Using Data Transformations for Low-latency Time Series Analysis

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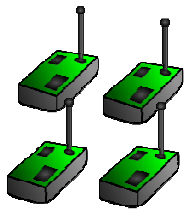
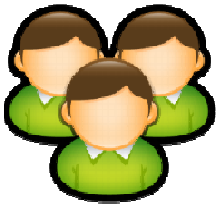
Time series data analytics



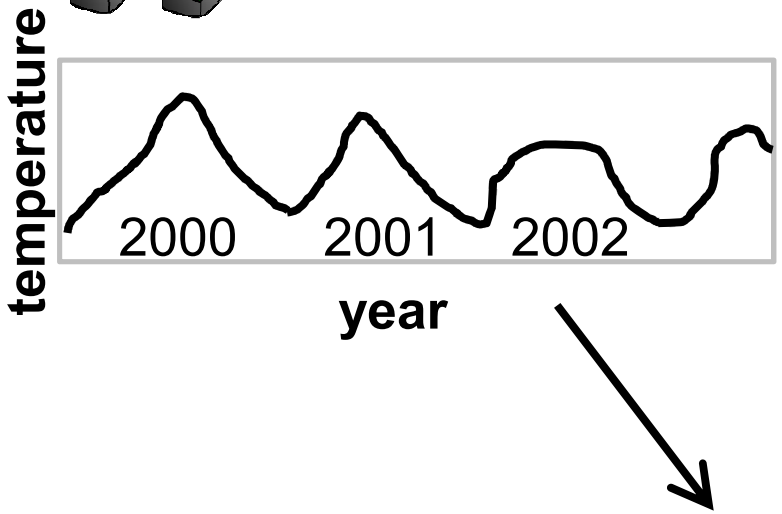
Time series data

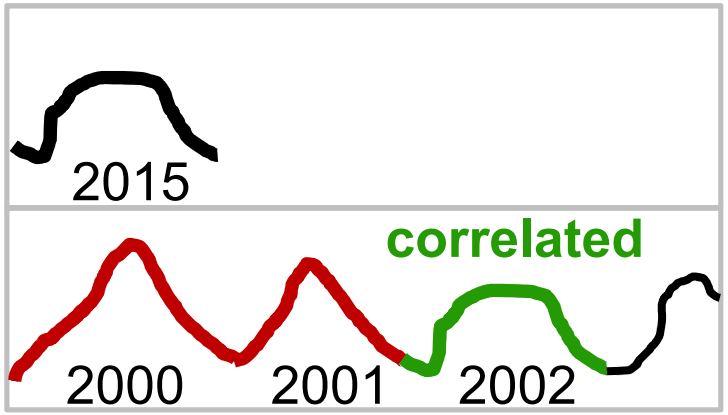
e.g., temperatures



Analytical queries

e.g., search for correlation





Time Series Database

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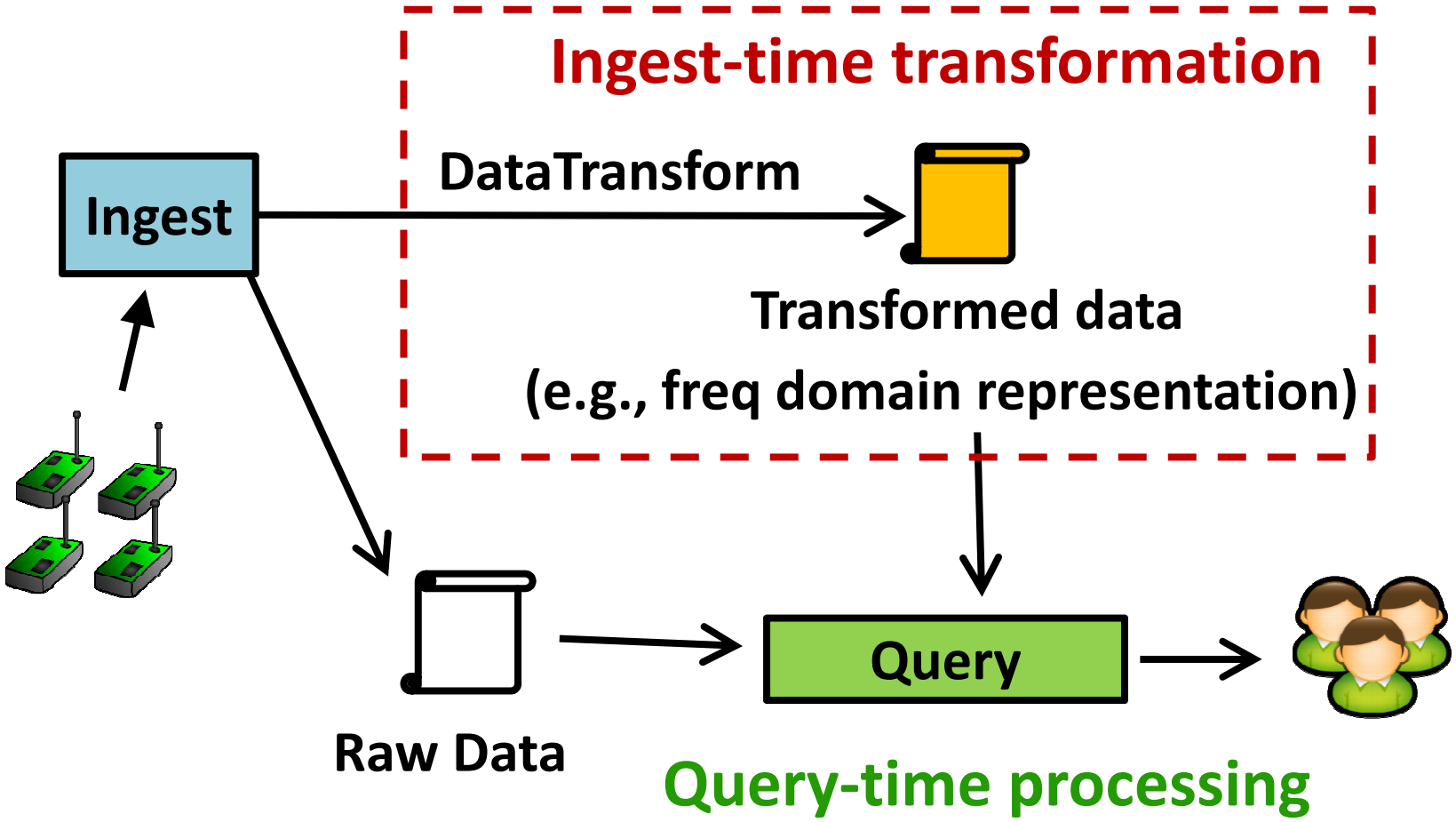
Goals and previous approaches

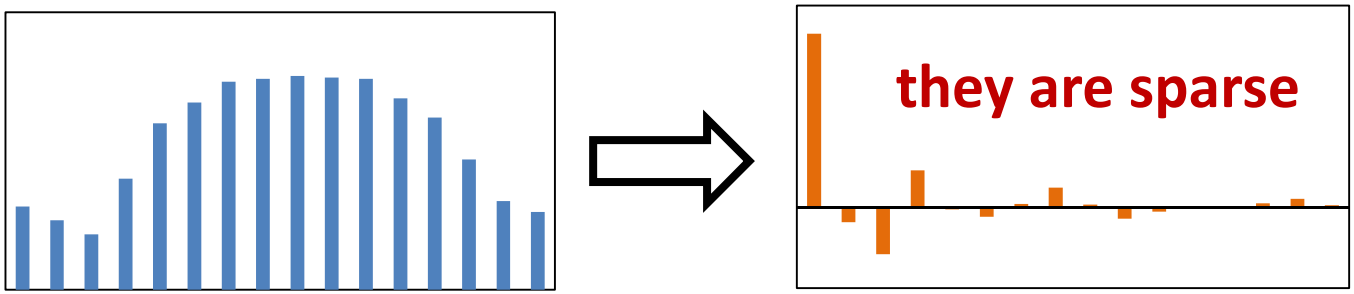
- Goals
  - Low latency queries
    - Sub-second latency for interactive queries
  - Handle large data size
    - Queries on both recent data and historical data
- Previous approaches
  - Archive data in compact forms [e.g., Cypress]
    - But, does not provide for low-latency interactive queries
  - Keep/use only recent data [e.g., Scuba]
    - But, excludes use of historical data
  - Provide approximate results via sampling [e.g., BlinkDB]
    - But, not for recent data or complex analytics

Data transformations at ingest



Data transformation examples

- Wavelet transform for temperature data
  - Frequency domain representation
  - Can calculate correlations directly from it
  - Data ranges can be approximated with few coefficients
    - Much smaller than raw data w/ small amount of error



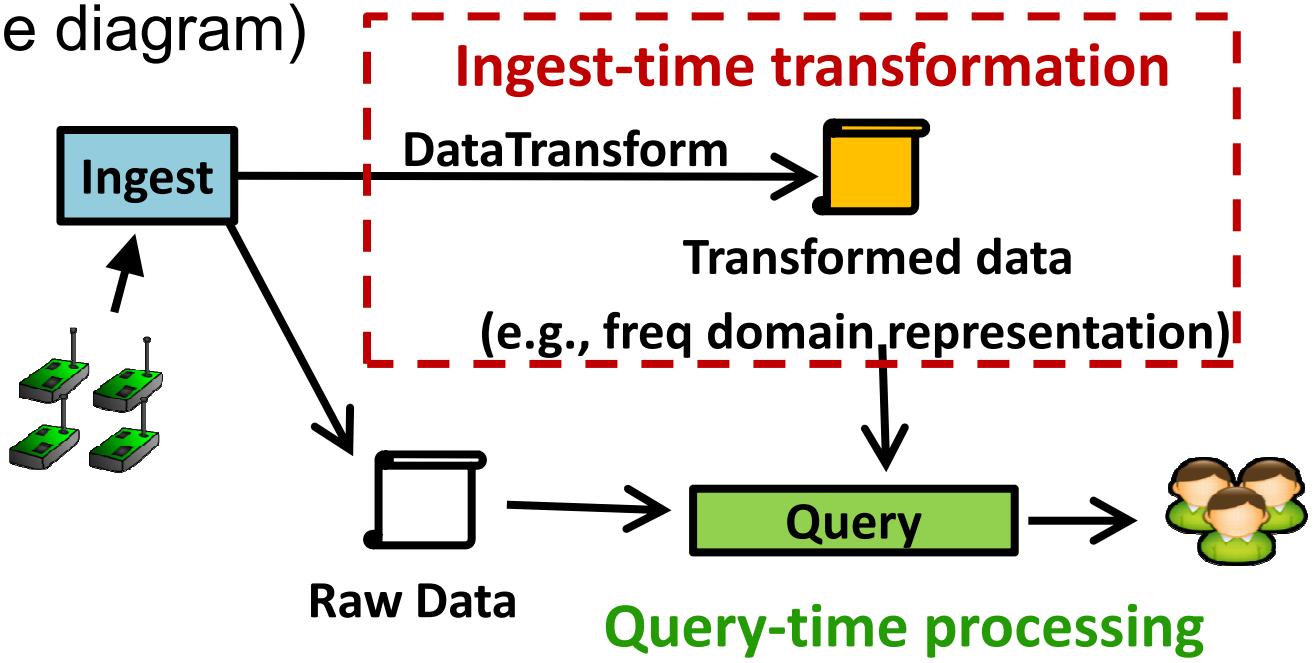
Temperatures **Wavelet coefficients**

- Other transformations implemented
  - Count-min sketch, ARMA model fitting, FFT, etc.

Aperture

- Timeseries DB with ingest-time transformation
  - User defined ingest-time transformations
  - Answer queries using transformed data

(same diagram)

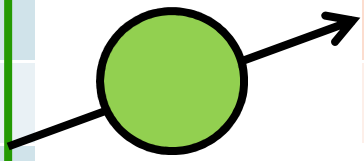


Ingest-time transformations

- Transform ingested data for every *window*
  - Window is a range of rows
- Generate and store windows of transformed data

Temperature table

city	date	value
PGH	1/1/2000	35.2
PGH	1/2/2000	36.3
...	...	...
PGH	12/31/2000	...
...	...	...



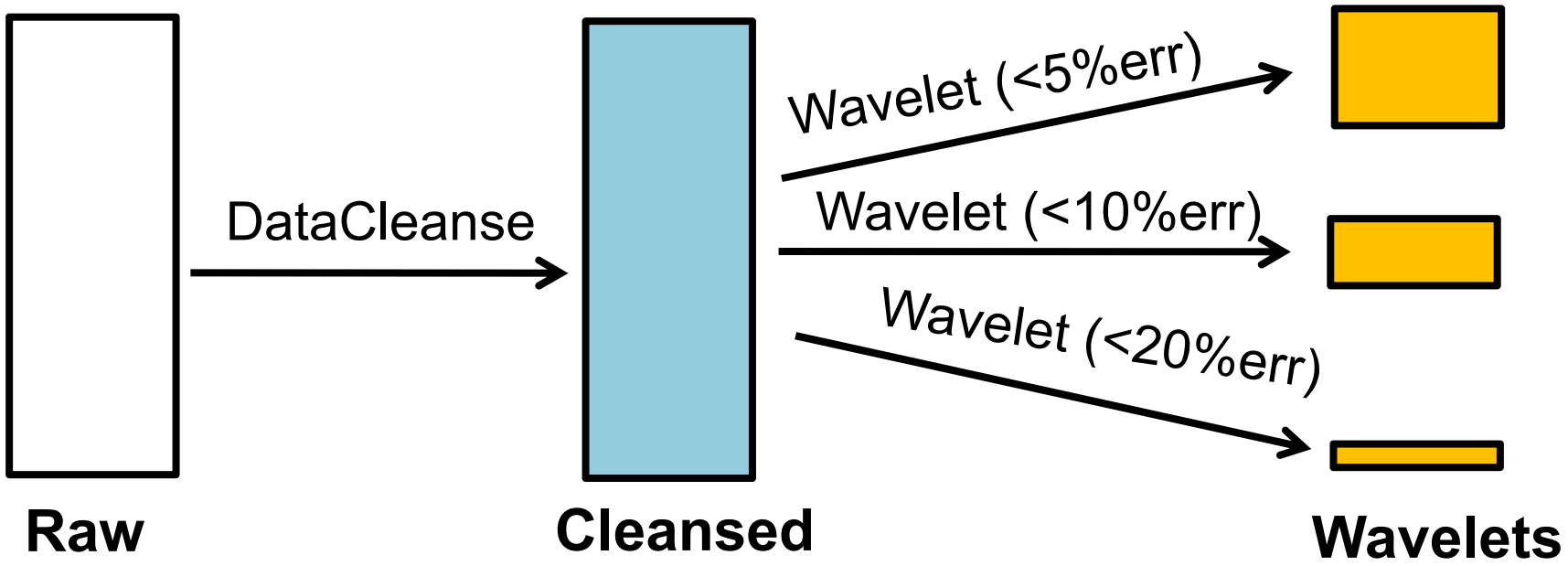
Wavelet table

city	date	wavelets
PGH	1/1/2000	<wavelets>
...	...	...

wavelet transform:
window size: 1 year,
error bound: 10%

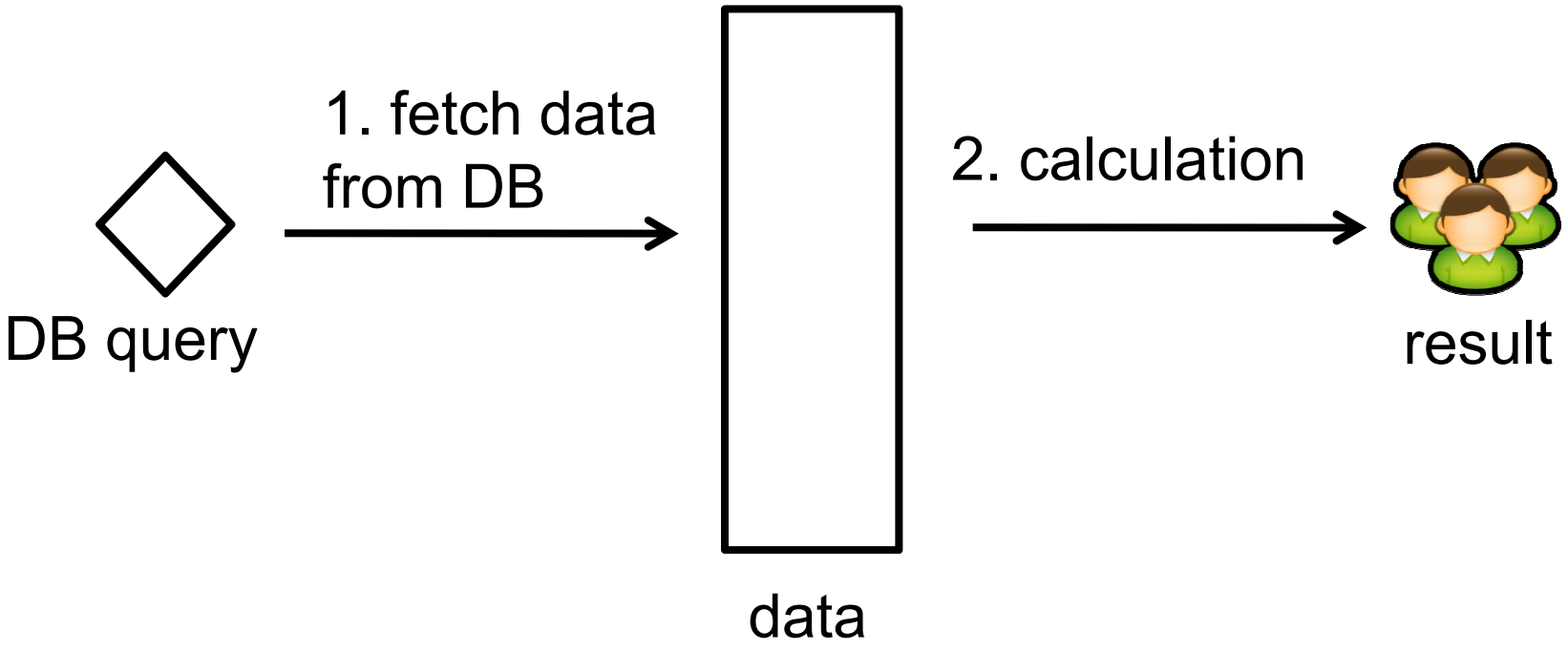
Ingest-time transformations

- Chained transformations
  - E.g., data cleansing then wavelets
- Multiple versions of transformed data
  - E.g., with different error bounds or window sizes



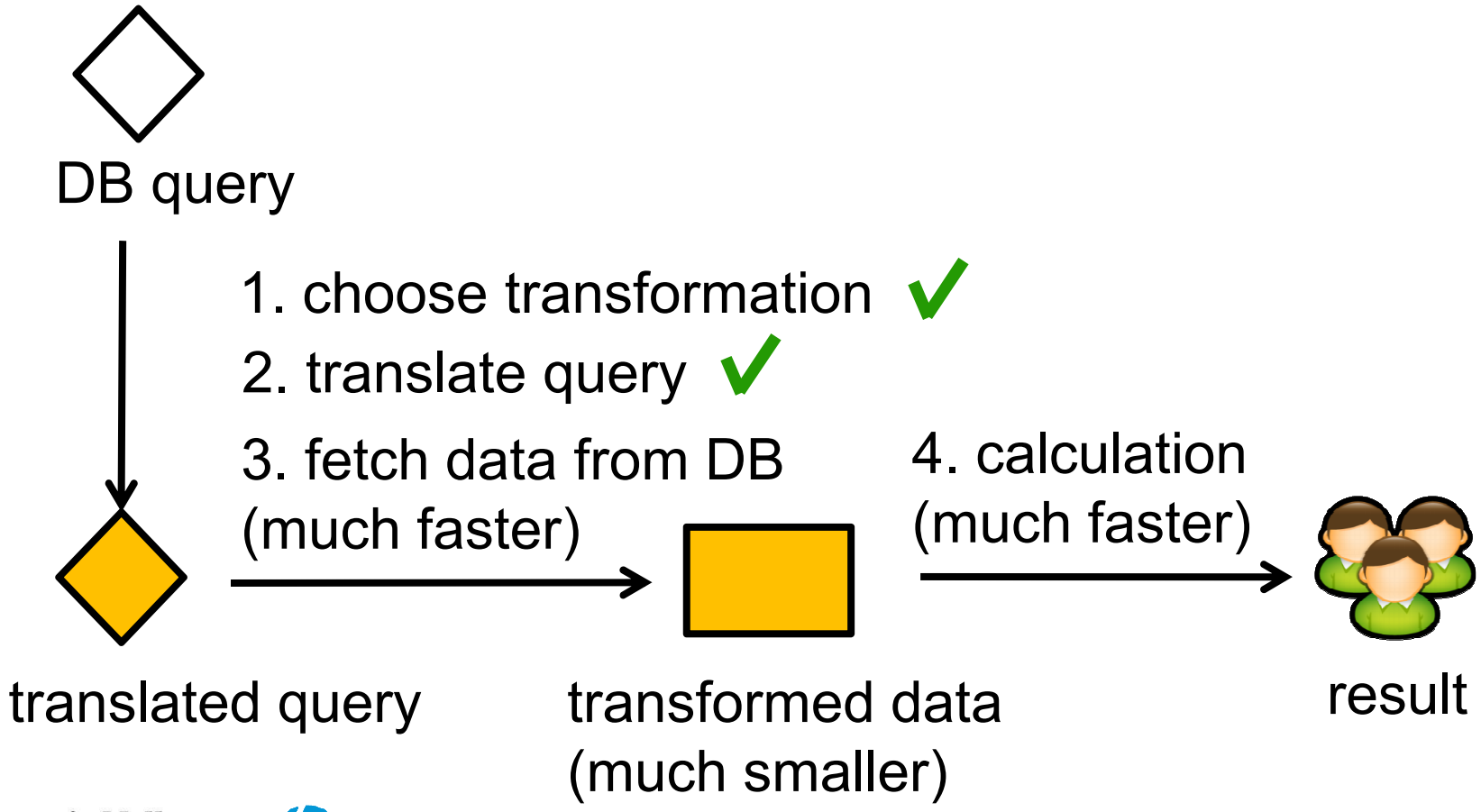
Query processing

- Workflow of analytical query tasks on raw data



Query processing

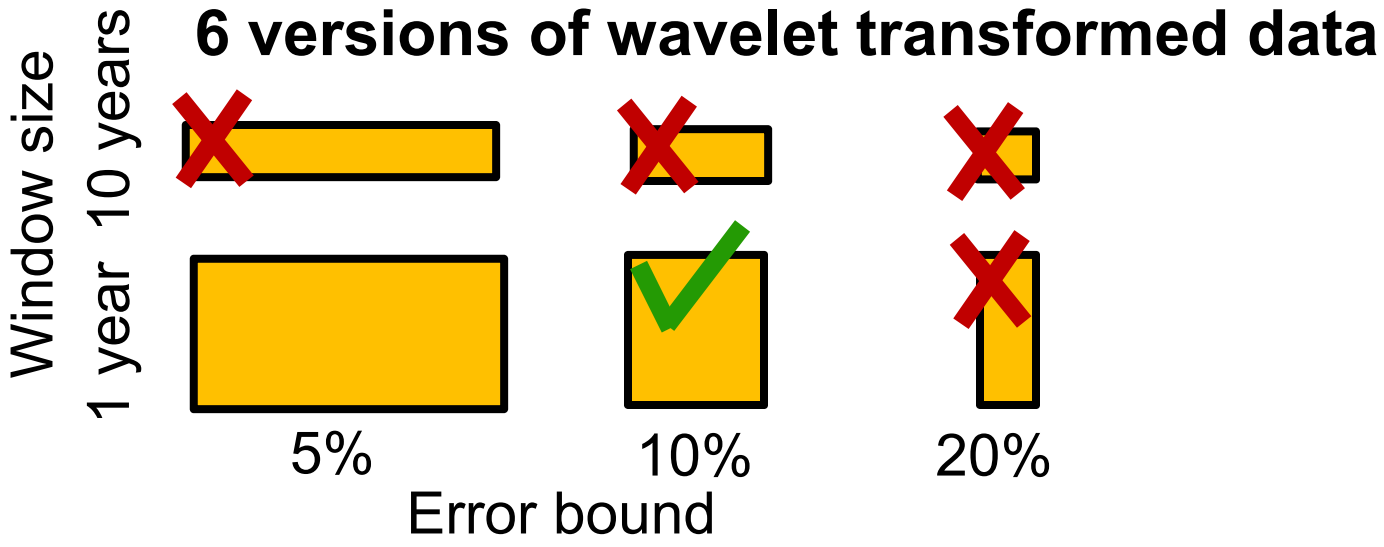
- Analytical query tasks using transformed data



Choosing transformation

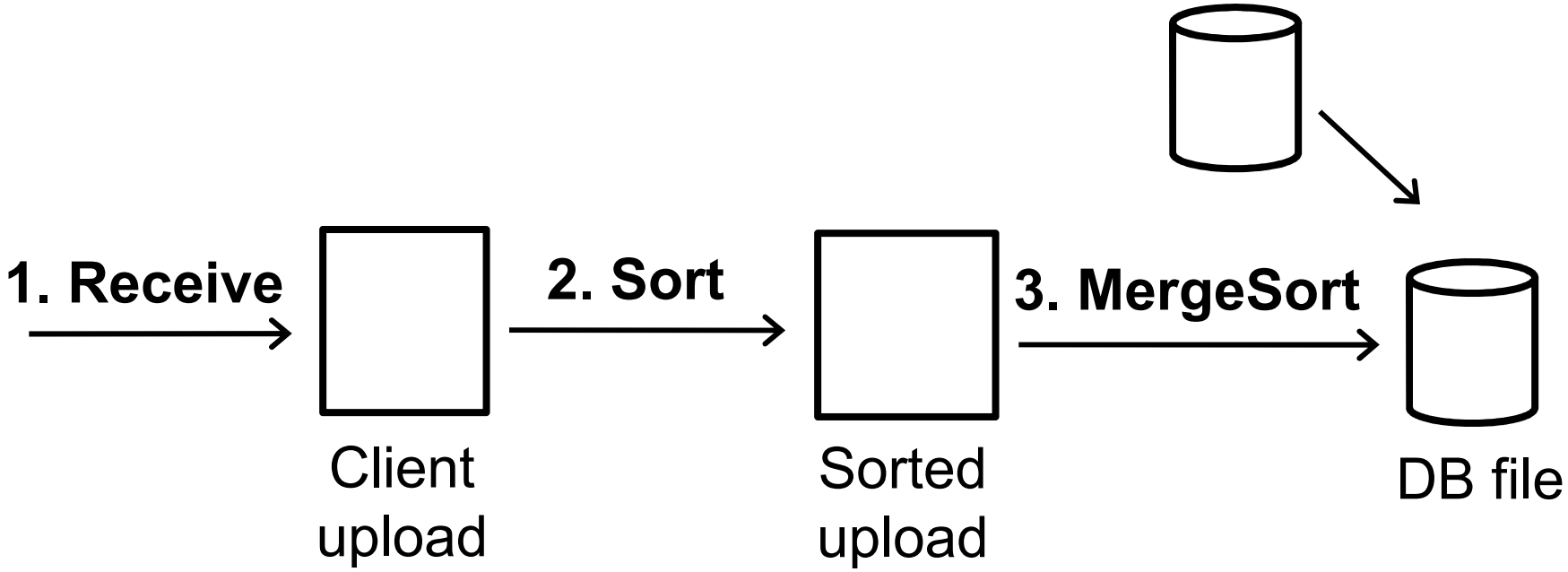
- Based on user-defined utility functions

```
If (not func == wavelet): utility = 0
If (window_size > 1 year): utility = 0
If (error_bound > 10%): utility = 0
utility = window_size * error_bound
```



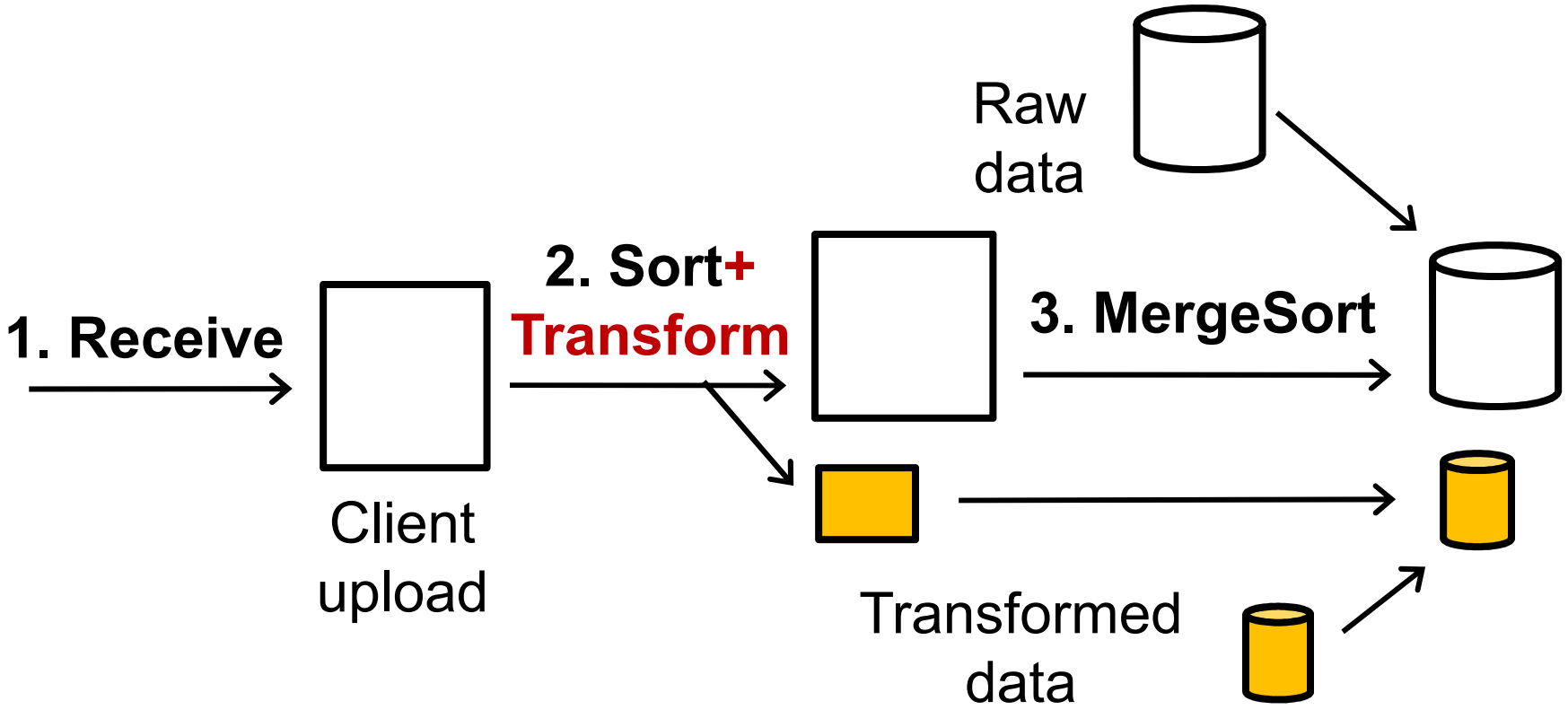
Aperture implementation

- Implemented on top of LazyBase [Cipar et al., Eurosys'12]



Aperture implementation

- Implemented on top of LazyBase [Cipar et al., Eurosys'12]
  - Extend Sort stage to Sort+Transform



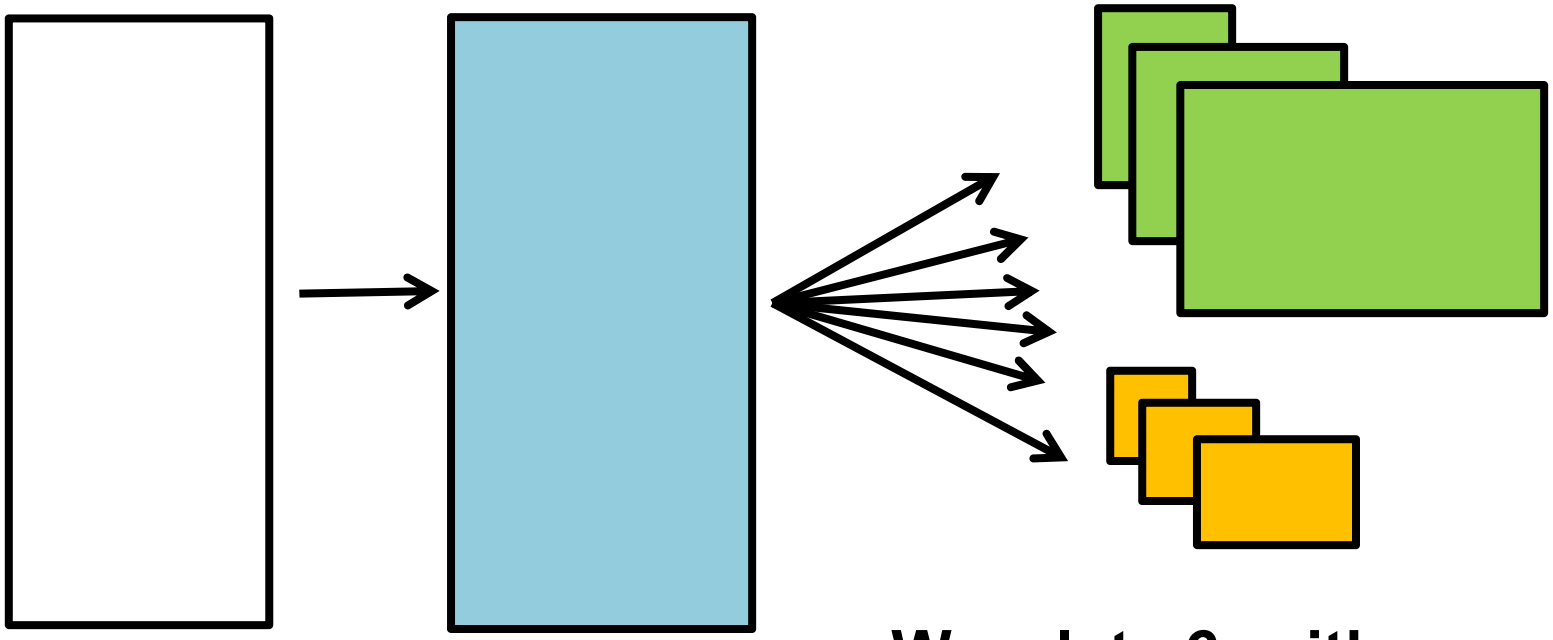
Evaluation setup

- Hardware information
  - HP ProLiant DL580 machines, each with
    - 60 Xeon E7-4890 @2.80GHz cores
    - 1.5 TB RAM
    - Running Fedora 19
  - One machine for the results in this talk
  - Multiple machines for scalability experiments

Evaluation: correlation search

- Dataset
  - Climatic data from National Climatic Data Center
  - Daily temperature, dew point, and wind speed from hundreds of stations since 1930s
- Table schemas
  - {**metric**, **station**, **date**, **value**}
  - 350 million rows in total
- Testing query task
  - Given 10 years of temperature data in station X
  - Find all data series with correlation > 0.8

Data transformations



Raw

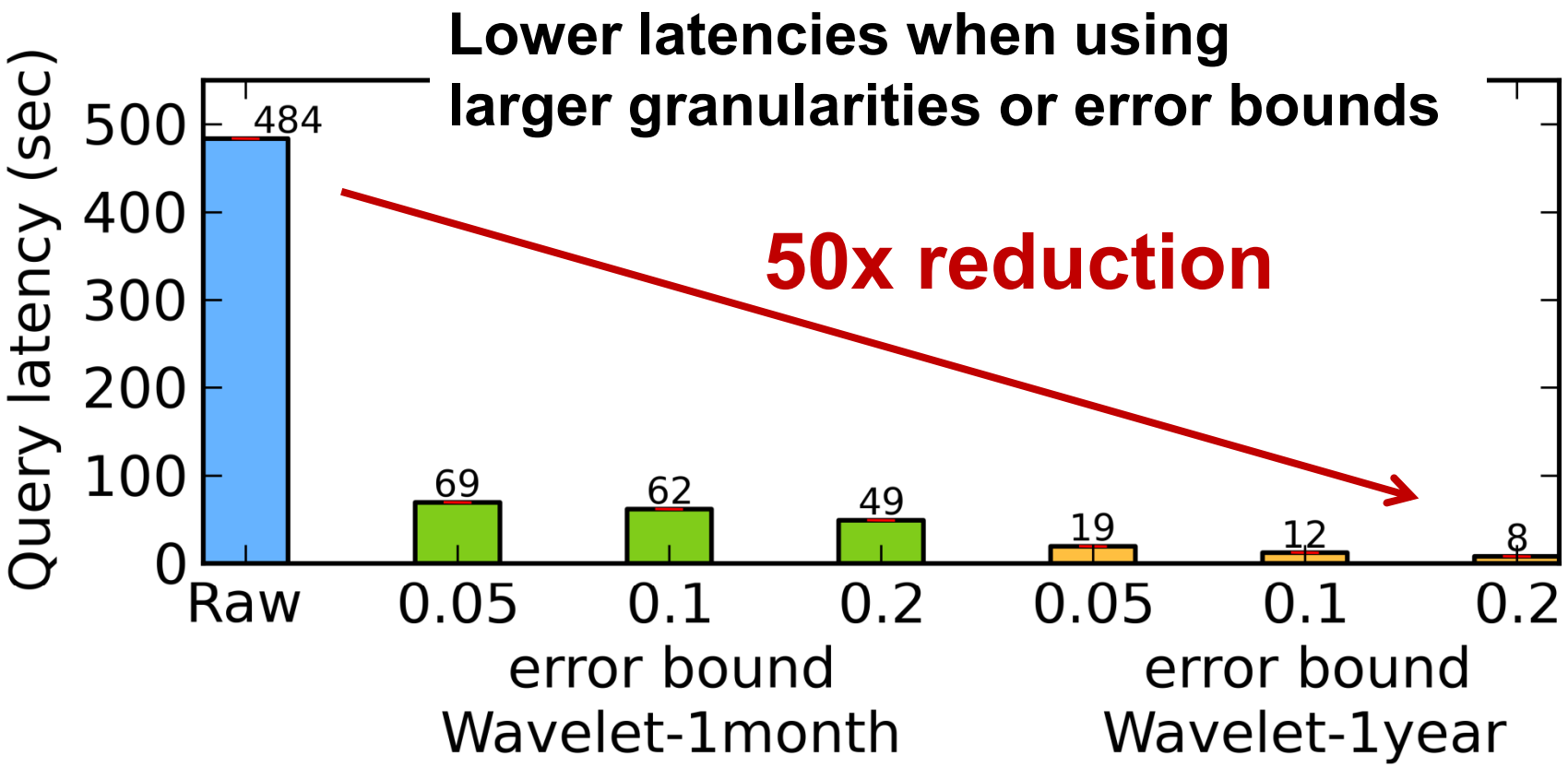
Cleansed

Wavelet x6, with

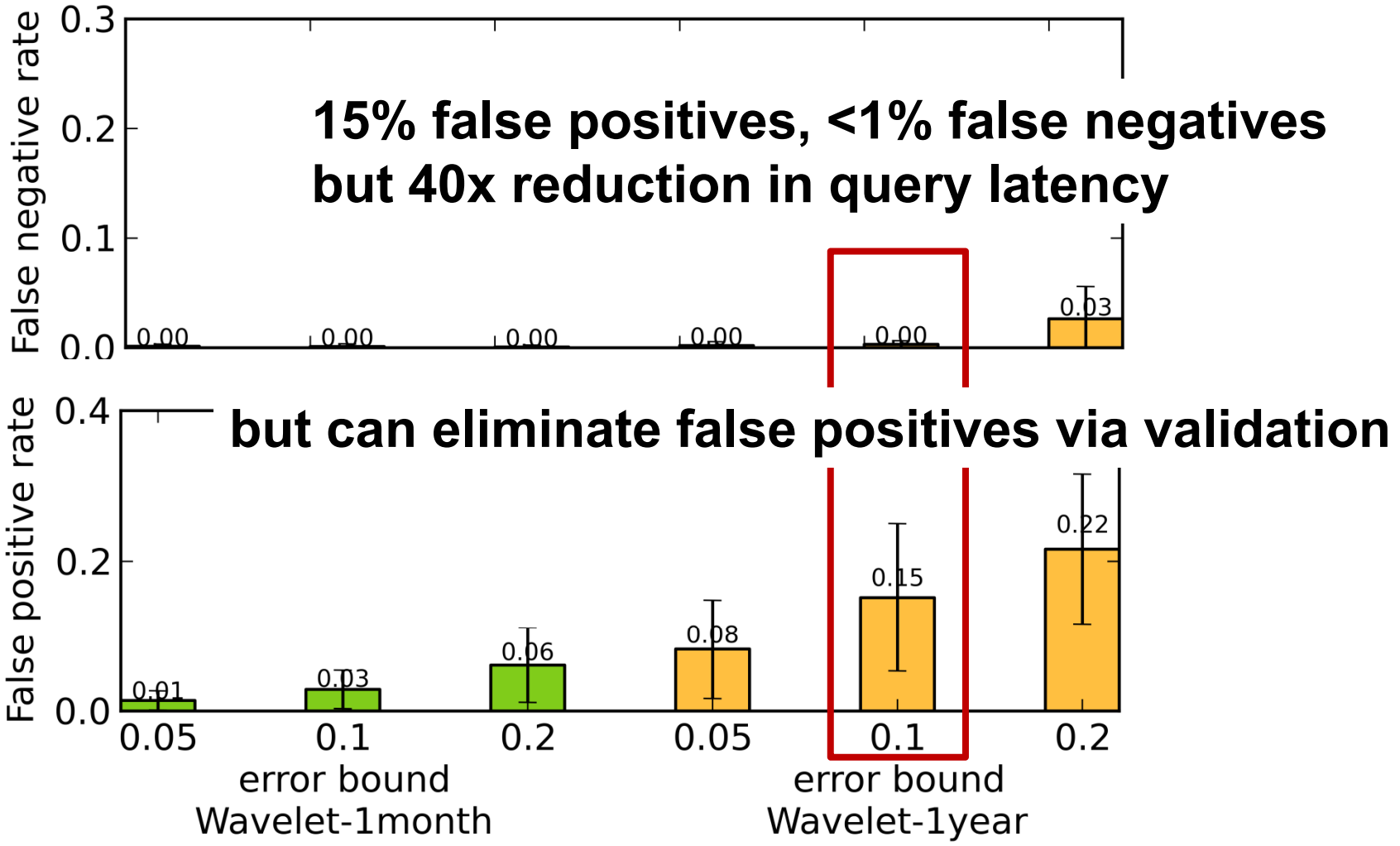
- window size: 1 month and 1 year
- error bound: 5%, 10%, and 20%

- **Only 4% overhead on ingestion throughput**

Query latencies



Errors of query results



Other use cases

- Event occurrence monitoring
  - Transform: event logs → count-min sketches
    - Bloom filter-like summaries
  - Query use: determine frequency of an event type
- Anomaly detection
  - Transform: observations → list of anomalies
  - Query use: find anomalies in a time range

Conclusions

- Aperture: ingest-time transformation for efficient time series data analytics
  - User-defined transformations when data ingested
  - Answer analytical queries using transformed data
- Many real-world use cases
  - 1~4 orders of magnitude reduction in query latency
  - Less than 20% query error
  - Less than 10% ingestion overhead