An Integrated Approach to Robust Processing of Spoken Situated Dialogue

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Talking robots ?

- Our long-term aim :

  « *Hi, I am C3-PO,Human Cyborg Relations.* »

- **Research goal** : building robots which are able to understand (and produce) *situated, spoken dialogue.*
- **Question** : How can we achieve that, given the current limitations of NLP technology ?

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Issues in spoken dialogue understanding

- Dialogue systems typically suffer from a lack of *robustness* and *adaptivity*.
- **Four issues** of particular importance :
  1. Difficulty of accommodating *spoken language phenomena* (disfluencies, fragments, etc.) in the dialogue system ;
  2. Pervasiveness of speech recognition errors ;
  3. Ambiguities arising at all processing levels ;
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Our approach in brief

- We present an **integrated approach** for addressing these questions, in the context of domain-specific dialogues for human-robot interaction.
- The approach is *fully implemented*, and integrated in a cognitive architecture for autonomous robots.
- We performed an extensive *evaluation* of our approach.

  $\Rightarrow$ The empirical results we obtained demonstrate **very significant improvements** both in *robustness* and in *accuracy* compared to the baseline.

The strategy in two steps

1. Allow for a **controlled relaxation** of the grammatical constraints to account for *spoken dialogue phenomena* and *speech recognition errors*.
2. Then apply a **discriminative model** on the resulting set of interpretations, in order to select the most likely one given the context.

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Spoken dialogue

Different levels of processing :

- **Auditory** : speech recognition
- **Grammatical** : syntactic structure, semantic structure

  "A grammar specifies the relation between well-formed syntactic structures and their underlying (linguistic) meaning"
- **Discourse** : contextual reference resolution (anaphora, ellipsis), rhetorical relation resolution, etc.

  "Discourse interprets utterance meaning relative to the context, establishing how it contributes to furthering the discourse"

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Open challenges

- **Robustness** in speech recognition :
  - noise, speaker independence, out-of-vocabulary words
  - poor performance of current ASR technology
- **Robustness** to ill-formed utterances :
  - partial, ungrammatical or extra-grammatical utterances
  - presence of various disfluencies (filled pauses, speech repairs, corrections, repetitions, etc.) in spoken dialogue.
- Pervasive **ambiguity** at all processing levels (lexical, syntactic, semantic, pragmatic)
- **Uncertainty** in contextual interpretation of utterances

Disfluencies in spoken dialogue : example

- Extract from a corpus of task-oriented spoken dialogue : *The Apollo Lunar Surface Journal*. [Audio file]

Example

Parker : That's all we need. Go ahead and park on your 045 <**okay**>. We'll give you an update when you're done.
Cernan : Jack is **[it]** worth coming right there ?
Schmitt : **err** looks like a pretty **go/** good location.
Cernan : okay.
Schmitt : We can sample the rim materials of this crater. **(Pause)** Bob, I'm at the **uh** south **uh** let's say east-southeast rim of a, **oh**, 30-meter crater - **err** in the light mantle, of course - up on the **uh** Scarp and maybe 300...**(correcting himself)** **err** 200 meters from the **uh** rim of Lara in **(inaudible)** northeast direction.

Software architecture

- Software architectures for "intelligent" robots are typically composed of several *distributed* and *cooperating* subsystems, such as :
  - communication ;
  - vision, perception ;
  - navigation and manipulation skills ;
  - deliberative processes (for planning, learning, reasoning).
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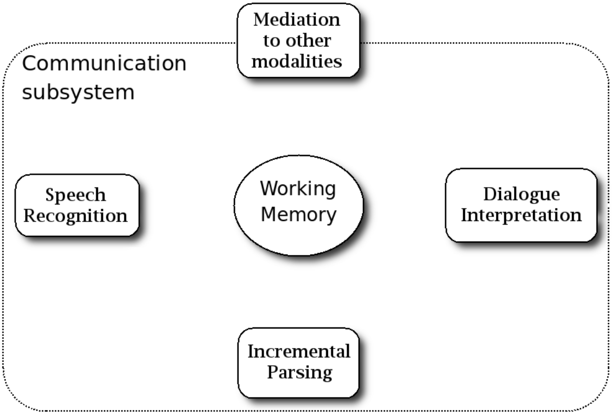
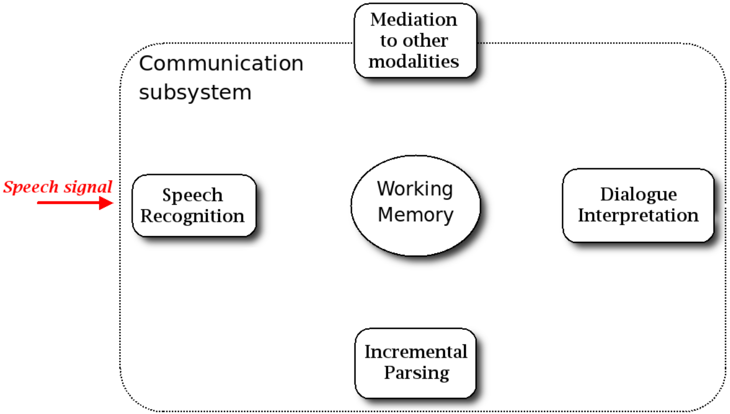


FIG.: Spoken dialogue comprehension

Communication subarchitecture



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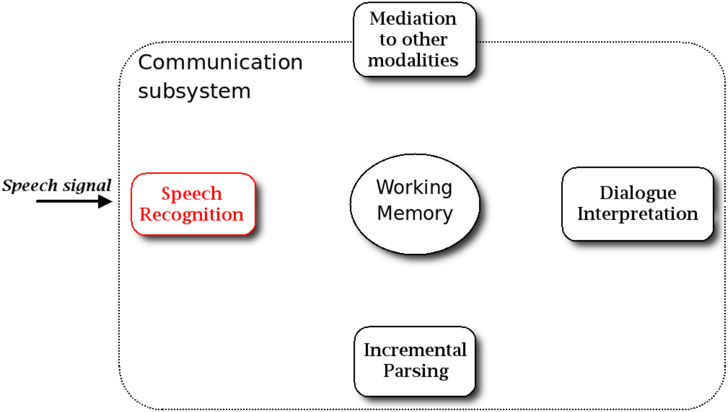

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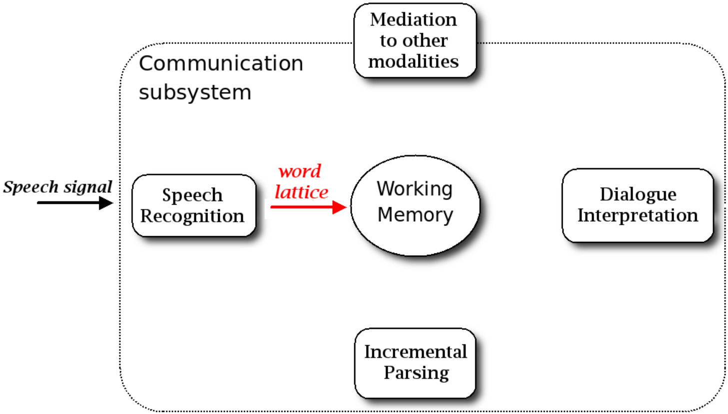

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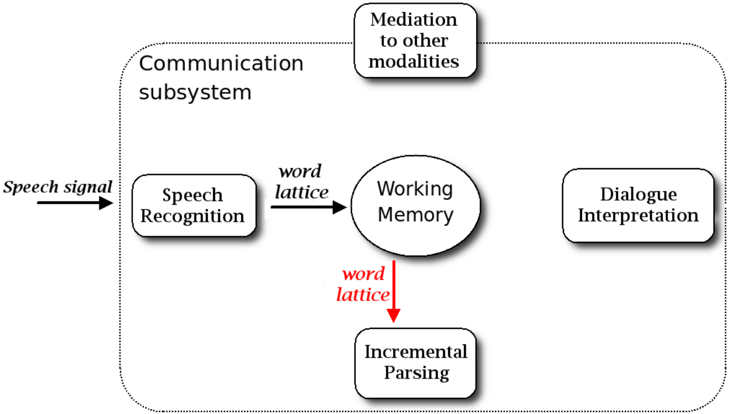

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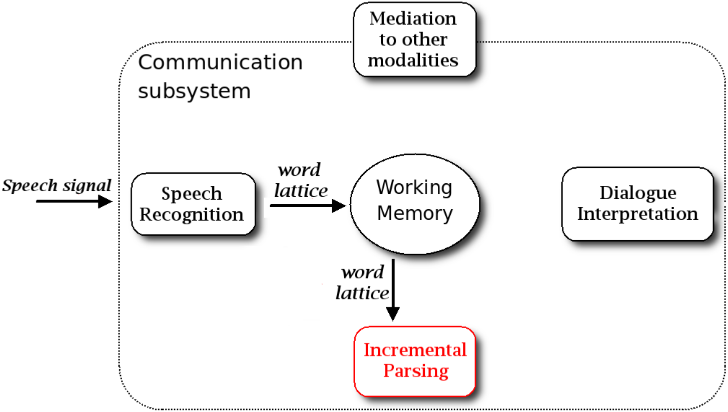

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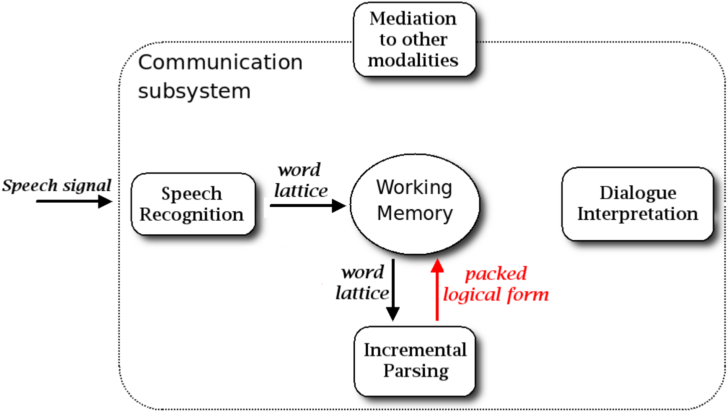

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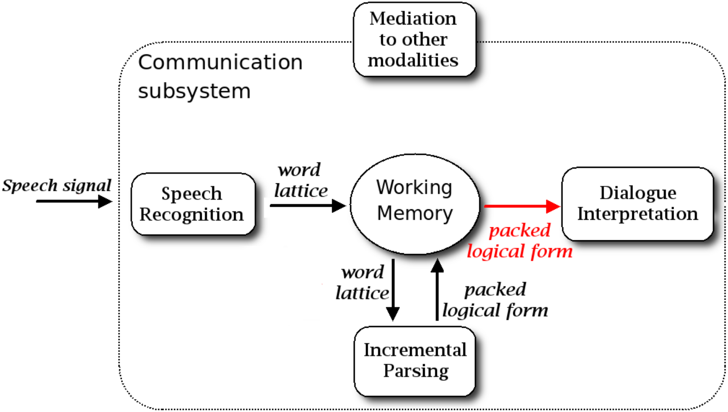

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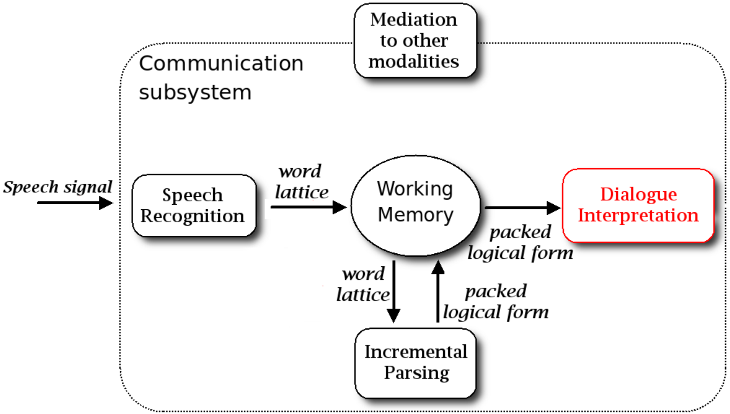

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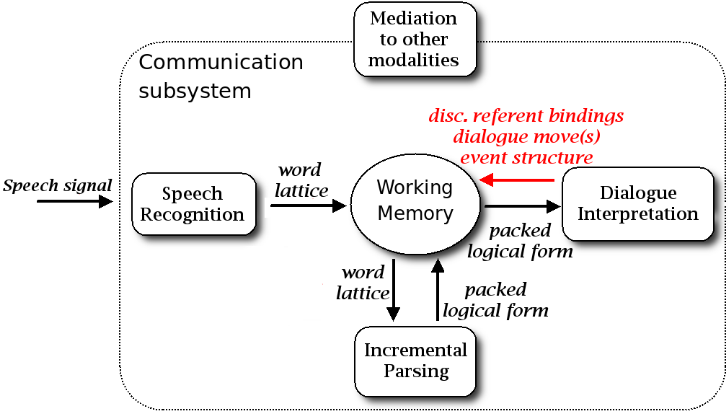

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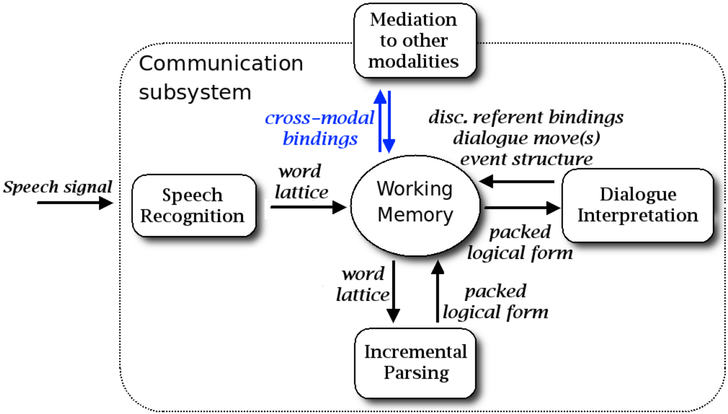

FIG.: Spoken dialogue comprehension : cross-modality

Robust parsing of spoken inputs

- Parsing spoken inputs is a difficult task
- The parser must be made robust to *ill-formed* and *misrecognised* inputs
- Three broad families of techniques can be used :
  - Shallow or partial parsing (concept spotting) ;
  - (pure) statistical approaches (HMMs, stochastic parsers) ;
  - Controlled relaxation of grammar rules.
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Implementation

- Practically, the relaxation is realised by introducing **non-standard CCG combinators** into the grammar
- The new rules are :
  - **Discourse-level composition rules**
    ⇒ to be able to combine discourse units ("fragments") ;
  - **"Paradigmatic heap" rules**
    ⇒ to account for repetitions and corrections ;
  - And **ASR correction rules**
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A simple example

$$\dfrac{\dfrac{\dfrac{\text{pick}}{\text{s/particle/np}} \qquad \dfrac{\dfrac{\text{cup}}{\text{up}}\ corr}{\text{particle}}}{\text{s/np}}> \qquad \dfrac{\dfrac{\text{the}}{\text{np/n}} \qquad \dfrac{\text{ball}}{\text{n}}}{\text{np}}>}{\text{s}}>$$

FIG.: CCG derivation of “pick cup the ball”.

Discriminative models

- The set of interpretations resulting from the parsing operation can be quite large.
- Why ?
  1. Multiple recognition hypotheses from the ASR ;
  2. Controlled relaxation of grammatical constraints ;
  3. And finally, language is inherently ambiguous, and spoken dialogue is no exception !
- We need a mechanism which filters out unlikely interpretations and only keeps the good one(s).

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Parse selection

- The task is defined as a function $F : \mathcal{X} \rightarrow \mathcal{Y}$ where the domain $\mathcal{X}$ is the set of possible inputs (in our case, $\mathcal{X}$ is the set of possible *word lattices*), and $\mathcal{Y}$ the set of parses.
- The function F, mapping a word lattice to its most likely parse, is then defined as :

$$F(x) = \underset{y \in \mathbf{GEN}(x)}{\operatorname{argmax}} \ \mathbf{w}^T \cdot \mathbf{f}(x, y) \qquad (1)$$

where $\mathbf{w}^T \cdot \mathbf{f}(x, y)$ is the inner product $\sum_{s=1}^{d} w_s \ f_s(x, y)$, and can be seen as a measure of the "quality" of the parse.

Discriminative models : learning

- How do we learn the parameters $\mathbf{w}$?
- We use a well-known algorithm from machine learning : a **perceptron**.
- The perceptron algorithm has proven to be very efficient and accurate for the task of parse selection
- **Problem** :we don't have any annotated corpora for our domain at our disposal
  ⇒ **Solution** : automatic *generation* of training examples from a small domain-specific grammar.

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- The accuracy of our discriminative model crucially relies on the selection of "good" features $\mathbf{f}(x, y)$ for our model
- That is, features which help *discriminating* the parses.
- They must also be relatively cheap to compute.
- In our model, the features are of four types :
  1. **semantic features** (substructures of the logical form) ;
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- The test suite is composed of 195 individual utterances collected during **Wizard-of-Oz experiments**.
- These experiments consist of a set of situated human-robot interactions relative to a shared visual scene.
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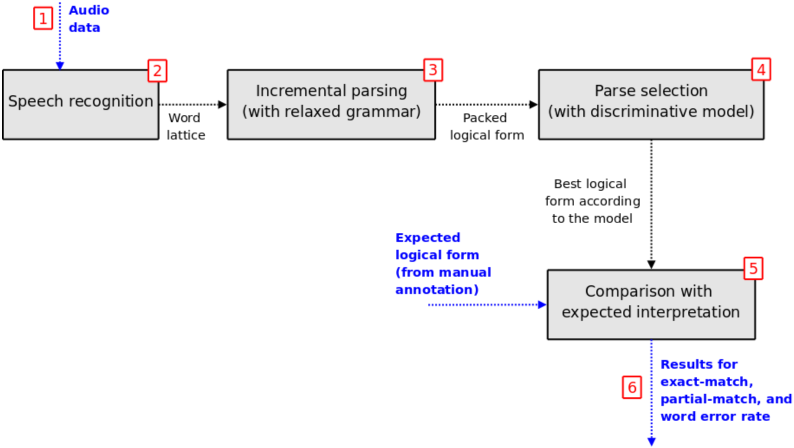

Evaluation results

	Precision	Recall	$\mathbf{F_1}$-measure
Baseline	40.9	45.2	43.0
Our approach	55.6	84.0	**66.9**

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   - Able to deliver both *deep* and *robust* dialogue processing
2. It is an **integrated** approach
   - Goes all the way from the speech signal up to the semantic & pragmatic interpretation
   - Interactions between various processing components
3. It is a **context-sensitive** approach
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   - Interactions between various processing components
3. It is a **context-sensitive** approach
   - *Context* is used at every processing step to guide the processing
   - Both an *anticipation* tool and a *discrimination* tool

Our approach in brief

1. It is a **hybrid symbolic/statistical** approach
   - Combination of fined-grained linguistic resources with statistical models
   - Able to deliver both *deep* and *robust* dialogue processing
2. It is an **integrated** approach
   - Goes all the way from the speech signal up to the semantic & pragmatic interpretation
   - Interactions between various processing components
3. It is a **context-sensitive** approach
   - *Context* is used at every processing step to guide the processing
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Contributions

1. A new model for **robust parsing of spoken inputs**, based on a relaxed CCG grammar coupled with a discriminative model exploring a broad range of linguistic and contextual features.
2. A fully working **implementation** for these two models, integrated into a cognitive architecture for autonomous robots. The implementation comes along with a complete set of training data and testing data.

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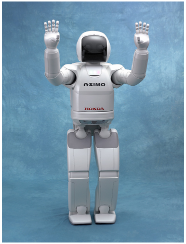
The end

Thank you for your attention ! !



⇒ **Questions, comments ?**

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