High-speed Training Using Binary Neural Networks

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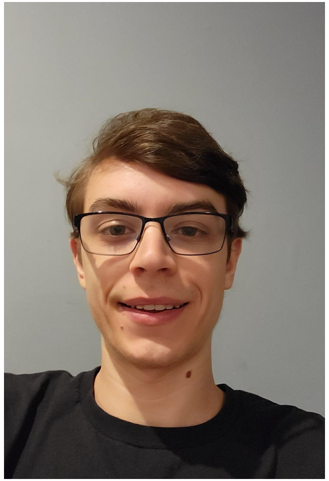
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Goals

- Training machine learning systems is currently very slow
  - Floating point chips take ~1 million transistors
- Recent work has shown promise by using simpler representations of numbers than the commonly used floating point ones.
  - Integer chips take ~300 thousand transistors
  - **Uses less power and have simpler arithmetic than floating point**
- Our goal: create and measure neural networks which only use binary or fixed-point numbers for both training and inference

Floating Point vs Fixed Point

Floating Point Numbers

- Current standard for ML and other computer applications
- **Think scientific notation e.g. $4.5*10^6$**
- Extremely precise with ability to store large range of numbers
- Contains sign, exponent and mantissa which needs to be normalized
- Uses ~1,000,000 transistors

Fixed Point Numbers

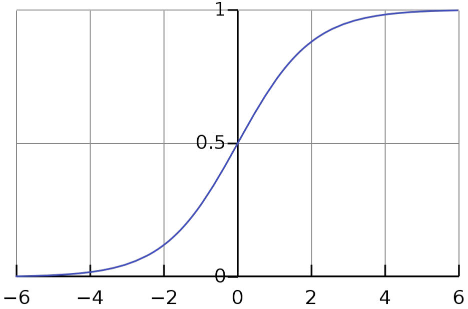
- **Regular decimal number**, contains an integer part (left of decimal point) and a fraction part (right of decimal point)
- Only uses ~300,000 transistors - much more efficient
- Limited range of numbers
  - A consideration we must make and test

Activation Functions - Sigmoid vs ReLU

Activation function: Helps network learn patterns; decides what to fire to next neuron

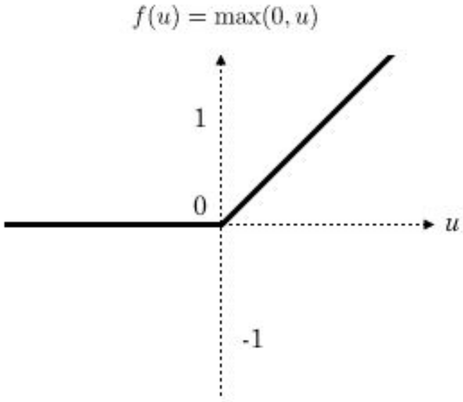
Sigmoid

- $$f(x) = \frac{1}{1 + e^{-x}}$$
- More complex but less efficient
- Outputs are constrained from 0 to 1



ReLU

- y = max(0, x)
- Less complex, more efficient
- Outputs approach infinity, leading to poor accuracy
- Requires another layer, like Softmax, to function accurately



Datasets - MNIST Digits and Fashion

MNIST Digits

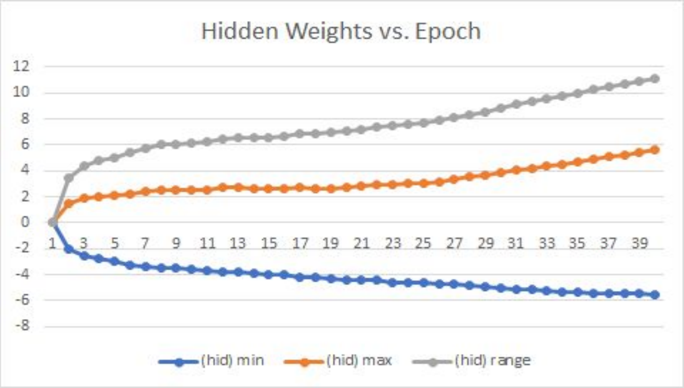
- Handwritten digits 0-9
- 28x28 grayscale image
- Easy to incorporate & train
- Highly Implemented with near perfect accuracy

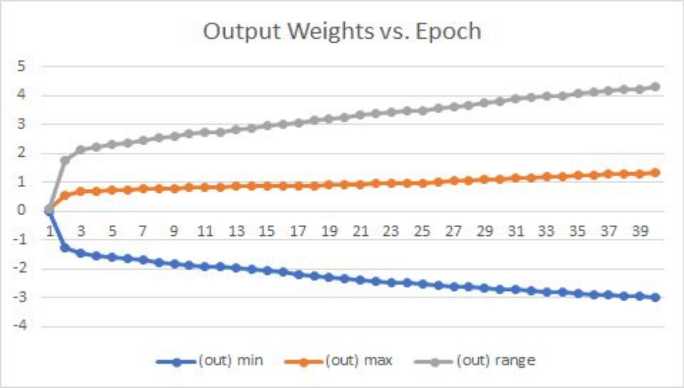
MNIST Fashion

- Articles of clothing Ex. Sneakers, shirts, dresses, etc.
- 28x28 grayscale image
- Easy to incorporate & difficult to train
- More applicable for CV tasks

Method - Weeks 1-5

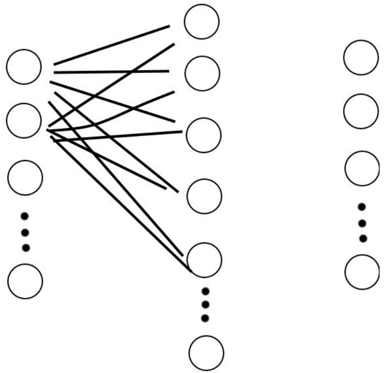
- Adapt the GoNN github repository for project (linear algebra library)
- Plot maxima and minima of the floating point weights to get dynamic range
- Check for accuracy plateau -> Lower bound for working range
- Implement fixed point matrix library (64 bit representation, sign bit, 15 bits preceding point, 48 bits following)





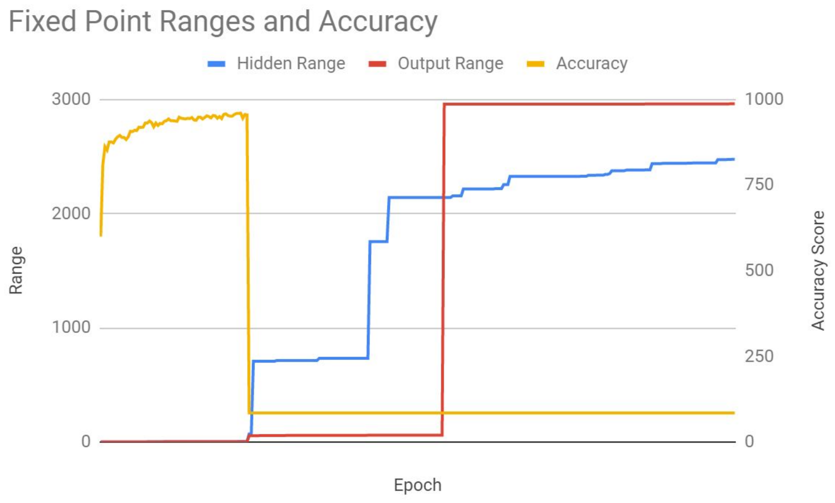
Method - Weeks 6-9

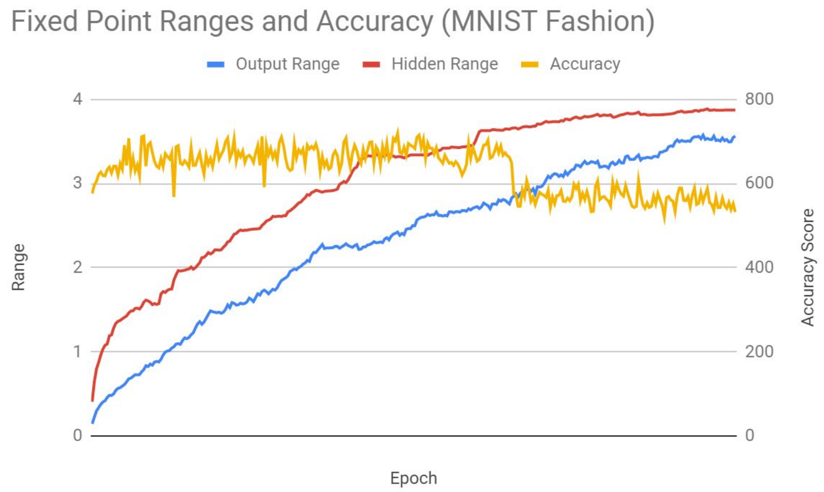
- Adapt activation function for fixed point representation (sigmoid)
- Analyze effects of number truncation (reduction of precision) on accuracy
- Begin Implementation of ReLU activation
- Apply fixed point schema to MNIST Digits and Fashion databases
- Collect and analyze accuracy and range data for fixed point models vs floating point



Issues

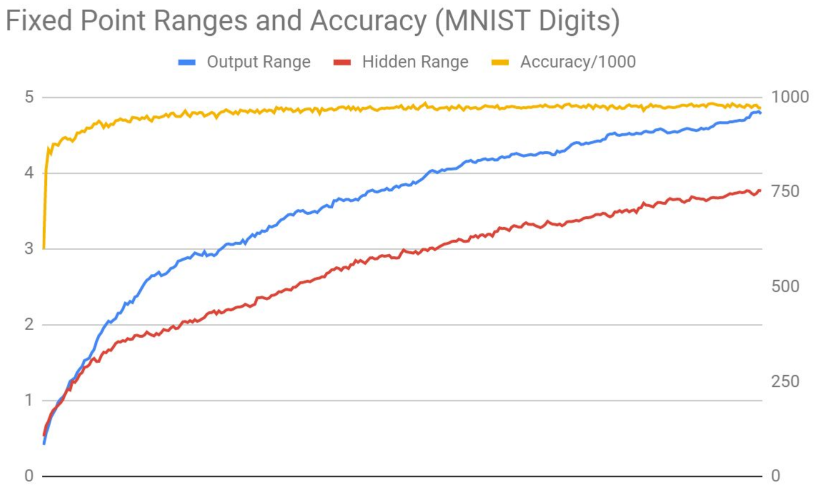
- Range does not converge, must find workable range for fixed point representation
- ReLU requires addition of SoftMax layer to function
- Sigmoid function within range overflows 64 bit fixed point representation, must be altered to function

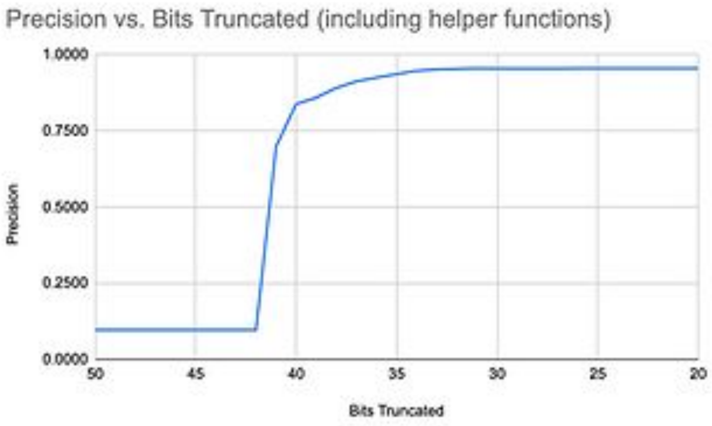


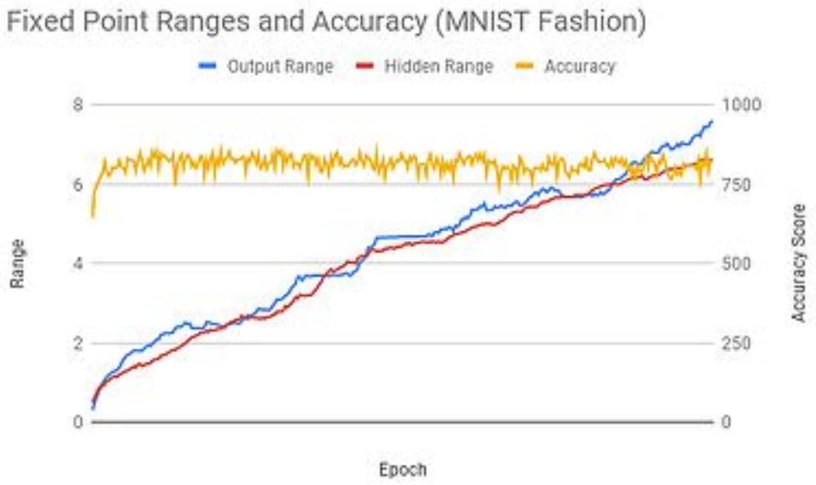


Results

- Accuracy drop of a maximum 3% compared to the floating-point network
- Dynamic range of 10 is very small, and much precision is not really necessary for accuracy. This is promising

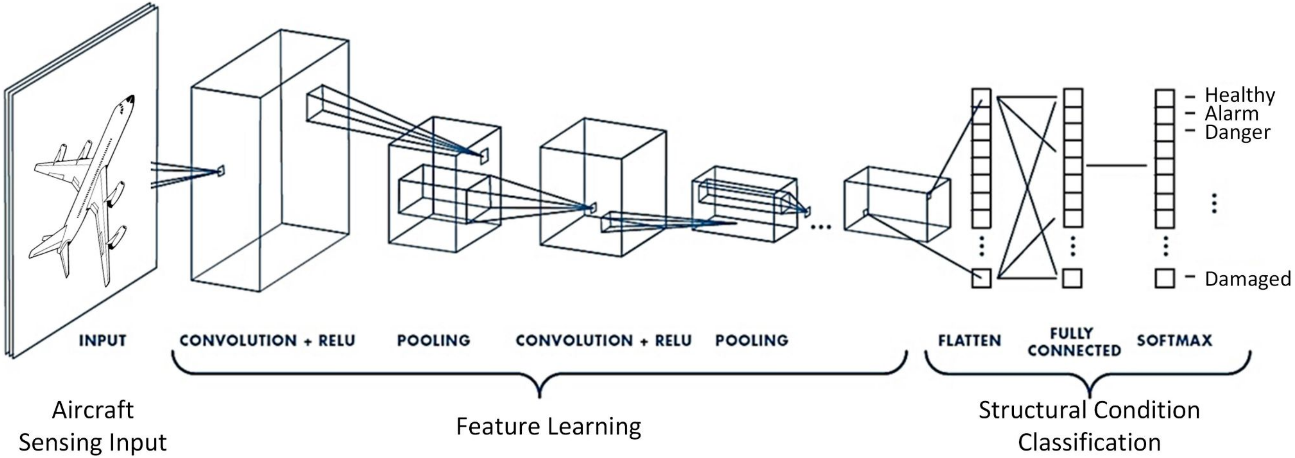






Further Research

- Apply fixed point schema to further databases
- Adapt code to wider variety of neural networks (modular layer sizes and numbers, new layer types like convolutional layers)
- Further testing of our ReLU implementation for efficacy vs Sigmoid



danielmaevsky.wixsite.com/winlab-binary-nn

Thank You!
Any Questions?