Chair of Communication Networks
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Master's Thesis

Towards a Digital Twin for Cloud-native Mobile Networks

Cloud computing and microservice-based architectures have empowered businesses to develop new highly reliable applications, that can adapt to variable workloads. In the context of 5G telco applications, both the research community and the industry has been exploring methods of using cluster orchestrators, such as Kubernetes (K8s) in mobile network deployments. More specifically, Multi-access Edge Computing and Fog computing for 5G networks represent use-cases where the principles of cloud computing can be applied, but meeting the requirements (especially regarding latency) proves challenging.

With the increased usage of cloud deployments for Radio Access Networks, cluster configuration gained importance, as an optimized configuration translates into higher performance, increased agility and better usage of the resources. Empirical, experience-based human heuristics can improve the cluster configuration, however they require advanced knowledge about the deployment and the direct intervention of the cluster operator.

The research community is currently exploring the steps towards an automated, data-driven cluster configuration: the behavior of the cluster is learned with Machine Learning (ML), the cluster behavior is simulated with different configurations and an optimizer chooses the best configuration. However, an optimised configuration is only applicable to the real-life cluster, if the simulation of the cluster behavior is highly accurate.

The goal of this Master's Thesis is to determine the net value added by building a Digital Twin of a k8s cluster. Therefore, it uses ML-based models for the simulation of three network functions compared to traditional “Hand-crafted models”. First, it implements new network functions such as the pod scheduler and the load balancer in an existing simulation framework for k8s cluster.

Second, the thesis compares classical, hand-crafted models for the simulation with data-driven methods. Namely, after implementing Load Balancing and Pod Scheduling in the simulator in the classical way, it also integrates already trained ML model equivalents of these functions.
In the end, performance metrics and accuracy of both appraoches are compared.

Advisors

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