Automated Storytelling via Causal, Commonsense Plot Ordering

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Abstract
Automated story plot generation is the task of generating a coherent sequence of plot events. Causal relations between plot events are believed to increase the perception of story and plot coherence. In this work, we introduce the concept of soft causal relations as causal relations inferred from commonsense reasoning. We demonstrate C2PO, an approach to narrative generation that operationalizes this concept through Causal, Commonsense Plot Ordering. Using human-participant protocols, we evaluate our system against baseline systems with different commonsense reasoning reasoning and inductive biases to determine the role of soft causal relations in perceived story quality. Through these studies we also probe the interplay of how changes in commonsense norms across storytelling genres affect perceptions of story quality.

1 Introduction
Automated story generation is a standing grand challenge of AI. One of the central challenges of automated story generation is causal progression such that the events of the story follow from events that have come before. Many prior approaches to plot generation relied on symbolic planning (Lebowitz 1987; Gervás et al. 2005; Porteous and Cavazza 2009; Riedl and Young 2010; Ware and Young 2011) that reason directly about causal enablement in the form of predicate precondition and post-condition matching. While these systems can guarantee causal entailment between story events, these approaches also require extensive domain knowledge engineering and limited vocabularies of events and characters.

Machine learning approaches to automated story generation can learn storytelling and domain knowledge from a corpus of existing stories or plot summaries. This theoretically allows them to overcome the knowledge engineering bottlenecks. However, neural language model based approaches to automated story generation learn probabilistic relationships between words, sentences, and events and thus have difficulty modeling causal entailment between actions and events. Additionally, stories need to remain consistent with respect to genre and commonsense norms.

In this paper, we consider the challenge of automatically generating narratives that have recognizable causal entailment between events. Specifically, we approach the problem of story generation as a plot-infilling (Ippolito et al. 2019; Donahue, Lee, and Liang 2020) where an outline of plot points are extracted from a source then elaborated upon. We introduce the concept of soft causal relations, where causal entailment between story events does not need to be strictly logically consistent, but draws upon people’s everyday commonsense understanding of whether one event tends to be preceded or succeeded by another.

We demonstrate an approach to story generation using soft causal relations in the C2PO (Commonsense, Causal Plot Ordering) system, which generates narratives via plot infilling using soft causal relations. Inspired by work on plot graph learning (Li et al. 2013), C2PO attempts to create a branching space of possible story continuations that bridge between plot points that are automatically extracted from existing natural language plot summaries. To create this branching story space, we iteratively extract commonsense causal inferences from the COMET (Bosselut et al. 2019) model of commonsense reasoning. Finally, once the space—a plot graph—has been constructed, we search the space for complete sequences.

Using human participation studies, we evaluate C2PO against baseline text infilling systems with different uses of commonsense reasoning and inductive biases to determine the role of soft causal relations on perceptions of story quality. We choose two story corpora in different genres: real-world mystery stories such as Sherlock Holmes—known for generally being consistent with everyday commonsense norms, and children’s fairy tales such as Hansel and Gretel—stories which usually shatter commonsense expectations. Through these studies we further explore the broader issue of how the change in commonsense norms across storytelling genres affects perceptions of story quality.

2 Background and Related Work
Narrative generation systems that use symbolic planning (Lebowitz 1987; Gervás et al. 2005; Porteous and Cavazza 2009; Riedl and Young 2010; Ware and Young 2011) explicitly ensure causal relations between actions via predicate calculus operations over explicitly modeled action pre-conditions and post-conditions. These symbolic proposition represent hard causal relations.

Neural language-model based approaches to story genera-
tion have typically overlooked causality or assumed it would emerge in the hidden state of neural networks. Roemmele and Gordon (2018) use LSTMs with skip-thought vector embeddings (Kiros et al. 2015) to generate stories. Similarly, Clark, Ji, and Smith (2018) introduce semantic event abstractions known as events and decompose storytelling into the problems of generating event sequence and elaborating the events into natural language. Tambwekar et al. (2019) extends this work by fine-tuning language models to achieve a given goal, though goals are not necessarily achieved in a causality-preserving way as in symbolic planning. Fan, Lewis, and Dauphin (2018) and Ammanabrolu et al. (2020b) pursue hierarchical approaches to story generation, wherein a prompt is first generated and then transformed into a text passage. Yao et al. (2019) break down the problem of story generation into that of planning out a story and then generating it from.

Ippolito et al. (2019) look at filling in missing parts from a story by conditioning a text generator on rare words, also attempting to achieve balance between novelty and coherence. Donahue, Lee, and Liang (2020) also attempt to model storytelling along these lines, training a language model to fill in the blanks given left and right contexts. None of these methods explicitly incorporate commonsense knowledge into story generation.

An alternative machine learning based approach to story generation introduced by Li et al. (2013) is to first learn a plot graph that can then be used as a constrained search space for a sequence of story events. Plot graphs are directed acyclic dependency graphs where each node represents a plot point or event and the arcs between nodes represent temporal constraints. Inspired by this approach, we also attempt to learn a branching story graph structure that can be searched; however, instead of learning the plot graphs from a crowdsourced text corpus, we construct this graph by extracting commonsense inferences about causally related events.

Approaches to automated story generation that incorporate commonsense resources include the following. Rashkin et al. (2018) present an annotation framework specifically designed to examine the mental states of characters in commonsense based stories. Guan, Wang, and Huang (2019) incorporate external commonsense knowledge sources to explicitly improve story ending generation and Mao et al. (2019). Guan et al. (2020) look at fine tuning pre-trained transformer based language models (Vaswani et al. 2017) on commonsense sources like ConceptNet (Speer and Havasi 2012) and the BookCorpus (Kiros et al. 2015). These works, however, focus on improving what they call logicality and grammaticality, translating largely to local coherence, as opposed to analyzing perceptions of causality or overall story quality.

3 Soft Causal Relations

A hard causal relation implies that some world state transitions that are illegal—e.g., a character John cannot shoot Xavier if John is not in possession of a gun and the two characters are physically co-located. In contrast, a soft causal relation is mediated by the assumed reader’s beliefs. That is, a soft causal relation is a reasonable expectation that (a) certain activities are needed to achieve a character’s goal, and (b) certain activities are in pursuit of future goals. The first clause draws on the psychological theory of the role of causality in story understanding by Trabasso and van den Broek (1985): readers attempt to understand “why” events occur by tracking causal relations as enablement—some event y cannot occur unless some preceding event x occurred. The second clause draws upon a theory of the role of character goal hierarchies in story understanding by Graesser, Lang, and Roberts (1991): readers attempt to understand “why” things happen by tracking and predicting character goal hierarchies. In both cases, whether an inference is made by reader is strongly dependent on what the reader’s beliefs about the world.

Commonsense knowledge is the set of commonly shared knowledge about how the world works. It enables us to form expectations about what will happen if we take certain courses of action and to infer things that likely happened in the past. Commonsense reasoning is the application of commonsense knowledge to specific contexts. Relevant to our work, commonsense reasoning might be applied to make inferences about what might have needed to have taken place for a character to arrive at a certain state—soft enablement—and what a reasonable next action would be based on what has happened so far—soft goal hierarchies.

Specifically for this paper, we use COMET (Bosselut et al. 2019) to model an assumed reader’s commonsense knowledge. COMET is a transformer-based language model designed for commonsense inference and is trained on ATOMIC (Sap et al. 2019). ATOMIC is a dataset containing 877k instances of information relevant for everyday commonsense reasoning in the form of typed if-then relations with variables. ATOMIC is organized into different relation types such as “needs”, “wants”, “attributes”, and “effects”. We specifically use the relations for “wants” and “needs”. An example of a cause using the wants relation is as follows, “if X tried to get away, then X wants to be free.” Likewise, an example of an effect using the needs relation is, “if X scaled the wall, then X needs to know how to scale the wall.”

In the next section we detail how we use the theory of soft causal relations, and COMET commonsense inferences about needs and wants, to generate stories. In section 5, we present the results of a human participant study that uses an evaluation of several systems in two distinct genres to probe how soft causal relations affect participant perceptions of story quality and coherence.

4 C2PO

This section presents the overall layout of C2PO. C2PO works by first extracting a set of high level plot points from a given textual story plot S and then generating a branching set of events that go between each high level plot point. The final story is obtained by walking the overall plot graph generated by joining each generated sub-graph.

4.1 Plot Extraction

The overall plot extraction process is described in Figure 1. In order to facilitate plot extraction, we propose a method that uses coreference resolution and information extraction to
identify a set of plot points following a single character. First, we extract all the coreference clusters using a pre-trained neural coreference resolution model (Clark and Manning [2016]). There can be multiple such clusters, each of which contains all mentions in the story belonging to a single possible character, we pick one of these clusters at random. Let $M = \{m_1, m_2, \ldots, m_n\}$ denote this cluster. Simultaneously, we also extract a set $R$ of $\langle subject, relation, object \rangle$ triples from the story text using OpenIE (Angeli et al., 2015).

Once we have both of the set of mentions for a character and the triples for the story, we align them, attempting to find the subset of triples $P \subseteq R$ that are relevant for a single character on the basis of their character-level positions within the original story text. Both the neural coreference model and OpenIE are information retrieval systems and so we can identify the character-level offset or position of the retrieved information in the original story text. Let $\text{pos}(\cdot)$ be a function that can do this. The set of plot points is $P = \{(s, r, o) : \text{pos}(m) = \text{pos}(s), \forall m \in M, (s, r, o) \in G\}$. The result is a sequence of relational tuples in which the character is the primary subject of the triple, ordered by when they first appeared in the original story text. Joining each triple together yields a subject-relation-object phrase which we refer to as a plot point.

### 4.2 Plot Graph Generation

Once we have extracted a set of plot points $P = \{p_1, p_2, \ldots, p_n\}$, we move on to plot graph generation as illustrated in Figure 2. A plot graph is generated for each pair of adjacent plot points $(p_i, p_{i+1}), i \in \{1, \ldots, n - 1\}$ and then linked together in the order the plot points first appear in $P$ to form a plot graph for an entire story.

The process to generate a plot graph between adjacent plot points $p_i, p_{i+1}$ is as follows. Starting from $p_i$, we use COMET (Bosselut et al., 2019) to generate candidate next events in the story. The $\text{wants}$ relation indicates a direct forward cause—a character has a want and therefore performs an action. We recursively query COMET to generate $k$ event candidates $n$ times going forward starting with $p_i$; let this be $G^f$. The $\text{needs}$ relation indicates backward enablement—a character needed something to be true to do an action. We recursively query COMET to generate $k$ event candidate $n$ times going backward from $p_2$; let this be $G^b$. This gives us two directed acyclic graphs as seen in Figure 2. The relations in $G^f$ and $G^b$ are weighted proportional to the likelihood score produced by COMET for each inference.

The next step is to look for the most optimal way to link $G^f$ and $G^b$ and computing the probability of reaching a node $u \in G^f$ looking at all nodes $\forall v \in G^b$. Let $P_{u, needs}(v | u)$ be the probability of generating event $e_2$ as determined by COMET under the $\text{needs}$ relation, conditioned on $e_1$, and $P_{u, wants}(v | u)$ be the same but under the $\text{wants}$ relation. We define this link’s weight as:

$$w(u, v) = \frac{P_{u, wants}(v | u)}{\alpha_u^w} + \frac{P_{u, needs}(v | u)}{\alpha_u^n}$$

were $\alpha_u^w$ and $\alpha_u^n$ are normalization constants. Here we set them equal to the probability of generating the word “to”, a word in ATOMIC common to both relations types. This process is repeated for all nodes until we have found a set of optimal links.

Finally, we link together the plot graphs for the entire sequence of plot points: $G = \cup_{p_1, p_2 \in P} (G^f_{p_1}, G^b_{p_2}) \cup_{p_1, p_2 \in P} (G^b_{p_1}, G^f_{p_2})$. The whole graph is rooted at the first plot point $p_1$, and linked such that $G^b_{p_n}$ is guaranteed to be reachable from every other node $G_{p_n}$.

### 5 Experiments

We evaluate on a story dataset with two genres—mystery stories and fairy tales—first introduced by Ammanabrolu et al. (2020a). The data is partitioned into train and test splits in a 8:2 ratio, and the train split used to train C2PO and two baseline models.

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2COMET can be replaced by any model designed for automated knowledge base completion and similarly ATOMIC can be swapped out by another commonsense reasoning knowledge base by selecting appropriate relations.

https://github.com/rajammanabrolu/WorldGeneration
Husband fears for her life
He scales wall
to escape
to avoid danger
to not be hurt
to be free
to get away
to be safe
to to know how to scale the wall
to get a scale
to know how to climb

to walk to the wall
to go to the wall

to get up

to get

to know how to

to climb

1 Husband fears for her life
2 He scales wall
3

Figure 2: A demonstration of the plot graph generation process. 1 and 2 respectively indicate adjacent, extracted plot points. Dotted lines represent the process finding the most optimal link between the backward plot graph and node 3.

| Mystery | Fairy Tale |
|---------|-----------|
| No. Stories | 569 | 695 |
| Sentences per story | 23.36 | 24.80 |
| Vocabulary size | 21,238 | 16,452 |

Table 1: Dataset statistics.

| C2PO | Commonsense | Storytelling |
|------|-------------|--------------|
| BERT+infill | ✓ | ✓ |
| Hier. Fusion | ✓ | ✓ |

Table 2: Inductive biases of each system.

(described below). A random set of 10 stories is chosen from each genre in the test set and high level plot points are extracted as described in Section 4. For each model and for each of set of high-level plot points and for each genre we generate three distinct stories for a total of \((3 \times 10 \times 2 \times 3 = 180)\) stories. We generate three stories for each combination of model, plot point set, and genre to account for variance in stories that can be produced by the same high level plot due to the branching nature of C2PO as well as variance in the baselines’ outputs. Standard automated language generation metrics such as perplexity and BLEU (Papineni et al. 2002) are known to be unreliable for creative generation tasks (Ammanabrolu et al. 2020b). The stories are thus evaluated using a human participant study, described below.

5.1 Baselines

We choose two baselines on the basis of the comparisons they afford (summarized in Table 2). Both are designed to perform text infilling tasks but differ based in their inductive biases. “Inductive biases” here specifically refer to a system’s ability to model commonsense knowledge and if they were originally designed for storytelling or not.

BERT+infill The first baseline is a BERT (Devlin et al. 2018) based model that has not strictly been designed for storytelling (though BERT is trained on a corpus that includes story texts) and then adapted to perform text infilling. Although large-scale pre-trained language models are known not to be great storytellers, mostly due to them being unable to stay on track for any extended period of time (See et al. 2019), they have demonstrated knowledge of factual commonsense information by virtue of the amount of data they have been trained on (Petroni et al. 2019). Our problem setting requires us to generate a section of text between two consecutive high level plot points at a time, reminiscent of approaches taken by Ippolito et al. (2019) and Donahue, Lee, and Liang (2020) that condition a language model on left and right contexts to fill in blanks in a story. We follow a similar setup for this baseline, using BERT (Devlin et al. 2018) conditioned to attend to both previous tokens—the preceding plot point—and future tokens—the following plot point—to generate sequences (Lawrence, Kotnis, and Niepert 2019). BERT+infill is fine-tuned using this methodology on the high-level plot points extracted from our training data. Despite being similar to these prior methods, we note that BERT+infill utilizes no storytelling domain knowledge in its architecture and boils down to simple masked language modeling with multiple mask tokens.

Hierarchical Fusion Fan, Lewis, and Dauphin (2018) train their system—consisting of a convolutional sequence-to-sequence network with self-attention (Ott et al. 2019)—on the Reddit Writing Prompt corpus, where human-contributed prompts are paired with human-contributed stories. The system learns to first generate a prompt and then transform it into a story. This model’s architecture is explicitly designed to tell stories and is suited for a type of storytelling wherein a prompt for a story is generated into a passage This type of training is particularly well suited to our setup of generating a story piece-by-piece using extracted high level plot points. We train the model from our training set using high level plots extracted from the stories as described in Section 4 as the prompts and sections in between each of these extracted plot points as the story.
We have 10 sets of high level plots per genre and three generated stories per each plot for each of the models. We recruited 351 human participants via Mechanical Turk. Criteria for enrollment included: (a) fluency in English, and (b) demonstrating an understanding of commonsense based causality in stories. To screen participants for the latter we asked them to predict potential next events that could reasonably occur in stories. To screen participants for the former we asked them a series of questions, each measuring a particular aspect of perceived story quality, comparing the C2PO generated model to one of the baselines. For each question they are asked to note down which story they preferred. The questions we use are adapted from Purdy et al. (2018) and have been used in multiple storytelling works as an indication of story quality (Tambwekar et al. 2019; Ammanabrolu et al. 2020b). Specifically, we ask:

- Which story's events occur in a more PLAUSIBLE ORDER?: as a proxy to indicate perceptions of overall causality within the story.
- Which story's sentences MAKE MORE SENSE given sentences before and after them?: to examine perceptions of local causality and commonsense reasoning in the story.
- Which story better follows a SINGLE PLOT?: for insight into perceptions of global coherence for the entire story.
- Which story is of HIGHER QUALITY?: as a measure of overall perceived story quality.
- Which story is more ENJOYABLE?: indicates value in the story.
- Which story better FITS A GENRE?: as a measure of how well the story matches commonsense knowledge specific to a genre, capturing the differences between the two genres we use.

For each of these questions, within a pairwise comparison, we perform a paired Mann-Whitney U test to assess statistical significance and additionally calculate Fleiss’ $\kappa$ (Kappa) value to measure inter-rater reliability.

### 6 Results and Analysis

There are a few dimensions along which we will attempt to analyze these results: (1) the inherent inductive biases of each model as seen in Table 2, (2) the two genres, and (3) the questions asked of the participants. The analysis will be performed hierarchically in the order just presented. Table 5 provides statistics on generated stories and Table 3 displays...
6.1 C2PO vs BERT+infill

Figures 3a and 3b show the percentages that participants preferred C2PO versus the BERT+infill system for each dimension and for each story genre. C2PO is preferred over BERT+infill in both genres and in all dimensions. All of these results are statistically significant ($p < 0.05$) with fair-to-moderate inter-rater reliabilities.

For the mystery genre the greatest differences in preferences are observed with respect to enjoyability and genre resemblance. The systems were most similar with regard to their ability to maintain a single plot. For the fairy tale genre the greatest differences are seen in the dimensions of plausibility of events and causality. For the mystery genre the greatest differences in preference are not significantly different for enjoyability and genre resemblance. The systems were most similar with regard to their ability to maintain a single plot for fairy tales than for mysteries. These three factors are also highly, positively correlated with each other and in terms of overall perceived story quality ($0.6 > r_s > 0.55$, $p < 0.01$ for all pairwise comparisons).

This provides evidence that the brand of commonsense reasoning-based causality brought to bear by C2PO-needs and wants—works well in the mystery genre. The mystery genre follows everyday commonsense norms whereas the fairy tale genre is more likely to stray from commonsense norms. It can thus be inferred that genre-specific or thematic commonsense knowledge is required to improve perceptions of genre resemblance and enjoyability but does little in terms of metrics assessing local and global coherence in terms of causality.

6.2 C2PO vs Hierarchical Fusion

Figures 4a and 4b show the percentages of participants that preferred C2PO to Hierarchical Fusion. For the mystery genre, C2PO was preferred for the dimensions of plausible ordering, making sense causally, maintaining a single plot, and overall story quality. These dimensions were significantly different ($p < 0.05$). The dimensions of enjoyability and genre resemblance were not significantly different, meaning no system did better than the other.

We see a similar pattern for fairy tale stories: C2PO is preferred to hierarchical fusion for the same dimensions as the mystery genre and are not significantly different for enjoyment and genre resemblance.

Across genres, there is a positive correlation between metrics relating to coherence and overall perceived story quality ($0.6 > r_s > 0.5$, $p < 0.05$ for each pairwise comparison using Spearman’s Rank Order Correlation). All also recall that...
the Hierarchical Fusion model contains an inductive bias for storytelling but does not model commonsense reasoning. This appears to indicate that genre resemblance and enjoyability are not dependant on causal, commonsense reasoning but rather on the how much the generated text “sounds like a story” but story quality still depends on overall coherence.

6.3 Broader Trends

There are two main trends that one can see across the models depending on their inductive biases (extent to which the models are trained for commonsense reasoning or storytelling). We observe these trends on the basis of the analysis presented so far as well as the examples of output stories found in Table[3] (1) Having commonsense reasoning abilities generally improves perceptions of local and global coherence in terms of causality with a caveat that what is perceived as commonsense can change across genres. When genre or domain specific commonsense knowledge matches “everyday” commonsense, it makes for an automated storyteller that is significantly more causal in nature. (2) Just commonsense reasoning without any sort of storytelling inductive bias incorporated—such as with pre-trained and finetuned language models which themselves have no real penchant for storytelling—into a model’s design doesn’t help, however, in terms of enjoyability and genre resemblance. The performance of Hierarchical Fusion in terms of enjoyability and genre resemblance—and the examples seen in Table[3]—appear to indicate that models designed for storytelling do a better job of maintaining the writing style of a story but struggle with causality.

7 Conclusions

We intend for the findings of this work to be utilized by researchers studying automated storytelling, a standing AI grandchallenge requiring creative, long-form language generation. We explore the effects of soft causal relations—reasonable expectations by a reader regarding a story’s progression—on human-based perceptions of overall story quality. We introduce C2PO as a way to use soft causal relations via transformer-based models trained for commonsense inference in storytelling.

A key insight from a human participant study, measuring a wide set of human perceived metrics, shows that the sum of the parts is indeed greater than the whole. Automated storytellers require both domain specific commonsense reasoning abilities as well as a storytelling inductive bias incorporated into the design of the system to perform well in terms of: local and global coherence on the basis of causality, enjoyability, genre resemblance, and overall story quality. Further, perceptions of causal, commonsense conforming coherence are highly correlated with overall story quality. We encourage future works build on these finding and more closely explore lines of research that use thematically relevant soft causal relations to improve automated storytellers.

References

Ammanabrolu, P.; Cheung, W.; Tu, D.; Broniec, W.; and Riedl, M. O. 2020a. Bringing Stories Alive: Generating Interactive Fiction Worlds. In 16th AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE-20). URL http://arxiv.org/abs/2001.10161.

Ammanabrolu, P.; Tien, E.; Cheung, W.; Luo, Z.; Ma, W.; Martin, L. J.; and Riedl, M. O. 2020b. Story Realization: Expanding Plot Events into Sentences. In Proceedings of the Thirty-Fourth AAAI Conference on Artificial Intelligence.

Angeli, G.; Premkumar, J.; Jose, M.; and Manning, C. D. 2015. Leveraging Linguistic Structure For Open Domain Information Extraction. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and
Bosselut, A.; Rashkin, H.; Sap, M.; Malaviya, C.; eliyilmaz, A.; and Choi, Y. 2019. COMET: Commonsense Transformers for Automatic Knowledge Graph Construction. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL).

Clark, E.; Ji, Y.; and Smith, N. A. 2018. Neural Text Generation in Stories Using Entity Representations as Context. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), 2250–2260. New Orleans, Louisiana: Association for Computational Linguistics. doi:10.18653/v1/N18-1204. URL https://www.aclweb.org/anthology/N18-1204.

Clark, K.; and Manning, C. D. 2016. Deep Reinforcement Learning for Mention-Ranking Coreference Models. In EMNLP.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv preprint arXiv:1810.04805.

Donahue, C.; Lee, M.; and Liang, P. 2020. Enabling Language Models to Fill in the Blanks. In Association for Computational Linguistics.

Fan, A.; Lewis, M.; and Dauphin, Y. 2018. Hierarchical Neural Story Generation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, 889–898. URL https://arxiv.org/pdf/1805.04833.pdf.

Gervás, P.; Díaz-Agudo, B.; Peinado, F.; and Hervás, R. 2005. Story plot generation based on CBR. Knowledge-Based Systems 18(4-5): 235–242.

Grässer, A.; Lang, K. L.; and Roberts, R. M. 1991. Question Answering in the Context of Stories. Journal of Experimental Psychology: General 120(3): 254–277.

Guán, J.; Huang, F.; Zhao, Z.; Zhu, X.; and Huang, M. 2020. A Knowledge-Enhanced Pretraining Model for Commonsense Story Generation. Transactions of the Association for Computational Linguistics.

Guán, J.; Wang, Y.; and Huang, M. 2019. Story Ending Generation with Incremental Encoding and Commonsense Knowledge. In Thirty-Third AAAI Conference on Artificial Intelligence (AAAI-19). URL https://arxiv.org/pdf/1808.10113.pdf.

Ippolito, D.; Grangier, D.; Callison-Burch, C.; and Eck, D. 2019. Unsupervised Hierarchical Story Infilling. In Proceedings of the First Workshop on Narrative Understanding, 37–43. Minneapolis, Minnesota: Association for Computational Linguistics. doi:10.18653/v1/W19-2405. URL https://www.aclweb.org/anthology/W19-2405.

Kiros, R.; Zhu, Y.; Salakhutdinov, R. R.; Zemel, R.; Urtasun, R.; Torralba, A.; and Fidler, S. 2015. Skip-thought vectors. In Advances in neural information processing systems, 3294–3302.

Lawrence, C.; Kotnis, B.; and Niepert, M. 2019. Attending to Future Tokens for Bidirectional Sequence Generation. 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), 1–10. Hong Kong, China: Association for Computational Linguistics. doi:10.18653/v1/D19-1001. URL https://www.aclweb.org/anthology/D19-1001.

Lebowitz, M. 1987. Planning Stories. In Proceedings of the 9th Annual Conference of the Cognitive Science Society, 234–242.

Li, B.; Lee-Urban, S.; Johnston, G.; and Riedl, M. O. 2013. Story Generation with Crowdsourced Plot Graphs. In Proceedings of the Twenty-Seventh AAAI Conference on Artificial Intelligence, AAAI’13, 598–604. AAAI Press. URL http://dl.acm.org/citation.cfm?id=2891460.2891543.

Mao, H. H.; Majumder, B. P.; McAuley, J.; and Cottrell, G. 2019. Improving Neural Story Generation by Targeted Common Sense Grounding. 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), 5988–5993. Hong Kong, China: Association for Computational Linguistics. doi:10.18653/v1/D19-1615. URL https://www.aclweb.org/anthology/D19-1615.

Martin, L. J.; Ammanabrolu, P.; Wang, X.; Hancock, W.; Singh, S.; Harrison, B.; and Riedl, M. O. 2018. Event Representations for Automated Story Generation with Deep Neural Nets. In Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18), 868–875. New Orleans, Louisiana.

Martin, L. J.; Ammanabrolu, P.; Wang, X.; Singh, S.; Harrison, B.; Dhuliawala, M.; Tambwekar, P.; Mehta, A.; Arora, R.; Dass, N.; Purdy, C.; and Riedl, M. O. 2017. Improvisational Storytelling Agents. In Workshop on Machine Learning for Creativity and Design (NeurIPS 2017), Long Beach, CA. URL https://nips2017creativity.github.io/doc/Improvisational(.-Agents.pdf.

Olson, J. S.; and Kellogg, W. A. 2014. Ways of Knowing in HCI. Springer Publishing Company, Incorporated. ISBN 1493903772.

Ott, M.; Edunov, S.; Baevski, A.; Fan, A.; Gross, S.; Ng, N.; Grangier, D.; and Auli, M. 2019. fairseq: A Fast, Extensible Toolkit for Sequence Modeling. In Proceedings of NAACL-HLT 2019: Demonstrations.

Papineni, K.; Roukos, S.; Ward, T.; and Zhu, W.-J. 2002. Bleu: a Method for Automatic Evaluation of Machine Translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, 311–318. Philadelphia, Pennsylvania, USA: Association for Computational Linguistics. doi:10.3115/1073083.1073135. URL https://www.aclweb.org/anthology/P02-1040.

Petroni, F.; Rocktäschel, T.; Riedel, S.; Lewis, P.; Bakhtin, A.; Wu, Y.; and Miller, A. 2019. Language Models as Knowledge Bases? 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), 2463–2473. Hong Kong, China: Associ-
Porteous, J.; and Cavazza, M. 2009. Controlling narrative generation with planning trajectories: The role of constraints. In Joint International Conference on Interactive Digital Storytelling, volume 5915 LNCS, 234–245. Springer. ISBN 3642106420. ISSN 03029743.

Purdy, C.; Wang, X.; He, L.; and Riedl, M. 2018. Predicting Generated Story Quality with Quantitative Measures. In AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE). URL https://aaaai.org/ocs/index.php/AIIDE/AIIDE18/paper/view/18106.

Rashkin, H.; Bosselut, A.; Sap, M.; Knight, K.; and Choi, Y. 2018. Modeling Naive Psychology of Characters in Simple Commonsense Stories. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 2289–2299. Melbourne, Australia: Association for Computational Linguistics. doi:10.18653/v1/P18-1213. URL https://www.aclweb.org/anthology/P18-1213.

Riedl, M. O.; and Young, R. M. 2010. Narrative Planning: Balancing Plot and Character. Journal of Artificial Intelligence Research 39: 217–267. URL https://www.cc.gatech.edu/~riedl/pubs/jair.pdf.

Roemmele, M.; and Gordon, A. S. 2018. An Encoder-decoder Approach to Predicting Causal Relations in Stories. In Proceedings of the First Workshop on Storytelling, 50–59. New Orleans, Louisiana: Association for Computational Linguistics. URL http://aclweb.org/anthology/W18-1506http://people.ict.usc.edu/~gordon/publications/NAACL-WS18A.PDF.

Sap, M.; Le Bras, R.; Allaway, E.; Bhagavatula, C.; Lourie, N.; Rashkin, H.; Roof, B.; Smith, N. A.; and Choi, Y. 2019. Atomic: An atlas of machine commonsense for if-then reasoning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, 3027–3035.

See, A.; Pappu, A.; Saxena, R.; Yerukola, A.; and Manning, C. D. 2019. Do Massively Pretrained Language Models Make Better Storytellers? In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), 843–861. Hong Kong, China: Association for Computational Linguistics. doi:10.18653/v1/K19-1079. URL https://www.aclweb.org/anthology/K19-1079.

Speer, R.; and Havasi, C. 2012. Representing General Relational Knowledge in ConceptNet 5. In Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC). ISBN 978-2-9517408-7-7.

Tambwekar, P.; Dhuliawala, M.; Martin, L. J.; Mehta, A.; Harrison, B.; and Riedl, M. O. 2019. Controllable Neural Story Plot Generation via Reward Shaping. In Proceedings of the 28th International Joint Conference on Artificial Intelligence. URL https://www.ijcai.org/proceedings/2019/829.

Trabasso, T.; and van den Broek, P. 1985. Causal Thinking and the Representation of Narrative Events. Journal of Memory and Language 24: 612–630.
8 Appendices

An example of a question used to screen participants on the basis of demonstrated everyday causal, commonsense reasoning:

1. Select all of the following events that are likely to happen after the following story event: “The man ran into a solid brick wall with handholds.”
   - The man broke through the wall.
   - The man climbed the wall.
   - The man flew over the wall.
   - The man made the wall disappear.

8.1 Experiment parameter details

Hyperparameters for training and finetuning the BERT, COMET, and hierarchical models are consistent with their respective work’s parameters, but we list them below where available. No additional hyperparameter tuning was conducted on any model.

| Parameter    | BERT  | COMET |
|--------------|-------|-------|
| embedding size | 768   | 768   |
| layers       | 12    | 12    |
| batch size   | 32    | 32    |
| learning rate | 0.00005 | 0.00025 |
| $\beta_1$    | 0.9   | 0.9   |
| $\beta_2$    | 0.999 | 0.999 |

When generating branches for the plot graphs with C2PO, we generate 3 branches recursively for a length of 3 times.
### 8.2 Example Generated Stories

| C2PO                                               | BERT+infill                                               | Hierarchical Fusion |
|----------------------------------------------------|-----------------------------------------------------------|---------------------|
| They live out at time seven years. Bearskin village is just came. Bearskin and family wants country. Bearskin only takes river gives valley. Bearskin gave purse of gold. Bearskin brothers also agreed. Bearskin with senior chief heads agreed. Bearskin daughter among elder sisters agrees. Bearskin promised return in three years. Bearskin they had had promised. Bearskin daughter was sisters agreed. Bearskin daughter sister married my family. Her sisters ridiculed her. Bearskin also always once reappeared. Bearskin who always is later left. Bearskin also becomes a Bearskin found devil again At end of seven years. Bearskin says and so says. Bearskin can sing now sings. Bearskin it has told him cries. He fulfill his promise. Bearskin polish grease nail nails. Bearskin polish cut boot. Bearskin helps clean burn wood cuts. Bearskin clip his nails. Bearskin boots and mr. Bearskin boots nails and boot. Bearskin leather leather toe boot. He is good. Bearskin brother had still also stood. Bearskin looked and then said. Bearskin claimed it did. Bearskin dropped his half of ring. Bearskin shifted and he changed. Bearskin and slowly transformed. Bearskin so gently lifted and turned. He was her bridegroom. | They live out at time seven years. Bearskin village is just came. Bearskin and family wants country. Bearskin only takes river gives valley. Bearskin gave purse of gold. Bearskin brothers also agreed. Bearskin with senior chief heads agreed. Bearskin daughter among elder sisters agrees. Bearskin promised return in three years. Bearskin they had had promised. Bearskin daughter was sisters agreed. Bearskin daughter sister married my family. Her sisters ridiculed her. Bearskin also always once reappeared. Bearskin who always is later left. Bearskin also becomes a Bearskin found devil again At end of seven years. Bearskin says and so says. Bearskin can sing now sings. Bearskin it has told him cries. He fulfill his promise. Bearskin polish grease nail nails. Bearskin polish cut boot. Bearskin helps clean burn wood cuts. Bearskin clip his nails. Bearskin boots and mr. Bearskin boots nails and boot. Bearskin leather leather toe boot. He is good. Bearskin brother had still also stood. Bearskin looked and then said. Bearskin claimed it did. Bearskin dropped his half of ring. Bearskin shifted and he changed. Bearskin and slowly transformed. Bearskin so gently lifted and turned. He was her bridegroom. | They live at time seven years. He was standing here in a large room. The door was wide open, and he looked down. He was n’t sure what he was seeing, but he was n’t sure what to think. Bearskin gave purse of gold. “ Hey , buddy , ” the man said , “ You’ve got to be kidding me. “ The man laughed , “ Yeah , buddy . “ I’ve been watch- ing this guy for a long time , buddy. Bearskin promised return in three years. “ What do you mean I’m here for you. “ “ Well , ” said the young boy , “ I’ll have you know this is n’t a bad idea. “ “ But , ” said the young girl , I was n’t in any trouble. Her sisters ridiculed her. What the hell. “ He was a man in a suit of black suit with a black tie. His face was red with sweat and a scar that was almost like lightning. Bearskin found devil again At end of seven years. “ Hey , man , what the Dom are you doing. “ I said as I looked around. “ I’m not sure , man , ” he said with an expression of ease , “ you’re not really my man. He fulfill his promise. The man was n’t exactly the most spinning man in the world. He was n’t the most spinning man in the world. He was n’t the most spinning man in the world , but he was n’t the most famous man in the world. Bearskin clip his nails. I was n’t the best on this wonders. I didn’t need any. There is n’t much time. He is good. “ So , what are you doing here. “ “ Oh , it ’s been a while since you’ve been in this business. “ “ I do n’t really know much about this. Bearskin dropped his half of ring. “ Sit. This is the greatest news ever noble. “ He exclaimed as he glaring off to his of- fice. He was her bridegroom. |
| Prince calls at time night. Prince and tries again calls. Prince that still wakes. Prince then knocks and asleep. He finds To his horror. Prince robert francis charles george leaps. Prince charles henry louis ru- pert. Prince joseph john frederick maurice victor. He leaps from tower. Prince an- thony or saint john leaves. Prince anthony nicholas edward lawrence. Prince edward nicholas james peter george. He wanders For years. Prince james edward thinks. Prince james john james. Prince alexander rupert james augustus george. He hears again her voice. Prince frederick leopold albert louis. Prince william william ru pert. Prince augustus ernest william. He leads their twins. | Prince calls at time night. Prince and tries again calls. Prince that still wakes. Prince then knocks and asleep. He finds To his horror. Prince robert francis charles george leaps. Prince charles henry louis rupert. Prince joseph john frederick maurice victor. He leaps from tower. Prince anthony or saint john leaves. Prince anthony nicholas edward lawrence. Prince edward nicholas james peter george. He wanders For years. Prince james edward thinks. Prince james john james. Prince alexander rupert james augustus george. He hears again her voice. Prince frederick leopold albert louis. Prince william william ru pert. Prince augustus ernest william. He leads their twins. | Prince calls at time night. He was sitting alone in the dark , surrounded by the many stars. He was alone , and this was it. He had been waiting for this moment , a long time ago. He finds To his horror. “ I’m not really sure where I got that from , but I just want to know where I got it. ” “ Oh , well it’s not a problem , you have to take it , just like I did. ” “ But no it’s not , it’s not like you could just give it to me. I’m not going to take it , but I do n’t want to be like it. It’s not like you have any idea why. ” “ You’re right , it’s not like you have the time. He leaps from tower. ” “ So , what. ” “ I’m not going to ask you any more questions about this. ” “ You’re going to be fine. He wanders For years. The sound of his phone being hung off the ground made him look up and see the phone. He had n’t seen her since she was eight. She was the most beautiful thing he’d ever seen. He hears again her voice. She’d been sitting here for days. Her hair was long and dark , her hair a long and vice mess , a long , long scar across her forehead. Her hair was long , her hair long and vice. He leads their twins. |
| Girl has clothes. Girl lives in dress. Girl know she can dress. Girl know still know she sees. Her wear rags. Girl not smile and talk. Girl never gets bad hair. Girl and most rarely smiles. She do kinds of hard work. Girl love to boy cry. Girl love girl get laugh. Girl do what will girls cry. Girl go cry to God. | Girl has clothes. Girl lives in dress. Girl know she can dress. Girl know still know she sees. Her wear rags. Girl not smile and talk. Girl never gets bad hair. Girl and most rarely smiles. She do kinds of hard work. Girl love to boy cry. Girl love girl get laugh. Girl do what will girls cry. Girl go cry to God. | Girl has clothes. The first few days were strike as hell. The first few days I woke up on a cold , damp night. My eyes were Small and my face looked as if I had been taller , bleeding , bleeding. I was just a little bit spriting and confused by the pain. Her wear rags. The room was dark. Not a single light was on. All the lights in the room were on. She do kinds of hard work. The door opened , a dark figure in the dark. I am here to kill you , sir. I am here to kill you , sir. Girl go cry to God. |

Table 6: Randomly selected examples of stories generated by the fairy models. Bolded sentences are the original extracted plot points.
Here is the plain text representation of the document as if you were reading it naturally:

| C2PO                                                                 | BERT+infill                                                                 | Hierarchical Fusion                                                                 |
|---------------------------------------------------------------------|------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|
| Holmes decides go. Holmes wants to go. Holmes begins to see something. Holmes begins to look around. Holmes notices has trouser knees. Holmes wants to clean up. Holmes begins to take a shower. Holmes wants to get ready. Holmes wants to walk to the store. Holmes taps in front of Wilson’s shop. Holmes tries to say hello. Holmes tries to say hello. Holmes himself still watches. Holmes again is house ghost watches. Holmes insists he took watch. Holmes taps in front of Wilson’s shop. Holmes smiles and eventually leaves. Holmes red cap now appears. Holmes silhouette finally stands. He calls Police Inspector Jones. | Holmes decides go. Holmes new friend initially stays. Holmes new son accepts goes. Holmes mother also stays. Holmes notices has trouser knees. Holmes himself still watches. Holmes again is house ghost watches. Holmes insists he took watch. Holmes taps in front of Wilson’s shop. “I’m not sure what’s happening to me, but I’m not sure.” “What?” “You’ve been in a heel for a few years, and you’ve been in a heel for nearly a month. He calls Police Inspector Jones.” | Holmes decides go. The room was silent. The air was heavy, and the room was quiet. Holmes notices has trouser knees. The young man was it going to be a father. His parents were n’t supposed to be a father. They had the best kids in the entire world. Holmes taps in front of Wilson’s shop. “I’m not sure what’s happening to me, but I’m not sure.” “What?” “You’ve been in a heel for a few years, and you’ve been in a heel for nearly a month. He calls Police Inspector Jones.” |
| Alec has room. Alec’s trousers are found. Alec’s trousers are found. Alec takes a shower. Alec begins to get dressed. Alec begins to go to room. Alec to room. Alec tries to eat. Alec starts drink water. Alec wants to have money. Alec wants to have a car. Alec throttle Holmes. Alec begins to be successful. Alec tries to buy a car. Alec tries to go to the car. Alec wants to be in a car. His father apparently twisting Holmes’s wrist. Alec begins to hurt someone. Alec tries to do something bad. Alec out of hand. | Alec has room. Alec back to says back says. Alec thinks back to go. Alec well that sure did too. Alec to room. Alec sees and also sees baldwin. Alec himself sees baldwin waits. Alec herself eventually enters. Alec throttle Holmes. Alec fletcher holmes thomas john thomas. Alec watson james smith. Alec james stew art john hacking. His father apparently twisting Holmes’s wrist. Alec getting out suddenly went outside. Alec said i always hesitated. Alec really only half even laughed. Alec out of hand. | Alec has room. I had been sitting in this room for a long time. I had never met a man before, but I had n’t been there when I was in here. I was not sure why I was in here. Alec to room. "What do you mean, it’s not real!" "Oh no. No. Alec throttle Holmes. This is not my first time writing. I’m in a bit late for this so it’s not the first time I’ve written anything but I’m not going to start it. I hope I did n’t mess up this. His father apparently twisting Holmes’s wrist. "Hey you, ” said refuge. "What. “What’s this thing. Alec out of hand. |
| Brunton had deduced insofar ritual’s meaning. Brunton tries to understand it. Brunton wants to learn. Brunton begins to look up. Brunton starts to look at trees. He had determined elm tree’s height. Brunton begins to take a break. Brunton starts to sleep. Brunton starts to get up. Brunton begins to approach someone. He had forced. Brunton starts to get something. Brunton starts to buy it. Brunton starts to go to the store. Brunton starts to find out what they want. He had chosen Rachel Howells. | Brunton had deduced insofar ritual’s meaning. Brunton then had fully understood. Brunton on first never thought. Brunton almost certainly knew. He had determined elm tree’s height. Brunton did then also stopped. Brunton saw d just immediately started. Brunton only still asked. He had had forced. Brunton two brothers too. Brunton wanted her twins. Brunton howell also wants twins. He had chosen Rachel Howells. | Brunton had deduced insofar ritual’s meaning. A little early to this. I was on unseen and was n’t quite sure about the first piece of writing. But I was n’t really sure how to 15 to the story and I’m not really sure how to improve. – – – He’d n’t seem like he should be. He had determined elm tree’s height. “This is a joke, ” said the old man. “It’s just a joke. ” “I do n’t believe it. He had forced. “This is the first time I’ve had this problem. ” “I said to myself as I stood up, my eyes wide and my head down with the realization of the situation I was in. I walked towards the door, my head down and the sound of a small wooden door being opened and a loud crack from the door echoed throughout the room. He had chosen Rachel Howells. |
| Wilder hired Hayes. Wilder begins to give orders. Wilder wants to follow up. Wilder begins to hear news. Wilder heard news. Wilder tries to learn more. Wilder starts to do well. Wilder wants to work hard. He confessed all. Wilder begins to go home. Wilder begins to sleep. Wilder wants to get ready. Wilder begins to go to the restaurant. He let his younger son stay at inn. Wilder starts to go to bed. Wilder tries wake up. Wilder wants to work. Wilder begins to have money. James Wilder seek his fortune. | Wilder hired Hayes. Wilder’s brothers family initially agreed. Wilder had resigned. Wilder sr announced d v. Wilder heard news. Wilder actually really cried. Wilder so alone has really wept. Wilder himself who only found sobs. He confessed all. Wilder and he refused. Wilder again is threatened. Wilder i again himself insisted. He let his younger son stay at inn. Wilder story was b. Wilder horror story by w. Wilder werewolf tale mr. | Wilder hired Hayes. “What is this.” he asked, as he walked to the door. A door with a large metal door that was like an egg. Wilder heard news. The tree was still, the tree’s spirits was a tree’s tree. The tree was still, the tree, its tree and the tree were still. The tree was still, a tree, its tree and its tree. He confessed all. He walked into the bar and took a seat. He took a long, long drag of the cigarette. “What have I done, ” he asked, “You have to stop me, ” and he leaned forward to take another puff. He let his younger son stay at inn. The man looked at me and smiled. The man looked at me and said, “You’re my only child, ” he said, “I’m not sure your father is n’t a bad man, ” he said. “I do n’t think I have the right to be like you, ” I said. James Wilder seek his fortune. |
| Colonel has behaviour. Colonel begins to get better. Colonel wants to get up. Colonel starts to go to the door. Colonel wants to walk to the lock. He would lock himself. Colonel begins to get in the car. Colonel starts to drive. Colonel begins to drink. Colonel wants get drunk. He shouting in drunken with pistol. Colonel tries to sleep. Colonel begins to get up. Colonel wants to go outside. Colonel wants to go to garden. He was found dead in garden pool. | Colonel has behaviour. Colonel was a must saw. Colonel is has did. Colonel not that was thought. He would lock himself. Colonel charles brown was. Colonel thomas and james a. Colonel thomas edward l. He shouting in drunken with pistol. Colonel general henry william miller killed. Colonel william andrew wilson acting. Colonel james edward richard stirling died. He was found dead in garden pool. | Colonel has behaviour. “You’re kidding me.” I shouted. “You’re joking about that. He would lock himself. “I’m sorry sir, but we do n’t have the time.” “You did n’t do this.” “We’re not here for that. He shouting in drunken with pistol. I’ve been on this planet for three years. It’s been a few weeks, and it’s been quite some time since I’ve been here. I’m here. He was found dead in garden pool. |

Table 7: Randomly selected examples of stories generated by the mystery models. Bolded sentences are the original extracted plot points.