End-to-end Conversation Modeling Track in DSTC6

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Abstract

This article explains the end-to-end conversation modeling track of the 6th dialog system technology challenges (DSTC6).

1 Introduction

End-to-end training of neural networks is a promising approach to automatic construction of dialog systems using a human-to-human dialog corpus. Recently, Vinyals et al. tested neural conversation models using OpenSubtitles [1]. Lowe et al. released the Ubuntu Dialogue Corpus [2] for research in unstructured multi-turn dialogue systems. Furthermore, the approach has been extended to accomplish task oriented dialogs to provide information properly with natural conversation. For example, Ghazvininejad et al. proposed a knowledge grounded neural conversation model [3], where the research is aiming at combining conversational dialogs with task-oriented knowledge using unstructured data such as Twitter data for conversation and Foursquare data for external knowledge. However, the task is still limited to a restaurant information service, and has not yet been tested with a wide variety of dialog tasks. In addition, it is still unclear how to create intelligent dialog systems that can respond like a human agent.

In consideration of these problems, we proposed a challenge track to the 6th dialog system technology challenges (DSTC6) [4]. The focus of the challenge track is to train end-to-end conversation models from human-to-human conversation and accomplish end-to-end dialog tasks in various situations assuming a customer service, in which a system plays a role of human agent and generates natural and informative sentences in response to user’s questions or comments given dialog context.

2 Tasks

In this challenge track, a system has to generate sentence(s) in response to a user input in a given dialog context, where it can use external knowledge from public data, e.g. web. The quality of automatically generated sentences is evaluated with objective and subjective measures to judge whether or not the generated sentences are natural and informative for the user.

This track consists of two tasks, i.e. main and pilot tasks as follows:

(1) Main task (mandatory): Customer service dialog using Twitter
Task A: Full or part of the training data will be used to train conversation models.

Task B: Any open data, e.g. from web, are available as external knowledge to generate informative sentences. But they should not overlap with the training, validation and test data provided by organizers.

Challenge attendees can select either A or B, or the both. The tools to download twitter data and extract the dialog text are provided to all attendees at this challenge track in DSTC6. The attendees need to collect the data by themselves. The data collected before Aug. 1st are available as trial data, and the official training/development data will be collected from Aug. 1st to 31st.

(2) Pilot task: Movie scenario dialog using OpenSubtitles
The OpenSubtitles are basically not task-oriented dialogs, but the naturalness and correctness of system responses will be evaluated.

3 Tool package

Data collection tools and a baseline system are available from

https://github.com/dialogtekgeek/DSTC6-End-to-End-Conversation-Modeling

Please follow the instruction in README.md of the package to use the tools. Sample models are also available from

https://www.dropbox.com/s/6jfpfxh3aakjvts/sample_twitter_models.tgz

which can be tested with an interactive demo in the package. The baseline system will respond to user utterances given by keyboard as follows.

```
$ cd ChatbotBaseline/demo
$ demo.sh --model sample_twitter_model_py3.best
--- do neural conversations ------
Loading model params from sample_twitter_model_py3.best
vocabulary size = 20000
--- start conversation [push Cntl-D to exit] ------
U: hello!
S: hi <USER> ! how can we help you today ?
U: i am thinking about buying a new car.
S: we can help you out with that ! what features are you looking for in your new car ?
U: i am looking for a minivan.
S: we ’d be happy to help you find one ! what ’s your budget ?
U: about 30000 dollars. do you have such minivans?
S: <URL>
U: okay, i will check that. thank you.
S: you ’re welcome . have a great day.
```

In the above example, we assume that the model file “sample_twitter_model_py3.best” is located in directory “ChatbotBaseline/demo”.

4 Data collection

4.1 Twitter data

In the twitter task, we use dialog data collected from multiple twitter accounts for customer services, where each dialogue consists of real tweets between a customer and an agent. A customer usually asks a question or complains something about a product or a service of the company, and an agent responds to the customer accordingly. In this challenge, each participant is supposed to develop a dialog system that mimics agents’ behaviors. The system will be evaluated based on the quality of
automatically generated sentences in response to customers’ tweets. For the challenge, we provide a
data collection tool to all participants so that they can collect the data by themselves because it is
basically not allowed to distribute twitter data to third parties. In this task, it is assumed that each
participant continues to collect the data from specific accounts in the challenge period. To acquire a
large amount of data, the data collection needs to be done repeatedly, e.g. by running the script once
a day, because the amount of data we can download is limited and older tweets cannot be accessed
as time goes by. At a certain point of time, we will provide an additional tool to extract subsets of
collected data for training, development (validation), and evaluation so that all the participants can
use the same data for the challenge. Until the official data sets are fixed, trial data sets are available to
develop dialog systems, which are selected from the data collected by each participant. But once the
official data sets are determined, the system needs to be trained from scratch only using the official
data sets. We plan to determine the training, development and evaluation sets with the following
amounts, where there are no overlaps between the data sets.

|                   | #twitter account | #dialog  | #utterance | Estimated release date |
|-------------------|------------------|----------|------------|------------------------|
| Training set      | 943              | ≈ 1M     | ≈ 2.2M     | 8/1                    |
| Development set   | 118              | ≈ 110K   | ≈ 280K     | 8/1                    |
| Evaluation set    | 118              | ≈ 500    | ≈ 1200     | 9/18                   |

Participants need to use data collection tool “collect_twitter_dialogs” included in the
provided package. Necessary steps are written in “collect_twitter_dialogs/README.md”
The trial data sets can be extracted from downloaded twitter dialogs using a data extraction script:
“make_trial_data.sh” in “tasks/twitter”.

4.2 OpenSubtitles2016

OpenSubtitles data is a collection of movie subtitles originally stored in
http://www.opensubtitles.org/. We use English subtitles in OpenSubtitles2016
corpus [6] on the web site:

http://opus.lingfil.uu.se/OpenSubtitles2016.php

The tar file can be downloaded via URL:

http://opus.lingfil.uu.se/download.php?f=OpenSubtitles2016/en.tar.gz

and decompressed by

$ tar xzvf en.tar.gz

The file size of “en.tar.gz” is approximately 18GB. It will need more disk space for storing the
decompressed files. The trial data sets can be extracted from the decompressed directory using a data
extraction script: “make_trial_data.sh” in “tasks/opensubs”.

|                   | #dialog | #utterance | Estimated release date |
|-------------------|---------|------------|------------------------|
| Training set      | ≈ 30M   | ≈ 60M      | 8/1                    |
| Development set   | ≈ 300K  | ≈ 600K     | 8/1                    |
| Evaluation set    | ≈ 500   | ≈ 1000     | 9/18                   |

5 Text preprocessing

Twitter dialogs and OpenSubtitles contain a lot of noisy text with specific expressions. Therefore,
text preprocessing is important to clean up and normalize the text. Moreover, all the participants
need to use the same preprocessing at least for target references to assure fair comparisons between
different systems in the Challenge.
5.1 Twitter data

Twitter data contains a lot of specific information such as twitter account names, URLs, e-mail addresses, telephone/tracking numbers and hashtags. This kind of information is almost impossible to predict correctly unless we use a lot of training data obtained from the same site. To alleviate this difficulty, we substitute those strings with abstract symbols such as <URL>, <E-MAIL>, and <NUMBERS> using a set of regular expressions. In addition, since each tweet usually starts with a twitter account name of the recipient, we just remove the account name. But if such names appear within a sentence, we leave them because those names are used as a part of sentence. We also leave hashtags because of the same reason. We also substitute user names with <USER>, for example,

Hi John, can you ... → Hi <USER>, can you ...

Actually, since the user’s name can be extracted from the attribute information of each tweet, we can replace it. Note that the text preprocessing is not perfect, and therefore there may remain original phrases, which are not replaced or removed successfully. The text also includes many abbreviations, e.g. “pls hlp”, special symbols, e.g. “(-:” and wide characters “©♥♣”, but they are left unaltered. The wide characters are encoded with UTF-8 in the text file. The preprocessing is performed by function “preprocess()” in python script “tasks/twitter/extract_twitter_dialogs.py”.

5.2 OpenSubtitles data

We basically follow the method in [3] to extract dialogs and preprocess the subtitle data. Consecutive two sentences are considered a dialog consisting of one question and one answer.

6 Dialog data format

6.1 Basic format

Each dialog consists of two or more utterances, where each line corresponds to an utterance given by user ‘U:’ or system ‘S:’ indicated at the head of each utterance. An empty line indicates a breakpoint of dialogs. The following text is an example of dialog data file.

U: hello !
S: how may I help you ?
U: nothing ...
S: have a good day !

U: your delivery timing & info leaves a lot to be desired . flowers ordered last wk for delivery yesterday are nowhere to be seen .
S: hello <USER> , i am sorry for the issue you are experiencing with us . please dm me so that i can assist you .

6.2 Evaluation data format

Evaluation data basically follows the basic format above, but it also contains partial dialogs that end with a system utterance. With this data, the dialog system has to predict the last utterance in each dialog, where the last utterance is considered the reference. Thus, the system can use the utterances before the last utterance as the context, and predict the last utterance, and is evaluated by comparing the predicted result with the reference.
6.3 System output format

Dialog systems are expected to read an evaluation data file and output the following file, where the reference is modified to have “S_REF:” header and a system prediction is appended, which starts with “S_HYP:”.

```
U: hello !                         (context)
S: how may I help you ?            (reference)
U: hello !                         (context)
S: how may I help you ?            (reference)
U: nothing ...                    :
S: have a good day !              (reference)
```

Note that the references will NOT be included in the official evaluation data as

```
U: hello !                         (context)
S:                                (empty reference)
U: hello !                         (context)
S: how may I help you ?            (empty reference)
U: nothing ...                    :
S:                                :
```

Therefore, the final result submitted to the challenge does not have to include the reference part starting with “S_REF:”.

6.4 Scoring

BLEU score can be computed for the system output if the file includes the references. A script “tasks/utils/bleu_score.py” are available to compute the score, which will report BLEU scores as the following result.
7 Evaluation

Each attendee has to submit a text file of system output to the organizer. The system outputs are evaluated with objective measures such as BLEU and METEOR, and also evaluated by human rating using crowd sources, in which human evaluators will rate the system responses in terms of naturalness, informativeness, and appropriateness.

8 Summary

This article described the end-to-end conversation modeling track of the 6th dialog system technology challenges (DSTC6). We will provide a detailed description of the baseline system, instruction of how to submit the results, and the human evaluation scheme.

References

[1] Oriol Vinyals and Quoc Le, “A neural conversational model,” arXiv preprint arXiv:1506.05869, 2015.
[2] Ryan Lowe, Nissan Pow, Iulian Serban, and Joelle Pineau, “The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems,” arXiv preprint arXiv:1506.08909, 2015.
[3] Marjan Ghazvininejad, Chris Brockett, Ming-Wei Chang, Bill Dolan, Jianfeng Gao, Wen-tau Yih, and Michel Galley, “A knowledge-grounded neural conversation model,” arXiv preprint arXiv:1702.01932, 2017.
[4] “DSTC6 Dialog System Technology Challenges,” https://github.com/dialogtekgeek/DSTC6-End-to-End-Conversation-Modeling, 2017.
[5] “DSTC6 Dialog System Technology Challenges,” http://workshop.colips.org/dstc6/, Accessed: 2017-06-01.
[6] Pierre Lison and Jörg Tiedemann, “Opensubtitles2016: Extracting large parallel corpora from movie and tv subtitles,” in Proceedings of the 10th International Conference on Language Resources and Evaluation, 2016.