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# Big Data Ingestion, Transformation and Orchestration

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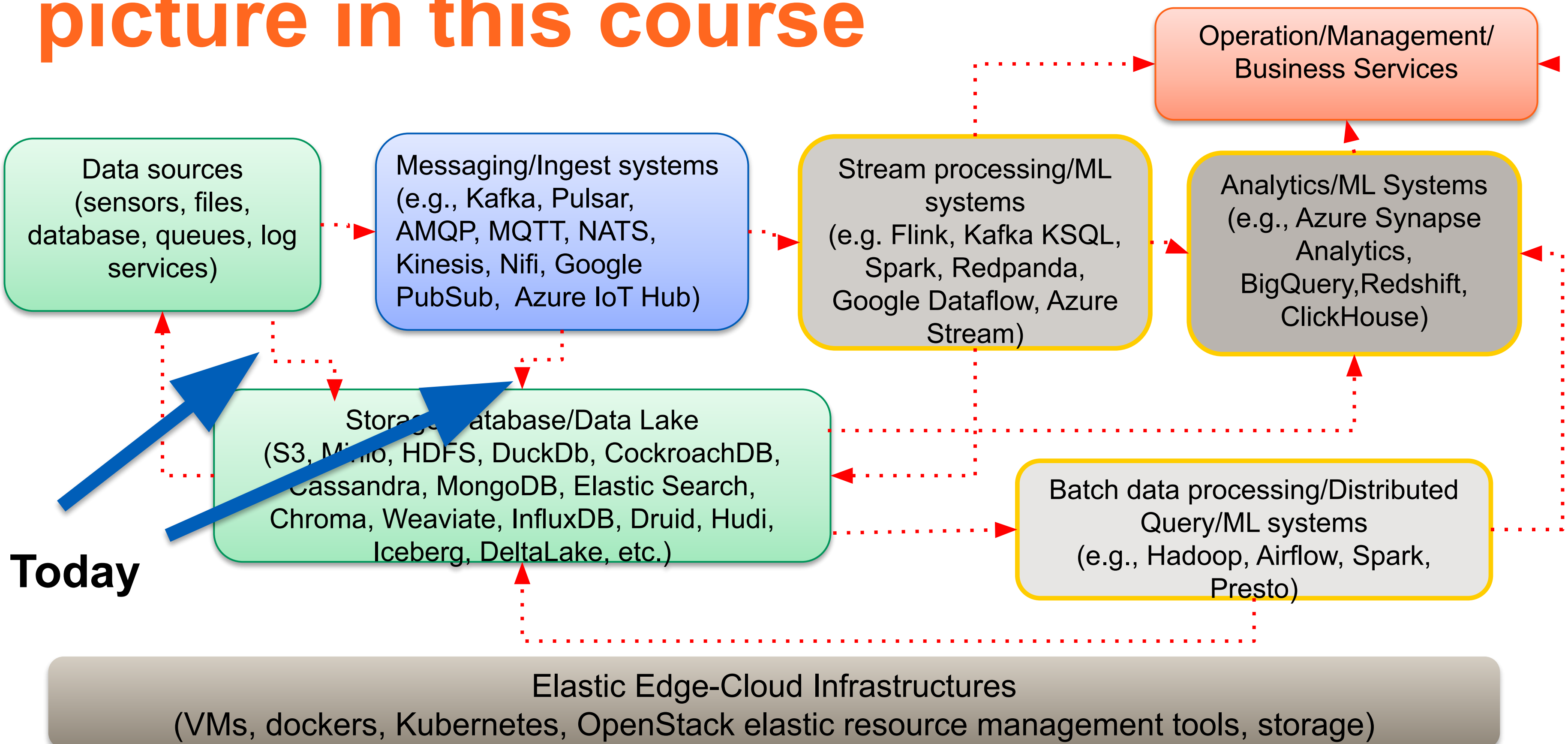
# Learning objectives

- Understand the overall design of data ingestion
- Study common tasks in data ingestion
- Understand and design efficient, robust data ingestion pipelines/processes
- Learn existing technologies/frameworks for your own design

# Big data at large-scale: the big picture in this course



# Ingestion systems

Data ingestion: move data from <u>different sources</u> into data platforms or selected data sinks/destinations

Data sources (files, databases,...)

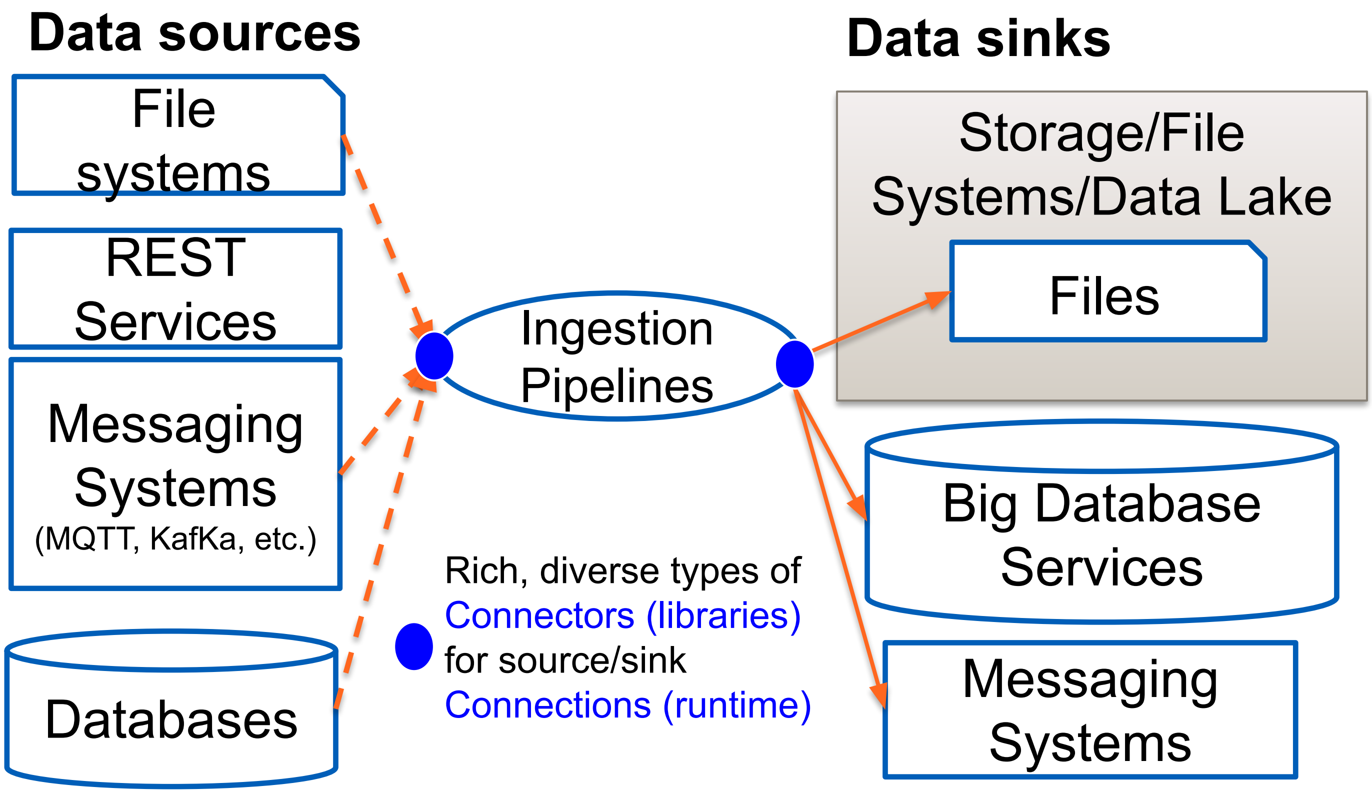

Data platform/ sink/destination

**Two important aspects:**

- tasks and non-functional requirements
- architectures, pipelines and service models

**Reusability and extensibility**

# Data sources and sinks




**Big data platform examples:**

Hadoop File systems
Google Storage
Amazon Storage

Druid
Google BigQuery
Hive
MongoDB
ElasticSearch
Cassandra
InfluxDB
Hudi
Kafka, Pulsar

# Diverse requirements from V* of big data

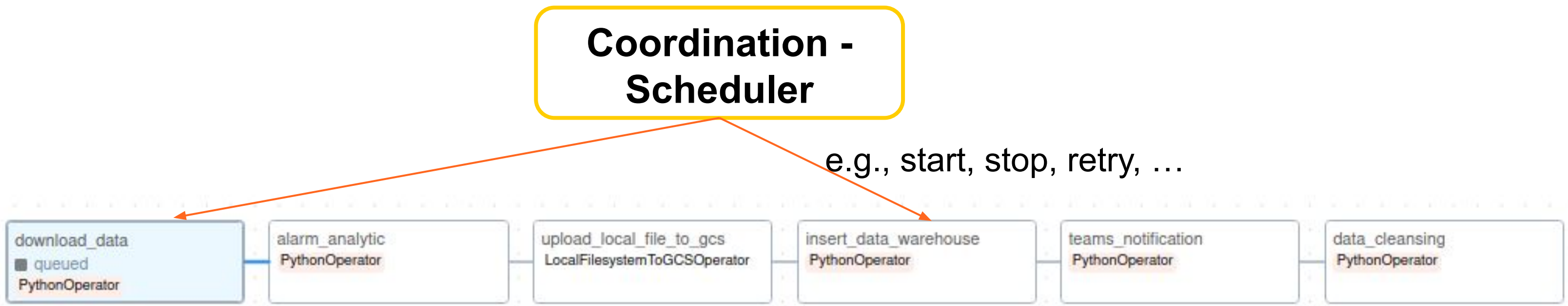
- **Requirements based on data characteristics**
  - structured, unstructured and semi-structured
  - speed, volume, accuracy, confidentiality, data regulation
- **Interact with data sources:**
  - Access APIs and protocols
    - *REST API, ODBC, SFTP, specific client libs*
    - *MQTT, AMQP, CoAP, NATS, Kafka,...*
  - Connection management:
    - *Performance, reliability and security*
- **How deep can a platform support complex requirements?**
  - e.g., able to go into inside of data elements (understanding the syntax and semantics of data)?

# Data transformation

- **Relation with ETL (Extract, Transform, Load)**
  - during ingestion, data transformation tasks might be needed
  - ETL has many operations to deal with the semantics/syntax of data and the business of data
- **Data transformation within ingestion**
- **Data transformation done after, within the (target) platform**
  - called ELT (load and then transformation)

**Performance, correctness and quality assurance**

# Ingestion needs task coordination




- **Big data ingestion involves**
  - many tasks
  - multiple tenants/users
  - ad-hoc, on-demand vs scheduled task pipelines
  - data movement in single vs cross data centers
- **Complex coordination techniques are used**
  - tasks are not in the same machine (executors) → data exchange among tasks (data dependencies)

# Ingestion tasks: common tasks and requirements

# Main tasks in ingestion

- **Key categories of tasks**
  - data access and extraction
  - data routing
  - data wrangling
  - data storing
  - lineage and observability for quality assurance/governance (quality check)
- **Consumer/user defined tasks vs platform tasks**
- **Other supports: compression, end-to-end security**

**They are different for batch vs near real time ingestions**

# Ingestion tasks implemented as extensible, composable connectors

- **Basic tasks for big data ingestion can be (re)used in different cases**
- **Support end-user goals**
  - enables the user to do many tasks through configurations and extensions
- **Enable pluggable approaches is important**

input data plugin/component → filter/extract/transform component → output data plugin/component

# Data access and extraction tasks

- **Access**
  - obtaining/copy data from sources
    - including change data capture (CDC)
  - often built based on common protocols and APIs
    - connector library: strongly related to data storage/database/datalake sink/source)
    - runtime connection management: maintain list of connections created from connectors
  - reusability is important!
- **Encryption, masking/anonymization**
  - might need to be done when accessing and extracting data
  - also during transfers of data
  - data security requirements, personally identifiable information

# Example with NETACT Log

29869;10/01/2017 00:57:56;;Major;PLMN-PLMN/BSC-xxxxxx/BCF-xxx/BTS-xxx;XYZ01N;ABC08;DEF081;BTS OPERATION DEGRADED;00 00 00 83 11 11;Processing

## Simple Grok

```
input {
file {
  path => "/tmp/alarmtest2.txt"
  start_position =>"beginning"
}
}
filter {
  grok {
     match => {"message" => "%{NUMBER:AlarmID};%{DATESTAMP:Start};%{DATESTAMP:End};%{WORD:Severity};%{NOTSPACE:NetworkType};%{NOTSPACE:BSCName};%{NOTSPACE:Sta
  }
}
output {
stdout {}
 csv {
     fields =>['AlarmID','Start','Stop','Severity','NetworkType','BSCName','StationName','CellName','AlarmInfo','Extra','AlarmStatus']
    path => "/tmp/test-%{+YYYY-MM-dd}.txt"
}
}
```

# Change data capture (CDC)

- **The principles:**
  - capture and ingest only new data by listening data changes
    - “new”: application-specific, e.g., based on time, value, and version.
  - leverage many features of databases (update, query, insert operations), data stream offsets and status notification (e.g., the availability of new files)
- **Implementation in different tools like Redhat Debezium, Hudi DeltaStreamer, Kafka Connect**

# Data wrangling

- **Convert/transform data from one form to another**
  - cleansing, filtering, merging, enriching, infering, and reshaping data
- **Require access to the data content!**
- **Key design choices**
  - do you support it during the ingestion or after the ingestion?
  - as a platform provider: are you able to do this?

# Data wrangling

- **In the context of big data platforms**
  - define or discover data schemas
  - automatic data wrangling: write pipelines/programs which do the wrangling
- **Wrangling programs provided by customers**
  - needs the platform to support debugging, monitoring and exception handling
  - runtime management for wrangling
- **Wrangling programs provided by platforms**
  - constraints in dealing with customer data

# Examples

**Write your own code with Pandas/Dask and Dataframe?**

**Automatically generate code for wrangling?**

```
Alarms={}
with open(sys.argv[1], 'rb') as csvfile:
    reader = csv.DictReader(csvfile)
    for row in reader:
        try:
            #print row['Started']
            alarm_time = datetime.strptime(row['Started'], '%d.%m.%Y %H:%M:%S')
            #diff =start_time - alarm_time
            #print "different time is ",diff
            if alarm_time  >=start_time:
                #print(row['RNW Object Name'], row['Severity'])
                typeOfAlarm = 0
                cleanSeverity = re.sub('\W+','',row['Severity'])
                if (cleanSeverity in mobifone.AlarmSeverity.keys()):
                    typeOfAlarm = mobifone.AlarmSeverity[cleanSeverity]
                #print ("Type of Alarm: ",typeOfAlarm)

                if row['RNW Object Name'] in Alarms:
                    #print "Again"
                    severies =Alarms[row['RNW Object Name']];
                    serveries[typeOfAlarm]=serveries[typeOfAlarm]+1
                else:
                    serveries =[row['RNW Object Name'],0,0,0,0,0,0]
                    serveries[typeOfAlarm]=serveries[typeOfAlarm]+1
                    Alarms[row['RNW Object Name']]=serveries;
        except:
            print "Entry has some problem"
            print row
        #timestamp =long(row['TIME'])
        #times.append(datetime.datetime.fromtimestamp(timestamp/1000))
        #times.append(long(row['TIME']))
        #signals.append(float(row['GSM_SIGNAL_STRENGTH']))
dataframe =pd.DataFrame(Alarms,index=mobifone.AlarmSeverityIndex).transpose()
alarmdata =dataframe.as_matrix();
#TODO print Alarms to fine
#only for debugging
print dataframe
dataframe.to_csv(outputFile, index=False)
```

# Data Wrangling: complex data transformation and processing

- **More complex data processing**
  - extract only important data
    - *feature engineering*
  - enrich data on the fly with external sources

**Example: extract vectors from images**

```python
class TowheeExtractor(BaseExtractor):
    def __init__(self):
        self.towhee_feature_extractor = (
            pipe.input('file_path')
                .map('file_path', 'img', ops.image_decode.cv2_rgb())
                .map('img', 'embedding', ops.image_embedding.timm(model_name='resnet50'))
                .map('embedding', 'embedding', ops.towhee.np_normalize())
                .output('embedding')
            )

    def get_model_name(self):
        return "resnet50"

    def feature_extractor(self, image_file):
        ##currently only a single figure so we have to get the first element
        embedding=self.towhee_feature_extractor(image_file).get()[0]
        return embedding
```

# Behind the scene: complex code & libraries hide low level distributed/parallel tasks

- **Complex distributed and parallel tasks for ingestion**
- **Complex coordination**
- **Underlying, internal task models:**
  - MapReduce model
  - embarrassingly parallel model
  - full direct acyclic graph (DAG) task model

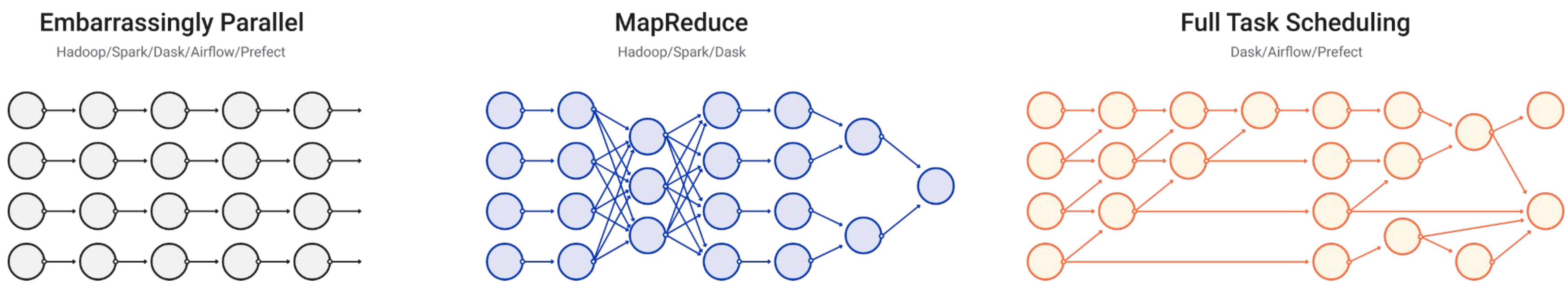
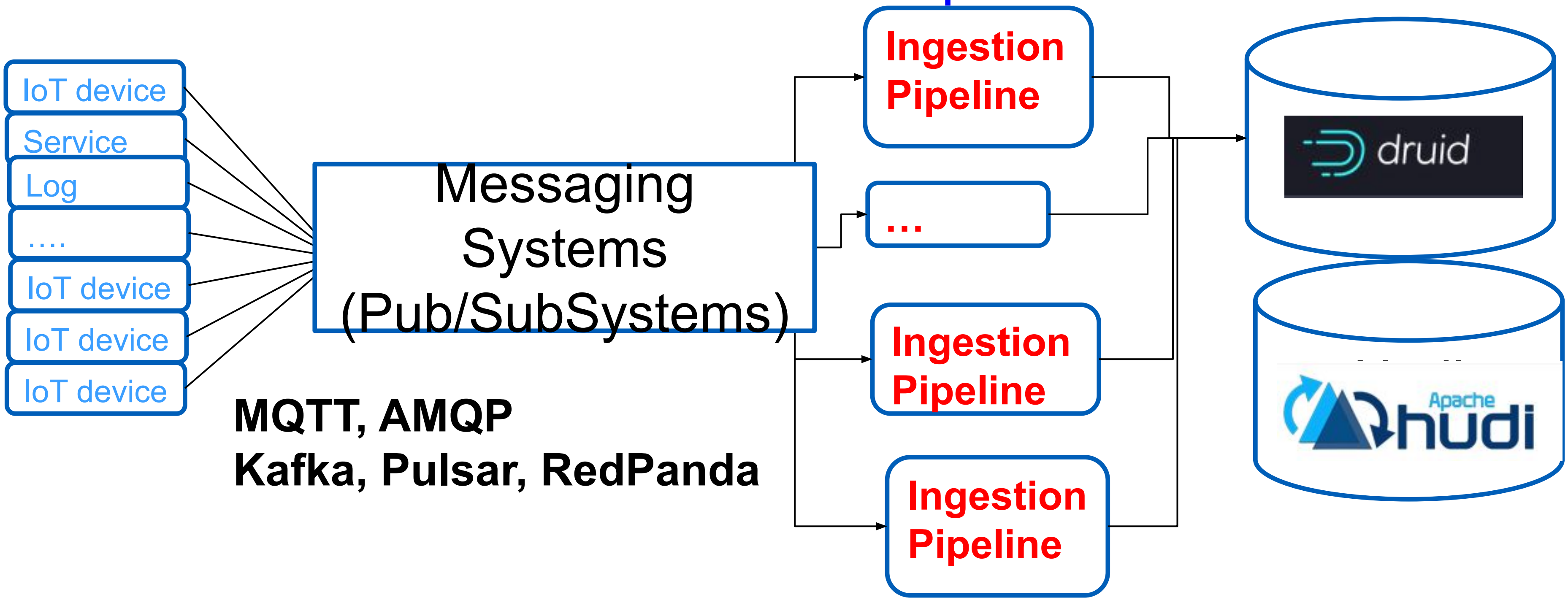


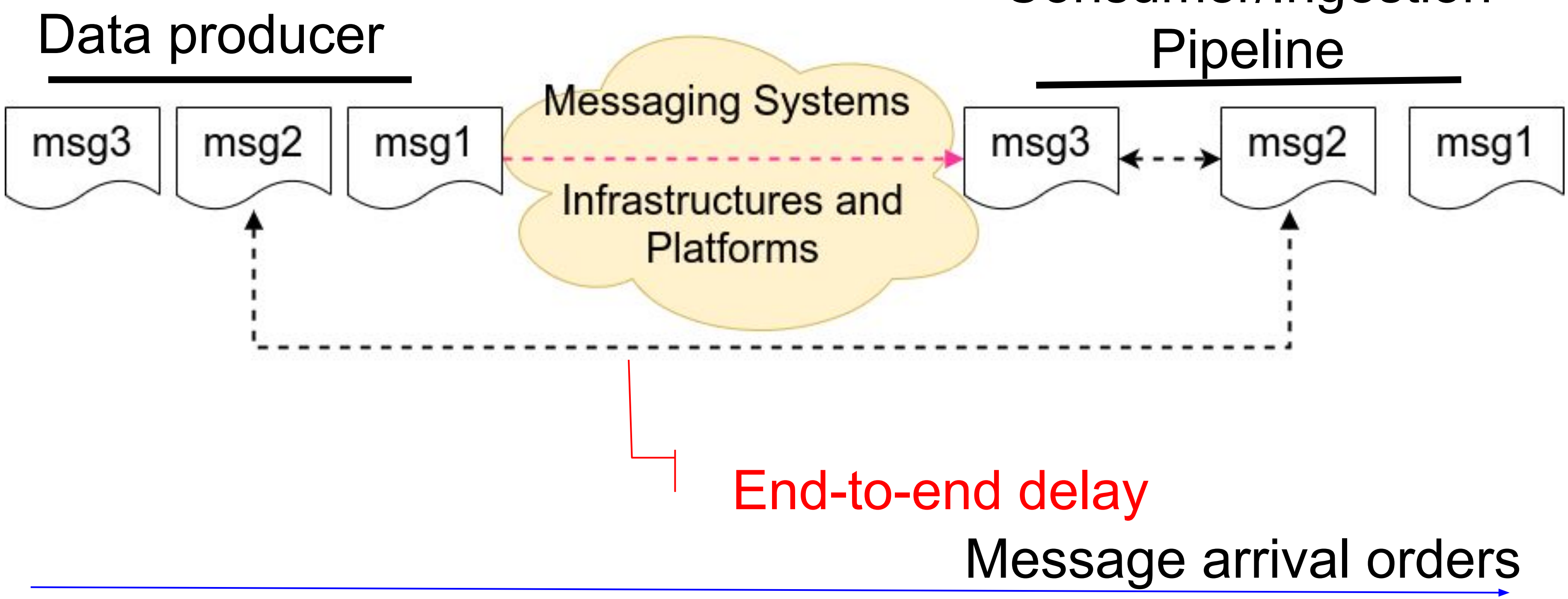

**Figure source:** https://docs.dask.org/en/stable/graphs.html

# Near real time ingestion

**Run as a service or arbitrary and can be complex**



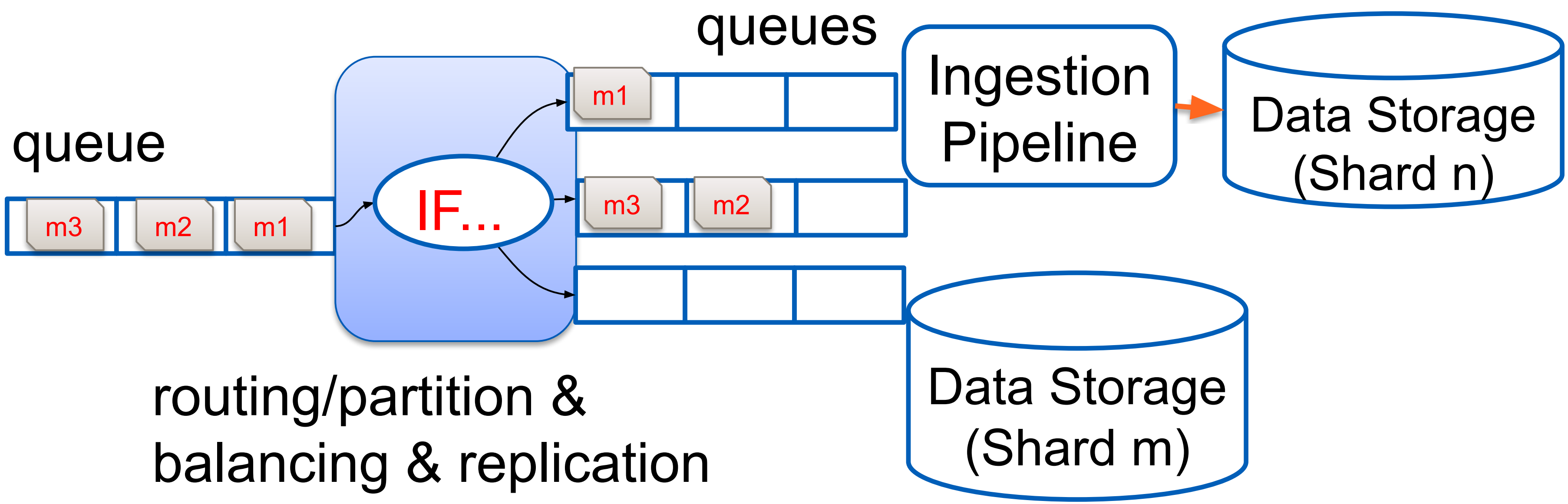
# Key issues in streaming data ingestion



# Some key issues for ingestion of streaming data

- **Late data, data out of order?**
- **Exactly once?**
- **Back pressure and retention**
  - for individual components or the whole pipelines
- **Scalability and elasticity**
  - changes in data streams can be unpredictable
- **Data quality**
  - fast processing, overhead

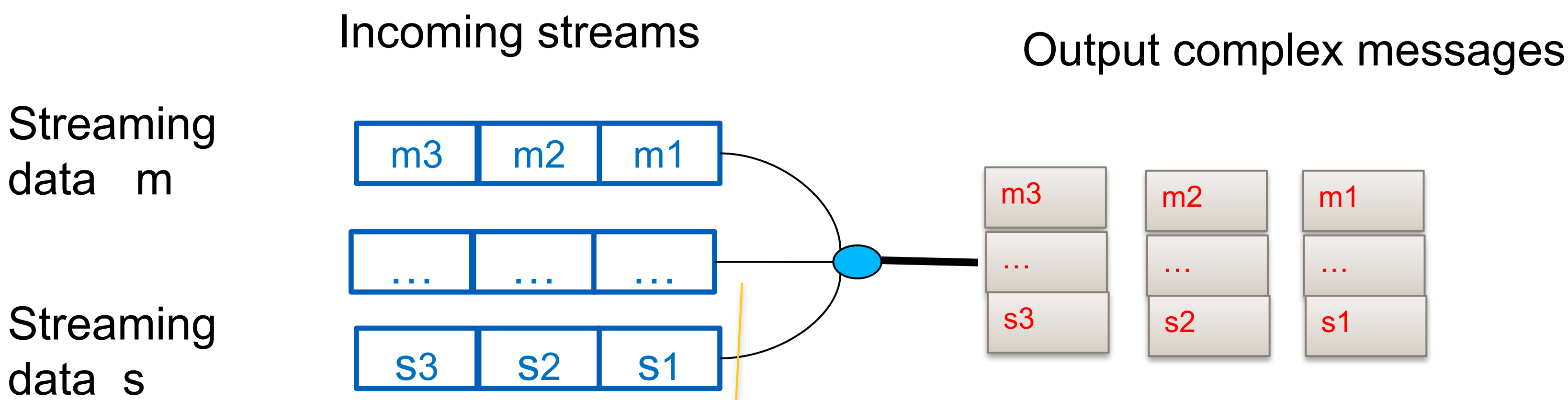
# Split (pub/sub) and partition with ingestion



# Some key issues

- **Multiple topics/streams of data**
  - speed and volume of data per topic vary
  - should not have duplicate data in data store
- **How to distribute topic/data to ingestion pipelines?**
  - application logics and performance
- **Where should we run the messaging system?**
- **Where and when should the elasticity be applied?**
  - computing resources + data resources (streams)

# Procesing data before ingestion requires some streaming techniques




E.g., basic processing for data rollup/summarization

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# Pipeline designs and execution models

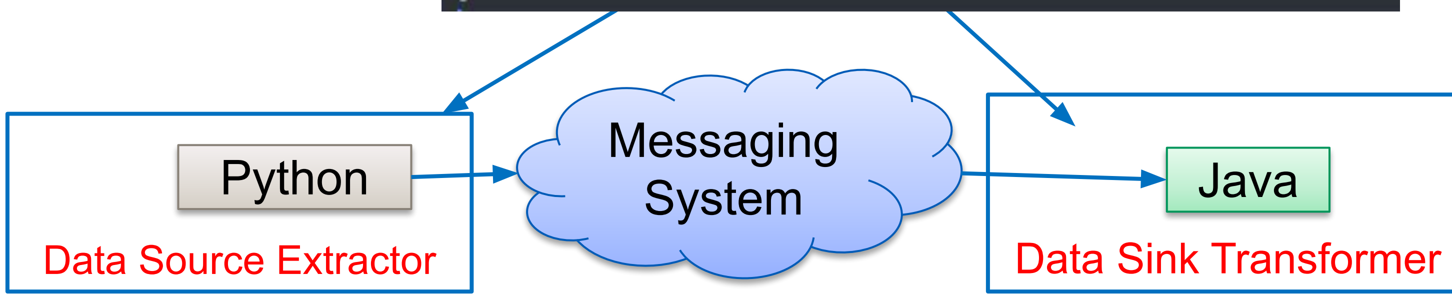
# Dealing with diverse data structures

- **the data sender/producer and the receiver/consumer are diverse**
  - implemented with different languages and software technologies
    - *need to guarantee the message syntax and semantics*
  - performance overhead due to data format conversion
- **Solutions:** don't assume! agreed in advance
  - agreed in advance $\Rightarrow$ within the implementation or with a standard
  - know and use tools to deal with syntax differences
- **Understanding the syntax allows some automatic transformations/quality checks**
- **But semantics are domain/application-specific**

# Example of interoperability in data transfer: Arvo

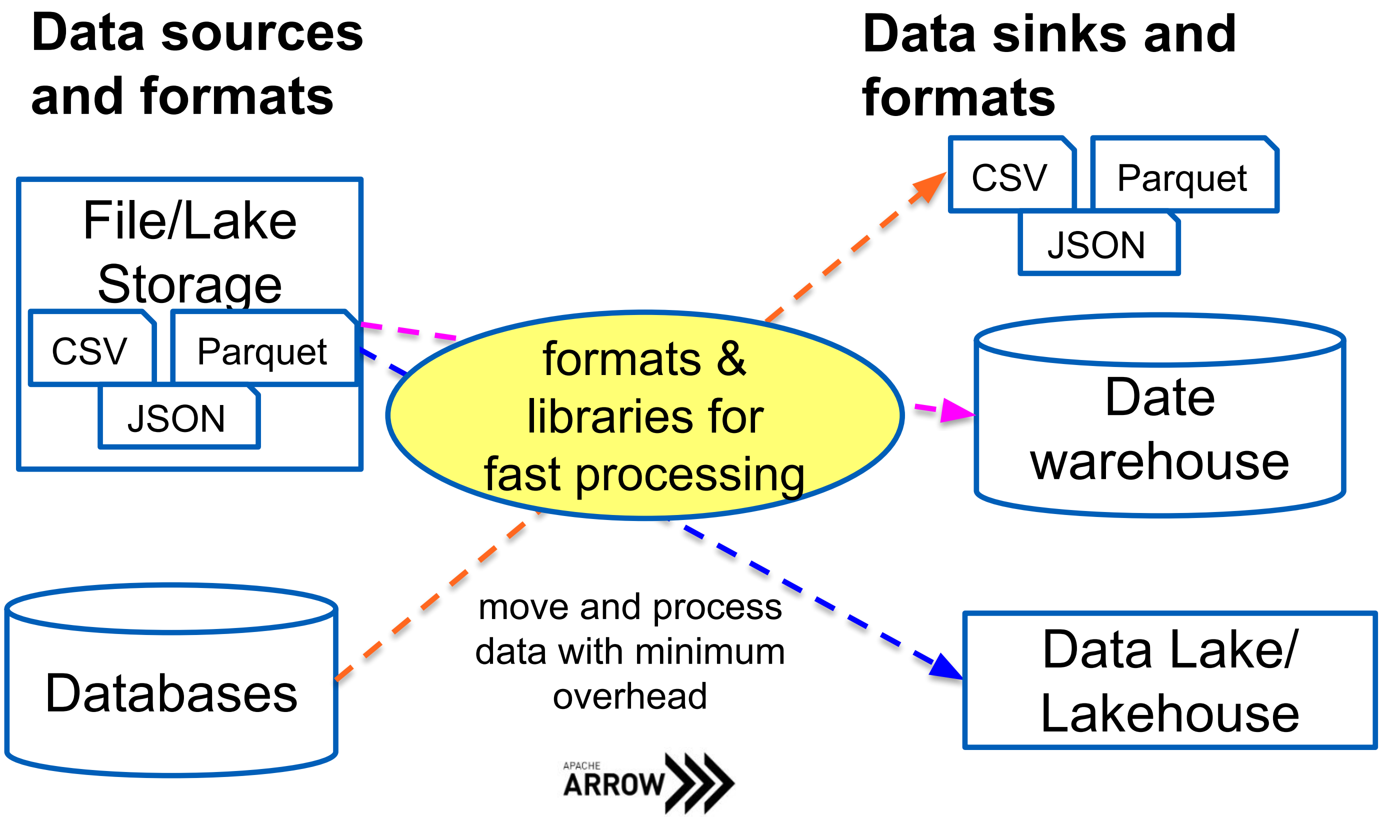
```
{
        "namespace": "bdp.courses.aalto.fi",
        "type": "record",
        "name": "event",
        "fields": [
            {"name":"station_id", "type":"string"},
            {"name":"datapoint_id", "type":"int"},
            {"name":"alarm_id", "type":"int"},
            {"name":"event_time", "type":"int"},
            {"name":"value", "type":"float"},
            {"name":"valueThreshold", "type":"float"},
            {"name":"isActive", "type":"boolean"}

        ]
}
```

**Syntax specification**
**https://avro.apache.org/**




**Also: Protobuf, JSON Schema**

# Interoperability in data processing in ETL




**Example: Apache Arrow**

In-memory columnar format

rich ecosystems

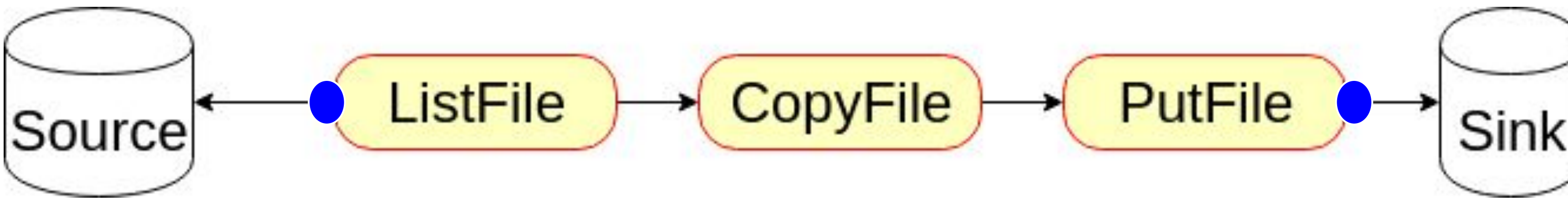
https://arrow.apache.org/

# Ingestion is not a single task!

# Ingestion pipelines/processes: architectures, composition, coordination, and tools

# Complex deployment and composition models

- **Understanding strong dependencies between protocols/APIs, security, performance and management**

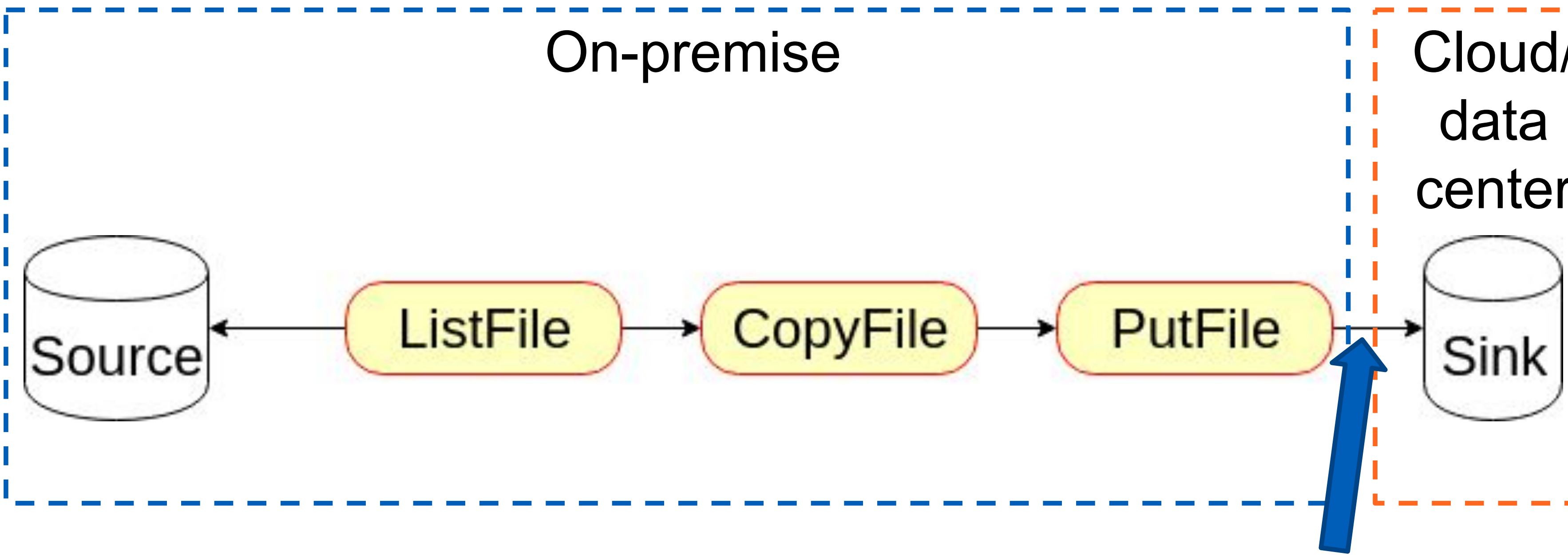



**Tenant/ user**

**Ingestion pipeline developer ( for whom?)**

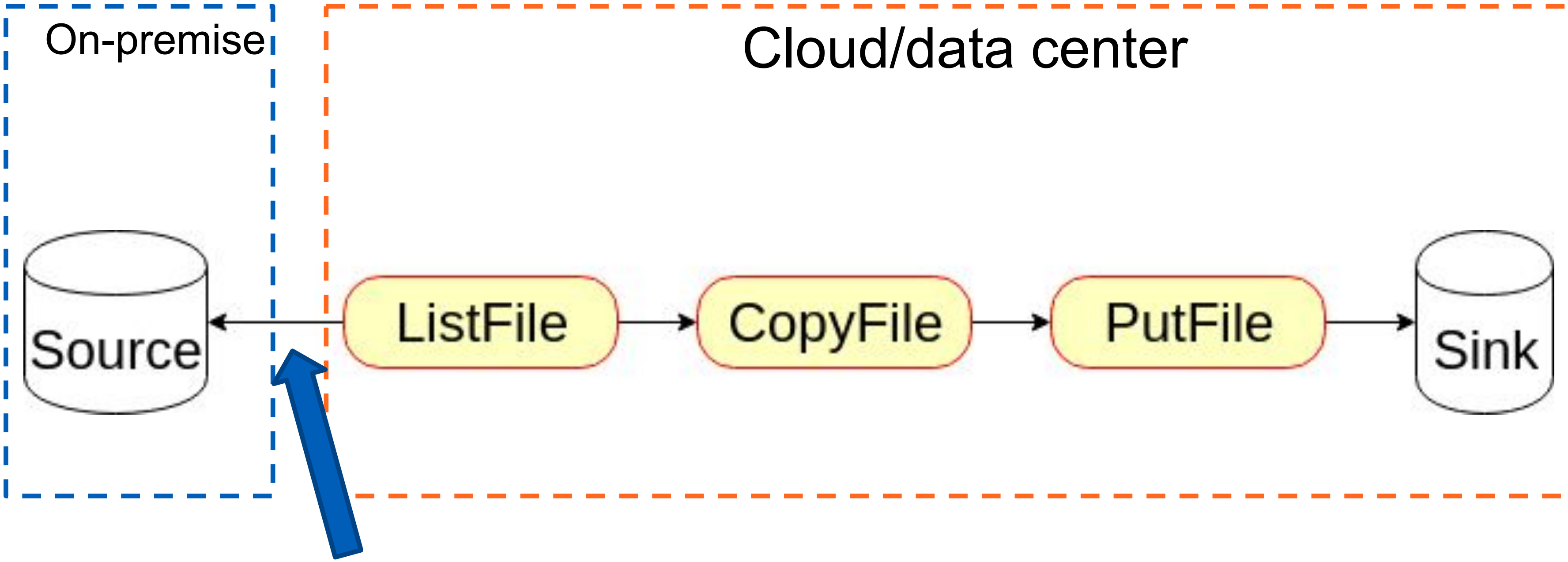
**Data store/platform provider**

# Complex deployment and composition models



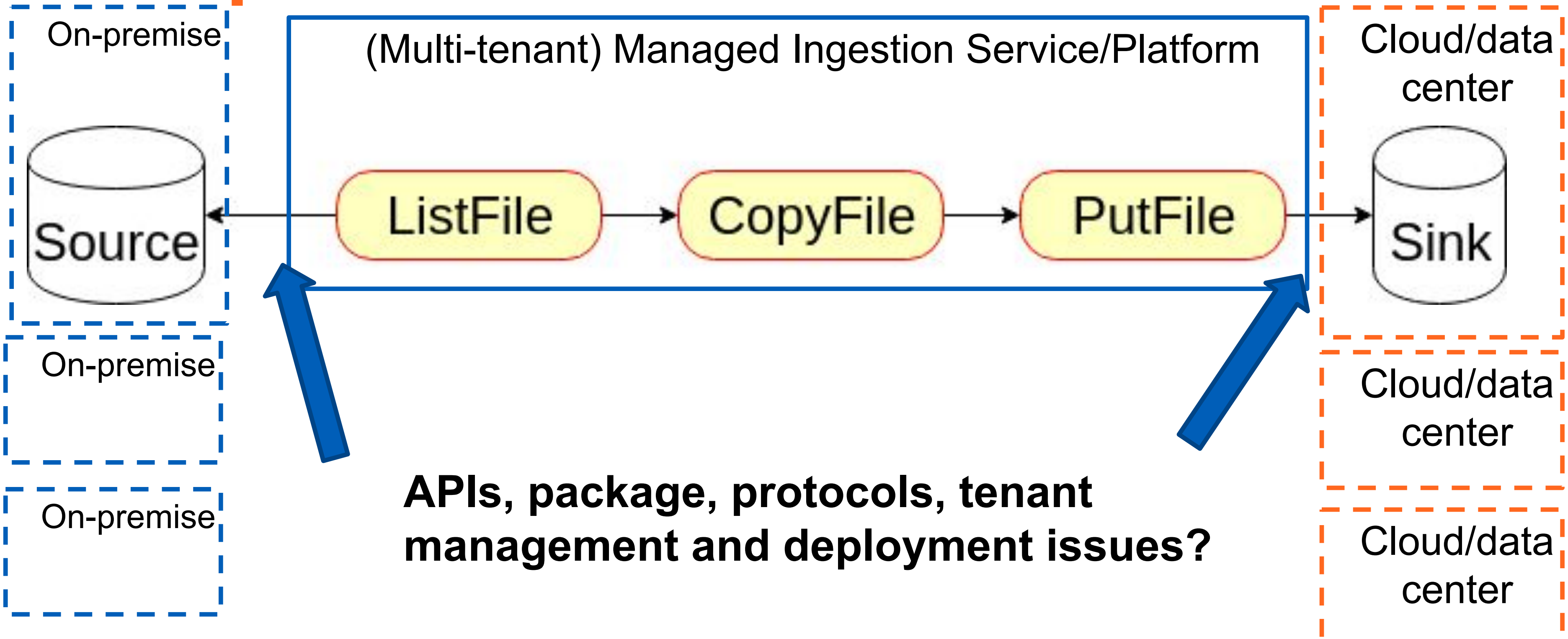

**APIs, protocols and deployment issues?**

# Complex deployment and composition models




**APIs, protocols and deployment issues?**

# Complex deployment and composition models

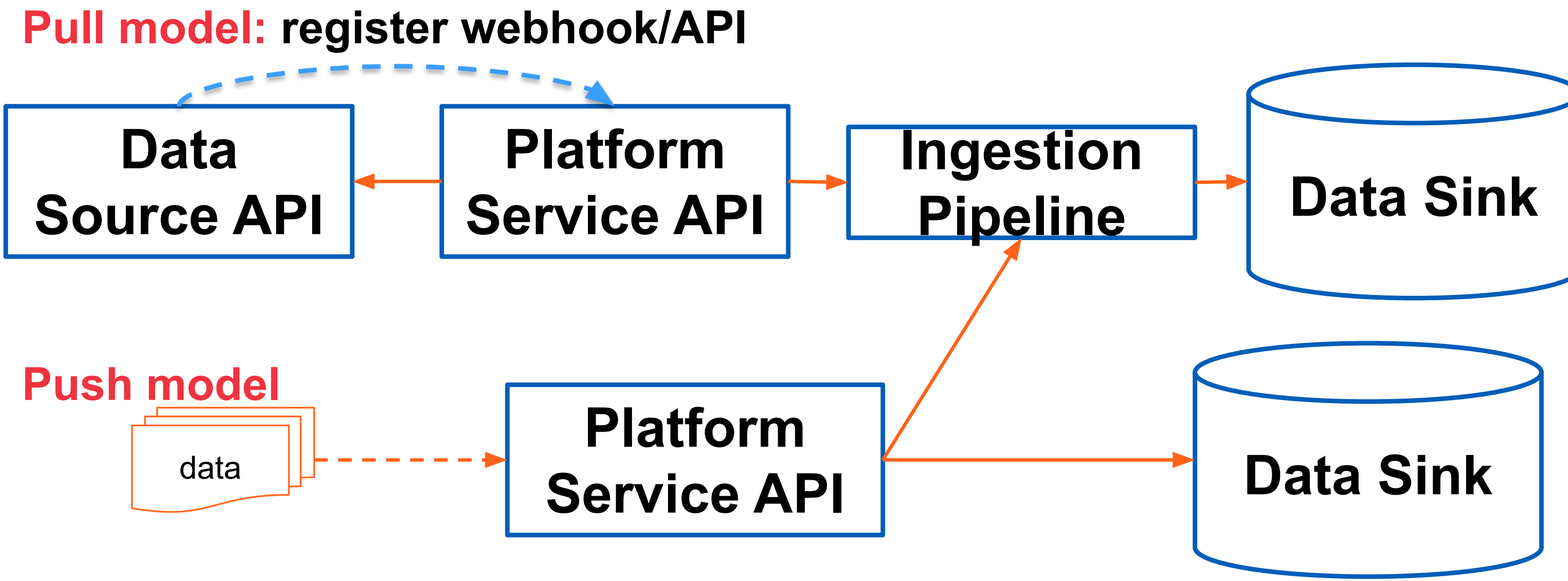



**APIs, package, protocols, tenant management and deployment issues?**

# Orchestrating batch ingestion pipelines

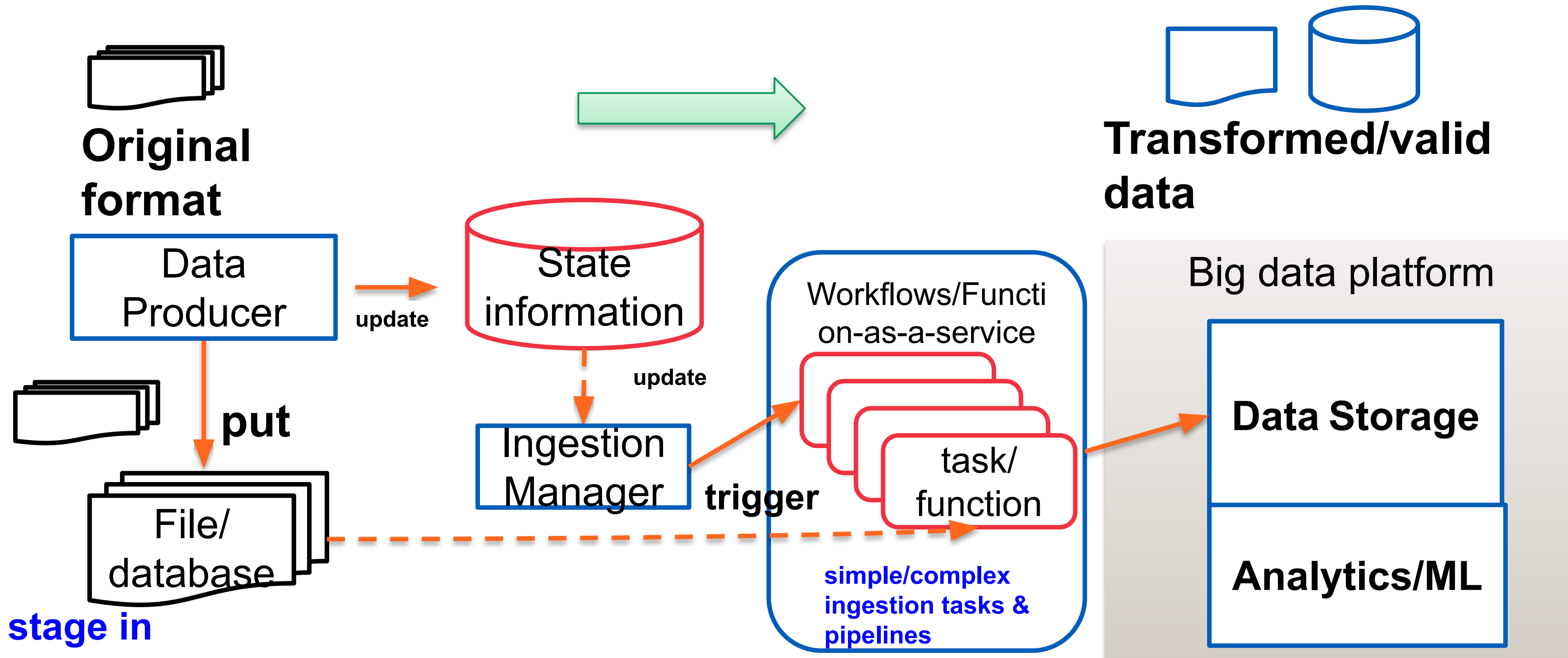
- **Data to be ingested is bounded**
  - files or messages are finite
- **Ingestion architectural styles**
  - (1) Direct APIs, (2) reactive pipelines, (3) tasks/workflows
- **Incremental ingestion**
  - dealing with the same data source but the data in the source has been changed over the time (related to change data capture)
- **Parallel and distributed execution**
  - use workflows and distributed  processing engines

# Simple, direct APIs for ingestion




**Try to analyze pros and cons for your platform!**

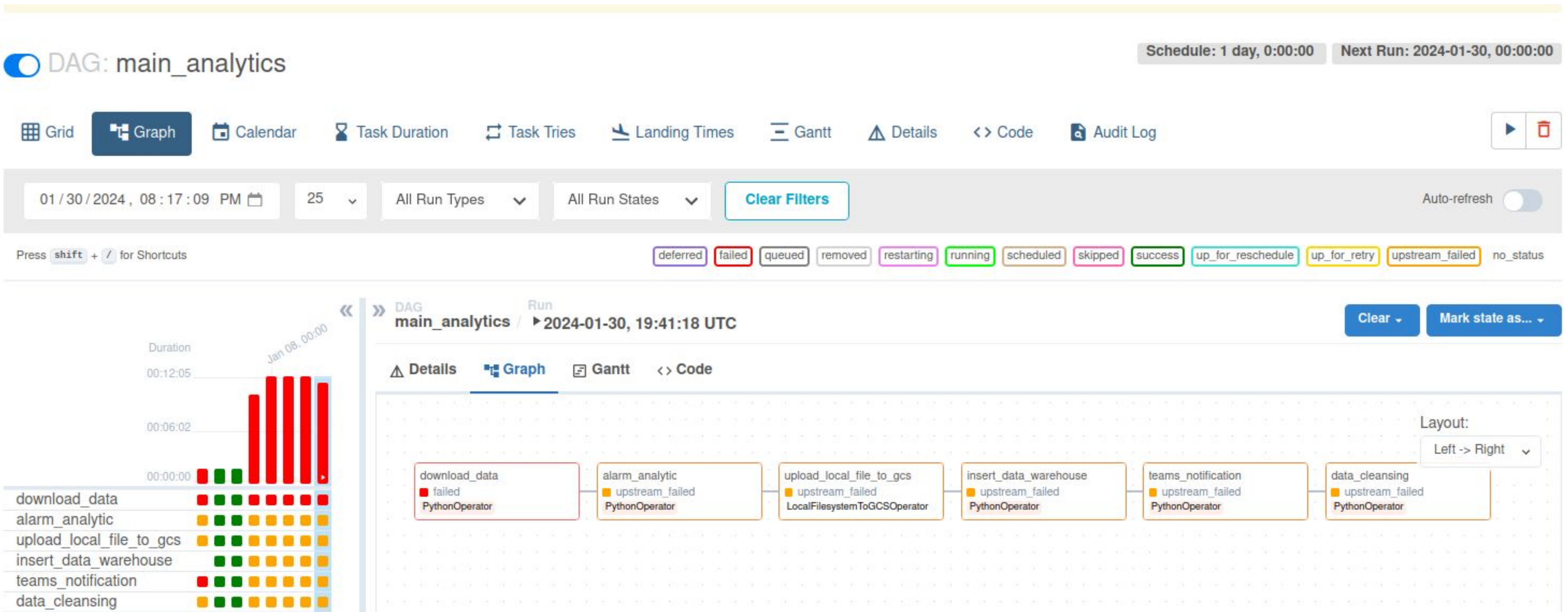
# Reactive pipelines with functions/workflows/containers



# Ingestion workflows orchestration

- **Different tasks**
  - access and copy, extract, covert, quality check, and write data
  - tasks are connected based on data or control flows
- **Workflows**
  - a set of connected tasks is executed by an engine
  - tasks can be scheduled and executed in different places
  - flexible designs
- **Different tenants have different service level agreements**
  - Performance, reliability, and cost.

# E.g., workflow based on scheduled time, with Apache Airflow

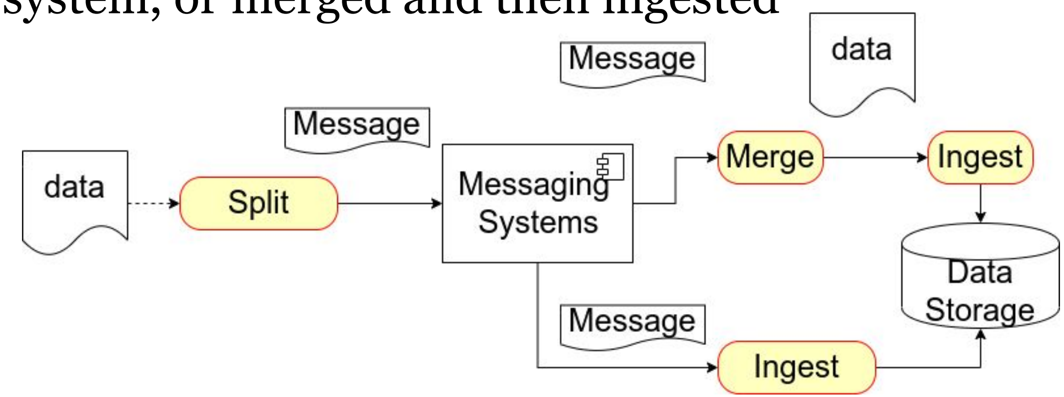


# Microbatching in data ingestion

- **Microbatching: we mean the strategy to deal with big dataset using batches of data (small chunks)**
  - not necessary the same as using batch systems to transfer small data in near realtime
- **Data is split into different chunks for ingestion**
  - using streaming or batch systems to transfer data chunks
  - chunks are ingested into the system, or merged and then ingested

**Example: with streaming system**

**Be careful with the data semantics/integrity!**



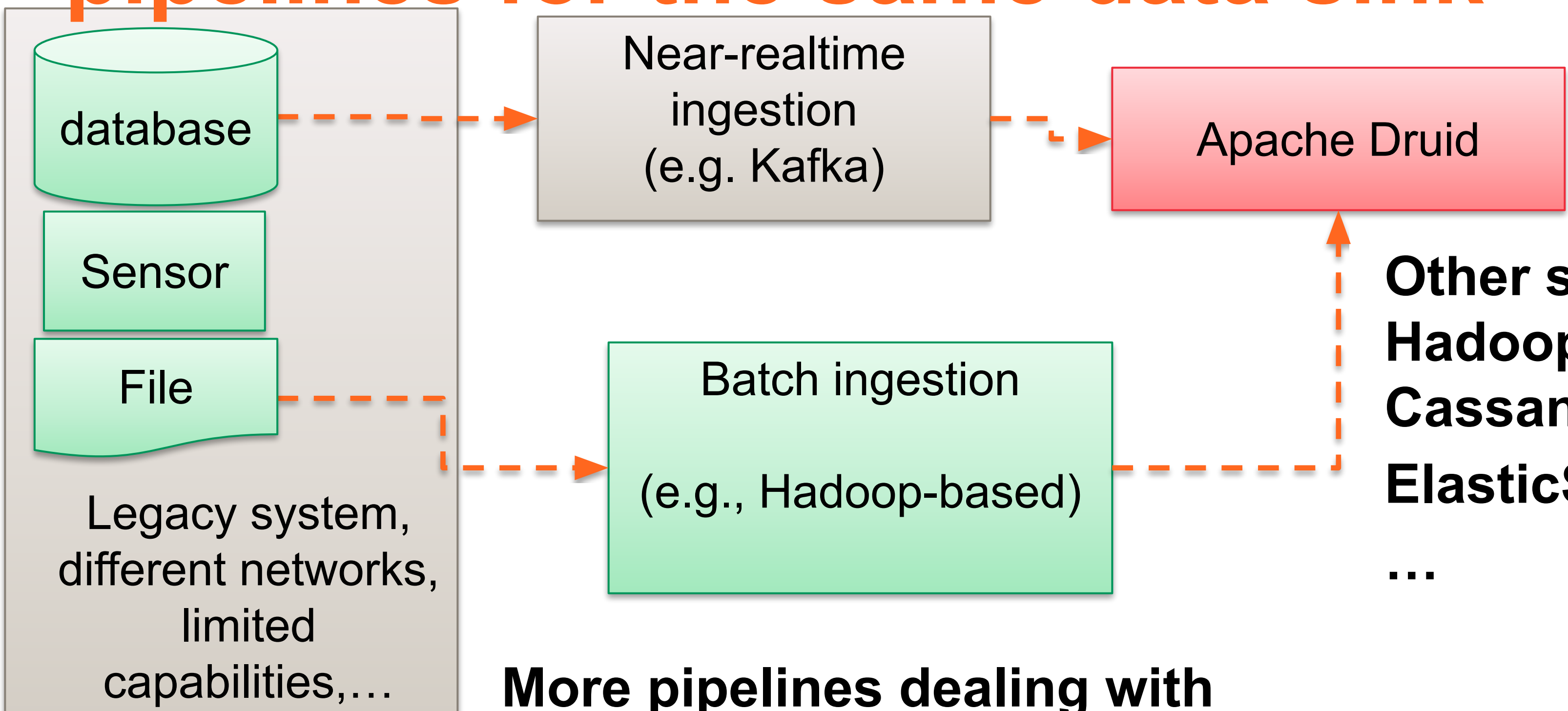
# Combining ingestion pipelines in big data platforms

- **Multiple types of pipelines for multiple types of tenants/users**
- **A tenant/user might need different integrated pipelines**

**⇒ Both batch and near-realtime ingestion are supported**

- **Complex architectural designs**
  - ingestion pipeline-to-pipeline needs “bridges”

# Supporting multiple types of pipelines for the same data sink

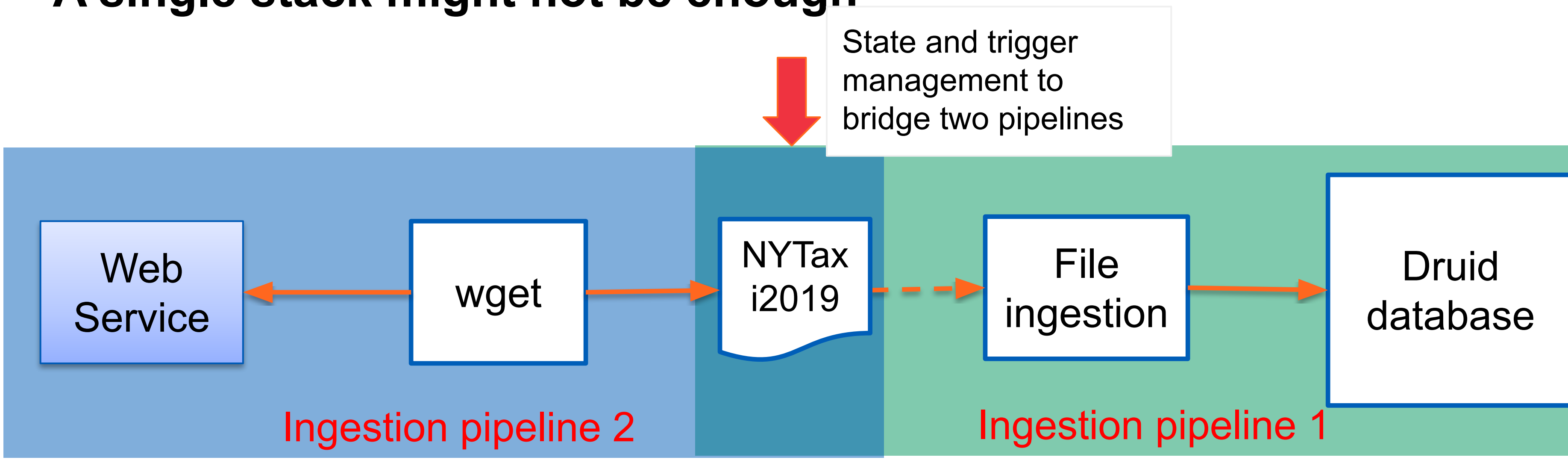



**Other systems: Hadoop, Cassandra ElasticSearch …**

**More pipelines dealing with different sources**

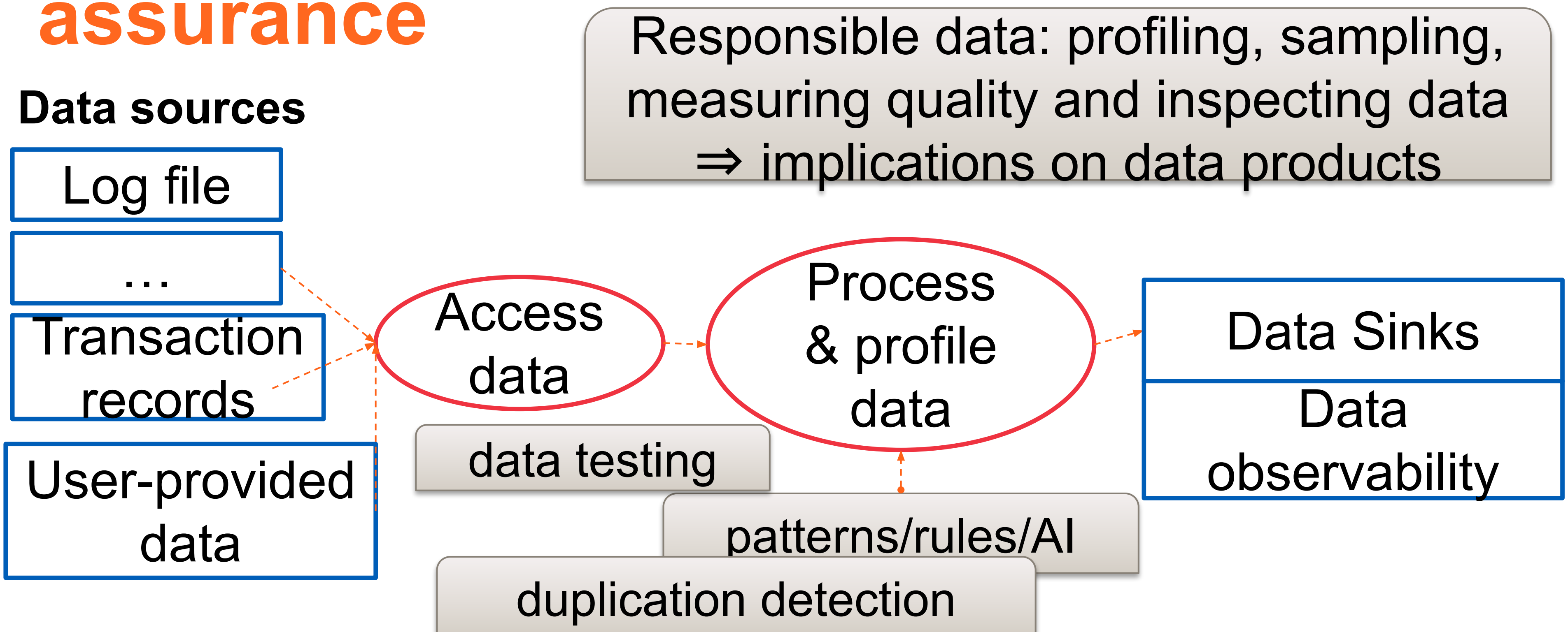
# Connecting different ingestion pipelines

**A single stack might not be enough**




**Real-world:**
**both pipelines and their connections are complex**

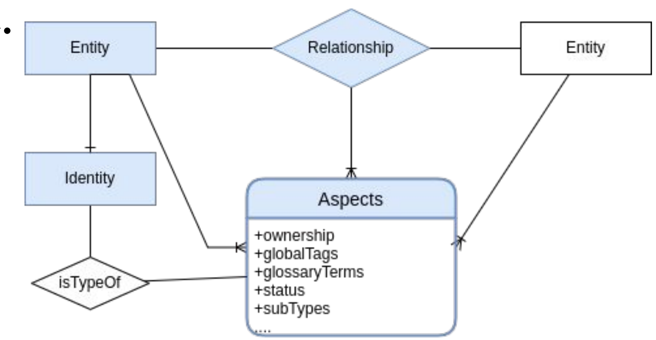
# Quality control/data regulation assurance




**Challenging issues: misinformation, GDPR, data quality, inappropriate content**

# Data lineage and observability (1)

- **FAIR principles** (https://www.nature.com/articles/sdata201618)
  - findable, accessible, interoperable, and reusable
- **Lineage/Provenance**
  - capture relevant information for understanding how data has been moved, transferred, processed, etc.
  - metadata models: W3C Provenance Model, DataHub, etc.
- **Key issues**
  - which metadata must be captured?
  - based on existing tools or your own?
- **Instrumentation/logging processes and automated data lineage → performance overhead!**




High level view of datahub see https://datahubproject.io/docs/metadata-modeling/metadata-model

# Data lineage and observability (2)

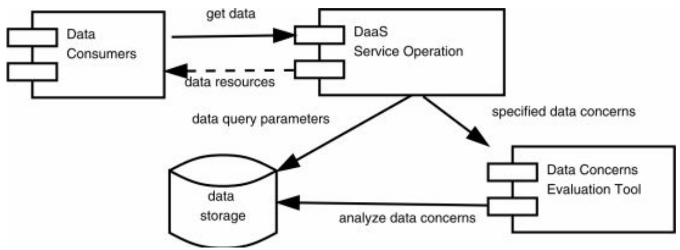
- **Data observability: the health about data**
  - near-real time metrics, offline checks and possible dashboards
  - similar to service observability, relying on traces, logs, metrics, etc.
- **Focus on data**
  - data metrics (volumes, data quality, schemas, lineage)
  - issues due to data problems
  - data ingestion processes/workflows
- **Some solutions**
  - validation of data against design schemas (e.g., Schema Registry in Kafka)
  - checks of realtime and offline data quality attributes → integrate with data ingestion processes or offline data profiling
  - integrated data quality tests in pipelines (e.g., data testing)

**Tools:** great expectations, OpenLineage, Microsoft Presidio, YData Profiling, aws deequ Public

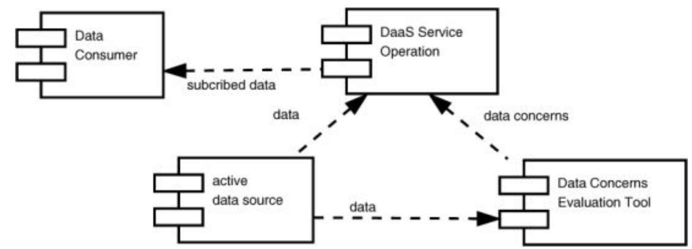
# Quality control/data regulation assurance (1)

## Design: dififerent evaluation modes

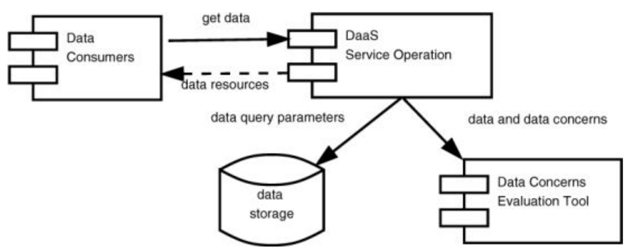
Pull, pass-by-reference model for evaluating data concerns




Push model for evaluating data concerns of active data sources




Pull, pass-by-value model for evaluating data concerns




**Source:** H. -L. Truong and S. Dustdar, "On Evaluating and Publishing Data Concerns for Data as a Service," *2010 IEEE Asia-Pacific Services Computing Conference*, doi: 10.1109/APSCC.2010.54.

# Quality control/data regulation assurance (2)

- **Before, after or during the ingestion/transformation**
- **In-process vs out-process**
  - in process: using libraries doing data quality very fast
  - out-process: a separate task in the workflow or external programs/services
- **Profiling, sampling, ML techniques for data quality**
- **Examples:**
  - Using a separate program like pydeequ Spark to check quality
    - *https://github.com/rdsea/bigdataplatforms/tree/master/tutorials/dataquality*
  - Anonymizing data
    - *https://microsoft.github.io/presidio/anonymizer/*

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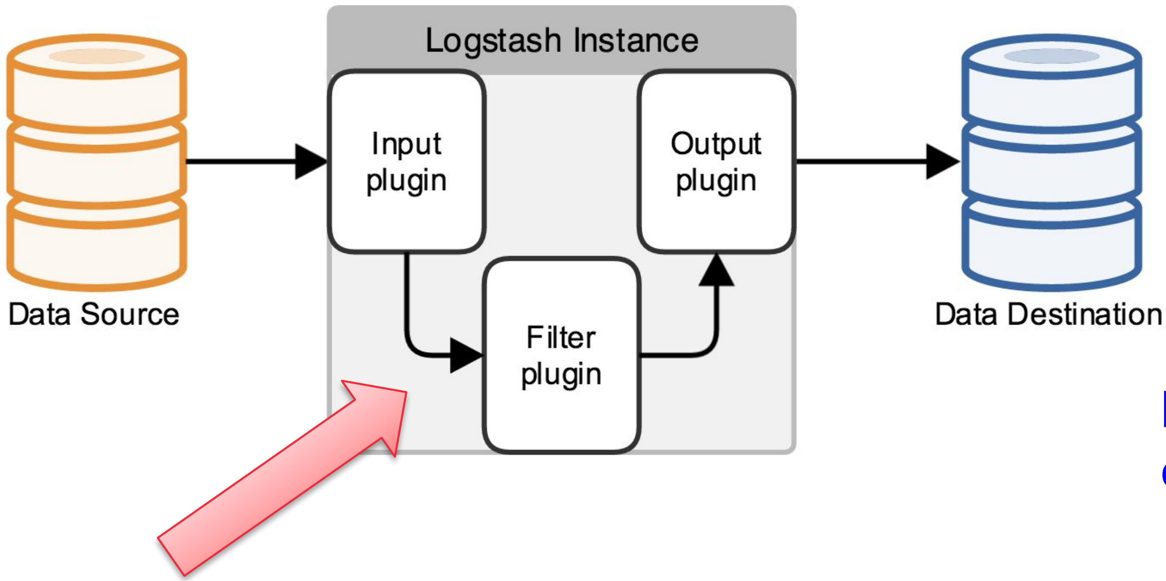
# Tooling for ingestion pipelines

# Tooling

- **Given different ingestion models, how do you deliver your ingestion tools/services?**
- **(Traditional) ways of REST API/specific client libraries**
  - upload using put/get operations
- **Workflows**
  - self-developed workflows vs automatically generated workflows
- **Pipelines are bundled into containers**
  - self-developed vs generic pipelines based on user configurations

# Design tools for ingestion processes: Logstash




```
input {
  file {
    path => "${MY_INPUT_DIR}/bts-data-alarm-2017.csv"
    start_position => "beginning"
  }
}
filter {
  csv {
    separator => ","
    columns => ["station_id","datapoint_id","alarm_id",
  }

}

output {
    stdout {}
    #...
}
```

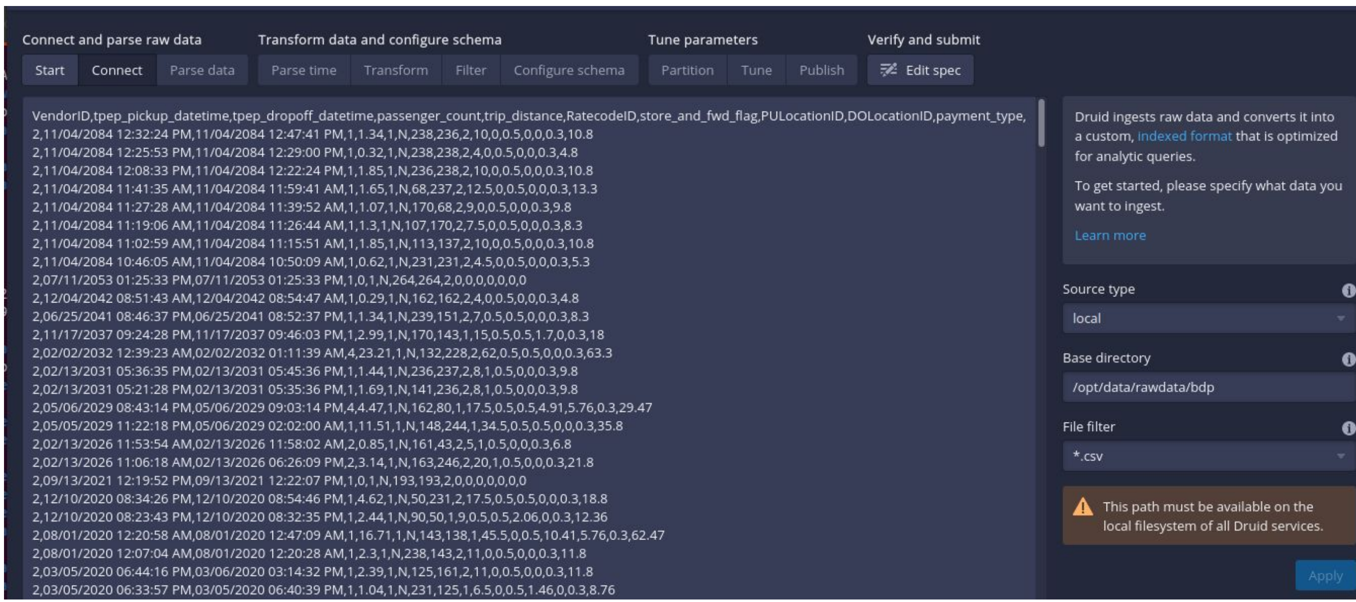
**Pipeline is defined in a configuration file**

**Pluggable approaches**

**Figure source:** https://www.elastic.co/guide/en/logstash/current/getting-started-with-logstash.html (from the previous version of Logstash)

# Design tools for ingestion processes: Apache Druid

## Allow the user to build the plan: select tasks, configuration, etc. and then generate ingestion pipelines



# Design tools for ingestion processes: Apache Nifi

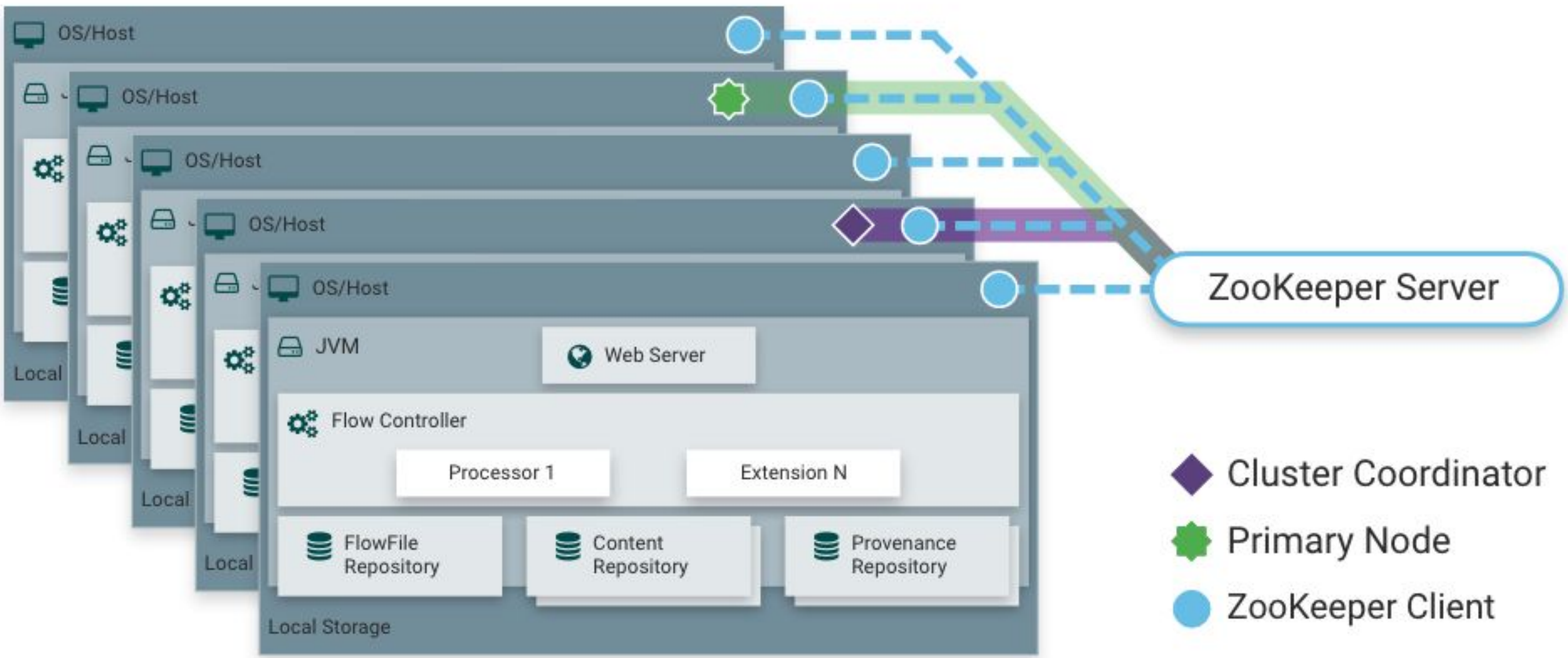
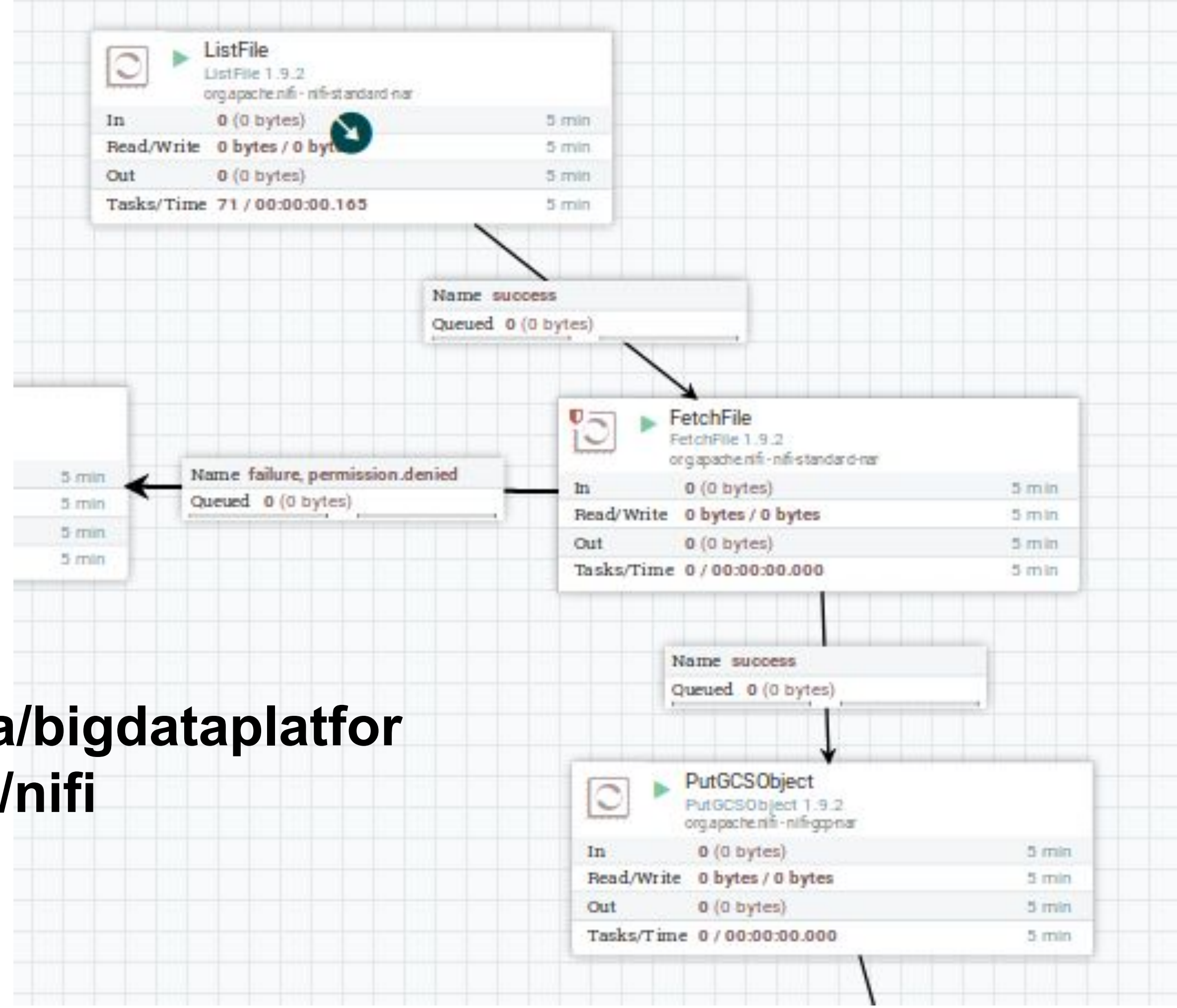



**Figure source:** https://nifi.apache.org/docs.html

# Design tools for ingestion processes: Apache Nifi - key concept

- Data is encapsulated into "FlowFile"
- Processor (Component) performs tasks
- Processor handle FlowFile and has different states
  - each state indicates the results of processing that can be used for establishing relationships to other components
- Processors are connected by Connection
- Connection can have many relationships based on states of upstream Processors

# Design tools for ingestion processes: Apache Nifi




**See the tutorial: https://github.com/rdsea/bigdataplatforms/tree/master/tutorials/nifi**

# Summary

- **Different designs of data ingestion for batch and streaming**
- **Ingestion is a complex pipeline**
  - many different sub tasks
  - complex requirements w.r.t performance, scale, failure handling
- **Different tools/stacks/services available**
  - share composable design principles, but different software models and deployments →explore them for your work
- **Do real-world designs**
  - hands-ons
  - complex designs but we do not need to "reinvent the wheel" → stay with core concepts and requirements to find the right tools!

# Thanks!

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