

# Assessing Dialog System User Simulation Evaluation Measures Using Human Judges

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## Abstract

Previous studies evaluate simulated dialog corpora using evaluation measures which can be automatically extracted from the dialog systems' logs. However, the validity of these automatic measures has not been fully proven. In this study, we first recruit human judges to assess the quality of three simulated dialog corpora and then use human judgments as the gold standard to validate the conclusions drawn from the automatic measures. We observe that it is hard for the human judges to reach good agreement when asked to rate the quality of the dialogs from given perspectives. However, the human ratings give consistent ranking of the quality of simulated corpora generated by different simulation models. When building prediction models of human judgments using previously proposed automatic measures, we find that we cannot reliably predict human ratings using a regression model, but we can predict human rankings by a ranking model.

## 1 Introduction

User simulation has been widely used in different phases in spoken dialog system development. In the system development phase, user simulation is used in training different system components. For example, (Levin et al., 2000) and (Scheffler, 2002) exploit user simulations to generate large corpora for using Reinforcement Learning to develop dialog strategies, while (Chung, 2004) implement user simulation to train the speech recognizer and understanding components.

While user simulation is considered to be more low-cost and time-efficient than experiments with human subjects, one major concern is how well the state-of-the-art user simulations can mimic human user behaviors and how well they can substitute for human users in a variety of tasks. (Schatzmann et al., 2005) propose a set of evaluation measures to assess the quality of simulated corpora. They find that these evaluation measures are sufficient to discern simulated from real dialogs. Since this multiple-measure approach does not offer a easily reportable statistic indicating the quality of a user simulation, (Williams, 2007) proposes a single measure for evaluating and rank-ordering user simulations based on the divergence between the simulated and real users' performance. This new approach also offers a lookup table that helps to judge whether an observed ordering of two user simulations is statistically significant.

In this study, we also strive to develop a prediction model of the rankings of the simulated users' performance. However, our approach use human judgments as the gold standard. Although to date there are few studies that use human judges to directly assess the quality of user simulation, we believe that this is a reliable approach to assess the simulated corpora as well as an important step towards developing a comprehensive set of user simulation evaluation measures. First, we can estimate the difficulty of the task of distinguishing real and simulated corpora by knowing how hard it is for human judges to reach an agreement. Second, human judgments can be used as the gold standard of the automatic evaluation measures. Third, we can validate the automatic

measures by correlating the conclusions drawn from the automatic measures with the human judgments.

In this study, we recruit human judges to assess the quality of three user simulation models. Judges are asked to read the transcripts of the dialogs between a computer tutoring system and the simulation models and to rate the dialogs on a 5-point scale from different perspectives. Judges are also given the transcripts between human users and the computer tutor. We first assess human judges' abilities in distinguishing real from simulated users. We find that it is hard for human judges to reach good agreement on the ratings. However, these ratings give consistent ranking on the quality of the real and the simulated user models. Similarly, when we use previously proposed automatic measures to predict human judgments, we cannot reliably predict human ratings using a regression model, but we can consistently mimic human judges' rankings using a ranking model. We suggest that this ranking model can be used to quickly assess the quality of a new simulation model without manual efforts by ranking the new model against the old models.

## 2 Related Work

A lot of research has been done in evaluating different components of Spoken Dialog Systems as well as overall system performance. Different evaluation approaches are proposed for different tasks. Some studies (e.g., (Walker et al., 1997)) build regression models to predict user satisfaction scores from the system log as well as the user survey. There are also studies that evaluate different systems/system components by ranking the quality of their outputs. For example, (Walker et al., 2001) train a ranking model that ranks the outputs of different language generation strategies based on human judges' rankings. In this study, we build both a regression model and a ranking model to evaluate user simulation.

(Schatzmann et al., 2005) summarize some broadly used automatic evaluation measures for user simulation and integrate several new automatic measures to form a comprehensive set of statistical evaluation measures. The first group of measures investigates how much information is transmitted in the dialog and how active the dialog participants are. The second group of measures analyzes the style of

the dialog and the last group of measures examines the efficiency of the dialogs. While these automatic measures are handy to use, these measures have not been validated by humans.

There are well-known practices which validate automatic measures using human judgments. For example, in machine translation, BLEU score (Papineni et al., 2002) is developed to assess the quality of machine translated sentences. Statistical analysis is used to validate this score by showing that BLEU score is highly correlated with the human judgment. In this study, we validate a subset of the automatic measures proposed by (Schatzmann et al., 2005) by correlating the measures with human judgments. We follow the design of (Linguistic Data Consortium, 2005) in obtaining human judgments. We call our study an assessment study.

## 3 System and User Simulation Models

In this section, we describe our dialog system (IT-SPOKE) and the user simulation models which we use in the assessment study. IT-SPOKE is a speech-enabled Intelligent Tutoring System that helps students understand qualitative physics questions. In the system, the computer tutor first presents a physics question and the student types an essay as the answer. Then, the tutor analyzes the essay and initiates a tutoring dialog to correct misconceptions and to elicit further explanations. A corpus of 100 tutoring dialogs was collected between 20 college students (solving 5 physics problems each) and the computer tutor, yielding 1388 student turns. The correctness of student answers is automatically judged by the system and kept in the system's logs. Our previous study manually clustered tutor questions into 20 clusters based on the knowledge (e.g., acceleration, Newton's 3rd Law) that is required to answer each question (Ai and Litman, 2007).

We train three simulation models from the real corpus: the random model, the correctness model, and the cluster model. All simulation models generate student utterances on the word level by picking out the recognized student answers (with potential speech recognition errors) from the human subject experiments with different policies. The **random model (ran)** is a simple unigram model which randomly picks a student's utterance from the real cor-

pus as the answer to a tutor’s question, neglecting which question it is. The **correctness model (cor)** is designed to give a correct/incorrect answer with the same probability as the average of real students. For each tutor’s question, we automatically compute the average correctness rate of real student answers from the system logs. Then, a correct/incorrect answer is randomly chosen from the correct/incorrect answer sets for this question. The **cluster model (clu)** tries to model student learning by assuming that a student will have a higher chance to give a correct answer to the question of a cluster in which he/she mostly answers correctly before. It computes the conditional probability of whether a student answer is correct/incorrect given the content of the tutor’s question and the correctness of the student’s answer to the last previous question that belongs to the same question cluster. We also refer to the real student as the **real student model (real)** in the paper. We hypothesize that the ranking of the four student models (from the most realistic to the least) is: *real*, *clu*, *cor*, and *ran*.

## 4 Assessment Study Design

### 4.1 Data

We decided to conduct a middle-scale assessment study that involved 30 human judges. We conducted a small pilot study to estimate how long it took a judge to answer all survey questions (described in Section 4.2) in one dialog because we wanted to control the length of the study so that judges would not have too much cognitive load and would be consistent and accurate on their answers. Based on the pilot study, we decided to assign each judge 12 dialogs which took about an hour to complete. Each dialog was assigned to two judges. We used three out of the five physics problems from the original real corpus to ensure the variety of dialog contents while keeping the corpus size small. Therefore, the evaluation corpus consisted of 180 dialogs, in which 15 dialogs were generated by each of the 4 student models on each of the 3 problems.

## 4.2 Survey Design

### 4.2.1 Survey questions

We designed a web survey to collect human judgments on a 5-point scale on both utterance and di-

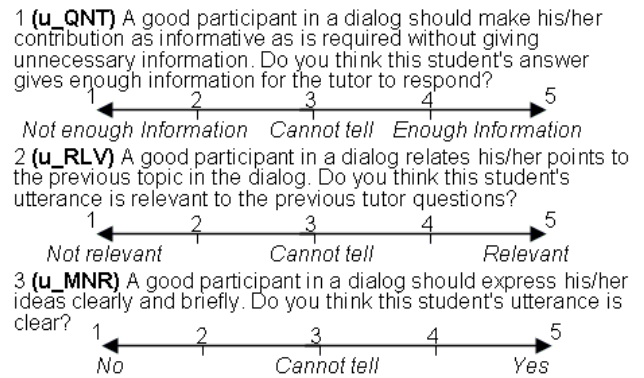


Figure 1: Utterance level questions.

alog levels. Each dialog is separated into pairs of a tutor question and the corresponding student answer. Figure 1 shows the three questions which are asked for each tutor-student utterance pair. The three questions assess the quality of the student answers from three aspects of Grice’s Maxim (Grice, 1975): Maxim of Quantity (**u\_QNT**), Maxim of Relevance (**u\_RLV**), and Maxim of Manner (**u\_MNR**). We do not include the Maxim of Quality because in our task domain the correctness of the student answers depends largely on students’ physics knowledge, which is not a factor we would like to consider when evaluating the realness of the students’ dialog behaviors.

In Figure 2, we show the three dialog level questions which are asked at the end of each dialog. The first question (**d\_TUR**) is a Turing test type of question which aims to obtain an impression of the student’s overall performance. The second question (**d\_QLT**) assesses the dialog quality from a tutoring perspective. The third question (**d\_PAT**) sets a higher standard on the student’s performance. Unlike the first two questions which ask whether the student “looks” good, this question further asks whether the judges would like to partner with the particular student.

### 4.2.2 Survey Website

We display one tutor-student utterance pair and the three utterance level questions on each web page. After the judges answer the three questions, he/she will be led to the next page which displays the next pair of tutor-student utterances in the dialog with the same three utterance level questions. The judge

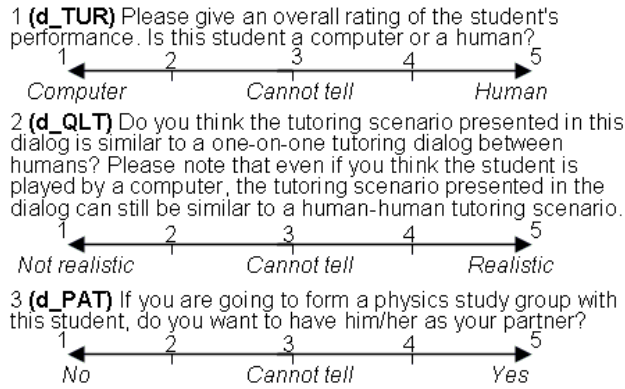


Figure 2: *Dialog level questions.*

reads through the dialog in this manner and answers all utterance level questions. At the end of the dialog, three dialog level questions are displayed on one webpage. We provide a textbox under each dialog level question for the judge to type in a brief explanation on his/her answer. After the judge completes the three dialog level questions, he/she will be led to a new dialog. This procedure repeats until the judge completes all of the 12 assigned dialogs.

### 4.3 Assessment Study

30 college students are recruited as human judges via flyers. Judges are required to be native speakers of American English to make correct judgments on the language use and fluency of the dialog. They are also required to have taken at least one course on Newtonian physics to ensure that they can understand the physics tutoring dialogs and make judgments about the content of the dialogs. We follow the same task assigning procedure that is used in (Linguistic Data Consortium, 2005) to ensure a uniform distribution of judges across student models and dialogs while maintaining a random choice of judges, models, and dialogs. Judges are instructed to work as quickly as comfortably possible. They are encouraged to provide their intuitive reactions and not to ponder their decisions.

## 5 Assessment Study Results

In the initial analysis, we observe that it is a difficult task for human judges to rate on the 5-point scale and the agreements among the judges are fairly low. Table 1 shows for each question, the percentages of

d_TUR	d_QLT	d_PAT	u_QNT	u_RLV	u_MNR
22.8%	27.8%	35.6%	39.2%	38.4%	38.7%

Table 1: Percent agreements on 5-point scale

pairs of judges who gave the same ratings on the 5-point scale. For the rest of the paper, we collapse the “definitely” types of answers with its adjacent “probably” types of answers (more specifically, answer 1 with 2, and 4 with 5). We substitute scores 1 and 2 with a score of 1.5, and scores 4 and 5 with a score of 4.5. A score of 3 remains the same.

### 5.1 Inter-annotator agreement

Table 2 shows the inter-annotator agreements on the collapsed 3-point scale. The first column presents the question types. In the first row, “diff” stands for the differences between human judges’ ratings. The column “diff=0” shows the percent agreements on the 3-point scale. We can see the improvements from the original 5-point scale when comparing with Table 1. The column “diff=1” shows the percentages of pairs of judges who agree with each other on a weaker basis in that one of the judges chooses “cannot tell”. The column “diff=2” shows the percentages of pairs of judges who disagree with each other. The column “Kappa” shows the un-weighted kappa agreements and the column “Kappa\*” shows the linear weighted kappa. We construct the confusion matrix for each question to compute kappa agreements. Table 3 shows the confusion matrix for d.TUR. The first three rows of the first three columns show the counts of judges’ ratings on the 3-point scale. For example, the first cell shows that there are 20 cases where both judges give 1.5 to the same dialog. When calculating the linear weighted kappa, we define the distances between the adjacent categories to be one<sup>1</sup>. Note that we randomly picked two judges to rate each dialog so that different dialogs are rated by different pairs of judges and one pair of judges only worked on one dialog together. Thus, the kappa agreements here do not reflect the agreement of one pair of judges. Instead, the kappa agreements show the overall observed agreement among every pair of

<sup>1</sup>We also calculated the quadratic weighted kappa in which the distances are squared and the kappa results are similar to the linear weighted ones. For calculating the two weighted kappas, see <http://faculty.vassar.edu/lowry/kappa.html> for details.

Q	diff=0	diff=1	diff=2	Kappa	Kappa*
d_TUR	35.0%	45.6%	19.4%	0.022	0.079
d_QLT	46.1%	28.9%	25.0%	0.115	0.162
d_PAT	47.2%	30.6%	22.2%	0.155	0.207
u_QNT	66.8%	13.9%	19.3%	0.377	0.430
u_RLV	66.6%	17.2%	16.2%	0.369	0.433
u_MNR	67.5%	15.4%	17.1%	0.405	0.470

Table 2: Agreements on 3-point scale

	score=1.5	score=3	score=4.5	sum
score=1.5	20	26	20	66
score=3	17	11	19	47
score=4.5	15	20	32	67
sum	52	57	71	180

Table 3: Confusion Matrix on d.TUR

judges controlling for the chance agreement.

We observe that human judges have low agreement on all types of questions, although the agreements on the utterance level questions are better than the dialog level questions. This observation indicates that assessing the overall quality of simulated/real dialogs on the dialog level is a difficult task. The lowest agreement appears on d\_TUR. We investigate the low agreements by looking into judges’ explanations on the dialog level questions. 21% of the judges find it hard to rate a particular dialog because that dialog is too short or the student utterances mostly consist of one or two words. There are also some common false beliefs among the judges. For example, 16% of the judges think that humans will say longer utterances while 9% of the judges think that only humans will admit the ignorance of an answer.

## 5.2 Rankings of the models

In Table 4, the first column shows the name of the questions; the second column shows the name of the models; the third to the fifth column present the percentages of judges who choose answer 1 and 2, can’t tell, and answer 4 and 5. For example, when looking at the column “1 and 2” for d\_TUR, we see that 22.2% of the judges think a dialog by a real student is generated probably or definitely by a computer; more judges (25.6%) think a dialog by the cluster model is generated by a computer; even more judges (32.2%) think a dialog by the correctness model is generated by a computer; and even

Question	model	1 and 2	can’t tell	4 and 5
d_TUR	real	22.2%	28.9%	48.9%
	clu	25.6%	31.1%	43.3%
	cor	32.2%	26.7%	41.1%
	ran	51.1%	28.9%	20.0%
d_QLT	real	20.0%	10.0%	70.0%
	clu	21.1%	20.0%	<u>58.9%</u>
	cor	24.4%	15.6%	<u>60.0%</u>
	ran	60.0%	18.9%	21.1%
d_PAT	real	28.9%	21.1%	50.0%
	clu	41.1%	17.8%	41.1%
	cor	43.3%	18.9%	37.8%
	ran	82.2%	14.4%	3.4%

Table 4: Rankings on Dialog Level Questions

more judges (51.1%) think a dialog by the random model is generated by a computer. When looking at the column “4 and 5” for d\_TUR, we find that most of the judges think a dialog by the real student is generated by a human while the fewest number of judges think a dialog by the random model is generated by a human. Given that more human-like is better, both rankings support our hypothesis that the quality of the models from the best to the worst is: *real*, *clu*, *cor*, and *ran*. In other words, although it is hard to obtain well-agreed ratings among judges, we can combine the judges’ ratings to produce the ranking of the models. We see consistent ranking orders on d\_QLT and d\_PAT as well, except for a disorder of cluster and correctness model on d\_QLT indicated by the underlines.

When comparing two models, we can tell which model is better from the above rankings. Nevertheless, we also want to know how significant the difference is. We use t-tests to examine the significance of differences between every two models. We average the two human judges’ ratings to get an averaged score for each dialog. For each pair of models, we compare the two groups of the averaged scores for the dialogs generated by the two models using 2-tail t-tests at the significance level of  $p < 0.05$ . In Table 5, the first row presents the names of the models in each pair of comparison. **Sig** means that the t-test is significant after Bonferroni correction; question mark (?) means that the t-test is significant before the correction, but not significant afterwards, we treat this situation as a trend; **not** means that the t-test is not significant at all. The table shows

	real-ran	real-cor	real-clu	ran-cor	ran-clu	cor-clu
d_TUR	sig	not	not	sig	sig	not
d_QLT	sig	not	not	sig	sig	not
d_PAT	sig	?	?	sig	sig	not
u_QNT	sig	not	not	sig	sig	not
u_RLV	sig	not	not	sig	sig	not
u_MNR	sig	not	not	sig	sig	not

Table 5: T-Tests Results

that only the random model is significantly different from all other models. The correctness model and the cluster model are not significantly different from the real student given the human judges’ ratings, neither are the two models significantly different from each other.

### 5.3 Human judgment accuracy on d\_TUR

We look further into d\_TUR in Table 4 because it is the only question that we know the ground truth. We compute the accuracy of human judgment as (number of ratings 4&5 on real dialogs + number of ratings of 1&2 on simulated dialogs)/(2\*total number of dialogs). The accuracy is 39.44%, which serves as further evidence that it is difficult to discern human from simulated users directly. A weaker accuracy is calculated to be 68.35% when we treat “cannot tell” as a correct answer as well.

## 6 Validating Automatic Measures

Since it is expensive to use human judges to rate simulated dialogs, we are interested in building prediction models of human judgments using automatic measures. If the prediction model can reliably mimic human judgments, it can be used to rate new simulation models without collecting human ratings. In this section, we use a subset of the automatic measures proposed in (Schatzmann et al., 2005) that are applicable to our data to predict human judgments. Here, the human judgment on each dialog is calculated as the average of the two judges’ ratings. We focus on predicting human judgments on the dialog level because these ratings represent the overall performance of the student models. We use six high-level dialog feature measures including the number of student turns (**Sturn**), the number of tutor turns (**Tturn**), the number of words per stu-

dent turn (**Swordrate**), the number of words per tutor turn (**Twordrate**), the ratio of system/user words per dialog (**WordRatio**), and the percentage of correct answers (**cRate**).

### 6.1 The Regression Model

We use stepwise multiple linear regression to model the human judgments using the set of automatic features we listed above. The stepwise procedure automatically selects measures to be included in the model. For example, d\_TUR is predicted as  $3.65 - 0.08 * WordRatio - 3.21 * Swordrate$ , with an R-square of 0.12. The prediction models for d\_QLT and d\_PAT have similar low R-square values of 0.08 and 0.17, respectively. This result is not surprising because we only include the surface level automatic measures here. Also, these measures are designed for comparison between models instead of prediction. Thus, in Section 6.2, we build a ranking model to utilize the measures in their comparative manner.

### 6.2 The Ranking Model

We train three ranking models to mimic human judges’ rankings of the real and the simulated student models on the three dialog level questions using RankBoost, a boosting algorithm for ranking ((Freund et al., 2003), (Mairesse et al., 2007)). We briefly explain the algorithm using the same terminologies and equations as in (Mairesse et al., 2007), by building the ranking model for d\_TUR as an example. In the training phase, the algorithm takes as input a group of dialogs that are represented by values of the automatic measures and the human judges’ ratings on d\_TUR. The RankBoost algorithm treats the group of dialogs as ordered pairs:

$$\mathcal{T} = \{(x, y) \mid \begin{array}{l} x, y \text{ are two dialog samples,} \\ x \text{ has a higher human rated score than } y \end{array}\}$$

Each dialog  $x$  is represented by a set of  $m$  indicator functions  $h_s(x)$  ( $1 \leq s \leq m$ ). For example:

$$h_s(x) = \begin{cases} 1 & \text{if } WordRatio(x) \geq 0.47 \\ 0 & \text{otherwise} \end{cases}$$

Here, the threshold of 0.47 is calculated by RankBoost.  $\alpha$  is a parameter associated with each indicator function. For each dialog, a ranking score is

calculated as:

$$F(x) = \sum_s \alpha_s h_s(x) \quad (1)$$

In the training phase, the human ratings are used to set  $\alpha$  by minimizing the loss function:

$$LOSS = \frac{1}{|T|} \sum_{(x,y) \in T} eval(F(x) \leq F(y)) \quad (2)$$

The *eval* function returns 0 if  $(x, y)$  pair is ranked correctly, and 1 otherwise. In other words, **LOSS** score is the percentage of misordered pairs where the order of the predicted scores disagree with the order indicated by human judges. In the testing phase, the ranking score for every dialog is calculated by Equation 1. A baseline model which ranks dialog pairs randomly produces a LOSS of 0.5 (lower is better).

While LOSS indicates how many pairs of dialogs are ranked correctly, our main focus here is to rank the performance of the four student models instead of individual dialogs. Therefore, we propose another Averaged Model Ranking (**AMR**) score. AMR is computed as the sum of the ratings of all the dialogs generated by one model averaged by the number of the dialogs. The four student models are then ranked based on their AMR scores. The chance to get the right ranking order of the four student models by random guess is  $1/(4!)$ .

Table 6 shows a made-up example to illustrate the two measures. *real\_1* and *real\_2* are two dialogs generated by the real student model; *ran\_1* and *ran\_2* are two dialogs by the random model. The second and third column shows the human-rated score as the gold standard and the machine-predicted score in the testing phase respectively. The LOSS in this example is  $1/6$ , because only the pair of *real\_2* and *ran\_1* is misordered out of all the 6 possible pair combinations. We then compute the AMR of the two models. According to human-rated scores, the real model is scored 0.75 ( $=(0.9+0.6)/2$ ) while the random model is scored 0.3. When looking at the predicted scores, the real model is scored 0.65, which is also higher than the random model with a score of 0.4. We thus conclude that the ranking model ranks the two student models correctly according to the overall rating measure. We use both LOSS and AMR to evaluate the ranking models.

Dialog	Human-rated Score	Predicted Score
real_1	0.9	0.9
real_2	0.6	0.4
ran_1	0.4	0.6
ran_2	0.2	0.2

Table 6: A Made-up Example of the Ranking Model

Cross Validation	d_TUR	d_QLT	d_PAT
Regular	0.176	0.155	0.151
Minus-one-model	0.224	0.180	0.178

Table 7: LOSS scores for Regular and Minus-one-model (during training) Cross Validations

First, we use regular 4-fold cross validation where we randomly hold out 25% of the data for testing and train on the remaining 75% of the data for 4 rounds. Both the training and the testing data consist of dialogs equally distributed among the four student models. However, since the practical usage of the ranking model is to rank a new model against several old models without collecting additional human ratings, we further test the algorithm by repeating the 4 rounds of testing while taking turns to hold out the dialogs from one model in the training data, assuming that model is the new model that we do not have human ratings to train on. The testing corpus still consists of dialogs from all four models. We call this approach the minus-one-model cross validation.

Table 7 shows the LOSS scores for both cross validations. Using 2-tailed t-tests, we observe that the ranking models significantly outperforms the random baseline in all cases after Bonferroni correction ( $p < 0.05$ ). When comparing the two cross validation results for the same question, we see more LOSS in the more difficult minus-one-model case. However, the LOSS scores do not offer a direct conclusion on whether the ranking model ranks the four student models correctly or not. To address this question, we use AMR scores to re-evaluate all cross validation results. Table 8 shows the human-rated and predicted AMR scores averaged over four rounds of testing on the regular cross validation results. We see that the ranking model gives the same rankings of the student models as the human judges on all questions. When applying AMR on the minus-one-model cross validation results, we see similar results that the ranking model reproduces hu-

	real		clu		cor		ran	
	human	predicted	human	predicted	human	predicted	human	predicted
d_TUR	0.68	0.62	0.65	0.59	0.63	0.52	0.51	0.49
d_QLT	0.75	0.71	0.71	0.63	0.69	0.61	0.48	0.50
d_PAR	0.66	0.65	0.60	0.60	0.58	0.57	0.31	0.32

Table 8: AMR Scores for Regular Cross Validation

man judges' rankings. Therefore, we suggest that the ranking model can be used to evaluate a new simulation model by ranking it against several old models. Since our testing corpus is relatively small, we would like to confirm this result on a large corpus and on other dialog systems in the future.

## 7 Conclusion and Future Work

Automatic evaluation measures are used in evaluating simulated dialog corpora. In this study, we investigate a set of previously proposed automatic measures by comparing the conclusions drawn by these measures with human judgments. These measures are considered as valid if the conclusions drawn by these measures agree with human judgments. We use a tutoring dialog corpus with real students, and three simulated dialog corpora generated by three different simulation models trained from the real corpus. Human judges are recruited to read the dialog transcripts and rate the dialogs by answering different utterance and dialog level questions. We observe low agreements among human judges' ratings. However, the overall human ratings give consistent rankings on the quality of the real and simulated user models. Therefore, we build a ranking model which successfully mimics human judgments using previously proposed automatic measures. We suggest that the ranking model can be used to rank new simulation models against the old models in order to assess the quality of the new model.

In the future, we would like to test the ranking model on larger dialog corpora generated by more simulation models. We would also want to include more automatic measures that may be available in the richer corpora to improve the ranking and the regression models.

## Acknowledgments

This work is supported by NSF 0325054. We thank J. Tereault, M. Rotaru, K. Forbes-Riley and the

anonymous reviewers for their insightful suggestions, F. Mairesse for helping with RankBoost, and S. Silliman for his help in the survey experiment.

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