

Advanced service-based data analytics: Models, Elasticity and APIs

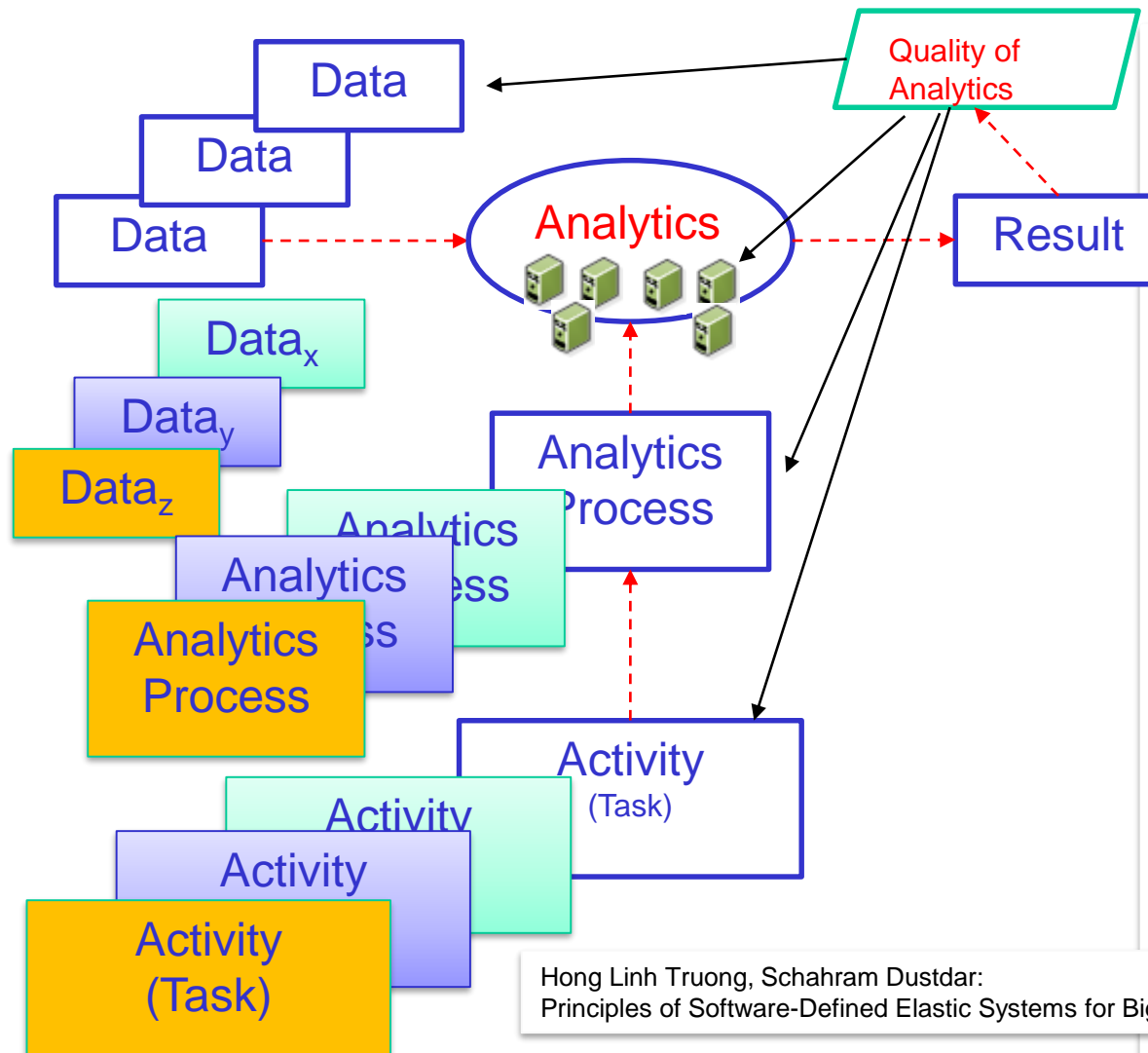
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[@linhsolar](#)

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

PRINCIPLES OF ELASTICITY FOR DATA ANALYTICS

Elasticity in (big) data analytics



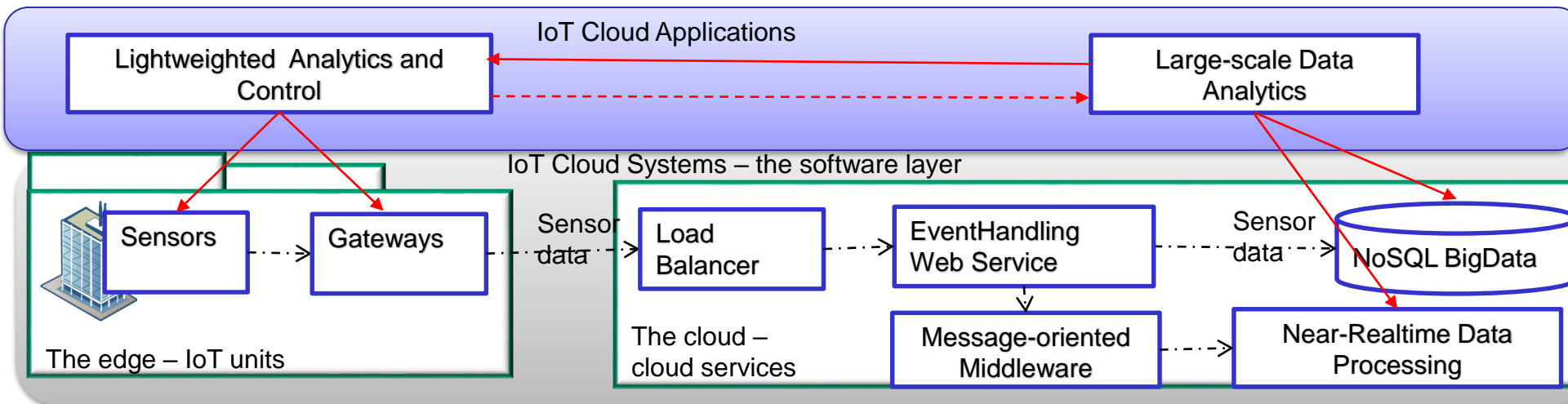
- **More data** → more compute resources (e.g. more VMs)
- **More types of data** → more activities → more analytics processes
- Change **quality of analytics**
 - Change quality of data
 - Change response time
 - Change cost
 - Change types of result (form of the data output, e.g. tree, table, story)

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

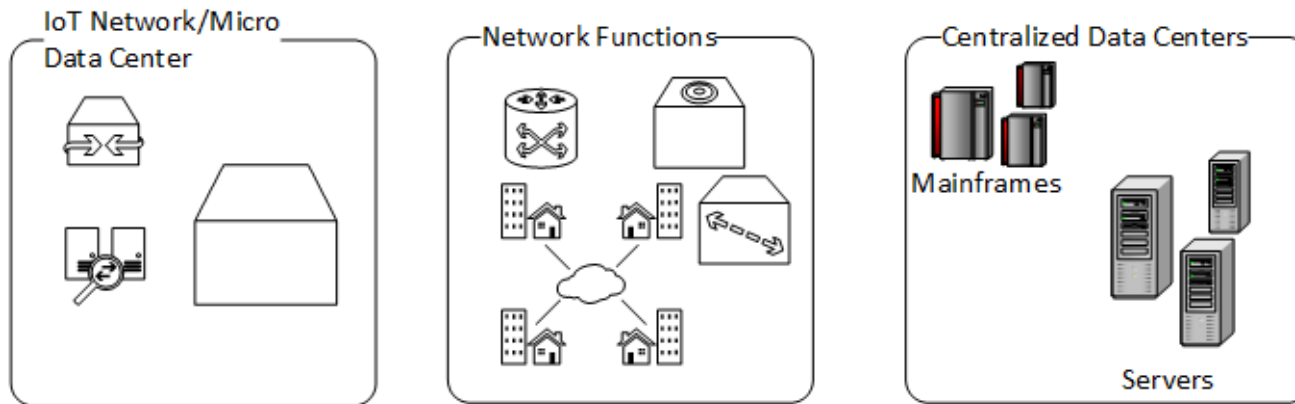


What should we do if suddenly many sensors send a lot of data?

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



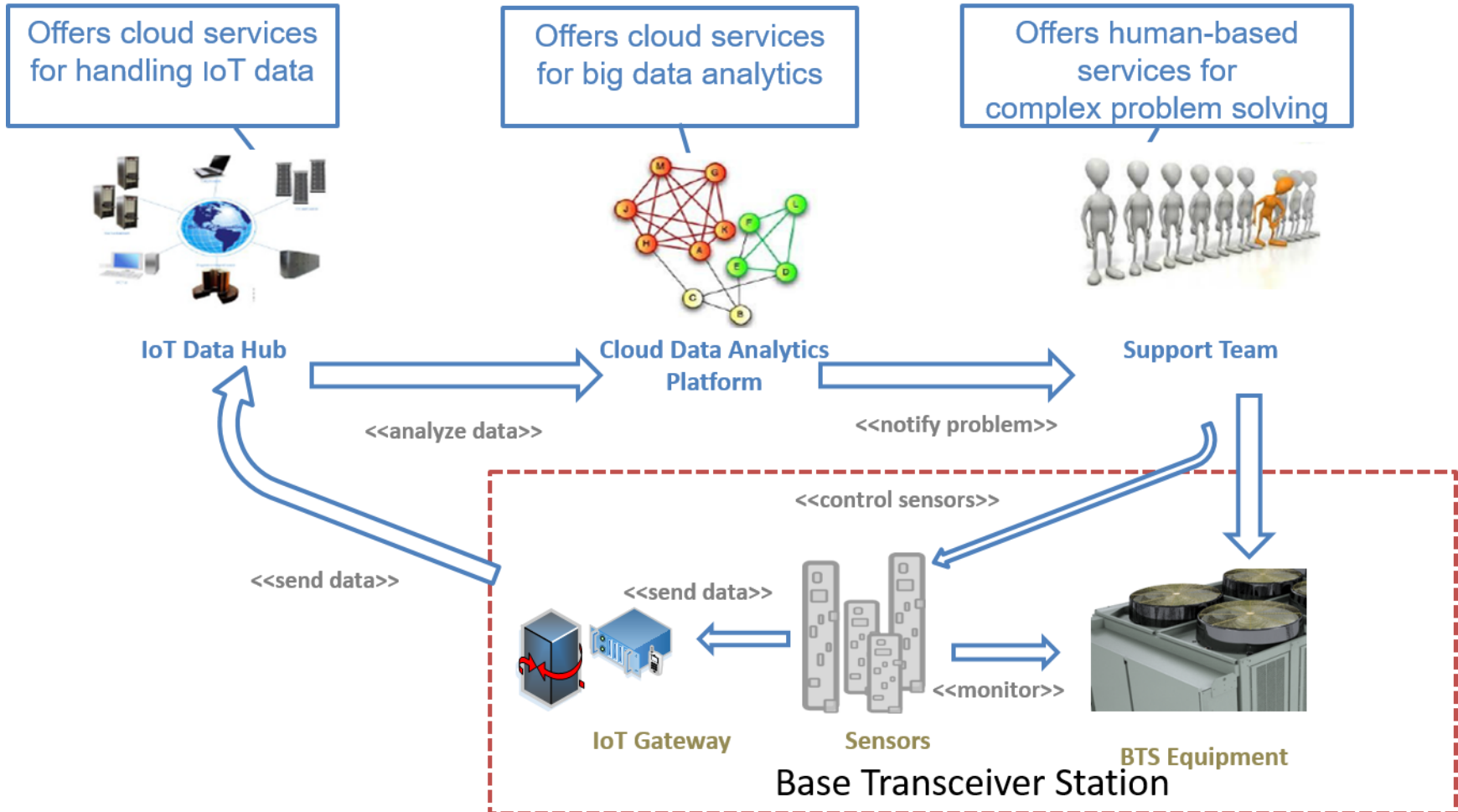
Elasticity Principles: Elasticity of quality of analytics

- 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

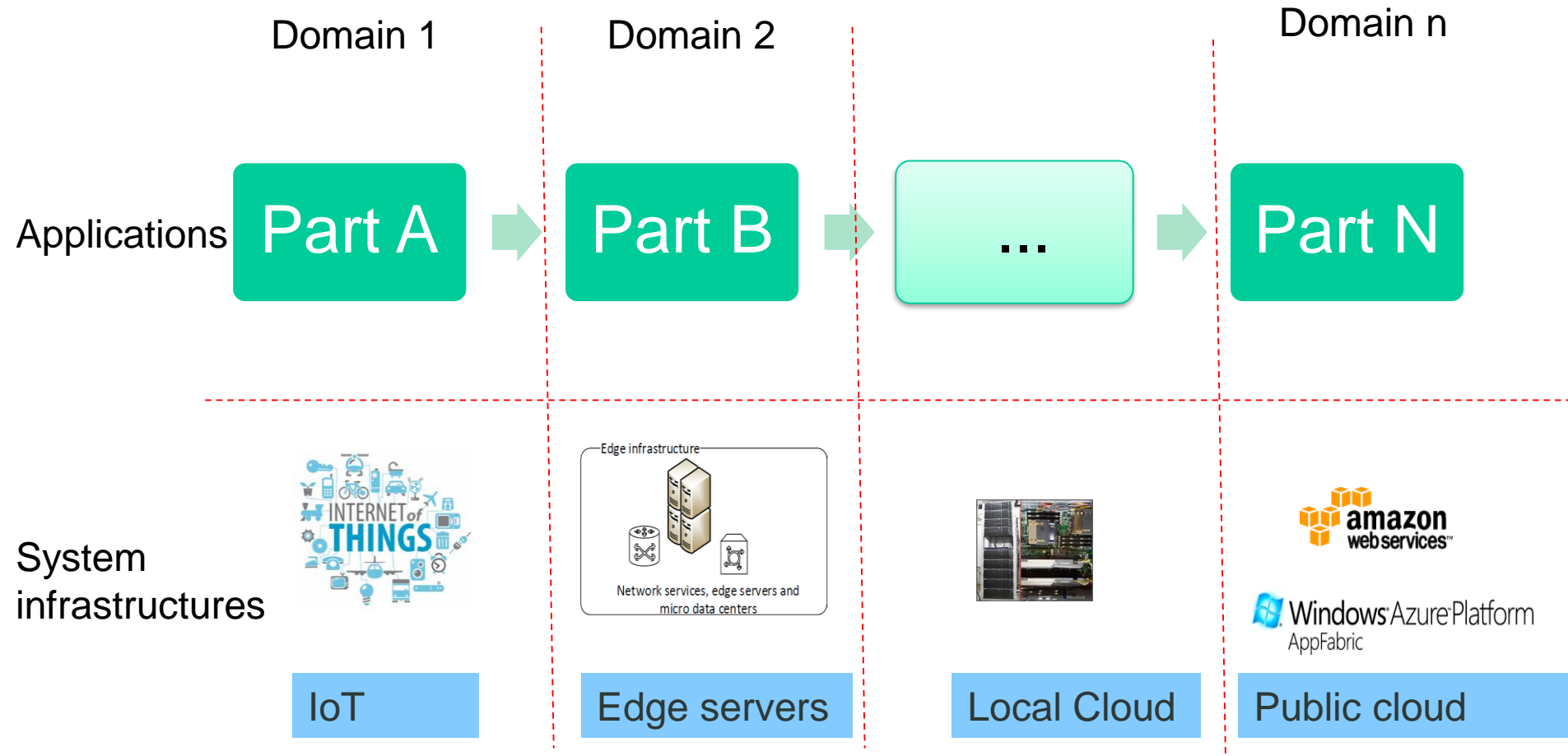
Able to cope with changes in quality of data, performance, cost and types of results at runtime

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

Recall -- Predictive Maintenance in Telcos



Advanced service-based data analytics -- fundamental concepts

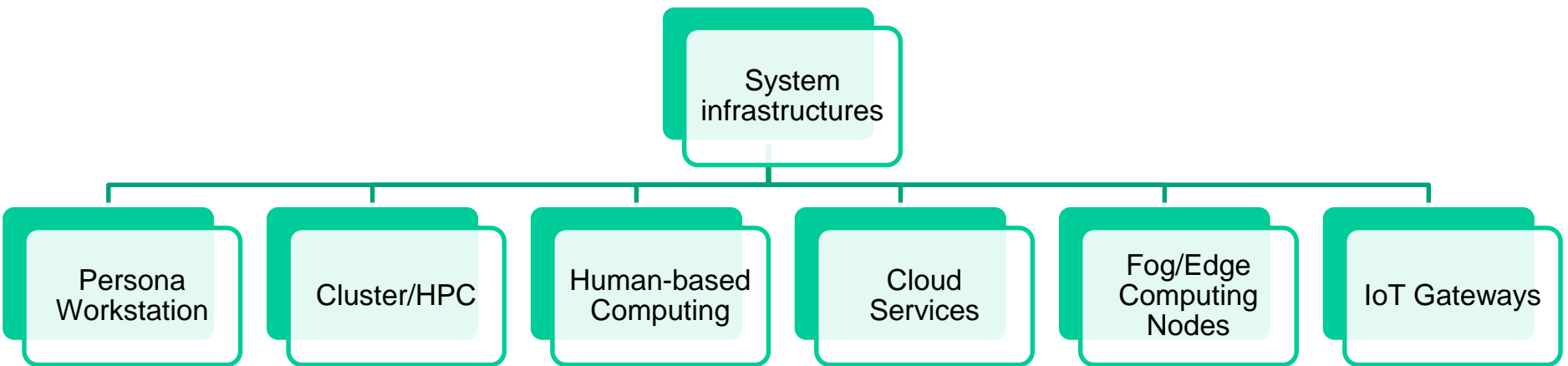


Design questions

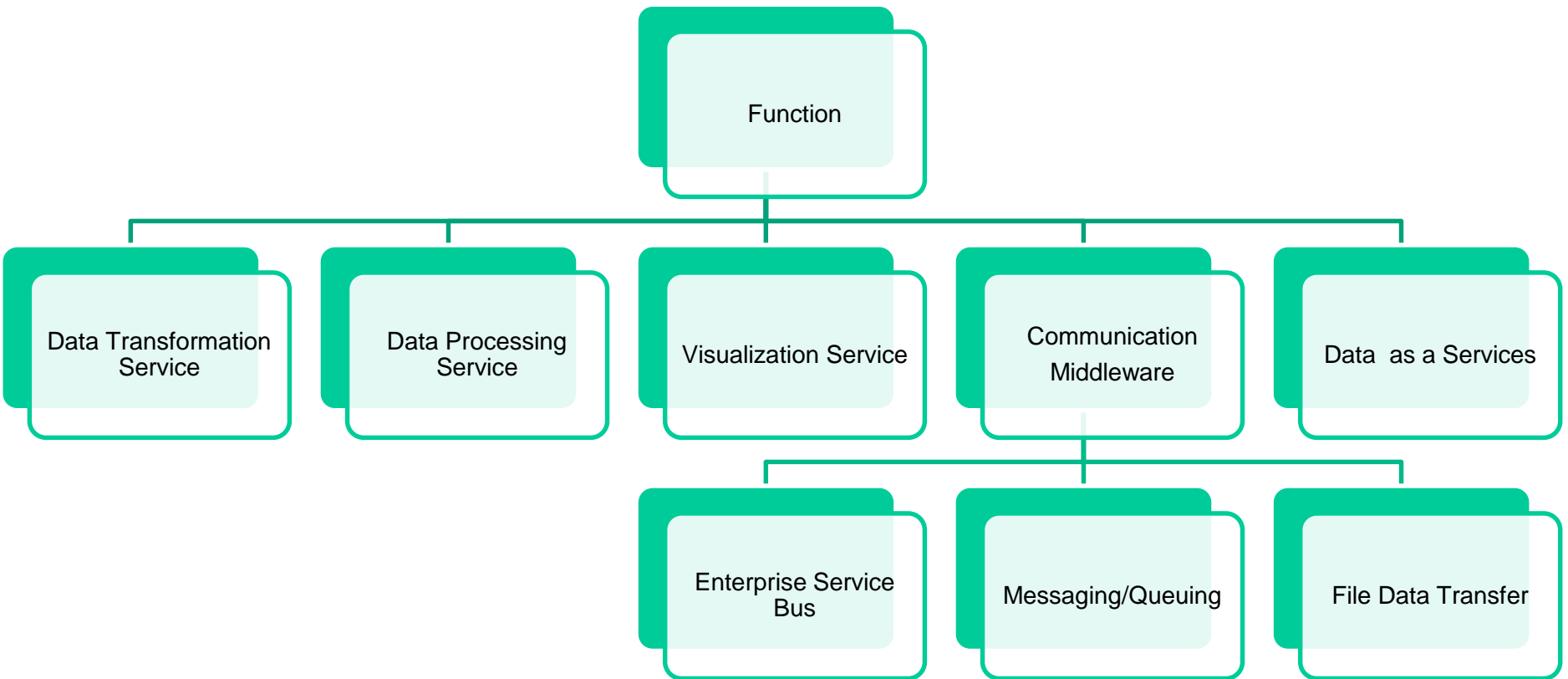
Part = a (composite) services/components

- 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?

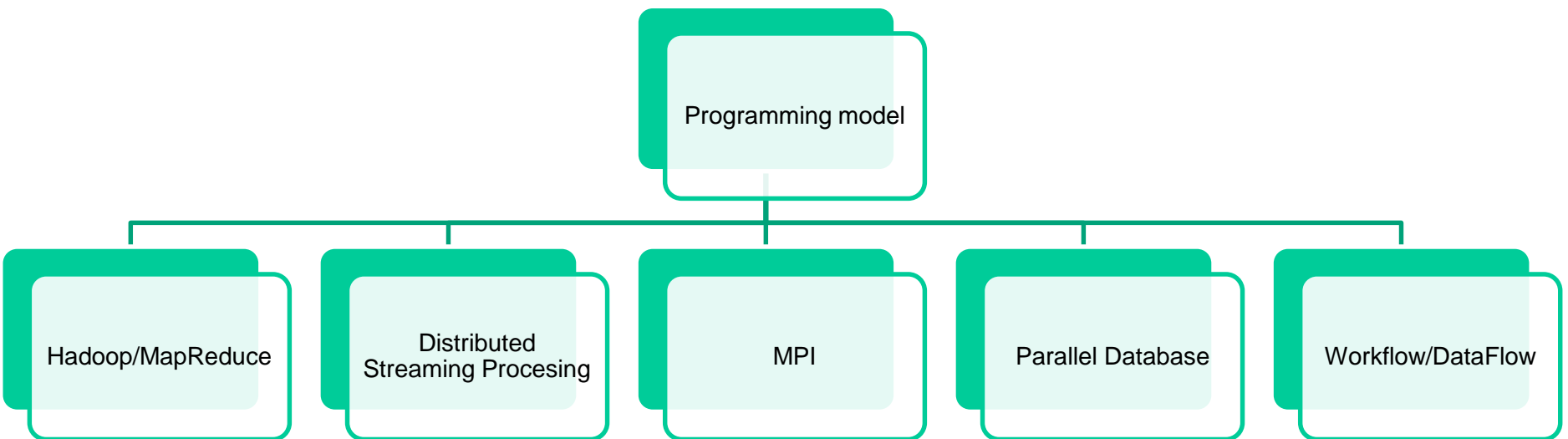
Fundamental concepts – system infrastructure unit



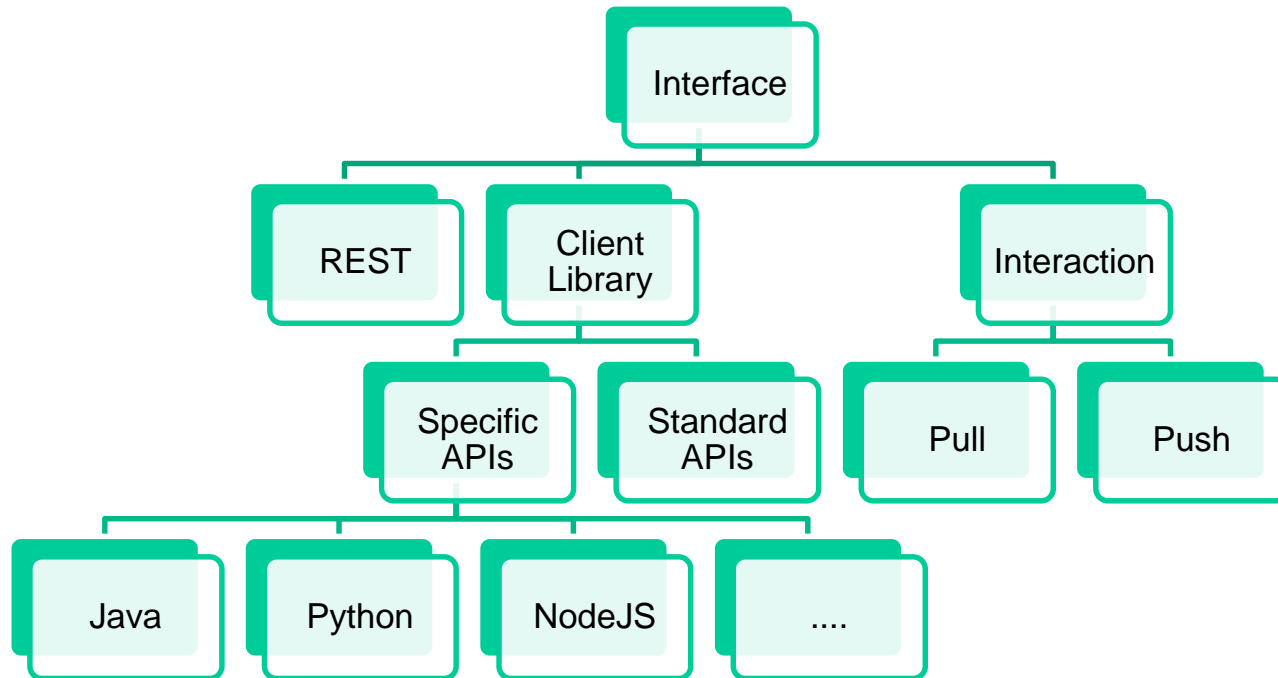
Fundamental concepts – unit functions



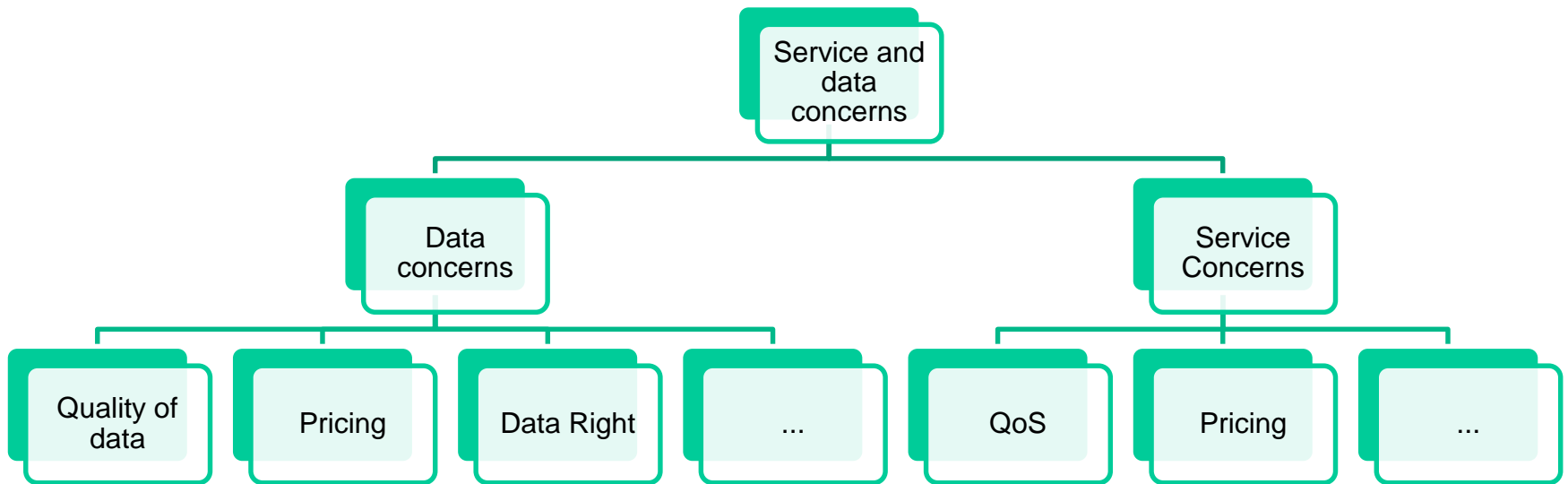
Fundamental concepts – programming model within units



Fundamental concepts – interfaces between services



Fundamental concepts – services and data concerns



You see we need to deal with many techniques and frameworks

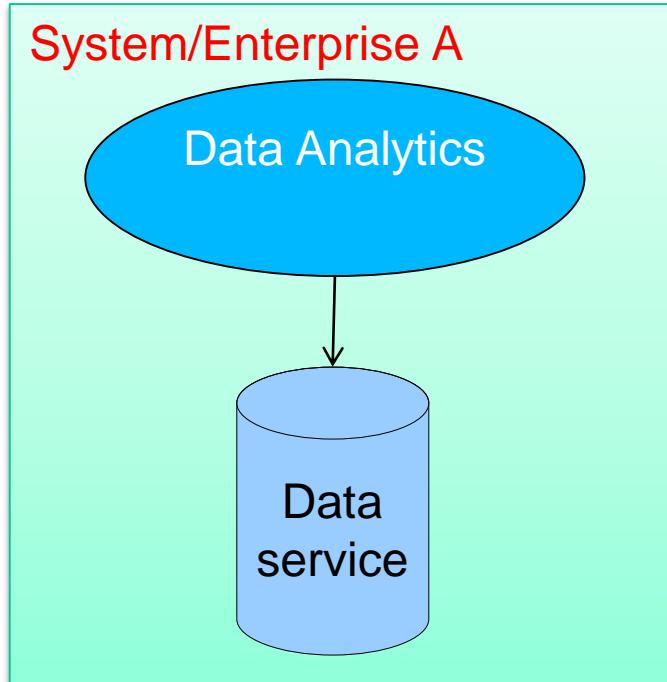
WE NEED TO START FROM DATA ANALYTICS WITHIN A SINGLE SYSTEM

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)

MapReduce + Google
File System

Yahoo S4

Hadoop + HDFS

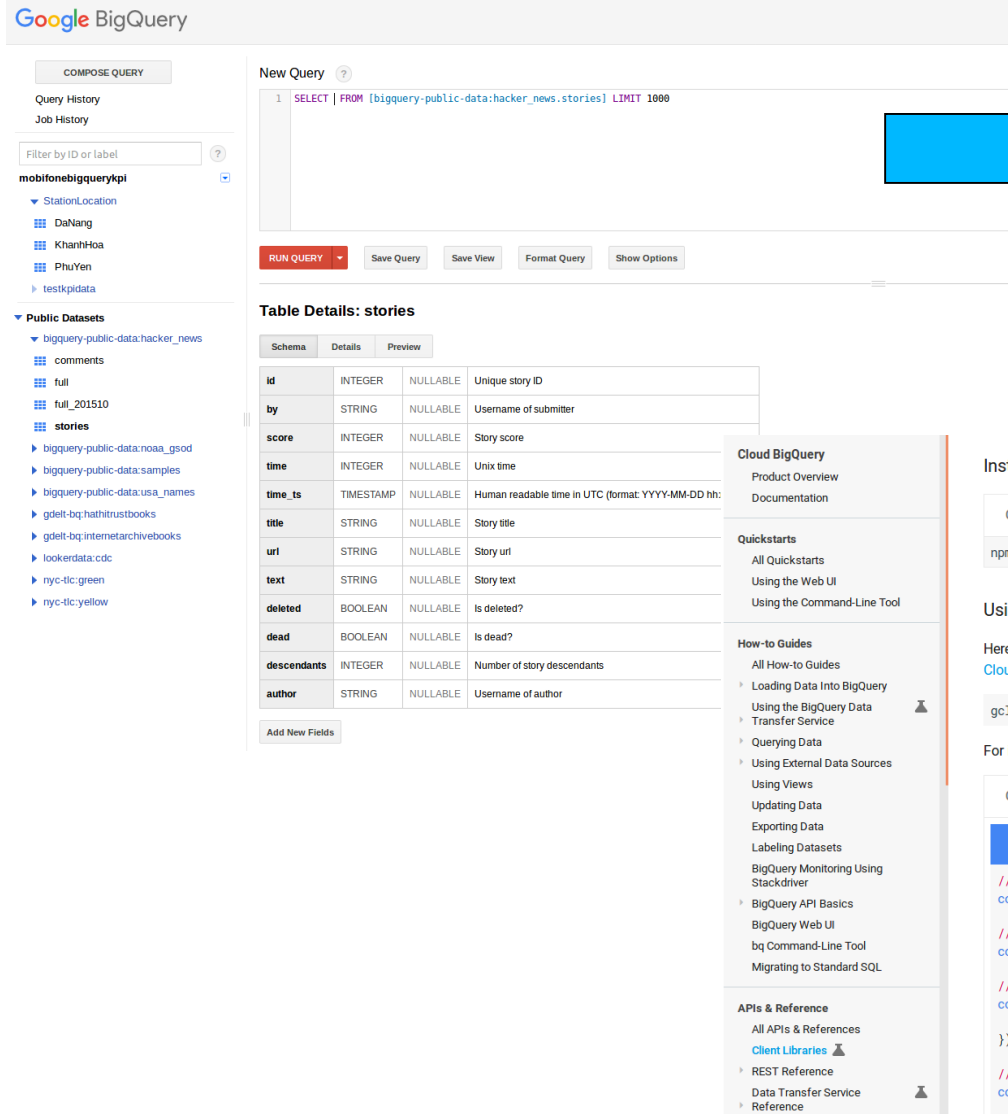
Spark

Dryad+LINQ

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 'COMPOSE QUERY' and a list of datasets under 'Public Datasets', including 'bigquery-public-data:hacker_news'. The main area shows a 'New Query' with the 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 table format.

Schema	Details	Preview	
id	INTEGER	NULLABLE	Unique story ID
by	STRING	NULLABLE	Username of submitter
score	INTEGER	NULLABLE	Story score
time	INTEGER	NULLABLE	Unix time
time_ts	TIMESTAMP	NULLABLE	Human readable time in UTC (format: YYYY-MM-DD hh:mm:ss)
title	STRING	NULLABLE	Story title
uri	STRING	NULLABLE	Story uri
text	STRING	NULLABLE	Story text
deleted	BOOLEAN	NULLABLE	Is deleted?
dead	BOOLEAN	NULLABLE	Is dead?
descendants	INTEGER	NULLABLE	Number of story descendants
author	STRING	NULLABLE	Username of author

On the right side of the interface, there's a sidebar with links to 'Cloud BigQuery' (Product Overview, Documentation), 'Quickstarts' (All Quickstarts, Using the Web UI, Using the Command-Line Tool), 'How-to Guides' (All How-to Guides, Loading Data Into BigQuery, Using the BigQuery Data Transfer Service, Querying Data, Using External Data Sources, Using Views, Updating Data, Exporting Data, Labeling Datasets, BigQuery Monitoring Using Stackdriver, BigQuery API Basics, BigQuery Web UI, bq Command-Line Tool, Migrating to Standard SQL), and 'APIs & Reference' (All APIs & References, Client Libraries, REST Reference, Data Transfer Service, 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

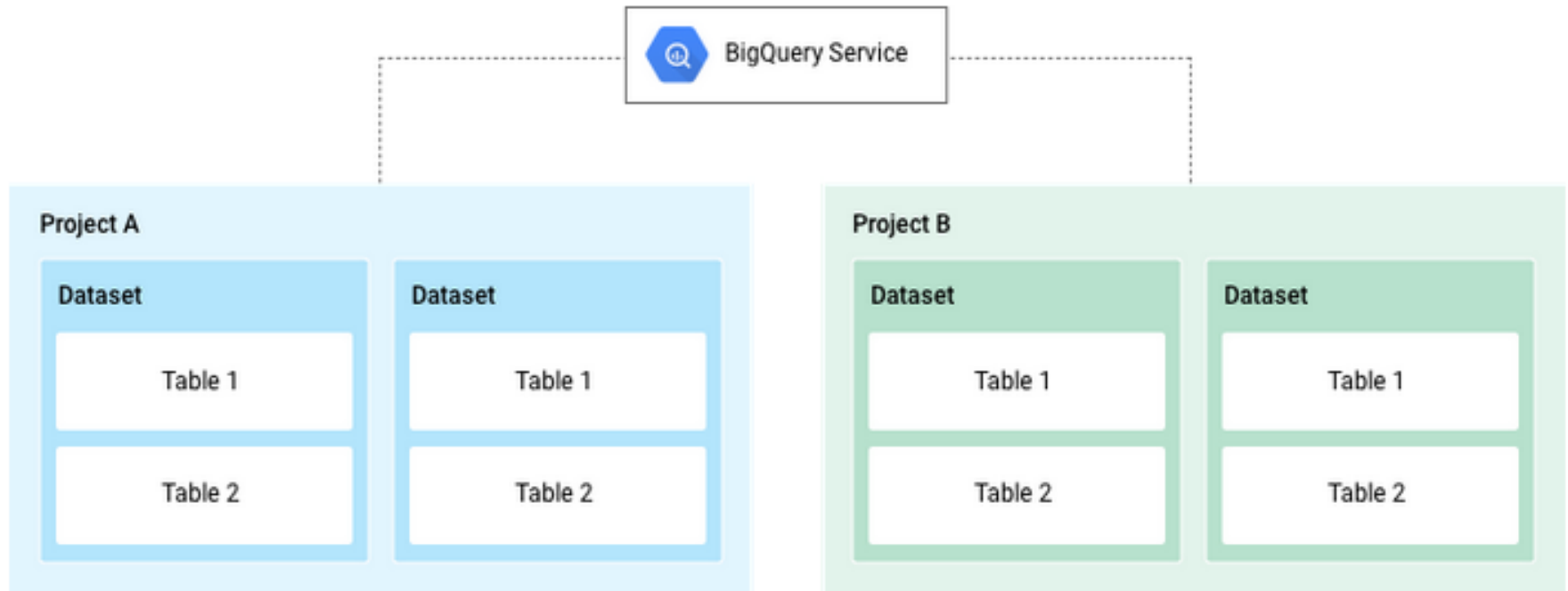
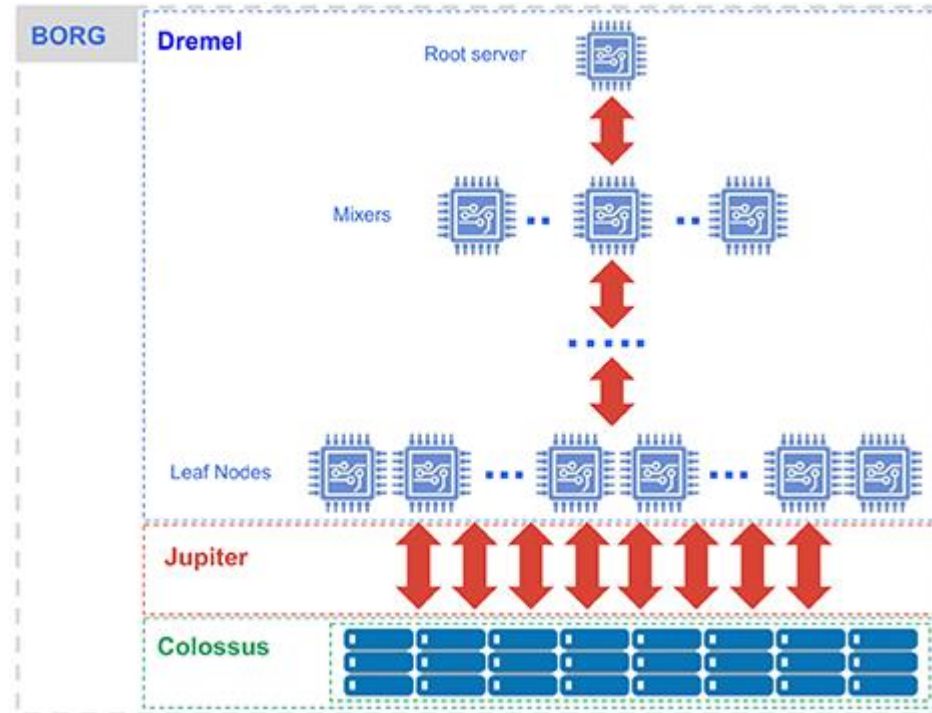


Figure 1: BigQuery structural overview

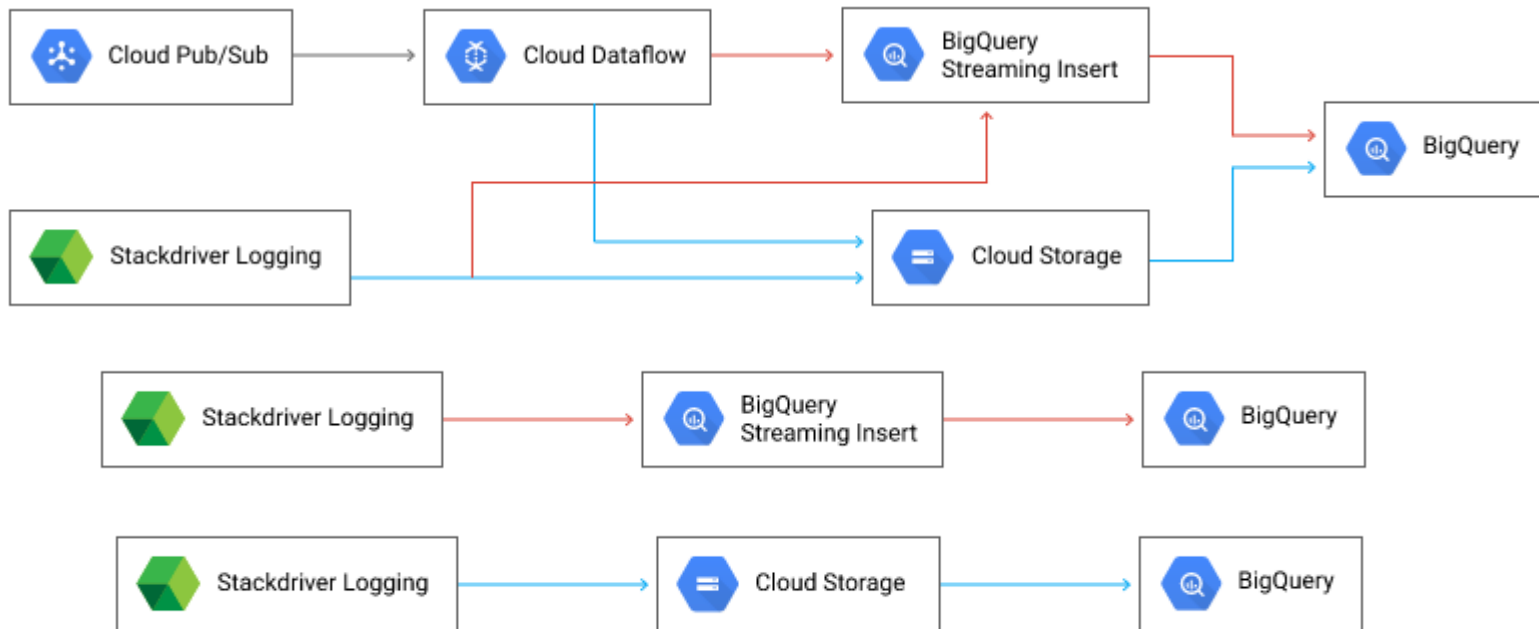
Source <https://cloud.google.com/solutions/bigquery-data-warehouse>

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? When?

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:~$

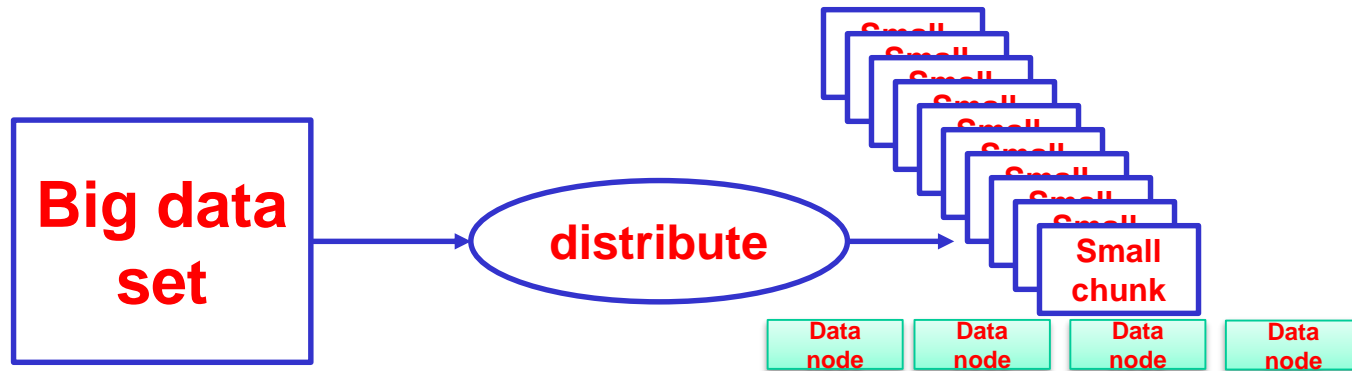
```



Hadoop File Systems

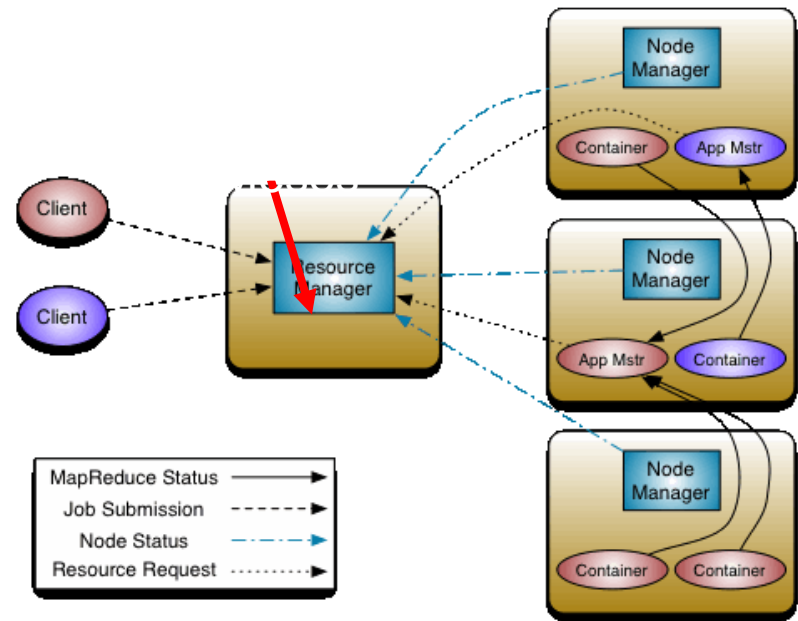
Example – Hadoop: complexity

- 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

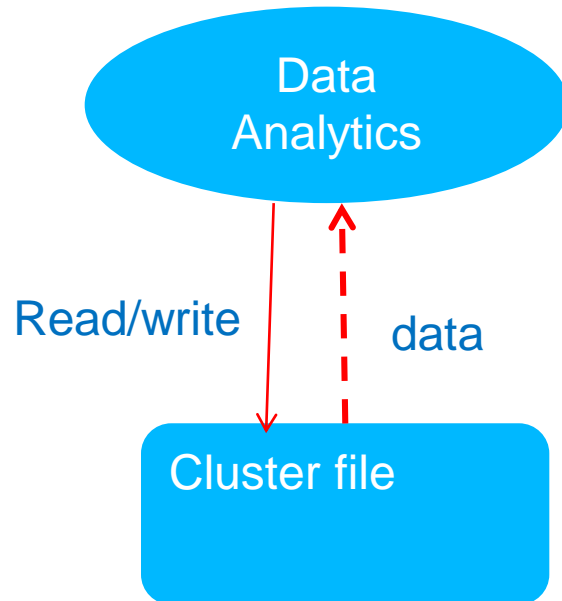
But why it might not be suitable for you? When?



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?

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

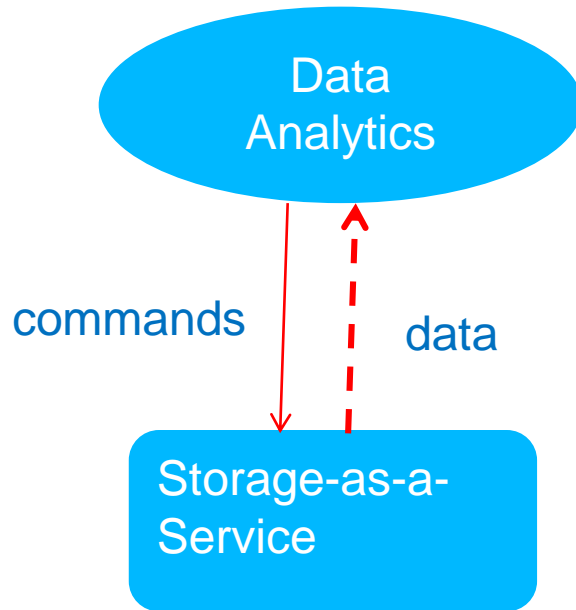
NFS

Lustre

Hadoop File System

Google file system

Data analytics across multiple systems – data service units



Interface

- Direct data transfer via REST/SOAP APIs

System

- Decouple between analytics and storage

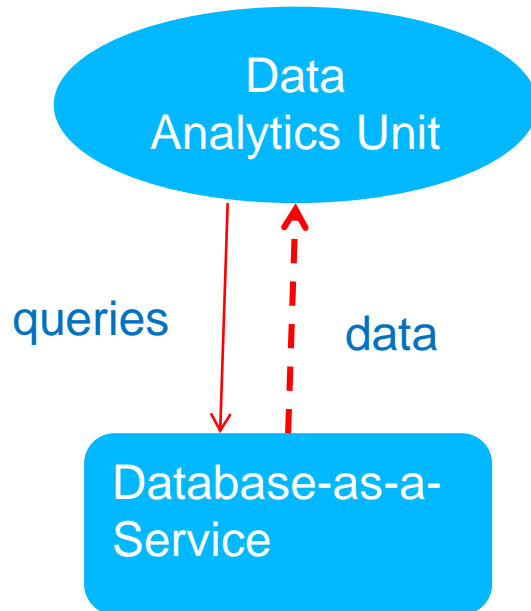
Programming model

- May require middleware for data transfer
- Request via SOAP/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/SOAP APIs
- Mainly for commands and results

System

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

Programming model

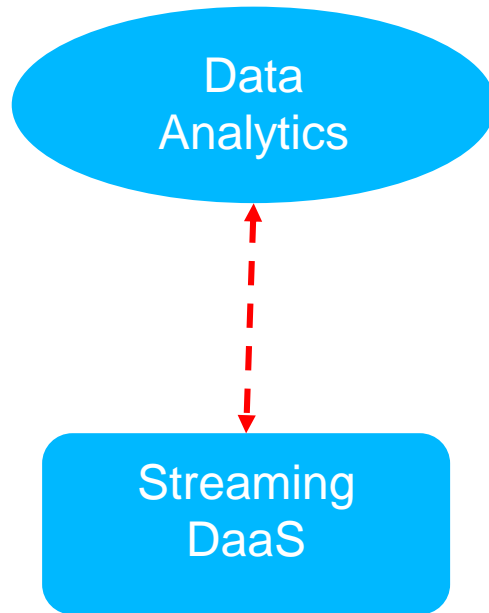
- Analytics can be done at both sides
- Analytic units can use any programming models
- Database-as-a-service can perform a lot of analytics
- Parallel database operations

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, ...

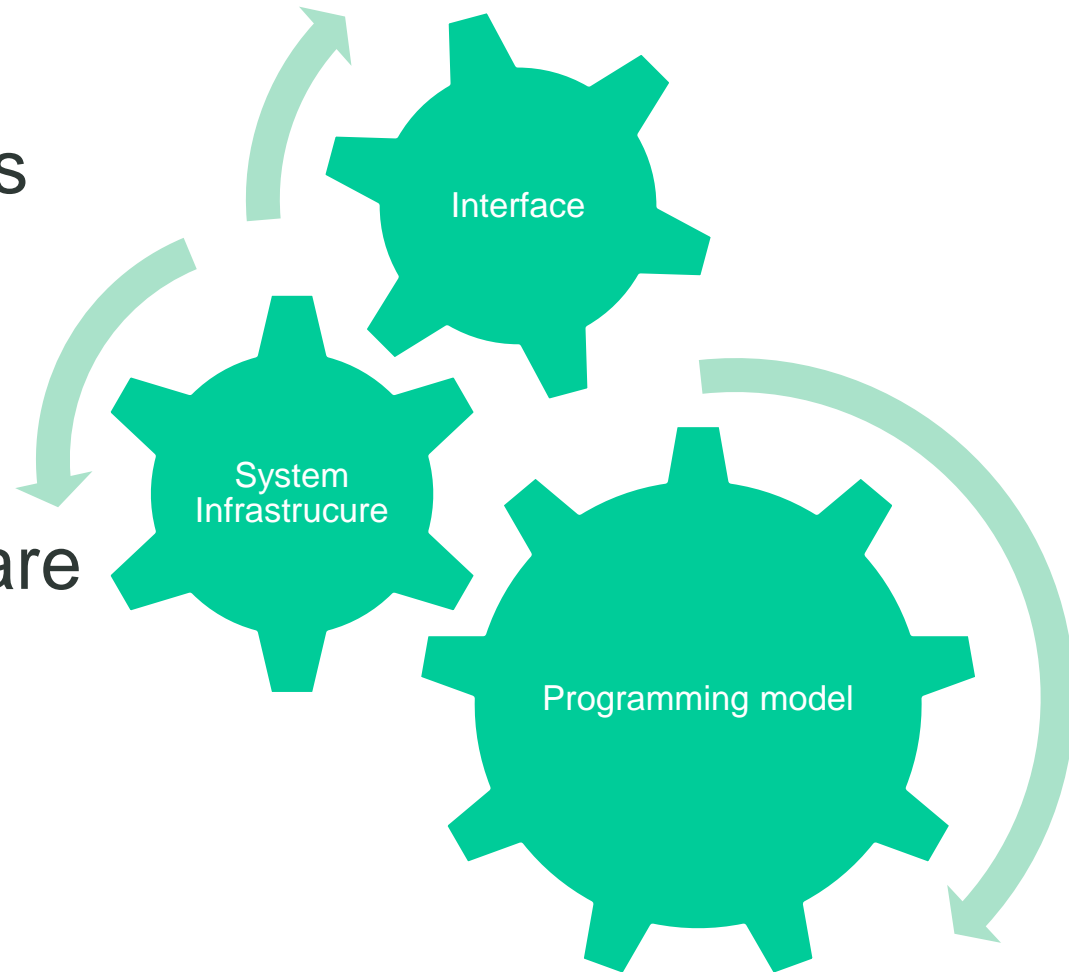
WHY SHOULD ANALYTICS UNITS BE „CLOSED“ TO DATA UNITS?

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?**

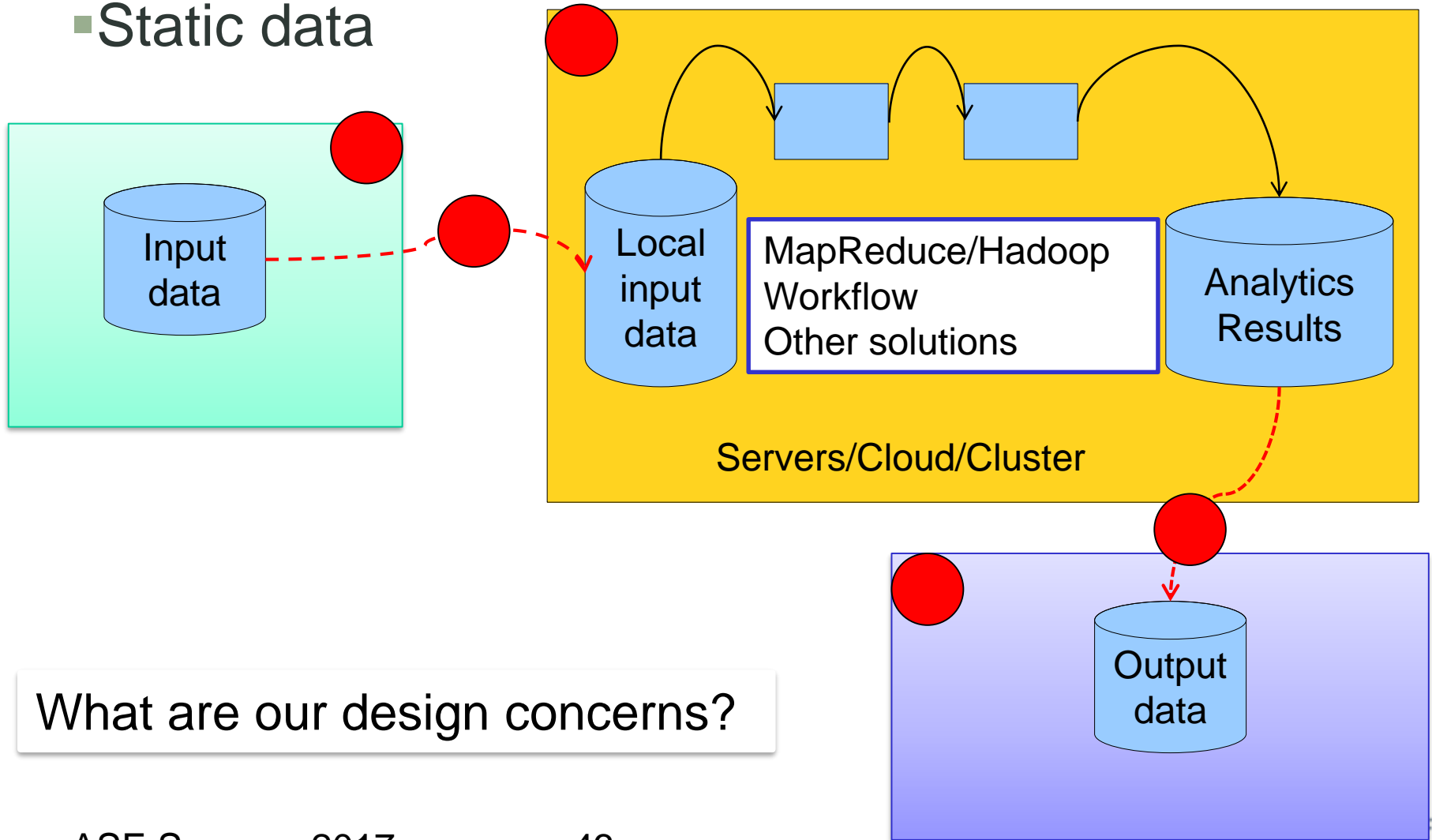
Data analytics across multiple systems – design choice

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



Data analytics across multiple systems – programming models (1)

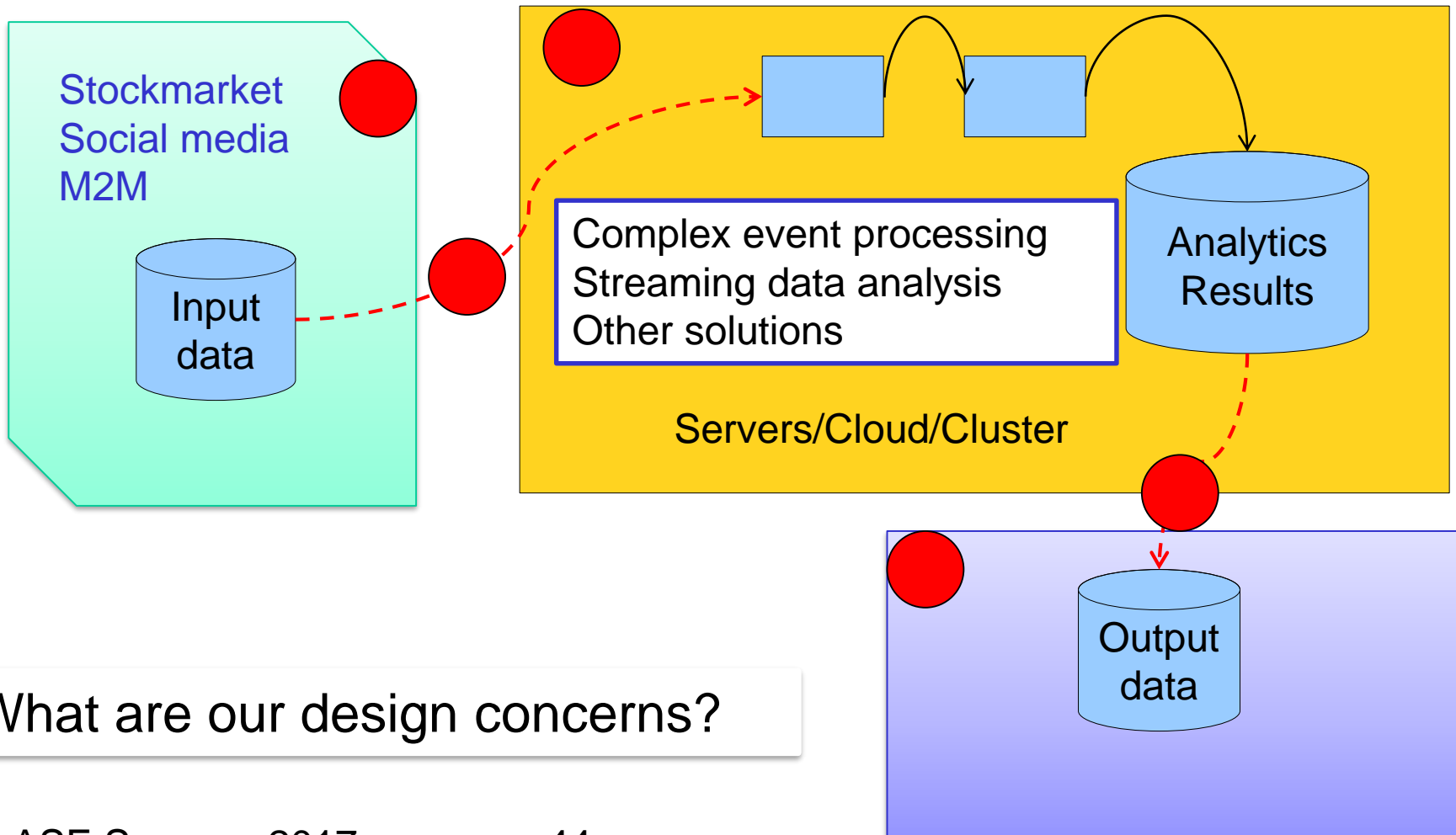
■ Static data



What are our design concerns?

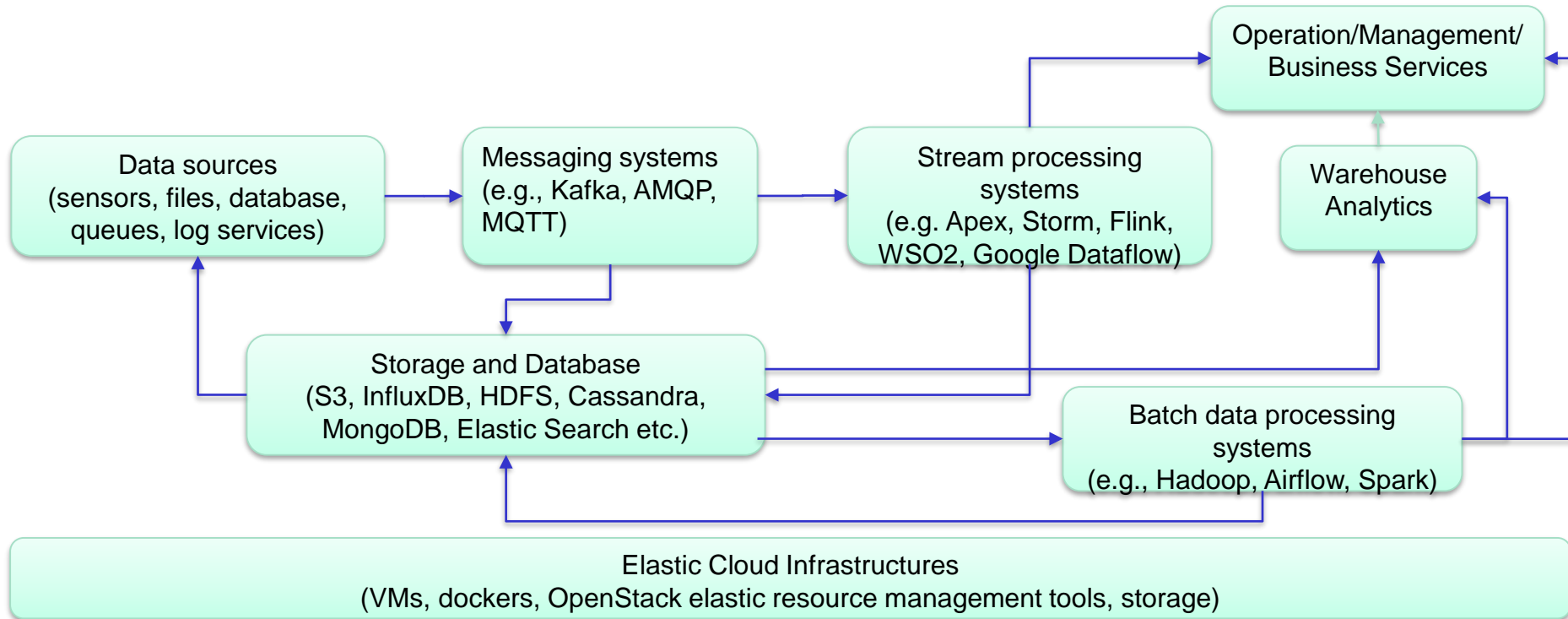
Data analytics across multiple systems – programming models (2)

■ 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

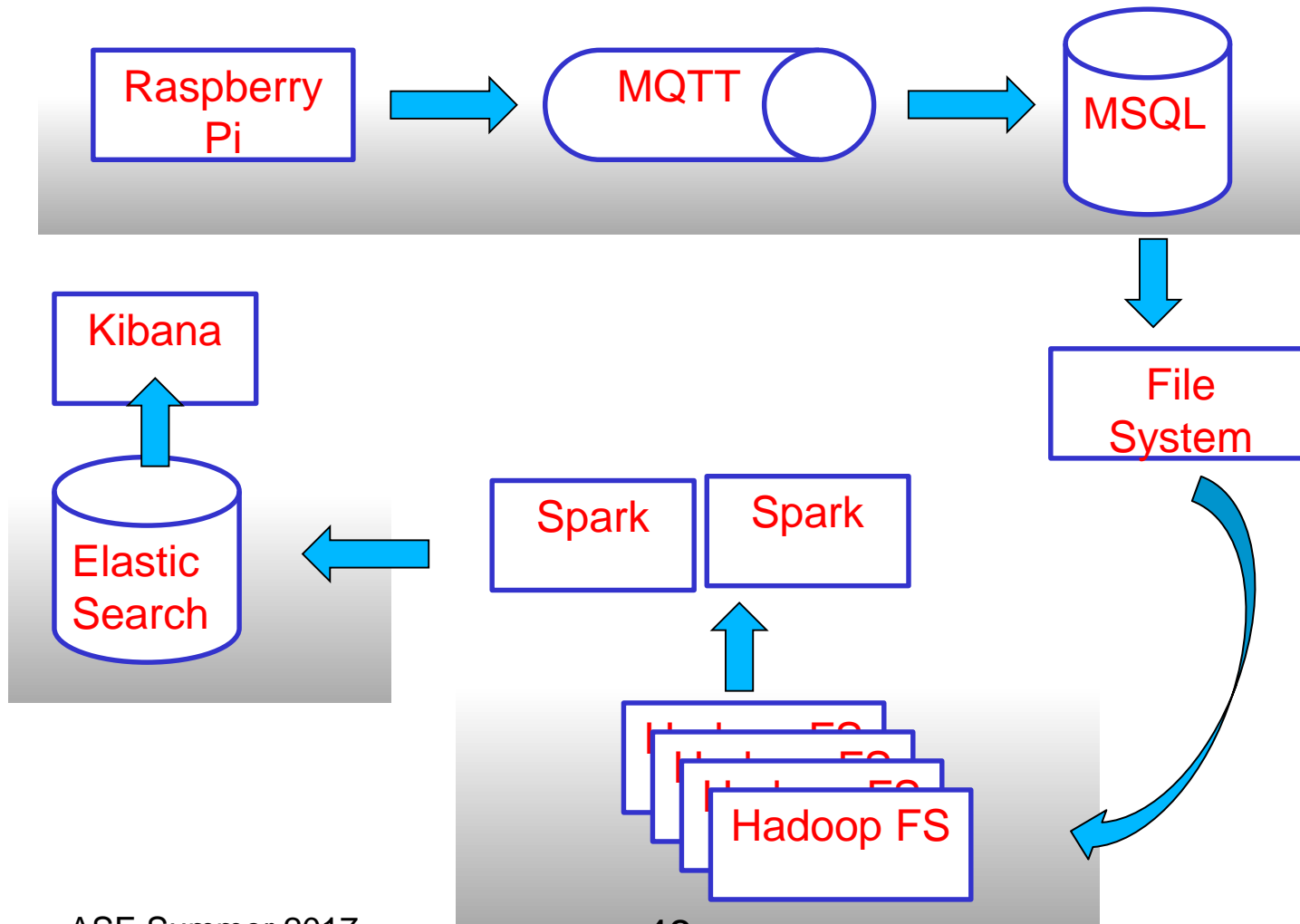


- **Requirements:**

- 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

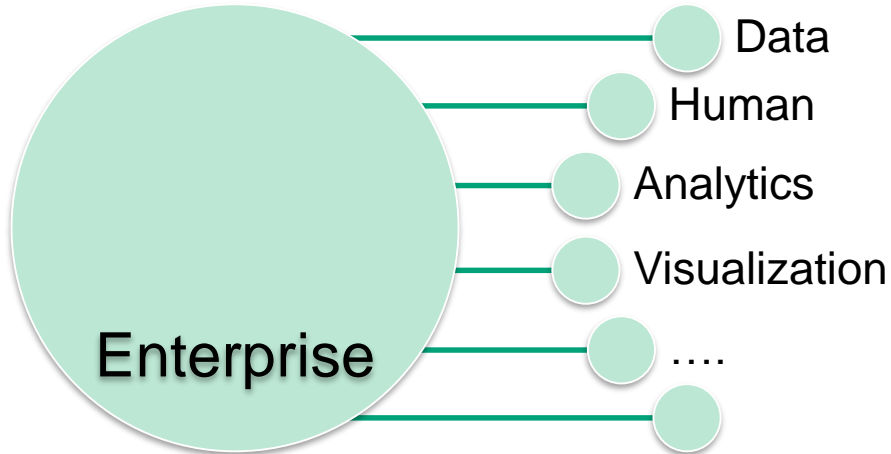


So many types of services from different providers. Anyway to simplify the management of services for the developer/operator?

API MANAGEMENT

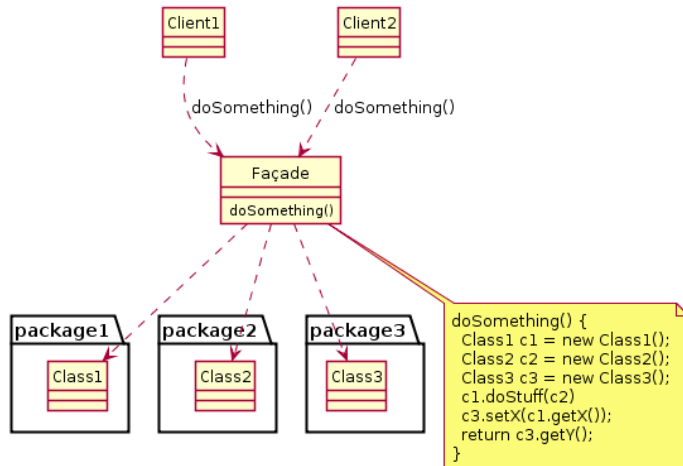
Ecosystem view for advanced service engineering

- 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 line connects the Enterprise to a sixth, unlabeled circle at the bottom.
- An API is an asset
 - We need to have lifecycle, pricing, management, etc.

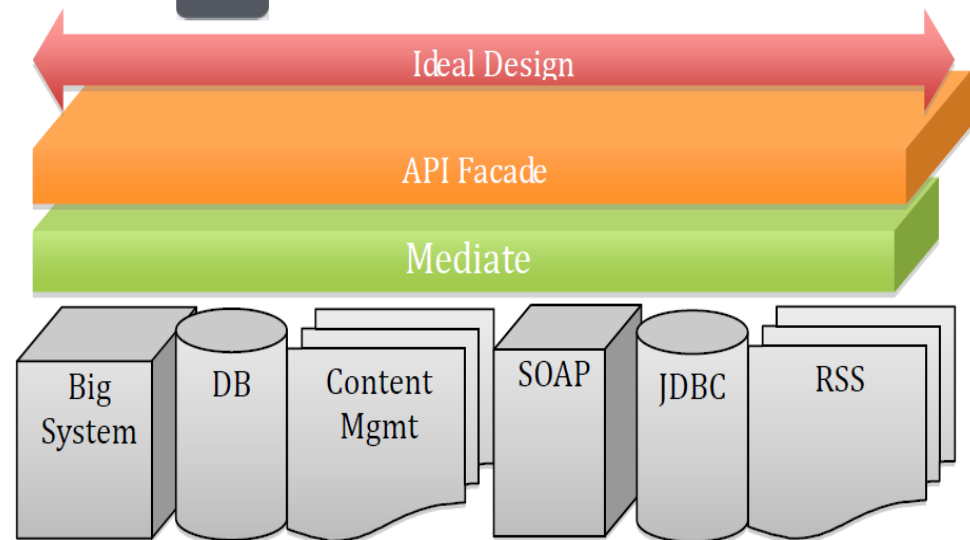
Check <http://www.apiacademy.co> for some useful tutorials

API Fasade

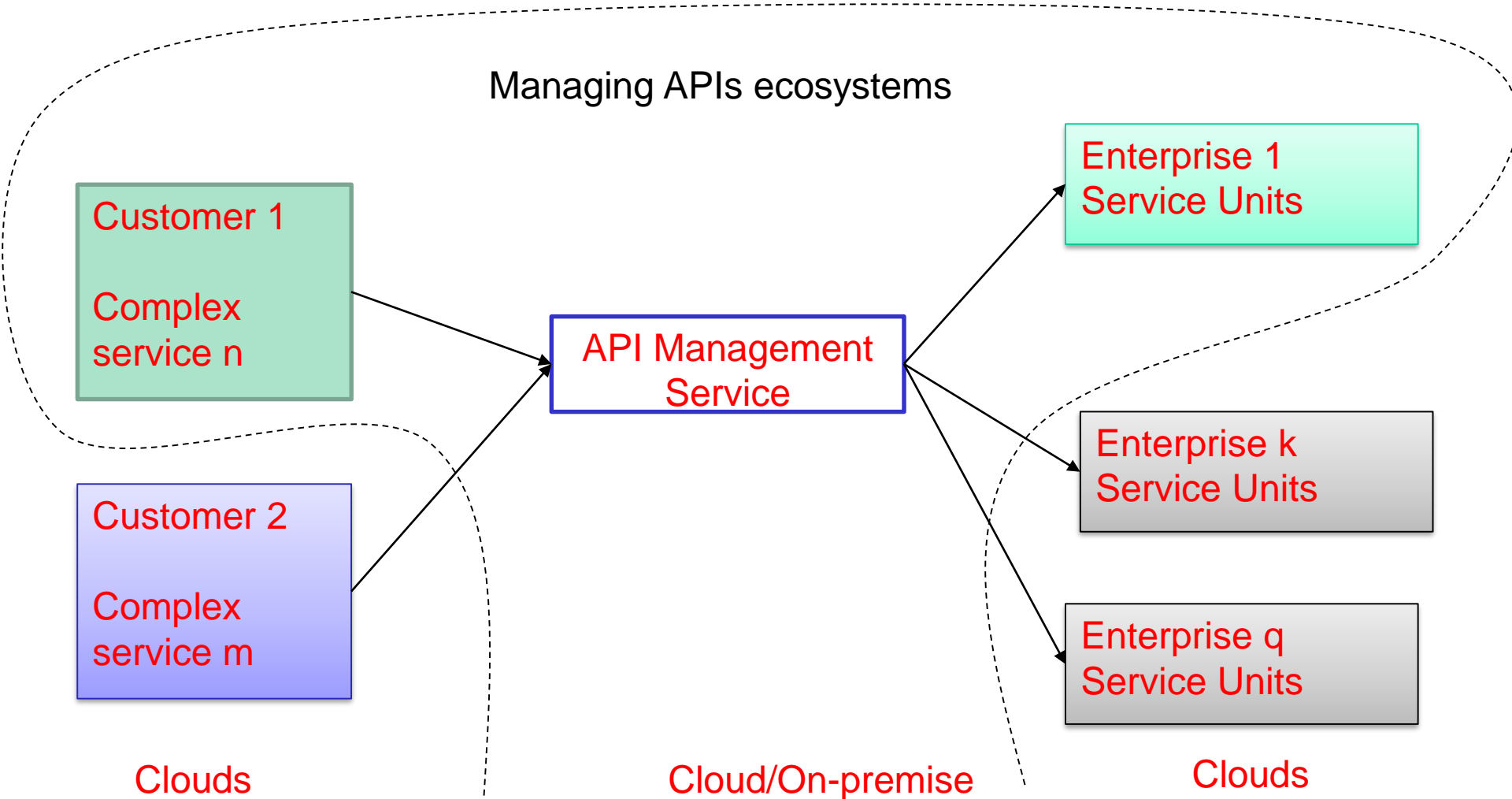


Source:
https://en.wikipedia.org/wiki/Facade_pattern

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

Prevent too many accesses?



```

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

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

How can we use API management for data/service contracts?

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.)

Some well-known frameworks

- <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

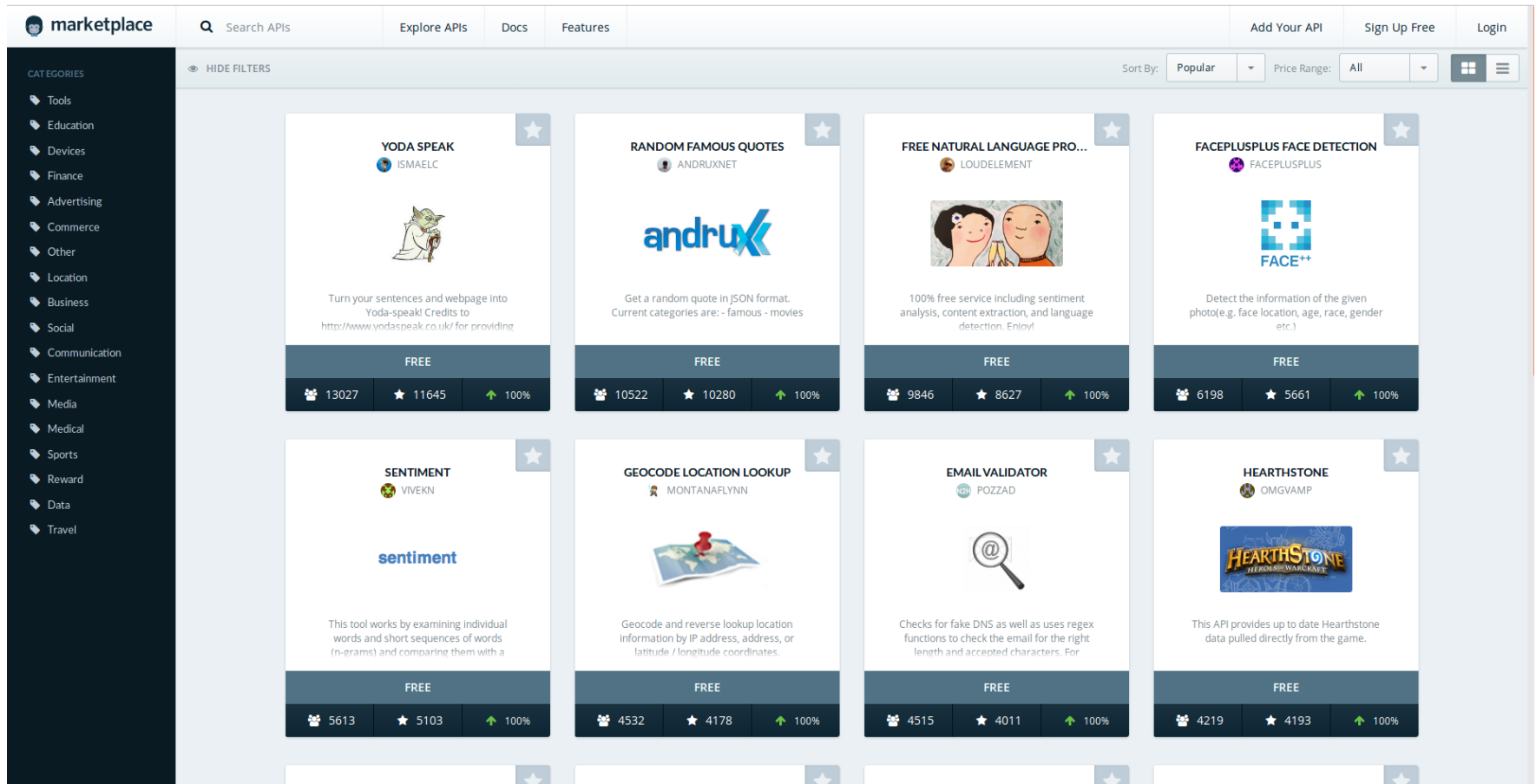
- Which APIs you need? Which ones are crucial for you to build complex services?
 - Data APIs
 - Data collection, Visualization, Analytics APIs
 - Communication
 - Coordination of tasks

→ 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 the 'marketplace' interface with a search bar and navigation tabs. A sidebar on the left lists categories such as 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.

API Name	Provider	Description	Free	Usage (Cat)	Rating (Star)	Uptime (%)
YODA SPEAK	ISMAELC	Turn your sentences and webpage into Yoda-speak! Credits to http://www.yodaspeak.co.uk/ 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

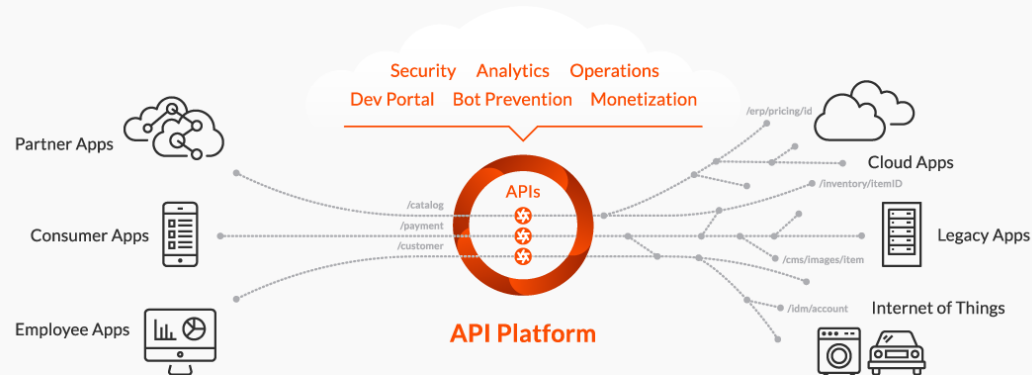
DEVELOPERS

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>

- 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
- Develop some patterns for data analytics across multiple systems
- Setup an API management platform for your work

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
3. Jerry Chou, Mark Howison, Brian Austin, Kesheng Wu, Ji Qiang, E. Wes Bethel, Arie Shoshani, Oliver Rübel, Prabhat, and Rob D. Ryne. 2011. Parallel index and query for large scale data analysis. In Proceedings of 2011 International Conference for High Performance Computing, Networking, Storage and Analysis (SC '11). ACM, New York, NY, USA, , Article 30 , 11 pages. DOI=10.1145/2063384.2063424 <http://doi.acm.org/10.1145/2063384.2063424>
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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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