18th USENIX Symposium on Operating Systems Design and Implementation

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Parrot: Efficient Serving of LLM-based Applications with Semantic Variable

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https://github.com/microsoft/ParrotServe

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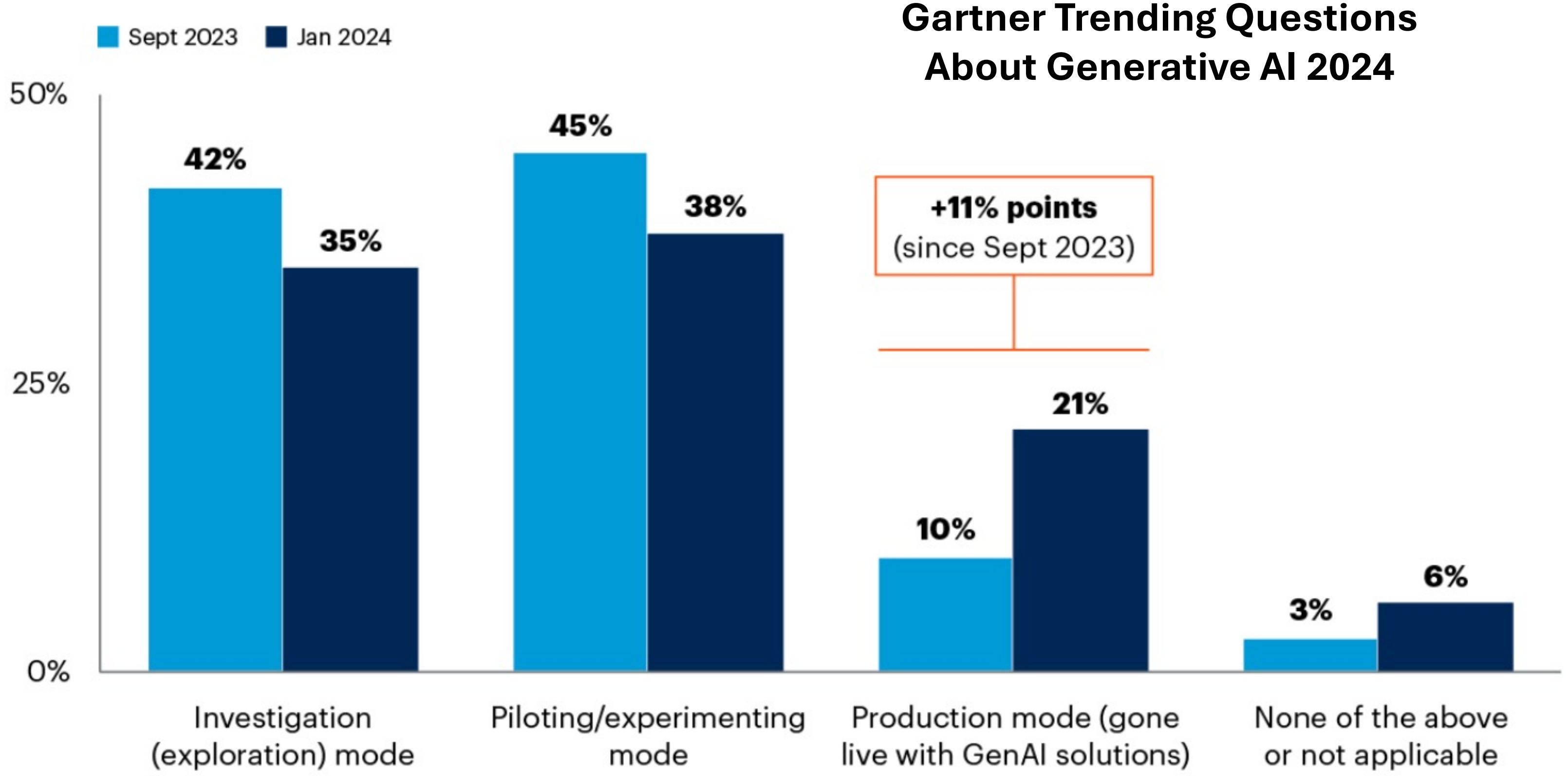
Paradigm Shift of Computer Programs

- A novel type of program (LLM + Code) are shaping the future
  - Ability of understanding semantics beyond bits
  - Complex planning

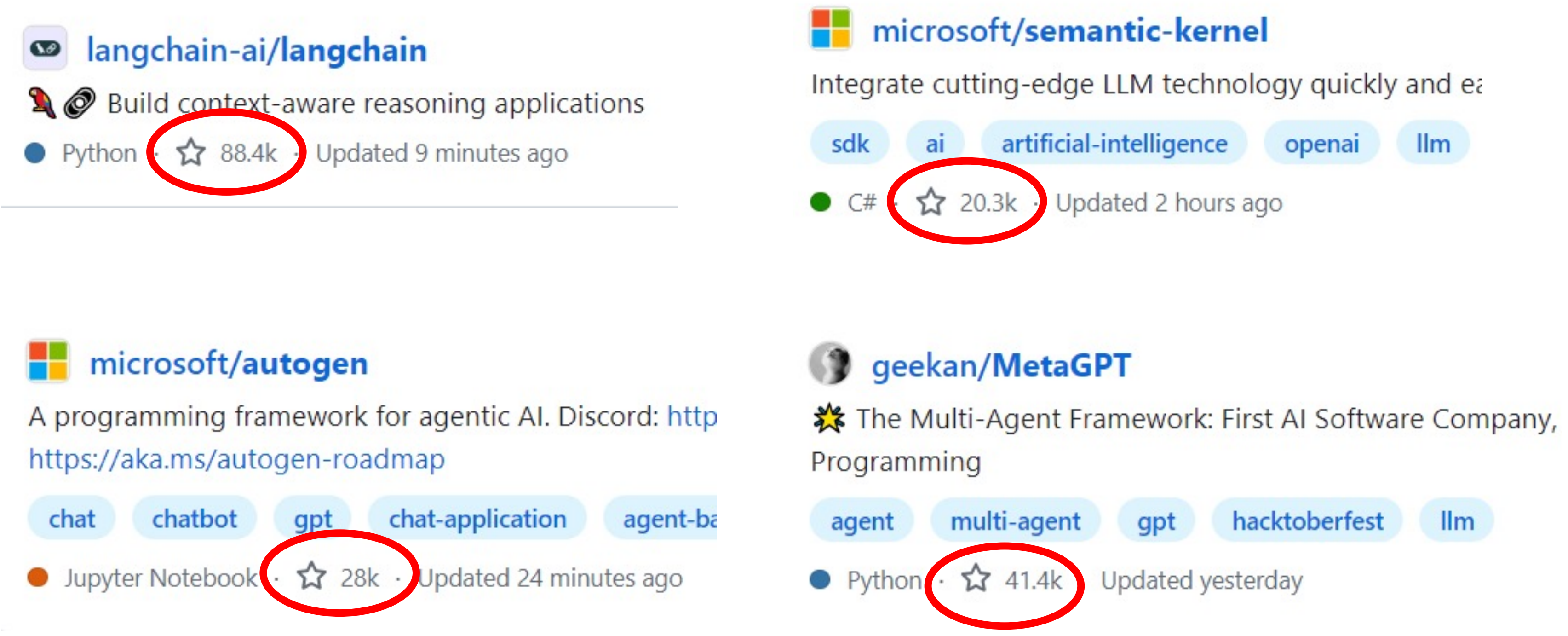
Gartner Trending Questions About Generative AI 2024



Increased Adoption of GenAI in production

Paradigm Shift of Computer Programs

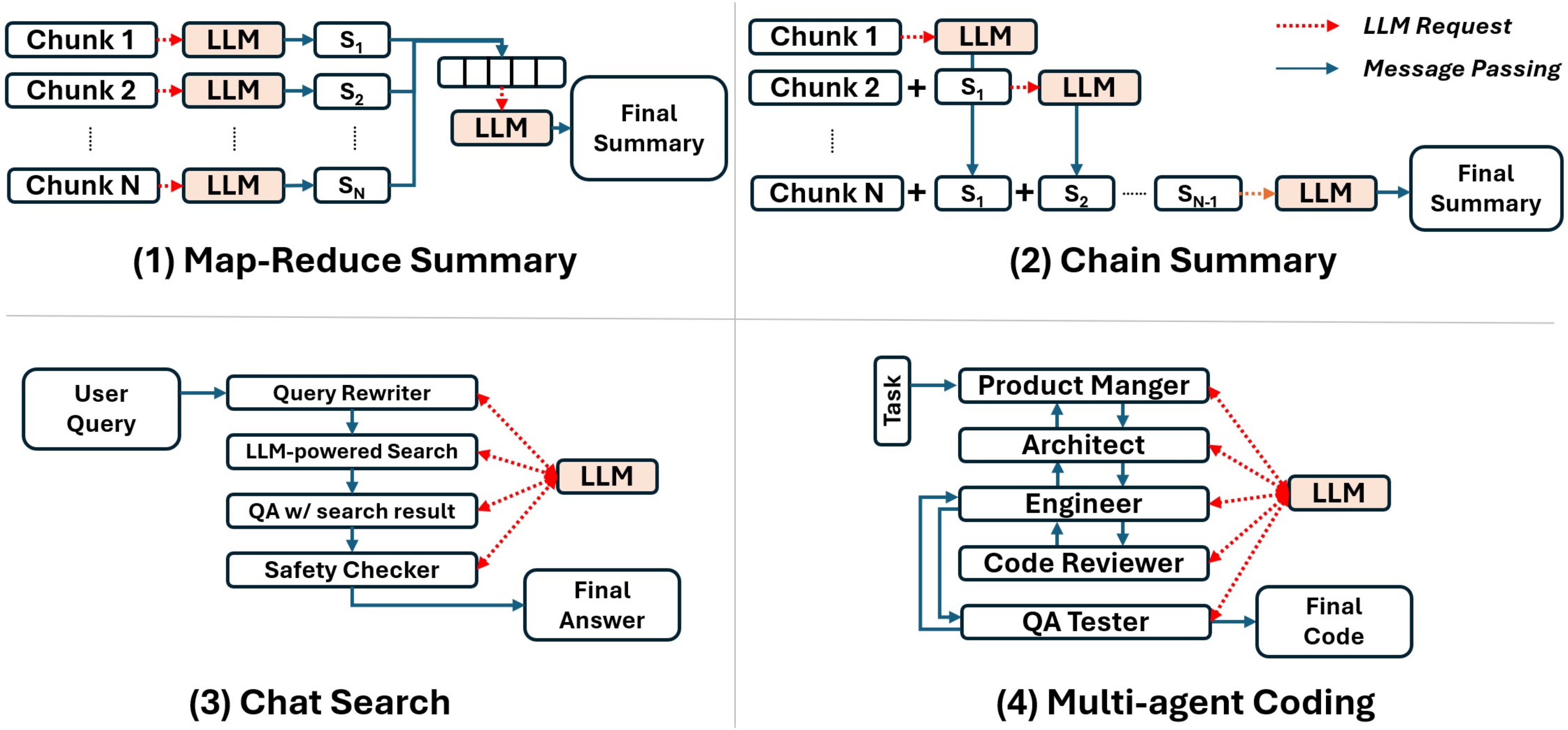
- A novel type of program (LLM + Code) are shaping the future
  - Ability of understanding semantics beyond bits
  - Complex planning



🔥Hot!

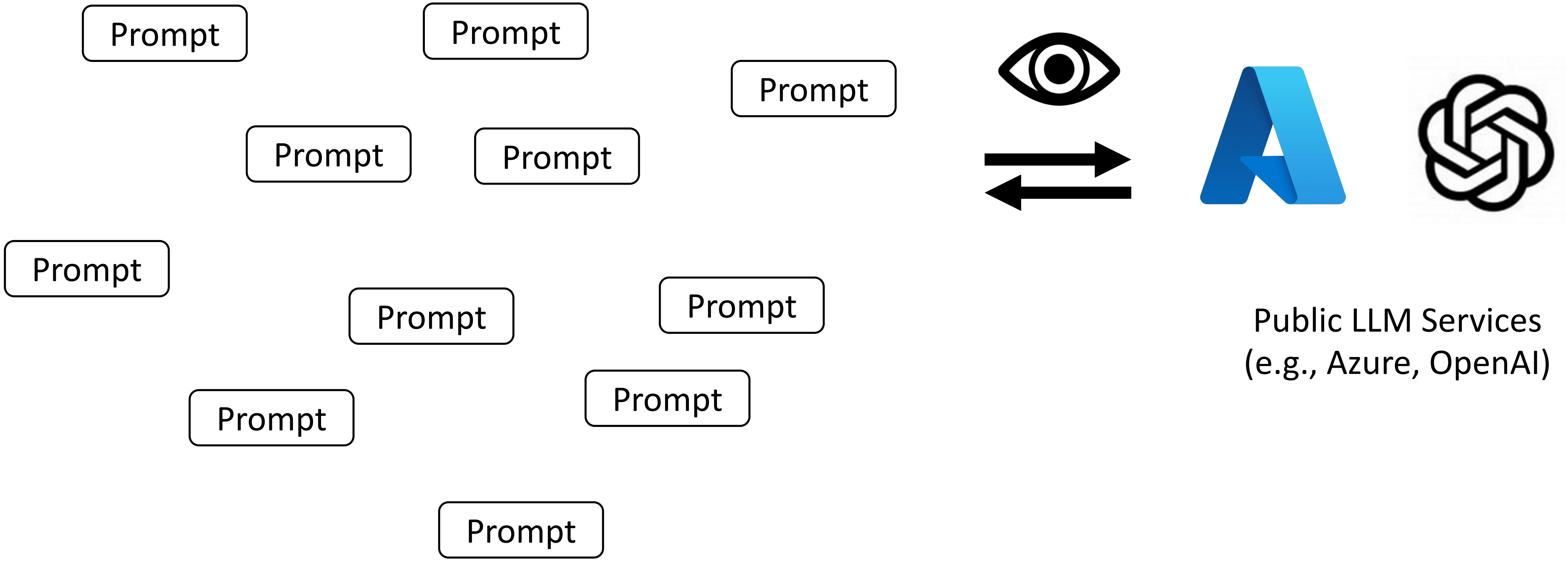
Diverse Workflows of LLM Apps (or Agents)

- High-quality LLM apps often need multiple LLM requests to collaborate in different workflows



From the view of Multi-tenant LLM Services

- Face a lot of independent prompt requests through OpenAI-style APIs



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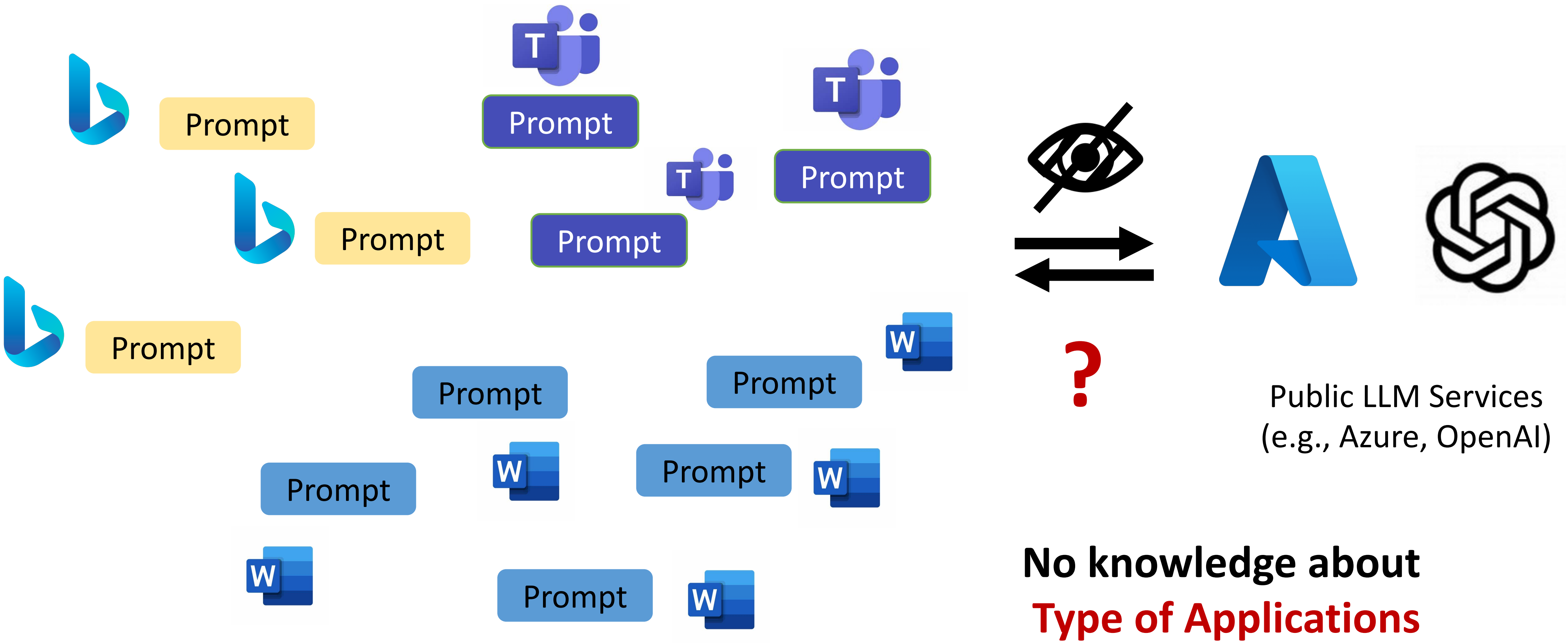
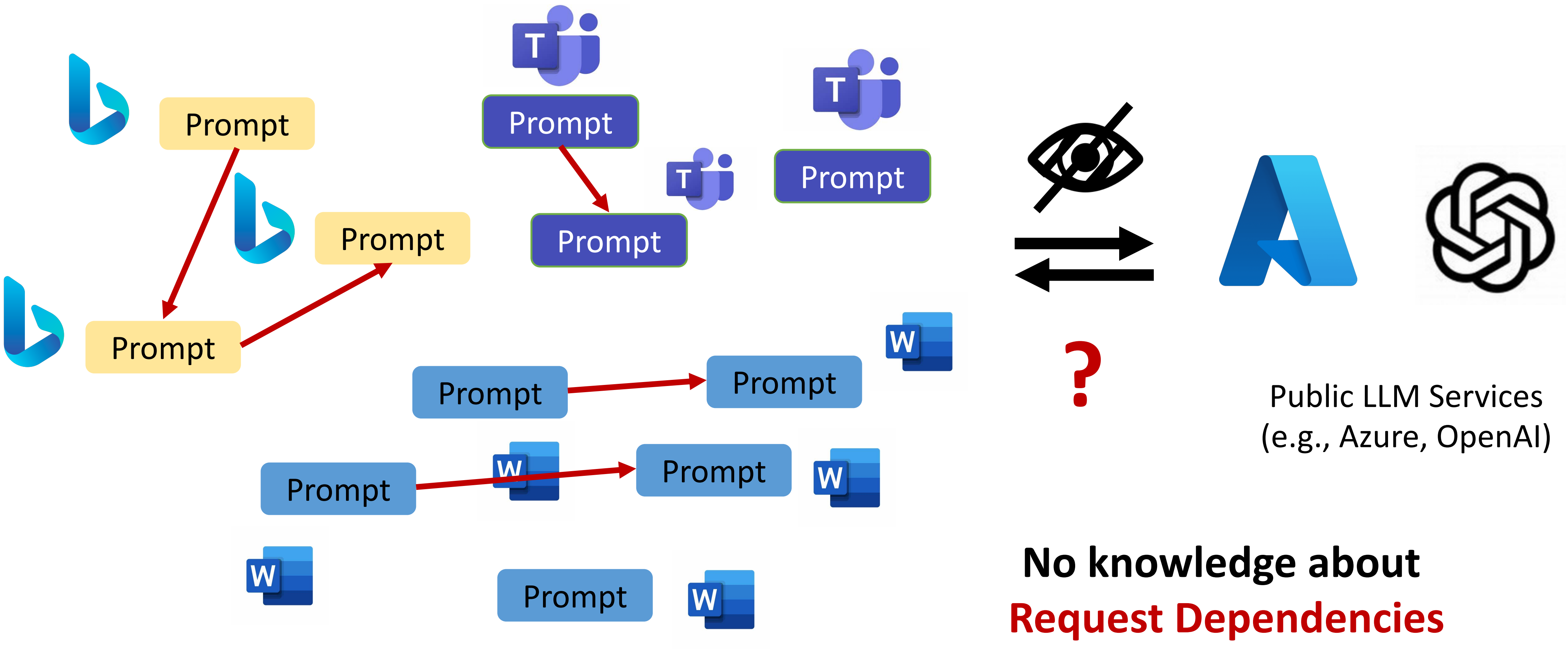


No knowledge about
Type of Applications

From the view of Multi-tenant LLM Services

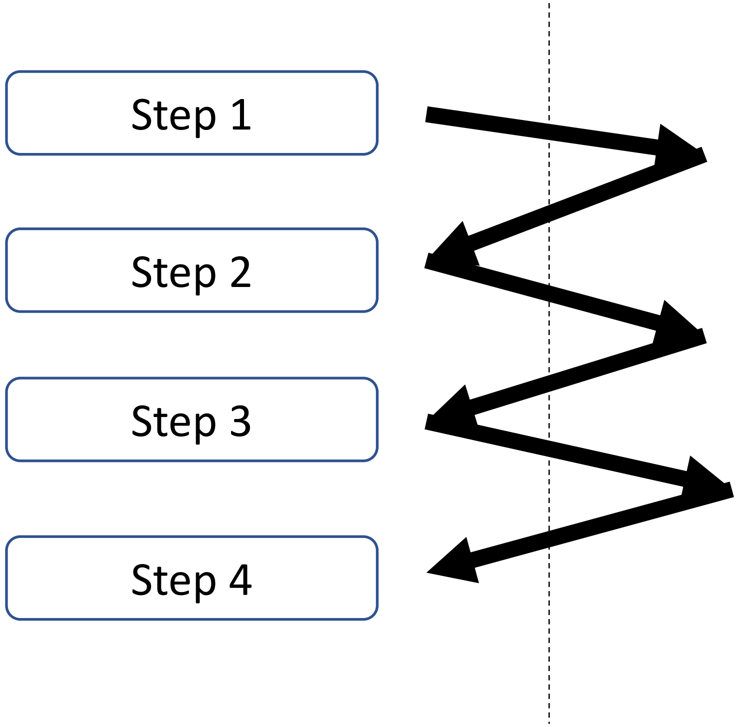
- Face a lot of independent prompt requests through OpenAI-style APIs



Problems of Lacking Application Knowledge

Internet

Multi-Request App has to use chatty submission



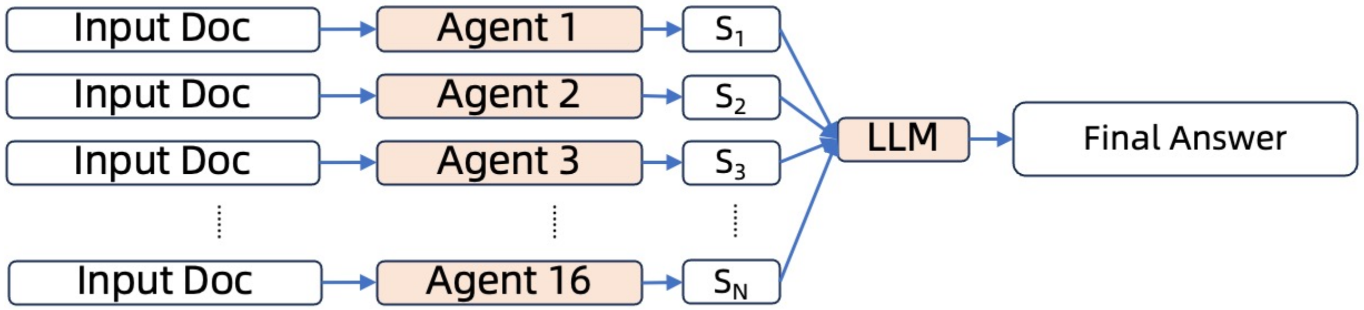
Public LLM Services
(e.g., Azure, OpenAI)

High Excessive Latency

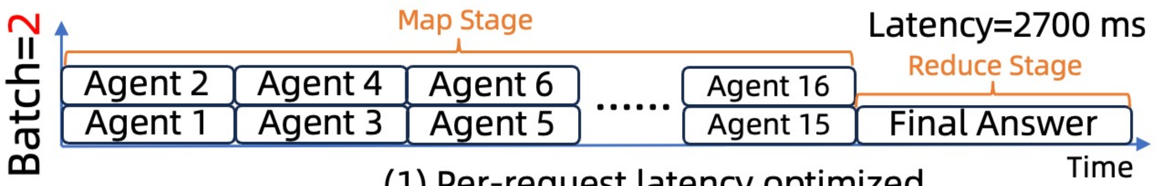
- 50~70% Non-GPU Time

- High Internet Latency
- Excessive Queuing Delay

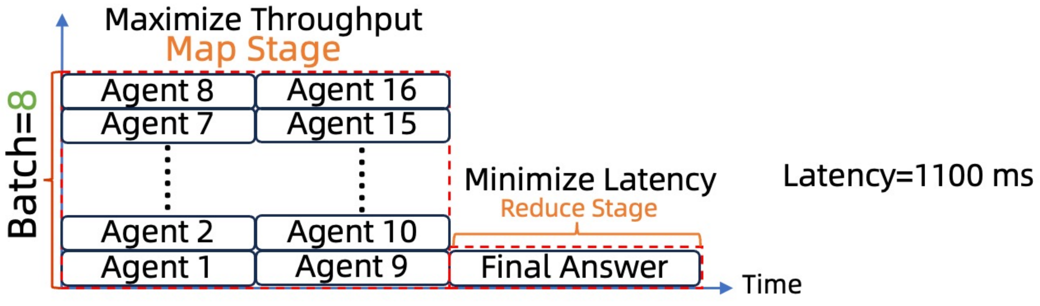
Problems of Request-centric LLM APIs



Misaligned
Scheduling Objectives



(1) Per-request latency optimized



(2) End-to-end latency optimized

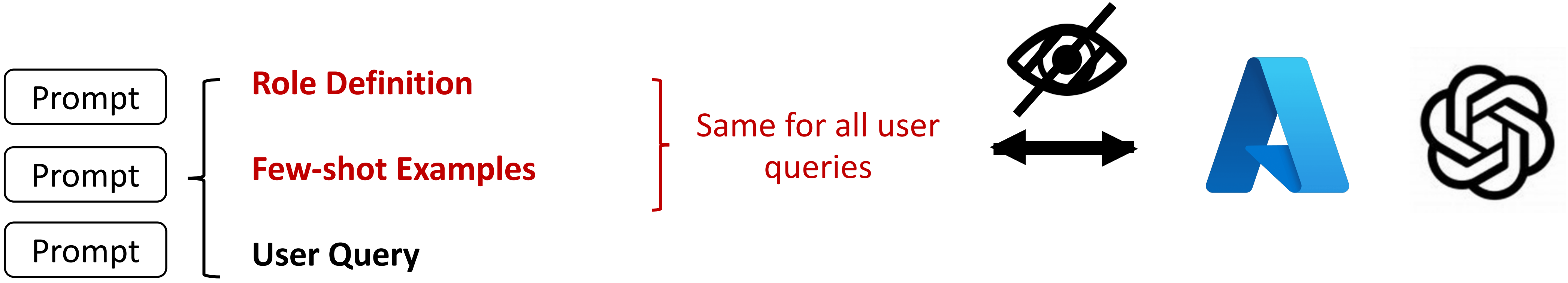
Small Batch Size for Low Per-Request Latency

Large Batch Size for Map Stage

Problem of Unknown Prompt Structure

- Existing LLM services receive ”rendered” prompt without structure info

Some apps use same prompt prefix for different user queries



Public LLM Services
(e.g., Azure, OpenAI)

No knowledge about
Shared Prompt Structure

Many Optimizations Not Applicable in Public LLM Services

- Public LLM Services face diverse applications

- Although there have some system optimizations
  - Sticky routing, DAG Scheduling, Prefix Sharing, ……

- But lacking essential information about applications
  - Have to blindly use a universal treatment for all requests

Our Goals in Parrot

- A unified abstraction to expose application-level knowledge
- Uncover correlation of multiple requests
- End-to-end optimization of LLM applications

Insight from Prompt Engineering

- Developers usually use prompt template to program LLM apps
- {{Placeholders}} are often used for inputs/outputs

You are an expert software engineer
Write the python code of {{input:task}}
Your Code: {{output:code}}

You are expert QA engineer, given code for {{input:task}}
{{input:code}}
Your write test cases: {{output:test}}

Key Abstraction: Semantic Variables

```python
@P.SemanticFunction
def WritePythonCode(task: P.SemanticVariable):
""" You are an expert software engineer.
    Write python code of {{input:task}}.
    Code: {{output:code}}
"""

@P.SemanticFunction
def WriteTestCode(
    task: P.SemanticVariable,
    code: P.SemanticVariable):
""" You are an experienced QA engineer.
    You write test code for {{input:task}}.
    Code: {{input:code}}.
    Your test code: {{output:test}}
"""

def WriteSnakeGame():
  task = P.SemanticVariable("a snake game")
  code = WritePythonCode(task)
  test = WriteTestCode(task, code)
  return code.get(perf=LATENCY), test.get(perf=LATENCY)
```

Semantic Variables

Data pipe that connects multiple LLM calls

Semantic Variables in Parrot Front-end

```python
@P.SemanticFunction
def WritePythonCode(task: P.SemanticVariable):
""" You are an expert software engineer.
    Write python code of {Input: task}
    Code: {Output: code}
"""
```

Prompt

```python
@P.SemanticFunction
def WriteTestCode(
    task: P.SemanticVariable,
    code: P.SemanticVariable):
""" You are an experienced QA engineer.
    You write test code for {Input: task}
    Code: {Input: code}
    Your test code: {Output: test}
"""
```

w/ Semantic Variables as Placeholders

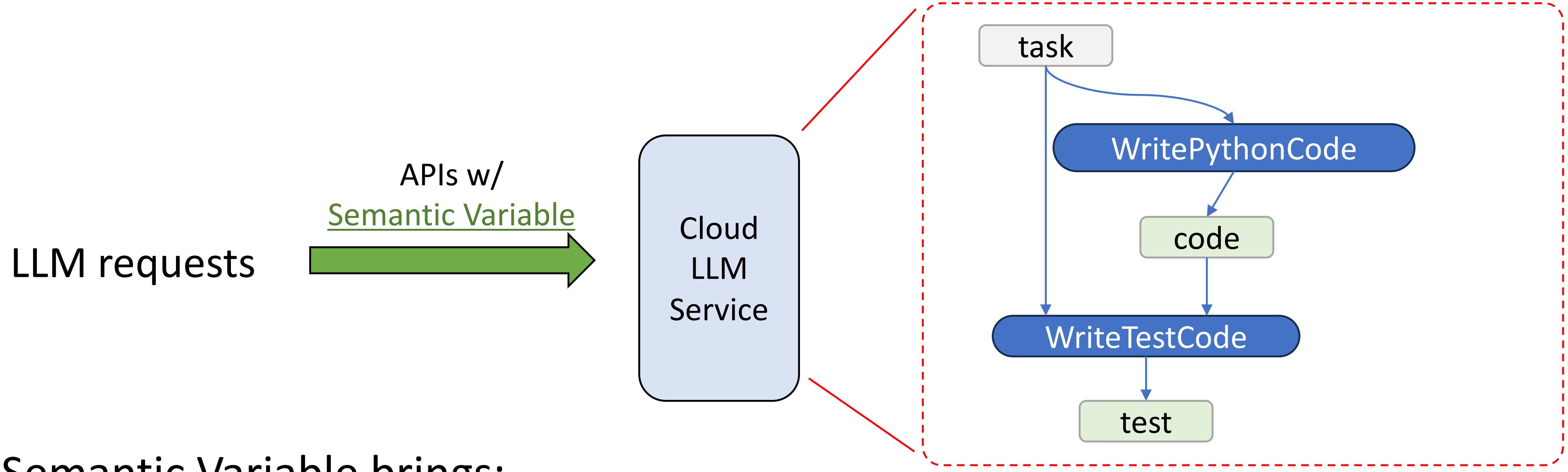
Prompt

```python
def WriteSnakeGame():
  task = P.SemanticVariable("a snake game")
  code = WritePythonCode(task)
  test = WriteTestCode(task, code)
  return code.get(perf=LATENCY), test.get(perf=LATENCY)
```

Data pipeline by connecting LLM Requests using Semantic Variables

Performance Criteria

Exposing Semantic Variable to Parrot LLM Service



Semantic Variable brings:

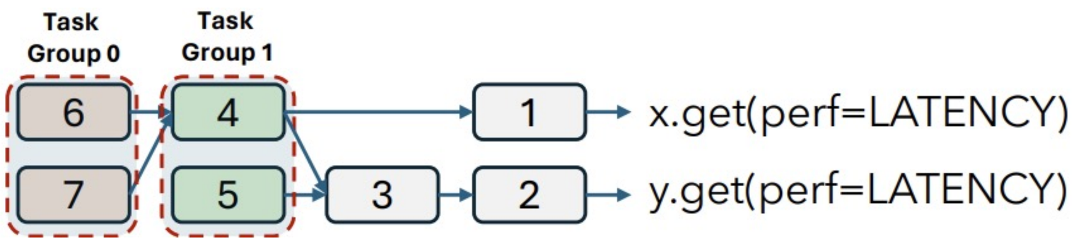
- DAG construction between requests
- Prompt structure analysis
- Data pipelining between requests

…

Parrot Overview

Optimization: App-centric Scheduling

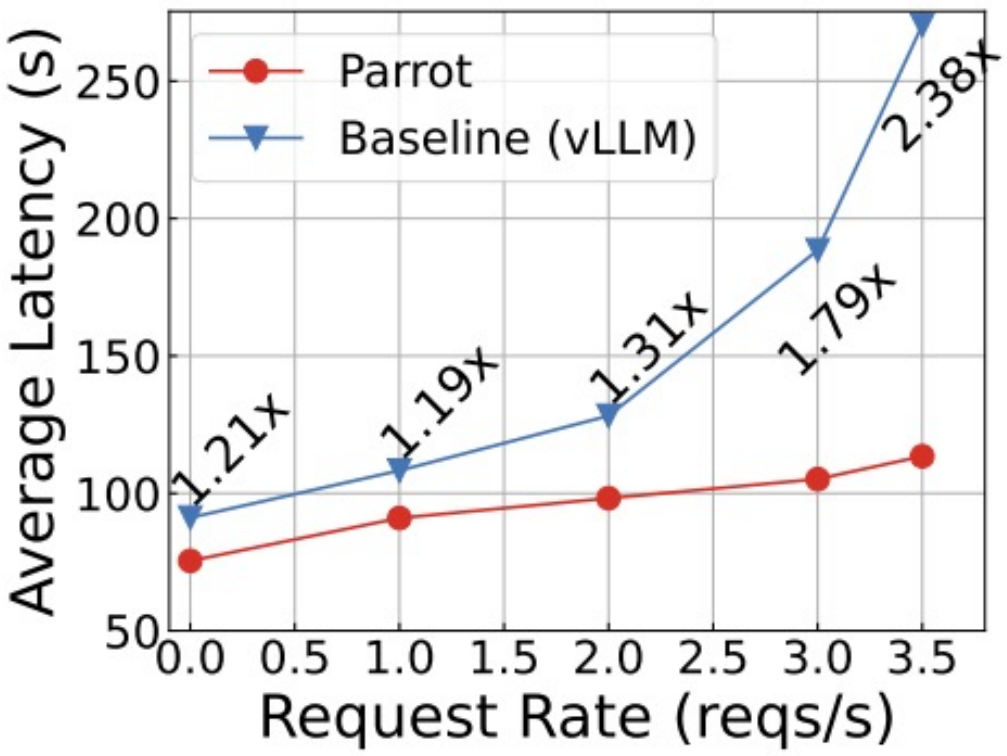
- With DAG of application requests & E2E requirement
- Derive the performance requirement of each LLM call



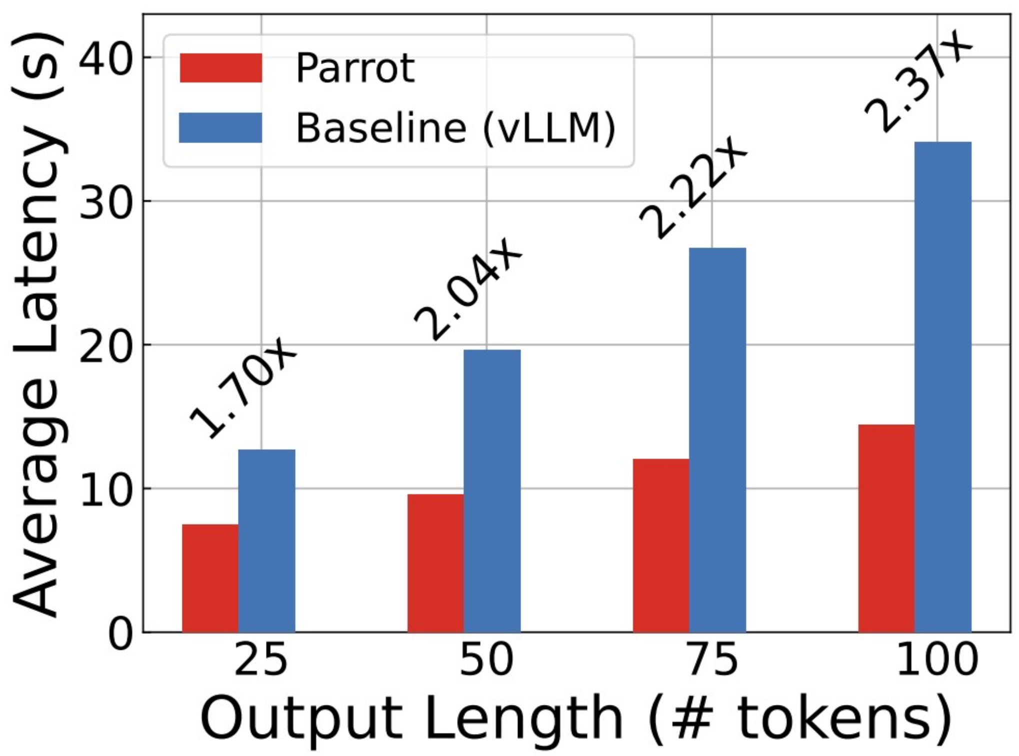
From the DAG, derive requests can be executed in parallel

Evaluation: Chain/Map-Reduce Summary

Chain Summary

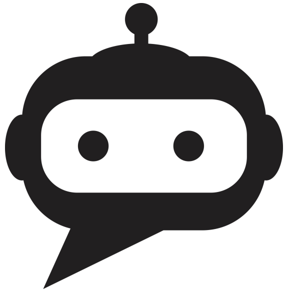


Map-Reduce Summary

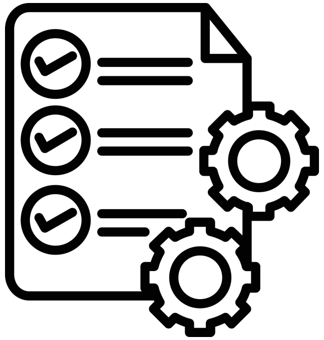


Optimization: Multi-app Serving

- Public LLM Service w/ apps with different performance criteria



Chatbot: Low Latency



Data Analytics: High Throughput

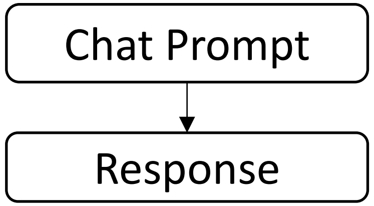
Batch Size	Small	Large

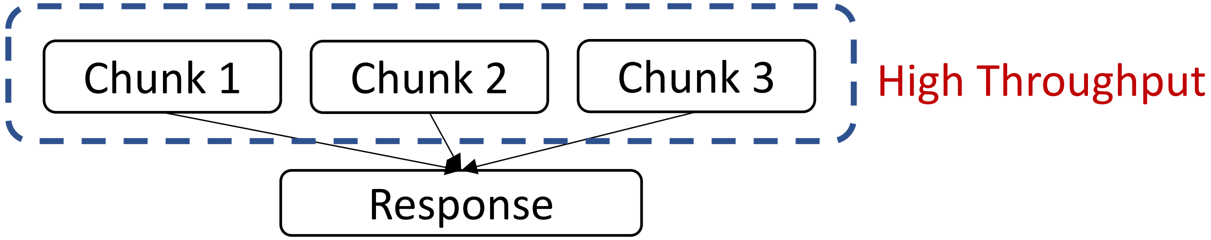
Conflict when scheduled to the same GPU engine

Optimization: Multi-app Serving

- Public LLM Service w/ apps with different performance criteria

Application DAG



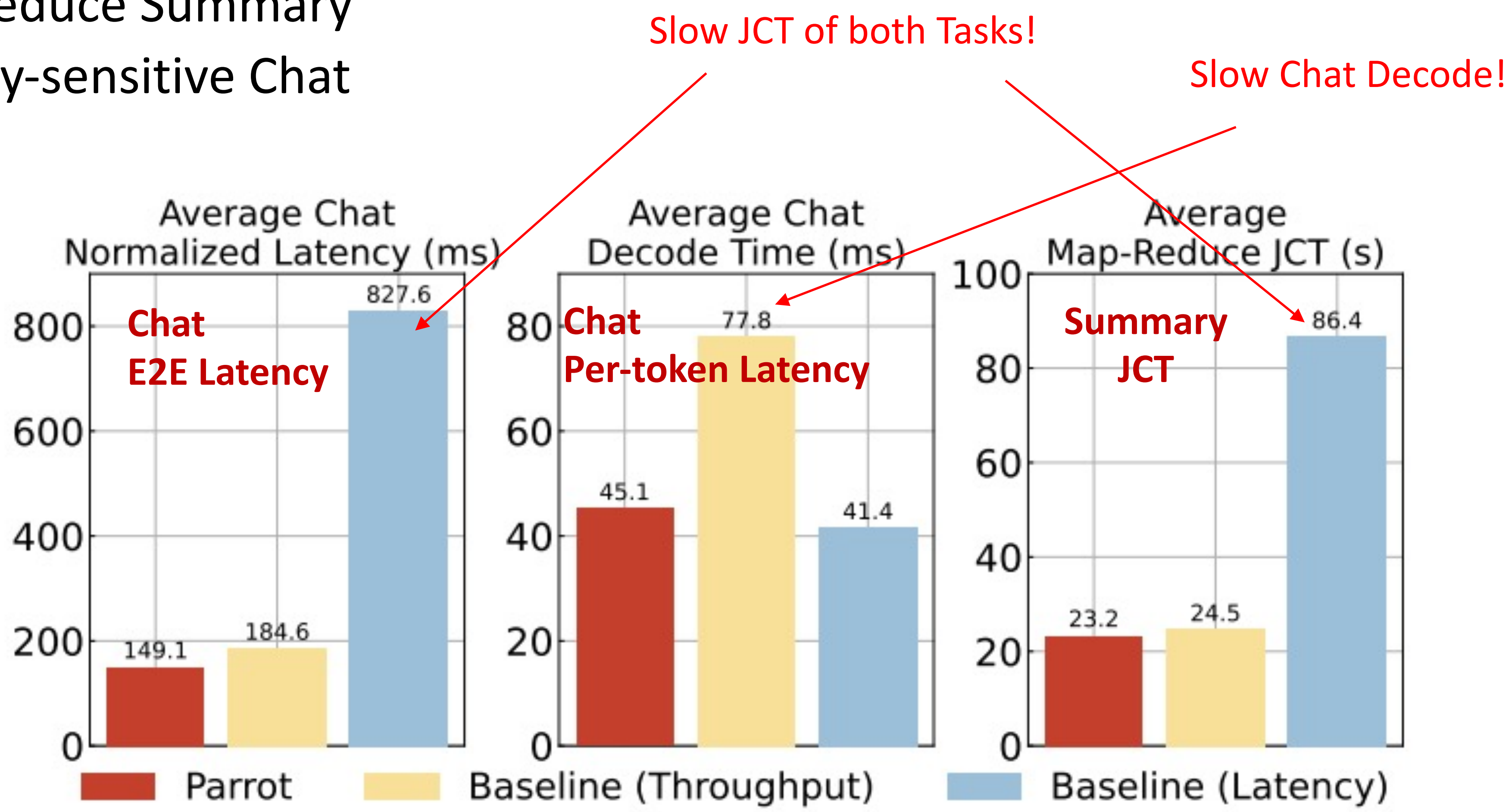


	Chatbot	Data Analytics
	response.get(perf=LATENCY)	response.get(perf=LATENCY)
	Chatbot: Low Latency	Data Analytics: High Throughput
Batch Size	Small	Large

Parrot can derive request-level scheduling goal from end-to-end requirement

Evaluation: Scheduling Mixed Workloads

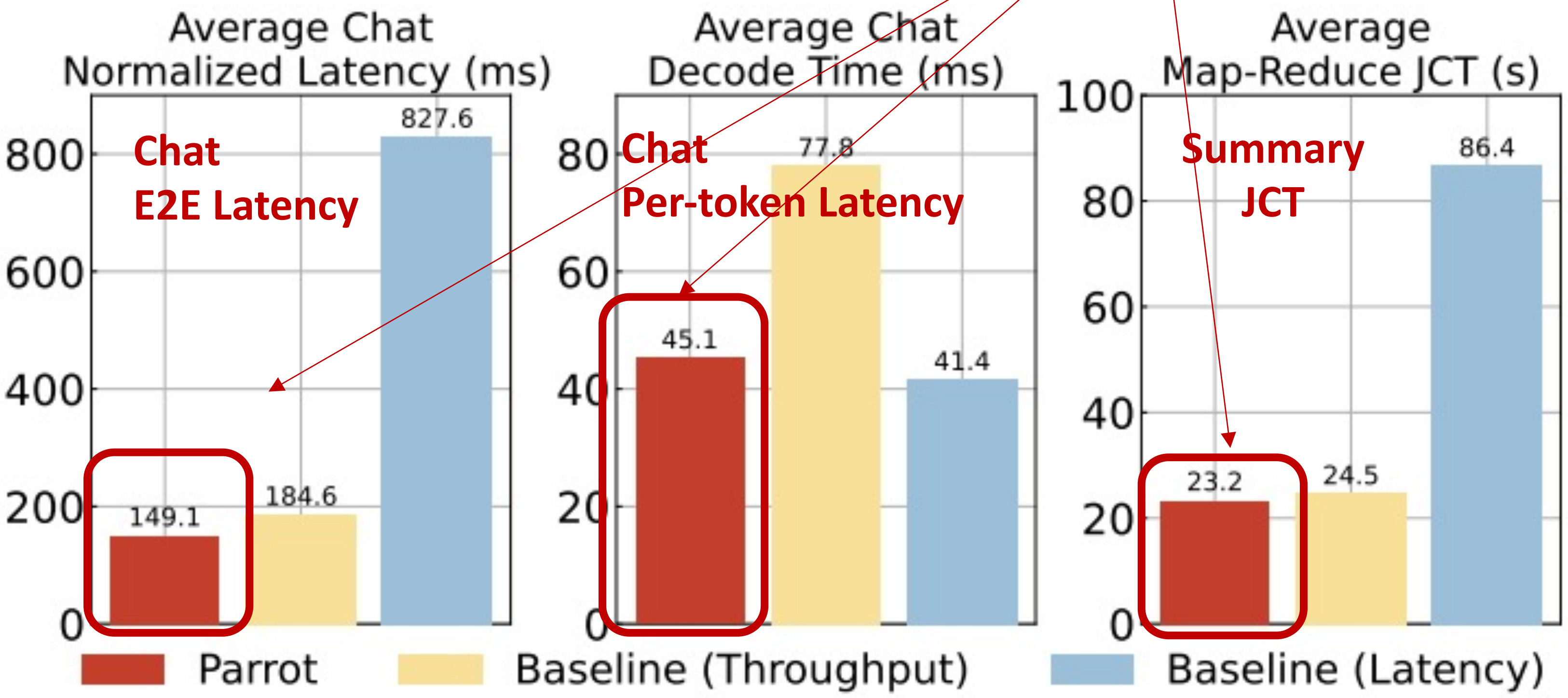
- Mixed workloads
  - Map-reduce Summary
  - Latency-sensitive Chat



Evaluation: Scheduling Mixed Workloads

- Mixed workloads
  - Map-reduce Summary
  - Latency-sensitive Chat

Parrot achieves low latency and high-throughput for both apps



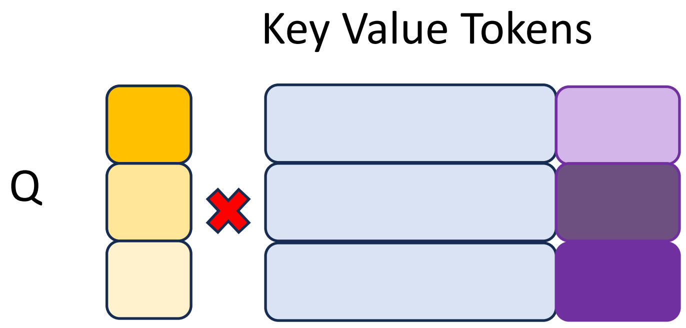
Optimization: Sharing Prompt Prefix

- With prompt structure, Parrot can **automatically** detect shared prefix

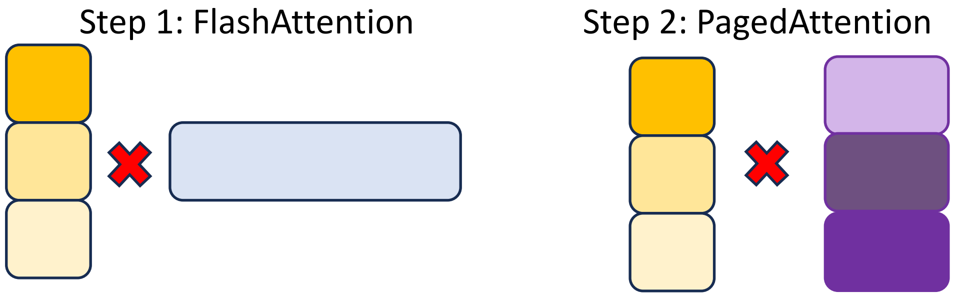
Prefix 1 Prefix 2

Your are expert of {task}, here are some examples: {example}, your response: {response}

- Optimized CUDA Kernel
  - Two-phase attention: avoid recomputing and reloading shared prefix



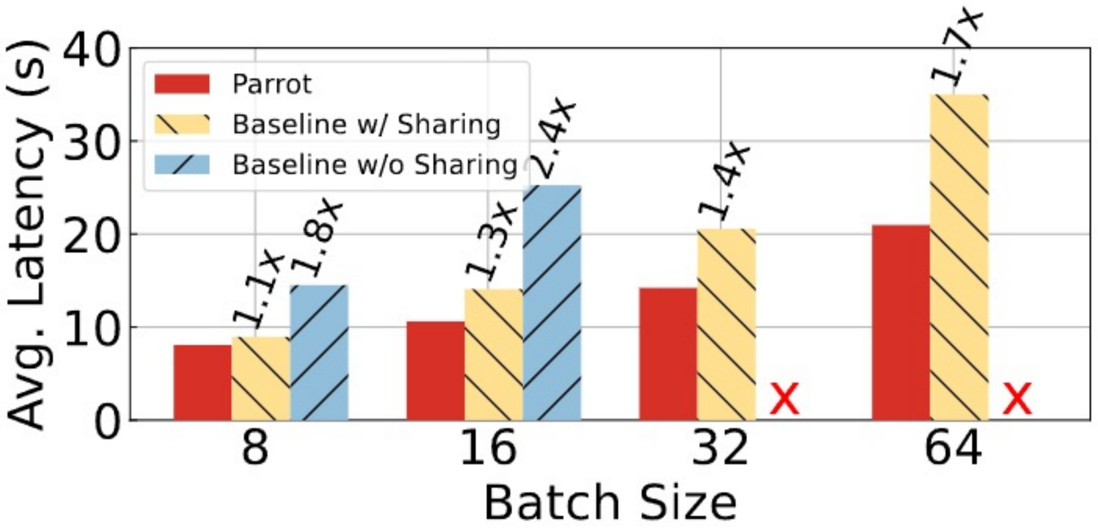
Standard Attention



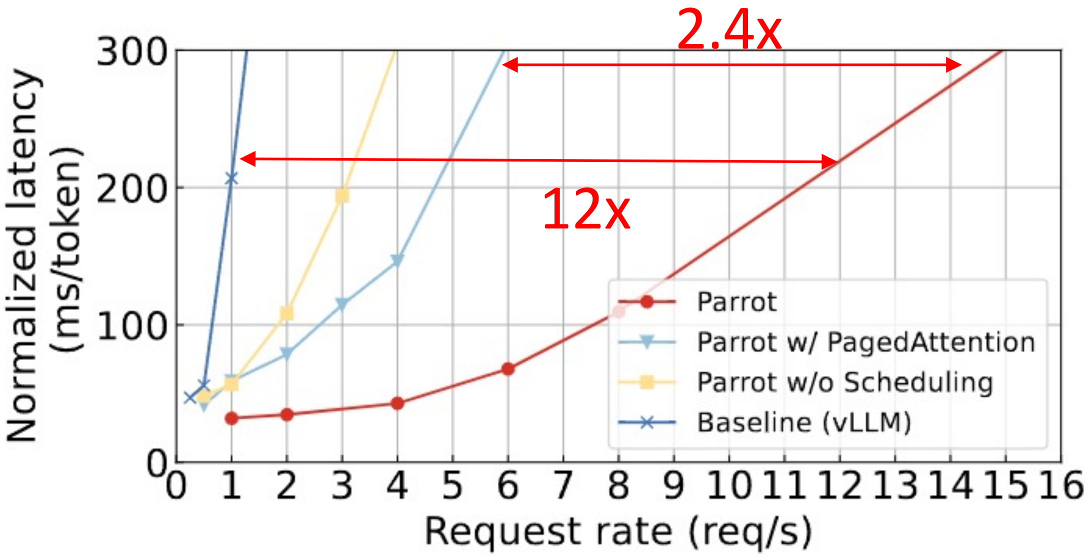
Our Algorithm

Evaluation: Popular Apps (Bing Copilot, GPTs)

Synthesized requests following Bing Copilot length distribution



Synthesized requests from 4 different popular GPTs applications



Summary

- Multi-tenant cloud LLM services running diverse apps
  - Lacking app knowledge misses many optimization opportunities
- Parrot: uses a unified abstraction Semantic Variable
  - To expose essential application-level information
  - End-to-end optimizations with dataflow analysis
- Evaluation shows order-of-magnitude efficiency improvement for practical use-cases

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