



TEAM
80

TM12.0

DEVREV AI AGENT 007

TOOLING UP FOR SUCCESS





DEMO

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Upload API Examples

Drag and drop file here
Limit 200MB per file • JSON

Browse files

examples.json 6.7KB

X

Submit

Valid Key Found!!

API Description Loaded ✓

Examples Loaded ✓

Choose Model

gpt-3.5-turbo

Prompting Technique ⓘ

None

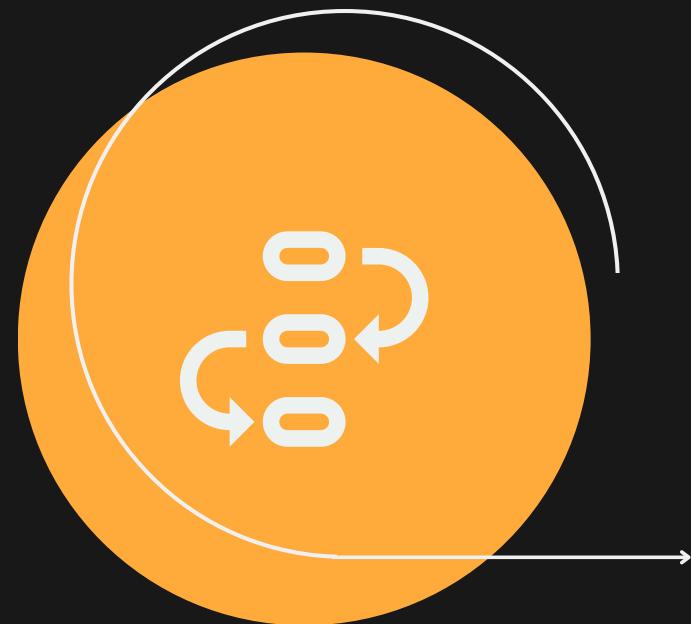
PRO

What is up? >

This screenshot shows a user interface for uploading API examples. At the top, there's a section for "Upload API Examples" with a "Drag and drop file here" input field, which has "examples.json 6.7KB" listed under it. Below this is a "Browse files" button and a close "X" button. A "Submit" button is also present. Below the file upload area, three green success messages are displayed: "Valid Key Found!!", "API Description Loaded ✓", and "Examples Loaded ✓". The "Examples Loaded ✓" message has a white cursor icon pointing towards it from the right side of the screen. Further down, there's a "Choose Model" dropdown set to "gpt-3.5-turbo", a "Prompting Technique" section with "None" selected, and a text input field containing "What is up?" with a right-pointing arrow button.



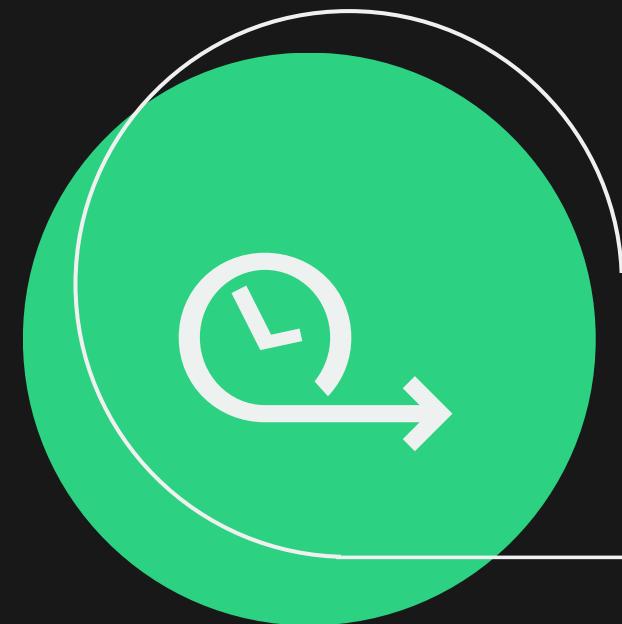
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METHODOLOGY



PERFORMANCE

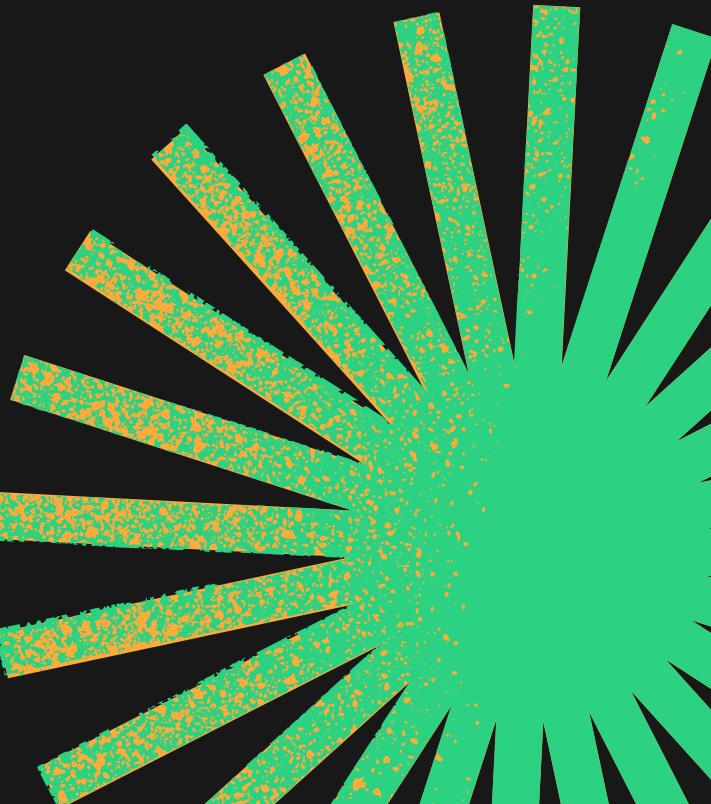


FUTURE
SCOPE



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METHODOLOGY

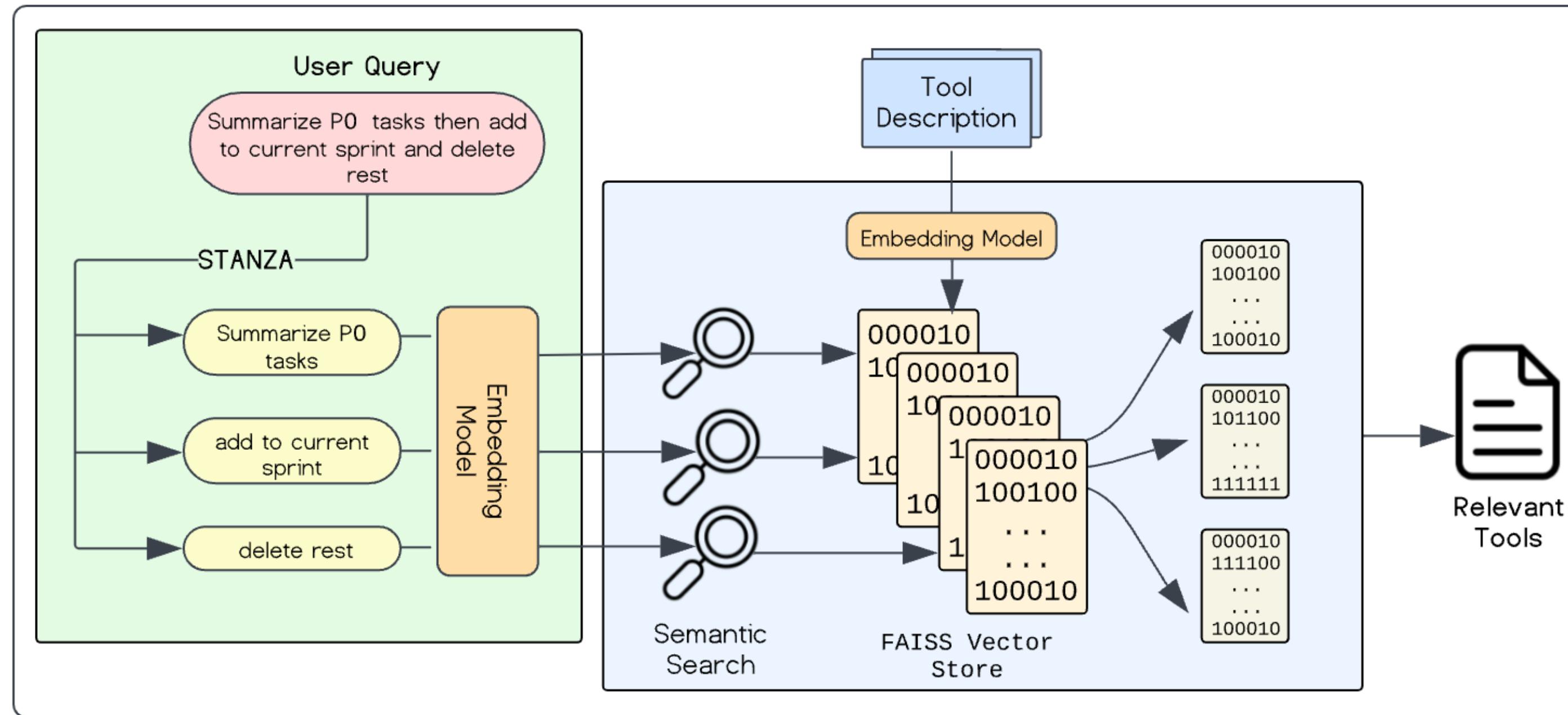




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TOOL RETRIEVAL

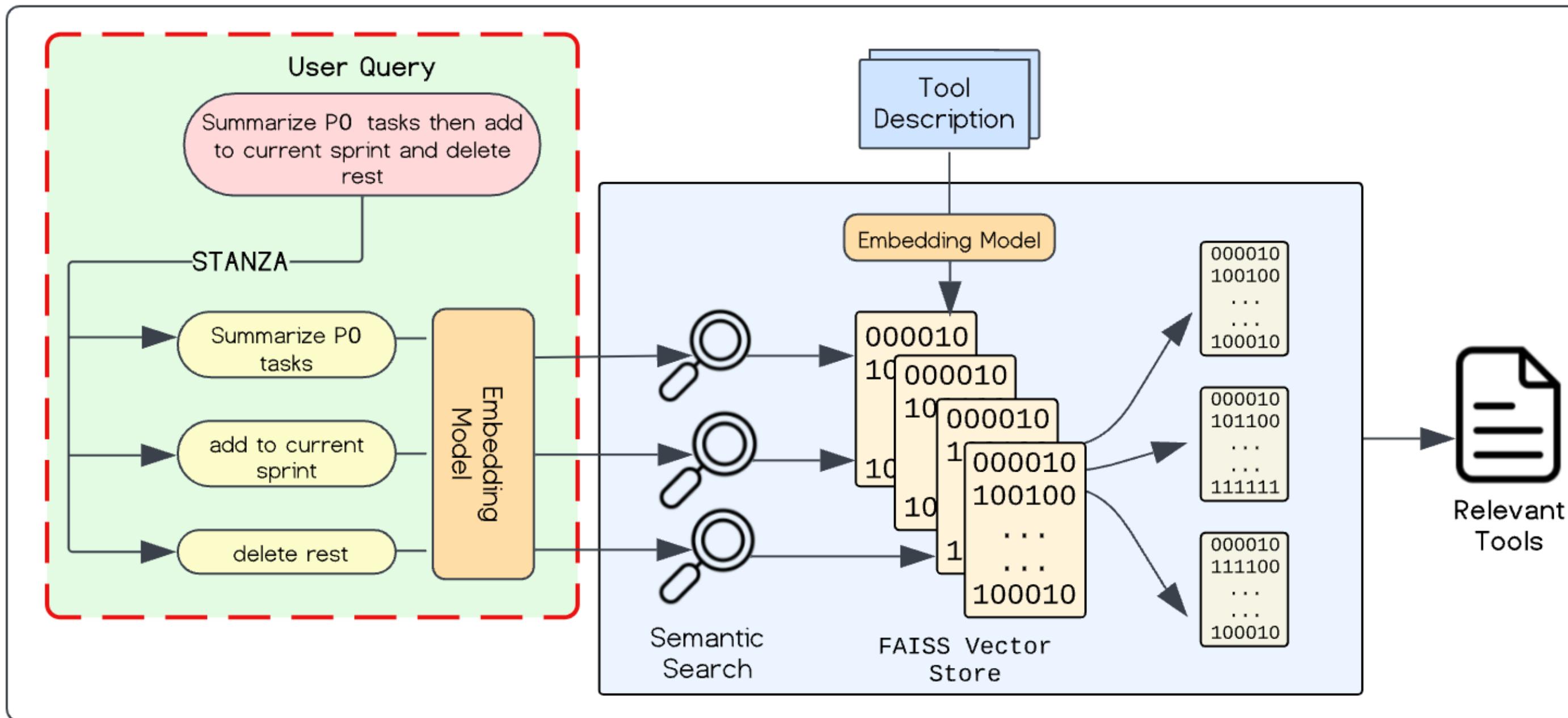




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TOOL RETRIEVAL

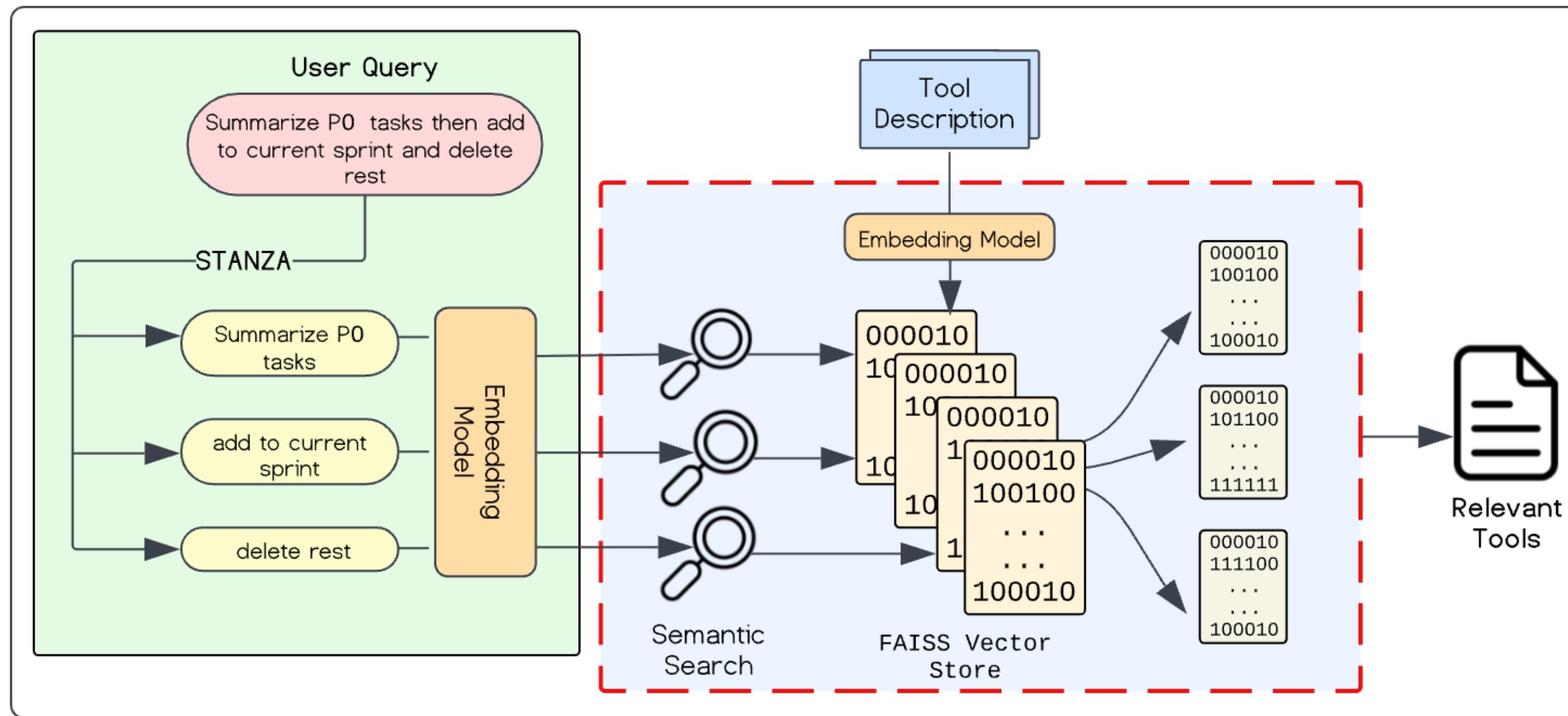




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TOOL RETRIEVAL





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ANSWER GENERATION



LLM SELECTION

- Chosen Model : **gpt-3.5-turbo**
- Offers best balance between accuracy and cost-efficiency

PROMPTING

- Prompts modulate model responses
- Our Method : **PIRO Prompting**
- Optimized for **gpt-3.5-turbo**



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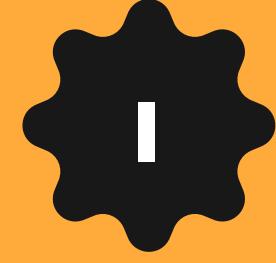


PIRO PROMPTING



PLANNING

Given the list of tools, we ask the model to create an ordered skeleton of tools it needs to solve the user query.



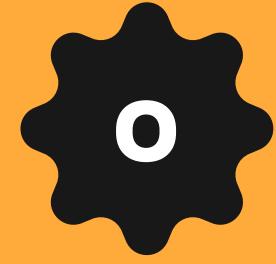
IMPROVEMENT

Provided the relevant tools and examples demonstrating their usage, we ask the model to improve its answer and rectify any argument errors



REFLECTION

For GPT3.5, the model reflects on its answer based on the given information about tools and their examples, to fix the solution, if required.



OPTIMIZATION

Finally, the model optimizes its solution, and removes any redundant API calls, and unnecessary arguments.



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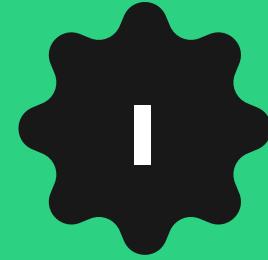


PIRO PROMPTING



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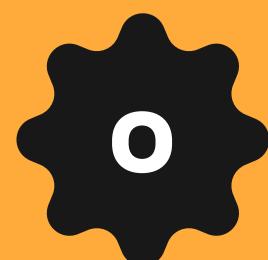
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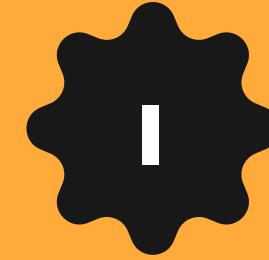


PIRO PROMPTING



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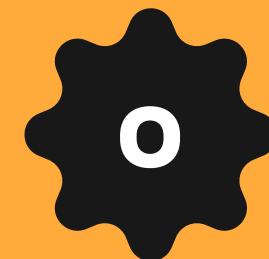
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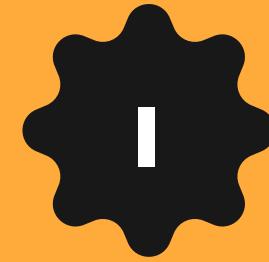


PIRO PROMPTING



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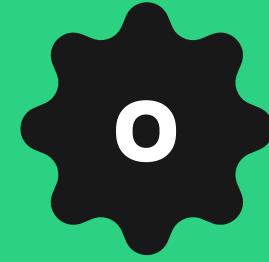
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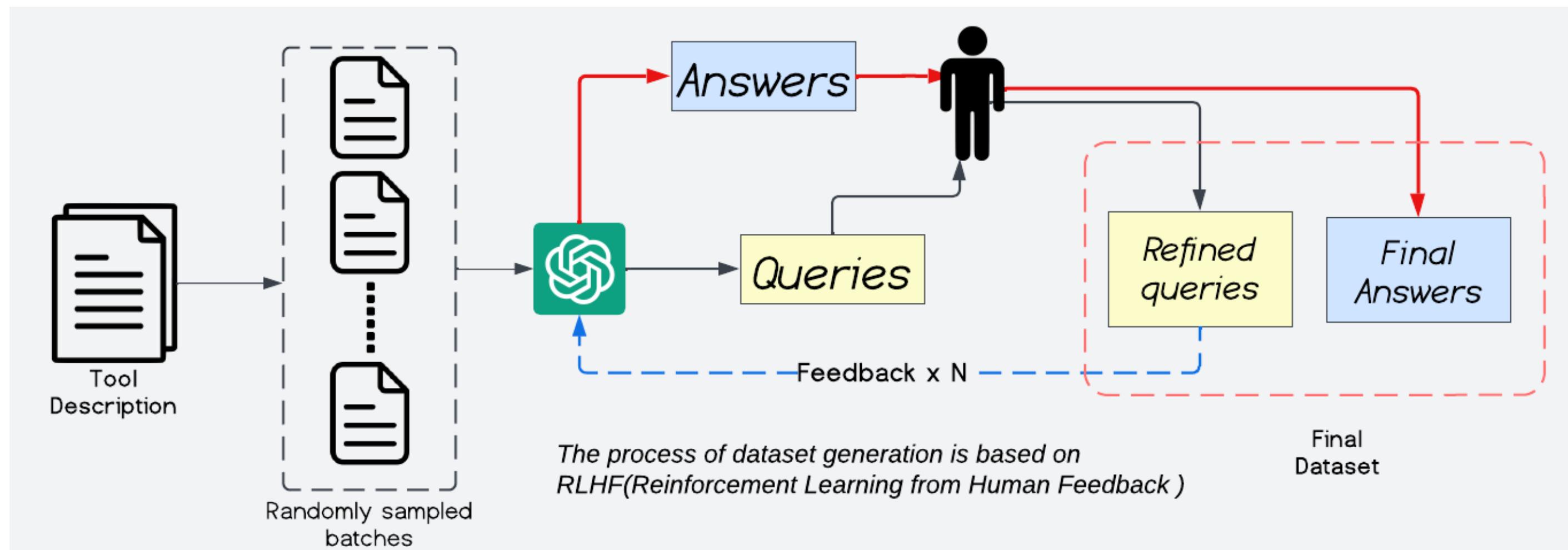


OPTIMIZATION

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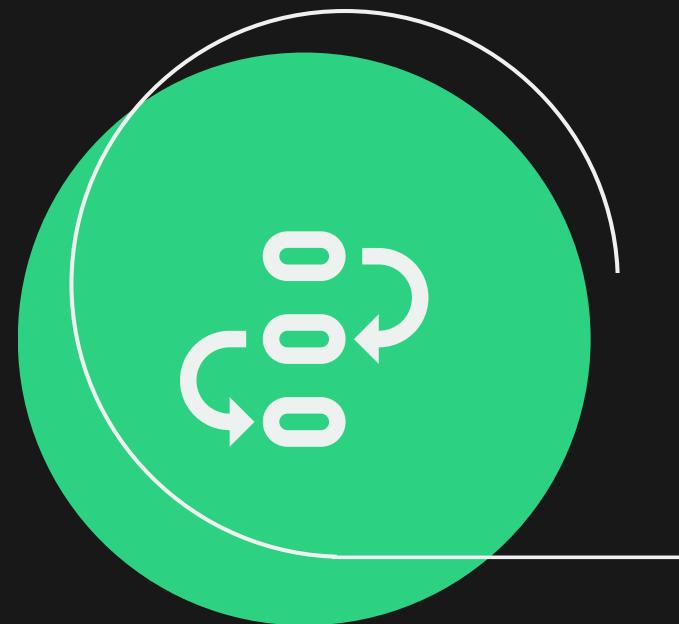


DATASET GENERATION





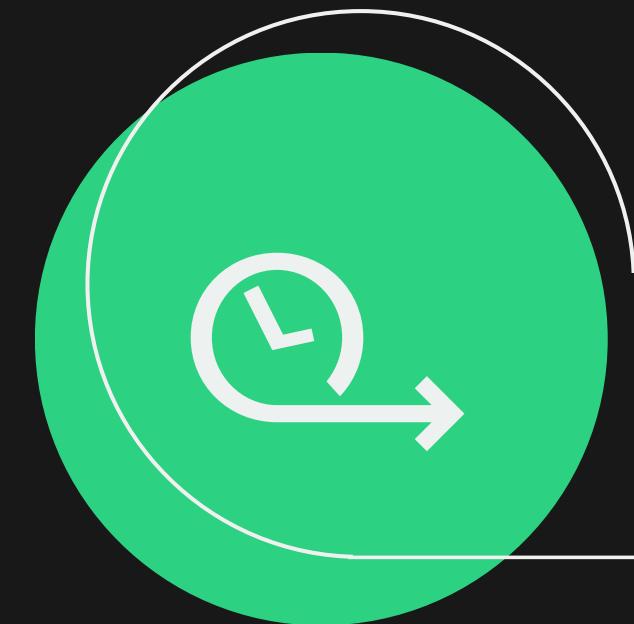
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METHODOLOGY



PIPELINE
PERFORMANCE

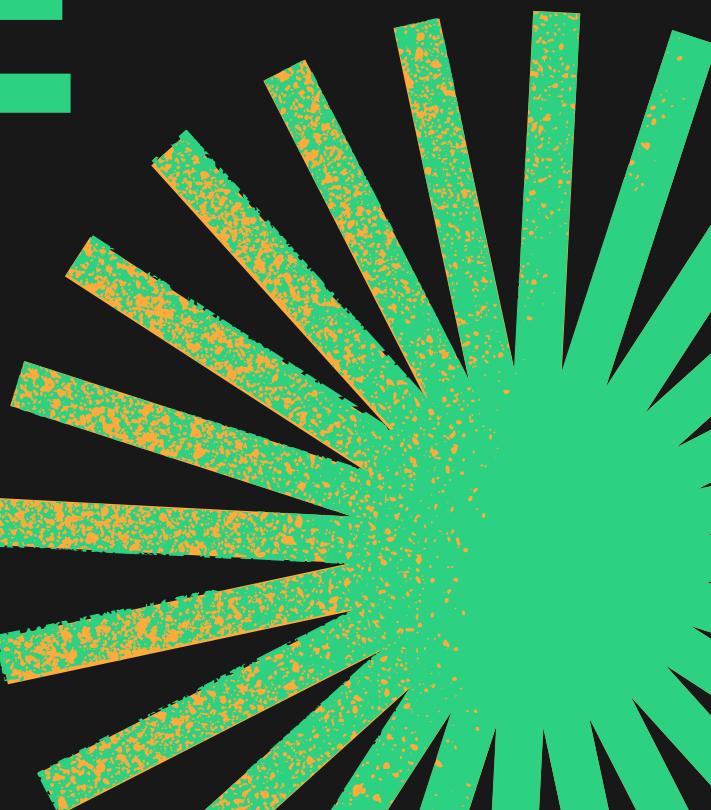


FUTURE
SCOPE



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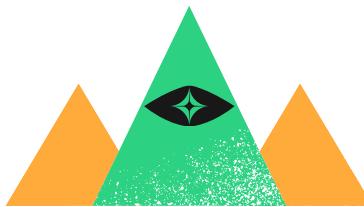
PIPELINE PERFORMANCE





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OUR PERFORMANCE



AVERAGE INFERENCE TIME

GPT 4 (with PRO)	30s
GPT 4 Turbo (with PRO)	39s
Human Performance	76s
GPT 3.5 Turbo(with PIRO)	19s

ACCURACY- D1* DATASET

GPT 4 Turbo	65%
Human Performance	80%
GPT 3.5 Turbo	65%

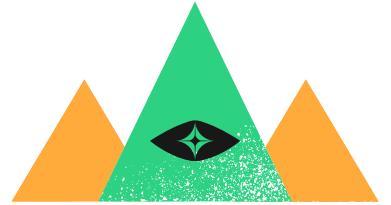
ACCURACY- D2* DATASET

GPT 4 Turbo	26%
Human Performance	46%
GPT 3.5 Turbo	24%

* D1 - Smaller DevRev Dataset; D2 - Larger DevRev Dataset



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INFERENCE COST

Model Name	Num Tokens	Cost/Query
GPT 4	5000	\$ 0.165
GPT 4 Turbo	5000	\$ 0.055
GPT 3.5 Turbo	6500	\$ 0.007



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HOW WE GOT HERE

Baseline

GPT 3.5 Turbo

25%



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HOW WE GOT HERE

Baseline	GPT 3.5 Turbo	25%
PRO prompting	GPT 3.5 Turbo	40%



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HOW WE GOT HERE

Baseline	GPT 3.5 Turbo	25%
PRO prompting	GPT 3.5 Turbo	40%
PIRO prompting	GPT 3.5 Turbo	55%



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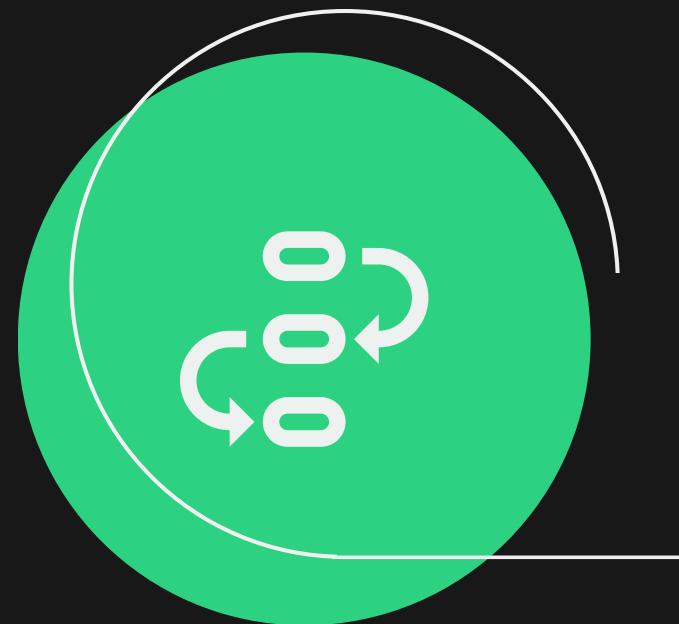


HOW WE GOT HERE

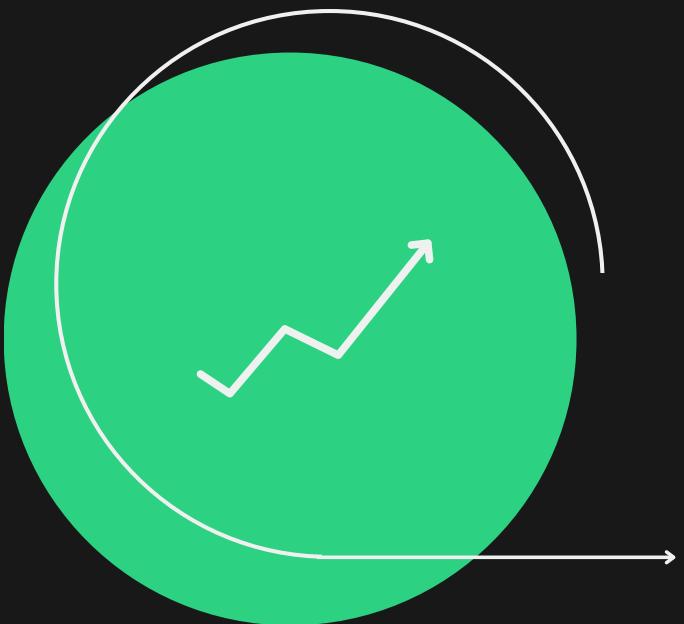
Baseline	GPT 3.5 Turbo	25%
PRO prompting	GPT 3.5 Turbo	40%
PIRO prompting	GPT 3.5 Turbo	55%
PIRO prompting+Stanza	GPT 3.5 Turbo	65%



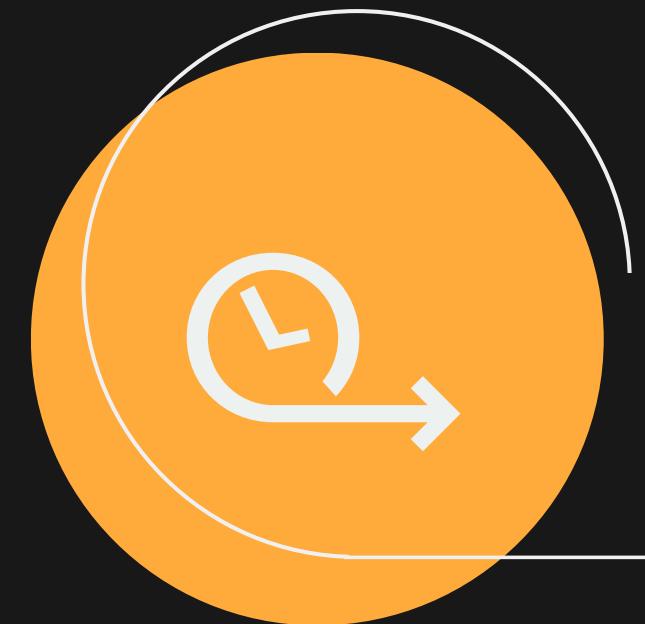
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METHODOLOGY



PIPELINE
PERFORMANCE

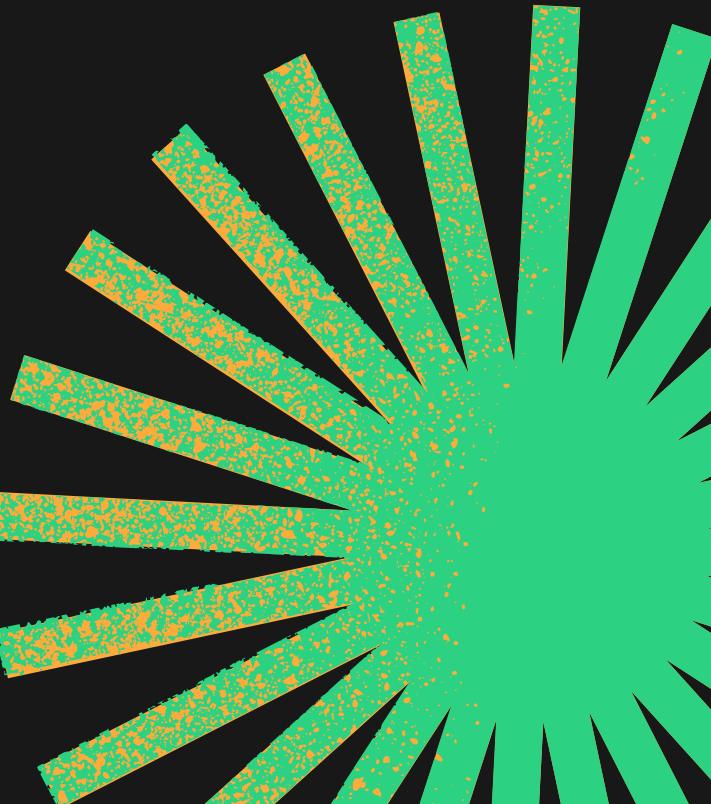


FUTURE
SCOPE



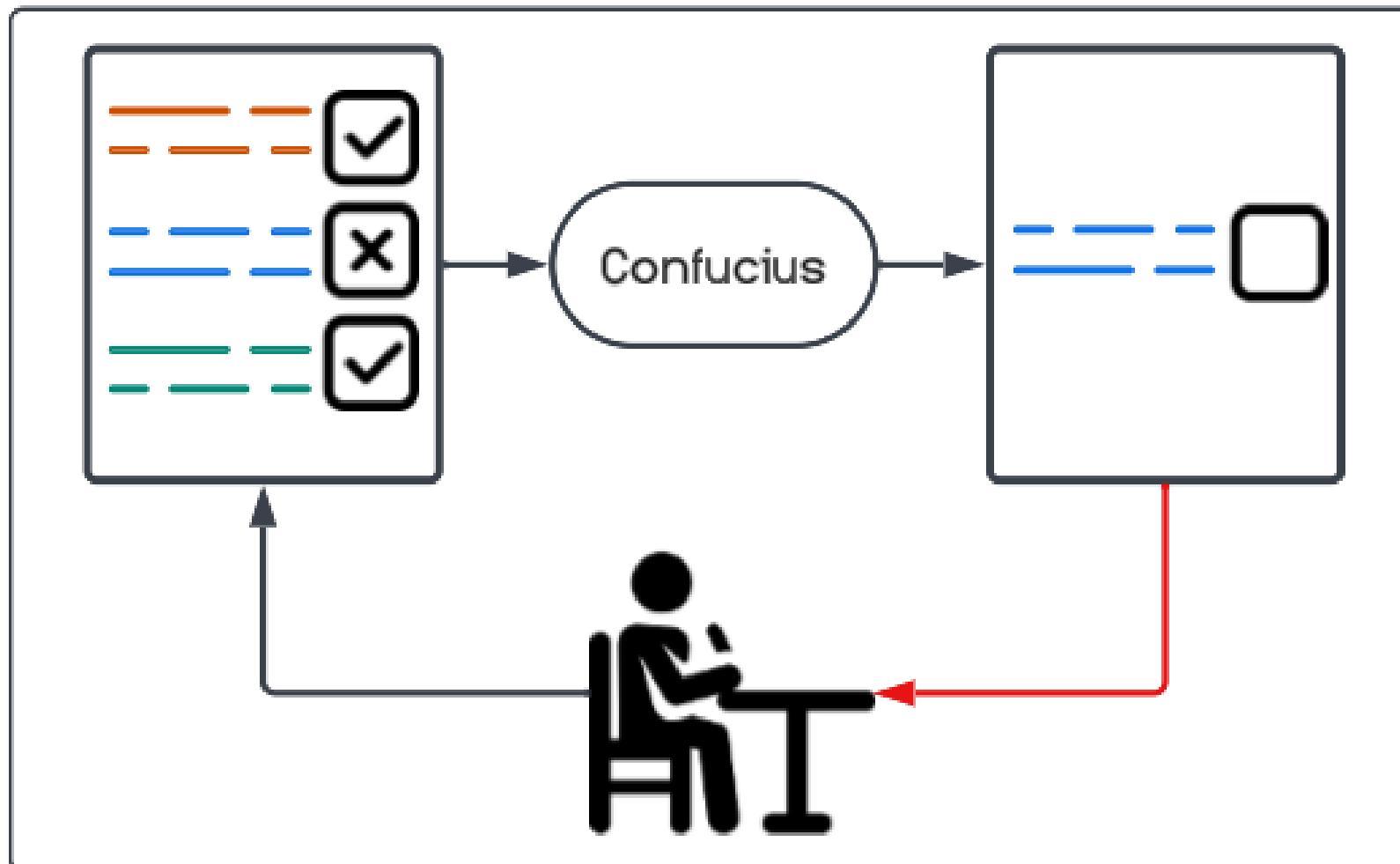
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FUTURE SCOPE





CONFUCIUS

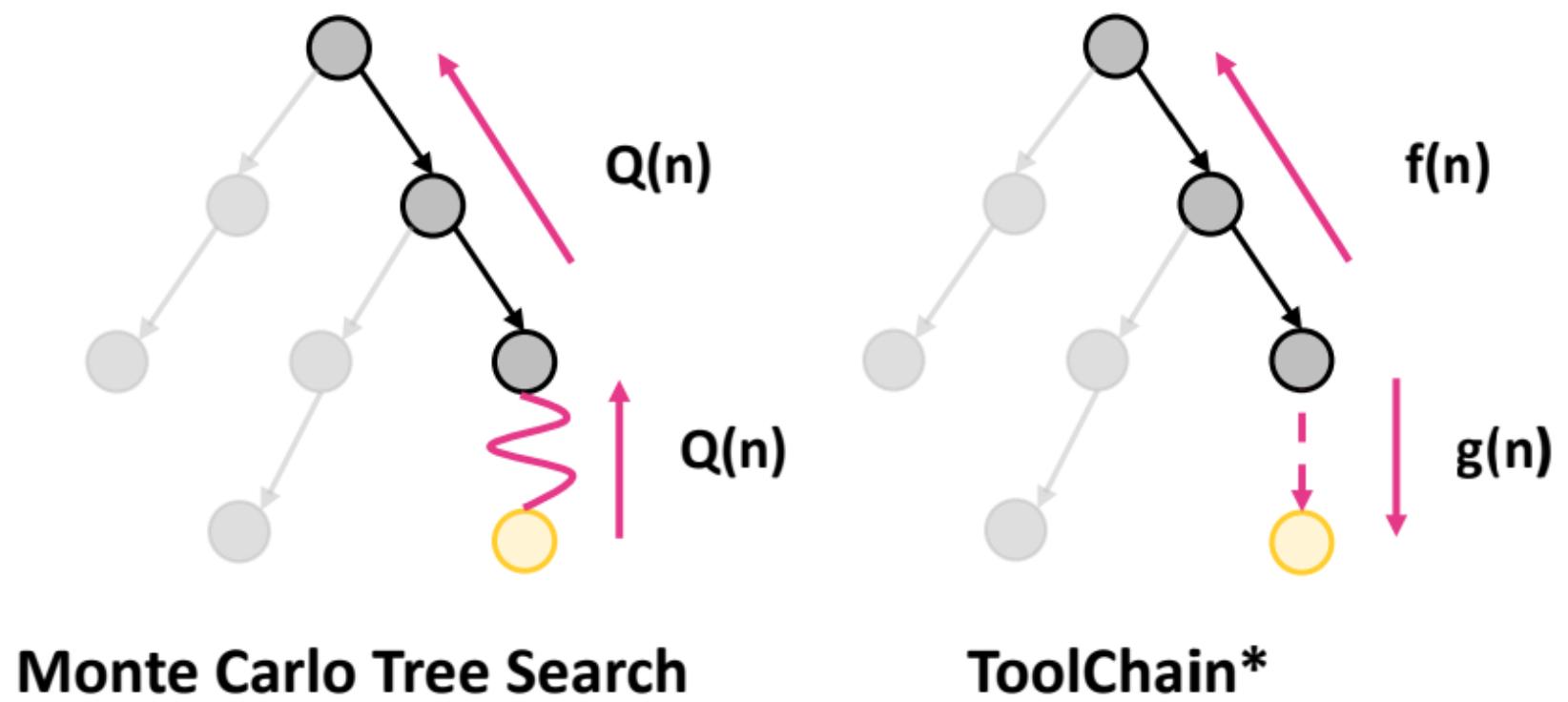


An overview of Confucius

- Confucius is a tool learning framework for LLMs
- Unlike existing self-instruction methods, Confucius takes the complexity of the tool into account during learning
- It emphasizes the tools that the model struggles with to make new test sets
- The model faces more questions based on the hardest tools



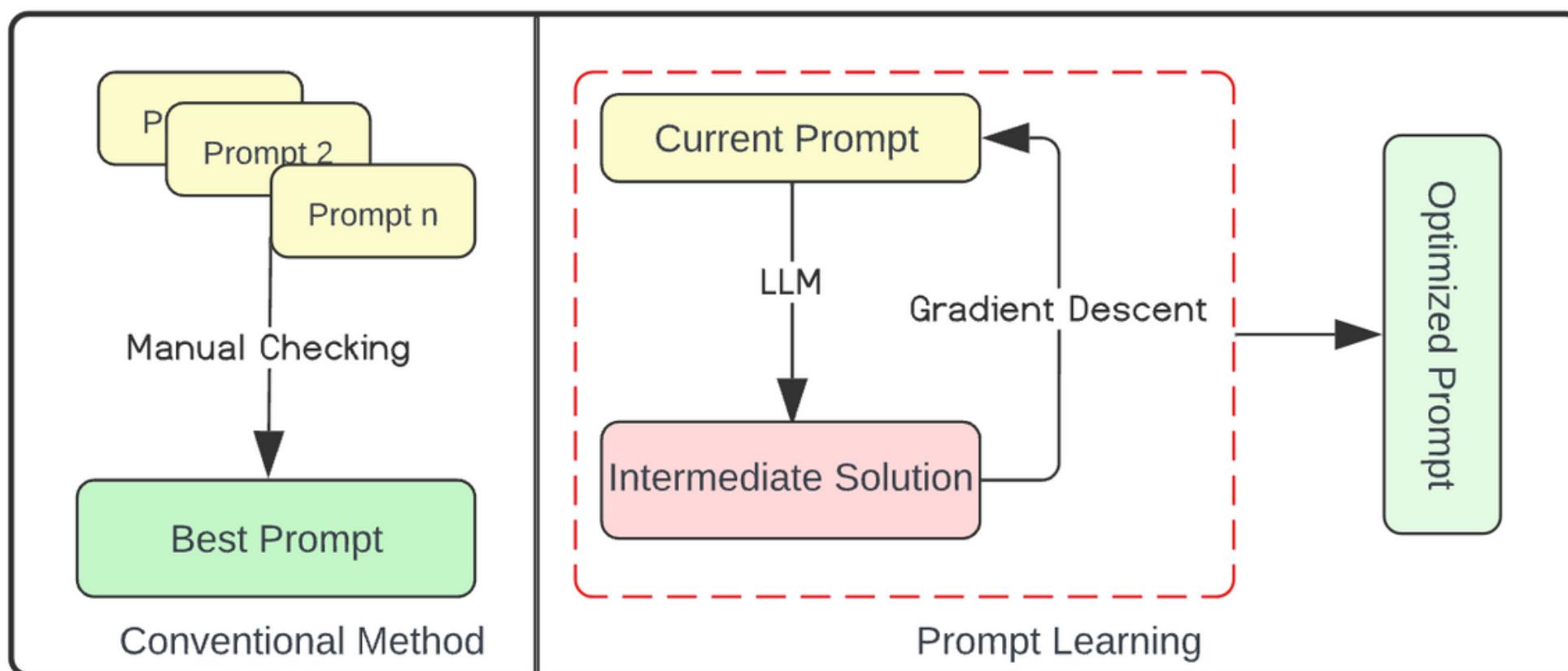
TOOLCHAIN*



- The available search space grows exponentially with the number of APIs.
- Toolchain* aims to make this search efficient.
- It uses the expected future cost to traverse trees.
- It is faster than popular traversal algorithms like DFS and MCTS.
- It also reduces snowball effects where one small error can render the entire solution incorrect.



PROMPT LEARNING



A comparison between prompt learning and the conventional method of prompt tuning

- Prompt learning arrives at the optimal prompt using gradient descent.
- Model weights are frozen, and only prompt parameters are learnt.
- Prompt parameters are learnt through likelihood maximization.
- This is cheaper and more stable than fine tuning.



THANK YOU!

Questions are Welcome



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