Rule2DRC: Benchmarking LLM Agents for DRC Script Synthesis with Execution-Guided Test Generation

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github.com/snu-mllab/Rule2DRC

Design rule checking is a manual bottleneck

Before a chip can be manufactured, its layout must satisfy thousands of geometric design rules.

- A foundry ships each rule as (i) a natural-language spec and (ii) an executable DRC script; a DRC engine runs the script on a layout and reports violations.
- Writing these scripts by hand needs a domain-specific language (KLayout, SVRF) *and* process expertise — and must be redone for every new node.

Natural-language rule r_i

Pad must be inside M4 and enclosed by M4 by at least 0.850 μm.

$\Longrightarrow$

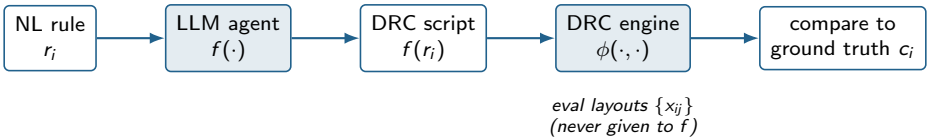
DRC script c_i (KLayout)

```
pad.enclosed(m4, 0.850.um)
  .output("PAD_M4_ENC", ...)
(pad - m4)
  .output("PAD_M4_ENC", ...)
```

Translating NL rules $\rightarrow$ correct DRC scripts is the bottleneck we target with LLM agents.

Task: natural-language rule $\rightarrow$ executable DRC script

An agent f sees only the NL rule r_i and outputs a script $f(r_i)$. We score it by execution, not code similarity.



- $\phi(x, c) \in \{0, 1\}$: does script c flag a violation on layout x?
- **Success rate** — generated and ground-truth outputs match on *every* eval layout.
- **Error rate** — fraction of scripts that hit a compile / runtime error.

Prior benchmarks: small, code-similarity, closed

Benchmark	Test rules	Test layouts	Execution eval	No eval layouts as input	Open source
DRC-SG (2022/23)	200	–	×	✓	×
AST-Guided SVRF (2025)	74	–	×	✓	×
DRC-Coder (2025)	7	29	✓	×	×
Rule2DRC (Ours)	1000	13921	✓	✓	✓

Code similarity misranks correct scripts.
One rule has many syntactically different but *behaviorally identical* implementations:

`nw.interacting(...)`	✓
`hv_ndiff.separation(...)`	✓
`hv_ndiff.sep(...)`	✓

same rule ⇒ code sim. ×, execution ✓

DRC-Coder uses execution, but needs ground-truth–labeled eval layouts *as agent input* — unrealistic in practice.

Rule2DRC: 1,000 tasks, 13,921 layouts, open-source

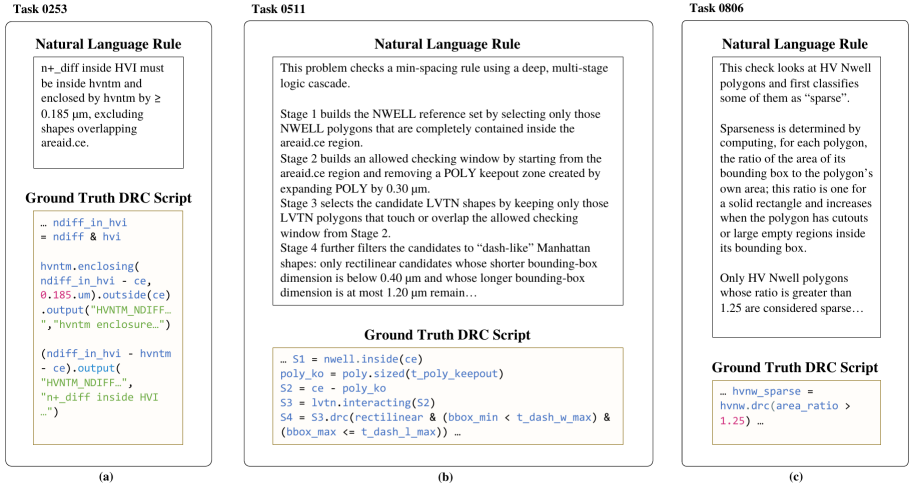
An order of magnitude larger than prior work, with execution-based scoring on KLayout / GDSII.

- **310** real rules extracted from the SkyWater130 PDK, with hand-built corner-case layouts.
- **490** synthetic multi-constraint rules — chained, multi-layer operations for advanced ($\leq$7 nm) nodes.
- **200** synthetic rules targeting under-used grammar — broadens DRC operator coverage.

Every task ships both passing and violating layouts

Including *hard negatives* that fail by the smallest margin (down to 1 nm) and topological corner cases. On average 13.9 eval layouts/task; 184 unique DRC methods across the benchmark.

Qualitative examples: one task per category



A (rule, script) pair from each category: (a) real SkyWater130 PDK rule, (b) synthetic multi-constraint, (c) synthetic niche-grammar.

Best-of-N: the hard part is *picking* the right script

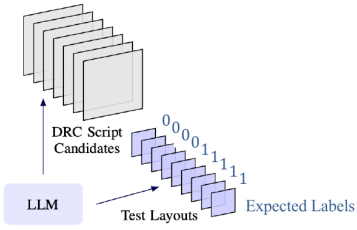
Sample N candidate scripts per task, then select the correct one.

- No ground-truth labels at selection time $\Rightarrow$ the agent must generate its own tests.
- Weak tests leave many candidates with identical outputs — correct and incorrect scripts hide in the same cluster.

Where prior selectors fall short

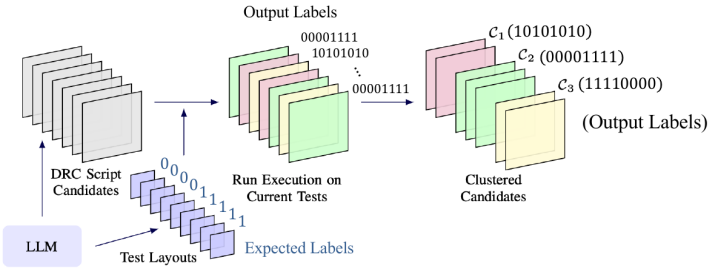
- **CodeMonkey** prunes to the top-3 early — can discard a candidate that only becomes distinguishable after more tests.
- **S*** spends tests on candidates that are *already* separated, leaving indistinguishable groups unexplored.

SplitTester: split indistinguishable clusters with targeted tests



1. Generate test layouts + expected labels.

SplitTester: split indistinguishable clusters with targeted tests



1. Generate test layouts + expected labels.
2. Run all candidates; cluster by identical outputs.

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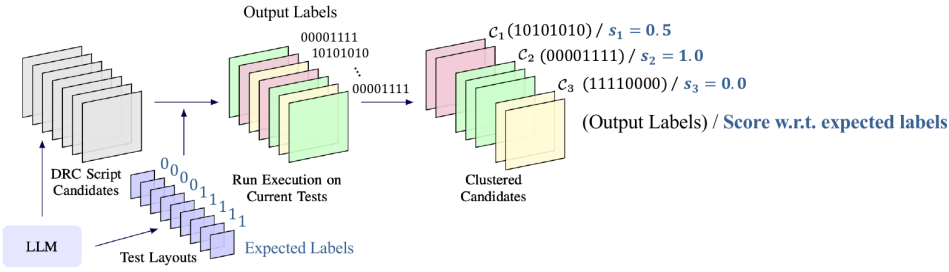

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3. Score each cluster vs. expected labels (s_i).

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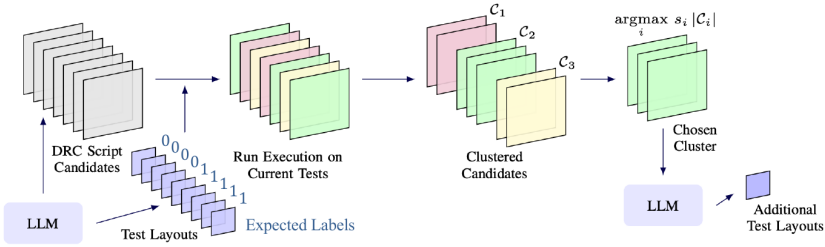

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2. Run all candidates; cluster by identical outputs.
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4. Split the large, high-scoring cluster ($\arg\max_i s_i|\mathcal{C}_i|$) with new tests.

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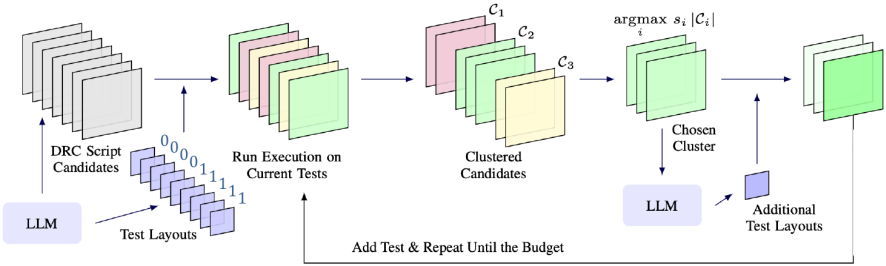

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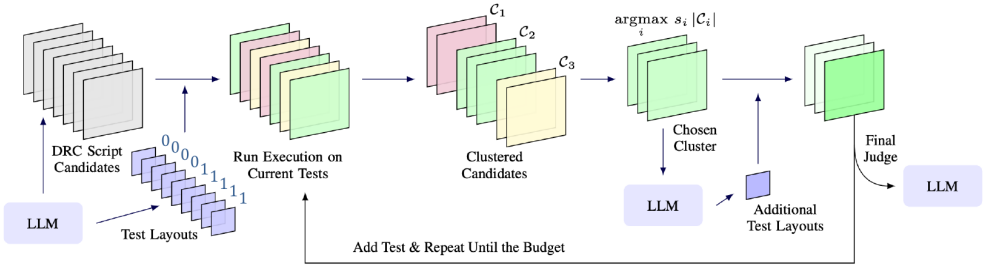

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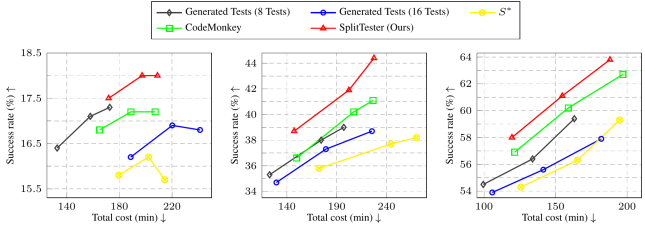
6. Judge LLM picks the best of the top-3.

SplitTester wins across models and budgets

	Qwen3-30B-Instruct		GPT-OSS-20B		GPT-OSS-120B	
Selector (Best-of-20)	Succ.↑	Err.↓	Succ.↑	Err.↓	Succ.↑	Err.↓
Single sample	14.1	61.9	16.9	66.9	32.5	48.5
CodeMonkey (best baseline)	17.2	38.6	41.1	14.1	62.7	4.2
SplitTester (Ours)	18.0	35.1	44.4	12.6	63.8	4.1
Oracle@20 (upper bound)	23.7	29.5	53.8	11.6	72.1	3.7



(a) Owen3-30B-A3B-Instruct-2507 (b) GPT-OSS-20B (c) GPT-OSS-120B

Pareto-optimal under runtime. Context: in-context KLayout API docs add +20%p pass@1 / +40%p pass@20 (used in all runs).

Conclusion

- **Rule2DRC** — the first large-scale (1,000 tasks / 13,921 layouts), execution-based, open-source benchmark for NL-rule → DRC script synthesis.
- **SplitTester** — clusters candidates by behavior and generates tests that split previously indistinguishable clusters, giving the best Best-of-N selection across three models while staying on the Pareto frontier.
- Benchmark, evaluation pipeline, and methods are open-sourced.

Thank you!

`github.com/snu-mllab/Rule2DRC`