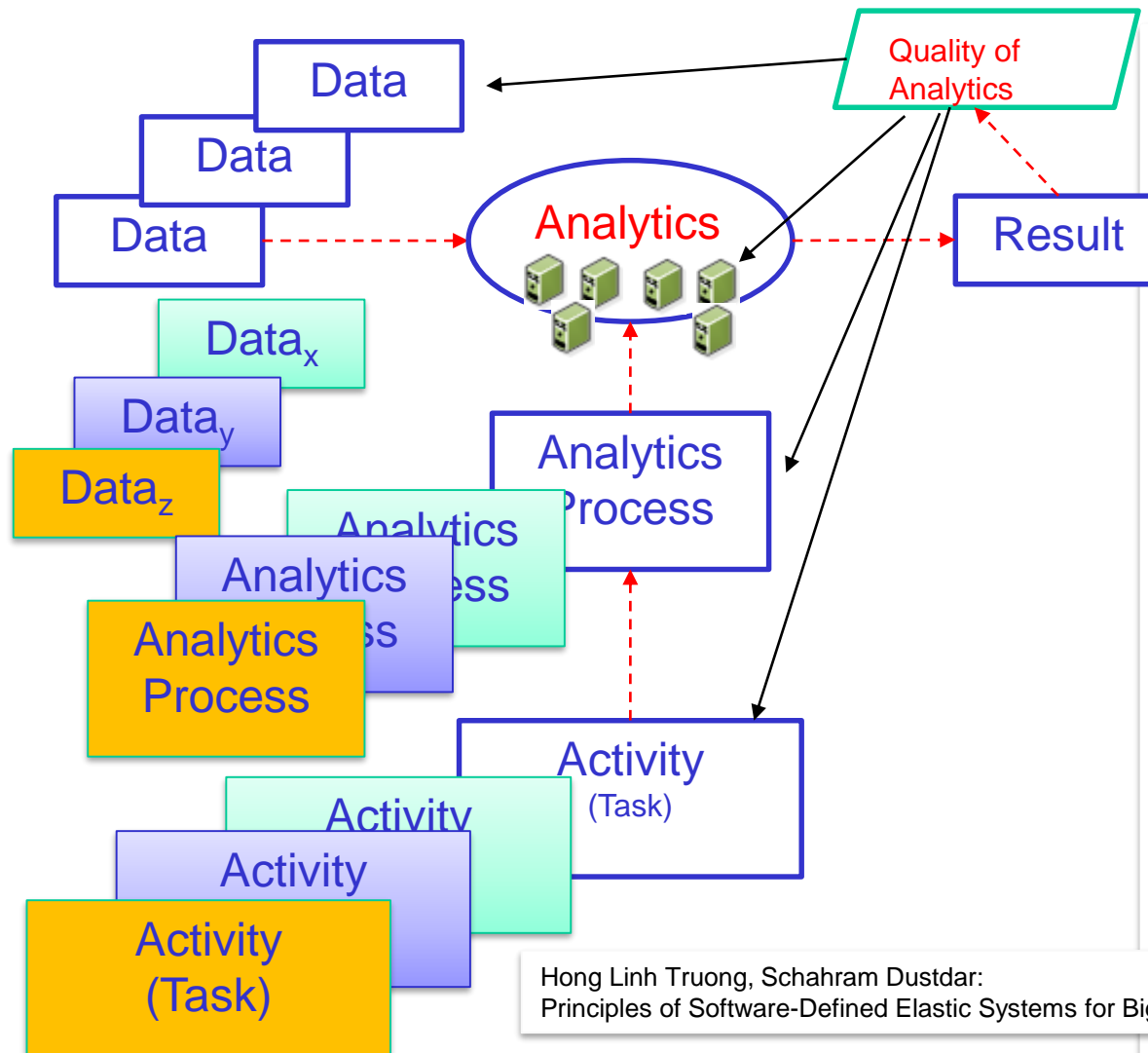


# Principles of Elasticity for Service systems

Hong-Linh Truong  
Faculty of Informatics, TU Wien

[hong-linh.truong@tuwien.ac.at](mailto:hong-linh.truong@tuwien.ac.at)  
<http://www.infosys.tuwien.ac.at/staff/truong@linhsolar>

# Elasticity in (big) data analytics

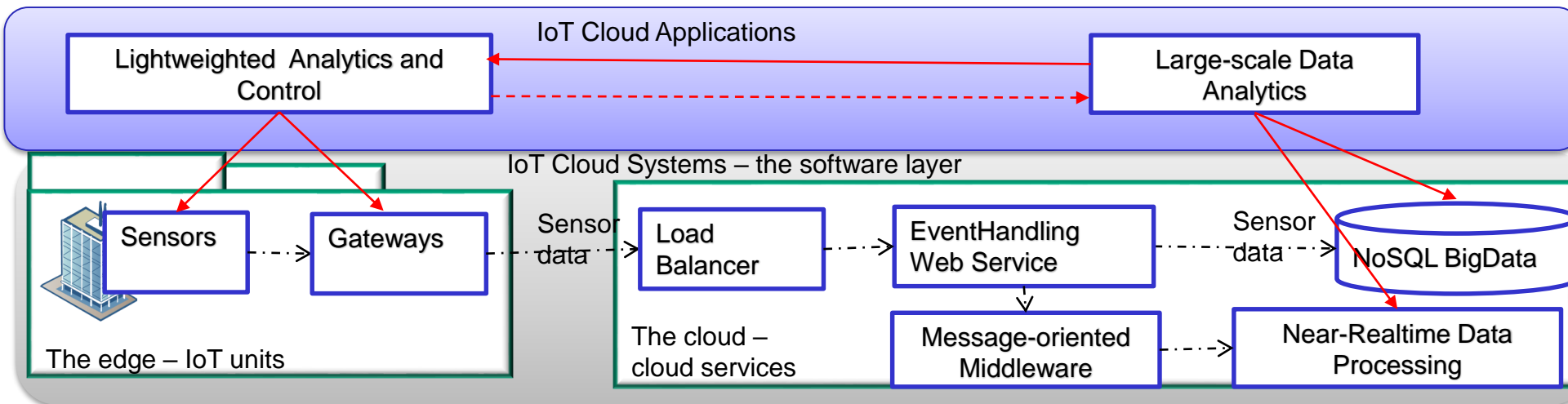


- **More data** → more compute resources (e.g. more VMs)
- **More types of data** → more activities → more analytics processes
- Change **quality of analytics**
  - Change quality of data
  - Change response time
  - Change cost
  - Change types of result (form of the data output, e.g. tree, table, story)

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

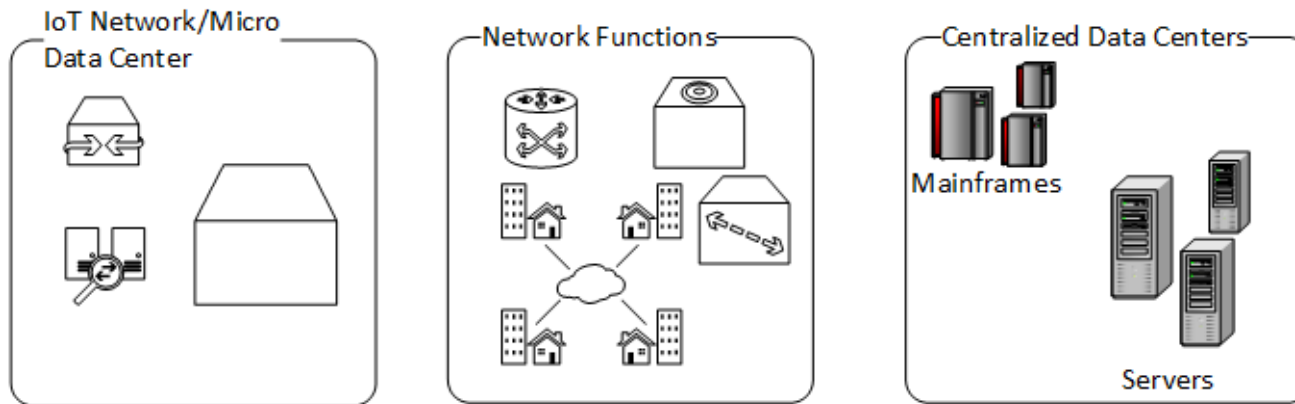


What should we do if suddenly many sensors send a lot of data?

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

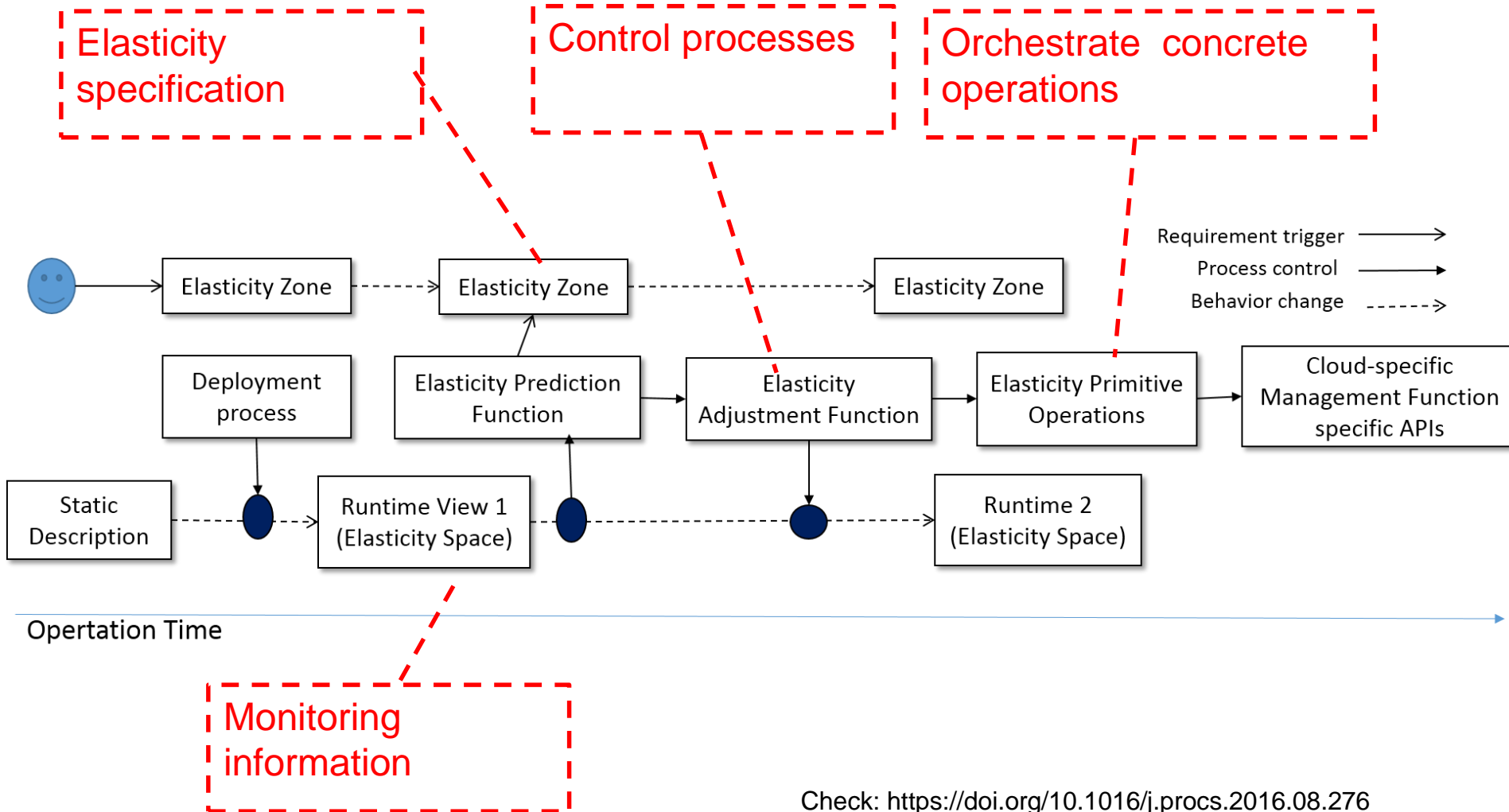


# Elasticity Principles: Elasticity of quality of analytics

- 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

# General software design concept: Lifecycle of applications and elasticity



Check: <https://doi.org/10.1016/j.procs.2016.08.276>

# Exercises

- Read mentioned papers
- Examine possible incidents in your data pipelines
- Examine how QoD evaluators can be integrated into different programming models for QoA-aware data analytics workflows
- Implement some QoD evaluators
- Develop techniques for determining places where QoD evaluators can be performed in your mini projects
- Support data elasticity management in your mini project

# Thanks for your attention

Hong-Linh Truong  
Faculty of Informatics, TU Wien  
[hong-linh.truong@tuwien.ac.at](mailto:hong-linh.truong@tuwien.ac.at)  
<http://www.infosys.tuwien.ac.at/staff/truong@linhsolar>