Abstract

The task of identifying and reasoning with circumstantial preconditions associated with everyday facts is natural to humans. It is unclear whether state-of-the-art language models (LMs) understand the implicit preconditions that enable or invalidate commonsense facts, such as A glass is used for drinking water. Despite their impressive accuracy on existing commonsense tasks. In this paper, we propose a new problem of reasoning with circumstantial preconditions, and present a dataset, called CoreQuisite, which annotates commonsense facts with preconditions expressed in natural language. Based on this resource, we create three canonical evaluation tasks and use them to examine the capability of existing LMs to understand situational preconditions. Our results show that there is a 10-30% gap between machine and human performance on our tasks. We make all resources and software publicly available.

1 Introduction

Improving a system’s ability to reason with commonsense knowledge is at the frontier of natural language processing (NLP) research, as it represents a beneficial component in question answering (Wang et al., 2019; Talmor et al., 2018), machine reading comprehension (Sakaguchi et al., 2020; Mostafazadeh et al., 2016), and dialogue systems (Adiwardana et al., 2020; Young et al., 2018). In the past couple of years, dozens of systems (Raffel et al., 2019; Khashabi et al., 2020; Liu et al., 2019; Devlin et al., 2018) and learning resources (Sap et al., 2019b; Mostafazadeh et al., 2020; Rudinger et al., 2020; Bhagavatula et al., 2020) have been proposed, focusing on various aspects of commonsense knowledge such as social interactions.

In cognitive studies, the theory of affordance (Gibson, 2000; Chemero, 2003) suggests that understanding the circumstances in which an action or fact is possible or impossible is a key aspect of human intelligence. For example, a glass may be used for drinking water, under an (implicit) assumption that water is in normal temperature, but it would generally not be used if the glass is shattered. Accordingly, we argue that for an NLP reasoner to understand common sense, it should comprehend the contextual preconditions associated with commonsense facts. Such contextual preconditions can naturally be categorized into two classes: the ones that enable the facts, and the ones that disable them.

In computational studies, few efforts have been made on the aforementioned contextualized commonsense reasoning, let alone supporting enabling and disabling circumstantial preconditions. Among those, a representative work by Rudinger et al. (2020) approach the problem from an inference perspective with soft assumptions as weakeners and strengtheners. Using soft assumptions, the model will only have access to the relative correlation between facts, and it is not explicitly being tested on the underlying preconditions of the fact. Relying on relative correlations is already a strong point of LMs, hence minimalizing the gain of using such soft assumptions. Instead, we propose to...
define the problem based on the crisp conditioning of disablers and enablers. Using this crisp conditioning forces the model learn the most fundamental preconditions of a fact, which it lacks, as opposed to just learning the correlated events. This significantly helps in effective reasoning with the preconditions and explaining the decision. Additionally, they lack the necessary binding of their preconditions to a symbolic knowledge representation, which is beneficial for neuro-symbolic reasoners (e.g. (Lin et al., 2019; Ma et al., 2019; Feng et al., 2020)).

Causal preconditions inferred from text have also been studied in previous work (e.g. (Mostafazadeh et al., 2020; Kwon et al., 2020)). However, as we discuss in Section 2, relying on available text and models that are trained on them is a futile effort for two reasons. First, as is the case in many other aspects of common sense, we rarely write them explicitly in our text. Second, even for those cases that we mention them in the text, the reasoning models have to infer the causation vs correlation for the preconditions by themselves.

This paper presents a systematic study on the problem of situational preconditions expressed in natural language. As the first contribution of this work, we define the new problem of reasoning with enabling and disabling preconditions associated with commonsense facts (Section 2). That is to say, given a commonsense fact, what are the preconditions which make the fact possible (enabling) or impossible (disabling) and vice versa. Reasoning systems relying on a commonsense knowledge base, should possess the skill to reason when to use and not to use each piece of the knowledge base. For example, given the fact “Glass is used for drinking water”, a system should know that it is only possible if the “water is not too hot”. Similarly, given the precondition that “the water is toxic”, a system must know that “Using the glass for drinking water” is no longer possible. We show how current SOTA models lack the necessary skill to understand circumstantial preconditions associated with everyday facts and lay the groundwork for our solution.

To foster related research, as illustrated in Fig. 1, as illustrated in Fig. 1, we develop CoreQuisite, a rich crowdsourced dataset with enabling and disabling preconditions of commonsense facts and actions (Section 3), as the second contribution of this paper. To gather CoreQuisite, we start by extracting publicly available everyday utility facts from ConceptNet (Speer et al., 2016). We design a crowdsourcing task to gather preconditions of the facts by asking the participants to provide short responses to the question: What makes the fact possible/impossible? for each of the facts. CoreQuisite contains 5.4K labeled preconditions, from 1K edges with “UsedFor” relation from ConceptNet (Speer et al., 2016), evenly distributed between enabling and disabling preconditions. Details of CoreQuisite collection and verification are discussed in Section 3.

The third contribution leads to a comprehensive NLP benchmarking based on CoreQuisite. To this end, we transform the collected dataset into three tasks on Preconditions: Natural Language Inference (P-NLI), Multiple-Choice Question Answering (P-MCQA), and Generation (P-G). This seeks to provide a comprehensive evaluation of the ability of natural language reasoners to understand circumstantial preconditions (Section 4). The three canonical tasks do not change the structure of the original problem, instead, they are designed such that they can solely evaluate the preconditions in different language processing mechanisms. Based on these three tasks, we examine the performance of a number of SOTA language models and reasoners, such as RoBERTa (Liu et al., 2019), TE (Parikh et al., 2016), UnifiedQA (UQA) (Khashabi et al., 2020), and BART (Lewis et al., 2019). Results show that existing methods largely fall behind human performance, therefore indicating the need for further research in order to improve the comprehension of contextual preconditions by commonsense reasoners (Section 5).

2 Preconditions in Commonsense Reasoning

**Problem Definition.** For a given common sense knowledge graph \((s,p,o) \in G\), where \(s\) and \(o\) are entities and \(p\) is the relation type, we define \(f = \text{lexic}(s,p,o)\) as a fact that contains the lexicalized version of the edge. We define the precondition \(P_f\) as set of situations (e.g. time, location, state, intent) that form the setting in which the fact can be fully understood by the humans. Based on this, we define an enabling precondition \((p^+_f \in P_f)\) as the precondition, in which the fact is considered possible and true by the average human. Similarly, we define a disabling precondition \((p^-_f \in P_f)\) as
the precondition, in which the fact is considered impossible and false by the average human.

The problem of reasoning with preconditions is attempted in two ways. First, given the fact \( f \) and a precondition \( p \) the system is expected to infer if the fact is still valid \( (p \in P_+^f) \) or not \( (p \in P_-^f) \); and second, given only the fact \( f \), the system is requested to compose a reasonable disabling \( (p_+^f) \) or enabling \( (p_-^f) \) precondition.

**Motivating Example.** Let’s focus on simple facts e.g. *A net can be used for catching fish* or *A glass is used for drinking water*. Table 1 represents examples to expose the NLP to our problem definitions. Here, the second problem is presented as text completion (rows 1, 2, 3), and first problem is presented as multiple-choice question answering (row 4).

No matter how the question is presented to the system, neither of GPT2 (Radford et al., 2019), and UnifiedQA (Khashabi et al., 2020) is able to meaningfully handle the problems. In fact, our study will further reveal that understanding such contextual preconditions is where SOTA language modeling technologies commonly fall short.

We believe that the main reason for such behavior lies in the training corpus of the language models. Although several previous research (e.g. (Nguyen et al., 2021; Mostafazadeh et al., 2016)) include instances of enabling preconditions of the facts, the system has to infer the causation vs correlation for the disabling preconditions by itself which is not explicit. For example, the model may have seen concepts like “drinking water”, “Glass”, and “shattering”, however beyond correlation between the concepts it has to deduce from lack of occurrence that “a broken glass cannot be used for drinking water”. As mentioned before, these resources do not explicitly include disabling preconditions.

**Facts of Interest.** Commonsense facts are commonly known to people and can be accepted by people without need for debate (Gunning, 2018). However, common sense facts in general are different from common facts as they are general-domain knowledge, common, and are about concepts (e.g. glass) rather than entities (e.g. a specific brand of glass) (Ilievski et al., 2020b). There has been various efforts in capturing and conceptualizing such commonsense knowledge (e.g. (Speer et al., 2016; Sap et al., 2019a; Ilievski et al., 2020a)). Here, we focus on such facts and the preconditions associated with them.

### 3 CoreQuisite

This section introduces the procedure of developing the CoreQuisite dataset. We will introduce the detailed processes of selecting relevant commonsense facts (Section 3.1), converting the facts to human-readable sentences (Section 3.2), collecting the preconditions for each fact using crowd-sourcing (Section 3.3), and steps to ensure high quality of the data (Section 3.4). Finally, we present the CoreQuisite data statistics (Section 3.5).

#### 3.1 Edge Selection

We extracted relevant commonsense facts from ConceptNet (Speer et al., 2016), given its breadth of knowledge and popularity in prior research. ConceptNet is a multilingual publicly available commonsense knowledge resource. It contains millions of assertions between concepts (e.g. “Glass”, “Drinking_water”, “Person”), and covers wide range of topics from the spatial, physical, and temporal aspects, to social and cognitive aspects of everyday life (e.g. “Glass” - Used for - “Drinking_water”).

We performed a pilot analysis of different knowledge types in ConceptNet to help us decide which of them are suitable to be annotated with preconditions. For this, we sampled 20 random edges for each type and checked how well one can annotate them with preconditions. Our analysis reveals that not all facts lend themselves naturally for annotation with enabling or disabling preconditions. Specifically, we observe that some relations (e.g., *Related To*) are underspecified in their meanings, and others, like *IsA*, are often truisms. Our investigation random samples of such relations revealed that it is difficult to come up with preconditions for them. Furthermore, we observe that some relations, like *CreatedBy*, can be annotated with enabling conditions, but not with disabling ones. The opposite is observed for *PartOf*.

Our investigation identifies the relations expressing utility (*UsedFor, CapableOf*), temporal knowledge (*Causes*), and desire/goal (*Desires*) (Ilievski et al., 2021) to be intuitive and representative for annotation of preconditions. We focus on the *UsedFor* relation, as its edges are most relevant for our task, and this relation is well-populated in ConceptNet. Yet, not all *UsedFor* edges can be an-
notated with preconditions, e.g., *Looking through telescope, Usedfor, viewing heavens*. Following this intuition, we computed correlation between a hand-annotated usefulness of the precondition statements, and the following quantitative scores: DICE metrics (e.g. salience) (Chalier et al., 2020), LM perplexity, and edge weights from ConceptNet. However, none of these scores had a strong correlation with whether an edge can be annotated with preconditions or not (see Appendix B.2 for the obtained correlations). Finally, we selected 1K *UsedFor* edges from ConceptNet based on uniform random sampling.

### 3.2 Edge Lexicalization

Each of the 1k selected edges is lexicalized using a combination of templates and masked LMs described by Ma et al. (2019) and Bouraoui et al. (2020). Similar to Ma et al. (2019), we use a combination of the templates for each relation (e.g. `[subject] is used for [object]`, `[subject] is used by [object]`) and use the perplexity score from the LM to select the best lexicalization for each edge. However, this method does not guarantee the selection of the best lexicalization as the perplexity score reflects the probability of the sentence tokens appearing in that specific order rather than the sentence’s grammatical correctness. To mitigate this issue, in addition to the above method, following (Bouraoui et al., 2020), we let the LM adjust the templates as well by adding one masked token to some templates (e.g. `[subject] is used [MASK] [object]`) and let the LM fill the mask before filling the *subject* and the *object* slots of the template.

### 3.3 Data Collection

We used Amazon Mechanical Turk (AMT) (Crowston, 2012) to collect data on preconditions for the lexicalized edges. Our data collection procedure is approved as exempt by Institutional Review Boards (IRB). For this, we ask the participants to provide enabling or disabling preconditions by providing short responses to the question: *What makes the fact possible/impossible?* for each of the lexicalized statements from ConceptNet. For financial reasons, in *CoreQuisite*, we collect 3 enabling and 3 disabling judgments for each fact. *CoreQuisite* does not try to exhaust all possible preconditions associated with each fact but rather serves as a resource for evaluation purposes. However, in some edges we get to near-saturation point (duplicate answers).

With this procedure, we collect 6K enabling and disabling preconditions. Further details on the data collection design, including annotator qualification, survey design and IRB submission details are given in Appendix A.

### 3.4 Quality Control

To ensure the quality of the responses, we used a mixture of automated and expert annotations. The automated quality control code implements a set of rules that we can easily check, such as not using negatives and not using pronouns (both were part of the instructions given to the annotators). However, it does not guarantee that all low-quality responses will be filtered out.

In addition, we leverage expert annotators to annotate the data gathered from crowd-sourcing. The goal here is to evaluate the usefulness of the collected responses. Here, for each recorded response we asked the annotator to classify the response into three categories, each representing a specific level of information in the response.

- **Truism** category, meaning, it is correct, but it is not specific to the situation (e.g. *being broken/functionable or being available/unavailable*).
- **Informative** category, meaning the response is correct.
and is adding information that is not mentioned in the prompt and is also not a truism (i.e., is specific). Finally, Irrelevant category, for any response that is not categorized as one of the previous two is considered in this category. For CoreQuisite, we remove the answers from Irrelevant category.

3.5 Dataset Statistics

The described data collection procedure resulted in a total of 3k enabling and 3k disabling preconditions for the 1k ConceptNet edges of type UsedFor. After filtering low-quality responses and the factual sentences that were marked as Invalid by expert collaborators, we ended up with around 5.4K high quality annotations. Our expert annotation results, on 10% of the 6K annotations, show that in 93% of the cases the crowd-sourced data contains informative responses, and only 5% of the responses are irrelevant.

Table 2 compares size of CoreQuisite with other available resources for preconditions. Although CoreQuisite is smaller in size, it is the only resource that gathers both enabling and disabling preconditions with full grounding onto knowledge graph edges.

| Dataset            | #En. | #Dis. |
|--------------------|------|-------|
| CoreQuisite        | 2.7K | 2.7K  |
| Rudinger et al. (2020)* | 44K  | 44K   |
| Mostafazadeh et al. (2020) | 277K | 0     |
| Kwon et al. (2020)  | 10K  | 0     |
| Speer et al. (2016) | 20K  | 0     |
| Sap et al. (2019a)  | 244K | 0     |

Table 2: Number of labeled enabling/disabling preconditions in resources. For details of numbers in this table see Appendix B.1.

strengtheners/weakeners

4 Tasks

Given the data collected in Section 3, we devise three tasks to showcase the possible ways one could use the CoreQuisite data to evaluate the current SOTA system’s understanding of circumstantial preconditions. We select P-NLI and P-MCQA as representative discriminative tasks, and P-G task as a generative task. These are three canonical tasks that different perspectives of an NLP system’s ability for commonsense reasoning. Table 3 summarizes the three tasks and provides an example for each of them. In the rest of this section, we explain each task in detail and discuss the steps to prepare it from the raw precondition data. This preparation is fully automatic, and no human annotation or supervision has been used.

4.1 P-NLI Task

Natural Language Inference (NLI) refers to tasks where given a sentence pair composed of a hypothesis and a premise, the system has to decide whether the hypothesis is true (entailment), false (contradiction), or undetermined (neutral) given the premise (Williams et al., 2018). Each of our preconditions (e.g., “water is clean” or “water is polluted”), in fact, can directly serve as a premise in the sense of NLI. Enabling preconditions correspond to entailment cases (e.g., “water is clean” entails “water is used for drinking”), whereas disabling preconditions can be annotated as contradictions (e.g. “water is polluted” contradicts “water is used for drinking”). The P-NLI task consists of 5.4K entries, which are well-balanced between entailment and contradiction cases.

4.2 P-MCQA Task

CoreQuisite can also be directly converted to a multiple-choice question answering (MCQA) task with little effort. In order to create the P-MCQA task, we process CoreQuisite in three steps. First, for each fact, each enabling (disabling) response is paired with three disabling (enabling) responses from the same statement. These three responses naturally act as negative samples (distractors), allowing us to have high-quality and fair questions, which is a notable challenge of creating multiple-choice questions effectively (Ma et al., 2021).
question of the MCQA instance is then formed by appending “What makes this possible?” or “... impossible?” to the lexicalized fact. Second, in order to have more distractors and increase the number of multiple-choice instances we applied the two negative sampling methods used by Lyu et al. (2020): Cosine Similarity Filtering, and Question/Answer Shuffling. Finally, in order to remove the annotation artifacts from the data, hence trivial instances, and prevent the models to exploit these artifacts instead of answering the questions, we used the Lite variation of the Adversarial Filtering method (introduced in Sakaguchi et al. (2020) and formalized in Le Bras et al. (2020)). This resulted in approximately 40K instances of multiple choice questions.

4.3 P-G Task

Despite our filtering efforts, it is possible that reasoning systems identify annotation artifacts in the data and solve the discriminative tasks for the wrong reasons, as a result of additional artifacts (Le Bras et al., 2020). Hence, we provide a third formulation as a generative commonsense reasoning task. In this task, we present the system with the exact question that was presented to the human annotators, thereby mimicking the human annotation task of writing down the precondition as a natural language sentence. We then evaluate the model’s response using the human responses as references.

5 Results and Discussion

We assess the novelty of our benchmark through evaluating representative NLP systems on the three tasks.

5.1 Experimental Setup

For each task, we start from available pre-trained models and evaluate their performance on the test set in zero-shot and fully-trained setups. To create the test set, we use a uniform random split of the edges that each instance stems from with [0.45, 0.15, 0.40] ratio of the data for train/dev/test. The rationale for splitting based on the edges instead of the task-instances is to prevent data leakage into the test sets through shared edges. The experiments are conducted on a commodity workstation with an Intel Xeon Gold 5217 CPU and an NVIDIA RTX 8000 GPU. For all the experiments, after loading the pre-trained model, we report results under two settings: (1) zero-shot results, and (2) fine-tuned from those models that are further fine-tuned on the whole training set.

P-NLI Setup For the pre-trained models, we use the huggingface (Wolf et al., 2020) library for the RoBERTa-large-MNLI model (Liu et al., 2019) and allennlp (Gardner et al., 2017) library for the TE model (Parikh et al., 2016). We evaluate each system’s performance by aggregating the F1-Macro score on the ground-truth labels and report the results on the unseen test subset of the data.

P-MCQA Setup For P-MCQA, we evaluate the systems’ performance based on their default evaluation protocols. For RoBERTa (Liu et al., 2019), we use the LM coupled with a linear regression layer as classification head. In this method, the LM is tasked with embedding each question/answer pair, and the classification head assigns a score to the pair. Later for each MC instance, the question/answer pair with the highest score is selected as the output choice. We report the accuracy score (code from (Pedregosa et al., 2011)) based on the output choices from the model. For UnifiedQA, we follow the original setting by Khashabi et al. (2020) to let the model conduct sequence-to-sequence generation based on the question. Then the choice is made by selecting the one that is closest to the generated answer from the candidate choices.

P-G Setup For the pre-trained models, UnifiedQA (UQA) (Khashabi et al., 2020) and BART (Lewis et al., 2019), we use the huggingface (Wolf et al., 2020) library implementations and evaluated the model in zero-shot and fully-trained setups.

To automatically evaluate the machine-generated answers of the models, we used Bleu-2 (Papineni et al., 2002) (code from (Bird et al., 2009)) and ROGUE-2 (Lin, 2004) (code from (Wolf et al., 2020)) metrics. We did not use methods with large n-gram match (e.g. Bleu-4) as they shown to be ineffectual for our case. We found two reasons for this behaviour. First, the small number of reference sentences (at most 3) made most of model’s output not matching any reference sentence. Second, relatively short reference sentences resulted in no 4-gram match that resulted in mostly zero scores.

For the human evaluation score, we sampled 100 responses and used a method similar to quality control method in Section 3.4 (here we consider the Simple responses as Informative), and report the
5.2 P-NLI Results
As in Table 4, both systems tend to get near-random results in the zero-shot setup. In case of the RoBERTa-large-MNLI model, although the zero-shot F1-Macro score is higher, it is far from human-level score (1.00). This observation that even models that are trained on large and diverse learning resources (e.g. MNLI (Williams et al., 2018)) are not able to perform well on the data in a zero-shot fashion, shows the novelty and uniqueness of CoreQuisite data.

In the Fine-tuned setup, both models tend to get higher scores that are close to the human-level performance. However, the slow saturation of the learning curve plot in Figure 2, further suggests the novelty of CoreQuisite knowledge. In addition, the high scores after fine-tuning may also be attributed to systems’ exploiting the annotation artifacts of data instead of actually learning to reason with preconditions. This claim will be further supported by the P-MCQA results.

5.3 P-MCQA Results
The second set of evaluation is for the P-MCQA task. The P-MCQA has all the intricacies of the original precondition data absent from the simple annotation artifacts that make it a better alternative to evaluate systems. As presented in Table 5, there is a significant gap between the ideal and machine performance in the P-MCQA benchmark that further supports the novelty of CoreQuisite and tasks stemming from it.

Error and Qualitative Analysis
After investigating the answers, we observe that even the promising large models tend to mistake questions about enabling and disabling cases. For example the UnifiedQA-Large model, mistakenly chooses a disabling response “Your car is out of fuel” for the enabling question “Gas are typically used for providing energy. What makes this possible?”. This might be explained by the fact that LMs tend to focus more on correlation of lexical occurrences and statistical patterns (e.g., gas and car/fuel), rather than the actual question. In addition, similar to Zhou et al. (2020), we observe that LMs lack understanding of linguistic permutations like negations, and lean toward positive words.

5.4 P-G Results
The third task tests a system’s generative commonsense reasoning with regard to the preconditions. According to results in Table 6, existing models fall short of obtaining promising BLEU scores even after fine-tuning. However, the human-annotations sheds more light on the results and show the relative comparison of the models.

| Model        | BLEU 0-Shot | Tune | ROGUE Tune | Humm Info. |
|--------------|-------------|------|------------|------------|
| UQA-sm       | 0.003       | 0.30 | 0.093      | 0.47       |
| UQA-bs       | 0.002       | 0.40 | 0.141      | 0.33       |
| UQA-lg       | 0.018       | 0.020| 0.014      | 0.52       |
| BART-bs      | 0.031       | 0.068| 0.104      | 0.26       |
| BART-lg      | 0.027       | 0.060| 0.103      | 0.10       |

Table 6: BLEU-2, ROGUE-2, and human evaluation Information score for results of SOTA systems on the P-G task

Our results are consistent with similar generation tasks (Rudinger et al., 2020), due to the small number of reference responses and relatively large...
space of correct responses that makes automatic evaluation of such machine responses an open problem (Chen et al., 2020).

**Error and Qualitative Analysis** Upon analysis of the results we noticed several patterns in the generated responses. First, models tend to generate pretty simple answers mostly discussing the existence or availability of the subject. For example, BART-base generated patterns such as “<subject> is closed” or “You have <subject>” which some were informative. Second, similar to P-MCQA task, the models tend to confuse enabling and disabling preconditions. For example, BART-large generated the enabling precondition “The clothes are is dirty” instead of disabling precondition for the fact “Washing clothes are used for making fresh again”.

### 6 Related Work

**Resources of Preconditions.** A few resources have provided representations for preconditions of facts. ConceptNet (Speer et al., 2016)’s HasPrerequisite relation, ATOMIC (Sap et al., 2019a)’s xNeed relation, and CauseNet (Heindorf et al., 2020) data can express concept dependencies, such as, e.g., before one bakes bread, they need to buy ingredients and go to a store. Instead of adding new edges, our work annotates existing edges with contextual preconditions, which helps reasoners understand when to use an edge and when not. ASER (Zhang et al., 2020) and ASCENT (Nguyen et al., 2021) extract edges from unstructured text together with their associated context. As such, their knowledge is restricted by information available in text, and they do not express disabling preconditions. It is also unclear to which extent their contextual edges express enabling preconditions, rather than coincidental information. GLUCOSE (Mostafazadeh et al., 2020) comes closer to our work, as they also extract enabling preconditions (e.g., Possession state that enables X) via crowdsourcing. Similarly, PeKo (Kwon et al., 2020) extract enabling preconditions between event pairs from available text. Yet, both GLUCOSE and PeKo do not explore disabling preconditions.

**Reasoning with Preconditions.** Few efforts have been made on evaluating commonsense reasoning with preconditions. Rudinger et al. (2020) focus on modeling weakeners and strengtheners of commonsense facts. Their work adds a utility sentence to the hypothesis-premise pair in NLI-style tasks and ask whether it weakens or strengthens the relationship of the pair. Our work differs as we focus on a crisp condition of enabling/disabling that is particularly useful in logic-like reasoning tasks (as opposed to probabilistic inference). In addition, our task allows the reasoning to be processed as canonical NLI and can benefit from existing NLI architectures instead of modifying them. Kwon et al. (2020) also uses their human-annotated data for precondition identification and generation tasks between pair of sentences. However their work’s limitations (only causal relations in available text) hinders the extent of their tasks.

More efforts have been put in neuro-symbolic reasoning, to allow reasoners to access external symbolic knowledge (e.g. (Verga et al., 2020; Ma et al., 2019; Lin et al., 2019; Feng et al., 2020)). These system mostly rely on their underlying decision making pipeline, based on LMs, to implicitly reason with the preconditions. However, as we showed, the LMs lack the skills to do so and do not filter each piece of the symbolic knowledge based on the relevance.

### 7 Conclusions and Future Work

We presented, CoreQuisite, a dataset of 5.4K collected enabling and disabling preconditions of everyday commonsense statements from ConceptNet. We utilize this resource to create three tasks for evaluating the ability of systems to reason over circumstantial preconditions, namely: P-NLI, P-MCQA, and P-G. Our evaluation shows that SOTA reasoners largely fall short below human performance, indicating the need for further investigation to develop precondition-aware systems.

Future work should also investigate the creation of precondition benchmarks for other statements besides utility, such as motivational or causal ones, or using weak-supervision to gather preconditions. Alternatively, we can leverage the contributed resource to develop generative models for automated context-aware KG construction (Sorokin and Gurevych, 2017).

**Ethical Considerations**

Though we may present this as we started from openly available data that is both crowdsourced and neutralized, however it still may reflect human biases (Mehrabi et al., 2021).

During our data collection we did not collect
any sensitive information, such as demographic or identity characteristics. We only limited the annotators to English-speaking users from mainly English-speaking countries such as US, which may add cultural bias to the data. However, neither our crowd annotators or the expert annotators noticed any offensive language in the questions or the responses.

Given the urgency of addressing climate change we have reported the detailed model sizes and runtime associated with all the experiments in Appendix C.

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A Data Collection Details

We used Amazon Mechanical Turk (AMT) (Crowston, 2012) to collect the CoreQuisite. This enabled us to coordinate the study and access a large pool of English-speaking participants as our study population. The AMT is especially suitable for this study as it can facilitate accessing a diverse population of participants which is necessary for any notion of commonsense. Our study on AMT consists of two parts: a tutorial that also serves as a qualification test and the main survey. In addition, we implemented two levels of quality control: in the first one we use a response checker code and in the second we use human annotators to ensure only high-quality responses wind up into the final data.

A.1 Main AMT Survey

In the main survey, the participants are given a set of question-units (sample in Fig. 4) each consists of a factual sentence (discussed in Section A.2) followed by a prompt question, then we ask participants to write their responses for each prompt question in the designated text box in front of the unit. The prompt questions are short questions that ask about the preconditions that enable or disable the factual sentence (e.g. what makes this possible?, when is this impossible?). The goal of this phase is to use the powers of crowdsourcing to capture as much information as needed to create a dataset of enabling and disabling conditions.

A.2 Gathering Factual Sentences

The first row in Fig. 3 summarizes the steps to create the factual sentences. Each factual sentence is a short sentence derived from an edge from a commonsense knowledge graph. The information on this knowledge graph is related to everyday situations such as usage of objects (A net is used for catching fish.), or capabilities of objects (Humans are capable of catching a bus.), etc. (Speer et al., 2016; Ilievski et al., 2020a; Sap et al., 2019a). In our case, the knowledge associated with each factual sentence is extracted from ConceptNet (Speer et al., 2016), a well known commonsense resource. To limit the scope of this work we only focus on UsedFor relations from ConceptNet, however, the method can be extended to any other relation from any other knowledge graph.

To convert the knowledge graph edges to human-readable factual sentences, we used automatic lexicalization methods, similar to (Ma et al., 2019; Bouraoui et al., 2020). In this method, we define a set of templates to convert the edge to a set of sentence candidates, then use the perplexity score of a language model to pick the best candidate for each edge. The lexicalization is explained in more details in Appendix 3.2.

Since ConceptNet’s knowledge is not perfect, some of the generated factual sentences may not fully make sense. Additionally, the automatic conversion of edges to the sentence is not perfect, hence some sentences may have odd grammar (e.g. An net is used for catch fish). Consequently, some of the question-units may be hard to understand or just be wrong. To help us find those question-units and ignore them in future iterations, each unit is presented with an adjacent checkbox labeled This does not make sense. The participant may choose to select the checkbox and skip answering that prompt. To make the payment structure fair for the participants, they will get paid regardless of their response.

A.3 Qualifying Participants

To ensure the participants can understand the task, we prepared detailed instructions that explain to the participants what they need to do and what are the criteria for a good vs bad response. For example, in the instructions, we ask participants to avoid using negative sentences or avoid using pronouns to refer to objects. The instruction is 366 words with an expected reading time of < 5 mins. Additionally, we have prepared a set of good/bad examples associated with each rule that can also be accessed in the tutorial. Each one of the good/bad
examples comes with a short explanation clarifying the reason for its good/bad rating.

The participants are then asked to take the qualification test as a check on whether they have read and understood the instructions. The qualification test contains 10 multi-choice questions (each with two choices); each containing a question-unit (similar to those that are used in the main survey) with two choices of the possible responses that one may give to them. We have carefully designed each multiple-choice question such that it tests the participants’ understanding of the rules individually and give them feedback on their wrong answers. For example, for the rule discouraging the use of negative sentences, we have two questions where the wrong answers contain a negative verb. After successfully passing the test, participants with acceptable scores are granted a qualification badge that allows them to engage in the main survey. It must be noted that the detailed instructions and the good/bad examples are both available in the main survey as a memory refresher for the participants.

B Results in More Details

B.1 Details of Data Statistics

For the GLUCOSE (Mostafazadeh et al., 2020) stats, we aggregated the total number annotated sentences in dimensions 1 to 8 which semantically contained causation and enablers.

The Rudinger et al. (2020) discusses preconditions in terms of strengthener/weakeners instead of enabling/disabling. For the sake of simplicity for stats in Table 2, we do not make this distinction and used the reported numbers from the Table 2 in their paper.

For Kwon et al. (2020) stats, we used the numbers from Table 3 in their paper.

Finally, for Speer et al. (2016) and Sap et al. (2019a) results, we used the numbers reported in Table 4 of (Ilievski et al., 2021)

B.2 Edge Selection Results

In this section, we provide further evidence to support the decision to use the UsedFor edges without any additional filtering. First, we showcase the lack of correlation between a hand-annotated usefulness indication of the precondition statements and existing quantitative methods/scores. Then, in a similar setup, we show that the UsedFor edges have a higher usefulness score.

For the first study, we only focus on UsedFor edges. For each metric, we randomly sample 20 edges in each percentile of the metric and hand-annotate the usefulness of sampled edges in each percentile. Then, for each percentile-metric, we report the percentage of edges that were considered useful for our study. The results in Table 7, summarizes the usefulness score for three of the percentile buckets for three of the metrics. For the perplexity score we used the RoBERTa (Liu et al., 2019) language model on the lexicalized edges, for the Salient score we used DICE metrics (Chalier et al., 2020), and for the weight score we use the weights from the ConceptNet (Speer et al., 2016) itself. The usefulness scores suggest that a higher score may or may not result in more useful edges which makes using them for filtering edges tricky. This study is by no means conclusive due to both the small sample sizes and a small number of trials, however, it led us to choose the edges solely based on relation type and leave further filterings to future work.

| Metric  | [0,10](%)   | [50,60](%) | [90,100](%) |
|---------|-------------|------------|-------------|
| Perp.   | 75          | 95         | 90          |
| Salient | 80          | 100        | 95          |
| Weight  | 95          | 90         | 90          |

Table 7: hand-annotated usefulness indication of the precondition statements for top/bottom/mid percentile buckets of the quantitative methods. The $[A, B]$ label indicates edges with the metric score in the range of $[A, B]$ percentile of the metric score.

For the second study, Table 8, we group edges based on their relations only and compute the usefulness score for each relation. The results showed that UsedFor edges tend to generally be more useful for our annotation task. This couple with the fact that UsedFor edges could be annotated with both enabling and disabling preconditions led us to focus on them for this study.

| Metric   | Score(%) |
|----------|----------|
| UsedFor  | 95       |
| CapableOf| 90       |
| RelatedTo| 40       |

Table 8: hand-annotated usefulness indication of the precondition statements three of the ConceptNet relations
B.3 NLI Mistakes

Table 9, lists some mistakes that each model made from the test subset of NLI task derived from CoreQuisite data.

As our version of NLI only consists of Entailment and Contradiction labels, we discuss the results using binary classification terminology.

C Model Sizes and Run-times

For table 4, Runtimes: TE=2hr, rbta=2.5hr and #params: TE=0.5M, rbta=356M. For table 5, Runtimes: rbta-base=1hr, rbta-large=2hr, uqa-small=1hr, uqa-base=4hr, uqa-large=20hr and #params: rbta-base=124M, rbta-large=355M, uqa-small=60M, uqa-base=222 M, uqa-large=737M. In table 1, Runtimes: uqa, gpt2=10min and #params: gpt2=1.5B. Finally in table 6, Runtimes: uqa-small=1hr, uqa-base=2hr, uqa-large=6hr and #params: uqa-small=60M, uqa-base=222 M, uqa-large=737M.
| **Model** | **Fact** | **Context** | **FP/FN** |
|-----------|----------|-------------|----------|
| TE        | You can typically use self adhesive label for labelling things. Acoustic ceiling is typically used for dampening sound. You can typically use self adhesive label for labelling things. | The self adhesive label runs out of glue. in rooms with noise above a certain decibel. Labeling things that are wet. | FP |
| roberta   | Farm is typically used for raising crops. You can typically use pets to provide companionship. Acoustic ceiling is typically used for dampening sound. | Enough rain should be available. the pet is dog. The sound is too loud | FN |

Table 9: Test results of SOTA systems on NLI task based on the *CoreQuisite*. FP: False Positive, FN: False Negative