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In-Memory Computing | SUMMIT 2017

Using In-Memory Computing to Create the Digital Twin: *A New Model for Stream Processing*

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A Brief Journey Towards the Digital Twin

Quick Review of Stream Processing

How In-Memory Data Grids Differ

What is a Digital Twin?

Implementing a Digital Twin with an IMDG

Data Ingestion and Time Windows

Examples of Implementing & Using Digital Twins

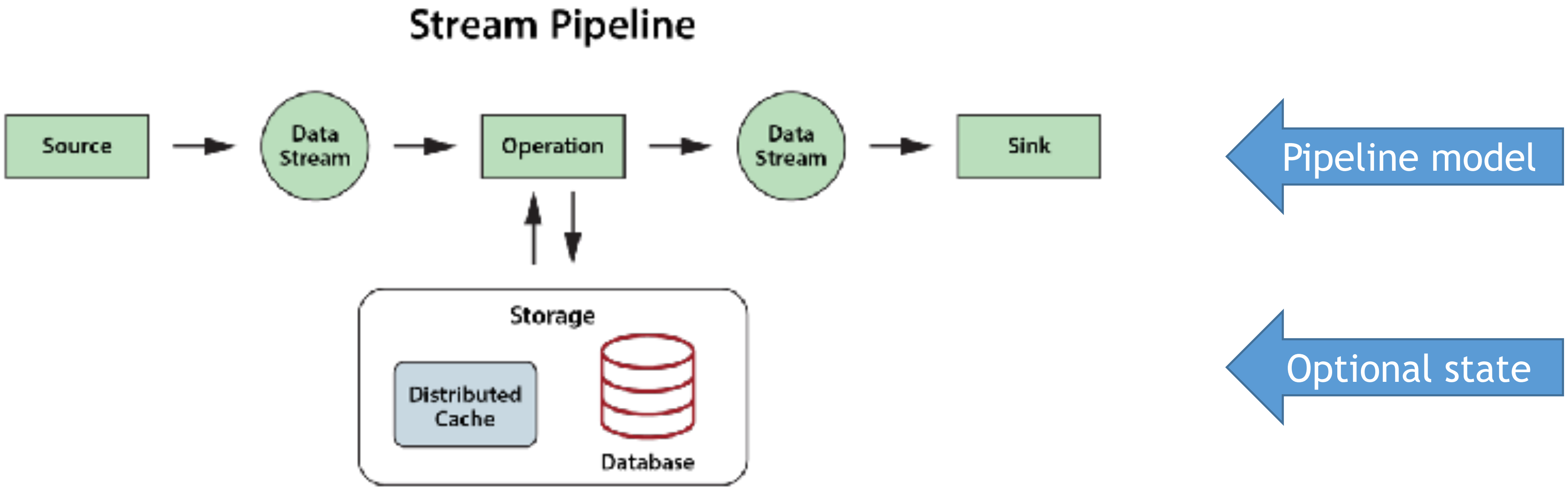
About the Speaker

- Dr. William Bain, Founder & CEO of ScaleOut Software:
  - Email: wbain@scaleoutsoftware.com
  - Ph.D. in Electrical Engineering (Rice University, 1978)
  - Career focused on parallel computing – Bell Labs, Intel, Microsoft
  - 3 prior start-ups, last acquired by Microsoft and product now ships as Network Load Balancing in Windows Server
- ScaleOut Software develops and markets **In-Memory Data Grids**, software for:
  - Scaling application performance with in-memory data storage
  - Analyzing live data in real time with in-memory computing
- Twelve years in the market; 440+ customers, 11,000+ servers

Basic Stream-Oriented Architecture

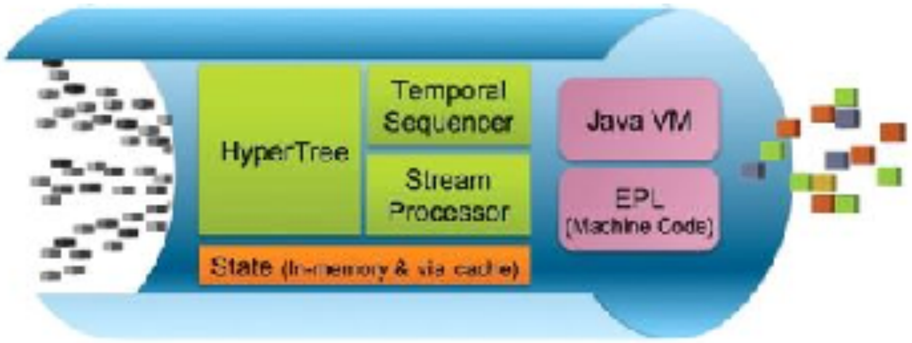
Stream-oriented platforms typically create a computing pipeline from data sources to sinks:

- Pipeline stages perform transformations often described by programming models as a sequence of extension methods.
- Usually access state data (in-memory and/or persistent) using an optional, separate storage tier.
- Examples: Apama (CEP), Apache Storm, Spark Streaming, Beam, and Flink



Complex Event Processing Architecture

- Example: Apama from Software AG
- Architecture (the Apama "Correlator"):
  - HyperTree: matches and filters incoming events
  - Temporal Sequencer: finds real-time correlations between events
  - Stream Processor: executes analytics on windows of events



- Programs can be written in EPL or Java; simple example of stock tracking in EPL:

```
monitor PriceRise{
    StockTick firstTick, finalTick;
    action onload() {
        on StockTick (symbol="IBM", price>210.5):firstTick {furtherRise();}
    action furtherRise() on StockTick (symbol="IBM",
price>firstTick.price*1.05):finalTick
        {send PlaceSellOrder("IBM", 100.0 to "Market");}
```

Illustration and code sample from "The Apama Platform," Software AG

Two Apache Platforms for Stream Processing

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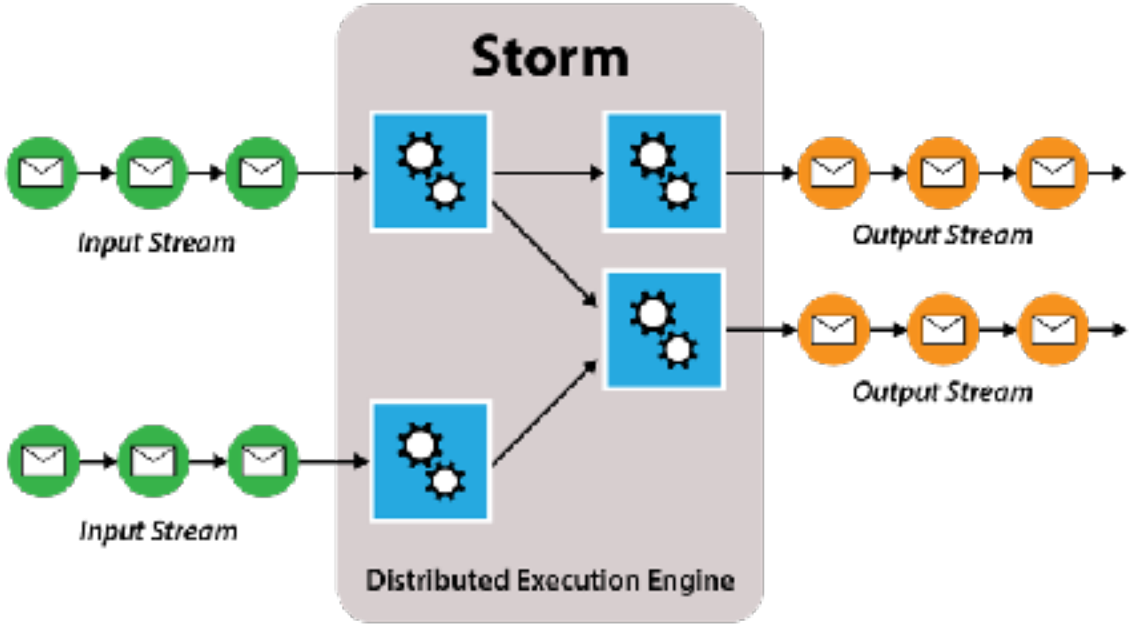
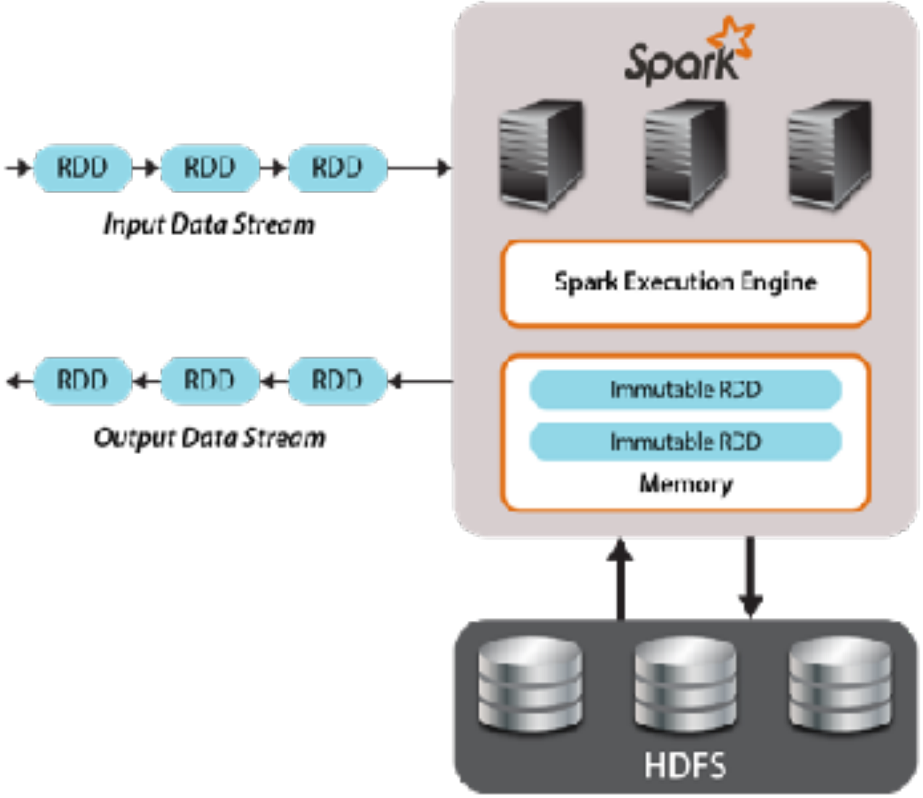
Task-parallel:



Data-parallel (micro-batched):



Stream Processing Model from Apache Beam

- Originally developed by Google.
- Provides unified, portable APIs for batch and stream processing.
- Relies on external execution platforms called "runners" (e.g., Apache Flink, Spark, Google Cloud Dataflow).
- Key elements:
  - Pipeline: data processing job as a directed set of steps
  - PCollection: the data inside a pipeline
  - Ptransform: an execution step in the pipeline (e.g., ParDo) or an IO step

Illustration from "Introduction to Apache Beam" by JB Onofre'

Apache Beam Code Examples (Java)

- Basic Dataflow model:

```
Pipeline p = Pipeline.create();              // create a pipeline
p.apply(TextIO.Read.from(“/path/to/…”)       // read input
 .apply(new CountWords())                    // do some processing
 .apply(TextIO.Write.to(“/path/to/…”);       // write output
p.run();                                     // run the pipeline
```

Simple example

- Example of advanced features (session windows):

```
Pcollection<KV<String, Integer>> scores = input
 .apply(Window.into(SessionWindows.of(Duration.standardMinutes(
        .triggering(AtWatermark()
            .withEarlyFirings(
                AtPeriod(Duration.standardMinutes(1)))
            .withLateFirings(AtCount(1)))
        .accumulatingFiredPanes())
 .apply(Sum.IntegersPerKey());
```

Apply transform

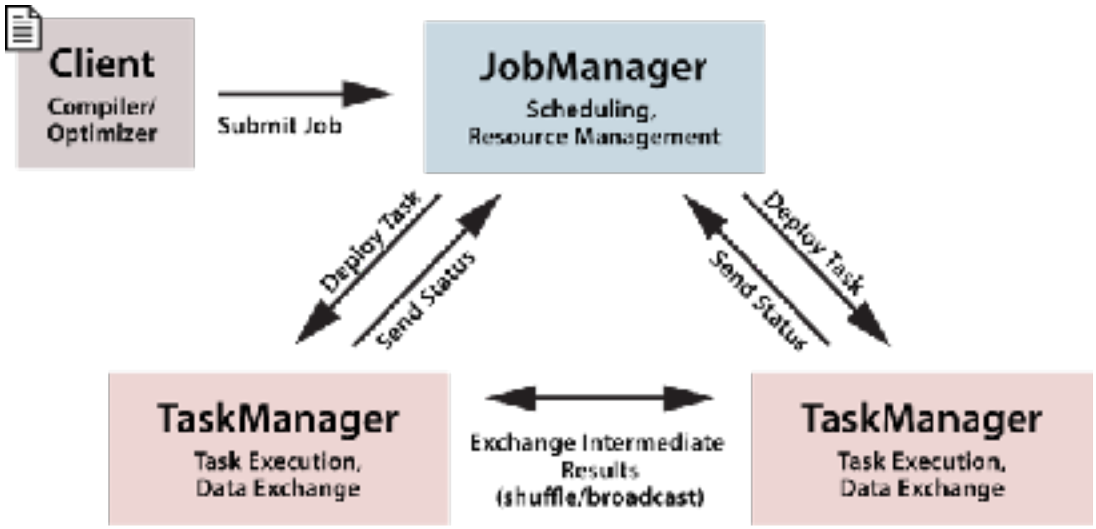
Analyze

Code samples from “Introduction to Apache Beam” by JB Onofre’

Stream Processing with Apache Flink

- Flink data flow:

- Flink architecture:



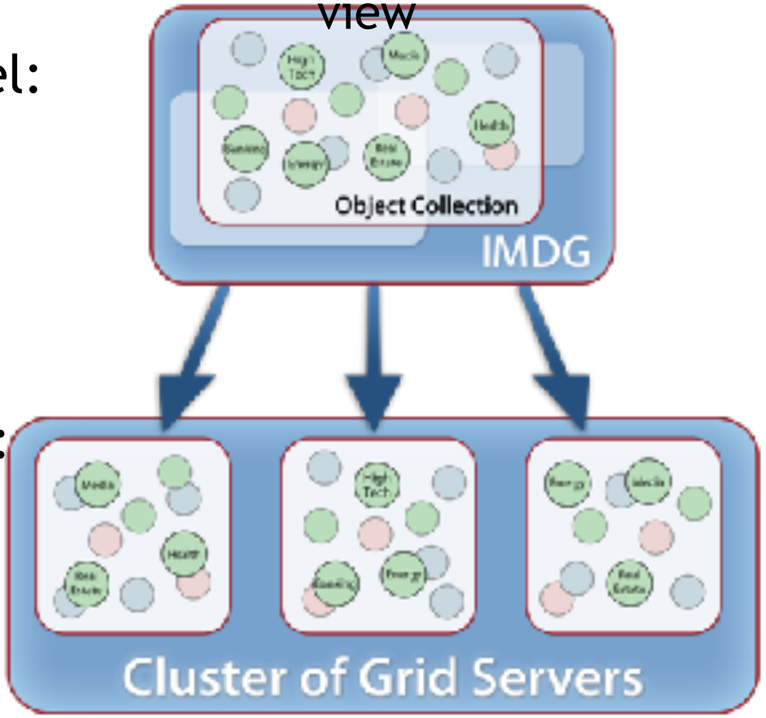
Illustrations from “Apache Flink: What, How, Why, Who, Where?” by Slim Baltagi

How In-Memory Data Grids Differ

IMDGs focus on integrating computing with state (vs. processing data streams with optional external state):

- IMDG provides scalable, hi-av storage for live data:
  - Stores and manages live state with object-oriented model:
    - Sequentially consistent data shared by multiple clients
    - Object-oriented collections by type
    - CRUD APIs for data access as key/value pairs
    - Distributed query by object properties
  - Has fast (<1 msec.) data access and updates
  - Designed for *transparent* scalability and high availability:
    - Automatic elasticity and load-balancing
    - Automatic data replication, failure detection, recovery
- IMDG integrates in-memory computing with data storage:
  - Leverages the computing power of commodity servers.
  - Computes where the data lives to avoid network bottlenecks.

Logical view

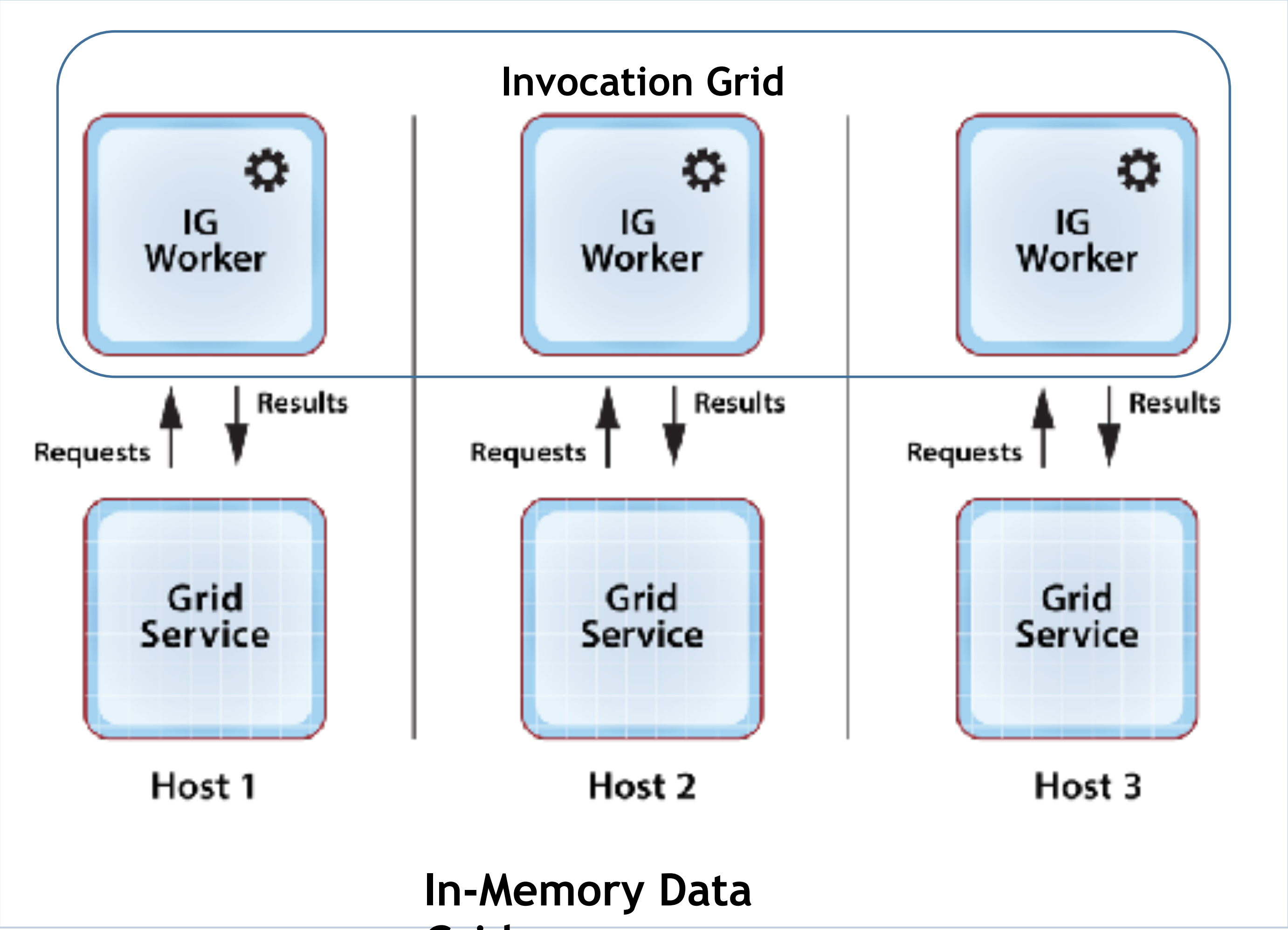


Physical view

Storage Model

Adding In-Memory Computing to an IMDG

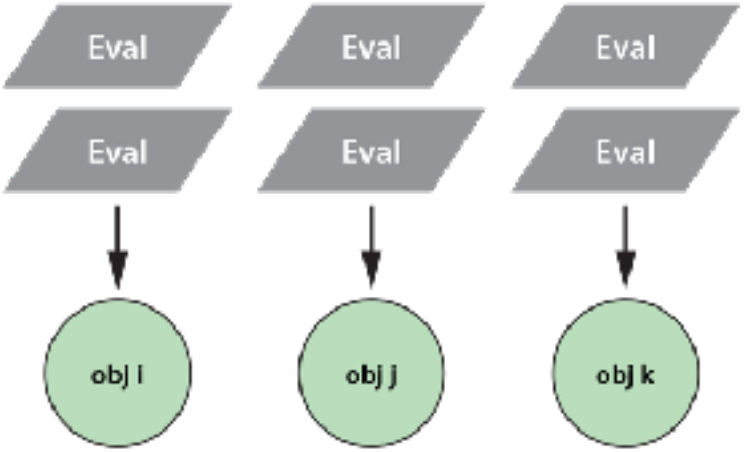
- Each grid host runs a worker process which executes application-defined methods.
    - The set of worker processes is called an *invocation grid*.
    - IG usually runs language-specific runtimes (JVM, .NET).
    - IMDG can ship code to the IG workers.
- Key advantages:
    - Avoids network bottlenecks by moving computing to the data.
    - Leverages IMDG's cores & hosts.
    - Isolates application code from grid service.



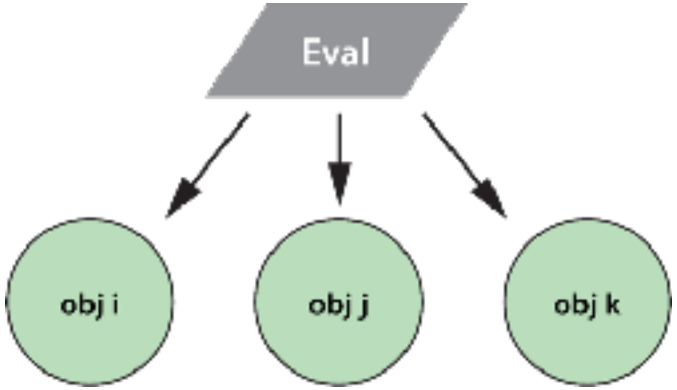
In-Memory Data Grid

IMDGs Perform Both Stream and Batch Processing

- IMDG leverages object-oriented storage model to execute methods on instances of stored objects.
- IMDG naturally integrates both stream-based and batch execution models:
  - Stream-based: execute method(s) on independent objects and sequentially on the same object.
  - Batch: execute a data-parallel method on a collection of objects.
  - Result: an implementation of the HTAP architecture



Stream-based execution

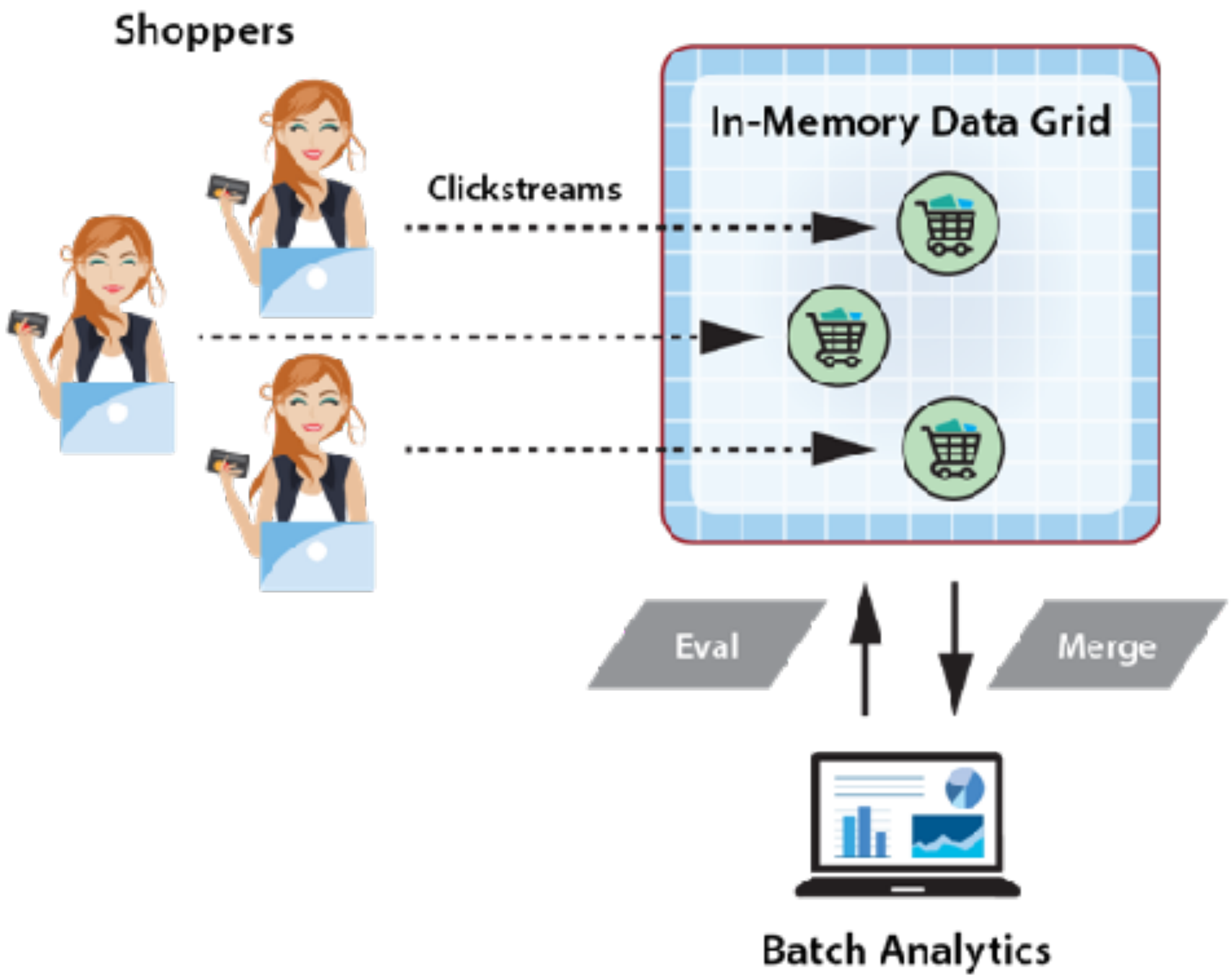


Batch (data-parallel) execution

Example of Combining Streaming and Batch

An Ecommerce site tracking web shoppers:

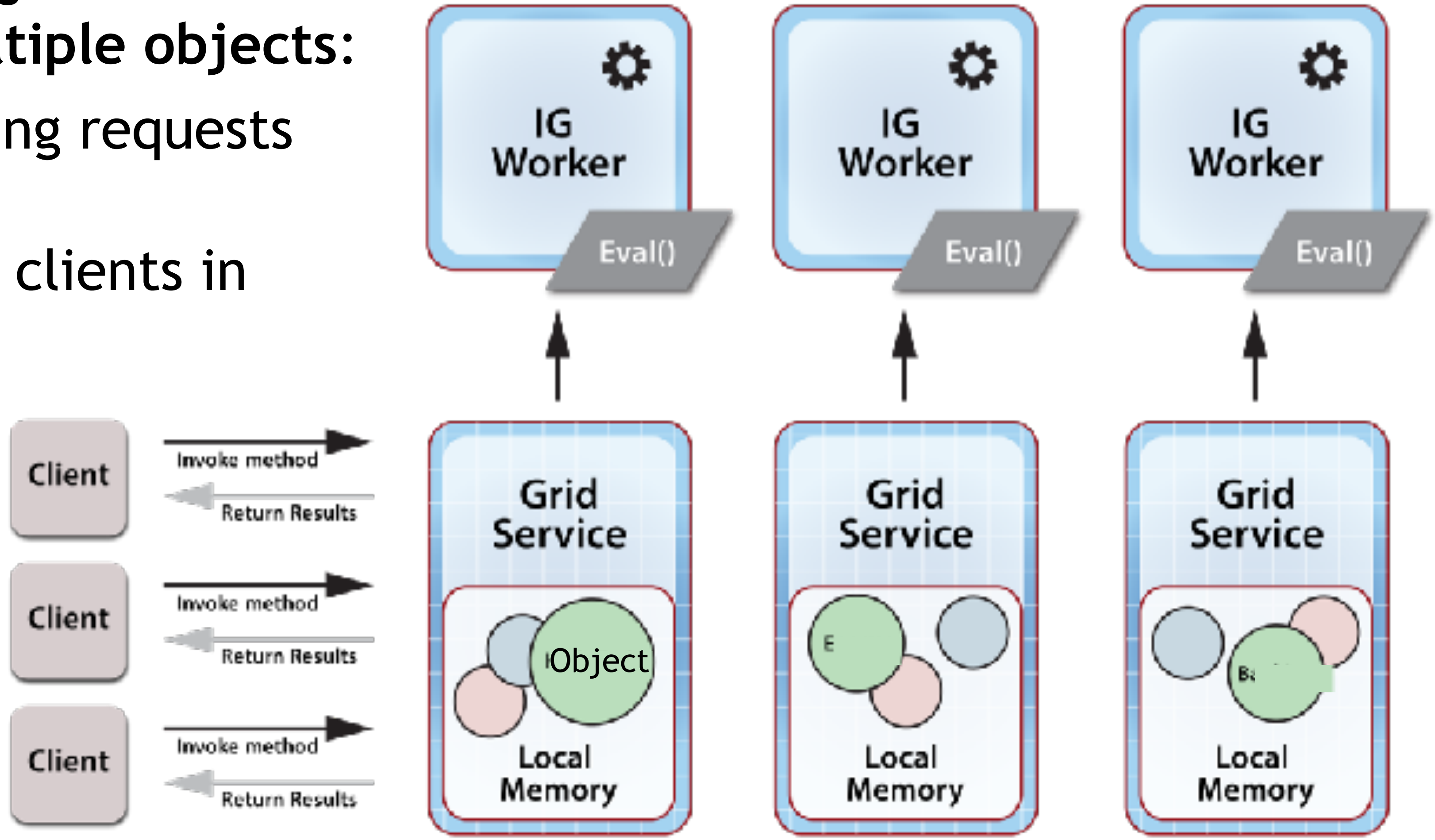
- IMDG manages clickstreams from shoppers by calling methods on individual objects to process click events.
  - Can immediately track shopper's actions.
- IMDG performs data-parallel, batch analytics on grid data to track aggregate trends.
  - Can determine best selling products, average basket size, etc.



Executing Multiple, Independent Requests

Method execution runs independently for multiple objects:

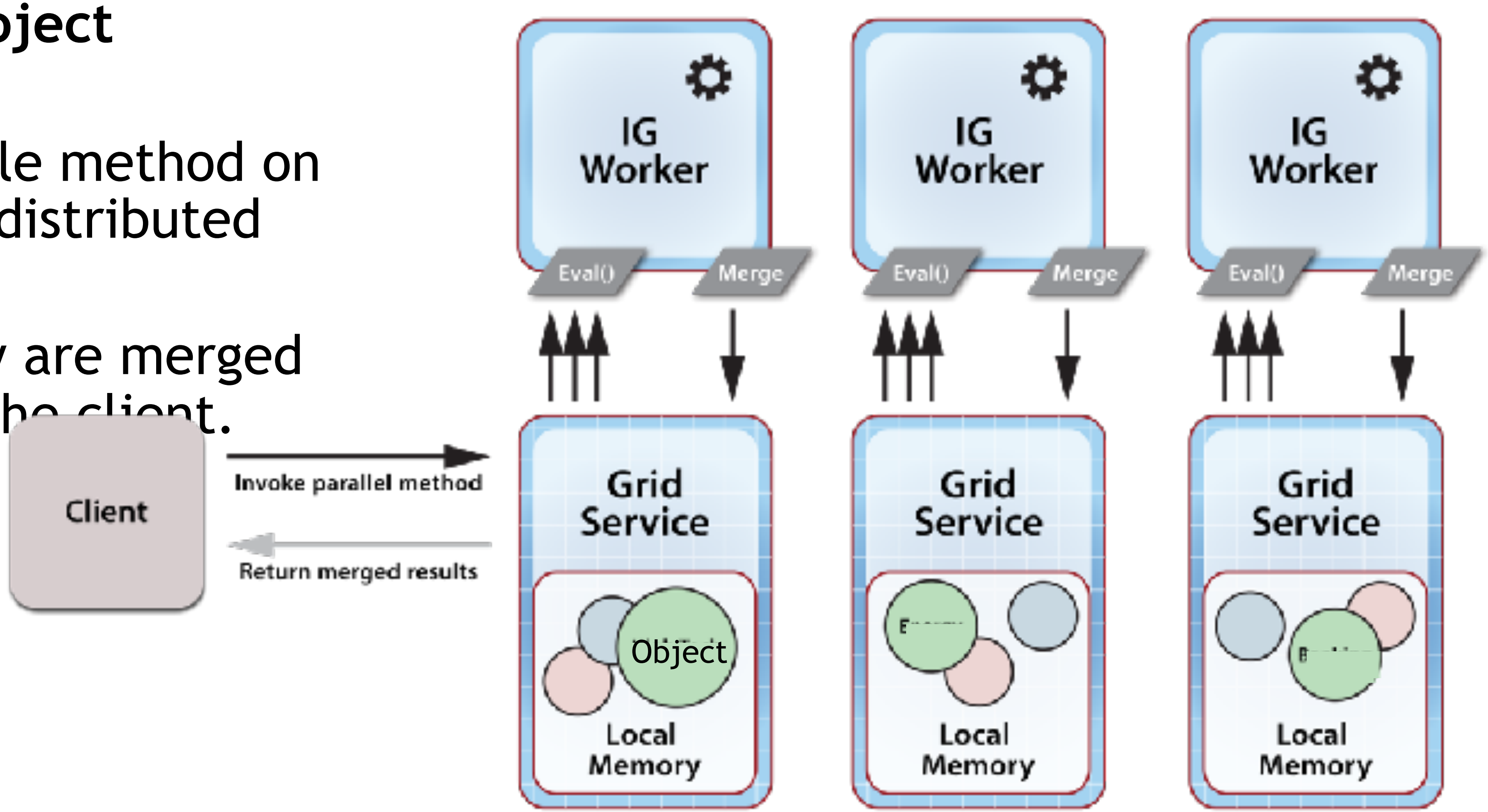
- IMDG handles streaming requests from a single client.
- Also handles multiple clients in parallel.



Executing a Data-Parallel Method

Method execution implements a batch job on an object collection:

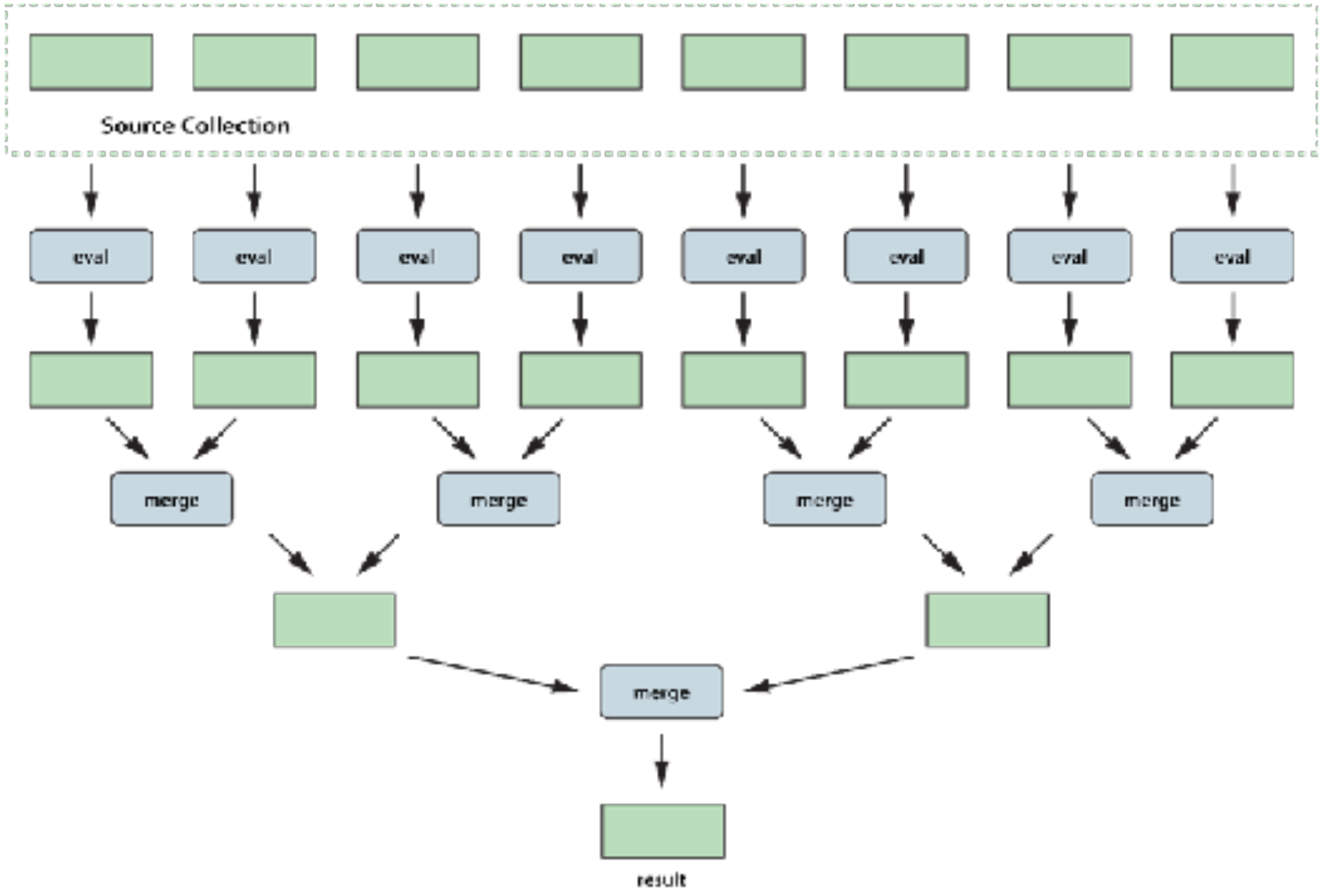
- Client runs a single method on multiple objects distributed across the grid.
- Results optionally are merged and returned to the client.



Basic Data-Parallel Execution Model

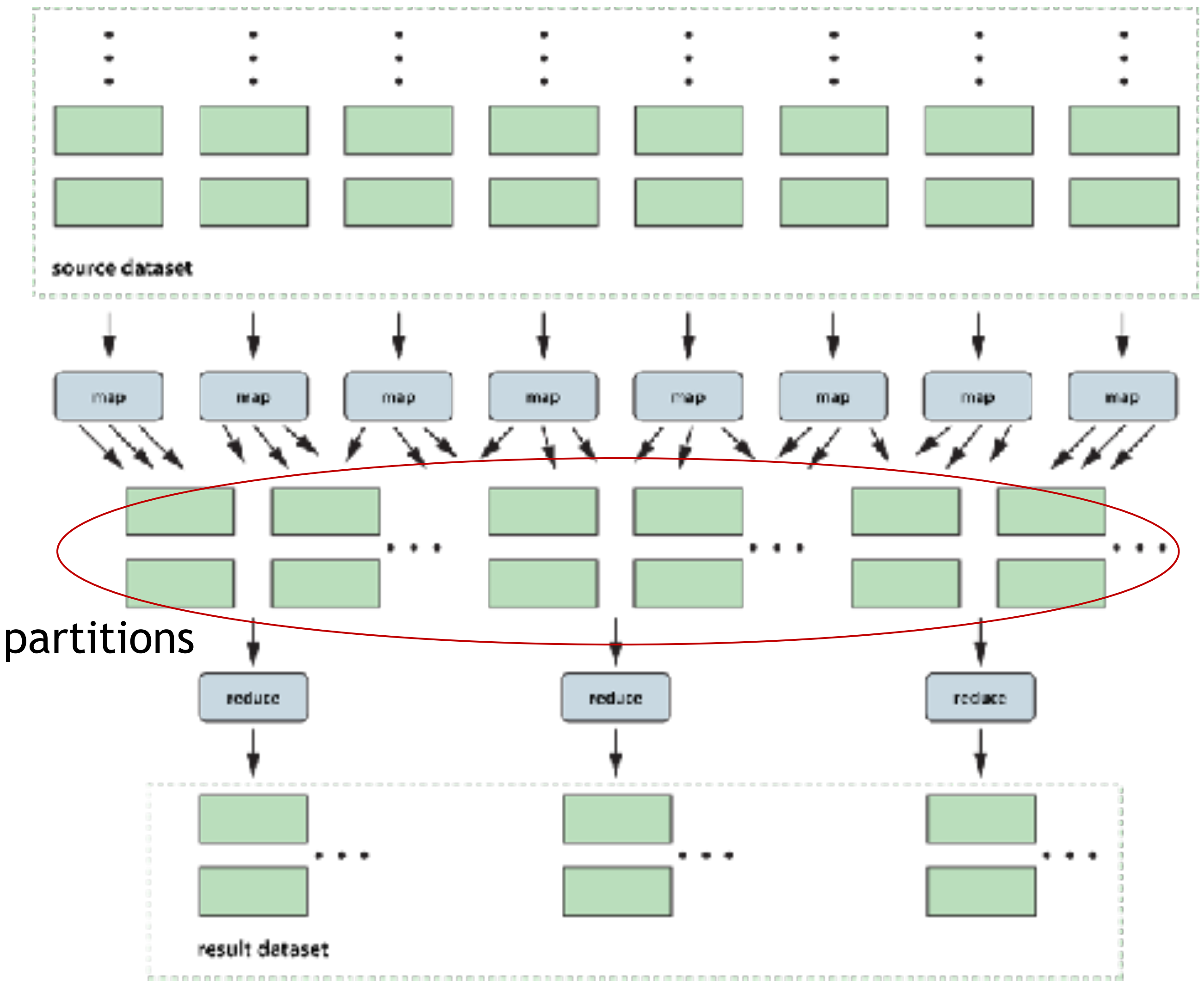
A fundamental model from parallel supercomputing:

- Run one method (“**eval**”) in parallel across many data items.
- Optionally **merge** the results.
  - Binary combining is a special case, but…
  - It runs in logN time to enable scalable speedup.



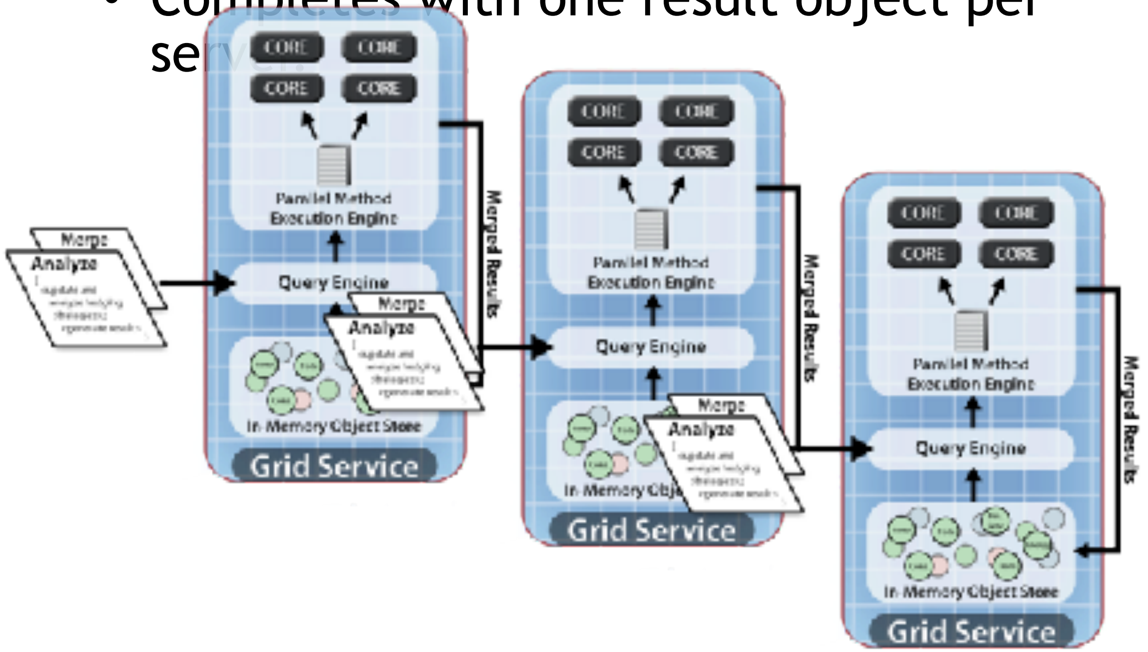
MapReduce Builds on This Model

- Runs in two data-parallel phases (map, reduce):
  - **Map** phase repartitions and optionally combines source data.
  - **Reduce** phase analyzes each data partition.
  - A global merge of the results is not performed.
- Classic example: word count
  - Source data items: lines of text
  - Mappers: emit {*word*, count} for all unique words.
  - Words are hashed to partitions.
  - Reducers sum counts and emit total counts for each word.

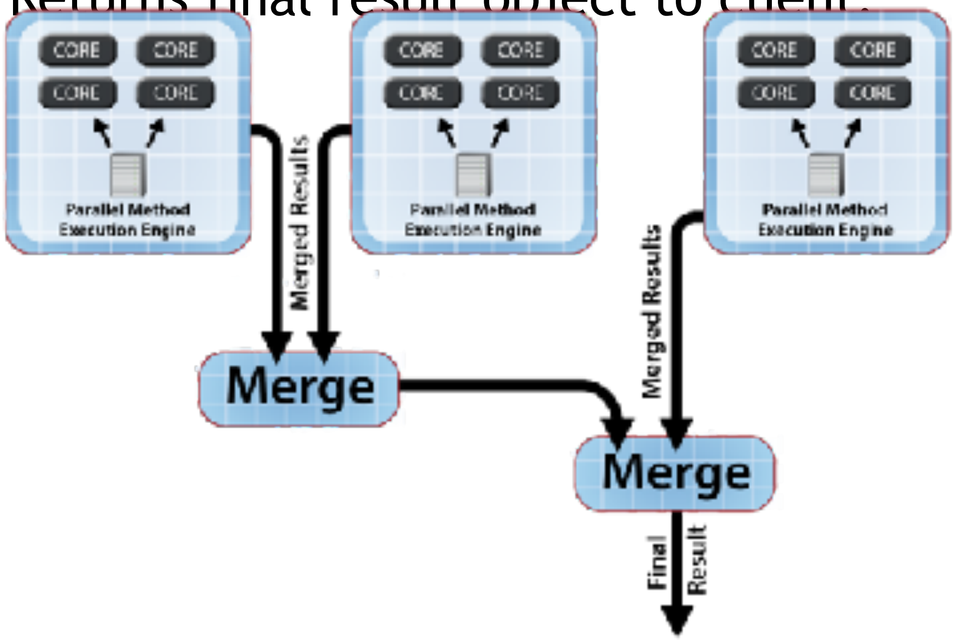


Data-Parallel Execution Steps

- **Eval** phase: each server queries local objects and runs eval and merge methods:
  - Accessing local objects avoids data motion.
  - Completes with one result object per server.



- **Merge** phase: all servers perform binary, distributed merge to create final result:
  - Merge runs in parallel to minimize completion time.
  - Returns final result object to client.



Ecommerce Code Sample(C#)

- Define shopping cart objects stored in the in-memory data grid (IMDG):

```
class ShoppingCartItem
{
    public string Name { get; set; }
    public decimal Price { get; set; }
    public int Quantity { get; set; }
}
```

Class for cart item

```
class ShoppingCart
{
    public string CustomerId { get; set; }
    public IList<ShoppingCartItem> Items { get; } = new
List<ShoppingCartItem>();
    public decimal TotalValue
    { get { return Items.Sum((item) => item.Quantity * item.Price); }}
    public decimal ItemCount
    { get { return Items.Sum((item) => item.Quantity); }}
}
```

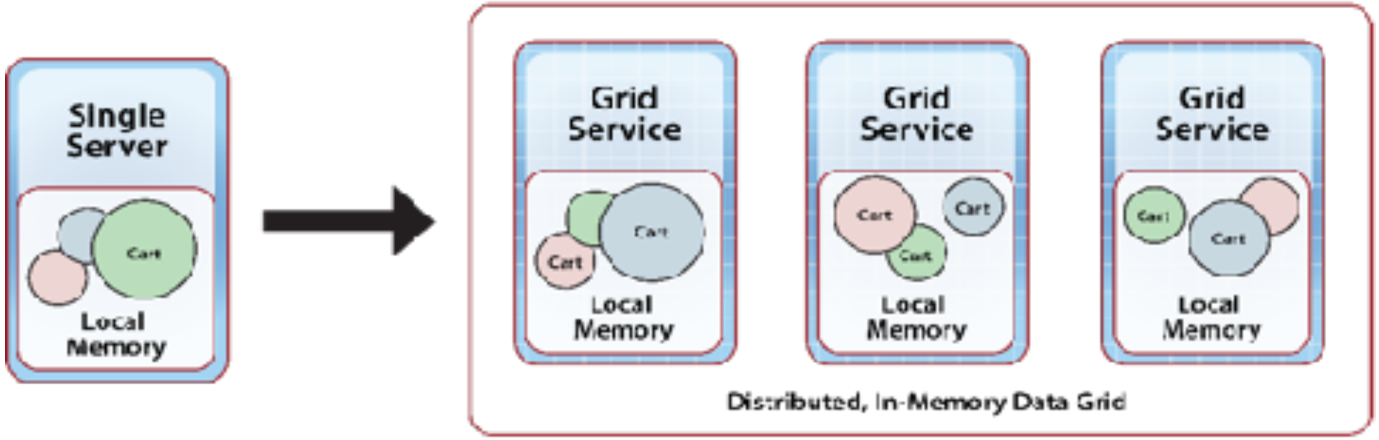
List of cart items

Loading the Shopping Carts into the Grid

- IMDG provides location-independent access using create/read/update/delete ("CRUD") APIs.

```
var carts = CacheFactory.GetCache("carts"); // Gets reference to a namespace
foreach (var cart in collection)
    carts.Add(cart.CustomerId, cart);        // CustomerId serves as key
```

- IMDG transparently distributes and load-balances the shopping carts across a cluster of servers or cloud instances.
- Allows an application to host much larger data sets than possible on a single server.



Posting a Click Event to the IMDG with ReactiveX

```
private static void PostCartItem()
{
    var nc = CacheFactory.GetCache("carts");

    var item = new ShoppingCartItem
    {
        Name = “Acme Snow Globe",
        Price = 7.50m,
        Quantity = 3
    };

    var key = nc.CreateKey("Jane Doe");

    nc.PostEvent(id: key,
                 eventInfo: "Add cart item",
                 payload: item.ToBytes());
}
```

Select namespace

Create item

Create key

Post event

Running a Streaming Method on a Single Object

```
// Initialization method is run when the invocation grid is first loaded:
public void Init_pipeline()
{
    // Set up a ReactiveX pipeline to handle adding shopping cart items:
    carts.GetEventSource()
        .Where(ev => ev.EventInfo == "Add cart item")
        .Select(ev => Tuple.Create(ShoppingCartItem.FromBytes(ev.Payload),
                ev.ObjectId.GetStringKey()))
        .Subscribe(HandleCartAddEvent);
}

public void HandleCartAddEvent(Tuple<ShoppingCartItem, string> addCartItemTuple)
{
    var custId = addCartItemTuple.Item2;
    var mycart = carts.Retrieve(custId, acquireLock: true) as ShoppingCart;
    mycart.Items.Add(addCartItemTuple.Item1);
    carts.Update(custId, mycart, unlockAfterUpdate: true);
}
```

Subscribe to stream

Add item to cart obj.

Running a Batch Data-Parallel Method

Filter objects

Invoke method

Merge results

```
finalResult = carts.QueryObjects<ShoppingCart>()
    .Where(cart => cart.TotalValue >= 20.00m)   // filter carts
    .Invoke(
        timeout: TimeSpan.FromMinutes(1), param: productName,
        evalMethod: (cart, pName) =>
        {
            var result = new Result();
            result.numCarts = 1;
            // see if the selected product is in the cart:
            if (cart.Items.Any(item => item.Name.Equals(pName)))
                result.numMatches++;
            return result;
        })
    .Merge(
        (result1, result2) =>
        {
            result1.numMatches += result2.numMatches;
            result1.numCarts += result2.numCarts;
            return result1; });
```

What Is a Digital Twin?

- Term coined by Dr. Michael Grieves (U. Michigan) in 2002 for use in product life cycle management
- Popularized in Gartner’s “Top 10 Strategic Technology Trends for 2017: Digital Twins” for use with IoT
- Definition: a digital representation of a physical entity; an encapsulated software object that comprises (per Gartner):
  - A model (e.g., composition, structure, metadata for an IoT sensor)
  - Data (e.g., sensor data, entity description)
  - Unique identity (e.g., sensor identifier)
  - Monitoring (e.g., alerts)
- Significance: focuses on modeling data sources
  - A basis for correlating and analyzing streaming data
  - A context for deep introspection and interaction

Examples of Digital Twins in IoT

Live System - Physical Objects | **Digital Twins**

(Autonomous) Vehicles

Vehicle subsystems for safety monitoring & predictive maintenance

Telemetry streams

Manufacturing floors and equipment

Networks of machine tooling for real-time interactive view and predictive maintenance

Immediate feedback

Wind turbines and wind farms

Collections of wind turbine components for remote operations and predictive maintenance

Tracking an Elevator: A Digital Twin Demonstration

Digital twin of an elevator implemented by Crossvale, Inc.:

Real-World Elevator

Elevator Specs	
Max People	10
Max Weight	1000 kg
Floors	8

Current Load	
People	Weight
4 people	320 kg

Actions
Open Door
Close Door
Ascend
Descend
Return to Lobby

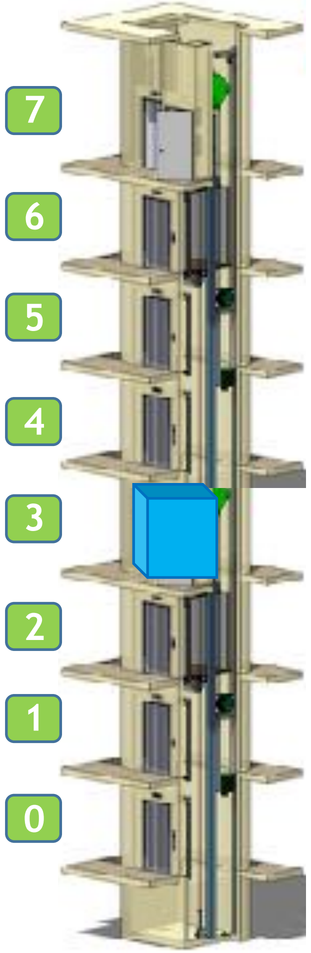
Telemetry Streams

Real-Time

Courtesy of:

CROSSVALE Operational Intelligence

Digital Twin



Monitoring Stats	
Elevator Position (cm)	720 cm
Floor position	3
Onboard Weight (kg)	320 kg
Power Consumption (kW)	High

Events
Operation Normal
Learning
Overweight
Descend Too-Fast
Ascend Too-Slow
Stuck Between Floors
Doors Stuck

Alerts
Check Cable
Vibration Limit Exceeded
Maintenance Required

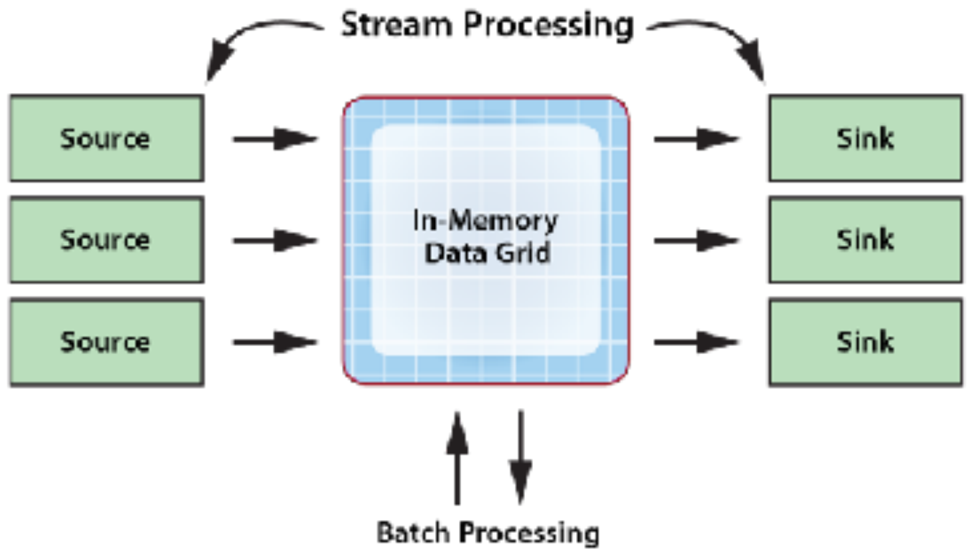
Some Applications for Digital Twins

A digital twin integrates incoming events with state information using domain-specific algorithms to generate alerts:

Application	State Information	Events	Logic	Alerts
IoT devices 	Device status & history	Device telemetry	Analyze to predict maintenance.	Maintenance requests
Medical monitoring 	Patient history & medications	Heart-rate, blood-pressure, etc.	Evaluate measurements over time windows with rules engine.	Alerts to patient & physician
Cable TV  	Viewer preferences & history, set-top box status	Channel change events, telemetry	Cleanse & map channel events for reco. engine; predict box failure.	Viewer recom-mendations, repair alerts
Ecommerce 	Shopper preferences & buying history	Clickstream events from web site	Use ML to make product recommendations.	Product list for web site
Fraud detection	Customer status & history	Transactions	Analyze patterns to identify probable fraud.	Alerts to customer & bank

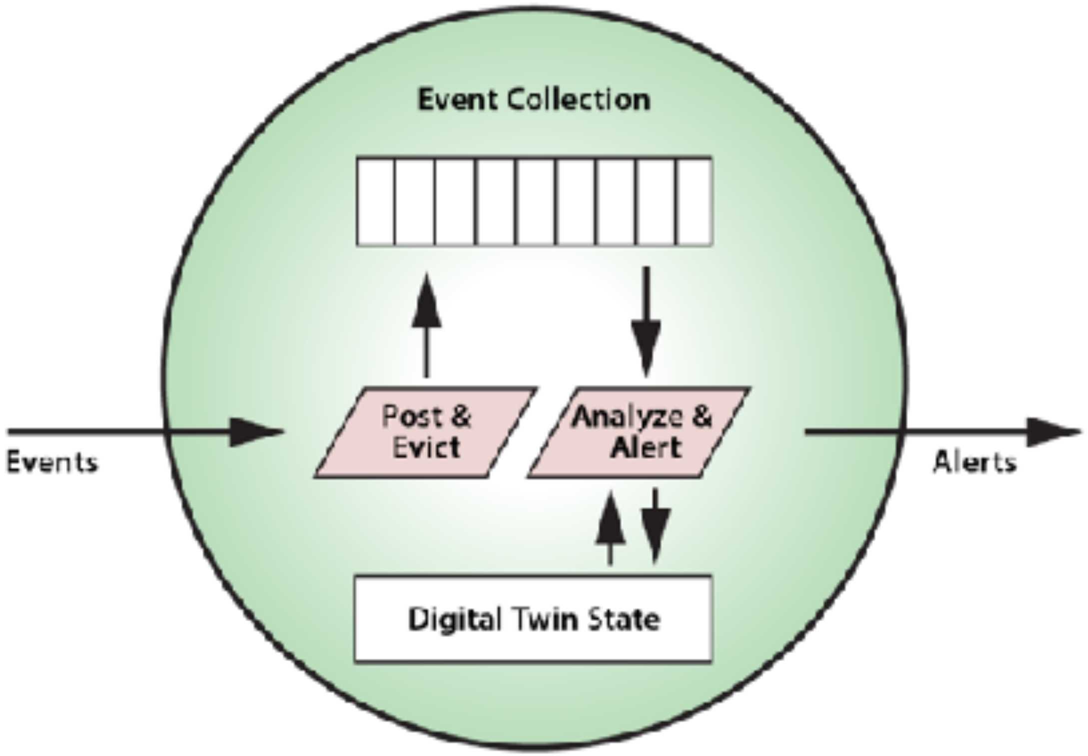
Why Use an IMDG to Host Digital Twins?

- Object-oriented data storage:
  - Offers a natural model for hosting digital twins.
  - Cleanly separates domain logic from data-parallel orchestration.
  - Provides rich context for processing streaming data.
  - Integrates streaming and batch processing.
- High performance:
  - Avoids data motion and associated network bottlenecks.
  - Fast and scales to handle large workloads.
- Integrated high availability:
  - Uses data replication designed for live systems.
  - Can ensure that computation is high av.



Modeling the Digital Twin with OOP

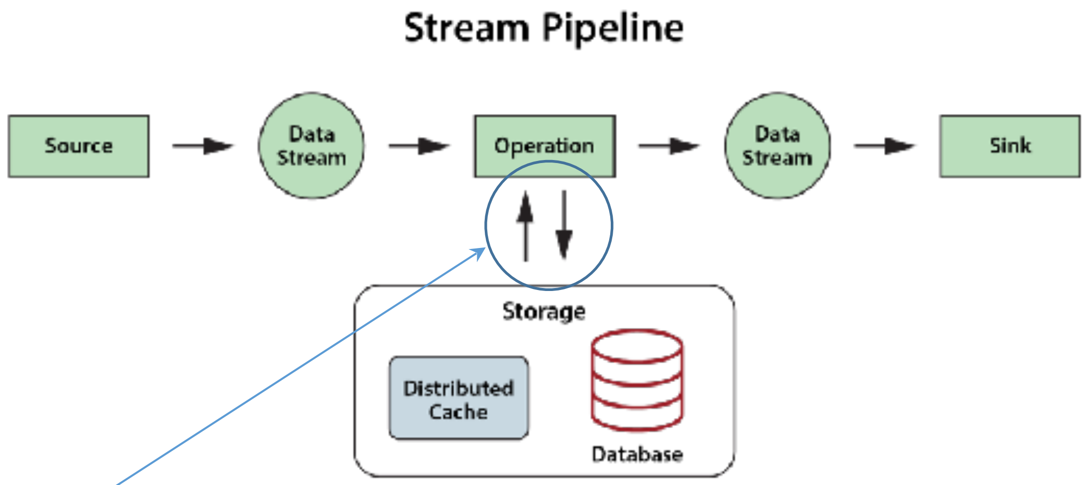
- Digital twin typically comprises:
  - An event collection
  - State information about the data source
  - Logic for managing events, updating and analyzing state, generating alerts
- Object oriented model:
  - Integrates event collection with state information.
  - Encapsulates domain-specific logic (e.g., ML, rules engine, etc.).
  - Runs code where the data lives (avoids data motion).
  - Delivers fast response times.



Comparison to Stream-Oriented Platforms

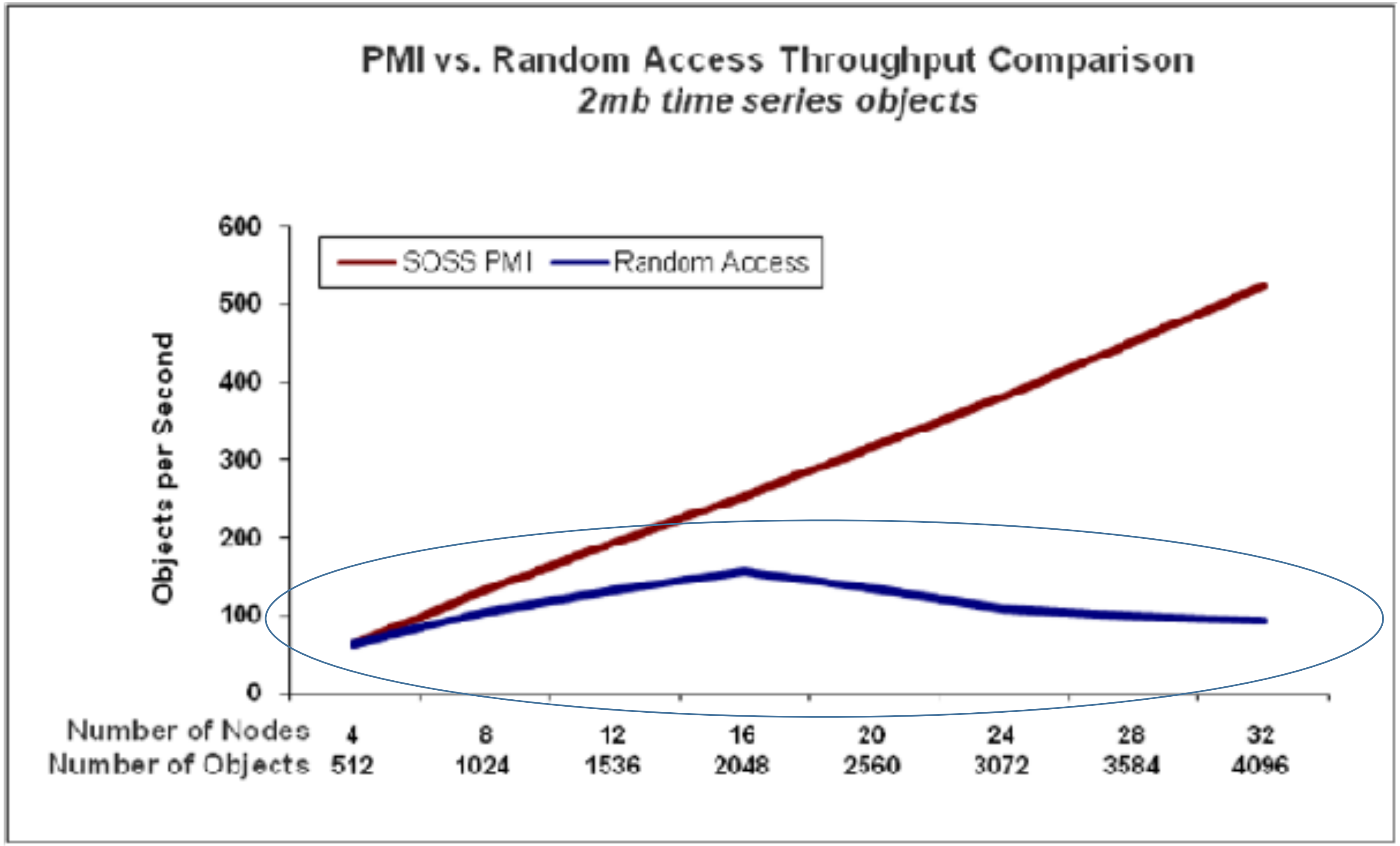
Stream-oriented platforms typically focus on analyzing the event stream:

- Lack specific support for building digital twins and managing their state & semantics:
  - Adds complexity in implementing digital twin models.
  - Can lack a clean separation between event orchestration and domain-specific code.
- Do not specifically integrate state management with stream processing:
  - Usually require state data to be accessed or updated using a separate storage tier.
  - Incur network delays which can lead to bottlenecks.



The Effect of Data Motion on Scaling

- Data motion creates a bottleneck that limits throughput.
- Avoiding data motion enables linear scalability for growing workloads => predictable, low latency.
- Example: back-testing stock histories in parallel

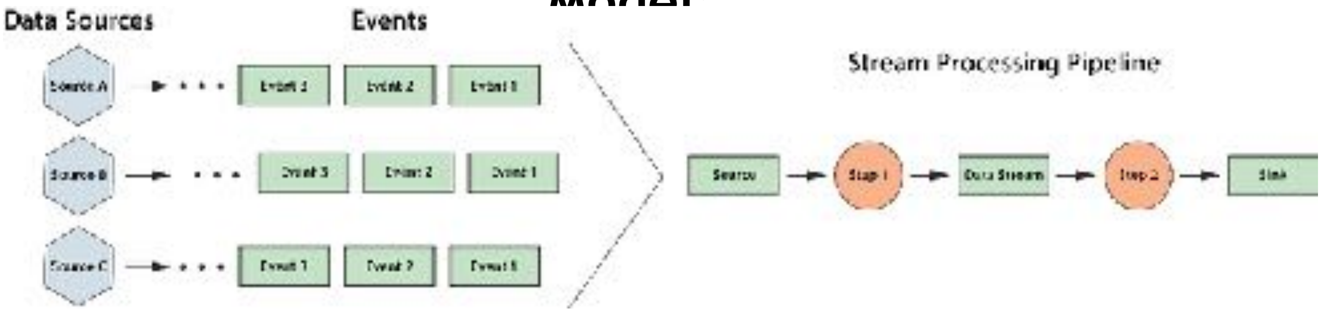


Comparison to Stream-Oriented Platforms

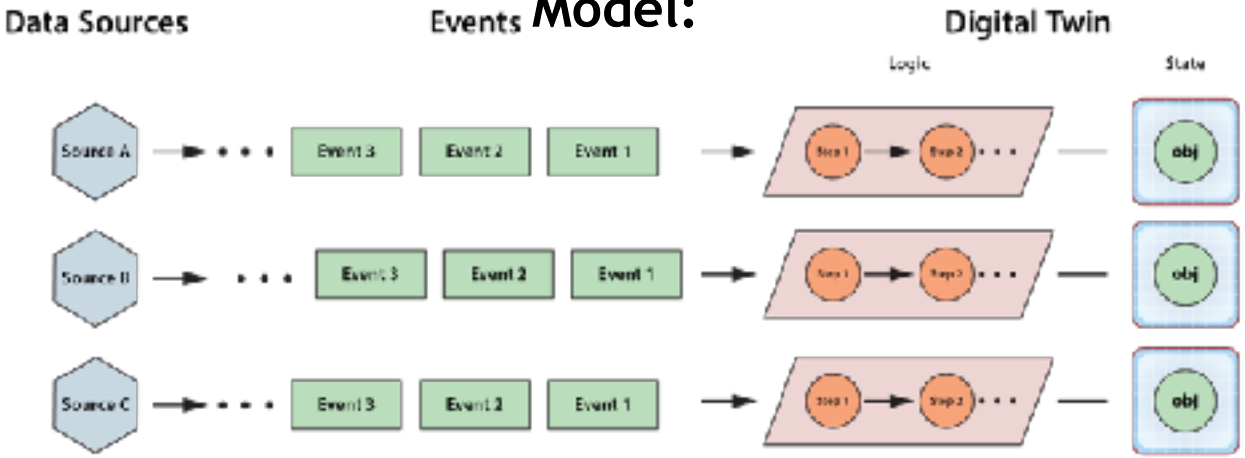
Some advantages of the digital twin model:

- Auto-correlates events from each data source:
  - Avoids the need to do this in the stream processing pipeline.
- Refactors processing steps to perform them in one location:
  - Avoids possible data motion between steps.
- Provides a basis for transparent scaling:
  - Leverages the grid's load-balancing of digital twin objects across the IMDG.

Stream-Oriented Model:



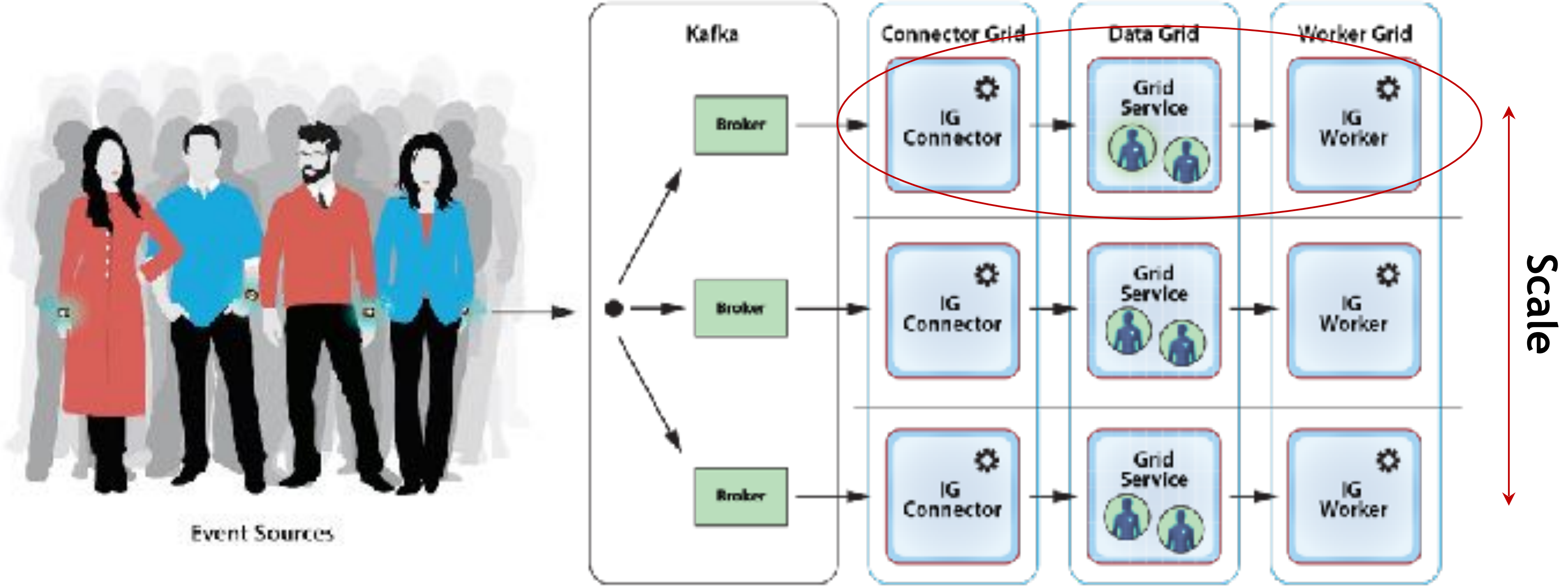
Digital Twin Model:



Ingesting Stream Data into an IMDG from Kafka

IMDG can transparently scale event reception from Kafka:

- IMDG can spawn multiple Kafka connectors in a “Connector Grid” to handle events in parallel.
- IMDG can spawn a “Worker Grid” to receive events and implement digital twin semantics.
- IMDG transparently scales as the workload grows.



IMDG uses key to direct events to grid host for associated digital twin object.

Code Sample (Java): Connecting an IMDG to Kafka

```
// Create a grid startup action to start Kafka connectors:
GridAction connectAction = new ConnectorGridBuilder("hr_cache")
     .addKafkaServerPropertiesPath(new File("server.properties"))
     .addConnectorProperties(new File[] {new File("sink.properties")})
     .build();
```

Kafka connect code

```
// Start the invocation grid and register the startup action:
InvocationGrid grid = new InvocationGridBuilder(“conn_grid")
     .setLibraryPath("Kafka").addJar("applicationClasses.jar")
     .addStartupAction(connectAction).load();
```

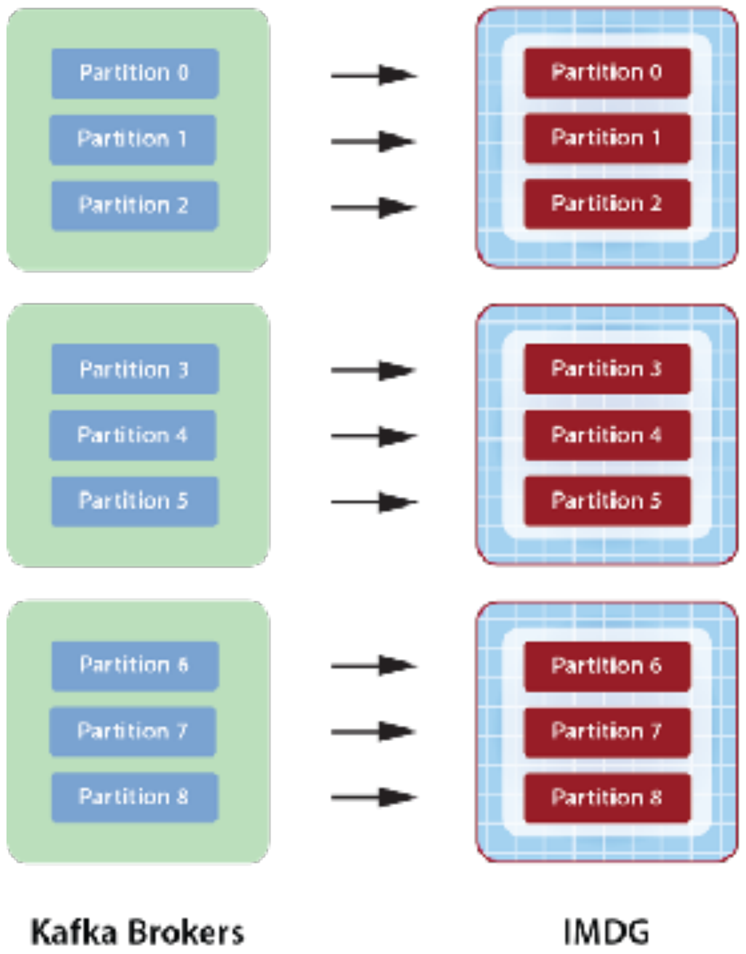
Load inv. grid

```
# Example of connect-grid-sink.properties:
name=grid-sink
connector.class=GridSinkConnector
key.converter=PassThroughConverter
value.converter=PassThroughConverter
topics=my_kafka_topic
grid.namedcache.name=mycache
```

Define properties

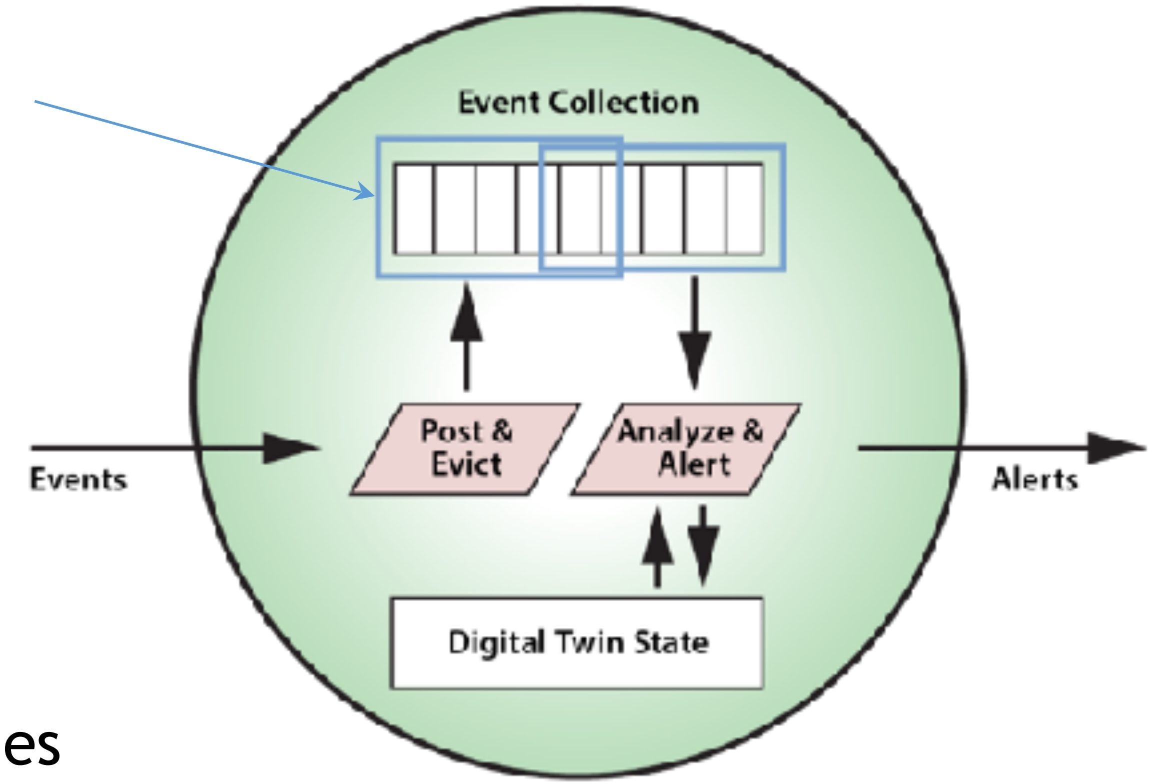
Using Kafka Partitions to Scale Event Handling

- Kafka offers partitions to scale out handling of event messages.
  - Partitions are distributed across brokers.
  - Brokers process messages in parallel.
- IMDG can map Kafka partitions to grid partitions.
- **This minimizes event handling latency.**
  - Avoids store-and-forward within IMDG.
- How?
  - IMDG specifies key mapping algorithm.
  - Application specifies # Kafka partitions.
  - IMDG listens to appropriate Kafka partitions (and handles membership changes).



Digital Twin Manages Time Windows of Events

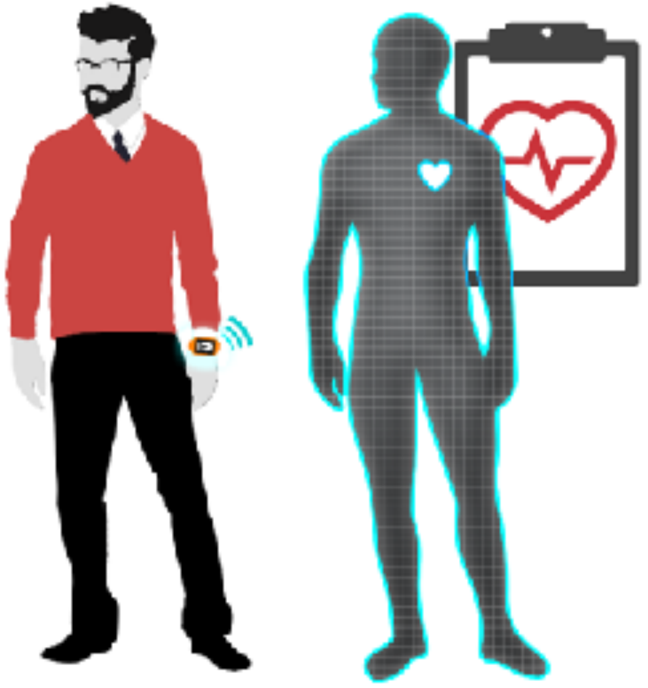
- Each digital twin object can host a time-ordered & windowed collection of events.
  - Can be implemented as a transform on the collection similar to streaming APIs (e.g. Beam)
- Event posting triggers eviction based on windowing policy.
- Time window manager implements multiple windowing policies, e.g.:
  - Sliding
  - Tumbling
  - Session
- Time window manager implements queries that supply windowed events for analysis.



Example: A Heart-Rate Monitoring Application

A simple medical application that monitors heart rate telemetry from a mobile device:

- Receives heart-rate telemetry events from patient's mobile device.
- Digital twin holds telemetry and patient's history/status.
- Event posting logic tracks these events within a collection in the digital twin.
- Analysis logic evaluates the events using time windows on the collection and with regard to the patient's history and status.
- In this example, it alerts a doctor when heart-rate exceeds age-specific threshold.
- Updates the patient's status.

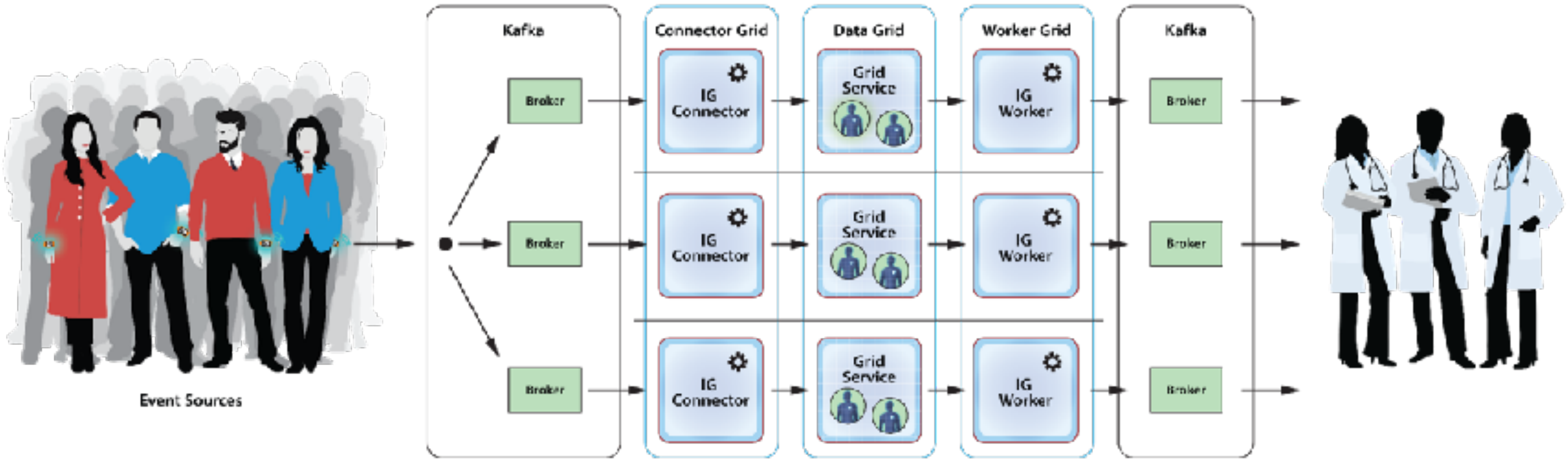


Patient

Digital Twin

Medical Monitoring & Alerting Architecture

- Heart-rate events flow to their respective digital twin objects for processing.
- The IMDG transparently scales to handle large numbers of patients.



Code Sample (C#): Heart-Rate Monitor

```
// Heart-rate event:
public class HeartRate
{
    public string PatientID { get; set; }
    public DateTime Timestamp { get; set; }
    public short BeatsPerMin { get; set; }
}

// Patient (the digital twin):
public class Patient
{
    public string Id { get; set; }
    public IList<HeartRate> HeartRates { get; set; }
    public DateTime Birthdate { get; set; }
    public int Age => (int)Math.Floor((DateTime.Now - Birthdate).TotalDays /
365);
    public bool HeartIssueDetected { get; set; }
}
```

Class for HR event

Class for patient

List of HR events

Code Sample (C#): Heart-Rate Monitor

```
// Set up a ReactiveX pipeline in the IMDG to handle incoming heart-rate
events:
heartMonGrid.GetEventSource()
    .Where(ev => ev.EventInfo == "Heart Rate Event") // look for heart-rate
events
    .Select(ev => HeartRate.FromBytes(ev.Payload))     // extract heart-rate
data
    .Subscribe(HandleHeartRateEvent);                // update digital-twin
```

Code Sample (C#): Heart-Rate Monitor

```
// Process an incoming heart rate event in the digital twin:
static void HandleHeartRateEvent(HeartRate heartRateEvent)
{
    var patient = heartMonGrid.Retrieve(heartRateEvent.PatientID,
acquireLock: true)
                      as Patient;

    // Obtain an enumerable windowing transformation of the event collection:
    var slidingHeartRates = new SlidingWindowTransform<HeartRate>(
                                         source: patient.HeartRates,
                                         timestampSelector: hr => hr.Timestamp,
                                         windowDuration: TimeSpan.FromMinutes(5),
                                         every: TimeSpan.FromMinutes(1),
                                         startTime: DateTime.Now -
TimeSpan.FromDays(1));

    slidingHeartRates.Add(heartRateEvent);        // add event and evict as
necessary
    AnalyzePatient(patient, slidingHeartRates); // analyze & update patient's
status
```

Transform the collection

Add event, analyze

Code Sample (C#): Heart-Rate Monitor

```
// Analyze patient's state and send an alert if necessary:
static void AnalyzePatient(Patient patient,
                           SlidingWindowTransform<HeartRate> slidingHeartRates)
{
    // See if there are any 5-minute periods in the past day when the average
    // heart rate is too high. We use the sliding windows to calculate a
    // moving average and vary the alert threshold depending on patient's age:

    foreach (var window in slidingHeartRates)
    {
        if (window.Count == 0) continue; // can't average zero elements

        var avg = window.Average(hr => hr.BeatsPerMin);
        if ((patient.Age > 50 && avg > 130) || avg > 160) {
            SendAlert($"{patient.Id} registers high heart rate at
{window.StartTime}!");
            patient.HeartIssueDetected = true;
        }
    }
}
```

Analyze time windows

A More Sophisticated Digital Twin Model

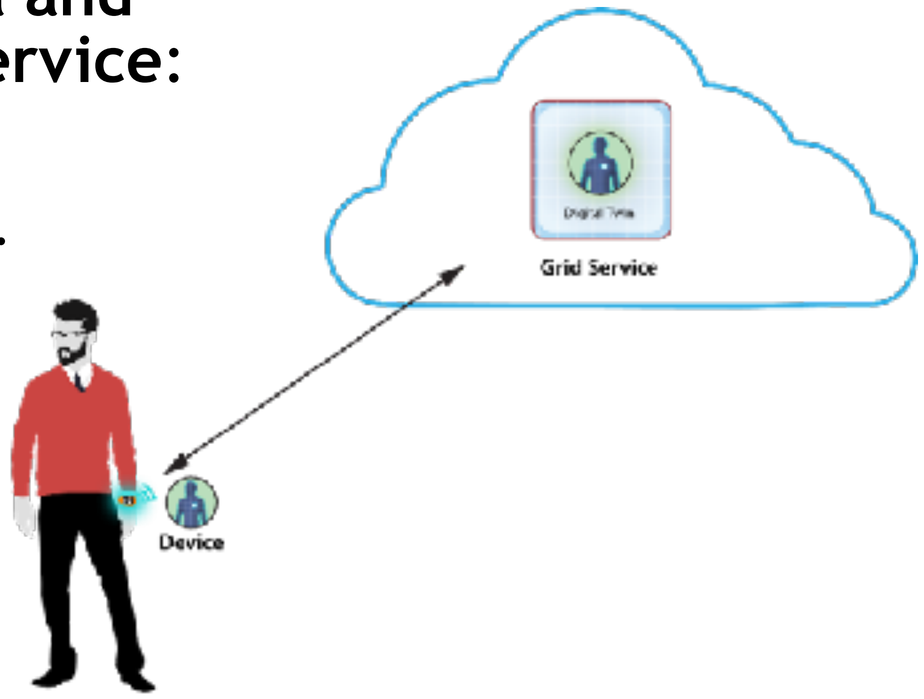
Example Model of Heart-Rate Monitoring for High Intensity Exercise Program

- Example of data to be tracked:
  - **Event collection**: time-stamped heart rate telemetry, type of exercise, specific parameters (distance, strides, altitude change, etc.)
  - **Participant background/history**: age, height, weight history, heart-rela medical conditions and medications, injuries, previous medical events
  - **Exercise tracking**: session history, average # sessions per week, average peak heart rates, frequency of exercise types
  - **Aggregate statistics**: average/max/min exercise tracking statistics for all participants
- Example of logic to be performed:
  - **Notify participant** if session history across time windows indicates need to change mix.
  - **Notify participant** if heart rate trends deviate significantly from aggregate statistics.
  - **Alert participant/medical personnel** if heart rate analysis across time windows indicates an imminent threat to health.
  - **Report** aggregate statistics.

Challenge: Edge vs. Grid Service

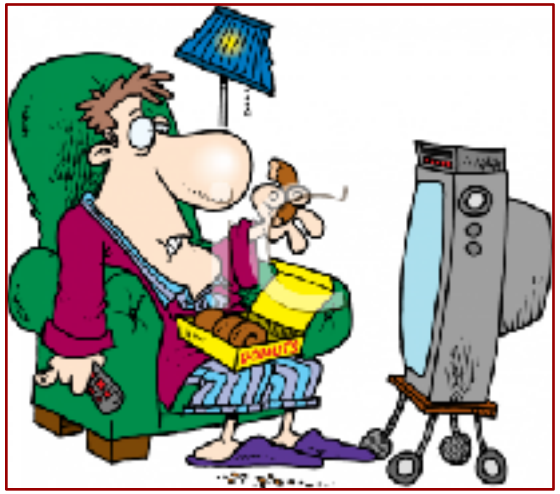
How partition the digital twin model's data and logic between edge devices and the grid service:

- Edge device:
  - Has limited storage and computing power, *but*…
  - Offers lowest latency to process events.
- Grid service:
  - Can run sophisticated algorithms.
  - Can store long event history.
  - Can track detailed state of the physical twin.
- Approach (akin to nervous system):
  - Perform tactical processing at edge for fast responsiveness.
  - Perform strategic processing in grid service.
- Software tools are needed for transparent migration.



Real-World Example: Tracking Cable Viewers

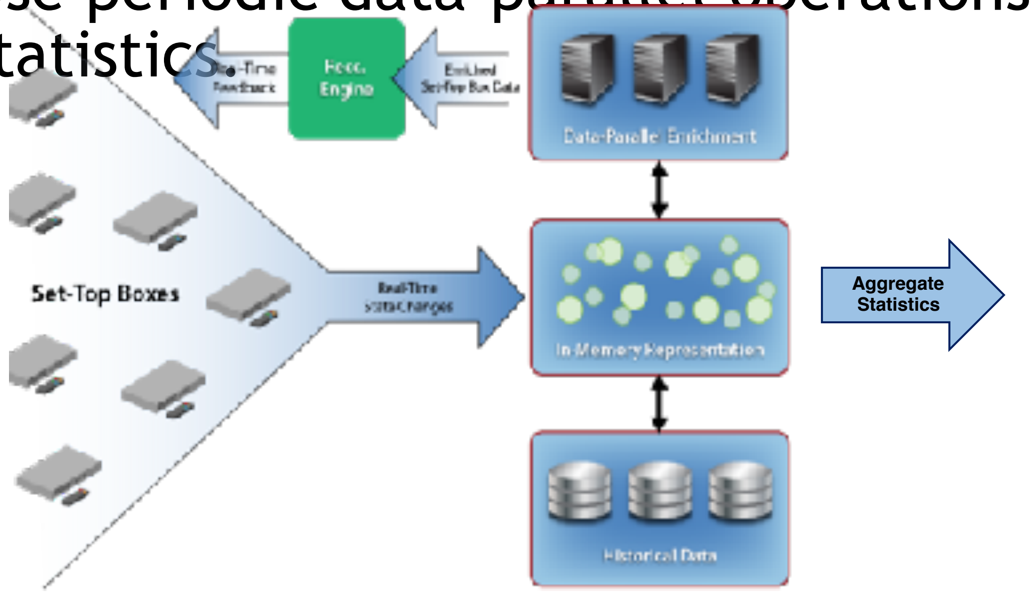
- **Cable Company's Goals:**
  - Make real-time, personalized upsell offers.
  - Immediately respond to service issues & hotspots.
  - Track aggregate behavior to identify patterns, e.g.:
    - Total instantaneous incoming event rate
    - Most popular programs and # viewers by zip code
- **Requirements:**
  - Track events from 10M set-top boxes with 25K events/sec (2.2B/day).
  - Correlate, cleanse, and enrich events per rules (e.g. ignore fast channel switches, match channels to programs) within 5 seconds.
  - Refresh aggregate statistics every 10 seconds.



Example: Tracking Cable Viewers

Solution:

- Each **set-top box** is represented as a digital twin object in the IMDG.
    - Holds raw & enriched event streams, viewer parameters, and box statistics.
- Use stream processing on box events to generate alerts for recommendation engine.
- Use periodic data-parallel operations on objects to generate aggregate statistics.



Real-Time Dashboard

AWS Simulation:
- 25 servers
- 30K events/sec
- <1 sec. latency for alerts
- 10s per batch update

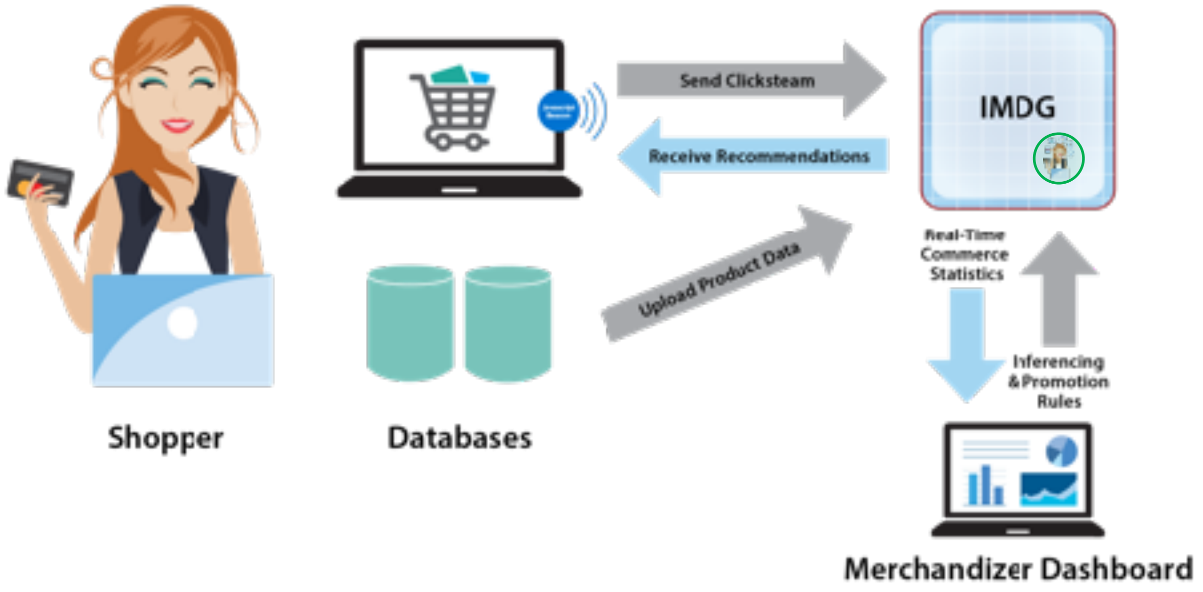
Example: Ecommerce Recommendations

- **Goals:**
  - Make real-time, personalized recommendations for an ecommerce web site:
    - Combine clickstream, shopper demographics, static recommendations
  - Track aggregate site performance, e.g.:
    - Shopper behavior (clicks-to-cart, basket size, …)
    - Merchandizing effectiveness (best selling products)
- **Requirements:**
  - Handle 500K+ simultaneous shoppers.
  - Return recommendations within 200 msec.
  - Refresh aggregate statistics every minute.

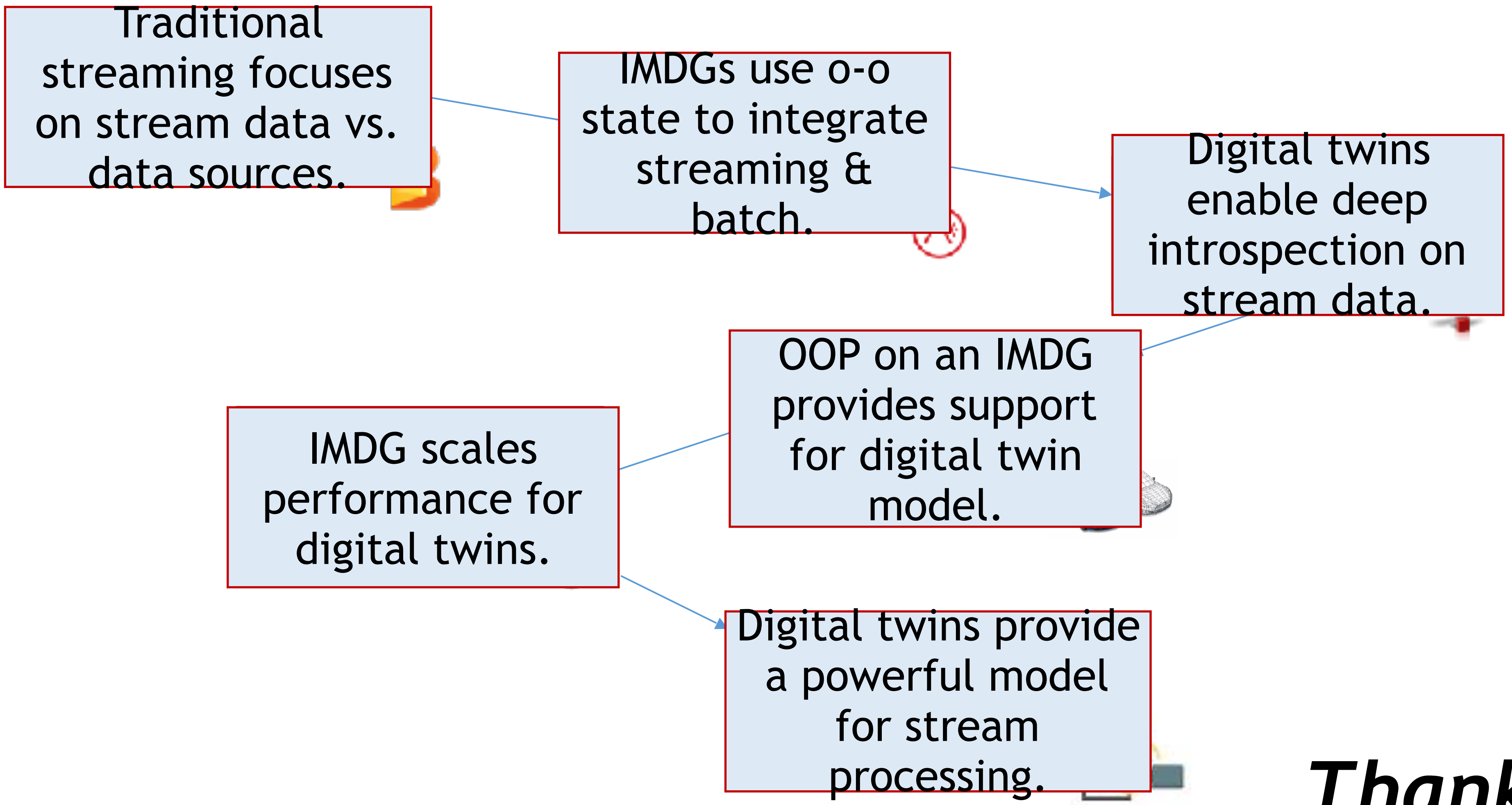
Example: Ecommerce Recommendations

Solution:

- Each **shopper** is represented as a digital twin object in the IMDG.
  - Holds clickstream events, shopper demographics, and ML parameters.
  - Note: digital twins can be used to represent people.
- Use stream processing on clickstream events to generate recommendations.
  - Analysis logic runs an ML algorithm in real-time to generate recommendations.
- Use periodic data-parallel operations on objects to generate aggregate statistics.



Recap of the Journey



Thank you!

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