Towards Question Format Independent Numerical Reasoning: A Set of Prerequisite Tasks

Swaroop Mishra¹, Arindam Mitra², Neeraj Varshney¹, Bhavdeep Sachdeva¹ and Chitta Baral¹

¹Arizona State University
²Microsoft Research

{srmishr1, nvarshn2, bssachde, chitta}@asu.edu, arindam.mitra@microsoft.com

Abstract

Numerical reasoning is often important to accurately understand the world. Recently, several format-specific datasets have been proposed, such as numerical reasoning in the settings of Natural Language Inference (NLI), Reading Comprehension (RC), and Question Answering (QA). Several format-specific models and architectures in response to those datasets have also been proposed. However, there exists a strong need for a benchmark which can evaluate the abilities of models, in performing question format independent numerical reasoning, as (i) the numerical reasoning capabilities we want to teach are not controlled by question formats, (ii) for numerical reasoning technology to have the best possible application, it must be able to process language and reason in a way that is not exclusive to a single format, task, dataset or domain. In pursuit of this goal, we introduce NUMBERGAME, a multifaceted benchmark to evaluate model performance across numerical reasoning tasks of eight diverse formats. We add four existing question types in our compilation. Two of the new types we add are about questions that require external numerical knowledge, commonsense knowledge and domain knowledge. While recently many QA datasets involving external knowledge have been proposed, ours incorporates them in a numerical reasoning setting. Other types in our compilation build upon existing data sets. For building a more practical numerical reasoning system, NUMBERGAME demands four capabilities beyond numerical reasoning: (i) detecting question format directly from data (ii) finding intermediate common format to which every format can be converted (iii) incorporating commonsense knowledge (iv) handling data imbalance across formats. We build several baselines, including a new model based on knowledge hunting using a cheatsheet. However, all baselines perform poorly in contrast to the human baselines, indicating the hardness of our benchmark. Our work takes forward the recent progress in generic system development, demonstrating the scope of these under-explored tasks.

1 Introduction

Neural language models powered by datadriven approaches have achieved human level performance across several NLP tasks. However, we still require machines that understand the world well enough to perform reasoning. This capability would give rise to new opportunities for real-world applications such as education, medicine, and scientific discovery [Clark and Etzioni, 2016] [Clark, 2015]. Additionally, numbers help us to reason in everyday tasks ranging from buying vegetables to reading newspaper to understanding economic situation, survey results, sports, climate change, and election. Since numbers make our conversation accurate, the skill to reason with them is of primary importance in understanding natural language. [Dehaene, 2011; Ravichander et al., 2019; Frank et al., 2008].

Several datasets have been proposed to foster research in numerical reasoning in natural language understanding and QA context. Examples include DROP [Dua et al., 2019b], EQUATE [Ravichander et al., 2019], MathQA [Amini et al., 2019] and the Mathematics dataset [Saxton et al., 2019]. But each of these focuses on a specific format. For example, DROP is in RC setting, EQUATE and MathQA are in NLI and QA setting respectively. Since numerical reasoning is generic and independent of any particular format, there exists a strong need for a benchmark which can evaluate abilities of models in performing question format independent numerical reasoning. Additionally, for numerical reasoning technology to have the best possible application, it must be able to process language and reason in a way that is not exclusive to a single format, task, dataset or domain. In pursuit of this goal, we introduce NUMBERGAME, a multifaceted dataset that builds upon existing datasets where we add some new types. Such a compilation by including datasets with limited training data is intended to encourage the development of general models that can address diverse question formats. For building a more practical numerical reasoning system, NUMBERGAME demands four additional capabilities beyond numerical reasoning (i) detect question format directly from data (ii) find intermediate common format to which every format can be converted (iii) incorporate commonsense knowledge (iv) handle data imbalance across formats.

It is now well understood that natural language understanding requires knowledge beyond that is present in the specific text one is trying to understand. This was emphasized when
the Winograd schema challenge was proposed [Levesque et al., 2012] and Marcus & Davis further emphasize this in their recent book [Marcus and Davis, 2019]. Indeed, several QA datasets have recently been proposed where answering requires reasoning with external knowledge of various kinds such as domain knowledge and commonsense knowledge [Bisk et al., 2019; Marino et al., 2019]. In our compilation, we add a significant number of QA pairs where external knowledge is needed to answer questions in numerical reasoning setting.

Even though Neural language models such as GPT [Rafford et al., 2018], BERT [Devlin et al., 2018] and RoBERTa ([Liu et al., 2019] have become standard tools across several language understanding tasks, they can not perform complex forms of reasoning, specifically numerical reasoning [Wallace et al., 2019]. Recently, several neuro-symbolic models have been proposed in response to the numerical reasoning datasets. Examples include NumNet+v2 [Ran et al., 2019], BERT Calculator [Andot et al., 2019] and tag-based multi-span extraction model [Efrat et al., 2019]. Though they have performed well on the DROP dataset, they are limited in terms of the type of questions and numerical operations they handle. Among those models, we selected NumNet+v2, the best one for which code is publicly available. We added a question type converter module on top of NumNet+v2 and created an initial baseline for our dataset. Noting that this model does not take into account external knowledge, we created an new enhanced architecture that first uses knowledge hunting (searching for the missing knowledge) [Banerjee et al., 2019; Mitra et al., 2019] with respect to a cheat sheet to identify the needed knowledge. This is inspired by the observation that cheat sheet makes the task easier for humans while solving math questions of various types. We then use this knowledge in the NumNet+V2 setting. This leads to an improved baseline.

Our contribution in this paper is as follows:

- We compile a multifaceted dataset involving eight different types and define a task to solve this in multi-task setting. In the process, we add four new types of data.
- We introduce questions that require external numerical knowledge, commonsense knowledge and domain knowledge in the QA setting.
- We create a baseline by extending the NumNet+V2 model to handle questions of various types together.
- We develop a model that uses knowledge hunting using a cheat sheet together with NumNet+V2; this leads to an improved baseline.

2 Related Works

Datasets for Numerical reasoning: Quantitative reasoning has been a challenging problem for a long time. Small question answering datasets were proposed to understand the quantitative aspect of natural language such as the template-based dataset which solved questions with equations as parameters [Kushman et al., 2014], addition-subtraction dataset [Hosseini et al., 2014] and arithmetic problems dataset [Koncel-Kedziorski et al., 2015]. Difficulty of questions were increased in subsequent datasets [Roy and Roth, 2016], [Upadhyay et al., 2016]. Later, larger datasets were created to facilitate deep learning research [Ling et al., 2017]. One of our focus in creating this dataset is to have simple question answering problems and minimize data repetition.

Neurosymbolic Models: NAQANet is the first neuro symbolic model proposed to solve the DROP dataset. It is a numerically-aware QANet model, which allows the reading comprehension system to generate three new answer types present in DROP. BERT Calculator uses the BERT embedding by separating the computation part from the neural network and using a calculator tool to do that. Tag-based multi-span extraction model introduces a novel approach to better understand multi-span questions. NumNet has a numerically-aware graph neural network which considers comparison information over numbers in the question and passage. We develop our model on top of NumNet+v2 which is the combination of NumNet+ and tag based multi-span extraction model.

Knowledge Retrieval: Elasticsearch has been shown to be successful in prior works for knowledge retrieval [Khot et al., 2019; Banerjee et al., 2019; Mitra et al., 2019]. We use elasticsearch and a heuristics ranking algorithm for extracting relevant information.

Multi-tasking Benchmarks: Several tasks in the BAbI dataset [Weston et al., 2015] were designed to act as prerequisites for any system that aims to be capable of interacting and conversing with a human. GLUE [Wang et al., 2018], a benchmark to evaluate the performance of models across a diverse set of NLU tasks, had the objective to favor and encourage models that share general linguistic knowledge across tasks. SuperGLUE [Wang et al., 2019] consists of more difficult language understanding tasks than the GLUE benchmark. ORB [Dua et al., 2019a] has an evaluation server which reports performance on seven diverse reading comprehension datasets, encouraging development of a single model for a wide variety of reading phenomena. QuAIL [Downey and Rumshisky, ] covers four domains (fiction, blogs, political news, and user story texts), demanding a system to handle both general and text-specific questions which are impossible to answer from pretraining data. DecaNLP [McCann et al., 2018] poses a challenge that spans ten tasks in multitask setting. It also introduces the Multitask Question Answering Network (MQAN) which jointly learns all tasks in decaNLP without any task-specific modules or parameters in the multitask setting. TS [Raffel et al., 2019] introduces a powerful mode that converts every language problem into a text-to-text format, taking forward the transfer learning paradigm. UnifiedQA [Khashabi et al., 2020] is a recent interesting work where the latest advances in language modeling are used to build a single pre-trained QA model. Our work, NUMBERGAME focuses on prerequisite tasks necessary to do question format independent numerical reasoning. It also demands detection of numerical reasoning question format directly from data and incorporation of
Ella and Lily are playing a game that requires 10 die. Find out the total number of faces in 10 die.

A die has 6 faces

60

Jacob and Lillian are running a km long race. Jacob finished the race when Lillian was 190 meters from the finish line. How many meters did Lillian cover till that time?

1000 meters make a km

810

A man can lift one box in each of his hands. How many boxes can a group of 5 people hold in total?

A human being has 2 hands

10

Table 1: Example questions where numerical knowledge required to answer is not explicitly provided in the question.

3 Data Creation

Our dataset consists of a variety of question types that involve numerical computation and reasoning. We carefully select eight setting that involve numerical reasoning such that each setting has distinct properties and one is not just an extension of others. We divide our dataset into two broad categories. First category includes novel datasets and second is a collection of existing datasets.

3.1 Novel Datasets

In this section, we describe datasets that we have created manually. Recently, a few datasets have been proposed in various areas like Visual Question Answering, Textual Question Answering that require external knowledge to answer the questions. Here, we create data in four different setting. Three of them require knowledge, specifically numerical common sense knowledge and the fourth one is a collection of completion based questions.

Daily Life Maths Requiring Numerical Common Sense Knowledge: This type includes questions that require some common sense numerical knowledge that is not explicitly provided in the question. Table 1 shows some examples of this category. This dataset creation process consists of two phases. First, we create a list of concepts that involve some common sense numerical knowledge such as ‘A dice has 6 faces’, ‘English language has 5 vowels’. Second, we form questions that leverage this numerical knowledge in various real world contexts. Using this two step approach, we create a total of 404 question and answer pairs.

Application of Maths requiring domain knowledge: This dataset includes problems which need the usage of rule-like numeric domain knowledge such as formulae. This sets a higher bar on the ability of a model to use numeric knowledge. However, language models which have succeeded in most question answering datasets have comparatively less accuracy on the AI2 Reasoning Challenge (ARC) which consists of grade-school level multiple-choice science questions [Clark et al., 2018]. In this dataset, we add a significant number of questions belonging to few simple concepts. This can help in assessing the capability of language models to solve science questions involving a small number of concepts. However, our dataset creation framework can be easily extended to create questions from a larger set of concepts. We create chemistry questions covering the concepts of balancing the reactions and molecular weight computation of compounds. We create such questions from a set of 90 reactions and 53 compounds. From Physics, we create numerical questions involving the speed, distance and time. Table 2 shows some examples of this category.

Table 2: Example questions where domain knowledge is required to answer a question.

Find the mass percentage of H in C6H6

Mass of C is 12 units and mass of H is 1 units

7.69

How many units of H2 are required to react with 2 units of C2H4 to form 2 units of C2H6

H2 + C2H4 = C2H6

2

A car covers 912 meters in 19 seconds. If bike’s speed is one fourth of the car. Find the distance covered by the bike in 4 seconds.

distance travelled = speed * time

48

Table 3: Example questions where qualitative relationships and quantities in multiple domains such as science and economics. We select a subset of Quarel questions that involve numerically comparable quantities, and introduce numbers in place of text representing qualitative relationship. A few examples of original Quarel questions and transformed questions are shown in Table 3. We accumulate a total of 807 questions of this kind.

Quantitative Comparison Requiring Common Sense Knowledge along with Numerical Common Sense: This type covers questions that involve numerical comparison between two quantities. QUAREL [Tafjord et al., 2019] is a dataset involving qualitative relationships and quantities in multiple domains such as science and economics. We select a subset of Quarel questions that involve numerically comparable quantities, and introduce numbers in place of text representing qualitative relationship. A few examples of original Quarel questions and transformed questions are shown in Table 3. We accumulate a total of 807 questions of this kind.

Completion type questions Completion is a type of question where a blank is required to be filled. We create such questions from the Arithmetic Word Problem repository [Roy and Roth, 2018][Roy and Roth, 2016][Roy and Roth, 2017] manually following a two step process. First, we introduce a blank in the question. Then, we reformulate the question such
that the blank takes place of the answer. We also create adversarial examples of this type. Table 4 shows some examples of this kind.

### 3.2 Collection of Existing Datasets

We compile questions from some of the existing datasets that involve numerical reasoning. In order to avoid adding repetitive questions and ensure high quality of out dataset, we filter questions following a five step procedure. First, we remove questions that do not have annotated answers. Second, we remove grammatically incorrect questions. Then, we eliminate problems which have high lexical overlap with rest of the dataset, thus ensuring that our dataset incorporates mostly unique concepts. Next, we rectify type mismatch issues such as, “there are 7.0 students” to “there are 7 students” as the number of students is not a float quantity. Finally, we discard invalid and inaccurate questions. We compile a total of four datasets was performed by three individuals.

**Reading Comprehension involving Implicit Math** Here, we select reading comprehension questions from DROP where the answer is not a numerical value but some sort of mathematical operation such as counting or sorting is required to answer the question. This category is inspired from the fact that many a times in real world some sort of math is implicitly required to answer a question.

**Quantitative NLI** Natural Language Inference (NLI) or Recognizing Textual Entailment (RTE) has been considered as a benchmark task in natural language understanding. Recently introduced EQUATE dataset has quantitative NLI problems combined from diverse sources. We use EQUATE to add NLI questions to our dataset.

**Arithmetic Word Problems** This dataset is a combination of algebra and arithmetic word problems. We collect problems from the Arithmetic Word Problem repository [Koncel-Kedziorski et al., 2016], SingleEq [Koncel-Kedziorski et al., 2015] and SimulEq-S [Kushman et al., 2014]. Using Spacy sentence similarity [Honnibal and Montani, 2017], we ensure that questions in this type don’t have high overlap with questions in completion type.

### 4 Combining all types of data

**Partitioning the dataset:** In a real world setting, number of problems in each type of data is different. Instead of undersampling or over-sampling data across types, we decide to keep them disproportionately to mimic the real world setting. Each type of data was randomly partitioned into training (70%), development (10%) and test (20%) set by ensuring that there is no data leakage among these splits. In order to ensure this for RC problems, we keep all questions of a passage in only one of the splits. Similarly, in other setting, questions which are very similar to each other are kept in only one of the splits. This way, we reduce the possibility of memorization by language models.

**Validation:** The validation of the test set of our novel datasets was performed by three individuals. We provided

---

1None of the authors were involved in this process
them questions and asked them to mark questions as either valid or invalid. A very small percentage of the data was marked as invalid which we later filtered out.

5 Data Analysis

We have performed data analysis in order to gauge the quality of our dataset.

Vocabulary Size: First, we calculate vocabulary size of each type by finding the number of unique words across all questions. Since our dataset is unbalanced in terms of question type, we find the average vocabulary size of the dataset by dividing vocabulary size with number of data in that type.

Which data has more average vocabulary size? As illustrated in Figure 2. Most of the question types belonging to the novel dataset category have relatively better average vocabulary size. This implies questions in those types have less repetitiveness.

| Data Type  | Problem                          | Train | Dev | Test |
|------------|----------------------------------|-------|-----|------|
| Type 1     | Missing Numerical Knowledge      | 282   | 41  | 81   |
| Type 2     | Maths in other domains           | 1131  | 164 | 325  |
| Type 3     | Quantitative comparison          | 564   | 81  | 162  |
| Type 4     | Completion Type                  | 770   | 110 | 220  |
| Type 5     | Reading comprehension with Explicit Math | 37949 | 5421 | 10842 |
| Type 6     | Reading Comprehension with Implicit Math | 22908 | 3272 | 6544 |
| Type 7     | Quantitative NLI                 | 6791  | 970 | 1941 |
| Type 8     | Arithmetic Word Problems         | 886   | 126 | 254  |

Table 5: Dataset size for all the question types across all splits

We expand on our vocabulary analysis to understand Figure 2 further. We dive deep to analyze different parts of speech. Figure 3 summarizes our analysis. Most of the novel datasets have more average number of nouns, verbs and adjectives implying there are more types of entities, actions and attributes. This further means that those data-sets are more diverse in nature.

Sentence Similarity Analysis We further extend our analysis to reinforce our inference from the word vocabulary analysis. We find cosine similarity of a sentence with every other sentence. Figure 6 and 7 illustrate the similarity analysis for various datasets.

Which data consists of most dissimilar sentences? As illustrated in Figure 6, most question sentences in Quarrer [Tafjord et al., 2019] have high similarity implying that data is repetitive. Same is true for majority of EQUATE data. From figure 7, it is evident that DROP also has high similarity among questions. We also analyze this similarity metric for our dataset and find that similarity among questions is significantly less. Some similarity boxes can be seen in the plot. They are mostly due to Type 2 data and partly due to Type 3. This implies that our dataset is far less repetitive than others. Also, in our dataset the repetition is sparse and is not equally distributed among the whole dataset unlike others. This way, our dataset is more diverse.

Why Type 2 questions have small vocabulary and high similarity? This is because, type 2 consists of math questions in other domains. Most of the questions in this category are chemistry questions in text book setting. Since we are limiting the number of concepts to two and questions in chemistry follow a pattern, this type results in comparatively less vocabulary and high sentence overlap.

6 Baseline Models

We evaluate our dataset using several baselines including heuristic baseline, extended NumNet+v2, bias-checking baseline, and human baseline. We use ExactMatch, and a numeracy-focused (macro-averaged) F1 score as evaluation metrics to compare model performance which has been used in prior works [Dua et al., 2019b].

Heuristic Baselines along with Type Oracle: We assume there is a type oracle that knows the question type. We add this to our heuristic baseline, since use of a single baseline across all eight types is not appropriate. In random baseline, we randomly select one of the options in case the question has multiple options (type 7 and type 3), a number between 0 to 100 for questions having a numerical answer and a random entity present in the passage for questions having a text segment from the passage as the answer. In the majority baseline, we select the most frequent answer for each type such as “Entailment” for NLI questions, 2nd option for questions having three options, most frequent number for questions having numerical answer and the major entity present in the passage for questions having span based answer.

Extended NumNet+v2 We convert every type of question to RC format because RC has a passage component that represents local facts relevant to the questions. This allows easy integration of external knowledge (global facts) to the passage with no risk of getting it mixed with the question. This is useful because some of our data needs knowledge and this setting will help models in providing knowledge. We add a type classifier module to do this task. We design type classifier heuristically. Then, we convert each of the question types to RC format. For NLI questions, we use the premise sentence as passage, hypothesis as the question and append the string “Entailment, contradiction or neutral?” to the question so that it has a span based answer. For other questions, we tokenize the question string into its constituent sentences and use a heuristic approach to split the question string into passage and question. Furthermore, for option based questions, we append all the options at the end of the question. Figure 5 illustrates the type conversion process.

Bias-checking Baselines Recently, many works have shown that some of the popular NLP datasets have annotation biases which are exploited by language models [Poliak et al., 2018]. In this baseline, we want to check if our dataset has any of those biases. We train our Extended NumNet+v2 model by heuristically removing the question completely and
Figure 1: Baseline Model overview depicting the various questions types and their answers.

| Type 1 | Type 2 | Type 3 | Type 4 | Type 5 | Type 6 | Type 7 | Type 8 |
|--------|--------|--------|--------|--------|--------|--------|--------|
| Random Baseline | 0 | 0 | 0.31 | 0.31 | 46.9 | 46.9 | 0 | 0 | 0.53 | 0.53 | 1.6 | 3.44 | 33.02 | 33.02 | 0.39 | 0.39 |
| Majority Baseline | 1.23 | 1.23 | 13.85 | 13.85 | 50 | 50 | 0.45 | 0.45 | 7.41 | 7.41 | 1.67 | 3.8 | 36.53 | 36.53 | 1.18 | 1.18 |
| Question-only Baseline | 1.23 | 1.23 | 13.23 | 13.23 | 23.21 | 25.07 | 0.45 | 0.45 | 6.01 | 6.12 | 20.86 | 25.14 | 32.82 | 32.82 | 2.36 | 2.36 |
| Context-only Baseline | 1.23 | 1.23 | 14.15 | 14.15 | 0 | 22.73 | 19.09 | 19.09 | 0.51 | 0.57 | 0.89 | 3.02 | 0 | 0 | 9.45 | 9.45 |
| Extended NumNet+V2 | 0 | 0 | 37.54 | 37.54 | 58.02 | 58.02 | 31.36 | 31.36 | 68.06 | 68.23 | 57.23 | 70.2 | 85.71 | 85.73 | 23.23 | 23.23 |
| Extended NumNet+V2 + Knowledge | 4.84 | 5.56 | 37.54 | 37.54 | 46.30 | 46.57 | 36.36 | 36.36 | 68.40 | 68.59 | 57.20 | 69.61 | 85.88 | 85.88 | 22.44 | 22.44 |
| Extended NumNet+V2 + Oversampling | 7.41 | 7.41 | 38.77 | 38.77 | 47.53 | 47.84 | 35.91 | 35.91 | 43.99 | 44.30 | 40.46 | 53.71 | 85.37 | 85.39 | 22.44 | 22.44 |
| Human baseline | 94.42 | 94.42 | 94.5 | 94.5 | 97.75 | 97.75 | 95.0 | 95.0 | 94.5 | 94.67 | 95.0 | 96.1 | 96.5 | 96.5 | 92.75 | 92.75 |

Table 6: Table showing the performance of various baselines on our test set across all data types

Figure 2: Distribution of average vocabulary in the data set.

replacing it with the word “question”. Similarly, we do the same by removing context. Context is different for different types such as passage in type 5 and type 6, premise in type 7, all sentences apart from question for type 8. Data which could not be split this way were converted manually.

Data Oversampling Baseline We try to tackle data imbalance by oversampling all types of data to the maximum size of all types.

Knowledge Hunting along with Extended NumNet+V2 We create a cheat-sheet by accumulating all types of external knowledge which are needed to solve questions of various types. We use elasticsearch to hunt relevant knowledge sentences. We further filter them using a heuristic threshold of relevance. We append this knowledge in the beginning of the passage so that continuity is not broken between passage and question. Figure 4 illustrates our approach.

Human Baseline: Human baseline was calculated on 100 samples of each type (81 of Type 1) from the test set by averaging the scores of four individuals.

7 Results and Discussion

Table 6 shows the performance of various baseline models on our test set. Performance of all the baseline models is significantly less than human baseline. Answering questions in eight different setting using a single model is indeed a challenging task. We find that, in some of the cases, the model fails to distinguish among the question types. For example, it gave a span based answer where a number was expected and vice versa in some cases.

Dataset Bias: We performed multiple experiments to evaluate bias in our dataset. All bias-check baselines did not perform well even with the help of a type oracle. This shows that our dataset has very less bias.
Figure 4: Knowledge Hunting augmented Model overview depicting the various questions types and their answers.

Figure 5: Conversion of various question types to reading comprehension format

| Type   | Original Question Setting                                                                 | Answer |
|--------|------------------------------------------------------------------------------------------|--------|
| Type 1 | In a football game, wristbands were given to every spectator for both their hands. In total 290 wristbands were distributed. How many people watched the game? | 145    |
| Type 2 | A train travelled at an average speed of 10 m/s to cover 60 meters. What is the total duration of the journey? | 6      |
| Type 3 | Tony has a beach ball that he loves to play with. He notices that the beach ball travels for 6 meters when he kicks it across the asphalt road and 4 meters when he kicks it across the gravel road. If he kicks it with the same force in each situation, which road is smoother? (A) gravel (B) Asphalt | (B)    |
| Type 4 | There are 22 walnut trees currently in the park, Park workers will plant walnut trees today. When the workers are finished there will be 55 walnut trees in the park. The workers planted _____ walnut trees today. | 33     |
| Type 7 | (*sentence 1*: “Sam had 9 dimes in his bank and his dad gave him 7 dimes”, *sentence 2*: “Sam has 16 dimes now”) (A) entailment (B) contradiction | Entailment |
| Type 8 | Sam had 79 dollars to spend on 9 books. After buying them he had 16 dollars. How much did each book cost? | 7      |

| Passage                                  | Question                                      | Answer |
|------------------------------------------|-----------------------------------------------|--------|
| In a football game, wristbands were given to every spectator for both their hands. In total 290 wristbands were distributed. How many people watched the game? | How many people watched the game? | 145    |
| A train travelled at an average speed of 10 m/s to cover 60 meters. What is the total duration of the journey? | What is the total duration of the journey? | 6      |
| Tony has a beach ball that he loves to play with. He notices that the beach ball travels for 6 meters when he kicks it across the asphalt road and 4 meters when he kicks it across the gravel road. If he kicks it with the same force in each situation, which road is smoother? (A) gravel (B) Asphalt | If he kicks it with the same force in each situation, which road is smoother? “Option 1” is gravel, “Option 2” is Asphalt. | Option 2 |
| There are 22 walnut trees currently in the park, Park workers will plant walnut trees today. When the workers are finished there will be 55 walnut trees in the park. The workers planted _____ walnut trees today. | The workers planted _____ walnut trees today. | 33     |
| (*sentence 1*: “Sam had 9 dimes in his bank and his dad gave him 7 dimes”, *sentence 2*: “Sam has 16 dimes now”) (A) entailment (B) contradiction | Sam had 9 dimes in his bank and his dad gave him 7 dimes. Sam has 16 dimes now. Entailment, contradiction or neutral? | Entailment |
| Sam had 79 dollars to spend on 9 books. After buying them he had 16 dollars. How much did each book cost? | How much did each book cost? | 7      |
Which question types are hard to solve? Our results show that type 1 which requires numerical commonsense knowledge, is the hardest question type. Similarly, Type 2, 4 and 8 appear to be comparatively harder from the rest. One pattern among these question types is that all of them expect the answer to be numeric. Numeric answer requires accurate calculation. So, models might have difficulty in learning the task with just data. This hypothesis is also justified from the drop in human performance for all these types.

Which question types are comparatively easier? Quantitative NLI has the best performance among all types. Also, performance on type 6 is better on type 5. Though both these datasets are inherited from the same parent. Models answer span based questions better as compared to numeric answers. Performance of model for type 3 questions further suggests that models find it easier to answer in an MCQ setting.

Do the knowledge retrieval help? Results show that knowledge help in improving performance of type 1, 2 and 4. It does not have significant difference for type 5, 6, 7, 8 which is as expected since questions of those types do not need external knowledge. This has been discussed in Section 3. However, seems like it acts as noise for type 3. Conditional knowledge retrieval might help to mitigate the adverse effect.

Does oversampling help to overcome data imbalance? Even though oversampling results in higher performance in certain types, specifically the ones with smaller training data, it results in significant drop in performance in the other extreme, i.e types with bigger training data. Oversampling disproportionately might help to resolve this issue.

8 Conclusion
We have compiled a multifaceted dataset involving eight different types of data and define a task to solve this dataset in multi-task setting. We introduce numerical reasoning questions that require external knowledge, commonsense knowledge and domain knowledge. Based on results, we infer that performing well across all the eight tasks is more challenging than existing tasks. Also, the effect of our baseline performance on providing external knowledge to a language model promises the benefit of using cheat sheet for those tasks which need knowledge. We expect this dataset and the task to motivate researchers to analyze the generalization capability of neuro symbolic models. Our future work will explore novel ways to do transfer learning in this multi task setting.

References
[Amini et al., 2019] Aida Amini, Saadia Gabriel, Peter Lin, Rik Koncel-Kedziorski, Yejin Choi, and Hannaneh Hajishirzi. Mathqa: Towards interpretable math word problem solving with operation-based formalisms. arXiv preprint arXiv:1905.13319, 2019.
[Andor et al., 2019] Daniel Andor, Luheng He, Kenton Lee, and Emily Pitler. Giving bert a calculator: Finding operations and arguments with reading comprehension. arXiv preprint arXiv:1909.00109, 2019.
[Banerjee et al., 2019] Pratyay Banerjee, Kuntal Kumar Pal, Arindam Mitra, and Chitta Baral. Careful selection of knowledge to solve open book question answering. arXiv preprint arXiv:1907.10738, 2019.
[Bisk et al., 2019] Yonatan Bisk, Rowan Zellers, Ronan Le Bras, Jianfeng Gao, and Yejin Choi. Piqa: Reasoning about physical commonsense in natural language. arXiv preprint arXiv:1911.11641, 2019.
[Clark and Etzioni, 2016] Peter Clark and Oren Etzioni. My computer is an honor student—but how intelligent is it? standardized tests as a measure of ai. AI Magazine, 37(1):5–12, 2016.
[Clark et al., 2018] Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge. arXiv preprint arXiv:1803.05457, 2018.
[Clark, 2015] Peter Clark. Elementary school science and math tests as a driver for ai: take the aristo challenge! In Twenty-Seventh IAAI Conference, 2015.
[Dehaene, 2011] Stanislas Dehaene. The number sense: How the mind creates mathematics. OUP USA, 2011.
[Devlin et al., 2018] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.
[Downey and Rumshisky, 2010] Anna Rogers Olga Koval- eva Matthew Downey and Anna Rumshisky. Getting closer to ai complete question answering: A set of prerequisite real tasks.
Dua et al., 2019a Dheeru Dua, Ananth Gottumukkala, Alon Talmor, Sameer Singh, and Matt Gardner. Orb: An open reading benchmark for comprehensive evaluation of machine reading comprehension. arXiv preprint arXiv:1912.12598, 2019.

Dua et al., 2019b Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. Drop: A comprehension benchmark requiring discrete reasoning over paragraphs. arXiv preprint arXiv:1905.00161, 2019.

Efrat et al., 2019 Avia Efrat, Elad Segal, and Mor Shoham. Tag-based multi-span extraction in reading comprehension. arXiv preprint arXiv:1909.13375, 2019.

Frank et al., 2008 Michael C Frank, Daniel L Everett, Evelina Fedorenko, and Edward Gibson. Number as a cognitive technology: Evidence from pirahá language and cognition. Cognition, 108(3):819–824, 2008.

Honnibal and Montani, 2017 Matthew Honnibal and Ines Montani. spacy 2: Natural language understanding with bloom embeddings, convolutional neural networks and incremental parsing. To appear, 7, 2017.

Hosseini et al., 2014 Mohammad Javad Hosseini, Hanaheh Hajishirzi, Oren Etzioni, and Nate Kushman. Learning to solve arithmetic word problems with verb categorization. In In Conference on Empirical Methods in Natural Language Processing (EMNLP), 2014.

Khashabi et al., 2020 Daniel Khashabi, Tushar Khot, Ashish Sabharwal, Oyvind Tafjord, Peter Clark, and Hanaheh Hajishirzi. Unifiedqa: Crossing format boundaries with a single qa system. arXiv preprint arXiv:2005.00700, 2020.

Khot et al., 2019 Tushar Khot, Ashish Sabharwal, and Peter Clark. What’s missing: A knowledge gap guided approach for multi-hop question answering. arXiv preprint arXiv:1909.09253, 2019.

Koncel-Kedziorski et al., 2015 Rik Koncel-Kedziorski, Hanaheh Hajishirzi, Ashish Sabharwal, Oren Etzioni, and Siena Dumas Ang. Parsing algebraic word problems into equations. Transactions of the Association for Computational Linguistics, 3:585–597, 2015.

Koncel-Kedzierski et al., 2016 Rik Koncel-Kedzierski, Subhro Roy, Aida Amini, Nate Kushman, and Hanaheh Hajishirzi. Mawps: A math word problem repository. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1152–1157, 2016.

Kushman et al., 2014 Nate Kushman, Yoav Artzi, Luke Zettlemoyer, and Regina Barzilay. Learning to automatically solve algebra word problems. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 271–281, 2014.

Levesque et al., 2012 Hector Levesque, Ernest Davis, and Leora Morgenstern. The winograd schema challenge. In Thirteenth International Conference on the Principles of Knowledge Representation and Reasoning, 2012.

Ling et al., 2017 Wang Ling, Dani Yogatama, Chris Dyer, and Phil Blunsom. Program induction by rationale generation: Learning to solve and explain algebraic word problems. arXiv preprint arXiv:1705.04146, 2017.

Liu et al., 2019 Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692, 2019.

Marcus and Davis, 2019 Gary Marcus and Ernest Davis. Rebooting AI: Building artificial intelligence we can trust. Pantheon, 2019.

Marino et al., 2019 Kenneth Marino, Mohammad Rastegari, Ali Farhadi, and Roozbeh Mottaghi. Ok-vqa: A visual question answering benchmark requiring external knowledge. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3195–3204, 2019.

McCann et al., 2018 Bryan McCann, Nitish Shirish Keskar, Caiming Xiong, and Richard Socher. The natural language decathlon: Multitask learning as question answering. arXiv preprint arXiv:1806.08730, 2018.

Mitra et al., 2019 Arindam Mitra, Pratyay Banerjee, Kuntal Kumar Pal, Swaroop Mishra, and Chitta Baral. Exploring ways to incorporate additional knowledge to improve natural language commonsense question answering. arXiv preprint arXiv:1909.08855, 2019.

Poliak et al., 2018 Adam Poliak, Jason Naradowsky, Aparajita Haldar, Rachel Rudinger, and Benjamin Van Durme. Hypothesis only baselines in natural language inference. arXiv preprint arXiv:1805.01042, 2018.

Radford et al., 2018 Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. URL https://s3-us-west-2.amazonaws.com/openai-assets/researchcovers/languageunsupervised/language_understanding_paper.pdf, 2018.

Raffel et al., 2019 Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. arXiv preprint arXiv:1910.10683, 2019.

Ran et al., 2019 Qiu Ran, Yankai Lin, Peng Li, Jie Zhou, and Zhiyuan Liu. Numnet: Machine reading comprehension with numerical reasoning. arXiv preprint arXiv:1910.06701, 2019.

Ravichander et al., 2019 Abhilasha Ravichander, Aakanksha Naik, Carolyn Rose, and Eduard Hovy. Equate: A benchmark evaluation framework for quantitative reasoning in natural language inference. arXiv preprint arXiv:1901.03735, 2019.
[Roy and Roth, 2016] Subhro Roy and Dan Roth. Solving general arithmetic word problems. *arXiv preprint arXiv:1608.01413*, 2016.

[Roy and Roth, 2017] Subhro Roy and Dan Roth. Unit dependency graph and its application to arithmetic word problem solving. In *Thirty-First AAAI Conference on Artificial Intelligence*, 2017.

[Roy and Roth, 2018] Subhro Roy and Dan Roth. Mapping to declarative knowledge for word problem solving. *Transactions of the Association for Computational Linguistics*, 6:159–172, 2018.

[Saxton et al., 2019] David Saxton, Edward Grefenstette, Felix Hill, and Pushmeet Kohli. Analysing mathematical reasoning abilities of neural models. *arXiv preprint arXiv:1904.01557*, 2019.

[Tafjord et al., 2019] Oyvind Tafjord, Peter Clark, Matt Gardner, Wen-tau Yih, and Ashish Sabharwal. Quarel: A dataset and models for answering questions about qualitative relationships. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 7063–7071, 2019.

[Upadhyay et al., 2016] Shyam Upadhyay, Ming-Wei Chang, Kai-Wei Chang, and Wen-tau Yih. Learning from explicit and implicit supervision jointly for algebra word problems. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 297–306, 2016.

[Wallace et al., 2019] Eric Wallace, Yizhong Wang, Sujian Li, Sameer Singh, and Matt Gardner. Do nlp models know numbers? probing numeracy in embeddings. *arXiv preprint arXiv:1909.07940*, 2019.

[Wang et al., 2018] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. Glue: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461*, 2018.

[Wang et al., 2019] Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. Superglue: A stickier benchmark for general-purpose language understanding systems. In *Advances in Neural Information Processing Systems*, pages 3261–3275, 2019.

[Weston et al., 2015] Jason Weston, Antoine Bordes, Sumit Chopra, Alexander M Rush, Bart van Merriënboer, Armand Joulin, and Tomas Mikolov. Towards ai-complete question answering: A set of prerequisite toy tasks. *arXiv preprint arXiv:1502.05698*, 2015.