In federated learning (FL), a set of distributed devices (e.g., smartphones or sensor nodes) cooperatively learn towards a specific goal. Thereby, devices train a local neural network (NN) with their private data and synchronize their knowledge with a server, therefore, benefitting from each other through jointly training. However, in real-world applications, the jointly trained model can be negatively affected by two effects: Firstly, not all devices have the same resources available for training, hence, the amount of training differs between devices. Secondly, data might be distributed in a non-independent and identically distributed (non-iid) fashion. Moreover, these two effects could be coupled, meaning that a specific set of devices (e.g., less capable devices) have access to a specific set of data samples (e.g., exclusive access to samples of a specific class).

The goal of this thesis is to study the effects of resource-correlated non-iid data in asynchronous FL. A first goal is to set up an asynchronous FL environment and study how baseline async. FL behaves in various types of data distributions (iid/non-iid/resource correlated non-iid) and different resource levels of devices. Usually, in an FL setting, not all devices are actively participating in the training. As a second step, it should be investigated how distribution effects can be mitigated by using "client selection" heuristics, i.e., selecting specific devices with specific data to perform training on their data.

Skills required for the thesis
- Programming skills (Python)
- Background on machine learning
- Experience with ML frameworks such as PyTorch or tensorflow is beneficial but not required

Skills acquired within the thesis
- In depth knowledge of FL with non-i.i.d. data
- Technical writing skills
- Work in a research environment

Language
The collaboration with the colleagues can be in English or German.

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