Grammatical Error Correction in Oral Conversation

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Abstract— We aim to provide grammar error feedback to learners. It is known that grammar error detection and feedback are challenging problems in written language, however, they become much more difficult tasks in oral conversation because it is difficult for a system to judge whether an error is due to grammar or automatic speech recognition (ASR). False alarms occur when a learner correctly utters a remark, but the system gives feedback implying an error. Minimizing the false alarm rate is especially critical in education applications because it is imperative that the tutor give correct instruction to learners. Thus, to reduce the false alarm rate in grammar error detection and feedback, we apply a partially observable Markov decision process (POMDP) when the system provides feedback about a learner's mistake. The POMDP models uncertainty between grammar errors and ASR errors. An additional advantage of our method is that “belief states” in POMDP can be used for learner models which indicate each individual learner's grammar comprehension level.

Key words: ASR, Artificial Intelligence, POMDP, ESL

I. INTRODUCTION

There has recently been a lot of work addressing errors made by English as Second Language (ESL) learners. As the development of technology attains newer heights, Human-Machine Interactions (HMI) has become predominant area of research. Artificial Intelligence as a formal discipline has been around for over thirty years. The goals of individual practitioners vary and change over time. Traditional Artificial Intelligence has tried to tackle the problem of building artificially intelligent systems from the top down. It tackled intelligence through the notions of thought and reason. Some of this work is based on engineering from first principle. The flavor of this work is quite different from that of traditional Artificial Intelligence.

Most of the work in the area of ESL error correction has addressed the task by building statistical models that specialize in correcting a specific type of a mistake. Figure 1 illustrates several types of errors common among non-native speakers of English: article, subject-verb agreement, noun number, and verb form.

Nowadays *phone/phones *has/have many functionalities, *included/including *Ø/a camera and *Ø/a Wi-Fi receiver.

Fig. 1: Examples of Representative ESL Errors.

In the example shown in Figure no.1, the agreement error on the verb “have” interacts with the noun number error: a correction system that takes into account the context may infer, because of the word “phone”, that the verb number is correct. For this reason, a system that considers noun and agreement errors separately will fail to identify and correct the interacting errors shown in Fig. no 1. Furthermore, it may also produce inconsistent predictions.

II. DESCRIPTION

Even though it is quite clear that grammatical errors interact, for various conceptual and technical reasons, this issue has not been addressed in a significant way in the literature. We believe that the reasons for that are two-fold: (1) Data: until very recently we did not have data that jointly annotates sufficiently many errors of interacting phenomena. (2) Conceptual: Correcting errors in interacting linguistic phenomena requires that one identifies those phenomena and, more importantly, can recognize reliably the interacting components (e.g., given a verb, identify the subject to enable enforcing agreement). The perception has been that this cannot be done reliably

The training and the test data contain 1.2M and 29K words, respectively. Although the corpus contains errors of other types, the task focuses on five types of errors. Table 1 shows the number of mistakes1 of each type and the error rates, i.e. the percentage of erroneous words by error type.

ERROR	NUMBER OF ERRORS AND ERROR RATE	
	TRAINING	TEST
Article	6658(2.4%)	690(10.0%)
Preposition	2404(2.0%)	311(10.7%)
Noun	3779(1.6%)	396(6.0%)
Verb Agreement	1527(2.0%)	124(5.2%)
Verb Form	1453(0.8%)	122(2.5%)

Table 1: Number of annotated errors in the CoNLL [6], 2013 shared task.

(Percentage denotes the error rates, i.e. the number of erroneous instances with respect to the total number of relevant instances in the data. For example, 10.7% of prepositions in the test data are used incorrectly. The numbers in the revised data set are slightly higher.)

III. METHODOLOGY

Here, we are using some learning techniques of Artificial Intelligence for identifying grammatical mistakes in oral conversation by user/person .The techniques are following;

- Learning by Analyzing Differences.
- Learning by Recording Cases.

So, individually explaining both the process below as these techniques plays a vital role in the execution of process till the end.

A. Learning by Analyzing Differences:

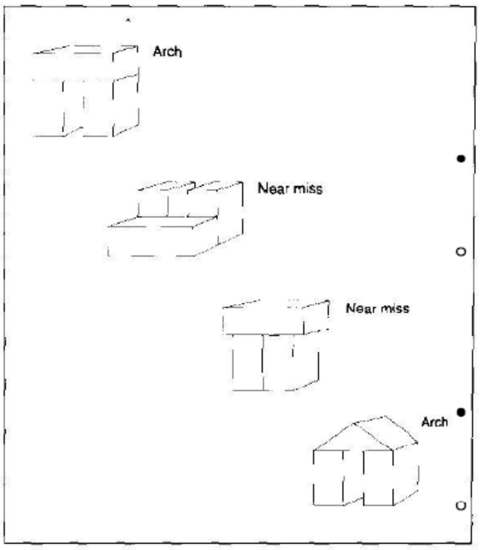

Fig. 2: A Sequence of Positive examples and near miss negative examples for learning about arches

- You cannot learn if you cannot know.
- Good teachers help their students by being sure that their students acquire the necessary representation
- You cannot learn if you cannot isolate what is important.
- Good teachers help their students by providing not only positive examples, but also negative and near misses

B. Procedure Specialize:

1) *If the example is near miss, use procedure Specialize:*
   - Match the evolving model to the example to establish correspondences among parts.
   - Determine whether there is single, most important difference between the evolving model and the near miss.
2) *If there is single, most important difference,*
   - If the evolving model has a link that is not in the near miss, use the require-link heuristic.
   - If the near miss has a link that is not in the model, use the forbid-link heuristic.
3) *Otherwise, ignore the example.*

C. Procedure Generalize:

1) *If the example is an example, use Generalize.*
   - Match the evolving model to the example to establish correspondences among parts.
   - For each difference, determine the different type:
2) *If a link point to a class in the evolving model different from the class to which the link point is an example,*
   - If the classes are a part of a classification tree, use the climb-tree heuristic.
   - If the classes form an exhaustive set, use drop-link heuristic.
   - Note: There will be situations where a model is not consistent with an example, even though the model is basically correct.

E.g. penguins are bird but cannot fly.
No altering principle: when an object or situation known to be an example fails to match a general model, create a special-case exception model.

D. Learning by Recording Cases:

A program that learns by recording cases generally makes use of consistency heuristic. According to consistency heuristic, a property of something can be guessed by finding the most similar cases from a given set of cases. For example, a computer is given the images of different types of insects, birds, and animals. If the computer is asked to identify a living thing which is not in the recorded list, it will compare the given image with already recorded ones, and will at least tell whether the given image is insect, bird or animal.

Learning by recoding cases technique is mainly used in natural language learning tasks.

During the training phase, a set of cases that describe ambiguity resolution episodes for a particular problem in text analysis is collected. Each case contains a set of features or attribute-value pairs that encode the context in which the ambiguity was encountered.

Moreover, each case is annotated with solution features that explain how the ambiguity was resolved in the current example. The cases which are created are then stored in a case base. Once the training is over, the system can use the case base to resolve ambiguities in new sentences. This way, the system acquires the linguistic knowledge.

IV. ALGORITHM FOR STORING AND EXECUTION OF LINGUISTIC DATA

A. For Storing Data In Database:

- CREATING DATABASE OF GRAMMATICAL SENTENCES AND A SEPERATE SET OF CASES FOR AMBIGUITY IN WORDS. (set primary key to the column sentences)

B. For Execution of Statements:

1) *Step 1: Declaring variables like userin, userout, strdata;*
2) *Step 2: if userin is equals to strdata*
   then userout = throw/execute the stored statement in that manner from database.
   Else if store it in database && check ambiguity words
   then usreout = throw/execute the statement by correcting it from the remaining data in database.
   else
   return userout = incorrect statement.
3) *Step 3: come out of the loop and terminate the process.*

V. CONCLUSION

This work presented the first successful study that jointly corrects grammatical mistakes. We addressed two pairs of interacting phenomena and showed that it is possible to reliably identify their components, thereby facilitating the joint approach. We described two joint techniques: learning by analyzing differences and learning by recording cases. In learning by analyzing difference we have to process i.e. procedure specialize and procedure generalize .Then we have in learning by recording cases we record sentences from the environment activities and match it with user input and throw it in correct form as a output.

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