A Bayesian Networks Approach to Plan Recognition for Interface Agents

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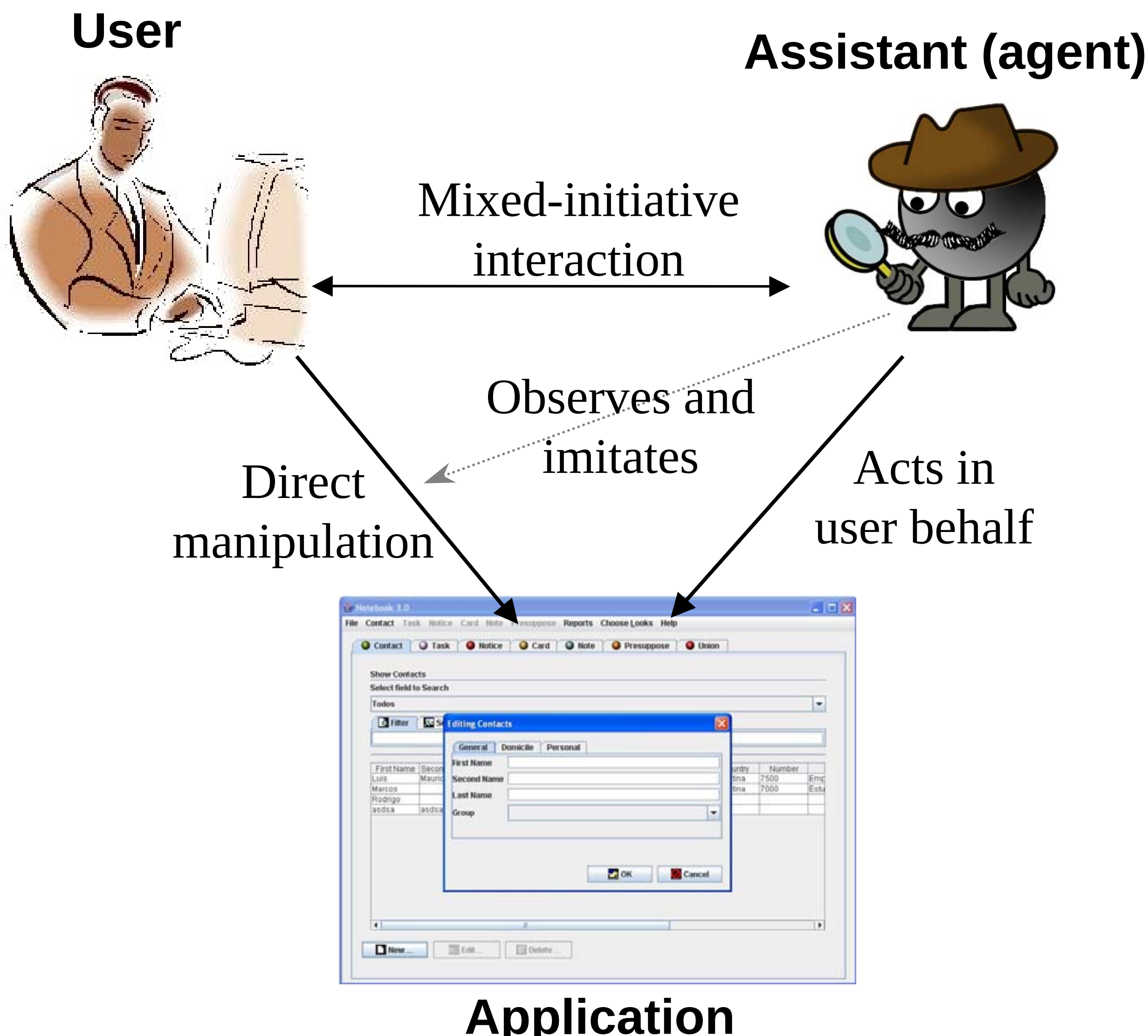
Agenda

- 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



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

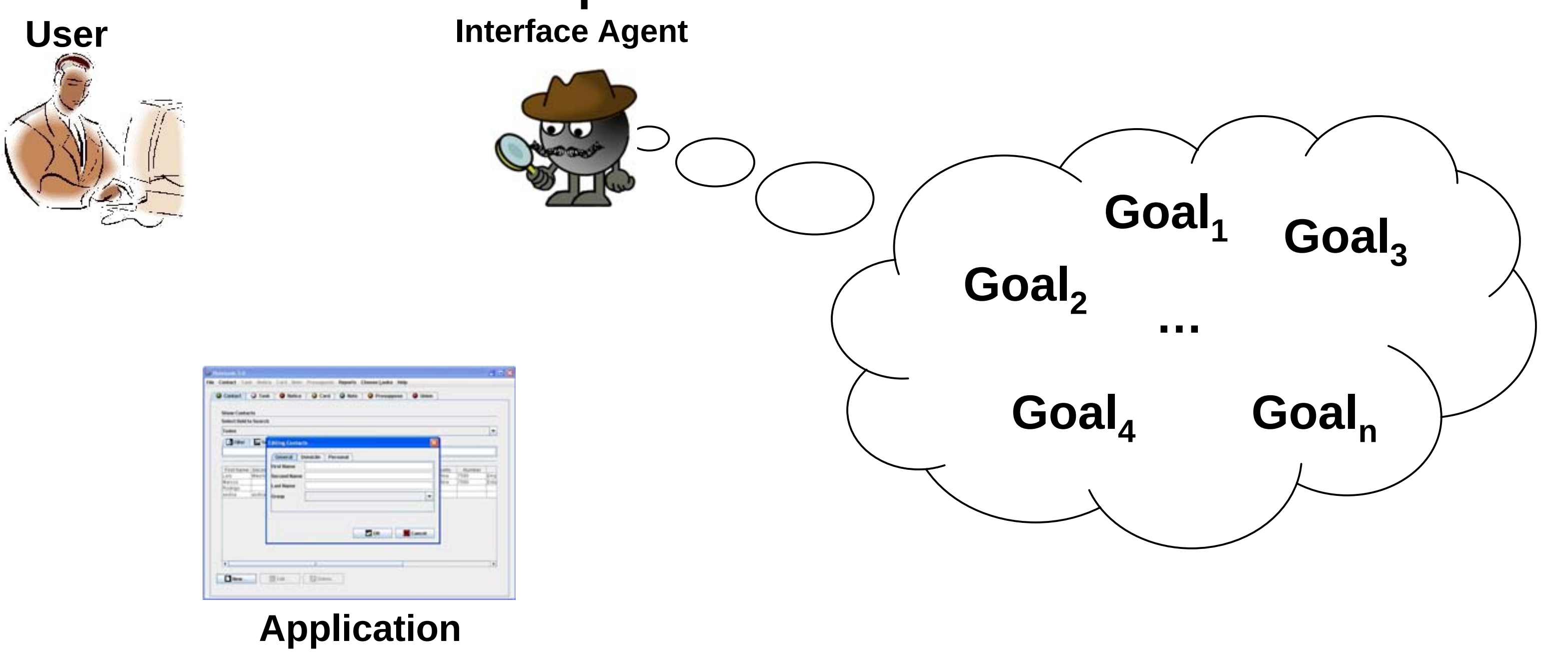
- Aims at identifying the goal (or intention) of the user based on the tasks he performs in a software application

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.



Plan Recognition – Basic Idea

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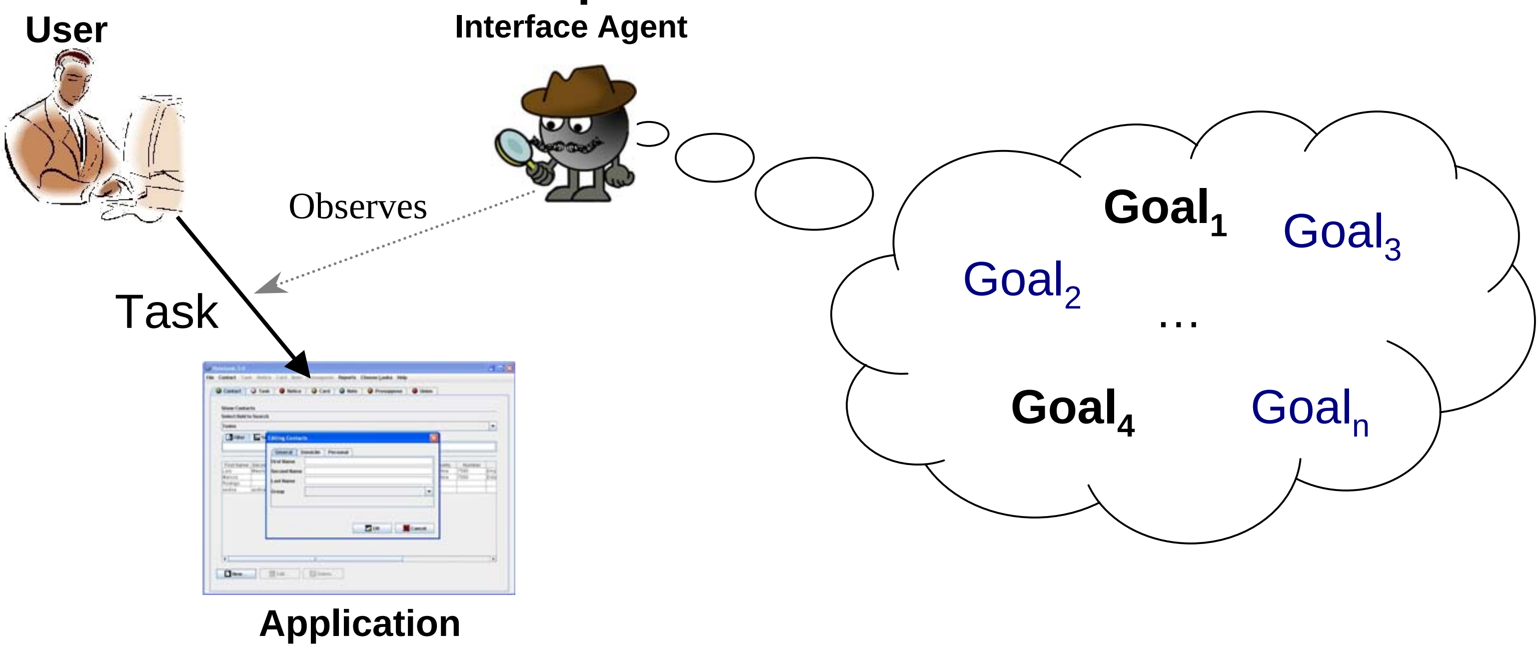


Aproaches to Plan Recognition

- 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

$$p(Vi\,/\,Vj) = \frac{p(Vj\,/\,Vi)\,p(Vi)}{p(Vj)}$$

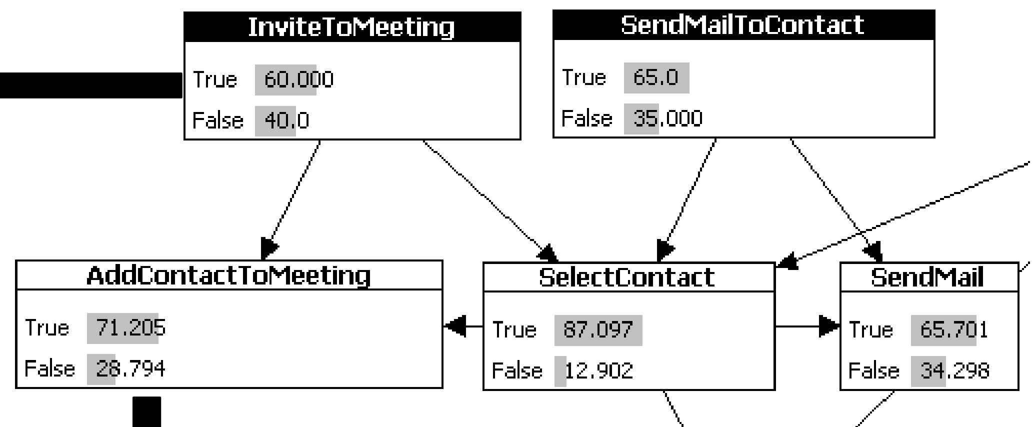
- Bayes' rule tells us how to update our belief about a hypothesis Vi in the light of new evidence Vj.
- p(Vi|Vj) is calculated by multiplying our prior belief p(Vi) by the likelihood p(Vj|Vi) that Vj will occur if Vi is true
- *Evidence*: collection of findings on some variables

Intention Graph

- Intention Graph G=<V,A,P,F,T>
  - 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 $v_1,...,v_n$, there is attached the potential table P_v encoding $p(v|v_1,...,v_n)$
  - 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

True	0.6
False	0.4



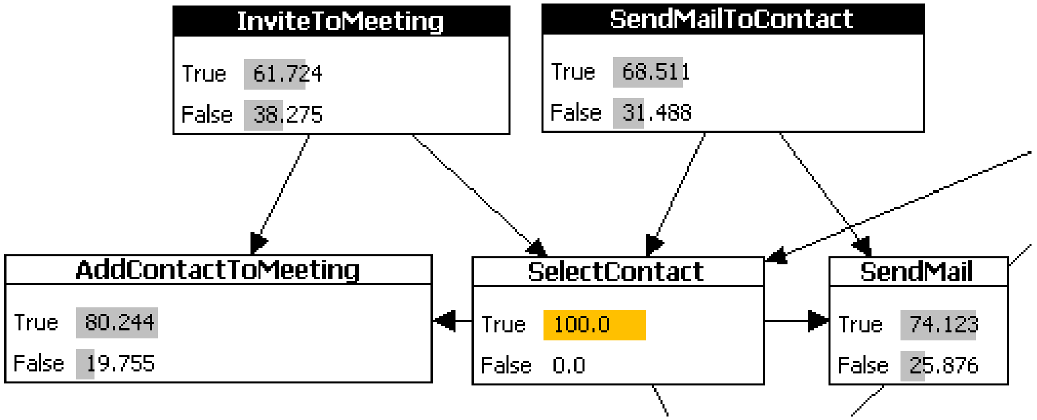
SelectContact	True		False	
InviteToMeeting	True	False	True	False
True	0.99	0.2	0.5	0.01
False	0.01	0.8	0.5	0.99

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



Overloaded Tasks and Multiple Interleaved Goals

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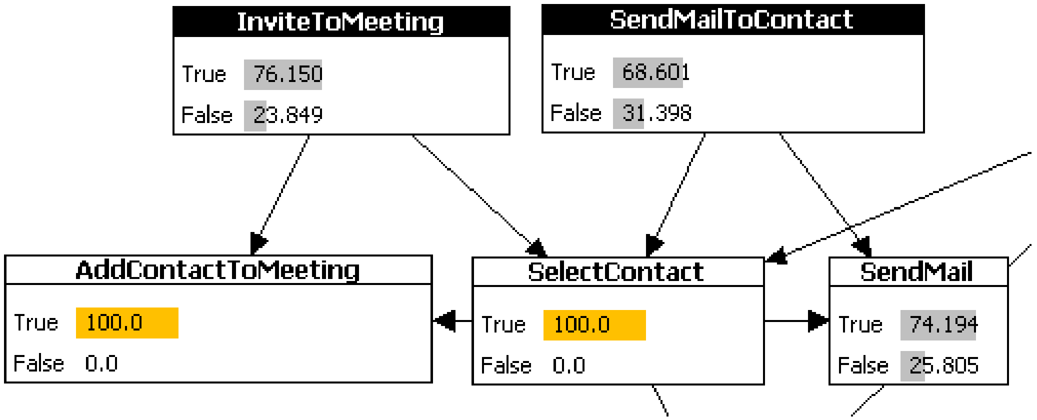

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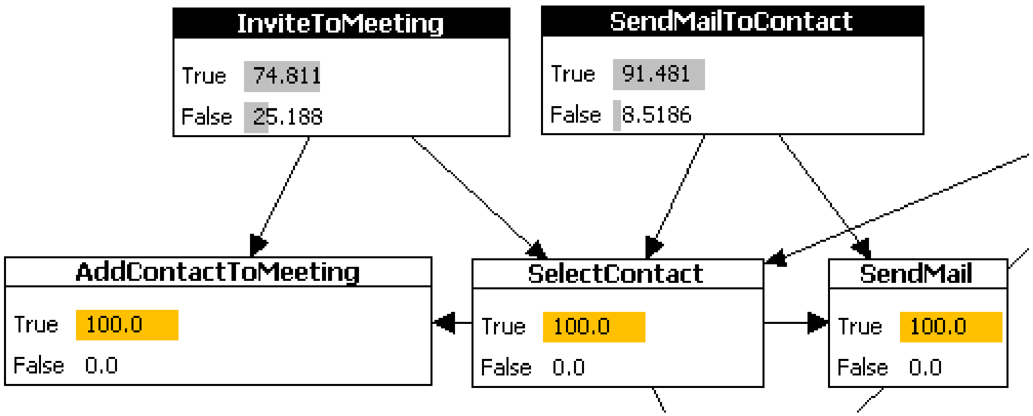
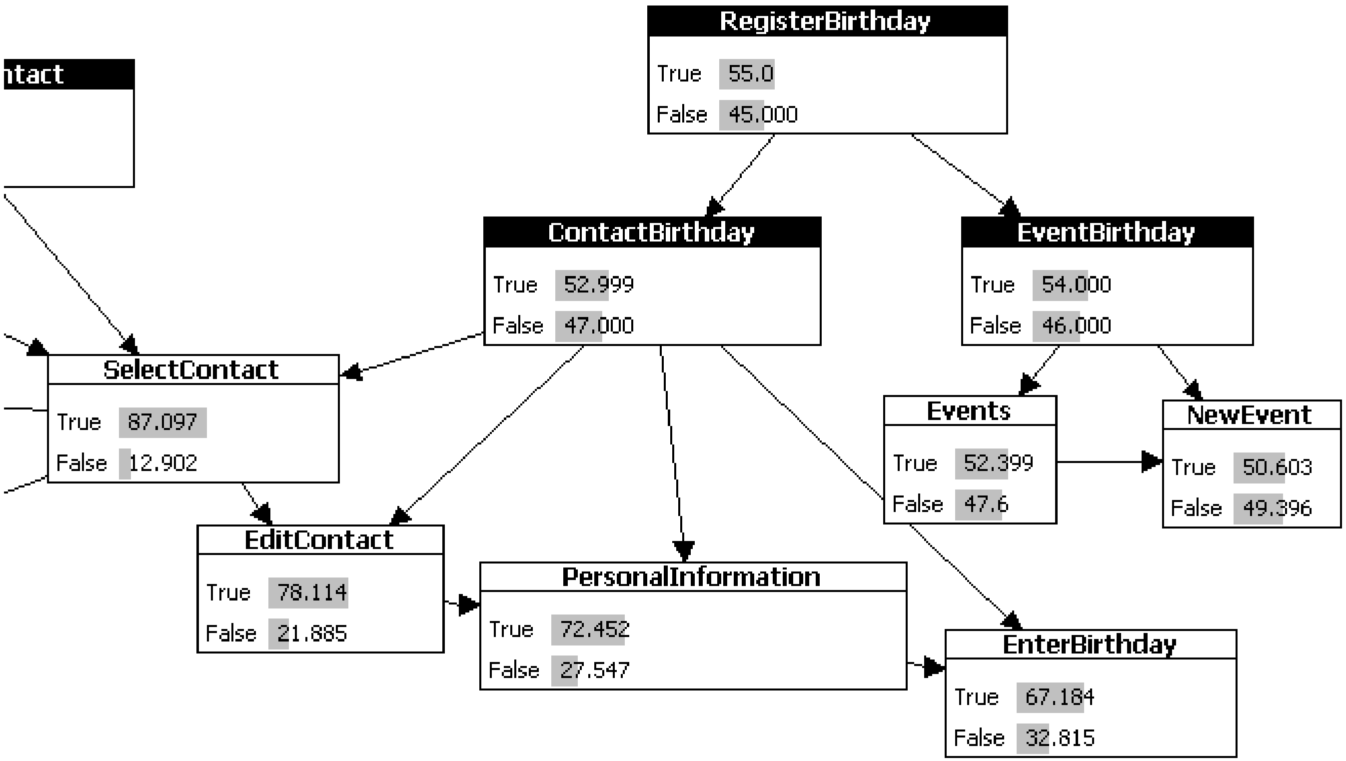
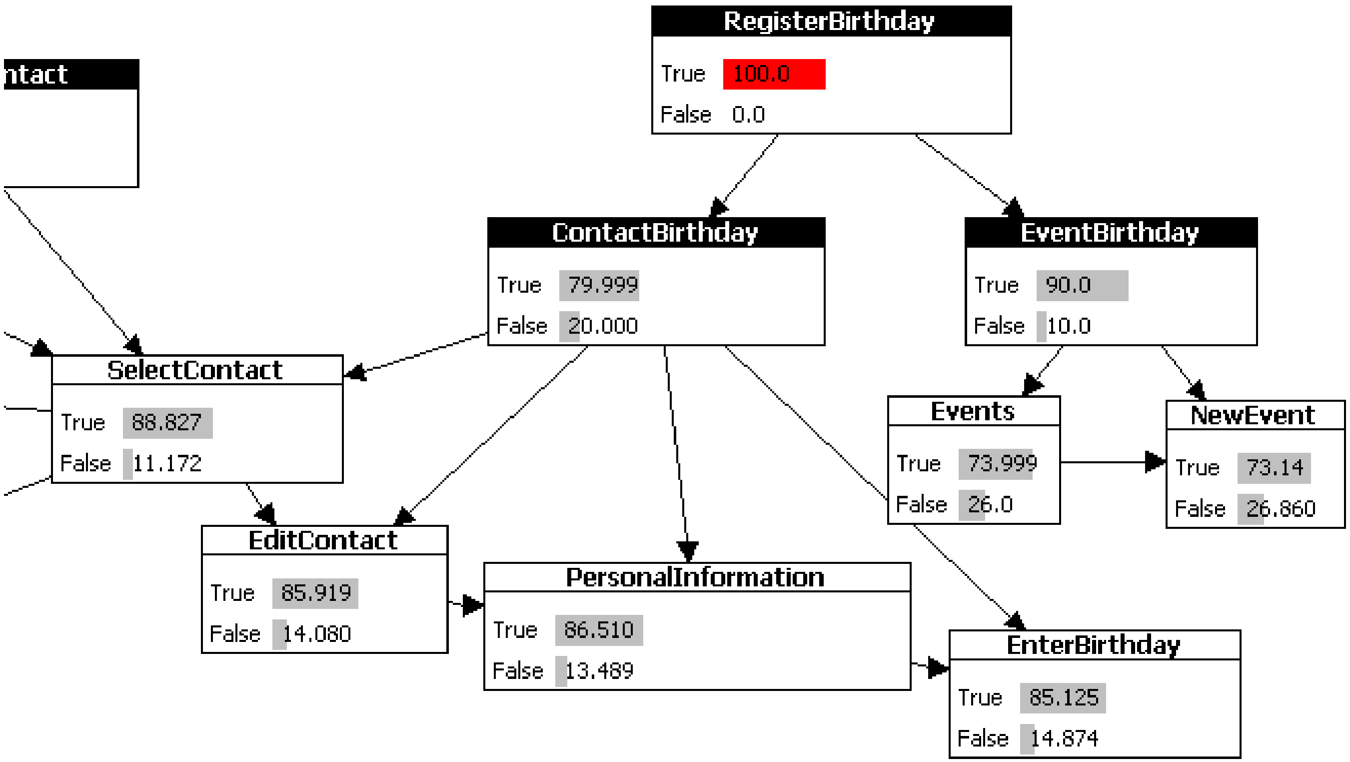


Multiple plans



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

$$p(N = k|conf) = \frac{n_k + z * y_k}{experiences_{new}}$$

Adaptation of probabilities

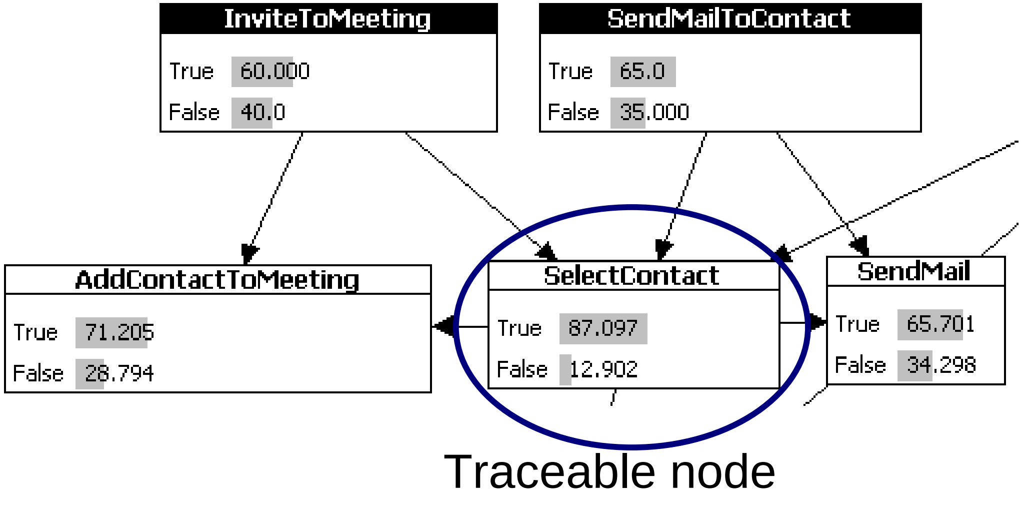
$$p(N = k|conf) = \frac{n_k + z * y_k}{experiences_{new}}$$

- 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
- $experiences_{new}$ = new count of experiences for n being in state k = $experiences_{old}$ + z

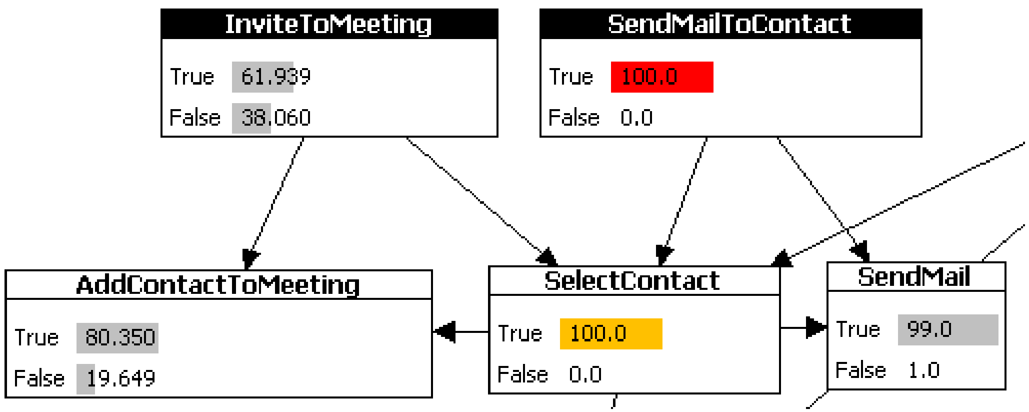
Intention Graph tuning

- Use the attributes of the tasks performed by the user to at building 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.

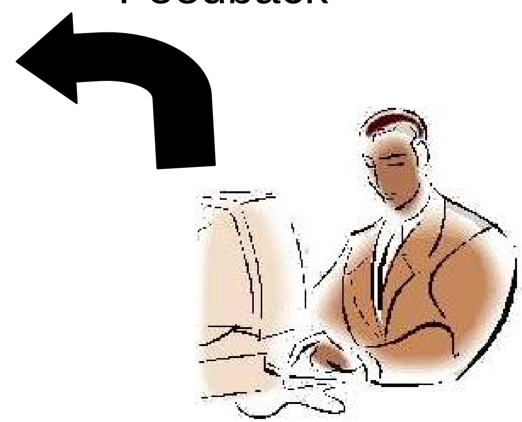
Intention Graph tuning



Intention Graph tuning



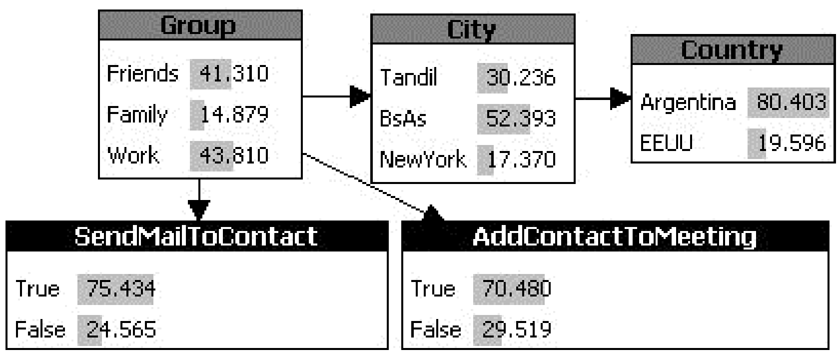
Feedback



Traceable node

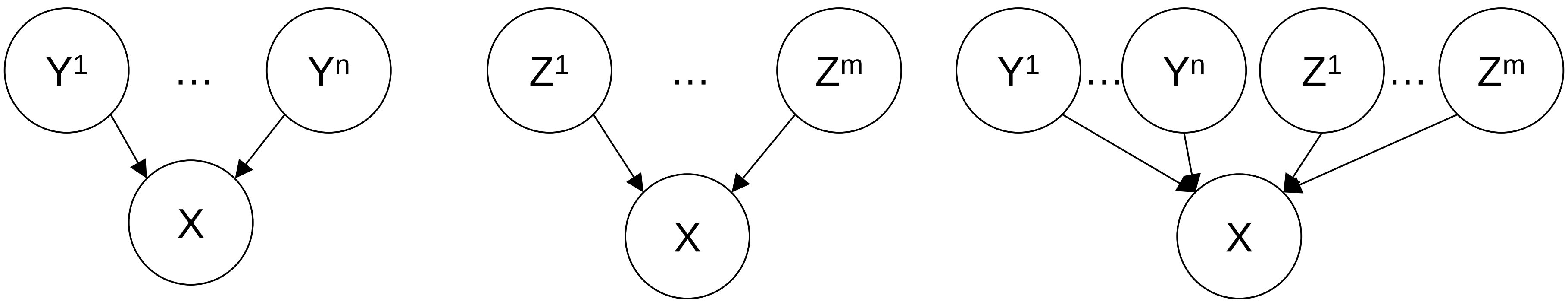
```
Friends, Tandil, Argentina, False, True
Work, BsAs, Argentina, True, False
...
```

Batch learning
+ Parametric learning



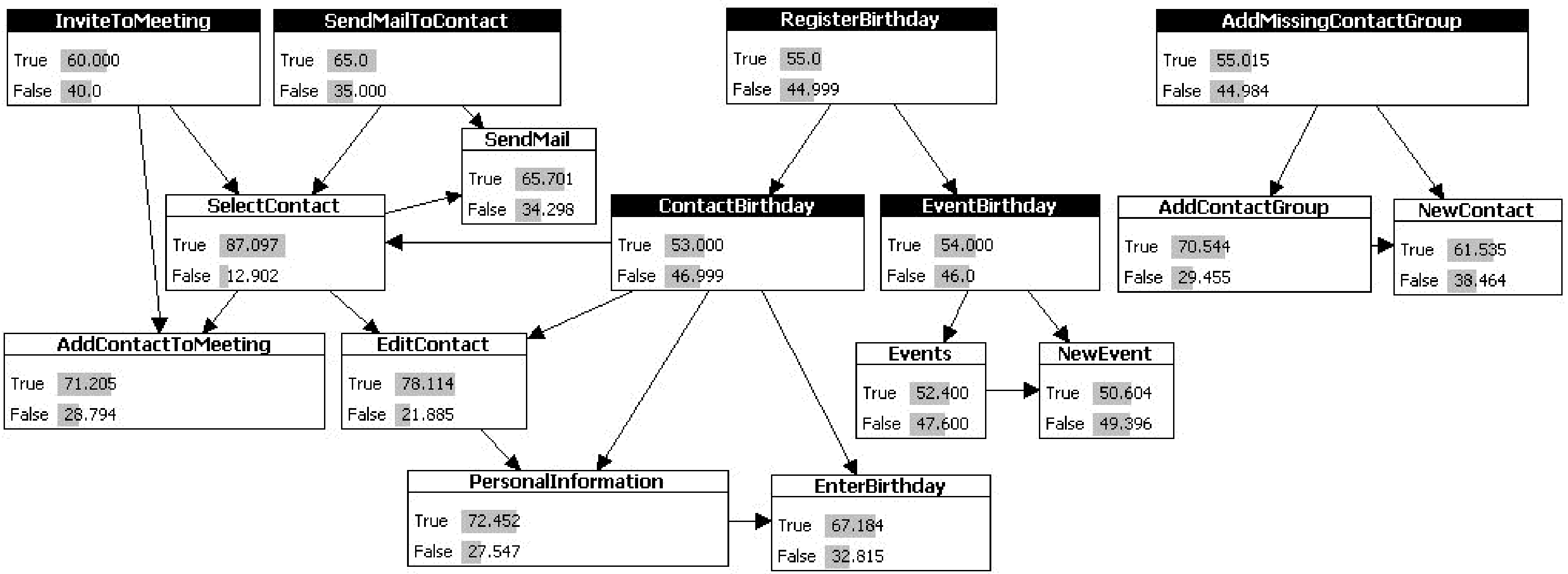
Intention Graph tuning

- Merging the learnt network into the Intention Graph

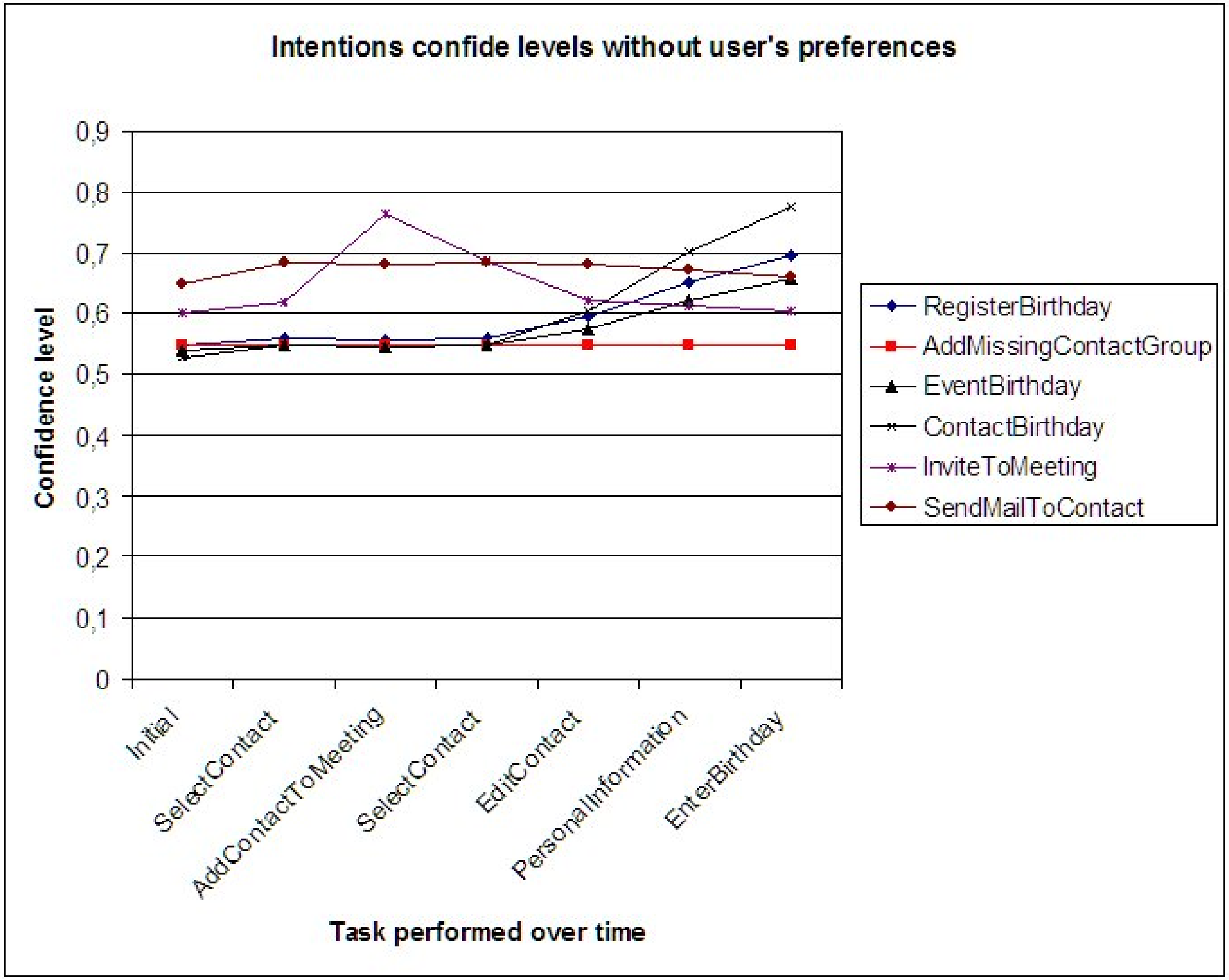


$$p(X_j|Y^1_{jY1},\ldots Y^n_{jYn},Z^1_{jz1},\ldots,\ Z^m_{jzm}) =$$
$$p(X_j|Y^1_{jY1},\ldots Y^n_{jYn}) * \pi +$$
$$p(X_j|Z^1_{jz1},\ldots,\ Z^m_{jzm}) * (1- \pi)$$

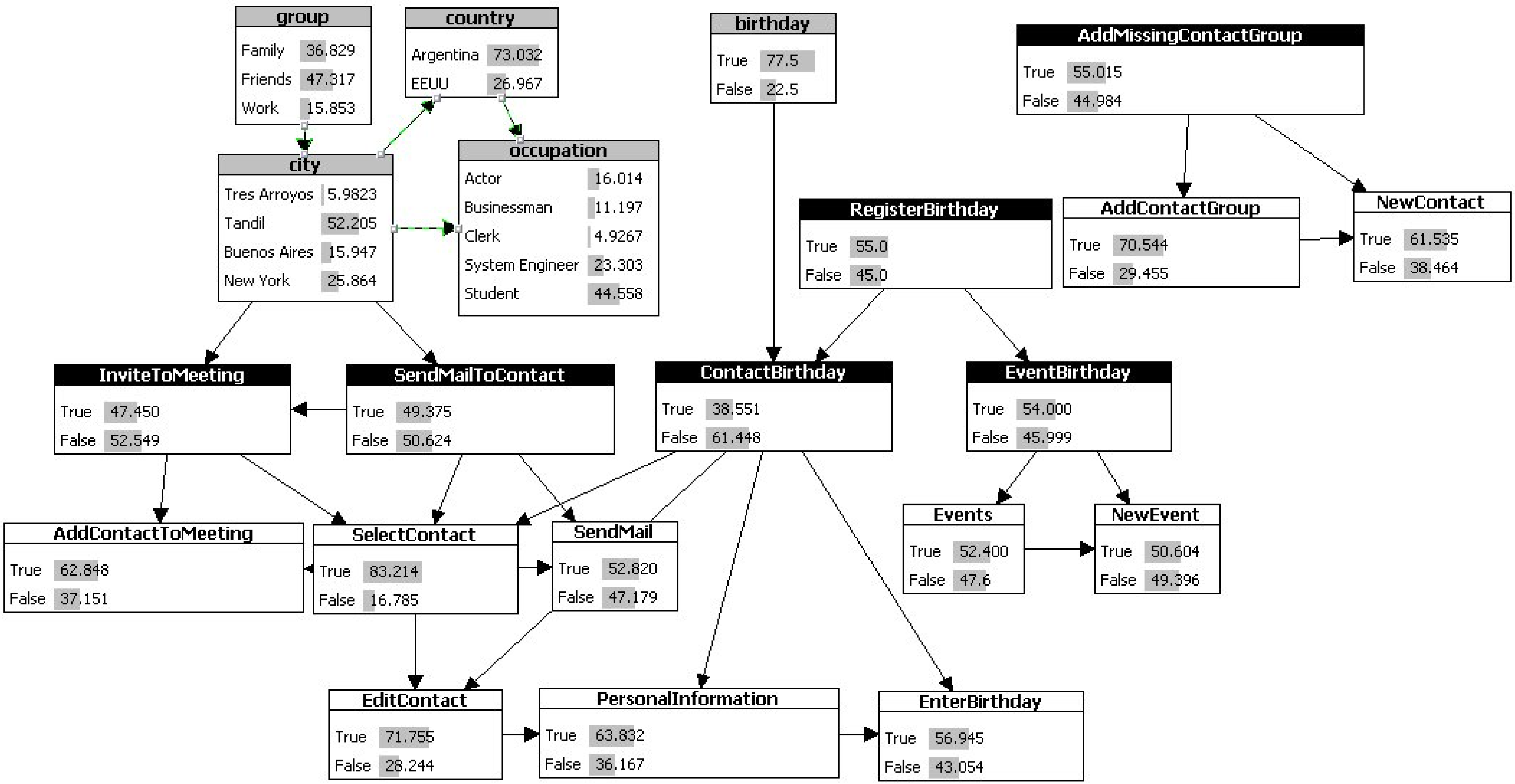
Example


InviteToMeeting
True 60.000
False 40.0
SendMailToContact
True 65.0
False 35.000
RegisterBirthday
True 55.0
False 44.999
AddMissingContactGroup
True 55.015
False 44.984
SendMail
True 65.701
False 34.298
SelectContact
True 87.097
False 12.902
ContactBirthday
True 53.000
False 46.999
EventBirthday
True 54.000
False 46.0
AddContactGroup
True 70.544
False 29.455
NewContact
True 61.535
False 38.464
AddContactToMeeting
True 71.205
False 28.794
EditContact
True 78.114
False 21.885
Events
True 52.400
False 47.600
NewEvent
True 50.604
False 49.396
PersonalInformation
True 72.452
False 27.547
EnterBirthday
True 67.184
False 32.815

Example

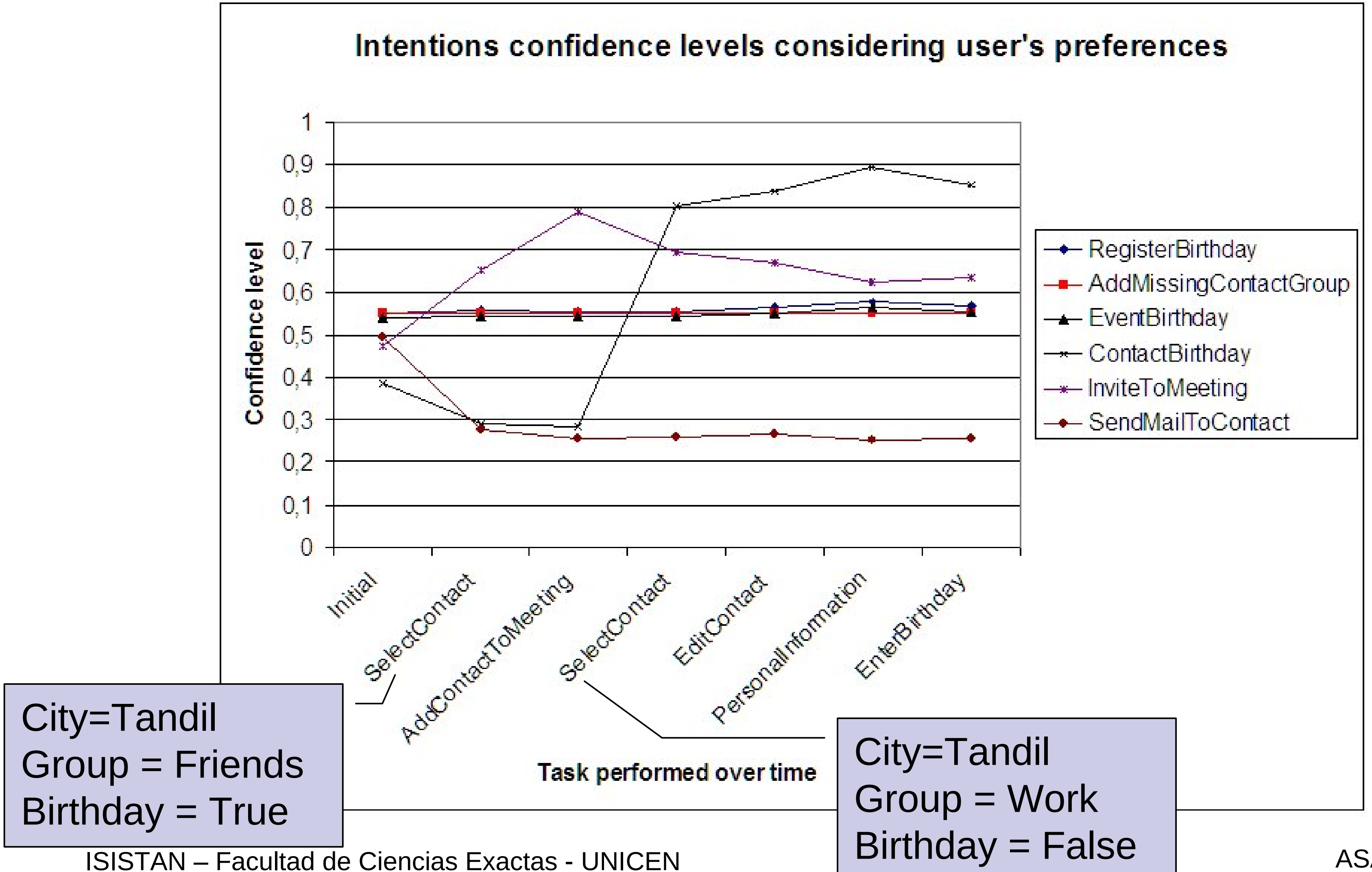

Intentions confide levels without user's preferences
Confidence level
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
Initial
SelectContact
AddContactToMeeting
SelectContact
EditContact
PersonalInformation
EnterBirthday
Task performed over time
RegisterBirthday
AddMissingContactGroup
EventBirthday
ContactBirthday
InviteToMeeting
SendMailToContact

Example



group
Family 36.829
Friends 47.317
Work 15.853
country
Argentina 73.032
EEUU 26.967
birthday
True 77.5
False 22.5
AddMissingContactGroup
True 55.015
False 44.984
city
Tres Arroyos 5.9823
Tandil 52.205
Buenos Aires 15.947
New York 25.864
occupation
Actor 16.014
Businessman 11.197
Clerk 4.9267
System Engineer 23.303
Student 44.558
RegisterBirthday
True 55.0
False 45.0
AddContactGroup
True 70.544
False 29.455
NewContact
True 61.535
False 38.464
InviteToMeeting
True 47.450
False 52.549
SendMailToContact
True 49.375
False 50.624
ContactBirthday
True 38.551
False 61.448
EventBirthday
True 54.000
False 45.999
AddContactToMeeting
True 62.848
False 37.151
SelectContact
True 83.214
False 16.785
SendMail
True 52.820
False 47.179
Events
True 52.400
False 47.6
NewEvent
True 50.604
False 49.396
EditContact
True 71.755
False 28.244
PersonalInformation
True 63.832
False 36.167
EnterBirthday
True 56.945
False 43.054

Example


Intentions confidence levels considering user's preferences
Confidence level
1
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
Initial
SelectContact
AddContactToMeeting
SelectContact
EditContact
PersonalInformation
EnterBirthday
Task performed over time
RegisterBirthday
AddMissingContactGroup
EventBirthday
ContactBirthday
InviteToMeeting
SendMailToContact
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 can not 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

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