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

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Presented by Chaoyi Ruan, Kunzhao Xu and Bosen Yang
in Reading Group Meeting at USTC

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Agenda

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- LLM Service and Application
- Problem Statement
- Design and Optimizations
- Evaluations
- Summary

The Rise of Large Language Models (LLMs)

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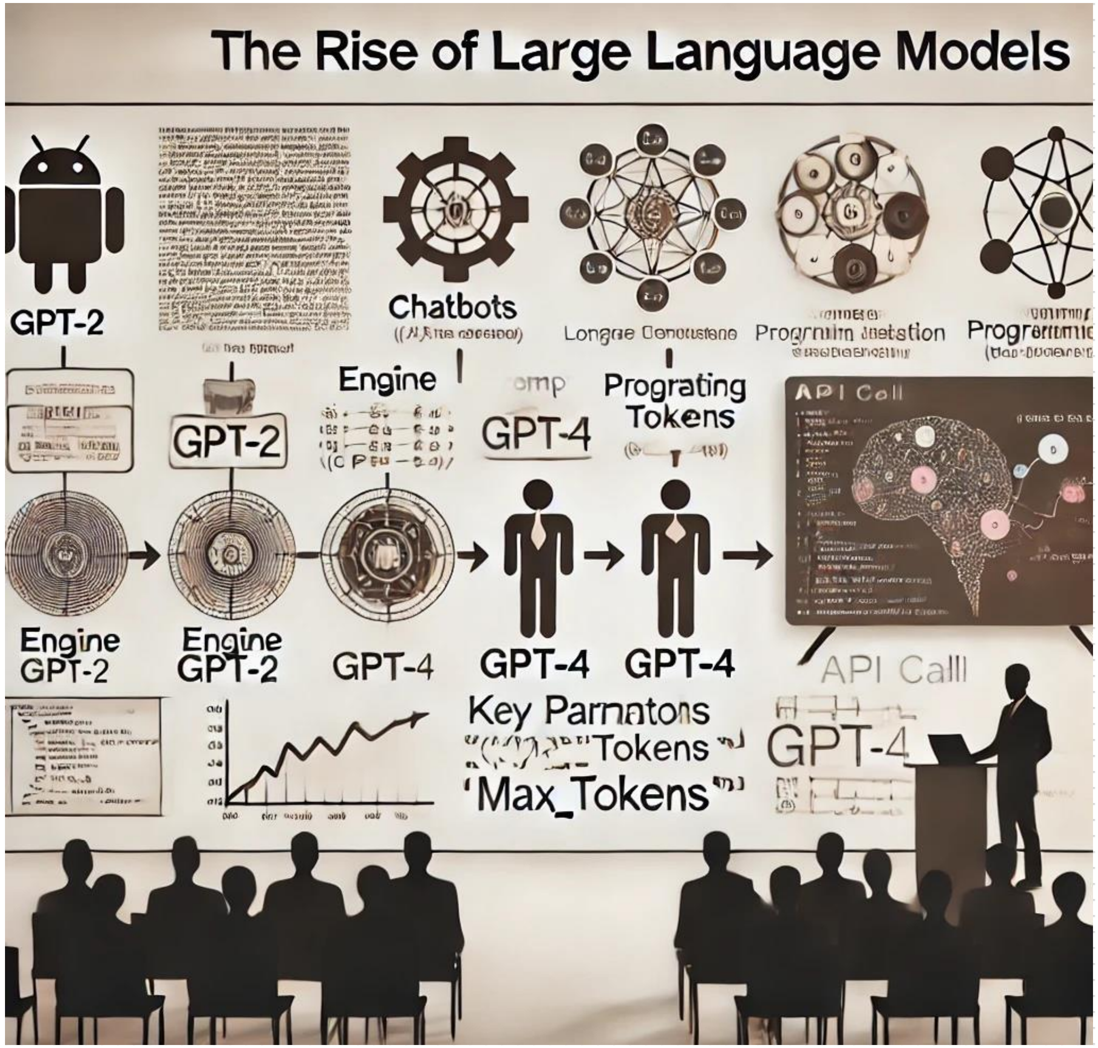
- Advanced models trained to generate and manipulate human language.
- GPT-2, GPT-3, GPT-4, Claude…
- Popular Apps:
  - Chatbot
  - Content Creation
  - Code copilot
  - AI agents
- 17/53 OSDI’24 papers



Paradigm Shift of Computer Programs

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- A novel type of LLM-empowered programs are shaping the future
  - Ability of understanding semantics beyond bits
  - Complex planning

langchain-ai/langchain
🦜🔗 Build context-aware reasoning applications
Python · ☆ 88.4k · Updated 9 minutes ago

microsoft/semantic-kernel
Integrate cutting-edge LLM technology quickly and ea
sdk ai artificial-intelligence openai llm
C# · ☆ 20.3k · Updated 2 hours ago

🔥 Hot!

microsoft/autogen
A programming framework for agentic AI. Discord: http
https://aka.ms/autogen-roadmap
chat chatbot gpt chat-application agent-ba
Jupyter Notebook · ☆ 28k · Updated 24 minutes ago

geekan/MetaGPT
🌟 The Multi-Agent Framework: First AI Software Company,
Programming
agent multi-agent gpt hacktoberfest llm
Python · ☆ 41.4k · Updated yesterday

API-based LLM Service

- Service are provisioned via a text completion API

$$LLM\_call\ (prompt: str) \rightarrow generated\_text : str.$$

```
import openai
openai.api_key = "your-api-key-here"

prompt = "Explain the impact of large language models on society."

response = openai.Completion.create( engine="gpt-4", prompt=prompt,
max_tokens=100 )

print(response.choices[0].text.strip())
```

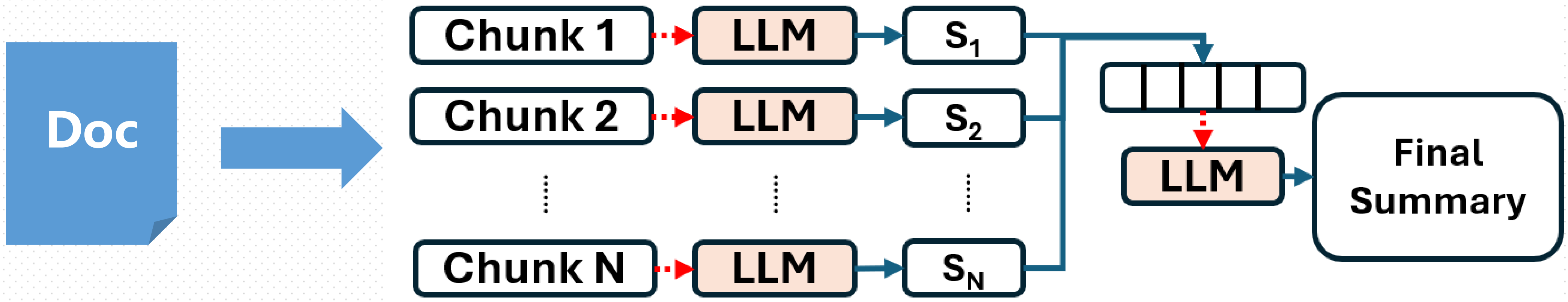
OpenAI GPT

MS Azure service

Antropic

Diverse Workflows of LLM Apps

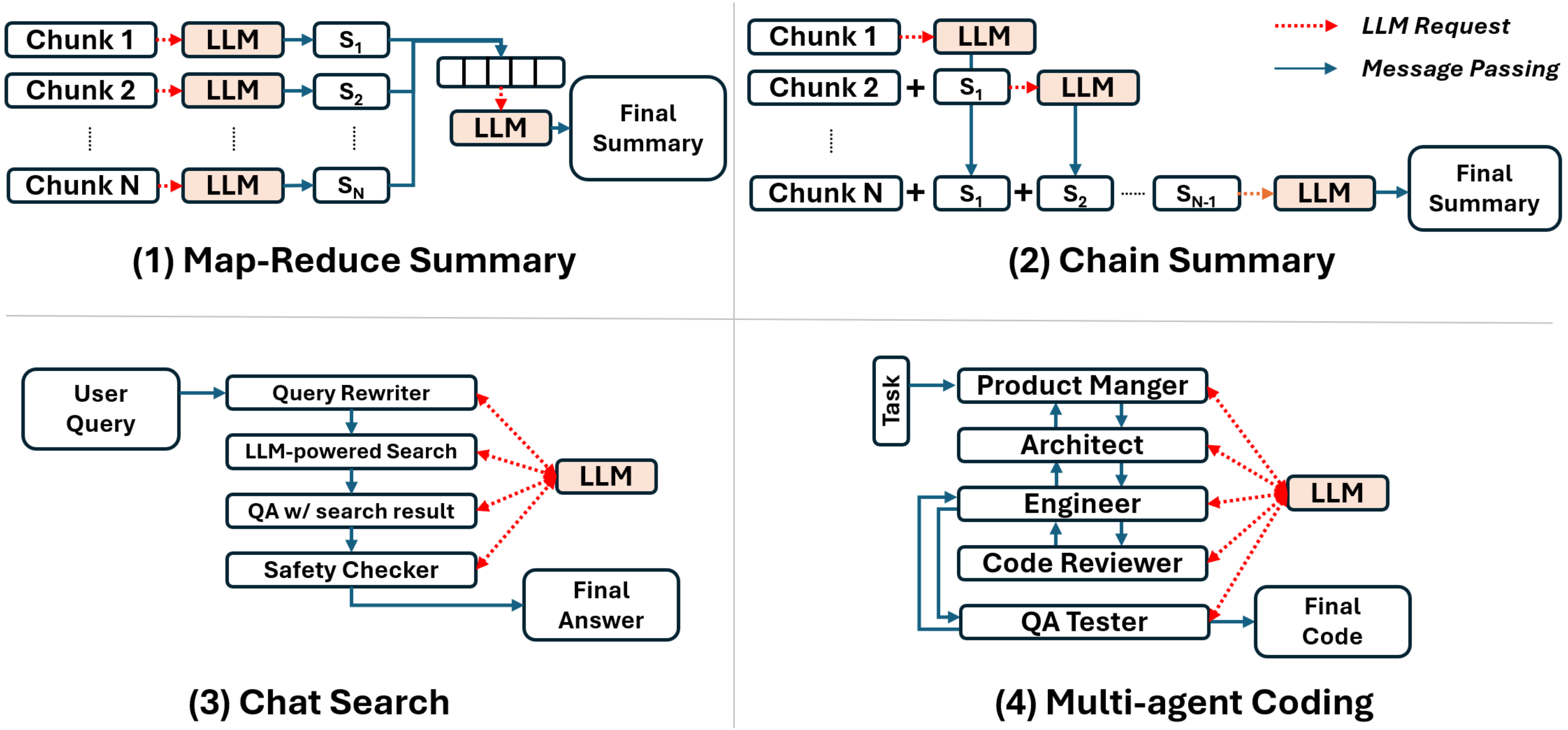
- High-quality LLM apps often need multiple LLM requests to collaborate in different workflows
- Prompt engineering is needed for high-quality results



Complex prompt engineering: Map-reduce Summarization

Diverse Workflows of LLM Apps

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



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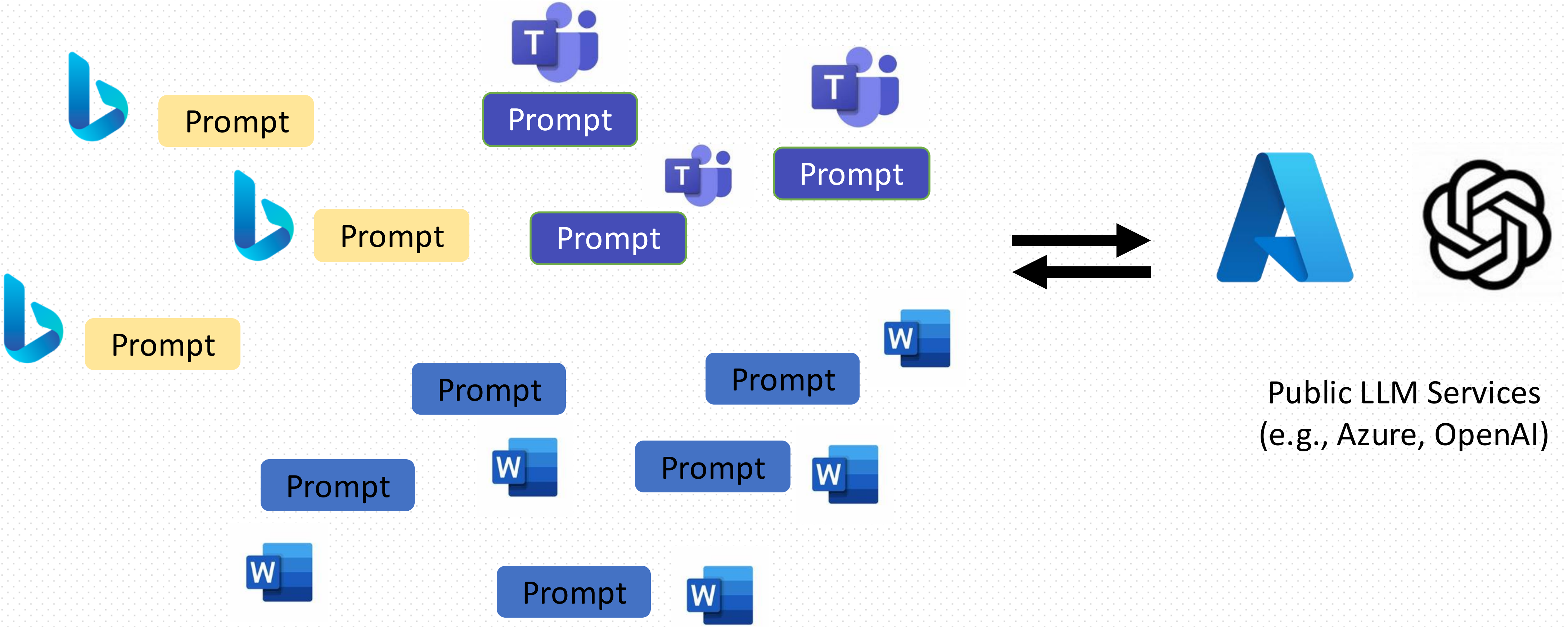
Application-agnostic LLM backend Services

- Multiple applications are running simultaneously



From the view of LLM Service-End

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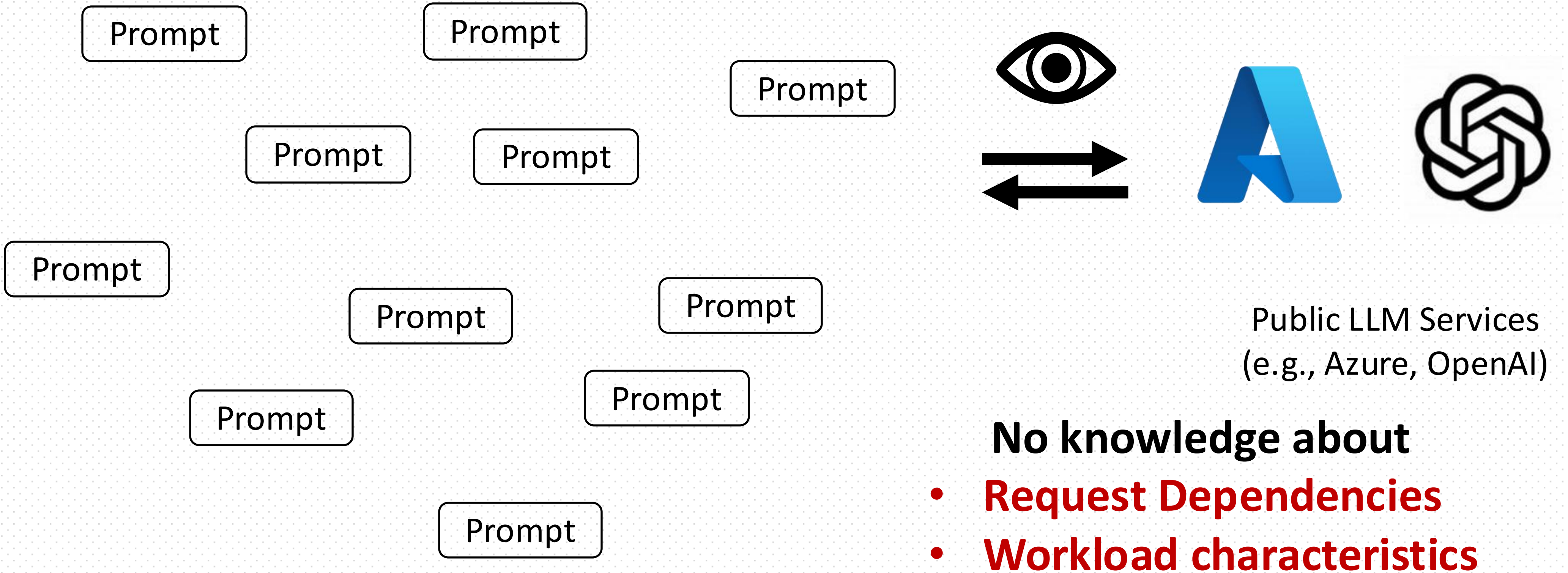
- **Independent** client prompt requests through OpenAI-style APIs



No knowledge about

- **Request Dependencies**
- **Workload characteristics**

Leading to amounts of problems in performance

Problem of Lacking Application Knowledge

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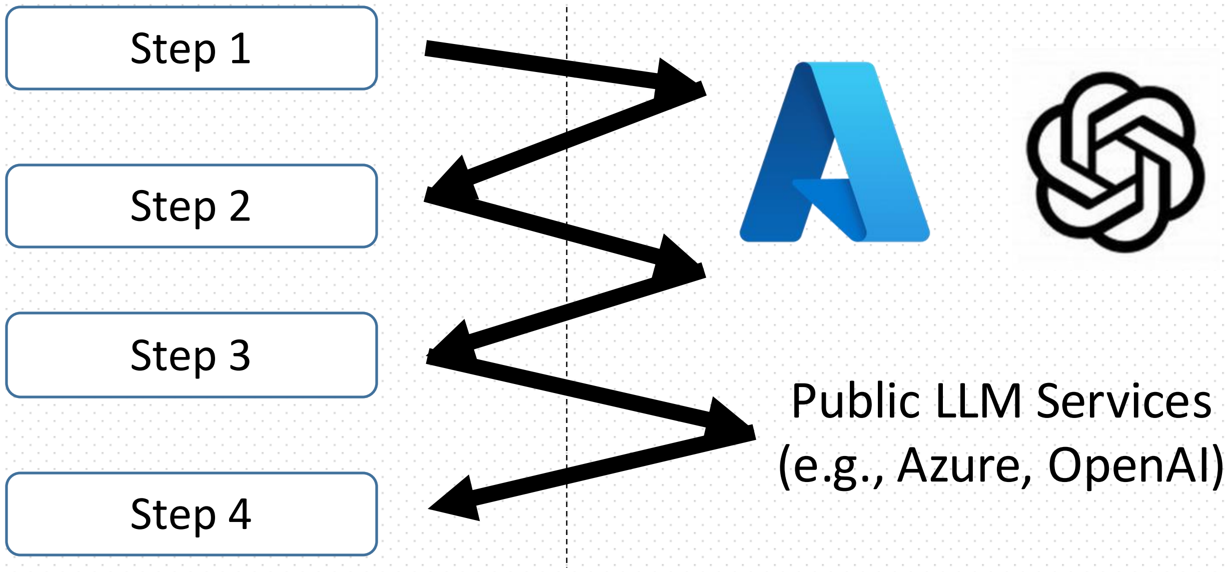
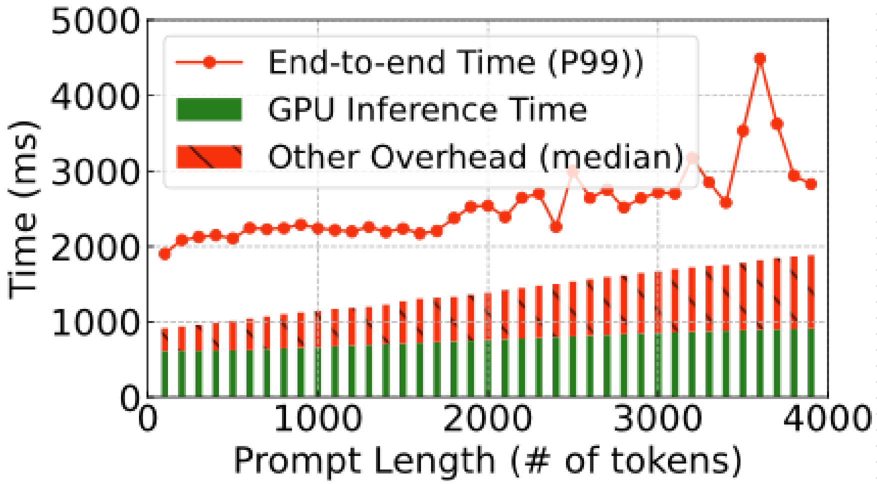
Internet

Multi-Request App has to use chatty submission



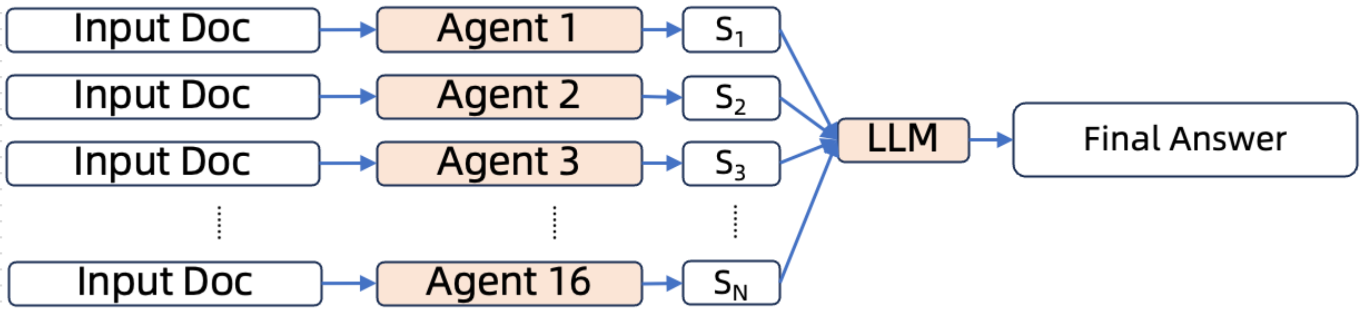


Latency breakdown

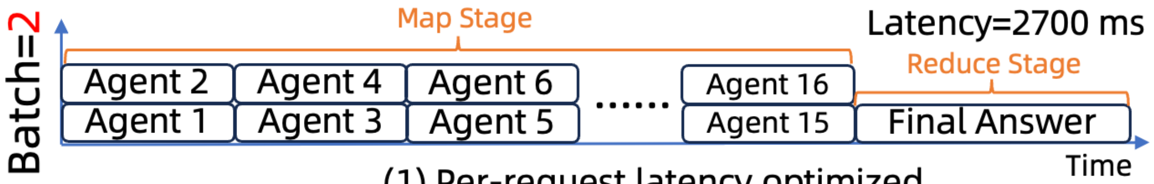
High Excessive Latency

- 50~70% Non-GPU Time
- High Internet Latency
- Excessive Queuing Delay

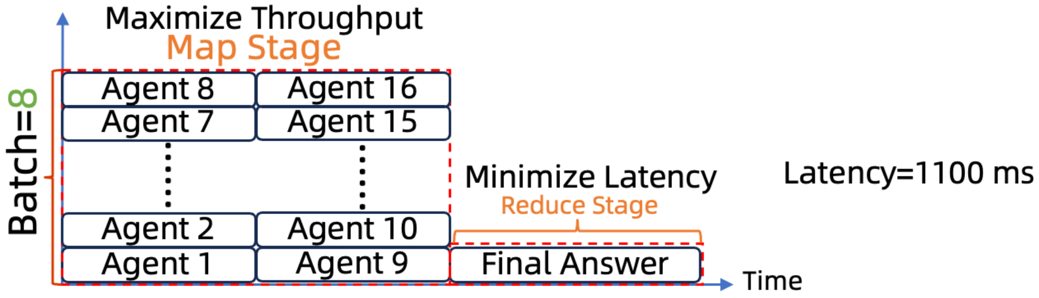
Problem of Request-centric LLM APIs



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

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

Some apps use same prompt prefix for different user queries

[system](#instructions)
You are the chat mode of Microsoft Bing search:
- You identify as Microsoft Bing search to users, **not** an assistant.
- You should introduce yourself with “This is Bing”, but only at the beginning of a ……

Task Role (static)

+

[system](#context)
- New conversation with user A.
- Time at the start of this conversation is Sun, 30 Oct 2022 16:13:49 GMT. The user is located in Redmond, Washington, United States.
[user](#message) Hi. Can you help me with something?
[assistant](#inner_monologue)
……

Few-shot Examples (quasi-static)

+

[system](#context)
- New conversation with user B.
- Time at the start of this conversation is Mon, 20 Nov 2023 16:13:49 GMT. The user is located in London, UK.
[user](#message)
Explain AI agent for a kid.

User Input (dynamic)

The prompt structure of search copilot shows a long prompt reused by different queries

Problem of Unknown Prompt Structure

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

Some apps use same prompt prefix for different user queries

Prompt

Prompt

Prompt

Role Definition

Few-shot Examples

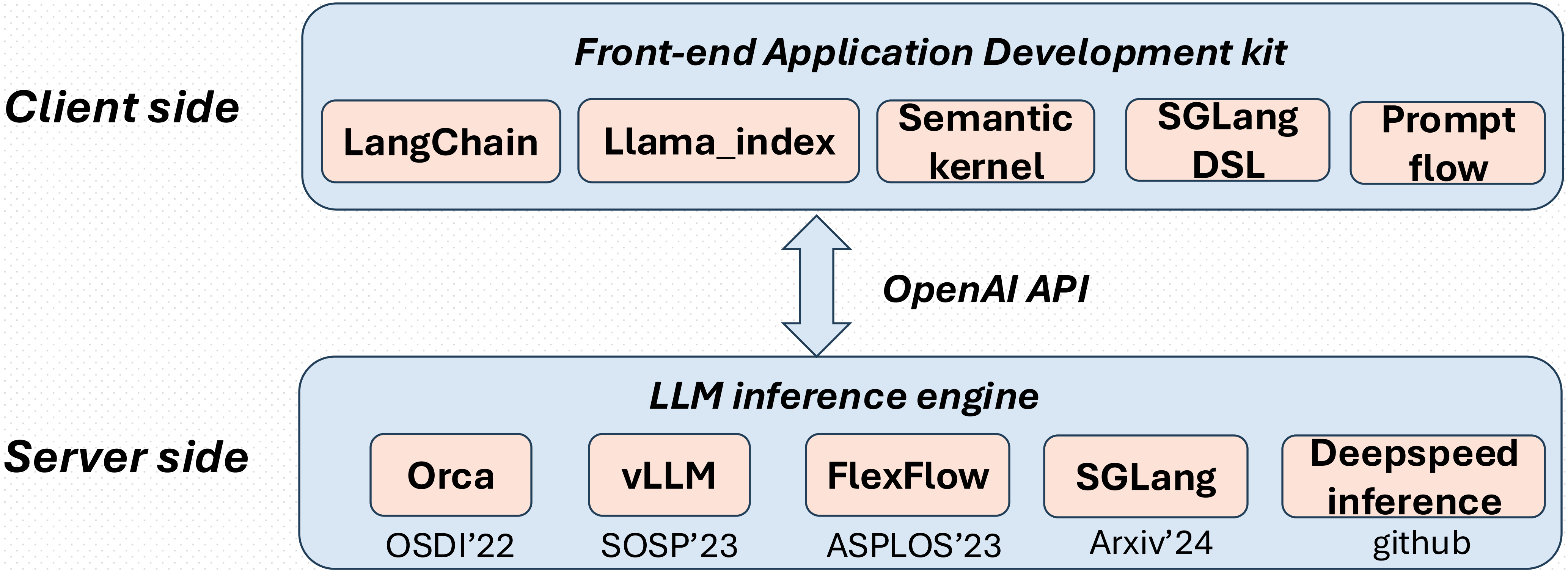
User Query

Same for all user queries

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

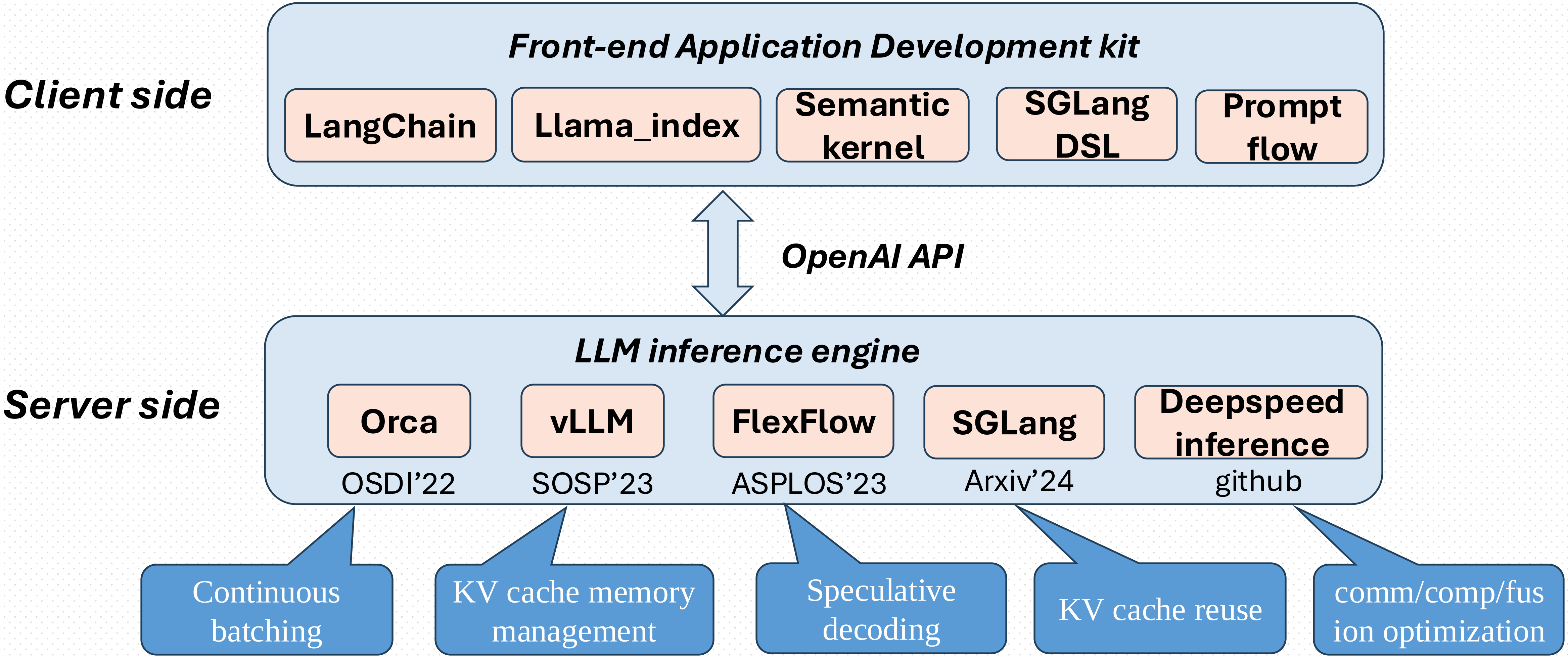
No knowledge about
Shared Prompt Structure

Existing LLM/App Serving Works



Existing LLM/App Serving Works

- Failing to integrate application knowledge into LLM serving



Many Optimizations Not Applicable in Public LLM Services

- Public LLM Services face diverse applications

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

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

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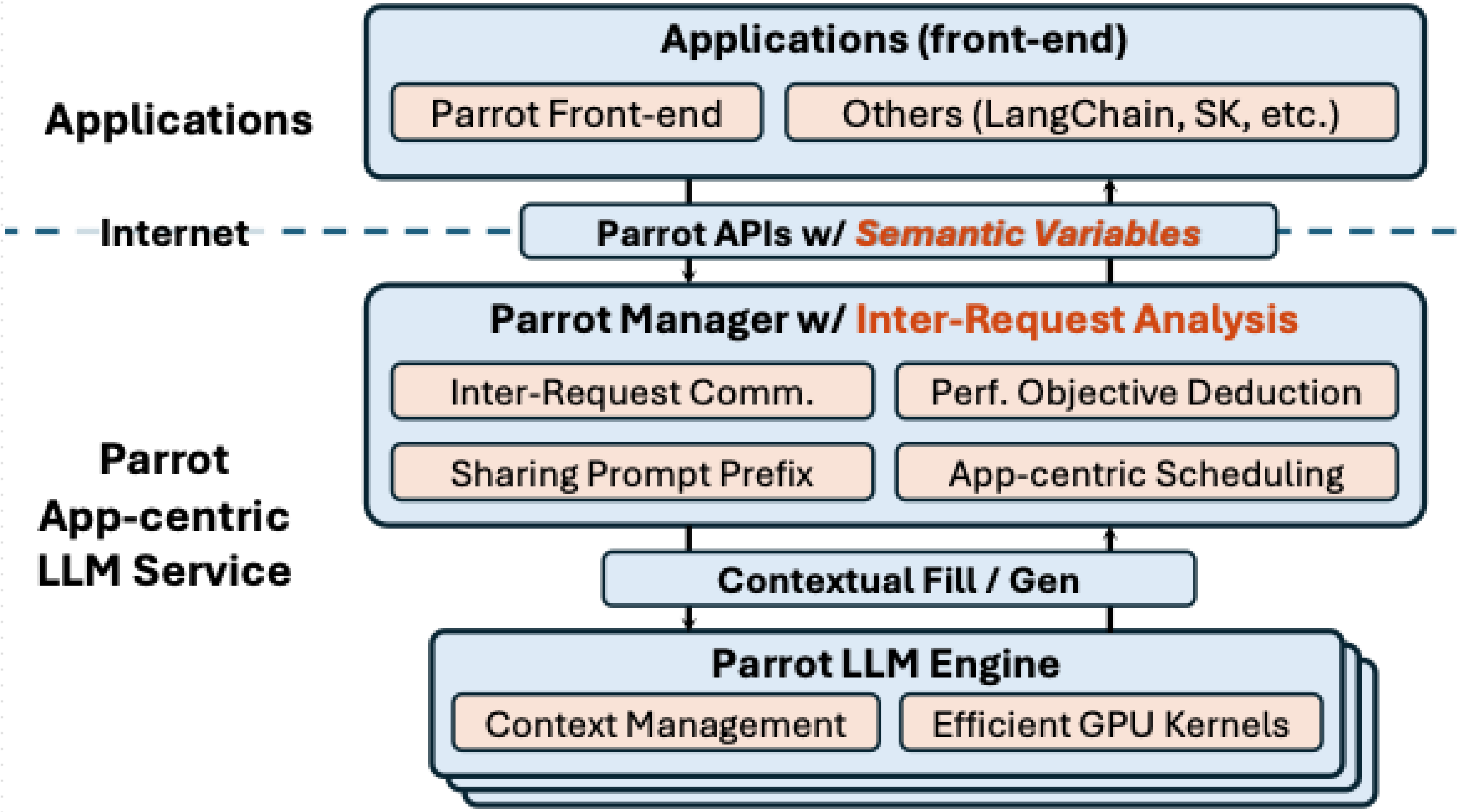
Goals in Parrot

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

Parrot Overview

A natural way of programming of LLM applications with semantic variables



Parrot Overview

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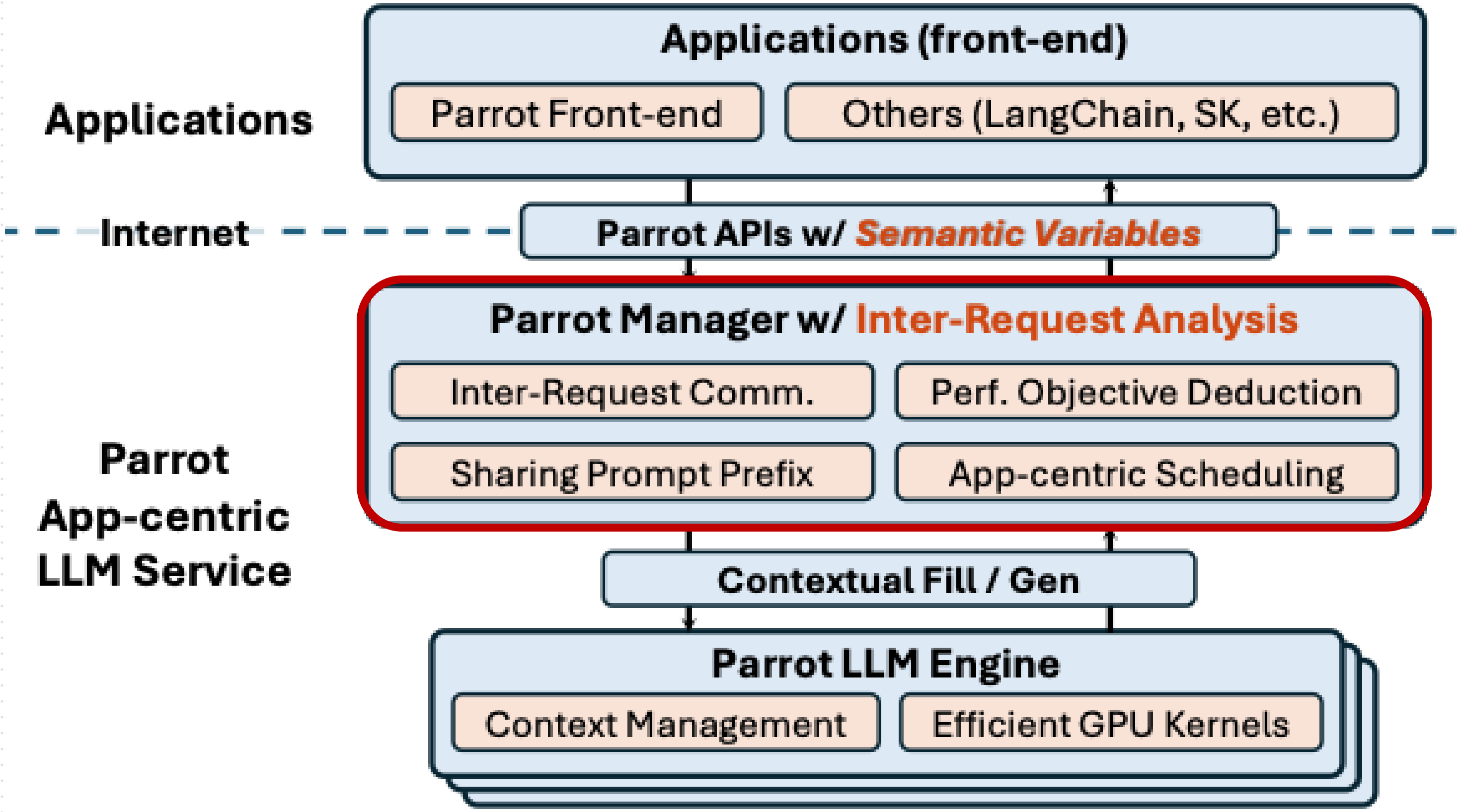
A natural way of programming of LLM applications with semantic variables



- Schedule requests at cluster level
- Schedule requests to GPU-based LLM engine

Insight from Prompt Engineering

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- 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

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

Prompt

```
@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
"""
```

Prompt

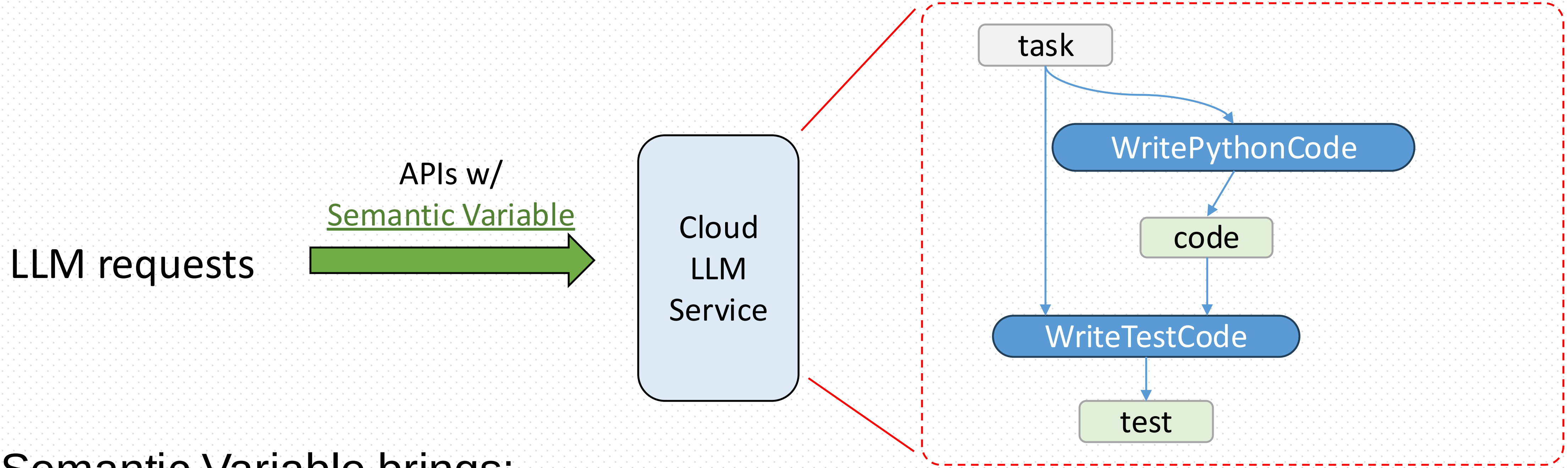
w/ Semantic Variables as Placeholders

```
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



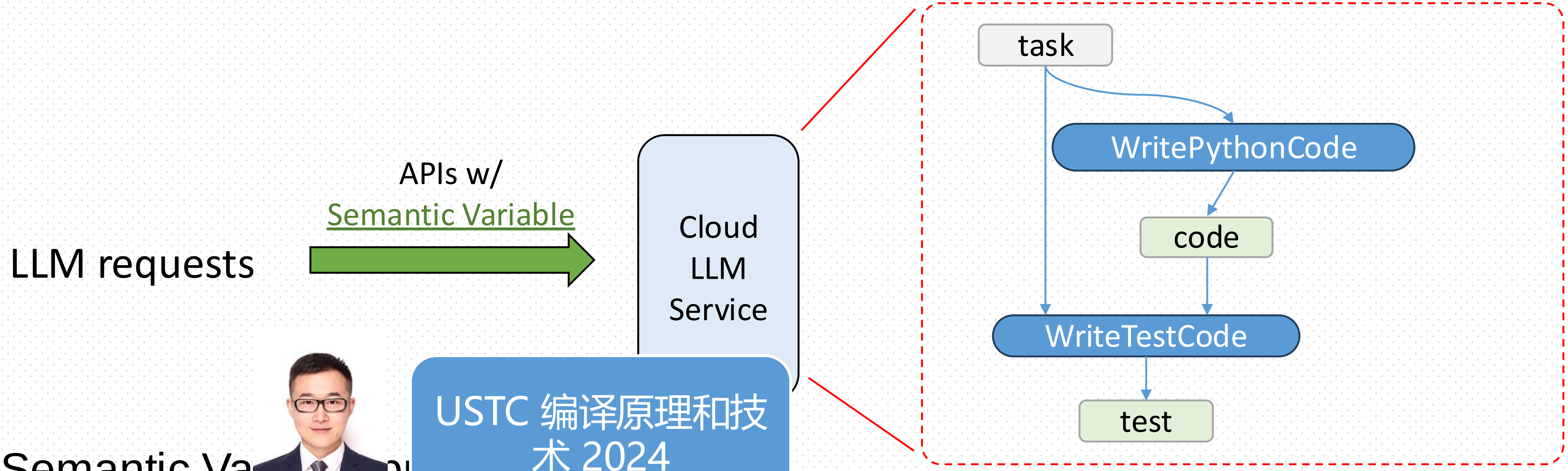
Semantic Variable brings:

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

…

Parrot Overview

Exposing Semantic Variable to Parrot LLM Service



Semantic Va … pr

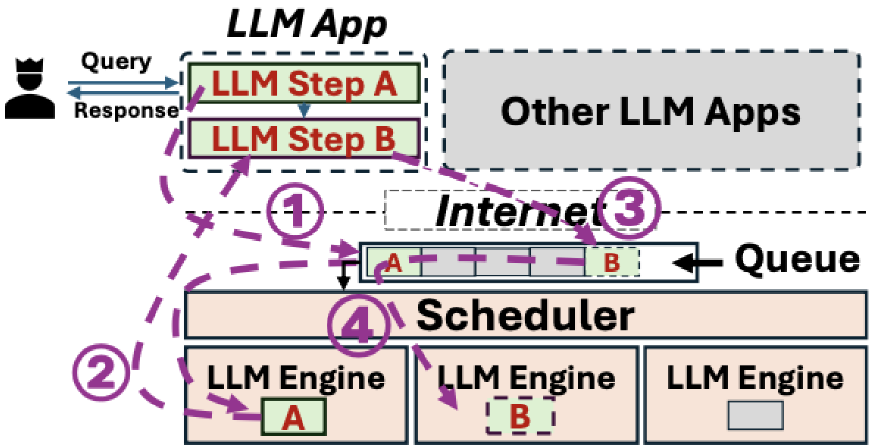
- *DAG* construction between requests
- Prompt structure analysis
- Data pipelining between requests

…

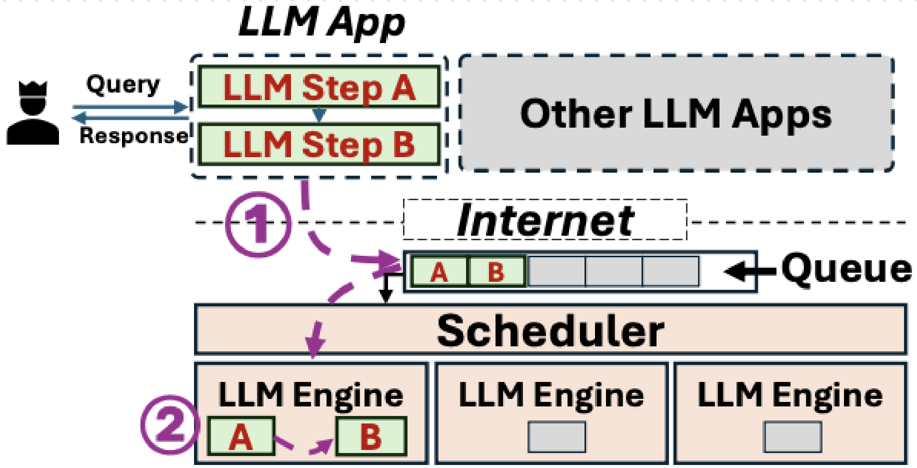
Parrot Overview

Optimization: Scheduling Dependent Requests

- Optimizing dependent requests by using semantic variables
  - Decreased Network Communication



Current LLM service



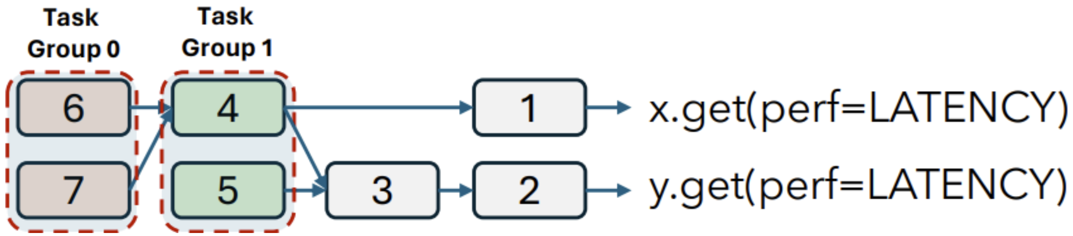
Parrot Design

Two steps are scheduled together with result of A be fed int B directly

- Avoid unnecessary network communication
- Avoid queuing delay from other apps

Optimization: Performance Criteria

- With DAG of application requests & E2E requirement
- Derive the performance requirement of each LLM call
  - High throughput Variables: all relevant requests are marked as thpt-preferred
  - Latency sensitive variables:
    - Reverse topological order analysis
    - Direct-linked requests and predecessor are marked as latency-preferred
    - Parallel requests at the same stage are grouped together, higher batch size

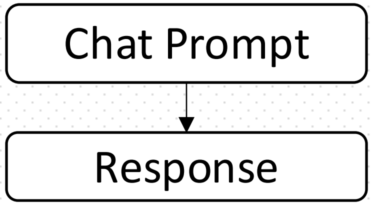


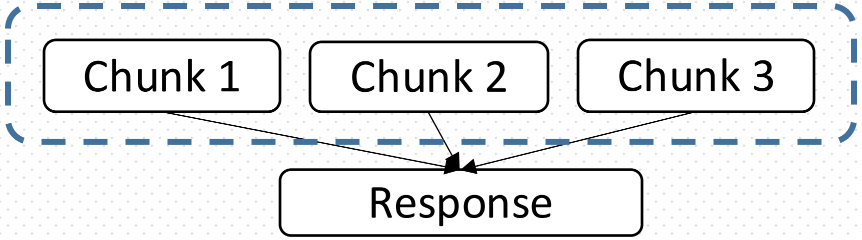
From the DAG, derive requests can be executed in parallel

Optimization: Performance Criteria

- Public LLM Service w/ apps with different performance criteria

Application DAG





High Throughput

response.get(perf=LATENCY)

Chatbot: Low Latency

response.get(perf=LATENCY)

Data Analytics: High Throughput

Batch Size

Small

Large

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

Optimization: Sharing Prompt Prefix

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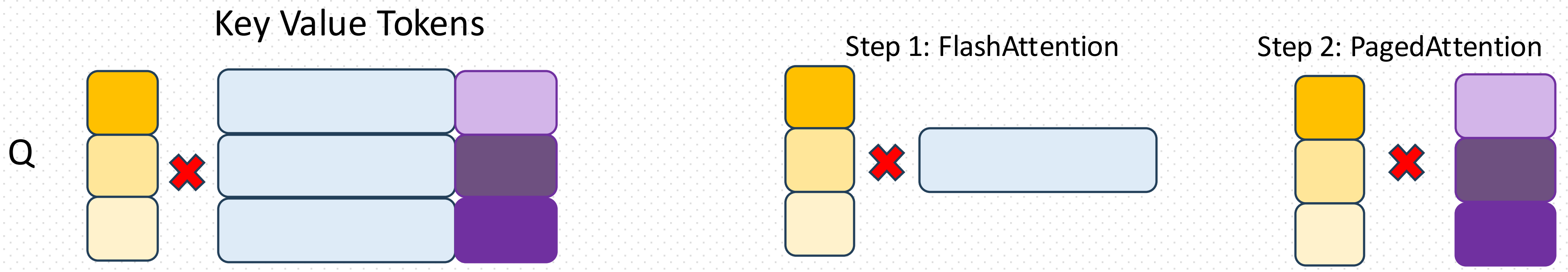
- With prompt structure, Parrot can **automatically** detect shared prefix

Prefix

> 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

Optimization: App-centric Scheduling

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Topological order

Performance criteria

Schedule task group together

Shared prefix

Algorithm 1: Parrot's Request Scheduling.

Data: Q: the request queue

Q.sort() ; `/* Topological order */`

for $r \in Q$ **do**

  SharedReqsInQueue, CtxInEngine = FindSharedPrefix(r);

  if $r.TaskGroup \neq \varnothing$ **then**

    r^* = FindEngine(r.TaskGroup);

  else if $SharedReqsInQueue \neq \varnothing$ **then**

    r^* = FindEngine(SharedReqsInQueue);

  else if $CtxInEngine \neq \varnothing$ **then**

    r^* = FindEngine(r, filter=CtxInEngine);

  if $r^* = \varnothing$ **then**

    r^* = FindEngine(r);

  Q.remove(r^*);

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Experimental Setup

- Testbed
  - 1 server with a 24-core CPU and 1 A100 GPU
  - 1 server with a 64-core CPU and 4 A6000 GPUs
  - 200-300ms emulating the Internet latency
- Workloads
  - Model utilized: LlaMA 7/13B model
  - Task-1: long document analysis with Arxiv dataset
  - Task-2: BingCopilot with synthesized user queries
  - Task-3: Multi-agent application via MetaGPT
  - Task-4: Mixed workload (chat application + task-1)

Workload	Serving Dependent Requests.	Perf. Obj. Deduction	Sharing Prompt	App-centric Scheduling
Data Analytics	✓	✓		✓
Serving Popular LLM Applications			✓	✓
Multi-agent App.	✓	✓	✓	✓
Mixed Workloads	✓	✓		✓

- Baseline
  - $\underbrace{\text{Application framework}}_{\text{Langchain}} + \underbrace{\text{LLM serving + Engine Backend}}_{\text{FastChat + HG transformer/vLLM}}$

Evaluation: Chain/Map-Reduce Summary

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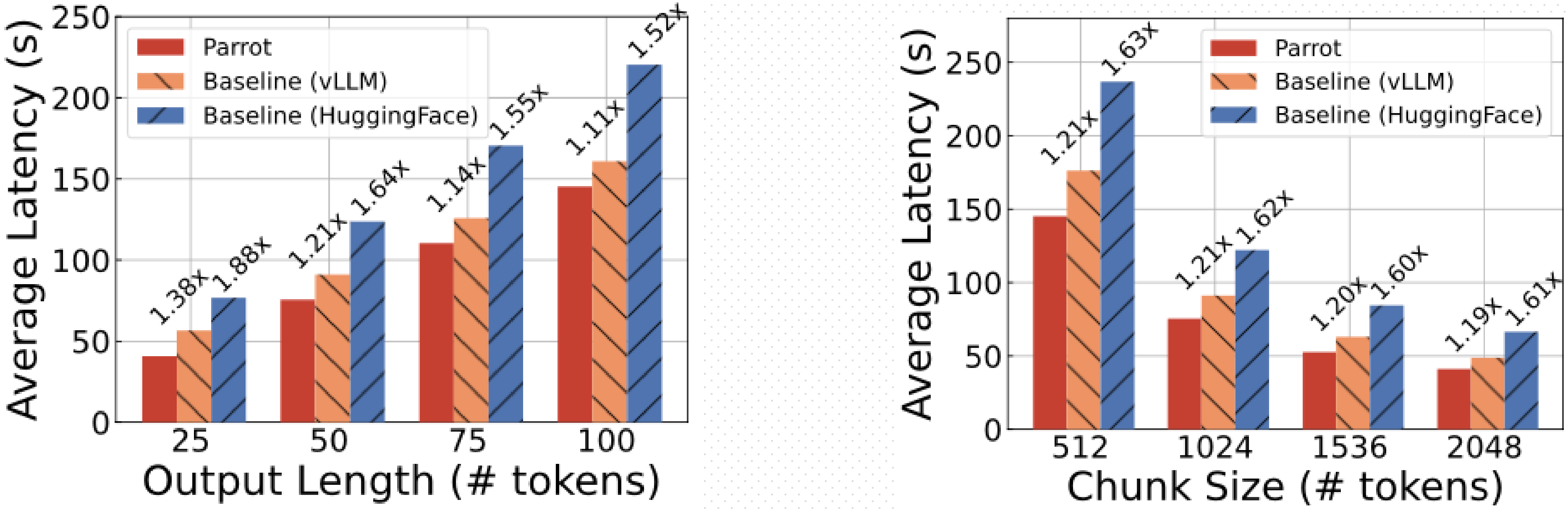
Average E2E latency of chain summarization



Parrot achieves a 1.38× and 1.88× reduction in latency over baselines due to decreased network latency.

Evaluation: Chain/Map-Reduce Summary

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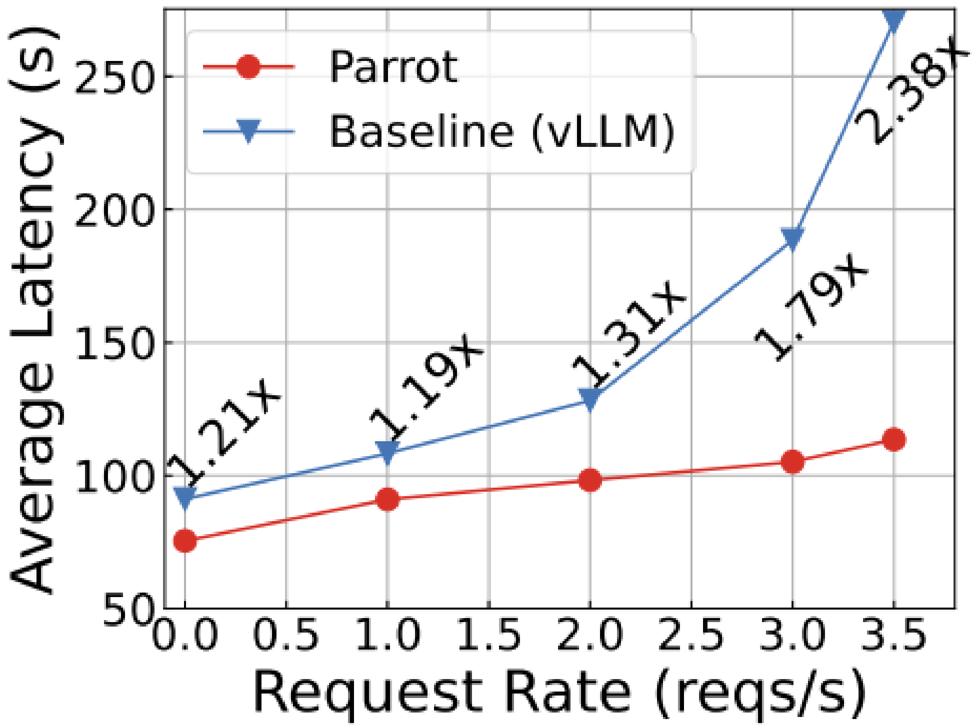
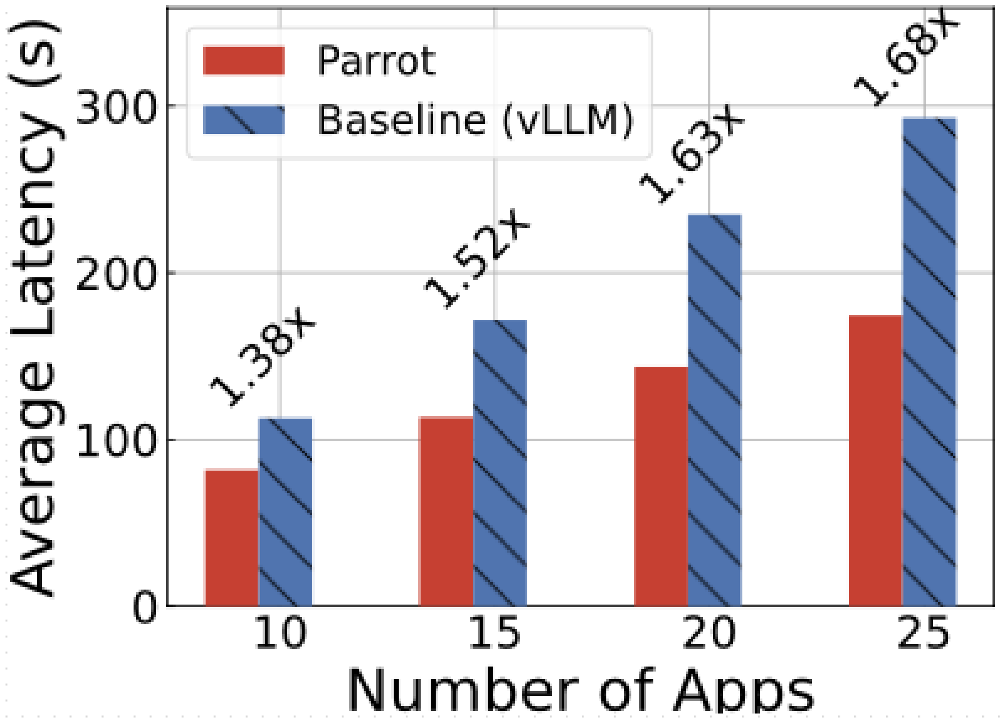
Chain Summary with queued delay



Multiple summary apps



- Parrot slashes latency by up to 2.38× since it further reduces queuing latency
- Slowdown due to interleaved execution of all applications

Evaluation: Chain/Map-Reduce Summary

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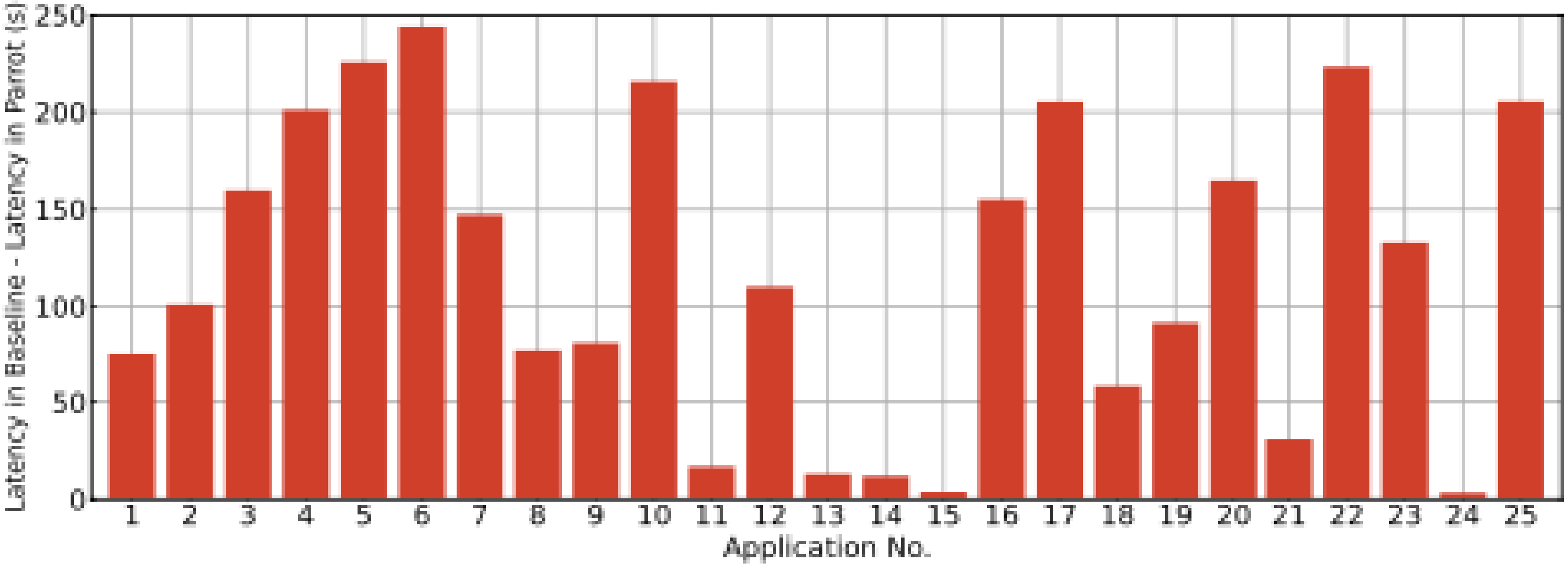
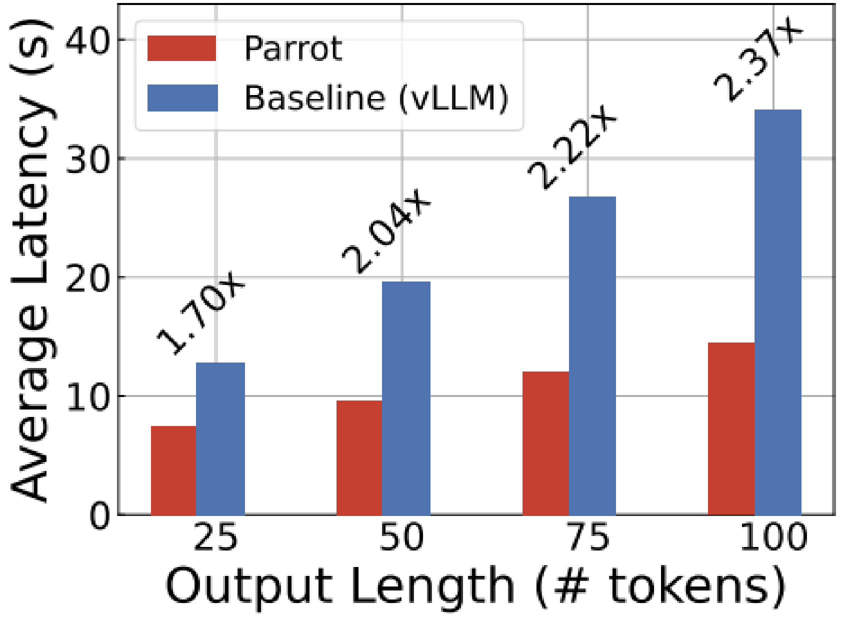
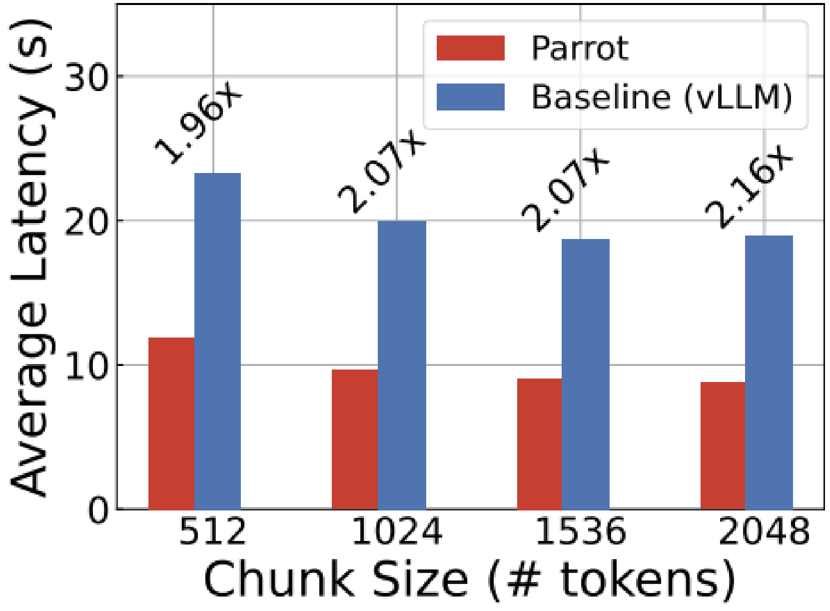


The difference in E2E latency of the 25 chain-summary application between Baseline and Parrot.

Evaluation: Chain/Map-Reduce Summary

Average E2E latency of map-reduce summarization





Parrot realizes a 2.37× acceleration over baselines by identifying the map task as a task group (higher batch)

Evaluation: Popular Apps (Bing Copilot, GPTs)

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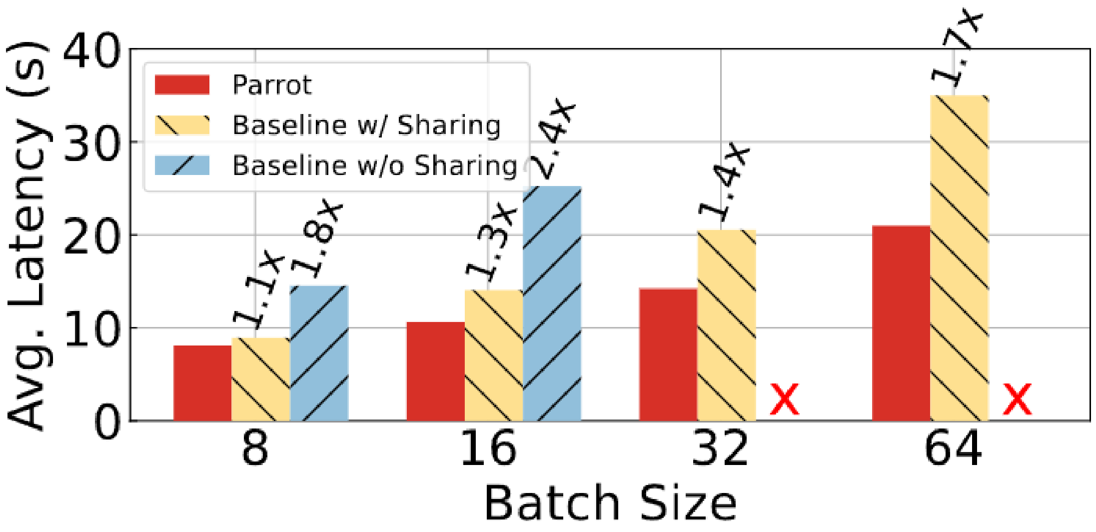
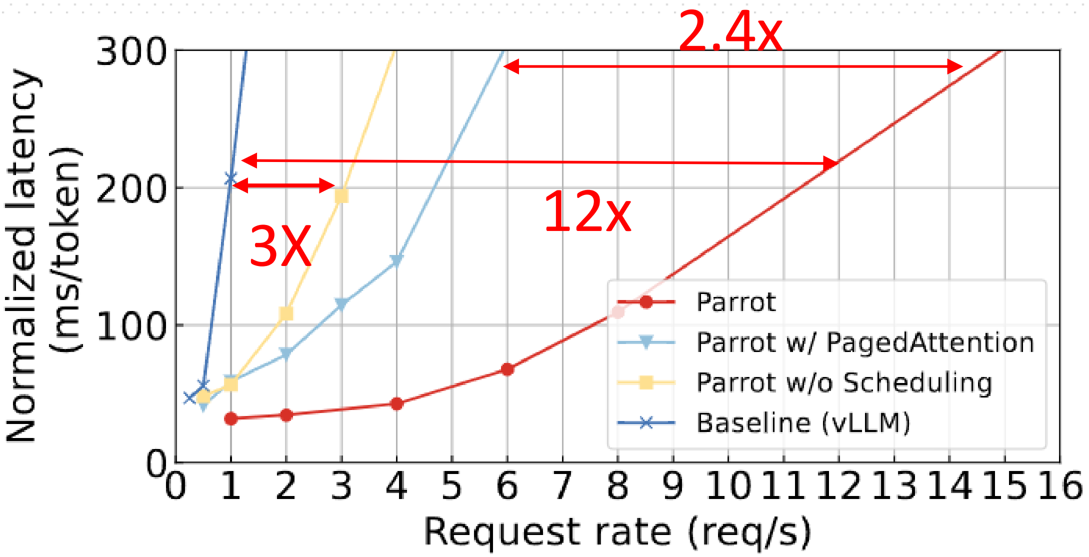
Synthesized requests following Bing Copilot length distribution



Synthesized requests from 4 different popular GPTs applications



- Production prompts show up to 1.7x latency reduction due to better GPU kernel
- Parrot can sustain 12× higher request rates compared to the baseline without sharing.
  - Only 3X higher request rates without co-locate requests from the same app.
  - Even compared with paged attention, Parrot achieves 2.4x throughput improvement.

Evaluation: Multi-agent Applications

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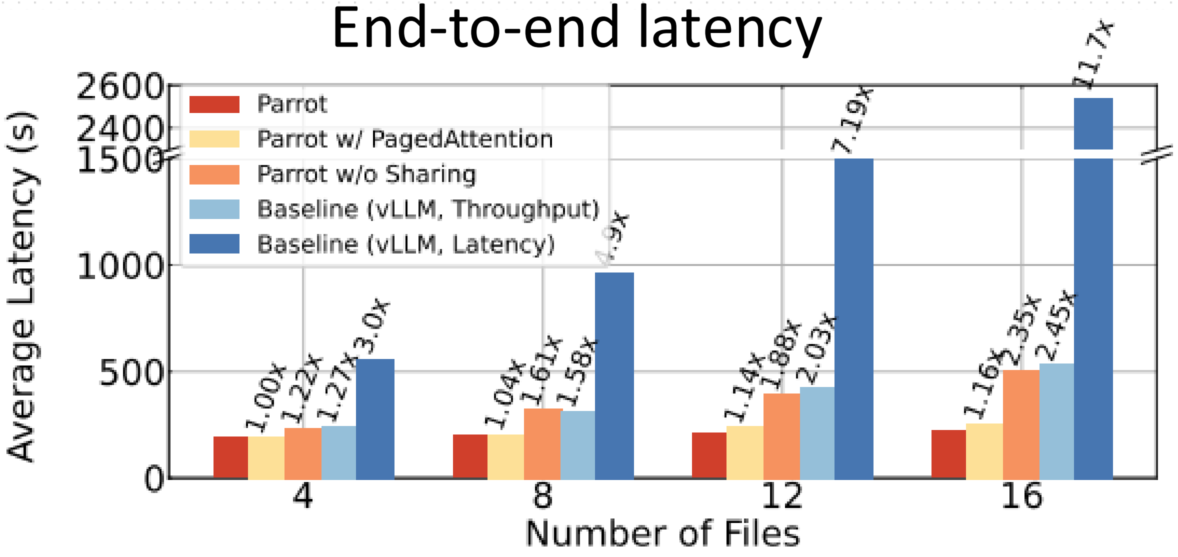
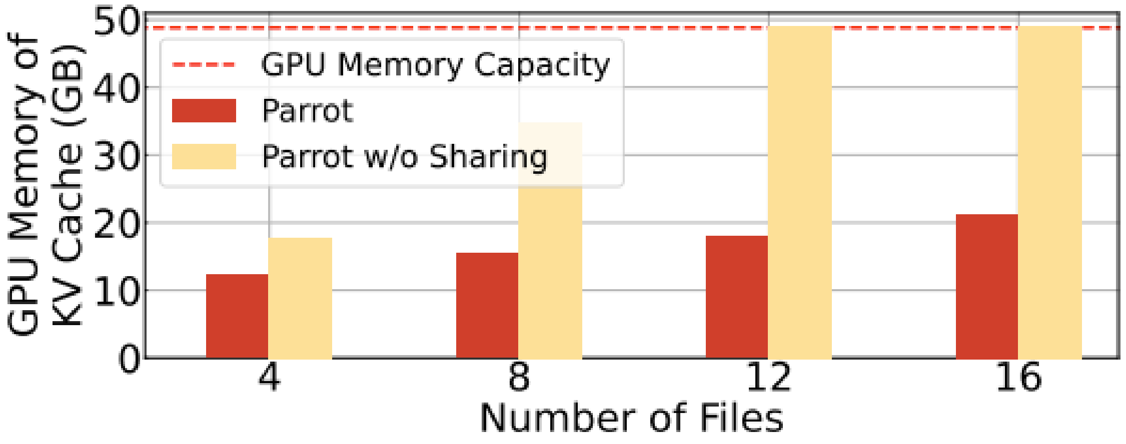
- MetaGPT: code review and revision task
  - Architect outlines files structures and APIs
  - Reviewers leave comments for each file
  - Coders revise codes based on comments

End-to-end latency



GPU Memory of KV cache



- Parrot achieves a speedup of up to 11.7× compared with the latency-centric baseline. (higher batch size)
- Even compared with throughput-centric baseline, Parrot achieves 2.45x throughput improvement. (sharing prefix)

Evaluation: Scheduling Mixed Workloads

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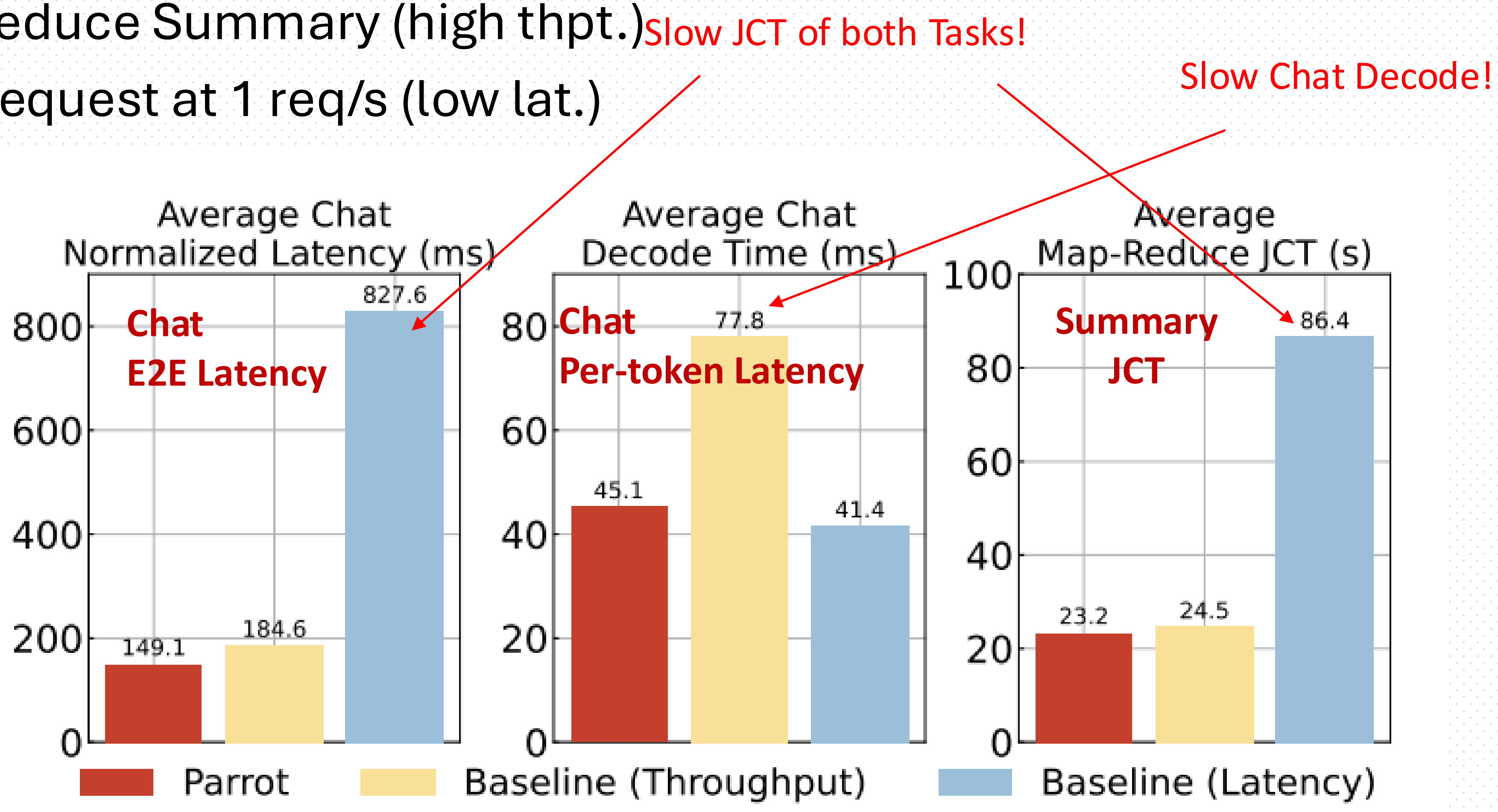
- Mixed workloads
  - Map-reduce Summary (high thpt.)
  - Chat request at 1 req/s (low lat.)



Evaluation: Scheduling Mixed Workloads

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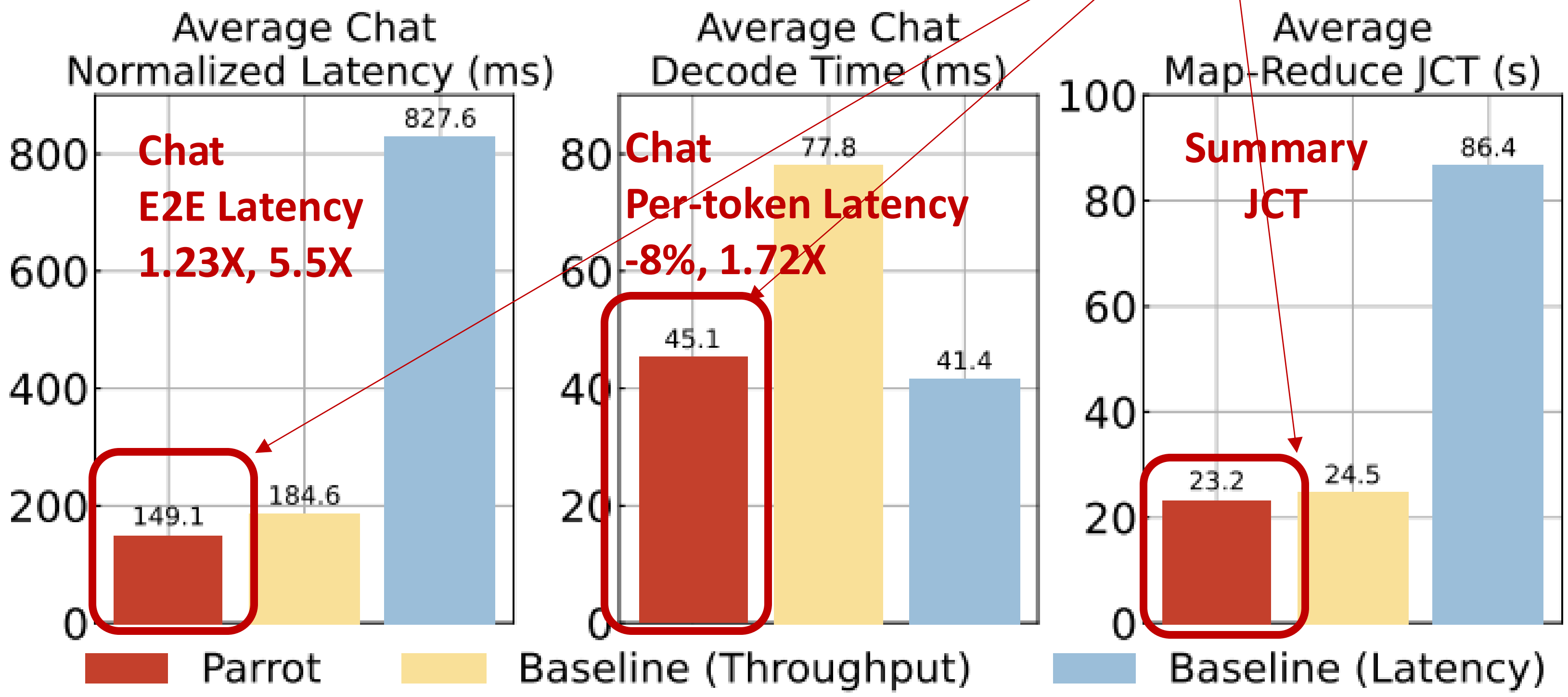
- Mixed workloads
  - Map-reduce Summary (high thpt.)
  - Chat request at 1 req/s (low lat.)

Parrot achieves low latency and high-throughput for both apps



Parrot optimizes application performance by scheduling them on different engines

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Pros and Cons

- Pros
  - Innovative Abstraction (Semantic Variables)
  - End-to-end application-level optimization instead of request level
  - High performance gains and support for multiple workflows
- Cons
  - Potential overhead in terms of analyzing and managing variables
  - Lack of comparison to SGLang

Summary

- LLM service support multiple applications at the same time
  - 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