Making The Most Out Of Large Language Models For Program Synthesis (when you want correct results)

Elizabeth Polgreen **University of Edinburgh SYNT 2024**

Is formal synthesis dead yet?



Two methods for making the most out of LLMs in synthesis:

Solving formal synthesis by guiding enumerative synthesis with LLMs

 Generating syntactically correct models for verification, via LLMs, synthetic programming elicitation and Max-SMT solvers

Guiding Enumerative Synthesis with Large Language Models





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CAV, Saturday 27th 4pm



Can LLMs solve formal synthesis problems?

Formal Program Synthesis

$\exists P \forall x. \sigma(P, x)$

Does there exist a function P such that, for all possible inputs x, the specification σ will evaluate to true for P and x.

 σ is a quantifier free formula in a background theory, e.g., Linear Integer Arithmetic

Can LLMs solve formal synthesis problems?



Single function benchmarks from the SyGuS competition, with function names removed and the full grammar from the logic permitted and a timeout of 180s

These are the results after some effort prompt engineering. Initial results were much worse.

Inv

Can LLMs solve formal synthesis problems?

Sort of.. but we think we can do better



Enumerative synthesis



Enumerative synthesis

Algorithms for formal synthesis

Counterexample Guided Inductive Synthesis



Combinatorial sketching for finite programs - Solar Lezama et al

Three approaches:

- 1. Prompt and verify
- 2. Use the LLM as pre-trained syntactic guidance
- 3. Use the LLM as an integrated syntactic oracle



Approach 1: prompt and verify



- This is not a prompt engineering paper!
- a small sample of benchmarks.
- The space is huge, a much bigger search could be done.

We took some prompt engineering techniques from the literature, and tested them on





[1] Better Zero-Shot Reasoning with Role-Play Prompting – Kong et al



[2] "What It Wants Me To Say": Bridging the Abstraction Gap Between End-User Programmers and Code-Generating Large Language Models – Liu et al





[3] Li, C., Wang, J., Zhang, Y., Zhu, K., Hou, W., Lian, J., Luo, F., Yang, Q., Xie, X.: Large language models understand and can be enhanced by emotional stimuli.



```
(synth-inv inv-f ((x Int) (y Int)))
(define-fun pre-f ((x Int) (y Int)) Bool (and (= x 1) (= y 1)))
(define-fun trans-f ((x Int) (y Int) (x! Int) (y! Int)) Bool (and (= x! (+
     x y)) (= y! (+ x y)))
(define-fun post-f ((x Int) (y Int)) Bool (>= y 1))
(inv-constraint inv-f pre-f trans-f post-f)
Please explain the constraints above.
```

[4] Chain-of-Thought Prompting Elicits Reasoning in Large Language Models – Wei et al

Ask for LLM explanation for invariant constraints [4]



```
(set-logic LIA)
(declare-var vr0 Int)
(declare-var vr1 Int)
(declare-var vr2 Int)
(constraint (>= (fn vr0 vr1 vr2) vr0))
(constraint (>= (fn vr0 vr1 vr2) vr1))
(constraint (>= (fn vr0 vr1 vr2) vr2))
(constraint (or (= vr0 (fn vr0 vr1 vr2)) (or (= vr1 (fn vr0 vr1 vr2)) (=
    vr2 (fn vr0 vr1 vr2))))
(check-synth)
You are a good synthesizer. Do you know what "(define-fun fn ((vr0 Int) (
    vr1 Int) (vr2 Int)) Int" is doing?
Write only one Lisp-like method "defun fn" without any built-in methods or
      arrays.
Requirements:
1. No built-in functions.
2. Never violate the SMT-LIB constraints above.
3. Pay attention to the define functions.
4. Ensure the response contains one and only one function.
5. Do not include any iterations, BitVec, or Int notations in the function
     body.
Write it correctly, or I will lose my job and 100 grandmothers will die.
    Don't disappoint me.
Write only one Lisp-like method "defun fn" that never violates the SMT-LIB
      constraints above.
```

You are close to the right answer. Take another guess. You have to try something different, think harder. Write a different Lisp method that never violates the SMT-LIB constraints above again.

Retry if the solution is incorrect



Number of iterations





- Iteration 1
- iteration 2
- Iteration 3
- iteration 4
- Iteration 5
- Iteration 6

Inv

We halt after 6 iterations, as number of new solutions tails off significantly

Results: prompt and verify







"Pre-trained" guidance from LLMs

If the LLM guesses are wrong, perhaps the solution is still in the neighborhood of those guesses?

Model that neighborhood as a probabilistic grammar.









probabilistic Context-Free Grammar

$P_G = (V, \Sigma, R, S, \mathbb{P})$:

- V is a set of nonterminal symbols
- Σ is a set of terminal symbols
- $R \subseteq V \times (V \cup \Sigma)^*$ is a set of production rules
- *S* is a start symbol
- \mathbb{P} is a probability mass function that assigns a probability $\mathbb{P}[r]$ to each $r \in R$

Top down enumeration



- Initialize expression with the Start symbol
- Repeatedly choose production rules to replace the left-most nonterminal in the current expression
- Choice is made by sampling from distribution over possible production rules
- Repeat until depth limit is hit or complete program is found

Top down enumeration



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- If depth limit: complete the program

Top down enumeration



- Initialize expression with the Start symbol
- Repeatedly choose production rules to replace the left-most nonterminal in the current expression
- Choice is made by sampling from distribution over possible production rules
- Repeat until depth limit is hit or complete program is found
- If complete, return for verification





- Queue stores partial programs with scores
- Initialize queue with the Start • symbol



Score = cost so far + estimate of cost to complete program



- Initialize queue with the Start symbol
- Pop partial program from queue with best score and expand





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 Queue stores partial programs with scores

- Initialize queue with the Start symbol
- Pop partial program from queue with best score and expand

[1] Accelerating search-based program synthesis using learned probabilistic models - Lee et al







- Initialize queue with the Start symbol
- Pop partial program from queue with best score and expand
- Repeat until complete program found







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Results: pre-trained guidance



- pass@1
- Prompt and verify
- pre-trained (top-down)
- pre-trained (A*)

VERIFY

■ cvc5



SYNTHESIZE

VERIFY

Comparison with unguided enumerators





- baseline (top down)
- baseline (A*)
- pre-trained (top-down)
- pre-trained (A*)

Inv

oracle





- partially enumerated programs
- counterexamples from previous iterations
- incorrect solutions from previous iteration

- Which we turn into: updated pCFG with new production rules and updated distributions

You are teaching a student to write SMT-LIB. The student must write a function that satisfies the following constraints: (constraint (>= (fn vr0 vr1 vr2) vr0)) (constraint (>= (fn vr0 vr1 vr2) vr1)) (constraint (>= (fn vr0 vr1 vr2) vr2)) (constraint (or (= vr0 (fn vr0 vr1 vr2)) (or (= vr1 (fn vr0 vr1 vr2)) (= vr2 (fn vr0 vr1 vr2)))) So far, the student has written this code: (define-fun fn ((vr0 Int) (vr1 Int) (vr2 Int)) Int (ite ?? ?? ??) Can you suggest some helper functions for the student to use to complete this code and replace the ?? You must print only the code and nothing else.

Sure, here are some helper functions:





Updating the pCFG:

- parse all helper functions, and update the pCFG distributions as before
- add any new helper functions as new production rules to any applicable nonterminal.







 Dynamically updating the probability distribution over grammar rules allows the oracle to make mistakes

Cheaper prompts!

•

Results: syntactic oracle



- pass@1
- Prompt and verify
- pre-trained (top-down)
- pre-trained (A*)
- syntactic oracle (top-down)
- syntactic oracle(A*)
- cvc5



Comparison with unguided enumerators



- baseline (top down)
- baseline (A*)
- syntactic oracle (top-down)
- syntactic oracle(A*)





Results: syntactic oracle



- pass@1
- Prompt and verify
- pre-trained (top-down)
- pre-trained (A*)
- syntactic oracle (top-down)
- syntactic oracle(A*)
- cvc5

Not quite as good.. but it is faster, and if we combine with the precalls to the LLM it gets a lot better...



Results: syntactic oracle



Combine standalone LLM with syntactic oracle

- pass@1
- Prompt and verify
- pre-trained (top-down)
- pre-trained (A*)
- syntactic oracle (top-down)
- syntactic oracle(A*)
- combined (top down)
- combined (A*)
- cvc5



Results: solving time



- pass@1
- Prompt and verify
- pre-trained (top-down)
- pre-trained (A*)
- syntactic oracle (top-down)
- syntactic oracle(A*)
- combined (top down)
- combined (A*)
- cvc5

Results

- Enumerative solvers are very good at problems with short solutions
- Conversely, LLMs are bad at problems with short solutions
- The pre-trained LLM guidance + enumerator is the best at long solutions
- The LLM alone performs poorly in the bitvector domain, but sees the biggest gains in combination with the enumerator



Related work

LLMs for program lifting [5]

- Spec restricted to $\exists P. \forall x. P(x) = Ref(x)$, where Ref is a reference implementation
- LLMs outperform enumeration (solving 99% of the benchmarks vs 94%) HYSYNTH [6]
- Uses an LLM to guide bottom-up search
- Reports similar results (LLM + search outperforms LLM and search)

[5] Verified Code Transpilation with LLMs – Bhatia et al [6] HYSYNTH: Context-Free LLM Approximation for Guiding Program Synthesis – Barke et al 71

Conclusions (part 1)

- But the combination of LLMs plus enumerative synthesis outperforms enumerative • synthesis, and stand-alone LLMs
 - (Even with naively implemented enumerators)

• LLMs are still not able to outperform state-of-the-art enumerative solvers by themselves



Two methods for making the most out of LLMs in synthesis:

- Solving formal synthesis by guiding enumerative synthesis with LLMs:
- Generating syntactically correct models for verification, via LLMs, synthetic programming elicitation and Max-SMT solvers





But can we be more ambitious?

Synthesis = Automatically generating code that satisfies the user's specification

Synthesis = Automatically generating code that satisfies the user's specification

(even natural language specifications)

Given a natural language description, generate a system model for verification





```
module main {
 // System description.
 var a, b : integer;
 init {
   a = 0;
   b = 1;
 next {
  a', b' = b, a + b;
 // System specification.
 invariant a_le_b: a <= b;</pre>
 // Proof script.
 control {
   induction;
   check;
```



Model a state machine describing a traffic light at a pedestrian crosswalk. This is a time triggered machine that assumes it will react once per second. It starts in the red state and counts 60 seconds with the help of the variable count. It then transitions to green, where it will remain until the pure input pedestrian is present. That input is generated by some other subsystem that detects when a pedestrian is present, and should be modelled as nondeterministic. When pedestrian is present, the machine transitions to yellow if it has been green for at least 60 seconds. ...

```
module TrafficLight {
  var sigG, sigR, sigY: boolean;
  var count, state: integer;
  var pedestrian: boolean;
  init {
    sigG = false; sigY = false; sigR = true;
    state = 0; count = 0; pedestrian = false; }
  procedure step()
    modifies sigG; modifies sigY; modifies sigR;
    modifies count; modifies state; {
    if (state == 0) {
        sigG = false; sigY = false; sigR = true;
        count = 0;
        if (count < 60) { count = (count + 1); }
    }
}
</pre>
```

• • •

Way beyond enumerative synthesis without serious user guidance.

Way beyond enumerative synthesis without serious user guidance.

Synthesis in UCLID5

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Elizabeth Polgreen University of California, Berkeley

Abstract

We describe an integration of program synthesis into UCLID5, a formal modelling and verification tool. To the best of our knowledge, the new version of UCLID5 is the only tool that supports program synthesis with bounded model checking, k-induction, sequential program verification, and hyperproperty verification. We use the integration to generate 25 program synthesis benchmarks with simple, known solutions that are out of reach of current synthesis engines, and we release the benchmarks to the community.

(even much smaller problems are out of reach of the state-of-the-art enumerative solvers)

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to synthesize called h at lines 16 and 17, and then uses h at line 18 to strengthen the existing set of invariants. Given this input, UCLID5, using e.g. cvc4 [2] as a synthesis engine, will automatically generate the function $h(x, y) = x \ge$ 0, which completes the inductive proof.

In this example, the function to synthesize represents an inductive invariant. However, functions to synthesize are treated exactly like any interpreted function in UCLID5: the user could have called h anywhere in the code. Furthermore, this example uses induction and a global invariant, however, the user could also have used a linear temporal logic (LTL)



What about LLMs?

Towards AI-Assisted Synthesis of Verified Dafny Methods

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In this paper, we demonstrate how to improve two pretrained models' proficiency in the Dafny verification-

Large language models show great promise in many domains, including programming. A promise is easy to make but hard to keep, and language models often fail to keep their promises, generating erroneous code. A promising avenue to keep models honest is to incorporate formal verification: generating programs' specifications as well as code, so that the code can be proved correct with respect to the specifications. Unfortunately, existing large language models show a severe lack of proficiency in verified programming. aware language. Using 178 problems from the MBPP dataset, we prompt two contemporary models (GPT-4 and PaLM-2) to synthesize Dafny methods. We use three different types of prompts: a direct Contextless prompt; a Signature prompt that includes a method signature and test cases, and a *Chain of Thought (CoT)* prompt that decomposes the problem into steps and includes retrieval augmentation generated example problems and solutions. Our results show that GPT-4 performs better than PaLM-2 on these tasks, and that both models perform best with the retrieval augmentation generated CoT prompt. GPT-4 was able to generate verified,

Related work suggests this is worth a try...



Syntax errors are a problem!



- Did not parse
- wrong
- mostly wrong
- half correct
- mostly correct
- totally correct



Syntax errors are a problem!

Results for GPT-4 [13][14], all pass@1 except Dafny



[13] What's wrong with your code generated by large language models? An Extensive Study - Duo et al [14] Towards AI assisted synthesis of verified Dafny methods - Misu et al

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Especially for very lowresource languages!!

> Tool specific verification/ specification languages



Given a natural language description, generate a system model for verification





module main { // System description. var a, b : integer; init { a = 0; b = 1;next { a', b' = b, a + b; // System specification. invariant a_le_b: a <= b;</pre> // Proof script. control { induction; check;



Synthetic Programming Elicitation and Repair for Text-to-Code in Very Low-Resource Programming Languages

Federico Mora¹ Justin Wong¹ Haley Lepe² Sahil Bhatia¹ Karim Elmaaroufi¹ George Varghese³ Joseph E. González¹ Elizabeth Polgreen⁴ ¹UC Berkeley ²MiraCosta Community College ³UCLA ⁴University of Edinburgh




Natural programming elicitation:

"asking non-programmers or novice programmers to express programs with the concepts and abstractions they find most natural" [7]

Coined by Brad Myers in 2004 [8]

Once you know what people "naturally" do, design for it.

[7] How statically-typed functional programmers write code - Lubin et al [8] Natural programming languages and environments – Myers et al



Synthetic programming elicitation: the same but for LLMs



Synthetic programming elicitation: the same but for LLMs



Prompt engineering: trying to persuade the LLM to do what you want



Our approach: observe what the LLM does, and design a DSL for the LLM.

Synthetic programming elicitation and repair



If the LLM goes wrong, and we can fix it with force, we do.



If we can't fix the errors, give the LLM guidance to get it back to the DSL

Overview



Design a DSL for the LLM Parse response generously

Repair via SMT solver

Repair via LLM

Overview



Design a DSL for the LLM Parse response generously

Repair via SMT solver

Repair via LLM



Synthetic programming elicitation:

- Collate a set of "training" data
 - Call LLM on all data
 - Analyse responses and choose language accordingly



- Participant: gpt-4-0613
- Data:
 - 82 UCLID5 regression tests
 - Each test consists of:
 - A description string
 - UCLID5 code
- Tasks (for each test):
 - Ask the LLM to write Python code that implements the test description



Synthetic programming elicitation:

- Collate a set of "training" data
- Call LLM on all data
- Analyse responses and choose language accordingly



Example task:

You are an expert user of FormalVerificationLibrary, a Python API for the formal modeling and verification of transition systems and procedures. Please write Python code using the FormalVerificationLibrary API that fits the description below. Do not worry if you do not remember the names of particular functions or classes. # The module has two integer variables and two bitvector variables. It should use inline assertions in the init block to check that we can correctly divide two integers.

The module has two integer variables and two bitvector variables. It should use inline assertions in the init block to check that we can correctly divide two integers, and correctly divide two bitvectors. It should check that signed and unsigned division report different results for very big bitvectors.







Synthetic programming elicitation:

- Collate a set of "training" data
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Example respose:





Another example task:

You are an expert user of FormalVerificationLibrary, a Python API for the formal modeling and verification of transition systems and procedures. Please write Python code using the FormalVerificationLibrary API that fits the description below. Do not worry if you do not remember the names of particular functions or classes.

A module with a single 1-bit bit-vector variable. The init block sets the variable to 3, which is larger than the width of the variable. A trivial invariant about that variable and a bmc check.







Another example response





Synthetic programming elicitation:

- Collate a set of "training" data
- Call LLM on all data
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Very object oriented!

When common Python uses a feature, the LLM will use it

Otherwise, the LLM will find a workaround using imports

None of the outputs were syntactically incorrect Python code (parsable)



Very object oriented!

When common Python uses a feature, the LLM will use it

Otherwise, the LLM will find a workaround using imports

None of the outputs were syntactically incorrect Python code (parsable)

Choosing the DSL

Note that there was no DSL for UCLID5 in Python like this before.





The DSL

- is a strict subset of Python
- code

Choosing the DSL

- every string in the DSL can be translated to syntactically correct UCLID5



• We can now use minimal prompting to interface to the LLM

Write python code to complete the following task:

[TASK]

Reply with your code inside one unique code block.

[Describe FormalVerificationLibrary]

Choosing the DSL

I can definitely do that. Here's the code:

[...]



Overview



Design a DSL for the LLM Parse response generously



Repair via LLM



• Given a response, parse it using a parser for Python



Python AST





• Given a response, parse it generously using an error-tolerant parser for Python









• Given a response, parse it generously using an error-tolerant parser for Python











Max-SMT encoding, inspired by [9]:

- For every static check in the DSL, for every node of the AST, generate a clause
- If all clauses are satisfied, the AST is in the DSL
- Find the maximum set of satisfiable clauses, and replace all other nodes with holes

[9] Finding Minimum Type Error Sources - Pavlinovic et al





Max-SMT encoding:

- For every static check in the DSL, for every node of the AST, generate a clause
- If all clauses are satisfied, the AST is in the DSL
- Find the maximum set of satisfiable clauses, and replace all other nodes with holes

- x is a bitvector
- is an integer
- x is an integer





Max-SMT encoding:

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Overview



Design a DSL for the LLM Parse response generously





Once we have a set of satisfiable clauses, we can use the satisfying model to repair (some of) the program:

Model-driven repair

• x is a ??

- 0 is an integer
- x is an integer



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Model-driven repair

• x is a ??

- 0 is an integer
- x is an integer

SAT when ?? is "integer"

If multiple assignments are valid, we use the one the SMT solver suggests.



Overview



Design a DSL for the LLM Parse response generously

Repair via SMT solver





Not everything can be repaired by the Max-SMT solver

```
module main {
var x: integer;
next {
   x' = y + 1;
}
invariant x_eq_y: x == 1;
control {
    induction;
    check;
    print_results;
```

LLM-driven repair

```
module main {
 var x: integer;
next {
    x' = ?? + 1;
 }
invariant x_eq_y: x == 1;
 control {
    induction;
    check;
    print_results;
```



If we can't repair the program from the model, we ask the LLM to repair the holes:

Fix the following Python code by replacing every occurrence of "??" with the correct code.

[CODE WITH HOLES]

Make sure your code completes the following lines [...]

LLM-driven repair

Overview



Design a DSL for the LLM Parse response generously

Repair via SMT solver

Repair via LLM

Loop repeats up to 5 times.



Eudoxus: ghost writing UCLID5

BOO

DEFIN

DEFINITION 1. A rectan the two sides which contain a

The expression, that a rectang AB, BC is of course a faulty or contained by the four sides of th considered merely as an abbrevia rectangle has for two of its adj AB, BC.

It can easily be proved one rectangle be equal to rectangle, the two rectangles

A rectangle, two of who two straight lines AB, CD, i rectangle contained by AB, denominated simply the rect

It is clear that the rect the rectangle CD, AB.

Also it may be noticed t rectangle AB, CD is equal t square on CD.

DEFINITION 1. Any part

The line which has been is often spoken of as the cir

The reason of this is that a ci part of the plane contained by circumference.

Half of a circle is called

It will be proved hereafter t divides it into two equal arcs.

DEFINITION 2. A straig circle is called a chord of the The straight line joining called the chord of the arc.

The figure formed of an called a segment of the circle

In the diagram the straight li BC, CA are chords of the circl AFB, BDC, CEA are arcs.

The straight line AB is the the arc AFB, and it is also the the arc ACB.

The figure formed of the ar and the chord BC is called the BFEC or BFAC, or more often BEC or BAC; and the figure for BC is called the segment BDC.

DEFINITION 1. That tude is called a point.

The word point is used ordinary language of the po Any mark made with such and is in some definite positi or a dot. Suppose such a si smaller it becomes the more but it is only when the spot point of vanishing altogethe position but has no magnitu definition of a point.

A point is generally dend for instance we speak of the p

DEFINITION 2. That neither breadth nor thick The extremities of a The intersections of

BOO

DEFIN

BOO

DEFIN

DEFINITION 1.

A figure of five sides one of six sides one of eight sides one of ten sides one of twelve side

DEFINITION 2. When ea rectilineal figure lies on one lineal figure, and each of the through one of the angular p figure is said to be inscribed second figure is said to be des

* Derived from πέντε "five," δώδεκα "twelve," respectively, and

BOOK V.

DEFINITIONS.

DEFINITION 1. If one magnitude be equal to another magnitude of the same kind repeated twice, thrice or any number of times, the first is said to be a multiple of the second, and the second is said to be an aliquot part or a measure of the first.

If one magnitude A be equal to m times another magnitude Bof the same kind (m being an integer, i.e. a whole number), A is said to be the mth multiple of B, and B the mth part of A.

If A be any multiple of B and if C be the same multiple of D, then A and C are said to be equimultiples of B and D.

The magnitudes treated of in Book V. are not necessarily Geometrical magnitudes: but they are assumed to be such that any magnitude can be supposed to be repeated as often as desired, in other words, that any multiple we please of a magnitude can be taken. They are assumed also to be such that any one taken twice is greater than it is alone; such quantities as those which are called in Algebra either negative or imaginary are excluded from consideration.

The capital letters A, B, C, D &c. will be used to denote magnitudes, and the small letters m, n, p, q &c. to denote whole numbers.

When a magnitude A is spoken of, the letter A is supposed to represent the magnitude itself.

DEFINITION 2. The relation of one magnitude to another of the same kind with respect to the multiples of the second or of aliquot parts of the second, which the first is greater than, equal to, or less than, is called the ratio of the first to the second.

It is difficult to convey a precise idea of "ratio" by a definition. The student will gradually acquire a firmer grasp of the meaning of the term as he proceeds. It is important to bear in mind that the difference between two magnitudes is not their ratio.




Results





When syntactic correctness is an issue, don't prompt or fine-tune to force the LLM to learn the rules you want it to.

Instead, use PL and formal techniques to meet the LLM in the middle

Conclusion (part II)



Related work

Giving the LLM feedback via compiler errors [10]

- Needs good compiler errors
- Not very effective for Dafny anyway[11]

Constrained Decoding [12]

- Limited to checks that you can encode in a grammar
- Works well if the LLM is *reasonably close* to the grammar you want?

[10] Fixing Rust Compilation Errors using LLMs - Deligiannis et al [11] DafnyBench: A Benchmark for Formal Software Verification – Loughridge et al [12] Efficient Guided Generation for Large Language Models – Willard and Louf

Conclusions

Not dead yet!



Conclusions

- Semantic and Syntactic correctness are still challenges for LLMs
 - especially in low resource languages and problem domains
- Formal methods and enumerative techniques might just be the answer to this!

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- Formal methods and enumerative techniques might just be the answer to this!

Guiding enumerative synthesis @CAV:



talk@CAV, Saturday 27th 4pm contact <u>Yixuan.Li.cs@ed.ac.uk</u>



