Spoken Language Understanding; a survey

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Summary

- THE SIGN TO MEANING PROCESS
- WORDS TO CONCEPTS (SEMANTIC CONSTITUENTS) TRANSLATION
- SEMANTIC GRAMMARS
- SEMANTIC COMPOSITION AND INFERENCE
- CONFIDENCE, CORPORA ANNOTATION AND LEARNING

THE SIGN TO MEANING PROCESS

Introduction

Epistemology, the science of knowledge, considers a datum as basic unit.

Semantics deals with the organization of meanings and the relations between sensory signs or symbols and what they denote or mean.

Computer epistemology deals with observable facts and their representation in a computer.

Natural language interpretation by computers performs a conceptualization of the world using computational processes for composing a meaning representation structure from available signs and their features.

Some problems and challenges in SLU

•meaning representation,

•definition and representation of signs,

•conception of relations between signs and meaning and between instances of meaning,

•processes for sign extraction, generation of hypotheses about units of meaning and constituent composition into semantic structures,

•robustness and evaluation of confidence for semantic hypotheses,

•automatic learning of relations from annotated corpora,

•collection and semantic annotation of corpora.

SLU and NLU

SLU and NLU share the goal and some types of signs of obtaining a conceptual representation of natural language sentences.

Specific to SLU is the fact that

•signs to be used for interpretation are coded into signals with other information such as speaker identity.

•spoken sentences often do not follow the grammar of a language; they exhibit self corrections, hesitations, repetitions and other peculiar phenomena.

•SLU systems contain an ASR component and must be robust to noise due to the spontaneous nature of spoken language, errors introduced by ASR and its difficulty in detecting sentence boundaries.

Meaning representation

Semantic theories have inspired the conception of *Meaning Representation Languages (MRL)*.

MRLs have a syntax and a semantic (Woods, 1975) and should, among other things:

represent intension and extension, with defining and asserting properties, use quantifiers as higher operators, lambda abstraction And make it possible to perform inference

Frame languages define computational structures (Kifer et al., JACM, 1995) and can be seen as cognitive structuring devices (Fillmore, 1968, 1985) in a semantic construction theory.

Frames as computational structures (intension)

A frame scheme with defining properties represents types of conceptual structures (intension) as well as instances of them (extension). Relations with signs can be established by attached procedures (S. Young et al., 1989).

{address

loc	TOWN
	……*attached procedures*
area	DEPARTMENT OR PROVINCE OR STATE
	……*attached procedures*
country	NATION
	……*attached procedures*
street	NUMBER AND NAME
	……*attached procedures*
zip	ORDINAL NUMBER
	……*attached procedures* }

Frame instances (extension)

A convenient way for asserting properties, and reasoning about semantic knowledge is to represent it as a set of *logic formulas*.

$$(\exists x)\left\{\begin{array}{l}\text{instance\_of}(x, \text{address}) \wedge \text{loc}(x, \text{Avignon}) \wedge \text{area}(x, \text{Vaucluse}) \wedge \\ \wedge\ \text{country}(x, \text{France}) \wedge \text{street}(x, \text{1 avenue Pascal}) \wedge \text{zip}(x, 84000)\end{array}\right\}$$

A frame instance (extension) can be obtained from predicates that are related and composed into a computational structure.

Frame schemata can be derived from knowledge obtained by applying semantic theories.

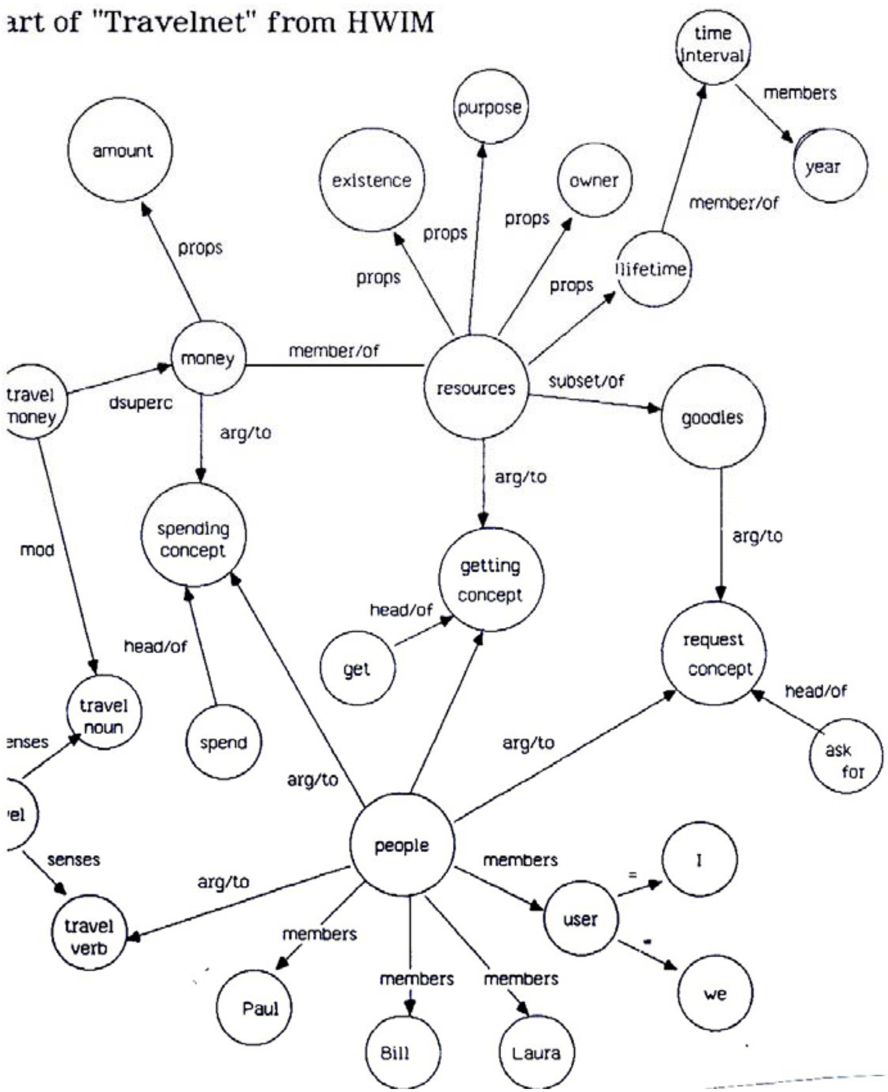
Interesting theories can be found, for example in (Jackendoff, 1990, 2002) or in (Brackman 1978, reviewed by Woods 1985)

Frame instance

Schemata contain collections of properties and values expressing relations. A property or a role are represented by a slot filled by a value

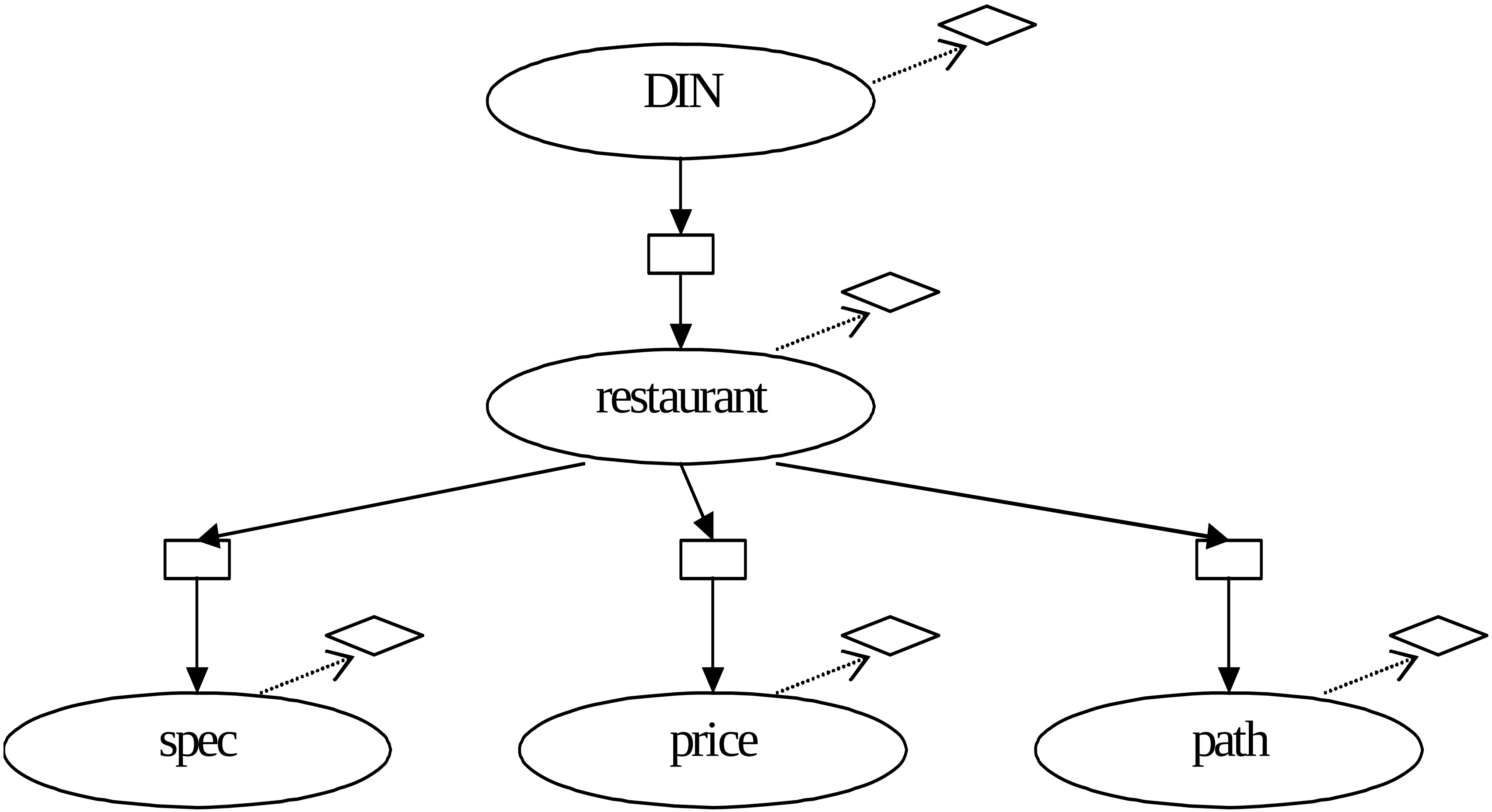
{a0001	
instance_of	address
loc	Avignon
area	Vaucluse
country	France
street	1, avenue Pascal
zip	84000
}	

Semantic networks



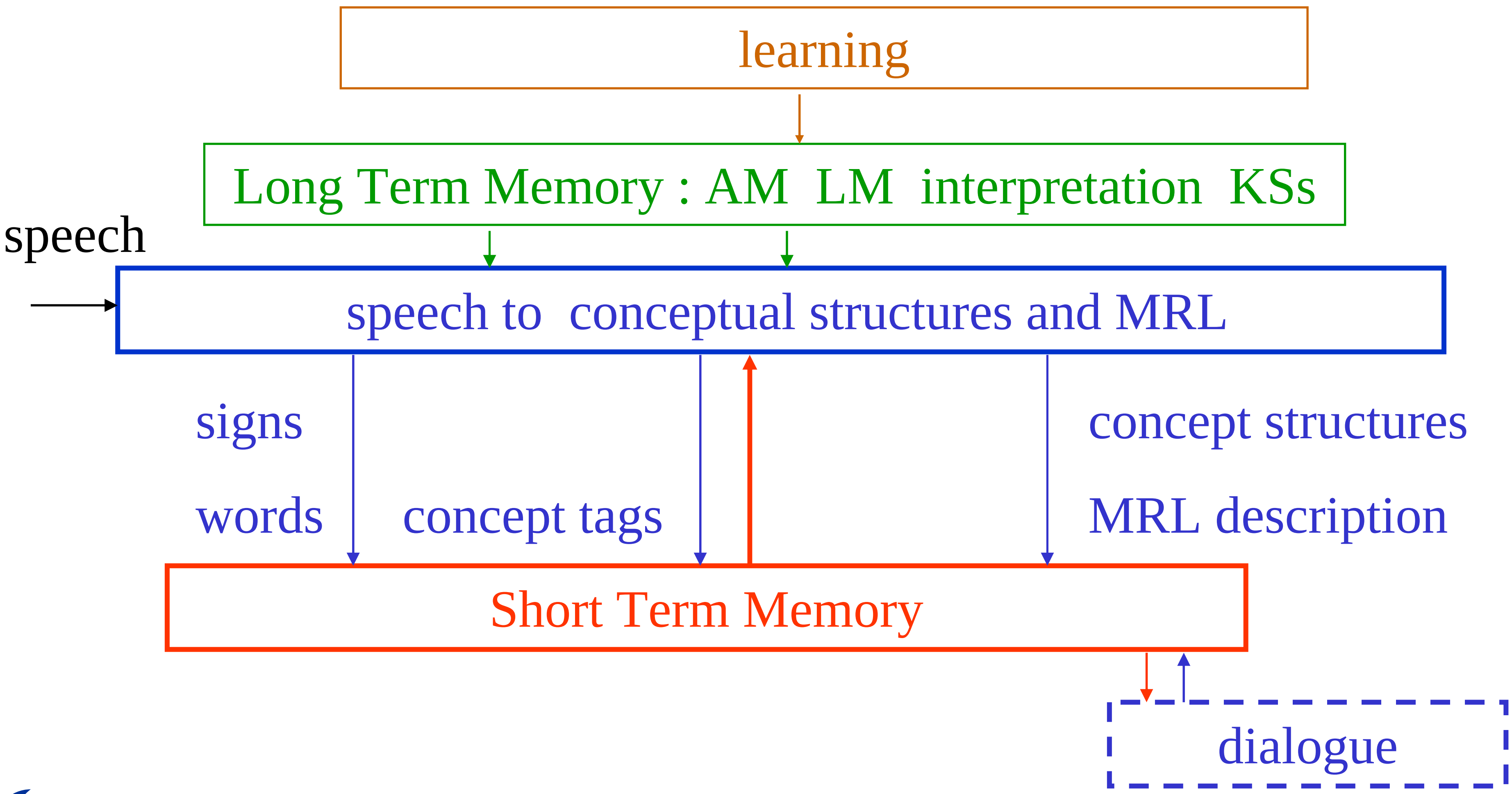
AUGMENTED ENTITY RELATIONS IN KL ONE

Entity relations plus structural descriptions represented by logic formulas are proposed in KL-ONE (Brachman, 1978).

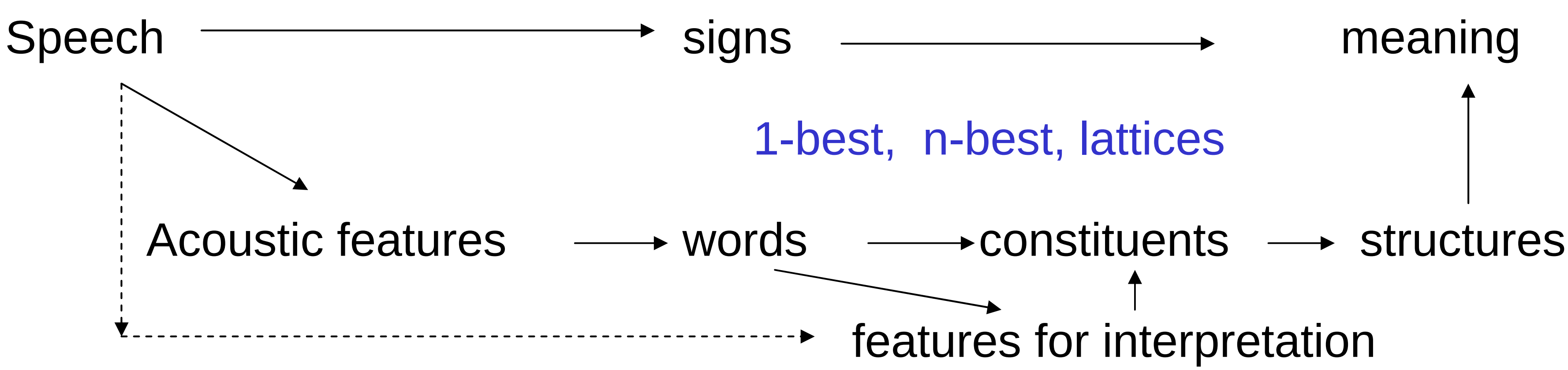


Process overview

An integrated solution: the blackboard architecture (Erman et al., ACM Comp. Surveys 1980)



Interpretation problem decomposition



Problem reduction representation is context-sensitive

Interpretation is a composite decision process. Many decompositions are possible involving a variety of methods and KSs, suggesting to consider a modular approach to process design.

Robustness is obtained by evaluation and possible integration of different KSs and methods used for the same sub-task.

Levels of processes and application complexity

Translation from words to basic conceptual constituents

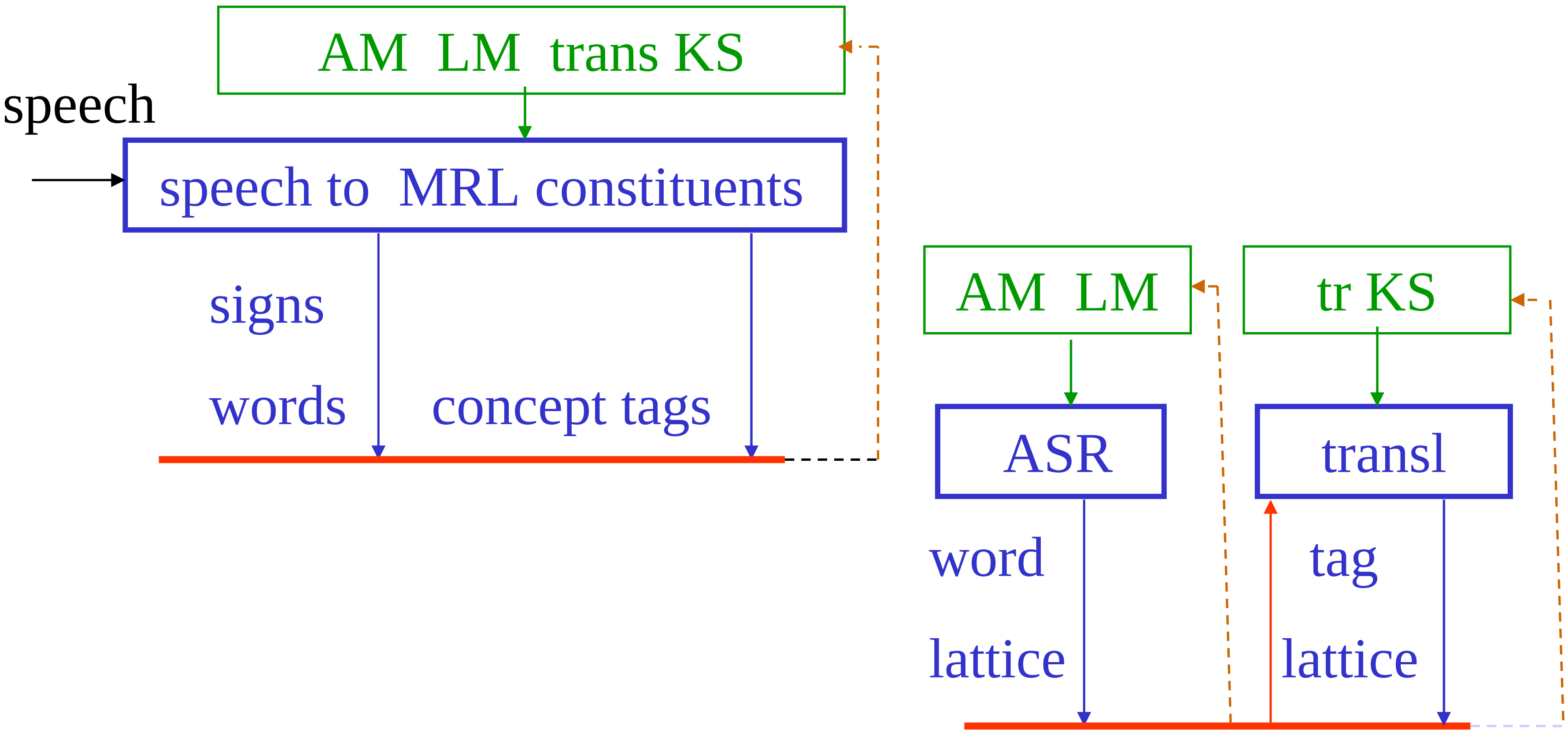
Semantic composition on basic constituents

Context-sensitive validation

Combination of level processes may depend on the application

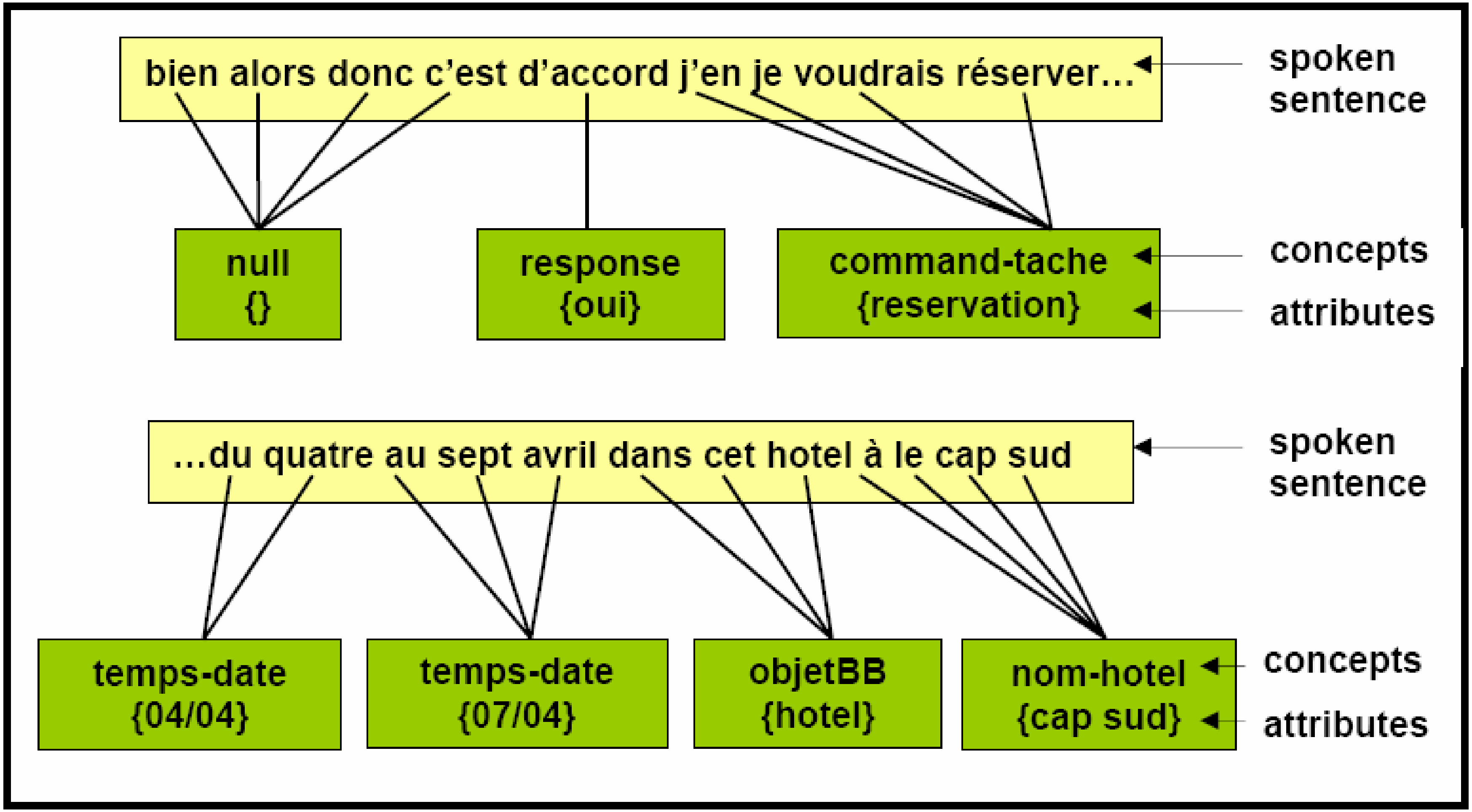
From signs to constituents

Hypothesize a lattice of concept tags for semantic constituents and compose them into structures. Detection vs. translation



WORDS TO CONCEPTS (SEMANTIC CONSTITUENTS) TRANSLATION

Generation of semantic constituent hypotheses



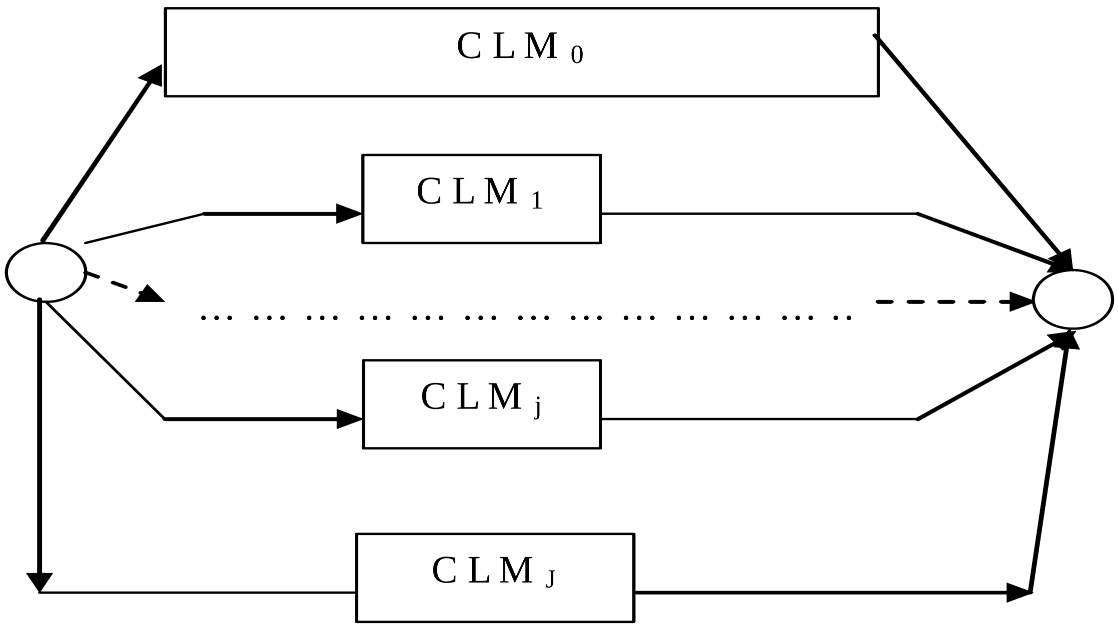
Finite-state conceptual language models

ASR algorithms compute probabilities of word hypotheses using finite state language models.

It is important to perform interpretation from a lattice of scored words and to take, possibly redundant, word contexts into account (Drenth and Ruber, 1997, Nasr et al., 1999). Other interesting contributions are in (Prieto et al., 1993, Kawahara et al., 1999).

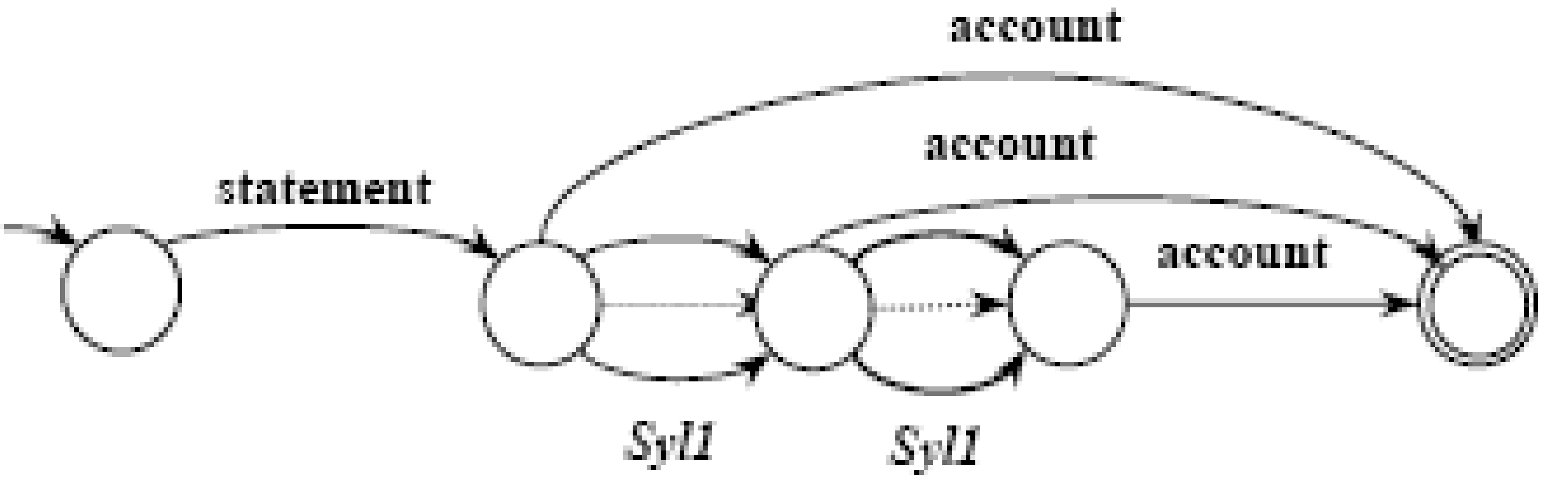
Finite state approximations of context-free or context-sensitive grammars (Pereira, 1990, reviewed in Erdogan, 2005), Finite state parser (TAG) with application semantics (Rambow et al. 2002).

Conceptual Language Models



This architecture is used also for separating in domain from out domain message segments (Damnati, 2007) and for spoken opinion analysis (Camelin et al., 2006). The whole ASR knowledge models in this way a relation between signal features and meaning.

noise tolerant modeles



Hypothesis generation from lattices

An initial ASR activity generates a word graph (WG) of scored word hypotheses with a generic LM.

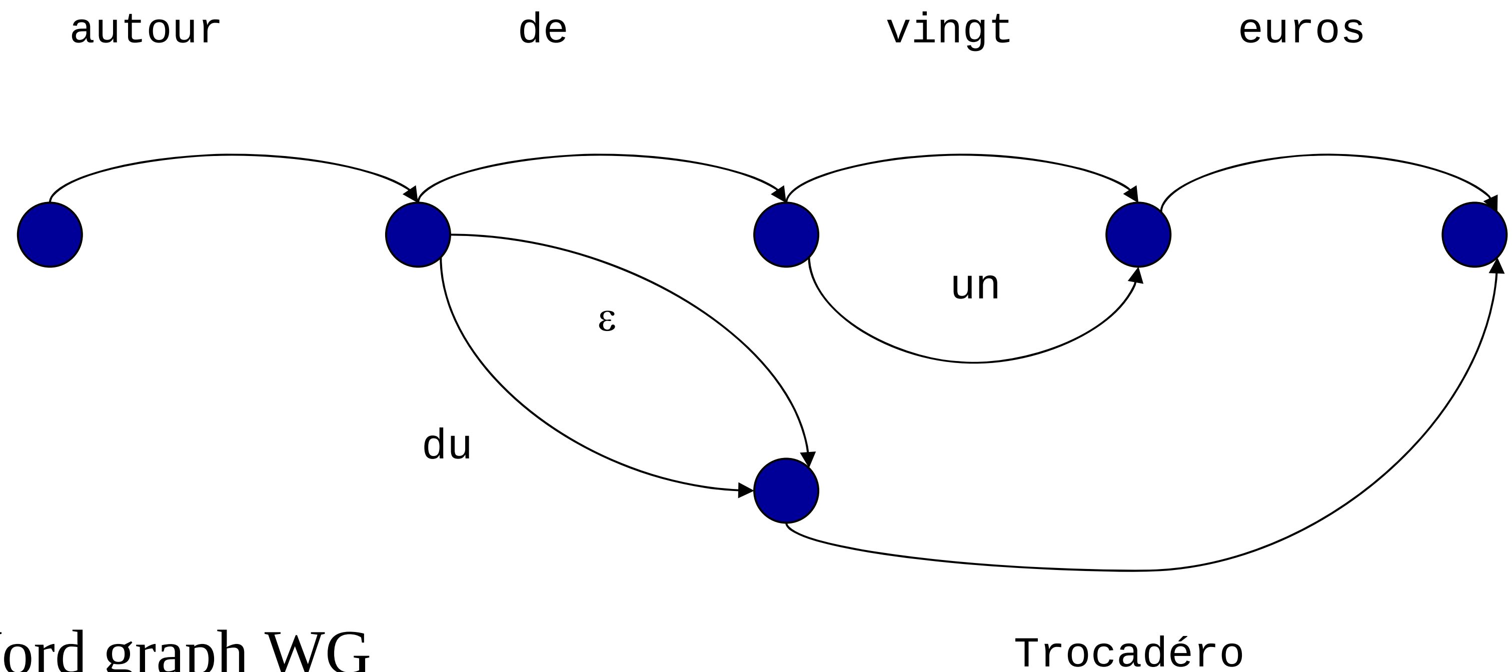
The network is composed with WG resulting in the assignment of semantic tags to paths in WG

$$\mathrm{SEMG} = \mathrm{WG}\ \mathrm{o} \left(\mathop{\mathrm{Y}}_{c=0}^{C} \mathrm{CLM}_c \right)$$

SWG=OUTPROJ(SEMG)

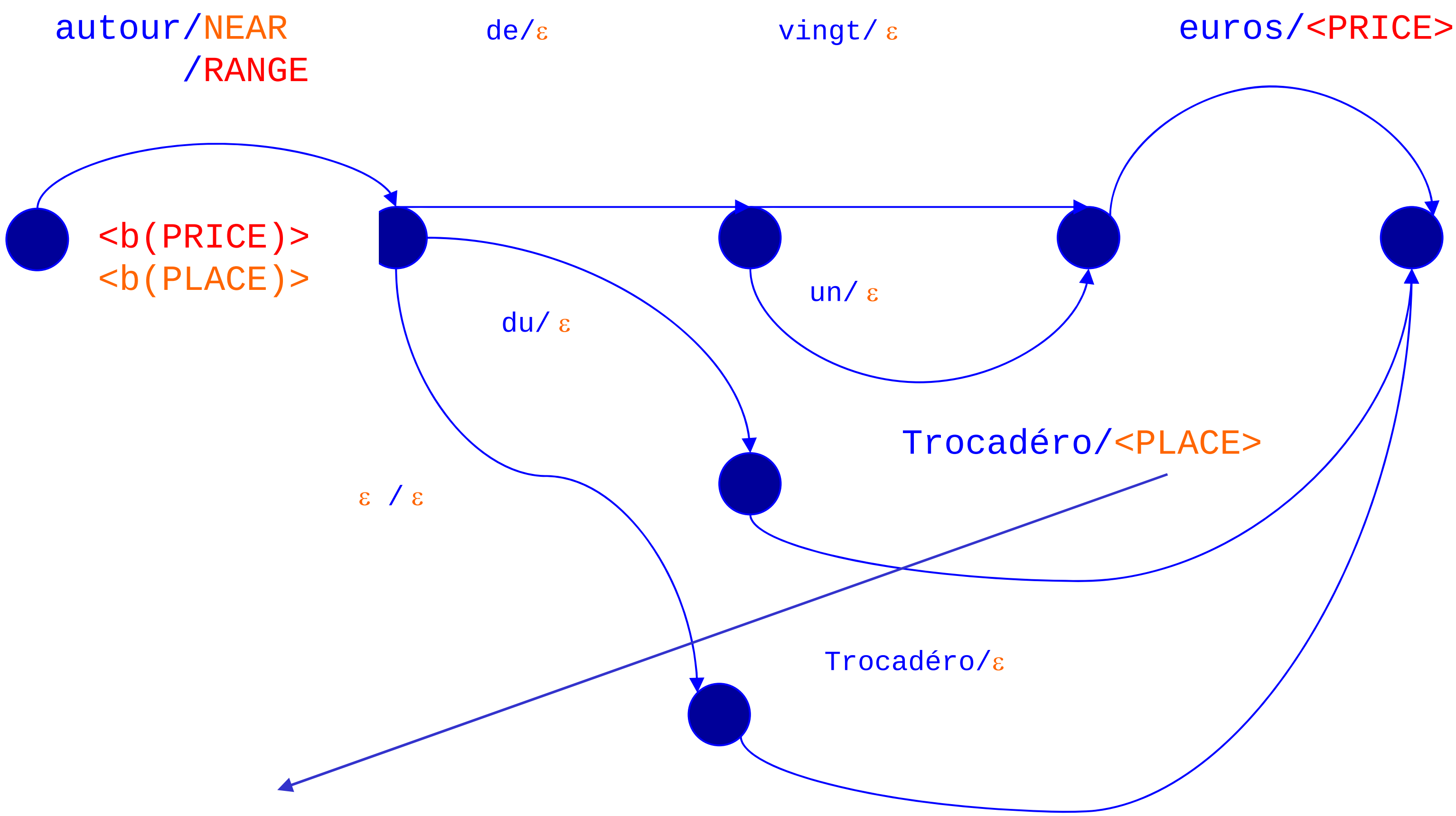
(Special issue Speech Communication, 3 2006, Béchet et al., Furui)

Word Graph



Word graph WG

Composition



$$\lfloor_{\text{Place}}\, \text{IN}(\lfloor_{\text{Thing}}\, \text{LOC}(\text{type} : \text{square}, \text{value} : \text{Trocadéro})\rfloor)\rfloor$$

NL - MRL translation

In (Papineni et al. , 1998) statistical translation models are used to translate a source sentence S into a target, artificial language T by maximizing the following probability :

$$\Pr(T|S) = \frac{\Pr(S|T)P(T)}{\Pr(S)}$$

The central task in training is to determine correlations between group of words in one language and groups of words in the other. The source channel fails in capturing such correlations, so a direct model has been built to directly compute the posterior probability P(T|S).

Intresting solutions also in (Macherey et al., 2001, Sudoh and Tsukada, 2005 for attribute/value pairs, LUNA)

CRF

Possibility of having features from long-term dependences

Results for LUNA from Riccardi, Raymond, Ney, Hann

$$p(y \mid x) = \frac{1}{Z(x)} \exp\left(\sum_{c \in C} \sum_{k} \lambda_k f_k(y_{i-1}, y_i, x, i) \right)$$

$$Z(x) = \sum_{y} \exp\left(\sum_{c \in C} \sum_{k} \lambda_k f_k(y_{i-1}, y_i, x, i) \right)$$

$$f_k(y_{i-1}, y_i, x, i) = \begin{cases} 1 & \text{if } y_i = ARRIVE.CITY \\ & \text{and } x_i \ldots x_{i-1} \text{ contain } \{\text{arrive} \mid \text{to}\} \\ 0 & \text{otherwise} \end{cases}$$

Method comparison and combination

- **Results on the French MEDIA corpus, LUNA project, NLU RWTH Aachen results**
- **Approaches:**
  - Linear chain CRF
  - FST
  - SVM
  - Log-linear on positional level
  - MT
  - SVM with tree kernel

Raymond C., Riccardi G. "Generative and Discriminative Algorithms for Spoken Language Understanding", Proc. INTERSPEECH, Antwerp, 2007.

Moschitti A., Riccardi G., Raymond C. "Spoken language understanding with kernels for syntactic/ semantic structures", Proc. IEEE ASRU, Kyoto, 2007.

Comparison

model	attribute		attribute/value	
	CER [%]	SER [%]	CER [%]	SER [%]
CRF	11.8	17.7	16.2	23.0
log-linear	14.9	22.2	19.3	26.4
FST	17.9	24.7	21.9	28.1
SVM	18.5	24.5	22.2	28.5
MT	19.2	24.6	23.3	27.6

Incremental oracle performance

model	attribute	
	CER [%]	SER [%]
CRF	11.8	17.7
+log-linear	9.8	15.6
+FST	8.3	13.8
+SVM	7.6	12.9
+MT	7.0	12.3

Sequential approach with 1-best ASR

Comparison of interpretation results obtained in the MEDIA corpus 1 best ASR output

	concept error rate (CER)
Conditional Random Fields	25.2 %
Finite State Transducers	29.5 %
Support Vector Machines	29.6 %

CER close to 20 when N-best concepts (N<10) are obtained with FSMs. Possiiblity of further imprevement by combination with CRFs and using dialog constraints

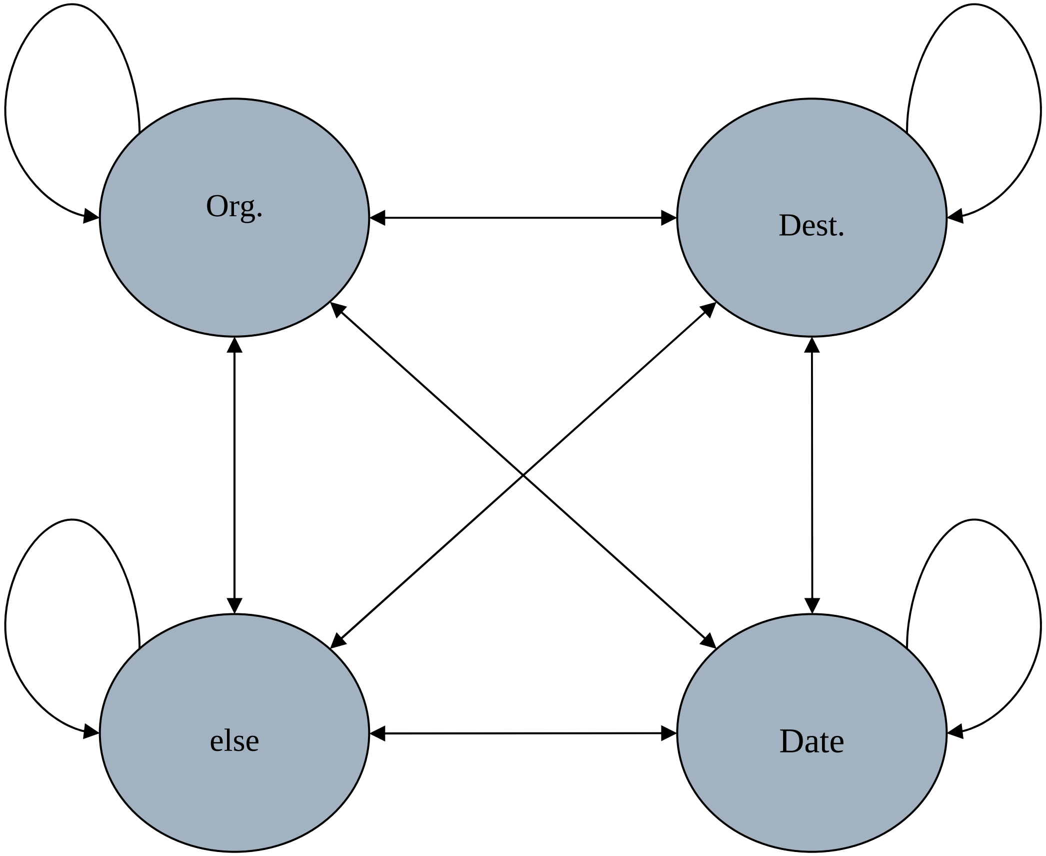
History

Systems developed in the seventies reviewed in (Klatt, 1977) and the eighties, early nineties (EVAR, SUNDIAL) mostly performed syntactic analysis on the best sequence of words hypothesized by an ASR system and used non probabilistic rules, semantic networks, pragmatic and semantic grammars for mapping syntactic structures into semantic ones expressed in logic form.

In the nineties, the need emerged for testing SLU processes on large corpora that could also be used for automatically estimating some model parameters. Probabilistic finite-state interpretation models and grammars were also introduced for dealing with ambiguities introduced by model imprecision.

Probabilistic interpretation in the Chronous system

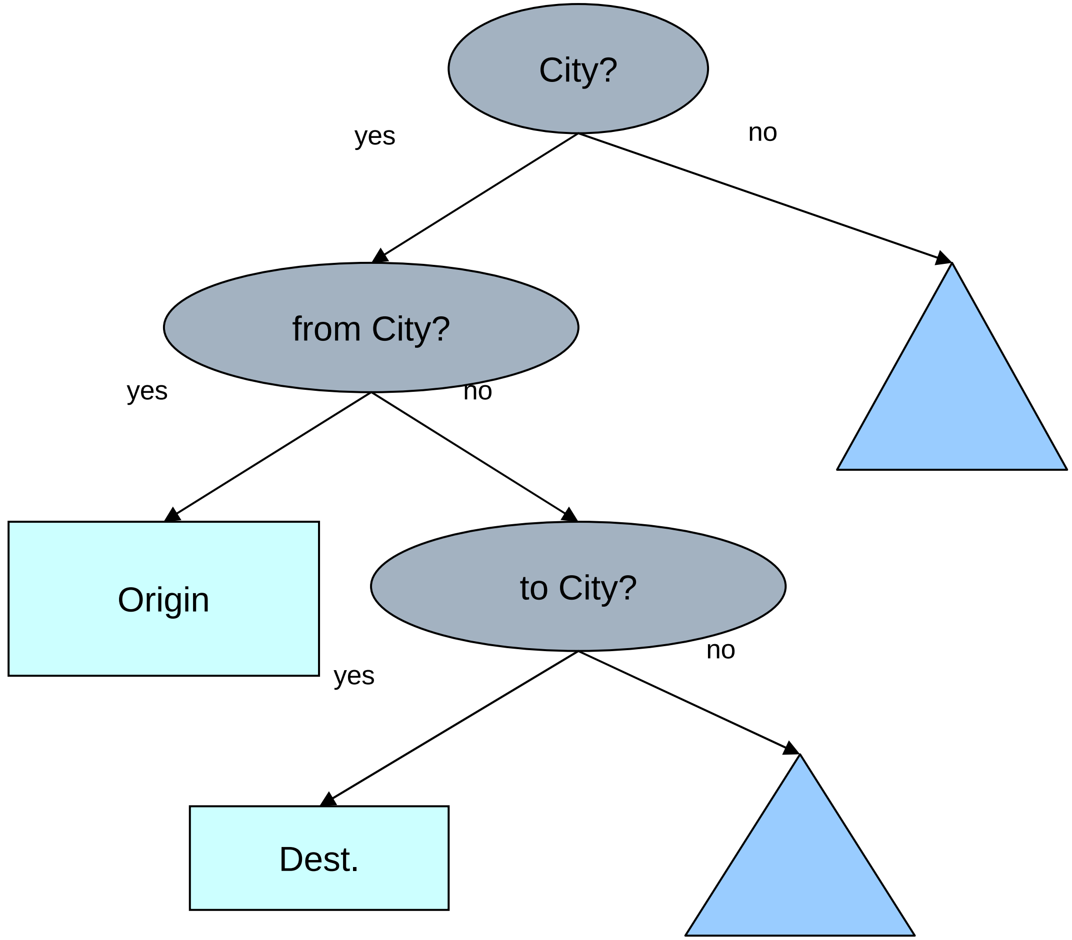
The probability P(CW) is computed using *Markov models* as



$P(CW)=P(W|C)P(C)$

(Pieraccini et al., 1991, Pieraccini, E. Levin, E. Vidal, 1993).

Semantic Classification trees



(Kuhn and De Mori, 1995)

SEMANTIC GRAMMARS

Interpretation as a translation process

Interpretation of written text can be seen as a process that uses procedures for translating a sequence of words in natural language into a set of semantic hypotheses (just constituents or structures) described by a semantic language.

W:[S[VP [V give, PR me] NP [ART a, N restaurant] PP[PREP near, NP [N Montparnasse, N station]]]]

Γ:[Action REQUEST ([Thing RESTAURANT], [Path NEAR ([Place IN ([Thing MONTPARNASSE])])]]

Interesting discussion in (Jackendoff, 1990) Each major syntactic constituent of a sentence maps into a conceptual constituent, but the inverse is not true.

Using grammars for NLU

Adding semantic building structures to cfg

Categorial grammars (Lambek, 1958)

Montague Grammars (Montague, 1974)

Augmented Transition Network Grammars (Woods 1970)

Semantic grammars for SLU (Woods, 1976)

Tree Adjoining grammars (TAG) integrate syntax and logic form (LF) semantics. Links can be established between the two representations and operations carried out synchronously (Shabes and Joshi, 1990).

Robust parsing (early ATIS)

A robust fallback module has been incorporated in successive versions (Delphi Bates et al., 1994).

The system developed at SRI consists of two semantic modules yoked together: a unification-grammar-based module called ”Gemini”, and the ”Template Matcher” which acts as a fallback if Gemini can't produce an acceptable database query (Appelt, 1996).

When a sentence parser fails, constraints on the parser are relaxed to permit the recovery of parsable phrases and clauses (TINA Seneff, 90). Fragments are then fused together.

Local parsing (Abney, 1991).

Stochastic semantic context-free grammars

The linguistic analyzer TINA, (MIT, Seneff, 1989), has a grammar written as a set of probabilistic context free rewrite rules with constraints.

The grammar is converted automatically at run-time to a network form in which each node represents a syntactic or semantic category.

The probabilities associated with rules are calculated from training data, and serve to constrain search during recognition (without them, all possible parses would have to be considered).

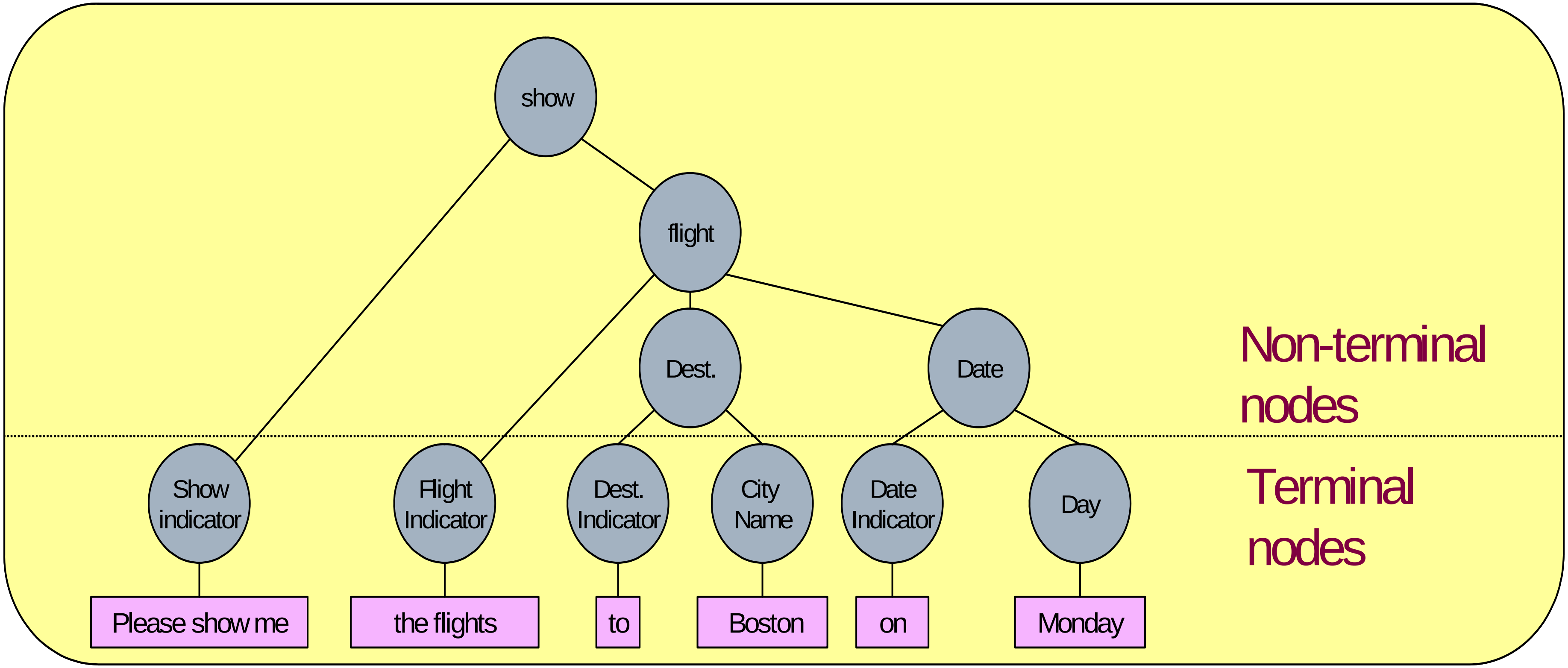
History grammars (Black et al., 1993)

Robust partial parser

Pragmetic grammars

```
S -> NP VP

NP -> PERSON_NP
NP -> FLIGHT_NP

PERSON_NP -> name
PERSON_NP -> pronoun
PERSON_NP -> determiner worker

FLIGHT_NP -> FLIGHT
FLIGHT_NP -> FLIGHT LOC_PHRASE

FLIGHT -> flight flight_num
FLIGHT -> determiner flight

LOC_PHRASE -> SOURCE_LOC
LOC_PHRASE -> DEST_LOC

VP -> VP1
VP -> VP1 TIME_PP

VP1 -> RESERVE_VP
VP1 -> DEPART_VP
VP1 -> ARRIVE_VP
```

Parsing with ATIS stochastic semantic gramamrs



Stochastic semantic context-free grammars

The Hidden Understanding Model (HUM) system, developed at BBN, is based Hidden Markov Models (Miller et al., 1994).

In the HUM system, after a parse tree is obtained, bigram probabilities of a partial path towards the root, given another partial path are used. Interpretation is guided by a strategy represented by a stochastic decision tree . The semantic language model employs *tree structured meaning representations*: concepts are represented as nodes in a tree, with sub-concepts represented as child nodes.

$$Pr(M|W) = Pr(W|M)Pr(M)/Pr(W)$$

M: meaning

Hidden vector state model

Each vector state is viewed as a hidden variable and represents the state of a push-down automaton. Such a vector is the result of pushing non-terminal symbols starting from the root symbol and ending with the pre-terminal symbol. Non-terminal symbols correspond to semantic compositions like FLIGHTS while pre-terminal symbols correspond to semantic constituents like CITY. (He and Young, 2006)

An example of state vector representing a path for a composition to the start symbol S is:

$$\begin{bmatrix} \text{CITY} \\ \text{FROM\_LOCATION\_} \\ \text{FLIGHTS} \\ \text{S} \end{bmatrix}$$

Microsoft stochastic grammar

Semantic structures are defined by schemata. Each schema is an object (Y.Y. Wang, A. Acero, 2003).

Object structures are defined by an XML schema. Given a semantic schema, a semantic CFG is derived using templates. Details of the schemata are learned automatically.

An entity is the basic component of a schema which defines relations among entities. An entity consists of a head, optional modifiers and optional properties defined recursively so that they finally incorporate a different sequence of schema slots. Each slot is bracketed by an optional pre-amble and post-amble which are originally place holders.

Concurrent or sequential use of syntax and semantic knowledge

Semantic parsing is discussed in (Tait, 1983).

A semantic first parser is described in (Lytinen, 1992).

a *race-based* parser is described in (McRoy and Hirst, 1990).

The Delphi system (Bobrow et al., 1990), contains a number of levels, namely, syntactic (using Definite Clause Grammar, DCG), general semantics, domain semantics and action.

Rules transform syntactic into semantic representations

Recent works introduce actions in parsers for generating predicate/argument hypotheses. Strategies for parsing actions are obtained by automatic learning from annotated corpora (FrameNet, VerbNet ….)

Predicate/argument structures and parsers

Recently, classifiers were proposed for detecting concepts and roles.

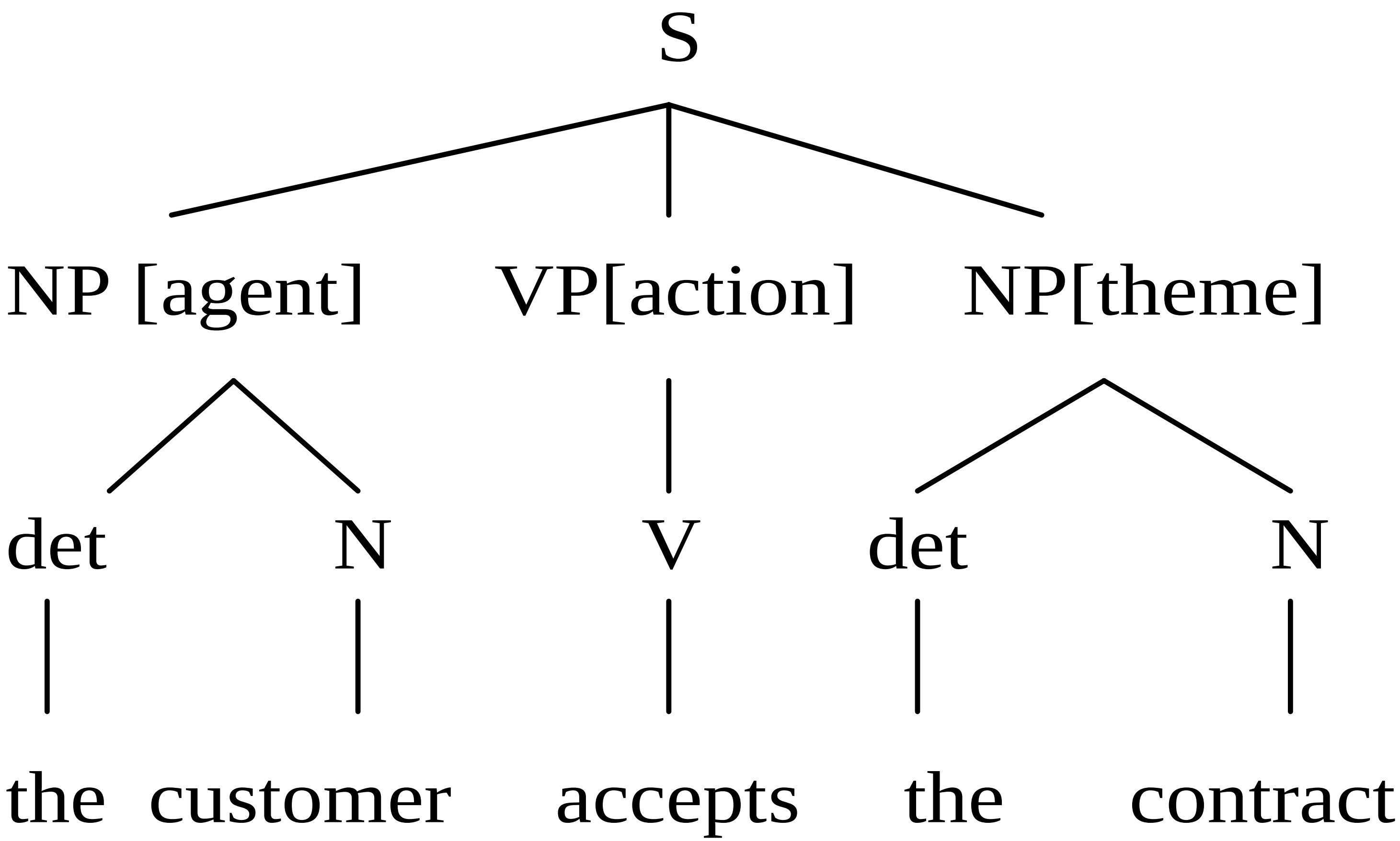
Such detection process was integrated with a stochastic parser (e.g. Charniak 2001).

A solution using this parser and tree-kernel based classifiers for predicate argument detection in SLU is proposed in (Moschitti et al. ASRU 2007).

Other relevant contributions on stochastic semantic parsing can be found in (Goddeau and Zue. 1992,   Goodman. 1996, Chelba and Jelinek, 2000, Roark, 2002, Collins, 2003)

Lattice-based parsers are reviewed in (Hall, 2005)

Semantic building actions in parsing



Use tree kernel methods for learning argument matching
(Moschitti, Raymond, Riccardi, ASRU 2007)

Important questions

There is no evidence yet that there is an approach that is superior to all others.

Where are the signs? Are they only words?

Many system architectures are ASR + NLU

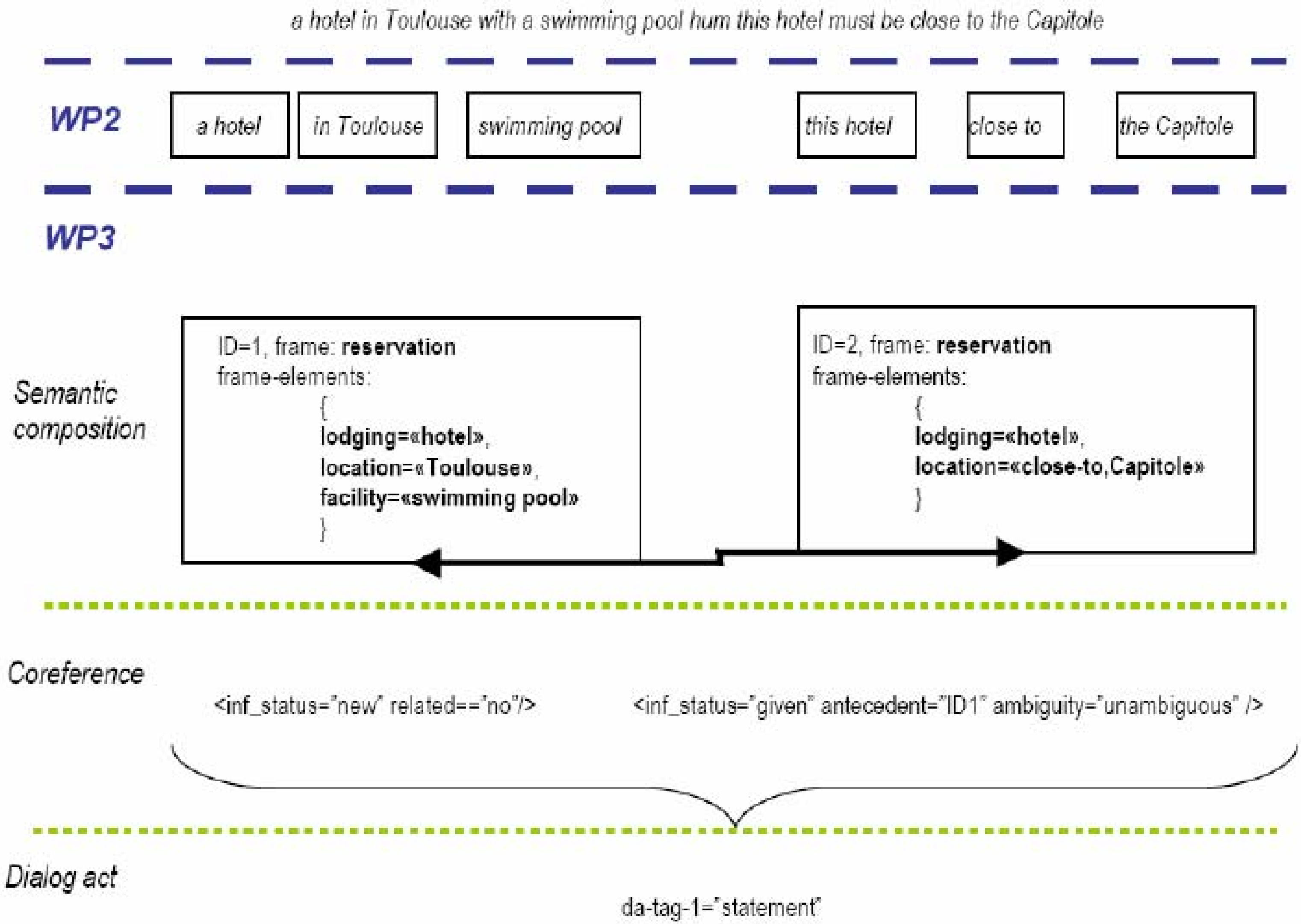
How effective is the use of syntactic structures with spoken language and ASR?

How important are inference and composition? Relevant NLU literature exists on these topics.

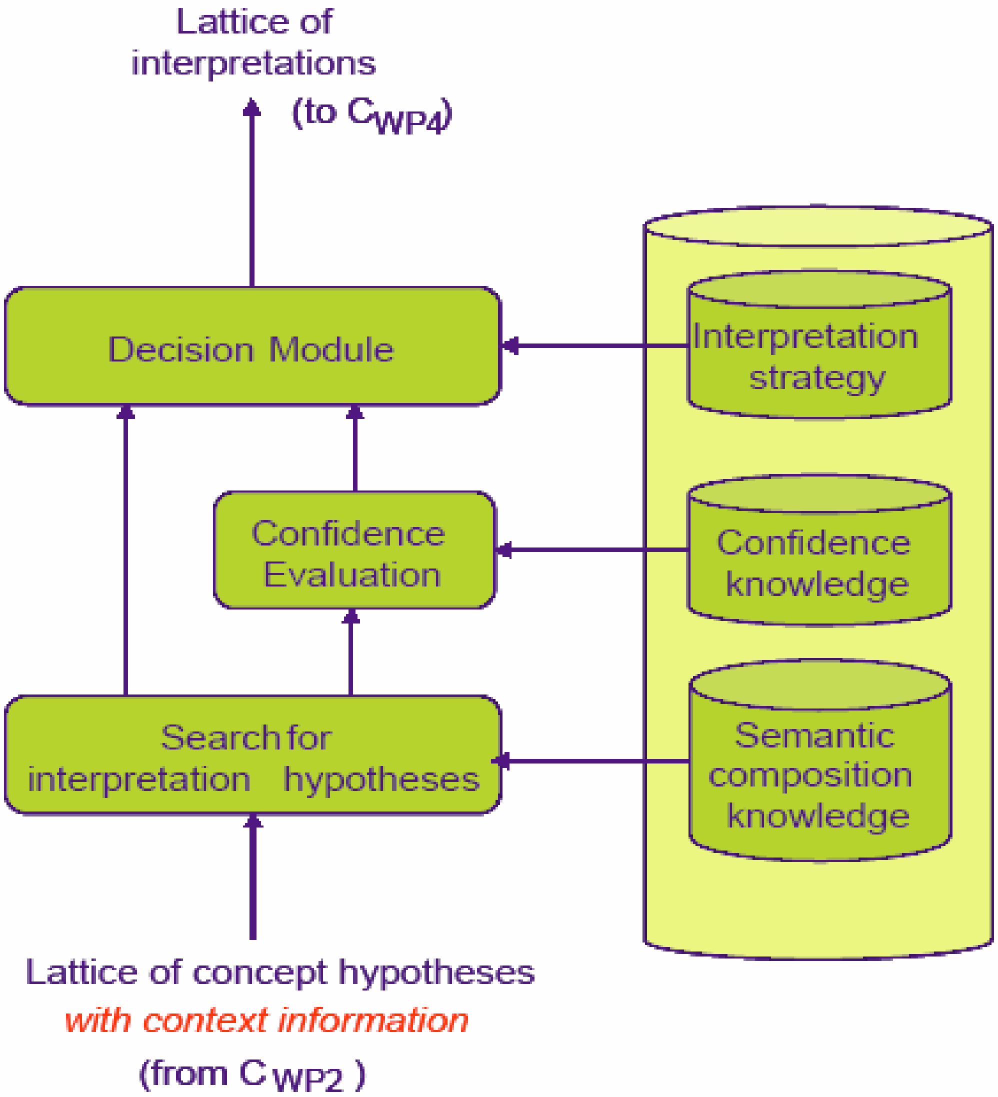
To what extent can they be used?

SEMANTIC COMPOSITION AND INFERENCE

Semantic composition and dependencies



From constituents to structures



Meaning representation models

Frame representation can be derived from semantic networks and logic
They are computational structures (Kifer et al., JACM, 1995) and also cognitive structuring devices (Fillmore, 1985) in a semantic construction theory.

In (Jackendoff 1990), major conceptual categories also called *semantic parts of speech* can be elaborated into a *function* and *arguments*.
Functions can be represented by action frames and arguments by roles

In KL-ONE (Brachman, 1978) each concept is characterized as a configuration of parts (roles) in specified relationships. Structured taxonomy with inheritance and action parts attached to concept nodes
Constraints on parts are represented by structural descriptions

Frame instances (extension)

A convenient way for asserting properties, and reasoning about semantic knowledge is to represent it as a set of *logic formulas*.

A frame instance (extension) is obtained from predicates that are related and composed into a computational structure.

Basic composition units are semantic constituents. They are hypothesized by a sequence labelling process using knowledge acquired by machine learning for which two main approaches have been followed.

Use of k-order generative probabilistic models of paired input sequences and label sequences, for instance hidden Markov models (HMMs) or multilevel Markov models. Generative models are trained to maximize the joint probability of the training data, which is not as closely tied to the accuracy metrics of interest.

Another approach views the sequence labelling problem as a sequence of classification problems, one for each of the labels in the sequence. The classification result at each position may depend on the whole input and on the previous k classifications.

The sequential classification approach can handle many correlated features, as demonstrated in work on maximum-entropy, and a variety of other linear classifiers, including winnow, AdaBoost, and support-vector machines. Furthermore, they are trained to minimize some function related to labeling error, leading to smaller error in practice if enough training data are available.

Conditional random fields (CRFs) bring together the best of generative and classification models. They can accommodate many statistically correlated features of the inputs, and they are trained discriminatively.

Conditional random fields (CRFs) bring together the best of generative and classification models. Like classification models, they can accommodate many statistically correlated features of the inputs, and they are trained discriminatively. But like generative models, they can trade off decisions at different sequence positions to obtain a globally optimal labeling.

If using different models the oracle error rate is reduced, it is worth investigating suitable combinations of methods and models for hypothesizing constituents (a sort of shallow parsing) and for composing them. Different combinations for different composition levels may lead to better results than just using a single approach.

Furthermore, useful confidence indicators can be obtained with multiple views;

LUNA FRAMES

Interpretation is problem solving performed by a composite decision process which replaces the set of attached procedures.

Problem reduction representation is context-sensitive. Many decompositions are possible involving a variety of methods and KSs, suggesting to consider a modular approach to process design.

Possible role instances are hypothesized from constituents and words. Composition is driven by the support of relations between supports of constituents (e.g. MEDIA specifiers hypothesized with CRFs)

Robustness is obtained by evaluation and possible integration of different KSs and methods used for the same sub-task.

$F_j\left[r_{jk}\left(G_x\left[r_{xk}\left(v_{xkh}\right)\right]\right)\right]$

Frame structures and slot chains

Instances of semantic structures are represented by slot chains (Koler, Pfeiffer, 1998)

$$F_j\left[r_{jk}\left(G_x\left[r_{xk}\left(v_{xkh}\right)\right]\right)\right]$$

$$\sigma\left(F_j, v_{xkh}\right) = \left\{\left(F_j, v_{xkh}\right) / \, r_{jk}\left(F_j, G_x\right) \wedge \sigma\left(G_x, v_{xkh}\right)\right\}$$

Composition

Γ_j : REQUEST.[agent(speaker), recipient (system), theme (KNOW [theme ITEM [theme (LODGING [])])])]

G_x : LODGING [ldg_structure (HOTEL[]), ldg_room (ROOM[]), ldg_lux (good)]

Obtained by inference after constituent detection

Speaker(user) $\wedge$ chambre-standing[bon] $\supset$

LODGING [ldg_structure (HOTEL[]), ldg_room (ROOM[]), ldg_lux (good)]

$\sup[R(\Gamma_j, G_x)]$

Support for Composition

REQUEST.[agent(speaker), recipient (system), theme (KNOW [theme ITEM [theme (LODGING [ldg_structure (HOTEL[]), ldg_room (ROOM[]), ldg_lux (good)])])]

Composition is performed if there is a support in the data for their relation

$$\sup \{R[\sup(\Gamma_j), \sup(G_x)]\}$$

Relation support have general word patterns (e.g. specificarion, inclusion…) which are often independent from the application domain

Soft constraints

In (Koller and Pfeffer, 1998) is noticed that one of the limits of the expressive power of frames is the inability to represent and reason about uncertain and noisy information.

In probabilistic frame-based systems, a frame slot S of a frame F is associated a facet Q with value Z: Q(F,S,V). A probability model is part of a facet as it represents a restriction on the values V.

It is possible to have a probability model for a slot value which depends on a slot chain, or, in general, on other values (Probabilistic version of structural descriptions)

Frame instance probability

It is shown (Koller, 1998) that it possible to construct a Bayesian network (BN) from a list of dependencies (F1.A<- F2.B) if the resulting dependency graph is acyclic. A Conditional Probability Table (CPT) is associated with each dependency).

The probability of a frame instance can be computed as follows:

$$P\left\{\Gamma_{i,j}, C_{i,j}, W_{i,j} \middle| Y_{i,j}\right\} = P\left[\Gamma_{i,j}\right]\left\{\prod_{k=1}^{K} \frac{P\left[W_k \middle| C_k, R(\gamma_{i,j,k})\right]}{P(W_k)}\right\} P\left[W_{i,j} \middle| Y_{i,j}\right]$$

Frame_instance , concepts_for_slots supports   relation_to_slot

Dependency graph with cycles

$Y_k \rightarrow W_k \rightarrow C_k \rightarrow \gamma_{i,j,k}$

$Y_\lambda \rightarrow W_\lambda \rightarrow C_\lambda \rightarrow \gamma_{i,j,\lambda}$

$Y_m \rightarrow W_m \rightarrow C_m \rightarrow \gamma_{i,j,m}$

Acoustic_evidence support concept filled-slot

If the dependence graph has cycles, then possible worlds can be considered. A general method for computing probabilities of possible worlds based on Markov logic networks (MLN) is proposed in (Richardson, 2006).

Probabilistic models of relational data

Probability of relational data can be estimated in various ways, depending on the data available and on the complexity of the domain.

For simple domains it is possible to use a naïve Bayes approach. Otherwise, it is possible to use the disjunctive interaction model (Pearl, 1988), or relational Markov networks (RMN) (Taskar, 2002)

Methods for probabilistic logic learning are reviewed in (De Raedt, 2003).

Frame-based resources

Predicate lexicon FrameNet (Lowe et al. 1997, Baker 1998, Fleischman 2003) ,

Verb lexicon PropBank (Palmer, 2003). ,

VerbNet (Kipper et al., 2000) is a a manually developed hierarchical verb lexicon based on the verb classification of Levin (1993). For each of 191 verb classes, including around 3000 verbs in total, VerbNet specifies the syntactic frames along with the semantic role assigned to each slot of a frame.

Semantic knowledge representation

Semantic descriptions may have connectives, co referential (descriptions attached to a slot are attached to another and vice-versa), declarative conditions. Attached procedures may perform different types of actions.

Verbs are fundamental components of natural language sentences. Roles can cases. Roles can also be properties of structured entities or arguments for functions. Descriptions based on predicate/argument structures can be derived.

Temporal representations can be made in higher order logic with lambda abstraction (Crouch and Pulman, 1993).
With procedural attachment, complex knowledge can be represented as in *schemata* (S. Narayanan, 1999)

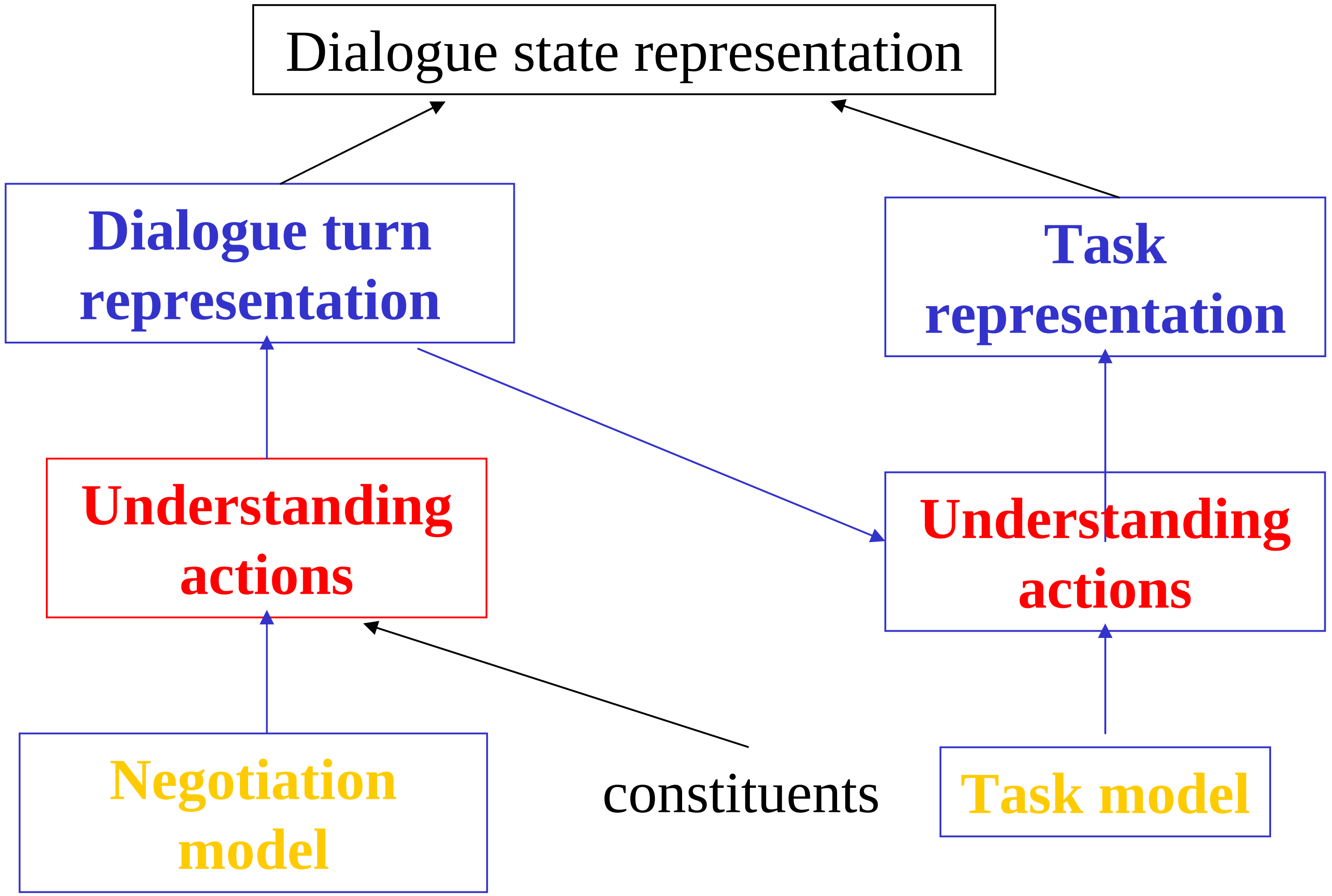
Other lexical resources

Partial parsing, also called *chunking*, is proposed for mapping the verb arguments onto subcategorization frames that can be extracted automatically, for example, from WordNet (Miller, 1995).

MindNet (Richardson et al., 1998) produces a hierarchical structure of semantic relations (*semrels*) from a sentence using a words in a machine readable dictionary.

DIALOGUE ACTS AND TASK REPRESENTATION

Short-term memory structures



Speech acts

Negotiation dialogues are characterized by a hierarchy of illocutory (speech) acts (Chang, 2004).

They are discourse actions identified by verbs, other lexical units or implied by other concepts expressed in a sentence.

These speech acts (SA) determine the sentence type. Various attempts have been made to identify SAs which are domain independent.

A possible taxonomy of them is formulated in the Dialogue Act Markup in Several Layers (DAMSL).

Speech acts

In (Cohen and Perrault, 1979), a notation of formulating dialogue acts as plan operators is proposed.

A negotiation dialogue follows a partially ordered plan represented by a Hierarchy of Tasks (HT) (Sacerdoti, ijcai75).

Each task is characterized by a SA whose effect is the instantiation, modification or finalization of conceptual structures required for performing transactions.

HT is a generative structure of possible sequences of SAs characterizing the sentences of a dialogue with which a system and a user negotiate for defining a possible transaction.

Speech acts

The main purpose of a service is to satisfy a user goal.

If a service can satisfy many goals, it has to hypothesize/identify actual user goals and, for each goal consider a mean to achieve it.

Such a mean can be a plan whose actions are executed following a policy and have the objective of gathering all the necessary details for specifying an instance of a goal which corresponds to a user intention

In the considered applicarions the goals are performing transactions and the dialogue involves negotiations represented by non-linear, partially ordered hierarchies of tasks whose possible sequences can be generated by rules

Negotiation dialogues

N_Dialogue := *Open* - Negotiation - Commit - *Close*

Negociation := Formulation (Formulation | Repair)*

Formulation := (*Assert* |Request | *Propose* | *Maybe*) (*Assert* | Request |*Propose* | *Maybe*)*

Request := (*Know* | *Reserve* | *Confirm*) (*Know* | *Reserve* | *Confirm*)*

Repair := (*Repeat* + *Hold* + *Correct*)* (*Repeat* + *Hold* *Correct* + Reject + *PartialReject*)

Commit := *Accept*

Dialogue turn representation

words	**c' est bien ça**
constituent	**command-dial[confirmation-demande]:**
Freme instance	**CONFIRM. [theme (ITEM)])]**

Task representation

SESSION [theme (TRANSACTION [], INFORMATION[])]

TRANSACTION [theme (RESERVATION[]), status (completeincomplete), proposed (Y,N)]

INFORMATION [theme (enum(LODGING []), enum (RESTAURANT [])))

RESERVATION [customer (PERSON []), theme (LODGING [] RESTAURANT []), time (PERIOD [])]

LODGING [loc [LOCATION], type [HOTEL], element [enum(ROOM)], facilities° [enum (FACILITY)], luxury° (value)]

………..

Understanding actions

REQUEST [agent (user), theme (ITEM[])] $\wedge$

$\neg$ EXIST_INSTANCE_OF (SESSION) ->

instantiate SESSION [theme INFORMATION[theme (ITEM.theme])]

where ITEM.theme is the value of the theme of ITEM

MODULAR SYSTEMS

Combinations of approaches NLU

Rule-based approaches to interpretation suffer from their brittleness and the significant cost of authoring and maintaining complex rule sets.

Data-driven approaches are robust. However, the reliance on domain-specific data is also one of the significant bottlenecks of data-driven approaches.

Combining different approaches makes it possible to get the best out of them. Simple grammars are used for detecting possible clauses, then classification-based parsing completes the analysis with inference (Kasper and Hovy, 1990).

Shallow semantic parsing was proposed by (Gildea and Jurafsky, 2002, Hacioglu and Ward, 2003, Pradhan et al. 2004)

Microsoft SLU

In (Wang et al., 2002), stochastic semantic grammars are combined with classifiers for recognizing concepts.

their combination with ROVER (the hypothesis which gets the majority of votes wins). SVM alone resulted to be the best even if ROVER is applied. Important improvement was found by replacing certain words with their semantic categories found by the parser.

Concepts detected in this way are used to filter the rules of the semantic grammar applied to find slot fillers

Colorado

A parser based on tagging actions producing non-overlapping shallow tree structures is proposed in (Hacioglu, K. (2004) , at lexical, syntactic and semantic levels to represent the language.

The goal is to improve the portability of semantic processing to other applications, domains and languages.

The new structure is complex enough to capture crucial (non-exclusive) semantic knowledge for intended applications and simple enough to allow flat, easier and fast annotation.

ATT

The use of just a grammar is not sufficient, (Bangalore et al.,) because recognition needs to be more robust to extragrammaticality and language variation in user's utterances and the interpretation needs to be more robust to speech recognition errors. For this reason, a class-based trigram LM is built with in-domain data.

In order to improve recognition rates, sentences are generated with the grammar to provide data for training the classifiers.

In (Shapire et al. 2005), authors explore the use of human-crafted knowledge to compensate for the lack of data in building robust classifiers.

IBM

In (Sarikaya et al, 2004), a system is proposed which generates an N-best (N=34) list of word hypotheses with a dialogue state dependent trigram LM and rescores them with two semantic models.

1 An Embedded context-free semantic Grammar (EG) is defined for each of 17 concepts and performs concept spotting by searching for phrase patterns corresponding to concepts.

2 A second LM, called Maximum Entropy (ME) LM (MELM), computes probabilities of a word, given the history, using a ME model.

SPEECH ACTS

Sentence boundary detection

Using prosody (Shriberg rt al., 2000)

Approaches to boundary detection have used finite-state sequence modeling approaches, including Hidden Markov Models (HMM) and Conditional Random Fields (CRF) (Roark et al. 2006)

Sentences are often short, providing relatively impoverished state sequence information.

A Maximum Entropy (MaxEnt) model that did not use state sequence information, was able to outperform an HMM by including additional rich information.

Features from (Charniak, 2000) parser were used.

Sentence classification

Call routing is an important and practical example of spoken message categorization.

In applications of this type, the dialog act expressed by one or more sentences is classified to generate a *semantic primitive action* belonging to a well defined set.

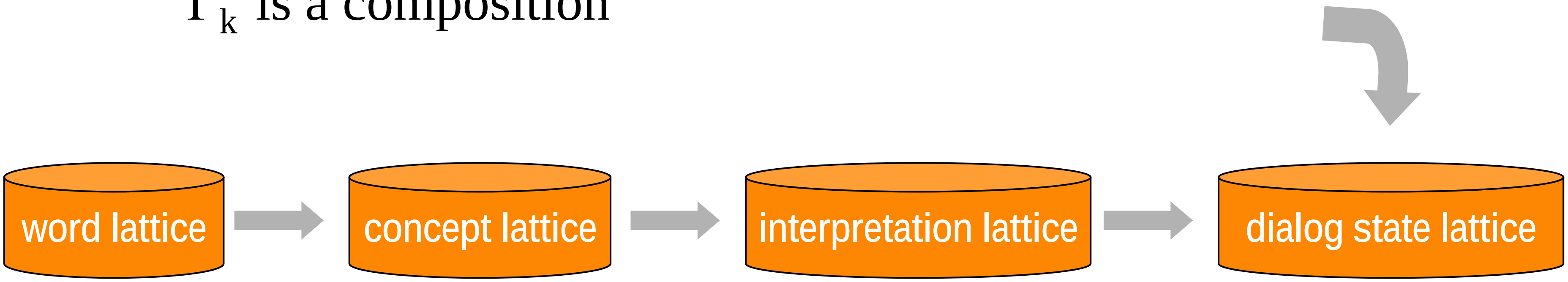
- Connectionist models (Gorin et al. 1995)
- SVD (Chu-Carroll and Carpenter, 1999)
- Latent Semantic Analysis (LSA) (Bellegarda 2002)
- SVM, cosine similarity metric (used in IR) and Beta-classifier (IBM, 2005, 2006)
- Cluster of sentences is proposed in (He and Young, 2006)

FT/LIA System 3000

Béchet et al. ICASSP 2007

Γ_k is a composition

$$P(S_k|\Gamma_k S_{k-1})$$



$$P(S|Y) = \sum_{\Gamma} P(S\Gamma|Y) = \sum_{\Gamma} P(S_k\Gamma_k|H_kY)P(H_k|Y)$$

$$P(S_k\Gamma_k|H_kY) \approx P(S_k|\Gamma_k S_{k-1}) \times \max_{W_k, C_k} P(\Gamma_k|C_k)P(C_k|W_k)P(W_k|Y_k)$$

CONFIDENCE AND LEARNING

unsupervised semantic role labelling

Interpretation modules have parameters estimated by automatic learning (Chronus, Chanel, HUM and successor systems)

Semantic annotation is time consuming. The process should be semi-automatic starting with bootstrapping (e.g., Hindle and Rooth, 1993; Yarowsky, 1995; Jones et al., 1999)

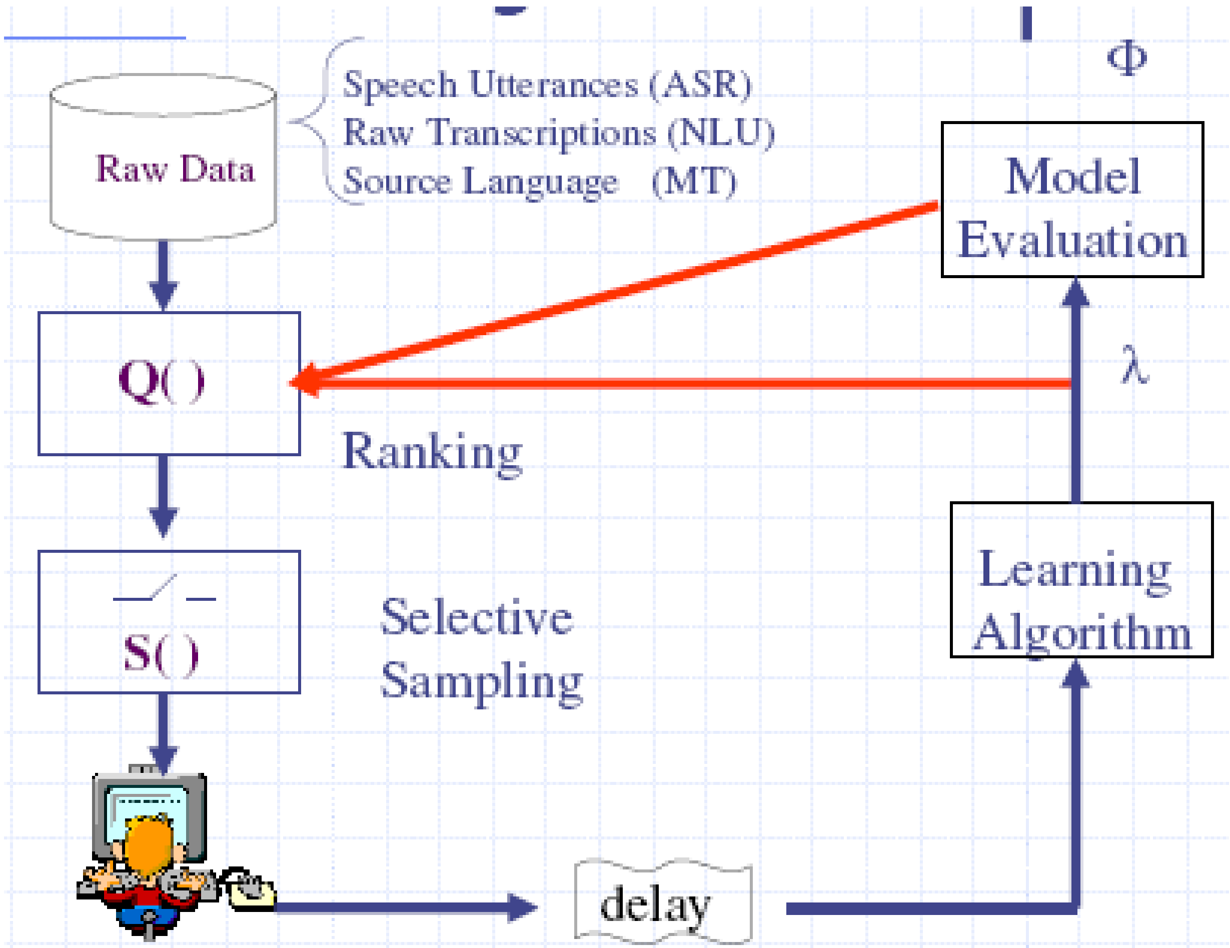
Initially make only the role assignments that are unambiguous according to a verb lexicon ((Kate and Mooney, 2007).

A probability model is created based on the currently annotated semantic roles.

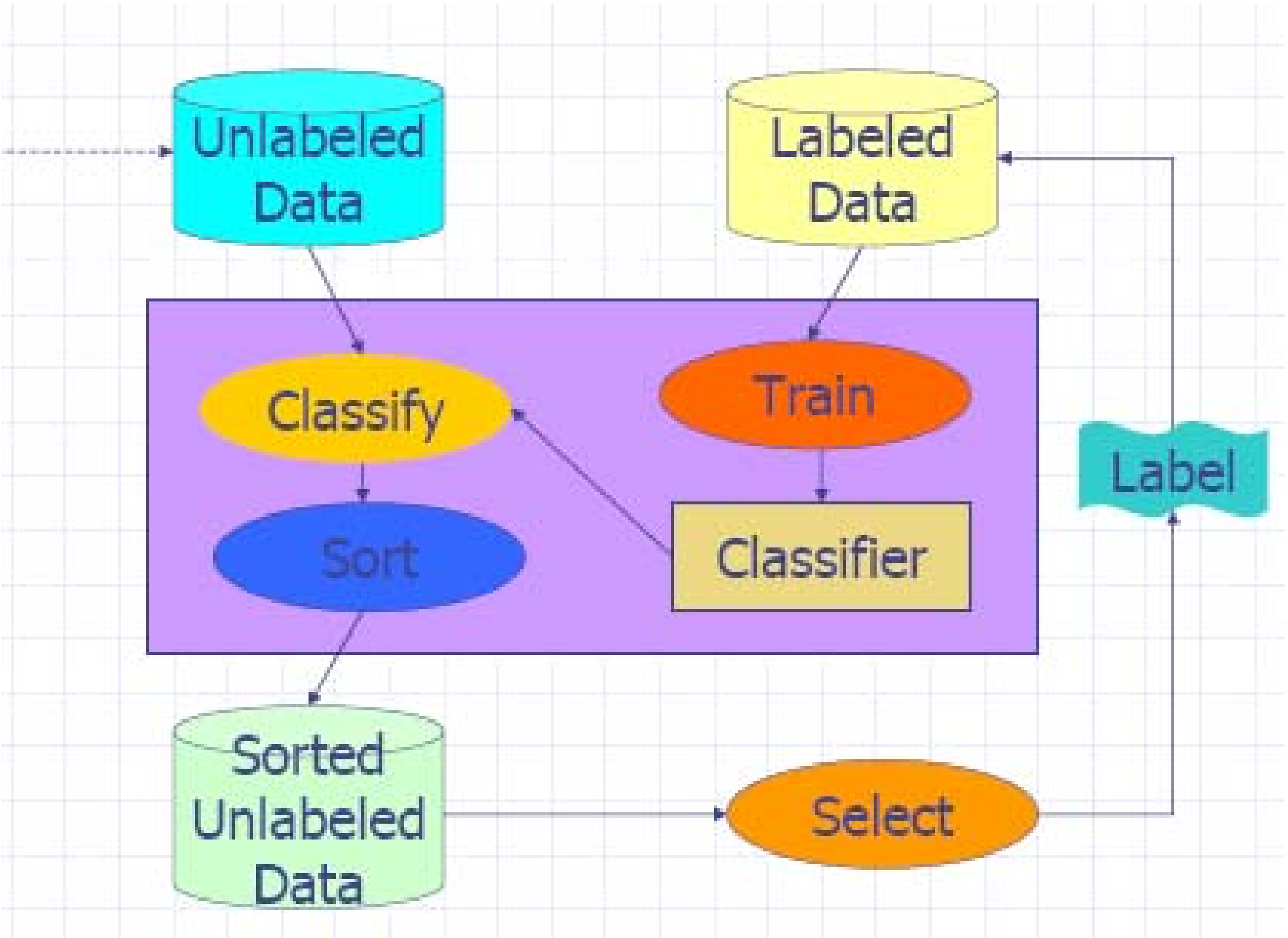
When unlabeled test examples are also available during training, a transductive framework for learning can further improve the performance on the test examples

Active Learning

Hakkani-Tür, Riccardi Gorin, 2002)



Certainty-Based Active Learning for SLU



Confidence

Evaluate confidence of components and compositions

$$P(\Gamma|\Phi_{conf})$$

Φ_{conf} represents the confidence indicators or a function of them.

Notice that it is difficult to compare competing interpretation hypotheses based on the probability $P(\Gamma|Y)$ where Y is a time sequence of acoustic features, because different semantic constituents may have been hypothesized on different time segments of stream Y.

Confidence measures

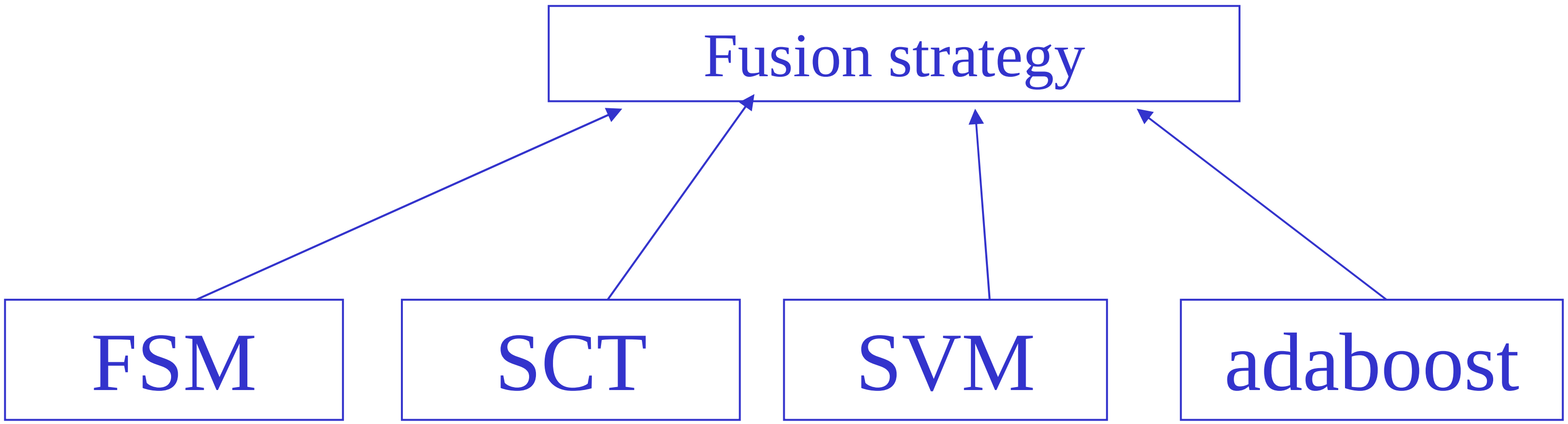
Two basic steps:

1) generate as many features as possible based on the speech recognition and/or natural language understanding process and

2) Estimate correctness probabilities with these features, using a combination model.

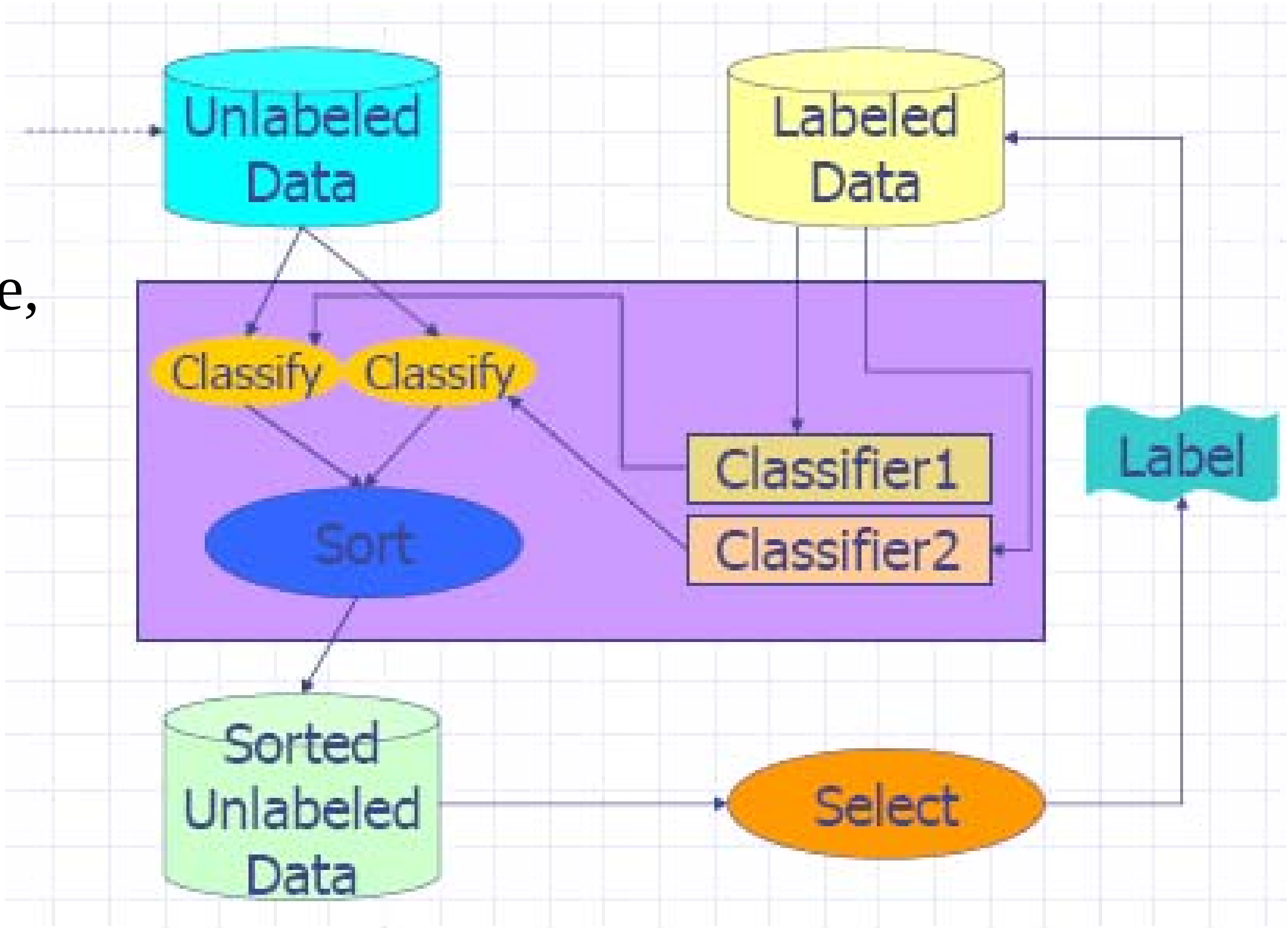
Define confidence-related situations

Consensus among classifiers and SFST is used to produce confidence indicators in a sequential interpretation strategy (Raymond et al. 2005, 2007). Classifiers used are SCT, SVM, adaboost. Committee-Based Active Learning uses multiple classifiers to select samples (Seung et al. 1992)



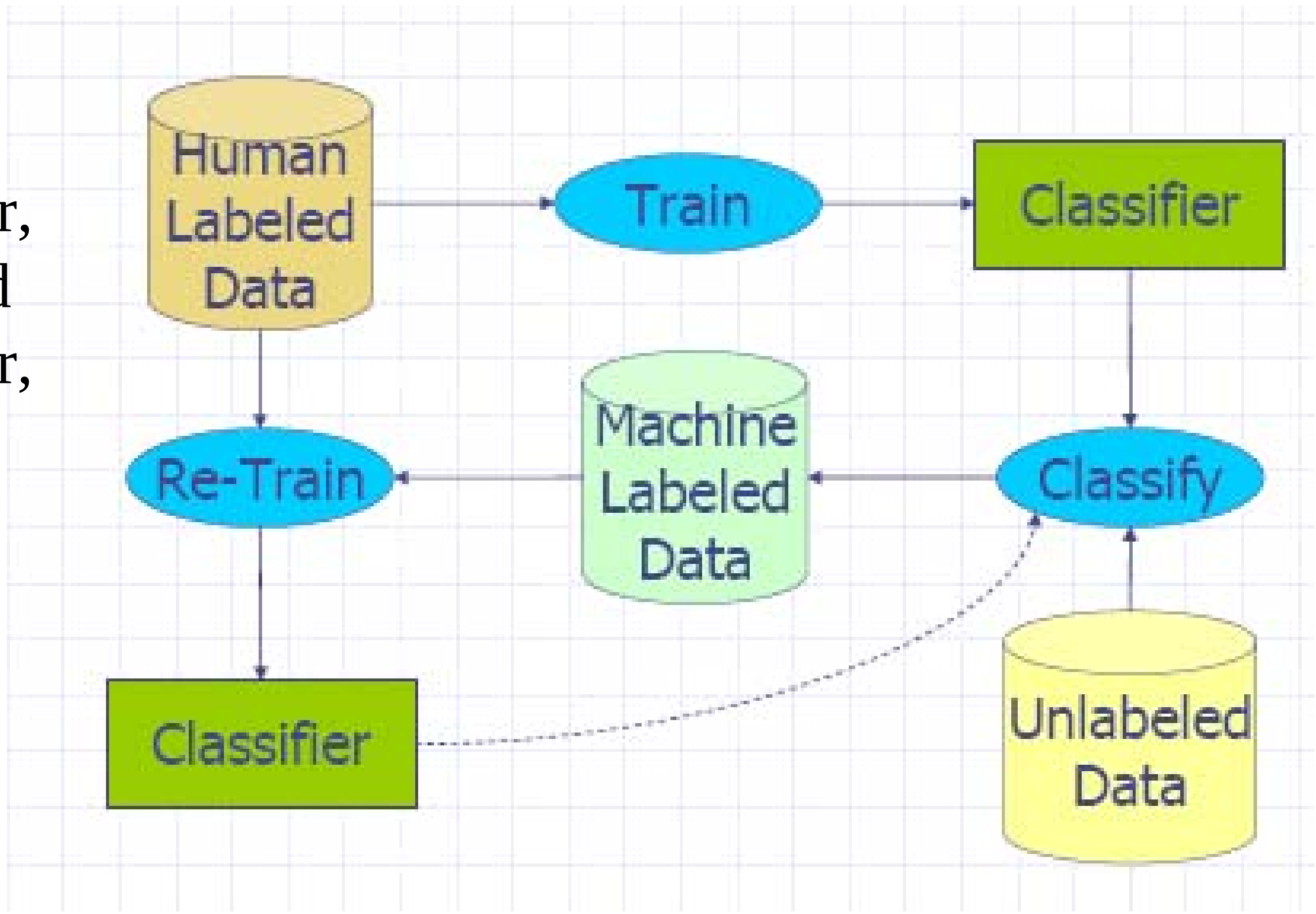
Committee-Based Active Learning

Call classification (Tur, Schapire, and Hakkani-Tür, 2003)



Unsupervised Learning

(Tur and Hakkani-Tür, Riccardi and Hakkani-Tür, 2003)



Co-Training

Assume there are multiple views for classification

1. Train multiple models using each view

2. Classify unlabeled data

3. Enlarge training set of the other using each classifier's predictions

4. Goto Step 1

Combining Active and Unsupervised Learning

Train a classifier using initial training data

While (labelers/data available) do

Select *k* samples for labeling using active learning

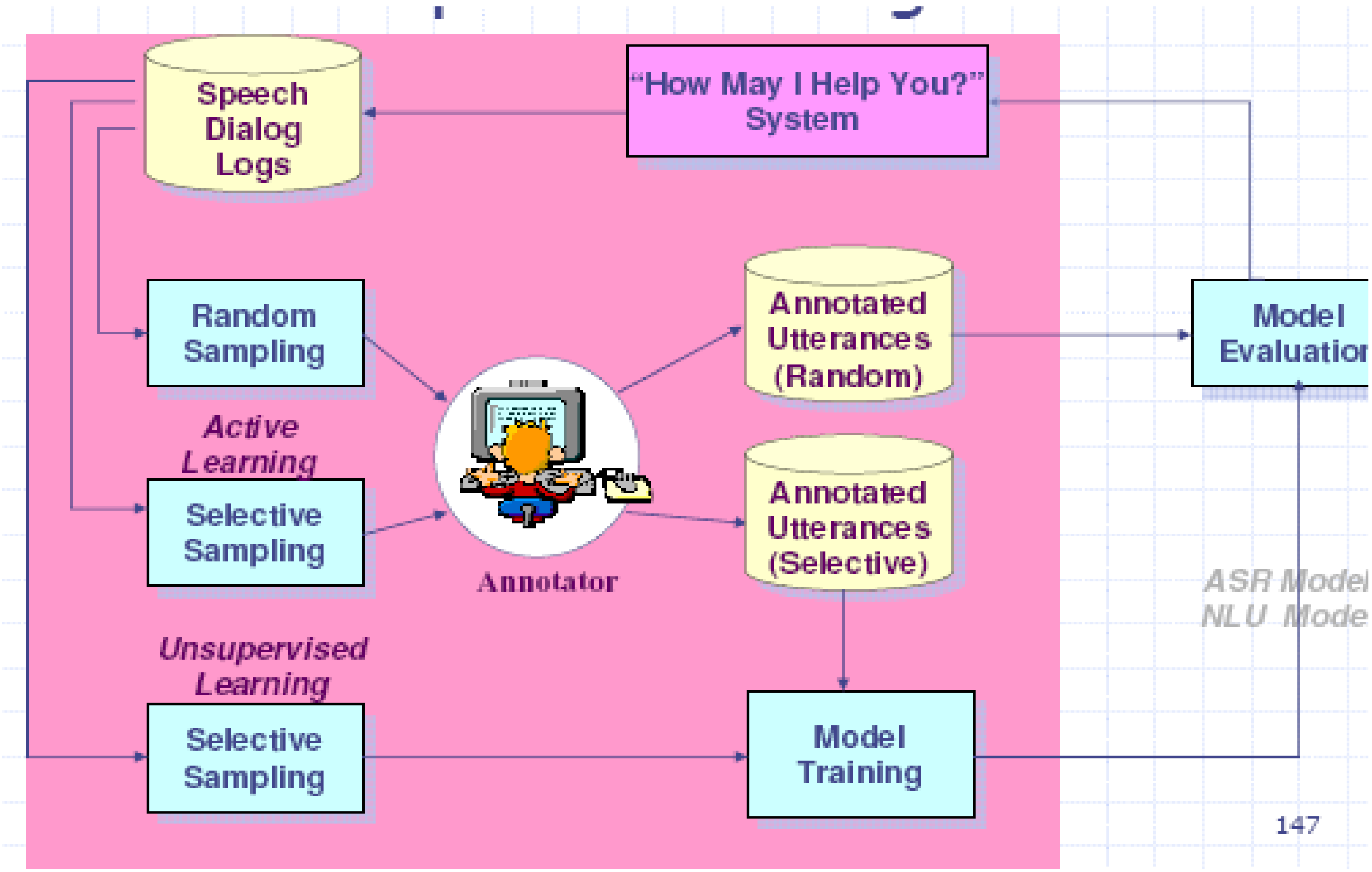
Label and add these selected ones to the training data and retrain

Exploit the unselected data using unsupervised learning

Update the pool.

Adaptive Learning in Practice

(Riccardi et al, 2005)



Solutions for applications

The simple use of semantic constituents is sufficient for applications such as call routing, utterance classification with a mapping to disjoint categories and perhaps to speech-to-speech translation and speech information retrieval.

Semantic composition is useful for applications like spoken opinion analysis, call routing with utterance characterization (finer-grain comprehension), question/answering, inquiry qualification.

A broad context is taken into account for context-sensitive validation in complex spoken dialog applications and inquiry qualification considering an utterance as a set of sub-utterances and the interpretation of one sub-utterance being context-sensitive to the others.

Conclusions

A modular SLU architecture can exploit the benefits of combined use of CRFs, classifiers and stochastic FSMs, which are approximations of more complex grammars.

Grammars should perhaps be used in conjunction with processes having inference capabilities.

Recent results and applications of probabilistic logic appear interesting, but its effective use for SLU still has to be demonstrated.

Annotating corpora for these tasks is time consuming suggesting that it is suitable to use a combination of knowledge acquired by a machine learning procedures and human knowledge.

Conclusions

Robustness,
incremental learning,
portability
are important and open issues.

SLU is not only used in human-machine dialogs. Other applications are for opinion analysis, indexing, summarization, retrieval.

When SLU is used in dialog, interpretation strategies should provide hypotheses with confidence indicators, taking into account dialogue context, communication principles, types of actions and goals, types of sources.

THANK YOU