Frustratingly Simple Entity Tracking with Effective Use of Multi-Task Learning Models

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Abstract

We present SET, a frustratingly Simple-yet-effective approach for Entity Tracking in procedural text. Compared with state-of-the-art entity tracking models that require domain-specific pre-training, SET simply fine-tunes off-the-shelf T5 with customized formats and gets comparable or even better performance on multiple datasets. Concretely, SET tackles the state and location prediction in entity tracking independently and formulates them as multi-choice and extractive QA problems, respectively. Through a series of careful analyses, we show that T5’s supervised multi-task learning plays an important role in the success of SET. In addition, we reveal that SET has a strong capability of understanding implicit entity transformations, suggesting that multi-task transfer learning should be further explored in future entity tracking research.

1 Introduction

Tracking an entity throughout procedural text, such as recipes or scientific processes, is challenging because this task requires a model to understand both surface and underlying dynamics of a process (e.g., Step 2 in Figure 1 implicitly mentions water). Recent work on entity tracking can be divided into two lines. One focuses on designing procedural text-specific fine-tuning architectures as entity tracking models need to make step-wise predictions (Gupta and Durrett, 2019b; Tang et al., 2020; Huang et al., 2021; Rajaby Faghihi and Kordjamshidi, 2021). For instance, TSLM (Rajaby Faghihi and Kordjamshidi, 2021) introduces time-stamp embeddings into RoBERTa (Liu et al., 2019) to ensure the model makes a specific prediction for each step of the procedure. The other line of work focuses on learning better representations for procedural text via domain-specific pre-training (Zhang et al., 2021; Bai et al., 2021; Shi et al., 2022). LEMON (Shi et al., 2022) achieves great performance by continuing pre-training BART (Lewis et al., 2020) on 1 million procedural paragraphs. Both lines of work effectively move this field forward, but all current solutions are domain-specific and require significant amounts of modeling effort and compute resources. This raises the question of whether entity tracking models can learn from out-of-domain NLP tasks given that cross-task transfer learning has been proven effective for many NLP tasks (Vu et al., 2020).

In this paper, we present SET, a Simple Entity Tracking approach, which benefits from the latest advances in multi-task transfer learning. This approach only requires fine-tuning T5 (Raffel et al., 2020), which is pre-trained a dozens of NLP tasks and has shown great cross-task generalizability (Raffel et al., 2020; Aribandi et al., 2022; Sanh et al., 2022). The key idea in this method is to frame entity tracking as tasks that T5 has been pre-trained on and thus facilitate knowledge transfer. Specifically, we formulate the two sub-tasks of entity tracking, state prediction and location prediction, as multi-choice and extractive QA problems, and then fine-tune T5 on each of them independently. Unlike previous methods which make architectural changes to encode the index of the queried step, we simply append the index to the question, like "What is the location of water in step 2?", which works well empirically.

As for the results, despite the simplicity of SET, we show that it performs on par or even better than the state-of-the-art methods on both scientific processes (ProPara; Dalvi et al., 2018) and recipes (Recipes; Bosselut et al., 2018). After a series of thorough analyses, we verify that entity tracking can significantly benefit from the multi-task learning in T5. In addition, we find that SET can well address the challenge of implicit entity transformations, indicating the necessity of further exploring multi-task transfer learning in future research of
2 SET: Simple Entity Tracking

2.1 Problem Definition

Entity tracking aims at monitoring the status of an entity throughout the procedure, e.g., a scientific process. The input of this task contains two items: 1) a procedure paragraph \( P \), composed of a sequence of sentences \( \{s_1, s_2, ..., s_T\} \); and 2) a set of procedure-specific entities \( \{e_1, e_2, ..., e_N\} \). Given the input, our goal is to predict the state and location of each query entity at each timestamp of the procedure, where state prediction and location prediction are traditionally framed as classification and span identification problems. An example from the ProPara dataset (Dalvi et al., 2018) is shown in Figure 1. The procedure is about “how to generate hydroelectricity” and the predicted state and location of the entity “water” in step 2 are “move” and “dam”, respectively.

2.2 Task Formulation in SET

SET is a simple T5-based fine-tuning model, which predicts entity state and location for each step of the procedure independently. As shown in Figure 1, we frame state and location predictions as multi-choice and extractive QA problems, respectively (see §3.1 for comparison with other formats).

For state prediction, we use the multi-choice QA format proposed in Khashabi et al. (2020). Given a query entity \( e_i \) and procedure \( P \), to predict the entity state at step \( t \), the input sequence is formatted as the concatenation of the template question “What is the state of \( e_i \) in step \( t \)?”, the candidate states, and the full procedure, in which we prepend the step index to each step of the procedure. The output is the name of the state, such as “move” or “exist”.

For location prediction, similar to Rajaby Faghihi and Kordjamshidi (2021), we frame it as an extractive QA problem. The input sequence is formatted as the concatenation of the question “Where is \( e_i \) located in step \( t \)?” and the indexed full procedure, with the text span “Other locations: none, unknown.” appended. This is because sometimes the entity locations are unknown or not explicitly mentioned in the procedure. The output is a text span extracted from the input sequence. Location prediction also requires the model to predict the initial location of the query entity (step 0), in this case, we substitute the input question to “Where is \( e_i \) initially located?”

3 Experiments

Datasets We experiment with two benchmark datasets of entity-tracking: ProPara (Dalvi et al., 2018) and Recipes (Bosselut et al., 2018). ProPara contains 488 scientific process-based procedural paragraphs (Figure 1) with 3.9 query entities in each procedure on average. The Recipes dataset includes 866 cooking recipes with an average of 8.6 ingredients per recipe. Note that previous work experiments with different splits of the Recipes dataset, here we follow the split of Zhang et al. (2021) as it is used in most of the recent work (Huang et al., 2021; Shi et al., 2022). More statistics on two datasets can be found in Table 5.

Evaluation Metrics ProPara performances are evaluated in two levels: sentence-level (Dalvi et al., 2018) and document-level (Tandon et al., 2018). The sentence-level evaluation focuses on three categories of questions: 1) Cat-1: Is entity \( e_i \) created (moved/destroyed); 2) Cat-2: When is entity \( e_i \) created (moved/destroyed); 3) Cat-3: Where is entity \( e_i \) created (moved/destroyed). The \( F_1 \) score of each category and the micro/macro averages of three categories are reported. The document-level evaluation inspects the input/output entities and their transformations from a procedure perspective. More details on these two evaluations are presented in Appendix C. For Recipes, following previous work (Zhang et al., 2021; Shi et al., 2022), we evaluate the location changes of each ingredient throughout the recipe.

Baselines & SET Implementation For ProPara, we compare with the top 5 approaches on its leaderboard. For Recipes, as mentioned previously, we compare with methods, which experiment on the same data split of Zhang et al. (2021). Due to the space limit, we refer readers to the corresponding paper of each baseline for further details. In terms of SET implementation, we use Huggingface Transformers (Wolf et al., 2020) to code the model, and choose T5-base and T5-large for experiments due to our limited computation budget. As for

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1. https://drive.google.com/drive/folders/1PYGLe7hSoCyfpKmPumeTy6jmPyONGz4
2. https://github.com/ytyz1307zhh/KOALA/issues/4
3. https://github.com/allenai/propara/blob/master/propara/evaluation/evalQA.py
4. https://github.com/allenai/aristo-leaderboard/blob/master/propara/evaluator
5. https://github.com/allenai/propara/blob/master/propara/evaluation/evalQA.py
**Table 1:** Document-level and sentence-level evaluation results on ProPara test set. The best performance is baseline (Zhang et al., 2021) for a fair comparison.

| Model          | PLM          | Document-level | Sentence-level |
|----------------|--------------|----------------|----------------|
|                |              | P   | R   | F1  | Cat-1 | Cat-2 | Cat-3 | macro | micro |
| NCET (Gupta and Durrett, 2019b) | ELMo         | 67.1 | 58.5 | 62.5 | 73.7 | 47.1 | 41.0 | 53.9 | 54.0 |
| DYNAPRO (Amini et al., 2020) | BERT<sub>Base</sub> | 75.2 | 58.0 | 65.5 | 72.4 | 49.3 | 44.5 | 55.4 | 55.5 |
| TSLM (Rajabzadeh and Gupta, 2021) | RoBERTa<sub>Large</sub> | 68.4 | 68.9 | 68.6 | 78.8 | 56.8 | 40.9 | 58.8 | 58.4 |
| KOALA (Zhang et al., 2021) | BERT<sub>Base</sub> | 72.2 | 64.4 | 70.4 | 78.5 | 53.3 | 41.3 | 57.7 | 57.5 |
| LEMON (Shi et al., 2022) | BART<sub>Large</sub> | 69.9 | 68.1 | 69.0 | 78.8 | 57.2 | 42.9 | 59.6 | 59.2 |
|                | BART<sub>Large</sub>† | 74.8 | 69.8 | 72.2 | 81.7 | 58.3 | 43.3 | 61.1 | 60.7 |
| SET (ours)     | T5<sub>Base</sub> | 73.8 | 64.6 | 68.9 | 76.2 | 59.6 | 42.4 | 59.4 | 58.8 |
|                | T5<sub>Large</sub> | 80.2 | 64.5 | 71.5 | 77.3 | 59.8 | 46.0 | 61.0 | 60.6 |

**Figure 1:** Overview of SET (Simple Entity Tracking). SET is a T5-fine-tuning model, which predicts entity state or location for each step of the procedure in a separate example. State prediction and location prediction are framed as multi-choice and extractive QA problems respectively in SET.

**3.1 Results and Analysis**

**How well does SET perform compared to existing methods?** We present the test set results of ProPara and Recipes in Table 1 and Table 2, respectively. For ProPara, with T5-large, our proposed method SET reaches the performance (-0.1 micro-F<sub>1</sub> on sent-level evaluation and -0.7 F<sub>1</sub> on doc-level evaluation) of the state-of-the-art model LEMON (Shi et al., 2022), which requires further pre-training BART<sub>Large</sub> on 1 million procedural paragraphs. For Recipes, SET outperforms all prior work with T5-base, and surpasses the previous state-of-the-art LEMON by 7.7 F<sub>1</sub> with T5-large.

**Does multi-task learning improve SET performance?** To investigate this question, we experiment with two variants of T5 as the backbone LM of SET<sup>7</sup>: 1) T5-v1.1<sup>8</sup>, a T5-like LM (with slight architecture changes) but is pre-trained on unlabeled corpus only without mixing in supervised downstream tasks; 2) T5-v1.1_{QA-FT}, the resulting LM after fine-tuning T5-v1.1 on the mixture of

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<sup>6</sup>We use the same random seed (1234) as the KOALA baseline (Zhang et al., 2021) for a fair comparison.

<sup>7</sup>We also experiment with UnifiedQA-v1/v2 (Khashabi et al., 2020, 2022). With suggested hyper-parameters, UnifiedQA does not performs significantly better than T5, so we defer further exploration on UnifiedQA to future work.

<sup>8</sup>https://huggingface.co/docs/transformers/model_doc/t5v1.1
We compare our QA formulation with two other step-input T5. The first formulation is called "T5, the benefits of multi-task learning can cross the task boundaries."

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| Model                  | P   | R   | F1  |
|------------------------|-----|-----|-----|
| NCET (Gupta and Durrett, 2019b) | 56.5 | 46.4 | 50.9 |
| IEN (Tang et al., 2020)    | 58.5 | 47.0 | 52.2 |
| KOALA (Zhang et al., 2021) | 60.1 | 52.6 | 56.1 |
| REAL (Huang et al., 2021)  | 55.2 | 52.9 | 54.1 |
| LEMON (Shi et al., 2022)   | 56.0 | 67.1 | 61.1 |

**SET (ours, T5-base)**

- **Model**: SET (ours, T5-base) | **P** | **R** | **F1** |
- **Data split**: all | **Model**: KOALA | **Cat-1** | **Cat-2** | **Cat-3** |
- **explicit** | SETT5-base | 76.2 | 59.6 | 42.4 |
- **implicit** | SETT5-large | 77.3 | 59.8 | 46.0 |
- **all** | SETT5_large | 84.3 | 76.4 | 49.7 |

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Table 3: Top: Comparison of different backbone LMs to investigate the impact of multi-task learning. Bottom: Comparison of different task formulations. Multi-task learning leads to a better entity tracking model, especially with the QA formulation.

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Table 4: Comparison of KOALA and SET on explicit and implicit entity transformations via the ProPara test set. Without specifically injecting domain knowledge, SET significantly outperforms KOALA on the implicit subset showing the effectiveness of multi-task learning.

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Three QA datasets including MultiRC (Khashabi et al., 2018), ReCoRD (Zhang et al., 2018), and BoolQ (Clark et al., 2019), which T5 is pre-trained on. The performance of these three LMs (T5-large size) on ProPara and Recipes test set is presented in the top section of Table 3. We can see that T5-v1.1 outperforms T5-v1.1 on both datasets by a large margin, indicating that multi-task learning on non-procedural-text tasks with similar formulation can benefit procedural text understanding. This finding was also verified by Rajaby Faghihi and Kordjamshidi (2021), which shows that SQuAD-fine-tuning can improve the performance on ProPara. In addition, the advantage of T5 over T5-v1.1QA-FT indicates that, under the "text-to-text" paradigm of T5, the benefits of multi-task learning can cross the task boundaries.

**How useful is the QA formulation for SET?**

We compare our QA formulation with two other task formulations proposed in the recent work for T5. The first formulation is called "step-input" (Shi et al., 2022; Gupta and Durrett, 2019a; Amini et al., 2020), where each pair of the query entity $e$ and procedure step $t$ is formulated as one instance, which is similar to our QA formulation. However, in "step-input" formulation, the state prediction is formulated as a classification problem, where the entity name is appended to the input, and no candidate answers are not provided. Moreover, the procedure is trimmed until step $t$ to specify the step index in the input. The second formulation is called "process-input" (Zhang et al., 2021; Gupta and Durrett, 2019b), where the model predicts entity states or locations in all steps in one instance. The input is the concatenation of entity $e$ and the full procedure, and the model decodes entity states and locations in all steps sequentially. The results of all three formulations are presented in the bottom section of Table 3. Our proposed QA formulation clearly outperforms the other two formulations on both datasets. When compared with the "step-input" formulation, the QA formulation allows the model to have the full context, and may benefit more from LM’s pre-training scheme (Li et al., 2019; Nagata et al., 2020). The "process-input" formulation works the worst in this comparison. With qualitative analyses, we find that it suffers from error propagation due to its autoregressive decoding, so future work may explore incorporating structural decoding (Tandon et al., 2018) into T5.

Does SET understand implicit entity transformations? To research this question, we split procedure steps into two subsets (explicit and implicit) based on whether the query entity is explicitly mentioned in the step. Then we evaluate the sentence-level performance of the model on both subsets. The comparison between SET and KOALA (Zhang et al., 2021), a competitive baseline that incorporating commonsense knowledge from ConceptNet,
is shown in Table 4. Although SET-T5-base slightly trails on the explicit subset, it significantly outperforms KOALA on the implicit subset (+13.1 F\textsubscript{1} on Cat-2 and +8.0 F\textsubscript{1} on Cat-3), which shows SET’s great capabilities on understanding inferred dynamics, and suggests that multi-task transfer learning should be an important part of future research on entity tracking.

4 Conclusion

We present SET, a simple T5-based fine-tuning approach for entity tracking. By reformulating entity tracking to QA problems, SET performs on par or even better than the state-of-the-art in-domain pre-training models. Our analyses show that multi-task learning on supervised tasks and QA reformulation is the key of SET achieving good performance as well as understanding challenging implicit entity transformations.

Limitations

Due to our limited computation budget, we do not experiment with larger T5 models such as T5-3B and T5-11B, so future work could look into extending SET to those larger T5 models or other multi-tasking models, including ExT5 (Aribandi et al., 2022) and MUPPET (Aghajanyan et al., 2021).

References

Armen Aghajanyan, Anchit Gupta, Akshat Shrivastava, Xilun Chen, Luke Zettlemoyer, and Sonal Gupta. 2021. Muppet: Massive multi-task representations with pre-finetuning. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 5799–5811, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Aida Amini, Antoine Bosselut, Bhavana Dalvi, Yejin Choi, and Hannaneh Hajishirzi. 2020. Procedural reading comprehension with attribute-aware context flow. In Automated Knowledge Base Construction.

Vamsi Aribandi, Yi Tay, Tal Schuster, Jinfeng Rao, Huaixiu Steven Zheng, Sanket Vaibhav Mehta, Honglei Zhuang, Vinh Q. Tran, Dara Bahri, Jianmo Ni, Jai Gupta, Kai Hui, Sebastian Ruder, and Donald Metzler. 2022. Ext5: Towards extreme multi-task scaling for transfer learning. In International Conference on Learning Representations.

Fan Bai, Alan Ritter, and Wei Xu. 2021. Pre-train or annotate? domain adaptation with a constrained budget. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 5002–5015, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Antoine Bosselut, Omer Levy, Ari Holtzman, Corin Ennis, Dieter Fox, and Yejin Choi. 2018. Simulating action dynamics with neural process networks. In Proceedings of the 6th International Conference for Learning Representations (ICLR).

Christopher Clark, Kenton Lee, Ming-Wei Chang, Tom Kwiatkowski, Michael Collins, and Kristina Toutanova. 2019. BoolQ: Exploring the surprising difficulty of natural yes/no questions. 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 2924–2936, Minneapolis, Minnesota. Association for Computational Linguistics.

Bhavana Dalvi, Lifu Huang, Niket Tandon, Wen-tau Yih, and Peter Clark. 2018. Tracking state changes in procedural text: a challenge dataset and models for process paragraph comprehension. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1595–1604, New Orleans, Louisiana. Association for Computational Linguistics.

Aditya Gupta and Greg Durrett. 2019a. Effective use of transformer networks for entity tracking. 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 759–769, Hong Kong, China. Association for Computational Linguistics.

Aditya Gupta and Greg Durrett. 2019b. Tracking discrete and continuous entity state for process understanding. In Proceedings of the Third Workshop on Structured Prediction for NLP, pages 7–12, Minneapolis, Minnesota. Association for Computational Linguistics.

Hao Huang, Xiubo Geng, Jian Pei, Guodong Long, and Daxin Jiang. 2021. Reasoning over entity-action-location graph for procedural text understanding. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 5100–5109, Online. Association for Computational Linguistics.

Daniel Hashabi, Snigdha Chaturvedi, Michael Roth, Shyam Upadhyay, and Dan Roth. 2018. Looking beyond the surface: A challenge set for reading comprehension over multiple sentences. In Proceedings
of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 252–262, New Orleans, Louisiana. Association for Computational Linguistics.

Daniel Khashabi, Yeganeh Kordi, and Hannaneh Hajishirzi. 2022. UnifiedQA-v2: Stronger generalization via broader cross-format training. ArXiv, abs/2202.12359.

Daniel Khashabi, Sewon Min, Tushar Khot, Ashish Sabharwal, Oyvind Tafjord, Peter Clark, and Hannaneh Hajishirzi. 2020. UNIFIEDQA: Crossing format boundaries with a single QA system. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 1896–1907, Online. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880, Online. Association for Computational Linguistics.

Xiaoya Li, Fan Yin, Zijun Sun, Xiayu Li, Arianna Yuan, Duo Chai, Mingxin Zhou, and Jiwei Li. 2019. Entity-relation extraction as multi-turn question answering. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1340–1350, Florence, Italy. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Masaaki Nagata, Katsuki Chouza, and Masaaki Nishino. 2020. A supervised word alignment method based on cross-language span prediction using multilingual BERT. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 555–565, Online. Association for Computational Linguistics.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. Journal of Machine Learning Research, 21(140):1–67.

Hossein Rajaby Faghiihi and Parisa Kordjamsheh. 2021. Time-stamped language model: Teaching language models to understand the flow of events. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 4560–4570, Online. Association for Computational Linguistics.

Victor Sanh, Albert Webson, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chauffin, Arnaud Stiegler, Arun Raja, Manan Dey, M Saifull Bari, Canwen Xu, Urnish Thakker, Shanya Sharma Sharma, Eliza Szoczechla, Tae-woon Kim, Gunjan Chhablani, Nihal Nayak, De-bajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Macina, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Teven Le Scao, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M Rush. 2022. Multitask prompted training enables zero-shot task generalization. In International Conference on Learning Representations.

Qi Shi, Qian Liu, Bei Chen, Yu Zhang, Ting Liu, and Jian-Guang Lou. 2022. Lemon: Language-based environment manipulation via execution-guided pretraining.

Niket Tandon, Bhavana Dalvi, Joel Grus, Wen-tau Yih, Antoine Bosselut, and Peter Clark. 2018. Reasoning about actions and state changes by injecting commonsense knowledge. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 57–66, Brussels, Belgium. Association for Computational Linguistics.

Jizhi Tang, Yansong Feng, and Dongyan Zhao. 2020. Understanding procedural text using interactive entity networks. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 7281–7290, Online. Association for Computational Linguistics.

Tu Vu, Tong Wang, Tsenduren Munkhdalai, Alessandro Sordoni, Adam Trischler, Andrew Mattarella-Micke, Subhansri Maji, and Mohit Iyyer. 2020. Exploring and predicting transferability across NLP tasks. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 7882–7926, Online. Association for Computational Linguistics.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierre Cistac, Tim Rault, Remi 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 Rush. 2020. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online. Association for Computational Linguistics.

Sheng Zhang, Xiaodong Liu, Jingjing Liu, Jianfeng Gao, Kevin Duh, and Benjamin Van Durme. 2018. Record: Bridging the gap between human and machine commonsense reading comprehension. ArXiv, abs/1810.12885.
A Appendix

B Dataset

For ProPara (Dalvi et al., 2018), following Zhang et al. (2021), the state prediction task includes five candidate states (Create, Destroy, Move, Exist and Outside). For Recipes (Bosselut et al., 2018), each ingredient has two possibilities (Exist or Absence) in each step of the recipe. Full data statistics on two datasets are presented in Table 5.

C Evaluation

Sentence-level evaluation Sentence-level evaluation measures the following questions for each target entity:

(a) Cat-1: Is entity created (destroyed, moved) in the process?

(b) Cat-2: When (step #) is entity created (destroyed, moved)?

(c) Cat-3: Where (location) is entity created (destroyed, moved to/from)?

Further, F1 scores for these questions are aggregated using micro/macro averages.

Document-level evaluation Document-level evaluation measures the following questions for each paragraph:

(a) What are the input entities to the process?

(b) What are the output entities of the process?

(c) What entity conversions occur, when (step #), and where (location)?

(d) What entity movements occur, when, and where?

The macro average of F1 scores for these questions will be used as the final score.

Merging State and Location Predictions As SET makes independent state and location prediction for each step of the procedure, there might be conflicts between adjacent state predictions (e.g., two Destroy states in a row), or same-step state and location predictions (e.g., the predicted state is Move while the after-step location is the same as the before-step location). To resolve these conflicts, we use the heuristic rules designed by Zhang et al. (2021), which works slightly better than applying off-line CRF decoding proposed in Gupta and Durrett (2019a).

| Dataset  | Statistics | Train | Dev  | Test | Total |
|----------|------------|-------|------|------|-------|
| Recipes  | # procedures | 693   | 86   | 87   | 866   |
|          | Avg. steps / proc. | 8.8   | 8.9  | 9.0  | 8.8   |
|          | Avg. entities / proc. | 8.6   | 8.8  | 8.5  | 8.6   |
| ProPara  | # procedures | 391   | 43   | 54   | 488   |
|          | Avg. steps / proc. | 6.8   | 6.7  | 6.9  | 6.8   |
|          | Avg. entities / proc. | 3.8   | 4.1  | 4.4  | 3.9   |

Table 5: Statistics of Recipes and ProPara.