SOUTHEAST UNIVERSITY 東南大學

计算机科学与工程学院
School of computer science and engineering

[NSDI'26] AVA: Towards Agentic Video Analytics with Vision Language Models

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https://github. com/I-ESC/Project-Ava

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11/17/2025

Team

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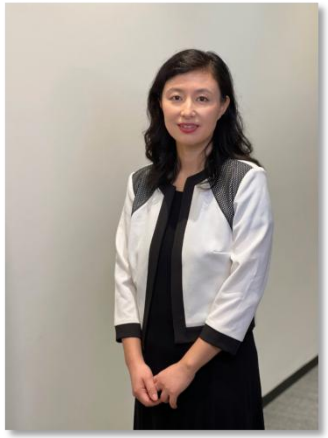

Lili Qiu
MSRA

Topic:

- Edge AI/ML analytics
- AI inference systems
- Mobile systems and AIoT

Top-tier computer system conferences:

- ISCA, ASPLOS, MobiCom, MobiSys, NSDI, OSDI, PLDI, EuroSys, SC, and PPoPP

- [NSDI'24] Vulcan: Automatic Query Planning for Live ML Analytics
- [NSDI'23] GEMEL: Model Merging for Memory-Efficient, Real-Time Video Analytics at the Edge
- [NSDI'23] RECL: Responsive Resource-Efficient Continuous Learning for Video Analytics
- [EuroSys'26] Scaling LLM Test-Time Compute with Mobile NPU on Smartphones
- [MobiCom'25] Confidant: Customizing Transformer-based LLMs via Collaborative Training on Mobile Devices

Outline

1 Background

2 Motivation

3 Design

4 Evaluation

5 Conclusion

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Background

- **Video analytics**

Object detection task

DNN-based model, e.g., YoLo

Video question answering task

Qusetion: *Why does the train stop for a while before moving again at the end of the video ?*

LLM/VLM

Answer: *The train stops for a scheduled stop at a station*

Video query task

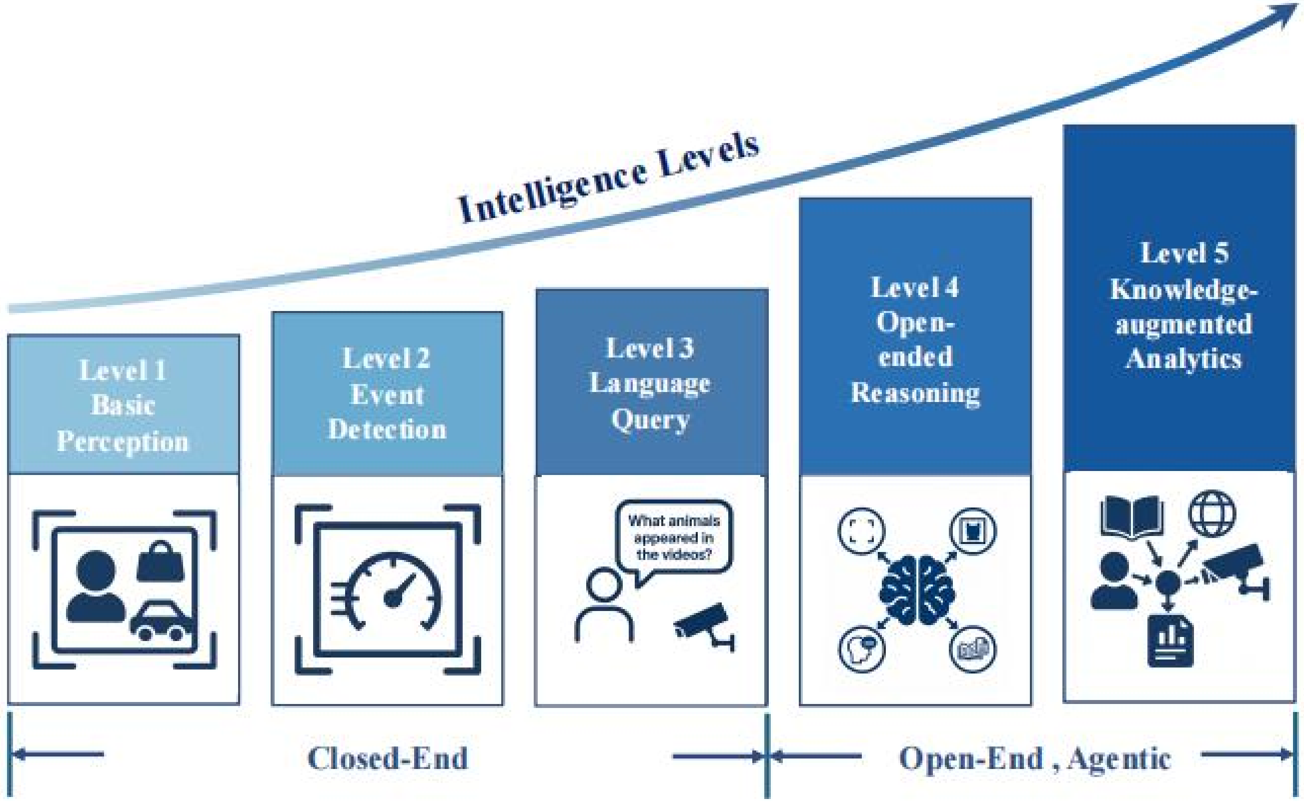
Query: *Can you confirm if the vehicle the uploaded image has been witnessed in Beijing?*

LLM/VLM

Knowledge graph

Answer: *Yes*

Background



Intelligence levels of video analytics systems

Closed-End video analytics system:

- **L1 ~ L3**
- **Predefined task/query, e.g., detection**
- **Domain-specific model, e.g., DNN**

CAT

Detection: YoLo

Level 1

Event detection: ActionFormer

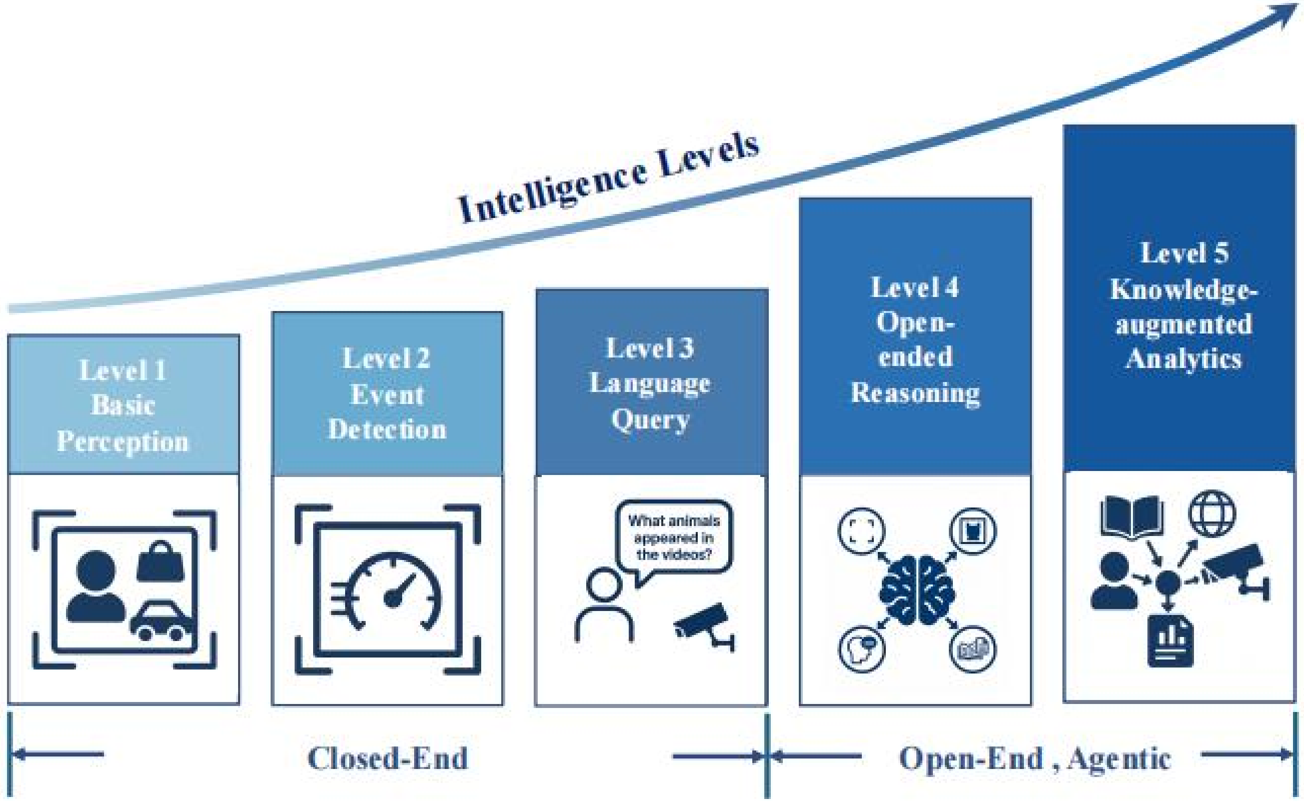
Level 2

Video query: CLIPBERT model

Level 3

Adaptability & Flexibility ✗

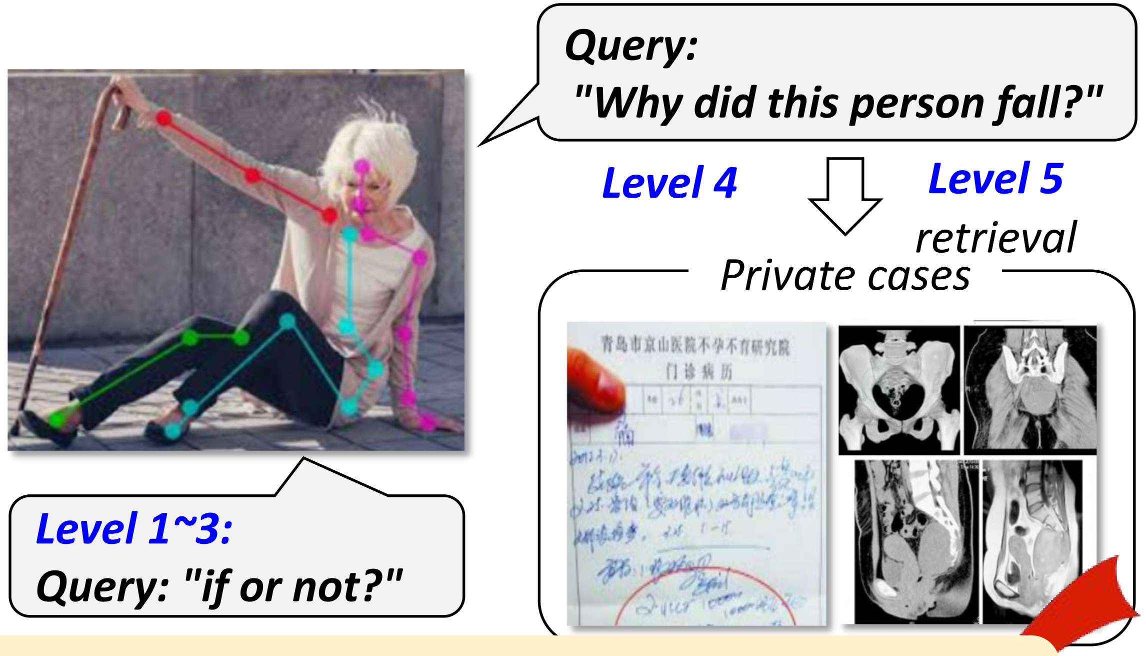
Background



Intelligence levels of video analytics systems

Open-end, Agentic video analytics system:

- L4 ~ L5
- Open and diverse tasks
- General model, e.g., LLM/VLM
- Complex query



Problem: how to achieve accurate and efficient video analytics for various tasks?

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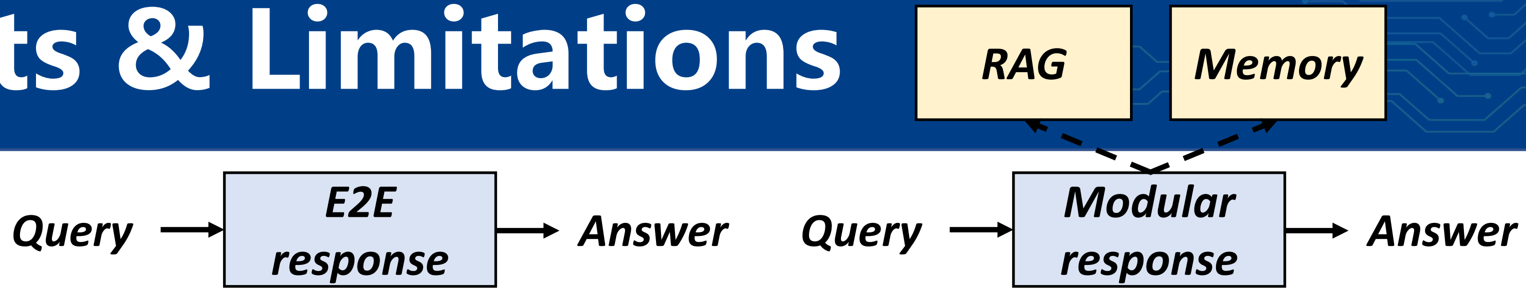
State-of-the-Arts & Limitations



	E2E response	Modular response
Closed-end analytics (L1~L3)	Vulcan [NSDI'24], RECL [NSDI'23], Gemel [NSDI'23], Ekya [NSDI'22]	Video-RAG [NeurIPS'25], VideoTree [CVPR'25], VideoAgent [ECCV'24], DrVideo [CVPR'25]
Open-end analytics (L4~L5)	VLMs like GPT-4o, Gemini, QwenVL and Phi	**[NSDI'26] AVA**

Limitation 1: Struggle to handle ultra-long videos (> 10 hours).

- L1 ~ L3: Rely on DNNs and process each video frame independently.
- L4 ~ L5: Traditional VLM limited inherent context window

Limitation 2: Struggle to handle open-end complex tasks.

- Predefined tasks, e.g., detection —> The limited agentic reasoning capabilities

Opportunity & Challenge

Limitation 1: Struggle to handle ultra-long videos.

Opportunity 1: Only a small portion of the frames are necessary to answer

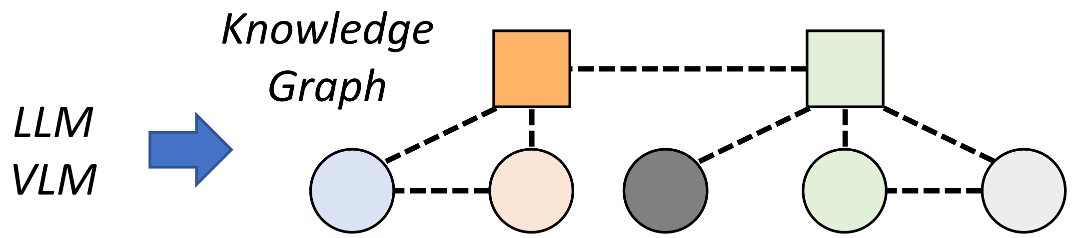
Short (1.4 minutes)		Medium (9.7 minutes)		Long (39.7 minutes)	
Total	Needed	Total	Needed	Total	Needed
2144.8	12.1 (0.5%)	13924.1	68.1 (0.4%)	66847.1	82.3 (0.1%)

Empolyed VideoMME benchmark and Qwen2-VL.

Challenge 1: How to extract useful information from ultra-long videos?

Limitation 2: Struggle to handle open-end tasks.

Opportunity 2: The LLM/VLM + knowledge graphs enables answering open-end questions.



Challenge 2: How to achieve accurate and efficient agentic searching on graph?

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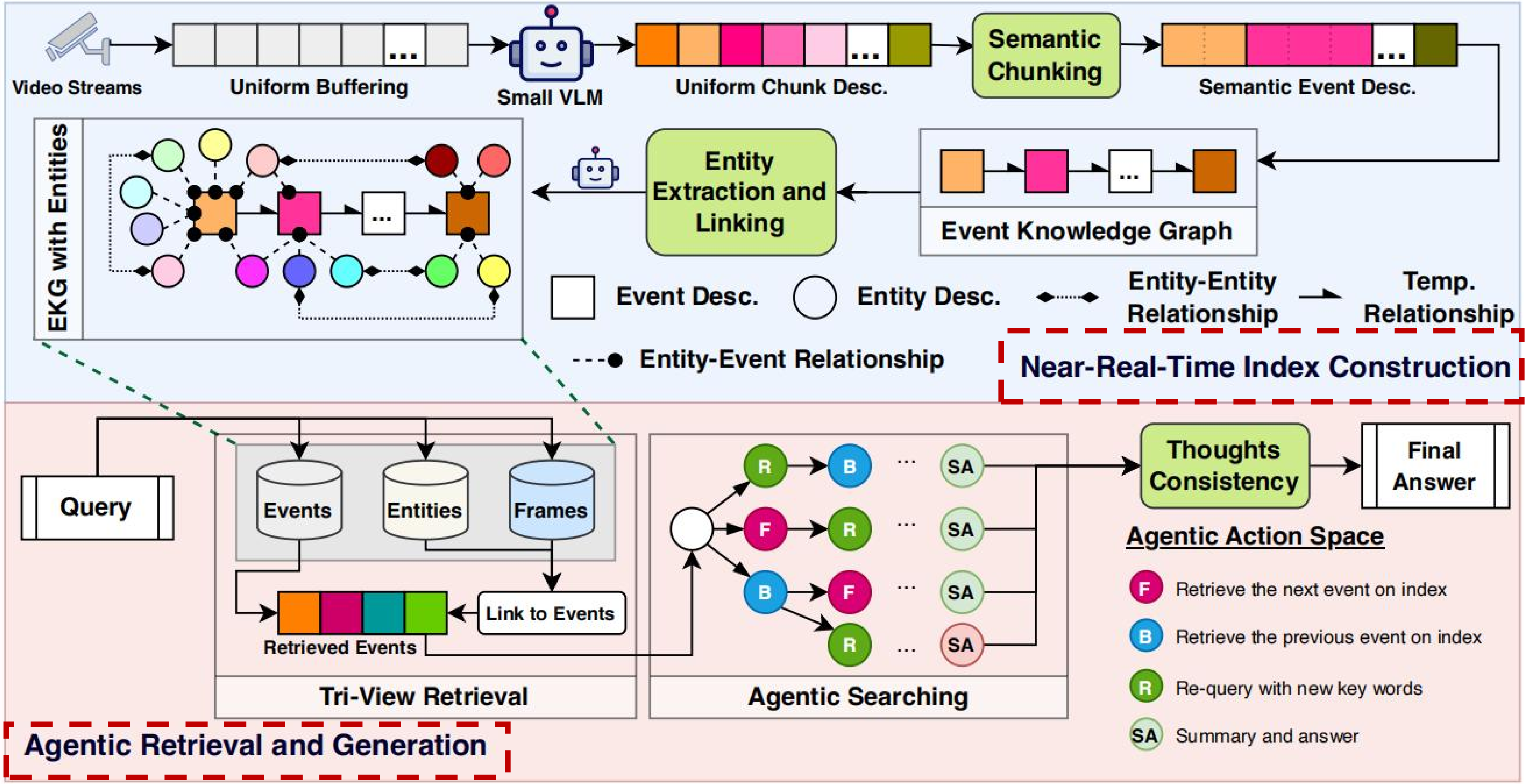
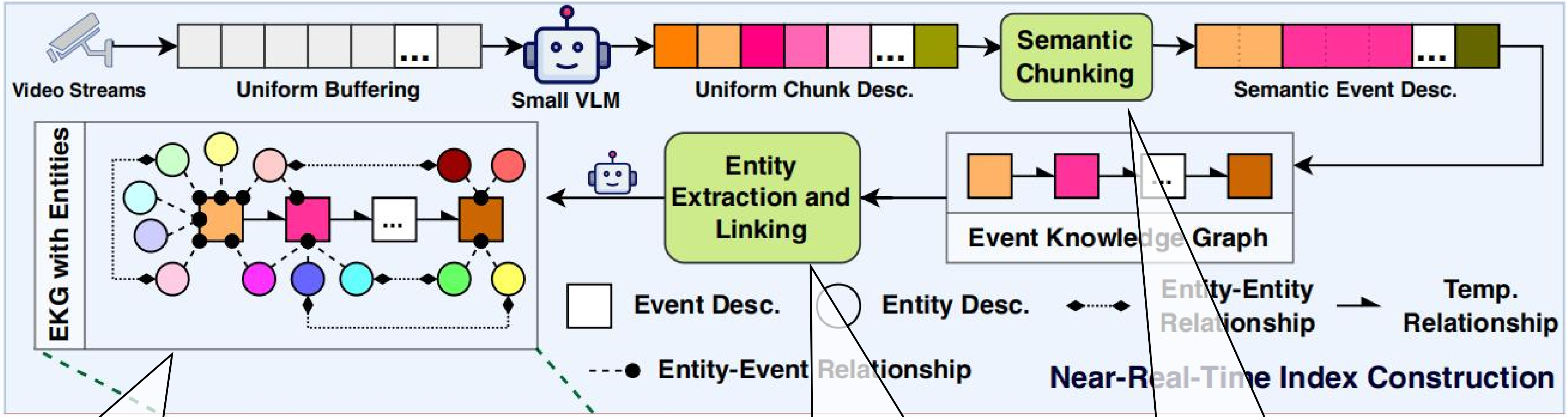
Overview



Video Streams
Uniform Buffering
Small VLM
Uniform Chunk Desc.
Semantic Chunking
Semantic Event Desc.
EKG with Entities
Entity Extraction and Linking
Event Knowledge Graph
Event Desc.
Entity Desc.
Entity-Entity Relationship
Temp. Relationship
Entity-Event Relationship
Near-Real-Time Index Construction
Query
Events
Entities
Frames
Link to Events
Retrieved Events
Tri-View Retrieval
R
B
F
SA
Agentic Searching
Thoughts Consistency
Final Answer
Agentic Action Space
F Retrieve the next event on index
B Retrieve the previous event on index
R Re-query with new key words
SA Summary and answer
Agentic Retrieval and Generation

Design 1: Near-Real-Time Index Construction



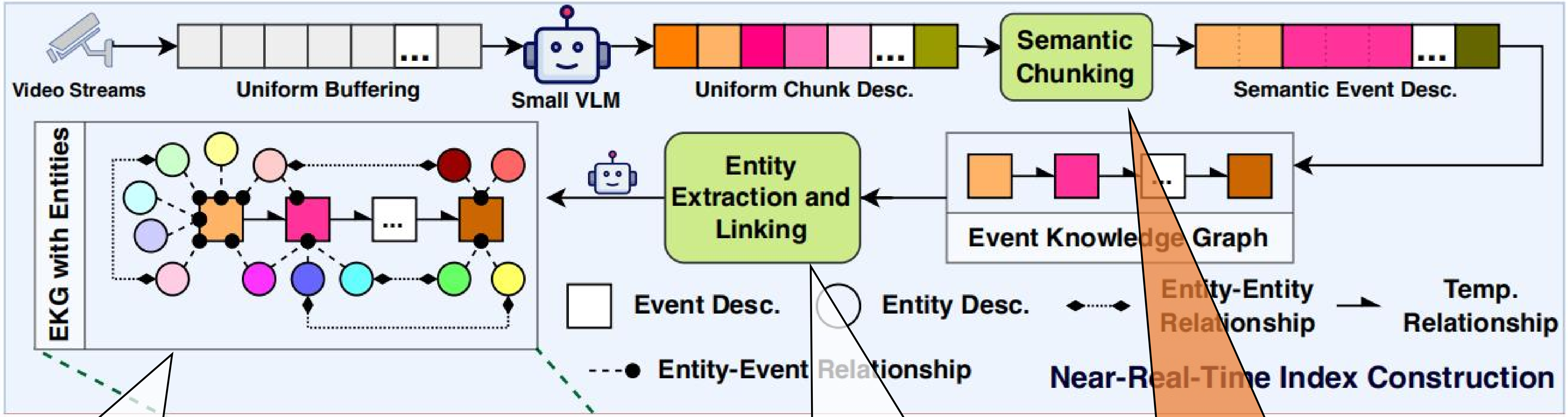
Model 3: Event Knowledge Graph with Entities

Model 2: Entity Extraction and Linking

Model 1: Semantic Chunking

Challenge 1: How to extract useful information from ultra-long videos?

Design 1: Near-Real-Time Index Construction



Model 3: Event Knowledge Graph with Entities

Model 2: Entity Extraction and Linking

Model 1: Semantic Chunking

Challenge 1: How to extract useful information from ultra-long videos?

Model 1: Semantic Chunking

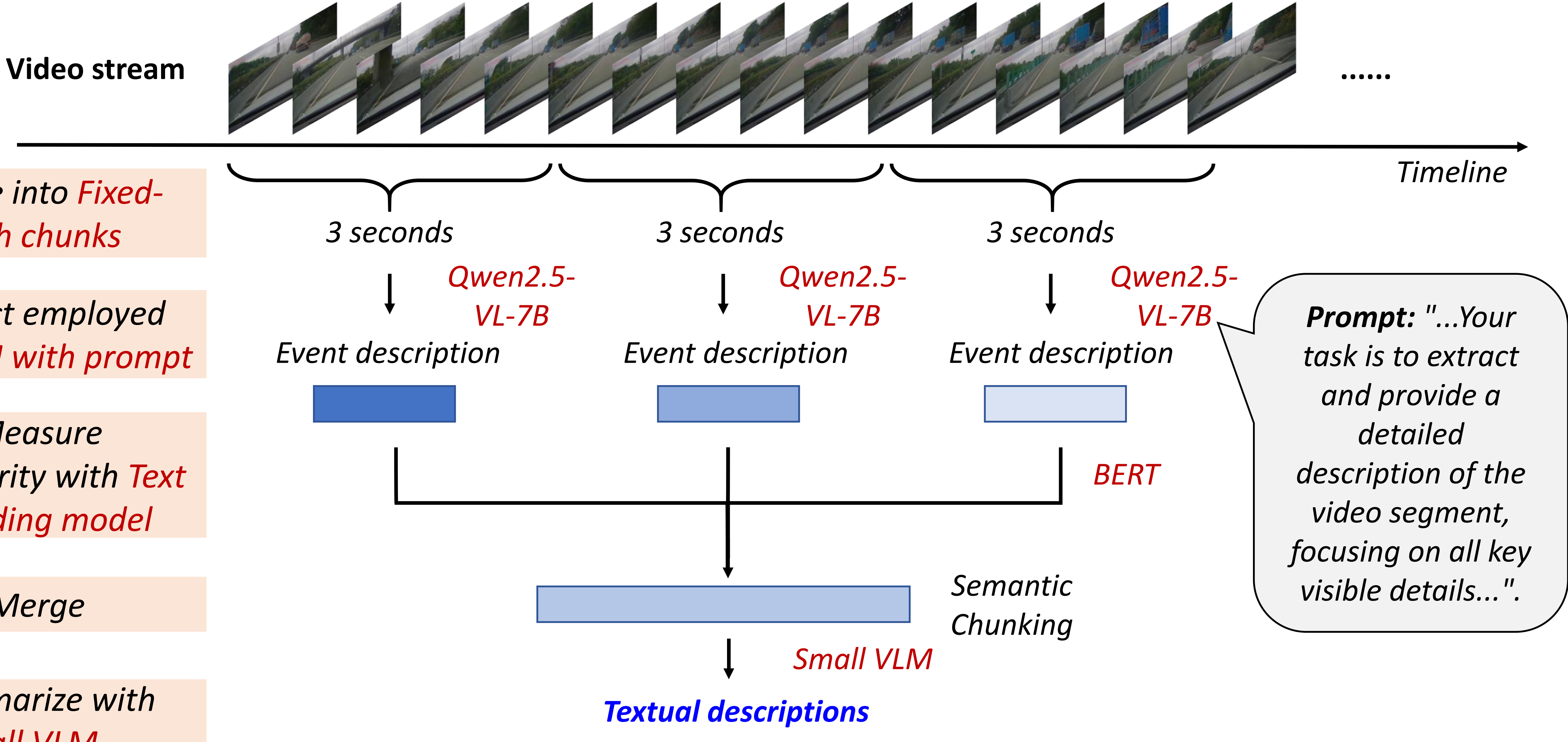
1. Divide into Fixed-length chunks

2. Extract employed Small VLM with prompt

3. Measure the similarity with Text embedding model

4. Merge

5. Summarize with Small VLM



Model 1: Semantic Chunking

Uniform Chunk Index

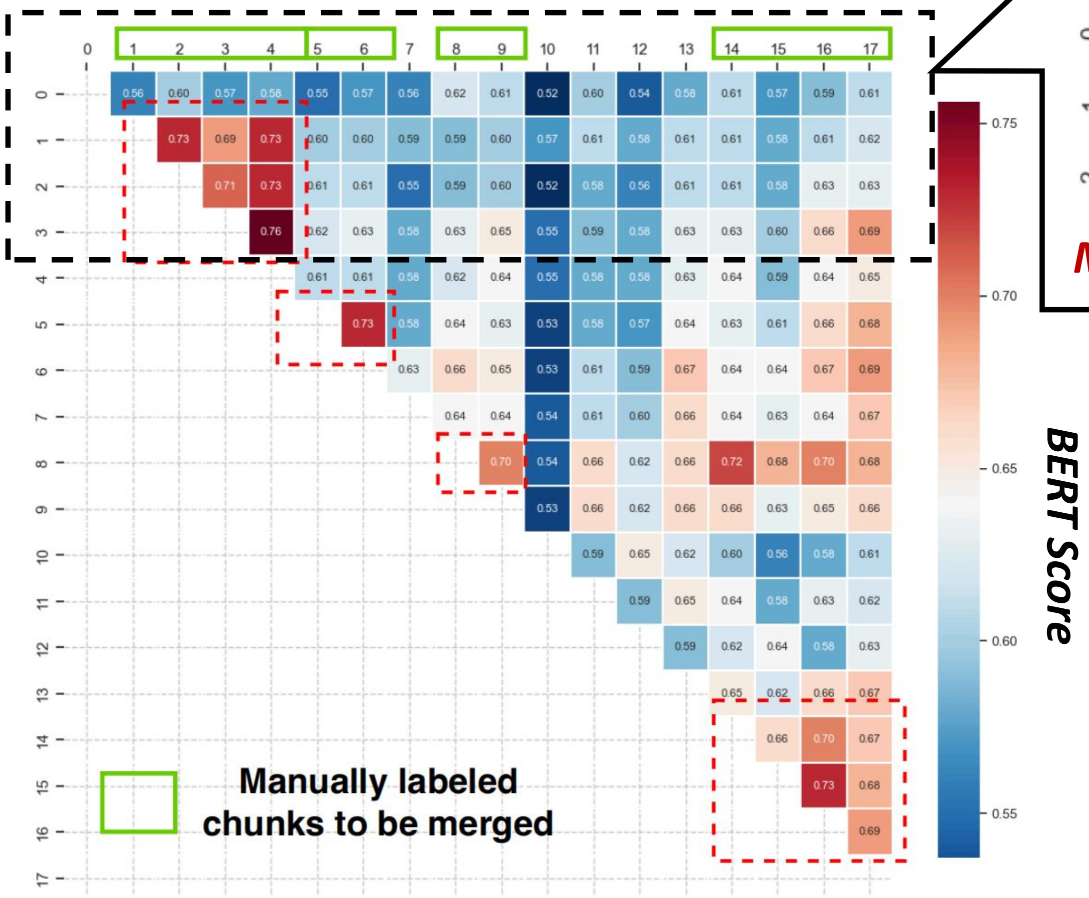
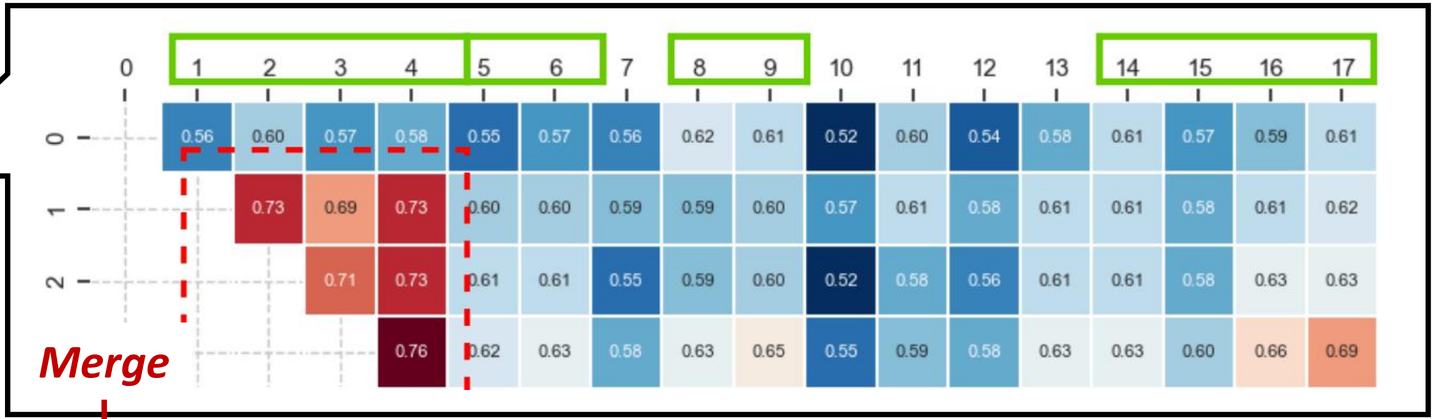


Figure: Merging uniform chunks into semantic chunks guided by the pairwise BERTScore distribution.

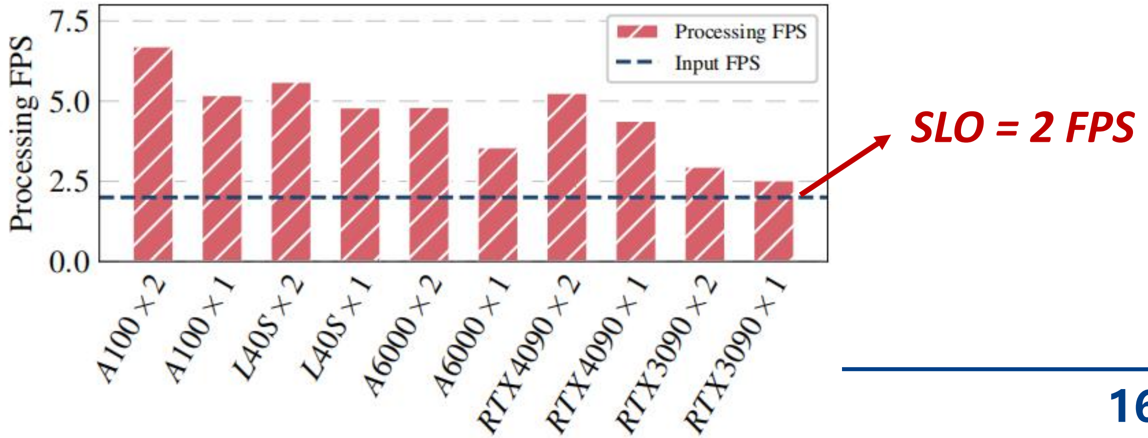


> predefined threshold → Merge 1, 2, 3, 4

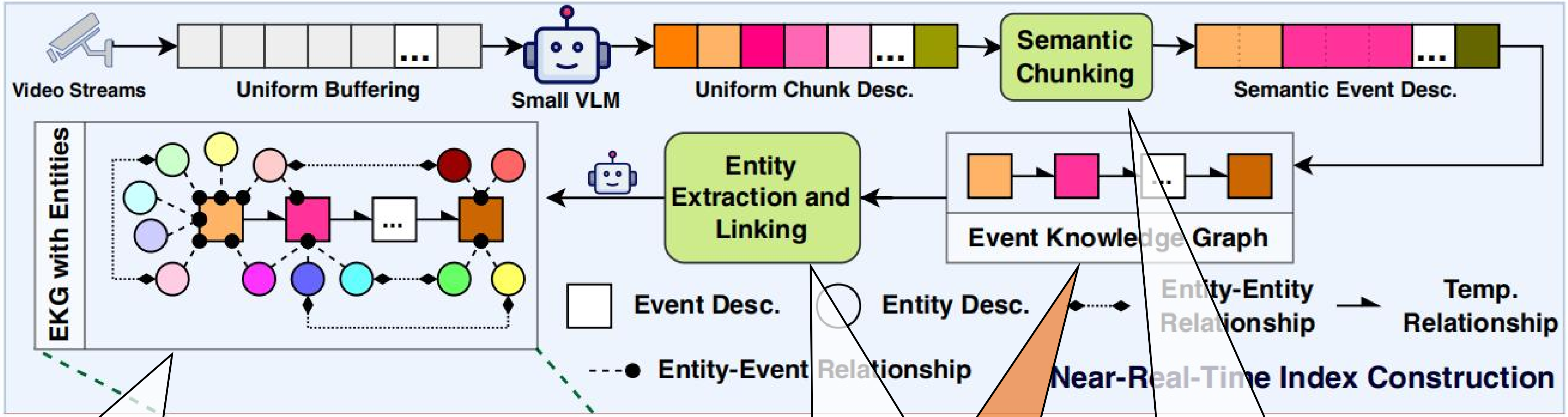
< predefined threshold → Not merge 4, 5

"......The semantic chunking process does not become a bottleneck in the near-real-time index construction phase."

- *Batch inference, maximize GPU utilization*



Design 1: Near-Real-Time Index Construction



Model 3: Event Knowledge Graph with Entities

Model 2: Entity Extraction and Linking

Model 1: Semantic Chunking

Event Knowledge Graph

...

An Example of Event Knowledge Graph

Semantic Chunk

00:04:10

Event 1

The environment is a grassy area with several feeding stations, including metalbowls and a hanging feeder,and a small wooden structure with dense greenery in the background......

Semantic Chunk

00:18:28

Event 2

... The rodent-like mammal, possibly a mouse or aracoon, is also consistently observed in the grassy outdoor area, moving around, and occasionally stopping to eat ..

Semantic Chunk

01:29:57

Event 3

.. during evening, a group ofracoon are captured, identifiable by their distinctive black and white striped tailsamd masked faces. A largeraninial likely a deer, ismoving closer..

Semantic Chunk

09:59:10

Event 4

... a small bird, likely a songbird, perched on theground near one of thebowls, moving around thebowl and pecking at theground. After a few momentsthe bird flies awav.

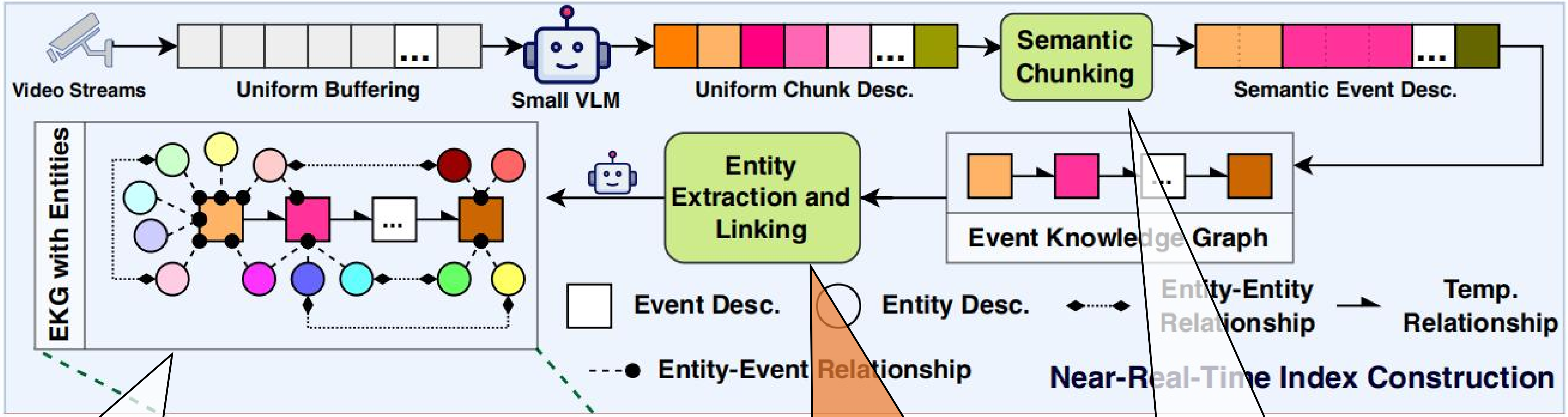
Semantic Chunk

11:21:23

Event 5

.. A small animal, possibly a squirrel or a similar rodent, is seen near the bird feeder, moving around the area and for aging and exploring the surroundings ...

Design 1: Near-Real-Time Index Construction



Model 3: Event Knowledge Graph with Entities

Model 2: Entity Extraction and Linking

Model 1: Semantic Chunking

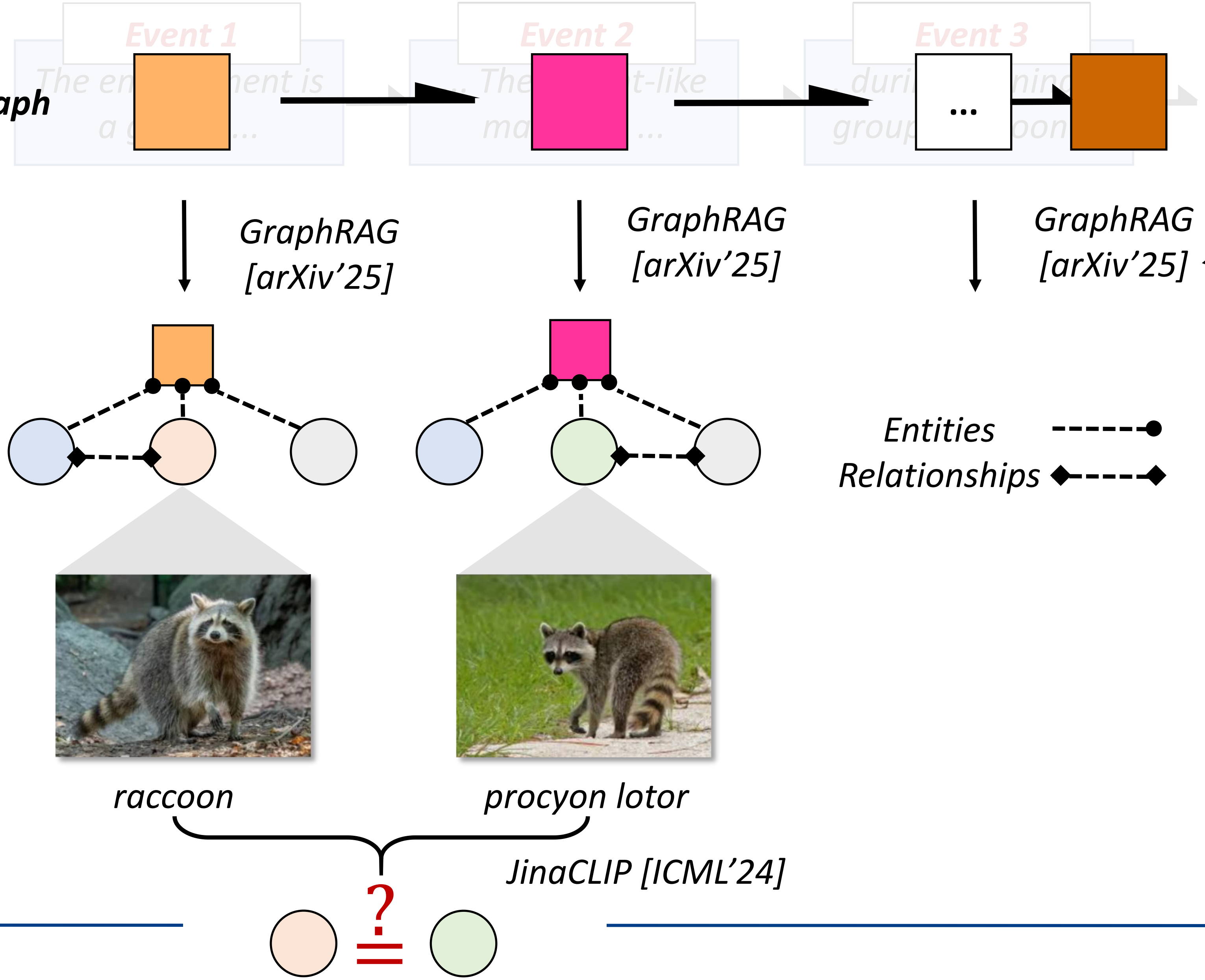
Challenge 1: How to extract useful information from ultra-long videos?

Model 2: Entity Extraction and Linking

Event knowledge graph

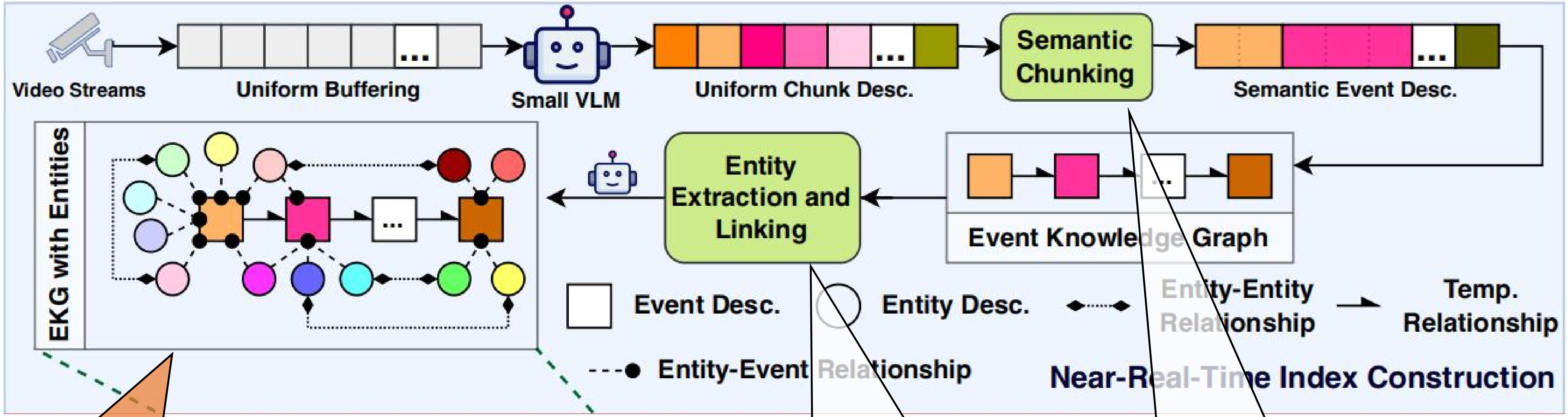
1. *Extract entity and relationships empolyed Small VLM with Prompt*

2. *De-duplicate and link employed Text Embedding Model*



***Prompt:** "...Your task is to extract and provide a detailed description of the video segment, focusing on all key visible details...".*

Design 1: Near-Real-Time Index Construction



Model 3: Event Knowledge Graph with Entities

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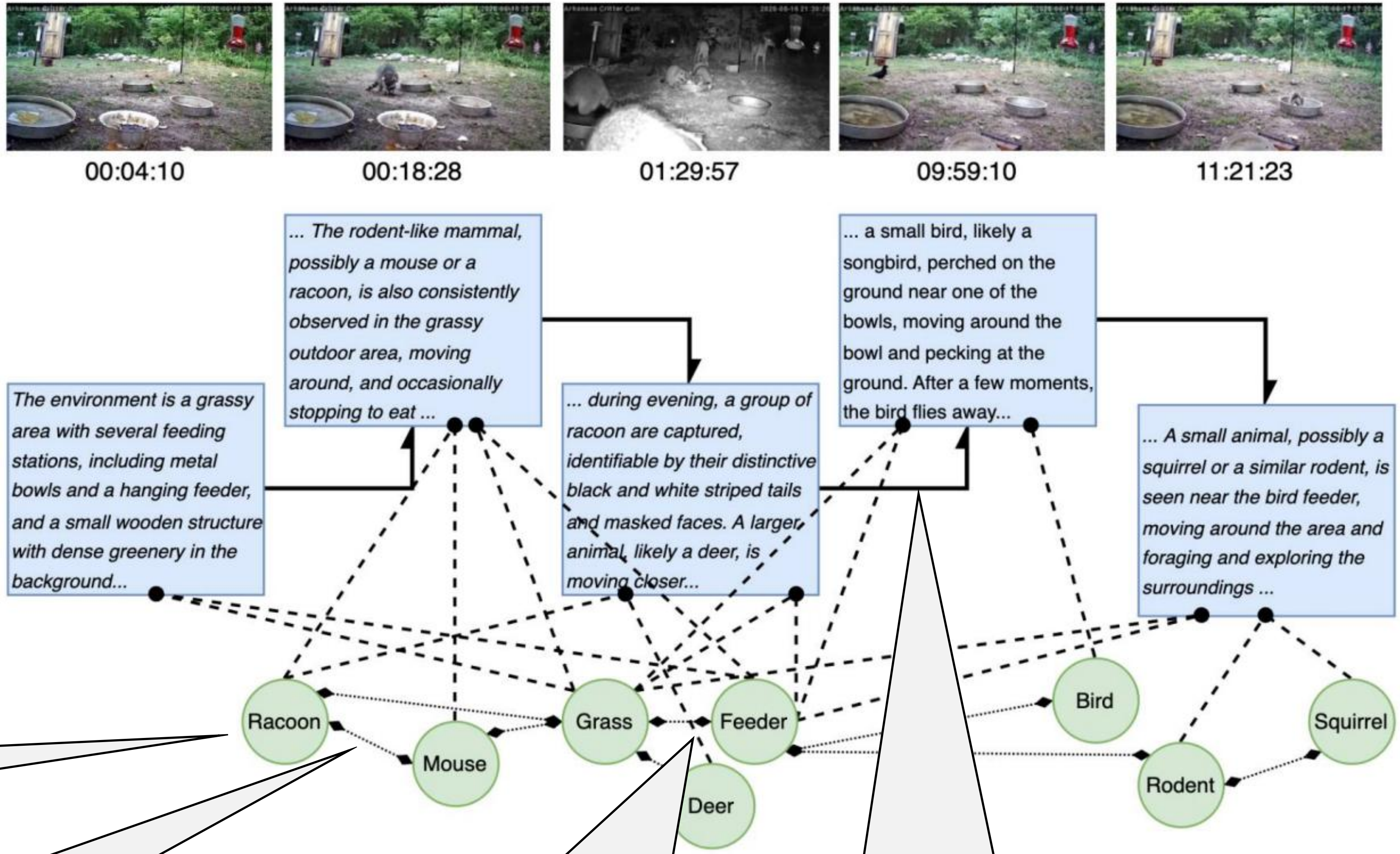
Challenge 1: How to extract useful information from ultra-long videos?

Model 3: Event Knowledge Graph with Entities

Wildlife monitoring video

Model 1

Model 2



Event Knowledge Graph

The temporally ordered set of events

The entities extracted from the video within each event

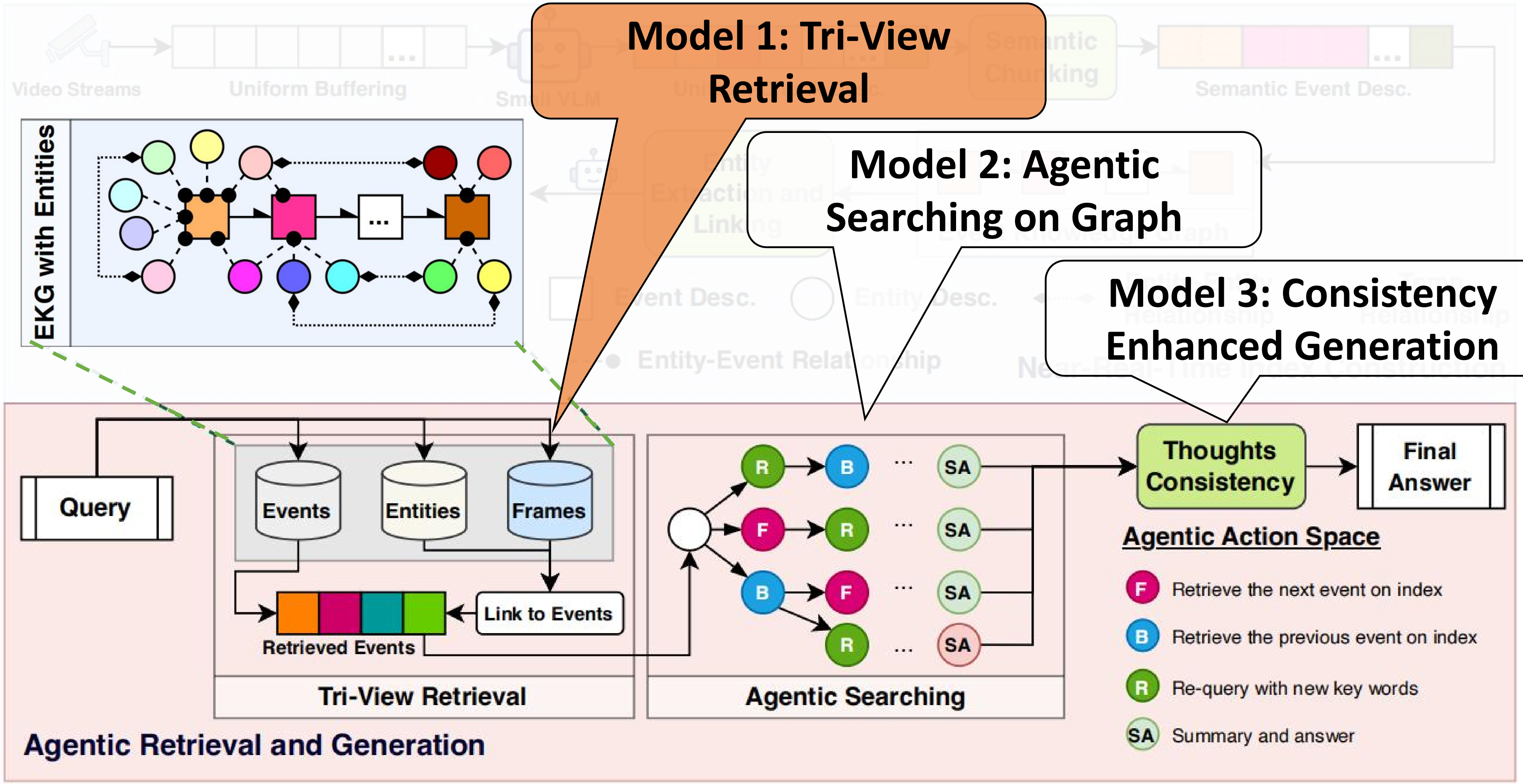
Three types of relationships:

1) semantic entity-entity relations

2) participation relations

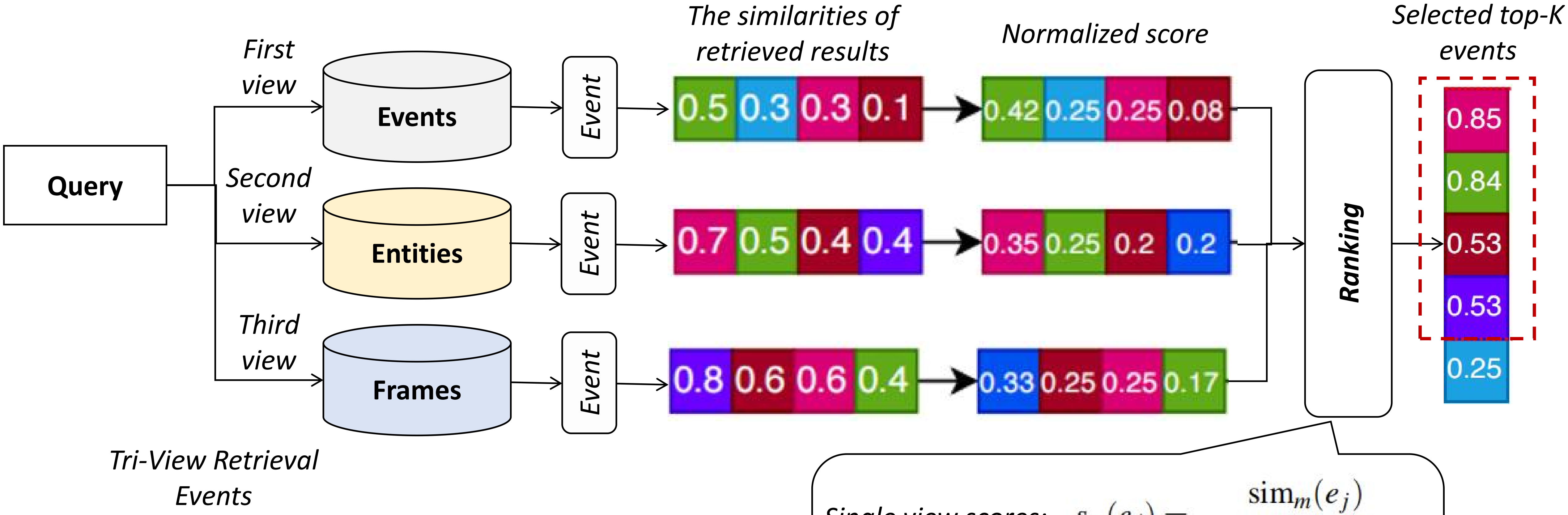
3) temporal event-event relations

Challenge 2: How to achieve accurate and efficient agentic searching on graph?



Model 1: Tri-View Retrieval

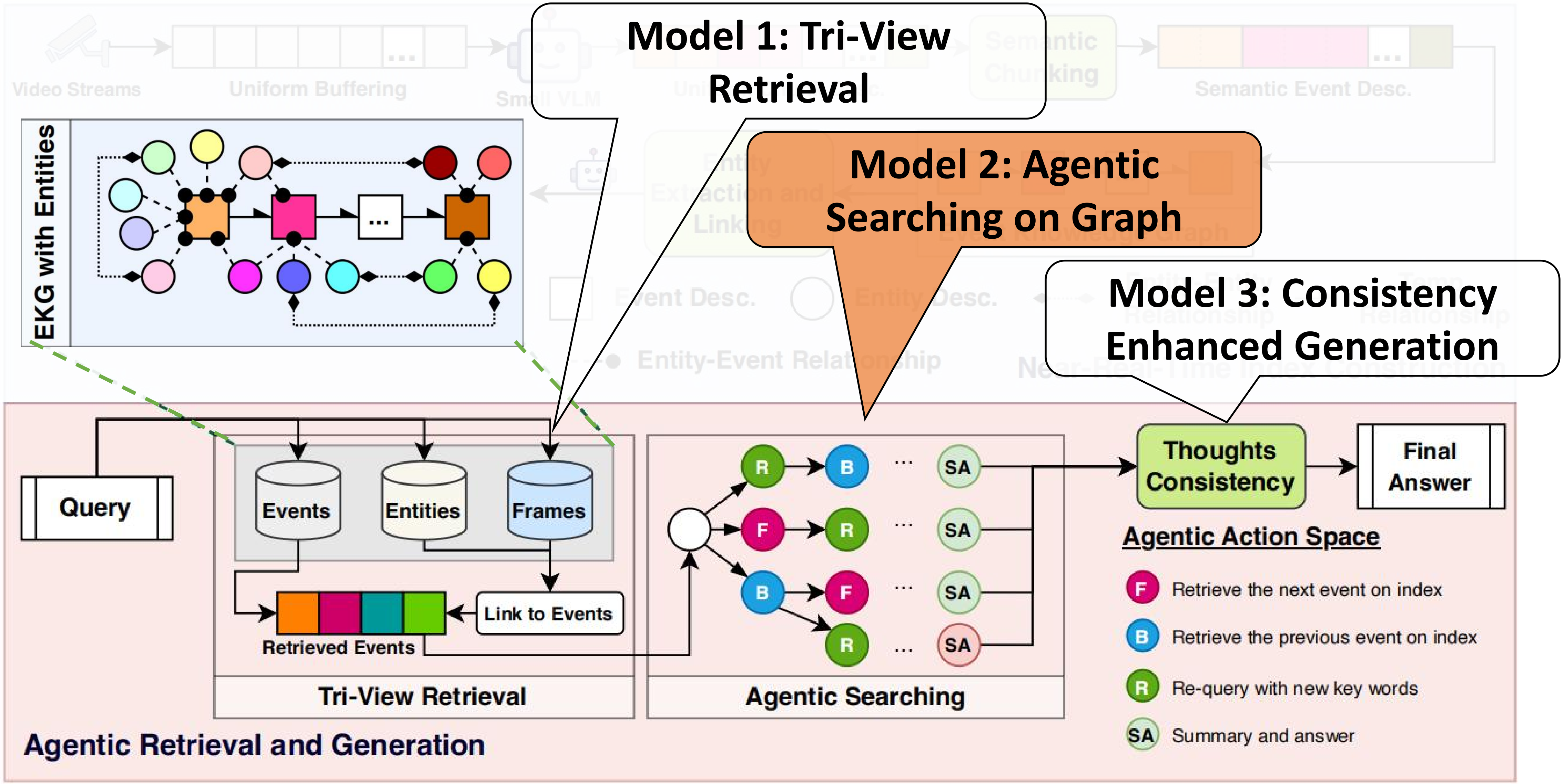
Key idea: *For a given query, simultaneous retrieval from three different views (i.e., event/entity/frame view) is performed to obtain more comprehensive and relevant information.*



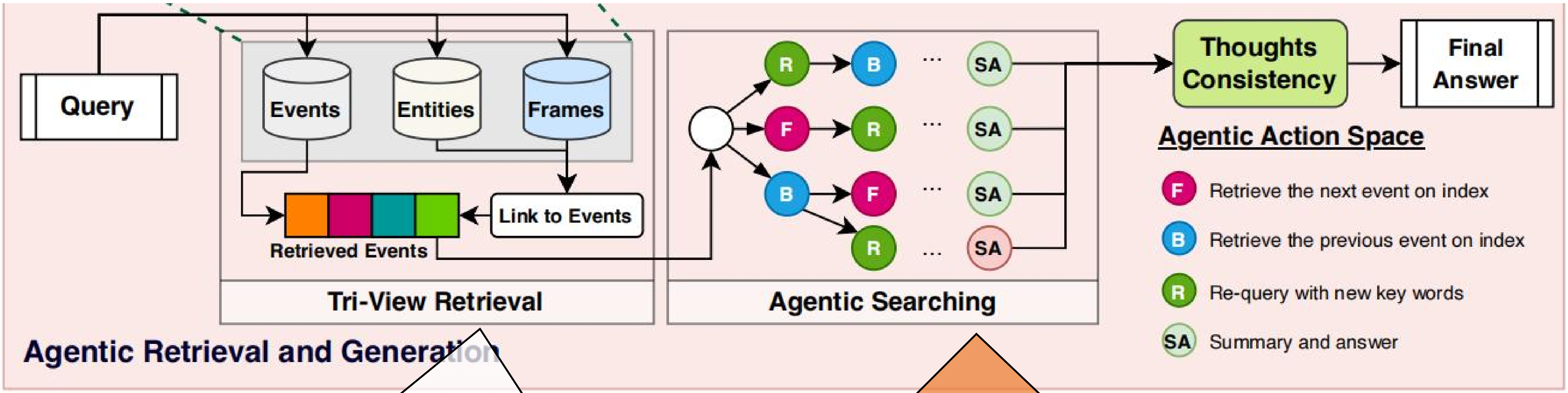
Single view scores: $$s_m(e_j) = \frac{\mathrm{sim}_m(e_j)}{\sum_{e_k \in \mathcal{E}_m} \mathrm{sim}_m(e_k)},$$

Tri-view scores: $$s(e_j) = \sum_m s_m(e_j),$$

Design 2: Agentic Retrieval and Generation



Model 2: Agentic Searching on Graph



Model 1: Tri-View Retrieval

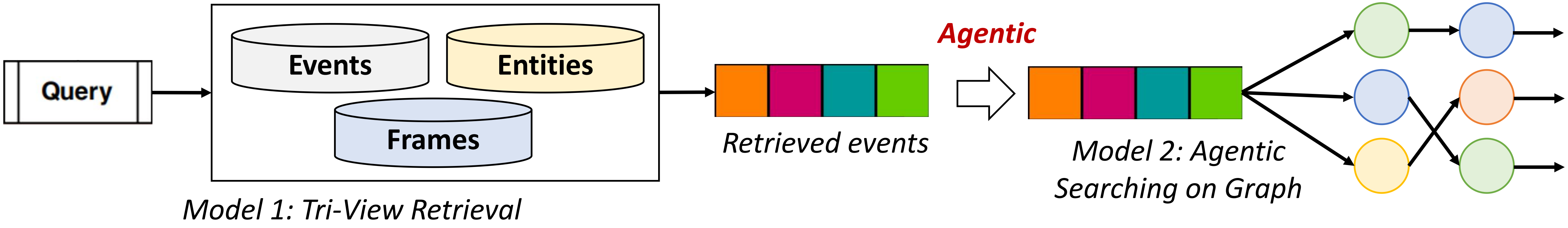
Agentic

Model 2: Agentic Searching on Graph

Closed-end query:
"Find all events with a raccoon"

Open-end query:
- *"Summarize all the abnormal activities that occurred in the past 10 hours."*
- *"What did the man do after he opened the fridge?"*

Model 2: Agentic Searching on Graph



Agentic action space:

F

1. Forward (F)

B

2. Backward (B)

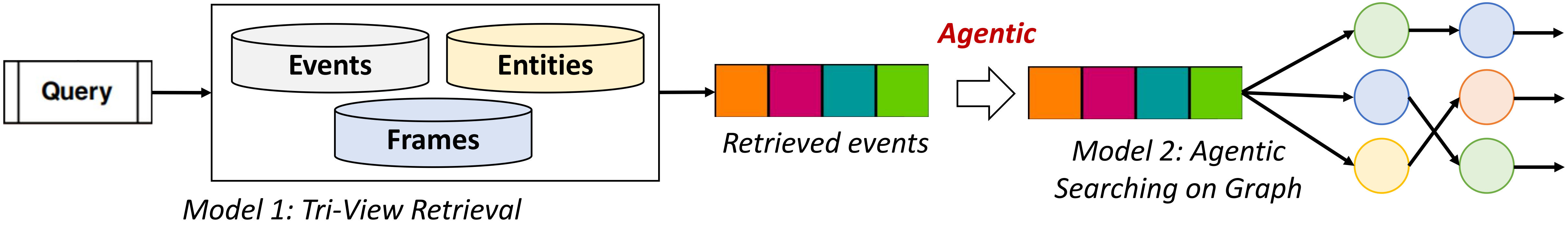
RQ

3. Re-query (RQ)

SA

4. Summary and Answer (SA)

Model 2: Agentic Searching on Graph

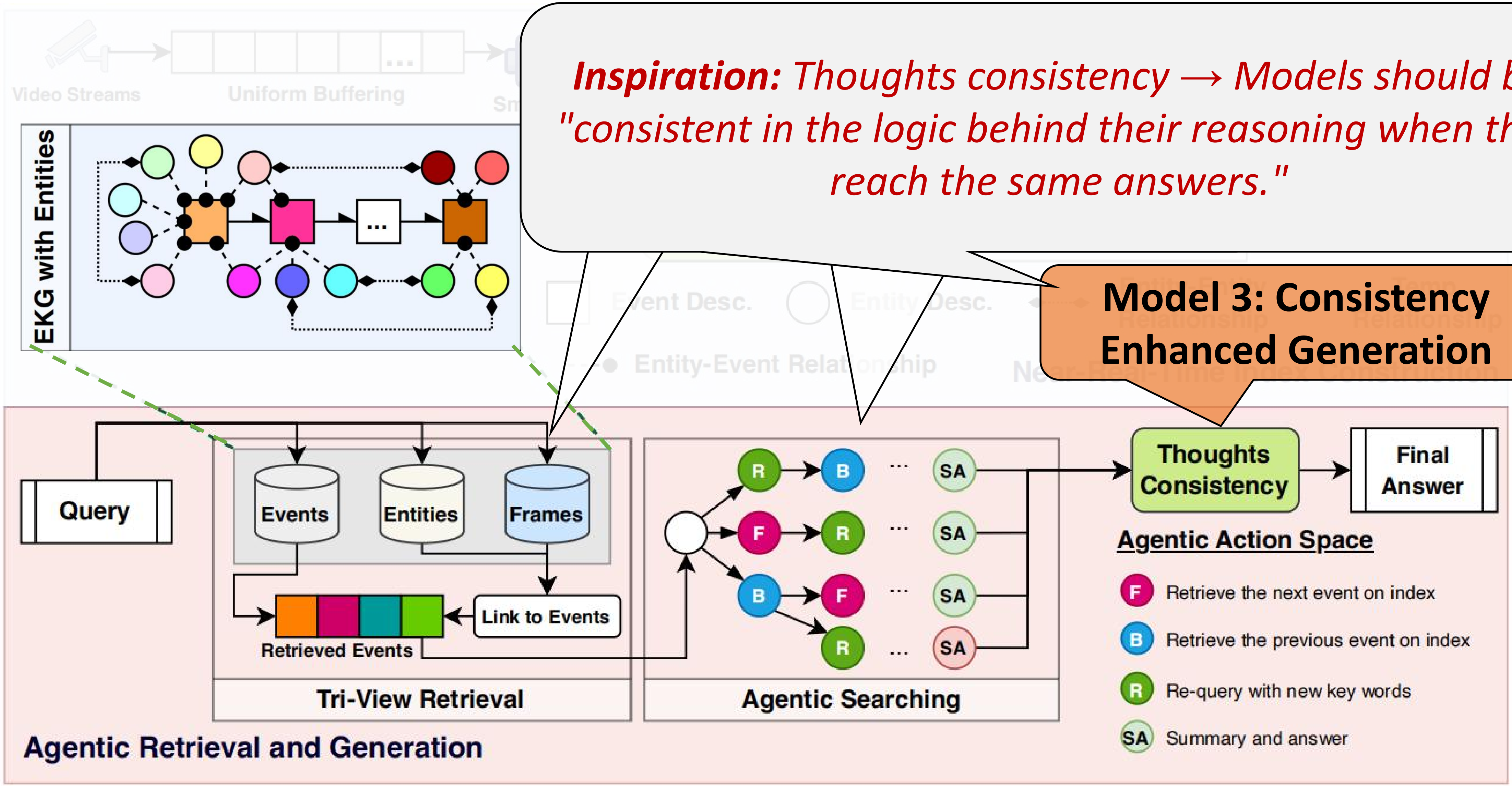


Qurey	Retrieved event	Agentic action space:	Enhanced event&describe
“那头独狼在发现废弃营地后，接下来去了哪里？”	”独狼-在营地边缘嗅探(时间: Day2 10:05)”	F 1. Forward (F)	“独狼-沿小溪向北移动(时间: Day2 10:28)”
“是什么原因导致鹿群在正午时分突然惊逃？”	“鹿群-突然惊逃-向东方(时间: Day3 12:15)”	B 2. Backward (B)	“金雕-从高空俯冲-掠过鹿群区域(时间: Day3 12:14)”
“评估一下该区域的人类活动强度。”	“研究人员-放置相机(时间: Day1 09:00)”	RQ 3. Re-query (RQ)	“评估一下该区域的人类活动强度，通过车、垃圾、灯光…”
“对比一下群体A和群体B的熊在觅食行为上的差异。”	“熊A-在树下翻找浆果；熊B-挖掘树根”	SA 4. Summary and Answer (SA)	“群体A更倾向于在白天…；群体B的觅食策略更多样化…”

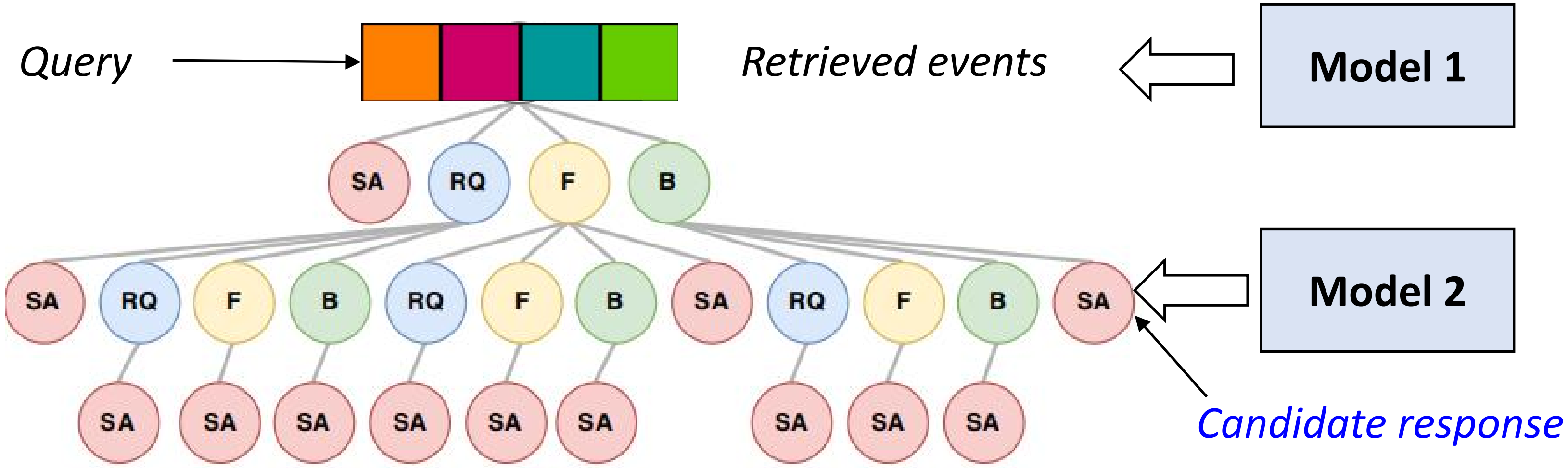
Overview

Inspiration: *Thoughts consistency → Models should be "consistent in the logic behind their reasoning when they reach the same answers."*

Model 3: Consistency Enhanced Generation



Model 3: Consistency Enhanced Generation



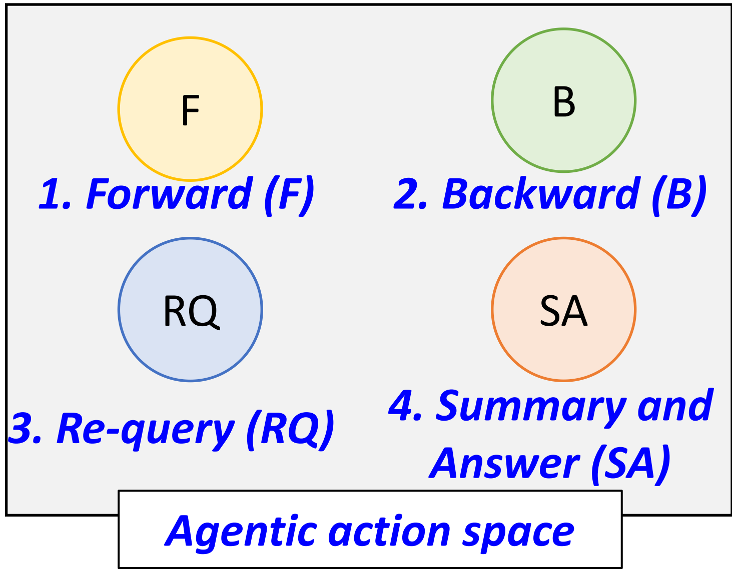
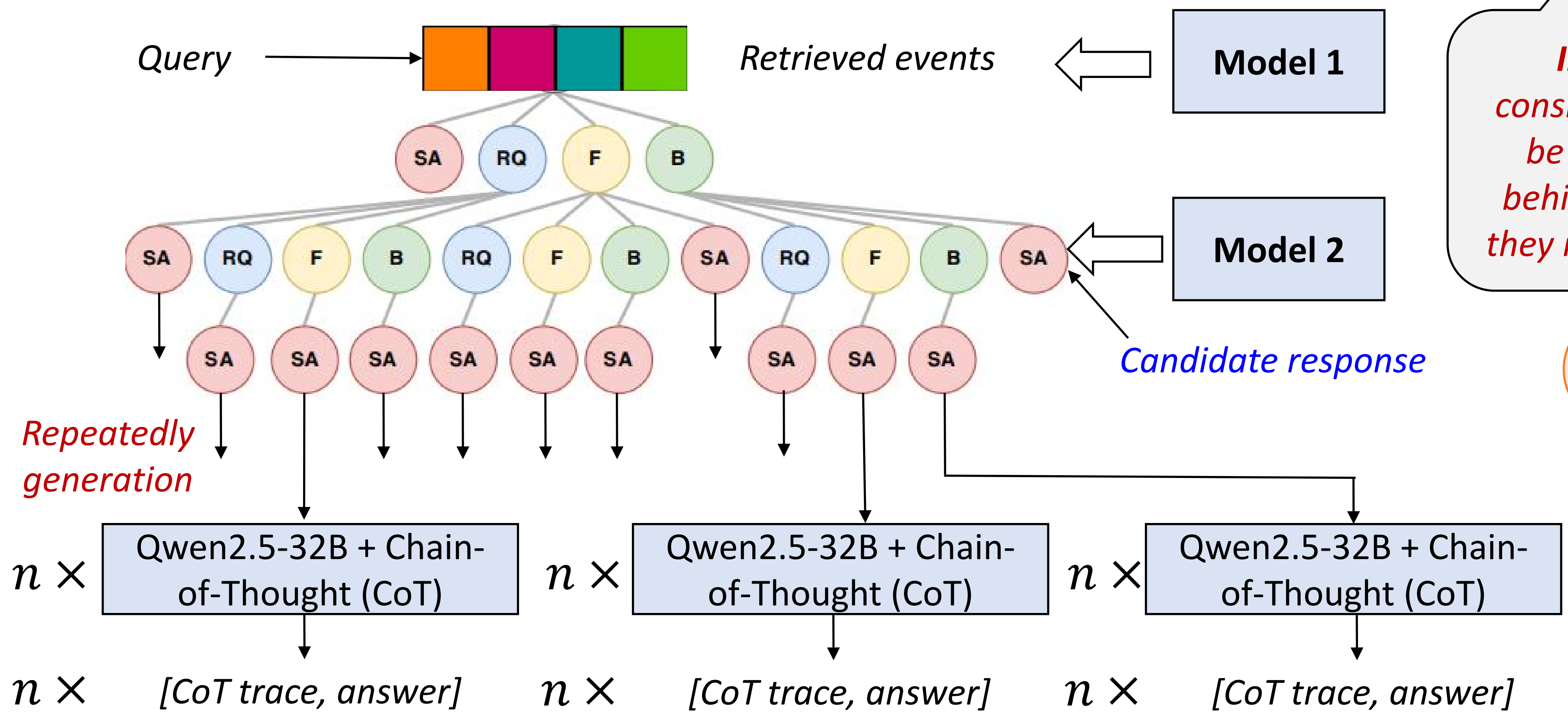


Figure 6: An example of agentic tree search with four actions and a depth of three, yielding 13 distinct pathways for information gathering and response generation.

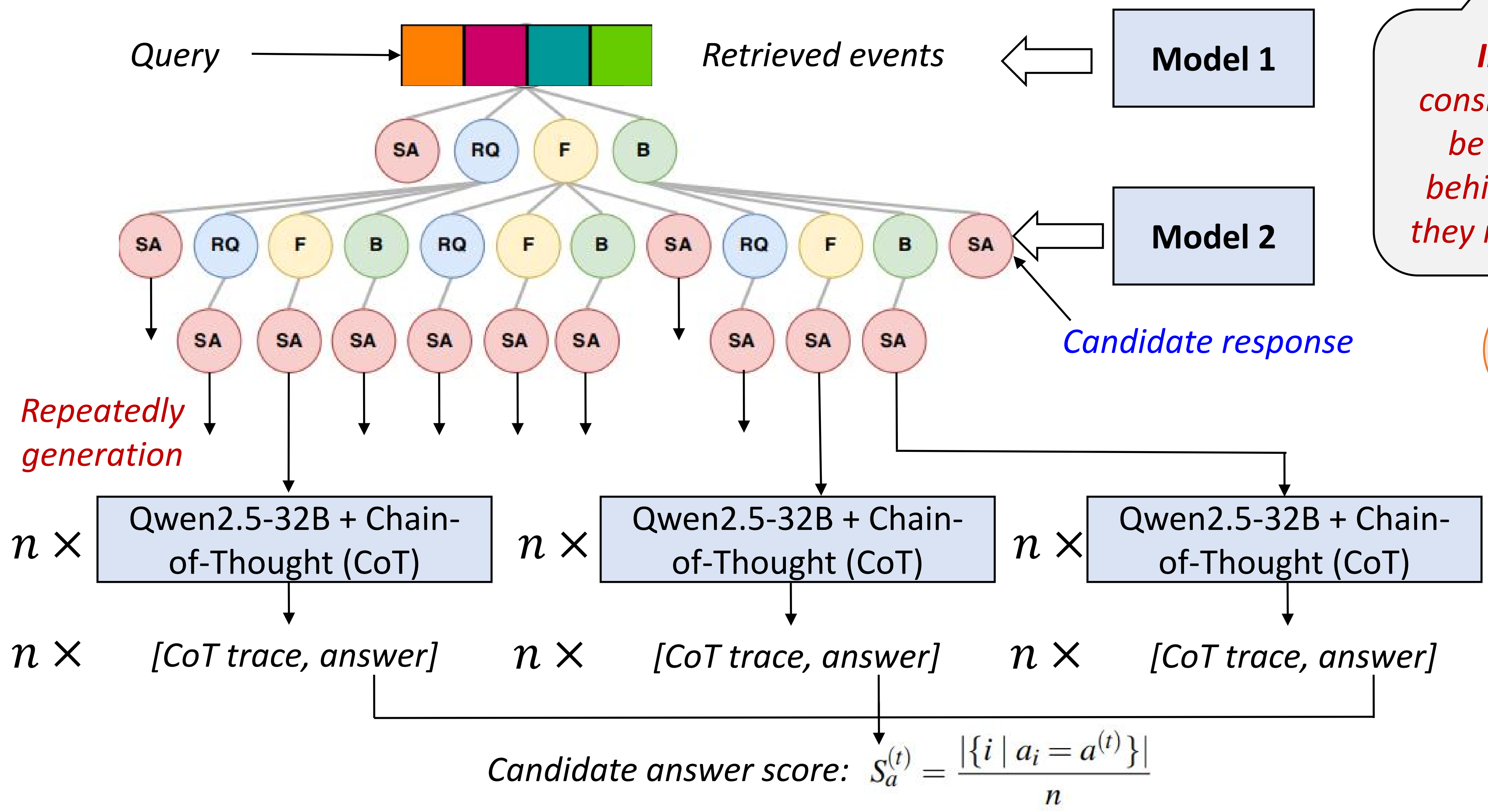
Model 3: Consistency Enhanced Generation



Inspiration: *Thoughts consistency → Models should be "consistent in the logic behind their reasoning when they reach the same answers."*

SA ***4. Summary and Answer (SA)***

Model 3: Consistency Enhanced Generation



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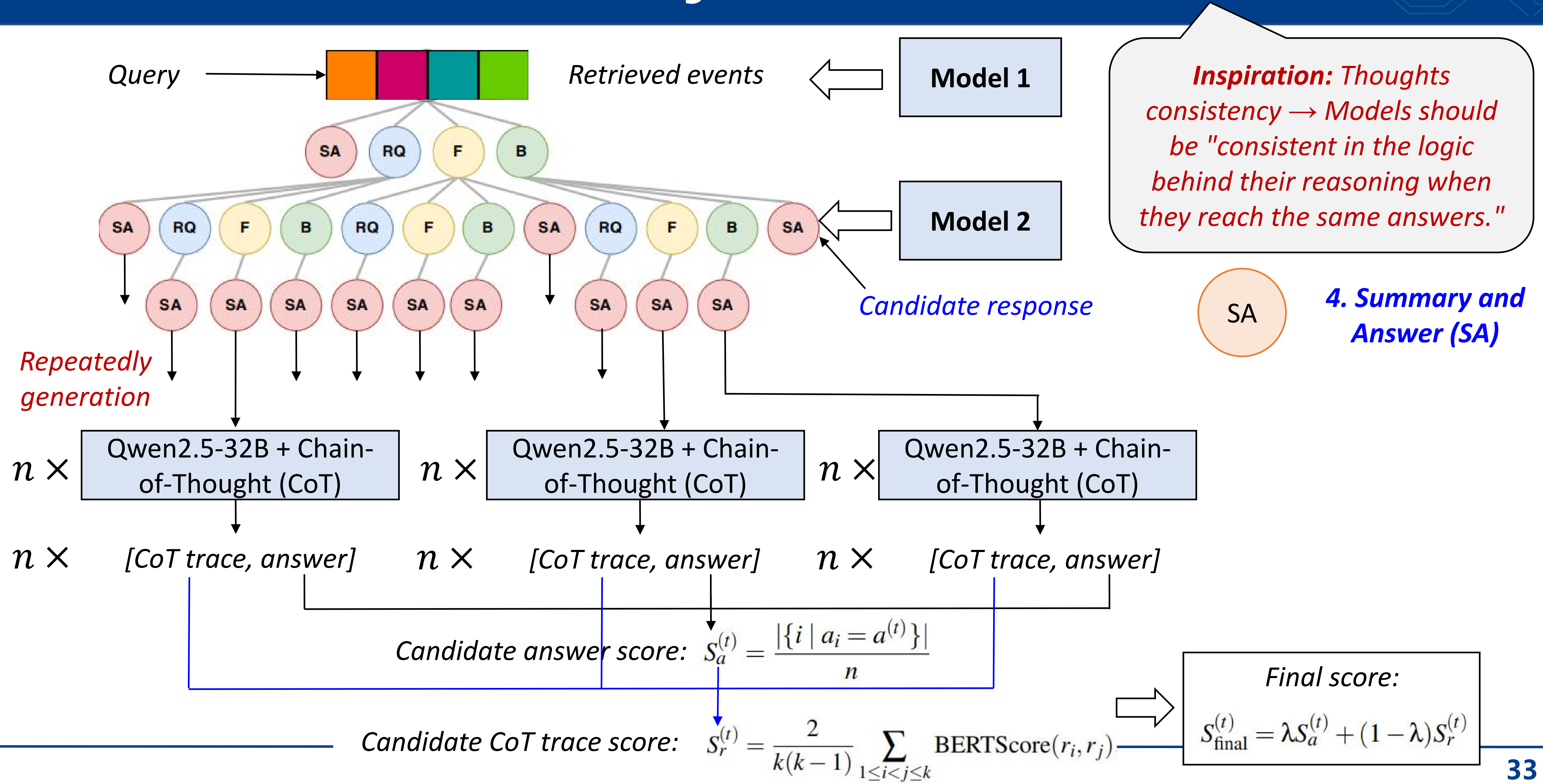
SA

4. Summary and Answer (SA)

Model 3: Consistency Enhanced Generation



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Evaluation Settings

Benchmarks:

- LVBench [ICCV’25]
  - 103 videos (4100 seconds/video)
  - 1549 questions
- VideoMME-Long [CVPR’25]
  - 300 videos (2400 seconds/video)
  - 900 questions
- AVA-100 [NSDI'26]
  - 8 videos (10 hours/video)
  - 120 questions

Baselines:

- VLM
  - GPT-4o
  - Gemini-1.5-Pro
  - Phi- 4-Multimodal
  - Qwen2.5-VL-7B
  - InternVL2.5-8B
  - LLaVA-Video-7B
- Video-RAG method
  - VideoTree [CVPR’25]
  - VideoAgent [ECCV’24]
  - DrVideo [CVPR’25]
  - VCA [ICCV’25]

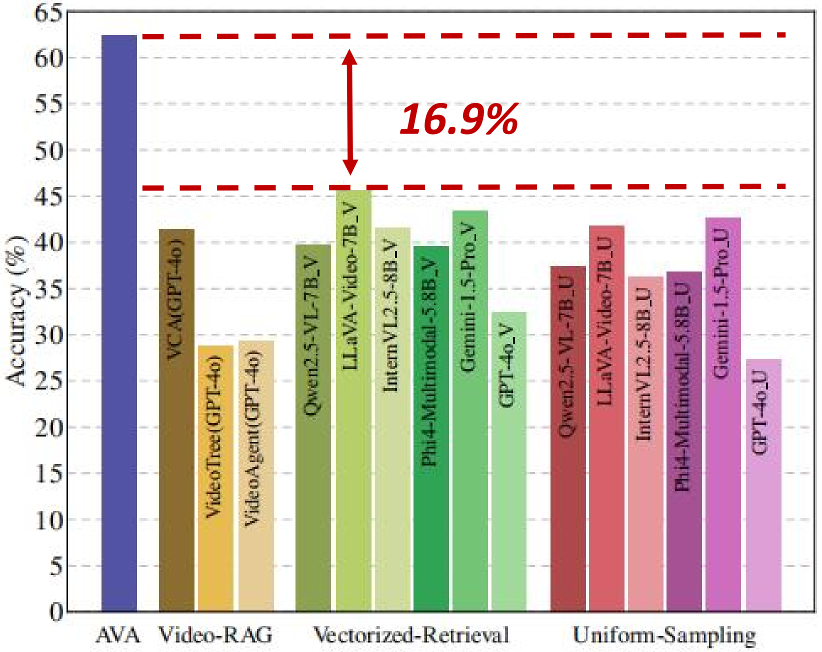
×

Two typical strategies:

- Uniform sampling
- Vectorized retrieval (top-K)

[1] [ICCV’25] Lvbench: An extreme long video understanding benchmark. In International Conference on Computer Vision
[2] [CVPR’25] Video-mme: The first-ever comprehensive evaluation benchmark of multi-modal llms in video analysis
[3] [NSDI'26] AVA: Towards Agentic Video Analytics with Vision Language Models
[4] [CVPR’25] Videotree: Adaptive tree based video representation for llm reasoning on long videos
[5] [ECCV’24] Videoagent: Long-form video understanding with large language model as agent
[6] [CVPR’25] Drvideo: Document retrieval based long video understanding
[7] [ICCV’25] Vca: Video curious agent for long video understanding

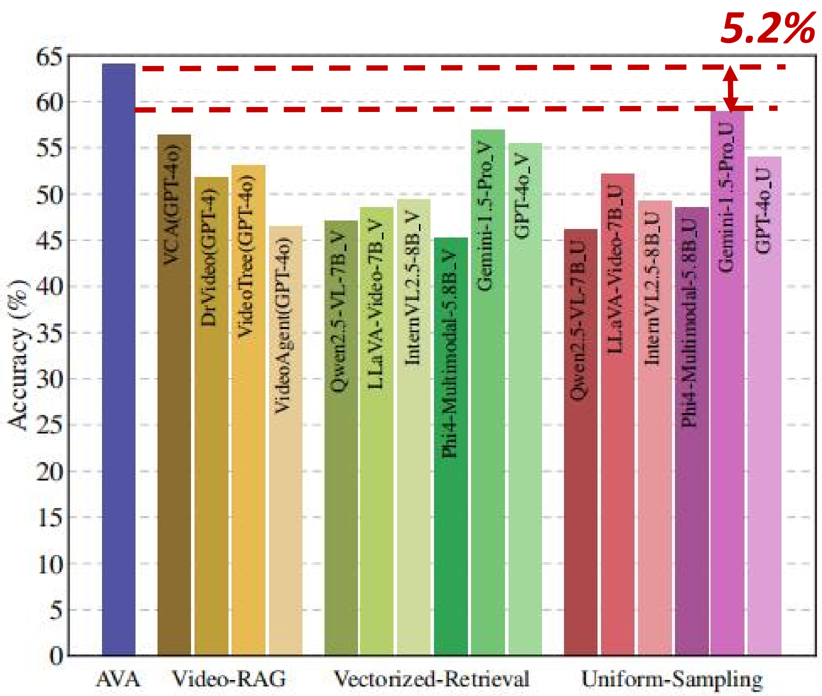
Overall Evaluation



Baseline 1: Video-RAG

Baseline 2: VLM

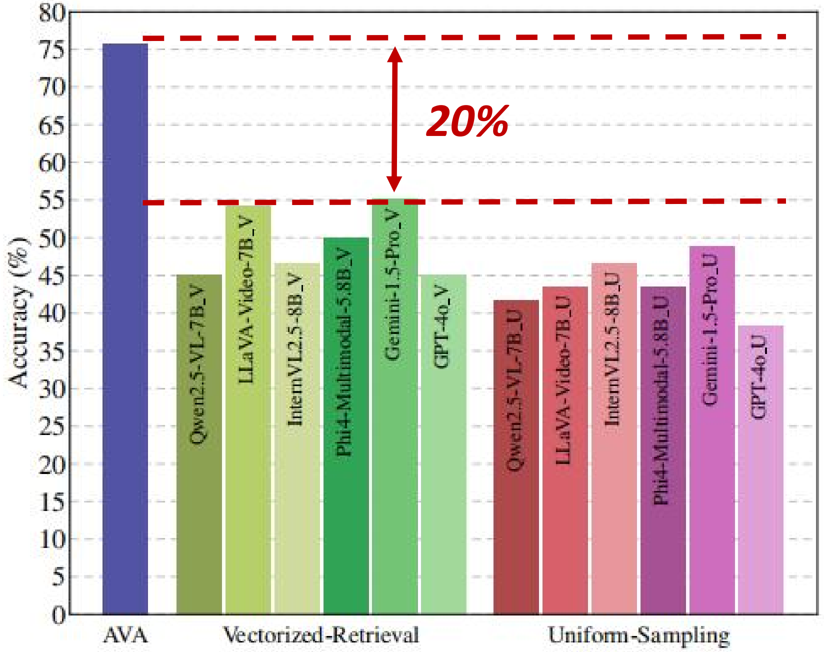
Benchmark 1: LVBench



Baseline 1: Video-RAG

Baseline 2: VLM

Benchmark 2: VideoMME-Long

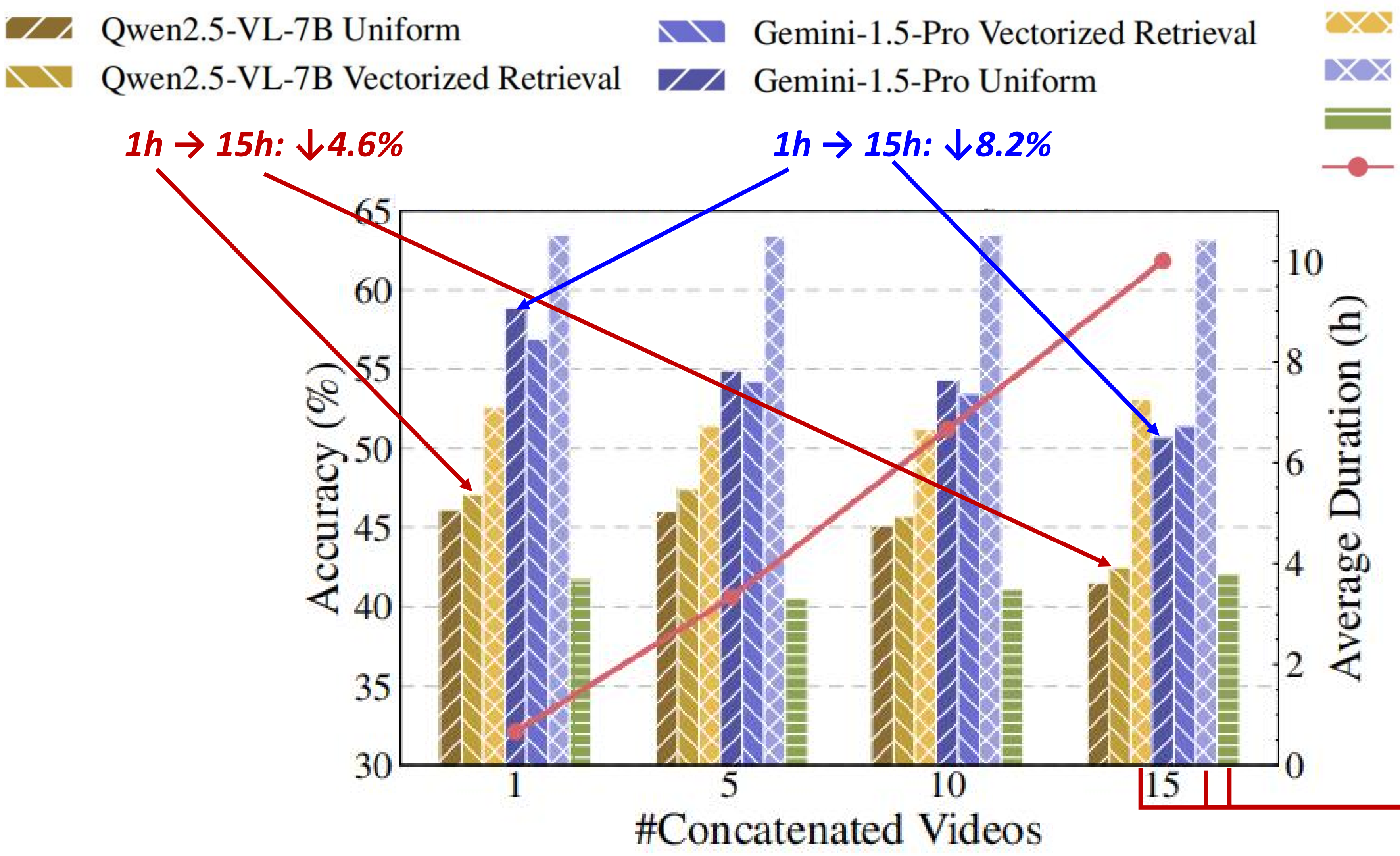


Baseline 2: VLM

Benchmark 3: AVA-100

AVA maintains robust performance for handling L4 video analytics tasks

Performance on Different Video Lengths



AVA consistently maintains stable performance across all video lengths

Figure: The accuracy achieved by AVA and the baselines across varying video lengths via concatenating videos from LVBench.

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Conclusion

- AVA, the first L4 video analytics system powered by VLMs, to the best of our knowledge.
- Near-real-time index construction and agentic retrieval and generation, enabling open-end analytics on extremely long video sources in near-real-time.
- AVA-100, a benchmark specifically designed for L4 video analytics systems

Thinking

- **Apply to our scenario**
  - Event Knowledge Graph
  —> Hierarchical memory (Episodic/semantic memory)
  —> Graph continual learning
  - Agentic Searching (action: F, B, RQ, SA)
  —> APIs: Resource allocation parameter search
- **More general**
  - [NSDI'26] AVA —> edgeAVA
  - Event Knowledge Graph (video/language) —> Multimodal data
- **Direct improvement**
  - F, B, RQ, SA —> More agentic action space
  - Near-real-time index construction (>2FPS) —> More real time

Thanks for your learning
Q & A