Weaver: Interweaving SQL and LLM for Table Reasoning

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Why is Table QA still Challenging?

- Tables contain both **structured** (numbers, fields) and **unstructured** (long text/images) data
- SQL is great for logic but fails at semantic inference
- LLMs handle semantics but struggle at structured logic

Example: "Which country had the most competitors?"

Driver	Constructor	Laps	Time
Alain Prost	Ferrari	64	1:18:31
Thierry Boutsen	Williams-Renault	64	39.092
Ayrton Senna	McLaren-Honda	63	1 Lap

SQL fails here $\rightarrow$ LLM helps with nationality inference

Existing SQL–LLM integration is rigid or shallow

Method	Strength	Limitation
Binder/BlendSQL	Integrate LLM into SQL	Fail on multi-step reasoning
H-STAR / Re-AcTable	Structured pruning	Struggles with row extraction
ProTrix	2-step reasoning	Limited flexibility

Key Issue: Fixed workflows lack adaptability to complex queries

Weaver dynamically interweaves SQL and LLM reasoning

LLM-generated dynamic execution plan:

Weaver first generates a **flexible step-by-step plan** that adapts to query complexity, then executes through dynamic interweaving of:

1. **SQL step** → Structured operations (filter, aggregate, join)
2. **LLM step** → Semantic reasoning (inference, understanding)
3. **Verification** → Ensures correctness

Back-and-forth reasoning:

SQL ↔ LLM ↔ SQL ↔ LLM

Phase 1: Preprocessing

Prepare the data:

- Extract metadata and constraints
- Identify table schema and data types
- Filter irrelevant columns

Table QA

1990 British Grand Prix

Rank	Driver	Constructor	Laps	TimeRetired
1	Alain Prost	Ferrari	64	1:18:31
2	Thierry Boutsen	Williams-Renault	64	39.092
3	Ayrton Senna	McLaren-Honda	64	43.088
4	Éric Bernard	Lola-Lamborghini	64	401:03:00

Question: which country had the most competitors?

Gold Answer: **Italy**

Pre-processed table ①

Relevant Columns: {Driver}

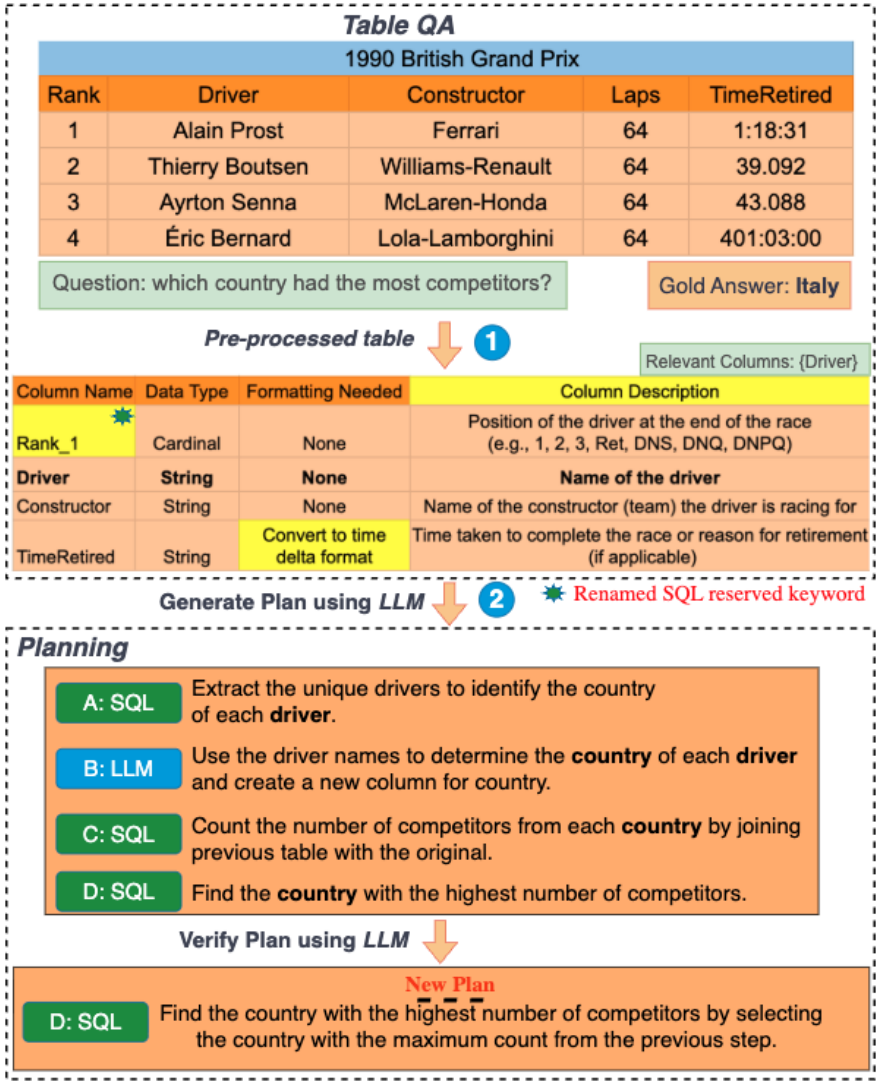
Column Name	Data Type	Formatting Needed	Column Description
Rank_1 ✸	Cardinal	None	Position of the driver at the end of the race (e.g., 1, 2, 3, Ret, DNS, DNQ, DNPQ)
Driver	**String**	**None**	**Name of the driver**
Constructor	String	None	Name of the constructor (team) the driver is racing for
TimeRetired	String	Convert to time delta format	Time taken to complete the race or reason for retirement (if applicable)

✸ Renamed SQL reserved keyword

Phase 2: Planning

LLM generates a dynamic execution plan:

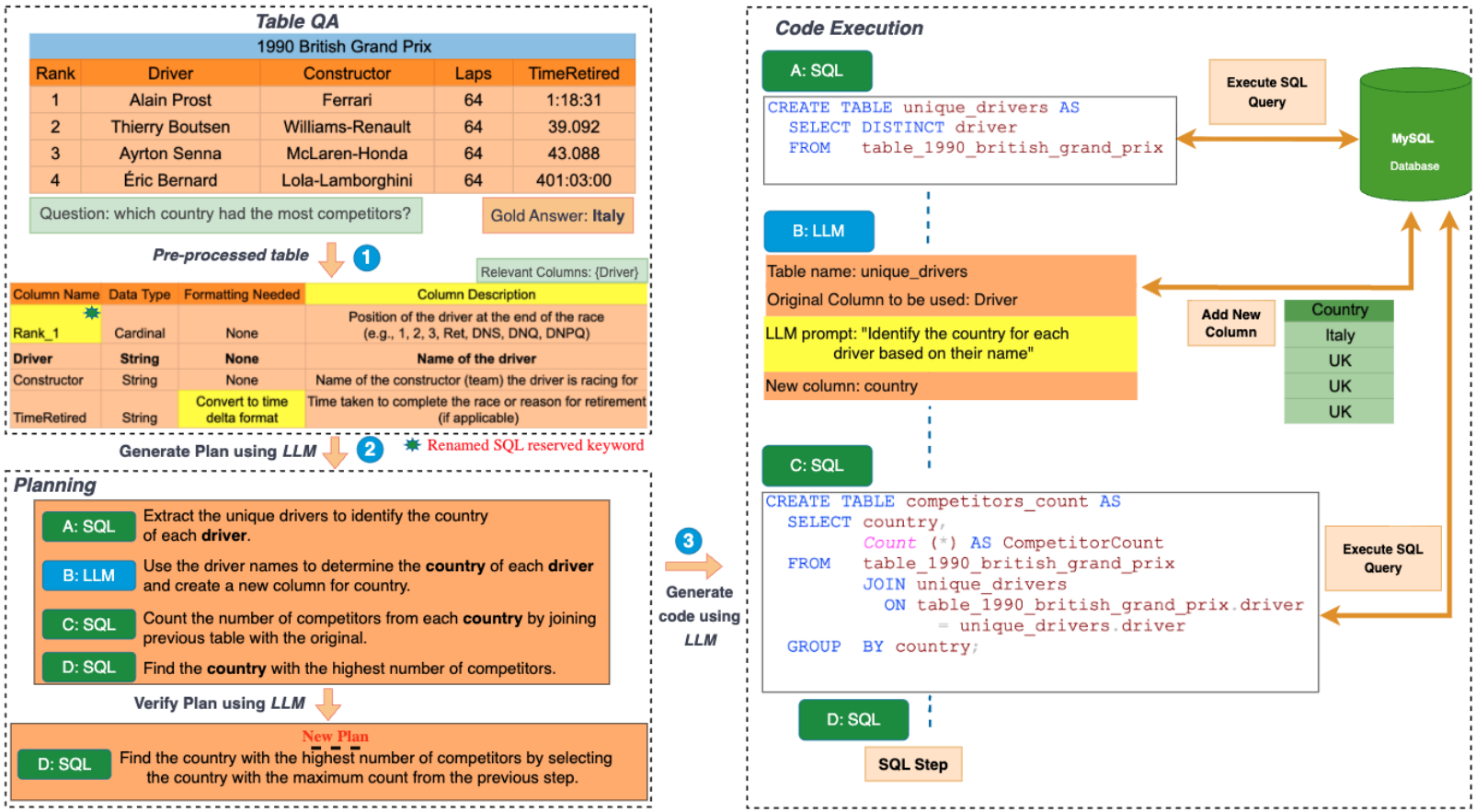
- Generate step-by-step execution plan
- Determine SQL vs. LLM operations for each step
- Adapt plan based on query complexity



Phase 3: Code Execution

Dynamic interweaving of SQL and LLM:

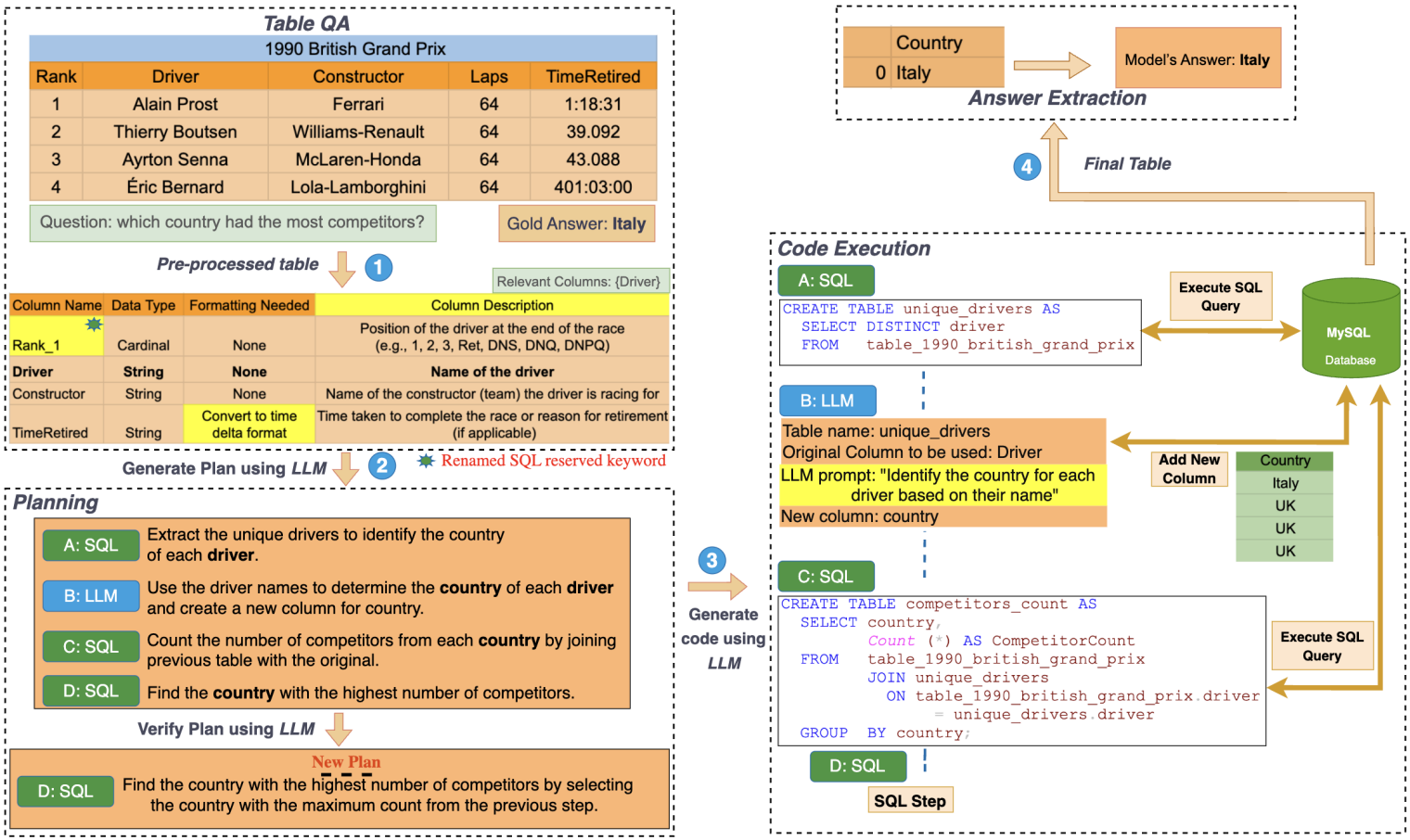
- Execute SQL queries on structured data
- Run LLM inference for semantic tasks



Phase 4: Answer Extraction

Generate final answer:

- Extract Answer from final table
- Format and validate the final answer



Example Walkthrough:

Question: Which country had the most competitors?

1. **SQL step:** Extract unique drivers

   `SELECT DISTINCT driver COUNT(*) FROM table`

2. **LLM step:** Infer country from `driver` column

   `"Alain Prost" → France, "Thierry Boutsen" → Belgium`

3. **SQL step:** Count competitors by country

   ```
   SELECT country, COUNT(*) as competitors
   FROM unique_drivers GROUP BY country
   ```

4. **Final Answer:** Italy

Key Benefit: Every step is transparent and interpretable

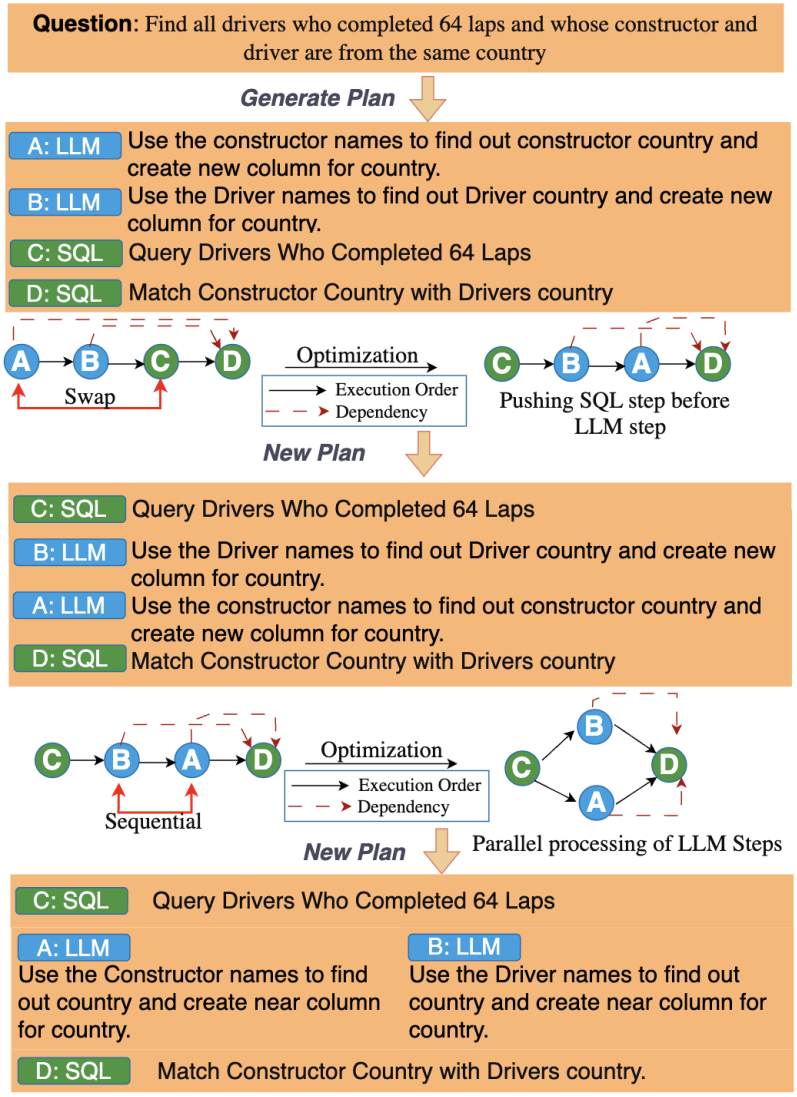
Planning Optimization for Fewer API Calls

Optimization strategies:

- **SQL reordering**
- **Parallelization**
- **Batch processing**

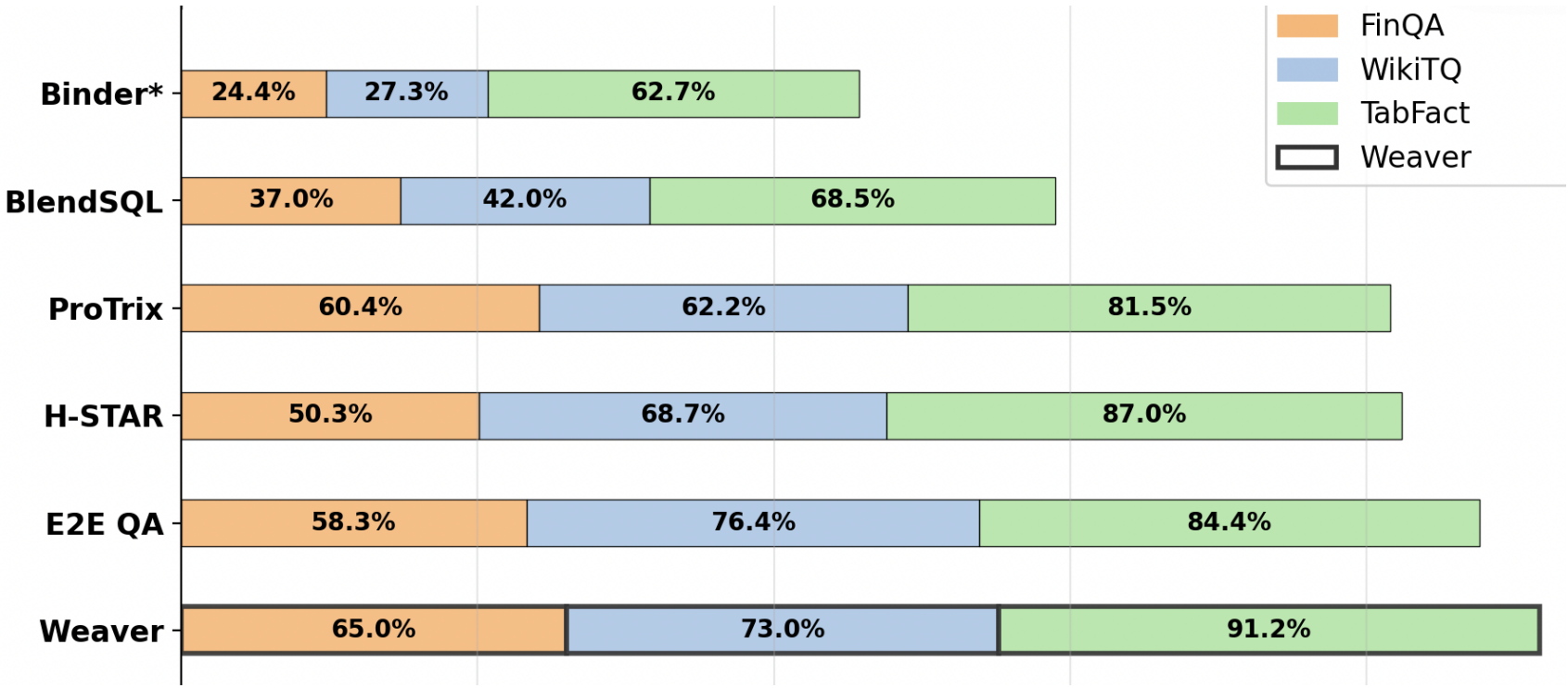
Result:

23% reduction in total steps with 1% accuracy loss



Weaver Outperforms State-of-the-Art

Performance on major benchmarks:



Key achievements:

- **+5%** accuracy improvement across datasets

Extends to Text + Image Tables

Multimodal Table QA Performance:

Dataset	Modalities	Accuracy Gain
MMTabQA	Text + Images	**+6.6%**
FinQA-MM	Tables + Passages	**+17.3%**
OTT-QA-MM	Tables + Passages	**+2.9%**

Highlight: Weaver handles reasoning across:

- Structured tables
- Unstructured text
- Embedded images

Unified framework for multimodal table reasoning

Efficacy & Efficiency

Efficiency:

- Average 6 API calls per query

Method	API Calls
Binder	50
H-STAR	8
Weaver	**5.5**

Efficacy:

- 28.1% accuracy improvement on large tables

Method	API Calls
H-STAR	35.9%
ProTrix	37.5%
Weaver	**65.6%**

Interpretability:

- Transparent step-by-step plan
- Intermediate tables visible
- Easy debugging and verification

Conclusion

Dynamic SQL–LLM weaving enables accurate, interpretable, and efficient Table QA

Key Takeaways:

- **Modular, interpretable pipeline** for hybrid table reasoning
- **5–10% accuracy gain** over state-of-the-art methods
- **Multimodal support** (text, image, table)
- **Flexible planning** adapts to query complexity

Link:

`coral-lab-asu.github.io/weaver`

Future Work

- Multi-table reasoning with joins across databases
- Multilingual table support (non-English tables)
- Hierarchical & nested data structures
- Integration with database systems