

LILaC: Late Interacting in Layered Component Graph for Open-domain Multimodal Multihop Retrieval

Joohyung Yun, Doyup Lee, Wook-Shin Han*

Multimodal Documents

- Real-world documents are often multimodal.
 - Examples of such multimodal documents include webpages, PDFs, presentation slides, etc.
- We refer to the elements that make up a document as *multimodal components*.
 - Correctly resolving the relationships between the components is a key factor in performing question-answering tasks.

Barack Obama 248 languages

Article Talk Read View source View history Tools

From Wikipedia, the free encyclopedia

"Barack" and "Obama" redirect here. For other uses, see Barack (disambiguation), Obama (disambiguation), and Barack Obama (disambiguation).

Barack Hussein Obama II^(b) (born August 4, 1961) is an American lawyer and politician who served as the 44th president of the United States from 2009 to 2017. A member of the Democratic Party, he was the first African-American president in U.S. history. Obama previously served as a U.S. senator representing Illinois from 2005 to 2008 and as an Illinois state senator from 1997 to 2004.

Obama was born in Honolulu, Hawaii. He graduated from Columbia University in 1983 with a Bachelor of Arts degree in political science and later worked as a community organizer in Chicago. In 1988, Obama enrolled in Harvard Law School, where he was the first black president of the *Harvard Law Review*. He became a civil rights attorney and an academic, teaching constitutional law at the University of Chicago Law School from 1992 to 2004. In 1996, Obama was elected to represent the 13th district in the Illinois Senate, a position he held until 2004, when he successfully ran for the U.S. Senate. In the 2008 presidential election, after a close primary campaign against Hillary Clinton,



Official portrait, 2012

44th President of the United States

In office
January 20, 2009 – January 20, 2017

Vice President Joe Biden

Preceded by George W. Bush

Succeeded by Donald Trump

United States Senator from Illinois

In office
January 3, 2005 – November 16, 2008

Preceded by Peter Fitzgerald

Succeeded by Roland Burris

Member of the Illinois Senate from the 13th district

In office

arXiv:1204.0162v2 [physics.pop-ph] 20 Apr 2012

The Proof of Innocence

Dmitri Krikschev¹
¹Cooperative Association for Internet Data Analysis (CAIDA),
University of California, San Diego (UCSD), La Jolla, CA 92039, USA

We show that if a car stops at a stop sign, an observer, e.g., a police officer, located at a certain distance perpendicular to the car trajectory, must have an illusion that the car does not stop, if the following three conditions are satisfied: (1) the observer measures just the linear but angular speed of the car; (2) the car decelerates and subsequently accelerates relatively fast; and (3) there is a short-time obstruction of the observer's view of the car by an external object, e.g., another car, at the moment when both cars are near the stop sign.

I. INTRODUCTION

It is widely known that an observer measuring the speed of an object passing by, measures not its actual linear velocity by the angular one. For example, if we stay not far away from a railroad, watching a train approaching us from far away at a constant speed, we first perceive the train not moving at all, when it is really far, but when the train comes closer, it appears to us moving faster and faster, and when it actually passes us, its visual speed is maximized.

This observation is the first building block of our proof of innocence. To make this proof rigorous, we first consider the relationship between the linear and angular speeds of an object in the top example where the object moves at a constant linear speed. We then proceed to analyzing a picture reflecting what really happened in the considered case, that is, the case where the linear speed of an object is not constant, but what is constant instead is the deceleration and subsequent acceleration of the object coming to a complete stop at a point located closest to the observer on the object's linear trajectory. Finally, in the last section, we consider what happens if at that critical moment the observer's view is briefly obstructed by another external object.

II. CONSTANT LINEAR SPEED

Consider Fig. 1 schematically showing the geometry of the considered case, and assume for a moment that C's linear velocity is constant in time t .

$$\alpha(t) \equiv \alpha_0 \quad (1)$$

Without loss of generality we can choose time units t such that $t = 0$ corresponds to the moment when C is at S. Then distance x is simply

$$x(t) = v_0 t. \quad (2)$$

Observer O visually measures not the linear speed of C but its angular speed given by the first derivative of angle α with respect to time t .

$$\omega(t) = \frac{d\alpha}{dt} \quad (3)$$

To express $\omega(t)$ in terms of $\alpha(t)$ and $x(t)$ we observe from triangle OCS that

$$\tan \alpha(t) = \frac{x(t)}{r_0} \quad (4)$$

leading to

$$\alpha(t) = \arctan \frac{x(t)}{r_0} \quad (5)$$

Substituting the last expression into Eq. (3) and using the standard differentiation rules there, i.e., specifically the fact that

$$\frac{d}{dt} \arctan \frac{x}{r_0} = \frac{1}{1 + \frac{x^2}{r_0^2}} \frac{dx}{dt} \quad (6)$$

where $f(t)$ is any function of t , but it is $f(t) = v_0/r_0$ here, we find that the angular speed of C that O observes

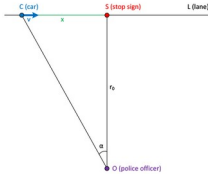
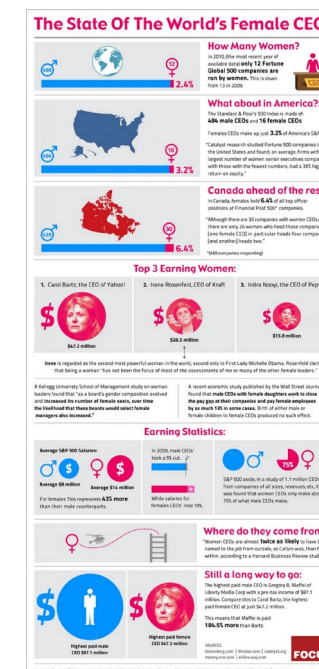


FIG. 1: The diagram showing schematically the geometry of the considered case. Car C moves along line L. Its current linear speed is v_0 , and the current distance from stop sign S is x . [CS] = x . Another road connects to L perpendicularly at S. Police officer O is located on that road at distance r_0 from the intersection, [OS] = r_0 . The angle between OC and OS is α .



An example of a multimodal webpage

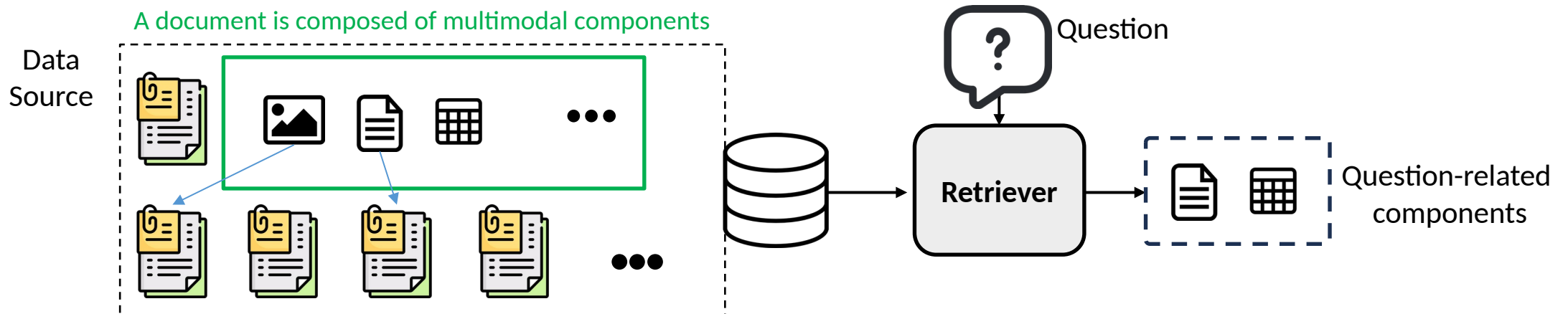
An example of a PDF file

An example of an infographic

Open-domain Multimodal Document Retrieval

Given a data source $\mathcal{D}$, a link mapping $\mathcal{L}$ and a query q , correctly retrieve a ranked list of components = $[C_1, \dots, C_{n_{ret}}]$. The goal for $\mathcal{R}$ is to contain the ground truth set of query-relevant components = $\{C_{gt_1}, \dots, C_{gt_r}\}$

- Data source $\mathcal{D} = \{D_1, \dots, D_{k_{doc}}\}$
 - Multimodal document $D = [C_1, \dots, C_{k_{comp}}]$
 - Component $C \in \{P, T, I\}$
 - Passage P : a natural language string
 - Table T : A matrix of natural language strings
 - Image I : A tensor of floating point numbers
- Link mapping $\mathcal{L} = \mathcal{C} \rightarrow \mathcal{D}$
 - $\mathcal{C}$: A set of all components within $\mathcal{D}$



In the mausoleum built by the Mughal emperor who married Mumtaz Mahal, how many slender minarets surround the central dome?

Four

Shah Jahan commissioned many monuments, including the Red Fort and the Taj Mahal, where his favorite consort Mumtaz Mahal is entombed.

The Taj Mahal is an ivory white marble mausoleum on the right bank of the river Yamuna in Agra, India.

Lossy Summarization

Shah Jahan commissioned many monuments, including the Red Fort, Shah Jahan Mosque and the Taj Mahal, where his favorite consort Mumtaz Mahal is entombed.

The picture captures a classic, head-on view of the Taj Mahal in Agra, India. The ivory-white marble mausoleum dominates the scene with its large central onion dome.

Minarets? Not a word about them!

TextRAG Retriever

Loss of hyperlinks



Everything's
crammed
into one
screenshot!

I see Shah Jahan...
but no trail to follow!

VisRAG Retriever

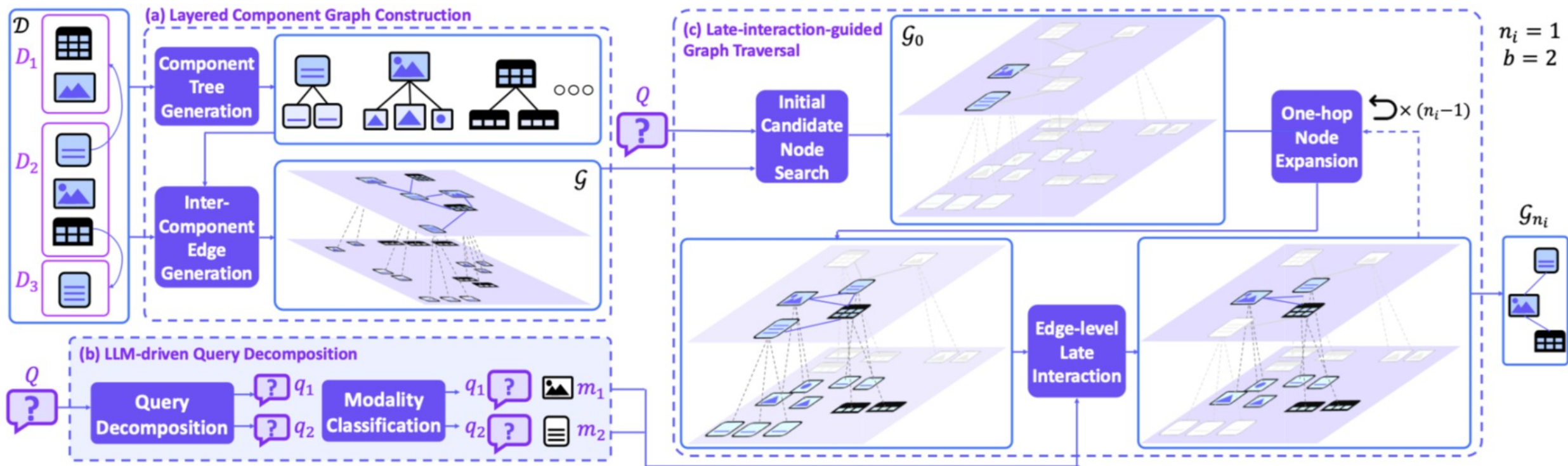
Key Aspects of Multimodal Document Retrieval

- **Preserve structure:** Model and exploit both inter-document links and intra-document relationships among components to maintain context and reasoning paths.
- **Modality awareness:** Identify which modality (text, table, figure/image) actually contains the evidence and route retrieval/scoring accordingly.
- **Granularity alignment:** Index and score at modality-appropriate levels—e.g., paragraph/sentence for text, table/row/cell for tables, and image/object/region for visuals.

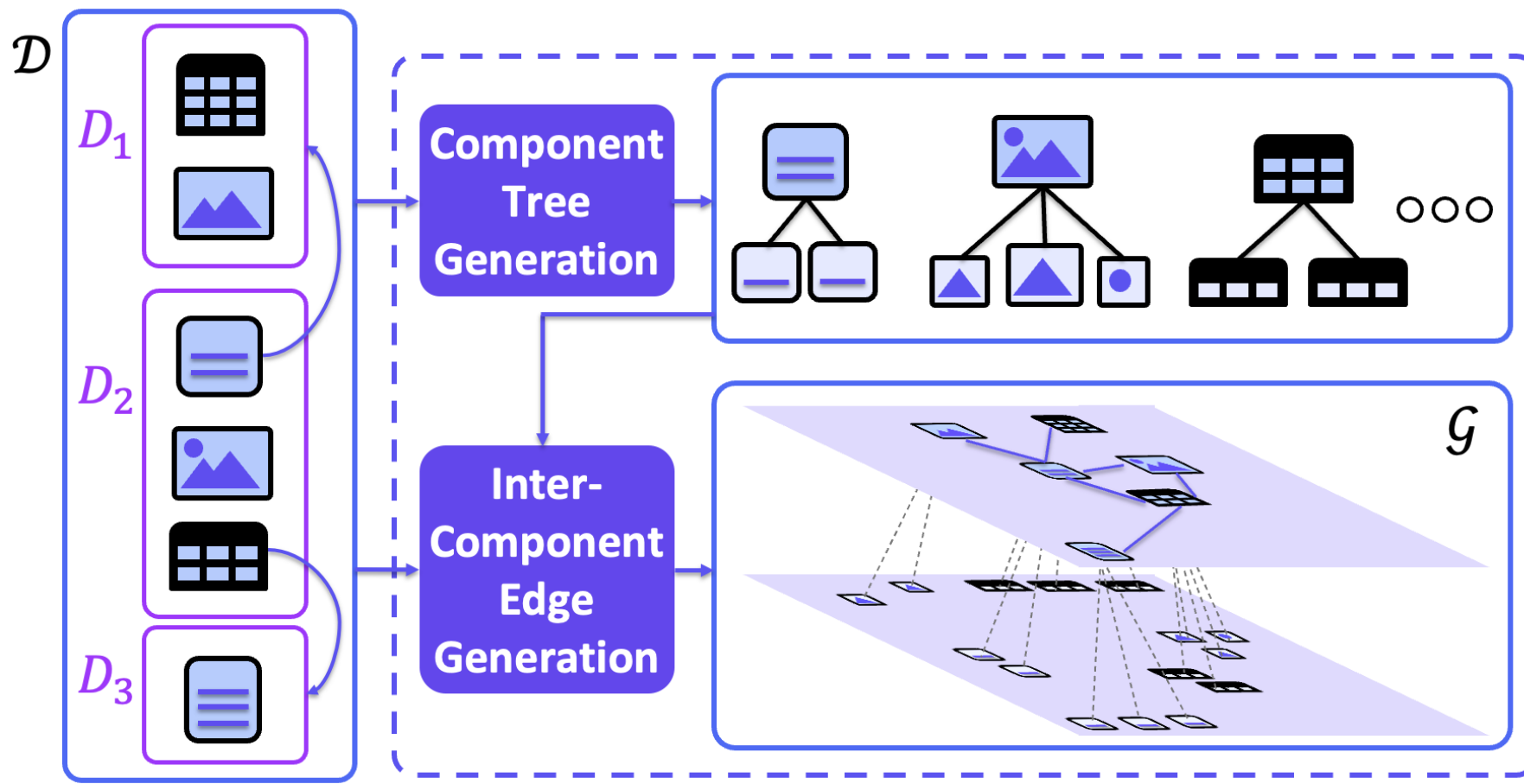
Key Ideas of Our Approach

- **Layered Component Graph**
 - Represents two granularities for each component.
 - Paragraph -> Sentences
 - Table -> Rows
 - Image -> Detected subimages
 - Expresses the link mapping and intra-document relationships as edges among components.
 - Uses multimodal embeddings to prevent any loss from modality conversion.
- **Retrieval Algorithm**
 - Fine-grained interaction with the graph and the query
 - Query decomposition
 - Late interaction

Overview of LLaC



Layered Component Graph Construction



Component Tree Generation

1. Break down components into subcomponents
 - Passage -> Split into sentences using SAT [1]
 - Table -> Split into rows
 - Image -> Detect subimages using MLLM
2. Connect each component with its subcomponents.

Inter-Component Edge Generation

Generate an undirected edge for

- Every pair of components within the same document.
- Every pair of component with its linked document's components.

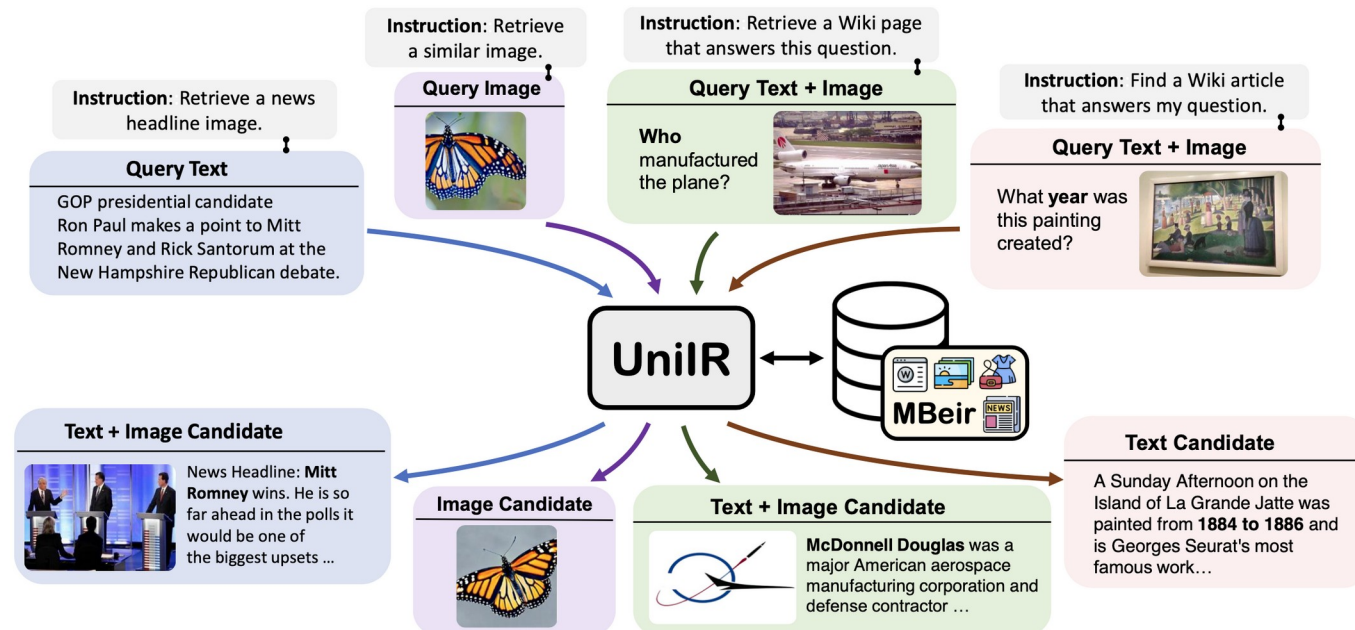
Background

Multimodal Embedders

Multimodal embedders embed a *natural language sequence*, an *image*, or a *combination of two* into a single vector.

Their retrieval setting includes an instruction for each retrieval.

- Instruction includes information about the target modality or target semantics of the retrieval.
- Such **instruction information is not given some cases** (e.g., our problem setting).

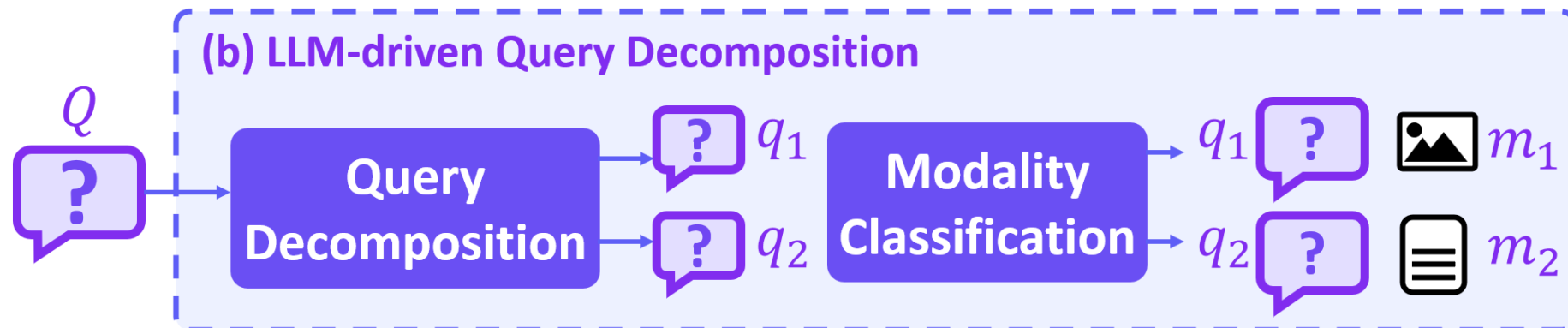


LLM-Driven Query Decomposition

A single query may include multiple evidences needed to locate multiple components. Such components may differ in their modalities.

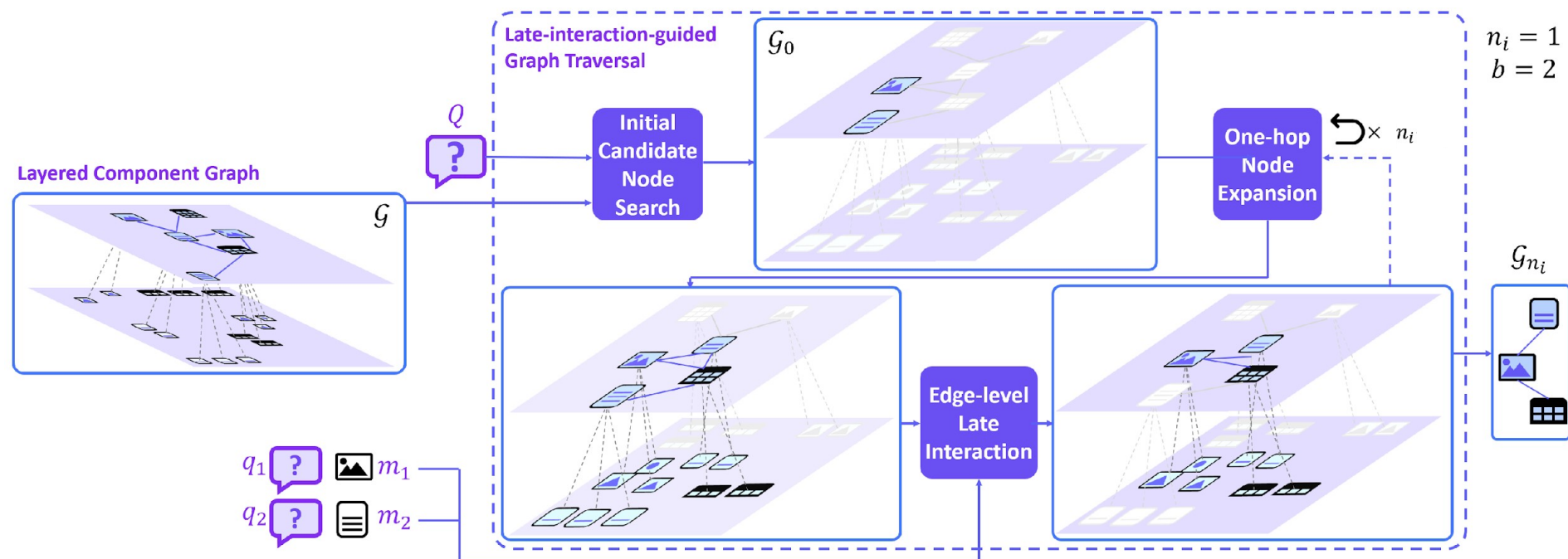
Idea:

- Decompose the given query so that each subquery contains fine-grained evidence for the target of retrieval.
- Estimate (i.e., classify) the target modality for each subquery, and use it to generate an instruction for each subquery embedding.



Late-Interaction-Guided Graph Traversal

1. Initiate the graph $\mathcal{G}_0$ by performing kNN search over the coarse-grained components using the coarse-grained query Q .
2. Iteratively (for n_i times)
 - 2.1. Expand the graph by performing a one-hop node expansion.
 - 2.2. Leave top- b query-relevant edges among the expanded graph.



Edge-level Late Interaction

Goal: Similarity calculation of a query and an edge

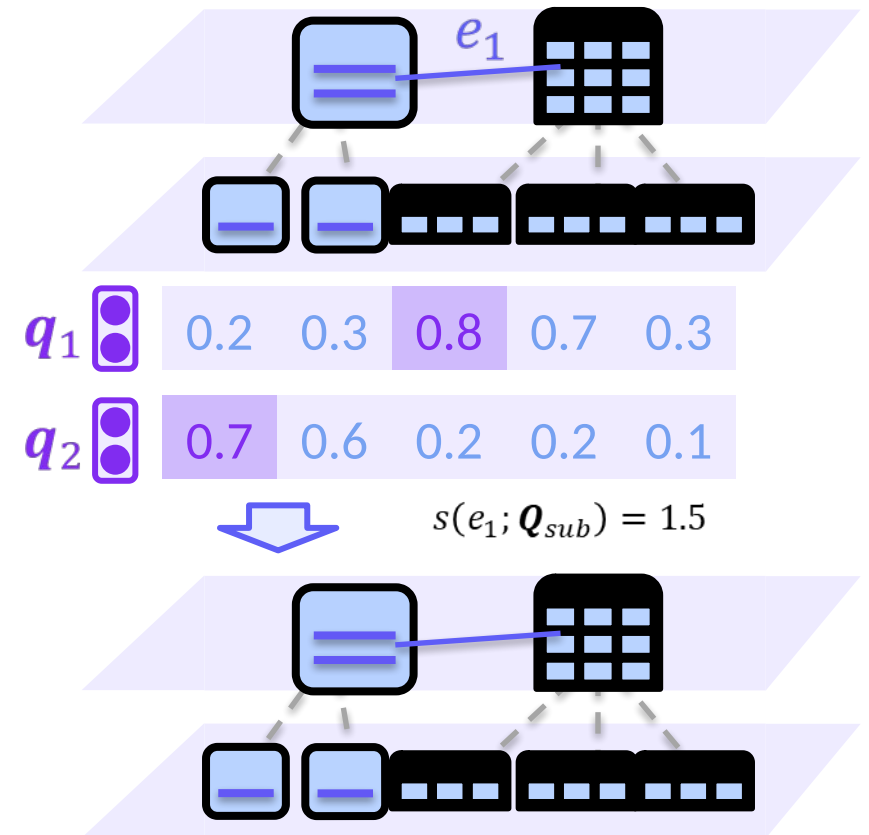
Input:

- Query embedding Q
 - Subquery embeddings $Q_{sub} = \{q_1, q_2, \dots, q_n\}$
- Edge $e = (C_a, C_b)$
 - Subcomponent embeddings $e_c = \{c_{a,1}, \dots, c_{a,k}\} \cup \{c_{b,1}, \dots, c_{b,l}\}$

Idea: Late-interaction-based score calculation

- A fine-grained subquery will show the highest cosine similarity with its corresponding target subcomponent.
- The edge similarity is the sum of all subcomponent scores.

$$s(e; Q_{sub}) = \sum_{q \in Q_{sub}} \max_{c \in e_c} \text{sim}(c, q)$$



Retriever Accuracy Comparison

- LILaC achieves state-of-the-art performance on all benchmarks.
- LILaC outperforms the previous VisRAG SOTA models, VisRAG-Ret and ColPali, by substantial margins of 12.39% and 9.85% in R@3, and 14.45% and 10.49% in MRR@10, on average, respectively.

Algorithm	Embedder Type	MP-DocVQA		SlideVQA		InfoVQA		MultimodalQA		MMCoQA	
		R@3	MRR@10	R@3	MRR@10	R@3	MRR@10	R@3	MRR@10	R@3	MRR@10
NV-Embed-v2	Text	67.85	61.91	88.49	79.55	86.21	80.86	60.19	67.86	46.16	41.45
VisRAG-Ret	Image	83.25	75.55	91.55	84.30	92.76	86.22	50.08	55.08	27.63	23.75
ColPali		80.71	74.86	89.39	81.55	88.30	82.76	58.73	65.05	36.24	32.33
LILaC (w/ mmE5)	Multimodal	61.25	55.30	77.52	68.80	75.09	69.86	54.79	59.02	48.88	40.30
LILaC (w/ UniME)		77.83	71.42	84.35	77.93	82.28	75.27	58.52	61.44	49.63	42.97
LILaC (w/ MM-Embed)		83.59	78.75	92.81	84.43	93.17	86.83	69.07	75.28	55.80	50.77

Table 1: Retrieval accuracy (Recall@3 ($R@3$) and $MRR@10$) of LILaC and its competitors on five benchmarks. The best score in each column is in **bold**. The in-domain fine-tuned settings are colored in orange .

End-to-End QA Accuracy Comparison

- LILaC achieves SOTA average end-to-end accuracy, with average EM and F1 scores of 52.00 and 58.79, respectively.
- 17.40% and 18.47% accuracy raise compared to the pre- 570 viously best-performing VisRAG setup, VisRAG 571 with Qwen2.5-VL

Algorithm	MLLM	MP-DocVQA		SlideVQA		InfoVQA		MultimodalQA		MMCoQA	
		EM	F1	EM	F1	EM	F1	EM	F1	EM	F1
NV-Embed-v2	Qwen2.5-VL 7B	56.51	63.16	53.77	64.41	60.72	63.40	37.23	43.85	28.05	34.67
VisRAG-Ret	MiniCPM V2.6	54.31	68.86	43.88	62.37	50.83	57.55	28.18	34.01	21.51	27.87
VisRAG-Ret	Qwen2.5-VL 7B	65.34	72.24	55.03	66.13	60.16	61.93	22.24	25.55	16.69	20.90
ColPali	Qwen2.5-VL 7B	64.46	71.16	53.77	64.54	58.07	60.38	23.59	27.37	18.07	22.30
LILaC (w/ mmE5)	Qwen2.5-VL 7B	52.96	59.53	50.89	59.07	50.12	53.12	40.72	47.46	33.90	40.38
LILaC (w/ UniME)	Qwen2.5-VL 7B	62.43	69.40	53.05	62.89	53.39	56.86	43.42	49.72	33.39	40.12
LILaC (w/ MM-Embed)	Qwen2.5-VL 7B	65.48	72.42	55.57	66.32	60.91	62.87	44.57	51.97	36.31	43.22

Table 2: End-to-end accuracy (EM and F1) of LILaC and its competitors for the 5 benchmarks. The best score in each column is in **bold**. Generation results corresponding to in-domain fine-tuned settings are colored in orange .

Thank You

Experiment Settings

Benchmarks:

- **DocVQA Benchmarks**
 - InfoVQA
 - MP-DocVQA
 - SlideVQA
- **Multimodal QA Benchmarks**
 - MultimodalQA
 - MMCoQA

Competitors

- VisRAG (ICLR'25)
- M3DocRAG (ArXiv'24)

Measurements

- **Component retrieval accuracy**
 - Recall@3
 - MRR@10
- **End-to-end accuracy**
 - Exact match (EM)
 - F1 score

Introduction

Multimodal (Text & Image) Data Source

- Most of real-world data are comprised of text and images.
- Images can play an irreplaceable role in answering some questions.
 - e.g., “Recommend me a white baby bike”
- However, most of prior works do not consider images

Barack Obama 248 languages

Article Talk Read View source View history Tools

From Wikipedia, the free encyclopedia

"Barack" and "Obama" redirect here. For other uses, see Barack (disambiguation), Obama (disambiguation), and Barack Obama (disambiguation).

Barack Hussein Obama II^(b) (born August 4, 1961) is an American lawyer and politician who served as the 44th [president of the United States](#) from 2009 to 2017. A member of the Democratic Party, he was the first [African-American](#) president in U.S. history. Obama previously served as a [U.S. senator](#) representing [Illinois](#) from 2005 to 2008 and as an [Illinois state senator](#) from 1997 to 2004.

Obama was born in [Honolulu](#), Hawaii. He graduated from [Columbia University](#) in 1983 with a [Bachelor of Arts](#) degree in political science and later worked as a community organizer in Chicago. In 1988, Obama enrolled in [Harvard Law School](#), where he was the first black president of the *Harvard Law Review*. He became a civil rights attorney and an academic, teaching constitutional law at the [University of Chicago Law School](#) from 1992 to 2004. In 1996, Obama was elected to represent the 13th district in the [Illinois Senate](#), a position he held until 2004, when he successfully ran for the U.S. Senate. In the 2008 presidential election, after a close primary campaign against Hillary Clinton,

Barack Obama

Official portrait, 2012

44th President of the United States

In office
January 20, 2009 – January 20, 2017

Vice President Joe Biden

Preceded by George W. Bush

Succeeded by Donald Trump

United States Senator from Illinois

In office
January 3, 2005 – November 16, 2008

Preceded by Peter Fitzgerald

Succeeded by Roland Burris

Member of the Illinois Senate from the 13th district

In office

A example Wikipedia page

Lightning Deals Top 100 Today's big deals Toys & Games Trending Fashion Pets

Filtered by Toys & Games

Clear Filters

Department Any Category > Toys & Games

All

Arts & Crafts

Baby & Toddler Toys

Building Toys

Collectible Toys

See more

Brands

Buffalo Games

Ceaco

Disguise

Educational Insights

See more

Customer Reviews

All

5 stars & up

4 stars & up

3 stars & up

2 stars & up

1 star & up

Price

All

Under \$25

Under \$50

Under \$100

Under \$200

\$200 & Above

Discount

All

10% off or more

25% off or more

50% off or more

70% off or more

Prime Programs

Lightning Deals

Top 100

Today's big deals

Toys & Games

Trending

Fashion

Pets

360°

Cyber Monday Deal

SAHJUNG Galaxy Tab A9+ Plus Kids Edition 11" 64G...
+5 colors/patterns

Cyber Monday Deal

Tomb Raider Audio Player Starter Set with Playtime...
+5 colors/patterns

Cyber Monday Deal

Barbie Camper Play DreamCamper Toy
89% claimed

Cyber Monday Deal

National Geographic Marble Run with Motorized Elevat...
2% claimed

Cyber Monday Deal

Drone for Kids and Beginners, SYMA X440 RC...
+3 colors/patterns
24% claimed

Cyber Monday Deal

SEREEED Baby Balance Bike for 1 Year Old Boys Girls 1...
+6

Cyber Monday Deal

Gooshow Kids Camera Toys for 3-8 Year Old Girls Boys...
Save 10% with coupon

Cyber Monday Deal

GlowCity Light Up Football - Light Up...
Save \$10.00 with coupon

An example Amazon page

Toys & Games > Tricycles, Scooters & Wagons > Balance Bikes

SEREEED Baby Balance Bike for 1 Year Old Boys Girls 12-24 Month Toddler Balance Bike, 4 Wheels Toddler First Bike, First Birthday Gifts

Visit the SEREEED Store

4.8 ★★★★★ 9,817 ratings | Search this page

Amazon's Choice

1 sustainability feature

30K+ bought in past month

Cyber Monday Deal

-26% \$37.98

List Price: \$50.99

No Import Charges & \$12.50 Shipping to Republic of Korea Details

Available at a lower price from other sellers that may not offer free Prime shipping.

Color: Green

Size Chart

Bike Type Balance Bike

Age Range (Description) Toddler

Brand SEREEED

Number of Speeds 1

Color Green

Wheel Size 6.7 Inches

Frame Material Aluminum

Suspension Type Rigid

Special Feature Lightweight

Included Components Balance Bike

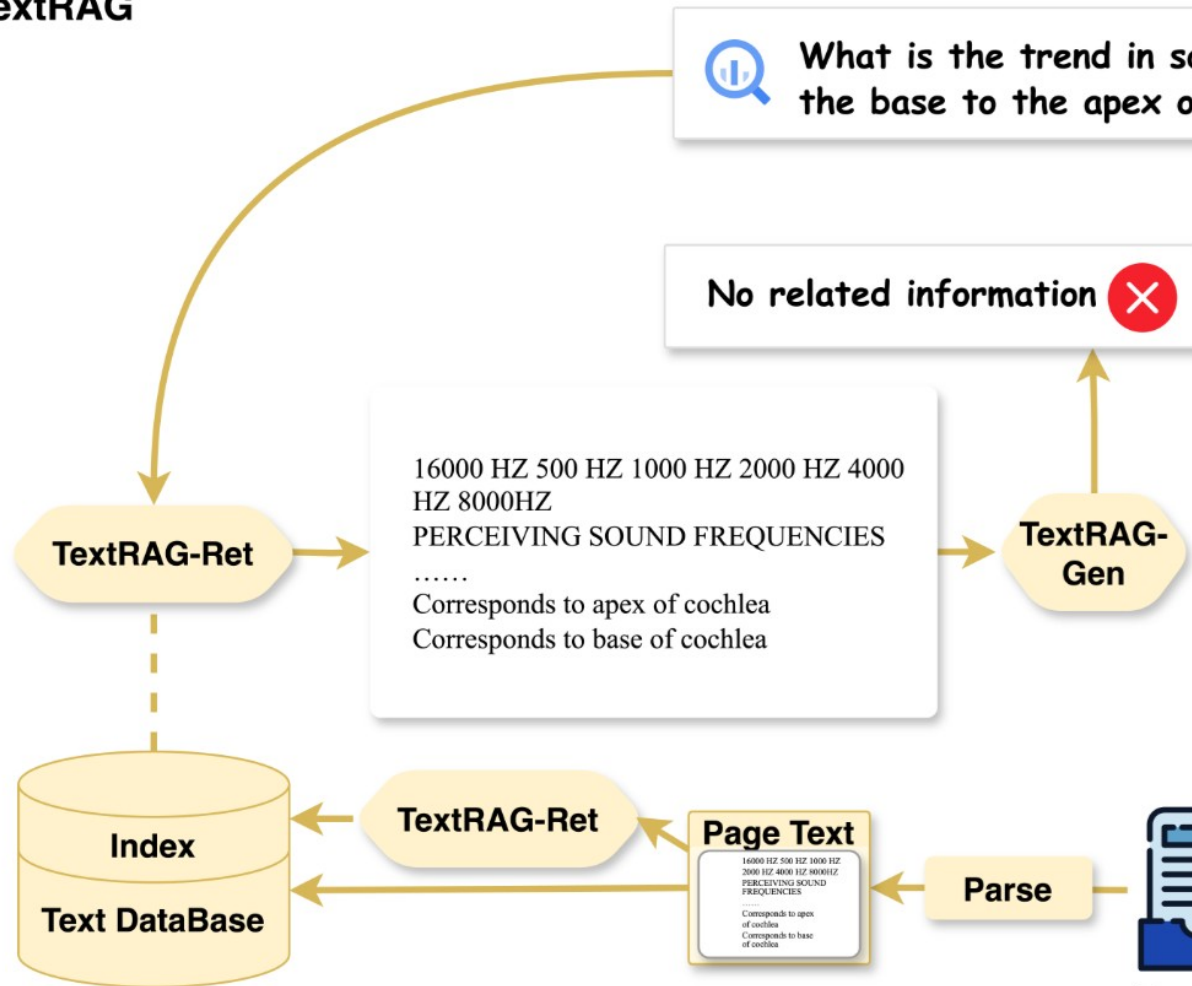
See less

Roll over image to zoom in

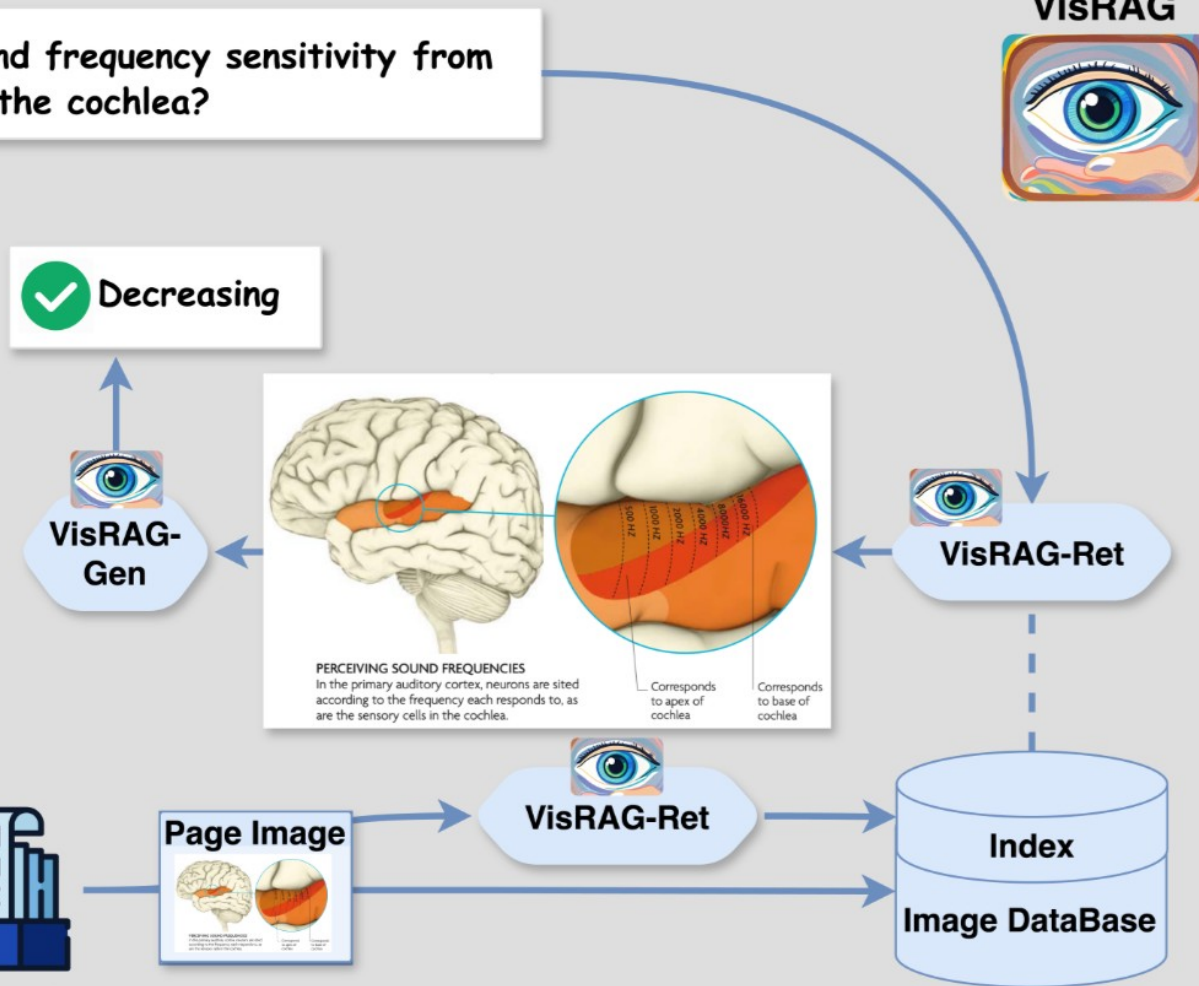
An example reddit page

Traditional Approaches: TextRAG and VisRAG

TextRAG



VisRAG



Ablation Study

- Employing the layered graph structure leads to notable average improvements - 7.33% in R@3 and 10.13% in MRR@10.
- Further employing query decomposition & late interaction shows incremental gains of 3.19% in R@3 and 4.7% in MRR@10.

Embedder Model	Variant	MP-DocVQA		SlideVQA		InfoVQA		MultimodalQA		MMCoQA	
		R@3	MRR@10	R@3	MRR@10	R@3	MRR@10	R@3	MRR@10	R@3	MRR@10
mmE5	LILaC ((w/o Query Decomposition) & Layered Graph)	48.90	43.97	75.91	68.13	65.60	58.55	42.99	46.92	41.22	34.51
	LILaC (w/o Query Decomposition)	60.81	55.02	74.14	67.58	67.70	60.01	45.15	51.12	44.18	36.62
	LILaC	61.25	55.35	76.80	68.99	68.91	61.18	54.78	59.32	48.54	40.22
UniME	LILaC ((w/o Query Decomposition) & Layered Graph)	52.12	45.31	81.47	71.22	83.57	77.07	47.68	49.06	45.78	38.41
	LILaC (w/o Query Decomposition)	77.83	71.27	83.45	75.70	85.11	78.01	52.18	54.01	47.11	39.85
	LILaC	77.83	71.39	84.35	77.93	85.53	78.81	58.43	61.32	49.45	42.91
MM-Embed	LILaC ((w/o Query Decomposition) & Layered Graph)	75.80	69.09	92.80	82.19	90.39	83.71	61.10	67.35	47.94	43.75
	LILaC (w/o Query Decomposition)	82.23	77.75	92.27	83.20	92.17	85.53	63.19	69.91	50.18	45.59
	LILaC	83.59	78.75	92.81	84.43	93.17	86.83	69.07	75.28	55.80	50.77

Table 3: Ablation study analyzing retrieval accuracy (Recall@3 and MRR@10) of different LILaC variants. Best scores per embedder and dataset are highlighted in bold.

Algorithm Runtime Analysis

- LILaC is approximately 20.76% slower than VisRAG, yet 18.24% faster than ColPali.
- Late-interaction-based subgraph retrieval step accounts for only about 48 ms (approximately 1.5% of the total runtime).
- The major performance bottleneck lies in the query de- composition phase, averaging 1,423 ms.

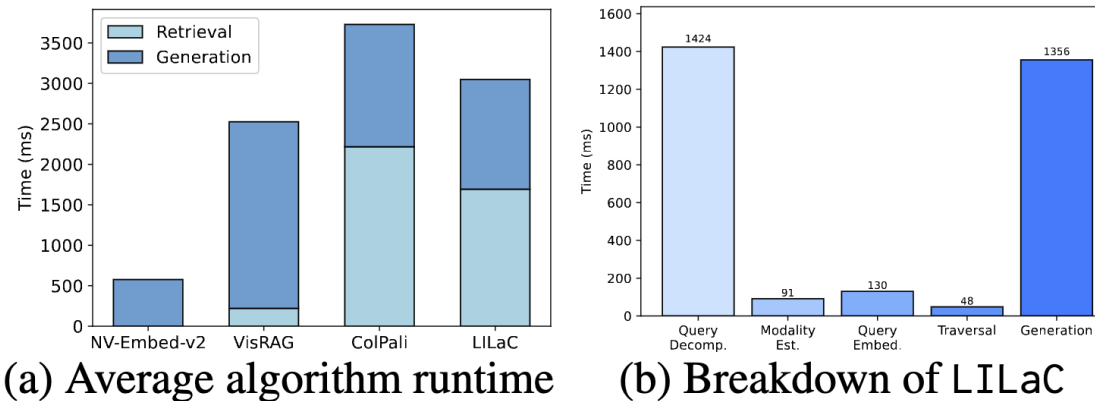


Figure 4: (a) Comparison of average algorithm execution times across different methods, and (b) detailed runtime breakdown of LILaC.

Next Research

Possible research directions

- Problem generalization
 - Expand the problem beyond Wikipedia setting
- **Multimodal retrieval improvement**
 - **Advanced graph construction**
 - **LLM-guided retrieval**
- Multimodal generation improvement

Current theoretical problems of LLaC

- Cannot retrieve components for which dependency resolution is needed.
 - Ineffective to retrieve long-hop evidences.
- > Currently performing a fine-grained error analysis.

Layerrec

