Generating Questions Automatically from Informational Text

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Abstract. Good readers ask themselves questions during reading. Our goal is to scaffold this self-questioning strategy automatically to help children in grades 1-3 understand informational text. In previous work, we showed that instruction for self-questioning can be generated for narrative text. This paper tests the generality of that approach by applying it to informational text. We describe the modifications required, and evaluate the approach on informational texts from Project LISTEN's Reading Tutor.

Keywords. Question generation, informational text, self-questioning, reading tutor, comprehension strategy instruction

Introduction

Good readers ask themselves questions during reading. Based on comprehension gains, self-questioning was the most effective reading comprehension strategy identified by the National Reading Panel [1]. So it would be useful for an intelligent tutor to automatically generate instruction for the self-questioning strategy to help students understand text. Ultimately we would like to generate effective self-questioning instruction automatically from any given text, focusing on children's text.

Previous work [2] used a two-step approach for generating instruction to model and scaffold the self-questioning strategy: first generate questions from the text, and then augment the questions into strategy instruction. It showed how to generate questions automatically from narrative text. Here we test the generality of that approach by extending it to another important genre: informational text.

Informational text is an important source of knowledge. Reading researchers have found that even young children can benefit from it, if taught the right strategy [3, 4].

Compared to narrative fiction, informational texts have different text structure and serve different reading goals [5]. For example, sentences (1) and (2) came from narrative and informational text, respectively.

(1) Peter thought it best to go away without speaking to the white cat.
(2) Rainbows are seen after it rains and the sun is out.

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As exemplified by sentence (1), narrative text involves characters, their behavior, and mental states that drive it. In contrast, informational text does not require characters. In addition, it places more emphasis on descriptions and explanations, which are often used to introduce objective phenomena, as in sentence (2).

The example below consists of a paragraph from the informational text “Life under the Sea Part 1 – the Meaning of Life,” followed by a question generated from the text.

Text: What does it mean to be “alive?” What is the difference, say, between an elephant and a boulder? This seems to be an obvious question but one that may be difficult to answer. All living things are not exactly alike. For example, not all living things breathe air, or have blood, or grow hair, like we do. Likewise, we can’t live under water like fish do.

Question: Why can’t we live under water like fish do?

The rest of this paper is organized as follows. Section 1 summarizes our previous work on question generation instruction from narrative text. Section 2 describes how we extend that work to handle informational text. Section 3 presents evaluation criteria and results. Section 4 discusses the generality and importance of the approach based on the evaluation results. Section 5 summarizes the contribution, lists some limitations of the approach, and points out future work.

1. Question generation for narratives

Our question generation task sits in the context of generating instruction for the reading comprehension strategy of self-questioning. The instruction includes four phases: describe, model, scaffold, and prompt the self-questioning strategy. Of these phases, modeling and scaffolding the strategy rely on question generation.

Previous work [2] described how to generate questions from narrative text and convert questions into modeling and scaffolding instruction. Given a piece of text, our question generation system transforms it into a situation model. The model of mental states is a partial simulation of the student’s own “theory of mind,” and thus the method creates a situation model of the textbase. A mental state expression (e.g., “think,” “regret”) indicates an opportunity to prompt strategy instruction. To model the self-questioning strategy for the student, the system transforms the sentence into a question, e.g., “Why did Peter think it best to go away without speaking to the white cat?” To scaffold the strategy, the system leads the student to construct a question by choosing a character, a question type, and a completer. For example,

Tutor: *Let’s make a question about ______ .*
(Peter; Mr. McGregor; the old mouse; the white cat)
Student: [The student chooses *Mr. McGregor* from an on-screen menu of 4 characters.]
Tutor: *Let’s ask a ___ (what; why; how) question.*
Student: [The student chooses *why*.]
Tutor: *Great! ‘Why’ questions can help you understand by making you think!*
Tutor: *Let’s complete your question: Why did Mr. McGregor ___ (try to put his foot upon Peter; try to find his way straight across the garden; think it best to go away without speaking to the white cat)?*

Student: [The student chooses *try to find his way straight across the garden*.]
Tutor: *I'm not sure Mr. McGregor tried to find his way straight across the garden. Would you like to try again?*

The character and completer choices are all extracted from the story. Constructible questions include system-generated questions and other combinations such as "How did Mr. McGregor try to put his foot upon Peter?" and "What did the white cat think?." "What" questions trigger different completers, not shown in the example.

How general is our question generation mechanism? We test it here by adapting it to informational text. We could not use exactly the same approach for informational text, because of its different text structure and vocabulary [6]. Therefore, we had to add knowledge to our question generation system to deal with two specific issues in informational text: the "where" of decisions about what sentences to use to generate questions; and the "how" of rules used for building the situation model, and question templates to map the text into questions.

2. Locating question opportunities in informational text

We generated questions of the same forms as for narrative text, and also of new forms.

2.1. Mental states in informational text

Our previous work relied on mental states to locate possible questioning points. By "mental states," we mean beliefs, states of knowledge, points of view, or suppositions. However, mental states are not as central in informational texts as in narrative texts, in terms of their role in understanding the main idea of the text. Using the same set of mental state expressions, we found that mental states occurred 1382 times in 162 narrative texts (8.5 mental expressions per text) from Project LISTEN's Reading Tutor [7] and 727 times in the 105 informational texts that we used as our training data (6.9 modal terms per text). This difference suggests that words and phrases indicating mental states occur more frequently in narrative text than in informational text, although the gap does not seem very big.

On the other hand, mental states may vary by text genre in terms of what relationships between clauses they represent (e.g., causal vs. coincidental vs. mood-setting). In narrative text, mental states are normally attached to a character in the story, as in "Peter thought." Moreover, mental states of a character tend to reveal the motivation of the character and thus are likely to indicate causal relationships to events involving the character. In contrast, informational text may not contain any character in the same sense as in narrative stories. However, it may still refer to agents' mental states (**boldfaced** here) as the motive force or result of some events or phenomena, e.g.:

(3) Fish have "noses" (called nares) that don't look anything like our own, yet their **purpose** is to smell chemicals in the water.

Informational text may also refer to mental states of people outside the text, such as the reader or author, e.g.:

(4) If you're an American citizen 18 years of age or older, you probably **think** you have the right to vote for presidential candidates in the national election.

Similarly, it may refer to beliefs of authoritative sources or the general public, e.g.:

(5) It is **thought** that they use this structure to detect prey, perhaps being able to distinguish the weak electrical signals given off by injured animals.

Thus mental state expressions appear in some – but not all – informational text.

2.2. Extension to other categories of question indicators in informational text

Based on our observations, we believe that using mental states as the only indicators of good questions will not suffice for informational text. Our criteria for selecting questioning indicators are that the indicator has to signal key information about the text and it should be feasible for an intelligent tutor to recognize and generate good questions. According to expert pedagogy, teaching text structure is important in comprehending informational text [e.g. 8, 9]. However, figuring out global text structure automatically is still an active research problem that has not been solved completely, so we started with discourse markers that indicate causal relationships (i.e., conditions and temporal context) and modality (i.e., possibility and necessity).

2.2.1. Causality: conditional and temporal contexts

Conditional and temporal context are very important in informational text. Compared to narratives, conditional context and temporal context in informational text are more likely to describe causation. For example, in sentence (2), the temporal expression “after it rains and the sun is out” describes a causal condition of the formation of a rainbow. Here is another example of conditional context (shown in **boldface**):

(6) **If humans removed all the kelp from the sea** soon all the other sea life would start to suffer as well.

To search for linguistic expressions that indicate conditional contexts, we enumerated 4 words and constructions we noticed in the training data as questioning points, namely “if,” “even if,” “only if,” and “as long as,” which occurred 37 times in the training data.

To find temporal expressions, we used the ASSERT semantic role labeler [10] to annotate the corpus. Then our system looks for expressions marked by the ARGM-TMP tag [11] for “temporal expression.” The system found 763 such temporal expressions in the training data. We noticed four kinds of temporal expressions in our training data: a general condition such as “after it rains and the sun is out,” a date or time such as “in 1999,” a duration of time such as “for several hours,” and a rhetorical relationship (at the same time) such as “while she was reading.” Here we focus only on the first type of temporal expression, which tends to indicate causality. To filter out the other three types of temporal expressions, we used regular expressions to detect dates, duration (i.e., started with the word “for”), and expressions that indicate things happening at the same time (i.e., started with the word “while”). We also noticed that some words about frequency such as “usually” and “sometimes” can lead to trivial “when”-questions, and they are often tagged individually with ARGM-TMP as in “[ARGM-TMP usually],” which is not as informative for our purpose of finding causality. To filter them out, we used a heuristic, namely ignore temporal expressions that contain only one word. This heuristic filtered out 35.8% (273) of the temporal expressions, yielding 490 questioning points about temporal contexts.

2.2.2. Linguistic modality: possibility and necessity

Linguistic modality such as possibility and necessity is also important in informational text. Linguistic modality is often expressed by auxiliary verbs. The most frequent auxiliary verbs can be hypothetical (e.g. "would"), predictive (e.g. "will"), or prescriptive (e.g. "should," "ought to," "must"). In sentence (7) below, the word "should" expresses goats' need for covered shelters. Thus a reasonable question to generate from this sentence is "Why should goats have covered shelters?"

(7) All goats **should** have covered shelters where they can escape the weather.

We identified 8 auxiliary verbs and constructions from the training data to extract modality patterns, including "would," "will," "should," "shall," "could," "ought to," "must" and "may." These constructions appeared 179 times in our training data.

2.3. Question generation process for informational text

Our system generates questions from the situation model, which it constructs using schema-building rules. The question generation system uses one rule for each type of target conditional, temporal or modality expression. Based on semantic categories of the target expressions, we defined 6 rules, which build various sub-contexts and store elements of statements in a situation model. For example, one schema-building rule for modeling temporal context can be paraphrased as "create a temporal context to store the when-statement; re-order existing temporal contexts based on time order."

We added 4 question templates to transform the information retrieved from situation models into questions. The question template for conditional context is "What would happen if <x>?" For temporal context, we used two templates: "When would <x>?" and "What happens <temporal-expression>?" For linguistic modality, we used "Why <auxiliary-verb> <x>?" Here <x> maps to semantic roles tagged with ARG0 (the agent), TARGET (the verb), ARG1 (the theme), and ARG2, if any. Since we aimed at questions about general conditions, which do not concern tense, we included auxiliary verbs such as "would" in the question templates. Therefore, we do not need morphology generation for verbs, as we did for narrative text questions. Table 1 shows questions generated from sentences (2), (6) and (7).

Table 1. Questions generated from temporal, conditional, and modality expressions.

Sentence number	Resulting question
(2)	a. When would rainbows be seen? b. What happens after it rains and the sun is out?
(6)	What would happen if humans removed all the kelp from the sea?
(7)	Why should all goats have covered shelters?

3. Results

We evaluated the quality of the generated questions by the same criteria we used for mental state questions, i.e., the question had to be grammatically correct and it had to make sense in the context of the text. These criteria describe plausible candidates that we considered worth showing to experts for review. To evaluate our approach, we used a separate set of 26 informational texts from the Reading Tutor as our test data, which did not overlap with the training data. The test data contained 444 sentences.

Table 2 summarizes the evaluation statistics and results. We hand-evaluated the questions in each of the three categories. To validate the evaluation result, we would have another rater and calculate inter-rater agreement.

Questions about conditional context can be classified into two kinds, depending on the semantic role of if-clauses. In the test data, three if-clauses turned out to be direct objects, as in "Scientists wondered **if meat-eating Tyrannosaurus rex had ever eaten Triceratops**." Others were adverbs, as in "**If humans removed all the kelp from the sea** soon all the other sea life would start to suffer as well." The implausible conditional questions were caused by unresolved coreference and ambiguity of "if" under different contexts. For example, the sentence "**If so**, then you have eaten kelp" resulted in an implausible question "What would happen if so?" by failing to resolve what "so" refers to. Also, some phrases like "as if" changed the meaning of "if" which in our case was defined to set a conditional context. The sentence "Sit beside a quiet pool of water and you'll soon see water striders skating as **if on ice**" resulted in the out-of-context question "What would happen if on ice?"

Questions about temporal information were rated lowest in terms of plausibility. 66.7% (20) of the implausible questions were due to parsing errors. For example, in the parsing result "If the pressure changes over a large area it can cause [ARG1 winds] to [TARGET blow] [ARGM-TMP in a huge circle]," the tagger erroneously tagged "in a huge circle" as a temporal expression, leading to the implausible question "What would happen when in a huge circle?" 33.3% (10) of the implausible questions came from undetected constructions that do not belong to the first type of temporal expressions, such as "at present" and "some day." For example, from the sentence "**At present** totem poles are sold to people who collect them and to museums," a question was "When would totem poles be sold to people who collect them and to museums?," which is not asking something that the sentence is intended to convey.

All the implausible modality questions we observed were caused by parsing errors (including coreference and negation errors). We use semantic roles as parameters to build the situation model, but sometimes the semantic roles are only partially tagged. For example, in "[ARG0 Skin cells] [ARGM-MOD must] [ARGM-DIS also] [TARGET make] [ARG1 sure] to keep harmful things out of the body," the incomplete semantic role labeling led to the partial question "Why must skin cells make sure?"

Table 2. Evaluation Results

Question type	Number of matched linguistic patterns	Number of generated questions	Percentage of plausible questions
Condition	15	15	86.7% (13/15)
Temporal information	44	88	65.9% (58/88)
Modality	33	77	87.0% (67/77)

4. Discussion

The goal of this paper is to extend our question generation approach for narrative fiction to handle informational text. This problem involves two issues: a) how well does the approach work on informational text? b) how much additional work does it take to extend question generation from narrative to informational text? Section 3 reported the quality of questions generated by the system. During the evaluation, we have noticed that some generated questions may not have explicit answers in the text, such as if-clauses as the direct object of a verb (e.g. "What would happen **if meat-eating Tyrannosaurus rex had ever eaten Triceratops**?"). This property makes the question itself interesting insofar as it gets the student to think about a possible result that could be caused by the condition, and the answers may not be obvious from the text. Similar to the case in narratives, the schema-building rules we used for informational text can be used for extracting answers and detecting questions with false premises, which is helpful for providing feedback to students in a complete instruction scenario. To adapt our approach to informational text, we kept the question generation process and same language technology tools, and we added three types of knowledge. Table 3 compares the knowledge we used for the two genres.

Generating good questions requires inference, which is a natural language understanding problem. We know that natural language understanding is "AI-complete" because of the inference problem. We do not attempt to solve the entire inference problem, but to identify some inferences that we know how to make. At the knowledge representation level, we built only partial situation models (i.e., about conditional and temporal context and modality). We looked for types of inferences that are feasible to extract and do not rely on world knowledge beyond the sentence (or story). The only information we needed for capturing important question indicators was knowledge of discourse markers such as if-constructions, temporal expressions, and auxiliary verbs.

Table 3. Comparison of question generation for informational text and narrative text.

Genre	**Linguistic patterns**	**Type of questions**	**Generation templates**
Narrative	mental state expressions	"What," "Why" and "How" questions about mental states	What did <character> <verb>?
			Why/How did <character> <verb> <complement>?
			Why was/were <character> <past-participle>?
Informational text	if-constructions	"What-would-happen-if" question about conditional context	What would happen if <x>?
	temporal expressions	"When-would-x-happen" question about temporal context	When would <x> happen?
		"What- happens-when" question about temporal context	What happens <temporal-expression>?
	auxiliary verbs	"Why" question about possibility and necessity	Why <auxiliary-verb> <x>?

5. Conclusion, Limitations and Future Work

In this paper, we tested the generality of our question generation approach by extending it to another genre: informational text. We described an approach to generate questions from informational text, which could then be used to generate modeling and scaffolding instruction for the reading comprehension strategy of self-questioning. We extended the question generation approach to informational text by adding three types of knowledge: a) discourse markers for locating opportunities for questions; b) schema-building rules for managing information in a situation model; c) question templates for converting information into questions. We proposed three types of questions for informational text: questions about conditional context, questions about temporal information, and questions about possibility and necessity. We also demonstrated how discourse markers, such as conjunctions and certain kinds of verbs, can be used as indicators of places to ask questions about text.

So far, we covered only three types of questions to generate from informational text. There are many other important features of informational text that can cause difficulty for young children, such as its non-linear text structure and implicit causality. In this paper, we explored discourse markers for causal implication. Future work includes extending the existing approach to include inference rules that can automatically discover implicit logical relationships in the text and build global text structures in order to generate other important questions (and their answers).

We showed the automatically generated questions from one example story to a reading expert for evaluation. Although the expert did not raise grammatical issues about the questions, she felt that most of them lacked pedagogical value. This result was surprising to us because the questions generated for narrative fiction had fared far better. In future work, we will try to find out what caused similar approaches to yield different pedagogical value in narrative fiction and informational text. We will also look for more educationally beneficial types of questions to generate.

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