Action Sequencing and Error Production in Stroke Patients with Apraxia
Behavioral Modeling using Bayesian Logic Networks

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Abstract: Individuals with Apraxia often suffer from cognitive impairments during the execution of activities of daily living (ADL). In this study, we used a statistical relational learning approach (Tenorth, 2011) to model the behavior of apraxic patients and neurologically healthy individuals (n = 14 in each group) during ADL performance. Video analysis indicated that apraxic patients committed more errors than control participants, typically committing omission, addition, and substitution errors. The results of the Bayesian Logic Network (BLN) approach indicate that the relevance of the nodes (i.e., actions) differed between the control participants and apraxia patients. Furthermore, there were more nodes in the patient group, which is likely a result of addition and substitution errors, or by alternative ways of solving the task using a different set of tools. Overall, the results of the present study highlight the variability inherent in ADL performance, which need to be considered when developing action and error prediction models.

1 INTRODUCTION

Stroke is most frequent neurological disease (WHO 1978). After a stroke incident as many as 24% of patients suffer from persistent impairments of praxic functioning (Bickerton et al., 2012), which often result in "*deficits in the execution of learned movement which cannot be accounted for by either weakness, incoordination, or sensory loss, or by incomprehension of or inattention to command*" (Geschwind, 1975, pp. 188). The most important characteristic of apraxia is that patients often retain sensorimotor functions and capabilities but their cognitive ability to carry out previously familiar tasks (e.g., dressing, preparing and eating meals and grooming) is adversely reduced (Goldenberg and Hagmann 1998).

The difficulty these patients experience in sequencing everyday tasks places great strain on patients' individual independence, their families, and the national healthcare systems which have to provide continuous support and care (Sunderland and Shinner, 2007).

In this paper, we present an approach for modeling and recognizing partially ordered ADL in healthy and apraxic populations. We apply statistical relational learning techniques to extract the joint probability distribution over the actions in an activity, their properties, and their pairwise ordering constraints. The resulting full-joint probability distributions elucidate relevant and important actions and ordering relations for a given task. We propose that this model can be used to classify and verify activities, identify relevant actions in an activity, and infer missing data.

2 BACKGROUND

2.1 Apraxia

Limb apraxia is a cognitive-motor characterized by impairment in the performance of skilled movement, and is operationally defined as a neurological disorder of learned purposive movement skill that is not explained by deficits of elementary motor or sensory systems (Rothi and Heilman, 1997), or by

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patients' inability to understand the tasks (Goldenberg, 2008); (Rothi and Heilman, 1997); (Liepmann, 1905). Apraxia is frequently caused by relatively large lesions in the territory of the left middle cerebral artery (MCA), resulting in plegia of the contralateral right hand. In the case of right hand plegia, the apraxia patient has the use of only the ipsilateral left hand. Further, apraxia does not only affect the side of the body opposite to the cerebral lesion (contralateral limb), but also the ipsilateral side.

2.2 Apraxia and Error Production

Research has demonstrated that apraxia patients have difficulty performing many activities of daily living, often committing errors during the action planning and execution (Buxbaum et al., 1998); (Schwartz et al., 1991; 1998). For example, apraxia patients will often omit an action (e.g., turn on the coffee maker without having inserted water) or use an inappropriate object (using a knife to stir a cup of tea) during the performance of ADL (Humpreys and Forde 1998); (Schwartz et al., 1998).

Errors of action can be broadly divided into *errors of omission* (the failure to execute critical actions or sequence of actions), and *errors of commission* (performing an action in an incorrect or inappropriate way) (Schwartz et al., 1991). The errors in the latter category can be further segmented into sequence errors (performing an action in the wrong order), additions (adding an extra component action), semantic errors (using a semantically related object instead of the correct one), perseverations (repeating an action or action sequence), and quality or spatial errors (using an inappropriate amount of ingredients or failing to use tools). A summary of the most common errors is shown in Table 1.

Several case studies have shown that some error types are more frequent than others (Morady and Humphreys, 2009); (Schwartz, 1995); (Schwartz et al., 1991; 1995; 1998); (Forde et al., 2004); (Morady and Humphreys, 2011); (Forde and Humphreys, 2000; 2002); (Humphreys and Forde, 1998). For example, patients with left- hemisphere stroke (LCVA; Buxbaum et al., 1998), right hemisphere stroke (RCVA; Schwartz et al., 1999) and patients with Action Disorganization Syndrome (ADS; Humphreys and Forde, 1998) general omit more steps and make more sequence errors during ADL performance. By comparison, addition errors, perseveration errors, quality or spatial errors, and semantic errors are less frequently observed than the more prominent errors.

3 MODELLING ACTION SEQUENCING AND ERROR PRODUCTION

Given the deficits in action sequencing and the errors in the movement quality in apraxic populations a model needs to be able to describe both low-level motor defects, (e.g., grasping an object with an inappropriate grip), and high-level errors (e.g., performing a task in a wrong sequence). A model should also be able to compare performance with prior observations of the same subject or to a reference group. The former comparison can be used to detect changes in the performance of an individual, whereas the latter comparison could be used to assess performance relative to individuals with similar (i.e., apraxic) or dissimilar (i.e., neurologically healthy) features.

3.1 Partially-ordered Tasks

Many of today's approaches for activity recognition are using sequence-based methods like Hidden Markov Models (HMMs; Patterson et al., 2005), Conditional Random Fields (CRFs; Vail et al., 2007) or Suffix Trees (Hamid et al., 2007). These models directly describe the observed sequences by local action transitions, and are based on the Markov assumption that the transition to the next action only depends on the current action.

However, there exists a great deal of freedom in how an ADL task can be performed, such that the same goal can be reached by significantly different action sequences. In these tasks, subsequent actions depend not only on the previous one, but on all actions that have already been performed, since they determine which other ones are still needed to complete the task at hand.

One example of a system that is able to model such a partial ordering among actions is the work of Shi and colleagues (Shi et al., 2004) that uses manually specified Dynamic Bayesian Networks to model behavior when calibrating a blood glucose monitor. However, this approach does not describe action properties (e.g., which object is manipulated, or which grasp is used) and as such does not allow for reasoning beyond the partial order of action types.

The model described in this paper differs from the aforementioned approaches in that it is able to describe complex tasks (including the partial order, but also other action properties like the types of manipulated objects), and is capable of *learning* a

Table 1: Summary of action errors often committed by apraxic individuals. Examples are drawn from the task of preparing two cups of tea used in the current experiment.

Error Type	Definitions	Example
Addition	Adding an extra component action that is not required in the action sequence	Adding instant coffee to the cup
Omission	An action sequence in which one step or subtask is not performed, despite the lack of any intention to omit the step or subtask	Turning on the kettle on without having inserted water
Perseveration	The unintentional repetition of a step or subtask	Adding more than one tea bag to a cup
Mislocation	An action that is appropriate to the object in hand but is performed in completely the wrong place	Pouring some liquid from the bottle onto the table rather than into the glass
Substitution	An intended action carried out with an unintended object	Pouring coffee grounds instead of sugar into the cup
Misestimation	Using grossly too much or too little of some substance	Pouring half of the milk jug contents into the cup

model from observed data. This latter point is especially important in the context of cognitive rehabilitation. Clinicians would be able to compare performance before and after rehabilitation to evaluate changes in the performance of individual apraxic patients, and contrast this to performance of apraxic patients with similar neurological backgrounds.

3.2 Bayesian Logic Networks

The Intelligent Autonomous Group (IAS) at the Technical University of Munich (TUM) has developed a model of action recognition that can handle the high degree of variation often observed in ADL tasks (Tenorth, 2011). The model is able to learn the partial ordering of actions in these ADL tasks using Bayesian Logic Networks (BLNs; Jain et al., 2009). By learning the models, they extract the joint probability distribution over the actions in an activity, their properties, and their pairwise ordering constraints. The results are statistical relational models that describe the partial order imposed on all actions in a task, as well as the general relations between consecutive actions and their properties.

From training data, partially-ordered models can learn which actions are relevant and which ordering relations are important, such that actions that occur in all observations of a task are considered more relevant than those that are only rarely observed, and ordering relations that consistently hold are also more likely to be important. Thus, the advantage of this approach is that the system is capable of *learning* such a model that is able to describe complex tasks including their partial order from observed data.

3.3 Modelling Partially-ordered Tasks

In this paper, we use Bayesian Logic Networks (BLNs; Jain et al., 2009) to represent and model the behavior of healthy and apraxic patients during ADL performance. Given space limitations we refer the reader to Jain et al., (2009) for more detailed methodological information.

In general, BLNs are statistical relational models that combine the expressiveness of first-order logics, necessary to describe the complex interactions between actions and the parameters associated with these actions, with the representation of probability in a probabilistic logical language.

The tasks and actions in the system are formally represented as follows. A set of tasks is denoted by T, which is described by a set of actions, A_t, a possibly empty set of action properties P_t, and an ordering relation O_t among the actions.

$$T = \{T_t \mid T_t = \langle A_t, P_t, O_t \rangle \}$$

Observation action sequences, S, are instances created by performing the task. A task model describes the partial order inherent in a given activity, and action sequences are the sequential samples following this partial order. Action sequences are described as:

$$S = \{S^T_s \mid S^T_s = \langle a_0, a_1, \ldots \rangle \}$$

Observed actions in an action sequence are denoted with the subscript index a_i, the prototypical actions in a task model have a superscript a^i. Action sequences are related to tasks via the *activityT* predicate.

$$activityT(S^T) = T$$

Each task model comprises of a set of n actions, which have one of m different types $A^0, \ldots A^m$.

$$A_t = \{ a^0, a^1, \ldots, a^n \}$$

$$\forall i \in [0, n] : actionT\,(a^i) \in \{ A^0, A^0, \ldots, A^m \}$$

Actions may have different properties like the object manipulated or the hand used to manipulate the object. P_t assigns a probability values to each property $\pi \in \Pi$ of each action a^i:

$$P_{t\,:}\, A_t \times \Pi \rightarrow \mathbb{R}$$

$$\Pi = \{ \pi_0, \pi_1, \ldots \pi_p \}$$

$$P_{ij} = P(\pi_j(a^i) = True)$$

For *action sequences*, this reduces to a simple indicator matrix that, for each action-property-pair, contains a probability value that this combination is present. In the case of reliable observations, this probability will be 1, in other cases it reflects the observation uncertainty. For *tasks*, P_t is more complicated and depends on the properties of the problem at hand.

The ordering relation O_t for a task T describes the probability that an action a^i is executed before an action a^j in the respective task context. The relative ordering of two actions is expressed using the *precedes* predicate defined as

$$\forall a_i,\ a_j \in S_s : (I < j) \Leftrightarrow \text{precedes}\ (a_i, a_j, S_s)$$

Figure 2 illustrates how a sequence 1-2-3-4-5 is translated into a set of pairwise ordering constraints. Sequences of observed actions are described by giving the types of actions (*actionT*), their ordering (*precedes*) and optionally their parameters (e.g., *objectActedOn*). For example

$$\begin{aligned}
&activity(Act_0) = MakeTea \\
&\wedge\ actionT\,(N_1) = N_1 \wedge objectActedOn\,(N_1, O_1) \\
&\wedge\ actionT\,(O_1) = \mathrm{O3} \\
&\wedge\ actionT\,(N_2) = N_3 \wedge actionT\,(N_3) = N4 \ldots \\
&\wedge\ precedes\,(N_1, N_2, Act_0) = True \\
&\wedge\ precedes\,(N_1, N_3, Act_0) = True \wedge \ldots \\
&\wedge\ precedes\,(N_1, N_2, Act_0) = True \wedge \ldots
\end{aligned}$$

From training data represented as such logical equations, the system learns Bayesian Logic Networks (BLN) using the implementation in the ProbCog statistical relational learning library.

A BLN is defined as a tuple $B = (D, F, L)$ which consists of the declarations of types and functions D, a set of fragments of conditional probability distributions F, and a set of hard logical constraints L as formulas in first-order logic. The fragments F describe dependencies between abstract random variables. Similar to the manner in which predicate logic abstracts away from the concrete entities in propositional logics, BLNs represent generic relations between classes of entities, as opposed to common Bayesian networks that represent probabilistic dependencies between concrete entities. While the structure of the conditional probability fragments is defined manually, the value domains and probabilities are learned from data. Due to the relational nature, the fragments become very compact and generic. The BLN fragment, consisting of random variables (oval nodes) and preconditions for the respective fragments to be applicable (rectangular nodes), that has been used in our experiments is shown in Figure 3. The fragment describes the dependencies between *precedes*(a_i, a_j, S_s, e, g), *actionT*(a^i), *objActedOn*(a^i), *toLocation*(a^i), and the group (patients or control).

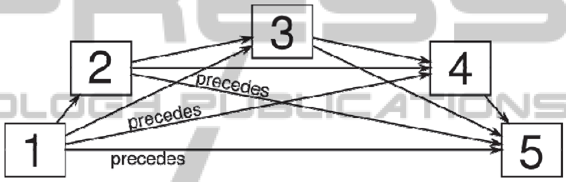

Figure 2: Describing the partial order in the sequence 1-2-3-4-5 by pairwise precedence relations.

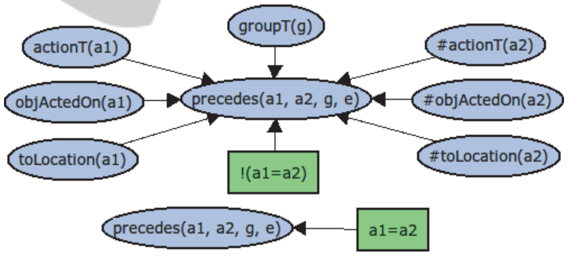

Figure 3: Model structure of the data with dependencies as conditional probability distribution fragments.

This fragment serves as a template for the construction of a ground network. For a given set of entities (i.e., observations of actions), the template is instantiated into a ground mixed network, expanding the abstract relations with the concrete domains of actions of objects. Learning BLNs requires determining the conditional probability tables in the fragments in F, which reduces to simply counting the relative frequencies of the relations in the training set.

4 EVALUATION

Fourteen patients (age = 55.86 y, SD = 12.94, 7 men, 7 women) with lesions following a single cerebrovascular accident (CVA) participated in the study. There were 3 left-handed and 11 right-handed patients. Fourteen healthy participants served as the control group (age = 38.53 y, SD = 14.74, 6 men, 8 women). None of the control participants had any history of neurological disorders or any constraints of upper limb movements. Eleven control participants were right-handed, and three control participants were left-handed.

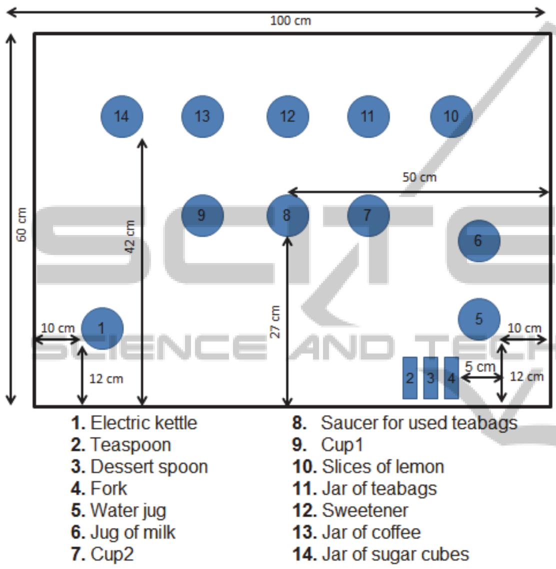

Figure 4: Experimental set up.

Subjects sat at a table with a dimension of 100 cm x 60 cm. The arrangement of the objects on the table is shown in Figure 4, with a total of 14 objects located on the work surface. Each participant was asked to perform a 2 cup tea making task, in which one cup of tea required milk and two sweeteners, and the other cup of tea required lemon and one sugar cube. Subjects were informed that all the things required to make the tea are on the table, and that they were to inform the experimenter if they required help stabilizing an object. Two trials were performed. Actions were recorded by a video camera (Panasonic HDC-SD909) located 45° to the right side of the table.

After data collection, the video data was annotated using a custom made visual labelling tool (Tenorth, 2011) and entered into the BLN learning tool in order to learn the conditional probabilities and domains of random variables from a given training database and the fragment network. Specific methodological information can be found in section 3.3.

5 RESULTS

5.1 Learning the Partial Order

Figure 5 depicts the conditional probabilities inside the *precedes*-node of the BLN. The visualizations contain all nodes that have a probability of at least 2E-6. The ellipse dimensions are proportional to the product of the marginal probabilities of the action components, the thickness of the edges is proportional to the conditional probability of the target given the origin times the probabilities of the target and origin nodes. Note that the node dimensions do not reflect the probability of the action/object/location combination in the task, which is why e.g. the node "Pour water to kettle" is smaller than the "Pour water to cup2" node (since "kettle" is less likely than "cup2").

In order to improve clarity, the redundant relations between actions have been pruned. That is to say, in instances in which P(*precedes(A;B)*) = 1, P(*precedes(A;C)*) = 1 and P(*precedes(B;C)*) = 1, the edge *A* - *C* was not drawn. As can be seen, the algorithm is able to successfully recover the partial-order structure from the data obtained from both healthy and patient populations. The nodes in Figure 2 have been arranged in a way that the more prominent ordering relations are pointing downwards.

The results of the BLN approach show that the relevance of the nodes (i.e., actions) is different between the two groups, indicated by the different sizes. There are more nodes in the patient group, which were caused by addition or substitution errors or by alternative ways of solving the task using a different set of tools. There are some very consistent orderings for apraxic patients, which can be seen by the very bold arrows between some of the actions. In total, however, there is more variation in how they perform the actions, which is visible by the heavily interconnected nodes. In comparison, control participants mostly added the ingredients before pouring water into the cups (indicative of a strong ordering relation), but the order in which the ingredients were added was not consistent (i.e., weak ordering relations). In total, they were much more consistent in how they performed the task and mostly completed the task without errors.

5.2 Error Types and their Frequency

Control participants successfully completed the task in 86% of trials (total 6 errors). Three errors were considered to be omission errors, where the

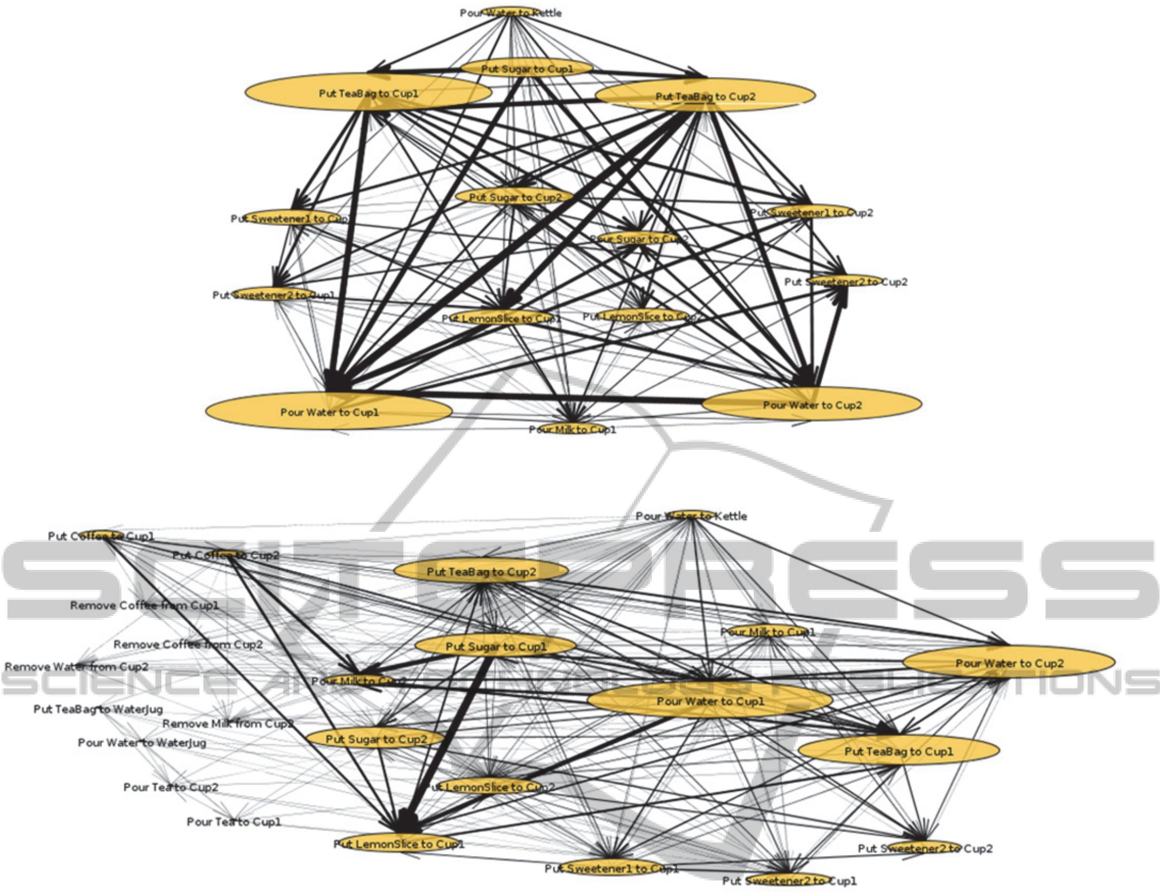

Figure 5: Learned dependencies in fourteen healthy controls (left) and apraxia patients (right).

participant failed to add sugar into cup2, and milk into cup1. Two errors were classified as substitution errors, where participants added two sugar cubes to cup2 and one sweetener to cup1. One error was classified as addition, where an extra sugar cube was added to cup2.

Figure 6 shows the proportions of errors during the tea making task for apraxic patients. Apraxia patients committed errors in 60% of trial, with a total of 38 errors recorded. Patients produced omission errors in 47% of error trials. Examples of omission errors include failing to pour water from the jug into the kettle, put tea bags into one or both cups, or adding sweetener to the cup that required it.

Errors of addition were also frequently committed (16% of errors), with patients adding coffee to a cup of tea, or putting sugar or lemon into the cup that did not require it. Patients committed substitution errors in 13% of trials, and typically added coffee instead of a teabag into either cup1 or cup2. There were also a small number of trials in which patients committed quality (11%), anticipation (8%), and mislocation (5%) errors.

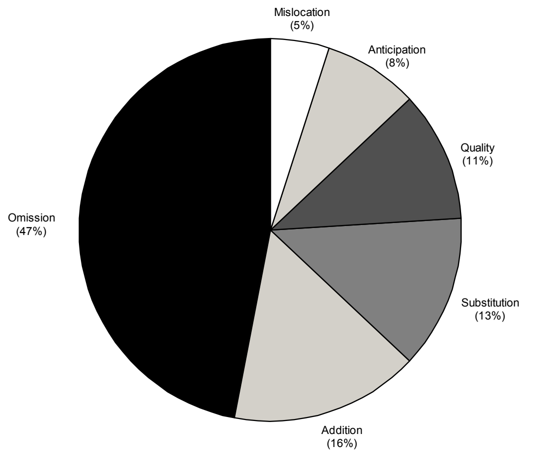

Figure 6: The distribution of errors by error type for patients with apraxia.

In sum, the error production results are consistent with previous research (Buxbaum et al., 1998); (Schwartz et al., 1998) demonstrating that omission errors are the most commonly committed type of errors during ADL. In addition, errors did not appear to be related to the laterality of lesion, hemiparesis, or aphasia type. Future research into error production in apraxic populations will continue to examine this issue, in order to ascertain the variables that correlate to error production.

Analysis also indicated that distractor objects located in the workspace influenced ADL behavior in 23.7% of trials. Interestingly, of the three distractor objects (i.e., jar of coffee, dessert spoon, fork), only the coffee jar influenced behavior, with patients adding coffee into a cup *instead* of a tea bag (substitution error) or adding coffee *and* a tea bag into a cup (addition error). This finding complements previous research (Moores et al., 2003); (Schwartz et al., 1998) suggesting that semantically related distractors compete for selection with appropriate target objects for action. More detailed analysis on a larger group of apraxia patients is needed to ascertain how the semantic relatedness of distractors influences action sequencing and error production during ADL performance.

6 CONCLUSIONS

In this paper, we presented a statistical relational learning approach to model the behavior of apraxic patients during ADL performance. Congruent with previous research (Buxbaum et al., 1998); (Schwartz et al., 1998) we found that apraxic patients committed more errors than control participants. The most frequently committed errors were omission, addition and substitution errors. These errors are recognizable by the nodes (i.e., actions) located in the upper left corner of the apraxic patient learned dependency visualizations (Figure 5).

The results of the BLN approach indicated that the relevance of the actions (i.e., nodes) differed between the controls and apraxics, with more nodes in the apraxic patient group. The larger number of nodes is due to errors associated with addition and substitution. The high degree of variation in action sequencing for this task resulted in a highly interconnected task graph.

Overall, control participants showed a strong ordering relation between some actions in the task. That said there was some flexibility in the order in which the ingredients were added. For example, in some trials participants first added the sugar and then lemon to cup2, and on other trials participants' added lemon and then sugar. This finding indicates a weak ordering relation between those actions. Control patients usually added milk at the very end of the task, both groups filled the kettle with water first.

The results of the present paper highlight the variability inherent in ADL performance, and indicate that the BLN approach is able to describe the partial order imposed on all actions in a task, including the general relations between consecutive actions and their properties. The presented models have been learned from annotated data and represent a joint probability distribution over not only the ordering, but also the types and properties of actions in the task. This distribution allows various inference tasks including classification into patient/control group, error prediction, inference of likely properties and types of individual actions, etc. We plan to investigate these possibilities in our future work and consider this a promising approach to behavioral modelling for use in cognitive rehabilitation.

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REFERENCES

Bickerton, W., Riddoch, M. J., Samson, D., Balani, A., Mistry, B., and Humphreys, G. W., (2012). Systematic assessment of apraxia and functional predictions from the Birmingham Cognitive Screen. *Journal of Neurology, Neurosurgery, and Psychiatry, 83*, 513-521.

Buxbaum, L. J., Schwartz, M. F., and Montgomery, M. W., (1998). Ideational apraxia and naturalistic action. *Cognitive Neuropsychology, 15,* 617-643.

Forde, E. M. E., Humphreys, G. W., and Remoundou, M., (2004). Disordered knowledge of action order in action disorganisation syndrome. *Neurocase, 10,* 19-28.

Geschwind, N., (1975). The apraxias: neural mechanisms of disorders of learned movements. *American Scientist, 63*, 188-195.

Goldenberg, G., (2008). Apraxia. In: Goldenberg, G. and Miller B. (Eds.), *Handbook of Clinical Neurology - Neuropsychology and Behavior (*pp. 323-338). Edinburgh: Elsevier.

Goldenberg, G., and Hagmann, S., (1998). Therapy of activities of daily living in patients with apraxia.

Neuropsychological Rehabilitation, 8(2): 123-141.

Hamid, R., Maddi, S., Bobick, A., and Essa, I., (2007). Structure from statistics-unsupervised activity analysis using suffix trees. *IEEEI, 206*, 7.

Humphreys, G. W. and Forde, E. M. E., (1998). Disordered action schema and action disorganisation syndrome. *Cognitive Neuropsychology, 15*, 771-811.

Jain, D., Waldherr, S., and Beetz, M., (2009). Bayesian Logic Networks. Technical report, IAS Group, Fakultät für Informatik, Technische Universität München.

Liepmann, H., (1905). *Ueber Störungen des Handelns bei Gehirnkranken*. Berlin: Karger.

Moores, E., Laiti., L., and Chelazzi, L., (2003). Associative knowledge controls deployment of visual selective attention. *Nature Neuroscience, 2*, 182-189.

Morady, K.., and Humphreys, G., (2009). Comparing action disorganization syndrome and dual-task load on normal performance in everyday action tasks. *Neurocase, 15*, 1-12.

Morady, K., and Humphreys, G., (2011). Multiple task demands in action disorganization syndrome. *Neurocase, 17*, 461-472.

Patterson, D., Fox, D., Kautz, H., and Philipose, M. (2005). Fine-grained activity recognition by aggregating abstract object usage. In *Ninth IEEE International Symposium on Wearable Computers, Proceedings,* 44-51.

Rothi, L. J. G., and Heilman, K. M., (1997). *Apraxia: The Neuropsychology of Action*. East Sussex (UK): Psychology Press.

Schwartz, M. F., (1995). Re-examining the role of executive functions in routine action production. *Structure and Functions of the Human Prefrontal Cortex, 769*, 321-335.

Schwartz, M. F., Buxbaum, L. J., Montgomery, M. W., Fitzpatrick-DeSalme, E., Hart, T., Ferraro, M., Lee, S. S., and Coslett, H. B., (1999). Naturalistic action production following right hemisphere stroke. *Neuropsychologia, 37*, 51-66.

Schwartz, M. F., Montgomery, M. W., Buxbaum, L. J., Lee, S. S., Carew, T. G., Coslett, H. B., Ferraro, M., Fitzpatrick-DeSalme, E., Hart, T., and Mayer, N., (1998). Naturalistic action impairment in closed head injury. *Neuropsychology, 12*, 13-28.

Schwartz, M. F., Reed, E. S., Montgomery, M., Palmer, C., and Mayer, N. H., (1991). The Quantitative Description of Action Disorganization After Brain-Damage - A Case-Study. *Cognitive Neuropsychology, 8*, 381-414.

Schwartz, M. F., Montgomery, M. W., Fitzpatrick-desalme, E. J., Ochipa, C., Coslett, H. B., and Mayer, N. H., (1995). Analysis of a disorder of everyday action. *Cognitive Neuropsychology, 12*, 863-892.

Shi, Y., Huang, Y., Minnen, D., Bobick, A., and Essa, I., (2004). Propagation networks for recognition of partially ordered sequential action. *cvpr, 02*, 862–869.

Sunderland, A. and Shinner, C., (2007). Ideomotor apraxia and functional ability. *Cortex, 43*, 359-367.

Tenorth, M., (2011). Knowledge processing for automous robots. Unpublished doctoral dissertation, Technische Universität München, München, Deutschland.

Vail, D. L., Veloso, M. M., and Lafferty, J. D., (2007). Conditional random fields for activity recognition. In *AAMAS '07: Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems*, 1-8. New York, NY, USA: ACM.

World Health Organization, (1978). *Cerebrovascular disease: a clinical and research classification*, Offset Series No. 43. Geneva: World Health Organization.