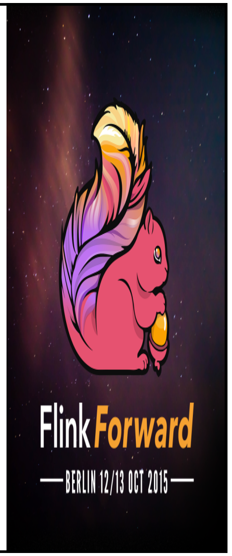
Flink vs. Spark

Flink Spark



Slim Baltagi @SlimBaltagi
Director of Big Data Engineering, Fellow
Capital One

Agenda

I. Motivation for this talk
II. Apache Flink vs. Apache Spark?
III. How Flink is used at Capital One?
IV. What are some key takeaways?

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I. Motivation for this talk

1. Marketing fluff
2. Confusing statements
3. Burning questions & incorrect or outdated answers
4. Helping others evaluating Flink vs. Spark

Capital One 3

1. Marketing fluff

Capital One 4

1. Marketing fluff

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2. Confusing statements

- "Spark is already an excellent piece of software and is advancing very quickly. No vendor — no new project — is likely to catch up. Chasing Spark would be a waste of time, and would delay availability of real-time analytic and processing services for no good reason." Source: MapReduce and Spark, Mike Olson. Chief Strategy Officer, Cloudera. December, 30th 2013 http://vision.cloudera.com/mapreduce-spark/
- "Goal: one engine for all data sources, workloads and environments." Source: Slide 15 of 'New Directions for Apache Spark in 2015', Matei Zaharia. CTO, Databricks. February 20th , 2015. http://www.slideshare.net/databricks/new-directions-for-apache-spark-in-2015

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3. Burning questions & incorrect or outdated answers

- "Projects that depend on smart optimizers rarely work well in real life." Curt Monash, Monash Research. January 16, 2015http://www.computerworld.com/article/2871760/big-data-digest-how-many-hadoops-do-we-really-need.html
- "Flink is basically a Spark alternative out of Germany, which I've been dismissing as unneeded". Curt Monash, Monash Research, March 5, 2015. http://www.dbms2.com/2015/03/05/cask-and-cdap/
- "Of course, this is all a bullish argument for Spark (or Flink, if I'm wrong to dismiss its chances as a Spark competitor)." Curt Monash, Monash Research, September 28, 2015. http://www.dbms2.com/2015/09/28/the-potential-significance-of-cloudera-kudu/

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3. Burning questions & incorrect or outdated answers

- "The benefit of Spark's micro-batch model is that you get full fault-tolerance and "exactly-once" processing for the entire computation, meaning it can recover all state and results even if a node crashes. Flink and Storm don't provide this…" Matei Zaharia. CTO, Databricks. May 2015http://www.kdnuggets.com/2015/05/interview-matei-zaharia-creator-apache-spark.html
- "I understand Spark Streaming uses micro-batching. Does this increase latency? While Spark does use a micro-batch execution model, this does not have much impact on applications…" http://spark.apache.org/faq.html

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4. Help others evaluating Flink vs. Spark

- Besides the marketing fluff, the confusing statements, the incorrect or outdated answers to burning questions, the little information on the subject of Flink vs. Spark is available piecemeal!
- While evaluating different stream processing tools at Capital One, we built a framework listing categories and over 100 criteria to assess these stream processing tools.
- In the next section, I'll be sharing this framework and use it to compare Spark and Flink on a few key criteria.
- We hope this will be beneficial to you as well when selecting Flink and/or Spark for stream processing.

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Agenda

I. Motivation for this talk

II. Apache Flink vs. Apache Spark?

III. How Flink is used at Capital One?

IV. What are some key takeaways?

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II. Apache Flink vs. Apache Spark?

1. What is Apache Flink?
2. What is Apache Spark?
3. Framework to evaluate Flink and Spark
4. Flink vs. Spark on a few key criteria
5. Future work

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1.What is Apache Flink?

Flink

- Squirrel: Animal. In harmony with other animals in the Hadoop ecosystem (Zoo): elephant, pig, python, camel,...
- Squirrel: reflects the meaning of the word 'Flink': German for "nimble, swift, speedy" which are also characteristics of the squirrel.
- Red color. In harmony with red squirrels in Germany to reflect its root at German universities
- Tail: colors matching the ones of the feather symbolizing the Apache Software Foundation. Commitment to build Flink in the open source!?

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1.What is Apache Flink?

- “Apache Flink is an open source platform for distributed stream and batch data processing.” https://flink.apache.org/
- See also the definition in Wikipedia:https://en.wikipedia.org/wiki/Apache_Flink

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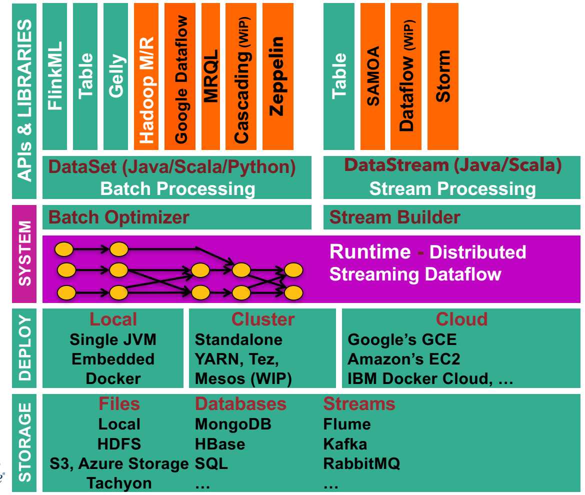
1.What is Apache Flink?



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2. What is Apache Spark?

- “Apache Spark™ is a fast and general engine for large-scale data processing.” http://spark.apache.org/
- See also definition in Wikipedia: https://en.wikipedia.org/wiki/Apache_Spark
- Logo was picked to reflect Lightning-fast cluster computing

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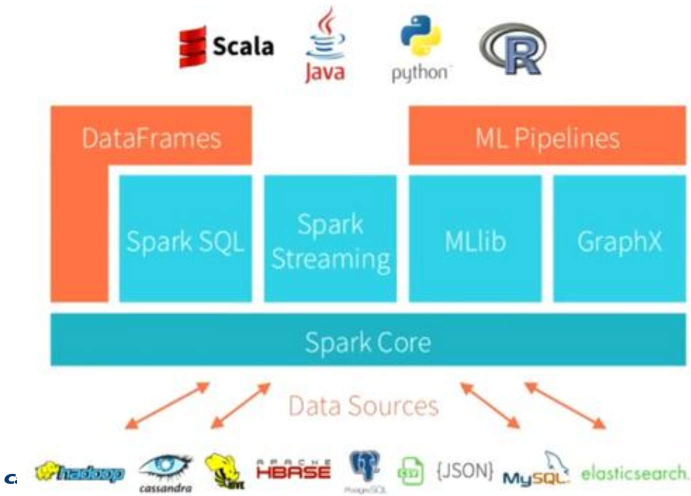
2. What is Apache Spark?



3. Framework to evaluate Flink and Spark

1. Background
2. Fit-for-purpose Categories
3. Organizational-fit Categories
4. Miscellaneous/Other Categories

1. Background

1.1 Definition
1.2 Origin
1.3 Maturity
1.4 Version
1.5 Governance model
1.6 License model

2. Fit-for-purpose Categories

2.1 Security
2.2 Provisioning & Monitoring Capabilities
2.3 Latency & Processing Architecture
2.4 State Management
2.5 Processing Delivery Assurance
2.6 Database Integrations, Native vs. Third party connector
2.7 High Availability & Resiliency
2.8 Ease of Development
2.9 Scalability
2.10 Unique Capabilities/Key Differentiators

2. Fit-for-purpose Categories

2.1 Security

2.1.1 Authentication, Authorization
2.1.2 Data at rest encryption (data persisted in the framework)
2.1.3 Data in motion encryption (producer ->framework -> consumer)
2.1.4 Data in motion encryption (inter-node communication)

2. Fit-for-purpose Categories

2.2 Provisioning & Monitoring Capabilities

2.2.1 Robustness of Administration
2.2.2 Ease of maintenance: Does technology provide configuration, deployment, scaling, monitoring, performance tuning and auditing capabilities?
2.2.3 Monitoring & Alerting
2.2.4 Logging
2.2.5 Audit
2.2.6 Transparent Upgrade: Version upgrade with minimum downtime

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2. Fit-for-purpose Categories

2.3 Latency & Processing Architecture

2.3.1 Supports tuple at a time, micro-batch, transactional updates and batch processing
2.3.2 Computational model
2.3.3 Ability to reprocess historical data from source
2.3.4 Ability to reprocess historical data from native engine
2.3.5 Call external source (API/database calls)
2.3.6 Integration with Batch (static) source
2.3.7 Data Types (images, sound etc.)
2.3.8 Supports complex event processing and pattern detection vs. continuous operator model (low latency, flow control)

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2. Fit-for-purpose Categories

2.3 Latency & Processing Architecture

2.3.9 Handles stream imperfections (delayed)
2.3.10 Handles stream imperfections (out-of-order)
2.3.11 Handles stream imperfections (duplicate)
2.3.12 Handles seconds, sub-second or millisecond event processing (Latency)
2.3.13 Compression
2.3.14 Support for batch analytics
2.3.15 Support for iterative analytics (machine learning, graph analytics)
2.3.16 Data lineage provenance (origin of the owner)
2.3.17 Data lineage (accelerate recovery time)

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2. Fit-for-purpose Categories

2.4 State Management

2.4.1 Stateful vs. Stateless
2.4.2 Is stateful data Persisted locally vs. external database vs. Ephemeral
2.4.3 Native rolling, tumbling and hopping window support
2.4.4 Native support for integrated data store

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2. Fit-for-purpose Categories

2.5 Processing Delivery Assurance

2.5.1 Guarantee (At least once)
2.5.2 Guarantee (At most once)
2.5.3 Guarantee (Exactly once)
2.5.4 Global Event order guaranteed
2.5.5 Guarantee predictable and repeatable outcomes(deterministic or not)

2. Fit-for-purpose Categories

2.6 Database Integrations, Native vs. Third party connector

2.6.1 NoSQL database integration
2.6.2 File Format (Avro, Parquet and other format support)
2.6.3 RDBMS integration
2.6.4 In-memory database integration/ Caching integration

2. Fit-for-purpose Categories

2.7 High Availability & Resiliency

2.7.1 Can the system avoid slowdown due to straggler node
2.7.2 Fault-Tolerance (does the tool handle node/operator/messaging failures without catastrophically failing)
2.7.3 State recovery from in-memory
2.7.4 State recovery from reliable storage
2.7.5 Overhead of fault tolerance mechanism (Does failure handling introduce additional latency or negatively impact throughput?)
2.7.6 Multi-site support (multi-region)
2.7.7 Flow control: backpressure tolerance from slow operators or consumers
2.7.8 Fast parallel recovery vs. replication or serial recovery on one node at a time

2. Fit-for-purpose Categories

2.8 Ease of Development

2.8.1 SQL Interface
2.8.2 Real-Time debugging option
2.8.3 Built-in stream oriented abstraction (streams, windows, operators , iterators - expressive APIs that enable programmers to quickly develop streaming data applications)
2.8.4 Separation of application logic from fault tolerance
2.8.5 Testing tools and framework
2.8.6 Change management: multiple model deployment (E.g. separate cluster or can one create multiple independent redundant streams internally)
2.8.7 Dynamic model swapping (Support dynamic updating of operators/topology/DAG without restart or service interruption)
2.8.8 Required knowledge of system internals to develop an application
2.8.9 Time to market for applications
2.8.10 Supports plug-in of external libraries
2.8.11 API High Level/Low Level
2.8.12 Easy to configuration
2.8.13 GUI based abstraction layer

2. Fit-for-purpose Categories

2.9 Scalability

2.9.1 Supports multi-thread across multiple processors/cores
2.9.2 Distributed across multiple machines/servers
2.9.3 Partition Algorithm
2.9.4 Dynamic elasticity - Scaling with minimum impact/ performance penalty
2.9.5 Horizontal scaling with linear performance/throughput
2.9.6 Vertical scaling (GPU)
2.9.7 Scaling without downtime

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3. Organizational-fit Categories

3.1 Maturity & Community Support
3.2 Support Languages for Development
3.3 Cloud Portability
3.4 Compatibility with Native Hadoop Architecture
3.5 Adoption of Community vs. Enterprise Edition
3.6 Integration with Message Brokers

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3. Organizational-fit Categories

3.1 Maturity & Community Support

3.1.1 Open Source Support
3.1.2 Maturity (years)
3.1.3 Stable
3.1.4 Centralized documentation with versioning support
3.1.5 Documentation of programming API with good code examples
3.1.6 Centralized visible roadmap
3.1.7 Community acceptance vs. Vendor driven
3.1.8 Contributors

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3. Organizational-fit Categories

3.2 Support Languages for Development

3.2.1 Language technology was built on
3.2.2 Language supported to access technology

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3. Organizational-fit Categories

3.3 Cloud Portability

3.3.1 Ease of migration between cloud vendors
3.3.2 Ease of migration between on premise to cloud
3.3.3 Ease of migration from on premise to complete cloud services
3.3.4 Cloud compatibility (AWS, Google, Azure)

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3. Organizational-fit Categories

3.4 Compatibility with Native Hadoop Architecture

3.4.1 Implement on top of Hadoop YARN vs. Standalone
3.4.2 Mesos
3.4.3 Coordination with Apache Zookeeper

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3. Organizational-fit Categories

3.5 Adoption of Community vs. Enterprise Edition

3.5.1 Open Source
3.5.2 Enterprise Support

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4. Miscellaneous/Other Categories

4.1 Best Suited for
4.2 Key use case scenarios
4.3 Companies using technology

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4. Flink vs. Spark on a few key criteria

1. Streaming Engine
2. Iterative Processing
3. Memory Management
4. Optimization
5. Configuration
6. Tuning
7. Performance

4.1. Streaming Engine

- Many time-critical applications need to process large streams of live data and provide results in real-time. For example:
  - ✓Financial Fraud detection
  - ✓Financial Stock monitoring
  - ✓Anomaly detection
  - ✓Traffic management applications
  - ✓Patient monitoring
  - ✓Online recommenders
- Some claim that 95% of streaming use cases can be handled with micro-batches!? Really!!!

4.1. Streaming Engine

Spark

- Spark's micro-batching isn't good enough!
- Ted Dunning, Chief Applications Architect at MapR, talk at the Bay Area Apache Flink Meetup on August 27, 2015

http://www.meetup.com/Bay-Area-Apache-Flink-Meetup/events/224189524/

- ✓Ted described several use cases where batch and micro batch processing is not appropriate and described why.
- ✓He also described what a true streaming solution needs to provide for solving these problems.
- ✓These use cases were taken from real industrial situations, but the descriptions drove down to technical details as well.

4.1. Streaming Engine

Flink

- "I would consider stream data analysis to be a major unique selling proposition for Flink. Due to its pipelined architecture, Flink is a perfect match for big data stream processing in the Apache stack." – Volker Markl

Ref.: On Apache Flink. Interview with Volker Markl, June 24th 2015
http://www.odbms.org/blog/2015/06/on-apache-flink-interview-with-volker-markl/

- Apache Flink uses streams for all workloads: streaming, SQL, micro-batch and batch. Batch is just treated as a finite set of streamed data. This makes Flink the most sophisticated distributed open source Big Data processing engine (not the most mature one yet!).

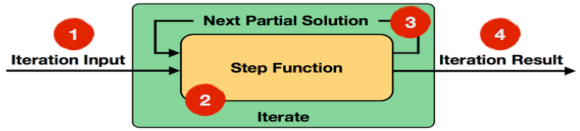
4.2. Iterative Processing

Why Iterations? Many Machine Learning and Graph processing algorithms need iterations! For example:

- **Machine Learning Algorithms**
  - ✓Clustering (K-Means, Canopy, …)
  - ✓Gradient descent (Logistic Regression, Matrix Factorization)
- **Graph Processing Algorithms**
  - ✓Page-Rank, Line-Rank
  - ✓Path algorithms on graphs (shortest paths, centralities, …)
  - ✓Graph communities / dense sub-components
  - ✓Inference (Belief propagation)

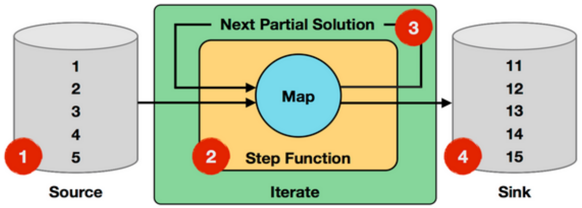
4.2. Iterative Processing

- **Flink's API offers two dedicated iteration operations: Iterate and Delta Iterate.**
- **Flink executes programs with iterations as cyclic data flows: a data flow program (and all its operators) is scheduled just once.**
- **In each iteration, the step function consumes the entire input (the result of the previous iteration, or the initial data set), and computes the next version of the partial solution**



4.2. Iterative Processing

- **Delta iterations run only on parts of the data that is changing and can significantly speed up many machine learning and graph algorithms because the work in each iteration decreases as the number of iterations goes on.**



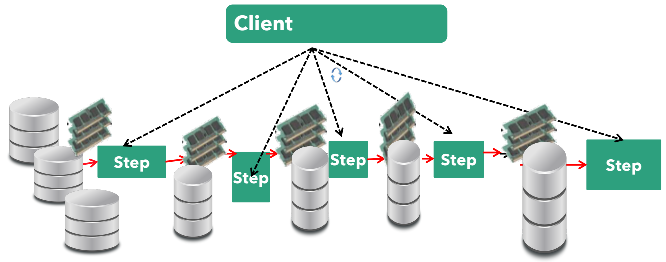
- **Documentation on iterations with Apache Flink**

http://ci.apache.org/projects/flink/flink-docs-master/apis/iterations.html

4.2. Iterative Processing

Non-native iterations in Hadoop and Spark are implemented as regular for-loops outside the system.

```
for (int i = 0; i < maxIterations; i++) {
     // Execute MapReduce job
}
```



4.2. Iterative Processing

- Although Spark caches data across iterations, it still needs to schedule and execute a new set of tasks for each iteration.
- Spinning Fast Iterative Data Flows - Ewen et al. 2012 : http://vldb.org/pvldb/vol5/p1268_stephanewen_vldb2012.pdf The Apache Flink model for incremental iterative dataflow processing. Academic paper.
- Recap of the paper, June 18, 2015http://blog.acolyer.org/2015/06/18/spinning-fast-iterative-dataflows/
- Documentation on iterations with Apache Flinkhttp://ci.apache.org/projects/flink/flink-docs-master/apis/iterations.html

4.3. Memory Management

- Question: Spark vs. Flink low memory available?
- Question answered on stackoverflow.comhttp://stackoverflow.com/questions/31935299/spark-vs-flink-low-memory-available
- The same question still unanswered on the Apache Spark Mailing List!! http://apache-flink-user-mailing-list-archive.2336050.n4.nabble.com/spark-vs-flink-low-memory-available-td2364.html

4.3. Memory Management

Features:

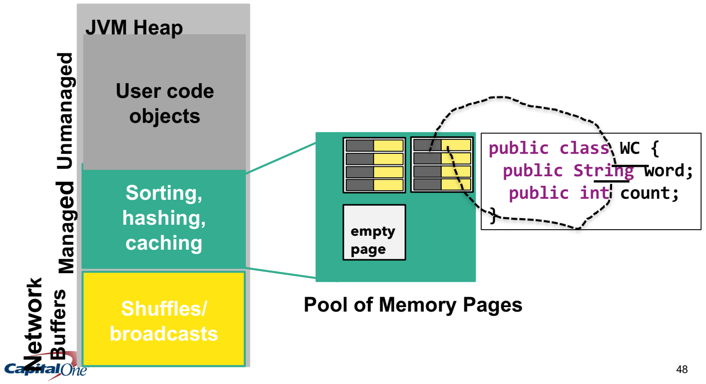
- C++ style memory management inside the JVM
- User data stored in serialized byte arrays in JVM
- Memory is allocated, de-allocated, and used strictly using an internal buffer pool implementation.

Advantages:

1. Flink will not throw an OOM exception on you.
2. Reduction of Garbage Collection (GC)
3. Very efficient disk spilling and network transfers
4. No Need for runtime tuning
5. More reliable and stable performance

4.3. Memory Management

Flink contains its own memory management stack. To do that, Flink contains its own type extraction and serialization components.



4.3. Memory Management

Flink

- Peeking into Apache Flink's Engine Room - by Fabian Hüske, March 13, 2015 http://flink.apache.org/news/2015/03/13/peeking-into-Apache-Flinks-Engine-Room.html
- Juggling with Bits and Bytes - by Fabian Hüske, May 11,2015 https://flink.apache.org/news/2015/05/11/Juggling-with-Bits-and-Bytes.html
- Memory Management (Batch API) by Stephan Ewen- May 16, 2015https://cwiki.apache.org/confluence/pages/viewpage.action?pageId=53741525
- Flink added an Off-Heap option for its memory management component in Flink 0.10: https://issues.apache.org/jira/browse/FLINK-1320

4.3. Memory Management

Spark

- Compared to Flink, Spark is still behind in custom memory management but is catching up with its project Tungsten for Memory Management and Binary Processing*:* manage memory explicitly and eliminate the overhead of JVM object model and garbage collection. April 28, 2014https://databricks.com/blog/2015/04/28/project-tungsten-bringing-spark-closer-to-bare-metal.html
- It seems that Spark is adopting something similar to Flink and the initial Tungsten announcement read almost like Flink documentation!!

4.4 Optimization

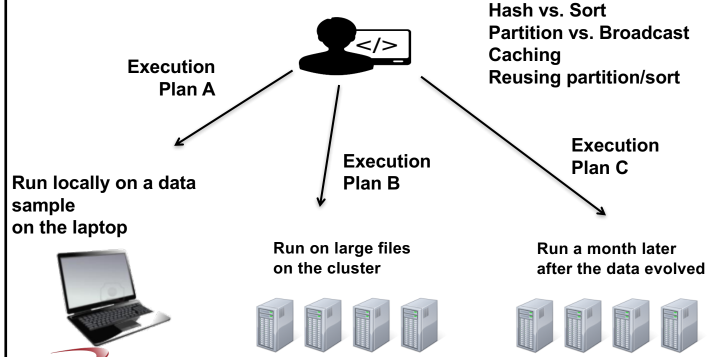
Flink

- Apache Flink comes with an optimizer that is independent of the actual programming interface.
- It chooses a fitting execution strategy depending on the inputs and operations.
- Example: the "Join" operator will choose between partitioning and broadcasting the data, as well as between running a sort-merge-join or a hybrid hash join algorithm.
- This helps you focus on your application logic rather than parallel execution.
- Quick introduction to the Optimizer: section 6 of the paper: 'The Stratosphere platform for big data analytics'http://stratosphere.eu/assets/papers/2014-VLDBJ_Stratosphere_Overview.pdf

4.4 Optimization

Flink

What is Automatic Optimization? The system's built-in optimizer takes care of finding the best way to execute the program in any environment.



4.4 Optimization

- In contrast to Flink's built-in automatic optimization, Spark jobs have to be manually optimized and adapted to specific datasets because you need to manually control partitioning and caching if you want to get it right.
- Spark SQL uses the Catalyst optimizer that supports both rule-based and cost-based optimization. References:
  - ✓ Spark SQL: Relational Data Processing in Sparkhttp://people.csail.mit.edu/matei/papers/2015/sigmod_spark_sql.pdf
  - ✓ Deep Dive into Spark SQL's Catalyst Optimizer https://databricks.com/blog/2015/04/13/deep-dive-into-spark-sqls-catalyst-optimizer.html

4.5. Configuration

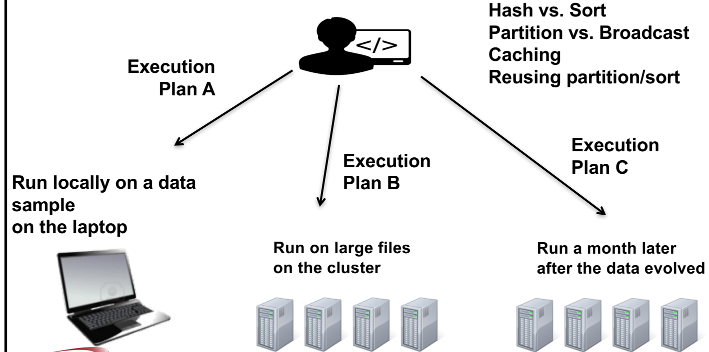
- Flink requires no memory thresholds to configure
  - ✓ Flink manages its own memory
- Flink requires no complicated network configurations
  - ✓ Pipelining engine requires much less memory for data exchange
- Flink requires no serializers to be configured
  - ✓ Flink handles its own type extraction and data representation

4.6. Tuning

- According to Mike Olsen, Chief Strategy Officer of Cloudera Inc. "Spark is too knobby — it has too many tuning parameters, and they need constant adjustment as workloads, data volumes, user counts change. Reference: http://vision.cloudera.com/one-platform/
- Tuning Spark Streaming for Throughput By Gerard Maas from Virdata. December 22, 2014 http://www.virdata.com/tuning-spark/
- Spark Tuning: http://spark.apache.org/docs/latest/tuning.html

4.6. Tuning

What is Automatic Optimization? The system's built-in optimizer takes care of finding the best way to execute the program in any environment.



7. Performance

- Why Flink provides a better performance?
  - ✓Custom memory manager
  - ✓Native closed-loop iteration operators make graph and machine learning applications run much faster.
  - ✓Role of the built-in automatic optimizer. For example: more efficient join processing.
  - ✓Pipelining data to the next operator in Flink is more efficient than in Spark.
- See benchmarking results against Flink here: http://www.slideshare.net/sbaltagi/why-apache-flink-is-the-4g-of-big-data-analytics-frameworks/87

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5. Future work

- The framework from Capital One to evaluate stream processing tools is being refined and will be published at http://www.capitalone.io/
- The assessment of the major open source streaming tools will be published as well as a live document continuously updated by Capital One.
- I also have a work in progress on comparing Spark and Flink as multi-purpose Big Data analytics framework
- Check my blog at http://www.SparkBigData.com
- Check also my slide decks on the Flink and Spark on http://slideshare.net/sbaltagi

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Agenda

I. Motivation for this talk
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III. How Flink is used at Capital One?

- We started our journey with Apache Flink at Capital One while researching and contrasting stream processing tools in the Hadoop ecosystem with a particular interest in the ones providing real-time stream processing capabilities and not just micro-batching as in Apache Spark.
- While learning more about Apache Flink, we discovered some unique capabilities of Flink which differentiate it from other Big Data analytics tools not only for Real-Time streaming but also for Batch processing.
- We evaluated Apache Flink Real-Time stream processing capabilities in a POC.

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III. How Apache Flink is used at Capital One?

- Where are we in our Flink journey?
  - ✓ Successful installation of Apache Flink 0.9 in our Pre-Production cluster running on CDH 5.4 with security and High Availability enabled.
  - ✓ Successful installation of Apache Flink 0.9 in a 10 nodes R&D cluster running HDP.
  - ✓ Successful completion of Flink POC for real-time stream processing. The POC proved that propriety system can be replaced by a combination of tools: Apache Kafka, Apache Flink, Elasticsearch and Kibana in addition to advanced real-time streaming analytics.

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III. How Apache Flink is used at Capital One?

- What are the opportunities for using Apache Flink at Capital One?
  1. Real-Time streaming analytics
  2. Cascading on Flink
  3. Flink's MapReduce Compatibility Layer
  4. Flink's Storm Compatibility Layer
  5. Other Flink libraries (Machine Learning and Graph processing) once they come out of beta.

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III. How Apache Flink is used at Capital One?

- Cascading on Flink:
  - ✓ First release of Cascading on Flink was announced recently by Data Artisans and Concurrent. It will be supported in upcoming Cascading 3.1.
  - ✓ Capital One is the first company verifying this release on real-world Cascading data flows with a simple configuration switch and no code re-work needed!
  - ✓ This is a good example of doing analytics on bounded data sets (Cascading) using a stream processor (Flink)
  - ✓ Expected advantages of performance boost and less resource consumption.
  - ✓ Future work is to support 'Driven' from Concurrent Inc. to provide performance management for Cascading data flows running on Flink.

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III. How Apache Flink is used at Capital One?

- Flink's compatibility layer for Storm:
  - ✓ We can execute existing Storm topologies using Flink as the underlying engine.
  - ✓ We can reuse our application code (bolts and spouts) inside Flink programs.
- Flink's libraries (FlinkML for Machine Learning and Gelly for Large scale graph processing) can be used along Flink's DataStream API and DataSet API for our end to end big data analytics needs.

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Agenda

I. Motivation for this talk
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III. What are some key takeaways?

- Neither Flink nor Spark will be the single analytics framework that will solve every Big Data problem!
- By design, Spark is not for real-time stream processing while Flink provides a true low latency streaming engine and advanced DataStream API for real-time streaming analytics.
- Although Spark is ahead in popularity and adoption, Flink is ahead in technology innovation and is growing fast.
- It is not always the most innovative tool that gets the largest market share, the Flink community needs to take into account the market dynamics!
- Both Spark and Flink will have their sweet spots despite their "Me too syndrome".

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Thanks!

- To all of you for attending!
- To Capital One for giving me the opportunity to meet with the growing Apache Flink family.
- To the Apache Flink community for the great spirit of collaboration and help.
- 2016 will be the year of Apache Flink!
- See you at FlinkForward 2016!

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