CURIE: An Iterative Querying Approach for Reasoning About Situations

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Abstract

Recently, models have been shown to predict the effects of unexpected situations, e.g., would cloudy skies help or hinder plant growth? Given a context, the goal of such situational reasoning is to elicit the consequences of a new situation (st) that arises in that context. We propose a method to iteratively build a graph of relevant consequences explicitly in a structured situational graph (st graph) using natural language queries over a finetuned language model (M). Across multiple domains, CURIE generates st graphs that humans find relevant and meaningful in eliciting the consequences of a new situation. We show that st graphs generated by CURIE improve a situational reasoning end task (WIQA-QA) by 3 points on accuracy by simply augmenting their input with our generated situational graphs, especially for a hard subset that requires back-ground knowledge and multi-hop reasoning.

1 Introduction

A long-standing challenge in reasoning is to model the consequences of a novel situation in a context. Consider these questions - Would it rain more if we plant more trees?, or What would help water to boil faster? - answering these questions requires comprehending the complex events such as plant growth and water boiling, where much of the information remains implicit (by Grice’s maxim of quantity (Grice, 1975)), thus requiring inference.

Tasks that require situational reasoning are increasingly observed by machines deployed in the real world - unexpected situations are common, and machines are expected to gracefully handle them. It is also essential for tasks such as qualitative reasoning (Tandon et al., 2019; Tafjord et al., 2019a), physical commonsense reasoning tasks (Sap et al., 2019; Bisk et al., 2020), and defeasible inference (Rudinger et al., 2020). Unlike humans, machines are not adept at such reasoning.

Prior systems that address situational reasoning take as input a context providing background information, a situation (st), and an ending, and predict the reachability from st to that ending either in a classification setting (e.g., Tandon et al. (2019) grounds the path on at most two sentences in the context) or recently, in a story-generation setting (Qin et al., 2019), where the goal is to generate an alternate ending when the original ending and a counterfactual situation are given. However, generating effects of situations in real-world scenarios, where the ending is typically unknown is still an open challenge. We also might need st-reasoning capabilities across multiple domains (beyond stories). Further, multiple types of consequences to a situation might have to be generated (e.g., positive and negative impacts or eventual and immediate

Figure 1: RQ1: CURIE generates situational graphs through iterative queries to a model, making the model’s knowledge of influences explicit (above; positive, and negative influence) iteratively. RQ2: Such graphs can improve situational reasoning QA when added to the QA input (below, where the context is a passage about erosion).
impacts), which requires outputs in a structured form.

To address these limitations, we propose CURIE— a generation framework that generalizes multiple reasoning tasks under a general situational reasoning framework. The task is illustrated in Figure 1: given some context and just a situation st (short phrase), our framework generates a situational reasoning graph (st-graph). At its core, CURIE constructs a reasoning graph based on the contextual knowledge that supports the following kinds of reasoning:

1. If st occurs, what will happen imminently/ eventually?
2. If st occurs, which imminent/ eventual effect will not happen?
3. What will support/ prevent the st?

As shown in Figure 1, our approach to this task is to iteratively compile the answers to questions 1,2,3 to construct the st-graph. Compared to a freeform text output obtained from an out-of-the-box seq-to-seq model, our approach gives more control and flexibility over the graph generation process, including arbitrarily reasoning for any particular node in the graph. Downstream tasks that require reasoning about situations can compose natural language queries to construct a st-reasoning graph that can be simply augmented to their input. In this paper, we ask the following two research questions:

**RQ1** Given a specific context and situation, can we iteratively generate a situational reasoning graph of potential effects?

**RQ2** Can the st-graphs generated by CURIE improve performance at a downstream task?

In response, we make the following contributions:

(i.) We present CURIE, the first domain-agnostic situational reasoning framework that takes as input some context and an st and iteratively generates a situational reasoning graph (§2). We show that our framework is effective at situational reasoning across three datasets, as validated by human evaluation and automated metrics.

(ii.) We show that st graphs generated by CURIE improve a st-reasoning task (WIQA-QA) by 3 points on accuracy by simply augmenting their input with our generated situational graphs, especially for a hard subset that requires background knowledge and multi-hop reasoning (§4). (Table 2).

![Figure 2: CURIE framework consists of two components: (i) a formulation that adapts datasets that allow st-reasoning for pretraining (ii) a method to iteratively build structured st-graphs using natural language queries over a fine-tuned language model (M).](image)

2 CURIE for Situational Reasoning

CURIE provides both a general framework for situational reasoning and a method for constructing st-reasoning graphs from pretrained language models. The overall architecture of CURIE is shown in Figure 2. CURIE framework consists of two components: (i) st-reasoning task formulation : a formulation that adapts datasets that allow situational reasoning (ii) st-graph construction : a method to fine-tune language model M to generate the consequences of a situation and iteratively construct structured situational graphs (shown in figure 1). In this section, we present (i) our task formulation (§2.1), (ii) adapting existing datasets for CURIE task formulation (§2.2), (iii) the learning procedure (§2.3), and (iv) the st-graph generation via inference (§2.4).

2.1 Task Formulation

We describe the general task formulation for adapting pretraining language models to the st-reasoning task. Given a context $T = \{s_1, s_2, \ldots, s_N\}$ with $N$ sentences, and a situation $st$, our goal is to generate an st-graph $G$ in this changed world.

An st-graph $G(V, E)$ is an unweighted directed acyclic graph. A vertex $v \in V$ is an event or a state such that it describes a change to the original conditions in $T$. Each edge $e_{ij} \in E$ is labeled with an relationship $r_{ij}$, that indicates whether $v_i$ positively or negatively influences $v_j$. Positive influences are represented via green edges comprising one of $\{entails, strengthens, helps\}$ and negative influences represented via red edges that depict one of $\{contradicts, weakens, hurts\}$. Our relation set is general and can accommodate various st-reasoning tasks. Given two nodes $v_i, v_k \in V$, if a path from $v_i$ to $v_k$ has more than one edge, we describe the effect c as eventual and a direct effect as imminent.
We obtain the training data for st-graph generation by decomposing an st-graph into a set of question-answer pairs. Each question comprises of the context $T$, a st-vertex $v_s$, a relation $r$, and the nature of the effect $c$. The output is an answer to the question, that corresponds to the target node $v_t$. An example is shown in Figure 1. Compared to an end-to-end approach to graph generation, our approach gives more flexibility over the generation process, enabling reasoning for any chosen node in the graph.

### 2.2 Generalizing Existing Datasets

Despite theoretical advances, lack of large-scale general situational reasoning datasets presents a challenge to train seq-to-seq language models. In this section, we describe how we generalize existing diverse datasets towards st-reasoning towards finetuning a language model $M$. If a reasoning task allows a context, a st-situation and can describe the influence of $st$ in terms of green and/or red edges, it can be seamlessly adapted to CURIE framework. Due to lack of existing datasets that directly support our task formulation, adapt the following three diverse datasets - WIQA, QUAREL and DEFEASIBLE for CURIE.

**WIQA**: WIQA task studies the effect of a perturbation in a procedural text (Tandon et al., 2019). The context $T$ in WIQA is a procedural text describing a physical process, and $st$ is a perturbation i.e., an external situation deviating from $T$, and the effect of $st$ is either helps or hurts. An example of WIQA to st-formulation is shown in Table 1.

**QUAREL**: QUAREL dataset (Tafjord et al., 2019a) contains qualitative story questions where $T$ is a narrative, and the $st$ is a qualitative statement. $T$ and $st$ are also expressed in a simpler, logical form, which we make use of because it clearly highlights the reasoning challenge. The effect of $st$ is either entails or contradicts (example in Table 1).

**DEFEASIBLE**: The DEFEASIBLE reasoning task (Rudinger et al., 2020) studies inference in the pres-
To reiterate our task formulation (§2.1), for a given $y$-sequences We model the conditional probability $p(Y_1, ..., Y_K | X)$ as a series of conditional next token distributions parameterized by $\theta$: as $p_{\theta}(y_i | x_i) = \prod_{k=1}^{M} p_{\theta}(y_k | x_i, y_i^{1:i-1})$.

### 2.4 Inference to Decode st-graphs
The auto-regressive factorization of the language model $p_{\theta}$ allows us to efficiently generate target event influences for a given test input $x_i$.

The process of decoding begins by sampling the first token $y_i^1 \sim p_{\theta}(y_1 | x_i)$. The next token is then drawn by sampling $y_i^2 \sim p_{\theta}(y_2 | x_i, y_i^1)$. The process is repeated until a specified end-symbol token is drawn at the $K$-th step. We use nucleus sampling (Holtzman et al., 2019) in practice. The tokens $(y_i^1, y_i^2, ..., y_i^{K-1})$ are then returned as the generated answer. To generate the final st-reasoning graph $G$, we combine all the generated graphs with CURIE (GEN): generating st graphs with CURIE

**Given:** curie language model $\mathcal{M}$.

**Result:** st graph $G$ where the $i^{th}$ node will be generated with the relation $r_i$ and the effect type $c_i$.

**Init:** $G \leftarrow \emptyset$

**for** $i \leftarrow 1, 2, ..., N_Q$ **do**

// Create a query
$x_i = \text{concat}(T, st, r_i, c_i);$ // Sample a node from the

/* Sample a node from the

(language model $\mathcal{M}$ */

$y_i \sim \mathcal{M}(x_i);$

/* Add the sampled node

and the edge to the

graph */

$G = G \cup (r_i, c_i, y_i);$

end

**return** $G$

### Table 2: Overview of experiments

| Research question | Training dataset | Test dataset | Task | Metrics |
|-------------------|------------------|--------------|------|---------|
| Can we generate good st graphs? (§3) | WIQA-st, QUARREL-st, DEFEASIBLE-st | WIQA-st, QUARREL-st, DEFEASIBLE-st | generation | ROUGE, BLEU |
| Can we improve downstream tasks? (§4.1, §4.2) | WIQA-st, WIQA-QA | WIQA-QA | finetuned QA | accuracy |

**Algorithm 1: IterativeGraphGen**

**Given:** Context passage $T$, a situation $st$, a set $R = \{(r_i, c_i)\}_{i=1}^{N_Q}$ of $N_Q$ tuples.

**Result:** st graph $G$ where the $i^{th}$ node will be generated with the relation $r_i$ and the effect type $c_i$. **Init:** $G \leftarrow \emptyset$

**for** $i \leftarrow 1, 2, ..., N_Q$ **do**

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and the edge to the

graph */

$G = G \cup (r_i, c_i, y_i);$

end

**return** $G$

### Table 3: Dataset wise statistics, we maintain the splits

| Dataset     | train | dev  | test  |
|-------------|-------|------|-------|
| WIQA        | 119.2k| 34.8k| 34.8k |
| QUARREL     | 4.6k  | 1.3k | 652   |
| DEFEASIBLE  | 200k  | 14.9k| 15.4k |
answers \( \{y_i\}_{i=1}^{N_Q} \) that had the same context and st pair \((T, st)\) over all \((r, c)\) combinations. We can then use generated answer \(st'\in \{y_i\}_{i=1}^{N_Q}\) as a new input to \(M\) as \((T, st')\) to recursively expand the st-graph to arbitrary depth and structures (Algorithm 1). One such instance of using CURIE st graphs for a downstream QA task is shown in §4.

### 3 RQ1: Establishing Baselines for st-graph Generation

This section reports on the quality of the generated st reasoning graphs and establishes strong baseline scores for st-graph generation.

We use the datasets described in section §2.2 for our experiments.

#### 3.1 Baseline Language Models

To reiterate, CURIE is composed of (i) task formulation component and (ii) graph construction component, that uses a language model \(M\) to construct the st-graph. We want to emphasize that any language model architecture can be a candidate for \(M\). Since our st-task formulation is novel, we establish strong baselines for the choice of language model. Our experiments include large-scale language models (LSTM and pretrained transformer) with varying parameter size and pre-training, along with corresponding ablation studies. Our \(M\) choices are as follows:

**LSTM Seq-to-Seq:**

We train an LSTM (Hochreiter and Schmidhuber, 1997) based sequence to sequence model (Bahdanau et al., 2015) which uses global attention described in (Luong et al., 2015). We initialize the embedding layer with pre-trained 300 dimensional Glove (Pennington et al., 2014)\(^1\). We use 2 layers of LSTM encoder and decoder with a hidden size of 500. The encoder is bidirectional.

**GPT:** We use the original design of GPT (Radford et al., 2018) with 12 layers, 768-dimensional hidden states, and 12 attention heads.

**GPT-2:** We use the medium (355M) variant of GPT-2 (Radford et al., 2019) with 24 layers, 1024 hidden size, 16 attention heads.

For both GPT and GPT-2, we initialize the model with the pre-trained weights and use the implementation provided by Wolf et al. (2019).

#### 3.2 Automated Evaluation

To evaluate our generated st-graphs, we compare them with the gold-standard reference graphs.

To compare the two graphs, we first flatten both the reference graph and the st-graph as text sequences and then compute the overlap between them. We use the standard evaluation metrics BLEU (Papineni et al., 2002), and ROUGE (Lin, 2004)\(^2\).

Our results indicate that the task of st generation is challenging, and suggests that incorporating st-reasoning specific inductive biases might be beneficial. At the same time, Table 4 shows that even strong models like GPT-2 struggle on the st-graph generation task, leaving a lot of room for model improvements in the future.

We also show ablation results for the model with respect to the context \(T\) (§2.1), by fine-tuning without the context. We find that context is essential for performance for both GPT and GPT-2 (indicated with w/o \(T\) in Table 4).

Further, we note that the gains achieved by adding context are higher for GPT-2, hinting that larger models can more effectively utilize the context.

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1https://github.com/OpenNMT/OpenNMT-py

2We use Sharma et al. (2017) for calculating the overlap.

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Table 4: Generation results for CURIE with baselines for language model \(M\). We find that context is essential for performance (w/o \(T\)). We provide these baseline scores as a reference for future research.

| Model (\(M\)) | BLEU | ROUGE |
|---------------|------|-------|
| WIQA-st       |      |       |
| LSTM Seq-to-Seq | 7.51 | 18.71 |
| GPT \(\sim\)(w/o \(T\)) | 7.82 | 19.30 |
| GPT-2 \(\sim\)(w/o \(T\)) | 10.01 | 20.93 |
| GPT           | 9.95 | 19.64 |
| GPT-2         | **16.23** | **29.65** |
| QUAREL-st     |      |       |
| LSTM Seq-to-Seq | 13.05 | 24.76 |
| GPT \(\sim\)(w/o \(T\)) | 20.20 | 36.64 |
| GPT-2 \(\sim\)(w/o \(T\)) | 26.98 | 41.14 |
| GPT           | 25.48 | 42.87 |
| GPT-2         | **35.20** | **50.57** |
| DEFEASIBLE-st |      |       |
| LSTM Seq-to-Seq | 7.84  | 17.50 |
| GPT \(\sim\)(w/o \(T\)) | 9.91  | 20.63 |
| GPT-2 \(\sim\)(w/o \(T\)) | 9.17  | 9.43  |
| GPT           | 10.49 | 21.79 |
| GPT-2         | **10.52** | **21.19** |
3.3 Human Evaluation

| Task          | GPT-2 (w/o \(T\)) | GPT-2 | No Preference |
|---------------|---------------------|-------|---------------|
| Relevance     | 23.05               | 46.11 | 30.83         |
| Reference     | 11.67               | 31.94 | 56.39         |

Table 5: Results of human evaluation. The numbers show the percentage(%) of times a particular option was selected for each metric.

In addition to automated evaluation, we perform human evaluation on the ablation (GPT-2 - w/o \(T\) and GPT-2 models) to assess the quality of generations, and the importance of grounding generations in context. Three human judges annotated 120 unique samples for relevance and reference, described next. Both models (with and without context) produced grammatically fluent outputs without any noticeable differences.

Relevance: The annotators are provided with the input of a procedural text \(T\), the \(st\), and the relational questions. The output events generated by GPT-2 (w/o \(T\)) and GPT-2 are also provided in random order. The annotators were asked, “Which system (A or B) is more accurate relative to the background information given in the context?” They could also pick option C (no preference).

Comparison with true event (reference): We measure how accurately each system-generated event reflects the reference (true) event. Here, the annotators saw only the reference sentence and the outputs of two systems (A and B) in a randomized order. We asked the annotators, “Which system’s output is closest in meaning to the reference?” They could also pick the options A, B, or C (no preference).

For relevance and reference comparison tasks (Table 5), we present the percentage of the count of human judges for each of the three categories. The table illustrates that GPT-2 performs better than GPT-2 (w/o \(T\)) on both the metrics. Particularly, GPT-2 not only performs better than GPT-2 (w/o \(T\)) but also much better than the “No Preference” option in the relevance metric. This means that GPT-2 generates target events that logically follow the passage and source events. The reference and relevance task scores together show that GPT-2 does not generate target events that are exactly similar to the reference target events, but they are correct in the context of the passage and the source event. This can happen due to linguistic variation in the generation, as well as the ability of the source event to influence multiple target events in the context of the passage. We study this in more detail in the error analysis presented below.

3.4 Error Analysis

Table 6 shows the error analysis on 100 random samples from the validation set. We found that for about 26% of samples, the generated event influence had an exact match with the reference, and about 30% of the samples had no overlap with the reference (category Wrong in Table 6). We found that for 20% of the cases, the generated target event was correct but was expressed differently compared to the reference text (Linguistic Variability class in Table 6). Furthermore, we observed that in 17% of cases, the generated target event was not the same as the reference target event, but was relevant to the passage and the question, as shown in the Related Event category in Table 6. In 5% of the samples (Polarity), the model generates events with opposite polarity compared to the reference. A small fraction (2%) of samples had incorrect gold annotations.

3.5 Consistency Analysis

Finally, we measure if the generated \(st\)-graphs are consistent. Consider a path of length two in the generated \(st\)-graph (say, A \(\rightarrow\) B \(\rightarrow\) C). A consistent graph would have identical answers to what does A help eventually i.e., “C”, and what does B help imminently i.e., “C”. To analyze consistency, we manually evaluated 50 random generated length-two paths, selected from WIQA-\(st\) development set. We observed that 58% of the samples had consistent output w.r.t to the generated output. We also measure consistency w.r.t. the gold standard, and observe that the system output is about 48% consistent. Despite being trained on independent samples, our \(st\)-graphs show reasonable consistency and improving consistency further is an interesting future research direction.

3.6 Discussion

In summary, our task formulation allows adapting pretrained language models for generating \(st\)-graphs that humans find meaningful and relevant. Automated metrics show the utility of using large-scale models and grounding the \(st\)-graph generation in context. We establish multiple baselines with
We hypothesize that \( \text{CURIE} \) can augment \( c \) and \( e \) with their influences, giving a more comprehensive picture of the scenario compared to the context alone. We use \text{CURIE} trained on WIQA-\( st \) to augment the event influences in each sample in the QA task as additional context.

More concretely, we obtain the influence graphs for \( c \) and \( e \) by defining \( R_{\text{fwd}} \) \( \equiv \{ \text{helps, imminent}, \text{hurts, imminent} \} \) and \( R_{\text{rev}} \) \( \equiv \{ \text{helped by, imminent}, \text{hurt by, imminent} \} \), and using algorithm 1 as follows:

\[
G(c) = \text{IGEN}(T; c, R_{\text{fwd}})
\]
\[
G(e) = \text{IGEN}(T; e, R_{\text{rev}})
\]

We hypothesize that WIQA-\( st \) graphs are able to generate reasoning chains that connect \( c \) to \( e \), even if \( e \) is not an immediate consequence of \( c \). Following Tandon et al. (2019), we encode the input sequence \text{concat} \( (T, c, e) \) using the \text{BERT} encoder \( E \) (Devlin et al., 2019), and use the [CLS] token representation \( \hat{h}_c \) as our sequence representation.

We then use the same encoder \( E \) to encode the generated effects \text{concat} \( (G(c), G(e)) \), and use the [CLS] token to get a representation for augmented \( c \) and \( e \) (\( \hat{h}_a \)). Following the encoded inputs, we compute the final loss as: \( L = \alpha \times L_1 + \beta \times L_2 \), where \( L_1 \) and \( L_2 \) represent the logits from \( \hat{h}_c \) and \( \hat{h}_a \) respectively, and \( L_1 \) and \( L_2 \) are their corresponding cross-entropy losses. \( \alpha \) and \( \beta \) are hyperparameters that decide the contribution of the generated influence graphs and the procedural text to the loss. We set \( \alpha = 1 \) and \( \beta = 0.9 \) across experiments.

**QA Evaluation Results** Table 7 shows the accuracy of our method vs. the vanilla WIQA-BERT model by question type and number of hops between \( cf \) and \( e \). We also observe from Table 7 that

| Error Class       | Description                                      | % | Question                                                                 | Reference            | Predicted                  |
|-------------------|--------------------------------------------------|---|-------------------------------------------------------------------------|----------------------|----------------------------|
| Polarity          | The predicted polarity was wrong but event was correct | 5% | What does ‘oil fields over-used’ help at eventually? | there is not oil refined | more oil is refined         |
| Linguistic        | The output was a linguistic variant of the reference | 20% | What does ‘fewer rabbits will become pregnant’ hurts at imminently? | more rabbits | more babies |
| Related Event     | The output was related but different reference expected | 17% | What does you inhale more air from the outside hurts at imminently? | there will be less oxygen in your blood | you develop more blood clo-ts in your veins |
| Wrong             | The output was completely unrelated               | 30% | What does ‘less nutrients for plants’ hurt at eventually? | more plants | more wine being produced |
| Erroneous Reference | The gold annotations were erroneous                | 2%  | What does ‘less rabbit rabbit mating’ hurt at imminently? | less rabbits | more babies |

Table 6: Examples of error categories. Error analysis is only shown for the incorrect outputs.

| Query Type | WIQA-BERT + CURIE | WIQA-BERT |
|------------|-------------------|-----------|
| 1-hop      | 78.78             | 71.60     |
| 2-hop      | 63.49             | 62.50     |
| 3-hop      | 68.28             | 59.50     |
| Exogenous  | 64.04             | 56.13     |
| In-para    | 73.58             | 79.68     |
| Out-of-para| 90.84             | 89.38     |
| Overall    | 76.92             | 73.80     |

Table 7: QA accuracy by number of hops, and question type. WIQA-BERT refers to the original WIQA-BERT results reported in Tandon et al. (2019), and WIQA-BERT + CURIE are the results obtained by augmenting the QA dataset with the influences generated by CURIE.
augmenting the context with generated influences from CURIE leads to considerable gains over WIQA-BERT based model, with the largest improvement seen in 3-hop questions (questions where the e and c are at a distance of three reasoning hops in the influence graphs). The strong performance on the 3-hop question supports our hypothesis that generated influences might be able to connect two event influences that are farther apart in the reasoning chain. We also show in Table 7 that augmenting with CURIE improves performance on the difficult exogenous category of questions, which requires background knowledge.

In summary, the evaluation highlights the value of CURIE as a framework for improving performance on downstream tasks that require counterfactual reasoning and serves as an evaluation of the ability of CURIE to reason about st-scenarios.

4.2 Zero-shot Evaluation

In addition to supervised augmentation, we also evaluate CURIE-M in a zero-shot setting. Towards this, we perform a zero-shot evaluation on QUARTZ (Tafjord et al., 2019b), a dataset for qualitative counterfactual reasoning. Each sample in QUARTZ consists of a question $q_i = \text{If the top of the mountain gets hotter, the ice on the summit will...}$, context $k_i = \text{ice melts at higher temperatures}$, the task is to pick the right answer from two options $a_i^1 = \text{increase}$, and $a_i^2 = \text{decrease}$. Since this task is setup as a qualitative binary classification task, CURIE cannot be directly adopted to augment the QA pairs like described in Algorithm 1.

For the zero-shot setting, we use CURIE-M fine-tuned on QUAREL-st as our language model. For an unseen test sample $(q_i, a_i^1, a_i^2, k_i)$, we select $a_i^1$ as the correct answer if $P_0(a_i^1 \mid x_i) > P_0(a_i^2 \mid x_i)$, and select $a_i^2$ otherwise (here $P_0$ stands for QUAREL-st). Our zero-shot CURIE-M achieves a 54% accuracy compared to supervised BERT model which achieves 54.7% accuracy. These results suggest that CURIE performs competitively at tasks while having no access to any supervision.

4.3 Discussion

In summary, we show substantial gains when a generated st-graph is fed as an additional input to the QA model. Our approach forces the model to reason about influences within a context, and then ask questions, which proves to be better than asking the questions directly.

5 Related Work

Closed-domain st reasoning : In NLP, a large body of work has focused on what-if questions where the input is a context, st, and an ending, and the task is to predict the reachability from st to the ending. The most common approach (Tandon et al., 2019; Rajagopal et al., 2020; Tafjord et al., 2019a) is a classification setting where the path is defined as more or less (qualitative intensities) over the sentences in the input context (a paragraph or procedural text with ordered steps). Such models do not generalize across domains because it is difficult to deal with changing vocabularies across domains. In contrast, our framework combines such diverse st-reasoning tasks under a general framework.

Open-domain st reasoning : Very recently, there has been interest in st reasoning from a retrieval setting (Lin et al., 2019) and a more common generation setting, attributed partially to the rise of neural generation models (Yangfeng Ji and Celikyilmaz, 2020). Qin et al. (2019) presents generation models to generate the path from a counterfactual to an ending in a story. Another recent dataset (Rudinger et al., 2020) proposes defeasible inference in which an inference (X is a bird, therefore X flies) may be weakened or overturned in light of new evidence (X is a penguin), and their dataset and task is to distinguish and generate two types of new evidence – intensifiers and attenuators. We make use of this dataset by reformulating their abductive reasoning setup into a deductive setup (see §2.2 for details).

Current systems make some simplifying assumptions, e.g. that the ending is known. Multiple st (e.g., more sunlight, more pollution) can happen at the same time, and these systems can only handle one situation at a time. Finally, all of these systems assume that the st happens once in a context. Our framework strengthens this line of work by dropping that assumption of an ending being given, during deductive st reasoning. In principle, our formulation is general enough to allow for multiple st and recursive reasoning as more situations unfold. Most importantly, our framework is the first to allow for st reasoning across diverse datasets, within a realistic setting where only the context and st are known.
6 Conclusion

We present CURIE, a situational reasoning that: (i) is effective at generating st-reasoning graphs, validated by automated metrics and human evaluations, (ii) improves performance on two downstream tasks by simply augmenting their input with the generated st graphs. Further, our framework supports recursively querying for any node in the st-graph. For future work, we aim to design advanced models that seeks consistency, and another line of research to study recursive st-reasoning as a bridge between dialog and reasoning.

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