Computer Networks Group University of Bamberg, Germany



# Federated Learning for Service Placement in Fog and Edge Computing WueWoWas 2023

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Manuel Dworzak, Marcel Großmann, Duy Thanh Le

Outline

**1** Introduction & Motivation

#### 2 Architecture

#### 3 Evaluation

4 Conclusion & Future Work

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Introduction & Motivation

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Architecture

**Evaluation** 

Conclusion

**Reference**:

# Orchestration

"Service Orchestration refers to the composition of system components to support the Cloud Providers' activities in arrangement, coordination and management of computing resources to provide Cloud services to the Cloud Consumers" [1].

# Autonomic Computing

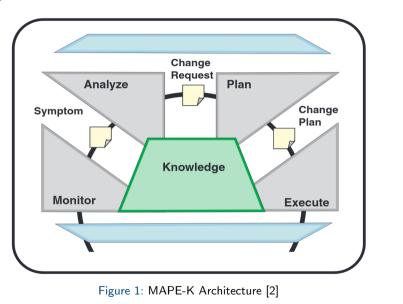
Autonomic Computing is a property of software systems that fulfill the following four properties, taken from [2].

- Self-configuring: The system shall dynamically configure itself to adapt to changing environments
- **Self-healing**: The system shall detect and react to errors
- Self-optimizing: The system shall optimally assign resources to improve overall system performance
- Self-protection: The system shall detect and react to hostile behavior



Introduction & Motivation Autonomic Computing MAPE-K Machine Learning SDN Architecture Evaluation Conclusion References

#### MAPE-K

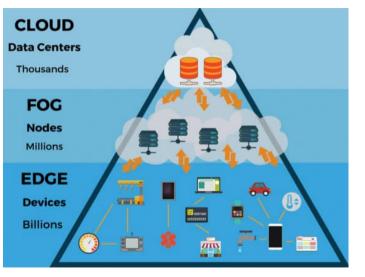


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Autonomic Comput MAPE-K Machine Learning SDN Architecture Evaluation

Conclusion

# **Computing Paradigms**





ntroduction & Motivation Autonomic Computi MAPE-K Machine Learning SDN Architecture Evaluation Conclusion References

Figure 2: Computing Paradigms [3]

## Learning Principles

The approximation theorem states that a feed-forward network with a linear output layer and at least one hidden layer with any "squashing" activation function can approximate any function from one finite-dimensional space to another with any desired non-zero amount of error provided that the network is given enough hidden units. [cf. 4]

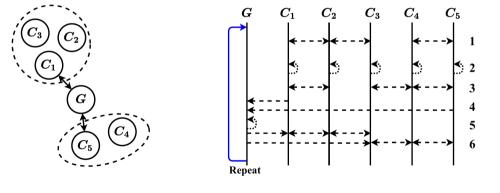
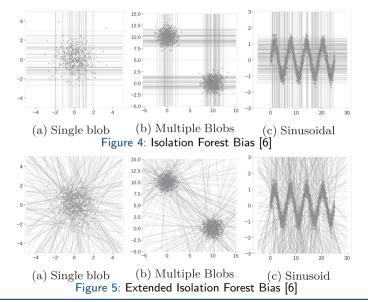


Figure 3: Federated Peer to Peer [5]

Motivation Autonomic Comp Machine Learning Neural Networks Isolation Forests SDN Architecture Evaluation Conclusion References

#### Isolation Forests





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# Comparison of Traditional and Software-Defined Networking

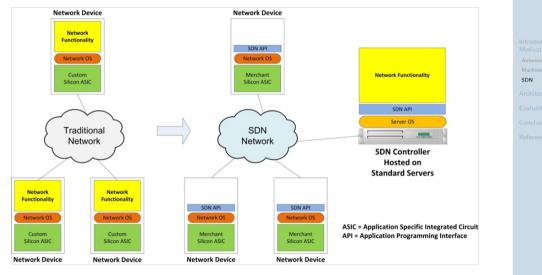


Figure 6: Difference Traditional and Software Defined Networking [7]

Outline

**1** Introduction & Motivation

#### 2 Architecture

#### 3 Evaluation

4 Conclusion & Future Work



ntroduction & Aotivation

#### Architecture

iolution Space Architecture L Workflow

Conclusion

# Solution Space

# Dynamic Event Handling

Dynamic Event Handling requires strong monitoring and data analysis processing.

#### Kubernetes' Scalability Considerations

The Kubernetes Scheduler scores fewer nodes when too many nodes are available: "Kubernetes calculates a figure using a linear formula that yields 50% for a 100-node cluster and yields 10% for a 5000-node cluster"<sup>1</sup>.

#### Support for Node Scalability

Our approach implements decentralized scoring such that every nodes scores itself to avoid running in such performance issues.

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ntroduction & Aotivation

Architecture

Solution Space

FL Workflow

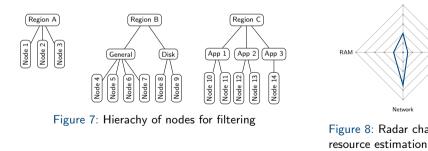
valuation

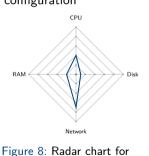
 $<sup>^{\</sup>rm 1} \rm https://kubernetes.io/docs/concepts/scheduling-eviction/scheduler-perftuning/#default-threshold$ 

# Intelligent Container Resource Estimation

A user enters the following three pieces of information for new deployments:

- A **hierarchy** for the application deployment
- A filled out chart rating about resource usage for each container
- The deployment configuration with the Docker container configuration

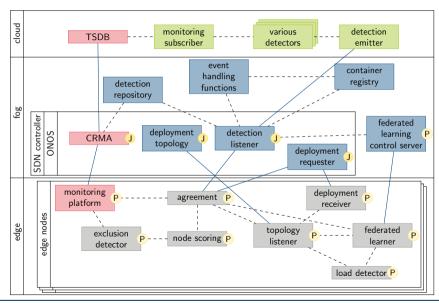






Solution Space

#### Architecture





Introduction Motivation Architecture Solution Space Architecture Cloud Layer Fog Layer Edge Layer FL Workflow Evaluation Conclusion References



The **machine learning** process aims to approximate a function that reflects the resource usage at the given time. A two layer neural network for function approximation receives the timestamp as input and returns the expected  $score_{resources}$  value, which averages the CPU and memory usage (cf. Equation 2.1).

 $score_{resources} = \frac{cpu\_usage + mem\_usage}{2}$ 



Introduction Motivation Architecture Solution Space Architecture Cloud Layer Fog Layer Edge Layer FL Workflow Evaluation Conclusion References

(2.1)



Concept of tainted nodes is taken from Kubernetes [8]. Taint detector checks if any node fulfills one of the following conditions:

- CPU Load over 60%
- Memory Load over 60%
- Disk Load over 60%



troduction & otivation

Architecture Solution Space Architecture

Cloud Layer

Edge Layer

FL Workflov

Evaluation

Conclusion



For each container and host, we use the following parameter to generate the Extended Isolation Forest:

- CPU usage
- Memory usage
- Disk usage
- Network RX/TX rates

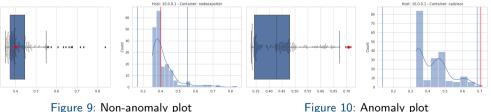
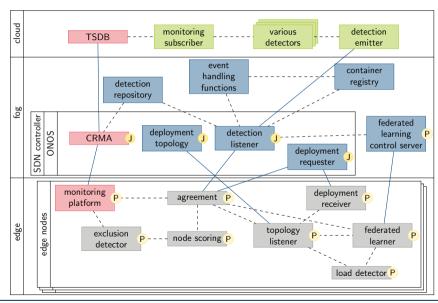


Figure 10: Anomaly plot



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#### Architecture





Introduction Motivation Architecture Solution Space Architecture Cloud Layer Fog Layer Edge Layer FL Workflow Evaluation Conclusion References

The *detection listener* is the P in our MAPE-K architecture. It reacts to the analysis done by the cloud layer by looking up event handlers in the *detection repository*. If we specify an event handler for the given scenario, the *detection listener* makes an HTTP call to the event handler URL.

The *deployment requester* deploys new containers and interacts with edge nodes for agreement and scoring.

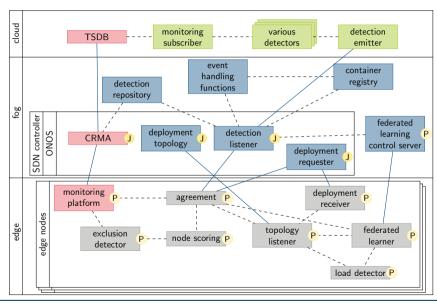
It needs to know the hierarchy for the application deployment with its container configurations.

With this resource estimation a service can be deployed on an appropriate node.



Architecture Solution Space Architecture Cloud Layer Fog Layer Edge Layer FL Workflow Evaluation Conclusion References

#### Architecture





ntroduction Notivation Architecture Solution Space Architecture Cloud Layer Fog Layer Edge Layer FL Workflow Evaluation Conclusion References

#### Edge Layer

As our **target devices** are **edge devices**, we also want to add factors like disk usage and network usage to the set of metrics M and calculate their utilization. Combining the exploitation factor f, where f is in [0,1], with the resource utilization equations, we finally calculate the overall node utilization score by Equation 2.2.

$$M = \{cpu, mem, disk, net\}$$

$$S_x = \frac{T_x - S_{req_x} - f * P_{req_x}}{T_x} \qquad for \ x \in M$$

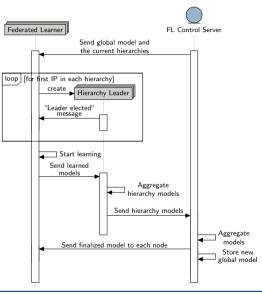
$$score_1 = \frac{\sum_{x \in M} S_x}{|M|}$$

$$(2.2)$$



Motivation Architecture Solution Space Architecture Cloud Layer Fog Layer Edge Layer FL Workflow Evaluation Conclusion References

# Federated Learning Workflow





Motivation Motivation Architecture Solution Space Architecture FL Workflow Evaluation Conclusion References



**1** Introduction & Motivation

#### 2 Architecture

#### 3 Evaluation

4 Conclusion & Future Work



ntroduction & Aotivation

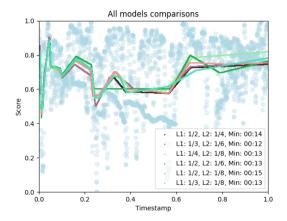
Architecture

Evaluation

FL Feature Importance

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#### Approximation of the Load Detection I





ntroduction & Aotivation

Architecture

Evaluation

FL Feature Importance

onclusion

References

Figure 11: Comparison of different approximations through the load detection function

# Approximation of the Load Detection II

#### Explanations

- Blue dots are the score values over time, the orange line is the approximated function.
- Layer 1 and 2 node count, given as a fraction, like 1/2 or 1/4
- Minimum load time is between 00:13 and 00:15 in this scenario.
- Difference between the configurations is mostly insignificant.
- The size of the layers does not make a significant difference in finding the minimum value



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Evaluation

FL Feature Importance

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**1** Introduction & Motivation

#### 2 Architecture

#### 3 Evaluation

4 Conclusion & Future Work



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Conclusion

# Reflection on Research Goals

#### Conclusion

- Evaluate the MAPE-K architecture for container orchestration
- Dynamic event handling
- Support for node scalability
- Intelligent container resource estimation

#### **Future Work**

- Container migration
- Constraints and goals (similar to DRAGON [9])
- Privacy and security
- Testing in real production environment



Introduction & Motivation Architecture Evaluation Conclusion

#### References

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Introduction Motivation Architecture Evaluation Conclusion References

# Questions ?



Introduction & Motivation Architecture Evaluation Conclusion

Manuel Dworzak manuel.dworzak@uni-bamberg.de Marcel Großmann marcel.grossmann@uni-bamberg.de Duy Thanh Le duy-thanh.le@uni-bamberg.de