

Apache Ignite - Using a Memory Grid for Heterogeneous Computation Frameworks

A Use Case Guided Explanation

Chris Herrera Hashmap

Topics

- Who Key Hashmap Team Members
- The Use Case Our Need for a Memory Grid
- Requirements
- Approach V1
- Approach V1.5
- Approach V2
- Lessons Learned
- What's Next
- Questions



Who - Hashmap



WHO

- Big Data, IIoT/IoT, AI/ML Services since 2012
- HQ Atlanta area with offices in Houston, Toronto, and Pune
- Consulting Services and Managed Services
 REACH
 - 125 Customers across 25 Industries

PARTNERS

Cloud and technology platform providers



Who - Hashmap Team Members



Jay Kapadnis Lead Architect Hashmap Pune, India



Akshay Mhetre Team Lead Hashmap Pune, India



Chris Herrera Chief Architect/Innovation Officer Hashmap Houston, TX

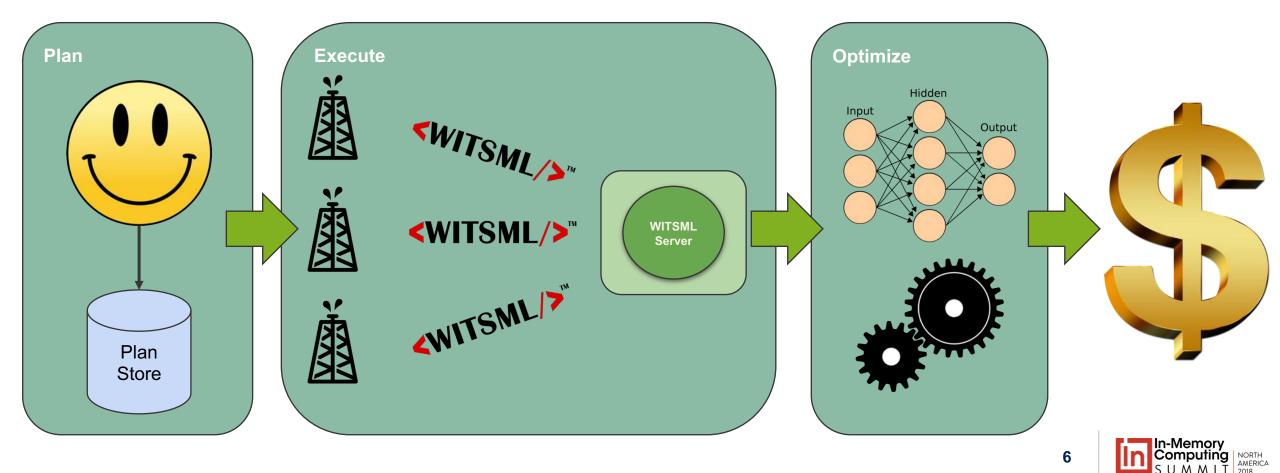


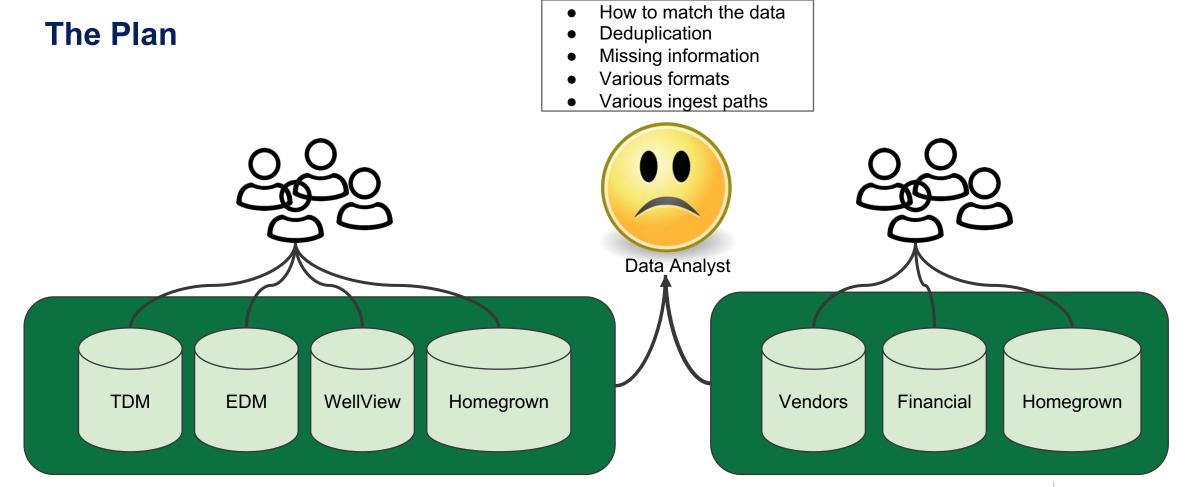
The Use Case

Oilfield Drilling Data Processing



The Process

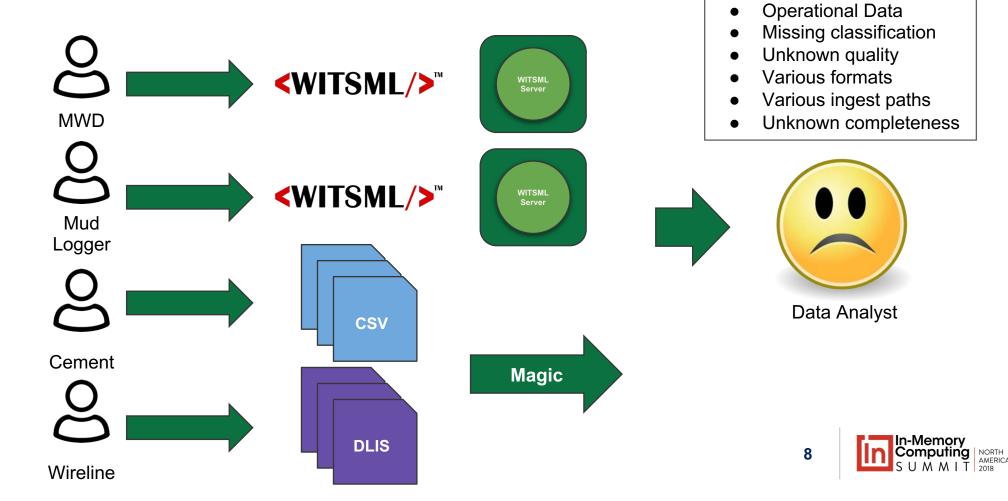




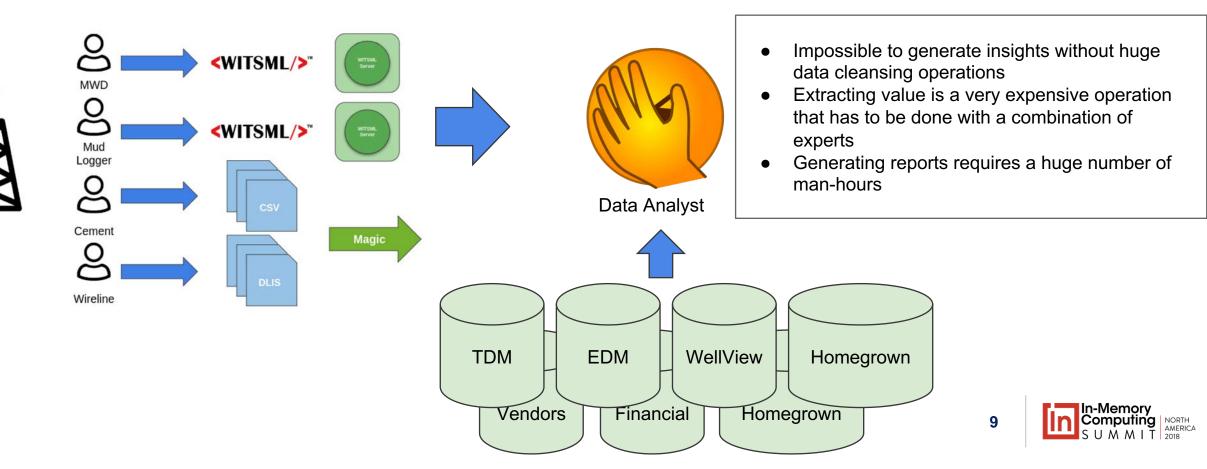


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Rig Site Data Flow



Oilfield Drilling Data Processing - Office

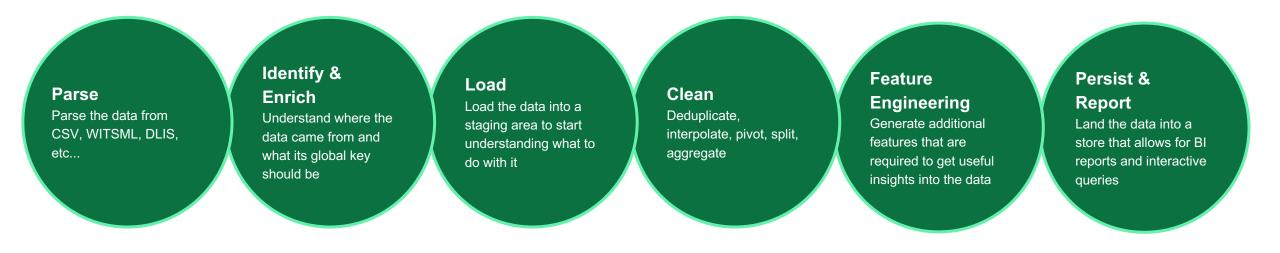


BUT WAIT...

There's More



We still have all the compute to deal with, some of which is very legacy code





Requirements

What do we have to do?



Functional Requirements

Cleaning and Feature Engineering (the legacy code I referred to)

- Parse WITSML / DLIS
- Attribute Mapping
- Unit Conversions
- Null Value Handling
- Rig Operation Enrichment
- Rig State Detection
- Invisible Lost Time Analysis
- Anomaly Detection



Non-Functional Requirements

Requirement		Description	
1	Heterogeneous Data Ingest	Very flexible irFlexible simple	ngest e transformations
2	Robust Data Pipeline	Easy to debugTrusted)
3	Extensible Feature Engineering	 Be able to sup computational 	oport existing frameworks / runtimes
4	Scalable	Scales upScales Down	
5	Reliable		essing workflow fails at a ot continue with a

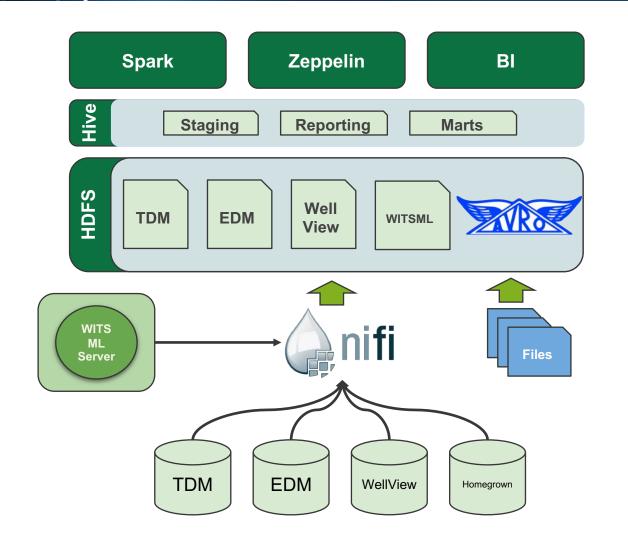


Approach V1

How Then?



Solution V1



- Heterogeneous ingest implemented through a combination of NiFi processors/flows and Spark Jobs
- Avro files loaded as external tables
- BI connected via ODBC (Tableau)
- Zeppelin Hive interpreter was used to access the data in Hive



Issues with the Solution

- Very Slow BI
- Tough to debug cleansing
- Tough to debug feature extractions
- A lot of overhead for limited benefit
- Painful data loading process
- Incremental refresh was challenging
- Chaining the jobs together in a workflow was very hard
 - Mostly achieved via Jupyter Notebooks
- In order to achieve the functional requirements, all of the computations were implemented in Spark, even if there was little benefit



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V1 Achieved Requirements

Requirement		Achieved	Description
1	Heterogeneous Data Ingest		 Very flexible ingest Flexible simple transformations
2	Robust Data Pipeline	\times	Hard to DebugHard to modify
3	Extensible Feature Engineering	\times	 Hard to support other frameworks Hard to modify current computations
4	Scalable	\times	 Scales up but not down
5	Robust	×	 Hard to debug

In-Memory Computing S U M M I T

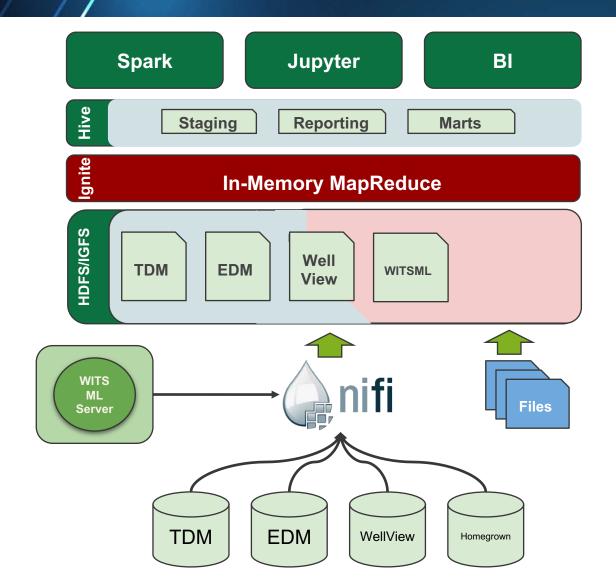
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Approach V1.5

An Architectural Midstep



A Quick Architectural Midstep (V1.5)



- Complicated an already complex system
- Did not solve all of the problems
- Needed a simpler way to solve all of the issues
- Ignite persistence was released while we were investigating this

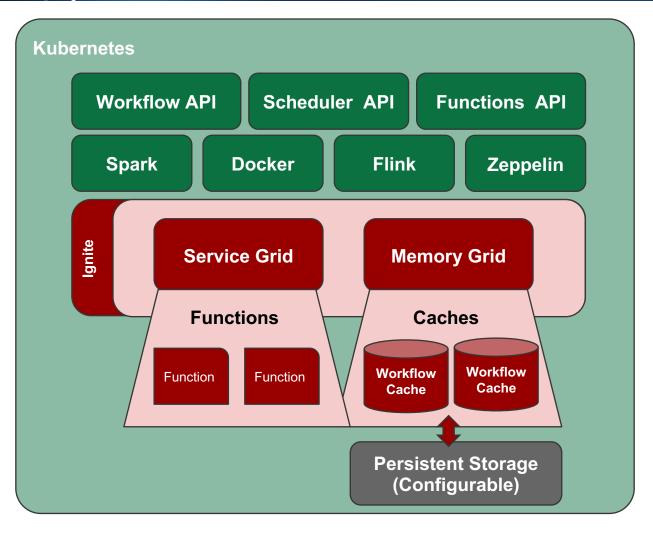


Approach V2

How Now?



Approach V2

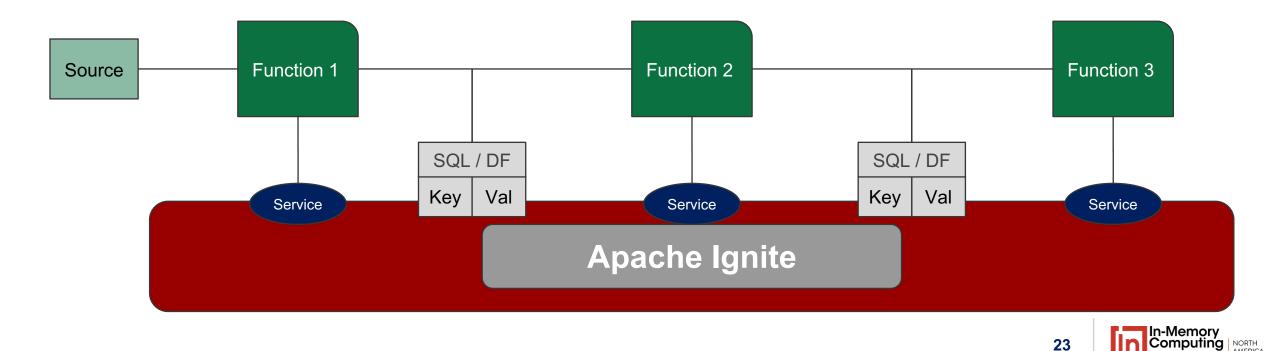


- Allows for very interactive workflows
- Workflows can be scheduled
- Each workflow is made up of functions (microservices)
- Each instance of a workflow workflow contains its own cache
- Zeppelin via the Ignite interpreter
- Workflows loaded data and also processed data



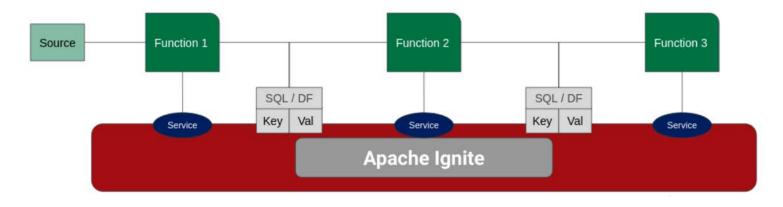
Approach V2 - The Workflow

- Source is the location the data is coming from
- The workflow is the data that goes from function to function
- Data stored as data frames can be queried by an API or another function



Approach – The Workflow

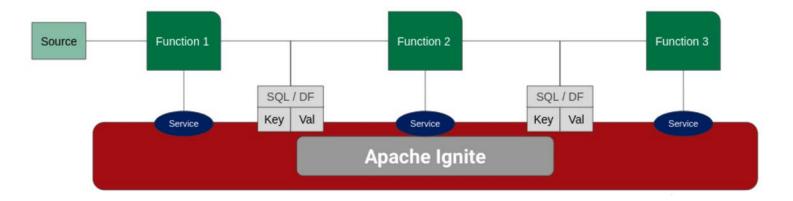
- Each function runs as a service using Service Grid
- The function receives input from any source
 - Kafka*
 - JDBC
 - Ignite Cache
- Once the function is applied, store the result into the Ignite cache store





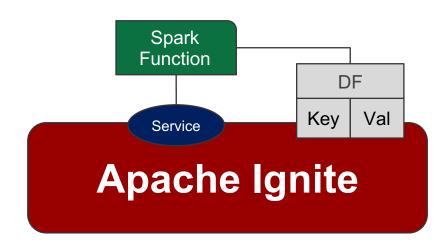
Workflow Capabilities

- Start / Stop / Restart
- Execute single functions within a workflow
- Pause execution to validate intermediate steps



Approach - Spark Based Functions - Persistence

- After each function has completed its computation the Spark DataFrame is stored via distributed storage
- Table name is stored as SQL_PUBLIC_<tableName>

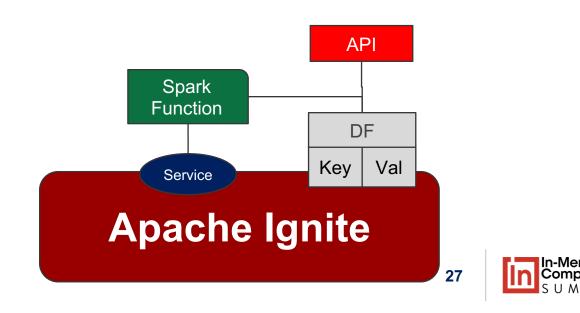


```
df.write
.format(FORMAT_IGNITE)
.option(OPTION_TABLE, tableName)
// table name to store data
.option(OPTION_CREATE_TABLE_PRIMARY_KEY_
FIELDS, "id")
.save()
```

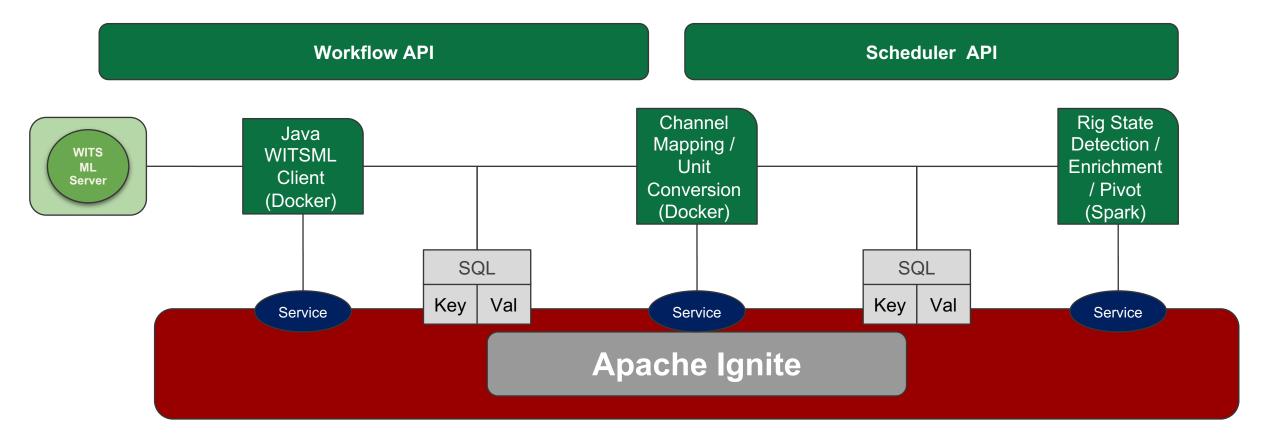
Approach – Intermediate Querying

- Once the data is in the cache, the data can be optionally persisted using the Ignite persistence module
- The data can be queried using the Ignite SQL grid module as well
- Allows for intermediate validation of the data as it proceeds through the workflow

val cache =
ignite.getOrCreateCache(cacheConfig)
val cursor = cache.query(new
SqlFieldsQuery(s"SELECT * FROM \$tableName
limit 20"))
val data = cursor.getAll



Approach - Applied to the Use Case



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V2 Achieved Requirements

Requirement		Achieved	Description	
1	Heterogeneous Data Ingest		Very flexible ingestFlexible transformations	
2	Robust Data Pipeline		Easy to debugEasy to modify	
3	Extensible Feature Engineering		Easy to addEasy to experiment	
4	Scalable		Scales upScales down	
5	Robust		Easy to debugReliable	



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Solution Benchmark Setup

- Dimension Tables already loaded
- 8 functions (6 wells of data 5.7 billion points)
 - Ingest / Parse WITSML
 - Null Value Handling
 - Interpolation
 - Depth Adjustments
 - Drill State Detection
 - Rig State Detection
 - Anomaly Detection
 - Pivot Dataset
- For V1 everything was implemented as a Spark application
- For V2 the computations remained close to their original format



Solution Comparison

V1 - Execute Time

• 9 Hours

Without WITSML Download

• 7 Hours

V2 - Execute Time

• 2 Hours

Without WITSML Download

• 22 minutes

19x Improvement V1 to V2



Lessons Learned

How Now?



Lessons Learned

- Apache Ignite is a great tool to speed up data processing without a wholesale replacement of technology
- Apache Ignite does have a learning curve, it is definitely worth doing an analysis beforehand to understand what it means to operationalize it
- Accelerating Hive via Ignite was not straightforward and, at times made it very difficult to debug the actual issues that we were facing
- Spatial querying, while great, is LGPL, so be aware of that before your specific implementation
- Understanding data locality in Ignite is crucial in larger data sets
- Ignite works very well inside of Kubernetes due to its peer-to-peer clustering mechanism
- The thin client JDBC driver does not have affinity awareness, so in multinode configurations, the thick client is preferred 33

What's Next

How Now?



What's Next

- Implementation of a UI on top of the computational framework
- Implementation of a standard set of "functions" that can be leveraged on top of the memory grid
- Implementation of streaming sources via Kafka Ignite Sink





Questions

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