SEMANTIC INTERPRETATION WITH ERROR CORRECTION

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\section*{ABSTRACT}

This paper presents a semantic interpretation strategy, for Spoken Dialogue Systems, including an error correction process. Semantic interpretations output by the Spoken Understanding module may be incorrect, but some semantic components may be correct. A set of situations will be introduced, describing semantic confidence based on the agreement of semantic interpretations proposed by different classification methods. The interpretation strategy considers, with the highest priority, the validation of the interpretation arising from the most likely sequence of words. If the probability, given by our confidence score model, that this interpretation is not correct is high, then possible corrections of it are considered using the interpretations emerging from the other sequences in the N-best lists.

This strategy is evaluated on a dialogue corpus provided by France Telecom R&D and collected for a tourism telephone service. Significant reduction in understanding error rate are obtained as well as powerful new confidence measures.

\section*{1. INTRODUCTION}

In a previous paper [1], a method has been proposed for obtaining interpretations of spoken sentences using stochastic finite state transducers (SFST). With these transducers an ordered set of N-best lists is obtained with concept-dependent language models (LM). Each list contains sequences of words which generate the same semantic interpretation but may have different acoustic and linguistic confidence. Semantic interpretations may be incorrect, but some semantic components may be correct. It is then useful for the dialogue manager to have the probability that each interpretation component is correct. This probability should be reliably estimated from situations describing the confidence with which results have been obtained. A set of situations will be introduced, describing semantic confidence based on the agreement of semantic interpretations proposed by different classification methods: decision-tree based classifiers (Semantic Classification Trees, SCT [2]) and large-margin classifiers using boosting (BoosTexter [3]) and Support Vector Machines (SVM-Torch, [4]).

In [5] a method has been proposed for computing the probability that an interpretation $\Gamma$ obtained from each sentence in a n-best list of conceptual interpretations is correct given the rank of the sentence and a set of acoustic, linguistic and semantic confidence features. The computation of this probability is often highly imprecise. A better strategy for selecting an interpretation is introduced in this paper by taking into account the results of redundant interpretation processes using different classifiers, using confidence measures taken mostly just on the words that support the generation of semantic constituent hypotheses. The interpretation strategy considers, with the highest priority, the validation of the interpretation arising from the most likely sequence of words. If the probability that this interpretation is not high, then possible corrections of it are considered using the interpretations emerging from the other sequences in the N-best lists.

\section*{2. KNOWLEDGE REPRESENTATION AND USE}

The type of applications considered in this paper are telephone services in which a user performs requests to a system. Following definitions and notations in [6], an example of user request is represented by an instance of a speech act of the type:

\begin{verbatim}
REQUEST(user,service,
INFORMREF(user,service,x,
(SATISFIES(Restaurant(x)),Path(PTH))))
\end{verbatim}

where REQUEST indicates an illocutionary speech act, user and service are the conversant entities, INFORMREF is a propositional content expressing the constraints of the request. In this example, the constraints apply to the request for instances $x$ of the semantic structure Restaurant in an area described by an instance PTH of the semantic structure Path. Other types of speech acts are INFORM, QUESTION.

In order for the service dialogue strategy to provide a suitable action, the speech understanding subsystem (SUS) has to hypothesize the type of dialogue act, and the propositional content. For this particular type of application, the conversant entities are constant and it may not be necessary to identify the user, although having some information about him/her might be useful.

The propositional content is obtained by the interpretation strategy of the SUS which generates the instance PTH and the fact that there is a request about a restaurant whose answer should satisfy PTH. Generation of semantic interpretation is a process of evidential reasoning in which composition and inference are based on semantic knowledge expressed by an appropriate formalism and on probabilities for computing the likelihood of a result given the imprecision of hypotheses and knowledge.

Most of the approaches proposed so far for Spoken Language Understanding (SLU) integrate semantic knowledge into a context-free semantic grammar and propose different algorithms for computing the probability $P(\Gamma, W)$ of a conceptual structure $\Gamma$ and a sequence of words $W$ [7, 8, 9]. Context-free semantic grammars

\begin{verbatim}
\section*{\textsuperscript{1}This research is supported by France Telecom’s R&D under the contract 021B178}
\end{verbatim}
have nonterminal symbols which represent semantic structures and can be rewritten into non-overlapping sequences of words.

Interesting books [10, 11] describe various types of semantic knowledge and their use. A common aspect of many of them is that it is possible to represent complex relational structures with non-probabilistic schemes that are more effective than context-free grammars. For example, in K-LONE [12] concept descriptions account for the internal structure with Role/Filler Descriptions, called Roles and for a global Structural Description (SD). Roles have substructures with constraints specifying types and quantities of fillers. SDs are logical expressions indicating how role fillers interact. Role descriptions contain value restrictions. Epistemological relations are defined for composing conceptual structures. They may connect formal objects of the same type and account for inheritance. It is important to point out that semantic knowledge is, in general, context-sensitive.

Instances containing token values are the basis for the inference performed by the dialogue strategy. The inference process uses ontologies and relations among semantic components and is based on algorithms for theorem proving or spreading activation on semantic networks. It is worth noticing that for representation formalisms like KL-ONE, inheritance can take place for concepts, roles as well as structural descriptions. Automatic reasoning is performed with these schemes using methods such as theorem proving, rule chaining or spreading activation. Evidential reasoning with these methods appear to be complex and often not feasible in a rigorous way.

3. SPEECH UNDERSTANDING STRATEGY

Following the semantic models presented in the previous section, the first step in the semantic interpretation process is to detect and extract the concepts (or speech acts) needed in order to fill the semantic structure considered. These concepts represent speech acts like:

- request_for_help, ask_for_repeat, ask_for_information,
- access_list_item, confirmation, negation, . . .
- and entities that are associated with specific values:
- restaurant_location, specialties, price, time, . . .

In order to detect such concepts from the ASR output, we use two kinds of models:

- text classifiers that are trained to label a string of words with one or several concept tags;
- regular grammars coded as Finite State Machines (FSMs), only on the concepts representing the entities with values. There is one FSM for each kind of entity (price, specialties, . . . ) that models all the different values accepted by the entity.

The general Speech Understanding strategy, presented in figure 1, can be described as follows:

1. the ASR module outputs a word graph;
2. a Structured N-best list of hypotheses [1] is extracted from the word graph, containing the n-best conceptual interpretations contained in the word graph as well as the n-best word hypothesis for each interpretation
3. the best hypothesis of the first interpretation is selected as the reference hypothesis W_{1,1};
4. each classifier processes W_{1,1} in order to output a string of concept tags;
5. a decision rule checks the agreement between the classifiers on the concept strings outputs;
6. if all classifiers agree, W_{1,1} with its concept string is transferred to the dialogue manager in order to build the semantic representation of the utterance;
7. if no total agreement is reached, an error correction module looks for the most reliable correction of W_{1,1} within the Structured N-best list. A score is given to the chosen correction, the utterance can be rejected according to a threshold on this score.

Before presenting the probabilistic model behind our error correction module, we describe first in the next section the classification tools used in the decision process.

4. SPEECH UNDERSTANDING WITH TEXT CLASSIFIERS

Several studies have shown that text classification tools (like Support Vector Machines or Boosting algorithms) can be an efficient way of labeling an utterance transcription with a semantic label such as a call-type [13] in a Spoken Dialogue context. This approach has two main advantages: firstly, the amount of human supervision is limited as no keywords or grammars have to be defined in order to characterize a concept. The only manual data needed is a training corpus containing, for each utterance, the string of concepts occurring in it. Secondly, classifiers are more robust to the noise generated by ASR errors and spontaneous speech effects. Indeed, they can be trained directly from ASR output and therefore model this noise.

In the proposed strategy we use three kinds of classifiers: a decision-tree based classifier (Semantic Classification Trees or SCT [2]) and two large-margin classifiers, one based on Support Vector Machine (SVM-Torch, [4]) and one implementing a boosting method of weak classifiers (BooTexter [3]). Because these tools are based on different classification algorithms with different input formats (bag-of-words or word-strings for example), they don’t always use the same information in order to characterize a label. Therefore, using them simultaneously and defining a voting decision rule, can increase the classification robustness.

![Fig. 1. Architecture of the error correction strategy](image-url)
5. ERROR CORRECTION PROBABILITIES

We present here the probabilistic model behind the error correction strategy presented in section 1.

Let $\Gamma_1$ be the most likely interpretation from the Structured N-best list and $W_{1.1}$ be the most likely sequence of words corresponding to $\Gamma_1$. Better semantic hypotheses have to be searched for in the other word sequence candidates only when there is a high probability that this search results in a better interpretation. It is thus important to find conditions for evaluating the probability that $\Gamma_1$ is correct. Furthermore, even when $\Gamma_1$ is incorrect, it is likely that it is partially correct and a better interpretation has to be found as a correction of the errors in $\Gamma_1$.

Let us consider only modifications $\Gamma_c = m_c(\Gamma_1)$. $\Gamma_c$ is an alternative in the Structured N-best list to $\Gamma_1$. The differences between these two interpretations (called modifications $m_c$) are insertions, substitutions or deletions of concepts between $\Gamma_1$ and $\Gamma_c$. Let $W_{c.1}$ be the best sequence of words expressing $\Gamma_c$.

In principle, semantic interpretations $\Gamma$ should be scored with the following probability, with $Y$ being the speech signal and $W_y$ the word graph:

$$P(\Gamma | Y) = P(\Gamma | W_y)P(W_y | Y)$$  (1)

The following approximation is proposed to find the best interpretation:

$$P(\Gamma_c | W_y) \approx P\{m_c | \Gamma_1, W_{1.1}, S_1, F(W_{1.1}, W_{c.1})\}$$

$$P(\Gamma_1 | W_y) \approx P\{\epsilon | S_1, F(W_{1.1})\}$$  (2)

$S_1$ is a confidence predicate about $\Gamma_1$. It is defined by agreement rules between the classifiers as presented in figure 1. Two levels of confidence are defined: high confidence ($\text{High}$) if all classifiers agree and low confidence ($\text{Low}$) if they don’t. $W_y$ is represented by $W_{1.1}$ and a set of measures or confidence predicates $F$ taken on $W_{1.1}$ and $W_{c.1}$. The confidence measures $F$ include acoustic and linguistic features as described in [5]. $\epsilon$ means that no correction is done on $\Gamma_1$.

Error correction $I_q$ can be seen as special type of inference in which a new interpretation $T_q(\Gamma_q)$ is obtained from the interpretation $\Gamma_q$ when some premise $P R_q$ is true. The general form for the q-th type of error correction is:

$$I_q : T_q \land P R_q \rightarrow T_q(\Gamma_q)$$

where $P R_q$ are expressions conditioning the application of a correction.

If corrections apply only to $\Gamma_1$, then: $\Gamma_q = \Gamma_1$ and $I_q = m_c(\Gamma_1)$. On the other hand, $I_q = \epsilon(\Gamma_1)$ means that $\Gamma_1$ is accepted.

Decision on applying corrections depends on the following probability:

$$P(T_q | P R_q) = \frac{P(P R_q | T_q)P(T_q)}{P(P R_q | T_q)P(T_q) + P(P R_q | \neg T_q)P(\neg T_q)}$$  (3)

where $\neg$ means negation.

All these probabilities are learned on a development corpus in the following way: firstly, a Structured N-best list is estimated on each utterance of the corpus. Secondly, each hypothesis of these lists is labeled with a tag indicating that the interpretation attached to the hypothesis is correct or not and with a set of confidence measures, as presented in [5]. Finally a decision-tree training is performed on these labeled hypotheses in order to separate the correct interpretations from the wrong ones.

Decision is based on the value of $P(T_q = \epsilon(\Gamma_1) | P R_q)$. Each path in the decision tree corresponds to a premise $P R_q$.

Each leaf has also associated counts from which the probability $P(T_q = \epsilon(\Gamma_1) | P R_q)$ can be estimated. If the probability is greater than a threshold, then $\Gamma_1$ is considered to be correct. If the probability that $\Gamma_1$ is correct is too low, then we look for the $T_q$ which maximizes the probability $P(T_q | P R_q)$. According to the probability obtained we can decide to either accept the correction or reject the utterance.

6. EXPERIMENTAL RESULTS

Experiments were carried out on a dialogue corpus provided by France Telecom R&D and collected for a tourism telephone service. The task has a vocabulary of 2200 words. The language model used is made of 44K words. The interpretation strategy was inferred using a development corpus containing 2.1k utterances. Performance was evaluated on a test corpus containing 1.7k utterances. The Word Error Rate (WER) on the development and test corpora, considering the best word sequence obtained only with the generic LM, were 25.83% and 26.98% respectively. The measure considered here is the Understanding Error Rate (UER) that is related to the tags and the values of the concepts detected. 15 concept tags are used in these experiments. In order to evaluate the performance of the classifiers alone, a Classification Error Rate (CER) has also been evaluated that just takes into account the concept tags but not their values.

<table>
<thead>
<tr>
<th>test</th>
<th>ref</th>
<th>asr</th>
<th>coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>best class</td>
<td>3.2%</td>
<td>9.6%</td>
<td>100%</td>
</tr>
<tr>
<td>agreement</td>
<td>-</td>
<td>5.8%</td>
<td>72%</td>
</tr>
</tbody>
</table>

Table 1. Classification Error Rate (CER) on the concept tags obtained by the best text classifier and by the agreement of all the classifiers. ref is the reference transcription of the utterances, asr is the output of the ASR module, coverage is the percentage of the corpus on which the classification results are given

Table 1 shows the CER results, on the test corpus, by means of the best text classifier. As we can see the performance is excellent on the reference transcriptions (around 97% of the tags are correct). This indicates that text classifiers are well suited for this understanding task. The drop in performance due to the noise generated by the ASR errors is also a strong indicator that a correction strategy needs to be added in order to recover some of these errors. If we look at the classification rate of the utterances that received a High confidence label (agreement of all the classifiers), we obtain a CER of 5.8% and the percentage of occurrences labeled with High confidence is 72%. This indicates that the agreement rule among the classifiers is a powerful confidence measure.

Table 2 presents the UER results obtained at different steps in our strategy: the column High shows the performance of the agreement decision rule (among the different classifiers). 72% of the test corpus utterances have been labeled with a high confidence. In this case we keep the first hypothesis extracted from the Structured N-best list (named $\Gamma_1, W_1$) and the UER on these utterances is only 6.2% (5% on the development corpus). On the other utterances, labeled with a Low confidence, the UER without error correction is 23.6% (27.2% on the development corpus). This result clearly
shows that agreement between classifiers is a very good predicate for estimating the confidence of an hypothesis.

By applying the error correction strategy presented in this paper, the UER drops to 18%, which is a relative improvement of 23.7% (34% of relative improvement on the development corpus). The overall drop in understanding errors is about 10% on the whole test corpus and 23% on the whole development corpus.

Furthermore we can use \( P(I_q | P_{Rel}) \) presented in section 5 in order to implement a rejection strategy: by fixing a threshold \( \delta \) on this probability, we can reject utterances that are labeled with low confidence. When all possible corrections \( I_q \) have a probability lower than \( \delta \), we can use this rejection strategy to estimate the best correction possible according to a set of acoustic, linguistic and semantic confidence measures is applied to the 1-best concept and word hypothesis. Results obtained on a dialogue corpus provided by France Telecom R&D and collected for a tourism telephone service show significant reduction in understanding error rate. Moreover, the error correction probabilities prove to be efficient new confidence measures that can be used in an utterance rejection decision rule.

8. REFERENCES


Table 2. Understanding Error Rate (UER) according to the conﬁdence given by the classiﬁers (High or Low) and the strategy used: \( (\Gamma_1, W_i) \) means that the 1-best hypothesis is chosen, \( (\Gamma_c, W_c) \) means that the error correction strategy is applied (only on the Low conﬁdence utterances). size indicates the % of the corpus labeled with High or Low conﬁdence. All reports the overall error correcting performance.

<table>
<thead>
<tr>
<th>Conf</th>
<th>High</th>
<th>Low</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Γ1, W1</td>
<td>6.2%</td>
<td>74.3%</td>
<td>100%</td>
</tr>
<tr>
<td>Γ2, W1</td>
<td>27.2%</td>
<td>25.7%</td>
<td>100%</td>
</tr>
<tr>
<td>Γ3, W1</td>
<td>17.8%</td>
<td>11.3%</td>
<td>9.7%</td>
</tr>
<tr>
<td>Γ1, Wc</td>
<td>10.9%</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Γ2, Wc</td>
<td>8.4%</td>
<td>25%</td>
<td></td>
</tr>
<tr>
<td>Γ3, Wc</td>
<td>9.7%</td>
<td>17.8%</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Conf</th>
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</thead>
<tbody>
<tr>
<td>Γ1, W1</td>
<td>100%</td>
<td>8.4%</td>
<td>72%</td>
</tr>
<tr>
<td>Γ2, W1</td>
<td>23.6%</td>
<td>28%</td>
<td>100%</td>
</tr>
<tr>
<td>Γ3, W1</td>
<td>18%</td>
<td>11.3%</td>
<td>9.7%</td>
</tr>
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</table>

Fig. 2 Understanding Error Rate vs. Utterance Rejection Rate with the error correction strategy on the test corpus

This rejection strategy is evaluated on figure 2 on the test corpus. As we can see, by fixing an operating point at 10% utterance rejection rate, the UER drops from 9.7% to 7.2% which is relative improvement of about 25%.

7. CONCLUSION

This paper presents an error correction strategy applied to semantic interpretation of utterances in a Spoken Dialogue context. Several classifiers are used in order to give confidence labels to interpretations output by the Spoken Language Understanding module. If the confidence is low, a decision-tree speciﬁcally trained in order to estimate the best correction possible according to a set of acoustic, linguistic and semantic conﬁdence measures is applied to the 1-best concept and word hypothesis. Results obtained on a dialogue corpus provided by France Telecom R&D and collected for a tourism telephone service show signiﬁcant reduction in understanding error rate. Moreover, the error correction probabilities prove to be efficient new conﬁdence measures that can be used in an utterance rejection decision rule.