AISB 2011

Computational Models of Cognitive Development

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George Tsoulas

THE UNIVERSITY of York

Foreword from the Convention Chairs

The AISB'11 call for symposium proposals particularly encouraged events drawing more strongly on the cognitive science aspect of the AISB remit. The result is a coherent programme with a very strong interdisciplinary character, which is also matched in the choice of plenary speakers. The three symposia looking at the interaction between Computing and Philosophy, the prospect of machine consciousness and the quest for a new, comprehensive intelligence test, form a coherent unit where the eternal questions of who we are and what makes us so are asked from a dual Human-Machine perspective. The Symposia on Active Vision, Computational Models of Cognitive Development and Human Memory for Artificial Agents demonstrate how better understanding of the nature and basis of cognitive processes can advance work on Artificial Intelligence and, inversely, how computational models of these processes can help better to understand them. The prominent multi-agent design and modelling paradigm links the Symposium on Social Networks and Multi-agent Systems with the one on AI and Games. Finally, the Symposium on Learning Language Models from Multilingual Corpora, which brings together some of the first attempts in this area, can also be seen through the prism of such a general notion in Philosophy and Linguistics as semiosis, and the dual role of sign and interpretant that text plays in translations.

We are delighted that after another ten successful years in its long history, the AISB convention is returning to the University of York. The 2011 convention takes place on the brand-new Heslington East campus, the result of a multi-million pound expansion that is now the new home of the Department of Computer Science, and hosts the Excellence Hub for Yorkshire and Humber, a new incubator for interdisciplinary research and interaction between academia and industry. The last few years have seen a strong involvement of the Computer Science Department in such interdisciplinary collaboration through the York Centre for Complex Systems Analysis (YCCSA), and we hope that this convention will provide a boost for more synergy between York departments, with other institutions conducting AI-related research in the region, and beyond. As the programme shows, we have also made an effort to promote cooperation with industry and use the convention to support school outreach. The convention format makes it perfect for establishing dialogue and collaboration in new areas of research, as well as across disciplines, and we hope that this year, it will play again this role to the full. We want to thank everyone who has contributed to it or otherwise made this event possible and wish all participants a fruitful and enjoyable time in York.

Dimitar Kazakov and George Tsoulas

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All Things Considered: Dynamic Field Theory Captures Effect of Categories on Children's Word Learning

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Abstract. Recent research demonstrates that both real-time variability in perceptual input and task demands influence young children's word learning and categorisation. The current study extends these findings by testing both children and a dynamic field theory (DFT) computational model in a category labelling task. Specifically, children and the model were introduced to multiple category members that were either moderately or highly variable. Both children and the model were better able to learn category labels when the individual category members were moderately variable. Overall, these findings have implications for both our understanding of children's categorisation and the use of computational models to investigate cognition more generally.

1 WORD LEARNING AND CATEGORISATION

In order to understand the world, children must learn to label and categorise objects in their environments; they do so astonishingly quickly [1]. The complexity of learning a single new word is well-documented [2]: children must not only parse the speech stream into individual words but also determine the meaning of a word from a seemingly infinite array of possible referents [3]. Children's ability to rapidly link a novel label to a novel object is known as fast mapping [4; 5; 6], however, as demonstrated by Horst & Samuelson [7], fast mapping is only one part of the word learning process. To have truly learned a word, children must be able to use that word after a delay or in a new context [8].

By the time children begin to learn words, they are already experienced categorisers. Each new word they encounter refers not just to a single object, but to a category of objects [9; 10]. For example, when a child learns that their family collie is called a "dog", she may also learn that their neighbours' poodle is a "dog", that her cuddly toy is a "dog" [11], and so on. Research in domains as diverse as motor development [12], phonological acquisition [13], and visual categorisation [14] has demonstrated that multiple and variable experiences facilitate learning [15; 16]. Further, variability among category members has also been shown to affect categorisation; that is, categorisation is facilitated by experience with multiple exemplars [17].

However, how variability among category members influences category label learning remains unclear. Recent research demonstrated that 30-month-old children exposed to multiple category members (exemplars) were significantly more likely to retain the category label after a 5-minute delay than children exposed to a single category member multiple times [18]. These data suggest that experience with multiple exemplars facilitates word learning. However, in this case the category members only varied in one feature (colour). The current research extends these findings both empirically and computationally with highly variable categories to further understand how categorisation influences word learning.

2 SUPPORTING EMPIRICAL DATA

2.1 Method

2.1.1 Participants

Twenty-four typically-developing, monolingual English-speaking 30-month-old children participated. 12 children were randomly assigned to the *narrow* condition, and 12 to the *variable* condition.

2.1.2 Stimuli

Known stimuli for all conditions consisted of 18 objects likely to be known to 30-month-old children (e.g., a toy chicken or a toy bike). Novel stimuli consisted of nine novel exemplars from three categories (examples are depicted in Figure 1). For children in the *narrow* condition, novel exemplars were moderately variable and differed only in colour. For children in the *variable* condition, novel stimuli were highly variable and differed in colour, shape and texture. For extension trials atypical exemplars from the novel categories were used. On the extension trials the same stimuli were used for both conditions.

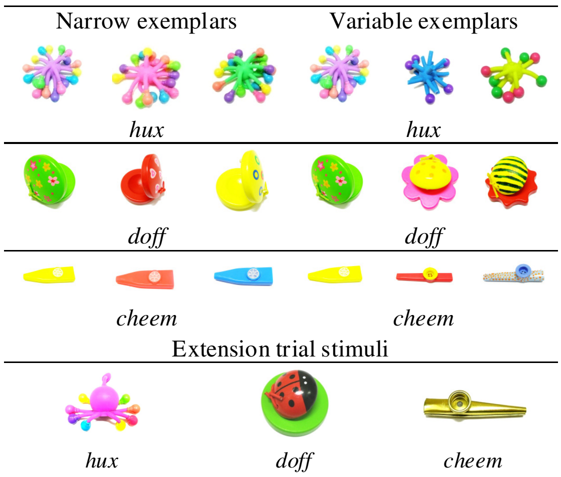

Figure 1. Novel stimuli used in the experiment

2.1.3 Procedure and design

The experiment consisted of three phases: referent selection (18 trials), retention (three trials) and extension (three trials). An example referent selection trial is depicted in Figure 2. On each referent selection trial children saw an array of three objects (two known, one novel) and were asked to get either the novel or one of the known objects (e.g., "can you get the *hux*?"). Overall, children received nine known name trials and nine novel name trials. Children received three trials per novel category (e.g., *hux*). Across trials, children saw novel categories with either *narrow* or *variable* exemplars.

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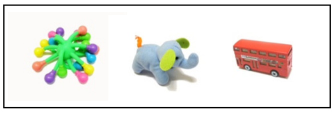
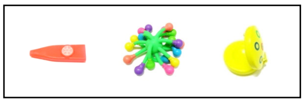


"Can you get the *hux*?"

Figure 2. Example referent selection trial

After a 5-minute break the test phase began. On each of the three retention test trials children saw an array of three objects (one from each of the just-encountered novel categories) and were asked to get each of the objects across trials (for an example, see Figure 3). Extension trials immediately followed and were identical to retention trials except that the atypical exemplars were used.



"Can you get the *hux*?"

Figure 3. Example retention trial

2.2 Results

2.2.1 Referent selection

Results are depicted in the left panel of Figure 4. All children were very good at referent selection. Children in both conditions chose the target object at significantly greater than chance levels on both known name trials (.33, all *p*s two-tailed, $t(11) = 10.51$, $p < .0001$, $d = 3.05$ and $t(11) = 17.42$, $p < .0001$, $d = 5.05$, respectively) and novel name trials ($t(11) = 5.95$, $p < .0001$, $d = 1.73$ and $t(11) = 15.58$, $p < .0001$, $d = 4.52$, respectively). Unpaired t-tests revealed no difference between conditions for either known or novel referent selection (known: $t(22) = -0.30$, *ns*; novel: $t(22) = -0.63$, *ns*.) Thus, whether children saw *narrow* or *variable* exemplars had no effect on referent selection.

2.2.2 Test trials

Results are depicted in the right panel of Figure 4. Data for test trials were submitted to a repeated measures ANOVA with Trial Type (retention, extension) as the repeated measure and Stimui (narrow, variable) as a between-subjects factor, The ANOVA revealed a significant interaction between Trial Type and Stimuli, $F(1, 22) = 7.86$, $p = .01$. To unpack this interaction, planned one-tailed *t*-tests against chance were performed. Only children in the *narrow* condition retained novel labels at levels significantly greater than chance, $t(11) = 4.73$, $p < .001$, $d = 1.38$. Importantly, this replicates Horst et al.'s [18] finding: experience with a category of objects clearly facilitates children's ability to retain labels. A planned, unpaired *t*-test revealed a significant difference between conditions, $t(22) = 2.84$, $p < .01$, $d = 1.22$. In contrast, only children in the *variable* condition extended the novel labels at levels greater than chance, $t(11) = 2.60$, $p < .05$, $d = 0.76$. Thus, encountering a variable category facilitates children's ability to extend labels to new category members [15].

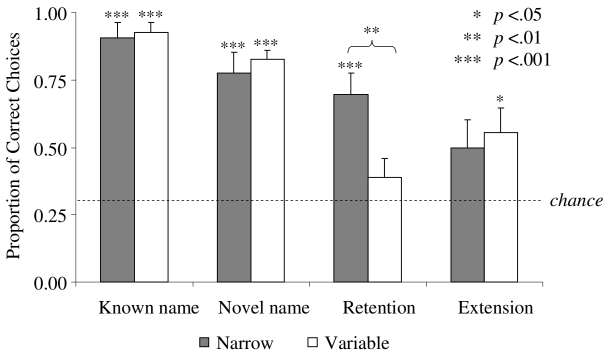


Figure 4. Experimental results

2.3 Discussion

Only children in the *narrow* condition retained novel category labels; however, these children did not extend this newly-learned label to a completely novel atypical category member. In contrast, children in the *variable* condition did not retain the novel labels but were nonetheless able to extend novel category labels. We explored this surprising result by simulating the task using a dynamic field theory model.

3 WORD LEARNING IN-THE-MOMENT

Dynamic Field Theory (DFT) is a formal instantiation of Dynamic Systems Theory (DST) [19] which has been successfully implemented to model children's decision-making processes in various motor and perceptual tasks [20; 21] as well as larger-scale robotic systems [22]. According to DST, behaviour is self-organising in the moment and is thus inextricably linked to real-time input, as well as just-past experience and longer-term learning history [23]. DST has been applied in many domains to explain hitherto puzzling phenomena; for example, the sudden disappearance of young children's stepping reflex [24], perseverative reaching in A-not-B tasks [25] and variable development of goal-directed reaching [12]. More recently, DST has been formalised in the DFT [26], a dynamic neural field framework in which self-sustaining, stable peaks of activation reflect self-organised behaviours. Critically, the DFT allows us to examine the interplay of multiple timescales underlying children's in-the-moment choices in experimental settings.

The goal of this simulation is to investigate whether small changes in stimuli in word learning tasks can give rise to better retention and extension of novel category labels. DFT models have successfully captured experimental data from looking tasks

[27] dimensional change card-sorting tasks [28] and novel noun generalisation tasks [29]. The current simulation adapts Faubel & Schöner's [22] feature binding DFT model of object recognition to a word learning context. If the simulation reflects the experimental data, this suggests that the apparently complex learning processes driving word learning may, in fact, depend on the simple, bottom-up, dynamic associative mechanisms that underlie DFT models.

3.1 The current simulation

3.1.1 Architecture

DFT models consist of continuous, topologically functional neural fields in which spreading activation governed by local excitation/global inhibition [30] generates localised, self-sustaining peaks of activation [31]. The current simulation, depicted in Figure 5, consists of two 2-dimensional dynamic neural fields; specifically, a perceptual layer coupled reciprocally to a memory layer. Activation in the perceptual layer is generated by input along the *label* and *object* dimensions. and is captured by the general equation below:

$$\tau\dot{u}_{o,l}(x,t) = -u_{o,l}(x,t) + h + S_{o,l}(x,t) + \int w(x-x')\sigma(u(x',t))dx' \qquad (1)$$

where $\dot{u}_{o,l}(x,t)$ is the rate of change of activation level across the object (o) and label (l) dimensions at location x, as a function of time (t) mediated by the timescale of the dynamics, τ. Current activation in the perceptual layer, $-u_{o,l}(x,t)$, receives external, experimenter-defined input, $S_{o,l}(x,t)$. Activation in the perceptual and memory layers is subject to excitatory and inhibitory interaction defined by a Gaussian kernel with weight w, and width σ. The resting level of the system is defined by h <0.

Units of representation are peaks of activation. The formation of a self-sustaining peak at any point in the perceptual layer represents a mapping between input along the object dimension and the label dimension. Activation from these peaks spreads to the memory layer, leaving a corresponding, slow-decaying memory trace. Activation in the memory trace acts as short-term memory, by feeding activation back to the perceptual layer, thus facilitating subsequent object-label mappings.

3.1.2 Stimuli and procedure

Known object stimuli were presented as inputs along the object dimension (length = 531 neurons) at intervals of at least 20 neurons. Novel object stimuli were presented at intervals of at least 20 neurons to their nearest known neighbour, with spacing between novel stimuli varying according to condition (see below). On every trial, each object stimulus was separated from its nearest neighbour by at least 75 neurons. Similarly, label stimuli were presented as inputs regularly spaced along the label dimension (length = 22 neurons). In the current model a single neuron on the label dimension was arbitrarily assigned to a single label. However, the model is sufficiently flexible for future work to explore further effects of categorisation, such as phonetic similarity of labels, or the global/basic distinction [32].

Variability in object inputs to the model reflects the variability in category structure encountered by children during the experiment. Specifically, the model is either presented with *narrow* category exemplars, in which novel object input is presented at the central category exemplar and two nearby locations, or with *variable* category exemplars, in which novel object input is presented at the central category exemplar and two more distant locations. For example, *narrow* stimuli might consist of input at locations 114, 115 and 116 along the *object* dimension, while *variable* stimuli might consist of input at positions 109, 115 and 121 along the *object* dimension.

Like the children, the model is presented with 18 referent selection, three retention and three extension trials, using dimensional cueing on each trial to distribute the presentation of stimuli and object labelling over time.

At the beginning of each referent selection trial, the model is presented with "known" cues located at the intersection between object and label for the two known objects, generating two stable peaks, and a "novel" cue at a specific location along the object dimension but generic along the label dimension (see Panel A of Figure 5). Thus, input for novel objects could correspond to any label.

Next, the model is presented with a ridge of input along the label dimension. This new label input intersects with either the existing "known" or "novel" object cues (see Panel B of Figure 5). Formation of a peak at any point in the perceptual layer is considered to reflect the model's choice of object in response to a given label; that is, when a peak is formed the model has fast mapped a label to an object. Note that both correct and incorrect choices are included in the analysis.

Object cues for test trials consist of three generic ridges of activation at the previously encountered novel object locations along the object dimension. The model then receives label input as during referent selection. The three subsequent extension trials are identical to retention trials except that the initial novel object cues are given at locations close to but not identical to the previously locations. Thus, during extension trials the model associates novel labels with completely new novel objects.

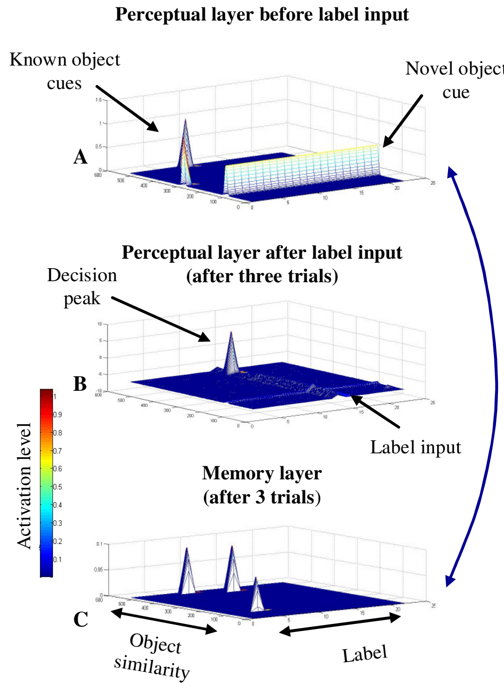


Figure 5. Architecture of the DFT model

3.2 Results

Simulation data are depicted in Figure 6. The model is very accurate on referent selection trials, both with narrow and variable categories. Like the children in our experiment, when the model is presented with *narrow* categories it correctly associates previously-encountered novel category members with previously-encountered novel labels on retention trials and does not associate completely novel, atypical exemplars with previously-encountered labels on extension trials. In contrast, like the children, when the model is presented with *variable* categories it does not associate previously-encountered novel category members with previously-encountered labels on retention trials and does associate completely novel atypical exemplars with previously-encountered labels on extension trials.. Thus, preliminary simulation data reflect children's behaviour in the word learning task, even reproducing the counterintuitive result in the *variable* condition.

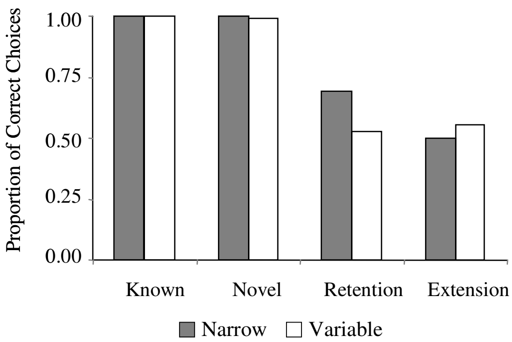


Figure 6. Simulation results

4 DISCUSSION

We have demonstrated both experimentally and computationally that word learning is susceptible to task effects; that is, small changes in stimuli during a fast-mapping task can dramatically influence retention and extension of novel labels. For example, when children encounter wide within-category variability, they do not show evidence of retaining a label for this category, despite being able to extend this label to a completely novel category member. A dynamic field simulation captures this phenomenon by repeated association of different perceptual input over time, generating a remarkably similar pattern of results.

This model offers considerable opportunity for further investigation of the interplay between category variation and word learning. For example, when a child sees an object, she is aware of its colour, shape and the visual components of its texture. In the current model, however, visual input is simplified and schematised: all visual input is collapsed across an overall "perceptual similarity" metric and presented to a single perceptual layer. The addition of further layers representing, for example, colour, shape and texture, allowing the separation of colour, shape and material inputs (cf. [22]), represents an important step towards understanding what constitutes "variability" for children learning to categorise. Comparable extensions of the model, for example taking into account motor feedback, and potential hybridisation with other connectionist architectures more commonly used in computer vision (for example, Self-Organising Maps, [33]), also offer opportunities for its deployment in an embodied agent.

These results have implications for our broader understanding of cognitive development. First, we have extended the DFT to reliably simulate children's fast mapping and word learning behaviour. Second, simulation data suggest that absence of evidence for a behaviour in one context does not imply that the behaviour will not be seen in a different context. Further, as DFT models are simple, associationist, spreading-activation networks, the present data lend further weight to the growing body of evidence suggesting that cognition develops in a bottom-up manner via associations learned from statistical regularities in the input, without recourse to innate learning mechanisms [34]. Taken together, the present data suggest a productive future direction for the integration of psychological and computational research in cognitive development.

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Self-production facilitates and adult input interferes in a neural network model of infant vowel imitation

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Abstract. It is well known that greater amounts of adult input facilitate a child's language development. Thus, one might expect that increased amounts of adult input would help an infant learn to accurately imitate the vowels of his/her native language. In addition, an infant's own production of sounds during cooing, babbling, etc. is known to be important to the development of speech abilities. We simulate infant vowel development using a neural network that contains a layer of auditory neurons, a layer of motor neurons, and bidirectional connections linking these perceptual and motor layers. During an initial babbling phase, the system produces random motor activations, hears the acoustic consequences of these motor activations, and adjusts the weights between its auditory and motor layers in a Hebbian fashion. In simulations, passive auditory input from an external "caregiver" is also included during the babbling phase, and is used to update existing auditory-motor connections. In a testing phase, the model is given adult vowels as auditory input and asked to imitate them. Results indicate that self-productions do promote the development of the ability to imitate, but, somewhat counter-intuitively, the more adult input this model receives during babbling, the less accurate its imitations are during test. Explanations and implications of this finding are discussed.[12]

1 INTRODUCTION

Numerous studies have shown that language input from caregivers has a positive effect on language acquisition. For example, a canonical finding is that the number of words a child hears from his/her caregivers predicts later vocabulary size and language test scores [1]. In the phonological domain, research suggests that infants tend to produce sounds that resemble those of the language spoken by their caregivers as opposed to other languages and to produce vocalizations that sound like those they have just recently heard [2-4] (but see [5] for a critical review).

For example, Kuhl & Meltzoff [2] presented 12- to 24-week old infants with recordings of a female adult producing exemplars of a single American-English vowel: /a/, /i/, or /u/. They recorded the cooing vocalizations produced by the infants during this exposure period. The infants' vocalizations were transcribed into broad phonetic categories and it was found that /a/-like vowels tended to correspond to sessions where adult /a/ vowels were played, /i/-like vowels tended to correspond to sessions where /i/ vowels were played, and /u/-like vowels tended to correspond to sessions where /u/ vowels were played. Understanding how this ability to imitate is achieved is important because the ability to imitate is thought to provide an important foundation for language learning in general [6]. It was proposed that two factors drove the observation in [2]: (1) perceptual re-organization based on hearing the auditory input and (2) learning of auditory-motor mappings based on self-production. These two factors were noted to be theoretically separable.

A number of connectionist modeling studies have demonstrated that artificial neural networks are sensitive to external input. Such work has shown how that input can be beneficial from the standpoint of helping the neural network develop language ability, including imitating the sounds of its ambient language. For example, Heintz et al. [7] show that a model consisting of a layer of auditory neurons and a layer of motor neurons, connected to each other by weighted Hebbian connections, can learn to correctly imitate adult vowels. In their model, a training trial consists of jointly presenting acoustic features of an adult vowel such as /i/ with the positions of vocal tract organs, such as the tongue and lips, required for the child to produce that same vowel.

Li, Zhao, and MacWhinney's connectionist word-learning model, DevLex-II [8], also learns the sounds of its language from external input and also contains layers (in their case phonological input, phonological output, and semantic layers) connected by weighted Hebbian connections. During training, the Hebbian weights between the phonological input and the semantic layers are updated in response to simultaneous presentation of phonological and semantic representations and the Hebbian weights between the semantic and the phonological output layers are also updated in response to simultaneous presentation of phonological and semantic representations. In addition to Hebbian weights between layers, each layer also has its phonetic or semantic features updated using a self-organizing map algorithm. Words are presented with frequencies corresponding to those observed in real caregivers' speech. After training, the model is successfully able to comprehend and produce words in its language.

Yoshikawa et al. [9] use a similar neural network architecture but a different training approach to model the development of vowel imitation ability. An auditory self-organizing map and a motor self-organizing map are linked to each other by Hebbian connections. The model is trained by having it produce a random action of a robotic vocal tract. A human "caregiver" judges whether the sound produced by the robot's vocal tract is similar to a vowel in their repertoire. If so, the human imitates the robot, and the first four formant frequencies of the human caregiver's imitation are fed to the model's auditory layer. The Hebbian connections between the auditory and motor layer are then

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updated to reflect the correspondence between the caregiver's production and the child's.

Westermann and Miranda [10,11] show that a model consisting of an auditory and a motor layer, again linked by weighted Hebbian connections but without self-organization of its perceptual and motor nodes' tunings to the external world, can learn to adapt its auditory percepts of vowels to the language-specific input it has heard (it also adapts those same percepts to reflect the auditory correlates of sounds produced during random babbling training trials). A unique feature of this model is that the correspondence between the sensory and motor pairings for a given speech sound is not assumed beforehand. The present study makes this same conservative assumption regarding what information is available to the child, but rather than focusing on changes in perceptual representations resulting from self-production and caregiver input, we focus on changes in imitation ability as a function of self-production and caregiver input. Given that modification of Hebbian auditory-motor connections based on adult input was sufficient to achieve language-specific perceptual reorganization, one might expect the same kind of mechanism to facilitate imitation.

The present study describes a connectionist model of vowel perception and production development. The model is tested on its ability to imitate adult vowels as in [2]. The approach is similar to some of the other connectionist models described above in that it contains an auditory neuron layer connected via Hebbian weights to a motor neuron layer. However, unlike some of the other models that are tested on the ability to imitate adult input, e.g. [7, 9], it makes the more conservative assumption that activations of the model's motor neurons can only be achieved (1) through the action of the model itself and subsequent perception of self-produced vocalizations or (2) through propagation of adult-generated activation on the auditory input layer via Hebbian connections to the motor layer. In other words, our study is novel because we test how well a model can learn to imitate when it is not given any direct information about which of its own motor articulations correspond to the adult targets. We systematically vary the number of adult-input trials to see how much passive adult stimulation acting through existing auditory-motor connections contributes to the model's development of the ability to imitate an adult. We hypothesized that, as [2] suggests, both self-production trials and passive-adult-input trials would contribute to learning.

2 METHOD

2.1 Auditory and motor neural networks

The model architecture is illustrated schematically in Fig. 1. It has two layers of neurons: an auditory layer and a motor layer. The auditory and motor layers are fully interconnected via modifiable weighted connections.

The auditory layer contains 25 neurons. Each node in the auditory layer has a set of weights to each acoustic input feature (relative first and second formants; see the Vowel Synthesis section below). A neuron's set of weights to input features defines the center of the neuron's receptive field; the closer an input gets to the center of the receptive field, the greater the activation of the neuron. An acoustic input activates the auditory neurons by multiplication (dot product) with these weights.

The motor layer contains 100 neurons. Each node in the motor layer has a receptive field defined by its set of weights to each upper vocal tract muscle (see the Vowel Synthesis section below).

A winner-takes-all function is applied to each layer of neurons before allowing its activation to spread to other layers and before making any Hebbian updates to the weights connecting the two layers. This prevents the auditory and motor representations from being heavily biased toward central regions in the input and output spaces, respectively.

During training, when the auditory and motor networks are simultaneously activated, the connection weights between two networks are updated according to the following Hebbian learning with decay rule:

$$W(t+1) = W(t) + \alpha(a \cdot m' - W) \tag{1}$$

where t is the current learning trial, $t+1$ is the next learning trial, W is a matrix representing the weights from each auditory node to each motor node, a is the vector representing the set of auditory neuron activations, m is the vector representing the set of motor neuron activations, and α is a learning rate parameter that starts at .1 and decreases by a factor of .99 on each learning trial until it reaches a minimum value of .01. Weights are initialized to zero at the start of training.

Prior to training, all auditory and motor receptive field weights are set to random uniformly distributed values. For the main model version, these receptive fields remain static throughout the course of training. In alternate model versions, the auditory receptive fields and/or the motor receptive fields are updated with each auditory input or motor production, respectively. This updating is done according using the standard self-organizing map algorithm [12]. The algorithm specifies that neurons in each layer be assigned locations on a square grid. On a given trial, the most activated node as well as its neighbours have their receptive field centers (i.e., their weights to acoustic features or muscle activations) modified to more closely resemble the current acoustic features or muscle activations. Such updates occur before the winner-takes-all function is applied.

2.2 Vowel data

The model simulations rely on a database of 4,022 synthesized vowels and a set of 30 real adult vowels.

The synthesized vowel database was created using the articulatory synthesis and formant and pitch extraction tools available as part of Praat, a free phonetics program [13]. Sounds were generated by randomly varying fourteen upper vocal tract muscle parameters related to the face, mouth, tongue, and pharynx. These were superimposed on a 1-second fixed pattern of lung volume and laryngeal muscle parameters. Praat uses these lung, larynx, and upper vocal tract parameters to define a system of masses and springs that represent the vocal tract boundaries in an adult female. Praat then derives the air pressures in this vocal tract model, which determine the synthesized vocal sound. Fundamental frequency (f_0), first formant frequency (F1), and second formant frequency (F2) traces were estimated for each resulting sound and sounds that did not contain at least 40 consecutive milliseconds where an f_0

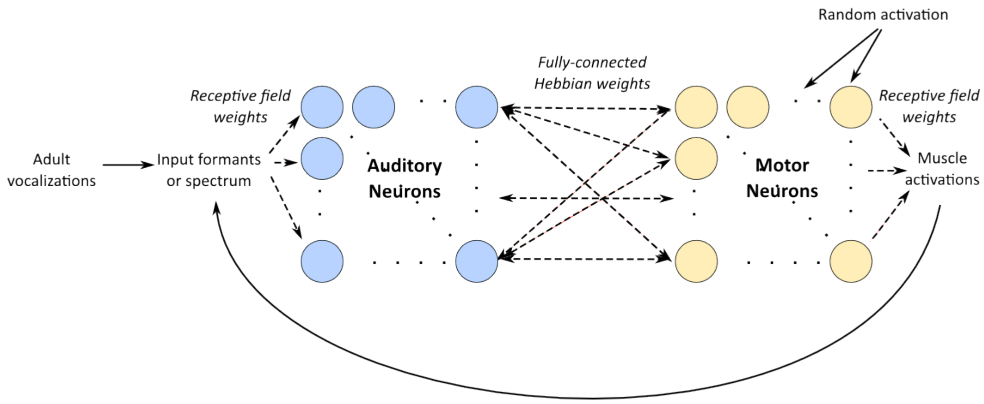

Figure 1. Schematic diagram illustrating the model architecture.

was detectable were discarded. For each remaining sound, we measured the mean F1 minus mean f_0 and mean F2 minus mean F1 over all portions of the sound where there were at least 40 consecutive ms of detectible f_0. Each database entry was thus comprised of a set of 14 muscle activation values and several acoustic measurements on the resulting sound.

Adult sounds consisted of 10 exemplars each of the English /a/ /i/ and /u/ vowels, produced by a female adult American English speaker. F1-f_0 and F2-F1 were obtained for these vowels using the same procedure as for the synthesized sounds. Relative formants were normalized to the combined range observed in the synthesized and human adult data.

2.3 Learning and test trials

Two types of learning experiences are modeled. The first type of learning trial is the infant production trial, which models the infant's experience of exploring his/her own motor capabilities and hearing the resulting sound. An infant production trial begins with a random activation of the model's motor neurons. This specifies a set of upper vocal tract muscle activations. The item in the synthesized vowel database that has muscle activations most similar to those specified by the winning motor neuron's receptive field is identified. The acoustic features associated with that vowel are then presented to the network, where they cause activation of the auditory layer. The auditory neurons are at the same time stimulated by activation propagating from the motor layer through the auditory-motor connection weights. At this point, both the auditory and motor layers of neurons are active, so the connection weights between them are updated according to the Hebbian learning rule described above. This concludes the infant production trial.

The second type of learning trial is the adult input trial, which models the infant's experience of hearing his/her caregiver vocalize. An adult input trial begins by choosing an item at random from the set of adult vowels. The acoustic features of that item are then presented to the model, which causes its auditory neurons to become active. This in turn causes activation to spread through the auditory-motor connection weights to the motor layer. At this point, both layers of neurons are active and their Hebbian connection weights are updated, concluding the adult input trial.

In the present study, different versions of the model were run, each with with differing amounts of adult input. In no-adult-input simulations, there were 500 infant-production training trials. In adult-input simulations there were either 600, 700, or 800 training trials; at each learning trial the probability of that trial being an adult input trial was proportional to the total number of training trials minus 500.

The model is tested on an imitation task. An imitation trial is initiated by presenting the model with acoustic features of an adult vowel. This activates the model's auditory neurons, which, via the auditory-motor connections, activate the model's motor neurons. The synthesized vowel that best matches the pattern of activation at the motor neuron level is then taken as the model's imitation. The Euclidean distance between the acoustic features of the imitated sound and those of the adult sound are then compared. Smaller distances indicate better performance. The model is tested on its imitation of each of the 30 adult vowels.

3 RESULTS

We ran a large number of simulations, systematically varying model parameters, specifically the number of adult input trials given in addition to the infant production trials and whether or not the auditory and motor layers had self-organizing receptive fields.

Prior to any training, it was common for all inputs to result in the same imitation sound, since the weights between the auditory and motor layers are initialized to zero. Across training, the model's ability to accurately imitate adult input improves as evidenced by the imitations' acoustic features becoming more similar to the input vowels' acoustic features. Figure 2 illustrates this change for one of the simulations. Measurement of the mean distance between the target input and the model's imitation in relative formant space corroborates this observation that performance improves with training (see the leftmost column of Fig. 3).

In contrast, increased amounts of adult input had a negative effect on performance. Figure 3 shows this detrimental effect of adult input for model versions in which receptive fields are static throughout training. This effect can be quantified statistically by regressing the change in mean imitation accuracy across training on the number of adult input trials, yielding $r = -.268$, $t(148) = -3.385$, $p < .001$. This effect also held when self-organization of auditory and/or motor layers was turned on and when using different acoustic input features, such as spectra.

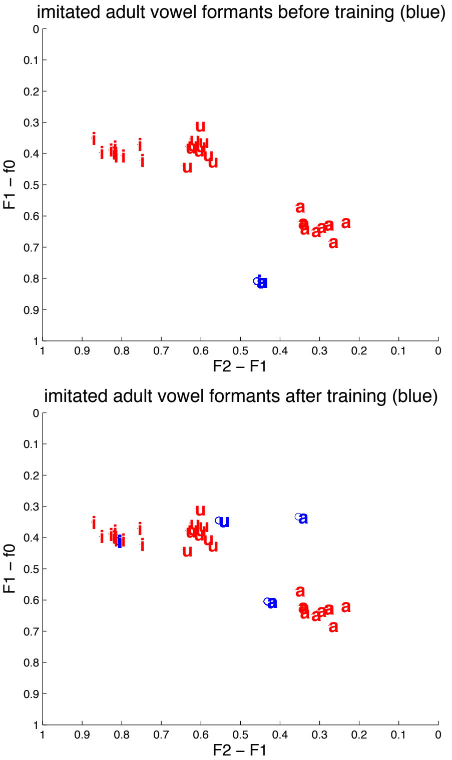

Figure 2. Imitated vowels' normalized formants for one of the model simulations before (above) and after (below) learning. Adult inputs are shown in red and the model's imitations are shown in blue. Letters indicate the adult vowel phone targets.

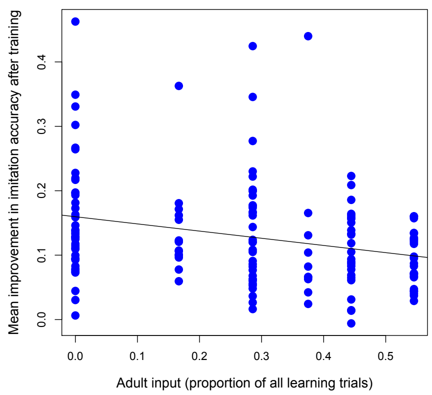

Figure 3. Model performance as a function of amount of adult input during training. Positive values on the y-axis indicate improvement from before training to after training.

4 DISCUSSION

The present study tested the hypothesis that modification of auditory-motor connections based on both self-production and passive adult input would improve performance of a neural network model on a vowel imitation task.

Results indicate that learning from self-productions is important to the model's development of imitation ability. This implies that random motor exploration and perception of the auditory correlates of that motor exploration can be a powerful driver of learning. An implication is that findings of infant vowel imitation in early infancy [2] may be explainable in large part on the basis of mappings achieved during self-production.

On the other hand, we found that modification to auditory-motor connections based on external inputs where the exact motor correspondence is unknown interferes with imitation performance. Given the numerous previous studies such as those reviewed in the Introduction finding that adult input plays a facilitative role in bringing children's language closer to that of their native language, our finding that adult input is associated with worse imitation accuracy is surprising.

One possible explanation is rooted in the fact that imitation in our model is a reinterpretation of the input stimulus within the developed system's own learned sensorimotor mappings. Every infant production trial provides by its nature the completely veridical mapping from motor representation to acoustic representation. In contrast, since adult input in this model does not accompany a known motor representation, adult input may amplify any errors in the model's current mappings. Thus, the present results show that the assumption made by other models [7-9] that the child knows the motor origins of the behavior it observes from a caregiver is nontrivial. Such an assumption makes a difference to performance, so its biological plausibility should be considered.

Since adult input is known to facilitate language learning but does not show such an effect in our model, what mechanisms could underlie its role in real children's language development? One possibility is that passive exposure to adult input affects learning not through modification of the auditory-motor connections but through reorganization of the perceptual system alone, e.g., through adjustment of receptive fields in the auditory system as shown by [14] and modeled in [15].

That being said, adult input effects on perception are not as strong for pre-recorded stimuli [14] and passive TV viewing is associated with reduced rates of language acquisition [16]. Since the TV does not respond differentially to child productions compared to caregiver inputs, which adapt dynamically to the state and abilities of the infant [17,18], the experience of an infant hearing speech on TV might be more like our model's experience hearing adult input. Thus, the finding here that adult input is not associated with increased language performance might not reflect merely a problem with the model but could potentially reflect how an infant might be expected to be affected by passive, non-contingent/non-adaptive input such as that from a TV or radio, especially when such exposure reduces the frequency of the infant's own vocal productions.

Another possibility is that the value of adult input is in actively reinforcing the infant and/or directing the infant's future motor exploration. Reinforcement may help an infant determine when to update neuronal connections, perhaps only updating connections that produce accurate imitations of an adult or updating connections when an adult has imitated the infant and so perceptual activation reflects both the self-vocalization and the caregiver's vocalization, as in Yoshikawa et al.'s model [9]. With regard to shaping exploration, in the model presented here as well as in [7, 9-11], motor activations are drawn completely at random and the entire range of possible motor activations is covered. The real infant, however, likely starts with a limited repertoire of vocal productions and expands on this. The direction of expansion could presumably be driven by auditory priming from adult input as well as by feedback in the form of perceptual, social, or other rewards [17-19].

Future computational modeling studies should expand on the foundations supplied by this and the handful of other neural network models of infant vocal imitation, to further explore various mechanisms by which external (i.e., adult) input might shape infant vocal development. For example, perhaps by modifying the model's perceptual representations of speech sounds but not modifying its auditory-motor connections, passive external input could improve performance. In another scenario, perhaps differential reinforcement of the model's productions might be used to adjust the amount of sensorimotor learning on a given trial or to influence where the model concentrates its motor exploration.

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Infants' Closed World Reasoning and Imitation as Evidence for Learning

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Abstract. Based on empirical evidence from developmental psychology (Gergely et al. 2002, Király et al. 2004), we outline a computational model for the reasoning claimed to explain preverbal infants' selective reenactment of observed novel instrumental action. Selective imitation evidences learning about new means actions. We set forth an argument for the possibility of modelling in terms of the event calculus (Kowalski & Sergot 1986) with constraint logic programming (van Lambalgen & Hamm 2005) as an inferential engine, which embody default reasoning with closed-world assumptions about actions and their effects. The argument is supported by a description of the main reasoning processes involved in the task, and by showing how these can be captured by the formalism.

1 Introduction.

The paper is structured as follows. We begin by introducing two developmental studies that bring evidence for early manifestations of human rationality in action. The first is the seminal task of Gergely and colleagues [15]. It emphasizes the selectivity of infants' imitative behavior, underlain by teleological interpretation of observations. A subsequent experimental manipulation by Király and her colleagues [26] provides a more fine-grained understanding of the social factors that modulate selectivity. In Section 3 we go on to highlight the empirical facts that demand an integrated explanation. We also introduce the developmentalists' theoretical account: 14-month-olds' imitative behavior is a rational manifestation of learning. The model adopts, and attempts to refine this perspective of the empirical data. Section 4 presents in a nutshell the reasoning framework that the model uses to explain the data. We detail the explanatory strategy, and spell out the features of the reasoning processes that lead to infants' exhibited behavior. Section 5 shows that these features are available in the formal environment of the event calculus with constraint logic programming. Drawing on a minimal package of formal technicalities, in Section 6 we describe the sequence of reasoning processes that would lead to action execution along the lines of the experimental results. The focus is on the most complex such sequence, hypothesized to underlie infants' behavior in the only experimental setup where learning is manifested. We conclude that a full-fledged formal model is possible and helpful, and we stress the points where more work needs to be done. The practical implementation of the model is a concrete direction for future research. Had we aimed to build a silicon-based system able to learn wisely (i.e. selectively) from observations of the environment, it would be beneficial to equip it with processing skills like the ones described (see also the related suggestions in [16]). Representing them in logic programming terms may be but a first step.

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2 The developmental experiments.

In [15] a head action is demonstrated by an adult to 14-month-old observers as a new way to turn on a light-box. The dependent measure is infants' performance of the novel action in the test phase. The experimental setup is as follows. The experimenter enters the room exhibiting behavioral signs of distress for being cold; she thus takes a scarf and wraps it around her shoulders. In one of the experimental conditions (HandsOccupied) she performs the novel action while holding the scarf, which would otherwise fall down. In the HandsFree condition she makes a knot tying the scarf around her; afterwards she places her free hands on the table next to the light-box. Consequently half the infants see that the demonstrators hands are occupied while executing the unusual head action (HandsOccupied condition), the other half observe her acting with hands visibly free (HandsFree condition). After a one-week delay subjects are given the chance to act upon the light-box themselves. Reenactment of the observed novel head action is selective between conditions: 69% of the infants in the HandsFree, and only 21% in the HandsOccupied. Interestingly, all infants, whether they reenacted the head touch or not, acted on the light-box with their hands.

In a further experiment Király and her colleagues [26] have shown that selectivity is contingent on a communicative action demonstration. This involves that throughout the demonstration session the experimenter behaves prosocially towards the infant seated in front of her, using non-verbal (eye contact, followed by gaze shift to the target object) as well as verbal ('Look, Baby, I'll show you something!) communicative-referential cues. The Communicative condition in [26] is similar to the original experimental setup in [15], and the results have been replicated (60% vs. 11% reenactment in the HandsFree vs. HandsOccupied condition). Interestingly however, when the novel action is performed aloof, without infant-directed gaze or speech, and spatially distant from the infant (Incidental condition), reenactment of the head touch is always below chance level, and there is no significant difference between the HandsFree and HandsOccupied conditions. In the Incidental condition infants' attention was triggered by a sound signal from the light-box, activated by another experimenter not visible to them. Demonstration started only when she indicated to the agent-experimenter that infants oriented toward the artifact. Only those infants who watched the full action demonstration were included in the analysis. Consequently failure to attend to the novel action is not a plausible explanation for the different patterns of results in the Communicative and Incidental conditions.

In Table 1 we plot the experimental results of the two studies. The findings of [15] are taken to belong to the Communicative setup. The Incidental columns only apply to [26].

Table 1. The experimental results under focus:
Gergely et al. 2002 (top rows), Kiraly et al. 2004 (bottom rows).

Infants' action performance	Communicative		Incidental	
	Hands Free	Hands Occupied	Hands Free	Hands Occupied
Head action	69%	21%	–	–
	60%	11%	11%	29%
No head action	31%	79%	–	–
	40%	89%	89%	71%

3 The empirical explanandum.

We lay emphasis on two aspects of infants' performance in these tasks. They constitute the primary motivation for the reasoning processes suggested to support behavior (see Section 4.2), and, consequently, for our choice of a formalism to model the data (see Section 5). First, infants' imitative behavior is goal-driven. Second, infants' selective performance of the novel observed action stands as evidence for observational learning.

We proceed with some terminological specifications. We then list what is to be explained in the tasks. Next, we relate the listed items to the two issues mentioned above. Finally we introduce the explanatory strategy to be pursued in modelling, and highlight its expected outcomes.

A *prepotent* action is a default response, most strongly associated with a certain outcome. It has priority over other response tendencies especially by virtue of developmental primacy. Commonsensically, human agents' default way to act upon artifacts is with their hands. Empirical results backup the claim: hands are prepotent agentive relata for instrumental action from very early ages. Infants tend to act on tools with their hands [27] (see also item (5) in the list below). Moreover, infants assign causal power to human hands when they observe them to be involved in goal-directed actions [39], [40], [41]. We will thus refer to hand actions as prepotent responses. A prepotent action is, until further evidence, optimal with respect to its goal: it is readily available in an agent's motor repertoire, hence it requires the least amount of processing effort. In this sense it provides the most efficient route to a physical desired end state. Accordingly, any alternative to a prepotent action is suboptimal. The crucial aspect of the described imitation studies is the novelty of the presented head action relative to a prepotent hand response.

So far we used the terms 'imitative behavior', 'imitation', and 'reenactment' to describe infants' behavior in the task. We now wish to call attention to the related notion of 'emulation'. The distinction between 'imitation' and 'emulation' upon observation of instrumental actions resides in the teleological status of the information that an observer reproduces from an observed agent [7]. Imitation refers to copying means actions. Emulation refers to copying goals, and bringing them about according to the observer's behavioral strategies. However, because of the hierarchical nature of means – ends relations, the contrast between imitation and emulation is not absolute. They can be understood as the two ends of a continuum of decreasing fidelity of action reproduction [57]. Along this lines, low fidelity of imitation places it closer to emulation, and thereby shows that goals are a driving force of imitative behavior. If goals are copied in emulation, they modulate imitation tendencies.

Taken together the items in the list below constitute the empirical explanandum that the model is engaged with. Items 2 to 4 characterize the kind of learning evidenced by imitative behavior. Items 5 and 6 support the claim that infants' imitative behavior is goal-driven.

1. The experimenter always turns on the light-box with a head touch (as if executing an action rule of the kind *For lighting up box contact box with head*);
2. If the experimenter's hands are occupied, infants reproduce the goal 'light-on' by enacting prepotent hand touch (as required by a prepotent action rule such as *For lighting up box contact box with hand*);
3. If the experimenter's hands are free, infants reproduce the goal 'light-on' by re-enacting head touch;
4. Unless the experimenter conveys communicative cues during demonstration, performance of head touch is below chance level, and the difference between conditions is not significant;
5. Action reproduction exhibits low fidelity. Infants' head actions appear in various forms, many times different from the demonstrated behavior (e.g. lifting up the light-box, touches with mouth/ nose/ cheek);
6. Across conditions, all infants enact hand touch at least once, always before reenacting head touch, i.e. prepotent rule is never fully or primarily inhibited[3].

Both the light-box and the action performed on it are new to the babies (criteria for novelty available in [34]). For this reason whatever interaction they may have with the artifact is a manifestation of observational learning broadly construed. In other words, both emulation and imitation characterize learning processes. However, there are several things that can be learnt upon observation of the experimenter's head-banging onto the light-box, e.g. about the affordances of the artifact (item 2), about new ways to make it work (3 in the list). The model focuses on the latter kind of learning, which manifests itself in imitative behavior. More specifically, it provides a computational framework for human infants' observational learning about means actions, when an alternative prepotent action for bringing about the goal is available. The imitative response that evidences such learning occurs selectively. Infants learn the observed new means action only when the agent's prepotent agentive relata are not involved in another goal-directed activity (item 3 in the list), and when the agent displays communicative signals (item 4 in the list).

Evidence abounds with respect to inter-species differences regarding learning from conspecifics by means of either imitation or emulation. The general line is that, unlike human children, primates focus primarily on the physical goal of demonstrated actions (namely, to obtain food), which they attempt to bring about most efficiently (although, see [58] for a slightly different pattern of results). The ones who behave similarly with children, i.e. imitate selectively, are enculturated (raised by humans). Their social abilities are more developed than the ones of individuals raised by conspecifics [1]. These primates by and large emulate the goal by means of a prepotent response. They reenact observed novel actions only when these facilitate obtaining the food, which is otherwise not accessible [2], [4], [23]. The robust difference between human infants and the other primates has been taken to make a case for pedagogy as a

[3] There are experimental manipulations that check precisely the factors influencing robustness of the performance of the prepotent response, e.g. [27].

human-specific method, extremely effective, of knowledge transmission among individuals [9].

3.1 A direction for the pursued explanation.

The question arises with respect to the cognitive mechanisms that support infants' imitative learning, and that, presumably, other primates lack. Two main answers have been proposed in the developmental psychology literature. One favors bottom-up processes; it links learning to direct perception of actions, access to prior experience, and motor resonance. From the other standpoint, a top-down approach focuses on interpretation of, and further computations over the perceived actions. Irrespective of the differences between the two, it is by now a commonplace that actions' goals are involved in imitative learning of goal-directed actions, for both human and non-human primates. For one, understanding observed instrumental actions is inherently tied to understanding their goals [15], [34], [35], [44], [60]. Non-human primates have a much easier task, because of the very restricted search space for goals [17]. Human infants' job, on the other hand, is tremendously more difficult, especially when confronted with novel actions. Furthermore, we wish to emphasize that the production of actions fit for one's goals, especially when those actions are not in one's motor repertoire, involves quite refined planning abilities. Bottom-up theories, like the ones based on action-effect associations [13], motor resonance or simulationist accounts [37], [50], [36], do not provide a satisfactory account for goal attribution to observed novel actions.

Consequently better sense may be made of the empirical explanandum above if the robust selectivity of performing novel means actions is explained in a top-down approach. The developmentalist explanatory strategy (e.g. [15], [45]) that we pursue in modelling belongs here. It claims that selective imitation is a form of rational behavior, supported by teleological (goal-centered) interpretation of the observed actions in the context of their occurrence [19]. Teleological interpretation means inferential action processing, grounded in the idea that observed (human) actions have a purpose ('the teleological stance with respect to action understanding' [8], [10], [19]). It results in understanding an action context in terms of relations between goals and means. Teleological reasoning is better able than the low level processes to explain goal attribution to novel actions, because it is not inherently tied to prior experience. Rather, it solves the problem of goal attribution through normative principles with a wide range of applicability, e.g. actions bring about goals most efficiently (see Section 4.2.1).

4 Spelling out the explanatory strategy.

The model elaborates the developmentalist explanation in two ways. First, it extends the notion of goals that drive teleological interpretation (see Section 4.2.2). It does so in order to capture the findings of [26], where social factors are shown to influence behavior. The claim is that infants' rational processing of teleological information involves non-physical factors. Already at that age, not just goals may be attributed to actions, but also intentions to observed agents (see [54] for arguments that infants are capable of thinking about others' intentions). Hence efficiency considerations need not be restricted to physical efficiency. The claim serves to explain the differential performance of social (human infants, enculturated chimpanzees) Vs. non-social primate species mentioned above.

Second, it adds to teleological interpretation an action planning component. We believe it to be necessary for an exhaustive explanation of infants' action production (their exhibited behavior). The interpretation of observed actions constrains infants' planning computations. The model aims to capture in a principled way the interaction between goal-centered interpretation of observed actions, and planning infants' own. The main formal tool for so doing is the use of integrity constraint on computations (see Section 5).

Such a strategy refines and clarifies the underlying top-down mechanisms of imitative behavior as a manifestation of learning in infancy. A full-fledged model that connects univocally the input variables to infants' behavioral output, by means of inferential processes, would corroborate the claims of the top-down approach. Moreover, because empirical evidence for primates' capacity for planning is scarce if not nonexistent, the formal work sets forth a direction for where the difference between humans and non-human primates may reside.

All in all, the account we set forth explains infants' performance in the test phase as a result of the computations in teleological interpretation of actions, and action planning. Teleological action interpretation starts with goal attribution. Because the inferential outcomes are uncertain, especially for novel actions, they require validation. This process is twofold. For one, infants generate an offline plan for the goal, based only on their prior knowledge. Second, in order to understand the action context, they need to understand in an integrated fashion the agent's plans for actions. This abductive process uses planning computations for a better understanding of the current situation. We use interchangeably the terms 'abduction' and 'plan recognition' to refer to it. Once a stable interpretation of the context is available, infants compute an online plan, which they execute. At all steps, derivations are guided by maintenance goals (see Section 4.2.2) expressed formally as integrity constraints. We elaborate on these stages in Section 6.

4.1 The cognitive abilities involved.

The proposed explanatory strategy requires that infants have a number of high-level cognitive skills. We discuss them in what follows. For each ability, we refer to empirical evidence showing its availability to children before the age of the subjects in the light-box tasks (i.e., 14 months). We do this as an argument that the model is psychologically well grounded.

An ample body of empirical evidence shows that from the first year of life infants use the teleological stance to understand actions. They exhibit a tendency to interpret actions as being *for* something. They specify in concrete terms this 'something' in the observed context as a justificatory reason for the action (e.g. [6], [8], [18], [19]). For instance, 12-month old babies were presented with an animated event of two differently sized circles moving on a computer screen. The big circle followed the small one in a heat-seeking fashion. Adults had catalogued this as a chasing event. The two circles disappeared from the screen before the babies could see any outcome. After habituation, they were presented with two test events. In one of them, the chaser makes an unnecessary detour as if 'changing its mind' with respect to catching the chasee. In the other test event, the chaser went on to follow the small circle, continuously reducing the distance between them. Infants' looking times were significantly longer in the latter, incongruent case, showing infants' surprise [6]. These results confirmed the hypothesis that infants expect actions to have goals, and that goals provide forward-looking sufficient reasons for the actions. Goals should justify actions in the given context.

A goal is a particular kind of physical causal effect of an action (but see Section 4.2.2 for a more nuanced understanding). Hence goal-centered reasoning about actions is supported by causal representations. In order to attribute goals to actions, and to understand some actions as means for some states of the world, one must have a grasp of physical causal relations. Empirical evidence demonstrates that infants reason in terms of causes and effects about motion events and qualitative state changes before 12 months of age [40]. Moreover, by 2 years, causal reasoning is co-opted for learning, e.g., about artifact functions [20].

Two principles that guide causal reasoning in infancy are of special interest to us (see Section 6): contact causality, and inertia. The former refers to the fact that observation of spatio-temporal contiguity between events signals a causal relation. The principle of inertia states that a property persists unless acted on by an outside force. We briefly introduce the empirical evidence that shows infants' reliance on the two causal principles. We begin with contact causality. Because of its early development (around 6 months of age [31]) and its generative power, it has been argued that it serves as the foundation of human causal understanding (see [40] for a critical discussion). When 7.5-month-olds observe repeatedly that contact between a moving object and a stationary one, is followed by the latter's being set in motion, they take the resulting motion state to be an effect of the contact event. This is evidenced by surprise if contact is not followed by motion, and if the second object starts to move although contact between the two is rendered impossible by the presence of a barrier [28]. The latter condition of surprise may also be taken as evidence for some rudimentary use of inertia in causal inferences. Just several months later, 10-month-olds' causal inferences show clearer signs of using the principle of inertia; the evidence becomes even more reliable in 1-year-olds [51]. For example, infants are surprised by objects moving rectilinearly, and change their rectilinear path (e.g., by making a sudden U-turn) without any interference.

Planning is a notable kind of goal-based reasoning, which leads to proactive behavior. It is particularly relevant in action production. Claxton and her colleagues [5] have proven that 10-month-olds already show an impressive level of sophistication in adapting the kinematics of their reaching actions to the particular goal they set in a given context (i.e. throwing a ball into a tub, or fitting it into a tube). The ability to plan motor responses for a desired outcome is therefore in place several months before infants engage selectively in imitation of observed novel means actions. We suggest that planning computations play a role not only in action production, but that they are recruited in the explanatory interpretation of the actions performed by an observed agent (see Section 6).

The other crucial aspect that we introduced in Section 3 was that selective imitative behavior attests observational learning. Human infants proneness to learn from conspecifics has been often taken to be a uniquely human feature [4], [9]. Aside from the physical factors that influence the differential imitation rate in HandsFree – HandsOccupied, selectivity of behavior is also shaped by social determinants. This requires credulity in the rationality, authority, and bona fide of observed agents. Only some agents trigger infants' credulity. In [61] it was shown, in an experiment in the same paradigm as the light-box tasks, that no learning occurs if the role of the experimenter is played by a same-aged peer, or by an older (3-4 years old) child. In [26] only agents with pro-social behavior, agents who communicate to the children, are granted a credulous perception of their suboptimal actions. Such results bring support for the developmentalist thesis of natural pedagogy [11]. The thesis holds that human communication is such that it allows the transmission of relevant, useful knowledge between individuals, and that human infants are adapted to play the receptive role by particular sensitivity to being addressed in communication. This is, infants' readiness to learn by imitation is a manifestation of the pedagogical stance with respect to observed human actions.

Given the cited empirical data, we conclude that an explanation of the experimental data on selective imitation that hinges on the capacities introduced above is not like putting the cog in infant cognition (cf. [21]).

These cognitive skills manifest themselves in the reasoning processes claimed to support behavior; Section 4.2 zooms in on the peculiarities of the processes. In Section 5 we go on to show how these abilities may be captured in a formal system. Section 6 details how the computations unravel.

4.2 Central features of the reasoning processes.

We propose that the processes that support observational learning by imitation are a form of closed world reasoning. Moreover, infants' goals are represented at different levels of abstraction. Relatedly, the selectivity of behavior is underlain by multi-level reasoning threads that go beyond object-level inferences, within the realm of physical causality.

Closed world reasoning refers to the use of assumptions in order to bring the inferential space to manageable dimensions, under time constraints. The basic format is the closed world assumption for reasoning about abnormalities – CWA_{ab}. It prescribes that, if there is no positive information that a given event occurs, one may assume it does not occur. In practice, these 'given events' are abnormalities with respect to the smooth, habitual running of a process. For example, if every day I cycle to university, having a flat tire is an abnormality. Before I observe it, my plan to go to the university need not take into account the possibility that it occurs. I can safely assume that I need everything there is to know about the journey from my house to the university. A similar intuition is expressed in [30] by referring to principles like the CWA_{ab} as "hidden auto-epistemic premises". Reasoning with such assumptions is defeasible, and its conclusions are open to revision. When new facts are added to the reasoning database, e.g., the observation of a flat tire, the conclusion previously licensed by CWA_{ab}, e.g., an action rule of the form *In order to go to university, mount on the bike*, may have to be retracted. In this sense the use of CWA is flexible, and closed world reasoning is non-monotonic. And it'd better be, for else, how would we ever learn anything new?

4.2.1 Goal-centered reasoning: interpretation and planning with closed world assumptions.

The basic aspect of action processing that may result, under certain conditions, in imitative behavior was hypothesized to be the use of the teleological stance for interpretive explanatory purposes [15]. Children's teleological interpretation of actions aims to make sense of the observed context. It does so by searching justificatory reasons for the actions observed. Goals provide the expected justifications. The processing involved in teleological interpretation is tripartite. It aggregates an observed action, relevant aspects of the context of observation, and a goal state [6], [19]. The inferential processes may be performed in two directions: attributing goals to observed actions (action-to-goal), and understanding observed actions as means for previously derived goals (goal-to-action). These processes constitute a normative appraisal of actions with respect to the goals that they are expected to bring about.

The concerns of goal-centered reasoning are well known in philosophy [14], logic and artificial intelligence [33], [46], or empirical sciences of the brain and mind [49], [10]. They threaten the attempts to make reasoning about goals explicit, both in the case of goal attribution and in the reverse direction of action planning. How is one to attribute goals to actions, or to plan ahead one's actions for one's goals, if one is faced with multifinality, equifinality, and quasi infinite possibilities of unexpected events? Nevertheless, despite computational complexity, even the youngest members of the human species show in their behavior the ability to bypass gracefully the problem.

One relevant attempt to explain this proneness and ease to reason about goals has been by resort to positing the use of constraining assumptions on inferences; their function is to reduce the inferential scope to manageable dimensions. An example of such a strategy is spotting causal relations of the kind 'x causes $y_1, y_2, \ldots, y_n$', and then picking y_k to be x's goal based on evaluation of the efficiency of x in bringing about y_k. An assumption of this kind was labeled either the principle of rational action, or the principle of efficiency, the two being used interchangeably. "The outcome (the effect) of an action may, or may not, be seen as the goal, depending on whether the outcome is judged to justify the action in the given situation. Such normative evaluation of actions is based on the principle of rational action (Csibra & Gergely, 1998; Gergely & Csibra, 2003), which allows for the assessment of the relative efficiency of the action performed to achieve the goal within the situational constraints given." ([10]: 7).

With certain reserves regarding a blunt equation of rationality with processing in terms of physical efficiency (see Section 4.2.2), we share the proposed strategy for dealing with reasoning about goals. More specifically, along the lines of [53] and [55], we propose that the inferential processes at work in the current task are guided by closed world assumptions. In this sense we take the principle of efficiency to be but one example of such an assumption. Should the explanatory attempt fail to provide a satisfactory teleological interpretation grounded in this principle, 'efficiency' may be understood with a wider scope where non-physical factors are taken into consideration (see Section 4.2.2). Thus, the assumptions are used flexibly.

Closed world assumptions require the reasoner to construct a minimal teleological interpretation of a situation. This process has been labeled reasoning *toward* an interpretation [53]. A useful formulation of the CWA for action interpretation is *All actions are forced to occur by the data.*. In the context of teleological evaluation 'the data' refers to the physical goals of actions. This formulation of the assumption captures the idea introduced above, that goals justify actions. More precisely, an action is forced to occur by its goal if it is the most efficient one, given contextual constraints, for the goal. Initially just the first-order physical features are relevant for considerations of actions' efficiency in bringing about goals.

The next step is the process of reasoning *from* this minimal interpretation [53]. For the tasks in question, this process refers to planning. The 'conclusions' of the inferential process are action rules that eventually lead the reasoner to action execution. The CWA_{ab} for planning prescribes that, *If there is no positive information that something is amiss, one can assume that nothing abnormal is the case and proceed to action according to prior knowledge*. Under a minimal interpretation, as far as they know, the infants in the described task may proceed to action. Closed world reasoning licenses action upon the artifact the way they already know how, i.e. enactment of the prepotent motor response of a hand touch.

4.2.2 *Multi-leveled goal representations: beyond physical efficiency.*

One way to understand the reasoning processes involved in the task is to see them as connecting goals represented at different levels of abstraction, and thereby supporting action performance. We introduce such a distinction between *maintenance* and *achievement* goals. The distinction arises from taking seriously the hierarchical nature of goal representations.

Agents have concrete *achievement goals*, or desires to make a certain state of the world come about. One's desire to submit a paper, or to turn on a light are good examples of this kind. In the suggested model, these are the kind of goals that infants reduce through backward reasoning to executable actions, both in the case of plan recognition (for the observed agent), and of the generation of their own action plans.

At a more abstract level[4], agents can have *maintenance goals*, which maintain the agent in some desired, stable, balanced relation with the ever changing state of the world. They refer thus to states that must remain true. Their function is to motivate agents to set achievement goals upon which to act.

This distinction originates in the AI literature with respect to autonomous intelligent agents and multiagent systems (e.g., [12], [22]). It is particularly useful for understanding the processes that underlie infants' imitation of novel suboptimal means actions. In short, the idea is that behavior may be suboptimal with respect to concrete goals, yet optimal for maintaining a certain relationship with the world.

Neither concrete, nor the more abstract goals are activated *ex nihilo*. Goals are elicited by things in the world. The conditions of activation specify in greater detail, narrow down as it were, the goal representation itself. The fact that goals are activated under some circumstances can be captured in a formal language by a conditional[5] representation: '*If* certain conditions obtain *then* a certain state of affairs is to be pursued'. Once the antecedent is made true by a certain context, the consequent must be made true by the reasoner. It is represented formally as an integrity constraint (see Section 5). Further reasoning derives an instance of the maintenance goal. This is set as the achievement goal to be pursued. Planning derivations then reduce it to action, which the reasoner executes.

The distinction between maintenance and achievement goal representations has significant consequences for the computational strategies used to reason with such goals. The continuous nature of maintenance goals manifests itself in that, once activated, their conclusions constrain the upcoming inferential processes. As such, reasoning is shaped by maintenance goals.

The model is developed on the empirically grounded assumption that infants' maintenance-goals in these tasks are:

1. *If* action *then* physical goal (i.e., assign goals to actions);
2. *If* communication *then* trust (i.e., trust communicating agents);
3. *If* trust *and* abduction with respect to physical goals fails *then* learn (i.e., learn from trustworthy agents whose actions do not bear a univocal plan assignment with respect to physical goals).

(1) expresses the teleological stance [19], [10], whereas (2) and

[4] The characterization of achievement goals as 'concrete', and of maintenance goals as 'abstract' refers to proximity, and distance, respectively, to concrete realization in action.

[5] The conditional as used here has a different semantics from the non-monotonic conditionals of logic programs, used to express infants' representations of action rules. See, for instance, the discussion about the semantics of integrity constraints in the Appendix to [30].

(3) flesh out the pedagogical stance [11]. (1) is an object-level goal – it accounts for a basic level of understanding actions in terms of the physical goals that they bring about. Thus it guides infants' reasoning across conditions, irrespective of manipulations of social factors. The second and third maintenance-goals, on the other hand, pertain to meta-reasoning. They involve thinking about the observed agent's intentions (e.g. potential pedagogical intention), and not simply about the goals of her actions. The constraint 'trust' is triggered by the communicative, prosocial manifestation of the observed agent[6]. If the agent is communicative, her actions may be trusted. The inability to provide a goal-framed object-level explanation for observations, and trust in the observed communicating agent, are prerequisites of learning. In case both obtain, actions may be interpreted as manifestations of the intention to convey new and relevant knowledge [11] about how to operate the light-box, and learnt.

4.2.3 Overriding what is known: learning as non-monotonic processing.

Although an optimal action response (the prepotent hand action) is always available to infants, under some conditions many of them reenact the observed suboptimal means action. This is learning by imitation. We emphasize a particularly significant feature of the reasoning that supports learning: non-monotonicity.

Learning amounts to overriding the prepotent response because of evidence for abnormalities. In order to make explicit that action rules can be overridden, we formulate them like *To bring about state s do action a, unless something abnormal is the case*. When there is positive evidence that something abnormal is the case, the optimal action a can be set aside. In such conditions performance of a suboptimal action does not deviate from rational behavior.

In the light-box tasks, the choice of suboptimal behavior with respect to physical efficiency may be seen as the result of violation of the CWA for action interpretation. More precisely, we suggest that in the Communicative-HandsFree setup the interpretation of the current context outputs an abnormality. If a certain observed action is not forced to occur by physical, object-level teleological processing of the context in which it occurs, it constitutes an abnormality.

But in a Communicative context, the maintenance goal 'trust' has been activated by the communicative agent. This means that the two conditions of the epistemic maintenance goal are both active. Therefore the constraint 'learn' is triggered, and it takes effect on infants' further computations.

Learning then means that if the interpretation of the current context calls for (e.g. by exhibiting a violation of the CWA in a communicative setting), then the database available for planning own actions should be augmented to include the action that generated the abnormality. The CWA_{ab} for planning no longer guides infants' online planning computation in the presence of an abnormality. The integrity constraint 'learn' requires the reduction of the achievement goal to the novel action (see Section 6). The prepotent rule for action is overridden. The novel action is thus a rational substitute for the prepotent response. Its reenactment is optimal with respect to infants' maintenance epistemic goal.

This flexible application of the CWA_{ab} for planning is an overt manifestation of the non-monotonic character of the human inferential strategies involved in observational learning about actions.

[6] More likely than not the conditions of activation of trust go beyond this plain treatment. Although a basic sort of trust seems to be indeed activated automatically, by plausibly low-level perceptual mechanism (cf. [11]; see also [59] for behavioral effects of trustworthiness judgments on adults facial processing) future work, both empirical and modelling-theoretical, is called for.

5 The logical formalism.

In [30] Kowalski makes the general point that agents "may use Logic to represent their beliefs about the way the world is, and to represent their goals for the way they would like the world to be". We intend to make use of the representational format of the event calculus [47], [48] and the computational resources of constraint logic programming (CLP) [24] for precisely these purposes. We model how young reasoners interpret the instrumental actions that they observe another human agent performing, thereby set achievement goals, and subsequently compute their own action plans. The model's working assumption is that the dynamic reasoning processes performed over representational structures expressed with the event calculus predicates output by means of CLP derivation rules the behaviors that infants exhibit in their task performance.

The event calculus was introduced by Kowalski and Sergot [29] as a formalism for representing events and their effects. Originally it was meant to address the concerns with respect to path planning in robotics, using logic programming as an inferential engine.

Constitutive features of the formalism composed of the event calculus language and CLP, furnish background reasons for its use in cognitive modelling. First, the expressive capacity of the event calculus is fairly good. Its causal predicates formalize two notions of cause, instantaneous and continuous [55]. $Initiates(action, property, time)$ and $Terminates(action, property, time)$ represent the instantaneous effects of actions. They are just what is needed to form causal representations with the principle of contact causality. $Trajectory(force, time, property, duration)$ expresses continuous causation, by linking a property to a force exerted over time that makes it be the case. It is a needed ingredient to represent infants' causal observations that are grounded by inertia. We reckoned these two principles to be essential for infants' causal processing in general (see Section 4.1). We are thus justified to believe that the formalism can capture the understanding of the world's dynamics necessary for performance in the light-box tasks (see the empirical evidence reviewed in Section 4.1). Some examples of infants' representations of the current context using the event calculus are provided in Section 6.

Second, the non-monotonic consequence relation specific to logic programming with the closed world assumption is computationally efficient [55]. It is less complex than other formalisms (e.g. classical logic) whose inapplicability to formal descriptions of actual human reasoning has been shown times and again (e.g. [3], [56]). Moreover, logic programming is also less complex than other non-monotonic logics, such as Reiter's default logic [42] because it does not involve consistency checks [55]. The logical notion of reduced complexity implies that, as a computational tool, it places lower demands on the processing capacities of working memory. Consequently it may serve well cognitive modelling endeavors.

Finally, the cognitive relevance of the event calculus with CLP has been demonstrated explicitly from a variety of perspectives: successful applications to discourse interpretation [55], formalization of cognitive tasks, which facilitated the derivation of predictions with respect to autistic subjects' performance on those tasks [38], or appealing implementations in neural networks [53]. The first example is particularly relevant because it exploits precisely the use of human cognitive capacities for planning in the construction of temporal meaning; thereby a cognitive formal semantics of tensed speech is provided based on a formalism for planning.

We argued in Section 4.2 that infants' inferential processes in the light-box tasks are a form of non-monotonic goal-centered closed world reasoning. Negation as failure (NAF) is the basic formal manifestation of closed world reasoning [53], [55]. It can be used to describe each of the three parameters of the formalism, i.e., syntactic, semantic, and notion of validity. Therefore the suggested logical formalism embeds closed world reasoning at each of these levels.

Syntactically, NAF is a rule of inference itself [30]. Moreover, the event calculus axiomatizes the commonsense principle of inertia. $\mathit{Happens}(e,t) \wedge \mathit{Initiates}(e,f,t) \wedge\ t < t^{'}\ \wedge \neg \mathit{Clipped}(t,f,t^{'}) \rightarrow \mathit{HoldsAt}(f,t^{'})$ is Axiom 2 in the set of the event calculus axioms in [55]. It is an expression of the principle of inertia with respect to instantaneous change. It states that unless there is explicit information about a causally relevant event in a given temporal interval ($\neg \mathit{Clipped}(t,f,t^{'})$), the resultant state of an event continues to hold. This serves well to formalize infant's inertial causal reasoning.

Semantically, NAF is linked to the idea that computations with the CLP inference rules are performed in minimal models [55], [53]. A model of a situation is minimal in the sense that the occurrences of events and their causal influences are restricted to what is required by the observed facts, and the axioms of the event calculus. Such minimal models are closed worlds. With respect to the meaning of truth connectives, it is especially worthwhile to emphasize that the $\rightarrow$ of logic programming is an excellent candidate for formalizing default action rules, open to revision (see Section 4.2.3).

From the standpoint of the definition of validity, CLP has a non-monotonic consequence relation. The addition of new information may defeat and lead to retraction or revision of previously held conclusions, such as previously known action rules. This allows flexible computations with the principle of inertia, and thereby it allows updates and changes in knowledge databases.

Consequently, the event calculus with CLP serves as a good representational and computational specification of practical reasoning with the features outlined throughout Section 4.2.

We use by and large the same version of the formalism as in [55] to model the processes that subserve imitative learning. Goal-centered reasoning about actions proceeds in two directions, by means of two inference rules: reasoning forward (as used in, e.g., attribution of goals to actions), and reasoning backward (from the inferred goals, as in planning)[7]. The main syntactic strategy in forward inferencing is unification using algorithms provided in [43]. Forward reasoning also manifests itself in cumulative application of the axioms of the event calculus to make inferences about properties of the world that hold at certain time points. Backward reasoning is the basic procedure to reduce a goal to subgoals, all the way down to executable actions. Infants' planning computations are essentially backward computations from goals. We suggested in Section 3.1 that they are also recruited in the process of action interpretation. Devising plan structures for an observed agent serves explanatory purposes. The isomorphism between planning and explanatory practices has been exploited before (e.g. by representing both processes in terms of the logical language of the event calculus in [47], [48]). We suggest that the young reasoners use abduction for teleological interpretation of observations in the light-box tasks in the form of plan recognition (see Section 6).

Activated maintenance goals are expressed as integrity constraints [55], [30] on subsequent derivations. They impose norms on how one interprets a set of observations and, consequently, on what one is willing to do. Integrity constraints require, or prohibit, certain movements in the reasoning strategies used.

6 The reasoning steps.

Finally, we detail the reasoning steps suggested to underpin infants' behavior in the light-box tasks. Table 2 provides a synopsis of the kinds of reasoning processes, and their inferential/ behavioral outputs.

Table 2. The reasoning processes involved in task performance.

Reasoning process	Database	Syntactic strategy	Outcome
Goal attribution	current observation	unification	goal hypotheses
Offline planning	prior knowledge	bwd. chaining from main goal	action rule (own)
Abduction (plan recognition)	updated current observation	bwd. chaining from both goals	action rule (agent's)
Online planning	updated current observation	bwd. chaining from main goal	action (agent's)

Infants behave as rational observers and, consequently, rational actors. The reasoning is two-staged: teleological interpretation of the observed context, and backward action planning. Computations are guided by meta-reasoning, which sets the maintenance socio-epistemic goals of infants. Interpretation is a psychological term to refer to model construction. Credulous reasoning engages in constructing a single, intended model [53]. This is a minimal model, whose construction is guided by closed world assumptions. The principle of efficiency of actions with respect to physical goals (referred to in Section 4.2.1) is one such assumption that regulates the process of goal attribution.The output from the interpretation stage shapes the computations involved in infants' planning of their own actions. It does so by outputting an achievement goal to be pursued. The activated integrity constraints regulate the goal-reduction derivations. These reasoning processes result in plan execution. This is infants' action performance, which constitutes the dependent variable in the tasks described. As such, goal-centered reasoning mediates between the experimental input variables and the behavioral output.

Upon action presentation infants individuate events and construct a database of current observations, which consists of a narrative of events, and a causal model. A clause in the narrative looks like $Happens(contact_{\text{head}}, t)$; it expresses infants' observation that the agent contacts the light-box with her head. The constitutive elements of the causal model are the principle of contact causality, and the principle of inertia. The former allows a clause such as $Happens(contact, t_1) \wedge \mathit{Initiates}(contact, light - on, t_2) \wedge t_1 < t_2$ to represent infants' observation that the light-on state is an effect of the contacting event. The latter licenses the use of the formula $\mathit{Trajectory}(scarf(on), s, warm, s + d)$ to express infants' inference that if the scarf is on the agent for some time, then she will feel warm.

The young reasoners open placeholders for actions' goals, and engage in goal attribution. The teleological stance integrity constraint looks like $?\mathit{Initiates}(action, goal, t)$ `succeeds`. It is resolved via

[7] Note the overlap with the psychological problematization of teleological action processing introduced in Section 4.2.1

forward inferential processes over the observed actions. These processes apply the unification algorithm [43], which results in concrete goals assigned to the observed actions. We suggest that in this first stage two goals are derived. Firstly, the agent is attributed the maintenance goal 'keep warm' triggered by the behavioral signs she conveys. It is reduced by backward reasoning to a concrete achievement goal of the kind 'action to the effect not-cold', or 'make warm'. Secondly, the unusual head contact causes the light activation (by contact causality). Since there is no other salient effect of the action the state 'light-on' is conjectured to be the achievement goal. Because novelty generates uncertainty, this goal is defeasible and it requires validation.

Validation is done via planning derivations. The first step is offline planning, whereby backward computations generate infants' motor plan for the uncertain achievement goal. The result is an action rule that allows exceptions. It reads as *Light-on, if hand contact and nothing abnormal is the case*. In other words, the goal activates the prepotent response most strongly associated with it. The rule is arrived at via backward reasoning from the goal 'light-on' over a database comprising only infants' prior knowledge; current observations are ignored. The computations here account for one of the components of the explanandum, namely that across conditions all infants perform a hand action on the light-box.

If state light-on is observed but hand contact is not, the action rule derived by offline planning is in conflict with the current observations. Conflict resolution amounts to searching in the observed context an abnormality with respect to infants' own action rule. The abnormality condition is expressed in the model as yet another integrity constraint, stating that simultaneous goals may provide exceptions to action rules: if hand is necessary for goal g_2 at t, then there is an abnormality of hand with respect to g_1 at t. More formally, IF $?x \neq hand, Initiates(hand, g2, t)$ `fails` THEN $?ab(hand, g1, t)$`succeeds`. The abnormality would provide an exception to the prepotent rule. This would explain agent's choice of an unusual action to the effect light-on. Infants engage in planning computations starting from both assigned goals. The process is abductive: it seeks an integrated action plan to be assigned to the observed agent who pursues more than one goal at a time. The conflict is resolved if that 'something abnormal being the case' that justifies the unusual action is found.

In the HandsOccupied condition the agent's side achievement goal 'make warm' reduces to the observed hand action with the scarf. Their continuous exertion of force on the scarf is necessary to bring about the agent's maintenance goal 'keep warm'. The integrity constraint above recommends it as an abnormality with respect to the prepotent rule. Because she couldn't have done otherwise, the agent's execution of an action rule like *Light-on if head contact* is justified. It is acceptable as the plan assigned to a rational agent in the exceptional conditions where she has two goals to pursue simultaneously. The reasoner, whose context is not exceptional (i.e., she does not have a side goal to accomplish), has no good enough reason to engage in further time-consuming computations. Thus infants execute the action computed in offline planning.

In the HandsFree condition, the object-level plan recognition endeavor fails because nothing (i.e., no side goal) forces the occurrence of the head action. It is impossible for infants to derive a univocal plan of actions for the observed agent. The CWA is violated. Her action choices are not justified in a minimal model where only the physical goals of actions are relevant: she could have done otherwise. The Communicative setup provides information about the potential pedagogical character of the demonstration. This furnishes a way to manage failed abduction. The activated 'trust' constraint sets infants in a learning-prone mode. It links the social notion of 'communication' with the epistemic notion 'learn' when the reasoner's abductive attempts fail. Their goal is now epistemic, and the criterion of physical efficiency in action performance can be overridden. The content of the knowledge conveyed by the agent is specialized to the abnormal means action performed with the head. The constraint 'learn' takes effect on infants' online planning computations. It constrains the reduction of the achievement goal 'light-on' to the novel, under-explained 'head-contact'. This is how imitation takes place, and how children learn a new way to use the light-box.

All in all, in a Communicative setting, infants are inclined to revise their own prepotent action-rule *Light-on, if hand contact and nothing abnormal is the case* upon observation of an under-explained novel head action to the effect 'light-on'.

7 Conclusions: wrapping up and further on.

As we showed through fleshing out the reasoning steps at work in the only experimental case where imitation is significant (Communicative–HandsFree), the modelling explanatory strategy allows a detailed perspective upon the kind of learning behavior exhibited by infants in the light-box tasks. It provides a red thread that connects the experimental manipulations with the findings. We have made at least some steps toward clarifying the complex interaction between action evaluation in terms of physical causality, and the inclusion of higher-order reasons for actions involving (communicative – pedagogical) intentions, that seem to support observational learning. The developmental trajectory of these complex reasoning skills is a proper avenue for future research, from which modelling should not be missing. Moreover, the model sets directions for explanations of the differences between human infants' and primates' performance in similar tasks. These may have to do with the cognitive capacity for planning and its use for action understanding, as well as with understanding the pedagogical intentions of conspecifics.

We have shown that infants imitation in the light-box paradigm qualifies as rational behavior that evidences selective learning. We did so by showing that it is supported by non-monotonic reasoning processes with closed world assumptions about actions' goals and agent's intentions. We briefly reviewed empirical evidence that shows 14-month-old infants' capacity for the required complex reasoning. The proposed approach recommends that the rationality of the exhibited behavior is to be formulated as efficiency with respect to socio-epistemic goals that bypass the more basic efficiency principle with respect to physical goals. We provided an informal description of the computations, and showed that they could be captured with the means made available by the formalism of the event calculus with CLP. Therefore we put forth an argument that the modelling enterprise is possible. The current formal approach should inspire research into the issue of practical implementations of the computations that lead to selective learning from action observations.

A lot more is left to be explained, from within the same perspective. For example, more needs to be added to the conditions of the 'trust' constraint on action interpretation; most likely it is not as simple as communicative agents trigger epistemic trust which thereby fosters learning new instrumental actions. The older the children grow, the more complex the activation conditions of trust based on social and epistemic factors is reckoned to be (see [32]'s study with 3-5-year olds, or [52] for a theoretical overview). The formalization is meant to facilitate integrated explanations for these phenomena, and to capture their evolution throughout development.

All in all the benefit of formalization is expected to manifest itself on at least two directions. First, by providing principled descriptions of the succession of internal states that connect the experimental input variables to the behavioral output, it corroborates and refines the claim of some developmental psychologists that infants behavioral performance is supported by reasoning processes. Second, such fine-grained explanations are expected to integrate various trends of related research, and to lead to new and precise experimental predictions. Hence the model is not only empirically well grounded, and thus psychologically plausible, but its further development is called for.

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Grasp Learning by Means of Developing Sensorimotor Schemas and Generic World Knowledge

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Abstract. We present a cognitive system in which grasping competences are coded by means of a formalisation of sensory motor schemas in terms of so called 'object action complexes' (OACs). OACs define the knowledge of the system via the effects and precondition of certain behavioural patterns, and also code the uncertainty associated with their execution. OACs are grounded through the observation and evaluation of individual executions generating 'experiments', and dynamically adapt through using these experiments for learning. Moreover, in parallel with the development and refinement of OACs, generic world knowledge is permanently generated by the system which affects the OACs on a meta level and provides a means for the generation of new competences and better generalisation. We present an example of a developing system executing OACs which code the grasping of known and unknown objects, and thereby illustrate (i) the refinement of OACs and (ii) building up generic world knowledge. We see this as particularly important since these interaction processes, although fundamental for human development, are usually difficult to observe by means of techniques in neurophysiology and developmental psychology.

1 Introduction

Cognitive development seems to proceed at a number of different levels of abstraction: for example there are low level developments such as perception-action control loops for basic sensorimotor skills involved in reaching, grasping, object manipulation, and walking; in parallel with this there are higher developments in the knowledge of objects, physical causality, and spatial relationships (these are more abstract than the lower level, and allow for application in a range of scenarios). There is a strong connection between these parallel tracks; higher-level knowledge seems to be abstracted from lower level context specific sensorimotor routines (see e.g. [31]), and seems to arrive after the acquisition of skills at the lower level. In the other direction, the higher level knowledge, once attained, can be used to improve the appropriate application and adjustment of lower level skills (see e.g. Piaget on the "support" [24, 25]). A major challenge is to explain (mechanistically) how this parallel development works. Such an explanation seems to be necessary in order to understand how such advanced abilities as tool-use develop ontogenetically in humans; contemporary opinion in psychology holds that advanced tool-use has its origins in infants' early exploratory interactions with objects and surfaces, and that the development from these precursors to advanced manipulations is gradual and continuous [19].

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In this paper we tackle one fragment of this development: that is the fragment related to grasping; at lower levels of abstraction we can learn specific sensorimotor routines for grasping specific objects, but at a higher level (and in parallel) we can learn more generic object knowledge which can improve the grasping of known objects, and also help us to grasp novel objects. More specifically we capture the sensorimotor skill of grasping within the framework of Object Action Complexes (OACs) (a formal framework introduced in [18, 38]). The formalism of OACs is a skeleton — which integrates existing concepts in the field of artificial intelligence as well as (behavioural and) cognitive robotics (see Sec. 2) — that can be used to formalise adaptive and predictive behaviours on different levels of the processing hierarchy. OAC executions generate empirical data in terms of so called 'experiments', and these lead to different kinds of learning which are clearly distinguished. This learning ensures grounding and leads to an ongoing improvement of the overall system through adaptation and learning. By that OACs should be able to reach from low level reactive actions to conscious planning through the experience of actions applied to objects in the world (for details, see [18]). In this paper, we will use this OAC concept to outline a framework for the development of sensorimotor skills associated with grasping as well as the parallel development of generic world knowledge.

As one innate grasping mechanism we make use of simple manually defined feature–action associations (see [27]) triggered by the early cognitive vision system [29]. These association are motivated by innate 'grasping reflexes' in infants although they differ in detail due to different embodiments (see [17] for a discussion of similarities and differences to infant's grasping). This initial 'grasping reflex' is coded as an object action complex OAC^{gen}. It becomes refined during its application in the exploration process through learning. In a process (described in detail in [17]) triggered by OAC^{gen}, world knowledge in terms of object shape knowledge is extracted. Once this shape knowledge is available to the system, object specific grasp knowledge is learned and coded in terms of a second OAC OAC_o^{grasp}. While OAC^{gen} codes generic feature grasp associations, OAC_o^{grasp} associates grasp knowledge with a specific learned object o based on the concept of grasp densities as outlined in [10]. OAC_o^{grasp} and OAC^{gen} code two different strategies associated with different branches of grasp research. While OAC^{gen} codes generic grasp affordances (see, e.g.,[30, 8, 5, 27] for work related to generic grasping), OAC_o^{grasp} addresses the grasping of specific objects (see, e.g., [4, 20, 15, 10]).

In this paper, we outline how these two kinds of OACs develop in parallel in a cognitive system, generate generic world knowledge and in particular support each other by making use of this developing generic world knowledge. This builds on existing work where we have shown that

- Innately defined feature action associations can already lead to rather high performance grasping [27].
- Both OACs are refined over time through learning processes associated with the OACs individually [27, 10].
- OAC^{gen} can be used to initiate the developmental process of OAC_o^{grasp} [17].

Building on this background, the current paper shows that convergence speed is a fundamental problem associated with OAC_o^{grasp} which is basically 'learning by heart' with only little generalisation by means of local interpolation (See Sec. 5.2). Furthermore, on the strength of our first experimental indications described here, we make the following speculative predictions

- OAC_o^{grasp} delivers the statistical material for the branching of OAC^{gen} into new OACs expressing new grasping affordances. This is done by finding indicative feature relations–grasp association in co-occurrence tables coding visual feature relation and the grasping success associated with grasps related to them (see Sec. 6.2).
- OAC_o^{grasp} and OAC^{gen} deliver the statistical material to fundamentally change the learning algorithm associated with OAC_o^{grasp} and by that lead to a faster convergence of OAC_o^{grasp}. This is done by using the co-occurrence statistics to refine kernels in the KDE approach [32] applied in the grasp density concept (See Sec. 6.1).
- Finally, at the end of the developmental process, OAC^{gen} (coding grasping without object knowledge) eventually becomes powerful enough to generate grasp densities close to the ones which are initially tediously learned by OAC_o^{grasp}, hence that there is no fundamental difference between grasping known and unknown objects anymore.

This paper will partly refer to already published work [27, 10, 17] while putting it in a developmental context, partly refer novel and ongoing work with new (and to a certain degree intermediate) results and partly make speculative predictions based on available data. The aim is to put existing and ongoing work in a wider context addressing the fundamental problem of learning of sensory motor schemas for tool use in an embodied robot system.

2 Sensorimotor schemas and object action complexes

The sensorimotor schema[3] as defined by Piaget and others [26, 9] is a dynamic entity that gathers together the perceptions and associated actions involved in the performance of a habitual behaviour. The schema represents knowledge generalised from all the experiences of that behaviour. It also includes knowledge about the context in which the behaviour was performed as well as expectations about the effects. During cognitive development these schemas are refined and combined. Object Action Complexes (OACs) are a formalisation of such schemas to be used in artificial cognitive systems (see [18]).

An OAC's definition is split into three parts, (1) a *symbolic description* consisting of a prediction function defined over an attribute space, together with a measure of the reliability of the OAC, and (2) an *execution specification* that defines how the OAC is executed by the embodied system and generates experience in terms of 'experiments' and (3) a specification of how the learning associated with the OAC is realised based on the 'experiments' generated by the executed OACs. More formally (see also Fig. 1):

[3] also called "sensorimotor process" [33], "skill" [13], or "perception-action routine" [19].

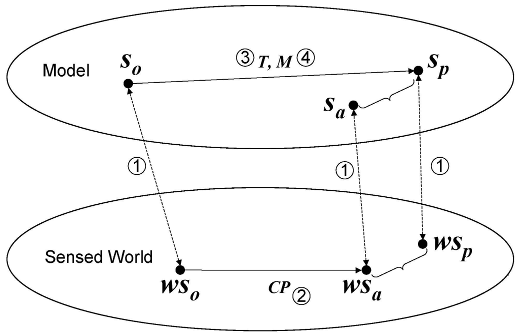


Figure 1: Graphical representation of an OAC and the OAC learning problems. This shows how the actual state ws_a (corresponding to s_a in the model) resulting from the execution of the control program *CP* diverges from the state s_p predicted by the OAC's prediction function T. This divergence drives the learning (i.e. refinement) of the OAC. For further explanation see text. Figure courtesy of Christopher Geib.

Definition 2.1 *An* ***Object-Action Complex (OAC)*** *is a triple*

$$(\mathtt{id}, T, M) \quad (1)$$

where:

- $\mathtt{id}$ *is a unique identifier for an execution specification,*
- $T : \mathcal{S} \to \mathcal{S}$ *is a prediction function defined on an attribute space* $\mathcal{S}$ *encoding the system's beliefs as to how the world (and the robot) will change if the control is executed , and*
- M *is a statistical measure representing the success of the OAC within a window over the past.*

An execution function `execute` (see below) can map an OAC $\mathtt{id}$ to an 'experiment' which is defined the following way:

Definition 2.2 *Given an attribute space* $\mathcal{S}$ *and an OAC with identifier* $\mathtt{id}$ *defined on* $\mathcal{S}$*, an* ***experiment*** *is a triple*

$$(s_o, s_p, s_a) \quad (2)$$

where:

- $s_o \in \mathcal{S}$*, captures the state of world before execution*
- $s_p \in \mathcal{S}$ *such that OAC* $\mathtt{id}$ *predicts that state* s_p *will result from its execution in* s_o*, i.e.,* $s_p = T_{\mathtt{id}}(s_o)$*, and*
- $s_a \in \mathcal{S}$ *such that* s_a *is observed as a result of actually executing OAC* $\mathtt{id}$ *in state* s_o*.*

Thus, an experiment is an *empirical event* by which OACs will be grounded in sensory experience.

As an empirical grounded event, such experiments can be used to update OACs in cycles of execution and learning based on evaluations of their success (see below). Note that sometimes an experiment is actually not used directly for learning but stored in some short term memory (see, e.g., [3]) until resources for learning are available (e.g., during 'sleeping phases').

The execution, i.e., the actual action associated to the OAC is defied as following:

Definition 2.3 `execute` *is a function that maps an OAC* id *to an experiment, i.e.,*

$$\texttt{execute} : id \to \texttt{expr} = (s_o, s_p, s_a). \tag{3}$$

The `execute` function is an operation that performs the OACs execution specification in the current world state, returning an experiment `expr`.

The definition of OACs as capturing both symbolic and control knowledge about actions highlights a number of learning problems that must be addressed for OACs to be effective. We note that while each of these learning problems can be addressed by recognising the differences between predicted states and those states actually achieved, they may still require different learning algorithms (e.g., Bayesian, neural network-like, parametric, non-parametric, etc.). It is up to the OAC designer to choose an appropriate learning mechanism.

As such, the following characterisations are intended to specify those aspects of the OAC that are modified through learning, not the method of learning. We consider four main learning problems, each of which is labelled by its respective number in Fig. 1. These are (1) learning control programs, (2) learning the prediction function, (3) learning the mapping from states of the real world to states of the model and (4) learning the prediction function's long term statistics. In our context, it is only the learning problems (1) and (4) which are of relevance, these are referred to by `updateCP` and `updateM` respectively. All learning functions take an experiment as an argument, e.g., `updateCP(expr)`.

3 Overview: Developmental process in a cognitive architecture

As mentioned in Sec. 1, cognitive development seems to proceed at a number of different levels of abstraction. Fig. 2 shows two such parallel tracks of development. On the bottom is the sensorimotor track which shows the development of lower level sensorimotor schemas (SMSs), which are observable in infant behaviour. Each node in the lower track corresponds to an SMS. A directed edge travels from each ancestor node to its descendents; for example the SMS for pulling a string descends from a basic grasping SMS. Some SMSs have more than one ancestor; for example an infant means-end behaviour will have as ancestors one SMS for the means and one for the goal. The top of Fig. 2 is the abstract track which shows the parallel development of the underlying world knowledge. Nodes in the upper track correspond to (for example) fragments of object knowledge which are common to a number of SMSs, and fragments of spatial relationships; these are gradually linked up as development progresses (to the right), to eventually form a more comprehensive knowledge of objects and space. We must stress here that the early fragments of object and spatial knowledge are likely to be very context specific, and strongly associated with the sensorimotor schemas they have been abstracted from. It is only after a long developmental process moving to the right in Fig. 2) that these fragments become more objective, and this developmental process must involve some sort of "representational redescription" [7]. The evidence from the psychology literature suggests that it is doubtful that very much objective knowledge is achieved during infancy, but rather that a high degree of context specificity persists [34, 36, 1, see for example].

For the lower track we see a developmental process in which a small set of innately defined SMSs lead to a large variety of SMSs through branching and specialisation. During this developmental process, the effects of the SMS become increasingly predictable and

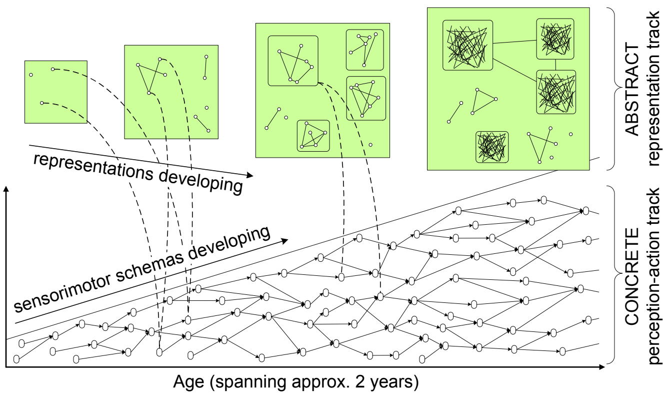


Figure 2: Conceptual diagram, overviewing infant developments on both a low level sensorimotor track and a higher level representational track; for explanation see text (Sec. 3).

can then be used more and more purposefully by the cognitive agent for the planning of behaviour. In parallel to (and triggered by) the development of individual SMSs more generic world knowledge is built up; as illustrated in the upper track of Fig. 2. This is done through the abstraction of empirical data gained during the execution of the SMSs on objects and associated actions. The central topic of this paper is the parallel development and interaction of observable sensorimotor schemas and the increasing abstract world knowledge which is based on the experiments generated by the OACs.

In our case an "innate" SMS is a generic grasping OAC (which would correspond to a single node to the lower left of Fig. 2). This OAC then branches as different objects are encountered, spinning off a new specific grasping OAC for each new object (in this paper three example objects are tackled). On the upper track we have representations of objects which are acquired in "object memory" (see Fig. 7), and also generic knowledge about the relations between low-level visual features and the existence of grasping affordances.

Figure 2 also illustrates (with dashed curves) links between the abstract and sensorimotor tracks; these links are bidirectional. To avoid clutter only six links are shown, but in reality all representational fragments will be linked to sensorimotor schemas. In one direction representations are linked to the schemas they have been generalised from (and hence can immediately link to actions which can manipulate the represented object or spatial relation). In our grasping system this means that the object representations, and general feature-grasping relationships have been abstracted from lower level interactions. In the other direction, more advanced schemas make use of the newly formed representations, for example in their description of the context in which a behaviour may be performed, or its effects, or the control policy followed during execution of the schema. In our grasping system this means that (i) the grasping of the three specific objects which the system has practised on will be able to make use of this more abstract knowledge once it is available, so the grasp success rate will be much higher once sufficient statistics are gathered on the general relationships between visual features and grasp success; (ii) the grasping of novel objects, using the generic grasp OAC will also leverage this generic knowledge leading it to also have a high degree of success.

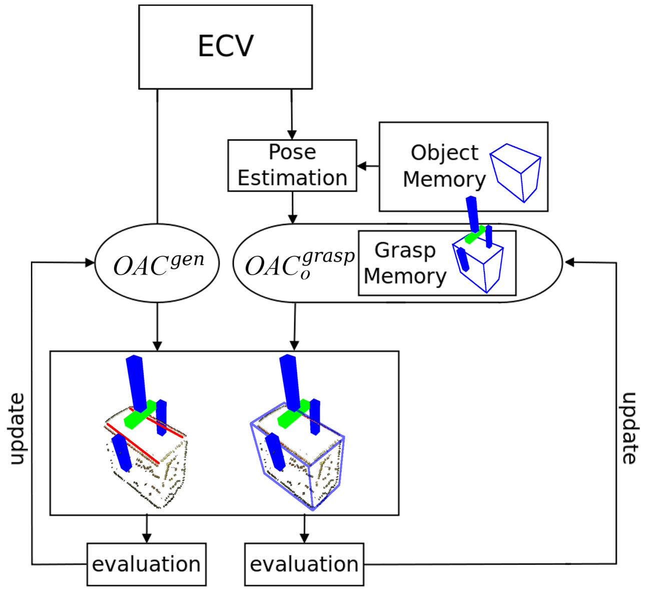


Figure 3: System architecture, see section 4.1

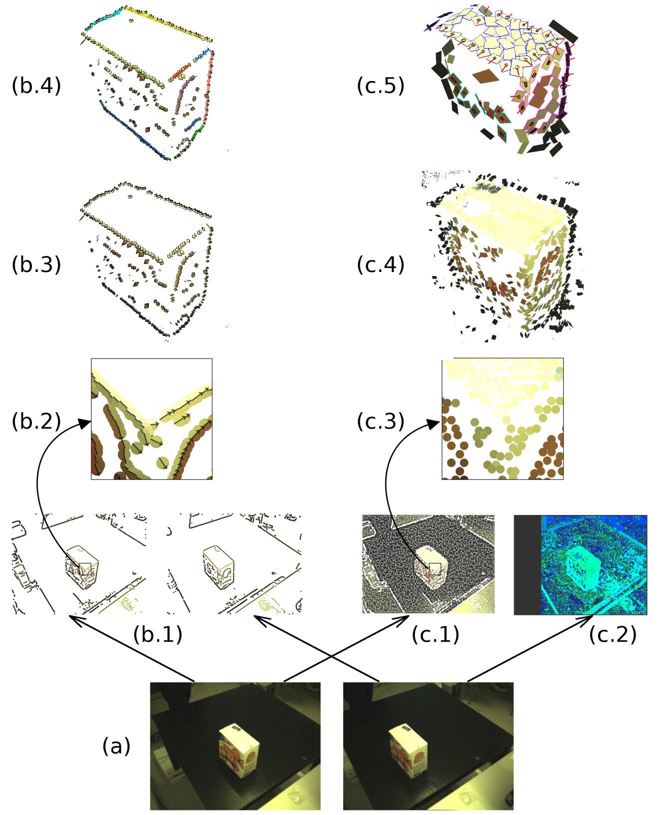


Figure 4: (a) an example stereo image pair. (b.1) 2D line segments for the left and the right image. (b.2) a detail from b.1. (b.3) 3D line segments. (b.4) 3D contours. (c.1) 2D texlets for the left image. (c.2) disparity image. (c.3) a detail from c.1. (c.4) 3D texlets. (c.5) 3D surflings.

4 Formalising grasping with and without object knowledge: OAC_o^{grasp} and OAC^{gen}

Grasping novel objects is one important example of sensorimotor schemas (SMS) (see, e.g., [26, 21]). An important property of an SMS is that it becomes grounded, refined and sometimes significantly modified during the developmental process. In this section we present the two OACs which formalise two sensorimotor schema associated with grasping, with and without object knowledge. Before we describe these two OACs in more detail in section 4.2 and 4.3, we give some basic information on the robot vision system in which the developmental process is taking place in section 4.1.

4.1 System in which development is taking place

In the system we envisage, the grasping process is organised as sketched in Fig. 3. The two OACs, OAC_o^{grasp} and OAC^{gen}, follow different paths. OAC^{gen} is based on combination of visual features computed by the early cognitive vision (ECV) system (described below). The output of the ECV system is used directly for producing grasping hypotheses (see also Fig. 11). In case of OAC_o^{grasp} the acquired image representation is compared against a database of stored object models, and once the pose estimation is done it is possible through OAC_o^{grasp} to access abstracted grasp knowledge for the known objects in the scene (see section 4.3). Suggested grasping hypotheses can be tested (both in simulation or with the real setup) and the results are used to continuously improve OAC_o^{grasp} and OAC^{gen}.

The visual representation extracted by the early cognitive vision (ECV) system [29] provides rich visual representations for edge structures, surfaces and junctions. Sparse 2D and 3D features, so-called *multi-modal primitives*, are created along image contours and textured areas. These 2D features represent a small image patch in terms of position, orientation and also appearance information (e.g., colour and phase). Primitives describing edge patches are called line segments, primitives describing textured surfaces are called texlets and primitives describing corners (intersections of edges) are called junctions. 2D primitives are matched across two stereo views, and pairs of corresponding 2D features permit the reconstruction of a 3D equivalent. The 2D and 3D primitives are organised into perceptual groups in 2D and 3D (called contours for line segments, or surflings for the texlets). The procedure to create visual representations (line segments and texlets) is illustrated in Fig. 4 on an example stereo image pair.

The sparse and symbolic nature of the multi-modal primitives allows for the coding of relevant perceptual structures that express relevant spatial relations in 2D and 3D [2]. The relations between contours (and also surflings) allow us to define grasping hypotheses (see section 4.2 and Fig. 11).

4.2 OAC^{gen}: Grasp affordances as feature relation - action associations

OAC^{gen} is used to gain physical control over unknown objects, a grasp computation mechanism based on previous work [27] is used. Pairs of 3D contours that share a common plane and have similar colours suggest a possible grasp (see Fig. 5b). The grasp location is defined by the position of one of the contours. Grasp orientation is calculated from the common plane defined by the two contours and the contour's orientation at the grasp location.

During execution, grasping hypotheses from co-planar contour pairs are computed. The initial attribute space is given by

$$s_o = (|\Omega|,\ (C_1, C_2), \texttt{statusGrasp}),$$

where $|\Omega|$ is the number of elements in the set Ω, and (C_1, C_2) is the concrete pair of extracted contours that was picked earlier. Recall that

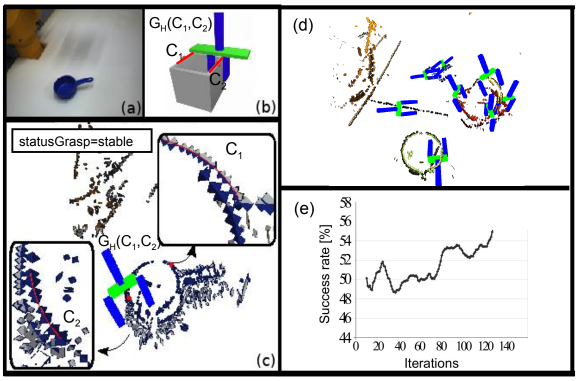


Figure 5: (a) The image of the scene captured by the left camera. (b) A possible grasping action type defined by using the two coplanar contours C_1 and C_2 shown in red. (c) A successful grasping hypothesis. The 3D contours from which the grasp was calculated are shown. Note that the information displayed is the core of an "expr". (d) A selected set of grasping hypotheses generated for a similar scene. (e) Change of performance as a result of the learning process.

$OAC^{gen} = (\mathtt{id}, T, M)$. The prediction function T in our context is trivial, since a stable grasp ($\mathtt{statusGrasp} = \mathit{stable}$) is predicted. M measures the percentage of successful grasps in a certain time window (see Fig. 5e).

The computed grasping hypothesis is then performed and the grasp status $s_a = \mathtt{statusGrasp}_{t+1}$ is sensed after picking up the object, resulting in an experiment (see Fig. 5c for the main components of an experiment):

$$\mathtt{expr} = \{s_o, \mathtt{statusGrasp}_{t+1} = \mathtt{stable}, \mathtt{statusGrasp}_{t+1}\}.$$

Each experiment can either be used directly for on-line learning, as in the following learning cycle:

while *true* **do**
  choose pair of contours C_1, C_2
  `expr=execute`(gen);
  `updateCP(expr)`;
  `updateM(expr)`;
  drop object
end

or stored in an episodic memory for off-line learning at a later stage by calling the function `updateCP` (see [27] for details). There we have shown that, based on these labelled experiences, we can learn an improved feature-based grasp generation mechanism. `updateCP` uses an artificial neural net to determine which feature relations predict successful grasps. Fig. 5e shows how the success rate increases when on-line learning is performed on the evaluated grasps. The learning is limited by the amount of grasp data available and by the noise that is present in the data. However, as the objects are unknown by the system, the performance is not expected to increase to nearly 100 % even if unlimited training data would be available.

4.3 OAC_o^{grasp}: Object specific grasping

OAC_o^{grasp} expresses affordance relative object-gripper configurations that yield stable grasps. The grasps we consider are parameterised by a 6D gripper pose composed of a 3D position and a 3D

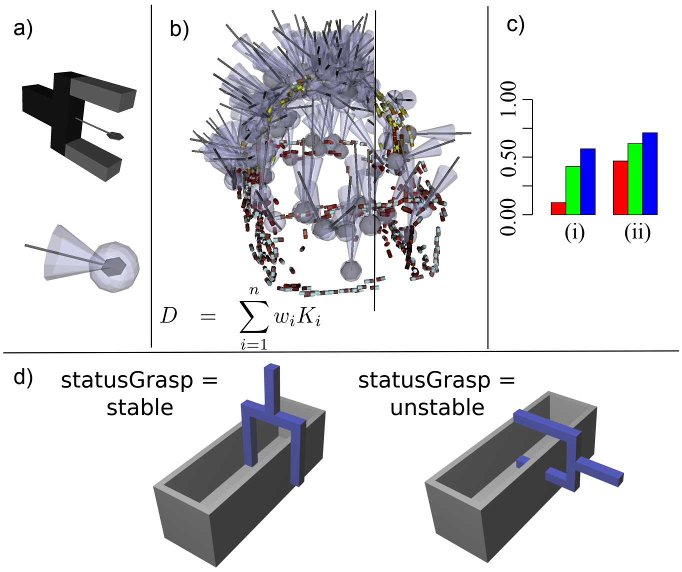


Figure 6: Grasping affordances are represented using kernel-based grasp densities. a) Iso-probable surface of a 'grasp kernel', and relation between a two-finger grasp and a kernel representing this specific grasp in the model. b) Kernel-based grasp density. The right-hand side shows lighter sampling for illustration purposes. D represents the density, while w_i and K_i represent the individual weights and kernels. c) Grasp success rates for the object 'basket' after different learning cycles (i) counting kinematic path planning errors as failures, and (ii) excluding such errors from the score. Red bars show the success rate of grasps before learning has been applied. Green bars correspond to grasps that have been drawn randomly from the learned grasp density. Blue bars correspond to the maximum-likelihood grasps from the learned grasp density. d) shows examples of a succeeding and a failing experiment. Figure adapted from [10], with kind permission by the authors.

orientation. Affordances are represented probabilistically with *grasp densities* [10], which correspond to continuous probability density functions defined on the 6D pose space. Their computational representation is non-parametric: A density is represented by a large number of weighted grasp observations. Density values are estimated by assigning a kernel function to each observation and summing the kernels [32]. An intuitive illustration of a grasp kernel is given in Fig. 6a and 6b illustrates a kernel-based grasp density.

OAC^{gen} is potentially applicable whenever the gripper is empty and an instance of object o is present in the scene. As in the previous example, the prediction function T always returns $\mathtt{statusGrasp} = \mathtt{stable}$. The attribute space $\mathcal{S}$ is defined by

$$\mathcal{S} = \{\mathrm{targetObj} = o, \mathtt{statusGrasp}\}. \tag{4}$$

Here, the state description includes an attribute $\mathrm{targetObj}$ that specifies which object model o is to be applied by the `execute` function; this model is chosen by processes external to the OAC. M is defined in such a way as to maintain cumulative outcome statistics of executions of this OAC, updated via `updateM` (see Fig. 6c).

The `execute` function is defined in such a way as to return an experiment

$$\mathtt{expr} = (s_o, \mathtt{statusGrasp}_{t+1} = \mathtt{stable}, \mathtt{statusGrasp}_{t+1}),$$

in s_a, the attribute `statusGrasp` is the observed status after the grasping attempt (see Fig. 6d). In addition, the data structures representing s_o, s_p and s_a may include further state information such as object and gripper poses. Such information is used, in particular, by `updateCP` to update the grasp density by integrating new experiments, which leads to increasingly reliable performance as can be seen in Fig. 6c.

5 Extraction of World knowledge by exploration

In this section we briefly describe the process of generating world knowledge by means of executing the generic and specific OACs. An important intermediate stage is sketched in Fig. 7. The top row in Fig. 7 represent the innate state of the system in which object and grasp memory is empty. It illustrates the usage of OAC^{gen} to grasp an unknown object based on the scene representation which is available in the iconic memory. Once an object is grasped, an object model is generated (see [17] for details). Subsequently the model can be used for pose-estimation in future scenes and thereby enable the association of actions to the specific object by OAC_o^{grasp} — this is illustrated in the bottom row in Fig. 7 representing a more advanced state of the system.

The experiments generated by the OACs coding object independent and object specific grasp knowledge are stored in the episodic buffer and are the basis for more abstracted representations in two respects. First, object dependent grasp knowledge is stored in the grasp densities (see section 5.2) and second, so called 'co-occurrence tables' store the statistics of feature relation - action associations (see section 5.3). Both kinds of knowledge are stored in the long term memory. Moreover, object shape knowledge is generated and also stored in the long term memory (see section 5.1).

5.1 Object shape knowledge

By successfully grasping a new rigid object initially (using OAC^{gen}) full physical control over it is achieved. This allows the object to be viewed from a variety of perspectives. From these views an accumulated description of multi-modal primitives is extracted. A detailed technical description of the accumulation process is given by Pugeault and Krüger, [28]. Besides other uses this generated shape description allows us to recognise the object in the scene and estimate its pose (see [11] for more information). The ability to estimate the object's pose is essential to be able to associate actions to the object as done by OAC_o^{grasp}.

5.2 Grasp Densities

The object specific grasp experiments generated by OAC_o^{grasp} are used to create grasp densities. The pose of each successful grasp defines one point in the 6-dimensional space and kernel density estimation is used to achieve a continuous density (see [10] and figure 6 for more details) based on the individual points. Once a grasp density is learned it can also be improved later on for instance by evaluating samples from it and use these to create a new, refined density which will lead to an improved success likelihood of OAC_o^{grasp}. Moreover, the grasp densities represent abstracted grasp knowledge which can be used for further learning, e.g., about how to improve the speed of convergence of the grasp densities (see section 6.1).

The width of each kernel is currently selected manually and depends on the specific use case. Typically they are chosen just large enough to ensure that neighbouring kernels overlap in order to ensure continuous density. The more detailed and fine grained the resulting density has to be, the more experiments are needed to ensure that the density is not incomplete and appears patchy. The level of detail depends one the usecase. When searching for a maxima it might be less critical how fine-grained the density is. For other investigations, e.g. as those described in section 5.3.1, it is beneficial to have a fine-grained density. As the density exists in a 6-dimensional space, the required number of experiments to reach a dense coverage grows quickly when a higher level of detail is required.

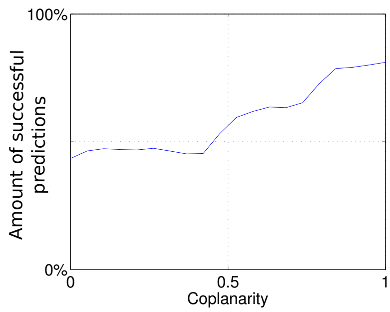


Figure 8: Using scenes containing one object, grasps have been created from pairs of contours using OAC^{gen} and compared against the grasps density associated with the object. This has been done using three different objects in total. The co-occurrence table shows the success likelihood of the grasps relative to the values of the feature-relations between the contours.

5.3 Co-occurrence tables

The experiments generated by OAC^{gen} can directly be used to improve the success likelihood of OAC^{gen} by calling the update function that is intrinsic to the OAC (illustrated in Fig. 3). Moreover, experiments generated by OAC_o^{grasp} are used to create so called co-occurrence tables (see Fig. 8 and 9) which represent projections of the grasp densities abstracted from the accumulated experiments. We discuss two different projections.

5.3.1 *Co-occurrence tables for* OAC^{gen}

The co-occurrence tables such as Fig. 8 store the values of relations between pairs of contours as well as the success likelihoods of grasps generated on these contour pairs and can thereby be used to improve the success likelihood of OAC^{gen}. Fig. 8 is based on grasps of three different objects and addresses coplanarity. It shows that coplanarity indeed seems to be an indicator for grasp affordances. Beside introducing additional relations, e.g. colinearity or cocolourity which is based on the colour-difference between those sides of the contours that face each other, also additional experiments using different objects will ensure that the statistic becomes more and more complete.

5.3.2 *Co-occurrence tables for* OAC_o^{grasp}

The kernels used in the grasp density approach in [10] are isotropic. This is unsatisfying in two respects. First, there is a certain arbitrariness in the selection of kernel parameters which requires manual selection. Second, it turns out that the convergence speed for the grasp densities is rather slow as many isotropic kernels are used to model the grasp affordances in sufficient detail. Both issues can be addressed when using the grasp densities as basis for the learning of the statistical dependencies of grasps in the vicinity of an already successfully tested grasp. More specifically, a simulation environment

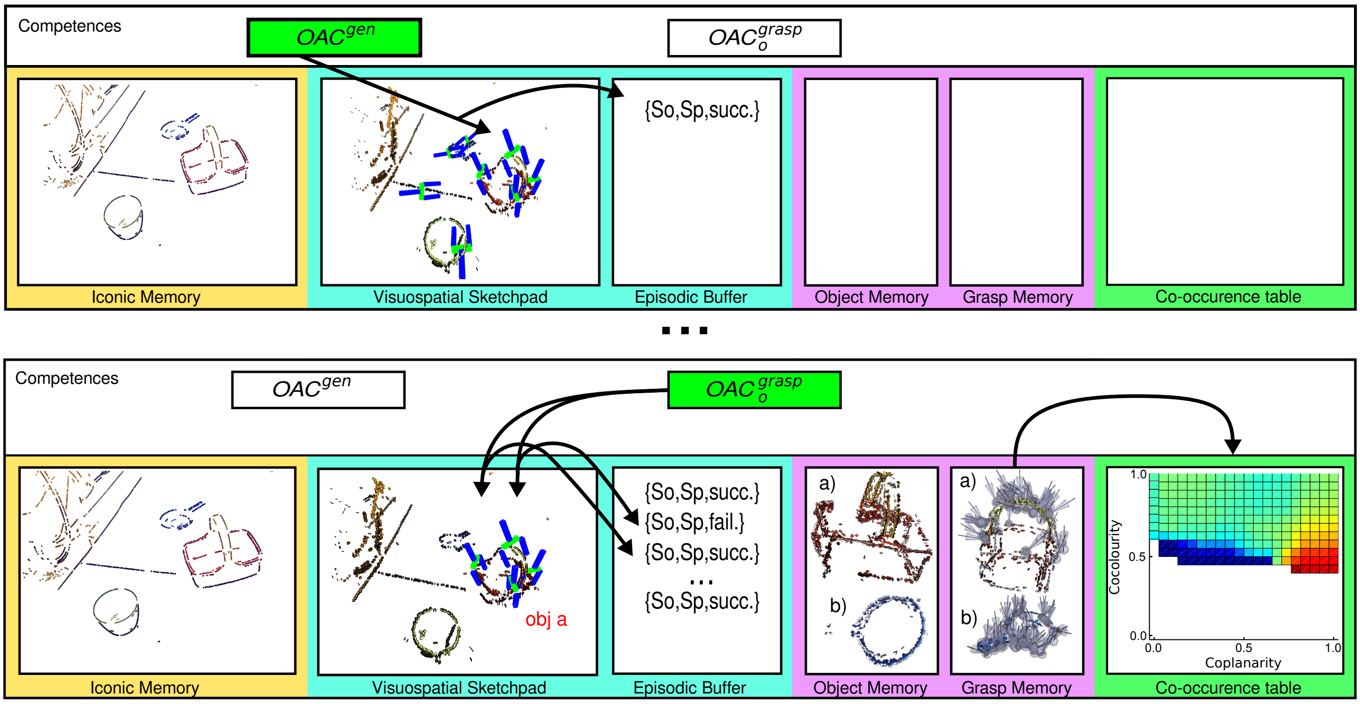
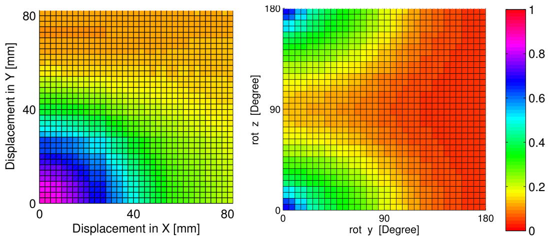


Figure 7: Illustration of how the system interacts by means of the two OACs interacting with the environment at two different stages of development. The top row represents this interaction at an innate state of development while the bottom row represents a more mature state.



(a) Translations (b) Rotations

Figure 9: Each successful grasp has been (a) translated or (b) rotated and subsequently its success likelihood is estimated using the grasp density associated with the object. This figure shows only the results for two dimensions of translation and rotation.

has been used to achieve a very dense grasp density, subsequently each successful grasp is transformed locally by a rigid body motion and using the density it is investigated whether the transformed action still would be successful. In order to reduce the complexity, only translations (see Fig. 9a) or rotations (see Fig. 9b) have been applied, not a combination of them. In these co-occurrence tables a clear anisotropy in the conditional probabilities are visible indicating that isotropic kernels are indeed a sub-optimal choice. In section 6.1 we argue that these co-occurrence tables can be used to define more optimal kernels.

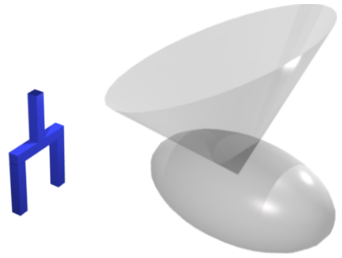
6 Interaction of the development of SMS and world knowledge

As indicated in Fig. 2, the SMSs and the generic world knowledge develop in parallel and complex interactions are to be expected. Making statements about this interactions in humans is difficult since only the change of behaviours, i.e., the executions of OACs/SMSs is directly observable. Statements of the change of internal representations are very difficult to achieve by means of neurophysiology. For example, it is virtually impossible to do single-cell recording experiments during development in awake behaving monkeys [23] (see also [16]). Developmental psychology can generate insights into that issue by means of sophisticated experiments. However, these insights are only indirect. Hence we find it to be valuable to look at such interactions in a developing robot system. This allows for making algorithmic problems explicit on a high level of detail.

In this section and based on the generic world knowledge accumulated by means of the OACs and abstracted in terms of grasp densities and co-occurrence tables as described in section 5, we intend to exemplify these interactions. First, we will discuss the need to improve the grasp density learning by means of learning more appropriate kernels in section 6.1. Then we discuss the role of co-occurrence tables for finding grasp affordances by means of statistics in section 6.2.

6.1 Kernel learning

The observations manifested in the co-occurrence tables in figure 9 lead to the idea of an anisotropic kernel where the iso-probable surface for the positional part becomes a ellipsoid rather than a sphere (see figure 10). We are currently working on developing these kernels in the density computation process. Besides having an empirical justification of the kernels themselves we also expect a much better convergence performance. The main benefit of the anisotropic kernel is that fewer kernels can be used to describe the density. As a direct consequence of this, we expect that fewer experiments are needed to achieve a "complete" density, which will then also speed up the convergence and will reduce the memory usage.



(a) Gripper (b) Kernel

Figure 10: (a) The orientation of the grasp corresponding to the mean-value of the kernel and (b) visualisation of how an anisotropic kernel could be formed.

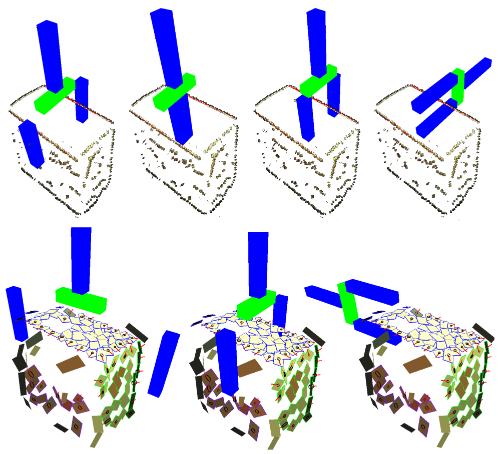


Figure 11: Top row: Grasping hypotheses derived from a pair of co-planar contours, (see section 4.2). Bottom row: Grasping hypotheses based on a single surface feature.

6.2 Co-occurrence tables as basis for justifying and improving grasp reflex

The co-occurrence tables also allow for a statistical justification of the originally hardwired behaviours as used in the execution of OAC^{gen}. Looking at the co-occurrence tables in Fig. 8 it becomes visible that the co-planarity relation is indeed indicative for successful grasps. It can be expected that the statistical analysis of the space of feature-relation action associations will reveal further indicative relations. In Fig. 11 besides edge pair related grasp affordances (top row) also surface related grasp affordances (bottom row) are shown. It is likely that many more indicative feature relation-grasp affordance relations do exist, potentially also for feature relations of very high order. Once enough grasp data in terms of grasp densities is available to the system even such higher order relations can be analysed. These can then be the basis for new OACs (i.e., branching OACs) coding more sophisticated grasp affordances.

Note that also in this context it is important to generate a large number of experiments and to integrate them in the co-occurrence tables. Hence the principle of ongoing learning on all levels as realised by the OACs is decisive for selecting the required material.

7 Related Work on Sensorimotor Schemas

Work on computational models of sensorimotor schemas includes several works on explicitly Piaget-inspired sensorimotor schemas [12, 6, 35, 22]; however, these either do not have objects to perceive (e.g. using sensorimotor schemas to navigate in mazes), or have objects that are only sensed in a binary way (present or not), and so these are not comparable with our work on gathering knowledge of objects. On the other hand, recent work on affordances [37], though not explicitly modelling sensorimotor schemas, is quite close to our work. Ugur et al. [37] use supervised learning to learn the patterns of visual features which are indicative of graspability (and other affordances). Given the appropriate selection of input features, and appropriate training data, this approach could implicitly capture relationships which are similar to our co-occurrence tables for example. However our approach is capturing and representing object knowledge more explicitly, and this should give greater generality in application.

In an alternative approach, Hart and Grupen [14] describe a Piagetian inspired framework for constructing adaptive robot control strategies. While our OACs place little restrictions on control programs or learning schemes, Hart and Grupen's approach limits the usable control programs to a specific set of functions and the learning scheme to reinforcement learning. The authors show how the Piagetian notions of assimilation and accommodation are implemented and give examples of their usage within their system. Most interestingly they allow composition of schemas; this goes beyond our current work, and if combined with our ideas of developing generic world knowledge, this could potentially facilitate the learning of sensory abstractions which capture relations among objects, or spatial relationships (i.e. a higher order of world knowledge). This would be the next logical step for the learning of world knowledge in the upper track of Fig. 2, and according to Piagetian theory it is through performing combinations of schemas that such knowledge is acquired [24, 25]).

8 Discussion

In this paper we demonstrated an important developmental process which is very hard to observe by means of developmental psychology or neurophysiology, namely the interaction of emerging generic world knowledge and developing sensory motor schemas. In this context, we have used the formalisation of sensory motor schemas in terms of object action complexes. We investigated two OACs coding grasping with and without prior object knowledge. Although still partly speculative, we could concretise potential interactions between developing generic world knowledge and the execution of OACs. In future work we will realise embodied systems in which such an interactive development will take place and we will further specify and quantify such interactions.

ACKNOWLEDGEMENTS

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Piagetian Autonomous Modeler

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Abstract. The Piagetian Autonomous Modeler (PAM) is a proposed architecture for a system that constructs an internal representation of a real or simulated environment based on its interaction with the environment. The novel aspects of PAM are: (1) how it spreads activation; (2) its use of two kinds of schemata (structural and behavioral) to connect the representational units (monads); (3) its use of multi-strategy inference to extend the internal model; (4) its use of a consolidation component to provide automaticity and forgetting; and (5) its evolution of successful behaviors through genetic techniques. The system is called Piagetian because it employs the notion of Monads (fundamental representational units), Schemata (patterns of structure and behavior), Assimilation (incorporating external elements) and Accommodation (modifying internal structures in accordance with environmental feedback) which are essential to the theories of Human Cognitive Development espoused by Piaget [7] [8].

1 BACKGROUND

The work in "*early developmental AI*" as surveyed by Guerin [17] is replete with examples of artificial intelligence computer programs that can interact with an environment, learn, and synthesize new concepts. Most prominent among them is Gary Drescher's seminal program, the Schema Mechanism [1], which employed the theories of Jean Piaget to demonstrate aspects of learning and planning in infant cognitive development.

The PAM architecture inter-connects and advances the work of earlier system architects such as Drescher [1], Heib & Michalski [2], Tecuci & Michalski [3], Holland et al. [4], Goldberg [5], Riesbeck & Schank [6], Chaput [14], and others.

This architecture is compatible with the developmental theory and embodied-social cognition theory of language learning as described by Kaplan, Oudeyer, and Bergen [22].

Although embodiment (sensing and acting upon the environment) is central to the PAM system, this work deliberately does not address attention, curiosity, motivation, drives, beliefs, desires or intentions. This omission was made in order to limit architectural concerns in the initial design of the system. These phenomena may be revisited in later phases as the PAM system evolves.

2 RESEARCH GOALS

The PAM effort is a multi-phased inquiry into early developmental AI which has several objectives:

(1) to replicate Piaget's sensorimotor and pre-operational stages of cognitive development including language acquisition;
(2) to create smarter computer systems based on Piaget's genetic epistemology that (a) are capable of modeling their environment, (b) exhibit stages of development, (c) predict transformations in their environments, (d) learn from failure, and (e) perform multistrategy inference;
(3) to explore the validity of the hypothesis that monads and schemata can be used to model a learner's environment;
and (4) to unify the work of Drescher and Michalski.

3 ARCHITECTURE

The PAM architecture described herein represents the first phase[1] of the research effort.

3.1. Assumptions

The system assumptions for PAM are:

(1) Human learners construct a mental model to represent (a) the structure of and (b) transformations within their environment.
(2) Monads and schemata are sufficient to construct a predictive model of an environment.
(3) The PAM system is implementable on existing computing technology.
(4) The system performs in real time, is resilient, available, and scalable.
(5) The system is domain agnostic. Any domain specific percept and effect assertions made to the system are irrelevant since all assertions are transformed into an internal representation of monads and schemata. Therefore, only the concurrence and recurrence of the assertions are salient.

3.2. Views

Figure 1 shows PAM interacting with its environment.
Figure 2 depicts the data tiers of the evolving model.
Figure 3 describes the structural and behavioral schemata that PAM employs.
Figure 4 shows a sample inference operation on a portion of the heterarchy.
Figure 5 shows the decomposition of the system elements by process and object.
Figure 6 shows the use cases for each system element.
Figure 7 shows the system elements as components exchanging data.
Figure 8 shows the actual data flows across the elements of the system.

3.3. Monads

A monad is a data structure which represents a percept, effect, or concept. Percepts represent encodings of sensor data from an external environment. Effects represent the status of actions that have been performed on the external environment. Concepts are internally synthesized monads which represent a completely new entity within the model arising from some underlying pattern of structure or behavior. Hence, a concept is

[1] Note that language acquisition is a long term goal and will not be addressed in phase 1.

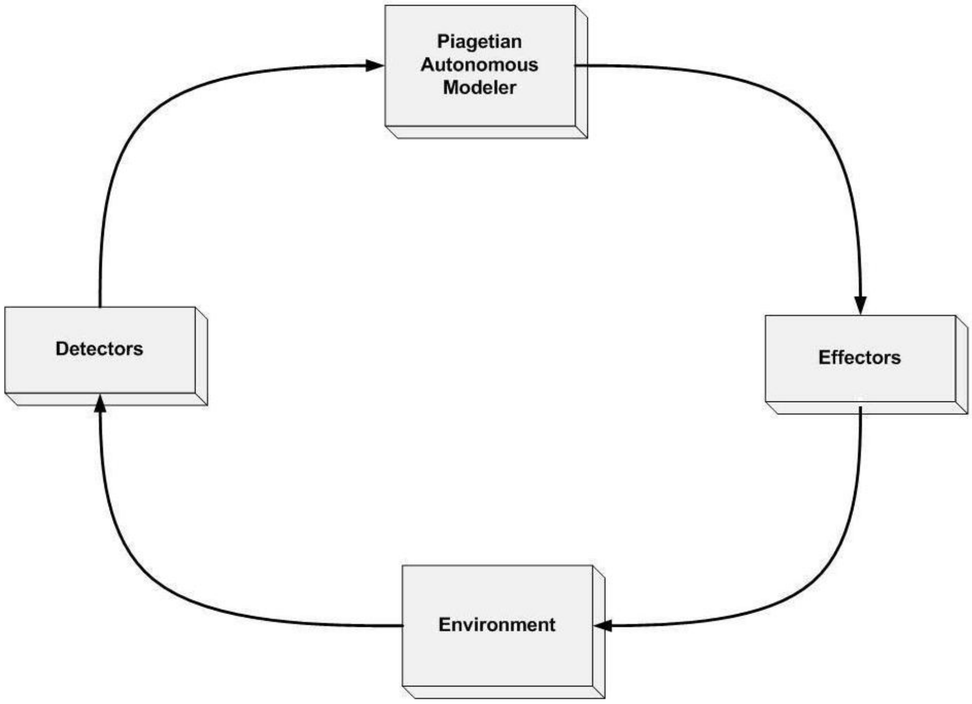

Figure 1. PAM Context view.

a schema. Schemata are structural relationships among monads, or behavioral patterns identifying transformations in the environment.

In Drescher's Schema Mechanism, concepts are called "Items" (which can be in a Boolean state of On or Off). Drescher's "items" correspond to "monads". In PAM monads are not Boolean and hence do not represent a binary On or Off state. Instead, they are continuous and use an activation time which denotes when they were last considered active. This strategy establishes an implicit notion of "decay" which is novel.

Monads actually have two activation times: fact activation and goal activation. These denote when they were last perceived or inferred (as a fact) and when they were last needed to enable a prediction (as a goal). Monads also contain the concept of Tier which sorts them into levels of abstraction and allows them to form hierarchies within the larger heterarchy[2].

3.4. Detectors and Effectors

To use PAM, one or more detector programs and one or more effector programs must be constructed. Each detector program provides PAM with continuous or discrete sensor data transformed into PAM's internal representation, percept monads.

When sense data arrive in the detector program, the program makes assertions in the model (Figure 2). Each assertion either creates a new percept monad or retrieves an existing percept monad, which is then marked active.

Each effector program allows PAM to issue commands to a device and retrieve feedback about the status of the command issued. The status (unknown, pending, executing, failure, or success) is asserted to PAM's model and its corresponding monad is created or retrieved and marked active.

[2] The model heterarchy is the sea of monads akin to Lenat's sea of assertions in Cyc[16].

3.5. Schemata

In contrast to Drescher's Schema Mechanism, which has one type of schema, PAM has two types of schema: structural and behavioral. The two types of schemata are needed because of the system's primary assumptions: that both structure and behavior exist in an environment, and that they are different. Structure pertains to the relationships among entities within the environment, while behavior pertains to the transformations occurring within the environment. Structural schemata are defined in PAM in order to allow PAM to perform inference above and beyond what would be encompassed by behavioral schemata alone because a human (our archetypal learner) can make subtle inferences which go well beyond predicting the effects of actions.

Drescher's schema consisted of a context, action, and result. PAM's schemata differ substantially (see Figure 3).

As behavior, a schema defines a predicate ***then(C, P, s)*** that posits: when the context ***C*** is true, the prediction ***P*** will also be true within a given time span ***s***. Thus, PAM's behavioral schemata contain a context and a prediction. The context contains two lists: enablers and impeders. The prediction also contains two lists: enables and impedes. Monads can be present in these lists within a behavioral schema.

As structure, a schema defines a relation $\boldsymbol{R(a_1..a_3, i)}$ among monad collections $\boldsymbol{a_j}$ in $\boldsymbol{a_1..a_3}$ at a given instant in time ***i***. PAM uses several types of structures including unary relations, binary relations, ternary relations, to form cases, events, types, plans, goals, and other concepts.

3.6. Activation

In PAM activation is defined as "recency," and therefore a system lifespan time function is used to mark active model entities. A system-wide activation interval parameter is also defined which demarcates the cutoff between active and inactive model entities.

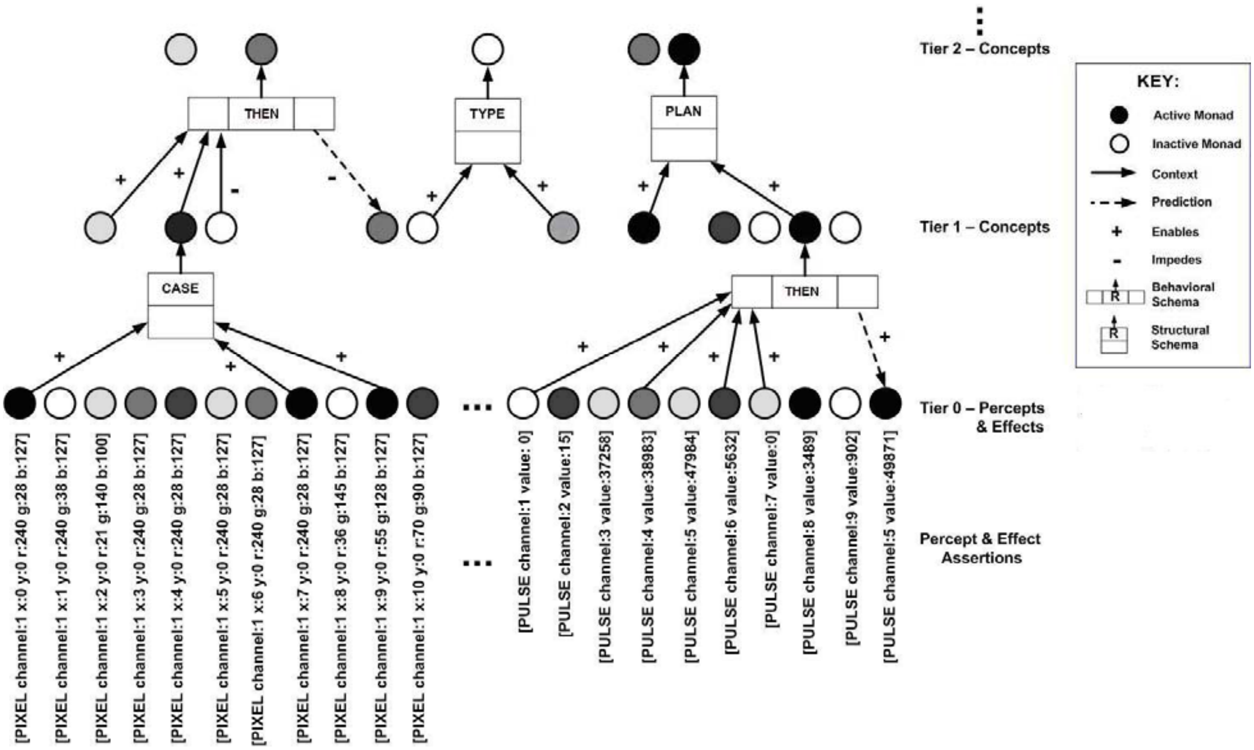

Figure 2. Assertions, monads and schemata.

The Tier Activator system element is responsible for activating monads representing structural schemata, and the Prediction Matcher system element is responsible for activating monads representing behavioral schemata. Percept monads are activated by Detectors and Effect monads are activated by Effectors.

3.7. Cases and Events

Holland et. al [4] describe mental models as "assemblages of synchronic and diachronic rules organized into default hierarchies and clustered into categories." The PAM system contains processing elements which use structural schemata to form synchronic (concurrent) and diachronic (sequential) relationships among monads.
As monads become activated within PAM, a concurrence associator process connects groups of concurrently active monads into "cases." A case represents a synchronic relationship (existing at one instant in time) as specified by Holland et. al.[4]. Similarly, a sequence associator process clusters monads into temporal "events." An event represents a diachronic relationship (existing across a period of time)[4].

3.8. Types and Plans

Cases represent instances of types (i.e., Classes). An inductor process synthesizes new types and clusters existing cases into these types. Types can also be clustered to form hierarchies of types. In a similar fashion events represent instances of plans. The inductor process aggregates events into newly synthesized plans, and may further form hierarchies of plans. Pickett & Oates [20] have done extensive work in concept formation -- as demonstrated by their work on the Cruncher. An incremental concept formation algorithm based on the Cruncher is used in the Inductor.

A reasoner processing element in PAM builds upon these cases, types, events and plans by using structural schemata to form other higher level relationships.

3.9. Inference

Ryszard Michalski [1] [3] [12] has long been involved in multistrategy learning and inference. His work has largely focused on logical models of inference in Artificial Intelligence systems. He and his co-authors have developed a method of inference involving Dynamically Interlaced Hierarchies. The premise is that language is organized into disparate hierarchies or taxonomies which are connected by traces (i.e., sentences, in PAM, cases). Inference then is simply a matter of performing transformations on traces (i.e., substitutions of words within sentences) according to the placement of the nodes (words) in the related hierarchies. (See Figure 4).

In their work on Multistrategy Inference, Heib and Michalski [2] define some basic knowledge generation transmutations which can be performed by making simple substitutions of select nodes in a case or event (referred to as a "trace" in the literature) from various related taxonomies within a model. By substituting constituent monads of a case (or event) according to specific transmutations, new cases (or events), and by extension new inferences, can be formed.

Hauser [13] defines thinking as navigating through the content of a word bank (a flat ontology, or heterarchy). "Navigation is the temporary activation of certain propositions in a potentially vast amount of content for purposes of inference and conceptualization (selecting what to say)." This view is consistent with Michalski's traces in Dynamically Interlaced Hierarchies.

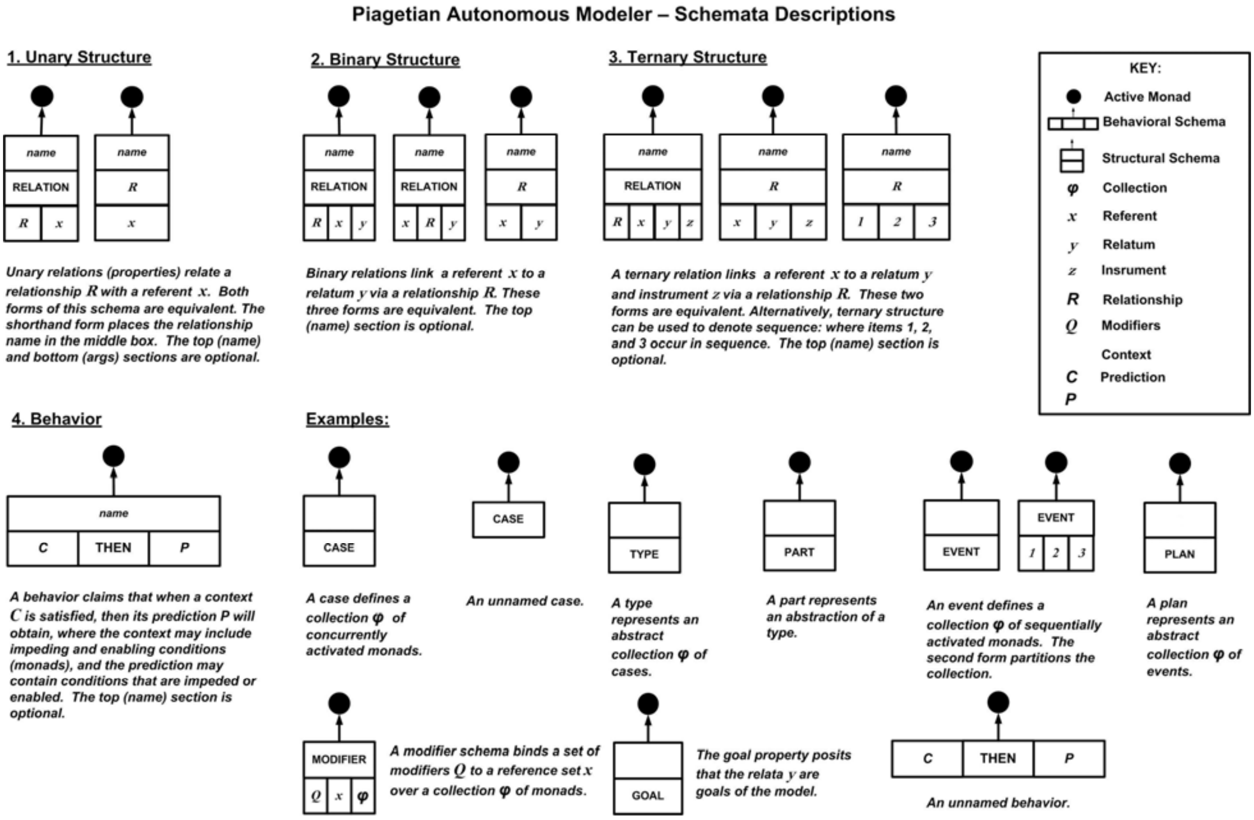

Figure 3. Schemata varieties in PAM.

Riesbeck & Schank [6] discuss the utility of Case based reasoning and implement a system to demonstrate their theories, Unfortunately, their system is largely constructed a-priori and does not employ dynamically constructed cases and events based on interaction with an environment. The Reasoner element in PAM is responsible for performing inference based on Michalski's theories of Inference [1] [3] [12]. This combination of interactionist model construction and multistrategy inference is novel.

Tecuci and Michalski [3] further define specific transmutations which can be applied to cases and events to make inferences: Generalization, Specialization, Abstraction, Concretion, Similization, Dissimilization, Agglomeration, Decomposition, Prediction, Explanation, Selection, Generation, Characterization, Discrimination, Association, Disassociation, Reformulation, Randomization, Insertion, Deletion, Replication, Destruction, Sorting, Unsorting.

3.10. Equilibration

Piaget [7] [8] discusses the notion of equilibrium and equilibration. Soros [9] also discusses the notion and use of equilibrium. For Soros, equilibrium occurs when predictions are consistently successful (with minor divergences). Disequilibrium, conversely, is when predictions are consistently failing [9]. Convergence with reality means trending towards more and more successful predictions. Divergence with reality means more and more failed predictions. (George Soros' theories of Human Uncertainty and Reflexivity are instructive here.)

Soros further theorizes that divergences occur in two ways: through Static and Dynamic Disequilibrium. Static Disequilibrium occurs when reality changes and the mental model does not change. Dynamic Disequilibrium occurs when a mental model changes but the underlying reality has not changed

The PAM system contains an Equilibrator component which modifies predictions based on prediction success or failure. The Equilibrator regulates the accuracy and consistency of the systems predictions. Failed predictions are refined to identify a failure cause through a process called Marginal Attribution (Drescher [1]).

In addition, PAM applies genetic techniques to successful predictions. Behavioral schemata which are successful in predicting outcomes of actions become candidates for genetic transformations such as crossover and mutation per Goldberg [5].

3.11. Consolidation

This component performs the automaticity and forgetting functions within PAM and serves to reclaim any low utility or useless model entities.

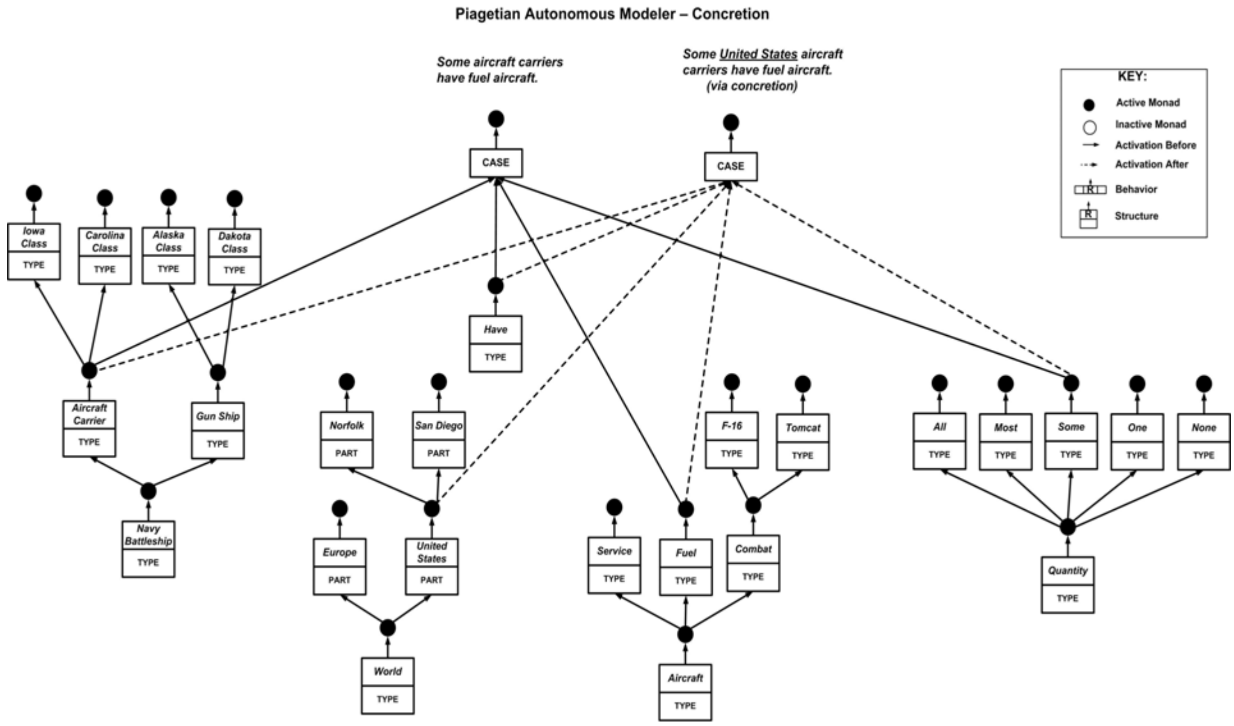

Figure 4. An inference example (adapted from Heib & Michalski [2]).

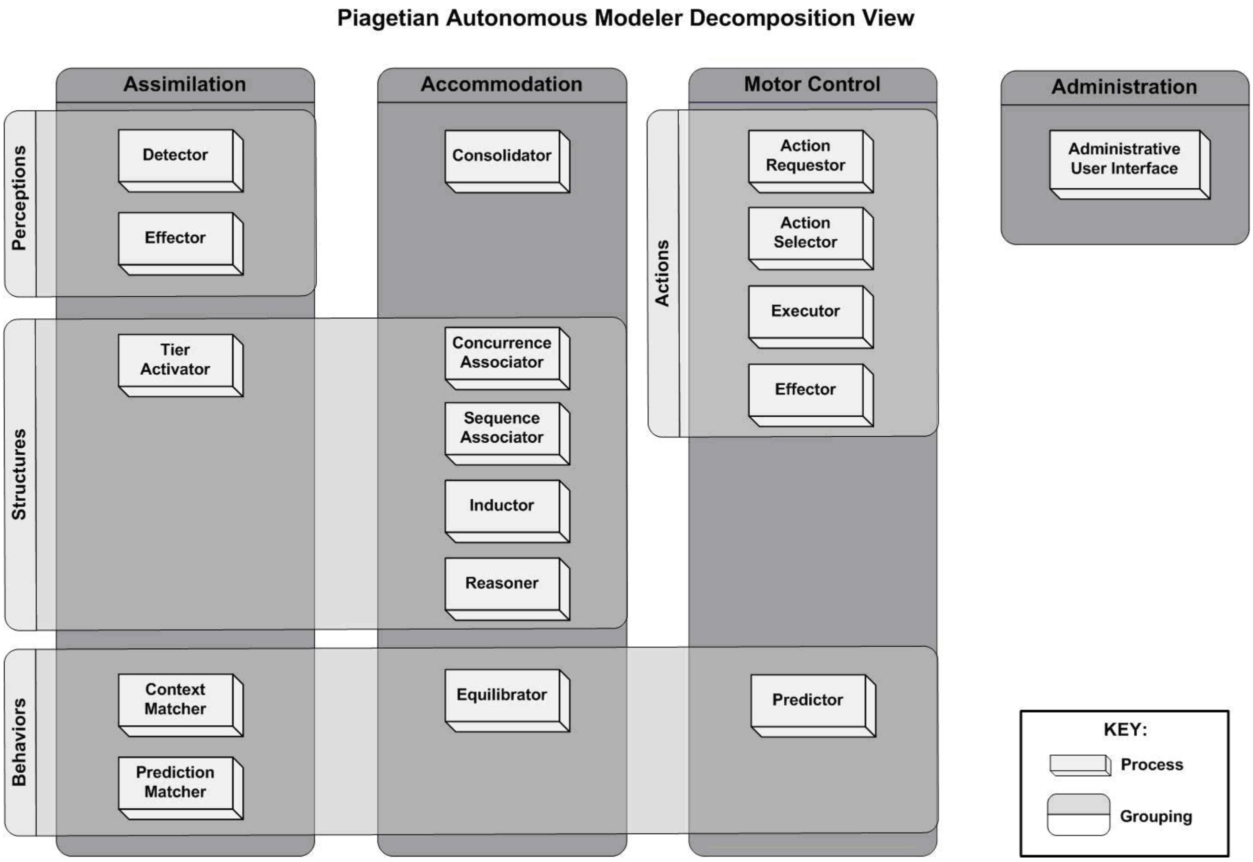

Figure 5. PAM Decomposition. Note that perception elements interact with the environment, structure elements activate and create new associations among structural schemata, behavior elements activate and reward behavioral schemata, and action elements determine which actions should be performed.

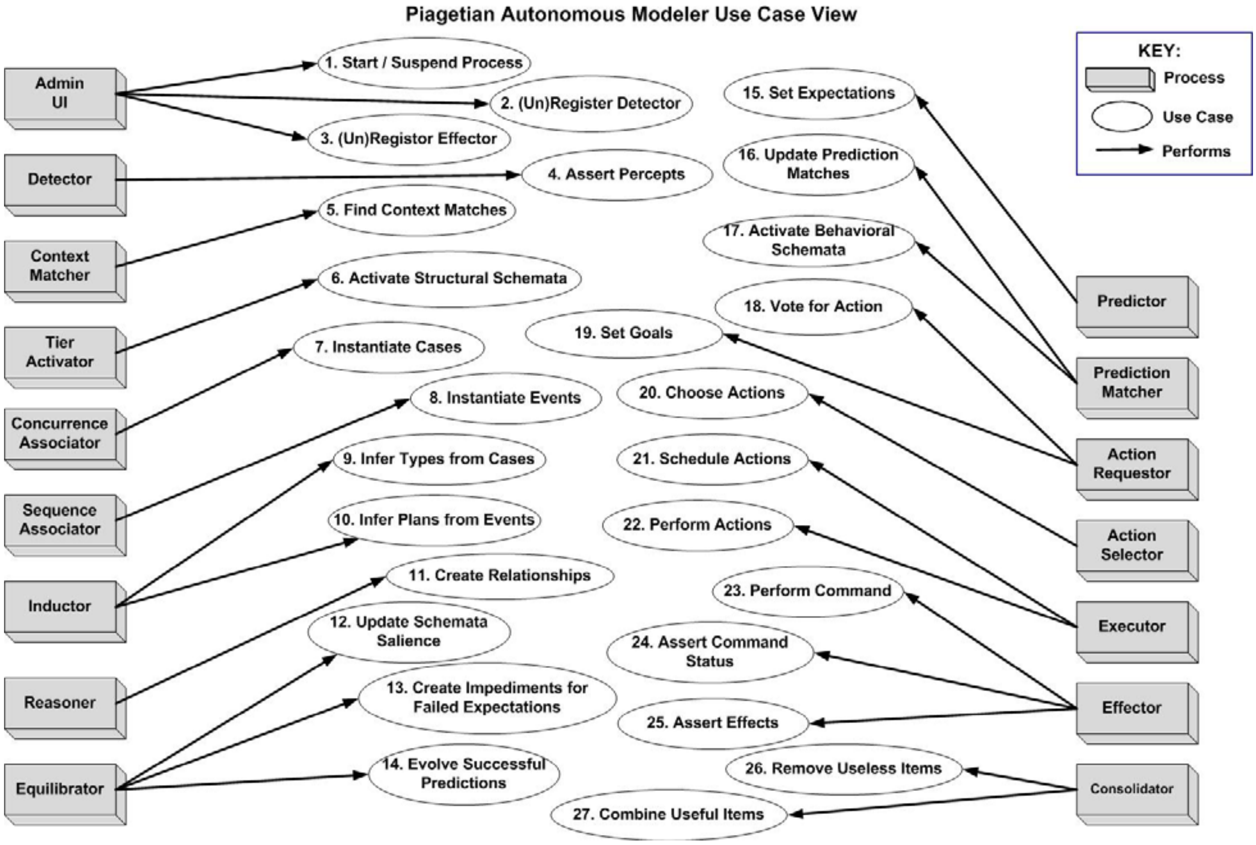

Figure 6. PAM Use Cases.

3.12 Components

(1) Detector. Transforms sensor data into activated percept monads within the model.
(2) Tier Activator. Activates the monads of structural schemata.
(3) Effector. Transforms actions into environmental commands, receives feedback on the execution status of the commands, and activates the corresponding effect monads within the model.
(4) Context Matcher. Matches behavioral schemata contexts with activated monads in the model. A context is satisfied when all enabling monads are active and no impeding monads are active.
(5) Prediction Matcher. Matches expectations (i.e., expiring predictions) to activated monads in the model, and when satisfied, activates the monads representing the behavioral schemata.
(6) Concurrence Associator. Creates "Cases" based on the concurrently activated monads in a lower tier.
(7) Sequence Associator. Creates "Events" based on the sequentially activated monads in a lower tier.
(8) Inductor. Aggregates "Cases" into "Types" and "Events" into "Plans".
(9) Reasoner. Infers new relationships using multiple strategies.
(10) Equilibrator. Revises behaviors according to failure and evolves behaviors according to success.
(11) Predictor. Sets an expiration time for a behavior's prediction (thereby creating an "expectation") based on actions the system has committed to undertake.
(12) Action Requestor. Bids for actions to be performed based on goals (inactive predicted monads), and satisfied behavior contexts.
(13) Action Selector. Decides which action to schedule for execution based on multiple biases [22].
(14) Executor. Invokes an action.
(15) Consolidator. Removes useless items and combines useful items.
(16) Administrative User Interface. Provides a system control dashboard and allows parameter adjustment.

4 EXPERIMENTS

Two experimental domains are proposed for this phase. A foraging domain (based on the Pioneer 3 DX robot simulation environment as described in Chaput [14]) , and a robot play domain (similar to Kaplan et. al. [22]) where a wireless mobile robot with audio and visual sensors can interact with various objects.

5 IMPLEMENTATION STATUS

The prototype is in the detailed design phase. It will be implemented using an agent platform and a database (either conventional SQL, high performance SQL, or NO-SQL).

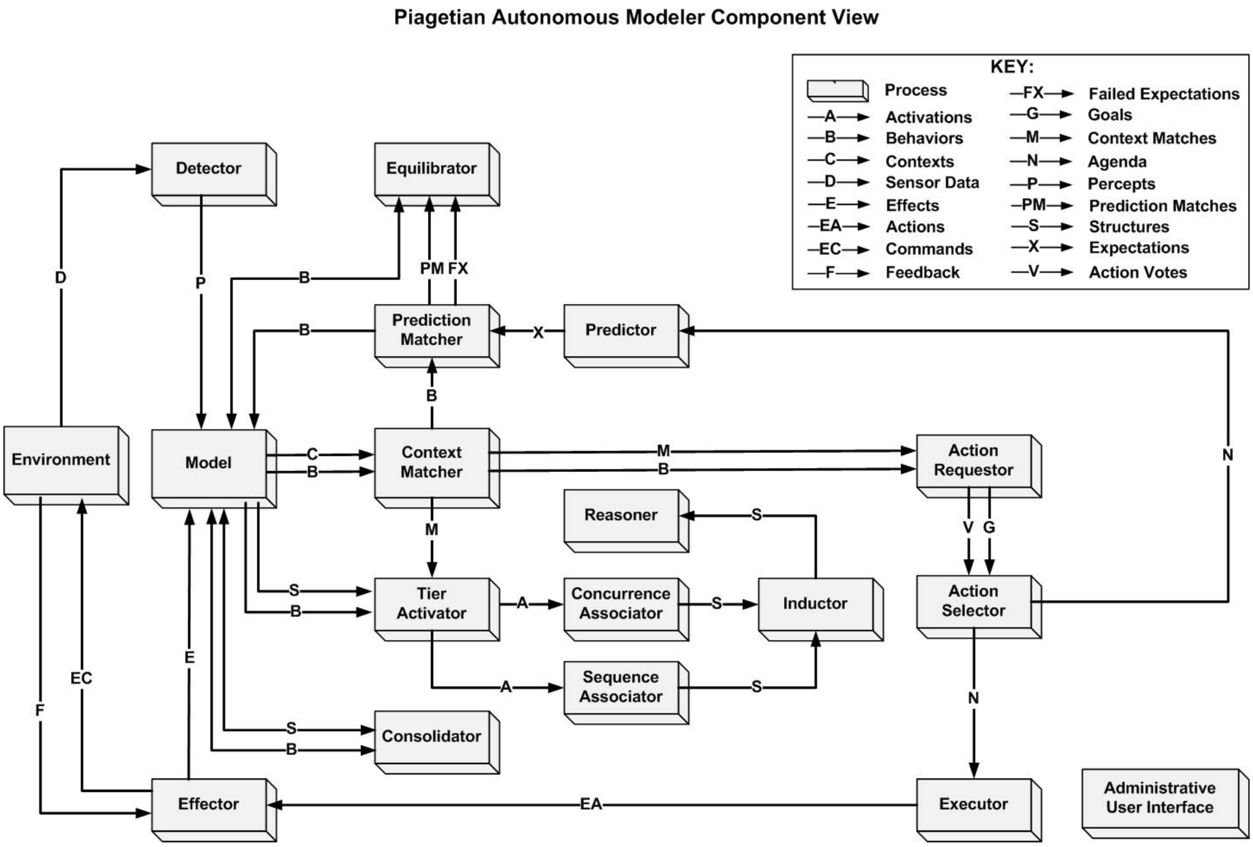

Figure 7. PAM Components.

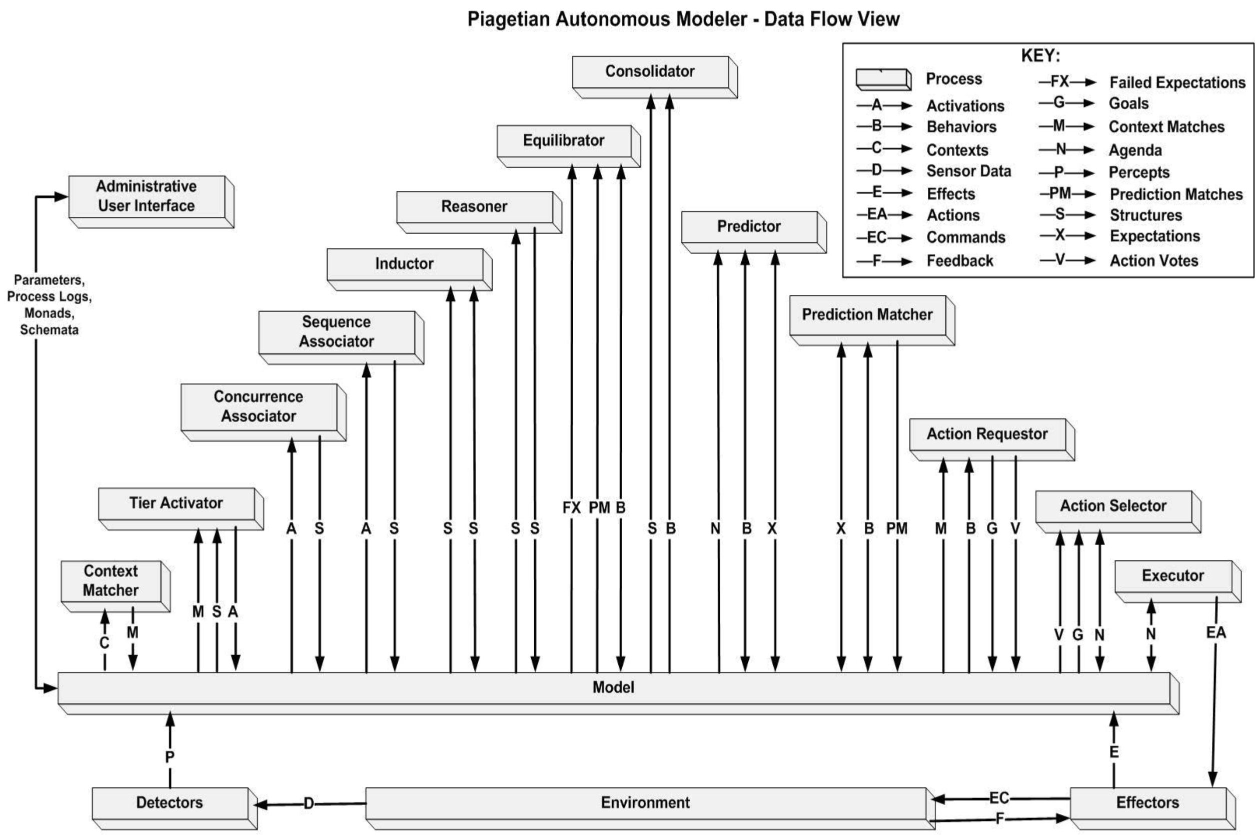

Figure 8. PAM Data Flow.

6 CONCLUSIONS & FUTURE WORK

The PAM architecture promises to be an exciting direction for experimentation in early developmental AI. In contrast to systems such as Chaput's CLA [14] which uses self organizing maps (SOMs), the PAM architecture seeks to exploit structural schemata, multi-strategy inference, cases, events and novel time based interconnections between percepts, action effects, and synthesized concepts.

7 ACKNOWLEDGEMENTS

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Using the Principles of Classical Conditioning to Learn Event Sequences

Timothy A. Furze [1] and **Brandon Bennett** [2]

Abstract. In order for an autonomous agent to interact rationally within its environment, it must have knowledge of that environment. Given that the wealth of knowledge that even small children evidently quickly acquire, it is infeasible for an agent to be directly encoded with much, if any, knowledge about the real world. This means that it would be best to instead imbue the agent with the ability to learn the knowledge for itself. Given the non-triviality of the problem of programming an agent with this ability, this paper looks at a system that qualitatively replicates one of the main psychological processes that biological agents use to learn about their environment, that of classical conditioning. Initial testing of the system shows results that are inconclusive but are encouraging. This leads to the conclusion that further work is needed to ascertain the utility of the approach.

1 INTRODUCTION

Classical Conditioning is a phenomenon of learning that begins during an early stage of development, according to Piaget's theory of cognitive development [18]. Due to its prevalence within animals it can be argued to be central to any agent's development of its understanding of its environment. The theory of classical conditioning, primarily introduced by Pavlov [17], allows for an agent to passively learn about its environment. The principal mechanism of classical conditioning is that of an agent learning to associate two stimuli that the agent observes as repeatedly occurring in pairs. The pair of stimuli is usually one stimulus that causes a reflex action in the agent and another stimulus that, if encountered in isolation prior to any pairing, would not cause any reflex.

By considering examples of stimuli pairings that would become associated through classical conditioning in a natural environment of a biological agent, the utility of such a mechanism to the agent can be seen. The smell of a particular food pairing with its taste and the sight of fire pairing with the sensation of heat are two examples of pairs of stimuli that a biological agent could conceivably learn to associate with one another in the course of its development in a natural environment. These sorts of examples suggest that classical conditioning can be seen as a mechanism to infer relationships between stimuli that can be treated as two aspects of the same, more complex, stimulus without the agent having any prior knowledge.

With this conception of classical conditioning in mind, it suggests that the mechanisms of classical conditioning could be used to infer relationships between pairs of events and so allowing the construction of patterns and sequences of events in an unsupervised manner with no prior knowledge. This paper introduces a system that uses a model of classical conditioning in order for an agent to learn to recognise increasingly complex sequences of events starting from a limited set of observed geometrical changes within its environment.

The system that was developed to test and expand on this theory, is comprised of three sub-systems that each provide data to one another forming a feedback loop to allow the system to find increasingly complex sets of patterns. The first sub-system reads a stream of events that describe simple geometrical changes within the observed scene and recognises patterns of those events that occur in its database of event patterns. The second sub-system takes both the base events and the instances of the recognised patterns and provides pairings of event instances that satisfy temporal and event complexity measures. The third sub-system takes the pairs of event instances and provides a list of those event pairs that should be considered significant to the first sub-system to use as its database of event patterns. The third sub-system uses a model of classical conditioning to decide which of the event pairs is significant.

The system was applied to the domain of visual extrinsic object motion (i.e. object tracking) in order to evaluate the system. The test that was done was that of a video of a person throwing a ball in the air. The prediction was that given the data derived from this scene, the system would infer that when the ball went up, that it would expect that the ball would later come down. This would be evidence of the system having developed a simplistic account of gravity.

This paper is structured as follows. Section 2 covers the background of the phenomena of classical conditioning and previous work in the learning and recognition of event sequences. Section 3 looks at the workings of the system that learns the event sequences and how this is done by modelling the mechanisms of classical conditioning. The work done to evaluate the system is presented in section 4. Concluding remarks and potential future directions for this work is then covered in section 5.

2 BACKGROUND

2.1 Classical conditioning

This theory is also known as Pavlovian Conditioning, named after Ivan Pavlov, one of the primary people who introduced the theory. Pavlov's widely-known experiments with dogs, first published in English in 1927 [17] were among the first experiments to demonstrate the collection of phenomena that are now collectively known as classical conditioning. Pavlov's famous experiment conducted with dogs was to create an audible tone (mostly a bell or metronome) immediately prior to the dogs having a substance directly placed into their mouth that would cause the reflex action of salivation (usually meat powder or a weak acid). This was done multiple times. The same audible tone was then presented to the dogs without the presentation of

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the substance. The result was that the dogs' salivary response was observable with the tone even when substance was not presented. This salivary response without the substance correlated with the number of presentations of the tone where the substance was jointly presented. Pavlov used this experiment and others like it to derive a theory of animal learning.

The derived theory of animal learning from this is that an arbitrary neutral stimulus can become associated with any non-neutral stimulus, (i.e. a stimulus that triggers a reflex response) based on their similar co-occurrence in time. Thus when the neutral stimulus is presented alone, the subject gives a similar response to the unconditioned response, as it has come to expect that the non-neutral stimulus will follow. In the literature around classical conditioning, the names of the stimulus and the responses have particular names. The neutral stimulus is known as the conditioned stimulus (CS) which in Pavlov's experiment corresponds to the generated tone. The non-neutral stimulus is termed the unconditioned stimulus (US) which in Pavlov's experiment corresponds to the substance placed in the dogs' mouths. The response to the non-neutral stimulus is called the unconditioned response (UR) which in Pavlov's experiment corresponds to the salivary reflex the dogs had to the substance. The response to the neutral stimulus after the association had been formed is the conditioned response (CR) which in Pavlov's experiment corresponds to the salivary response the dogs had to the tone when the substance was not present.

There are several phenomena that have been observed in the interaction of CSs and USs. The most notable of these are: Acquisition, Extinction, Reacquisition, Blocking, Secondary Conditioning, The Inter-Stimulus Interval, Intermittent Stimulus Facilitation and Conditioned Inhibition.

- **Acquisition** – Acquisition is the process whereby the CS becomes associated with the US and thus the CR. This is the phenomenon that was discussed above. The strength of the association (e.g. measured by the amount of saliva produced) is a sigmoid-like function of the number of reinforcements of the CS (i.e. the number of presentations of the CS where the US follows).
- **Extinction** – Extinction is the process whereby a CS that is already associated with the US is repeatedly and consistently presented to the subject without the US. The strength of the association is weakened and eventually returns to the same level of association as observed prior to acquisition.
- **Reacquisition** – Reacquisition is the name given to the phenomenon where a previously extinguished CS-US association is acquired again. During reacquisition, it takes a fewer number of reinforcements to re-acquire the same strength association than it did the previous time that association was acquired.
- **Blocking** – Blocking is where a previously conditioned CS stops a second CS from acquiring an association with the US (i.e. demonstrating a CR) when the two CSs are reinforced simultaneously.
- **Secondary Conditioning** – Secondary Conditioning is where a secondary CS can be conditioned to elicit a CR through reinforcement only with a primary CS (where the primary CS has been reinforced with the US). This effect is typically weak as the extinction of the primary CS will happen while the secondary CS is being conditioned.
- **The Inter-Stimulus Interval** – The inter-stimulus interval is the time between the start of the CS and the start of the US. This time gives rise to several situations that affect the acquisition process. This leads to two modes of acquisition, Delay and Trace conditioning. Delay conditioning is where the CS overlaps or finishes immediately before the US appears. Trace conditioning is where the CS finishes with a period of inactivity before the US appears. The inter-stimulus interval affects the rate of acquisition of a CS-US association. The rate follows a curve where small intervals are negligible, it then rapidly moves up to a peak and then gently decays, similar to the curve of a log-normal distribution. The difference between delay and trace conditioning is that the latter has a much faster decay after the peak.
- **Intermittent Stimulus Facilitation** – During conditioning, a longer inter-stimulus interval gives a weaker CR. If a second CS is presented between the first CS and the US, the CR of the first CS is stronger.
- **Conditioned Inhibition** – Conditioned Inhibition refers to an effect where a CS can be made to create an inhibitory effect on a CS-US association. This can be demonstrated in the following experiment: two CSs, CS_1 and CS_2 are conditioned separately to associate with the US. A third CS, CS_0, is then non-reinforced simultaneously with CS_1. Presenting CS_0 simultaneously with CS_2 will then not elicit a CR.

Ever since classical conditioning became widespread in the discourse of psychology, there has been numerous models of classical conditioning that vary in complexity and fidelity. The most well-known model is Rescorla and Wagner's model that was presented in 1972 [22]. This model has served as the basis of later models [12, 30]. The Rescorla-Wagner model works by calculating a difference between the current association strength and what the new trial implies it should be. The rate of learning is based on the salience of both the CS and the US. More recently, there has been a trend to use artificial neural networks to model classical conditioning [26, 25, 10, 7]. Balkenius and Morén [2] presented a comparative study of a number of modern models, including artificial neural network based models, those based on Rescorla and Wagner's model, among others.

2.2 Event sequence learning

Research into learning patterns of event sequences mainly comes from two different fields of computer science research, namely data mining and computer vision. Data mining applies the algorithms that learn event sequences to discover important frequent sequences of events from data that has a temporal component. For example, within the domain of shopping, finding rules that state that certain items have a tendency to be bought at the same time during particular points in the day, or customers who bought one specific item later return to buy another specific item. The main work in the area of mining rules of association (independent of a temporal context) is the work by Agrawal [1]. Work more directly involved with mining associations in a temporal domain is the work of Mannila [13], among others [31, 8, 19]. This work looks to mine sequential patterns of events that appear frequently. This area of data mining as a whole looks more on optimising time, space and I/O write complexity rather than trying to optimise the output rules themselves. Therefore this area, while being relevant in that it attempts to find the same sort of output, is not fully relevant to the work of this paper as the emphasis of the field is more on optimising computational resources rather than trying to have the rules more closely match that of human experience.

Computer vision research in this area more looks at optimising the output itself against a calculated ground-truth with computational efficiency as a secondary goal. One of the influential works in this field, though looks at recognition rather than direct learning is that of Ivanov and Bobick [9] who presented the idea of finding patterns as being akin to parsing a stochastic variant of a context-free grammar. This allowed the powerful idea of looking for events at different levels of abstraction, which is used in this current work. Another important work in the area is that of Stauffer and Grimson [28], who extended their seminal work in object tracking [27] to learn classifications of activity sequences by applying statistical methods to determine co-occurrences.

One approach that has been particularly successful in learning event sequences is to use Inductive Logic Programming. Inductive Logic Programming [15], or ILP, is a branch of machine learning that, through a variety techniques, attempts to find generalised logical rules that explain a set of specific relations. Typically, the rules are expressed as first-order horn clauses. While the technique has been used in the data mining aspect of event sequence learning [19], it has had a larger impact on the computer vision aspect. There have been two prominent works that have used the ideas of ILP to learn event sequences. The first of these is Needham et al. [16], in which the system presented is able to learn from observation only, the rules to a number of simple games, such as paper-scissors-stone. This was accomplished by using an ILP system (PROGOL) [15] to learn generic rules that state the required action given a particular game state. The second work is that of Fern et al. [6], which does not directly use an ILP system, as the authors came to the conclusion that first-order logic horn clauses was a poor representation to use for learning temporal event sequences. However, many of the ideas of ILP were used on a language specifically developed by the authors to represent temporal events. This event system was then used to learn to recognise a variety of verbs from the system being presented a video of that action.

While the system does use first-order logic as to represent its events, the system presented by this paper does not use ILP. The reason for this is two-fold. Firstly, ILP systems in wide use are batch-based programs, where the learning happens in a separate phase to the recognition and all the data the system is required to learn from is required before any recognition can be done. The second reason ILP could not be used by the current system is that ILP requires examples to be labelled as either positive or negative examples of a particular concept, meaning ILP methods are supervised learning methods. The system presented by this paper is an unsupervised system.

3 THE SYSTEM

The purpose of the system is to find sequences of events that are temporally associated with each other by utilising the theories of classical conditioning. This utilisation of the theory of classical conditioning makes one important divergence from most theories of classical conditioning, namely that this system does not assume the need for there to be a reflex-causing stimulus at all, and that a neutral stimulus can gain association with another neutral stimulus via the same mechanism. The reflex response to particular stimuli and the response of stimuli conditioned to them allows for the effects of this association to be measured.

There is evidence that supports this particular divergence. The first piece of evidence is in the phenomenon of classical conditioning known as secondary conditioning, as described in the previous section. This supports the divergence by showing that an association can occur between two conditioned stimuli and that there is nothing inherent in the nature of non-neutral stimuli that causes this association effect to happen. Another piece of supporting evidence is in Rescorla's substantiation of the S-S interpretation of conditioning [21]. The S-S (stimulus-stimulus) interpretation of conditioning states that the CS becomes associated with the US, as opposed to the S-R (stimulus-response) interpretation where the CS becomes associated with the UR. This supports the divergence as it shows that it is not a direct back-propagation of the response when two stimuli become associated.

The remainder of this section describes how the system operates. The system comprises of three component sub-systems that feed data between each other. Figure 1 shows the modules and the data that is passed between them.

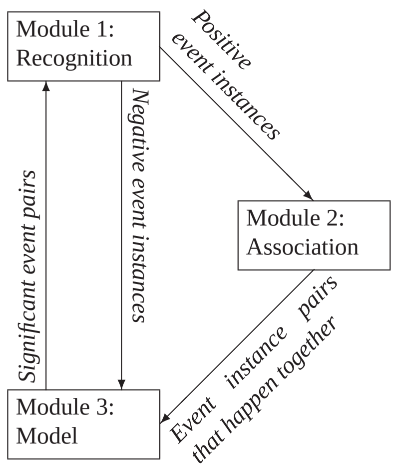

Figure 1. The three sub-systems and the data flows between them.

As input to the system, the system takes a series of time-ordered bounding boxes for each object of interest in the observed scene. In the case of the experiment, this input data would be the bounding boxes for the ball and the person. This is then processed to find geometrical changes, which are used as events to be passed to the first sub-system.

The first sub-system takes the stream of basic events and compares these events with a database comprising of event patterns to be recognised as more complex events. The sub-system recognises both positive and negative instances of these complex events. Positive complex event instances are those event patterns where a pattern is observed. Negative complex event instances are those events where the first half of a pattern is observed, but the latter half of the pattern does not follow.

The second sub-system then identifies and outputs pairings of the positive events whose temporal relationship satisfies a set of criteria such that they can be said to happen together. Only those events that have an equal pattern length are compared for reasons of efficiency.

The third sub-system has two input sources. The first input source is the instances of the identified event pairings with the second input source being the negative complex event instances. To these inputs, the sub-system applies a functional model of classical conditioning. In the model, instances from first input source are treated as positive reinforcements and the instances from the second input are treated as negative reinforcements. This results in a list of pairs of types event instances (both complex and basic) together with a measure of their association strength. The pairs that have a high association strength measure are then fed back to the first sub-system. In the first sub-system, these pairings are treated as a single composite event and are added to the database of events that the first sub-system recognises. Should the association strength of an event pairing that has been allocated a composite event subsequently weaken such that it is no longer considered to have a high association strength, its corresponding composite event is removed from that same list of events.

3.1 The recognition sub-system

The recognition system recognises two types of event instance, atomic events and composite events. Atomic event instances are generated through an analysis of processed sensor data provided as input. The recognition system for atomic events is an expansion of the system presented by dos Santos et al. [5]. Composite event instances are generated by matching their component events against the list of generated events. Composite events may have either atomic events or composite events as their component events but for reasons of computational efficiency, both component events of a composite event must be of equal recursive depth. In other words, the depth of atomic events is zero; the depth of composite events comprising of two atomic events is one; and the depth of a composite event comprising of two composite events that each both comprise of two atomic events is two.

The sub-system outputs positive and negative instances of events. Positive event instances are instances of event pairings that have been observed to happen. Negative event instances are instances of event pairings that were expected to happen but did not. An event is expected to happen when the first component event of a composite event happens, but the second was not observed to happen. By those definitions, all atomic events are positive event instances. The positive event instances are passed to the association sub-system whereas the negative event instances are passed directly to the model of classical conditioning.

The external input to the recognition system used within this paper is data that represents the extrinsic motion of objects within the agent's field of view (i.e. objects moving around a scene, rather than the movement of sub-components of the object while the object itself is static). This data is split into temporal frames. In each frame each object is represented as a bounding box labelled with an identifier unique to that object. It is expected that the system is general enough to be applicable to different domains.

For each frame, a set of state information regarding the objects present within the frame is generated. The set of state variables initially includes the x and y position of the centre of each box. The remainder of the state variables are based on each pair of objects. Each pair of objects has four state variables that describe their relationship. The first state variable is the distance between the centres of each box. The next state variable represents one of the mutually exclusive possible states of *"A is coalescent with B"* (which means that the boxes of the two objects A and B overlap to the extent that the two objects cannot be reliably distinguished), *"A is externally connected with B"* (the two boxes are touching but do not significantly overlap) or *"A is disconnected with B"* (the two boxes are distinctly separate). These three possible states are based on a variant of the region connection calculus [20, 24]. The third state variable represents one of the possible mutually exclusive states *"A is to the left of B"*, *"B is to the left of A"* or *"Both A and B are in-line in the X axis"*. The final state variable represents one of the possible mutually exclusive states *"A is above B"*, *"B is above A"* or *"Both A and B are in-line in the Y axis"*.

After these states have been generated for a frame, they are compared with the states of the previous frame. Based on the changes in each state type, multiple atomic events are generated based on each atomic event's logical definition encoded within the system. Figure 2 lists the names and English definitions of the events that can be generated. Note that the last two events are generated by comparing the lists of objects present in a frame rather than from any of the states generated. These atomic events are those that have been identified as being pertinent to the test domain of the extrinsic motion of objects.

- `Approaching(X,Y)` – `X` and `Y` are approaching each other.
- `Receding(X,Y)` – `X` and `Y` are receding from each other.
- `Static(X,Y)` – The distance separating `X` and `Y` does not change.
- `MergeR(X,Y)` – `X` is merging with `Y` on the right of `Y`.
- `MergeL(X,Y)` – `X` is merging with `Y` on the left of `Y`.
- `MergeT(X,Y)` – `X` is merging with `Y` on the top of `Y`.
- `MergeB(X,Y)` – `X` is merging with `Y` on the bottom of `Y`.
- `EmergeR(X,Y)` – `X` is emerging from `Y` on the right of `Y`.
- `EmergeL(X,Y)` – `X` is emerging from `Y` on the left of `Y`.
- `EmergeT(X,Y)` – `X` is emerging from `Y` on the top of `Y`.
- `EmergeB(X,Y)` – `X` is emerging from `Y` on the bottom of `Y`.
- `MakeCR(X,Y)` – `X` has made contact with `Y` on the right of `Y`.
- `MakeCL(X,Y)` – `X` has made contact with `Y` on the left of `Y`.
- `MakeCT(X,Y)` – `X` has made contact with `Y` on the top of `Y`.
- `MakeCB(X,Y)` – `X` has made contact with `Y` on the bottom of `Y`.
- `BreakCR(X,Y)` – `X` has broken contact with `Y` on the right of `Y`.
- `BreakCL(X,Y)` – `X` has broken contact with `Y` on the left of `Y`.
- `BreakCT(X,Y)` – `X` has broken contact with `Y` on the top of `Y`.
- `BreakCB(X,Y)` – `X` has broken contact with `Y` on the bottom of `Y`.
- `MoveRight(X)` – `X` has moved right.
- `MoveLeft(X)` – `X` has moved left.
- `MoveUp(X)` – `X` has moved up.
- `MoveDown(X)` – `X` has moved down.
- `Lost(X)` – Object `X` has ceased to be detected.
- `Found(X)` – Object `X` has been newly detected.

Figure 2. The event types that the system uses to describe the transition between the states of one frame and the states of the next for the domain of extrinsic motion.

The list of atomic events is then compared with the list of composite event types (which is initially empty and is grown by the feedback from the model of classical conditioning sub-system). Where an atomic event is the first event of a composite event that appears in the list, an event instance of the type of the matched composite event is generated and is marked as being a potential event (as the second sub-event has yet to be observed). A potential event is an event that is believed to be currently ongoing but there is not the evidence to know for sure. The generated potential event is then recursively compared with the list of composite event types to generate further potential events of increasing complexity.

After the potential events have been generated, they need to be grown to so they can represent their true observed duration. The set of both the atomic and potential events of the time in-between the current and previous frame are compared with the events that were generated when the now-previous frame was the current frame. Where the same event has been generated in both consecutive frames, the event token of the event in the previous frame is extended to cover the current time frame of the event and the duplicate newly generated event instance is removed.

At the next stage, the list of potential events that are within a predetermined window of time before the current frame is compared to the list of atomic events that were generated during the current frame. If any of the atomic events are the second event of a potential event, the potential event instance in its entirety is replaced with an actual event as that potential event has now been confirmed. The set of newly confirmed potential events is then recursively compared with the list of potential events to generate further confirmed events of increasing complexity.

Where a potential event has yet to see its second event, but the first event has finished and its finishing time was longer ago than the width of the predetermined window of time before the current frame, then the potential event is classed as a negative event instance and is passed as such to the model of classical conditioning.

These stages outlined above are repeated for every subsequent pair of frames provided as input. Note that the system has been designed to be able to be used in an on-line manner. This on-line nature was required so that the system may continuously learn new associations throughout the lifetime of the agent.

3.2 The association sub-system

The purpose of the association system is to systematically record each pairing of event instances that are temporally close enough together that, based on defined criteria, they can be said to happen together.

The criteria that define the notion of two events happening together is based on the modes of conditioning that are a part of the inter-stimulus interval phenomena of classical conditioning, namely delay and trace conditioning. Delay conditioning notes that the period of the conditioned stimulus can either stop at the start of, or overlap, the period of the unconditioned stimulus. Whereas trace conditioning shows that end of the conditioned stimulus can have a short gap before the start of the conditioned stimulus, though the longer the gap the slower any association is formed. These ideas suggest for criteria for the notion of two events happening together, either the two events must temporally overlap or that the first event must have its finishing point within a defined window of time before the beginning of the second.

Due to these criteria, the association sub-system calculates its pairings based on whether an event is starting, stopping or continuing. An event instance is considered to be starting if the event that was generated in the current frame but not in the previous frame. An event instance is considered to have stopped if was generated in the previous frame but not in the current frame. An event instance is considered to be continuing if it was generated in both the current frame and the previous frame.

For every starting event that the recognition system generates, the association system records the list of events that occurred within the defined window of time before the current frame including those that are ongoing. Where an event is ongoing, it is marked as so in the list.

As each event finishes, the association system looks for all the occurrences of that event in the list of event pairings and notes its finishing time against those listings, removing the marker that it is a continuing event. As the parings get to the stage where both events have finished, they are passed to the model of classical conditioning sub-system.

Figure 3 depicts the moving window and 12 intervals of events. Each interval is inclusive at both ends, so for instance, event interval 1 is over six time steps. The current time step is marked as t, meaning that in the diagram, event 12 has not started happening yet. In the diagram, event 8 is starting, event 7 is stopping and events 5 and 11 are continuing. W is the length of time of the window; again, this is inclusive at both ends so that the system would generate an pairing instance for events 8 and 9. In fact, for this diagram only 3 of all possible pairings of the events would not be generated, being 3&8, 3&12 and 9&12. The density of the events is for illustration purposes and in the practical example of the test case, the events are more sparse.

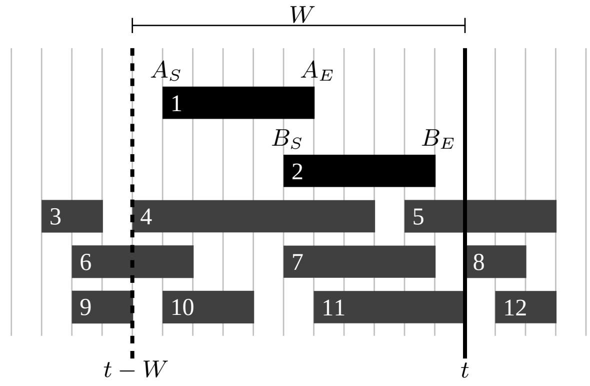

Figure 3. A demonstration of the window in relation to a series of events. Note that the vertical grouping of event intervals in the diagram is arbitrary.

3.3 The model of classical conditioning

The purpose of the model of classical conditioning as a sub-system is to create a mapping from a list of instances of event pairings and a list of negative event instances to a measure of the association strength for that pairing each event type present. While the other parts of the system also are responsible for modelling some of the phenomena of classical conditioning, it is this sub-system that attempts to model the main phenomena.

The model presented by this paper is a relatively simplistic model that does not claim to be able to compete neither on fidelity nor on complexity with those models that were developed as an exercise in of themselves. This raises the question of why the effort was undertaken to produce a new model at all, after all, if there are better models already in existence, why was one of these models not implemented instead? The reason is due to the divergence in the theory stated at the beginning of this section, that neutral stimuli can associate together without the presence of a reflex-causing stimulus. All of the models that have been encountered make the assumption that there is a natural strength of reflex of the reflex-causing stimulus that can be propagated across an association and is available to be factored into the calculation of the association strength. This assumption means that they cannot be used in this system. This is due to the very definition of being neutral stimulus, they cause no reflex action and so do not have any measure of the strength of reflex that could be propagated. So the model in this system attempts to be a proof-of-concept model.

The two inputs of the sub-system, the list of event pairings from the association sub-system and the list of negative event instances from the recognition sub-system, represent the twin notions of reinforcements and non-reinforcements. This sub-system treats them as such in the modelling.

The model was primarily developed through examining and attempting to approximate in a function, the response curves of the various phenomena as described in [2]. While this approach does not attempt to provide any explanatory power, it does allow for the desired responses. This approach has led to the production of three functions that determine different aspects of the association strength. All three functions are designed so that they perform in an iterative manner. In other words, the functions output the amount the current association strength (Y_N) should be changed by (δY), rather than calculating the new association strength (Y_{N+1}) directly. This means that only the current association strength needs to be stored in memory rather than retaining all the inputs to each of the functions. Note that the association strength is real-valued and constrained to the range $0 \leq Y \leq 1$. The new association strength is updated according to equation 1.

$$Y_{N+1} = Y_N + \delta Y \tag{1}$$

The first function, shown in equation 2, models the curve observed in the acquisition phenomenon. This function is applied for each reinforcement of an event pairing. As described previously in the background section, the acquisition phenomenon follows a sigmoid-like curve. In the equation, δX is the amount one reinforcement instance is to be counted (this is normally equal to 1), k_1 is a constant representing the learning rate of acquisition and Z is the output of the functions that model the effect of a change in the inter-stimulus interval.

$$\delta Y = Z \frac{(1 - Y_N)e^{k_1 \delta X} + Y_N - 1}{e^{k_1 \delta X} + Y_N + \frac{2}{Y_N} - 3} \tag{2}$$

The next function, shown in equation 3, models the effect of extinction. This function is applied for each non-reinforcement (i.e. a negative event instance) the sub-system receives for a given pair of events. Note that the functions that model the effect of changes in the inter-stimulus interval are not applied to the extinction function. This is because in the case of a negative instance, the size of the second event is not available, this means there is no inter-stimulus interval to be measured and so the functions cannot be applied. [2] did not provide any description of the extinction decay curve, however, Pavlov provided a small sample of data in lecture 4 of [17] that suggests a linear decay. In the equation, δX is the amount one non-reinforcement instance is to be counted (this is normally equal to 1) and k_2 is a constant representing the learning rate of extinction.

$$\delta Y = -k_2 \delta X \tag{3}$$

The final functions, are the functions that model the change in response due to changes in the inter-stimulus interval. These functions are only applied when dealing with reinforcements, as opposed to non-reinforcements. The reason that these functions have not been merged into equation 2 is due to the complexity of the equations. To allow for these functions to alter the output of acquisition function, its output is constrained to $0 \leq Z \leq 1$. As described previously in the background section, the phenomena due to changing the inter-stimulus interval suggests a curve similar to the curve of the log-normal distribution. In these equations, Z is the factor that the output of the acquisition function is to be multiplied by, I and J are intermediary values used to allow the function to be shown in a simpler form, A_S is the start time of the first event, A_E is the end time of the first event, B_S is the start time of the second event, B_E is the end time of the second event and W is the defined size of the moving window. Figure 3 shows these variables in relation to the pair of events 1 and 2 in that diagram.

$$I = \frac{1}{2} - \left(\frac{\max\left(0, \frac{A_E - B_S}{B_E - B_S}\right)}{2} \right) + \left(\frac{\max\left(0, \frac{B_S - A_E}{W}\right)}{2} \right) \tag{4}$$

$$J = \max\left(0, \left(|B_S - A_S| - 2I\right)\right) \tag{5}$$

$$Z = \frac{2(2 - I)e^{\frac{-2(\ln(J) - 1)^2}{(2+I)^2}}}{J(2 + I)\sqrt{\frac{\pi}{2}}} \tag{6}$$

When an association strength goes above a certain defined threshold, that pairing is added to the list of rules that the first sub-system uses to recognise as a composite event. If a pairing drops below the threshold through the extinction processes, that pairing is removed from the list.

This feedback of information is one of the central ideas of the system as it both allows for patterns of arbitrary length to be built up yet does not allow any combinatorial explosion to take place. It also has to be recognised that this can mean that the more complex the composite event the system needs to learn, the more examples it requires. This means that this list builds up simple representations first, creating the event representations that have a minimum description length before updating them with longer ones as required. With the ability to remove sequences that no longer have a strong enough evidence base, the system is able to retract locally maximal artifacts that are due to coincidences.

4 EVALUATING THE SYSTEM

The intention of the system was for it to passively learn about its presented environment without any initial data regarding that environment. To this end, the system was tested to see if it could find any patterns of events that can be argued to be semantically important with reference to the environment. The domain of extrinsic object motion was chosen due to its prevalence within computer vision and that it was the domain used by the work of dos Santos et al. [5] that formed one of the bases of this work. The domain also allows for the use of the principles of physical mechanics to form predictions.

The environment that was chosen was that of observing a person repeatedly throwing a ball in the air and catching it. The prediction was that the system would find a pattern of events that would represent the ball being thrown upwards followed by it falling downwards. This would mean that the system has come to expect (and through the system of potential events, generates expectations) that whenever the ball moves upwards, it will at some point come down again, this would be an expectation of gravity to enact on the ball.

Note that this application domain may appear to be similar to the application domain presented Bennett et al. [3]. However, this is not the case. The domain in Bennett et al. [3] used a basketball-like domain with multiple moving people as well as a moving ball as a source of complex movement to test the capabilities of the presented tracking system. The domain of the current paper uses a single, static person and a moving ball to allow for a domain simple enough to allow for a testable prediction to be made of what the system should learn.

An approximately 2:45 minute video (5006 frames at 30fps) was shot of a person throwing a ball in the air. This video was then hand-processed using the ViPER annotation tools [4, 14] so that the extrinsic motion of the relevant objects within the viewer could be extracted without need for an object tracking system, so that the inaccuracies of a tracking system could be avoided. The tracking data was then converted into a suitable format and input into to the system. The system was run with a window size of 30 frames, a rule association strength threshold of 0.85 and equation constants k_1 and k_2 set at 3 and 0.1 respectively.

The list of rules that had been generated by the system after it had completed processing every frame had 30 rules. None of these rules were compound rules. On inspection of the list of all association strengths, the majority of the associations were for compound events, and some were only marginally outside the threshold.

Figure 4 shows those pairings of events that were above the threshold. These are a mixture of encouraging results with a couple of anomalous results. For an effect that was reasonably expected, there is the tendency of groupings of related concepts. For example, results 2 to 5 indirectly imply that when static(A,B) holds that static(B,A) holds and that when an object A makes contact with the bottom of an object B, then object B has made contact with the top of object A. The knowledge of these implications is not coded into the system in any capacity as each atomic event is independently searched for and generated.

The main encouraging results given the prediction made, is that of 7 & 8 and 11 to 14. 7 & 8 show that the system is expecting for the ball to be receding from the person when it is moving up, and 11 to 14 show that the system expects that when the ball emerges from the bounding box of the person, that it also breaks contact with the box.

The majority of the anomalous results relate to the relations showing various types of stasis. A number of these can be explained by the nature of the recorded video. The video recording was of a relatively low quality, which included the movement being jerky in places. The prevalence of the static events could be attributed to this. This throws up the question of the utility of recording the stasis events at all.

One interesting and unexpected rule is number 29. It was unexpected as the person does not make many movements other than with the arms. This result is due to the person moving their arms up above their head to throw the ball up. This makes the bounding box of the person taller and so the centre point of the bounding box moves up.

1. `staticX(personA), moveDown(personA)`
2. `static(personA, ball), makeCB(personA, ball)`
3. `static(ball, personA), makeCB(personA, ball)`
4. `static(personA, ball), makeCT(ball, personA)`
5. `static(ball, personA), makeCT(ball, personA)`
6. `staticX(personA), moveRight(personA)`
7. `moveUp(ball), receding(personA, ball)`
8. `moveUp(ball), receding(ball, personA)`
9. `moveLeft(ball), static(personA, ball)`
10. `moveLeft(ball), static(ball, personA)`
11. `emergeB(personA, ball), breakCB(personA, ball)`
12. `emergeT(ball, personA), breakCB(personA, ball)`
13. `emergeB(personA, ball), breakCT(ball, personA)`
14. `emergeT(ball, personA), breakCT(ball, personA)`
15. `moveLeft(ball), approaching(personA, ball)`
16. `moveLeft(ball), approaching(ball, personA)`
17. `static(personA, ball), mergeB(personA, ball)`
18. `static(ball, personA), mergeB(personA, ball)`
19. `static(personA, ball), mergeT(ball, personA)`
20. `static(ball, personA), mergeT(ball, personA)`
21. `staticX(ball), staticY(ball)`
22. `staticX(personA), staticY(ball)`
23. `staticX(personA), moveDown(ball)`
24. `staticY(personA), moveDown(ball)`
25. `staticX(personA), staticY(personA)`
26. `staticX(personA), moveRight(ball)`
27. `staticX(ball), moveRight(ball)`
28. `staticX(ball), moveDown(ball)`
29. `moveUp(personA), moveUp(ball)`
30. `staticX(personA), moveLeft(personA)`

Figure 4. The resultant pairs of events that the system considered to be compound events after processing all the input data.

5 CONCLUSIONS AND FURTHER WORK

The results found in testing the system presented in this paper appear to be inconclusive but encouraging. The best explanation that can be offered for the lack of composite rules is that the video used was too short to give the system the time that would be needed to see these rules gain a high enough association strength to be included. The results are encouraging though, as several parts that would be required for a full composite rule that would expect gravity to enact on the ball are present.

Further work in the short term would be to re-run the experiment for a longer period of footage that is recorded with higher quality equipment. From this, a more concrete conclusion could be formed.

Beyond that, the first area of improvement to the system would be to create a model of classical conditioning that models a greater number of the phenomena in better quality. For instance, reacquisition, blocking and inhibitory phenomena are not implemented in the model presented.

Within a wider field, the system could be adapted to also model operant (instrumental) conditioning, this could be done by adding in agent actions as events in the system along with reward and punishment events. The work by Touretzky et al. [29, 23] may be useful in assisting work towards this goal.

It can be observed that animals learn both passively and actively. It is argued that an effective agent must be able learn using both modes. For instance, an animal can associate the sound of a rock slide with the sight of falling rocks. It can also be learn to actively avoid being hit by a rock. Only when both passive and active learning are together can the animal associate the sound of a rock slide with danger, without actually being caught in a rock slide. For another example, consider using a hairdryer to move a toy sailing ship. For a planning system to decide that course of action, the agent would need to have passively associated air currents with moving sailing ships and observed that the action of activating a hairdryer causes an air current.

During the development of the system, a question kept surfacing about randomised outcomes to event sequences. How should the system deal with event sequences where the outcome event is not deterministic but can be one of a set of outcomes? For an example, the rolling of a die; here there is a definite sequence of events leading up to the outcome. However there is not a single outcome but a definite set of outcomes. For example, one would not expect a seven to appear on a standard six-sided die. There are methods that do learn stochastic event sequences [11] but these operate in a batch manner. If it is possible for the system presented in this paper to learn stochastic events, then the system would be capable of adapting its existing hypotheses as new examples of the patterns of events are presented. This system, when combined with an extension to account for instrumental conditioning, could, in an unsupervised manner, dynamically learn about how an agent expects its environment to behave, in a way that allows adaptation to changes in that environment.

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