Table Learning w/ LLM

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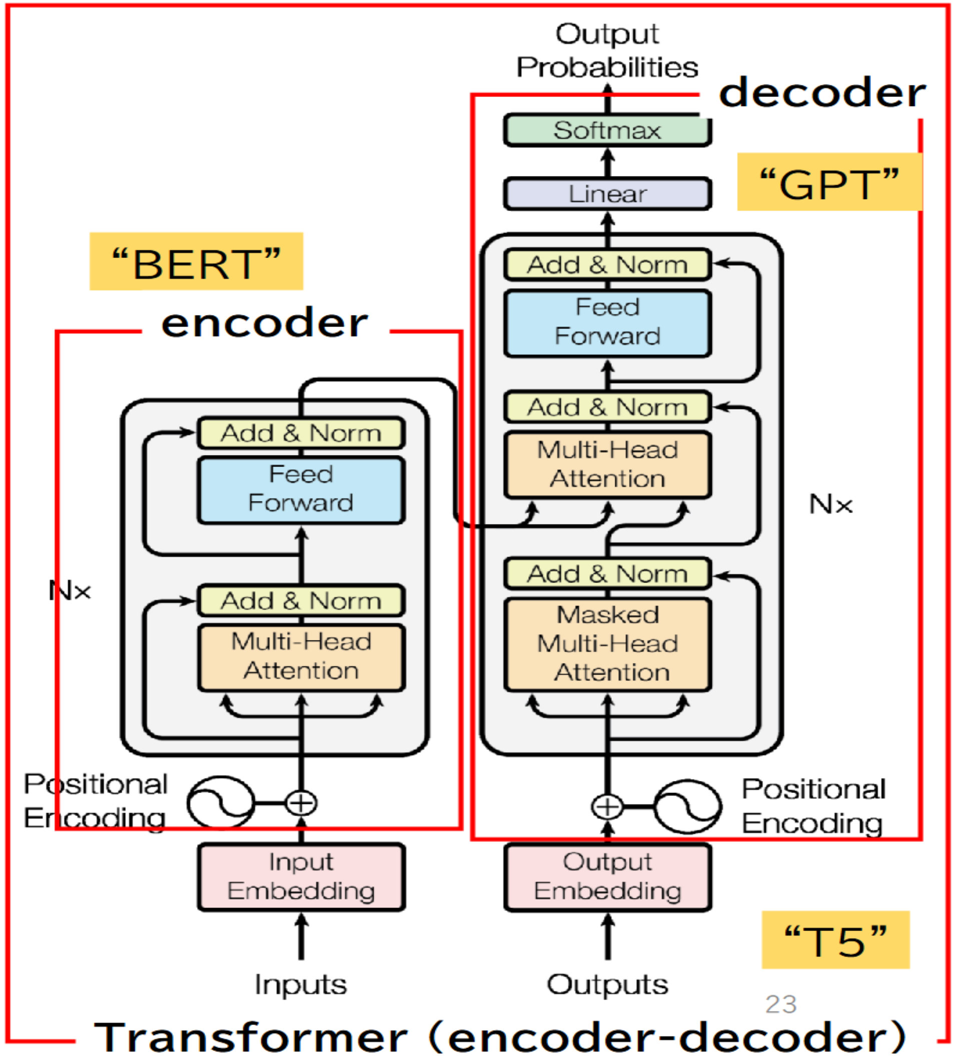
Outline

- **Background**
- Classical methods vs. LLM
- Table Learning w/ LLM
  - w/ Finetuned LLM
  - w/o Finetuned LLM

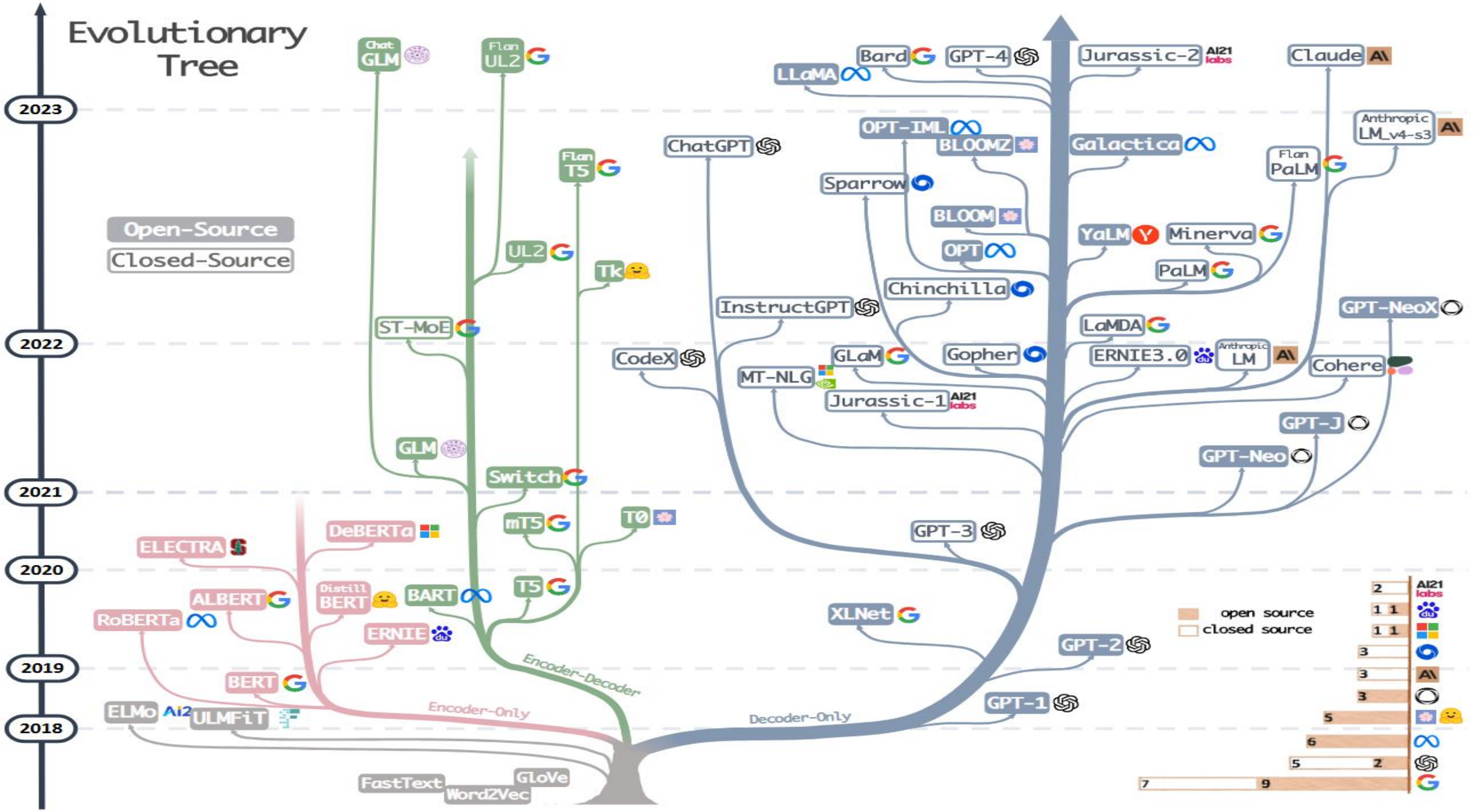
Transformer: The Cornerstone of LLMs



- Self-Attention Mechanism
- Encoder Generates contextualized representations for each input token.
- Decoder Generates the output one sequence token at a time
- Can be used individually or combined together.

Vaswani A, Shazeer N, Parmar N, et al. Attention is all you need[J]. Advances in neural information processing systems, 2017, 30.

LLM Development History



Yang J, Jin H, Tang R, et al. Harnessing the power of llms in practice: A survey on chatgpt and beyond[J]. ACM Transactions on Knowledge Discovery from Data, 2024, 18(6): 1-32.

LLM in Context Learning

(a) Few-shot

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?
A: The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A:

(Output) The answer is 8.

(b) Few-shot-CoT

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?
A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A:

(Output) The juggler can juggle 16 balls. Half of the balls are golf balls. So there are 16 / 2 = 8 golf balls. Half of the golf balls are blue. So there are 8 / 2 = 4 blue golf balls. The answer is 4.

(c) Zero-shot

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: The answer (arabic numerals) is

(Output) 8

(d) Zero-shot-CoT

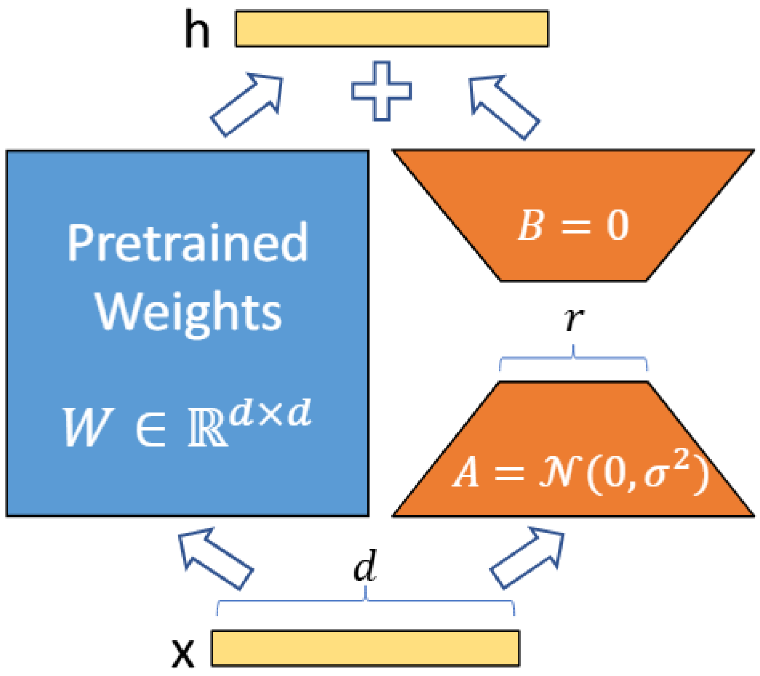
Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: ***Let's think step by step.***

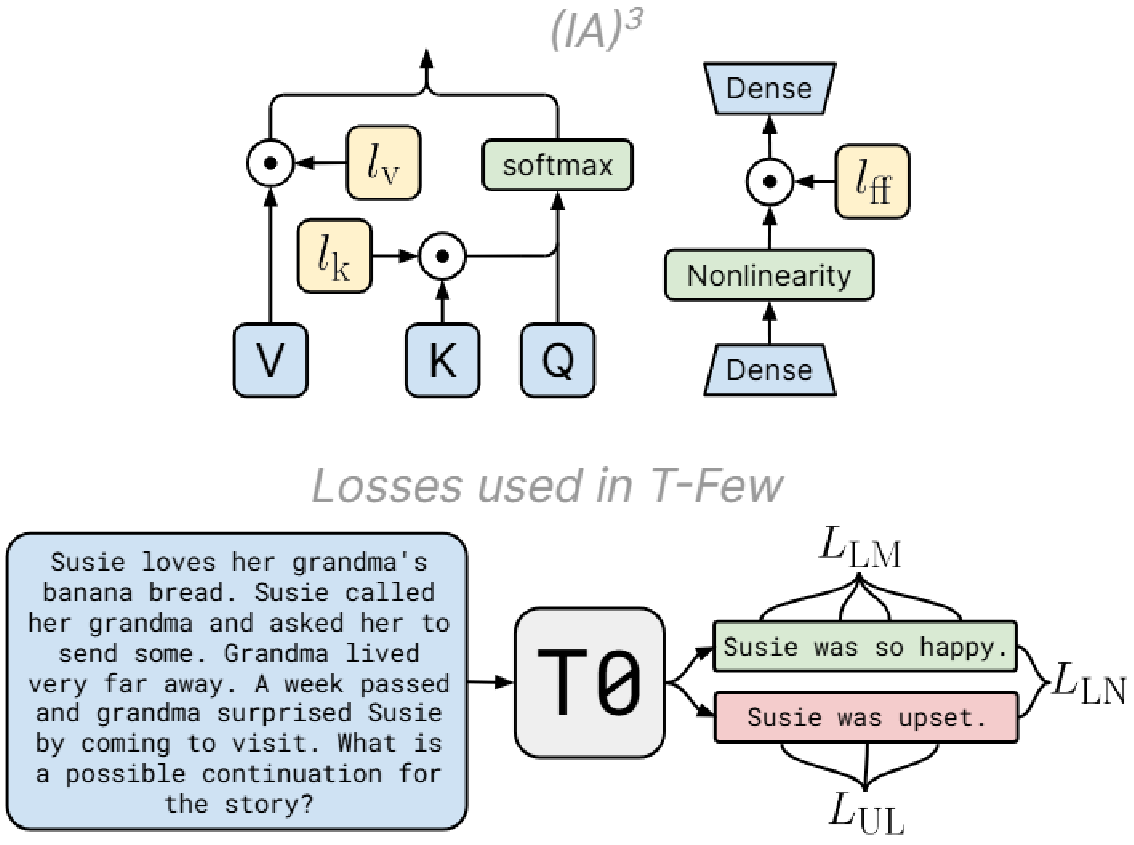
(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls.

- Frozen LLMs
- Zero-Shot
- Few-Shot
- Chain-of-Thought

Kojima T, Gu S S, Reid M, et al. Large language models are zero-shot reasoners[J]. Advances in neural information processing systems, 2022, 35: 22199-22213.

LLM Finetune: PEFT (Parameter-Efficient Fine-Tuning)





- LoRA

Hu E J, Shen Y, Wallis P, et al. Lora: Low-rank adaptation of large language models[J]. ICLR, 2022, 1(2): 3.

- IA3

……

Liu H, Tam D, Muqeeth M, et al. Few-shot parameter-efficient fine-tuning is better and cheaper than in-context learning[J]. Advances in Neural Information Processing Systems, 2022, 35: 1950-1965.

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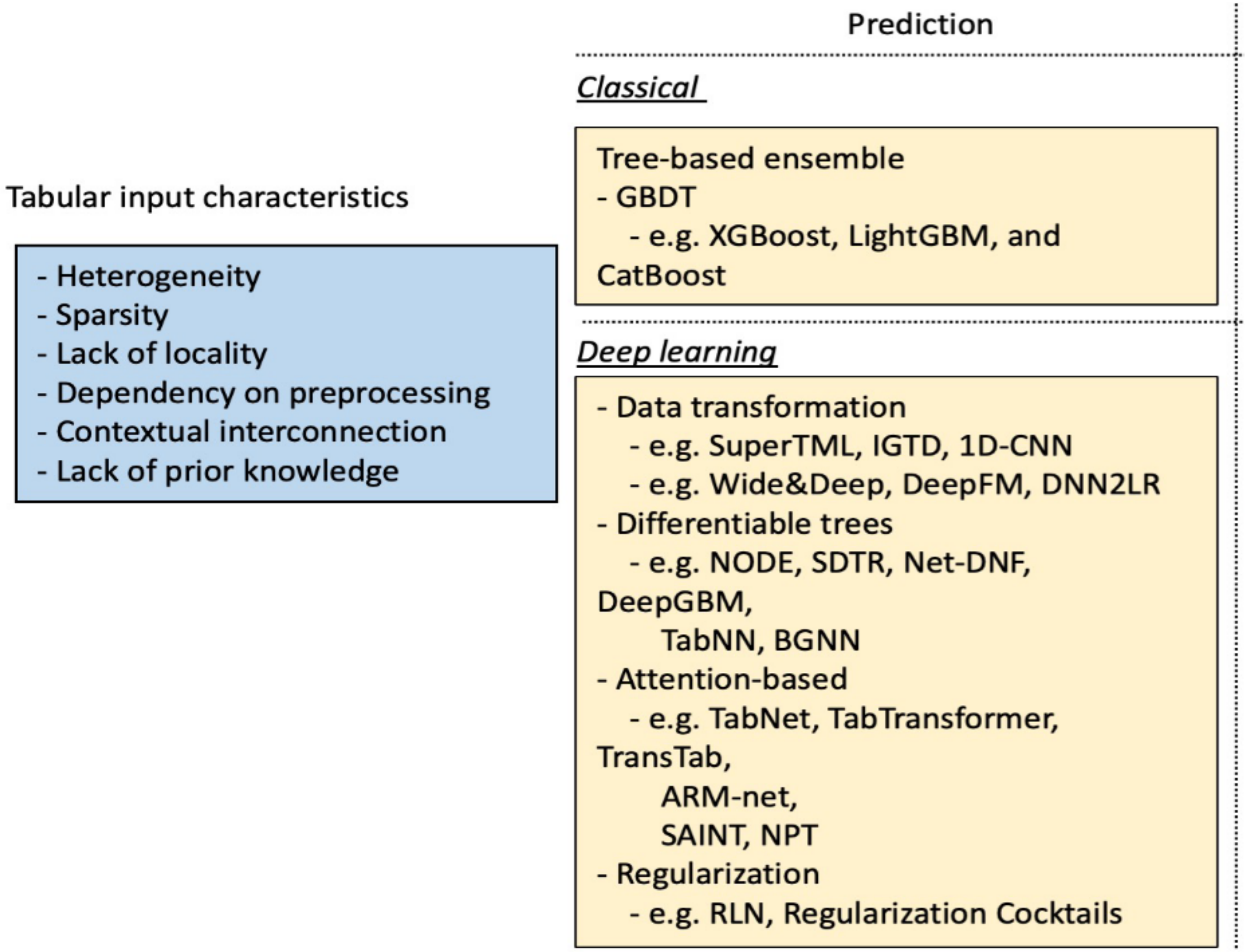
Classical Methods for Table Learning

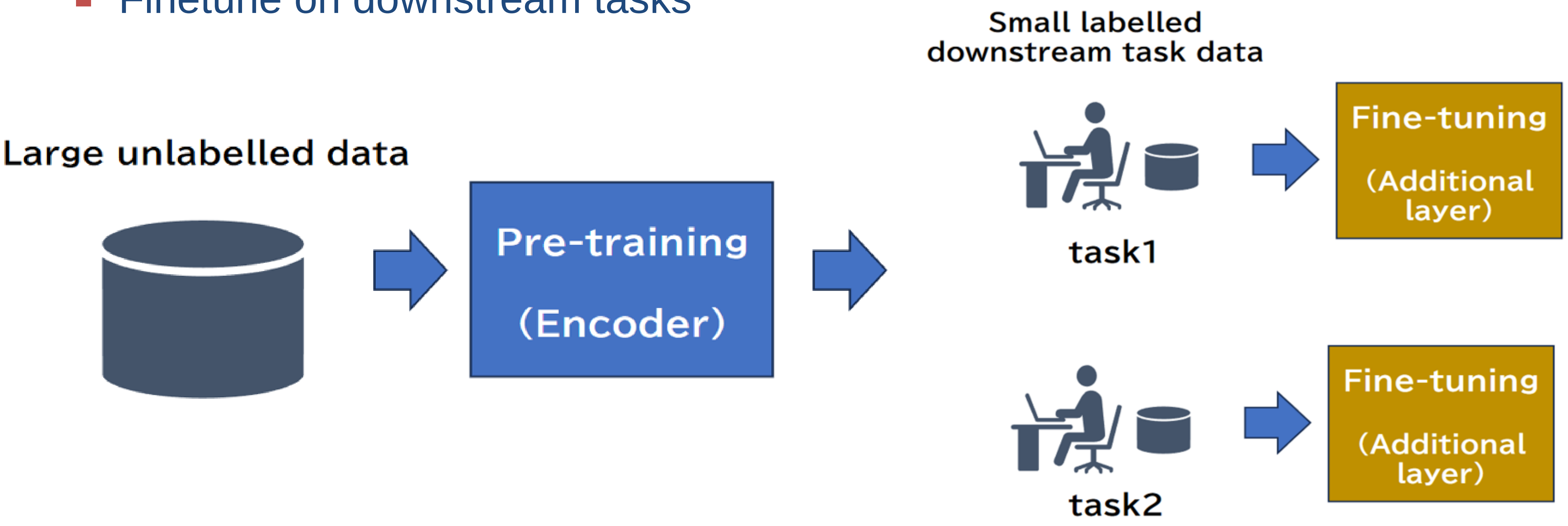


- Only focus on Prediction for simple.
- Data preprocessing requires manual feature engineering.
- Semantic understanding is insufficient.

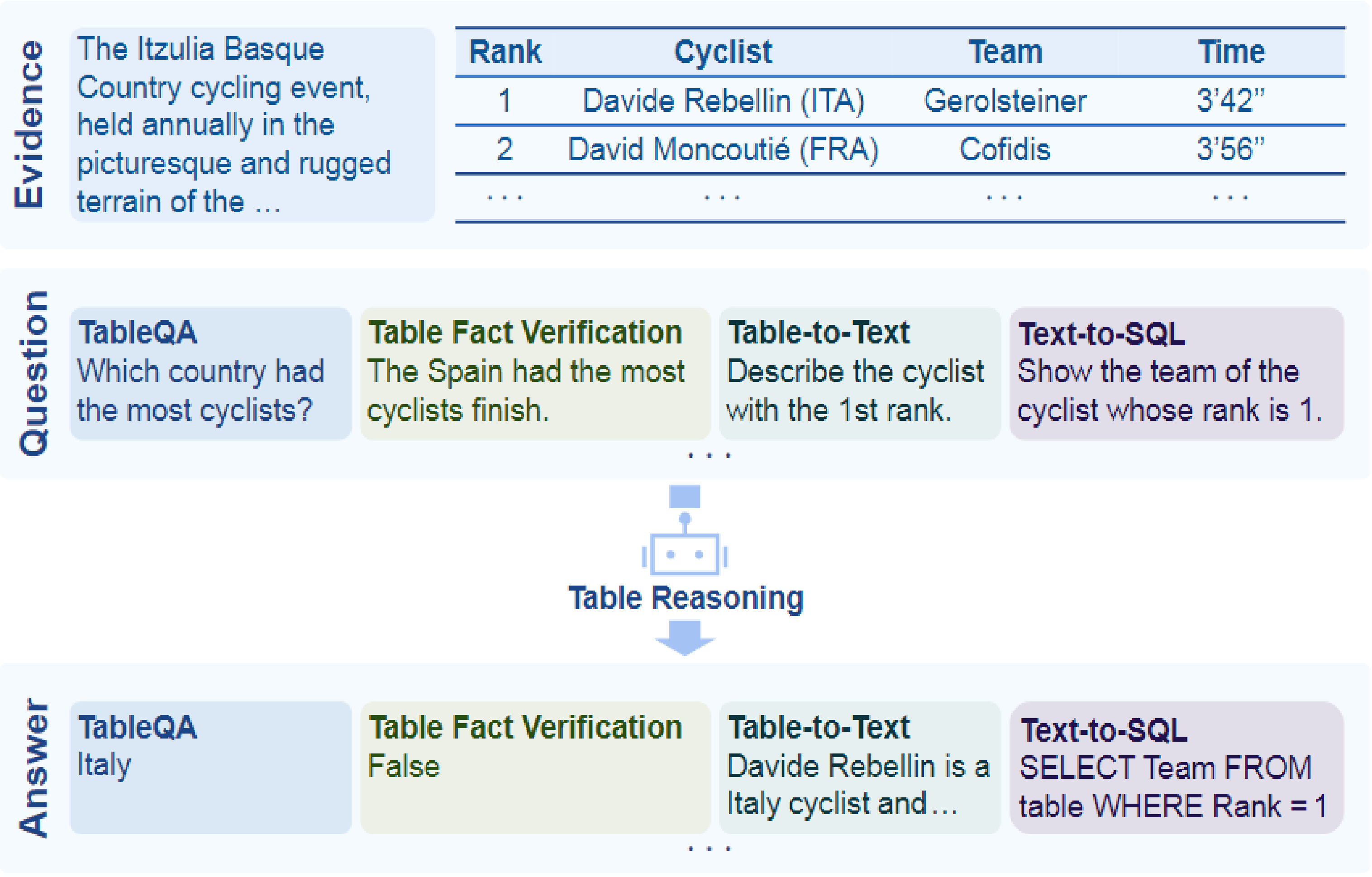
Fang X, Xu W, Tan F A, et al. Large Language Models (LLMs) on Tabular Data: Prediction, Generation, and Understanding--A Survey[J]. arXiv preprint arXiv:2402.17944, 2024.

Encoder For tables

- Pretrain-and-Finetune (“BERT-like”)
  - Learning good table representation (embedding) with table pretraining tasks
  - Finetune on downstream tasks



Why LLM is Promising for Table Learning



- Tabular data can be easily serialized as text for LLM processing.
- LLM excelling in zero-shot or few-shot scenarios.
- LLM offer strong interpretability and flexibility.

Zhang X, Wang D, Dou L, et al. A survey of table reasoning with large language models[J]. Frontiers of Computer Science, 2025, 19(9): 199348.

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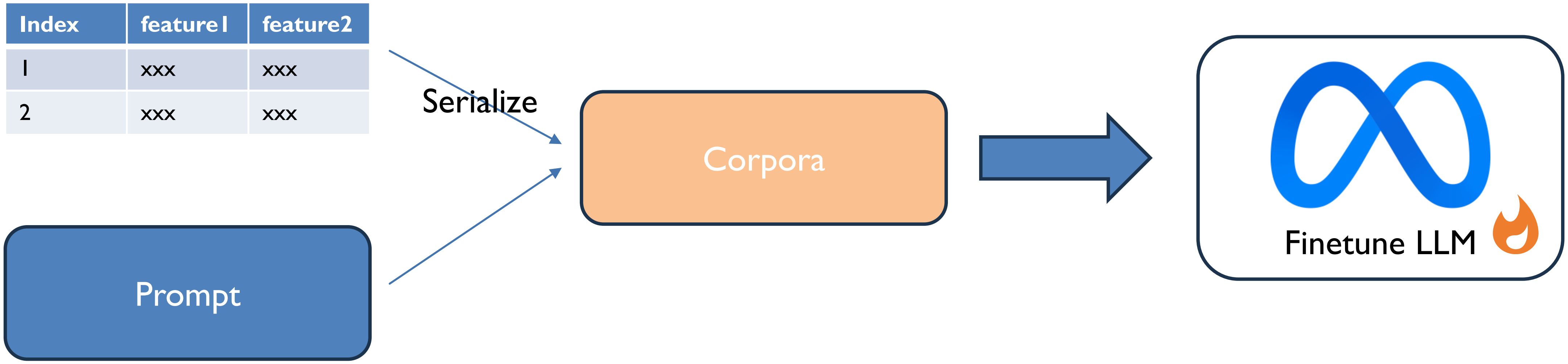
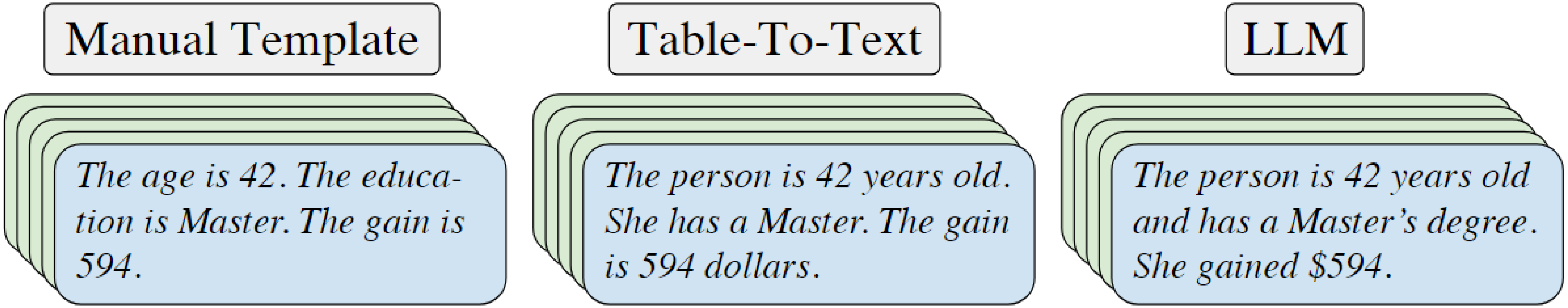
Overview

- How to serialize table data into text data?
- How to construct an effective prompt?
- Which PEFT method should be selected?



TabLLM: Serialize Table Data

- How to serialize table data into text data?
  - Text Template: An textual enumeration of all features as "The column name is value."
  - Table-To-Text: Use a specialized table-to-text generation model.
  - Text LLM: Use an LLM for table-to-text generation.
  - Json format, LaTex format, Markdown format……



Hegselmann S, Buendia A, Lang H, et al. Tabllm: Few-shot classification of tabular data with large language models[C]//International Conference on Artificial Intelligence and Statistics. PMLR, 2023: 5549-5581.

TabLLM: Construct Prompt

- How to construct an effective prompt?
  - Use dataset-relevant prompt

Bank Dataset:

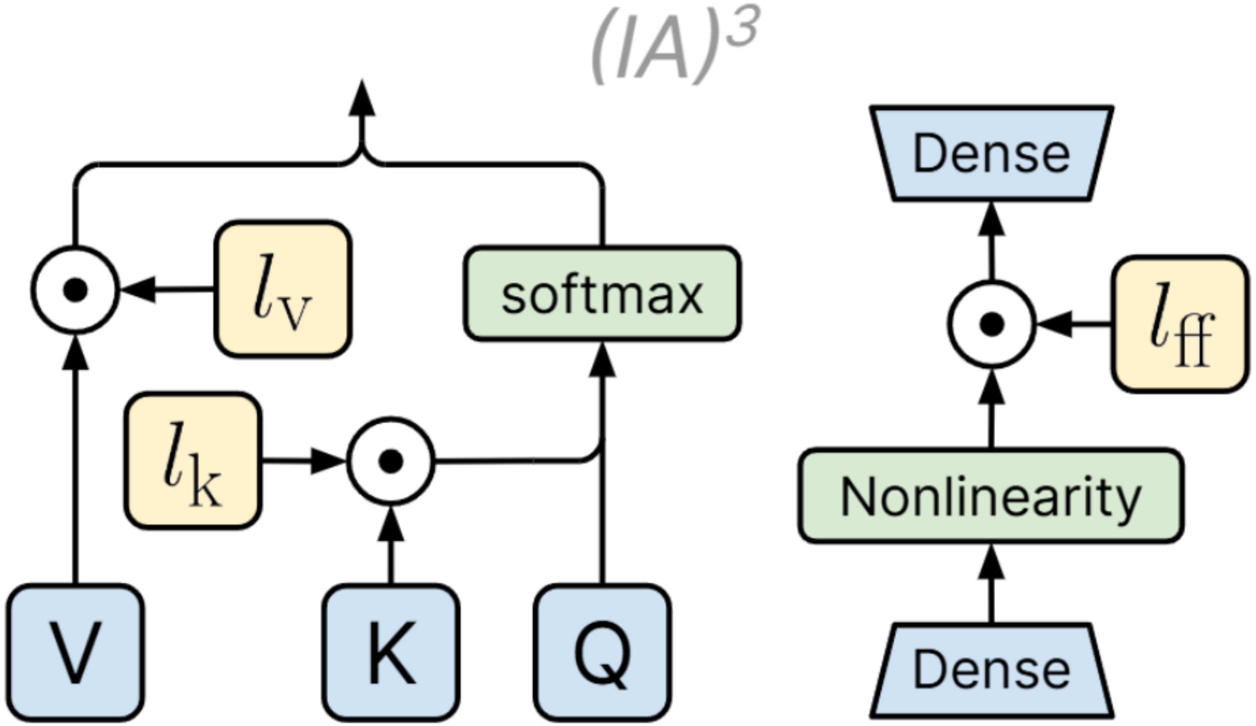
```
answer_choices: 'No ||| Yes'
jinja: '{{serialization}}

Does this client subscribe to a term
deposit? Yes or no?
Answer:
|||
{{ answer_choices[label] }}'
```

Heart Dataset:

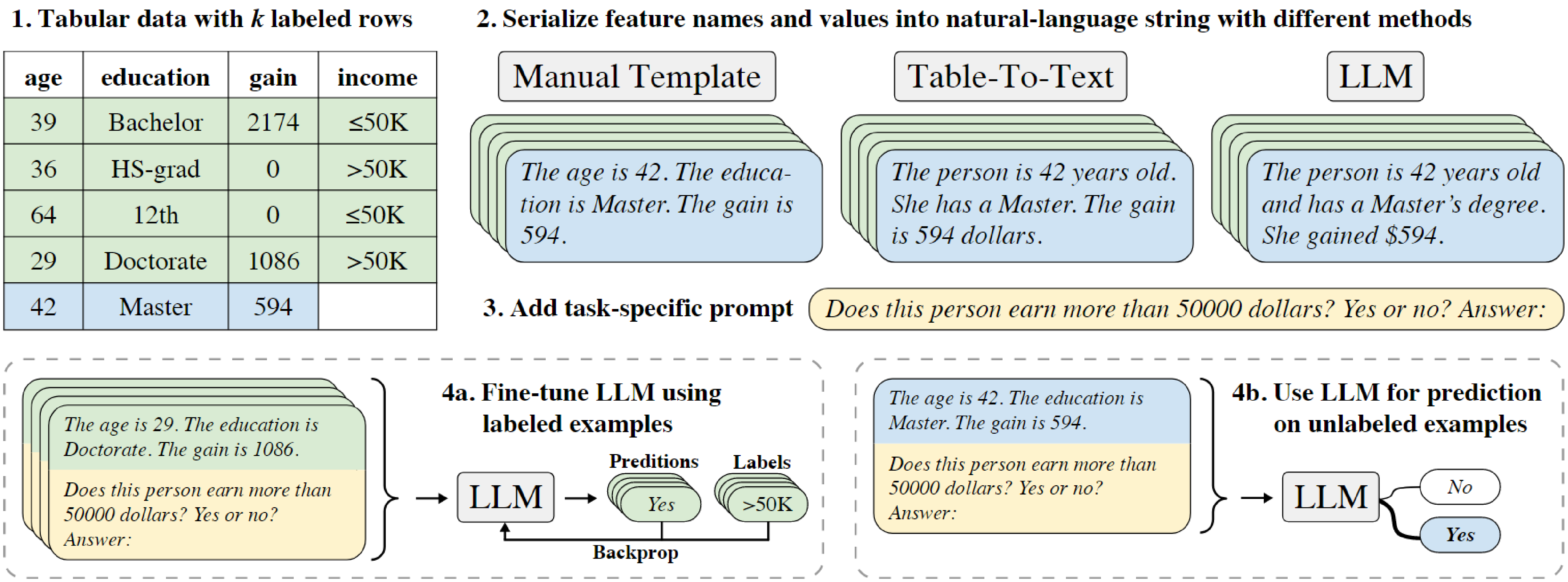
```
answer_choices: 'No ||| Yes'
jinja: '{{serialization}}

Does the coronary angiography of this
patient show a heart disease? Yes or
no?
Answer:
|||
{{ answer_choices[label] }}'
```

TabLLM: Choose a Proper PEFT Method

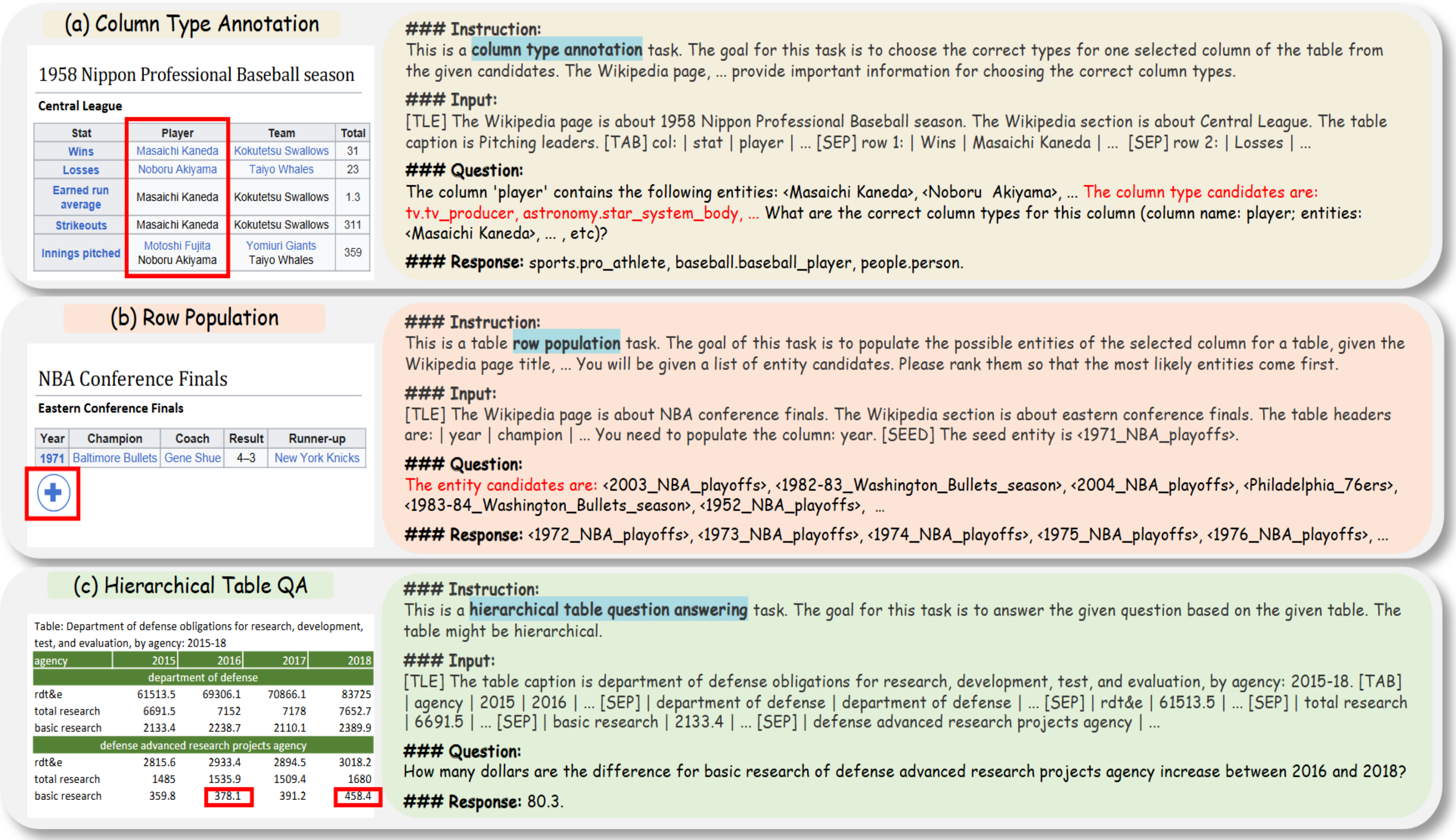
- Which PEFT method should be selected?
  - Here TabLLM has chosen IA3 for finetuning LLM.



TabLLM Pipeline



TableLlama: Serialization & Prompt

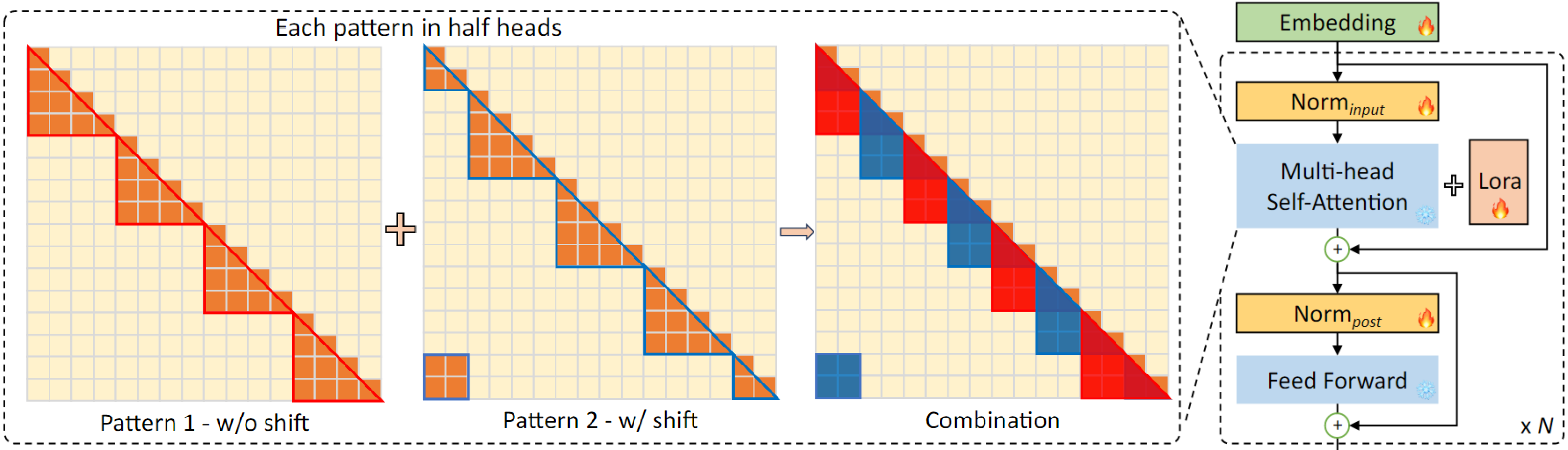


- Table interpretation
- Table augmentation
- Question answering
- Fact verification
- ……

Zhang T, Yue X, Li Y, et al. Tablellama: Towards open large generalist models for tables[J]. arXiv preprint arXiv:2311.09206, 2023.

TableLlama : Choose a Proper PEFT Method

- Which PEFT method should be chosen?
  - Here TableLlama has chosen LongLoRA for finetuning LLM.

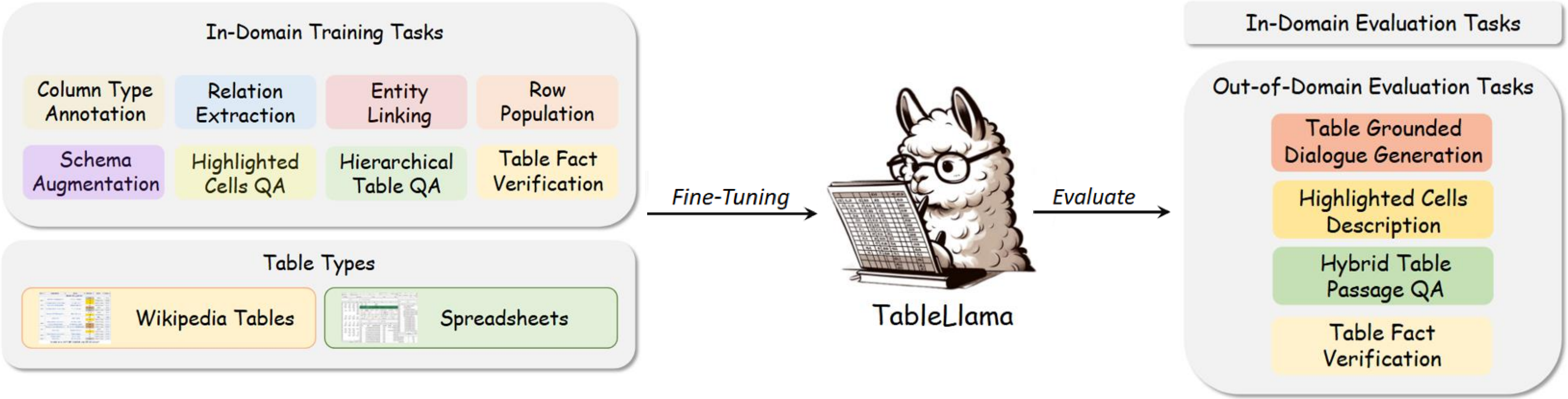


(a) Shifted sparse attention *(b) Low-rank adapt*

Chen Y, Qian S, Tang H, et al. Longlora: Efficient fine-tuning of long-context large language models[J]. arXiv preprint arXiv:2309.12307, 2023.

TableLlama Pipeline

- In-Domain and Out-of-Domain Evaluation
  - In-Domain: train the generalist table model.
  - Out-of-Domain: test generalization ability.



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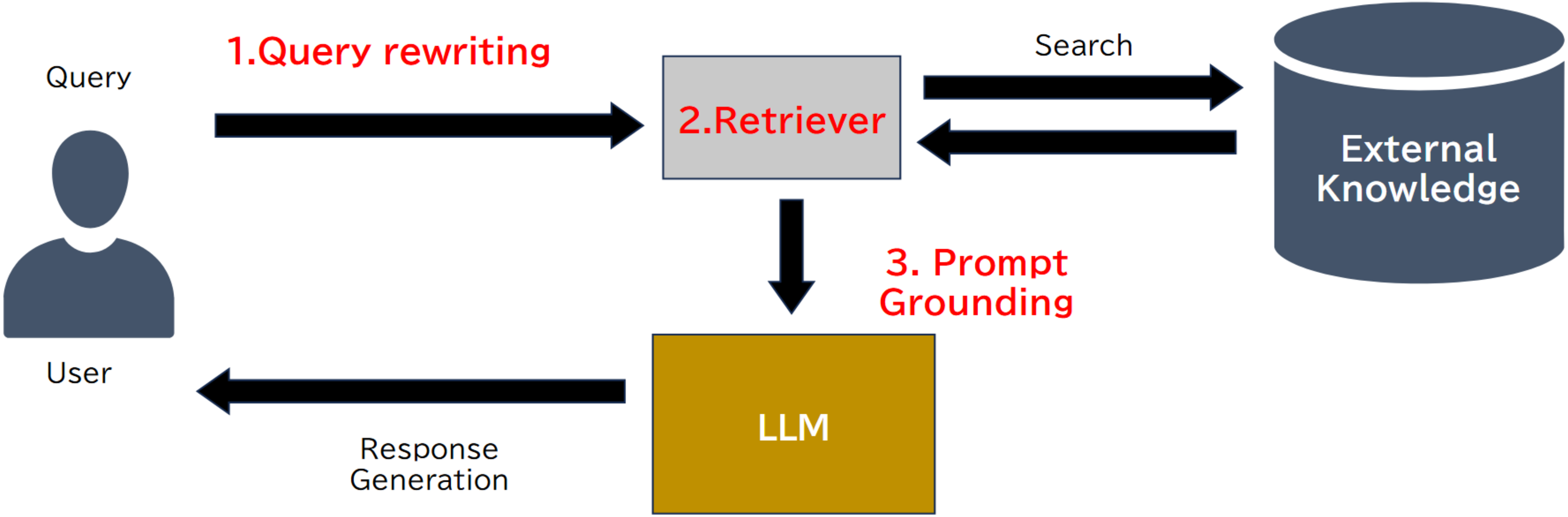
Why Non-Finetune?

- High resource consumption: even using fine-tuning techniques, the entire model must be loaded.
- High costs: Fine-tuning models on large-scale tabular data is very costly.
- State-of-the-art LLMs often do not support fine-tuning.

VS

Retrieval-based Method

- What is RAG (Retrieval-Augmented Generation)?
  - RAG is an efficient way to on-demand get external knowledge



Retrieval-based Method

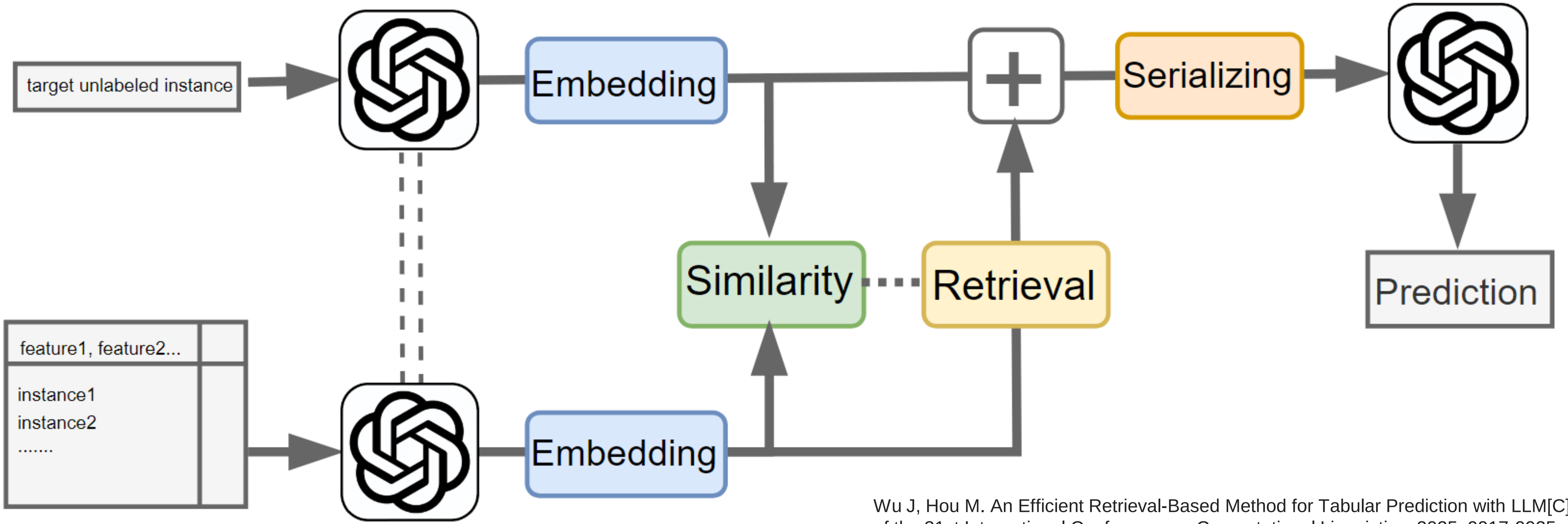
- Intuition: There is some association between certain data within the same table.
- Knowledge is also in tables!
- In context learning (ICL) is very important!

Income table				
id	Name	Education	Age	Gain
1	Tom	High school	30	27000$
2	John	Master	25	89000$
3	Lily	Master	27	75000$

People with the same educational background tend to have similar incomes.

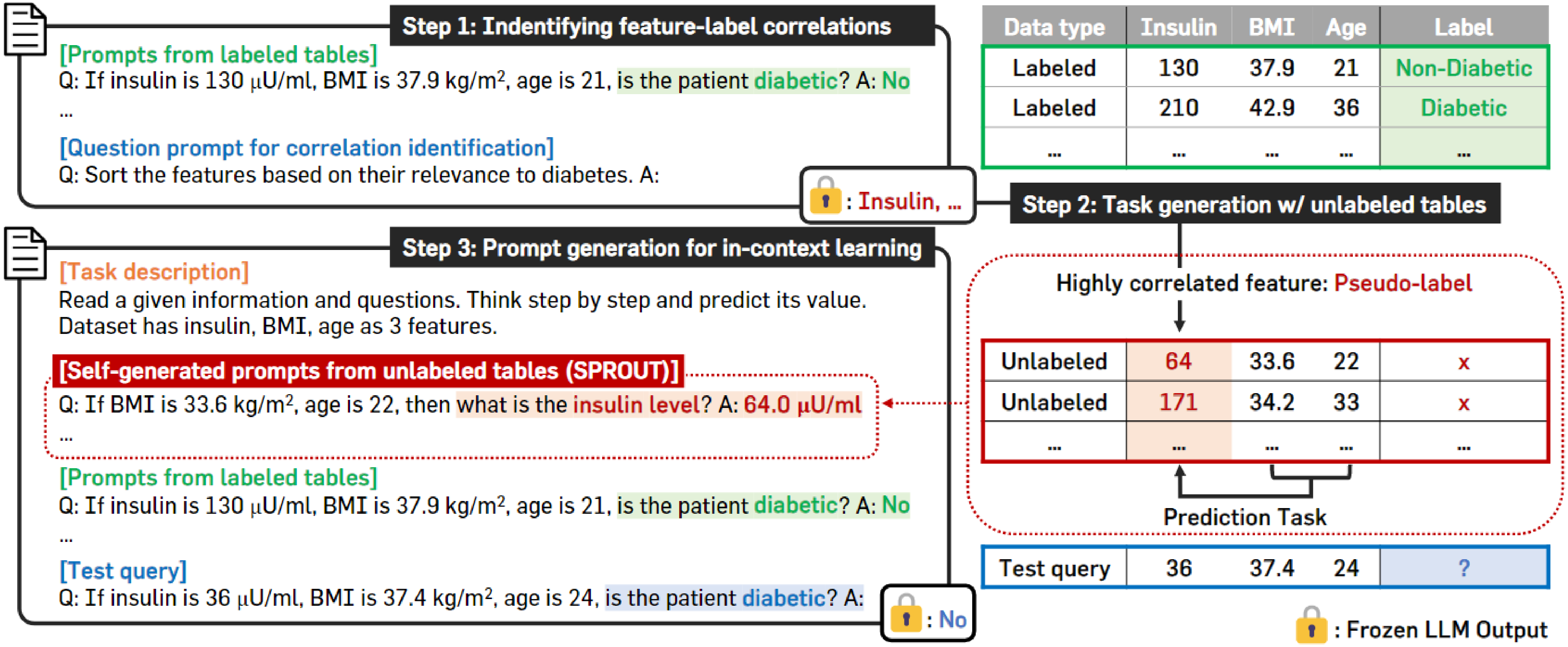
Simple Retrieval Method Example

- Retrieve similar instances.
- Few-shot prompt for LLM prediction.



Wu J, Hou M. An Efficient Retrieval-Based Method for Tabular Prediction with LLM[C]//Proceedings of the 31st International Conference on Computational Linguistics. 2025: 9917-9925.

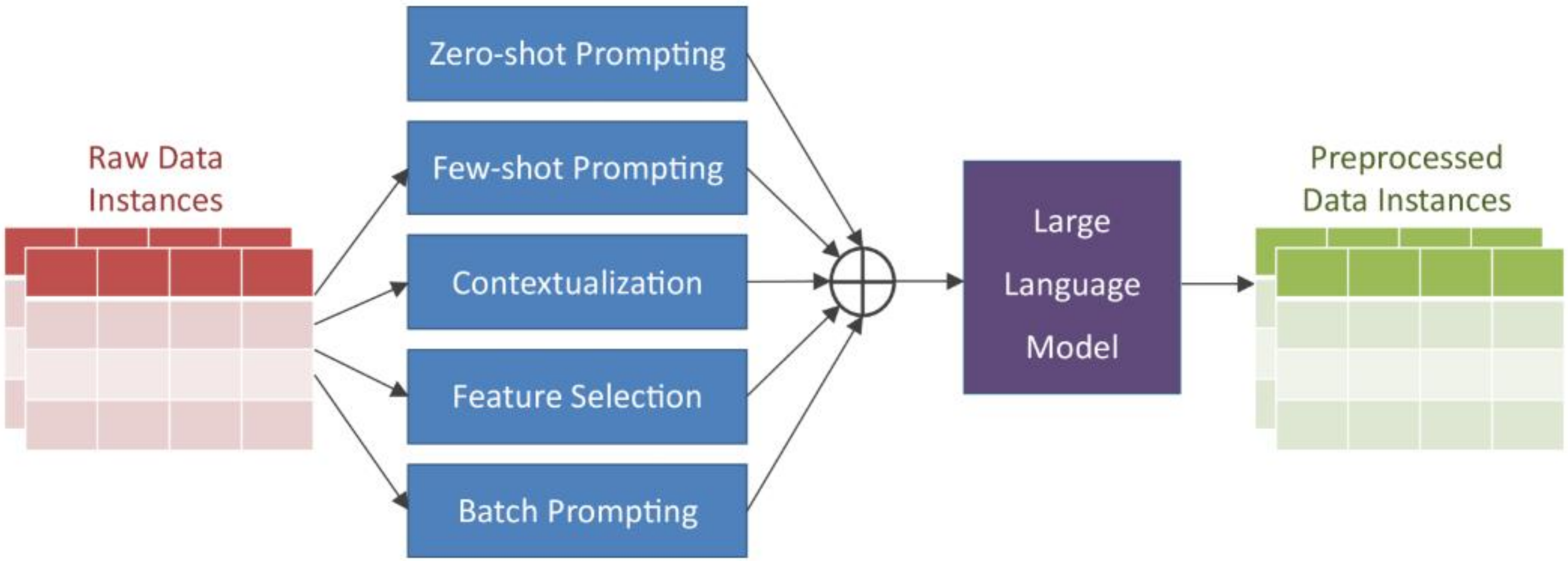
Retrieval Method Example in Limited Labeled Samples



Nam J, Song W, Park S H, et al. Semi-supervised tabular classification via in-context learning of large language models[C]//Workshop on Efficient Systems for Foundation Models@ ICML2023. 2023.

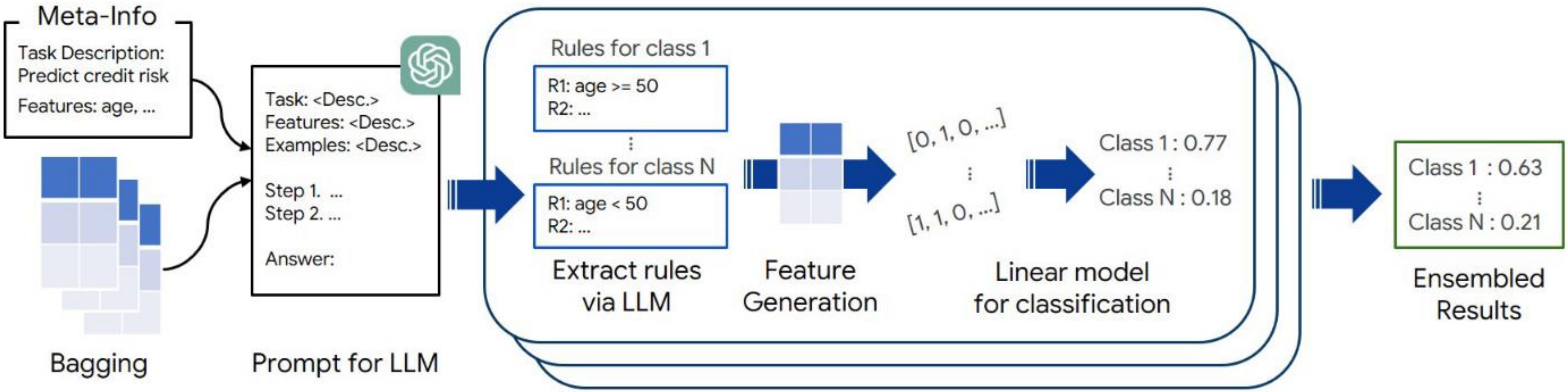
Data Augmentation/Filtering Method

- Intuition: LLM can automatically capture latent patterns and relationships within the data.
- High-quality prompts are required.
- LLM may not be the backbone of the pipeline.



FeatLLM: LLM as Feature Engineer

- LLMs can identify and extract the most relevant features for classification/regression tasks.
- Simple MLP can be used as classifiers and regressors.



Han S, Yoon J, Arik S O, et al. Large language models can automatically engineer features for few-shot tabular learning[J]. arXiv preprint arXiv:2404.09491, 2024.

Conclusion

- Strengths
  - Extensive knowledge coverage
  - Effective in-context learning and zero-shot capabilities
  - Strong performance in interactive text generation tasks

- Weakness
  - Relatively slow response times
  - High operational cost
  - Limited effectiveness with:
    - Mathematical task
    - Large tables

Challenges

- Can LLMs be integrated with traditional tree-based methods and deep learning approaches?

- Analyzing tabular data row by row with a large model incurs enormous cost, how can this cost be reduced?

- How can relational (multi-table) data be analyzed using LLMs?

Thanks for your time.

QA.