DIRECT: Direct and Indirect Responses in Conversational Text Corpus

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Abstract

We create a large-scale dialogue corpus that provides pragmatic paraphrases to advance technology for understanding the underlying intentions of users. While neural conversation models acquire the ability to generate fluent responses through training on a dialogue corpus, previous corpora have mainly focused on the literal meanings of utterances. However, in reality, people do not always present their intentions directly. For example, if a person said to the operator of a reservation service ‘I don’t have enough budget.’, they, in fact, mean ‘please find a cheaper option for me.’ Our corpus provides a total of 71,498 indirect–direct utterance pairs accompanied by a multi-turn dialogue history extracted from the MultiWoZ dataset. In addition, we propose three tasks to benchmark the ability of models to recognize and generate indirect and direct utterances. We also investigated the performance of state-of-the-art pre-trained models as baselines.

1 Introduction

We create a large-scale dialogue corpus that discloses users’ hidden intentions to advance techniques for natural language understanding in dialogue systems. Neural conversation models have been able to generate high-quality responses (Zhao et al., 2020; Zhang et al., 2020) and achieve dialogue state tracking (Hosseini-Asl et al., 2020; Lin et al., 2020). These previous studies have been based on the literal meanings of user utterances. Little attention has been given to the implied intention of the utterances considered.

However, during conversation, humans often respond to others with indirect expressions, without directly telling them their requests or intentions (Searle, 1979; Brown et al., 1987). When humans receive an indirect response, they infer the intention implied in the response based on context, such as dialogue history. For example, in the example of operator–user dialogue in Figure 1, the user responds with ‘I don’t have enough budget’ to the operator’s utterance of ‘Would you like to make a reservation for this restaurant?’ If the operator only considers the literal meaning, they would repeat the question. However, based on the dialogue history, the operator would infer that the user wants a cheaper restaurant and thus suggest an option to satisfy the user’s preference. Our experiments revealed that even a state-of-the-art dialogue system (Yang et al., 2021) degrades the quality of response generation for indirect utterances. Such a pair of user utterances and hidden intentions is categorized into the class of pragmatic paraphrases, which emerge in conversations depending on the context. To realize dialogue systems for communicating with users at the human level, the systems should process the pragmatic paraphrases to address the true intentions of the user.

In this study, we release a corpus of direct and indirect responses in conversational text, DIRECT, which contains 71,498 pairs of indirect and direct responses. We expand the commonly used dialogue corpus of MultiWoZ (Eric et al., 2020), a multi-domain and multi-turn task-oriented dialogue

https://github.com/junya-takayama/DIRECT
corpus. The MultiWoZ corpus is created using the Wizard-of-Oz method, in which the user and system speak alternately. For each user’s utterance, we use crowdsourcing to collect ‘an utterance that is more indirect than the original utterance’ and ‘an utterance that is more direct than the original utterance’. Hence, DIRECT provides triples of paraphrases: original utterances, indirect utterances, and direct utterances.

We designed three benchmark tasks using this corpus to evaluate the model’s ability to recognize and generate pragmatic paraphrases. As baselines, we investigated the performance of state-of-the-art pre-trained models, BERT (Devlin et al., 2019) and BART (Lewis et al., 2020), for benchmark tasks.

2 Related Work

Paraphrases have been applied in a dialogue system’s research in the context of data augmentation (Hou et al., 2018; Gao et al., 2020). Despite its importance in understanding users’ intentions, the pragmatic paraphrases have been overlooked. Only a few recent studies have focused on pragmatic paraphrases to advance the understanding of users’ intentions. Pragst and Ultes (2018) proposed a rule-based approach to automatically construct a corpus consisting of pairs of indirect and direct utterances. They demonstrated that the neural conversation model could accurately extract utterances with opposing directness. Because of their rule-based approach, patterns of indirect/direct utterances in their corpus are limited. Louis et al. (2020) used crowdsourcing to build a corpus comprising indirect answers to Yes/No questions, annotating whether the answers were Yes or No. This corpus provides natural answers written by crowdsourcing workers; however, it is limited to context-free Yes/No questions. In contrast to these studies, DIRECT provides natural utterances written by humans with rich dialogue histories. Furthermore, it covers various types of utterances.

While there are several paraphrase corpora (Dolan and Brockett, 2005; Lan et al., 2017), all have focused on context-free paraphrases. Hence, none provide pragmatic paraphrases that emerge in contexts. Corpora for natural language inference are also relevant to our study (Giampi- colo et al., 2007; Marelli et al., 2014; Bowman et al., 2015). Similar to the paraphrase corpora, they do not provide contexts. This means that these corpora rely on world knowledge to determine whether a text entails a hypothesis. In contrast, context is a crucial element in determining paraphrasal relationships in pragmatic paraphrases. Our DIRECT is the first corpus that provides large-scale pragmatic paraphrases. It would be a valuable resource also for research on paraphrase identification and generation to make a step forward from literal paraphrases.

3 DIRECT Corpus

A pragmatic paraphrase is a pair of texts that have equivalent outcomes in a given context, which frequently emerge in conversations. Expanding a dialogue corpus is a promising approach for building a corpus that collects such pragmatic paraphrases as such a corpus is conversational by nature and often provides conversation histories. Specifically, we employed MultiWoZ 2.1 (Budzianowski et al., 2018; Eric et al., 2020) and collected pragmatic paraphrases using crowdsourcing.

We describe how we collected pragmatic paraphrases in Section 3.1 with careful quality control as described in Section 3.2. Section 3.3 describes the statistics of the collected corpus. Section 3.4 presents a comparative analysis between our corpus and existing paraphrase corpora using conventional paraphrase identification models.

3.1 Direct and Indirect Response Collection

MultiWoZ is a multi-domain, task-oriented dialogue corpus annotated with dialogue act tags and dialogue states, comprising 10,438 dialogues. Each dialogue involves alternate utterances by a user and system; the total number of utterances is 71,524.

We used Amazon Mechanical Turk, a crowdsourcing service, to expand MultiWoZ with pragmatic paraphrases. The workers first received instructions, as presented in Table 1, and some examples of the task. Then, the workers were shown dialogue histories extracted from MultiWoZ, as illustrated in Figure 2. Based on the given conversation histories, the workers input indirect and direct responses that have the same intent as the specified user response in the dialogue (written in red in Figure 2) into the input forms at the bottom.

https://www.mturk.com/

The original MultiWoZ data contains dialogues between a person acting as the ‘system’ and another acting as the ‘user.’ We presented the former as the ‘operator’ in our user interfaces to prevent the workers from misunderstanding the corresponding utterances that were automatically generated.
**Instructions**

Read the following dialogue between the USER and the OPERATOR, please rephrase the USER’s response written in red letters into two different types of speech, following the instructions below.

**Type-1 (Direct)**: a more direct response that expresses the same intention as the original response

**Type-2 (Indirect)**: a more indirect but natural response that expresses the same intention as the original response

‘Indirect response’ means, for example, a response to a Yes/No question that does not contain a ‘Yes’ or ‘No’, or a response that does not directly refer to the action you want the other person to do or your desire. If you have trouble rephrasing, click the ‘Hints’ button. You can see the goals that ‘USER’ must achieve in that interaction.

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Table 1: Instructions for workers

We assumed that workers should be able to develop indirect and direct responses based only on the dialogue histories. If they did not understand the intent of the utterance that they were required to paraphrase, we provided an option to refer to the goal of the user as ‘Hints’ (upper part of Figure 2). Such goals were extracted from the MultiWoZ.

We targeted the utterances of the ‘user’ in MultiWoZ for paraphrasing because users primarily express their needs and preferences. We assumed the average time per post to be 1 minute and set the average reward at $0.12 USD ($7.2 USD per hour).

As a result, we collected 71,498 indirect–direct pairs. We divided the corpus into training and test data in the same manner as in the settings of MultiWoZ. Note that our corpus is a parallel corpus, comprising indirect and direct responses, but it can also be used with the original MultiWoZ responses, i.e., triples of indirect, original, and direct responses are also extractable.

**Examples** Table 2 presents the examples of the collected pragmatic paraphrases. In the upper example, the user asks for a restaurant in a moderate price range. The indirect response is ‘I don’t want to overspend but remember its also vacation,’ which requires an understanding that ‘its also vacation’ is a paraphrase of ‘not too cheap’, as explicitly stated in the direct response in this context. In the lower example, the phrase ‘Do you know of any in town?’ in the indirect response paraphrases ‘Can you find me a guesthouse...?’ in this context.

**3.2 Quality Control**

We carefully created the **DIRECT** corpus to collect high-quality pragmatic paraphrases by pre-screening workers. We also conducted a quality assessment.

**Worker Selection** Prior to formal data collection, we carefully selected crowd workers to avoid trivial paraphrases by replacing or shuffling some words. Specifically, we posted a pilot consisting of 2 tasks. We automatically rejected workers whose average word-level Jaccard index between indirect and direct responses exceeded 0.75. We also manually observed sampled paraphrases. We then chose workers to ask for actual tasks that passed these automatic and manual quality assessments. In total, we obtained 536 workers to exclusively complete the tasks.

**Quality Assessment** After completing paraphrase collection, we used the same crowd workers to assess the quality of the collected pragmatic paraphrases for 7,372 dialogues from the test set. We showed the workers utterances for assessment with their dialogue histories. The paraphrased utterances, presented as Response-A and Response-B, were also shown to the worker, of which indirect or direct labels were closed. Using a binary label, the workers first judge whether paraphrased utterances have the same intention as an original utterance. The workers then determined whether Response-A or Response-B was more direct. If the workers could not make a decision, they were allowed to choose a ‘no difference’ label.

We assumed the average time per post to be 30 seconds, and set the reward at $0.06 USD ($7.2 USD per hour). Five workers were assigned to each
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| speaker | utterance |
|---------|-----------|
| SYSTEM | Would you like to pick a different type of food? |
| USER | Yes, what about British food please. |
| SYSTEM (original) | What price range are you comfortable with? |
| USER (indirect) | I don’t want to overspend but remember it’s also vacation. |
| USER (direct) | Can you choose something that is not too expensive and not too cheap. |
| SYSTEM | Do you have a preference as to what area of town you dine in? |
| USER | I need a place to stay in the north |
| SYSTEM | OK, I’m seeing a lot of choices in hotels. Is there anything else you need in the hotel that would help narrow it down |
| USER (original) | I’d really like to stay in a guesthouse. I heard the ones in Cambridge are very nice. |
| USER (indirect) | I’m thinking of staying in a guesthouse. Do you know of any in town? |
| USER (direct) | Can you find me a guesthouse in Cambridge? |
| SYSTEM | How about the Acorn Guesthouse? It is rated 4 stars and is in the moderate price range. |

Table 2: Examples of DIRECT corpus. ‘USER (indirect)’ and ‘USER (direct)’ are the responses created by the crowd worker based on ‘USER (original)’.

| Metric | Value [words] |
|--------|---------------|
| Vocabulary size (Indirect) | 6,273 |
| Vocabulary size (Direct) | 4,664 |
| Length (Indirect) | 15.59 |
| Length (Direct) | 12.38 |
| Keep (Indirect-to-Direct) | 5.33 |
| Add (Indirect-to-Direct) | 7.04 |
| Delete (Indirect-to-Direct) | 10.26 |

Table 3: Quality assessment results

3.3 Statistical Analysis

We reveal the characteristics of pragmatic paraphrases in the DIRECT corpus using case-insensitive token-level analyses. Table 4 presents the word-based statistics on our corpus (except the test data). First, the vocabulary size of indirect responses was much larger than that of direct responses. This implies that even for utterances with the same intent, there are more diverse expressions in the indirect responses than in the direct responses. The average number of words in utterances was 15.59 for indirect utterances and 12.38 for direct utterances. Wilcoxon’s test (Wilcoxon, 1945) confirmed that the difference in the average number of words in utterances was statistically significant at the level of 0.1%. Figure 3 shows the histogram of differences in lengths between indirect and direct responses, where the distribution spreads to both positive and negative ranges. This implies that simply shortening a sentence does not necessarily make an utterance more direct.

Next, we investigate the number of words that need to be replaced to transform an indirect response into a direct one. We computed three metrics of ‘Keep’, ‘Delete’, and ‘Add’. ‘Keep’ is the average number of words kept when rewriting indirect responses to direct, ‘Add’ is the number of words that need to be added and ‘Delete’ is the

4For tokenization, we used word_punct_tokenize() method of the nltk (https://www.nltk.org/) library.
number of words that need to be deleted. Table 4 demonstrates that ‘Keep’ is smaller than ‘Add’ and ‘Delete.’ This indicates that more than half of the words need to be replaced to transfer an indirect response into a direct response.

Finally, Table 5 presents the top 20 most frequent trigrams that appear in indirect and direct responses. Indirect and direct responses use distinctive expressions. Frequent trigrams of direct responses contain verbs that directly convey what the user wants an operator to do, such as ‘book’ and ‘find’, as well as phrases that refer to specific objects, such as ‘the reference number’. On the contrary, trigrams of indirect responses contain phrases of ‘is there any’ and ‘I think that’, which do not appear in the counterpart.

![Figure 4: Histograms of cosine similarities of sentence embedding (encoded by Sentence-BERT) for paraphrase pairs.](image)

![Figure 5: Percentages of paraphrased pairs recognized as paraphrases by BERT fine-tuned on MRPC and Twitter URL paraphrase corpus.](image)

![Figure 6: Percentages of paraphrased pairs recognized as paraphrases by BERT fine-tuned on PAWS.](image)

### 3.4 Model-based Analysis

In this section, we investigate how the DIRECT corpus differs from existing paraphrase corpora using state-of-the-art paraphrase identification models.

First, we compute the cosine similarity between paraphrase pairs in DIRECT, MRPC (Dolan and Brockett, 2005), and Twitter URL Paraphrase corpus (Lan et al., 2017) using Sentence-BERT\(^5\) (Reimers and Gurevych, 2019). Figure 4 shows the histograms, which confirms DIRECT provides more paraphrase pairs with lower cosine similarities than the MRPC and Twitter URL Paraphrase corpus. Sentence-BERT is expected to address the literal meaning of a sentence through its pre-training via STSBenchmark (Cer et al., 2017). The large volume of paraphrases with lower similarities confirms that DIRECT provides paraphrases beyond literal similarity.

Next, we investigate whether a paraphrase identification model trained on existing paraphrase corpora transfers to DIRECT. Specifically, we calculated the percentage of paraphrase sentence pairs that are recognized as paraphrases using the paraphrase identification model. Figures 5 and 6 show the results where BERT (Devlin et al., 2019) was

\(^5\)We used the ‘stsb-roberta-base’ model available at https://www.sbert.net/.
We designed three tasks using the DIRECT Word Scrambling (PAWS) (Zhang et al., 2019), has the lowest percentage of pairs recognized as paraphrases for both BERT models: only 64.9% and 35.3%, respectively. This indicates that pragmatic paraphrases in DIRECT are exclusive to existing paraphrase corpora and are difficult to recognize via models trained on literal paraphrases.

4 Benchmark Tasks

We designed three tasks using the DIRECT corpus to benchmark the models’ ability to handle pragmatic paraphrases. Specifically, we design an indirect-to-direct transfer task (Section 4.1), direct-to-indirect transfer task (Section 4.2), and directness prediction task (Section 4.3). We also evaluated state-of-the-art pre-trained models for these tasks as baselines.

4.1 Indirect-to-direct Transfer Task

Task Description and Motivation Indirect-to-direct transfer is the task of transforming an indirect response into a direct response while preserving its intent under the context, i.e., the dialogue history. This task allows the ability of a certain model to accurately interpret the intent of an indirect response to be evaluated. A possible application of this task is the pre-editing of utterances for task-oriented dialogue systems. By transforming the user’s indirect utterances into direct utterances that are easier to interpret before inputting them into the model, the response generation quality is expected to improve.

Baselines We employed BART (Lewis et al., 2020) as the baseline model for this benchmark. The architecture of the baseline model is shown in Figure 7 (a). We added new special tokens ‘<user>’, ‘<system>’, and ‘<query>’ such that the model can distinguish between utterances in the dialogue history and the response to transform. We first added a ‘<query>’ tag to the beginning of the indirect response to the transformation. Then, for the dialogue history, we added ‘<user>’ and ‘<system>’ at the beginning of user utterances and system utterances, respectively. These utterances are concatenated in the order of appearance in the dialogue history and input into the BART encoder. We fine-tuned the model using cross-entropy loss.

For implementation, we used the transformers (Wolf et al., 2020) library. The pre-trained model we used was ‘facebook/bart-base’. We used the AdamW (Loshchilov and Hutter, 2019) optimizer for training, with a learning rate of 2e-5. The batch size was 8, owing to the GPU memory size. We randomly sampled 2,000 dialogues from the training data as a validation set and used the rest for training. Through 30 epochs of training, the model with the lowest validation loss was used to evaluate the test data.

We also constructed a model that disregards dialogue history (BART without history) to investigate the effects of context. In addition, we trained a transformer model (Transformer w/ history) from scratch on only the DIRECT corpus to investigate the effects of pre-training. The transformer model has the same architecture as the BART, comprising six self-attention layers of the encoder and decoder.

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6We used ‘bert-base-cased’ model in transformers library https://huggingface.co/transformers/ (version 3.5.1).
7https://huggingface.co/facebook/bart-base
8We chose the value that gives the lowest validation loss.
9GeForce RTX 2080 Ti, 11 GB Memory
### Table 6: Evaluation results of the indirect-to-direct task

| Model               | BLEU  | Perplexity |
|---------------------|-------|------------|
| Transformer w/ history | 25.23 | 2.66       |
| BART w/o history    | 32.51 | 2.15       |
| BART w/ history     | 33.77 | 2.16       |

### Results and Discussion

Table 6 presents the BLEU score (Papineni et al., 2002) and Perplexity of each model. For the BART-based models, the model using dialogue history has a higher BLEU score, as expected, because pragmatic paraphrases are context-dependent. Comparing BART and transformer with dialogue history, the former largely outperformed the latter. This result confirms that pre-training is also crucial in this task.

Examples of generated direct responses are presented in Table 7. In the upper example, the BART model successfully interprets the phrase ‘the best place’ in the indirect response as an expression of the price range, while the transformer without pre-training failed in this interpretation. The context is particularly important in the indirect response in the lower example. In fact, the BART w/o history model generated a sentence with the opposite intent to the reference. Conversely, the two models that use dialogue history generate sentences with the same intent as the reference.

### Table 7: Examples of generated direct responses in the indirect-to-direct transfer task.

**Indirect response**

- Transformer w/ history: I want it to be the best place in town.
- Transformer w/o history: Can you find me an attraction in town?
- Reference: I was hoping for a much more expensive place if possible.

**Systenm**

- Transformer: Can you find me something expensive?
- Transformer w/o history: Can you find me an attraction in town?
- Reference: I was hoping for a much more expensive place if possible.

### Table 8: Evaluation results of the direct-to-indirect task

| Model               | BLEU  | Perplexity |
|---------------------|-------|------------|
| Transformer w/ history | 19.84 | 3.06       |
| BART w/o history    | 27.12 | 2.39       |
| BART w/ history     | 26.52 | 2.34       |

### Results and Analysis

Table 8 shows the BLEU and Perplexity. The fine-tuned BART models achieved higher BLEU scores and lower perplexity Compared to the indirect-to-direct task, the direct-to-indirect task is more challenging as it requires a more complex understanding of the dialogue context and user intent.
than the transformer without pre-training, which again confirms the effectiveness of pre-training.

Overall, the performances of all models were lower in this task than in the indirect-to-direct transfer task. Moreover, dialogue history did not improve the BLEU score and perplexity in the BART model. These results imply that direct-to-indirect transfer is more difficult than the indirect-to-direct task. As our statistical analyses presented in Section 3.3, indirect responses have a larger vocabulary and are longer on average. Hence, we conjecture that even the fine-tuned BART model does not acquire the ability to properly transform the direct response into an indirect one, regardless of the availability of the dialogue history. As seen from Table 9, the response generated by all models failed to preserve the intent of the direct response. More sophisticated models are desired to achieve direct-to-indirect transformation.

4.3 Directness Prediction Task

Task Description and Motivation This task aims to estimate the degree of directness of an utterance. This technology allows the rephrasing of utterances predicted as indirect into direct utterances using an indirect-to-direct transfer model or by asking users to clarify their intentions before inputting the utterance into a dialogue system.

In DIRECT, each dialogue history has a triple response: the original response from MultiWoZ, an indirect response, and a direct response. These responses can be ordered in descending order of directness as direct, original, and indirect responses. In this task, a model takes a response as an input and predicts the degree of directness.

Baselines We employ BERT as the baseline, where a response to predict its directness and dialogue history is input. The architecture is shown in Figure 7 (c). The output of the final layer corresponding to the ‘[CLS]’ token is input into a linear layer, followed by a sigmoid function. The final output is regarded as the score indicating the directness of the response.

As discussed in Section 3.3, there is a remarkable difference in the frequency of words between the direct and indirect responses. We also employ a simple bag-of-words-based linear regression model to investigate the usefulness of word-level features in predicting directness.

We use pointwise and pairwise settings to train the model, which are typically used in learning-to-

Table 10: Performance of the directness prediction task

| Model               | Loss  | Exact | Kendall tau |
|---------------------|-------|-------|-------------|
| BERT w/o history    | Pointwise | 0.755 | 0.803 |
| BERT w/o history    | Pairwise | **0.816** | **0.846** |
| BERT w/ history     | Pointwise | 0.784 | 0.804 |
| BERT w/ history     | Pairwise | 0.813 | 0.841 |
| LR w/o history      | Pointwise | 0.540 | 0.616 |

As evaluation metrics, we compute the percentage of exact matches between a ranking based on the predicted scores and the gold standard. We also evaluate Kendall’s tau between the predicted and gold standard and report the average.

We implemented the BERT-based model using ‘bert-base-cased’ with the transformers library, and the linear regression model using ‘linear_model.LinearRegression’ with the scikit-learn library, and the linear regression model using ‘linear_model.LinearRegression’ with the scikit-learn library.

Results and Analysis Table 10 shows the results. The BERT models disregarding dialogue history achieved higher scores than the models that use dialogue history. As revealed in Section 3.3, indirect and direct responses have largely different vocabulary and phrases, which may be clues for predicting the degree of directness. Nonetheless, the percentage of an exact match remains at 0.814 and a more sophisticated model is desired to effectively employ the dialogue history. The exact match rate for the linear regression model (LR w/o history) was 0.540, which was much higher than the chance rate of 0.167. This indicates that the bag-of-words-based model is useful for predicting directness, although it is not as good as BERT-based models.

Finally, we evaluated the performance of the response generation for the indirect and direct re-

10https://scikit-learn.org/stable/
responses identified by the best model in Table 10. The model predicted 1,842 responses as indirect and 5,530 responses as direct.\(^\text{11}\) We generated system responses to each of the indirect and direct user responses using the model proposed by Yang et al. (2021), which is the most advanced end-to-end response generation model for task-oriented dialogues. The BLEU scores of the indirect and direct responses were 10.25 and 14.09, respectively. This result confirms that direct utterances are easier for the dialogue system to respond accurately, while indirect utterances are more difficult.

5 Conclusion

We created DIRECT, a dialogue corpus providing 71,498 pairs of pragmatic paraphrases with context. In addition, we proposed three benchmark tasks and showed the performance of state-of-the-art pre-trained models as the baseline.

In a future, we will apply DIRECT to a task-oriented dialogue system to handle indirect responses in an end-to-end manner. We also intend to investigate the relations between pragmatic paraphrases and other features of dialogue acts and belief states.

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