ScaleOut Software

Webinar:

Digital Twins: The Next Generation in Stream-Processing and Real-Time Analytics

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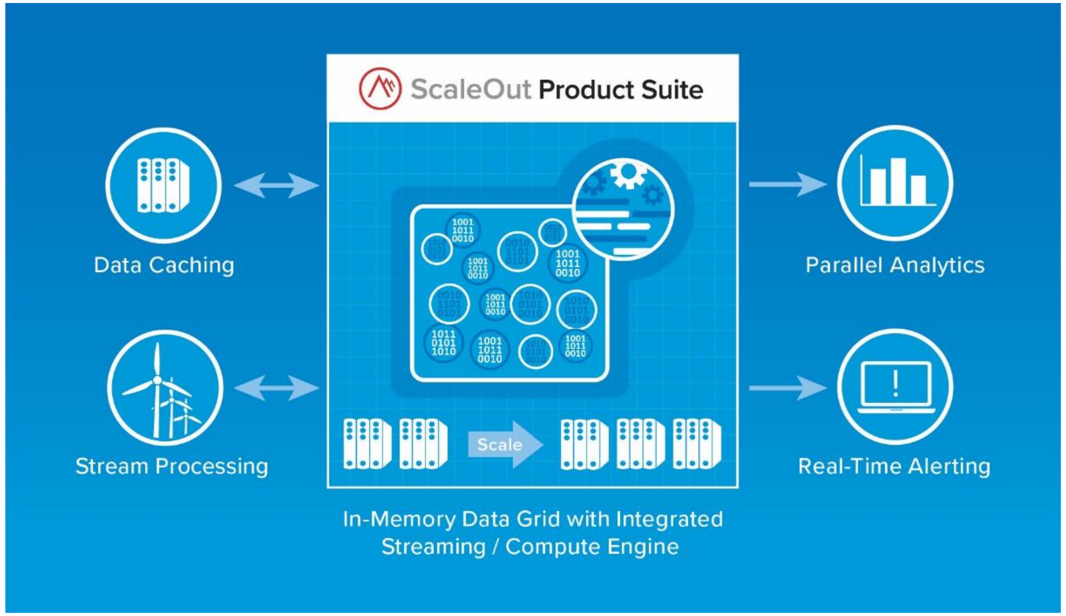
December 11, 2018

Agenda

- About ScaleOut Software
- Our core technologies: software for in-memory data grids and computing
- Challenges for stream-processing
- A solution: the digital twin model
- Running digital twins on an IMDG
  - Advantages
  - Comparison to traditional approaches
- IoT example with C# code using ScaleOut Digital Twin Builder™
- IoT example with Java code incorporating data-parallel feedback

About ScaleOut Software

- Develops and markets **In-Memory Data Grids**, software middleware for:
  - **Scaling application performance** and
  - **Providing operational intelligence** using
  - **In-memory data storage and computing**
- Dr. William Bain, Founder & CEO
  - Career focused on parallel computing
  - Bell Labs, Intel, Microsoft
- Eleven years in the market:
  - 450+ customers, 10,000+ servers
- Sample customers:



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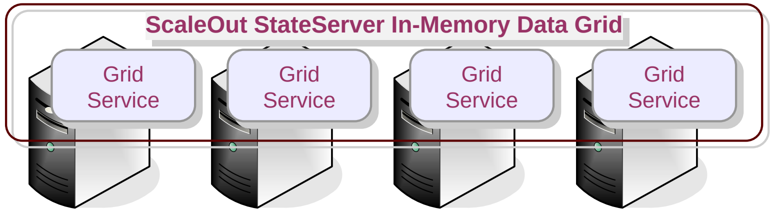
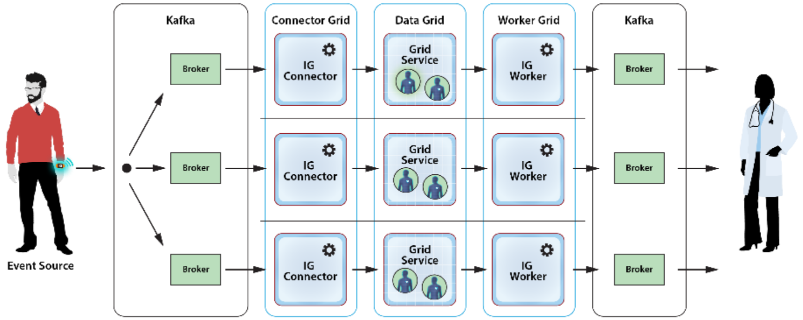
ScaleOut Software's Products

- **ScaleOut StateServer® & ScaleOut GeoServer®**
  - In-Memory Data Grid (IMDG) for Windows and Linux
  - Application scaling with strong consistency & high av
  - APIs in Java, C#, C/C++
  - Deployable on-premises and in public clouds (Azure, AWS)
  - Global data replication and remote data access
  - Released in 2005; now in 5th major version



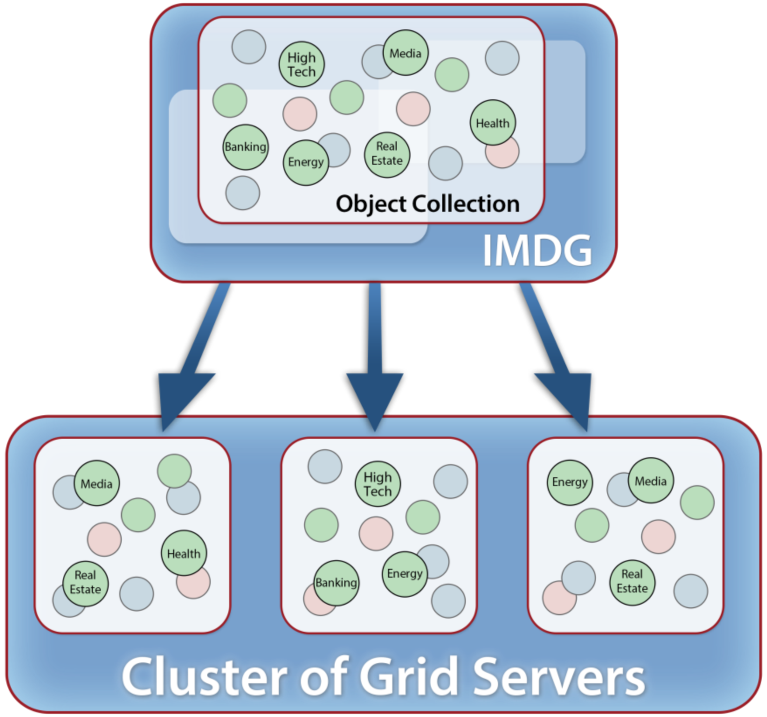
- **ScaleOut StreamServer™ & ScaleOut Digital Twin Builder™**
  - Stateful stream-processing with digital twins
  - Simplified development for digital twins in Java, C#
  - Support for ReactiveX APIs, Kafka, and Azure IoT
  - Integrated IMDG and in-memory compute engine
  - Real-time, data-parallel analytics



Core Technology: IMDG + IMC

- **In-Memory Data Grid (IMDG):** cluster-hosted software which provides fast, distributed in-memory storage for live data:
  - Uses object-oriented, key/value storage model
  - Location-transparent access to data by multiple clients
  - Create/read/update/delete APIs for Java/C#/C++
  - Parallel query by object properties
- **In-Memory Computing:** integrated software-based compute engine for streaming & data-parallel ops
  - Runs o-o methods on live data with low latency
  - Avoids network bottlenecks by computing in the IMDG.
- **Both**: Transparent scalability and high availability:
  - Automatic load-balancing across commodity servers
  - Automatic data replication, failure detection, and recovery

Logical view



Physical view

IMDG Storage Model

How an IMDG Can Integrate Computation

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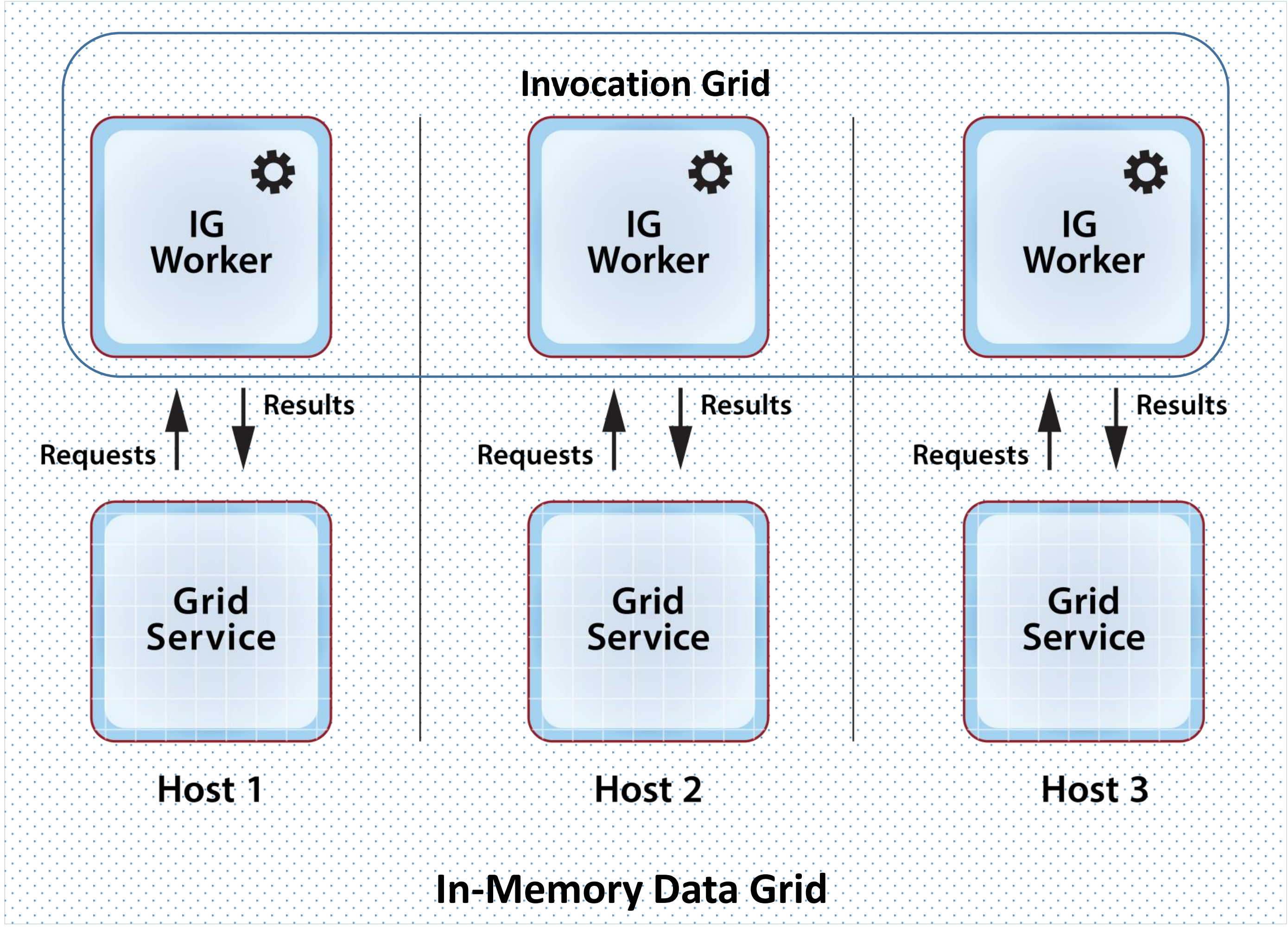
- Each grid host runs a worker process which executes application-defined methods on stored objects.
    - The set of worker processes is called an *invocation grid (IG)*.
    - IG usually runs language-specific runtimes (JVM, .NET).
    - IMDG can ship user code to the IG workers.
- Key advantages for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



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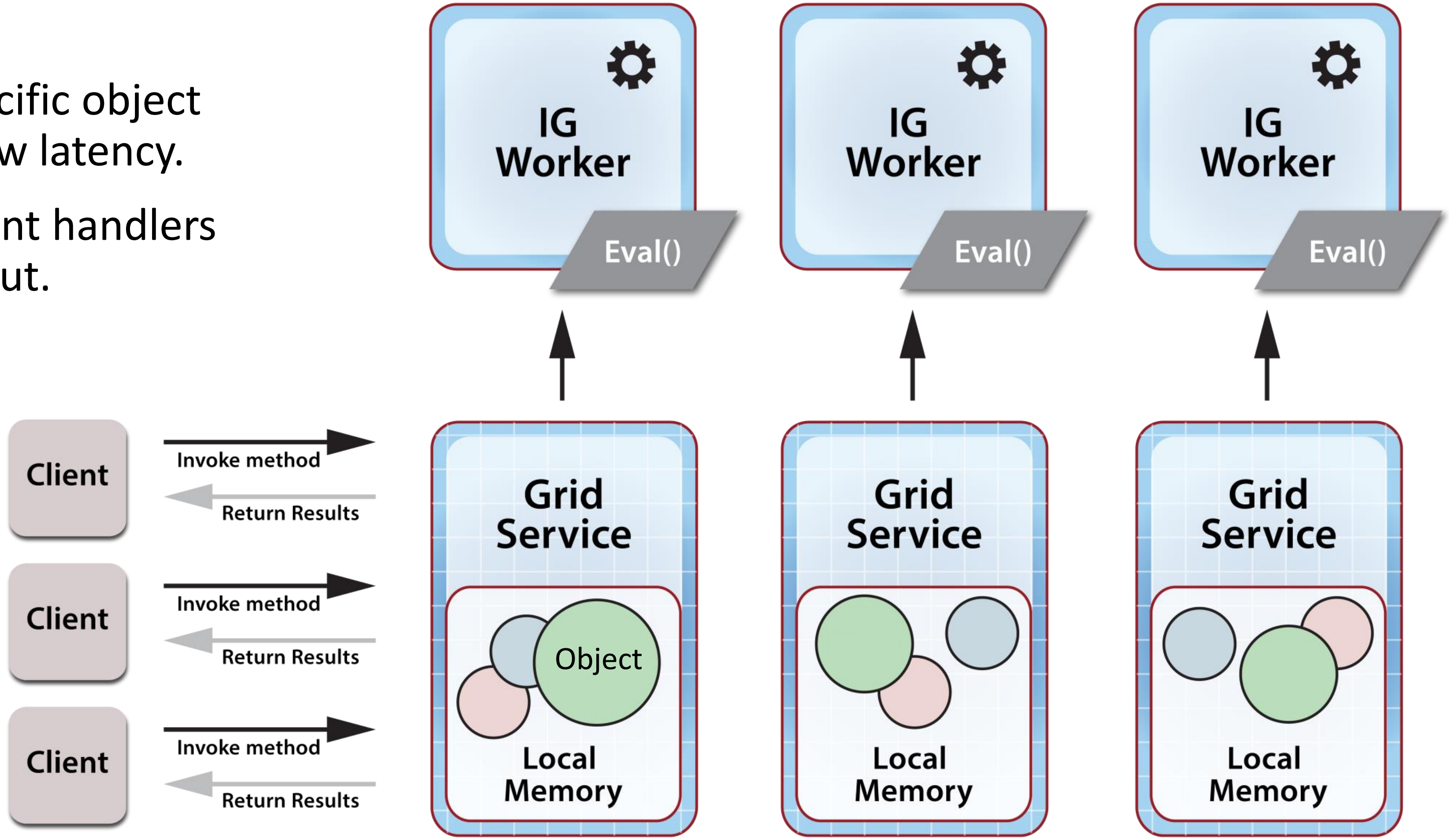
IMDG Runs Handlers for Stream-Processing

Event handlers run independently for each incoming event:

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



IMDG Also Runs Data-Parallel Computations

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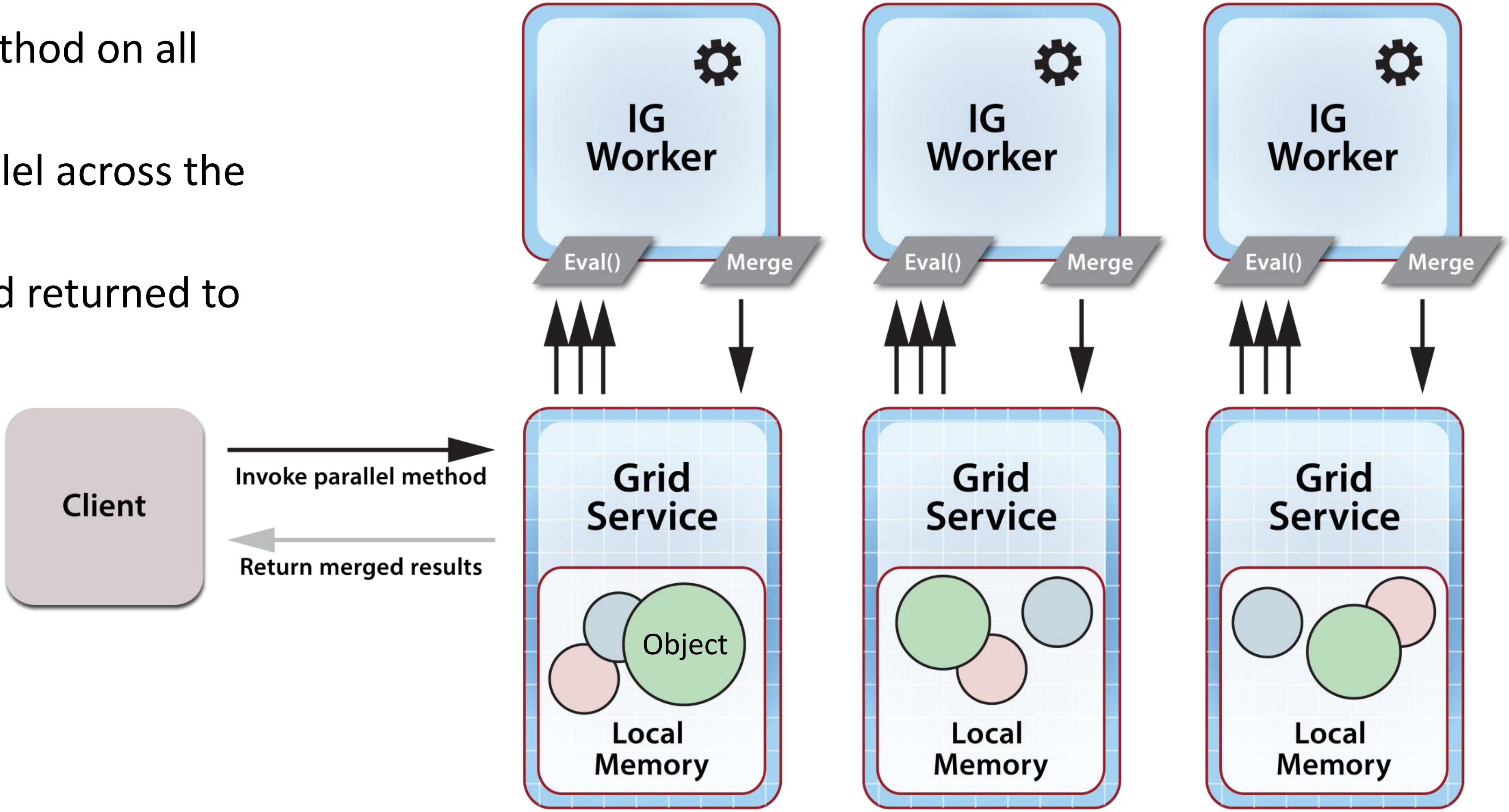
Method execution implements a parallel operation on a stored object collection:

- 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.

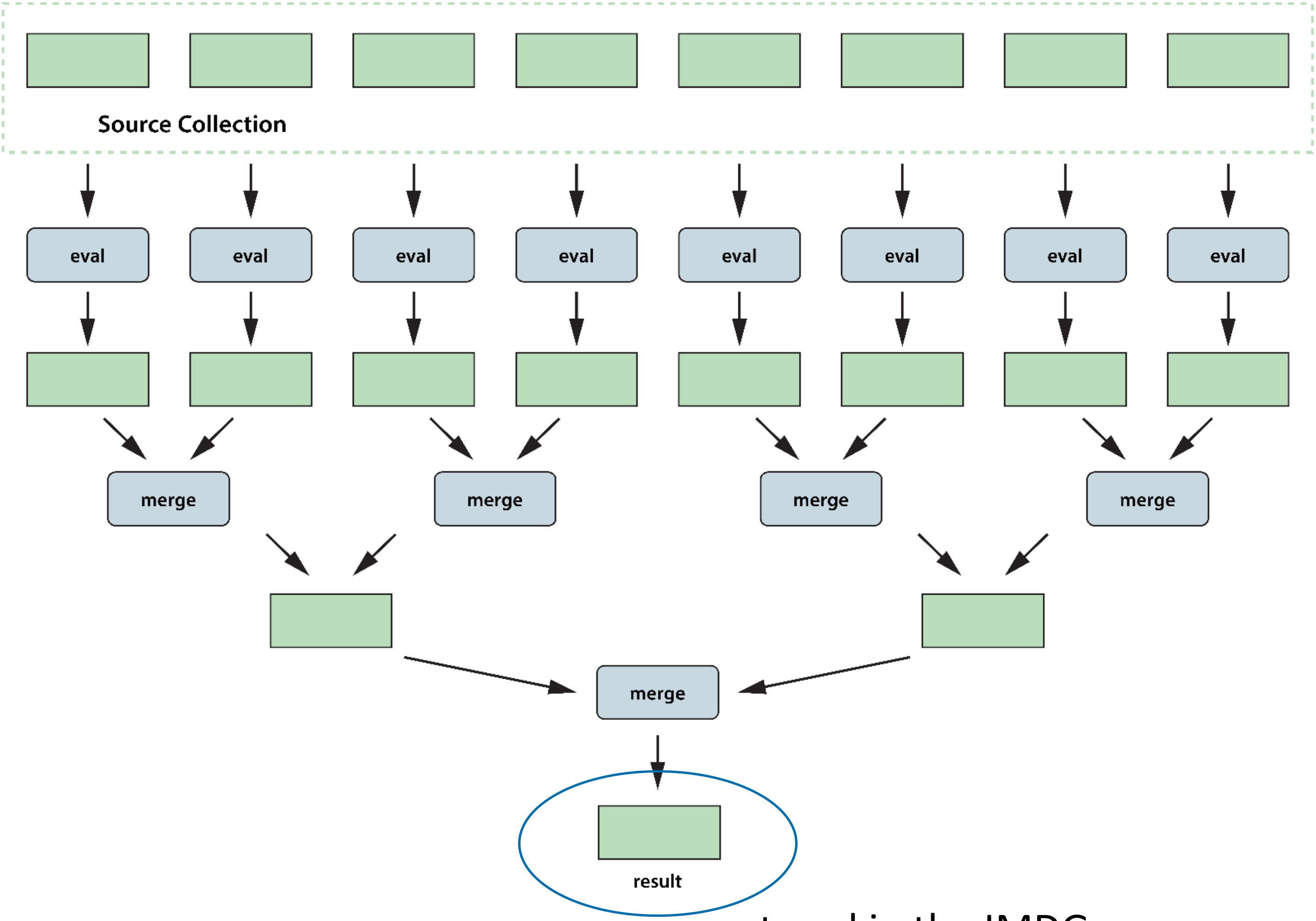


A Basic Data-Parallel Execution Model

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

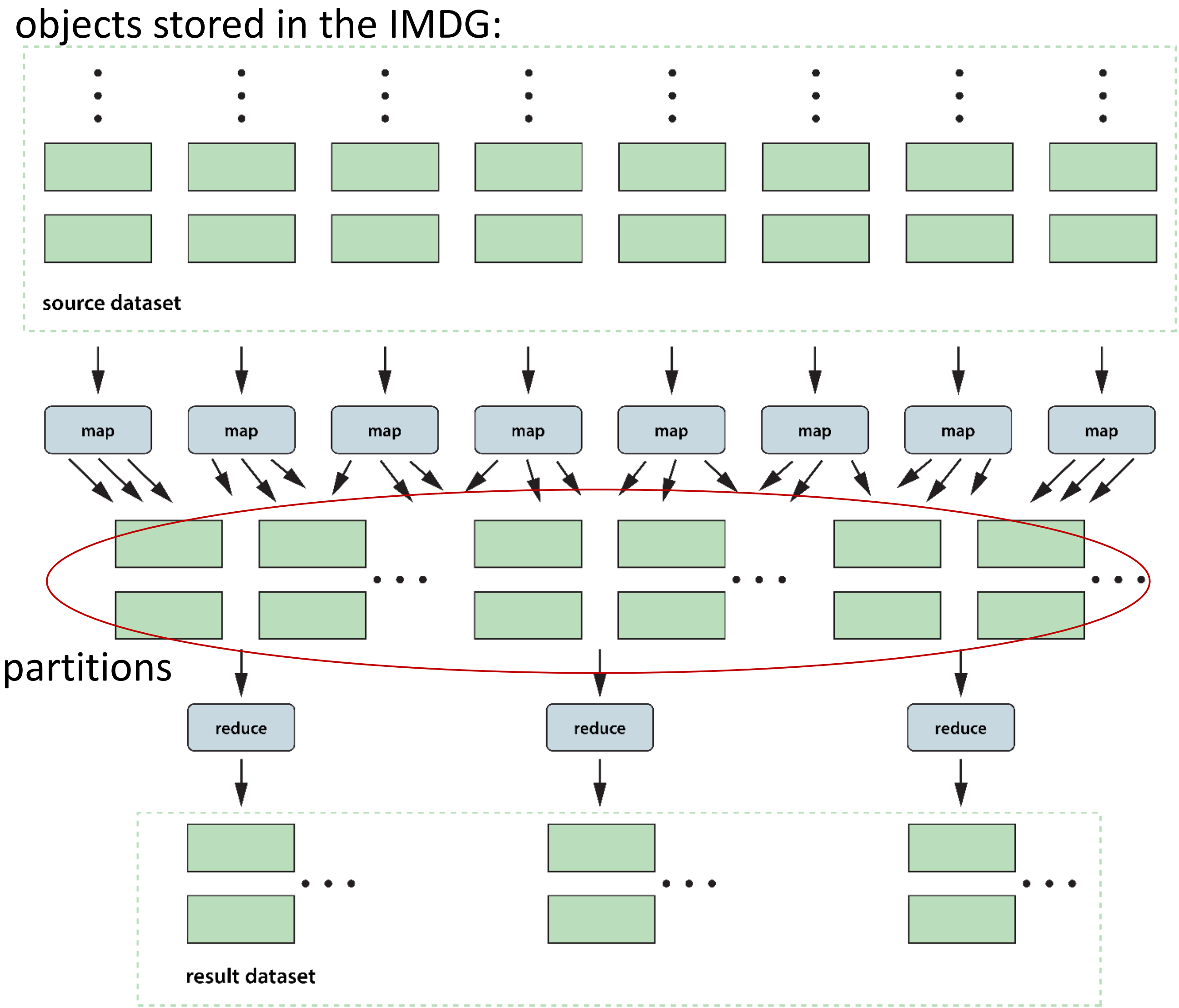
objects stored in the IMDG:



stored in the IMDG

Example: MapReduce Computation

- Implements “group-by” computations on *live* data.
- Example: “Determine average RPM for all wind turbines by region (NE, NW, SE, SW).”
- Runs in two data-parallel phases (map, reduce):
  - **Map** phase extracts, repartitions, and optionally combines source data.
  - **Reduce** phase analyzes each data partition in parallel.
  - Returns results for each partition.



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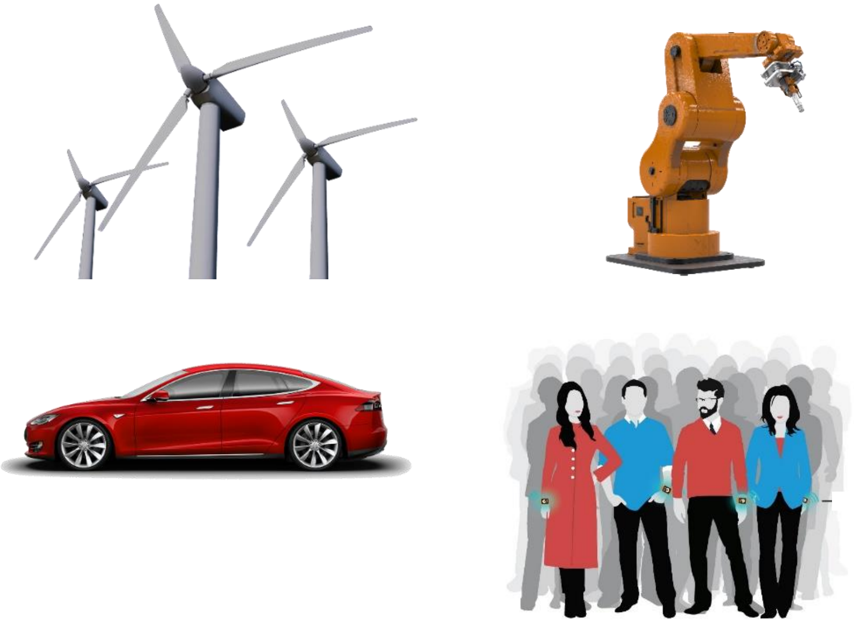
Goals for Stream-Processing

- **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

- **Challenge**: How can we track the dynamic state of data sources to enhance real-time analysis?



Event Sources

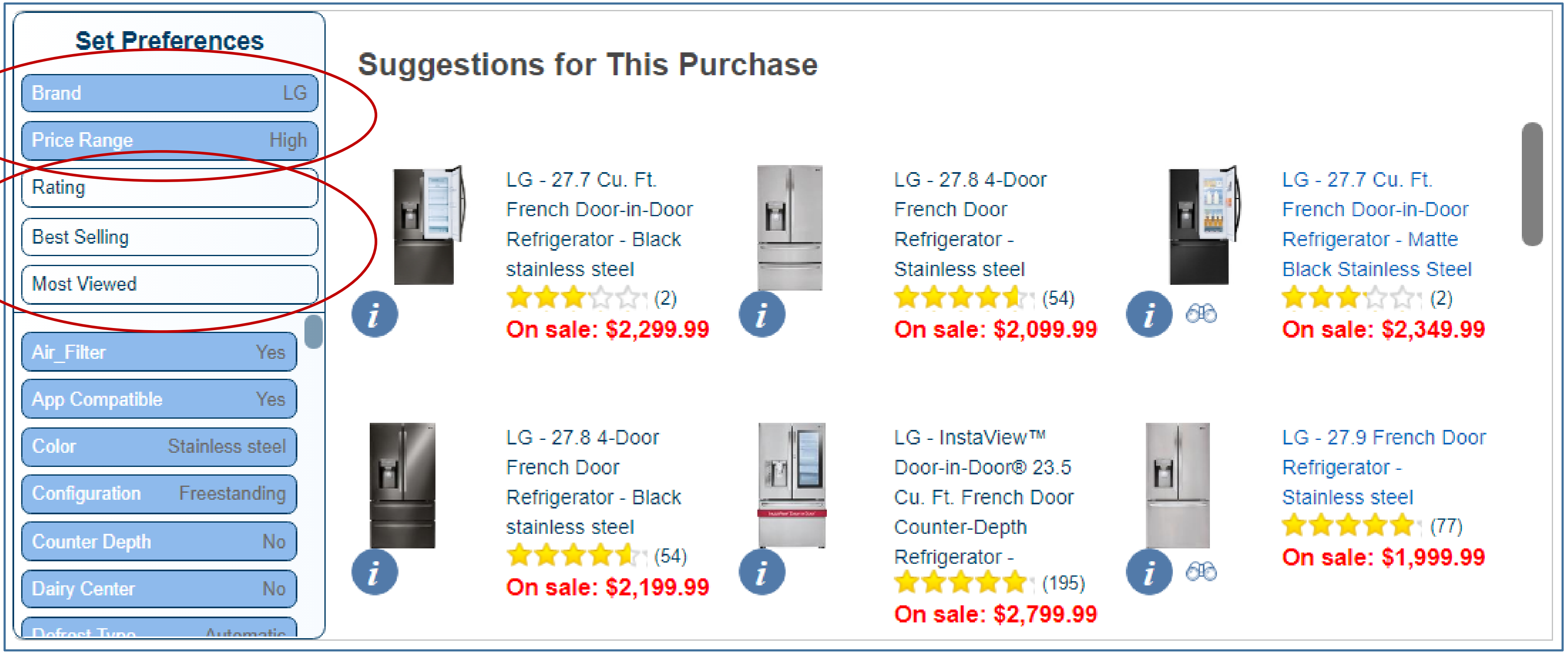
Example: Ecommerce Recommendations

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.
- To be effective, analysis should:
  - Take into account the shopper's preferences and demographics.
  - Use aggregate feedback on collaborative shopping behavior.

Real-Time Recommendations

- Requires *stateful* stream-processing to analyze each click and respond in <100ms:
  - Can accept input with each event on shopper's preferences and track these preferences.
  - Can analyze aggregate behavior and provide feedback on best-selling products.



Set Preferences

Brand	LG
Price Range	High
Rating	
Best Selling	
Most Viewed	
Air_Filter	Yes
App Compatible	Yes
Color	Stainless steel
Configuration	Freestanding
Counter Depth	No
Dairy Center	No
Defrost Type	Automatic

Suggestions for This Purchase

- LG - 27.7 Cu. Ft. French Door-in-Door Refrigerator - Black stainless steel ★★★☆☆ (2) On sale: $2,299.99
- LG - 27.8 4-Door French Door Refrigerator - Stainless steel ★★★★½ (54) On sale: $2,099.99
- LG - 27.7 Cu. Ft. French Door-in-Door Refrigerator - Matte Black Stainless Steel ★★★☆☆ (2) On sale: $2,349.99
- LG - 27.8 4-Door French Door Refrigerator - Black stainless steel ★★★★½ (54) On sale: $2,199.99
- LG - InstaView™ Door-in-Door® 23.5 Cu. Ft. French Door Counter-Depth Refrigerator - ★★★★★ (195) On sale: $2,799.99
- LG - 27.9 French Door Refrigerator - Stainless steel ★★★★★ (77) On sale: $1,999.99

Real-Time, Aggregate Metrics

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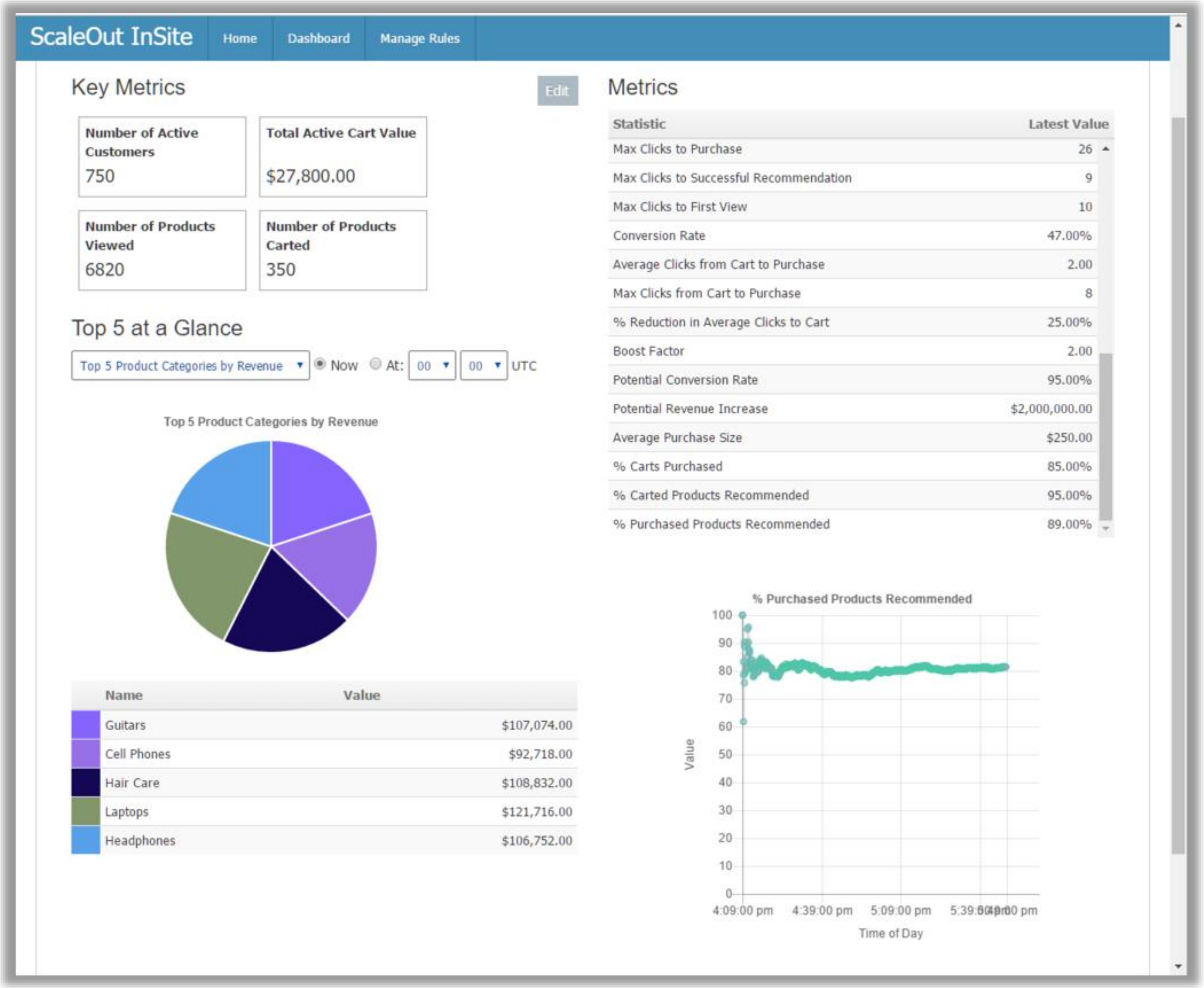
- Dynamically aggregates statistics for all shoppers:
    - Track real-time shopping behavior.
    - Chart key purchasing trends.
    - Enable merchandizer to create promotions dynamically.
- Combined statistics can be shared with all shoppers:
    - Allows shoppers to obtain collaborative feedback.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



Key Metrics

Number of Active Customers 750	**Total Active Cart Value** $27,800.00
Number of Products Viewed 6820	**Number of Products Carted** 350

Top 5 at a Glance

	Name	Value
🟪	Guitars	$107,074.00
🟪	Cell Phones	$92,718.00
⬛	Hair Care	$108,832.00
🟩	Laptops	$121,716.00
🟦	Headphones	$106,752.00

Metrics

Statistic	Latest Value
Max Clicks to Purchase	26
Max Clicks to Successful Recommendation	9
Max Clicks to First View	10
Conversion Rate	47.00%
Average Clicks from Cart to Purchase	2.00
Max Clicks from Cart to Purchase	8
% Reduction in Average Clicks to Cart	25.00%
Boost Factor	2.00
Potential Conversion Rate	95.00%
Potential Revenue Increase	$2,000,000.00
Average Purchase Size	$250.00
% Carts Purchased	85.00%
% Carted Products Recommended	95.00%
% Purchased Products Recommended	89.00%

Challenges for Stream-Processing

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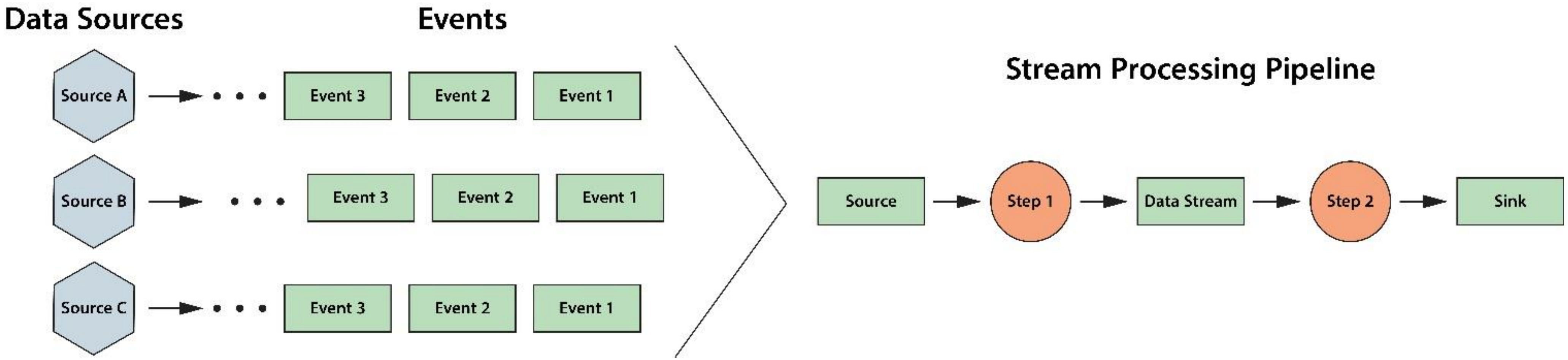
- Basic stream-processing architecture is a pipeline (or acyclic graph):



- **Challenges** unmet by traditional architectures:
    - 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?

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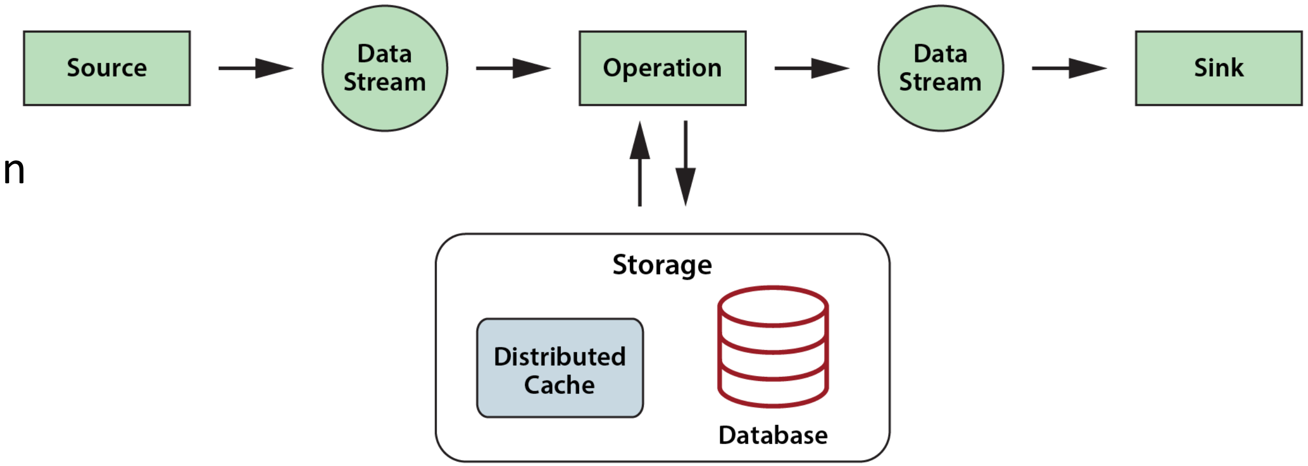
Adding Context to Stream-Processing

- 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

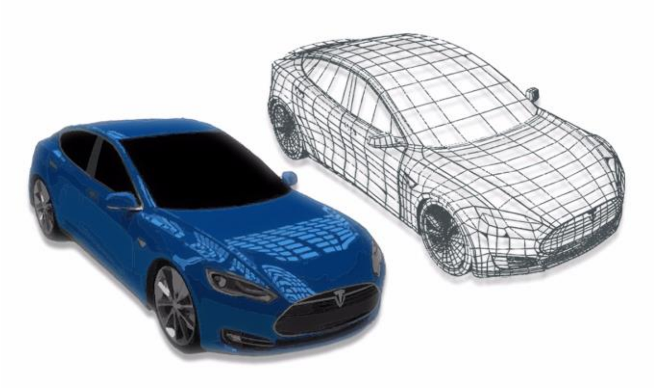


- **Problems**:
  - Data stores for managing state information are not integrated into the pipeline.
  - This adds complexity and creates a network bottleneck.
  - Does not address need for data-parallel analytics.

How can we efficiently combine stream-processing with state (context) to enable real-time analytics, simplify design, and maximize performance?

A Solution: the “Digital Twin” Model

- 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)



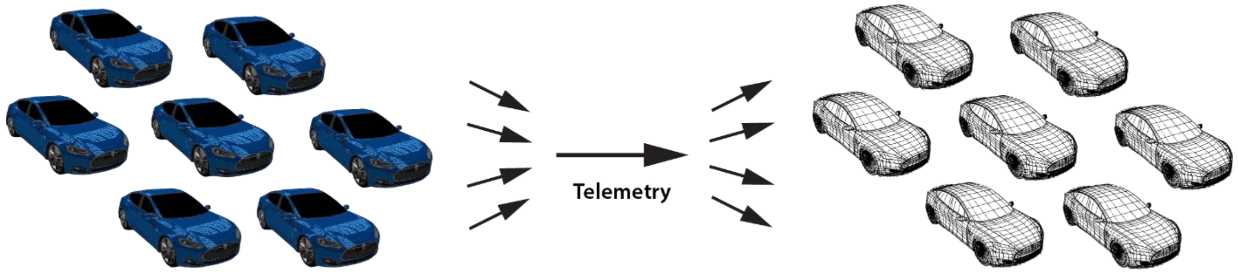
- **Significance**: focuses on modeling data sources
  - A basis for correlating and analyzing streaming data
  - A context for deep introspection and interaction

Many Uses of the Term “Digital Twin”

Although created by Michael Grieves for product life cycle management (PLM)…

- The term “digital twin” has several interpretations, for example:
  - **Digital twin** as used in PLM and product-line engineering (from Marc Lind, SVP Aras Corp.)
    - A virtual version of a physical entity
    - Adds context to interpret the time-series data streaming back from the field
  - **Azure digital twin**: spatial graph of spaces, devices, and people for modeling relationships in context
  - Azure IoT **device twin**: JSON document that stores per-device state information (metadata, conditions)
  - AWS **device shadow**: cloud-based repository for per-device state information with pub/sub messaging

- **ScaleOut’s use of digital twin**:
  - Object-oriented model of a data source (or higher-level entity) for use in real-time streaming analytics
  - **Benefit:** *enables* real-time streaming analytics which is:
    - Fast and scalable
    - Easy to use



Examples of Digital Twins in IoT

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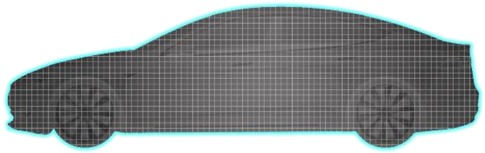
Live System – Physical Objects

Digital Twins

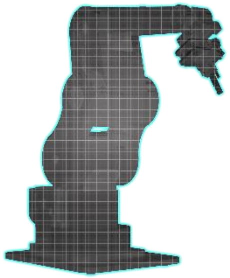
(Autonomous) Vehicles



Vehicle subsystems for safety monitoring & predictive maintenance

Telemetry streams

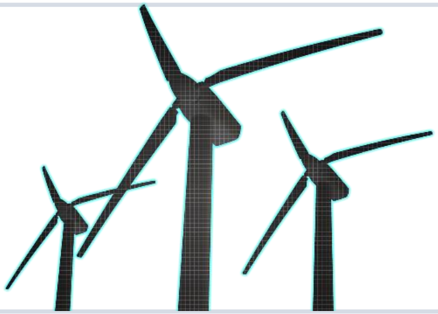
Manufacturing floors and equipment



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

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Creating Digital Twins with OOP

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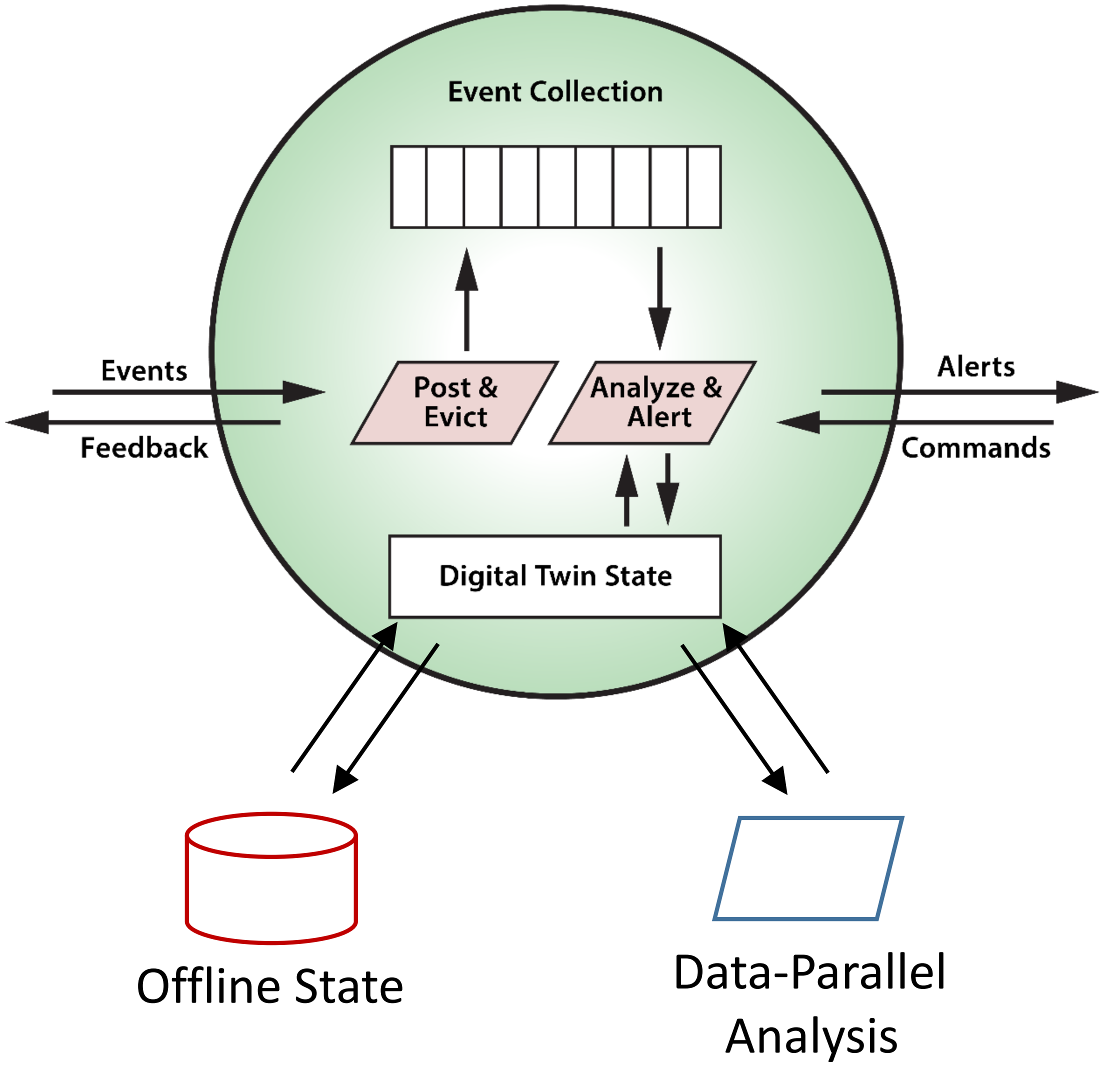
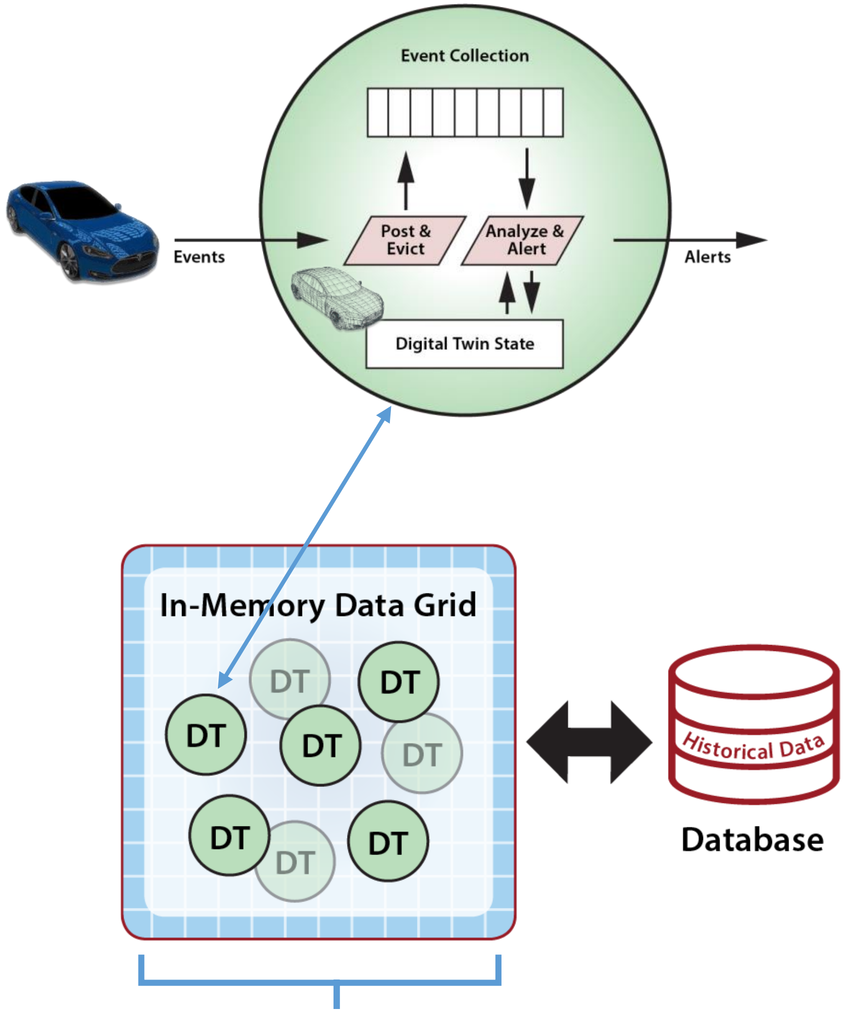
- A digital twin **model** represents a type of data source (e.g., a wind turbine).
- Each digital twin **instance** represents a specific physical data source (e.g., wind turbine 73).
- Digital twin typically comprises:
  - An event collection
  - State information about the data source
  - Logic for managing events & commands, updating & analyzing state, generating alerts
- Object oriented model:
  - Holds source's dynamic state information.
  - Encapsulates domain-specific logic (e.g., ML, rules engine, etc.).
  - Runs code where the data lives (avoids data motion) for fast response times.
  - Enables data-parallel analysis.



Using an IMDG to Host Digital Twins

The IMDG:

- Can host thousands of digital twins as objects.
- Can post incoming events to their respective digital twin objects.
- Can run the twin's event handler method with low latency:
  - Event handler uses and updates in-memory state.
  - Event handler can manage an event collection and use time windows for its analysis.
  - Event handler can use/update off-line state.
  - Event handler optionally generates alerts and feedback to its digital twin.
- Also can run data-parallel methods to analyze all digital twins in real-time.
  - Collects and reports periodic aggregate statistics.
  - Results can be used for both alerting and feedback.



Data-parallel analysis

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Why Use an IMDG to Host Digital Twins?

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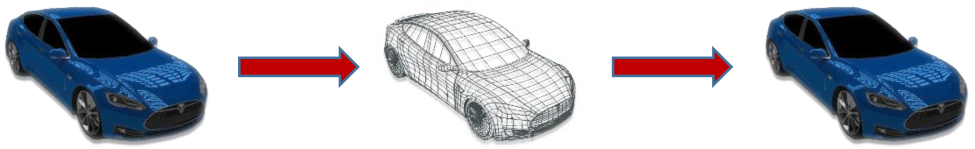
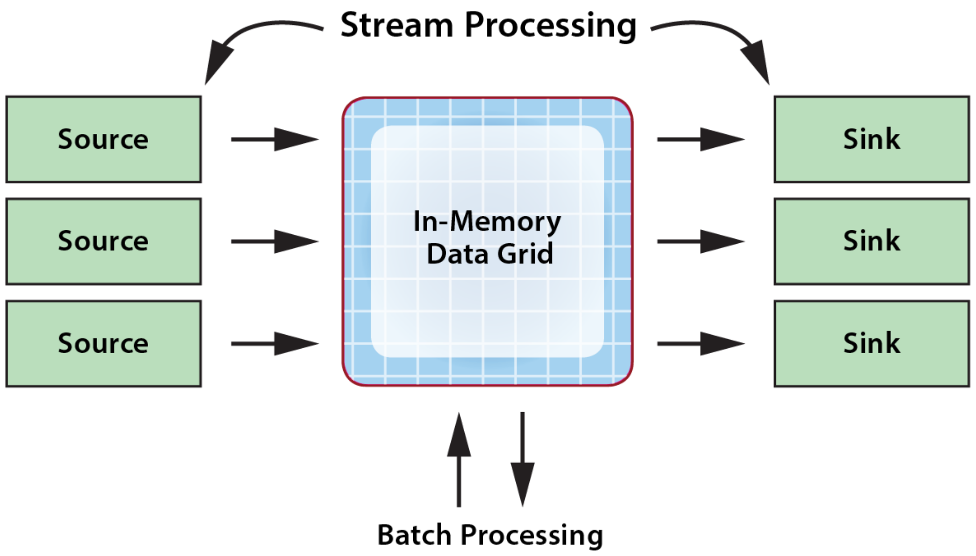
- **Object-oriented data storage**:
    - Offers a natural model for hosting digital twins.
    - Cleanly separates domain logic from data-parallel orchestration.
    - Provides rich context for correlating and processing streaming data.
    - Allows easy addition of specialized analysis algorithms (rules, ML, etc.)
    - Integrates streaming 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.





Stream Processing

Source

Source

Source

In-Memory Data Grid

Sink

Sink

Sink

Batch Processing

Comparison to Traditional Architecture

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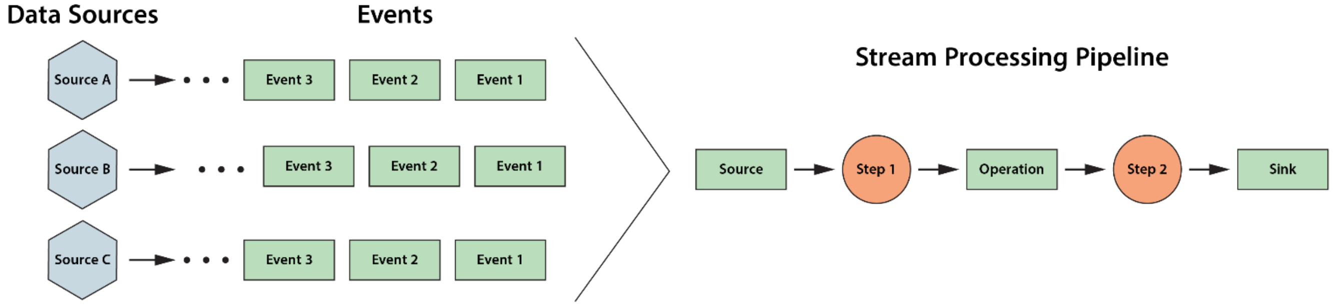
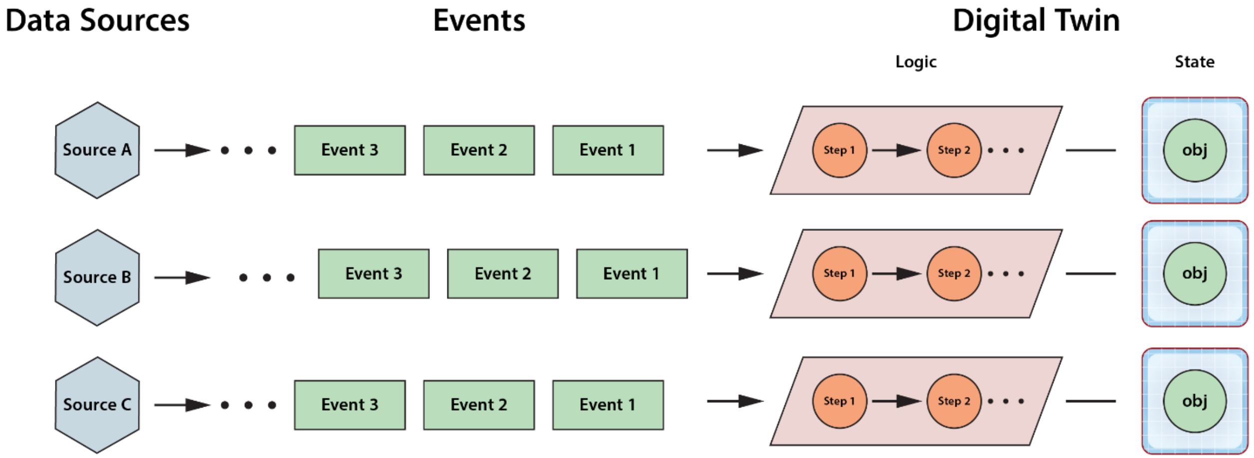
An IMDG:

- Avoids the need to correlate events from each data source in the stream processing pipeline:
  - Reduces application complexity.
  - Eliminates network bottlenecks.
- Refactors processing steps to perform them in one location:
  - Allows application encapsulation.
  - Avoids data motion between pipeline stages.
- Provides a basis for transparent scaling:
  - Leverages the grid's load-balancing of digital twin objects across the IMDG.
- Enables data-parallel analytics.

Stateless Stream-Oriented Model:



Digital Twin Model:



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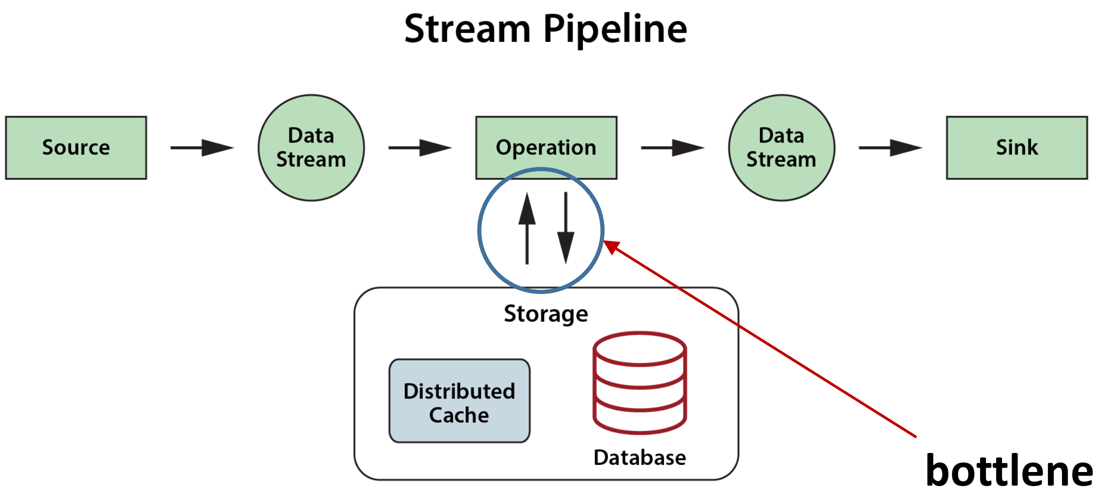
Important to Avoid Network Bottlenecks

- Hosting digital twins in an IMDG avoids network bottlenecks associated with accessing a database or networked cache in a stream-processing pipeline.
  - External data storage requires network access to obtain an event's context.
  - Network bottleneck prevents scalable throughput.



Stream Pipeline

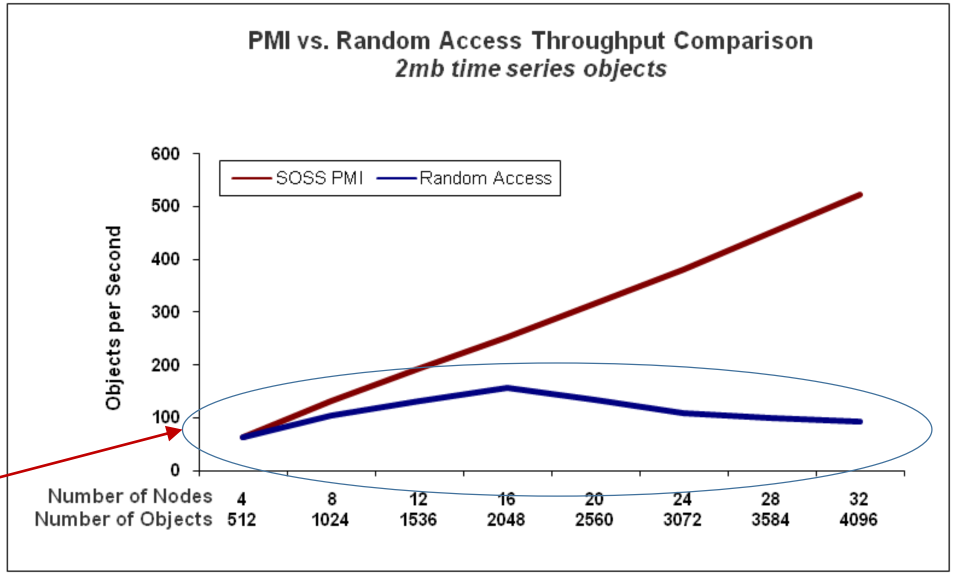
Source → Data Stream → Operation → Data Stream → Sink

Storage

Distributed Cache

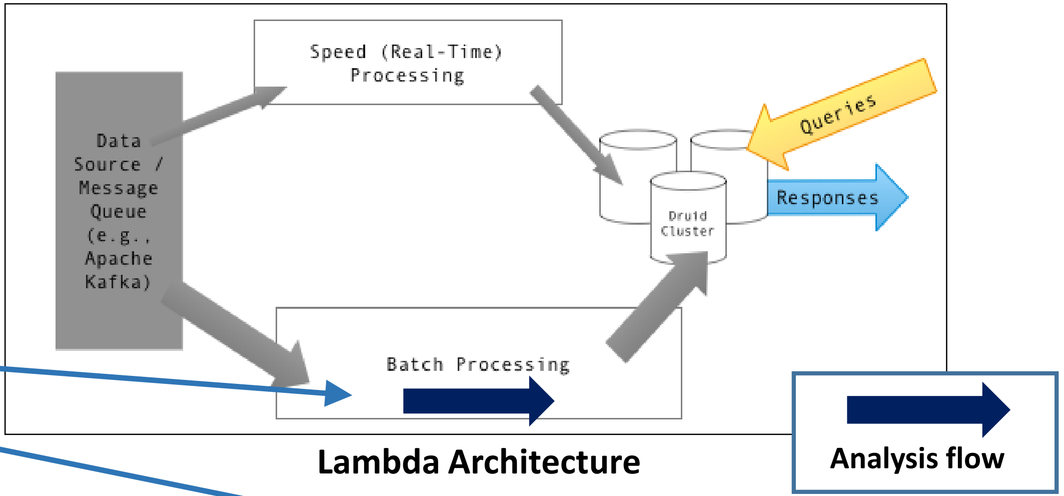
Database

bottleneck

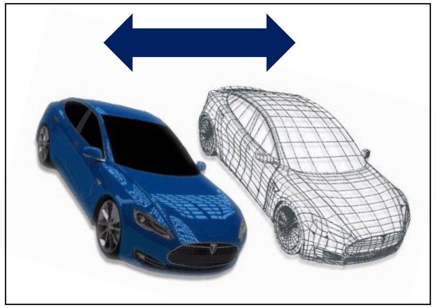


Moves Streaming Analytics into Real Time

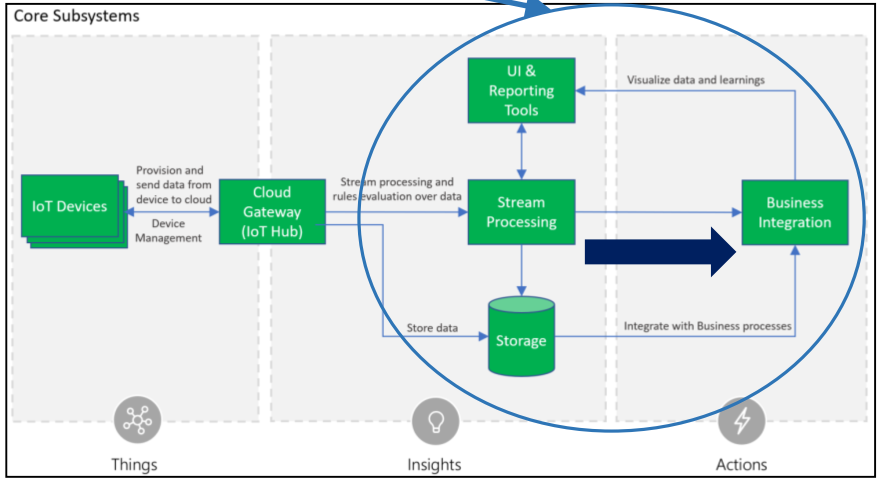
- Lambda architecture separates stream-processing (“speed layer”) from data-parallel analytics (“batch layer”).
- Performance limitations keep streaming analytics in the batch layer.
- This prevents real-time responses with deep introspection.
- ScaleOut’s digital twin model running on ScaleOut StreamServer’s IMDG+IMC enables:
  - **Deep introspection** in the speed layer
  - **Real-time feedback** from event analytics
  - Data-parallel analytics to detect aggregate trends in real time



Lambda Architecture



ScaleOut StreamServer



Example: Microsoft Azure IoT Services Architecture

Many 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

Example: Tracking a Fleet of Vehicles

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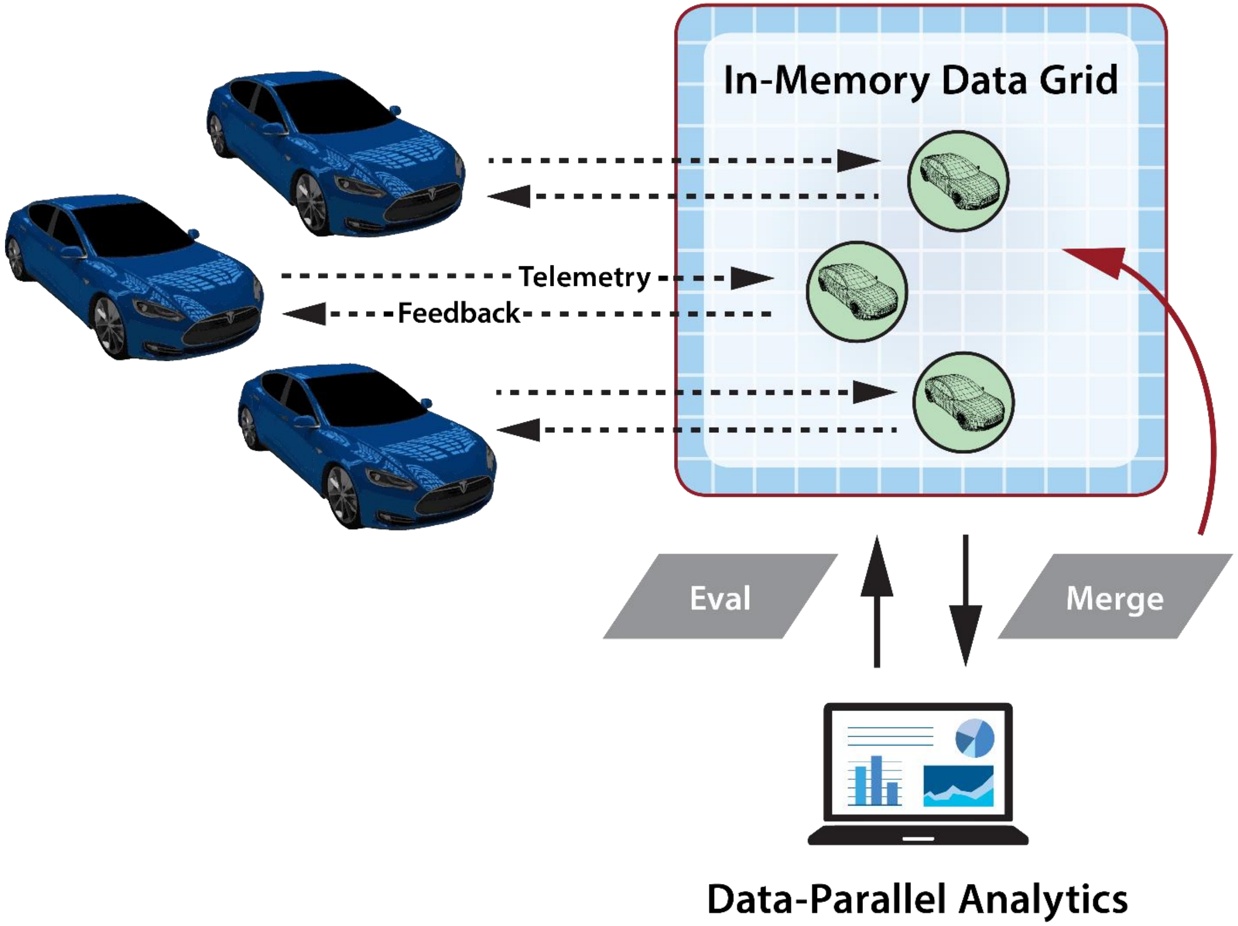
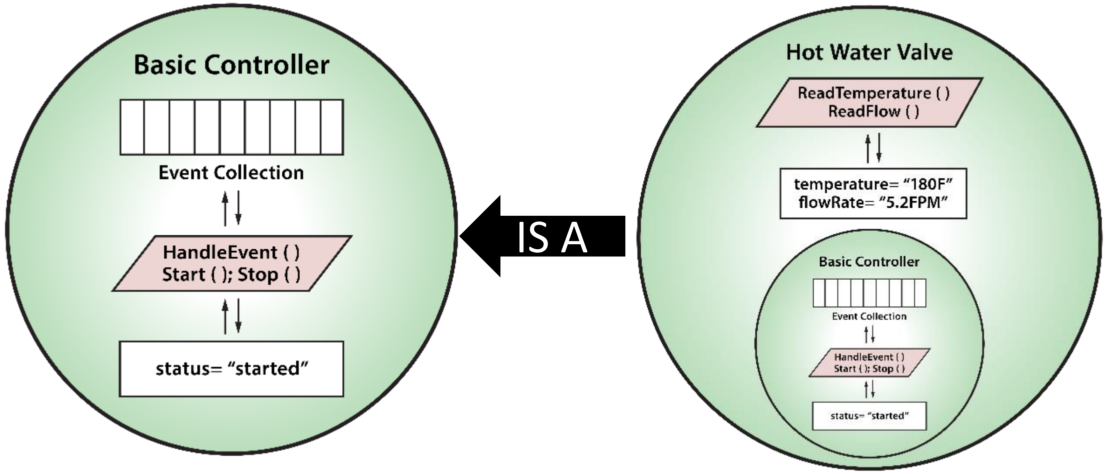
- **Goal**: Track telemetry from a fleet of cars or trucks.
  - Events indicate speed, position, and other parameters.
  - Digital twin object stores information about vehicle, driver, and destination.
  - Event handler alerts on exceptional conditions (speeding, lost vehicle).

- 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.



OOP Techniques Simplify Digital Twins

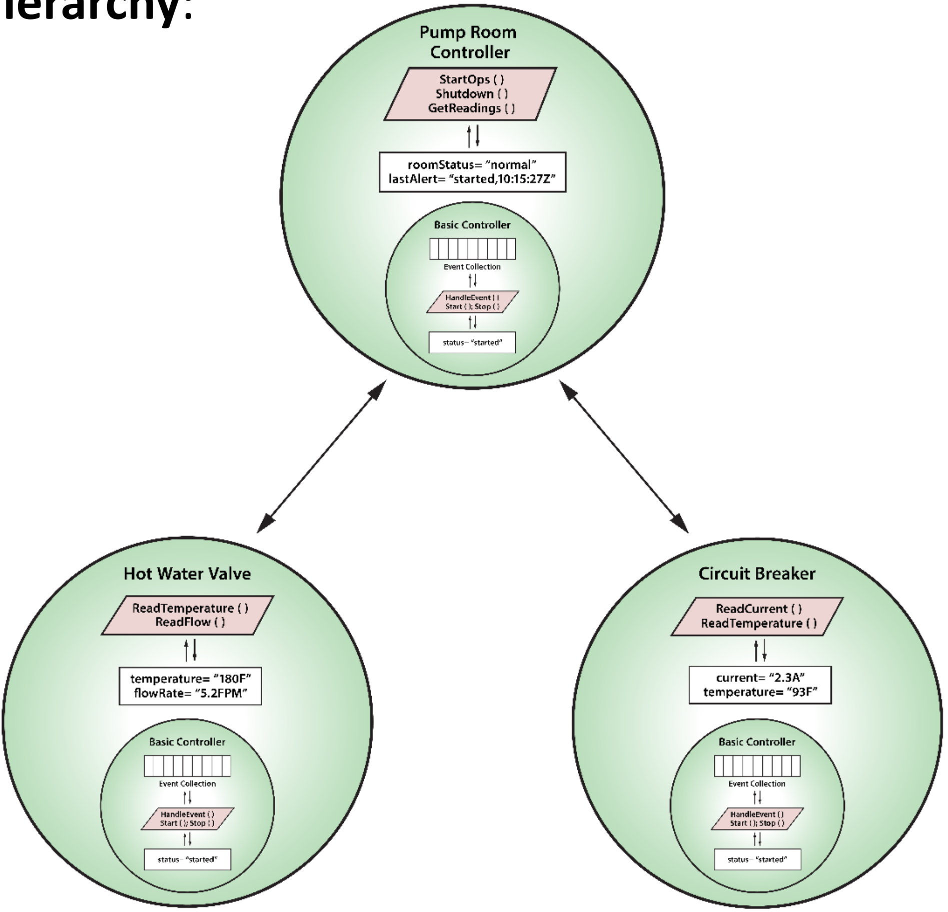
- Digital twin objects can use **inheritance** to create specialized behaviors:



Base Class

Sub-Class

- Instances of objects can be organized in a **hierarchy**:



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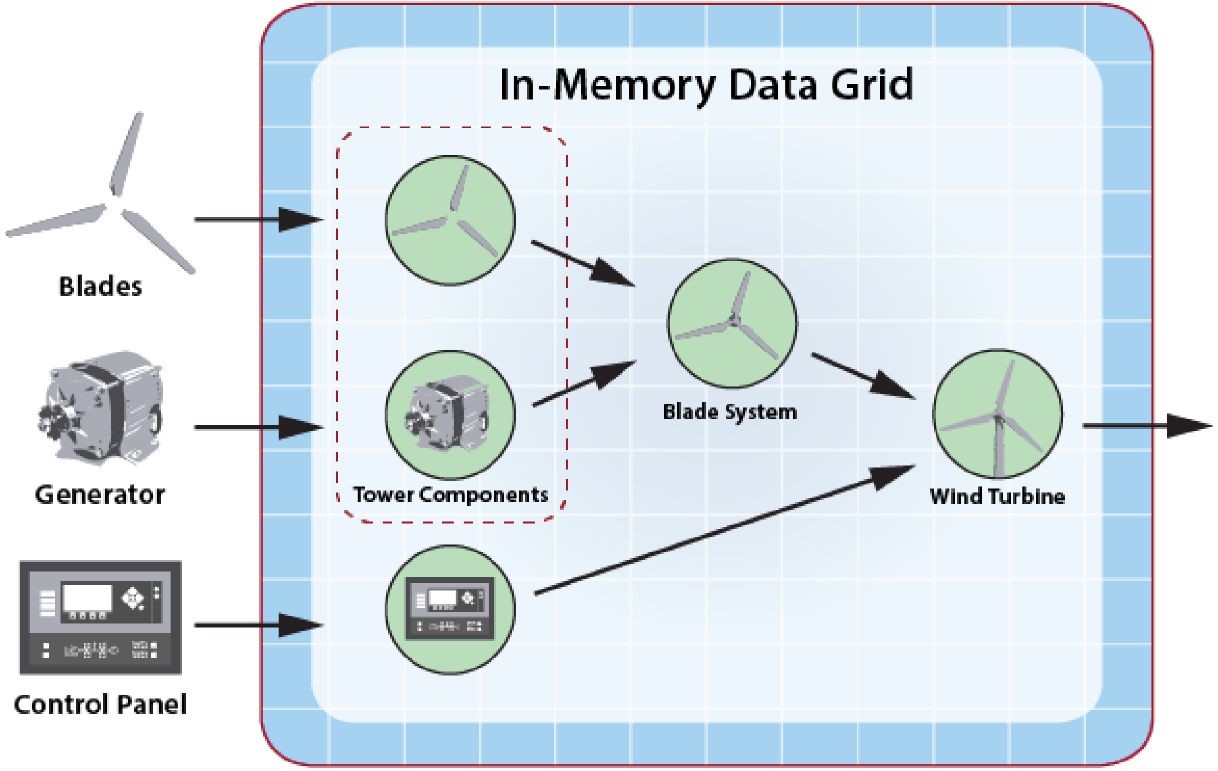
Using Digital Twins in a Hierarchy

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.

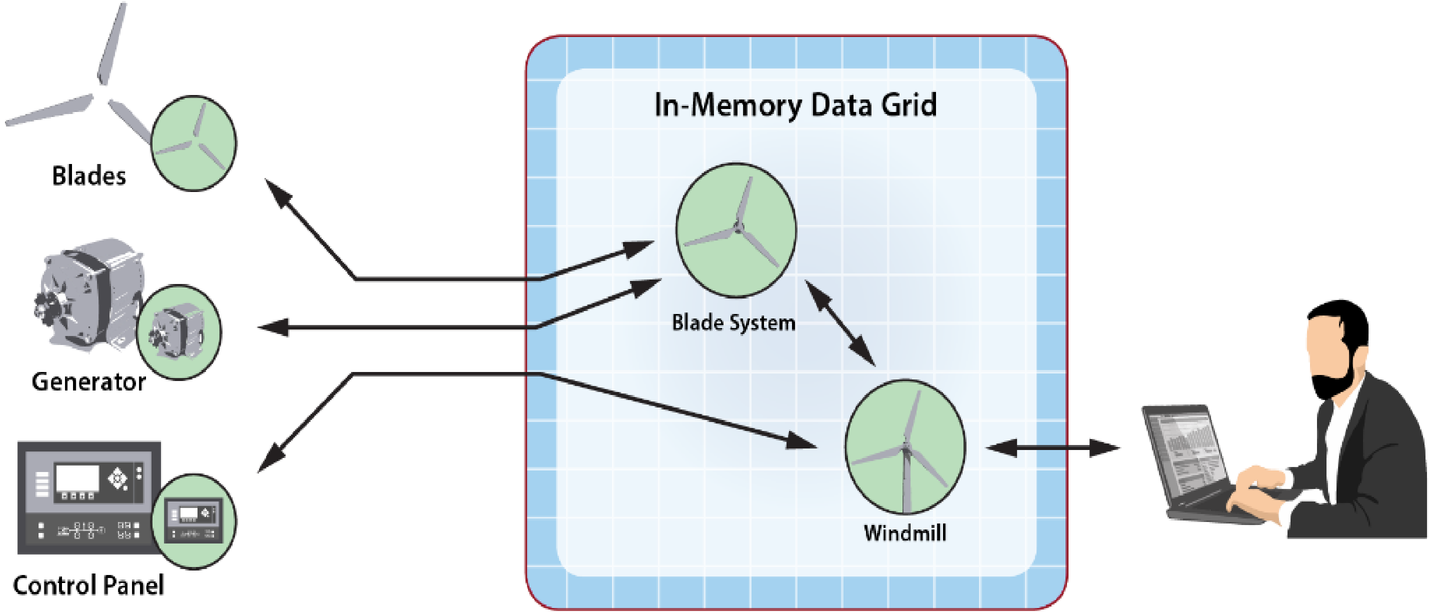


Example: Hierarchy of Digital Twins for a Wind Turbine

Digital Twins Simplify Migration to Edge

ScaleOut Software

- Migration of stream-processing intelligence to the edge is an ongoing trend driven by continuous advances in technology.
- Constructing software components as o-o digital twins simplifies migration:
  - Makes software decomposition independent of execution location.
  - Avoids rewriting code for execution at the edge; can leverage containers.

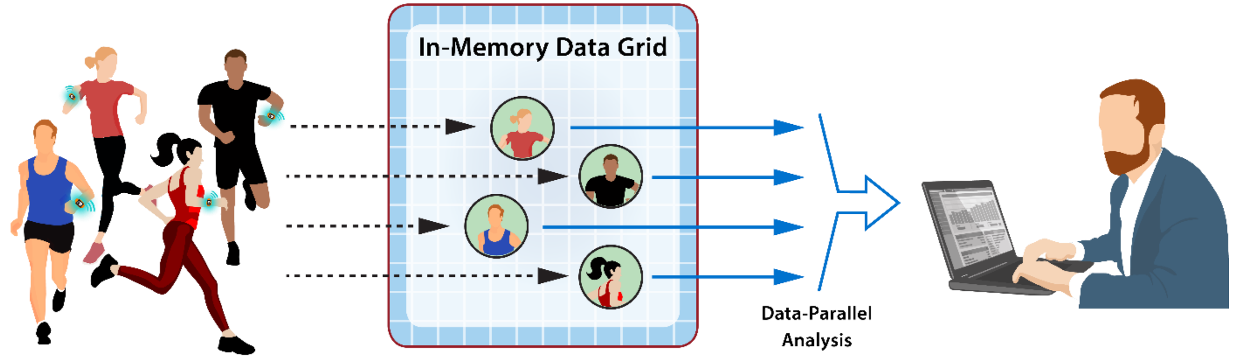


Digital Twins Enable Data Parallel Analysis

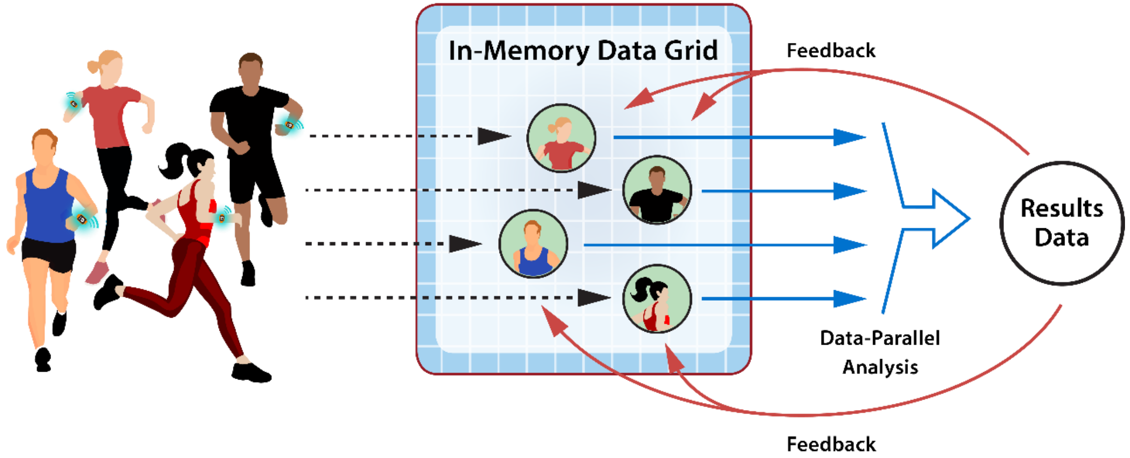
ScaleOut Software

- 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.



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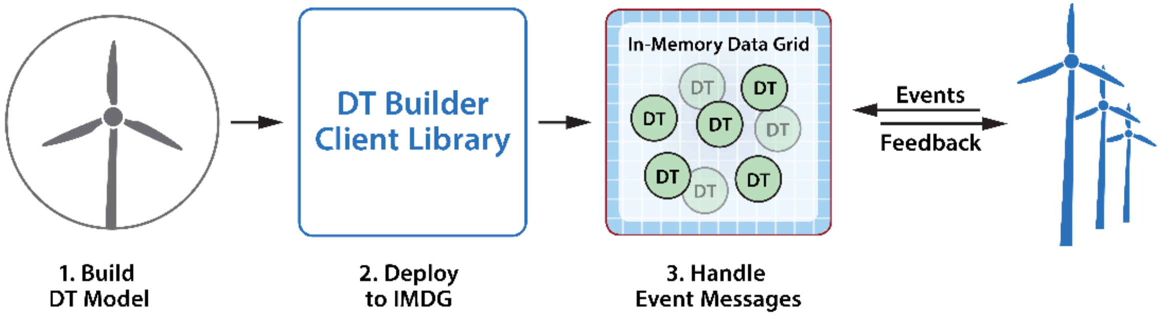
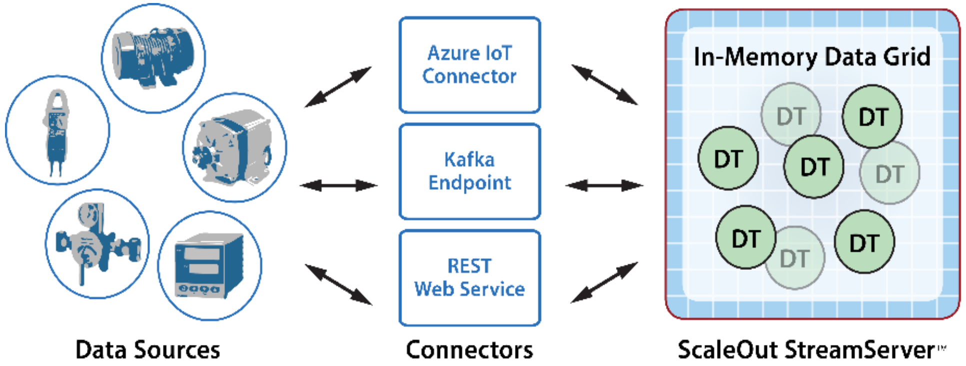
ScaleOut Digital Twin Builder™ Toolkit

- API libraries for building digital twin models in Java and C#
- Deployment libraries for hosting in ScaleOut StreamServer



- Connectors to Kafka, Azure IoT, and REST



Sample Application (C#)

- Goal: Illustrate use of digital twin to analyze temperature telemetry from a wind turbine.
- Digital twin tracks:
  - *Parameters*: model, pre-maintenance period based on model, max. allowed temperature, max. allowed over-temp duration (normal and pre-maintenance)
  - *Dynamic state*: time to next maintenance, over-temp condition and its duration
- Message processing:
  - Determines onset of and recovery from over-temp condition
  - Alerts at maximum allowed duration
  - Logs incidents for time-windowing analysis

Block Island Wind Farm

Sample State Object (C#)

```
[JsonObject]
public class WindTurbine : DigitalTwinBase
{
    // physical characteristics:
    public const string DigitalTwinModelType = "windturbine";
    public WindTurbineModel TurbineModel { get; set; } = WindTurbineModel.Model7331;
    public DateTime  NextMaintDate { get; set; } = new DateTime().AddMonths(36);
    public const int MaxAllowedTemp = 100; // in Celsius
    public TimeSpan  MaxTimeOverTempAllowed = TimeSpan.FromMinutes(10);
    public TimeSpan  MaxTimeOverTempAllowedPreMaint = TimeSpan.FromMinutes(2);

    // dynamic state variables:
    public bool TrackingOverTemp      { get; set; }
    public DateTime OverTempStartTime { get; set; }
    public int NumberMsgsWithOverTemp { get; set; }

    // list of incidents and alerts:
    public List<Incident> IncidentList { get; } = new List<Incident>();
}
```

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Sample Message Processor (Outer Loop)

```
 public override ProcessingResult ProcessMessages(ProcessingContext context,
     WindTurbine dt, IEnumerable<DeviceTelemetry> newMessages)
{
    var result = ProcessingResult.NoUpdate;

    // determine if we are in the pre-maintenance period for this wind turbine model:
    var preMaintTimePeriod  = _preMaintPeriod[dt.TurbineModel];
    bool isInPreMaintPeriod = ((dt.NextMaintDate
             - DateTime.UtcNow) < preMaintTimePeriod) ? true : false;

    // process incoming messages to look for over-temp condition:
    foreach (var msg in newMessages) {
        // if message reports a high temp indication, track it:
        if (msg.Temp > WindTurbine.MaxAllowedTemp)
            <track over-temp condition>
        else if (dt.TrackingOverTemp)
            <resolve over-temp condition>
    }
    return result;}
```

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Track or Resolve Over-Temp Condition

ScaleOut Software

```
// track over-temp condition:
{dt.NumberMsgsWithOverTemp++;

if (!dt.TrackingOverTemp) {
    dt.TrackingOverTemp  = true; dt.OverTempStartTime = DateTime.UtcNow;
    <add a notification to the incident list> }

TimeSpan duration = DateTime.UtcNow - dt.OverTempStartTime;

// if we have exceeded the max allowed duration for an over-temp, send an alert:
if (duration > dt.MaxTimeOverTempAllowed ||
       (isInPreMaintPeriod && duration > dt.MaxTimeOverTempAllowedPreMaint)) {
    var alert = new Alert(); <fill out the alert message>;
    context.SendToDataSource(Encoding.UTF8.GetBytes(JsonConvert.SerializeObject(alert)));
    <add a notification to the incident list> }}
```

```
// resolve the condition and reset our state:
{dt.TrackingOverTemp = false; dt.NumberMsgsWithOverTemp = 0;
 <add a notification to the incident list> }
```

Deploying the Model

- Deploy the WindTurbine model to ScaleOut StreamServer:

```
ExecutionEnvironmentBuilder builder = new ExecutionEnvironmentBuilder()
    .AddDependency(@"WindTurbine.dll")
    .AddDigitalTwin<WindTurbine, WindTurbineMessageProcessor,
        DeviceTelemetry>(WindTurbine.DigitalTwinModelType);
```

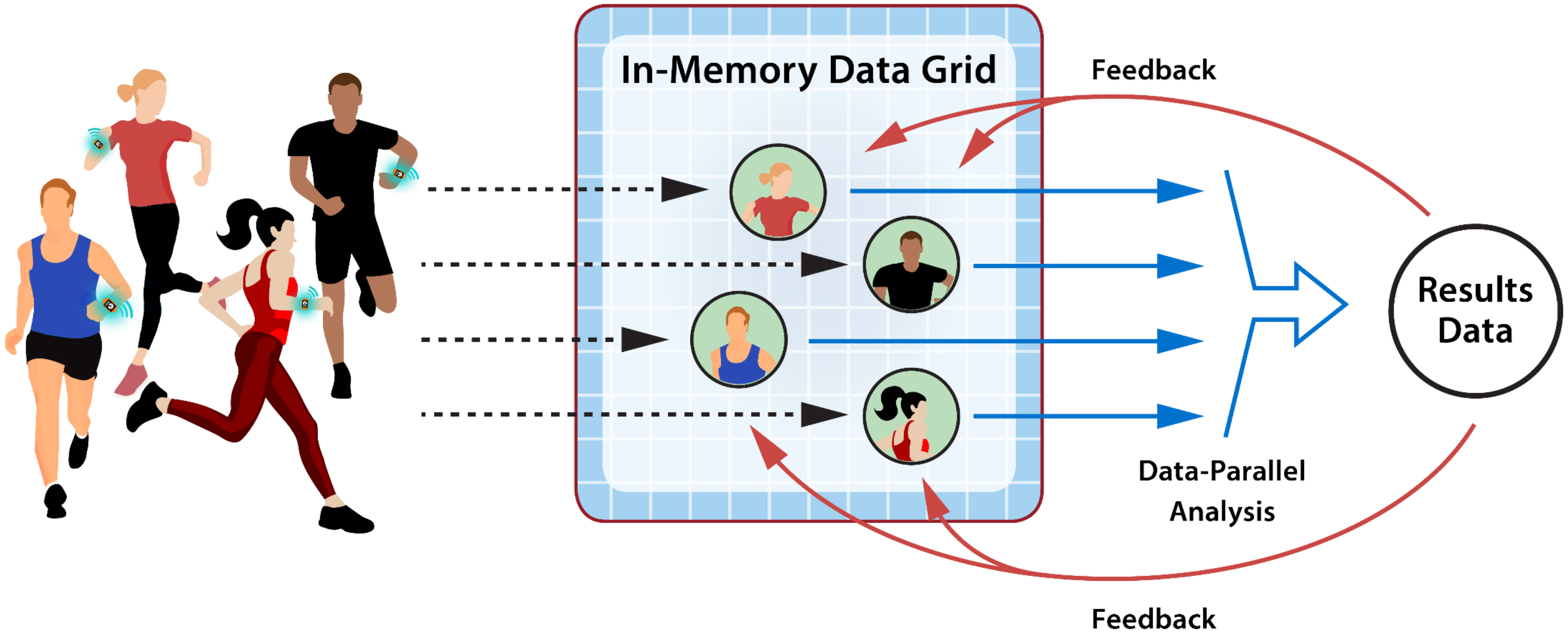
- Connect to a data source (Azure IoT Hub):

```
EventListenerManager.StartAzureIoTHubConnector(
     eventHubName               : _eventHubName,
     eventHubConnectionString: _eventHubConnectionString,
     eventHubEventsEndpoint   : _eventHubEventsEndpoint,
     storageConnectionString : _storageConnectionString,
     consumerGroupName         : "");
```

Example: Heart-Rate Watch Monitoring

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

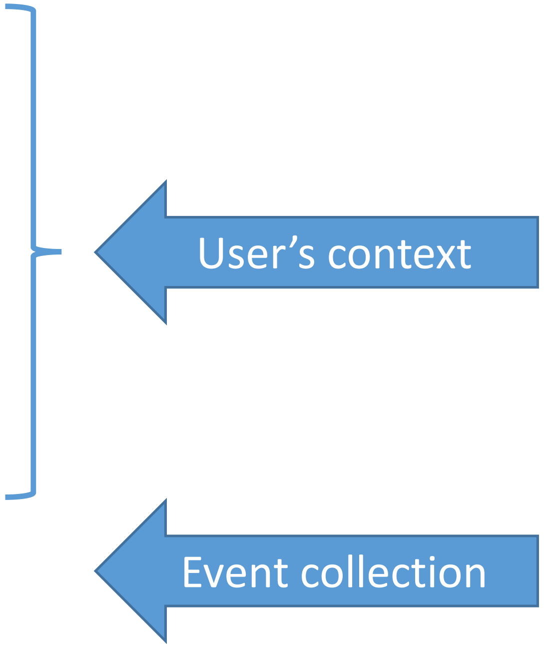
- Heart-rate events flow from smart watches to their respective digital twin objects for analysis.
- The analysis uses wearer’s history, activity, and aggregate statistics to determine feedback and alerts.



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;
    ...}
```



Events & Alerts

ScaleOut Software

- 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;
    ...}
```

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Event Analysis

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

```
private static void processMessage(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

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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.

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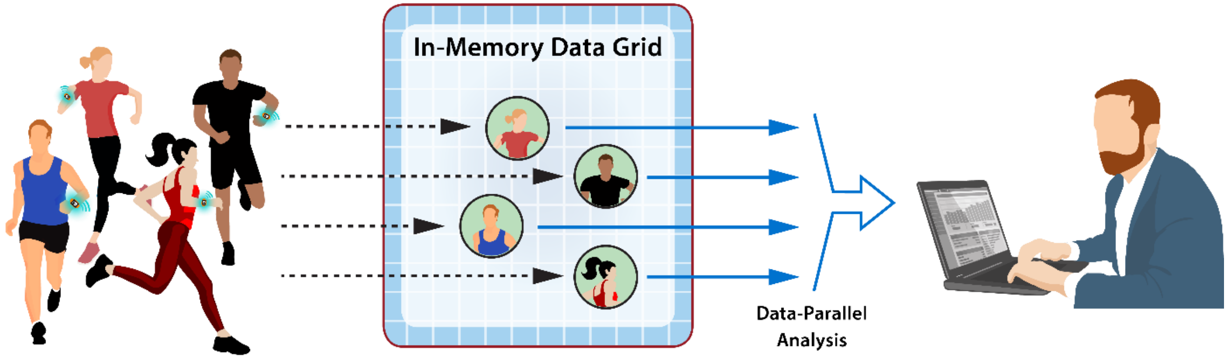
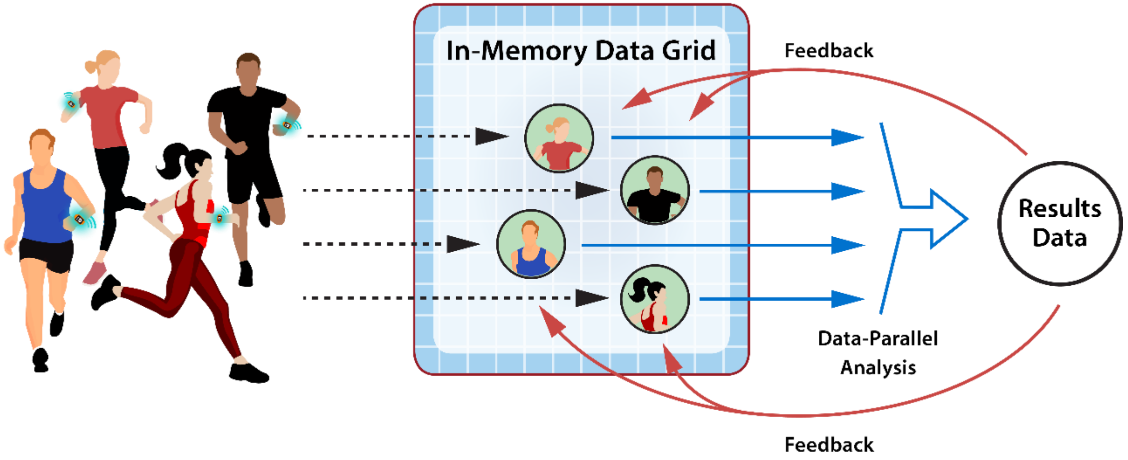
Data Parallel Analysis Across all Digital Twins

ScaleOut Software

- 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

ScaleOut Software

- 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

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Computing Aggregate Data (2)

ScaleOut Software

- 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

ScaleOut Software

- 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

Wrap-Up

Digital Twins: The Next Generation in Stream-Processing and Real-Time Analytics

- **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.
- **Stateful stream-processing using digital twin models in ScaleOut StreamServer**:
  - Automatically correlates incoming events and processes them in parallel.
  - Enables integrated stream-processing and real-time analytics.

Thank you!

For more information:

- ScaleOut Software: www.scaleoutsoftware.com
- ScaleOut Digital Twin Builder User Guide: https://static.scaleoutsoftware.com/docs/ScaleOut_Digital_Twin_Builder_User_Guide.pdf
- ScaleOut blog: https://www.scaleoutsoftware.com/news-blog/
- Java Digital Twin Builder libraries: github.com/scaleoutsoftware/JavaDigitalTwinCore
- .NET Digital Twin Builder libraries: www.nuget.org/packages/Scaleout.Streaming.DigitalTwin.Deployment/
- REST Digital Twin message service: hub.docker.com/r/scaleout/dtbuilder_webmessenger/