Measuring the ‘I don’t know’ Problem through the Lens of Gricean Quantity

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Abstract
We consider the intrinsic evaluation of neural generative dialog models through the lens of Grice’s Maxims of Conversation (1975). Based on the maxim of Quantity (be informative), we propose Relative Utterance Quantity (RUQ) to diagnose the ‘I don’t know’ problem. The RUQ diagnostic compares the model score of a generic response to that of the reference response. We find that for reasonable baseline models, ‘I don’t know’ is preferred over the reference more than half the time, but this can be mitigated with hyperparameter tuning.

1 Introduction
Evaluating chatbots an active area of research, in part due to the open-ended nature of these systems (Sedoc et al., 2019; Hashimoto et al., 2019; Li et al., 2019; Mehri and Eskenazi, 2020; Deriu et al., 2020). One theoretical framework for analyzing conversations is Grice’s Maxims of Conversation (1975). Grice originally analyzed conversations between humans, but there has been some exploration in the context of evaluating dialog systems as well (Qwaider et al., 2017; Jwalapuram, 2017).

The categories of maxims are: Quantity, Quality, Relation, and Manner. We discuss each of them and the ways a chatbot might violate them.

QUANTITY Do not give more or less information than required. This could be violated by rambling, or by not answering a question (fully). Answering ‘I don’t know’ when a better answer is known also falls under this category.

QUALITY Do not say anything that is false, or for which you do not have evidence. This is violated by lying.

RELATION Be relevant. This is violated by off topic responses.

MANNER This is the least concise of the categories, but can be summarised as ‘communicate clearly.’ Disfluent responses violate this.

We propose a new diagnostic measure to directly evaluate the Gricean maxim of QUANTITY called relative utterance quantity (RUQ). This diagnostic checks to see if the model favors a generic response (such as ‘I don’t know’) over the reference it was trained on.

2 ‘I don’t know’ (IDK) problem
Neural chatbots have a tendency to produce safe, generic responses, such as ‘I don’t know’ (Serban et al., 2016; Li et al., 2016a). Such responses contribute nothing to the conversation, and the repetition of the phrase is annoying to users. If a system responds ‘I don’t know’ when it could have given a better or more informative answer, this is by definition a violation of QUANTITY.

3 Relative Utterance Quantity (RUQ)
Through this lens of the IDK problem as a QUANTITY violation, we propose a method for diagnosing it. We compare the model score of producing ‘I don’t know,’ to the model score of producing the reference. This can be done on the training data, or the test data. Particularly on the training data, we should expect the model to ‘know’ the data it was trained on and to give a higher score to the reference it was trained on than to ‘I don’t know.’

We propose two diagnostic measures which compute the Relative Utterance Quantity of a system: (1) We plot the average model score for each token across sentences. We compare the original reference, beam search output, and two IDK variants: ‘I don’t know,’ and ‘I don’t know what to do.’ This allows for the visualization of the relative gap in scores at different points in the sentence. (2) We

1This was also observed to be a common response.
compute the (length normalized) model score for both ‘I don’t know.’ and the reference of each training prompt, and count how many times the reference is preferred. We denote the later as RUQ score. Both measures generalize to other generic responses.

4 Evaluation Metrics

4.1 Standard Automatic Metrics

Standard automatic metrics in the dialog community measure some form of similarity between the produced response and a reference. These metrics assume that the reference is good, and a response similar to it will be good as well.

We use the single-reference and multi-reference automatic evaluation evaluation framework for DailyDialog released by Gupta et al. (2019), which is computed using NLG-EVAL (Sharma et al., 2017). We primarily consider multiple-reference METEOR (Lavie and Agarwal, 2007). See §A.2 for full results on all metrics. For reading ease, we reports metrics scaled between 0 and 100 rather than 0 and 1.

5 Data

Following Khayrallah and Sedoc (2020), we train and evaluate on DailyDialog (Li et al., 2017), as released by ParlAI (Miller et al., 2017b). DailyDialog is a high quality corpus with multiple references for evaluation. We train on the ~80,000 turns of English-learners practicing ‘daily dialogues’ in various contexts, e.g., chatting about vacation or food.

We also use Entropy-Based Data Filtering (Csányi et al., 2019), which filters out high entropy utterances with the goal removing generic utterances. We use their recommended filtering threshold of 1.0 and ‘IDENTITY’ clustering. We filter based their ‘source’, ‘target’, and ‘both’ settings. We consider ‘target’ as the baseline since they report it works best.

6 Models

Following Khayrallah and Sedoc (2020), we train Transformer (Vaswani et al., 2017) chatbots in fairseq using parameters from the FLORES benchmark for low-resource MT (Guzmán et al., 2019): 5-layer encoder and decoder, 512 dimensional embeddings, and 2 encoder and decoder attention heads. The default regularization parameters are 0.2 label smoothing, 0.4 dropout and 0.2 attention & relu dropout.

6.1 Hyperparameter Sweep

There are some kinds of regularization that are not universally considered in dialog – label smoothing (Szegedy et al., 2016) and subword vocabularies (Sennrich et al., 2016) are not often used and popular toolkits for dialog (i.e. Hugging Face (Wolf et al., 2019) and ParlAI (Miller et al., 2017a)) do not expose label smoothing. Beginning with the parameters described in §6, we perform a hyperparameter sweep of regularization parameters.

We sweep SentencePiece (Kudo and Richardson, 2018) vocabulary size (1k,4k,8k,16k), learning rate (1e-2, 1e-3, 1e-4), dropout (0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6), attention & relu dropout (0.0, 0.1, 0.2, 0.3, 0.4), and label smoothing (0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8).

We use multiple-reference METEOR for model selection. We denote models trained using DailyDialog as DD and models trained on the entropy filtered data as FILTERED. We denote models trained using the FLORES hyperparameters as BASE, and the best model from the hyperparameter search for each data type (as determined by multiple-reference METEOR) is denoted as BEST.

We report the multi-reference METEOR scores for the BASE and BEST systems in Table 1. We report hyperparameters of these models and their performance on the full set of automatic metrics in §A.2. For the DailyDialog data we find that hyperparameter tuning can improve multiple-reference METEOR from 12.7 (DD-BASE) to 17.8 (DD-BEST).

We perform the same hyperparameter sweep after performing entropy filtering (Csányi et al., 2019) on the data, but we find that the best model is still DD-BEST. Without hyperparameter tuning,
entropy filtering improves performance by 0.5 on multi-reference METEOR, but the improvement by hyperparameter sweeping is much larger (5.1 points). While we did a very thorough sweep (including values we expected to perform poorly), there are some general takeaways: Using a subword vocabulary (of 4-8k) is a good idea. Label smoothing amount interacts with BPE size, but some amount of label smoothing should also be used.

7 Relative Utterance Quantity

In this section we report the different methods of analysis, and discuss their implications.

7.1 RUQ Plots

We show plots for the four models in Figure 1. We plot the token normalized model score for reference and ‘I don’t know.’ For additional comparison, we also plot the model scores for the beam-search output and ‘I don’t know what to do.’ Overall, we observe that for the BASE models the IDK’s are higher probability than the reference, even on the training data. This is problematic, because the model is ranking a response that is not providing enough QUANTITY of information higher than ‘I don’t know’ despite the fact that it should know the training data.

The relative difference in probabilities is much better in DD-BEST than DD-BASE, particularly on the training set. Simply entropy filtering the data alone does not fix the problem.

7.2 RUQ scores

We summarize QUANTITY in a single statistic by counting how many times the reference has a higher probability than ‘I don’t know.’ Filtering the data improves how often the reference is preferred to ‘I don’t know’, but not by as much as the hyperparameter sweep does.

|          | DD | FILTERED |
|----------|----|----------|
| BASE     | 28.5% | 37.9%    |
| BEST     | 95.3% | 94.2%    |

Table 2: RUQ scores on the training data. Filtering the data improves how often the reference is preferred to ‘I don’t know’, but not by as much as the hyperparameter sweep does.
For both DD-BASE and FILTERED-BASE, IDK is preferred over the reference response the model was trained on more than half of the time.

8 Discussion

The relative rankings of these systems by RUQ is the same as the relative rankings by multiple reference METEOR, but we note that computing RUQ on the training data does not require a particular (multi-reference) test set like most automatic evaluation metrics. RUQ simply diagnoses how well the model learned the training data compared to a generic response.

The preference of the model to produce IDK when it has a better response is not only a QUANTITY violation, but is also indicative of a fundamental problem with the models themselves, and should be fixed before decoding time (either by correcting the data, or by correcting the model).

Csáky et al. (2019) argue that the IDK problem is due to the one-to-many/many-to-one nature of dialog training data—if a single response can apply to many different responses, this will become the model’s canonical response. Therefore their entropy filtering method they removes these one-to-many/many-to-one pairs, by removing high entropy responses. While this data filtering does mitigate the problem somewhat, we found that our baseline model trained on the entropy filtered data (FILTERED-BASE) preferred IDK over the reference more than half the time.

9 Limitations

Strong regularization might prevent the model from memorizing the training data, but in such a case the model should also be prevented from overfitting on ‘I don’t know.’

In this work we are comparing systems all trained on the same or similar data, with similar architectures and with different hyperparameters, specifically regularization parameters. This mimics a setting where a single researcher would like to do model selection, but we do not consider system evaluation, and leave that to future work.

10 Related Work

Grician Maxims in Dialog Systems Jwalapuram (2017) propose a Gricean human evaluation dialog. The evaluator is asked to rate performance on a Likert scale for each category. Qwaider et al. (2017) consider the QUANTITY, RELATION, and MANNER maxims in for ranking community question answers. They use other NLP tools to evaluate if the response has key elements or named entities (QUANTITY/RELATION), has high semantic similarity (RELATION) and includes/excludes positive/negative polarity terms (MANNER).

Chatbot evaluation As discussed in §4 automatic evaluations for dialog typically measure lexical or semantic similarity between a produced response and a reference, under the assumption that the reference is a good response and responses similar to it will be good as well. Since there are often multiple valid responses to a prompt, this can be extended to multiple references too. In contrast, in this work we compare a model’s score of a reference to a model’s score of a generic response.

HUSE (Hashimoto et al., 2019) considers the model score combined with human judgements to evaluate diversity and quality, classifying if a response is human- or machine-generated. Our work does not consider human judgements, and compares the model score of a generic response to the reference response.

Mitigating the IDK Problem A variety of approaches have been proposed to mitigate the IDK problem. These include active post-processing methods such as MMI (Li et al., 2016a), training data filtration (Csáky et al., 2019), reinforcement learning (Li et al., 2016b) and unlikelihood training (Welleck et al., 2020). In our work, we propose an intrinsic model diagnostic other than perplexity.

MMI Maximum Mutual Information (MMI) was proposed as a ‘Diversity-Promoting Objective Function’ for dialog (Li et al., 2016a), but we argue this was actually tackling a relevancy problem, since MMI-bibi encourages the prompt to be predictable from the response, by using a reverse direction model. That method did improve performance, though recent work found it to be detrimental (Khayrallah and Sedoc, 2020).

Copying in Machine Translation Ott et al. (2018) found that copying was being over represented in the output of RNN NMT models. They
used an analysis similar to RUQ plots where they compare the probability of the beam search translation to the probability of copying the source. They also consider the probability at each position in the output, and find that a translated sentence is unlikely to start copying, but once it starts it keeps copying. In our analysis, we find IDK has a relatively high probability from the start, though for some models the gap does widen over the course of the sentence.

11 Conclusion

We consider a Gricean approach to chatbot evaluation, reframing the IDK problem as a violation of the maxim of QUANTITY leading to a new measure—Relative Utterance Quantity (RUQ), which allows researchers to diagnose if their method is violating this particular conversational principle.
References

Richárd Csáky, Patrik Purgai, and Gábor Recski. 2019. Improving neural conversational models with entropy-based data filtering. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5650–5669, Florence, Italy. Association for Computational Linguistics.

Jan Deriu, Don Tuggener, Pius von Däniken, Jon Ander Campos, Alvaro Rodrigo, Thiziri Belkacem, Aitor Soroa, Eneko Agirre, and Mark Cieliebak. 2020. Spot the bot: A robust and efficient framework for the evaluation of conversational dialogue systems. In EMNLP.

Gabriel Forgues, Joelle Pineau, Jean-Marie Larchevêque, and Réal Tremblay. 2014. Bootstrapping dialog systems with word embeddings. In Modern Machine Learning and Natural Language Processing at NeurIPS.

H. P. Grice. 1975. Logic and Conversation, pages 41 – 58. Brill, Leiden, The Netherlands.

Prakhar Gupta, Shikib Mehri, Tiancheng Zhao, Amy Pavel, Maxine Eskenazi, and Jeffrey Bigham. 2019. Investigating evaluation of open-domain dialogue systems with human generated multiple references. In Proceedings of the 20th Annual SIGdial Meeting on Discourse and Dialogue, pages 379–391, Stockholm, Sweden. Association for Computational Linguistics.

Francisco Guzmán, Peng-Jen Chen, Myle Ott, Juan Pino, Guillaume Lample, Philipp Koehn, Vishrav Chaudhary, and Marc’Aurelio Ranzato. 2019. The FLORES evaluation datasets for low-resource machine translation: Nepali–English and Sinhala–English. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6098–6111, Hong Kong, China. Association for Computational Linguistics.

Michael Alexander Kirkwood Halliday. 1989. Spoken and Written Language. Language education. Oxford University Press.

Tatsunori Hashimoto, Hugh Zhang, and Percy Liang. 2019. Unifying human and statistical estimation for natural language generation. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1689–1701, Minneapolis, Minnesota. Association for Computational Linguistics.

Prathyusha Jwalapuram. 2017. Evaluating dialogs based on grice’s maxims. In Proceedings of the Student Research Workshop Associated with RANLP 2017, pages 17–24, Varna. INCOMA Ltd.

Huda Khayrallah and João Sedoc. 2020. SMRT Chbots: Improving non-task-oriented dialog with Simulated Multiple Reference Training. In Findings of the 2020 Conference on Empirical Methods in Natural Language Processing, Online. Association for Computational Linguistics.

Ryan Kiros, Yukun Zhu, Russ R Salakhutdinov, Richard Zemel, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Skip-thought vectors. In C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, editors, Advances in Neural Information Processing Systems 28, pages 3294–3302. Curran Associates, Inc.

Taku Kudo and John Richardson. 2018. SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 66–71, Brussels, Belgium. Association for Computational Linguistics.

Batia Laufer and Paul Nation. 1995. Vocabulary Size and Use: Lexical Richness in L2 Written Production Applied Linguistics, 16(3):307–322.

Alon Lavie and Abhaya Agarwal. 2007. METEOR: An automatic metric for MT evaluation with high levels of correlation with human judgments. In Proceedings of the Second Workshop on Statistical Machine Translation, pages 228–231, Prague, Czech Republic. Association for Computational Linguistics.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016a. A diversity-promoting objective function for neural conversation models. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 110–119, San Diego, California. Association for Computational Linguistics.

Jiwei Li, Will Monroe, Alan Ritter, Dan Jurafsky, Michel Galley, and Jianfeng Gao. 2016b. Deep reinforcement learning for dialogue generation. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1192–1202, Austin, Texas. Association for Computational Linguistics.

Margaret Li, Jason Weston, and Stephen Roller. 2019. Acute-eval: Improved dialogue evaluation with optimized questions and multi-turn comparisons.

Yanran Li, Hui Su, Xiaoyu Shen, Wenjie Li, Ziqiang Cao, and Shuzi Niu. 2017. DailyDialog: A manually labelled multi-turn dialogue dataset. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 986–995, Taipei, Taiwan. Asian Federation of Natural Language Processing.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.
Shikib Mehri and Maxine Eskenazi. 2020. **USR: An unsupervised and reference free evaluation metric for dialog generation.** In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 681–707, Online. Association for Computational Linguistics.

Alexander Miller, Will Feng, Dhruv Batra, Antoine Bordes, Adam Fisch, Jiasen Lu, Devi Parikh, and Jason Weston. 2017a. **ParlAI: A dialog research software platform.** In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 79–84, Copenhagen, Denmark. Association for Computational Linguistics.

Alexander H. Miller, Will Feng, Adam Fisch, Jiasen Lu, Dhruv Batra, Antoine Bordes, Devi Parikh, and Jason Weston. 2017b. **Parlai: A dialog research software platform.**

Myle Ott, Michael Auli, David Grangier, and Marc'Aurelio Ranzato. 2018. **Analyzing uncertainty in neural machine translation.** In Proceedings of the 35th International Conference on Machine Learning, volume 80 of Proceedings of Machine Learning Research, pages 3956–3965, Stockholmsmässan, Stockholm Sweden. PMLR.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. **Bleu: a method for automatic evaluation of machine translation.** In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Mohammed R. H. Qwaider, Abed Alhakim Freihat, and Fausto Giunchiglia. 2017. **TrentoTeam at SemEval-2017 task 3: An application of grice maxims in ranking community question answers.** In Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017), pages 271–274, Vancouver, Canada. Association for Computational Linguistics.

Vasile Rus and Miha Lintean. 2012. **A comparison of greedy and optimal assessment of natural language student input using word-to-word similarity metrics.** In Proceedings of the Seventh Workshop on Building Educational Applications Using NLP, pages 157–162, Montréal, Canada. Association for Computational Linguistics.

João Sedoc, Daphne Ippolito, Arun Kirubarajan, Jai Thirani, Lyle Ungar, and Chris Callison-Burch. 2019. **ChatEval: A tool for chatbot evaluation.** In Proceedings of the 2019 Conference of the North American Workshop of the Association for Computational Linguistics (Demonstrations), pages 60–65, Minneapolis, Minnesota. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. **Neural machine translation of rare words with subword units.** In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

Iulian V. Serban, Alessandro Sordoni, Yoshua Bengio, Aaron Courville, and Joelle Pineau. 2016. **Building end-to-end dialogue systems using generative hierarchical neural network models.** In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, AAAI’16, page 3776–3783. AAAI Press.

Shikhar Sharma, Layla El Asri, Hannes Schulz, and Jeremie Zumer. 2017. **Relevance of unsupervised metrics in task-oriented dialogue for evaluating natural language generation.** CoRR, abs/1706.09799.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. 2016. **Rethinking the inception architecture for computer vision.** In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 2818–2826.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. **Attention is all you need.** In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, Advances in Neural Information Processing Systems 30, pages 5998–6008. Curran Associates, Inc.

Sean Welleck, Ilia Kulikov, Stephen Roller, Emily Dinan, Kyunghyun Cho, and Jason Weston. 2020. **Neural text generation with unlikelihood training.** In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2019. **Huggingface’s transformers: State-of-the-art natural language processing.** ArXiv, abs/1910.03771.
A Appendix

A.1 Standard Automatic Metrics

In § A.2 we report the full automatic evaluation results of the 14 metrics across both the single reference and multi-reference evaluation from the the multi-reference automatic evaluation framework for DailyDialog released by Gupta et al. (2019), which is computed using NLG-EVAL (Sharma et al., 2017). This include word-overlap metrics: BLEU (Papineni et al., 2002), METEOR (Lavie and Agarwal 2007), and ROUGE-L (Lin 2004) as well as embedding based metrics: SkipThought (Kiros et al., 2015), embedding average (Forgues et al., 2014), vector extrema and Greedy Matching (Rus and Lintean, 2012). For reading ease, we reports metrics scaled between 0 and 100 rather than 0 and 1.

A.1.1 Lexical Diversity

The Gricean maxims focus on ensuring cooperation between speakers, but there is more to a conversation than cooperation—especially in an open ended conversation that might be had with a chatbot. This is where additional desiderata may come in to play, such as interestingness. One (indirect) automatic way of measuring interestingness is lexical diversity (Halliday, 1989; Laufer and Nation, 1995), by computing the n-gram type/token ratio (Li et al., 2016a). We use the same spaCy tokenization used in the automatic evaluation scripts (Appendix A).

A.2 Full Results

Table 3 shows the hyperparameters for each system. Table 4 and Table 5 show the evaluation against the multiple references for the word based and embedding based metrics. Table 6 and Table 7 show the evaluation against the original single reference for the word based and embedding based metrics. Table 8 shows the lexical diversity, and Table 9 shows the RUQ sores.

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8 github.com/prakharguptaz/multirefeval
9 github.com/Maluuba/nlg-eval
10 spacy.io
11 github.com/Maluuba/nlg-eval
### Table 3: Hyperparameters for each of the four models we consider.

| Data        | Params | bpe | lr  | dropout | otherdropout | labelsmooth |
|-------------|--------|-----|-----|---------|---------------|-------------|
| DD BASE     | 4      | 0.001 | 0.4 | 0.2     | 0.2           |             |
| DD BEST     | 4      | 0.001 | 0.0 | 0.1     | 0.4           |             |
| FILTERED BASE | 4   | 0.001 | 0.4 | 0.2     | 0.2           |             |
| FILTERED BEST | 2    | 0.001 | 0.0 | 0.1     | 0.2           |             |

### Table 4: Word-overlap based metrics on multiple references.

| Data       | Params | Average Max Sentence BLEU | Corpus BLEU | METEOR | ROUGE |
|------------|--------|---------------------------|-------------|--------|-------|
|            |        | BLEU1 | BLEU2 | BLEU3 | BLEU4 | BLEU1 | BLEU2 | BLEU3 | BLEU4 |        |       |
| DD BASE    | 27.8   | 14.7  | 10.3  | 7.9   |        | 48.1  | 25.6  | 16.2  | 11.2  | 12.7   | 34.3  |
| DD BEST    | **33.9**  | **21.9**  | **17.7**  | **15.3**  |        | **53.9**  | **36.1**  | **28.9**  | **25.1**  | **17.8**  | **39.7**  |
| FILTERED BASE | 27.8 | 14.0  | 9.4   | 7.0   |        | 46.9  | 24.1  | 14.6  | 9.8   | 13.2   | 33.4  |
| FILTERED BEST | 31.7 | 19.1  | 14.9  | 12.7  |        | 51.0  | 32.8  | 25.5  | 21.8  | 16.9   | 37.2  |

### Table 5: Embedding based metrics on multiple references.

| Data       | Params | Cosine Similarity | SkipThought | Embed. Avg. | VectorExtrema | GreedyMatching |
|------------|--------|-------------------|-------------|-------------|---------------|----------------|
| DD BASE    |        | 72.4              | 90.8        | 62.9        |                | 77.2           |
| DD BEST    |        | **73.8**          | **92.2**    | **65.4**    |                | **79.3**       |
| FILTERED BASE |     | 71.9              | 91.2        | 62.2        |                | 77.0           |
| FILTERED BEST |     | 72.8              | 91.6        | 62.7        |                | 77.9           |

### Table 6: Word-overlap based metrics on the single reference test set.

| Data       | Params | Average Max Sentence BLEU | Corpus BLEU | METEOR | ROUGE |
|------------|--------|---------------------------|-------------|--------|-------|
|            |        | BLEU1 | BLEU2 | BLEU3 | BLEU4 | BLEU1 | BLEU2 | BLEU3 | BLEU4 |        |       |
| DD BASE    | 15.3   | 7.6   | 5.6   | 4.5   |        | 12.9  | 6.3   | 4.1   | 3.0   | 6.7    | 20.6  |
| DD BEST    | **24.3**  | **16.7**  | **14.3**  | **12.8**  |        | **23.2**  | **16.7**  | **14.2**  | **12.9**  | **11.9**  | **29.2**  |
| FILTERED BASE | 15.9 | 7.4   | 5.2   | 4.1   |        | 15.8  | 7.5   | 4.7   | 3.3   | 7.2    | 20.4  |
| FILTERED BEST | 22.1 | 14.0  | 11.8  | 10.5  |        | 22.9  | 15.8  | 13.2  | 11.8  | 11.1   | 26.6  |

### Table 7: Embedding based metrics on the single reference test set.

| Data       | Params | Cosine Similarity | SkipThought | Embed. Avg. | VectorExtrema | GreedyMatching |
|------------|--------|-------------------|-------------|-------------|---------------|----------------|
| DD BASE    |        | 65.3              | 86.3        | 50.6        |                | 71.3           |
| DD BEST    |        | **68.2**          | **88.5**    | **54.7**    |                | **74.6**       |
| FILTERED BASE |     | 64.9              | 86.9        | 50.2        |                | 71.3           |
| FILTERED BEST |     | 67.0              | 87.7        | 52.3        |                | 73.1           |
| Data   | Params | 1-grams | 2-grams | 3-grams |
|--------|--------|---------|---------|---------|
| DD     | BASE   | 2.4     | 10.3    | 18.8    |
| DD     | BEST   | 3.5     | 18.0    | 35.5    |
| FILTERED | BASE | 2.3     | 10.7    | 20.1    |
| FILTERED | BEST | **3.8** | **18.3** | 34.6    |

Table 8: Type/Token ratios.

| Data   | Params | RUQ-train | RUQ-test |
|--------|--------|-----------|----------|
| DD     | BASE   | 28.5      | 12.2     |
| DD     | BEST   | **95.3**  | **35.7** |
| FILTERED | BASE | 37.9      | 15.5     |
| FILTERED | BEST | 94.2      | 32.5     |

Table 9: RUQ scores on the train and test data.