A Step Toward Deep Online Aggregation

Nikhil Sheoran[1,*], Supawit Chockchowwat[2,*], Arav Chheda[2], Suwen Wang[2], Riya Verma[2], Yongjoo Park[2]

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[2] CreateLab @ University of Illinois at Urbana-Champaign,
[*] Equal Contribution

Today’s big data ecosystems

FLOW

kafka

STORM

STORE

ceph

hadoop

FORMAT

AVRO™

Apache orc™

Parquet

COMPUTE

APACHE Spark™

Microsoft® SQL Azure™

cassandra

amazon REDSHIFT

HIVE

Google BigQuery

VIZ

+ a b l e a u®

Periscope Data

QlikView

Various systems across different aspects of big data processing

motivation

How to enable quick processing for large volumes of data?

A Step Toward Deep Online Aggregation

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In this work, we take a step toward *Deep OLA* with *evolving data frames* (edf), a novel data model to offer OLA for nested ops—op(...(op(data)))—by representing an evolving structured data (with converging estimates) that is *closed* under set operations. That is, op(edf) produces yet another edf; thus, we can freely apply successive operations to edf and obtain an OLA output for each op. We evaluate its viability with Wake, an edf-based OLA system, by examining against state-of-the-art OLA and non-OLA systems. In our experiments on TPC-H dataset, Wake produces its first estimates 4.93× faster (median)—with 1.3× median slowdown for exact answers—compared to conventional systems. Besides its generality, Wake is also 1.92× faster (median) than existing OLA systems in producing estimates of under 1% relative errors.

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CCS Concepts: • **Information systems** → **Database query processing**; **Online analytical processing engines**; *Relational parallel and distributed DBMSs*; **Uncertainty**; **Relational database model**; • **Mathematics of computing** → *Time series analysis*; • **Theory of computation** → **Streaming models**.

Scaling for faster insight

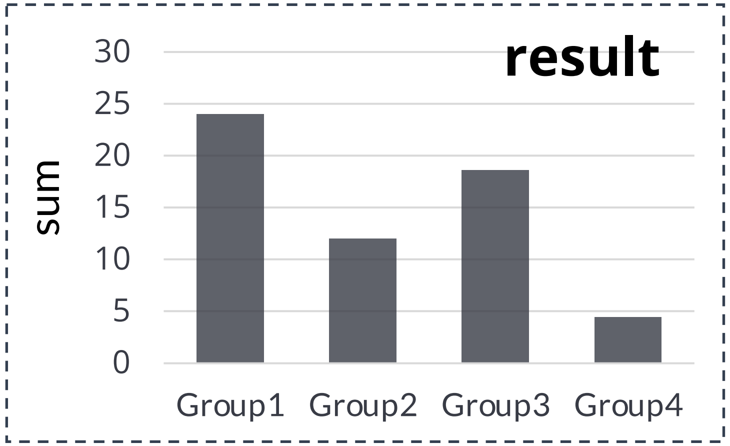
Input: Data

System:

Output:

?

waiting



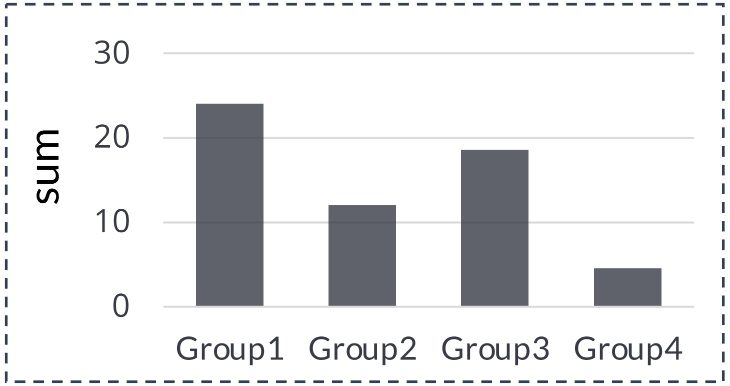
More VMs for the system, the more quickly we get a result

Alt: Predict final result from *partial processing*

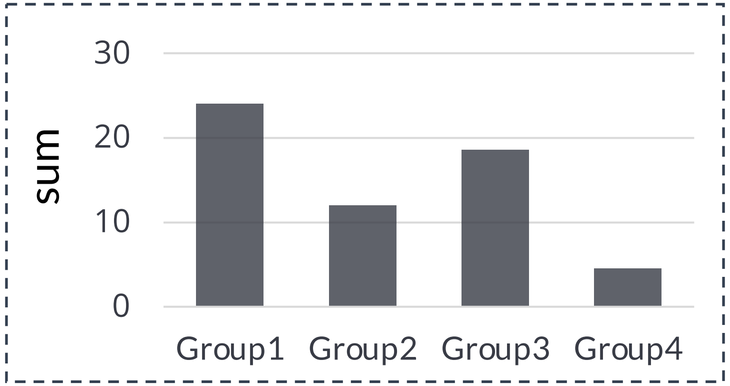
Input: Data

System: Online Aggregation

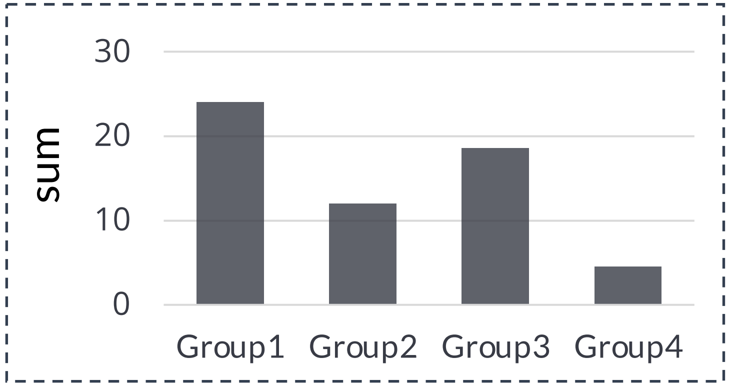
result in 1s



result in 2s



exact result in 10s



Initial results often provide enough information

Currently, limited to *simple queries*

```
lineitem = read_csv('...')
# item count for each order
order_qty = lineitem.sum(qty, by=orderkey)
# select only the large orders
lg_o          order_qty.filter(sum_qty > 300)
# fi                                  rder sizes
lg_order_cus
qty_per_cust = lg_order_cust.sum(sum_
top_cust = qty_per_cust.sort(sum_qty, desc=True).limit(100)
```

cannot apply these subsequent OPs

Can we continuously update each data frame?

key concept

How to represent online aggregation results?

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Types *closed* under operations

Integers are *closed* under addition

- `(1 + 3) + 3 = 4 + 3`

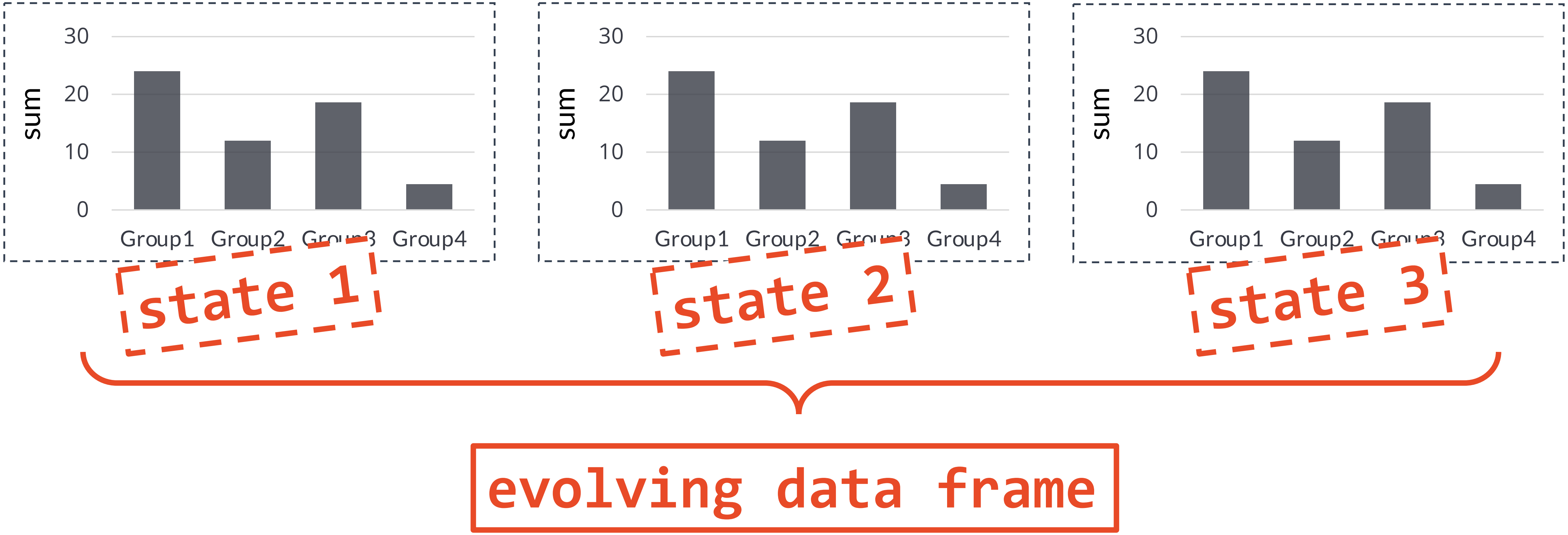
Relations (or tables) are *closed* under relational operations

- `lineitem = pandas.read_csv('lineitem.csv')`
- `order_qty = lineitem.sum(qty, by=orderkey)`
- `lg_orders = order_qty.filter(sum_qty > 300)`

We need an **OLA type** *closed* under OLA operations

How to represent an *evolving* object?

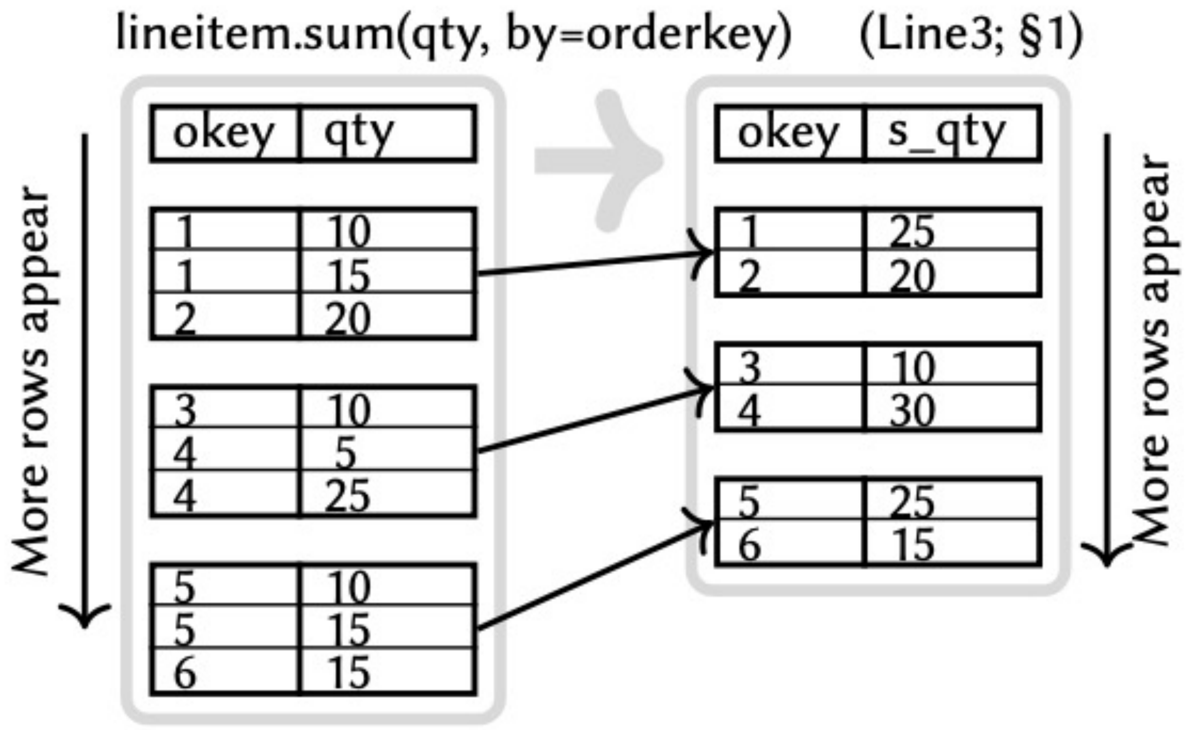
result in 1s **result in 2s** **exact result in 10s**



How are these individual **states** transformed?

Case 1: order-preserving local operation

Input: `lineitem` (*sorted on* `orderkey`) **OP:** sum `qty` by `orderkey`



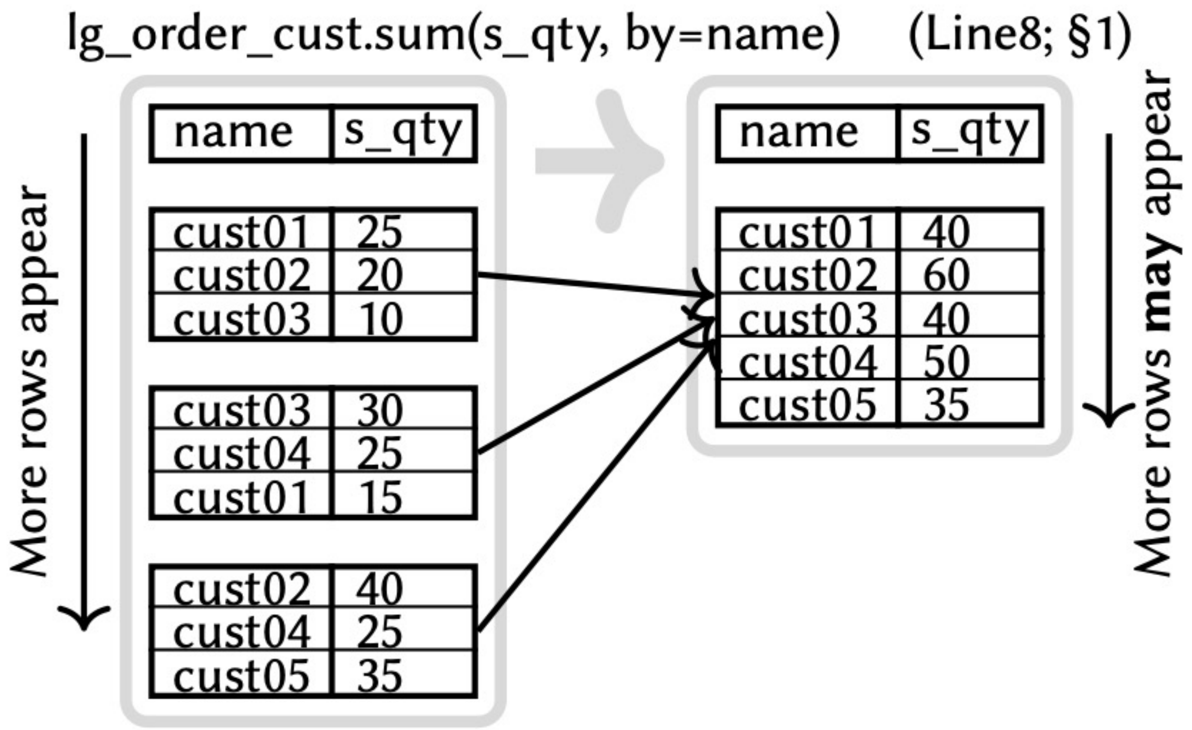
Properties:

1. More rows may appear

incremental processing

Case 2: shuffling with inference

Input: `lg_order_cust` (*sorted on* `orderkey`) **OP:** sum `s_qty` by `name`



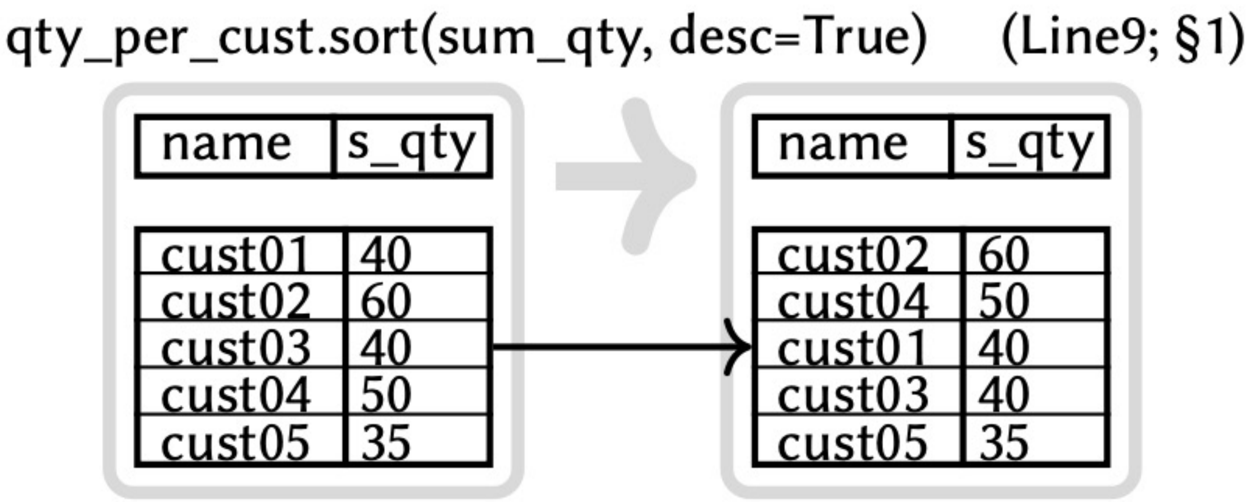
Properties:

1. More rows may appear
2. Attribute values may change
3. Values may need scaling (= **prediction**)

merge into existing results

Case 3: shuffling without inference

Input: `qty_per_cust` **OP:** sort by `sum_qty`



Properties:

1. More rows may appear
2. Attribute values may change
3. ~~Values may need scaling (= **prediction**)~~

complete refresh

Summary: Only a few transformation patterns

Types of Transformation:

- Case 1: order-preserving OP
- Case 2: shuffle with inference
- Case 3: complete refresh

In *transformed* output:

1. More rows may appear
2. Attribute values may change
3. Values may need scaling

New concepts introduced:

cardinality growth (query progress vs cardinality)
mutable attributes (values can change or not)

internal processing

How to represent states and efficiently generate new states?

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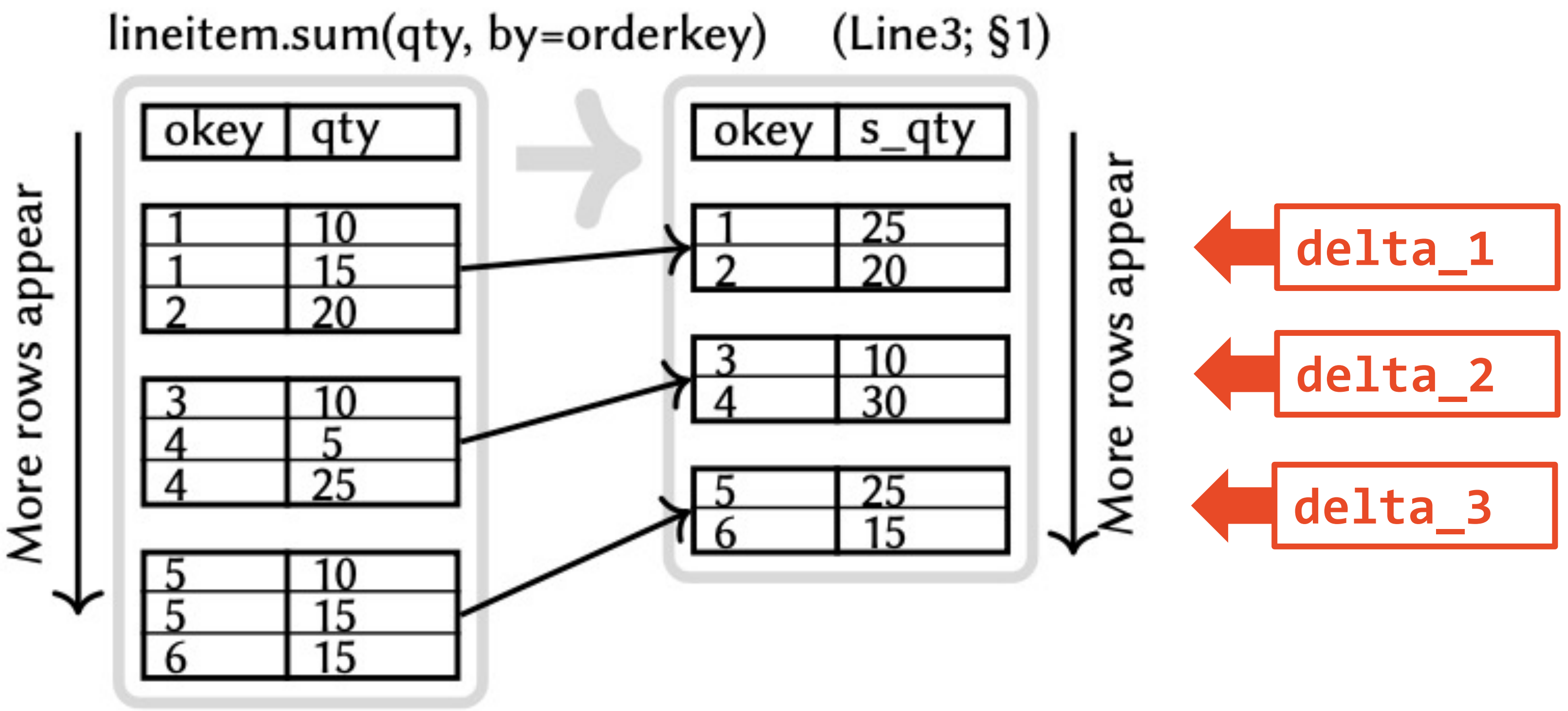
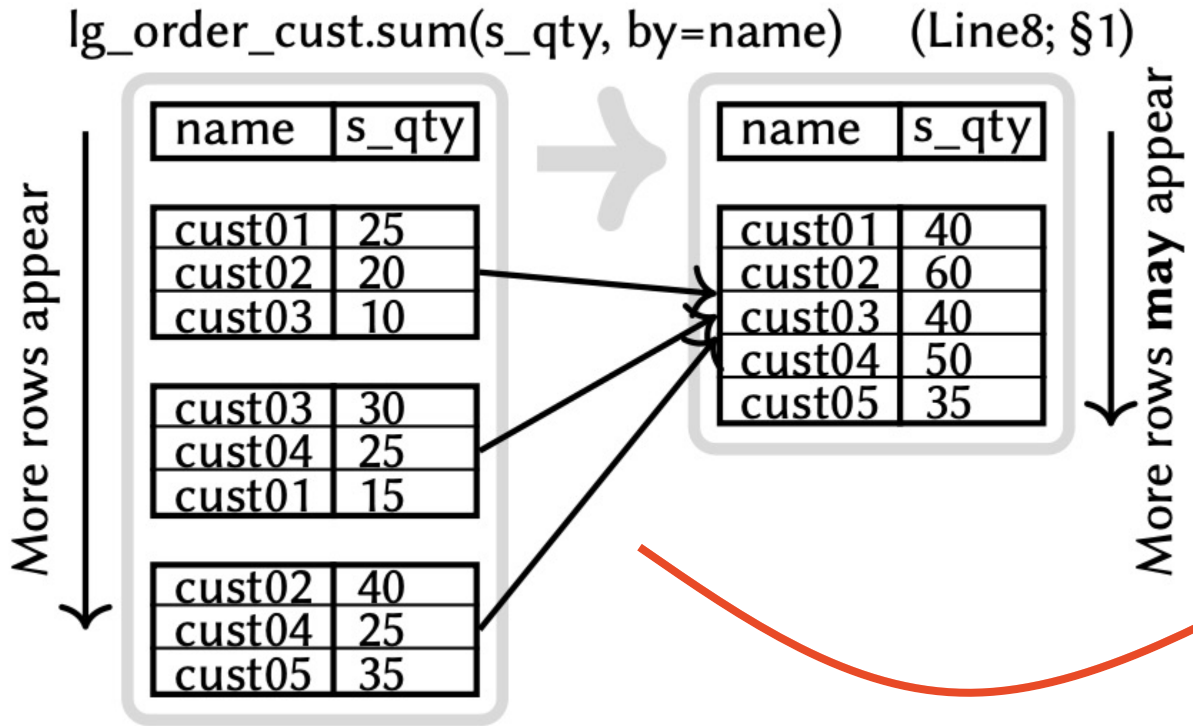
Case 1: order-preserving local operation



state_k = delta_1 ∪ delta_2 ∪ … ∪ delta_k

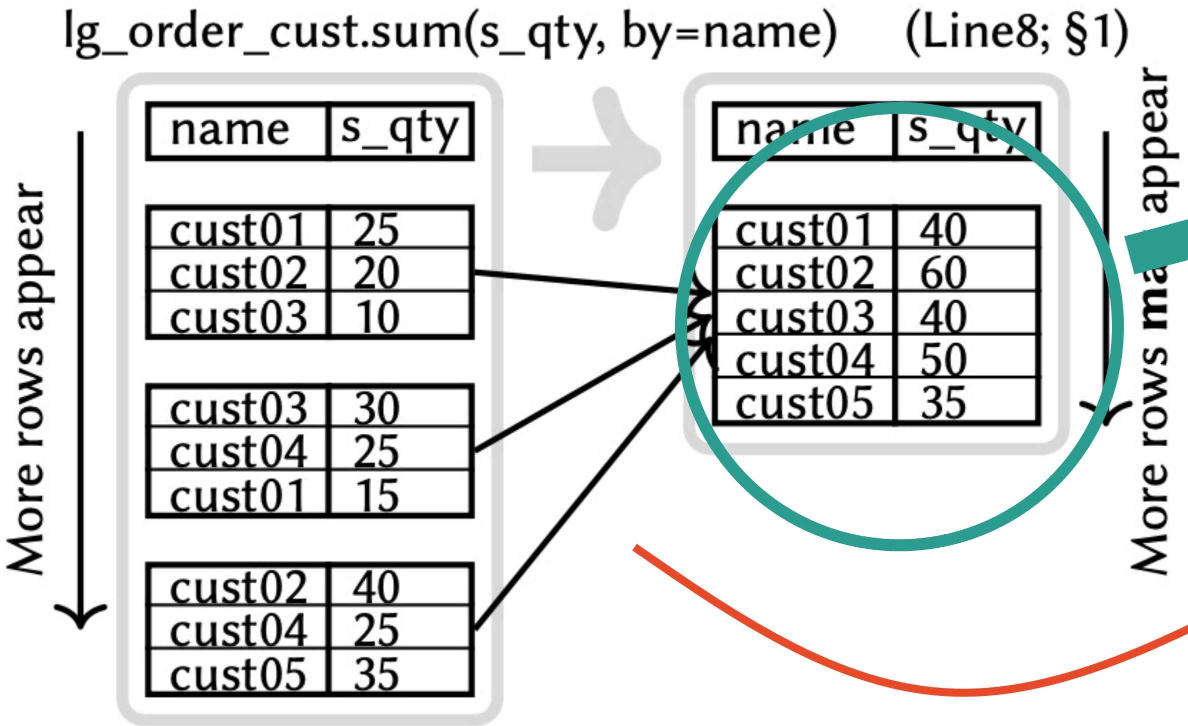
Case 2: shuffling with inference (1/2)



Each merge creates a new ***version*** of state

`state_k = version_k` *(after scaling)*

Case 2: shuffling with inference (2/2)



These values need **scaling** w.r.t. *current input size*

Each merge creates a new ***version*** of state

The values are scaling with (**est total input size** / current size)

Case 3: shuffling without inference

Input: `qty_per_cust` **OP:** sort by `sum_qty`

qty_per_cust.sort(sum_qty, desc=True) (Line9; §1)

name	s_qty
cust01	40
cust02	60
cust03	40
cust04	50
cust05	35

name	s_qty
cust02	60
cust04	50
cust01	40
cust03	40
cust05	35

`state_k = version_k` *(without scaling)*

putting it together

How can a user use it end-to-end?

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Evolving Data Frame and Operations

Our Earlier Example

```
lineitem = read_csv('...')
# item count for each order
order_qty = lineitem.sum(qty, by=orderkey)
# select only the large orders
lg_orders = order_qty.filter(sum_qty > 300)
# find the customers with biggest order sizes
lg_order_cust = lg_orders.join(orders).join(customer)
qty_per_cust = lg_order_cust.sum(sum_qty, by=name)
top_cust = qty_per_cust.sort(sum_qty, desc=True).limit(100)
```

Operations generating *edf*

```
read := data_source -> edf
edf_op := (edf, op) -> edf
op  := agg(attrs, by) | filter(predicate)
     | map(function) | join(df, options)
agg := sum | count | avg | count_distinct | min | max
     | var | stddev
```

OLA operation on an edf generates edf

Cardinality and Aggregate Inference Logic

- Given the states of an edf, generate a user-consumable query output.
  - Growth: group sizes may grow in a non-linear way as more input data are processed *(Cardinality estimators)*
  - Coverage: the number of groups covered may also increase over time *(Cardinality estimators)*
  - Operation: different types of aggregations requires different estimations *(Aggregate estimators)*

obtain estimation of final result

Confidence Interval for Deep OLA

- Compute "uncertainty" for all mutable attributes.
  - Different techniques for different aggregation operations e.g. variance of OLS parameter, central limit theorem, etc.
- Propagate uncertainty through OLA operations.
  - Linearize using a first-order taylor expansion and compute covariance matrix.
- Compute confidence intervals from final uncertainty.
  - Use Chebyshev's inequality for final CI estimate.

confidence interval on estimation

Putting together (first four EDFs)

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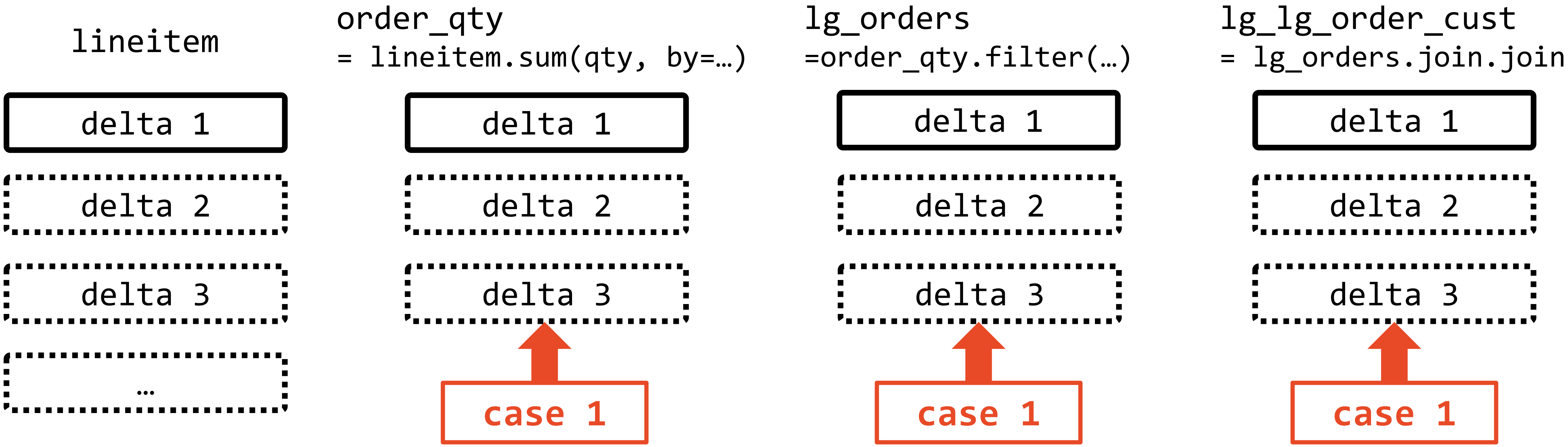
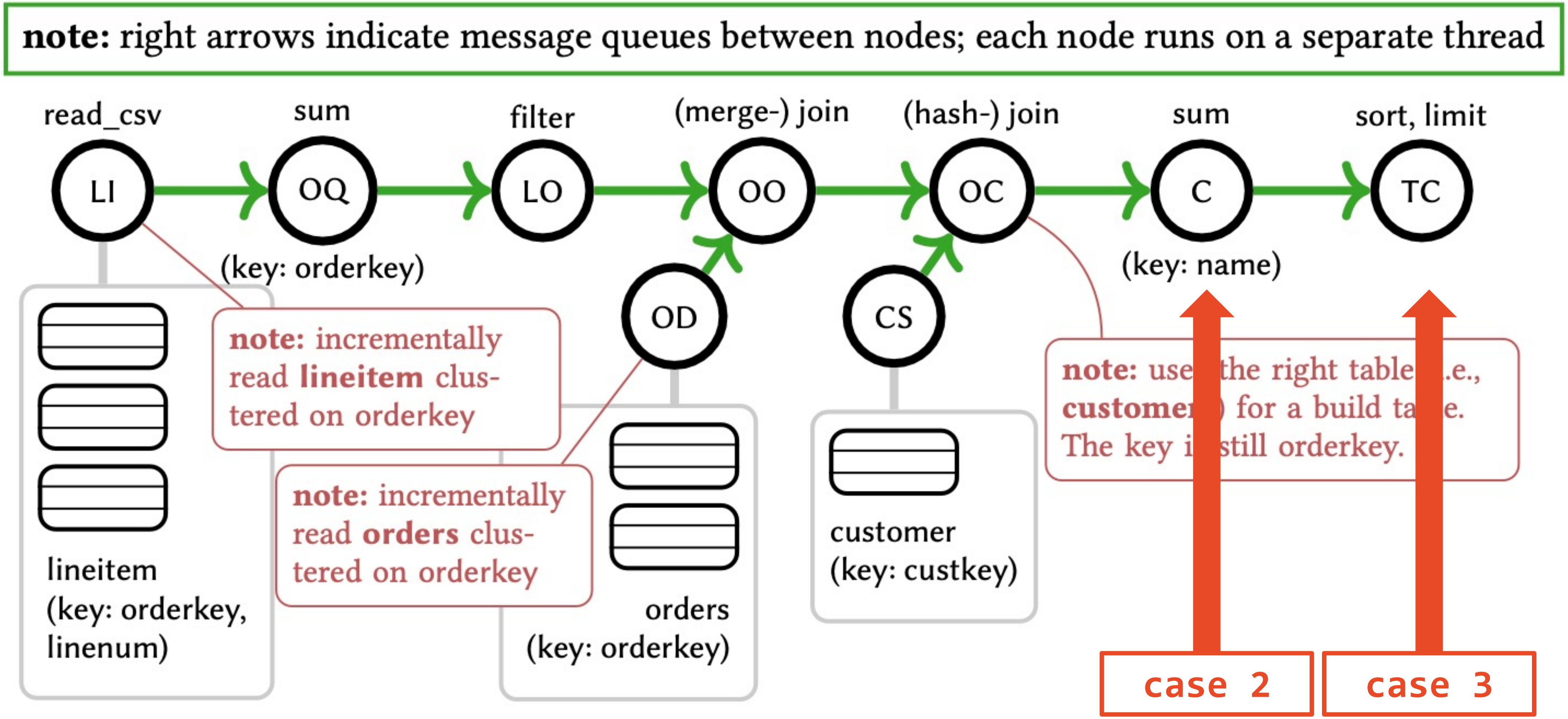


Complete data flow



evaluation

How much is the computation overhead and approximation error?

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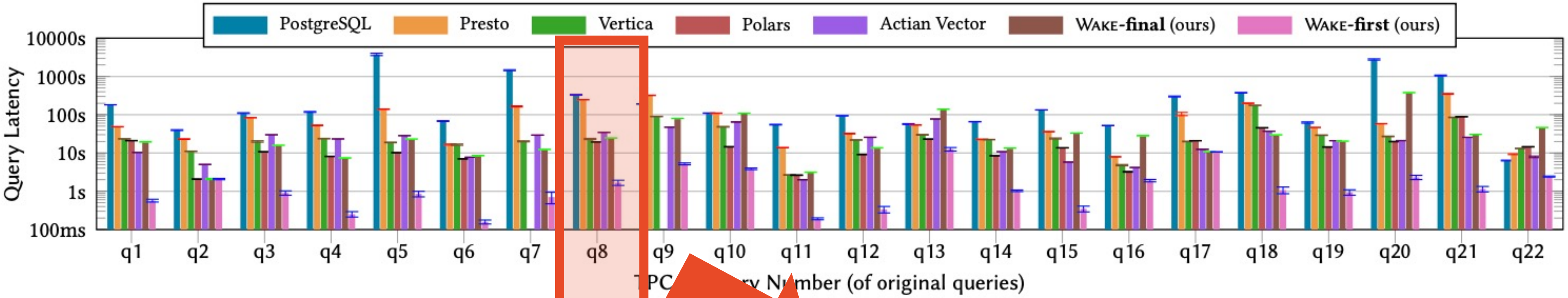
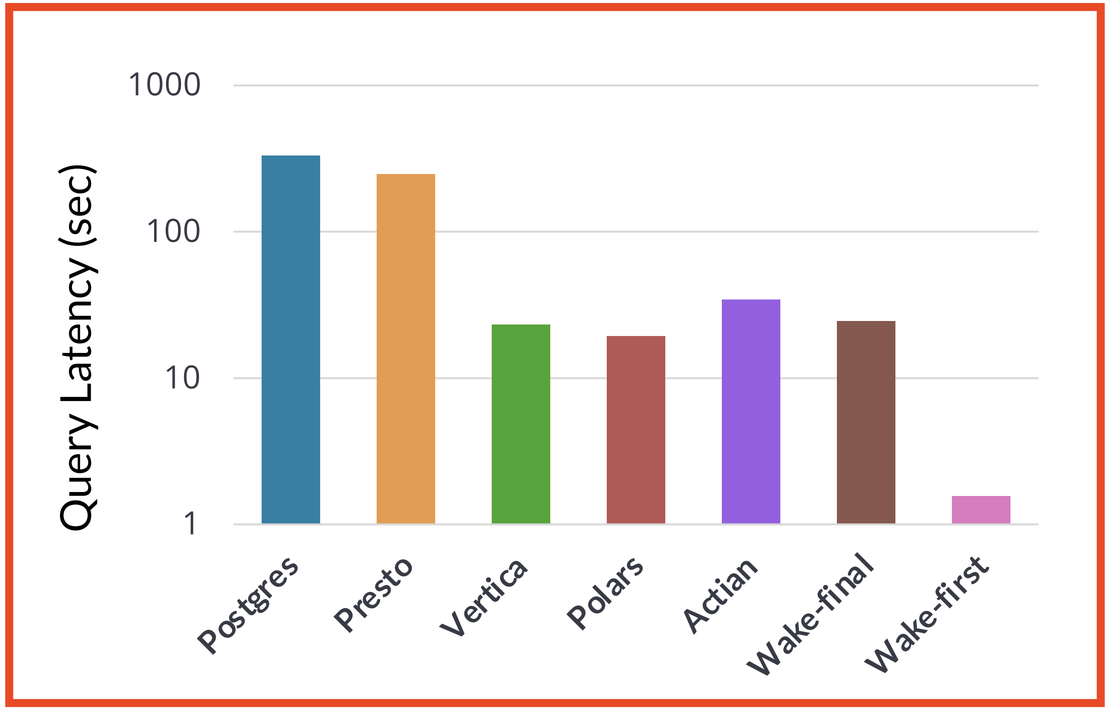
Our OLA system delivers answers quickly




```
select o_year,
  sum(...) / sum(...) as mkt_share
from (
  select
    year(o_orderdate) as o_year,
    l_extendedprice * (1 - l_discount) as volume,
    n2.n_name as nation
  from
    part, supplier, lineitem, orders, customer,
    nation n1, nation n2, region
  where ...
  ) as all_nations
group by o_year
order by o_year;
```

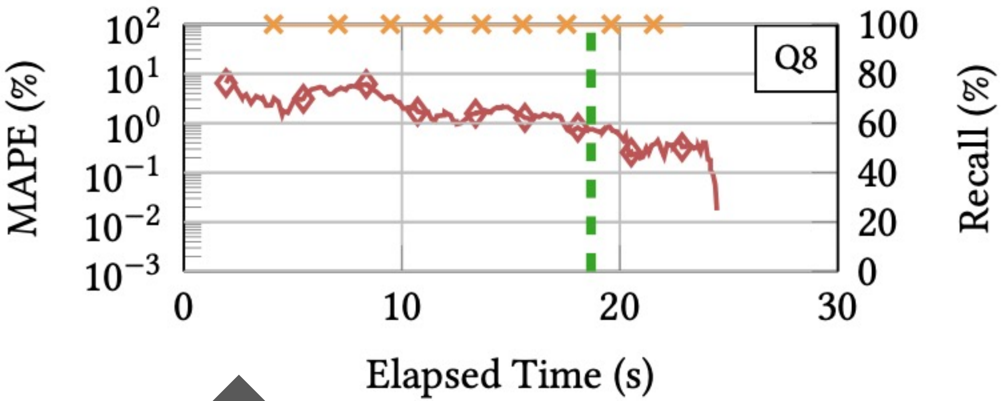
Q8



Our errors decrease quickly

Q8

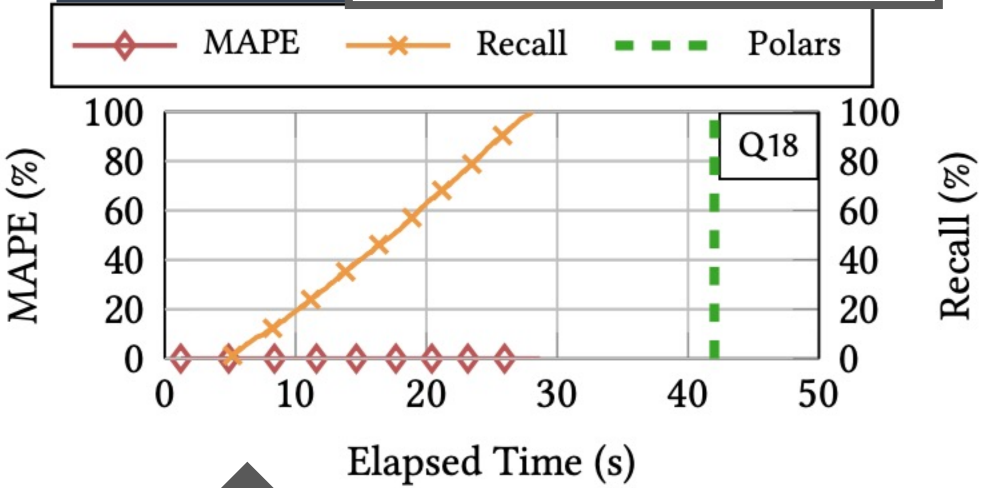
- All rows are present
- Attr values improve



- Our result has a complete row set
- The errors decrease quickly

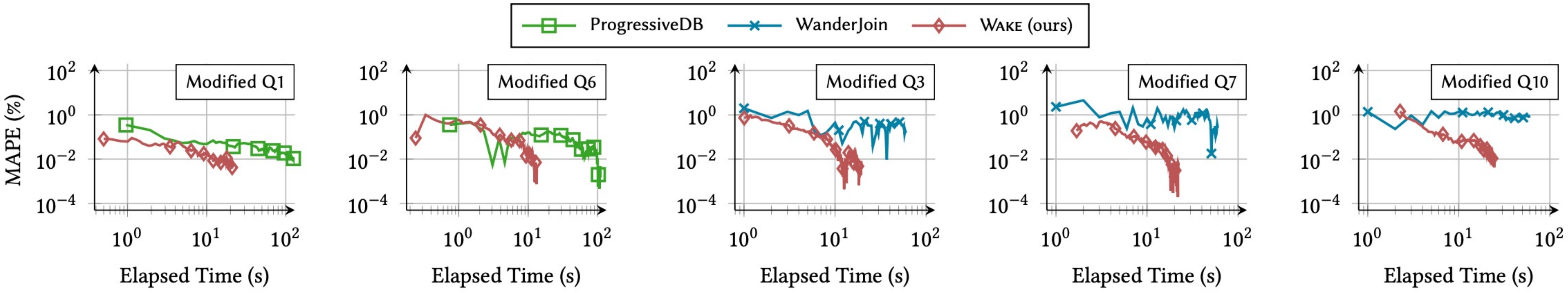
Q18

- Attr values are exact
- More rows appear



- Attr value errors are zero
- Result set increase

Faster & more *accurate* than existing OLA



(a) vs ProgressiveDB (using single-table Q1 and Q6) **(b) vs WanderJoin (using same modified Q3, Q7, and Q10 as in [50])**

- The lower, the better *(we are lower)*
- **Reason 1: we are highly parallel** **Reason 2: our final answers are exact**

Conclusion: A Step Toward Deep OLA

- **First OLA** for processing arbitrarily **nested queries**
- Motivation: A **new type** for OLA
- Proposed *Evolving Data Frame* (EDF)
- EDF, consisting of multiple states, is *closed* under OPs
- Evaluation: ***low latency***, ***high accuracy***, and ***improvement over STOA***

Thank you!