

EAI Challenge in NeurIPS 2025

Team SingaX

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Our Team



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Overview of the solution by Team SingaX

Areas we aim to tackle

- Prompt optimization — Generate better output
- Inference generation — Generate output candidates
- Output verification — Iterate/select best output

Our observation: ambiguity in prompts causes confusion in LLM reasoning

- LLM explicitly express confusion

```
But in the OPEN description, it says "toggle off the target object first if want to open it" - this is confusing.
```

- “Conflicting” ambiguity

```
However, the problem says: "Do not output redundant states." and "A redundant state means a state that is either not necessary or has been satisfied before without broken."
```

```
But note: the initial state has the fruits inside the fridge. To get them on the countertop, we must:
```

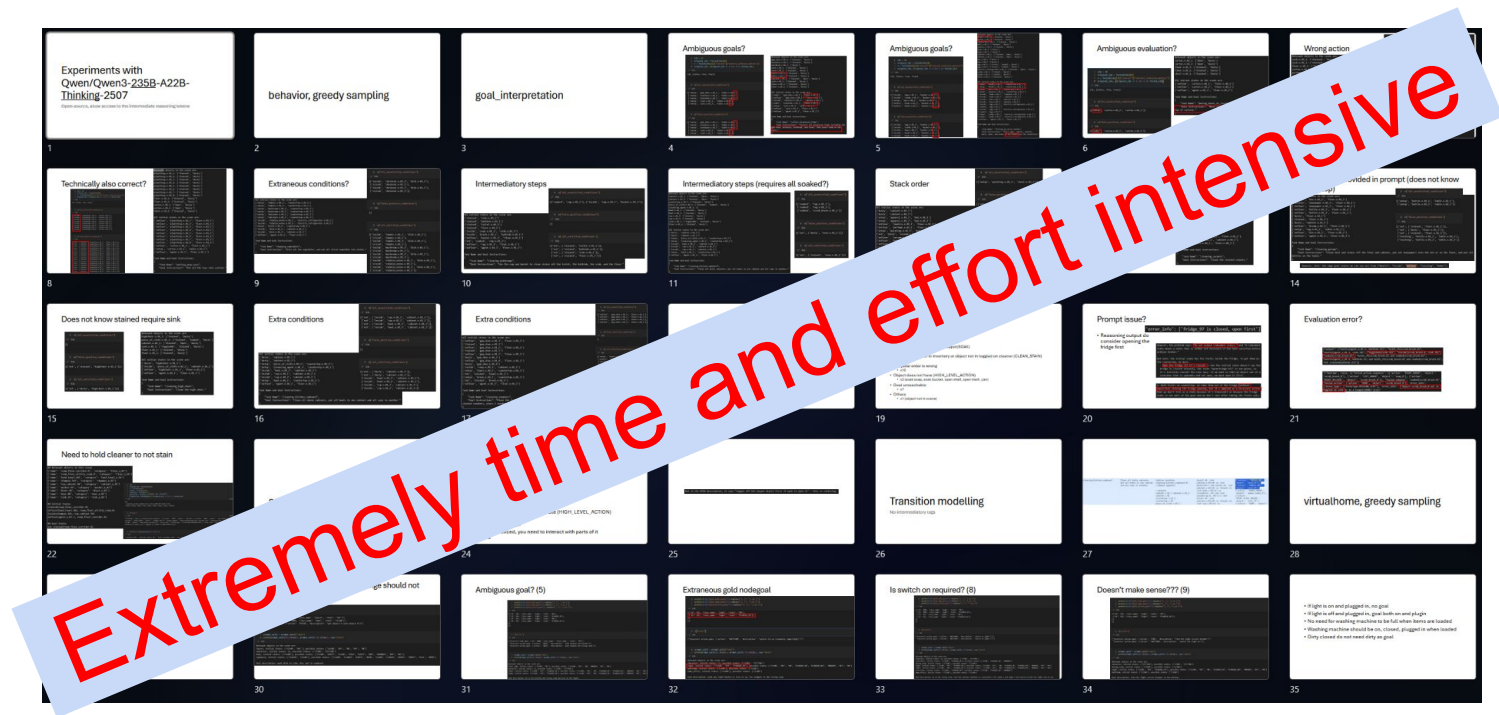
```
- Open the fridge (if it's closed) -> but the initial state doesn't say the fridge is closed? Actually, the state "open(fridge.97)" is not given, so it's initially closed? The rule says: if we want to take an object out of a container that is openable and not open, we must open it first.
```

```
1. Both fruits on countertop: we take them out of the fridge (without explicitly stating the fridge opening, but it's implied as a necessary action that we don't list as a state because it's transient? or because the fridge state is not part of the goal and we don't care after taking the fruits out).
```

```
'error_info': ['fridge_97 is closed, open first']
```

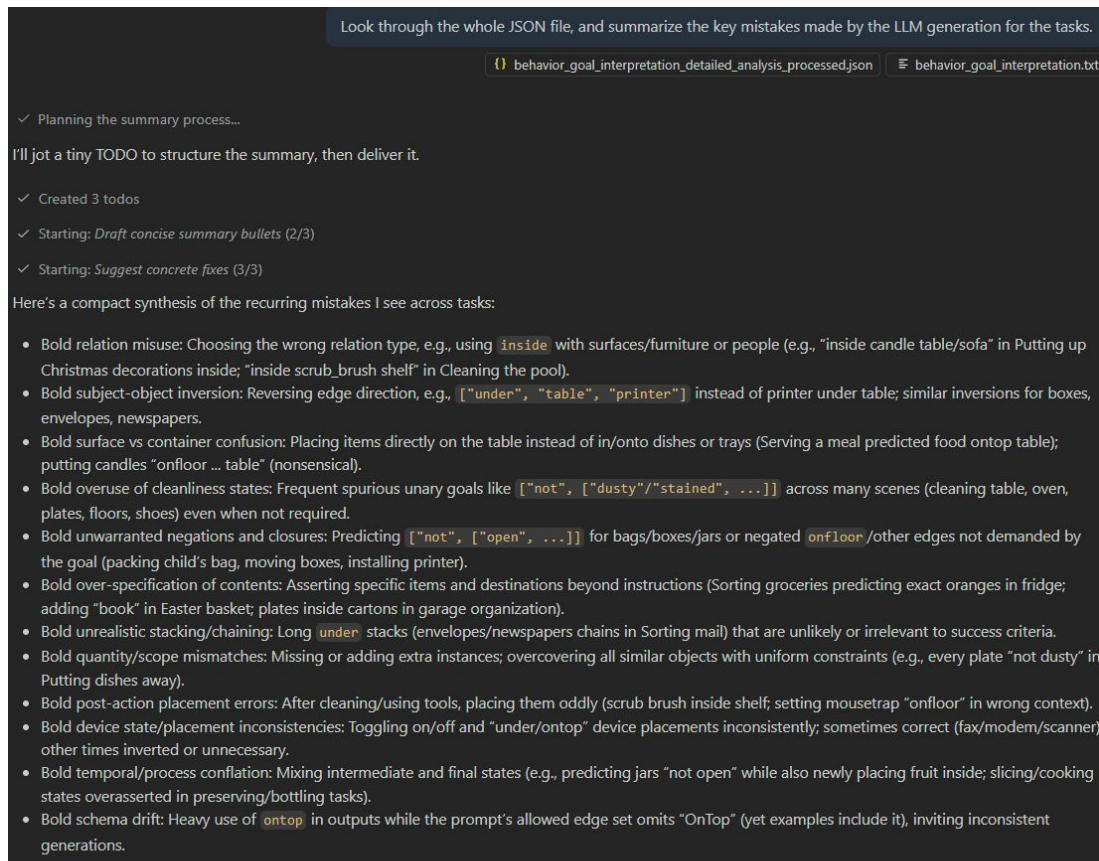
We should reduce the ambiguity in prompts, but how?

- **Manual approach:** identifying common errors from logs



Preliminary idea: one automated way is... asking LLMs to do this

- GPT-5 agent on VS-Code Co-pilot extension
- “Look through the whole JSON file, and **summarize** the key mistakes made by the LLM generation for the tasks.”
- Attach log file
- Long context window: ingest entire log file



```
Look through the whole JSON file, and summarize the key mistakes made by the LLM generation for the tasks.
behavior_goal_interpretation_detailed_analysis_processed.json behavior_goal_interpretation.txt

✓ Planning the summary process...
I'll jot a tiny TODO to structure the summary, then deliver it.

✓ Created 3 todos

✓ Starting: Draft concise summary bullets (2/3)

✓ Starting: Suggest concrete fixes (3/3)

Here's a compact synthesis of the recurring mistakes I see across tasks:

- Bold relation misuse: Choosing the wrong relation type, e.g., using inside with surfaces/furniture or people (e.g., "inside candle table/sofa" in Putting up Christmas decorations inside; "inside scrub_brush shelf" in Cleaning the pool).
- Bold subject-object inversion: Reversing edge direction, e.g., ["under", "table", "printer"] instead of printer under table; similar inversions for boxes, envelopes, newspapers.
- Bold surface vs container confusion: Placing items directly on the table instead of in/onto dishes or trays (Serving a meal predicted food ontop table); putting candles "onfloor ... table" (nonsensical).
- Bold overuse of cleanliness states: Frequent spurious unary goals like ["not", ["dusty"/"stained", ...]] across many scenes (cleaning table, oven, plates, floors, shoes) even when not required.
- Bold unwarranted negations and closures: Predicting ["not", ["open", ...]] for bags/boxes/jars or negated onfloor /other edges not demanded by the goal (packing child's bag, moving boxes, installing printer).
- Bold over-specification of contents: Asserting specific items and destinations beyond instructions (Sorting groceries predicting exact oranges in fridge; adding "book" in Easter basket; plates inside cartons in garage organization).
- Bold unrealistic stacking/chaining: Long under stacks (envelopes/newspapers chains in Sorting mail) that are unlikely or irrelevant to success criteria.
- Bold quantity/scope mismatches: Missing or adding extra instances; overcovering all similar objects with uniform constraints (e.g., every plate "not dusty" in Putting dishes away).
- Bold post-action placement errors: After cleaning/using tools, placing them oddly (scrub brush inside shelf; setting mousetrap "onfloor" in wrong context).
- Bold device state/placement inconsistencies: Toggling on/off and "under/ontop" device placements inconsistently; sometimes correct (fax/modem/scanner), other times inverted or unnecessary.
- Bold temporal/process conflation: Mixing intermediate and final states (e.g., predicting jars "not open" while also newly placing fruit inside; slicing/cooking states overasserted in preserving/bottling tasks).
- Bold schema drift: Heavy use of ontop in outputs while the prompt's allowed edge set omits "OnTop" (yet examples include it), inviting inconsistent generations.

```


Prompt Induction: Learning from History or Mistakes \Rightarrow Better Instructions

- “Improve the prompts to address the issues”
- Attach prompt file
- LLM agent directly applies patch to the system prompt file
- Distinct from existing prompt optimization works (e.g., [1,2]), we directly use the verifier logs as feedback during the prompt improvement step

```
Improve the prompt to address the issues
behavior_goal_interpretation.txt

✓ Preparing next steps after patch...
Next, I'll patch the prompt to add guardrails and fix the schema.

✓ Starting: Patch prompt schema/casing (2/4)
behavior_goal_interpretation.txt +40 -4

✓ Completed: Patch prompt schema/casing (2/4)
I updated the prompt to fix schema and add guardrails.

• Bold schema/casing: Standardized to lower-case tokens for all states and relations; added ontop to the allowed relation set; tightened JSON shape to exactly {"node goals": [...], "edge goals": [...]} with lists only.
• Bold allowed sets: Node states now restricted to {"cooked", "open", "frozen", "dusty", "stained", "sliced", "soaked", "toggled_on"}; edge relations to {"nextto", "inside", "onfloor", "ontop", "touching", "under"}; not wrapper required for negations.
• Bold semantics rules: Clear constraints for inside (containers only), ontop (support surfaces), onfloor (floor only), under directionality, and symmetry of nextto / touching. Prevents subject-object inversions and surface/container confusions.
• Bold minimality: Explicitly forbid speculative cleanliness/open/negated states unless the task demands them; discourage blanket assertions and unrealistic stacks; require matching counts and plausible placements.
• Bold validation checklist: Deduplication, no invented objects/IDs, final states only (not intermediate steps).
• Bold examples: Tiny snippets to disambiguate printer-under-table, serving on dishes, and jars without forced closure.

File changed: behavior_goal_interpretation.txt

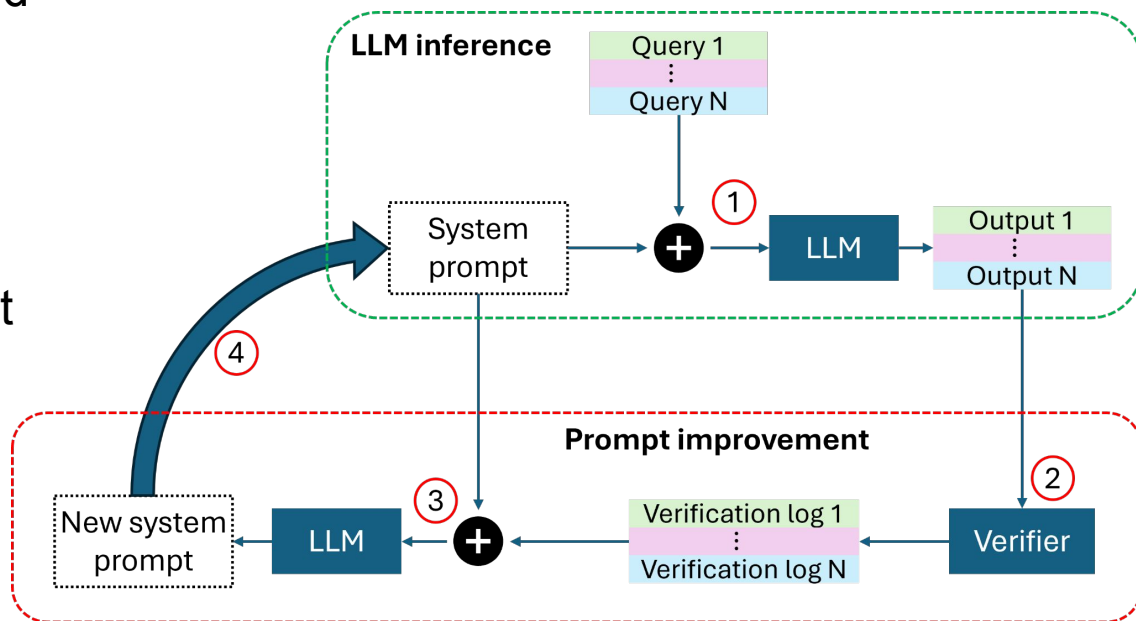
Want me to regenerate prompts or run a small batch to sanity-check reductions in false positives (e.g., serving, sorting mail, installing printer)?
```

[1] Zhou et. al. (2023). Large language models are human-level prompt engineers. In Proc ICLR.

[2] Guo et. al. (2025). Evoprompt: Connecting llms with evolutionary algorithms yields powerful prompt optimizers. arXiv:2309.08532.

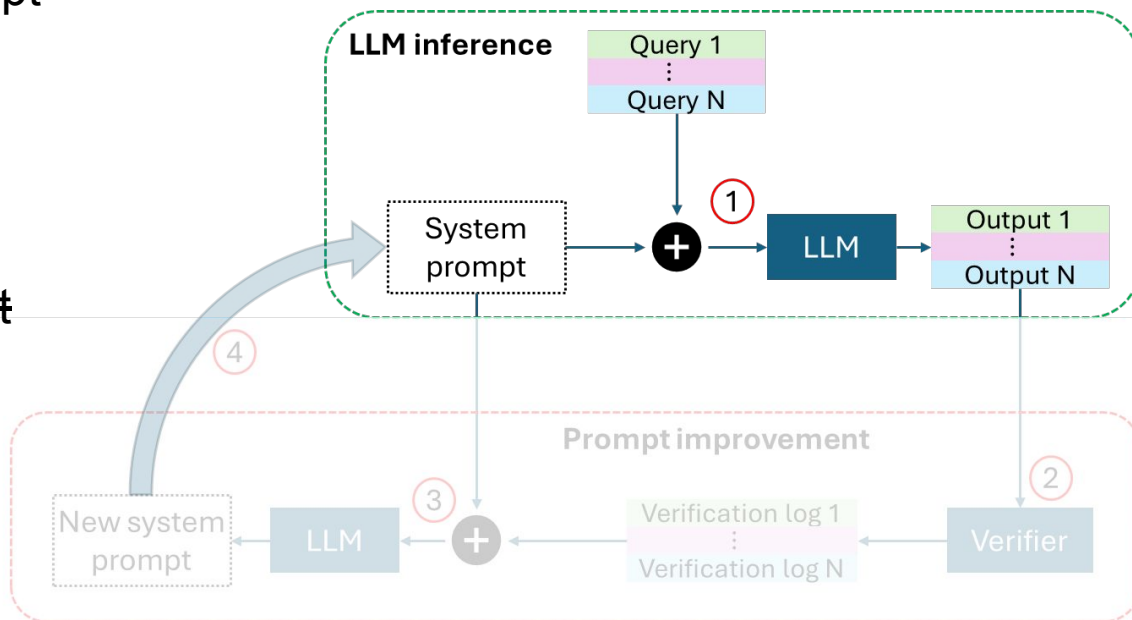
Overall pipeline of **Iterative Prompt Induction** (Development phase)

1. Use initial system prompt and generate initial LLM outputs
2. Pass LLM outputs through verifier
3. Put all verifier logs in-context into LLM, and ask LLM to improve system prompt
4. Repeat step 1 onwards with new system prompt (as required)



Overall pipeline (**Test phase**) — When verifier is not available

1. Use **improved** system prompt and generate LLM outputs
- ~~2. Pass LLM outputs through verifier~~
- ~~3. Put all verifier logs in context into LLM, and ask LLM to improve system prompt~~
- ~~4. Repeat step 1 onwards with new system prompt (as required)~~



Evaluate on actual large LLM: Clear improvements across the board

	behavior			virtualhome		
	dev set			dev set		
	Default prompt	Ours		Default prompt	Ours	
goal_interpretation (f1)	79.7	82.3	+ 2.6	43.6	61.1	+17.5
subgoal_decomposition (task sr)	69.0	77.0	+ 8.0	90.5	92.9	+ 2.4
action_sequencing (task sr)	79.0	84.0	+ 5.0	65.9	77.0	+11.1
transition_modeling (f1)	67.9	84.5	+16.6	47.3	81.0	+33.7
transition_modeling (sr)	86.0	98.4	+12.4	75.0	97.9	+22.9
avg_perf	76.2	83.7		65.3	80.1	

Improved prompts also work well on small LLMs

Table 2: Overview of results (%) on the evaluation phase. V: VirtualHome, B: BEHAVIOR.

Model	Goal Interpretation		Action Sequencing				Subgoal Decomposition				Transition Modeling				Average Perf.		Overall Perf.
	F_1		$TaskSR$		$ExecSR$		$TaskSR$		$ExecSR$		F_1		$PlannerSR$		$ModuleSR$		
	V	B	V	B	V	B	V	B	V	B	V	B	V	B	V	B	
Qwen 3 4B (+ Optimized Prompt)	23.9	39.7	58.4	39.0	67.0	56.0	54.9	43.0	79.1	54.0	30.3	35.9	43.5	46.0	43.53	40.66	42.09
	38.6	30.6	63.7	41.0	74.6	51.0	55.7	55.0	79.8	70.0	68.8	52.0	47.0	70.0	53.98	46.90	50.44
	(↑ 14.7)	(↓ 9.1)	(↑ 5.3)	(↑ 2.0)	(↑ 7.6)	(↓ 5.0)	(↑ 0.8)	(↑ 12.0)	(↑ 0.7)	(↑ 16.0)	(↑ 38.5)	(↑ 16.1)	(↑ 3.5)	(↑ 24.0)	(↑ 10.4)	(↑ 6.2)	(↑ 8.4)
Qwen 3 8B (+ Optimized Prompt)	23.4	69.7	58.4	44.0	69.5	58.0	58.9	40.0	81.3	50.0	38.3	53.7	80.2	73.0	49.99	54.26	52.13
	39.5	73.3	67.9	56.0	80.7	65.0	61.1	56.0	82.7	70.0	81.0	63.7	92.5	91.0	63.81	65.66	64.74
	(↑ 16.1)	(↑ 3.6)	(↑ 9.5)	(↑ 12.0)	(↑ 11.2)	(↑ 7.0)	(↑ 2.2)	(↑ 16.0)	(↑ 1.4)	(↑ 20.0)	(↑ 42.7)	(↑ 10.0)	(↑ 12.3)	(↑ 18.0)	(↑ 13.8)	(↑ 11.4)	(↑ 12.6)
Qwen 3 14B (+ Optimized Prompt)	24.8	71.0	66.0	46.0	82.1	58.0	62.5	45.0	82.1	53.0	43.0	59.6	63.5	44.0	51.64	53.45	52.54
	41.5	73.0	65.5	57.0	80.9	65.0	66.3	66.0	86.6	78.0	79.9	64.6	82.4	83.0	63.61	67.45	65.53
	(↑ 16.7)	(↑ 2.0)	(↓ 0.5)	(↑ 11.0)	(↓ 1.2)	(↑ 7.0)	(↑ 3.8)	(↑ 21.0)	(↑ 4.5)	(↑ 25.0)	(↑ 36.9)	(↑ 5.0)	(↑ 18.9)	(↑ 39.0)	(↑ 12.0)	(↑ 14.0)	(↑ 13.0)
Qwen 3 32B (+ Optimized Prompt)	28.0	65.5	63.2	59.0	77.3	71.0	65.9	47.0	86.3	55.0	45.4	62.5	76.2	78.0	54.48	60.44	57.46
	39.4	68.5	67.4	63.0	81.1	72.0	66.3	66.0	85.7	79.0	78.2	68.3	84.4	89.0	63.60	69.04	66.32
	(↑ 11.4)	(↑ 3.0)	(↑ 4.2)	(↑ 4.0)	(↑ 3.8)	(↑ 1.0)	(↑ 0.4)	(↑ 19.0)	(↓ 0.6)	(↑ 24.0)	(↑ 32.8)	(↑ 5.8)	(↑ 8.2)	(↑ 11.0)	(↑ 9.1)	(↑ 8.6)	(↑ 8.9)
Qwen 3 30B A3B (+ Optimized Prompt)	26.80	79.10	69.30	53.00	81.50	68.00	61.10	56.00	83.90	66.00	36.70	49.70	82.10	69.00	54.15	61.86	58.01
	42.80	69.70	70.00	54.00	83.60	65.00	64.30	73.00	86.10	88.00	75.60	61.50	92.60	88.00	65.30	67.86	66.58
	(↑ 16.00)	(↓ 9.40)	(↑ 0.70)	(↑ 1.00)	(↑ 2.10)	(↓ 3.00)	(↑ 3.20)	(↑ 17.00)	(↑ 2.20)	(↑ 22.00)	(↑ 38.90)	(↑ 11.80)	(↑ 10.50)	(↑ 19.00)	(↑ 11.15)	(↑ 6.00)	(↑ 8.6)

Main changes in improved prompts via our interactive induction

- Rules and checklist
- Templates for common tasks

However, LLMs can still hallucinate and make mistakes

- Double check templates for correctness
- Add in a few more rules
- *Minimal manual effort*, as LLM has already done the bulk of the work

```
8. If you want to apply an action on an object, you should WALK to it.

9. If an object is placed with a grabbable container, the container must be OPEN.

Rules and recipes to avoid common mistakes (follow strictly):

R1. Always WALK before acting on an object.
- Before applying ANY action to an object, first WALK to that object.
- You may skip WALK only if the input explicitly states the character is already at the object.

R2. Use PLUGIN only when required by the state.
- Use PLUGIN only if the device has HAS_PLUG and its node state is PLUGGED.
- If it is already PLUGGED_IN (or no plug state is given), do not use PLUGIN.

R3. Canonical action sequences (maintain this order):
- Power and use an electric device (e.g., computer, light, stove): WALK device → (PLUGIN if PLUGGED_OUT) → SWITCHON device → THING.
- Washing hands/dishes: WALK faucet or sink area → SWITCHON faucet/sink → WASH → RINSE.
- Getting a drink: WALK container (cup/glass) → GRAB container → OPEN → POUR → DRINK.

R4. Containers and access:
- If an object is INSIDE a CLOSED container, WALK the container to it and OPEN it.

R5. Goal-aligned final actions:
- For "character is ON to X": make SIT or LIE on X the last action.
- For "character is FACING/CLOSE to X": include TURNTO/LOOKAT/GO TO X.

R6. Avoid redundancy and no-ops:
- Do not repeat the same action on the same object consecutively.
- Do not act on irrelevant objects (e.g., WASH faucet itself).

R7. Prefer WALK over FIND when IDs are provided.
- Since inputs include object IDs, directly WALK to the target object.

R8. Never include <character> as an action object.
- The subject is always the character; action arguments must be objects.

Submission checklist (verify before outputting):
- Every acted-on object has a preceding WALK unless NEAR is explicitly used.
- Devices to be used are SWITCHON before TYPE/WATCH/other usage.
- For washing: WASH occurs before RINSE.
- For items inside containers: OPEN precedes GRAB/PUTIN/PUTBACK.
- No duplicate consecutive actions on the same object; stop after the first successful action.
- Output is a pure JSON array with correct action objects and correct IDs.
```

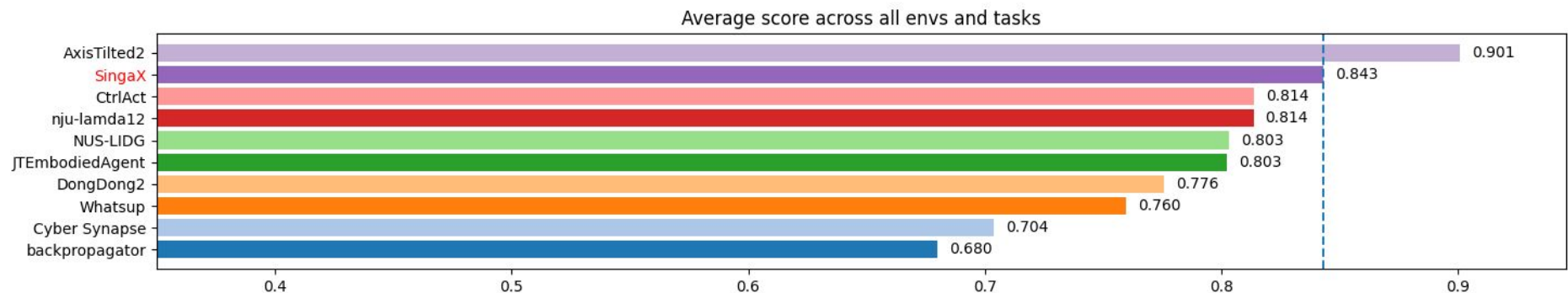
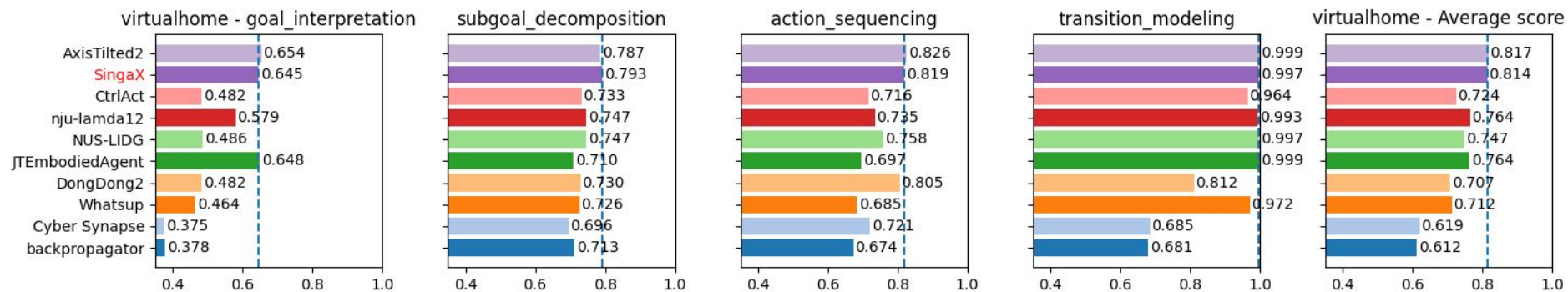
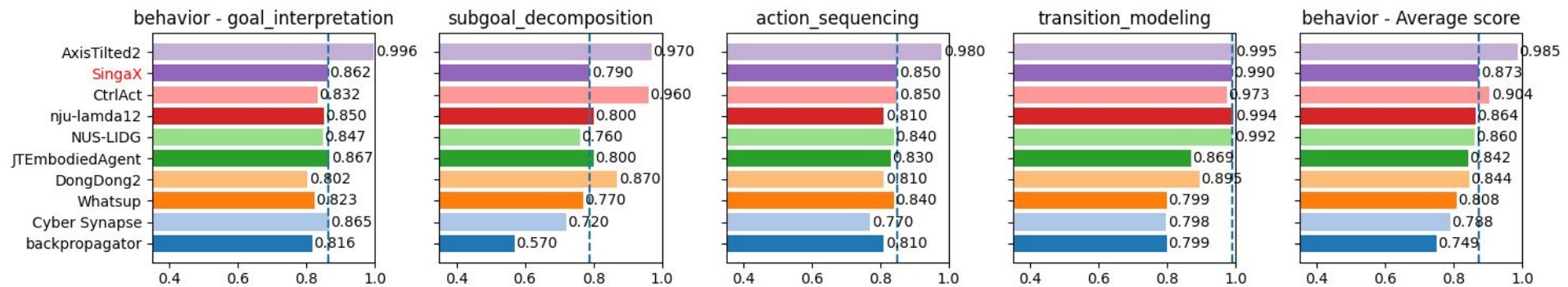
Further improvements (Test set)

	behavior			virtualhome			
	dev/test set			dev set		test set	
	Default prompt	Ours	Ours + edits	Default prompt	Ours	Ours	Ours + edits
goal_interpretation (f1)	79.7	82.3	86.2	43.6	61.1	46.5	64.5
subgoal_decomposition (task sr)	69.0	77.0	79.0	90.5	92.9	72.6	79.3
action_sequencing (task sr)	79.0	84.0	85.0	65.9	77.0	70.8	92.0
transition_modeling (f1)	67.9	84.5	98.9	47.3	81.0	96.0	99.5
transition_modeling (sr)	86.0	98.4	99.0	75.0	97.9	98.5	99.9
avg_perf	76.2	83.7	87.3	65.3	80.1	71.8	81.4

Key strength — Cost effective

- Training-free
- Only require 1 round of query using dev set
- Qwen3-235B-Thinking total cost: 3.75 USD in dev phase, and 17.41 USD in test phase.

Environment	Task	Dev set			Test set		
		Mean token length		Cost for task (\$)	Mean token length		Cost for task (\$)
		Prompt	Output		Prompt	Output	
behavior	goal_interpretation	1216	5717	0.36	2119	5229	0.35
	subgoal_decomposition	2657	12014	0.75	3683	8851	0.58
	action_sequencing	3415	8188	0.53	3701	7298	0.50
	transition_modeling	3414	10399	0.66	3660	8352	0.57
virtualhome	goal_interpretation	1874	7706	1.65	2994	5513	5.46
	subgoal_decomposition	3056	7225	1.58	3571	8386	8.14
	action_sequencing	2256	5264	1.16	3336	5777	5.75
	transition_modeling	3635	9902	1.88	5398	8681	8.70
Total cost				3.75			17.41



Remaining performance gap in behavior env

- Some problems have specific ground truth
- Cannot be resolved without overfitting to specific problems

```
1 v["all_unsatisfied_conditions"]  
✓ 0.0s  
[['ontop', 'gym_shoe.n.01_1', 'table.n.02_2'],  
 ['ontop', 'necklace.n.01_1', 'table.n.02_2'],  
 ['ontop', 'notebook.n.01_1', 'table.n.02_2'],  
 ['ontop', 'sock.n.01_1', 'table.n.02_2'],  
 ['ontop', 'sock.n.01_2', 'table.n.02_2']]
```

```
1 v["false_positive_conditions"]  
✓ 0.0s  
[['ontop', 'gym_shoe.n.01_1', 'table.n.02_1'],  
 ['ontop', 'necklace.n.01_1', 'table.n.02_1'],  
 ['ontop', 'notebook.n.01_1', 'table.n.02_1'],  
 ['ontop', 'sock.n.01_1', 'table.n.02_1'],  
 ['ontop', 'sock.n.01_2', 'table.n.02_1']]
```

```
Relevant objects in the scene are:  
gym_shoe.n.01_1: ['Stained', 'Dusty']  
necklace.n.01_1: ['Stained', 'Dusty']  
notebook.n.01_1: ['Dusty']  
sock.n.01_1: ['Stained', 'Dusty']  
sock.n.01_2: ['Stained', 'Dusty']  
table.n.02_1: ['Stained', 'Dusty']  
table.n.02_2: ['Stained', 'Dusty']  
cabinet.n.01_1: ['Stained', 'Open', 'Dusty']  
sofa.n.01_1: ['Stained', 'Dusty']  
floor.n.01_1: ['Stained', 'Dusty']  
floor.n.01_2: ['Stained', 'Dusty']
```

```
All initial states in the scene are:  
['under', 'gym_shoe.n.01_1', 'table.n.02_1']  
['onfloor', 'gym_shoe.n.01_1', 'floor.n.01_2']  
['inside', 'necklace.n.01_1', 'cabinet.n.01_1']  
['under', 'notebook.n.01_1', 'table.n.02_2']  
['ontop', 'sock.n.01_1', 'sofa.n.01_1']  
['onfloor', 'sock.n.01_2', 'floor.n.01_1']  
['onfloor', 'agent.n.01_1', 'floor.n.01_1']
```

Task Name and Goal Instructions:

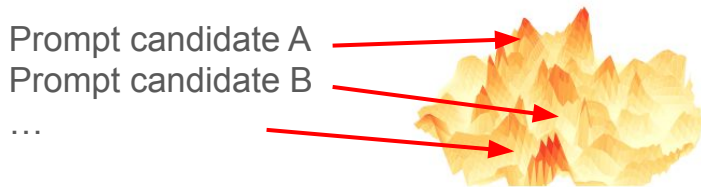
```
{  
  "Task Name": "collect_misplaced_items",  
  "Goal Instructions": "Collect all misplaced items including the  
gym shoe, necklace, notebook, and socks. Then place them on the  
table."  
}
```

Other stuff we tried

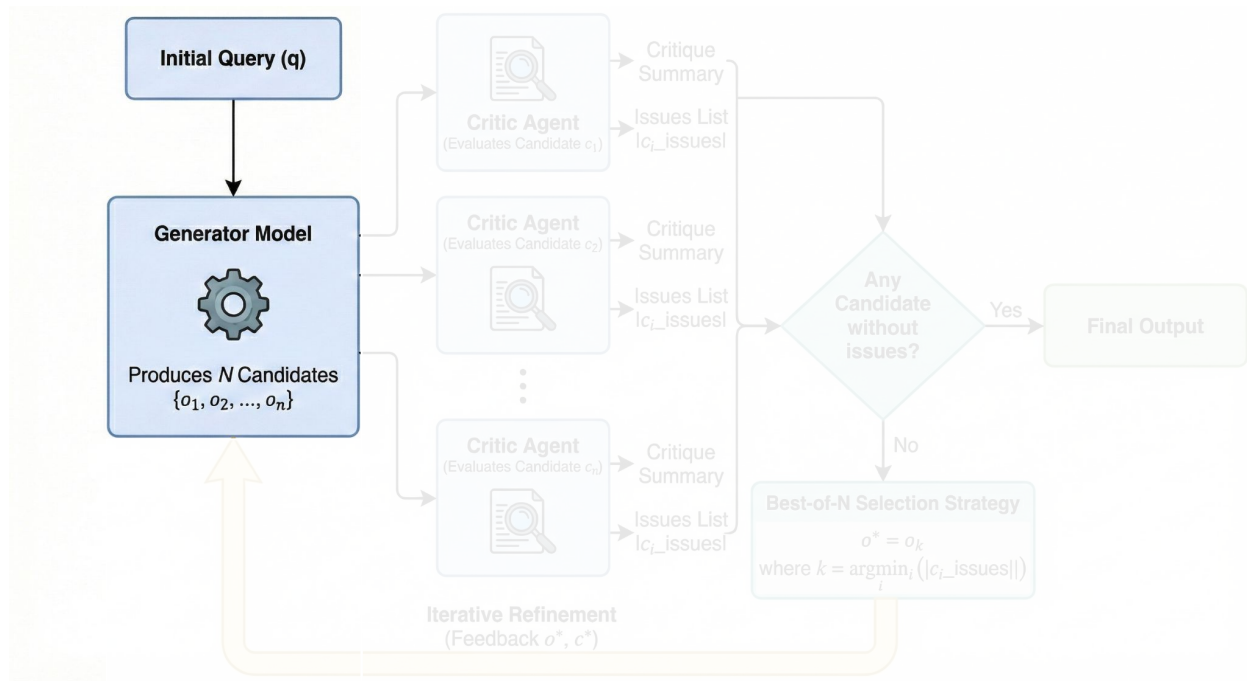
Prompt Optimization

We optimize the prompts used for each task in the following manner:

1. Use the LLM to generate 200 different possible prompt candidates (candidate pool) from the original prompts given by the organizer.
2. Project each prompt into a latent semantic embedding space using an off-the-shelf embedding model.
3. Apply Bayesian Optimization (BO) over the prompt candidates:
 - a. Progressively estimates the approximate performance landscape and retrieves the prompt that has the best performance estimate from this landscape.
4. Yields approximately 4-5% improvements.



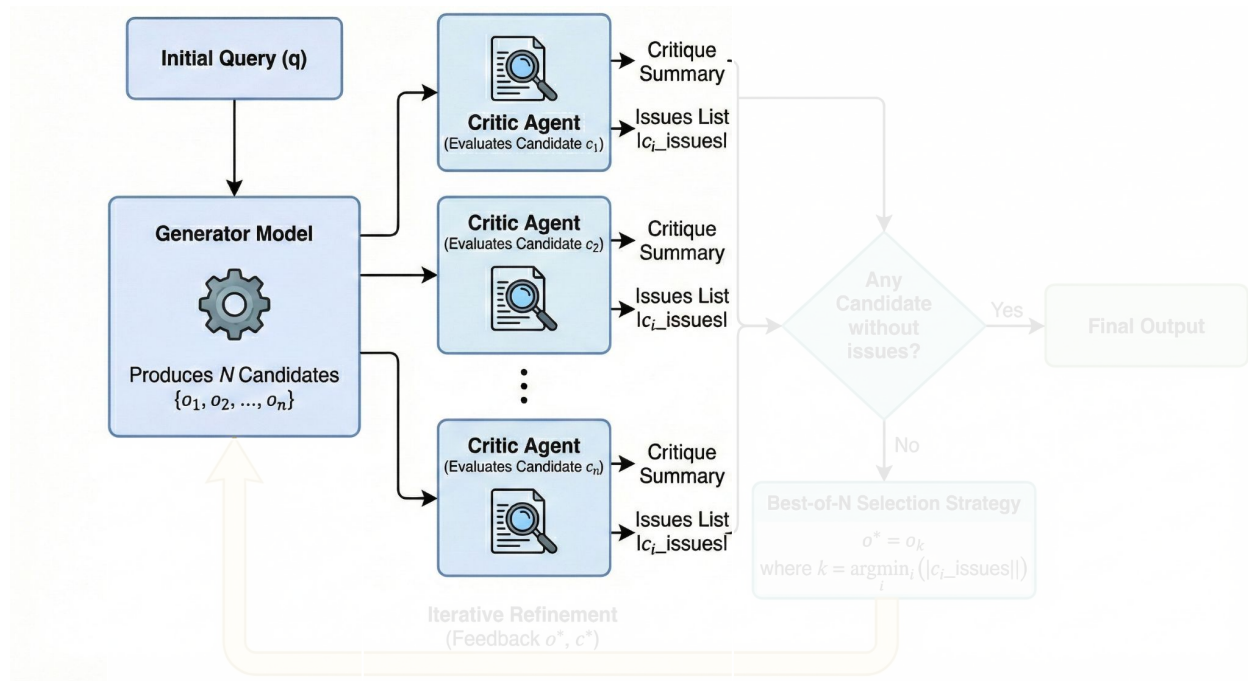
Critic Best-of-N (Critic BoN) Framework



1. Generation Phase:

Given the initial query, the generator model produces N candidate outputs.

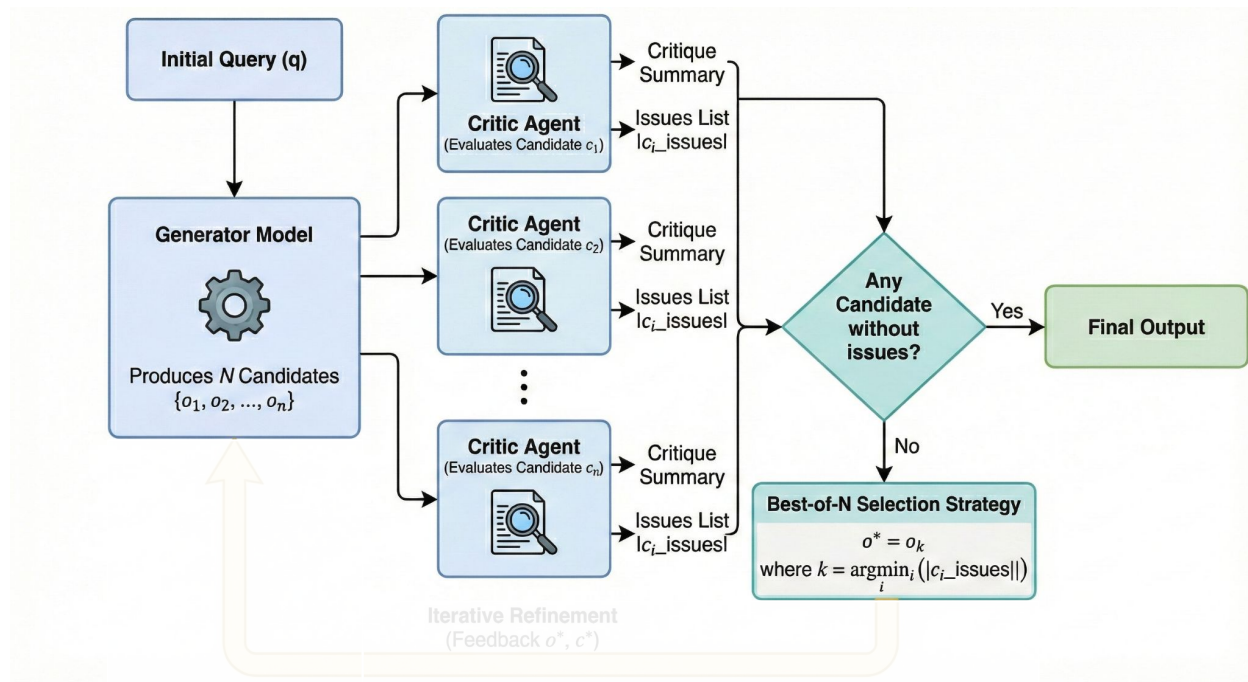
Critic Best-of-N (Critic BoN) Framework



2. Critic Phase:

A Critic Agent checks every candidate against a predefined checklist and outputs any identified issues.

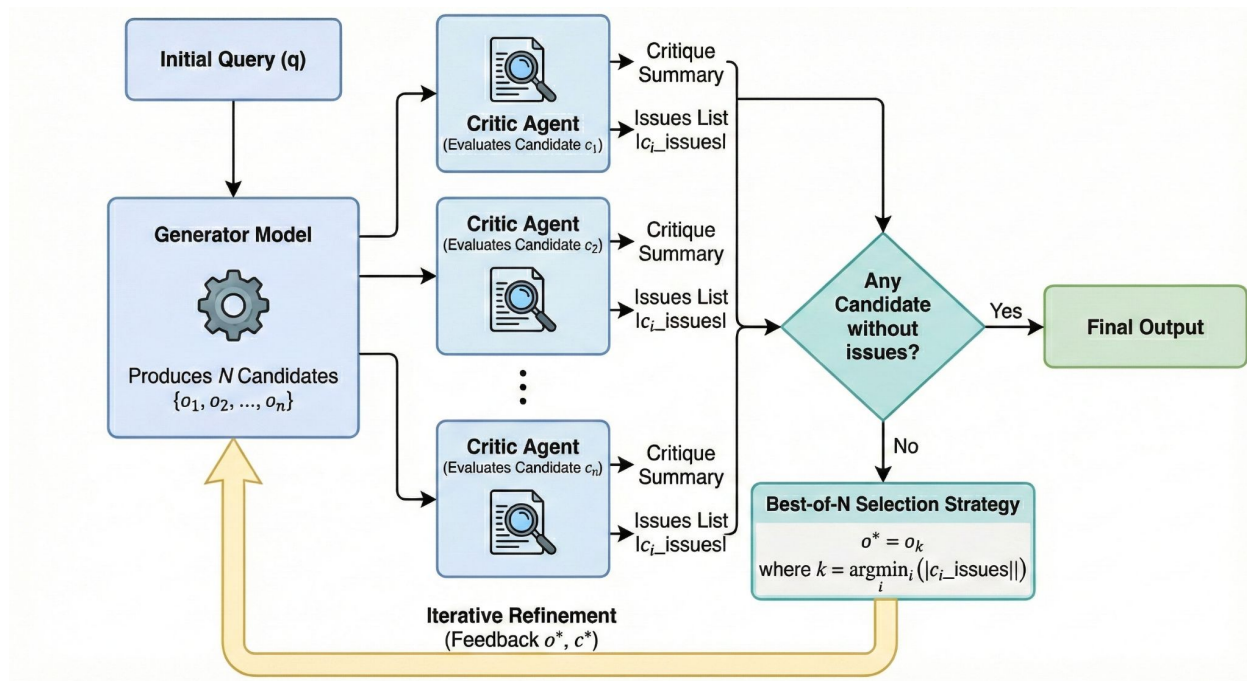
Critic Best-of-N (Critic BoN) Framework



3. Decision Logic:

- (a) If a candidate has zero issues, it is accepted as the final output.
- (b) If all candidates contain errors, the framework defaults to the Best-of-N strategy.

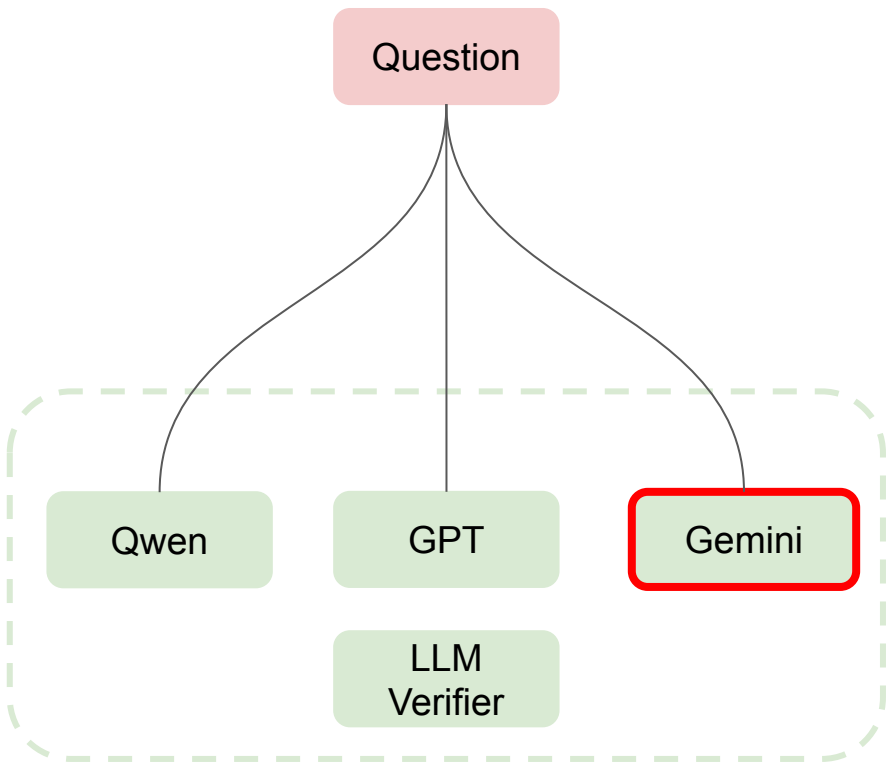
Critic Best-of-N (Critic BoN) Framework



4. Refinement Loop:

The selected candidate and its corresponding critique are provided to the generator model, which then iteratively refines its output based on this feedback.

Multi-Model Best-of-N at Test Time



- Baseline BoN: Sample N answers from one LLM and let a verifier pick the best.
- Multi-Model BoN: For each question, query three heterogeneous LLMs (Qwen, GPT, Gemini) and treat their outputs as N=3 candidates.
- Verifier selection: An LLM verifier scores candidates on JSON format, constraint satisfaction, and task quality, then selects the best answer.
- Benefit: Better robustness and accuracy from model diversity, with no extra training.

Thank you for your time!