A Model for Attention-Driven Judgements in Type Theory with Records

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A knowledge representation framework for robots



 Information fusion: interactively combining, comparing and reasoning with information from perceptual and conceptual domains A knowledge representation framework for robots



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- Layered approach (Kruijff et al., 2007)
 - meaning representations are modular and independent
 - interfaces to mediate between the levels

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 - meaning representations are modular and independent
 - interfaces to mediate between the levels
- TTR (Cooper, 2012; Cooper et al., 2014): from types of sensory readings to types of information states (ISs) (Dobnik et al., 2014)

Why TTR?

- Agent centred: an agent makes judgements that an object a is of type T or a : T
- Type system is learned as agent interacts with its environment (perception, Dobnik et al. (2013)) and other agents (dialogue, (Larsson, 2013))
- Open to revision as agent enters new environments or dialogue contexts
- Convergence of the type system across agents is ensured by being located in the same perceptual and linguistic contexts
- A different view in computational linguistics but a standard view in mobile robotics (Dissanayake et al., 2001)





Rich type system:

а	=	ind ₂₆		а	:	Ind
sr	=	[[34,24],[56,78]]	:	sr	:	list(list(Real))
loc	=	[45,78,0.34]		loc	:	list(Real)

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- Component types: s : Left and s : Table-Left-Chair



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- Sub-typing: Chair ⊆ Object ⊆ Physical entity ⊆ Entity and if s : Chair then s : Object, s : Physical entity and s : Entity
- ► Component types: *s* : *Left* and *s* : *Table-Left-Chair*
- Dependent types: s : Table-Left-Chair and s : Table and s : Left



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- An agent with n types can make n judgements of each situation
- A learning agent is faced with 2^n possible assignments $n = 3, 2^3 = 8$: {}, { T_1 }, { T_2 }, { T_3 }, { T_1, T_2 }, { T_1, T_3 }, { T_2, T_3 } and { T_1, T_2, T_3 }



- Sub-typing can be inferred by comparing record structures
- (Hough and Purver, 2014) organise types in a lattice by subtype relation for incremental inference
- Allows us to prune sub-types of an incompatible type
- Taxonomic or categorical relations
- Do humans judge situations from most general to most specific?



- Require priming what to expect in the current state given the knowledge about the world.
- ► Thematic relations: spatial, temporal, causal or functional relations between individuals occuring in the same situations Lin and Murphy (2001); Estes et al. (2011)
- Type resources (Cooper, 2008) that are employed and learned in different situational contexts



- What drives the creation of resources/thematic relations?
- How are bundles of types selected and primed in particular situational contexts?
- How can we model them computationally for an application of TTR in a situated robot?





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Attention



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- Top-down attention: consciously directed and task dependent/primed
- A shared resource that can spread across multiple tasks to different degrees depending on the difficulty of the task and attention policy (Kahneman, 1973)
- What are the conditions under which the perception of task irrelevant distractors is prevented and at what stage?

Attention driven judgements



Load Theory (LT) (Lavie et al., 2004):

- Perceptional selection: the more perceptual load the less capacity to perceive distractor objects
- Cognitive control: active processing prioritisation of task-relevant stimuli and reduction of perceived distractors

Attention driven judgements



- Load Theory (LT) (Lavie et al., 2004):
 - Perceptional selection: the more perceptual load the less capacity to perceive distractor objects
 - Cognitive control: active processing prioritisation of task-relevant stimuli and reduction of perceived distractors
- Attention driven judgements:
 - Pre-attentive
 - Task and context induced

Pre-attentive judgements



- Perceptional selection mechanism of LT
- Iconic representations Harnad (1990)
- Ullman (1984): basic representations of visual environment and visual routines
- Segmentation of a visual scene into entities and background

Pre-attentive judgements



- Perceptional selection mechanism of LT
- Iconic representations Harnad (1990)
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- Segmentation of a visual scene into entities and background
- Linked to agent's biology and embodiment, sensors and actuators: finite in number and "basic"
- Fundamental to the agent's basic operation: made continuously
- The judgements are pushed to the IS at a rate determined by LT

Task-induced and context-induced judgements



- Cognitive control mechanism of LT
- An agent is making a cup of tea in the kitchen on the second floor at FLOV
- Task-induced judgements: primed by a default set of objects and actions associated with the task
- Context-induced judgements: primed by the context in which the task is taking place
- Both kinds of judgements interact
- Making a judgement belonging to a task or a context primes the agent to further judgements of that task or context

Control mechanism for TI and CI judgements



- Organisation of agent's type inventory in memory according to thematic relations (Lin and Murphy, 2001; Estes et al., 2011)
- How is type inventory organised this way used in making primed typed judgements following the LT?

Cognitive states



- An agent experiences the world through perception, embodiment and linguistic interaction
- Experiencing tasks and contexts, an agent forms associations between types co-occuring in its memory
- Associations clusters are modelled as cognitive states
- An agent is not conscious of its states
- ... but they prime the agent to particular types of situations
- An agent may be in one or more state at the same time
- ► A particular type may be associated with more than one state



Relations between states are computationally more tractable than relations between types

- States are built bottom up as agent discovers new situations
- Constrained by the environment in which it operates
- Can only discover a finite set of states in its lifetime
- Has a strong learning bias for making generalisations



- Latent Dirichlet Allocation (LDA) Blei et al. (2003): document.word := topic and memory.type := state
- Hierarchical Dirichlet Process Teh et al. (2006) for unknown number of topics/states



We need...

- Update mechanism for the posterior distribution over states
- A decision mechanism regarding which types to be primed to based on the posterior probability distribution over states

Posterior probability over states



- Probability of states at t-1
- ► The task and context judgements the agent has made following the priming at t - n, n is the length of history
- Pre-attentive judgements at t reflecting perceptual change in its world

$$P(s_t | Pre_t, Task_{t-1}, Cont_{t-1}, AS_{t-1}) = \eta \times P(Pre_t, Task_{t-1}, Cont_{t-1}, AS_{t-1} | s_t) \times P(s_t)$$



Assuming conditional independence:

$$P(s_t | Pre_t, Task_{t-1}, Cont_{t-1}, AS_{t-1}) = \eta \times P(Pre_t | s_t) \times P(Task_{t-1} | s_t) \times P(Cont_{t-1} | s_t) \times P(AS_{t-1} | s_t) \times P(s_t)$$



- Select $s_t \in S$ with the maximum a posteriori probability
- Load the types from s_t into short-term memory
- ► + and -:
 - + simple
 - agent assumes it is only in 1 state
 - may end up switching between two states

Priming of types, II



- Rank and prune the state set using the posterior probability: active relevant states (AS)
- The threshold determined by available resources: perceptual selection and cognitive control
- Renormalise the probability distribution over AS
- Compute a posterior probability over the set of types in AS using a Bayes optimal classifier
- Using the posterior probability over types, rank and prune the set of types
- Load the set of unpruned types into working memory



$$P(T_{i,t}|Pre_t, Task_{t-1}, Cont_{t-1}, AS_{t-1}) = \sum_{s_i \in AS_t} P(T_i|s_i) \times P(s_i|Pre_t, Task_{t-1}, Cont_{t-1}, AS_{t-1})$$



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 $+\,$ A type is associated with more than one state

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Probability of a type

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 $+\,$ A type is associated with more than one state

 $+\,$ More than one state may be active at one time



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- $+\,$ A type is associated with more than one state
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- + Types and states as associated probabilistically: $P(T_i|s_i)$



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- + Several states may be maximising a probability of a particular type



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- $+\,$ A type is associated with more than one state
- + More than one state may be active at one time
- + Types and states as associated probabilistically: $P(T_i|s_i)$
- + Several states may be maximising a probability of a particular type
- $+\,$ The system is more stable in making decisions than argmax



- + The more judgements we make the more we reduce the ambiguity of being in several states.
- Calculating posterior probabilities of types in active states is computationally more expensive than calculating probabilities of states
- $+\,$ The aggressiveness of the pruning criteria: Load Theory

Conclusions and future work



 Attention-driven type judgements in an interacting agent inspired by discovery of thematic relations and sharing of cognitive resources

Conclusions and future work



- Attention-driven type judgements in an interacting agent inspired by discovery of thematic relations and sharing of cognitive resources
- Agent maintains:
 - a distribution set of cognitive states
 - a distribution over set of types in the active states
 - the number of active states is controlled by available cognitive resources

Conclusions and future work



- Attention-driven type judgements in an interacting agent inspired by discovery of thematic relations and sharing of cognitive resources
- Agent maintains:
 - a distribution set of cognitive states
 - a distribution over set of types in the active states
 - the number of active states is controlled by available cognitive resources
- A general problem for agent making classification:
 - visual search in robotics (Sjöö, 2011; Kunze et al., 2014)
 - situated dialogue: disambiguation of speakers utterances/topic priming
 - situated dialogue: generating new utterances/topic modelling

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