MINTS – A General Framework and Tool for Supporting Test-suite Minimization

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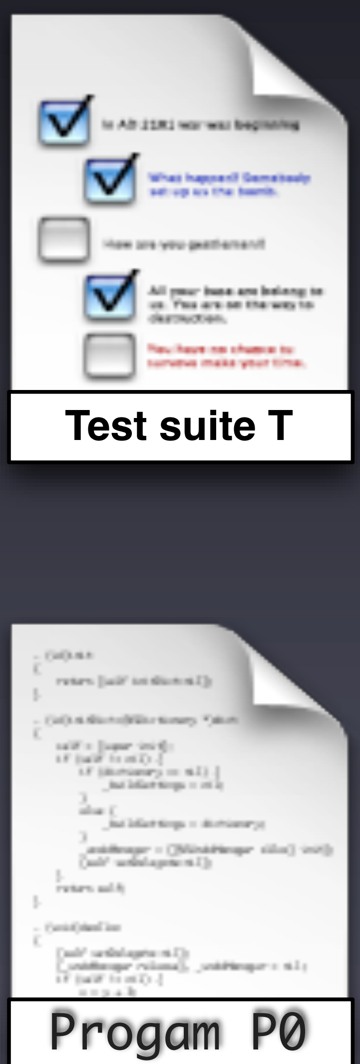
Regression Testing



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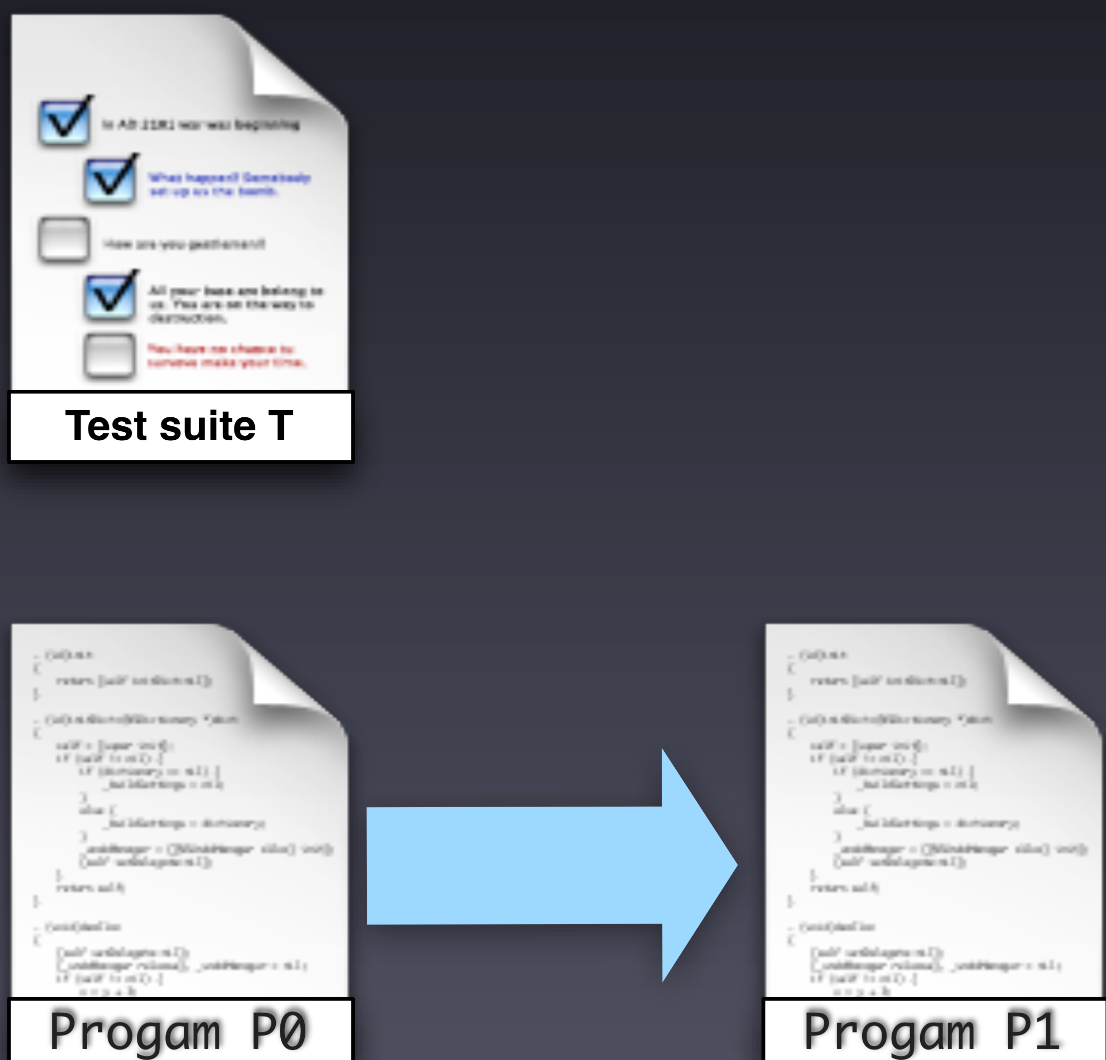

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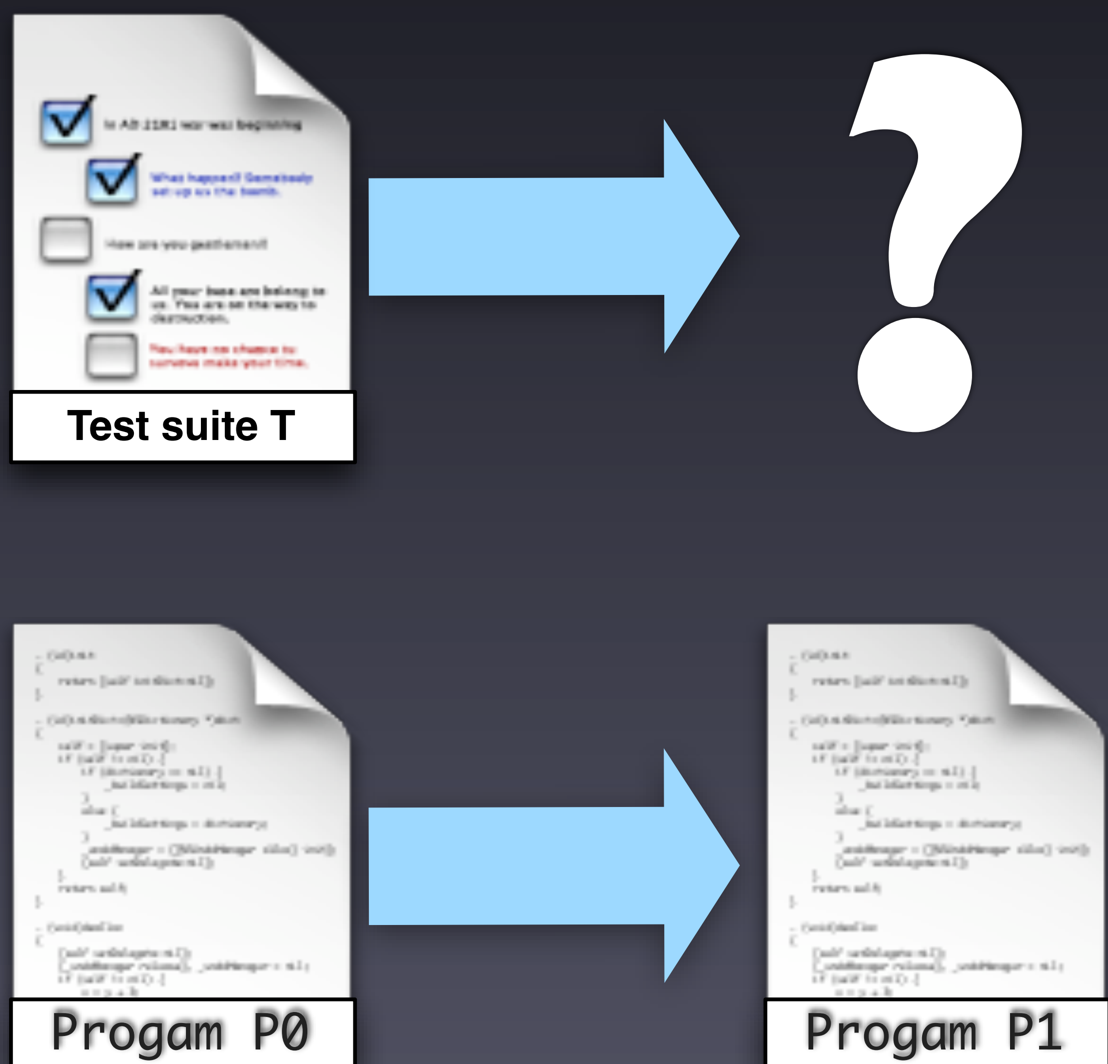

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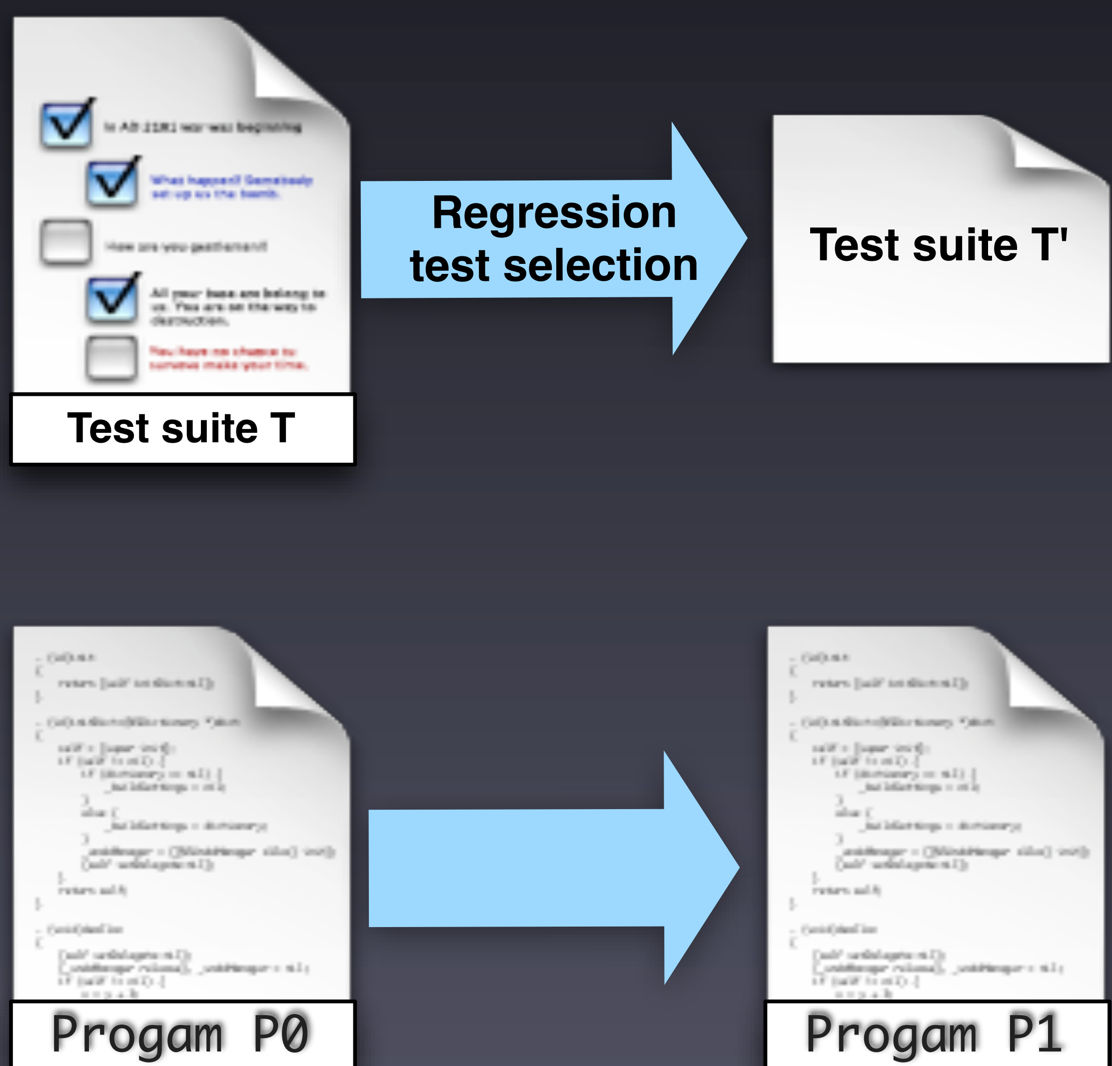

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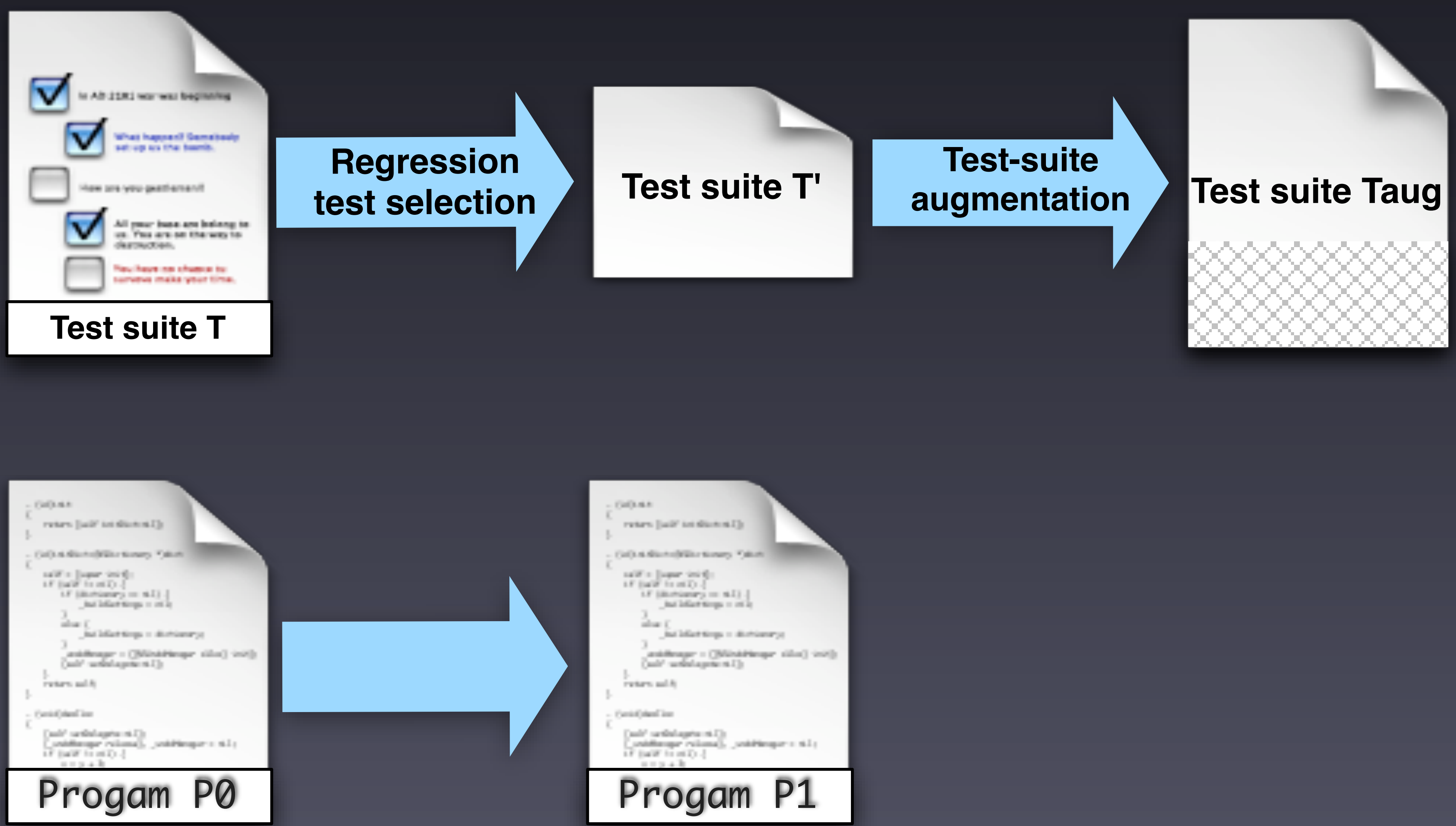

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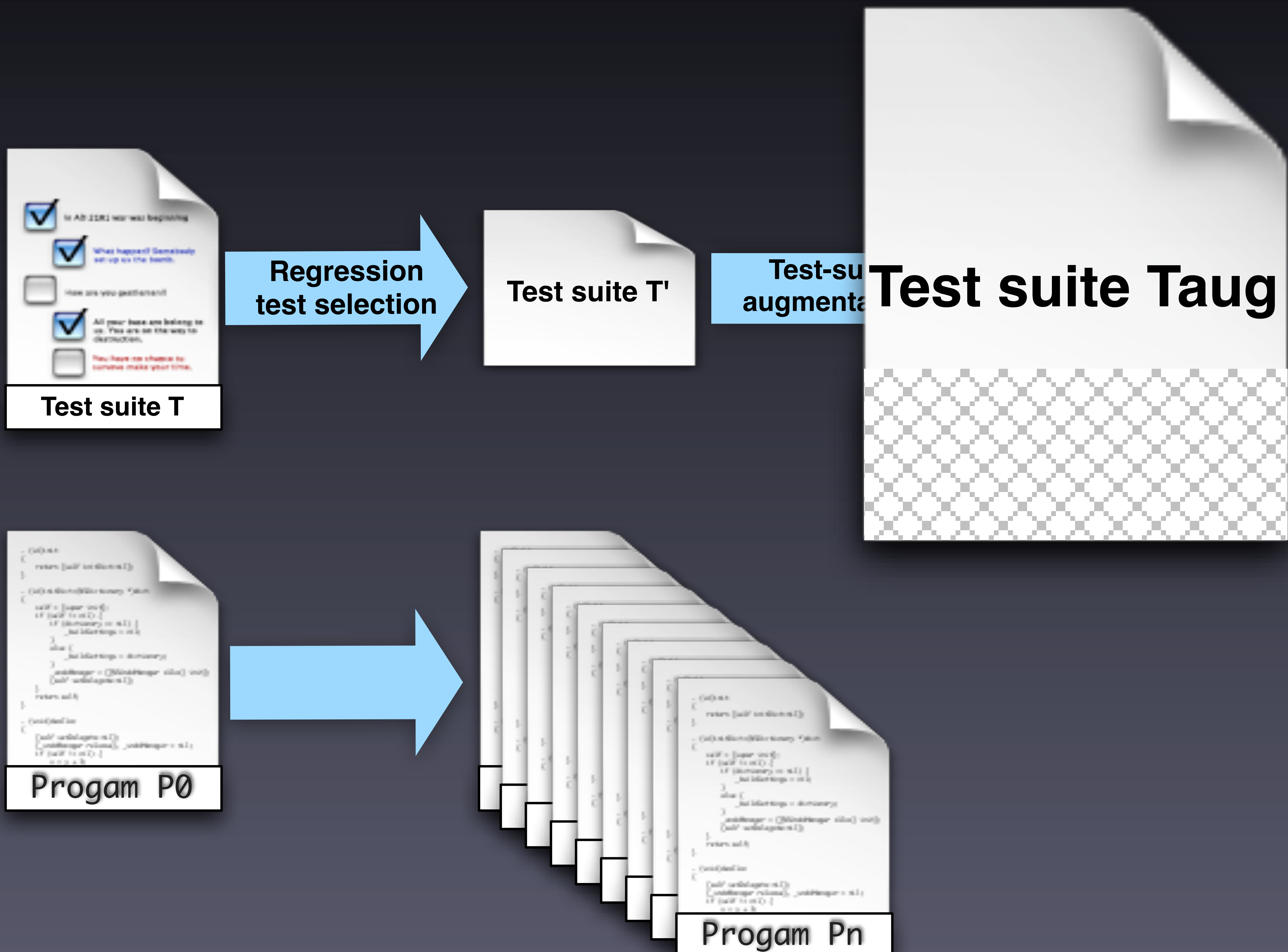
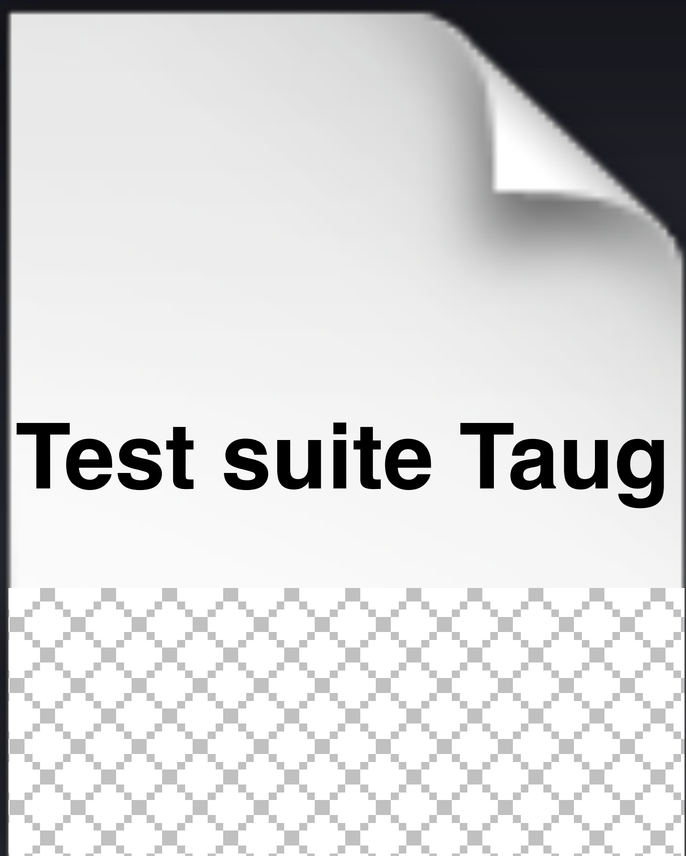


Test Suite Minimization



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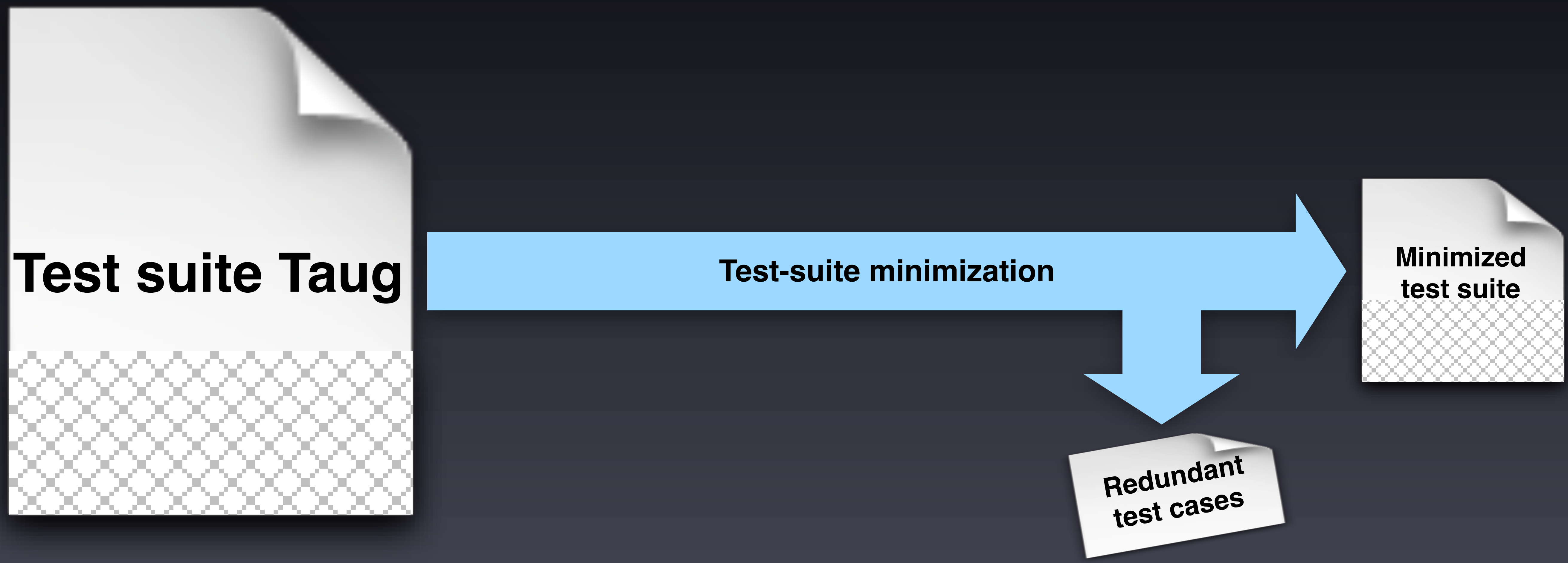

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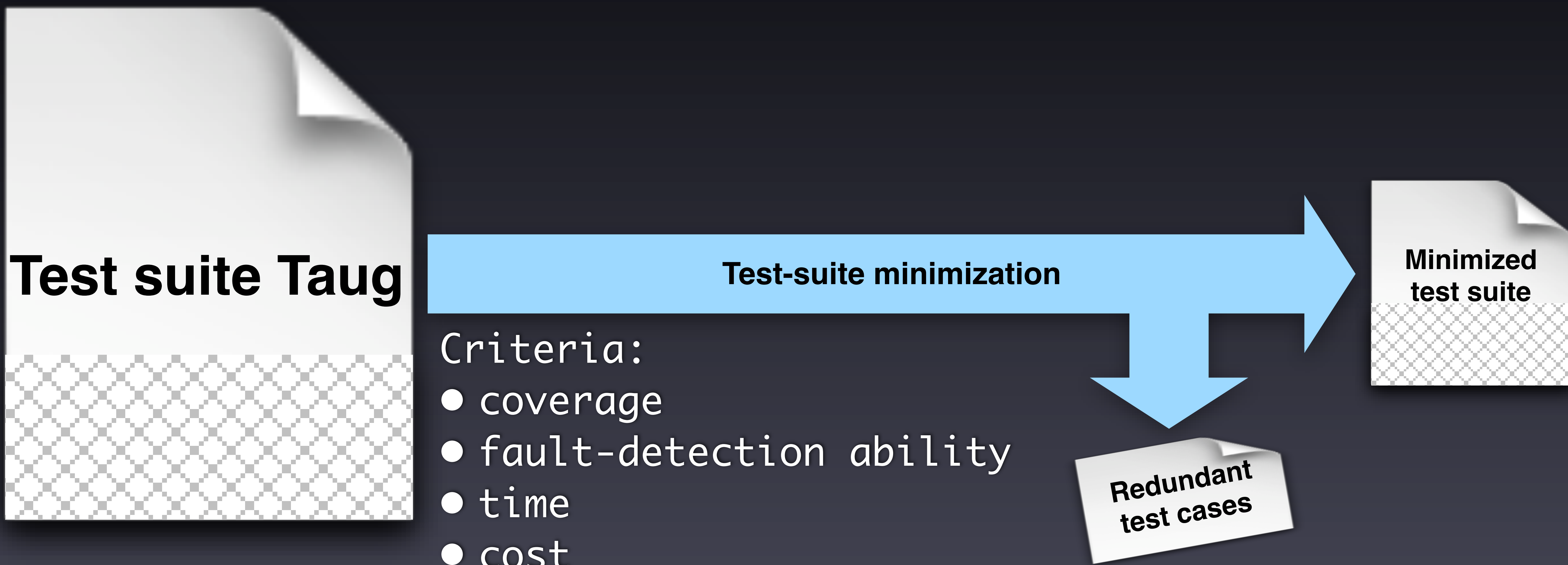
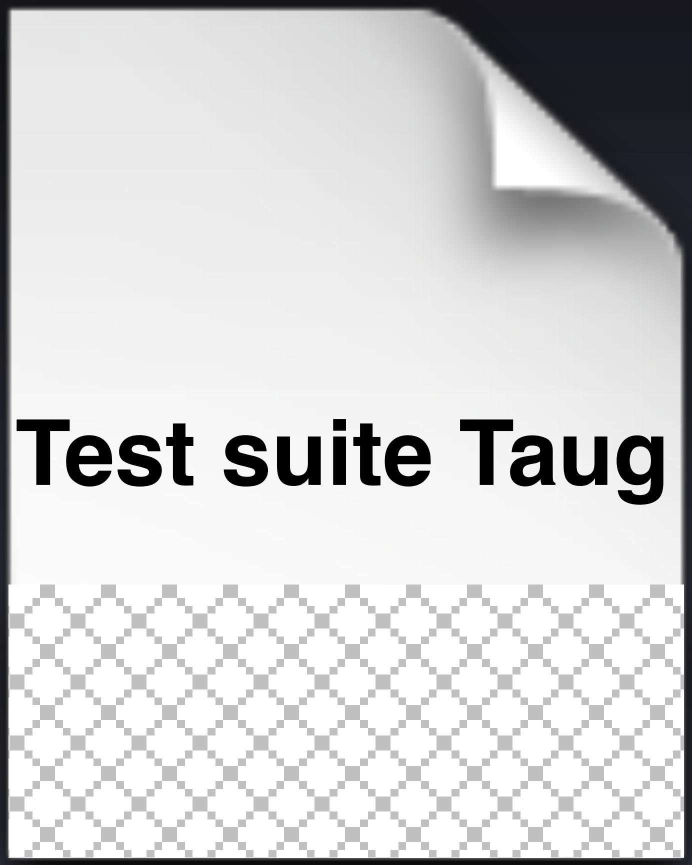


Criteria:

- coverage
- fault-detection ability
- time
- cost
- ...

A Simple Example



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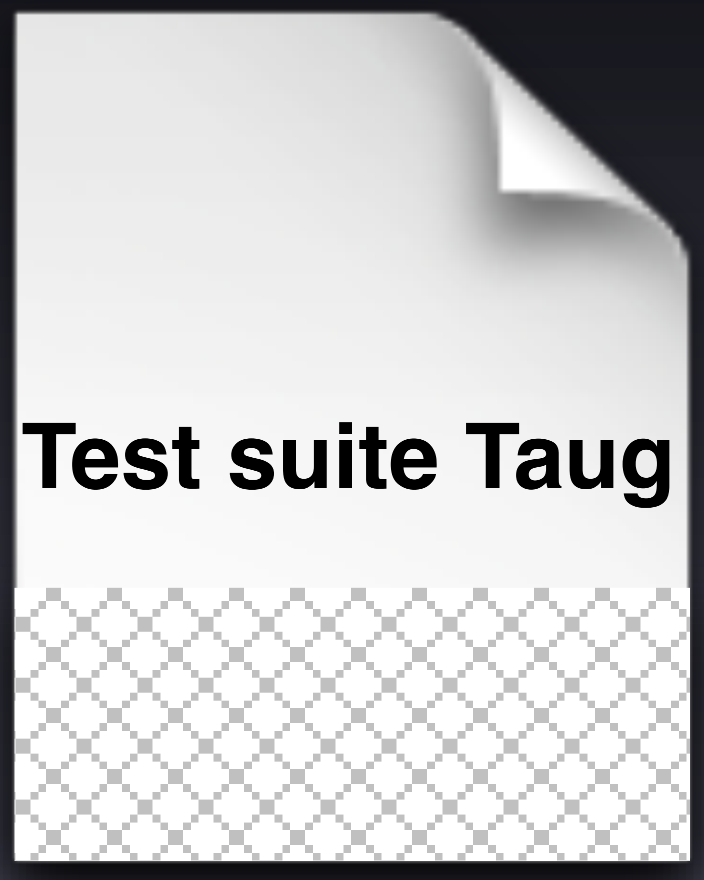

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Minimize test suite while maintaining the same level of coverage

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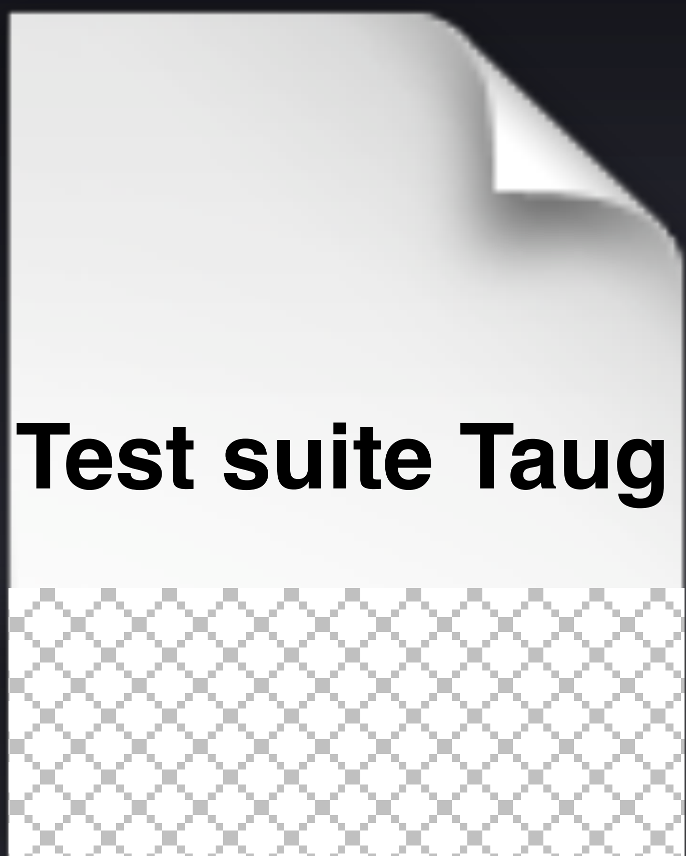

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A More Realistic Example

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Relevant parameters:

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2. Requirements to cover: R = {stmt1, stmt2, stmt3}

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Criteria of interest:

C1 – maintain coverage

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C1 – maintain coverage

C2 – minimize time to run

C3 – minimize setup effort

C4 – maximize fault detection

State of the Art

- Several approaches in the literature (e.g., [HGS93],[H99],[MB03],[BMK04],[TG05])
- Two main limitations:
  - Single criterion
    (typically, coverage)
  - Approximated
    (problem is NP-complete)
- Only exception is [BMK04]: two criteria, but still limited in terms of expressiveness

Our Contribution

MINTS – novel technique (and freely-available tool) for test-suite minimization that:

- Lets testers specify a wide range of multi-criteria test-suite minimization problems
- Automatically encodes problems in binary ILP form
- Leverages different ILP solvers to find optimal solutions in a “reasonable” time

Outline

- Introduction
- Our technique
- Empirical evaluation
- Conclusion and future work

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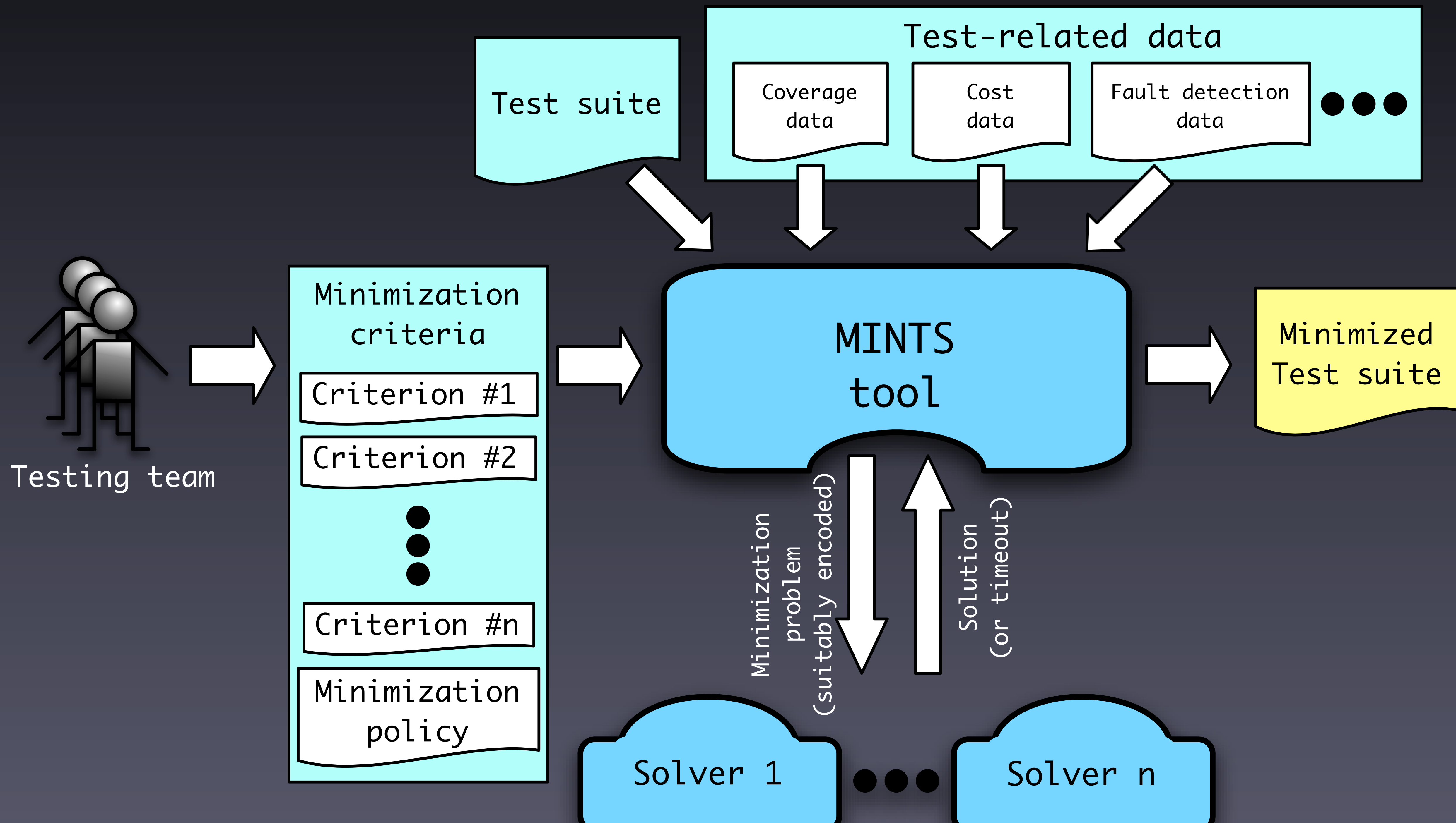

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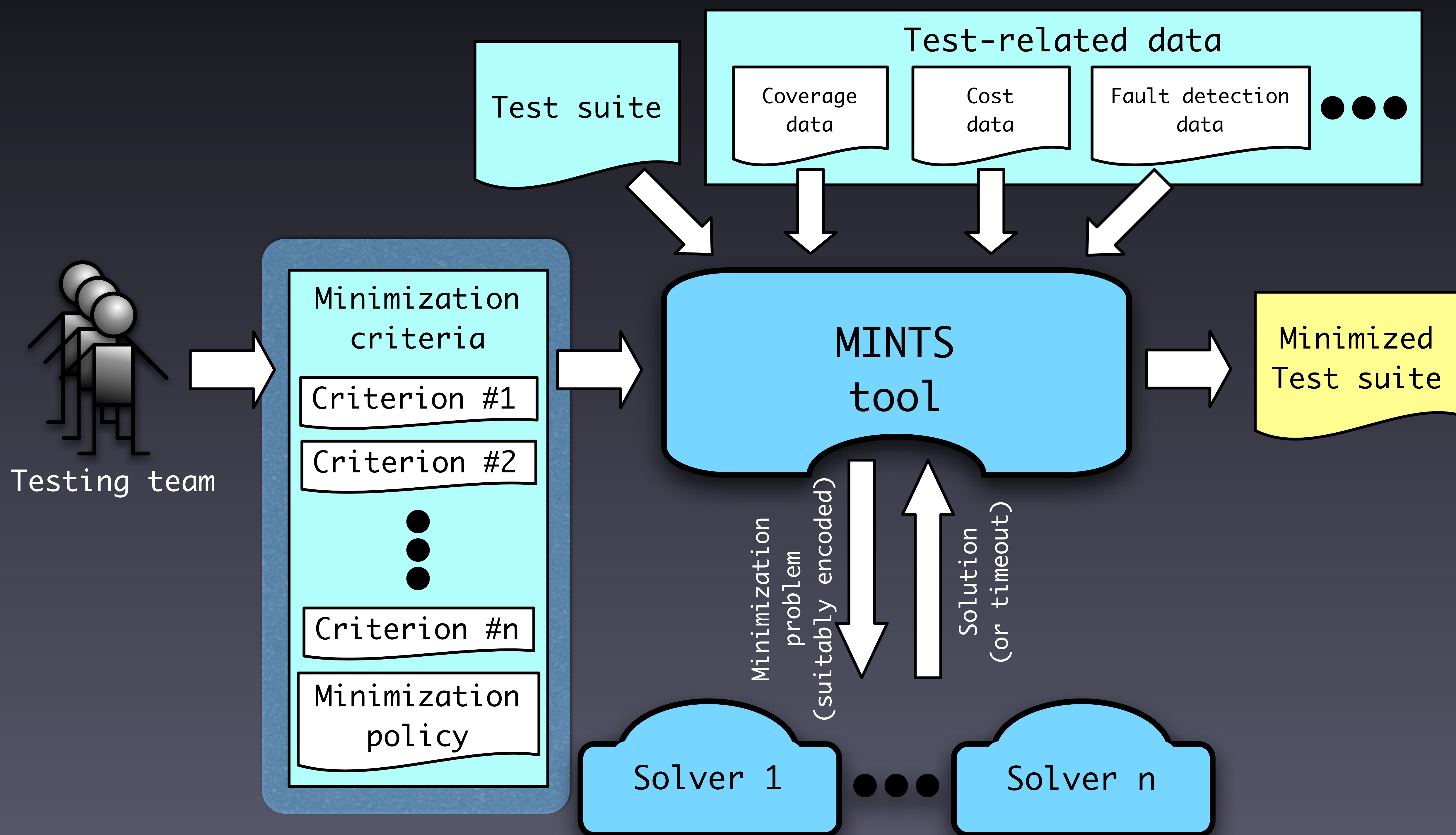

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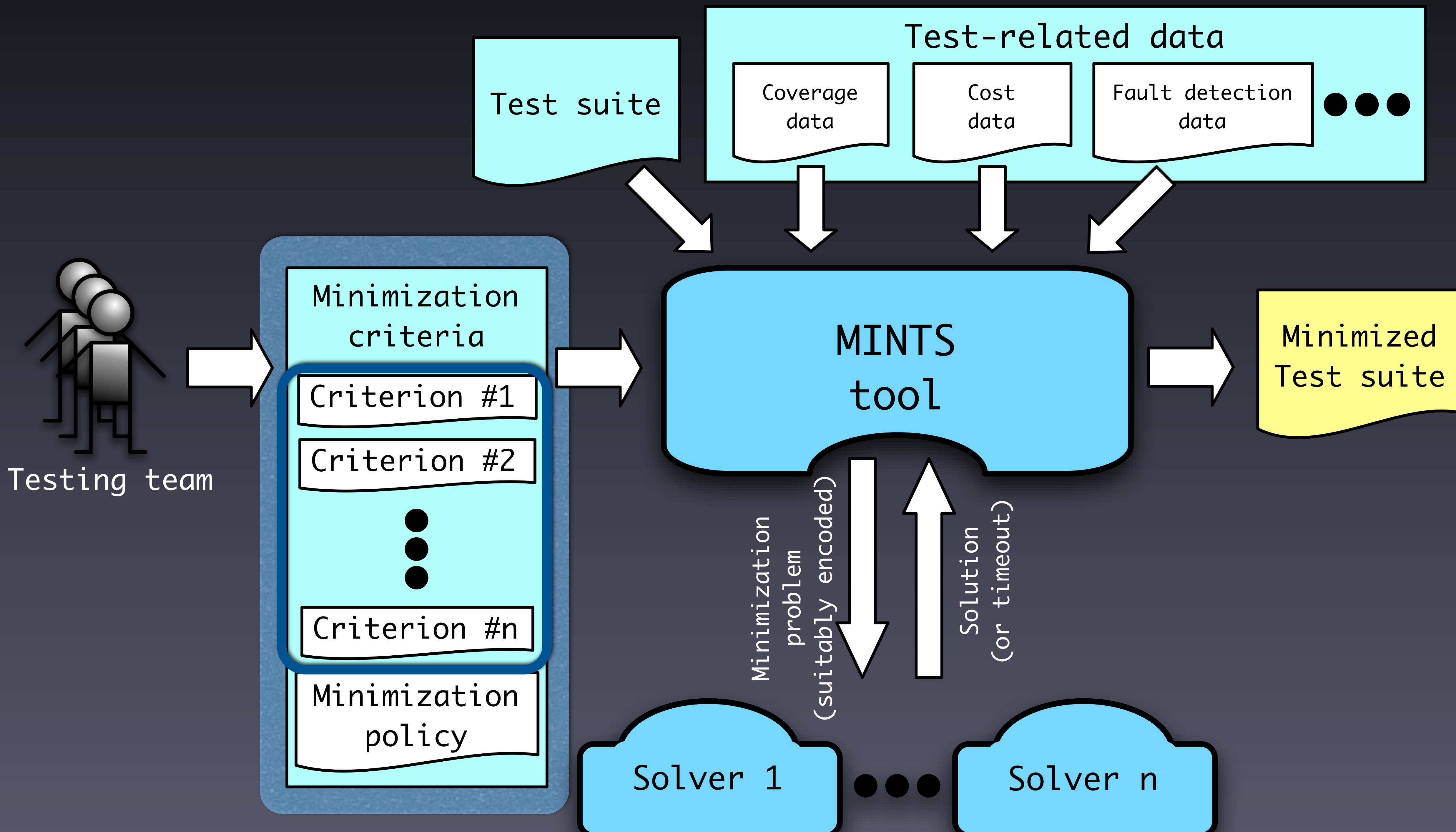

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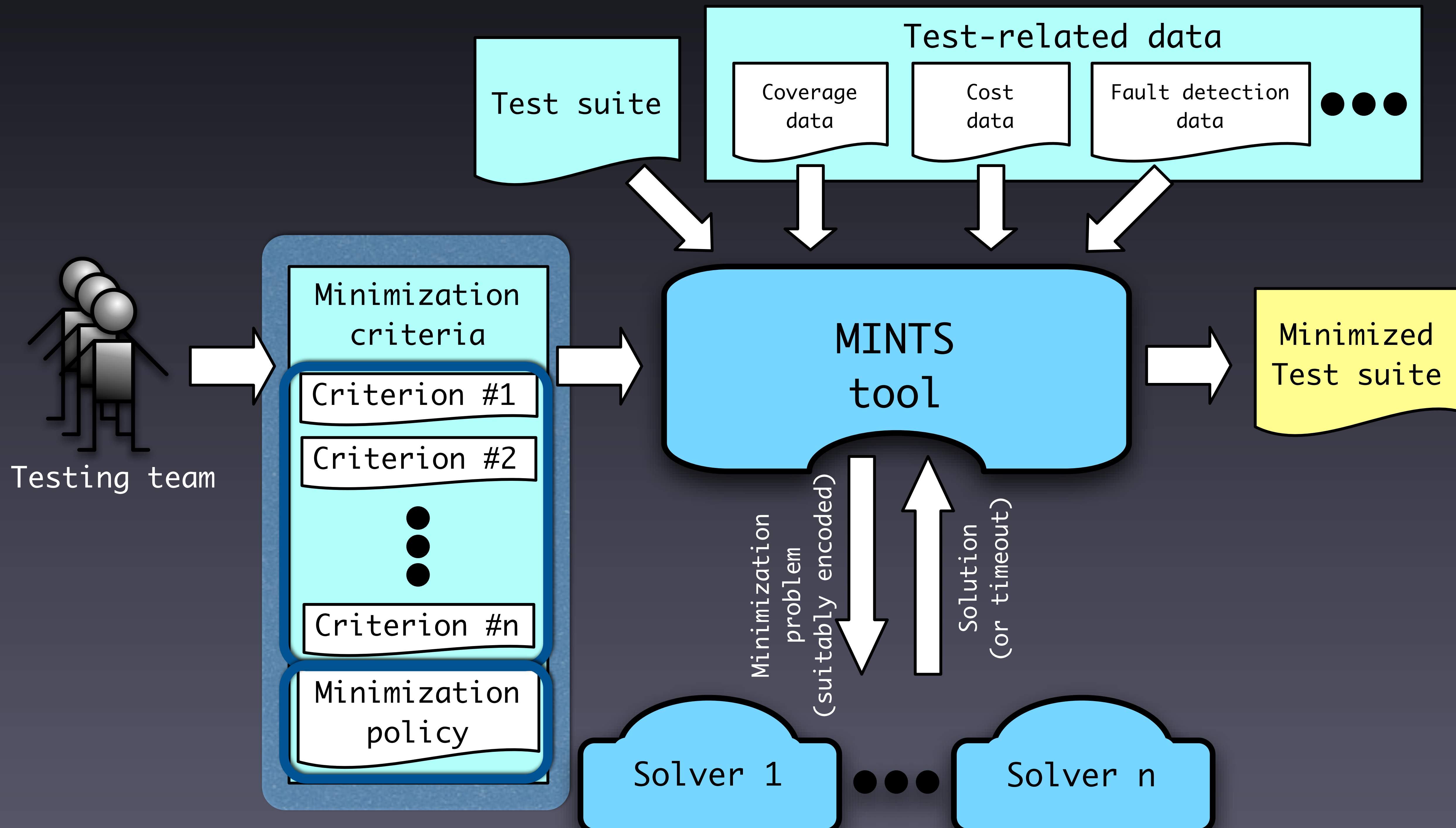

Minimization Criteria

- Absolute criteria
  - Introduce a <u>constraint</u>
  - Example: C1 – Maintain statement coverage
- Relative criteria
  - Introduce an <u>objective</u>
  - Example: C2 – Minimize time to run
- Note: the same set of data can be used for either type of criteria

Minimization Policy

- Defines how to combine different objectives
- Weighted
- Prioritized
- Hybrid

Minimization Policy

- Defines how to combine different objectives
- Weighted
  - Testers associate a weight to each objective
  - Weights indicate relative importance
  - Example: very limited man power:
    C2 – minimize time to run ➡ 0.1
    C3 – minimize setup effort ➡ 0.8
    C4 – maximize fault detection ➡ 0.1
- Prioritized
- Hybrid

Minimization Policy

- Defines how to combine different objectives
- Weighted
- Prioritized
  - Testers specify a priority order for each objective
  - Priorities indicate order of processing
  - Example: C3 ➡ 1, C2 ➡ 2, C4 ➡ 3:
    $S1 \subseteq 2^T$ = min setup effort
    $S2 \subseteq S1$ = min testing time
    $S3 \subseteq S2$ = max fault detection
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C2 – minimize time to run
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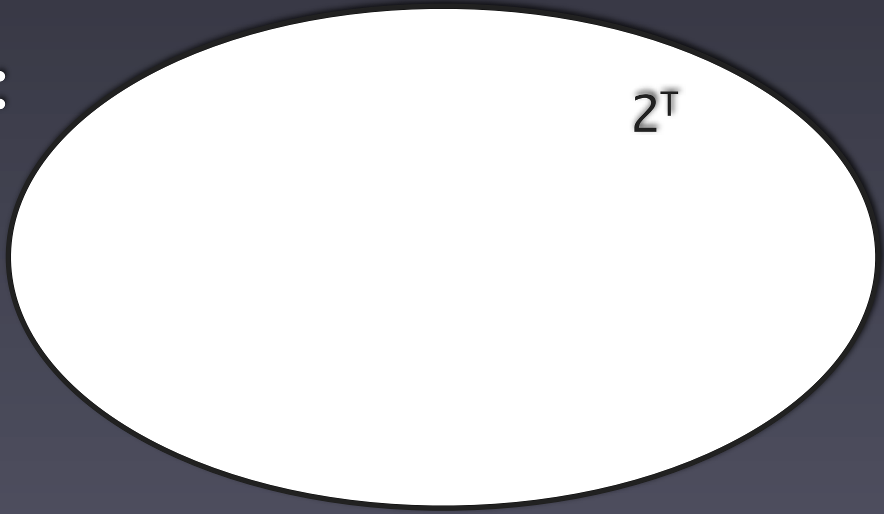

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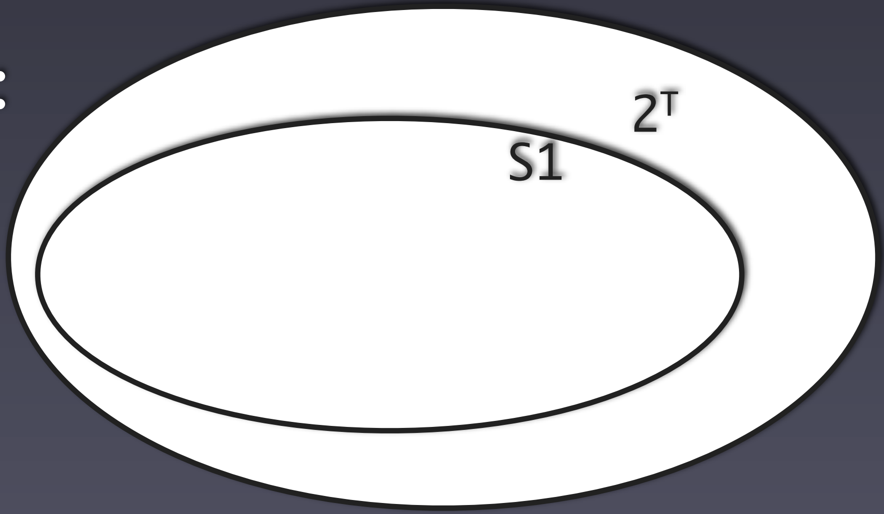

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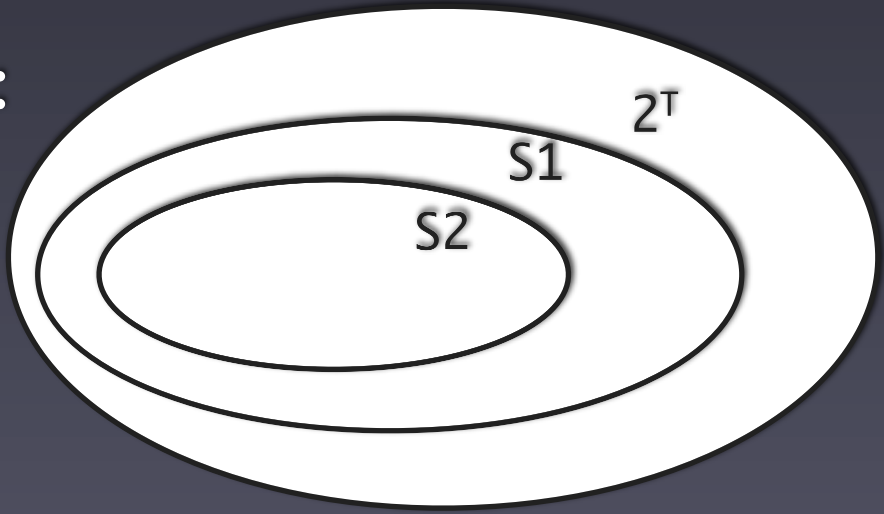

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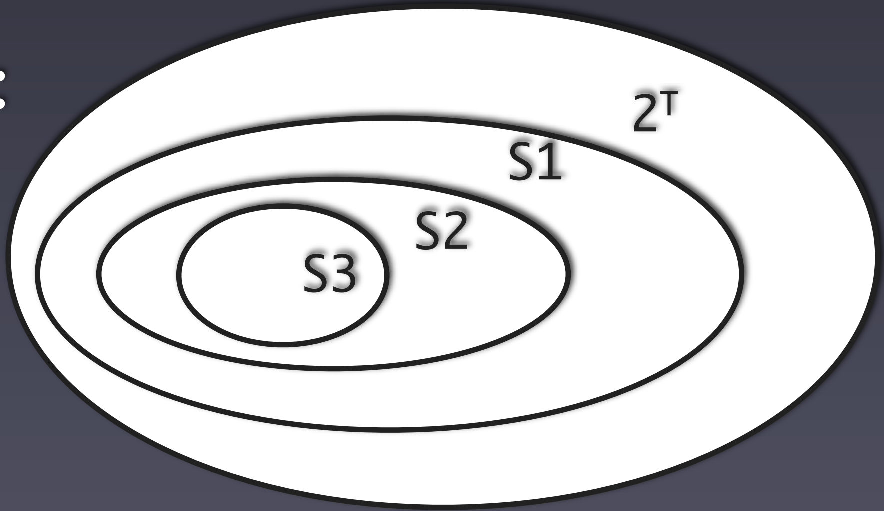

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Minimization Policy

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  - Testers cluster objectives into groups and
    - assign weights to objects within group
    - assign priorities to groups

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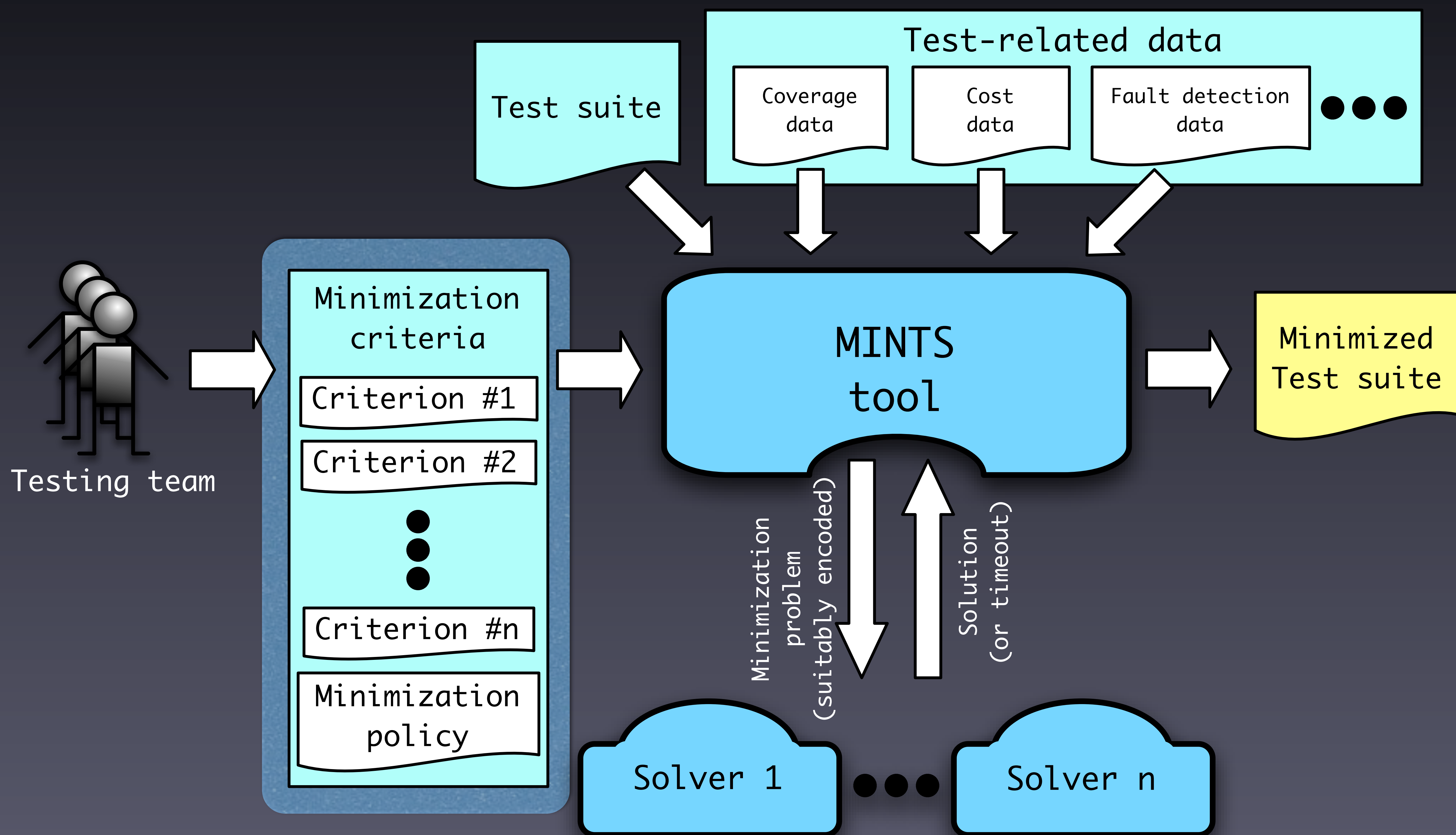

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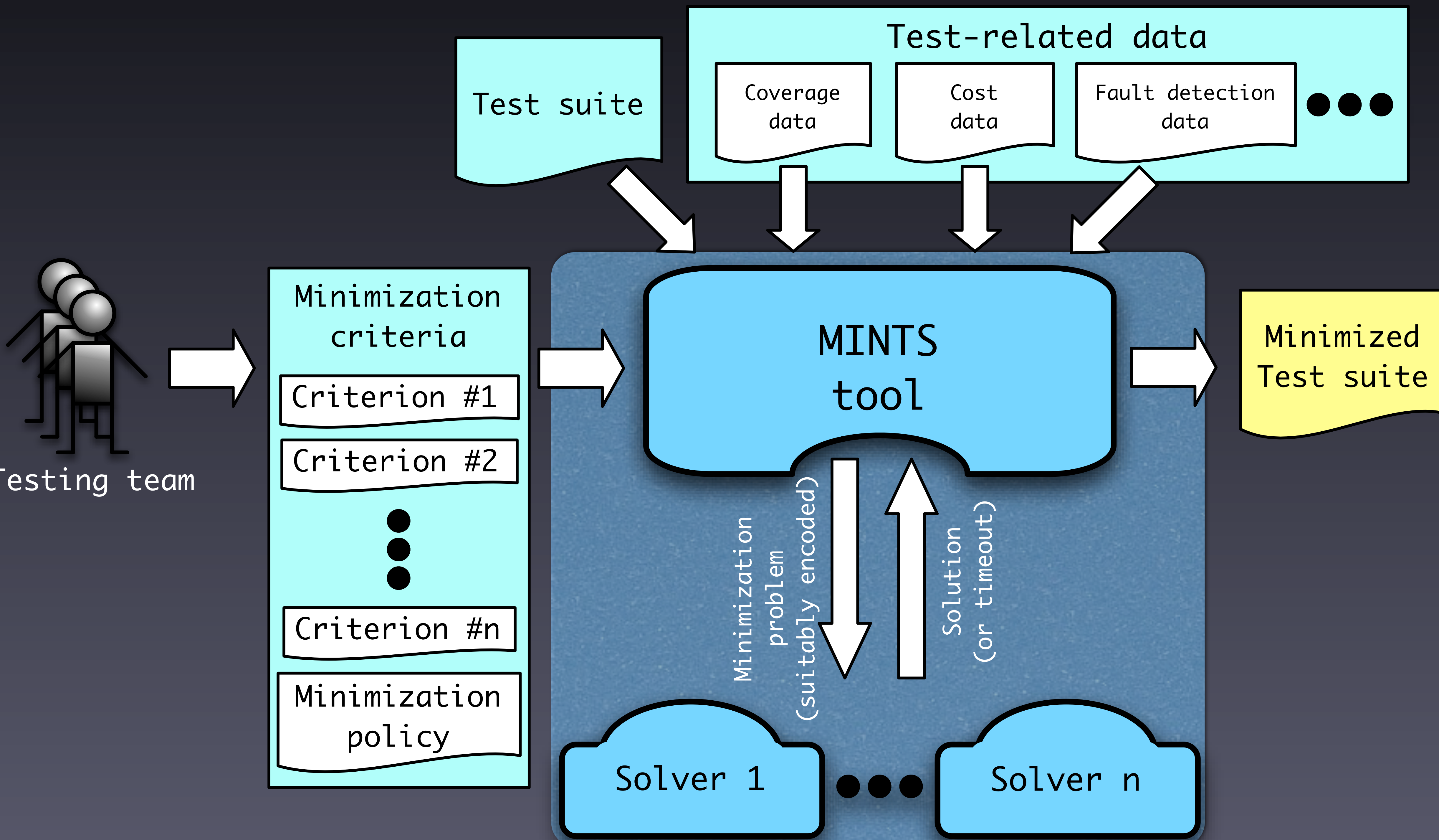

Multi-criteria minimization as a binary ILP problem: Encoding

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For example:

Criterion #1: (maintain coverage)

$$\sum_{j=1..4} d_{1,j}\ o_j = o_1 + o_3 \ge 1$$
$$\sum_{j=1..4} d_{2,j}\ o_j = o_1 + o_2 \ge 1$$
$$\sum_{j=1..4} d_{3,j}\ o_j = o_3 + o_4 \ge 1$$

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- Relative criteria (type x): $\min/\max \sum_{j=1..|T|} \text{norm}(d_{x,j}) o_j$
  $(\sum_{j=1..|T|} \text{norm}(d_{,j}) = 1)$

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For example:

Criterion #2 (minimize time to run):
$\min \sum_{j=1..4} \text{norm}(d_{3,j}) o_j = .5o_1 + .1o_2 + .36o_3 + .04o_4$

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  - Weighted: $\{\alpha_j\}$, $1 \le j \le$ #relative criteria

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Multi-criteria minimization as a binary ILP problem: Weighted policy

Given

- n relative criteria involving test data d_{x1}, ..., d_{xn}
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Multi-criteria minimization as a binary ILP problem: Weighted policy

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MINTS encode the minimization problem as

minimize

$\sum_{i=1..n} \alpha_i \sum_{j=1..|T|} norm(d_{xi,j}) o_j$

under the constraints

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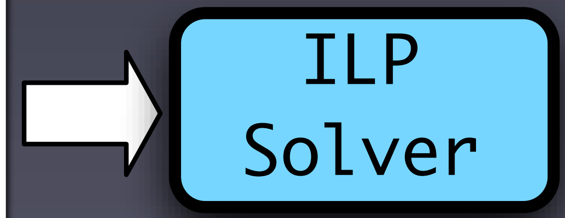

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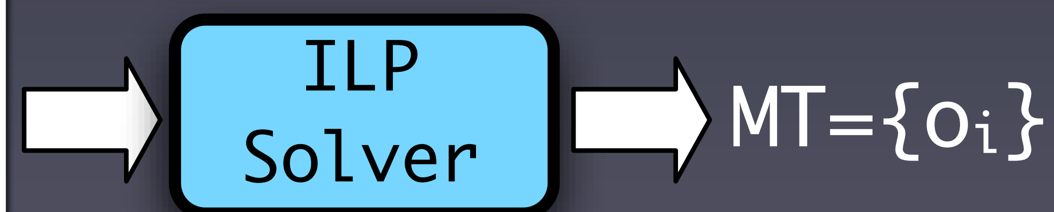

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$0.1(.5o_1+.1o_2+.36o_3+.04o_4) + 0.8(.13o_1+.48o_3+.39o_4) - 0.1(.3o_1+.17o_2+.42o_3+.08o_4)$

Under the constraints

$o_1 + o_3 \geq 1,\ o_1 + o_2 \geq 1,\ o_3 + o_4 \geq 1$

$\Rightarrow MT = \{0,1,1,0\}$

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- Empirical evaluation
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- Goal: assess usefulness and practicality of the approach
- RQ1: How often can MINTS find an optimal solution “quickly”?
- RQ2: How does MINTS compare with a heuristic approach?
- RQ3: How does the use of a specific solver affect MINTS’s performance?

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Experimental Subjects and Solvers Considered

Subject	LOC	COV	#Test Cases	#Versions
tcas	173	72	1608	5
schedule2	307	146	2700	5
tot_info	406	136	1052	5
schedule	412	166	2650	5
replace	562	263	5542	5
print_tokens	563	194	4130	5
print_tokens2	570	197	4115	5
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- Solvers:
  Four SAT-based pseudo-Boolean and two pure ILP solvers

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Overall, 400 minimization problems covering a wide spectrum

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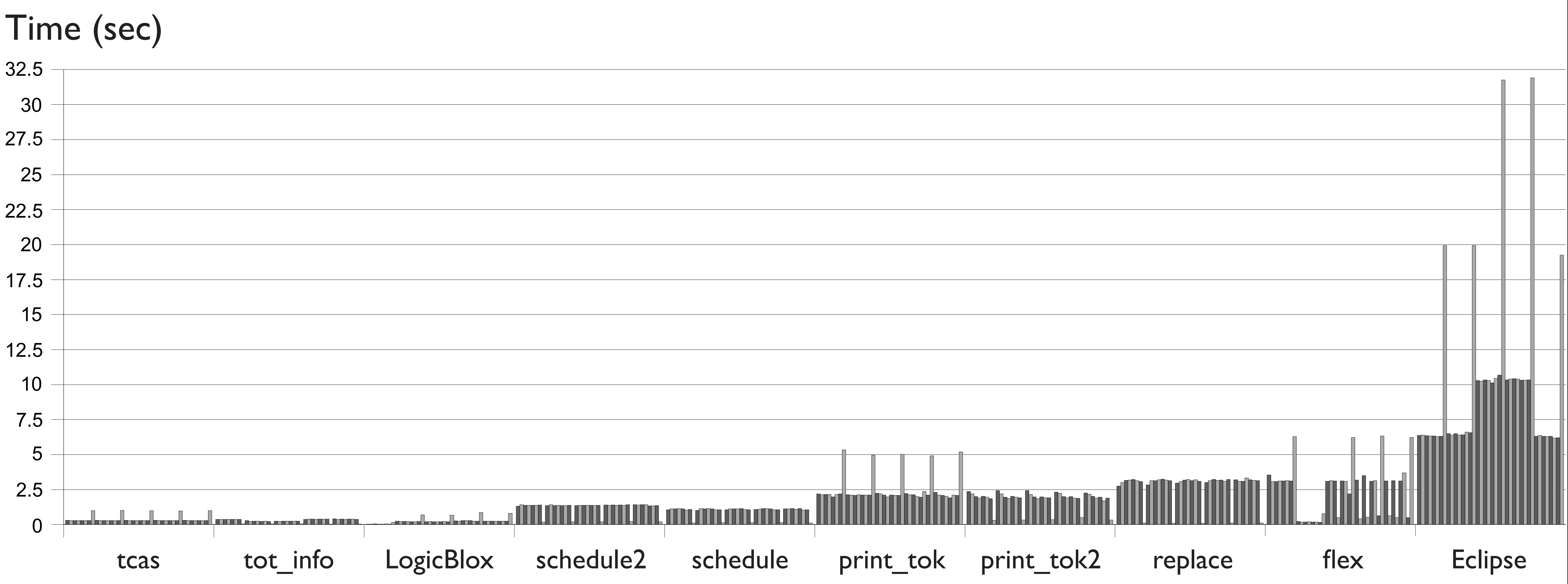

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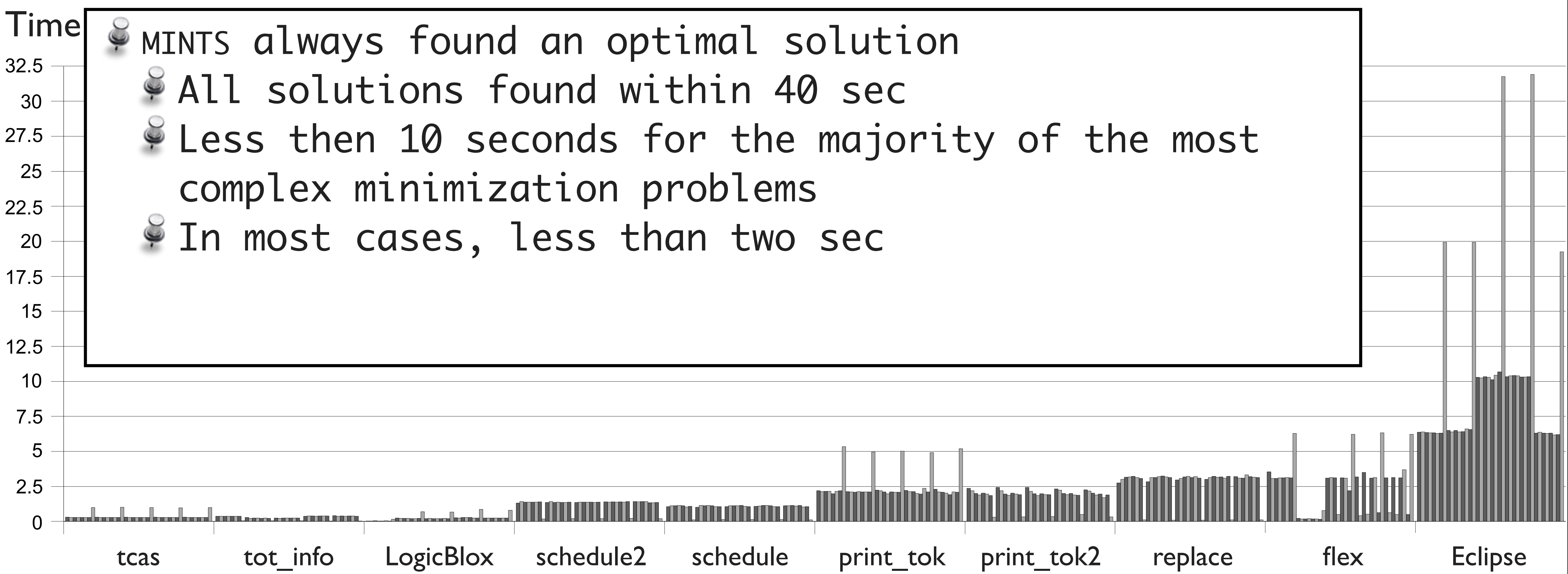

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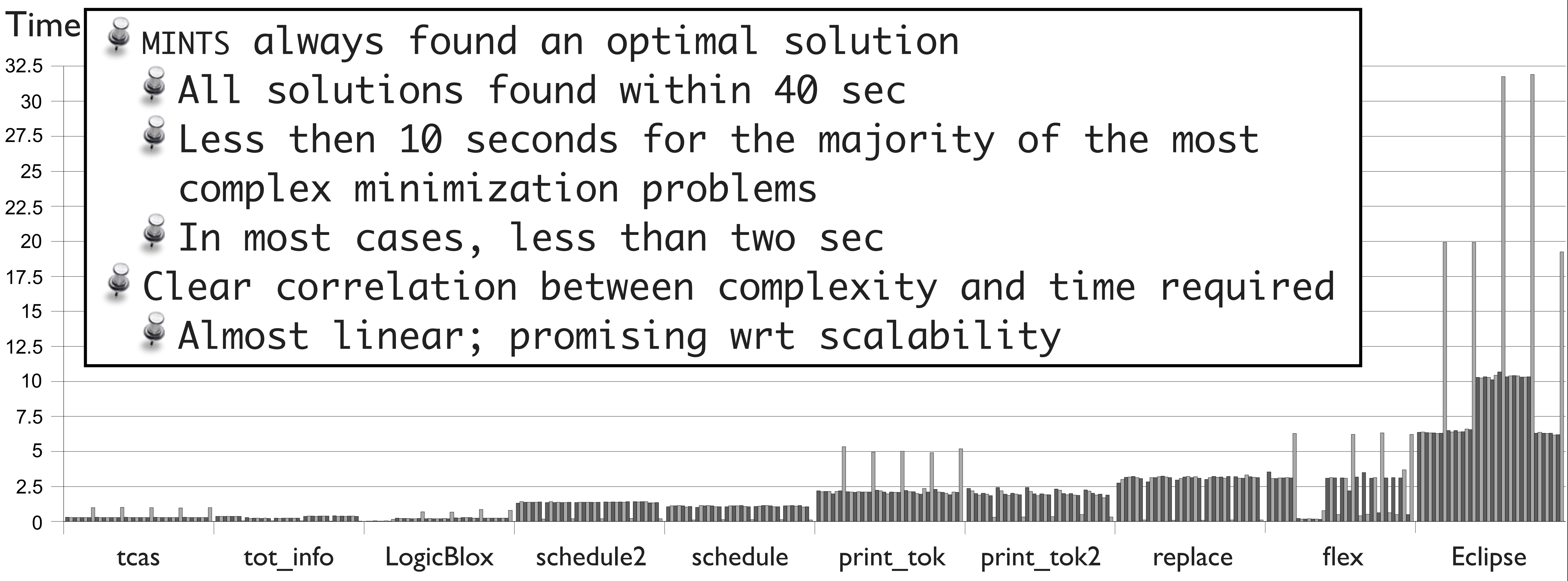
- Clear correlation between complexity and time required
  - Almost linear; promising wrt scalability



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- Both found solutions to all problems in a few seconds
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RQ2: How does MINTS compare with a heuristic approach?

Eclipse version	Original T's size	HGS	MINTS	Difference
3.0.1	2460	656	418	238 (36%)
3.0.2	2467	651	423	228 (35%)
3.1	3621	851	553	298 (35%)
3.1.1	3681	833	532	301 (36%)
3.1.2	3681	656	406	250 (38%)

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Future work

- Additional experimentation
- Study solvers' performance to go beyond the black box
- Extension of MINTS to include prioritization

Thank You!