Intent Formalization

PBE is not always enough

Pros

- Ease of use
- Broader base of users
- Error detection

Cons

- Ambiguity in intent
- Lack of Formal Guarantee

One needs to formally specify the desired behavior of the target program!

int f(int x, int y)
{
z = 0;
i = x;
while (i) {
z = z + y;
i = i - 1;
}
return z;
}

PBE:

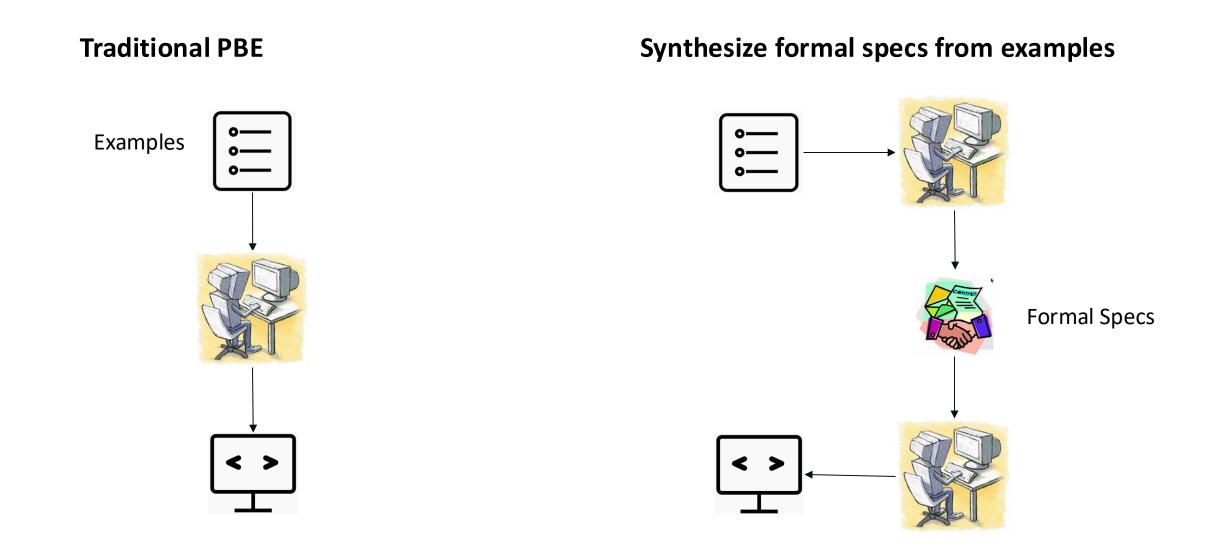
x	у	out
1	1	1
2	3	6
2	-1	-2
4	0	0
3	4	12

Formal spec: $out = x \cdot y$

Who is going to write the formal specification?

- Most users are not trained to write specifications using logics or other rigorous mathematical languages
- The synthesizer is sneaky and always finds a workaround (e.g., an infinite loop) for an incomplete specification

Examples to the rescue!



From Examples to RegEx

Regular Expressions

Regular expressions are a *syntactic tool* for defining *regular languages*

- Common feature in many languages; but the basics of regular expressions are much simpler than what you see in languages like Perl or Python
- String literals combined by choice and star
- "Regular" languages: Regular expressions can be represented as deterministic finite automata (DFA), and vice versa

alice@example.com bob.smith@company.org charlie123@mail.co.uk david@my-email.com



^[a-zA-Z0-9._%+-]+@[a-zA-Z0-9.-]+\.[a-zA-Z]{2,}\$

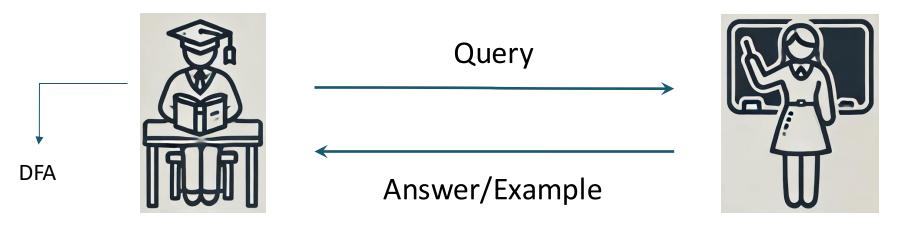
(123) 456-7890 987-654-3210 (555) 123-4567 111-222-3333



 $((d{3}))s?|d{3}[-.s])d{3}[-.s]?d{4}$



Angluin's L* Algorithm (1987)



Student (Synthesizer)

Minimally Adequate Teacher (User)

Membership Query

- Is the string *s* accepted by the target language?
- Answer: yes/no

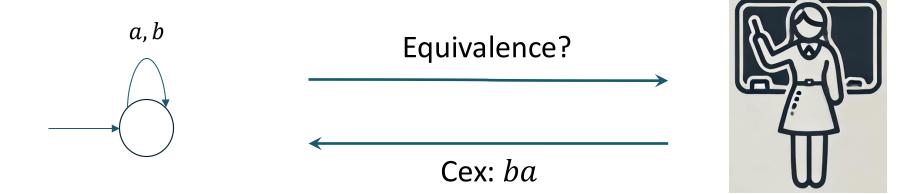
Equivalence Query

- Does the candidate DFA match the target language?
- Answer: yes/counterexample
- Done if the answer is yes!

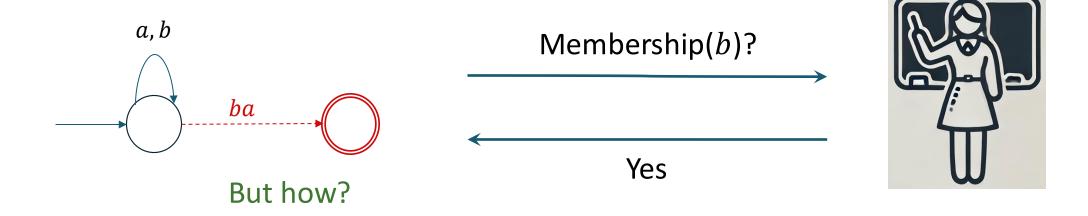
Idea: maintain a candidate DFA

- 0. Represent the DFA as an Observation Table (ignored)
- 1. Start with a simple hypothesis DFA (usually an empty state machine).
- 2. Use equivalence queries to check if the current hypothesis matches the target DFA.
- 3. If not match, use membership queries to refine the DFA with respect to the counterexample.
- 4. Repeat from step 2 until it correctly recognizes the language.

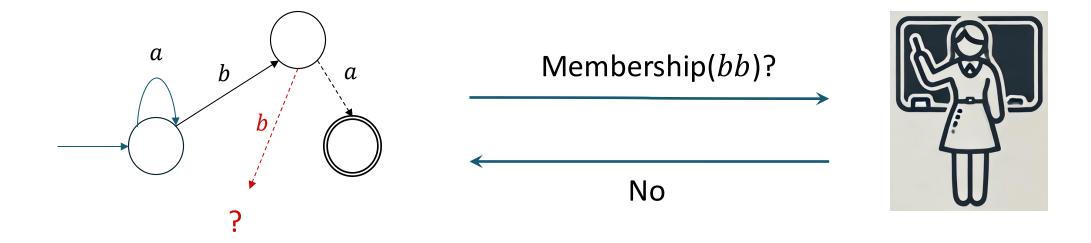
Alphabet: $\{a, b\}$



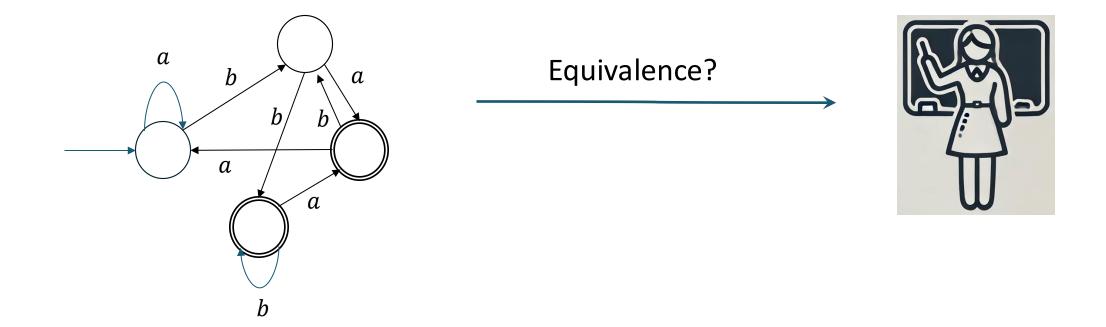
Alphabet: $\{a, b\}$



Alphabet: $\{a, b\}$



After several rounds of queries...

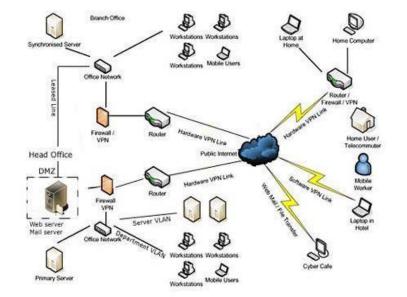


Model Learning

"Even though faster algorithms have been proposed since then, the most efficient learning algorithms that are being used today all follow Angluin's approach of a minimally adequate teacher (MAT)." – Frits Vaandrager

Comparative Synthesis

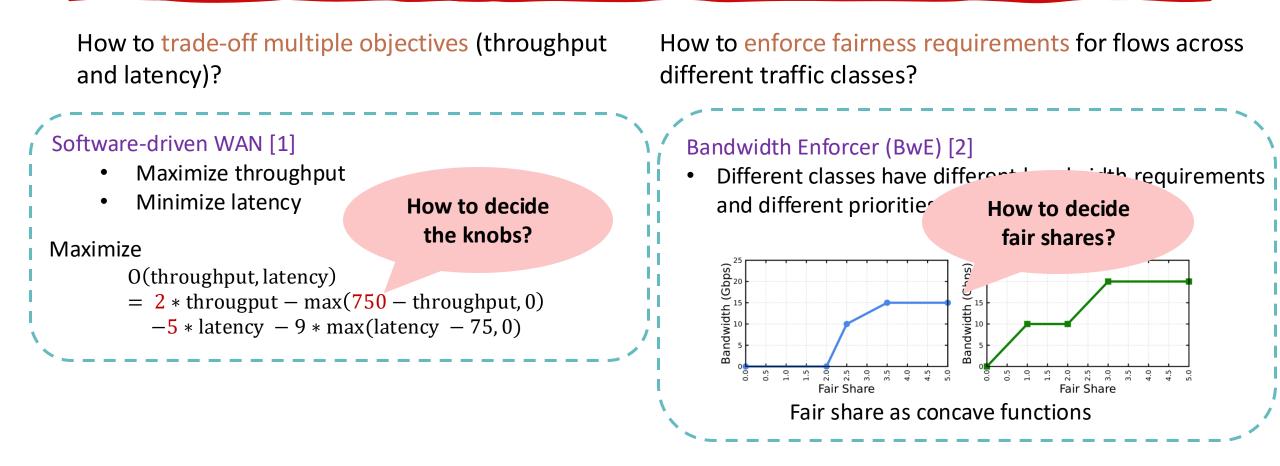
Motivation: Network Design



- Plenty of source-destination pairs
- Multiple paths per s-d pair
- Multiple traffic classes
- Capacity/security restriction
- Given demand, figure out allocations

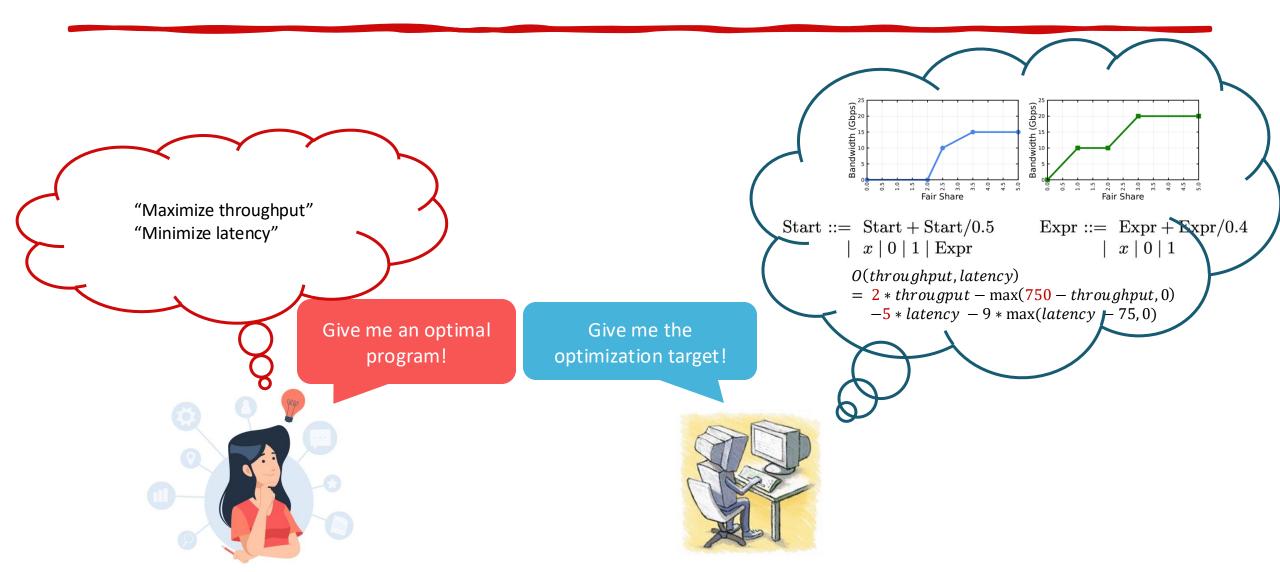
It is not too hard to find a mediocre network design.

But what is the optimal solution?

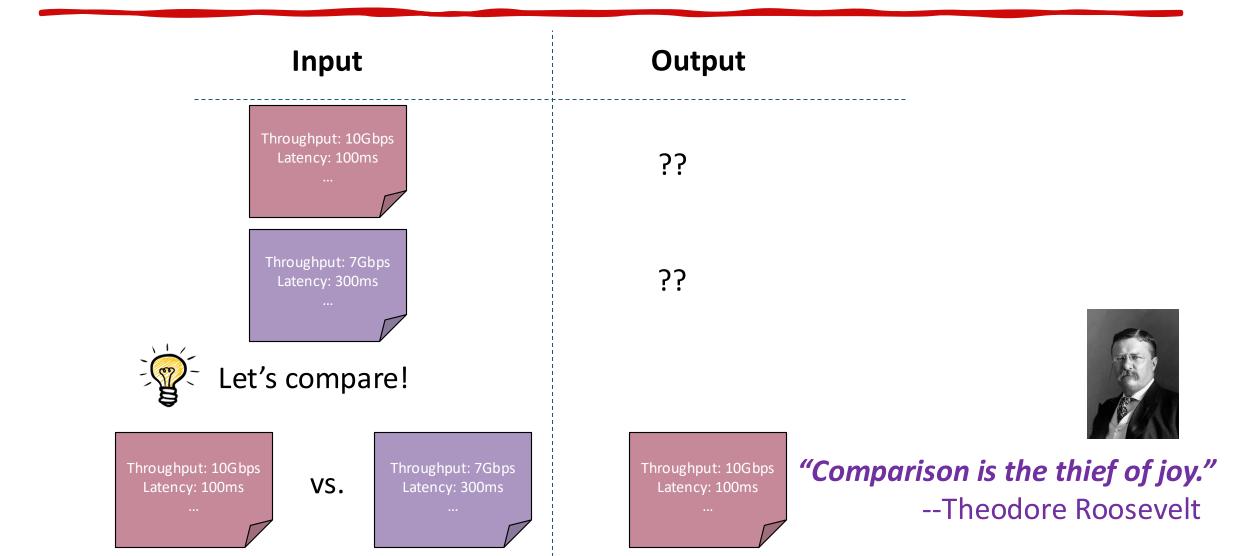


[1] Achieving High Utilization with Software-Driven WAN. [Hong et al., SIGCOMM'13] [2] BwE: Flexible, Hierarchical Bandwidth Allocation for WAN Distributed Computing. [Kumar et al., SIGCOMM'15]

The synthesis conundrum remains

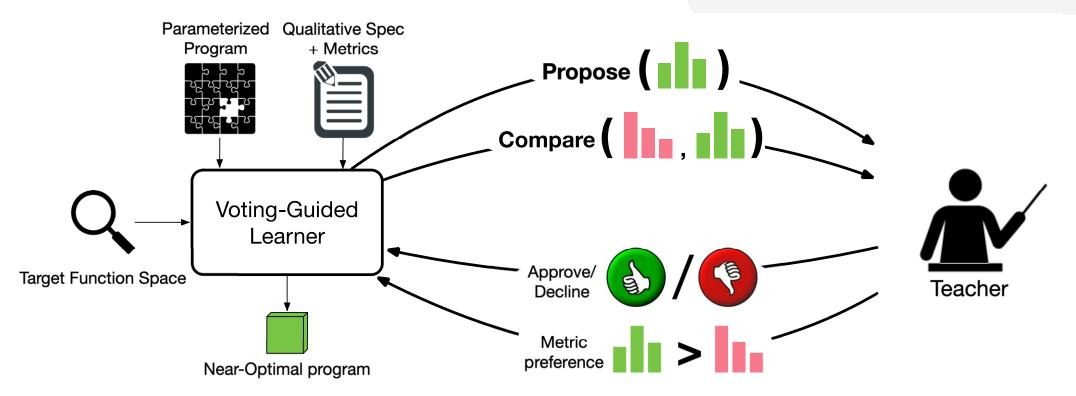


But didn't we have PBE?



Net10Q: Comparative Synthesis for Natural Decision

Spend a budgeted number of queries and to produce a near-optimal program from the perspective of the teacher



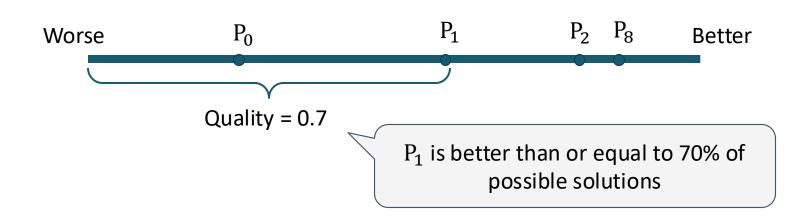
w/ Yanjun Wang, Chuan Jiang, Zixuan Li, Sanjay Rao. [HotNets'19 + POPL'23]

Quality of Solution

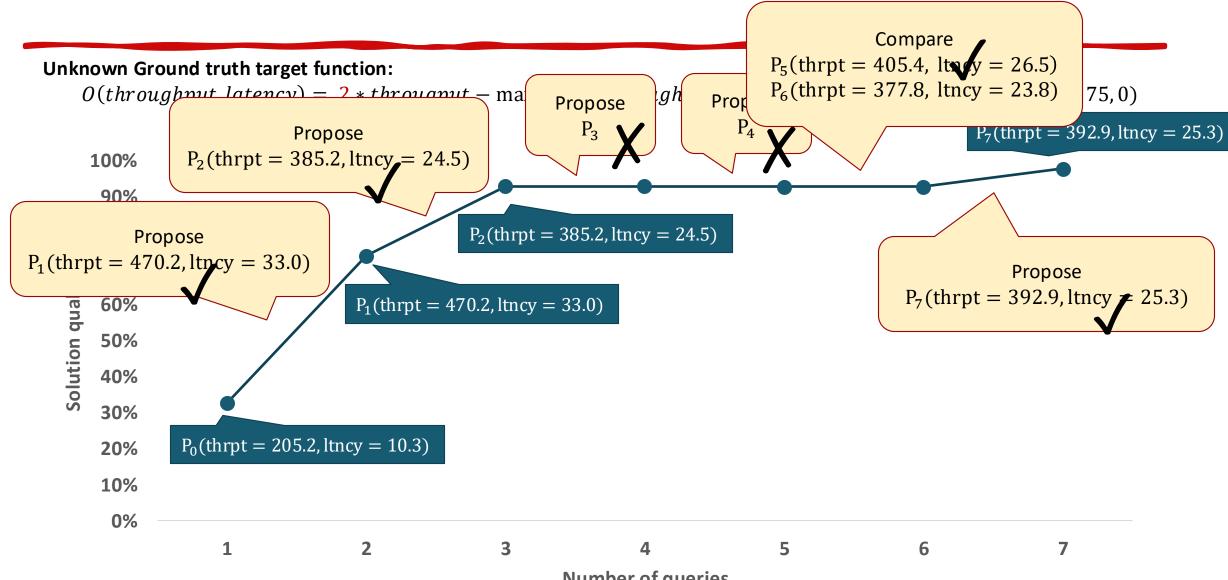
How close a solution is to the ground truth optimal?

Quality of Solution:

The "relative rank" of the solution among all solutions



Computing the exact quality can be expensive, we estimate the quality by sampling



Number of queries

How does the synthesizer work?

A Voting-Guided Learning Algorithm

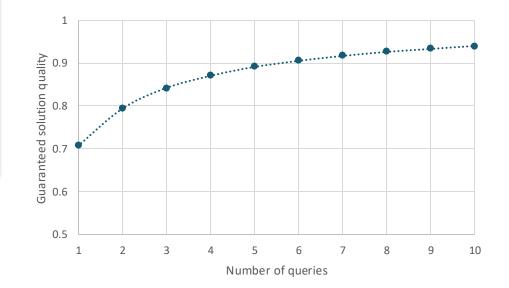
- Maintains a Pareto candidate set
- Each query can prune the search space, one way or the other
- Greedily prune the candidate set by making the *most informative* query (i.e., maximizing the worst-case space cut)
- Re-generate more candidates when the candidate set becomes too small

Convergence Guarantee

(How fast does the output solution approach the optimal?)

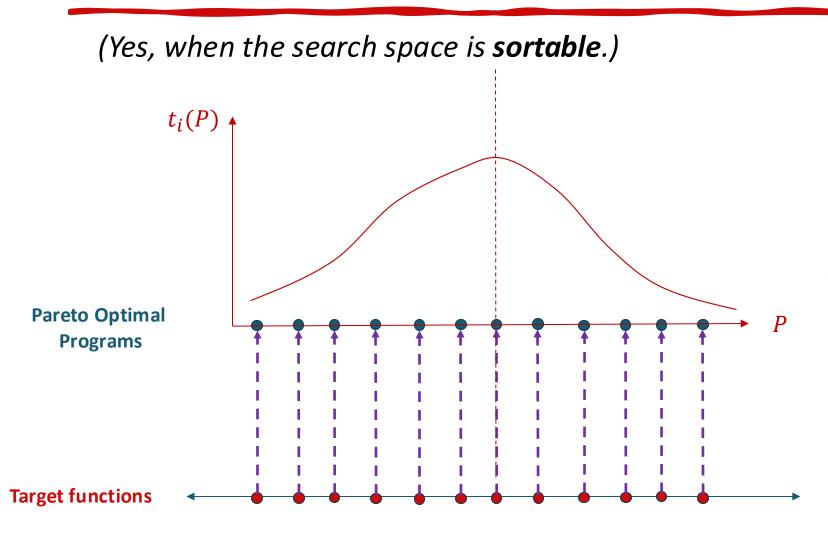
Theorem

The voting-guided learning algorithm guarantees a **logarithmic** rate of convergence. (the median quality of solution is at least $2^{\frac{-1}{n+1}}$ after *n* queries). The bound is tight.



Proof idea: Every query discards at least one randomly generated candidate.

Can the algorithm converge faster?



Example

If there are two competing metrics (e.g., *throughput* and *latency*) such that for each metric continued improvement leads to diminishing marginal utility, the search space is *sortable*.

Can the algorithm converge faster?

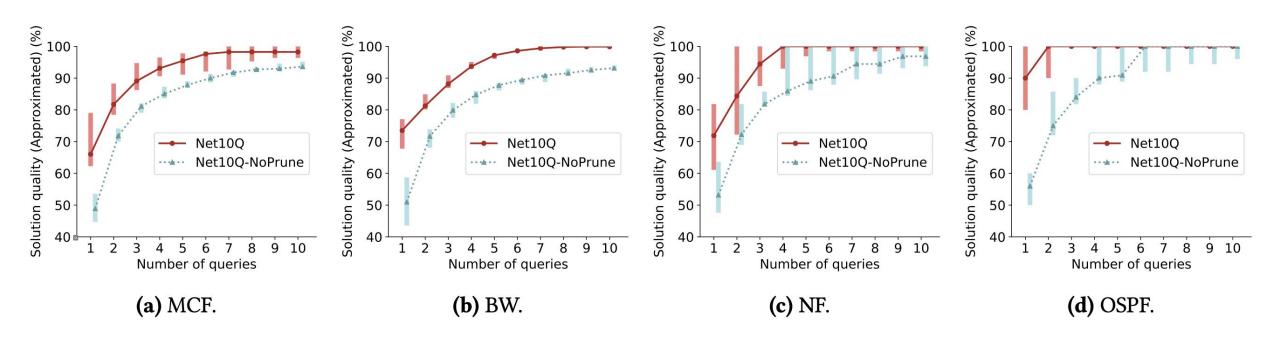
(Yes, when the search space is sortable.)

Theorem

When the target function space is *sortable*, the voting-guided learning algorithm guarantees a *linear* rate of convergence. (the median quality of solution is at least $1 - \frac{1}{\Omega(1.5^n)}$ after *n* queries). The bound is tight.

Proof idea: Every query discards at least one third of the candidates from the current PCS pool.

Oracle-based Evaluation (Perfect Oracle)



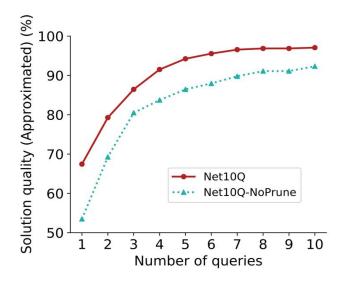
Net10Q performed constantly better than Net10Q-NoPrune

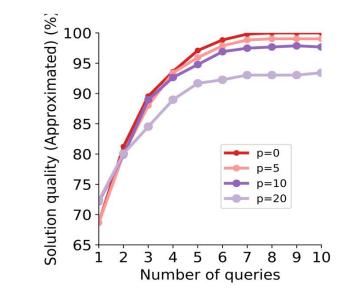
Oracle-based Evaluation (Imperfect Oracle)

Imperfect oracle model:

assigns a random reward that is sampled from a normal distribution (tunable by p)

Net10Q vs. Net10Q-NoPrune (p=10)

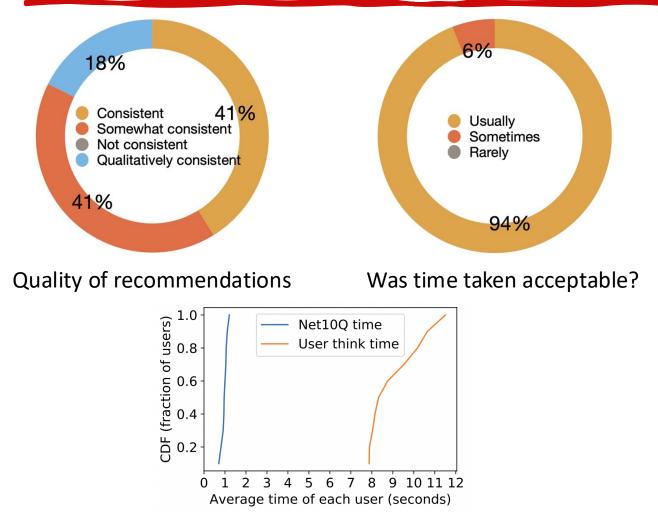




Net10Q can handle moderate feedback inconsistency

(BW on CWIX)

User Feedback



Average time per query across users

Qualitative Comments

- Most users are satisfied with *Net10Q*'s recommendations and response time.
 - "The study was well done in my opinion. It put the engineer/architect in a position to make a qualified decision to try and chose the most reasonable outcome." — an expert user

Can we learn formal specification from natural languages?

- Again, examples are not comprehensive, and good examples can be very expensive.
- Accurate specification may call for excessive examples
- "Natural language will always remain the basic interpretation of, and reservoir for, the development of the artificial formalized languages of science." – Doris Bradley

Pre-LLM Age

FRET:

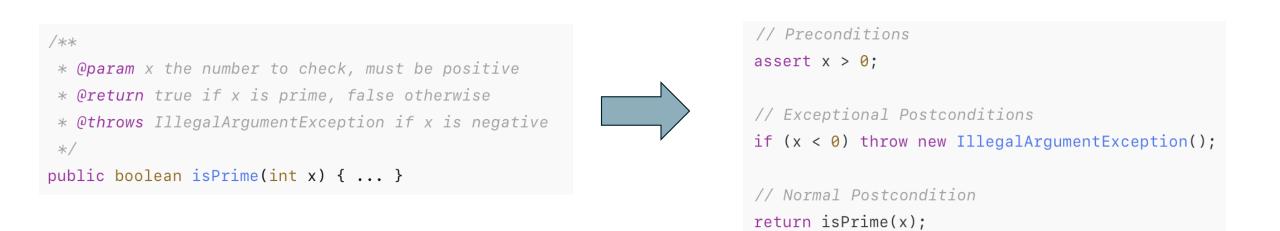
Controlled Natural Language to Metric Temporal Logic (MTL)

Create Requirement			T	ASSISTANT	TEMPLATES	GLOSSARY
Requirement ID REQ1-SEPARATION	Parent Requirement ID	Project ICAROUS	•	ENFORCED: in every inte the interval if <i>((horizonta</i> <i>))</i> is true and any point in	al_distance <= 250) & ()	vertical_distance <= 50
Rationale and Commen	ts		^) & (vertical_distance < every trigger, RES must h trigger (i.e., at trigger, trig than trigger+3, then RES	= 50)) becomes true (from hold at some point with dis ger+1,, or trigger+3). If	m false). REQUIRES: for stance <= 3 from the
Rationale					тс	
hazard zone of an intrud	g alert must be raised within 3 sec der (250 feet horizontal and 50 fee				M n norizontal_distance <= 2 == 50)), n = 3, Response =	
Requirement Description				Diagram Semantics		~
A requirement follows the senten information on a field format, clic	nce structure displayed below, where fields a	are optional unless indicate	d with "*". For			
SCOPE	CONDITIONS COMPONENT* SHALL*	TIMING RESPONSES*	0	Formalizations		
In flight mode, when (horizontal_distance <=250) & (vertical_ within 3 seconds satisfy warning_alert		_distance <=50) the ai	rcraft shall	Future Time LTL		~
				Past Time LTL		~
			SEMANTICS	SIMULATE		

Conrad et al. A Compositional Proof Framework for FRETish Requirements[CPP'22]

Pre-LLM Age

Jdoctor: translating Javadoc to JML-style specifications



Blasi et al. Translating Code Comments to Procedure Specifications [ISSTA'18]

Pre-LLM Age

Pros

- Pattern matching for semi-structured languages, which is predictable, understandable and adaptable
- Low computational cost

Cons

- Limited generalization
- Limited handling of ambiguities
- Manually defined patterns

NLP is the bread and butter of LLMs!

Can Large Language Models Write Good Property-Based Tests? **Clarify When Necessary: Resolving Ambiguity Through Interaction with LMs** Finding Inductive Loop Invariants using Large Language Models Can Large Language Models Transform Natural Language Intent into Formal Method Postconditions? **Tell Me More! Towards Implicit User Intention Understanding of**

USER INTENT RECOGNITION AND SATISFACTION WITH LARGE LANGUAGE MODELS: A USER STUDY WITH CHATGPT

SpecGen: Automated Generation of Formal Program Specifications via Large Language Models

Language Model Driven Agents

Can Large Language Models Reason about Program Invariants?

Open Question: How to evaluate LLMgenerated specs?

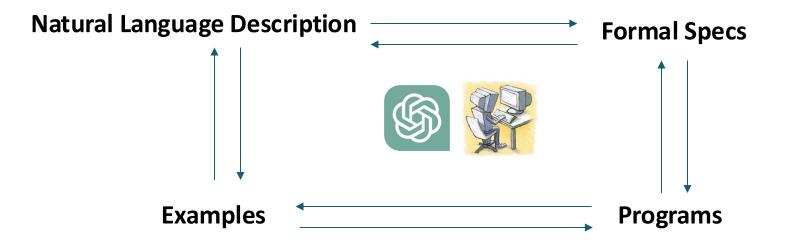
Shuvendu Lahiri proposed the notions of soundness and completeness with respect to a set of input-output tests T:

- Soundness: all tests in T satisfy ϕ
- **Complete measure:** if (i, o') is a mutation from a test $(i, o) \in T$, how likely (i, o') is *inconsistent* with ϕ

Problems

- Higher completeness measure is not always better (e.g., x > 1.04562 is likely overfitting; x > 1 is more natural)
- What if test cases are not available (how about generate test cases?)

Open Question: What's the best paradigm?

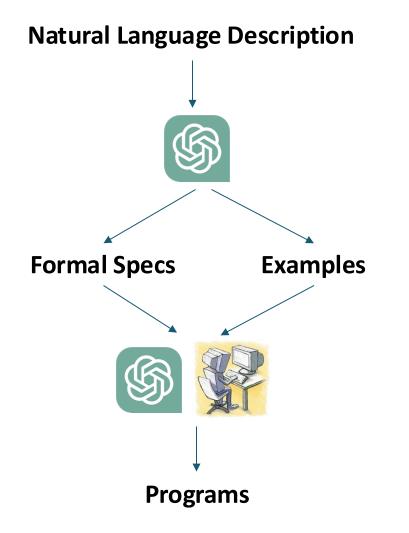


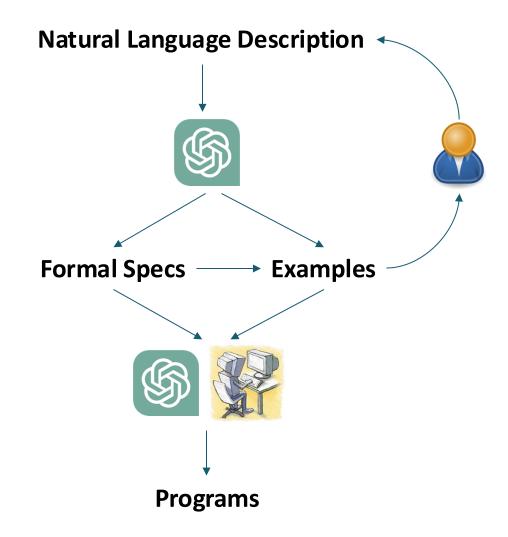
Natural Language Description



Programs

Natural Language Description **Formal Specs** Programs





Workflow n?



Figure out your own workflow for your project!