Dyna-bAbI: unlocking bAbI’s potential with dynamic synthetic benchmarking

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Abstract

While neural language models often perform surprisingly well on natural language understanding (NLU) tasks, their strengths and limitations remain poorly understood. Controlled synthetic tasks are thus an increasingly important resource for diagnosing model behavior. In this work we focus on story understanding, a core competency for NLU systems. However, the main synthetic resource for story understanding, the bAbI benchmark, lacks such a systematic mechanism for controllable task generation.

We develop Dyna-bAbI, a dynamic framework providing fine-grained control over task generation in bAbI. We demonstrate our ideas by constructing three new tasks requiring compositional generalization, an important evaluation setting absent from the original benchmark. We tested both special-purpose models developed for bAbI as well as state-of-the-art pre-trained methods, and found that while both approaches solve the original tasks (>99% accuracy), neither approach succeeded in the compositional generalization setting, indicating the limitations of the original training data.

We explored ways to augment the original data, and found that though diversifying training data was far more useful than simply increasing dataset size, it was still insufficient for driving robust compositional generalization (with <70% accuracy for complex compositions). Our results underscore the importance of highly controllable task generators for creating robust NLU systems through a virtuous cycle of model and data development.

1 Introduction

Considerable progress has been made recently in natural language understanding (NLU), driven largely by advances in model pre-training (Devlin et al., 2019; Raffel et al., 2020) and the development of large-scale NLU benchmarks across a wide range of tasks (Wang et al., 2018, 2019; Liang et al., 2020). Such successes, however, have coincided with the discovery of various shortcomings in existing human curated datasets, largely related to annotation artifacts (Gururangan et al., 2019).
et al., 2018), or systematic biases that create shortcuts that can inflate model performance and harm generalization.

In order to overcome these issues, two avenues of research have recently gained traction: 1) the development of dynamic benchmarks (Potts et al., 2021; Kiela et al., 2021) where, in contrast to conventional static benchmarks, evaluation and data collection are performed in an agile manner and conducted interactively with humans and models in a rapidly evolving feedback loop and; 2) renewed interest in synthetic benchmarks (Lake and Baroni, 2018; Sinha et al., 2019; Clark et al., 2020; Ruis et al., 2020) that allow for absolute control over the data creation process in order to help understand the strengths and weaknesses of existing models on targeted tasks and language phenomena.

Story understanding is a particularly important domain for research on dynamic and synthetic benchmarks; it is a core competency for NLU systems (McClelland et al., 2020; Dunietz et al., 2020), but the scale and annotation detail required make human data collection prohibitively costly. However, the main synthetic resource for story understanding remains the bAbI task suite (Weston et al., 2016), which is saturated by models reaching near-perfect performance (Liu et al., 2021), and further limited by exploitable biases in the data (Kaushik and Lipton, 2018). Despite its creators’ initial intentions, bAbI has largely remained a static benchmark limited to a small subset of the tasks potentially possible to generate within the bAbI “micro-world”. Accordingly, two natural questions arise: (Q1) is near-perfect model performance on the original bAbI tasks a reliable indicator of story understanding competence?; (Q2) are there still interesting challenges to discover inside the broader bAbI task space that help identify weaknesses in current models and drive modeling innovation?

To answer these questions, we employ a dynamic synthetic benchmarking approach on bAbI, combining the benefits of the agile approach of recent dynamic benchmarks with the scale and control provided by synthetic datasets. As illustrated in Figure 1, in dynamic synthetic benchmarks the data generator itself is designed for agile development, enabling experimentation with increasingly complex tasks and a wider range of linguistic phenomena. Constructing challenging tasks is a challenge in and of itself, requiring precise control over the reasoning patterns underlying each question. To meet these requirements, we developed a new task generator for bAbI called Dyna-bAbI2.

Using Dyna-bAbI, we first devise new splits that systematically test compositional generalization across tasks; as shown in Fig. 1c, we test models on novel combinations (line 10 question on right) of concepts seen at training, like co-reference and object tracking (left). We find that training on the original bAbI tasks (hereafter: bAbI 1.0) is not sufficient for models to attain good compositional generalization. Though general purpose pre-trained models far outperform special-purpose (non-pre-trained) architectures developed for bAbI, they still suffer a 30-50% drop in accuracy compared to the non-pre-trained models which suffer a 50-80% drop. Both types attain near perfect performance on the original tasks, suggesting that bAbI 1.0 is not challenging enough to differentiate between the two classes of models (Q1).

We next investigate how different enhancements of training data affect compositional generalization: (a) injecting more questions into bAbI 1.0, and (b) generating new, more diverse training samples. Compared to question injection, we find that diverse training data better facilitates compositional generalization, as well as being more data efficient. However, neither approach drives reliable compositional generalization; a representative state-of-the-art (SOTA) model, T5 (Raffel et al., 2020), demonstrates a lack of robustness to novel combinations and also exhibits knowledge inconsistency, for example, correctly answering certain types of questions, but systematically failing to answer equivalent question paraphrases. These results suggest that there remain many important challenges within the broader bAbI task space (Q2).

To sanity-check the quality of our new tests compared with bAbI 1.0, we employ the notion of concurrence proposed by Liu et al. (2021); concurrence is a measure of correlation between models’ performance on a synthetic task and their performance on an existing, non-synthetic NLU benchmark. We find high concurrence between our new challenge tasks and the widely used SQuAD dataset (Rajpurkar et al., 2016), in contrast to bAbI

3 Implemented in Python for improved accessibility compared with the original Lua implementation (https://github.com/facebookarchive/bAbI-tasks).
1.0 which achieved low concurrence.

Giving the continued interest in using bAbI 1.0 to evaluate new modeling approaches (Banino et al., 2020, 2021; Schlag et al., 2021), our new challenge splits and the Dyna-bAbI task generator contribute to more reliably guiding future efforts. While we focused on bAbI, our results apply more generally, telling a cautionary tale about the limits of static synthetic datasets, and motivating the development of controllable task generators for dynamic synthetic benchmarking.

2 Related Work

Our work brings together two promising areas of current research: dynamic benchmarking such as Dynabench (Kiela et al., 2021) that address many existing issues with static benchmarks (Bowman and Dahl, 2021), and synthetic benchmarking, which is widely used for high-precision and data-intensive problems such as relational and logical reasoning (Sinha et al., 2019; Clark et al., 2020; Betz et al., 2021), robot planning (Banerjee et al., 2020), instruction following and language grounding (Long et al., 2016; Lake and Baroni, 2018) among many others (Richardson et al., 2020; Khot et al., 2021). Most approaches to synthetic benchmarking focus on model development on a static benchmark, and are not designed to facilitate agile and highly controlled task space exploration, which is our focus here. The recent gSCAN dataset (Ruis et al., 2020) and later extensions (Qiu et al., 2021; Wu et al., 2021) can be seen as an example of a synthetic benchmark “going dynamic”. Our work differs in terms of target domain (story understanding as opposed to multi-modal language grounding), and we further focus attention on a more general research direction of intentional, a-priori design of NLU benchmarks for agile development.

We address the domain of story understanding as a particularly core (and data-intensive) capacity underlying language use (McClelland et al., 2020), thought to require constructing and manipulating situation models of entities and their relations as they unfold throughout discourse (Zwaan, 2016; Tamari et al., 2020). Procedural text datasets (Dalvi et al., 2018; Tandon et al., 2020) are closely related in that they provide detailed annotation of entities and state changes, and have mostly focused on relatively small and static benchmarks using human collected data. Overall, recent works identify a lack of benchmark tasks which systematically probe the situation models constructed by NLP systems processing discourse-level texts (Sugawara et al., 2021).

The bAbI benchmark (Weston et al., 2016) is seen as highly relevant in terms of objective (targeting situation modelling) (Dunietz et al., 2020), but has been viewed critically due to its constrained nature and exploitable artifacts (Kaushik and Lipton, 2018). Our work focuses on improving the evaluation in bAbI through compositional generalization, widely used across NLP to more rigorously probe model robustness (Finegan-Dollak et al., 2018; Keysers et al., 2020; Gontier et al., 2020; Yanaka et al., 2021), but to our knowledge still not applied to story understanding or bAbI.

3 Synthetic Dynamic Benchmarking on bAbI

3.1 Dyna-bAbI

What makes a synthetic benchmark dynamic? We think of a dynamic synthetic benchmark as a highly controllable task generator, enabling rapid exploration of interesting areas of task space. The original bAbI 1.0 simulator code does not readily facilitate such exploration; each of the bAbI 1.0 tasks is generated by a hard-coded script which does not neatly expose “dials” to manipulate interesting generation aspects such as question difficulty or compositionality.

Accordingly, we developed Dyna-bAbI, a Python-based version of the original simulator. Dyna-bAbI facilitates control of task generation through a configuration file, effectively abstracting away much of the underlying implementation complexity. The configuration file allows users to specify high-level task parameters such as the concepts set, passage length, and filtering conditions to mine for harder/rarer examples. We also modularized the code to facilitate adding new questions and other concepts more easily.

In this next sections we describe the underlying structure of the bAbI 1.0 tasks, and how we combine them using Dyna-bAbI to create more complex compositional generalization tasks.

3.2 bAbI task structure

A task in bAbI 1.0 is a set of train, validation and test splits. Each split is a set of instances, where an instance is a tuple $(p, q, a)$=(passage,
question, answer). Passages are generated using a micro-world simulator, by sampling a valid sequence of world events from an event set \( \mathcal{E}^* \) and generating a linguistic description of them. By default, linguistic descriptions are generated by a simple sentence-level mapping from an event to a natural language sentence. For example, the event \( \text{move(john, park)} \) could be translated to “John moved to the park.” Some tasks also incorporate more complex linguistic mappings between events and sentences, such as co-reference: the event sequence \( \text{move(john, park), move(john, kitchen)} \) could be mapped to “John moved to the park. Then he went to the kitchen.”

We denote the set of possible linguistic mappings by \( \mathcal{L}^* \). Finally, a valid question-answer pair \((q,a)\) over \( p \) is sampled from question set \( \mathcal{Q}^* \). In bAbI, splits are usually generated using a subset of possible events, linguistic constructs and questions; we denote these as \( \mathcal{E}, \mathcal{L}, \mathcal{Q}, \) respectively. We can then define the concept set of a specific split, \( \mathcal{C} = \mathcal{E} \cup \mathcal{L} \cup \mathcal{Q} \). Instances also include a set of supporting facts \((f)\), or the relevant lines from which \( c \) can be derived (see Fig. 1). The support composition \((f_c)\) is the set of events and linguistic constructs contained in \( f \) (see examples in §4.2), and is useful for characterizing compositionality performance (§3.4).

### 3.3 Original bAbI 1.0 tasks

Our focus here is on a particular subset of 12 bAbI 1.0 tasks evaluating aspects of story understanding. Table 1 summarizes them, detailing \( \mathcal{E}, \mathcal{L}, \mathcal{Q} \) for each task. For \( \mathcal{L} \), we list only complex constructs beyond the default event-sentence mapping (which is present in every task). See Appendix A.1 for additional details on task construction. Not all of the story understanding tasks are considered. For example, tasks 14 and 20 address time reasoning and agent motivations, and we leave their integration for future work.

### 3.4 Compositional generalization on bAbI

As can be seen in Table 1, many possible task configurations are not covered by the original benchmark; which directions should be explored? We focus on out-of-distribution (OOD) robustness, which is increasingly seen as a vital evaluation criteria across AI/NLP research (Shanahan et al., 2020; Hendrycks et al., 2020). In particular, we target the OOD capacity for compositional generalization; the ability to systematically generalize to test inputs containing novel combinations of more basic elements seen at training time (Partee et al., 1995; Lake et al., 2017). For example, a model that has learned basic object tracking and co-reference separately (tasks 2 and 11, see Fig. 1c) could be expected to solve tasks requiring a mixture of both object tracking and co-reference (Fig. 1c, line 10 question on right side). Compositional tasks are absent from bAbI 1.0 which features only IID test sets (independent, identically distributed).

**Table 1:** Subset of 12 bAbI 1.0 tasks considered here. Each task is characterized by the possible events, linguistic constructs and questions that can occur in instances. POSS (possession) is short for GRAB and DROP events. Statistics based on training sets. A large space of task configurations remains unexplored.

| Task | Events | Linguistic Constructs | Questions | Avg. sents. & supp. facts per story |
|------|--------|-----------------------|-----------|-------------------------------------|
| 1    | MOVE   | -                     | where-P   | 6, 1                                |
| 2    | MOVE,  | -                     | where-O   | 15.52, 2                            |
| 3    | MOVE,  | -                     | where-was-O | 51.9, 3                           |
| 4    | MOVE,  | -                     | give-qs   | 20.1, 1                             |
| 5    | MOVE,  | -                     | yes-no    | 6.27, 1                             |
| 6    | MOVE   | -                     | counting  | 8.67, 2.33                         |
| 7    | MOVE,  | -                     | list      | 8.75, 1.94                         |
| 8    | MOVE   | NEGATE                | yes-no    | 6, 1                                |
| 9    | MOVE   | INDEF                 | yes-no    | 6, 1                                |
| 10   | MOVE   | CO-REF                | where-P   | 6, 2                                |
| 11   | MOVE   | CONJ.                 | where-P   | 6, 1                                |
| 12   | MOVE   | CONJ.                 | -         | 1                                   |
| 13   | MOVE   | CO-REF                | where-P   | 6, 2                                |

**Compositional task generation.** To create compositional generalization tasks in practice, we create training (and validation) splits composed of \( M \) sub-tasks with concept sets \( \{C^i_{\text{train}}\}_{i=1}^M \), and a test set \( C_{\text{test}} \) such that \( C_{\text{test}} \neq C^i_{\text{train}} \forall i \), but \( C_{\text{test}} = \bigcup_{i=1}^M C^i_{\text{train}} \). In other words, each training sub-task can be thought of focusing on a particular subset of test concepts, so models are exposed to all test concepts at training time, but not to all combinations of them (Yanaka et al., 2021).

**Task difficulty.** We hypothesize that support composition \((f_c)\) and supporting fact set size

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3 Weston et al. (2016) noted that transfer learning was an important goal out of the original work’s scope.
(\{f\}) are main factors underlying a particular instance’s difficulty, and especially novel support compositions not seen at training time. Additionally, the difference between train and test splits results in potentially harder distractors, as test-time distractors appear in novel contexts.

Our notions of concept and support composition resemble atoms and compounds in DBCA, a related study on compositionality (Keysers et al., 2020). While DBCA enables automatic creation of compositional train and test splits, we opt here for a more human-interpretable representation that allows more precise manual control of the combinations of concepts a model is exposed to at train and test time.

Quality comparison vs. bAbI 1.0 tasks. Intuitively, good synthetic datasets help drive the development of better modelling approaches. Our new compositional tasks might be harder than bAbI 1.0, but how do we know whether they are a more useful target? To provide a preliminary answer to this question, we adopt the notion of concurrence as a quality measure (Liu et al., 2021). Two benchmarks are said to have high concurrence when they rank a set of modelling approaches similarly. Concurrence offers a way to formalize the intuition above, as high concurrence between a synthetic and natural language benchmark suggests that the synthetic benchmark could have driven similar innovations. We follow the setup of Liu et al. (2021) using SQuAD for the natural language benchmark.4 Notably, bAbI 1.0 achieved very low concurrence with SQuAD; for example, pre-training consistently yields large gains on SQuAD, but on bAbI 1.0, both pre-trained and non-pre-trained models achieve perfect performance on many tasks. The low concurrence thus suggests that bAbI 1.0 may be an unreliable benchmark for model development, and highlights the importance of improving its quality.

4 Experiments

With the controllable task generation afforded by Dyna-bAbI, we can now create datasets probing deeper story understanding capabilities of models.

We present two main experiments targeting the following questions:

• Exp. 1: (q1.a) What role does model architecture play in the capacity for compositional generalization? (q1.b) What is the concurrence of our compositional tasks with real datasets, compared with bAbI 1.0?
• Exp. 2: (q2) How do training data quantity and diversity affect compositional generalization?

Data

For our experiments we created 4 kinds of splits over three subsets of bAbI 1.0 tasks, summarized in Table 2. We denote a subset of tasks T, and consider \(T_2 = \{2, 11\}, T_7 = \{1, 2, 3, 5, 11, ..., 13\}, \) and \(T_{12} = \{1, 2, 3, 5, ..., 13\}.\)

- **concat** splits are simply concatenations of the official data for the tasks \(T.;\) for example, pre-training consistently yields large gains on SQuAD, but on bAbI 1.0, both pre-trained and non-pre-trained models achieve perfect performance on many tasks. The low concurrence thus suggests that bAbI 1.0 may be an unreliable benchmark for model development, and highlights the importance of improving its quality.

| Split    | Type   | Avg. length | Size     | Avg. suppl. fact set size |
|----------|--------|-------------|----------|--------------------------|
| concat(T2) | Train  | 10.76       | 18,000   | 2                        |
| inject(T7) | Train  | 23.25       | 190,158  | 1.42                     |
| diverse(T7) | Train  | 20          | 17,000   | 2.17                     |
| inject(T12) | Train  | 15.97       | 368,831  | 1.28                     |
| diverse(T12) | Train  | 20          | 24,772   | 2.45                     |
| mix(T2)    | Test   | 13.25       | 1,000    | 2.05                     |
| mix(T7)    | Test   | 20          | 3,000    | 2.50                     |
| mix(T12)   | Test   | 20          | 6,000    | 3.70                     |

Table 2: Splits used for our experiments. All except the original data (concat) are created with Dyna-bAbI.

4 Liu et al. (2021) consider a set of 20 modelling approaches used on SQuAD, including 10 pre-trained and 10 non-pre-trained methods.
reference) are only seen with MOVE events.

- mix are test splits generated using rejection sampling like diverse, and consist of instances which may feature events, linguistic constructs and questions from any of the considered tasks. As a result, questions in mix splits require novel/more complex reasoning patterns compared to those seen at training time.

See appendix A.1 for examples and extended details on task generation.

4.1 Exp. 1: Can training on bAbI 1.0 facilitate compositional generalization?

For this experiment, we compared models on \(T_2\) and \(T_7\), since they allow for a direct conversion to an extractive QA format, thus enabling us to use the same concurrence measurement framework of Liu et al. (2021).

Models. We considered 3 classes of models:

- Non-pre-trained specialized architectures for bAbI 1.0 including EntNet (Henaff et al., 2017) and STM (Le et al., 2020), the latter being current SOTA on bAbI 1.0.
- Non-pretrained general-purpose QA methods, such as BiDAF (Seo et al., 2017).
- General purpose pre-trained approaches including RoBERTa (Liu et al., 2020) and T5 (base) (Raffel et al., 2020).

The last two categories are comprised of the 20 models evaluated in Liu et al. (2021), with the addition of T5 to the last group. For implementation details, see appendix A.2.

Results & Analysis

Experiment results are summarized in Table 3. All models perform well in IID settings, but performance drops considerably in OOD settings, including for the SOTA STM model. Pre-trained models fare better on the OOD splits, but still suffer large drops for the harder 7 and 12-task OOD splits.

Architecture alone is not a significant compositionality driver (q1.a). The large OOD performance gap between pre-trained and non-pre-trained models indicates that pre-training plays a much greater role than specialized architectures for QA performance, adding to similar findings in other NLP domains (Hendrycks et al., 2020). The results raise questions about special purpose relational reasoning architectures that continue to be developed today: the poor OOD performance suggests that such models may not be fulfilling their intended design. Either way, we believe these results underscore the importance of rigorous evaluation to verify that modelling motivations are borne out in practice (Aina et al., 2019).

Compositionality increases concurrence (q1.b). As can be seen in the Fig. 2 plots, increasing compositionality is correlated with increased concurrence. In particular, the 7-task OOD split yields high concurrence with the SQUAD benchmark, comparable to other natural language as well as purpose-built synthetic datasets considered in Liu et al. (2021), which feature \(r, \tau\) (Pearson and Kendall correlation functions, resp.) in the ranges \([0.87, 0.99]\) and \([0.77, 0.94]\), respectively. Our results extend the findings of Liu et al. (2021); they demonstrated the existence of high concurrence synthetic benchmarks, we additionally suggest a guiding principle for how to create them (compositional generalization).

4.2 Exp. 2: enriching bAbI 1.0 training data

The results above suggest that the bAbI data in their current form may not be rich enough to drive compositional generalization. In this experiment we probe this question, enriching the training data.

\(^3\) Tasks 6-10 require generative QA, for answering yes-no, count and list questions.

\(^6\) As of November 11, 2021.
Table 3: Experiment 1. OOD evaluation exposes large differences between pre-trained and non-pre-trained models, and also achieves high concurrence with the SQuAD benchmark. We report [min,max] concurrence for bAbI 1.0.

Table 4: Enriching the training data. Injecting knowledge to the original bAbI tasks doesn’t substantially improve compositionality. Sampling more structurally diverse instances yields more significant improvements, though is still limited, especially for more complex compositions.

Discussion and error analysis

Figure 3 breaks down the performance of T5 on mix(T12) after training on diverse(T12). The heatmaps plot performance across various support compositions \((f_c)\) occurring in the test data, subdivided by the number of required supporting facts \(n\) per question. Performance on support compositions seen at training time (blue frames) shows that such implicit inferences are indeed challenging for models trained on the concat splits (see appendix A.5 for details). Perhaps the inject splits supplementing the original tasks with questions providing relevant information will improve compositionality performance? Table 4 displays the result of this experiment; performance in the mix setting is improved only marginally, even though the amount of training data increases 3-fold (Table 2).

Sampling structurally diverse training data. As shown in Table 2, though inject splits significantly increase dataset size, their diversity remains low: most questions require only one or two supporting facts. Therefore, we next enrich training data through sampling more structurally diverse samples. This method is known to improve data efficiency for both compositional generalization as well as IID settings (Oren et al., 2021). As can be seen in Table 4, training on the diverse splits yields a more significant improvement; similar to the findings of Oren et al. (2021), sampling more diverse training data leads to greater generalization as well as much improved data efficiency. However, as the error analysis of the next section shows, performance on compositional generalization is still fundamentally limited.

The relatively low performance of diverse trained models in the “3+” column for concat splits is predominantly due to length discrepancies at train and test time: concat contains some very long stories which are challenging for the model trained on the uniform length and shorter diverse stories.
is generally high, indicating the importance of training pattern diversity for better generalization. The plots indicate that T5 shows some ability to generalize to new support compositions, especially for lower \( n \). Furthermore, certain question types appear to be more learned more robustly; for list and count questions, performance remains relatively high even for larger \( n \) and across novel \( f_c \). We hypothesize that such questions may be easier as simple counting rules suffice to reach an answer, and these are “close to the surface”; unlike other events that may implicitly convey information, in our stories, changes of possession are always explicit in the text.

In general however, the plots indicate that T5 is far from robust compositional generalization:

**Performance deteriorates with increased complexity.** Performance is near perfect for simple compositions (\( n \leq 2 \)) but deteriorates significantly for more complex cases (e.g., center and right plots).

**Inconsistent knowledge.** The discrepancy between the relatively high performance on where-\( P \) questions compared with very low performance on yes-no questions suggests that models aren’t learning consistent knowledge representations. E.g., if a model answers \( y \) correctly to some “Where is \( p \)?” question, we would expect it to answer “yes” correctly for the same question in yes-no format, “Is \( p \) at \( y \)?”. We present further empirical support for this finding in appendix A.6.

**Performance below chance for certain question types.** The heatmaps expose a particularly challenging class of yes-no questions involving disjunctions over indefinites (center and right plots, bottom right); accuracy for such questions is close to zero. See appendix A.7 for an example instance.

## 5 Future work & conclusions

Our work opens up multiple new directions for future research. Dyna-bAbI is readily extendable, for systematic probing of more diverse linguistic phenomena. A beneficial first step could include integration of other bAbI tasks such as spatial reasoning and agent motivations. That said, our experience suggests that the design of truly scalable synthetic and dynamic benchmarks poses significant theoretical and engineering challenges, warranting deeper research on their own right.

Our results raise new questions about the viability of learning robust situation models using standard question-answering training methods, and our datasets present new modelling challenges for future efforts.

Additionally, Dyna-bAbI can naturally complement parallel work probing the the situation representations constructed by neural language models (Li et al., 2021), by facilitating tailored data generation for specific questions, thus broadening and deepening the scope of possible research.

In conclusion, we introduced Dyna-bAbI, a new framework for highly controllable bAbI task generation. We used it to create compositional
generalization datasets providing new modelling challenges for state-of-the-art neural language models. More broadly, our results underscore the importance of agile development of benchmarks themselves, beyond only the models solving them.

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A Appendix

A.1 Extended task construction details

This section provides further details of the training and test splits used for our experiments.

Table 5 enumerates the basic “building blocks”, or concepts underlying the tasks, as presented in §3.2.

Tables 6 and 7 detail the concept sets for each of the sub-tasks comprising the training and test sets, for the $T_2$, $T_7$ and $T_{12}$ groups of tasks.

As can be seen from the tables, the main sources of compositionality are:

- Following the bAbI 1.0 task structure, at training time, all of the more complex linguistic constructs are seen only with MOVE events (and none of the other event types).
- Similarly, at training time, yes-no questions are always seen only with MOVE events (and none of the other event types), and with the INDEF or NEGATE linguistic constructs (but not others, such as COREF).
- where-was-O questions are never seen in stories with GIVE events.

A.1.1 Example instances

Figure 4 shows examples from each of the 4 types of splits used in our experiments. The concat instance is from the original bAbI 1.0 task 5. The inject data contains the same passages as concat, but adds supplementary questions on agent and object locations. diverse instances contain more diverse support compositions ($f_c$), but certain combinations are held out. In particular, diverse instances only feature non-default linguistic mappings with MOVE events, never with POSS (GRAB or DROP) or GIVE. In the mix instances, all combinations of support compositions are possible, as shown in the example which features possession (POSS) events along with co-reference.

A.1.2 Long instances in the bAbI 1.0 tasks

For the T5 experiments, we used a slightly modified version of the bAbI 1.0 tasks, where we trimmed all training and validation examples that didn’t fit into the 512-token input window. This resulted in trimming 1,585 training instances and 175 validation instances from $T_7$ and $T_{12}$ (common to both sets). These data points are not consequential as our analysis focuses on the effects of compositionality and not story length; all instances in diverse and mix are substantially shorter than the 512-token maximum input window size.

A.2 Implementation details

T5. We use the publicly available HuggingFace pre-trained T5-base implementation (Wolf et al., 2020). We fine-tune T5 for 12 epochs on our bAbI data, using the Adam optimizer (Kingma and Ba, 2017), an initial learning rate of $5 \times 10^{-5}$ and training batch size of 8.

STM. We used the official STM implementation, with the only change being a batch size of 32 instead of 128, due to technical constraints.

EntNet. We re-implemented the model in PyTorch, similarly using a batch-size of 32. Following the official Lua reference implementation, we used 20 memory units each with dimension 100. We used the SGD optimizer.

For both the EntNet and STM, we trained models for 200 epochs, and took the best of 10 tries, following Henaff et al. (2017).

For the 20-model concurrence benchmark, refer to Liu et al. (2021) for model details, as we used the same experimental setup.

For the T5 experiments, we used the PyTorch Lightning (Falcon et al., 2019) trainer implementation, and Weights & Biases (Biewald, 2020) for experiment tracking and artifacts management.

A.3 Inoculation experiment results

To rule out the hypothesis that certain patterns may be too hard for models to learn, we follow the inoculation methodology presented in Liu et al. (2019): after training on the original tasks, we fine-tune the T5 on small amounts of OOD data (disjoint from the test data), and evaluate performance as a function of “inoculation dose”. As can be seen in Fig. 5, we find that performance quickly (with only 500 additional inoculation samples per question type) reaches over 90% accuracy on both the mix($T_7$) and mix($T_{12}$) challenge sets. These results support the hypothesis that the training data is not rich enough, indicating clearly that the model is capable of quickly learning to solve the challenge.

10https://github.com/thaihungle/SAM
11https://github.com/facebookarchive/MemNN/tree/master/EntNet-babi
| Events  | Template                      | Example                   | Notes                      |
|---------|-------------------------------|---------------------------|----------------------------|
| MOVE    | P {moved} to the L.           | John traveled to the park.|                            |
| GRAB    | P {grabbed} the O.            | Mary picked up the apple. |                            |
| DROP    | P {dropped} the O.            | Daniel dropped the milk.  |                            |
| GIVE    | P1 {gave} P2 the O.           | John handed Mary the apple.|                            |

**Linguistic Constructs**

|           |                           |                           |                           |
|-----------|---------------------------|---------------------------|---------------------------|
| COREF     | P (MOVE|GRAB|DROP)                  | John went to the garden.  | Co-reference              |
| Following that, {he} (MOVE|GRAB|DROP). | Following that, he moved to the store |                          |
| CONJ      | P1 and P2 {moved} to the L1. | Jeff and Fred went to the cinema. | Conjunction               |
| COMPOUND  | P1 and P2 {moved} to the L1. | Jeff and Fred went to the cinema. | Compound co-reference     |
| NEGATE    | P is not at the L.          | Julie is not in the park. | Negation                  |
| INDEF     | P is either at the L1 or the L2. | John is either in the park or the school. | Indefinite expression    |

**Questions**

|                      | Where is P?                     | Where is John?             | Where is the O?                       | Where is the football?       |
|----------------------|---------------------------------|-----------------------------|--------------------------------------|-------------------------------|
| where-O              | Is P at the L?                  | Where was the O before the L? | Is John at the park?                 | Where was the football before the hallway? |
| where-was-O          | What is P carrying?             | What is John carrying?      |                                      |                               |
| yes-no               | Who gave the O to P2?           | Who gave the O?             |                                      |                               |
| list                 |                                  | Who received the O?         | Who did P1 give the P2 to?           | Who gave the football to John? |
| counting             | How many objects is P carrying? | How many objects is John carrying? |                                   |                               |
| give-qs              | What did P1 give to P2?         |                              |                                      |                               |

**Table 5:** Details of the events, linguistic constructs and questions constituting the bAbI tasks covered in this work. Words in {brackets} are drawn from a small set of synonyms.

**Figure 4:** Example instances from each of the 4 types of splits used in our experiments.
### Table 6: Concept sets for the $T_2$ and $T_7$ sub-set of the original bAbI tasks, and the new tasks generated with Dyna-bAbI. Train sub-task numbering follows the original bAbI numbering. The inject and diverse tasks inherit the same concept set from the original tasks, and additionally “I”, “D” denote question types included only in the inject or diverse tasks, respectively. “I/D” denotes question types included in both.

| Sub-task | Type | Move | Grab | Drop | Give | Co-reference | Conjunction | Compound c-ref. | where-P | where-O | where-was-O | give |
|----------|------|------|------|------|------|--------------|-------------|----------------|---------|---------|-------------|------|
| 1        | Train | ✓    |       |       |       |              |             |                |         |         |             |      |
| 2        | Train | ✓    | ✓    |       |       |              |             |                |         |         |             |      |
| 3        | Train | ✓    | ✓    | ✓    |       |              |             |                |         |         |             |      |
| 5        | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |         |         |             |      |
| 11       | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |         |         |             |      |
| 12       | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |         |         |             |      |
| 13       | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |         |         |             |      |
| mix($T_2$) | Test | ✓    | ✓    | ✓    | ✓    |              |             |                |         |         |             | ✓   |
| mix($T_7$) | Test | ✓    | ✓    | ✓    | ✓    | ✓            |             | ✓              |         |         |             | ✓   |

### Table 7: Concept sets for the $T_{12}$ sub-set of the original bAbI tasks, and the new tasks generated with Dyna-bAbI. Train sub-task numbering follows the original bAbI numbering. The inject and diverse tasks inherit the same concept set from the original tasks, and additionally “I”, “D” denote question types included only in the inject or diverse tasks, respectively. “I/D” denotes question types included in both.

| Task | Type | Move | Grab | Drop | Give | Co-reference | Conjunction | Compound c-ref. | Negation | Indefinite | where-P | where-O | where-was-O | yes-no | counting | list | give |
|------|------|------|------|------|------|--------------|-------------|----------------|----------|------------|---------|---------|-------------|-------|----------|------|------|
| 1    | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 2    | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 3    | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 5    | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 6    | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 7    | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 8    | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 9    | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 10   | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 11   | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 12   | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| 13   | Train | ✓    | ✓    | ✓    | ✓    |              |             |                |          |            |         |         |             |      |          |      |      |
| mix($T_{12}$) | Test | ✓    | ✓    | ✓    | ✓    | ✓            |             | ✓              |          |            |         |         |             | ✓    |          |      |      |
# Supporting facts

| # supporting facts | # samples | Evaluation accuracy |
|--------------------|-----------|---------------------|
| 1                  | 334       | 53.3 93.4 86.8      |
| 2                  | 833       | 45.7 73.3 72.4      |
| – (including give) | 99        | 3.03 7.07 12.12     |
| 3                  | 1832      | 19.4 37 53.8        |
| – (including give) | 468       | 4.27 7.05 30.3      |

Table 9: Breakdown of model performance on mix(T7) for questions including GIVE events in the supporting fact set. The poor performance indicates that training on the bAbI 1.0 data does not facilitate generalization to novel compositions of GIVE.

in particular we focus on GIVE events. As noted in §4.2, compositions involving GIVE are intuitively challenging as they entail multiple inferences which are not explicit in the text: the actors share the same location, and the possession of the object being given is transferred from the giver to the recipient. The only task in concat(T7) featuring GIVE events is task 5, which never asks about the locations of actors or objects, but only about the participant roles in the event (e.g., who was the giver or recipient; see Fig. 1 example from task 5).

To measure this intuition empirically, we analyze a subset of 567 questions including GIVE events in the supporting facts set. As shown in Table 9, performance for all models on questions including GIVE is extremely low, far below performance for questions without it. Qualitative analysis indicates many failure cases follow the pattern shown in the right-side example of Fig. 1c, question on line 10: the location of an entity (e.g., Daniel) must be inferred via the known (co-)location of a second participant in the GIVE event (e.g., Jeff). These results strengthen the hypothesis that standard QA training on the original bAbI data does not drive strong event comprehension in models.

A.6 Extended error analysis: knowledge inconsistency

This section presents further analysis of the knowledge consistency of the T5 model trained on the diverse(T12) data when evaluated on the challenge set mix(T12).

We collected all yes-no questions from mix(T12) for which the answer was “yes”, yielding 446 questions in total. For each such (question, answer) pair, of the form (“Is person at the location?”, “yes”), we created an equivalent pair in the format of a where-P question, (“Where is person?”, location).
| where-P (→) | correct | incorrect |
|-------------|---------|-----------|
| yes-no (↓)  |         |           |
| correct     | 209     | 4         |
| incorrect   | 145     | 88        |

Table 10: Confusion matrix displaying knowledge inconsistencies in T5. We pose a question in two formats: (1) yes-no: “Is X at L? yes” vs (2) where-P: “Where is X?’ L’. We find performance is considerably higher for questions posed in the where-P format, indicating the model isn’t learning the equivalence of both forms.

Ideally, we would expect a model to be agnostic to equivalent phrasings of a question. However, as displayed in Figure 10, we find that T5 is considerably more accurate for questions posed in the where-P format, likely due to exposure to a larger variety of such questions at training time. Figure 6 shows a characteristic example: T5 correctly answers in the where-P format, but wrongly answers “maybe” for the yes-no format, thrown off by the distractor indefinite phrase in sentence 3. The pattern of answering “maybe” to questions about the location of an actor mentioned in an indefinite is commonly observed in training.

These results highlight a limitation of text-to-text QA models such as T5: their story representation may be highly coupled with the input question. This form of representation stands in contrast to more human-like narrative comprehension which is thought to involve the construction of situation models; structured representations of entities and their relations as depicted by the text. Situation models are not dependent on a-priori knowledge of a particular question, and are thought to constitute a representational substrate supporting more systematic inferential generalization.

A.7 Extended error analysis: double disjunctions

As the shown in the §4.2 error analysis, a particularly difficult class of questions are double disjunctions over indefinite expressions. Figure 7 displays a typical example from mix(T_{12}), where the locations of two actors are given in indefinite form (sentences 3 and 19), and are also known to be co-located, since they share the location of the object “football”, as inferred from sentences 18 and 20. Hence it is possible to infer their location as the intersection of the two indefinite expressions (here “bedroom”). Rather than answering “yes” to the question “Is John in the bedroom?”, T5 invariably answers “maybe” for such cases. This pattern is likely due to the fact that in the training data “maybe” is a typical answer for yes-no questions about actors mentioned by indefinite expressions (task 10 in bAbI 1.0).