Effect of Sample Difficulty on Time-to-First-Spike Networks

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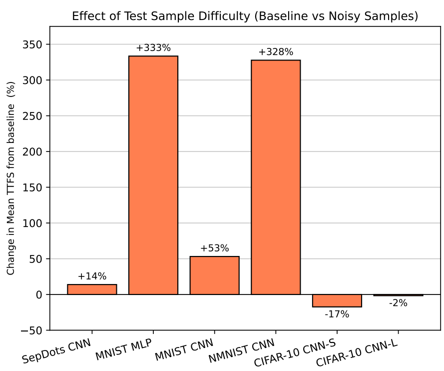
Neuroscientific experiments have shown that human reaction time decreases under simpler task conditions [1, 2, 3]. Conventional deep learning models fail to capture this virtue: they use exactly the same amount of resources for simple input data, as for samples with high class ambiguity or low signal-to-noise ratio. Spiking Neural Networks (SNNs) do have the characteristic that latency and efficiency might vary for each individual input. This is especially true for SNNs that use a Time-to-First-Spike (TTFS) paradigm (a.k.a. latency coding), where the desired output is dictated by its first output [4]. Such networks can be trained to process input as quick as possible. The question is whether their reaction times will then depend on sample difficulty.

In this study, we show that TTFS-SNNs trained on visual classification tasks are indeed in line with the two main findings captured in the neuroscientific Drift Diffusion Model: response time increases with sample difficulty and misclassified samples use relatively high response times [1].

In addition, we found that training on more difficult samples, though resulting in a higher accuracy, also leads to an increase in response time for all samples, including simple ones. There is thus a clear tradeoff between accuracy and reaction speed. This phenomenon can be explained by the regularizing effect of more difficult samples, which results in an overall decrease of the network weights, causing a slower increase in neuron potentials.

Experiments include both a controlled artificial decision task, SepDots, as well as well known computer vision benchmarks: MNIST, N-MNIST and CIFAR-10. Task difficulty was simulated by adding different kinds of noise to the input. SNNTorch [5] was used to train discrete time LIF variants of both MLP and CNN architectures.



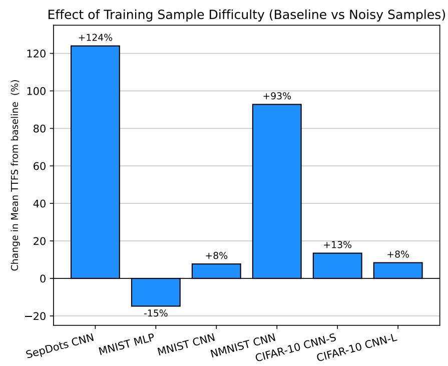


Figure 1: The difference of Time-to-First-Spike (TTFS) in % for difficult samples as compared to the baseline. The left figure shows TTFS mostly increases when noise is added to the test input. The right figure shows that for SNNs trained with noisy samples, the TTFS also increases.

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