A Transformer-Based User Satisfaction Prediction for Proactive Interaction Mechanism in DuerOS

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ABSTRACT
Recently, spoken dialogue systems have been widely deployed in a variety of applications, serving a huge number of end-users. A common issue is that the errors resulting from noisy utterances, semantic misunderstandings, or lack of knowledge make it hard for a real system to respond properly, possibly leading to an unsatisfactory user experience. To avoid such a case, we consider a proactive interaction mechanism where the system predicts the user satisfaction with the candidate response before giving it to the user. If the user is not likely to be satisfied according to the prediction, the system will ask the user a suitable question to determine the real intent of the user instead of providing the response directly. With such an interaction with the user, the system can give a better response to the user. Previous models that predict the user satisfaction are not applicable to DuerOS which is a large-scale commercial dialogue system. They are based on hand-crafted features and thus can hardly learn the complex patterns lying behind millions of conversations and temporal dependency in multiple turns of the conversation. Moreover, they are trained and evaluated on the benchmark datasets with adequate labels, which are expensive to obtain in a commercial dialogue system. To face these challenges, we propose a pipeline to predict the user satisfaction to help DuerOS decide whether to ask for clarification in each turn. Specifically, we propose to first generate a large number of weak labels and then train a transformer-based model to predict the user satisfaction with these weak labels. Moreover, we propose a metric, contextual user satisfaction, to evaluate the experience under the proactive interaction mechanism. At last, we deploy and evaluate our model on DuerOS, and observe a 19% relative improvement on user satisfaction.

1 INTRODUCTION
DuerOS from Baidu Inc. is a commercial spoken dialogue system that serves millions of users, through conversations, to complete a series of tasks such as acquiring weather forecasts, such as searching for flight information and playing music. Like Alexa, Google Assistant, and other modern conversational systems, DuerOS processes a user utterance and responses to the user by a pipeline of the following modules: an automatic speech recognition (ASR) module [12, 23], a language understanding (LU) module [33], a knowledge graph (KG) module [26, 27], an information retrieval (IR) module [13], a natural language generation (NLG) module [4, 18, 30], a dialogue manager (DM) module [6, 17, 20] and a text-to-speech (TTS) module [21]. However, the users interacting with DuserOS voice assistant may experience frictions due to various reasons: 1) Automatic Speech Recognition (ASR) errors, such as misrecognizing the user utterance as some unrecognizable tokens, 2) Natural Language Understanding (NLU) errors, such as misunderstanding the user utterance that aims to play a song as intending to play a short video, 3) and user errors, such as speaking of playing a song as stopping playing a song. To ensure the success of a conversational system, it is essential to fix these frictions to let users have a more seamless and engaged experience.

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CCS CONCEPTS
• Computing methodologies → Discourse, dialogue and pragmatics.

KEYWORDS
Dialogue System, Transformer-based Model, User Satisfaction Prediction

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the error correction module can only avoid a small fraction of user frictions. (Specially, it can fix only around 10% of the user frictions in DuerOS.) The remaining frictions in the system can still make the users hard to enjoy a seamless experience. Moreover, the correction may be wrong and further confuses the user.

A better way to address these frictions is to proactively interact with the user (i.e., ask the user a clarification question and get his/her answer to this question) when the system recognizes that the candidate response might fail to satisfy the user. With the interaction with the user, the system can prepare a better response. Specifically, the system first uses a predictor to predict the user satisfaction with the candidate response. According to the user satisfaction, the system decides whether to ask for clarification or directly give this candidate response. Instead of correcting the user utterance directly, asking for clarification is a better way for the system to interact with the user when the system cannot determine the real intent of the user. In addition, some users in DuerOS tend to modify a previous utterance in hopes of fixing an error in the previous turn (which may be an error from the user or the system) to get the right results, but some users may give up or change to another intent when facing an error. Accordingly, asking a suitable question may guide a part of the users to find good rephrases to interact with the system.

Based on the above reasons, we consider it is necessary to adopt such a proactive interaction mechanism in DuerOS, where one key challenge task is to decide whether to ask for clarification in each turn. A common solution of this task [1, 3, 24] is to predict the user satisfaction with the candidate response that decides whether to ask for clarification in each turn. Though these works have been demonstrated their effectiveness in the offline datasets, it is hard to directly deploy them to DuerOS since more complex user dialogues that cover millions of domains make these methods hard to predict an accuracy user satisfaction in a commercial dialogue system. Furthermore, previous works usually adopt the turn-level user satisfaction to evaluate the user experience in a commercial dialogue system which is based on the information within the same turn. However, when deploying the proactive interaction mechanism to the DuerOS, turn-level user satisfaction cannot be adopted to evaluate the user satisfaction in our scenario since the evaluation should be based on the user utterance and the system response in the sequential turn as well. For example, we need to use the information of the sequential turn to determine whether the additional clarification question disturbs the user.

The challenges we face in this paper are summarized as follows:

- **Labels are not sufficient.** In DuerOS, there exists only a few users or expert annotators to support a few labels on user sessions. Accordingly, how we can improve the model over time with a few labels is a challenge to us.
- **Complex patterns lie behind different types of data.** The data available for our task is various, including structured data (such as the result item) and text data (such as the queries parsed by the ASR module). Moreover, the task handled by a commercial dialogue system is diverse and the data patterns behind these tasks become complex. Accordingly, it is challenging to effectively extract the patterns from the data to predict the user satisfaction.

2 RELATED WORK

Our work touches on three strands of research: proactive interaction mechanism in spoken dialogue system, weak label generation process, and transformer-based model.

2.1 Proactive interaction mechanism in spoken dialogue system

Proactive interaction mechanism is a widely studied research topic in spoken dialogue systems, which contains two key challenge tasks: When (i.e., whether to ask for clarification in each turn) and how (i.e., clarification query generation) to ask for clarification. There are many works focusing on the clarification query generation problem in the spoken dialogue systems [19, 25, 31]. However, few researchers focus on whether to ask for clarification in each turn of the spoken dialogue systems, particularly in a commercial dialogue system. For example, Hakkani-Tur et al. [9] propose a rule-based method to combine the signals from the ASR and LU module to predict whether to ask for clarification. In addition, Kotti et al. [16] extract the features from ASR and LU module and train a linear model with provided labels to predict the user satisfaction with the candidate response to help the system decide whether to ask for clarification in each turn. Recently, Alok et al. [1] propose a hypothesis rejection module that adopts a deep model with the user utterance and a series of handcrafted features from the NLU module to predict whether the system rejects the NLU result or directly give a response to the user in Alexa. When rejecting the
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Figure 1: The flow chart for the dialogue system. The system first generates a candidate response that consists of a result item and a voice response (the blue boxes). If the predictor predicts that the user is not likely to be satisfied with the candidate response, the system will ask a suitable question to determine the real intent of the user (the red boxes) instead of providing the candidate response to the user (the blue dotted box).

2.2 Weak Label Generation Process

To automatically generate the weak labels of the user satisfaction with the candidate response, we estimate the user satisfaction with the system response in each turn. Different from the user satisfaction prediction with the candidate response, when estimating the user satisfaction with the system responses, we can use the user utterance and user actions after the current turn, which contains the information of the user feedback to the system response in the current turn.

In the previous work, user satisfaction is a subjective measure of a user’s experience in a dialogue system, which indicates whether the user’s desire or goal is fulfilled. There is two-level user satisfaction in spoken dialogue systems: dialogue level user satisfaction which is to estimate whether the system response satisfies the user at the end of a user dialogue or session, and turn level user satisfaction which is to estimate whether the system response satisfies the user in each turn. To evaluate the turn-level user satisfaction on a spoken dialogue system or intelligent assistants, Hashemi et al. [10] first propose to extract the user intent from the user utterances and embed it into the query embeddings. Based on the intent-sensitive query embeddings, they measure the turn-level user satisfaction. In addition, Bodigutla et al. [2] proposes a new response quality annotation scheme, which introduces several domain-independent features to estimate user satisfaction, which improves generalizability to conversations spanning over multiple domains. Furthermore, Bodigutla et al. [3] propose a BiLSTM based model that automatically weighs each turn’s contribution towards the dialogue-level user satisfaction to jointly estimate the turn-level and dialogue-level user satisfaction.

In our work, we adopt a linear model with cross-domain handcrafted features to predict turn-level user satisfaction, which is used as the weak label of our model. In other words, we assume that if a user is not satisfied with the system response in one turn, proactively interacting with the user may bring a better experience to the user than directly giving this response. Moreover, a large number of weak labels enable us to train a deep neural network to explore more complex patterns from the user sessions that predict the user satisfaction with the candidate response.

2.3 Transformer-based Model

Transformer is first proposed by Vaswani et al. [28], which is solely based on an attention mechanism. It is more parallelizable and therefore being more computationally efficient compared with RNN or CNN. Transformer is effective for a wide range of problems. The most notable success is BERT [8] which is a transformer-based pre-trained model that works well on a wide range of natural language processing (NLP) tasks after fine-tuning, such as question-answering and natural language inference. Transformer-based models are also effective for relational reasoning [32], multi-agent reinforcement learning [29], and improving the click-through rate (CTR) in recommendation systems [5]. Notice that our task is closely connected to NLP (since there is text data in the dialogue system) and CTR prediction (since we need to predict the preference of the...
Figure 2: A high-level overview of our method. There are two stages in our solution to the user satisfaction prediction problem:
1) Weak label generation process: We first collect anonymous user log data and turn-level user satisfaction labels annotated by humans. Based on these data and handcrafted features, we train a linear model to generate weak labels for unlabeled data.
2) User satisfaction prediction process: We use dialogue-level features from user sessions and generated weak labels to train a transformer-based model to predict user satisfaction with the candidate response. Finally, we deploy the user satisfaction predictor to the online system that decides whether to ask a question for clarification in each turn.

4 METHOD

We show a high-level overview of our method in Figure 2. Specifically, there are two steps in our solution to predict the user satisfaction with the candidate response: 1) Weak label generation process: We first collect a small amount of anonymized user log data with the labels annotated by the expert annotators. Based on these data and handcrafted features, we train a linear model to generate weak labels. 2) User satisfaction prediction process: We use dialogue-level features in user sessions and a large number of weak labels to train a transformer-based model to predict the user satisfaction with the candidate response. Finally, we deploy the user satisfaction predictor to the online system that decides whether to ask for clarification or give the candidate response to the user in each turn.
With a large number of samples and the weak labels generated (e.g., certain words in the next turn’s utterance indicate that the user is unhappy), we train a transformer-based predictor to infer the user satisfaction ex post. Notice that this is an inference for user satisfaction with the candidate response \( r_n \) based on the features \((t_1, t_2, ..., t_n)\). The architecture of the transformer-based model is shown in Figure 3. The model contains two parts: (1) In the first part, the model adopts two stacks of transformer blocks to learn the patterns in each turn, where the first stack is used to extract features from the interactions between the query and the voice response which are text features, and the second stack is to extract features from the interactions between the domain-intent, the slot, the result item, and the query-response. The output of the first part is the embedding vector of each turn. (2) In the second part, the model adopts scaled dot-product attention [28] to extract features from the interactions between the current turn and the previous turns.

In the first part, the query and the voice response are processed by a query-response embedding layer followed by a position embedding layer, which follows Vaswani et al. [28]. Then, the embeddings are fed to the first stack of transformer blocks, each of which consists of a multi-head attention layer, a layer-norm layer, a feed-forward layer, and another layer-norm layer (cf. Figure 3 Center). The first stack of transformers block models the interaction between the query and the voice response. This architecture is helpful for the predictor to identify the mismatch between the query and the voice response which may indicate an erroneous response and the dissatisfaction of the user. Then, we use the second stack of transformer blocks with a similar architecture to extract the error patterns from the interactions between the structured features (the slot \(s_i\), the domain-intent \(d_i\), the item \(m_j\)) and the output vectors of the first stack of transformer blocks (i.e., the representation of the query \(q_i\) and response \(r_j\)). Finally, the output of the first part is the embedding vector of each turn \( E_i \).

In the second part, the input of the scaled dot-product attention consists of query, key and value, where query is the embedding vector of the current turn (denoted by \( Q \), key is the embedding vector of the current turn (denoted by \( Q \), value is the embedding vector of the current turn (denoted by \( Q \)).
vectors of the previous turns (denoted by $K$), and value is also the embedding vectors of the previous turns (denoted by $V$). The output (denoted by $O$) of attention is a weighted sum of the value, where the weight matrix is determined by query and its corresponding key.

$$O = \text{softmax}(\frac{QK^T}{\sqrt{d}})V$$

where $d$ is usually set to a large value in our case to scale the dot product attention.

At last, we use a fully-connected layer followed by reduce max function to find the error patterns in the interactions between the current turn and the previous turns. With the softmax function, the model outputs the probability $p(l_0|t_1,t_2,...,t_n)$. In addition, we use the cross entropy between the prediction $p(l_0|t_1,t_2,...,t_n)$ and the weak label $\hat{l}$ as the loss function.

### 4.4 Large-batch training

There are two potential problems in the above training process with weak labels: 1) Training a transformer-based model with a large amount of data is time-consuming. Moreover, when deployed online, the model needs to be frequently retrained (e.g., for every two weeks) using the updated data, which places a higher requirement of training efficiency. Retraining is necessary since the system is consistently updated in practice (e.g., the change of system settings or the update of the knowledge base). The update may result in a shift of the data distribution and degrade the performance of the old predictor. 2) The noise in the training data (induced from the weak label generation) slows down the learning and affects the generalization of the model. Specifically, for gradient-based methods, the noisy labels may lead to the wrong direction of the gradient. The model optimized through successive erroneous gradient steps may lead to a poor local minimizer and therefore poor generalization.

To solve the above problems, we propose to use a large batch size (LB) in the training process. For the first problem, LB accelerates the training process especially when the model is trained on multiple machines. LB reduces the number of passes through the model to iterate over all the training samples once. Also, LB is more suitable for parallelization across multiple machines. For the second problem, too many noisy samples in a batch may result in an incorrect gradient update, and successive erroneous gradient updates may lead to a deviation from the gradient updates using the true gradient which is assumed to result in correct generalization. Here, we use true gradient to refer to the gradient calculated on the samples with correct labels. In the training process, if the batch size is large enough, the noise ratio (i.e., the percentage of samples with incorrect labels) in a batch will not be too large and thus the gradient will be close to the true gradient with large probability. This may result in a better generalization. In general, we find that LB leads to better generalization when there are noisy samples.

### 5 MEASURE USER EXPERIENCE IN DUEROS

Though DuerOS collects the feedback from users by an app, the amount of the feedback is too few to be adopted to evaluate the performance of the model and the user experience. Previous works usually adopt turn-level user satisfaction (TUS) to measure user experience in a commercial dialogue system. However, TUS cannot be adopted to evaluate the user satisfaction in our scenario since the evaluation should be based on the user utterance and the system response in the sequential turn as well. Accordingly, we propose a new metric, contextual user satisfaction (CUS), to evaluate the user experience in our scenario. Specifically, we first evaluate the user experience in our scenario. Generally, we first evaluate the TUS by two ways: 1) use the linear model to automatically rate each turn on a continuous $[0-1]$ scale, 2) rate some specific turns on a discrete $[0-1]$ scale from expert annotators. For the above example in Figure. 1, the linear model would rate the turn “Hey Xiaodu, play the song show me love” as a score 0.87, while the expert annotators rate this turn as 1, which indicates that the user is satisfied with the system response and has a good experience. In contrast, if the system misrecognizes the user utterance as “play the song show up” in this turn and plays the song show up, the linear model rates this turn as a score 0.4 and the expert annotators rate this turn as 0, which indicates the system does not fulfill the user requirement. Then, we use TUS to calculate CUS by taking account of the contextual information around the turn when the system ask for clarification. Specifically, when the system proactively asks a question, there are two steps to estimate the user experience.
First, we estimate whether the user is satisfied with the clarification question. Second, we estimate whether the new response from the system satisfies the user. When the user is not satisfied with the clarification question or the system response after the clarification, we consider the question disturbs the user. Accordingly, we estimate the user experience (denoted by \( r_n \)) when the system asks for clarification by the following equation,

\[
r_c = r_n \times r_{n+1}.
\]  

(2)

where \( r_n \) is the rating of the user satisfaction in the turn when the system asks for clarification and \( r_{n+1} \) is the rating of user satisfaction in the turn after the clarification.

6 EXPERIMENT

In this section, we conduct experiments on three real datasets and evaluate our model online on DuerOS. We aim to answer the following questions:

Q1: How does the weak label generator perform?

Q2: How does our transformer-based model perform compared with the other baselines on the three datasets?

Q3: How do different designs influence the performance of our model?

Q4: How does training using a large batch size (LB) perform compared with training using a small batch size (SB)?

Q5: How does our transformer-based model perform when we deploy it on DuerOS?

6.1 Offline experiments

6.1.1 Dataset. We conduct experiments on three industrial datasets of different scales, which are collected from DuerOS. The training and the validation data of the three datasets are extracted from different months (June, July, and August respectively). The training data of the three datasets contains 18M, 32M, and 5M samples respectively. The validation data of each dataset contains 250K samples. The training data and the validation data are all labeled by expert annotators, which can be regarded as the ground truth. For clarity, we summarize these statistics in Table 2.

6.1.2 Metrics and hyperparameters. In our experiment, we use the area under the curve (AUC) and the conditional label accuracy (CLA) as the evaluation metrics. AUC is the area under the ROC curve, and CLA is the maximum recall when precision is larger than a specified value (which is set to 85% in this paper). Accuracy is the percentage of correct predictions. In our experiments, we binary our prediction according to a threshold and then calculate the classification accuracy given the true labels, where we tune the threshold by grid searching to maximize the accuracy.

We train the weak label generator with 10k training samples from the expert annotators. Then we implement our model based on Tensorflow and use the Adam optimizer. We apply a grid search for hyperparameters: the number of layers in two transformer blocks is searched in \( \{1, 2, ..., 8\} \) and the embedding size of each vector in the embedding layer is chosen from \( \{90, 120, ..., 1800\} \). Besides, the number of turns in our model is chosen from \( \{1, 2, ..., 10\} \). (cf. Figure 3). The selected hyperparameters of the model are listed in the Table 4.

6.1.3 Baselines. We compare our transformer-based model (TBM) with the following baselines:

- **Trans-Text**. Trans-Text [9] is a simple but efficient user satisfaction prediction method based on parsed rules. This method takes the semantic similarity and time interval between two turns, word confidence in the query, and frequency of occurrence of the user queries into consideration.
- **TDU**. TDU [33] is a BiLSTM-based deep neural net model in Alexa that predicts both turn-level and dialogue-level user satisfaction.
- **CNN and LSTM**. We also implement several popular architectures: CNN (following Text-CNN in Kim [14]) and LSTM [11]. We train the models with these architectures using the same training sets (including the weak labels).

6.1.4 Results. In the subsequent paragraphs, we first present the performance of the weak label generator. Then, we present the performance comparison between the baselines and the transformer-based model on the three datasets, and an ablation study of our model. At last, we compare the performance of LB and SB on Dataset 1.

The performance of weak label generator (Q1). We show the accuracy of the weak labels from the generator on the three datasets in Table 3. We have the following observations on the experimental results:

- Based on the available ground truth, we can evaluate the accuracy of our weak label generator, which is around 84% for the three datasets. It demonstrates that the weak label generator performs well on the three large datasets.
- When training using the generated weak labels, the transformer-based model obtains good performance in the three validation sets (with weak labels). This demonstrates the weak labels generalize well across the data.
- However, we observe that the performance of our model on the testing sets (with true labels) is slightly worse than that on the validation sets. This demonstrates the gap between weak labels and true labels, which motivates us to further improve the accuracy of the weak labels in the future.

Performance comparison (Q2). We show the experimental results on the three datasets in Table 3. We have the following observations on the experimental results:

- Transformer-based model outperforms all the other baselines on Dataset 1 and Dataset 2. In particular, compared with TDU, the performance of our model has improved by 7.4% in AUC (or 19% in CLA) on Dataset 1, and 1.2% in AUC (or 15% in CLA) on Dataset 2. The success of our model is due to the design of the transformer-based model that effectively extracts the information from structured and text data by modeling the interactions between the features and learns the temporal dependencies between turns by modeling the interactions between the features in current turn and those in previous turns.
- On Dataset 3, the AUC of the transformer-based model is slightly worse than that of TDU. However, the CLA of our model is still better than other baselines. Notice that the number of samples in Dataset 3 is smaller than that of Dataset 1 and Dataset 2, which indicates that our model is suitable for scenarios with a large number of training samples.
Table 2: Scales of the three datasets and the statistics of the weak labels.

|           | Dataset 1 | Dataset 2 | Dataset 3 |
|-----------|-----------|-----------|-----------|
| #samples in training set | 18M | 32M | 5M |
| #samples in validation set | 250K | 250K | 250K |
| #samples in testing set | 1K | 1K | 1K |
| Accuracy of the weak labels | 0.833 | 0.832 | 0.846 |
| Performance of our model on the validation sets (AUC) | 0.765 / 0.060 | 0.742 / 0.058 | 0.737 / 0.041 |
| Performance of our model on the testing sets (AUC) | 0.754 | 0.797 | 0.754 |

Table 3: The performance comparison between the baselines and our model on testing sets.

| Model         | Dataset 1 (AUC / CLA) | Dataset 2 (AUC / CLA) | Dataset 3 (AUC / CLA) |
|---------------|-----------------------|-----------------------|-----------------------|
| Trans-Text    | 0.724 / 0.050         | 0.668 / 0.045         | 0.643 / 0.020         |
| LSTM          | 0.765 / 0.060         | 0.742 / 0.058         | 0.737 / 0.041         |
| CNN           | 0.734 / 0.051         | 0.742 / 0.042         | 0.725 / 0.048         |
| TDU           | 0.754 / 0.071         | 0.787 / 0.052         | 0.767 / 0.045         |
| TBM (ours)    | **0.810 / 0.085**     | **0.797 / 0.060**     | **0.754 / 0.053**     |

Table 4: Hyperparameters in the model

| Hyperparameters                  | Value                  |
|----------------------------------|------------------------|
| LR                               | $1.2 \times 10^{-5}$   |
| The number of turns              | 5                      |
| Embedding size                   | 240                    |
| Threshold                        | 0.7                    |
| The numbers of the first stack of the transformers | 8                      |
| The numbers of the second stack of the transformers | 4                      |

- The rules in Trans-Text are carefully designed by experts and the model is not trained using data (and therefore weak labels). This model is shown to be effective in practice and being deployed on many real dialogue systems (e.g., AT&T Spoken Dialog System). Nevertheless, Trans-Text is not as good as the other baselines.

Ablation study (Q3). Here, we study the role of two stacks of transformer blocks, how the number of the transformer blocks in the two stacks (i.e., the number of the transformer blocks for text data and the transformer blocks for structured data) in our model affects the performance. Moreover, we also explore the temporal dependency between turns in the model that affects the performance. We perform the ablation study on Dataset 1 and show the results in Table 5. We have the following observations:

- First, we train the model with only the first stack of transformer blocks (for text data) or the second stack of transformer blocks (for structured data) separately. The AUC and the accuracy of the two ablated versions with a single stack are lower than the transformer-based model. This demonstrates that extracting the information from both the structured and text data using the transformer-based model improves the performance.

- We also test the model with the different number of transformer blocks (using $N = 4$ or 8). We find that a shallow structure for the first stack of transformer blocks (for text data) degrades the performance while a shallow structure for the second stack of transformer blocks (for structured data) does not significantly influence the performance.

- With the different number of turns in a user session feeding to the model, we find that when the number of the user turns is smaller than 5 in TBM, the performance of the model degrades. However, when the number of the user turns is more than 5 in TBM, there is no significant performance improvement of the model. It indicates that the user satisfaction in the current run has a strong relationship with the last four user turns. In other words, the temporal dependency between the current turn and the last four turns may exist and can be used to predict the user satisfaction with the candidate response. It may be caused by the reason that the user always has a similar intention in a continuous dialogue.

The performance comparison between LB and SB (Q4). We compare LB and SB on Dataset 1. For LB, we set the batch size to 12000 and the learning rate to 0.012. For SB, we set the batch size to 1024, and the learning rate to 0.001. The optimizers for both SB and LB are Adam [15], and the learning rates in both settings are tuned separately. In addition, we feed 100k data to the model in one epoch. In LB, each batch costs 0.224 and each epoch costs 330s. In SB, each batch costs 0.13s and each epoch costs 2285s.

We show the loss and the AUC during the training in Figure 4. We can see that the optimization for LB is faster (with only 20 epochs to converge) and results in higher AUC on testing data, which indicates that the model trained using LB performances better than using SB.

6.2 Online experiments (Q5)

With the encouraging results on the three real datasets, we perform online experiments on DuerOS. We deploy this model to the DM module of DuerOS to control whether to ask a clarification question or directly give the candidate response to the user. Before presenting the results, we first introduce the experiment setup for the online experiments.

Experiment setup and evaluation metrics. We use A/B testing, which is originated from Deininger [7] and widely used to
perform controlled experiments with two or more variants in real-world systems. In our experiments, we partition the users into 70/10/10/10 groups for four variants: In the first group, there is no user satisfaction predictor, i.e., the system directly provides the candidate response to the user. In the second group, we use Trans-Text as the user satisfaction predictor. In the third group, we use TDU as the user satisfaction predictor. In the fourth group, we adopt the transformer-based model as the user satisfaction predictor. In addition, we train each model with the training samples in the last week and update them every day. All experiments lasted for two weeks to avoid daily fluctuations.

We measure the online performance for each model using the contextual user satisfaction (CUS) where the label comes from expert annotators (cf. Section 5). To estimate CUS, we first sample the same number of user queries (1000 queries) from the queries in each group. Then, we extract the context for each query (e.g., 10 turns before the query, 10 turns after the query, and the candidate response), manually annotate whether it is a satisfied query for each sample and calculate the CUS for the target turn.

**Results.** The average CUS ratings across samples for the four groups (without a user satisfaction predictor, Trans-Text, TDU and the transformer-based model) are 0.654, 0.662, 0.668 and 0.684 respectively. We see that the transformer-based model achieved the best performance gain in terms of CUS, which is consistent with previous offline experiments. Given these promising results, our model has been successfully deployed to the DM module of DuerOS, serving hundreds of millions of user queries on a daily basis.

### Table 5: Ablation study.

| #Turns | Structured Transformer | Text Transformer | AUC   | Accuracy |
|--------|------------------------|-----------------|-------|----------|
| $T = 5$ | $N = 4$                | $N = 8$         | 0.810 | 0.720    |
| $T = 5$ | Null                   | $N = 8$         | 0.698 | 0.710    |
| $T = 5$ | $N = 4$                | Null            | 0.678 | 0.710    |
| $T = 5$ | $N = 8$                | $N = 8$         | 0.811 | 0.718    |
| $T = 4$ | $N = 4$                | $N = 8$         | 0.780 | 0.704    |
| $T = 5$ | $N = 4$                | $N = 8$         | 0.810 | 0.724    |
| $T = 10$ | $N = 4$               | $N = 8$        | 0.809 | 0.722    |
| $T = 20$ | $N = 4$               | $N = 8$        | 0.808 | 0.721    |

**Figure 4:** The loss and AUC during the training when using LB and SB.

### 7 CONCLUSION

In this paper, we propose a transformer based model to predict the user satisfaction for proactive interaction mechanism in a large-scale dialogue system (DuerOS), where we design a transformer-based model to predict the user satisfaction that helps the system decide whether to ask a user a clarification question. Specifically, we generate a large number of weak labels according to the user’s interactions with the system in the current turn and the next turn. Based on these weak labels, we propose a transformer-based model to extract information from both the structured and text data and grasp the temporal dependency between the current turn and the previous turns for prediction. We also find using a large batch size is empirically more effective in the training when the data is noisy. Furthermore, we conduct experiments on three large datasets and deploy the model to a large-scale spoken dialogue system. We evaluate the proactive interaction mechanism by a new metric (contextual user satisfaction), which can measure the user experience when the system asks a clarification question to the user. The result indicates the effectiveness of our method.

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