

# BenchCLAMP: A Benchmark for Evaluating Language Models on Semantic Parsing

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## Abstract

We introduce **BenchCLAMP**, a **Benchmark** to evaluate **Constrained L**anguage **M**odel **P**arsing, which produces semantic outputs based on the analysis of input text through constrained decoding of a prompted or fine-tuned language model. Developers of pretrained language models currently benchmark on classification, span extraction and free-text generation tasks. Semantic parsing is neglected in language model evaluation because of the complexity of handling task-specific architectures and representations. Recent work has shown that generation from a prompted or fine-tuned language model can perform well at semantic parsing when the output is constrained to be a valid semantic representation. BenchCLAMP includes context-free grammars for six semantic parsing datasets with varied output meaning representations, as well as a constrained decoding interface to generate outputs covered by these grammars. We provide low, medium, and high resource splits for each dataset, allowing accurate comparison of various language models under different data regimes. Our benchmark supports both prompt-based learning as well as fine-tuning, and provides an easy-to-use toolkit for language model developers to evaluate on semantic parsing.

## 1 Introduction

Large pretrained language models when fine-tuned on target data can achieve state-of-the-art performance on a host of NLP tasks (Liu et al., 2019; Raffel et al., 2020; Wang et al., 2021; He et al., 2021). Models like GPT-3 (Brown et al., 2020), Codex (Chen et al., 2021) and T0 (Sanh et al., 2021) have also shown impressive zero- and few-shot performance, when prompted with task descriptions and examples. Research on large language models is commonly validated by performance on downstream NLP tasks. Past work has evaluated new pretrained language models on classification, extraction, and generation (Liu et al., 2019; He

et al., 2021). However, semantic parsing is generally not considered a testbed for such evaluation since most state-of-the-art systems involve dataset-specific model architectures and meaning representation constraints.

Recently, Shin et al. (2021) and Scholak et al. (2021) have shown that standard generation from a fine-tuned or few-shot prompted language model can perform competitively in semantic parsing tasks, when the output of the language model is constrained to produce valid meaning representations. However, it is still challenging to set up constrained generation for a new dataset and language model due to the variation in meaning representations and model-specific tokenization. In this paper, we introduce a new benchmark called BenchCLAMP (Benchmark for Constrained Language Model Parsing) that covers six semantic parsing datasets with four different meaning representations. We release context-free grammars for each dataset and provide a toolkit to perform efficient constrained decoding to generate valid meaning representations. Our benchmark reduces the barrier for language model developers to evaluate on semantic parsing. The benchmark is made available at [https://github.com/microsoft/semantic\\_parsing\\_with\\_constrained\\_lm](https://github.com/microsoft/semantic_parsing_with_constrained_lm).

## 2 Related Work

**Language Models for Semantic Parsing** Recent work has shown that one can generate an analysis of a natural language sentence, such as a semantic parse, by asking a large language model to continue a prompt that includes the sentence (Chen et al., 2021; Li et al., 2021; Schucher et al., 2021). We refer to this as “language model parsing.” To avoid ill-formed analyses, it is possible to *constrain* the generation so that the generated output satisfies hard task-specific constraints. Shin et al. (2021) showed that constrained generation from

Dataset	Metric	Example Representation
SMCalFlow (Andreas et al., 2020) TreeDST (Cheng et al., 2020)	Lispress Match	(Yield (Event.start (FindNumNextEvent (Event.subject_? (?~= "meeting")) 1L)))
MTOP (Li et al., 2021)	Exact Match	[IN:Get_Message [SL:Type_Content video] [SL:Sender Atlas]]
Overnight (Wang et al., 2015)	Denotation Match	(call listValue (call getProperty en.block.block1 (string color)))
Spider (Yu et al., 2018) CoSQL (Yu et al., 2019)	Test suite Execution	SELECT born_state FROM head GROUP BY born_state HAVING count(*) >= 3

Table 1: List of datasets covered by BenchCLAMP, along with evaluation metric and an example representation. For SMCalflow and TreeDST, we use the Lispress format (lisp-like serialization format for programs) of the data released by (Platanios et al., 2021).

few-shot-prompted GPT-3 and fine-tuned BART models outperformed task-specific semantic parsing architectures in low-resource settings. Scholak et al. (2021) were able to achieve state-of-the-art performance in SQL prediction by fine-tuning a T5-3B model (Raffel et al., 2020) and using constrained decoding. As the above works used different evaluation settings, it is hard to see which techniques work best under different data regimes.

**NLP Benchmarks** Multiple benchmarks have been introduced to track progress on specific NLP tasks, and to encourage multi-task learning using diverse datasets. The GLUE (Wang et al., 2018) and SuperGLUE (Wang et al., 2019) benchmarks are widely used by language model developers to evaluate model efficacy. However, these benchmarks focus on classification and span extraction, and do not include structured prediction tasks like semantic parsing. Our benchmark fills this gap.

### 3 Datasets

**Data Splits** BenchCLAMP includes six popular semantic parsing datasets with a varied set of meaning representation formalisms (details in Table 1). For each dataset, we create the following splits:

1. We create **three low-resource train splits** of 500 examples, each sampled from the training portion of the dataset. We create a single low-resource development set of 50 examples sampled from the development portion of the dataset. We always report mean of these splits.
2. We similarly create **a medium-resource train split** of 5000 examples paired with a dev set of 500 examples.
3. We consider **a high-resource split** with the entire training set of the dataset, paired with the

medium-resource development set.

To make it feasible for researchers to evaluate large pretrained models on BenchCLAMP, we randomly sample 2000 examples from the test set of each dataset, and evaluate test performance on this smaller set. We use the full test set in cases where there are less than 2000 examples. We also release a smaller randomly-sampled 100-example test set for each dataset to evaluate models accessed through costly API calls like GPT-3 and Codex. Results on a 100-example test set will have wide error bars and should be used with caution. See Appendix D for a discussion on result variance. We allow for the evaluation on full test sets of the datasets to compare with state of the art results. For datasets that do not release public test sets, like SMCalflow, Spider, and CoSQL, we treat the development set as the test set, and sample 10% of the training set and treat it as the development set for splits creation. For datasets which include dialogue interactions, we ensure that all turns of a dialogue belong to the same split. The Overnight train set was already small (< 5k examples), so we do not have a separate medium split for it.

**Grammars** We release context-free grammars for all datasets to constrain generation to valid meaning representations. For SMCalflow and TreeDST, we use the Lispress-format datasets released by Platanios et al. (2021). We create a non-terminal corresponding to each type present in the training data. For each (sub-)expression with type  $t$ , we add a production rule with the non-terminal for  $t$  generating the non-terminals of its component (sub-)expression types, or component terminal plan fragments. For MTOP, we induce a simple type system on the meaning representation, and then follow a similar procedure to extract the grammar.

For all data splits, we use the full training data to derive the grammar. We envision that in realistic scenarios, the grammar will be provided by a domain developer, and hence will have complete coverage of the domain (even when some plan fragments might not have appeared in the low-resource dataset). We also add results with grammars induced from low-resource splits in Appendix C.

We use a publicly available SQL grammar (antlr, 2022) for Spider and CoSQL. For each example, we add schema-specific constraints to the grammar to generate consistent table and column names.

## 4 Experimental Setup and Results

We use BenchCLAMP to fine-tune and evaluate five language models with varying number of parameters: T5-base (220M), T5-large (770M), T5-3B (3B), BART-large (406M) and CodeT5-base (220M). The input to our model is the utterance concatenated with the string representation of the context (conversation context, database schema, etc.), and the output is the semantic parse. We evaluate two large GPT-based language models: GPT-3 and Codex, using few-shot prompting on the 100 example test sets. For each input (utterance concatenated with context) we select a set of 20 relevant examples from the training set using BM25 (Rubin et al., 2021). We create a prompt using these examples, following the template in Shin et al. (2021) and limiting the total length of the prompt to be 1500 tokens. This leaves room in GPT-3’s buffer to generate an output of up to 548 tokens. Details of the input format and training are provided in Appendices A and B.

We use the code released by Shin et al. (2021) to support constrained generation of semantic representations. At each step, the prefix generated until that point is incrementally parsed by Earley’s algorithm (Earley, 1970) to determine the set of legal next tokens, which is used for subsequent token generation. We extend their method to support all autoregressive language models and sequence-to-sequence models. Unless otherwise mentioned, we always use constrained decoding to report metrics.

**Impact of Context** The datasets in BenchCLAMP require a model to use a variety of contexts. SMCalflow, TreeDST and CoSQL datasets all have conversational context. Spider and CoSQL have database schema context which informs the target SQL prediction. BenchCLAMP allows us to perform a controlled investigation of the effect

Conv. Context	SMCalfFlow			TreeDST		
	Low	Med	High	Low	Med	High
No context	37.0	63.8	72.9	42.4	68.4	76.0
Last agent utt.	<b>42.6</b>	70.7	80.6	<b>59.6</b>	82.7	87.9
Last user & agent utt.	40.0	<b>71.5</b>	<b>81.3</b>	58.8	<b>86.2</b>	<b>90.0</b>

Table 2: Effect of conversational context on the performance of fine-tuned T5-large (without constraints)

Conversational Context	DB values?	Low	Med	High
No context	no	21.3	35.9	34.4
	yes	25.3	38.9	40.3
Last interaction	no	24.1	40.4	39.1
	yes	<b>28.2</b>	44.2	44.4
All interactions	no	24.3	36.8	43.0
	yes	24.9	<b>44.9</b>	<b>48.8</b>

Table 3: Performance of BART-large (without constraints) on the CoSQL dataset with varying context.

of context. Table 2 shows that while using the last agent and user utterance is helpful for all settings, the low-data regime does even better when using only the last agent utterance; without more data, training struggles to learn how to utilize (or ignore) the additional context. We find similar results for CoSQL in Table 3. Also, SQL prediction always benefits from including database values in the context along with the database schema information. Input formats are detailed in Appendix A. The best settings for context for each data regime is used for all subsequent experiments.

**Few-Shot Prompt Structure** In the few-shot prompting scenario, we manipulate the context choice and ordering of examples in our prompt to Codex. The results in Table 4 show that ordering the most relevant example at the end closest to the generation heads is helpful in the low-data regime, indicating that GPT-3 and Codex pay more

Prompt Order	Conv. Context	Low	Med
Random	No context	35.7	52.0
Best First	No context	34.3	<b>53.0</b>
Best Last	No context	<b>36.7</b>	52.0
Best Last	Last agent utt.	34.0	41.0
Best Last	Last user & agent utt.	26.0	31.0

Table 4: Lisspress match accuracy of the Codex language model on the SMCalflow dataset with different prompt order and conversational context.

LM	SMCalflow			TreeDST			MTOp (en)			Overnight (blocks)	
	Low	Med	High	Low	Med	High	Low	Med	High	Low	High
GPT-3 <sup>†</sup>	28.7	42.0	48.0	37.7	59.0	65.0	49.0	61.0	62.0	49.3	50.0
Codex <sup>†</sup>	36.7	52.0	58.0	46.3	60.0	64.0	53.0	64.0	69.0	58.0	59.0
T5-base	41.6	69.7	78.6	62.0	85.8	89.4	55.8	80.6	84.3	<b>64.4</b>	63.9
CodeT5-base	37.3	67.5	81.1	56.8	84.4	90.0	46.0	75.0	81.7	60.4	65.2
BART-large	42.5	71.4	<b>83.0</b>	61.1	86.4	89.8	59.3	81.8	84.0	61.2	63.7
T5-large	46.3	73.1	82.1	<b>64.2</b>	<b>87.2</b>	90.1	57.2	81.7	85.2	62.8	<b>68.9</b>
T5-3B	<b>48.7</b>	<b>75.9</b>	<b>83.0</b>	64.1	<b>87.2</b>	<b>90.3</b>	<b>61.2</b>	<b>82.4</b>	<b>86.0</b>	63.2	66.2
T5-large unconstrained	42.6	71.5	81.3	59.6	86.2	90.0	53.4	81.4	85.6	62.1	68.7

Table 5: Performance of language models on 4 non-SQL datasets. <sup>†</sup> indicates few-shot prompted and evaluated on the 100 example test set. Remaining LMs are finetuned and evaluated on 2k example test sets. We also show the performance of T5-large with unconstrained decoding to illustrate the contribution of constraints. Metrics are dataset-specific (see Table 1). The best score in each column is boldfaced.

LM	Spider			CoSQL		
	Low	Med	High	Low	Med	High
T5-base	33.8	56.8	58.9	26.8	42.7	43.4
CodeT5-base	37.6	58.0	62.2	27.3	46.2	48.2
BART-large	42.5	62.7	63.9	29.1	48.8	51.5
T5-large	44.1	65.5	66.5	32.1	52.4	55.5
T5-3B	<b>48.6</b>	<b>70.3</b>	<b>72.3</b>	<b>34.7</b>	<b>56.4</b>	<b>56.2</b>
T5-large unconstr.	42.4	64.6	65.7	30.7	50.0	53.8

Table 6: Test suite execution accuracy of fine-tuned language models on two SQL datasets.

Dataset	Current State of the Art	Our T5-3B
SMCalflow	80.4 (Platanios et al., 2021)	<b>83.7</b>
TreeDST	88.1 (Platanios et al., 2021)	<b>91.5</b>
MTOp (en)	<b>86.4</b> (Pasupat et al., 2021)	86.0
Overnight (blocks)	65.2 (Cao et al., 2019)	<b>66.2</b>
Spider	<b>75.5</b> (Scholak et al., 2021)	72.2
CoSQL	<b>56.9</b> (Scholak et al., 2021)	52.3

Table 7: Comparison of our finetuned T5-3B model with current state of the art models on full test sets. We report exact match accuracy for Spider and CoSQL to match the settings of previous work. The best score in each row is boldfaced.

attention to the recent past. In higher data regime, all prompt examples are almost equally relevant, hence the order does not matter as much. We find that context does not help; one of the reasons being that we can fit fewer examples in the prompt if we need to include context for each example.

**Effect of Constraints** Tables 5 and 6 show the effect of constraints while generating from finetuned T5-large model. We find that constrained

decoding is most beneficial in low-data regimes, giving on average 2.7% gain over unconstrained decoding. In the high-resource setting, the average gain is less than 1%, suggesting that the full data is nearly sufficient to learn the constraint system.

**Benchmarking Language Models** We show the performance of all language models on all BenchCLAMP datasets in tables 5 and 6. We find that performance increases with model size for most fine-tuned language models. Few-shot prompting of GPT-3 and Codex are still not on par with finetuned models. For non-SQL datasets, even smaller language models reach close to the best performance in the high resource setting. However, for Spider and CoSQL, model size seems important in all data settings. This is likely because the model has to reason about the database schema to generate SQL queries, making it a harder learning problem.

**Comparison with State of the Art** Table 7 compares our T5-3B model with the best-performing models in the literature. We outperform state-of-the-art models on the SMCalflow, TreeDST and Overnight-blocks datasets. For Spider and CoSQL, our scores are lower than the state of the art, although they follow a CLAMP approach. This is likely because we use a general SQL grammar to constrain decoding, whereas the SQL in these datasets covers only a small fraction of the SQL grammar. We believe using a more constrained grammar will improve performance.

## 5 Conclusion

We introduce a benchmark comprising six semantic parsing datasets with varying meaning representations. We support few-shot prompting, fine-tuning

and constraint decoding for all autoregressive language models and sequence-to-sequence models on these datasets. We hope that this work will encourage language model developers to consider semantic parsing as a test-bed in future work.

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## A Format for Model Inputs

For experiments related to fine-tuned language models with SMCalfFlow and TreeDST with last user and agent utterance as context, the input to the model has the format  $l | a | u$ , where  $u$  is the input natural language utterance,  $l$  is the last user utterance,  $a$  is the last agent utterance and  $|$  is a separator symbol. When using only last agent utterance as context, the input is  $a | u$ , and for using no context, the input to the model is simply  $u$ .

We use the the following format for Spider and CoSQL:  $c, d, u$ , where  $c$  is any conversational context if applicable,  $d$  is a rendering of the database schema with or without values and  $u$  is the user utterance. We use the database schema representation used in (Scholak et al., 2021) for  $d$ . For  $c$ , we concatenate the past utterances in the conversational context with the separator symbol  $|$ .

Our few shot prompting experiments use the prompt template of (Shin et al., 2021). The input to the model has the following format:

*Let’s translate what a human user says into what a computer might say.*

Human:  $uc_1$

Computer:  $p_1$

Human:  $uc_2$

Computer:  $p_2$

...

Human:  $uc$

Computer:

where  $uc$  is the rendering of context and utterance into text according to the strategy described for finetuning experiments. For the  $i$ th prompt example, we refer to its context and utterance rendering as  $uc_i$ , and its semantic parse as  $p_i$ .

## B Training Details

For fine-tuning experiments, we train the language models with batch size 32 for 10 000 steps using AdaFactor (Shazeer and Stern, 2018), saving a checkpoint every 5000 steps. We use 1000 linear warmup steps and then linear decay the learning rate to 0. We tune all models with learning rates  $10^{-4}$  and  $10^{-5}$ , except for T5-3B for which we only used  $10^{-4}$  to save compute. The best performing checkpoint on the dev set is used to report scores on the test set.

Constraint Grammar	SMCalfFlow		TreeDST	
	Low	Med	Low	Med
Unconstrained	42.6	71.5	59.6	86.2
Induced from train split	45.6	73.1	62.3	87.2
Induced from full train	46.3	73.1	64.2	87.2

Table 8: Effect of different grammar induction data on the Lispress match constrained decoding accuracy of fine-tuned T5-large.

## C Grammars induced from Low Resource Splits

The grammars released for SMCalfFlow, TreeDST and MTOP were induced using the full train dataset. This grammar is then used even with low and medium resource train splits. We expect the grammar will be provided by a developer of the domain and hence will cover all valid representations. However, for the sake of completeness, we report here the impact of using grammar induced from the corresponding train sets. Table 8 shows the results with constrained decoding with train split induced grammar, and compares the performance with unconstrained decoding and decoding with grammar induced from full train set. The gains from constraints drop by 1–2% for low resource splits when using train split induced grammar instead of full train induced grammar. It does not affect results for the medium resource splits.

## D Variance of Results

All low-resource results in the main paper are a mean of the three training data splits. Table 9 reports the average standard deviation for each model over the three low resource splits, averaged over four datasets. We find a high standard deviation of GPT-3 and Codex; one of the factors being the small size of the test set being used for evaluation of prompted language models (100 examples). Finetuned models show relatively low variance, consistently having standard deviation lower than 2%.

## E More dataset details

We release data splits for all domains of Overnight and all languages in MTOP. But for brevity, we benchmark on a single domain of Overnight (blocks) and a single language from MTOP (English). All other datasets used in the benchmark are in English.

<b>Model</b>	<b>Avg. Standard Deviation</b>
GPT-3	4.7
Codex	3.2
T5-base	1.2
CodeT5-base	1.1
BART-large	1.4
T5-large	2.0
T5-3B	1.5

Table 9: Standard deviation of the scores for each language model over the three low resource splits, averaged over non-SQL datasets.

We did not evaluate few shot prompted GPT-3 / Codex on SQL datasets. The input sequences for these datasets are very long, since it has to include an encoding of the database schema with values. As a result, we can accommodate only a couple examples in the prompt for GPT-3 / Codex, which is not sufficient for good few shot prompted performance.