Cross-Domain Reasoning via Template Filling

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Abstract

In this paper, we explore the ability of sequence to sequence models to perform cross-domain reasoning. Towards this, we present a prompt-template-filling approach to enable sequence to sequence models to perform cross-domain reasoning. We also present a case-study with commonsense and health and well-being domains, where we study how prompt-template-filling enables pretrained sequence to sequence models across domains. Our experiments across several pretrained encoder-decoder models show that cross-domain reasoning is challenging for current models. We also show an in-depth error analysis and avenues for future research for reasoning across domains.

1 Introduction

Humans often need to reason across different domains for several day-to-day decisions. For instance, Are leafy greens good for people with history of blood clots? Answering this question requires commonsense understanding that leafy greens are high in vitamin-K and a related health domain knowledge that people with history of blood clots are prescribed blood thinners and vitamin-K inhibits blood thinner action, increasing blood clots. Answering questions like these present an unique challenge - it requires knowledge in both commonsense and health and well-being domains as well as the ability to reason across them correctly and coherently.

We formally define this as the cross-domain reasoning task, as one where the reasoning chain spans across multiple domains. While humans are adept at reasoning across domains, research in cognitive science shows that they often have different processing preferences for individual domains, and it is dependent on domain specific expertise and their reliability of intuition for reasoning across domains (Pachur and Spaar, 2015; Oktar and Lombrozo, 2020). Whether machines can do such cross-domain reasoning is still an open question.

Our goal in this work to is explore whether we can train NLP models that can effectively reason across domains in a situation. Cross-domain reasoning in NLP literature has been primarily addressed via knowledge bases (KB) (Mendes et al., 2012). Recently, pretrained NLP models have shown immense promise for reasoning applications in several tasks such as commonsense reasoning (Bosselut et al., 2019b; Shwartz et al., 2020b), defeasible reasoning (Madaan et al., 2021), procedural knowledge (Rajagopal et al., 2021) and rule-based reasoning (Clark et al., 2020). Inspired by findings in cognitive science and the current advances in reasoning systems, our work extends this line of investigation to study whether pretrained sequence-to-sequence models (SEQ-TO-SEQ) can be used to reason across knowledge that connects diverse domains.

We model the cross domain reasoning challenge as a prompt-based template filling task (prompt-template-filling) where a SEQ-TO-SEQ model is trained to fill a template that connects concepts

code and data will be released soon

Figure 1: An example of prompt-template-filling. We propose an approach for cross-domain reasoning via filling templates guided by prompts. In this example, each prompt signifies a concept from a different domain (activity from commonsense domain and disease from health and well-being domain).
across domains. Figure 1 shows an example of our approach. In our use-case, we evaluate whether LMs can effectively reason across commonsense domain and health and well-being domain. Towards this, our contributions in this paper are two-fold. First, we present a dataset of cross-domain cloze style templates and corresponding sentences that are valid completions of the template. The slots in the templates are open-ended and are not restricted to any particular vocabulary. Our prompt-template-filling approach models the cross-domain reasoning challenge as a SEQ-TO-SEQ task where given a template, the goal of the model is to produce meaningful completed sentences for the template. The concept in each slot in the template is provided via a prompt, which indicates an abstraction of the nature of the slot from a particular domain. In figure 1, the first prompt indicates a commonsense concept activity and the second slot indicates a health concept disease, facilitating cross-domain reasoning. Our experiments on reasoning across commonsense and health domain shows that SEQ-TO-SEQ models show reasonable ability for cross-domain reasoning. We also present an in-depth error analysis along with our empirical analysis, leaving several open avenues for future research.

To summarize, (i) we present the first prompting based approach to enable SEQ-TO-SEQ perform cross-domain reasoning that uses prompts to specify domain specific concepts to fill templates (prompt-template-filling). (ii) For the use-case of reasoning across the commonsense and health and well-being domain, we present a dataset and a corresponding study on the ability of prompt-template-filling to enable SEQ-TO-SEQ to reason cross-domain.

2 Dataset
To investigate whether SEQ-TO-SEQ models are effective at cross domain reasoning, we collect a dataset of templates that are composed of cross-domain reasoning chains and corresponding sentences that matches the template. Figure 2 shows an example of a sample from our dataset. Each template in our dataset is composed of the following basic units:

1. **concept slot**: contains an abstract category form of a concept from one of the domains.
2. **qualifier**: a word or phrase that describes the nature of the effect of concept of one domain on the other (e.g. higher, lower,...)
3. **explanation**: this optional field consists of a free-form explanation that explains the reasoning across the concepts from the different domains.

For our use-case, we use the commonsense domain and the health and well-being domain. In
AI, it is a long-standing challenge to address commonsense reasoning with approaches ranging from building commonsense knowledge bases (Matuszek et al., 2006; Speer and Havasi, 2013) and neural-network based approaches (Sap et al., 2019; Bosselut et al., 2019a). There has also been specialized knowledge resources for reasoning in the health and well-being domain (Bodenreider, 2004; Schmidt and Gierl, 2000). Both these domains have seen immense research over the years, motivating us to choose them for exploring cross-domain reasoning for our use-case.

For the use-case to reason across commonsense and health and well-being, we collect a set of template \((x)\) and its corresponding expansions \((y)\) based on this overall schema of reasoning across commonsense and health and well-being domain. An example is shown in figure 2. Each template has at least one concept slot, one from each domain (people eating leafy vegetables from commonsense domain and blood clot from the medical domain in the example shown in the figure). A qualifier slot optionally specifies how the concept in a domain interacts with the concept from other domain. In the example in figure 2, higher risk indicates the qualifier. The template also includes an optional explanation slot that specifies in free-form text how leafy vegetable intake is connected to blood clots.

### Table 1: Examples from our dataset.

| Template | Sentences |
|----------|-----------|
| {person_at_location} has a (higher/lower) risk of {disease} because {reason_for_risk} | Person who lives in a city has a higher risk of depression - because of stress due to noise. Person who lives near a village has a lower risk of respiratory illness - because of lower pollution. |
| {person_taking_prescription} has a higher risk of {disease} due to {reason} | Someone on steroids have a higher risk for heart disease because - steroids compromise heart pumping. People on insulin have a lower risk of hyperglycemia - because of lower glucose levels. |
| {food_item_1} should not be consumed with {food_item_2} because {reason} | Steak should not be consumed with mashed potatoes because - pairing fried foods with starchy carbohydrates increases the risk of diabetes. Pizza should not be consumed with French fries because proteins require - a much different stomach environment than starches for proper digestion. |
| A change in behavior such as {behavior_change} is often associated with {a_medical_condition} because {reason_for_condition} | A change in behavior such as becoming more sedentary is - often associated with obesity because less activity leads to less calorie burning. A change in behavior such as no longer drinking coffee is often - associated with diminished insomnia because less caffeine equals improved sleep. |
| When severe symptoms like {a_symptom} for a {a_medical_condition} shows up, immediately one should perform {an_action} | When severe symptoms like confusion or disorientation for heatstroke show up, immediately - one should perform cooling actions, such as applying cooling towels. When severe symptoms like unconsciousness for a heart attack show up, immediately - one should call 911 and perform CPR while awaiting help. |
| People often do {an_activity} before going to bed in night to prevent risk of {disease}. This is because {reason_for_activity} | People often do reading before going to bed in night to prevent risk of insomnia. - This is because doing some light reading helps lull you to sleep. People often do teeth brushing before going to bed in night to prevent risk of tooth decay. This is because brushing removes cavity-causing plaque from teeth. |

[2] https://www.mturk.com/  
[3] https://www.cdc.gov/  
[4] https://www.webmd.com/  
[5] https://www.healthline.com/  
[6] https://www.mayoclinic.org/
template-sentence pairs with about 3600 unique templates.

3 Prompt Template-Filling Framework

Early NLP systems have often relied with templated rule-based systems (Riloff, 1996; Brin, 1998; Agichtein and Gravano, 1999; Craven et al., 2000) due to their simplistic nature. Compared to machine learning methods, they were often rigid (Yih, 1997). Despite their rigidity, template based systems are often easy to comprehend, and lend themselves to easily incorporate domain knowledge (Chiticariu et al., 2013). Our goal is to combine the strengths of both template-based systems and recent pretrained SEQ-TO-SEQ models for the task of cross-domain reasoning.

In our prompt-template-filling formulation, we setup the template filling task as a prompt-tuning task inspired by the recent advances in prompt-tuning. Prompt-based approaches have achieved state-of-the-art performance in several few-shot learning experiments (Brown et al., 2020; Gao et al., 2021; Le Scao and Rush, 2021). Table 3 shows an example of our task setup. The template filling task takes an input template $x$, containing one or more template slots represented as spans ([[MASK]]) as input, and produce an expanded sequences $y$ as output. Given a template $x$, the task is to model $p(y|x)$. Since there could be multiple sentences in the output $y$, we concatenate these sentences as one for model training.

In comparison to approaches such as Donahue et al. (2020), our approach does not strictly enforce that that sentences only fill missing spans of text. Rather, the expanded sentences can have additional modifications. For instance, for the following input template - {person_at_location} has a {higher/lower} risk of {disease} because {reason_for_risk}, a valid sentence is person who lives in the city has a higher risk of depression due to noise. In this example, the word because does not match the output sentence phrase due to but it is considered a valid output for the template.

3.1 Training

Given a template $x \in \mathcal{X}$ and its corresponding expansion $y \in \mathcal{Y}$, we can train any sequence-to-sequence model that models $p_\theta(y|x)$. Towards this, we use a pretrained sequence-to-sequence model $M$ to estimate the filled template $y$ for an input $x$. We model the conditional distribution $p_\theta(y | x)$ parameterized by $\theta$: as

$$p_\theta(y | x) = \prod_{k=1}^{M} p_\theta(y^k | x, y^1, \ldots, y^{k-1})$$

where $M$ is the length of $y$.

4 Experiments

In this section, we describe the experimental setup, baselines for our approach. Since our approach is agnostic to the pretrained encoder-decoder architecture type, we perform experiments on several state-of-the-art seq-to-seq models.

4.1 Experimental Setup

Following experimental setup for similar reasoning tasks (Rudinger et al., 2020), we use the ROUGE metric (Lin, 2004) as our automatic metric. To perform the evaluation, we compare the generated sentence for the template against the gold annotations in our dataset. We remove the template words from the output before the comparison for ROUGE to avoid inflating the scores. All the experiments were performed on a cluster of 8 NVIDIA V100 GPUs.

4.2 Models

We follow the same experimental settings across the baseline and our approach for all the models. We initialize all the models with their pretrained weights. We use commonly used encoder-decoder architectures for our experiments - BART-BASE, BART-LARGE, T5-BASE. The model settings are given below:

- **BART-BASE**: This pretrained encoder-decoder transformer architecture is based on Lewis et al. (2020). It consists of 12 transformer layers each with 768 hidden size, 16 attention heads and overall with 139M parameters.
The first blank is \textit{person_at_location}.
The second blank is \textit{higher/lower}.
The third blank is \textit{disease}.
The fourth blank is a \textit{reason_for_risk}.

\textbf{[MASK]} has a \textbf{[MASK]} risk of
\textbf{[MASK]} because \textbf{[MASK]}

\begin{table}[h]
\centering
\begin{tabular}{|l|l|l|}
\hline
\textbf{Template} & \textbf{Output} \\
\hline
The first blank is \textit{person_at_location}. & Person who lives in a city
The second blank is \textit{higher/lower}. & has a higher risk of depression
The third blank is \textit{disease}. & because of stress due to noise
The fourth blank is a \textit{reason_for_risk}. & \\
\textbf{[MASK]} has a \textbf{[MASK]} risk of & \\
\textbf{[MASK]} because \textbf{[MASK]} & \\
\hline
\end{tabular}
\caption{Task Setup. Each concept category is given as a prompt to the input and the slots are represented via the \textbf{[MASK]} token. The task for SEQ-TO-SEQ is to generate the \textit{output}}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|l|l|l|}
\hline
\textbf{Model} & \textbf{Template} & \textbf{Output} \\
\hline
BERT \textbf{[MASK]} & \textbf{[MASK]} has a \textbf{[MASK]} risk of & Person who lives in a city
& \textbf{[MASK]} because \textbf{[MASK]} & has a higher risk of depression
& & because of stress due to noise
\hline
SPL TOKEN \textbf{[S]person_at_location[/S]} & \textbf{[S]higher/lower[/S]} risk of & Person who lives in a city
& \textbf{[S]disease[/S]} because & has a higher risk of depression
& \textbf{[S]reason_for_risk[/S]} & because of stress due to noise
\hline
\end{tabular}
\caption{Task Setup for baselines. In the first baseline, we query the BERT MLM model to check if cross-domain knowledge is already present. In our second baseline, we use special tokens to indicate the start and end of each slot. In both the case, the SEQ-TO-SEQ is trained to generate the output.}
\end{table}

• **BART-LARGE**: Larger version of BART-BASE, consisting of 24 transformer layers, 1024 hidden size, 16 heads and 406M parameters.

• **T5-BASE**: The T5 model is also a transformer encoder-decoder model based on Raffel et al. (2020) with 220M parameters with 12-layers each with 768 hidden-state, 3072 feed-forward hidden-state and 12 attention heads.

4.3 Baseline Methods

• **BERT \textbf{[MASK]}**: To understand whether pretrained models contain the knowledge already, we try a masked language modeling baseline where we query the template using \textbf{[MASK]} tokens.

• **SPL TOKEN**: In this approach, we use the special token approach (SPL TOKEN) (Donahue et al., 2020), where we indicate the start and end of each template slot in the input and generate the output sentence.

Table 4 shows the baseline setup of the models for our task with a corresponding example.

4.4 Results

The results across various pretrained encoder-decoder approaches are shown in table 5. In this table, we see that on average, BART models perform better than T5 models on average. We hypothesize this might be an effect of their pretraining task choices and corresponding datasets. We also observe that \textbf{PROMPT} based models outperform the SPL TOKEN based approach. For all of the models and baselines, we used the greedy decoding strategy.

N-gram metrics such as \textbf{ROUGE} are known to be limited, specifically for reasoning tasks. To assess the quality of generated output, three human judges annotated 100 unique samples for correctness - that indicates how many samples were correct from a human perspective.

We used our best performing BART-BASE model for this evaluation. In this experiment, a sentence generated by the SEQ-TO-SEQ for a given template was given to a human judge and they
were asked to evaluate whether the sentence was correct, given the template. The judges were asked to refer to the same sources as the human annotators to verify the correctness. The inter-annotator agreement on graph correctness was substantial with a Fleiss’ Kappa score (Fleiss and Cohen, 1973) of 0.73. From our evaluation, we found that human judges rated about 69% of the sentences to be correct given a template. Both the automated and human evaluation suggests that there is ample room for further improving cross-domain reasoning ability of SEQ-TO-SEQ models.

5 Error Analysis

In this section, we analyze in detail how well language models perform cross-domain reasoning. Automated metrics such as ROUGE are restrictive in terms of understanding the reasoning abilities and we complement our automated evaluation with manual error analysis. For this analysis, we randomly select 100 samples from the validation set predictions where the ROUGE scores were low. We observe the following categories of errors that language models exhibit. Table 6 shows the common type of errors and a corresponding example for each type.

Error Type - Correct but not in gold (17%) : In several cases, we observe that the output produced by the language models are correct despite not matching the gold answer. This phenomenon is evident when the input template contains multiple possible answers. While the gold answer in the example shown in Table 6 (first row) fills the template using smoking, the language models generates an answer that relates to kidney damage. While correct, the automated metrics score this answer lower.

Error Type - Wrong commonsense concept (8%) : In this category of error, the model generates the wrong specification for the given slot. For instance (second row in table 6), the model mistakenly assumes person taking less medication as a socioeconomic condition.

Error Type - Generic Explanation (53%) : In several cases, the model resorts to generic explanation that are obvious. A generic explanation repeats the same information as the rest of sentence as an explanation, thereby not providing any new information compared to the rest of the sentence. In the example shown in Table 6 (row 3), the explanation because of the strain of the heart is already clear from the concept chest pain.

Error Type - Factually Incorrect (22%) : Factually correctness is one of the biggest challenges in NLP applications (Petroni et al., 2020; Pagnoni et al., 2021). The incorrect factual information is also acute for cross-domain reasoning applications as well. As shown in the example (row 4 in table 6), the model incorrectly generates that people with flu diagnosis should do exercise.

Our errors highlight the difficulty of the task for language models. This leaves room for several research questions that requires future work. Overall, cross-domain reasoning is still an uphill task for language models with promising directions.

6 Related Work

Knowledge Bases : Knowledge Bases (KBs) have been the predominant approach to perform cross-domain reasoning in the past. Some of the prominent cross domain knowledge bases include DBPedia (Mendes et al., 2012), YAGO (Suchanek et al., 2007) and NELL (Mitchell et al., 2018). Most of these knowledge bases despite being cross-domain, the focus is primarily on the encyclopedic knowledge. In our work, we focus on ability of SEQ-TO-SEQ for cross-domain reasoning, which can be viewed as a complementary approach to KBs.

Language Models for Knowledge Generation: Using pretrained language models to generate knowledge has been studied for commonsense reasoning tasks. (Sap et al., 2019; Bosselut et al., 2019b; Shwartz et al., 2020a; Bosselut et al., 2021). Our work closely aligns with Bosselut et al. (2019b, 2021). Compared to Bosselut et al. (2019b), our focus in this work to extend this line of work from only commonsense reasoning to perform reasoning cross domain.

Language Model Infilling : Our work also closely relates to the language model infilling work in the literature such as Fedus et al. (2018) and (Donahue et al., 2020). Compared to these works which only look at cloze-test infilling, our work aims to expand templates that cannot be directly modeled as cloze-style. Our work is also related to the story generation efforts such as Yao
| Model         | Type           | ROUGE-1 | ROUGE-2 | ROUGE-L |
|--------------|----------------|---------|---------|---------|
| BERT-BASE    | [MASK]         | 5.33    | 0.72    | 4.94    |
| BERT-LARGE   | [MASK]         | 8.05    | 0.63    | 7.85    |
| T5-BASE      | SPL TOKEN      | 14.00   | 2.71    | 12.58   |
| T5-BASE      | PROMPT         | 14.01   | 2.60    | 12.57   |
| BART-BASE    | SPL TOKEN      | 17.17   | 5.60    | 16.32   |
| BART-BASE    | PROMPT         | 18.89   | 5.87    | 17.96   |
| BART-LARGE   | SPL TOKEN      | 19.54   | 7.57    | 18.49   |
| BART-LARGE   | PROMPT         | 20.58   | 7.32    | 19.58   |

Table 5: Overview of the results compared to baselines. The table shows that BART-BASE performs better than T5-BASE model and BART-LARGE outperforms both.

| Error Type | Template                                                                                     | Gold Answer                                                                                   | Generated Answer                                                                 |
|------------|--------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|
| Correct but not in gold | Children who are exposed to [environmental_factor] are often at a higher risk for [disease] because [reason] | Children exposed to second hand smoke are at a higher risk for lung disease because of breathing in the cigarette smoke | Children who are exposed to lead paint are often at a higher risk for kidney failure because lead causes kidney damage |
| Wrong commonsense concept | People with [certain_socioeconomic_condition] are at higher risk of [disease] as they are more exposed to [reason] | Person who often inhales a lot of dirt is at a higher risk of hay fever because of allergen content. | Person who often does less medications is at a higher risk of hay fever because the drug can help clear it up |
| Generic Answer | When people with [certain_co-morbidities] shows [symptoms], this is because of [reason_for_patient_state] | When people with diabetes shows lethargy, this is because of high glucose levels. | When people with heart disease shows chest pain, this is because of the strain on the heart |
| Factually Incorrect | People with a [health_condition] should do [an_activity] because [reason] | People with a cardiovascular disease should do exercise since exercise burns excess fat | People with a flu diagnosis should do exercise |

Table 6: Error Analysis based on the BART-BASE-PROMPT model. We select 100 samples from the validation set and each row shows an example of each class of error.

et al. (2019); Fan et al. (2018); Ippolito et al. (2019); Rashkin et al. (2020) but our application differs from them in that we focus on cross-domain reasoning instead of content planning for stories.

There has also been efforts to transfer knowledge cross-domain via transfer learning (Min et al., 2017; Wiese et al., 2017; Deng et al., 2018) but our work focuses on cross-domain reasoning in the same input sample unlike transfer learning based approaches.

7 Conclusion and Future Work

In this paper, we present a novel prompt-template-filling approach that adapts language models to perform cross-domain reasoning via prompting. To study this, we present a dataset via a use-case of reasoning across commonsense and health and well-being domain. Through both automated and human metrics, we find that there is immense room for progress towards improving language models’ capability for cross-domain reasoning. For future work, we want to extend this work for multiple other cross-domain scenarios and understand the nature of cross-domain reasoning in depth.

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