Modeling Performance in Open-Domain Dialogue with PARADISE

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Abstract There has recently been an explosion of work on spoken dialogue systems, along with an increased interest in open-domain systems that engage in casual conversations on popular topics such as movies, books and music. These systems aim to socially engage, entertain, and even empathize with their users. Since the achievement of such social goals is hard to measure, recent research has used dialogue length or human ratings as evaluation metrics, and developed methods for automatically calculating novel metrics, such as coherence, consistency, relevance and engagement. Here we develop a PARADISE model for predicting the performance of Athena, a dialogue system that has participated in thousands of conversations with real users, while competing as a finalist in the Alexa Prize. We use both user ratings and dialogue length as metrics for dialogue quality, and experiment with predicting these metrics using automatic features that are both system dependent and independent. Our goal is to learn a general objective function that can be used to optimize the dialogue choices of any Alexa Prize system in real time and evaluate its performance. Our best model for predicting user ratings gets an $R^2$ of .136 with a DistilBert model, and the best model for predicting length with system independent features gets an $R^2$ of .865, suggesting that conversation length may be a more reliable measure for automatic training of dialogue systems.

1 Introduction

Over the last ten years there has been an explosion of work on spoken dialogue systems, along with an increased interest in open-domain systems that engage in casual conversations on popular topics such as movies, books and music. These systems aim to socially engage, entertain, and even empathize with their users [35, 21, 67]. Since the achievement of such social goals is hard to measure, recent
work has used dialogue length and human ratings as evaluation metrics [23,27,43].
Other work has focused on automatically calculating novel metrics such as coherence, consistency, relevance and engagement, using supervised models, or measures based on language model probabilities and word embedding cosine similarity [30,32,31,22,33,5,16,63,62] inter alia.

This paper develops a PARADISE-style dialogue evaluation model [57,59,49,48], for a particular type of open-domain dialogue system, namely systems that compete in the Alexa Prize (AP) [13,35,9,34,18,36,14,1,8,15]. The evaluation criteria for the AP explicitly specifies that systems will be evaluated on a combination of ratings from real users and the length of conversations: the “Grand Challenge” goal is conversations that last for twenty minutes and get an average rating of 4 out of 5 [51]. Real users can initiate AP conversations by saying Let’s talk to any Alexa device. They are then randomly assigned to an AP system, and, at the end of the conversation, are asked for a user satisfaction rating: On a scale of 1 to 5, how interested are you in talking to this socialbot again?: Because about 20% of users provide ratings, reliably predicting user satisfaction (ratings) would be valuable. Since the AP also aims for “long and engaging” conversations, conversation length is a second measure of dialogue quality. Conversation length makes particular sense in the context of the Alexa Prize, where real users choose when to stop the conversation. We thus experiment with predicting both user ratings and conversation length for Athena, a dialogue system that has been an AP finalist for the last two years [18,36,2]. In the 20/21 semi-finals, Athena’s average overall rating was 3.62 and average length was 2.12 minutes.

Previous work on open-domain dialogue has been trained on large-scale, unconstrained, freely available corpora, such as Twitter [41,7,12], Reddit [11], Open Subtitles [24], and Film Scripts [42,60]. More recent models are trained on controlled, crowd-sourced datasets, which are shorter and text-based to facilitate collection, training and evaluation, with lengths of 2-4 exchanges for Empathetic Dialogues [39], 4 exchanges for Daily Dialogue [28], 6 exchanges for PersonaChat [65], and 10 exchanges for Topical Chat [17]. Conversations with AP systems are much longer: in recent challenges conversations average more than 20 exchanges in length, with some as long as 200 exchanges. AP conversations are also a very different genre, due to the requirement that AP systems must carry out real-time, spoken conversations with hundreds of thousands of users, and respond to any

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{conversation_lengths.png}
\caption{Conversation Lengths in Exchanges}
\end{figure}

\footnote{1 We use the term exchanges, also known as adjacency pairs, since in AP parlance, a turn consists of both a user and system utterance, while a turn is a single user or system utterance in the typical usage in the spoken dialogue community.}
topic that the user might bring up, including recent events. AP systems are expected
to recognize and use up-to-date knowledge about sports and athletes, movies and TV
shows and their actors, characters and directors, as well as books and their authors,
and music, bands and musicians [15, 44, 3]. Thus, AP systems require mechanisms
beyond training on static open-domain dialogue corpora [41, 66, 4, 38, 20].

Section 2 describes our corpus of Athena dialogues. Section 3 describes our
experimental setup, and Section 4 presents both quantitative and qualitative results.
We discuss related work throughout the paper where it is relevant, and sum up our
results and future work in Section 5. We show that the best model for predicting
user ratings results in an $R^2$ of 0.135, while a model predicting conversation length
using Athena Independent features results in an $R^2$ of 0.862. These results suggest that
conversation length could be a more reliable indicator of dialogue quality in large
scale open-domain dialogue corpora that have been collected using interactions with
real users. We expect these results to generalize to other AP systems and be useful
for optimizing the system’s dialogue policy using reinforcement learning.

2 Athena Dialogue Corpus

We sampled a corpus of ~32K rated Athena dialogues from 2021. Figure 1 shows that many conversations
are very short, often only consisting of one exchange,
where the user seems to have invoked the AP skill by accident. The average conversation length is around
20 exchanges, with some conversations as long as 200
exchanges. The conversation ratings in Figure 2 shows
that highly rated conversations dominate, with a me-
dian of 4 and an average of 3.7.

We expected a strong correlation between
length and rating but surprisingly, Row 1 of Ta-
ble 1 shows that these two metrics are only weakly
(but significantly) correlated. We also examine the
correlations of dialogue acts indicating user sat-
isfaction (compliments) or dissatisfaction (com-
plaints), illustrated in Figure 3 and used as fea-
tures in Section 3. While all correlations are sig-
nificant, the largest is between length and com-
pliments, similar to findings in previous work on AP dialogues [43]. User utterances
such as these have also been used as the basis for open-domain evaluation models
such as FED, based on contextualized queries to DialogGPT for language model
probabilities [31, 66].
Figure 4 provides examples of short conversations. Each row counts as an exchange, so the first conversation is of length 3 (it includes Exchange 2 where the user says “alexa stop”). The second conversation is length 5. A conversation of length 1 only includes the greeting in Exchange 0. We believe that conversations of length < 5 don’t justify any rating at all, and that understanding how dialogue behaviors affect ratings requires modeling the ratings of users who experienced enough of a conversation to judge its quality. We therefore only model conversations that are at length ≥ 5, since greeting the user and asking their name takes ~4 exchanges. See Figure 4. The final corpus has a median length of 17 exchanges and an average length of 23.7 exchanges.

Figure 5 and Figure 6 illustrate Athena conversations. Sub-dialogues are logged by topic and response generator and most conversations consist of multiple topics, some initiated by Athena, and others by the user. Each topic uses different types and amounts of content, and supports different conversation styles. Athena supports “niche” topics such as astronomy, nutrition, and comic books along with popular topics such as music, animals, movies and video games. Figure 5 shows a sub-dialogue about comic books. Figure 6 shows a sub-dialogue about movies.

| Ex | Topic | User | Athena |
|----|-------|------|--------|
| 0  | intro | chat with me | Hi, this is an Alexa Prize Socialbot. I hope you had a good weekend. How’s it going. |
| 1  | intro | good | Okay, can’t wait to get to know a thing or two about you. I don’t think we’ve had a chance to meet yet. Would you like to tell me your name? |
| 2  | intro | alexa stop | |
| 0  | intro | talk to me | Hi, this is an Alexa Prize Socialbot. I hope your week is off to a good start. How are you doing? |
| 1  | intro | good | Okay, can’t wait to get to know a thing or two about you. I don’t think we’ve had a chance to meet yet. Would you like to tell me your name? |
| 2  | intro | colin | Okay, got it. It’s nice to meet you, Colin! Did you watch the fireworks on Sunday? |
| 3  | intro | yes | Awesome! Unfortunately I couldn’t go out and barbecue because I’m stuck in the cloud. But I hope you were able to celebrate! Anyway, What are some of the things you like to do in your free time. |
| 4  | intro | stop | |

Fig. 4 Two short conversations: the first (length 3) was rated 5, the second (length 5) was rated 3. Conversations of length ≥ 5 are included in our training data while those of length ≤ 5 are not.

A qualitative analysis of the goodness of topical sub-dialogues suggests that topic alone should have a large effect on user ratings. However, each conversation only

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2 In accordance with the AP Challenge rules, the shared conversations in Figure 4, Figure 5 and Figure 6 are between Athena and UCSC undergraduates rather than real users.
Ex. | Topic | User | Athena
---|---|---|---
18 | comics | oh really | I am familiar with DC and marvel. Who is your favorite character?
19 | comics | captain marvel | What about captain marvel do you like?
20 | comics | how she’s like super empowering | In general, why are you interested in comic books?
21 | comics | because they’re fun to read | That makes sense. I love comic books because they take you into another world with many different adventures. How often do you read them?
22 | comics | i probably read one every week | Okay. I wish I had more time to read comics. Would you say you’re an MCU expert? Like, I mean, have you seen most of the movies?
23 | comics | yeah all of them | There’s a ton of cool marvel characters in all the movies, it’s hard to pick a single favorite character. How about Thor? I think Chris Hemsworth did a really good job playing him in the MCU. What do you think? Do you also think he did a good a job?
24 | comics | i also think he did a good job | Yeah! Chris Hemsworth has been playing Thor for the past 8 years in 8 different marvel movies. Don’t you find that a little bit intriguing?
25 | comics | i think it is | My thoughts exactly. Here’s a little trivia about the actual comic book character. Thor has actually been in 7187 different comic books.
26 | comics | i did not know that | I was wondering. Tell me. If you could pick a character from DC to crossover into the Marvel Cinematic Universe, who would you pick and why?
27 | comics | yes scarlet witch | Yeah, that makes sense. I would pick the iconic hero Superman. The DC movies always make him look drab, but the Marvel movies are more colorful, so Superman would fit right in. Anyhow, that’s enough from me. I’m interested in your opinion. If you could have any one superpower from any superhero whatsoever, what would it be and why?
28 | comics | scarlet witch is power because she can live things and do things with her mind | Yeah, I get that. I would definitely have the ability to fly like Superman. Being able to just take off at light speed and get anywhere I want in no time would be amazing. Anyway, I think it’s cool that marvel comics has been around for so long. Marvel published a Generic Comic Book, in order to trademark the names “Super-Hero” and “Super-Villain”
29 | comics | i know that DC is one of the biggest and most famous comic distributors out there. | Did you ever wonder if DC actually stands for anything? It actually stands for Detective Comics, so when you say “DC Comics,” you’re really saying Detective Comics Comics.
30 | comics | that’s pretty funny | ...

Fig. 5 Sub-dialogue on the comics book topic of a rated 5 conversation totaling 41 exchanges.

has one rating. We approximate topic ratings with three heuristic scoring functions that take into account the conversation rating, the length of the sub-dialogues for each topic, and the length of user utterances in topical sub-dialogues, assuming that longer user utterances indicate greater engagement. For each function, we create a population of scores over all conversations and then sum them and standardize them
| Ex | Topic | User       | Athena                                                                 |
|----|-------|------------|------------------------------------------------------------------------|
| 36 | movies| no i have one | I really like the Actor Eddie Murphy. Have you seen any of his movies? |
| 37 | movies| no         | I really like the Movie Black Panther. Have you seen that movie?       |
| 38 | movies| no         | Scarlett Johansson did a really good job in her role in the Avengers. Scarlett Johansson wanted the role of Black Widow so much that she dyed her hair red to convince producers that she was right for the part. |
| 39 | movies| i don't care | Black Panther has actors David S. Lee and Winston Duke in it. What's your opinion of their performances? |
| 40 | movies| i don't care | I believe I read that Black Panther is directed by Ryan Coogler. Sometimes a director's unique voice really comes through in their work, do you think that happened in this case? |

Fig. 6 Sub-dialogue on the movies topic of a rated 1 conversation totaling 41 exchanges. Figure 5 includes "i don't care" as a complaint.

Fig. 7 Z-scores of Ratings by Topic, for 3 different scoring functions

by calculating their Z-scores (standardized value). Figure 7 shows the Z scores for each topic for each scoring function. The first function (in blue in Figure 7) simply multiplies the number of exchanges on a topic by the rating of that conversation, and then sums the scores over the whole population of conversations. The second function (in orange in Figure 7) down-weights the effect of the length of the conversation by taking the square root of the length and then multiplying by rating. The third function multiplies each product by an additional factor of average user utterance length (in green in Figure 7). The relative ranking of topics changes little over the three functions, but hobbies, which has shorter conversations, but longer user utterances, moves from 5th place to 2nd when user utterance length is taken into account. Despite the shorter conversations, users appear to find the hobbies topic, where Athena discusses what they like to do in their free time, very engaging.
3 Experimental Setup

Our dataset consists of 32,235 conversations split (~80/10/10) into training (25,794), development (3,229), and test (3,212). Our goal is to develop models capable of predicting the goodness of a conversation using regression models trained to predict either user ratings or conversation lengths. We also experiment with predicting dialogue outcomes in terms of length by only using features from the first 10 or 15 utterances in the conversation, to investigate whether we can make reliable predictions as the conversation unfolds, which could be then used as state variables for dialogue policy optimization, as in previous work on problematic dialogue prediction [19, 26, 56]. Given the AP goal of “long and engaging” conversations, a problematic dialogue is one that is short.

The plot of conversation ratings in Figure 2 has a mean of 3.7 and a median of 4. Figure 1 shows a long tail for conversation lengths, with only 3% of conversations longer than 75 exchanges (2.52 standard deviations above the mean of 23.7). We represent these longer conversations as if they had length 75.

We develop features as real-time automatic proxies for Athena’s performance that are specific to Athena as well as dialogue quality features that we expect to generalize, as summarized in Table 2 [59, 45, 29]. We use frequencies to ensure that features don’t indirectly encode conversation length. Previous work on PARADISE included many such features, e.g. Reprompts counted system utterances where a question was repeated, and Apologies counted system utterances apologizing for misunderstanding [52, 53]. We standardize each feature with their Z-scores so their distribution has a mean of 0 and a standard deviation of 1. This prevents the relative scales of features from impacting model performance and, for linear models, indicates the relative importance of each feature with the magnitude of the weight assigned to it.

User Utterance Features. To represent user utterances we calculate the median number of words in each response (LengthMedian in Table 2), expecting longer responses to indicate greater engagement. To capture user behaviors at a general level, we use two types of dialogue act tags [52]. First, we utilize all the MIDAS dialogue act tags (MIDAS%) from Athena’s NLU [18, 64]: these are used by the dialogue manager to condition Athena’s conversational behaviors. These include DAs identifying the user responding negatively to a question or criticizing the system.

Athena also uses a second level of fine-grained dialogue acts. These Social Dialogue Acts (SDAs) identify specific actions, feelings, and intents in the user’s speech. Some SDAs are grouped as negative (SDA_complaint) or positive feedback (SDA_compliment), as shown in Figure 3. Rows 2 to 4 in Table 1 show these independent measures of dialogue quality have a lower correlation with ratings and a higher correlation with length. Other SDAs, such as SDA_dev_command, identify

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3 We carried out pilot experiments on binary classifiers by treating conversations rated 1 and 2 as bad, and conversations rated 5 as good, but these barely performed above the baseline.
cases where the user request can only be satisfied outside the AP skill, such as requests to play some music or to turn down the volume. These requests result in an Apology from Athena. Other features count dialogue acts where users ask Athena to repeat herself (Repeat%), and where user abuse Athena or engage in profanity (Abuse%), which may correlate with lower ratings. We also create features measuring user utterances on prohibited topics of conversation (Red%), which result in Athena saying I am not the best person to discuss that with.

**Topic Features.** Some users would be expected to inherently find certain topics more interesting and the analysis in Section 2 suggests Athena’s performance is better on some topics. Thus, we include Athena dependent features representing the fraction of the conversation spent on each topic (e.g. TOPIC_FREQ_movies), as well as the median number of exchanges overall topics (TOP_DIST_MEDIAN). A high median indicates that the user found most topics engaging.

Figure 5 and Figure 6 in Section 2 provide examples of Athena conversations that illustrate several of these features. For example, exchanges 18 and 26 in Figure 5 shows the user saying Oh really and I didn’t know that, which are classified as compliments and contribute to the SDA_compliments for that conversation. Even though comic books is one of the less highly rated topics in Figure 7, this user is engaged, contributing long utterances, which are captured by the feature LengthMedian. The dialogue was 41 exchanges long, so the 13 comic exchanges here are represented by the feature Topic_Freq_comics having the value of 13/41. Figure 6 shows a sub-dialogue on the movies topic. Despite movies being Athena’s highest rated topic (see Figure 7), this user is not engaged. Exchanges 37 and 38 illustrate negative answers from the user (MIDAS_neg_answer), and exchanges 39 and 40 illustrate complaints. The LengthMedian is low due to the many short user utterances. The TOPIC_FREQ_movies value is 5/41.

**Model Setup.** We train regression models using Support Vector Regression models (SVR), Decision Tree and Random Forest models, Multi-layer Perceptron models (MLP), and Transformers. Our models are implemented using the Scikit-Learn Python package [37] and Huggingface Transformers.

- **Linear Regression.** Most linear regression experiments were done using ordinary least squares linear models. We also experimented with ridge and lasso regression models but they either matched or under-performed the least squares model.
- **SVR.** We used a Support Vector Regression model with a kernel containing a non-linear radial basis function. We also tuned the regularization parameter (traditionally denoted C) for these models. A larger value of C optimizes for a decision boundary which separates the data more accurately, but with smaller margins, whereas a smaller value of C optimizes for a larger margin around the decision boundary, but allows more misclassified points. When predicting rating, we found that a regularization parameter of 0.1 returned the best results. For conversation length, a regularization parameter of 10 performed best.
- **Decision Tree and Random Forest.** When using the Decision Tree and Random Forest regression models, we ran experiments with maximum allowed depths of 5 and 10, as well as an unbounded maximum depth. For length, the unbounded
depth trees consistently performed the best, but limiting the maximum depth to 5 performed best when predicting rating.

- **MLP.** When predicting conversation rating, we found that the performance of the Multi-layer Perceptron algorithm was poor when the hidden layers were large. So we used a model with just 5 hidden nodes in a single hidden layer. For conversation length, we raised the maximum number of training epochs to 1000 and used a structure consisting of two hidden layers, the first of which contained 100 hidden nodes, the second containing 50 hidden nodes. We also tried single hidden layer models with 50, 100, and 150 hidden nodes, but these alternatives performed worse. In all cases, the "reLu" activation function was used at each hidden node.

- **DistilBERT.** DistilBERT is a lightweight Transformer[50] model based on the BERT-base[10] model. DistilBERT is trained by distilling BERT base so that it is smaller, faster, and cheaper, yet has only marginally lower performance. Compared to BERT, DistilBERT has 40% less parameters, runs 60% faster, and achieves 95% of BERT’s performance on the GLUE[61] language understanding benchmark. We initialize DistilBERT using the pre-trained weights available through Huggingface Transformers.

**4 Results**

We train each regression model using the features described in Section 3 and report mean squared error (MSE), the coefficient of determination ($R^2$), and the Pearson correlation ($r$) for each model below.

| Model                  | MSE  | $R^2$ | $r$   |
|------------------------|------|-------|-------|
| SVR                    | 1.799| 0.025 | 0.252**|
| Decision Tree          | 1.767| 0.042 | 0.210**|
| Random Forest          | 1.743| 0.056 | 0.237**|
| Multi-layer Perceptron | 1.726| 0.065 | 0.258**|
| Least Squares Linear   | 1.709| 0.074 | 0.272**|
| DistilBERT Transformer | 1.597| 0.135 | 0.370**|

Table 3 Results of regression models trained to predict the user provided ratings. ** indicates significant $r$ correlation at $p \leq .01$. We found it surprising that user ratings, one of the main evaluation criteria for the Alexa Prize, should be so challenging to predict, even given thousands of training examples[43]. One reason might be subjectivity in user ratings[51]. In previous work, a controlled study with UCSC undergrads showed that user personality and

*github.com/huggingface/transformers
user expectations of a spoken SocialBot, affected ratings. Athena ratings for conversations of lengths < 5 also provides evidence for user subjectivity, given that we believe that these conversations are too short to justify any rating at all. The top plot in Figure 8 shows that most users rate conversations of length < 5 with a 1 but there is large variance ($\sigma^2 = 2.51$), while the variance for the whole training set is 1.85. The 5000 conversations of length 1, which only consisted of a greeting, were all rated 1. Figure 8 showed short conversations of length 3 and 5. The variance in ratings for conversations of lengths 3 & 4, at the bottom of Figure 8, clearly suggests an effect of user personality or subjectivity. This is why we filter out these conversations from our training data. In other settings, it would be possible to normalize user ratings according to the ratings distribution for a particular user (rater), but only about 20% of AP users actually carry out multiple dialogues with Athena. While Alexa users may talk to an AP system repeatedly, the random assignment of users to systems means an individual system is not likely to see the same user twice.

As a final point, it is well known that the performance of ASR varies on an individual basis, and that ASR error and ASR confidence scores are predictive of user satisfaction and conversation length. However AP systems do not have access to acoustic properties or gold-standard transcriptions of user utterances, and therefore cannot model ASR error.

**Predicting Conversation Length.**

We expect better results for predicting conversation length, given the correlation in Table 1 of length with independent measures of user satisfaction (compliments). Recent work by Shalyminov et al. also shows that conversation length performs as well as user ratings for reinforcement learning in AP conversations. However, it is important when predicting conversation length, to ensure that features are represented in such a way to avoid indirectly encoding length. We thus only use features calculated as frequencies and medians. We also conduct ablation studiess to show that individual features are not indirectly encoding length.

Table 4 shows, for each model and feature set, surprisingly good mean squared error (MSE), and $R^2$ and $r$ values. A model based on the DistilBERT architecture achieved the lowest MSE at 8.20 for Athena dependent features and the highest $R^2$ at 0.975. However, these models also are likely to rely on many Athena independent features as suggested by the decision tree model shown in Figure 9. The top node splits on the SDA_compliments feature. The sub-branch of the tree we include in the figure shows that the SDA_compliments feature is highly predictive of dialogue length, as the model chooses to split on that feature multiple times. The Athena dependent features representing topics such as video games and music are not selected for model splits until the third layer of the tree. This may also reflect user subjectivity in their interests in different topics.
### Table 4

| Model                  | Athena Specific Features | Athena Independent Features |
|------------------------|--------------------------|-----------------------------|
|                        | MSE | $R^2$   | $r$ | MSE | $R^2$   | $r$ |
| Least Squares Linear   | 95.82 | 0.684 | 0.827** | 249.23 | 0.179 | 0.425** |
| Decision Tree          | 55.03 | 0.819 | 0.909** | 80.69 | 0.734 | 0.866** |
| Random Forest          | 24.91 | 0.918 | 0.959** | 41.78 | **0.862** | 0.929** |
| SVR                    | 24.90 | 0.918 | 0.959** | 106.63 | 0.649 | 0.824** |
| Multilayer Perceptron  | 18.38 | 0.939 | 0.970** | 54.24 | 0.821 | 0.907** |
| DistilBERT Transformer | 08.20 | **0.975** | 0.995** | 43.00 | 0.842 | 0.920** |

**Table 4** Results of regression models trained to predict the length of the conversations for Athena Dependent and Athena Independent features. A ** indicates a significant $r$ correlation at $p \leq .01$.

Fig. 9 Second, Third and Fourth layers of the Decision Tree predicting Conversation Length using Athena Dependent Features, with an $R^2$ model fit of 0.819 (see RHS of Row 2 of Table 4).

The z-scores in Figure 7 suggest that length prediction should benefit from topic features. Some topics such as music may be popular in any system, but topic performance is clearly Athena Dependent, reflecting whether large scale training data on that topic is present in corpora such as Topical Chat [17, 20], whether high quality topical data is in WikiData or sources like IGDB, and the human effort put into that topic. Thus, it is surprising that the RHS of Table 4 shows that the Athena Independent features achieve excellent performance, with an $R^2$ value of 0.862 using a Random Forest model. Since SDA features can be calculated for any dialogue system, these results imply that the Athena Independent models are very general.

Fig. 10 Top 3 layers of a Decision Tree predicting Conversation Length using Athena Independent Features, with an $R^2$ model fit of 0.734 (LHS of Row 2 of Table 4).
Table 5 Results of an ablation study using the Decision Tree model. ** indicates significant $r$ correlation at $p \leq .01$.

Predicting Length from Initial Sequences. We also explore whether initial segments of the dialogue can predict conversation length, as in early work on task-oriented dialogue. Examination of our corpus suggests that some users are adversarial, some conversations just go poorly from the start, or some users suffer from particularly poor ASR due to dialect or native language [47]. Such predictions can be added to the dialogue state table and used for reinforcement learning [19, 26, 56]. We experiment with initial segments of length 10 and 15, given that the median conversations length is 17 exchanges.

We first trained and tested logistic regression by binning conversations lengths into two bins, one for lengths less than the median, and another for lengths greater
Table 6 Results of logistic regression models trained to predict whether or not the conversation length would be less or greater than the median. A ** indicates a significant correlation at $p \leq .01$.

| Model            | First 10 exchanges | First 15 exchanges |
|------------------|--------------------|--------------------|
|                  | MSE | $R^2$ | $r$ | MSE | $R^2$ | $r$ |
| Least Squares Linear | 0.211 | 0.154 | 0.394** | 0.149 | 0.402 | 0.634** |
| Decision Tree    | 0.226 | 0.095 | 0.508** | 0.086 | 0.656 | 0.828** |
| SVR              | 0.192 | 0.228 | 0.549** | 0.100 | 0.597 | 0.775** |
| Random Forest    | 0.159 | 0.361 | 0.612** | 0.047 | 0.812 | 0.902** |
| Multi-layer Perceptron | 0.174 | 0.301 | 0.579** | 0.081 | 0.676 | 0.827** |

We then experiment with conversation length binned into increments of 10 exchanges up to 70, with one final bin for conversations that were 70 exchanges or longer. These models use the same features as those in Table 6. The best performing Random Forest model after 15 turns of conversation results in an $R^2$ of 0.456. Thus it performs fairly well at predicting how long the conversation will be in terms of 10 exchange chunks. Additional features and further tuning could easily lead to even better results.

Table 7 Results of regression models trained to predict conversation length bins of size 10. A ** indicates a significant correlation at $p \leq .01$.

| Model            | First 10 exchanges | First 15 exchanges |
|------------------|--------------------|--------------------|
|                  | MSE | $R^2$ | $r$ | MSE | $R^2$ | $r$ |
| Least Squares Linear | 2.586 | 0.144 | 0.381** | 2.186 | 0.276 | 0.526** |
| Decision Tree    | 3.159 | 0.045 | 0.439** | 2.768 | 0.084 | 0.554** |
| SVR              | 2.430 | 0.196 | 0.510** | 2.035 | 0.326 | 0.620** |
| Random Forest    | 2.168 | 0.283 | 0.556** | 1.645 | 0.456 | 0.683** |
| Multi-layer Perceptron | 2.269 | 0.249 | 0.536** | 2.035 | 0.326 | 0.612** |

We then experiment with conversation length binned into increments of 10 exchanges up to 70, with one final bin for conversations that were 70 exchanges or longer. These models use the same features as those in Table 6. The best performing Random Forest model after 15 turns of conversation results in an $R^2$ of 0.456. Thus it performs fairly well at predicting how long the conversation will be in terms of 10 exchange chunks. Additional features and further tuning could easily lead to even better results.

5 Conclusion and Future Work

Our initial aim was to create a model that could predict the evaluation metrics that AP systems optimize for, namely dialogues that are “long and engaging”, in the style of work on PARADISE and Interaction Quality [57,49]. The setting of the AP supports the collection of thousands of user ratings at the end of a conversation; these should be a valuable indication of how engaging a dialogue is. We created predictive models of the ratings using Athena dependent dialogue features, but the best $R^2$ value was 0.139. We then showed that the variance in ratings of dialogues that are too short
to merit a rating, shows that there is great deal of subjectivity in these ratings [51]. In other settings, this subjectivity could be accounted for by normalizing ratings for each user [6], but only about 20% of AP users engage in multiple dialogues with Athena. Other work on AP systems modelled user individual differences such as Big Five personality, and user propensity to take the initiative [13, 8]. Athena models user topical preferences already, and e.g. makes inferences that interest in a sport like hiking may indicate an interest in a topic such as nature, or that interest in a topic like food may indicate interest in a topic such as nutrition. It seems clear that further work on personalized models of the user could be fruitful for better predicting user ratings [46].

However, the length metric is less subjective because users are volunteers, and only converse at length if they are engaged in the conversation. Results for predicting conversation length with a DistilBert model achieves an $R^2$ of 0.975, using Athena Dependent features. Results for predicting length with Athena Independent features are also excellent with an $R^2$ of 0.862 for a Random Forest model.

We also train models to predict length based on initial sequences of the dialogue of lengths 10 and 15. This ability is important for using length prediction in real-time to affect a dialogue system’s behavior. The best $R^2$ is 0.34 for a model that only had access to the first 10 exchanges of a conversation, and the best $R^2$ is 0.740 for a model that had access to the first 15 exchanges.

We believe that better results are possible, with additional features representing conversational behaviors. Features such as user response time might indicate confusion or a lack of interest, while our previous work showed that system response time directly affects user ratings [18]. Another speech feature missing from our models are ASR confidence scores and actual ASR error rates [47]. In future work, we will use the length predictor in the representation of dialogue state and condition the dialogue policy on predicted length. We would also like to test our model on other AP systems and conversational agents.

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