**Abstract**

Scripts - standardized event sequences describing typical everyday activities - have been shown to help understand narratives by providing expectations, resolving ambiguity, and filling in un-stated information. However, to date they have proved hard to author or extract from text. In this work, we demonstrate for the first time that pre-trained neural language models (LMs) can be finetuned to generate high-quality scripts, at varying levels of granularity, for a wide range of everyday scenarios (e.g., bake a cake). To do this, we collected a large (6.4k), crowdsourced partially ordered scripts (named proScript), which is substantially larger than prior datasets, and developed models that generate scripts with combining language generation and structure prediction. We define two complementary tasks: (i) edge prediction: given a scenario and unordered events, organize the events into a valid (possibly partial-order) script, and (ii) script generation: given only a scenario, generate events and organize them into a (possibly partial-order) script. Our experiments show that our models perform well (e.g., F1=75.7 on task (i)), illustrating a new approach to overcoming previous barriers to script collection. We also show that there is still significant room for improvement toward human level performance. Together, our tasks, dataset, and models offer a new research direction for learning script knowledge.

1 Introduction

Scripts, originally introduced by Schank and Abelson (1975), represent structured commonsense knowledge about prototypical events in everyday situations/scenarios such as bake a cake and fuel a car (Figure 1). However, while scripts have been shown to help understand narratives by providing expectations, resolving ambiguity, and filling in un-stated information (Chambers and Jurafsky, 2008; Modi et al., 2017, inter alia), they have proved hard to author or extract from text, with only small script databases available (Regneri et al., 2010; Chambers, 2017; Ostermann, 2020).

In this work, we show for the first time that pre-trained neural language models (LMs) can be adapted to generate high-quality scripts, including appropriately partial ordering events where a specific temporal ordering is required only when it is necessary. LMs have previously been shown to successfully generate stories (Rashkin et al., 2020), summaries (Lewis et al., 2020), and commonsense facts (Bosselut et al., 2019; Hwang et al., 2020). Here we investigate their application to script generation. First, we collect large amount (6.4k) of partially ordered script from crowdsourcing with a similar but simplified collection method (Ciosici et al., 2021). We call the dataset as proScript (PaRtial Order SCRIPt for generaTion), and this is substantially larger than prior (crowdsourced) dataset such as DeScript (Regneri et al., 2010) that
has 40 scripts. Since the granularity of scripts (and the events) are inherently vague and subjective (Modi et al., 2016), we collected wider variety of micro and macroscopic scripts than previous datasets. Additionally, temporal duration of each event is also annotated (e.g., *take the cake out of the oven* typically takes one minute in the *bake a cake* script), which will potentially link script knowledge with temporal reasoning in future work.

Second, with the collected data, we introduce two complementary tasks: **script edge prediction** and **entire script generation**. In the edge prediction task, given a scenario and unordered intermediate events, models must organize the events as a valid partial-order script. On the other hand, the script generation task is to generate intermediate events and the partial-order of those events for a given scenario. This task requires both natural language generation (for nodes) and graph structure prediction (for edges).

Finally, based on our proposed dataset, we develop models for both edge prediction and entire script generation tasks. As Chambers (2017) has revealed that models trained and evaluated on missing events prediction (i.e., *narrative cloze*) are insufficient to assess script knowledge, our evaluation scheme evaluates the entire script. We compare the models against baselines, and show that our models outperform the baselines for both the edge prediction and the script generation tasks. Nonetheless, there is a significant room for improvement toward human-level performance – e.g., for edge prediction, the best model achieves 75.71 of F1 score while human achieves 89.28, and for script generation, the best model obtains a graph edit distance of 4.97 (i.e., number of human edits), while human-created scripts achieve 2.98 on average.

Our contributions are thus:

- A new dataset (**proScript**) of crowdsourced scripts that is substantially larger than prior (manually crafted) datasets
- Two complementary task definitions against **proScript**
- Two new models for these tasks, providing the first demonstration that generative models can be successfully applied, although it is still significantly below human levels

2 Related Work

**Script as narrative chain**  Mooney and DeJong (1985) and Chambers and Jurafsky (2008, in-
don et al., 2016; Peng et al., 2018; Zhai et al., 2019; Rashkin et al., 2020). Our work is related to story generation in terms of generating higher-level agenda (or plot) of a story. However, a main difference between stories and scripts is that stories often require surprising and incidental sequence of events as well as description about character’s mental states and landscape depiction that make the story attractive for readers, whereas our script generation expects generating essential core events (Chambers, 2017) in partial order.

## 3 Definitions

**proScript** We define proScript as a directed acyclic graph (DAG), $G(V, E)$ with a given scenario $(s)$, where $V$ is a set of essential events $\{v_1, ... v_i, ... v_n\}$ and $E$ is a set of temporal ordering constraints between events $\{e_{ij}\}$ which means that the events $v_i$ must precede the event $v_j$ ($v_i \prec v_j$).\(^1\) DAGs effectively encode the partial-ordering of core events—crucial for representing events which can be performed in any order. For example, in a *bake a cake* scenario, one can “gather the ingredients” and “turn on the oven” in any order (Figure 1). We emphasize that scripts should not include non-core events such as discourse related events (e.g., reporting verbs) as Chambers (2017) proposed. In proScript, we also exclude alternative events in a proScript DAG. For example, in a *bake a cake* scenario, “get ingredients” and “buy ingredients” are alternative events with each other because either one is only necessary in the scenario. By excluding alternative events, we can resolve ambiguity of the edges in partial order structure as temporal relations or alternative paths. Regneri et al. (2010) and Modi et al. (2016) do not discriminate this ambiguity.\(^2\)

With the definition, we introduce proScript task in two complementary settings: script edge prediction and entire script generation.

**Edge Prediction** The script edge prediction task is to predict a set of partial-ordered edges $(E)$ of the script $(G(V, E))$, given a scenario and a set of unordered intermediate events $v \in V$.

\(^1\)Technically, proScript is a transitive reduction of a DAG. In short, transitive reduction of $G$ does not have any short cut edges between nodes. In proScript, we add a single root node $(v_r)$ and scenario $(s)$ as a unique leaf node.

\(^2\)In proScript, we focus on events and the (partial-) ordering, and we leave participants/arguments identification for future work.

## Script Generation

The script generation task is to predict a partial order script $G(V, E)$, but only the scenario is given. Models are additionally expected to generate events $(V)$ in natural language.

## 4 Datasets

**Source of Scenarios** We collected scenarios from ROCStories (Mostafazadeh et al., 2016), DeScript (Wanzare et al., 2016), and VirtualHome (Puig et al., 2018). As ROCStories consists of sentences instead of scenarios, we extract phrases that match the manually curated patterns “want(ed) to ...”, “need(ed) to ...”, “look(ing) to ...” and that do not include personal pronouns or person’s name. The 2,565 scenarios we collected include both high-level long-term ones (e.g., open a small business) and fine-grained short-term ones (e.g., sign into an email account). DeScript consists of 40 daily scenarios (e.g., making coffee) and we use all of them. VirtualHome is constructed to learn activities interactively in a household in a 3D simulated world. It has 233 indoor tasks (e.g., turn on light) and we include them as scenarios.

**Crowdsourcing proScript** For the collected scenarios, we crowdsourced the corresponding proScript on the Amazon Mechanical Turk. Our crowdsourcing procedure is similar but simplified method to (Ciosici et al., 2021). First, crowdworkers are required to describe five to seven core events that they are essential for the given scenario (Chambers, 2017) with the estimated time it takes to complete each event. In the second question, they are asked to sort them in possibly partial order (=DAG), which represents the proScript for the scenario.

Due to the complex nature of this crowdsourcing procedure, it is crucial to maintain the quality. To identify and filter out noisy instances, two different workers are asked to sort the same set of events in partial order (i.e., the same as the second question described above). According to our manual analysis, we decided to retain scripts that have at least 65.0 F1 score between the workers.\(^3\) To collect proScript with both micro and macroscopic scenarios, we iteratively picked two adjacent events in the DAGs and use them as a source of finer-grained scenarios.

\(^3\)In our crowdsourcing tasks, we maintained a pay rate of 12$/hr or higher. For example, crowd workers were paid $0.8 for the script creation and $0.4 for the validation.
Dataset Statistics In total, we collected 6,414 valid scripts that include 311,502 pairs of events, and we split the proScript into training (3,252 scenarios), development (1,085), and test set (2,077). The training and development sets consist of scenarios collected from ROCStories, and the test set consists of those from ROCStories, Describe, and VirtualHome. This helps us evaluate in- and out-of-domain performance.

The average number of events in proScript scenarios is 5.45 and the maximum degrees of DAGs in the training set are distributed as follows: 2,198 scripts (67.6%) for degree 1, 915 scripts (28.1%) for degree 2, 108 scripts (3.3%) for degree 3, 31 scripts (0.9%) for degree 4 and above.

Figure 2 shows the normalized histogram of the typical time to take for each script in proScript dataset. Most of the scripts take between a minute and an hour (e.g., “go to bathroom”, “buy some new clothes”), while there are a reasonable amount of high-level long-term scripts (e.g., “find a new job”, “open a small business”).

5 proScript Edge Prediction

5.1 Models

For the proScript edge prediction task (§3), we implement a two-step approach baseline (pairwise model) and compare it with our proposed end-to-end neural method (proScript_edge-pred).

Pairwise Model We implement a two-step baseline where we train a binary classifier to predict the precedence between pairs of events, followed by building a partial order script \( \hat{G} \) by aggregating the predicted relations across all pairs of events.

Formally, the classifier takes a pair of events \((v_i, v_j)\) and predicts the precedence \( \hat{e}_{ij} \) – i.e. the event \( v_i \) precedes \( (\prec) \) \( v_j \).

\[
\hat{e}_{ij} = p(v_i \prec v_j | v_i, v_j)
\]

Scores by the classifier are used as weights to create an adjacency matrix of \( G \) which is then automatically converted into a partial-order script with heuristics – when \( G \) contains a cycle, we iteratively remove edges by choosing the one with minimum weight until we get a valid DAG.

proScript_edge-pred We propose an an end-to-end neural model, which takes all the (unordered) events \((v)\) and the scenario \((s)\) as the input \((x)\) and predicts the edges \((E)\) in a partial-order script \((\hat{G})\) at one time. To represent \( E \) in a linear format \((y)\), we use DOT, a graph description language as shown in Figure 3.\(^4\) By flattening the nodes and edges of \( G \) (and \( \hat{G} \)), we apply neural encoder-decoder models. Formally, flattened unordered events and scenario as \( x \) are embedded as continuous representation (\( \text{emb}(x) \)) by the encoder, then the decoder will generate tokens \((y)\) as follows:

\[
p(y_1, \ldots, y_N | x_1, \ldots, x_M) = \prod_{n=1}^{N} p(y_n | \text{emb}(x_1, \ldots, x_M), y_1, \ldots, y_{n-1}).
\]

Compared to the pairwise model, the proScript_edge-pred model uses information from all the events jointly to build partial-order script with a broader context.

5.2 Evaluation Metrics

Given \( G(V, E) \) as a predicted (partial order) script and \( \hat{G}(V, E) \) as the correct (oracle) script, the F1

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\(^{4}\text{Madaan and Yang (2020) have previously shown that finetuned LMs can generate valid DOT language.} \)
Table 1: Results for proScript edge prediction task. In this table, proScript refers to proScript_{edge-pred}.

| Models              | F1   | P    | R    | F1   | P    | R    | F1   | P    | R    | F1   | P    | R    |
|---------------------|------|------|------|------|------|------|------|------|------|------|------|------|
| random              | 21.30| 21.08| 21.72| 21.03| 20.52| 20.84| 21.32| 21.27| 21.58|      |      |      |
| Pairwise (RoBERTa)  | 65.75| 67.05| 64.71| 65.29| 64.97| 65.89| 59.06| 60.44| 57.98|      |      |      |
| Pairwise (T5)       | 70.96| 71.93| 69.76| 67.64| 69.44| 66.18| 69.50| 71.41| 67.96|      |      |      |
| proScr (11B-100)    | 56.05| 56.58| 55.75| 52.26| 52.91| 51.89| 54.98| 55.67| 54.59| 49.16| 49.76| 48.33|
| proScr (11B-1k)     | 65.98| 66.49| 65.71| 60.55| 61.24| 60.15| 64.64| 65.40| 64.20| 55.89| 56.51| 55.54|
| proScr (Large)      | 66.25| 66.89| 65.83| 63.64| 64.22| 63.27| 65.76| 66.38| 65.35| 61.23| 61.76| 60.91|
| proScr (11B-all)    | 78.20| 78.48| 78.14| 75.71| 75.93| 75.72| 77.75| 78.03| 77.71| 73.37| 73.54| 73.46|
| Human               | 89.32| 89.60| 89.21| 89.28| 89.91| 88.86| 90.04| 90.54| 89.74| 88.71| 89.44| 88.18|

5.3 Experiments

Setup For the binary classifier (pairwise model), we use two variants of the Transformer (Vaswani et al., 2017): RoBERTa-large (Liu et al., 2019) and T5-11B (Raffel et al., 2020).

When training (i.e., fine-tuning) RoBERTa, we use a grid-search for choosing the best hyper-parameters from the best performed model on the development set: epochs {1, 2, 3}, learning rate {1e-5, 1e-6, 1e-7}, batch size {16, 24, 32}. For training the T5 model as the pairwise model, we followed a default set of hyper-parameters that are recommended in Raffel et al. (2020).

For the proScript_{edge-pred} model, we use the T5 with different model sizes (Large and 11B) and training sizes (100, 1k, and all 3.2k) to see how these factors affect the performance. We followed a default set of hyper-parameters for the T5 models.

Results The results are shown in Table 1. We find that the pairwise and proScript_{edge-pred} models significantly outperform the random baseline where the edges are randomly assigned. The proScript_{edge-pred} T5-11B model outperforms the pairwise T5-11B model. This indicates that the proScript_{edge-pred} model benefits from a larger context from the input to predict edges more accurately, although there is still a significant room for improvement toward human-level performance. Regarding the difference between in and out of domain, we find that the in-domain performance is higher than the out-of-domain performance, whereas human performance is robust regardless of the domain difference. We also see that the training set (100, 1k, all) and model sizes (Large, 11B) significantly affect the performance of proScript_{edge-pred}.

Figure 4 shows the performance of the pairwise (T5-11B) model, proScript_{edge-pred} (T5-11B) and human according to the maximum degree of the script (DAG).

6 proScript Generation

6.1 Models

proScript_{gen} The proScript generation task combines natural language generation (i.e. generating events in natural language) with structure prediction over the generated events (i.e. organizing the events into a DAG). Our approach (proScript_{gen}) is to formulate it as an end-to-end problem, similar to the proScript_{edge-pred}
for the proScript edge prediction task (§5.1). Given a scenario (s) and the number of events to generate in the script, proScript_gen generates events and edges for the partial-order script (\(\hat{G}\)) in DOT language (Figure 5). Formally, we use the same encoder-decoder framework (eq.2) except that a scenario and number of steps to generate are described in natural text as \(x\) and the decoder is expected to generate events as well as the edges (as \(y\)) in the script.

**Transfer learning from WikiHow data** Transfer learning often helps improve the performance when it is (pre-)trained on a similar task (Peters et al., 2018; Devlin et al., 2019). As additional resource for pre-training proScript_gen, we use procedural texts extracted from WikiHow, which contains 130k instances of a sequence of essential steps for a given topic in various categories (e.g., health, finance, hobbies, etc.). It is important to note that all the procedures in WikiHow are formatted as sequences rather than a partial-order. We refer to this approach as proScript_gen-transfer.

**Pipeline approach** An alternative approach is to use proScript_gen followed by the proScript_edge-pred model. The approach relies on proScript_gen to generate a set of events but allows to fix the predicted edges via the proScript_edge-pred model. We refer to this approach as proScript_gen-pipe, and study whether it can improve the performance over proScript_gen.

### 6.2 Evaluation Metrics

Chambers (2017) emphasizes the importance of human annotation for evaluating script knowledge. However, human evaluation for the proScript generation task is challenging because it involves natural text generation and structured prediction. As in the text generation tasks such as machine translation and text summarization, there are several possible correct answers. Therefore, we use two complementary evaluation metrics for the proScript generation task: (i) graph edit distance, and (ii) pairwise comparison. These are the absolute and relative measures of performance, respectively. Graph edit distance (Abu-Aisheh et al., 2015) computes the distance between two graphs. Formally, given two graphs \(G_1\) and \(G_2\),

\[
\text{GED}(G_1, G_2) = \min_{G_1, \ldots, G_k \leftarrow G_2} \sum_{i=1}^{k} \text{cost}(d_i)
\]

where \(d_1, \ldots, d_k\) is a list of graph edit operations from \(G_1\) to \(G_2\). The operations include deletion, insertion, and replacement for vertex and edge. Each operation has its cost and we set the cost to be 1 for all the operations in our evaluation for simplicity. We use the graph edit distance between a model-generated script and the revised script by human annotators. The graph edit distance is indicative of the quality of the generated scripts; higher-quality scripts must have smaller graph edit distances to the gold-standard (i.e., they require a smaller number of human revisions). In addition, we also employ pairwise human judgments where we ask human annotators to compare the scripts generated by proScript_gen with those from the other approaches.

### 6.3 Experiments

**Setup** For our proScript_gen, we use T5-11B. Similarly to the proScript_edge-pred, we follow the default set of hyper-parameters recommended in (Raffel et al., 2020). For proScript_gen-transfer, we pre-train the proScript_gen with the 130k procedures, and finetune it on the proScript dataset. For the proScript_gen-pipe, we first obtain the actions generated by proScript_gen (ignoring the edges), and use the set of events as input for proScript_edge-pred, which is trained (see §5.3) to predict the edges.

As defined in §3, we use graph edit distance and pairwise judgments to evaluate the quality of the generated scripts. For computing graph edit distances, we select 500 scripts (250 for dev and test sets) and ask crowdworkers to revise the generated scripts as necessary (e.g., add/delete/replace the
| Split       | Models            | Edit Dist | V-Del | V-Ins | V-Rep | E-Del | E-Ins | E-Rep |
|------------|-------------------|-----------|-------|-------|-------|-------|-------|-------|
| dev        | proScript_gen     | 4.73      | 0.426 | 0.192 | 0.581 | 1.558 | 1.308 | 0.671 |
|            | proScript_gen-transfer | 4.79     | 0.337 | 0.195 | 0.679 | 1.491 | 1.281 | 0.775 |
|            | proScript_gen-pipe | 4.88      | 0.397 | 0.159 | 0.560 | 1.705 | 1.407 | 0.661 |
|            | Human             | 2.78      | 0.155 | 0.161 | 0.144 | 1.123 | 1.011 | 0.199 |
| test       | proScript_gen     | 4.97      | 0.581 | 0.142 | 0.656 | 1.668 | 1.184 | 0.709 |
|            | proScript_gen-transfer | 5.03     | 0.438 | 0.213 | 0.775 | 1.713 | 1.402 | 0.835 |
|            | proScript_gen-pipe | 5.10      | 0.594 | 0.143 | 0.671 | 1.880 | 1.292 | 0.787 |
|            | Human             | 2.85      | 0.168 | 0.217 | 0.154 | 1.223 | 1.091 | 0.209 |
| test (in domain) | proScript_gen     | 4.57      | 0.513 | 0.158 | 0.633 | 1.471 | 1.108 | 0.687 |
|            | proScript_gen-transfer | 5.03     | 0.339 | 0.299 | 0.649 | 1.575 | 1.496 | 0.677 |
|            | proScript_gen-pipe | 5.10      | 0.561 | 0.147 | 0.630 | 1.765 | 1.217 | 0.744 |
|            | Human             | 2.98      | 0.168 | 0.211 | 0.149 | 1.223 | 1.091 | 0.206 |
| test (out domain) | proScript_gen     | 4.07      | 0.659 | 0.124 | 0.681 | 1.894 | 1.270 | 0.735 |
|            | proScript_gen-transfer | 5.76     | 0.549 | 0.115 | 0.916 | 1.867 | 1.296 | 1.013 |
|            | proScript_gen-pipe | 5.81      | 0.659 | 0.116 | 0.795 | 1.961 | 1.267 | 0.941 |
|            | Human             | 3.03      | 0.168 | 0.149 | 0.130 | 1.340 | 1.074 | 0.189 |

Table 2: Results for proScript generation task (dev, test, in-domain test and out-of-domain test set). We measure the average graph edit distance between generated script and the two human revisions (lower the better). We also show the average number of each graph edit operation ({Delete, Insert, Replace} × {Vertex, Edge}).

Random (edge) baseline shows 11.06 edit distance for the dev set and 10.95 for the test set.

In pairwise judgments, we compare the scripts generated by proScript_gen with those from the other approaches. We randomly select 150 pairs, and ask three crowdworkers to judge whether the script generated by proScript_gen is better, worse, or equal to the other (i.e. transfer, pipeline, or human). We use majority vote to decide the final pairwise human judgment between the two scripts.

**Results** The pairwise judgment result is shown in Figure 6. We see that the pipeline and transfer models show slight preference over the proScript_gen (except pipeline-dev), although the difference is not large. We also see that the transfer model constantly have more preference over the proScript_gen than the pipeline model in both dev and test sets. Regarding the pairwise comparison with human-created plans, proScript_gen still has a significant room for improvement toward human level.

Table 2 shows the average graph edit distance between the generated script and the human revisions. We find that neither transfer nor pipeline help to improve the graph edit distance over proScript_gen, indicating that proScript_gen is already a strong baseline (see examples in Appendix). The reason of no improvement by the transfer approach may be because WikiHow consists of sequences rather than partially ordered steps. No improvement by the pipeline approach indicates that the proScript_gen can directly generate valid script
in both events and edges. Further studies for improvements are needed for future work.

In terms of the edit types, many of the edits are edge-related, suggesting that proScript and the variants are all good at generating events but struggles with ordering them. Regarding in- and out-of domains in the test sets, we observe that proScript and the variants have slightly better performance for in-domain scripts than out-of domain, while human created scripts are not affected by domains. These findings are consistent with the result in the edge prediction task (§5.3).

Figure 7 shows a histogram of the graph edit distance. It is evident that human created scripts are corrected less often than scripts generate by proScript, whereas the scripts from proScript and the variants often have a large number of edits (e.g., 4 or more). It is interesting to see that fewer number of scripts have 1 to 3 edits (except scripts created by human). The reason is because one simple revision tends to yield multiple graph edits (e.g., one node insertion yields multiple edge insertions).

**Error Analysis** We performed manual error analysis for the scripts generated by each model. We selected 40 random scripts that have non-zero graph edit distance and classified the human revisions into 7 types: (1) incorrect order, (2) missing event, (3) irrelevant/redundant event, (4) order by context, (5) granularity, (6) paraphrased event, and (7) wrong correction (examples are shown in Table 3).

Table 3: Examples for each revision type.

| Revision types       | generated script (subgraph)                                                                 | revised script (subgraph)                                                                 |
|----------------------|-------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| incorrect order      | get off the car → drive to the zoo → put clothes in dryer → place clothes into dryer → dry clothes | drive to the zoo → get off the car → put clothes in dryer → dry clothes                   |
| irrelevant/redundant | get a visa → ... → get off the plane → trip to a foreign country                           | get off the plane → get a visa (on arrival) → trip to a foreign country                  |
| order by context     | get out of the bed → go to the kitchen                                                      | go out of the bed → open the bedroom door → go to the kitchen                            |
| granularity          | move into new apartment                                                                    | move to a new apartment                                                                    |

Table 4: Revision type distribution (%) by each model.

| Revision types               | proScript | Transfer | Pipeline | Human |
|-----------------------------|-----------|----------|----------|-------|
| crucial errors (edge)       | 15.79     | 21.62    | 24.32    | 10.00 |
| incorrect order (node)      | 5.26      | 2.70     | 2.70     | 0.00  |
| irrelevant/redundant event (node) | 10.53   | 13.51    | 2.70     | 0.00  |
| order by context (edge)     | 31.58     | 32.43    | 40.54    | 33.33 |
| granularity (node)          | 31.58     | 24.32    | 21.62    | 26.67 |
| paraphrased event (node)    | 0.00      | 0.00     | 5.41     | 6.67  |
| wrong revisions (node)      | 5.26      | 5.41     | 2.70     | 23.33 |

Approximately, the first three types indicate that the script has crucial errors, the next three types are trivial revisions where both generated and revised scripts are plausible. The last type of revision is the one where the revised script is wrong (or worse).

Table 4 shows the statistics of each error type. We see that edge-related revisions are more frequent than node-related revisions. This is consistent with the results in graph edit distance. Overall, we find that minor revisions are more frequent than crucial errors, indicating that proScript and the variants generates reasonably good scripts. In contrast, crucial errors are quite rare in human created scripts, indicating a significant room for future innovation.

### 7 Conclusions

We show for the first time that pre-trained neural language models can be adapted to generate partial order scripts. We collect 6,400 partially ordered script from crowdsourcing (proScript), which is substantially larger than prior manually crafted datasets. With the proScript dataset, we introduced two complementary task and models, providing the first demonstration that generative models can be successfully applied to script generation, although it is still below human performance. We believe that proScript dataset and models would advance future work on various NLP tasks such as story generation, machine comprehension, temporal reasoning, and high-level planning.
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A.1 Plans generated by proScript_gen

We show some example scripts generated by proScript_gen in Figure 8.

A.2 Reproducibility

For the POP model, we use a single CPU with 4GB memory. This model does not require any training procedure. For training RoBERTa-large as a pairwise model, we use Quadro RTX 8000 (48GB memory), which takes around 4.5 hours to train a model. RoBERTa-large consists of 355M parameters with 24 layers, 1,024 of hidden embedding size, and 16 of the attention heads. T5-large model has 770M parameters with 24-layers, 1024-hidden-state, 4096 feed-forward hidden-state, and 16 attention heads. T5-11B models has 11B parameters with 24-layers, 1,024 of hidden embed-

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Scenario: play the organ
- find sheet music to play
- sit down at the organ bench
- warm up on the organ
- play the music on the organ

Scenario: drink a glass of milk
- walk to the kitchen
- open the refrigerator
- remove milk from refrigerator
- close the refrigerator
- pour milk into pot to warm a bit
- pour milk into glass to drink
- raise glass to lips

Scenario: audition for a musical
- research local musicals
- find out when the musicals are auditioning
- look up directions to the musical
- practice reading lines with friends
- practice reading lines before bed
- show up to auditions

Figure 8: Example scripts generated proScriptGen.