H2020 TAILOR -Foundations of Trustworthy AI -
Integrating Reasoning, Learning and Optimization

Black-box Precondition Inference through Constraint Acquisition

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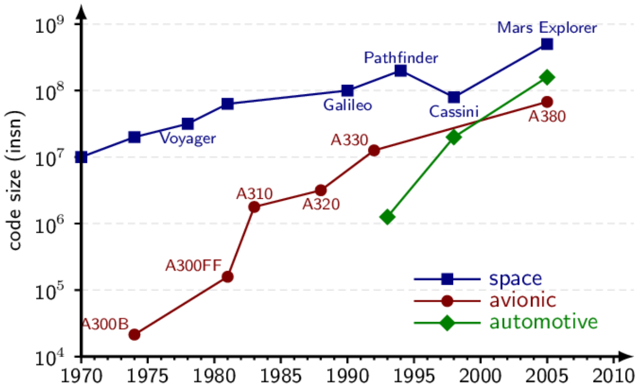
More Complex Software Everywhere

- Software in all domains

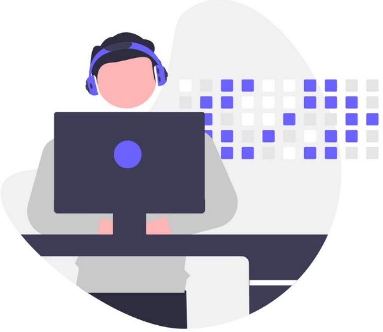
- Bigger and more complex



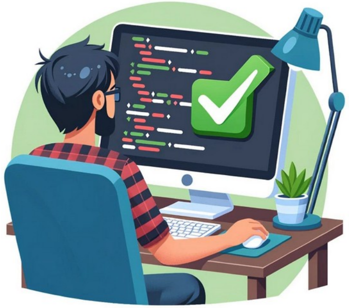
More Complex Software Everywhere

– Softw

– Bigge



Coding is hard



Checking is even harder

Secure Code by Automated Analysis

Help Analysis and Improve Confidence in Software

- Testing

- Formal Verification
  - E.g., Precondition / postconditon
    - Enable to scale to big code
    - Almost never given in practice

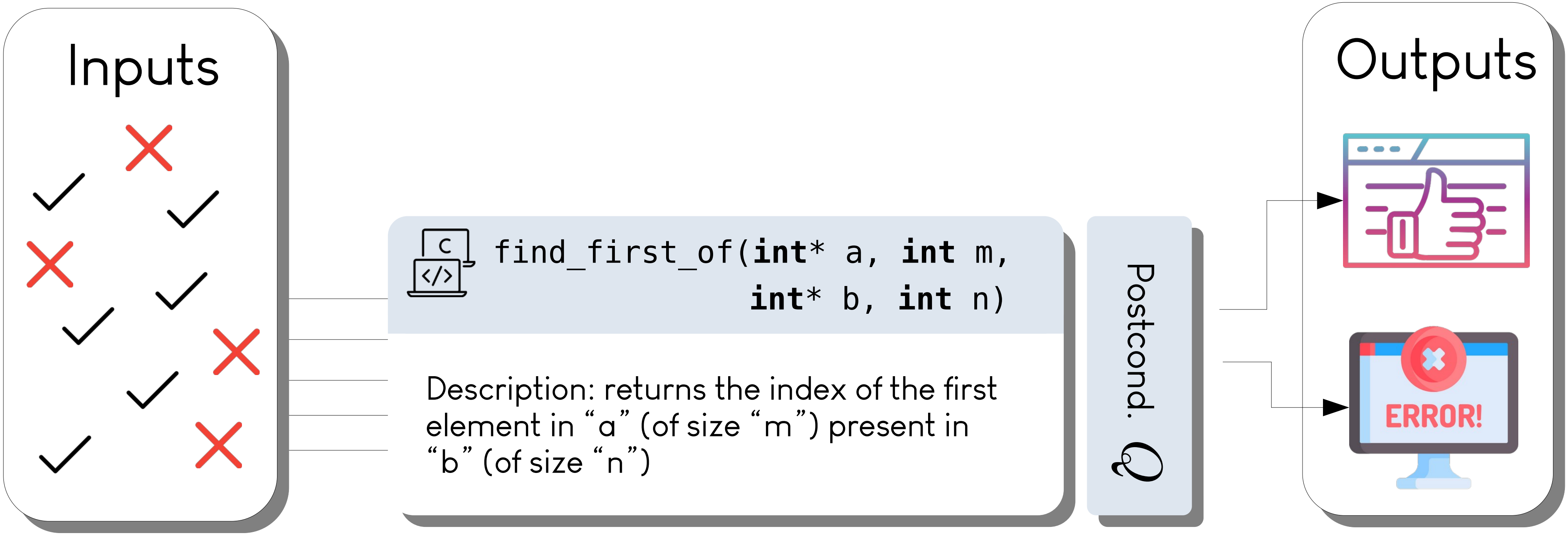
frama C Software Analyzers

ASTRÉE

BINSEC

CPA

Dream: Infer Preconditions



Dream: Infer Preconditions

Inputs

$$valid(a) \land valid(b)$$

```c
find_first_of(int* a, int m,
              int* b, int n)
```

Description: returns the index of the first element in “a” (of size “m”) present in “b” (of size “n”)

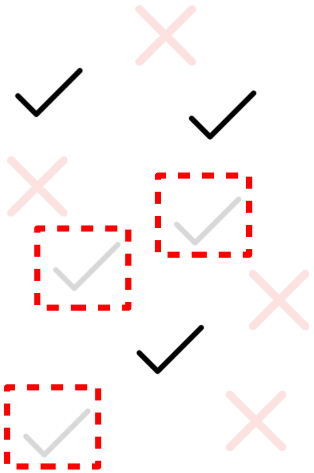
$Q = true$

Outputs

Undecidable problem: Rice theorem (1953)

Dream: Infer Preconditions

Inputs



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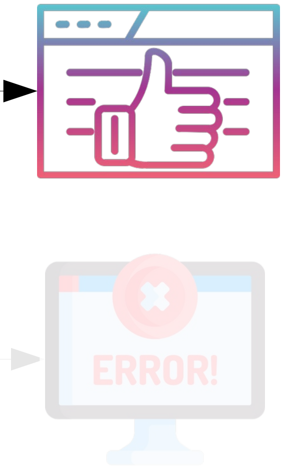

Undecidable problem: Rice theorem (1953)

Dream: Infer The Weakest Precond.

$$[m > 0 \Rightarrow valid(a)]$$
$$\land$$
$$[m > 0 \land n > 0 \Rightarrow valid(b)]$$

Inputs

```c
find_first_of(int* a, int m,
              int* b, int n)
```

Description: returns the index of the first element in “a” (of size “m”) present in “b” (of size “n”)

$Q = true$

Outputs

Undecidable problem: Rice theorem (1953)

State-of-the-art

Execution Based (Daikon, PIE, Gehr et al.):

- 👍 Does not need the source code
- 👎 No clear guarantees

Data-Driven Precondition Inference with Learned Features

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Code Based:

- 👎 Need the source code
  - scalability issues • code not available
- 👍 Clear guarantees

Counterexample-Guided Precondition Inference*

Mohamed Nassim Seghir and Daniel Kroening
Computer Science Department, University of Oxford

Goal

Execution Based (Daikon, PIE, Gehr et al.):

- Does not need the source code
- Clear guarantees

Constraint Acquisition Based Precond. Inference

Code Based:

- Need the source code
  - scalability issues • code not available
- Clear guarantees

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Counterexample-Guided Precondition Inference*

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Constraint Acquisition

Constraint Programming

Hard to design models

Constraint Acquisition

Version Space Learning (Mitchell, 82)

Bessiere, C., Koriche, F., Lazaar, N., & O'Sullivan, B. (2017). Constraint Acquisition. Artificial Intelligence, 244, 315-342.

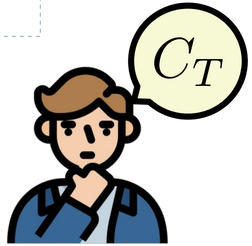
Conacq: Active Constraint Acquisition

Hypothesis:
The target concept $C_T \subset B$

$B = \{c_1, ..., c_k\}$

Conjunctions of constraints from B

Oracle

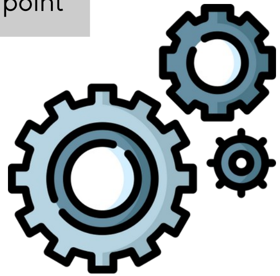


stakeholder

query

yes / no

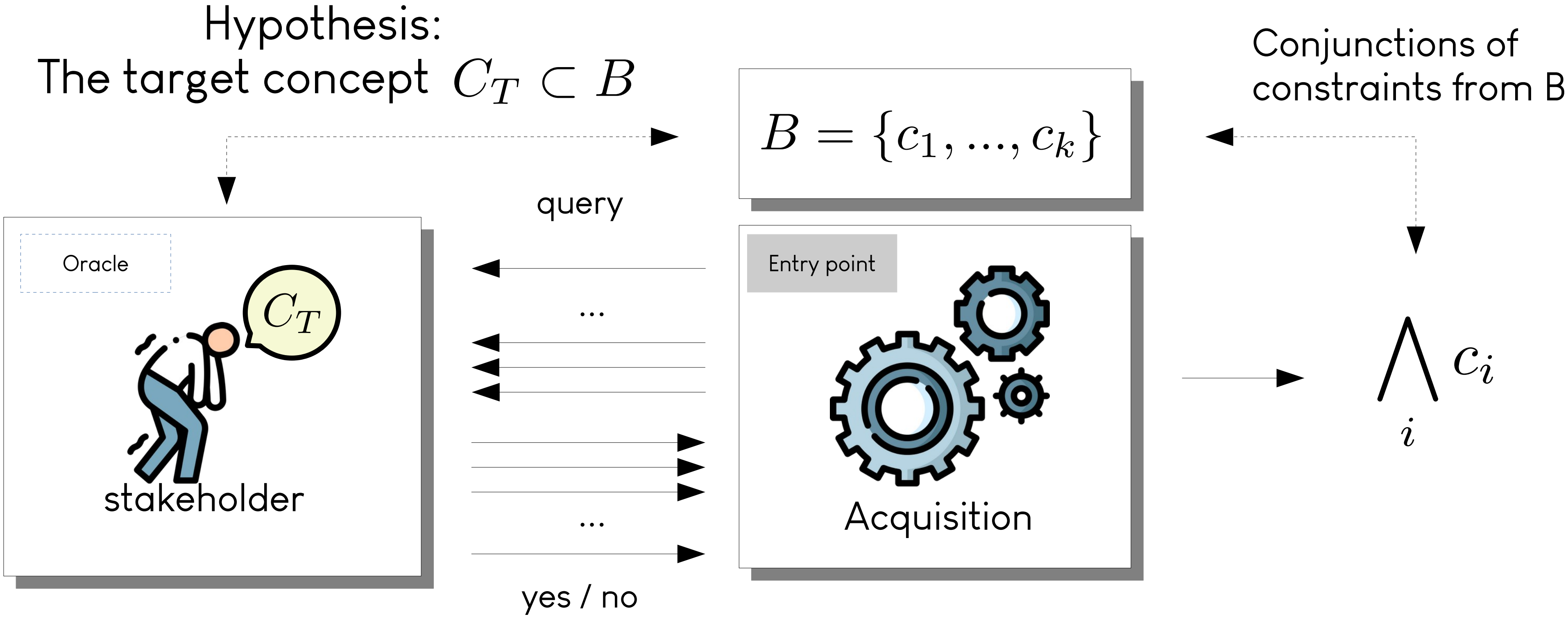
Entry point



Acquisition

$\bigwedge_i c_i$

Careful: too many queries



Adapting Constraint Acquisition

Human user → Executable under analysis

↳ No limitation on the queries nb.

Query → Function inputs (args, global vars)

Constraints → B : Constraints over ptr and int

Preprocess (passive mode)

↳ Generates likely to be interesting queries

The Constraint Language

New constraints

Overlap(str1, str2)

strlen(str) > 0

Constraints for memory-related precond.:

Method not limited to memory-related precond.

$$
\begin{array}{lll}
C & := & C \vee C \mid A \mid \neg A \\
A & := & valid(p) \mid alias(p, q) \mid deref(p, g) \\
 & \mid & i = 0 \mid i < 0 \mid i \leq 0 \mid i = j \mid i < j \mid i \leq j
\end{array}
$$

$$valid(p) \equiv p \neq NULL$$

$$alias(p, q) \equiv p = q$$

$$deref(p, g) \equiv p = \&g$$

p, q : pointer variables

i, j : integer (signed and unsigned) variables

g : global variables (of any type)

The Bias

Constraints for memory-related precond.:

$$
\begin{array}{lcl}
C & := & C \vee C \mid A \mid \neg A \\
A & := & valid(p) \mid alias(p,q) \mid deref(p,g) \\
 & \mid & i = 0 \mid i < 0 \mid i \leq 0 \mid i = j \mid i < j \mid i \leq j
\end{array}
$$

Method not limited to memory-related precond.

From language to bias B:

↳ The bias is a finite set → Which disjunctions to include ?

↳ Proposal: max. size of disjunctions depending on the function prototype – especially number of integer inputs

Preprocess

Positive (e^+) vs Negative Queries (e^-)

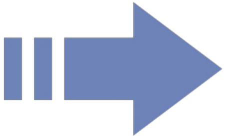
- **All constraints** incoherent with e^+ are not in the solution
- **At least one constraint** incoherent with e^- is in the solution

Generate positive queries first to remove a lot of constraints

- How to generate positive queries ?

Preprocess

- Goal of developers : software should work
  - Usually they handle well usual cases
- Generate queries where code likely behave correctly



Generate first queries with ≤ 1 one non valid, aliasing or deref pointers

PreCA

NEW

```
Call the preprocess

while true do
    Generate an informative query
    if no-query then «we converged»
    Submit query to the oracle(F, Q)
    if answer is yes then
        Bottom-up-inference()
    else
        Top-down-inference()
```

How Oracle answers queries ?

- Run function F under query
- If $ret \not\models Q$ or  → no
- If   → ukn
- Otherwise → yes

Back To Our Example

```
find_first_of(int* a, int m, int* b, int n)
```

Description: returns the index of the first element in “a” present in “b”

Postcondition: $Q = true$

- Variables : a, m, b, n
- Heuristics : max. Horn clause size = 3
- $[m > 0 \Rightarrow valid(a)] \wedge [m > 0 \wedge n > 0 \Rightarrow valid(b)]$

Theoretical Analysis

PreCA guarantees

↳ If B is expressive enough → ∅ or Precond.

↳ ⊕ If oracle never answers "unk" → Weakest precond.

These are good theoretical guarantees

↳ SOTA executions based methods, from programming language community, have no clear guarantees

Evaluation

Dataset: 94 learning tasks • compiled C functions (string.h, arrays, arithmetic ...)

Evaluation:

1 hour

	PreCA		Daikon, PIE, Gehr et al		P-Gen
$Q = true$	92%	VS	At most 52%	VS	74%
$Q \neq true$	41%		At most 23%		34%

PreCA better in 5s than concurrent tools in 1 hour

Problem

What happens if horn clauses heuristics fails?

B is not expressive enough

~~If B is expressive enough~~ $\rightarrow$ ~~$\varnothing$ or Precond.~~

~~$\oplus$ If oracle never answers “unk”~~ $\rightarrow$ ~~Weakest precond.~~

Better handling of disjunctions

C_T is a conjunctions of constraints from B, i.e.,

$$C_T \subset B$$

$\longrightarrow$

C_T is a conjunction of disjunctions of B's constraints, i.e.,

$$C_T = \{d_i\}_{i \in I}$$

$$d_i = \bigvee_j a_j \quad \text{with} \quad a_j \in B$$

⇒ We say that C_T is $\bigvee$-representable by B

Disjunctive Constraint Acquisition

NEW

Key points :

- MSSes induce a partition
- Check classification of one element per MSS

Deduce the classification of all the domain

Algorithm 1: DCA

In : A nonempty complete bias B
Out : A conjunction of disjunctions of constraints from B

begin
  $L \leftarrow \top$
  foreach $M \in \textsc{Mss}_B$ **do**
    pick $e \in sol(M)$
    if $\texttt{ask}(e) \neq yes$ **then**
      $L \leftarrow L \wedge \neg M$
  return L

Theoretical analysis

Proposition : DCA generates informative queries only

Remark: Informativeness must be extended because of disjunctive behaviors. Some queries which were not informative in CA is informative now.

Theorem : If C_T is $\bigvee$-representable by B then DCA infers a concept L s.t., $L \equiv C_T$

⊕ Terminates, result agrees with all tested queries

Theoretical analysis

Proposition : DCA generates informative queries only

Remark: Informati… …iors. Some
queries which were…

Theorem : If … …A infers a
constraint ne…

DCA have the same good properties as CA

Terminates, result agrees with all tested queries

DCA for Precondition Inference

	Min bias				Avg bias				Max bias			
	1s	5s	5 mins	1h	1s	5s	5 mins	1h	1s	5s	5 mins	1h
PreCA	34/60	45/60	48/60	48/60	32/60	44/60	46/60	46/60	24/60	36/60	44/60	45/60
↳ No disj	21/60	21/60	21/60	21/60	21/60	21/60	21/60	21/60	20/60	21/60	21/60	21/60
↳ $\|disj\| \leq 2$	38/60	43/60	44/60	44/60	35/60	42/60	44/60	44/60	21/60	38/60	44/60	44/60
↳ $\|disj\| \leq 3$	30/60	44/60	48/60	48/60	26/60	43/60	46/60	46/60	18/60	31/60	42/60	44/60
↳ $\|disj\| \leq 4$	30/60	43/60	48/60	48/60	26/60	42/60	45/60	46/60	18/60	29/60	35/60	40/60
↳ $\|disj\| \leq 7$	30/60	43/60	48/60	48/60	27/60	42/60	45/60	45/60	18/60	28/60	35/60	35/60
↳ $\|disj\| \leq 10$	30/60	43/60	48/60	48/60	27/60	42/60	45/60	45/60	17/60	27/60	35/60	35/60
↳ *Omniscient*	38/60	45/60	48/60	48/60	34/60	44/60	46/60	46/60	26/60	40/60	43/60	45/60
DCA	40/60	45/60	51/60	54/60	38/60	45/60	49/60	51/60	31/60	42/60	47/60	51/60

↳ Over each bias DCA infers in 5mins more preconditions than PreCA in 1h

↳ DCA is even more efficient than $\text{PreCA}_{\text{Omniscient}}$

Results Bench 2 (precond. inference)

	Min bias				Avg bias				Max bias			
	1s	5s	5 mins	1h	1s	5s	5 mins	1h	1s	5s	5 mins	1h
PreCA	34/60	45/60	48/60	48/60	32/60	44/60	46/60	46/60	24/60	36/60	44/60	45/60
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↳ $\lvert disj \rvert \leq 2$	38/60	43/60	44/60	44/60	35/60	42/60	44/60	44/60	21/60	38/60	44/60	44/60
↳ $\lvert disj \rvert \leq 3$	30/60	44/60	48/60	48/60	26/60	43/60	46/60	46/60	18/60	31/60	42/60	44/60
↳ $\lvert disj \rvert \leq 4$	30/60	43/60	48/60	48/60	26/60	42/60	45/60	46/60	18/60	29/60	35/60	40/60
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↳ $\lvert disj \rvert \leq 10$	30/60	43/60	48/60	48/60	27/60	42/60	45/60	45/60	17/60	27/60	35/60	35/60
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DCA	40/60	45/60	51/60	54/60	38/60	45/60	49/60	51/60	31/60	42/60	47/60	51/60

↳ Over each bias DCA infers in 5mins more preconditions than PreCA in 1h

↳ DCA is even more efficient than $\text{PreCA}_{\text{Omniscient}}$

An example from MbedTLS

PreCA with Conacq cannot do it in 1h

```
int mbedtls_md_finish(mbedtls_md_context_t *ctx,
                      unsigned char *output);
```

Description: Delete structures of selected MD

Postcondition: $Q = \text{“}ret = 0\text{”}$

```
typedef enum {
    MBEDTLS_MD_NONE=0,    /**< None. */
    MBEDTLS_MD_MD5,       /**< MD5 */
    MBEDTLS_MD_SHA1,      /**< SHA-1 */
    MBEDTLS_MD_SHA224,    /**< SHA-224 */
    MBEDTLS_MD_SHA256,    /**< SHA-256 */
    MBEDTLS_MD_SHA384,    /**< SHA-384 */
    MBEDTLS_MD_SHA512,    /**< SHA-512 */
    MBEDTLS_MD_RIPEMD160, /**< RIPEMD-160 */
} mbedtls_md_type_t;
```

DCA result:

- #queries: 416
- convergence time: 6 min 41s
- Solution (simplified):

$$valid(ctx) \wedge valid(md\_info) \wedge$$
$$\neg alias(ctx, md\_info) \wedge valid(md\_ctx) \wedge$$
$$\left(\begin{array}{l} type = 1 \vee type = 2 \vee type = 3 \vee \\ type = 4 \vee type = 5 \vee type = 6 \vee type = 7 \end{array} \right)$$
$$\wedge \quad valid(output)$$

Conclusion

AI contributions

- 1st adaptation of CA for prog. analysis
  - new use case for CA
  - no user (no limit for queries nb)
- Translate core concepts :
  - Set of constraints
- Extend CA & new algorithm

Opens new research directions for CA

Prog. analysis contribs

New efficient precond. inference tool

- Good guarantees
- Outperforms concurrent tools

\+

- Does not need the source code

Thank you for your attention

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https://gregoiremenguy.github.io/