A Machine Learning Approach to the Classification of Dialogue Utterances

Toine Andernach
Parlevink Group, Department of Computer Science
University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands
anderlac@cs.utwente.nl

Abstract. The purpose of this paper is to present a method for automatic classification of dialogue utterances and the results of applying that method to a corpus. Superficial features of a set of training utterances (which we will call cues) are taken as the basis for finding relevant utterance classes and for extracting rules for assigning these classes to new utterances. Each cue is assumed to partially contribute to the communicative function of an utterance. Instead of relying on subjective judgments for the tasks of finding classes and rules, we opt for using machine learning techniques to guarantee objectivity.

1 Introduction

In tasks such as determining a taxonomy of dialogue acts or a set of rules for assigning dialogue acts to utterances, researchers often rely on subjective judgments or on classifications already available in literature (Hinkelman 1990), (Seligman, Fais & Tomokiyo 1994), (Litman & Passonneau 1995), (Carletta 1996 (forthcoming)).

In this paper, we will present an alternative approach to dialogue act classification in which as many classification decisions as possible are taken automatically, i.e. without intervention of a human being. The advantages of this approach over more traditional approaches are the consequent behavior of the machine and the ability to combine different knowledge sources much faster than people can. Our approach differs from superficial approaches like (Hinkelman 1990), (Seligman et al. 1994) and Schmitz & Quantz (1995) in that the the set of dialogue acts and dialogue act rules are automatically learned from a training corpus by machine learning techniques.

In section 2 we will first give a brief description of the context of the research, the SCHISMA project. In section 3 and 4 we will discuss the role of surface linguistic information relevant for dialogue act classification in general and in SCHISMA respectively. Section 4 also presents cue patterns as a means for objectively representing surface linguistic information.

In our approach, cue patterns are the input for an unsupervised classification algorithm which outputs classes of cue patterns and which is discussed in section 5.1. These classes, together with the cue patterns are input for a supervised classification algorithm discussed in section 5.2. This algorithm derives rules which describe the classification yielded by unsupervised learning. The number and complexity of the rules can be used as a measure of the quality of the classification yielded by unsupervised learning. Sections 6 and 7 contain conclusions and future work respectively.

2 The context: the SCHISMA project

In SCHISMA we aim at developing a natural language keyboard dialogue system which interfaces a database containing information about theater performances. The interface should allow
people to enquire about performances in general, to tune in to a specific performance and, if desired, make a reservation for this performance. Research until now has concentrated on various aspects of realizing such a theater information and booking system such as the building of a Wizard of Oz environment for the acquisition of a corpus of dialogues for this domain, analysis and tagging of the dialogue corpus, recognition of domain-specific concepts, syntactic analysis and dialogue modeling. The utterances used as examples in this paper are all taken from the corpus of simulated man-machine dialogues yielded by the Wizard of Oz experiments.

In SCHISMA, we consider a dialogue to be a sequence of turns of two speakers. The word Speaker is used in the general sense of the word: a language user. A turn is an uninterrupted stream of language by one speaker. A turn consists of utterances: linguistically identifiable units. Typically, typed or written dialogues utterances are divided by punctuation marks and conjunctives. A dialogue act is a communicative function expressed by a dialogue utterance.

3 The role of surface elements: cue patterns

Many of our insights are based on Conversation Analysis (CA) (Sacks, Schegloff & Jefferson 1978). Conversational analysis is rule-governed and the underlying idea is that shared knowledge of these rules (or conventions) most often enables conversants to have smooth flowing and coherent conversations with one another.

Like CA we assume that there is a strong interdependence between speakers’ wishes and the way they chose their utterances, i.e. between form and function of utterances in a dialogue. The more we can rely on superficial information to exploit this rather complex interdependence (see (Hinkelman & Allen 1989)), the more computationally attractive this will be.

A surface-linguistic way of determining dialogue acts has already been suggested by several researchers. Hinkelman & Allen (1989) use patterns of linguistic features to suggest a range of speech act interpretations for an utterance. The dialogue act classification rules they formulated, express linguistic conventions.

Seligman et al. (1994) describe an approach to speech act interpretation in the context of a speech translation system; they restrict their attention to communicative goals which can be explicitly expressed via so-called conventional surface cue patterns rather than deep intentions. We will use the following definitions of the terms cue patterns, cue and cue value (based on (Seligman et al. 1994):

cue pattern a configuration (tuple) of one or more cue-cue value pairs

cue any aspect of the surface syntax or morphology of a language

cue value an instantiation of a cue

Cues must not be confused with cue words; The latter term will be used for special words which contribute to the communicative function of an utterance (see section 4). We will adopt this way of representing linguistic knowledge by cue patterns because these structures are very suitable for our purpose of automatically classifying dialogue utterances.

4 Describing the data: cues in SCHISMA

In this section we will discuss the utterance cues which are used as the empirical basis for dialogue act classification in SCHISMA.
The initial set of cues used for dialogue act interpretation is given in table 1. This set of cues is based on cues used in literature (Utterance Type, Cue Word) and on intuitions about their usefulness; Subject Type, First Verb Type and Second Verb Type are selected because of their potential informativity on kinds of agents and actions. The optimal set of cues and cue values however, can not a priori be selected; they will be the result of the iterative process of cue set construction, tagging, testing, interpretation and updating (see section 5).

Furthermore, the extraction of cue patterns from utterances is not done automatically; a parser which could identify the cue pattern of all utterances in our corpus is not yet available. We are, however, writing a grammar for the Schisma domain and use the left-corner parser for PATR-II developed at SIL (PCPATR) (Shieber 1986). Recent uses of the parser showed that no principle problems need be expected in automating cue pattern extraction; the set of cues and their potential values concern objectively observable linguistic elements.

(1) is taken from the corpus and is represented by the cue pattern in table 2:

\[
\text{Example 1. } \text{ik wil graag meer weten over de voorstelling 'Antigone'.}
\]

| Cue            | Description                                                                 |
|----------------|----------------------------------------------------------------------------|
| Utterance Type | the mood of an utterance or the syntactic category in case of a phrase     |
| WH-word?       | the presence or absence of a wh-word                                       |
| Subject Type   | the type of the subject of an utterance (if present)                       |
| Cue Words      | words which change the communicative function (if present)                 |
| First Verb Type| the type of the first verb in the utterance (if present)                   |
| Second Verb Type| the type of the second verb in the utterance (if present)                  |
| Question mark? | the presence or absence of a question mark                                 |

Table 1. Cues and their potential values

The cue pattern in table 2 expresses that (1) has a declarative utterance type, does not contain a wh-word nor a question mark, has a first person pronoun as subject, willen as first verb type, a cognitive verb as second verb type and contains the cue word graag.

4.1 Utterance type

The first cue we discuss is utterance type (UT). The corpus contains utterances with an utterance type which more or less corresponds to sentence mood and utterances which do not.

Table 3 gives an overview and a description of the utterance types in Schisma.
### Table 3. Utterance Types

| Label | Description |
|-------|-------------|
| DEC   | finite verb in second sentence position and no wh-word |
| WHQ   | wh-word in initial position |
| YNQ   | a finite verb in initial position and a subject in second position |
| IMP   | a 1st pers. sing. or 3rd pers. sing. verb in initial position |
| PRE   | (one or more) prepositional phrases |
| NOM   | (one or more) nouns, noun phrases or proper names |
| ADJ   | (one or more) adjectives, adverbs or numbers |
| THA   | thank |
| GRE   | greet |
| CON   | confirmations, negations |
| EXC   | interjections, emotives, exclamations |
| MIS   | miscellaneous |

Many utterances in the corpus are regular declarative sentences (DEC). They are defined as having a finite verb in second sentence position and no wh-word in (a constituent in) sentence initial position. An example from the corpus is (2):

**Example 2.** *Ik wil graag een reservering.*

YNQ utterance types are assigned to utterances with a finite verb in sentence initial position and a subject in second position.

All utterances which contain a wh-word in (a constituent in) initial sentence position are considered to be of type WHQ. IMP utterance type is assigned to utterances with a first person singular or third person singular verb in sentence initial position. Furthermore, the utterance should not contain a subject. Another instance of IMP utterance type concerns utterances with an infinite verb in sentence-initial position. The IMP utterance type roughly corresponds to the traditional imperative sentence mood.

Utterances types which do not correspond to one of the conventional sentence moods as described above typically consist of a (sequences of) phrases (multiple PPs or multiple NPs), polite thanking and greeting utterances and typically short forms like confirmations, negations, interjections and exclamations.

(3) is an example of utterance type PRE from the corpus:

**Example 3.** *En op 18 maart?*

Note that although (3) is not a strict PP, we consider it to be one; conjunctives like *en* and *of* are considered to be absent for the task of determining utterance types. This also applies to conventional utterance types. While (3) only contains a rather atomic PP, there are also cases in which the PP has a complex structure. Utterance type NOM is assigned to (sequences of) Ns and/or NPs. Most utterances tagged with this utterance type consist of one noun. They function either as answer to former questions or as prompts to provide all instances of a certain domain type but complex NPs do also occur. A collection of ADJ(P)s, ADV(P)s and Numericals is represented in the ADJ type. Again, most of the occurrences are one word utterances, consisting of a number or an attitude adverb.
The kind of utterances belonging to the CON type (negation markers also belong to this class), THA type, EXC type (which also contains exclamatives and interjections) and GRE type should be obvious. The utterance type MIS functions as a kind of a garbage collector; all utterances which cannot be classified as one of the utterance types above are covered by this type.

4.2 Other cues

Another cue for the communicative function of utterances is the presence of a wh-word (WH). This cue might seem to be superfluous because of the presence of the WHQ utterance type. However, wh-words do not necessarily occur in utterances with a wh-question type. (4) has a YNQ Utterance Type and contains the wh-word wie.

Example 4. Wbet u wie dat stuk heeft geschreven?

Like WH, The use of Question Mark (QM) as potential cue is not as trivial as it might seem to be. After a closer look at the corpus we found that utterances with a WHQ or a YNQ utterance type are not always ended with a question mark as we might expect. On the other hand, many utterances with utterance type DEC do have a question mark:

Example 5. 2 zei ik toch?

The cue Subject Type (ST) is only applicable to utterances with utterance types WHQ, YNQ and DEC. We distinguished the following superficial subject types:

- NPs referring to artists, performances, tickets, discounts etc. like Herman Finkers
- First person personal pronouns like ik referring to the speaker
- Second person personal pronouns like u referring to the hearer
- Third person personal pronouns like het
- Interrogative pronouns like welke, wanneer etc.
- Demonstrative pronouns like dit and dat
- Others

Another kind of cues for the function of utterances in discourses are Cue Words (CW). Most cue words are realized as modal adverbs or adverbial phrases. graag for example, can be translated as like to. In dialogue however, it is often used as a more general politeness marker like in (6):

Example 6. Ik wil graag naar Mini en Maxi.

While used in a declarative utterance, graag intuitively strengthens the wish for information or action. (6) shows that cue words can be very subtle indications for speaker intentions in discourse, very often in combination with other cues in utterances.

The last cues are First and Second Verb Type (FVT/SVT). The corpus contains both utterances with and without verbs. After analyzing the corpus, we found the following main kinds of verbs:

- verbs like to reserve, to be, to have and to know
- domain verbs, which only have domain objects as their arguments
- task verbs, which have at least one argument which refers to a dialogue partner
Many utterances contain more than one verb and most do not contain more than two. Therefore, we assume that the types of the first two verbs are the most relevant ones.

In the next sections we will discuss our way of automatically classifying dialogue utterances.

5 Towards the automatic classification of dialogue utterances

The central idea of our approach to dialogue act classification is to automatically derive dialogue acts and dialogue act rules from a corpus. We would like to prevent human subjective judgments as much as possible because people are not very good at deriving rules from a rather large set of examples, like a corpus of dialogue utterances. Litman & Passonneau (1995) for instance, found in an experiment that performance of individual speakers varied widely when they were asked to indicate segment boundaries in discourses, a task comparable to the one at hand.

We also experienced these problems in our attempts to tag the Schisma corpus with dialogue act labels; it appeared to be very difficult to consequently determine the dialogue act of an utterance because there were no strict criteria available to decide when to assign which dialogue act label. This complexity of dialogue act classification (also noted by Hinkelman & Allen (1989)) lends us more support for our choice to use algorithms implemented in computer programs instead. Furthermore, a machine can do the job much faster.

The term classification is often used in two senses: it either means assigning a class (element of an existing set of classes) to a new case, or finding the classes themselves from a given set of unclassified cases. The latter is often called unsupervised classification as opposed to the former supervised classification in which the set of classes must be provided beforehand. In this section we will propose a way of using both kinds of classification in determining the dialogue act of a given utterance.

After having tagged the whole dialogue corpus yielded by the Wizard of Oz experiment (64 dialogues) with relevant cues already discussed in section 4 the corpus was converted to the generic mark-up language SGML. This converted corpus served as the input for scripts to create sub-corpora for the different kinds of algorithms used.

First, the utterances in the corpus (2351) were randomly split in a training set which consisted of 75% (i.e. 1763) of all utterances and a test set of 25% (i.e. 588) of all utterances.

After that, an unsupervised classification algorithm was applied to the training set to automatically discover dialogue acts (see section 5.1). The output consists of a list of all cue patterns in the training set together with their class (see section 5.2).

Then, we applied a supervised classification algorithm to the output of the unsupervised classification algorithm to extract a reduced dialogue act rule set. The rules yielded by the supervised classification algorithm had the form of if-then rules. In the following sections, we will discuss the classification process in the training phase and the testing phase in more detail.

5.1 Unsupervised classification

Unsupervised classification (also called clustering) is concerned with the automatic discovery of classes in data. Classification is based on the fact that some cases are more like each other than the rest of the cases.
Methodology We used the program *AutoClass* (Cheeseman & Stutz 1995) in which a method for unsupervised learning is implemented. AutoClass is an unsupervised Bayesian classification system that seeks a maximum posterior probability classification. In the AutoClass approach, class membership is expressed probabilistically; every item is considered to have a probability that it belongs to each of the possible classes.

AutoClass allowed us to automatically find the set of classes that is maximally probable with respect to cue patterns in the training set. These classes should resemble classes which we would indicate as dialogue acts.

However, Cheeseman & Stutz (1995) stress the fact that the discovery of important classes in data is rarely a one shot process. Instead, it is:

“(...) a process of finding classes, interpreting the results, transforming and/or augmenting the data, and repeating the cycle.”

(Cheeseman and Stutz 1995:62)

This implies the intervention of an expert to judge the intermediate results and to transform or augment the data if necessary: the number or kind of cues, the number of AutoClass trials or some other parameters could be changed. Cheeseman & Stutz (1995) also stress the need for a strong interaction between the classification program and the expert, because their contributions to the classification process are complementary; the program can handle a huge amount of data with a high speed, while the expert has domain knowledge.

Instead of the intervention of a human being however, we could also look for ways to automatically judge the appropriateness of the set of classes, for instance by taking the highest common factor of the results of multiply applying AutoClass to different (randomly generated) training sets.

AutoClass Input consisted of the 75% training set of cue patterns. The cues chosen for the first experiment were *Speaker*, *UtteranceType*, *SubjectType*, *FirstVerbType* and *QuestionMark*. AutoClass was instructed to report on the best two classifications found. AutoClass reports contained information about the strength of the classes found and the relative importance of the cues for a specific class. Furthermore, both case and class descriptions were given for every cue pattern in a certain class. The results of the first runs of AutoClass on our training corpus will be discussed in the following section.

Results We let AutoClass generate five classifications of which the two best were stored. These two yielded ten and seven classes respectively, for 206 different cue patterns in the training set, i.e. about 20 and 30 cue patterns in each class.

We will now focus on the classification which yielded seven classes and informally discuss the kind of cue patterns in every class. Class 0 can be roughly identified as consisting of cue patterns for which SubjectType=’n’ (no subject present) or UtteranceType=’n’ (Nouns and NPs). In the former respect this class is similar to Class 6. Class 0 and Class 6 utterances together can be informally characterized as all utterances without a subject.

Class 1 only consists of UtteranceType=’d’ patterns (declarative utterances) and does both contain Client and System utterances. Other patterns in this class typically have SubjectType=’a’ or ‘p’ (artist or performance) or FirstVerbType=’z’ or ‘d’ (a form of to be or a domain verb). The features of Class 1 can roughly be characterized as Information supplying utterances about domain objects.

Class 2 cue patterns have either UtteranceType=’w’ or ‘y’ (wh-utterances and yes/no utterances) and SubjectType=’i’ or ‘e’ (first person or second person pronouns). A suitable common
description for the cases in Class 2 is questions concerning actions of one of the conversation participants or states in which they are.

Class 3 patterns only contain Client utterances with UtteranceType='w' or 'y'. In this latter sense, they are related to Class 2. The main distinction however, is that Class 3 patterns all concern Client questions about facts in the domain. Note that System questions about domain facts do not occur in the corpus.

Class 4 utterances are tagged with UtteranceType='d'. Most of them also have SubjectType='e' (second person pronoun), which means that most of the Class 4 utterances are Information supplying utterances about actions of the other conversation participant or the state where he is in. Strange enough, we also found some patterns in Class 4 which at first sight, are not similar to the other cases.

Most of the Class 5 utterances are both UtteranceType='d' and SubjectType='i' (first person pronoun) utterances. Some others have SubjectType='t' (demonstrative pronoun) instead of 'i'. Most Class 5 Client utterances have FirstVerbType='w'. These are the utterances in which Clients express a wish.

Table 4 shows the relative strength of the classes found. This measure is based on the mean probability of instances belonging to each class and provides a heuristic measure of how strongly each class predicts its instances.

| Class | Relative class strength |
|-------|-------------------------|
| 0     | 0.596                   |
| 1     | 0.705                   |
| 2     | 0.167                   |
| 3     | 0.067                   |
| 4     | 1.000                   |
| 5     | 0.331                   |
| 6     | 0.199                   |

Table 4. Relative class strength

It is clear from table 4 that classes 4 and 1 are the strongest and class 3 is the weakest class. Together with the observations of the classified data, the information given in table 4 can be used in the process of deciding which classes are going to be used in the eventual system.

Table 5 shows the relative influence of each cue in differentiating the classes from the overall set of cue patterns.

| Cue | Relative influence |
|-----|--------------------|
| Sp  | 0.270              |
| Ut  | 0.859              |
| St  | 1.000              |
| Fvt | 0.881              |
| Qm  | 0.248              |

Table 5. Relative influence of cues
The cues Question Mark and Speaker appear to have little influence compared to the other three cues whose influence is about three to four times as great. This information can be used for new trials of AutoClass with fewer cues, omitting cues with little influence. Information about the influence of the values of each cue is also generated by AutoClass. This can also be used for new trials with other cue values.

In the next section we will discuss supervised classification and the way we applied it to our dialogue corpus.

5.2 Supervised classification

To gain more insights in the results of unsupervised classification, supervised classification has been applied to the output of the unsupervised classification algorithm yielding a reduced dialogue act rule set. A set of cue patterns with their classes can be regarded as a set of rules in which the number of cue patterns equals the number of rules. The goal of supervised classification is then, to reduce the number of rules i.e. to extract generalizations from the data. Such a reduced rule set should allow us to assign classes to new cue patterns.

Methodology We used the supervised classification program CN2 (Clark & Boswell 1991) which induces if-then rules. It is designed to work well for domains where there might be noise, which is the case in our domain; instead of using normal significance testing or entropy which favor rules which cover examples of only one class, it uses the so-called Laplace accuracy which does not have a downward bias; rules which cover many examples of one class and a few examples of another class are preferred to rules which cover a few examples of only one class.

We applied CN2 to the same training set of cue patterns as we used for discovering classes by unsupervised learning. CN2’s application in SCHISMA takes as first input the fixed set of cues and their potential values and the set of classes (dialogue acts) to be learned. The second input consists of the training data, i.e. a set of cue patterns together with their class yielded by the unsupervised classification phase. The output of CN2 is a set of if-then rules, which predict classes given one or more cue–cue value expressions.

We consider the number of rules relative to the number of different cue patterns as one indication of the quality of the rule set. More specifically, the lower this number the more general the rule set. We call this metric the specificity index (SI):

\[ SI = \frac{\# \text{rules} - \# \text{classes} + 1}{\# \text{cue pattern types} - \# \text{classes} + 1} \]

The underlying idea of this index is that maximum abstractness is obtained if SI approaches zero, i.e. if few rules describe many CPTs. SI can be used to compare the abstractness of different rule sets.

Results Applying CN2 resulted in a set of 44 rules for 206 different cue patterns types (CPTs) with an SI of 0.19. Two of the rules are shown in figure 1 (cue names and value names are changed to improve readability):

The first rule informally expresses that if an utterance contains a subject which is a second person pronoun and a question mark, than it will be assigned class 2, i.e. it is a question concerning an action of one of the conversation participants or state which he is in (see section
IF SUBJECTTYPE = 2nd person pronoun AND QUESTIONMARK = yes THEN CLASS = 2 [0 0 96 0 0 0 0]

IF UTTERANCETYPE = Noun/NounPhrase THEN CLASS = 0 [109 0 0 0 0 0 0]

Figure 1. CN2 Rules

5.1. The second rule expresses that all utterances which only consist of a noun or noun phrase are assigned class 0.

Due to the fact that we chose to generate an unordered rule set instead of an ordered one for reasons of interpretability, a partial cue pattern could give rise to more than one class. Suppose that the rules in figure 1 were the only ones and that an unknown cue pattern matched with both of them. In that case, the distributions would be summed and frequencies calculated; Class 2 would have a probability of 96/205 and Class 0 of 109/205 which means that Class 0 would be assigned to the unknown cue pattern, because of its higher probability.

Table 6 expresses the accuracy with which the rules generated from the training set describe the unsupervised classification of the test set.

| Actual\Predicted | 0 | 1 | 2 | 3 | 4 | 5 | 6 | Accuracy |
|------------------|---|---|---|---|---|---|---|----------|
| 0                | 146 | 0 | 0 | 1 | 0 | 0 | 0 | 99.3 %   |
| 1                | 3 | 131 | 0 | 0 | 0 | 0 | 0 | 97.8 %   |
| 2                | 0 | 75 | 0 | 0 | 0 | 0 | 0 | 100.0 %  |
| 3                | 2 | 0 | 0 | 66 | 0 | 1 | 0 | 95.7 %   |
| 4                | 6 | 0 | 0 | 78 | 2 | 0 | 0 | 90.7 %   |
| 5                | 1 | 0 | 0 | 0 | 43 | 0 | 0 | 97.1 %   |
| 6                | 0 | 0 | 0 | 0 | 0 | 33 | 1 | 100.0 %  |

Table 6. Evaluation results of the set of supervised classification rules

The accuracy of the rules for a certain class \( c \) can be expressed by the ratio of the number of well-predicted cue patterns and the total number of cue patterns in \( c \). This metric is also called precision. Table 6 shows the number of cue patterns for every possible pair of actual and predicted classes. The accuracy as defined above is included in the last column.

6 Conclusions

As was already noted by Cheeseman & Stutz (1995) (see section 5.1) and as we experienced ourselves, our way of automatically finding dialogue utterance classes from a corpus of training utterances is not a one shot process: it requires iteratively training and testing with varying sets of cues and cue values. In this process, the combination of domain knowledge of the expert and the objectivity and computational power of the machine is necessary.
The classification results described however, are promising; the classes yielded by the unsupervised classification algorithm can be interpreted intuitively; for the task of predicting client and system actions, however, the classes might be too general. More specific classes will be obtained if the number of initial classes for AutoClass is increased.

The information about the relative influence of cues and classes generated by AutoClass is very useful for the training-testing cycle. The problem of finding the optimal set of cues and cue values to train the algorithms will also be solved during this cycle.

Furthermore, as shown by the evaluation results in Table 6 the supervised classification algorithm found an acceptable general and accurate set of rules for the classes yielded by the unsupervised classification algorithm.

7 Future Work

At this moment, we are in the cycle of testing different sets of cues and their values, generating and interpreting classes, generating rules for deriving classes and re-testing on the basis of the results. In parallel, a grammar is written which should allow us to automatically extract cue patterns from the utterances in the training corpus.

In the near future, we will test alternative ways of supervised and unsupervised classification in SCHISMA. We will use the unsupervised classification program package C4.5 (Quinlan 1993) which can both yield rules and decision trees. It has some extra features like n-folded cross-validation and the consultation of the decision tree and rules. Regarding unsupervised classification, we are currently working on the generation of Kohonen Maps for discovering classes in the training corpus. The results will be compared with the AutoClass results.

Another aspect paid attention to, is the use of context information in the classification process. One could argue that at least some context information is necessary for finding useful classes of dialogue utterances. We will test this hypothesis by adding the class of cue pattern n-1 as a cue to cue pattern n for all cue patterns in the training set. Another possible way of using local context information is applying an n-gram analysis to the classes of all cue patterns in the training set. To approximate the conditional probability \( P \) that utterance \( n \) falls in class \( c \) given the classes of \( m \) previous utterances deleted interpolation (Jelinek 1990) will be used. This approach is similar to the one adopted by Reithinger (1995) in the VERBMOBIL project and has already been applied with promising results.

References

Beun, R.-J. (1989), The Recognition of Declarative Questions in Information Dialogues, PhD thesis, Instituut voor Perceptie Onderzoek, Eindhoven, The Netherlands.
Carletta, J. (1996 (forthcoming)), ‘Assessing agreement on classification tasks: the kappa statistic’, Computational Linguistics.
Cheeseman, P. & Stutz, J. (1995), Bayesian classification (autoclass): Theory and results, in U. Fayyad, G. Piatetsky-Shapiro, P. Smyth & R. Uthurusamy, eds, ‘Advances in Knowledge Discovery and Data Mining’, The AAAI Press, Menlo Park, pp. 61–83.
Clark, P. & Boswell, R. (1991), Rule induction with cn2: Some recent improvements, in ‘Machine Learning - Proceedings of the Fifth European Conference (EWSL-91)’, pp. 151–163.
Hinkelmann, E. (1990), Linguistic and Pragmatic Constraints on Utterance Interpretation, PhD thesis, University of Rochester, Rochester.
Hinkelmann, E. & Allen, J. (1989), Two constraints on speech act ambiguity, in ‘27th Annual Meeting of the Association for Computational Linguistics: Proceedings of the Conference’, ACL, pp. 212–219.
Jellinek, F. (1990), Self-organized language modeling for speech recognition, in A. Waibel & K.-F. Lee, eds, ‘Readings in Speech Recognition’, Morgan Kaufmann, pp. 450–506.
Litman, D. & Passonneau, R. (1995), Combining multiple knowledge sources for discourse segmentation, in ‘33rd Annual Meeting of the Association for Computational Linguistics: Proceedings of the Conference’, ACL.
Quinlan, J., ed. (1993), C4.5: Programs for Machine Learning, The Morgan Kaufmann in Machine Learning, Morgan Kaufmann Publishers, Inc., San Mateo, California.
Reithinger, N. (1995), Some experiments in speech act prediction, in ‘Working Notes AAAI Spring Symposium Series’, AAAI, Stanford University, California, USA, pp. 126–131.
Sacks, H., Schegloff, E. & Jefferson, G. (1978), A simplest systematics for the organization of turn-taking in conversation, in J. Schenkein, ed., ‘Studies in the Organization of Conversational Interaction’, Academic Press, New York.
Schmitz, B. & Quantz, J. (1995), Speech-event types in automatic dialogue interpreting, in ‘Submitted to Proceedings of TMIF’.
Seligman, M., Fais, L. & Tomokiyo, M. (1994), A bilingual set of communicative act labels for spontaneous dialogues, Technical Report TR-I-0081, ATR, Kyoto.
Shieber, S. (1986), An introduction to unification-based approaches to grammar, CSLI Lecture Notes 4, CSLI, Stanford, CA.