Deep Learning in Medical Imaging

--deep learning is complex and continuously evolving

--pre-processing: extraction of meaningful features

--using algorithms, we can directly extract features

Neural Networks

--using bias and weights, linear equations can be set up to model a decision

--take the form

--*h* is a non-linear activation function; “classifier” if function is monotonic, bounded, conts.

--sign(x) is most common as is tanh(x)

--single layer can be described as a single function; the network is a linear comb. Of these

--ALL functions can be approximated using a single layer only

--weights are setup to minimize (y-yhat)2, this will create a somewhat ideal decision network

--using back propagation and gradient functions, we can find the pathway that best minimizes the functions we need

--using a long chain rule, the input layer gradient can be determined for any number of layers, each with an additional chain rule term added

Deep Learning

--with just a gradient, we cannot perform deep learning truly

--Rectified Linear Unit (ReLU(x) = x iff x >=0 || Leaky ReLU(x) = ax iff x<0, =x iff x>=0)

--originally we couldn’t go deeper than three layers with any effect

--determine sub-gradient for each kind of problem, to minimize function

--convolution and pooling layers enable us to model locality and abstraction

--by comparing network to the desired output on each forward pass, loss function lets us know what needs to be modified and tells us how well we are doing

--convolution🡪pooling (making matrix smaller) 🡪 convolution 🡪 connecting

Common Mistakes

--cannot put bias in the data, leads to optimistic results

--must use validation set to determine over-fitting

--once any minimum is reached, the training will stop, so multiple training runs are usually necessary to allow for the right minimum to be found

--regularization must also be used (dropout, weight-sharing, multi-task learning)

Architectures in Deep Learning

--Autoencoders: use contracting and expanding branch to find representations of input of lower dimensionality

--Generative Adversarial Networks: employs two networks to learn a representative distribution from the training data; a generator network creates new images, and discriminator network tries to differentiate real images from generated images

--Google’s inception network: uses an inception block that essentially allows to compute convolutions and pooling operations in parallel

--Ronneberger’s U-Net: breakthrough toward automatic image segmentation, consists of contracting and an expanding branch, and enables multi-resolution analysis

--ResNets: designed to enable training of very deep networks; residual block introduced taking form of

--Variational Networks: Variational Unit that can describe a single update step of

--Recurrent Neural Networks: processing of long term dependencies

Advanced Deep Learning Concepts

Data Augmentation: common sources of variation are explicitly added to data samples;

Precision learning: strategy to include known operators into the learning process; counterintuitive idea for most recognition tasks

Adversarial Examples: input to neural network as a possible weak spot that could be exploited by an attacker; using different objective functions allows for different types of attacks

Deep Reinforcement Learning: deep networks are used as flexible function approximators representing learning theory

Image Segmentation

Identifying an organ via machine learning networks

Image Registration

Finding specific points on an image that differ from others; we need to understand how to find good feature descriptors