In-Memory Computing SUMMIT | NORTH AMERICA 2018

Integrating Data-Parallel Analytics into Stream-Processing Using an In-Memory Data Grid

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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
- Thirteen+ years in the market; 450+ customers, 12,000+ servers

Agenda

How In-Memory Computing Creates the Next Generation in Stream-Processing

- Goals and challenges for stream-processing
- Adding context: stateful stream-processing
- Overview of in-memory data grids (IMDGs)
- Digital twin model for stateful stream-processing
- Why use an IMDG: integrated event processing and data-parallel analysis
- Example use cases
- Detailed code sample: runners with smart watches
- Performance benefits

Goals for Stream-Processing

- **Goals**:
  - Process incoming data streams from many (1000s) of sources.
  - Analyze events for patterns of interest.
  - Provide timely (real-time) feedback and alerts.
  - Provide data-parallel analytics for aggregate statistics and feedback.
- **Many applications**:
  - Internet of Things (IoT)
  - Medical monitoring
  - Logistics
  - Financial trading systems
  - Ecommerce recommendations




Event Sources

Example: Ecommerce Recommendations

1000s of online shoppers:

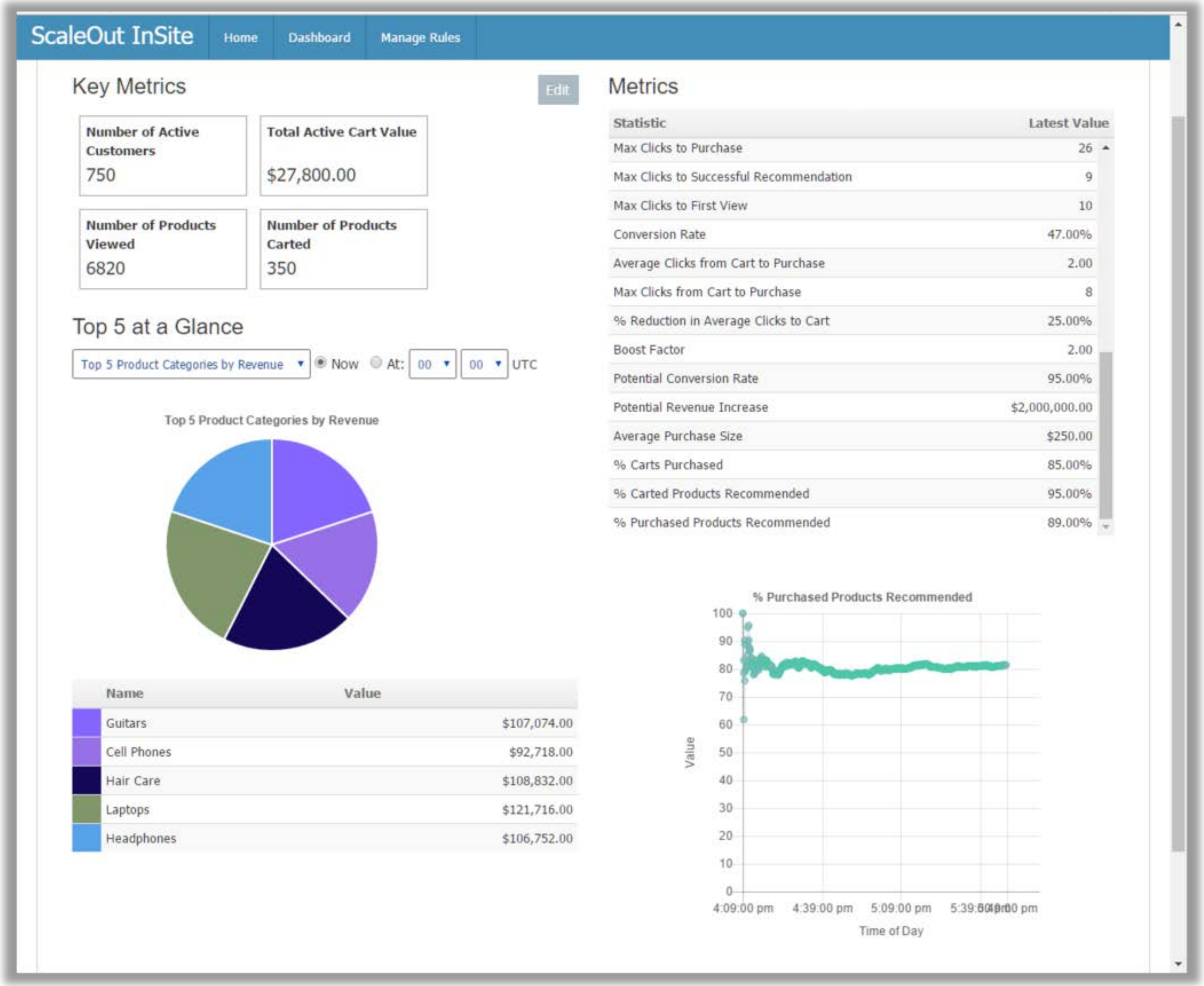
- Each shopper generates a clickstream of products searched.
- Stream-processing system must:
  - Correlate clicks for each shopper.
  - Maintain a history of clicks during a shopping session.
  - Analyze clicks to create new recommendations within 100 msec.
- Analysis must:
  - Take into account the shopper’s preferences and demographics.
  - Use aggregate feedback based on collaborative shopping behavior.

Providing Recommendations in Real Time

- Requires scalable stream-processing to analyze each click and respond in <100ms:
  - Accept input with each event on shopper's preferences.
  - Provide aggregate feedback on best-selling products.

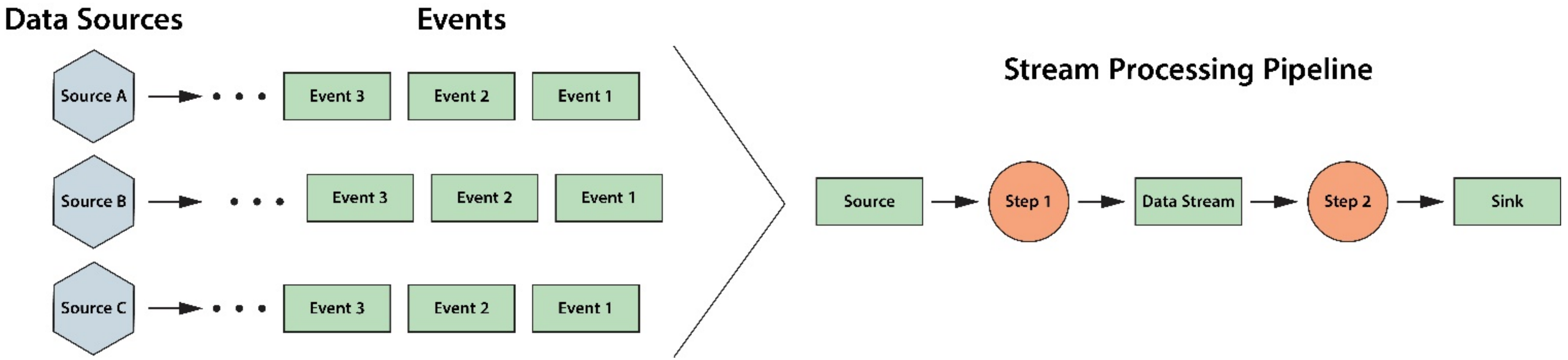
Providing Aggregate Metrics

- Must aggregate statistics for all shoppers:
  - Track real-time shopping behavior.
  - Chart key purchasing trends.
  - Enable merchandizer to create promotions dynamically.
- Aggregate statistics can be shared with shoppers:
  - Allows shoppers to obtain collaborative feedback.
  - Examples include most viewed and best selling products.



Challenges for Stream-Processing Architectures

- Basic stream-processing architecture:

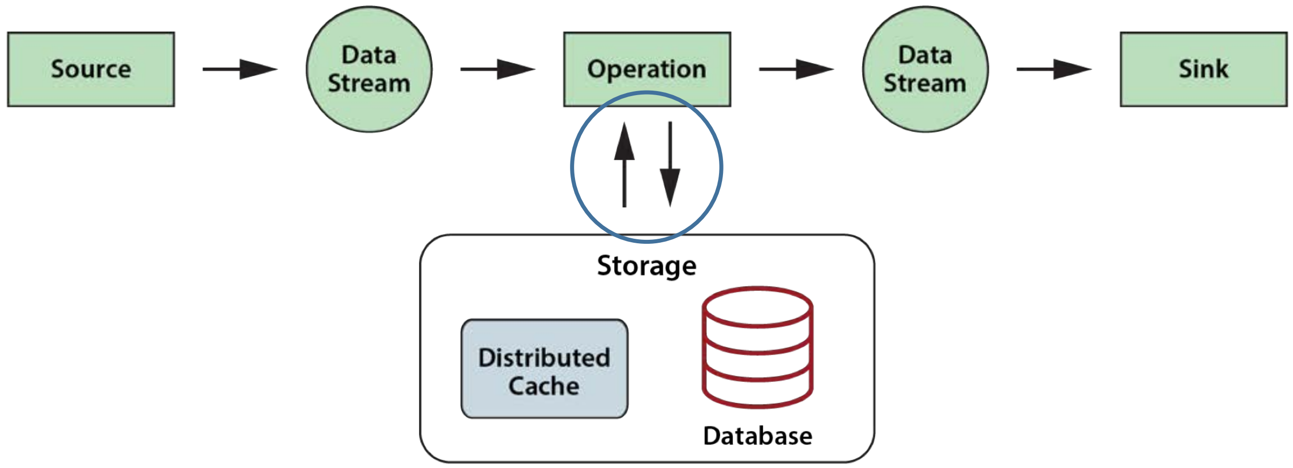


- Challenges:
  - How efficiently correlate events from each data source?
  - How combine events with relevant state information to create the necessary context for analysis?
  - How embed application-specific analysis algorithms in the pipeline?
  - How generate feedback/alerts with low latency?
  - How perform data-parallel analytics to determine aggregate trends?

Adding Context to Stream-Processing

- Stateful stream-processing platforms add “unmanaged” data storage to the pipeline:
  - Pipeline stages perform transformations in a sequence of stages from data sources to sinks.
  - Data storage (distributed cache, database) is accessed from the pipeline by application code in an unspecified manner.
  - Examples: Apama (CEP), Apache Flink, Storm

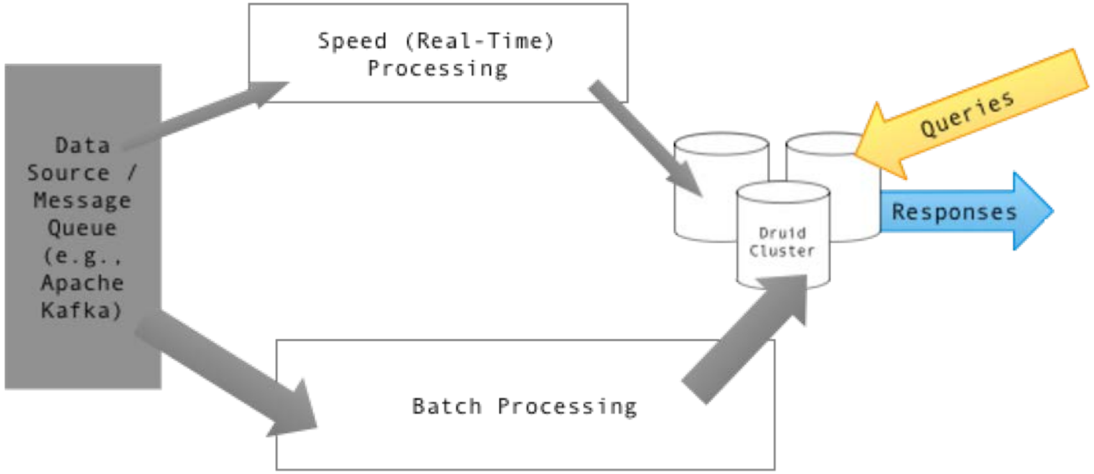
Stream Pipeline



- Problems:
  - There is no software architecture for managing state information.
  - This adds complexity to the application.
  - Creates a network bottleneck.
  - Does not address need for data-parallel analytics.

Lambda Architecture: Batch Parallel Analytics

- Lambda architecture separates stream-processing ("speed layer") from data-parallel analytics ("batch layer").
- Creates queryable state, but:
  - Does not enhance context for stateful stream processing.
  - Does not perform data-parallel analytics online for immediate feedback.
  - Does not lead to a "Hybrid Transactional and Analytics Processing" (HTAP) architecture.



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How combine stream-processing with state to simplify design, maximize performance, and enable fast data-parallel analytics?

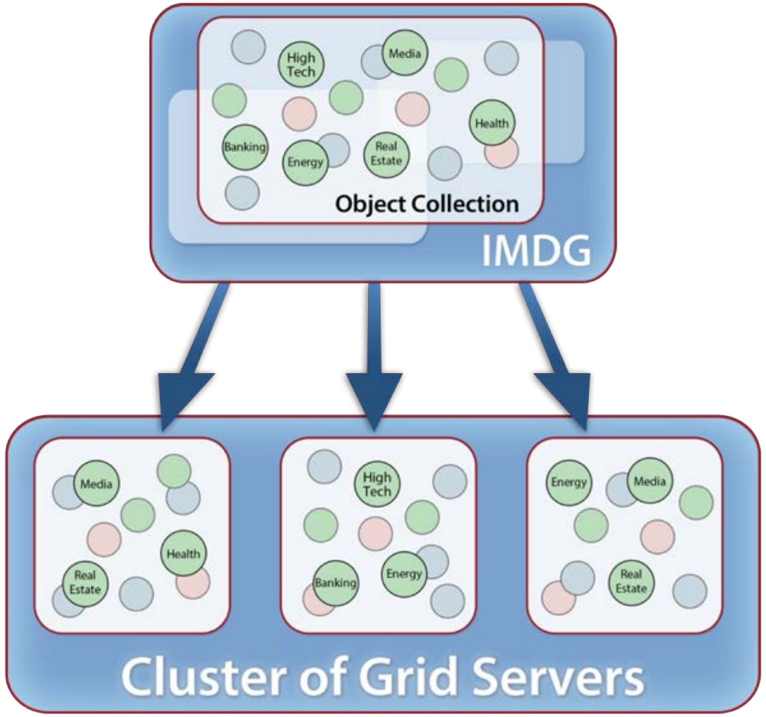
In-Memory Data Grid (IMDG)

IMDG provides a powerful platform for stateful stream-processing.

What is an IMDG?

- IMDG stores live, object-oriented data:
  - Uses a key/value storage model for large object collections.
  - Maps objects to a cluster of commodity servers with location transparency.
  - Has predictably fast (<1 msec.) data access and updates.
  - Designed for *transparent* scaling and high availability
- IMDG integrates in-memory computing with data storage:
  - Uses object-oriented execution model.
  - Leverages the cluster's computing power.
  - Computes where the data lives to avoid network bottlenecks.

Logical view

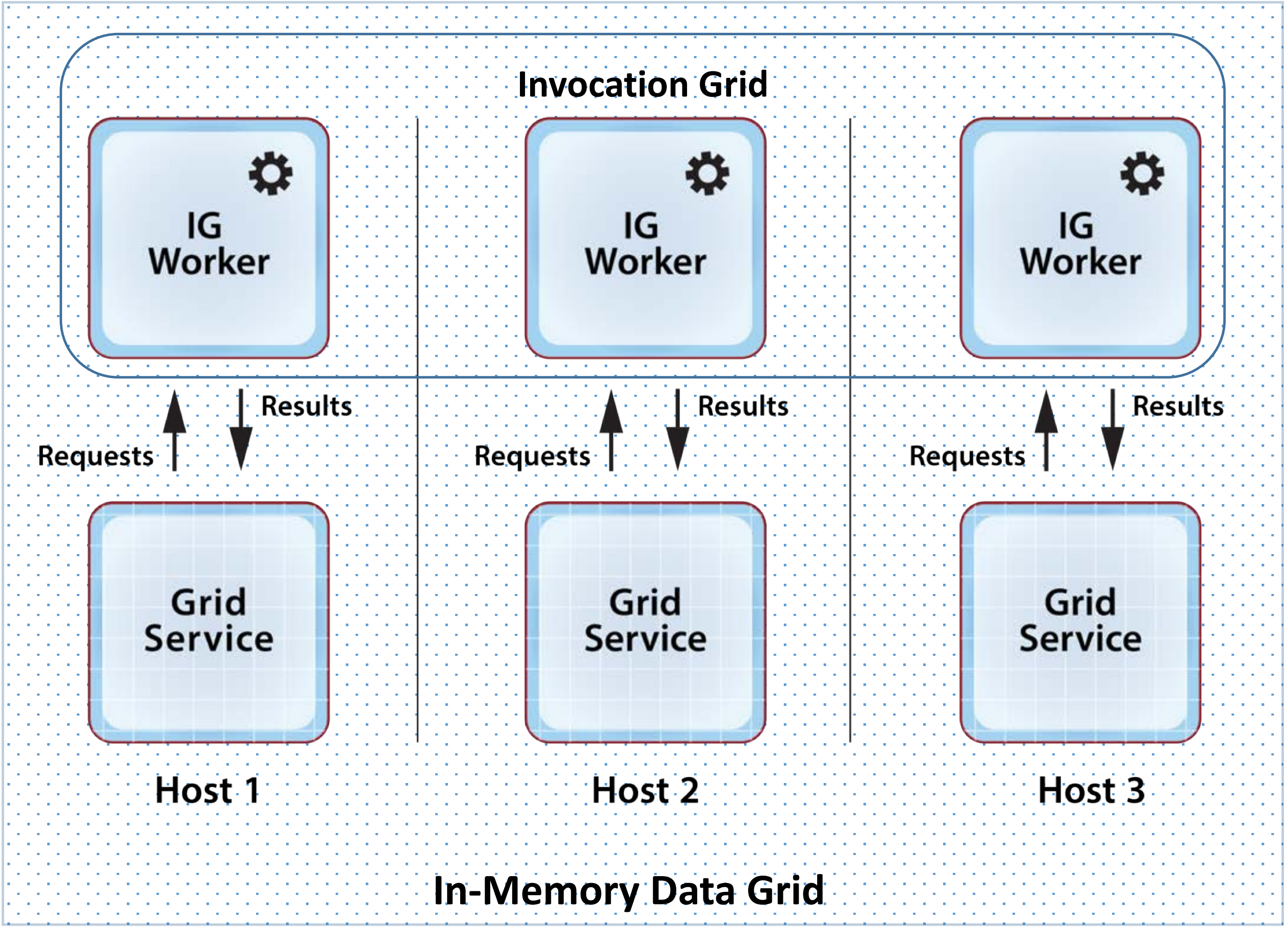


Physical view

IMDG Storage Model

How an IMDG Can Integrate Computation

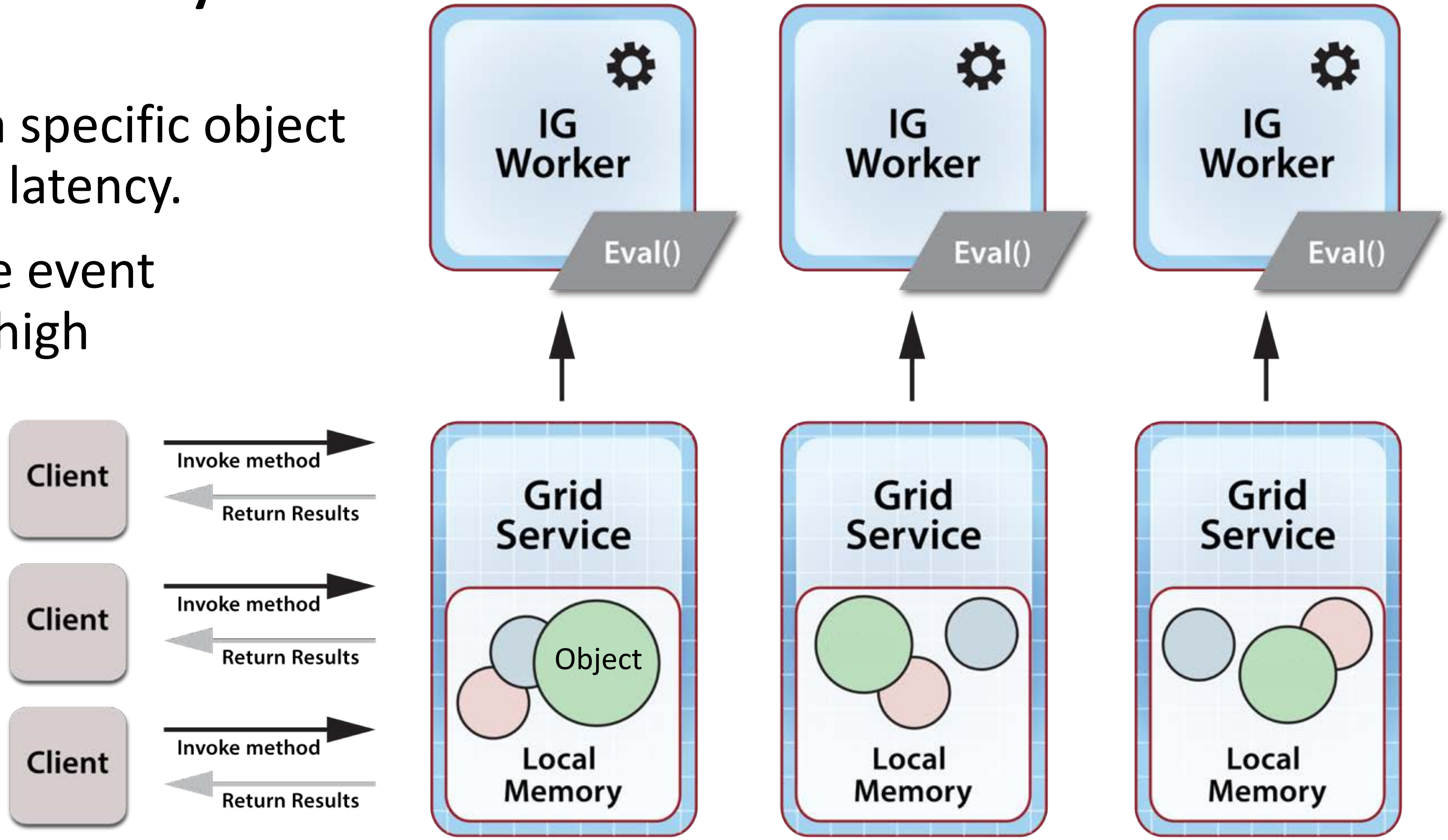
- Each grid host runs a worker process which executes application-defined methods on stored objects.
  - The set of worker processes is called an *invocation grid (IG)*.
  - IG usually runs language-specific runtimes (JVM, .NET).
  - IMDG can ship code to the IG workers.
- Key advantages for IGs:
  - Follows object-oriented model.
  - Avoids network bottlenecks by moving computing to the data.
  - Leverages IMDG's cores & servers.



IMDG Runs Event Handlers for Stream-Processing

Event handlers run independently for each incoming event:

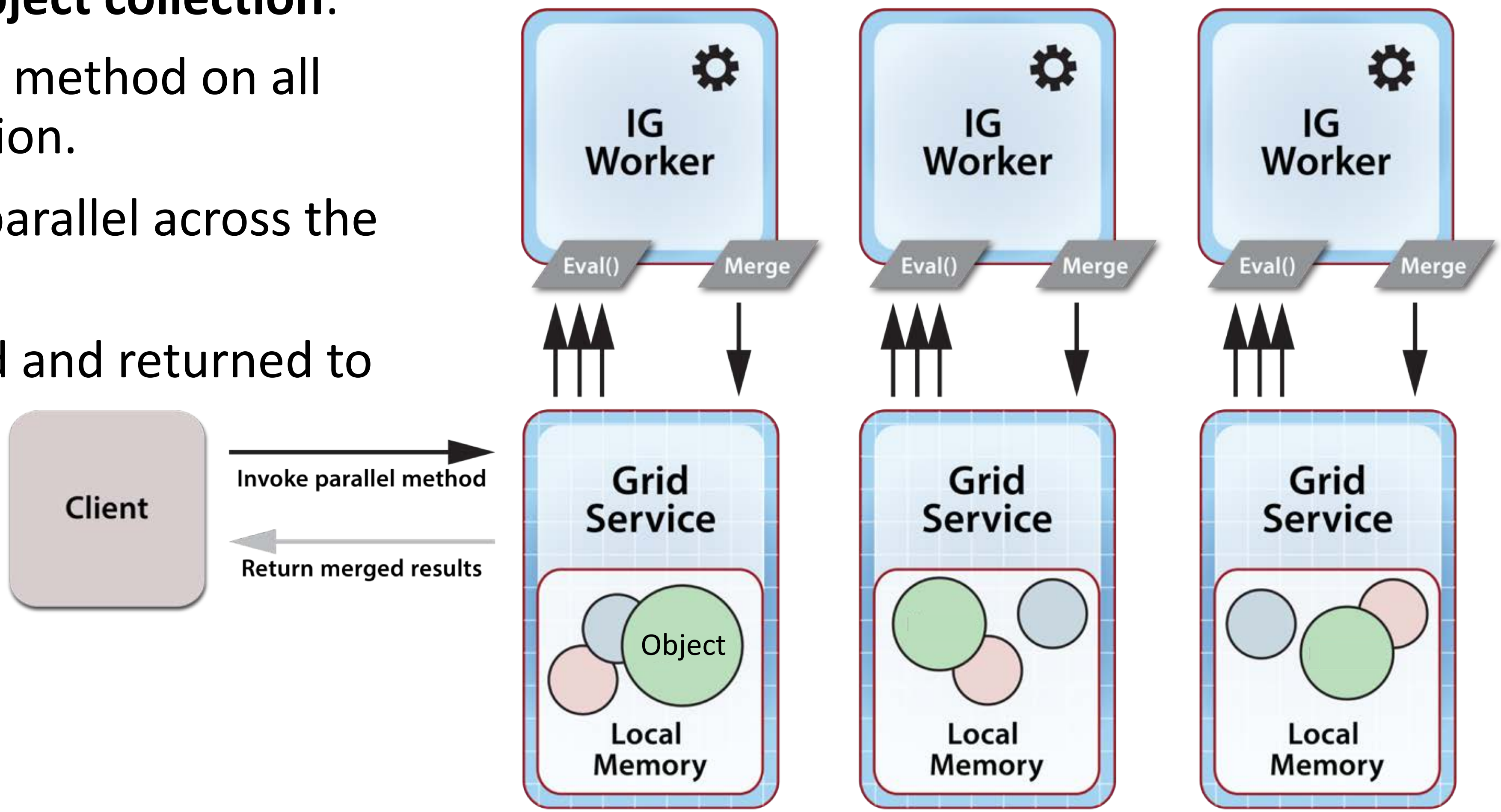
- IMDG directs event to a specific object using ReactiveX for low latency.
- IMDG executes multiple event handlers in parallel for high throughput.



IMDG Executes Data-Parallel Computations

Method execution implements a parallel op. on an object collection:

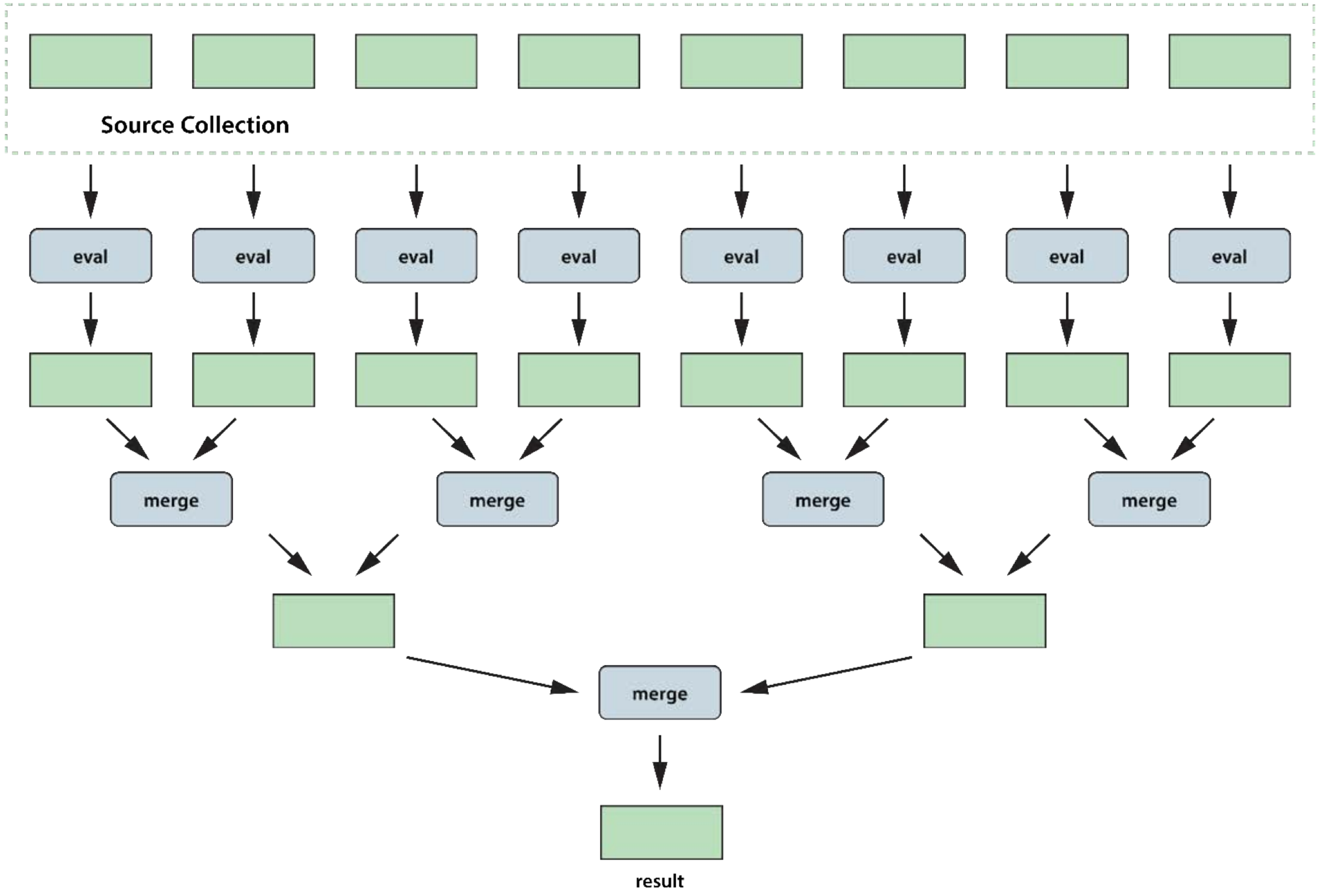
- Client runs a single method on all objects in a collection.
- Execution runs in parallel across the grid.
- Results are merged and returned to the client.
- Runs with lower latency than batch jobs.



A Basic Data-Parallel Execution Model

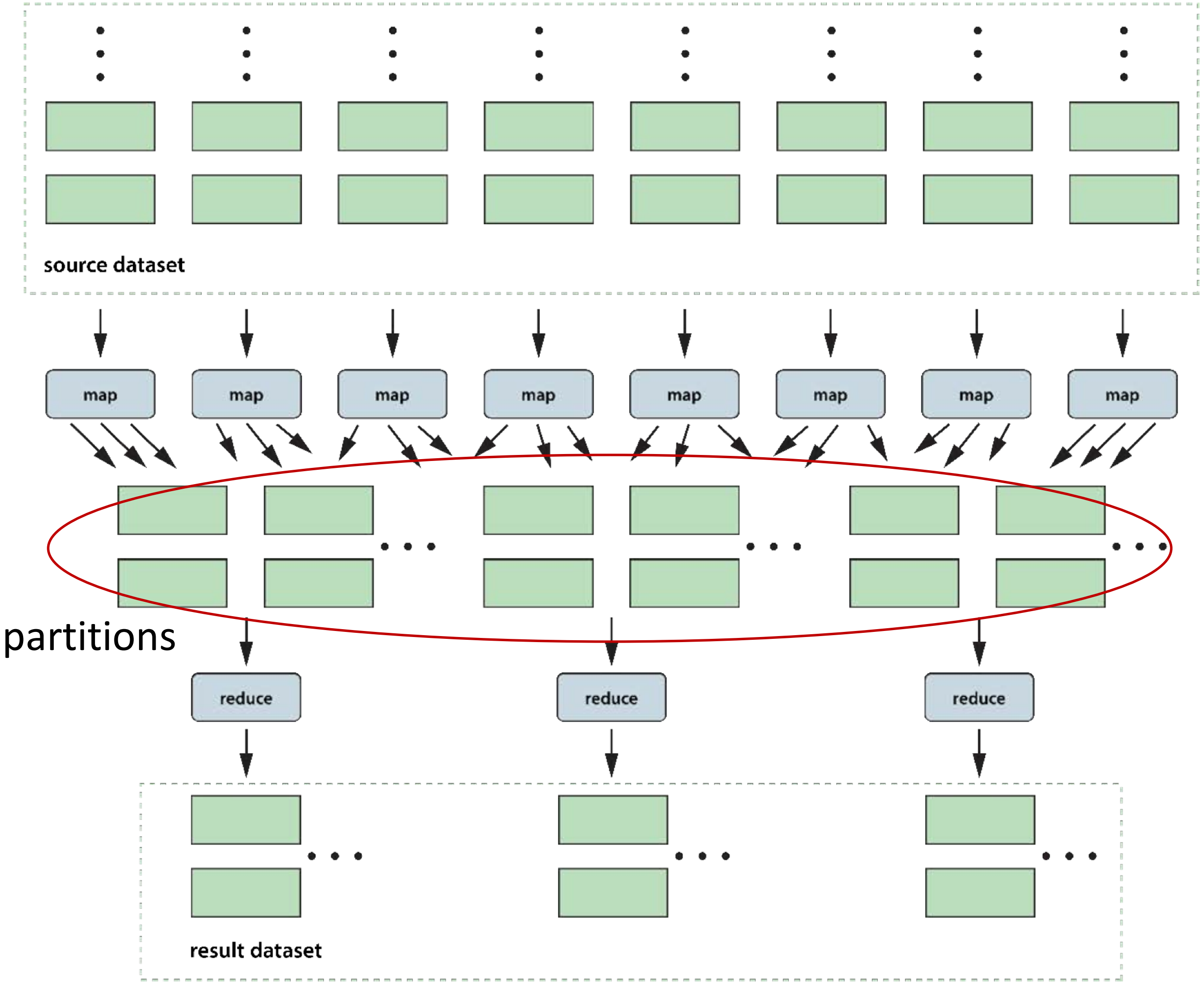
A fundamental model from parallel supercomputing:

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



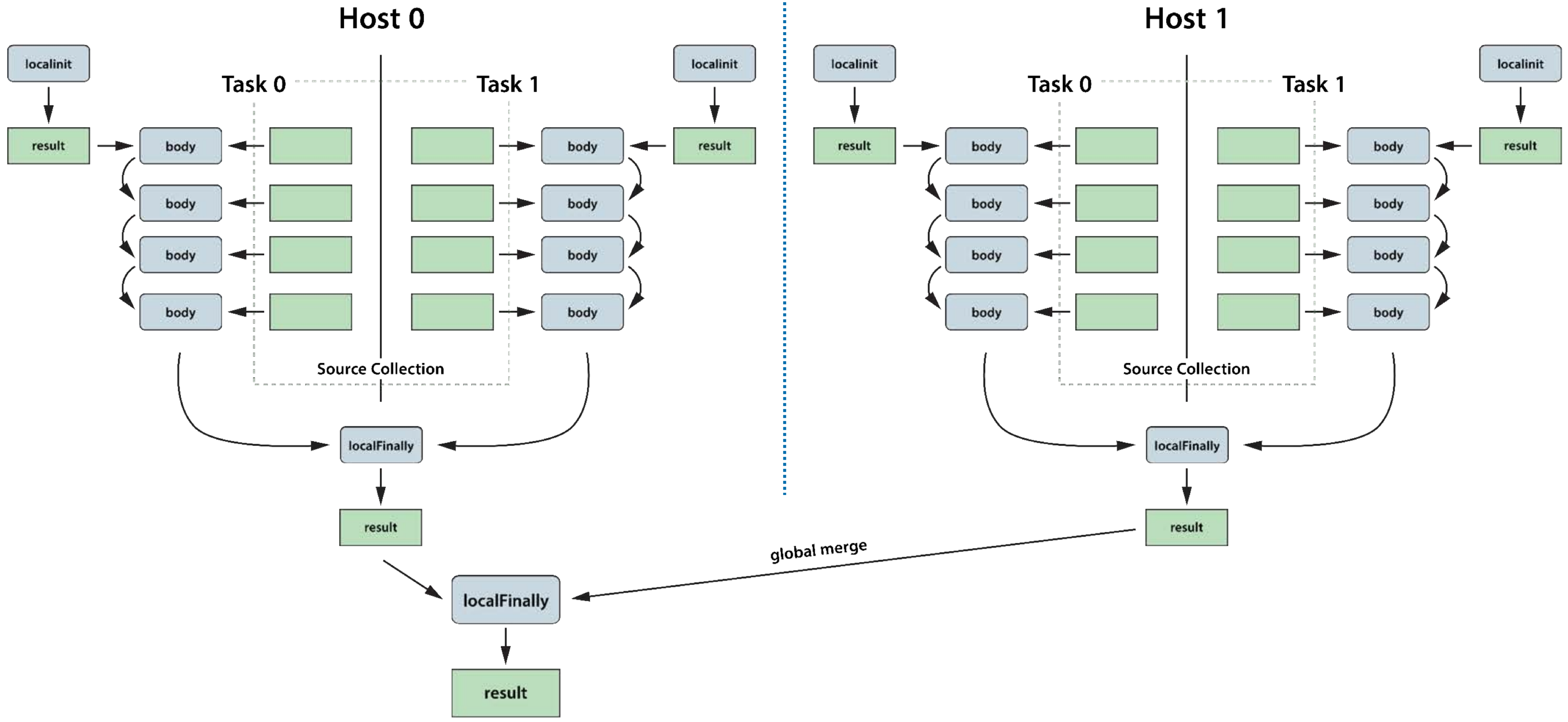
MapReduce Builds on This Model

- Implements "group-by" computations.
- Example: "Determine average RPM for all windmills by region (NE, NW, SE, SW)."
- Runs in two data-parallel phases (map, reduce):
  - **Map** phase repartitions and optionally combines source data.
  - **Reduce** phase analyzes each data partition in parallel.
  - Returns results for each partition (no merging).



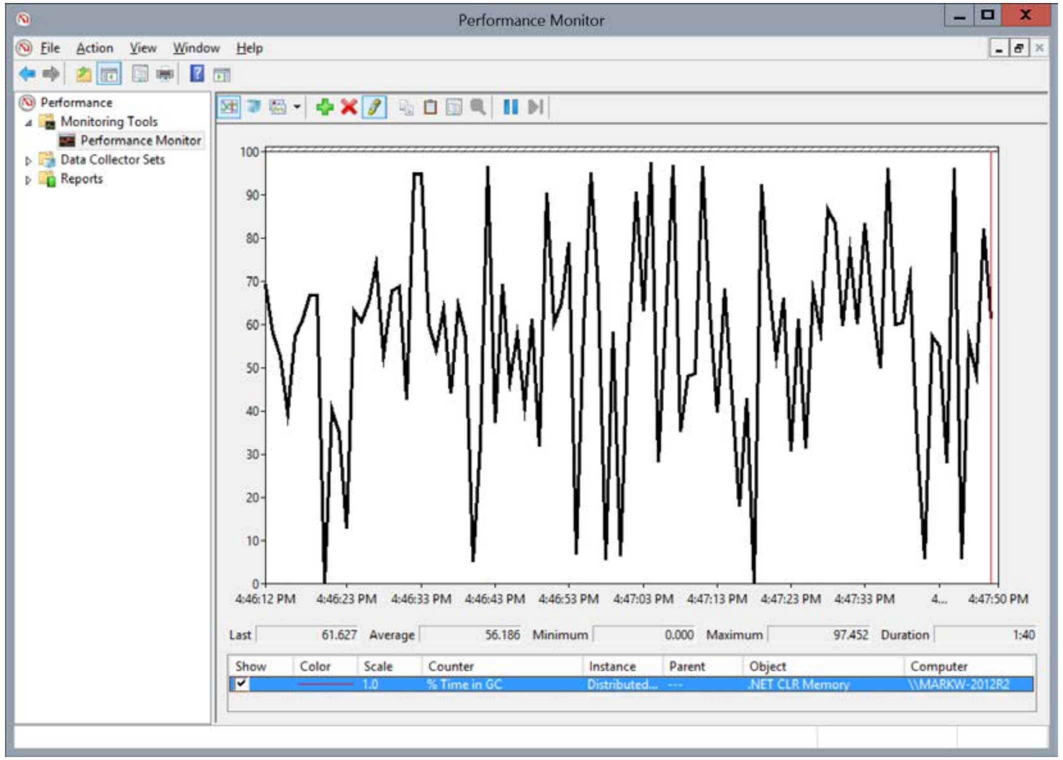
Distributed ForEach: Another Data-Parallel Model

- Body code performs **eval** and iterative **merge** to reduce garbage collection:

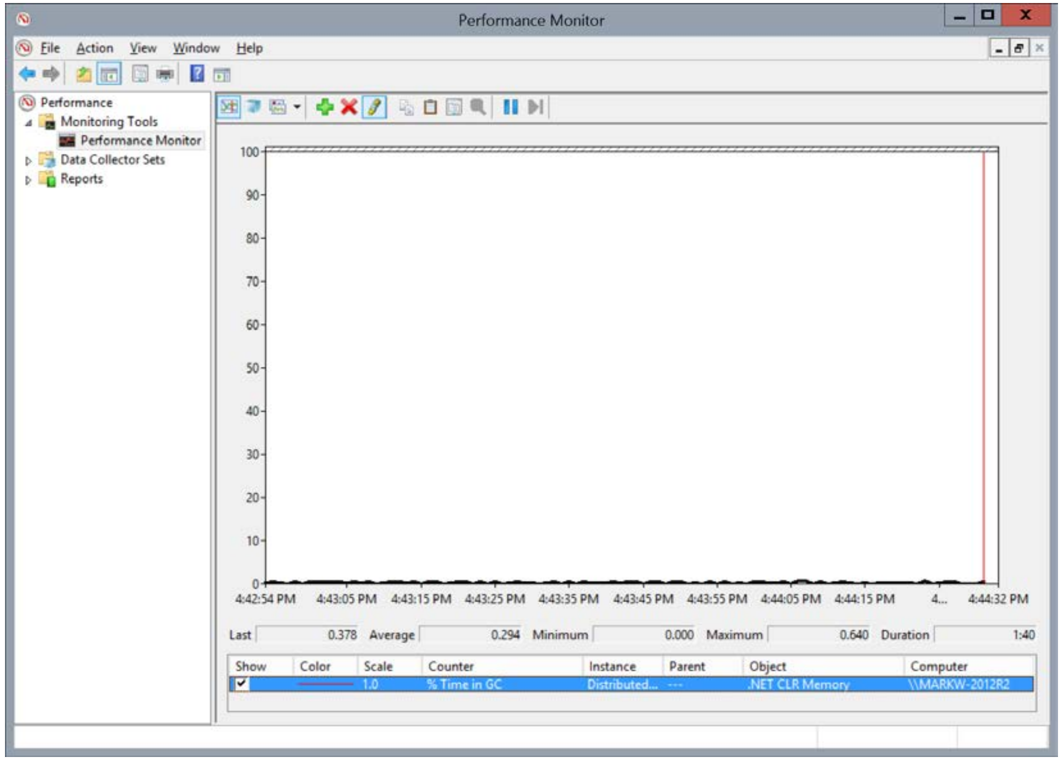


Reduced GC Time with Distributed ForEach

PMI

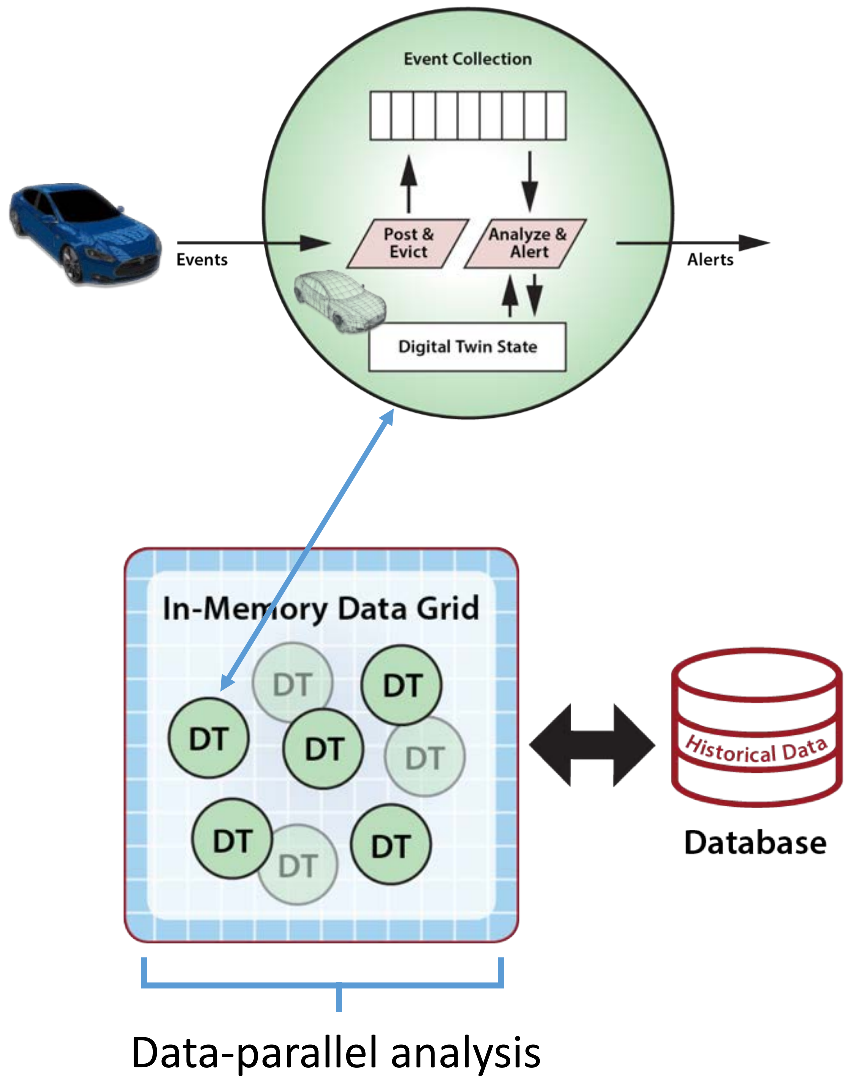


Distributed ForEach



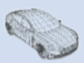
Stream-Processing with the Digital Twin Model

- Created by Michael Grieves; popularized by Gartner
- Represents each data source with an IMDG object that holds:
  - An event collection
  - State information about the data source
  - Logic for analyzing events, updating state, and generating alerts
- Benefits:
  - Offers a structured approach to stateful stream-processing.
  - Automatically correlates incoming events by data source.
  - Integrates all relevant context (events & state).
  - Enables easy deployment of application-specific logic (e.g., ML, rules engine, etc.) for analysis and alerting.
  - Provides domain for aggregate analysis and feedback.



Some Applications for Digital Twins

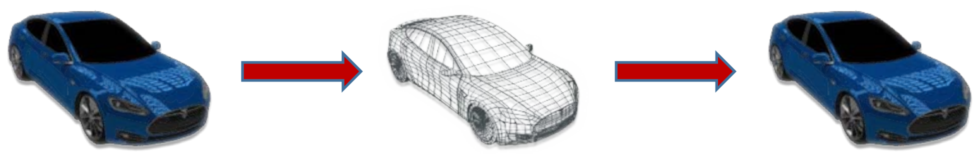
A digital twin correlates incoming events with context using domain-specific algorithms to generate alerts:

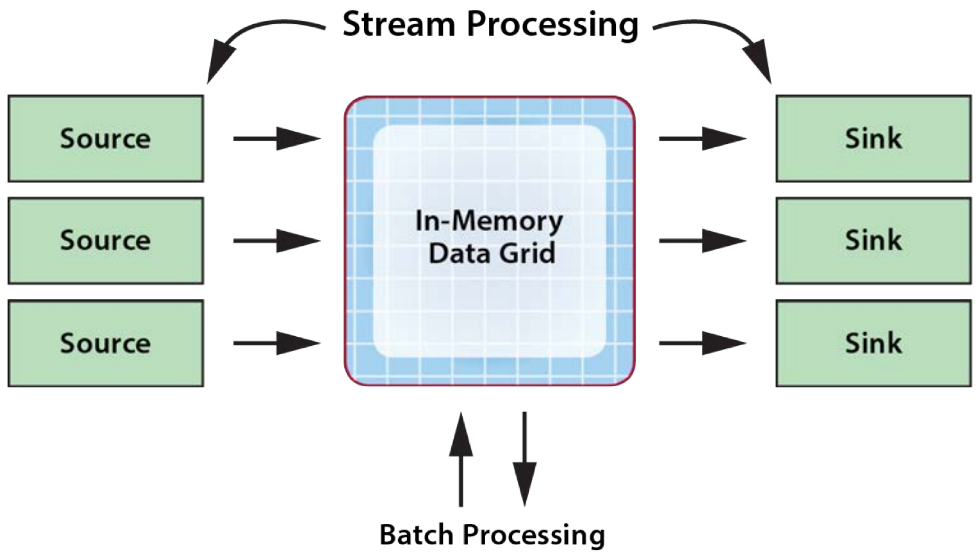
Application	Context	Events	Logic	Alerts
IoT devices 	Device status & history	Device telemetry	Analyze to predict maintenance.	Maintenance requests
Medical monitoring 	Patient history & medications	Heart-rate, blood-pressure, etc.	Evaluate measurements over time windows with rules engine.	Alerts to patient & 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?

IMDG provides an excellent DT plaftorm:

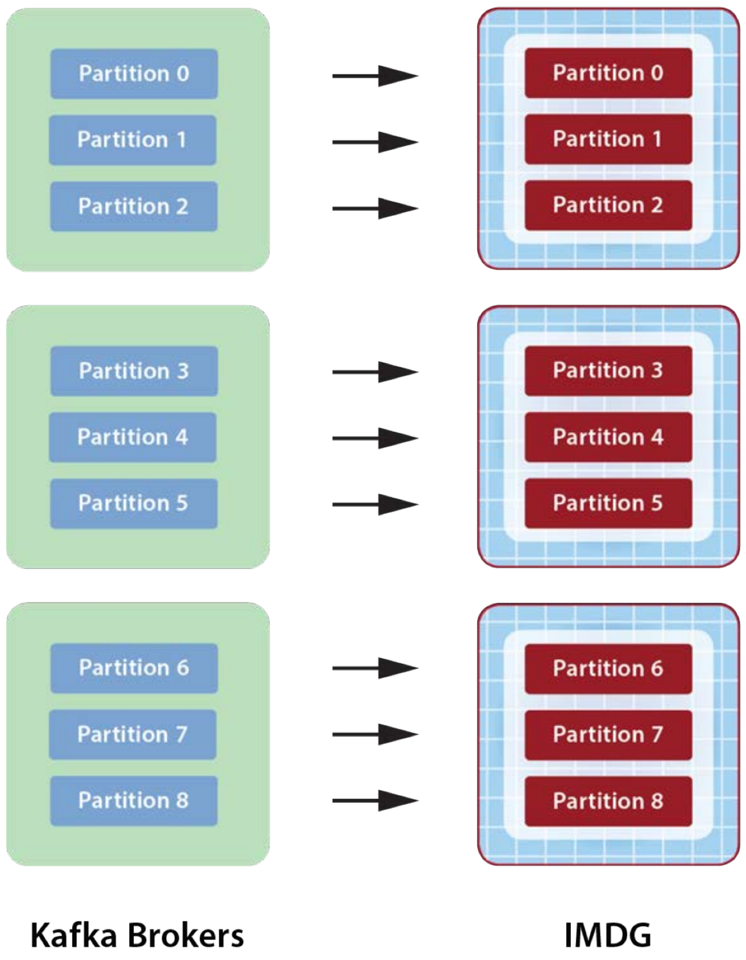
- Scalable, object-oriented data storage:
  - Offers a natural model for hosting digital twins.
  - Cleanly separates domain logic from data-parallel orchestration.
- Integrated, In-memory computing:
  - Automatically correlates incoming events for analysis.
  - Enables both stream and data-parallel 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.





Scaling Event Ingestion with Kafka

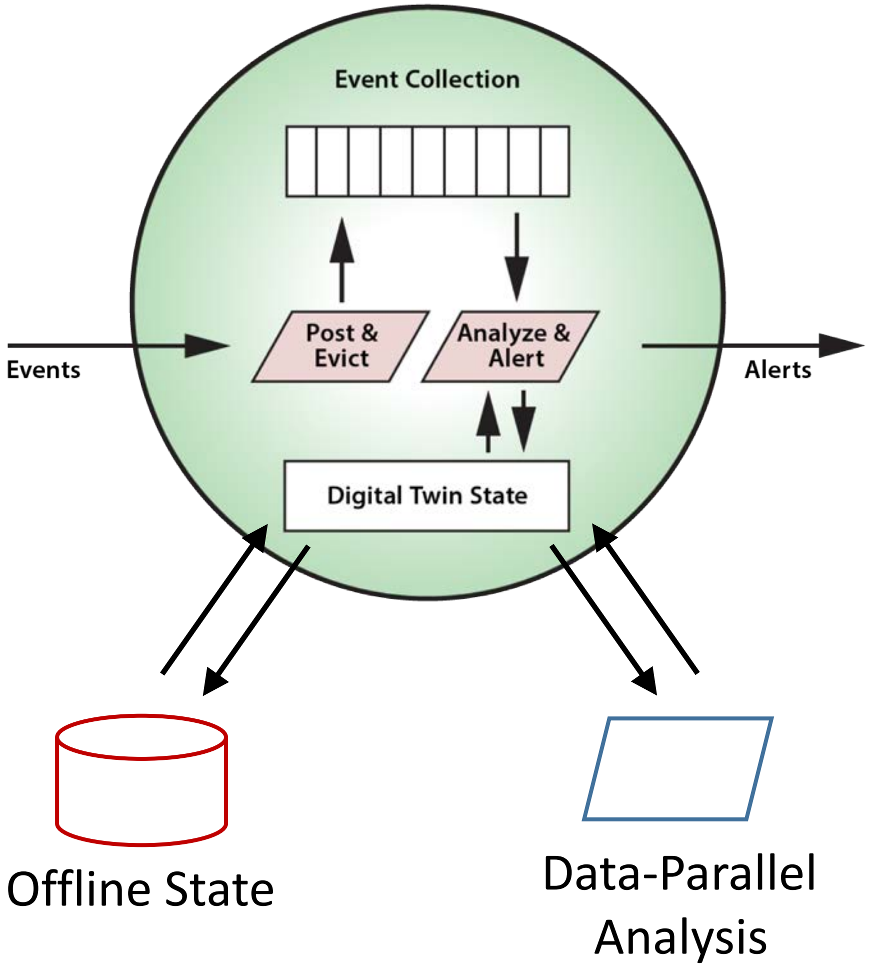
- IMDG partitions digital twin objects across servers.
- Kafka offers partitions to scale out handling of event messages.
  - Partitions are distributed across brokers.
  - Brokers process messages in parallel.
- IMDG can map Kafka partitions to grid partitions:
  - IMDG specifies event-mapping algorithm to Kafka.
  - IMDG listens to appropriate Kafka partitions.
- **This minimizes event handling latency**.
  - Avoids store-and-forward within IMDG.



Integrating Event and Data-Parallel Processing

The IMDG:

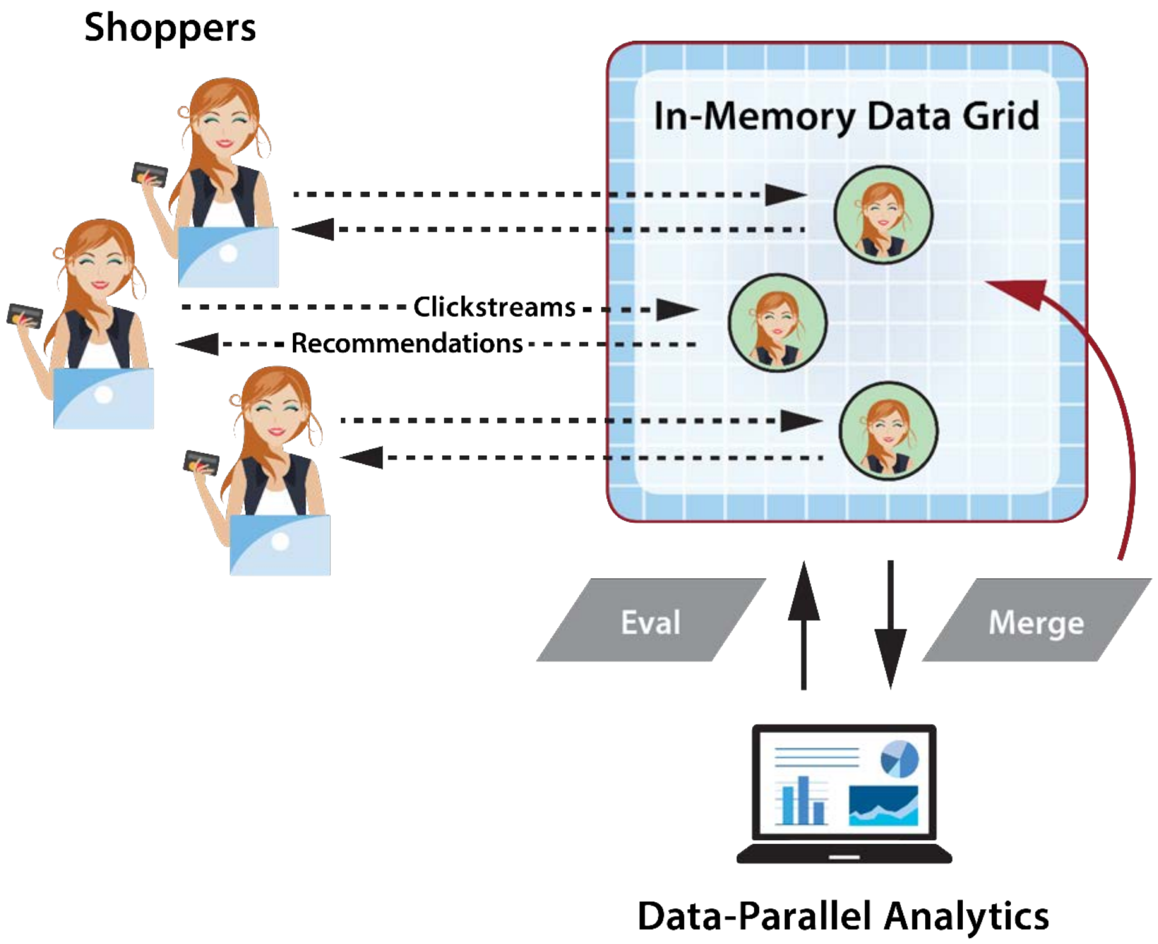
- Posts incoming events to its respective digital twin object.
- Runs the twin's event handler method with low latency.
  - Event handler manages the event collection and can use time windows for analysis.
  - Event handler uses and updates in-memory state.
  - Event handler can use/update off-line state.
  - Event handler optionally generates alerts and feedback to its data source.
- Runs data-parallel methods to analyze all digital twins in real-time.
  - Results can be used for both alerting and feedback.



Example: Ecommerce Shopping Site

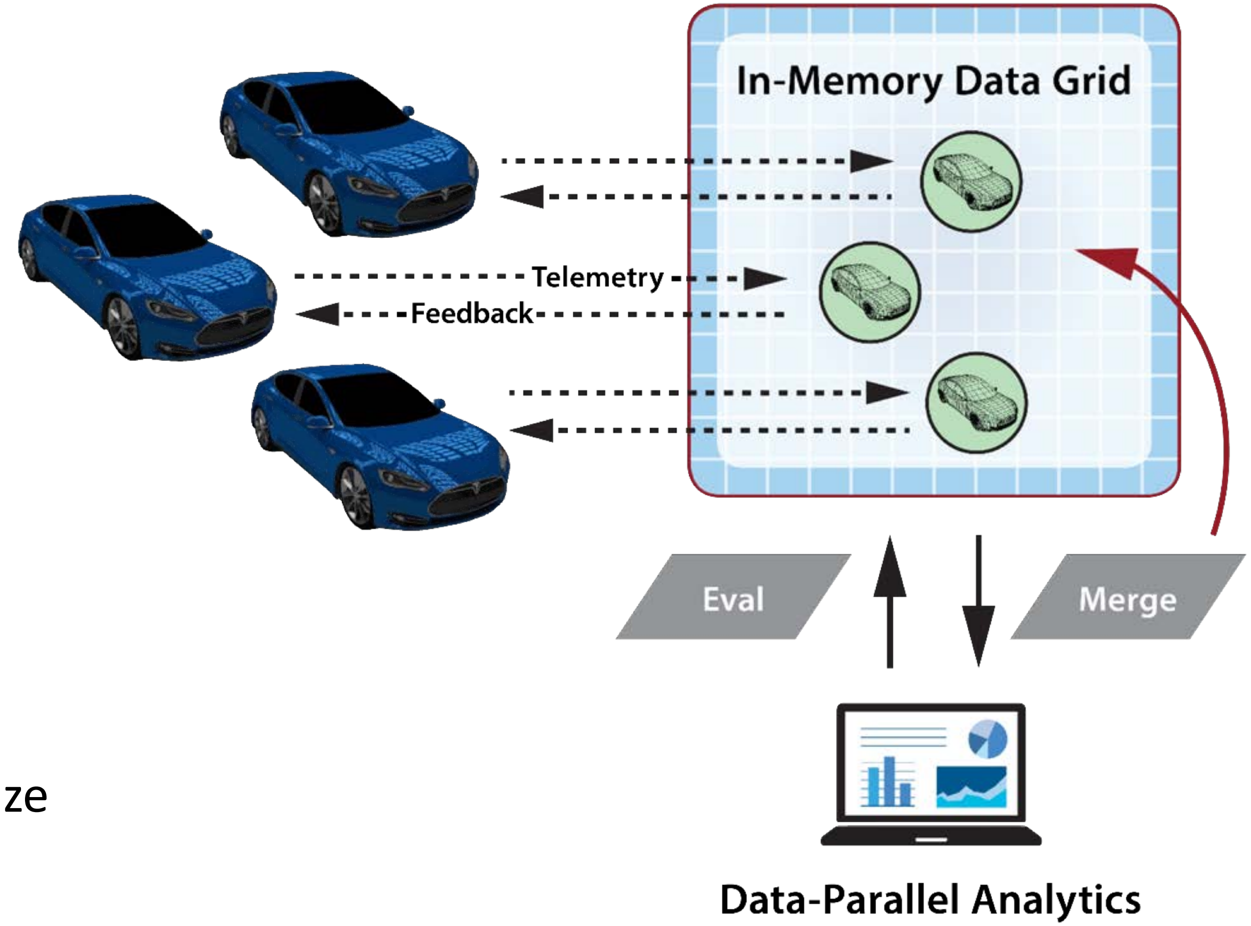
Tracks web shoppers and provides real-time recommendations:

- Each DT object holds clickstream of browsed products, preferences, and demographics.
- Event handler analyzes this data and updates recommendations.
- Periodic data-parallel, batch analytics across all shoppers determine aggregate trends:
  - Examples include best selling products, average basket size, etc.
  - Used for analysis and real-time feedback



Example: Tracking a Fleet of Vehicles

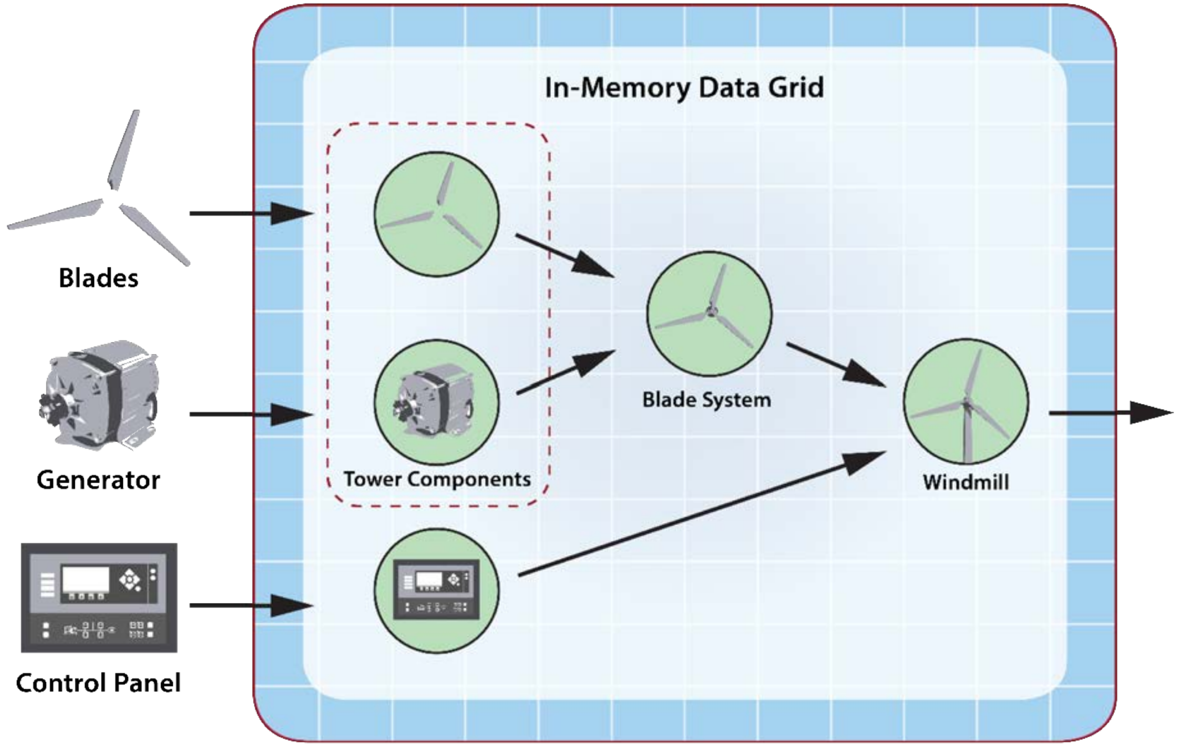
- **Goal**: Track telemetry from a fleet of cars or trucks.
  - Events indicate speed, position, and other parameters.
  - Digital twin object stores information about vehicle, driver, and destination.
  - Event handler alerts on exceptional conditions (speeding, lost vehicle).
- Periodic data-parallel analytics determines aggregate fleet performance:
  - Computes overall fuel efficiency, driver performance, vehicle availability, etc.
  - Can provide feedback to drivers to optimize operations (e.g., avoid congested areas).



Using Digital Twins in a Hierarchy

Tracks complex systems as hierarchy of digital twin objects:

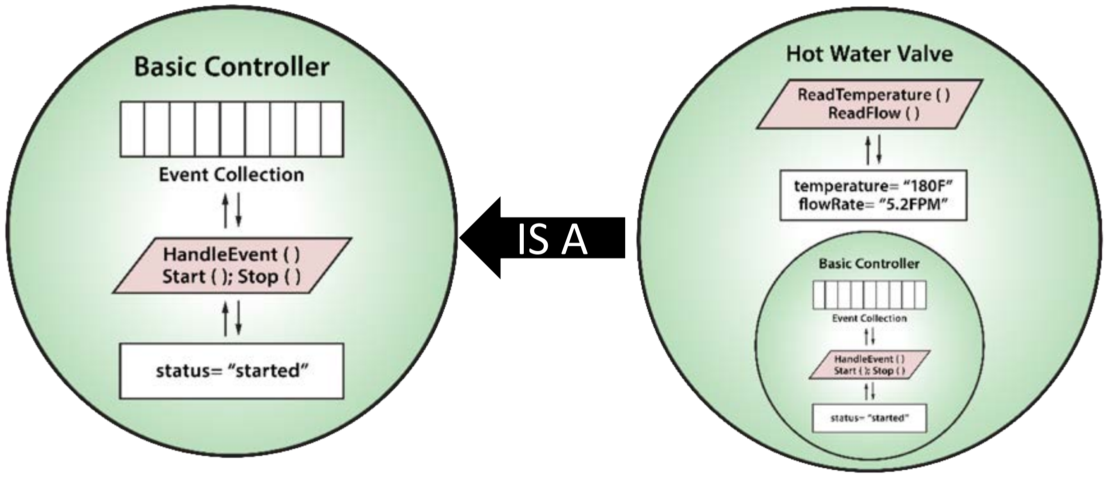
- Leaf nodes receive telemetry from physical endpoints.
- Higher level nodes represent subsystems:
  - Receive telemetry from lower-level nodes.
  - Supply telemetry to higher-level nodes as alerts.
  - Allow successive refinement of real-time telemetry into higher-level abstractions.



Example: Hierarchy of Digital Twins for a Windmill

OOP Techniques Simplify Building Digital Twins

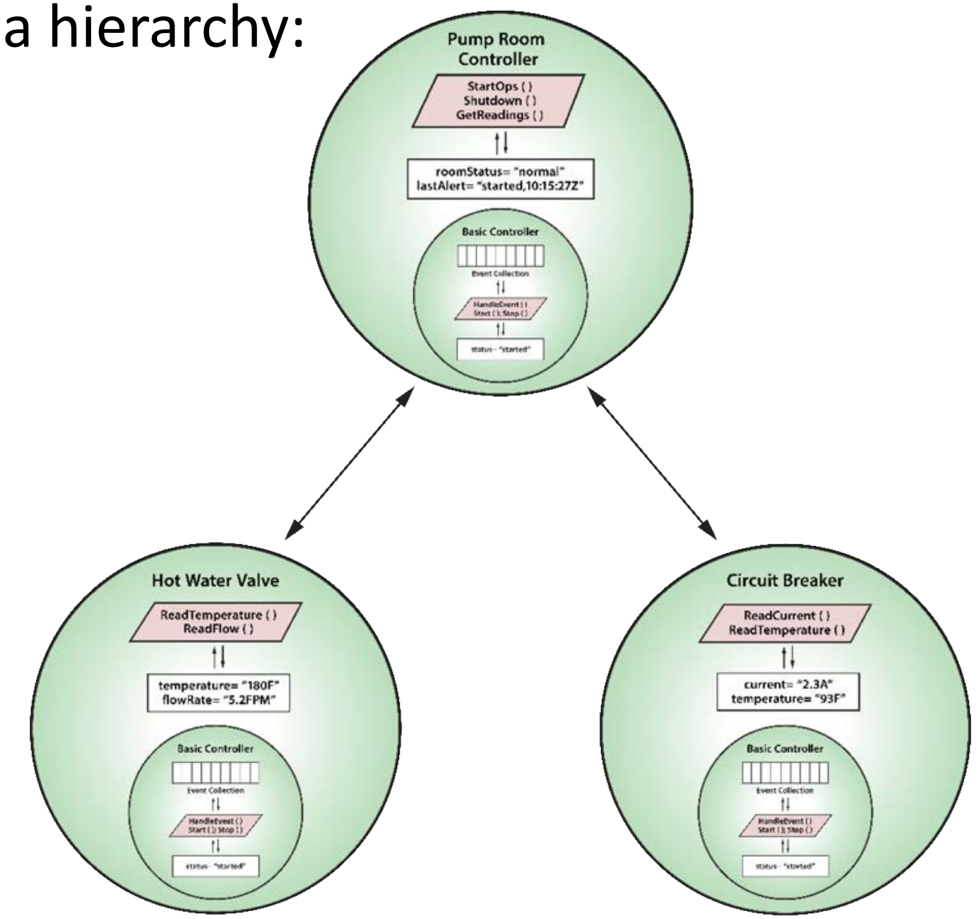
- Digital twin objects can use inheritance to create specialized behaviors:



Base Class

Sub-Class

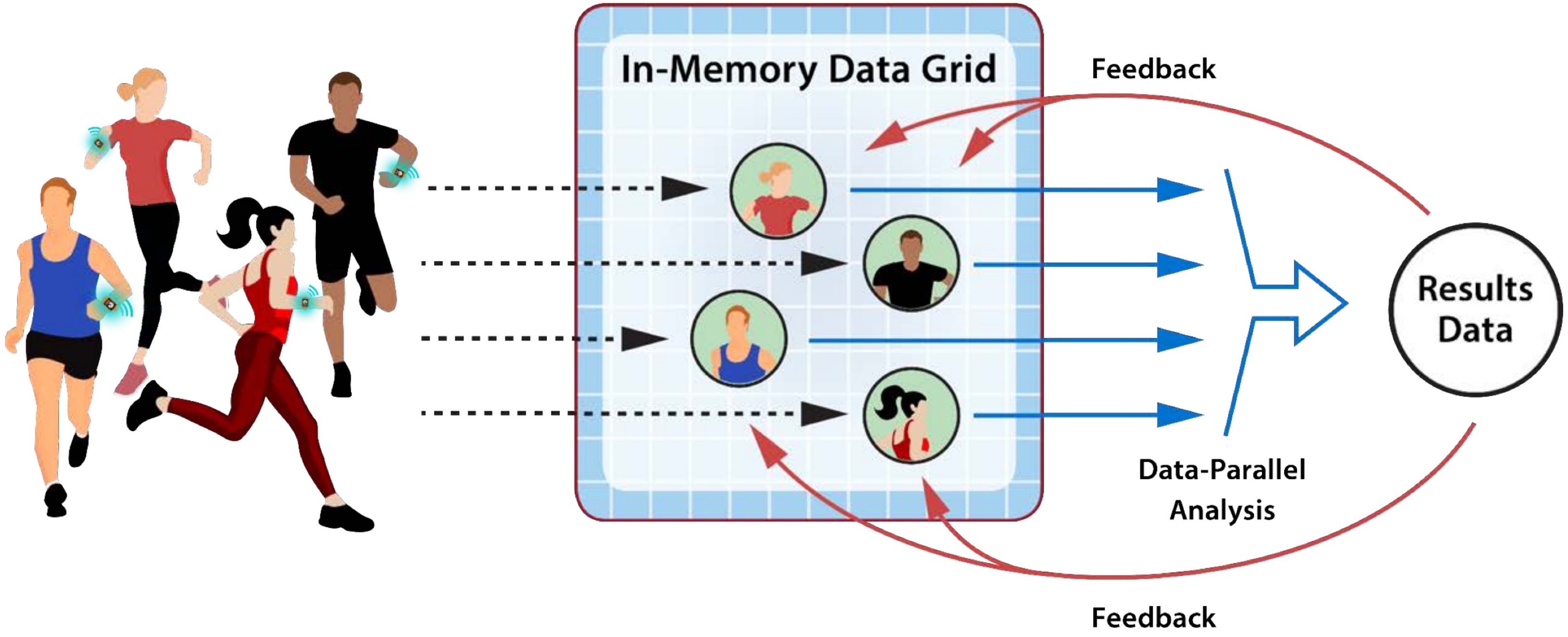
- Instances of objects can be organized in a hierarchy:



Detailed Example: Heart-Rate Watch Monitoring

Goal: Track heart-rate for a large population of runners.

- Heart-rate events flow from smart watches to their respective digital twin objects for analysis.
- The analysis uses wearer's history, activity, and aggregate statistics to determine feedback and alerts.



Digital Twin Object (Java)

- Holds event collection and user’s context (age, medical history, current status, etc.):

```
public class User implements Serializable {
    private int _id;
    private double _height;
    private double _bodyWeight;
    private Gender _gender;
    private int _age;
    private int _averageHr;
    private WorkoutProgress _status;
    private int _sessionAverageMax;
    private List<Medication> _medications;
    private List<Long> _heartIncidents;
    private List<HeartRate> _runningHeartRateTelemetry;
    private long _alertTime;
    private boolean _alerted;
    ...}
```

User’s context

Event collection

Events & Alerts

- Event holds periodic telemetry sent from watch to IMDG:

```
public class HeartRateEvent {
    private int _userId;
    private int _heartRate;
    private long _timestamp;
    private WorkoutType _workoutType;
    private WorkoutProgress _workoutProgress;
    private Event _event;
    ...}
```

- Alert holds data to be sent back to wearer and/or to medical personnel:

```
public class HeartRateAlert {
    private int _userId;
    private String _alertType;
    private String _params;
    ...}
```

Setting Up a ReactiveX Pipeline on the IMDG

- Define a ReactiveX observer that runs on every server in the IMDG:

```
public class HeartRateObserver implements Observer<Event>, Serializable {
    @Override public void onNext(Event event) {
        HeartRateEvent hre = HeartRateEvent.fromBytes(event.getPayload());
        hre.setEvent(event);
        User.processRunningEvent(hre);} ...}
```

Call application

- Create an invocation grid that Initializes the ReactiveX observer at startup:

```
Pipeline pipeline = new Pipeline(“userCache”, “userGrid”);
GridAction action = pipeline.createRemoteObserverAction("userObserver",
                        new HeartRateObserver());
InvocationGrid grid = new InvocationGridBuilder(“userGrid”)
                             .addJar("./bin/appcode.jar")
                             .addStartupAction(action)
                             .load();
```

Initialize observer

Event Handler and Event Posting

- Posting an event to the ReactiveX observer :
  - The key determines which server receives the event for posting.

```
pipeline.postEvent(makeKey(UserId),"heartRateEvent", HeartRateEvent.toBytes(
                       new HeartRateEvent(last, System.nanoTime(),
                       WorkoutType.Running, WorkoutProgress)));
```

- Handling an event posted to the ReactiveX observer on DT twin's server :

```
 private static void processRunningEvent(HeartRateEvent hre) {
    CachedObjectId id = hre.getId();
    User u = (User)cache.retrieve(id, false);
    ...
    executeRunningWorkoutAnalytics(hre, u);
    ...
    cache.update(id, u);}
```

Retrieve DT object

Analyze event

Update DT object

Event Analysis

- Handles an event for an active user doing a running workout:

```
private static void executeRunningWorkoutAnalytics(HeartRateEvent hre, User u) {
      long start = twoWeeksAgo();
      long sessionTimeout = threeHours();
      SessionWindowCollection<HeartRate> swc = new
          SessionWindowCollection<>(u.getRunningHeartRateTelemetry(),
          heartRate -> heartRate.getTimestamp(), start, sessionTimeout);
      swc.add(new HeartRate(hre.getHeartRate(), hre.getTimestamp()));

      int total = 0; int windowCount = 0;
      for(TimeWindow<HeartRate> window : swc) {
          int avg = 0;
          for(HeartRate hr : window) {avg += hr.getHeartRate();}
          total += (avg/window.size());
          windowCount++;}
      u.setAverageHr(total/windowCount);
      u.analyzeAndCheckForAlert(hre);}
```

Create time windows

Add event

Analyze event history

Analyze user's context

Analysis Techniques Enabled by Digital Twin

Enable detailed heart-rate monitoring for a high intensity exercise program:

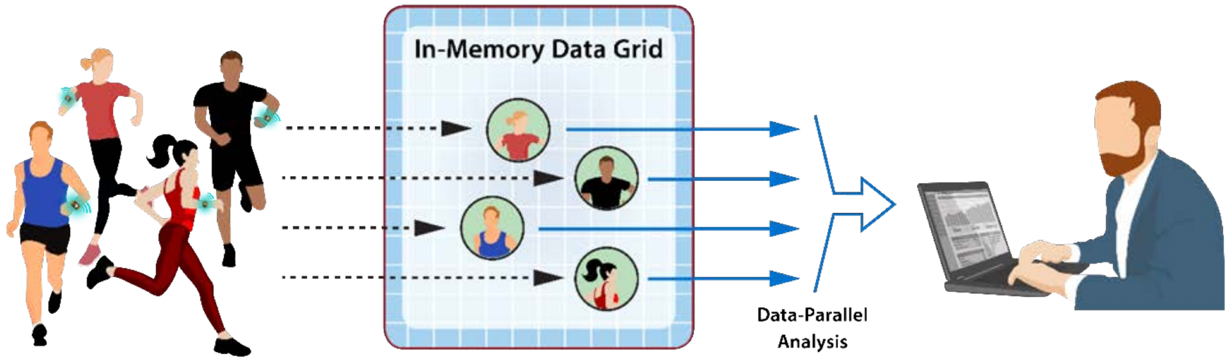
- Example of data to be tracked:
  - **Exercise specifics**: type of exercise, exercise-specific parameters (distance, strides, altitude change, etc.)
  - **Participant background/history**: age, height, weight history, heart-related medical conditions and medications, injuries, previous medical events
  - **Exercise tracking**: session history, average # sessions per week, average and 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 to analysts and/or users.

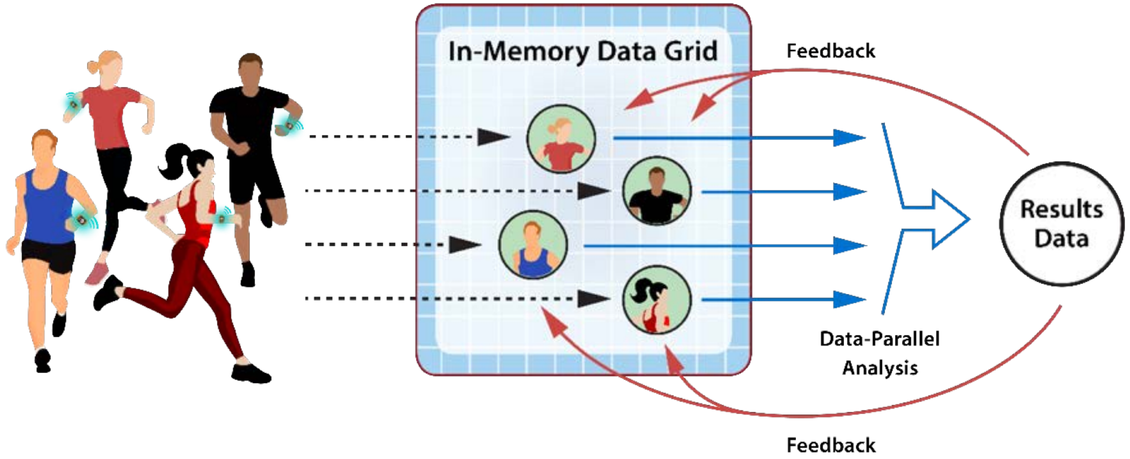
Data Parallel Analysis Across all Digital Twins

- Uses IMDG's in-memory compute engine to create aggregate statistics in real time.

- Results can be reported to analysts and updated every few seconds.



- Results can be used as feedback to event analysis in digital twin objects and/or reported to users.



Computing Aggregate Data

- Performs a data-parallel computation using the IMDG's `Eval` and `Merge` methods:

```
public class AggregateStatsInvokable implements Invokable<User, Integer,
    AggregateStats> {
    @Override
    public AggregateStats eval(User u, Integer numUsers) {
        AggregateStats userStats = new AggregateStats(numUsers);
        userStats.merge(u);
        return userStats;
    }

    @Override
    public AggregateStats merge(AggregateStats mergedStats,
                                AggregateStats u) {
        mergedStats.merge(u);
        return mergedStats;
    }
}
```

Eval method

Binary merge method

Computing Aggregate Data (2)

- Computes running average of heart-rate by categories:

```
public void merge(AggregateStats user) {
    numEvents += user.getNumEvents();
    totalHeartRate18to34 += user.getTotalHeartRate18to34();
    totalHeartRate35to50 += user.getTotalHeartRate35to50();
    totalHeartRateOver50 += user.getTotalHeartRateOver50();
    count18to34 += user.getCount18to34();
    count35to50 += user.getCount35to50();
    countOver50 += user.getCountOver50();

    totalHeartRateBmiUnderWeight += user.getTotalHeartRateBmiUnderWeight();
    totalHeartRateBmiNormalWeight += user.getTotalHeartRateBmiNormalWeight();
    totalHeartRateBmiOverweight += user.getTotalHeartRateBmiOverweight();
    countUnderweight += user.getCountUnderweight();
    countNormalWeight += user.getCountNormalWeight();
    countOverWeight += user.getCountOverWeight();
}
```

Creates Groups

Running the Data-Parallel Computation

- Uses a single method to run a data-parallel computation and return results.
- Publishes merged results to an IMDG object for access by user objects and/or analysts.

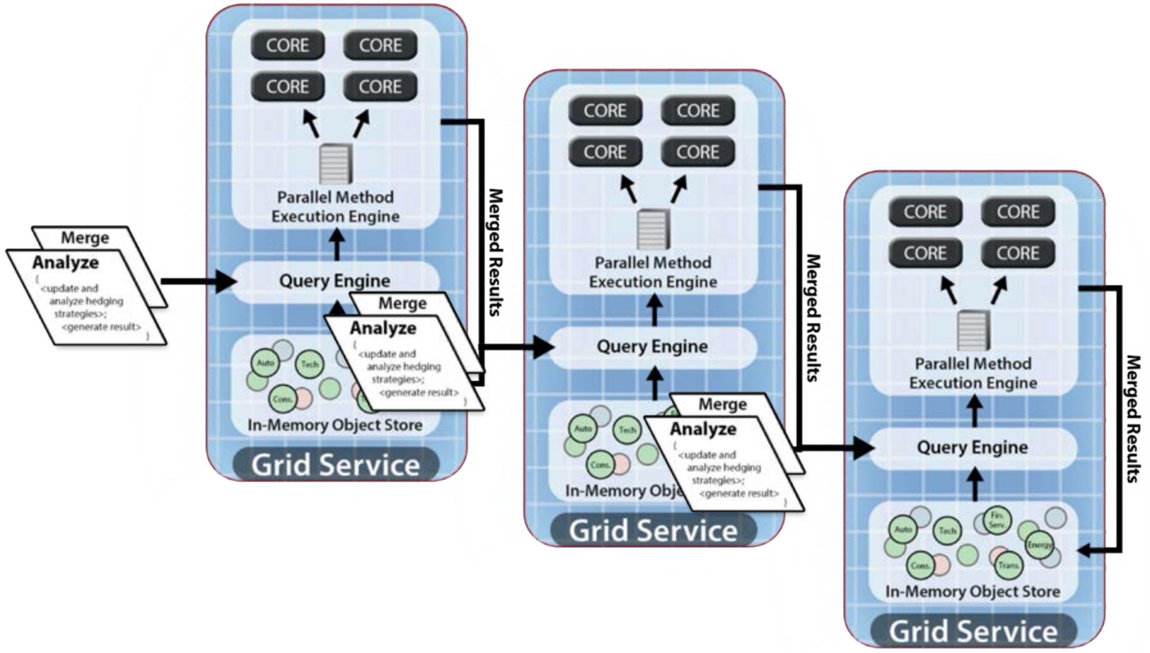
```
public void run() {
    NamedCache usersCache = CacheFactory.getCache(“userCache”);
    NamedCache statsCache = CacheFactory.getCache(“statsCache”);
    AggregateStats stats;

    InvokeResult<AggregateStats> result =
        usersCache.invoke(AggregateStatsInvokable.class, null, _numUsers,
            TimeSpan.fromMilliseconds(10000));

    stats = result.getResult();
    statsCache.put(“globalStats”, stats);
}
```

Invoke data-parallel op

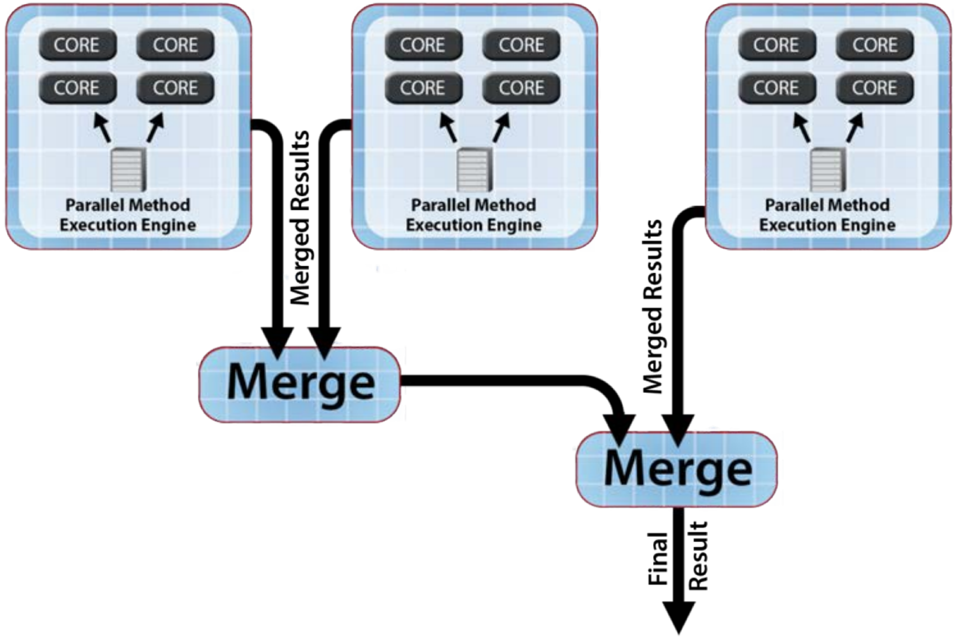
Store result in IMDG

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.

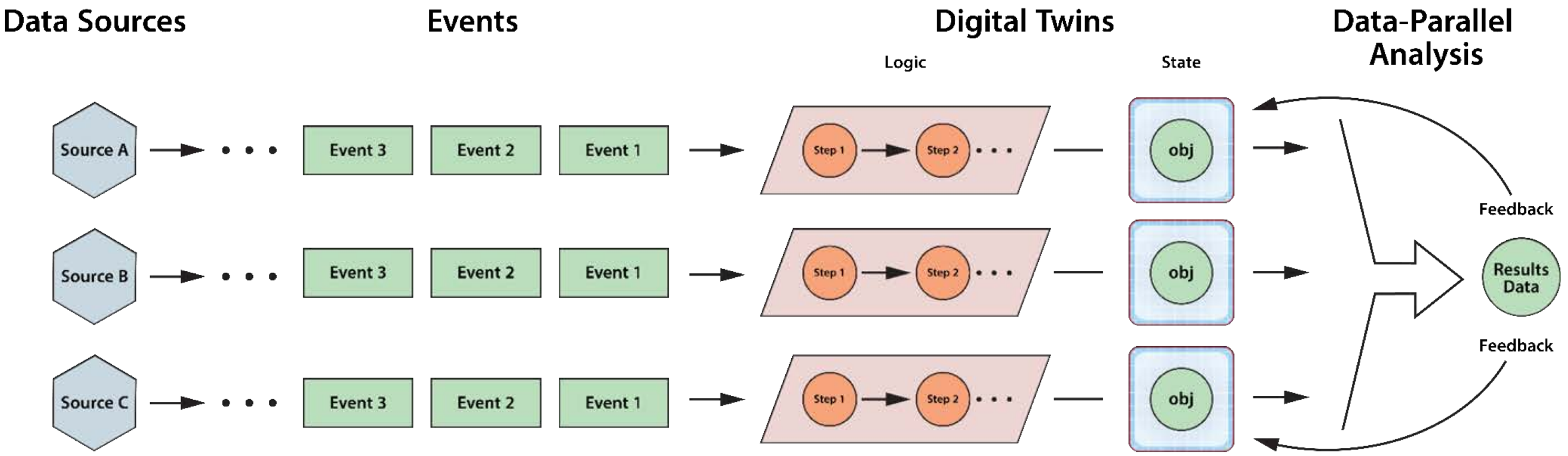


- **Merge** phase: all servers perform binary, distributed merge to create final result:
  - Merge runs in parallel to minimize completion time.
  - Returns final result object to client.



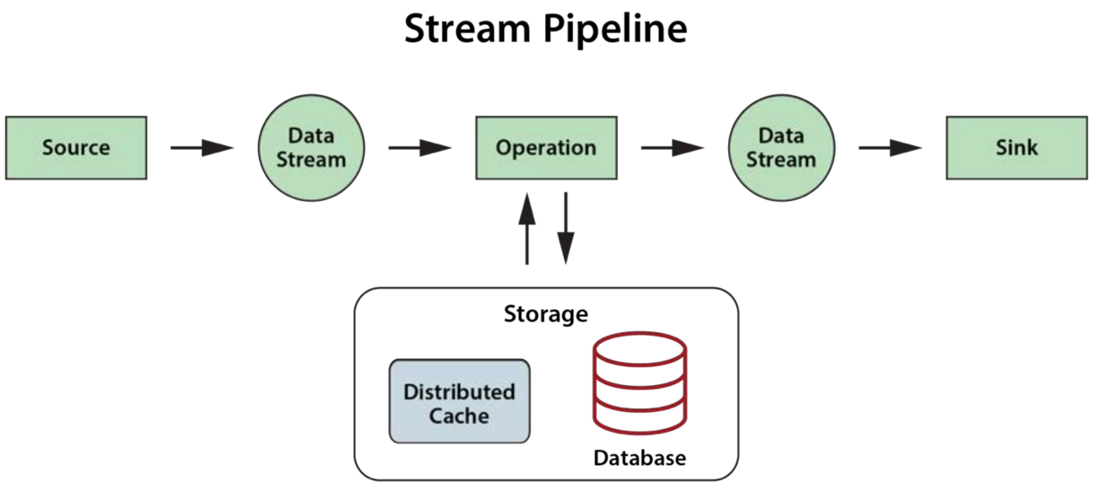
Predictable, Scalable Performance

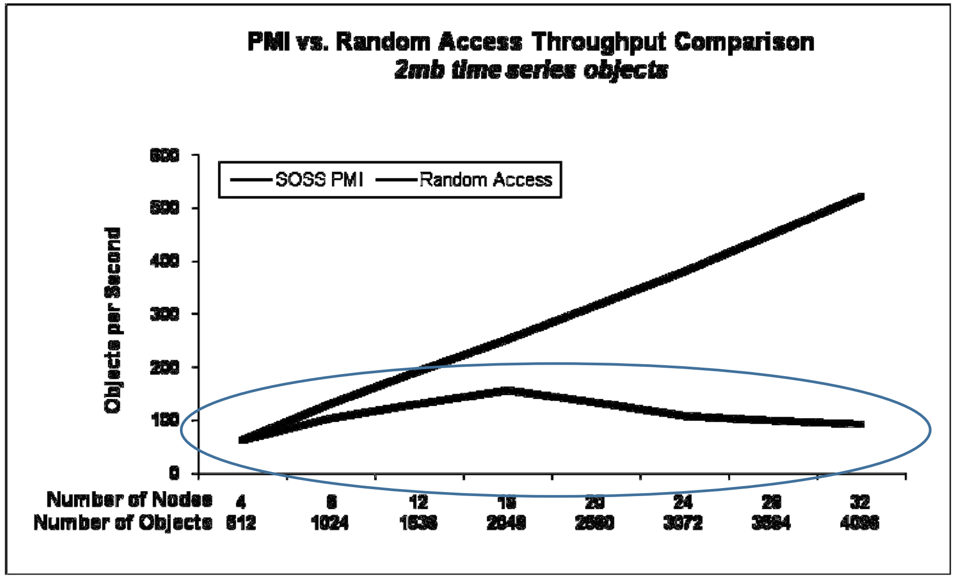
- Digital twin model enables the IMDG to scale both event-handling and integrated data-parallel analysis.
  - Correlating events to digital twin objects creates an automatic basis for performance scaling:
    - For event analysis
    - For data-parallel analysis
  - It enables access to each event's context without requiring a network access.
  - It also co-locates and encapsulates application-specific code using o-o techniques.



Avoids Network Bottlenecks

- Digital twin model avoids network bottlenecks associated with using an IMDG as a networked cache in a stream-processing pipeline.
  - External data storage requires network access to obtain an event’s context.
  - Network bottleneck prevents scalable throughput.





Wrap-Up

Digital Twins: The Next Generation in Stateful Stream-Processing

- **Challenge**: Current techniques for stateful stream-processing:
  - Lack a coherent software architecture for managing context.
  - Can suffer from performance issues due to network bottlenecks.
- **The digital twin model**:
  - Offers a flexible, powerful, scalable architecture for stateful stream-processing:
    - Associates events with context about their physical sources for deeper introspection.
    - Enables flexible, object-oriented encapsulation of analysis algorithms.
  - Provides a basis for aggregate analysis and feedback.
- **Scalable, data-parallel computing with an IMDG**:
  - Automatically correlates incoming events and processes them in parallel.
  - Implements integrated (real-time), aggregate analysis for immediate feedback.

In-Memory Computing for Operational Intelligence

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