Learning Reusable Probabilistic User-System Models for Human-Computer Dialogue Simulation

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Abstract: We propose an approach to learn reusable probabilistic models for simulating human-computer task-oriented dialogues at the intention level, trained from different corpora using a two-pass clustering technique and temporal models. In order to predict system behavior we use a hidden Markov model and to predict human behavior we use a dynamic Bayesian network. Finally, we propose an evaluation method to measure the realism of the generated artificial dialogues.

1. Project Proposal

Spoken dialogue systems allow computers to interact with humans using speech. However, a major drawback is due to the fact that dialogue data is required to build a system to engage users in natural and effective conversations - and such a system is required for collecting the data!

Levin and Pieraccini formulated the problem as a Markov decision process and introduced the concept of *dialogue simulation* [4], see figure 1.

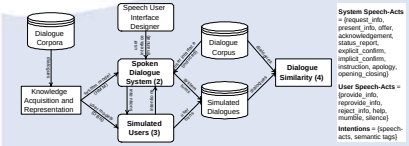

Fig. 1. Architecture of the dialogue simulator

- **Motivation**: To reuse annotated data collected from different dialogue systems in order to generate more explorative data for a particular system, useful for early optimization and evaluation.
- **Goal**: To characterize a human-computer dialogue simulator useful since early development.
- **Previous Work**: Task-dependent models [1,4-6].
- **Research Gap**: A task-independent approach at the intention level, see tables 1 and 2.

Dimension \ Work	Previous	Proposed
Task	Dependent	Independent
User Models	Single-class (Markov Chains)	Multi-class (DBN)
System Model	Intentions (N-grams, HMM)	Intentions (HMM)
Evaluation	# Turns per Goal	Dialogue Similarity (HMMs)

Table 1. Previous and proposed work

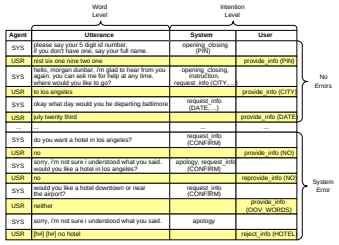

Table 2. Conversation at word/intention level

2. The System Model

- **Problem**: To learn a system model based on small amounts of data from different systems.
- **Task of the System Model**: To simulate a *speech recognizer* and *dialogue manager*, given a speech user interface for a particular application.
- **Solution**: A Hidden Markov Model (HMM) $\lambda = (S, A, B, \pi, \sigma)$, where S is the state set (system turns), A the state transitions, B the observations (intentions), π and σ are the initial and final distributions (begin-end conversation); see figure 2a.
- **Reusability**: In order to train the parameters we use data obtained with *state clustering*, using the *one-pass* clustering as illustrated in figure 2b.

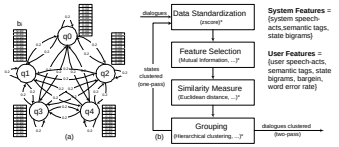

*Fig. 2. (a) HMM to predict system behavior, (b) Two-pass clustering technique (*baseline)*

3. Reusable User Models

- **Problem**: To learn user models based on small amounts of data from different systems.
- **Task of the User Models**: To simulate user intentions including confusions and dialogue history.
- **Solution**: A Dynamic Bayesian Network (DBN) $\lambda = (Z_t^i, D, B, A, \pi)$, where Z_t^i represent the i-th variables at time t, D the conditional independence relations $Parents(Z_t^i)$, B the conditional probabilities $P(Z_t^i|Parents(Z_t^i))$, A the transition model $P(Z_t^i|Z_{t-1}^i)$, and π the prior distribution $P(Z_0^i)$. Figure 3 shows a manually designed network, which will be learnt from data as in [2].
- **Reusability**: To learn the structure-parameters we use dialogues clustered (representing kinds of users), using a *two-pass* clustering, see figure 2b.

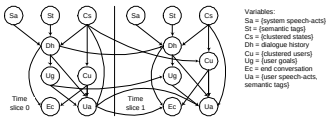

Fig. 3. DBN to predict user behavior

4. Evaluation Method

- **Problem**: Lack of a criterion to evaluate artificial human-computer dialogues.
- **Solution**: A similarity measure based on the symmetric distance of two smoothed HMMs, each HMM trained with a different set of dialogues. For instance, λ_1 represents real dialogues and λ_2 represents simulated dialogues (see equation 1), where S is the set of states, A is the transition matrix, B is the observation matrix (speech-acts) and D_{KL} is the Kullback-Leibler distance.
- **Utility**: Computing $D_{sys}(\lambda_1, \lambda_2)$ with system speech-acts and $D_{usr}(\lambda_1, \lambda_2)$ with user speech-acts, we can observe both systems and users similarity. Figure 4 shows comparisons between real dialogues (CMU Communicator 2001) and simulated dialogues (1000, using a simulator as in [1]).

$$D(\lambda_1, \lambda_2) = \sum_{s \in S} [D_{KL}(P(A_s|\lambda_1) \parallel P(A_s|\lambda_2)) + D_{KL}(P(B_s|\lambda_1) \parallel P(B_s|\lambda_2))] \quad (1)$$

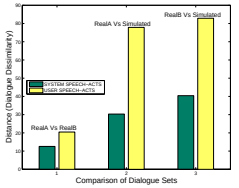

fig. 4. Dialogue similarity

5. Current/Future Work

- In this work in progress we have described an approach to learn reusable models, trained on annotated data [7] for stochastic simulation [3].
- Later work consists in the application of this approach to learn optimal dialogue strategies within a reinforcement learning framework.

References

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