中国人民大学
RENMIN UNIVERSITY OF CHINA

# 利用大模型提升学生工程实践能力

张静

中国人民大学

# 大模型时代

- 以Transformer为基础的语言大模型、代码大模型、多模态大模型，在自然语言、代码以及图像理解与生成方面展现出令人惊叹的能力


自然语言

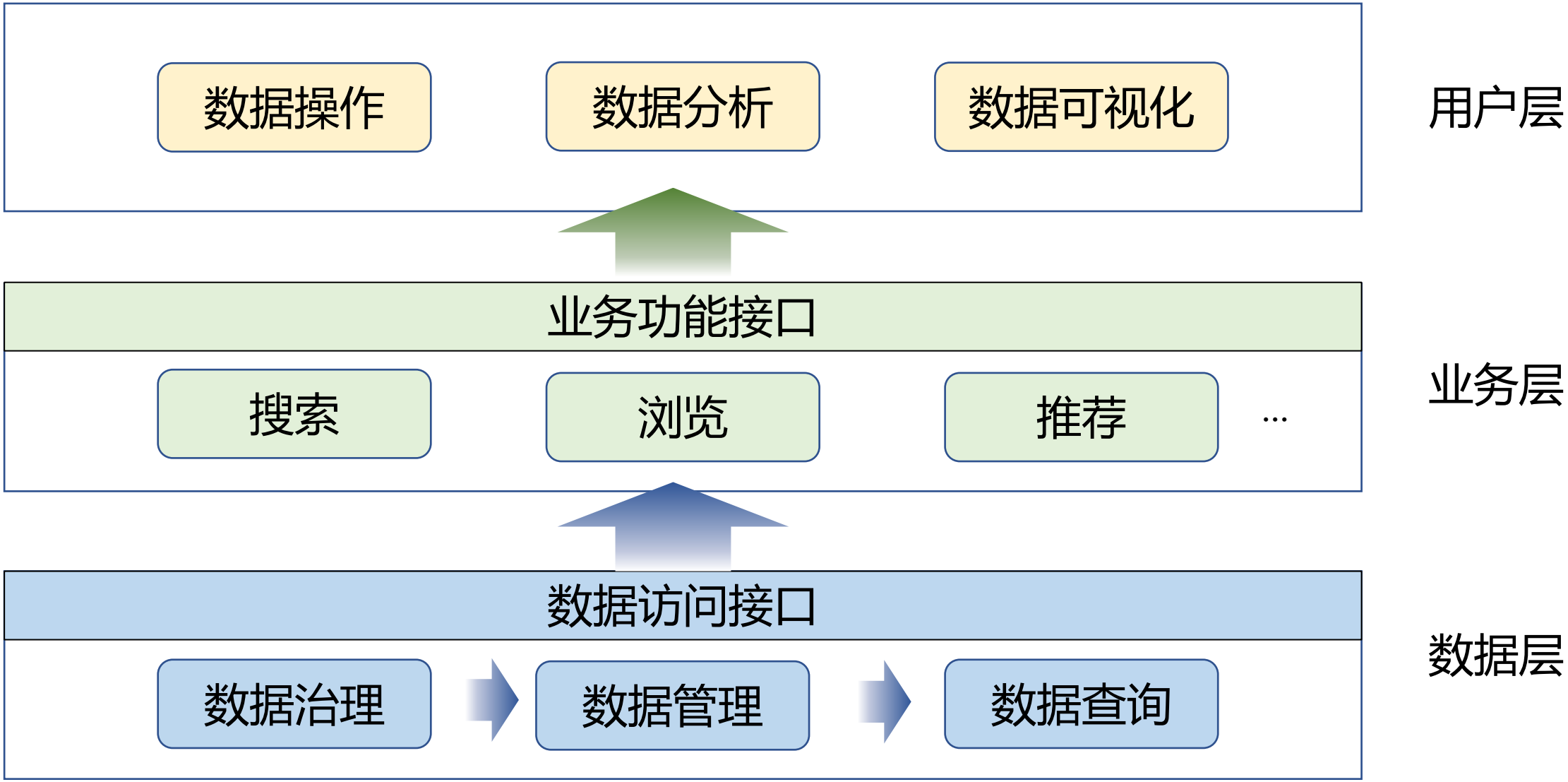
```
<script>
(function(){
    var bp = document.createElement('script');
    var curProtocol = window.location.protocol.split(':')[0];
    if (curProtocol === 'https'){
   bp.src = 'https://zz.bdstatic.com/linksubmit/push.js';
  }
  else{
  bp.src = 'http://push.zhanzhang.baidu.com/push.js';
  }
    var s = document.getElementsByTagName("script")[0];
    s.parentNode.insertBefore(bp, s);
})();
</script>
```

代码

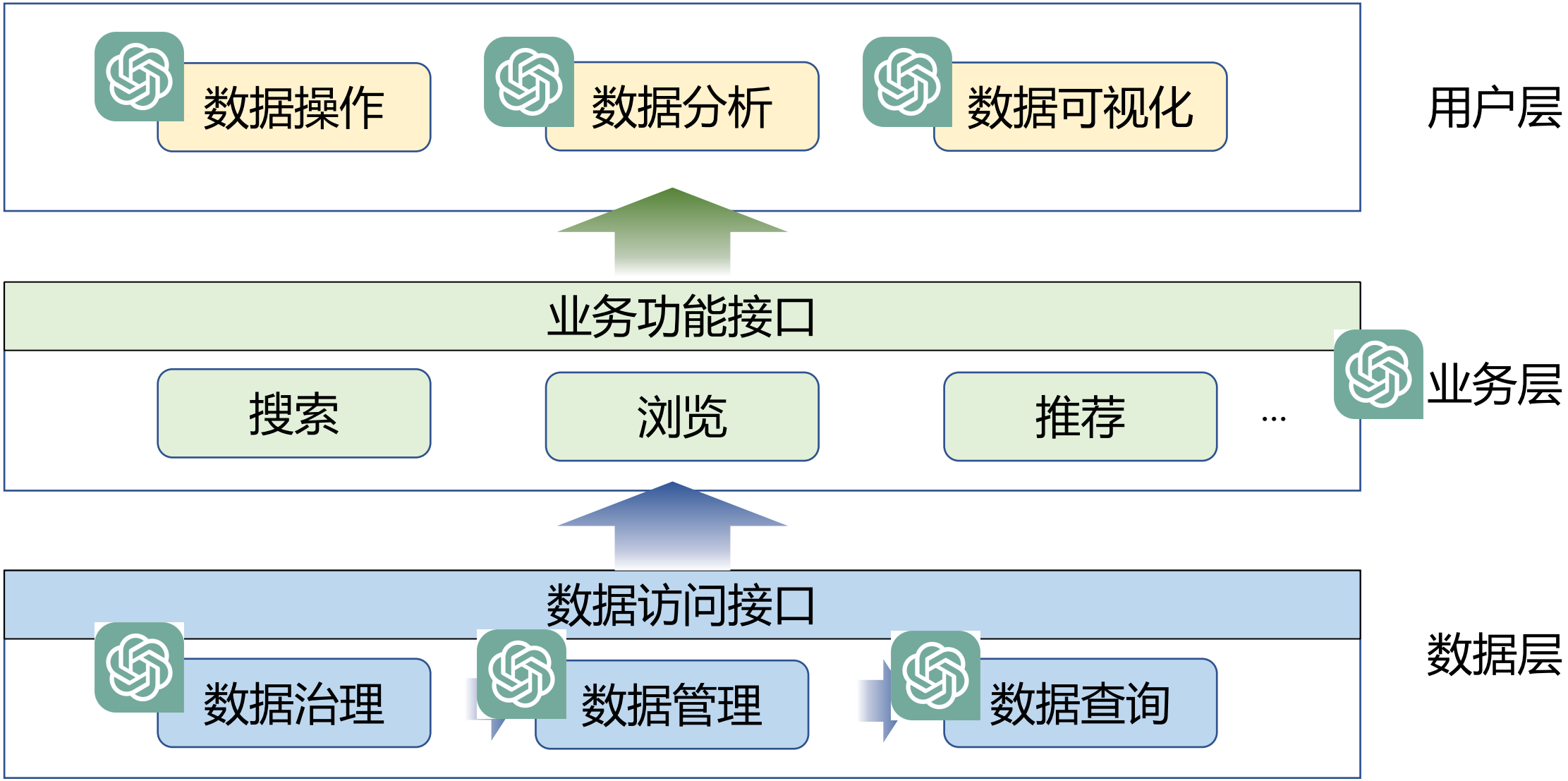

图像

- 大模型可以辅助教学资源开发、智能课堂助手、作业批改
- 本报告探讨大模型对本科教育中提升学生工程实践能力可能发挥的作用

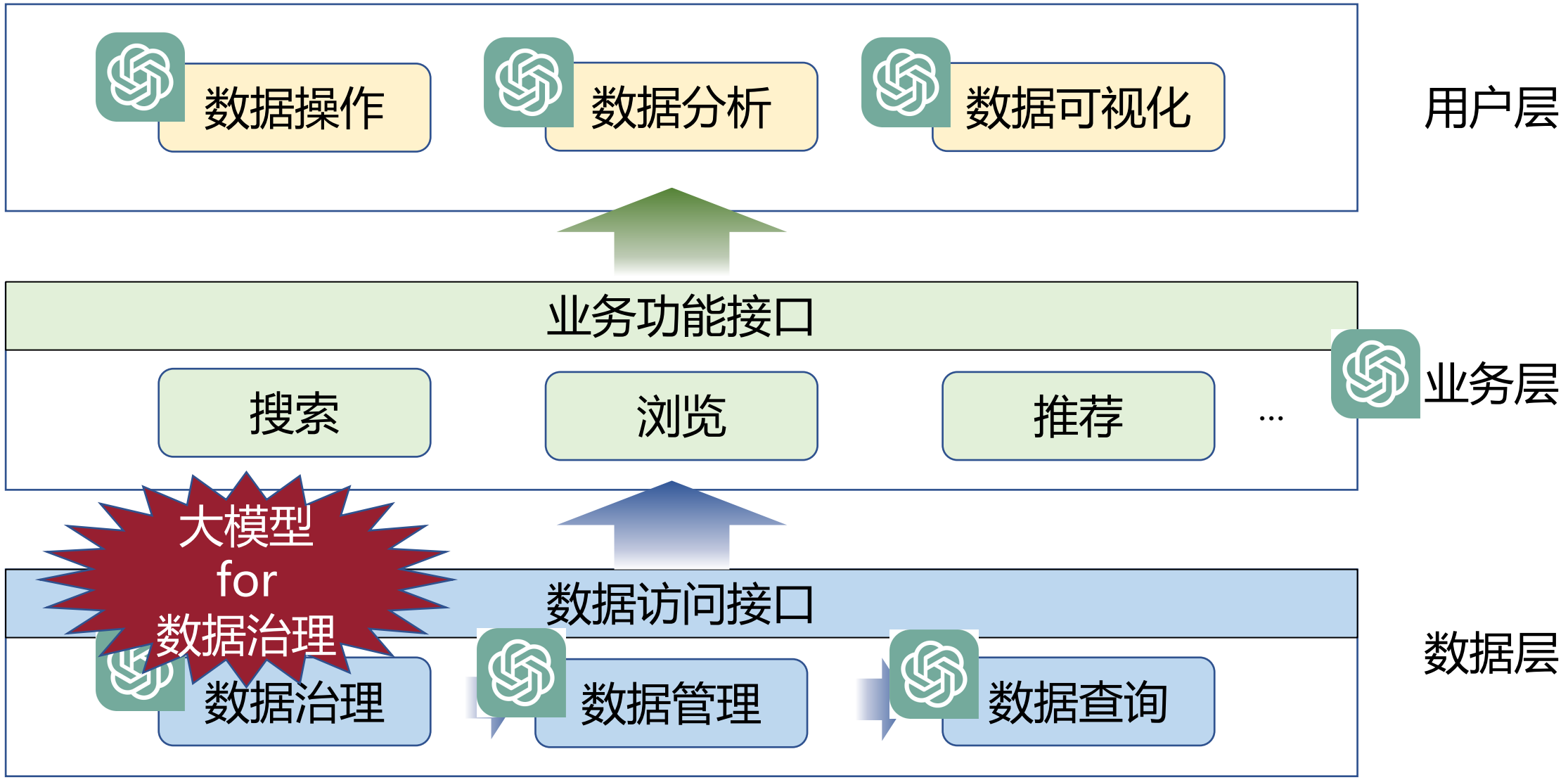
# 工程开发流程


数据操作
数据分析
数据可视化
用户层
业务功能接口
搜索
浏览
推荐
...
业务层
数据访问接口
数据治理
数据管理
数据查询
数据层

# 工程开发流程

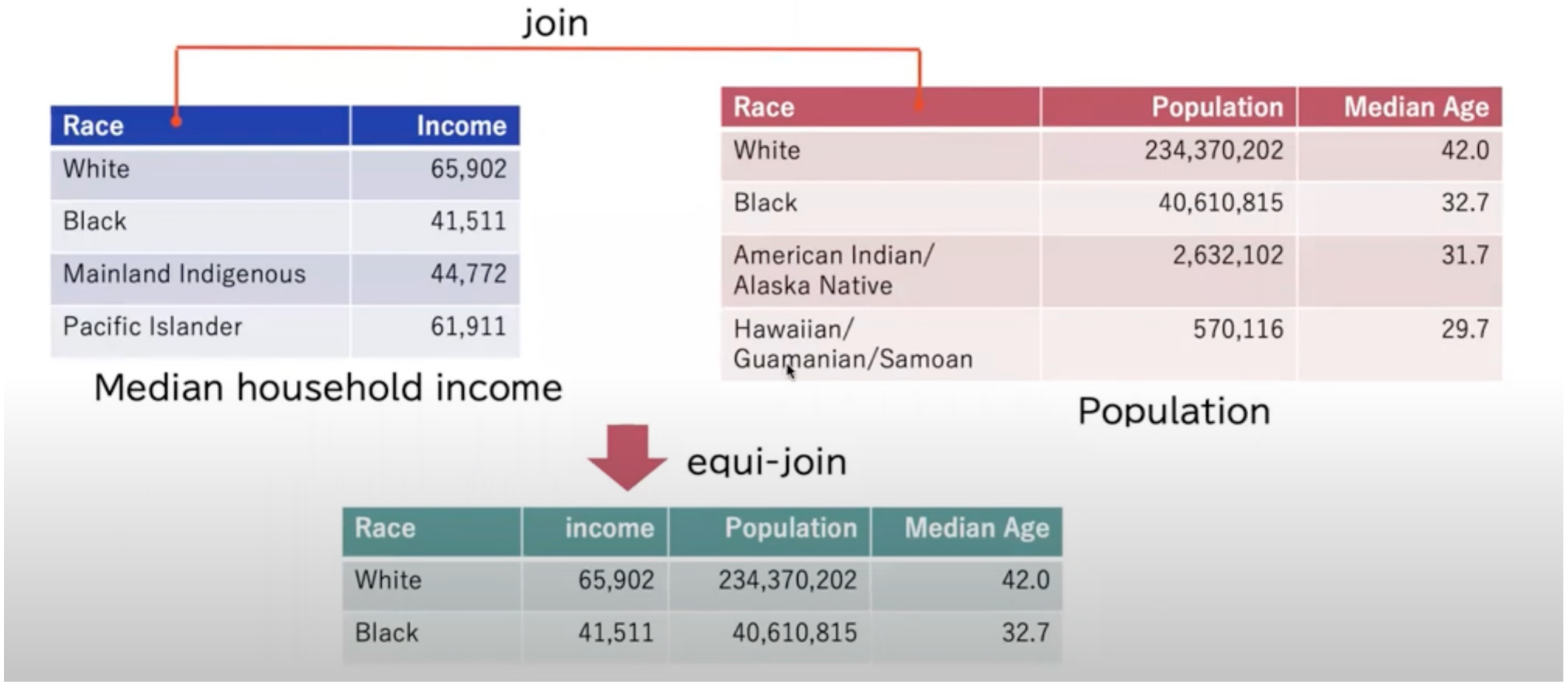

数据操作
数据分析
数据可视化
用户层
业务功能接口
搜索
浏览
推荐
...
业务层
数据访问接口
数据治理
数据管理
数据查询
数据层

# 工程开发流程


数据操作
数据分析
数据可视化
用户层
业务功能接口
搜索
浏览
推荐
...
业务层
大模型
for
数据治理
数据访问接口
数据治理
数据管理
数据查询
数据层

# 表格数据链接

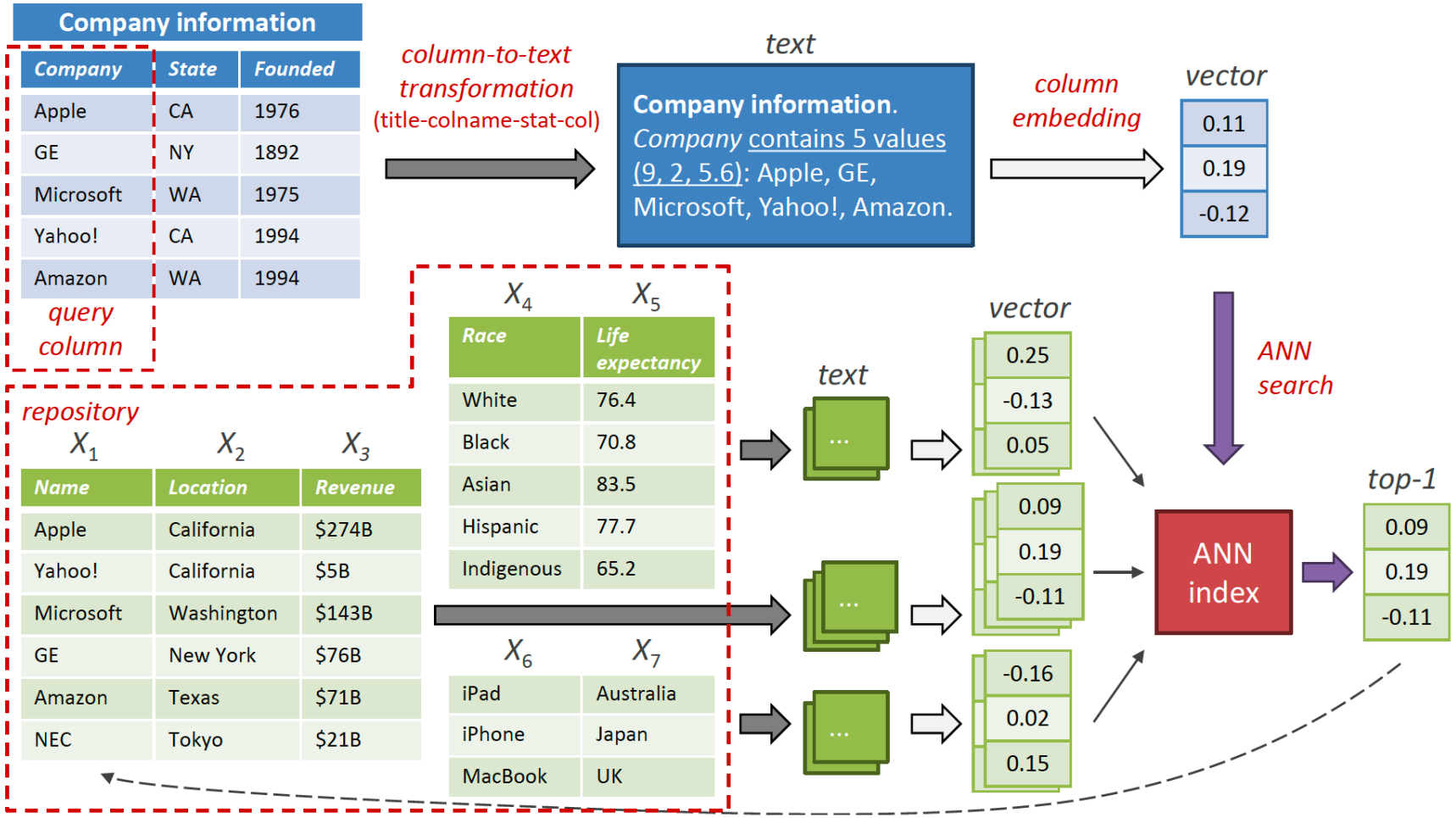
**任务**: 多个关系型表格自动链接




Yuyang Dong, Chuan Xiao, Takuma Nozawa, Masafumi Enomoto, and Masafumi Oyamada. DeepJoin: Joinable Table Discovery with Pre-Trained Language Models. Proc. VLDB Endow. 16, 10 (June 2023), 2458–2470.

# 表格数据链接

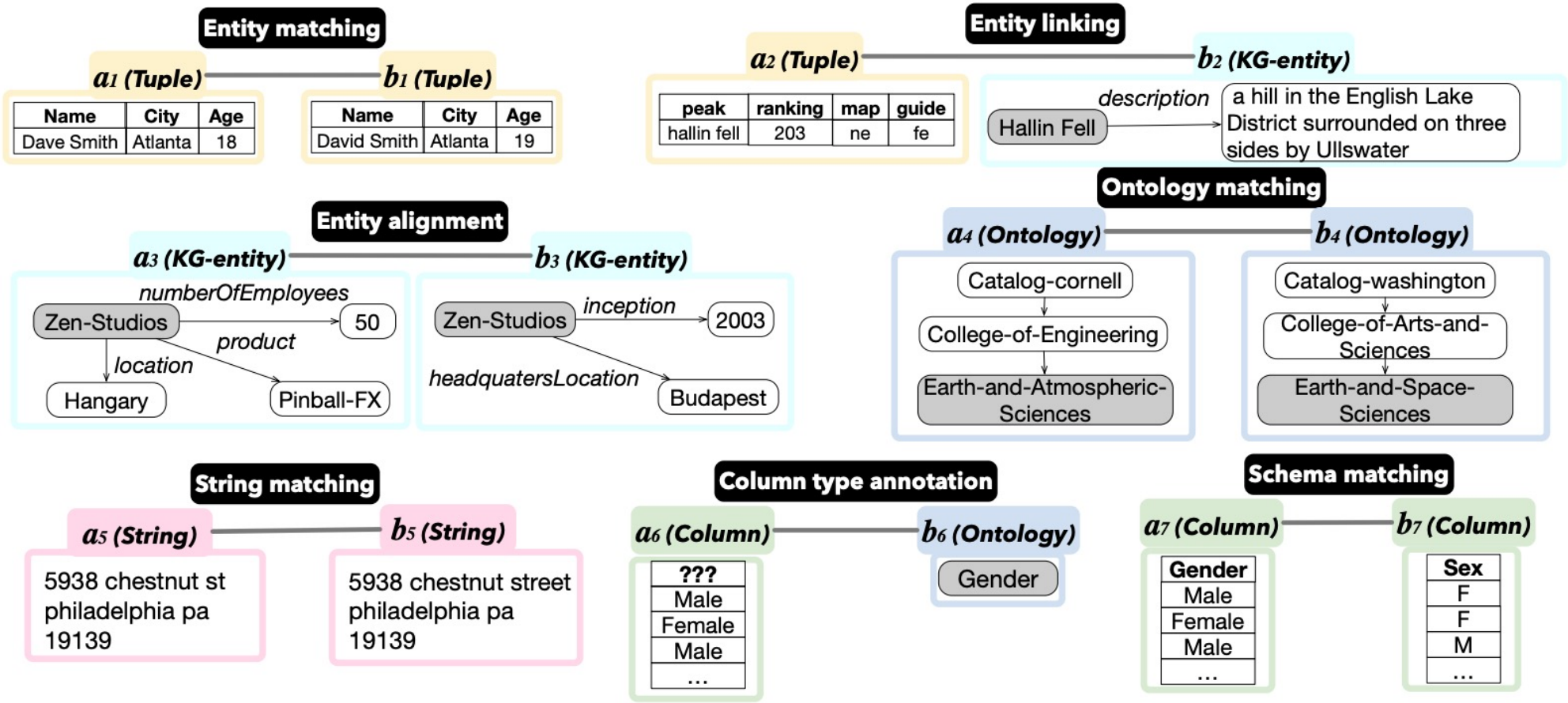
**解决方法**: DeepJoin - 基于表格嵌入的检索




Yuyang Dong, Chuan Xiao, Takuma Nozawa, Masafumi Enomoto, and Masafumi Oyamada. DeepJoin: Joinable Table Discovery with Pre-Trained Language Models. Proc. VLDB Endow. 16, 10 (June 2023), 2458–2470.

# 数据匹配多任务

**任务：**判断两个元素 (字符串、三元组、列、实体) 是否一致

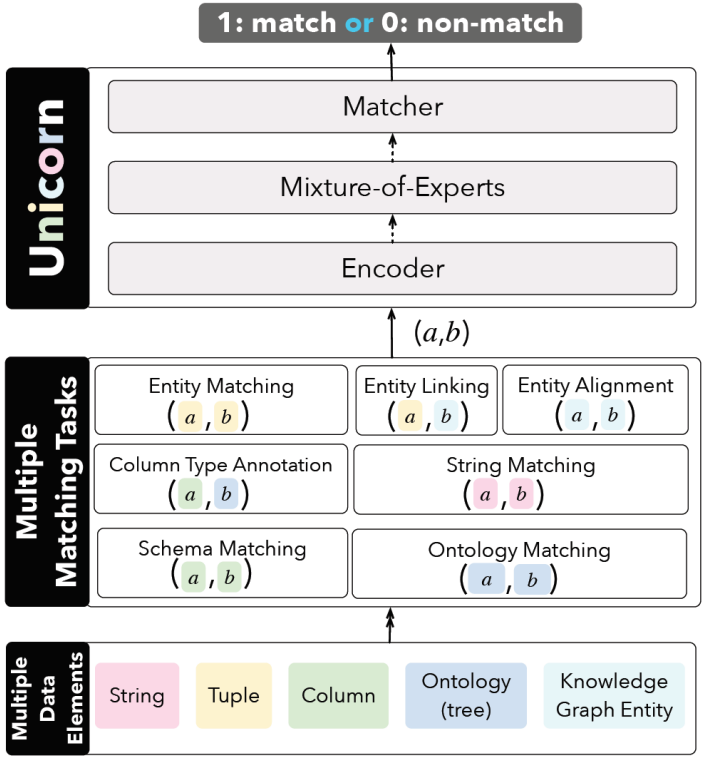


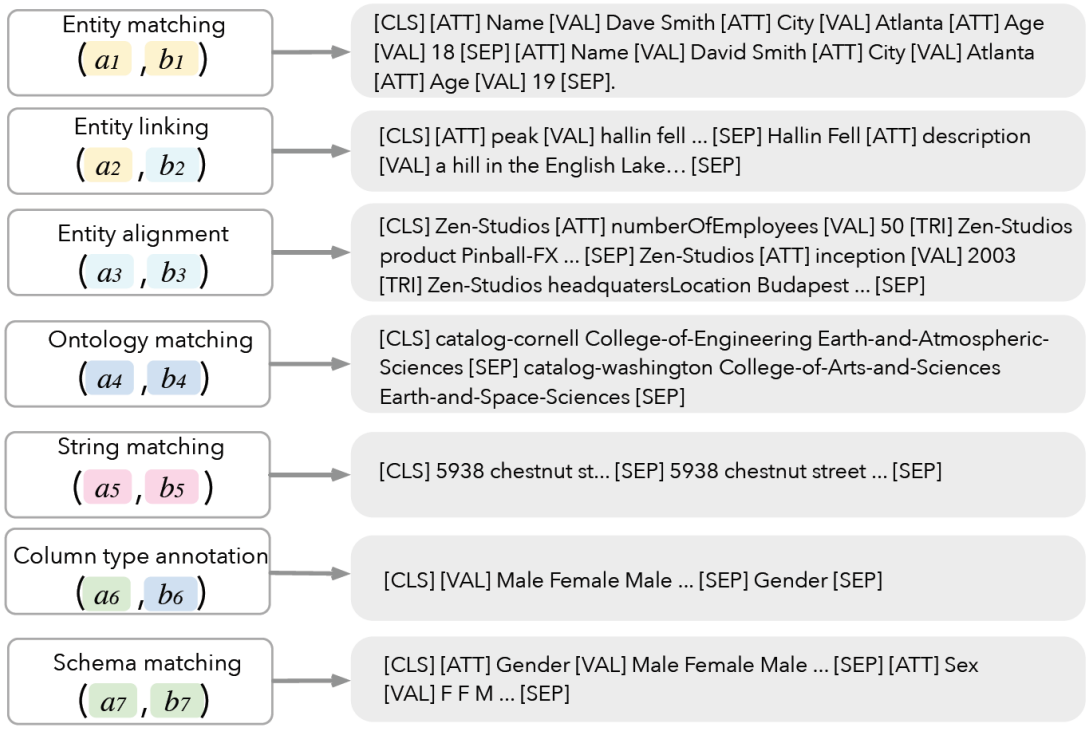

Jianhong Tu, Ju Fan, Nan Tang, Peng Wang, Guoliang Li, Xiaoyong Du, Xiaofeng Jia, Song Gao. Unicorn: A Unified Multi-tasking Model for Supporting Matching Tasks in Data Integration. SIGMODE 2023.

# 数据匹配多任务

**解决方法：**Unicorn 是一个用于数据集成领域**数据匹配**任务的统一模型

- Unicorn 由统一的编码器，专家混合层，匹配器组成
- 编码器将输入的数据对(a, b)编码为统一的表示向量。
- 专家混合层融合不同任务的专家知识,匹配器判断(a, b)是否匹配




- 将数据匹配任务中的数据对序列化为统一的文本序列

Jianhong Tu, Ju Fan, Nan Tang, Peng Wang, Guoliang Li, Xiaoyong Du, Xiaofeng Jia, Song Gao. Unicorn: A Unified Multi-tasking Model for Supporting Matching Tasks in Data Integration. SIGMODE 2023.

# 数据匹配多任务

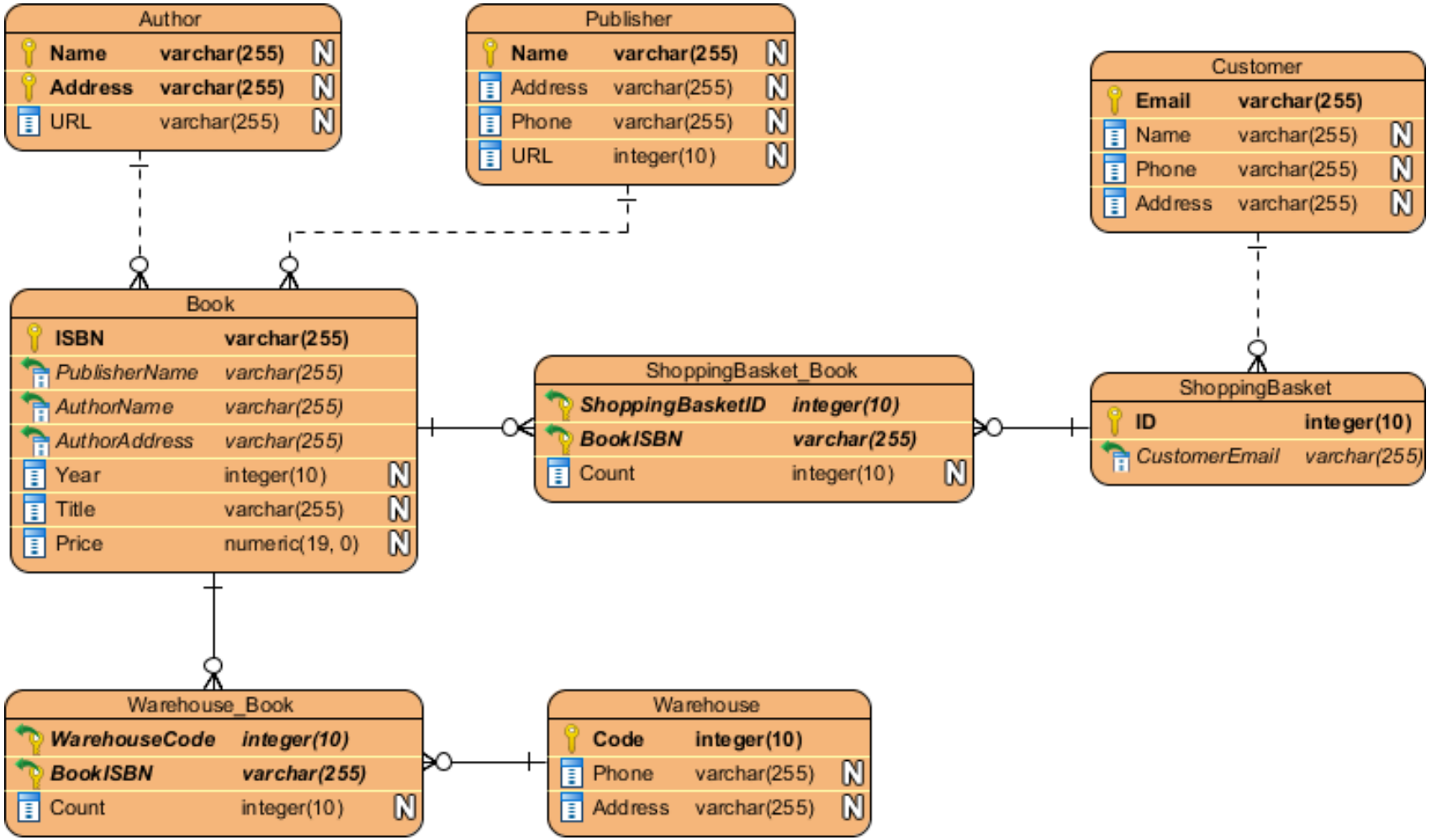
## 实验结果：

| Type | Task | Metric | Unicorn w/o MoE | Unicorn | Unicorn ++ | Previous SOTA (Paper) |
|---|---|---|---|---|---|---|
| EM | Walmart-Amazon | F1 | 85.12 | 86.89 | **86.93** | 86.76 (Ditto [30]) |
| | DBLP-Scholar | F1 | 95.38 | 95.64 | **96.22** | 95.6 (Ditto [30]) |
| | Fodors-Zagats | F1 | 97.78 | **100** | 97.67 | **100** (Ditto [30]) |
| | iTunes-Amazon | F1 | 94.74 | 96.43 | **98.18** | 97.06 (Ditto [30]) |
| | Beer | F1 | 90.32 | 90.32 | 87.5 | **94.37** (Ditto [30]) |
| CTA | Efthymiou | Acc. | 98.08 | 98.42 | **98.44** | 90.4 (TURL [10]) |
| | T2D | Acc. | 98.81 | 99.14 | **99.21** | 96.6 (HNN+P2Vec [5]) |
| | Limaye | Acc. | 96.11 | 96.75 | **97.32** | 96.8 (HNN+P2Vec [5]) |
| EL | T2D | F1 | 79.96 | 91.96 | **92.25** | 85 (Hybrid I [20]) |
| | Limaye | F1 | 83.12 | 86.78 | **87.9** | 82 (Hybrid II [20]) |
| StM | Address | F1 | 97.81 | 98.68 | 99.47 | **99.91** (Falcon [39]) |
| | Names | F1 | 86.12 | 91.19 | **96.8** | 95.72 (Falcon [39]) |
| | Researchers | F1 | 96.59 | 97.66 | **97.93** | 97.81 (Falcon [39]) |
| | Product | F1 | 84.61 | 82.9 | **86.06** | 67.18 (Falcon [39]) |
| | Citation | F1 | 96.34 | 96.27 | **96.64** | 90.98 (Falcon [39]) |
| ScM | FabricatedDatasets | Recall | 81.19 | **89.6** | 89.35 | 81 (Valentine [27]) |
| | DeepMDatasets | Recall | 66.67 | 96.3 | 96.3 | **100** (Valentine [27]) |
| OM | Cornell-Washington | Acc. | 90.64 | **92.34** | 90.21 | 80 (GLUE [15]) |
| EA | SRPRS: DBP-YG | Hits@1 | 99.46 | 99.67 | 99.49 | **100** (BERT-INT [46]) |
| | SRPRS: DBP-WD | Hits@1 | 97.11 | 97.22 | 97.28 | **99.6** (BERT-INT [46]) |
| **AVG** | | | 90.8 | 94.21 | **94.56** | 91.84 |
| **Model Size** | | | 139M | 147M | 147M | 995.5M |

- Unicorn与每个任务特定方法的效果持平，在多个任务上甚至优于特定方法

Jianhong Tu, Ju Fan, Nan Tang, Peng Wang, Guoliang Li, Xiaoyong Du, Xiaofeng Jia, Song Gao. Unicorn: A Unified Multi-tasking Model for Supporting Matching Tasks in Data Integration. SIGMODE 2023.

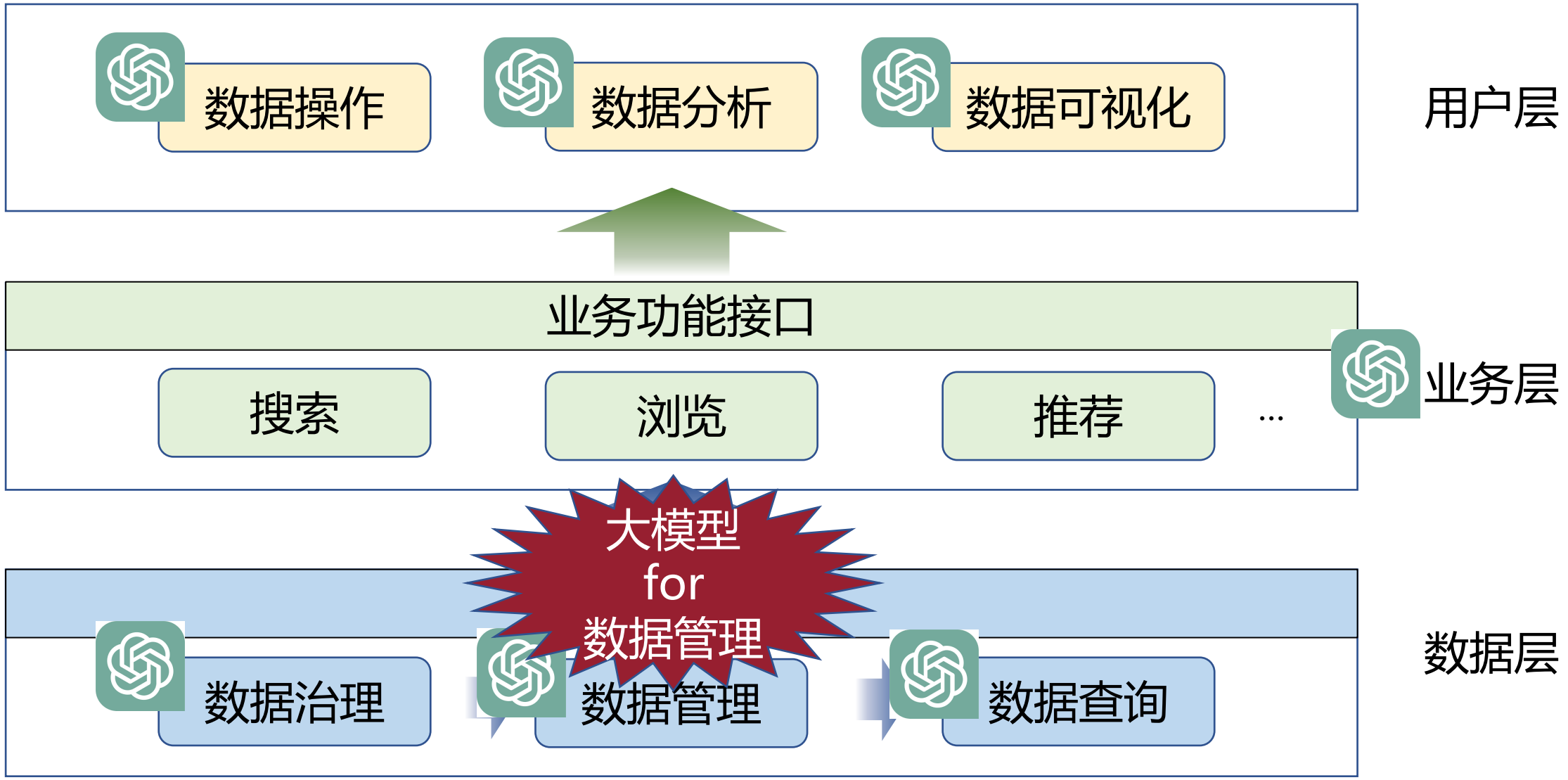
# 工程能力培养：辅助学习实体关系（ER）图




- ER图的作用
  - 数据库设计
  - 数据库调试
  - 数据库创建和修补
  - 帮助收集需求

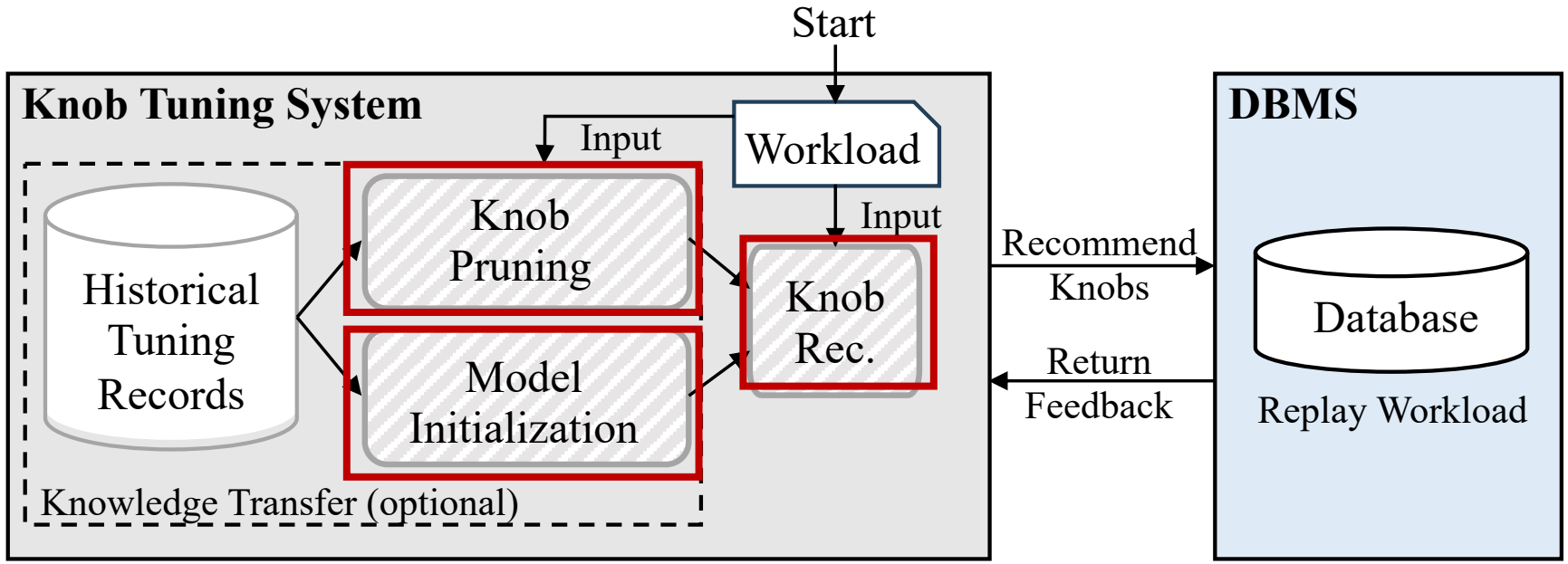
- 手动设计实体关系
- 自动检测关系合理性

# 工程开发流程


数据操作
数据分析
数据可视化
用户层
业务功能接口
搜索
浏览
推荐
...
业务层
大模型
for
数据管理
数据治理
数据管理
数据查询
数据层

# 数据管理

**任务：数据库参数调优**，对负载的执行效率进行优化




调参系统包含三个关键组件：参数修剪、模型初始化、参数推荐

- **参数修剪**旨在选择关键参数，并确定它们的合理取值范围
- **模型初始化**着眼于在参数推荐方法中初始化可学习的模型，加快收敛速度
- **参数推荐**是调参系统的核心，针对具体的工作负载提供合适的参数配置建议

Yiyan Li, Haoyang Li, Zhao Pu, Jing Zhang, Xinyi Zhang, Tao Ji, Luming Sun, Cuiping Li, Hong Chen. Is Large Language Model Good at Database Knob Tuning? A Comprehensive Experimental Evaluation. https://arxiv.org/abs/2408.02213

# 数据管理

## 解决方法：探索每个组件的大模型提示学习方法的可能性

**Knob Pruning**

**Task Description:**
Select the 10 most important knobs from the provided and give their range of values for the current tuning task in order to optimize the throughput metric.

**Candidate Knobs:**
"innodb_thread_concurrency": {
"max": 1000,
"min": 0,
"type": "integer",
"description": "Defines the maximum number of threads permitted inside of InnoDB."
},
……

**Workload and Database Information:**
- Workload: OLTP, SYSBENCH Read-Write Mixed Model, Read-Write Ratio = 50%, threads = 32.
- Data: 13 GB data contains 50 tables and each table contains 1,000,000 rows of record.
- Database Kernel: RDS MySQL 5.7.
- Hardware: 8 vCPUs and 16 GB RAM.

**Output Format:**
Knobs should be formatted as follows:

```
{
    "knob_name": {
      "max": MAX_Value,
      "min": Min_Value,
      "type": "integer"
    },
    or
    "knob_name": {
      "enum_values": [
        "value1",
        ......
      ],
      "type": "enum"
    }
}
```

**1.任务描述**：LLM 的目标
**2.候选参数**：候选参数详细信息
**3.工作负载和数据库信息**：工作负载、数据特征、数据库及硬件环境的关键细节
**4.输出格式**：LLM 的响应格式，列出被选中的参数名称、取值范围和参数类型

**1.任务描述**：概述了 LLM 的目标。
**2.参数优化示范**：作为提示中的示范案例
**3.环境**：数据库内核和硬件信息,还有每个内部指标和可调参数的文本描述
**4.当前工作负载信息**：工作负载类型、读写比例和数据统计等
**5.输出格式**：LLM 响应的格式要求
**6.当前配置**：参数默认值,作为优化起点
**7.数据库反馈**：默认配置下执行工作负载的性能和内部指标

**Model Initialization / Knob Recommendation**

**Task Description:**
Recommend optimal knob configuration based on the inner metrics and workload characteristics in order to optimize the throughput metric.

**Demonstration for Knob Refinement:**
- Current Configuration (input):
{ "thread_cache_size" : 50, …, "innodb_log_file_size" : 512M }
- Inner Metrics (input):
{ "lock_timeouts" : 0, …, "dml_updates" : 27356 }
- Refined Configuration (output):
{ "thread_cache_size" : 75, …, "innodb_log_file_size" : 1024M }

**Environments:**
- Database Kernel: RDS MySQL 5.7.
- Hardware: 8 vCPUs and 16 GB RAM.
- Inner Metrics: 1.load_average. In Unix computing, the system load is ameasure of the amount of computational work that a computer system performs.
……
- Knobs: 1. innodb_thread_concurrency. Controls the maximum number of concurrent threads that InnoDB can use for executing queries.
……

**Information about Current Workload:**
- Workload: OLTP, SYSBENCH Read-Write Mixed Model, Read-Write Ratio = 50%, threads = 32.
- Data: 13 GB data contains 50 tables and each table contains 1,000,000 rows of record.

**Output Format:**
Strictly utilize the aforementioned knobs, ensuring that the generated configuration are formatted as follows:
{ "knob_name": knob_value, …… }

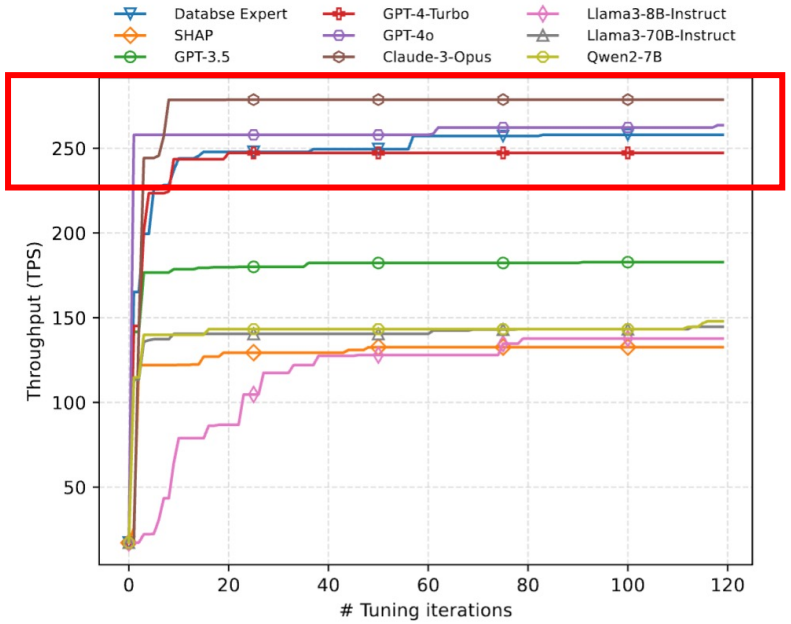
**Current Configuration:**
{ "tmp_table_size": 16777216, …… }

**Database Feedback:**
- Throughput : 100
- Inner Metrics: lock_timeouts = 0, …, dml_updates = 22692

Yiyan Li, Haoyang Li, Zhao Pu, Jing Zhang, Xinyi Zhang, Tao Ji, Luming Sun, Cuiping Li, Hong Chen. Is Large Language Model Good at Database Knob Tuning? A Comprehensive Experimental Evaluation. https://arxiv.org/abs/2408.02213

# 数据管理

## 实验结果：




| Type | Model | ODP | PE | TES | Speedup |
|---|---|---|---|---|---|
| Traditional Method | VBO | 154.73 | 0% | 316 | 0% |
| | VBO + Mapping | 154.37 | -0.23% | 279 | 11.71% |
| | RGPE + Model Ensemble | 158.02 | **0.42%** | **215** | **42.67%** |
| | DS-DDPG + Pre-training | **162.15** | 33.10% | 313 | -216.16% |
| Closed Source LLM | VBO + GPT-3.5 | 127.68 | -17.48% | 176 | 44.30% |
| | VBO + GPT-4-Turbo | **152.01** | **-1.93%** | 84 | 73.41% |
| | VBO + GPT-4o | 126.65 | -18.29% | 90 | 71.51% |
| | VBO + Claude-3-Opus | 126.09 | -18.65% | **2** | **99.37%** |
| Open Source LLM | VBO + Llama3-8B-Instruct | 153.16 | -1.19% | **90** | **71.51%** |
| | VBO + Llama3-70B-Instruct | **154.68** | **-0.03%** | **90** | **71.51%** |
| | VBO + Qwen2-7B | 153.58 | -0.74% | 100 | 68.35% |

| Type | Method | IR TPS | ODP | TES |
|---|---|---|---|---|
| Traditional Method | Default | - | 17.45 | - |
| | DDPG | - | 120.71 | **99** |
| | SMAC | - | **157.25** | 375 |
| | VBO | - | 155.10 | 316 |
| Closed Source LLM | GPT-3.5 | 16.38 | 116.62 | 24 |
| | GPT-4-Turbo | **145.06** | **155.30** | **9** |
| | GPT-4o | 117.96 | 126.05 | 13 |
| | Claude-3-Opus | 26.70 | 148.51 | 23 |
| Open Source LLM | Llama3-8B-Instruct | 20.90 | 125.88 | 25 |
| | LlaMa3-70B-Instruct | 28.84 | 145.12 | **3** |
| | Qwen2-7B | **143.58** | **154.94** | 14 |

**参数修剪：**

Claude-3-Opus, GPT-4o, GPT-4-Turbo
超越数据库管理员

**模型初始化：**

语言模型通过生成初始配置来大幅
加快贝叶斯优化方法的收敛能力

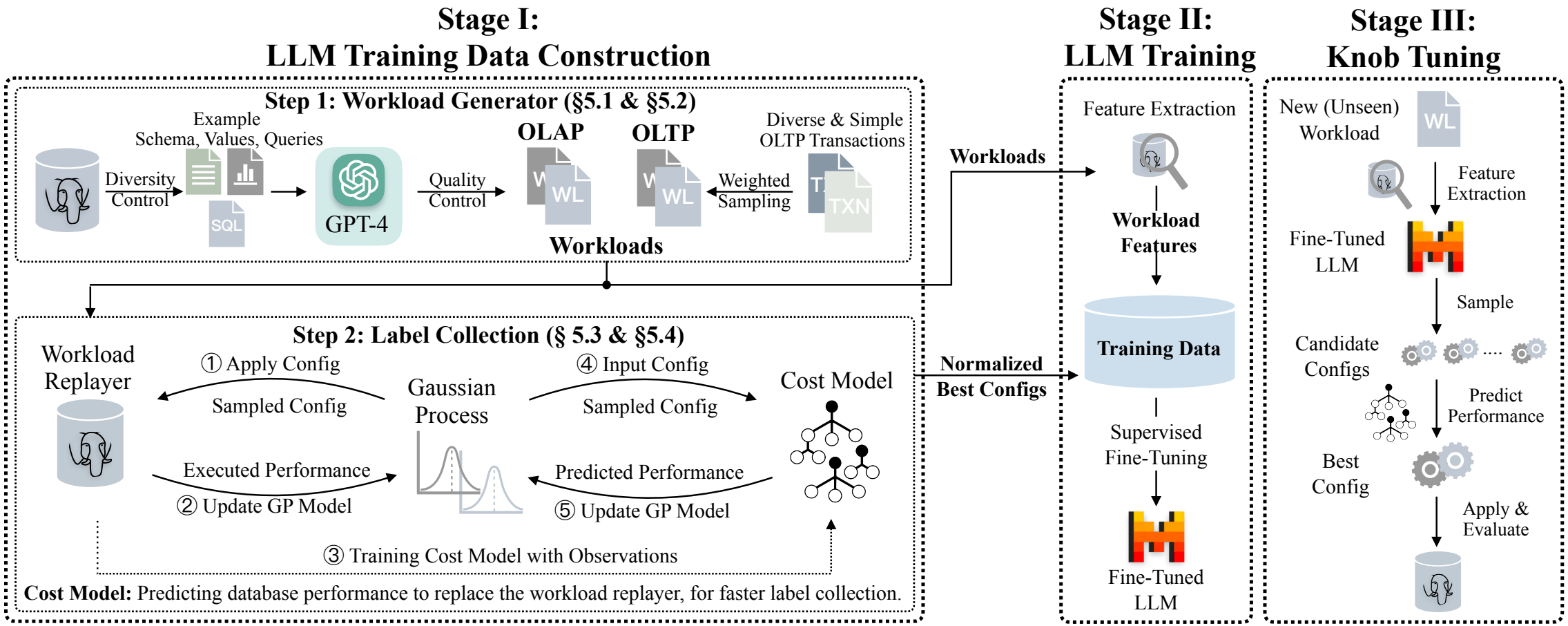
**参数推荐：**

语言模型能够在大幅减少的迭代
次数内找到优异的参数配置

Yiyan Li, Haoyang Li, Zhao Pu, Jing Zhang, Xinyi Zhang, Tao Ji, Luming Sun, Cuiping Li, Hong Chen. Is Large Language Model Good at Database Knob Tuning? A Comprehensive Experimental Evaluation. https://arxiv.org/abs/2408.02213

# 数据管理

## 解决方法：参数调优的大模型微调方法




Xinmei Huang, Haoyang Li, Jing Zhang, Xinxin Zhao, Zhiming Yao, Yiyan Li, Zhuohao Yu, Tieying Zhang, Hong Chen, Cuiping Li. LLMTune: Accelerate Database Knob Tuning with Large Language Models. https://arxiv.org/pdf/2404.11581

# 数据管理

## 实验结果

| Methods | TPC-H [67] | | JOB [35] | | SSB | | SSB-flat | | TPC-DS | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Δ (%) ↑ | T (min) ↓ | Δ (%) ↑ | T (min) ↓ | Δ (%) ↑ | T (min) ↓ | Δ (%) ↑ | T (min) ↓ | Δ (%) ↑ | T (min) ↓ |
| HEBO | 71.5/- | 1381.7/- | 51.8/- | 766.4/- | 41.7/- | 732.4/- | 46.3/- | 823.8/- | 39.2/- | 749.9/- |
| + Cost Model | 68.8/58.2 | 91.2/99.8 | 49.2/33.6 | 82.3/91.5 | 39.2/34.6 | 83.8/89.3 | 43.1/29.2 | 84.5/92.4 | 37.6/29.2 | 88.9/98.7 |
| + Workload Mapping | 72.5/70.2 | 328.7/739.7 | 51.3/50.7 | 308.2/428.2 | 42.3/42.0 | 280.3/439.4 | 46.6/44.3 | 266.1/547.6 | **40.9**/**40.4** | 254.8/563.1 |
| + Model Ensemble | 72.3/**71.5** | 234.6/662.6 | 52.1/**51.9** | 241.4/491.0 | 43.5/42.2 | 199.0/345.2 | 47.3/**46.9** | 213.7/490.2 | 39.6/40.0 | 321.8/462.4 |
| SMAC | 69.8/- | 1182.5/- | 50.0/- | 724.7/- | 40.0/- | 634.2/- | 43.9/- | 794.3/- | 38.7/- | 712.9/- |
| + Cost Model | 67.3/43.1 | 67.3/78.6 | 48.8/29.6 | 50.2/67.8 | 37.6/22.6 | 49.5/45.8 | 41.2/33.8 | 48.9/55.1 | 37.0/29.8 | 43.5/59.8 |
| + Workload Mapping | 70.4/67.7 | 374.4/896.8 | 52.3/51.5 | 283.2/567.3 | 40.9/40.1 | 289.8/413.8 | 46.2/45.9 | 315.2/515.8 | 39.7/38.6 | 223.4/632.4 |
| + Model Ensemble | 70.3/70.5 | 289.3/658.4 | 51.9/51.7 | 249.9/493.2 | 43.4/**43.3** | 179.6/323.1 | 47.1/46.7 | 284.3/563.3 | 39.9/39.1 | 213.6/549.8 |
| CDBTune | 68.8/- | 965.4/- | 48.4/- | 489.5/- | 38.8/- | 320.3/- | 45.5/- | 723.4/- | 36.9/- | 698.4/- |
| + Cost Model | 66.9/38.9 | 63.2/70.9 | 47.3/29.8 | 49.6/81.4 | 38.0/23.1 | 48.8/54.9 | 40.5/22.0 | 42.1/52.9 | 36.6/19.6 | 53.2/76.8 |
| + MP (w/ online tuning) | 71.2/68.9 | 569.4/698.3 | 49.2/49.2 | 198.4/378.4 | 42.2/37.7 | 235.1/352.9 | 47.3/46.1 | 312.4/536.9 | 38.6/37.0 | 258.3/589.8 |
| + MP (w/o online tuning) | 47.8/37.5 | 634.7/702.9 | 42.3/32.5 | 178.9/267.9 | 29.5/18.1 | 184.9/213.4 | 42.3/30.1 | 72.1/378.1 | 39.4/22.5 | 103.9/409.6 |
| OpAdviser | **73.4**/67.3 | 579.3/638.9 | 52.2/49.1 | 328.8/391.0 | 43.9/36.3 | 219.6/380.2 | 47.1/45.2 | 412.5/456.3 | 40.1/39.1 | 283.1/312.5 |
| DB-BERT | 70.9/- | 523.1/- | 51.3/- | 299.0/- | 40.0/- | 202.8/- | 44.3/- | 438.6/- | 38.2/- | 232.4/- |
| GPTuner | 72.0/- | 301.2/- | 51.3/- | 213.8/- | **44.9**/- | 178.3/- | 47.3/- | 233.5/- | 39.2/- | 193.4/- |
| E2ETune | 72.5/71.0 | **19.8**/**20.9** | **52.8**/50.9 | **12.3**/**15.4** | 44.0/42.5 | **9.8**/**8.9** | **47.4**/46.1 | **13.9**/**9.2** | 40.1/39.9 | **9.9**/**11.8** |

- 微调的参数调优大模型调优速度最快，且能实现与传统调优方法相媲美的性能改善效果
- 超越经典的贝叶斯调优方法、基于知识迁移的模型初始化、利用大模型的参数修剪方法

Xinmei Huang, Haoyang Li, Jing Zhang, Xinxin Zhao, Zhiming Yao, Yiyan Li, Zhuohao Yu, Tieying Zhang, Hong Chen, Cuiping Li. LLMTune: Accelerate Database Knob Tuning with Large Language Models. https://arxiv.org/pdf/2404.11581

# 工程能力培养：辅助学习数据库调优经验

**LLM Output**

Recommendations for Further Tuning

1. **Increase Buffer Pool Size:**
   - Current: 13GB
   - Recommendation: Increase to 14GB if the system has sufficient memory available to further reduce disk reads.

2. **Optimize Read-Ahead:**
   - Metrics: buffer_pool_read_ahead (0)
   - Adjust`innodb_read_ahead_threshold` to 24 to improve sequential read performance.

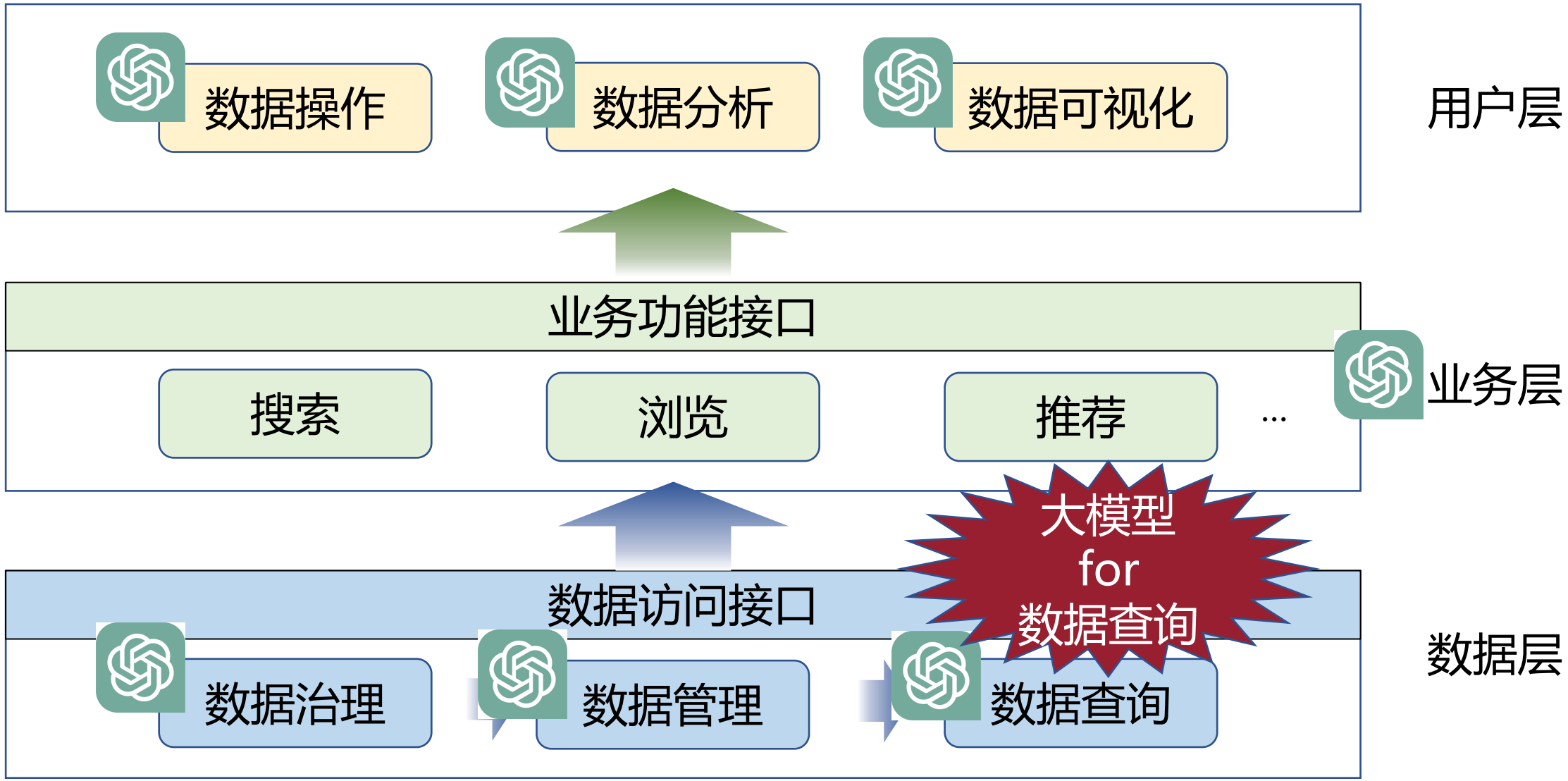
3. **Increase Write I/O Threads:**
   - Current: 16
   - Metrics: os_data_writes (2104005120), innodb_dblwr_writes (628)
   - Recommendation: Increase to 32 to improve write throughput.

……

- 语言模型能够以“思维链”的方式,为每个参数调整提供详细的理由和考虑因素。
- 与传统的“黑箱”方法相比,语言模型在参数调优中展现出了更好的可解释性。这不仅增强了实际应用性,也提高了结果的可靠性。
- 通过阐述推荐的原因,语言模型还可以帮助数据库管理员做出更明智的决策,促进参数推荐过程的协作和高效。

Yiyan Li, Haoyang Li, Zhao Pu, Jing Zhang, Xinyi Zhang, Tao Ji, Luming Sun, Cuiping Li, Hong Chen. Is Large Language Model Good at Database Knob Tuning? A Comprehensive Experimental Evaluation. Under Review

# 工程开发流程

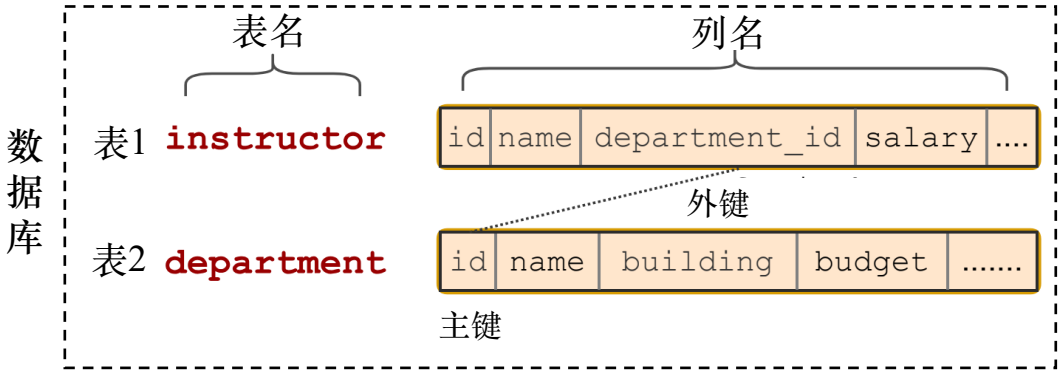

数据操作
数据分析
数据可视化
用户层
业务功能接口
搜索
浏览
推荐
...
业务层
大模型
for
数据查询
数据访问接口
数据治理
数据管理
数据查询
数据层

# Text-to-SQL

**任务：**给定一个数据库，将自然语言问题转化为SQL语句

Text-to-SQL任务的核心挑战包括：

- 理解用户的自然语言查询意图，包括查询的关键词、条件、排序等要求。
- 将自然语言中提及的实体（如表名、列名）和关系（如列与列之间的关系）正确地映射到数据库的相应元素上。
- 生成复杂查询，包括多表连接、子查询、聚合操作等。




自然语言查询：哪些部门的平均讲师工资高于总体平均水平，请列出这些部门的名称和预算？

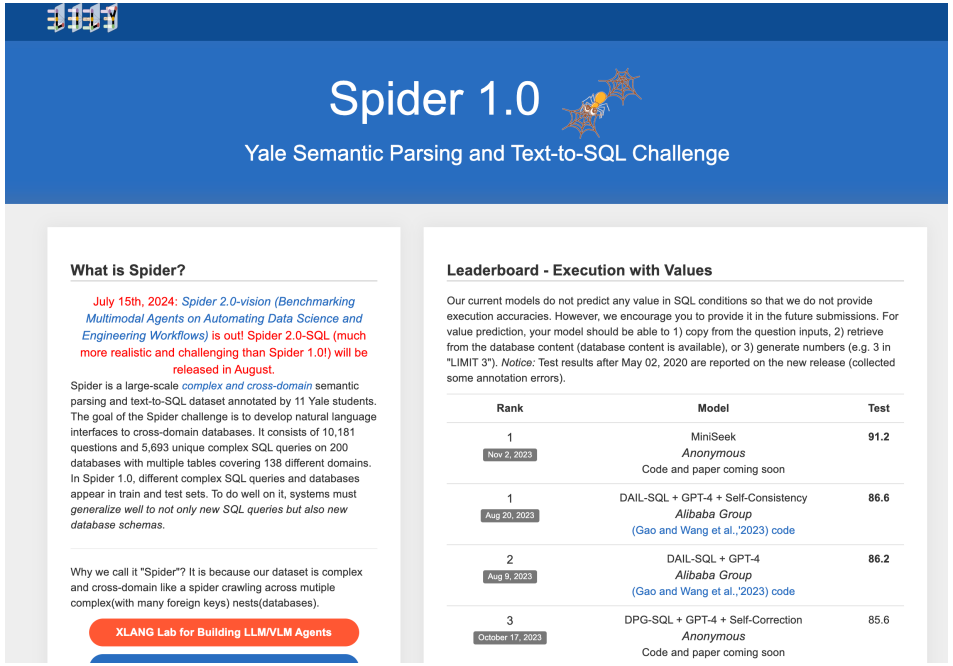
Text-to-SQL 方法

SQL查询

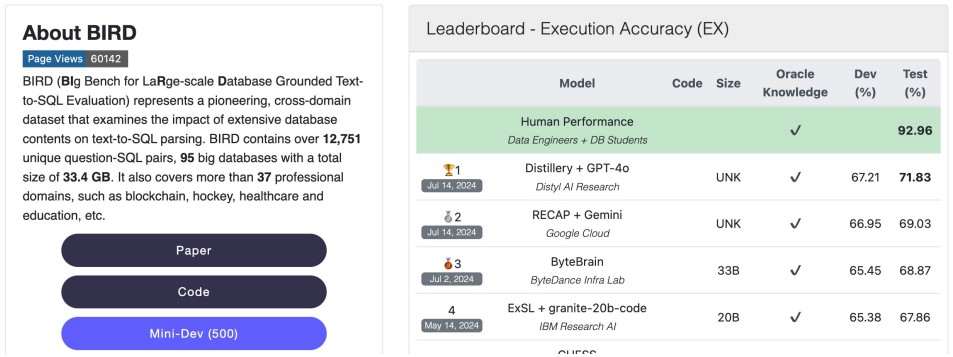
```
SELECT T2.name, T2.budget
FROM instructor as T1 JOIN department as
T2 ON T1.department_id = T2.id
GROUP BY T1.department_id
HAVING avg(T1.salary) >
    (SELECT avg(salary) FROM instructor)
```

# Text-to-SQL数据集

国际公认的Spider和BIRD等数据集，提供了丰富的<数据库，自然语言查询，SQL>样本，用于评估




https://yale-lily.github.io/spider


https://bird-bench.github.io

Spider是第一个跨领域且大规模的text2sql数据集，包含了10,181条文本到SQL数据对和200个独立的数据库，内容覆盖了138个不同领域。

BIRD引入三个额外的挑战，即处理大规模和混乱的数据库值、外部知识推理和优化生成SQL的执行效率。

# Text-to-SQL评测指标

评价Text-to-SQL方法的性能主要依赖两个指标：精确匹配率（EM）和执行准确率（EX）

1. **精确匹配率（Exact Set Match，EM）**：衡量生成的SQL与标准SQL在语法树层面的一致性，其局限在于无法识别语义等价但结构不同的SQL查询，可能导致假负例。
2. **执行准确率（Execution Accuracy，EX）**：通过比较生成SQL与标准SQL在数据库上执行结果的一致性来评估。可能会将语义不同但偶然产生相同结果的SQL视为正确，导致假正例。

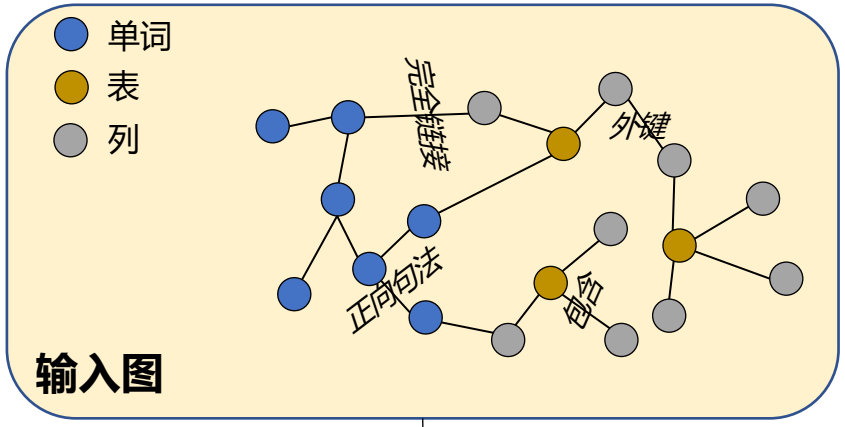
为全面评估Text-to-SQL模型性能，可综合使用EM和EX两个指标，并引入以下补充指标：

1. **测试组件准确率（Test Suit Execution Accuracy）**：针对EX指标的假正例问题，TS通过比较生成SQL与标准SQL在不同数据库实例上的执行结果，以判断其语义等价性。
2. **有效效率得分（Valid Efficiency Score）**：衡量生成SQL的执行效率，以评价模型输出的性能。

这些补充指标有助于更精确地评估模型（学生）的SQL撰写能力

# 基于编码器-解码器模型的训练方法

- **编码器**：将用户的自然语言查询和数据库信息整合成**图结构**，使用图编码器为图中的每个节点（包括数据库的表、列和自然语言查询中的单词）编码，捕获结构信息。
- **解码器**：生成相应的SQL查询。为了确保生成的SQL查询不仅语义上正确而且遵循SQL的语法规则，采用受语法限制的序列解码器，考虑SQL语法的约束，如正确的关键字顺序、括号匹配等。




编码

图编码器

基于语法树的序列解码器

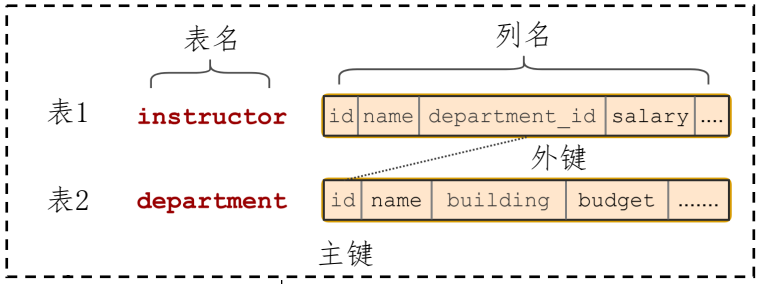
解码

```
SELECT T2.name, T2.budget
FROM instructor as T1 JOIN department as
T2 ON T1.department_id = T2.id
GROUP BY T1.department_id
HAVING avg(T1.salary) >
    (SELECT avg(salary) FROM instructor)
```

# 基于生成式语言模型的微调方法

- 随着T5、GPT、BART的出现，Text-to-SQL被视为序列到序列的转换问题，在包含自然语言查询和数据库信息的输入序列上进行微调，直接生成SQL查询。

**数据库信息：**




将数据库信息序列化为文本

instructor: id, name, department_id, salary … | department: id, name…

**自然语言查询：**
哪些部门的平均讲师工资高于总体平均水平，请列出这些部门的名称和预算？

**自然语言查询+数据库信息**
（输入序列）

哪些部门的平均讲师. . . | instructor: id, name, department_id …

输入

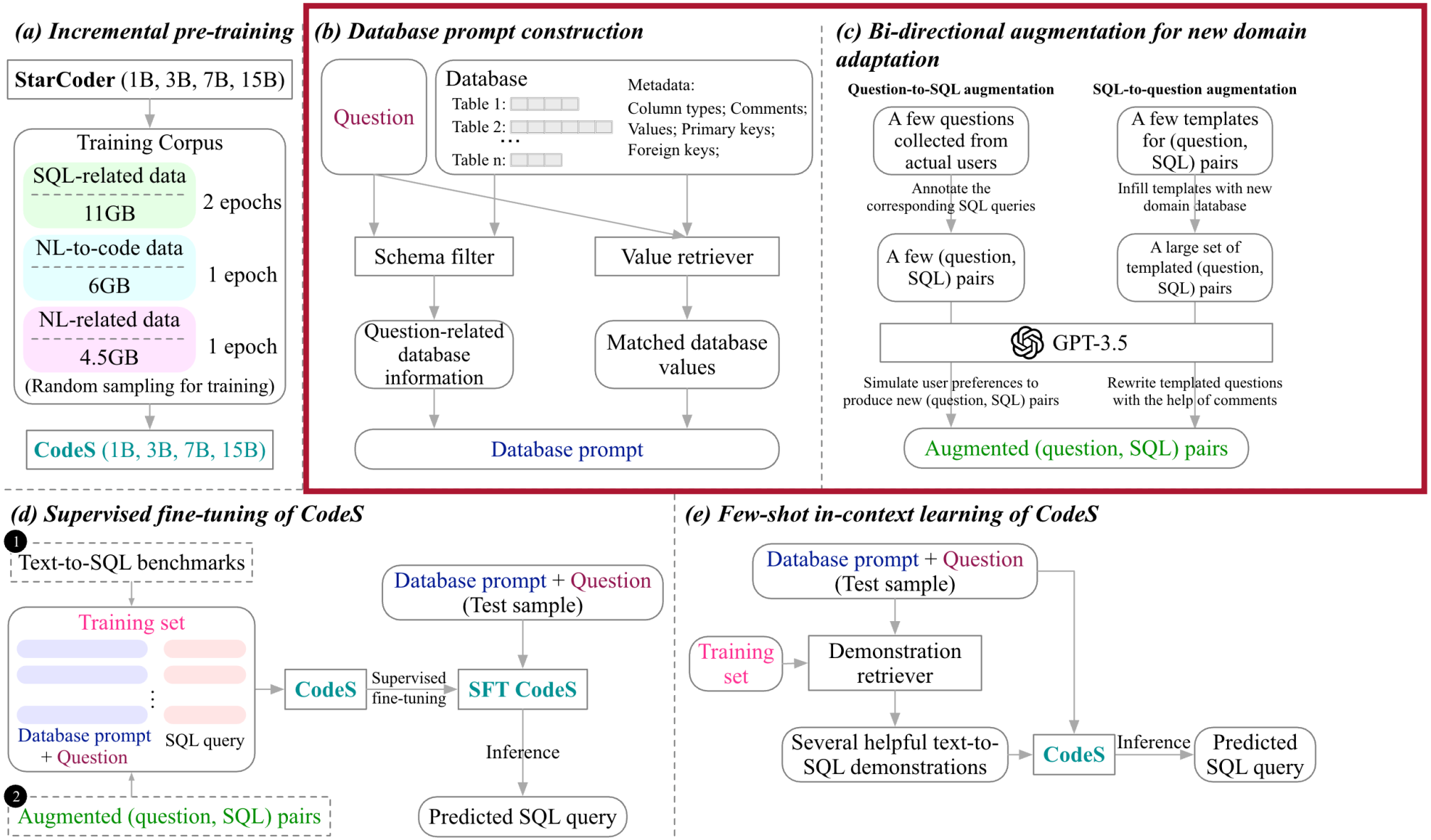
序列到序列的生成式语言模型（如T5和BART）

输出

**SQL查询**（输出序列）

```
SELECT T2.name, T2.budget
FROM instructor as T1 JOIN department as
T2 ON T1.department_id = T2.id
GROUP BY T1.department_id
HAVING avg(T1.salary) >
    (SELECT avg(salary) FROM instructor)
```

# Codes：大模型微调方法




Haoyang Li, Jing Zhang, Hanbing Liu, Ju Fan, Xiaokang Zhang, Jun Zhu, Renjie Wei, Hongyan Pan, Cuiping Li, Hong Chen. CodeS: Towards Building Open-source Language Models for Text-to-SQL. SIGMOD 2024

# 基于大语言模型的提示方法

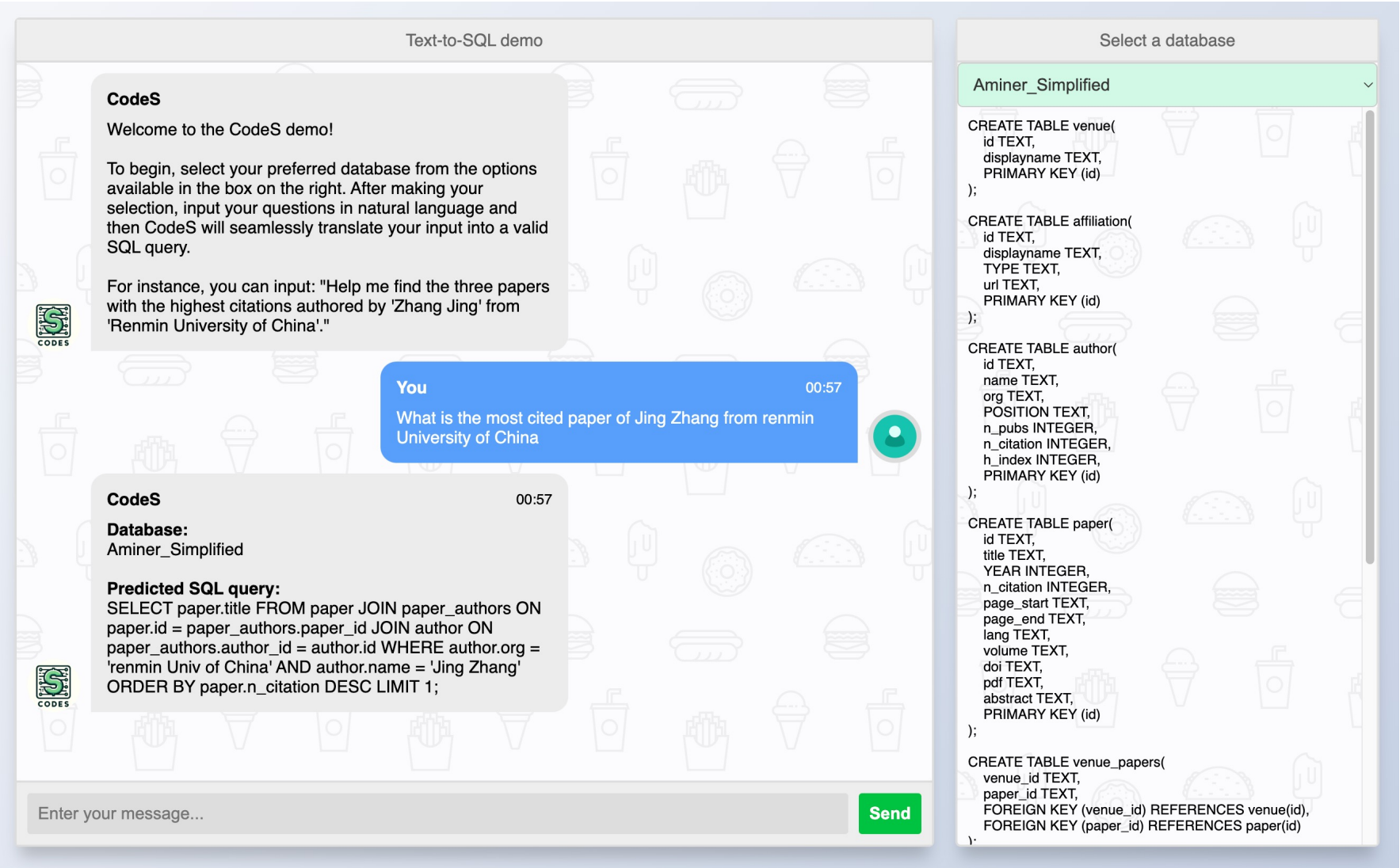
指令：明确告诉模型需要执行的任务

- 利用如GPT-4等大语言模型的zero-shot和few-shot上下文学习能力，通过设计合适的提示词来引导模型完成任务，无需模型微调。
- 通常将任务分解为多个子任务，每个子任务使用特定提示词来解决，最终模型整合这些子任务的结果以生成SQL查询。

1-shot 示例：提供了一个完整的text-to-SQL示例，包括<数据库信息，自然语言查询，SQL查询>的三元组，以指导模型了解任务格式和预期输出。

测试样例：给出了测试用的数据库信息和自然语言查询，但不包括对应的SQL查询。

# 工程能力培养：辅助学习SQL




Text-to-SQL任务的应用场景广泛：

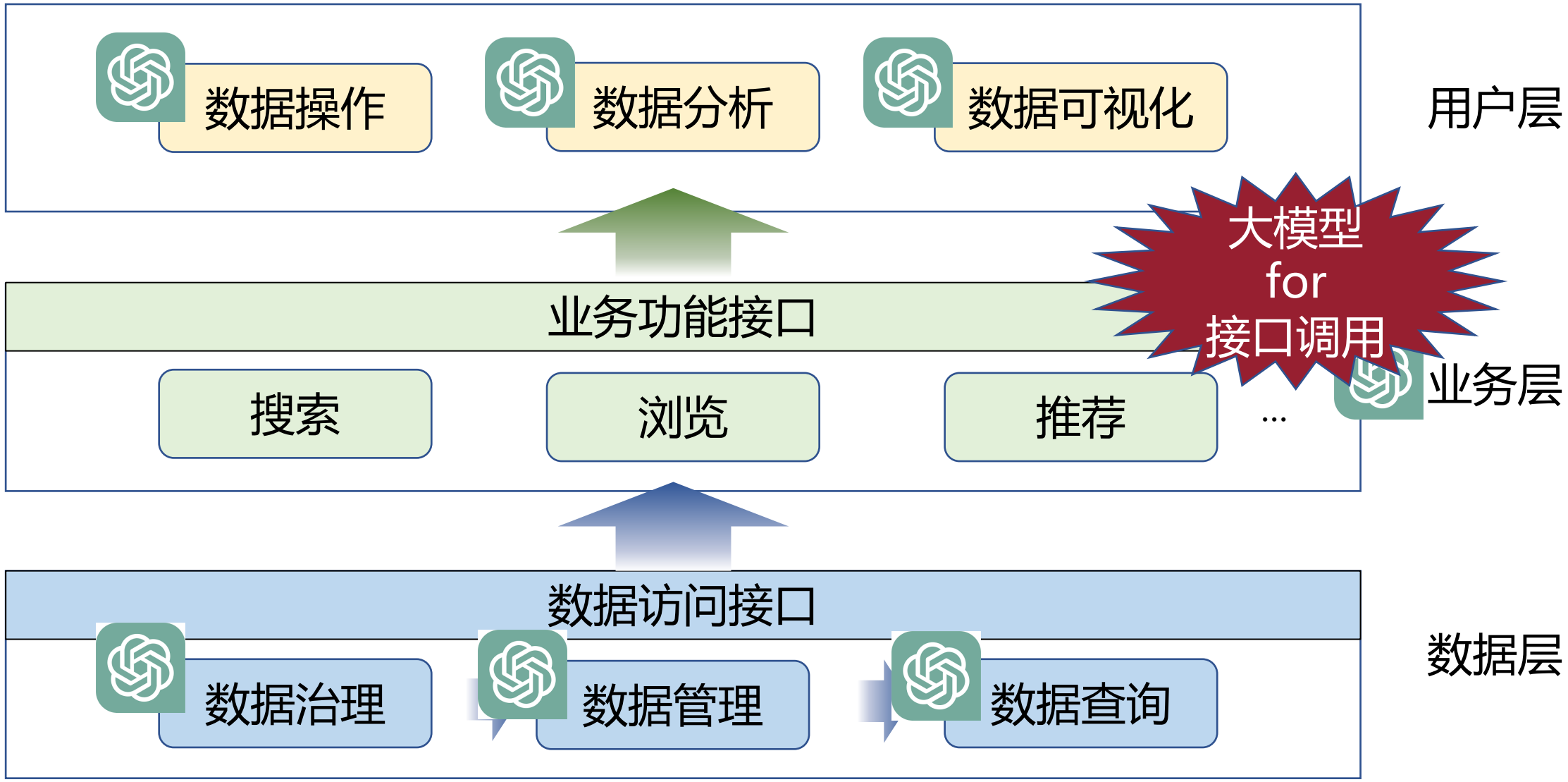
1. **商业智能（BI）**：允许非技术背景的商业分析师通过自然语言查询企业数据库，快速获取决策支持信息。

2. **数据工程师降本增效**：辅助数据工程师撰写SQL。

3. **教育**：帮助学习SQL的学生验证他们的查询是否正确，或者提供查询示例；帮助教师出题。

**Demo:** https://github.com/RUCKBReasoning/text2sql-demo

# 工程开发流程


数据操作
数据分析
数据可视化
用户层
大模型
for
接口调用
业务功能接口
搜索
浏览
推荐
...
业务层
数据访问接口
数据治理
数据管理
数据查询
数据层

# 例子：学术挖掘与检索系统AMiner的接口调用

业务问题: 纽约大学Yann LeCun引用最高的论文的引用数是多少?

数据访问接口

| ID | API name | Type | Parameter(s) | Return |
|---|---|---|---|---|
| 1 | searchPerson | fuzzy | name, organization, interest | [person_id, name, num_citation, interest, num_pubs, organization] |
| 2 | searchPublication | fuzzy | publication_info | [pub_id, title, year] |
| 3 | getCoauthors | exact | person_id | [id, name, relation] |
| 4 | getPersonInterest | exact | person_id | list of interests |
| 5 | getPublication | exact | pub_id | abstract, author_list, num_citation |
| 6 | getPersonBasicInfo | exact | pub_id | person_id, name, gender, organization, position, bio, education_experience, email |
| 7 | getPersonPubs | exact | person_id | [authors_name_list, pub_id, title, num_citation, year] |

Yann LeCun, NYU ➤ searchPerson ➤ [{ person_id: ec0f***jsk, person_name: Yann LeCun, ... }]

ec0f***jsk ➤ getPersonPubs ➤ [{ pub_id : al4k***8fa, ...}, { pub_id : 79pa***rjk, ...}, { pub_id : q2f4***n3c, ...}...]

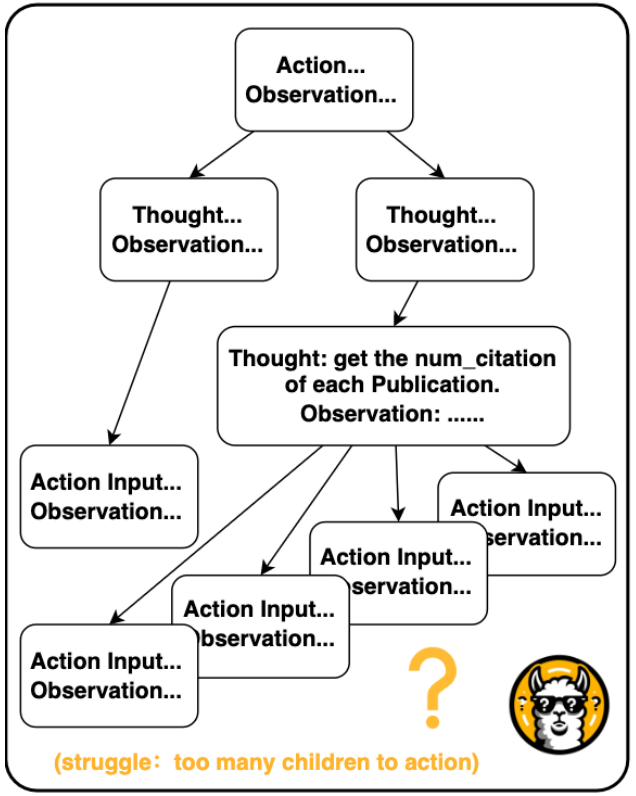
al4k***8fa
79pa***rjk
q2f4***n3c
➤ getPublication ➤ [{ title: Efficient Backprop, citation: 7145}, { title: Deeplearning, citation: 79904}, { title: The Minist Database, citation: 7592}...]

# 大模型接口调用

业务问题: 纽约大学Yann LeCun引用最高的论文的引用数是多少?

检索并执行:
API依赖问题


DFSDT
推理效率太低



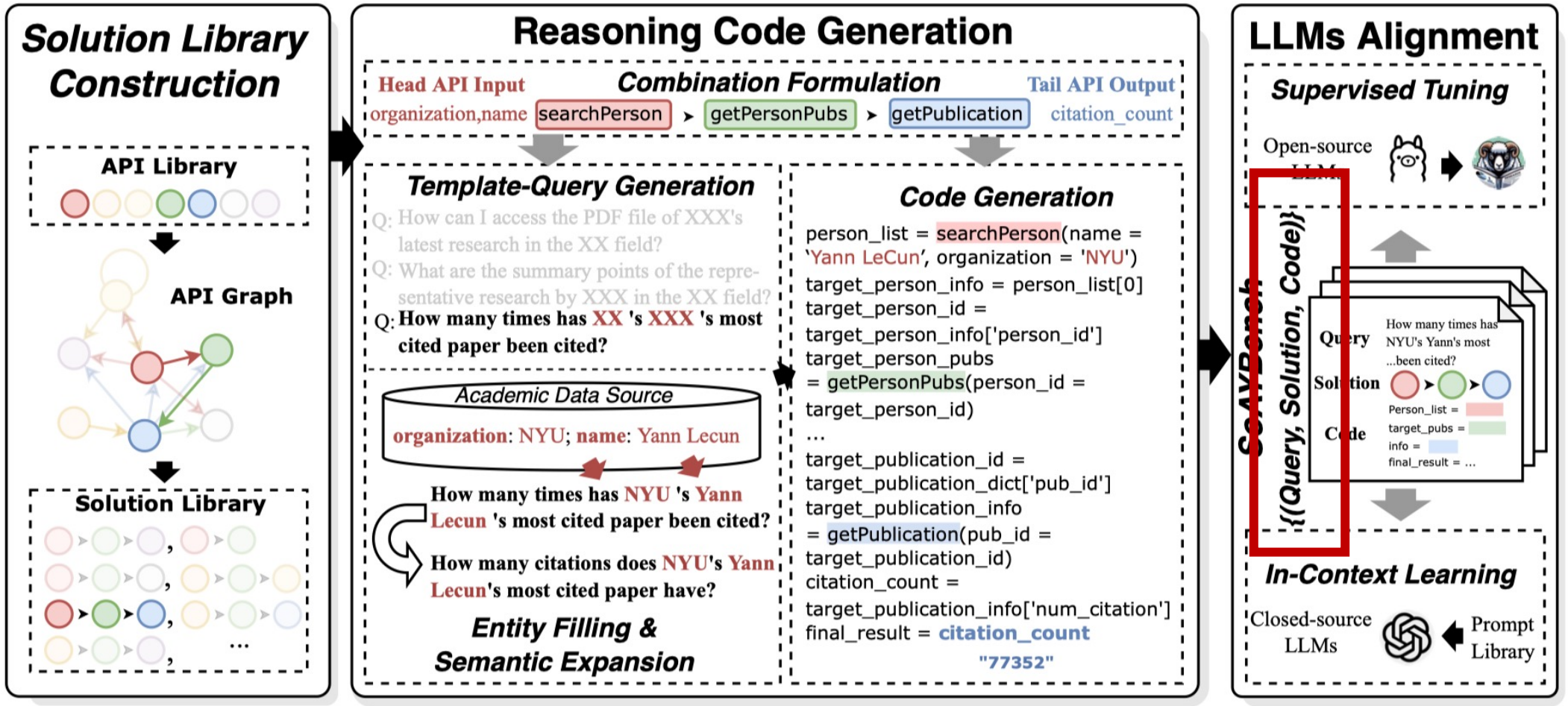


SoAy:

预定义Solution以及
Solution-based代码生成

# SoAy：大模型接口调用解决方法

业务问题: 纽约大学Yann LeCun引用最高的论文的引用数是多少?




Yuanchun Wang, Jifan Yu, Zijun Yao, Jing Zhang, etc. SoAy: A Solution-based LLM API-using Methodology for Academic Information Seekinghttps://arxiv.org/pdf/2405.15165

# 大模型接口调用

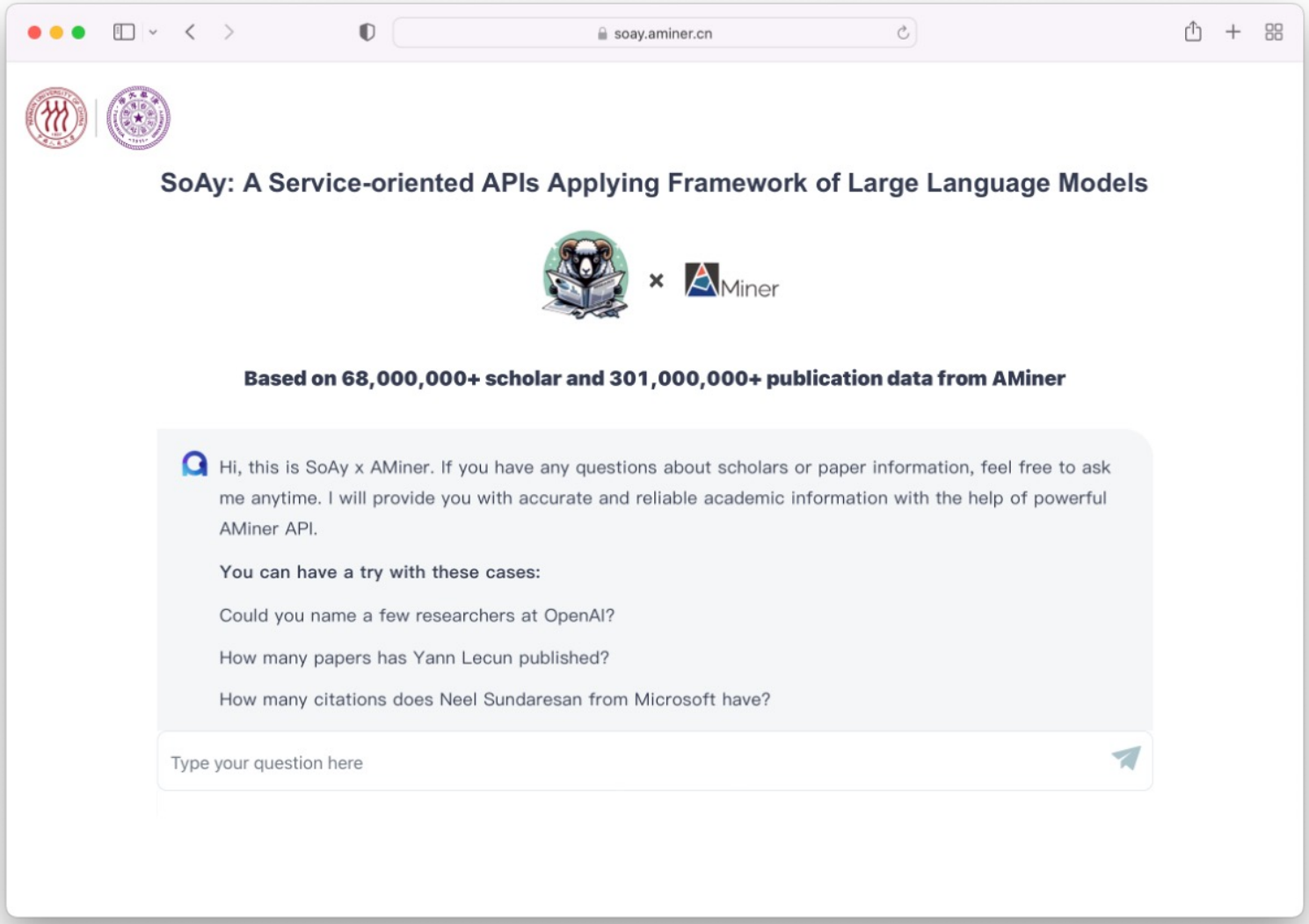
## 实验结果

微调模型优于GPT-4, 效率也提升很多

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| SoAyGPT | 3.5 | one-hop | 27.78±8.70 | 15.97±7.73 | 3.47±0.00 | 13.19±7.80 | 39.58±9.12 | 67.36 | 67.30 |
| | | two-hop | 33.84±4.94 | 9.60±4.75 | 6.06±2.81 | 13.13±7.12 | 37.37±5.06 | 71.21 | |
| | | three-hop | 22.22±6.43 | 12.70±5.91 | 9.52±4.42 | 13.10±6.72 | 42.46±6.00 | 64.68 | |
| | 3.5-16k | one-hop | 28.47±11.67 | 15.28±6.12 | 1.39±0.00 | 17.36±7.78 | 37.50±9.07 | 65.97 | 66.76 |
| | | two-hop | 35.86±6.01 | 7.32±3.41 | 5.30±2.18 | 15.91±7.16 | 35.61±4.65 | 71.46 | |
| | | three-hop | 23.02±7.16 | 10.32±4.99 | 8.33±3.42 | 17.46±7.37 | 40.87±6.26 | 63.89 | |
| | 4 | one-hop | 0.00±0.00 | 0.00±0.00 | 1.39±0.00 | 2.78±0.00 | 95.83±5.70 | 95.83 | 86.57 |
| | | two-hop | 15.91±4.71 | 1.26±0.00 | 9.34±1.07 | 2.02±1.69 | 71.46±3.74 | 87.37 | |
| | | three-hop | 6.75±0.00 | 0.40±0.00 | 14.68±1.68 | 1.98±0.00 | 76.19±3.25 | 82.94 | |
| SoAyLLaMA | Chat-7B | one-hop | 0.00±0.00 | 0.00±0.00 | 0.00±0.00 | 0.69±0.00 | 99.31±2.94 | 99.31 | 85.76 |
| | | two-hop | 0.00±0.00 | 0.00±0.00 | 20.20±3.84 | 2.53±1.97 | 77.27±2.70 | 77.27 | |
| | | three-hop | 0.00±0.00 | 0.00±0.00 | 9.92±3.56 | 3.17±2.50 | 86.90±2.72 | 86.90 | |
| | Code-7B | one-hop | 0.69±0.00 | 0.00±0.00 | 0.69±0.00 | 5.56±4.37 | 93.06±7.50 | 93.75 | 88.95 |
| | | two-hop | 0.25±0.00 | 3.28±0.00 | 7.07±2.75 | 4.80±3.69 | 84.60±5.18 | 84.85 | |
| | | three-hop | 0.40±0.00 | 0.00±0.00 | 4.76±2.14 | 5.16±4.57 | 89.68±6.54 | 90.08 | |
| | Code-13B | one-hop | 0.00±0.00 | 0.00±0.00 | 1.39±0.00 | 0.00±0.00 | 98.61±4.03 | 98.61 | **92.74** |
| | | two-hop | 0.00±0.00 | 2.27±0.00 | 14.14±2.14 | 0.51±0.00 | 83.08±3.32 | 83.08 | |
| | | three-hop | 0.00±0.00 | 0.00±0.00 | 2.38±2.86 | 0.40±0.00 | 97.22±4.28 | 97.22 | |

| **Method** | 7B | 13B | 3.5 | 3.5-16k | 4 |
|---|---|---|---|---|---|
| ToolLLaMA | 45.10 | / | / | / | / |
| GPT-DFSDT | / | / | 39.12 | 53.73 | 70.92 |
| SoAyGPT | / | / | 6.15 | 6.40 | 26.05 |
| SoAyLLaMA-Code | 1.12 | 1.35 | / | / | / |

# 工程能力培养：业务建模



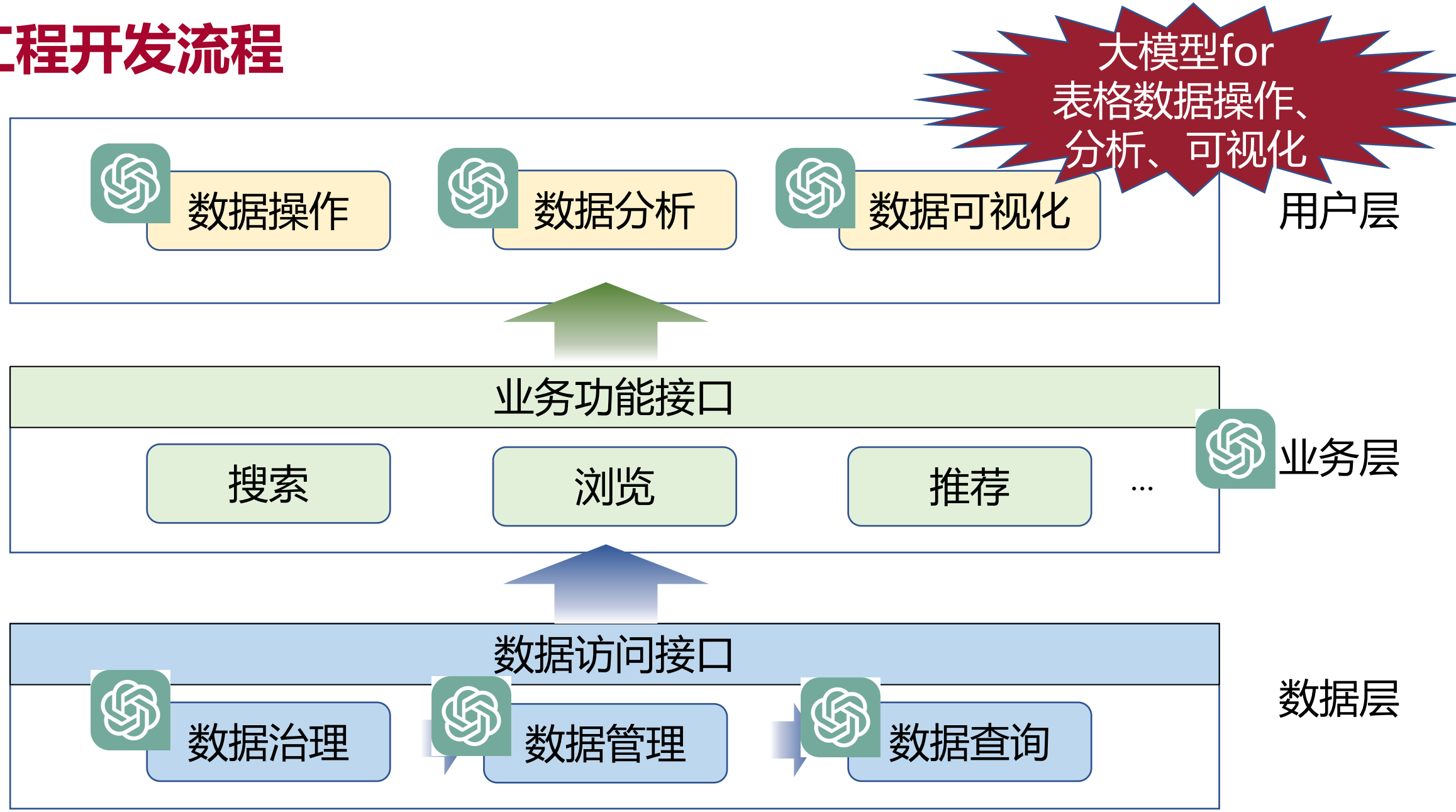

大模型接口调用的应用场景广泛：

1. **商业智能（BI）**：允许非技术背景的商业分析师通过自然语言组合数据访问接口，灵活搭建业务功能。

2. **教育**：帮助学习软件工程业务建模的学生验证他们建模并实现的业务功能是否正确。

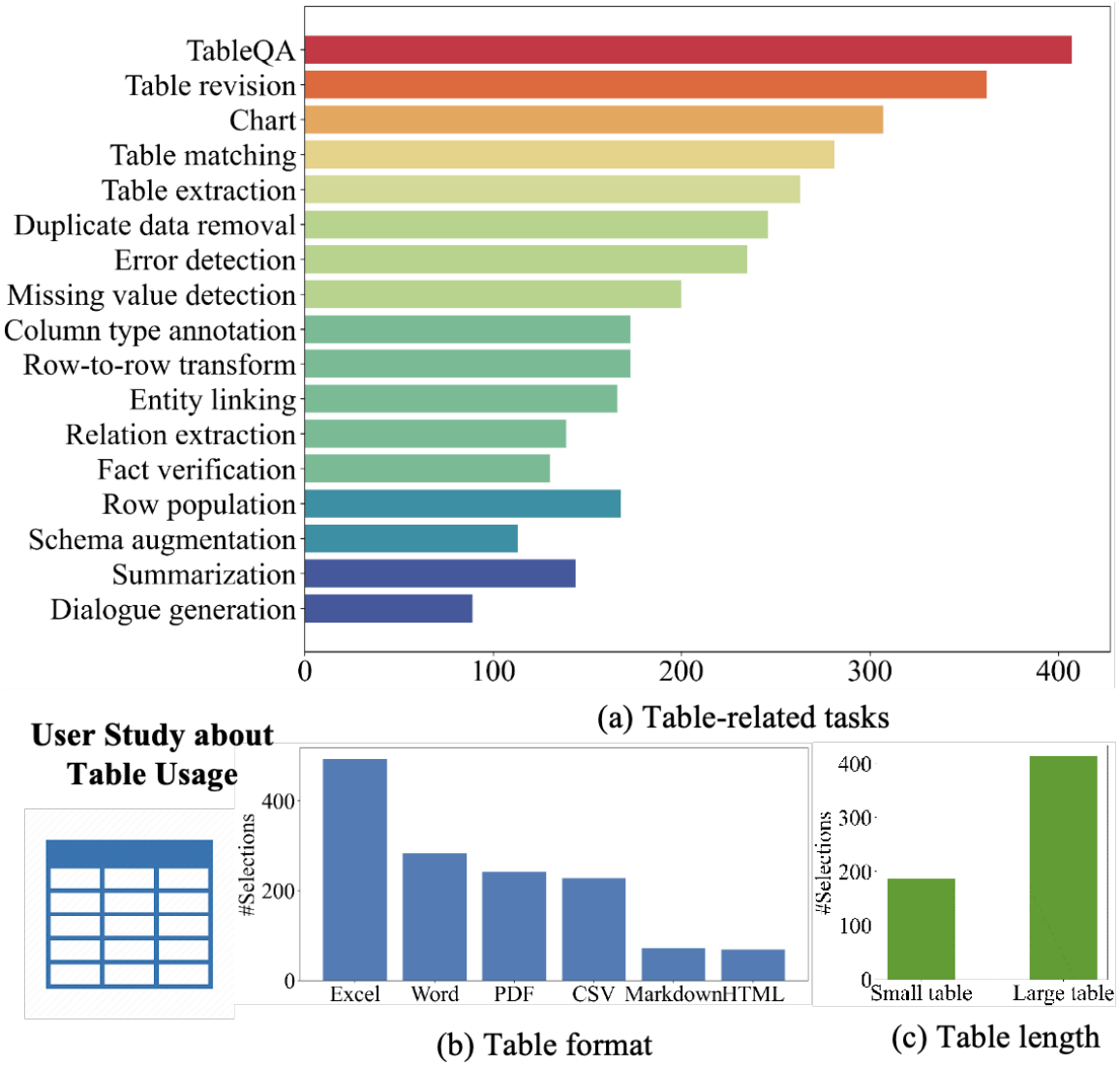
**Demo:** http://soay.aminer.cn

# 工程开发流程


大模型for
表格数据操作、
分析、可视化
数据操作
数据分析
数据可视化
用户层
业务功能接口
搜索
浏览
推荐
...
业务层
数据访问接口
数据治理
数据管理
数据查询
数据层

# 表格数据相关任务

- **多样的操作需求：**用户偏好的任务涉及广泛的操作，不仅包括表格问答，还有查询、更新、合并、分析、绘制图表等。




Xiaokang Zhang, Jing Zhang, Zeyao Ma, etc. https://arxiv.org/pdf/2403.19318

# 合成数据方法一：扩展COT

丰富现有基准数据的推理过程（COT），促进语言模型的训练。

| ID | Employer | #Employees |
|---|---|---|
| 1 | Medline | 1,200 |
| 2 | MPD | 422 |
| 3 | Amcor | 350 |
| 4 | FSD 79 | 287 |
| 5 | Univ. of SML | 220 |
| 6 | ME School D. | 213 |
| 7 | M. High School | 211 |
| 8 | Village of M | 183 |

**Benchmark**

**Question:** how many employers have at least 300 employees?

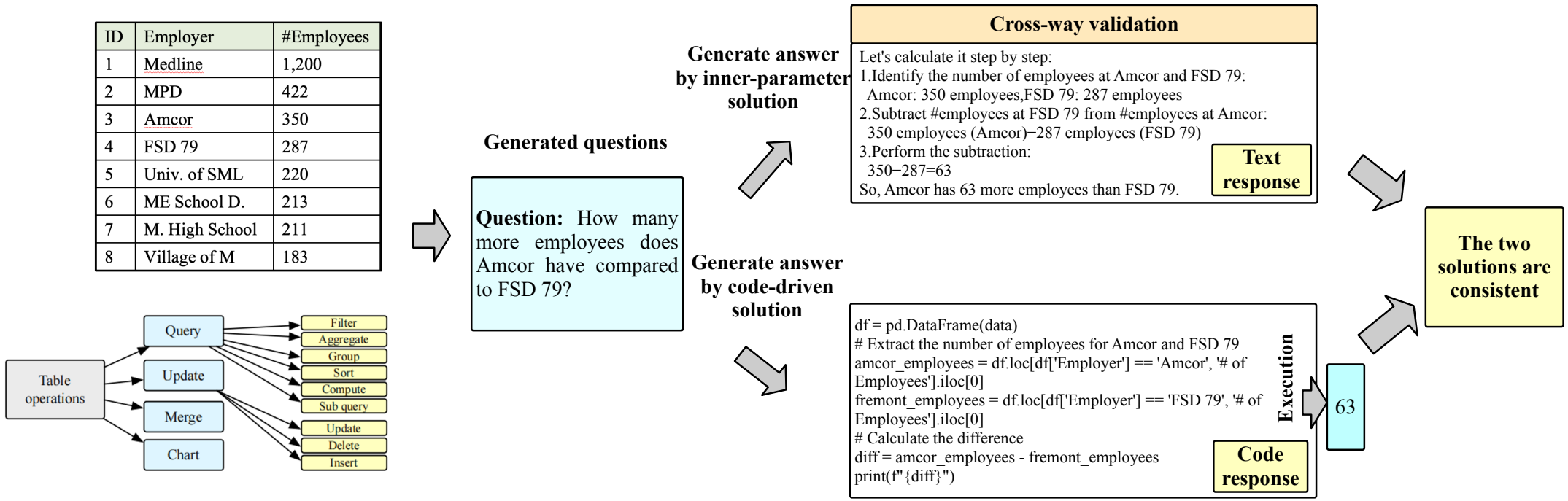
**Answer:** 3

**Reasoning process extending**

Let's go through each row of the table:
1.Medline: #employees is 1,200, which is greater than 300.
2.MPD: #employees is 422, which is greater than 300.
3.Amcor: #employees is 350, which is greater than 300.
4.FSD 79: #employees is 287, which is less than 300.
5.Univ. of SML: #employees is 220, which is less than 300.
6.ME School D.: #employees is 213, which is less than 300.
7.M. High School: #employees is 211, which is less than 300.
8.Village of M: #employees is 183, which is less than 300.
Based on this analysis, we can conclude that there are 3 employers with at least 300 employees: Medline, MPD, and Amcor.

# 合成数据方法一：原子操作与一致性检查

为了增加训练数据的多样性和覆盖度，提供给大模型表格**原子操作列表**
并采用**交叉验证策略**从提供的表格数据中自动生成新的问题和答案。




**定理:**

（1）如果 A 和 B 是从同一分布中抽取的,并且 $P(Ya) = P(Yb) = p > ½$，那么一致性检查的表现优于单独推理，即 $P(Y|E) \geq P(Ya)$。

（2）如果 A 和 B 进一步是从独立分布中抽取的，这种效果将更明显(从期望值的角度来看)。

# 表格数据大模型

## 实验结果

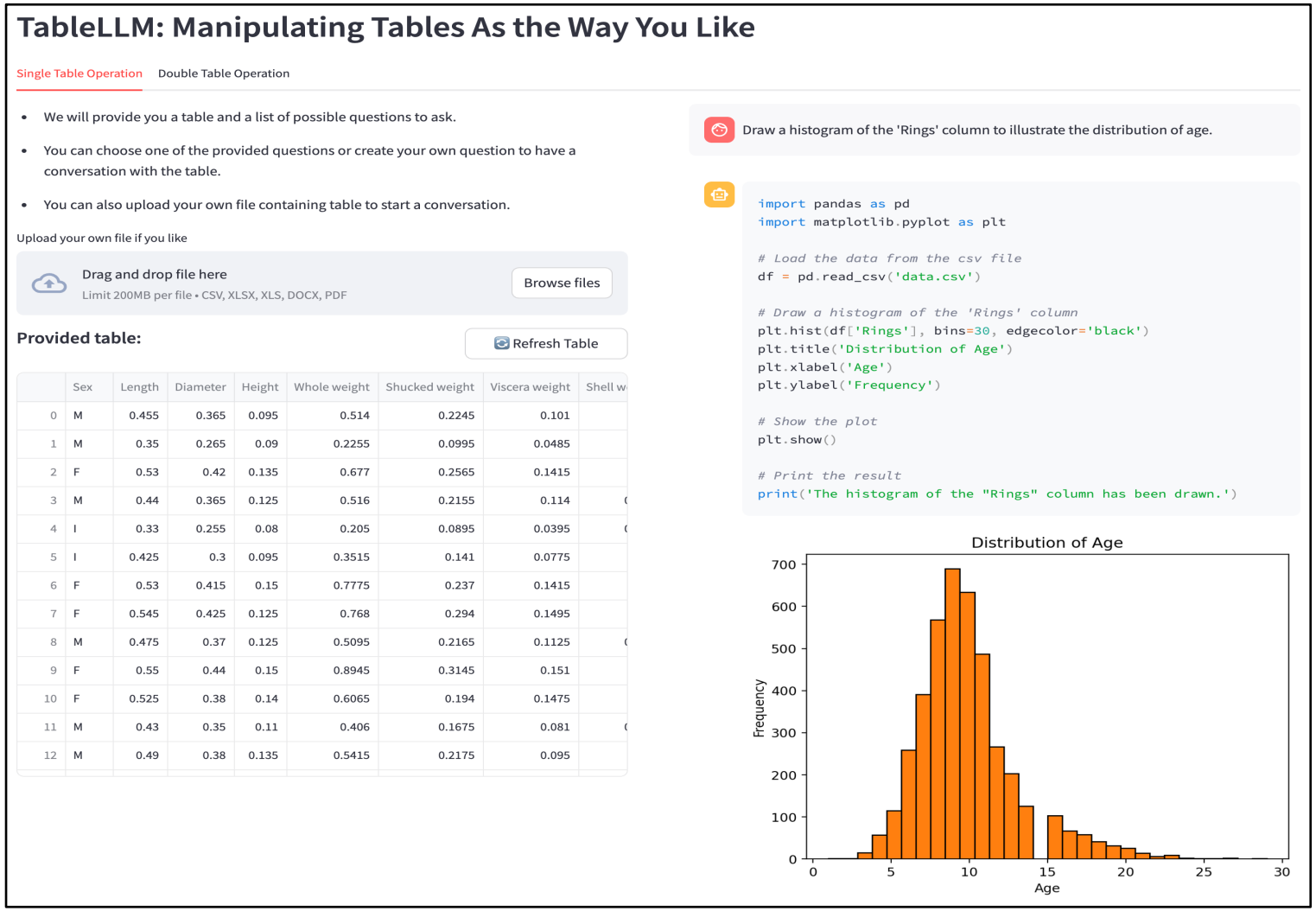
TableLLM 在表格操作任务上超越GPT-4

**Table 2: Overall evaluation in both document-embedded and spreadsheet-embedded tabular data scenarios (%)**

| Model | Document-embedded tabular data | | | | Spreadsheet-embedded tabular data | | | Average accuracy | Inference times |
|---|---|---|---|---|---|---|---|---|---|
| | WikiTQ | TAT-QA | FeTaQA | OTT-QA | WikiSQL | Spider | Our created | | |
| TaPEX | 38.55 | – | – | – | 83.90 | 15.04 | – | 45.83 | 1 |
| TaPas | 31.60 | – | – | – | 74.20 | 23.05 | – | 42.95 | 1 |
| TableLlama | 24.01 | 22.25 | 20.47 | 6.39 | 43.70 | – | – | 23.36 | 1 |
| Llama2-Chat (13B) | 48.82 | 49.63 | 67.73 | 61.50 | – | – | – | 56.92 | 1 |
| GPT-3.5 | 58.45 | 72.13 | 71.18 | 60.80 | 81.70 | 67.38 | 77.08 | 69.82 | 1 |
| GPT-4 | **74.09** | **77.13** | **78.35** | **69.50** | 84.00 | 69.53 | 77.83 | **75.78** | 1 |
| CodeLlama (13B) | 43.44 | 47.25 | 57.24 | 49.72 | 38.30 | 21.88 | 47.58 | 43.63 | 1 |
| Deepseek-Coder (33B) | 6.48 | 11.00 | 7.12 | 7.44 | 72.50 | 58.40 | 73.92 | 33.84 | 1 |
| StructGPT (GPT-3.5) | 52.45 | 27.53 | 11.80 | 13.96 | 67.80 | **84.80** | – | 43.06 | 3 |
| Binder (GPT-3.5) | 61.61 | 12.77 | 6.85 | 5.13 | 78.60 | 52.55 | – | 36.25 | 50 |
| DATER (GPT-3.5) | 53.40 | 28.45 | 18.26 | 13.03 | 58.20 | 26.52 | – | 32.98 | 100 |
| TableLLM (7B) | 58.77 | 66.88 | 72.64 | 63.11 | 86.60 | 82.62 | 78.83 | 72.68 | 1 |
| TableLLM (13B) | 62.40 | 68.25 | 74.50 | 62.51 | **90.70** | 83.40 | **80.83** | 74.66 | 1 |

* Underline represents the runner up.

# 工程能力培养：业务建模




| | Sex | Length | Diameter | Height | Whole weight | Shucked weight | Viscera weight | Shell w |
|---|---|---|---|---|---|---|---|---|
| 0 | M | 0.455 | 0.365 | 0.095 | 0.514 | 0.2245 | 0.101 | |
| 1 | M | 0.35 | 0.265 | 0.09 | 0.2255 | 0.0995 | 0.0485 | |
| 2 | F | 0.53 | 0.42 | 0.135 | 0.677 | 0.2565 | 0.1415 | |
| 3 | M | 0.44 | 0.365 | 0.125 | 0.516 | 0.2155 | 0.114 | |
| 4 | I | 0.33 | 0.255 | 0.08 | 0.205 | 0.0895 | 0.0395 | |
| 5 | I | 0.425 | 0.3 | 0.095 | 0.3515 | 0.141 | 0.0775 | |
| 6 | F | 0.53 | 0.415 | 0.15 | 0.7775 | 0.237 | 0.1415 | |
| 7 | F | 0.545 | 0.425 | 0.125 | 0.768 | 0.294 | 0.1495 | |
| 8 | M | 0.475 | 0.37 | 0.125 | 0.5095 | 0.2165 | 0.1125 | |
| 9 | F | 0.55 | 0.44 | 0.15 | 0.8945 | 0.3145 | 0.151 | |
| 10 | F | 0.525 | 0.38 | 0.14 | 0.6065 | 0.194 | 0.1475 | |
| 11 | M | 0.43 | 0.35 | 0.11 | 0.406 | 0.1675 | 0.081 | |
| 12 | M | 0.49 | 0.38 | 0.135 | 0.5415 | 0.2175 | 0.095 | |

大模型表格数据操作、分析与可视化的应用场景广泛：

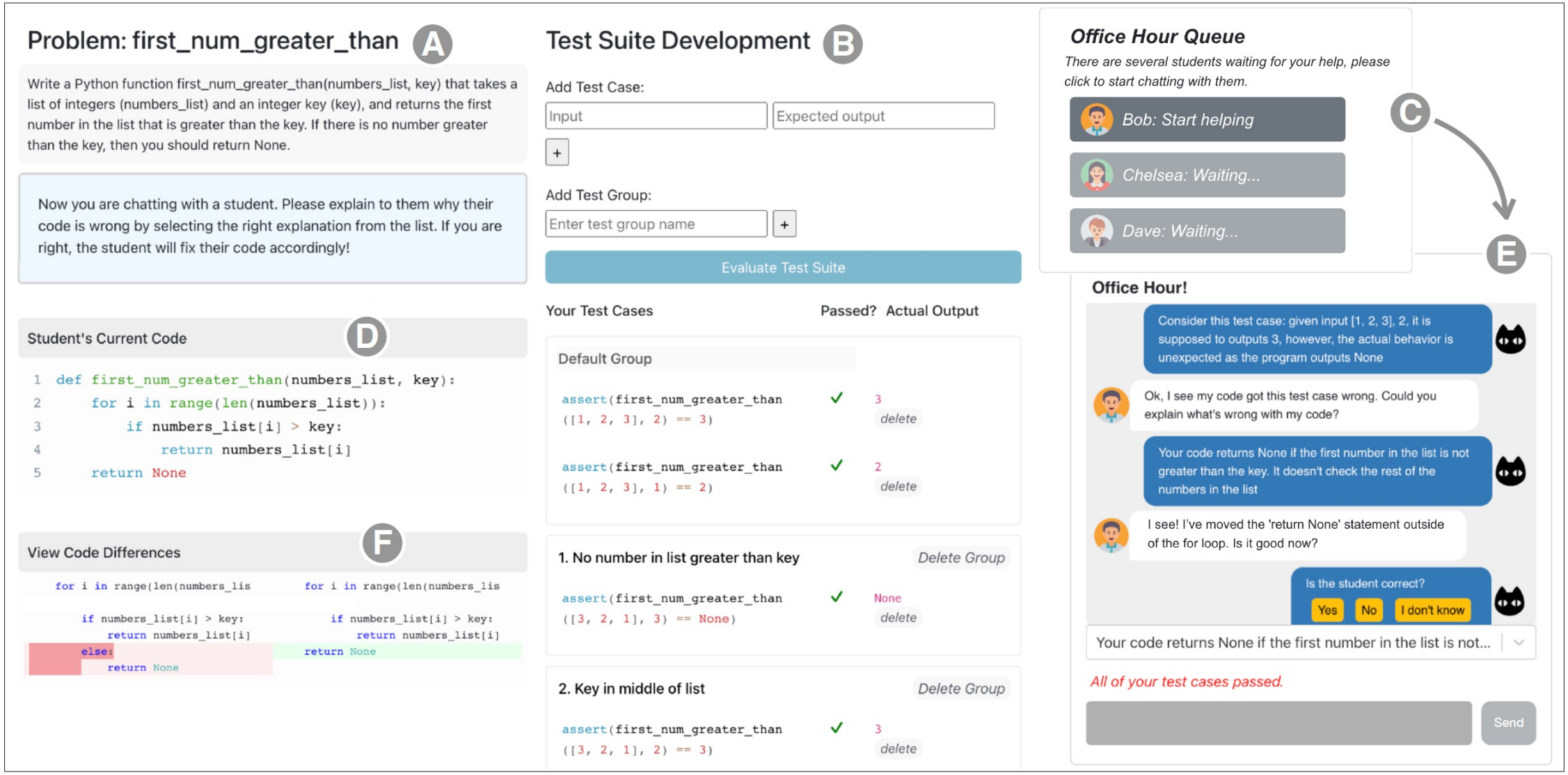
1. **商业智能（BI）**：允许非技术背景的商业分析师通过自然语言直接操作表格、挖掘信息。

2. **教育**：帮助学习数据分析工具（Python、Matplotlib、Sklearn、Pandas）的学生验证他们撰写分析代码是否正确。

**Demo:** https://tablellm.github.io/

# 代码理解能力提升: 更强大的代码大模型与项目级编程助手

# Debug能力的提升：学生当助教，写Test Case，给修Bug建议






Qianou Ma, Hua Shen, Ken Koedinger, Tongshuang Wu. Teach Programming in the AI Era? Using LLMs as a Teachable Agent for Debugging. AIED 2024

# 总结：利用大模型提升学生工程实践能力

- **数据层**
  - 大模型for数据治理、数据管理与数据查询
  - 辅助ER图、DBA、SQL的学习
- **业务层**
  - 大模型for接口调用
  - 辅助软件工程业务建模的学习
- **用户层**
  - 大模型for表格数据操作、分析与可视化
  - 辅助数据分析工具的学习
- **更强大的通用代码模型**：提升代码理解能力
- **特定应用**：提升Debug能力

**未来可能**：深度结合教学理论与教学实践与大模型，开发专业教具，提升工程能力

# 感谢聆听!