

Computational Approaches to False-Belief Tasks

In order to gain more understanding of the underlying dynamics of ToM, computational models can help to identify the essential variables that give rise to correct predictions. We will here focus on three models concerned with explicit (Goodman et al., 2006) and implicit (Berthiaume, Onishi, & Shultz, 2008) false-belief tasks and a Human-Robot Interaction (HRI) setting (Ferreira, Milliez, Lefevre, & Alami, 2015). While ToM has also been addressed with help of inverse reasoning, e.g. inversion of Partially Observable Markov Decision Processes (POMDP) (Baker, Saxe, & Tenenbaum, 2011), these approaches have not been applied to a false-belief setting.

A probabilistic account of ToM has been developed by Goodman et al. (2006). With the help of Bayesian networks, two models, the copy theorist (CT) and the perspective theorist (PT), are compared. Both of these models incorporate variables representing the world state, beliefs and desires of an actor, while only the perspective theorist has access to a variable indicating visual access. Manually defined, discrete probability distributions over mutual influences of these variables allow for the derivation of a posterior distribution over beliefs and desires given the observed events and actions. Additionally, the surprise about an observation can be determined. As the CT is less complex, it is not able to represent a false-belief, resulting in a high level of surprise when Sally is looking into the original box. The PT on the other hand, predicts the false-belief correctly. Due to hand-picked probability distributions and the additional information of visual access, the PT succeeds in the false-belief task. However, the superimposed structure, simplicity of the model and lack of temporal dynamics prohibit reliable conclusions about the applicability of this model.

In contrast to the probabilistic viewpoint Berthiaume et al. (2008) approached the implicit ToM, the idea that humans automatically and implicitly track others' mental states, with a neural network. To train networks with different numbers of hidden unit layers, they presented the models with the state and action data of an implicit Sally-Anne version. The training data was corrupted by adding incorrect samples. While networks with no hidden units were not able to capture false-beliefs, deeper networks could more reliably predict the behavior of the agents. Due to the nature of neural networks, the performance increased with an increasing amount of training samples. Furthermore, the results hint that the networks represented the statistics of the generated training data, with error rates matching the added noise. Although implicit knowledge should be more intuitive than explicit, conscious reasoning, it is dubious that this ability does only depend on correlations of observations. Instead, the internal motivation to predict the actions of other agents and to engage in interaction seems to be an important factor.

The examples introduced above function on the basis of belief-desire inference on the one hand and correlations on the other hand. As stated in the introduction, we propose taking a sensorimotor approach towards false-belief inferences. One recent example of this idea has been introduced by Ferreira et al. (2015) in a HRI setting. Applying two independent POMDP for the robot and human action space respectively, which use estimates of visual and reachable space to determine hidden state information, this system is able to interact with a human in a false-belief setting. By comparing manually designed and learned behavior, the authors conclude that learning results in faster and more reliable predictions. Furthermore, a system that incorporates knowledge about the humans belief space reacts faster towards misunderstandings. Nevertheless, the differences in performance between belief incorporation and its absence are not significant. The advantages in conversation speed might be balanced by the additional computational load during the learning period. Additionally, the focus lies on successful communication while predictive power and a deeper analysis of the system are not presented.

A Sensorimotor Approach to Social Inference

The application oriented approach towards false-belief inference based on visibility and reachability by Ferreira et al. (2015), points towards the explanatory power of sensorimotor signals in a social context. Even Goodman et al. (2006) and Berthiaume et al. (2008) conclude that visual access is an important factor. Without this variable, both belief and desire are not sufficient to account for false-belief inferences.

Thus, we propose that the theoretical considerations concerning ToM in such simple false-belief tasks as the Sally-Anne test need to be revised. Instead of high-level reasoning

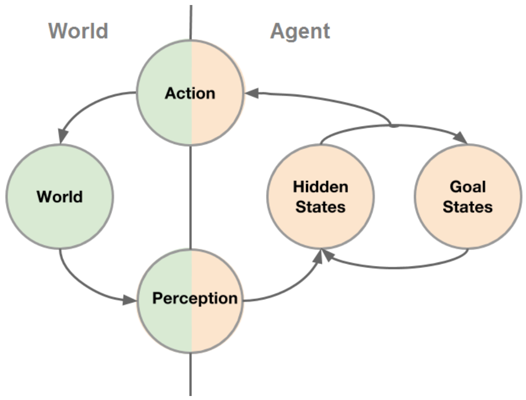

Figure 1: A simplified version of active inference: The agent is connected to the world through sensorimotor channels. Actions are chosen to minimize the distance between approximated hidden state and goal state distributions. The hidden states are thought to represent hidden causes of events in the world.

about mental states we suggest that tracking of SMCs and affordances over time is the primary factor for successful inference.

Inspired by the ideas of predictive coding (Kilner, Friston, & Frith, 2007) and active inference (Friston, Mattout, & Kilner, 2011) in the context of social cognition, we propose a generative model of optimal action selection which can also be employed for optimal action prediction of a co-actor. According to active inference, the human mind is prone to minimize uncertainty about the world state and sees actions as an inferential process to fit internal state distributions to goal distributions. The coupling between an agent and the world is accomplished through sensorimotor channels as shown in Figure 1. Since both actions and hidden causes can give rise to changes in the world, the hidden state distributions are approximating these hidden causes.

Assuming that interaction partners are equipped with a similar probabilistic inference machine, others' actions can be predicted with help of prior knowledge about their social SMC signals and hidden and goal states. Since the consideration of other agents reduces uncertainty about future world states significantly, these automatic mechanisms might account for many aspects of social cognition. Implicit tracking of others' sensory input and affordances is vital for both low-level and high-level interaction. We propose that failing in false-belief task is less caused by the lack of ToM than by the inability to identify and memorize others' social SMC histories. In this case, estimates of the hidden state distributions of the co-actor are impaired and have to be approximated by ones own internal distributions at the current time. As the hidden state distributions differ in the context of false-belief tasks, such an assumption leads to incorrect inferences. In the following, we will introduce a generative model that can imitate both of these behaviors.

The Model

Our generative model is based on a joint distribution over observations and hidden states. Actions based on the current hidden state estimates will have an effect on the actual environment. Optimal action selection is performed in two steps. Firstly, the current observations are incorporated into the distribution over hidden states. Secondly, the optimal action, which minimizes the distance between a given goal distribution and the updated hidden state distribution, is sought. The found optimal action is then executed. In a Bayesian fashion, prior beliefs can be incorporated into the hidden state distribution and affect action selection in a top-down manner. In a further step, this model can be used to predict the actions of an interaction partner by using the same mechanisms but different distributions over hidden states. Thus, instead of inferring beliefs and desires, action prediction is based on approximations of hidden states that represent SMC signals.

Mathematical Notation To clarify the mathematical notation, let $\mathbf{v} \in \mathbb{R}^n$ be a column vector of dimension n and $\mathbf{v}^T$ denote the transpose. Equivalently, let $\mathbf{M} \in \mathbb{R}^{n,m}$ represent a matrix with n rows and m columns. The dimensions of a vector are indexed by v^i for $i \in [1,..n]$, while a matrix entry is indexed by $m^{i,j}$ for $i \in [1,..n]$ and $j \in [1,..m]$. Furthermore, let the index $t \in [1,..T]$ indicate the time step ranging from 1 to T, such that $\mathbf{v}_t$ is a vector at time t. The time index for a single vector in a set of N vectors $\{\mathbf{v}_t\}_N$ is represented by $\mathbf{v}_{t,k}$ for $k \in [1,..N]$.

Our generative model consists of a discrete vector representing the actual world state $\mathbf{w} \in \mathbb{R}^{N_w}$. Due to the noise inherent in perceptual channels, let an observation $\mathbf{o} \in \mathbb{R}^{N_o}$ be a representation of the world state with added noise such that for each dimension i we have

$$o_t^i = w_t^i + \varepsilon^i, \quad \varepsilon^i \sim \mathcal{N}(0, \sigma_i), \tag{1}$$

where $\mathcal{N}(\mu, \sigma)$ denotes the normal distribution with mean μ and variance σ and σ_i is the variance belonging to the ith dimension. Let the hidden states be represented by a set of N_s normal distributions, denoted by $\{\mathbf{s}_t\}_{N_s}$, and each kth hidden state consist of N_f features such that

$$\mathbf{s}_{t,k} \sim \mathcal{N}(\mu_k, \Sigma_k), \tag{2}$$

with mean $\mu_k \in \mathbb{R}^{N_f}$ and covariance matrix $\Sigma_k \in \mathbb{R}^{N_f,N_f}$. Finally, an agent is equipped with a set of N_a actions a_k for $k \in [1,..N_a]$ that produce changes in the environment.

Integration of new observations In this discrete setting, the joint probability distribution over hidden states and observations $P(\mathbf{o}_t, \{\mathbf{s}_t\}_{N_s})$ at time t is defined as a mixture of Gaussians

$$P(\mathbf{o}_t, \{\mathbf{s}_t\}_{N_s}) = P(\mathbf{o}_t | \{\mathbf{s}_t\}_{N_s}) P(\{\mathbf{s}_t\}_{N_s}) \tag{3}$$

$$= \sum_{k=1}^{N_s} P(\mathbf{o}_t | \mathbf{s}_{t,k}) P(\mathbf{s}_{t,k}). \tag{4}$$

Assume that the conditional distribution of the observation given the hidden states is multinomial distributed. Let the parameters of this distribution be a linear combination of the observations with a weight vector $\mathbf{u}_i \in \mathbb{R}^{N_o}$ that depends on the respective hidden state such that

$$P(\mathbf{o}_t|\mathbf{s}_{t,k}) = \frac{\mathbf{u}_k^T \mathbf{o_t}}{\sum_{l=1}^{N_s} \mathbf{u}_l^T \mathbf{o_t}}. \tag{5}$$

If the weight vectors have been determined, through learning or manual design, the update of the joint distribution $P(\mathbf{o}_{t+1}, \{\mathbf{s}_{t+1}\})$ is accomplished by inserting the new observation $\mathbf{o}_{t+1}$ into Eq. 3.

Optimal action selection Action selection is based on the minimization of the distance between a given goal distribution $P_{goal}(\mathbf{o}^*_{t+1}) \sim \mathcal{N}(\mathbf{o}^*_{t+1}, \sigma_{goal}\mathbf{I})$ and the joint probability distribution $P(\mathbf{o}_{t+1}, \{\mathbf{s}_t\}_{N_s})$. Let this distance be defined as the L^2 vector norm of the distance between the mean vectors of both distributions. Since this model is operating in a defined action space, let us assume, that an action a_k produces a discrete, deterministic hidden state $\hat{\mathbf{s}}_{t+1} = Q(\mathbf{s}_{t+1}|\{\mathbf{s}_t\}_{N_s}, a_k)$, where Q denotes a transition function. Then, Eq. 4 at time $t+1$ turns into

$$P(\hat{\mathbf{o}}_{t+1}, \hat{\mathbf{s}}_{t+1}) = \sum_{k=1}^{N_s} P(\hat{\mathbf{o}}_{t+1}|\hat{\mathbf{s}}_{t+1}) \mathcal{N}(\hat{\mathbf{s}}_{t+1} : \mu_k, \Sigma_k), \tag{6}$$

where $\mathcal{N}(\hat{\mathbf{s}}_{t+1} : \mu_k, \Sigma_k)$ denotes the kth Gaussian evaluated at $\hat{\mathbf{s}}_{t+1}$. Define $\mathbf{p} \in \mathbb{R}^{N_s}$ to be a vector consisting of the evaluations of the N_s Gaussian distributions. Then, the approximated observation is given by

$$\hat{\mathbf{o}}_{t+1} = \mathbf{U}^{-T}\mathbf{p}, \tag{7}$$

where the matrix $\mathbf{U}$ consists of the stacked weight vectors $\mathbf{u}$. The optimal action is therefore selected by determining which resulting approximate observation minimizes the L^2 vector norm

$$a^* = \underset{a_k,\ k \in [1,..N_a]}{\operatorname{argmin}} \ ||(\hat{\mathbf{o}}_{t+1}|a_k) - \mathbf{o}^*_{t+1}||_2^2. \tag{8}$$

When the optimal action is performed, it results in a change of the environment as follows

$$\mathbf{o}_{t+1} = P(\mathbf{o}_{t+1}|\mathbf{s}_{t+1}) Q(\mathbf{s}_{t+1}|\{\mathbf{s}_t\}_{N_s}, a^*). \tag{9}$$

Action prediction Up to this point, the discussion was focused on the optimal action selection for a single agent. In a joint setting, the same mechanism can be used to predict the action of a co-actor. If the observing agent memorizes not only its own past hidden state distributions, but also those of its partner, the observer can use its internal models to make inferences based on this information. As we assume the hidden states to represent SMC signals and affordances, many of the hidden states are either identical or complementary, such that the tracking of the additional states is computationally cheap. Thus, we assume that any agent keeps a memory over its own hidden states up to the current time T, i.e. $\{\mathbf{s}_{1:T}\}^{own}$, and an approximation of its partners hidden states, i.e. $\{\hat{\mathbf{s}}_{1:T}\}^{other}$. This approximation is based on the information made available by the observations and prior assumptions. Since the perceptual channels of the observed agent are inaccessible, the input can only be estimated. But as both agents share the same environment, these estimations can be made under low uncertainty.

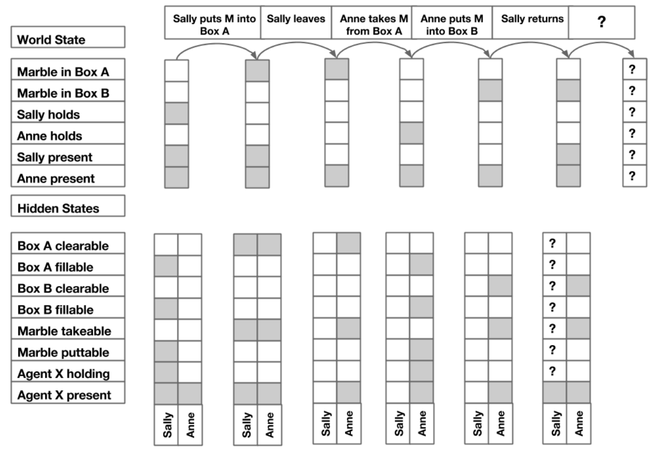

Figure 2: The Sally-Anne story enacted by our generative model. For the purpose of visualization, the noise has been removed. Dark squares indicate a value of 1 and white squares a value of 0. In the upper row, the dynamics of the story in the world state are depicted, while the lower row shows the hidden states of both agents in the view of Anne. Since Sally is gone for several time steps, her hidden states are unknown to Anne.

Experiment

The main goal of this work is to demonstrate that low-level sensorimotor signals can account for inferences in a false-belief task which are usually explained by high-level reasoning based on ToM. As the generative model presented above allows predictions of others' actions based on approximations of hidden states which represent these low-level signals, we can apply it to the Sally-Anne test. Following the idea of past affordance tracking, suggested by Brincker (2014), we aim to show that both passing and failing this false-belief task can be accounted for by prior assumptions about others' past affordances. In this scenario, we need to incorporate the two agents Sally and Anne, the objects box A, box B and marble and finally the room itself.

World Representation In order to test our generative model in a false-belief setting, we need to specify the variables world state and hidden state and the transition function describing effects of applied actions. While the former two variables are defined to be binary, with feature 0 = false and 1 = true, the later represents changes in the hidden states and world state.

Let the world state be defined as a vector with $N_w = 6$, representing the features *marble in box A*, *marble in box B*, *marble held by Sally*, *marble held by Anne*, *Sally present* and *Anne present*.

Furthermore, let each hidden state consist of $N_f = 9$ features, *box A is clearable*, *box A is fillable*, *box B is clearable*, *box B is fillable*, *marble is takeable*, *marble is puttable*, *room is leavable*, *agent X is holding* and *agent X is present*.

Finally, let the $N_a = 4$ actions be defined as *agent X takes marble from box Y*, *agent X puts marble into box Y*, *agent X leaves room* and *agent X enters room*, where X $\in$ {Sally, Anne} and Y $\in$ {A, B}.

We defined the parameters of the Gaussian distribution in the mixture model and the mapping parameters of the multinomial distribution and the transition function manually. In a more application oriented setting, these parameters could also be learned either with help of learning by demonstration or self-learning.

Sally-Anne test As our generative model is generally applicable, we were able to let the model itself enact the Sally-Anne story instead of predefining the variables manually. By defining the goal observations at each time point t according to the Sally-Anne story, the model determined the optimal action and updated the distributions in accordance with the mechanisms described above. This procedure was iteratively performed up to the point, where Sally returns to the scene. Fig. 2 illustrates the Sally-Anne story in this format.

What will Sally do next?

Upon Sally's return, we ask the question "What will Sally do next?". In order to answer this question, we made use of Anne's inferential model since this agent has knowledge about the current situation and Sally's past hidden states. Given that Sally has been absent, her hidden state representation at time t, i.e. $\{\hat{\mathbf{s}}_t\}^{Sally}$ is unknown to Anne. However, with the aim to predict her next action given that she wants to hold the marble, the hidden states need to be approximated. Anne has two alternatives. Either she replaces the missing information with her own representation at time t

$$\{\hat{\mathbf{s}}_t\}^{Sally} = \{\mathbf{s}_t\}^{Anne} \tag{10}$$

or she recalls Sally's representation at time $\tau < t$ when Sally was last present in the room, i.e.
$\tau = \max_{t'}(t' \in [1, ...t] : \{\hat{\mathbf{s}}^9_{t'}\}^{Sally} == 1 | t' < t)$,

$$\{\hat{\mathbf{s}}_t\}^{Sally} = \{\hat{\mathbf{s}}_\tau\}^{Sally}. \tag{11}$$

While this approach is similar to the copy theorist (Eq. 10) and the perspective theorist (Eq. 11) as introduced by Goodman et al. (2006), notice that our approach is not based on the notion of beliefs and desires. Furthermore, we introduce temporal dynamics which make a fluent interaction possible, while Goodman et al. (2006) work in a static environment with predefined variables and distributions. Since our idea is not following the TT approach but the ideas of ST, our agents can not be viewed as theorists. Therefore, we denote the approach of Eq. 10 as *mapping* and the past affordance incorporation in Eq. 11 as *tracking*.

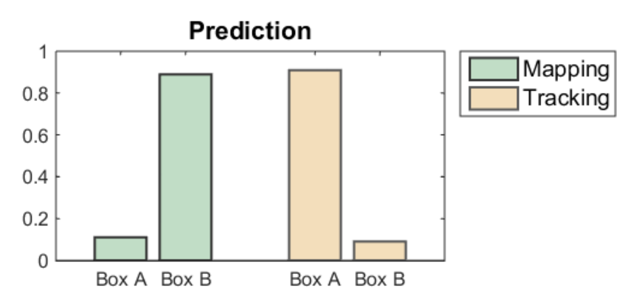

Figure 3: Predictions of the box that Sally would select based on Anne's generative model. To the left, the mapping approach demonstrates that the inference of a false-belief fails, while the tracking approach to the right correctly predicts the box into which Sally had put the marble before leaving.

Results

For the sake of reliability, we performed $N = 1000$ trials of the Sally-Anne test. Due to the induced noise in the mapping from world state to observation and the variance of the Gaussian distributions representing the hidden states, the model did occasionally fail to complete the Sally-Anne story up to the point where Sally returns, i.e. it selected incorrect actions. These trials were omitted and replaced by a newly generated, successful trial. The average of the predicted location where Sally will look for the marble is depicted in Fig. 3 for both the mapping and the tracking approach. While the mapping approach incorrectly predicted that Sally would look at the actual location in 89 % of all trials, the tracking approach correctly inferred Sally's behavior in 91 % of all trials. These results match closely those found in e.g. healthy (tracking) and autistic (mapping) children as reported in Baron-Cohen et al. (1985).

Discussion

In this work, we presented a generative model based on social SMCs which can be employed for both optimal action selection and prediction. Instead of mental state, belief and desire inferences, we hypothesize that SMCs can account for complex social behavior such as the recognition of a false-belief. In this context, the tracking of others' past affordances gives rise to successful inferences, while a failure of these basic sensorimotor functions results in incorrect predictions.

Why would the inference and tracking of others' SMCs be of advantage compared to belief and desire inferences? First of all, the two approaches have not to be seen as contradictory but as complementary. While the social SMC approach might be involved to a great extent in social behavior, high-level reasoning is also a non-negligible part of interaction. Instead, we argue for a shift from pure ToM reasoning towards the integration of essential, sensorimotor functions. As shown in this work, social SMC signals can account for complex interaction scenarios, while a lack or impairment of these functions leads to the impoverished social capabilities found in infants and autistic children. A focus on the entanglement between low- and high-level cognition in a social context might reveal important information for medical and therapeutic research.

One could argue that the memory of the world state alone would result in the same predictions. Instead of inferring an affordance space, the mere knowledge where the marble had been when Sally was present could suffice. It is important to keep in mind, that the world and agent are two separate entities, coupled through sensorimotor channels. Thus, the agent has no direct access to the location of the marble but only to the hidden state representation of hidden causes in the environment. Without the inference of the co-actor's representation, successful prediction is impaired since the representations of observer and observed are entwined but not identical.

How can such representations of others be acquired? Similar to other computational approaches towards false-belief tests, such as Berthiaume et al. (2008) and Goodman et al. (2006), we defined many parameters manually. However, with a sufficient amount of training data, the model could be learned in an adaptive fashion and be generally applicable in dynamic interaction scenarios. As two agents share a considerable amount of the hidden state space, shared latent variable models are one method that could be applied to this method. While Ferreira et al. (2015) implemented a dynamic, socially interactive system, they did not account for this redundancy in the data. A putative future extension of the presented model is therefore an actively learning system which detects shared and individual latent manifolds in the action space that effectively encode action possibilities. Such an approach is both data efficient and reduces the complexity of high-dimensional interaction spaces. Models based on social SMCs can then be employed in interactive agents that are able to master complex scenarios as e.g. a false-belief setting.

Conclusions

The Theory of Mind has a long tradition to account for complex, social behavior. Mental state inferences and the reasoning about beliefs and desires are viewed as a mile stone in mental development. Advances of the idea of embodied intelligence however have started to give a complementary explanation of social phenomena. In this work, we demonstrated how the tracking of others' SMCs and affordances can be involved in certain false-belief inferences. This low-level approach to high-level cognition can clear the way for artificial agents in which social intelligence emerges naturally through the coupling between action and perception. Furthermore, a deeper insight in the underlying dynamics of social interaction results in valuable information for medical and psychological research and applications. In conclusion, sensorimotor signals are vital for social interaction. Their incorporation into theoretical frameworks of social intelligence is an important step towards an embodied understanding of social communication.

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