

# Big data service systems: Models, Elasticity, and Platforms

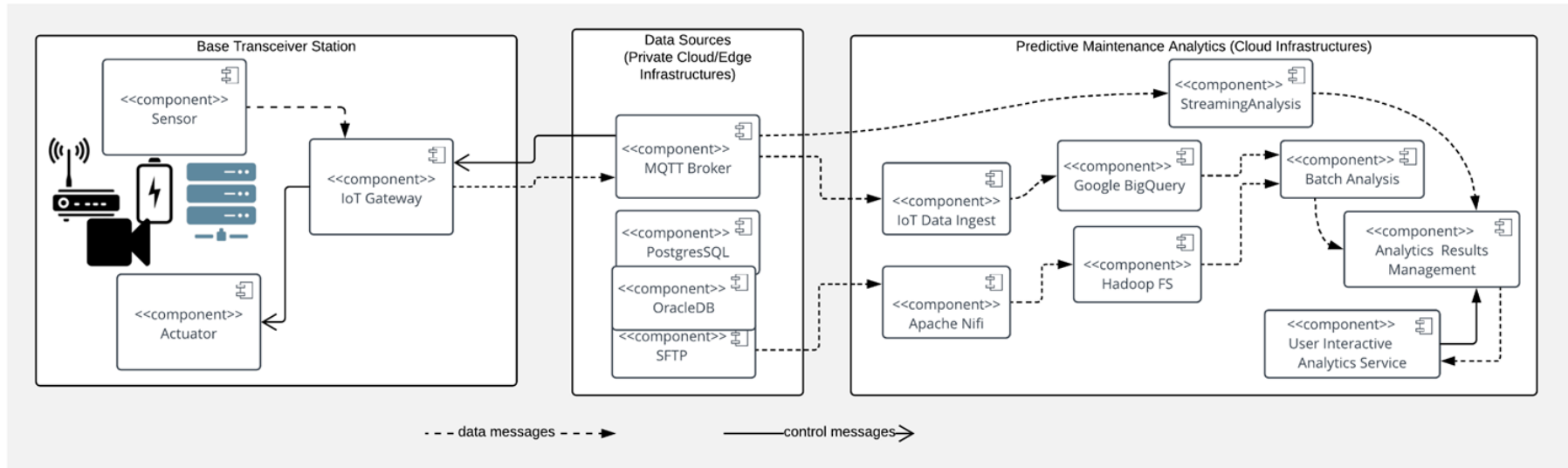
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[@linhsolar](mailto:linhsolar)

- Data analytics within a single system
- Data analytics across multiple systems
- APIs management and big data systems
- Principles of elasticity for advanced service-based data analytics

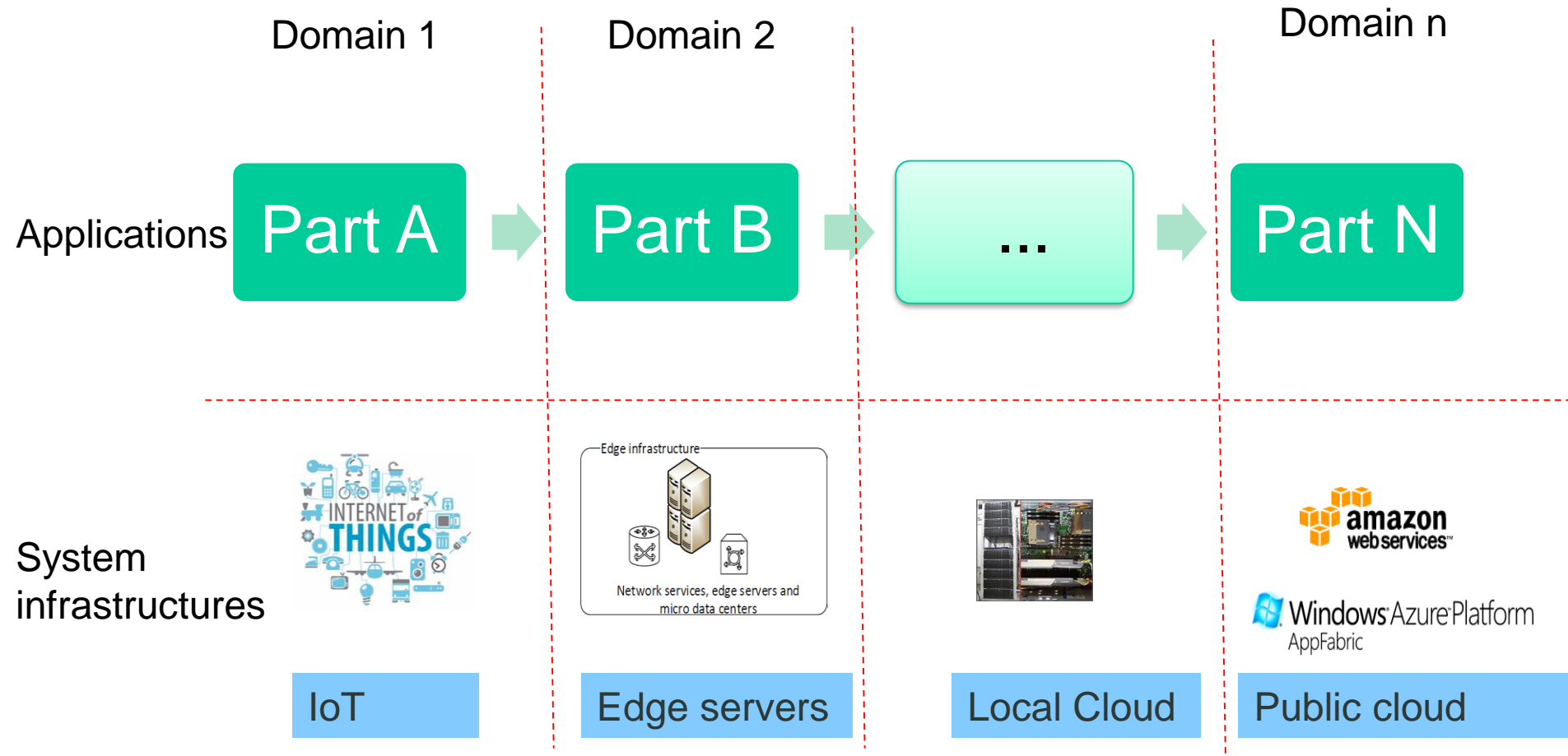
# **Advanced service-based analytics – which are fundamental engineering questions?**

# Predictive Maintenance in Telcos



- Complex types of data
- Various services
- Complex analytics/data processing algorithms

# Advanced service-based data analytics -- fundamental concepts

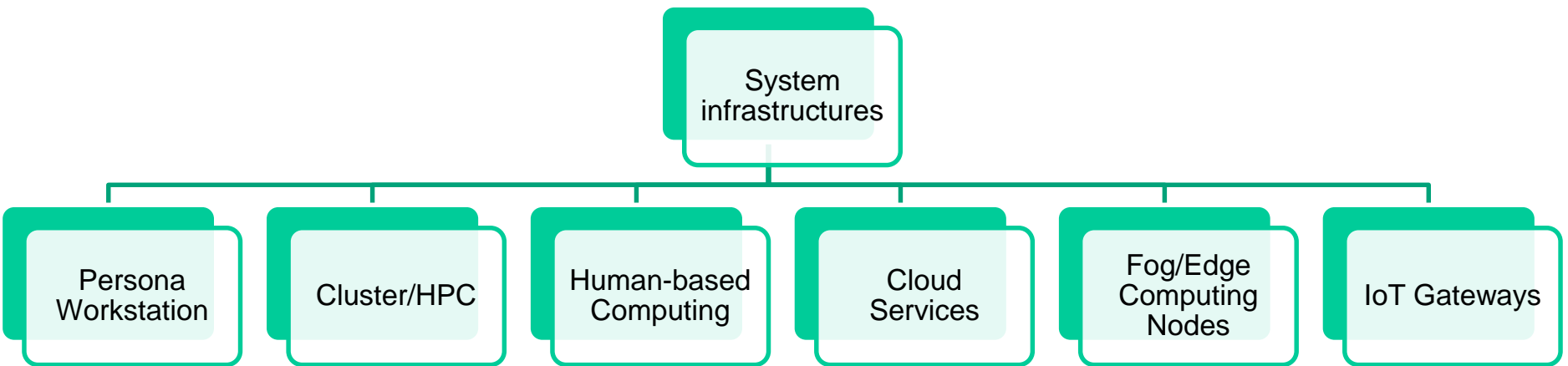


# Design questions

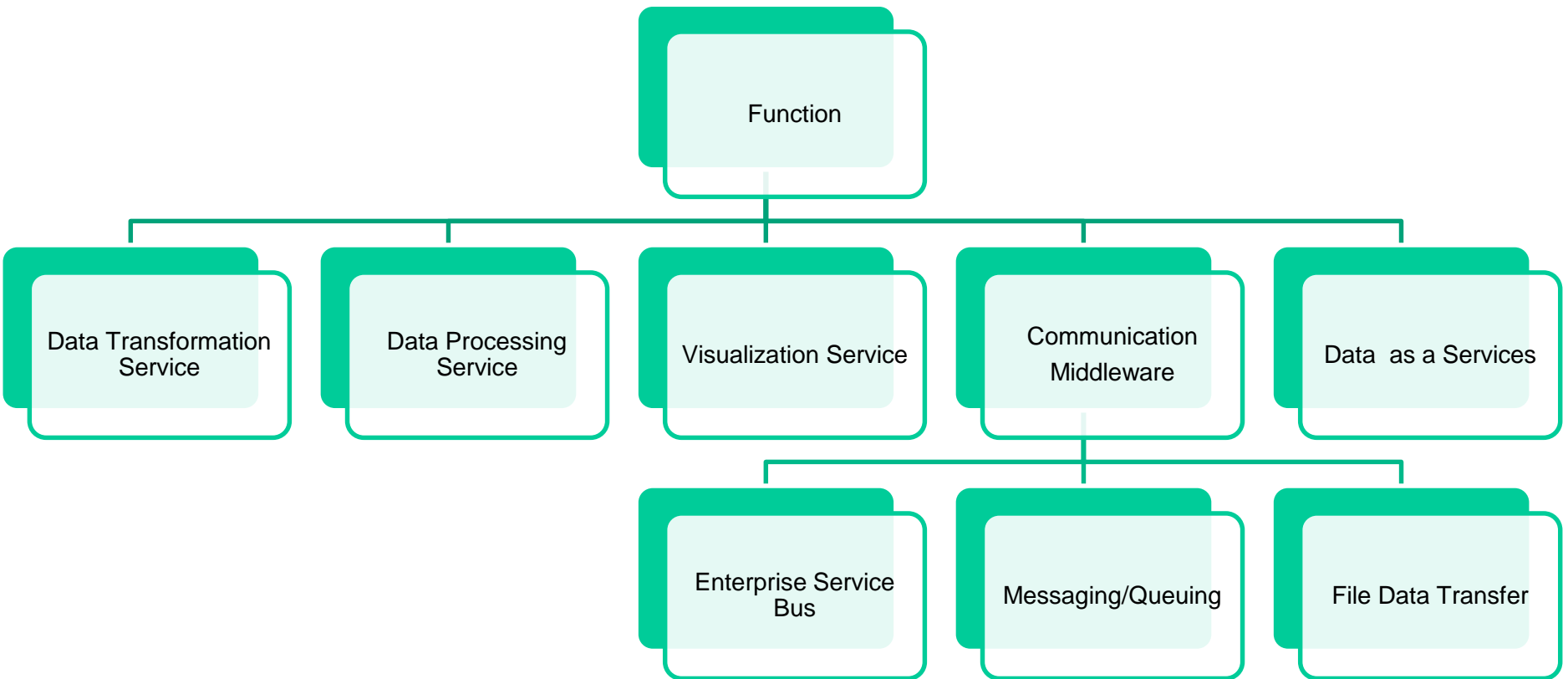
Part = a (composite) services/components

- Which system **infrastructures** are used?
- Which **interfaces/APIs** are suitable for services?
- Which **programming models** are used within services?
- Which **non-functional parameters** are important and how to measure them?

# Fundamental concepts – system infrastructure unit

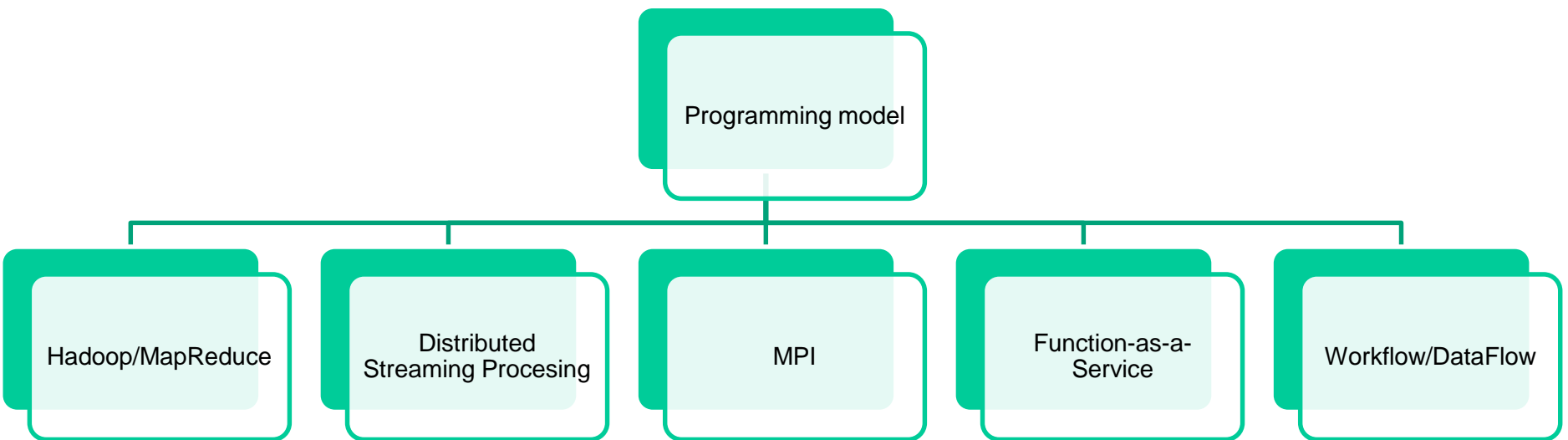


# Fundamental concepts – unit functions

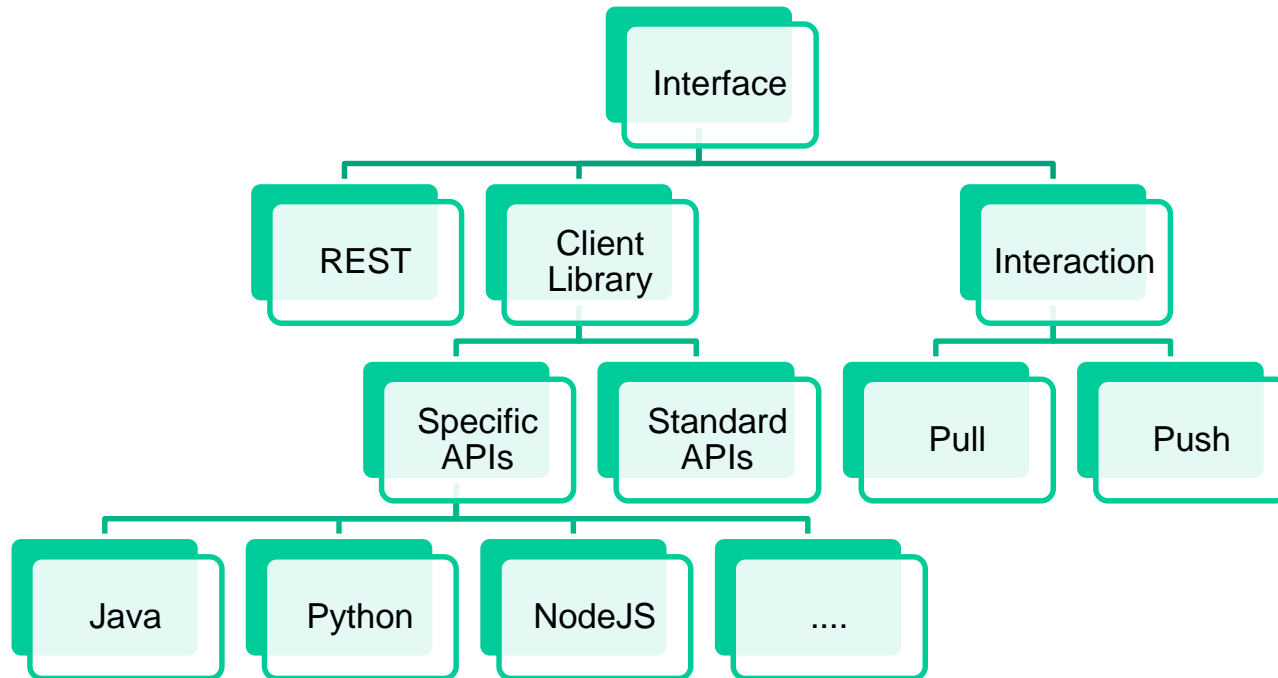




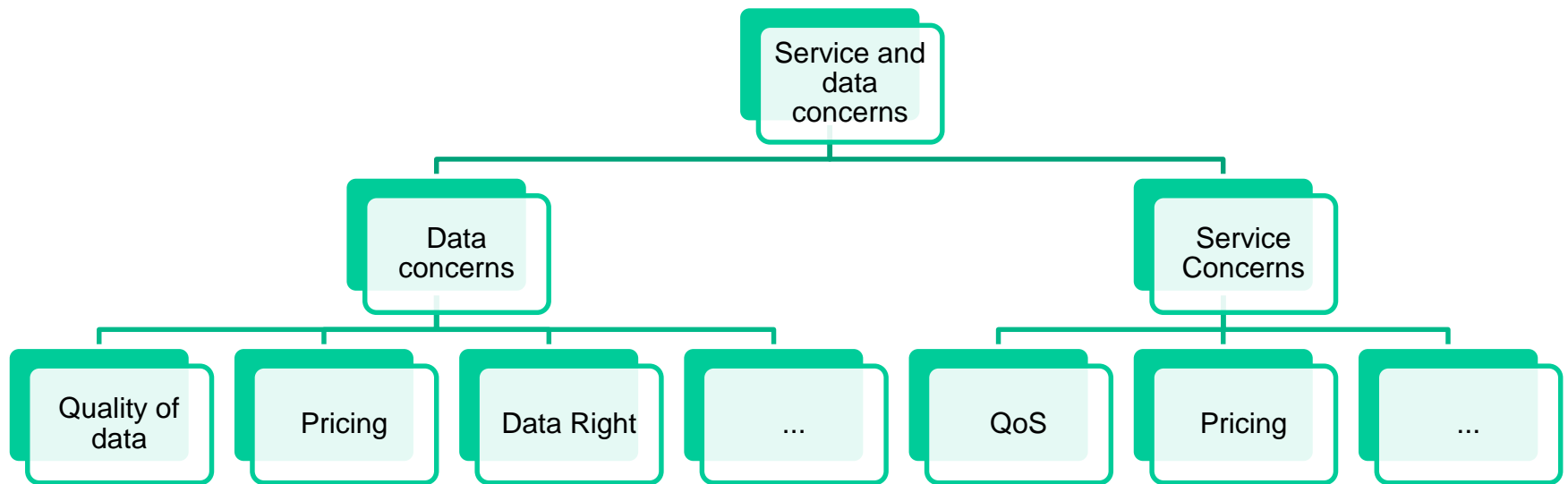
# Fundamental concepts – programming model within units



# Fundamental concepts – interfaces between services



# Fundamental concepts – services and data concerns



**You see we need to deal with many techniques and frameworks**

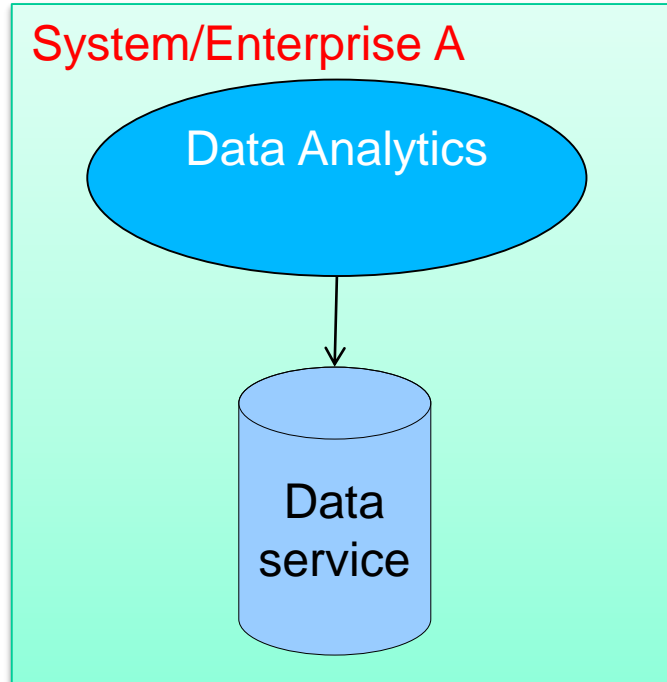
# **WE NEED TO START FROM DATA ANALYTICS WITHIN A SINGLE SYSTEM**

**What is our understanding about a single system?**

**Location and enterprise boundary?**

**Within a virtual infrastructure owned by a single organization?**

# Data analytics within a single (technical) system



- In a single domain
  - Tightly coupled computing infrastructures
    - E.g., in the same cloud
  - Computation and data are close
  - Several concerns can be by-passed
  - They can be complex

# Data analytics within a single system – some examples

Message Passing Interface (MPI) + Cluster-based File system

Parallel Database (SQL/NonSQL)

Big Query

Azure HDInsight

Hadoop + HDFS

Apache Spark

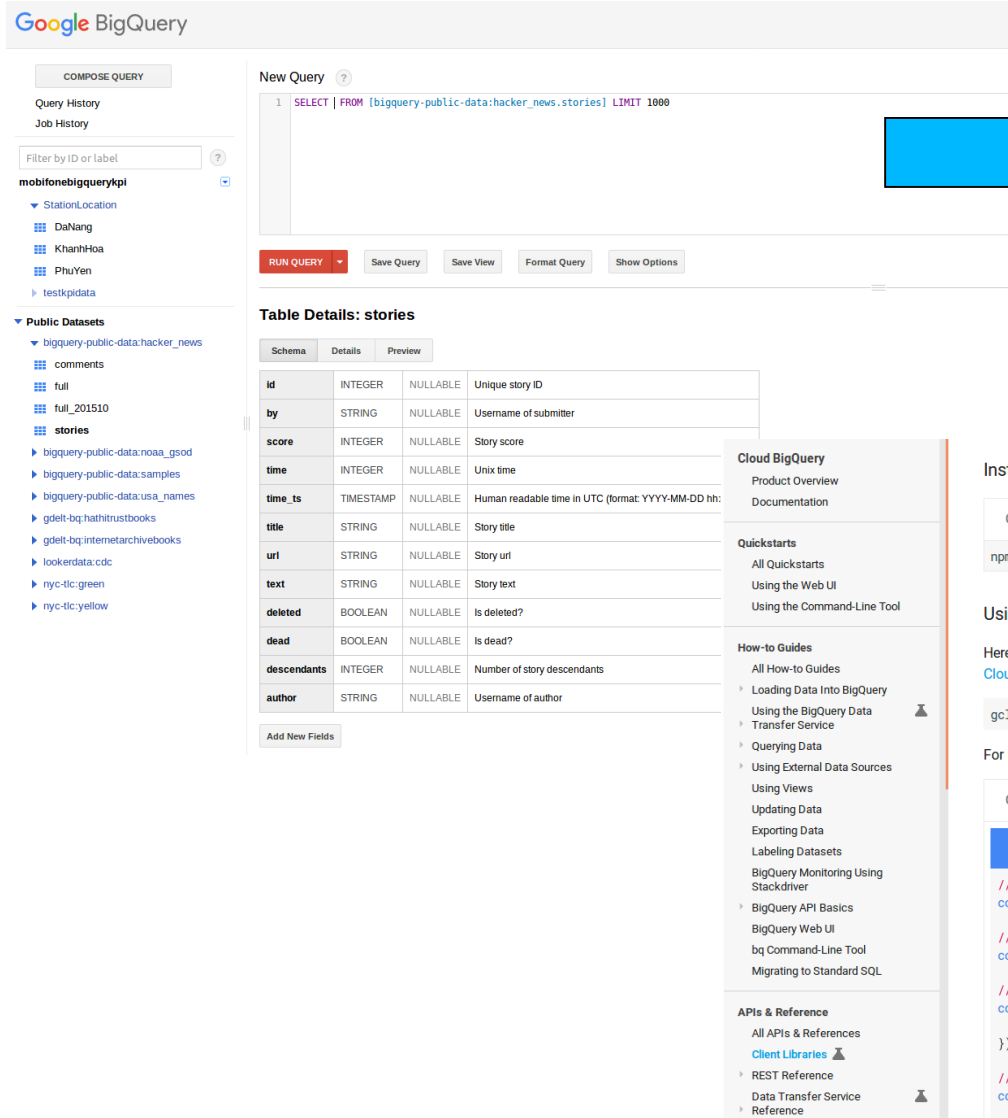
Amazon RedShift

Scientific/Business Workflow

A short, good overview in Chapter 6: Cloud Programming and Software Environments, Book: Distributed and Cloud Computing – from Parallel Processing to the Internet of Things, Kai Hwang, Geoffrey C. Fox and Jack J Dongarra, Morgan Kaufmann, 2012



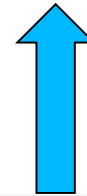
# Example - BigQuery (1)



The screenshot shows the Google BigQuery web interface. On the left, there's a sidebar with navigation options like 'COMPOSE QUERY', 'Query History', and 'Job History'. Below that, a list of datasets is shown, including 'mobifonebigquerykpi' and 'Public Datasets'. The main area displays a 'New Query' with a SQL query: `SELECT * FROM [bigquery-public-data:hacker_news.stories] LIMIT 1000`. Below the query editor, there are buttons for 'RUN QUERY', 'Save Query', 'Save View', 'Format Query', and 'Show Options'. To the right of the query editor, the 'Table Details: stories' are shown in a tabular format with columns like 'id', 'by', 'score', 'time', 'time\_ts', 'title', 'uri', 'text', 'deleted', 'dead', 'descendants', and 'author'. A sidebar on the right contains links to 'Cloud BigQuery' documentation, 'Quickstarts', 'How-to Guides', and 'APIs & Reference'.



Google  
BigQuery



## Installing the client library

C# GO JAVA NODE.JS PHP PYTHON RUBY

```
npm install --save @google-cloud/bigquery
```

## Using the client library

Here's an example of how to use the client library. To run it on your local workstation you must first install the [Google Cloud SDK](#) and authenticate by running [the following command](#):

```
gcloud auth application-default login
```

For information about authenticating in other environments, see the [Google Cloud Platform Auth Guide](#).

C# GO JAVA NODE.JS PHP PYTHON RUBY

[VIEW ON GITHUB](#)

[FEEDBACK](#)

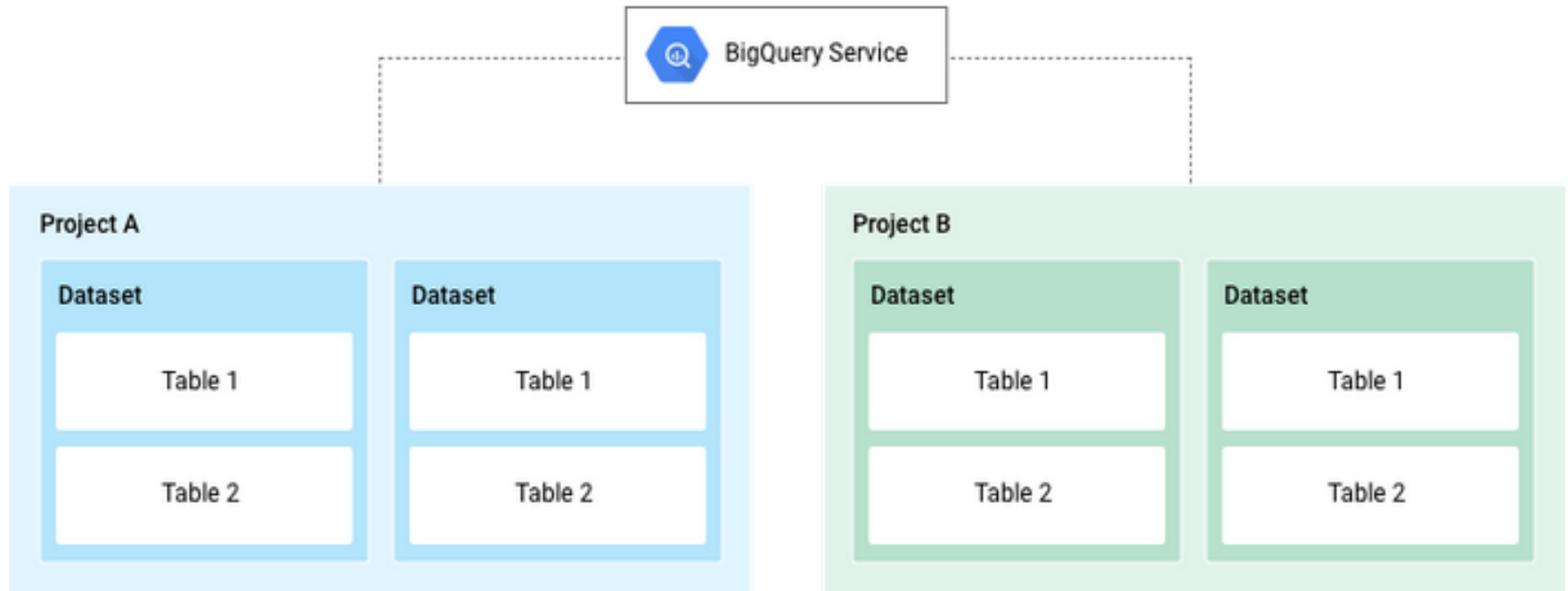
```
// Imports the Google Cloud client library
const BigQuery = require('@google-cloud/bigquery');

// Your Google Cloud Platform project ID
const projectId = 'YOUR_PROJECT_ID';

// Instantiates a client
const bigquery = BigQuery({
  projectId: projectId
});

// The name for the new dataset
const datasetName = 'my_new_dataset';
```

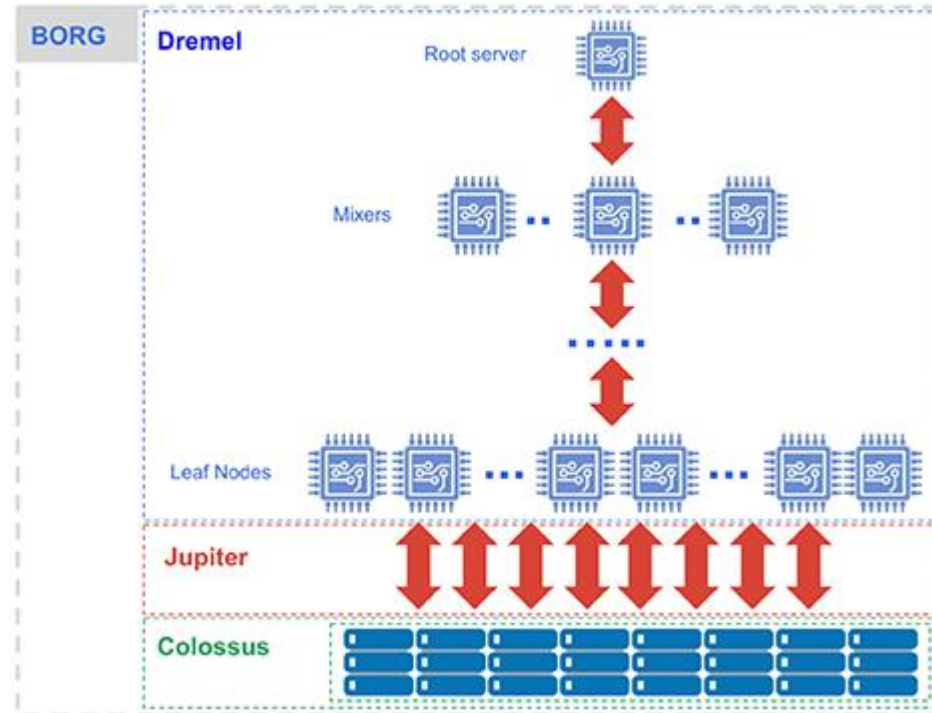
# Example – BigQuery: complexity



**Figure 1:** BigQuery structural overview

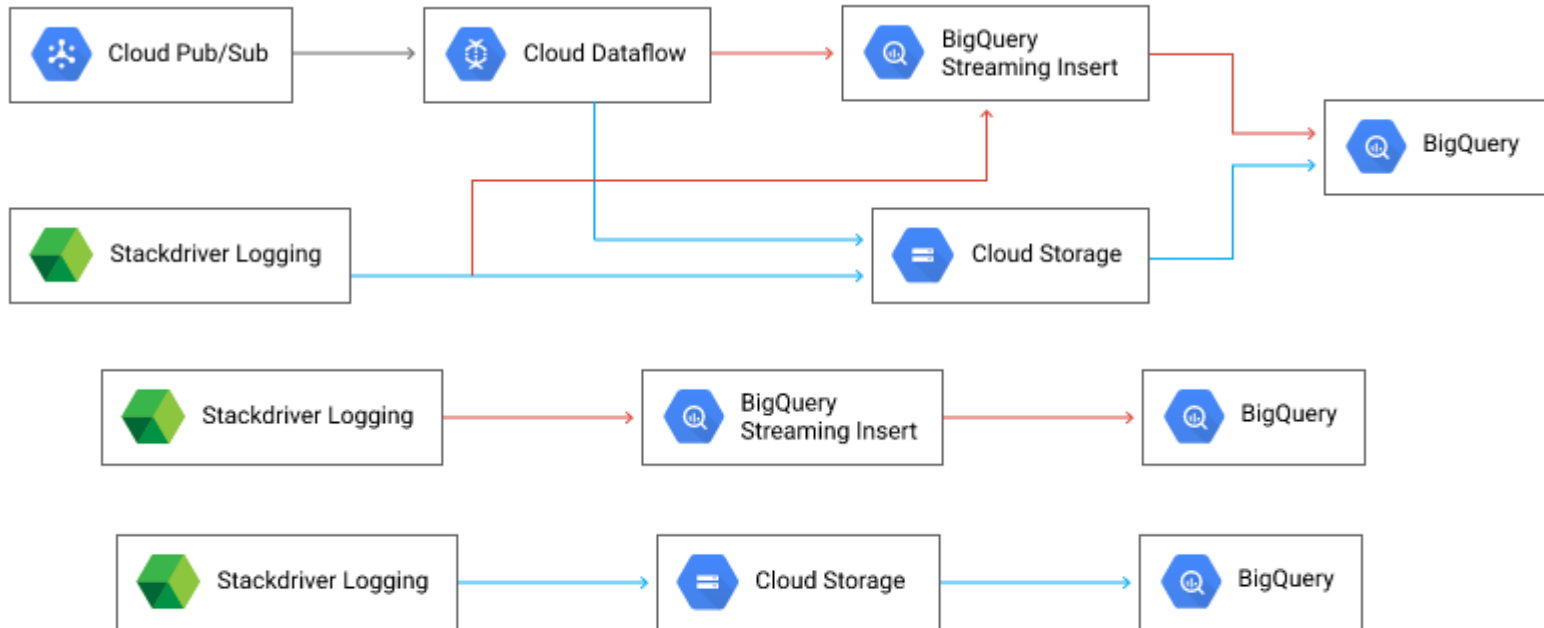
Source <https://cloud.google.com/solutions/bigquery-data-warehouse>

# Example – BigQuery: complexity



Source: <https://cloud.google.com/blog/big-data/2016/01/bigquery-under-the-hood>

# Example – BigQuery: complexity



Source: <https://cloud.google.com/solutions/architecture/optimized-large-scale-analytics-ingestion>

But why it might not be suitable for you?

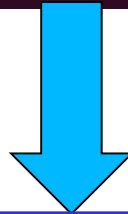
# Example - Hadoop

```

truong@bachphu-spark-m: ~
The programs included with the Debian GNU/Linux system are free software;
the exact distribution terms for each program are described in the
individual files in /usr/share/doc/*/copyright.

Debian GNU/Linux comes with ABSOLUTELY NO WARRANTY, to the extent
permitted by applicable law.
truong@bachphu-spark-m:~$ ls
aa  linh.csv  spark-warehouse  tt.py
truong@bachphu-spark-m:~$ hadoop fs -ls /user/truong
17/05/18 21:03:20 INFO gcs.GoogleHadoopFileSystemBase: GHFS version: 1.6.0-hadoop2
Found 4 items
drwxr-xr-x  - truong hadoop      0 2017-05-17 14:29 /user/truong/.sparkStaging
-rw-r--r--  2 truong hadoop    8945 2017-05-12 07:42 /user/truong/aa
drwxr-xr-x  - truong hadoop      0 2017-05-12 07:40 /user/truong/output
-rw-r--r--  2 truong hadoop    8945 2017-05-12 07:41 /user/truong/part-r-00000-9f88111c-f139-40e5-ac06-53a6e283cd40.csv
truong@bachphu-spark-m:~$ hadoop fs -copyFromLocal aa /user/truong/test.csv
17/05/18 21:04:00 INFO gcs.GoogleHadoopFileSystemBase: GHFS version: 1.6.0-hadoop2
truong@bachphu-spark-m:~$

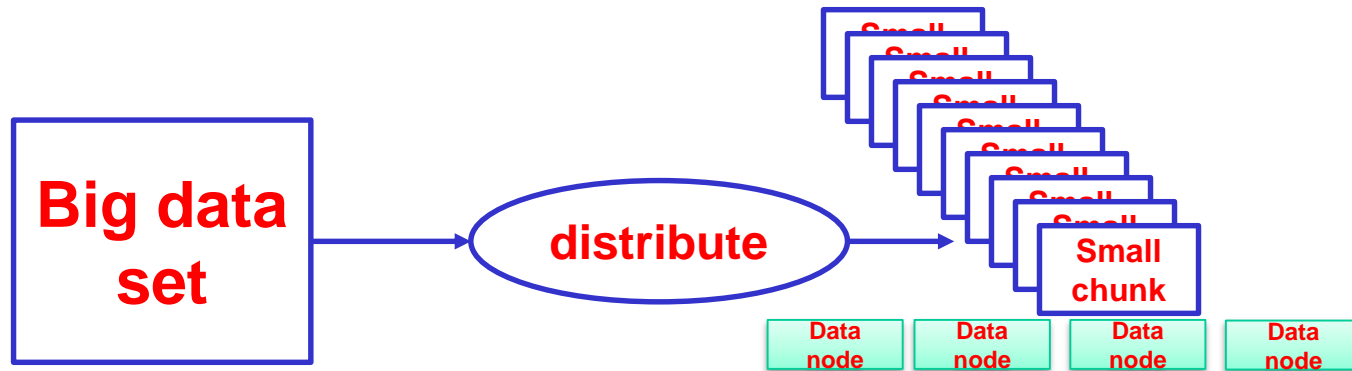
```



Hadoop File Systems

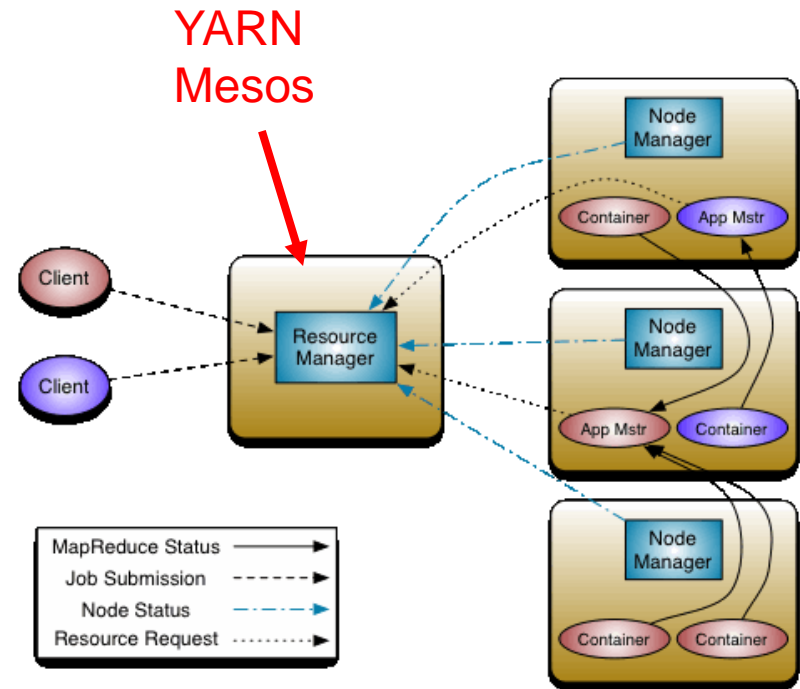
# Example – Hadoop: complexity

- Distributing data into multiple nodes/machines is the key!  
Why?
- Hadoop provides a parallel file system – Hadoop File Systems
  - Deal with hardware failures, support data locality, streaming data access
  - Like traditional file systems with new features for big data
- Key principles:



# Example – Hadoop: complexity

- Several computers are used to setup Resource Manager and Node Manager
- You write the tasks and you submit the tasks



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

# Example – Hadoop: simple

```
spark =
SparkSession.builder.appName("sp_AlarmTypePerday").getOrCreate()
df
=spark.read.csv("hdfs://test/Alarm_nodeB_DN_9_Jan.csv",header=True,
inferSchema=True)
newdf = df.select(['Alarm Number','Started','Canceled'])
newdf.show()
```

Submission  
command  
line  
(your local  
machine)

```
gcloud dataproc jobs submit pyspark
--cluster cluster-spark Test.py
```

cluster-spark  
(Google spark installation with n  
nodes)

Google  
cloud

```
spark-submit --master
spark://master-node:7077 Test.py
```

master-node

Slave  
node

Slave  
node

Slave  
node

Slave  
node

Slave  
node

But why it might not be suitable for you? When?



# Similar questions

- With ElasticSearch, MongoDB, Cassandra, etc. within a single system → they can be very large and scalable!
- But when are they not enough? When are they not suitable for us?

# Bigdata-as-a-Service for ASE

- Two viewpoint
  - Develop services for bigdata-as-a-service
  - Develop services utilizing bigdata-as-a-service
- Important issues
  - Design concepts and architectural patterns
  - Microservices
  - Data access protocols
- Abstraction
  - Data service units and data concerns
  - Performance concerns

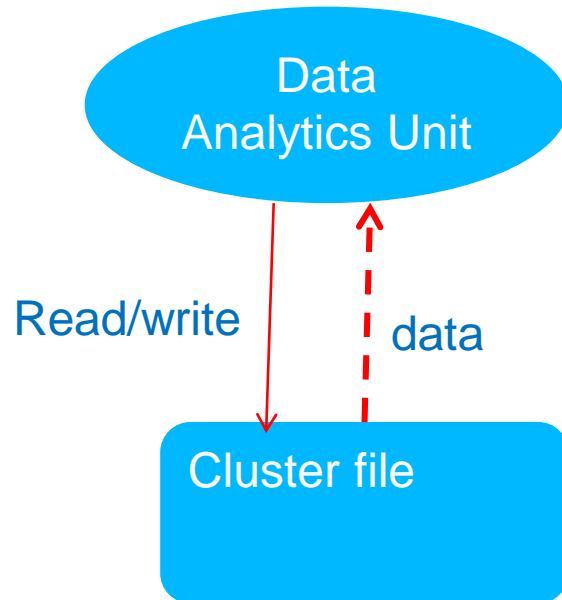
# Data Analytics Unit: Characteristics

A blue oval containing the text 'Data Analytics Unit' in white.

Data  
Analytics Unit

- Can be simple or complex
  - E.g., a python program based on scikit-learn or a pySpark program or a workflow
- Can be written in different program languages
- Can be deployed and run “as a service”
  - Clear input & output

# Data analytics across multiple systems – data service units



## Interface

- Read/write data via direct , low-level read/write via IO

## System

- Cluster or cluster of clusters
- Can be very large

## Programming model

- Usually parallel processing

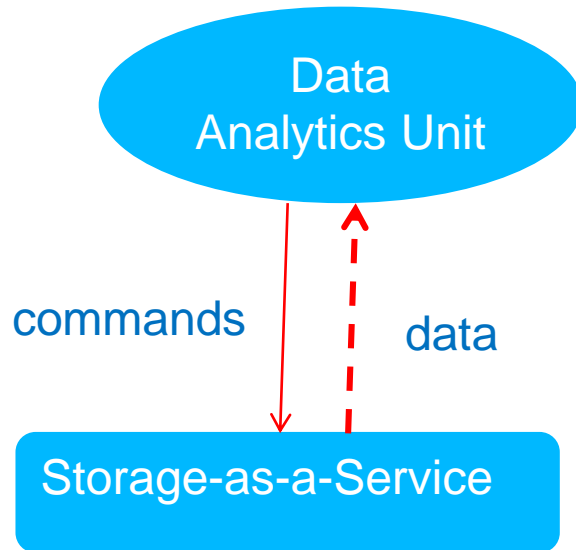
NFS

Lustre

Hadoop File System

Google file system

# Data analytics across multiple systems – data service units



## Interface

- Direct data transfer via REST APIs

## System

- Decouple between analytics and storage

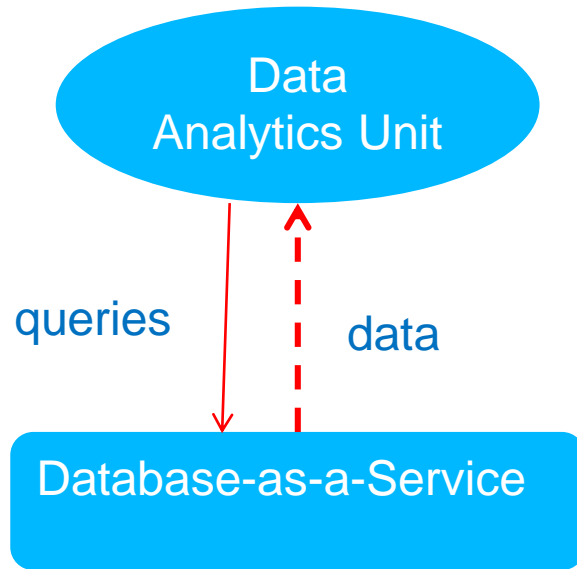
## Programming model

- May require middleware for data transfer
- Request via REST
- Real data transfer done by external middleware
- A rich set of programming models can be used

Amazon S3  
(SOAP/REST API)

Google Storage Service  
(REST API)

# Data analytics across multiple systems – data service units



## Interface

- REST APIs
- Mainly for commands and results

## System

- Decouple between analytics unit and database
- Database as a service can be very large

## Programming model

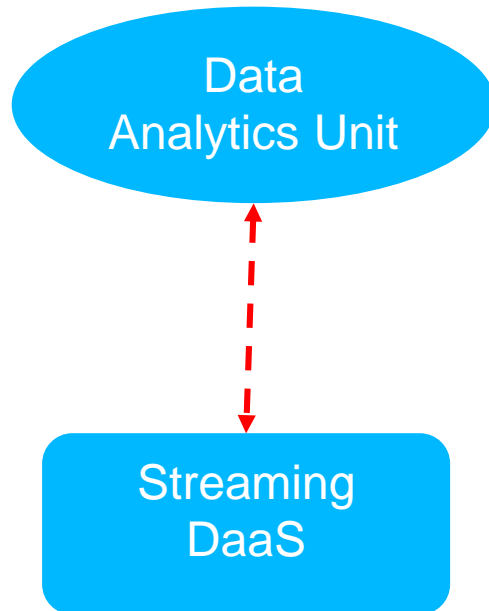
- Analytics can be done at both sides
- Analytic units can use any programming models
- Database-as-a-service can perform a lot of analytics
  - Parallel database operations

## Technology

MongoDB/MongoLab  
 Amazon DynamoDB  
 Amazon SimpleDB  
 Cloudant Data

SkySQL  
 Amazon RDS  
 Microsoft SQL Azure  
 Clustrix DBaaS

# Data analytics across multiple systems – data service units



## Interface

- Data transfer can be uni or bi-direction
- Streaming data protocols

## System

- Both systems for DaaS and for analytics units can be very large

## Programming model

- Can be any

## Technology

StormMQ, RabbitMQ,  
CloudMQTT, Google Data  
Hub, Azure Data Hub, ...

# **WHY SHOULD ANALYTICS UNITS BE „CLOSED“ TO DATA UNITS?**

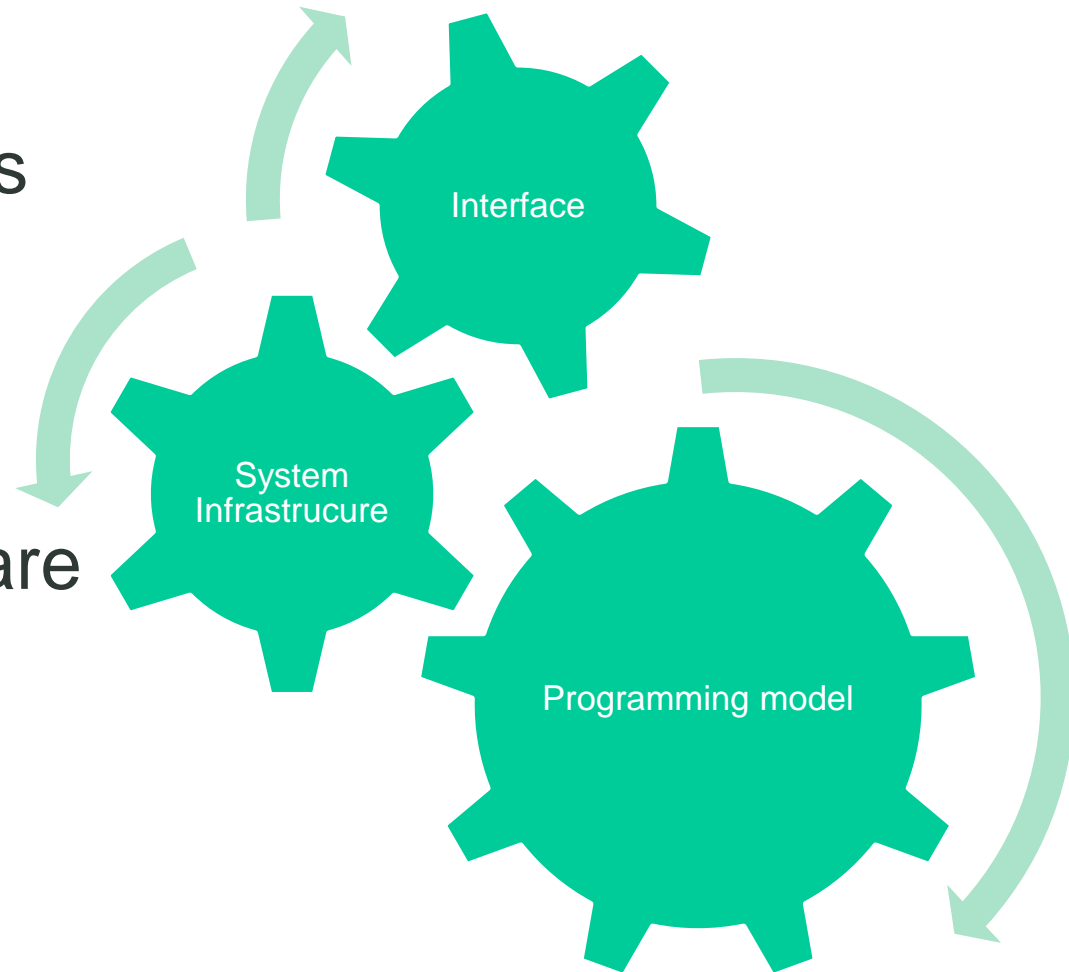


# **WHICH CONCERNS COULD BE IGNORED IN SINGLE SYSTEM DATA ANALYTICS?**

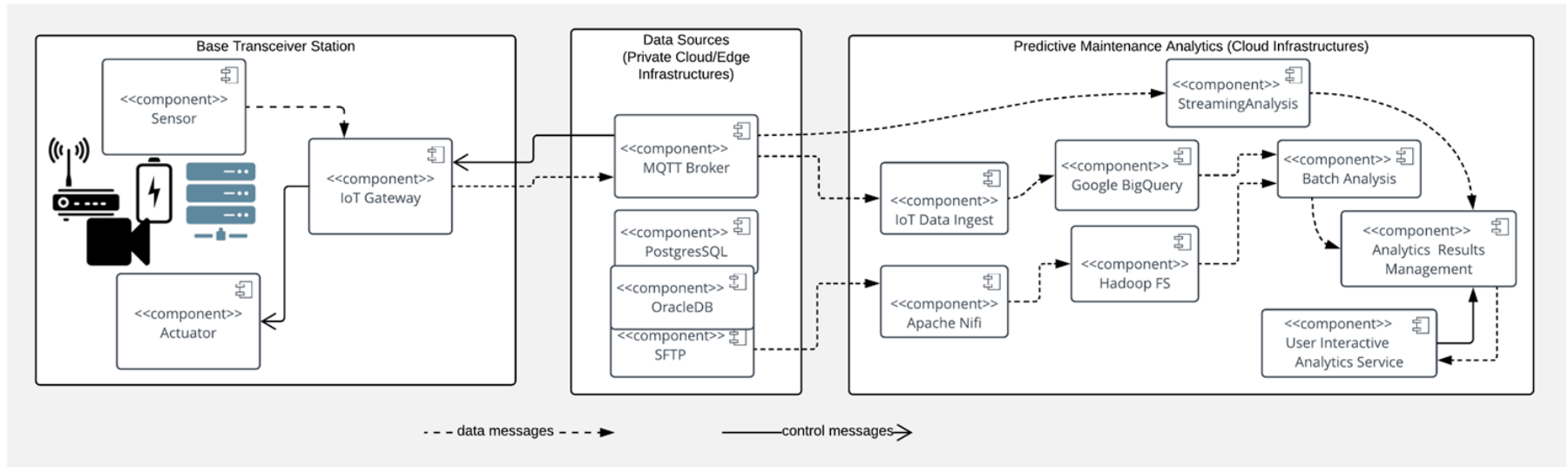
**WHICH ARE THE ISSUES THAT WE NEED  
TO CONSIDER WHEN OUR DATA UNITS  
ARE IN DIFFERENT SYSTEMS?**

# Data analytics across multiple systems – design choice

- Programming models for data analytics service
- Data service units
- Supporting middleware units



# Data analytics across multiple systems - example

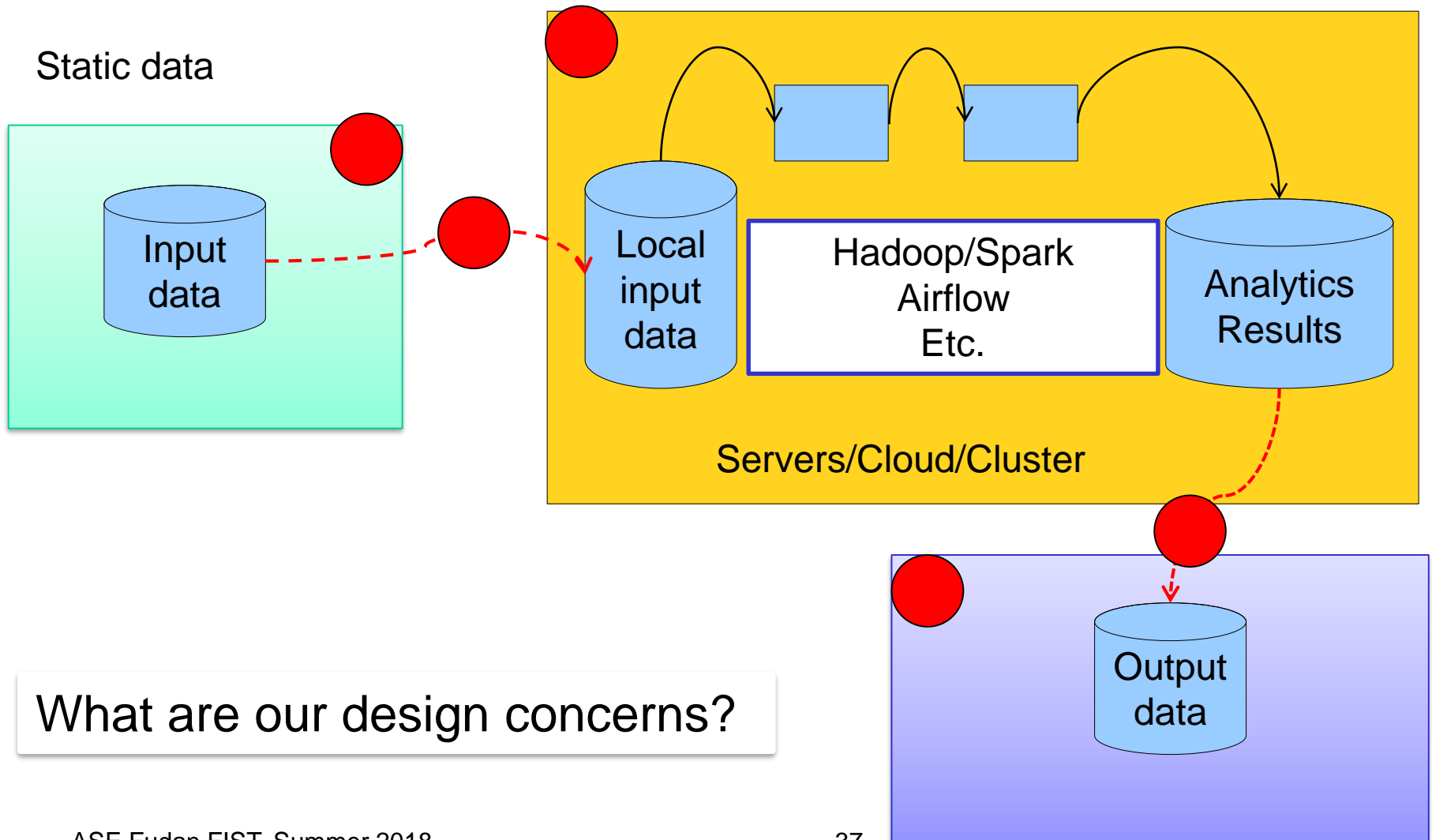


How many systems?

Programming languages?

Type of data?

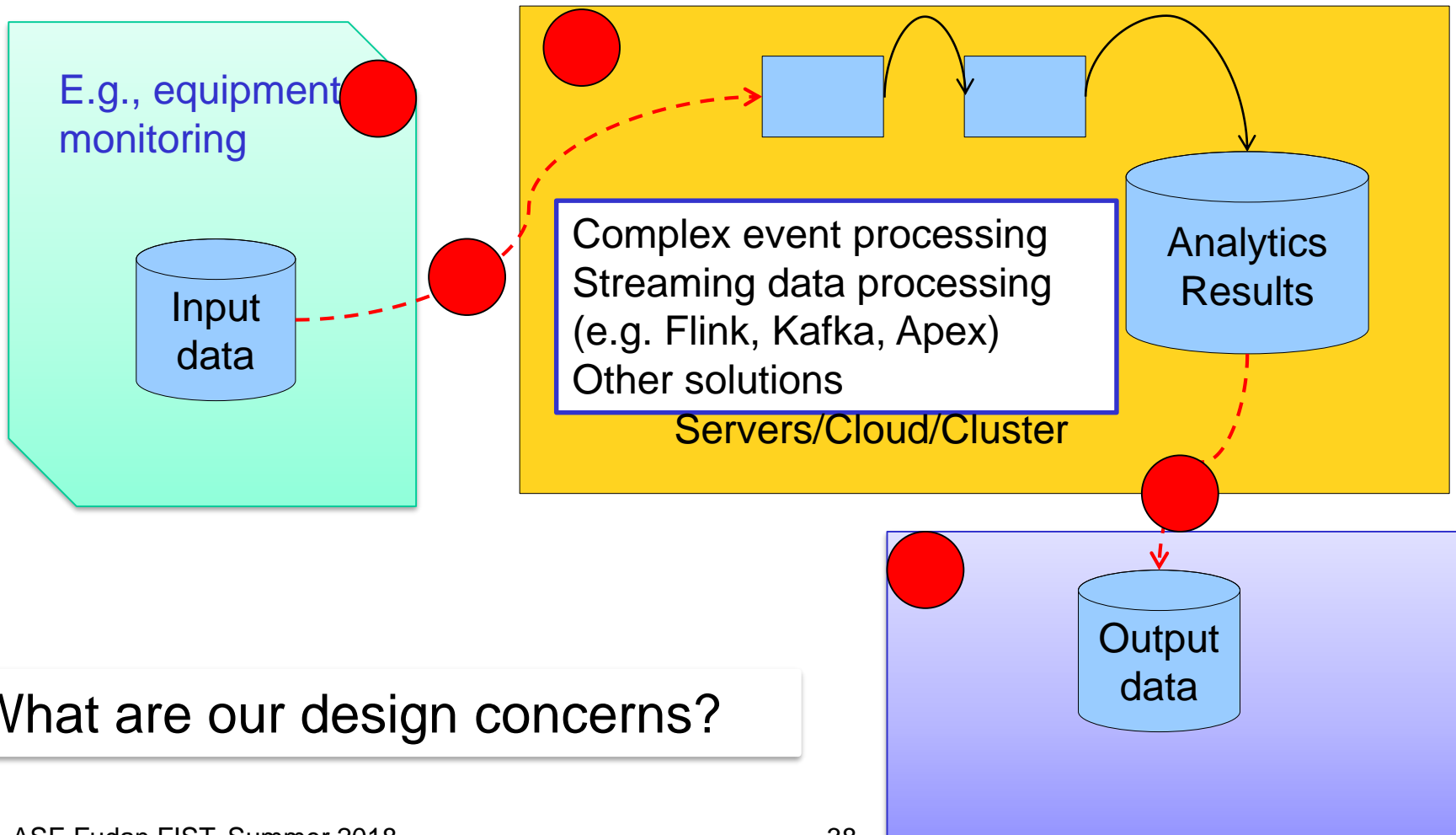
# Data analytics across multiple systems – programming models (1)



What are our design concerns?

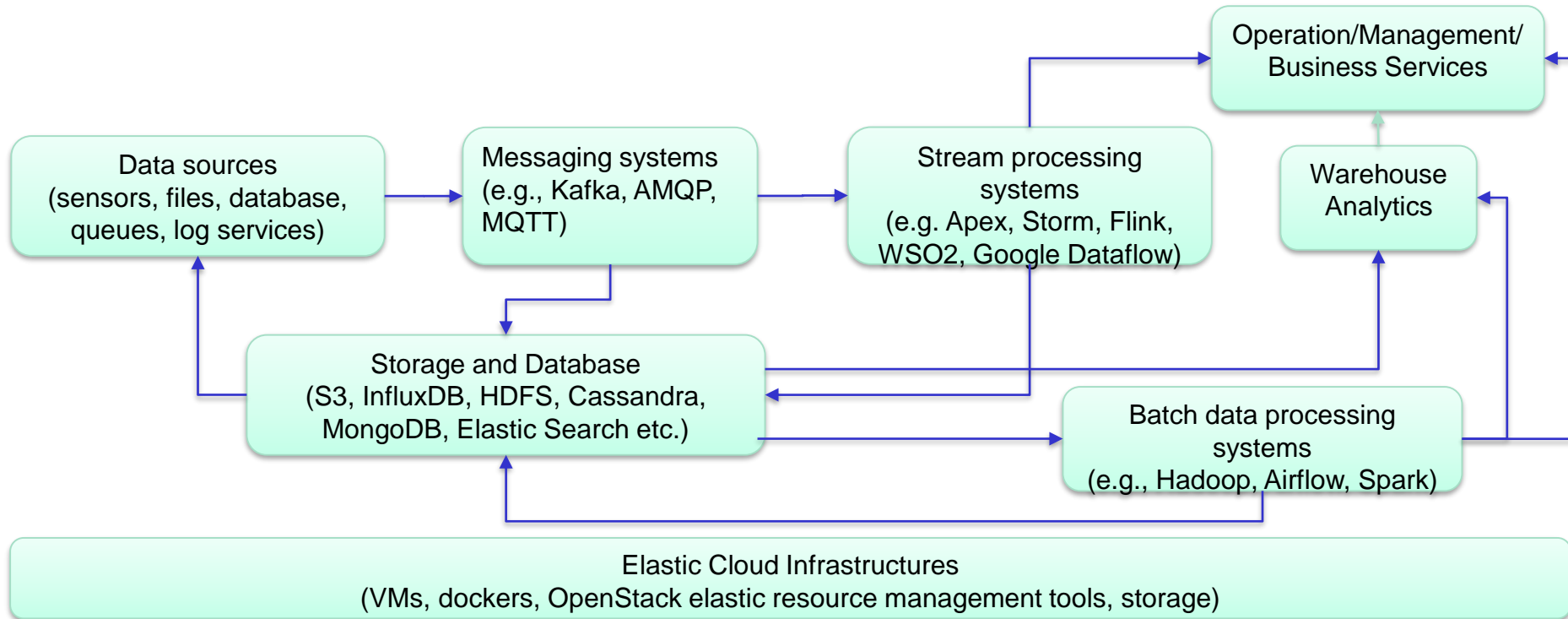
# Data analytics across multiple systems – programming models (2)

## Near-realtime data



What are our design concerns?

# Cloud services and big data analytics



Very complex problems due to software complexity, infrastructures management and service providers

# Case studies

- Monitoring equipment and environments
  - Electricity, temperature, air conditioner breakdown, etc.
- Using MQTT and MySQL

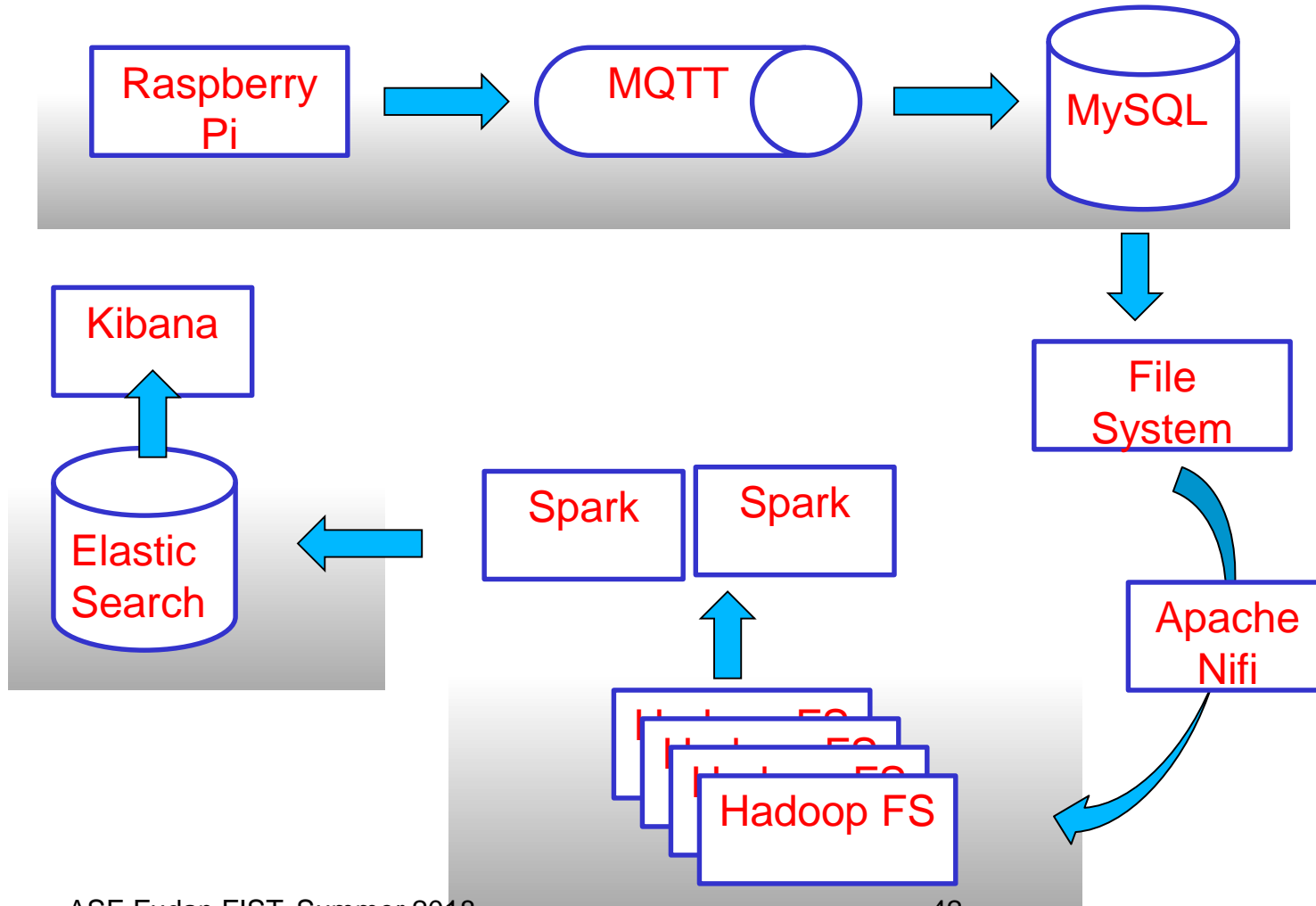


- **Requirements:**
  - Now would like to do big data analytics (for certain type of problems) – offline per day
  - Do not want to manage the big data analytics system
  - Not worry about data privacy/regulation



What would you recommend for solving the requirements?

# Example – Legacy then how to deal with big data analytics

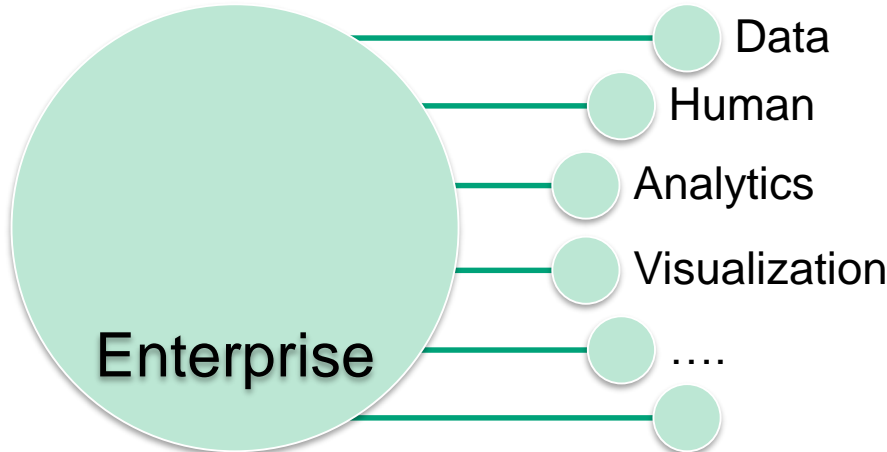


So many types of services from different providers. Anyway to simplify the management of services for the developer/operator?

# **API MANAGEMENT AND BIG DATA**

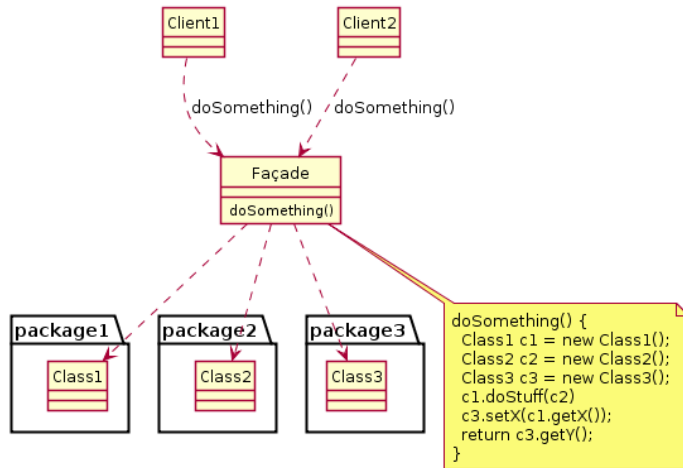
# Ecosystem view for advanced service engineering

- Complex data analytics applications → need to understand potential service units from an **ecosystem perspective**
  - Interdependent systems: Social computing, mobile computing, cloud computing, data management, etc.
  - Different functions (analytics, visualization, communications, etc.)
  - Too many different types of customers (and their interactions)
  - Blending vertical and horizontal analytics

- APIs are key! Why?
    - Enable access to data and function from entities in your ecosystem
    - Virtualization
- 
- The diagram illustrates an 'Enterprise' as a large light green circle on the left. Five horizontal lines connect it to a series of smaller light green circles on the right. The circles are labeled from top to bottom: 'Data', 'Human', 'Analytics', 'Visualization', and '....'. A final unlabeled circle is at the bottom, connected by a line.
- An API is an asset
    - We need to have lifecycle, pricing, management, etc.

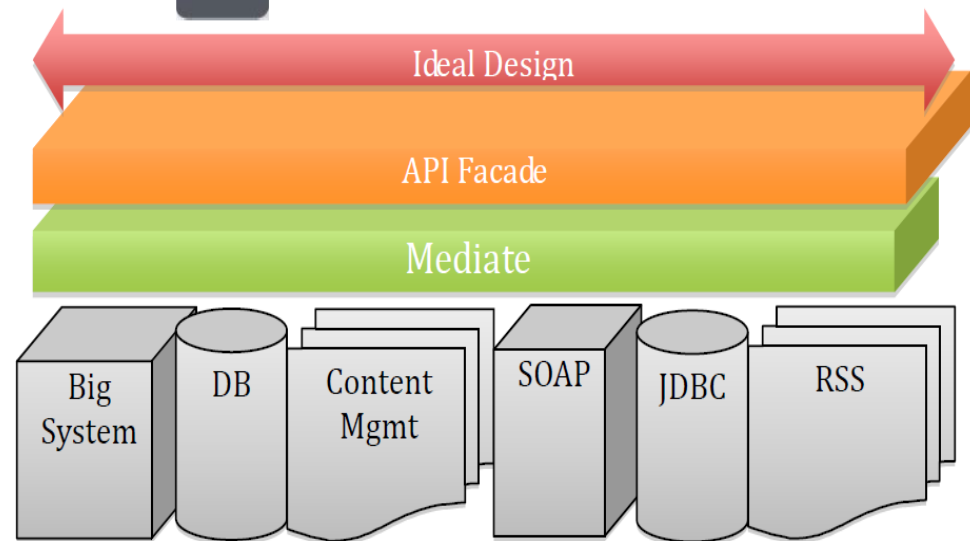
Check <http://www.apiacademy.co> for some useful tutorials

# API Fasade

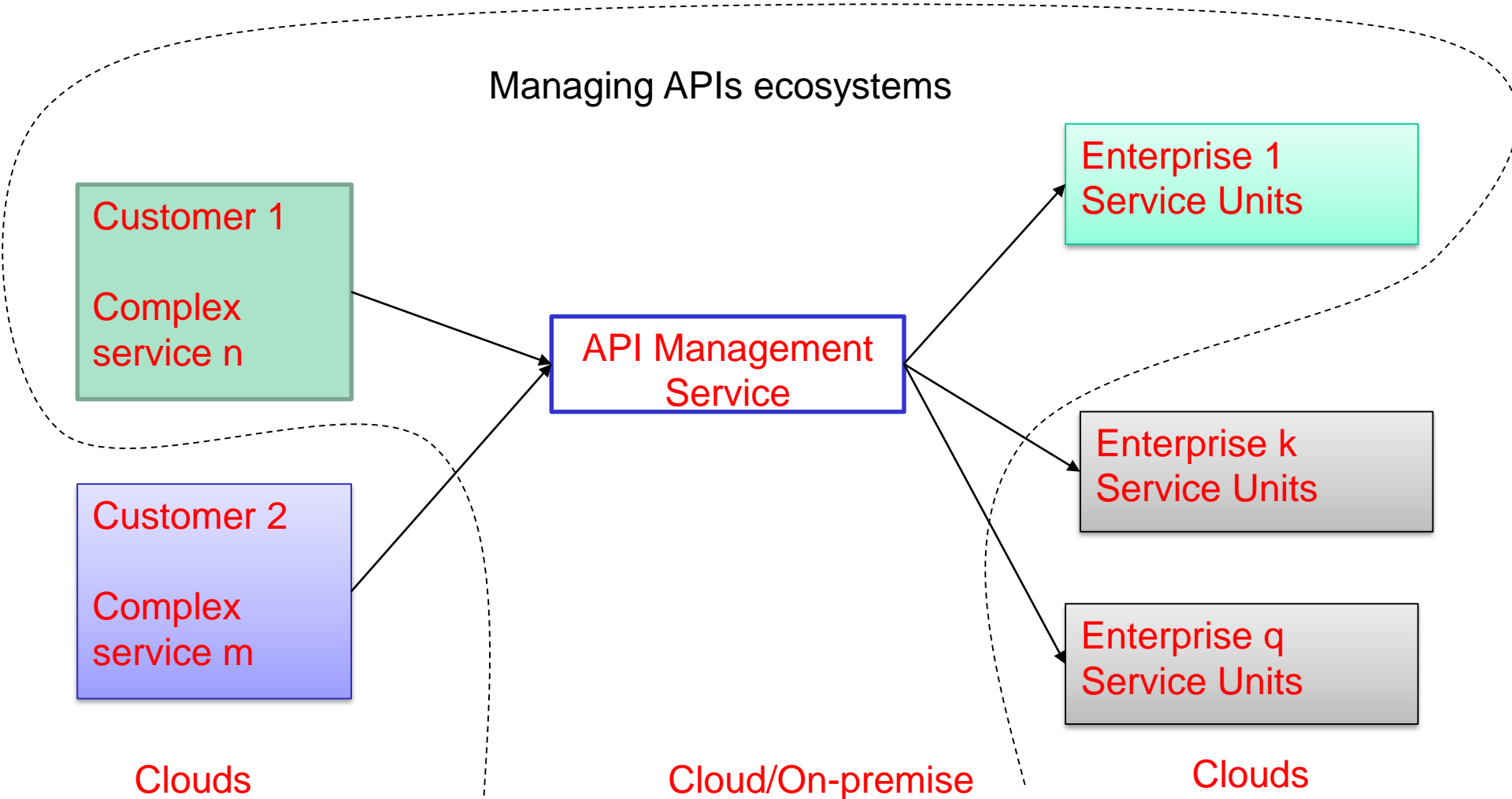


Source:  
[https://en.wikipedia.org/wiki/Facade\\_pattern](https://en.wikipedia.org/wiki/Facade_pattern)

Source: Web API Design, Brian Mulloy  
<http://apigee.com/about/resources/ebooks/web-api-design>



# API management & APIs as a service





# Development of APIs

- Not just the functions behind the APIs
  - This we have learned since a long time
- Emerging (business/service) management aspects
  - Usage control and security
  - Any where from any device for any customer
    - Interfaces (communications, inputs/output formats)
  - APIs as a service:
    - Availability and reliability of APIs are important – think APIs are similar to a service that your client will consume

# Issues on APIs management

- Publish
  - Business and operation planning
    - API usage schemes (e.g., pricing, data concerns)
    - API payload transform policies
    - API throttling
  - API publish and discovery (like service discovery?)
- Management
  - Management roles in enterprises, versions, etc.
- Monitoring and analytics
  - monitoring and analytics information (availability, types of customers, usage frequencies, etc.)
- Microservices and IaC: e.g., with Kubernetes

# Some well-known frameworks

- <https://konghq.com/>
- <http://apigee.com>
- Oracle API management:  
<http://www.oracle.com/us/products/middleware/soa/api-management/overview/index.html>
- <http://wso2.com/api-management/>
- <http://www.ca.com/us/lpg/layer-7-redirects.aspx>
- <https://www.mashape.com/>
- <http://apiaxle.com/>

# Build your own APIs ecosystem

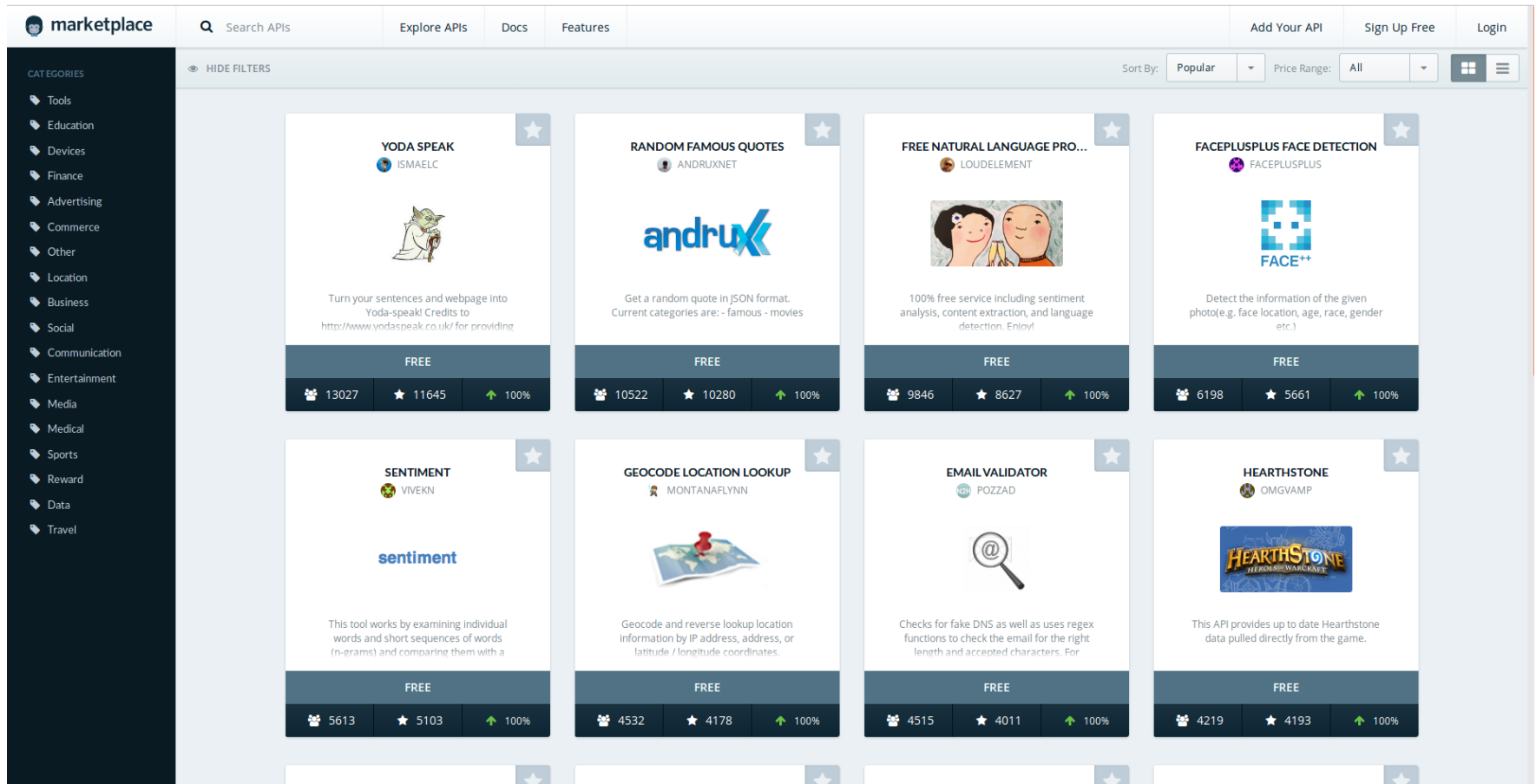
- Which APIs you need? Which ones are crucial for you to build complex services?
  - Data APIs
    - Data collection, Visualization, Analytics APIs
  - Communication
  - Coordination of tasks

→ API management for IoT?

(<http://ubiquity.acm.org/article.cfm?id=2822873>)

- API marketplaces → your APIs
- Using existing API platforms to manage your APIs

# Examples of an API marketplace



The screenshot displays a marketplace interface for APIs. On the left is a sidebar with categories: Tools, Education, Devices, Finance, Advertising, Commerce, Other, Location, Business, Social, Communication, Entertainment, Media, Medical, Sports, Reward, Data, and Travel. The main area shows a grid of API cards, each with a star icon in the top right corner. The cards are as follows:

API Name	Provider	Description	Free	Usage (Cat)	Rating (Star)	Uptime (Green)
YODA SPEAK	ISMAELC	Turn your sentences and webpage into Yoda-speak! Credits to <a href="http://www.yodaspeak.co.uk/">http://www.yodaspeak.co.uk/</a> for providing	FREE	13027	11645	100%
RANDOM FAMOUS QUOTES	ANDRUXNET	Get a random quote in JSON format. Current categories are: - famous - movies	FREE	10522	10280	100%
FREE NATURAL LANGUAGE PRO...	LOUDELEMENT	100% free service including sentiment analysis, content extraction, and language detection. Enjoy!	FREE	9846	8627	100%
FACEPLUSPLUS FACE DETECTION	FACEPLUSPLUS	Detect the information of the given photo(e.g. face location, age, race, gender etc.)	FREE	6198	5661	100%
SENTIMENT	VIVEKN	This tool works by examining individual words and short sequences of words (n-grams) and comparing them with a	FREE	5613	5103	100%
GEOCODE LOCATION LOOKUP	MONTANAFLYNN	Geocode and reverse lookup location information by IP address, address, or latitude / longitude coordinates.	FREE	4532	4178	100%
EMAIL VALIDATOR	POZZAD	Checks for fake DNS as well as uses regex functions to check the email for the right length and accepted characters. For	FREE	4515	4011	100%
HEARTHSTONE	OMGVAMP	This API provides up to date Hearthstone data pulled directly from the game.	FREE	4219	4193	100%

# Use API Management for your mini project?



WHY API PLATFORM

PRODUCTS

CUSTOMERS

COMMUNITY

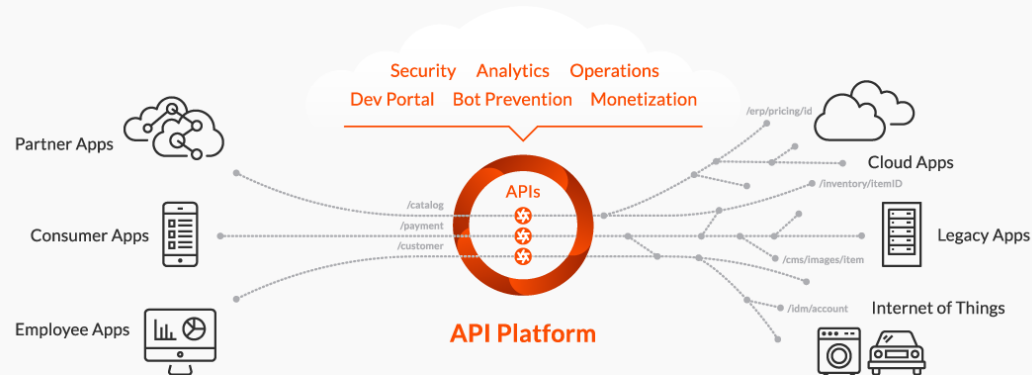
DEVELOPERS

[SIGN UP FREE](#)

[SIGN IN](#)

## Manage your APIs anywhere

Design, secure, analyze, and scale your APIs with the Apigee API platform



From <https://apigee.com>

What would be the relationship  
between API management and big  
data?

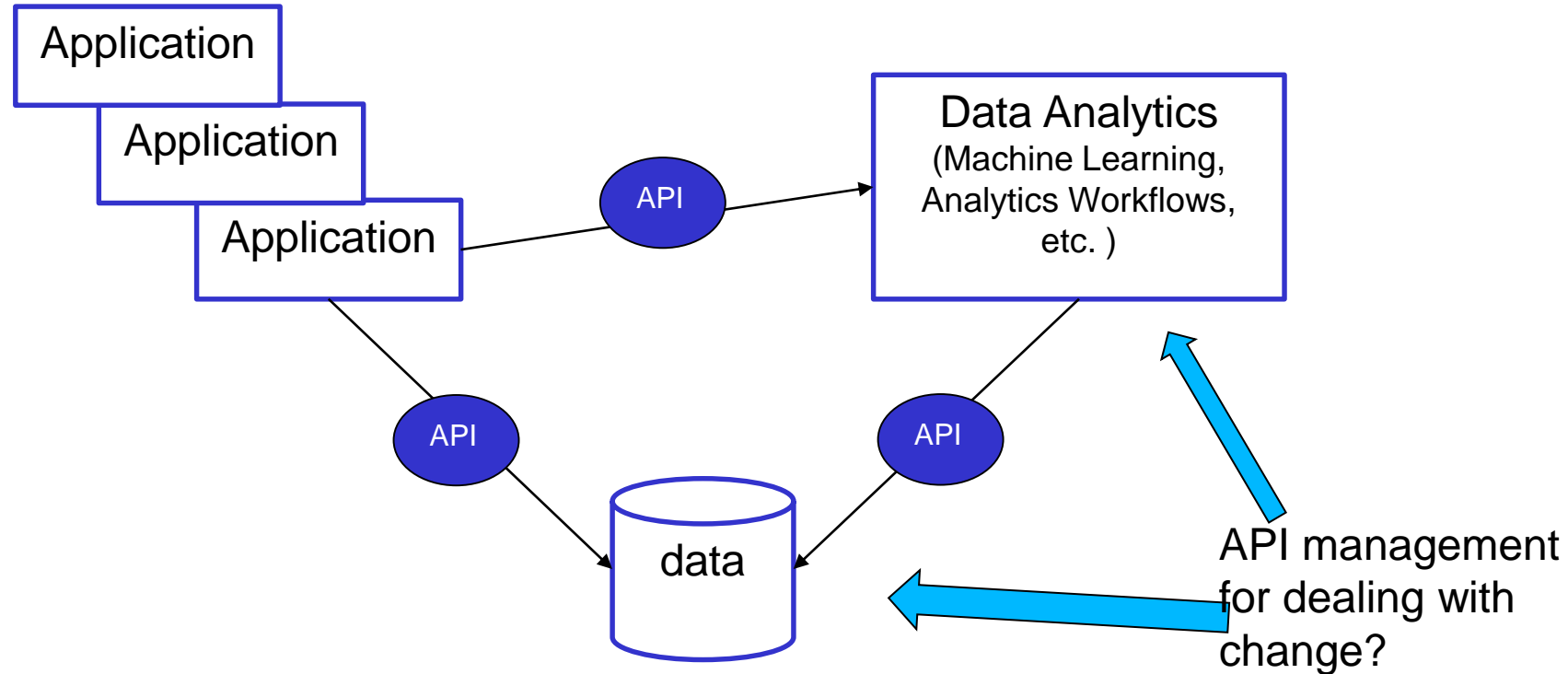
## Aspects:

- Data access and contract
- New source of data
- Data analytics



# Changes in Application, Analytics and data

All are changing internally. Can we keep the API remains and new APIs are added



# Example of Architecture Design from Amazon

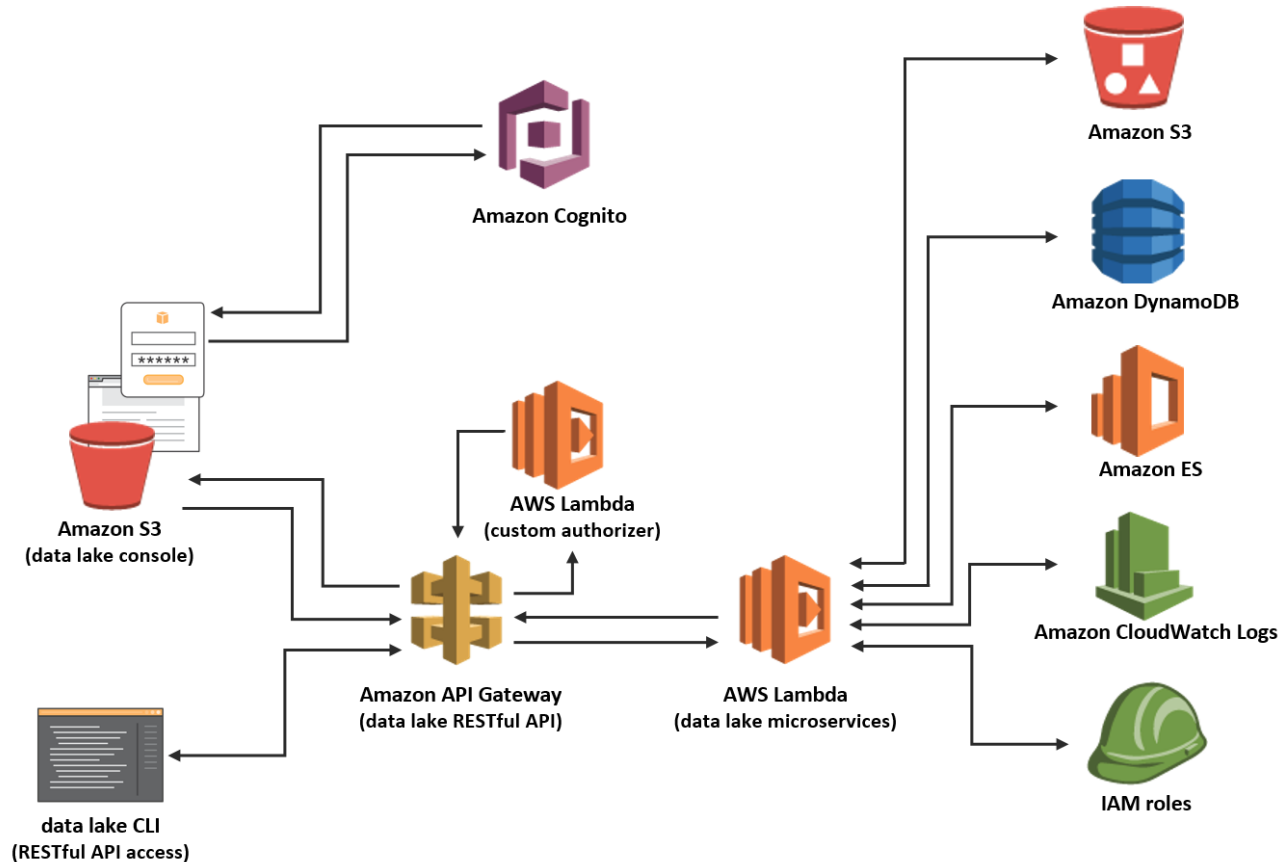
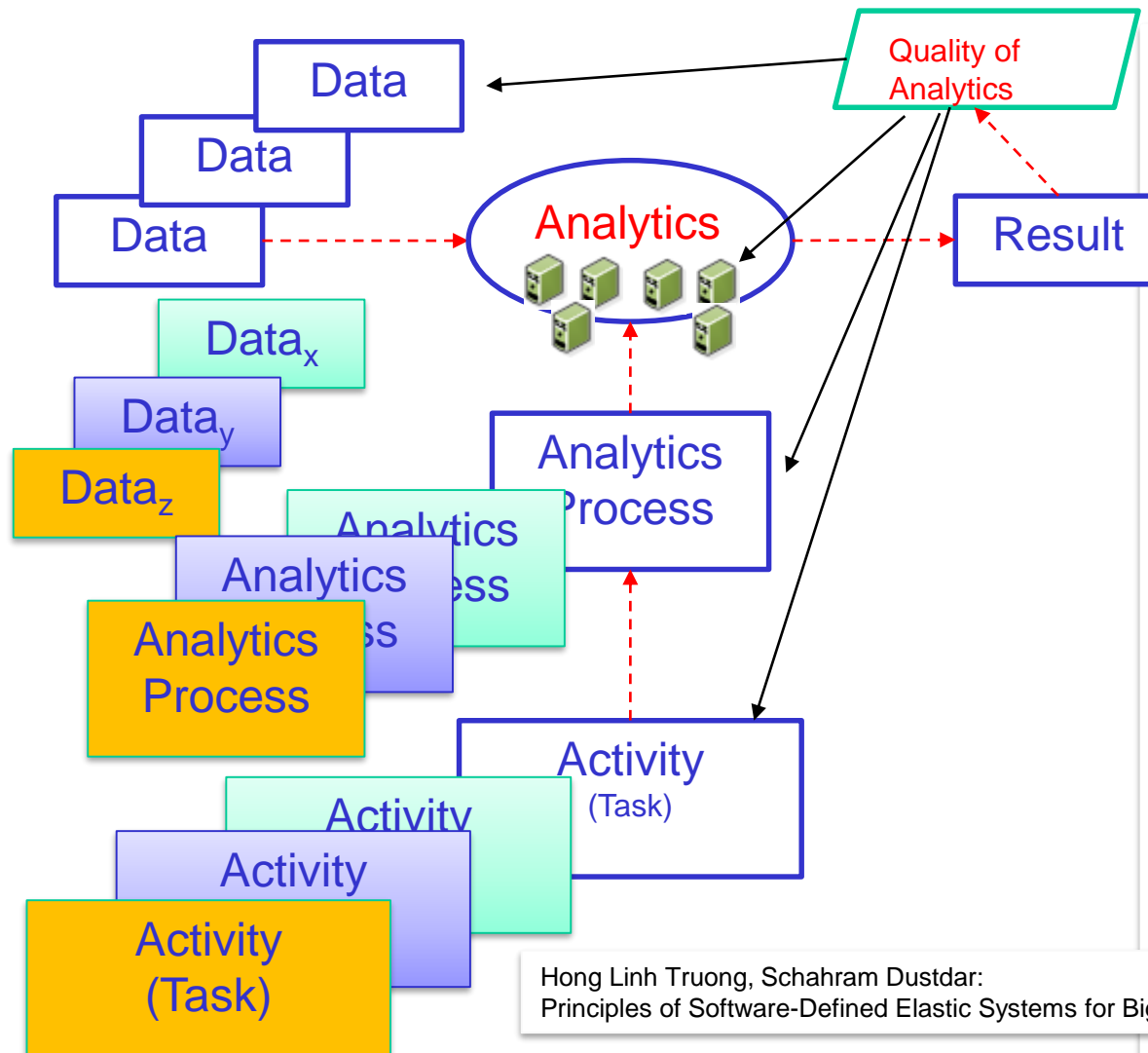


Figure source: <https://aws.amazon.com/answers/big-data/data-lake-solution/>

# PRINCIPLES OF ELASTICITY FOR BIG DATA SYSTEMS

# Elasticity in (big) data analytics

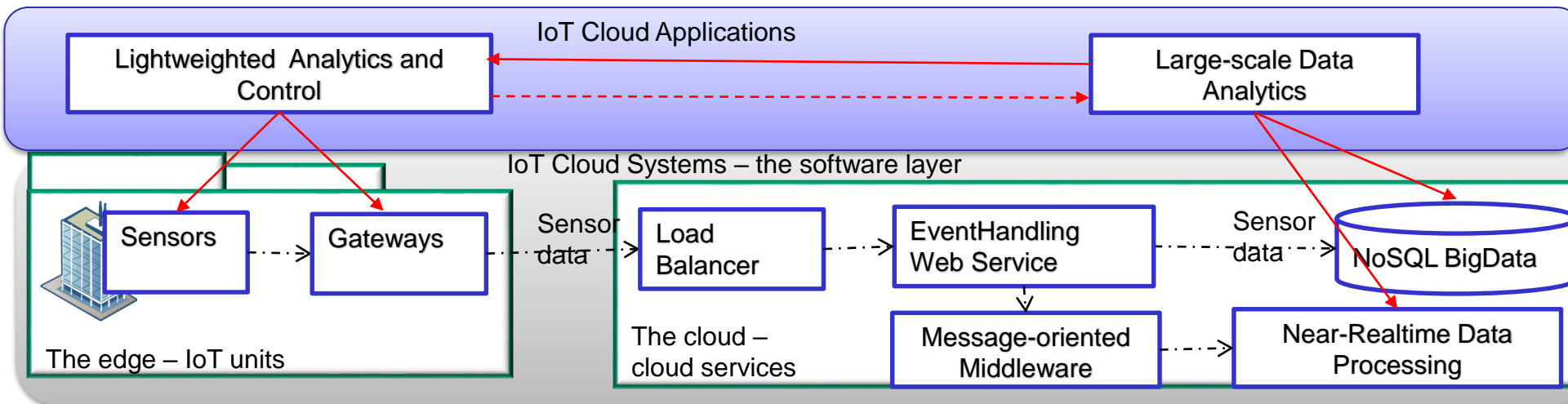


- **More data** → more compute resources (e.g. more VMs)
- **More types of data** → more activities → more analytics processes
- Change **quality of analytics**
  - Change quality of data
  - Change response time
  - Change cost
  - Change types of result (form of the data output, e.g. tree, table, story)

Hong Linh Truong, Schahram Dustdar:  
Principles of Software-Defined Elastic Systems for Big Data Analytics. IC2E 2014: 562-567

# Elasticity in slices of IoT, Network functions and cloud resources

## Application example

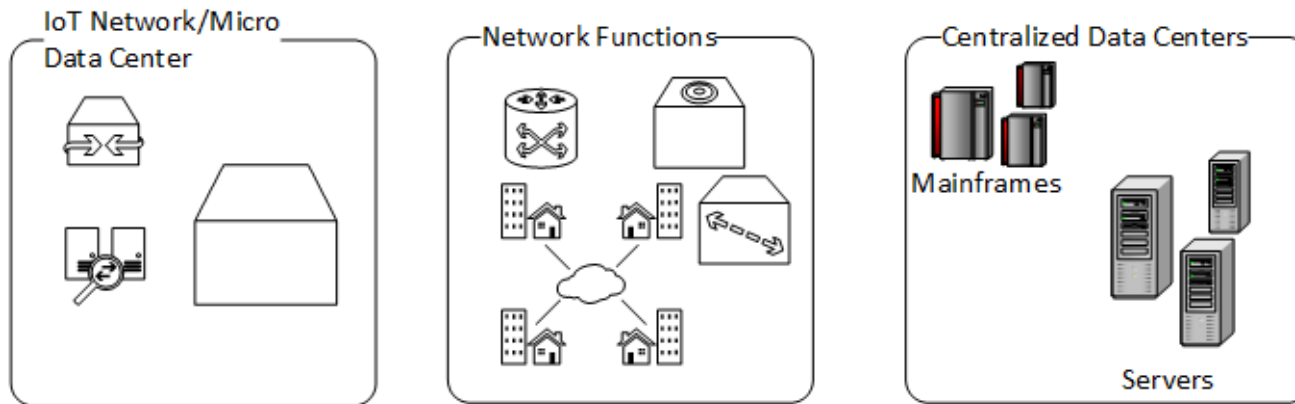


What should we do if suddenly many sensors send a lot of data?

What if you know that “5 minutes from now,  $10 \cdot n$  sensors will be started?

# Elasticity in slices of IoT, Network functions and cloud resources

„IoT + Network functions + Clouds“



What if in the “network functions” we can create VMs or perform network traffic engineering?

Elasticity principles can be used to support dynamic quality of analytics

# Elasticity Principles: **Elasticity of data and analysis processes**

- Multiple types of objects from different sources with complex dependencies, relevancies, and quality
- Different data and algorithms models for analyzing the same subject
- New analytics subjects can be defined and analytics goals can be changed
- Decide/select/define/compose not only data but also analysis pipelines based on existing ones

Management and modeling of elasticity of data and processes during the analytics



# Elasticity Principles: **Elasticity of data resources**

- Data provided, managed and shared by different providers
- Data associated with different concerns (cost, quality of data, privacy, contract, etc.
- Static data, open data, data-as-a-service, opportunistic data (from sensors and human sensing)
- Distributed big data and multiple data owners

Data resources can be taken into account in an elastic manner: similar to VMs, based on their quality, relevancy, pricing, etc.



# Elasticity Principles: Elasticity of humans and software as computing units

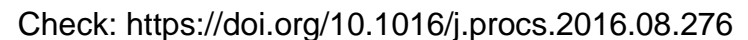
- Human in the loop to solve analytics tasks that software cannot do
- Human-based compute units can be scaled up/down with different cost, availability, and performance models
- Human-based compute units + software-based compute units for executing analysis pipelines
- Elasticity controls can be also done by humans

Provisioning hybrid compute units in an elastic way for computing/data/network tasks as well as for monitoring/control tasks in the analytics process

# Elasticity Principles: **Elasticity of quality of analytics**

- Definition of **quality of analytics**
  - Trade-offs of time, cost, quality of data, forms of output
- Using quality of analytics to select suitable analysis processes, data resources, computing units
- Multi-level control for the elasticity based on quality of analytics

Able to cope with changes in quality of data, performance, cost and types of results at runtime



- Read mentioned papers
- Analyze the relationships between programming models and system infrastructures for data analytics across multiple domains
- Examine <http://cloudcomputingpatterns.org> and see how it supports data analytics patterns
- Mini project:
  - Develop data analytics with suitable frameworks and APIs for your project

# Data analytics within a single system

## Some papers

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2. Leonardo Neumeyer, Bruce Robbins, Anish Nair, Anand Kesari: S4: Distributed Stream Computing Platform. ICDM Workshops 2010: 170-177
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6. Yingyi Bu, Bill Howe, Magdalena Balazinska, Michael D. Ernst: HaLoop: Efficient Iterative Data Processing on Large Clusters. PVLDB 3(1): 285-296 (2010)

# Thanks for your attention

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