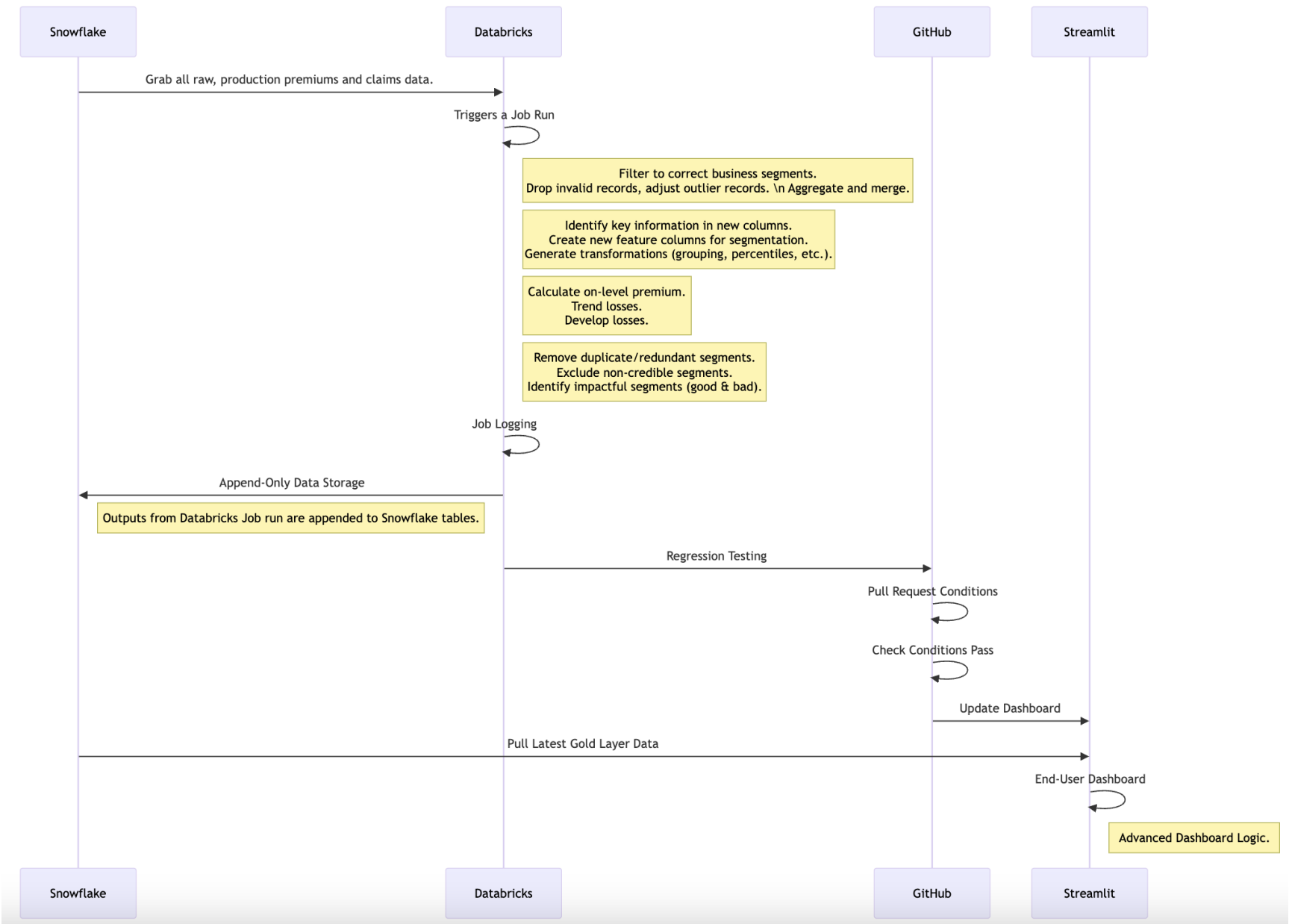
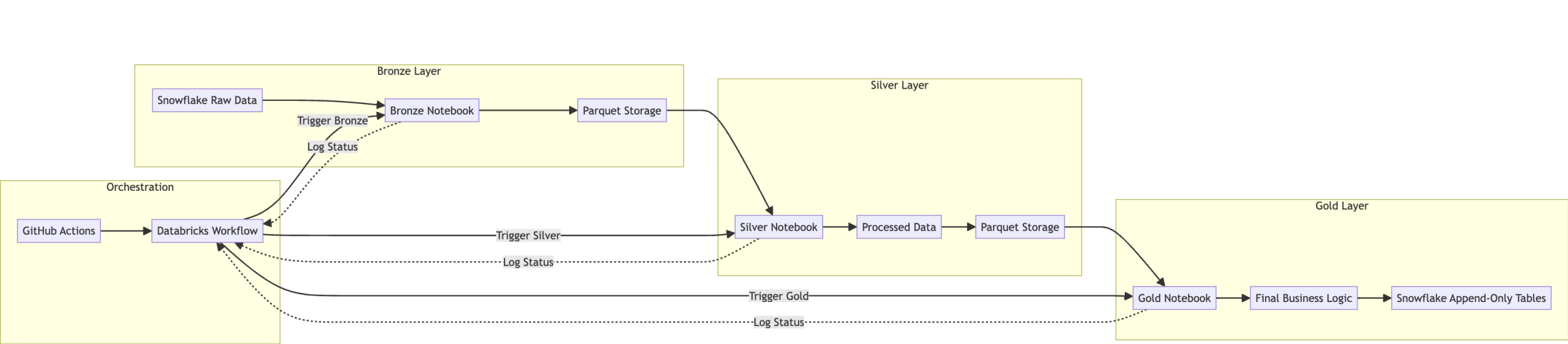


Sample Sequence Diagram of E2E Architecture



Sample Flow Chart of Medallion Architecture



Idempotency

∞ -loop

The output remains the same for each execution given the same input.

static input

Function

static output

Idempotency is necessary for application testing.

Idempotency is typically an essential characteristic of data engineering pipelines.

Non-Idempotent

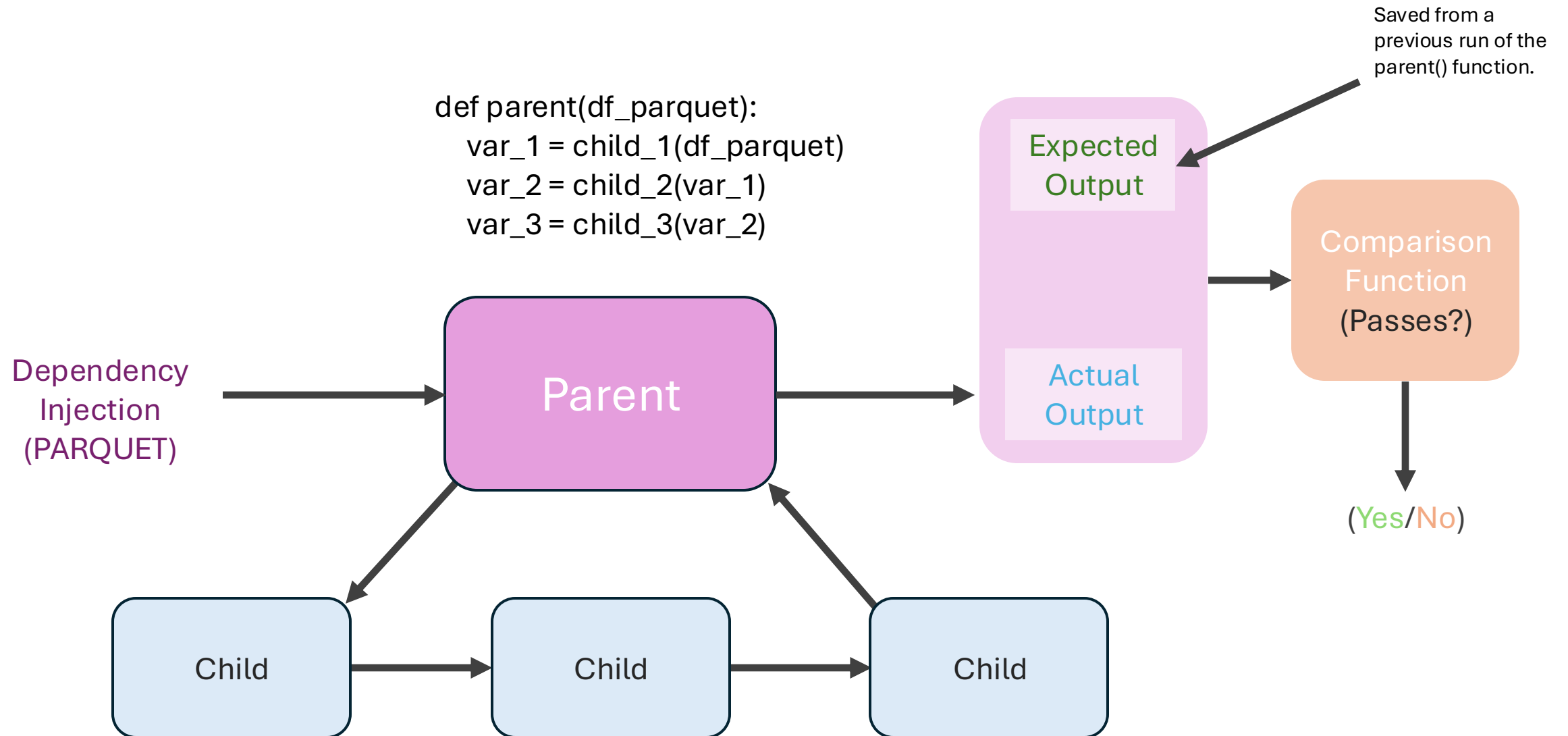
```
def func(float_val):  
    float_val += random_int()  
    return float_val
```

Idempotent

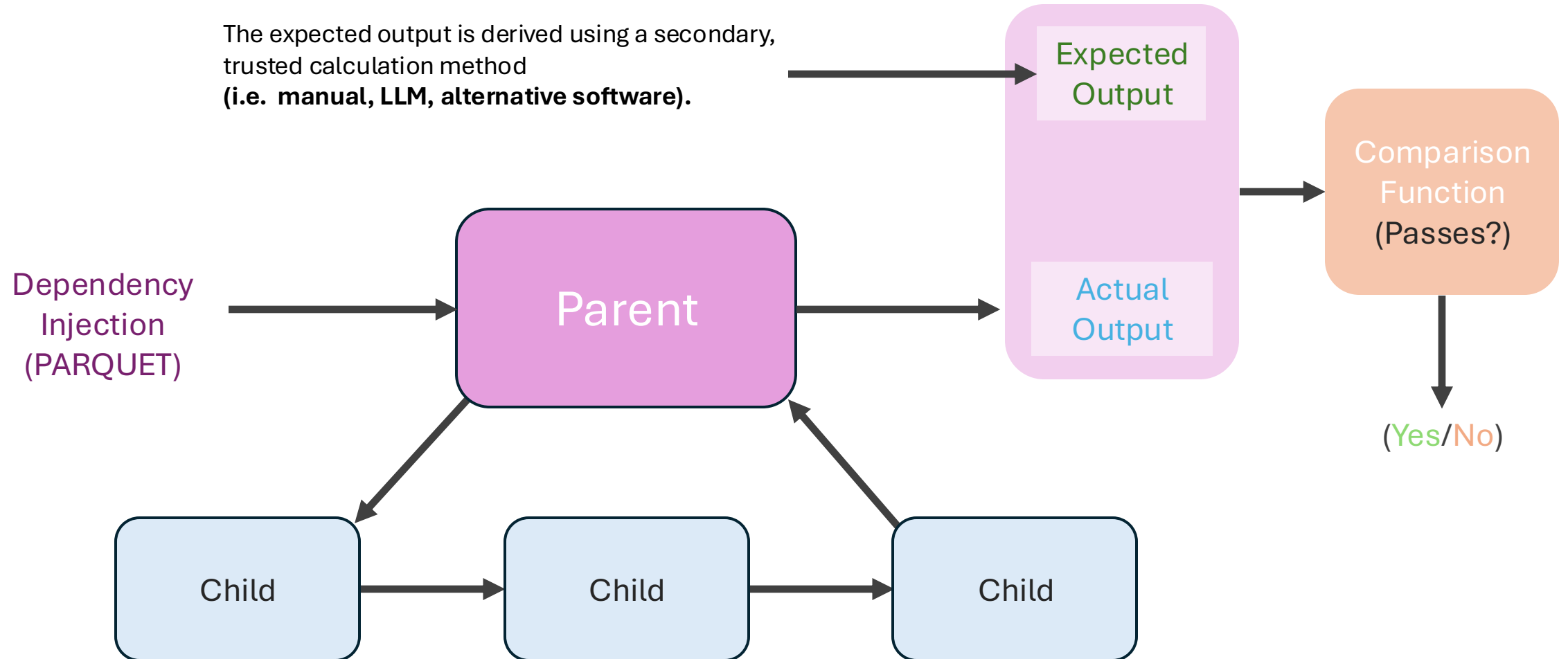
```
def func(float_val):  
    return float_val
```

Integration **Snapshot** Testing (Analytics Engineering)

```
def parent(df_parquet):  
    var_1 = child_1(df_parquet)  
    var_2 = child_2(var_1)  
    var_3 = child_3(var_2)
```



Integration Unit Testing



Alternative Testing

“Good software is well-tested software.”



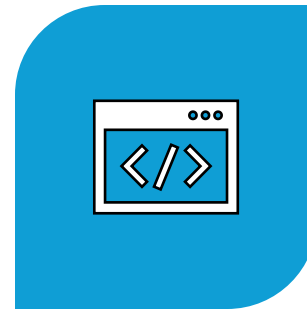
1. SMOKE TESTING

Does it run?



2. PERFORMANCE TESTING

Is it fast?



3. UI TESTING

Does the UI
operate as
expected?



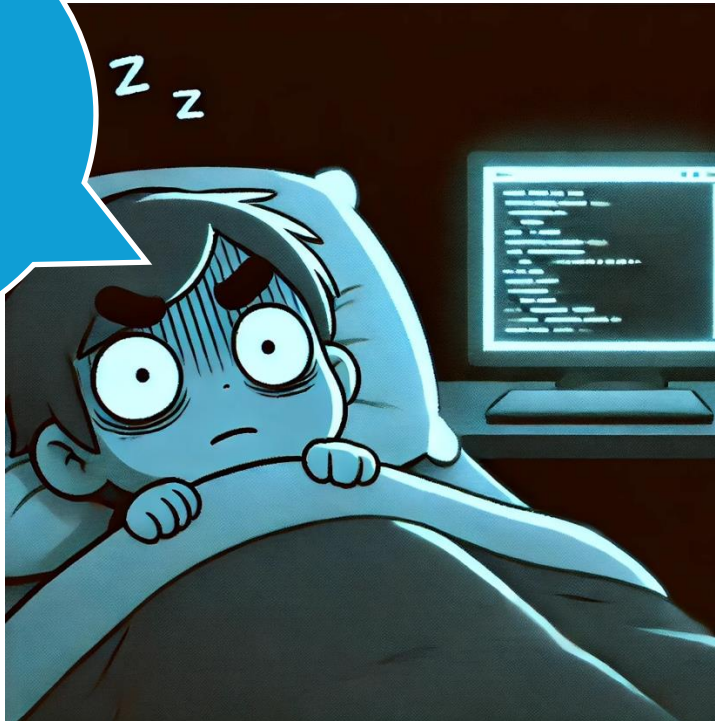
4. PROPERTY TESTING

Does it fit within the
bounds of an
expected output?

Snapshot Testing

- Probably not conceptually validated (using a previous out as a test case).
- **Fickle:** Needs to be changed often.
- Must be updated with each functional change.
- Verifies that only non-functional changes have occurred (i.e., refactors).
- Should only be updated with peer review.

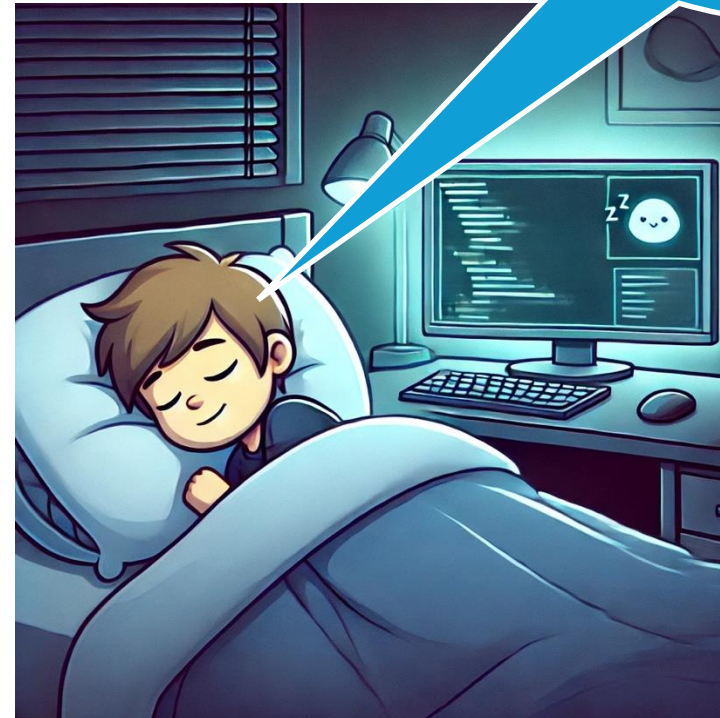
I hope James and Hannah didn't secretly update that snapshot test for our whole pipeline without checking our dashboard first.



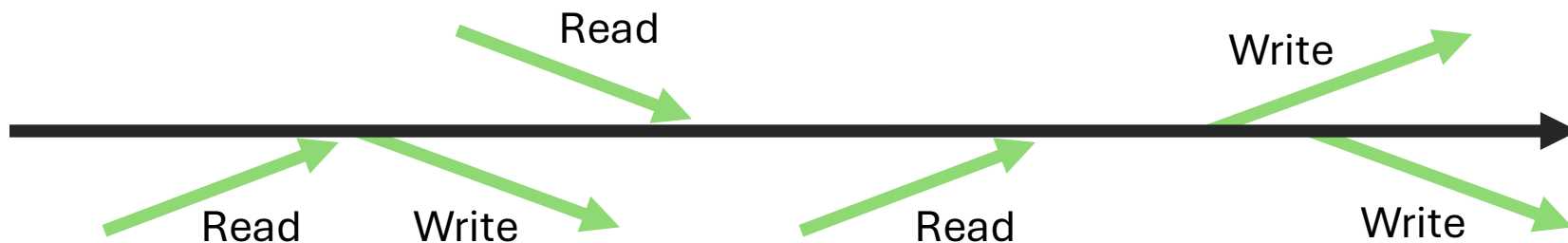
Unit Testing

- Conceptually validates a function is performing correctly.
- Ideally, these are written for critical building blocks of a software.
- Helps developers sleep at night.

Sleep is easy when I know my core functionality is conceptually validated via unit tests.

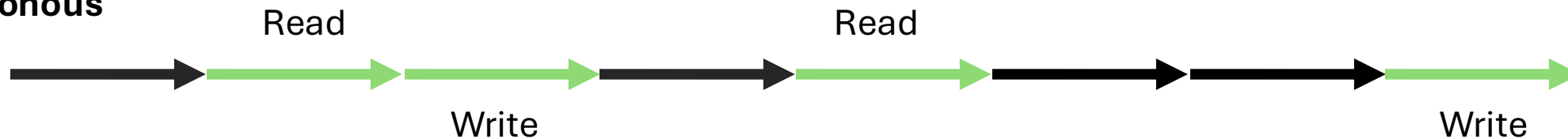


Asynchronous

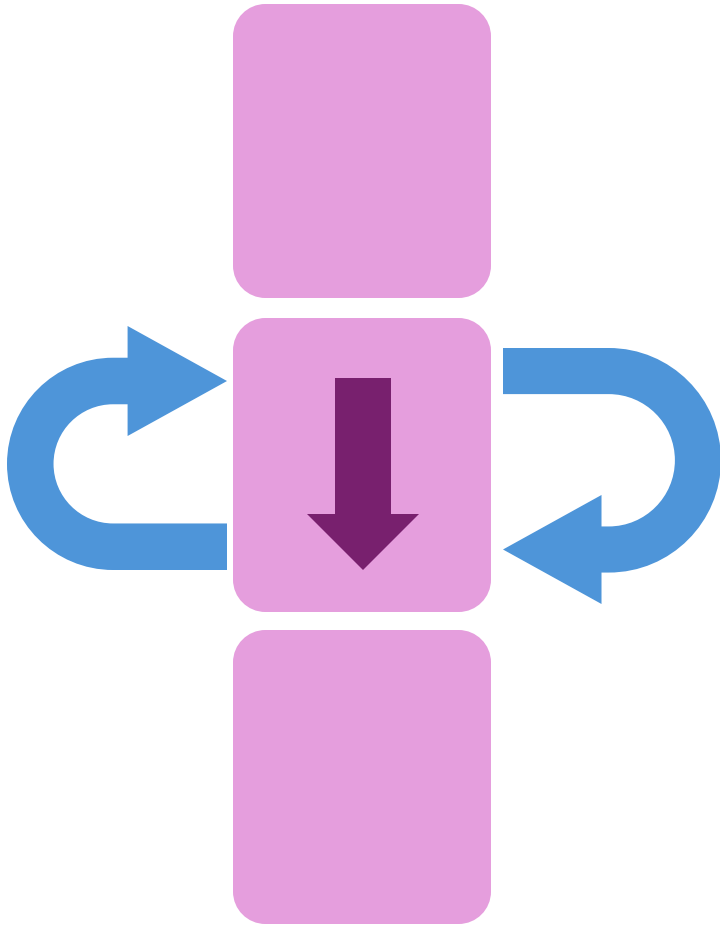


Asynchronous reads and writes run operations on separate threads decrease the runtime of the data pipeline.

Synchronous

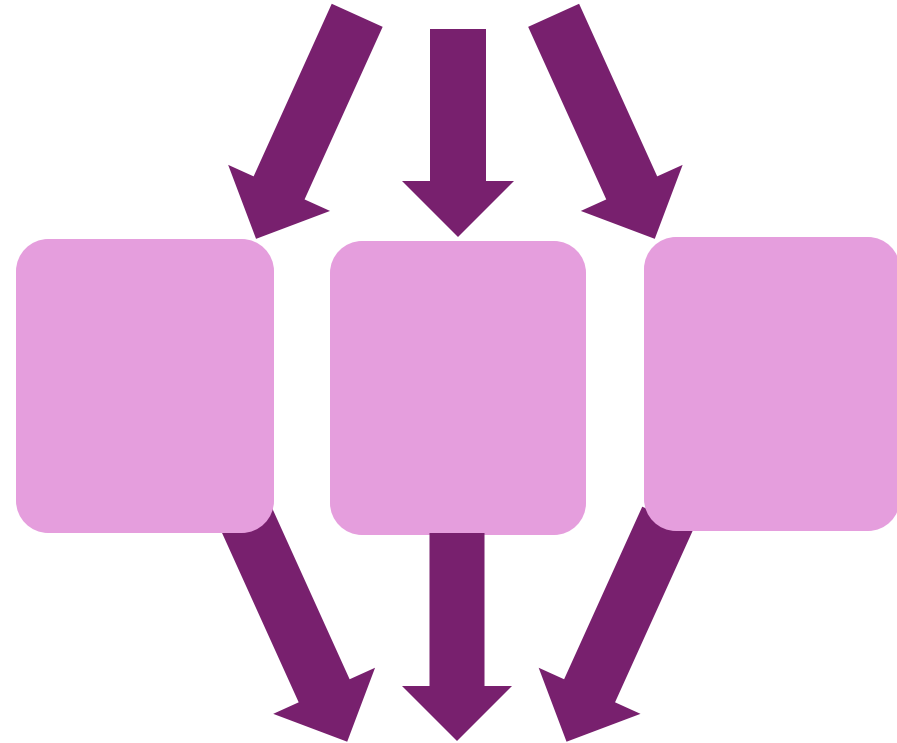


Chunking



Time Complexity: $O(n)$
Space Complexity: $O(1)$

Parallelization

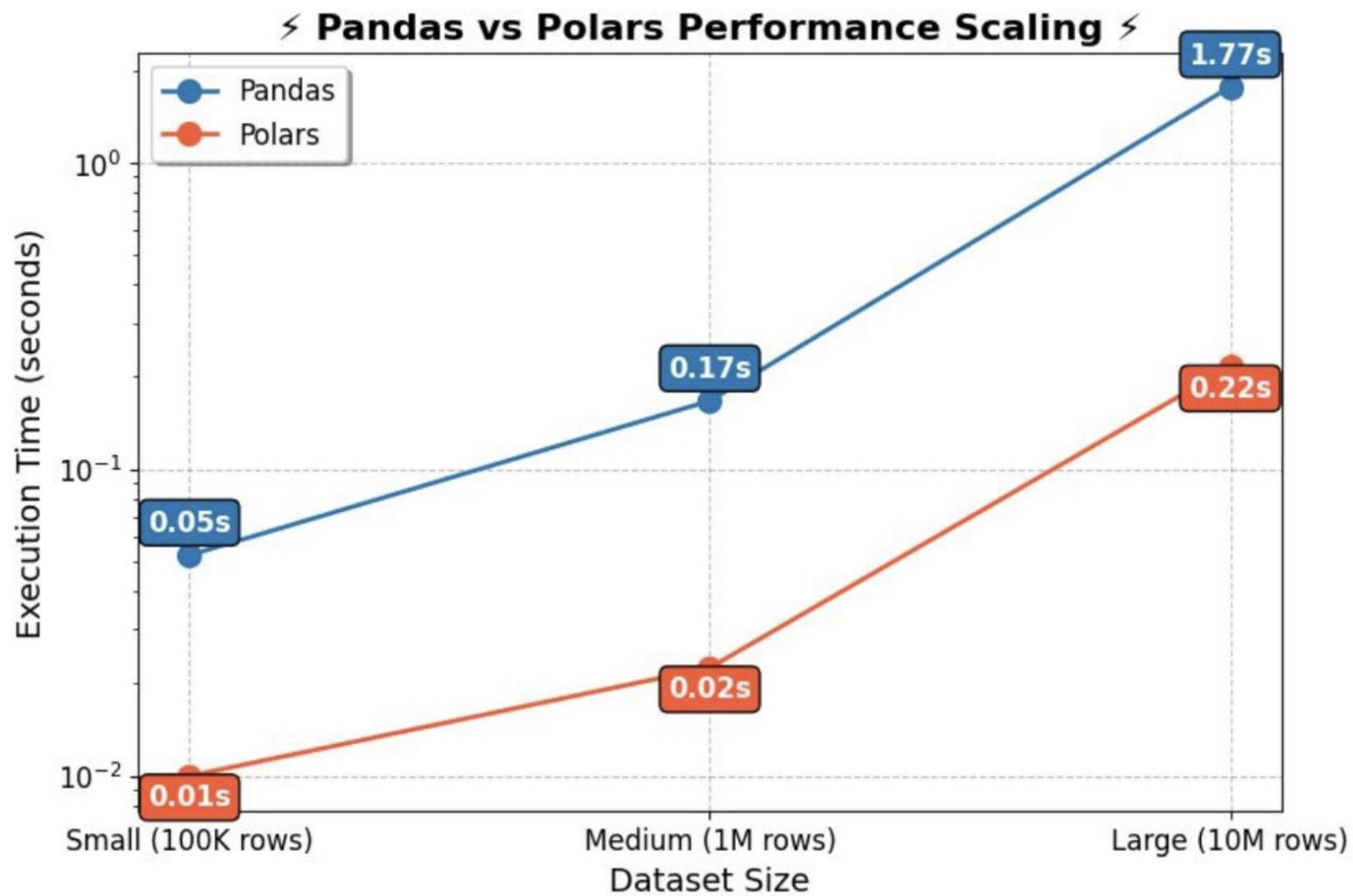


Time Complexity: $O(1)$
Space Complexity: $O(n)$

Programming Language Trade-Offs

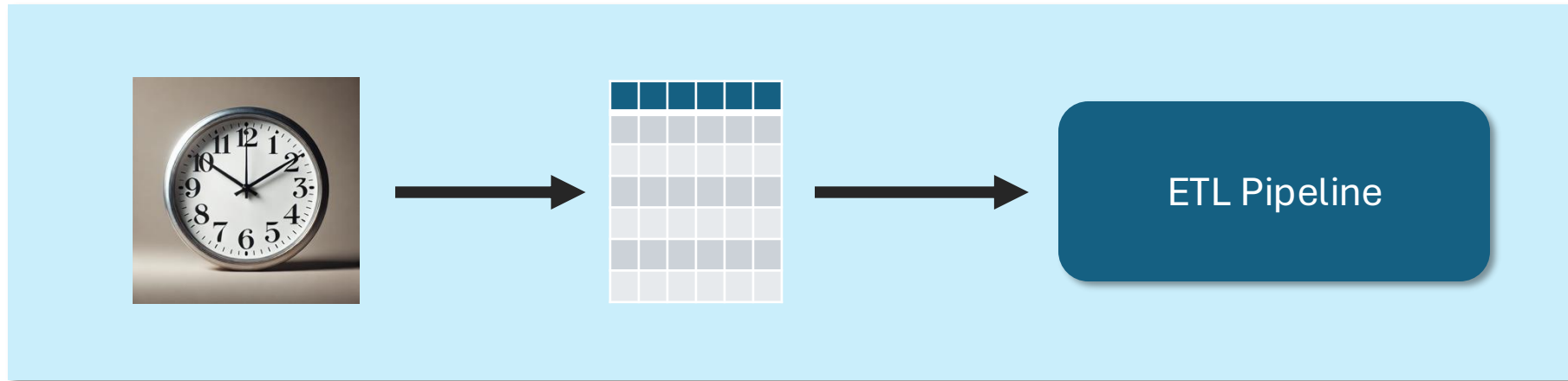
Use Case	Pandas	Polars	PySpark	SQL
Small datasets (<10M rows)	✓ Best	✓ Faster	✗ Overkill	✓ Good for querying
Large datasets (>10M rows, fits in RAM)	✗ Memory issues	✓ Efficient	✓ Good	✓ Good
Big Data (TB-scale, distributed)	✗ Impossible	✗ Limited	✓ Best	✓ Best
Parallel processing	✗ Single-threaded	✓ Multi-threaded	✓ Distributed	✓ Query optimizations
Complex ETL	✓ Simple	✓ Efficient	✓ Distributed pipelines	✓ SQL transformations
ML/Statistical modeling	✓ Best for ML	✓ Works	✗ Spark ML (limited)	✗ Not ideal
Cloud-based processing	✗ Local only	✗ Local only	✓ Cloud (Databricks, EMR)	✓ Cloud-native (BigQuery, Snowflake)

Pandas VS. Polars

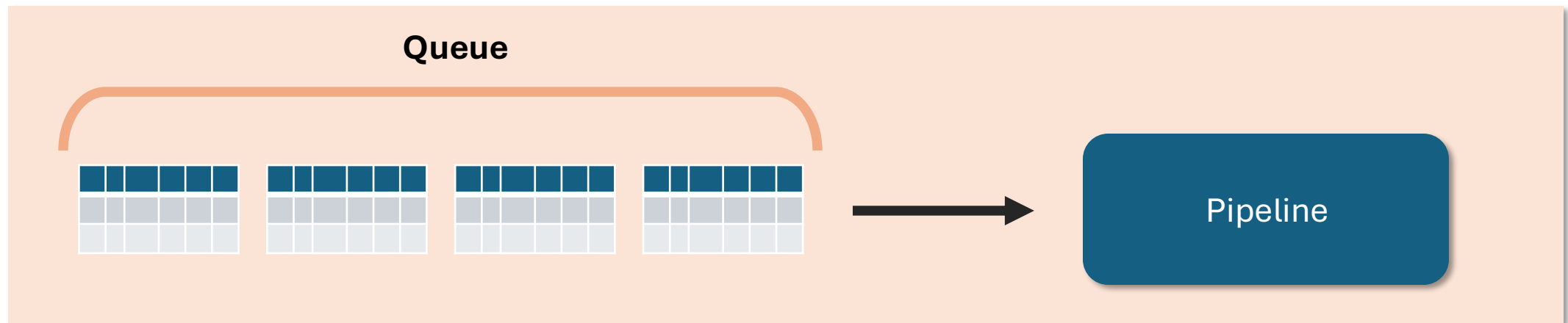


Batch or Stream Processing

Batch



Stream



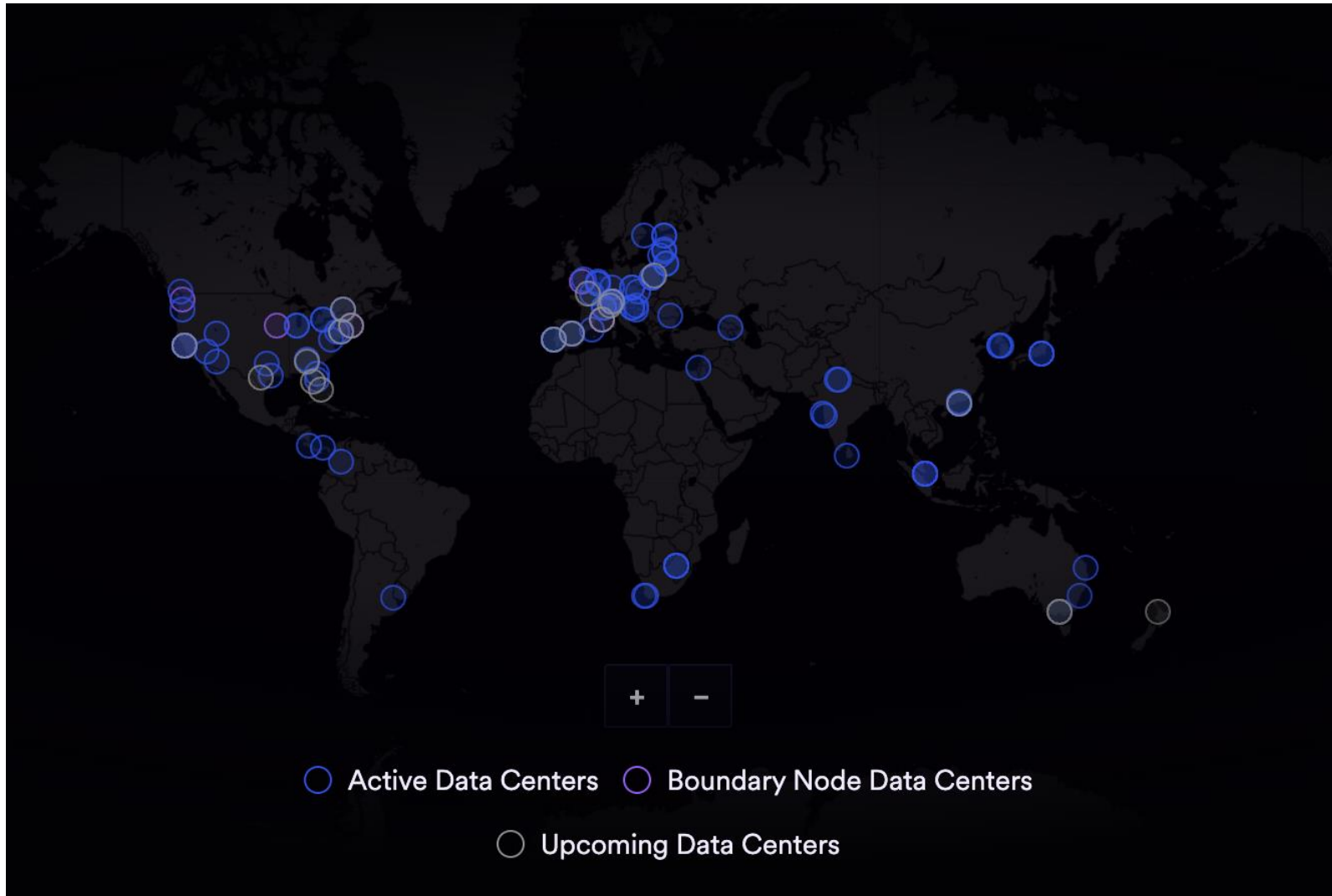
Vectorization

PyArrow

Numpy

Pandas

CI/CD



Cloud Provider as
State Machine
Replication for
Byzantine Fault
Tolerance



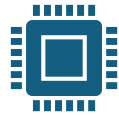
Subnets consist of 13 or more nodes. This allows for variable decentralization.



Latency is < 2 seconds.



Egress (query calls) doesn't need to go through consensus.

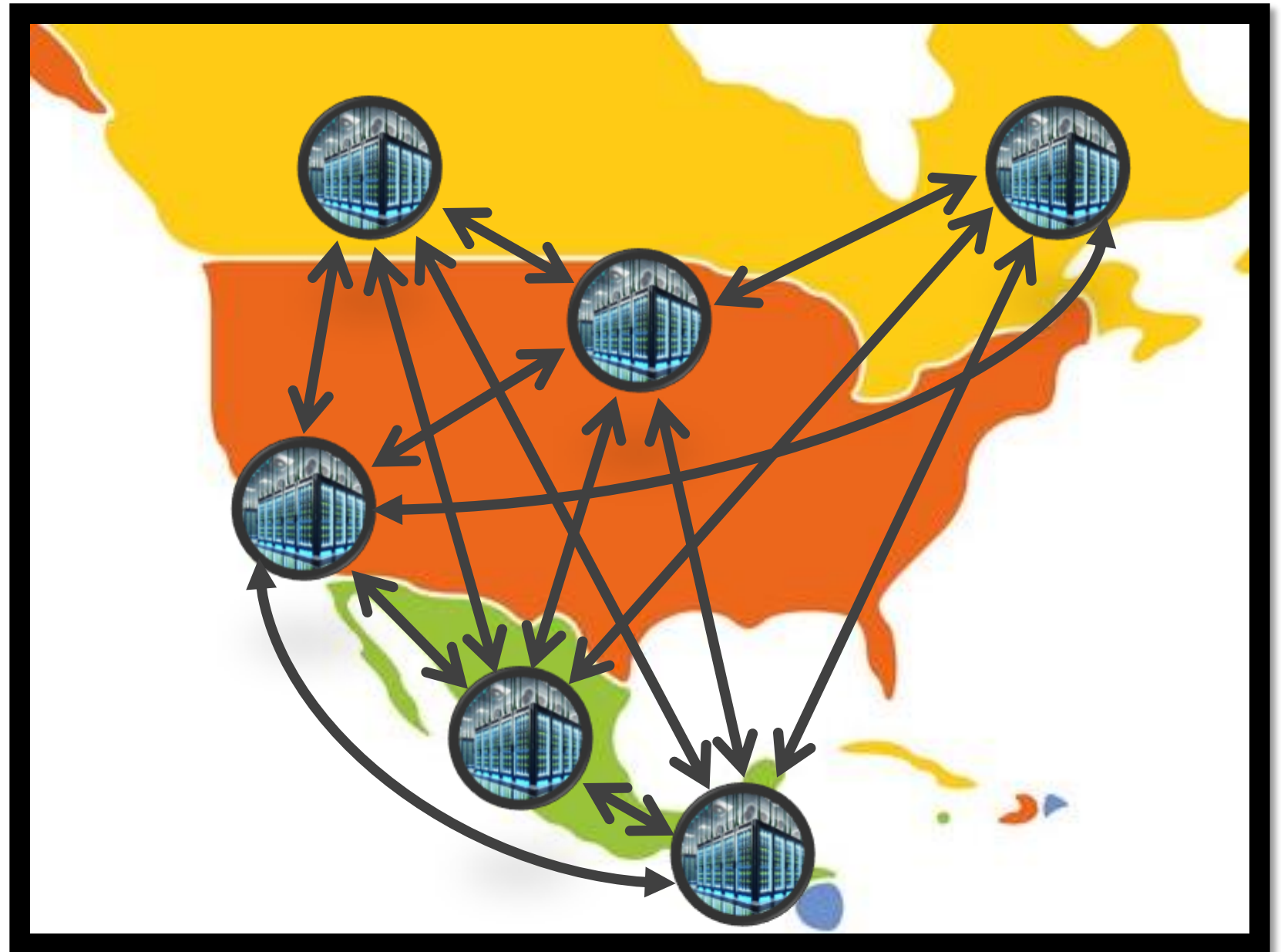


Reverse gas:

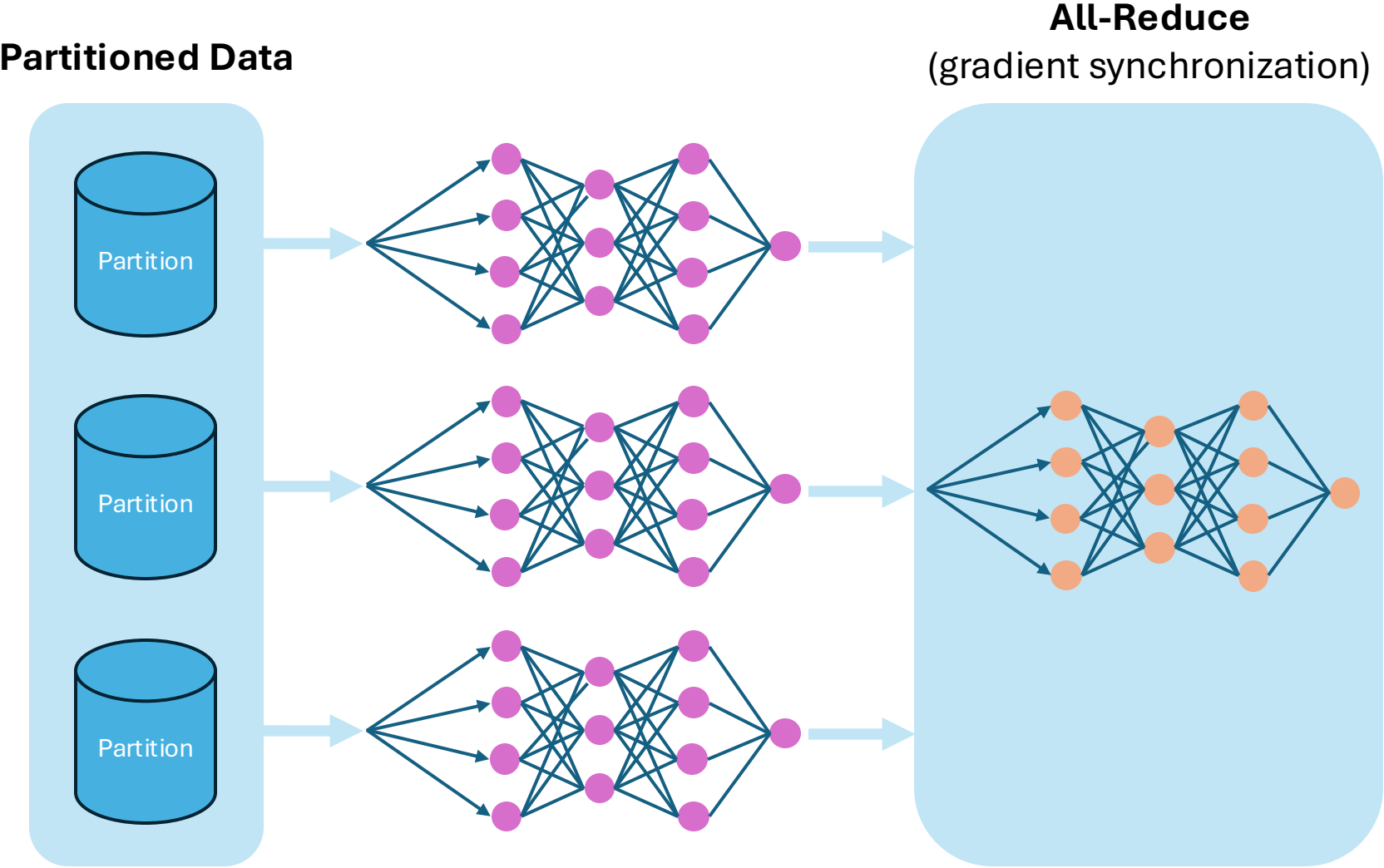
Developers pay for gas fees, and end-users can use the blockchain without needing to pay in ICP (like a normal website).



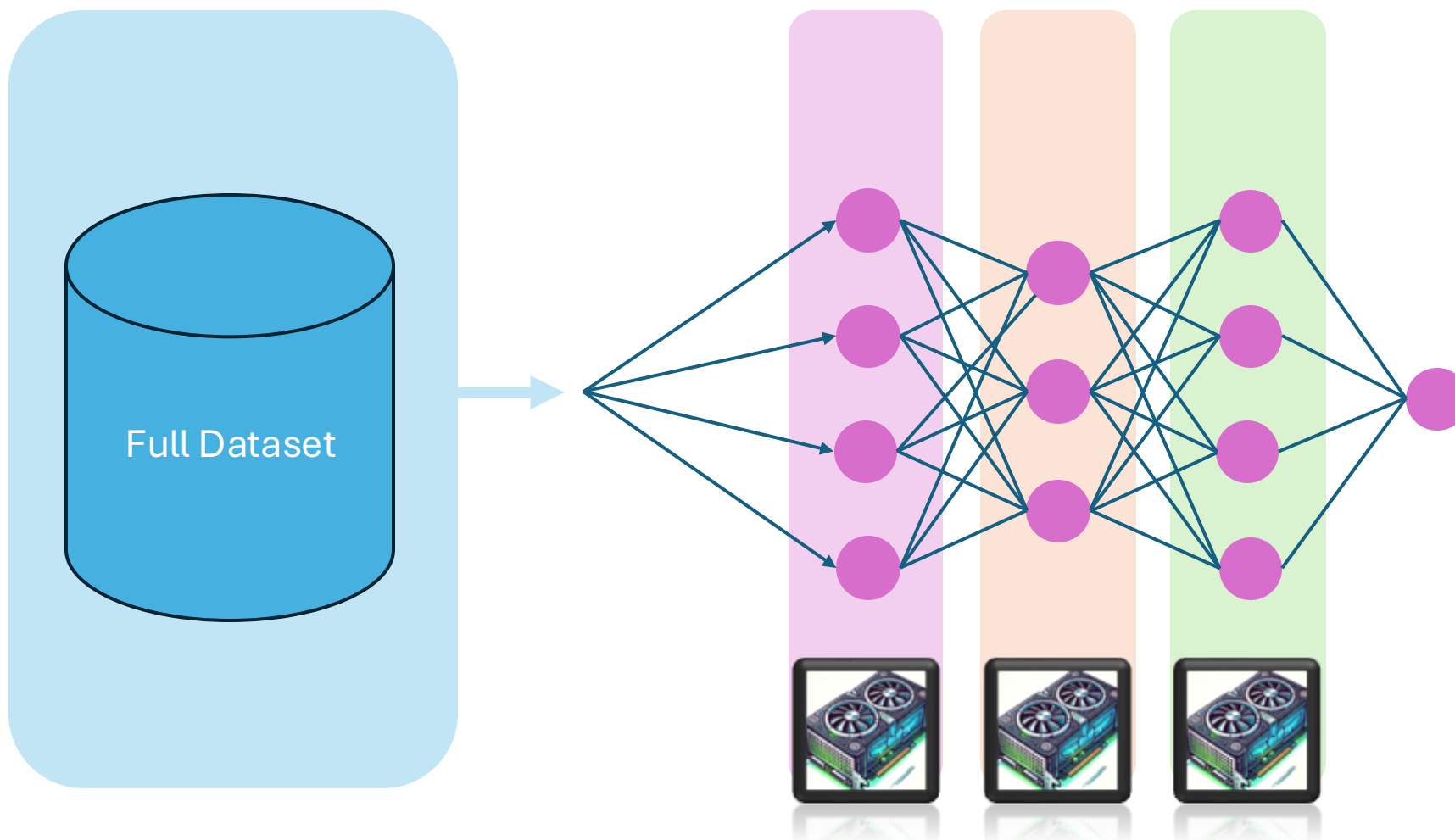
Software becomes immune to cyber hacks or datacenter outages due to any cause of failure.



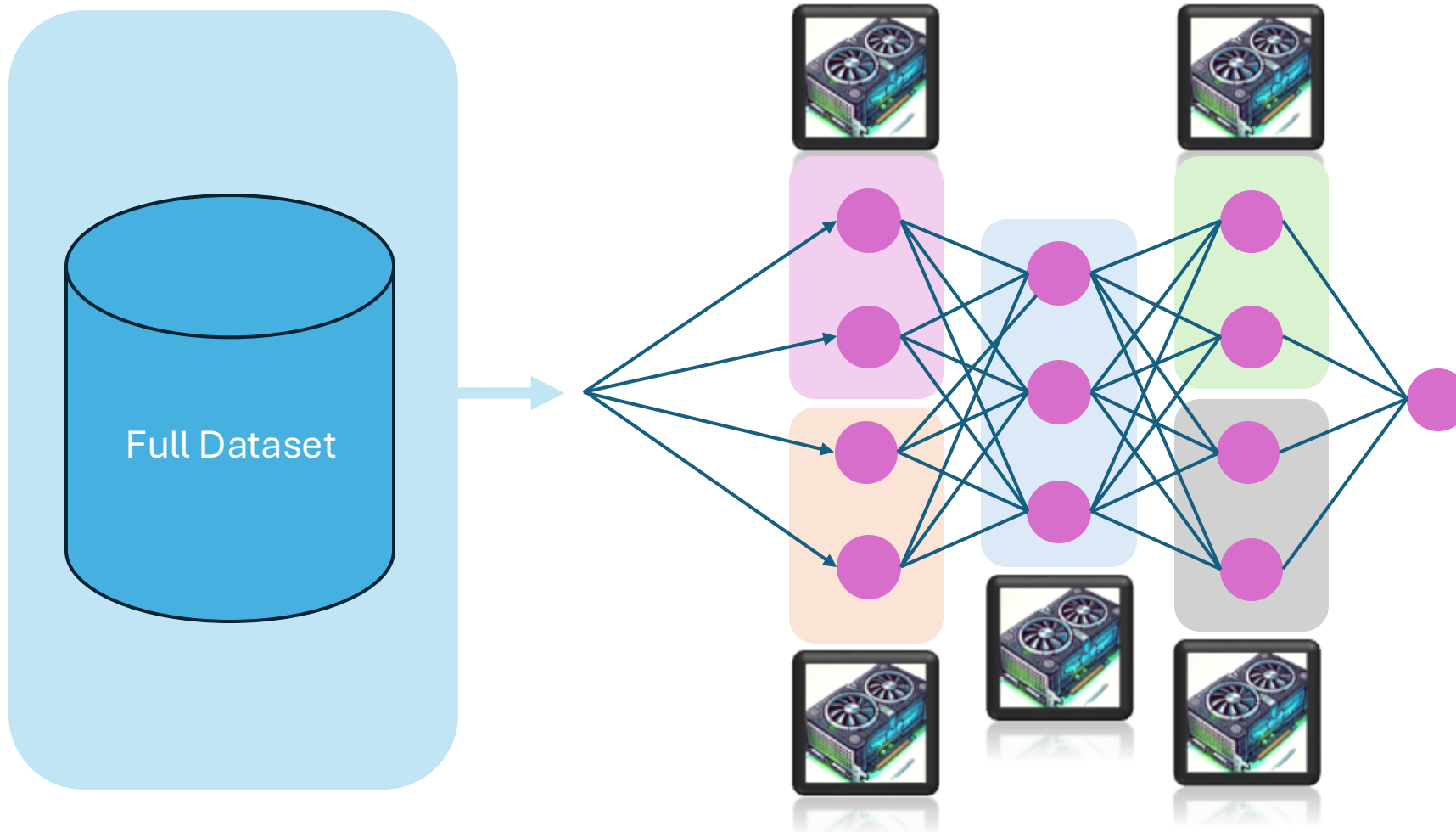
Distributed Data Parallel Training



Model Parallel Training



Tensor Parallel Training



RAG: Retrieval Augmented Generation

Example DL Project