

Bespoke-Card: Why Tune When You Can Generate? Synthesizing Workload-Specific Cardinality Estimators



Johannes Wehrstein, Anton Winter, Timo Eckmann, Carsten Binnig
Technical University Darmstadt, Germany

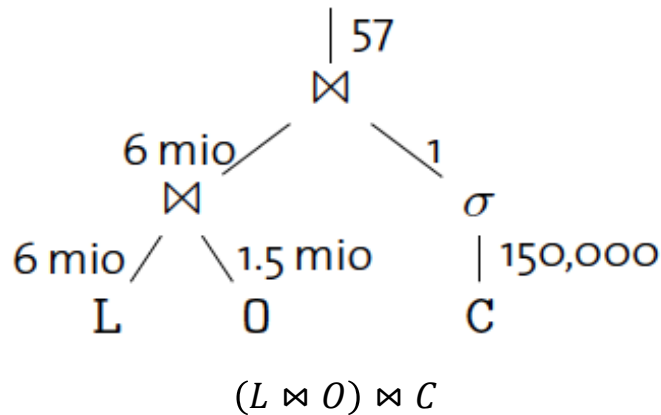


SYSTEMS



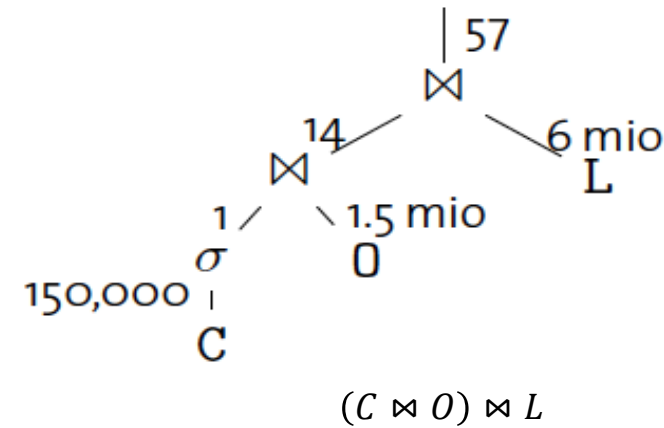
Query Optimization in a nutshell

Determines join-orders, physical operator selections...



Intermediate Cardinalities:

13.65 M



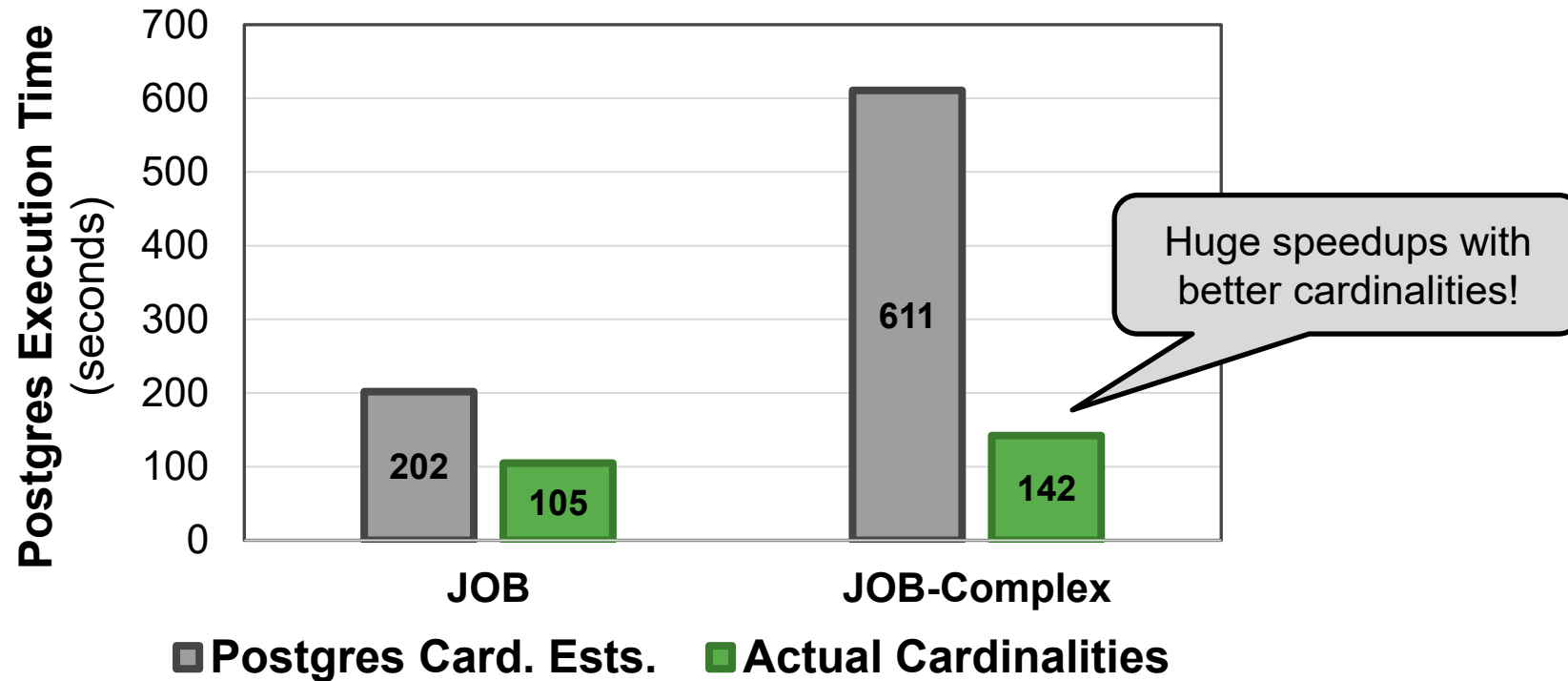
Intermediate Cardinalities:

7.65 M

Decision between plans decided by cardinality estimates

Cardinality Estimation sits at the core of Query-Optimization

Accurate Cardinalities Are Important



What is the problem with existing cardinality estimators?

Pitfalls of existing approaches

Independence assumption:

City	Country
Darmstadt	Germany
Darmstadt	USA
Paris	France
London	GB
...	...

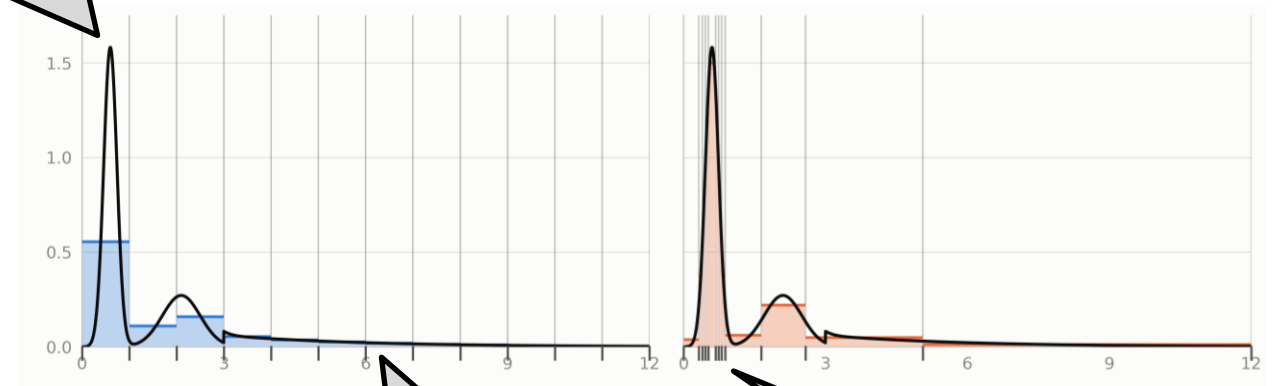
Columns are correlated!
Traditional 1-D Hists / ...
assume independence

Pre-sized statistics:

Not capturing peak

*Equi-Width Histogram
(12 bins)*

*Optimal Binning
(12 bins)*



Useless bins

Bins sized to
where it matters

Classical approaches are inaccurate

Existing Estimation Methods

Classical Approaches (synopses and sampling)

👍 Fast

OK Limited accuracy (simplifying assumptions)

👎 General purpose

Can't adapt to the workload!

Learned Approaches (data-driven, wl-driven, foundational)

👍 Higher Accuracy (tuned to wl)

👎 Expensive & slow

👎 Very limited (e.g. mostly cannot handle strings)

In practice hard to use
(limited SQL, too costly)

Classical approaches still dominating production

Bespoke-Card: The best of two worlds

Low-overhead
of classical estimators

+

Accuracy
of wl-tuned learned
estimators



**Workload-specific (“Bespoke”)
Classical Estimators**

Histograms with
optimized bin
boundaries

Cross-Column
statistics for cols
queried together

Column/Predicate
specific sampling
methods

Workload-aware
substring / filter
stats

Synthesizing Bespoke-Cardinality Estimators

**Workload
Information**
+
**Database
Statistics**

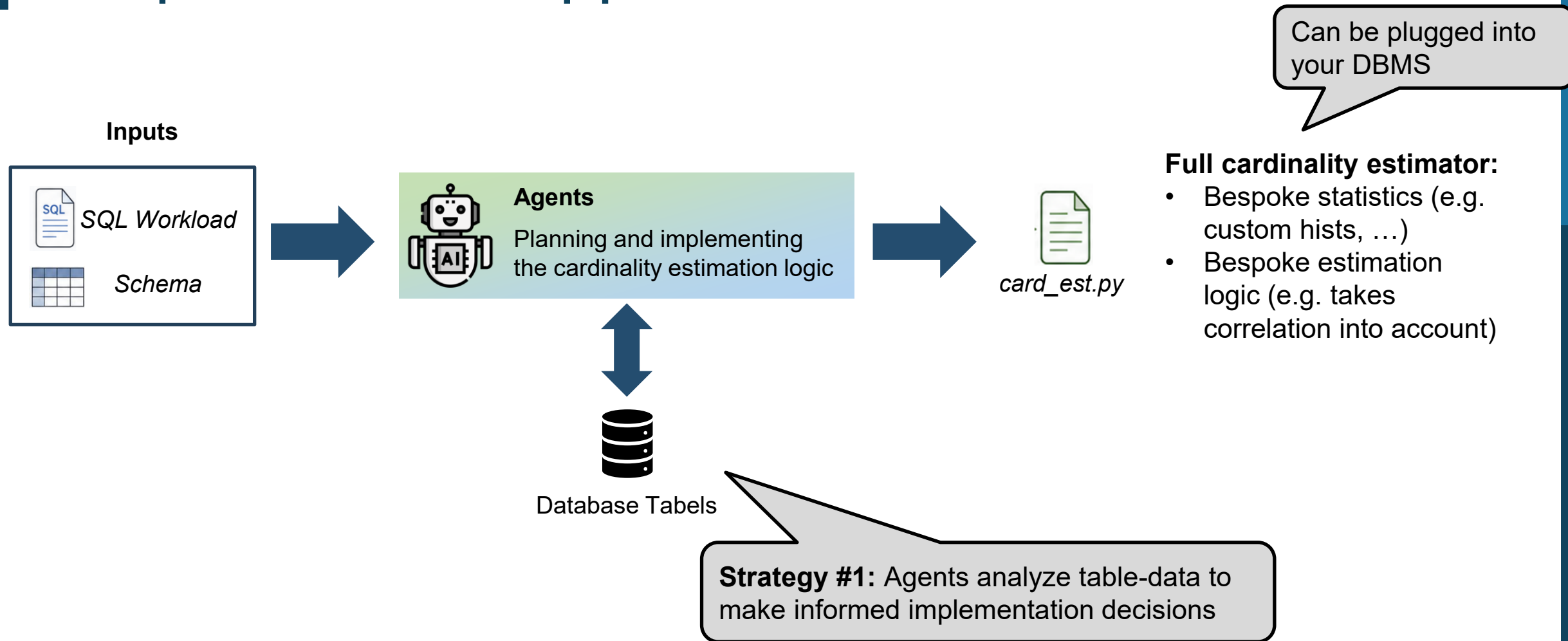


**Bespoke
Cardinality
Estimator**

```
def populate_stats(self, tables: list):  
    # populate bespoke histograms  
    # perform bespoke sampling  
  
def estimate(self, tables: list,  
             filters: list, joins: list) -> int:  
    # query hist / sampling / ... logic  
    est_rows = ...  
  
    return est_rows
```

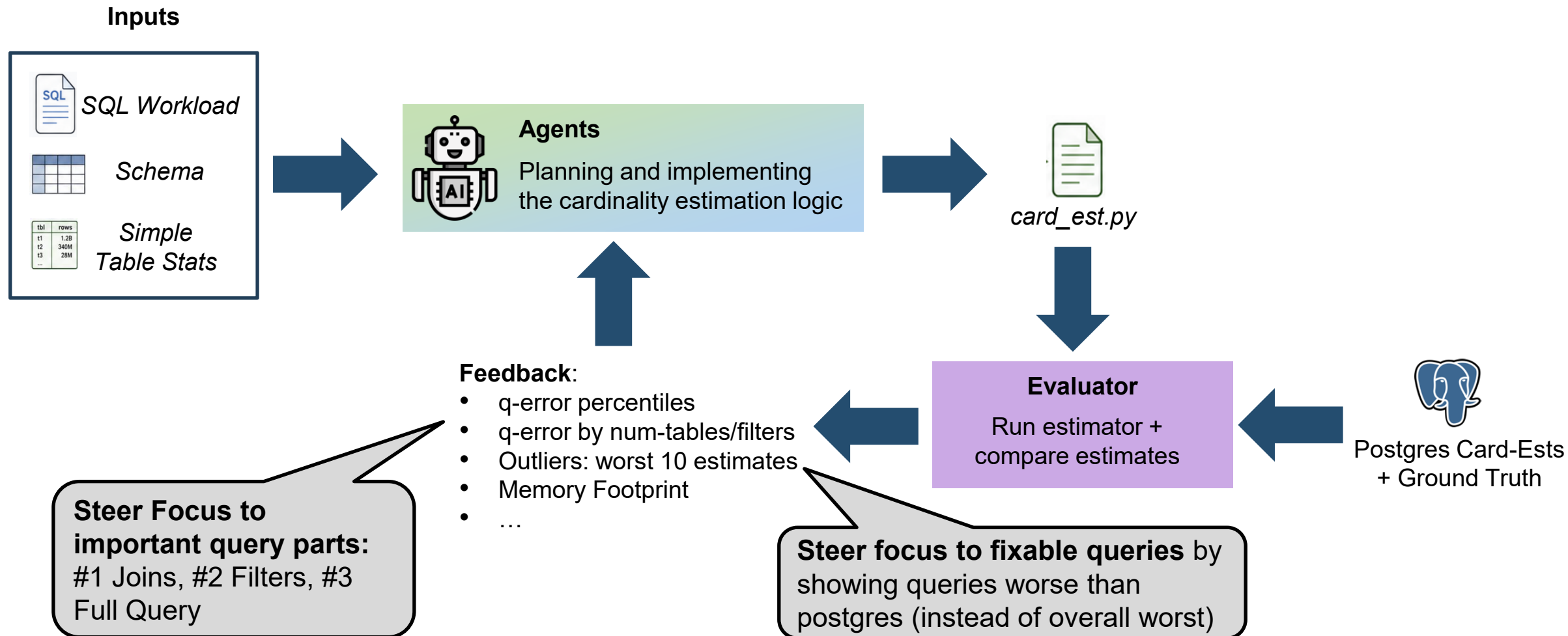
Statistics, hists, ...
designed for the workload!

Bespoke-Card: Approach



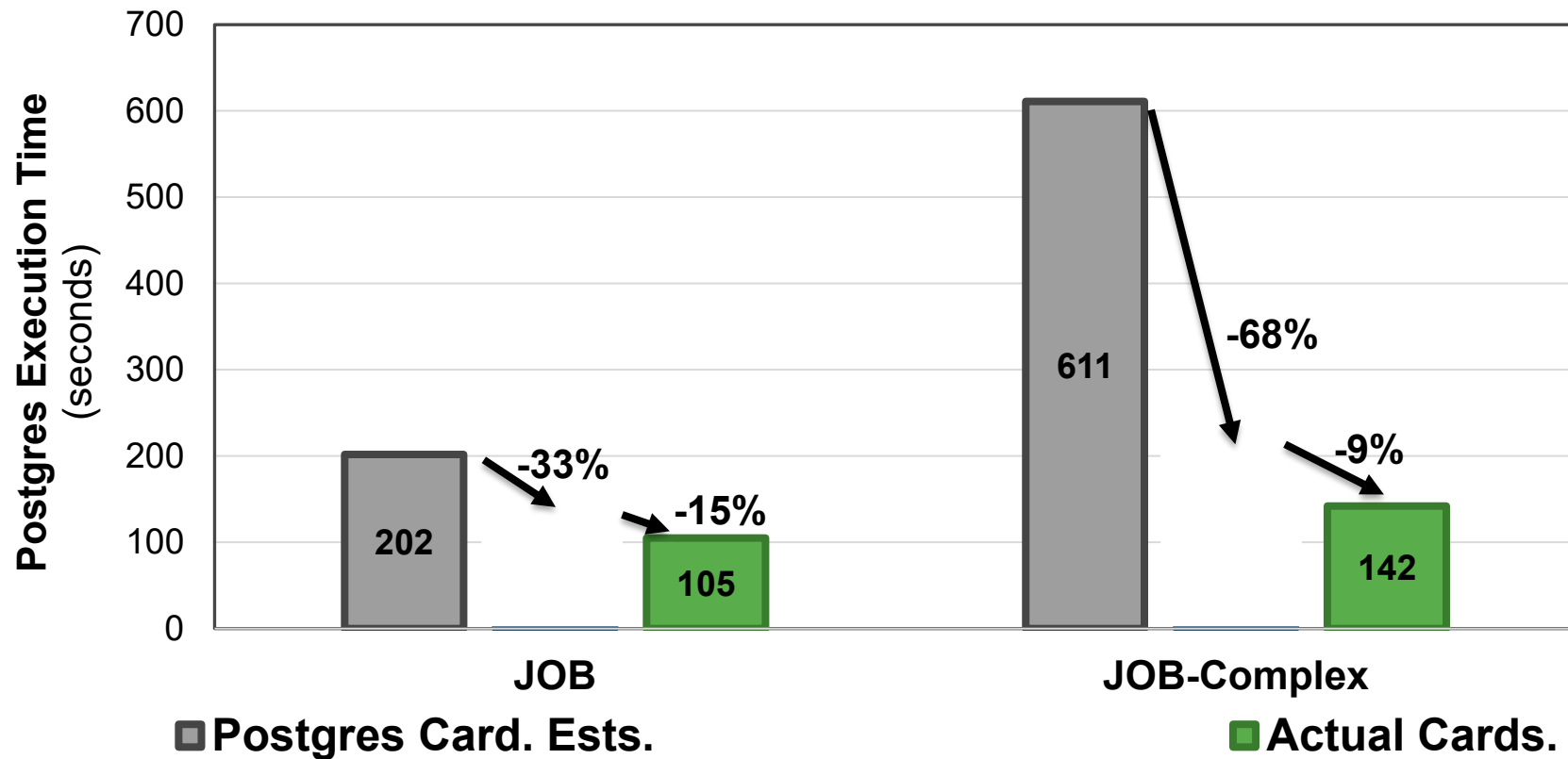
Agents implement estimator with distributions in mind

Strategy #2: Targeted Feedback (optional)



Targeted feedback ensures forward progress

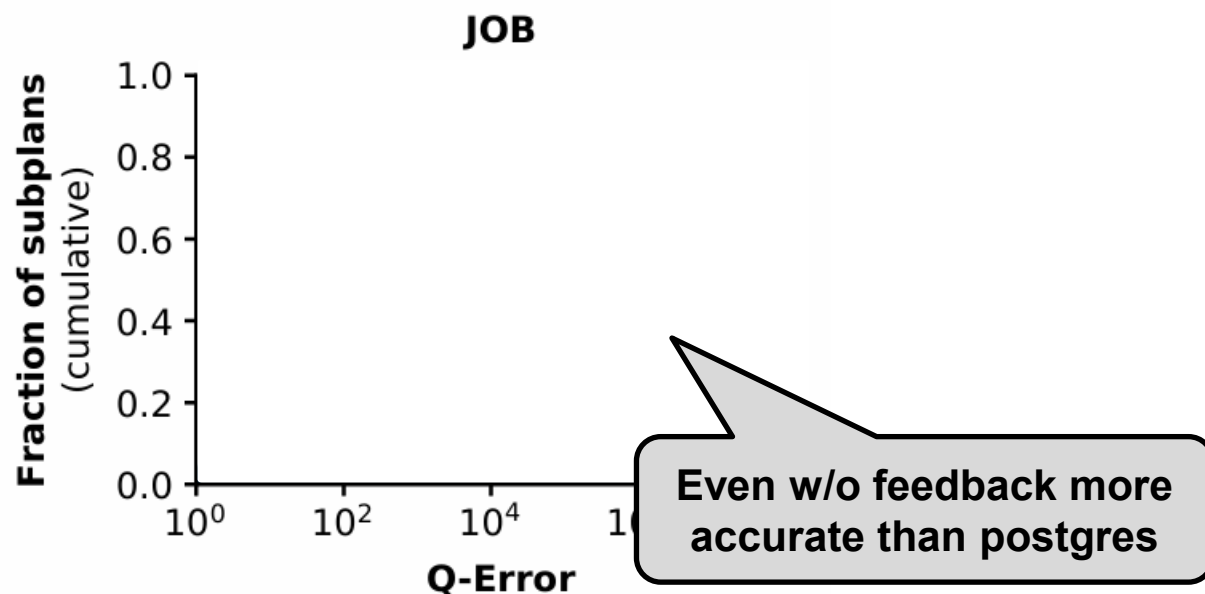
Bespoke-Card



Bespoke-Card: LLM synthesized cardinality estimator

Bespoke-Card reduces runtime by 33% (JOB), 68% (JOB-Complex)

Estimation Accuracy: Q-Error



WL	System	q5	q50	q95
JOB	PostgreSQL (16)	1.50	190.5	132k
	Bespoke-Card	1.24	11.5	1k

Improvements increase in tail distribution

Synthesis Cost & Time

Initial Implementation (JOB):

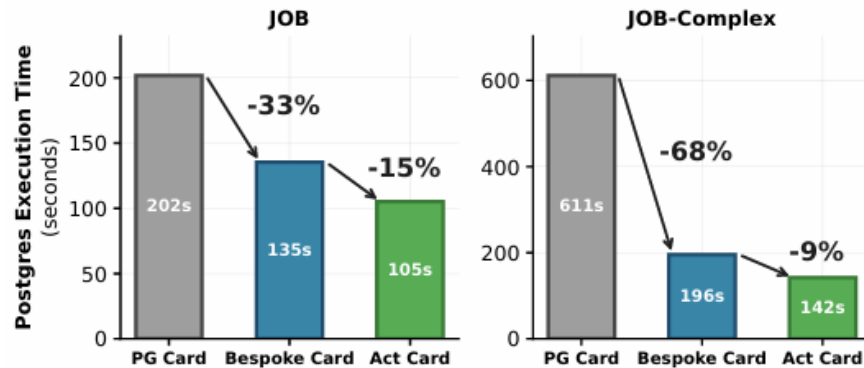
- 25 LLM Turns
- \$ 0.67
- <10mins

Feedback Stages (JOB):

- 63 LLM Turns
- \$ 9.07
- <60mins

**Q-Errors orders of magnitude lower
for less than \$10**

Bespoke-Card



- **Workload-aware classical** cardinality estimators are orders of magnitude **more accurate** than PG
- **LLM Agents** can effectively design and implement bespoke-cardinality estimators (<\$10)
- End-to-end runtimes reduce drastically (-33% on JOB, -68% on JOB-Complex)



Learn more:

github.com/DataManagementLab/BespokeCard

- Paper 📄
- Source code 📁
- Synthesized Engines 🚀

Synthesize full DB Engines?

*Tuesday Research 2 (Cloud-Native Data Systems)
“Bespoke-OLAP”*



SynnoDB synthesizes workload-specific database systems that deliver orders-of-magnitude performance improvements.

synnodb.com