Abstract

User Satisfaction Estimation (USE) is crucial in helping measure the quality of a task-oriented dialogue system. However, the complex nature of implicit responses poses challenges in detecting user satisfaction, and most datasets are limited in size or not available to the public due to user privacy policies. Unlike task-oriented dialogue, large-scale annotated chitchat with emotion labels is publicly available. Therefore, we present a novel user satisfaction model with domain adaptation (USMDA) to utilize this chitchat. We adopt a dialogue Transformer encoder to capture contextual features from the dialogue. And we reduce domain discrepancy to learn dialogue-related invariant features. Moreover, USMDA jointly learns satisfaction signals in the chitchat context with user satisfaction estimation, and user actions in task-oriented dialogue with dialogue action recognition. Experimental results on two benchmarks show that our proposed framework for the USE task outperforms existing unsupervised domain adaptation methods. To the best of our knowledge, this is the first work to study user satisfaction estimation with unsupervised domain adaptation from chitchat to task-oriented dialogue.

1 Introduction

The developed task-oriented dialogue system has achieved great success for various business situations, such as virtual assistants and information-seeking systems with domain knowledge (Deriu et al., 2021). However, a dialogue chatbot with limited model capability sometimes fails to understand queries correctly and even annoys users with the wrong response. User Satisfaction Estimation (USE) is able to detect user satisfaction and enable adjustment of the strategy of the system. Liu et al. (2021) implemented a smooth handoff from the machine to a human agent when USE estimates a negative emotion from a user. When USE detects good user feedback in the deployment environment, chatbots can utilize this information to learn and improve continuously (Hancock et al., 2019).

In recent years, the USE in dialogue systems is always considered in the classification task. Previous works (Sun et al., 2021; Deng et al., 2022) show that data-driven pre-trained models can learn good exchange-level representations from task-oriented corpora and predict correct user satisfaction. Unfortunately, most user satisfaction datasets are very limited in size (Saha et al., 2020; Shi and Yu, 2018) or not publicly available due to user privacy policies (Wang et al., 2020). Moreover, it is time-consuming and expensive to conduct human evaluation experiments or crowd-sourcing for user satisfaction in a real-world task-oriented application.

Compared to the task-oriented dataset, the chitchat corpora from social media is easy-to-get but without explicit chatting targets. The underlying difference in linguistic patterns between the chitchat and task-oriented dialogue makes it difficult to utilize the chitchat dataset in the USE task directly. Therefore, unsupervised domain adaptation from chitchat to task-oriented dialogue is valuable and challenging in user satisfaction tasks.

As shown in Figure 1, we collect two dialogue sessions from human-human chitchat and human-machine task-oriented dialogue. In the chitchat, people talk around one topic and explicitly express their intents with emotions. In task-oriented dialogue, the user and system have explicit actions where the user wants to achieve his goal, and the system uses the background knowledge following the presetting actions. But users tend to implicitly show their emotions and are comfortable with the fulfillment of their goals.

To tackle the domain difference, we propose a novel USMDA framework and implement USE
with unsupervised domain adaptation from chitchat to task-oriented dialogue. On the one hand, the model reduces the domain discrepancy of turn representations between chitchat and task-oriented dialogue datasets. On the other hand, the model learns satisfaction signals in context features from chitchat, and learns user actions in the task-oriented system with an additional Dialogue Action Recognition (DAR) task. Moreover, the framework utilizes the pseudo-labeling approach (Lee, 2013) to label the most confident predictions and build a stronger USE model.

To the best of our knowledge, our paper is the first attempt to explore the USE with domain adaptation from chitchat to task-oriented dialogue. In this work, we make the following contributions:

- We propose the USMDA framework to perform user satisfaction estimation with unsupervised domain adaptation from chitchat to task-oriented dialogue.
- The result shows that user actions and invariant dialogue-related features improve the performance of the USE model within an unsupervised domain adaptation setting.
- The results on two datasets demonstrate that the proposed framework in the USE task achieves better results than other domain adaptation approaches.

2 Problem Definition

We formulate the task of user satisfaction estimation with domain adaptation from chitchat to task-oriented dialogue. Given a set of chitchat and task-oriented dialogue sessions, each session contains $N$ utterances $\{u_1, u_2, \ldots, u_N\}$. We split the $N$ utterances into $\frac{N}{2}$ exchange turns $x_i = (u_{2i-1}, u_{2i})$.

Each exchange turn is a communication either between multiple users or between user and system. Each exchange turn in chitchat is annotated with a satisfaction label $y_i^c$ and each exchange turn in a task-oriented dialogue has a user action $a_i^t$. Our goal is to train a USE model using labeled chitchat data $S$ and unlabeled task-oriented dialogue data $T$ to predict the correct satisfaction label $y_i^t$ on $T$.

3 Framework

This section introduces how to train a user satisfaction model with unsupervised domain adaptation. Figure 2 shows the overall architecture of our proposed framework USMDA with four different parts, including (1) dialogue Transformer encoder to capture a representation of each exchange-turn in the dialogue, (2) joint learning for USE with DAR, (3) reducing domain discrepancy between different distributed datasets, (4) predicting pseudo labels in the task-oriented dialogue, and retraining the model with the top-k pseudo labels.

3.1 Dialogue Transformer encoder

Chitchat and task-oriented dialogue samples are mixed in one batch $X$, which is fed into the shared backbone BERT (Devlin et al., 2019) to extract the exchange-level representation $e_i$ of each exchange.
where $\alpha$ denotes the hyperparameter to balance USE and DAR tasks.

3.3 Domain discrepancy

The framework uses maximum mean discrepancy (MMD) (Gretton et al., 2012; Long et al., 2015) to measure the distance between chitchat and task-oriented dialogue dataset distributions. MMD computes the distance between two exchange-level representations with Gaussian kernel, i.e., $k(e_i^s, e_j^t) = \exp(-||e_i^s - e_j^t||^2)$. Finally, we combine the joint learning loss and MMD as the overall loss:

$$\mathcal{L} = \mathcal{L}_{Joint} + \beta \left( \frac{4}{|X|^2} \sum_{i=1}^{|X|} \sum_{j=1}^{|X|} k(e_i^s, e_j^t) \right)$$

where $e_i^s$ and $e_j^t$ are two exchange-level representations from chitchat and task-oriented dialogue, $\beta$ denotes the hyperparameter balancing the joint-learning loss and MMD, and $|X|$ is the size of a mixed batch $X$.

3.4 Pseudo-labeling

After joint learning and reducing domain discrepancy, the user satisfaction model makes the satisfaction prediction $\hat{y}_i^t$ on each exchange turn $x_i^t$ from task-oriented dialogue. We measure the confidence of predictions by predicted scores. As shown in Figure 3, the top-k instances with the highest predicted scores are set as pseudo labels for retraining.

4 Experiments

4.1 Datasets and evaluation metrics

We conduct the proposed framework on the chitchat dataset EmoryNLP (Zahiri and Choi, 2018) and two task-oriented dialogue datasets: MultiWOZ 2.1 (MWOZ) (Eric et al., 2020) and Schema Guided Dialogue (SGD) (Rastogi et al., 2020). Moreover, we use the sampled 1000 dialogues from each of the MWOZ and SGD datasets, which are annotated with a five level satisfaction scale by Sun et al. (2021). The seven emotions in chitchat and five rating scores in task-oriented dialogue datasets are mapped into the coarse-grained labels “dissatisfied/neutral/satisfied” following existing work (Deng et al., 2022; Zahiri and Choi, 2018). For the DAR task, the MWOZ dataset is labeled with 21 actions by Eric et al. (2020), and the SGD dataset has 12 actions from Rastogi et al. (2020). We use the EmoryNLP dataset as a labeled source dataset and randomly choose 300 dialogues from each of the task-oriented dialogue datasets as unlabeled target datasets. The remaining 700 labeled dialogues from each task-oriented dialogue dataset are used for testing.

Following most existing work on emotion recognition in conversation, we report Macro-F1 and Micro-F1 scores for evaluating USE performance. Macro-F1 takes the average of all the per-class F1, and Micro-F1 computes the F1 of the aggregated contributions of classes.
### 4.2 Other models

We use the BERT model as our baseline model and the backbone for our proposed method for a thorough comparison. The following related models with task-oriented dialogue pretraining or different unsupervised domain adaptation methods are implemented:

- **ToD Bert (Wu et al., 2020)** is pretrained with masked-language modeling strategy and response selection task on nine task-oriented dialogue datasets.

- **WDGRL (Shen et al., 2018)** learns domain invariant representations by reducing empirical Wasserstein distance with an adversarial strategy.

- **DANN (Ganin et al., 2016)** uses domain adversarial training to learn the features that can not discriminate in domain adaptation. The DANN method is most widely used for unsupervised domain adaptation task in natural language processing.

### 5 Results and Analysis

#### 5.1 Overall performance

Table 1 shows primary experiment results, including the following models: (1) the baseline model and ToD Bert using only the source chitchat dataset, (2) several models with domain adaptation strategies and access to the user actions from the target data, (3) the BERT-based model with supervised learning on task-oriented datasets as upper bound.

We made the following notable observations:

(1) Our unsupervised domain adaptation strategy is effective in improving the performance for USE on two task-oriented dialogue datasets. USMDA leads to a significant improvement in Macro-F1 of 5.29% on MWOZ and 15.35% on SGD, and a performance improvement in Micro-F1 of 2.99% on MWOZ and 8.76% on SGD. Our proposed framework USMDA successfully solves the domain shift problem for USE from chitchat to task-oriented dialogue. USMDA, without any satisfaction labels in task-oriented data, achieves a competitive Micro-F1 48.50% on MWOZ, which is comparable to the upper bound model with supervised learning.

(2) Our framework USMDA achieves the best performance with domain adaptation for two datasets. On average, the models with domain adaptation have better performance than the baseline model. This suggests that the domain-invariant dialogue-related features boost the performance of the user satisfaction model. Compared to other domain adaptation approaches, USMDA leads to a comparatively significant improvement. We demonstrate that our proposed framework USMDA to learning domain-invariant dialogue-related features is more effective than WDGRL and DANN.

(3) Baseline model, using only source chitchat samples, does not perform competitively. Even though ToD-BERT is pretrained with nine task-oriented dialogue datasets, it has a subpar performance without domain adaptation in the USE task. The unsatisfactory results without domain adaptation suggest that specific domain features are valuable and necessary for USE in task-oriented dialogue.

#### 5.2 Ablation study

To understand the impacts of different individual parts in our domain adaptation strategy, we conduct an ablation study on three simplified modules of our proposed framework (see Table 2). We can observe that by removing any module, this results in worse performance. Removing joint learning leads to the most significant loss in Micro-F1 by 6.96% on SGD. This indicates that user actions throughout the dialogue reflect user satisfaction and are important dialogue-related specific features in task-oriented dialogue.

Table 2 shows that the improvement transfers well across both datasets. Learning transferable features using MMD is beneficial because dropping MMD impairs the performance by 1.17% Macro-F1 and 0.85% Micro-F1 on SGD. Moreover, removing the pseudo-labeling degrades the performance...
Table 2: Ablation study of USMDA on pseudo-labeling, joint learning and MMD. A negative value means a performance loss by removing module.

| Module       | Macro | Micro | Macro | Micro |
|--------------|-------|-------|-------|-------|
| w/o pseudo   | -5.33 | -0.58 | -3.88 | -1.20 |
| w/o MMD      | -0.37 | -0.26 | -1.17 | -0.85 |
| w/o joint    | -0.22 | -0.50 | -6.27 | -6.96 |

by 3.9-5.3% Macro-F1 and 0.6-1.2% Micro-F1, indicating the benefits of the data-centric approach to the USE task.

5.3 Discussion and future work

Compared to the kernelized method MMD, the WDGRL and DANN are adversarial training strategies. Table 1 shows that WDGRL improves the model performance only slightly and that DANN does not always lead to the increased target domain performance. While traditional adversarial training strategies are sometimes unable to gain improvements with pre-trained language models, simple MMD is efficient at learning domain-invariant features. Our proposed framework achieves impressive results on the two fixed datasets. In the future, we will evaluate this framework on real-life scenarios.

6 Conclusion

We adopt joint-learning, MMD, and pseudo-labeling with domain adaptation to improve the strong USE model in task-oriented dialogue. The results show that domain adaptation with user actions is effective in the USE task. MMD has positive effects on overall performance by learning domain-invariant dialogue-related feature representations. The pseudo-labeling is important for USE with unsupervised domain adaptation. Our proposed USMDA framework has comparable results like the supervised model, encouraging future work addressing domain adaptation in the USE task.

Acknowledgements

The BMW Group supported the content of this work. We thank Davide Cadamuro and the reviewers for the invaluable feedback.

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A Appendix

A.1 Datasets

We perform experiments on dialogue corpora, using 713 dialogues from EmoryNLP, 1000 dialogues from MWOZ, and 1000 dialogues from SGD. A dialogue session is divided into dialogue windows. The number of considered exchange-level turns in a dialogue window is four.

| EmoryNLP          | Emotion | Satisfaction |
|-------------------|---------|--------------|
| Monica: Hey.      | Neutral | Neutral      |
| Rachel: Hey.      | Neutral | Neutral      |
| Monica: How’s the big anniversary dinner? | Neutral | Neutral |
| Rachel: Well, we never actually got to dinner. | Sad | Unsatisfied |
| Monica: Ohhh, nice. | Sad    | Unsatisfied  |
| Rachel: No, we kinda broke up instead. | Sad | Unsatisfied |
| Monica: What?!    | Scared  | Unsatisfied  |
| Rachel: God, Monica it’s on the ceiling. | Scared | Unsatisfied |

Table 3: Chitchat example from EmoryNLP.

EmoryNLP: EmoryNLP is an annotated chitchat dataset with fine-grained and coarse-grained emotions from the TV show, Friends. The EmoryNLP contains seven emotions: (1) Positive: powerful, joyful, peaceful, (2) Negative: mad, sad, scared, and (3) Neutral: neutral.

MWOZ: Multi-Domain Wizard-of-Oz 2.1 is a multi-domain task-oriented dialogue dataset. It contains dialogue utterances, user goals, and system actions over seven domains.

SGD: Schema-Guided Dialogue has multi-domain task-oriented dialogues over 16 domains and provides a challenging testbed for dialogue state tracking. SGD contains multiple schemas with a dynamic set of slots for task-oriented dialogue.

A.2 Training and hyperparameters

For the backbone of USMDA, we use the implementation of the BERT-base uncased model and of the ToD-Bert model from huggingface1. Both models are 768-dimensional Transformer self-attention encoders with 12 layers. The dialogue-level Transformer is a standard Transformer encoder with 2 layers.

We run each experiment four times with different seeds and calculate the average performance. The adamW optimizer is implemented with a learning rate of 2E-5, and the training epoch size is 2.

A.3 Dialogue Examples

The annotated chitchat and task-oriented dialogue examples are presented in Tables 3, 4.

A1https://huggingface.co/
System: Okay, there is an American Airlines outbound flight that will leave at 11:40 am and the return flight will leave at 9:30 am. The cost of the ticket will be only $163.

| USER: When is the arrival time of my return flight and to which airport it arrives? |
|---------------------------------|
| System: The destination airport is Dulles International Airport and the flight will arrive at 1:42 pm. |

| USER: Sounds good to me. |
|--------------------------|
| System: Do you want me to book tickets for this flight? |

| USER: Yup, please book 1 ticket in economy class which should be a refundable one, since my plan might change later on. |
| System: Okay! Please can you confirm me that you wish to fly from Atlanta to Washington in American Airlines on March 10th at 11:40 am and the return journey will be on March 14th at 9:30 am and you wish to book only 1 Economy ticket, right? |

| USER: Yup, you’re right. Is it a zero stops flight? |

| SGD | Action | Satisfaction |
|-----|--------|--------------|
| System: Okay, there is an American Airlines outbound flight that will leave at 11:40 am and the return flight will leave at 9:30 am. The cost of the ticket will be only $163. | Offer | - |
| USER: When is the arrival time of my return flight and to which airport it arrives? | Request | Neutral |
| System: The destination airport is Dulles International Airport and the flight will arrive at 1:42 pm. | Inform | - |
| USER: Sounds good to me. | Select | Satisfied |
| System: Do you want me to book tickets for this flight? | Offer | - |
| USER: Yup, please book 1 ticket in economy class which should be a refundable one, since my plan might change later on. | Affirm | Neutral |
| System: Okay! Please can you confirm me that you wish to fly from Atlanta to Washington in American Airlines on March 10th at 11:40 am and the return journey will be on March 14th at 9:30 am and you wish to book only 1 Economy ticket, right? | Confirm | - |
| USER: Yup, you’re right. Is it a zero stops flight? | Affirm | Satisfied |

Table 4: Task-oriented dialogue example from SGD.