Weakly and Strongly Constrained Dialogues for Language Learning

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Abstract

We present two dialogue systems for language learning which both restrict the dialog to a specific domain thereby promoting robustness and the learning of a given vocabulary. The systems vary in how much they constrain the learner's answer : one system places no other constrain on the learner than that provided by the restricted domain and the dialog context ; the other provides the learner with an exercise whose solution is the expected answer. The first system uses supervised learning for simulating a human tutor whilst the second one uses natural language generation techniques to produce grammar exercises which guide the learner toward the expected answer.

1 Introduction

Work on dialog based tutors for language learning includes both chatbot systems which maintain a free flowing dialog with the learner (Shawar and Atwell, 2007; Jia, 2004) and form-focused dialog systems which restrict the learner answer e.g., by providing her with an answer template to be filled in for the dialog to continue (Wilske and Wolska, 2011). While the former encourages language practice with a virtual tutor and requires a good knowledge of the language, the latter focuses on linguistic forms and usually covers a more restricted lexical field thereby being more amenable to less advanced learners.

In these notes, we describe a dialog architecture which (i) supports both free-flowing and form-focused man/machine dialog ; and (ii) ensures that in both cases, dialogs are restricted to a specific lexical field. The free-flowing dialog system uses supervised classification techniques to predict the system dialog move based on the learner's input and does not explicitely constrain the learner's answer. In contrast, the dialog system for intermediate learners provides an exercise which the learner must solve to construct her answer.

To restrict the dialog to a specific domain and to improve system robustness, we make use of a finite-state automaton (FSA) describing the range of permissible interactions within a given domain. This FSA serves to guide the collection of human-human interactions necessary to train the classifier ; to verify and if necessary to adjust the system's predicted answer ; and to support the generation of the exercise provided in the form-focused dialog engine.

2 Finite State Automaton and Domain Representation

To support focused dialog and promote robustness, we make use of the FSA depicted in Figure 2. This FSA models a generic sequence of (System Question, Learner Answer, System Reaction) turns instantiating 4 main question/answer patterns and two possible system reactions.

The system question systematically formulates a question which explicitly lists a set of possible answers.

The learner's answer is then classified into four main types. It selects one of the proposed answers ; it chooses another alternative not mentioned in the system's question ; it indicates that the learner does not know the correct answer or does not understand the question ; or it meets neither of these categories.

Finally, for each answer, the system can continue the dialogue by making a "confirmation" which is used to reassure the learner in the free dialogue system and to provide some feedback in the guided dialogue system ; or just by "informing" to the learner of the correct answer before getting into the next question.

Given a specific domain, this generic FSA is

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>S:Welcome to my house!, I'm the cat. Do you want
to play with me?   || ask(ready)
>L:Ok.       || answer(ready)
>S:Great! How are you doing? || ask(health)
>L: I'm doing very well, thanks!
|| answer(health, pref-option)
>S: Awesome!  || confirm(health,pref-option)
>S: Come! I want to show you the kitchen!
|| inform(health)
>S:In the kitchen we prepare lunch. I prepare
soup very often. Do you prefer soup or salad?
|| ask(pref-meal)
>L:I prefer salad.
|| answer(pref-meal,pref-option)
>S:So do I! || confirm(pref-meal,pref-option)
>S:I also love cheese. || inform(pref-meal)
>S:Where do we usually keep the cheese?
|| ask(cheese where)
>L:In the fridge || answer(cheese where,pref-option)
>S:You are right || confirm(cheese where,pref-option)
>S:In the fridge || inform(cheese where)
...
>S:Thanks for this little chat! See you soon
|| quit
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FIGURE 1 – Example of a dialog (translated from French to English)

instantiated differently for each question/answer pair making up a dialog. In particular, in the current demonstration system, it is instantiated to model a dialog situated in the kitchen of a virtual world. Figure 1 shows an example dialog.

3 Situated Dialogues for language learning

Our dialog systems for language learning are integrated in a serious game called I-FLEG (Interactive French Learning Game, (Amoia et al., 2012)) in which the learner can trigger grammar exercices and interactive dialog sessions by clicking on the objects present in the virtual world.

IFLEG integrates the two dialog systems for language learning mentioned above namely, a "free answer dialog system" where the learner answer is guided only by the preceding dialog exchanges ; and a "guided dialog system" which restricts the set of permissible answers by providing the learner with an exercise whose solution provides a possible answer given the current dialog context.

3.1 Data collection

To provide the training data necessary to train the free dialog system, we conducted a Wizard-of-Oz experiment where language learners were invited to engage in a conversation with the wizard, a French tutor. In these experiments, we followed the methodology and used the tools for data collection and annotation presented in (Rojas-Barahona et al., 2012a). Given an FSA specifiying a set of 5 questions the learner had to answer, the wizard guided the learner through the dialog using this FSA. The resulting corpus consists of 52 dialogues and 1906 sentences.

3.2 Free answer Dialogue System

The free answer dialogue system simulates the behavior of the wizard tutor by means of a Logistic-Regression classifier, the FSA and a generation-by-selection algorithm. The system first uses the FSA to determine the next question to be asked. Then for each question, the Logistic-Regression classifier is used to map the learner answer to a system dialog act. At this stage, the FSA is used again, in two different ways. First, it is used to ensure that the predicted system dialog act is consistent with the states in the FSA. In case of a mismatch, a valid dialog act is selected in the current context. In particular, unpredicted "preferred options" and "do not know" learner answers are detected using keyword spotting methods. If the classifier prediction conflicts with the prediction made by key word spotting, it is ignored and the FSA transition is prefereed.

Second, since the system has several consecutive turns, and given that the classifier only predicts the next one, the FSA is used to determine the following system dialog acts sequence. For instance, if the predicted next system dialog act was "confirm", according to the FSA the following system dialog act is "inform" and then eiher the next question encoded in the FSA or "quit".

Training the simulator To train the classifier, we labeled each learner sentence with the dialog act caracterising the next system act. The features used for trainig included *context features* (namely, the four previous system dialogue acts) and the set of *content words* present in the learner turns after filtering using tf*idf (Rojas Barahona et al., 2012b). Given the learner input and the current dialog context, the classifier predicts the next system move.

Generation by Selection Given the system move predicted by the dialog manager, the system turn is produced by randomly selecting from the training corpus an utterance annotated with that dialog move.

3.3 Guided dialogue system

Unlike the free answer dialogue, the guided dialogue strongly constrains the learner answer by suggesting it in the form of a grammar exercise.

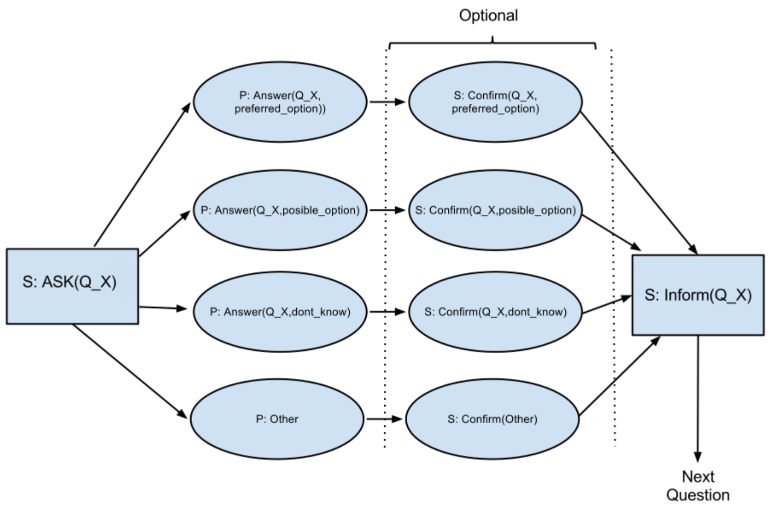

FIGURE 2 – Finite-state automata that defines the different states in the dialog for each question Q_X. S defines the system, and P the learner.

In the guided dialogue system, the dialogue paths contained in the training corpus are used to decide on the next dialogue move. In a first step, learner's moves are labelled with the meaning representation associated to them by the grammar underlying the natural language generator used to produce IFLEG grammar exercises. Given a sequence S/L contained in the training corpus with S, a system turn and L the corresponding learner's turn, the system then constructs the exercise providing the learner's answer using the methodology described in (Perez-Beltrachini et al., 2012). First, a sentence is generated from the meaning representation of the learner answer. Next, the linguistic information (syntactic tree, morpho-syntactic information, lemmas) associated by the generator with the generated sentence is used to build a shuffle, a fill-in-the-blank or a transformation exercise. Here is an example interaction produced by the system :

S : Vous préférez la soupe ou le fromage ? (*Do you prefer soup or salad ?*)
Please answer using the following words : { je, adorer, le, soupe }

This dialogue setting has several benefits. The dialogue script provides a rich context for each generated exercise item, learners are exposed to example communicative interactions, and the system can provide feedback by comparing the answer entered by the learner against the expected one.

4 Sample Dialogue

In this demo, the user will be able to interact with both dialogue systems, situated in the kitchen of a virtual world, and where the tutor prompts the learner with questions about meals, drinks, and various kitchen related activities such as floor cleaning and food preferences.

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