Tree kernel and Feature Vector Methods for Formal Semantic Requests Classification

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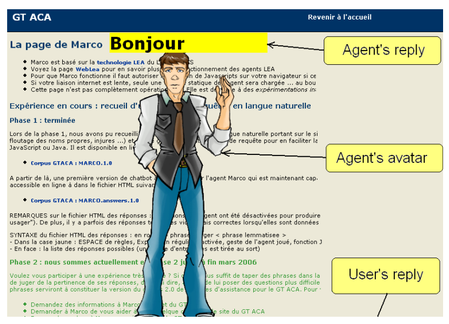
Introduction

Context: assistance to novice computer users with an Embodied Conversational Agent

Input: Natural Language request

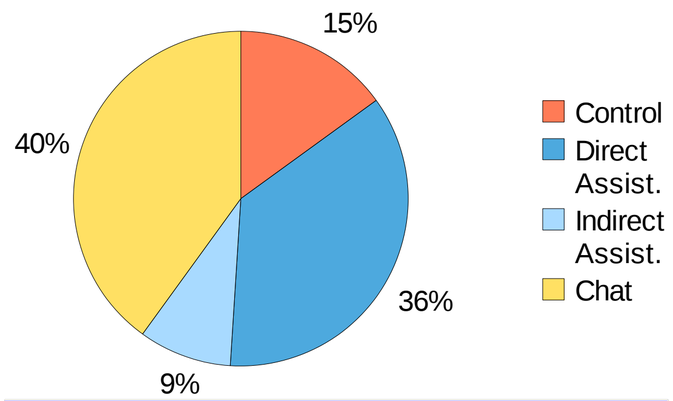
Output: Relevant multimodal reaction

Objective: preliminary step of automatic identification of the conversational activity of the request.



Resources used

- Four distinct categories of requests according to their conversational activities
- A formal representation of requests based on nested schemes (237 schemes available)
- 11,000 NL users' requests and their automatically generated formal representation: 1,070 requests manually associated to an activity



R_{ex} = *"Click on the little red button"*

Structure-based classification

Methodology: tree kernel approach – a request = a tree

$$k(R_1, R_2) = \sum_i h_i(R_1) h_i(R_2) = \sum_{r_1 \in \mathcal{R}_1, r_2 \in \mathcal{R}_2} S(r_1, r_2)$$

Applicable since:

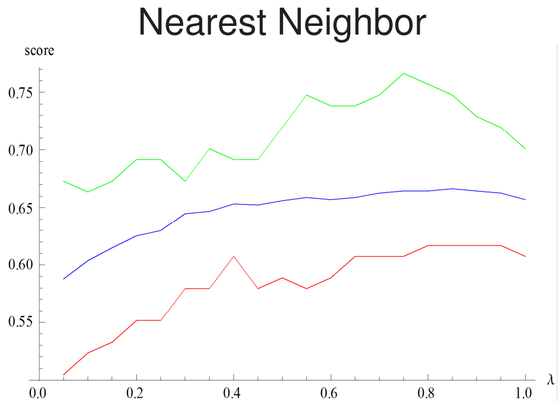
- the fields of a request are always in the same order;
- the number of fields is the same for any given head (*e.g.* Click);
- partially analyzed requests = tree with a root having N elements.

But specificities requiring modifications:

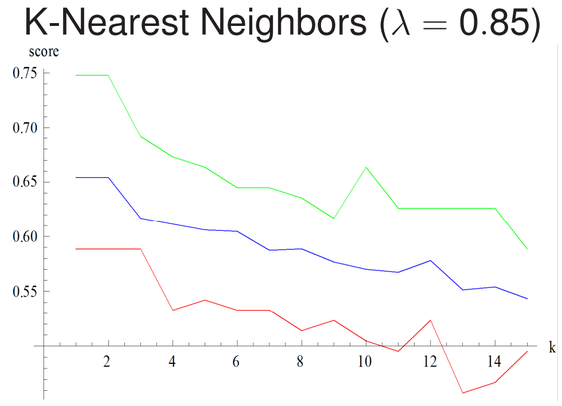
- terminal values in subtrees;
- multiple values fields: number of fields and their order vary;
- k is dependent on the complexity of the request ⇒ normalization
- very peaked kernel function (small modifications = big impact) ⇒ weight dependent on the number of subtrees.

Results: using leave-one-out

Nearest Neighbor



K-Nearest Neighbors ($\lambda = 0.85$)



(top = best score, middle = mean score, bottom = minimum score)

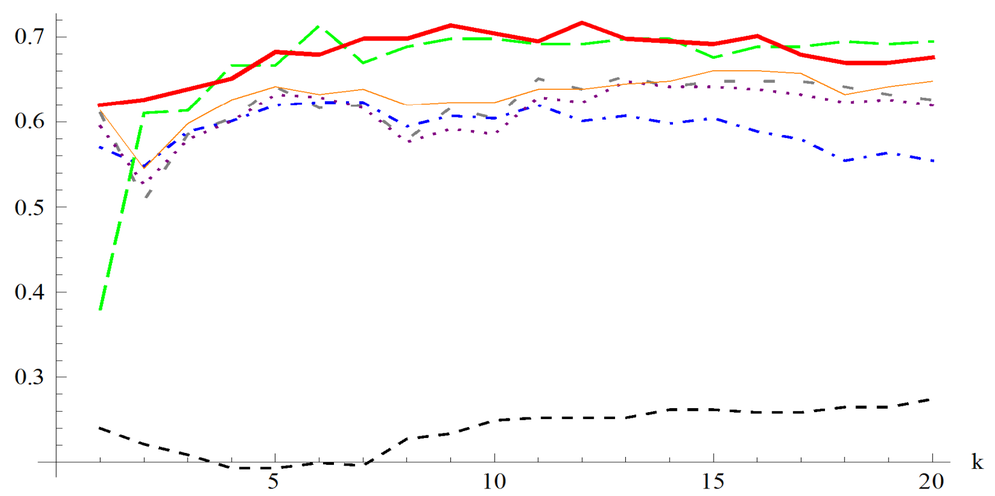
Semantic-based classification

Methodology: vectors matrix approach – a request = a vector

scheme	NEG	ASK	…	Click	Modify	…	person	object	…
R_{ex}	0	0	…	1	0	…	0	1	…

Results:

- KNN method ($K \in [\![1, 20]\!]$) with different distances:



Bray-Curtis (thick), correlation (long dashed), Canberra (thin), Euclidian (dashed), Manhattan (dotted), Hamming (dot dashed), Chebyshev (dashed)

- Other classification methods (using leave-one-out):

ID	Classification method	Overall score
sem1	**Naive Bayes (kernel estim.)**	**74.4%**
sem2	Decision tree (C4.5)	71.1%
sem3	Adaboost Naive Bayes (kernel estim.)	71.1%
sem4	Bayes Net	64.9%
sem5	Decision Table	71.0%
sem6	Adaboost C4.5	71.7%
sem7	KNN (K=12, Bray-Curtis dist.)	70.4%

Combination of classifiers

ID	Classification method	Overall score
-	Baseline	40.2%
ker	Nearest Neighbours	65.4%
sem1	Naive Bayes (kernel estim.)	74.4%
sem1+ker	Decision Table	74.4%
sem1+sem2	C4.5	75.2%
sem[1-7]	**Decision Table**	**76.1%**
sem[1-7]+ker	Decision Table	76.1%

- Combination of semantic classifiers increases performance from 74.4% to 76.1%
- The tree kernel approach isn't helping: no improvement

Conclusion and perspectives

- Results not outstanding but enough for a complementary method
- Structure of a request seems not essential in the conversational activity identification

Considering application of same methods with:

- Only correctly represented formal requests (manual transcription)
- Thinner level of granularity for conversational activities (ex: question about the possibility of an action)

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