AGACY Monitoring: Hybrid model for activity recognition and uncertainty handling

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Outline

- Motivation and problematic
- State of the arts of activity recognition methods
- The propsed solution
- Evaluation results
- Conclusion and future work

Motivation

- **Clear interest is devoted to monitor the Daily Living Activities (DAL) of persons living alone:**
  - Several applications need to know the DAL of the users for different purposes (healthCare, security, …)
- **The main aim of any application based on DAL recognition is to help the user or to improve his life**
  - Example: an application that sends alarm when detecting the user's fall

Problematic

- **Raw sensor data are usually the input of a model for activity recognition**
- **Several problems can occur in real world deploiement (hardware failure, energy depletion , ..)**
  - ➢ Sensor data become imprecise and uncertain

➢ **The problematic is:**

- How to manage with these uncertainty values in a hybrid model?
- How to exploit these values in the process of the activity recognition ?

State of the art for activity recognotion

- **Two main approaches for the activity recognition:**
  - Data driven based model:
    - Advantages: can be applied for a broad range of sensors
    - Drawbacks:
      - Need a large amount of training data to set up a model
      - Need a human effort to label the training data
  - Semantic based models:
    - Advantages: provide a powerful representation model
    - Drawbacks:
      - Their application is for a limitrd number of sensors
      - They are based on the specification of human experts

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State of the art for activity recognotion

- Combining semantic and data driven approaches is a promising research direction according to two recent surveys [Ye and al. 2012][M. Ziaeefard and al. 2015]

Model\ criteria	Semantic method	Data driven method	Handling uncertainty from sensors	Remark
SmartFABER[D. Riboni and al. 2016]	OWL2 ontology	Any Supervised technique	No	This is the first paper that proposes a new algorithm to detect activity instances based on hybrid model
FABER [D. Riboni and al. 2015]	Fisrt order logic	Markov Logic Networks (MLN)	No	----
FALLRisk [F. De Backere and al. 2015]	Ontology	Any machine learning method	No	This system aims specially to detect the fall of the user. It integrates several Fall detection systems and it filters their results
[R. Helaoui and al. 2013]	OWL2 ontology + logLinear + Descrition logic	Any machine learning method	No	This paper handles the uncertainty merely occurring in the semantic method
COSAR [D. Riboni and al. 2009]	Ontology	Any supervised technique	No	The combining between data driven and semantic methods serves to filter the result of the data driven method

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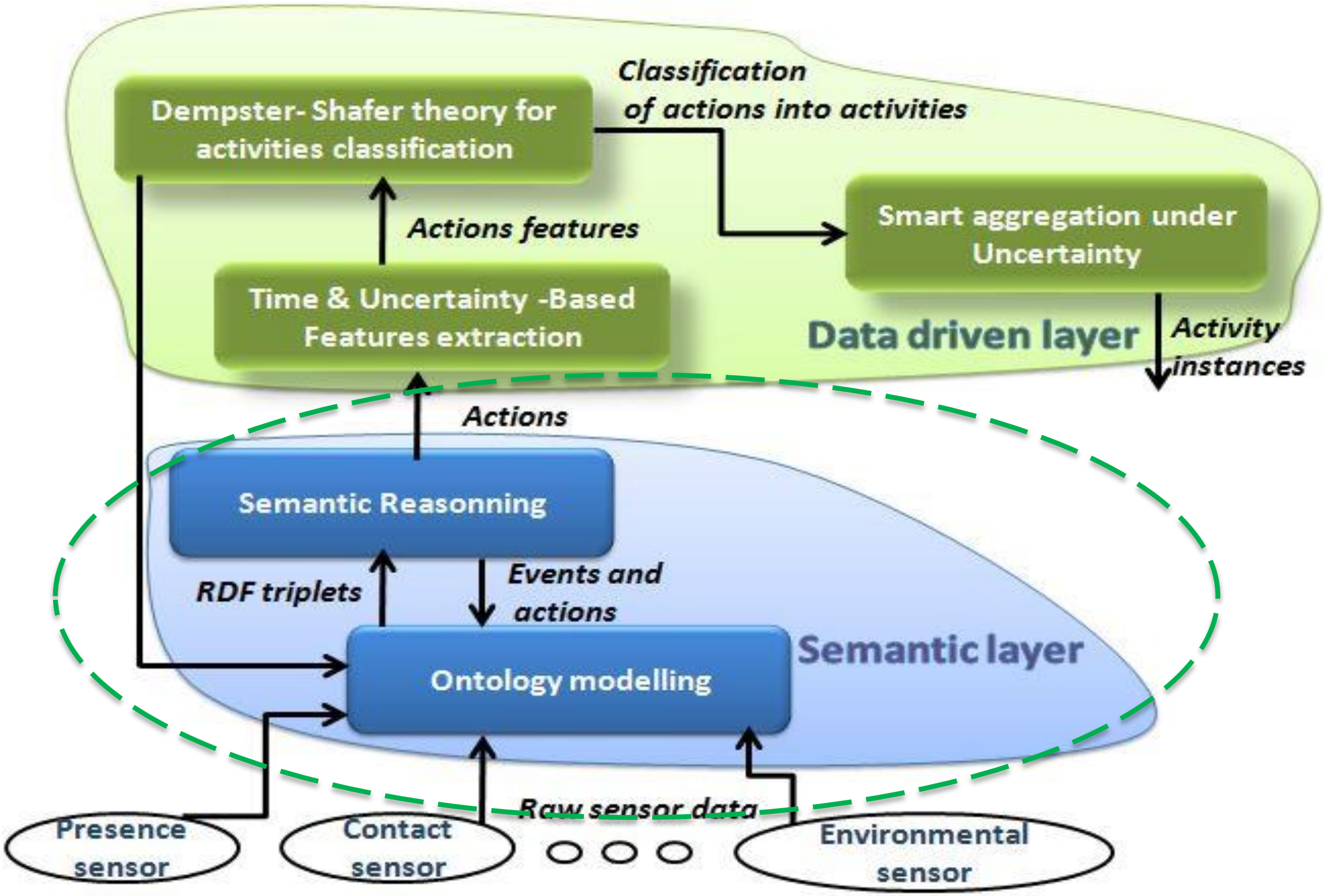
The proposed solution: The propsed model



Semantic Layer: Semantic Reasonning

1. Inferring events

- An event instance is defined as follows:
  - ev(ei, ti, ci) ➔ the event with label ei is happened in the timestamp ti with the certainty value ci
- The events and their certainty values are deduced by applying possibility *logic:*
  - The premise is a set of sensors data combined with logic operators.
  - The conclusion is the event

Example of rule for inferring the event instance sitOnChair

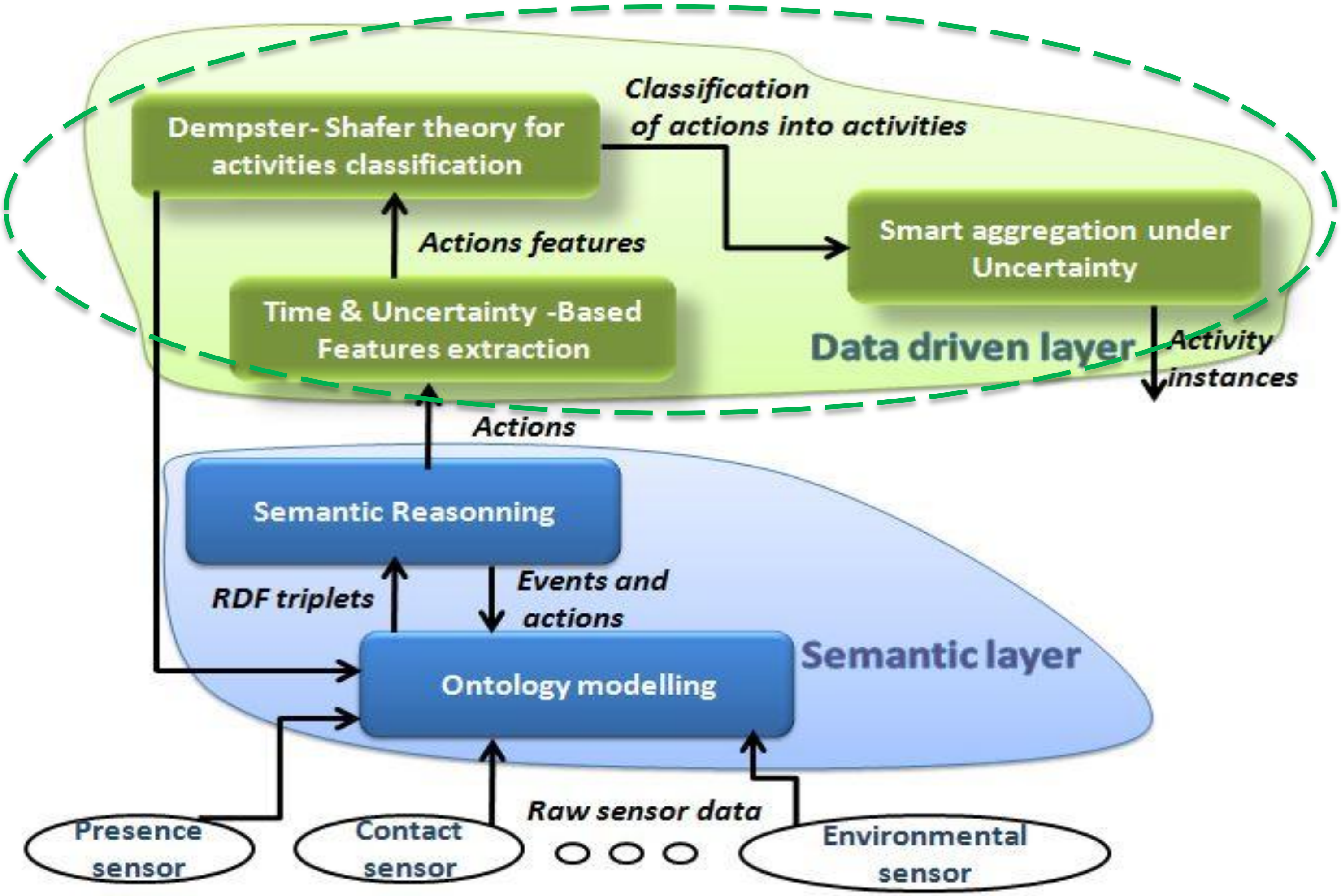
$\forall$ se_1, se_2 $\in \{Sensors\}$ and t_1, t_2 $\in \{Time\}$, p $\in \{Person\}$
(p hasLocomotion [**a Uncertainty; uncertaintyLevel** n_1**; relatedObject SitOn; relatedTime** t_1**; accordingTo** se_1]
$\wedge$
(p hasObject [**a Uncertainty; uncertaintyLevel** n_2**; relatedObject Chair; relatedTime** t_2**; accordingTo** se_2])
$\longrightarrow$ ev(SitOnChair, t_1, min(n_1, n_2))

Semantic Layer: Semantic Reasoning

2. Inferring actions

- An action instance is defined as follows:
  - act(aci, ti, ci) ➔ the action with label aci is happened in the timestamp ti with the certainty value ci
- The actions and their certainty values are deduced by applying the *possibility logic :*
  - The premise is a set of events combined with logic operators:
  - The conclusion is the action

The proposed solution: The model



Data driven Layer:Time and Uncertainty based features extraction

- **An action aci is represented by a time window Si where:**
  - Ds: the duration of Si
  - Si contains a sequence of actions produced before aci during Ds and aci itself
  - This time window is converted to a feature vector of aci that contains essentially:
    - The label of the represented feature Ki
    - The sequence of the actions in Si
    - A proposed weight value that represents the offset effect of time and uncertainty of the actions in Si to aci:

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Data driven Layer:Dempster-shafer for activity classification

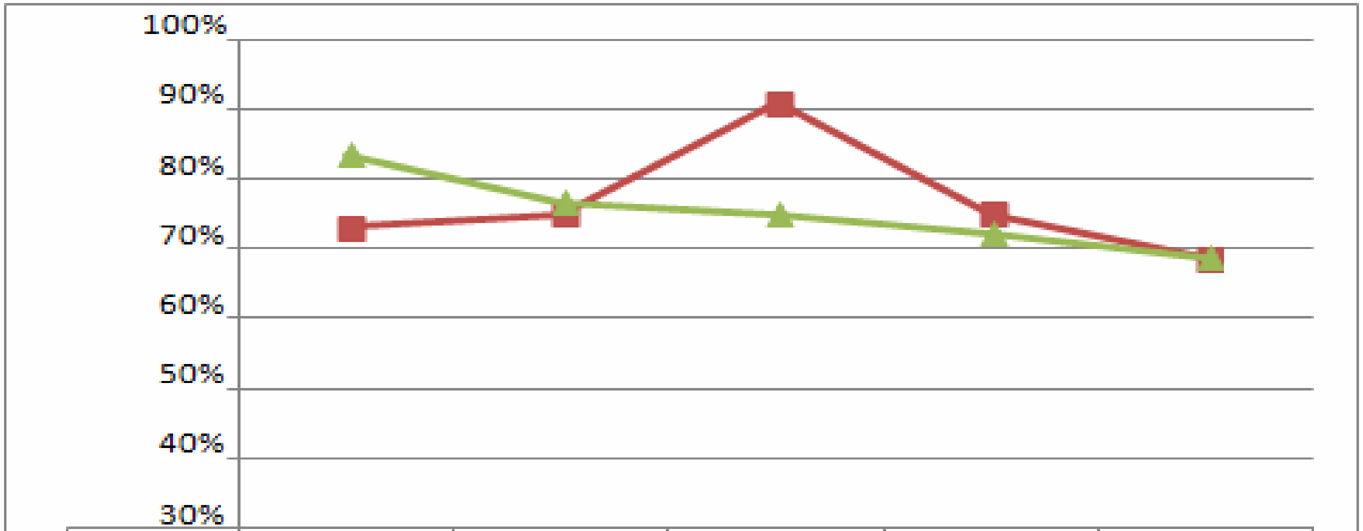
- Recently a great interest has been paid to apply Dempster-shafer (DS) as a machine learning technique for activity classification:
  - It has proved better result than Naïve Baise and J48 Tree [S. Mckeever and al. 2011, F. Sebbak and al. 2014, Q. Chen and al. 2014]
- The model is used through a directed acyclic graph, where:
  - The named evidences in DS are actions in AGACY monitoring
  - The called the hypothesis in DS are features in AGACY monitoring
  - The activities are the output with their uncertainty values
- The uncertainty values of activities are computed based on the uncertainty values of the features and the mass function defined in DS

Evaluation

AGACY monitoring: Dataset

- A prototype system of AGACY-Monitoring has been implemented using JAVA
- The system was tested with the Opportunity dataset[1]. The dataset contains from AGACY-Monitoring perspective:
  - Homogeneous sensor data (level 4)
  - Events (level 3)
  - Actions (level 2)
  - Activities (level 1): Relaxing, CoffeeTime, SandwichTime, and CleanUp. They have been done by three persons S10, S11, and S12 with three different routines each (ADL1-3)
- The dataset does not contain uncertainty values about sensor data (level 4)
  - ➢ Erroneous sensor data was injected in the dataset annotated with low uncertainty values [0…0,4]

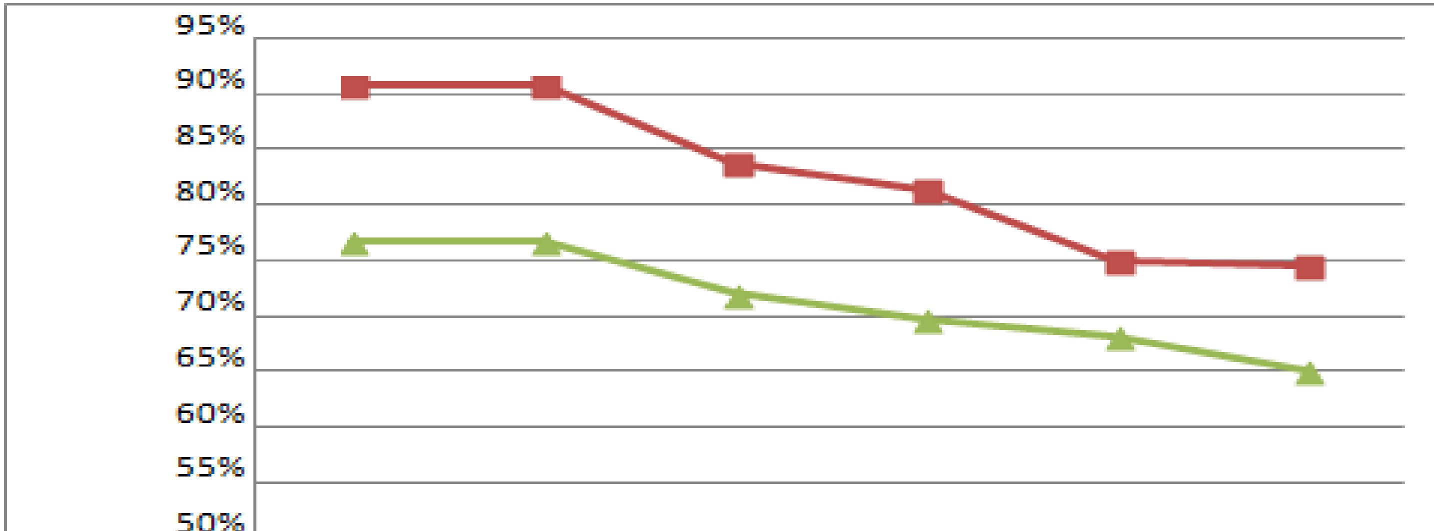
AGACY-Monitoring: Experiments



Tw size	60 s	120 s	180 s	240 s	300 s
DS	73%	75%	91%	75%	69%
SVM	84%	77%	75%	72%	69%

Average recognition precision for all subject over the three routines with different values of the size n of the time window (Tw)

AGACY-Monitoring: Experiments



UEF	0/5	1/5	2/5	3/5	4/5	1
DS	91%	91%	84%	81%	75%	74%
SVM	77%	77%	72%	70%	68%	65%

Average recognition precision for all subject over the three routines for varying frequency of uncertain event (UEF). The value 1/5 means there is one uncertain sensor data for five correct ones. 1 means there is one uncertain sensor data for one correct

AGACY-Monitoring: Experiments

- We compared the performance of AGACY monitoring regarding that of the hybrid model in [Helaoui, R., and al. 2013]
- The system has been applied with the same dataset (without erroneous sensor data and uncertainty values)

All users	AGACY Monitoring	[14]
Precision	0,91	0,91
recall	1	0,65

- the two systems have the same average precision recognition
- AGACY Monitoring outperforms the second system within recall value

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AGACY-Monitoring: Experiments

- **Result resume :**
  - AGACY-Monitoring with a suitable time window is very performing (Precision = 0,91 with n= 180s)
  - Generally DS is more efficient than SVM:
    - For time windows shorter or longer than 180s, DS tends to become less efficient: DS is efficient where time window are properly proportioned to the activities
    - SVM gives better results for short time window (n<=120s), but with the increase of n value, the accuracy of classification gets worse
  - The system is able to efficiently handle sensor data uncertainty:
    - Despite the dataset half contains uncertain sensor data, the system is able to predict the activity with a good precision level (74%)

Conclusion and Future work

- Proposition of AGACY Monitoring as a hybrid model for activity recognition
- AGACY Monitoring handles uncertainty of sensor data
- The proposal shows promising results
- ➢ Dynamic window size ?
- ➢ Multi users activities recognition ?

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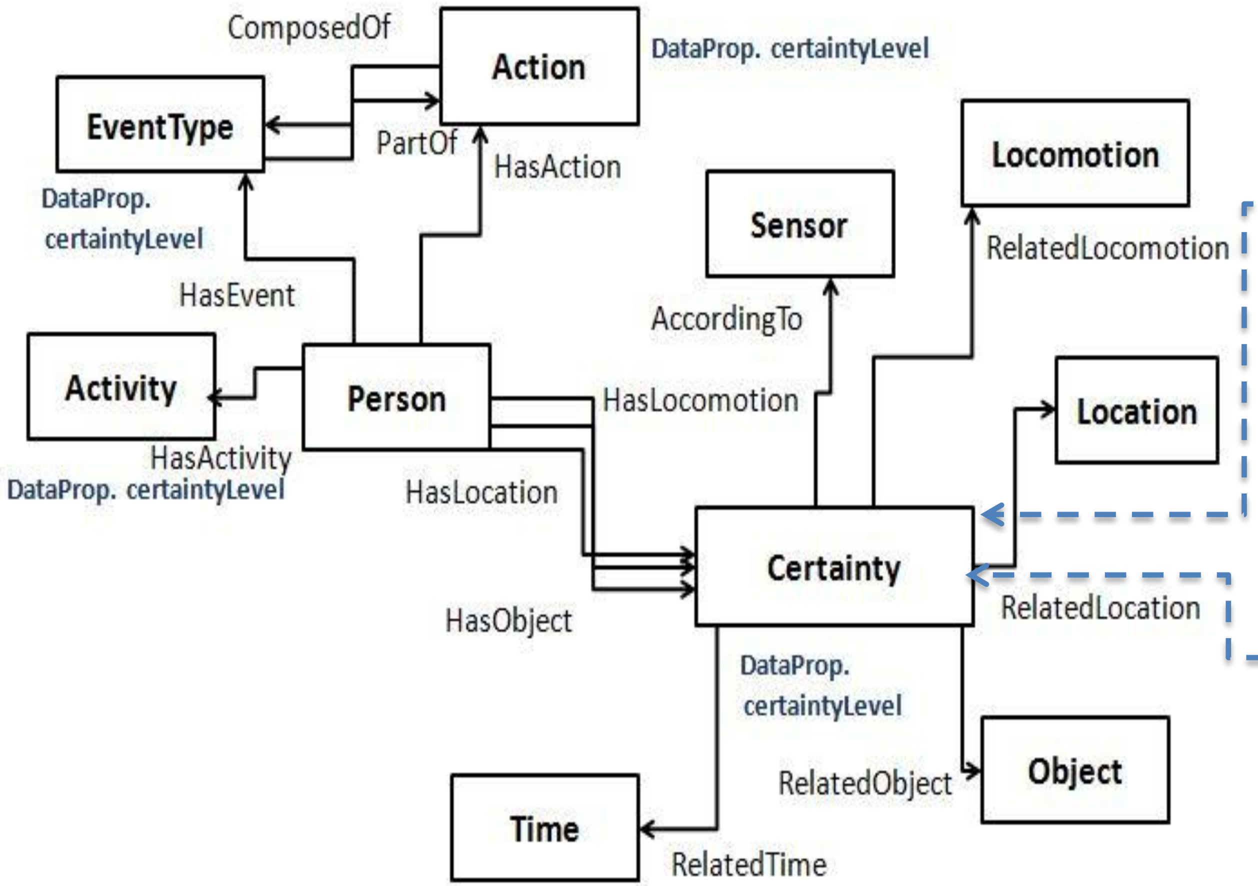
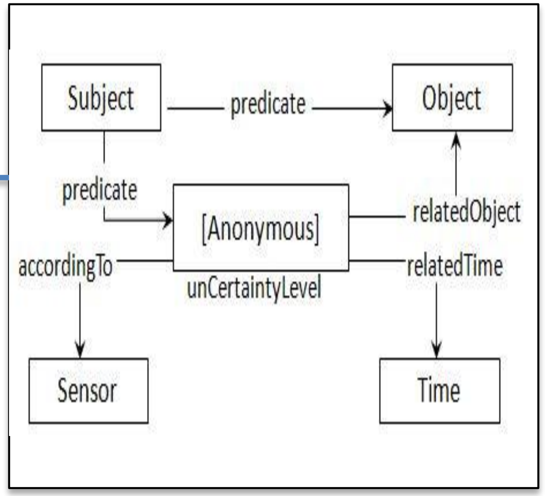
Thank you

Semantic Layer: Ontology modelling



- To model the uncertainty we have applied the proposed modelization in [H. aloulou and al. 2015] where the uncertainty is attached to the predicate

- The only difference is that we have attached the time besides than the sensor, the object, and the subject



Exerpt of the ontology model with certainty

Data driven Layer:Time and Uncertainty based features extraction

- **The proposed weight of the feature vect**

$$F_{k_i}(S_i) = \sum_{act_j(Ac_j,t_j,c_j)\in S_i} c_j \times Fact_{x,t_i-t_j} \times f_{k_i}(act_j(Ac_j,t_j,c_j))$$

- A factor of time distance between actions. cj*Fact must be always<=cj

- =1 if aci is a part of the execution of the feature Ki
- =0 else

- 1st case: the estimated duration of the activity is in term of minutes or hours so :

$$Fact_{x,t_i-t_j} = \exp(-\chi(t_i - t_j))$$

- ti-tj Is expressed in hours

- 2nd case: the estimated duration of the activity is in terms of seconds:

$$Fact_{x,t_i-t_j} = \frac{1}{\chi(t_i - t_j)}$$

- If (x*(ti-tj))>1 where ti-tj is expressed in seconds)
- Else Fact =1