Probabilistic Dialogue Models for Dynamic Ontology Mapping

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Introduction

- Agents communicate to perform tasks that they cannot accomplish alone.
- To communicate means to exchange messages that convey meanings encoded into signs for transmission.
- To understand a message, a receiver should be able to map the signs in the messages to meanings aligned with those intended by the transmitter.
- Agents should agree on the terminology used to describe the domain of the interaction:
  - ontologies specify the terminology
- Having a shared ontology can be a strong assumption in an open environment:
  - agents may come from different backgrounds, and have different ontologies, designed for their specific needs

Introduction

- In this sort of environment, communication implies ontology mapping.
- In an open environment, it is impossible to know which agents will take part in the interactions.
- Agents have to map ontologies dynamically when needed.
- However, agents may meet infrequently and only for interactions on specific topics.
- A full ontology mapping would be a waste of resources:
    - only the terms that are needed for the interaction should be mapped

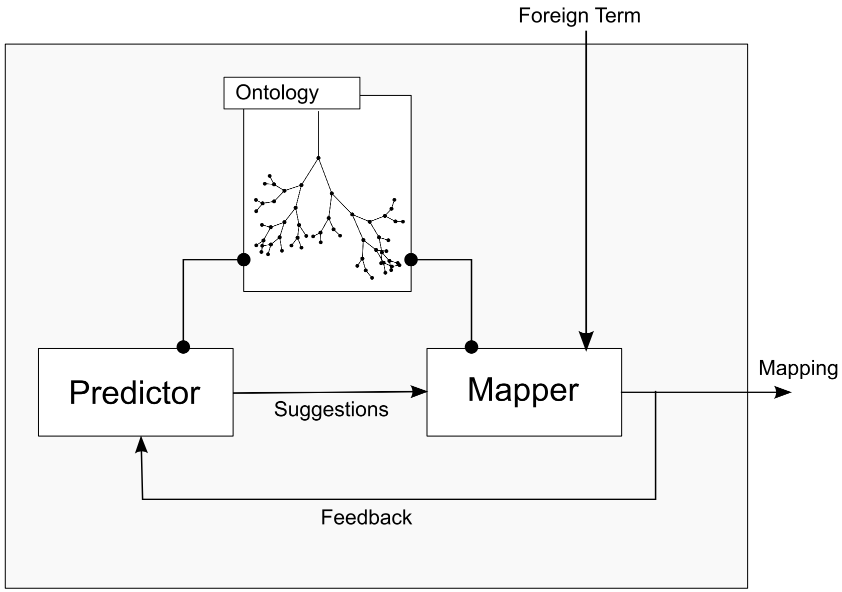
Ontology Mapping and interactions

- Usually, a term $t_j \in O_1$ is mapped to another term $w_i \in O_2$ comparing the term t_j with all the terms in O_2
- However, during an interaction it is often possible to avoid all these comparisons.
- A term in a received message is unlikely to refer to an entity completely unrelated with the context of the dialogue.
- Intuitively, the type of interaction, the specific topic and the messages already exchanged bind the content of a message to a set of possible expected entities.

Probability and Uncertainty in Ontology Mapping

- Probabilities are often used in ontologies to express the uncertainty of static relation between entities
- In this work, probability is used to *predict* the content of received messages in specific interactions.
- The repetition of similar interactions provide the information needed to compute the probability distribution of the entities.
- The predictions are used as *suggestions* for an Ontology Mapping system that must match foreign terms with local ones.
- The use of suggestions:
  - Reduce the number of comparisons to perform, improving its efficiency
  - Reduce the ambiguities, excluding terms that are unrelated to the interaction.

General Structure



- The *predictor* learns the probabilities of terms received as feedback from the Mapper
- The predictor provides suggestions to the Mapper

Predicting the terms in messages

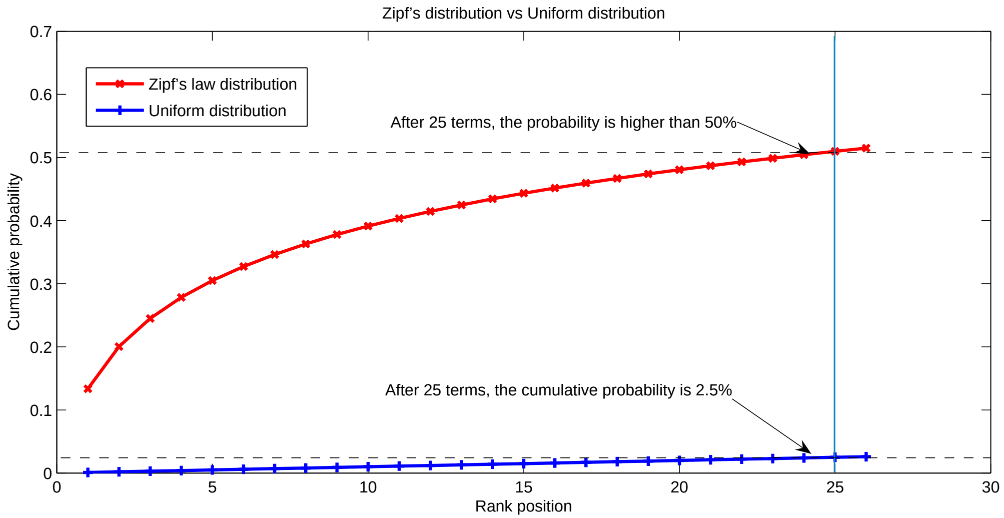
- Suppose an agent receives a message $m_k(\ldots, w_i, \ldots)$, where $w_i \notin L_a$, where L_a is the agent's ontology.
- The mapping algorithm (the "oracle") must find what entity, represented in the agent's ontology by t_m, was encoded in w_i by the transmitter.
- *The aim of this work is to specify a method for choosing the smallest set* $\Gamma \subseteq L_a$ *of terms to compare with* w_i*, given a probability of finding the matching term* $t_m \in L_a$.
- We assume that t_m exists in L_a.
- Let $p(t_j)$ be the probability that the entity represented by $t_j \in L_a$ was used in the i^{th}slot inside m_k.
- The oracle will find t_m if $t_m \in \Gamma$, am event that has a probability:

Definition

$p(t_m \in \Gamma) = \sum_{t_j \in \Gamma} p(t_j)$

- The core issue is how to find the probabilities of the entities that can be used in a message $m_k(\ldots, w_i, \ldots)$.

Exploiting term distribution



- If all terms are equiprobable, then $p(t_m \in \Gamma)$ will be proportional to $|\Gamma|$, as in the blue line in the graph.
- If the probability is distributed unevenly, we can obtain a higher probability for smaller Γ.
- For example, if $p(t_j)$ is distributed according to Zipf's law, the probability of finding t_m follow the red line in the graph.
- For $|L_a| = 1000$, then $p(t_m \in \Gamma) \geq 0.5$ for $|\Gamma| = 25$.

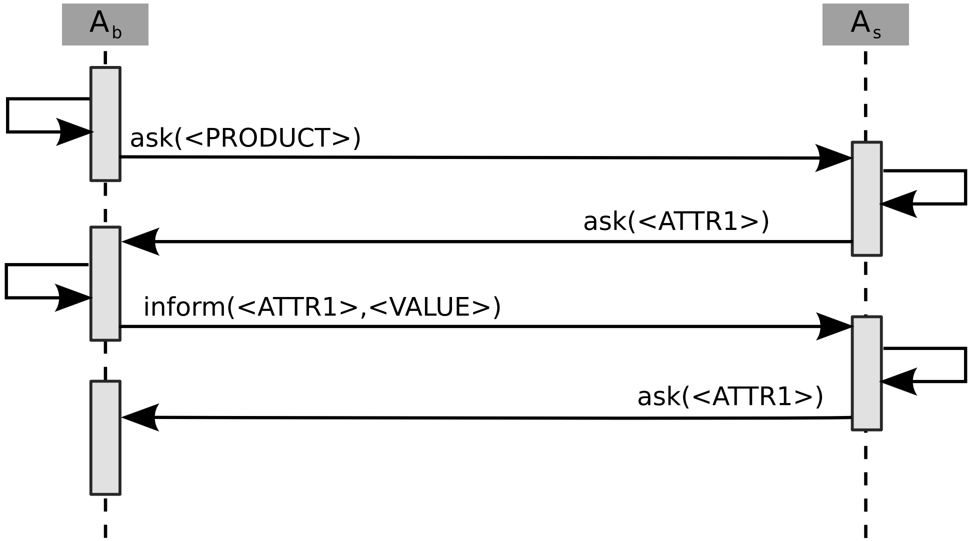
Assertions

- The possible values for a slot are modelled by M assertions
- Each assertion assigns a probability to the hypothesis that the matching entity for the slot belongs to a set Ψ:

Definition

$$A_j^{\langle \mathtt{Ni,A} \rangle_{\mathtt{R}}} \doteq Pr\left(slot\_value \in \Psi\right) \quad (1)$$

Example Scenario



A protocol for the purchase of a product: the buyer ask the product, and the vendor asks for some specs before making an offer.

How to obtain assertions

- Assertions are created and updated every time a protocol is executed.
- The predictor uses the feedback from the mapper to create the assertions
- The frequencies of the mappings are used to compute dynamically the probabilities in the assertions.

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If the purchase protocol is used by the buyer a number of time with different vendors, the frequencies of the terms appeared in the slot `ask<product>` are:

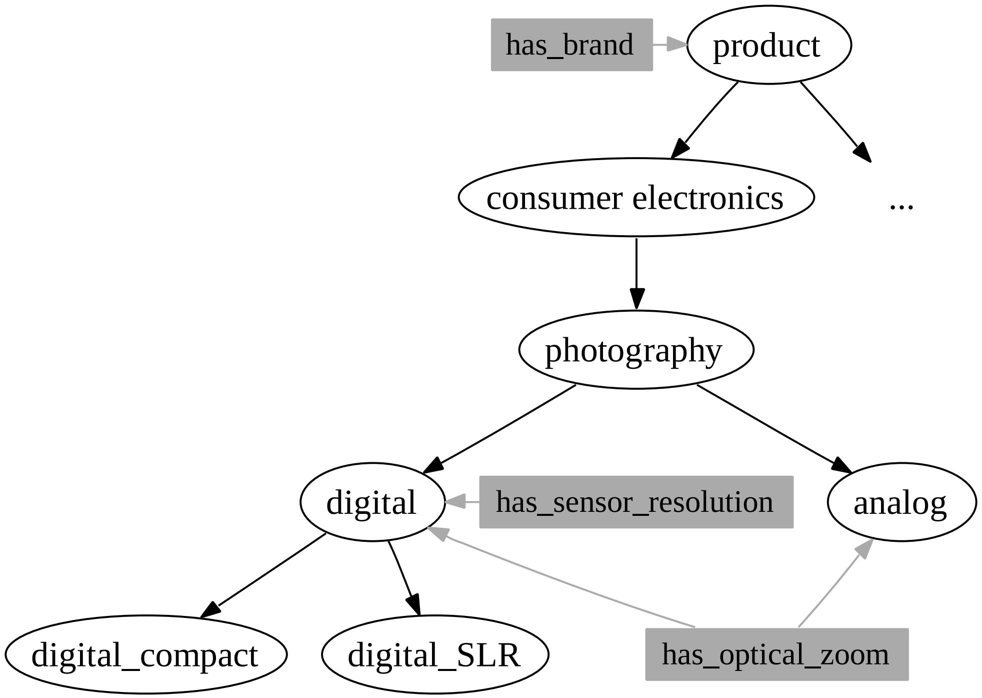
ask<product>	*Laptop*	*digital_SLR*	**Total**
has_brand	4	5	9
has_cpu	6	0	6
has_ram	6	0	6
has_hard_disk	4	0	4
has_weight	3	1	4
has_optical_zoom	0	5	5
has_sensor_resolution	**0**	**6**	6
Total	**23**	**17**	40

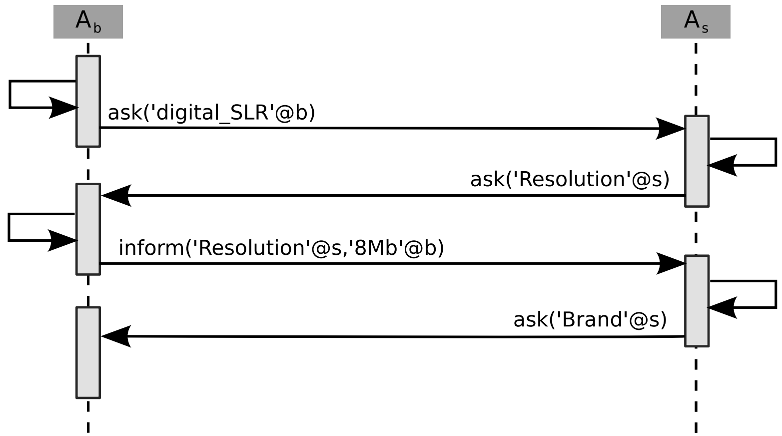
Ontology Relations

It is possible to use the ontological relations between terms in the dialogue. During the interaction, the system:

- makes hypotheses about the possible relations between the terms.
- try to prove them using the ontology,
- generalise them,
- update the frequencies of the successful hypotheses.

Ontology Relations





Example

For example, if the protocol is used for buying a Digital_SLR, when the message `ask('Resolution')`arrives, the *predictor* receives as feedback the mapped value '`has_sensor_resolution`' for the foreign term and generates a set of relations between the terms that have appeared:

`isSubClass(has_sensor_resolution,digital_SLR), ...,isInstance(has_sensor_resolution, digital_SLR),...,hasDomain(has_sensor_resolution,Digital_SLR)`

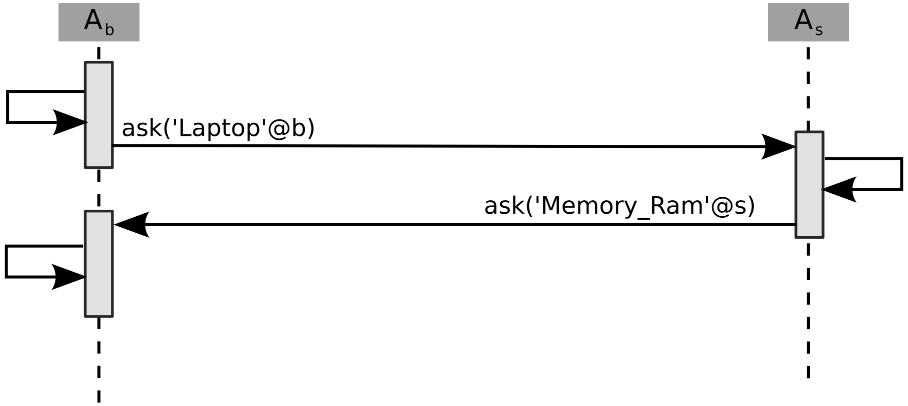
Stored relation

- Then the system tries to prove all the generated relations
- In proved relations, the values are replaced with the dialogue slot that contained the entity.
- The stored relation keeps track of the frequency with which they have been proved in the dialogues.

Example

`hasDomain(has_sensor_resolution, digital_SLR)` can be proved: the stored `hasDomain` relation is between the slot in the sent `ask(<Product>)` message and the `ask(<ATTR*>)` received from the seller.

Example of use



The purchase protocol is used for buying a laptop. We want to predict the content of the `ask(<ATTR>)` message: the mapper will compare the foreign term `Memory_Ram` only with these suggestions, and find the correct mapping with a probability higher thatn 90%.

Simple frequencies

$\langle \texttt{ask,1} \rangle_{\texttt{nb}}$	*Laptop*	*digital_SLR*	**Total**
has_brand	4	5	9
has_cpu	**6**	**0**	**6**
has_ram	6	0	6
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has_weight	3	1	4
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The probability of a term in a slot can be computed simply by its frequency.

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The probability of a term in a slot can be computed simply by its frequency.

Example

$A_1)\ Pr\left(slot\_value \in \{\text{"}has\_cpu\text{"}\}\right) = \frac{6}{40} = 0.15$

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The information provided by these simple assertions is rather poor, as it is not possible to exploit any contextual information: the probability of terms not related with the context can be the same.

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Example

$A_2)\ Pr\left(slot\_value \in \{\text{"}has\_sensor\_resolution\text{"}\}\right) = \frac{6}{40} = 0.15$

Conditional frequencies

$\langle \texttt{ask,1} \rangle_{\texttt{nb}}$	*Laptop*	*digital_SLR*	**Total**
has_brand	4	5	9
has_cpu	6	0	6
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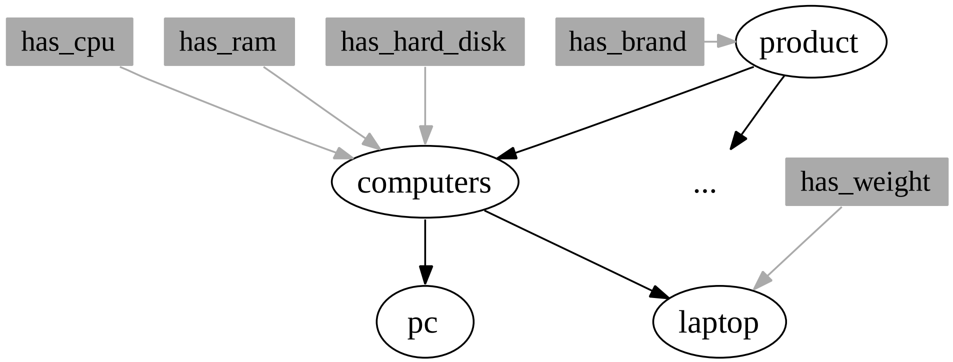
The probability computed using the frequency of a term conditional to the value of another term provides more information:

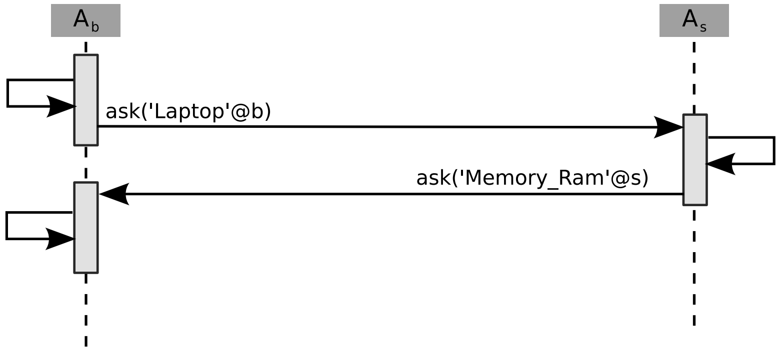
Example

A_3) $Pr\left(slot\_value \in \{\text{"}has\_cpu\text{"}\} \mid \text{"}\langle PRODUCT\rangle = Laptop\text{"}\right) = \frac{6}{23} = 0.260$

A_4) $Pr\left(slot\_value \in \{\text{"}has\_sensor\_resolution\text{"}\} \mid \langle PRODUCT\rangle = \text{"}Laptop\text{"}\right) = \frac{0}{23} = 0.0$

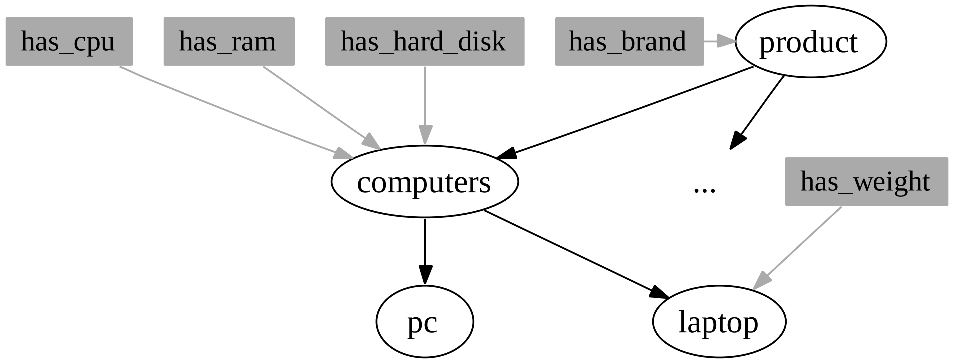
Relation assertions

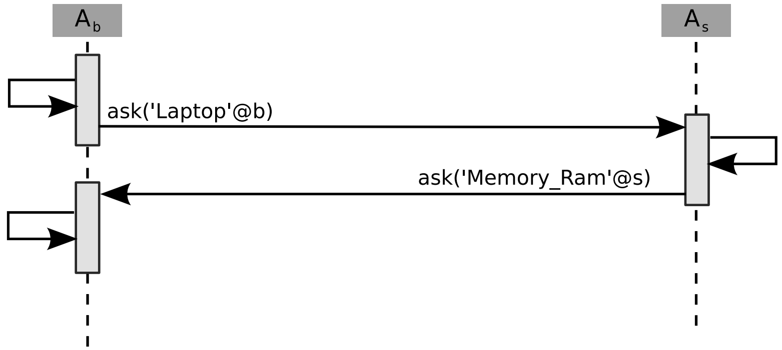




- The relations stored for the slot are instantiated, replacing the references with the values of the already filled slots
- The remaining variables are unified with the entities in the ontology that satisfy the predicate

Relation assertions





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Example

The relation `hasDomain(X, <PRODUCT>)` becomes: `hasDomain(X, Laptop)`.
The system searches the entities in the ontology that satisfy the relation:
`{has_cpu, has_ram, has_hard_disk, has_brand, has_weight}`
The assertion becomes:
$A_5)\ \ Pr(slot\_value \in \{has\_cpu, has\_ram, has\_hard\_disk, has\_brand, has\_weight\}) = 1$

Computing term probabilities

1. Probabilities given to sets are uniformly distributed among the members: according to the *principle of indifference*, the probability of mutually exclusive elements in a set should be evenly distributed.
2. Hence, the probability of an entity t_i is computed by summing over all its probabilities, and dividing the sum by the sum of all the probabilities given by assertions regarding the slot:

Definition

$$p\left(t_i\right) = \frac{\sum A_j\left(slot\_value \in \{t_i\}\right)}{\sum A_k} \quad (2)$$

Computing term probabilities

Example

To compute the probability of `has_cpu`.

Group all the assertions about the term

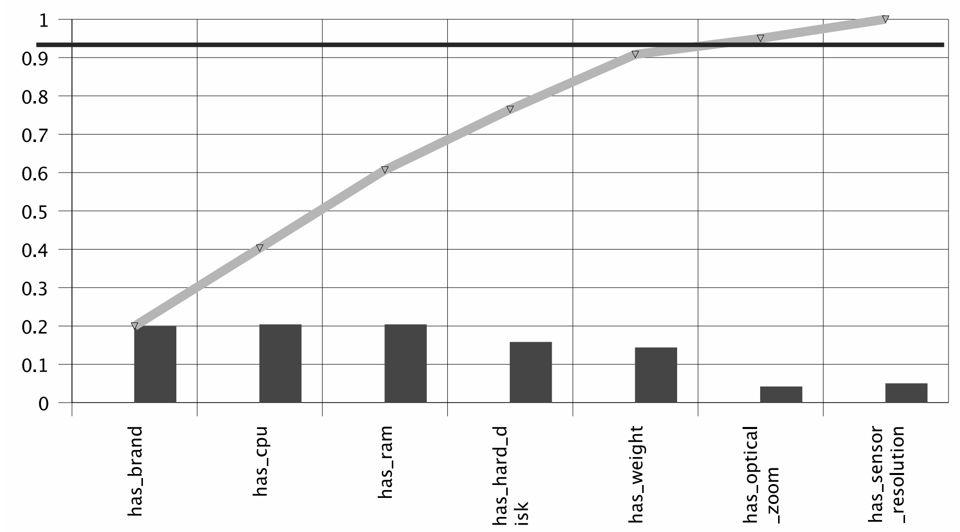
$A_1)$ $Pr\left(\langle \texttt{ask}, 1\rangle_{\texttt{nb}} \in \{''has\_cpu''\}\right) = \frac{6}{40} = 0.15$

$A_3)$ $Pr\left(\langle \texttt{ask}, 1\rangle_{\texttt{nb}} \in \{''has\_cpu''\} \mid sent\_ask = ''Laptop''\right) = \frac{6}{23} = 0.260$

$A_5)$ $Pr(slot\_value \in \{has\_cpu, has\_ram, has\_hard\_disk, has\_brand, has\_weight\}) = 1$

$$P(has\_cpu) = \frac{A_1 + A_3 + \frac{A_5}{5}}{A_1 + \ldots + A_N} = \frac{0.15_1 + 0.26 + 0.2}{3} = 0.203$$

Choosing the terms



- The probabilities are computed for all the terms
- The terms are ordered in descending order of probability
- The first N terms whose cumulative probability reaches the chosen threshold are used as suggestions

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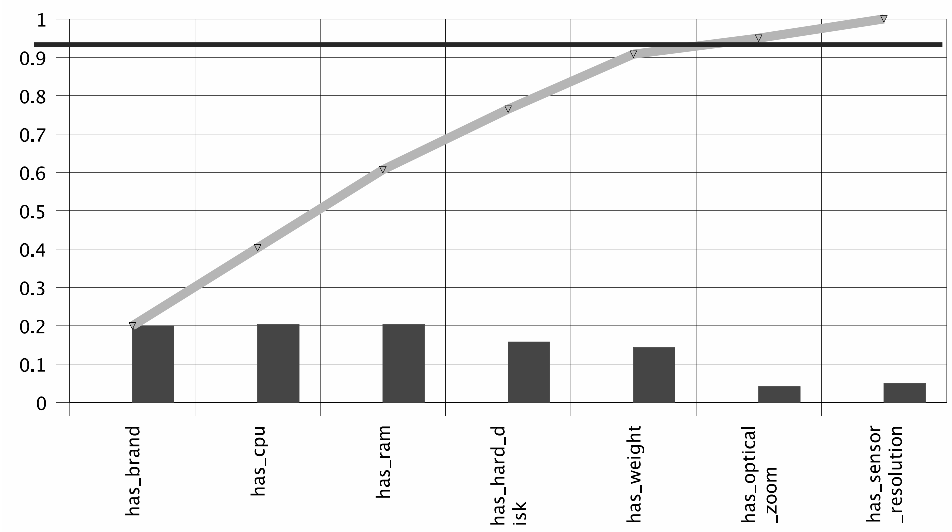

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Example

In this case, with a threshold of 95%, the terms `has_brand`, `has_cpu`, `has_ram`, `has_hard_disk`, `has_weight` are kept and passed to the mapper as suggestions. The terms `has_optical_zoom` and `has_sensor_resolution` are discarded.

Conclusions

- We showed an approach for improving dynamic ontology mapping that exploits knowledge about interactions to reduce the waste of resources employed to verify unlikely similarities between unrelated terms
- Traditional approaches aim at finding all the possible mappings between the ontologies, so that any possible interaction can occur.
- Our goal is pragmatic: only the mappings required for the interactions that take place need to be found.
- In the standard approach, an ontology mapper oracle compares the "foreign" terms with all the terms in the agent's ontology, although most of the compared terms are not related.
- However, the terms that appear in messages are not all equally probable: given the context of the interaction, some will be more likely than others.
- The use of protocols allows us to collect consistent information about the mappings used during an interaction

Thanks

Thanks for your attention

Any question?