FAIRYTAILOR: A MULTIMODAL GENERATIVE FRAMEWORK FOR STORYTELLING

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ABSTRACT

Storytelling is an open-ended task that entails creative thinking and requires a constant flow of ideas. Natural language generation (NLG) for storytelling is especially challenging because it requires the generated text to follow an overall theme while remaining creative and diverse to engage the reader. In this work, we introduce a system and a web-based demo, FairyTailor, for human-in-the-loop visual story co-creation. Users can create a cohesive children’s fairytale by weaving generated texts and retrieved images with their input. FairyTailor adds another modality and modifies the text generation process to produce a coherent and creative sequence of text and images. To our knowledge, this is the first dynamic tool for multimodal story generation that allows interactive co-formation of both texts and images. It allows users to give feedback on co-created stories and share their results. We release the demo source code for other researchers’ use.

Keywords  Automated Story Generation · Natural Language Generation · Multimodality · Human-in-the-loop

Introduction

Automated story generation strives to generate compelling stories automatically [Fan et al., 2018]. A story consists of sentences describing a series of events. Story generation introduces compelling challenges to existing Natural Language Generation models. Compared to more constrained text generation tasks, such as machine translation and summarization, which follow existing content, story text generation has an open-ended nature. It requires diversity and creativity while adhering to a continuous narrative.

Multimodal content is prevalent in social media posts, news articles, and commercials. Among the audio, videos, and pictures modalities, images are the most common modality to accompany textual content. Adding images can enrich the content and catch readers’ attention. Therefore, semi-automatically generating a multimodal story can produce more attractive results, especially for young readers, and augment short stories.

An interactive writing platform can support writers by suggesting new ideas and continuing previous content. It can offer exciting and entertaining directions that are nevertheless relevant to the writer’s work. Moreover, it can alleviate writers’ inertia and keep them motivated and involved in writing. Giving writers full editing power to control the final story’s content keeps the users engaged.

A challenging story generation aspect is sustaining long-term memory and producing coherent text within an overall theme [Jain et al., 2017]. Another major challenge is that while adhering to a general theme and tone, stories must evolve their composition and progress to new directions.

Current storytelling models are limited to focus on text modality [Fan et al., 2018; Yao et al., 2018; Ippolito et al.].
Figure 1: FairyTailor user’s co-created story. User’s text has no background, versus machine-generated text has a blue background.

There are several previous work methods for controllable story generation [Fan et al., 2018; Yao et al., 2018; Ippolito et al., 2019; Wang et al., 2020] that aim to produce coherent text with an appealing plot. Topic conditioned models produce stories from a compact topic input [Fan et al., 2018; Yao et al., 2018]. The advantage of the topic encoding is that it can create a concise, progressing storyline [Yao et al., 2018]. However, since the Seq2Seq model tends to focus on recently generated text and specific parts of the prompt, the plot derails from the storyline within the few (3-5) generated sentences [Yao et al., 2018]. It also frequently generates similar sentences without any sense of progression [Fan et al., 2018]. Storyline conditioned models propose tighter conditioning during the story generation by continuously directing the start to a specific ending [Ippolito et al., 2019; Wang et al., 2020]. The Unsupervised Hierarchical Story Infilling [Ippolito et al., 2019] conditions the language model on keywords that are probable to appear between the beginning and the ending of the story. The Narrative Interpolation for Generating and Understanding Stories [Wang et al., 2020]
generates several candidates and re-ranks them to take the one with the best overall coherence. Our approach mixes ideas from both topic and storyline controlled models by augmenting extracts from the dataset with automatically generated keywords and continuously re-ranking the text generation.

Story visualization architectures retrieve \cite{ravi2018} or generate \cite{li2019} images to illustrate a given story, i.e., a multi-sentence paragraph. Coherent Neural Story Illustration (CNSI) \cite{ravi2018} suggests an encoder-decoder framework that can retrieve a coherent sequence of images from visualGenome \cite{krishna2016} by predicting images’ feature representations from encoded sentences and parse tree extractions \cite{ravi2018}. StoryGAN can generate a coherent sequence of images dependent on the text by concatenating the current sentence with contextual information vector encoded from the entire story \cite{li2019}. Other text-to-image generation models such as BigGAN \cite{brock2018}, stackGAN \cite{zhang2017} and DALL-E \cite{ramesh2021} evaluate their results on various text sources. As detailed in subsection 3.2.2, we favor image retrieval since they align better with user interaction times and our free-form textual content was not descriptive enough to generate valuable images. We retrieve images independently according to story pieces and use a broad image dataset that corresponds to our intended stories’ genre.

Even though there are no multimodal architectures for storytelling that we are aware of, combining vision and language for a joint representation is addressed by several successful models. MVAE \cite{wu2018} consists of one VAE model that assumes conditional independence of modalities to use product-of-experts (PoE) and reduce the number of parameters. The VAEGAN model \cite{wu2019} uses a VAE for text and a GAN for images on a modified multimodal objective that minimizes variational divergences \cite{wu2019}. As part of the pretrain-then-transfer approach, ViLBERT \cite{lu2019} aims to serve as a common platform for visual grounding. It has two separate streams for visual and textual inputs that interact through co-attentional transformer layers \cite{lu2019}.

Previous approaches to generate stories suffer from repetition \cite{fan2018}, are unable to consistently condition on a theme \cite{yao2018} and struggle to produce a grounded, evolving storyboard \cite{tambwekar2019b, wang2020, lippolito2019}. Story visualization often requires specific, informative text \cite{li2019}, and takes significantly longer than image retrieval on our one-GPU compute resource to create relevant images. To address these problems in story text generation and story visualization, we offer a multimodal story generation platform that collaborates with writers. A similar interactive writing platform is STORIUM \cite{akoury2020}, an online collaborative storytelling community. However, it is intended for text completions of long stories that follow the STORIUM narrative format \cite{akoury2020}.

Our proposed multimodal story-generating framework aims to generate creative and coherent short tales by taking advantage of multimodal robust representation of stories, decoder-based transformer architecture \cite{radford2018, du2020} and controllable text generation. Multimodal frameworks have been proven successful over their unimodal counterparts on various downstream tasks \cite{wu2019, lu2019}. Transformer models such as GPT-2 \cite{radford2018}, GPT-3 \cite{brown2020} and TransformerXL \cite{dai2019} have successfully used decoder transformer blocks \cite{li2018} to generate diverse, stable text. Controllable generation have encouraged generation of coherent texts \cite{fan2018, yao2018, lippolito2019, wang2020}. Therefore, it seems promising to compare and evaluate our multimodal generative framework on the complex story-generation task.

### 3 Data Collection and Data Wrangling

In this section, we describe the datasets and pre-processing used for creating the benchmark system and the final design. We evaluated several sources of data for each modality. A detailed data analysis is available in Appendix C.

#### 3.1 Text datasets

To help finetuning models, we tried data from an open-source dataset and from a manually collected text collection. Reddit WritingPrompts \cite{fan2018} is an open-source dataset that provides a writing prompt before each story. The stories are varied in their subjects, language and writers. The manually collected dataset consists of public domain children’s books from Project Gutenberg that are suitable for young readers. These books are handpicked and cleaned before use.

To fit Reddit WritingPrompts data to our text generation style and adjust it to the transformer model pre-requisites \cite{radford2018}, we pre-process and clean the data to: trim stories to 1000 words, clean special characters and symbols, remove offensive words, filter stories that were classified as having a negative sentiment, merge prompt and corresponding story to one pair and add end-of-sentence between them and at the end of the story.

From approximately 300K stories, we train the benchmark model on 35K prompt-and-story pairs that were predicted to express positive sentiment. To predict the tonality of a given story, we use a pre-trained BERT \cite{devlin2018} with an added GRU layer that is fine-tuned on the IMBD dataset for a sentiment analysis regression task. The model returned a value from 0-1, representing extremely negative to positive sentiment. The selected stories have a sentiment score above 0.9.
We handpick Gutenberg books relevant to fairy tale generation (complete list available at Appendix A). We further clean the data by splitting stories into 500 tokens extracts, removing redundant new lines, metadata, offensive language, and special characters, and adding a generated prompt before each extract to keep a prompt-story structure and encourage controllable coherent generation.

We use approximately 9K 500-token extracts to fine-tune the benchmark model for the second time, after Reddit WritingPrompts, and to fine-tune the final model for the first and only time. We do not train the final model on Reddit WritingPrompt because of the unpredictable nature of stories. Even after filtering stories, many were unsuitable for our intended young audience.

3.2 Image datasets

For image retrieval, we assessed several open-source resources to find a varied dataset that includes sceneries, people, and animals that are more closely related to fairy tales. After evaluating COCO [Chen et al., 2015], Unsplash [Unsplash, 2020] and Flickr30k [Young et al., 2014] caption-image datasets, we use Unsplash due to images relative objects’ diversity and landscapes nature.

4 System Architecture

We present two evolving architectures that we used in the process of this work. Our benchmark model [4.1] introduced multimodal generation but suffered from repetition, inconsistency, and negative sentiments. We mitigated those flaws in our final model [4.2] by improving the framework and changing the data.

4.1 Benchmark Design

The benchmark model shown in Figure 2 generates text and accordingly retrieves images. The architecture introduces a novel multimodal element. The images guide the text generation process by re-ranking the generated story samples by how coherent and relevant the retrieved images are. Another feature is the automatic text ranking performed after text generation that tests the generations’ readability, diversity, and sentiment.

We perform two fine-tuning rounds of the GPT-2 model [Radford et al., 2018] using the huggingface library [Wolf et al., 2019]. The first is on Reddit WritingPrompt [Fan et al., 2018] to fine-tune the model to a prompt-story template. The second is on our individually collected children’s books dataset to adapt the model to a younger audience.

To encourage creativity while maintaining consistent text generation, we tested the top-k random sampling method (k = 50) that was used in the Hierarchical Neural Story Generation model (with k = 10) [Fan et al., 2018], but the results were repetitive. We decided to use Nucleus Sampling [Holtzman et al., 2019] instead.

For image retrieval, the benchmark architecture extracts frequent nouns from the generated text to retrieve corresponding images from Flickr30K [Plummer et al., 2017] caption-image dataset.

4.2 Final Design

Testing the benchmark model revealed a few flaws that we approach in our final model. First, The text completions are often repetitive, incoherent, inappropriate, and dark. Second, the independently retrieved images are inconsistent (e.g., might get a different female figure each time). To improve upon the benchmark generation, we revise both the text generation and the image retrieval methods. The final model is shown in Figure 5.

4.2.1 Text Modality

We added several re-ranker metrics to significantly increase the ranker’s role and score texts according to their readability, positiveness, diversity, simplicity, coherency, and tale-like manner. The re-ranker computes the min-max normalization (1) to rescale each feature across all generated texts so that all features contribute equally.

\[
scaled\_scores = \frac{\text{scores} - \text{min(scores)}}{\text{max(scores)} - \text{min(scores)}}
\]
Furthermore, we increased the re-ranker frequency. To maintain a coherent text generation, we re-rank after each end-of-sentence token. By re-ranking, we only keep the better half of the generation and filter out the rest. The following text measures contribute to the re-ranking:

**Readability** calculates the length of sentences and length of words to estimate how complex the text is.

\[ \text{readability} = 0.5 \times \text{word_chars} + \text{sent_words} \]  
(2)

Where `word_chars` and `sent_words` are equal to -10 if number of words and number of sentences are zero respectively. The 0.5 multiplier gives a higher rank to the number of words per sentence.

**Positive Sentiment** uses SentiWordnet [Baccianella et al., 2010] to compute the positivity polarity. SentiWordnet assigns sentiment scores to each WordNet [Fellbaum, 1998] synonym group. WordNet is popular for information retrieval tasks and does not require pre-training. Since we do not have a supervised sentiment dataset for tales, SentiWordNet predictions were more accurate than neural nets trained on different datasets.

**Diversity** calculates the fraction of unique words from the total number of words.

\[ \text{diversity} = \frac{\text{len(set(filtered_words))}}{\text{len(filtered_words)}} \]  
(3)

`filtered_words` are word tokens that exclude stop words (e.g., at, in, is) and punctuation. The score is equal to zero if there are no filtered words.

**Simplicity** calculates the fraction of tale-like characteristic words in the given text.

\[ \text{simplicity} = \frac{\text{len(set(filtered_words) \cap freq_words)}}{\text{freq_words}} \]  
(4)

`freq_words` are precalculated to represent seven percent of the most frequent words in the collected Gutenberg fairy tales corpus.

**Coherence** calculates the Latent Semantic Analysis (LSA) similarity within the story sentences compared to the first sentence. The calculation includes three steps:

1. Computing the LSA embedding of the tf-idf document-term matrix per sentence. 
   \[ \text{embeddings} = \text{embedder(text_sentences)} \]

2. Computing the pairwise cosine similarity for each sentence against all other sentences.
   \[ \text{similarity} = \text{cosine_similarity(embeddings)} \]

3. Computing the final similarity score by comparing the first sentence to the rest of the sentences: 
   \[ \text{sum(similarity[0][:1])] \]

"Tale like" computes the KL divergence loss between a preset GPT-2 and a fine-tuned GPT-2 generated texts’ predictions. A higher score is better since it usually implies that the text is more similar to the fine-tuned distribution and different from the preset GPT-2 distribution. The computation consists of the following steps:

1. Tokenizing and encoding the text to `tokens_ids` to prepare it for the forward pass.
2. Computing the logits of the present model `logits_preset` and of the fine-tuned model `logits_finetuned` with forward pass on `tokens_ids`.
3. Returning the difference score according to the KL-divergence loss between the two models logits: 
   \[ \text{torch.nn.KLDivLoss(logSoftmax(logits_preset)), logSoftmax(logits_finetuned))} \]

**4.2.2 Image Modality**

We evaluated three open-source implementations for text to image synthesis, BigGAN [Brock et al., 2018], stackGAN [Zhang et al., 2017] and Dall-E [Ramesh et al., 2021]. To generate images with bigGAN, we extracted image categories (i.e., animal and object names) from the generated text. However, bigGAN’s limitation to 1000 categories [Brock et al., 2018] prohibited the generation of relevant scenes. StackGAN and Dall-E accept any text input. However, since the text is usually unstructured and not descriptive of a scene, the resulting images were often noisy and distorted (Figure 3). Furthermore, image generation times were significantly longer than image retrieval. One GPU image generation time ranged from 4-30 seconds per image versus image retrieval, which took 0.5-2 seconds per image.

**Figure 3:** StackGAN’s generations for the caption: "several men standing outside of small airplane with man retrieving luggage from cart.”

Therefore, we remained with the image retrieval method, but with a different dataset and an improved retrieval method. We use [Radford et al., 2021] to transform the images and generated text to the same latent space. Per-retrieval, we compute the cosine similarity of the text embeddings and the images embeddings. The computation returns the images’ ids of the highest-scoring images. The retrieval searches over 2M Unsplash pre-computed embeddings to find the best match to the query.

To achieve a coherent look of story images we fine-tune a neural style transfer model [Johnson et al., 2016] on several target images shown in Figure 4.

https://github.com/haltakov/natural-language-image-search
https://github.com/lucidrains/DALLE-pytorch
https://github.com/hanzhanggit/StackGAN-Pytorch
https://github.com/huggingface/pytorch-pretrained-BigGAN
https://github.com/unsplash/unsplash-datasets
https://github.com/unsplash/unsplash-datasets
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To improve overall story generation, the framework can generate multiple stories and rank them by their images' consistency. The images' consistency metric is calculated by summing the KL divergence of ResNet classification predictions of image pairs. A lower score indicates a smaller difference, which is better.

Figure 5: Final Model Architecture. The system generates text while re-ranking, retrieves images from Unsplash dataset, applies style transfer [Johnson et al., 2016] and then re-ranks stories according to the story's visual consistency.

5 Prototype "FairyTailor"

FairyTailor is a user interface to access the final multi-modal framework and allow story co-creation. A human writer can start in multiple ways: from scratch, by using a random story primer, or by entering minimal content such as a story title. FairyTailor then offers various modes of autocomplete to assist the writer.

The web platform skips some of the final design steps to allow for fast user interaction. We use CSS transforms instead of the style transfer neural model, and we do not evaluate stories by the consistency of their image (since we generate one story at a time).

Autocomplete. The faster, more straightforward text autocomplete immediately returns the three completions generated by the fine-tuned model. It may generate empty or irrelevant completions.

High-Quality Autocomplete. Instead of generating three text completions, the framework generates ten texts, ranks them, and returns the top three. The framework scores texts according to their readability, positiveness, diversity, simplicity, coherency, and tale-like manner. The scoring metrics are detailed in sub-section 4.2.
can use the HTML to review aspects of the generated
story, such as the ratio of generated vs. user-inputted text
and number of images.

6 Experiment, Evaluation & Discussion

Since we used a custom, newly collected dataset and our
demo’s goal is story co-creation, the most suitable eval-
uation practice is human evaluations [Tambwekar et al.
2019a][Akoury et al., 2020]. Automated metrics such as
Perplexity [Jelinek et al., 1977], BLEU [Papineni et al.
2002] and BLEURT [Sellam et al., 2020] are unsuitable to
measure creativity and coherence without reference texts.

We use the FairyTailor prototype and a questionnaire
to solicit feedback on the user interface and the generated
stories. The feedback questions expand on the evaluation
form on the website to understand the user’s journey until
they freeze and submit their story. We further analyze the
users’ published stories to verify the efficacy of the genera-
tions. We check the ratio of generated vs. user inputted
text and the text to image ratio.

6.1 Qualitative Evaluation

We collected feedback on the demo with story generation
experts that have done similar work. The demo’s added
value from their experienced perspective is summarized
in Appendix F.

In addition, we performed structured human evaluations
with thirteen students and professionals (six males and
seven females). The interviewees included two under-
graduate students in Biology Engineering and Computer
Science, a Computer Science graduate student, five Com-
puter Science Ph.D. students, two Natural Language Pro-
cessing researchers, a global marketing executive, a soft-
ware engineer, and a technical product manager.

The questionnaire form can be found in Appendix B. It is
split into two parts to evaluate: (1) storytelling back-
ground which checks whether the user has written stories
before, and in what context and (2) user feedback on the
generated story (e.g., ranking the story’s flow and qual-
ity), the interface (e.g., the use of autocomplete versus
high-quality autocomplete and the use of images), and the
overall experience (e.g., asks what the user liked and did
not like).

The generated story questions are based on Predicting
Generated Story Quality with Quantitative Measures
[Purdy et al., 2018]. They were designed for automated
story evaluations and were previously tested on similar
tasks.

6.2 Feedback and Results

Participants’ insights revealed what is enjoyable and what
should be improved. The participants commented on the
strengths and weaknesses of the interface and the multi-
modal framework completions after playing with the plat-
form for a 5-10 minutes.

Demo Interface. Overall, the participants found the demo
highly engaging. A few users mentioned that the short text
autocompletes that are not full sentences encouraged them
to press autocomplete again, and they were less likely to
delete those shorter completions.

Autocomplete Versus High-Quality Autocomplete. The
autocomplete and high-quality autocomplete options
demonstrate the difference between the ablated version of
the framework and the iterated, final one. Users who tried
both indicated that the high-quality autocompletes, which
take advantage of the final framework, are significantly
better and were willing to wait longer for generations. It
emphasizes the benefits that the final model’s modifica-
tions provide.

Multimodal Framework Completions. A third of the
submitted stories did not include images because users
found them irrelevant to the story, or they did not think
their style fits the story they had in mind. The same hap-
ened with text completions. If the tone, vocabulary, or
ideas that the completion suggested did not fit what the
users had in mind, they did not incorporate it.

Published Stories. The average scores of published co-
created stories are clarity: 3.4, coherence: 3.5, creativity:
3.7 out of 5. Most of the participants highlighted the ben-
eficial creativity of the platform and its fairy tail-y nature.

6.3 Discussion

We found that people are excited about interactive writing
and enjoyed prompting autocomplete. Some of the sup-
portive comments include: "I have a big interest in litera-
ture, so this is very fun" and "I love the highly engaging,
very polished user interface". Flexibility was key for an
enjoyable experience. People liked having control over the
content, the placement of the texts and images and the
timing of the completions.

6.3.1 Strengths

Since our goal is co-creation of stories with human-in-
the-loop, many questions were on the demo user inter-
face. Users highlighted the ease of use and the design of
the platform. It is best to use the platform when users
are open-minded. One of the users mentioned: "Though I
did not know where my story was going initially, the au-
tocomplete helped me find a direction". Prompting auto-
completes is likely to generate different suggestions each
time, thus helping writers guide the story.

6.3.2 Weaknesses

Some users did not use images because their style or con-
tent did not fit their stories. The image retrieval is re-
stricted to the images dataset and thus do not fit every
scenario. Most users indicated they declined to use the suggested (simple) autocompletion 50%-75% of the times they prompted it because it was repetitive or did not fit their motif. However, for users who used the high-quality autocompletes, the numbers were significantly lower, ranging from 0-25% of the times declining suggestions. This shows, that spending time on content quality matters, and that faster high-quality models are key to future success.

6.3.3 Improvements

During the interviews we also collected features on how we could help improving the user experience with FairyTailor overall.

- Adding other modes of user interaction, such as changing the image style-transfer style.
- Adding endings completions, since regular autocompletes do not try to summarize or direct the current story.
- A leaderboard of the highest-scoring published stories.
- An option for user-provided text examples to fine-tune the language model and adapt the style and probable vocabulary to the users’ intended writing style.

7 Conclusion and Future Work

We find that participants enjoyed engaging with FairyTailor to co-create a variety of stories and would use such systems again. FairyTailor is especially beneficial for beginning writers, who find it hard to start and do not envision a specific storyboard in mind. Users mentioned that the completions’ creativity helped them find a direction and maintain a continuous flux of ideas.

The platform is helpful for user testing and automated story evaluations. When the user submits a story, the platform saves its content along with an outlined feedback form. Researchers can quickly evaluate the ratio of generated versus inputted text and inserted images ratio with simple analytics. The platform is publicly available[7] for other researchers to deploy their work and user-test a story generation model quickly.

The image modality is novel among other story generation platforms. The images add a touch to the story and are especially prevalent in children’s books. When image completions are relevant, users tend to incorporate them. Published stories that included images were ranked higher overall; users who used images praised the images’ role in improving their co-generated story’s quality.

From conducting our experiments, we think that the canon of future work in multimodal story generation should include the following ideas and challenges:

**User-specific completions.** Currently, the autocomplete function is the same for all users. It only changes according to content. However, users’ writing style and goals vary. When users have a specific storyboard in mind, the platform might never get what they envisioned and generate irrelevant completions. Incorporating an interactive feedback loop can mitigate this problem. The deletions or unused autocompletes can guide the model to the users’ intentions and produce user-centered results.

**Storyboard completions.** Currently, autocompletes do not explicitly follow a storyboard and are not designated for the beginning, middle, or ending of the story. Suppose a user indicates a need to end or evolve the story by providing a goal-driven storyboard in advance or signaling while writing. In that case, it will be beneficial to have directed autocompletions that follow these cues.

**Image generation versus image retrieval.** For generality purposes, it is valuable to generate images according to input, assuming that generated images will be of high quality as retrieved images are and rendered in a suitable time frame.

**Faster is better.** A technical challenge for interactive human-AI multi-modal co-creation is not only to develop models of higher text/image quality but also models of fast inference time to allow interactive rates during the creation process.

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Appendices

A  Collected Gutenberg Stories’ Titles

The Happy Prince, Andersen’s Fairy Tales, The Blue Fairy Book, The Adventures of Pinocchio, Myths Retold by Children, Household Tales, Indian Fairy Tales, Fairy Tales Second Series, MERRY STORIES AND FUNNY PICTURES, Childhoods Favorites and Fairy Stories, The Wonderful Wizard of Oz, Celtic Tales, Our Children, The Little Lame Prince, The Prince and Betty, The Adventures of Sherlock Holmes, Peter Pan, The Secret Garden, The Jungle Book, The Adventures of Tom Sawyer, A Little Princess, Little Women, Just So Stories, Moby Dick, Treasure Island, The Idiot, A Tale of Two Cities, My Man Jeeves, Sense and Sensibility, The Time Machine, Comic History of the United States, The Velveteen Rabbit, The Book of Dragons, The Snow Image, The Magical Mimics in Oz, Folk Tales from the Russian, Snow-White or The House in the Wood, Dramatic Reader for Lower Grades, A Christmas Hamper, Aesop Fables, My Fathers Dragon, The Peace Egg and Other tales, Indian Why Stories, Folk-Tales of the Khasis, The Paradise of Children, Wonder Stories, The Best American Humorous Short Stories, Hindu Tales from the Sanskrit, The Tale of Johnny Town-Mouse, The Little Red Hen, East of the Sun and West of the Moon, Among the Forest People, True Stories of Wonderful Deeds, English Fairy Tales, Simla Village Tales Or Folk Tales from the Himalayas, Japanese Fairy Tales, Plain Tales of the North, The Wind in the Willows, The Louisa Alcott Reader. A Supplementary Reader for the Fourth Year of School, A Wonder Book for Girls and Boys, Tanglewood Tales, The Pig Brother and Other Fables and Stories, The Worlds Greatest Books, Vol 3, Goody Two-Shoes, The Marvelous Exploits of Paul Bunyan, Christmas Every Day and Other Stories, The Childrens Book of Thanksgiving Stories.

B  FairyTailor User Test Template

FairyTailor, available at fairytailor.org, is a visual story co-creation platform created by MIT & IBM. Users can create a cohesive story by weaving automatically generated texts and retrieved images with their input.

*Required

1. Email Address*
2. Have you written stories before? If yes, elaborate on the intended audience and the stories’ structure*
3. Paste the URL of your story (created after pressing "submit story" at the bottom)*
4. Do you agree with the following statement?* (Choose one of strongly Disagree, Somewhat Disagree, Neither Agree nor Disagree, Somewhat Agree, Strongly Agree) [Purdy et al, 2018]
   • Autocompletes exhibit CORRECT GRAMMAR
   • Autocompletes occur in a PLAUSIBLE ORDER
   • Autocompletes MAKE SENSE given sentences before and after them.
   • Autocompletes AVOID REPETITION
   • Autocompletes use INTERESTING LANGUAGE
   • This story is of HIGH QUALITY.
   • This story is ENJOYABLE.
   • This story follows ONE OVERALL THEME.
5. When prompted, how often did you decline to use the suggested completions?*
   • Never
   • For 25% of completions
   • For 50% of completions
   • For 75% of completions
   • Always
6. Did you use autocomplete (Tab) or High-Quality autocomplete (shift + Tab)?*
   • Mostly autocomplete (Tab)
   • Mostly HQ autocomplete (shift + Tab)
   • Both
   • Other: __
7. Please elaborate on your choice above*
8. Did you use images? Why?*
9. What did you like?*
10. What not so much?*
11. Other comments/ suggestions?

C Data Analysis

The datasets were analyzed to validate their diversity. Each text dataset was inspected to look at the number of sentences (Figure 7), the Part-Of-Speech (POS) tagging (Figure 8) and the least frequent (Figure 9) and most frequent (Figure 10) words.

The number of sentences’ distributions in Figure 7 verifies that our dataset mostly includes shorter stories as the ones we aim to produce. The children’s stories corpus has a higher quantity of longer stories, leading to a higher mean of 71 sentences per children’s story versus Reddit’s mean of 48 sentences.

The Part-Of-Speech (POS) tagging distributions in Figure 8 displays higher concentrations of verbs and nouns than adjectives, as expected. Interestingly, in both stories’ corpora, the mean number of adjectives is approximately 35% of the mean number of verbs or nouns. That high ratio might reflect the vivid, artistic nature of storytelling.

The least frequent words’ distributions in Figure 9 shows that the Reddit corpus has a more diverse vocabulary than the children’s stories corpus. Almost 50% of Reddit’s vocabulary consists of infrequent words in comparison to 40% in children’s stories.

The most frequent words displayed in Figure 10 word clouds show the characteristic old-fashioned style of children’s stories. Old, upon, and shall are among the most frequent words in fairy tales, whereas terms like world, people, eyes are common in Reddit stories. Prevalent words such as I, time, and you appear in both corpora.

![Figure 7: Number of sentences in text datasets.](image)

![Figure 8: Part-Of-Speech (POS) tagging distributions.](image)
Figure 8: Part of speech (POS) tagging of Verb, Noun and Adjective (Adj) in text datasets.

Figure 9: Frequency of the least frequent words in text datasets.

Figure 10: 50 Most frequent words in text datasets.
D  Benchmark and Final Model Generated Stories

*Provided prompt: I was wearing my flowery jammies when suddenly a cockroach fell right on top of my head. Even though I was inside, people down the street heard me scream.*

![Image of a rooster, a woman, and a pencil with a note]

I was standing in front of the little school with the white fence, and I heard a noise in the distance. It sounded like a bell. I looked up and saw a big red rooster, about five feet long, standing right in front of me. It peered at me with an enormous mouth and a big black eye. “Well, how do you like that rooster, Miss?” the rooster asked me. I didn’t know what to do. I didn’t have any friends, but I did have a neighbor who was very nice. I lived in the neighborhood called Parson’s Point, and we lived there on a farm that I built in the woods. The rooster looked at me with its enormous mouth and pointed at me. “That’s my rooster” I said. “What do you think it is?” the rooster asked. “A rooster!” I said. “it is a rooster” said the rooster.

**Figure 11:** Benchmark model: Example of a generated story

*Provided prompt: The Truth is Written in the Stars*

![Image of several paintings]

There were once upon a time, long before the writing of the Epistles was known, a mighty kingdom whose name was in every hand of the people a kingdom of stars. And among them, in the midst of the shining city of Cyrene, was a beautiful maiden, so long ago as the time of the poet, when the world was but half its present size. Her name, for which it was named, was Aurora. But she was not the only one of the stars in the sky in whom the light of prophecy had fitted a sweet spot. She was loved and respected by the entire race of mortals, a godlike beauty, and an angelic beauty, as is shown in the following letter. ”Aurora loved you very much.”

"I dare say that she did," sighed a most melancholy-looking fellow.

**Figure 12:** Final model: Example of a generated story
E FairyTailor Screenshots

(a) Landing Page

Your Story Title

Click to write something awesome...

(b) Random Preset Story

Christmas by the Beach

This is a story about a joyful Christmas morning when the holiday spirits were high, by a quaint and beautiful beach house. There was such a sense of adventure and freshness of spirit in it!

Figure 13: Users can start writing from scratch or use preset examples.
Figure 14: Users can publish their created stories, give feedback and share stories with others.

F Feedback from Story Generation Experts

- **Controllable Neural Story Plot Generation via Reinforcement Learning** [Tambwekar et al., 2019b] co-author, Professor Mark Riedl: The main innovation is the refined, web-based interactive demo that works with writers to create stories.

- **STORIUM: A Dataset and Evaluation Platform for Machine-in-the-Loop Story Generation** [Akoury et al., 2020] first author, Nader Akoury: The main difference is the reachability of FairyTailor to any writer, outside of the STORIUM platform, and the ability to write narratives and stories’ of any structure. In addition, STORIUM autocompletes do not suggest images.

- **Creative Writing with a Machine in the Loop: Case Studies on Slogans and Stories** [Clark et al., 2018] first author, Elizabeth Clark: The significant distinctions are the writing flexibility and the intuitive options menu that enables adding images and texts.

- **Creative Help: A Story Writing Assistant** [Roemmele and Gordon, 2015] first-author, Dr. Melissa Roemmele: The dominant strength is the analysis platform that can be used for evaluation thanks to the editable autocompletes and user-inputted content. The images are also novel in comparison to existing story generation platforms.