Introduction to Neural Networks

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Outline

1. Introduction
   - Logistic Regression
   - Maximum Likelihood Estimation
   - Motivations for Neural Networks
2. Structure and Design
3. Estimation and Application
4. Other Neural Architectures
   - Recurrent Neural Networks
   - Convolutional Neural Network
   - Deep Learning

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- This is super useful for neural nets, as we'll discuss later.

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- Often work in terms of log likelihood

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- Less useful for inference (and causal inference), but this is changing

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- More flexible estimation techniques allow computers to learn functional forms
- Neural networks are "universal approximators" and can learn arbitrarily complex functional forms

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- *Examples on the board...*

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- More training data translates into a more robust model

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- General goal: Minimize how wrong you are

Estimation

- Estimation is done with an algorithm called *backpropagation*
- Similar to MLE, except now we search over parameters to *minimize* the loss function
- Updates to the individual parameters in the model are typically done via *gradient descent*
- Similar to Newton-Raphson, but doesn't require inverting a Hessian and requires more iterations to converge - in big data applications, often faster (smaller but quicker steps)

Application

Clone or download the files from the github repo:

https://github.com/klintkanopka/nn_workshop

Feed-Forward Neural Networks

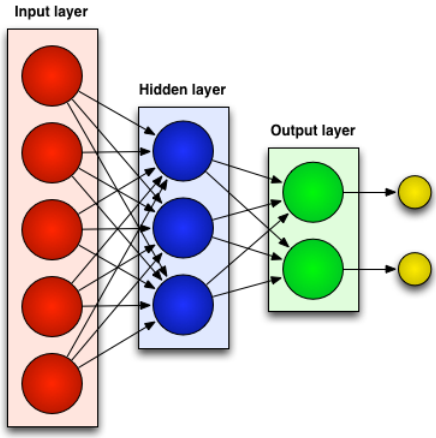

Figure 1: Feed-Forward Neural Network. Image Credit: Joseph Wilk

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    - Long Short Term Memory (LSTM)

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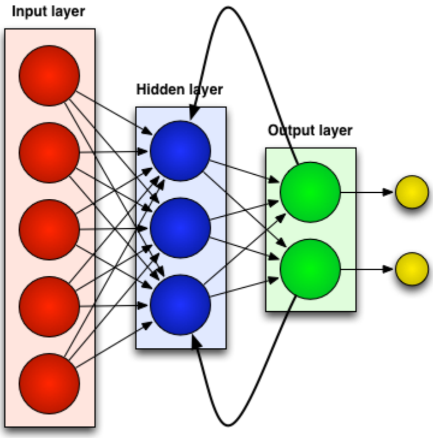

Figure 2: Recurrent Neural Network. Image Credit: Joseph Wilk

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- These windows are called filters and can learn to detect features in the input

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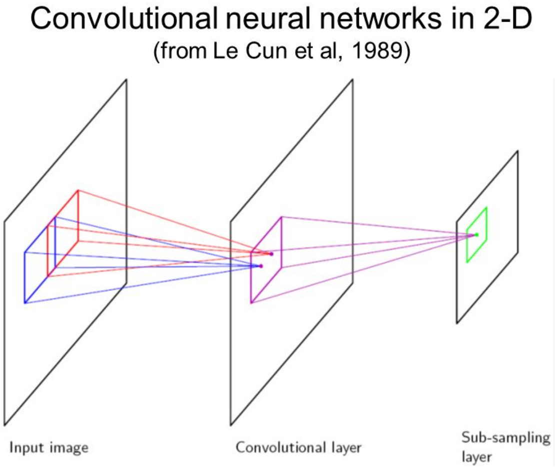

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- Signal processing

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- Leverages huge amounts of data
- Trained/run on cloud servers with GPUs/TPUs
- Good word to stick into things you want to get published or funded

I'm Done

Thank you for your attention.

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To download today's materials:
https://github.com/klintkanopka/nn_workshop