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Realtime Data Processing with Pentaho Data Integration (PDI)

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Change log (if you want to use it):

Date	Version	Author	Changes
9/7/2017	0.1	Alexander Schurman	Initial document
9/21/2017	0.2	Alexander Schurman	Adding samples
3/25/2019	2	Alexander Schurman	Updates Pentaho 8+
3/9/2020	2.1	Alexander Schurman	Updates for Pentaho 9.0

Contents

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Overview

This document covers some best practices on real-time data processing on big data with Pentaho Data Integration (PDI). In it, you will learn reasons to try this PDI implementation, and some of the things you should and should not do when implementing this solution.

Our intended audience is solution architects and designers, or anyone with a background in realtime ingestion, or messaging systems like Java Message Service (JMS), RabbitMQ, or WebSphere MQ.

The intention of this document is to speak about topics generally; however, these are the specific versions covered here:

Software	Version(s)
Pentaho	8.x, 9.0

The Components Reference in Pentaho Documentation has a complete list of supported software and hardware.

Before You Begin

Before beginning, use the following information to prepare for the procedures described in the main section of the document.

Prerequisites

This document assumes that you have some knowledge of messaging systems such as Kafka, Amazon Kinesis, IBM RabbitMQ or MQ, Message Queue Telemetry Transport (MQTT), Advanced Messaging Query Protocol (AMQP), or JMS, as well the Hadoop Data File System (HDFS), microbatching, and Spark.

Use Cases

Use cases employed in this document include the following:

Use Case 1: Immediate Data Push to Customers

> *Marc wants to use a messaging system or channel that will push data to customers as soon as it is received. It will then be the customers' responsibility to collect and store or process the data.*
>
> *See Use Case 1 later in the document for the solution.*

Use Case 2: Event Messaging

> *Janice is using a messaging system like JMS or RabbitMQ to send an event message that will trigger a process of Extract/Transform/Load (ETL) alerts. In Janice's case, the data is not part of the message.*
>
> *See Use Case 2 later in the document for the solution.*

PDI Transformation

Successful PDI transformation of your data involves several considerations. This section contains preliminary information you will need to understand before you encounter the solutions to the use cases from the introduction of this document.

You can find information on these topics in the following sections:

- How PDI Works
- Neverending Transformations

How PDI Works

PDI is designed to work as a flow of data. In fact, it may be useful to think of PDI as a series of pipes through which water flows and is joined with other flows, mixed, and so on. Water pipes do not really know how much water is in their source, but no matter how big the source, if you keep the water flowing, eventually all the water will be processed. In a water pipe system, if any junctions or containers slow down or block the flow of water, then all the water in the pipe before that point will slow down in a chain reaction.

PDI joins, merges, and mixes data in the same way: all the data will eventually be processed as long as the data keeps flowing without blockages. The size of the "pipe" in PDI is directly linked to the number of data records, and to the amount of memory needed to hold all those records[1].

The key to successfully transform your data with high performance is to understand which PDI steps slow or block your flow.

Problem Steps and Situations

Some steps and situations you should pay close attention to include:

- **Sort step**: To sort rows, you first must collect all the rows. The flow of data can be blocked here until you have collected all the rows, so no data will move to the next step until all the data is received. [2]
- **Joins and stream lookup**: When a stream of data depends on another stream, pay attention to where the reference records come from, since all the reference records will be needed in memory before the data can move ahead.
- **Split and rejoin on the same flow**: When you split one flow and then recombine it, make sure the flow is not slowed or stopped in one of the flows, because that will likely slow or block the other flow as well.

[1] PDI has a configuration setting called **RowSet size** to control the number of records in the pipe.

[2] Pentaho's microbatch strategy reduces the risk because the microbatch is executed on a different thread/executor. Therefore, it will not affect the incoming data.

Neverending Transformations

A neverending transformation is a process that starts, and continuously awaits new data. All the steps continue running, awaiting new data.

How to Implement a Neverending Transformation

In a PDI transformation, the input steps collect and push the data records through the stream. There are currently many input steps that support constant data flow:

- **Kafka consumer** step
- **Kinesis consumer** step
- **JMS consumer** step (which can connect to things like RabbitMQ and IBM WebSphereMQ)
- **MQTT consumer**[3]
- **AMQP consumer** step
- **User Defined Java Class** step

Where to Run a Neverending Transformation

Although there are many different places you can execute your neverending transformation, choose the best option for your use case based on your organization's needs, fault tolerance, resources, and available infrastructure.

Table 1: Locations

Location	Details
Adaptive Execution Layer (AEL) Spark	Pentaho 8 introduced Spark Streaming integration. You can use any of the consumer or producer steps, such as Kafka. New releases will include new input/output technologies.
Pentaho Server or Carte Server	When you execute the transformation this way, you can use the API to track the status. In case of failure, you will need to create a process to detect and handle your next steps.
Kitchen/Pan	This technique issues a specific Java Virtual Machine (JVM) for the process, with specific memory settings for the process required. It is not possible to get execution statistics unless you include the code in the transformation design, either with database logging, Simple Network Management Protocol (SNMP), or another custom implementation. In case of failure, the JVM will be terminated, and a wrapping operating system (OS) batch process will be necessary to handle your next steps.

[3] Native in Pentaho 8 and 9, and available for Pentaho 7 as a plugin from the Pentaho Marketplace

How to Stop a Neverending Transformation

To stop a neverending transformation gracefully, it is important to stop consuming incoming records and allow the rest of the transformation steps to process the records through the pipe.

In the **Abort** step, you will find a set of options to control how to stop the transformation. In our case, we will focus on the **Stop input processing** option, which stops all the input steps, while allowing any records already retrieved or initiated to be processed.[4]

The **Abort** step can be placed in the parent or microbatch transformation with a logic for when it should be triggered.

Here are two techniques to illustrate this:

Technique 1

Main process

1. Add a separate data stream.
2. Call the **Action** stream and listen for actions like a **STOP** action, for example.

Sub-Transformations (microbatches)

3. The **Action** stream will evaluate the message and call the **Abort** step

[4] When the process is executed in Carte or Pentaho server, the ETL monitoring page has a STOP link that can be used to simulate the ABORT processing input records.

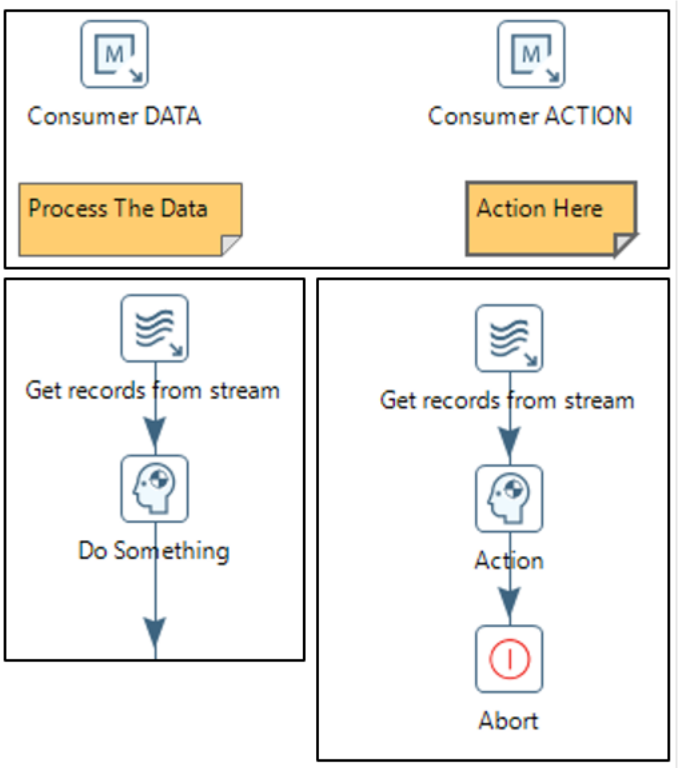


Figure 1: Technique 1 for Neverending Transformations

Technique 2

In this method, the main stream consumer consumes different topics.

The stream consumer will require you to define a microbatch transformation process that defines the flow for the **Action** we want to perform, based on the action type.

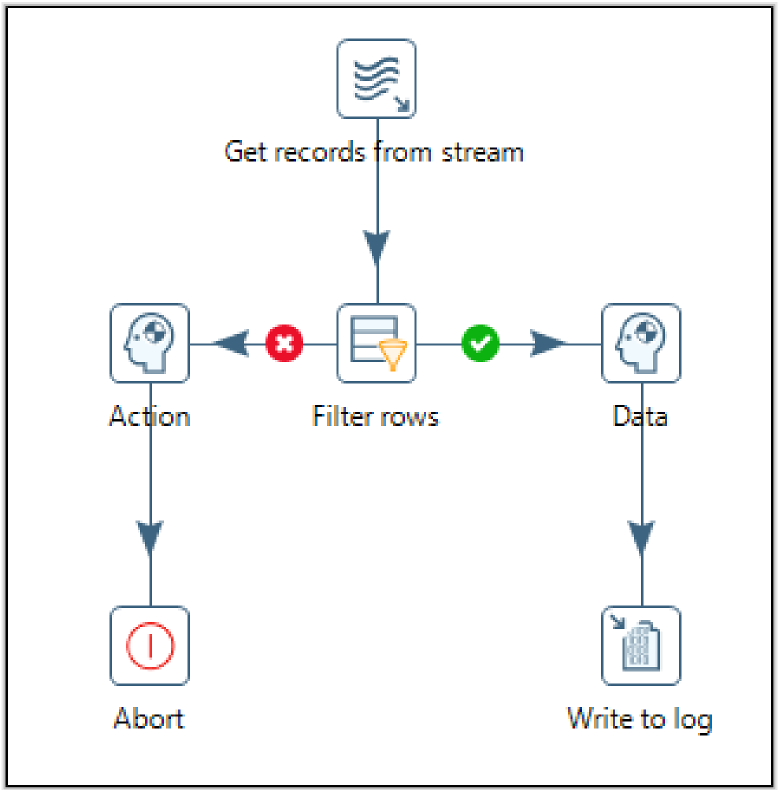


Figure 2: Technique 2 for Neverending Transformations

Managing Data Duplication

Data duplication and reprocessing is an important part of real-time data processing.

Handle data duplication detection and management outside of the real-time data processing, because it may require additional steps or processes that could slow down your data processing. This slowdown may cause your data processing to move even slower than the number of records per second received, causing a records traffic jam.

Streaming Solution

Streaming-driven solutions are usually designed for a single purpose. Data can come from a broker, channel, or socket, and the architecture in this type of implementation most commonly includes Kafka or MQTT.

There are two approaches to designing this solution:

- Focus on collecting and storing the data as it comes in and process it in microbatching.
- Process the data as it is received, transform it, and then store it.

You can find the similarity in how data is collecting from the messages/channel and pushed to the processing/storing in the Neverending Transformations section of this document.

The key to making your solutions successful is being able to cope with the required data throughput. This means you need to measure the solution execution at the data volumes and speed you require.

We recommend you test your process with at least 10-20% above your real data volume and speed requirements.

Split your data stream into two parts by following lambda architecture best practices:

- The **first stream** will be dumped directly into a data bucket such as HDFS, Amazon Simple Storage Service (S3), or other, which can be used for:
  - Batch processing
  - Model building
  - Processing asynchronous data chunks
- The **second stream** can be used for:
  - Realtime processing
  - Data decisions based on window events
  - Gathering statistics
  - Alerting

Because realtime processing may cause data duplication, gaps, missing records that arrive late, and other unique issues, you may want to reprocess in batch mode towards the end of your process so that you can rebuild your data while realtime data continues to arrive.

Pentaho 8 introduced stream processing capabilities. It can process data incoming from Kafka Source and create microbatching processes. The design solution works in the Pentaho engine or in Spark Streaming.

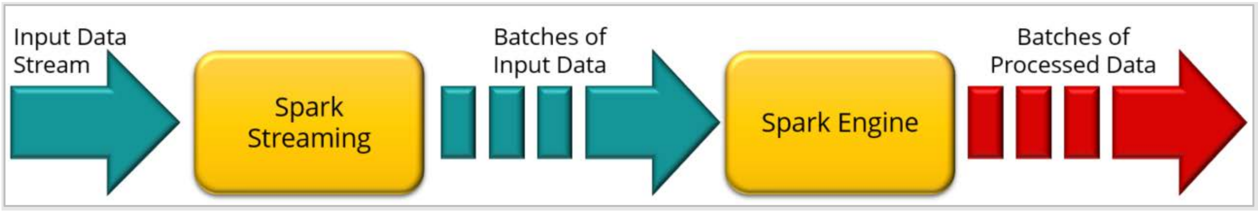


Figure 3: Pentaho Stream Processing

Setting Up Stream Processing example

To set up and use stream processing:

1. Use a **Kafka Consumer** step to continuously listen to Kafka topics for messages.
2. Enable long-running stream data processing by setting parameters in the **Kafka Consumer** step for the size of your configurable microbatch of data.
3. Use a **Get Records from Stream** step to process a microbatch of a continuous stream of records.
4. Process and blend retrieved messages using other steps running in the Kettle engine or in AEL Spark.
5. When you use AEL Spark, use Spark Streaming to microbatch the streaming data.
6. Publish to Kafka from the Kettle engines using a **Kafka Producer** step, or in parallel from AEL Spark.

Here is an example of how the messages move and how that relates to the movement of your data:

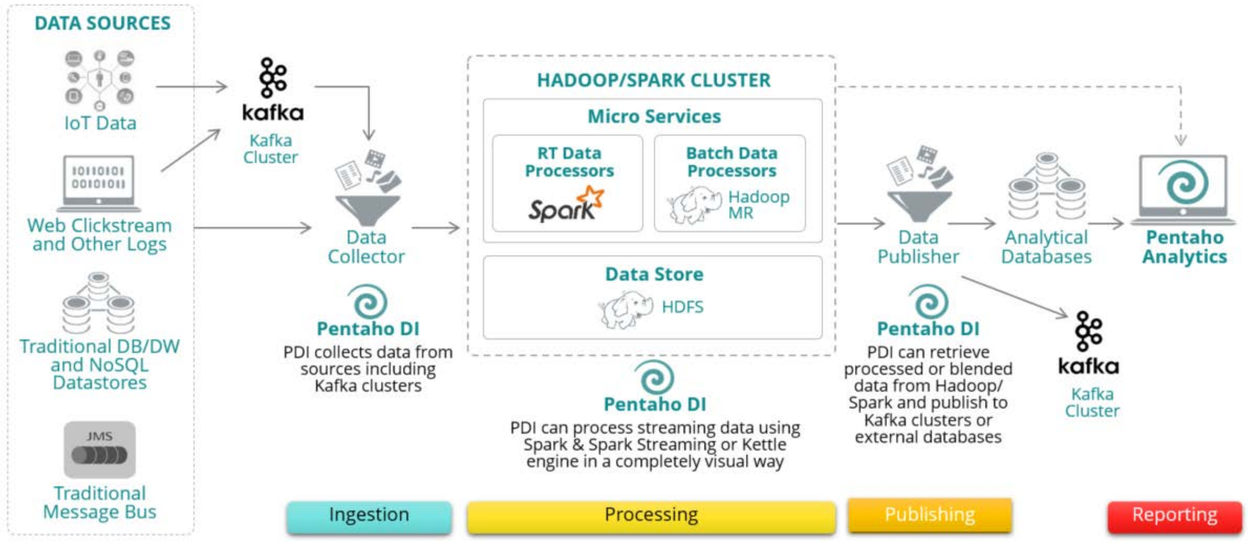
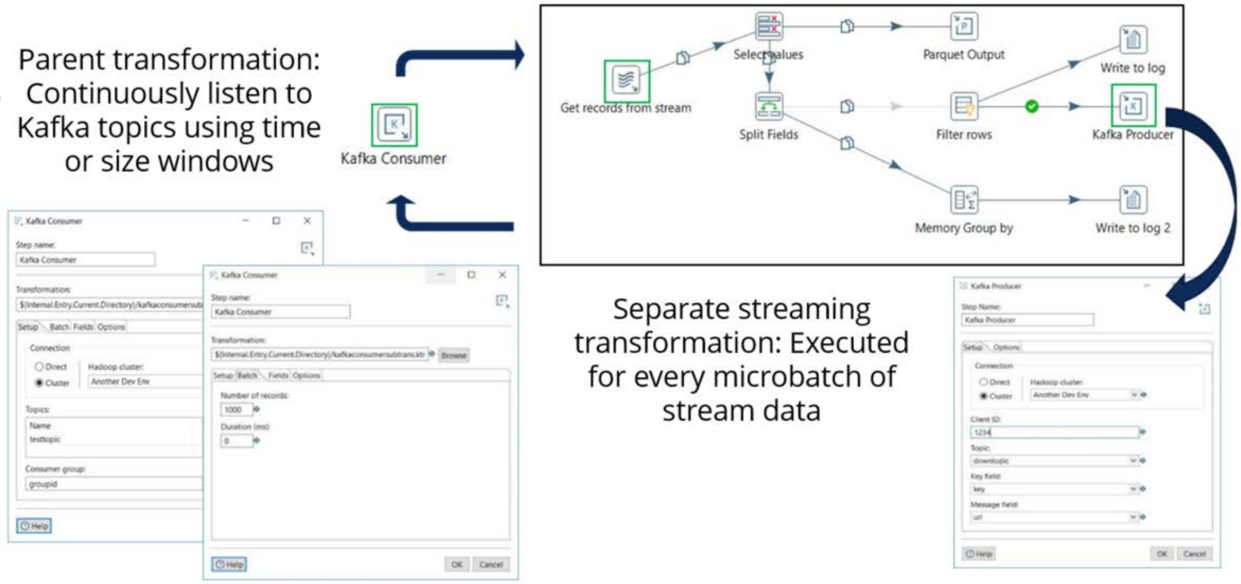

DATA SOURCES
IoT Data
Web Clickstream and Other Logs
Traditional DB/DW and NoSQL Datastores
JMS
Traditional Message Bus
kafka
Kafka Cluster
Data Collector
Pentaho DI
PDI collects data from sources including Kafka clusters
HADOOP/SPARK CLUSTER
Micro Services
RT Data Processors
Spark
Batch Data Processors
Hadoop MR
Data Store
HDFS
Pentaho DI
PDI can process streaming data using Spark & Spark Streaming or Kettle engine in a completely visual way
Data Publisher
Analytical Databases
Pentaho Analytics
Pentaho DI
PDI can retrieve processed or blended data from Hadoop/ Spark and publish to Kafka clusters or external databases
kafka
Kafka Cluster
Ingestion
Processing
Publishing
Reporting

Figure 4: Stream Processing Data Flow

An illustration of the potential PDI transformation you could use:



Parent transformation: Continuously listen to Kafka topics using time or size windows

Separate streaming transformation: Executed for every microbatch of stream data

Kafka Consumer

Step name: Kafka Consumer

Transformation: ${Internal.Entry.Current.Directory}/kafkaconsumersub

Setup | Batch | Fields | Options

Connection: ○ Direct ● Cluster — Hadoop cluster: Another Dev Env

Topics: Name — testtopic

Consumer group: groupid

Kafka Consumer

Step name: Kafka Consumer

Transformation: ${Internal.Entry.Current.Directory}/kafkaconsumersubtrans.ktr

Setup | Batch | Fields | Options

Number of records: 1000

Duration (ms): 0

Kafka Producer

Step Name: Kafka Producer

Setup | Options

Connection: ○ Direct ● Cluster — Hadoop cluster: Another Dev Env

Client ID: 1234

Topic: downtopic

Key field: key

Message field: url

Figure 5: PDI Transformation for Streaming

In the above illustration:

- **Kafka Consumer** is where you collect the raw data with all its settings in real time. This step calls a subtransformation which will represent the microbatching processing.
- **Get Records from Stream** is the input step for the subtransformation and has information like key, message, partition, offset, and others.
- The remaining steps are the specific processes that need to be done: writing to HDFS in text, Avro or Parquet; and parsing and creating new messages to be pushed through **Kafka Producer** to Kafka on a different topic.

It is very important to have error handling on any of the steps that could cause a message parsing fatal error.

Related Information

Here are some links to information that you may find helpful while using this best practices document:

- Amazon
    - Kinesis
- Apache
    - Kafka
    - Spark Streaming
- IBM
    - MQ
    - RabbitMQ
- JMS
- Lambda Architecture
- MQTT
- Pentaho
    - Abort
    - Pentaho Components Reference
    - Pentaho Marketplace
    - Performance Tuning
    - Third-Party Monitoring with SNMP
    - Transformations
- Realtime Streaming Data Aggregation

Finalization Checklist

This checklist is designed to be added to any implemented project that uses this collection of best practices, to verify that all items have been considered and reviews have been performed.

Name of the Project:____

Date of the Review:____

Name of the Reviewer:____

Item	Response	Comments
Did you check for problem steps that might slow down your data flow?	YES________ NO________	
Did you set up a neverending transformation using the best practices explained in this document?	YES________ NO________	
Did you create an event-driven solution?	YES________ NO________	
Did you create a data-driven solution?	YES________ NO________	