

# Natural Language Processing: RAG, Tools

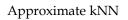
HSE Faculty of Computer Science
Machine Learning and Data-Intensive Systems

Murat Khazhgeriev



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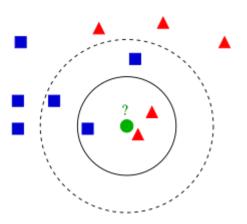
- Approximate kNN
- Retrieval-Augmented Generation (RAG)
- Introducing graphs to the system
- Agents

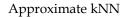






# Vanilla kNN







# Hierarchical Small Navigable World (HNSW)

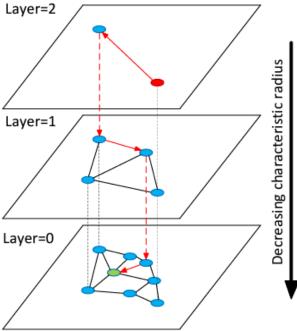
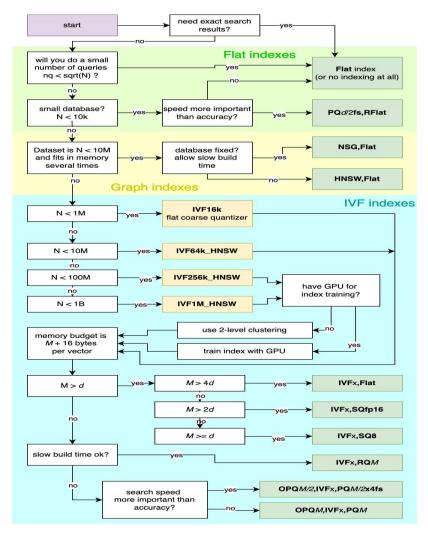


Fig. 1. Illustration of the Hierarchical NSW idea. The search starts from an element from the top layer (shown red). Red arrows show direction of the greedy algorithm from the entry point to the query (shown green).



## **FAISS**



Source: https://github.com/facebookresearch/faiss/wiki/Guidelines-to-choose-an-index

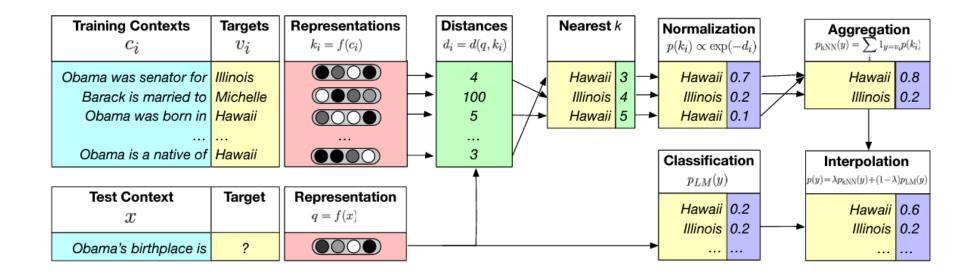


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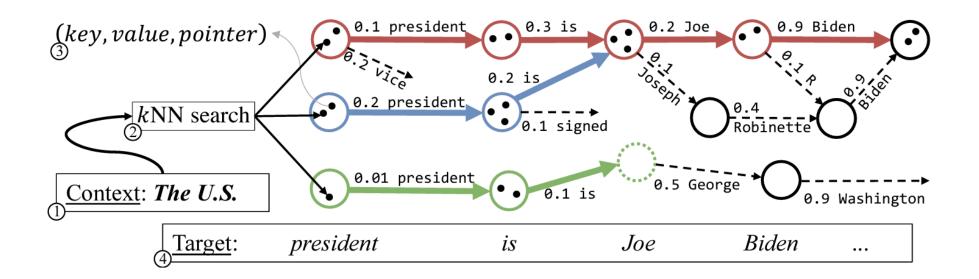
# Generalization through Memorization: Nearest Neighbor Language Models



$$p(y|x) = \lambda p_{kNN}(y|x) + (1 - \lambda) p_{LM}(y|x)$$

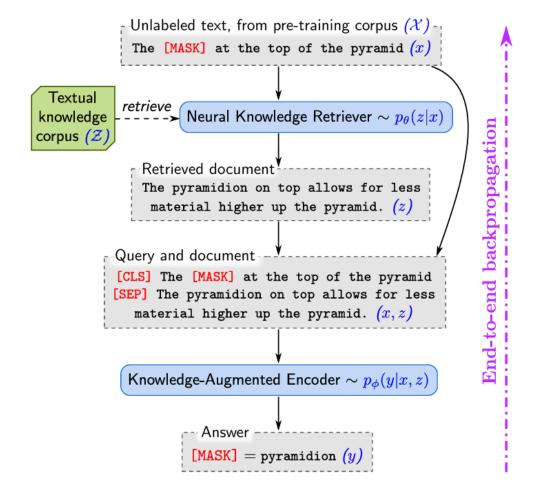


# Neuro-Symbolic Language Modeling with Automaton-augmented Retrieval





# REALM: Retrieval-Augmented Language Model Pre-Training



Weighted probability for each neighbor is the answer:

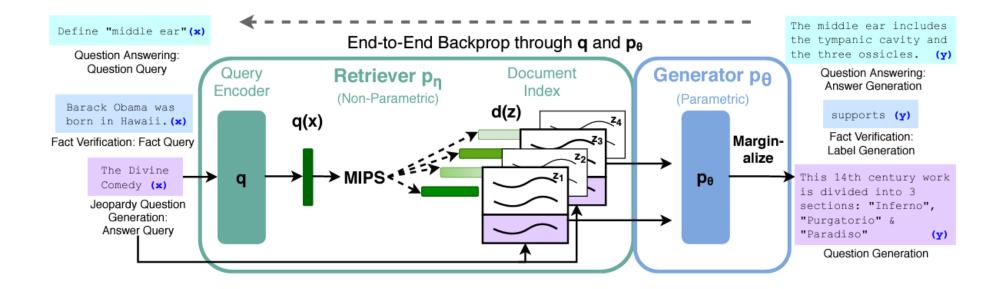
$$p(y \mid x) = \sum_{z \in \mathcal{Z}} p(y \mid z, x) p(z \mid x).$$

The closer retrieved data, the more weight it has:

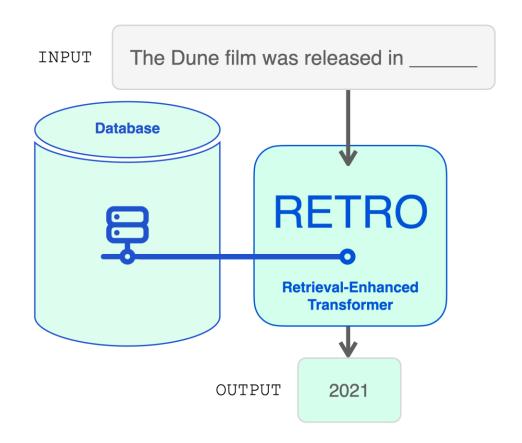
$$\begin{split} p(z \,|\, x) &= \frac{\exp f(x,z)}{\sum_{z'} \exp f(x,z')}, \\ f(x,z) &= \texttt{Embed}_{\texttt{input}}(x)^{\top} \texttt{Embed}_{\texttt{doc}}(z), \end{split}$$



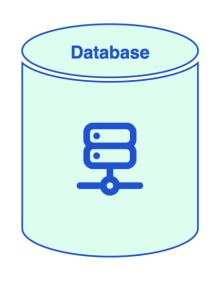
# Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks





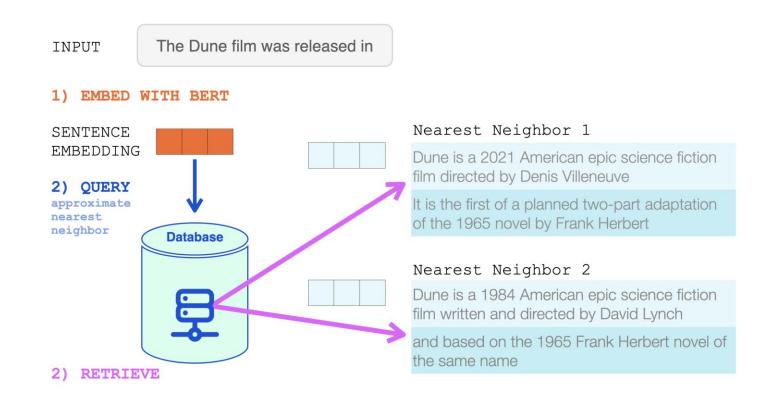




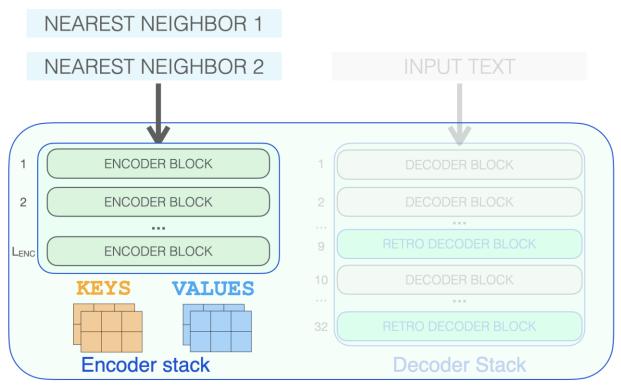


Key (BERT sentence embedding)	Value (text. neighbor and completion chunks. Each up to 64 tokens in length)	
	Dune is a 2021 American epic science fiction film directed by Denis Villeneuve	NEIGHBOR
	It is the first of a planned two-part adaptation of the 1965 novel by Frank Herbert	COMPLETION
	Dune is a 1965 science fiction novel by American author Frank Herbert	NEIGHBOR
	originally published as two separate serials in Analog magazine	COMPLETION



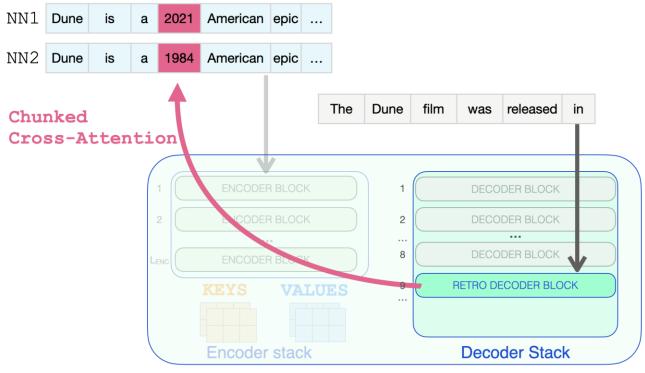






**RETRO Transformer** 

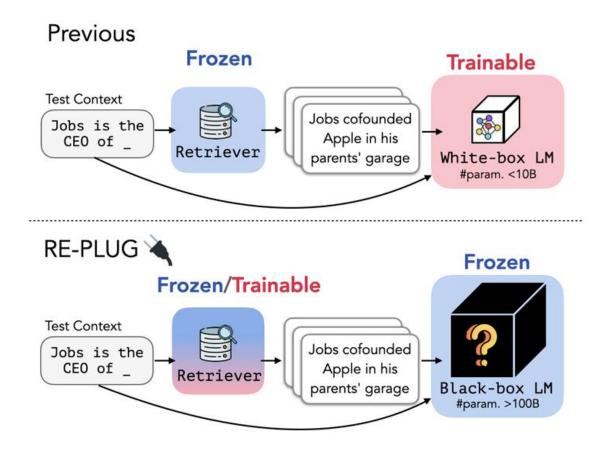




**RETRO Transformer** 

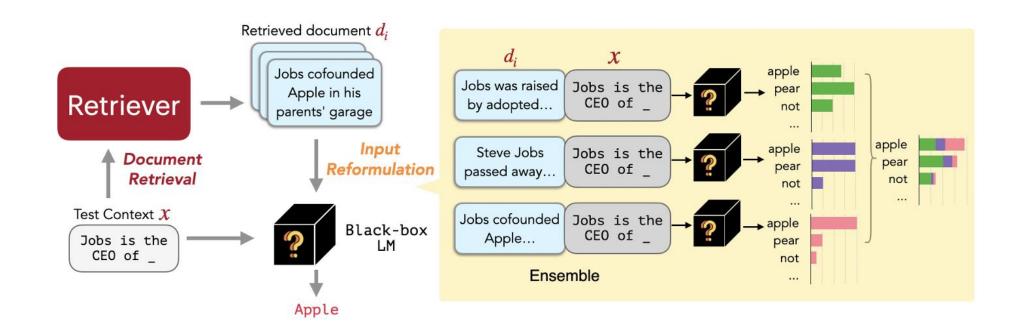


# REPLUG: Retrieval-Augmented Black-Box Language Models





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# Retrieval meets Long Context Large Language Models

Model	Seq len.	Avg.	QM	QASP	NQA	QLTY	MSQ	HQA	MFQA
GPT-43B	4k	26.44	15.56	23.66	15.64	49.35	11.08	28.91	40.90
+ ret	4k	29.32	16.60	23.45	19.81	51.55	14.95	34.26	44.63
GPT-43B	16k	29.45	16.09	25.75	16.94	50.05	14.74	37.48	45.08
+ ret	16k	29.65	15.69	23.82	21.11	47.90	15.52	36.14	47.39
Llama2-70B	4k	31.61	16.34	27.70	19.07	63.55	15.40	34.64	44.55
+ ret	4k	36.02	17.41	28.74	23.41	70.15	21.39	42.06	48.96
Llama2-70B	16k	36.78	16.72	30.92	22.32	<b>76.10</b>	18.78	43.97	48.63
+ ret	16k	37.23	<b>18.70</b>	29.54	23.12	70.90	23.28	44.81	50.24
Llama2-70B	32k	37.36	15.37	31.88	23.59	73.80	19.07	49.49	48.35
+ ret	32k	39.60	18.34	31.27	24.53	69.55	26.72	53.89	<b>52.91</b>
Llama2-7B	4k	22.65	14.25	22.07	14.38	40.90	8.66	23.13	35.20
+ ret	4k	26.04	16.45	22.97	18.18	43.25	14.68	26.62	40.10
Llama2-7B	32k	28.20	16.09	23.66	19.07	44.50	15.74	31.63	46.71
+ ret	32k	27.63	17.11	23.25	19.12	43.70	15.67	29.55	45.03

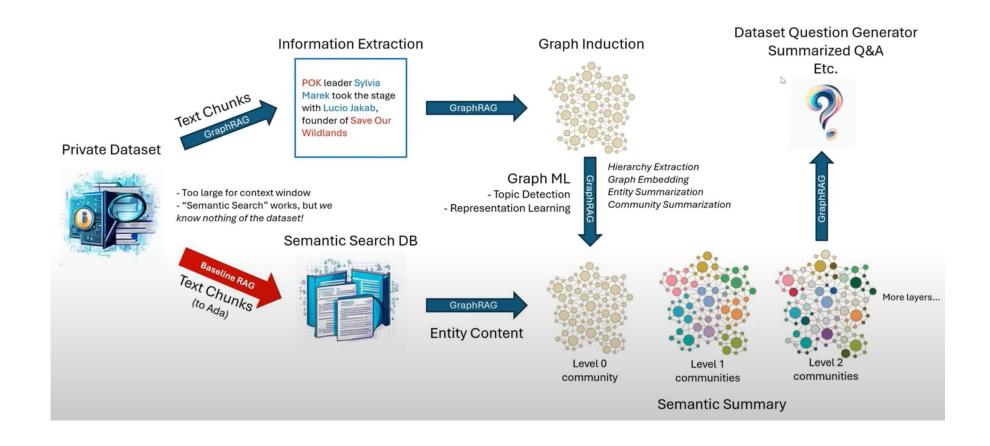


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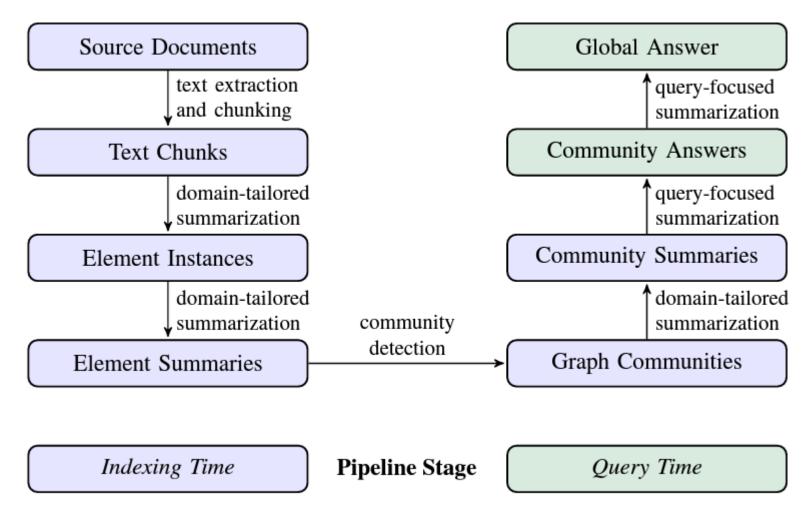


## From Local to Global: A Graph RAG Approach to Query-Focused Summarization





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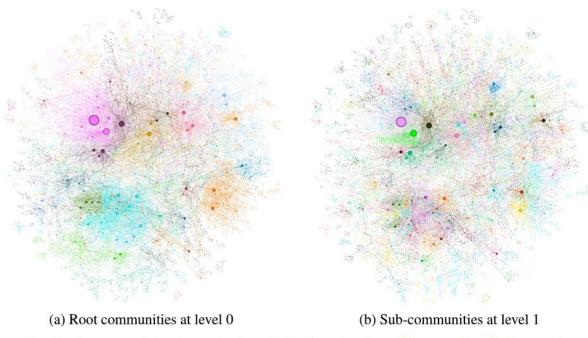


Figure 3: Graph communities detected using the Leiden algorithm (Traag et al., 2019) over the MultiHop-RAG (Tang and Yang, 2024) dataset as indexed. Circles represent entity nodes with size proportional to their degree. Node layout was performed via OpenORD (Martin et al., 2011) and Force Atlas 2 (Jacomy et al., 2014). Node colors represent entity communities, shown at two levels of hierarchical clustering: (a) Level 0, corresponding to the hierarchical partition with maximum modularity, and (b) Level 1, which reveals internal structure within these root-level communities.



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(a) Screenshot from the demonstration interface.

(b) Corresponding text given to the model.

Figure 1: An observation from our text-based web-browsing environment, as shown to human demonstrators (left) and models (right). The web page text has been abridged for illustrative purposes.



Table 1: Actions the model can take. If a model generates any other text, it is considered to be an invalid action. Invalid actions still count towards the maximum, but are otherwise ignored.

Command	Effect				
Search <query></query>	Send <query> to the Bing API and display a search results p</query>				
Clicked on link <link id=""/>	Follow the link with the given ID to a new page				
Find in page: <text></text>	Find the next occurrence of <text> and scroll to it</text>				
Quote: <text></text>	If <text> is found in the current page, add it as a reference</text>				
Scrolled down <1, 2, 3>	Scroll down a number of times				
Scrolled up <1, 2, 3>	Scroll up a number of times				
Тор	Scroll to the top of the page				
Back	Go to the previous page				
End: Answer	End browsing and move to answering phase				
<pre>End: <nonsense, controversial=""></nonsense,></pre>	End browsing and skip answering phase				



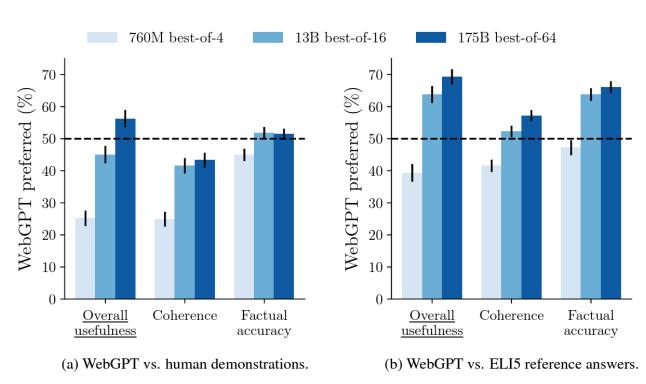


Figure 2: Human evaluations on ELI5 comparing against (a) demonstrations collected using our web browser, (b) the highest-voted answer for each question. The amount of rejection sampling (the n in best-of-n) was chosen to be compute-efficient (see Figure 8). Error bars represent  $\pm 1$  standard error.

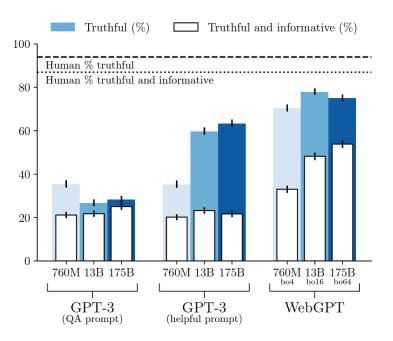


Figure 3: TruthfulQA results. The amount of rejection sampling (the n in best-of-n) was chosen to be compute-efficient (see Figure 8). Error bars represent  $\pm 1$  standard error.



# Toolformer: Language Models Can Teach Themselves to Use Tools

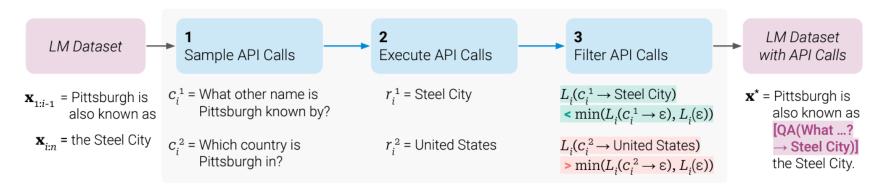


Figure 2: Key steps in our approach, illustrated for a *question answering* tool: Given an input text  $\mathbf{x}$ , we first sample a position i and corresponding API call candidates  $c_i^1, c_i^2, \ldots, c_i^k$ . We then execute these API calls and filter out all calls which do not reduce the loss  $L_i$  over the next tokens. All remaining API calls are interleaved with the original text, resulting in a new text  $\mathbf{x}^*$ .



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# Toolformer: Language Models Can Teach Themselves to Use Tools

Your task is to add calls to a Question Answering API to a piece of text. The questions should help you get information required to complete the text. You can call the API by writing "[QA(question)]" where "question" is the question you want to ask. Here are some examples of API calls:

Input: Joe Biden was born in Scranton, Pennsylvania.

Output: Joe Biden was born in [QA("Where was Joe Biden born?")] Scranton, [QA("In which state is Scranton?")] Pennsylvania.

**Input:** Coca-Cola, or Coke, is a carbonated soft drink manufactured by the Coca-Cola Company.

Output: Coca-Cola, or [QA("What other name is Coca-Cola known by?")] Coke, is a carbonated soft drink manufactured by [QA("Who manufactures Coca-Cola?")] the Coca-Cola Company.

Input: x

Output:

Figure 3: An exemplary prompt  $P(\mathbf{x})$  used to generate API calls for the question answering tool.

Source: https://arxiv.org/abs/2302.04761



# Toolformer: Language Models Can Teach Themselves to Use Tools

The New England Journal of Medicine is a registered trademark of [QA("Who is the publisher of The New England Journal of Medicine?") → Massachusetts Medical Society] the MMS.

Out of 1400 participants, 400 (or [Calculator(400 / 1400)]  $\rightarrow$  0.29] 29%) passed the test.

The name derives from "la tortuga", the Spanish word for [MT("tortuga") → turtle] turtle.

The Brown Act is California's law [WikiSearch("Brown Act") → The Ralph M. Brown Act is an act of the California State Legislature that guarantees the public's right to attend and participate in meetings of local legislative bodies.] that requires legislative bodies, like city councils, to hold their meetings open to the public.

Figure 1: Exemplary predictions of Toolformer. The model autonomously decides to call different APIs (from top to bottom: a question answering system, a calculator, a machine translation system, and a Wikipedia search engine) to obtain information that is useful for completing a piece of text.

Source: https://arxiv.org/abs/2302.04761



## HuggingGPT: Solving AI Tasks with ChatGPT and its Friends in Hugging Face

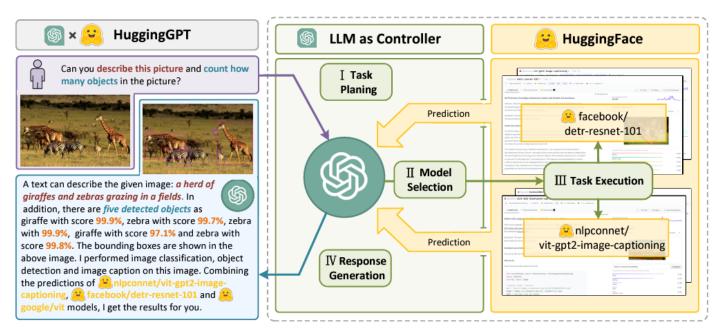


Figure 1: Language serves as an interface for LLMs (e.g., ChatGPT) to connect numerous AI models (e.g., those in Hugging Face) for solving complicated AI tasks. In this concept, an LLM acts as a controller, managing and organizing the cooperation of expert models. The LLM first plans a list of tasks based on the user request and then assigns expert models to each task. After the experts execute the tasks, the LLM collects the results and responds to the user.





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