Exploration of Interval Neural Networks for Handling Uncertainty

Abstract Interval arithmetic provides a tool for propagating uncertainty through computations. However, its application to uncertainty quantification in neural networks remains under-explored, in part due to concerns that forward-propagated intervals may become uninformative. This work explores these concerns through systematic empirical investigation, analyzing whether choices in activation functions, loss formulations, and training objectives allow interval neural networks to achieve high classification accuracy while providing calibrated, meaningful uncertainty estimates. We trained a feedforward neural network with point-valued weights on interval-valued inputs, formed by perturbing each input pixel by a known ε, and propagated these intervals through the forward pass using interval arithmetic. Several interval-aware loss formulations were explored, each computing the loss at both interval bounds and back-propagating through the midpoint of the resulting interval-valued loss, with most configurations incorporating a width regularization term to encourage informative intervals. We defined three notions of calibration: midpoint, width-accuracy, and coverage, and used them to evaluate the resulting output intervals on an MNIST binary classification task. Our experiments examined which configurations produced intervals that are both informative and calibrated, and which did not, with the goal of laying the groundwork for applying calibrated interval neural networks in higher-stakes settings.

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