

mSCAN: A Dataset for Multilingual Compositional Generalisation Evaluation

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Abstract

Language models achieve remarkable results on a variety of tasks, yet still struggle with compositional generalisation benchmarks. The majority of these benchmarks evaluate performance in English only, leaving us with the question of whether these results generalise to other languages. As an initial step to answering this question, we introduce mSCAN, a multilingual adaptation of the SCAN dataset. It was produced by a rule-based translation, developed in cooperation with native speakers. We then showcase this novel dataset on some in-context learning experiments, with the multilingual large language model BLOOM as well as gpt3.5-turbo.

1 Introduction

Humans learn quickly by easily recombining previously known concepts in unseen settings. Several benchmarks have been designed to empirically investigate whether neural networks are equipped with similar abilities (Lake and Baroni, 2018; Keysers et al., 2020; Hupkes et al., 2020; Kim and Linzen, 2020). Such benchmarks are composed of tasks in which the training data and the test data have different and carefully chosen distributions. Recent work used these benchmarks to evaluate pre-trained large language models (LLMs) and showed that despite their remarkable success on many other tasks they still struggle with compositional generalisation (Qiu et al., 2022).

The majority of the research on compositional generalisation has focussed on English data and models — but do compositional generalisation abilities differ across languages? Indeed, it has been argued that the performance of a model in English is not a guarantee that it will work “equally or even reasonably well” in other languages (Bender, 2011). On top of that, compositional generalisation itself is not guaranteed to work uniformly across human languages (Bittner, 1995).

Furthermore, the exploration of cross- and multilingual compositional generalisation could benefit the expansion of language technology to low-resource languages and settings (Chaabouni et al., 2021), as a potential approach to overcome the need for huge amounts of data that neural models require.

With ever-increased scale, some large language models have shown great performance on downstream tasks while only conditioned on a few examples, and without updating their parameters. This is known as in-context learning, a paradigm in which some very large models such as GPT-3 and PaLM have been shown to manifest reasoning abilities when prompted in specific ways, including in multilingual settings (Shi et al., 2022). Despite these promising perspectives, it does not currently stand as an alternative to fine-tuning. Some recent research has sought to investigate compositional generalisation within the in-context learning paradigm, showing it gets outperformed by smaller fine-tuned models.

As a means to further the study of compositional generalisation in multiple languages, we introduce mSCAN (multilingual SCAN), an adaptation of the SCAN benchmark into French, Hindi, Mandarin Chinese and Russian. We also provide for each language both the original SCAN benchmark splits (add_jump, add_turn_left, length) as well as the Maximum Compound Divergence splits (Keysers et al., 2020).

We also present preliminary experimental results using mSCAN in an in-context learning paradigm on BLOOM and gpt3.5-turbo.

Following the GenBench taxonomy (Hupkes et al., 2023), the primary motivation for this work can be characterised as intrinsic given its primary function to provide a means to evaluate compositional generalisation in multilingual settings. Similarly to the original SCAN benchmark, the source of the distribution shift is fully generated and its

Motivation					
<i>Practical</i>	<i>Cognitive</i>	<i>Intrinsic</i>	<input type="checkbox"/>	<i>Fairness</i>	
Generalisation type					
<i>Compositional</i>	<i>Structural</i>	<i>Cross Task</i>	<i>Cross Language</i>	<i>Cross Domain</i>	<i>Robustness</i>
<input type="checkbox"/>					
Shift type					
<i>Covariate</i>	<i>Label</i>	<i>Full</i>		<i>Assumed</i>	
<input type="checkbox"/>					
Shift source					
<i>Naturally occurring</i>	<i>Partitioned natural</i>	<i>Generated shift</i>		<i>Fully generated</i>	<input type="checkbox"/>
Shift locus					
<i>Train–test</i>	<i>Finetune train–test</i>	<i>Pretrain–train</i>		<i>Pretrain–test</i>	<input type="checkbox"/>

Figure 1: GenBench evaluation card

type is covariate. Moreover, the in-context set-up of our experiments places the shift locus between the pre-train and test stages though we note that the data can also be used in a fine-tuning setup in the future.

2 Background

Pre-trained multilingual models seek to address the challenge of low-resource languages, by leveraging the pre-training and the hope that high-resource languages will help lower-resource ones. Large-scale multilingual language models have achieved impressive performance across typologically distinct languages (Ruder et al., 2021). Yet, the cross and within-language performance of downstream tasks on such models remain correlated to their amount of language-specific pertaining data (Lauscher et al., 2020).

However, if scaling up the amount of pre-training data might improve cross-lingual generalisation, it might come at a price when it comes to compositional generalisation. Kim et al. (2022) have questioned the reported benefits of pre-training on compositional generalisation benchmarks and have observed a case of inverse scaling, where the performance degradation on COGS actually increases with the amount of pre-training data.

In a further study on the impact of model scale on compositional generalisation, Qiu et al. (2022) compared fine-tuning, prompt-tuning and in-context learning on multiple compositional generalisation datasets and observed that for in-context

learning, the performance is correlated with model size. However, it is worse than for fine-tuned, smaller models. Datasets they used included COGS and the Compositional Freebase Question dataset or CFQ (Keysers et al., 2020), which consists of questions and answers in natural language, as well as accompanying SPARQL queries against a knowledge base. (Qiu et al., 2022)

Hosseini et al. (2022) evaluated four model families for in-context learning on multiple semantic parsing benchmarks. Despite their observation that the larger models tend to do better, they report that the in-context learning performance on SCAN and CFQ is very small for the models tested.

MCWQ (Cui et al., 2022), a multilingual variant of CFQ, is the first adaptation into multiple languages of a compositional generalisation benchmark. It was created with the use of neural machine translation. Wang and Hershovovich (2023) have shown that using neural machine translation to translate already existing benchmarks entails “critical semantic distortion”, and favour a rule-based translation of the MCWQ dataset.

The MSGM benchmark (Shi et al., 2022) investigates the mathematical reasoning abilities of LLMs in multilingual settings, by providing data in ten different languages. Even though the decomposition of SCAN commands closely resembles that of arithmetic operations, the MSGM differs in that it does not specifically target the capacity of the model to map forms to a representation of meaning. As such, there has not yet been any investigation specifically targeting the compositional

generalisation abilities of multilingual models in an in-context setting.

3 The mSCAN dataset

Our goal was to adapt the Simplified version of the CommAi Navigation dataset or SCAN (Lake and Baroni, 2018) to languages that belong to typologically diverse families and typically are represented in varying proportions in the training data of multilingual models. The languages selected also have different language scripts: Latin, Cyrillic and Devanagari. The original SCAN consists of a set of navigation commands in English such as “jump left”, and their corresponding sequence of actions, such as LTURN JUMP. It is a synthetic dataset: the natural language commands are generated by a phrase-structure grammar, and the actions are produced by applying a semantic interpretation function. As such, it is akin to a semantic parsing task.

3.1 Generation methodology: a grammar based-transduction

Following (Wang and Hershcovich, 2023), we translate SCAN in a rule-based manner.

The method we used consists of a set of English grammar rules, their accompanying transduction rules and word mappings.

We used the context-free grammar shown in Figure 2, which is exactly equivalent to the one from (Lake and Baroni, 2018), only differing in notation. We also used the interpretation function as provided in their work. The SCAN grammar does not have recursion and generates an unambiguous and finite set of 20910 natural language commands to action sequence pairs.

Native speakers of French, Mandarin Chinese, Russian and Hindi were asked to provide the corresponding interpretation function in their language. We consequently manually built the transduction functions, which were applied to the English parse trees. The resulting parse trees were then formed into our translated commands by word mappings.

For instance, for French translations, we first parsed the English text using the original SCAN grammar, given in Figure 2, to produce an English parse tree. This parse tree can be transduced into a French parse tree using the transduction rules given in Figure 3. These transduction rules tell us that, for instance, S AND S and S AFTER S should be translated word-for-word, and the translation

of “and” is “et”, and “after” is “après”. They also tell us that French distinguishes between “turn left” (translated as “tourner à gauche”) and “turn around left” (translated as “tourner autour par la gauche”).

```

C -> S AND S | S AFTER S | S
S -> V TIMES | V
V -> ACTION VECTOR DIR
    | TURN VECTOR DIR
    | D | ACTION
D -> ACTION DIR | TURN DIR

ACTION -> 'walk' | 'look'
        | 'run' | 'jump'
TURN -> 'turn'
VECTOR -> 'around' | 'opposite'
DIR -> 'left' | 'right'
TIMES -> 'twice' | 'thrice'
AFTER -> 'after'
AND -> 'and'

```

Figure 2: English SCAN grammar

Upon the completion of generation, a sample was manually checked by the native speakers for meaning preservation.

3.2 Splits

We do not introduce a novel way to split our dataset and rather choose to directly reproduce already existing splits on mSCAN.

3.2.1 SCAN splits

The original SCAN dataset contains multiple types of splits, each aimed to test distinct levels of compositional ability: the “simple” split is a random subset of the data, and the “length” one targets commands with corresponding action sequences that are longer than any example seen during training, and finally, the “primitive” split, which tests whether a primitive only encountered in isolation during training can be used adequately novel combinations at test time.

3.2.2 Maximum Compound Divergence Splits

The MCD splits were introduced by (Keysers et al., 2020) with their distribution-based compositionality assessment (DBCA). It consists of a method to measure whether a dataset has been split adequately to test for compositional generalisation, as well as a method to construct such splits. The main principles of the DBCA are that (1) all the atoms or primitive elements existing in the test set should also be present in the training set, and in a distribution as similar as possible, and (2) that

```

# Non-terminals
[S AND S] -> [S] [AND] [S]
[S AFTER S] -> [S] [AFTER] [S]
...
[ACTION VECTOR DIR] -> [ACTION] [VECTOR]
[DIR]
[ACTION LEFT] -> [ACTION] 'a gauche'
[ACTION RIGHT] -> [ACTION] 'a droite'
...

# Terminals
'and' -> 'et'
'after' -> 'apres'
'turn' -> 'tourner'
'right' -> 'par la droite'
'left' -> 'par la gauche'
...

```

Figure 3: English to French transduction rules

the distribution of compounds (ways of composing the atoms) should be as different as possible between the training and the test set. Intuitively, this method seeks to ensure that what is measured is how the atoms are composed into new compounds and that the compositions are challenging enough so that the model cannot rely on anything else than its capacity to generalise compositionally.

(Keysers et al., 2020) applied MCD to SCAN, and we replicate these splits exactly in mSCAN: each line of the respective test, train and evaluation sets in mSCAN is a direct translation of the corresponding line in the English-language MCD SCAN split.

We make mSCAN_fra, mSCAN_hin, mSCAN_rus and mSCAN_cmn and their accompanying splits, available as a public dataset available on the Hugging Face platform¹.

4 Experiment

4.1 Models

The BigScience Large Open-Science Open-access Multilingual Language Model or BLOOM, (Workshop et al., 2023) is a Transformer-based language model with 176 billion parameters. As an autoregressive LLM, it is trained to generate text from a prompt. It was trained on 46 languages and 13 programming languages.

We also ran a small experiment on the OpenAI model gpt3.5-turbo, accessed via the OpenAI REST API, between 2023/10/23 and 2023/10/26.

4.2 Prompt design

Our approach focussed on the selection methodology of the in-context examples. Our goal was to adapt and mimic the principle underlying the original SCAN benchmark. That is, to test for compositional generalisation, the context examples should not contain the combinations of the test case.

¹<https://huggingface.co/datasets/CLMBR/mSCAN>

We therefore randomly select the in-context examples from the training sets of our splits and the test case from the corresponding test sets. For example, a certain number of examples is sampled from the French add_jump training set, and its corresponding test case comes from the French add_jump test set. This example is cut out to only include the natural language commands and the start of the output sequence token (“OUT:”), therefore prompting the model to generate the adequate sequence of instructions as the output.

An EOS token was added at the end of each example and provided to the model as a stopping criterion parameter.

An example of a prompt is provided in Figure 4.

```

<s>IN: jump right thrice and turn
      opposite left OUT: I_TURN_RIGHT
      I_JUMP I_TURN_RIGHT I_JUMP
      I_TURN_RIGHT I_JUMP I_TURN_LEFT
      I_TURN_LEFT </s>

<s>IN: walk after walk opposite left OUT
      : I_TURN_LEFT I_TURN_LEFT I_WALK
      I_WALK </s>

...

<s>IN: turn around left twice and look
      around left thrice OUT:

```

Figure 4: Example of a prompt in English

4.3 Set-up

Due to the context-size restrictions of the BLOOM model, we set the number of context examples to 8. In the original add_primitive SCAN splits, the primitive is over-represented in the training set by 10%. We imitate this in our set-up by manually adding the primitive to the context examples once, and by having removed the primitive from our train set, which ensures that the sampled remaining 7 in-context examples do not contain it. Therefore,

the full prompt consists of 8 examples, of which one contains the primitive and 7 do not, and a test case that includes the primitive. We use greedy decoding for generation to provide a baseline.

5 Results

5.1 BLOOM

Because BLOOM was not trained with an end-of-sequence token, we truncated generated outputs to their expected length. Despite this adjustment, our results get zero exact match accuracies, that is, none of the full output sequences was equal to the correct answer. This is consistent with the results observed by Hosseini et al. (2022).

For a finer-grained measure of model performance than exact match accuracy, we measured the minimum edit distance between the truncated outputs and the target strings.

Table 1 shows the average minimum edit distance compared to the expected output length on 100 runs on the simple, MCD1, length and add_jump splits for each language. There is no result for add_jump on Hindi and Russian due to the encoding being larger than the maximum supported size for these experiments.

It is important to emphasise that there was no exact match, both for the original version of SCAN as well as for our mSCAN multilingual variants, meaning that the model has a 0% accuracy. We can observe however that there is a similar amount of error across languages.

As expected, the simple split achieves the best results, and Russian did not achieve a similar performance as the other languages, which are officially part of the BLOOM training corpus. Surprisingly, there is little difference between English and Hindi, while the model seems to do slightly better on Mandarin and French.

Despite Russian not being an official language part of the training data of BLOOM, we ran the experiments on our mSCAN_rus and we included it with the others.

5.2 GPT 3.5

Unlike with BLOOM, we obtained a few exact sequence matches with gpt-3.5-turbo but they are few, with less than 10% per language over the five languages including English. In this experiment again, Mandarin seems to achieve slightly better results. From these observations, it also appears that

the model has the most difficulty with the length split.

The average edit distance results are better than those with BLOOM but display a similar pattern, with the model seeming to struggle the most on the length split and Mandarin achieving slightly better results. As expected, the model seems to be more successful with Russian than BLOOM.

6 Discussion

6.1 Pre-training data contamination

In the in-context set-up, the data from the pre-training corpus cannot be controlled. This means that there is a possibility that the compositional generalisation training set or the whole dataset itself could have been used. Given that BLOOM specifies the content of its training corpus, we are at least guaranteed that it has not learned the English SCAN dataset or that there was some test contamination. As we introduce mSCAN with this paper, it could not have been a part of the training data.

However, there is no guarantee the original SCAN has not been seen during the pre-training of the ChatGPT model. Given that we are not able to check the pre-training data, the data distribution shift is only *assumed* in this case.

6.2 In context-examples selection

It is acknowledged that prompting variations such as the format or order of prompts can have an influence on the in-context learning performance. Our context example selection methodology is rudimentary. A recent study found that the selection of in-context examples affects compositional generalisation performance, by showing that randomly selecting in-context leads to an accuracy gap compared to fine-tuned models (An et al., 2023). They argue that a careful selection of the in-context examples will “fully reveal the potential of in-context learning”. They define three requirements for in-context examples: structural similarity, diversity and complexity. They show that this helps compositional generalisation. In the case of SCAN, the structural similarity factor is not as relevant, given the basic nature of the grammar (there are no complex structures such as in COGS). The diversity and complexity factors are not controlled in our experiment, given that we sample from the train set without looking at the number of distinct primitives included. For this reason, our set-up does not follow the principle that the primitives in the test

Model, language \ split	simple (13.55)	mcd1 (18.03)	length (30.04)	add_jump (14.58)	
BLOOM	cmn	5.04	8.28	13.82	7.16
	eng	9.32	11.65	19.15	10.53
	fra	7.69	11.85	16.26	7.95
	hin	8.63	11.10	18.72	
	rus	12.04	15.60	27.21	
gpt-3.5-turbo	cmn	4.52	7.95	14.83	5.81
	eng	5.51	8.75	16.32	6.65
	fra	5.63	9.39	17.00	7.26
	hin	6.47	10.17	17.50	8.17
	rus	5.67	9.51	17.70	7.26

Table 1: Average edit distance for each language and split, on BLOOM and gpt-3.5-turbo. The numbers reported in the column headings correspond to the average expected output length. Note that BLOOM produced 0 exact matches.

Language \ split	simple	mcd1	length	add_jump
cmn	10	6	0	6
eng	7	7	0	1
fra	4	4	0	1
hin	0	0	1	2
rus	3	0	0	4

Table 2: Number of exact matches over 100 queries of gpt-3.5-turbo

case should be covered by the in-context examples. Instead, we expect the model to be able to infer the mapping to SCAN instructions from context as the instructions closely match their natural language counterparts (e.g., walk is mapped to I_WALK).

Other research uses a least-to-most prompting strategy: prompts consist of instructions telling explicitly the model to decompose the task into subproblems and showing it how to solve them sequentially (Zhou et al., 2023). The number of in-context examples in our experiment was constrained by the context size of the model in the BLOOM experiment. To work around this, the least-to-most method uses intermediate representations in the form of Python expressions, mapping for example “look twice” to “LOOK*2” instead of “LOOK LOOK”. The authors show that the model is able to expand from the Python expression with high accuracy, but further investigation of the potential consequences of these intermediate representations could be pursued.

6.3 Compositional Generalisation and different languages

We observed that there was no large variation between how the different languages performed in

our in-context setup, except for Mandarin Chinese, which has slightly better results. Given the limited scope of our experiments, this observation should be confirmed by further investigation. If these results hold then, they would be in contrast with previous findings, where in some NLP tasks, generative models (including BLOOM) perform better on higher-resource languages and languages that are in the Latin script (Ahuja et al., 2023).

6.4 Possibilities for future work

In addition to investigating different strategies for in-context example selection and systematically conducting the experiments on a larger scale than what this work presents, future work could involve adapting more realistic natural language tasks to multiple languages. Indeed, the subset of natural language covered by SCAN is small and its interpretation is more akin to arithmetic expressions than naturally occurring language. As such, it does not make it possible to evaluate for more sophisticated linguistic abstraction (Kim and Linzen, 2020). Adapting COGS to other languages would be an extensive process, requiring the construction of language-specific grammars.

It would also be worth doing experiments with

fine-tuning on multilingual models such as mBART (Liu et al., 2020) or mT5 (Xue et al., 2021).

A systematic study of the interactions between (a) the size of language-specific pretraining data, and (b) both compositional and cross-lingual generalisation, would be an important contribution.

7 Conclusion

The majority of the research on compositional generalisation is focussed on English, leaving open the question as to whether its findings can generalise across languages. As an initial step towards this exploration, we introduce mSCAN, a multilingual adaptation of the SCAN dataset, produced using rule-based translation, with rules developed in cooperation with native speakers. We then showcase this novel dataset on some in-context learning experiments, with the multilingual large language model BLOOM.

Limitations

Due to the synthetic nature of the SCAN dataset, the translations in other languages do not aim to capture naturalness or fluency.

This dataset was created with the aim of expanding compositional generalisation evaluation to multiple languages. We evaluate BLOOM, a model carefully designed for multilingualism, trained on a meticulously curated corpus. Despite these two points, more typologically diverse and low-resource languages are absent from our dataset and our evaluation.

Finally, the scale of the experiments reported in this paper was limited by different factors, including the cost and time of inference, and the maximum context size of 1000 tokens of BLOOM. As such, larger-scale experiments would be needed to form a basis for comparison with other benchmark results.

Acknowledgements

We would like to thank the native speakers for their precious help with this work: Sofia Ahmed, Catalin Gangalic, Qingxia Guo, Sanjana Sharma, Onur Tuna, and Shengqi Zhu.

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