Acquiring Commonsense Knowledge during Collaborative Storytelling

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Abstract. Conversational agents that engage children in collaborative storytelling need a collection of domain knowledge to formulate its responses. However, the current manual processes of collecting, annotating and extracting data from a corpus of unstructured text is time-consuming that often impedes the population of a knowledge base. An alternative is to design the agent as a teachable peer that can continuously learn from its human users. In this paper, we describe a storytelling agent that can expand its domain knowledge base by learning new assertions from its story-based conversation with children. We also use conversations as a means of validating the acquired knowledge. Results showed that the agent can achieve a recall value from 83% to 94% in extracting capabilities, property and instance relations while encountering difficulty in identifying assertions that describe the location of story events. Analysis of the conversation logs showed that the performance of the agent is affected by how children describe the characters and events in their stories.

1. Introduction
Knowledge acquisition (KA) refers to the extraction of knowledge from a data source to feed the information requirements of an NLP task, such as question-answering systems [1], dialogue or conversational systems [2, 3], and text understanding and generation. Decades of research in KA have seen the utilization of varying approaches, including crowdsourcing [4, 5], information and relation extraction [6, 7, 8, 9], and more recently, knowledge embeddings [10]. These are aimed at addressing the manual process of collecting, annotating and extracting data from a corpus of unstructured text which often impedes the population of a knowledge base or an ontology.

Ontology learning is a type of KA that applies (semi-) automatic construction approaches to provide software agents with semantic knowledge in a particular domain [11]. It includes extending an existing ontology by adding new binary semantic relations or assertions, resolving duplicates and revising incorrect assertions. Thus, acquiring knowledge to populate ontologies has been repeatedly described as a time-consuming effort and often left to knowledge engineers.

Everyday human-to-human communication is a means by which we can share knowledge with one another. Children can learn new concepts and their relations from storytelling. Much like how a child learns new concepts from stories, we can enable a software agent to continuously learn new knowledge from its conversations with children. The emergence of conversational interfaces pose an opportunity for software agents to acquire commonsense assertions from children’s input. Such unstructured text may contain useful knowledge about children’s perception of the world they live in and which software agents can use as leverage when engaging in collaborative storytelling with children.
In this paper, we present our work in expanding the ontology of a conversational storytelling agent (CSA) by learning new assertions from its dialogue with children. Section 2 provides an overview of commonsense ontology and CSA. While children’s input may be expressed in simple sentences, these still require correct sentence parsing to identify concepts and the type of semantic relation present in the text. Furthermore, in the process of extraction, the presence of duplicate and contradictory information cannot be avoided but should be properly handled [6]. Section 3 describes the identification, extraction and validation of assertions. Section 4 presents our results and findings, followed by lessons learned in acquiring commonsense knowledge through story-based conversations.

2. Related Works
A commonsense ontology contains concepts and relations that are relevant and make sense in a particular domain such as children’s stories. Following ConceptNet [12], knowledge is represented as a semantic network containing binary assertions of the form relation(concept1, concept2). Concepts are abstract or general ideas that can be classified according to semantic categories, namely entities, objects, locations, actions and attributes. In the context of storytelling, the semantic categories are used to model different real-world concepts that children are familiar with. These include story characters, places, objects, events and abstract ideas (emotions).

Ontology population is concerned with adding new assertions into the ontology for use in natural language processing tasks such as story generation. Of primary importance to ontology population is the set of semantic relations that can exist between two concepts. Among the 20+ relations defined in ConceptNet [13], a set of relations relevant to children’s stories include those that describe entities (isA, partOf, hasProperty, usedFor and locationOf) and event causality (capableOf, receiveAction and effectOf).

Extracting relations from documents is crucial to ontology population in order to provide the knowledge requirements for automated story generation and conversational interfaces [3, 14]. The ConceptNet ontology used in MakeBelieve [15] sourced its assertions through the Open Mind Common Sense (OMCS) project [13]. SUMO Stories [16] represented story elements such as characters, objects, location and events in the Suggested Upper Merged Ontology (SUMO) [17]. Story Sense [18] generates stories with blanks and uses children’s answers to gain new assertions that can be used to generate more stories. The work of [9] utilized a predefined set of relation extraction templates to extract conceptual relations from children’s stories.

In these works, they found that children’s narratives have various characteristics that affect the extraction quality and content of the ontology. OMCS [13] is crowdsourced from adults and may extract concepts that are not suitable for children. SUMO Stories [16] need to balance between what is truth and modeling fictional elements typically found in children’s stories. Story Sense [18] found that children may have their own sense of what can be considered as true in their imaginative story world. Samson [9] had to work with dialogues as these contain relevant information about the story plot, character relationships and event causality.

Conversational storytelling agents (CSA) can bring life to virtual environments by formulating interesting and engaging responses to human utterances [14, 19]. They can also provide assistance to children during the story construction process [20, 21]. During the collaboration, CSAs can play varying roles including facilitator, tutor, co-author and teachable peer. A teachable peer is a kind of a pedagogical agent where learning can be achieved by teaching others [22]. In this role, the CSA has the knowledge level of a younger peer, giving the child the responsibility to teach new concepts and clarify misconceptions of the agent regarding elements of the story. CSAs also employ dialogue moves to elicit details about story characters and events, and then provide feedback to acknowledge the child’s input, pumps to urge the child to expound on his/her input, and hints to help the child to formulate the next story text. These were adapted by [20] from the intelligent software tutor of [23].
3. Knowledge Acquisition
Knowledge acquisition aims to identify and extract new assertions of the form \( \text{relation}(\text{concept1}, \text{concept2}) \) from a child’s input and to store these into the ontology that serves as the CSA’s knowledge base. We present the design of the ontology and the knowledge acquisition process in this section.

3.1. Ontology Design
The ontology has two components: global and local ontology. The global ontology contains assertions from the work of [24] and crowdsourced assertions that have confidence scores above the set threshold. These assertions can be used by the CSA to contribute to storytelling by giving hints on possible story text.

The local ontology, shown in Table 1, acts as a temporary repository of new assertions. Each assertion has a corresponding confidence score (CS) which is initially set to 0. The score may increase or decrease during validation with children. The confidence score is the basis for deciding when an assertion can be moved to the global ontology. The ID indicates the source of the assertion and is tracked so that the child cannot participate in the validation of his/her own assertion.

| ID | Concept 1 | Relation       | Concept 2 | CS |
|----|-----------|----------------|-----------|----|
| 1  | laptop    | hasProperty    | black     | 0.3|
| 1  | grandmother | capableOf     | love      | 0.5|
| 2  | cake      | hasProperty    | big       | 0.1|

3.2. Acquisition Process
A conversation is comprised of a set of dialogue turns. The agent and the child take turns formulating an input or a response. The child can give four types of input, namely command to instruct the CSA to start or end the storytelling session, answer to respond to a question posed by the CSA, silence when the child does not know the answer or is stuck during storytelling, and story text. The agent then formulates corresponding dialogue moves (feedback, pump, hint) as a response to the child’s input.

As a teachable agent, the CSA leverages on the story text input to dynamically learn new assertions. Knowledge acquisition proceeds as follows (see Figure 1). When a child’s input has been identified as a story text, the CSA applies a set of patterns containing parts-of-speech tags and word dependencies to detect the presence of candidate semantic relations. Examples of these patterns are shown in Table 2.

Assertions are then extracted and compared against the local ontology. If the assertion already exist in the ontology, the corresponding confidence score is incremented by 1. Otherwise, the assertion is considered new and is added to the local ontology with a confidence score of 0.

3.3. Validation Process
Knowledge validation, shown in Figure 2, is performed using the suggestion and follow-up dialogue moves. The phrasing of these dialogues should give the impression that the agent is collaborating in the task by proposing story text embedded with one or more assertions that need to be validated. Given an input sentence \( S \), the agent selects a word \( w \) (where \( w \in S \) and \( \text{POS}(w) = \text{noun} \)) and uses this to perform the following query on the local ontology:
\((w, \text{relation}, \text{concept2})\) or \((\text{concept1}, \text{relation}, w)\)

The query result \(R\) is a set of assertions \(\{A_1, A_2, \ldots, A_n\}\) that contains \(w\) as one of the concepts. The CSA selects \(A_i\) (where \(A_i \in R\)) and formulates a suggested story text. For example, if \(w = \text{"baby"}\) and \(A_i = \text{capableOf(cry, baby)}\), the response is “What if ‘baby cries’?”

**Figure 1.** KA process to populate the local ontology. Orange nodes are new assertions from an input story text.

**Table 2.** Extraction patterns using both parts-of-speech tags and word dependencies.

| Relation     | Concept1 | Keyword | Concept2 |
|--------------|----------|---------|----------|
| isA          | nsubj    | be      | attr     |
| hasA         | nsubj    | have    | dobj     |
| capableOf    | nsubj    | aux     | ROOT     |
| capableOF    | nsubj    |         | ROOT     |
| capableOF    | ROOT     | agent   | pobj     |
| receivesAction | nsubjpass | auxpass | ROOT     |
| receivesAction | ROOT     | det     | dobj     |
| atLocation   | nsubj    | go      | advmod   |
| atLocation   | nsubj    | in | at  | pobj     |

**Figure 2.** KV process. Orange nodes are new assertions; gray nodes are moved from the local to the global ontology.
Table 3. Annotated template for generating a multi-assertion suggestion.

| Template | (1) (2) a (3) to make a (4). |
|----------|-------------------------------|
| Word     | capableOf(1, 2)               |
| Relations| receivesAction(3, 2), usedFor(3, 4) |
| Example  | capableOf(Peter, carve)       |
| Assertions| receivesAction(plane, carve), usedFor(plane, gift) |
| Text     | (Peter) (carved) a (plane) to make a (gift). |

A positive input from the child increases the confidence score for $A_i$. A negative input, however, triggers a follow-up dialogue move, specifically, “Why not? Don’t you like it or do you think it is wrong?” This is necessary to differentiate between an invalid assertion (from the child’s perspective) versus the child’s non-acceptance of the suggested story text to be included as part of his/her story. An invalid assertion merits a decrease in the corresponding confidence score, while a non-acceptance of the suggested story text does not effect its value.

A suggested story text can contain more than one assertion sourced from the ontology using an annotated template as shown in Table 3. An annotated template includes a set of word relations indicating the semantic relations between the numbered variables to be used in filling up the slots. This approach is adapted from [25]. The agent iterates through all the word relations and queries the ontology to find matching assertions until it can fill-up the template slots to generate a response. When the child gives a negative response to a multi-assertion suggestion, the CSA generates a follow-up dialogue that also contains multiple assertions as illustrated in Table 4. The child then selects which of the assertions, i.e., capableof(dog, study) or usedFor(book, study), is incorrect.

Table 4. An example log showing multiple assertions used in a follow-up dialogue.

| Turn | Agent | Child |
|------|-------|-------|
| 1    | What if the dog used book for study? | No |
| 2    | Why not? Don’t you like it or is it wrong? | Wrong |
| 3    | Which one is wrong? | A |
|      | A. Dog can study | |
|      | B. Book used for study | |
|      | C. All of them | |

4. Test Results
12 children who are between the age of 7 to 11 years old were invited to conduct a one-on-one storytelling session with the CSA. In this section, we present the test results that assess the CSA’s ability as a teachable agent by learning new assertions from children.

4.1. Knowledge Acquisition
To assess the performance of the CSA as a teachable peer, we measured its precision and recall values in extracting assertions from children’s inputs. The results are shown in Table 5. True positive (TP) refers to correct extraction of assertions, false positive (FP) refers to incorrect assertions and false negative (FN) are assertions that were not extracted. Given these, precision is computed as the number of correctly extracted assertions (TP) over the total number of extracted assertions (TP+FP). Recall is computed as the number of correctly extracted
Table 5. Performance results in extracting assertions from children’s input.

| Relation        | TP  | FP  | FN  | Precision   | Recall  | F-Score   |
|-----------------|-----|-----|-----|-------------|---------|-----------|
| isA             | 17  | 15  | 1   | 53.13%      | 94.44%  | 68.00%    |
| hasA            | 10  | 4   | 3   | 71.43%      | 76.92%  | 74.07%    |
| hasProperty     | 43  | 13  | 8   | 76.79%      | 84.31%  | 80.37%    |
| capableOf       | 46  | 26  | 9   | 63.89%      | 83.64%  | 72.44%    |
| atLocation      | 1   | 9   | 19  | 10.00%      | 5.00%   | 6.67%     |
| receivesAction  | 44  | 14  | 14  | 75.86%      | 75.86%  | 75.86%    |
| desires         | 0   | 0   | 2   | 0.00%       | 0.00%   | -         |
| instanceOf      | 12  | 1   | 42  | 92.31%      | 22.22%  | 35.72%    |
| usedFor         | 1   | 3   | 2   | 25.00%      | 33.33%  | 28.57%    |
| **Total**       | 174 | 85  | 100 |             |         |           |

The F-Score is the harmonic mean of the precision and recall values and is used to measure the accuracy of the test.

Stories that children share mostly revolve around entity (characters and objects) descriptions and actions. The agent’s corresponding responses using pumps such as “What happens next” and “Tell me more then” are specifically designed to elicit such story details. Story text expressed in subject-verb-object and adjective-noun phrases are then extracted as hasProperty, capableOf and receivesAction relations, thus their high recall and F-score values. In particular, the CSA performs well in extracting hasProperty (see Table 6).

Table 6. Sample story text with hasProperty relations.

| Line | Story Text                                    | Assertions                        |
|------|----------------------------------------------|-----------------------------------|
| 1    | harry is a dark little boy while cookie is a tall handsome man | [isA(harry, boy)]                 |
|      |                                              | [hasProperty(boy, dark)]          |
|      |                                              | [hasProperty(boy, little)]        |
|      |                                              | [isA(cookie, man)]                |
|      |                                              | [hasProperty(man, tall)]          |
|      |                                              | [hasProperty(man, handsome)]      |
| 2    | pepper and cookie are the smartest           | students in class                 |
|      |                                              | [isA(pepper, student)]            |
|      |                                              | [isA(cookie, student)]            |
|      |                                              | [hasProperty(student, smart)]     |
| 3    | students are mean to people who fail         | [hasProperty(student, mean)]      |

The low precision and recall values can be attributed to the different ways that children express their ideas and the presence of grammar errors in their story text. Misspellings, lack of punctuation marks and the use of common nouns as proper nouns can lead to incorrect POS tagging and dependency parsing by spaCy. The agent missed a number of named entities in the story of P12 shown in Table 6, such as pepper and cookie in line 2, which could be extracted as instanceOf(pepper, dog) and instanceOf(cookie, dog). This is because spaCy did not consider these common nouns as named entities. The agent also encountered difficulty in extracting atLocation relations using the extraction patterns in Table 2 with the lowest precision and recall values of 10% and 5%, respectively.

Another way to evaluate the CSA’s performance is by looking at the precision and recall values for each participant’s story, as shown in Table 7. P7 has the highest precision but the
Table 7. Precision and recall values in extracting assertions from participant’s story.

| Child | TP  | FP  | FN  | Precision   | Recall   | F-Score  |
|-------|-----|-----|-----|-------------|----------|----------|
| P1    | 2   | 3   | 1   | 40.00%      | 66.67%   | 50.55%   |
| P2    | 16  | 10  | 6   | 61.54%      | 72.73%   | 66.67%   |
| P3    | 5   | 2   | 2   | 71.43%      | 71.43%   | 71.43%   |
| P4    | 31  | 13  | 10  | 70.45%      | 75.61%   | 72.94%   |
| P5    | 10  | 2   | 2   | 83.33%      | 66.67%   | 74.07%   |
| P6    | 31  | 7   | 23  | 81.58%      | 57.41%   | 67.39%   |
| P7    | 2   | 0   | 11  | 100.00%     | 15.38%   | 26.66%   |
| P8    | 15  | 5   | 6   | 75.00%      | 71.43%   | 73.17%   |
| P9    | 11  | 10  | 9   | 52.38%      | 55.00%   | 53.66%   |
| P10   | 16  | 11  | 7   | 59.26%      | 69.57%   | 64.00%   |
| P11   | 10  | 7   | 18  | 58.82%      | 35.71%   | 44.44%   |
| P12   | 25  | 15  | 2   | 62.50%      | 92.59%   | 74.63%   |
| Total | 174 | 85  | 100 |             |          |          |

lowest recall. While the CSA did not commit any errors in extraction, it missed 11 sentences with candidate assertions which affected the recall value. A trace of the conversation log showed that P7 typed the whole story in a single dialogue turn:

Once upon a time, there was a mermaid named Janesa. she wished to become a human one day ... she was told to drink a potion at dawn. when she drank it she became a human! she met a prince and they got married after a week.

However, the agent extracted assertions only from the last sentence, `receivesAction(prince, meet)` and `instanceOf(week, date)`, and missed a number of candidate assertions such as `capableOf(wish, mermaid)`, `capableOf(drink, mermaid)` and `receivesAction(potion, drink)`.

4.2. Knowledge Validation

Validating crowdsourced knowledge is a crucial step in the knowledge acquisition task. To validate the crowdsourced assertions in its local ontology, the agent uses the `suggestion` and `follow-up` dialogue moves. To vary the types of responses, the CSA uses a weighted randomizer to calculate the ratio between the frequency of use of a dialogue move and the total number of dialogue turns made by the agent. As seen in Table 8, feedback and pumps are used more often, comprising nearly 90% of the agent’s dialogue turns. When the CSA cannot find an assertion from its local and global ontology for a given input word to fill-up an annotated template, it resorts to using general pumps ("Tell me more then") and specific pumps ("I don’t know much about ... Please help me learn more.").

Furthermore, only 29 (54.72%) of the total attempts by the agent to formulate a suggestion were realized as actual responses. Analysis of the logs showed that hints and suggestions often fail when the selected template requires more than one assertion. In the conversation logs of P5, P6 and P8, hints and suggestions were not used because the CSA encountered multiple failures during the session. When a failure occurs, the event chain and dialogue history are refreshed and the conversation has to start anew.

The last experiment aims to determine if the CSA is using assertions acquired from one child and validating this with another child. Two evidences were found in the logs shown in Table 9. In the first instance, the agent learned from P8 that a `dog` is `capableOf` performing the action `find`, which it validated by asking P11. In the second instance, the CSA learned from P4 that a `boy` can be located in the `countryside`, thus making the suggestion to P12.
Table 8. Frequency of use vis-a-vis CSA’s attempts to formulate the dialogue moves.

| Dialogue Move | Actual Use | Attempts |
|---------------|------------|----------|
|               | Count | Frequency | Total | Actual ÷ Attempt |
| Feedback      | 81    | 27.36%    | 119   | 68.06%           |
| General Pump  | 72    | 24.32%    | 72    | 100.00%          |
| Specific Pump | 100   | 33.78%    | 100   | 100.00%          |
| Hint          | 14    | 4.73%     | 43    | 32.56%           |
| Suggestion    | 29    | 9.80%     | 53    | 54.72%           |
| Total         | 296   | 100.00%   |        |                  |

Table 9. Excerpts of logs showing knowledge acquisition and validation across users.

| Child | Text | Assertion |
|-------|------|-----------|
| P8    | Child: ... and the dog found a human ... | [capableOf(dog, find)] |
| P11   | Child: (talks about dog) Agent: What if dog can find? | |
| P4    | Child: a boy living in a countryside loved ... | [atLocation(boy, countryside)] |
| P12   | Child: (talks about boy) Agent: What if boy was near countryside? | |

5. Conclusion

We presented the use of story-based conversations as a means for a conversational agent to acquire and to validate assertions from children. A two-level ontology is used to separate validated knowledge (global ontology) from newly acquired knowledge (local ontology) that are yet to undergo validation. The agent suggests story text as a means of soliciting confirmation from a child on the correctness of an assertion. The confidence score associated with an assertion in the local ontology is updated through this exchange and is also used to determine when an assertion can be moved to the global ontology. The resulting ontology is mostly comprised of assertions that describe story entities and their actions. These are represented by the relations hasProperty, capableOf and receivesAction. Variances in the linguistic and storytelling abilities of children led to F-score values ranging from 75% - 95% for the most common semantic relations. Low recall values for atLocation and instanceOf relations can be attributed to the difficulty in detecting locations and named entities from the input text.

Current research in neural conversational models are investigating the use of knowledge graphs to provide conversational agents with domain knowledge [2, 3, 14]. These can be explored as strategies to extract commonsense knowledge from children’s input text. Allowing children to provide explanations beyond the current “no” and “don’t like” responses to follow-up questions can also be explored as another avenue for enriching the local ontology.

While suggestions are the primary means by which the agent can validate the correctness of an assertion in its local ontology, our experiments show that only 55% of the attempted suggestion dialogue moves were realized as responses. This is due to the limited number of assertions in the ontology that can be used to fill-up the annotated response templates and the variances in the topics and themes of the stories that children share with the agent. Further experiments should therefore be conducted to expand the knowledge base with new assertions and to validate existing assertions.
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