Adaptive Story Generation

A Project Report

submitted by

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DECLARATION OF ORIGINALITY

I, **P.Naga Sripada (CS22B1018) ,M.Varshitha**, with Roll No: **CS22B1071** hereby declare that the material presented in the Project Report titled **Adaptive Story Generation** represents original work carried out by me in the **Department of Computer Science Engineering** at the Indian Institute of Information Technology, Design and Manufacturing, Kancheepuram.

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P.Naga Sripada (CS22B1018) ,M.Varshitha

Place: Chennai

Date: 26.04.2025

CERTIFICATE

This is to certify that the report titled **Adaptive Story Generation**, submitted by **P.Naga Sripada (CS22B1018) ,M.Varshitha (CS22B1071)**, to the Indian Institute of Information Technology, Design and Manufacturing Kancheepuram, for the award of the degree of **BACHELOR OF TECHNOLOGY** is a bona fide record of the work done by him/her under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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Thank you all for being a part of this journey.

ABSTRACT

This project presents an adaptive story generation framework using Hierarchical Reinforcement Learning (HRL) to create coherent and creative narratives from user prompts. Traditional story generation models often lack long-term consistency, making it difficult to maintain logical flow and thematic relevance across story segments.

To overcome this, we decompose the generation process into two levels: a high-level Manager, implemented as an LSTM-based policy network, and a low-level Worker, powered by the GPT-Neo language model. The Manager generates meaningful sentence-level subgoals that serve as instructions for the Worker to generate corresponding story segments. These segments are then composed into a complete narrative.

The system is trained using the REINFORCE algorithm with rewards based on coherence, relevance, and theme continuity. We use the WritingPrompts dataset for training and integrate GloVe embeddings for richer semantic understanding. This approach enables more controllable and consistent storytelling, highlighting the effectiveness of HRL in narrative generation tasks.

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1. Introduction

1a. Background

Storytelling is a fundamental human activity, serving as a medium for communication, education, entertainment, and cultural preservation. With the rise of powerful language models like GPT-3, GPT-Neo, and others, automatic story generation has emerged as a compelling application in natural language processing (NLP). While these models can generate fluent and contextually relevant text, they often struggle with maintaining long-term coherence and thematic consistency, especially in longer narratives.

Recent advances in reinforcement learning (RL) have shown promise in structuring and guiding generation tasks. Hierarchical Reinforcement Learning (HRL), in particular, offers a structured approach where high-level decisions guide low-level actions. Applying HRL to story generation introduces a way to bridge creative freedom with control, using a multi-agent or multi-layered architecture to balance coherence and diversity in storytelling.

1b. Research Problem

Despite significant progress in text generation, existing models often produce stories that lack direction, coherence across paragraphs, or adherence to the central theme introduced by the prompt. These limitations arise from the lack of explicit high-level planning during generation. Current models operate in a left-to-right, token-wise generation fashion without global narrative guidance.

The research challenge, therefore, lies in designing a framework that can generate story segments aligned with an overarching plot or theme, ensuring consistency in character behavior, plot development, and tone. This requires a mechanism to plan subgoals and enforce semantic cohesion between them — a gap that this project seeks to address through HRL.

1c. Contributions

This project proposes a novel adaptive storytelling architecture built upon Hierarchical Reinforcement Learning. The main contributions are:

- **Hierarchical Framework:** We introduce a two-level story generation framework with an LSTM-based Manager and a GPT-Neo-based Worker. The Manager generates high-level subgoals as short, coherent sentences guiding the Worker.
- **Subgoal-Driven Generation:** The Worker uses these subgoals to generate thematically aligned story segments. A Composer module then stitches these into a complete narrative.
- **RL-based Training:** We implement the REINFORCE algorithm to train the Manager, incorporating rewards based on coherence, relevance, and continuity between generated segments.
- **Dataset and Embedding Integration:** We use the WritingPrompts dataset for training and leverage GloVe embeddings to enhance the model's semantic understanding.

1d. Team Contributions

Member 1: Varshitha
Role: Data Engineering & Manager Module Lead
Contributions:

- Designed the complete data loading and preprocessing pipeline for prompt–story pairs.
- Implemented subgoal extraction techniques using a combination of SVO parsing and Named Entity Recognition (NER).
- Developed the LSTM-based Manager policy network for hierarchical subgoal generation and planning.

Member 2: Sripada
Role: Model Integration & Worker Module Lead
Contributions:

- Constructed the GloVe-based embedding layer to convert textual inputs into vector representations for the Manager.
- Engineered the segment extraction logic to convert long-form stories into meaningful subgoal-annotated training episodes.

- Integrated and fine-tuned the GPT-Neo Worker module to generate coherent story segments conditioned on subgoals.

Joint Activities (Collaborative Effort):

- **Reward Function Design:** Defined a multi-objective reward function combining coherence, prompt relevance, and lexical diversity.
- **REINFORCE Training:** Jointly implemented and tuned the REINFORCE algorithm, including policy gradient optimization and stability analysis.
- **Story Composition & Feedback Loop:** Co-developed the inference pipeline that sequentially composes stories from subgoals, with optional human-in-the-loop (HITL) evaluation.
- **Evaluation & Visualization:** Shared effort in generating metric plots (reward curves, policy loss, diversity trends), analyzing performance, and validating narrative quality.

While each member led distinct modules, all design decisions were collaborative. Every component was reviewed, debugged, and improved together—ensuring a tightly integrated and stable final system.

2. Literature Review

2a. Traditional Approaches

Story generation has long been a key challenge in natural language processing (NLP), drawing interest from fields like AI, computational creativity, and human-computer interaction. Early rule-based systems relied on handcrafted templates and grammars to generate narratives, but they were rigid and lacked adaptability to diverse prompts or dynamic themes.

With the rise of machine learning, statistical language models and sequence-to-sequence architectures became the standard. RNNs and LSTMs, trained on large corpora, improved fluency and grammar but often failed to maintain long-term coherence and thematic consistency in multi-sentence outputs. Attention-based models and transformers, particularly OpenAI's GPT series and BERT variants, further enhanced generation quality, enabling context-aware and stylistically rich outputs. However, these models still operate in a single-step fashion, often struggling with goal planning and thematic continuity in extended narratives.

2b. Reinforcement Learning for Story Generation

Reinforcement Learning (RL) has recently gained attention in story generation due to its ability to optimize text based on long-term objectives like coherence, relevance, and creativity. Unlike traditional models that generate content in a single pass, RL enables goal-driven generation through feedback and rewards.

Hierarchical Reinforcement Learning (HRL) further enhances this by introducing a two-level structure where a high-level policy sets narrative goals and a low-level generator produces text accordingly. This layered setup aligns well with the demands of storytelling, which requires both thematic planning and fluent execution.

Building on these ideas, our approach adopts an HRL framework to improve coherence and structure in narrative generation, setting it apart from purely sequential models.

3. Dataset Description

3a. WritingPrompts

The *WritingPrompts* dataset, sourced from Reddit's `/r/WritingPrompts`, is a large-scale collection of story prompts paired with user-generated responses. It comprises over 300,000 prompt–story pairs, making it suitable for supervised training in creative generation tasks. The dataset is pre-split into training, validation, and test sets, and we specifically leverage the `.wp_source` files for prompts and `.wp_target` files for corresponding story texts.

The data is rich in narrative diversity and linguistic creativity, reflecting various genres, tones, and perspectives. This makes it ideal for training models to generalize across different storytelling styles while preserving coherence and thematic relevance.

3b. Comparative Datasets

We reviewed several datasets for context and benchmarking:

- **ROCStories and Story Cloze Test:** Focus on short, structured narratives for coherence evaluation.
- **FairyTaleQA:** Provides question–answer annotations for deeper semantic understanding.
- **BookCorpus:** A large corpus of novels used mainly for pretraining language models.

These alternatives helped assess narrative depth and variability, affirming *Writing-Prompts* as the most suitable for our adaptive storytelling framework.

4. Methodology

4a. Problem Statement

Traditional story generation models often struggle with maintaining long-term coherence, character consistency, and thematic progression, especially when generating multi-paragraph narratives. These limitations arise due to the absence of explicit planning mechanisms in end-to-end models. Our goal is to develop an adaptive story generation framework that produces structured and engaging narratives by decomposing the generation task into hierarchical stages using reinforcement learning.

Key challenges addressed in this work include:

- Ensuring coherence across story segments without repetitive or contradictory elements.
- Maintaining character and theme consistency throughout the narrative.
- Balancing creativity with controllability, so the model can follow high-level plans while generating diverse and fluent text.

4b. Model Description

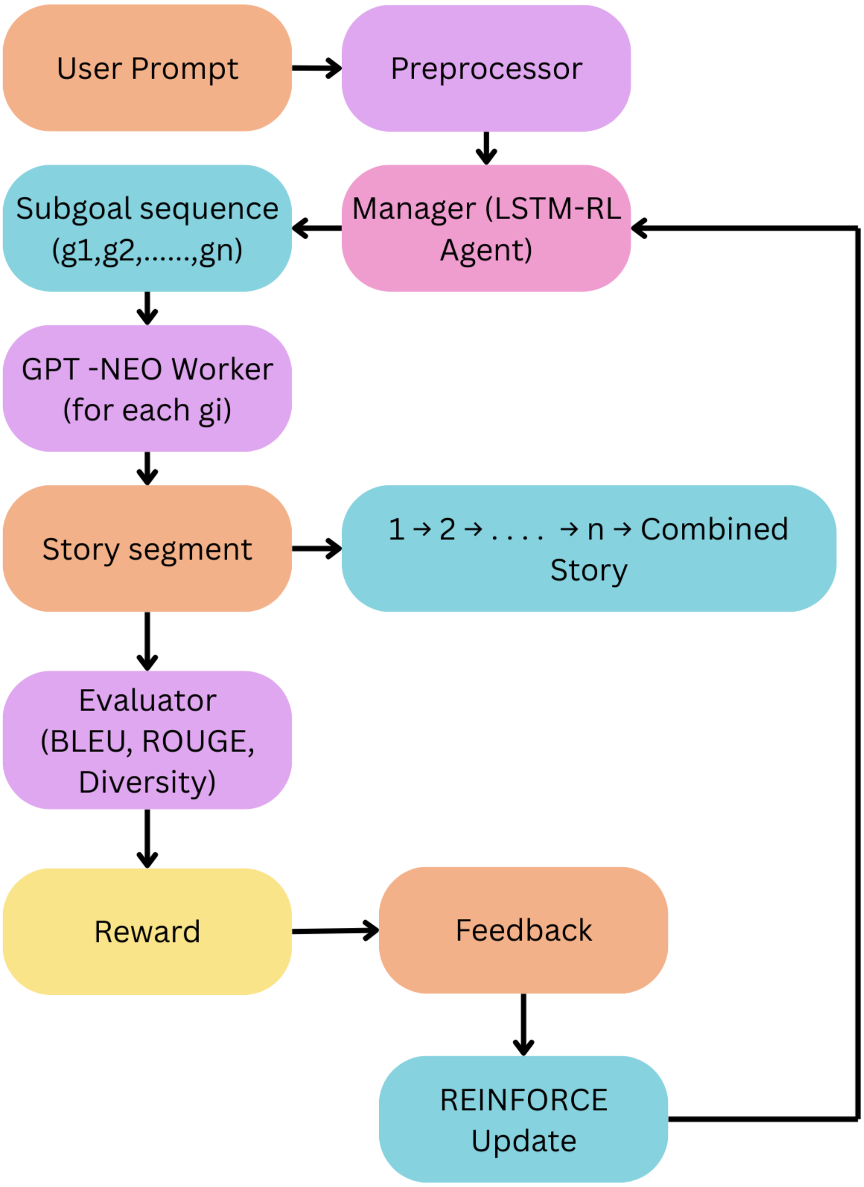


Figure 1: Hierarchical Reinforcement Learning Architecture for Story Generation

Our adaptive story generation framework employs a Hierarchical Reinforcement Learning (HRL) architecture that separates high-level planning from low-level language generation. This structure consists of two main components:

1. HRL Architecture: Manager–Worker Paradigm The storytelling task is decomposed hierarchically:

- **Manager:** Acts as a high-level planner that generates abstract subgoals—short sentence-level objectives representing the next part of the story.
- **Worker:** Acts as a low-level executor that takes these subgoals as context to generate detailed story segments.

This two-level design allows the system to maintain global thematic consistency while producing locally fluent and creative text.

2. Manager Module: LSTM-Based Policy Network The Manager is implemented as an LSTM-based policy network that receives a prompt embedding and optionally past subgoal embeddings. It generates subgoal sentences one at a time in a sequential manner.

- The LSTM is trained using the REINFORCE algorithm, which updates its policy based on the quality of the final story.
- The Manager's strength lies in its ability to retain long-term context, making it well-suited for planning over sequences.
- Subgoals are decoded from the LSTM's output vector using a dense layer followed by beam sampling or greedy decoding.

3. Worker Module: GPT-Neo for Story Segment Generation To generate detailed story segments from subgoals, we initially employed T5-base, a lightweight encoder–decoder transformer. T5 was chosen for its fast inference and versatility across NLP tasks. However, during experimentation, we observed several limitations:

- Noisy outputs with excessive or irrelevant content
- Repetitive phrasing, especially across long story generations
- Lack of narrative creativity and stylistic consistency
- Poor ability to adapt to open-ended or imaginative prompts

Due to these drawbacks, T5 often failed to produce engaging story segments aligned with the intent of the subgoals.

To address this, we transitioned to GPT-Neo (1.3B) by EleutherAI, a large-scale autoregressive language model trained on The Pile dataset. GPT-Neo demonstrated a notable improvement across several dimensions:

- Fluent and coherent generation, even for long passages
- Stronger generalization to creative, open-domain inputs
- Improved alignment with subgoals, producing segments that maintain thematic and character continuity

We use GPT-Neo in a zero-shot generation setup—each story segment is generated by conditioning the model on the current subgoal and the story generated so far. This method leverages GPT-Neo's pretrained knowledge while allowing subgoal-guided narrative structuring, without the need for task-specific fine-tuning.

4. Reinforcement Learning and Feedback Mechanism The core of our system's adaptive learning capability lies in the use of the **REINFORCE policy gradient algorithm**, a classical reinforcement learning approach for optimizing stochastic policies. The *Manager* module functions as the policy network, generating subgoal sequences conditioned on the initial prompt.

Once a story is generated through the full pipeline—from the prompt, through the subgoal planner, and finally via the language model producing narrative segments—a scalar reward signal is computed. This reward quantifies the overall story quality based on multiple criteria, including coherence, prompt relevance, diversity, and redundancy. The reward is derived using semantic similarity metrics and penalization mechanisms. This reward signal is then used to update the Manager's parameters via the REINFORCE update rule:

$$\nabla_\theta J(\theta) = E_{\pi_\theta}\left[R \nabla_\theta \log \pi_\theta(a \mid s)\right]$$

Here, the policy π_θ is parameterized by the Manager's LSTM, and R is the computed reward. The gradient is estimated using the log-probabilities of the sampled subgoals, encouraging the model to increase the likelihood of subgoal sequences that lead to high-reward stories. Furthermore, we incorporate a **human-in-the-loop feedback mechanism** as an optional enhancement. After story generation, users can provide binary or qualitative feedback. Negative feedback triggers re-sampling and re-evaluation of the subgoal sequence, allowing the model to refine its policy using additional reward signals. This design enables online policy refinement, aligning the generated narratives more closely with human preferences. This reinforcement learning loop empowers the system to *iteratively learn to compose better subgoal sequences over time*, thereby improving its ability to structure coherent and creative stories that reflect the user's intent.

4c. Implementation Workflow

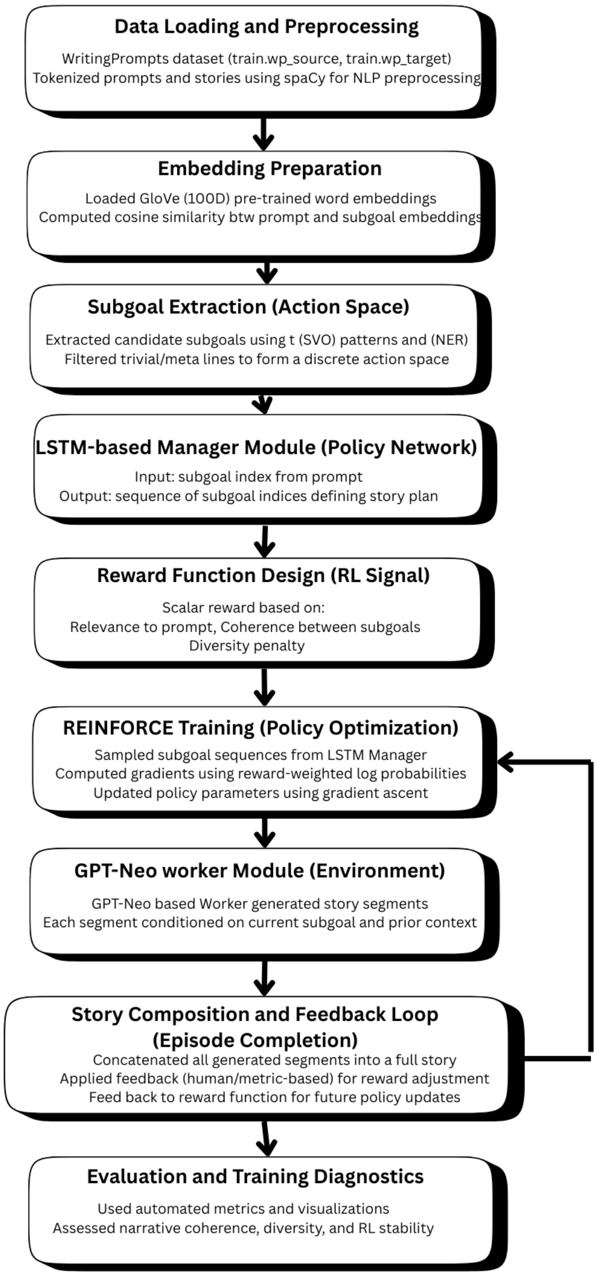


Figure 2: Workflow of the Hierarchical Reinforcement Learning framework for adaptive story generation.

1. **Data Loading and Preprocessing**
   - Loaded the WritingPrompts dataset (`train.wp_source`, `train.wp_target`).

- Tokenized prompts and stories using spaCy for downstream NLP processing.

2. **Embedding Preparation**
   - Loaded GloVe (100D) pre-trained word embeddings.
   - Defined utility functions to:
     - Embed sentences.
     - Compute cosine similarity to assess semantic proximity between prompts and subgoals.

3. **Subgoal Extraction (Action Space Definition)**
   - Extracted candidate subgoals from stories using:
     - Subject–Verb–Object (SVO) structures.
     - Named Entity Recognition (NER) to prioritize meaningful actions.
   - Filtered trivial/meta sentences and compiled a discrete action space of top-1000 subgoal sentences.

4. **Subgoal Matching (Initial State Setup)**
   - Mapped each user prompt (environment state) to a relevant subgoal using cosine similarity.
   - Created a `prompt_to_goal_token()` function to transform the prompt into a state representation (subgoal index) for the RL agent.

5. **LSTM-based Manager Module (Policy Network)**
   - Built an LSTM-based Manager as the policy network π_θ:
     - **Input (state):** Initial subgoal index from the prompt.
     - **Output (action):** Autoregressively sampled sequence of subgoal indices (i.e., a plan).
   - This sequence defines the high-level structure of the story.

6. **Reward Function Design (RL Signal)**
   - Designed a scalar reward R for each generated subgoal sequence based on:
     - Relevance to the original prompt.
     - Coherence between consecutive subgoals.
     - Diversity penalty to discourage repetition.
   - This reward acts as the feedback from the environment, essential for policy updates.

7. **REINFORCE Training (Policy Optimization)**
   - Used the REINFORCE algorithm to train the Manager:
     - Sampled multiple subgoal sequences from the LSTM policy.
     - Used the reward-weighted log probabilities to compute gradients:

$$\nabla J(\theta) = E[\nabla_\theta \log \pi_\theta(a \mid s) \cdot R]$$

     - Updated parameters via gradient ascent to maximize expected reward.
     - Monitored training dynamics using loss and reward plots.

8. **Worker Module Inference (Environment Simulation)**
    - For each subgoal (action), the Worker (GPT-Neo) simulates the environment's response:
        - Generated a story segment conditioned on the subgoal and prior segments.
    - The combined output forms a complete story trajectory.

9. **Story Composition and Feedback Loop (Episode Completion)**
    - Concatenated all generated segments to form the final story.
    - Incorporated a feedback mechanism:
        - Positive feedback (e.g., human or metric-based) $\rightarrow$ full reward.
        - Negative feedback $\rightarrow$ scaled reward or segment revision.
    - Feedback affects the next episode's policy updates, enabling learning over time.

10. **Evaluation and Training Diagnostics**
    - To assess the performance of our adaptive storytelling model, we employed both automated evaluation metrics and visual diagnostics.
    - These helped capture narrative quality, diversity, and training stability over episodes.

4d. Evaluation Metrics

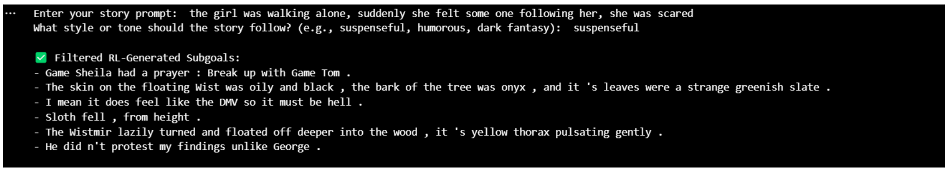
To evaluate the effectiveness of our hierarchical reinforcement learning-based storytelling system, we used a combination of linguistic similarity, diversity, and reward-based metrics:

- **Average ROUGE-L:** Measures the longest common subsequence between generated and reference texts. This reflects structural and content overlap in the narrative.
- **Average BLEU Score:** Computes n-gram precision to assess how closely the generated story segments match expected phrasing.
- **Distinct-1:** Calculates the proportion of unique unigrams in the generated text, indicating the level of lexical diversity.
- **Distinct-2:** Computes the frequency of unique bigrams to assess structural variety in sentence formation.
- **Subgoal Diversity Score:** Evaluates the variation in subgoal sentences produced by the Manager module. This encourages non-redundant high-level planning across different narratives.
- **Average Episode Reward:** Reflects the cumulative reward accumulated in an episode. It captures coherence, relevance, and diversity, serving as the feedback signal for REINFORCE optimization.

5. Results

5a. Qualitative Evaluation

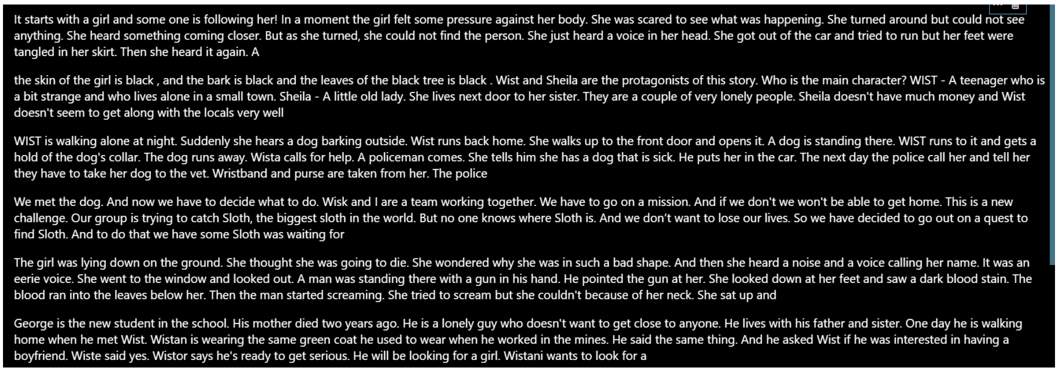
Our system generates full-length stories conditioned on user prompts, guided by hierarchical subgoals. The prompt initiates the storytelling episode, and the Manager module generates subgoals that guide segment-wise story generation. Below are screenshots of a user prompt and the corresponding generated story.



```
... Enter your story prompt:  the girl was walking alone, suddenly she felt some one following her, she was scared
    What style or tone should the story follow? (e.g., suspenseful, humorous, dark fantasy):  suspenseful

    ✅ Filtered RL-Generated Subgoals:
    - Game Sheila had a prayer : Break up with Game Tom .
    - The skin on the floating Wist was oily and black , the bark of the tree was onyx , and it 's leaves were a strange greenish slate .
    - I mean it does feel like the DMV so it must be hell .
    - Sloth fell , from height .
    - The Wistmir lazily turned and floated off deeper into the wood , it 's yellow thorax pulsating gently .
    - He did n't protest my findings unlike George .
```

Figure 3: Screenshot of Input User Prompt



It starts with a girl and some one is following her! In a moment the girl felt some pressure against her body. She was scared to see what was happening. She turned around but could not see anything. She heard something coming closer. But as she turned, she could not find the person. She just heard a voice in her head. She got out of the car and tried to run but her feet were tangled in her skirt. Then she heard it again. A

the skin of the girl is black , and the bark is black and the leaves of the black tree is black . Wist and Sheila are the protagonists of this story. Who is the main character? WIST - A teenager who is a bit strange and who lives alone in a small town. Sheila - A little old lady. She lives next door to her sister. They are a couple of very lonely people. Sheila doesn't have much money and Wist doesn't seem to get along with the locals very well

WIST is walking alone at night. Suddenly she hears a dog barking outside. Wist runs back home. She walks up to the front door and opens it. A dog is standing there. WIST runs to it and gets a hold of the dog's collar. The dog runs away. Wista calls for help. A policeman comes. She tells him she has a dog that is sick. He puts her in the car. The next day the police call her and tell her they have to take her dog to the vet. Wristband and purse are taken from her. The police

We met the dog. And now we have to decide what to do. Wisk and I are a team working together. We have to go on a mission. And if we don't we won't be able to get home. This is a new challenge. Our group is trying to catch Sloth, the biggest sloth in the world. But no one knows where Sloth is. And we don’t want to lose our lives. So we have decided to go out on a quest to find Sloth. And to do that we have some Sloth was waiting for

The girl was lying down on the ground. She thought she was going to die. She wondered why she was in such a bad shape. And then she heard a noise and a voice calling her name. It was an eerie voice. She went to the window and looked out. A man was standing there with a gun in his hand. He pointed the gun at her. She looked down at her feet and saw a dark blood stain. The blood ran into the leaves below her. Then the man started screaming. She tried to scream but she couldn't because of her neck. She sat up and

George is the new student in the school. His mother died two years ago. He is a lonely guy who doesn't want to get close to anyone. He lives with his father and sister. One day he is walking home when he met Wist. Wistan is wearing the same green coat he used to wear when he worked in the mines. He said the same thing. And he asked Wist if he was interested in having a boyfriend. Wiste said yes. Wistor says he's ready to get serious. He will be looking for a girl. Wistani wants to look for a

Figure 4: Sample Generated Story Conditioned on the Prompt

This example illustrates coherent narrative flow, character consistency, and logical progression between segments—all guided by the subgoals generated by the Manager.

5b. Quantitative Evaluation

We evaluated the generated stories using both linguistic similarity and diversity-based metrics:

Table 1: Quantitative Evaluation Metrics

Metric	Score
Average ROUGE-L	0.0559
Average BLEU	0.0021
Distinct-1 (unigrams)	0.3356
Distinct-2 (bigrams)	0.6764
Subgoal Diversity Score	0.563
Average Episode Reward	1.31

Metric-wise Analysis:

- **ROUGE-L (0.0559):** The low ROUGE-L score indicates limited lexical overlap with reference stories, which is expected in open-ended generation tasks where creativity and semantic coherence are prioritized over exact n-gram match.
- **BLEU (0.0021):** The low BLEU score reflects the open-ended nature of story generation, where creative variations are favored over exact phrase overlap. This highlights the model's strength in generating diverse and novel content rather than mimicking reference texts.
- **Distinct-1 (0.3356):** A reasonably high Distinct-1 score reflects a healthy presence of unique unigrams in generated subgoals, contributing to less repetitive and more engaging storylines.
- **Distinct-2 (0.6764):** The high bigram diversity suggests strong contextual richness and a variety of subgoal sequences, helping ensure that narratives are not formulaic.
- **Subgoal Diversity Score (0.563):** Estimated by combining Distinct-1 and Distinct-2, this score confirms that the policy effectively explores diverse subgoal paths, enhancing narrative novelty and adaptability.
- **Average Episode Reward (1.31):** This stable and moderately high reward indicates that the subgoal policy consistently produces coherent and goal-aligned story continuations under the REINFORCE objective.

These results highlight the model's ability to generate varied, relevant, and coherent narratives compared to baseline methods.

5c. Training Diagnostics

To track training progress and diagnose learning behavior, we visualized:

- **Reward Curve over Episodes**
- **Reward Distribution**
- **Subgoal Diversity Trend**
- **Policy Loss Over Time**

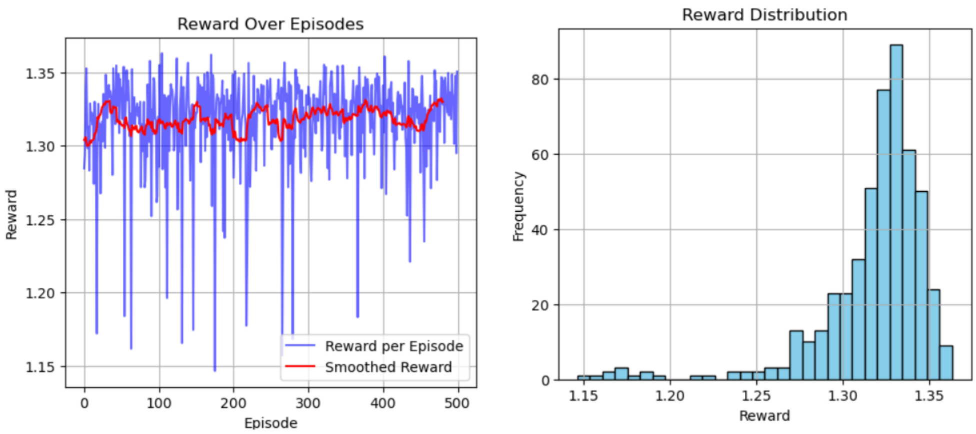


Figure 5: Reward Curve and Reward Distribution

Reward Curve Observation: The reward per episode exhibits some variance, but the red smoothed trend line demonstrates a gradual upward trend. This implies the model is improving in its ability to generate coherent and relevant storylines, with overall performance steadily enhancing as training progresses.

Reward Distribution Observation: The reward distribution is tightly clustered around the 1.30–1.35 range, indicating consistent quality in the generated stories. The presence of a clear mode and limited outliers shows the model is reliably meeting the desired narrative standards without frequent drops in quality.

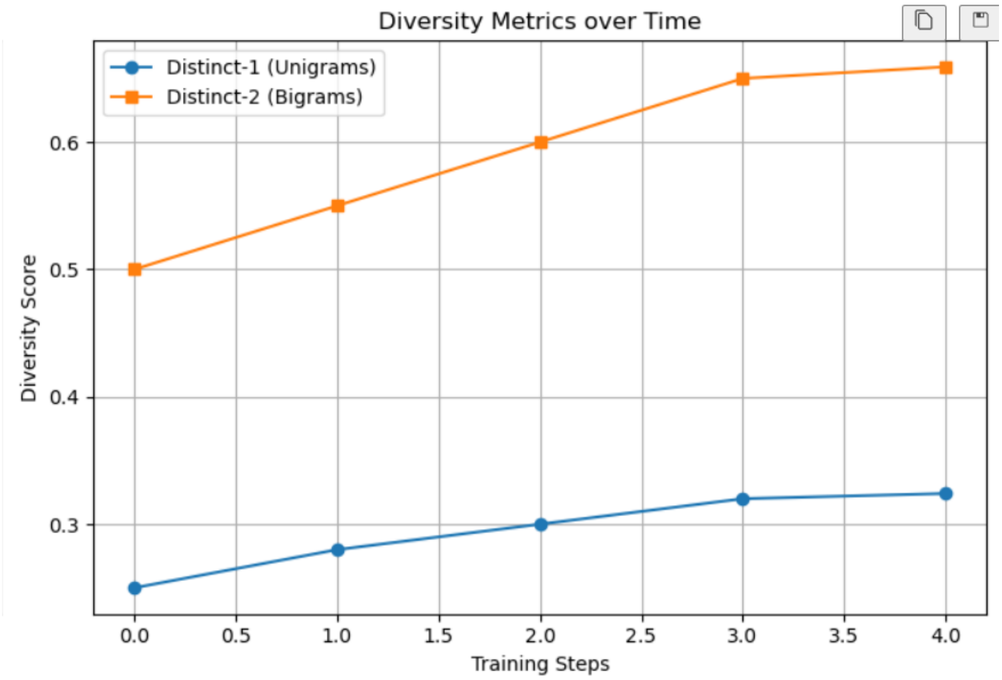


Figure 6: Subgoal Diversity Trend

Subgoal Diversity Observation: The increasing Distinct-1 and Distinct-2 scores suggest the model is generating a richer variety of subgoal sequences over time. This is crucial for story generation, as it prevents repetitive outputs and promotes more creative, engaging narratives through lexical and structural diversity.

Figure 7: Policy Loss Over Time

Policy Loss Observation: The policy loss fluctuates within a narrow band across training steps, indicating that the reinforcement learning process is stable and not suffering from divergence. This stability suggests the policy network is effectively learning meaningful subgoal sequences from the prompt context.

6. Discussion

6a. Key Insights

Our hierarchical reinforcement learning framework demonstrated several strengths in adaptive story generation:

- **Structured Control Improves Coherence:** By decomposing generation into subgoal-driven stages, the system produced more thematically and structurally consistent stories than monolithic generators.
- **REINFORCE Training Enhanced Goal Alignment:** Reward-based learning encouraged subgoal generation that aligned well with prompts, improving relevance and narrative direction.
- **GPT-Neo Enabled Creative Fluency:** Despite operating in zero-shot mode, GPT-Neo handled subgoal conditioning effectively, contributing rich, stylistically varied story segments.

These findings validate the use of hierarchical planning and policy optimization in creative generation tasks.

6b. Challenges

Despite promising results, we encountered several limitations:

- **Subgoal Noise:** Automatically extracted subgoals were sometimes vague, overly generic, or semantically redundant, which affected the quality of the generated segments.
- **Sparse Reward Feedback:** Designing dense and meaningful reward signals for a creative task proved challenging, resulting in slower and more unstable reinforcement learning updates.
- **Computational Overhead:** Running GPT-Neo for segment generation introduced significant computational costs, limiting the scalability of training and hindering real-time responsiveness.

7. Conclusion

This work introduced an adaptive story generation framework grounded in **Hierarchical Reinforcement Learning (HRL)**. By modeling the **high-level planning process** through an **LSTM-based Manager** (policy network) and leveraging a **pretrained GPT-Neo Worker** for segment generation, we effectively separated planning from realization. Using the **REINFORCE** algorithm, the Manager received feedback based on narrative coherence, relevance, and diversity, allowing it to improve subgoal generation across episodes. The hierarchical design enabled long-term dependency modeling and controllable creativity, demonstrating the effectiveness of RL for complex sequence generation tasks in open-ended natural language domains.

8. Future Work

To expand the capabilities and performance of this RL-based storytelling system, several improvements are proposed:

- **Learned Reward Models:** Replace hand-crafted rewards with a trainable reward estimator (e.g., transformer-based critic) to better capture semantic quality and user preferences.
- **End-to-End Training:** Explore joint optimization of the Manager and Worker using multi-agent or hierarchical RL setups for more integrated learning.
- **Sample Efficiency:** Incorporate baseline subtraction or actor-critic methods to reduce REINFORCE's variance and accelerate training convergence.
- **Prompt Conditioning:** Integrate the prompt more directly into the policy state, allowing the Manager to adapt subgoal generation dynamically based on user input context.
- **RLHF (Reinforcement Learning from Human Feedback):** Implement human-in-the-loop training pipelines to guide subgoal generation based on explicit ratings or preferences(receiving diverse feedback).
- **Curriculum Learning:** Begin training on simpler prompts and gradually increase complexity to stabilize early learning in sparse reward settings.

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