Advanced Data Processing Techniques for Distributed Applications and Systems

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What this lecture is about?

- Large-scale data analytics
- Advanced messaging
  - Apache Kafka
- Advanced data analytics with streaming data processing
  - Main common features
  - Stream processing examples with Apache Apex
- Advanced data analytics with workflows
  - Data pipeline with Beam
  - Complex workflows with Airflow

Analytics-as-a-service

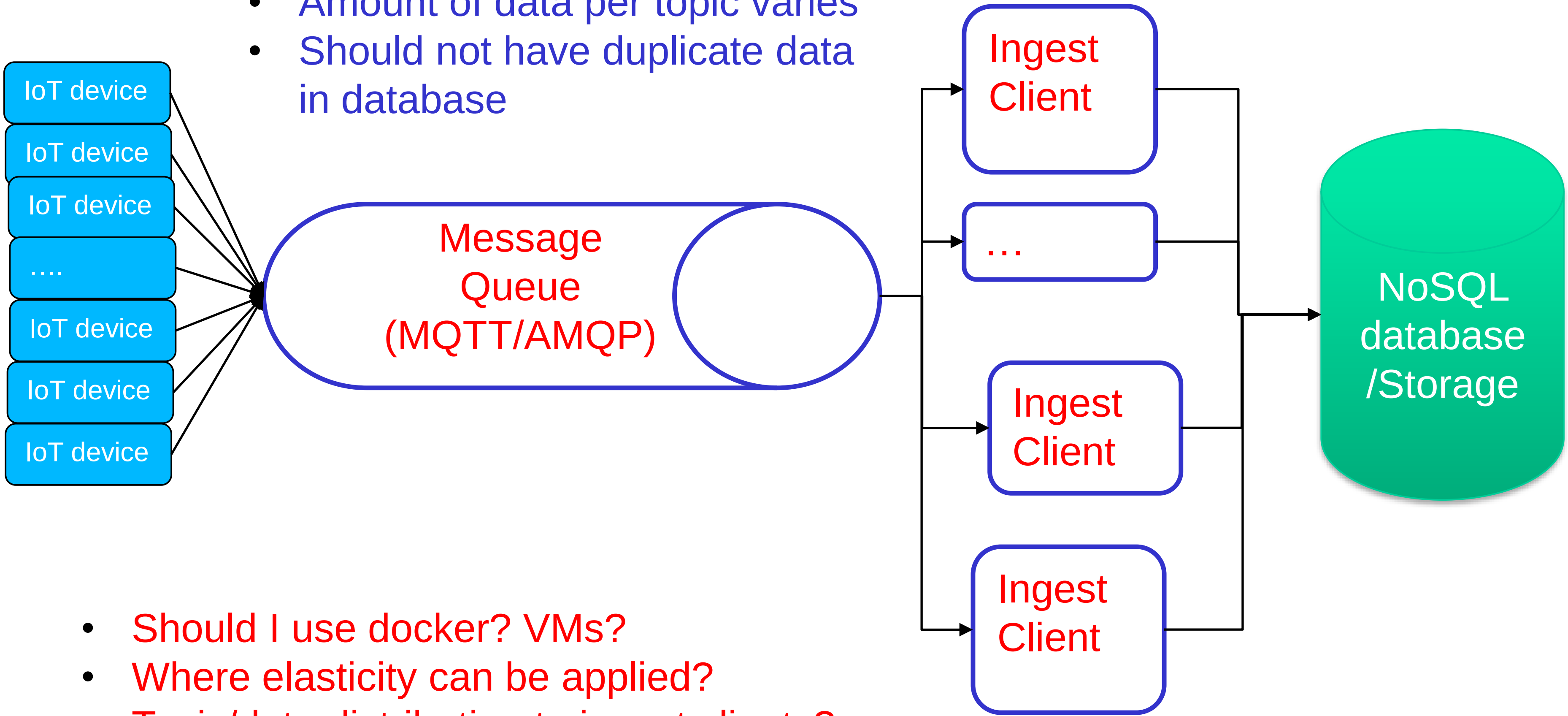
- Goals
  - Developers, Service Providers & Infrastructure Providers:
    - Understand and manage services systems
  - Service Providers:
    - Understand customers and optimize business
- Examples
  - Analyze monitoring information, logs, user activities, etc.
  - Predict usage trends for optimizing business
- Techniques → Big data analytics
  - Handle and process big data at rest and in motion

Key issues in large-scale data analytics

- Collect/produce messages from distributed application components and large-scale monitoring systems
  - Cross systems and cross layers
- Need scalable and reliable large-scale messaging broker systems
- Require workflow and stream data processing capabilities
- Integrate with various different types of services and data sources

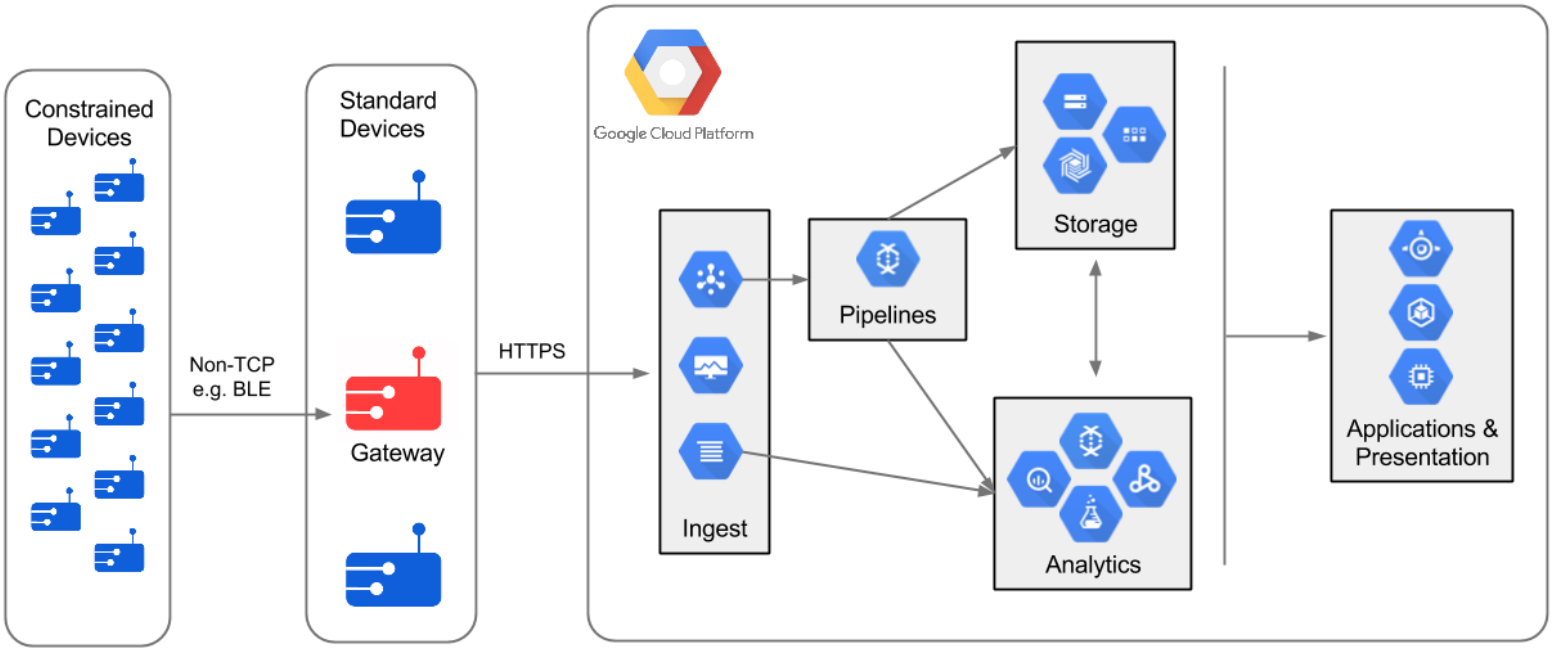
Example from Lecture 4

- Multiple topics
- Amount of data per topic varies
- Should not have duplicate data in database



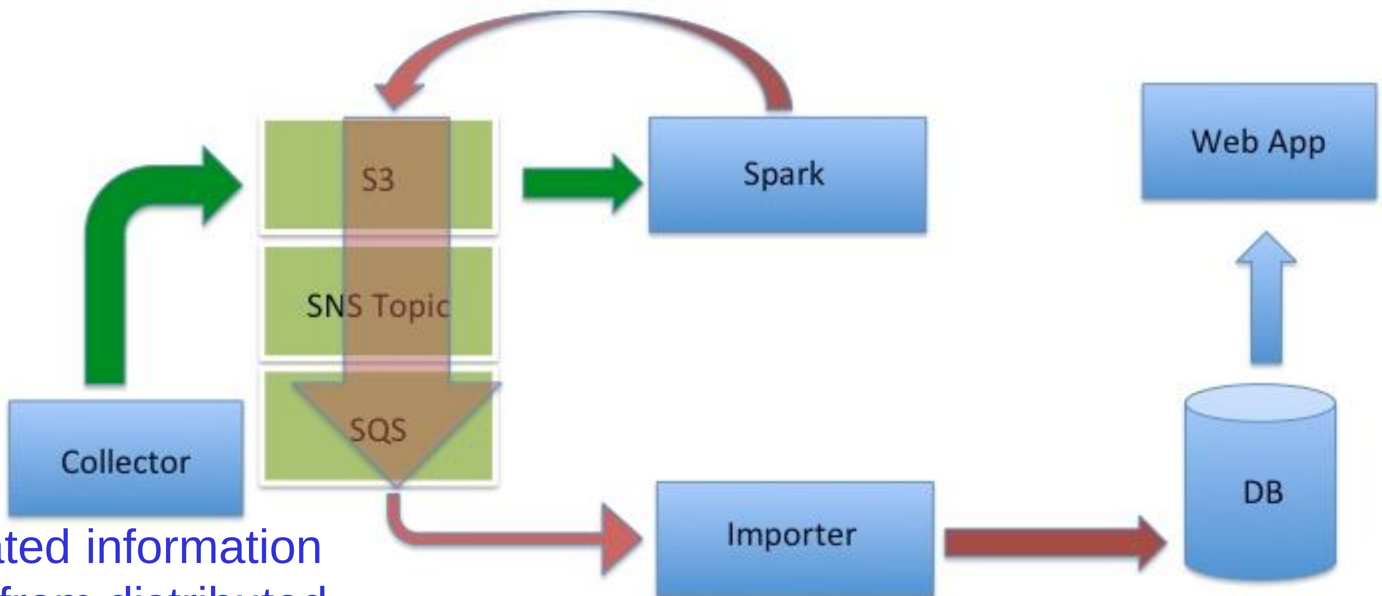
- Should I use docker? VMs?
- Where elasticity can be applied?
- Topic/data distribution to ingest clients?

Implementation atop Google cloud



Source: https://cloud.google.com/solutions/architecture/streamprocessing

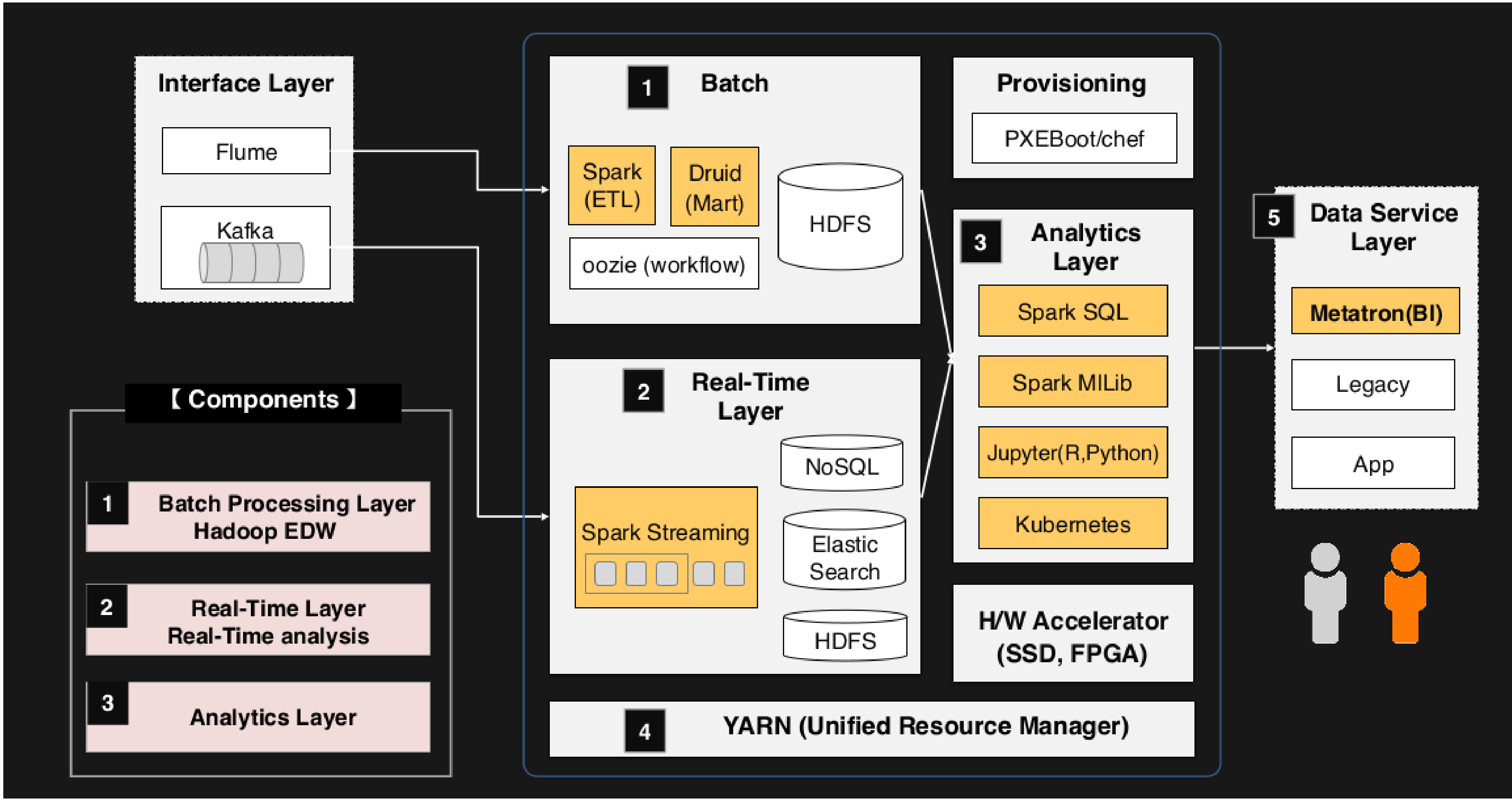
Example: monitoring and security



Security-related information and metrics from distributed customers

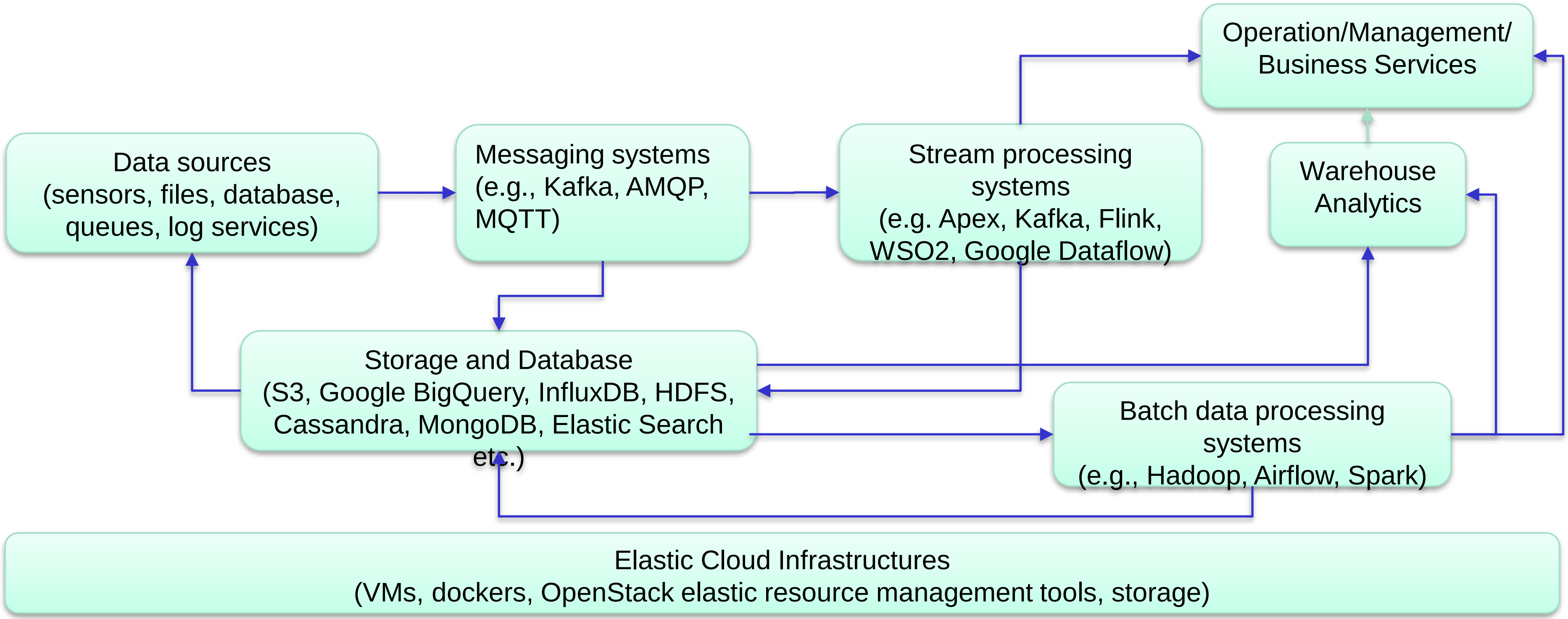
Source: http://highscalability.com/blog/2015/9/3/how-agari-uses-airbnbs-airflow-as-a-smarter-cron.html

Example: Bigdata analytics in SK Telco



Source: Yousun Jeong https://www.slideshare.net/jerryjung7/stsg17-speaker-yousunjeong

Cloud services and big data analytics



Recall: Message-oriented Middleware (MOM)

- Well-supported in large-scale systems for
  - Persistent and asynchronous messages
  - Scalable message handling
- Message communication and transformation
  - publish/subscribe, routing, extraction, enrichment
- Several implementations

Amazon SQS

JMS

MQTT

CloudMQTT

Apache Kafka

RabbitMQ
Messaging that just works

Recall: Workflow of Web services

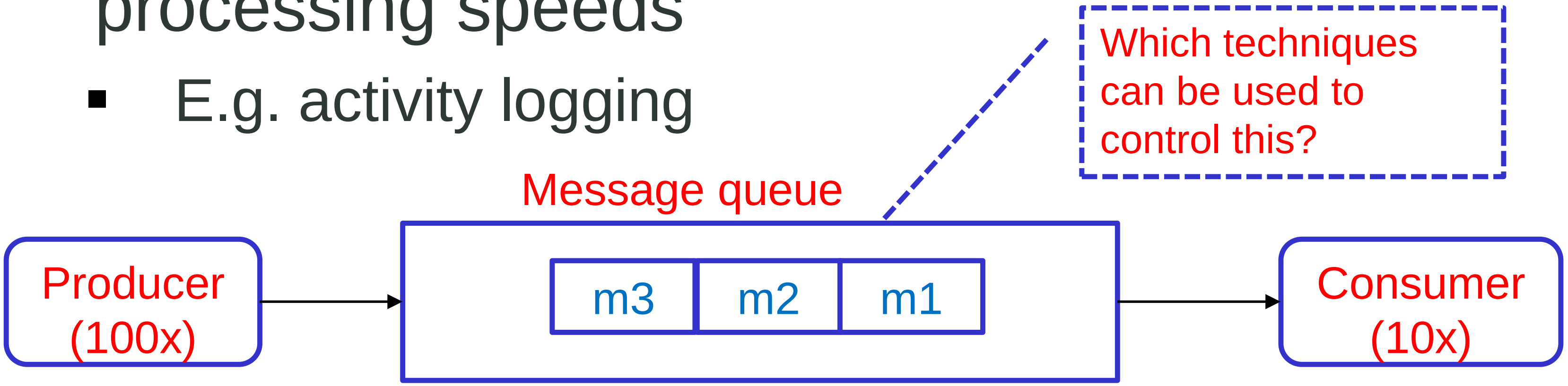
- You learn it from the Advanced Internet Computing course
- Typically for composing Web services from different enterprises/departments for different tasks → many things have been changed in the cloud environment
- For big data analytics and Analytics-as-a-Service
  - Tasks are not just from Web services

http://kafka.apache.org/ , originally from LinkedIn

APACHE KAFKA

Some use cases

- Producers generate a lot of realtime events
- Producers and consumers have different processing speeds
  - E.g. activity logging



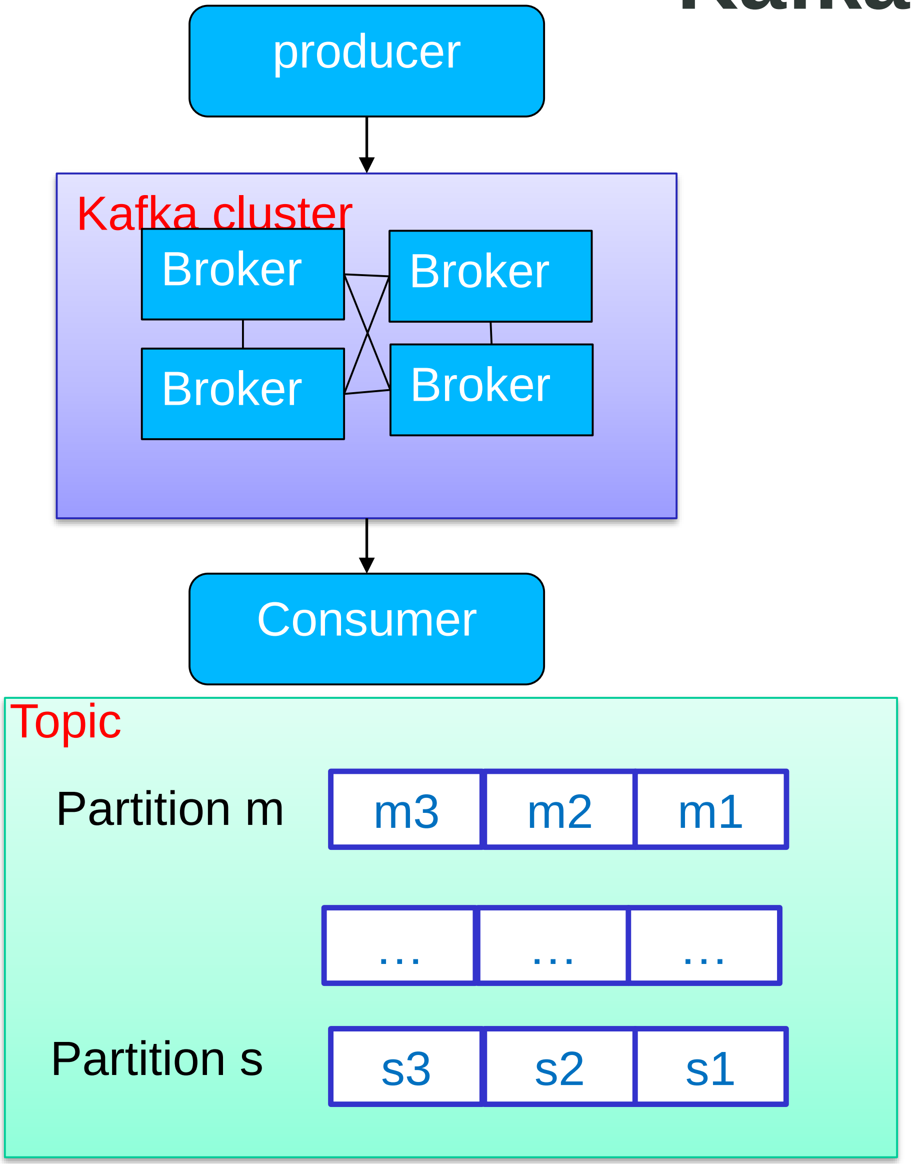
- Rich and diverse types of events
  - E.g. cloud-based logging
- Dealing with cases when consumers might be on and off (fault tolerance support)

More than message broker

- Messaging features
  - For transferring messages
    - Other frameworks in the ecosystem: RabbitMQ, Mostquitto
- Streaming processing
  - Streaming applications handle data from streams
  - Read and write data back to Kafka messaging brokers
  - Other frameworks in the ecosystem: Apache Flink and Apache Apex
- High-level SQL-style: KSQL
  - Other possibilities: SQL-liked + Java in Apache Flink

Kafka Messaging

Kafka Design

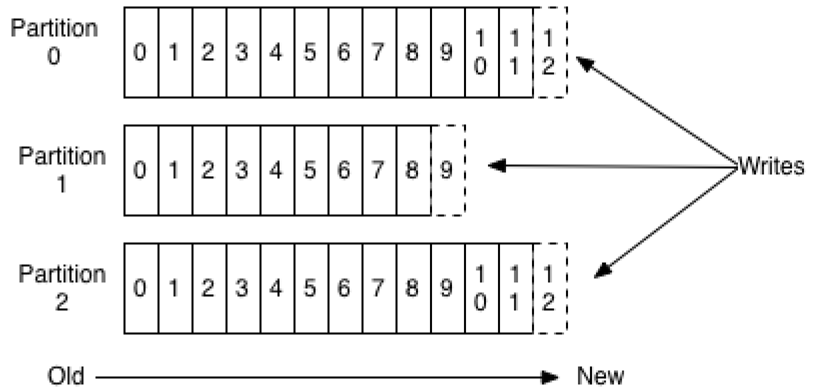


- Use cluster of brokers to deliver messages
- A topic consists of different partitions
- Durable messages, ordered delivery via partitions
- Online/offline consumers
- Using filesystem heavily for message storage and caching

Messages, Topics and Partitions

- Ordered, immutable sequence of messages
- Messages are kept in a period of time (regardless of consumers or not)
- Support total order for messages within a partition
- Partitions are distributed among server

Anatomy of a Topic



Source: http://kafka.apache.org/documentation.html

Consumers

- Consumer pulls the data
- The consumer keeps a single pointer indicating the position in a partition to keep track the offset of the next message being consumed
- Why?

→ allow customers to design their speed

→ support/optimize batching data

→ easy to implement total order over message

→ easy to implement reliable message/fault tolerance

Example of a Producer

```java
public SimpleProducer( String url, String inputfile, String topic ) {
    Properties props = new Properties();
    props.put("bootstrap.servers", url);
    props.put("client.id", "rdsea.io.training.demo");
    props.put("key.serializer", "org.apache.kafka.common.serialization.IntegerSerializer");
    props.put("value.serializer", "org.apache.kafka.common.serialization.StringSerializer");
    producer = new KafkaProducer<Integer,String>(props);
    this.topic = topic;
    this.inputfile =inputfile;
}

public void run() {
    int messageNo = 1;
  //read data from file:
    try {
        Reader in = new FileReader(inputfile);
        Iterable<CSVRecord> records = CSVFormat.RFC4180.withFirstRecordAsHeader().parse(in);
        for (CSVRecord record : records) {

            JsonObject event = new JsonObject();
            event.addProperty("USERPHONE", 6645);
            event.addProperty("TIME", Long.parseLong(record.get("TIME")));

            event.addProperty("lat", Float.parseFloat(record.get("LATITUDE")));
            event.addProperty("lon", Float.parseFloat(record.get("LONGITUDE")));

            event.addProperty("GSM_BIT_ERROR_RATE", Float.parseFloat(record.get("GSM_BIT_ERROR_RATE")));
            event.addProperty("GSM_SIGNAL_STRENGTH", Float.parseFloat(record.get("GSM_SIGNAL_STRENGTH")));
            //a simple way to handle missing data is to skip the record
            if (!record.get("LOC_ACCURACY").equals("")) {
                event.addProperty("LOC_ACCURACY", Float.parseFloat(record.get("LOC_ACCURACY")));
            } else {
                continue;
            }
            if (!record.get("LOC_SPEED").equals("")) {
                event.addProperty("LOC_SPEED", Float.parseFloat(record.get("LOC_SPEED")));
            } else {
                continue;
            }

            String eventString = "{\"event\": " + event + "}";
            try {
                        producer.send(new ProducerRecord<Integer,String>(topic,messageNo,eventString)).get();
                } catch (ExecutionException e) {
                        // TODO Auto-generated catch block
                        e.printStackTrace();
                }
                System.out.println("Sent message: (" + messageNo + ", " + eventString + ")");
```

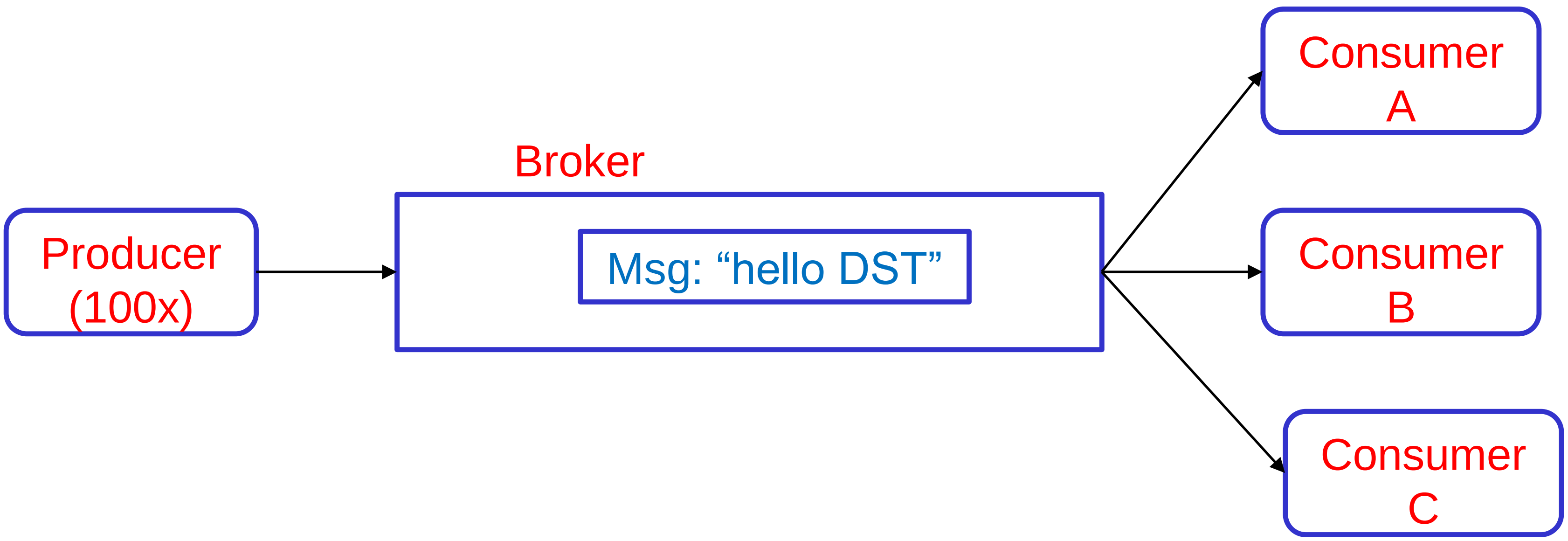
Example of a consumer

```
public class SimpleConsumer {
    private final KafkaConsumer<Integer, String> consumer;
    private final String topic;
    private final int pollNr;
    public SimpleConsumer(String url, String topic, int pollNr) {

        Properties props = new Properties();
        //just use standard example configuration
        props.put(ConsumerConfig.BOOTSTRAP_SERVERS_CONFIG, url);
        props.put(ConsumerConfig.GROUP_ID_CONFIG, "RDSEA Simple Consumer");
        props.put(ConsumerConfig.ENABLE_AUTO_COMMIT_CONFIG, "true");
        props.put(ConsumerConfig.AUTO_COMMIT_INTERVAL_MS_CONFIG, "1000");
        props.put(ConsumerConfig.SESSION_TIMEOUT_MS_CONFIG, "30000");
        props.put(ConsumerConfig.KEY_DESERIALIZER_CLASS_CONFIG, "org.apache.kafka.common.serialization.IntegerDeserializer");
        props.put(ConsumerConfig.VALUE_DESERIALIZER_CLASS_CONFIG, "org.apache.kafka.common.serialization.StringDeserializer");

        consumer = new KafkaConsumer<Integer, String>(props);
        this.topic = topic;
        this.pollNr = pollNr;
    }

    public void readData() {
        consumer.subscribe(Collections.singletonList(this.topic));
        ConsumerRecords<Integer, String> records = consumer.poll(pollNr);
        for (ConsumerRecord<Integer, String> record : records) {
            System.out.println("Received message: (" + record.key() + ", " + record.value() + ") at offset " + record.offset());
        }
    }

        public static void main(String[] args) {
                // TODO Auto-generated method stub
                if (args.length < 3) {
            System.out.println("Usage: SimpleProducer kafka_broker  topic nr");
            System.exit(0);
        }
                int pollNr =Integer.valueOf(args[2]);
        SimpleConsumer consumer = new SimpleConsumer(args[0], args[1], pollNr);
        consumer.readData();
        }

}
```

Message delivery

- Still remember message delivery guarantees?
  - At most once
  - At least once
  - Exactly once

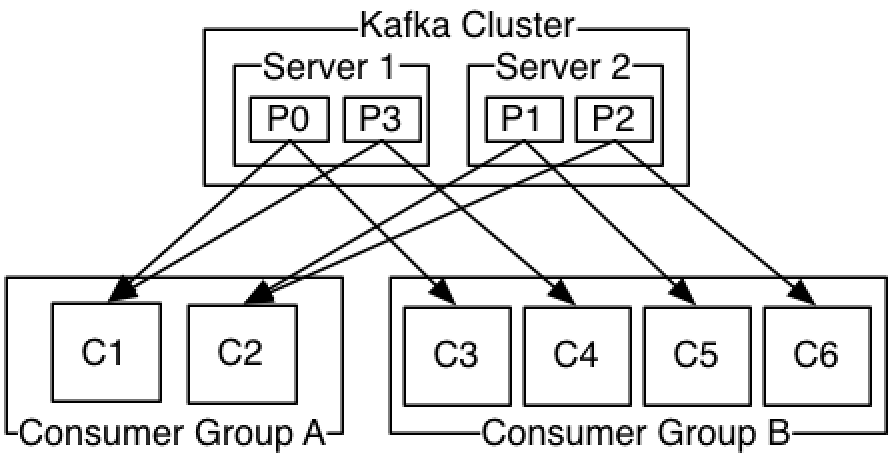
What does it mean exactly one?



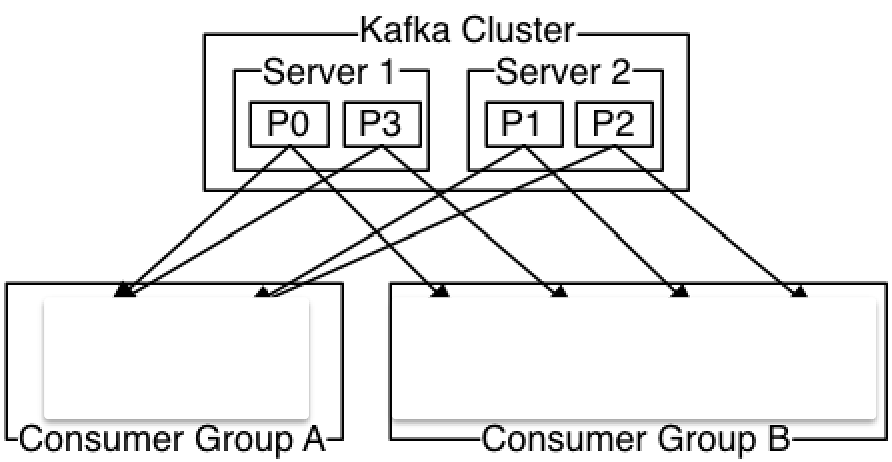
- Producer: Idempotent delivery → no duplicate entry in the log
- Transaction-like semantics: either message to ALL partition topics or not at all
- Consumer behavior management

Scalability and Fault Tolerance

- Partitions are distributed and replicated among broker servers
- Consumers are organized into groups
- Each message is delivered to a consumer instance in a group
- One partition is assigned to one consumer



http://kafka.apache.org/documentation.html#majordesignelements

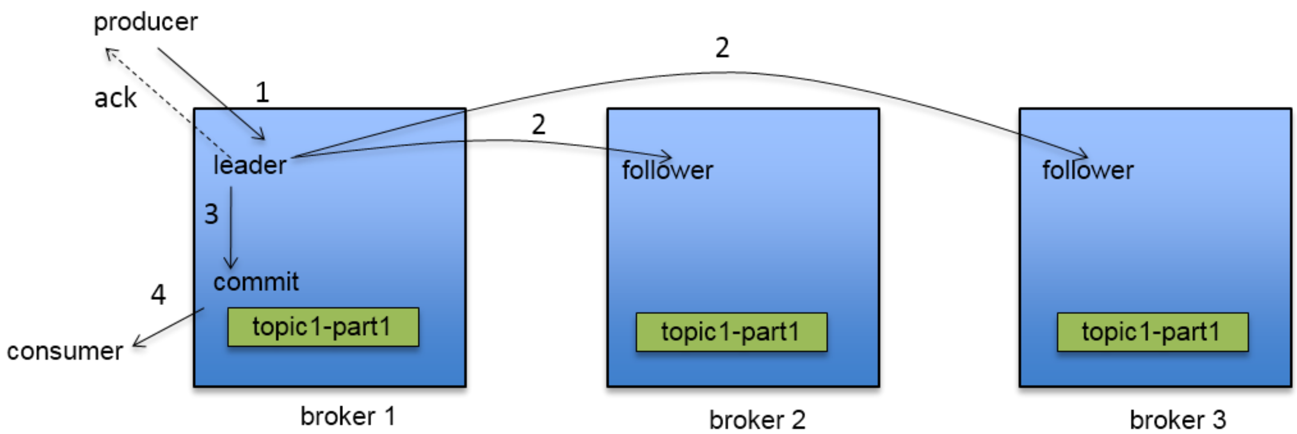


Partitions and partition replication

- Why partitions?
  - Support scalability
    - enable arbitrary data types and sizes for a topic
    - enable parallelism in producing and consuming data

- But partitions are replicated, why?
  - For fault tolerance

Partition Replication



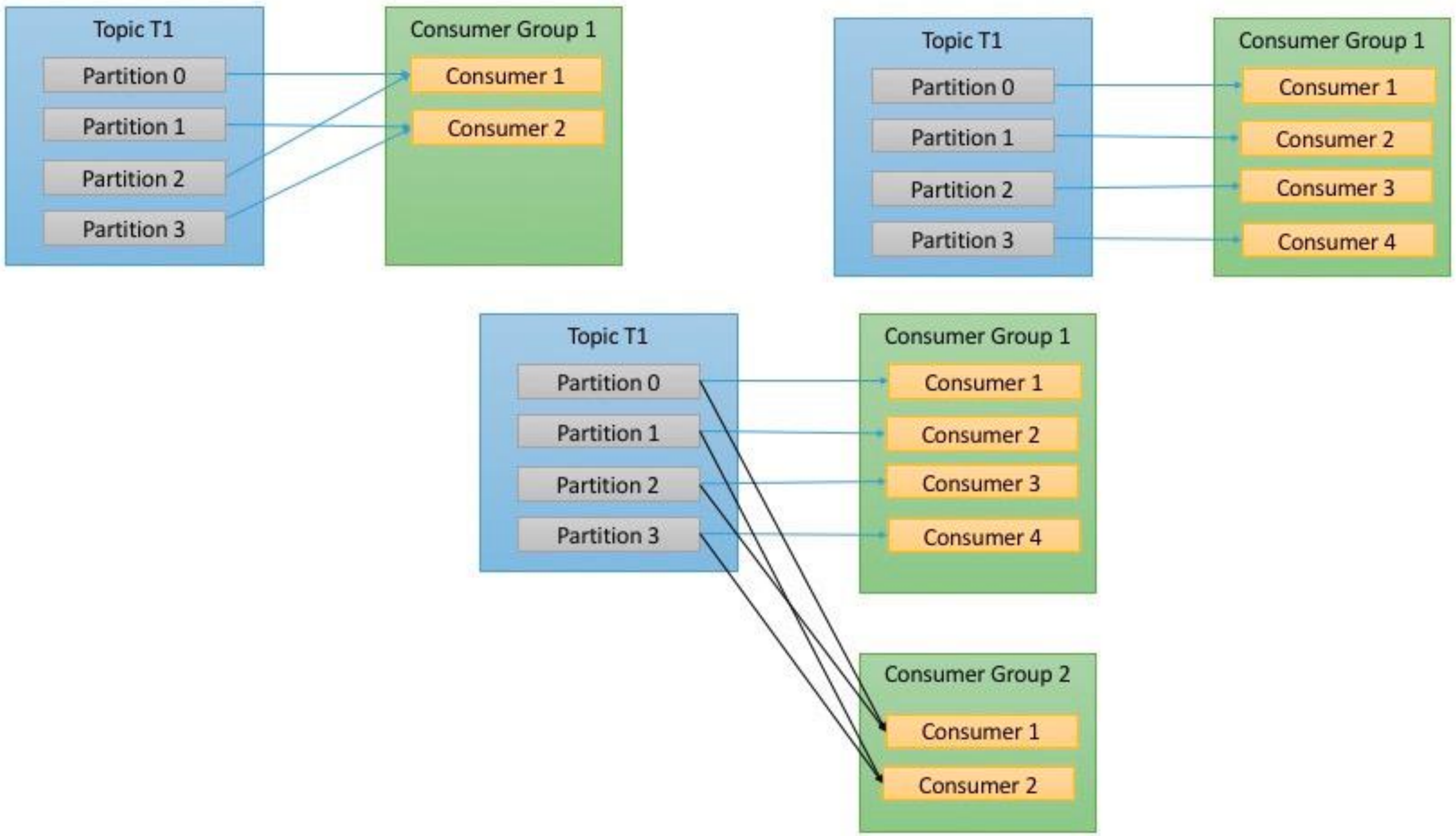
Source: http://de.slideshare.net/junrao/kafka-replication-apachecon2013

The leader handles all read and write requests

Consumer Group

- Consumer Group: a set of consumers
  - is used to support scalability and fault tolerance
  - allows multiple consumers to read a topic
- In one group: each partition is consumed by only consumer instance
  - Combine „queuing“ and „publish/subscribe“ model
- Enable different applications receive data from the same topic.
  - different consumers in different groups can retrieve the same data

Group rebalancing



Source: https://www.safaribooksonline.com/library/view/kafka-the-definitive/9781491936153/ch04.html

Key Questions/Thoughts

- Why do we need partitions per topic?

→ arbitrary data handling, ordering guarantees, load balancing

- How to deal with high volume of realtime events for online and offline consumers?

→ partition, cluster, message storage, batch retrieval, etc.

- Queuing or publish-subscribe model?

→ check how Kafka delivers messages to consumer instances/groups

Kafka vs RabbitMQ

Source: Philippe Dobbelaere and Kyumars Sheykh Esmaili. 2017. Kafka versus RabbitMQ: A comparative study of two industry reference publish/subscribe implementations: Industry Paper. In Proceedings of the 11th ACM International Conference on Distributed and Event-based Systems (DEBS '17). ACM, New York, NY, USA, 227-238. DOI: https://doi.org/10.1145/3093742.3093908

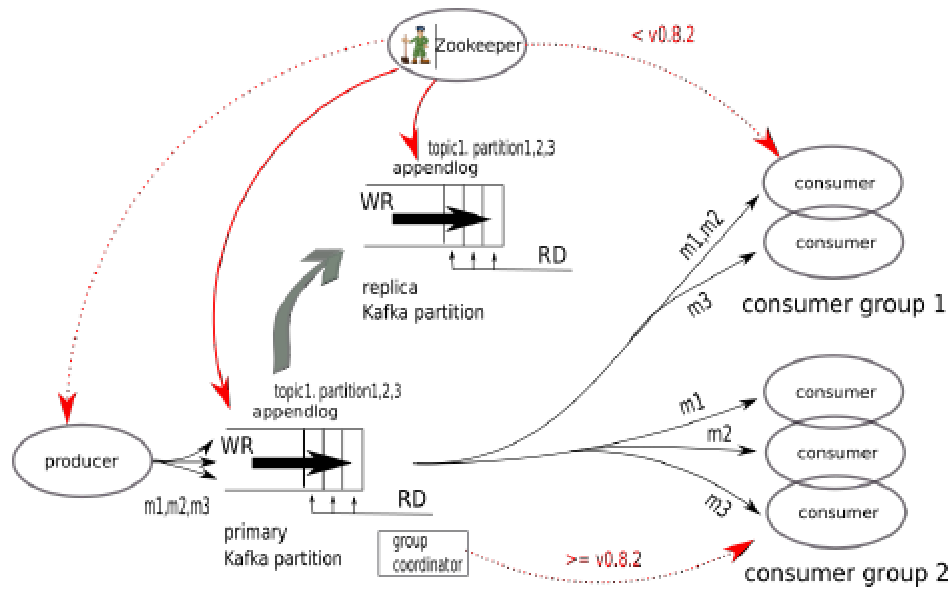


Figure 1: Kafka Architecture

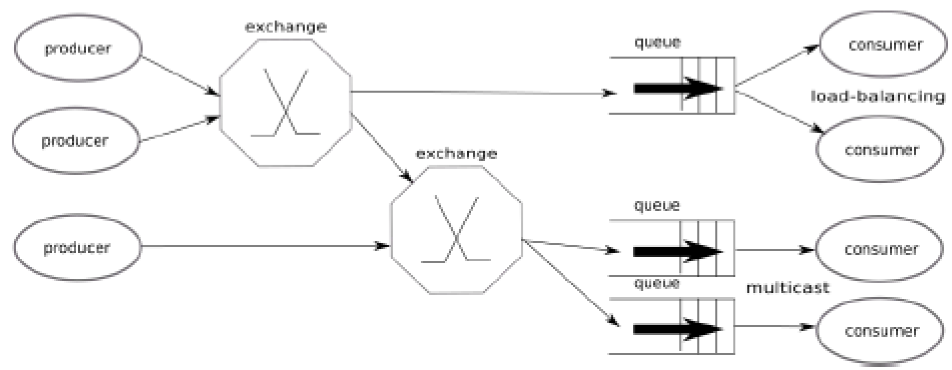
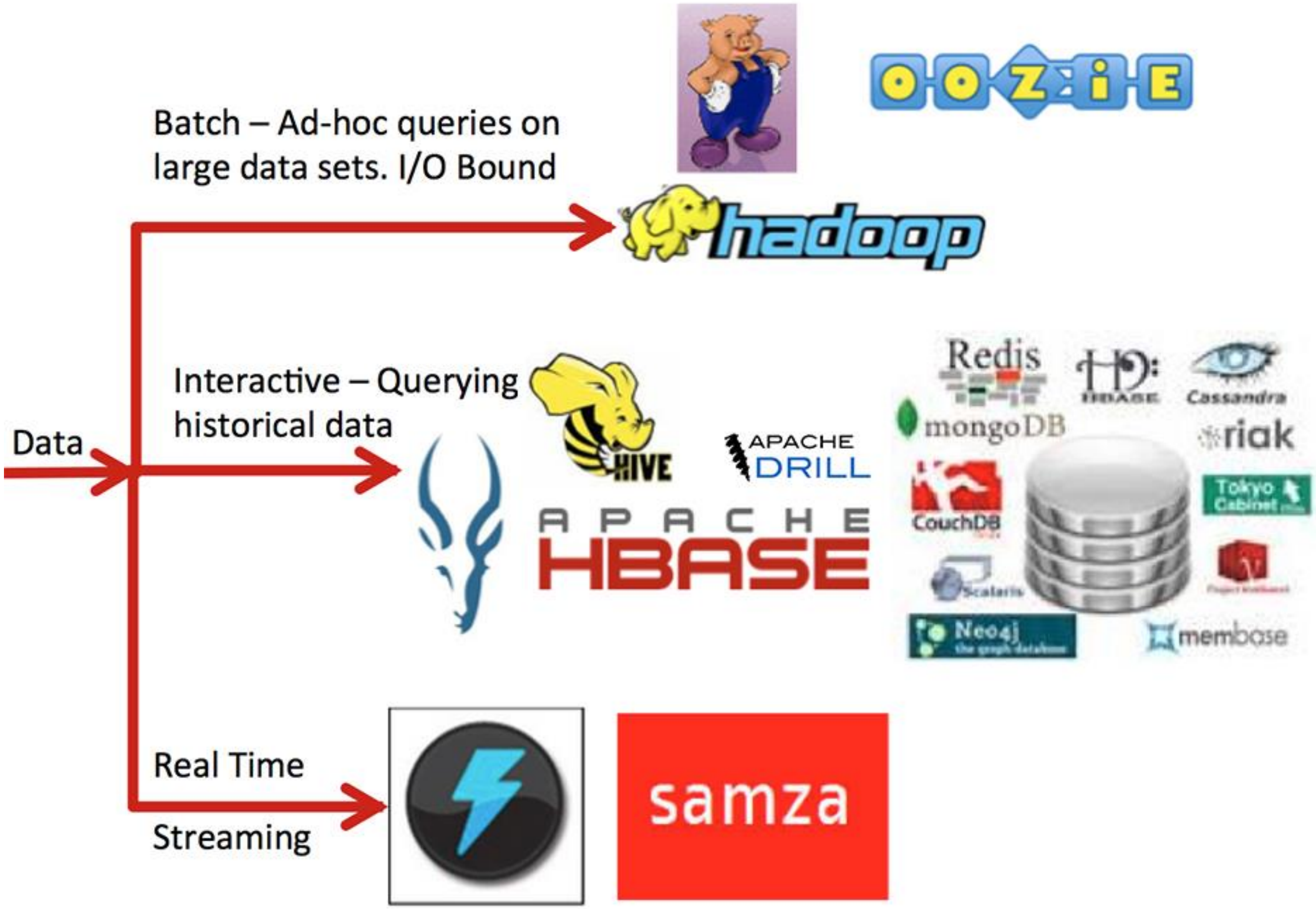


Figure 2: RabbitMQ (AMQP) Architecture

STREAMING DATA PROCESSING

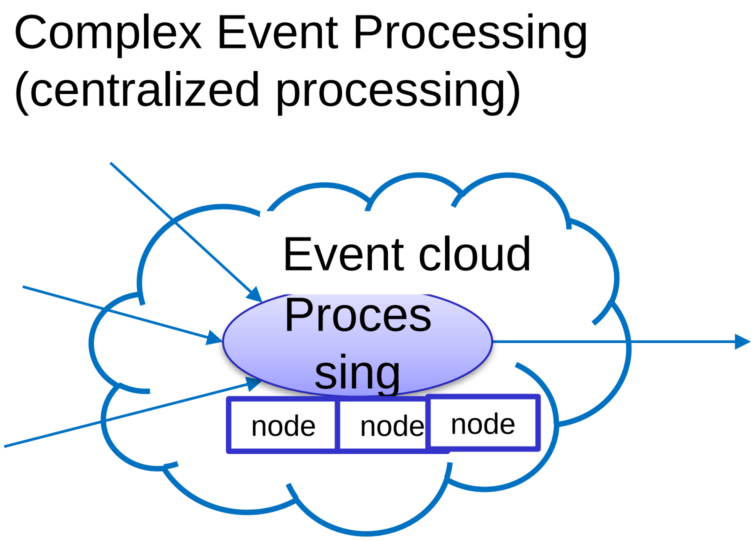
Batch, Stream and Interactive Analytics

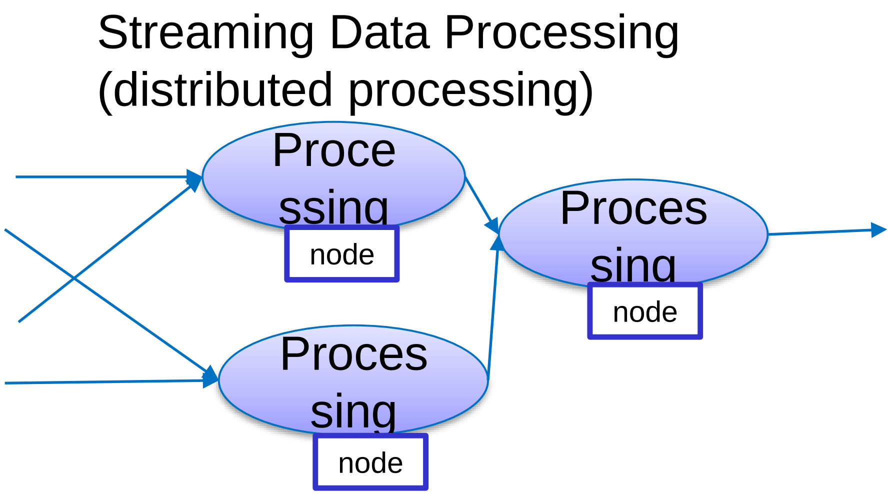


Source: https://dzone.com/refcardz/apache-spark

Recall: Centralized versus distributed processing topology

Two views: streams of events or cloud of events

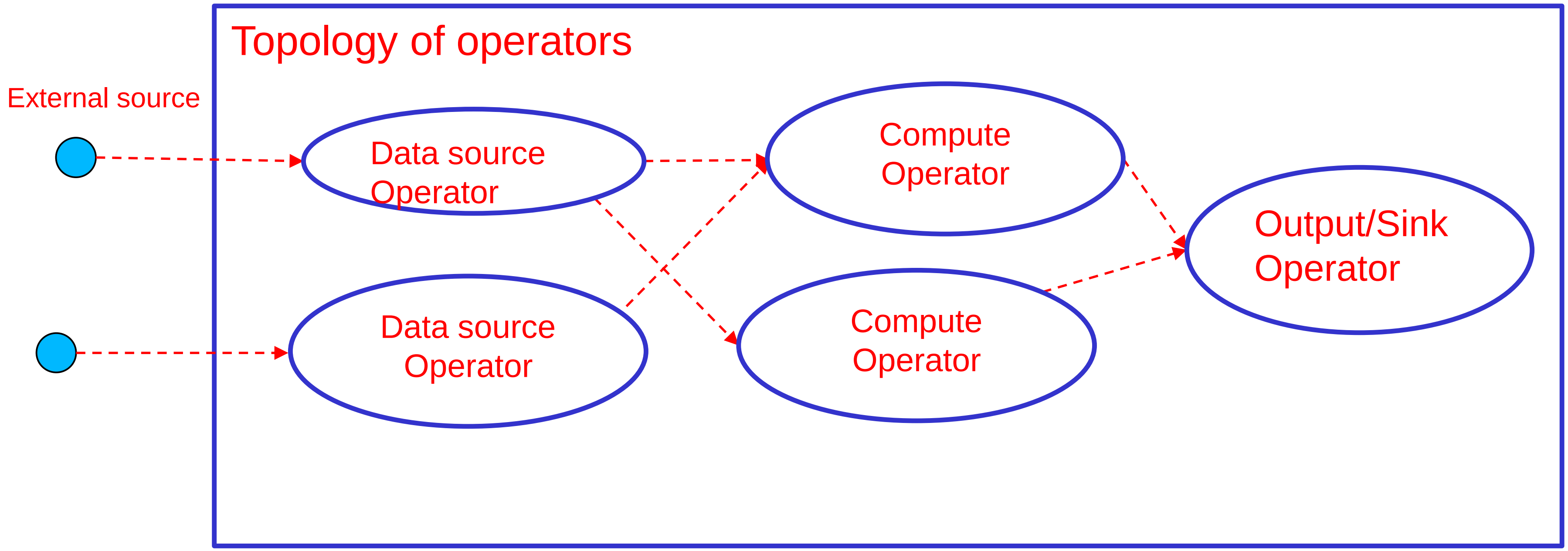




Usually only queries/patterns are written

Code processing events and topologies need to be written

Structure of streaming data processing programs



- Data source operator: represents a source of streams
- Compute operators: represents processing functions
- *Native* versus *micro-batching*

Key concepts

- Structure of the data processing
  - Topology: Directed Acycle Graph (DAG) of operators
  - Data input/output operators and compute operators
  - Accepted various data sources through different connectors
- Scheduling and execution environments
  - Distributed tasks on multiple machines
  - Each machine can run multiple tasks
- Stream: connects an output port from an operator to an input port to another operator
- Stream data is sliced into windows of data for compute operators

Implementations

- Many implementation, e.g.
  - Apache Storm
    - https://storm.apache.org/
  - Apache Spark
    - https://spark.apache.org/
  - Apache Apex
    - https://apex.apache.org/
  - Apache Kafka and Apache Flink

Check:
http://www.cakesolutions.net/teamblogs/comparison-of-apache-stream-processing-frameworks-part-1

http://www.cakesolutions.net/teamblogs/comparison-of-apache-stream-processing-frameworks-part-2

Key common concepts

- Abstraction of streams
- Connector library
  - Very important for application domains
- Runtime elasticity
  - Add/remove (new) operators (and underlying computing node)
- Fault tolerance

Abstraction of Data Streams

- Data stream is the key abstraction

Recall:
Data stream: a sequence/flow of data units
Data units are defined by applications: a data unit can be data described by a primitive data type or by a complex data type, a serializable object, etc.

In Apache Apex: a stream of atomic data elements (tuples)

In Apache Kafka: data element is <Key,Value> tuple

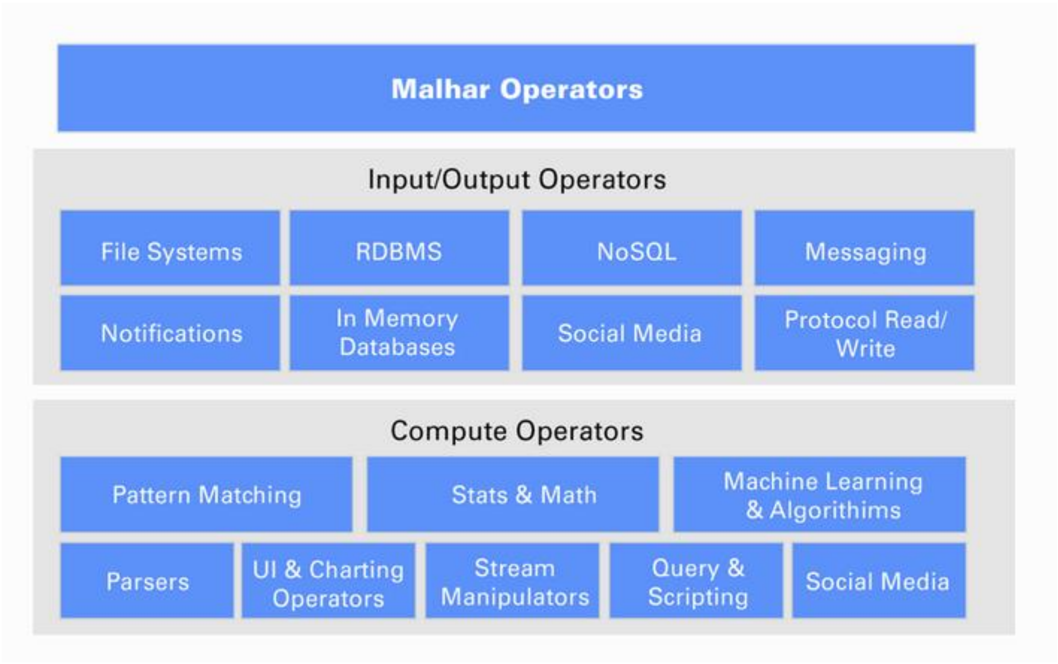
Example of an Apex application in Java

```java
/**
 *
 * @author truong
 */
public class VietcontrolMQTTInput extends AbstractMqttInputOperator{
public final transient DefaultOutputPort<String> out;

    public VietcontrolMQTTInput() {
        this.out = new DefaultOutputPort<>();
        //out.emit("Test message");
    }
    @Override
    public void emitTuple(org.fusesource.mqtt.client.Message msg) {
        System.out.println("topic: "+msg.getTopic());
        byte[] data =msg.getPayload();
        String v = new String(data, Charset.forName("UTF-8") );
        System.out.println(v);
        out.emit(v);
    }

}
```

```java
@ApplicationAnnotation(name="MySecondApplication")
public class BTSApplication implements StreamingApplication
{
  String topic ="apextest";
  QoS qos;

    public BTSApplication() {
        this.qos = QoS.AT_MOST_ONCE;
    }
  @Override
  public void populateDAG(DAG dag, Configuration conf)
  {

      System.out.println("Start the application by connecting to MQTT");
      MqttClientConfig btsmqttConfig = new MqttClientConfig();

      btsmqttConfig.setHost("localhost");
      btsmqttConfig.setPort(1883);
      btsmqttConfig.setUserName("guest");
      btsmqttConfig.setPassword("guest");
      btsmqttConfig.setCleanSession(true);
      //creating input operator
      VietcontrolMQTTInput btsInput = dag.addOperator("input", VietcontrolMQTTInput.class);
      btsInput.setMqttClientConfig(btsmqttConfig);
      System.out.println("Subscribe topics");
      btsInput.addSubscribeTopic(topic, qos);
      //just a simple example to output the data to the console
      ConsoleOutputOperator cons = dag.addOperator("console", new ConsoleOutputOperator());
      cons.setSilent(false);
      System.out.println("Just create one single stream");
      dag.addStream("test", btsInput.out, cons.input).setLocality(Locality.CONTAINER_LOCAL);

  }
}
```

Processor/Operators

- Streaming applications are built with a set of processors/operators: for data and computation



Source: https://apex.apache.org/docs/malhar/

- Some common data operators (related to other lectures)
  - MQTT
  - AMQP
  - Kafka

Why are the richness and diversity of connectors important?

Time and stream processing

Can you explain the time notion and the roles?

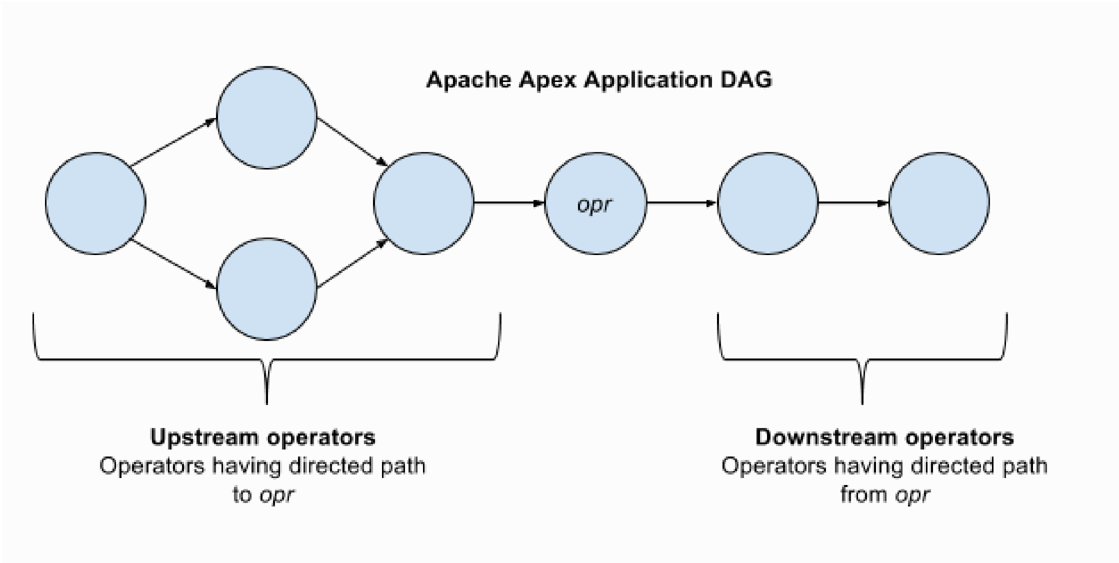
Fault tolerance

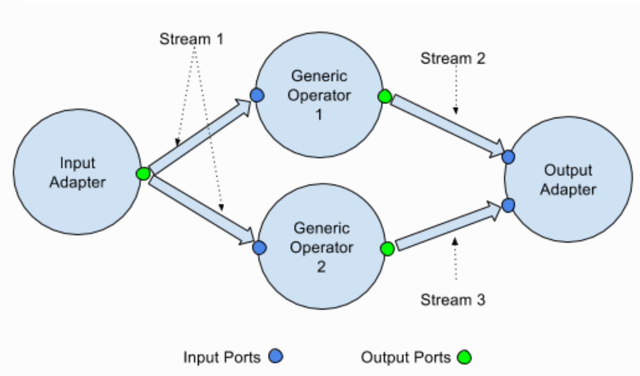
- Recovery
  - At least once
  - At most once
  - Exactly once
  - E.g. Kafka Streams: Exactly once and at least once

- Note the difference between messaging and processing w.r.t fault tolerance

Some (interesting) features of Apache Apex

DAG of Operators



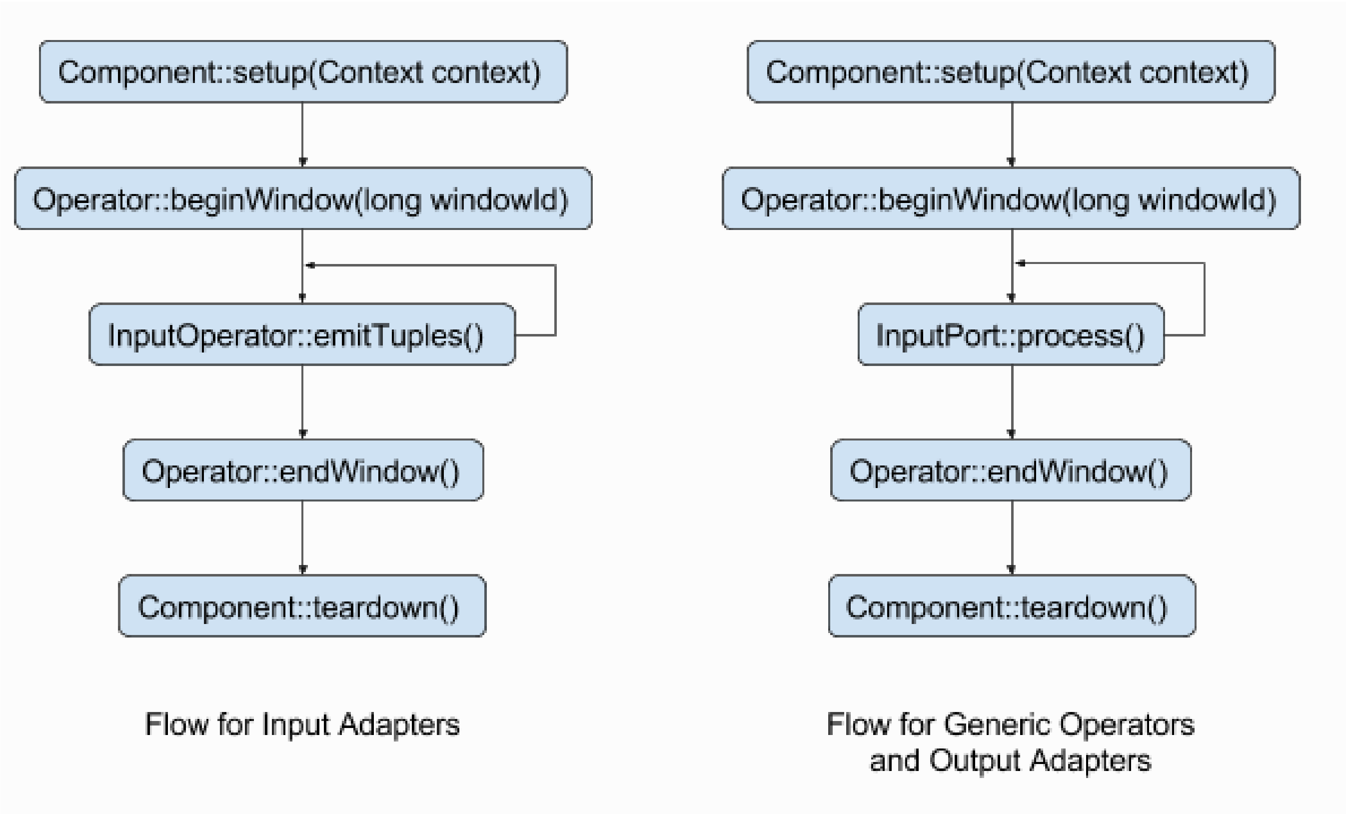


Source: https://apex.apache.org/docs/apex-3.6/operator_development/

- Ports: for input and output data
- Data in a stream: streaming windows

Processing data in operators

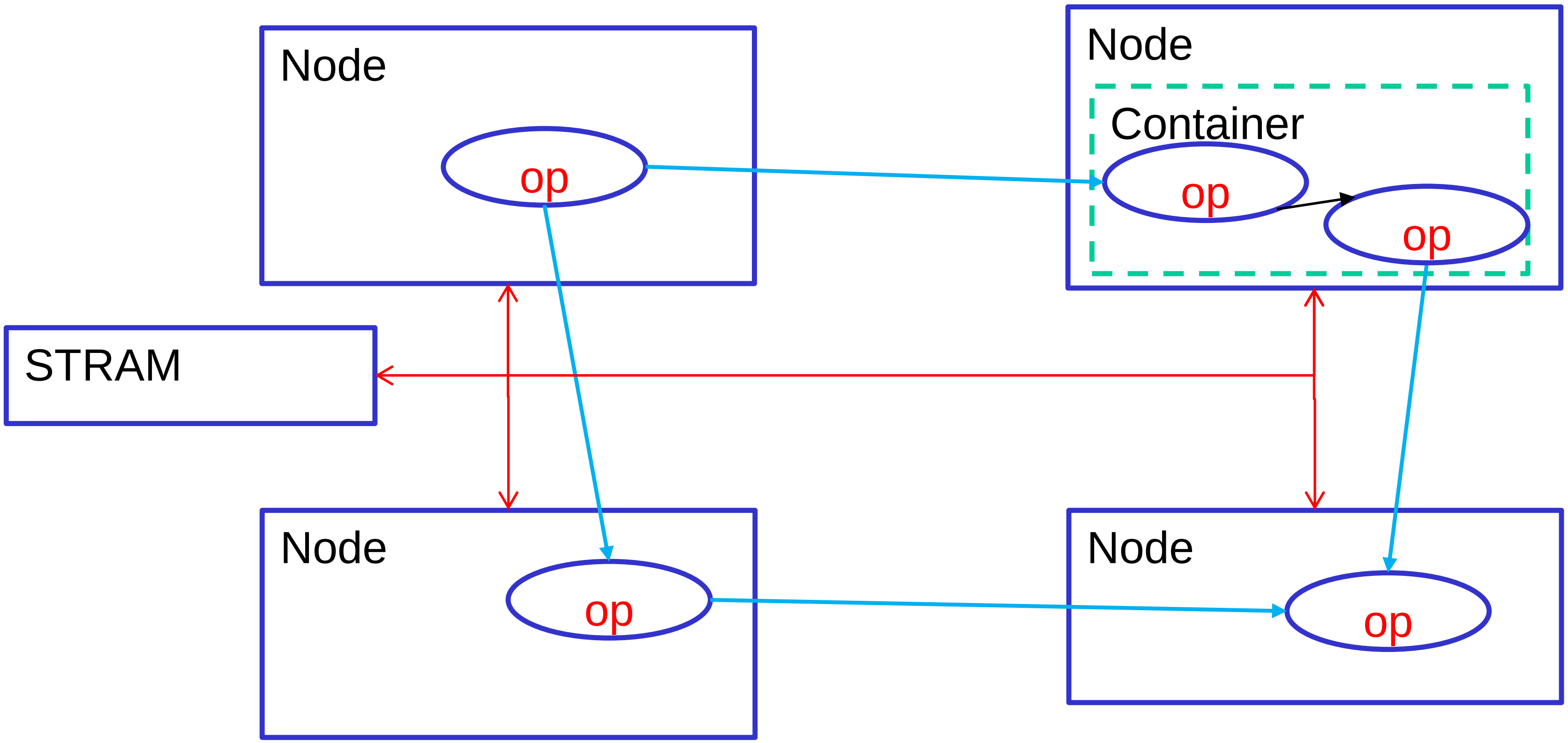
Different types of Windows: GlobalWindows, TimeWindows, SlidingTimeWindows, etc.



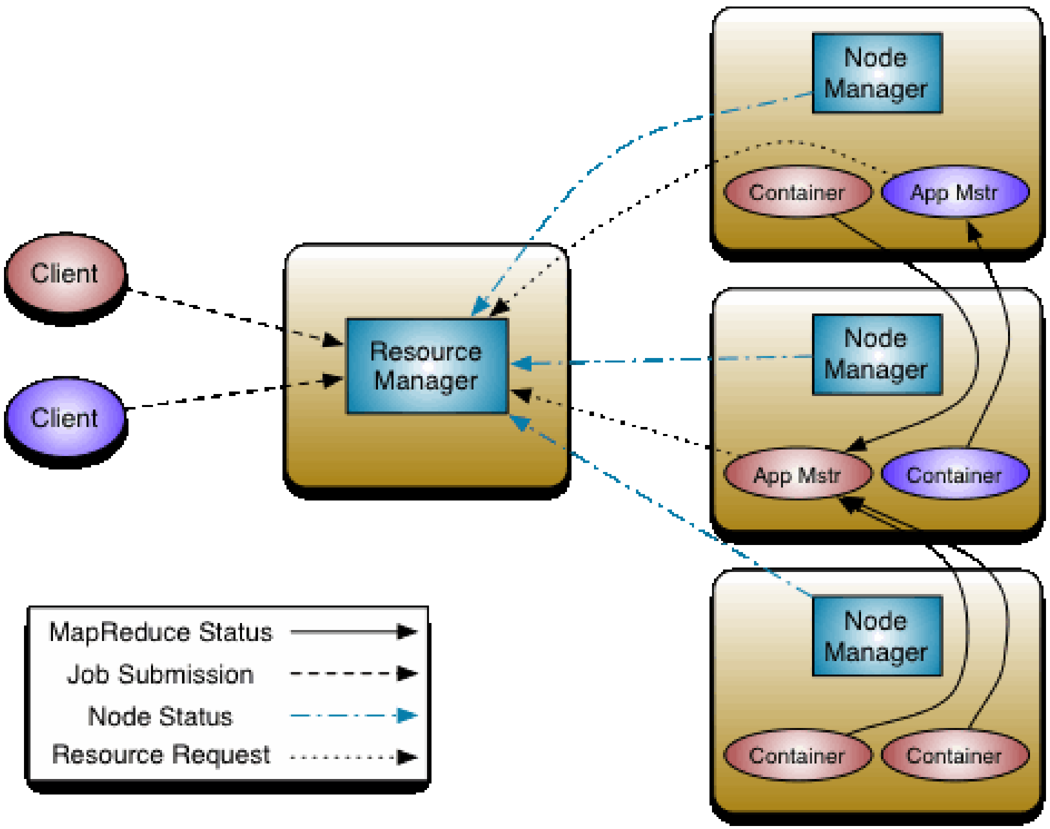
Source: https://apex.apache.org/docs/apex/operator_development/

Execution Management

- Using YARN for execution tasks
- Using HDFS for persistent state



Understand YARN/Hadoop to understand Apex operator execution management



Source: http://hadoop.apache.org/docs/current/hadoop-yarn/hadoop-yarn-site/YARN.html

Scalability

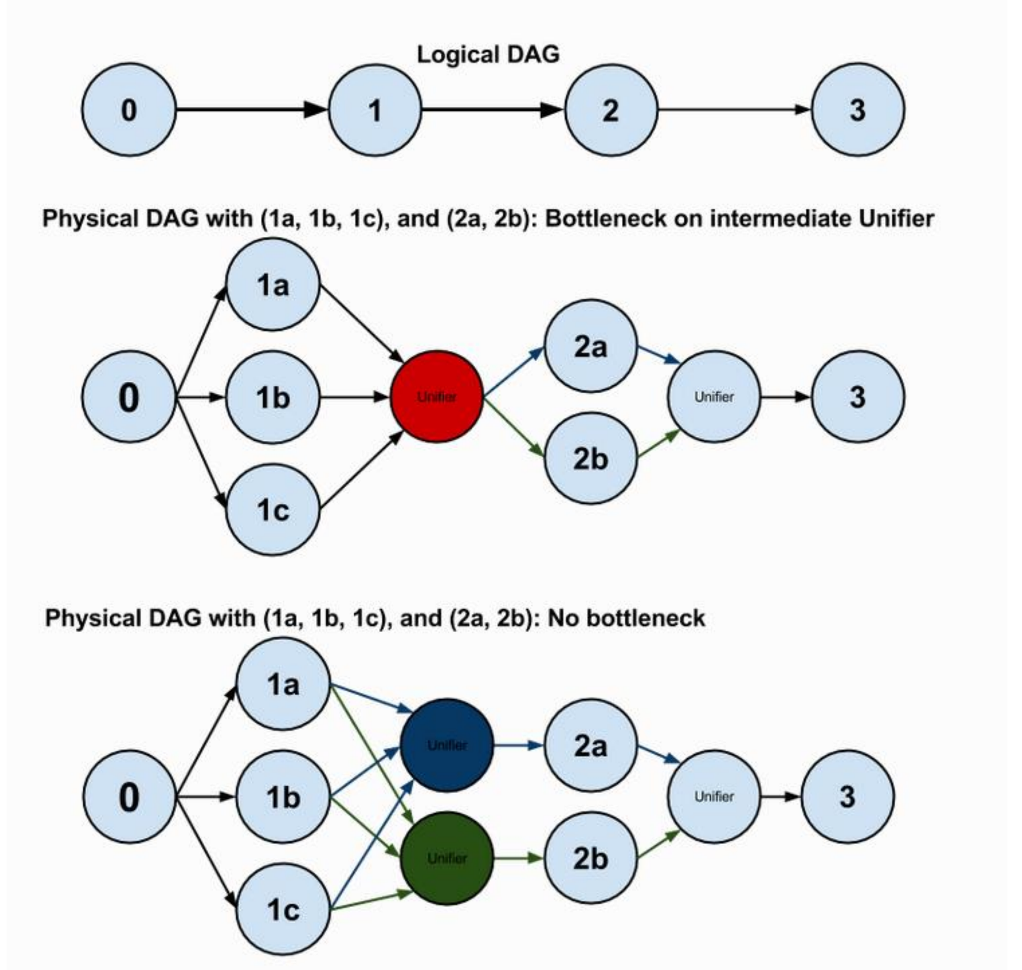
- Locality configuration for deployment of streams and operators
- Affinity and anti-affinity rules
- Possible localities:
  - THREAD_LOCAL (intra-thread)
  - CONTAINER_LOCAL (intra-process)
  - NODE_LOCAL (inter-process but within a Hadoop node)
  - RACK_LOCAL (inter-node)

Operators Fault tolerance

- Checkpoint of operators: save state of operators (e.g. into HDFS)
  - @Stateless no checkpoint
  - Check point interval: CHECKPOINT_WINDOW_COUNT
- Recovery
  - At least once
  - At most once
  - Exactly once

Example of Partitioning and unification in Apex

- Dynamic Partition
  - Partition operators
  - Dynamic: specifying when a partition should be done
  - Unifiers for combining results (reduce)
- StreamCodec
  - For deciding which tuples go to which partitions
  - Using hashcode and masking mechanism



Source: https://apex.apache.org/docs/apex/application_development/#partitioning

Fault tolerance – Recovery in Apex

- At least once
  - Downstream operators are restarted
  - Upstream operators are replayed
- At most once
  - Assume that data can be lost: restart the operator and subscribe to new data from upstream
- Exactly once
  - https://www.datatorrent.com/blog/end-to-end-exactly-once-with-apache-apex/

Exercise

How to make sure no duplication results when we recover End-to-End Exactly Once?

How to use hash and masking mechanism to distributed tuples?

How to deal with data between operators not in a CONTAINER_LOCAL or in THREAD_LOCAL

ADVANCED WORKFLOWS/DATA PIPELINE PROCESSING

Use cases

- Access and coordinate many different compute services, data sources, deployment services, etc, within an enterprise, for a particular goal
- Implementing complex „business logics“ of your services
- Analytics-as a service: metrics, user activities analytics, testing, e.g.
  - Analytics of log files (generated by Aspects in Lecture 3)
  - Dynamic analytics of business activities

Workflow and Pipeline/data workflow

- Workflows: a set of coordinated activities
  - Generic workflows of different categories of tasks
  - Data workflows → data pipeline

    „a pipeline is a set of data processing elements connected in series, where the output of one element is the input of the next one"

    Source: https://en.wikipedia.org/wiki/Pipeline_%28computing%29
- We use a pipeline/data workflows to carry out a data processing job

Example of Pipeline in Apache Beam

```java
Pipeline p = Pipeline.create(options);

// Concepts #2 and #3: Our pipeline applies the composite CountWords transform, and passes the
// static FormatAsTextFn() to the ParDo transform.
p.apply("ReadLines", TextIO.read().from(options.getInputFile()))
 .apply(new CountWords())
 .apply(MapElements.via(new FormatAsTextFn()))
 .apply("WriteCounts", TextIO.write().to(options.getOutput()));

p.run().waitUntilFinish();
```

Source: https://github.com/apache/beam/blob/master/examples/java/src/main/java/org/apache/beam/examples/WordCount.java

Example with Node-RED

http://nodered.org

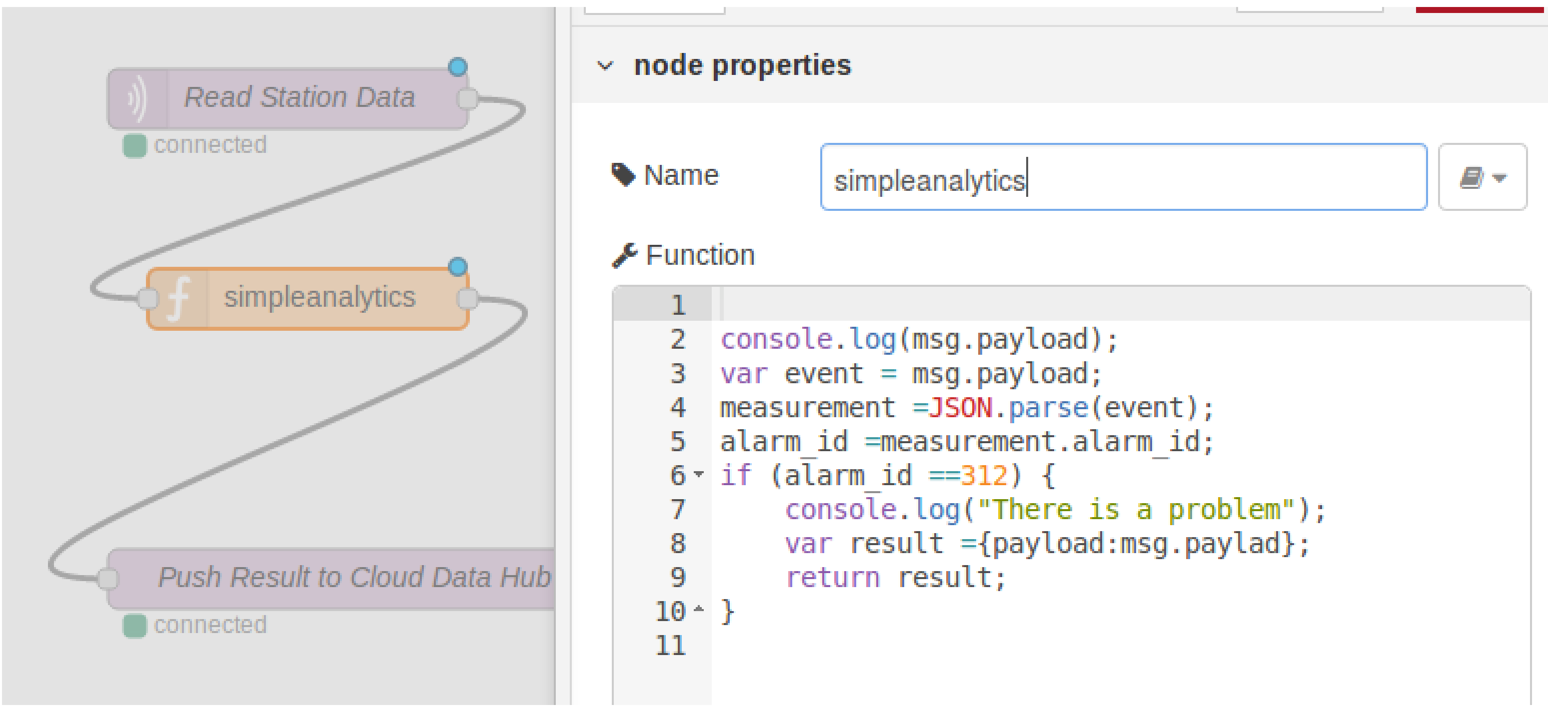
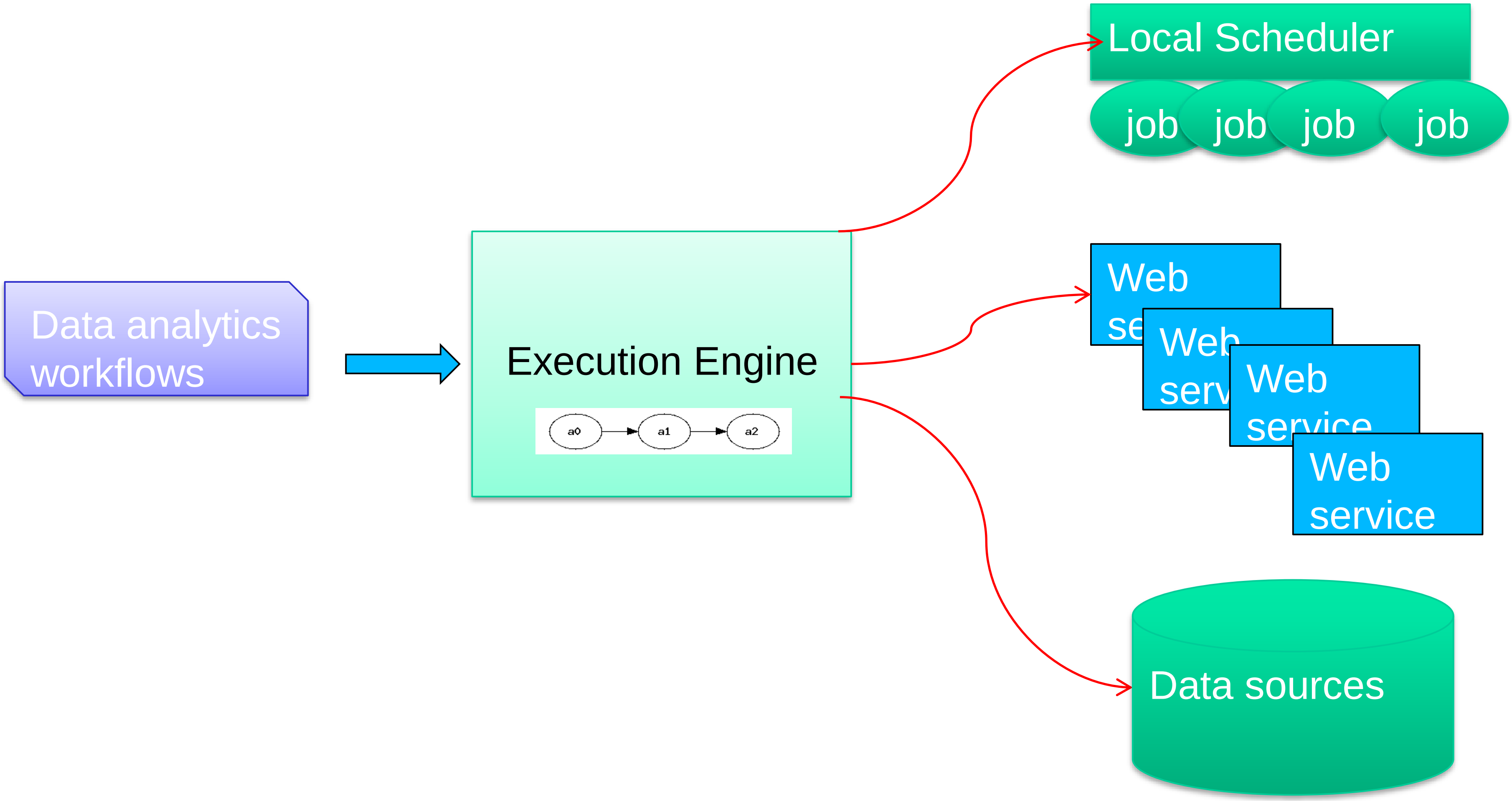


Figure source: Hong-Linh Truong, Enabling Edge Analytics of IoT Data: the Case of LoRaWAN, The 2018 Global IoT Summit (GIoTS) 4-7 June 2018 in Bilbao, Spain

Data analytics workflow execution models



Workflow and Pipeline/data workflow

- But analytics have many more than just data processing activities
  - Storage: where is the data from? Where is the sink of data?
  - Communication of results
    - is software or human the receiver of the analytics results?:
    - Software: messaging, serverless function, REST API, Webhook?
    - People: Email, SMS, …
  - Visualization of results: which tools?

Your are in a situation:

- Many underlying distributed processing frameworks
  - Apex, Spark, Flink, Google
- Work with different underlying engines
- Write only high-level pipelines
- Stick to your favour programming languages

Apache Beam

- Goal: separate from pipelines from backend engines

Read data analytics → Post-processing result → Store analysis result

Apache Apex™ | Flink | Apache Spark™ | Dataflow

Apache Beam

- https://beam.apache.org/
- Suitable for data analysis processes that can be divided into different independent tasks
  - ETL (Extract, Transform and Load)
  - Data Integration
- Execution principles:
  - Mapping tasks in the pipeline to concrete tasks that are supported by the selected back-end engine
  - Coordinating task execution like workflows.

Basic programming constructs

- Pipeline:
  - For creating a pipeline
- PCollection
  - Represent a distributed dataset
- Transform

  [Output PCollection] = [Input PCollection] | [Transform]

  - Possible transforms: ParDo, GroupByKey, Combine, etc.

A simple example with Google Dataflow as back-end engine

```
import apache_beam as beam
from apache_beam.options.pipeline_options import PipelineOptions

p = beam.Pipeline(options=PipelineOptions())

entries = p | 'ReadHadoopResult' >> beam.io.ReadFromText('gs://.../ElectricityAlarm
/electricity_alarm_frequency-2017-05-11-00-vn.csv')
class ExtractAlarmFrequency(beam.DoFn):
  def process(self, elements):
    ....
    return ....
frequency = entries| beam.ParDo(ExtractAlarmFrequency())
frequency | 'write' >> beam.io.WriteToText('gs://.../ElectricityAlarm')
result = p.run()
result.wait_until_finish()
```

Beam SQL

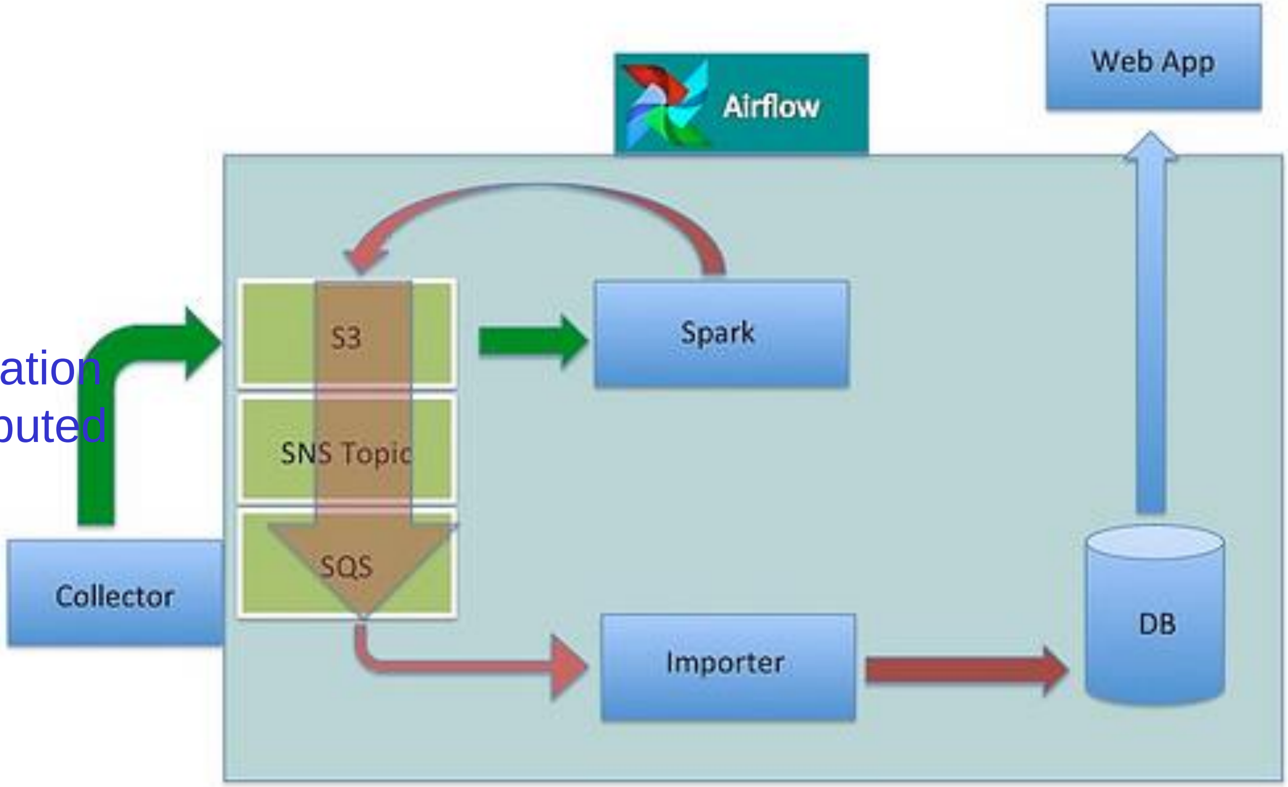
- https://beam.apache.org/documentation/dsls/sql/
- High level SQL-like statements
- Combine with Java APIs
- Common features
  - Aggregation functions
  - Windows
  - User-defined functions

But what if you need diverse types of tasks with various back-end services?

→ Workflow systems

Example of using workflows

Security-related information and metrics from distributed customers



Source: http://highscalability.com/blog/2015/9/3/how-agari-uses-airbnbs-airflow-as-a-smarter-cron.html

Representing and programming workflows/data workflows

- Programming languages
  - General- and specific-purpose programming languages, such as Java, Python, Swift

- Descriptive languages
  - BPEL and several languages designed for specific workflow engines

Key requirements for us in the Cloud

- Rich connectors to various data sources
- Computation engines
- Different underlying infrastructures
- REST and message broker integration

Example with Apache Airflow

Airflow from Airbnb

- http://airbnb.io/projects/airflow/
- Features
  - Dynamic, extensible, scalable workflows
  - Programmable language based workflows
    - Write workflows as programmable code
- Good and easy to study to understand concepts of workflows/data pipeline

Many connectors

subpackage	install command	enables
all	`pip install apache-airflow[all]`	All Airflow features known to man
all_dbs	`pip install apache-airflow[all_dbs]`	All databases integrations
async	`pip install apache-airflow[async]`	Async worker classes for gunicorn
devel	`pip install apache-airflow[devel]`	Minimum dev tools requirements
devel_hadoop	`pip install apache-airflow[devel_hadoop]`	Airflow + dependencies on the Hadoo
celery	`pip install apache-airflow[celery]`	CeleryExecutor
crypto	`pip install apache-airflow[crypto]`	Encrypt connection passwords in met
druid	`pip install apache-airflow[druid]`	Druid.io related operators & hooks
gcp_api	`pip install apache-airflow[gcp_api]`	Google Cloud Platform hooks and ope
jdbc	`pip install apache-airflow[jdbc]`	JDBC hooks and operators
hdfs	`pip install apache-airflow[hdfs]`	HDFS hooks and operators
hive	`pip install apache-airflow[hive]`	All Hive related operators
kerberos	`pip install apache-airflow[kerberos]`	kerberos integration for kerberized ha
ldap	`pip install apache-airflow[ldap]`	ldap authentication for users
mssql	`pip install apache-airflow[mssql]`	Microsoft SQL operators and hook, su
mysql	`pip install apache-airflow[mysql]`	MySQL operators and hook, support a
password	`pip install apache-airflow[password]`	Password Authentication for users
postgres	`pip install apache-airflow[postgres]`	Postgres operators and hook, support
qds	`pip install apache-airflow[qds]`	Enable QDS (qubole data services) sup
rabbitmq	`pip install apache-airflow[rabbitmq]`	Rabbitmq support as a Celery backend
s3	`pip install apache-airflow[s3]`	`S3KeySensor`, `S3PrefixSensor`
samba	`pip install apache-airflow[samba]`	`Hive2SambaOperator`
slack	`pip install apache-airflow[slack]`	`SlackAPIPostOperator`
vertica	`pip install apache-airflow[vertica]`	Vertica hook support as an Airflow ba
cloudant	`pip install apache-airflow[cloudant]`	Cloudant hook
redis	`pip install apache-airflow[redis]`	Redis hooks and sensors

Airflow Workflow structure

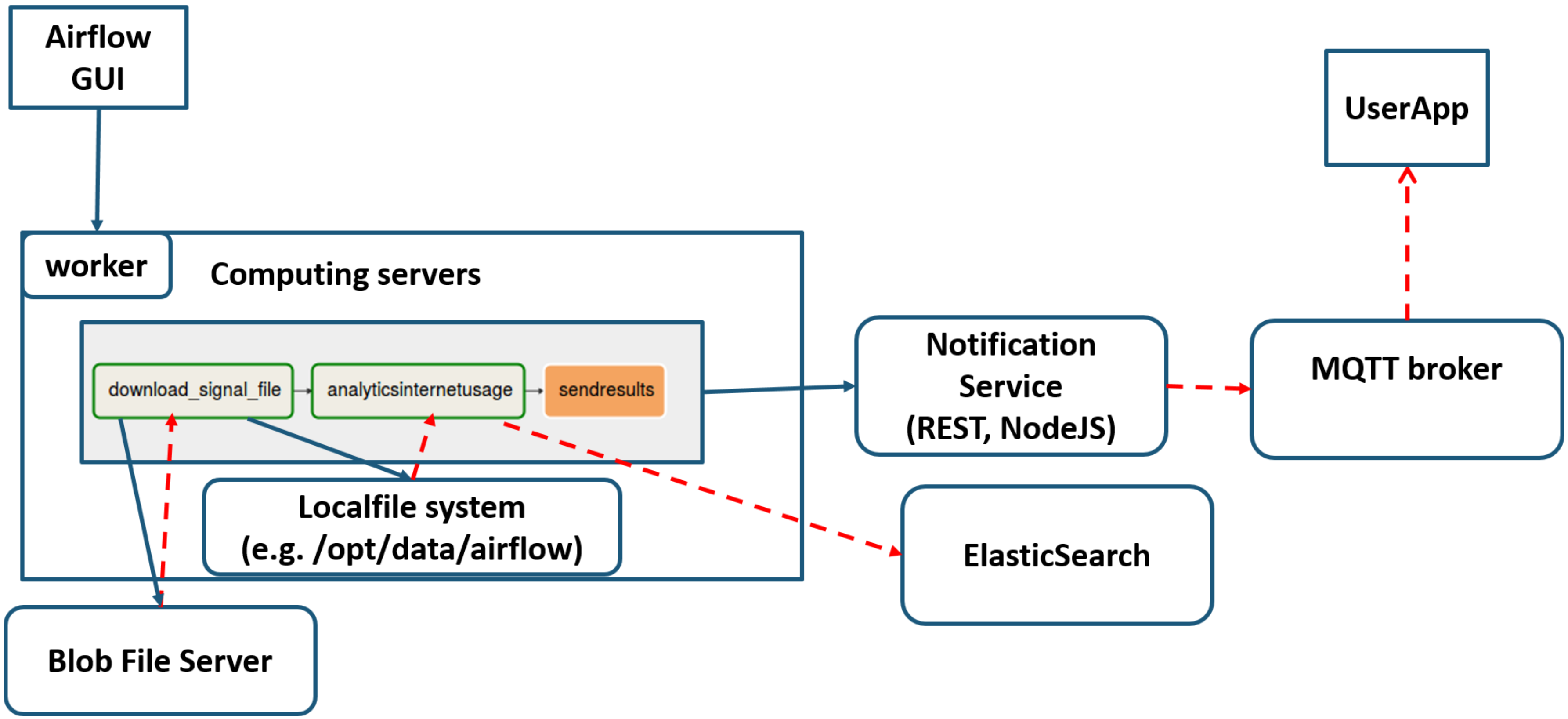
- Workflow is a DAG (Direct Acyclic Graph)
  - A workflow consists of a set of activities represented in a DAG
  - Workflow and activities are programed using Python – described in code
- Workflow activities are described by Airflow operator objects
  - Tasks are created when instantiating operator objects

Airflow from Airbnb

- Rich set of operators
  - So that we can program different kinds of tasks and integrate with different systems

- Different Types of operators for workflow activities
  - BashOperator, PythonOperator, EmailOperator, HTTPOperator, SqlOperator, Sensor,
  - DockerOperator, HiveOperator, S3FileTransferOperator, PrestoToMysqlOperator, SlackOperator

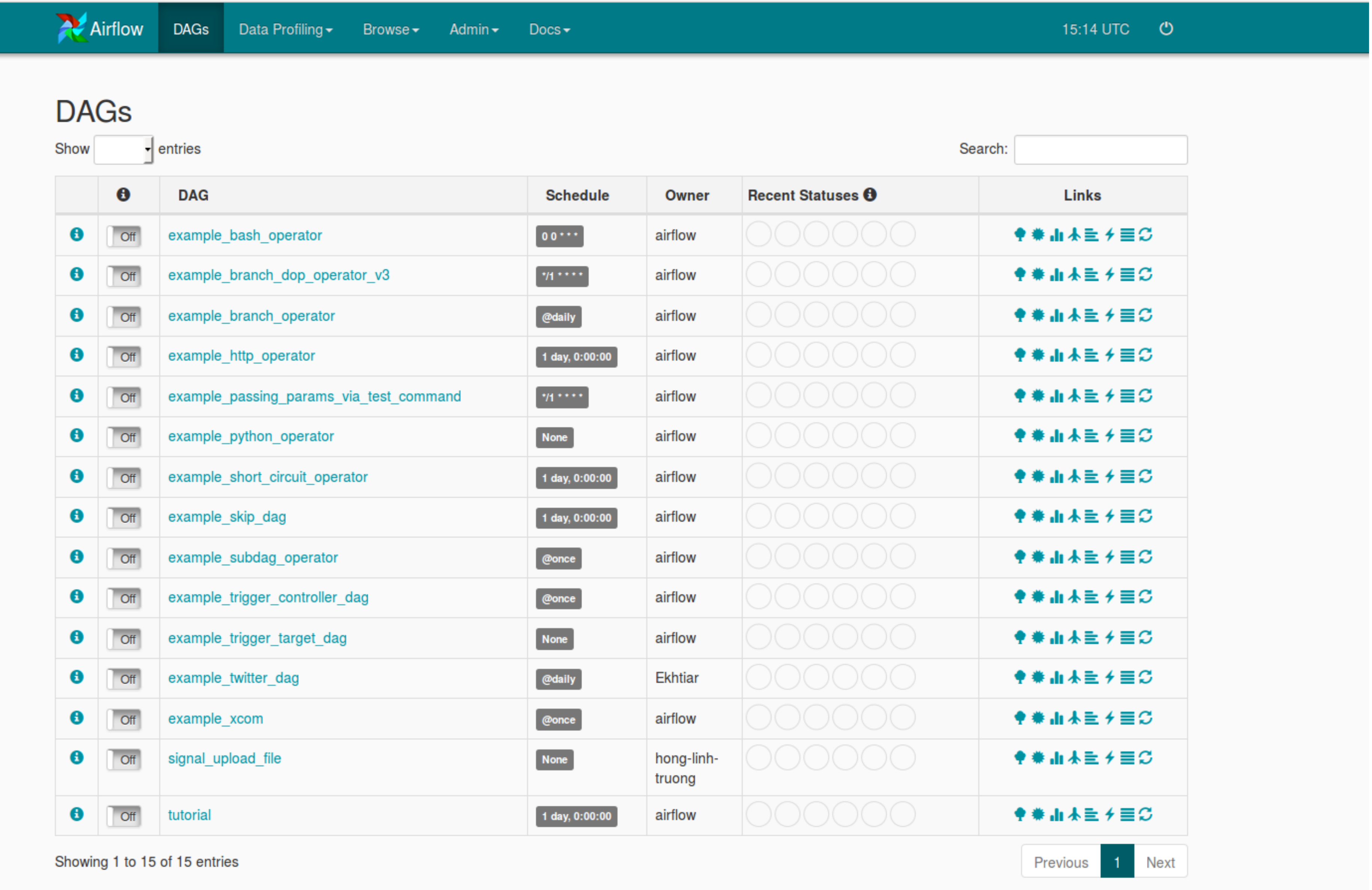
Example for processing signal file



Example for processing signal file

```
DAG_NAME = 'signal_upload_file'

default_args = {
    'owner': 'hong-linh-truong',
    'depends_on_past': False,
    'start_date': datetime.now(),
}

dag = DAG(DAG_NAME, schedule_interval=None, default_args=default_args)


stations=["station1", "station2"]

def checkSituation(**kwargs):
    f = 'f'
    t = 't'
    return t

downloadlogscript="curl  file:///home/truong/myprojects/mygit/rdsea-mobifone-training/data/opensignal/sample-Oct182016.csv -o /opt/data/air

t_downloadlogtocloud=  BashOperator(
    task_id="download_signal_file",
    bash_command=downloadlogscript,
    dag = dag
    )


t_analytics=  BashOperator(
    task_id="analyticsinternetusage",
    bash_command="/usr/bin/python /home/truong/myprojects/mygit/rdsea-mobifone-training/examples/databases/elasticsearch/uploader/src/uploa
    dag = dag
    )
t_sendresult =SimpleHttpOperator(
    task_id='sendresults',
    method='POST',
    http_conn_id='station1',
    endpoint='api/update/credit',
    data=json.dumps({"userphone": "066412345","credit":10}),
    headers={"Content-Type": "application/json"},
    dag = dag
    )

t_analytics.set_upstream(t_downloadlogtocloud)
t_sendresult.set_upstream(t_analytics)
```

Examples



DAGs

Show entries Search:

		DAG	Schedule	Owner	Recent Statuses	Links
	Off	example_bash_operator	0 0 * * *	airflow		
	Off	example_branch_dop_operator_v3	*/1 * * * *	airflow		
	Off	example_branch_operator	@daily	airflow		
	Off	example_http_operator	1 day, 0:00:00	airflow		
	Off	example_passing_params_via_test_command	*/1 * * * *	airflow		
	Off	example_python_operator	None	airflow		
	Off	example_short_circuit_operator	1 day, 0:00:00	airflow		
	Off	example_skip_dag	1 day, 0:00:00	airflow		
	Off	example_subdag_operator	@once	airflow		
	Off	example_trigger_controller_dag	@once	airflow		
	Off	example_trigger_target_dag	None	airflow		
	Off	example_twitter_dag	@daily	Ekhtiar		
	Off	example_xcom	@once	airflow		
	Off	signal_upload_file	None	hong-linh-truong		
	Off	tutorial	1 day, 0:00:00	airflow		

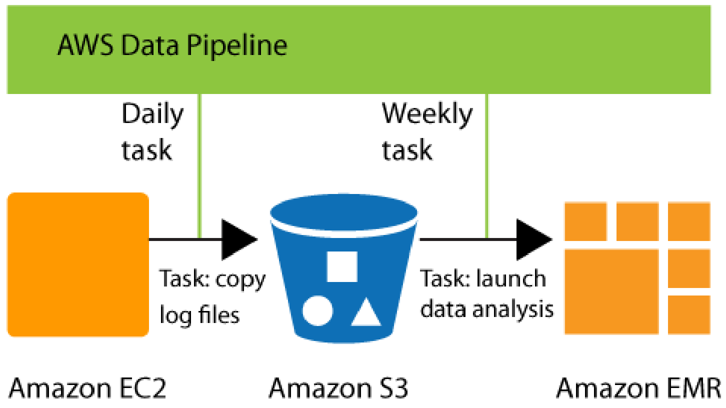
Showing 1 to 15 of 15 entries

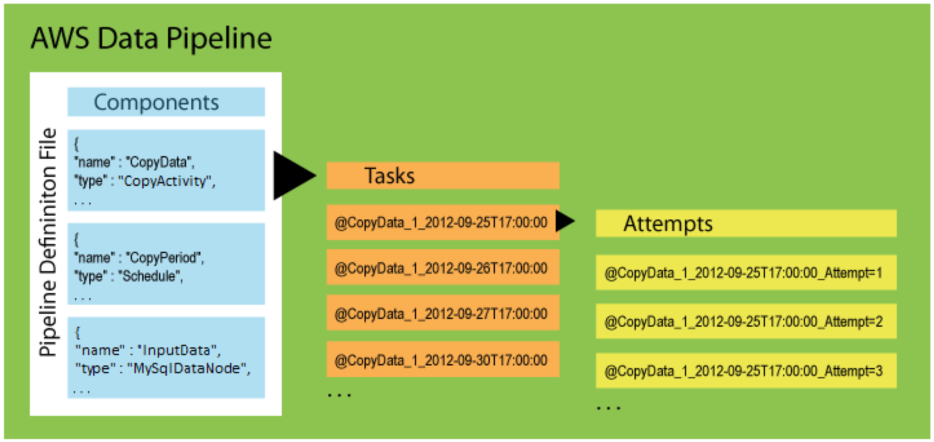
Previous 1 Next

Elasticity control for Workflows/Data Flows

- How to scale the workflows?
- Scheduling in a large resource pool (e.g., using clusters)
- Elasticity controls of virtualized resources (VMs/containers) for executing tasks
- Distributed Task Queue, e.g. Celery
    - http://docs.celeryproject.org/en/latest/getting-started/brokers/index.html
    - Job description/request sent via queues
    - Results from jobs can be stored in some back-end

Other systems, e.g., AWS Data Pipeline





http://docs.aws.amazon.com/datapipeline/latest/DeveloperGuide

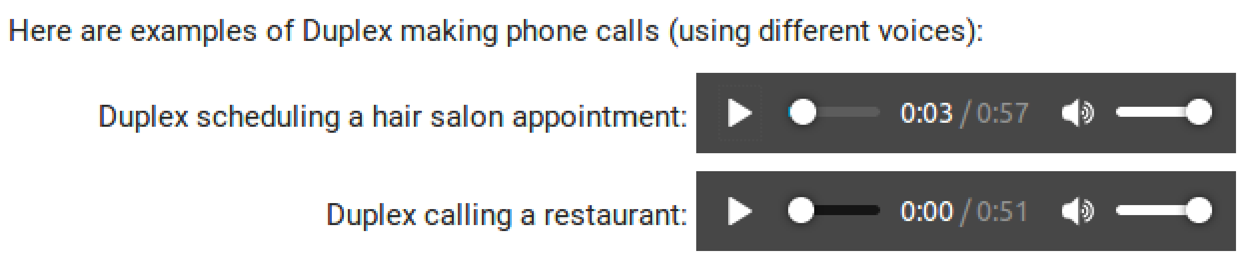
Hybrid service design

- Stream analytics triggers datapipes?
- Stream analytics triggers workflows?
- Stream analytics triggers serverless functions?
- And another way around?

Communicating results

- How to communicate results to the end user or other components?
- Software integration with protocols and interactions in previous lectures
- People: conversational commerce
  - More than just using SendGrid, Applozic, etc.

Source: https://developer.amazon.com/alexa-voice-service



Source: https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html

Summary

- Analytics-as-a-service for large-scale distributed applications and big data analytics require different set of tools
- Kafka, Apache Apex and Airflow are just some of the key frameworks
  - There are a lot of tools
- Need to understand common concepts and distinguishable features
- Select them based on your use cases and application functionality and performance requirements
- Exercises:
  - a small application utilizing Kafka/MQTT and Apache Apex
  - Log analytics using AOP and Kafka and Airflow

Further materials

- http://kafka.apache.org
- http://www.corejavaguru.com/bigdata/storm/stream-groupings
- https://cloud.google.com/dataflow/docs/
- http://storm.apache.org/
- https://azure.microsoft.com/en-us/documentation/articles/hdinsight-storm-iot-eventhub-documentdb/
- https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-102
- https://medium.com/walmartlabs/how-we-embraced-the-new-release-of-apache-kafka-9cf617546bb6
- https://hevodata.com/blog/exactly-once-message-delivery-in-kafka/
- https://dzone.com/articles/kafka-clients-at-most-once-at-least-once-exactly-o

Thanks for your attention

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