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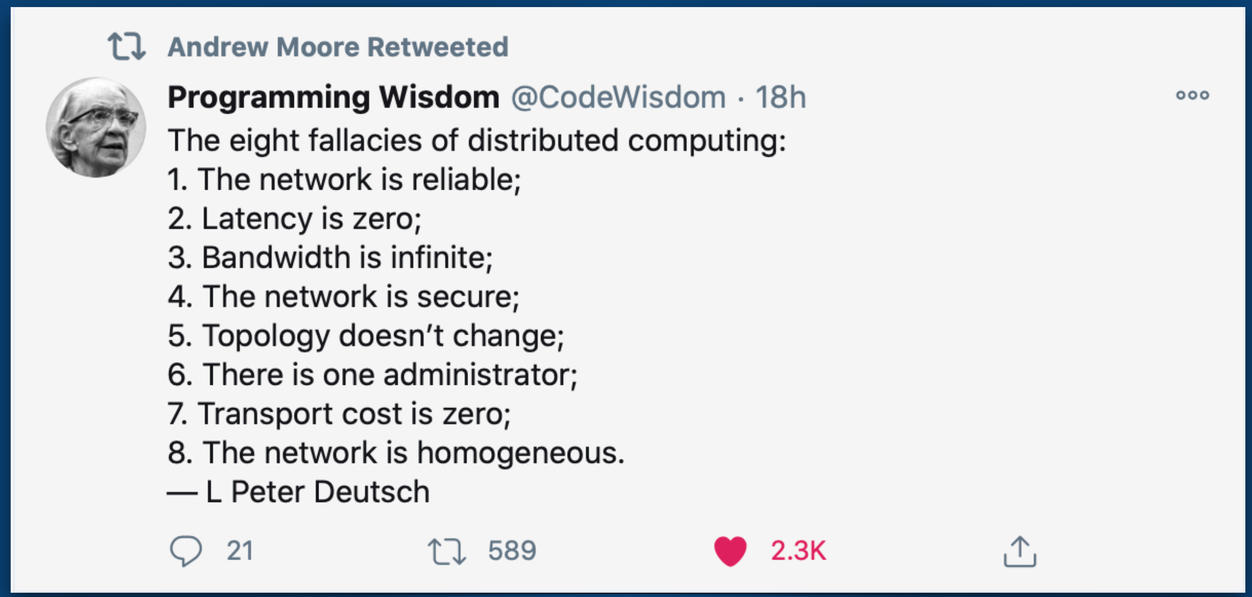
PICCOLO

Information-Centric Dataflow

Re-Imagining Reactive Distributed Computing

Dirk Kutscher, Laura Al Wardani, T M Rayhan Gias
ACM ICN-2021



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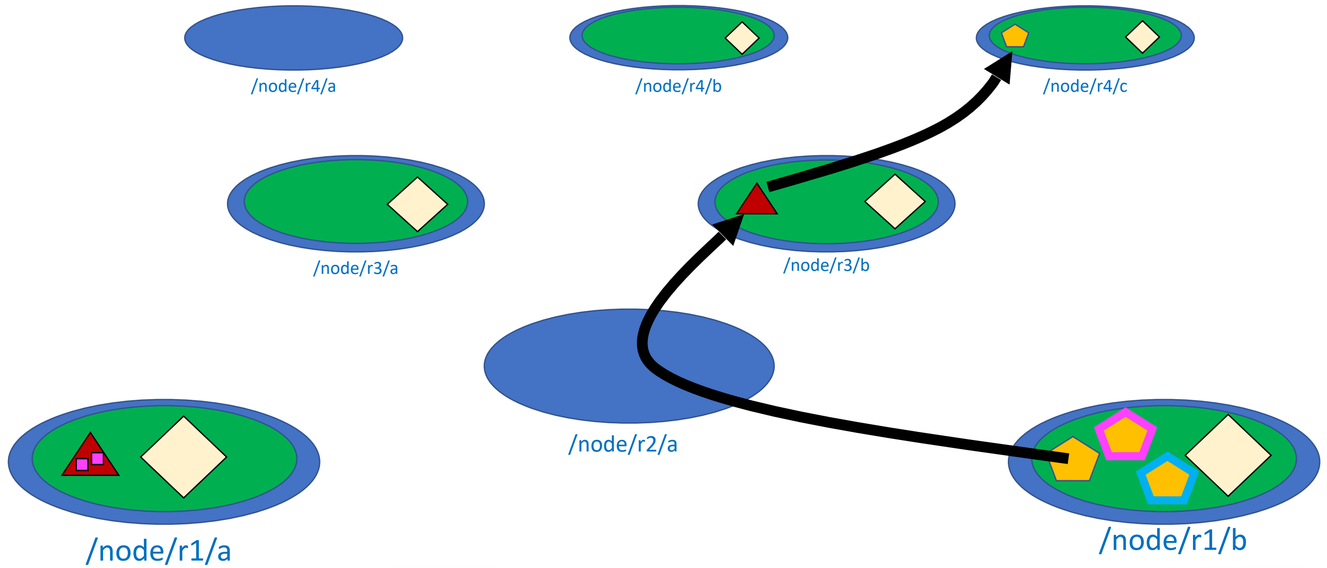
Distributed Computing

Many Different Types of Interactions

- Message passing
- Remote Method Invocation
- Dataset synchronization
- Key-value store



Compute First Networking: Distributed Computing meets ICN

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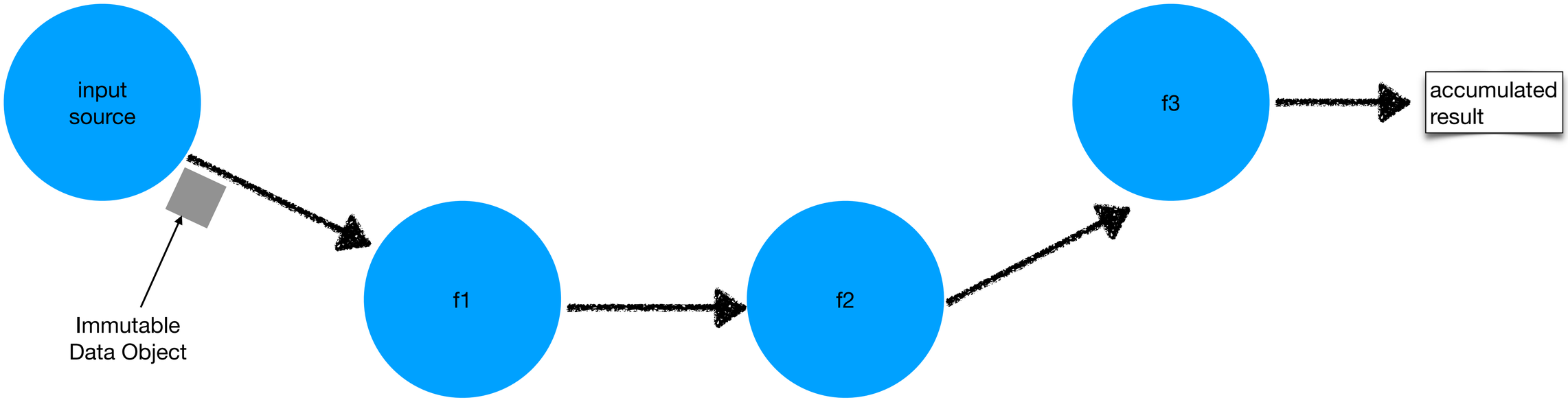
Dataflow

Structured Distributed Data Processing



Dataflow

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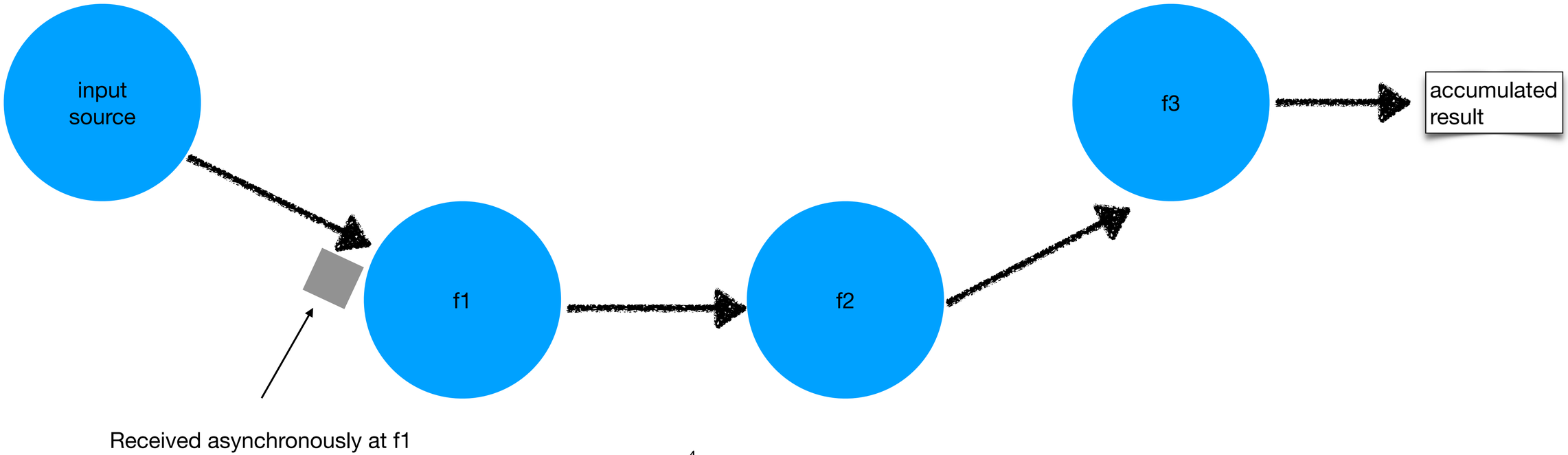

Dataflow

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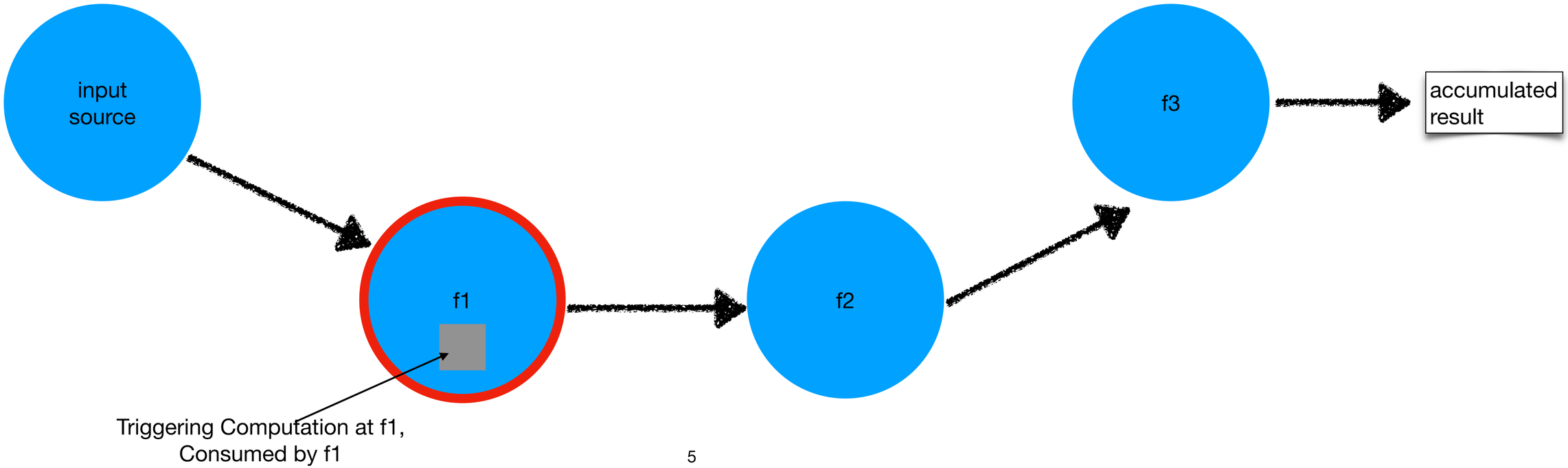

Dataflow

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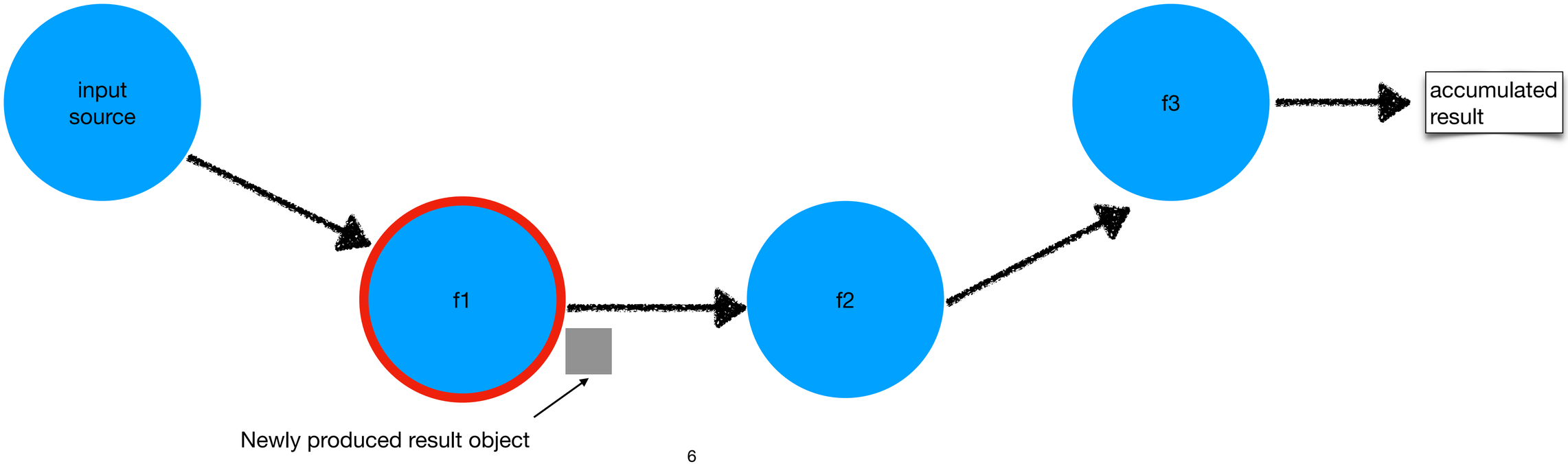

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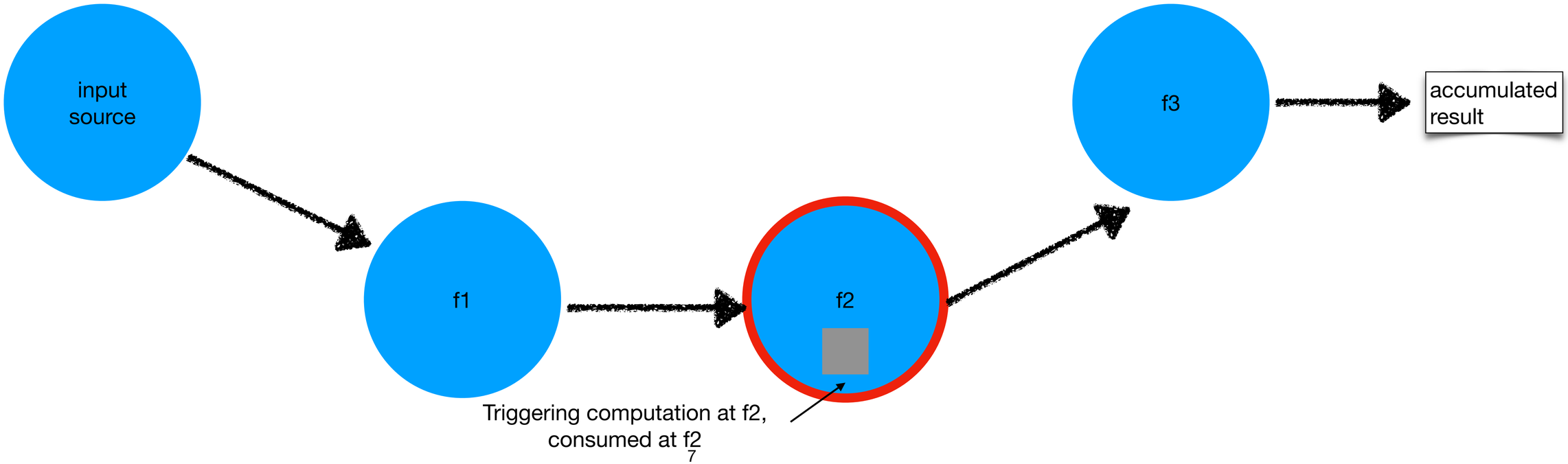

Dataflow

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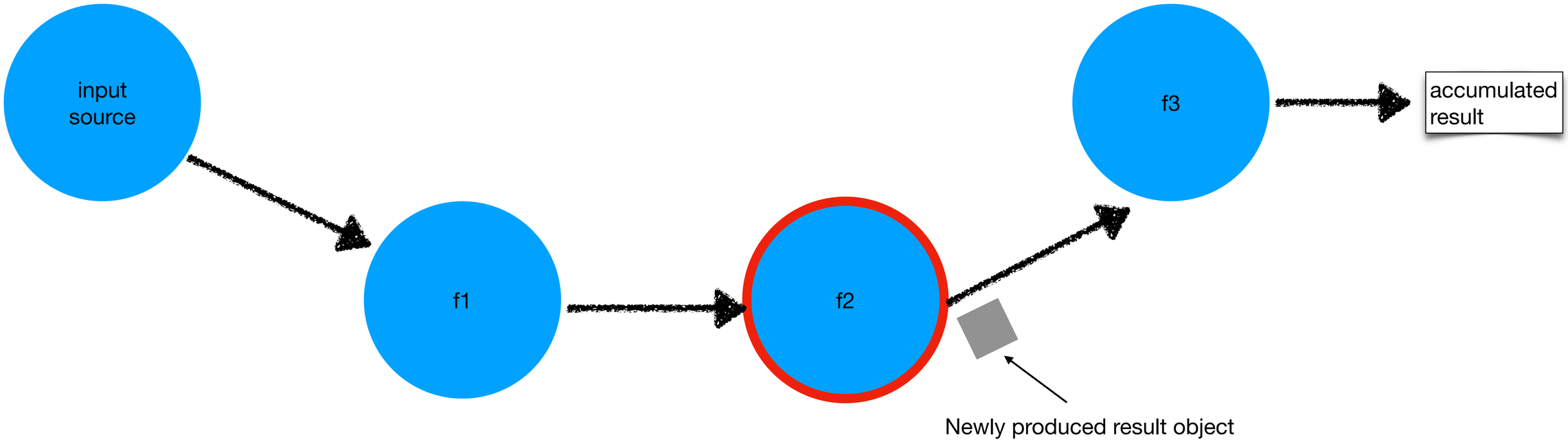

Dataflow

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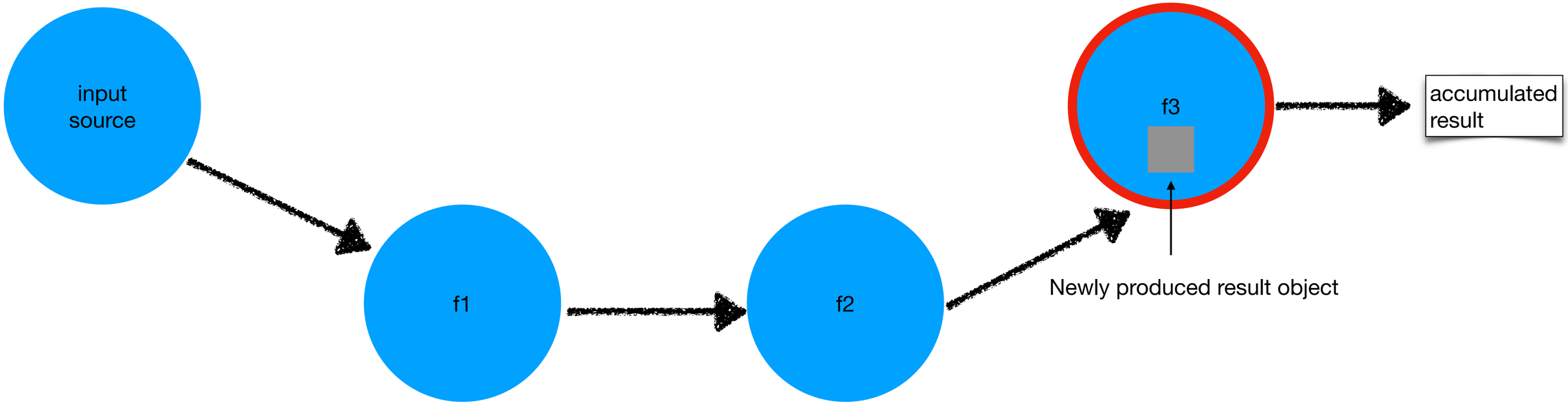

Dataflow

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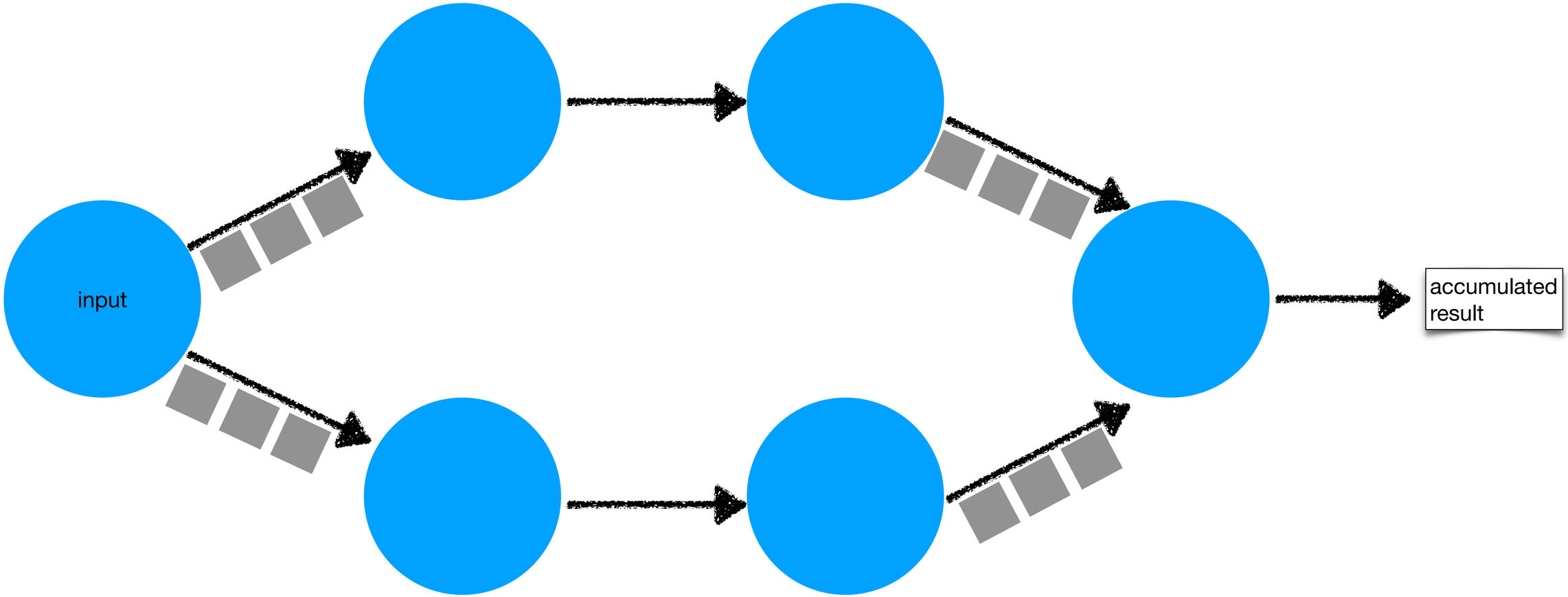

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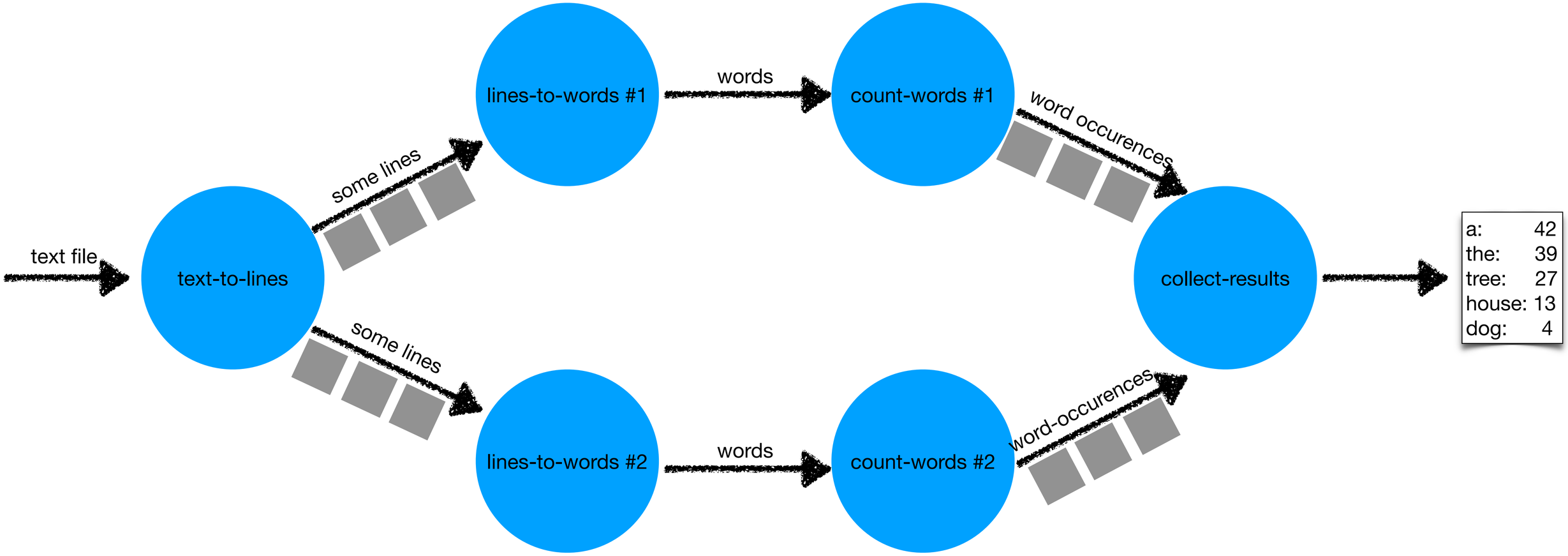
Dataflow

Poster Child Example: word-count

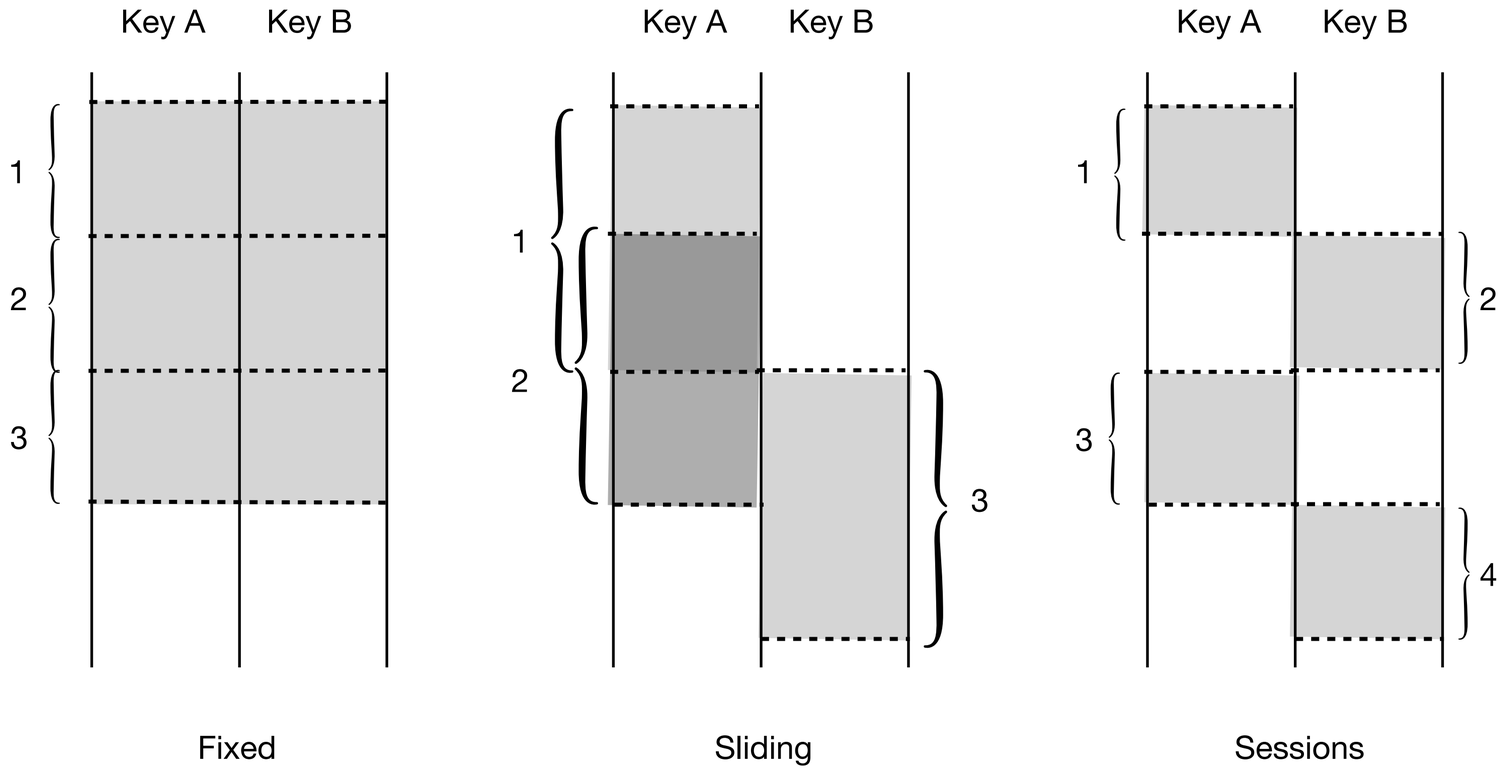
```
text-to-lines -> lines-to-words -> word-count ->
    ↪ collect-results
```



Dataflow Concepts

Batch & Stream Processing

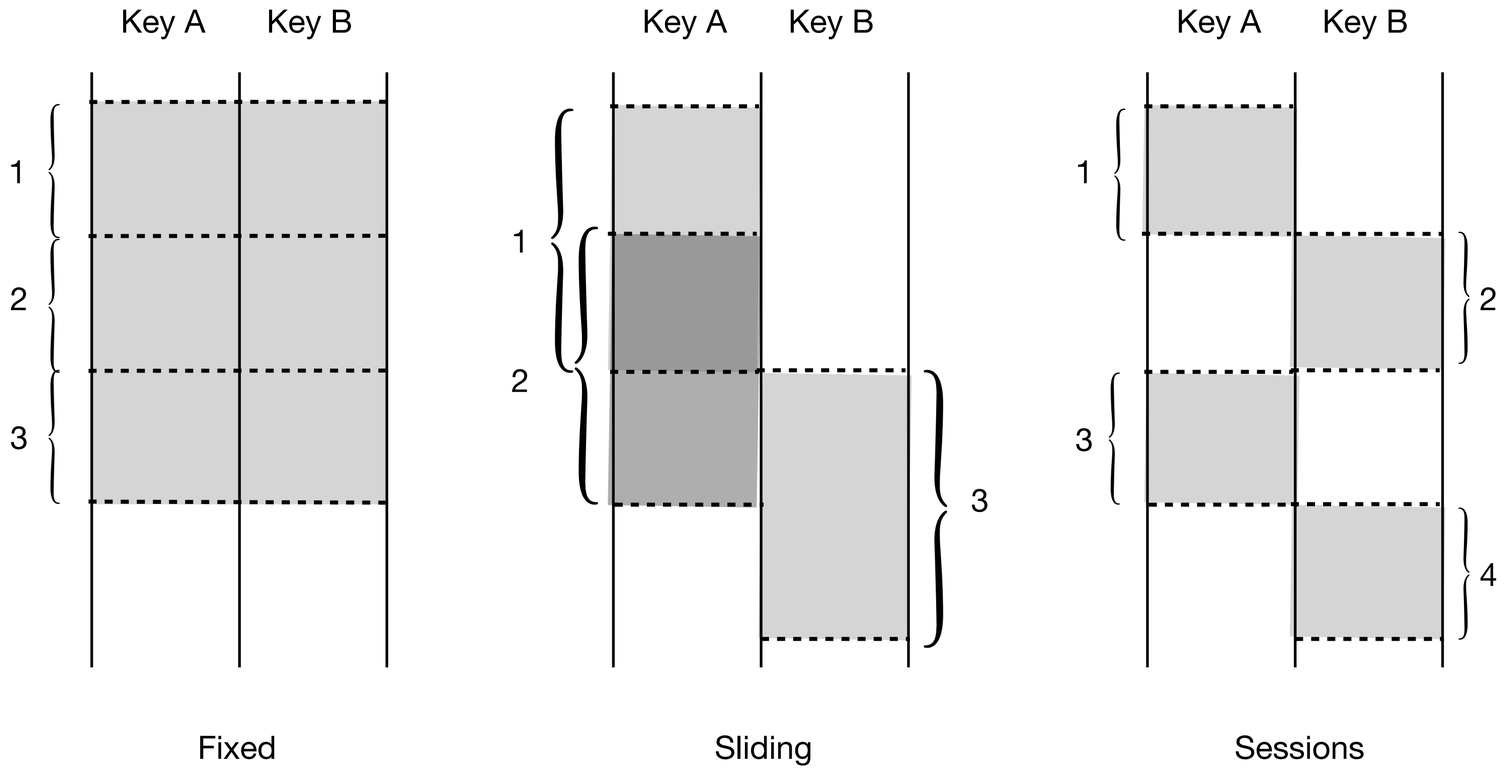
- Data objects as asynchronous events
  - Stream processing: each data object processed independently (unbounded)
  - Batch processing: grouping of data objects (bounded)



Dataflow Concepts

Windowing

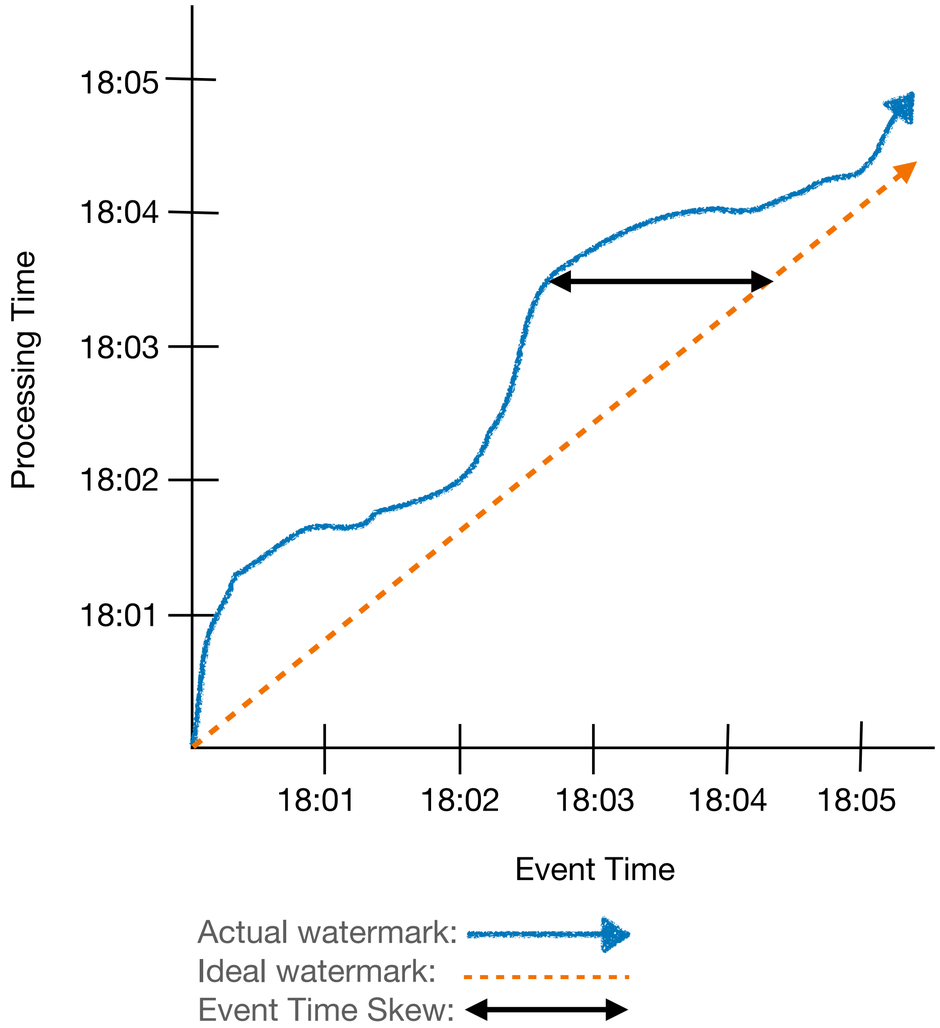
- Slicing data sets for processing as a group (aggregation)
- One data item can be assign to more than one group
- Directing data to specific consumers



Dataflow Concepts

Timing

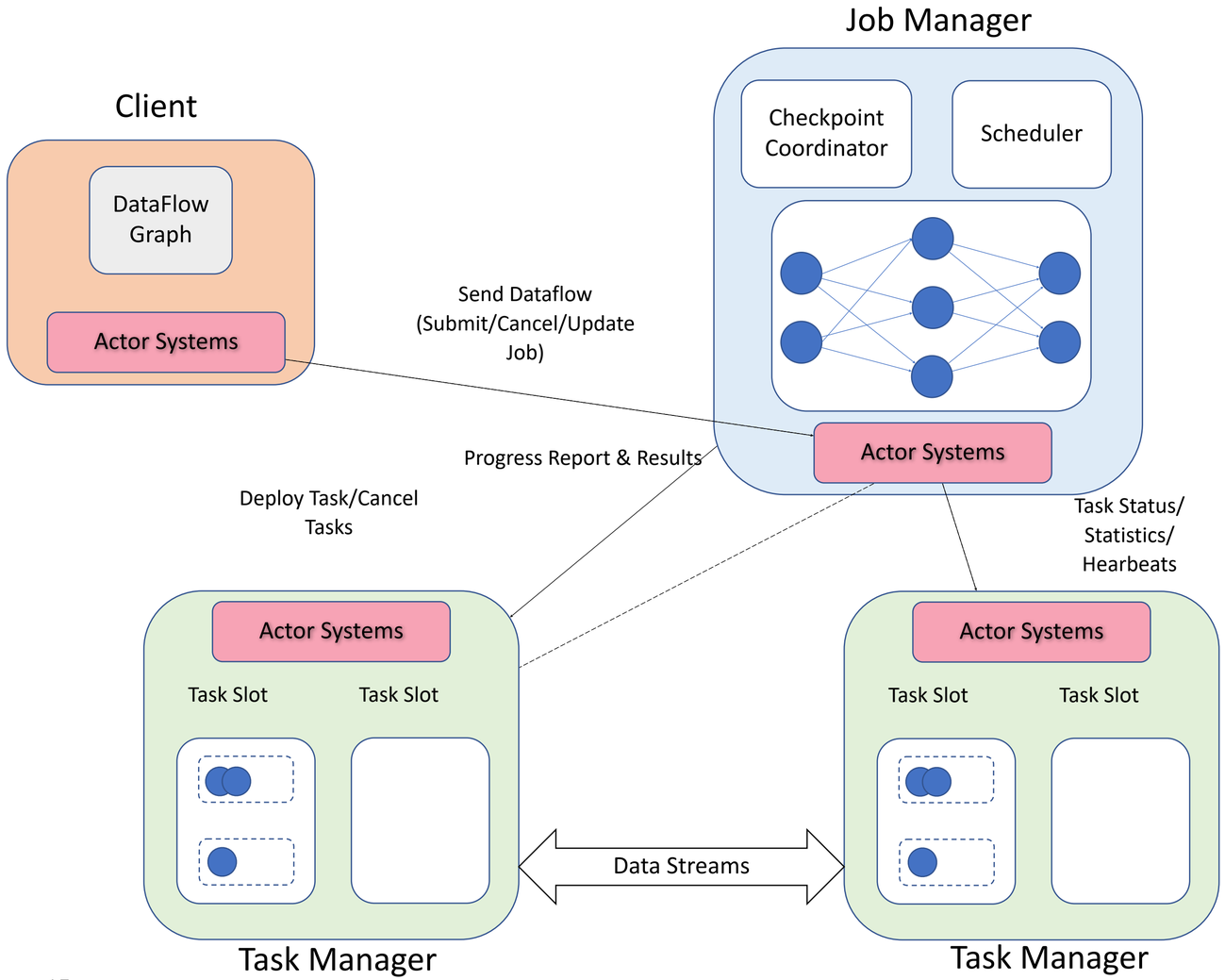
- Elastic data processing
- Asynchronous sourcing
- Unpredictable transport and processing delays
- Ideally: processing matches production rate
- Task of a Dataflow system: adjust processing graph to production rate and "real-time requirements"



Dataflow

Mainstream Implementations

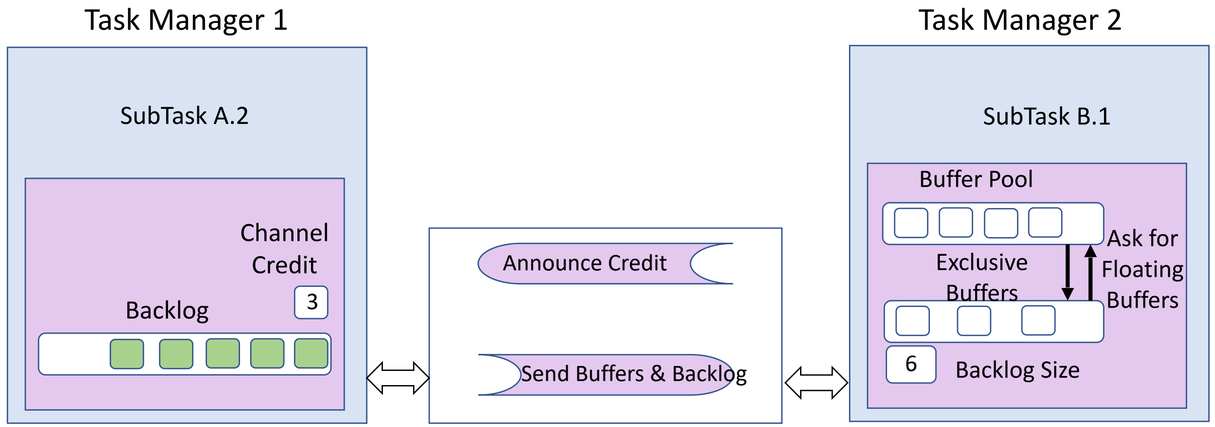
- Apache BEAM
  - Unified programming model for data processing pipelines
- Dataflow runners
  - Execution environments for Dataflow applications
  - Apache Flink, Samza, Spark
  - Google Cloud Dataflow



Dataflow

Transport and Back Pressure

- Example: Apache Flink
- Connections connect task managers, not tasks
- Need to regulate upstream processing rates



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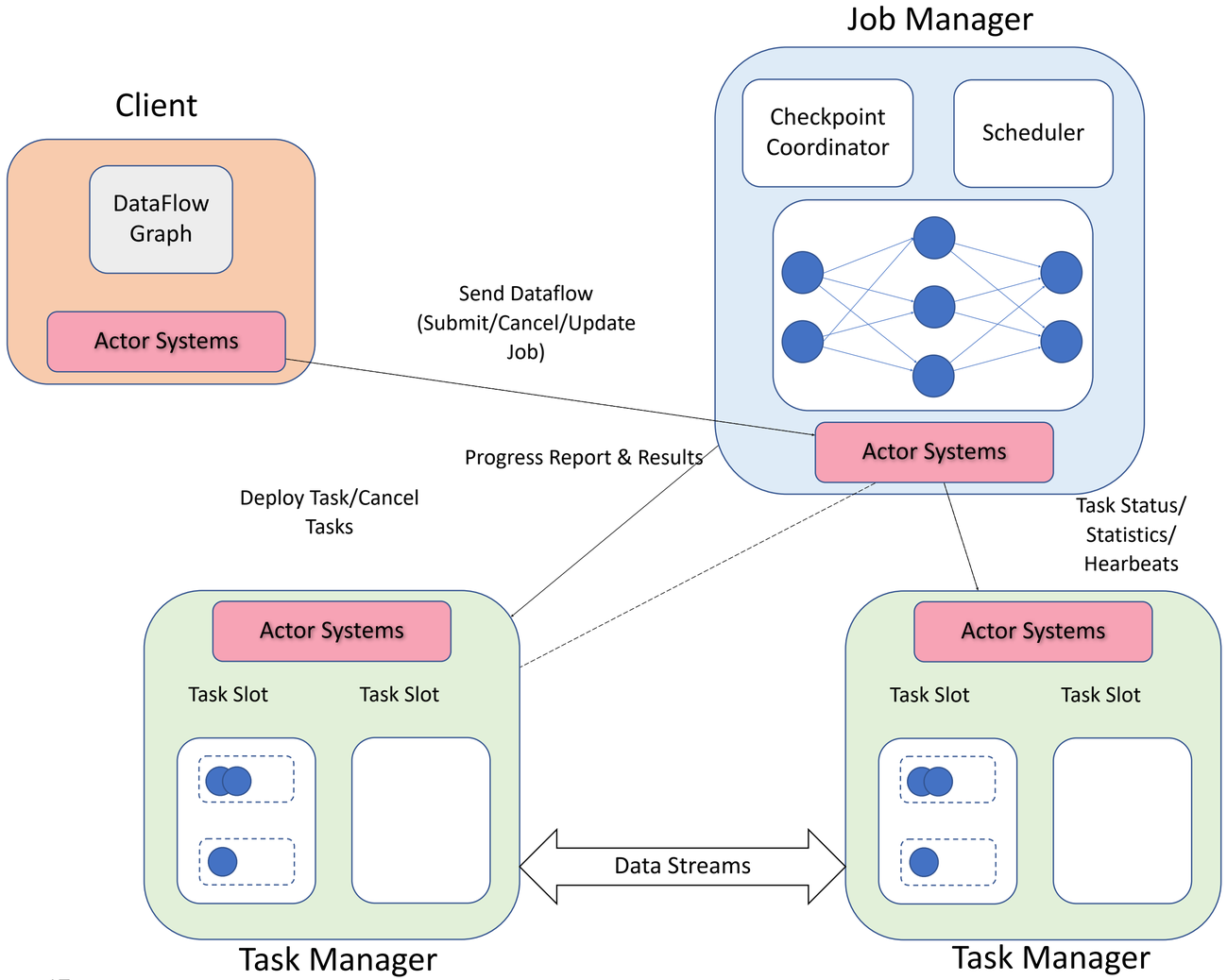
Problem Statement

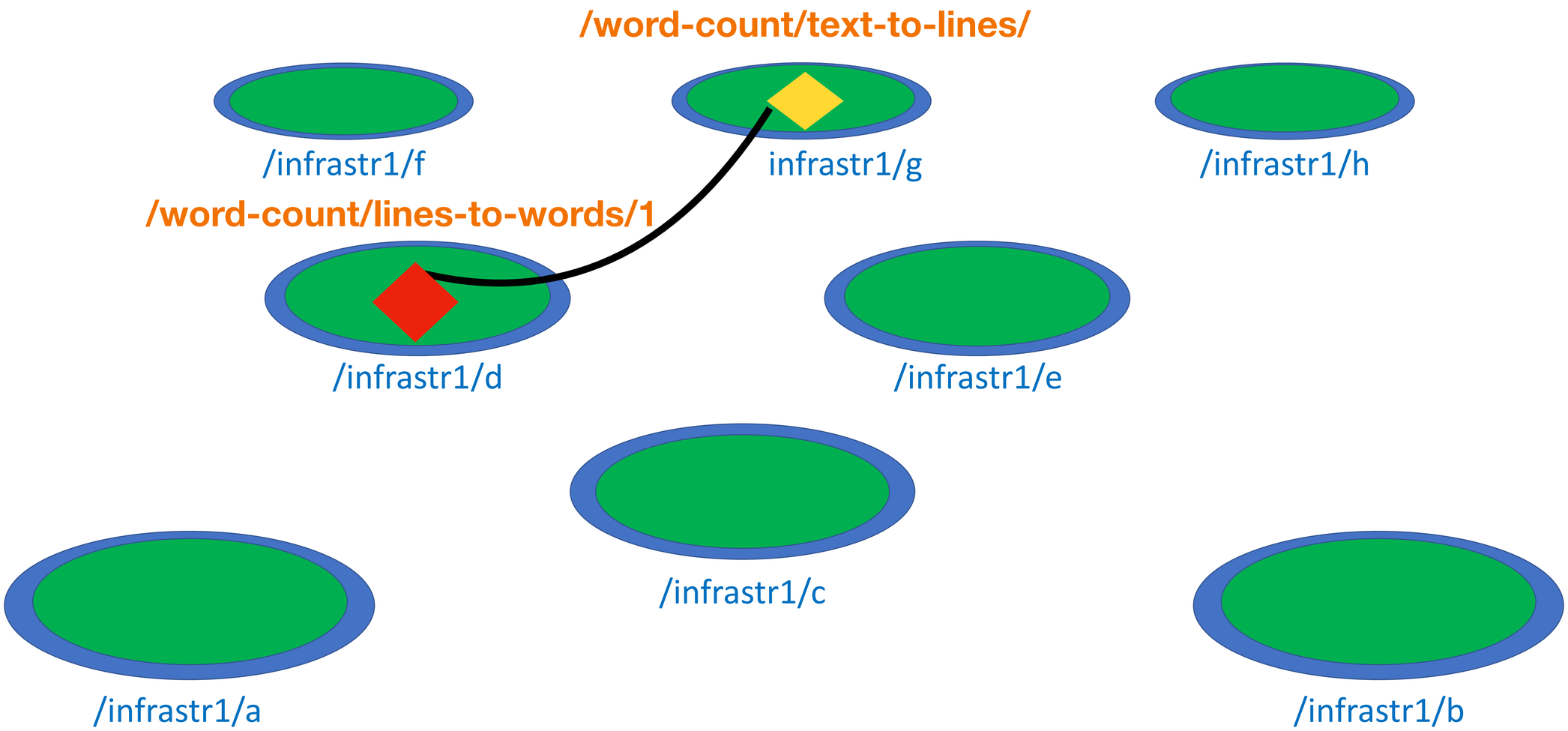
Overlays, Pipes, Address Mappings, Orchestration

- **Overlays do not match the inherent logic of processing immutable data objects**
  - Data is locked into connections
  - Connections are virtual channels between IP hosts
  - Orchestrator required to track resources, maintain mappings of task relationships to connections between hosts
- **Elastic Dataflow requires agile function instantiation, flow graph updates etc.**
- **Performance is a function of upstream data rates, network throughput, processing speed**
  - Limited visibility into root causes of performance problems at orchestrator



IceFlow

Information-Centric Dataflow



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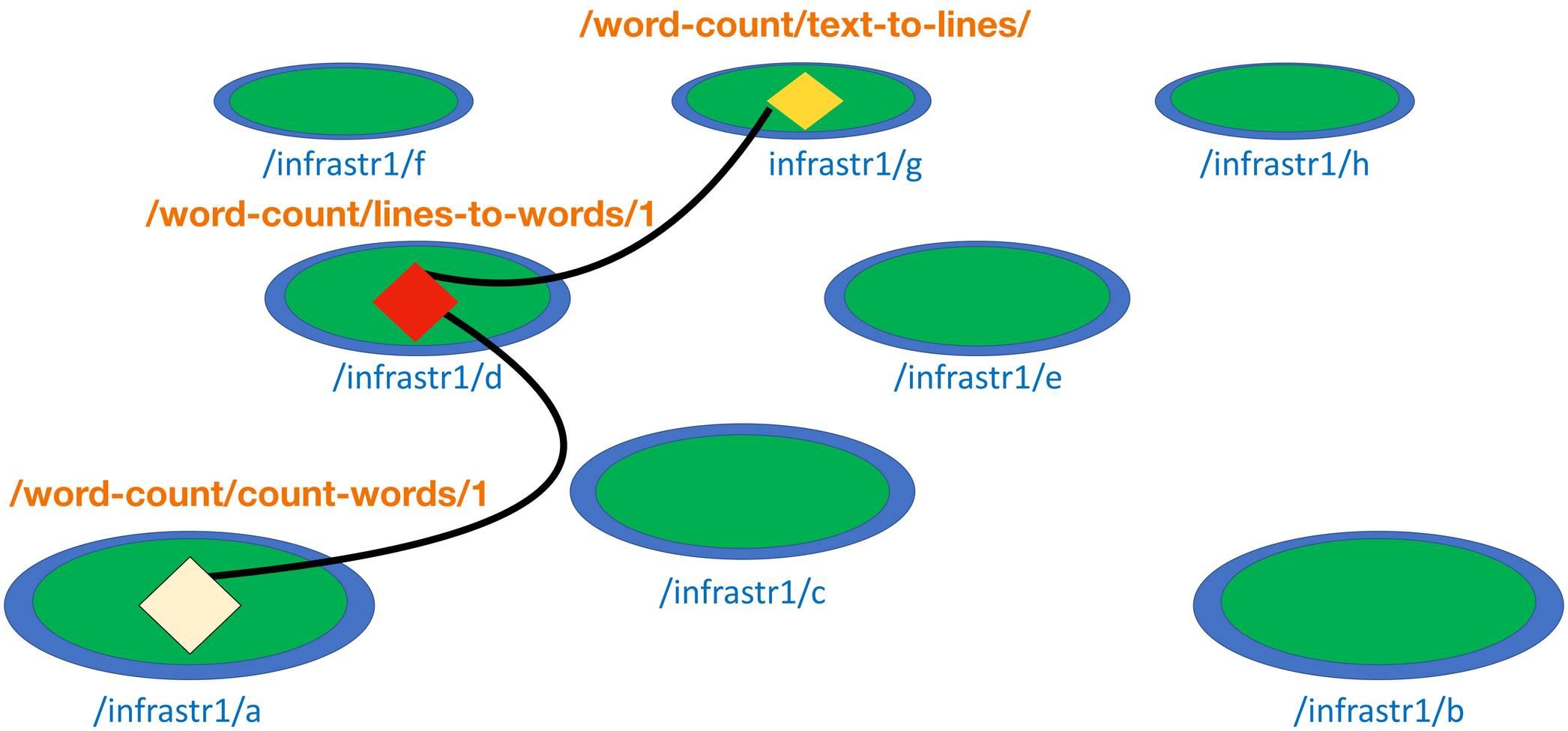
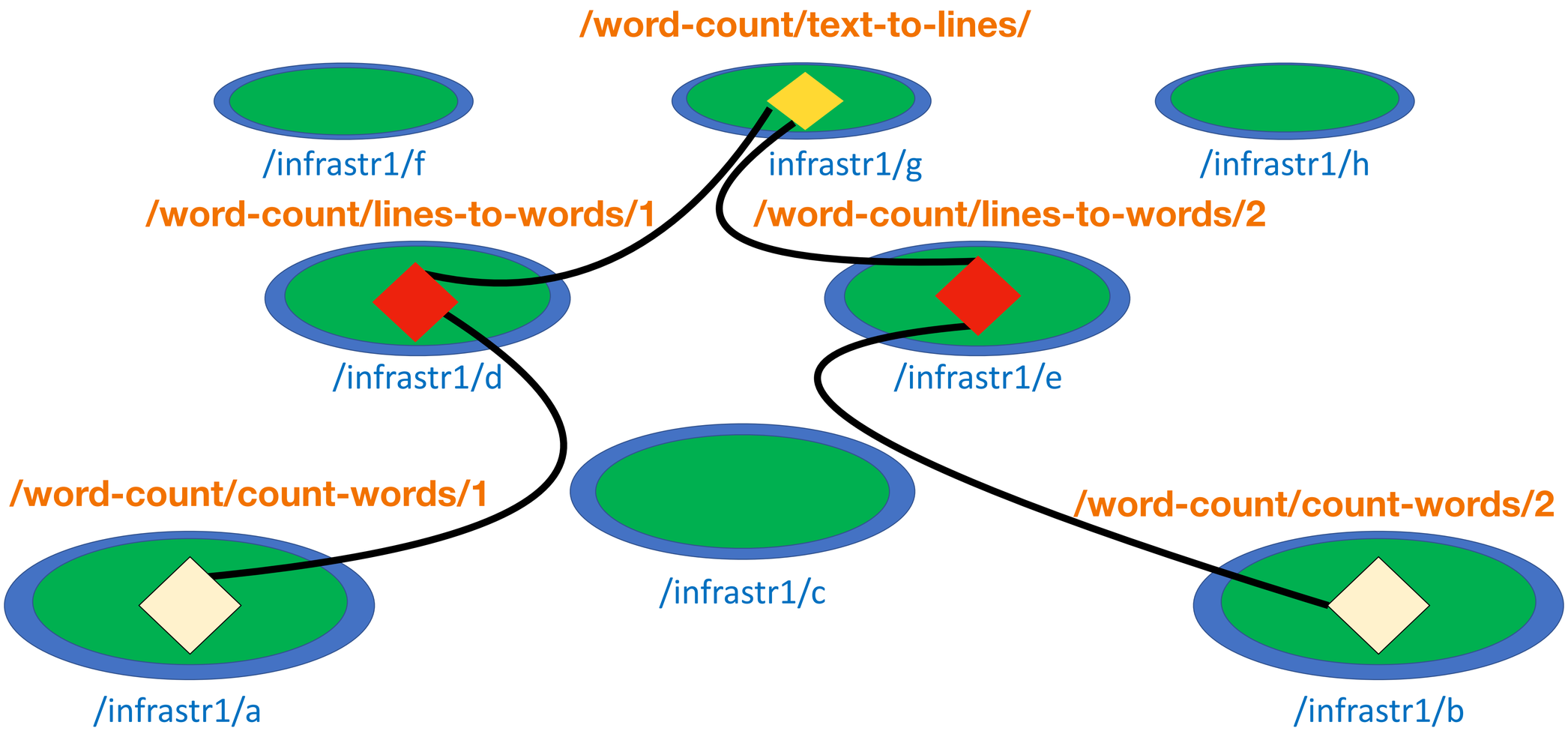


IceFlow

Information-Centric Dataflow



IceFlow

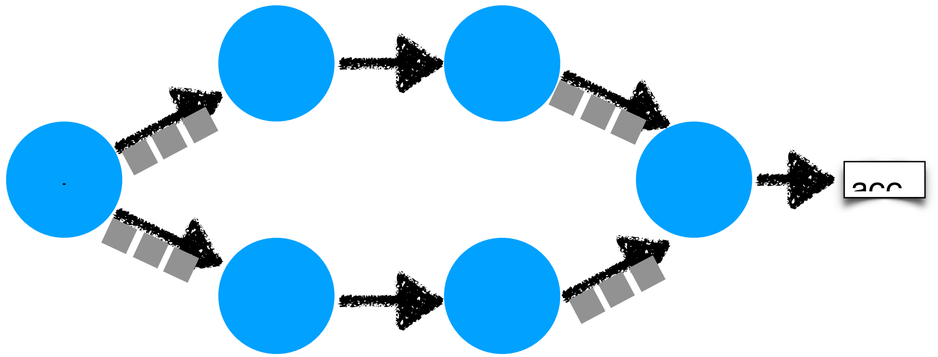
Concepts

- **Just Names**
  - For infrastructure
  - And for actors
- **Computation results as Named Data Objects**
  - Usual ICN properties...
- **Asynchronous data production**
  - Consumer has to know when data is available
- **Flow control**
  - Some coupling between consumers and producers
- **Garbage collection**
  - producers may be resource-constrained
  - cannot keep data forever

```
/[app]/[actor]/[instance]/data/[partition]/[object]
```

app	the name of the application
actor	the name of a Dataflow actor
instance	actor instance number
partition	monotonically increasing partition number to structure data objects on the producer's side
object	monotonically increasing sequence number

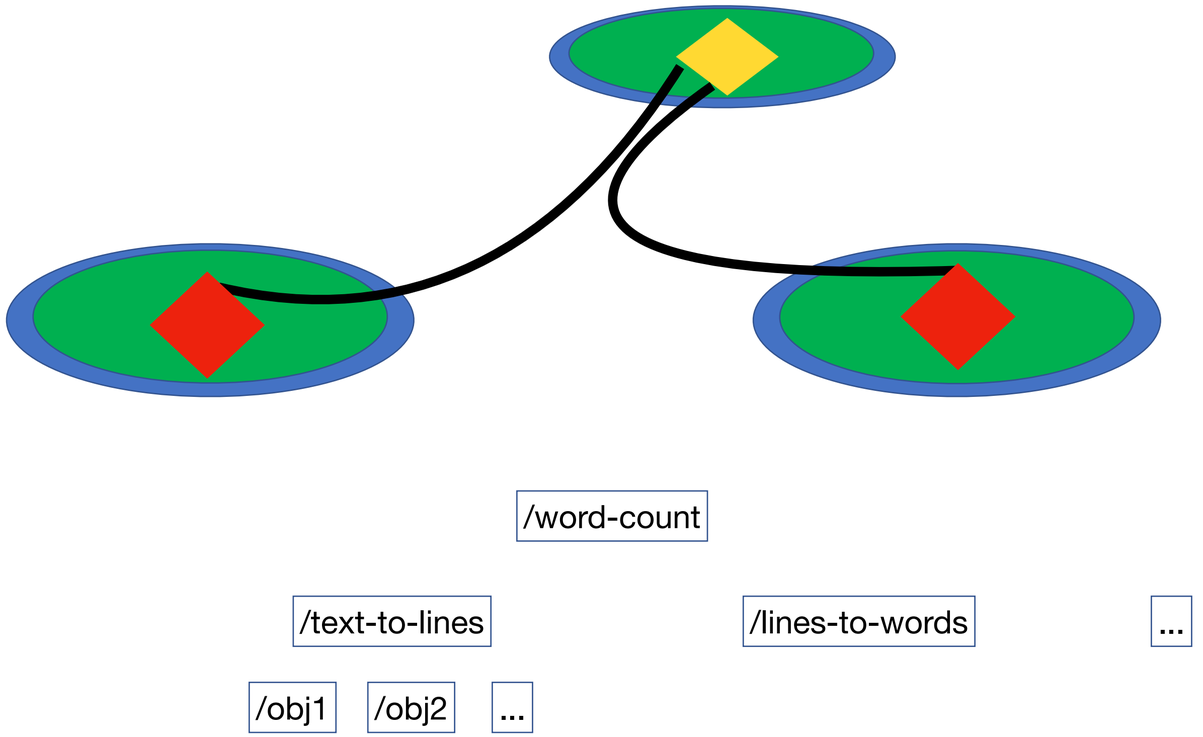
```
/word-count/text-to-lines/1/data/1/1
/word-count/lines-to-words/2/data/3/27
```



IceFlow Operation

Dataset Synchronization

- Producers produce data under a known prefix
  - Consumers subscribe to prefix
  - And learn update new input data
- Ideally: one prefix for whole application ("word-count")
  - Everyone could learn about all data in the app context
  - For practical reasons: need indirection
  - One prefix per consumer group



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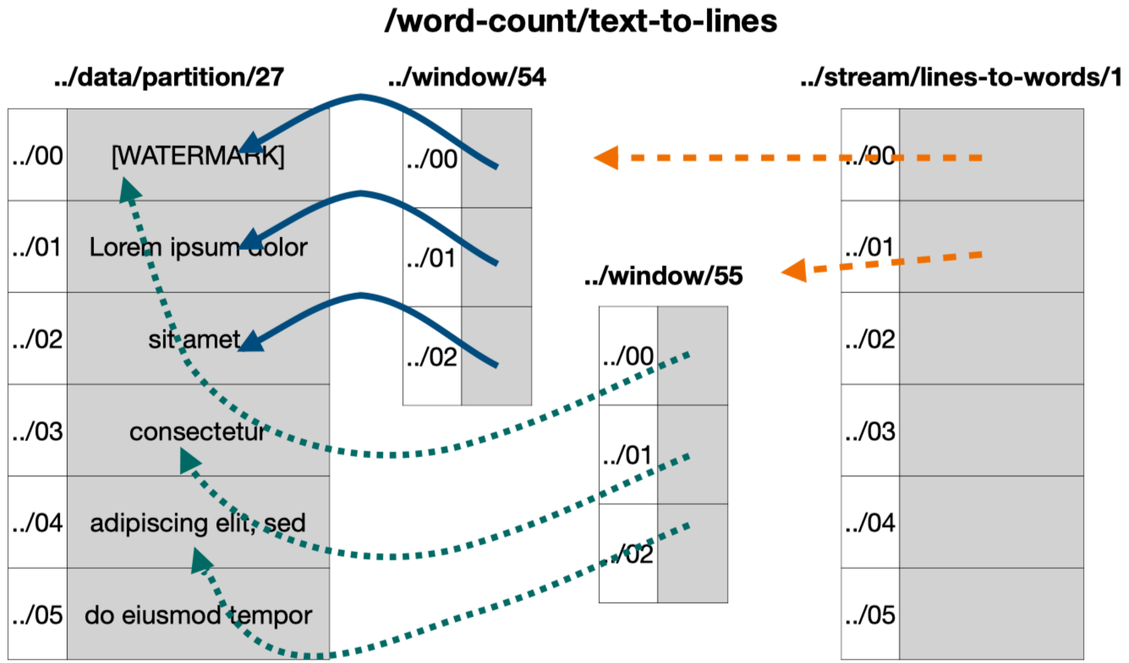
IceFlow

Windows and Result Sharing

- Need more flexibility to re-use computation results in different contexts
  - Group data objects in windows
  - Group windows under per-consumer name prefixes



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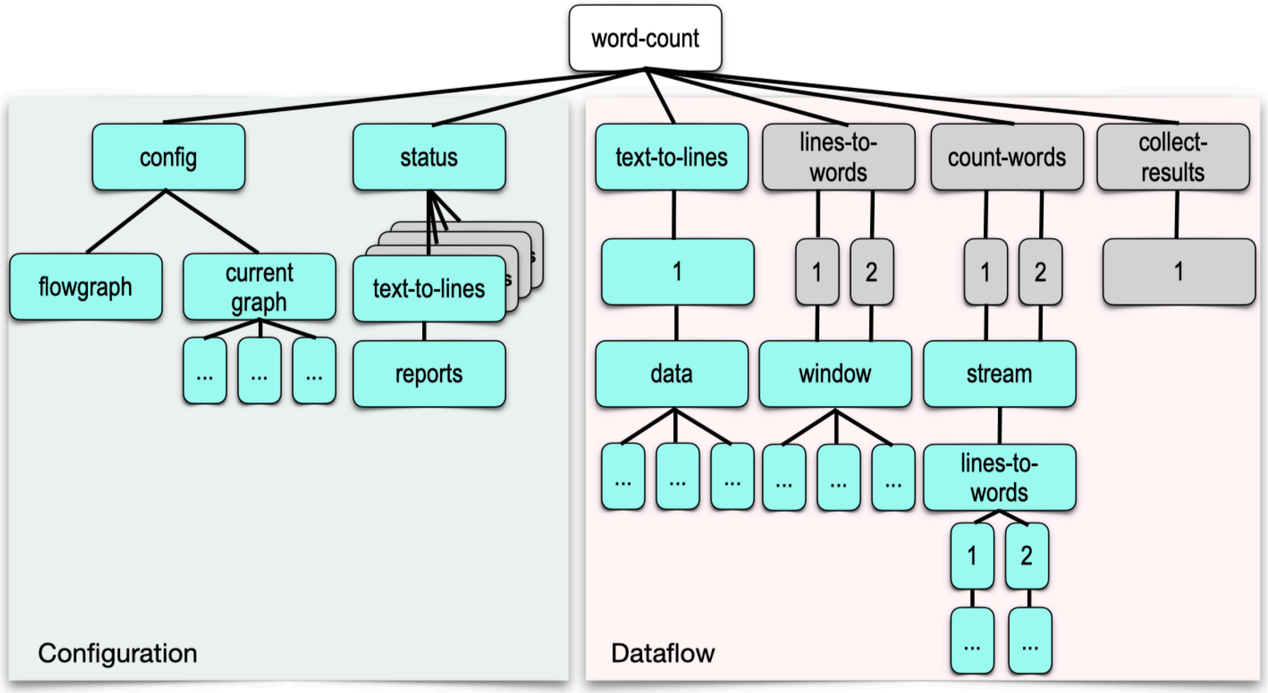
Dataflow data and configuration

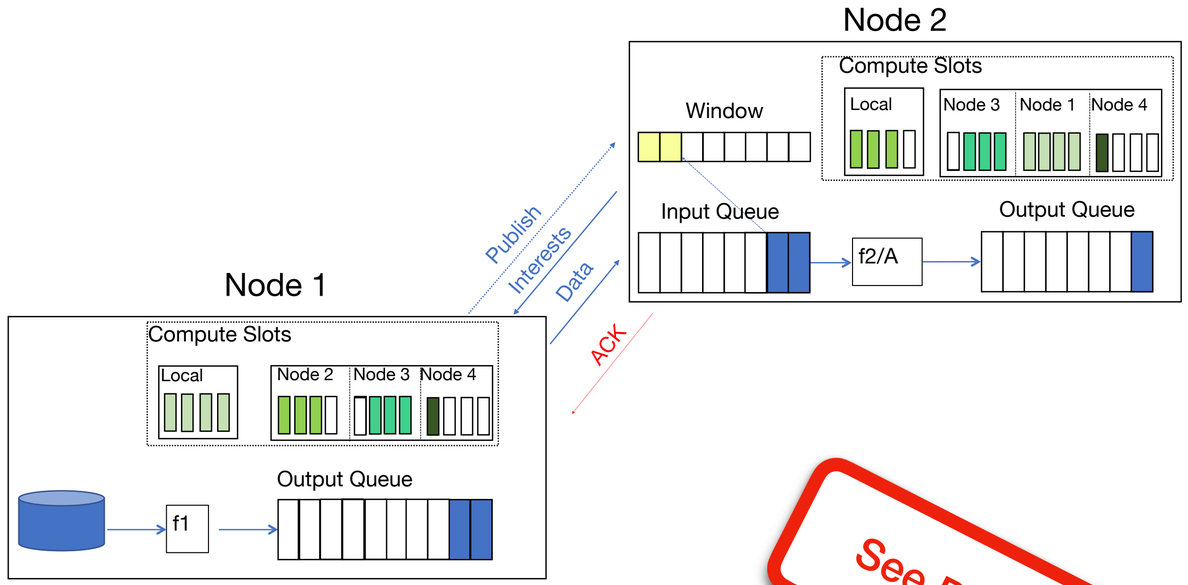
- Need additional shared information
  - Static application flowgraph
  - Actual current dynamic flowgraph
- Also: loose coupling between consumers and producers
  - Consumers reports: what windows have been processed
  - So that producer can advance
- Result: share namespace with Dataflow data and configuration info
  - Some config info represented in CRDTs (like in CFN)



IceFlow

Resource Management

- IceFlow can be smarter than receiver-driven AIMD
  - No need to fetch data that cannot be processed at throughput speed
  - "Receive Window"
- Producers should not overrun consumers
  - Output queue occupancy...
  - When consistently full: trigger scale-out



See Demo!

IceFlow

Insights So Far

- **Todays Dataflow systems are powering many data science applications**
- Overlay approach
  - Usual address mapping and virtual circuit issues
  - Limited data sharing
  - Centralized orchestration
- **Real opportunity for redesigning distributed data processing with ICN**
  - Elegant name-based approach: no mappings, no resolution – just data
  - Direct sharing of computation results
  - Potentially better visibility into network performance
- **Dataset synchronization in principle the right approach**
  - NDN Psync performance not great in experiments (NFD)
  - Also requires multicast forwarding strategy
- **Additional mechanisms needed**
  - Name-based routing (NLSR should be fine)
  - Failure recovery