TVRecap: A Dataset for Generating Stories with Character Descriptions

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Abstract

We introduce TVRecap, a story generation dataset that requires generating detailed TV show episode recaps from a brief summary and a set of documents describing the characters involved. Unlike other story generation datasets, TVRecap contains stories that are authored by professional screenwriters and that feature complex interactions among multiple characters. Generating stories in TVRecap requires drawing relevant information from the lengthy provided documents about characters based on the brief summary. In addition, by swapping the input and output, TVRecap can serve as a challenging testbed for abstractive summarization. We create TVRecap from fan-contributed websites, which allows us to collect 26k episode recaps with 1868.7 tokens on average. Empirically, we take a hierarchical story generation approach and find that the neural model that uses oracle content selectors for character descriptions demonstrates the best performance on automatic metrics, showing the potential of our dataset to inspire future research on story generation with constraints. Qualitative analysis shows that the best-performing model sometimes generates content that is unfaithful to the short summaries, suggesting promising directions for future work.1

1 Data is available at https://github.com/mingdachen/TVRecap

1 Introduction

Story generation is the task of generating a coherent narrative. Due to its open-ended nature, increasing efforts have been devoted to constrained settings to facilitate reliable evaluation of computational models, such as generating stories from short prompts (Fan et al., 2018) and story continuations (Mostafazadeh et al., 2016) with various constraints (Akoury et al., 2020). In this work, we are interested in generating stories that accord with descriptions about the characters involved. The task is akin to writing stories based on true events or historical figures. For example, when writing historical fiction, writers use facts in biographies of historical figures (i.e., character descriptions) (Brown, 1998). In a similar vein, cognitive psychologists observed that in order for narrative text to be compelling, it has to base its characters on real-world details such that readers can form emotional attachments to them even if the events occurring in the text are not realistic (Oatley, 1999; Green et al., 2003). In either case, computational models for this task can offer assistance in proposing possible stories constrained by relevant documents.

To this end, we create a story generation dataset TVRecap that generates detailed TV show episode recaps from a brief summary of the episode and a set of lengthy character descriptions. We construct TVRecap from fan-contributed websites, which allows us to collect 26k episode recaps covering a variety of genres. An example from TVRecap is shown in Figure 1. The dataset is challenging in that it requires drawing relevant information from the lengthy character description documents based on the brief summary. Since the detailed episode recaps are constrained by character descriptions, it also can evaluate neural models’ ability to maintain consistent traits or goals of particular characters during generation.

In addition, by considering generating the brief summary from the detailed recap, we show that TVRecap is a challenging testbed for abstractive summarization. To evaluate the faithfulness of the generated stories to the brief summaries, we propose a metric that uses the perplexities from the summarization model trained on our dataset.

Empirically, we characterize the dataset with several nearest neighbour methods and oracle models, finding that the use of the brief summaries and the character descriptions generally benefits model performance. We find that our non-oracle models are competitive compared to nearest neighbour models,
suggesting promising future directions. We also benchmark several large pretrained models on the summarization version of our dataset, finding that they perform worse than an extractive oracle by a large margin despite the fact that the dataset favors abstractive approaches. Human evaluation reveals that without character descriptions, models tend to dwell on each event separately rather than advancing the plot, whereas using character descriptions improves the interestingness of the generated stories. Qualitatively, we show that models are able to generate stories that share similar topics with the summaries, but they may miss events in the summaries, leading to unfaithful generations.

We summarize our contributions below:

1. We construct a story generation dataset of 26k instances and show (both qualitatively and quantitatively) that it has several unique challenges.

2. We show that inverting our dataset provides a challenging testbed for abstractive summarization. Models trained on the inverted dataset can be used in evaluation for the original dataset, namely to determine whether generated stories are faithful to their input summaries.

3. We empirically characterize the story generation dataset and the summarization version of our dataset with several nearest neighbour methods, oracle models, and pretrained models, showing the challenges of these tasks and suggesting future research directions.

2 The TVR ECAP Dataset

In this section, we will describe how we construct TVR ECAP and compare it to other story generation datasets. An instance in TVR ECAP is comprised of three components: (1) a detailed episode recap, (2) a brief summary of the episode, and (3) character descriptions, i.e., a set of documents describing the characters involved in the episode. The detailed episode recap delineates the events that occurred in the corresponding episode, which is usually written by fans after watching the episode. The documents about the characters contain biographical details and possibly personality traits. The summary either summarizes the whole episode or talks about the setup of the episode (to avoid spoilers).

An example instance is shown in Figure 1, which comes from an episode of the TV show “The Simpsons”. As there are relevant details mentioned in the character descriptions, generating the detailed recap requires drawing information from the lengthy character descriptions about the two characters. Moreover, due to the fact that the brief summary only depicts the setup of the episode, completing the story also necessitates using information in the character descriptions. That is, the character description information is expected to be useful for both filling in details that are not present in the brief summary as well as, for some of the instances, generating a plausible ending for the story.

2.1 Dataset Construction

We construct TVRECAP from two fan-contributed websites: Fandom2 (FD) and TVMegaSite3 (TMS). We collect brief summaries and detailed episode recaps for several long-running soap operas from TVMegaSite and other TV shows from Fandom. We collect character descriptions from Fandom.4 Since the pages on Fandom have hyperlinks pointing to the character pages, we use the hyperlinks to connect episodes to the characters involved. For TVMegaSite, where there are no such hyperlinks, we use string matching to find the characters. To ensure the quality of this dataset, we filter out episodes based on several criteria. See the appendix for more details on the criteria and the string matching algorithm.

We report detailed statistics about TVRECAP in Table 2. As shown in the table, there are systematic differences between FD and TMS in terms of length of detailed episode recaps, summaries, and character descriptions, among others. We note that the character descriptions for TMS also come from FD. Considering the differences, we train and evaluate models on the two splits separately in experiments. Since the summaries in Fandom are shorter and likely only depict the setups of the detailed recaps, we conduct a human evaluation to check the fraction of setups in the summaries, finding that 61.7% of the summaries are setups.5

We verify the diversity of topics covered in TVRECAP, finding that FD covers far more genres than TMS with the most frequent occupying only 15% of episodes (see the appendix for more details). We randomly split the datasets into train/dev/test sets. For TMS, we additionally filter out instances

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2https://www.fandom.com/
3http://tvmegasite.net/
4Data from Fandom is available under Creative Commons licenses and we have received permission from the owners of tvmegosite.net to publish their data for use with attribution.
5We sample 60 episodes with 2 episodes per show.
Washed-up actor Troy McClure gets pulled over for erratic driving, due to the fact he’s driving without his corrective lenses. When Troy goes to the DMV to get his license changed so that he won’t be required to wear glasses anymore, he offers to take Selma Bouvier to dinner if she will let him pass the eye test.

After dinner at the Pimento Grove, photographers notice Troy leaving with a human woman (rumors about a romantic abnormality initially destroyed Troy's career). The next day, Troy’s agent calls and says that he can get work again if he continues seeing human women. Troy continues dating Selma to help his career. On his agent’s advice, Troy asks Selma to marry him. Troy gets a part in ‘Planet of the Apes’ the musical …

Selma Bouvier

== Introduction ==
Selma Bouvier (born February 28, 1952) is one of Marge's older chain-smoking twin sisters. She works at the DMV and possesses a strong dislike for her brother-in-law, Homer, …

Selma’s favorite film actor was reportedly Troy McClure, to whom she was briefly married, before discovering that it was just a publicity stunt by McClure …

== Personality ==
Selma and Patty tend to be cynical and are noted for their addiction to tobacco smoking…

Troy McClure

== Introduction ==
Troy McClure (born May 8th, 1955) is a cheesy B-movie actor who had fallen on hard times …

== Biography ==
… To cover this up, he began a relationship with Selma Bouvier, whom he had met when she gave him an eye test at the Department of Motor Vehicles. This revived his career, leading him to star in Stop the Planet of the Apes, I Want to Get Off!, a musical version of the film Planet of the Apes …

2.2 Dataset Comparison

We compare TVRECAP to other story generation datasets in Table 1. Unlike ROCStories (Mostafazadeh et al., 2016) and WritingPrompts (Fan et al., 2018) where the inputs to models are either the first few sentences or short prompts, TVRECAP has character descriptions as extra constraints, making the task of generating the reference stories from the inputs less open-ended and therefore more feasible.

Since STORIUM (Akoury et al., 2020) has character descriptions and other information as constraints, it is the most comparable resource to TVRECAP. Our dataset differs from STORIUM in the following aspects:

1. Our dataset has more stories, more characters,
and longer character descriptions.

2. The stories in STORIUM often have detailed descriptions about environments and character utterances, whereas the stories in TVRECAP mostly narrate events that happened without these details. While this leads to shorter stories in TVRECAP, it also prevents the task from conflating generating events and generating other kinds of details in story generation.

3. Due to the fact that the plots in STORIUM are gamified and crafted by amateur writers, 89.8% of stories in STORIUM are unfinished. The stories in our dataset are created and refined by professional screenwriters (though the prose is written by fans, who are presumably amateurs).

4. Stories in STORIUM are turn-based, where each turn is written from the perspective of a particular character and is composed by one player, so the stories often lack direct interactions among characters, unlike TVRECAP. More details are in the appendix.

5. Unlike other story generation datasets, there is an episodic structure among the stories in TVRECAP, which can potentially be used to improve the modeling of characters.

Moreover, models trained on TVRECAP can potentially complement those from STORIUM by merging all the characters’ turns in STORIUM into a coherent narrative. We also quantitatively demonstrate that the source inputs and the output stories are more directly related in our dataset than STORIUM. Details are in the appendix.

**Summarization.** By considering generating the brief summary from the detailed episode recap, we can view TVRECAP as an abstractive summarization dataset. We simply use the detailed episode recap as the source input and the summary as the target output and leave the integration of character descriptions to future work. We compare it to other abstractive summarization datasets, finding that it favors abstractive approaches. In addition, unlike most other summarization datasets, our dataset focuses on stories. These two characteristics make our dataset a potentially valuable contribution for the summarization community. More details are in the appendix.

Table 3: Two excerpts in detailed recaps from TVRECAP that correspond to different episodes in the TV show “The Simpsons”. The excerpts involve interactions between Homer and Selma where Selma consistently shows a strong dislike for Homer, matching the character description in Figure 1.

3 Challenges and Modeling Approaches

3.1 Challenges

TVRECAP poses several challenges for story generation models. One set of challenges relates to consistency in character modeling. Since the episode recaps are constrained by character descriptions, the dataset provides opportunities to evaluate neural models’ ability to maintain consistent personalities or goals of particular characters during generation. The consistency of personalities and goals is related to the notion of “character believability” (Bates et al., 1994; Riedl and Young, 2010), which has been deemed important for composing convincing stories. We illustrate this challenge with two excerpts in Table 3: the strong dislike that Selma has shown for Homer matches her description and is consistent across episodes. Solving this challenge requires models to first identify related information in the lengthy character descriptions based on the plot and integrate it into the generated narrative. We aim to incorporate this idea into the design of our models.

3.2 Approach

We follow Fan et al. (2019) to take a hierarchical story generation approach. The generation process is broken into two steps that use two separately parameterized models: a text-to-plot model and a plot-to-text model. The text-to-plot model first generates detailed plots based on the inputs, and then conditioned on the plots the plot-to-text model generates detailed stories. In this paper, we define the plots as linearized semantic role labeling (SRL) structures. More details on SRL are in the appendix.

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6We label a story as unfinished if it has no completion date.
For example, a plot may be as follows:

\[
\begin{align*}
\langle \text{VERB} \rangle \text{spots} \langle \text{ARG0} \rangle \text{Mummy Pi} \\
\langle \text{ARG1} \rangle \text{how messy the car is} \langle \text{SEP} \rangle \\
\langle \text{VERB} \rangle \text{clean} \langle \text{ARG0} \rangle \text{the car}
\end{align*}
\]

where \langle \text{SEP} \rangle is a special token used to separate SRL structures for different sentences.

**Text-to-Plot Model.** During training, we use the oracle plots, i.e., the SRL tags extracted from the reference recaps. During test time, we use BM25 (Robertson et al., 1995) to find the most similar plot in the training set from the same show based on either the summaries or the detailed recaps (as an oracle baseline).\(^7\) If a show is not present in the training set, we search over the whole training set.

**Plot-to-Text Model.** Our models are based on the sequence-to-sequence transformer architecture (Vaswani et al., 2017). Similar to Rothe et al. (2020) that uses pretrained BERT-like models to initialize sequence-to-sequence models, we use the pretrained RoBERTa-base model (Liu et al., 2019) as the decoder.\(^8\) For the encoder, we choose to use a one-layer randomly initialized Longformer (Beltagy et al., 2020) due to the lengthy inputs and computational constraints. We randomly initialize other parameters and finetune the whole model during training.

Given a plot, we use the neural models to generate sentence by sentence as we find this yields better performance than generating the whole detailed recap. When doing so, we concatenate the SRL tags for the adjacent sentence of the target sentence with the SRL tags for the target sentence. This gives similar performance to showing the SRL tags for the entire detailed recap but is much more efficient (due to shorter sequence lengths). Because the character descriptions are lengthy, we use BM25 to retrieve the most salient information from character descriptions (i.e., one sentence) for each sentence in the detailed recap. We note that during test time, when the text-to-plot model retrieves plots from the training set, we also use the corresponding selected character descriptions.

The pipeline that retrieves relevant character information and then adapts it based on the plot is the first step that we take to simulate a writing system that can dynamically update its belief about particular characters based on the given relevant documents. This differs from prior work on entity representations for story generation (Clark et al., 2018) that does not consider character descriptions as we do.

The inputs to plot-to-text models contain two sources: plots and character descriptions. Since there could be multiple entries corresponding to different characters in the character descriptions, we include a type embedding to differentiate different entries and sources in the input. Similar approaches have been used to represent table entries in neural models (Dhingra et al., 2019; Herzig et al., 2020; Yin et al., 2020). For example, for Figure 1 the inputs are

\[
\begin{align*}
\langle \text{SEP} \rangle_0 \text{Troy McClure’s} \ldots_0 \langle \text{SEP} \rangle_1 \text{Selma Bouvier} \\
\langle \text{SEP} \rangle_1 \text{Selma’s favorite film} \ldots_1 \langle \text{SEP} \rangle_2 \\
\end{align*}
\]

where the subscripts indicate the ID of the type embedding and we always prepend the character names to the corresponding selected character descriptions. The final vector representation of the input is the summation of subword unit embeddings, positional embeddings, and the type embeddings. Conditioned on the input representations, we train the RoBERTa decoder on the reference recaps using a cross-entropy loss.

Due to computational constraints, for the Longformer encoder, we use the global attention on the \langle \text{SEP} \rangle tokens, and use the encoded representations for the summary, the SRL tags, and the \langle \text{SEP} \rangle tokens in character descriptions as the input to decoders.

### 4 Experiments

We perform experiments for both story generation and summarization.

#### 4.1 Setup

For both story generation and summarization, we use a batch size of 200, beam search of size 5 with n-gram blocking (Paulus et al., 2018) where probabilities of repeated trigrams are set to 0 during beam search,\(^2\) and report BLEU (BL) (Papineni et al., 2002)
et al., 2002), ROUGE-1 (R1), ROUGE-2 (R2), and ROUGE-L (RL) (Lin, 2004) scores. For story generation, we additionally report perplexities of the summaries given the generated stories using the summarization models. We will refer to this metric as “PL”. This metric evaluates the faithfulness of the generated stories to the summaries. Lower PL suggests better faithfulness. When computing PL, we use the Pegasus model (Zhang et al., 2020) finetuned on our dataset as it has the best test set perplexities. More details on hyperparameters are in the appendix.

4.2 Results

Story Generation. We report results for FD and TMS in Tables 4 and 5, respectively. We report several return-input baselines on the test sets to show the benefits of using neural models as plot-to-text models. We report PL on the test sets as an approximated lower bound of this metric. We do not report PL on return-input baselines as the output detailed recaps involve SRL sequences, which are not natural language, and therefore the results are not comparable to others.

On the development sets, adding summaries and oracle character descriptions generally improves performance by a significant margin, showing that the extra information aids generation.

Regarding the test set results, we find that (1) the return-input baselines show that the performances of our neural models are non-trivial; (2) while the oracle nearest neighbour baselines achieve competitive performance to our non-oracle neural models, the non-oracle neural models are consistently better than the non-oracle baselines, showing promising results for future research on our datasets. We note that the return-input baselines involving character descriptions display much worse results than other return-input baselines because they are lengthy, which leads to low precision.

Summarization. We report results in Table 6. We report the performance of an extractive oracle where for each sentence in the reference summary, we pick a sentence in the detailed episode recap that maximizes the average of the three ROUGE scores compared against the summary sentence. While recent pretrained models, such as Pegasus, have outperformed the oracle extractive approaches by a large margin on datasets with a high degree of abstractiveness (e.g., XSum (Narayan et al., 2018)), the results in the table show that our dataset is still challenging for these pretrained models.

It is also interesting to see that while Pegasus is best for Fandom, it is not best on TVMegaSite. This may be because TVMegaSite has longer summaries than Fandom. Also, the performance of BART-base is comparable to that of BART-large on Fandom and is better than Pegasus and BART-large on TVMegaSite. This is likely because there is a limited amount of data with similar writing style in pretraining, resulting in little benefit of using larger models for this downstream task. We provide this abstractive summarization task to the community as a challenging dataset for future work.

5 Analysis

5.1 Human Evaluation

To measure the impact of including different components in TVRECAP, we conduct a human evaluation. We show two generated stories from different models along with the corresponding brief summary and ask annotators to choose which story they prefer according to two aspects: (1) which generation is more relevant to the summary; (2) which story is more interesting.

We make two comparisons: “oracle plot” vs. “oracle plot+summary” for studying the benefits of using summaries (“Prefer summary”), and “oracle plot+summary” vs. “oracle plot+summary+oracle char. desc.” for studying the benefits of using character descriptions (“Prefer char. desc.”). We sample instances from the FD development set because the average lengths in FD are shorter, and we only show annotators the first 100 tokens of the texts as we expect it to be challenging to annotate lengthy texts. We use Amazon Mechanical Turk (AMT) and collect 20 annotations per question for each comparison with 6 workers involved (shown in Table 7 as “crowdsourced annotations”). We (the authors) also annotate 50 instances per comparison using the same interface as AMT (shown in the table as “expert annotations”).

To ensure annotation quality, we hire workers with master qualification and pay them with a target hourly wage of $12.
### Table 4: Fandom results. The results for the return-input baselines and the neural models are indicated by “(Return)” and “(NN)” respectively. The best result in each column for each split (excluding the references) is boldfaced.

|                  | BL (%) | R1 (%) | R2 (%) | R3 (%) | PL (%) |
|------------------|--------|--------|--------|--------|--------|
| **Development set results** |        |        |        |        |        |
| (NN) Nearest neighbour plot + summary + char. desc. | 7.1    | 40.7   | 11.0   | 39.6   | 32.3   |
| (NN) Oracle plot | 21.2   | 52.8   | 24.1   | 51.8   | 23.1   |
| (NN) Oracle plot + summary | 24.5   | 54.3   | 25.6   | 55.2   | 20.8   |
| (NN) Oracle plot + summary + oracle char. desc. | **28.4** | **63.0** | **32.8** | **61.2** | **17.9** |
| **Test set results** |        |        |        |        |        |
| (Return) reference | 100.0  | 100.0  | 100.0  | 100.0  | 12.9   |
| (Return) oracle plot | 3.6    | 43.9   | 19.7   | 41.9   | -      |
| (Return) oracle plot + summary | 5.4    | 48.5   | 20.5   | 46.2   | -      |
| (Return) oracle plot + oracle char. desc. | 1.2    | 11.0   | 4.6    | 10.6   | -      |
| (Return) oracle plot + oracle char. desc. + summary | 1.2    | 11.0   | 4.7    | 10.6   | -      |
| (NN) Nearest neighbour detailed recap | 5.1    | 41.1   | 9.3    | 39.6   | 31.2   |
| (NN) Oracle nearest neighbour detailed recap | 4.8    | 41.2   | 10.8   | 39.9   | 28.5   |
| (NN) Oracle plot + summary + oracle char. desc. | **24.5** | **54.3** | **25.6** | **55.2** | **20.8** |
| (NN) Oracle plot + summary + oracle char. desc. + summary | **28.4** | **63.2** | **32.9** | **61.5** | **18.2** |

### Table 5: TVMegaSite results. The results for the return-input baselines and the neural models are indicated by “(Return)” and “(NN)” respectively. The best result in each column for each split (excluding the references) is boldfaced.

|                  | BL (%) | R1 (%) | R2 (%) | R3 (%) | PL (%) |
|------------------|--------|--------|--------|--------|--------|
| **Development set results** |        |        |        |        |        |
| (NN) Nearest neighbour plot + summary + char. desc. | 10.7   | 43.5   | 14.9   | 42.9   | 20.7   |
| (NN) Oracle plot | 26.4   | 60.5   | 34.0   | 60.0   | 17.0   |
| (NN) Oracle plot + summary | 28.3   | 64.3   | 36.1   | 63.9   | 16.4   |
| (NN) Oracle plot + summary + oracle char. desc. | **30.9** | **68.3** | **44.0** | **67.5** | **15.7** |
| **Test set results** |        |        |        |        |        |
| (Return) Reference | 100.0  | 100.0  | 100.0  | 100.0  | 13.9   |
| (Return) Oracle plot | 7.1    | 53.1   | 22.3   | 52.4   | -      |
| (Return) Oracle plot + summary | 13.6   | 62.9   | 25.6   | 62.0   | -      |
| (Return) Oracle plot + oracle char. desc. | 1.1    | 12.3   | 5.1    | 11.9   | -      |
| (Return) Oracle plot + oracle char. desc. + summary | 1.2    | 12.4   | 5.1    | 12.0   | -      |
| (NN) Nearest neighbour detailed recap | 6.6    | 49.8   | 16.0   | 49.2   | 26.3   |
| (NN) Oracle nearest neighbour detailed recap | 7.5    | 49.9   | 18.5   | 49.3   | 25.8   |
| (NN) Oracle plot + summary + oracle char. desc. | 7.3    | 50.6   | 17.6   | 49.8   | 25.3   |
| (NN) Oracle plot + summary + oracle char. desc. + summary | **28.1** | **67.0** | **40.9** | **66.2** | **18.3** |

### Table 6: Test results for summarizing detailed episode recaps. The best result in each column for each domain (excluding the oracle) is boldfaced.

|                  | BL (%) | R1 (%) | R2 (%) | R3 (%) |
|------------------|--------|--------|--------|--------|
| **Fandom**       |        |        |        |        |
| Extractive oracle | 8.3    | 37.0   | 11.3   | 30.9   |
| BART-base        | 5.2    | 31.2   | 7.3    | 25.5   |
| BART-large       | 5.4    | 30.7   | 7.6    | 25.3   |
| Pegasus          | **5.7** | **31.3** | **7.7** | **25.6** |
| **TVMegaSite**   |        |        |        |        |
| Extractive oracle | 16.9   | 35.8   | 20.9   | 33.6   |
| BART-base        | **8.3** | **43.8** | **12.6** | **42.3** |
| BART-large       | 8.1    | 43.2   | 12.3   | 41.8   |
| Pegasus          | 7.7    | 43.5   | 12.6   | 42.1   |

### Table 7: Human annotation results analyzing the effect of including different components in the inputs. The percentage is the fraction of annotations that favor the models to include the corresponding component. The numbers in parentheses are the number of positive annotations divided by the total number of annotations.

|                  | Relevancy | Interesting |
|------------------|-----------|-------------|
| **Expert annotations** |          |             |
| Prefer summary    | 60.0% (30/50) | 40.0% (20/50) |
| Prefer char. desc. | 54.0% (27/50) | 70.0% (35/50) |
| **Crowdsourced annotations** |          |             |
| Prefer summary    | 50.0% (11/20) | 55.0% (10/20) |
| Prefer char. desc. | 55.0% (11/20) | 55.0% (11/20) |

When examining annotations, we find that models without using character descriptions tend to generate sentences that use the word “but” to negate what has been said in the earlier part of the sentence, leaving the sentence dwelling on each event separately rather than advancing the plot (see Sec. 5.2 for examples). To quantify this observation, we compute the frequency of the word “but” per sentence for the reference stories, “oracle plot+summary”, and “oracle plot+summary+oracle char. desc.”. The results are 0.13, 0.53, and 0.24, respectively.
5.2 Generation Examples

We display the generation examples in Table 8 where we find that generations from both models generally share similar topics and character names with the summaries and the references. For example, for the first instance, both generations are about a battle that concerns Elfman, Evergreen, and Rustyrose. However, as observed in the human evaluations, the “oracle plot+summary” model suffers from meaningless negation. For example, see the second generation example, where the highlighted texts keep negating the earlier plot development. While the “Oracle plot+summ.+oracle char.” model does not have this problem, it is still not faithful to the summary. Specifically, both the summary and the reference mention that Chuck needs Serena’s help for his new club opening, but the generation states that “Serena is conducting the club opening” and “Blair asks her to help”. This is likely caused by the model’s inability to understand the states of each character (possibly due to the fact that our models generate at the sentence level) and to effectively integrate multiple sources of information into a coherent narrative.

6 Related Work

Early methods in computational modeling for story generation rely on handwritten rules (Mechan, 1977; Liu and Singh, 2002) to structure narrative. Recent work has explored different approaches to improve the quality of story generation systems, including commonsense knowledge (Mao et al., 2019; Guan et al., 2020), automatically extracted key words (Peng et al., 2018) and key phrases (Orbach and Goldberg, 2020; Rashkin et al., 2020), event-based representations (Martin et al., 2018), and plot graphs (Li et al., 2013).

As our model involves plot generation and character modeling, it is related to work on plot planning (Riedl and Young, 2010; Li et al., 2013; Martin et al., 2018; Yao et al., 2019; Jhamtani and Berg-Kirkpatrick, 2020), character modeling (Clark et al., 2018; Liu et al., 2020), and the interplay between the two (Riedl and Young, 2010). Our work is different in that it explicitly requires performing inference on lengthy documents about characters.

There have been other datasets built from TV shows, such as summarizing TV show character descriptions (Shi et al., 2021), constructing knowledge bases (Chu et al., 2021), summarizing TV
show screenplays (Chen et al., 2021), entity tracking (Chen and Choi, 2016; Choi and Chen, 2018), coreference resolution (Chen et al., 2017; Zhou and Choi, 2018), question answering (Ma et al., 2018; Yang and Choi, 2019), speaker identification (Ma et al., 2017), sarcasm detection (Joshi et al., 2016), emotion detection (Zahiri and Choi, 2017; Hsu and Ku, 2018), and character relation extraction (Yu et al., 2020).

7 Conclusion

We constructed a story generation dataset of 26k stories where each instance is comprised of a detailed episode recap, a summary, and several character descriptions. We quantitatively and qualitatively illustrate several unique challenging aspects of this dataset. In addition, we show that by generating the summary from the detailed recap, the dataset can serve as a challenging tested for abstractive summarization. We also propose a metric based on the summarization model trained on our dataset for evaluating the faithfulness of the generated stories to the summaries. Empirically, we benchmark several nearest neighbour models and oracle models, showing that the summaries and the character descriptions are helpful in generating better stories, which are verified by human evaluations. We also benchmark several pretrained models on the summarization version of our dataset, showing that there is room for improvements.

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### Table 9: Statistics of train/dev/test splits for Fandom and TVMegaSite.

|          | Fandom |       |       | TVMegaSite |       |       |
|----------|--------|-------|-------|------------|-------|-------|
|          | Train  | Dev   | Test  | Train       | Dev   | Test  |
| # shows  | 106    | 104   | 106   | 7          | 7     | 9     |
| # episodes | 10833 | 1320  | 1430  | 11586      | 1452  | 2392  |

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### A Dataset Construction

#### String Matching Algorithm.
For example, for the character name “John Doe”, valid mentions are itself, “John”, “J.D.”, and “JD” due to the writing style on TVMegaSite. While this matching algorithm may lead to extra characters aligned to particular episodes, it at least includes all characters that are actually involved in the episode.

#### Episode Filtering Criteria.
We filter out episodes if (1) an episode contains fewer than 3 characters (to avoid stories that do not involve many character interactions); or (2) the detailed recap has fewer than 200 word tokens (ensuring that stories have enough details); or (3) the brief summary has fewer than 20 word tokens (to ensure that there is sufficient information given as the input).

### B Detailed Statistics for TVRECAP

#### Statistics for Train/Dev/Test Splits
We show train/dev/test splits for Fandom and TVMegaSite in Table 9.

#### Table 10: Dataset statistics for TVRECAP

|          | TVRECAP (Fandom) |             |             |
|----------|------------------|-------------|-------------|
|          | summ.            | uni.        | tri.        |
|          | char. desc.      | 34.3        | 3.4         | 0.8         | 0.3         |
|          | char. desc. \ sum. | 88.1        | 48.3        | 16.7        | 6.2         |
|          | sum. \ char. desc. | 54.3        | 45.4        | 16.3        | 6.1         |
|          | char. desc. \ sum. | 0.5         | 0.6         | 0.4         | 0.2         |
|          | char. desc. \ sum. | 88.7        | 48.9        | 17.1        | 7.4         |
| TVRECAP (TVMegaSite) | | | |
|          | summ.            | 61.7        | 14.7        | 3.0         | 1.2         |
|          | char. desc.      | 93.4        | 56.9        | 17.3        | 3.2         |
|          | char. desc. \ sum. | 32.7        | 44.2        | 16.1        | 3.1         |
|          | sum. \ char. desc. | 0.9         | 2.0         | 1.8         | 1.0         |
|          | char. desc. \ sum. | 94.3        | 58.9        | 19.1        | 4.2         |
|          | STORIUM          | 72.5        | 24.7        | 5.4         | 1.2         |

#### Table 11: Fraction (%) of n-grams in the output stories that also appear in the source inputs. Higher fraction of overlapping n-grams indicates that the two are more directly related. For TVRECAP, we vary different kinds of inputs.

#### Detailed Statistics for FD and TMS.
We show detailed dataset statistics for FD and TMS in Table 10.

#### C Detailed Comparison to STORIUM

STORIUM lacks direction interactions among characters. We quantify this phenomenon in STORIUM by computing the frequency of occurrences of characters in each turn excluding the character that owns the turn, and the frequency is 0.8 on average with 50.4% of the turns absent such occurrences. In contrast, TV shows advance plots by interactions among characters.

Source Inputs and Output Stories are More Closely Related in TVRECAP than STORIUM. To quantitatively illustrate the extent of relatedness between the source inputs and the output stories, we compute the n-gram overlap ratio (i.e., fraction of n-grams in the output stories that also appear in the source inputs) between the inputs and outputs where higher ratios indicate that the two are

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12 We use string matching to detect the occurrences of characters as in the way we construct our dataset.
Table 12: Genres for TV shows in Fandom (left) and TVMegaSite (right).

| Genre      | Count | (Fraction) |
|------------|-------|------------|
| Comedy     | 45    | 15.0%      |
| Drama      | 36    | 14.5%      |
| Action     | 32    | 13.4%      |
| Adventure  | 27    | 11.8%      |
| Children   | 25    | 9.1%       |
| Fantasy    | 15    | 7.0%       |
| Science-Fiction | 14 | 6.2%     |
| Crime      | 12    | 3.9%       |
| Family     | 11    | 3.8%       |
| Anime      | 10    | 3.7%       |
| Romance    | 9     | 3.2%       |
| Supernatural | 4 | 1.5%     |
| Horror     | 3     | 1.0%       |
| Mystery    | 3     | 0.9%       |
| Music      | 2     | 0.6%       |
| Medical    | 2     | 0.6%       |
| Legal      | 1     | 0.3%       |
| History    | 1     | 0.3%       |

Table 13: Genres in Fandom and their corresponding numbers and percentages of episodes.

| Genre      | Count (Fraction) |
|------------|------------------|
| Drama      | 15430 (44.6%)    |
| Romance    | 8341 (24.1%)     |
| Family     | 7686 (22.2%)     |
| Medical    | 3144 (9.1%)      |

Table 14: Genres in TVMegaSite and their corresponding numbers and percentages of episodes.

| Genre      | Count (Fraction) |
|------------|------------------|
| Drama      | 5385 (15.0%)     |
| Comedy     | 5214 (14.5%)     |
| Action     | 4793 (13.4%)     |
| Adventure  | 4220 (11.8%)     |
| Children   | 3280 (9.1%)      |
| Science-Fiction | 2524 (7.0%)   |
| Anime      | 2239 (6.2%)      |
| Fantasy    | 1949 (5.4%)      |
| Romance    | 1408 (4.0%)      |
| Family     | 1355 (3.8%)      |
| Crime      | 1139 (3.2%)      |
| Supernatural | 729 (2.0%)  |
| Medical    | 480 (1.3%)       |
| Horror     | 309 (0.9%)       |
| Mystery    | 299 (0.8%)       |
| Thriller   | 240 (0.7%)       |
| Music      | 220 (0.6%)       |
| History    | 47 (0.1%)        |
| Legal      | 19 (0.1%)        |

D Genres

To demonstrate the diversity of topics covered in TVRECAP, we report distributions of genres in Table 12, Table 13, and Table 14. While TVMegaSite has a relatively small number of genres, Fandom covers far more genres with the most frequent occupying only 15% of episodes.

E Hyperparamters

Because our plot-to-text models work at the sentence level, leading to many training instances for both FD and TMS (i.e., 0.5 million and 1.5 million sentences respectively), we train these plot-to-text models for 10 epochs without early stopping. During generation, we set the minimum number of decoding steps to 24 and the maximum number of decoding steps to 48.

As for summarization, we benchmark pretrained BART-base, BART-large (Lewis et al., 2020), and Pegasus (Zhang et al., 2020). As the average length of the detailed recaps is much longer than the default maximum sequence length of these pretrained models, we extend the maximum sequence length to 4096. When doing so, we randomly initialize new positional embeddings for BART. Since Pegasus uses Sinusoidal positional embeddings, we simply change the default value of maximum sequence length. We train the models for 15 epochs and perform early stopping on the dev set perplexities. During generation, we limit the minimum decoding step to be 50 and 300, and the maximum decoding step to be 100 and 600 for FD and TMS respectively. The minimum decoding steps roughly match the average length of the summaries in FD and TMS.

F Comparison to Other Summarization Datasets

We briefly compare our dataset to three summarization datasets: CNNDM (Hermann et al., 2015),
We report n-gram overlap ratio (i.e., fraction of n-grams in the output stories that also appear in the source inputs) and length statistics in Table 15. The n-gram overlap ratio is usually used as an indicator of the abstractiveness of a summarization dataset. Lower ratio indicates a higher degree of abstraction. CNNDM favors extractive approaches, whereas XSum is known for its abstractiveness. We also compare to MNews because it shares similar input and output lengths as our dataset. As shown in the table, our dataset tends to be more abstractive. In addition, unlike other summarization datasets, our dataset focuses on stories. These two characteristics make our dataset a potentially valuable contribution for the summarization community. Comparison to other abstractive summarization datasets is in Table 16.

G Details of Semantic Role Labeling

We use a pretrained model from Shi and Lin (2019) to generate SRL tags of the detailed episode recaps. We eliminate the SRL tags for sentences that do not contain ⟨ARG0⟩ or only contain pronouns to avoid ambiguity. For each sentence, we also only keep the SRL tags that correspond to the first verb that appears in the sentence to avoid the SRL tags being too specific, so there will be a balanced burden between the text-to-plot model and the plot-to-text model. In addition, following Goldfarb-Tarrant et al. (2020), we discard SRL tags of generic verbs.

The list of verbs we discard is as follows: “is”, “was”, “were”, “are”, “be”, “’s”, “’re”, “’ll”, “can”, “could”, “must”, “may”, “have to”, “has to”, “had to”, “will”, “would”, “has”, “have”, “had”, “do”, “does”, “did”.

We also eliminate arguments that are longer than 5 tokens.

G.1 Human Evaluation

Evaluating the PL Metric. To verify the efficacy of our proposed metric PL, we compute accuracies and F1 scores between the PL metric and the human annotations (we use the expert relevancy annotations from both comparisons in human evaluation results). We consider BL as a baseline metric by computing the generation against the brief summaries. When reporting results for PL and BL, we consider two variants: one that uses the truncated generation and the other one that uses all the tokens in the generation. We show the results in Table 17. While PL and BL show similar performance in the non-truncated setting, we find that in the truncated setting PL outperforms BL significantly, showing that PL is a promising metric for evaluating the faithfulness of generated story. We speculate that the discrepancy is likely caused by the fact that the annotations were collected based on the truncated generations.

G.2 Generation Examples

We show generation examples in Table 18 and Table 19.
Table 16: Statistics for datasets focusing on abstractive summarization for long-form text or dialogue. The numbers are averaged over instances.

| Domain                  | # instances | # tokens (input) | # tokens (summary) | Domain               |
|-------------------------|-------------|------------------|--------------------|----------------------|
| Long-form text summarization datasets |             |                  |                    |                      |
| Multi-News          | 56.2k       | 2103.5           | 264.7              | News                 |
| RottenTomatoes      | 3.7k        | 2124.7           | 22.2               | Reviews              |
| arXiv               | 215k        | 4938.0           | 220.0              | Science              |
| PubMed              | 113k        | 3016.0           | 203.0              | Science              |
| GovReport          | 19.5k       | 9409.4           | 553.4              | Government Reports   |
| TVRecap             | 29.0k       | 1868.7           | 221.6              | Television Series    |

| Dialogue-related summarization datasets | | | |
| SAMSum               | 16.4k       | 83.9             | 20.3               | Chitchat             |
| QMSum               | 1.8k        | 9069.8           | 69.6               | Meetings             |
| MediaSum            | 463.6k      | 1553.7           | 14.4               | News Interviews      |
| SummScreen          | 26.9k       | 6612.5           | 337.4              | Television Series    |

Table 17: Accuracies and $F_1$ scores when evaluating the automatic metrics against human annotations. The best performance in each column is in bold.

|          | Acc. | $F_1$ |
|----------|------|-------|
| BL       | 55.9 | 35.1  |
| BL (trunc. gen.) | 50.0 | 32.4  |
| PL       | 55.0 | 34.5  |
| PL (trunc. gen.) | **61.4** | **49.6** |
Elfman and Evergreen, after much struggle, lose to Rustyrose and his imagination-based Magic. In the meantime, Gray, Lucy, Cana and Loke have been overpowered by Caprico alone. Loke decides to take him on by himself because of his mysterious Magic.

| Summary | Reference | Oracle plot + summ. + oracle char. desc. |
|---------|-----------|------------------------------------------|
| Elfman and Evergreen encounter a cliff as they run away from Rustyrose’s Bel-cusas the Thunderclap. Rustyrose appears shortly afterwards and expands on the idea of "The Ultimate World of Magic", saying that all those who can not use Magic and the trash in the guilds are useless. However, Rustyrose outsmares them despite their teamwork. He proceeds to explain the nature of his Magic, Arc of Embodiment, and then finishes the two off with Tower of Dingir. Meanwhile, Natsu awakes with his scarf and clothes reverted to normal by Wendy. Upon thanking Wendy, he picks up the scent of Zalty, the masked man he met back in Galuna Island. On the Magic Council warship, Doranbolt, formerly known as Mest Gryder, appears before Lahar who is ordering people to repair the damaged ship. Doranbolt reports to Lahar about the events on Tenrou Island Lahar warns him that Gran Doma, the Chairman, is very strict and would likely eliminate those who he believes are wrongdoers without a trial and he might resort to using Etherion once more. In the battle against Caprico, Loke tells the others to leave and look for Caprico’s teammates while he battles Caprico himself. At first, Lucy did n’t want to leave. This action makes Caprico slightly recognize her. He discovers that Caprico’s Magic enables him to capture and summon humans and that Caprico has no master.

Table 18: Complete generation for the first examples.
| Summary | Reference | Oracle plot + summ. + oracle char. desc. |
|---------|-----------|----------------------------------------|
| Chuck is preparing for his new club opening and enlists Serena’s help, but Blair begins to feel left out. Jenny, the new Queen at Constance, struggles between proving herself and her friendship with Eric, and Dan feels inferior after watching one of Olivia’s movies. Meanwhile, Lily tries to respect Rufus’ Halloween traditions. | Lily wants to get rid of Jenny’s old clothes, including one of the dresses she made, but Jenny insists that all of her clothes fit her perfectly and wants to keep them. At The Empire, Chuck tells Blair how the hotel is doing in terms of bookings. Blair says that if he opens the club, it will bring in business and make bookings go up. She suggests an 80s themed party but Chuck shoots down the idea. Blair, suspicious that Chuck is still angry over her lying to him to get the NYU freshman toast (in Enough About Eve), tells him that she apologized and they should move on. He explains that he needs to do things his way and leaves to meet with his accountant. When he’s gone, Blair calls a party planner to plan the opening of the club. At the loft, Nate has brought Dan the Endless Knights trilogy starring Olivia. He tells Dan about how Patrick Roberts, who plays her boyfriend in the movies, was actually her boyfriend in real life. Dan seems unfazed, until he gets a Gossip Girl blast with a picture of Olivia getting some condoms. She’s annoyed because Serena did n’t break up Olivia and Dan like she was asked to. KC explains that Olivia needs to be with Patrick, because otherwise he’s headed for a serious career stall and becoming irrelevant. She instructs Serena to break the two up, or else she’ll be stuck running pointless errands for the rest of her life. On the way to school, Eric and Jenny discuss Halloween. Jenny tells him they have to find a party or else risk handling out candy with Rufus, when they run into her minions. Eric goes off to find Jonathan and Jenny begins bossing her minions around. She tells them to move, not wanting to risk looking weak to her minions, and they do. As they walk off, Jonathan tells Eric that she’s changing. Eric defends Jenny, saying it’s only a mask for school and Jonathan Back at the loft, Nate and Dan are watching the Endless Knights trilogy. Dan watches one of the sex scenes and begins to get uncomfortable. Nate asks if he’s okay, and Dan tries to play it cool when Olivia calls. He pretends to be sick to buy some time to finish the films and think things over. Blair goes to see Serena at KC’s office. She tells her that she already hired a party planner, but Serena is confused since Chuck wanted to wait until after the holidays to open the club... | Jenny wants to keep them, and all of her friends get out of the way to get her out of there. At The Empire, Chuck tells Blair how Serena is coming back to town in Los Angeles to see her ex. Blair says that if he opens the club, it’s an opening opportunity, and Chuck says he will. She suggests an 80s themed party, but Chuck is not interested, as she’s taking a break from the party. Afterwards, she tells him that she knows about her lying to him over the phone and that she is n’t going to give up. He tells her that he needs to do things his way, and she agrees to do it the next day before he leaves. Back at the VDW’s, Blair calls a party planner to tell everyone that she’s going to the party. At the loft, Nate has brought Dan everything he’s ever wanted to know about Rufus and Jenny. He tells Dan how Serena broke up with him at the bar, and that she’s trying to move in with him. Dan replies that he gets a Gossip Girl blast every day, and that’s why she’s so obsessed with The Spectator. Serena threatens to break up Olivia and Dan if she does n’t break up with him at some point. At the VDW’s, Olivia needs to be with Patrick because she feels like he needs her for something. She instructs Serena to break the two up, and once she does, the two begin to break up. On the way back to school, Eric and Jenny discuss Halloween and agree that it’s the perfect way to celebrate. Jenny tells him they have to figure out a way to get through the party, and Rufus asks where they’re going. Eric goes off to find Jonathan, and he’s surprised to find her at the table with all of her friends. She tells them to move, and they do, and Eric tells her not to do anything stupid and to do what’s right. At The Palace, Jonathan tells Eric that she’s changing, and he tells him that they should move in together. Eric defends Jenny, saying it’s only a matter of time before he’s exiled, and Serena says it is. Back at the loft, Nate and Dan are watching the Endless Knights snorakatomy and discuss Dan’s plans for the night. Dan watches one of the sex scenes and begins to get jealous of Chuck’s lack of sex appeal, but Dan breaks up with him and leaves. Nate calls and asks if he’s okay, and Rufus says it’s fine if he leaves. He pretends to be sick and she goes over to ask if he needs to spend the time with her and Rufus... |

Table 19: Part of the generated text for the second examples. Due to space constraints, we only show the beginnings of the generated stories and the reference story.