DATA TO INSIGHT CENTER
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Crossing Analytics Systems: Case for Integrated Provenance in Data Lakes

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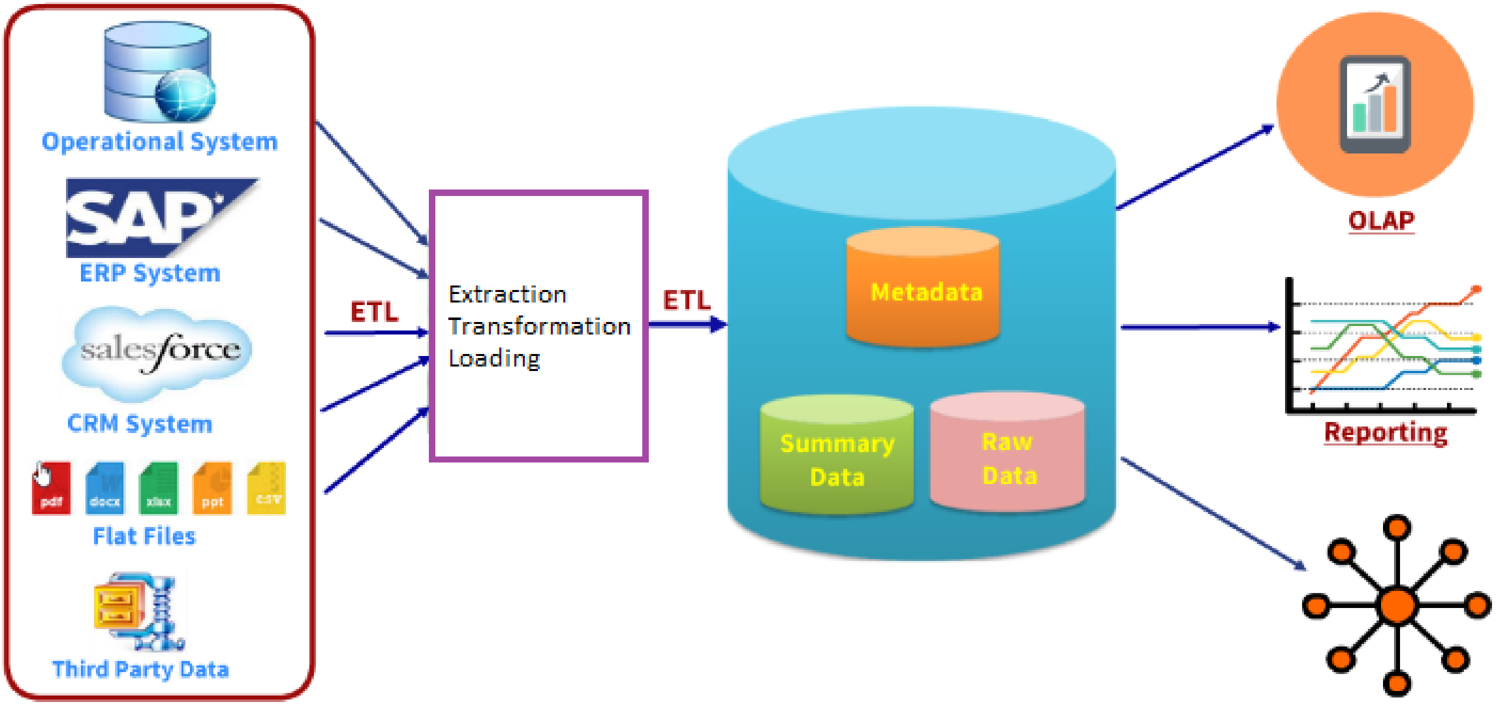
The **Data Lake** has arisen within last couple of years as conceptualization of data management framework with flexibility to support multiple data processing tools needed for truly Big Data analytics.

Data Warehouse

- Supports multidimensional analytical processing
  - Online Analytical Processing (OLAP) or Multidimensional OLAP
- Numeric facts (measures) categorized by dimensions creating vector space (OLAP cube).
- Interface is matrix interface like Pivot tables
- Schema is star schema, snowflake schema
- Storage is largely relational database

Data Warehouse Architecture



- ETL: Extraction, Transformation, Load

Credit: https://www.linkedin.com/topic/data-warehouse-architecture

Challenging the Warehouse: Big Data

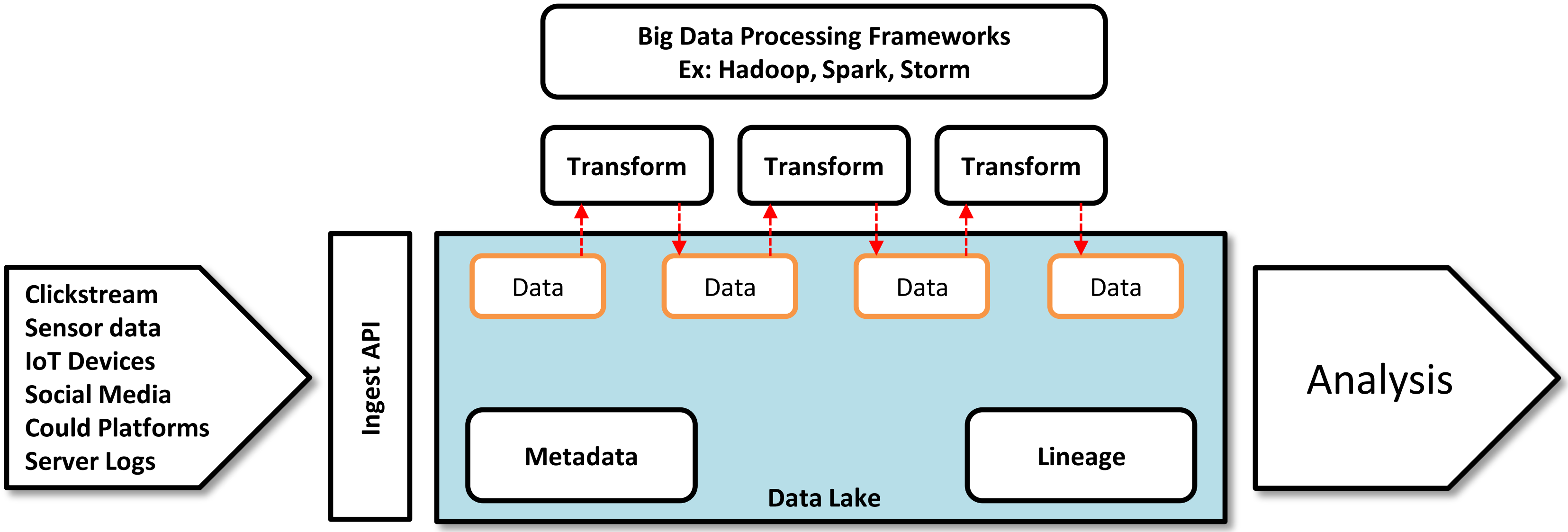
- From numerous sources
  - social media, sensor data, IoT devices, server logs, clickstream etc.
- Not all numeric (quantitative) thus differently structured
  - Structured, semi-structured, unstructured
- Continuously generated or archived

Suitability of Data Warehouse for Today's Big Data

- ETL imposes burden
  - Schema on write
  - Inflexibility/inefficiency at ingest time
  - Information loss upon schema translation
- Weak fit for popular Big Data analytical tools (e.g., Spark, Hadoop) and data serving platforms (e.g., HDFS, S3)

Data Lake

- A scalable storage infrastructure with no schema enforcement at ingest
- Data ingested in raw form: no loss
- Schema-on-read
- Integrated Transformations
  - With e.g., Hadoop, Spark



Data Lake Challenges

- Increased flexibility leads to harder manageability
  - Differently typed data can be easily dumped into the Data Lake
  - Data products can be in different stages of their lifecycle: raw, half processed, processed etc.
  - Can easily turn into “data swamps”
- Requires traceability!!..
  - Provenance can help

Data Provenance

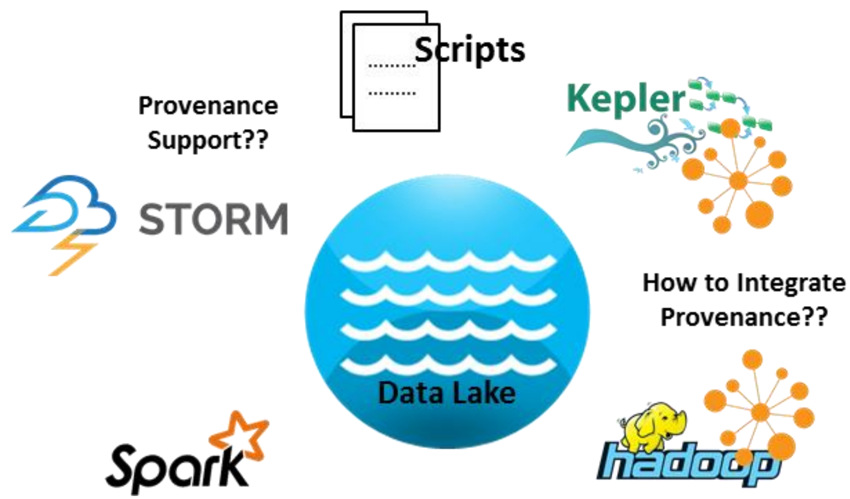
- Information about activities, entities and people who involved in producing a data product
- Standards
  – OPM
  – PROV
- If a Data Lake ensures that every data product’s provenance is in place starting from data product’s origin, critical traceability can be had

What provenance perspective could bring to a Data Lake?

- Track origins of data, chained transformations
- Contribute to reuse determinations of trust and quality
- React!! Minimally constrain what enters a Lake?

Challenges in Provenance Capturing

- Chains of Transformations
  - Different analytics systems: Hadoop, Spark etc.
- Need is end to end **integrated provenance across transformations**
- System specific provenance collection methods are less useful
  - Integration/stitching problems
  - E.g.: RAMP, HadoopProv for Hadoop

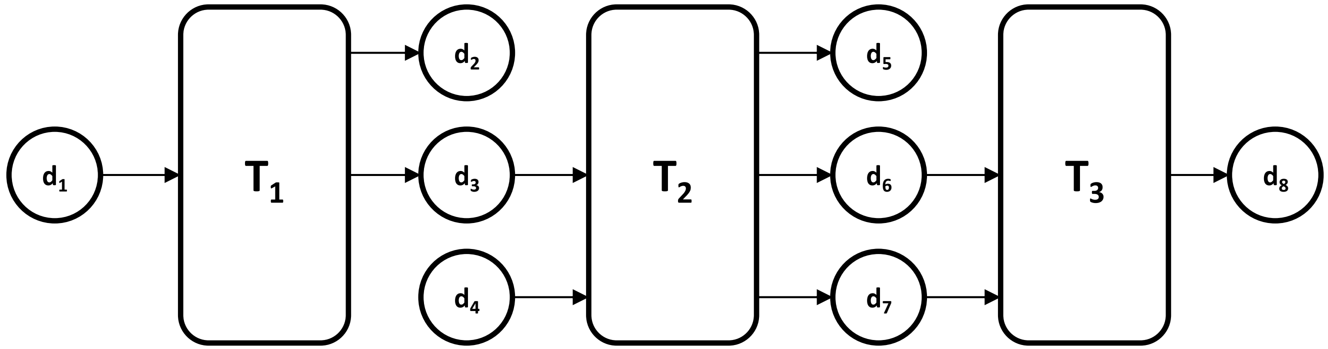


Solution to minimal lake governance

- All components in lake ***stream*** provenance to central provenance subsystem
  - Stores provenance for long term queries
  - Monitors provenance stream in real time
- ***Event*** in stream represented by ***edge*** in provenance graph
- Global lake wide policy: Uniform Persistent ID (PID) (Handle, UUIDs, DOIs) attached to all data objects in Data Lake
  - required to guarantee integrated provenance

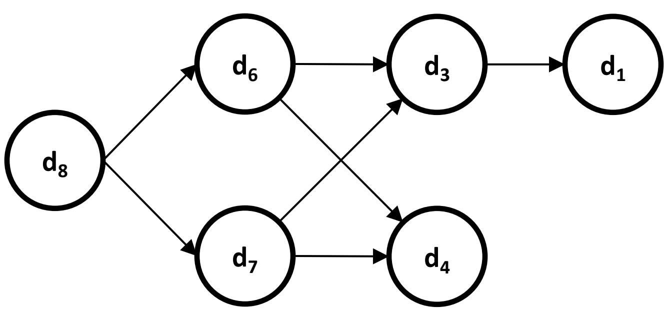
Model

Chain of transformations sharing Ids

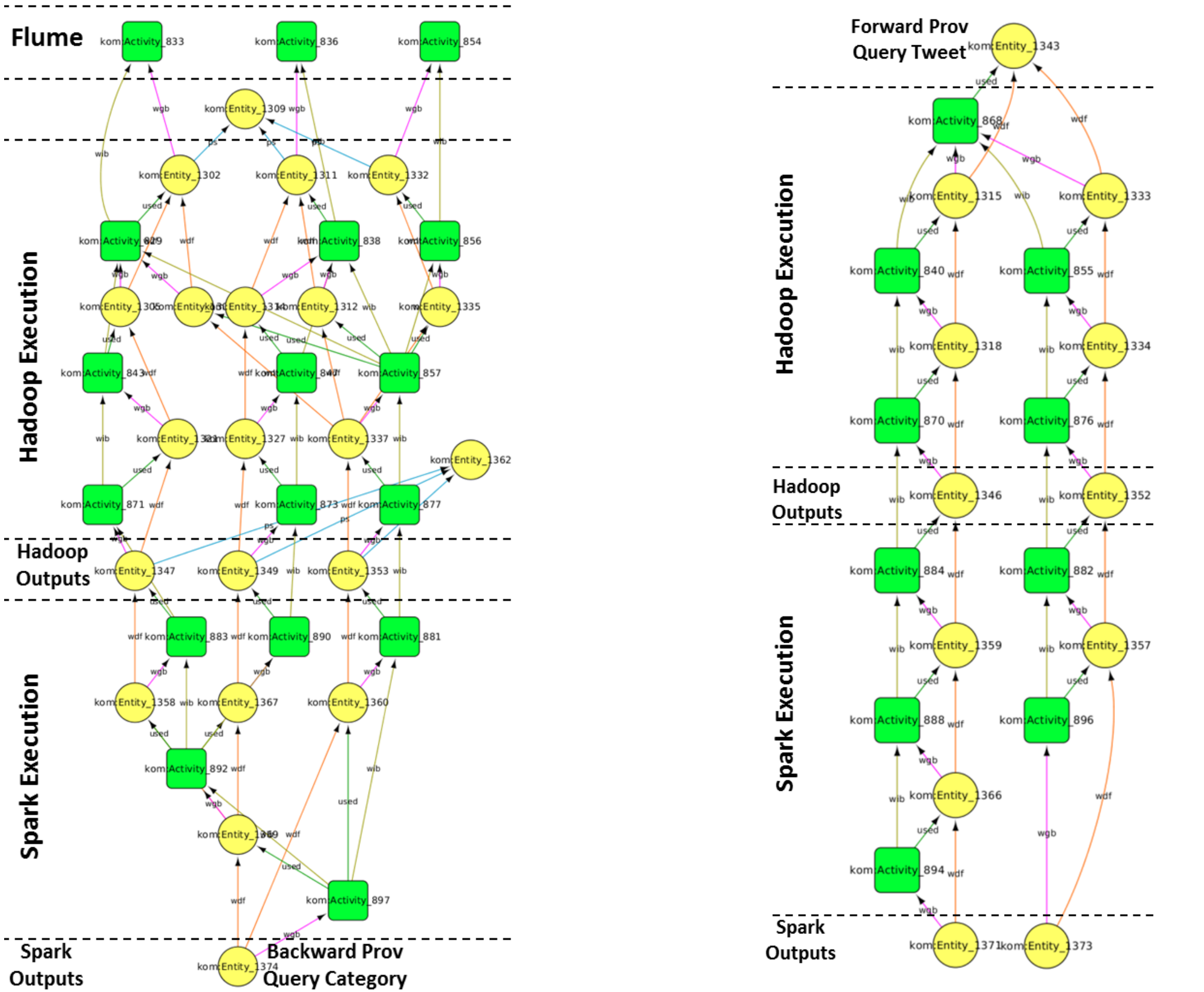


- PID assigned to all data objects
  - granularity
- Transformations T_1, T_2, and T_3
  - Distributed
  - May use different frameworks

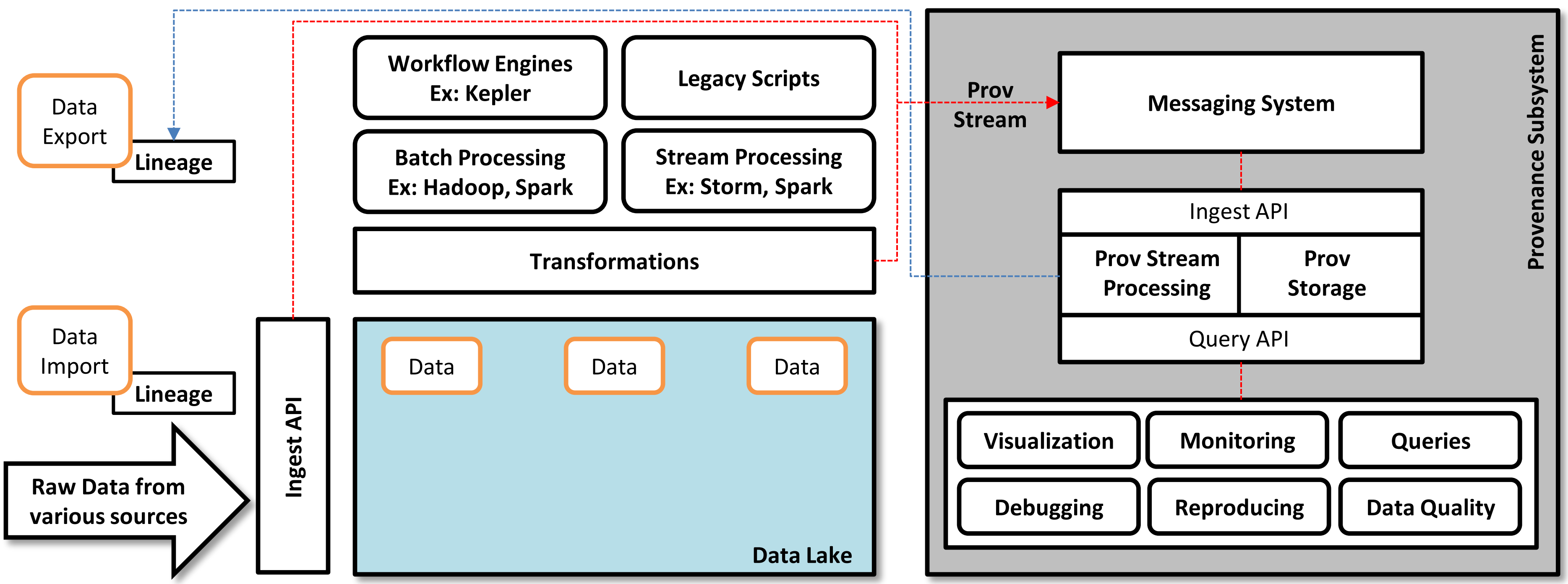
Backward provenance from central provenance store



Provenance traces integrate across systems of Data Lake

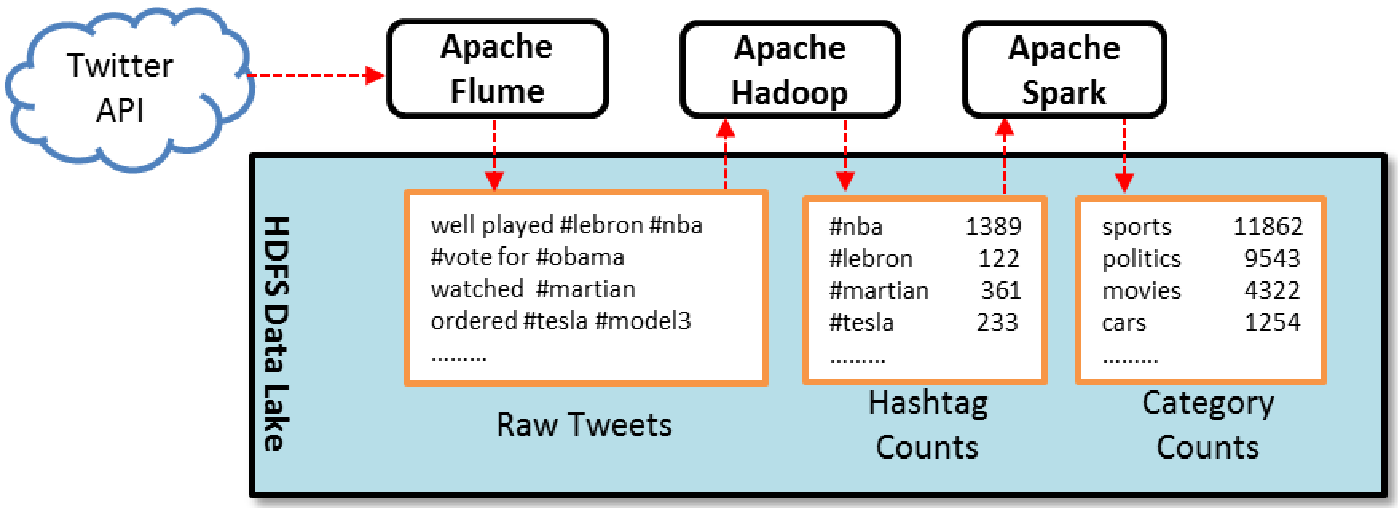


Reference Architecture



- Real-time provenance stream processing
- Stored provenance for long term usage

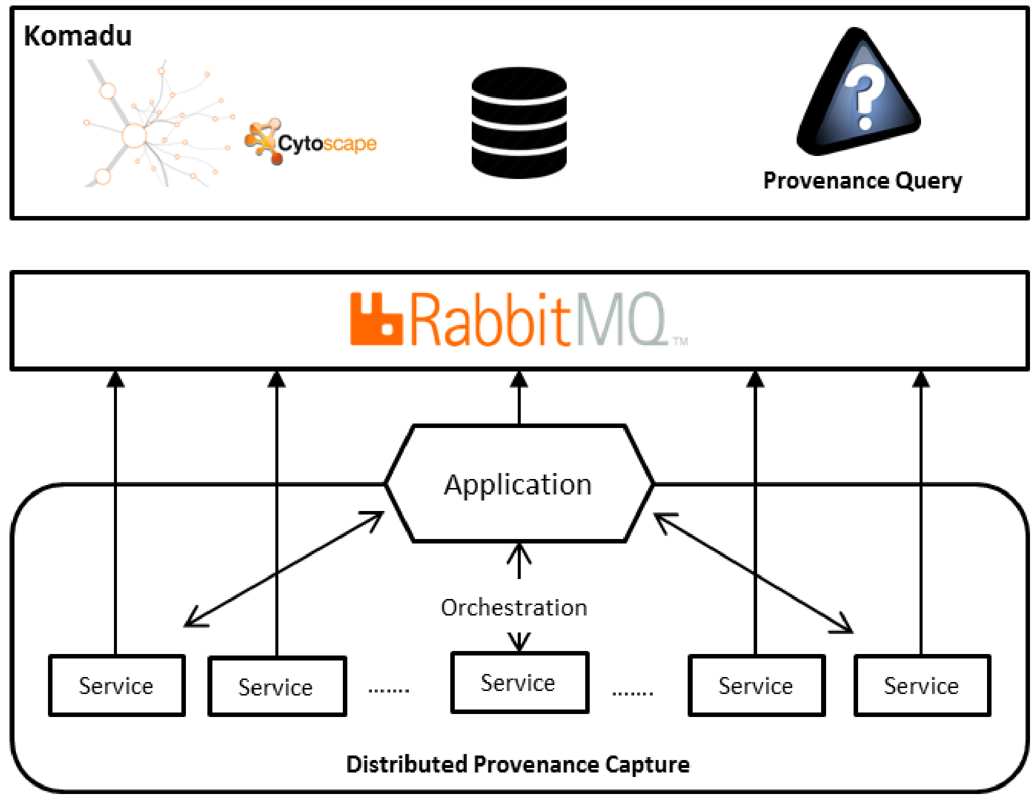
Prototype Use Case



- Different frameworks used
  - Flume: Captures tweets and write into HDFS
  - Hadoop Job: Computes hashtag counts
  - Spark Job: Computes category counts

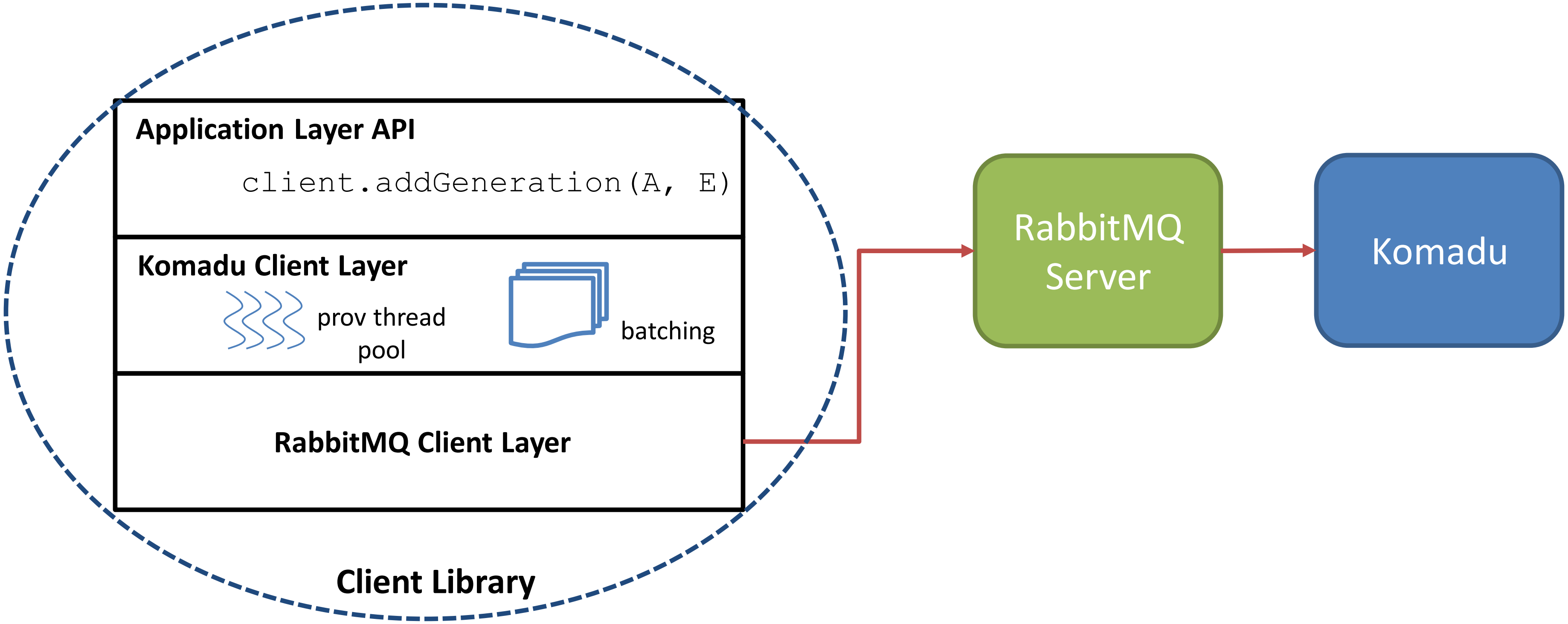
Central provenance store

- Uses Komadu
  - A distributed provenance collection tool
  - Visualization, Custom Queries



I. Suriarachchi, Q. Zhou and B. Plale (2015). Komadu: A Capture and Visualization System for Scientific Data Provenance. *Journal of Open Research Software* 3(1):e4

Client Library



- Log4j like API for provenance capture
- Dedicated thread pool in provenance layer
- Batching to minimize network overhead

Use case evaluation

- Flume, Hadoop and Spark jobs instrumented using Komadu client libraries
- Jobs stream provenance events into central provenance store (Komadu)
- Persistent IDs (UUID) assigned for each data object at entry to data lake; PID persists thereafter with data object

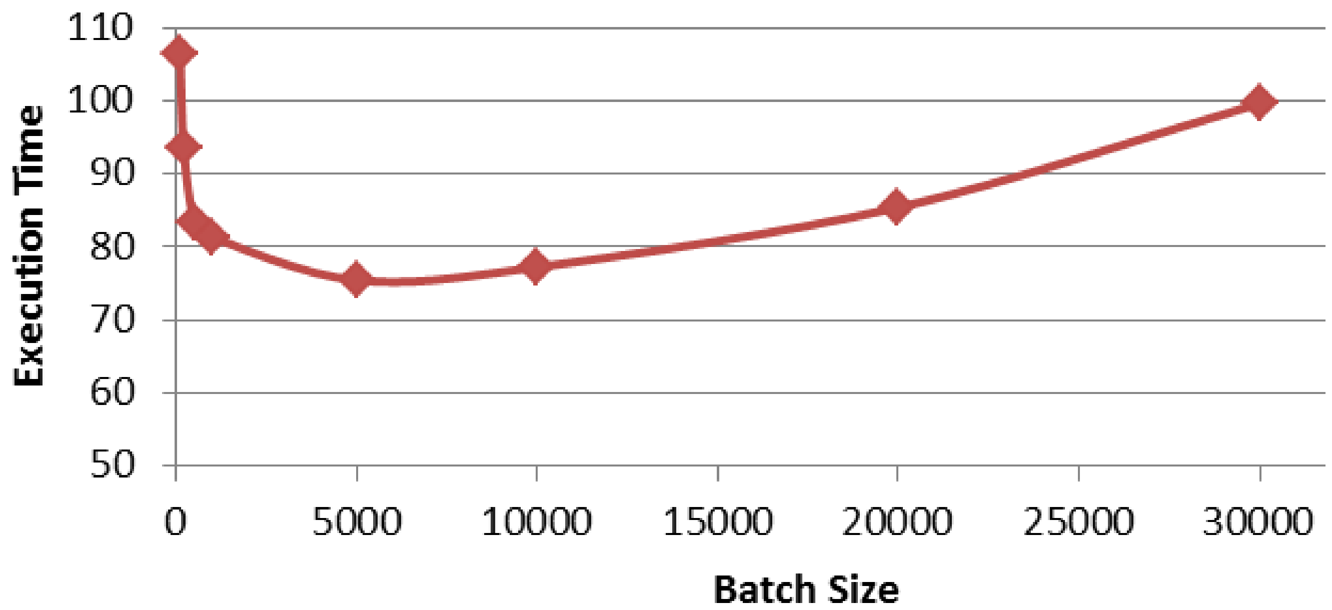
Use case evaluation: experimental environment

- 5 small VM instances, 2 2.5GhZ cores, 4 GB RAM, 50 GB local storage
- 4 VM instances used for HDFS cluster
- 3.23 GB Twitter data collected over 5 days running Flume on master node
- Hadoop and Spark set up on top of HDFS cluster
- Separate instance for RabbitMQ and Komadu

Use case evaluation: Metrics

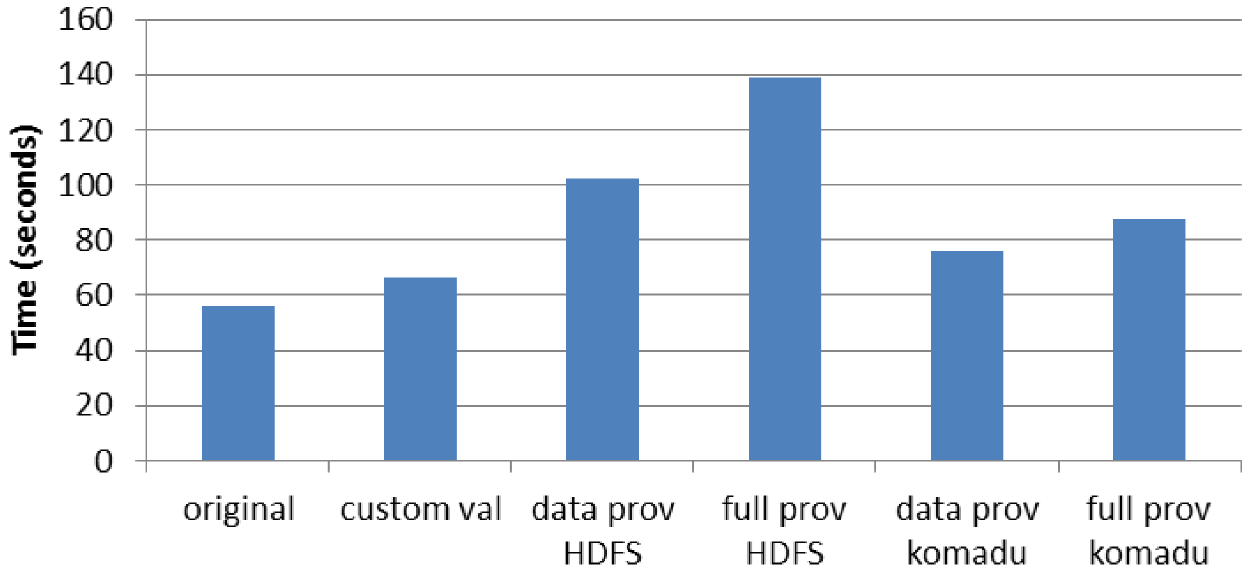
- Batch size:
  - impact of batch size on provenance capture efficiency. Measured by total execution time for Hadoop using provenance event batching mechanism in Komadu library
- Overhead of provenance capture:
  - Measured against total tool-specific execution time
  - measure overhead of customized value field (in key value pair)
  - Measure overhead of provenance capture for Hadoop and Spark

Batch Size Test



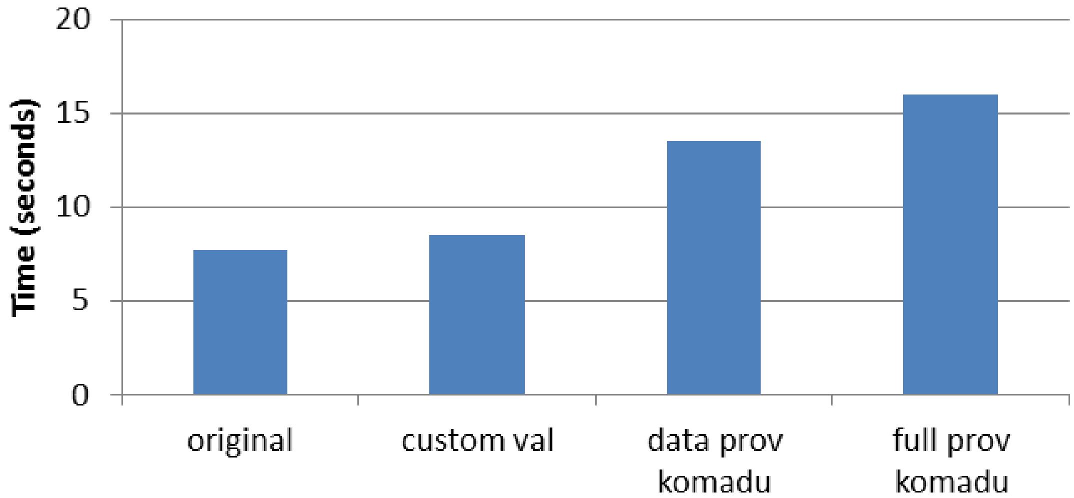
- Hadoop job execution times with varying batch sizes
- Optimal batch size: ~5000 KB

Overhead: Hadoop



- custom val: emits PID with key value pair
  as (#nba, <2, ***id***>) instead of (#nba, 2)
- data prov HDFS: writes provenance into HDFS, used by HadoopProv and RAMP

Overhead: Spark



- Higher provenance capture overhead compared to Hadoop

Future Work

- Performance overhead is prohibitively high
  - decouple PID assignment from execution? Examine granularity
- Live provenance stream processing for real time monitoring/reaction
- Explore minimal provenance at on-line rates and more comprehensive provenance at off-line rates

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