Physical signals are continuous and need to be sampled to enable their use in any digital system. To enable signal reconstruction, the sampling rate has for years been dictated by the Nyquist rate. This lower bound induces large amounts of data samples which, in this era of information technology, easily result in massive amounts of data which can hardly be transferred, stored, and/or processed anymore. The main question that we faced to solve these challenges is:

*Can we sample below the well-known Nyquist rate, but still extract the information we need to fulfill the system’s task?*

Medical applications are an example in which reduction of the sampling rate has major advantages. Sampling less diminishes the radiation exposure of a CT-scan, reduces the acquisition time for taking an MRI, and facilitates portable cheap ultrasound devices.

We developed a machine learning algorithm that is able to learn sub-Nyquist sampling patterns which extract the necessary information from the signal. We tested the algorithm on ultrasound acquisitions for different imaging tasks, and observed that learned task-adaptive sampling patterns did actually deviate from conventional uniform sampling schemes. While the system’s task failed for uniformly sub-Nyquist sampled data, our task-adaptive sampling schemes permitted fulfillment of this task.