

# Big Data Processing Platforms/Systems



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AIM3 - Scalable Data Science

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# Introduction



- Collecting huge amounts of data
  - Data must be processed
  - Mostly analysts can make use out of data
  - Big data does not fit into MS Excel any more
- Big data platforms
  - Started with Google MapReduce paper (2004)
  - Followed by open source implementation and Hadoop ecosystem
  - Later platforms/systems focused on specialized use cases
    - Streaming
    - Graph
    - Machine Learning
    - Relational Processing

## BIG DATA LANDSCAPE 2017



# Timeline

2004

- Map-reduce

2006

- Hadoop

2008

- Hive

2009

- Graph-Lab

2010

- Pregel
- S4
- Storm
- Spark

2011

- Stratosphere

2012

- Impala
- Presto

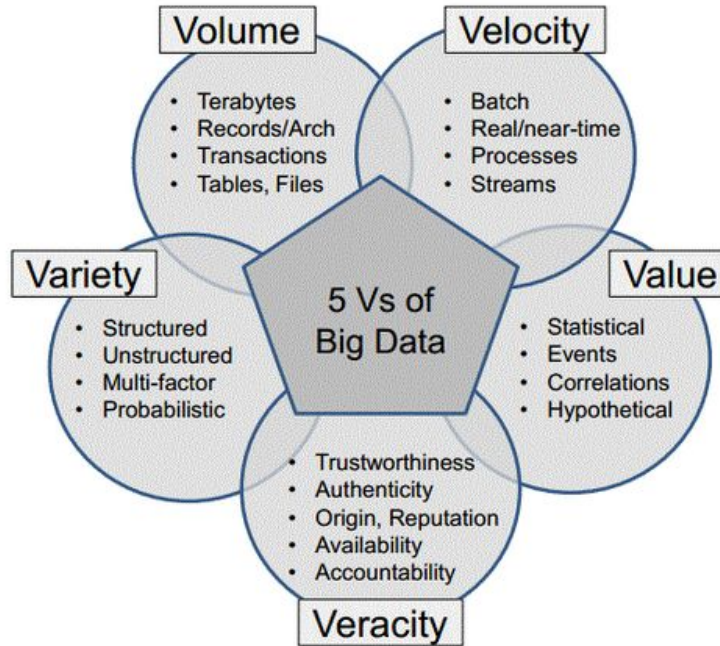
2014

- Spark SQL
- Flink

# Classification of Big Data Systems

- Data Type (record, graph, ...)
- Data Source (batch, stream)
- Processing Technique (data parallel, graph parallel, task parallel)
- Interactiveness (algorithms, ad-hoc queries)
- Licence (commercial, open-source, in-house solutions)

# Big Data - 5 Vs



[ Chandarana, Parth, and M. Vijayalakshmi. "Big data analytics frameworks.", 2014 ]

# Important factors

- Efficiency
- Scalability
- Fault tolerance
- Data I/O Performance
- Iterative Task Support
- Maturity
- Ease of use
- Programming languages supported
- Libraries

# Hadoop MapReduce



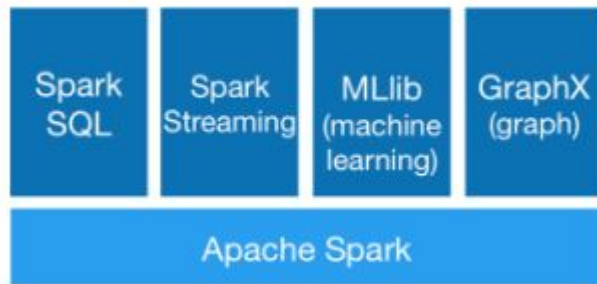
- Inspired by Google's MapReduce
- Processes data from HDFS (inspired by Google's GFS)
- Functional approach: *map()* and *reduce()* functions
- Fault tolerant: recomputes results from failed nodes
- Efficient: scales out well
- Difficult to implement complex algorithms
- Expensive for specific tasks (writes intermediate results to disk)



# Spark



- UC Berkeley, AMPLab 2009
- Both stream and batch processing
- Introduces RDD
- Extends MapReduce by operators (join, filter etc) and transformations
- Several APIs in various programming languages
- Several domain specific APIs
  - Relational Processing (Spark SQL)
  - Graph processing (GraphX)
  - Machine Learning algorithms
- Fault tolerance due to Lineage of RDD
- Efficient due to in-memory processing assumption
- Iterations: data stays in memory



[ <https://spark.apache.org> ]

# Flink



- TU Berlin (DIMA) and other research groups, 2009
- Both stream and batch processing
- Generalization of MapReduce
  - Introduces PACTs (operators such as join, group, etc)
- Provides several APIs in various programming languages
- Also provides domain specific APIs
  - Relational processing
  - Graph processing
  - Machine learning algorithms
- Fault tolerance by checkpointing
- Efficiency due to relational world optimizations
- Native iteration support (Bulk & delta)

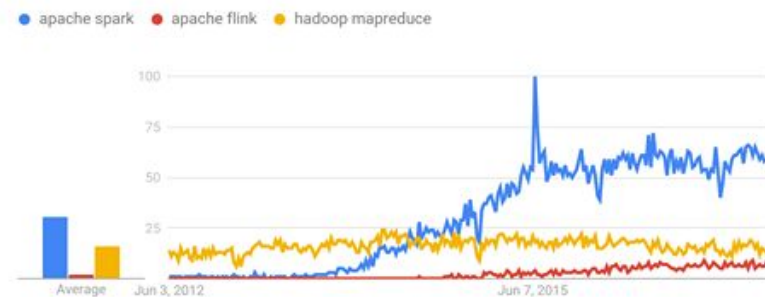
SQL

Table API

DataStream / DataSet API

Stateful Stream Processing

# Overview - Acceptance



	Spark	Flink	Hadoop
Open Source Contributors <sup>1</sup>	1082	319	98 (+ proprietary)
Conference	Spark Summit	Flink Forward	Hadoop Summit
Use cases	Amazon, NASA JPL, Yahoo!, ...	Alibaba, Bouygues, Zalando, ...	Yahoo!, Facebook, Twitter, ...
Meetup members	362,044	16,923	1,305,024
Meetups <sup>2</sup>	607	41	2,010

1 github.com statistics, accessed May 2017

2 meetup.com, accessed May 2017

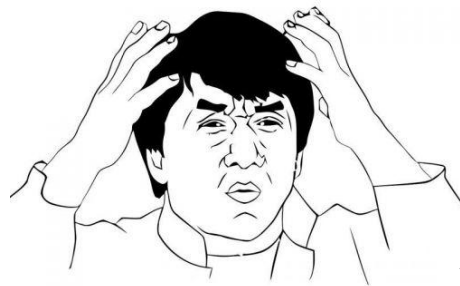
# Evaluation from Academia

- Spangenberg, Norman, Martin Roth, and Bogdan Franczyk. "Evaluating new approaches of big data analytics frameworks.", 2015
  - Flink faster for graph processing, data mining algorithms & relational queries
  - Spark faster for batch processing
- Marcu, Ovidiu-Cristian, et al. "Spark versus flink: Understanding performance in big data analytics frameworks.", 2016
  - Spark faster for large graph processing
  - Flink faster for batch and small graph processing (also using less resources)

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[ <http://i3.kym-cdn.com/photos/images/original/000/185/168/misc-jackie-chan-l.png> ]



# Evaluation from Industry (Zalando)

- Zalando chose Flink over Spark for their internal analytics platform

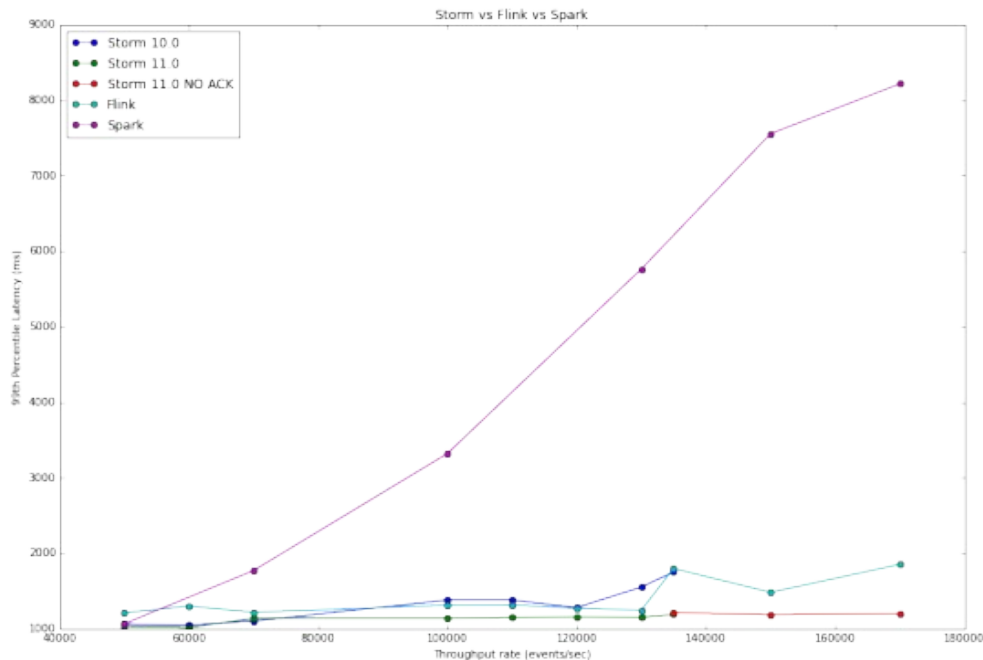
## Flink for Saiki

Why did we end up choosing Apache Flink to be Saiki's stream processing framework? Here are our reasons:

- Flink processes event streams at high throughputs with consistently low latencies. It provides an efficient, easy to use, key/value based state.  
Flink is a true stream processing framework. It processes events one at a time and each event has its own time window.
- Complex semantics can be easily implemented using Flink's rich programming model. Reasoning on the event stream is easier than in the case of micro-batching. Stream imperfections like out-of-order events can be easily handled using the framework's event time processing support.  
Flink's support is perceivably better than Spark's. We have direct contact to its developers and they are eager to improve their product and address user issues like ours. Flink originates from Berlin's academia, and a steady flow of graduates with Flink skills from Berlin's universities is almost guaranteed.

[ <https://tech.zalando.com/blog/apache-showdown-flink-vs.-spark> ]

# Evaluation from Industry (Yahoo!)

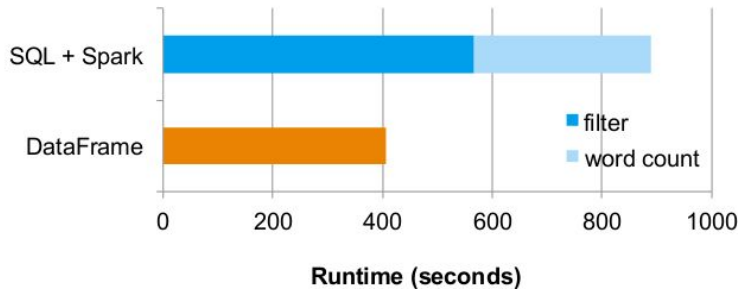


throughput vs latency

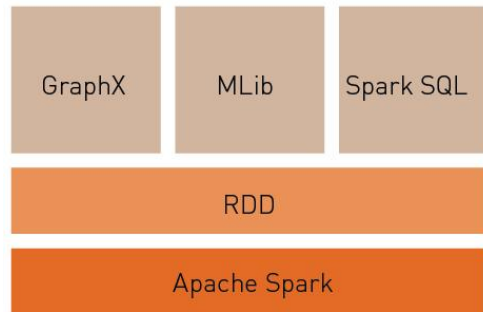
- Yahoo! compared Storm, Spark and Flink streaming
- For them, Flink and Storm performed better (probably due to Spark's micro-batching)

# Spark SQL

- Adds a new Abstraction on top of RDDs
- DataFrame API
  - Inspired by R's data frames and Python's Pandas
  - Fixed schema (supports complex data types)
  - Supports UDFs
  - Inherits fault tolerance from RDDs
- Outperforms SQL + native RDDs
- User friendlier API
  - Also suitable for machine learning algorithms



[ Spark SQL, SIGMOD 2015 ]

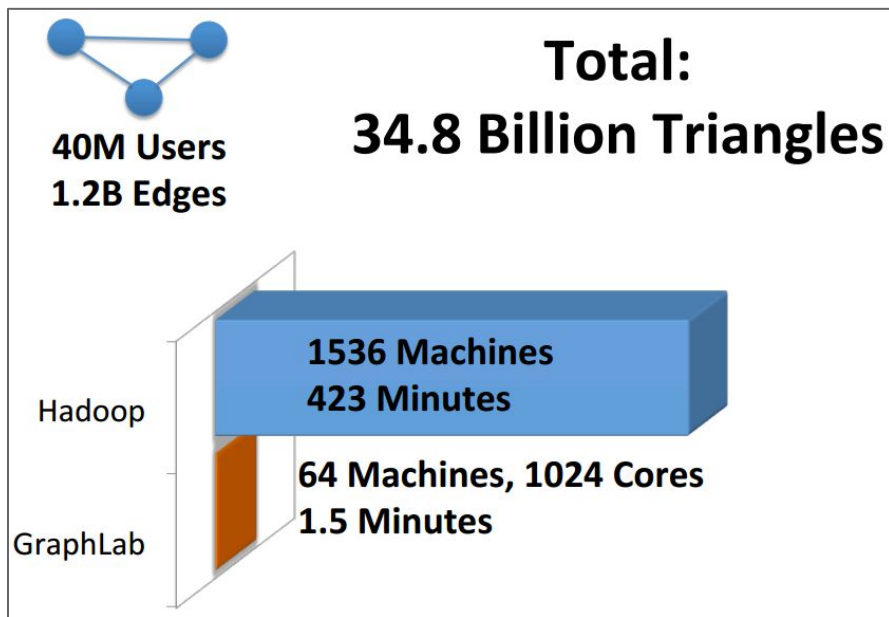




# GraphLab



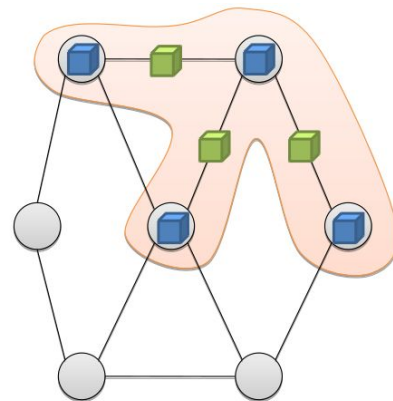
- Carnegie Mellon University 2010, Graphlab (now Turi acquired by Apple)
- Hadoop MapReduce not suited for graph computations
  - Data representation
  - Iterations
- Researchers needed faster graph computation for their experiments
- GraphLab introduces:
  - Data abstraction
  - Update functions
  - Scheduler
  - Consistency model



# GraphLab (cont'd)



- Introduces *SFrame* and *SGraph*
  - *SFrame* is an efficient disk-based data structure
  - *SGraph* is a graph abstraction that stores vertices and edges in *SFrames*
- “Think like a Vertex.” - Malewicz et al. (SIGMOD 2010)
  - Update functions are applied within the scope of a vertex
- Bulk vs asynchronous processing
  - Bulk: Computation in phases - Google Pregel 2010
  - Asynchronous - GraphLab 2010
    - Often race conditions
    - Difficult fault tolerance
    - Faster ML Algorithm convergence
- Ensures sequential consistency



[Carlos Guestrin 2013]

# Relational Processing Systems

System	Initiated by	Features	Suitable for
Apache Hive	Facebook	-HiveQL query language -Build on top of Hadoop MR	Interactive analytics
Apache Pig	Yahoo!	- PigLatin query language - Build on top of Hadoop MR	Algorithms
Impala	Cloudera	-SQL as interface -combines hadoop ecosystem with rel. proc. -multi user queries	Data warehousing
Presto	Facebook	-fast interactive queries -combines mult. sources	Data warehousing

# Google VS ASF

Google	Apache	Type
GFS	HDFS	Filesystem
MapReduce	Hadoop MapReduce	Processing
Pregel	Giraph	Graph processing
Big Table	HBase	Database
Borg	Mesos	Cluster management
Chubby	Zookeeper	Cluster management
Dremel	Drill	Query engine

[ <https://mapr.com/blog/5-google-projects-changed-big-data-forever/> ]

# Other aspects

- Michael Stonebraker, “One Size Fits All”: An Idea Whose Time Has Come and Gone
  - Need of specialized domain specific systems
- Frank McSherry, McSherry, Frank, Michael Isard, and Derek Gordon Murray. "Scalability! but at what COST?." HotOS. 2015.
  - Many tasks can be solved without big data platforms, if programmed correctly

# Conclusion

- Big data revolution started with Google's MapReduce paradigm
- Many big data systems live and evolve inside the Hadoop ecosystem
- Hadoop MapReduce was found to be unsuited for certain tasks
- Newer systems generalize MapReduce paradigm
  - More operators
  - More efficiency
  - Enhance user experience
  - Several domain specific libraries/APIs (relational, graph, ML)
- Newer systems often provide compatibility with older
- Open source systems are extensible
- Different big data systems are suited for different use cases
- Some problems can still be solved without big data systems

# Spark Demo

- Temperatures (remember homework?)

# Literature

- Marcu, Ovidiu-Cristian, et al. "Spark versus flink: Understanding performance in big data analytics frameworks." Cluster Computing (CLUSTER), 2016 IEEE International Conference on. IEEE, 2016.
- Spangenberg, Norman, Martin Roth, and Bogdan Franczyk. "Evaluating new approaches of big data analytics frameworks." International Conference on Business Information Systems. Springer International Publishing, 2015.
- Stonebraker, Michael, and Ugur Cetintemel. "" One size fits all": an idea whose time has come and gone." Data Engineering, 2005. ICDE 2005. Proceedings. 21st International Conference on. IEEE, 2005.
- McSherry, Frank, Michael Isard, and Derek Gordon Murray. "Scalability! but at what COST?." HotOS. 2015.