Complex Activity Recognition Using Context-Driven Activity Theory and Activity Signatures

Saguna, Saguna, Arkady Zaslavsky, and Dipanjan Chakraborty. "Complex activity recognition using context-driven activity theory and activity signatures." ACM Transactions on Computer-Human Interaction (TOCHI) 20.6 (2013): 32.

Introduction

- Accurate activity recognition is challenging because human activity is complex and highly diverse.
- Each human complex activity has more than one subactivity, called atomic activity
- They propose Context-Driven Activity Theory (CDAT) using Markov chains and probabilistic analysis to recognize complex activity.

Challenge

- Complex activities can have a different sequence each time they performed.
- There arises a need to assimilate these atomic activities and context activities performed by the user.
- They need to minimize the amount of training data required as well as the precess of its annotation.

Contributions

- They use their novel Context-Driven Activity Theory (CDAT) to build complex activities definitions and develop a mechanism which combines domain knowledge and activity data collected from real-life experimentation.

- They discover complex activity signatures for different users and associations between atomic activities, context, and complex activities using Markov chains and probabilistic analysis.

Context-Driven Activity Theory

1. Atomic Activity and Complex Activity definitions

- Atomic activity: Atomic activity, A, is defined as a unit-level activity which cannot be broken down further

- Context attribute: A context attribute is defined as any type of data at time t that is used to infer an activity or a situation. It's represented as C_i^t.

- Complex activity:

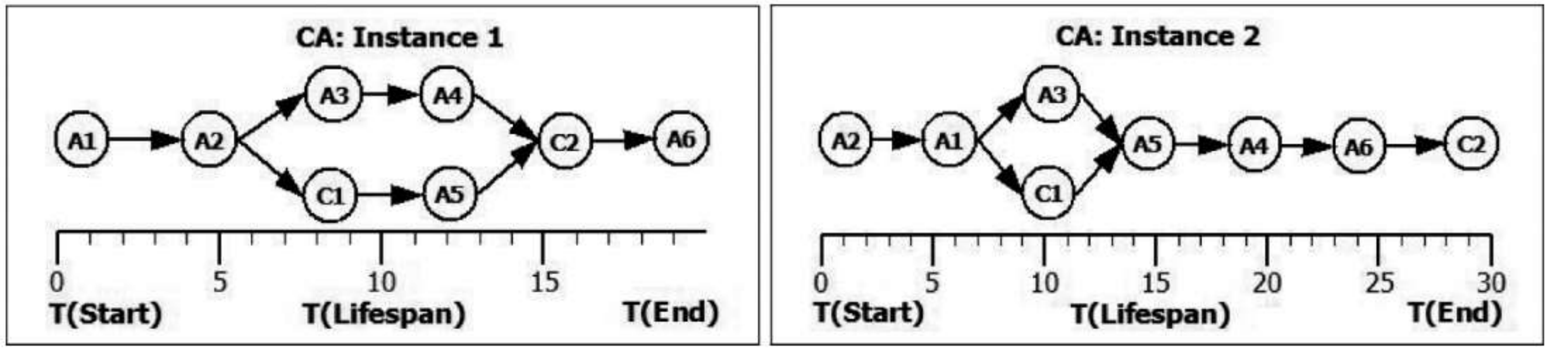

Fig. 2. An example complex activity which can be performed in two different ways: Instance 1 and Instance 2.

Context-Driven Activity Theory

2. Context and atomic activity reasoning to infer complex activities

- Each complex activity has a set of atomic activities, γ A, and a set of context, ρ C,as mentioned in the previous definitions

Table II. Complex Activity Examples

CA_k ($\omega_{CA_k}^{T}$)	γA ($w_{CA_k}^{A_i}$)	ρC ($w_{CA_k}^{C_i}$)	Core γA and ρC	A_S, C_S	A_E, C_E	T_S, T_E, T_L (minutes)	$T_L$range (minutes)
Cooking omelette for breakfast in kitchen (0.59)	A_3: walking (0.10), A_2: standing (0.10), A_5: fridge (0.05), A_{18}: eggs (0.10), A_{21}: frypan (0.10), A_6: vegetable drawer (0.07), A_{17}: slicer (0.10), A_{11}: salt (0.10), A_{23}: whisker (0.08), A_{10}: knife (0.10), A_9: plate: (0.10)	C_2: kitchen (0.19), C_7: kitchen light on (0.12), C_{14}: stove on (0.19), $\neg C_{14}$: stove on (0.19), $\neg C_7$: kitchen light on (0.12), $\neg C_2$: kitchen (0.19)	A_3, A_2, A_{18}, A_{21}, A_{11}, A_{23}, A_9 and C_2, C_7, C_{14}	C_2, A_{18}, A_5, A_{21}, A_{23}	$\neg C_7$, A_9, $\neg C_{14}$	07:06, 07:22, 16	10-20
Preparing coffee in office kitchen (0.65)	A_3: walking (0.25), A_2: standing (0.25), A_{32}: coffee mug (0.25), A_{33}: coffee machine (0.25)	C_2: kitchen (0.3), C_7: kitchen light on (0.3), $\neg C_7$: kitchen light on (0.13), $\neg C_2$: kitchen (0.26)	A_3, A_2, A_{32}, A_{33}, C_2				

$$\omega_{CA_k} = \frac{\sum_{i=1}^{N} w_{CA_k}^{A_i} + \sum_{i=1}^{N} w_{CA_k}^{C_i}}{2}$$

$$\omega_{CA_k} \geq \omega_{CA_k}^{T}$$

Discovering Activity Signatures and Generat

- Complex activity definitions are created by finding the associations between each atomic activity and its corresponding parent complex activity.

1. Associations between atomic and complex activities for different users.

    - The associations involve the calculation of individual probabilities of start, end and other atomic activities for a complex activity

    - Then the atomic activities whose values are equal to or higher than the required threshold are used for creating the activity definition for the respective complex activity

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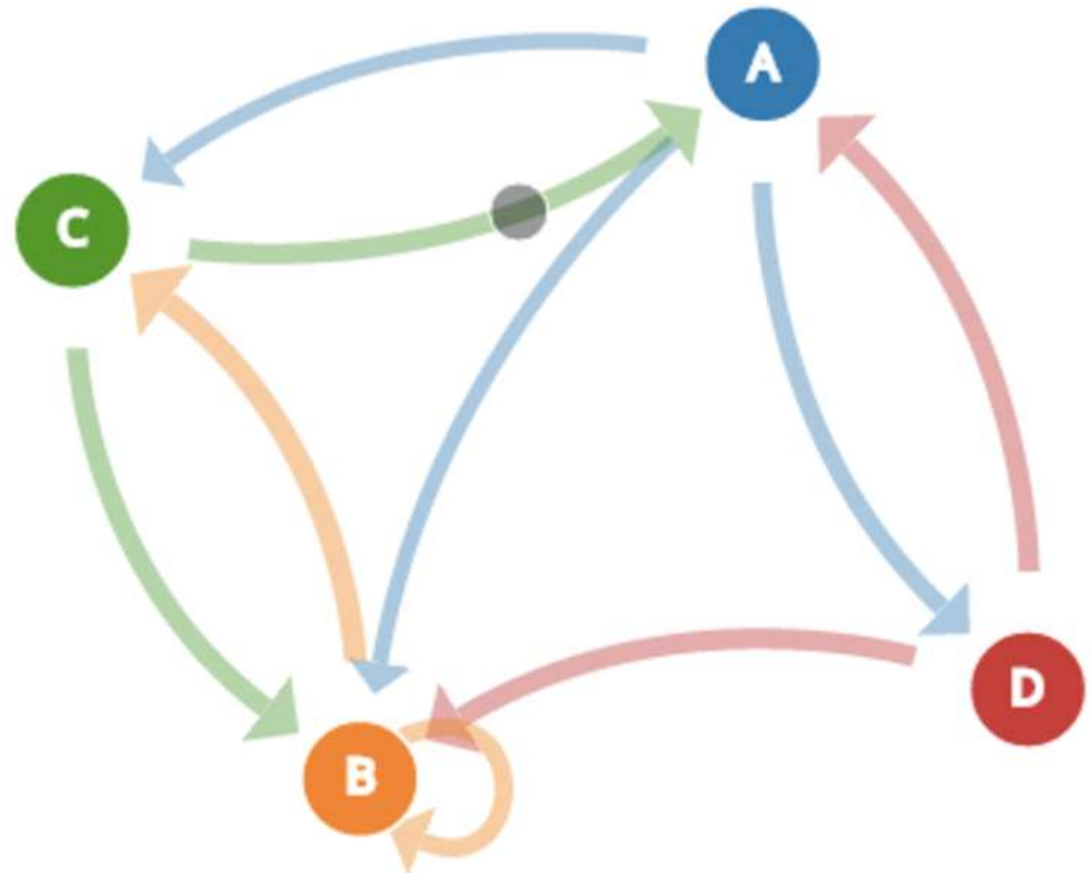


2. Associations between different atomic

$$Pr((X_1,\, X_2,\, \ldots\, X_t) = (x_1,\, x_2,\, \ldots\, x_t) \mid X_1 = x_1) = p_{x_1 x_2} p_{x_2 x_3} \cdots p_{x_{t-1} x_t}. \tag{3}$$

- Associations between atomic activities involves the calculation of conditional probabilities and transition probabilities ($p_{i\,j}$) for different pairs of atomic activities within each complex activity.

- Then they used Markov chains for discovering these associations between pairs of atomic activities for a complex activity

Discovering Activity Signatures and Generat

3. Discovering complex activity signatures of users

- Based on the previous probability calculations, they build complex activity signatures for each complex activity corresponding to individual users.

- the complex activity signature for CA is A3 → A2 → A5 → A18 → A3 → A2 → A21 → A3 → A2 → A6 → A3 → A2 → A17 → A23 → A23 → A10 → A21 → A9

- They use Markov chains to discover activity signatures by calculating the path probabilities for each complex activity.

Complex Activity Recognition Algorithm

ALGORITHM 2: Complex Activity Recognition after Probabilistic Analysis and Discovered Complex Activity Signatures

Input: A_i, C_i, S_i.
Output: CA_k.
Initialization:
findStartAtomicActivity(A_i, C_i);
check for current situation S_i ;
findComplexActivitiesList(S_i)
foreach (CA_k) **do**
  if $A_i == A_S$ **then**
    $add(CA_{list} \longleftarrow CA_i = (\gamma A, \rho C, A_S, A_E, C_S, C_E, T_L))$
  end
end
return CA_{list} ;
findComplexActivity(A_i, C_i)
foreach ($CA_{list} \longleftarrow CA_k$) **do**
  while $timecounter < T_{L_{max}}^{CA_k}$ **do**
    if ($A_i == element\ in\ \gamma A_i$ **then**
      add $A_i \longrightarrow \gamma A_i$ **and** recalculate $w_{CA_k}^{A_i}$ using recomputed weights
    end
    if ($C_i == element\ in\ \rho C_i$ **then**
      add $C_i \longrightarrow \rho C_i$ **and** recalculate $w_{CA_k}^{C_i}$ using recomputed weights
    end
  end
  if ((A_E, C_E *found for* CA_i) **and** ($\rho C_i and \gamma A_i$ *are complete* **and** $\omega_{CA_k} \geq \omega_{CA_k}^{T}$ **and** *complex activity signature matched*)) **then**
    $foundCA_k$
  end
  return CA_k ;
end

Experimentation and Results Validation

- They initially consider two subjects for the duration of 21 days, with an average of 8 hours daily. The experiments were performed from 8:00 am to 12:00 pm and from 2:30 pm to 9:30 pm.
- They identified 16 complex activities and used their CDAT to define them.
- They gave their subjects an Android phone to record the activities manually, which involved adding a count for each occurrence of a complex activity in the corresponding hour.
- Users were asked to keep the record simply for establishing the ground truth, which enabled them to measure the accuracy of their algorithm.

Experimentation and Results Validation

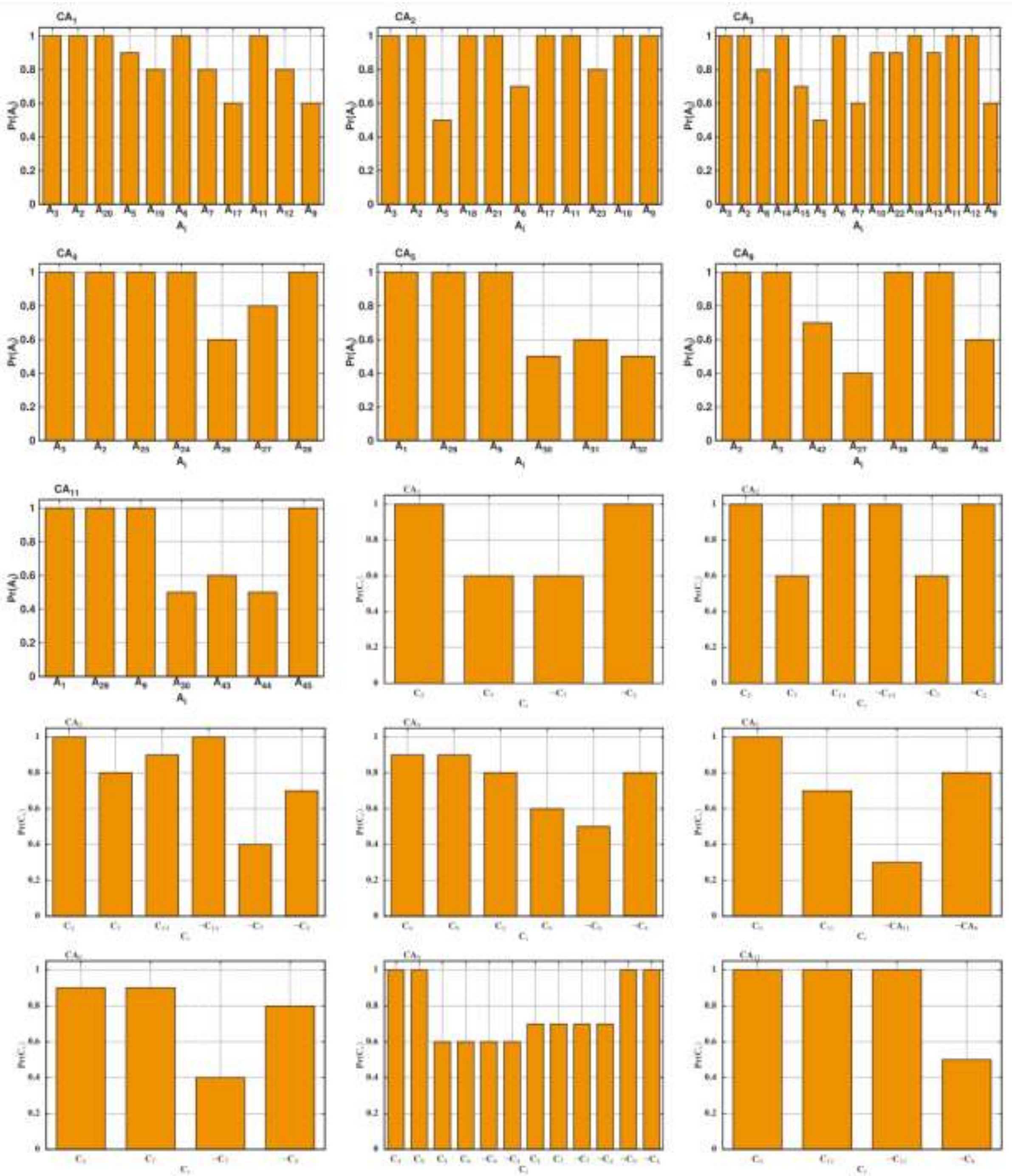
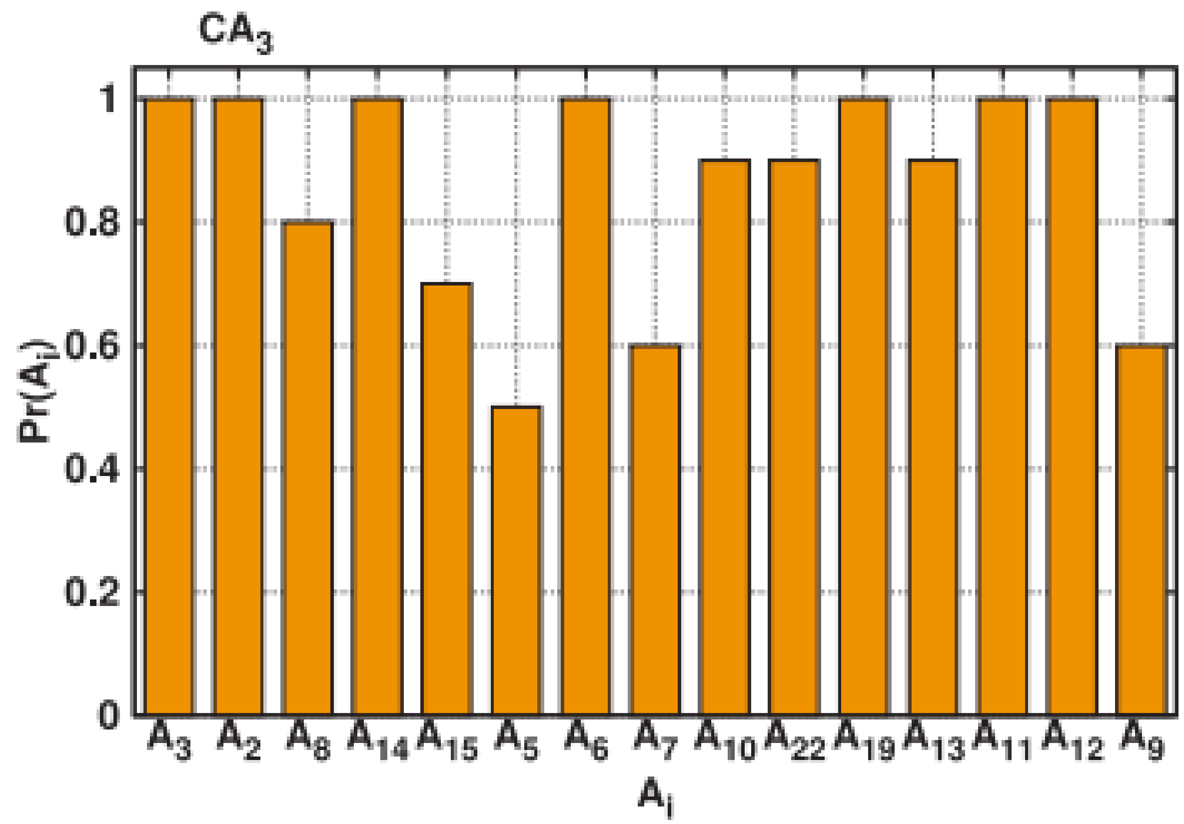


Fig. 6. Atomic activity and context attribute probabilities for eight complex activities from Table V.



Atomic Activity A_i	Description
A_1	Sitting
A_2	Standing
A_3	Walking
A_4	Running
A_5	Fridge
A_6	Vegetable_Drawer
A_7	Vegetable_Basket
A_8	Freezer
A_9	Plate
A_{10}	Knife
A_{11}	Salt
A_{12}	Pepper
A_{13}	Seasoning
A_{14}	Oven
A_{15}	Pizza_Tray

Experimentation and Results Validation

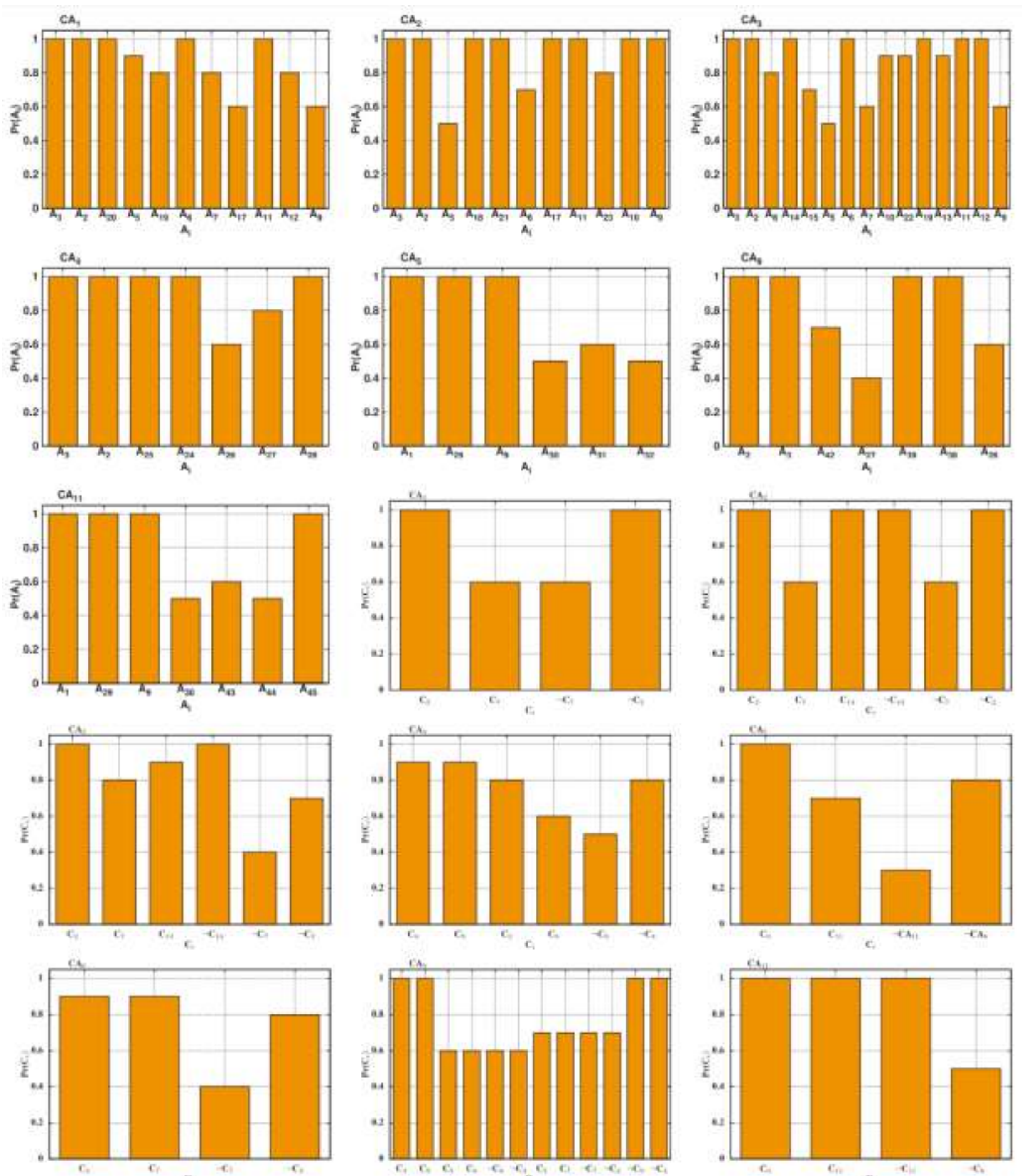


Fig. 6. Atomic activity and context attribute probabilities for eight complex activities from Table V.

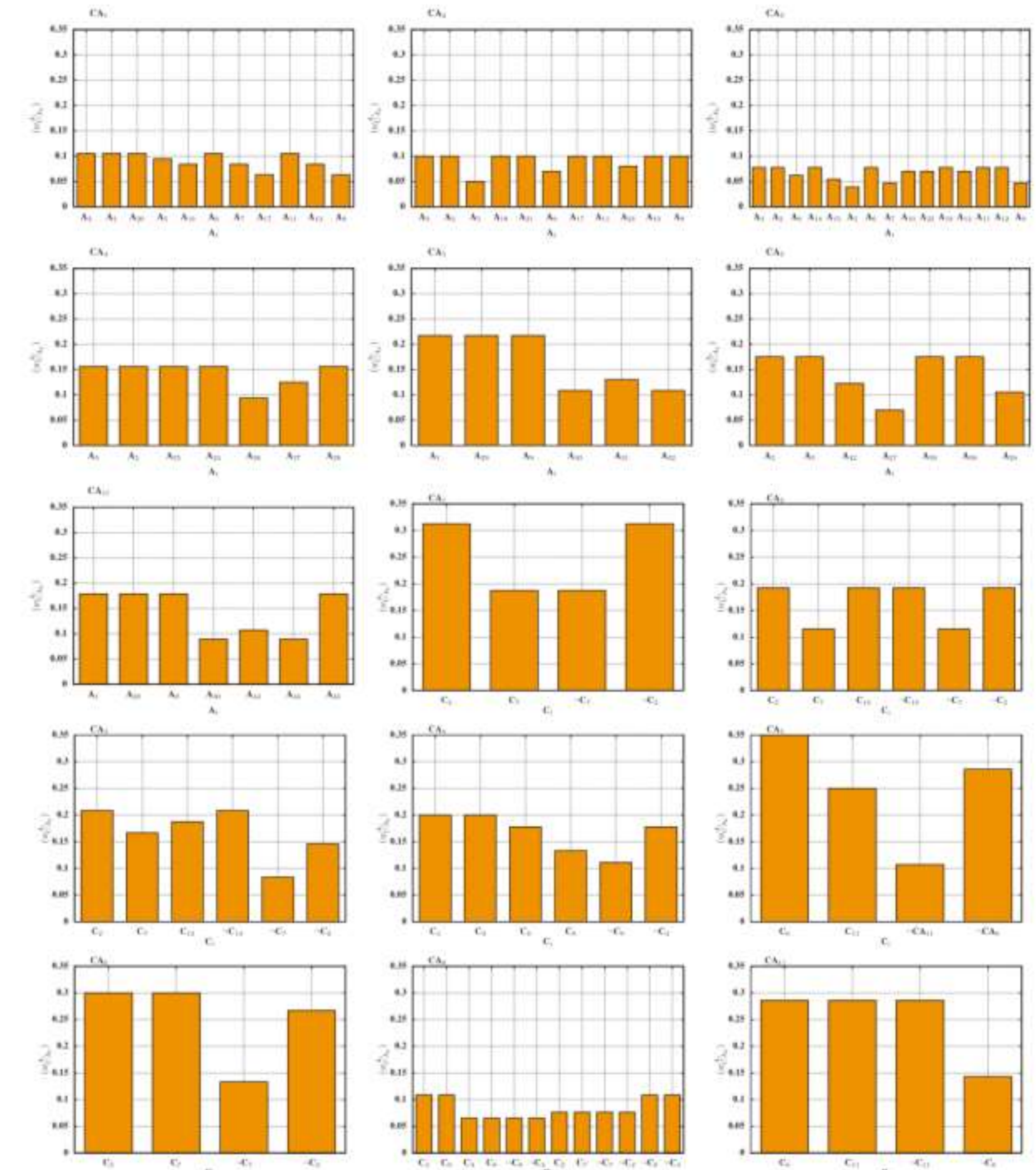


Fig. 7. Atomic activity and context attribute weights for eight complex activities from Table V. These share similar distribution, as shown in Figure 6. Similarly, weights were computed for all other complex activities.

Experimentation and Results Validation

Table III. Complex Activity Signatures for User 1

Complex Activity CA_k	Complex Activity Signature with Atomic Activities γA_i	Complex Activity Signature with Context ρC_i	Path Probability (γA_i) (ρC_i)
Making Sandwich CA_1	$A_3 \rightarrow A_2 \rightarrow A_{20} \rightarrow A_3 \rightarrow A_2 \rightarrow A_5 \rightarrow A_{19} \rightarrow A_6 \rightarrow A_3 \rightarrow A_2 \rightarrow A_7 \rightarrow A_{17} \rightarrow A_{11} \rightarrow A_{12} \rightarrow A_9$	$C_2 \rightarrow C_7 \rightarrow \neg C_7 \rightarrow \neg C_2$	(0.85) (0.87)
Making Omelette CA_2	$A_3 \rightarrow A_2 \rightarrow A_5 \rightarrow A_{18} \rightarrow A_3 \rightarrow A_2 \rightarrow A_{21} \rightarrow A_3 \rightarrow A_2 \rightarrow A_6 \rightarrow A_3 \rightarrow A_2 \rightarrow A_{17} \rightarrow A_{23} \rightarrow A_{23} \rightarrow A_{10} \rightarrow A_{21} \rightarrow A_9$	$C_2 \rightarrow C_7 \rightarrow C_{14} \rightarrow \neg C_{14} \neg C_7 \rightarrow \neg C_2$	(0.81) (0.84)
Making Pizza CA_3	$A_3 \rightarrow A_2 \rightarrow A_8 \rightarrow A_3 \rightarrow A_2 \rightarrow A_{14} \rightarrow A_{15} \rightarrow A_3 \rightarrow A_2 \rightarrow A_5 \rightarrow A_6 \rightarrow A_3 \rightarrow A_2 \rightarrow A_7 \rightarrow A_{10} \rightarrow A_{22} \rightarrow A_3 \rightarrow A_2 \rightarrow A_5 \rightarrow A_3 \rightarrow A_2 \rightarrow A_{19} \rightarrow A_{13} \rightarrow A_{11} \rightarrow A_{12} \rightarrow A_9$	$C_2 \rightarrow C_7 \rightarrow C_{14} \rightarrow \neg C_{14} \neg C_7 \rightarrow \neg C_2$	(0.82) (0.95)
Getting Ready CA_4	$A_3 \rightarrow A_2 \rightarrow A_{25} \rightarrow A_{24} \rightarrow A_3 \rightarrow A_2 \rightarrow A_{26} \rightarrow A_3 \rightarrow A_2 \rightarrow A_{27} \rightarrow A_3 \rightarrow A_2 \rightarrow A_{28}$	$C_4 \rightarrow C_9 \rightarrow C_3 \rightarrow C_8 \rightarrow \neg C_8 \rightarrow C_4 \rightarrow \neg C_9 \rightarrow \neg C_4$	(0.67) (0.60)
Eating Breakfast CA_5	$A_1 \rightarrow A_{29} \rightarrow A_9 \rightarrow A_{30} \rightarrow A_{31} \rightarrow A_{32}$	$C_6 \rightarrow C_{11} \rightarrow \neg C_{11} \rightarrow \neg C_6$	(0.95) (0.98)
Preparing Coffee CA_6	$A_3 \rightarrow A_2 \rightarrow A_{32} \rightarrow A_{33} \rightarrow A_{32}$	$C_2 \rightarrow C_7 \rightarrow \neg C_7 \rightarrow \neg C_2$	(0.98) (1.0)
Drinking Coffee CA_7	$A_1 \rightarrow A_{32}$	C_{12}	(1.0) (1.0)
Watching Videos CA_8	$A_1 \rightarrow A_{36} \rightarrow A_{37} \rightarrow \neg A_{37}$	C_{13}	(0.95) (1.0)
Laundry CA_9	$A_{38} \rightarrow A_3 \rightarrow A_2 \rightarrow A_{26} \rightarrow A_3 \rightarrow A_2 \rightarrow A_{42} \rightarrow A_3 \rightarrow A_2 \rightarrow A_{27} \rightarrow A_3 \rightarrow A_2 \rightarrow A_{39}$	$C_4 \rightarrow C_9 \rightarrow C_3 \rightarrow C_8 \rightarrow \neg C_8 \rightarrow C_2 \rightarrow C_7 \rightarrow \neg C_7 \rightarrow C_4 \rightarrow \neg C_9$	(0.73) (0.68)
Cleaning Kitchen CA_{10}	$A_2 \rightarrow A_{40} \rightarrow A_{41} \rightarrow \neg A_{40}$	$C_2 \rightarrow C_7 \rightarrow \neg C_7 \rightarrow \neg C_2$	(0.75) (0.84)
Eating Dinner CA_{11}	$A_1 \rightarrow A_{29} \rightarrow A_9 \rightarrow A_{30} \rightarrow A_{43} \rightarrow A_{44} \rightarrow A_{45}$	$C_6 \rightarrow C_{11} \rightarrow \neg C_{11} \rightarrow \neg C_6$	(0.80) (0.85)
Working on Presentation CA_{12}	$A_1 \rightarrow A_{47} \rightarrow A_{36} \rightarrow A_{46} \rightarrow \neg A_{46}$	C_{13}	(0.67) (0.95)
Working on Document CA_{13}	$A_1 \rightarrow A_{47} \rightarrow A_{36} \rightarrow A_{48} \rightarrow \neg A_{48}$	C_{13}	(0.55) (0.98)
Searching the Internet CA_{14}	$A_1 \rightarrow A_{47} \rightarrow A_{36} \rightarrow A_{49} \rightarrow \neg A_{49}$	C_{13}	(0.57) (0.85)
Jogging in the Gym CA_{15}	$A_4 \rightarrow A_{50} \rightarrow \neg A_{50}$	C_{12}	(0.85) (0.95)
Going to Work CA_{16}	$A_{51} \rightarrow A_3$	$C_1 \rightarrow C_{19} \rightarrow C_{12}$	(1.0) (1.0)

Experimentation and Results Validation

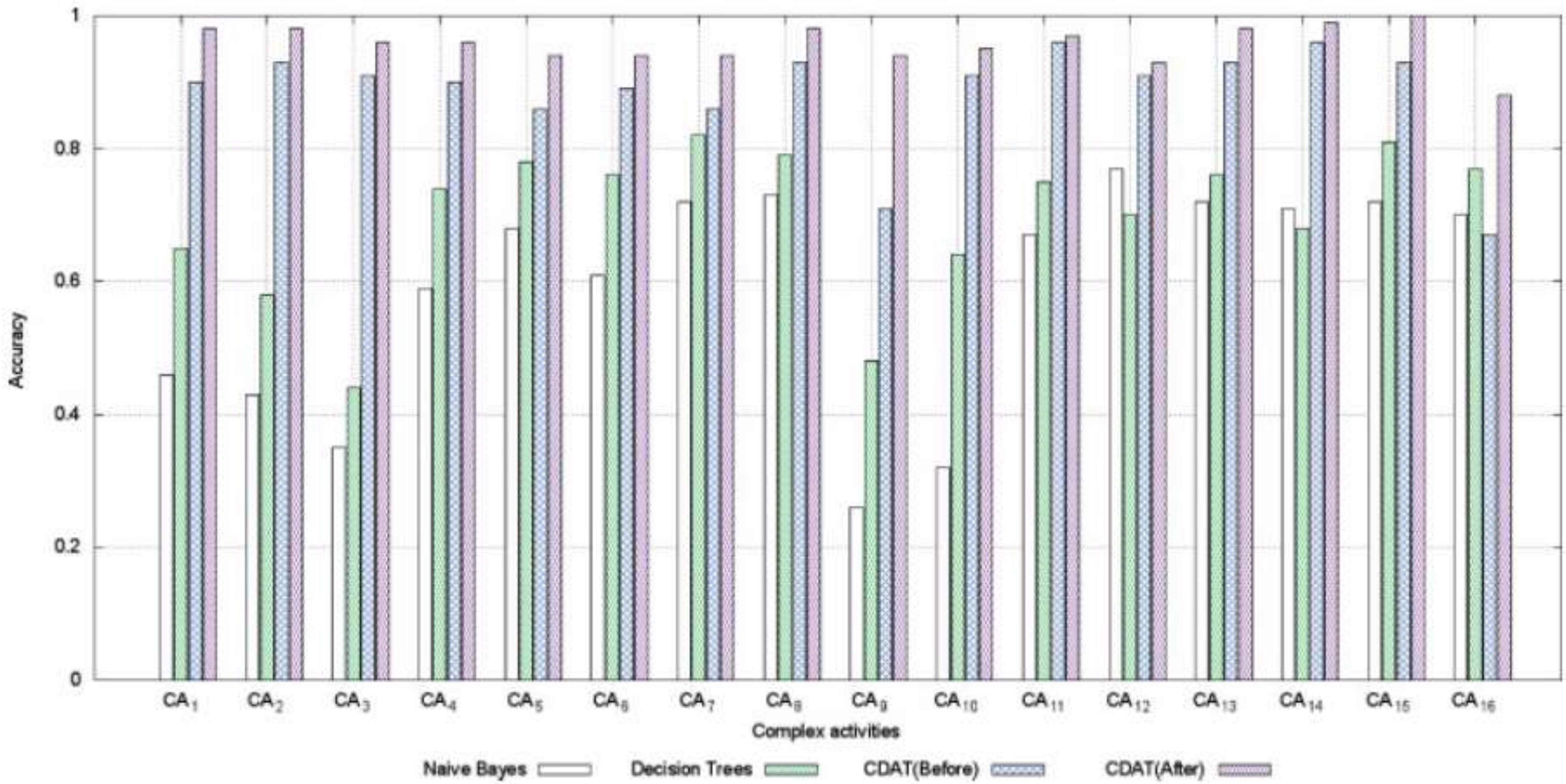


Fig. 8. Complex activity recognition accuracy: (1) CDAT from Section 6.1 as "Before," (2) updated CDAT from Section 6.3 as "After," (3) decision trees (J48), and (4) naive Bayes (NB).

Experimentation and Results Validation

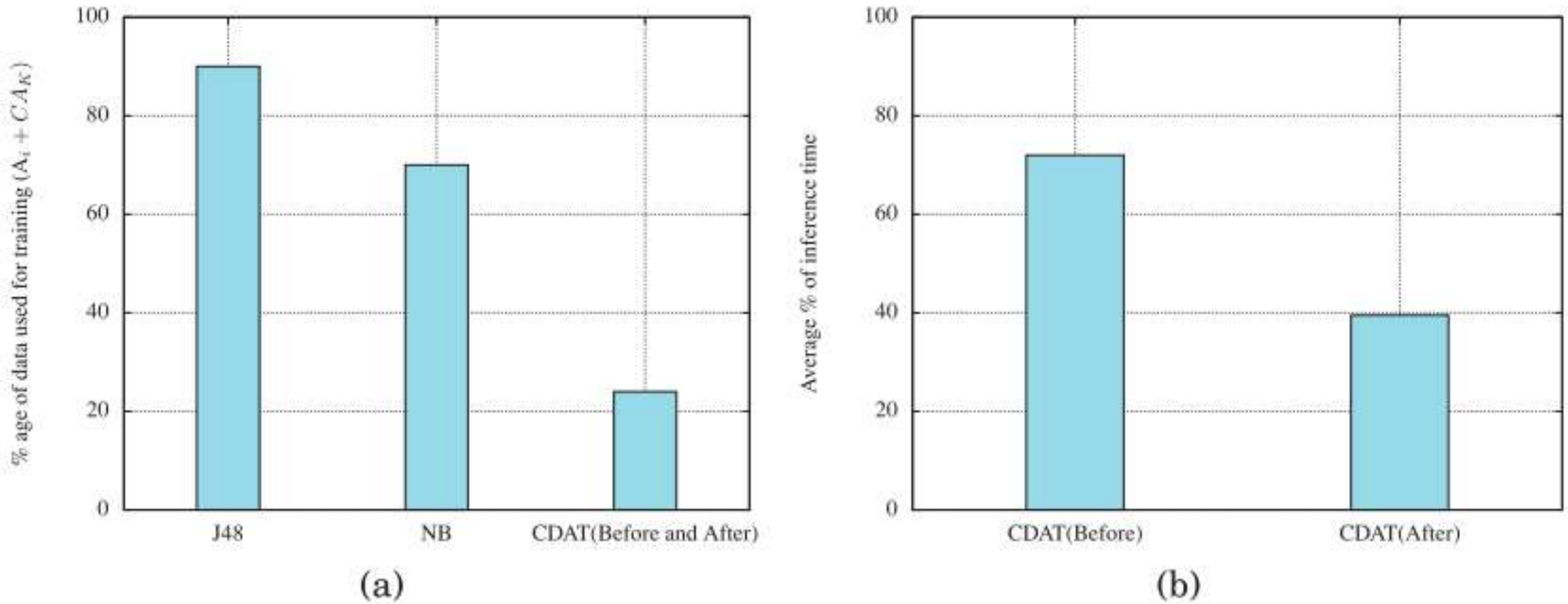


Fig. 10. (a): Training data used for atomic activities and complex activities for decision trees (J48), naive Bayes (NB), and CDAT (Before and After). (b): Average percentage of time for inferring complex activities for CDAT (Before) and CDAT (After).

Conclusions

- They use probabilistic analysis and Markov chains to discover complex activity signatures, assign weights to atomic activities, and update complex activity definitions within their CDAT
- Their average accuracy is higher than another machine learning algorithms.
- They are able to reduce the amount of training data, atomic activities and context attributes used.