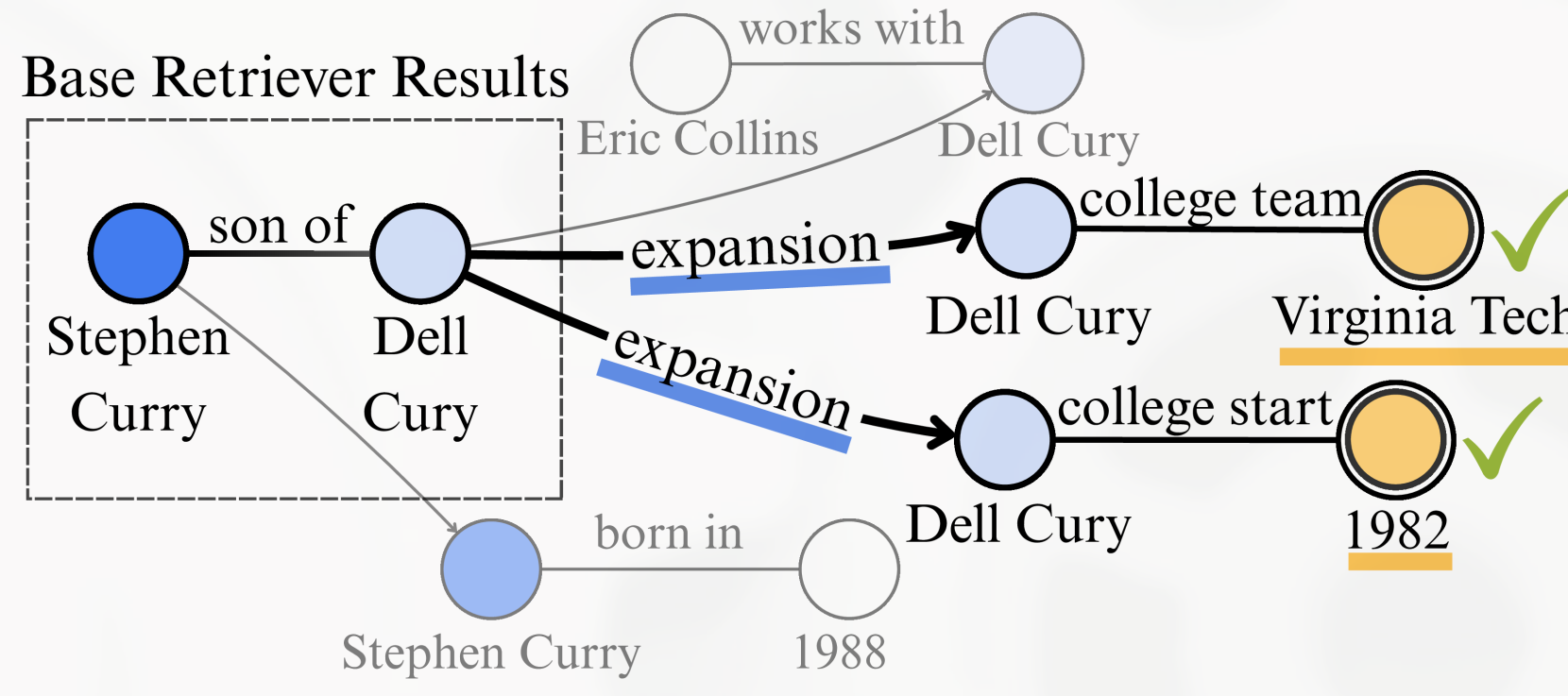


Multi-hop QA Example

“In what year did Stephen Curry’s father join the team from which he started his college basketball career?”



- A base retriever cannot, by design, retrieve all necessary information in a single step
- Graph expansion enables retrieval of subsequent hops
- Guides the system toward the correct answer without using an LLM

[TL;DR] Why GEAR?

Task: Multi-hop Question & Answering

- 🔍 **State-of-the-art retrieval performance:** $\geq 17\%$ relative \uparrow for R@5 on MuSiQue vs HippoRAG w/ IRCot
 → Leads to more than 35% relative \uparrow for end-to-end QA F1
- 🦋 **Less computational LLM workload:** achieves best performance in less iterations, and sometimes w/o using multi-step agent
- 🧠 **Neuroscience-inspired framework:** modelling the communication between *hippocampus* and *neocortex* in the brain

A Walk-through

When did the location of the basilica which is named for the same saint that the Bremen Cathedral is named for become a country?

Offline Index Building Stage

For each passage $c_i \in \mathbf{C} = \{c_1, c_2, \dots, c_C\}$, an LLM extracts a triple set, such that each triple is uniquely linked to one single passage.

1. Base Retrieval

For a query \mathbf{q} , $\mathbf{C}'_q = h_{\text{base}}^k(\mathbf{q}, \mathbf{C})$ is a list of passages given by the retriever, implemented as BM25, SBERT, or a mix of both.

- \mathcal{P}_1 Bremen Cathedral
- \mathcal{P}_2 Münster Cathedral
- \mathcal{P}_3 Basilica of the Sacred Heart
- \mathcal{P}_4 Saint Justin’s Church, Frankfurt-Höchst
- \mathcal{P}_5 Alatri Cathedral

2. Reader

An LLM reads \mathbf{C}'_q and summarises knowledge triples, outputting a collection \mathbf{T}'_q of triples: the *proximal triples*.

- \mathcal{T}'_1 (Bremen Cathedral, dedicated to, St. Peter)
- \mathcal{T}'_2 (Alatri Cathedral, dedicated to, Saint Paul)
- \mathcal{T}'_3 (Alatri Cathedral, co-cathedral of, Diocese Anagni-Alatri)
- \mathcal{T}'_4 (Bremen, is located in, Germany)

3. tripleLink

Initial nodes \mathbf{T}_q for graph expansion are identified by linking each triple in \mathbf{T}'_q to a triple in \mathbf{T} , using the *tripleLink* function.

- \mathcal{T}_1 (Bremen Cathedral, dedicated to, St. Peter)
- \mathcal{T}_2 (Alatri Cathedral, dedicated to, Saint Paul)
- \mathcal{T}_3 (Diocese of Macerata-Tolentino-Recanati-Cingoli-Treia, type, co-cathedral)
- \mathcal{T}_4 (Bremen, part of, Germany)

4. Graph Expansion

The primary component of graph expansion is *Diverse Triple Beam Search*. Here, we

Retriever	MuSiQue			2Wiki			HotpotQA		
	R@5	R@10	R@15	R@5	R@10	R@15	R@5	R@10	R@15
ColBERTv2	39.4	44.8	47.7	59.1	64.3	66.2	79.3	87.1	90.1
HippoRAG	41.0	47.0	51.4	75.1	83.2	86.4	79.8	89.0	92.4
BM25	33.8	38.5	41.3	59.5	62.7	64.1	74.2	83.6	86.3
+ NaiveGE	37.5	45.5	48.4	65.0	70.7	71.8	79.1	89.1	91.9
+ SyncGE	<u>44.7</u>	<u>52.6</u>	<u>57.4</u>	70.5	76.1	79.3	<u>87.4</u>	<u>93.0</u>	<u>94.0</u>
SBERT	31.1	37.9	41.6	41.2	48.1	51.5	72.1	79.3	84.0
+ NaiveGE	32.2	41.4	45.4	45.1	54.0	57.3	76.1	84.7	88.8
+ SyncGE	41.6	51.3	54.2	54.8	64.9	70.7	84.1	89.6	92.8
Hybrid	39.9	46.3	49.1	60.0	65.8	66.6	77.8	85.8	89.7
+ NaiveGE	41.8	49.4	53.0	63.0	70.8	72.6	80.6	89.4	92.7
+ SyncGE	48.7	57.7	61.2	<u>72.6</u>	<u>80.9</u>	<u>82.4</u>	87.4	93.3	95.2
IRCot (BM25)	46.1	<u>54.9</u>	57.9	67.9	75.5	76.1	87.0	92.6	92.9
IRCot (ColBERTv2)	47.9	54.3	56.4	60.3	86.6	69.7	86.9	92.5	92.8
HippoRAG w/ IRCot	<u>48.8</u>	54.5	<u>58.9</u>	<u>82.9</u>	<u>90.6</u>	<u>93.0</u>	<u>90.1</u>	<u>94.7</u>	<u>95.9</u>
GEAR	58.4	67.6	71.5	89.1	95.3	95.9	93.4	96.8	97.3

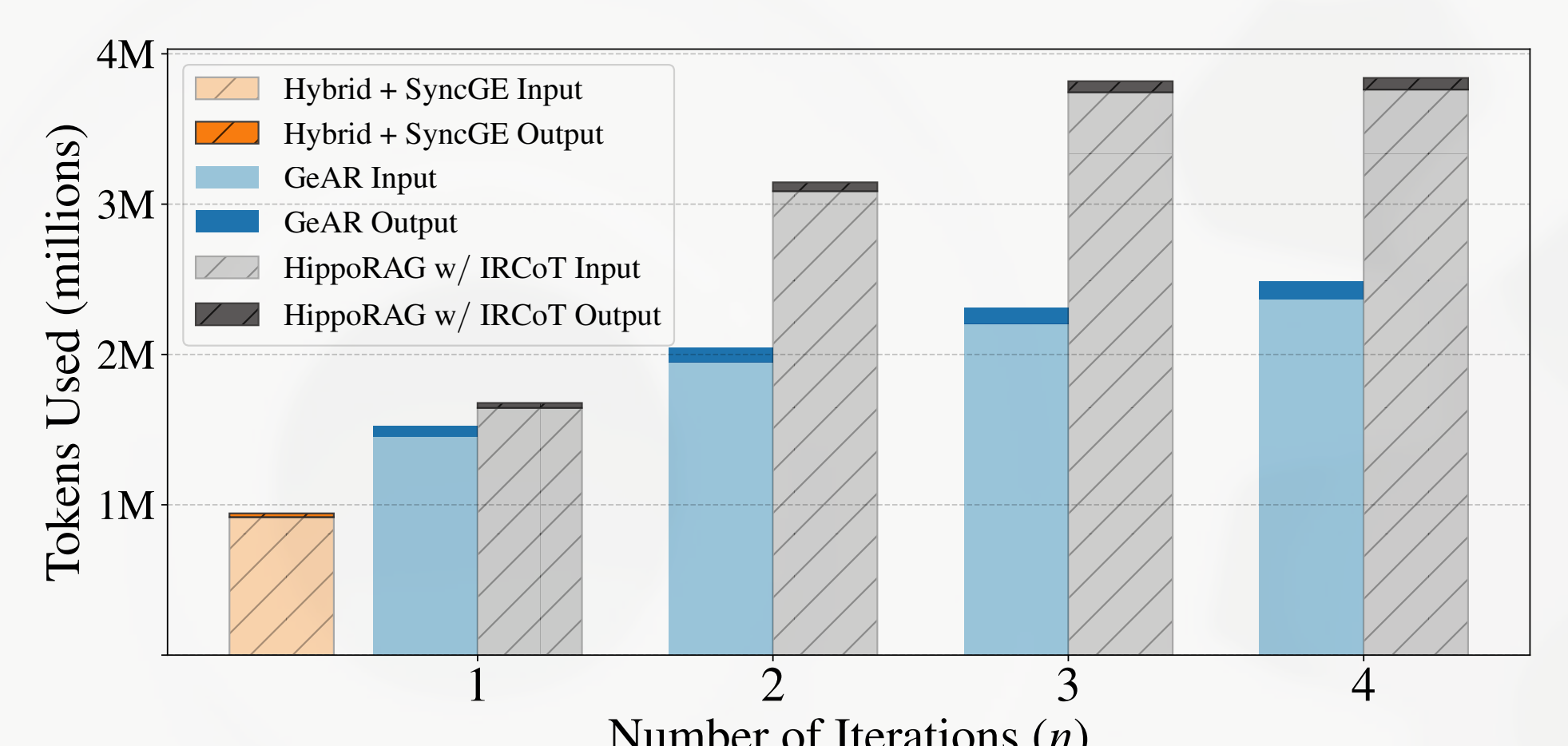
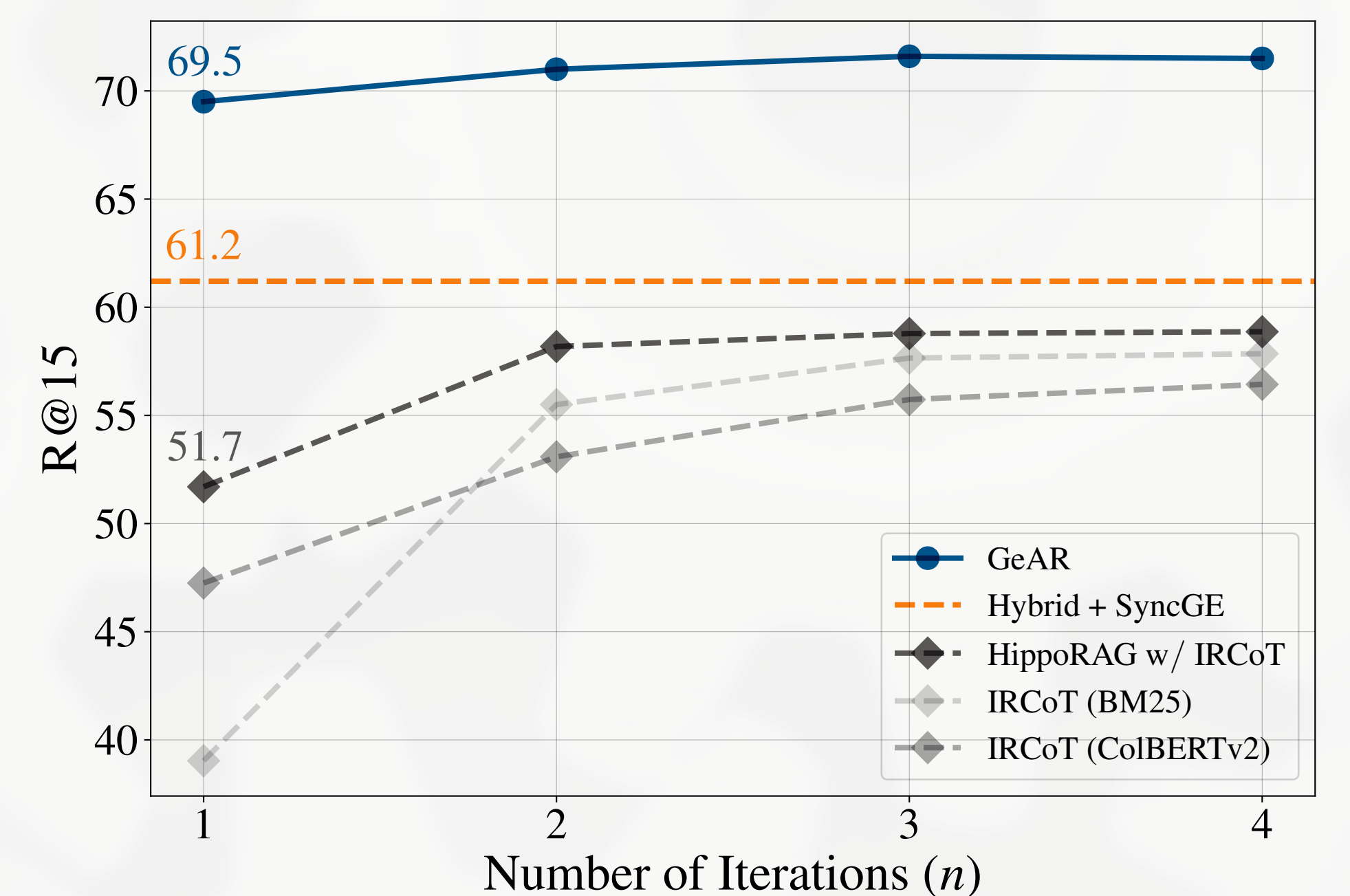
What makes GEAR work?

- [GE] Graph expansion on top of a base retriever
- [SyncGE] LLM for locating initial nodes for GE—synergetic behaviour between LLM and GE \gg NaiveGE
- [Diversity Weights] Introducing diversity weight for triple beam search



Is GEAR efficient?

- GEAR requires fewer iterations than the competition to reach its maximum recall performance
- GEAR is more efficient in terms of LLM token utilisation
- Even for a single iteration, GEAR uses fewer tokens than HippoRAG w/ IRCot, with substantially higher Recall@15



Metric	Dataset	w/ Diversity	w/o Diversity
R@5	MuSiQue	48.7	47.0
	2Wiki	72.6	68.2
	HotpotQA	87.4	85.0
R@10	MuSiQue	57.7	53.9
	2Wiki	80.9	76.0
	HotpotQA	93.3	92.2
R@15	MuSiQue	61.2	58.4
	2Wiki	82.4	77.4
	HotpotQA	95.2	94.3