A Bayesian Networks Approach to Plan Recognition for Interface Agents

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Agenda

- Interface Agents
- Plan Recognition
- Proposed model of user’s intentions
- Example
- Conclusions
Interface Agents

- Assist users in a personalized manner
- Learn interests, preferences, goals and needs of the user
- Should consider the status of the user’s attention and the uncertainty about the user’s goals
  - ability to recognize or predict opportune moments for gaining the user’s attention
Interface Agents

- User
- Assistant (agent)

Mixed-initiative interaction

- Direct manipulation
- Observes and imitates
- Acts in user behalf

Application
Interface Agents

- Two ways of detecting user’s intention
  - Asking the user
    - Is a direct way of accessing to his/her intentions
    - We run the risk of disturbing him/her
    - Slows down the interaction
    - Interrupts the user’s line of thought
  - Inferring from context
    - Information obtained from user’s interaction with the application is on a low level compared to the user’s intention
Plan Recognition - Objective

- Aims at identifying the goal (or intention) of a subject based on the actions he performs in an environment.
Plan Recognition - Objective

- Aims at identifying the goal (or intention) of the user based on the tasks he performs in a software application.
Plan Recognition – Inputs and outputs

- Inputs:
  - a set of goals the agent expects the user to carry out in the domain,
  - a set of plans describing the way in which the user can reach each goal,
  - an action observed by the agent.

- Output:
  - foretelling the user's goal, and determining how the observed action contributes to reach it
Plan Recognition – Basic Idea

- narrow the number of possible goals the agent believes the user is pursuing by observing the actions the user performs.
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Aproaches to Plan Recognition

- Consistency
  - Determine which of an input set of goals is consistent with the observed tasks
  - A goal G is consistent with a task sequence T if T might have been executed in service of G

- Probabilistic
  - Select as a candidate intention that with the higher probability in light of the evidence at each moment
Plan Recognition for Interface Agents

- We have to consider several issues:
  - The uncertainty related to the moment in which the user starts a new plan
  - Overloaded tasks
  - Noisy tasks
  - Interruptions and plan abandonment
  - Multiple interleaved goals
  - Multiple plans
  - Adaptation to the user
Model of User’s Intentions

- Intention Graph
  - models the intentions the user can pursue in the domain
  - represents a context of execution
    - the set of tasks that the user has performed recently, and will influence the confidence the agent will have in any intention that the user could be pursuing.
  - materialized by a Bayesian Network
    - Knowledge representation capable of capturing and modeling dynamically the uncertainty of user-application interactions
Bayes Theorem

\[ p(V_i / V_j) = \frac{p(V_j / V_i)p(V_i)}{p(V_j)} \]

- Bayes' rule tells us how to update our belief about a hypothesis \( V_i \) in the light of new evidence \( V_j \).
- \( p(V_i|V_j) \) is calculated by multiplying our prior belief \( p(V_i) \) by the likelihood \( p(V_j|V_i) \) that \( V_j \) will occur if \( V_i \) is true.
- *Evidence*: collection of findings on some variables
Intention Graph

Intention Graph $G = \langle V, A, P, F, T \rangle$

- A set of variables $V$, where each variable can be of the type:
  - Task: a variable representing a task of the application
  - Goal: a variable representing a goal the user can pursue while using the application
  - Context: a variable representing attributes or properties of tasks in the application
- A set of directed edges $A$ between variables
- Each variable has a finite set of mutually exclusive states
- The variables together with the directed edges form a directed acyclic graph (DAG).
- To each variable $v$ in $V$ with parents $v_1, \ldots, v_n$, there is attached the potential table $P_v$ encoding $p(v|v_1, \ldots, v_n)$
- A fading function $F$ for evidence introduced in the network
- A set of $T$ traceable nodes, which is a subset of the nodes in $V$
Intention Graph

<table>
<thead>
<tr>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>0.4</td>
</tr>
</tbody>
</table>

- **InviteToMeeting**
  - True: 60.000
  - False: 40.00

- **SendMailToContact**
  - True: 65.0
  - False: 35.000

- **AddContactToMeeting**
  - True: 71.205
  - False: 28.794

- **SelectContact**
  - True: 87.097
  - False: 12.902

- **SendMail**
  - True: 65.701
  - False: 34.298

- **SelectContact**

<table>
<thead>
<tr>
<th>InviteToMeeting</th>
<th>True</th>
<th>False</th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>True</td>
<td>0.99</td>
<td>0.2</td>
<td>0.5</td>
<td>0.01</td>
</tr>
<tr>
<td>False</td>
<td>0.01</td>
<td>0.8</td>
<td>0.5</td>
<td>0.99</td>
</tr>
</tbody>
</table>
Intention Graph

- Confidence level: probability of a (task or intention) node of being in state “true”
Overloaded Tasks and Multiple Interleaved Goals

- Overloaded task: a task that the user can perform to achieve multiple goals
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Multiple plans
Multiple plans
Noisy Tasks and changes in the user’s goal

- Fading function
  - Gradually forget past observations
- Soft evidence
  - Use a probabilistic distribution to set evidence in Bayesian Networks
- Ex.: decrement evidence by a constant factor
- Allowing to gradually forget past observation, the agent not only would be able to manage changes in the goal of the user, but also will allow it to forget the execution of noisy tasks, that are tasks that do not belong to the main goal the user is pursuing.
Adaptation of probabilities

- Adapt the CPTs established by the designer to a particular user
- User Feedback declaring his intention
- Fractional updating [Jensen2001]
  - Statistical approach
  - Experience count

\[
p(N = k | conf) = \frac{n_k + z \times y_k}{\text{experiences}^{\text{new}}}
\]
Adaptation of probabilities

\[ p(N = k | \text{conf}) = \frac{n_k + z \times y_k}{\text{experiences}_{\text{new}}} \]

- $N=$ node
- $k=$ state
- conf = $pa(N)$ configuration
- $z =$ probability of conf
- $n_k =$ probability of $N$ being in state $k$
- $y_k =$ probability of query $N$ being in state $k$
- $\text{experiences}_{\text{new}} =$ new count of experiences for $n$ being in state $k = \text{experiences}_{\text{old}} + z$
Intention Graph tuning

- Use the attributes of the tasks performed by the user to build an interaction history.
- Traceable node: node of the Intention Graph in which we want to register such attributes.
- Find new relations between these attributes and the nodes in the Intention Graph.
  - Batch learning and Parametric learning for Bayesian Networks.
Intention Graph tuning

[Diagram with tables and nodes labeled InviteToMeeting, SendMailToContact, AddContactToMeeting, SelectContact, and SendMail]
Intention Graph tuning

 InviteToMeeting
 True 61.939
 False 38.060

 SendMailToContact
 True 100.0
 False 0.0

 AddContactToMeeting
 True 80.350
 False 19.649

 SelectContact
 True 100.0
 False 0.0

 SendMail
 True 99.0
 False 1.0

 Friends, Tandil, Argentina, False, True
 Work, BsAs, Argentina, True, False
 ...

 Feedback

 Traceable node

 Batch learning
 + Parametric learning

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Merging the learnt network into the Intention Graph

\[ p(X_j|Y_1^{j_{Y_1}}, \ldots Y_n^{j_{Y_n}}, Z_1^{j_{Z_1}}, \ldots, Z_m^{j_{Z_m}}) = \]
\[ p(X_j|Y_1^{j_{Y_1}}, \ldots Y_n^{j_{Y_n}}) * \pi + \]
\[ p(X_j|Z_1^{j_{Z_1}}, \ldots, Z_m^{j_{Z_m}}) * (1- \pi) \]
Example
Example

Intentions confidence levels without user's preferences

Confidence level

Task performed over time
Example
Example

City = Tandil
Group = Friends
Birthday = True

City = Tandil
Group = Work
Birthday = False
Summary and Conclusions

- Inferring the goal of the user from observations of his actions
  - A problem of inference under conditions of uncertainty.
- Non-probabilistic approaches cannot decide to what degree the evidence supports any particular goal hypothesis.
  - Important issue to consider so that the agent could be able to rank different possible explanations supported by the set of performed actions.
- We presented a probabilistic model of user intentions
  - Able to deal with some common problems of plan recognition
  - Able to adapt to a particular user of the software application
Summary and Conclusions

- The incorporation of the user's preferences allow a better distinction of the actual intention of the user.
- The confidence level of finished intentions gradually decrements to its original value due to the fading function for evidence.
References


