DCH-2: A Parallel Customer-Helpdesk Dialogue Corpus with Distributions of Annotators’ Labels

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ABSTRACT
We introduce a data set called DCH-2, which contains 4,390 real customer-helpdesk dialogues in Chinese and their English translations. DCH-2 also contains dialogue-level annotations and turn-level annotations obtained independently from either 19 or 20 annotators. The data set was built through our effort as organisers of the NTCIR-14 Short Text Conversation and NTCIR-15 Dialogue Evaluation tasks, to help researchers understand what constitutes an effective customer-helpdesk dialogue, and thereby build efficient and helpful helpdesk systems that are available to customers at all times. In addition, DCH-2 may be used for other purposes, for example, as a repository for retrieval-based dialogue systems, or as a parallel corpus for machine translation in the helpdesk domain.

KEYWORDS
dialogue; evaluation; helpdesk; corpus;

1 INTRODUCTION
Companies have call centers and helpdesks for their products and services to help their customers whenever they encounter problems. If the helpdesk staff can be replaced completely by intelligent dialogue systems, this would mean a lot of cost savings from the companies’ viewpoint. More importantly, this would enable a 24-hour, wait-free, efficient and homogeneous helpdesk service for the customers. However, existing natural language dialogue systems are not effective enough to completely replace humans. Effective helpdesk systems should understand the customer’s problem, gather the necessary context, and provide a solution to the problem through minimal interactions.

To help researchers build effective dialogue systems for helpdesk applications, we have constructed a Chinese-English parallel corpus of customer-helpdesk dialogue, with dialogue-level and turn-level annotations. The dialogue-level annotations are given as distributions of dialogue quality scores as rated by multiple annotators, while the turn-level annotations are given as distributions over nugget types: that is, whether a turn states the problem the customer is facing, whether it provides useful information for solving it, or whether it shows that the problem has been solved (details to follow in Section 4.3).

Our data set, DCH-2 (Dialogues between a Customer and a Helpdesk - Version 2) was constructed through our effort as the organisers of the NTCIR-14 Short Text Conversation (STC-3) [9] and NTCIR-15 Dialogue Evaluation (DialEval-1) [10] tasks. These two tasks offered the same subtasks: the Dialogue Quality (DQ) subtask and the Nugget Detection (ND) subtask. In the DQ subtask, participants were required to estimate, for each test dialogue, the gold dialogue quality score distributions; in the ND subtask, participants were required to estimate, for each turn in the dialogue, the gold distribution over nugget types. The DCH-2 dialogue corpus contains the DCH-1 corpus (training data used at STC-3), the STC-3 test dialogues (additional training data used at DialEval-1), and the DialEval-1 test dialogues. However, DCH-2 may also be useful for researchers working on tasks other than the DQ and ND tasks. For example, retrieval-based helpdesk response systems may find our data useful as a knowledge repository; Chinese-English machine translation systems may leverage DCH-2 as a parallel corpus for the helpdesk domain.

2 RELATED WORK
The DARPA COMMUNICATOR Program that evaluated spoken dialogue systems in the travel planning domain [8] produced the Communicator 2000 Corpus, which consists of 662 dialogues based on nine different systems, with per-call survey results on dialogue efficiency, dialogue quality, task success and user satisfaction. Unlike DCH-2, these task-oriented dialogues focused on a structured task, and they evaluated these dialogues based on how they filled the key slots (e.g., “origin,” “destination,” “date”).

Lowe et al. [2] released the Ubuntu Dialogue Corpus, which contains 930,000 human-human dialogues extracted from Ubuntu chats. They focus primarily on unstructured dialogues like we did in DCH-2. However, while they automatically disentangled the chats to form dyadic dialogues, their original chat logs usually involve more than two parties, which makes it different from our dyadic customer-helpdesk DCH-2 dataset. They formed a response selection test data set by setting aside 2% of the corpus and forming (context, response, flag) triplets based on this set. Here, context is the sequence of utterances that appear prior to the response in the dialogue; response is either the actual correct response from the dialogue or a randomly chosen utterance from outside the dialogue (but within the test set); flag is one for the correct response and zero for incorrect responses. For each correct response, they generated nine additional triplets containing different incorrect responses. Thus, response selection systems are given a context and ten choices of responses, and required to select one or more responses. They use recall at $k$ as the evaluation measure, where $k$ is the size of the set of responses selected by the system and therefore “recall at 1” reduces to accuracy. Note that this evaluation setting does not require annotations for defining the gold standard. They do not consider ranked lists of responses.

One novelty of DCH-2 is that both the gold DQ and gold ND data are provided as distributions of labels rather than a single consolidated labels. A gold DQ distribution is defined over an ordinal scale (namely, Likert scale scores): the task of estimating such a
distribution is known as the *ordinant quantification* task [3–5]. In contrast, a gold ND distribution is defined over nominal classes (namely, nugget types); hence, the task of estimating this distribution should probably be called *nominal quantification*. The reason why we preserve the distribution of labels given by multiple annotators is that these assessments are inherently subjective. If a user of DCH-2 prefers to evaluate DQ and ND tasks in a deterministic way, they can easily take the most frequent class from each of our gold distribution and treat it as the gold class for ordinal and nominal classification tasks.

The Dialogue Breakdown Detection Challenge (DBDC) data sets [1, 7] also contain turn-level annotations that can be used for evaluating ordinal quantification. The dialogues are chats between a system and human (in English and in Japanese), and each system turn is labelled with a distribution over three ordinal classes, namely, breakdown, possible breakdown, and not a breakdown. While the organisers of DBDC used nominal quantification measures (namely, Jensen-Shannon Divergence and Mean Squared Error) despite the ordinal nature of their classes, subsequently they examined nominal quantification measures used in the aforementioned NTCIR tasks, namely, Normalised Match Distance (NMD) and Root Symmetric Normalised Order-aware Distance (RSNOD) [6]. They reported that RSNOD is suitable for evaluating DBDC systems. Section 5 discusses a tool we have released for computing these measures.

### 3 Dialogues

DCH-2 is a data collection based on real (i.e., human-human) customer-helpdesk dialogues. We crawl Weibo, a Chinese microblog service, to obtain customer-helpdesk dialogues, because many technology company accounts handle users’ inquiries on Weibo publicly.

The dialogues in DCH-2 were crawled in three batches, with the same approach. The first batch (3700 dialogues) was crawled in 2016, and these dialogues formed a dialogue corpus namely DCH-1. The second batch (390 dialogues) crawled in 2018 were used as the test collection in NTCIR-14 STC-3 NDDQ subtasks [9]. The third batch (300 dialogues) was crawled in 2020, and was used as the test collection of NTCIR-15 DialEval-1 Task [10].

#### 3.1 Dialogue Crawling

We detail the mining process of the first batch (3,700 dialogues) as follows.

1. We collected an initial set of Weibo accounts by searching Weibo account names that contained keywords such as “assistant” and “helper” (in Chinese). We denote this set by $A_0$.

2. For each account name $a$ in $A_0$, we added a prefix “@” to $a$ and used the string as a query for searching up to 40 conversational threads (i.e., initial post plus comments on it) that contain a mention of the official account. While the organisers of DBDC used nominal quantification measures (namely, Jensen-Shannon Divergence and Mean Squared Error) despite the ordinal nature of their classes, subsequently they examined nominal quantification measures used in the aforementioned NTCIR tasks, namely, Normalised Match Distance (NMD) and Root Symmetric Normalised Order-aware Distance (RSNOD) [6]. They reported that RSNOD is suitable for evaluating DBDC systems. Section 5 discusses a tool we have released for computing these measures.

Weibo’s interface for conversational threads is somewhat different from Twitter’s: comments to a post are not displayed on the main timeline; they are displayed under each post only if the “comments” button is clicked.
Table 1: DCH-1 and DCH-2 dialogue corpus statistics.

|                         | DCH-1 [11]                     | DCH-2                                                                 |
|-------------------------|--------------------------------|----------------------------------------------------------------------|
| Data timestamps         | Jan. 2013 - Sep. 2016          | Jan. 2013 - Sep. 2016 (DCH-1 corpus) Oct. 2016 - Apr. 2018 (NTCIR-14 STC-3 NDDQ test dialogues [9]) Apr. 2018 - Jul. 2019 (NTCIR-15 DialEval-1 test dialogues [10]) |
| #Chinese dialogues      | 3,700                          | 4,390 (DCH-1 + 390 STC-3 + 300 DialEval-1)                            |
| #English translations  | 1,264 (34%)                    | 4,390 (100%)                                                          |
| #Helpdesk accounts      | 161                            | 161                                                                  |
| Avg. #turns/dialogue    | 4.162                          | 4.201                                                                 |
| Avg. turn length (#chars) | 48.31                         | 54.541                                                                |
| # Annotators per dialogue | 19                             | 20                                                                   |

Please give your ratings by looking at the entire dialogue, rather than specific parts of it.

**Dialogue**

| CNUG | Customer: 我的TI商用快半个月了都不能用，系统也设定没有更新。 阅读没有问题。@锤子科技 @锤子科技客服 @锤子科技产品部 请问有个说法 北京/开通... |
|------|----------------------------------------------------------------------------------------------------------------------------------|
| HNUG | Helpdesk: 您好,为了保证您的信息安全，我们升级了系统的安全加密算法，请您登录 http://www.example.com 上线的『系统更新服务』软件后，使用此软件进行系统更新即可。具体操作方法请您点击此处，点击此处链接。 |

| CNUG | Customer: 好了谢谢 |
|------|------------------|
| HNUG | Helpdesk: 不客气 |

**Question**

- Task Accomplishment: The customer's problem has been solved.
  - 2 (strongly agree)
  - 1 (somewhat agree)
  - 0 (neither agree nor disagree)
  - -1 (somewhat disagree)
  - -2 (strongly disagree)

- The customer is satisfied at the end of the dialogue. (Note: this is NOT about the customer's general satisfaction with the product/service or the company)
  - 2 (strongly agree)
  - 1 (somewhat agree)
  - 0 (neither agree nor disagree)
  - -1 (somewhat disagree)
  - -2 (strongly disagree)

- The customer and the helpdesk interact effectively to solve the problem efficiently.
  - 2 (strongly agree)
  - 1 (somewhat agree)
  - 0 (neither agree nor disagree)
  - -1 (somewhat disagree)
  - -2 (strongly disagree)

Figure 2: The interface of the annotation tool. The Chinese dialogue on the left is the same as Figure 1.

although we used account names in A as seeds for searching the dialogue corpus, we obtained dialogues involving not only these accounts but also subaccounts of these accounts. For example, when the customer mentions “ABCD Company Helpdesk,” a subaccount called “ABCD Company Helpdesk Beijing” might actually respond to it. Such dialogues are also included in DCH-2; thus it actually covers helpdesk accounts that are outside A.

(4) As $D_0$ is too large for annotation, we sampled 3,700 dialogues from it based on the dialogue lengths. For $i = 2, 3, \ldots, 6$, we randomly sampled 700 dialogues that contained $i$ turns. In addition, we randomly sampled 200 that contained $i = 7$
turns; we could not sample 700 dialogues for \( i = 7 \) as \( D_0 \) did not contain enough dialogues that are very long.

(5) To remove the privacy information in the dialogues, we replaced telephone numbers with 123456789, and replaced email addresses with XXX@YYY.com.

When crawling the second batch (390 dialogues) and the third batch (300 dialogues), we utilise the same account names in A as keywords to crawl from Weibo using the same crawling approach. However, we use different timestamps to filter the search results in different batches. In the first batch, we only crawl dialogues with the timestamps between January 2013 to September 2016. The timestamps of the second batch are between October 2016 to August 2018, and the timestamps of the third batch are between September 2018 to August 2020.

We utilised a similar method as the step (4) to sample dialogues based on the number of turns for the second batch (390 dialogues) and the third batch (300 dialogues). The second batch has 65 dialogues that contained 7 turns, and the third batch has 30 ones. For \( i = 2, 3, \ldots, 6 \), there are the same amount of the dialogues that contained \( i \) turns.

### 3.2 English Translations

We hired professional translators to manually translate all the original Chinese dialogues into English. Hence DCH-2 is a completely parallel corpus. As we shall describe in Section 4, the dialogue-level and turn-level annotations were performed solely based on the Chinese part of the corpus; since DCH-2 is a parallel corpus, we assume that these annotations perfectly reflect the nature of the translated English dialogues as well.

Figure 1 shows an actual dialogue from DCH-2, with its English version.

#### 3.3 DCH-2 Dialogue Corpus Statistics

Table 1 provides the statistics of the dialogues in DCH-2, together with those of its predecessor, DCH-1.

### 4 ANNOTATIONS

This section describes how we obtained the dialogue-level and turn-level annotations. The former was used as the gold data for the DQ subtask of NTCIR-14 STC-3 and NTCIR-15 DialEval-1; the latter was used as the gold data for the ND subtask of the above NTCIR tasks.

#### 4.1 Annotators

We followed the same approach to annotate all the dialogues in DCH-2, but the dialogues were annotated in two groups. In 2018, we annotated the first 4,090 of 4390 dialogues with 19 annotators\(^2\). Note that DCH-1 was annotated by three annotators in a different way in 2016 [11], but the 2016 annotations are not related to DCH-2. We revised the annotation criteria and annotated DCH-1 again in 2018 with the approach introduced in this section. In 2019, we annotated the rest 300 dialogues with 20 annotators. We hired Chinese undergraduate students and graduate students from Waseda University as annotators. Each annotator was asked to annotate all the dialogues in each group, so each dialogue was annotated by either 19 or 20 annotators. An initial face-to-face instruction and training session for the annotators was organised by the first author of this paper at Waseda University. Each annotator was paid about 1,200 Japanese Yen per hour. We developed a web-based annotation tool for the annotation. Subsequently, the annotators were allowed to do their annotation work online using a web-browser-based tool at their convenient location and time. Figure 1 shows a screenshot of the web-based annotation tool. The order of dialogues to annotators was randomised; given a dialogue, each annotator was instructed to first read the entire dialogue carefully, and then complete the dialogue quality annotation criteria described in Section 4.2; finally, the annotators classified the nugget types for each dialogue turn, where nugget types were defined as described in Section 4.3.

#### 4.2 Dialogue Quality Annotations

By Dialogue Quality (DQ) annotation, we mean manual quantification of the quality of a dialogue as a whole. Specifically, we introduce the following three dialogue quality scores for three different criteria.

- **A-Score** : Task Accomplishment (The customer’s problem has been solved)
- **S-score** : Customer Satisfaction (The customer is satisfied at the end of this dialogue.)
- **E-score** : Dialogue Effectiveness (The customer and the helpdesk interact effectively to solve the problem efficiently.)

The annotators were asked to choose from the following options: 2 (strongly agree), 1 (somewhat agree), 0 (neither agree nor disagree), -1 (somewhat disagree), -2 (strongly disagree).

#### 4.3 Nugget Type Annotations

In Nugget Detection (ND) annotations, annotators were asked to identify nuggets for each dialogue, where a nugget is an turn that helps the Customer transition from the current state (where the problem is yet to be solved) towards the target state (where the problem has been solved). Figure 3 reflects our view that accumulating nuggets will eventually solve Customer’s problem. The official definition of nuggets is:

1. A nugget is a turn by either Helpdesk or Customer;
2. It can neither partially nor wholly overlap with another nugget;
3. It helps Customer transition from Current State (including Initial State) towards Target State (i.e., when the problem is solved).

Compared to the traditional nugget-based information access evaluation approaches, there are two unique features in nugget-based helpdesk dialogue evaluation:

- A dialogue involves two parties, Customer and Helpdesk;
- Even within the same utterer, nuggets are not homogeneous, by which we mean that some nuggets may play special roles. In particular, since the dialogues we consider are task-oriented (but not closed-domain, which makes slot filling approaches infeasible), there must be some nuggets that represent the state of accomplishing the task and those that represent the state of identifying it.

\(^2\)We hired 20 annotators, but one did not complete the job. Thus, we ended up with 19 annotators.
Based on the above considerations, we defined the following four mutually exclusive nugget types:

**CNUG0** Customer’s *trigger nuggets*. These are nuggets that define customer’s initial problem, which directly caused customer to contact Helpdesk.

**HNUG** Helpdesk’s *regular nuggets*. These are nuggets in helpdesk’s turns that are useful from Customer’s point of view.

**CNUG** Customer’s *regular nuggets*. These are nuggets in customer’s turns that are useful from helpdesk’s point of view.

**HNUG+** Helpdesk’s *goal nuggets*. These are nuggets in helpdesk’s turns which provide the customer with a solution to the problem.

**CNUG+** Customer’s *goal nuggets*. These are nuggets in customer’s turns which tell helpdesk that customer’s problem has been solved.

**CNAN** Customer’s *not a nugget*. It means that the current customer turn does not help towards problem solving.

**HNAN** Helpdesk’s *not a nugget*. It means that the current helpdesk turn does not help towards problem solving.

Note that each nugget type may or may not be present in a dialogue, and multiple nuggets of the same type may be present in a dialogue.

### 4.4 DCH-2 Annotation Statistics

Table 2 shows the statistics of the dialogue-level and turn-level annotations provided in DCH-2. Table 3 shows the inter-annotator agreement of DCH-2 measured by Krippendorff’s $\alpha$ coefficient. It can be observed that the agreement among the annotators is not high, which reflects the highly subjective nature of this annotation task. Evaluating such a customer-helpdesk dialogue is even subjective and difficult for human, and often there is no such thing as the ground truth: different people may have different opinions about the dialogue.

It should be stressed that our annotation task is not like document relevance assessments, and that it is inherently highly subjective. In a previous study [11], the authors found that annotators usually have different interpretation about evaluating such complicated customer-helpdesk dialogues. For example, when a user encounter a software bug, the helpdesk may promise to fix this problem in the next version. Some annotators think it is acceptable, but the other do not. Thus, we believe that hiring many assessors and preserving their different viewpoints in the data set, is more important than trying to force them into reaching an agreement. We hired 19 or 20 annotators for each dialogue, so that the distributions that may preserve different viewpoints are formed by the annotations. For example, the customer satisfaction annotation of a dialogue may be “15 of 20 dialogues strongly agree that the customer was satisfied by the dialogue, but the other annotators somewhat agree it”.

### 5 UTILISING DCH-2

#### 5.1 Distribution

To obtain DCH-2 from us for research purpose use, please contact the authors and sign a user agreement form first.

#### 5.2 Task

To utilise DCH-2, researchers may follow the task setting in NTCIR-15 DialEval-1 [10] to train and test estimators that can automatically evaluate customer-helpdesk dialogues. Since the dialogues have both nugget annotations and quality annotations, there are two subtasks available: Nugget Detection (ND) and Dialogue Quality (DQ). The ND subtask requires to automatically classify the nugget type for each dialogue turn, and the DQ subtask is to estimate the three quality scores based on the criteria introduced in Section 4.2. Also, since DCH-2 is a fully parallel data set that contains both Chinese dialogues and English dialogues, it can be used for other purposes, such as exploring the difference between Chinese task-oriented dialogues and English task-oriented dialogues.

#### 5.3 Evaluation

Instead of evaluating both ND and DQ subtasks as simple classification problems using metrics like accuracy, we recommend the researchers to estimate the probability distributions on all the quality scores or nugget types to incorporate the highly subjective
nature of dialogue evaluation. For example, a customer satisfaction estimator may output something like 70% strongly agree with 30% somewhat agree. To evaluate the effectiveness of the estimators, the distance between the estimated distribution and the golden distribution formed by the annotators can be calculated. Specifically, for the DQ subtask (an ordinal quantification task), we recommend using Normalised Match Distance (NMD); a special case of the Earth Mover’s Distance (EMD) and the Root Symmetric Normalised Order-aware Divergence (RSNOD). For the ND subtask (a nominal quantification task), we recommend using Jensen-Shannon Divergence (JSD) and Root Normalised Sum of Squares (RNSS) [6]. Also, if a researcher wants to use DCH-2 to evaluate DQ and/or ND tasks under the NTCIR task settings, they can utilise our Python evaluation script to compute the official evaluation measure scores. The evaluation tool will be distributed along with DCH-2 data set.

6 CONCLUSIONS

We have described DCH-2, a parallel-corpus of 4,390 customer-helpdesk dialogues with dialogue-level dialogue quality annotations and turn-level nugget annotations. The data set is available at https://dialeval-2.github.io/DCH-2/. We described how we constructed the test collection and the philosophy behind it.

For the upcoming NTCIR-16 DialEval-2 task, DCH-2 will be used as the training data for participants. However, as we have discussed in Section 1, it may be leveraged for other purposes.

Table 2: DCH-2 annotation statistics. Each dialogue was annotated independently by either 19 or 20 annotators.

(a) Total number and ratio of dialogue quality labels over all 4,390 dialogues

| Task accomplishment | -2 | -1 | 0  | 1  | 2  |
|---------------------|----|----|----|----|----|
| Customer satisfaction| 13937 (16.649%) | 15497 (18.513%) | 33810 (40.389%) | 13659 (16.317%) | 6807 (8.132%) |
| Dialogue effectiveness| 12877 (15.383%) | 14829 (17.715%) | 36754 (43.906%) | 13334 (15.929%) | 5916 (7.067%) |

(b) Total number and ratio of turn-level nugget type labels over all 4,390 dialogues

| Task accomplishment | Trigger | Regular | Goal | Not-a-Nugget |
|---------------------|---------|---------|------|--------------|
| Customer turns      | 71925 (37.17%) | 71115 (37.60%) | 8079 (4.15%) | 43186 (22.22%) |
| Helpdesk turns      | N/A     | 93542 (59.41%) | 25397 (30.33%) | 8552 (10.21%) |

Table 3: Inter-rater agreement of DCH-2. Measured by Krippendorf’s \( \alpha \) coefficient.

| Task accomplishment | 0.301 |
| Customer satisfaction | 0.213 |
| Dialogue effectiveness | 0.323 |
| Nugget | 0.395 |

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