The main idea of Federated Learning is the heterogeneity of data. While this sounds like data-level parallelism, I would like to focus on the structure of Cross-Silo Federated Learning within the scope of heterogeneity. I have not narrowed down to a particular algorithm for this structure. I intend to narrow the topic between now and the annotation portion of this project.

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