An Atlas of Cultural Commonsense for Machine Reasoning

Anurag Acharya, 1 Kartik Talamadupula, 2 Mark A Finlayson 1

1 School of Computing and Information Sciences
Florida International University
2 IBM Research

{aacharya, markaf}@fiu.edu, krtalamad@us.ibm.com

1 Introduction

In the past few years, there have been major advancements in the field of question answering (QA) systems (Richardson, Burges, and Renshaw 2013; Rajpurkar et al. 2016; Both et al. 2016; Singh et al. 2018; Gan and Ng 2019; Fan and Ferrucci 2019; Qu et al. 2019; Zafar et al. 2020) within the field of natural language processing (NLP). The majority of the current work in the field is focused on improving the performance of existing systems; and researchers have looked at different ways in which these systems can be made more accurate and human-like in both their responses as well as their methodology. Incorporating commonsense knowledge and reasoning into NLP systems is one such area of recent focus (Davis and Marcus 2015; Lin, Sun, and Han 2017; Ostermann et al. 2018; Tandon et al. 2018; Tandon, Varde, and de Melo 2018; Trinh and Le 2018; Merkhofer et al. 2018); and a large body of recent work has focused on the creation, curation, and use of large-scale commonsense knowledge bases and knowledge graphs (Speer and Havasi 2012; Sap et al. 2019b; Bosselut et al. 2019). Importantly, these types of knowledge acquisition efforts have a long history in and have been of great use to a wide variety of AI systems (Wollmer et al. 2013; Bouchoucha, He, and Nie 2013; Shi et al. 2017; Olteanu, Varol, and Kiciman 2017; Sap et al. 2019a; Liu et al. 2020).

Commonsense knowledge in one form or another seems to be a prerequisite for natural, human-like, and intelligent interaction with the world. For example, if a person hits a wall and is able to punch a hole through it, almost all humans will safely assume that it was probably made of dry-wall and not concrete. One is able to make this inference without having any information about the wall, its construction, material, etc. Such reasoning—while considered so common among humans that it is taken for granted—is actually much harder to replicate in automated systems (Clark et al. 2018; Boratto et al. 2018). The ability to incorporate such commonsense knowledge into various NLP tasks can vastly improve the quality of the returned responses, as well as the accuracy of the work done in the field (Marcus 2018).

The importance of commonsense knowledge bases and repositories is clear from the volume of recent work that makes use of resources such as ConceptNet (Speer, Robyn 2020; Speer, Chin, and Havasi 2016; Speer and Havasi 2012) to imbue NLP systems with worldly knowledge obtained from humans. A key contribution along these lines was ATOMIC (Sap et al. 2019b), which tackles the task of incorporating commonsense reasoning into NLP tasks by generating an atlas of “if-then” rules that taken together produce behavior akin to commonsense reasoning. Work such as ATOMIC and COMET (Bosselut et al. 2019) has made commonsense knowledge more accessible to the current generation of state-of-the-art NLP techniques; and the progress and pitfalls of these resources have been catalogued recently (Sap et al. 2020).

One glaring omission in all of this prior work has been the lack of focus on context-contingent aspects of commonsense knowledge; that is, most prior work views common sense as a universal monolith. However, we know that this is not the case, and in this paper we focus on one highly relevant type of context-specific commonsense knowledge, namely cultural commonsense. Consisting of ritualistic, geographical, and social knowledge, cultural commonsense plays a large but hidden role in humans’ day-to-day social interactions.

For example, let us consider a very simple social setting: You are invited to a wedding. How long do you expect to be...
gone for? For most people in the United States or the wider Western world, the answer would probably be at least a few hours: probably half a day, starting in the early afternoon. However, for many people in India, the obvious answer is that you will probably have to lay aside several days—perhaps even a week—for the whole event. Such socially-conditioned knowledge is inherently obvious to people from the respective cultures; and hints at the differences in commonsense knowledge across cultural and social settings, particularly when it comes to ritualistic practices.

This paper builds on prior work on systematizing commonsense knowledge for use in NLP tasks by demonstrating a proof-of-concept scheme for gathering cultural commonsense in a format similar to previous approaches like ATOMIC. Specifically, we start by studying the extensive prior literature on cultural knowledge and ritual practices; and select a short list of three rituals to focus on for our demonstration. We selected three different national groups that are diverse in their ritualistic practices, and conducted a pilot experiment via a survey. We report on the results of the survey, and showcase what a truly cultural commonsense knowledge repository might look like. We hope that this work spurs future research on incorporating cultural and social commonsense knowledge into NLP systems across a wide range of tasks.

2 Related Work

While the concept of incorporating cultural knowledge into commonsense is fairly unique, there have been several previous works that have laid the groundwork for it by building commonsense reasoning systems. We build on the ATOMIC (Sap et al. 2019b) system and knowledge repository, where crowdsourced commonsense information was used to build an atlas for if-then reasoning. ATOMIC builds a knowledge graph containing inferential knowledge regarding 24,000 “short events”. The dataset is then used on the social question answering system SocialIQA (Sap et al. 2019c), which shows an increase in performance using the commonsense knowledge from ATOMIC.

Another prominent line of work is on building and analyzing the AI2 Reasoning Challenge (ARC) (Clark et al. 2018). ARC consisted of a dataset of almost 8,000 science questions in English. This dataset was split into the Easy set and the Challenge set; and the Challenge set consisted of questions that neither a retrieval-based algorithm nor a word co-occurrence algorithm were able to answer correctly. Later, Boratko et al. (2018) more precisely analyzed the ARC knowledge, defining 7 knowledge types and 9 reasoning types, as well as triple annotating 192 ARC questions. They concluded that more work needed to be done on initial query formulation.

In addition to these, there have been several other efforts in the field of commonsense reasoning. Espinosa and Lieberman (2005) introduced Eventent, which deals with inferring temporal relations between commonsense events. Related work was done by Rashkin et al. (2018), who built a system called Event2mind—a commonsense inference system on events, intents, and reactions. Furthermore, Speer, Chin, and Havasi (2016) have built an updated version of ConceptNet (Liu and Singh 2004), a practical commonsense reasoning toolkit, which is now a multilingual graph of general knowledge. Another relevant work in the field is the Webbuild 2.0, a fine-grained commonsense knowledge distillation (Tandon, De Melo, and Weikum 2017). Several of the other important pieces of work done in the field of commonsense have been reviewed by Davis and Marcus (2015), which lays out the uses, successes, challenges, approaches and possible future work in the field of commonsense reasoning. Apart from these applications, Gordon and Hobbs (2017) lay out a formal theory of commonsense psychology and how people assume others think, while Lake et al. (2017) put forward their argument as to how we can go about building machines that learn and think like people. There are several other noteworthy works like Cyc (Lenat 1995) and Ordinal commonsense inference (Zhang et al. 2017).

The Stanford Question Answering Dataset (SQuAD) (Rajpurkar et al. 2016) consists of 100k+ questions and a reading comprehension dataset; these were collected from 536 highly-ranked Wikipedia articles split into 23,215 paragraphs, with numerous questions and answers. They contrast 3 types of tasks: 1. reading comprehension (RC): read a passage, select a span that answers, 2. Open-domain QA: answer a question from a large set of documents, and 3. Cloze datasets: predict a missing word in a passage.

There have also been several efforts to facilitate Question Answering (QA) systems and commonsense knowledge by building datasets. The seminal work in this was by Sap et al. (2019c), which introduces a benchmark dataset for social and emotional commonsense reasoning. It consists of almost 45k multiple-choice items with one context (a sentence), one question, and three answers. This crowdsourced dataset is available for researchers to download and use. The MCTest dataset (Richardson, Burges, and Renshaw 2013) consists of multiple-choice reading comprehension questions comprised of short (150-300 words) fictional stories which were targeted at 7 year olds. The dataset had a total of 500 stories and 2000 questions (4 questions per story). The above systems and data are just key examples; many other QA and commonsense reasoning systems and datasets have been created in the field (Roemmele, Bejan, and Gordon 2011; Levesque, Davis, and Morgenstern 2012; Talmor et al. 2018; Hirschman et al. 1999; Trischler et al. 2016; Dunn et al. 2017; Joshi et al. 2017; Clark 2015; Welbl, Liu, and Gardner 2017; Hermann et al. 2015).

3 Cultural Knowledge and Rituals

The primary focus of this work is to encode cultural knowledge as an essential part of commonsense knowledge. To do this, we need to first find ways to collect cultural knowledge across a variety of cultural groups. However, this is not straightforward, since cultural knowledge can be fairly arbitrary and complex across groups. Prior literature from the study of cultural groups (see Section 2) seems to suggest that it is hard enough just to define culture given the array of complexities and nuance; however, it is even harder to identify the knowledge that comes along with it and to differentiate across cultural groups. Furthermore, as cultural
norms and practices are so varied across various groups, it is hard to find knowledge structures that can be clearly compared across different groups. The first task, therefore, is to find topics that are relatively common across different groups; and that can be compared in a like-for-like fashion, thus demonstrating the relevance of culture-dependent representation of commonsense knowledge.

3.1 Rituals

We first detail our search for a cultural marker that can be consistently compared across different cultural groups. After a survey of the extant literature, we decided to focus on rituals as the markers that are commonly represented across cultures. There are several definitions of ritual, and the concept often comes entangled with religion and rites (Braun and McCutcheon 2000, p. 259-262). For the purposes of this work, we consider two definitions: a broad one and a narrow one. Broadly defined, ritual is simply a “culturally defined set of behavior” (Leach 1968). More specifically, however, a widely accepted definition is by Turner (1973), who defines ritual as:

“...a stereotyped sequence of activities involving gestures, words, and objects, performed in a sequestered place, and designed to influence preternatural entities or forces on behalf of the actors’ goals and interests”

While studying rituals in detail is beyond the scope of this work, there are several reasons for focusing on rituals as indicators of cultures. First, rituals are well-studied and quite a bit of prior work exists for us to build on. Prior work has identified not just specific rituals, but also the genres and types of rituals and their variance across cultures, etc. (Durkheim and Swain 2008; Turner 1973; Bell 1992, 1997). There is also a rich body of literature on the analysis of cultural practices for various rituals across several cultures, clearly indicating a strong concomitance between cultures. While there is a large breadth of work that looks at rituals, the various taxonomies of rituals show some basic categories previously outlined, and the variance in the extent of their observance across cultures, another crucial decision is in selecting specific rituals as markers of cultural knowledge. There were several factors that we had to consider while making this decision. First and foremost, we needed activities whose names or keywords are used in multiple cultures. For example, a ritual like Passover cannot be used since it is highly specific to Judaism and Jewish cultures. It would make no sense to ask “What are your cultural practices with regards to Passover?” of a Hindu or a Muslim. Furthermore, the more specific the keywords, the easier it is for a QA system to associate its knowledge to that activity. As an example, “Catholic Christmas Mass” is a highly denomination- and group-specific ritual, and will exhibit very little variation across cultures. A second factor that we needed to consider in order to ease the data collection process was the selection of activities that have fairly concise and telegraphic names. For instance, it is confusing to probe a participant in a study about “the kinds of things you do before a sports game popular in your culture; even though this is an activity that is fairly widespread and at the same time variable across cultures. Instead, we are seeking rituals that can be described in just a few words, and bring a very specific activity or event to mind. Our choice of rituals is intended to primarily ease the collection of crowdsourced data—we thus pick activities that may have different practices across different cultural groups, but are likely to be found in all of them. We take guidance from the analysis of Bell (1997) and use the following six rituals as our target rituals in this work:

1. Wedding: wedding, marriage, marry, matrimony, nuptials, wedlock, union, hymeneals (rite of passage)
2. Funeral: funeral, burial, cremation, interment, entombment, obsequy (rite of passage)
3. Coming of Age: becoming a man, becoming a woman, manhood, womanhood, adulthood (rite of passage)
4. Birth: childbirth, delivery, birthing, childbearing, parturition, nativity (rite of passage)
5. New Year (calendrical rite)
6. Birthday: name day, natal day (rite of passage)
Out of these six, we use the first three for our pilot experiment that is reported here (see Section 5.2 for details). These rituals all have the advantage that across cultural groups, there are not too many diverse ways of naming or expressing them, and the meaning is evident to most human subjects answering our survey.

4 Methodology

In this section, we outline the process of gathering the ritual-based cultural knowledge for our work. We first elucidate on the target cultures; followed by the details of our pilot experiment; and then the survey questionnaire that we used. We share these details both to describe our method, as well as to enhance the reproducibility of the work.

4.1 Selecting Target Cultures

For this study, we focused on three specific target groups—Americans (people from the United States of America), Indians (people from India), and Filipinos (people from the Philippines)—based on a number of factors. Firstly, all three countries use English as one of their major languages, either officially or unofficially; since our study was to be conducted in English, this was a key requirement. Secondly, Amazon Mechanical Turk has a high presence of workers from these three countries (Difallah, Filatova, and Ipeirotis 2018). While this does not affect the pilot experiment, the planned second phase of the study will be conducted via Amazon’s Mechanical Turk platform, and so it was essential that we consider the demographics of the crowd-workers. Moreover, this trio of groups also allows us to have a unique contrast and high degree of cultural variation. The US-Philippines data is a potential source for contrast in terms of variations of Christianity-based cultures; while the India-Philippines data can be a contrast between the differences in Asian cultures. In addition to this, the fact that the United States and India are large and diverse countries consisting of various cultures allows us to capture a varied amount of data in terms of rituals.

4.2 Pilot Experiment

For the pilot experiment, we collected data from a small number of participants for three rituals: coming of age, wedding, and death rites/funeral. We collected two unique sets of responses per ritual per culture, for a total of 18 unique responses. Participants were recruited based on personal contact by email, and all participants were over the age of 18. Each person only filled out one survey to ensure that every recorded response was unique. The identification of cultural group membership was done based on self-identification by the participants, based on a demographic questionnaire that preceded the main survey.

The participants took the survey using an online form, which was hosted on our university servers so that no commercial third party collected any information about the participants. The actual survey consisted of a series of questions that are modifications of the ATOMIC (Sap et al. 2019b) question set (see Section 4.3 for details). The questions remained the same across rituals and cultures, with only the initial prompt changing, so as to keep the method as consistent as possible. The survey was conducted asynchronously and all participants were compensated for their time.

We were also extremely cognizant of the ethical aspects of our study. The details of the study were reviewed by the Institutional Review Board (IRB) of Florida International University. The proposed study was deemed Exempt Research, and given approval to proceed. No step of the study—excepting internal preparations—were carried out prior to obtaining this approval. No personally identifiable information was collected from the participants, and all IRB requirements were met and followed during the course of the study.

4.3 Survey Questionnaire

The survey questionnaire was divided into two sections: the self-identification questionnaire, and the survey proper.

Self-identification Questions We based the self-identification questionnaire primarily on the College Students Knowledge and Belief (Clark and Barrows 1981) survey’s questionnaire. Portions of the questionnaire relevant to our current study were modified to suit our purposes, and the wording changed to be consistent with contemporary terminology. This self-identification questionnaire was further modified to prioritize the targeted countries with regard to language and religion. The options for these two fields were based on most likely answers given the demographics of those populations. The updated questionnaire asked participants about their place of birth,
languages used, and religion; it also asked these questions about their primary caregivers in order to ascertain the degree to which the participants were immersed into their identified culture.

**Event-specific Questions** For the main survey, a prompt specifying the ritual event under consideration was first shown, and the participants were asked a set of questions pertaining to the specific event; see the layout of the form in Figure 1 for details. The questions asked were the following:

1. Where does this event typically happen?
2. When does this event typically happen?
3. How long does this event typically last?
4. How many people typically participate in an event like this?
5. Who are the important people involved in this event? (Maximum 5)
6. Is one or more of the important people the focus of this event?
7. Who are the people who are the focus of this event? (check all that apply)

Question 7 only appeared if participants answered “Yes” to Question 6, and the list was automatically populated from the answers of Question 5.

**Person-specific Questions** After the event-specific questions, the participants were asked to answer questions that involved the specific persons mentioned in the events (as part of their responses). This part of the survey was adapted from ATOMIC (Sap et al., 2019b). Questions were divided into three temporal categories—before the event, during the event, and after the event. We considered four types of questions: 1. intent & reaction; 2. need & want; 3. effects; and 4. attributes. These four types evolved into 11 questions on the survey form, as shown in Figure 1. In terms of the presentation of the questions, the terms PersonX or PersonY were replaced by the actual names that participants provided in Question 5, in order to make the questions feel more natural to the survey participants. These person-specific questions were repeated for each person that the survey participant deemed “important” to a given event.

### 5 Results

In this section, we detail the findings of our pilot study. We first report on the demographics of the survey participants, particularly with an eye towards cultural background; and then recount and discuss the responses to the survey.

#### 5.1 Demographics

There were a total of 18 individuals who participated in the study. Only information that was deemed necessary for the purposes of the experiment was collected from participants. For example, we did not collect gender and age for this study, as we decided they were not relevant.

| **BEFORE THE EVENT** |
|-----------------------|
| Does this person typically have an intent in causing the event? |
| What is this person’s typical intent in causing the event? |
| Does this person typically need to do anything before this event? |
| What does this person typically need to do before this event? |

| **DURING THE EVENT** |
|----------------------|
| Does this person typically use something during the event? |
| What things does this person typically use during this event? |

| **AFTER THE EVENT** |
|---------------------|
| How would this person be described as a consequence of the event? |
| Does this person typically want to do something after this event? |
| What does this person typically do after this event? |
| What is the typical effect of the event on this person? |
| What does this person typically feel after this event? |

Table 1: Questions asked of the survey participants for each important person associated to an event in their responses.

**Geography** Out of the 18 participants, there were six people each born in the USA, India, and The Philippines. Of those born in India, two are now living in the USA; and of those born in the Philippines, four currently live in the USA and one lives in New Zealand. Every respondent born in the USA said that they still lived there. Only two participants indicated that their caregivers were born in a country other than where they were born. While all the participants that identified as American (from the USA) resided in the USA; in the case of Indian and Filipino participants, it was a mix of them living in India and the Philippines respectively, as well as in the USA. However, these participants still identified only as Indian or Filipino, and not the hyphenated identities Indian-American and Filipino-American respectively. Of the participants who said they lived in the USA, five were from the Southeast, three from the Northeast, two from the Midwest, and one from the West. Among the ones living in India, three lived in Central India, and one in the Northeast. The person living in the Philippines lived in the National Capital Region.

**Religion** Since a lot of rituals have a basis in religion—to the extent that they are often intertwined (Goody, 1961; Geertz and Banton, 1966; Bell, 1992)—it is important to ensure a diversity of religious practice among the respondents. To ensure that we had this wide representation, we made a distinction in the religion the participants practiced growing up versus the religion they practice now (Figure 2b)). The reasoning behind this was that the religion that respondents practiced while growing up is important in terms of their knowledge of various rituals. Of the participants in the study, 9 said they grew up practicing some form of Christianity; 6 practicing Hinduism; 1 Islam; 1 Buddhism; and 1 said they grew up not practicing any religion (N = 18). This is encapsulated in Figure 2a). In terms of religion currently
practiced, 7 said they still practiced some form of Christianity; 5 said they practiced Hinduism; 4 said they did not practice any religion and/or were atheist; 1 practiced Buddhism; and 1 practiced other religion (Unitarian Universalism).

Among participants who identified as Americans, 3 said they grew up practicing some form of Christianity (Protestant, Roman Catholic, and Lutheran); 1 Islam; 1 Buddhism; and 1 participant said they grew up non-religious or atheist. For every participant, it was the case that either one or both of their caregivers (parents/grandparents/etc.) practiced the religion that the participant themselves grew up practicing. However, only 2 participants said that they were still practicing some form of Christianity; 3 said they were non-practicing or non-religious or atheist, and 1 said they practiced “other” religion (Unitarian Universalism). Among participants who identified as Indians, all 6 said they grew up Hindu, and both their caregivers also practiced Hinduism. Only 1 participant said they are no longer religious. Among participants who identified as Filipinos, all 6 said they grew up practicing some form of Christianity, with 5 of them growing up practicing Roman Catholicism and 1 Anglicanism, with their caregivers also practicing the same religions. Of them, 1 said they now practiced Buddhism, while the rest remained some form of Christian; although one switched from Anglican to Lutheran.

**Language** Among the N = 18 participants, 6 identified their native language as English; 5 as Filipino/Tagalog; 4 as Hindi; and 1 each as Marwari, Marathi, and Kapampangan. Of these, only 1 person said their caregivers’ native language was different from their own (Arabic). However, 10 participants said they used English to communicate with their friends now; 4 Hindi; and 4 Filipino/Tagalog. More importantly, 2 participants said they spoke to their family in a language other than their or their caregivers’ native language; both of these identified as Indian.

### 5.2 Ritual Survey Responses

For our pilot study, we collected 2 responses per ritual (R = 3, see Section 3.2 for a list) per cultural group (C = 3). Since there are not enough data points yet in our pilot experiment to conduct a quantitatively significant study, we instead present a qualitative analysis of the data collected thus far. We focus on the 3 rituals for which we collected data.

**Wedding** The most significant difference seen in the responses for the wedding ritual was that while participants from the USA and the Philippines said weddings typically lasted a few hours, Indian participants responded by saying that weddings lasted multiple days (Table 2). This is an excellent example of the type of knowledge that is collected by our work, where a machine can now leverage this information to have commonsense that is culturally sensitive and correct. This also suggests that with more data, more such variations in the way rituals are conducted across cultures can be documented and understood by NLP systems.

All participants gave similar responses in terms of the important people for a wedding: the bride, the groom, and their...
Cultural differences in wedding ritual.

- In the United States, the bride plans the wedding.
- In India, the bride gets to know her groom’s family.
- In the Philippines, the bride buys a dress.

Cultural differences in funeral ritual.

- In the United States, a funeral usually takes place in a church or a funeral home.
- In India, a funeral usually takes place at a cremation or funeral grounds.
- In the Philippines, a funeral usually takes place at home.

Figure 4: Qualitative examples of culturally aware commonsense knowledge obtained by our study.

| Culture | Wedding | Coming-of-Age | Funeral |
|---------|---------|---------------|---------|
| US      | Few hours | Varies        | Few hours |
| IN      | Several days | Few Hours     | 13 days |
| PH      | Few hours | Varies        | 4-10 days |

Table 2: Lengths of rituals per culture in number of days. US - United States, IN - India, PH - Philippines.

Parents. There were also differences recorded in the role of the bride in different cultures, as highlighted in Figure 4(a). Participants from the USA and the Philippines said the bride would focus on the wedding planning part of the event, like dresses and so forth; while the Indian participants focused on the cultural aspects of the wedding, as well as the fact the bride might have to get to know the groom’s family, and possibly the groom himself. This is another key piece of knowledge to come out of our study, and highlights another difference amongst cultural groups. It would be extremely unlikely for a bride to not know the groom’s family, let alone the groom himself, in a typical US wedding; while this is still reasonably prevalent in Indian society. The effects of the event and the consequences on the people in the event were shown to be similar across cultures, suggesting that there are some parts which are naturally universally common for a specific ritual such as a wedding.

Funeral. There were noticeable differences recorded in the way participants from different cultural groups said funerals were observed in their cultures, as encapsulated in Figure 4(b). The American participants said that funerals were often held in churches, while Filipino and Indian participants said they usually took place at home or at designated funeral homes/grounds. Similarly, the data suggested American funerals lasted a few hours; Filipino ones a few days; while Indian funeral rites lasted 13 days (Table 1). All participants agreed that the number of guests and their roles were varied. Moreover, the participant response seemed to suggest Indian funerals had more ritualistic rites to be performed compared to the other two cultural groups. These findings validate our expectation that rituals can give us a peek into cultures and how they vary; and how commonsense knowledge cannot truly be complete without including cultural nuances. As with weddings, the effects of the event (funeral) on the people were described similarly by participants across cultures as “sad”, suggesting once again that despite the difference in ritualistic aspects, there is a universal commonality among major life events.

Coming of Age. For this ritual, both Indian and American participants reported that they observe no coming-of-age rituals as such; while the Filipino participants said they observed a small family reunion and/or celebration. They used adjectives like “happy” and “proud” to express how the person coming of age felt. An American participant focused on practicalities, and said it was expected that a person start being independent and look for a job once they turn eighteen.

While the data observed with respect to this ritual in our small sample size does not seem to indicate many differences, we know that some communities in both the USA and India do observe coming-of-age rituals; with celebrations like Quinceañera being observed in the former (Cantu 1999); and Upayan (for boys) and Ritusuddhi (for girls) being observed in the latter (Gray 1979; Smith 1986). These are data points that we would expect to see as we scale up the data collection process.

6 Conclusion & Future Work

In this paper, we presented the setup and results of a pilot experiment aimed at collecting cultural information from diverse groups about different life rituals; all aimed at creating a repository of cultural commonsense knowledge. Such knowledge can greatly improve the ability of AI systems to exhibit human-like performance, and address gaps in their current knowledge. We showcased some interesting qualitative results that can have implications for NLP tasks. The task of injecting cultural sensitivity in commonsense reasoning, while being crucial to developing a true human-like AI, has not been broached in the field. We expose this gap and in order to bridge it, perform the difficult task of choosing a suitable cultural marker that would work within existing frameworks of commonsense knowledge. While the data we have collected thus far will not at this point directly improve the performance of QA or other NLP tasks, the work presented here allows for scale-up into a full dataset. We are currently in that process; we are also evaluating existing
datasets to design benchmarks that require the use of cultural commonsense.

7 Acknowledgements
This project was funded by an IBM Faculty Award awarded to Dr. Finlayson.

References
Bell, C. 1992. *Ritual theory, ritual practice*. Oxford University Press.

Bell, C. M. 1997. *Ritual: Perspectives and dimensions*. Oxford University Press on Demand.

Boratko, M.; Padigela, H.; Mikikilineni, D.; Yuvraj, P.; Das, R.; McCallum, A.; Chang, M.; Fokoue-Nkoutche, A.; Kapaniapthi, P.; Mattei, N.; Musa, R.; Talamadupula, K.; and Witbrock, M. 2018. A Systematic Classification of Knowledge, Reasoning, and Context within the ARC Dataset. In Proceedings of the Workshop on Machine Reading for Question Answering (MRQA) at ACL 2018, 60–70.

Bosselut, A.; Rashkin, H.; Sap, M.; Malaviya, C.; Celikyilmaz, A.; and Choi, Y. 2019. COMET: Commonsense Transformers for Automatic Knowledge Graph Construction. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 4762–4779.

Both, A.; Diefenbach, D.; Singh, K.; Shekarpor, S.; Cherix, D.; and Lange, C. 2016. Qanary—a methodology for vocabulary-driven open question answering systems. In *European Semantic Web Conference*, 625–641. Springer.

Bouchoucha, A.; He, J.; and Nie, J.-Y. 2013. Diversified query expansion using conceptnet. In Proceedings of the 22nd ACM international conference on Information & Knowledge Management, 1861–1864.

Braun, W.; and McCutcheon, R. 2000. *Guide to the Study of Religion*. Bloomsbury Publishing.

Cantú, N. E. 1999. La quinceañera: Towards an ethnographic analysis of a life-cycle ritual. *Southern Folklore* 56(1): 73.

Clark, J.; and Barrows, T. 1981. College students’ knowledge and beliefs: A survey of global understanding .

Clark, P. 2015. Elementary school science and math tests as a driver for AI: take the aristo challenge! In *AAM*, 4019–4021. Citeseer.

Clark, P.; Cowhey, I.; Etzioni, O.; Khot, T.; Sabharwal, A.; Schoenick, C.; and Tafjord, O. 2018. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv preprint arXiv:1803.05457 .*

Cliford, G. 1973. The Interpretation of Cultures: Selected Essays.

Davis, E.; and Marcus, G. 2015. Commonsense reasoning and commonsense knowledge in artificial intelligence. *Communications of the ACM* 58(9): 92–103.

Dean, K. 1997. Ritual and space. *Civil Society in China, Armonk: ME Sharpe* 172–192.

Difallah, D.; Filatova, E.; and Ipeirotis, P. 2018. Demographics and dynamics of mechanical Turk workers. In *Proceedings of the eleventh ACM international conference on web search and data mining*, 135–143.

Dunn, M.; Sagun, L.; Higgins, M.; Guney, V. U.; Cirik, V.; and Cho, K. 2017. Searchqa: A new q&a dataset augmented with context from a search engine. *arXiv preprint arXiv:1704.05179 .*

Durkheim, E.; and Swain, J. W. 2008. *The elementary forms of the religious life*. Courier Corporation.

Espinosa, J.; and Lieberman, H. 2005. Eventnet: Inferring temporal relations between commonsense events. In *Mexican International Conference on Artificial Intelligence*, 61–69. Springer.

Fan, J. J.; and Ferrucci, D. A. 2019. Scoring candidates using structural information in semi-structured documents for question answering systems. US Patent 10,223,441.

Gan, W. C.; and Ng, H. T. 2019. Improving the robustness of question answering systems to question paraphrasing. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 6065–6075.

Geertz, C.; and Banton, M. 1966. Religion as a cultural system .

Goody, J. 1961. Religion and ritual: the definitional problem. *The British Journal of Sociology* 12(2): 142–164.

Gordon, A. S.; and Hobbs, J. R. 2017. A formal theory of commonsense psychology: How people think people think. Cambridge University Press.

Gray, J. N. 1979. Keep the Hom fires burning: sacrifice in Nepal. *Social Analysis: The International Journal of Social and Cultural Practice* (1): 81–107.

Hermann, K. M.; Kocisky, T.; Grefenstette, E.; Espeholt, L.; Kay, W.; Suleyman, M.; and Blunsom, P. 2015. Teaching machines to read and comprehend. In *Advances in neural information processing systems*, 1693–1701.

Hirschman, L.; Light, M.; Breck, E.; and Burger, J. D. 1999. Deep read: A reading comprehension system. In *Proceedings of the 37th annual meeting of the Association for Computational Linguistics*, 325–332.

Joshi, M.; Choi, E.; Weld, D. S.; and Zettlemoyer, L. 2017. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. *arXiv preprint arXiv:1705.03551 .*

Lake, B. M.; Ullman, T. D.; Tenenbaum, J. B.; and Gershman, S. J. 2017. Building machines that learn and think like people. *Behavioral and brain sciences* 40.

Leach, E. R. 1968. *A runaway world?* Oxford University Press.

Lenat, D. B. 1995. CYC: A large-scale investment in knowledge infrastructure. *Communications of the ACM* 38(11): 33–38.

Levesque, H.; Davis, E.; and Morgenstern, L. 2012. The winograd schema challenge. In *Thirteenth International
Conference on the Principles of Knowledge Representation and Reasoning. Citeseer.
Lin, H.; Sun, L.; and Han, X. 2017. Reasoning with heterogeneous knowledge for commonsense machine comprehension. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, 2032–2043.
Liu, H.; and Singh, P. 2004. ConceptNeta practical commonsense reasoning tool-kit. BT technology journal 22(4): 211–226.
Liu, W.; Zhou, P.; Zhao, Z.; Wang, Z.; Ju, Q.; Deng, H.; and Wang, P. 2020. K-BERT: Enabling Language Representation with Knowledge Graph. In AAAI, 2901–2908.
Marcus, G. 2018. Deep learning: A critical appraisal. arXiv preprint arXiv:1801.00631.
Merkhofer, E.; Henderson, J.; Bloom, D.; Strickhart, L.; and Zarrella, G. 2018. Mitre at semeval-2018 task 11: Commonsense reasoning without commonsense knowledge. In Proceedings of The 12th International Workshop on Semantic Evaluation, 1078–1082.
Olteanu, A.; Varol, O.; and Kiciman, E. 2017. Distilling the outcomes of personal experiences: A propensity-scored analysis of social media. In Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, 370–386.
Ostermann, S.; Roth, M.; Modi, A.; Thater, S.; and Pinkal, M. 2018. Semeval-2018 task 11: Machine comprehension using commonsense knowledge. In Proceedings of the 12th International Workshop on Semantic Evaluation, 747–757.
Qu, C.; Yang, L.; Croft, W. B.; Scholer, F.; and Zhang, Y. 2019. Answer interaction in non-factoid question answering systems. In Proceedings of the 2019 Conference on Human Information Interaction and Retrieval, 249–253.
Raijpurkar, P.; Zhang, J.; Lopyrev, K.; and Liang, P. 2016. Squad: 100,000+ questions for machine comprehension of text. arXiv preprint arXiv:1606.05250.
Rashkin, H.; Sap, M.; Allaway, E.; Smith, N. A.; and Choi, Y. 2018. Event2mind: Commonsense inference on events, intents, and reactions. arXiv preprint arXiv:1805.06939.
Richardson, M.; Burges, C. J.; and Renshaw, E. 2013. Mctest: A challenge dataset for the open-domain machine comprehension of text. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, 193–203.
Roemmele, M.; Bejan, C. A.; and Gordon, A. S. 2011. Choice of Plausible Alternatives: An Evaluation of Commonsense Causal Reasoning. In AAAI spring symposium: logical formalizations of commonsense reasoning, 90–95.
Sap, M.; Gabriel, S.; Qin, L.; Jurafsky, D.; Smith, N. A.; and Choi, Y. 2019a. Social bias frames: Reasoning about social and power implications of language. arXiv preprint arXiv:1911.03891.
Sap, M.; Le Bras, R.; Allaway, E.; Bhagavatula, C.; Lourie, N.; Rashkin, H.; Roof, B.; Smith, N. A.; and Choi, Y. 2019b. ATOMIC: An Atlas of Machine Commonsense for If-then Reasoning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, 3027–3035.
Sap, M.; Rashkin, H.; Chen, D.; Le Bras, R.; and Choi, Y. 2019c. Social IQA: Commonsense Reasoning about Social Interactions. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 4453–4463.
Sap, M.; Schwartz, V.; Bosselut, A.; Choi, Y.; and Roth, D. 2020. Commonsense Reasoning for Natural Language Processing. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: Tutorial Abstracts, 27–33.
Shi, F.; Chen, L.; Han, J.; and Childs, P. 2017. A data-driven text mining and semantic network analysis for design information retrieval. Journal of Mechanical Design 139(11).
Singh, K.; Radhakrishna, A. S.; Both, A.; Shekarpour, S.; Lytra, I.; Usbeck, R.; Vyas, A.; Khikmatullaaev, A.; Punjani, D.; Lange, C.; et al. 2018. Why reinvent the wheel: Let’s build question answering systems together. In Proceedings of the 2018 World Wide Web Conference, 1247–1256.
Smith, B. K. 1986. The unity of ritual. Indo-Iranian Journal 29(2): 79–96.
Speer, R.; Chin, J.; and Havasi, C. 2016. Conceptnet 5.5: An open multilingual graph of general knowledge. arXiv preprint arXiv:1612.03975.
Speer, R.; and Havasi, C. 2012. Conceptnet 5. Tiny Transactions of Computer Science.
Speer, Robyn. 2020. ConceptNet in Context. Invited talk at the Reasoning for Complex QA (RCQA) Workshop at AAAI 2020.
Talmor, A.; Herzig, J.; Lourie, N.; and Berant, J. 2018. CommonsenseQA: A Question Answering Challenge Targeting Commonsense Knowledge. CoRR abs/1811.00937. URL http://arxiv.org/abs/1811.00937.
Tandon, N.; De Melo, G.; and Weikum, G. 2017. Webchild 2.0: Fine-grained commonsense knowledge distillation. In Proceedings of ACL 2017, System Demonstrations, 115–120.
Tandon, N.; Mishra, B. D.; Grus, J.; Yih, W.-t.; Bosselut, A.; and Clark, P. 2018. Reasoning about actions and state changes by injecting commonsense knowledge. arXiv preprint arXiv:1808.10012.
Tandon, N.; Varde, A. S.; and de Melo, G. 2018. Commonsense knowledge in machine intelligence. ACM SIGMOD Record 46(4): 49–52.
Trinh, T. H.; and Le, Q. V. 2018. A simple method for commonsense reasoning. arXiv preprint arXiv:1806.02847.
Trischler, A.; Wang, T.; Yuan, X.; Harris, J.; Sordoni, A.; Bachman, P.; and Suleman, K. 2016. Newsqa: A machine comprehension dataset. arXiv preprint arXiv:1611.09830.
Turner, V. W. 1973. Symbols in African ritual. Science 179(4078): 1100–1105.
Ulrich, W. L. 1984. HRM and culture: History, ritual, and myth. *Human resource management* 23(2): 117–128.

Underhill, A. 2000. An analysis of mortuary ritual at the Dawenkou site, Shandong, China. *Journal of East Asian Archaeology* 2(1): 93–127.

Welbl, J.; Liu, N. F.; and Gardner, M. 2017. Crowd-sourcing multiple choice science questions. *arXiv preprint arXiv:1707.06209*.

Wöllmer, M.; Weninger, F.; Knaup, T.; Schuller, B.; Sun, C.; Sagae, K.; and Morency, L.-P. 2013. Youtube movie reviews: Sentiment analysis in an audio-visual context. *IEEE Intelligent Systems* 28(3): 46–53.

Zafar, H.; Dubey, M.; Lehmann, J.; and Demidova, E. 2020. IQA: Interactive query construction in semantic question answering systems. *Journal of Web Semantics* 100586.

Zhang, S.; Rudinger, R.; Duh, K.; and Van Durme, B. 2017. Ordinal common-sense inference. *Transactions of the Association for Computational Linguistics* 5: 379–395.