Fact-in-a-Box: Hiding Educational Facts in Short Stories for Implicit Learning

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Abstract: Generating stories on-demand is one of the covered tasks in Natural Language Generation. Stories are being used in every culture by any age. They have been used for different purposes, such as entertainment and the education of children. They are an effective way of indirectly providing students with valuable facts that are easier embedded in their memory. We propose an approach for embedding facts into existing or automatically generated stories, given a specific target audience and a story context. As proof of concept, we implemented a framework called Fact-in-a-Box to hide facts in existing stories or a human-like generated text through a customized user. The framework is based on a fine-tuned model for children as the target audience and fixes the story context to animals. Instructors can apply the approach to deliver facts to the learner in an exciting yet informative way. The framework is composed of two modules, one for selecting the most relevant story and the other one to embed the fact in it. We tested the proposed approach using an experiment to test the learning gain of children and a survey for adults to evaluate the language of the resulting stories and the concept itself. The performance was relatively good in hiding facts inside an existing story where children could correctly re-convey 50% of the complex facts and 80% of the simpler tasks.

1 INTRODUCTION

Natural Language Generation (NLG) covers a wide range of diverse tasks, including generating stories on-demand, providing endless possibilities for entertainment and education. Intelligent tutoring systems can provide students with instant feedback, increasing education quality. Stories are an effective way of indirectly providing students with valuable facts that are easier embedded in their memory. They are used in classrooms to promote critical thinking and enhance learning (Alhussain and Azmi, 2021). NLG can be a more cost-effective tool than hiring authors to write informative yet interesting tales for kids.

We propose an approach for embedding preselected facts into existing or automatically generated stories, given a specific target audience and a story context. Our main goal was to be able to implicitly hide and deliver knowledge or facts without the conscious awareness of the target audience. Pre-trained models like Generative Pre-trained Transformer (GPT) 2 (Radford et al., 2019), and 3 (Brown et al., 2020) are used to fine-tune the involved downstream NLG tasks and obtain accurate results based on the intended context. We rely on pre-trained transformer-based models to overcome the shortcomings of Seq2Seq, RNN, and LSTM for maintaining the coherence and story flow. As proof of concept, we implement a fine-tuned model for children as the target audience and fix the story context to animals. Further modifications were done to enhance the model to make conditional text predictions based on the user's selection. As proof of concept, we implement our approach into a framework called Fact-in-a-Box, to hide facts in existing stories or a human-like generated text through a customized user interface based on the target audience and the specified context. The framework contains two interaction modes one for the educator responsible for content creation and one for the student for receiving implicit learning.

To embed a fact in a story, the framework is divided into two modules. The first module is a *Base Story Selector*; it contains existing stories and can generate new stories. The latter task is not the focus of this presented paper. It takes as input the fact from the user and selects from the available/generated stories the most relevant to it. The selection approach is

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applied using TF-ID (Salton, 1983), and Cosine Similarity (Pang-Ning et al., 2005) methods. The second module is the *Fact Embedder*, which selects the best position for adding the fact in the selected story. Cosine Similarity is used to calculate the similarity between the story sentences and the fact.

Given the fact list and their intended context as input, the framework produces the output story text with the information embedded. This work demonstrates how beneficial combining NLG and fact embedding may be in the education domain. The proposed project goes beyond animal-based stories directed at children and expands to educational and training systems. Instructors can apply the approach to deliver facts to the learner in an exciting yet informative way. We tested the proposed approach in two phases: 1) an experiment to test the learning gain of 5 children and 2) a survey for 40 adults to evaluate the language of the resulting stories and the concept itself. The proposed framework performance was relatively good in hiding facts inside an existing story where children could correctly re-convey 50% of the complex facts and 80% of the simpler tasks. The proposed approach can be expanded to a broader domain by using more complex stories than children's stories to reach a broader audience.

Several works are done regarding story generation that can be found in (Alhussain and Azmi, 2021) On the other hand, there are lots of approaches for unconventional learning mediums to accompany traditional face-to-face classes and computer-assisted learning (Akturk, 2022). These include gamification (Nadi-Ravandi and Batooli, 2022), online learning (Mastan et al., 2022), immersive learning (Bizami et al., 2022), and indirect learning. Indirect learning is achieved when knowledge is acquired by watching a movie, reading a book, or doing a seemingly daily life activity. While indirect learning can happen unintentionally, it can be harnessed by developing educational systems that intentionally convey implicit knowledge through the chosen mediums. Different use-cases for this implicit learning have been investigated. For example, movies are used for STEM education (Kangas et al., 2017), language education (Obloberdiyevna and Odilkhonovna, 2022), soft skills (Belda-Medina, 2022), and physical education (Fu et al., 2022), to name a few. (Faidley, 2021) explores education through different pop culture mediums, e.g., movies, tv shows, and memes. Storytelling has always been used as a tool for teaching language and morals by both caregivers and educators (Abdalrahman, 2022; Purnama et al., 2022; Nicolaou, 2023; Ratih et al., 2022; Hofman-Bergholm, 2023; Quah and Ng, 2022).



Figure 1: Overview of the Fact-in-a-Box Story Generation.

In this work, we focus on providing a generic tool for automatically generating indirect learning material to intentionally convey information to learners in an implicit manner in the form of short stories.

2 FACT-IN-A-BOX OVERVIEW

Hiding information inside an existing or generated text is challenging as many variables should be taken care of otherwise, the text would not make any sense. Our proposed framework enables the problem of embedding words or hiding information within an already-existing story or a newly generated story. Fig. 1 gives an overview of the proposed architecture. Given the chosen input facts to be learned, a story is selected. The facts are then embedded in an appropriate location inside the story based on two scoring criteria. We will go into the details of each of the two main modules in the following.

2.1 Base Story Selector

There are two approaches to choosing a story to use as a basis for embedding the facts. We can either generate a story from scratch based on the input facts or choose existing stories to embed the facts. The former is a pure NLG approach requiring heavy computational power and story tuning. The latter benefits from relying on existing stories adhering to the plot generation rules of stories. When depending on existing stories, the challenge is choosing a suitable story to match the facts. While the authors also investigate generating stories using GPT-2, in the presented work, we focus on choosing a fitting story from a database of existing stories. We categorize the global dataset into smaller topically-clustered and difficultyclustered datasets. We have different datasets for stories about animals, crimes, fairytales, etc., and other datasets for young children's stories, teenagers, and adults¹. We rely on two metrics to choose a matching story based on the input prompt from the story database: TF-IDF and cosine similarity.

Before applying the TF-IDF technique, we cleaned the text by removing extra white spaces, converting all the text into lowercase, removing digits, and removing stop words. Lastly, we added the stemming of the words, which is the process of converting similar words into a single word, e.g., running and runs would be converted to run. This improves the calculations of the TF-IDF function to focus on the essential parts only rather than calculating misleading information and preventing the function from diverging from the critical information. Then after passing the list of inputs, each input is passed into the TF-IDF function with each story, and the maximum probability score is chosen. This score resembles the most likely fitting story for the input fact. This process is repeated for the rest of the inputs. Also, the highest-scoring story appearing for each input is chosen as the story to embed these facts in. The other approach is similar to TF-IDF but applies cosine similarity instead. We are trying to find a matching story that would make our input fit in the sentence without being placed incorrectly and without affecting the story's flow and the text's coherence. For this reason, we propose another way to find the matching story by calculating the cosine similarity scores for each input with every sentence in the story. We first split our story into a list of sentences. The function is then calculated by encoding each sentence to have them as vectors so that the function can be applied. Accordingly, the score is calculated for each input n times where n is the number of sentences in a story. We calculate a list of probabilities that we sum for each story. We pick the highest probability scores to find the most fitting stories in our dataset. Then, we calculate the total score for each fact from our input and store it for each story, respectively. The final stage for picking the base story is choosing a story randomly from the list of highest probabilities. This ensures different outputs every time the story generator is run and avoids producing repetitive, boring results.

2.2 Fact Embedder

The Fact Embedder is responsible for choosing appropriate locations within the base story to embed the different facts. This is done by relying on the cosine similarity lists already calculated by the Base Story Selector. Each sentence in the story is encoded, and we generate a combined list of cosine similarities between every sentence in the story and each input fact. This yields a list of probability scores for each input fact. We then randomly choose one of the maximum three scores for each fact. Again, this is to ensure non-determinism and enable different generated stories. The same fact-embedding approach is applied when inserting facts into auto-generated new stories.

3 FACT-IN-A-BOX DESIGN

Fact-in-a-Box in a box was designed in a simple manner. The aim of the initial prototype was not to introduce any design elements that might affect the results of measuring the learning gain from the embedded facts.

3.1 User Interface and Features

The developed user interface is a web application with two different interaction modes: an educator mode for content creation and a student mode for indirect or implicit learning. In the following, we will discuss each mode's different features/views.

Educator Mode - Content Creation

The Educator Mode consists of three main views: Story Selection, Fact Input, and Story Browsing. Story Selection is an optional feature. Educators can use it to choose a specific story from the dataset or upload their own story as the base story for the fact embedding. This step can be skipped if a story should be automatically selected. The Fact Input of Fact-in-a-Box is shown in Fig 2. Educators can input the four facts they want to teach learners. The educator should also specify the protagonist animal to improve the base story selection process. After confirming, the facts are used as a basis for selecting the base story or the educator's input story. The Fact Embedder then inserts the facts in the suitable locations in the story before displaying the generated story in the Story Browsing view. In this view, the facts are highlighted for the educator to evaluate their location. The educator can then confirm the generated story or rerun the process.

¹https://libguides.stcc.edu/c.php?g=886516&p=6370592

Natural Lan	guage Generation For Hiding Learning Information
Fact 1:	
Fact 2:	
Fact 3:	
Fact 4:	
Select an Animal:	Boa 🗸
	Generate
	Story generation page

Figure 2: The Fact Input View of Fact-in-a-Box.

Student Mode - Indirect Learning

The *Student Mode* currently consists of the *Story Reading* view, where learners are presented with different stories the educator assigns. Students can switch between the different stories.

3.2 Implementation Details

The main aim was to implement a rapid prototype as a proof-of-concept to the proposed idea of fact hiding for implicit learning. Thus, we implemented a basic architecture for the proposed approach relying on readily available and easy-to-use tools. We used Python and Google Colaboratory to build the backend of Fact-in-a-Box, and Flask API² to build the web app. Flask is a Python-based microweb framework. Flask is classified as a micro-framework since it does not require using specific tools or libraries. It lacks a database abstraction layer, form validation, or other components relying on pre-existing third-party libraries to perform common operations. Thus, Flask is used for building the UI that links with the back-end code rather than using other frameworks that might slow down the story generation process in Google Colab's environment. We are using it for both our generation and running the server. We used Ngrok³ to host the local webserver to the internet.

4 EVALUATION AND EXPERIMENT

Our goal was to hide some facts regarding a specific topic in a story to help a specific group of individu-

als better retain the information. We wanted to evaluate whether our approaches yield the intended results of giving information to individuals without explicitly mentioning them and without giving the users the feeling that they are on a learning endeavor. As proof of concept, we chose to test our Fact-in-a-Box approach on the target group of young children, i.e., generating stories with easy difficulty. Children were chosen as they are the most obvious target group for such a tool, especially in its initial phases. Children have an amazing capacity for retaining knowledge and, at the same time, are the most adverse age group to sitting and receiving it (Chau, 2008). As we are dealing with children, we decided to constrain the target information to be learned to four facts. We restrict the global story dataset to stories topically related to animals. The already existing stories were scraped "Folklore and Mythology Electronic Texts" (Ashliman, 1996) that were all related to animals to test the model for only one domain. All scraped books were cleaned, filtered, and processed.

4.1 **Pilot Experiment**

We experimented with measuring the children's ability to recall the information they read in the story and how much information they could retain. We also tested their ability to explicitly state the facts we embedded inside the story.

4.1.1 Experiment Design and Setup

The experiment aimed to give clear insights into children's perceptions of the application. Accordingly, we choose a small sample size for this initial evaluation. We invited 9 children ages seven and nine. We needed to evaluate their reading ability before starting the experiment, and this was crucial to ensure they could extract and understand knowledge from reading texts to conduct our experiment. Four children did not meet this criterion and were thus excluded from the experiment.

After that, each child was given the same three generated stories to read. Each of the stories had four facts, but they had variable lengths. The order of the three stories was counterbalanced in a Latin square manner. The experiment consisted of four question groups that serve as evaluation metrics. (1) A regular post-test to measure the learning gain of the children from the story with respect to the intended learning facts. Each child is given the same two questions about the facts embedded in the three stories. (2) Children were asked for three facts they learned from the story about the protagonist's animal to evaluate how well they recognized the included facts. (3) Mislead-

²https://flask.palletsprojects.com/en/2.2.x/

³https://ngrok.com/



Figure 3: S_1 with the input facts highlighted.

ing information contradicting the story's context was embedded in one of the cases to see whether the children would retain it or not. This helped us understand whether the proposed model can influence the children's judgment of the story.

4.1.2 Results

We will present the three generated stories, S_1 , S_2 , and S_3 , with their learning facts, the post-test questions, and the results of the experiment on this story. The input facts are highlighted in the generated stories to display where the model predicted and embedded each fact. The model outputs a story that revolves around a specific protagonist animal: elephants, kangaroos, and lions, respectively.

- 1. The generated story S_1 is shown in Fig. 3. The following post-test questions were asked:
 - "Do you find elephants gentle creatures?": The reason behind asking this question is that the context of the story implies that elephants were causing harm to rabbits. However, we mentioned in our facts that elephants were kind, so we wanted to see if the effect of our input as it was placed by the model early at the beginning of the story would influence the children's understanding.
 - "Do Elephants feed on grass?": This question was clear as we needed to measure how well the children retained the relatively easy question or will they encounter difficulty.
 - "Mention three facts about the elephant from the story you have just read.": Here, we are trying to estimate how much information the child can understand and receive from our input.



Figure 4: S_2 with the input facts highlighted.

To analyze the results of the answers to the survey questions of the S_1 , we investigated the children who said" No" to specific questions. We found that the reason for answering" No" in the first story was the story's context, describing elephants in a way that they harmed another animal (rabbit). Hence, the answer was" No", as the elephant hurts another animal, so it cannot be gentle. The second question was easy, and all the kids scored correctly except for one. When we investigated the results of the first question, we found that the story had already mentioned that" elephants eat leaves" before we stated that" elephants eat grass". Almost every child stated that" elephants are huge" and that" the elephants drink a lot of water". Still, although four facts were embedded in the story, all the children could not state three facts and only recalled two.

- 2. The generated story S_2 is shown in Fig. 4. The following post-test questions were asked:
 - "Are Kangaroos adapted to hot environment?": This question was fairly indirect to ask the children; however, we needed to see how well they answered this question to measure their ability to capture the information if it has been stated at a higher linguistic level.
 - "What do Kangaroos feed on?": This question was clear as we needed to measure how well the children retained the relatively easy question or will they encounter difficulty.
 - "Mention three facts about the Kangaroos from the story you have just read.": Here, we are trying to estimate how much information the child can understand and receive from our input.

As expected in the answers to the survey questions of the second story, no child could answer the first question, but all children easily managed to answer the second.

- 3. The generated story S_2 is shown in Fig. 4. The following post-test questions were asked:
 - "Is the lion the king of the forest": We wanted to investigate the children's ability to receive in-

Г	One afternoon, a Lion had just finished his meal and decided to take his afternoon nap a <mark>s lions</mark>				
L	sleep a lot . The Lion had just closed his eyes, when a Gnat saw him Now, this Gnat, though				
L	active and young, was also haughty and over-confident He was extremely daring and he				
L	attacked the Lion The Lion was very angry and woke up with a start But the Gnat did not stop				
L	He kept stinging the Lion's nose, eyes and ears The Lion roared in pain He tried to crush the				
L	Gnat but all his attempts went in vain The Gnat had no pity on the poor beast as the lions is				
L	strong At last, the poor Lion la exhausted and bleeding on the ground <mark>because the lion is the</mark>				
L	king of the jungle. The Gnat, extremely pleased on his victory over the King of the Forest,				
L	hovered over the spot, praising himself and feeling joyful <mark>as the lion is fearless</mark> His pleasure				
L	blinded him so much, that while flying, he suddenly got stuck in a Spider-web No matter how				
L	much he tried, the Gnat could not escape Thus, the Gnat who had defeated the mighty Lion				
	became the prey of the Spider				

Figure 5: S_3 with the input facts highlighted.

formation from our model when they received a relatively straightforward fact.

- "Is the lion powerful?": This question contradicts the story's context, where the lion was defeated by another animal. Still, we wanted to check if the child could see the lion as powerful and if it would affect his judgment.
- "Mention three facts about the lion from the story you have just read.": Here, we are trying to estimate how much information the child can understand and receive from our input.

The first question got three "No" answers. The reasoning behind Child 2's answer was that the lion was defeated in the story by the Gnat; hence it is not powerful. Same for Child 4 and 5 mentioned that the lion could not stop the Gnat. This left only 2 children with "Yes", supporting our claim that implicitly affecting the children's decisions, lets them obtain information that is not accurate. All the children could identify that" the lion is the king of the forest" in the second question we asked them. Finally, we received an average of two facts out of the 3 for all the children.

The pilot experiment results showed that all the children could identify at least two out of four facts in each story. And they received clear and mentioned facts with a rate of up to 80 percent. Accordingly, we found that we could involve false information to the children, and around 50% were able to verify its authenticity even though it conflicted with the actual storyline. Finally, The linguistic difficulty of the sentences greatly affected the children's ability to answer the questions. This was yielded from the open-ended discussion conducted with the children after the experiment, where they pinpointed some sentences as too complicated.

4.2 Human Evaluation of Stories

Following the proposed approaches presented in (Sai et al., 2022), we also evaluated the generated stories using human evaluation. To test the quality of the generated stories, we surveyed a group of 40 adults. They

Table 1: Summary of the results of the subjective evaluation.

	(Q1)	(Q2)	(Q3)	(Q4)
S_1	40% very good (5) avg = 3.9	yes = 75%	yes = 85%	yes = 75%
S_2	42.5% very good (5) avg = 4.1	yes = 75%	yes = 85%	yes = 75%
S_3	42.5% very good (5) avg = 4.1	yes = 75%	yes = 85%	yes = 87.5%

were mainly asked to (Q1) evaluate the story's grammar (Likert scale from 1 (lowest) to 5), (Q2) whether there are repetitions in some places (yes/no), (Q3), whether a child will be able to identify the facts, and (Q4) whether they would read it to a child as it's a good source for learning facts. The summary of the results can be found in Table 1. S_3 surprisingly scored better in (Q4). The results strengthen the position of our approach and claim in being able to convey the hidden facts within the text, making it unnoticeable to the reader that there is something off or misplaced with the text he is reading without being to identify that a certain part of the text was hidden explicitly.

5 CONCLUSION

We have shown that NLG and story generation may be beneficial in domains like education and fact embedding. We implemented an approach to embed facts in related stories. We proposed a framework called Fact-in-a-Box as a proof of concept that contains two different interaction modes one for educators and one for students. It contains animal-based stories directed to children. The process starts by taking the fact as input from the educator and goes to the story selector module to select the most relevant story to it. The selection is done using two methods TF-IDF and Cosine Similarity. After the story is selected, the fact embedder module that adds the fact between the available sentences by selecting the best position. In the end, the generated story could be shown to the student. We tested our proposed approach by evaluating the learning gain of some students and conducted a survey for adults to evaluate the language of the resulting stories and the concept itself.

In the future, we want to apply more testing for the different modules of the application. In addition, we want to enhance the performance of the story generation module and include different domains. We will also add a quizzing module, where educators can define quizzes in the *Educator Mode*. In the *Student Mode*, students will then be able to take a quiz after reading a specific story, if a quiz is defined for it.

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