What Table Representation Learning Brings to Data Systems

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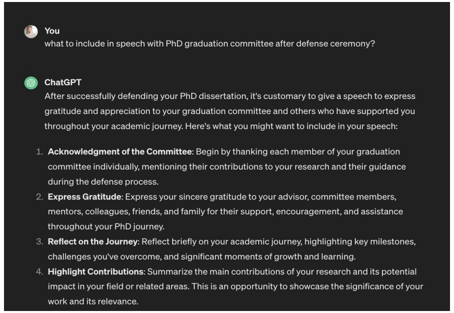
5 December 2024

CWI

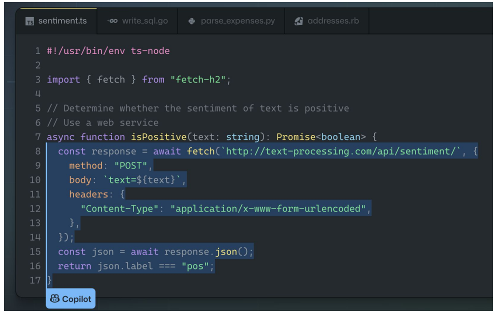
The Impressive Capabilities of Transformers

Transformer-architecture leveraged for applications over images, text, code:

Generating funny dog images



Writing graduation speech

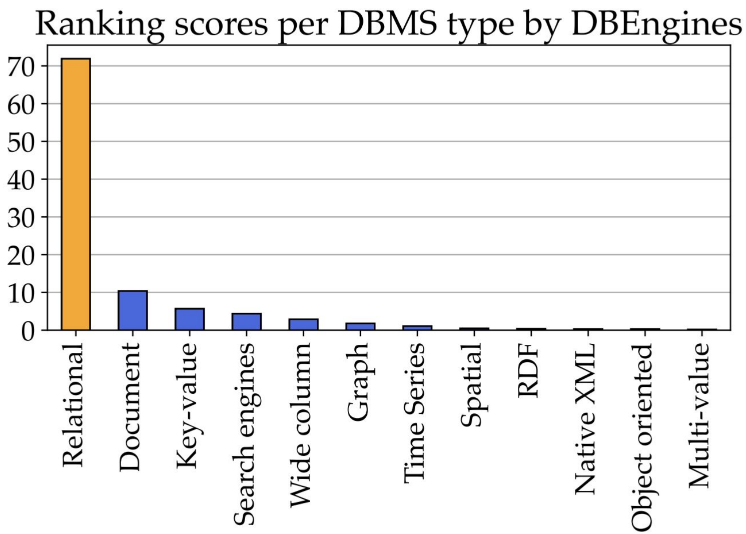


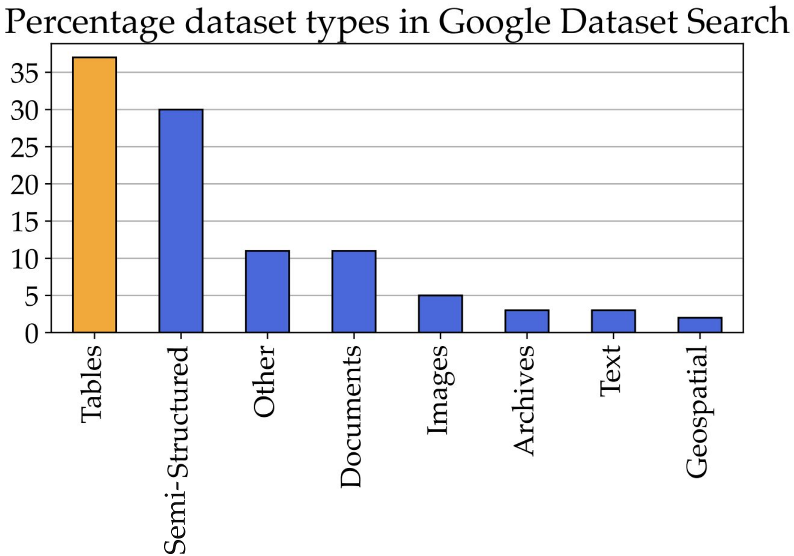
Completing code

What about tables?

We have LLMs... why not analyze docs?

Tables Dominate the Data Landscape

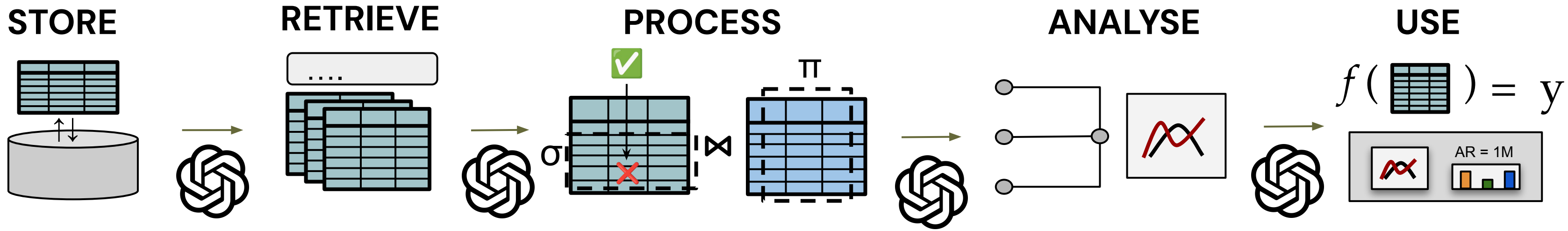




Potential of Table Representation Learning

Available... but also: fresh, structured, domain, data!

High value use-cases, e.g. *data analysis:* many tables, many tasks!



- indexing
- query execution
- compression

- search
- validation
- exploration

- transformation
- augmentation
- cleaning

- aggregation
- statistics
- visualization

- insight extraction
- machine learning
- dashboarding

Relational data: rich and challenging

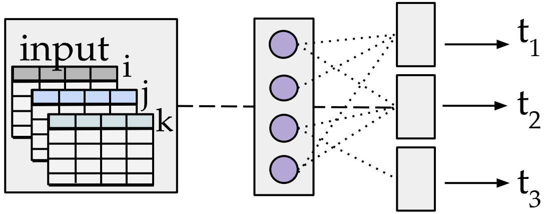
Diverse in dimensions, structure, cleanliness and semantics…

crop rotation : Tabelle

Nr	ID	seed rate	yield	crop	cultivar	pre crop	pre-pre crop	pre-pre-pre	soil type	precipita	tempera	comment
1	68		91	winter wheat		sugar beets	beans		sandy loam, loe	636	9,6	wb, sg,
2	68		100	winter wheat		sugar beets	rotation fallow		sandy loam, loe	636	9,6	cultivation
3	68		97	winter wheat		sugar beets	fallow land (5,5y)		sandy loam, loe	636	9,6	1993-1996
4	136		95	winter wheat		oats	sugar beets		sandy loam, loe	636	9,6	
5	136		96	winter wheat		potatos	sugar beets		sandy loam, loe	636	9,5	cultivation
6	136		107	winter wheat		sugar beets	maize		sandy loam, loe	636	9,5	1991-1994
7	136		107	winter wheat		sugar beetsn	summer wheat	maize	sandy loam, loe	636	9,5	
8	136		82	winter wheat		oats	sugar beets	sugar beets	sandy loam, loe	636	9,5	organic
9	136		77	winter wheat		potatos	sugar beets		sandy loam, loe	636	9,5	organic
10	136		85	winter wheat		sugar beets	maize	maize	sandy loam, loe	636	9,5	organic
11	136		84	winter wheat		sugar beets	summer wheat	sugar beets	sandy loam, loe	636	9,5	organic
12	57	371	98	winter wheat	Sperber	sugar beets	winter barley	winter wheat	sandy loam, loe	635		wb, ww
13	57	365	98	winter wheat	Sperber	potatos	sugar beets	summer barle	sandy loam, loe	635		cultivation, weed
14	57	365	105	winter wheat	Sperber	sugar beets	maize	maize	sandy loam, loe	635		1987-1992
15	57	365	97	winter wheat	Sperber	sugar beets	winter wheat	sugar beets	sandy loam, loe	635		
16	39	433	90	winter wheat	Okapi	summer barley			sandy loam, loe	690	8,5	oats, cultivation, weec
17	39	433	100	winter wheat	Okapi	oats			clay, silt	690	8,5	1982-1986
18	39	433	97	winter wheat	Okapi	winter wheat			clay, silt	690	8,5	

	2019			delta		
	Profit	Quantity	Sales	Quantity	Sales	Profit
Overall	128.9k	13.3k	1.0m	36.5%	36.2%	30.9%
France	35.1k	3.9k	308.4k	33.8%	33.2%	8.7%
Austria	7.5k	299.0	24.6k	13.3%	11.9%	40.8
Belgium	4.2k	202.0	17.3k	23.2%	82.7%	98.6%
Denmark	-1.3k	86.0	2.8k	4.9%	-21.1%	22.9%
Zealand	-245.0	15.0	242.7			
South Denmark	-362.9	40.0	1.3k	33.3%	-7.7%	41.1
Sonderborg	-45.4	6.0	87.5			
Odense	-280.3	30.0	1.1k	0.0%	-20.1%	54.5
Esbjerg	-37.3	4.0	88.7			
Hovedstaden	-0.7k	31.0	1.3k	-40.4%	-40.9%	35.4%
Copenhagen	-0.7k	31.0	1.3k	0.0%	-29.5%	23.1
Frederiksberg	232.1	11.0	1.1k			
Finland	36.0k	2.4k	216.5k	-79.6%	-81.4%	-86.2%
Germany	-3.9k	152.0	7.2k	15.0%	46.3%	32.9%
Ireland	10.6k	1.4k	109.7k	17.8%	101.6%	-152.5%
Italy	-11.6k	0.6k	23.7k	37.5%	37.2%	57.6%
Netherlands	2.9k	135.0	12.9k	46.3%	12.6%	2.5%
Norway	-1.0k	74.0	1.8k	229.3%	230.8%	162.8%
Portugal	20.6k	1.2k	99.1k	-29.5%	-79.2%	82.4%
Spain	-9.4k	360.0	15.6k	46.7%	12.9%	27.1%
Sweden	2.2k	84.0	7.3k	143.2%	167.7%	-128.7%
Switzerland	36.8k	2.4k	194.0k	5.0%	-25.6%	-29.1%
United Kingdom	1.3k	48.0	4.0k	66.4%	66.4%	32.7%
Wales	1.9k	118.0	6.6k	-5.9%	-30.2%	-28.7%
Scotland	33.6k	2.2k	183.4k	0.9%	-54.6	-55.5

Goal TRL: map tables to some consistent input. Learn some representation that helps detect patterns relevant to given task(s).



Today...

1 The power of table and column **semantics**

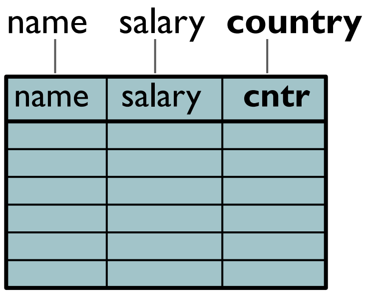
2 What we need to **make TRL work**

3 Towards **end-to-end data analysis** tools

The power of table and column semantics

Essential understanding of a table comes through its columns.

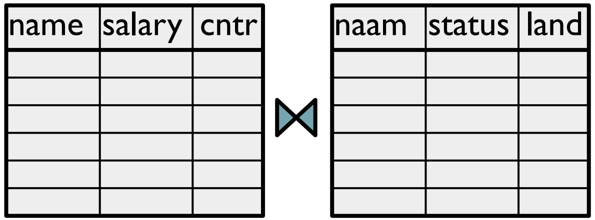
Semantic column types: what and why?



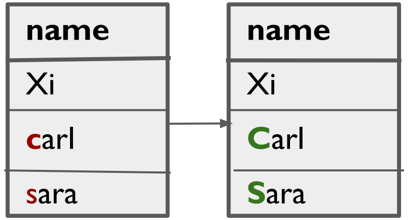
Looks easy, but….

- Undescriptive header?
- Messy values?
- Diverse data types?

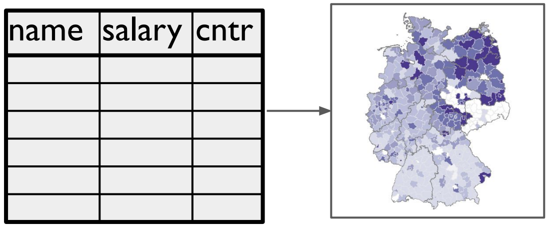
Semantic column types dictate operations *sensible* to perform on them:



Join tables on “name” and “country” columns



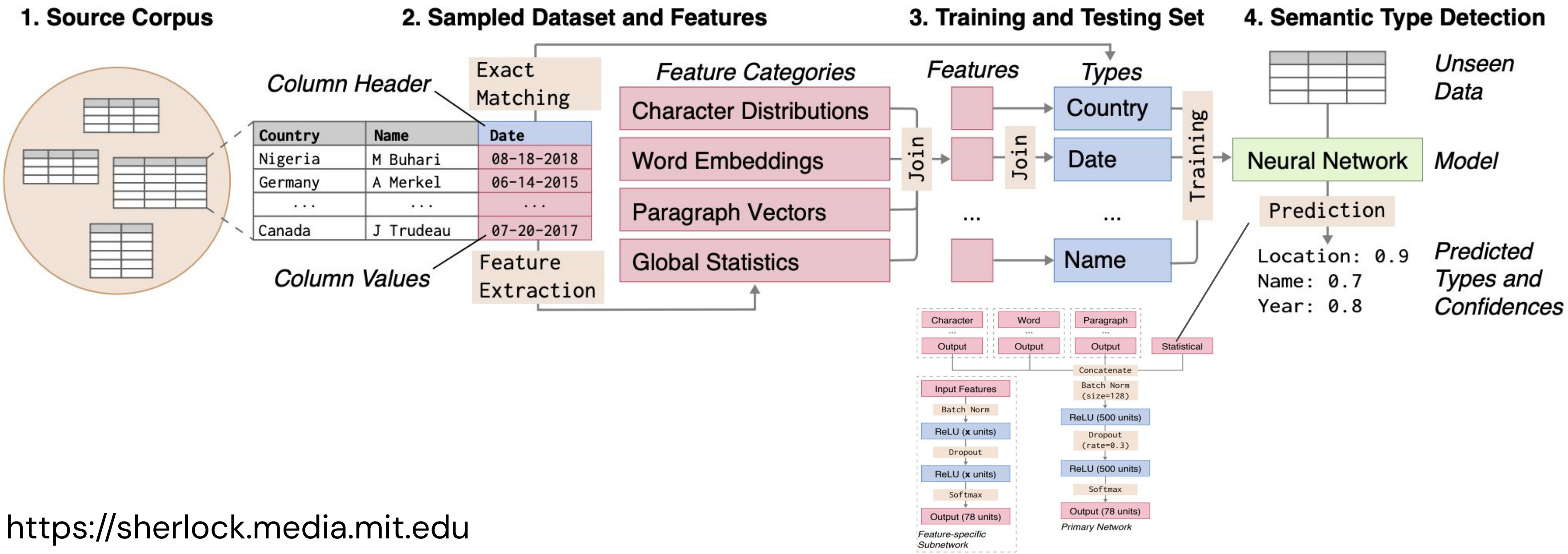
Capitalize “name” columns



Plot “country” data

Sherlock: Column Type Detection with DL

Prior: string matching (header/values) w/ **regex** or dict: robust? scale? accurate?



https://sherlock.media.mit.edu

Sherlock: A Deep Learning Approach to Semantic Data Type Detection. Hulsebos, Hu, Bakker, et al., KDD 2019.

How well does Sherlock detect types?

78 semantic types (name, address, etc).

Method	F_1 Score	Runtime (s)	Size (Mb)
Machine Learning			
Sherlock	0.89	0.42 (±0.01)	6.2
Decision tree	0.76	0.26 (±0.01)	59.1
Random forest	0.84	0.26 (±0.01)	760.4
Matching-based			
Dictionary	0.16	0.01 (±0.03)	0.5
Regular expression	0.04	0.01 (±0.03)	0.01
Crowdsourced Annotations			
Consensus	0.32 (±0.02)	33.74 (±0.86)	–

Examples of misclassifications.

Examples	True type	Predicted type
Low Precision		
81, 13, 3, 1	Rank	Sales
316, 481, 426, 1, 223	Plays	Sales
$, $$, $$$, $$$$, $$$$$	Symbol	Sales
Low Recall		
#1, #2, #3, #4, #5, #6	Ranking	Rank
3, 6, 21, 34, 29, 36, 54	Ranking	Plays
1st, 2nd, 3rd, 4th, 5th	Ranking	Position

Challenges

- Numeric data
- Non-mutually exclusive types

Don’t we have LLMs now?

“Table-tuned” LLM (but not for semantic type detection) [1]:

Zero-Shot		Few-Shot	
GPT-3.5	+table-tune	GPT-3.5	+table-tune
0.332	**0.449**	0.528	**0.538**

Sherlock model: ~0.88 F1.

LLM (GPT-3.5) w/ more examples and specific context [2]:

	F_1-score	Precision	Recall
DoDuo-VizNet∗	0.876	89.4%	87.2%
Sherlock∗	0.954	96.2%	94.6%
TaBERT	0.321	32.6%	32.0%
DoDuo-Wiki	0.440	59.2%	45.4%
Chorus	**0.891**	**91.2%**	**88.8%**

Sure, GPT-x might do better..
but w/ **billions** of params vs **thousands**!

Representation Learning (LM trained on type detection) [3]:

Method	F1	P	R
Sherlock (only entity mention) [17]	78.47	88.40	70.55
TURL + fine-tuning (only entity mention)	88.86	90.54	87.23
TURL + fine-tuning	**94.75**	**94.95**	**94.56**
w/o table metadata	93.77	94.80	92.76
only table metadata	90.24	89.91	90.58

[1] TableGPT: Table-tuned gpt for diverse table tasks. P. Li et al, VLDB, 2024
[2] *CHORUS: Foundation Models for Unified Data Discovery and Exploration*. Kayali, et al. VLDB, 2024.
[3] TURL: Table understanding through representation learning. Xiang Deng, et al., ACM SIGMOD Record, 2022.

Semantics for optimizing data systems

Example: column semantics -> correlations.

Cardinality estimation

Learned Cardinalities:
Estimating Correlated Joins with Deep Learning

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Can Large Language Models Predict Data Correlations from Column Names?

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Cornell Database Group
Ithaca, NY, USA
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Compression

Lightweight Correlation-Aware Table Compression

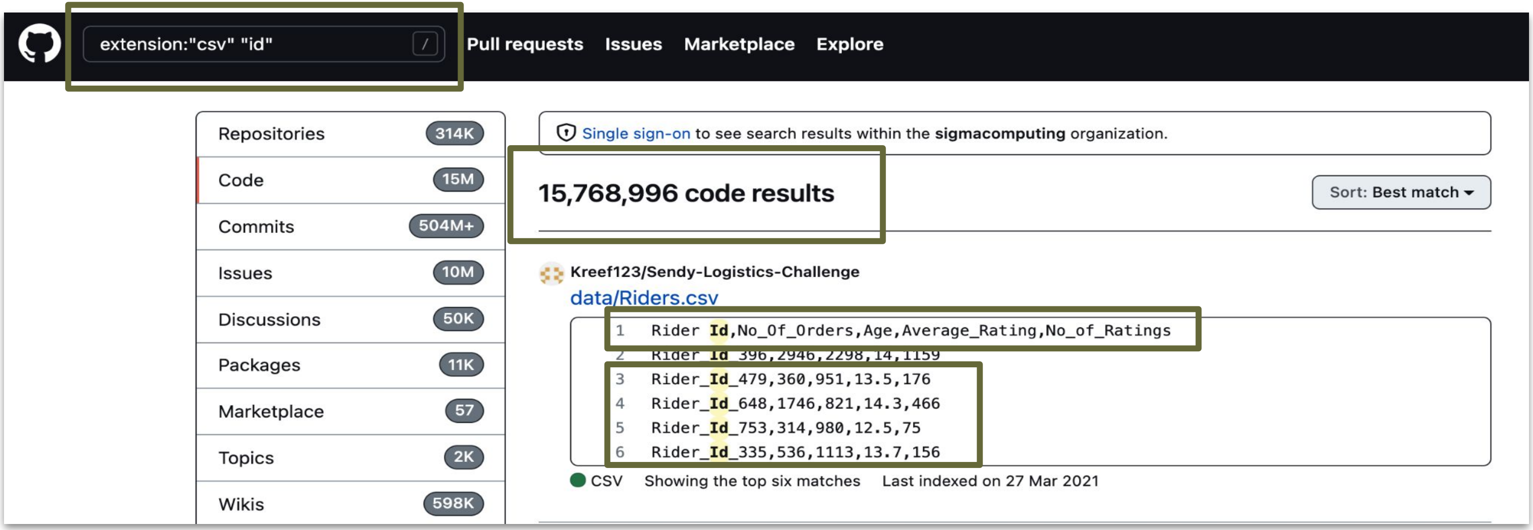
Mihail Stoian, Alexander van Renen, Jan Kobiolka, Ping-Lin Kuo, Josif Grabocka, Andreas Kipf
{mihail.stoian, alexander.van.renen, jan.kobiolka, ping-lin.kuo, josif.grabocka, andreas.kipf}@utn.de
University of Technology Nuremberg

What we need to make TRL work

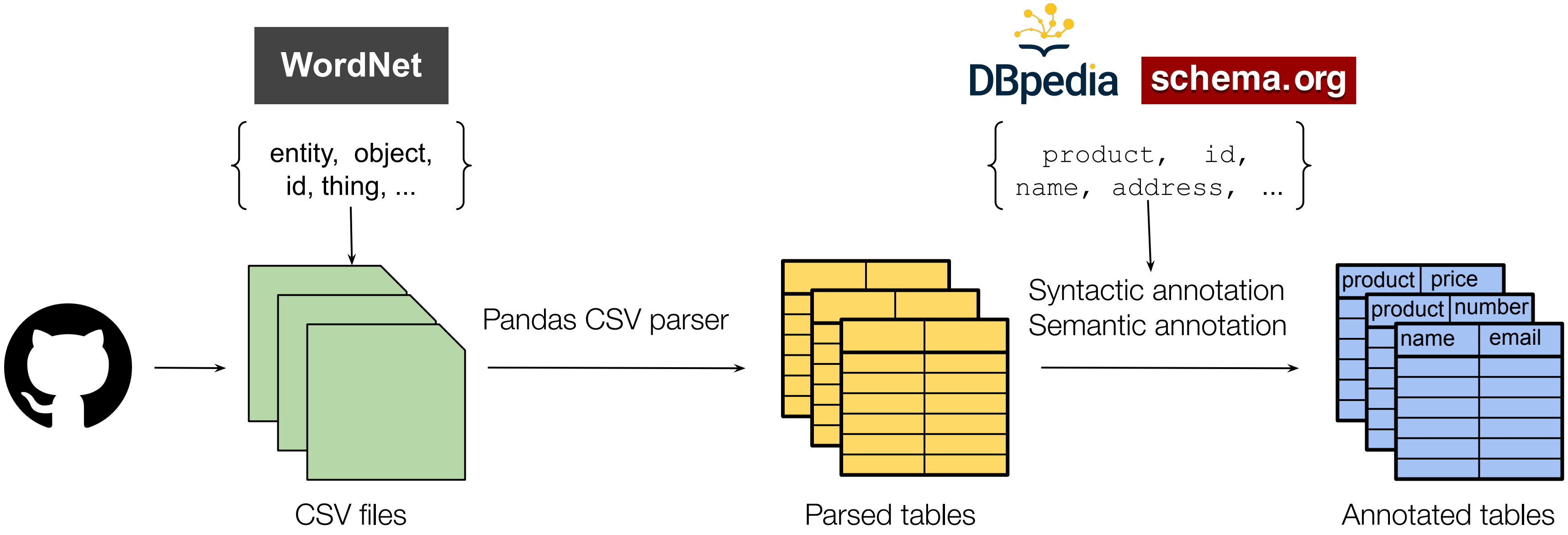
As LLM scaling laws
reach their limits:
it is all about the
“quality” of the data,
and the “tricks” we apply.

What Data Do We Need?

- Web/WikiTables → Web applications. Web tables ≠ DB tables…
- Data tasks on offline tables? GitHub as a data source?



GitTables: a new large corpus with tables



https://gittables.github.io

GitTables: A large-scale corpus of relational tables. Hulsebos, Demiralp, & Groth. SIGMOD, 2023.

Using GitTables

- >1M tables and 800K CSV files.
- Wider+taller, and lots of IDs; more representative.
- Useful for *semantic column type detection* and *schema completion*:

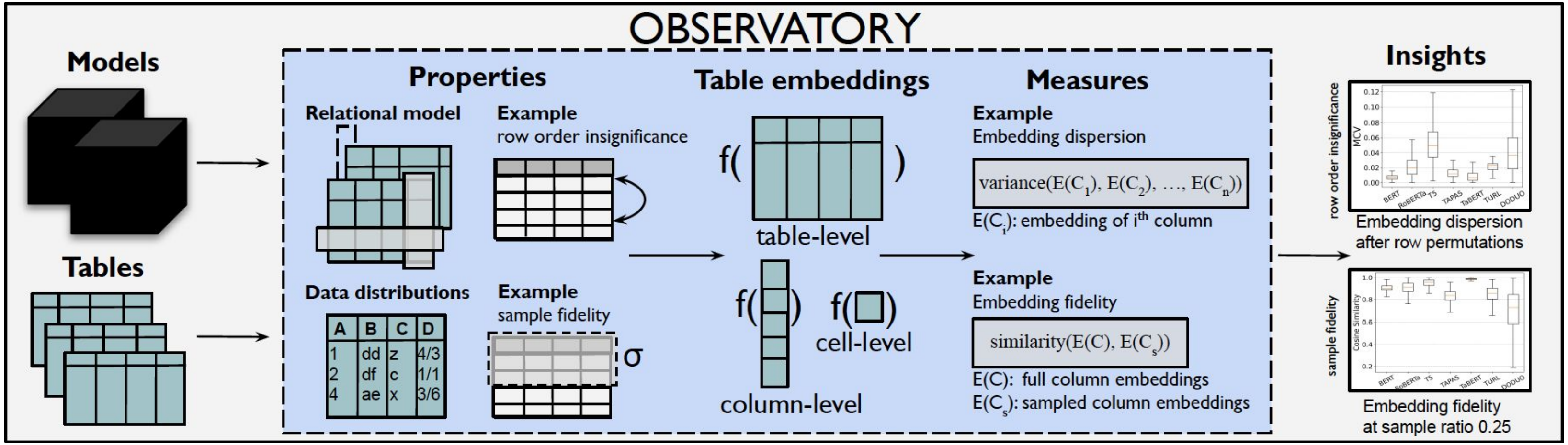
Header prefix	Suggested completion
payment_id, customer_id	review_id, product_id, product_parent, product_title, …
id, company	ReceivablePaymentHeader, ReceivablePayment, Status, Customer, BankEntity, …
id, name, location	phone, email, uid, active, ad_organization_id, …

Used for join discovery, CSV parsing, KG enhancement, retrieval eval, etc.
Other corpora to bridge the “realism gap” e.g. **SchemaPile**, **BIRD**, **Spider**.

Do ‘tableLM’ **tricks** capture relational properties?

Tables ≠ natural language

Studying neural table embeddings through **Codd’s relational model.**



Observatory: Characterizing Relational Table Embeddings. Cong, Hulsebos, Sun, Groth, Jagadish, VLDB, 2024.

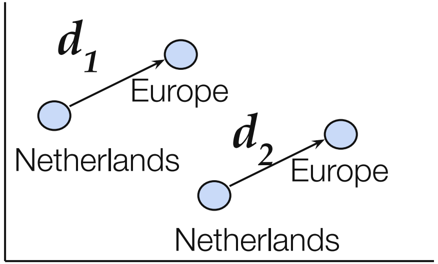
Example Property: Functional Dependencies

Given table with FD: X=country → Y=continent

ID	name	country	continent
1	Kathryn	Netherlands	Europe
2	Oscar	Netherlands	Europe
3	Lee	Canada	North America
4	Roxanne	USA	North America
5	Fern	Netherlands	Europe
6	Raphael	USA	North America
7	Rob	USA	North America
8	Ismail	Canada	North America

We argue that:

- FD relations interpretable as *translation* between embeddings E($\pi X(s)$) and E($\pi Y(s)$)
- Model preserves FD if $d(E(\pi X(s)), E(\pi Y(s))) = d(E(\pi X(t)), E(\pi Y(t)))$ where *d* preserves magnitude+direction (L1/L2-norm).
- Intuitively:



Current Architectures Often Fall Short...

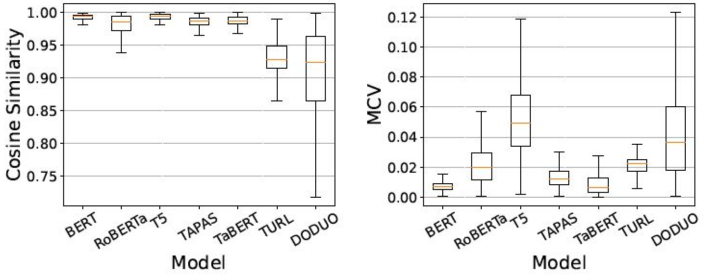
Turns out, most models do not preserve FDs!

RM [4] also has straightforward properties:

A *relation* then consists of a set of tuples, each tuple having the same set of attributes. If the domains are all simple, such a relation has a tabular representation with the following properties.

(1) There is no duplication of rows (tuples).
(2) Row order is insignificant.
(3) Column (attribute) order is insignificant.
(4) All table entries are atomic values.

Measure by avg cosine similarity of col embeddings across row permutations.



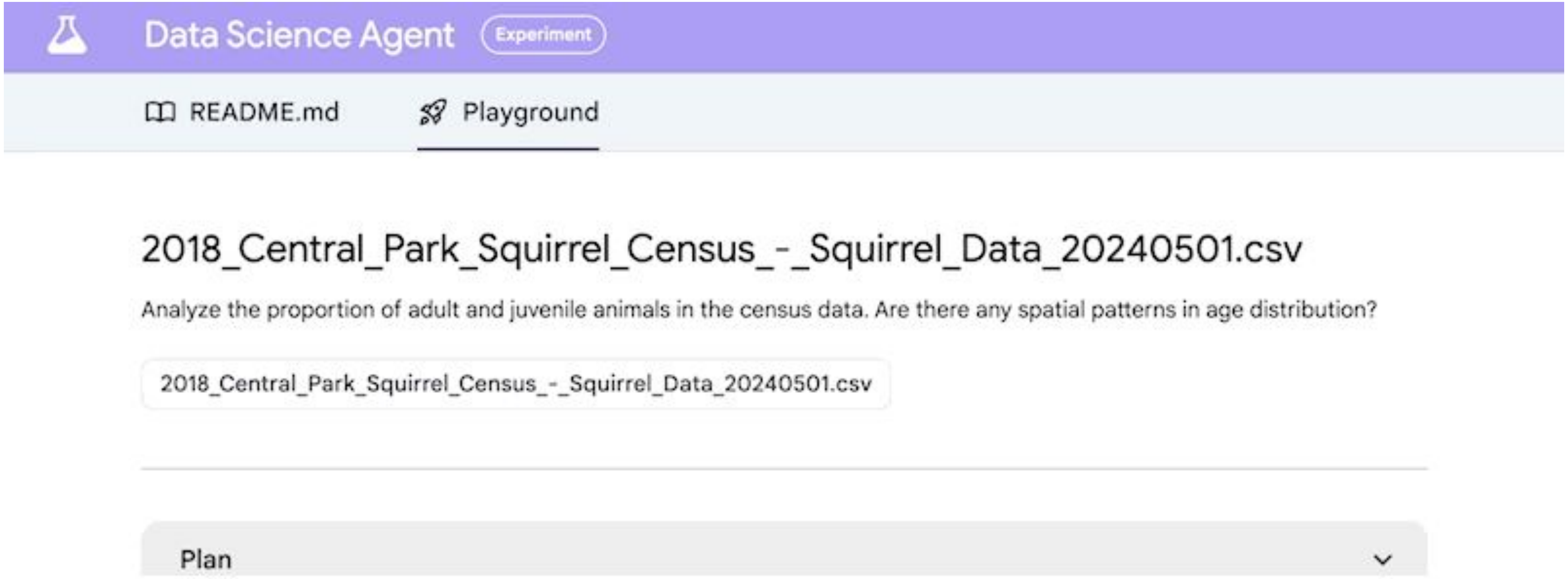
row order robustness

Impact downstream tasks: **row shuffling affects 34%** semantic column types!

Extending the Database Relational Model to Capture More Meaning, Codd, 1979.

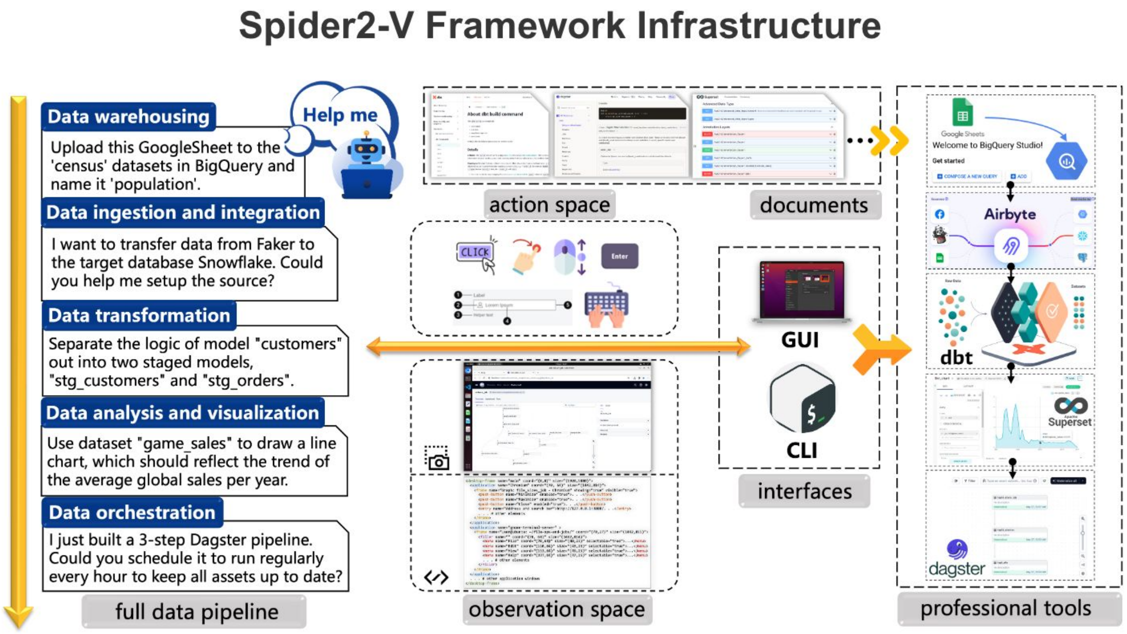
Towards end-to-end data analysis systems

End-to-end DS goes far beyond "automl"



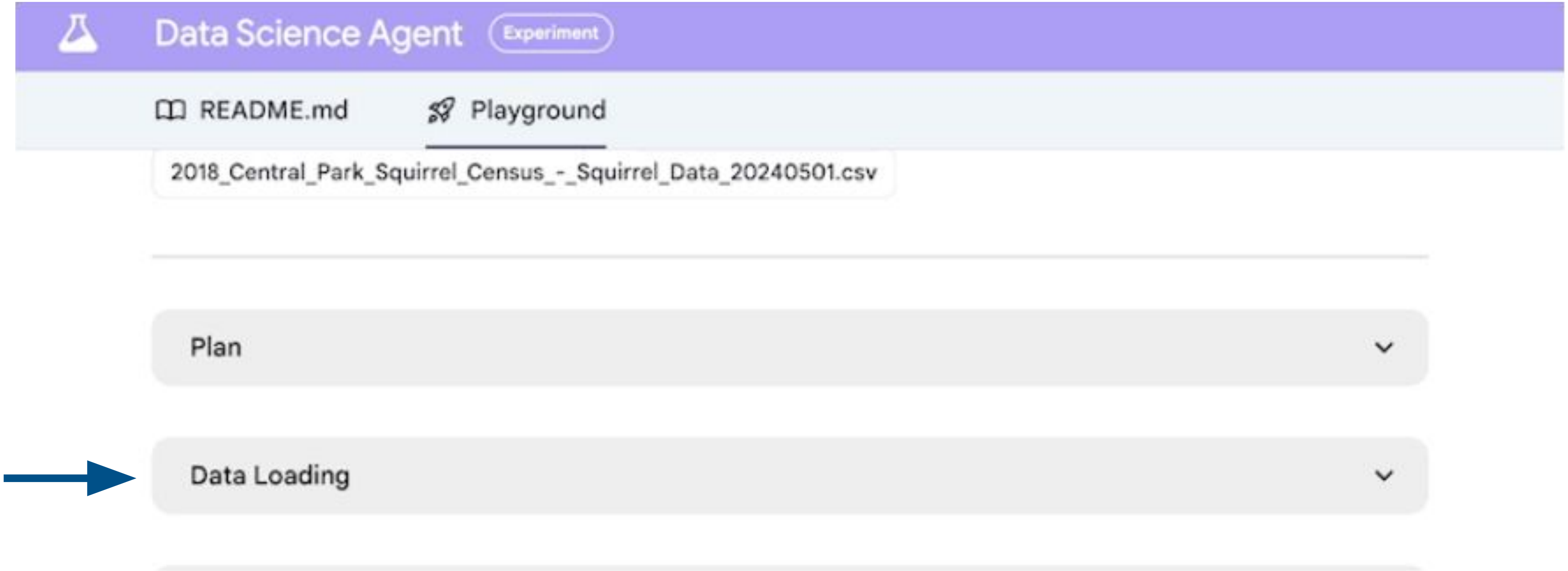
Typically lots of text-to-code (e.g. SQL) involved!

From DS codegen to **DS GUI** agents



Spider2-V: How Far Are Multimodal Agents From Automating Data Science and Engineering Workflows? Ruisheng Cao, et al., NeurIPS Datasets & Benchmarks 2024

Sounds cool, how do we get there?



Who or what is doing data analysis, it will need the right data first.

Finding the right data
for basic questions or
deep analysis
is *still* not easy.

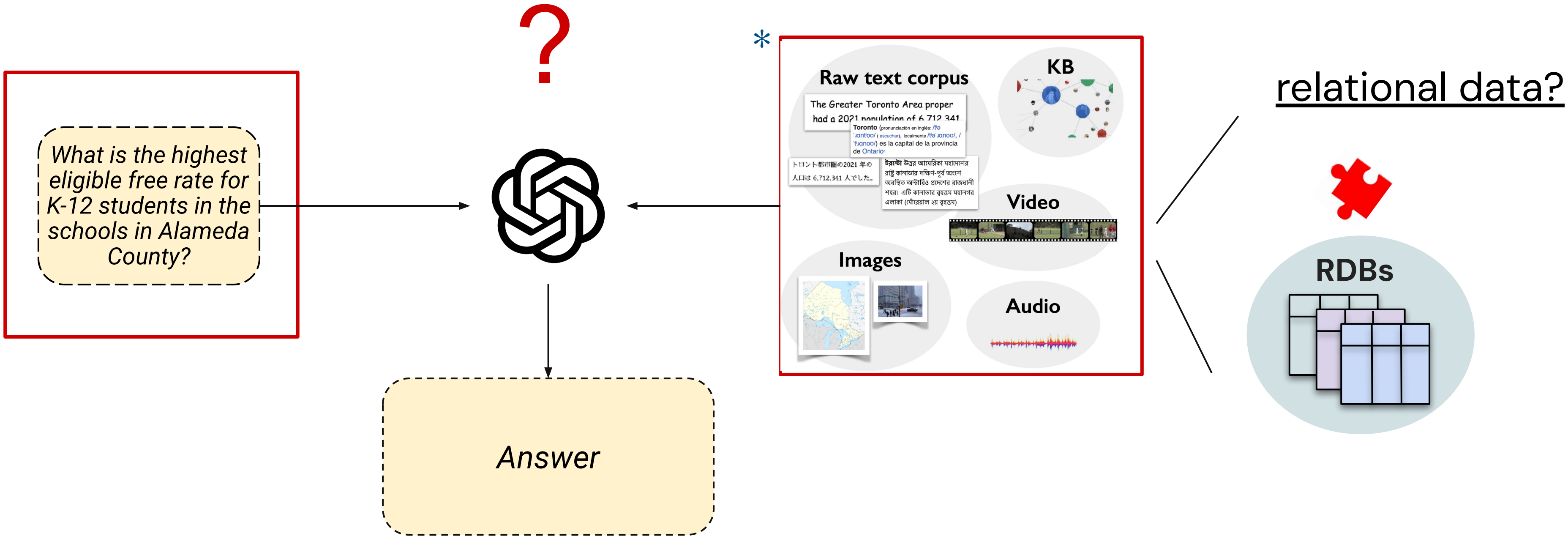
Asking LLMs complex questions

What is the highest eligible free rate for K-12 students in the schools in Alameda County?

*"…. To determine the highest free rate specifically in Alameda County schools, **you'd generally need data from specific school districts or schools in the area**, as this rate can vary widely depending on the socio-economic demographics of each district. …" **

*Generated with chatgpt on 6 October 2024

We need “specific” data to ground LLMs

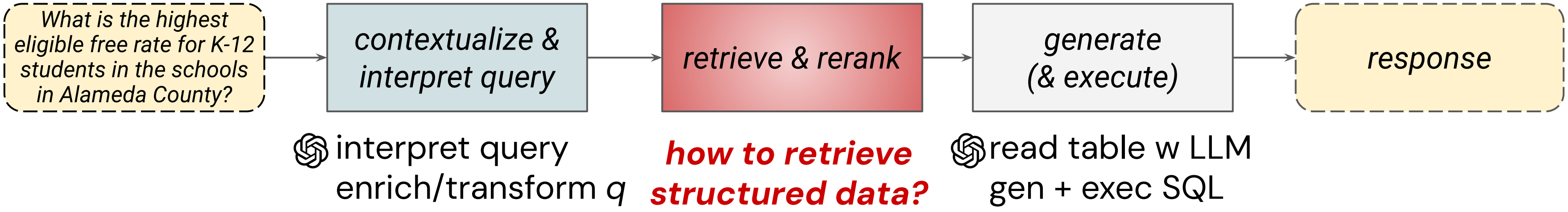


Queries & RAG pipeline

"Which urban Japanese prefecture is not associated with thorny trees?" [table lookup]

"Shane Hall ran a total of 190 races between the year of 1995 - 2008" [aggregate & compare]

"What is the highest eligible free rate for K-12 students in the schools in Alameda County" [aggregate]



Retrieval is difficult, but crucial…

“.. keep in mind that a good RAG system is really hard to build.

If your **retrieval system is mediocre**,
the **retrieval can easily distract LLMs**…

There is still a long way to go.” - Wenhu Chen (Univ of Waterloo)

Methods for table retrieval

① Embed tables in corpus

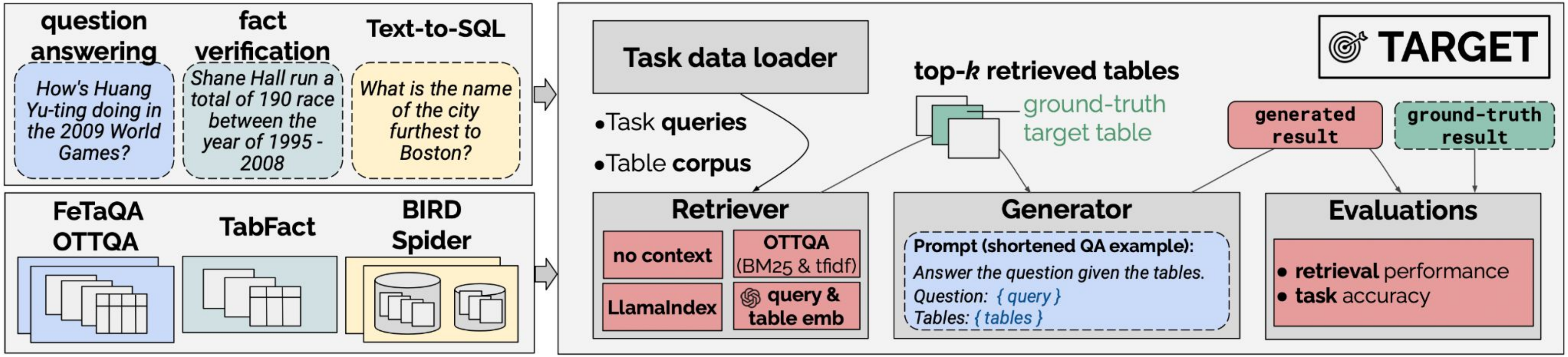
- BM25 / TF-IDF (sparse lexical representations)
- Generate summary/metadata → embed summary + table
- "Naive" embedding of table (header / header+rows) and query

② Embed query

③ Similarity search (e.g. cosine similarity) to identify top-*k* relevant tables

But how effective are these? How robust across datasets and tasks? No one really knows!

TARGET: Benchmarking Table Retrieval for Generative Tasks



https://target-benchmark.github.io (`pip install target_benchmark`)

TARGET: benchmarking Table Retrieval for Generative Tasks, Ji, Parameswaran, Hulsebos.
Table Representation Learning workshop NeurIPS, 2024.

TARGET insights

Method	Question Answering						Fact Verification			Text-to-SQL					
	OTTQA			FeTaQA			TabFact			Spider			BIRD		
	R@10	s	SB	R@10	s	SB	R@10	s	P/R/F1	R@1	s	EX	R@1	s	EX
No context	-	-	0.414	-	-	12.495	-	-	0.578/0.42/0.44	-	-	0	-	-	0
OTT-QA BM25	**0.955**	0.001	0.606	0.082	0.001	1.631	0.338	0.001	0.75/0.26/0.39	0.635	0.001	0.385	0.709	0.001	0.181
w/o table title	0.443	0.001	0.529	0.084	0.001	1.555	0.331	0.001	0.75/0.26/0.38	0.5	0.001	0.376	0.535	0.001	0.164
OTT-QA TF-IDF	0.950	0.001	0.425	0.083	0.001	1.639	0.336	0.001	0.75/0.26/0.38	0.622	0.001	0.474	0.640	0.001	0.227
w/o table title	0.43	0.001	0.593	0.083	0.001	1.527	0.322	0.001	0.75/0.25/0.37	0.492	0.001	0.376	0.491	0.001	0.164
LlamaIndex	0.458	0.354	0.507	0.435	0.396	13.745	**0.827**	0.297	0.73/0.34/0.47	0.735	0.198	0.559	0.937	0.228	0.311
OpenAI embedding	0.950	0.190	0.599	**0.722**	0.200	17.64	0.779	0.189	0.76/0.51/0.61	0.768	0.193	0.602	0.926	0.199	0.317
header only	0.950	0.189	0.61	0.718	0.18	17.66	0.781	0.187	0.75/0.48/0.58	**0.833**	0.175	0.646	**0.958**	0.191	0.323

- BM25/TF-IDF **less effective than for text**, only works with descriptive table name.
- Table **rows can "distract" embeddings**, particularly in RDBs as seen in practice.
- Generating summary/metadata can help, but **not all tables easy to LLM-summarize**.

Still much to explore...

- What is the right input of (meta)data to not "distract" embedding?
- How do we route to proper data source, interpret the task, etc?
- **The reality in practice is much harder**:
  - How do methods perform on more *challenging tasks & datasets*?
  - Closing semantic gap *e*(query) and *e*(table); most public datasets relatively "easy" match between query and tables.
  - Relational databases are large → in-DB schema and table retrieval.

Roadmap for TARGET

Take aways...

- **Tables are everywhere,** serving **high-value use-cases** in e.g. gov, health, finance.
- **Tables ≠ natural language**: tables come with **specific properties** (e.g. relational).
- Capabilities of **"foundation" models should extend to tables & relational DBs**.
- For this, we need the **right data**, and the **right "tricks"**.
- For any data analysis system, human or agentic; **retrieval is key** (e.g. tables, context).

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Hulsebos, M., Hu, K., Bakker M., et al. "Sherlock: A deep learning approach to semantic data type detection." ACM SIGKDD 2019.
Hulsebos, M., Demiralp, C., Groth, P. "GitTables: A large-scale corpus of relational tables." SIGMOD 2023.
Cong, T., Hulsebos M., Groth, P., Jagadish, H. "Observatory: Characterizing embeddings of relational tables." VLDB 2024.
Ji, X., Parameswaran, A., Hulsebos., M. "TARGET: Benchmarking Table Retrieval for Generative Tasks." TRL @ NeurIPS 2024.