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School of Science

Service and Integration Models in Big Data Platforms

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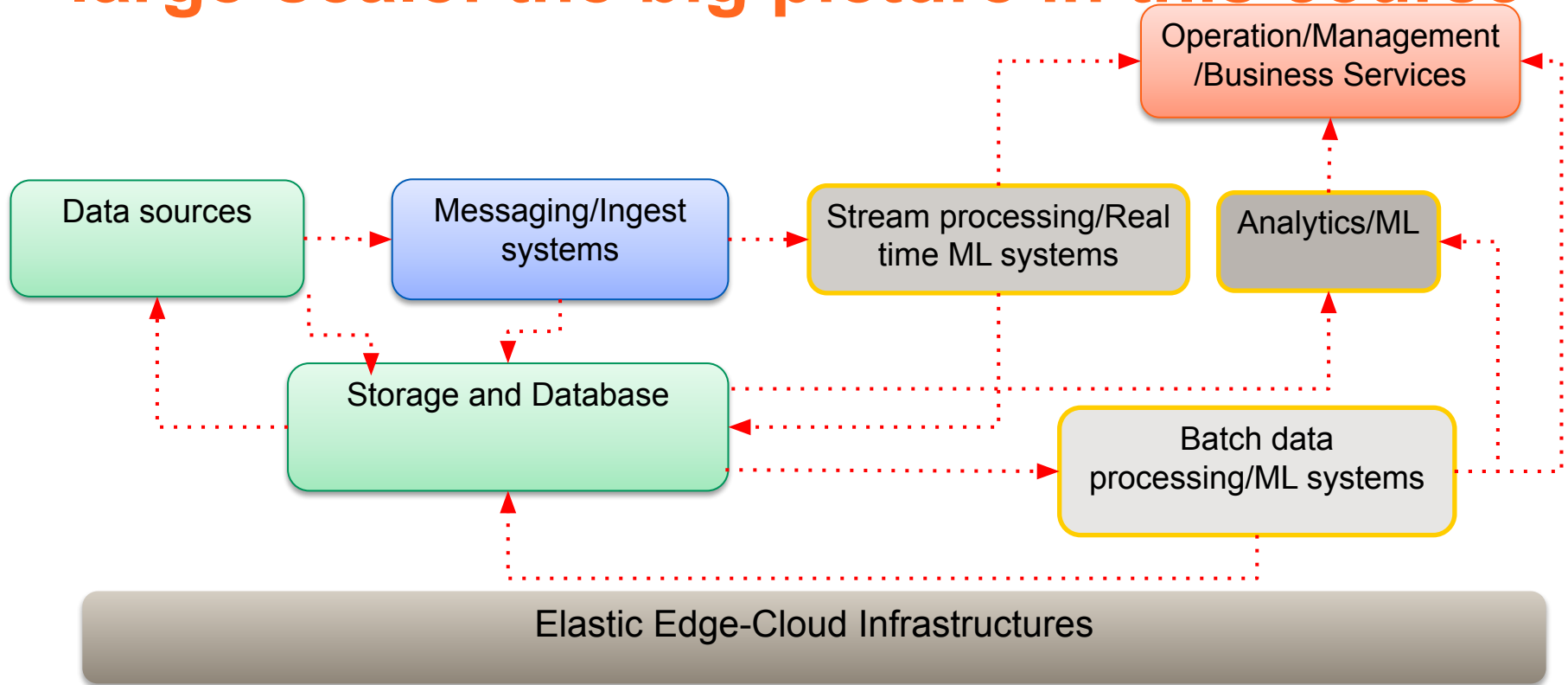
Learning objectives

- **Understand common ways to bring data into platforms**
- **Study service requests and data partition for optimizing integration models**
- **Understand the role of service discovery and consensus**
- **Establish the links to follow-up lectures**

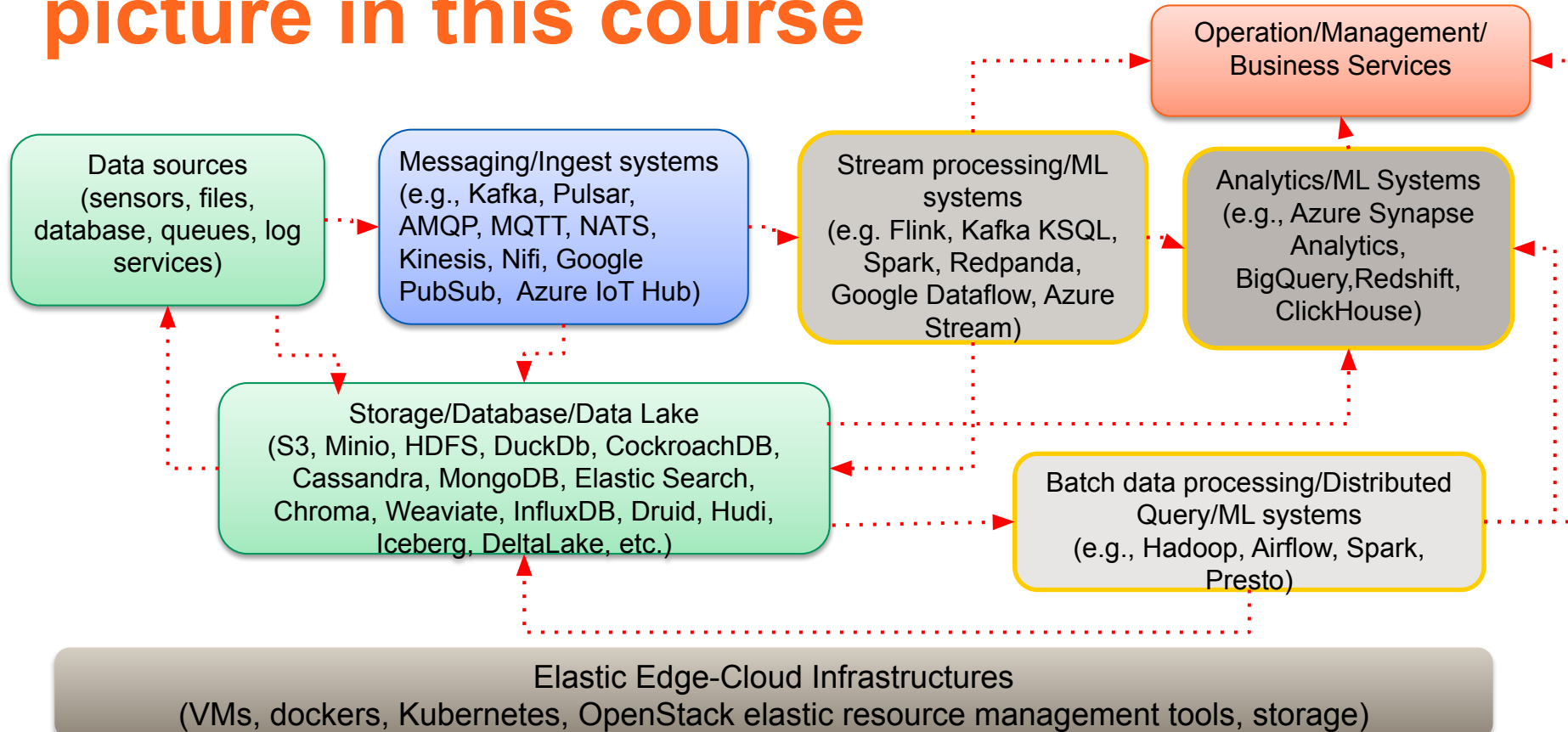
Recall

- **Platforms must facilitate exchanges between many stakeholders centered around data products**
- **Platform services support many types of interactions with different protocols and APIs**
- **Some important aspects of interactions**
 - APIs for encapsulating low-level details
 - protocols for interoperability
 - performance management
 - service/data discovery

Basic building blocks for big data at large-scale: the big picture in this course



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

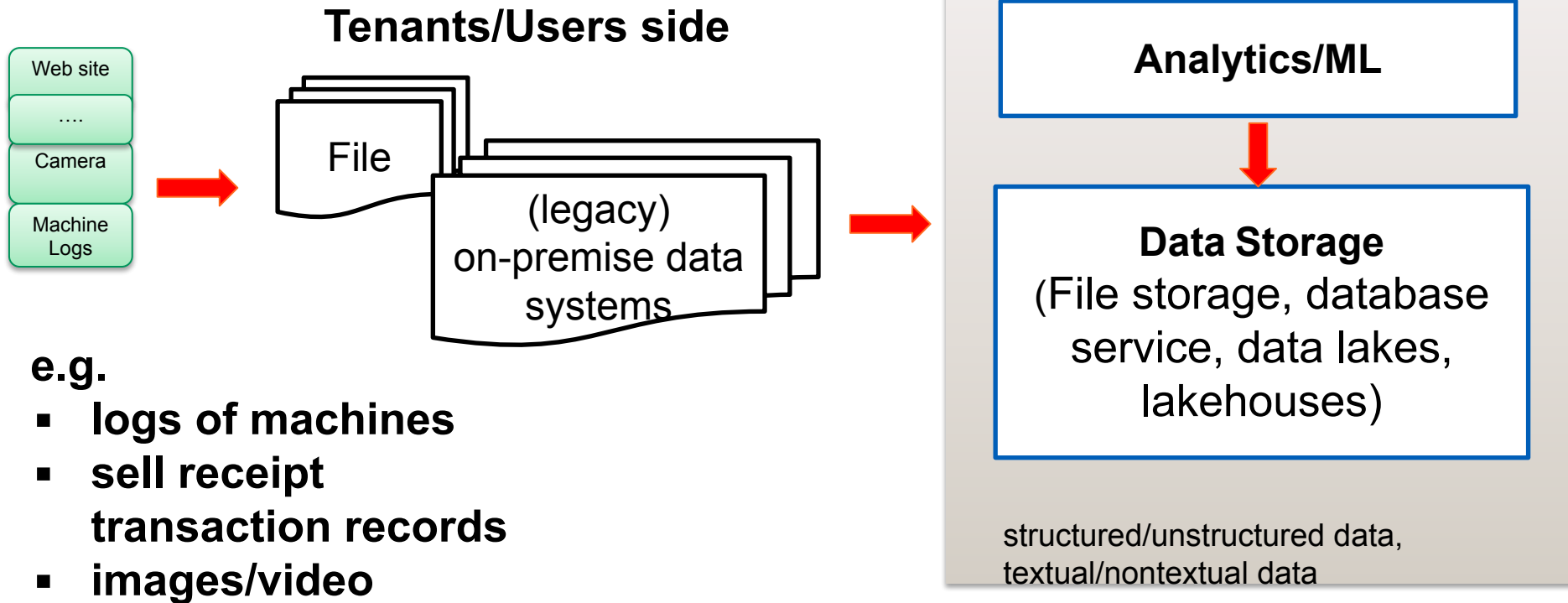




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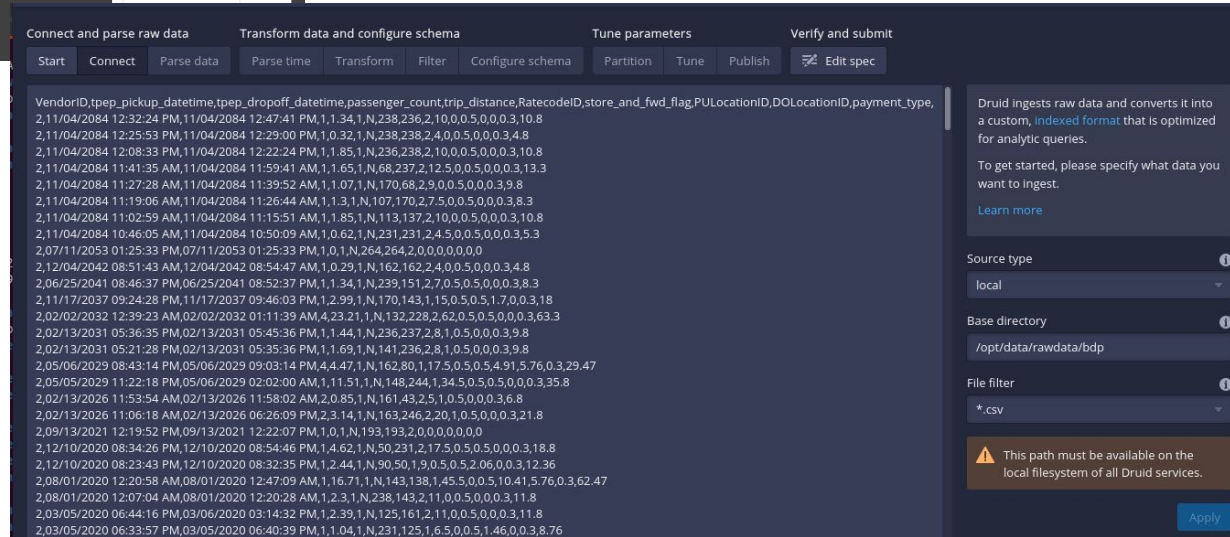
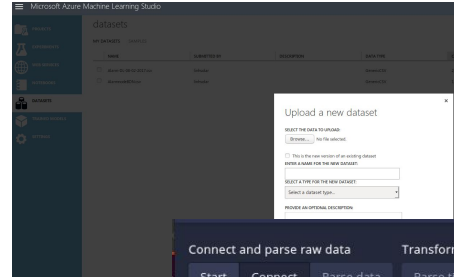
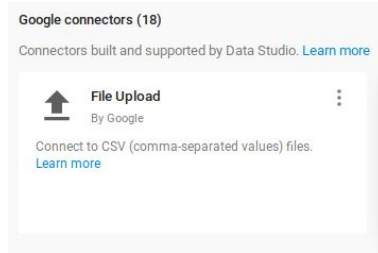
Basics of moving big data into the platform

Integrate files/static datasets/sources into platforms



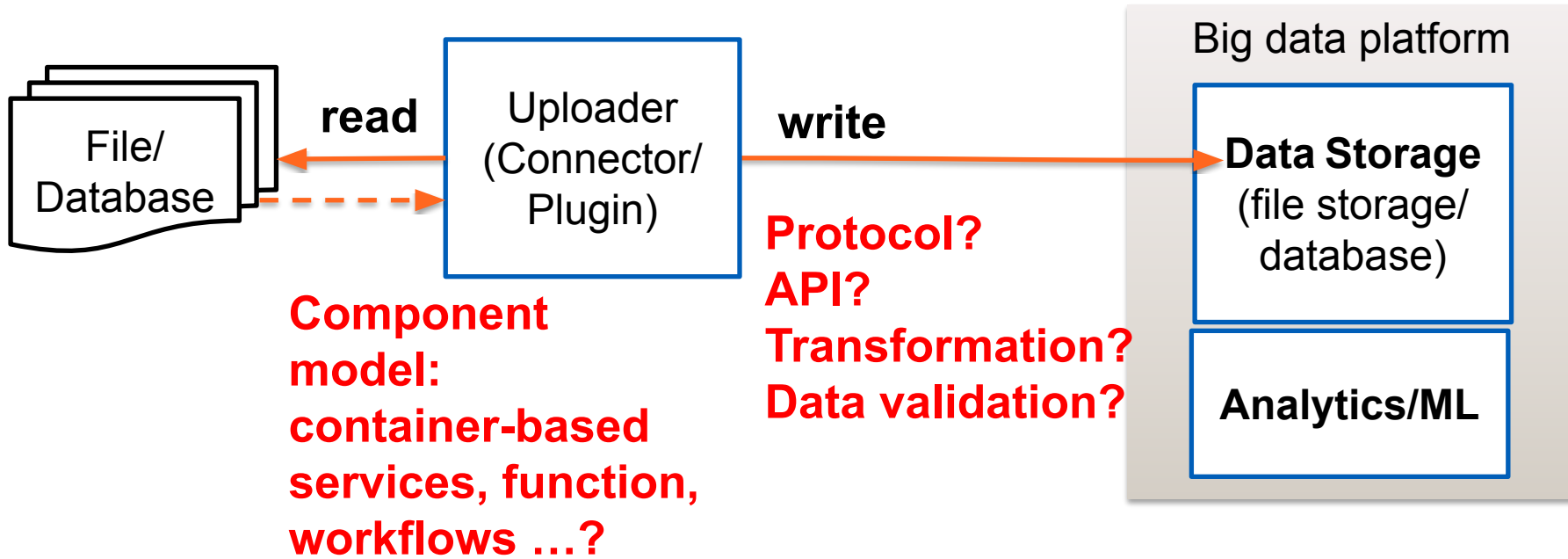
First obstacle: ingesting big data into cloud data storage/database services

What would be a good way?
Using Flask/FastAPI REST API?



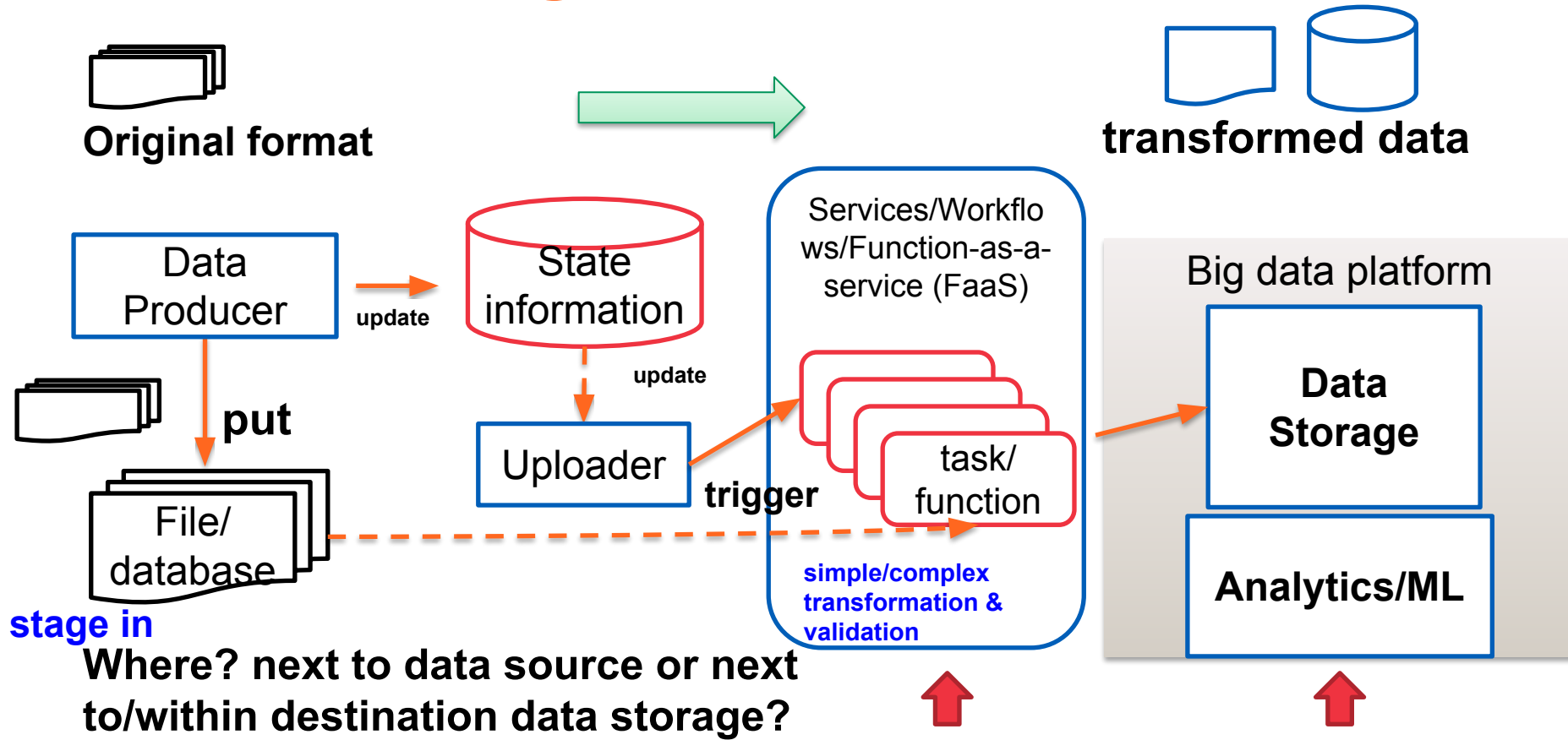
e.g., upload data into the
cloud storage and run
machine learning

Complex design details



- Practical issues for optimization:
 - Handle very big files vs a lot of small files
 - Different transformation/integration models

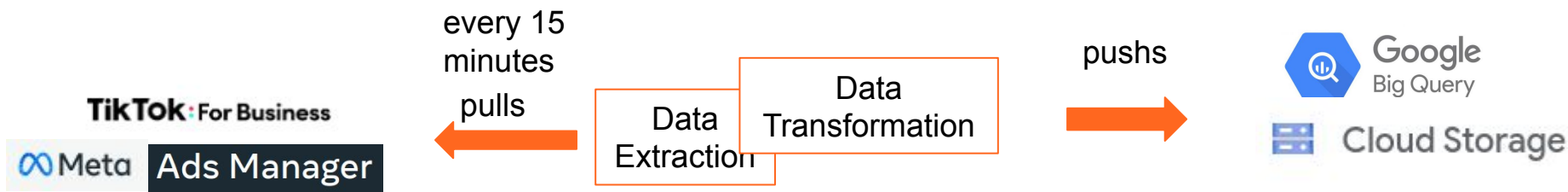
Complex design details



Several ways of implementation

- **REST/gRPC APIs for uploading**
 - APIs for calling/running batch of jobs
- **File transfers and ingestion**
 - move files into a stage space and run parallel tasks to process data files
- **Containerized microservices moving files**
 - detect and move files
- **Cron/workflow tasks**
 - Workflows, Serverless/Function-as-a-service
- **Complex design, including task management for multi tenants/users**

Simple example: a Customer Data Platform



Say we want to store data into Google Storage in different spaces:

- hot, warm, cold and archive

We need uploaders and also movers (moving data between different spaces). Mapped into specific technologies:

- **Cloud Run:** microservices/containers whose APIs can be triggered based on events
- **Cloud Function:** as serverless/function-as-a-service
- **Cloud Composer (Airflow):** a workflow engine
- **bare Containers/VMs:** write your own code, do your own way

Parallel/distributed processing

- **Individual data file/dataset is big**
 - parallel/distributed processing for single file
 - using suitable models
 - *MapReduce, Workflow, etc.*
- **Multiple files/datasets but small individuals**
 - parallel/distributed processing of tasks
 - task for a single file
 - *multi-thread, Dask, etc.*
- **Change data capture and failure handle could be tricky**
- **Bursty/ephemeral data processing**

Remember
we have a
lot of data
(files)



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Check the simple example in

<https://github.com/rdsea/bigdataplatfroms/tree/master/tutorials/queuebaseddataingestion>

Integrate streaming data sources into platforms



(near real-time) streaming protocols/frameworks

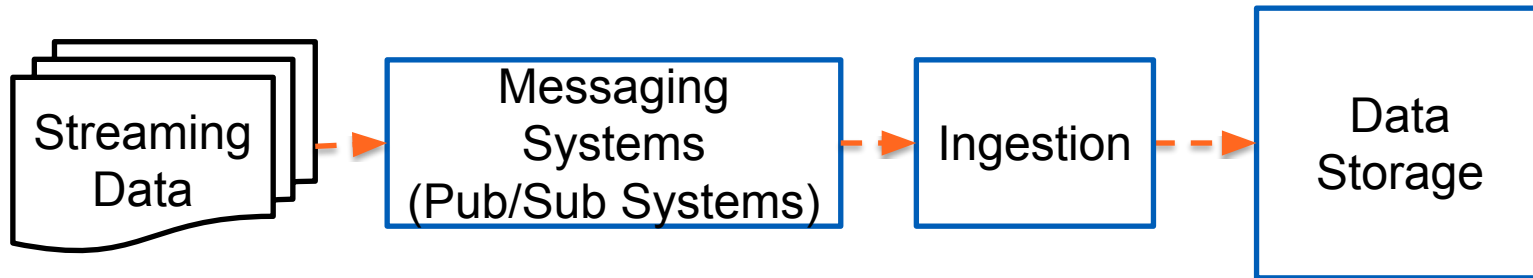
Big data platform

Data Storage
(file storage/
database)

Quick check

“A big data platform monitors network usage of devices from million+ customers. We have different levels: **Sensor/Customer, Node (concentrator of multiple customers), Agent (concentrator of multiple Nodes) and the whole network. In a region, the real operator can generate 1.4 billion records per day ~ 72GB per day”**

How do I move streaming data into the cloud?



Protocol?
Data format
Message structure

Real-world technologies

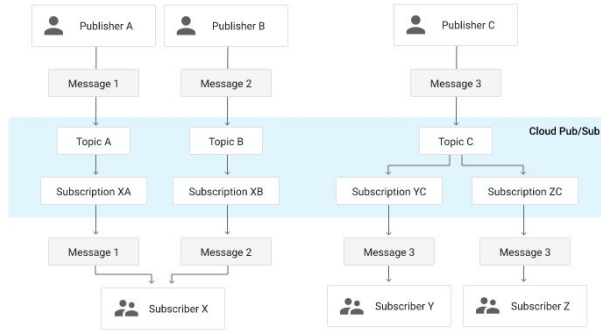


Figure source: <https://cloud.google.com/pubsub/docs/overview>

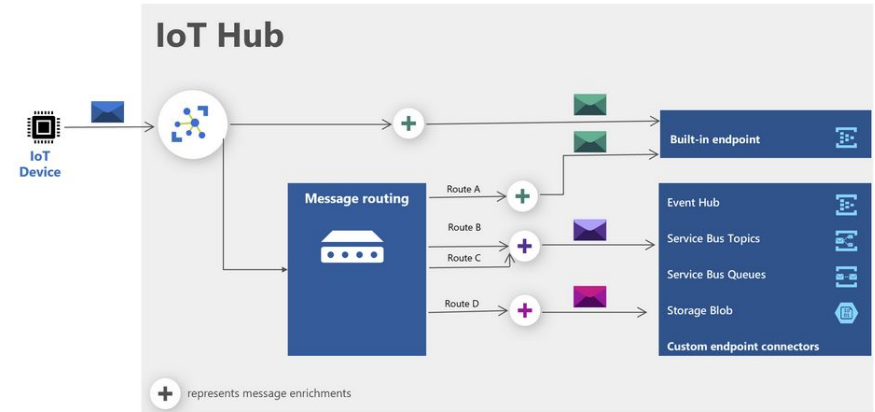


Figure source: <https://docs.microsoft.com/en-us/azure/iot-hub/iot-hub-message-enrichments-overview>

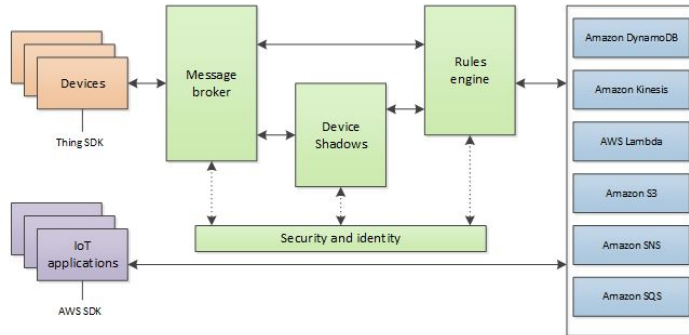


Figure source: <https://docs.aws.amazon.com/iot/latest/developerguide/aws-iot-how-it-works.html>

Do you see common concepts/terms?

Some important protocols

- **Protocols**
 - AMQP, MQTT, NATS (<https://nats.io/>)
- **Systems**
 - Apache Kafka, Apache Pulsar, Apache RocketMQ, RedPanda, Google PubSub
- **Distinguish between “protocols” and “specific frameworks”**
 - how would they affect your design?

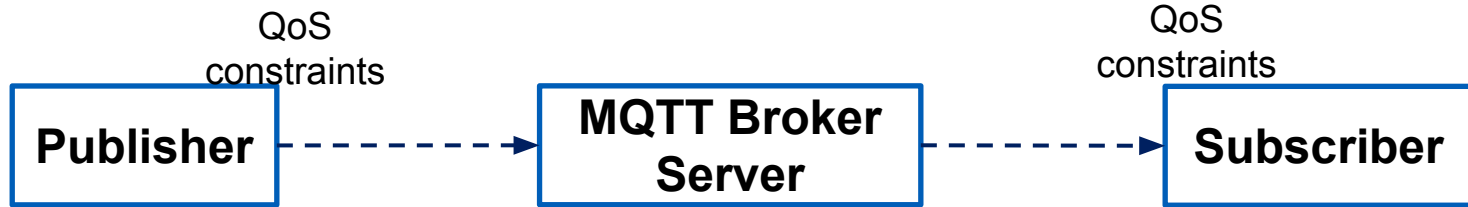
AMQP - Overview

- **Protocol for message-oriented middleware**
 - Not language- or platform- specific
 - For Java, C#, Python,
- **Binary wire-level protocol for message exchange, rather than APIs**
- **<http://www.amqp.org>**
- **We use it for *big data movement and tasks coordination***

MQTT Overview

- <https://mqtt.org/>
- **OASIS Standard**
 - ISO/IEC 20922:2016 (Message Queuing Telemetry Transport (MQTT) v3.1.1)
- **IoT/M2M connectivity protocol atop TCP/IP**
- **MQTT brokers enable publish/subscribe messaging systems**
 - Publisher can publish a message within a topic that can be subscribed by many Subscribers
- **We use it mostly for *big data movement***

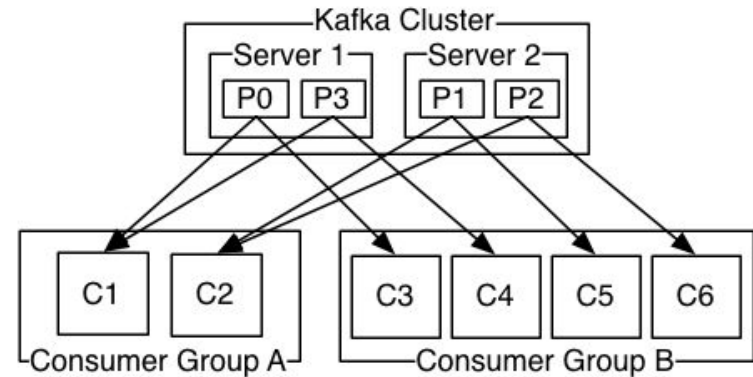
Model and Implementation



- **Different programming languages for OS/devices**
- **Implementation examples**
 - Mosquitto (<http://projects.eclipse.org/projects/technology/mosquitto>)
 - docker pull eclipse-mosquitto
 - Paho: <http://www.eclipse.org/paho/>
 - RabbitMQ: <https://www.rabbitmq.com/>
 - Cloud providers: <http://cloudmqtt.com> (offer a free instance)
 - Cluster of MQTT brokers: VerneMQ (<https://vernemq.com/>), EMQ (<https://www.emqx.io/>)

Apache Kafka

- <http://kafka.apache.org/>
 - originally from LinkedIn, not a protocol!
- **Some components are commercialized by Confluent**
 - <https://www.confluent.io/>
- **Widely used for big data use cases**
 - including message processing in large-scale enterprise service platforms



Figures source: <https://kafka.apache.org/documentation.html>

So which one you think is suitable for this?

“A big data platform monitors network usage of devices from million+ customers. We have different levels: Sensor/Customer, Node (concentrator of multiple customers), Agent (concentrator of multiple Nodes) and the whole network. In a region, the real operator can generate 1.4 billion records per day ~ 72GB per day”

Hybrid data processing architectures

Batch processing, micro-batching, and streaming

- **Batch processing**

- data to be processed: complete with a large size
- high throughput but also high latency
- triggered by scheduled/manual time or by data completion (size or time)

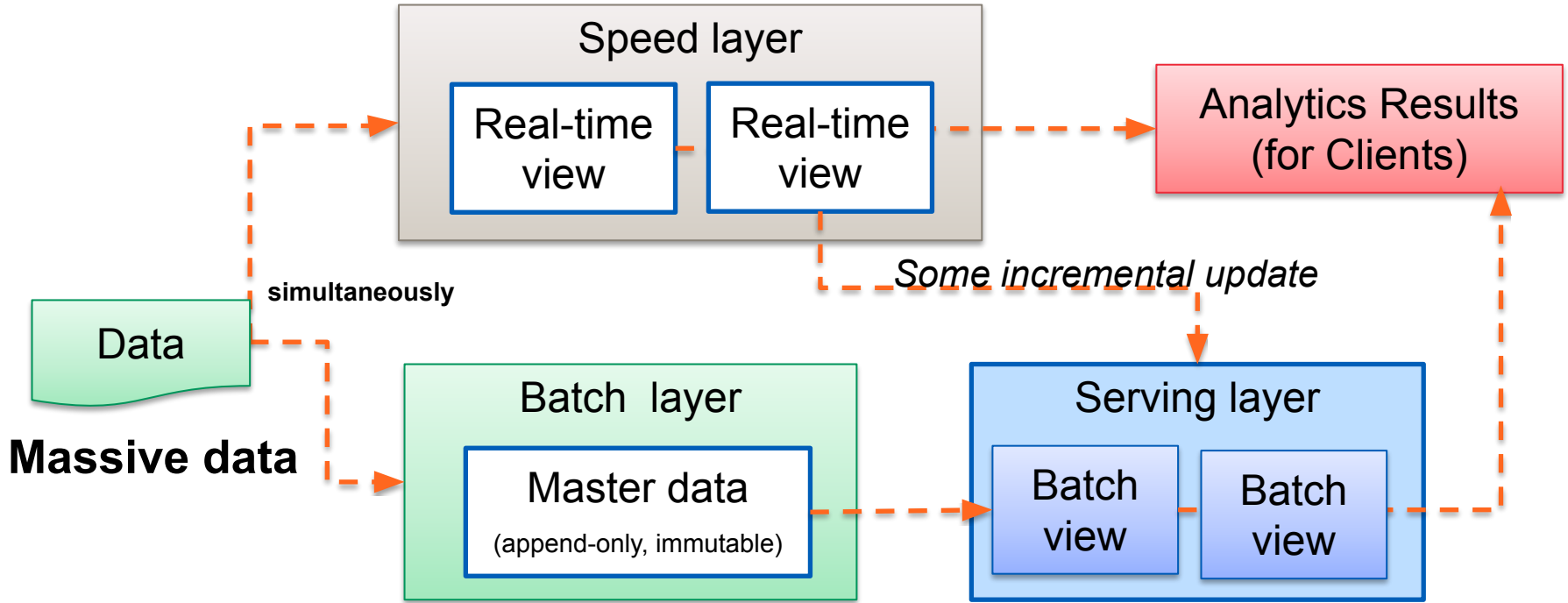
- **Micro-batching**

- data to be processed: small; collected over a short, regular time; small batches
- near real-time and low latency

- **Streaming**

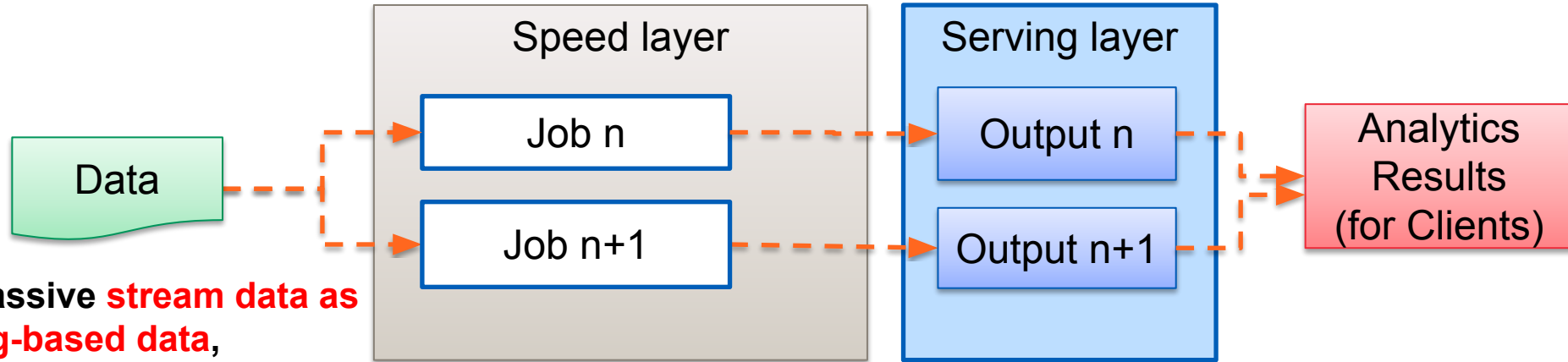
- data to be processed: as soon when it arrives; record-by-record
 - very low latency and real time
-

Lambda architectural style



Check: <https://docs.microsoft.com/en-us/azure/architecture/data-guide/big-data/>
<https://www.oreilly.com/radar/questioning-the-lambda-architecture/>

Kappa architectural style



Massive stream data as log-based data, retained enough for different analytics needed

Job n: analytics/processing

Can switch from version n to version n+1 using a single software stack

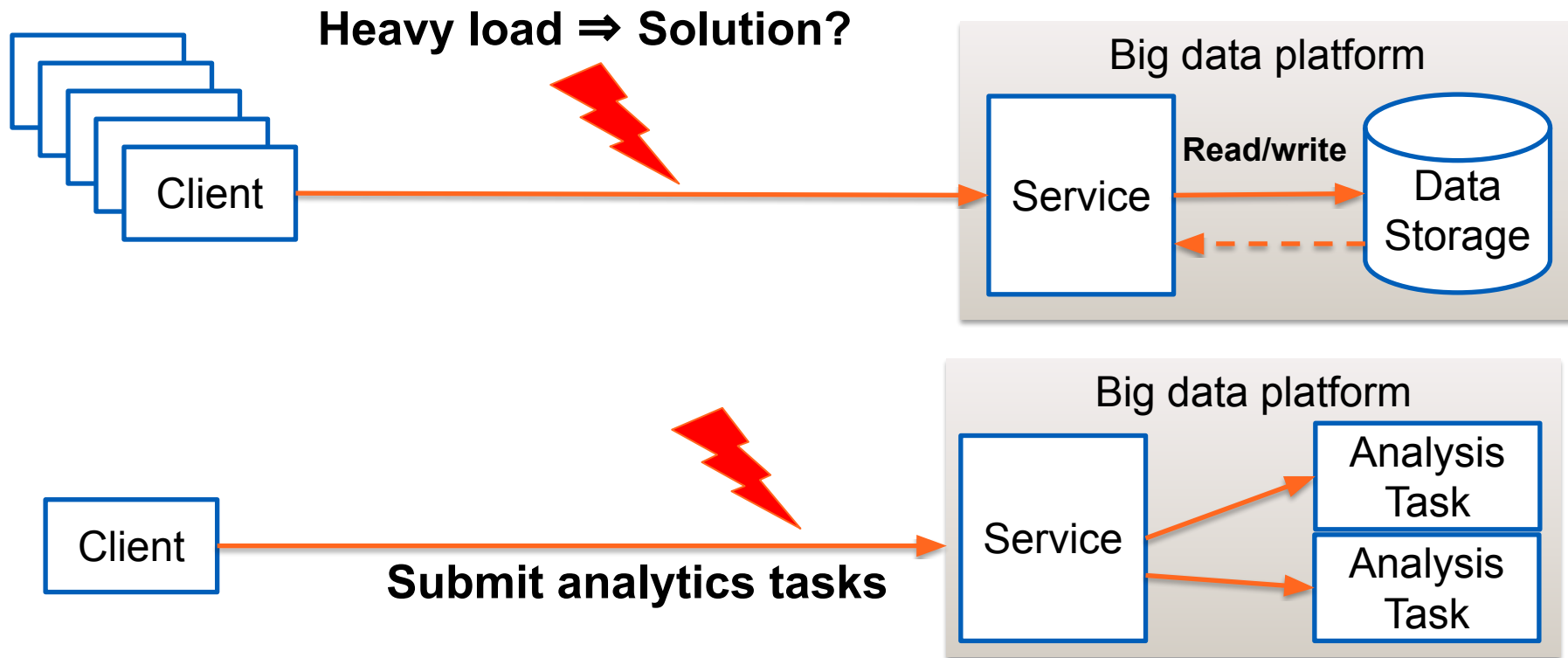
Check: <https://milinda.pathirage.org/kappa-architecture.com/> & <http://radar.oreilly.com/2014/07/questioning-the-lambda-architecture.html>

Recall:

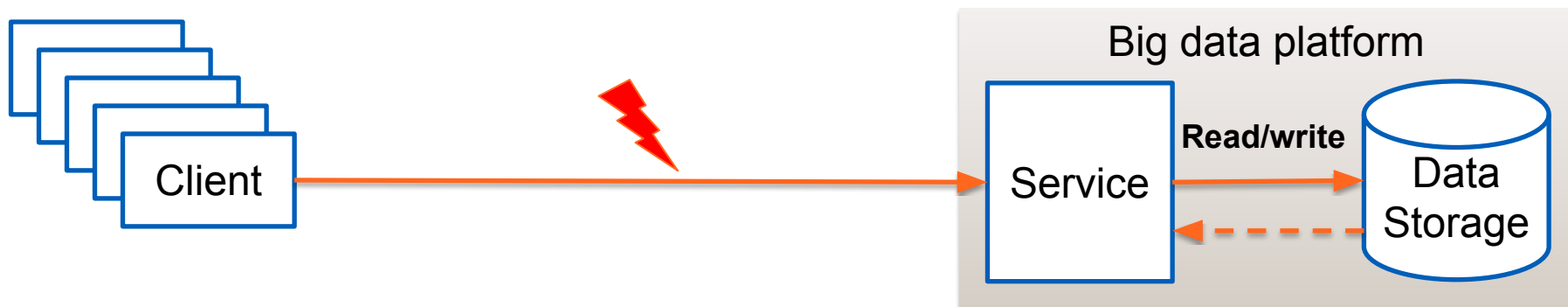
“A big data platform monitors network usage of devices from million+ customers. We have different levels: **Sensor/Customer, Node (concentrator of multiple customers), Agent (concentrator of multiple Nodes) and the whole network. In a region, the real operator can generate 1.4 billion records per day ~ 72GB per day”**

Optimize data service requests and functionalities → handling “unlimited vs limited amount of data”

Concurrent contention



Back-pressure or elasticity



Back-pressure: control, drop, and buffer

Prevent too many accesses?

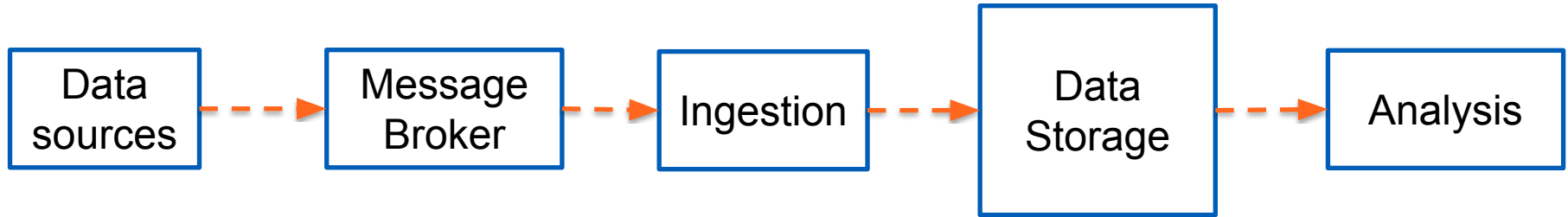


A related situation: prevents clients to retry a (failed) operation

<http://martinfowler.com/bliki/CircuitBreaker.html>

<https://msdn.microsoft.com/en-us/library/dn589784.aspx>

Scaling in every place of big data pipelines



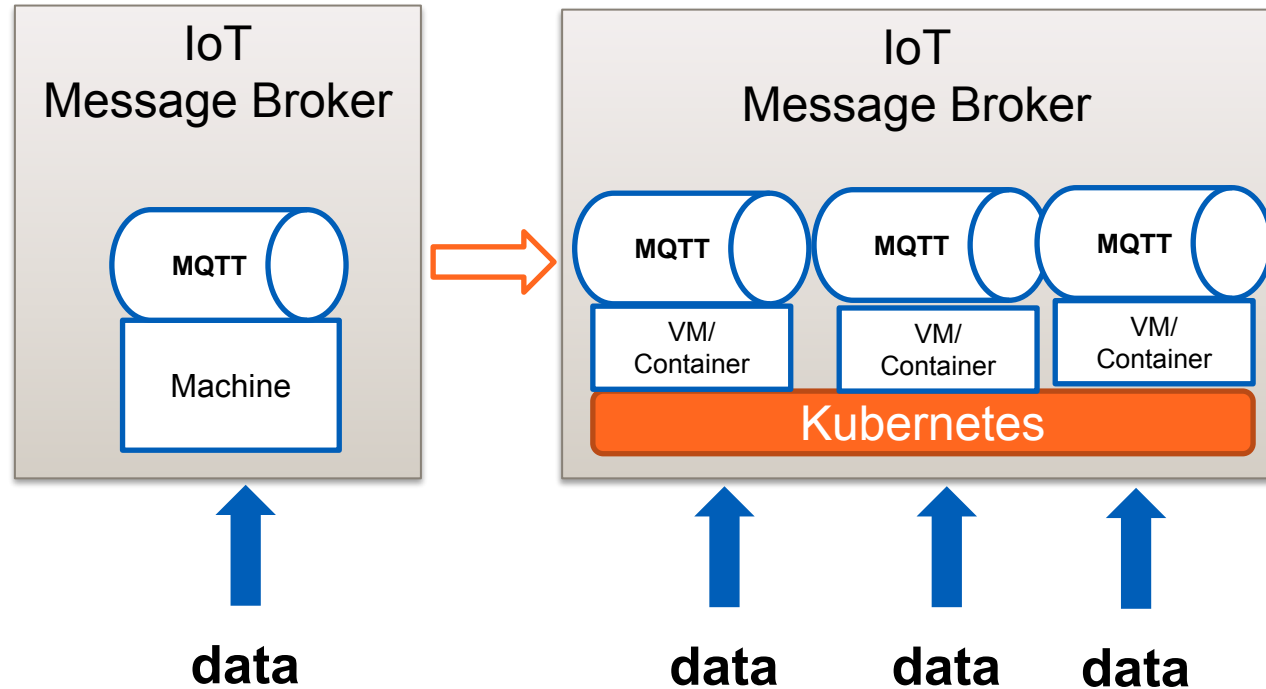
- **Scaling**

- disk spaces for file storage
- resources for data ingestion
- resources for data analysis

**Happen at
different times
and location**

Scaling middleware nodes

- Increase the number of brokers when more data arrive
- Provide dedicated brokers on-demand



Example: scaling compute nodes for data analysis

MonitoringJobsVM InstancesConfigurationWeb Interfaces

Name	Role
thebasecluster-m	Master
thebasecluster-w-0	Worker
thebasecluster-w-1	Worker
thebasecluster-w-2	Worker
thebasecluster-w-3	Worker

SSH

MonitoringJobsVM InstancesConfigurationWeb Interfaces

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thebasecluster-w-3	Worker
thebasecluster-w-4	Worker
thebasecluster-w-5	Worker

SSH

Equivalent REST

4 nodes

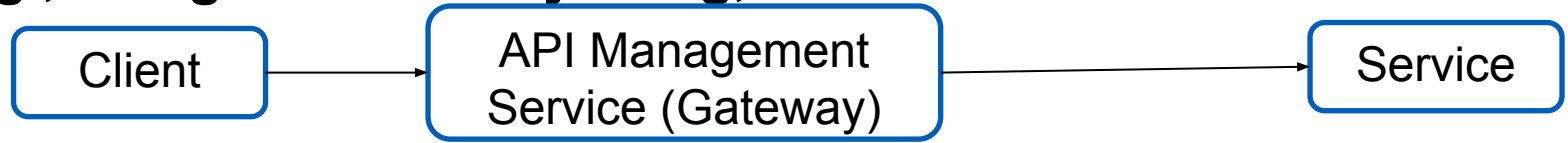
On-demand change

Name	thebasecluster
Region	europe-north1
Zone	europe-north1-a
Autoscaling	Off
Scheduled deletion	Off
Enhanced flexibility mode	Off
Master node	Standard (1 master, N workers)
Machine type	n1-standard-2 (2 vCPU, 7.50 GB memory)
Primary disk type	pd-standard
Primary disk size	500 GB
Worker nodes	6
Machine type	n1-standard-1 (1 vCPU, 3.75 GB memory)

6 nodes

Throttling principle

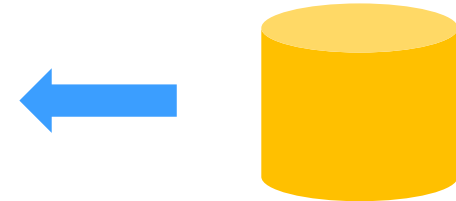
- **Drop strategy: disable too many accesses and disable unessential services**
 - dynamic vs static configuration
- **E.g., using API Gateway Kong, Kubernetes**



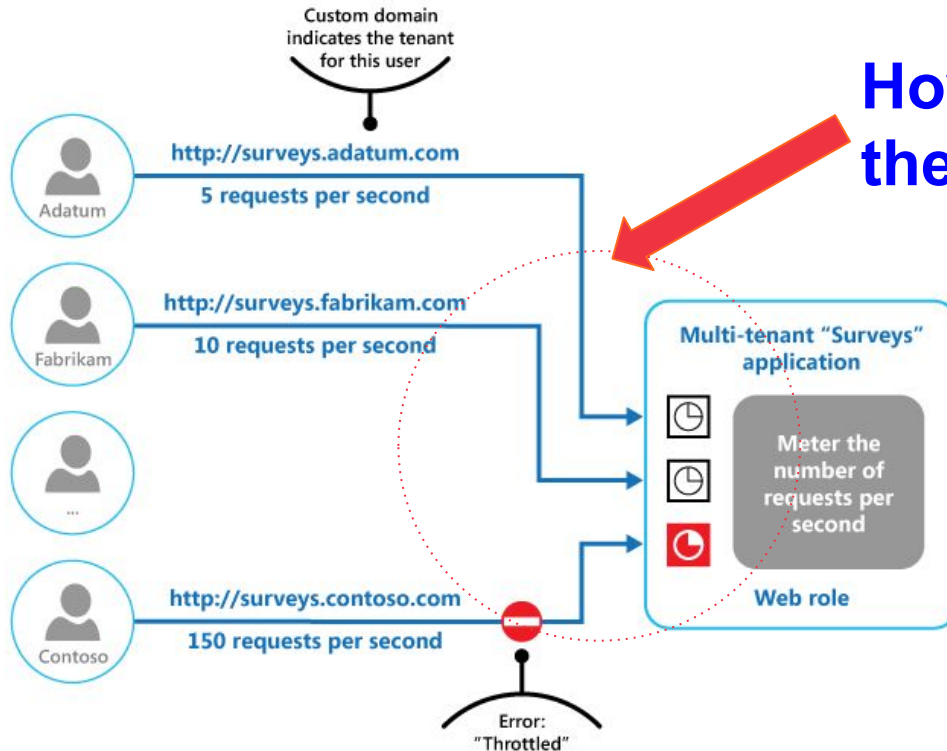
Code:
<http://www.django-rest-framework.org/api-guide/throttling/#how-throttling-is-determined>

```
REST_FRAMEWORK = {  
    'DEFAULT_THROTTLE_CLASSES': (  
        'rest_framework.throttling.AnonRateThrottle',  
        'rest_framework.throttling.UserRateThrottle'  
    ),  
    'DEFAULT_THROTTLE_RATES': {  
        'anon': '100/day',  
        'user': '1000/day'  
    }  
}
```

Tenant profile/SLA



Example of throttling based on roles



How would you do this in the big data platform?

Big Data Platforms implement “business service models”/SLA for tenants

Figure source:

<https://msdn.microsoft.com/en-us/library/dn589798.aspx>

Using tasks and queue-based load leveling pattern

Affects the internal design of the service in the big data platforms

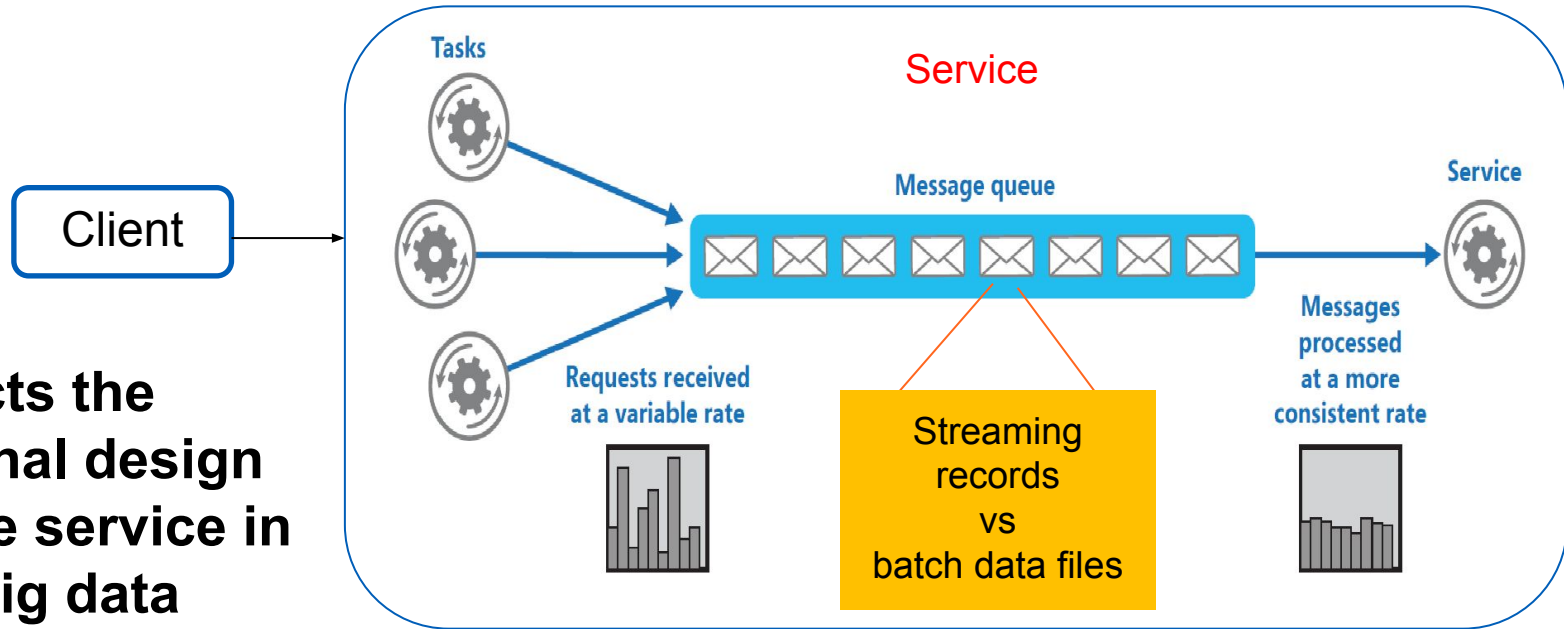
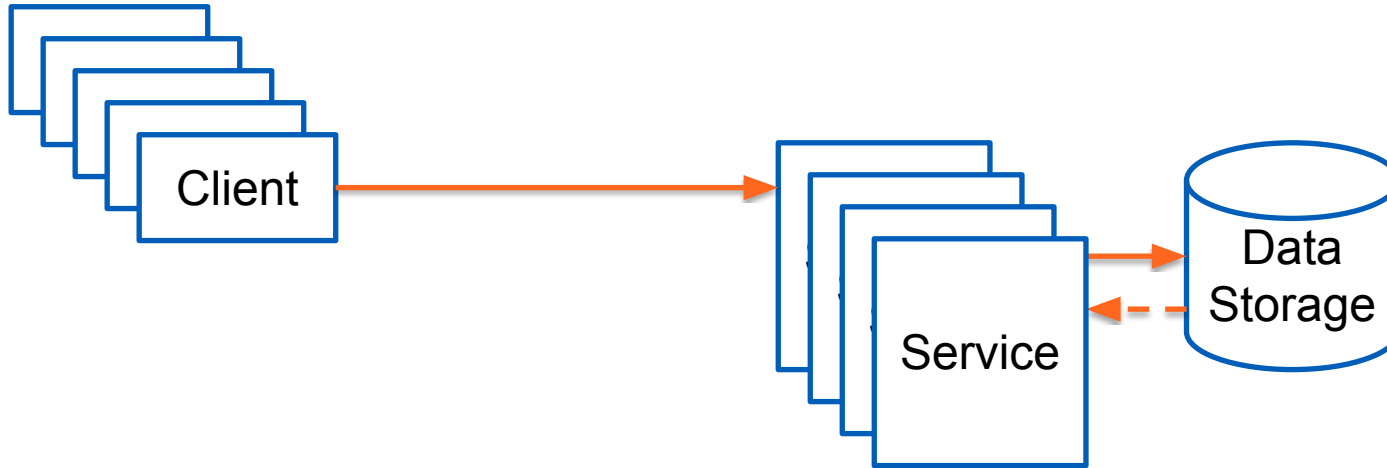


Figure source: <https://msdn.microsoft.com/en-us/library/dn589783.aspx>

Heavy load between service serving request and data storage



Elastic solution: scale out or up

Using multiple instances of services and queues

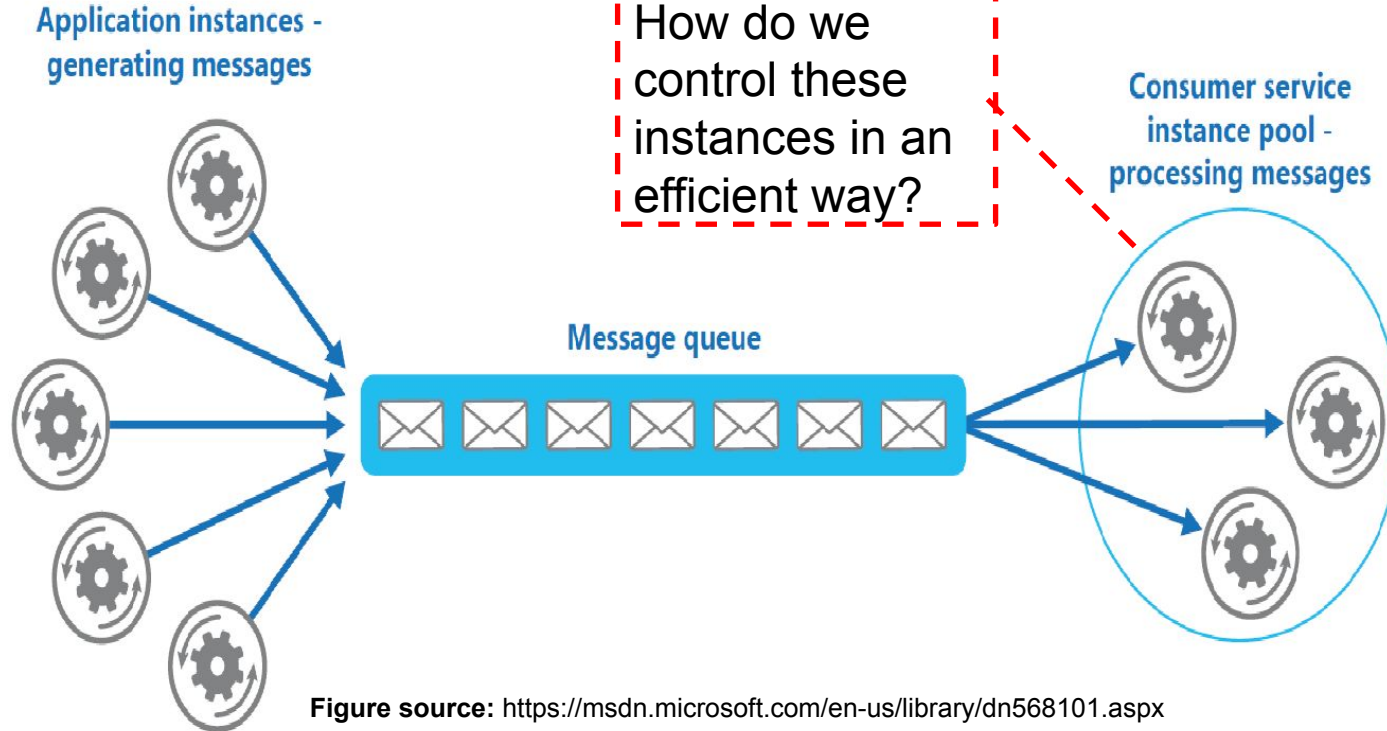


Figure source: <https://msdn.microsoft.com/en-us/library/dn568101.aspx>

Discovery and consensus

Where are available services and data?

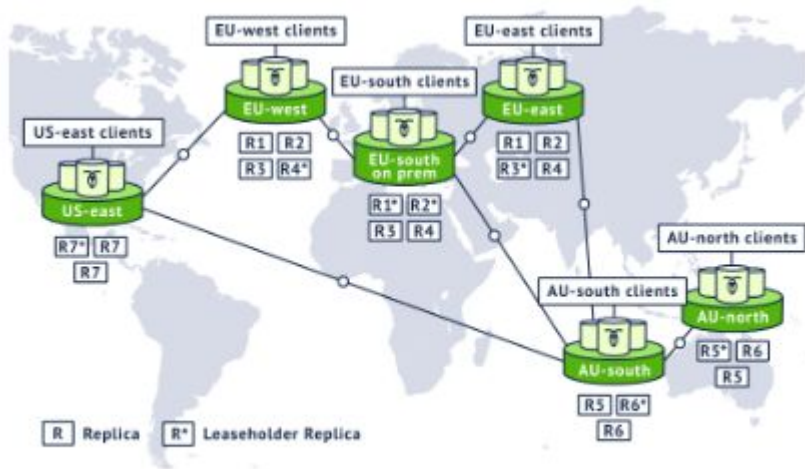


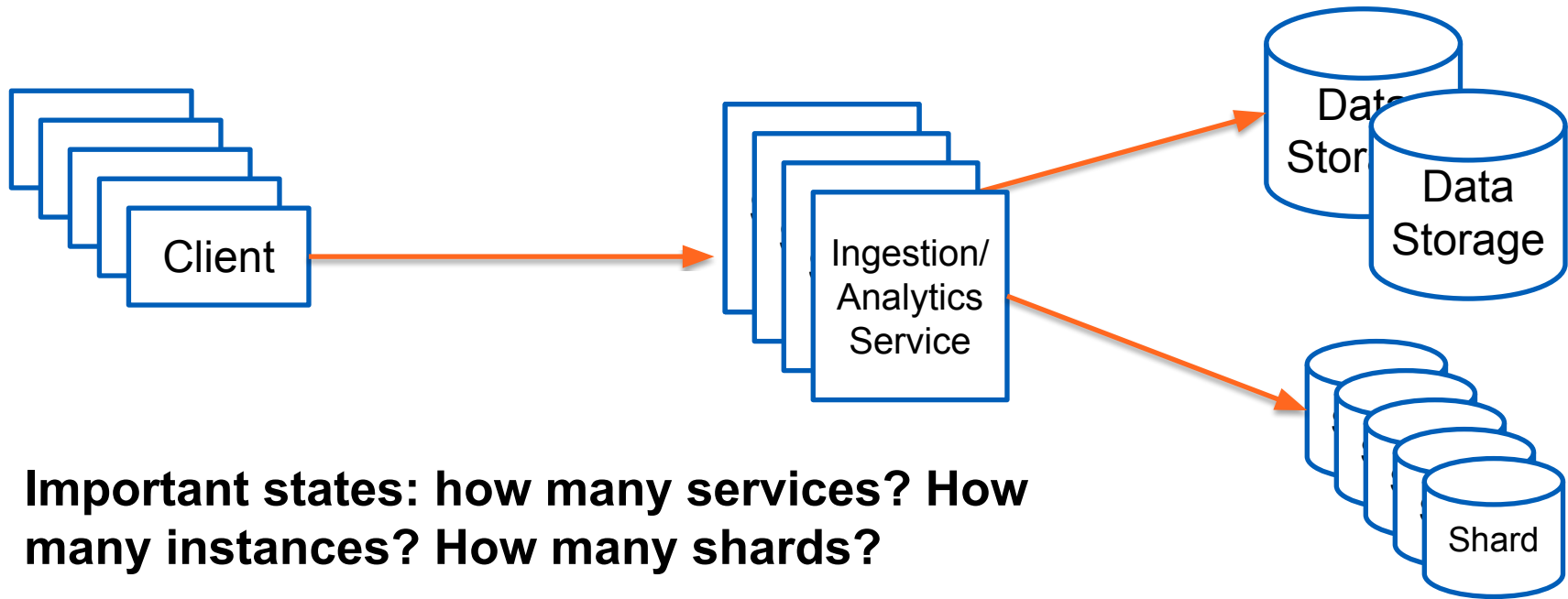
Figure 1: A global CockroachDB cluster

Figure source: Taft et al., CockroachDB: The Resilient Geo-Distributed SQL Database, <https://dl.acm.org/doi/pdf/10.1145/3318464.3386134>

“At the time of writing, our largest **Druid** cluster deployment uses more than 100 nodes for Historical processes and about 75 nodes for MiddleManager processes. We ingest over three million events per second and respond to over 250 queries per second. We keep seven days of queryable data in Druid Historical nodes and two years of data retention in S3 deep storage.”

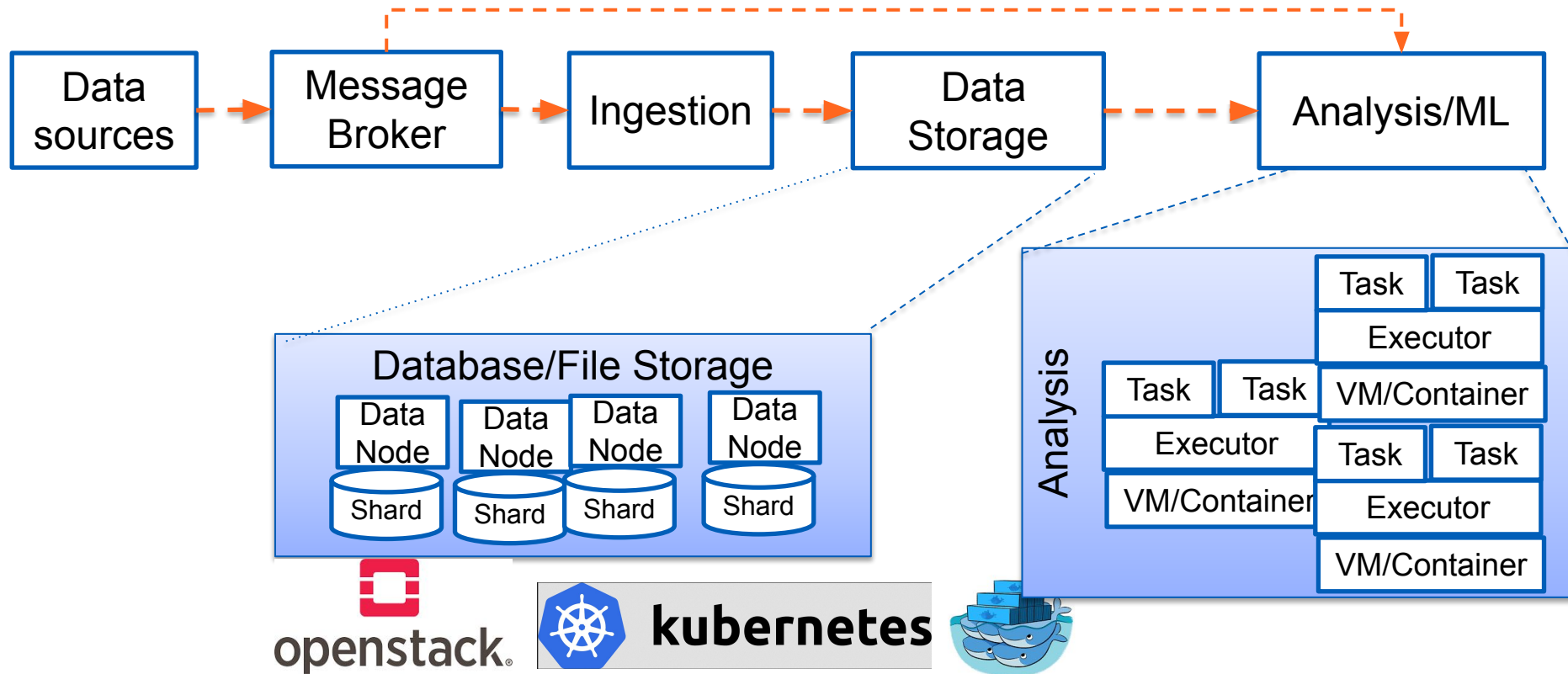
Source: November 8, 2021,
<https://www.confluent.io/blog/scaling-apache-druid-for-real-time-cloud-analytics-at-confluent/>

We can create a lot of instances or we can create new services



Important states: how many services? How many instances? How many shards?

Runtime view of some components



Multiple instances

- **A building block of big data platforms can have many services and a service can have many instances**
 - e.g., for replication and load balancing
 - a database service (e.g. MongoDB) has multiple data nodes, each responsible for a subset of shards/partitions
 - a processing engine (e.g., Spark or Airflow) can have many nodes, each executes different tasks of a process
- **The same component can have many instances deployed**
 - e.g., dedicated deployment of MongoDB for different customers

Service state management

- **Service information**

- include states and other important configuration information
- many instances
- cross different infrastructures/data centers

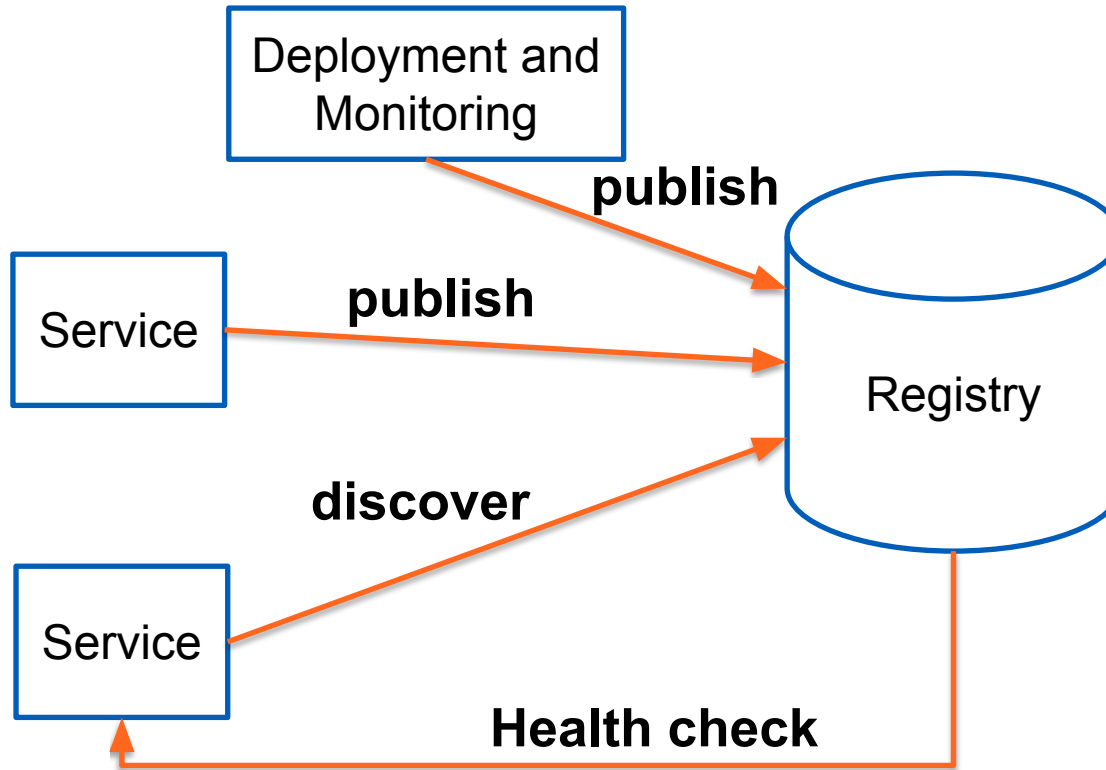
- **Related components**

- services themselves
- monitoring component, deployment component, orchestration controllers

- **Lifecycle: very dynamic in elastic environments**

- *Start, run, shutdown, restart, scale*

Service Discovery principle



- **Key requirements**

- fast
- consistent
- secure
- cross data centers
- simple APIs

But what about data discovery?

- **Approach 1**
 - pre-defined mapping: e.g., using consistent hashing
- **Approach 2**
 - discover relevant services and then ask relevant services about metadata about data
- **Approach 3**
 - use a dedicated data discovery service and ask the service for metadata about data

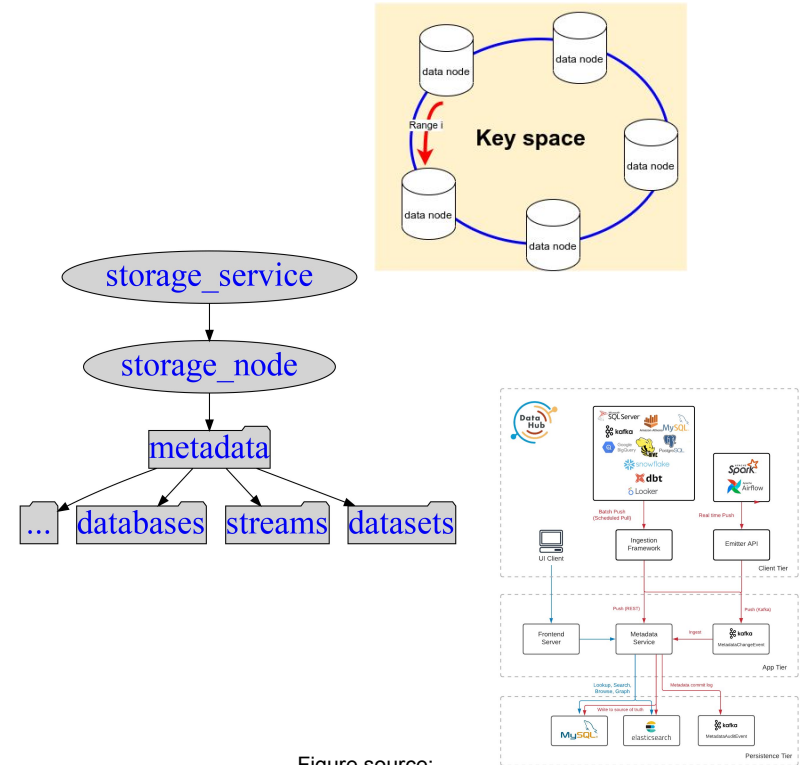


Figure source:
<https://datahubproject.io/docs/architecture/architecture>

Example:

<https://github.com/rdsea/bigdataplatforms/tree/master/tutorials/servicediscovery>

Consensus for big data platforms

- **Consensus is about to agree on something**
- **Very important for replication and fault tolerance in big data platforms**
 - distributed lock, master selection
- **Scope**
 - platform level and service component levels
 - single data center or cross-data center
- **We will have to deal with them in several frameworks for big data, e.g. Apache Spark, Hadoop and Kafka**

Distributed coordination

- A lot of algorithms, etc.
 - Paxos family
- Well-known in the cloud

Notes from the paper: “server replication (SR), log replication (LR), synchronization service (SS), barrier orchestration (BO), service discovery (SD), group membership (GM), leader election (LE), metadata management (MM) and distributed queues (Q)”

TABLE 4. PATTERNS OF PAXOS USE IN PROJECTS

Project	Consensus System	Usage Patterns								
		SR	LR	SS	BO	SD	GM	LE	MM	Q
GFS	Chubby			✓				✓	✓	
Borg	Chubby/Paxos	✓				✓		✓		
Kubernetes	etcd						✓		✓	
Megastore	Paxos		✓							
Spanner	Paxos	✓								
Bigtable	Chubby						✓	✓	✓	
Hadoop/HDFS	ZooKeeper	✓						✓		
HBase	ZooKeeper	✓		✓			✓		✓	
Hive	ZooKeeper			✓					✓	
Configurator	Zeus								✓	
Cassandra	ZooKeeper					✓		✓	✓	
Accumulo	ZooKeeper		✓	✓					✓	
BookKeeper	ZooKeeper						✓		✓	
Hedwig	ZooKeeper						✓		✓	
Kafka	ZooKeeper						✓	✓	✓	
Solr	ZooKeeper							✓	✓	✓
Giraph	ZooKeeper		✓		✓				✓	
Hama	ZooKeeper				✓					
Mesos	ZooKeeper							✓		
CoreOS	etcd					✓				
OpenStack	ZooKeeper					✓				
Neo4j	ZooKeeper			✓				✓		

What if they do not fit into your big data platforms?

Source: Ailidani Ailijiang, Aleksey Charapkov and Murat Demirbasz , Consensus in the Cloud: Paxos Systems Demystified, <http://www.cse.buffalo.edu/tech-reports/2016-02.pdf>

What you should do this week

- Look at the list of data sources and start think which data sources you will use for your study
- Lambda and Kappa architecture styles
- Check and play with basic ingestion: simple queue, MQTT/AMQP (from the cloud background)
- Brush up patterns for scaling and failure handling
- Look at how service discovery and consensus are implemented in big data systems

Note: *materials/links are in our git and slides*

Thanks!

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rdsea.github.io